PRISONS AND POLLUTANT PLUMES:

A SPATIAL ANALYSIS OF LULU COEXISTENCE

by

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Prison facilities and other locally unwanted land uses (LULUs) lead to a number of health, environmental, and socio-economic impacts on the local community. Prison facilities and other LULUs tend to be sited in locations where less wealth and social capital are available to contest their installation. This causes an increased burden on the local population. The purpose of this study is to address the relationship between prisons, other LULUs, and the health impact on the surrounding community using interdisciplinary approaches including regression analysis, plume analysis, and geographic information science. Using a combination of the U.S. Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI), a prison facilities database, and available census data, plume modeling and risk assessment were performed for North Carolina, Pennsylvania, and Texas. The chemicals evaluated are benzene, toluene, ethylbenzene, and xylene (BTEX), known respiratory irritants. The Areal Locations of Hazardous Atmospheres (ALOHA) plume dispersion model was used in this analysis. Risk assessment was performed using an R coded regression analysis evaluating socio-demographic variables, health variables, and prison and TRI facilities to output an air quality value based on the EPA's Air Quality Index (AQI). Using the air quality index that accounts for both physical

and socioeconomic characteristics allowed the results to be compared across states and minimized the risk of bias from urban-rural divides.

Location analysis was completed using a combination of multinomial regression and probability analysis to assess the relationship between the location of prisons and the location of other LULUs. The results of this analysis were inconclusive however it provided insight into the relationship between income and placement of both prisons and TRI facilities. A Poisson distribution was performed to evaluate the likelihood of TRI facilities being placed in counties with and without prisons as well. This analysis indicated that counties with prisons have a higher probability of receiving TRI facilities.

Counties in Texas, North Carolina, and Pennsylvania were selected using a linear regression analysis to assess the relationship between socioeconomic factors and the annual AQI for each county. Income, the percent of housing that is renter occupied, the percent of the population employed, and the percent of asthma related Medicare expenses are the socioeconomic factors most related to air quality. In Texas, the highest modeled AQI was present in the county with a prison facility while in Pennsylvania and North Carolina, the non-prison county yielded the highest modeled AQI. The difference between these modeled AQIs was small for both Pennsylvania and North Carolina; however, in Texas the difference between values was approximately 50 AQI points.

Plume analysis was performed using the combined stack and fugitive air emissions for TRI facilities as the emissions source. The plume dispersion models indicated that the BTEX facilities considered are unlikely to pose a serious health risk to the populations in the surrounding area with few exceptions. Plumes were only able to be generated for facilities with the greatest emissions due to limitations in the model’s short-range accuracy. This indicates that while the toxins being considered are respiratory irritants, they are unlikely to strongly influence the health of the local populations or prison inmates through direct emissions. The largest dispersion radius calculated was approximately 61 yards indicating that the probability of adverse exposure to toxins from target facilities is minimal.

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Master of Science in Geography

By

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DEDICATION

This thesis is dedicated to Murray.

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CHAPTER 1: INTRODUCTION

Locally unwanted land uses (LULUs) can be described as any facility that is unsightly or detracts from the perceived value of an area including but not limited to "airports, water treatment facilities, electrical plants, wastewater facilities, and correctional facilities" (Torrens, 2008, p.16). The location of prisons and other LULUs remains a topic of debate in the United States. Placement of any LULU is associated with a perceived decrease in local property values and a perceived increase in crime rates due to the undesirable nature or appearance of the structures. These changes in perception are greatest in the immediate area of the facilities and decrease with distance from the site (Myers and Martin, 2004), which has strengthened the role of Not In My Backyard (NIMBY) organizations in affluent communities while potentially marginalizing low income communities (Myers and Martin, 2004; Stewart et al., 2014). In addition to the perceived community changes associated with LULU placement, many industrial and commercial facilities emit hazardous toxins into the air and impose these toxins on the surrounding community. These toxins, expelled at the surface level, interact with the human and biological environment without the knowledge or consent of the population. In many cases these chemicals, or their derivatives, are carcinogenic, respiratory irritants, or otherwise harmful to the physical health of the exposed population While industrial LULUs are problematic for all downwind populations, the inmate population in prisons is unable to make decisions about their housing locations, unable to enter and leave the facility at will, and cannot communicate their opinions and experiences to the authorities in charge of LULU siting and legislation.

State prison facilities were selected as target sites for this study. The target facilities do not offer a work release or similar program that permits inmates to spend time outside of the facility. Indoor air quality in prison facilities is well documented and studied (March et al., 2000;

Ofungwu, 2005; Urrego et al., 2015; Reis et al., 2016), however the literature for outdoor air quality in prison facilities is sparse. Poor ventilation, cigarette smoking, and overcrowding contribute to conditions such as tuberculosis (TB), asthma, and chronic obstructive pulmonary disease (COPD) (March et al., 2000; Ofungwu, 2004; Binswanger et al., 2009; Vinkels Melchers et al., 2013; Reis et al., 2015; Urrego et al., 2015). While these factors are controlled and regulated, the impact of external airborne contaminants on inmate and staff health is not well established. Another risk factor that impacts inmates, more than staff or residents of the surrounding community, is the dependence on facility health services. Corrections health care does not provide inmates with the option to seek alternative care or a second opinion in the same way that a private citizen can.

Benzene, toluene, ethylbenzene, and xylene (BTEX) are the target chemicals for this study. BTEX chemicals are mild respiratory irritants and also precursors to ozone which is a more severe respiratory irritant. Data on the emissions of BTEX is readily available through the U.S. Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI). Health outcomes data regarding asthma and COPD is also freely available through the Medicare public record system while socioeconomic information is available through the U.S. Census. Prison facilities were selected as the target sites because they perform a dual role in this study due to their unique position as both a LULU and also a distinct residence with an immobile population.

Using the previously mentioned data sources, this study generated a predictive air quality index at the county level for all study sites. This model is representative of health risks related to social, demographic, and pollutant variables. Plume dispersion modeling was also used to predict exposure to BTEX from EPA TRI facilities. The combination of these models assessed whether the siting of a prison places the inmates and surrounding community at higher risk of exposure to

BTEX, ozone, and presumably other toxins. Inmates are also considered a vulnerable population because they lack control of their environment and their daily lives. For this reason, it is important to study the implications of external activities on the health and wellbeing of the prison's residents.

This study examines three broad study areas to reflect the diverse climatic and environmental regions within the United States. The study areas selected for analysis are within the 48 contiguous states due to data availability restrictions. At the state level, the study areas are Pennsylvania, North Carolina, and Texas (Figure 1.1), and, as detailed later, specific counties in each state were identified for in-depth analysis.

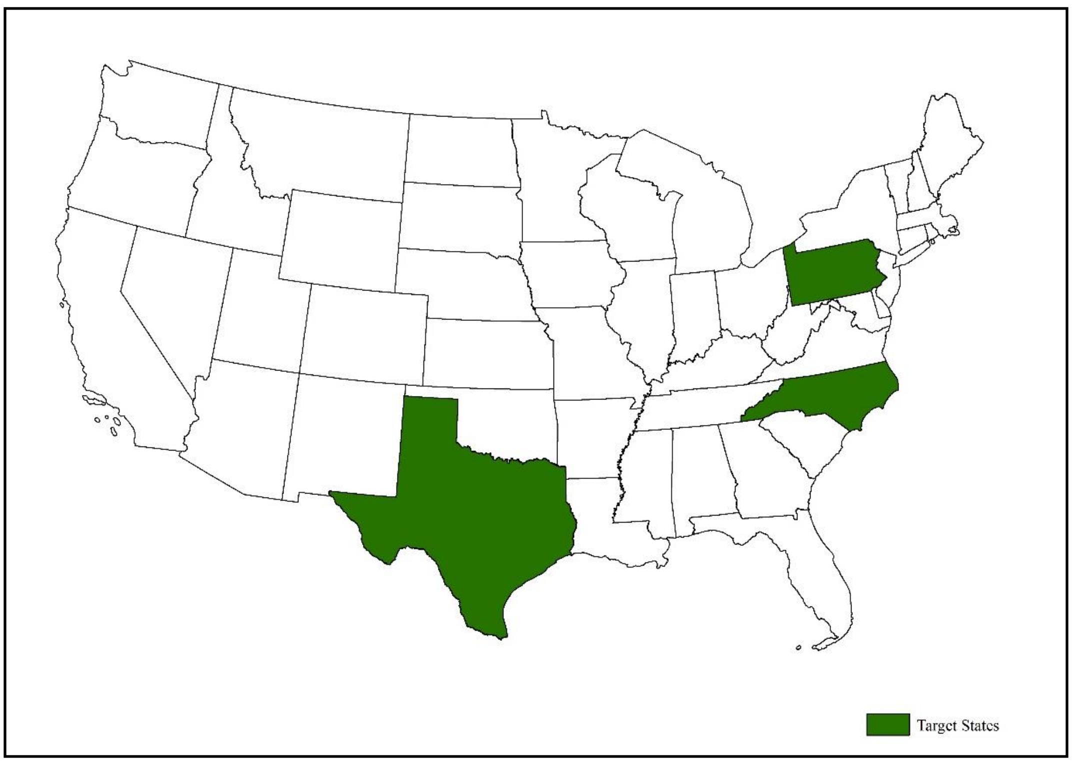

Figure 1.1: Broad study sites considered at the state scale.

Pennsylvania was selected due to the historic coal and oil extraction economy within the state as well as its role in shaping the state prison system within the United States. The United States has historically followed either the Auburn (New York) or Pennsylvania prison designing systems when constructing new prison facilities. The Pennsylvania System, commonly referred to as "separate confinement," required each inmate to remain in his/her individual cell for the duration of the sentence, communicating only with visitors and prison staff members. Inmates in this system also performed trade-type labor, such as carpentry, from their cells (Rubin, 2017b). In contrast, the Auburn (New York) System, commonly referred to as the "congregate system," required inmates to perform industrial-type labor in a collective setting during the day and remain in their separate cells outside of working hours (Rubin, 2017a). Historically, these systems were dominant in prison architecture in the United States and continue to influence the design of new correctional facilities. However, contemporary prison architecture and security use a combination of both systems to achieve the optimal balance between safety and functionality in prison facilities. North Carolina was selected because of the location of East Carolina University. This study aims to benefit the residents of North Carolina in accordance with the goals of the University of North Carolina system and East Carolina University. Selection of North Carolina also facilitates field work in any future aspects of this study. Texas was selected because of the large number of state prison facilities as well as the prevalence of fracking and other forms of natural gas and oil extraction throughout the state.

Given the issues presented earlier, this study aims to address the following research questions within the three states chosen:

1. What is the spatial relationship between the placement of prisons, the placement of other LULUs, and the risk of exposure to airborne toxins? What socioeconomic factors influence this relationship?
2. What are the differences between exposure in a prison county compared to a non-prison county and are those differences statistically significant?

3. To what extent does respiratory health correlate with the predicted toxic exposure?

CHAPTER 2: LITERATURE REVIEW

2.1: Prison and LULU Siting

The placement of state prison facilities in the United States is a topic of great contention. Construction requirements for state managed facilities are subject to the same state and federally mandated bid process as any other municipal building; however, the location of the facility is not prescribed in the legislation. In many states, rural municipalities request the placement of a prison facility in their jurisdictions with the hope that the construction and staffing needs of the facility will provide an economic stimulus to the community in the form of jobs and local purchases (Hoyman and Weinberg, 2006; Russell, 2017). The construction of a prison requires a significant amount of local labor and material which will benefit the community and, as a state institution, the construction costs will be financed through the state government rather than becoming a burden on the local population. These nuances of state construction projects make the bid for a prison of strategic advantage to a poor and/or rural community. The staffing of the prison also creates numerous jobs which could be allocated to residents, boosting the labor force and local spending (Hoyman and Weinberg, 2006). Both aspects of constructing a state prison facility in a rural municipality support the immediate economic benefits a facility could provide to the community. However, these factors do not account for potential social and demographic impacts of the placement. Placement of a prison, or another LULU, alters the perception of the surrounding area. The placement of a LULU of any type within or near an area creates a perceived increase in crime rates and perceived decreases in property values, but these are not necessarily validated by government reporting and statistics (Myers and Martin, 2004). These perceived changes can motivate the wealthier segment of the population to arrange to leave the community, leaving those attached to the community or without means to leave in a declining area. Eason (2010) reports results consistent with Hoyman and Weinberg (2006) indicating that the placement of prisons is largely a rural phenomenon impacting areas with higher than average minority populations. On the other hand, prison siting can serve as an effective economic stimulus for an area by creating tens or hundreds of jobs (depending upon facility size and population) which is consistent with Hoyman and Weinberg (2006) and provides advantages to an impoverished population (Eason, 2010).

The placement of prisons and other LULUs is governed by local zoning laws which account for the property type, potential risk to residents, and the benefits of the facility. In 1986, an academic study suggested a sealed bid auction mechanism as a method for determining the location of toxin-emitting LULUs. The mechanism included parameters to control for construction and property cost, willingness of the municipality to support the project, and the financial viability of the facility in each location (Kunreuther and Kleindorfer, 1986). The suggested process gives a small advantage to areas with lower property values and less expensive labor costs, but also accounts for the ability of the municipality to approve and contribute to the construction (Kunreuther and Kleindorfer, 1986). Although never implemented in the United States, the implication of this mechanism is the increased likelihood of a noxious facility being placed in the same area as existing LULUs due to the decreased property values in the area.

The location of LULUs has been a topic of concern relating to environmental justice for decades in both the government and the private sector. Executive Order 12898, issued in 1994, mandated that the EPA and other federal agencies reexamine their practices regarding the regulation and placement of facilities and measures impacting human health. The order particularly focused on the uneven burden placed on minority and impoverished communities by contemporary practices (The President, 1994). After the executive order was implemented, however, the spatial distribution of facilities was only corrected across large areas. While at the state and federal level LULUs are placed in a random pattern, examination of the county or local level indicates that the facilities are still clustered (Moore, 2017). Moore's (2017) study indicates that while the large-scale changes were successful following E.O. 12898, at a finer scale (20 km or less), no change occurred after the implementation of E.O. 12898. Studies by Stewart et al. (2014) and Al-Kohlani and Campbell (2016) are consistent with this concept. Stewart et al. (2014) examined the unequal environmental burdens placed on affluent and disadvantaged communities in Santa Clara, CA. Results indicate that the highest environmental burdens (including highway placement, industrial LULU construction, and similar activities) were concentrated in low-income and minority communities rather than dispersed throughout the area. The study by Al-Kohlani and Campbell (2016) indicates similar results and concludes that the concentration of LULUs in a single location minimizes the overall burden of property values and also mitigates any political backlash that results from infringing on affluent areas.

The locations of prison facilities and other LULUs are designed to minimize the wider environmental burden while also preserving the integrity of affluent areas (Hoyman and Weinberg, 2006; Stewart et al., 2014; Al-Kohlani and Campbell, 2016). Placement of both types of facilities in concentrated locations meets both of these needs while also providing economic stimulus to the local population (Hoyman and Weinberg, 2006; Eason, 2010). While these facilities all create an economic benefit for the local population, the inmate population remains disenfranchised and receives only the environmental burden of concentrated LULU placement. Both inmates and community residents are subjected to the toxins and health impacts associated with exposure, but the inmates are unable to change location (even daily), voice concerns, or adequately report their health issues (Russell, 2017). Russell (2017) examined the placement of the Pennsylvania State Correctional Institution (SCI) at Fayette on land that concurrently serves as an active coal mine and is located adjacent to active coal ash dumping grounds for the mining facility. She found that prison construction was approved where other forms of residential construction were not due to health concerns (Russell, 2017). These results indicate that the consideration for inmate health is held to a lower standard than private citizens despite the inability of inmates to adjust to their environment.

2.2: Indoor and Outdoor Air Quality

Indoor and outdoor air quality in prison facilities poses a significant risk to the incarcerated population and to the facility staff. Studies regarding indoor air quality in prisons name several key factors impacting the health of inmates. Close quarters and overcrowding contribute significantly to the increased transmission rate for diseases in prison facilities relative to outside populations (Urrego et al., 2015) while poor ventilation increases the residence time of airborne chemicals and diseases beyond what is expected under normal conditions (Urrego et al., 2015; Reis et al., 2016).

Ventilation and overcrowding serve as critical influences on disease transmission within prison facilities and to outside populations. A 2000 study by March et al. determined that inmates in a Barcelona prison reported TB transmissions rates 50 times greater than the non-incarcerated population. The study determined that this rate creates a major public health concern for both the incarcerated and surrounding populations and that the transmission is directly related to the overcrowded conditions rather than prior residences of the inmates (March et al., 2000). Transmission of TB and other infections also occurs over a short time period with the highest incidences of infection occurring in local jails rather than state and federal prison facilities

(Lambert et al, 2016). TB transmission to staff and visitors also poses a significant risk to the outside population because, unlike inmates, these groups are not confined to the facility (Lambert et al., 2016).

The poor ventilation in prison facilities is well studied and documented from both the perspective of chemical and disease transmission. Carbon dioxide (CO_2) gas concentration is a common and established indicator of ventilation within any facility with higher concentrations of CO_2 indicating poor gas exchange throughout the facility (Wood et al., 2014). A 2015 study in Brazil examined the ventilation and air exchange within three prison facilities (141 cells total with greater than single occupancy) to assess the direct impact of ventilation on TB transmission (Urrego et al., 2015). They discovered that, of the 141 cells, only three met the World Health Organization (WHO) standard for acceptable minimum air exchange and that increasing the air exchange would decrease transmission rates of TB by 38.2% (Urrego et al., 2015).

A study in a New Jersey correctional facility used a similar technique to quantify and examine several airborne toxins and disease transmission after numerous complaints were made regarding the air quality and inmate health within the facility (Ofungwu, 2005). The study examined BTEX, tuberculosis, CO_2, and several other metal and organic airborne toxins within the facility, and noted that most contaminants present were within both EPA and New Jersey Public Employees and Occupational Safety and Health Program (PEOSH) levels for the entire facility. However, benzene, trichloroethylene, and tetrachloroethylene were all detected throughout the facility and, in several locations, they exceeded the EPA recommended levels for residential safety (Ofungwu, 2005, p. 137). These results indicate that contamination is present in the prison facility, however, it is being addressed in the form of staff safety rather than addressing the health and safety concerns for inmates exposed to the toxins 24 hours every day.

The study also demonstrated that, while measured concentrations were within the 1989 EPA guidelines, the hazard index and worst-case risk assessments both exceeded regulatory standards (Ofungwu, 2005) indicating that while toxin concentrations were in compliance with regulations, the anticipated risk assessment can exceed the regulatory standards. Ofungwu (2005) noted that two possible sources of contamination were likely contributing to the pollutant levels. The first was the storage of chemicals inside the facility coupled with inmate habits (such as smoking) which release airborne toxins. The second probable source was subsurface contamination of the soil and water with volatile organic compounds (VOCs) resulting in emissions entering the facility from volatilization of soil and water borne chemicals (Ofungwu, 2005, 141), a cause that is consistent with the zoning practices questioned by Russell (2017).

Despite the extensive study of indoor air quality, the literature regarding outdoor air pertains only to general impacts and urban development rather than the prison system. The implications of particulate matter on respiratory health have been studied extensively and provide strong evidence that fine particulate matter negatively affects the respiratory system. A study considering the Los Angeles area determined through computer modeling that, while particulate matter does impact the respiratory system, it correlates more closely with increased risk of heart disease (Jerrett et al., 2005). The study assessed both the viability of several interpolation techniques and the impact of ozone and fine particulate matter on the mortality rate in Los Angeles. Ostro et al. (2009) reported similar findings when analyzing a cohort of teachers in California. The study aimed to examine the effect of long-term exposure to fine particulate matter, without differentiation of natural and anthropogenic origins, and the reported cause of the 2,600 reported deaths within the cohort (Ostro et al., 2009). The study found a positive relationship between increased levels of fine particulate matter and increased risk of death associated with cardiopulmonary conditions (Ostro et al., 2009). A study by Cao et al. (2011) found similar results in China when examining the impact of particulate matter, nitrogen dioxides, and sulfur dioxides on the health and cardiopulmonary mortality rates in cities. The study focused on 17 urban provinces in China and used the 1991 China National Hypertension Follow-up Survey for initial data and follow-up exams in 1999 and 2000 to assess change in health. The study was limited to urban regions due to the presence of ambient monitoring equipment (Li et al., 2018). In all three case studies, the long-term exposure to air pollutants produced negative health impacts for the participants. While these influences are key to understanding health implications, inmates are not able to limit their own exposure to the same contaminants.

2.3: Pollutant Health Impacts

While there is little reporting of the relationship between prison placement and the siting of other LULUs nearby, the increased prevalence of asthma and COPD in inmates relative to a comparable non-institutionalized population indicates that there are influences acting on the health of the prison population, even though inmates frequently come from underprivileged backgrounds which introduce respiratory conditions prior to incarceration (Binswanger et al., 2009). VOCs potentially influence the asthma and COPD rate in two ways, directly as a respiratory irritant of minor concern and indirectly through the facilitation of surface-level ozone formation. Ozone is a known and significant respiratory irritant at surface level. For this reason, the emissions from TRI facilities in close proximity to prison facilities could cause an increase in respiratory disease.

Most studies in this area also emphasize the impact of traffic related emissions on air quality over the impact of point source emissions. A 2014 report by Guarnieri and Balmes indicates that traffic emissions have an impact on respiratory health, particularly for sensitive groups, however the combination of these pollutants with other airborne allergens increases the risk of health impacts. With Binswanger et al.'s (2009) description of the inmate population, many incarcerated persons would be considered part of the sensitive population. This indicates that inmates are both more exposed to the contaminants without the ability to mitigate this and also more susceptible to health impacts due to their environment.

2.4: Inmate Health and Health care

Asthma, COPD, and TB (with TB transmission being one of the best documented and most prevalent prison-related health conditions) are prevalent respiratory conditions in the prison environment due to overcrowding, poor ventilation, limited screening practices, and lifestyle prior to incarceration (Binswanger et al., 2009; Vinkels Melchers et al., 2013; Urrego et al., 2015; Reis et al., 2016). Beyond the inability of inmates to adjust their lifestyle or location to meet the demands of new environmental burdens, the prison health care system also limits their ability to mitigate or treat medical conditions.

Confinement in a correctional facility prevents an inmate from relocating away from hazardous living conditions, seeking secondary medical care (Bryant, 2013), or expressing concerns about their environment or potential land use changes which will impact their lives directly (Russell, 2017). The state correctional health care system is required to offer comparable care to health care services offered to private citizens, however internal restrictions required to maintain the safety of medical staff in a prison setting effectively prevent this standard from being met (Bryant, 2013). In the private and public sectors, effective medical treatment is the priority of health care services. In the prison setting, the priority is staff and inmate safety which permits medical staff a large degree of discretion in treatment options with particular emphasis on narcotics and other controlled substances (McGrath, 2002; Bryant, 2013). “Prisoners often have no recourse for inadequate or negligent medical treatment, as their health care providers and jailers are often protected by the doctrine of qualified immunity” (McGrath, 2002, p. 651), a sentiment which demonstrates that the health of inmates is not the primary concern of medical staff. McGrath (2002) also stated that, in the rare instance that charges were brought to court related to ineffective or negligent treatment, they were dismissed by summary judgement with no remediation efforts or changes to treatment resulting from the case. The prioritization of safety for staff is not unwarranted but has a strong potential to result in insufficient medical care for inmates (McGrath, 2002; Bryant, 2013).

Coupled with the disparity between prison health care and public health care, a larger percentage of prison inmates exhibit chronic respiratory diseases, including asthma and COPD, than a comparable population of private citizens (Binswanger et al., 2009). Binswanger et al. (2009) used the national census of inmates for 2002 and 2004 which was the best available data for the time. In contrast, a study by Harzke et al. (2010) used the Electronic Medical Record (EMR) system for Texas to examine the health of inmates in the Texas Department of Criminal Justice (TDCJ). Like Binswanger et al. (2006), Harzke et al. (2010) demonstrated that the incidence of chronic respiratory conditions was significantly higher within state correctional institutions than in a comparable population outside of the facility. Two key contributing factors to this health disparity are the living conditions within a state correctional facility and the prior medical history of many incarcerated people. Many prisoners come from disadvantaged or impoverished environments, leading to poor medical care and minimal preventative care prior to incarceration (Binswanger et al., 2009). Many inmates come from environments where proper nutrition and preventative medicine are unavailable, previously used tobacco products and other illicit drugs, and were subjected to a number of other environmental stressors that resulted in chronic conditions prior to incarceration (Binswanger et al., 2009). These conditions are frequently aggravated by the conditions in a prison setting and potentially by exposure to airborne toxins associated with the outdoor environment.

The Eighth Amendment provides prisoners protection from cruel and unusual punishment while in custody. In the case of inmate health care, a staff member must act with deliberate indifference (a level of disregard that exceeds negligence but is not necessarily malicious in intent) towards the inmate's wellbeing for this to be invoked (Helppie-Schmieder, 2016). Currently the outdoor air quality of a facility and the placement of noxious facilities nearby are not considered an undue burden on the incarcerated population. Helppie-Schmieder (2016) and Russell (2017) argue that the imposition of toxins by industrial emissions infringes upon the prisoners' protection from cruel and unusual punishment because they are unable to voice concerns about their environment or enact lifestyle changes (including preventative treatment) to protect themselves from the exposure.

Despite the limited research regarding outdoor air quality in prisons and its influence on inmate health, progress is being made with regard to cases of healthcare and exposure within the prison systems. Estelle v. Gamble (1976) established the standard of deliberate indifference with regard to medical claims of cruel and unusual punishment. Since this decision, cases ranging from toxin exposure to medical care in prisons have begun to reshape legislation regarding the concept of cruel and unusual punishment. Cases such as Helling v. McKinney (1993) established the role of secondhand tobacco smoke as a form of cruel and unusual punishment due to increased respiratory health and carcinogenic impacts on non-smoking inmates. The role of indoor air quality as a cruel and unusual punishment (Helling v. McKinney, 1993) establishes the precedent that environmental conditions can adversely impact inmate health to a severe extent. More recently Brown v. Plata (2011) establishes the systematic nature by which air quality is causing undue suffering to inmates in the California correction system. These cases begin the process of establishing air quality and exposure to environmental toxins as a cause for undue suffering to an extent that it meets the standard of deliberate indifference.

2.5: Plume Analysis Model

Modeling the dispersion of the target toxins can provide a better estimate of the risk distribution associated with chemical exposure and proximity to prisons than the traditional fixed width buffer method. Chakraborty et al. (2011) suggest that plume analysis of pollutant dispersion will provide the most accurate representation of chemical dispersion, with regard to previous use of fixed radius buffers and coincident analysis for a more defined zone of exposure. Plume analysis accounts for environmental and atmospheric conditions as well as the chemical properties when assessing the plume direction and shape, allowing the analysis to be more consistent with the conditions at the time of monitoring. There are several models that are useful in modeling the spatial characteristics of plumes. Maantay et al. (2009) discuss the use of a modified version of the American Meteorological Society/ Environmental Protection Agency Regulatory Model (AERMOD), a computer modeling program designed to generate plume surfaces for a chemical contaminant using multiple sources. Chakraborty et al. (2011) and Chakraborty and Armstrong (1997) present similar studies using the Areal Locations of Hazardous Atmospheres (ALOHA) model which incorporates a user-friendly interface for single source assessment. While these models are different in purpose, the application of either can generate chemical plume footprints at a sufficient level to assess exposure levels for surrounding populations.

Chakraborty et al. (2011) effectively used the ALOHA plume dispersion model to evaluate the potential impacts of accidental chemical emissions. The model includes an ArcGIS tool to convert the plume footprint output into a compatible vector file to complete GIS analysis on the model (Chakraborty and Armstrong, 1997; Chakraborty, 2001; Jakala, 2007; Chakraborty et al., 2011). Chakraborty and Armstrong (1997) also performed a plume and buffer analysis using the ALOHA model to determine impacts of TRI facilities on the surrounding communities. The study compared the results of fixed-radius circular buffers with plumes generated by the ALOHA model to determine the spatial impact of TRI facilities on the local population to assess more detailed assessment of exposure. Chakraborty (2001) also applied the ALOHA model to assess variations in exposure based on race and income. The study found that minority populations and impoverished populations were exposed to a disproportionate level of chemicals emitted from nearby TRI facilities (Chakraborty, 2001). The studies by Chakraborty and others indicate that the ALOHA model, though less intensive than AERMOD, can be accurately applied to multi-site plume analysis with viable results. Maantay (2002) also suggests that the incorporation of GIS-based plume analysis allows studies to adjust to the necessary spatial scale based on the available data.

2.6: Summary

The research questions presented earlier attempt to address both the social and physical implications of prison and LULU siting for both the inmates and the community at large. This review of the literature illustrates the importance of addressing the impact of LULUs on the local population, particularly immobilized populations such as prisoners, and the lack of information on outdoor exposure to potential toxins of these populations. While models exist to measure the extent of exposure, they have not been applied to document the combination of risk assessment and exposure levels. Based on the available research, it is likely that modeling both the social influences on exposure and the physical influences will provide a better understanding of the relationship between LULUs and the health of the surrounding population.

CHAPTER 3: METHODOLOGY

An interdisciplinary methodology was employed in this study to address: 1) the spatial relationship between prisons and other LULUs at the county level (location analysis), 2) the variations in exposure to airborne toxins between counties with prisons and without them (specific site selection), and 3) the correlation between exposure and respiratory health impacts (plume analysis). The interdisciplinary approach allows for both physical, environmental, and social influences on air quality to be considered collectively, producing a holistic approach. As shown in Figure 3.1, the location analysis addresses the coexistence of prisons and LULUs both collectively for all three states and for each state individually. The subsequent specific site selection and plume analysis models were performed at finer scales to increase specificity. The data and methods employed for each are described in detail in this chapter.

This study employs a combination of statistical and geographic information system (GIS) methodologies to assess air pollution risk and plume dispersion analysis. A combination of GIS and statistical methods was used to create a regression model for toxin exposure risk and to create a categorical model assessing the presence of a prison and/or TRI site in each county. Plume dispersion modeling was undertaken using the ALOHA dispersion model in combination with GIS techniques. Data management occurred in both R and GIS.

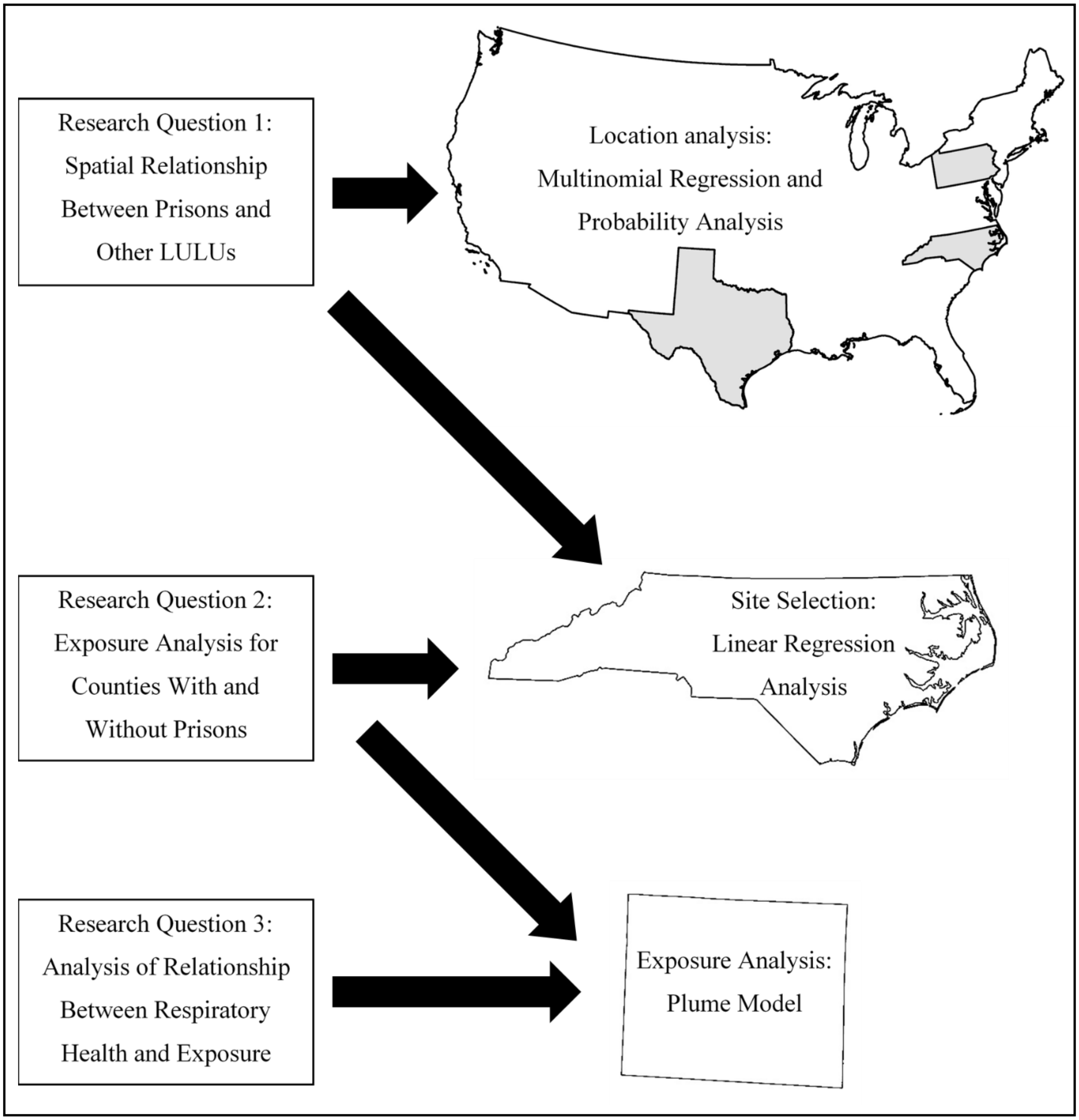

Figure 3.1: A workflow diagram of the methods performed in this study and the associated research question(s) each technique is addressing

3.1: Variable Selection.

Several data sources were used within this study to represent a broad array of physical, social, economic, and health conditions at the county level. All data was acquired for the year 2012 to align with the state prison dataset to ensure a consistent analysis, and data was directly downloaded, stored on a local computer hard drive, and retained on a portable back-up drive to mitigate the potential for corruption of files.

3.1.1: Socioeconomic Variables

The first research question addresses the relationship between prisons, other LULUs, and socioeconomic indicators at the county scale. To address this question, it is important to consider both the physical causes of airborne toxin exposure as well as the socioeconomic factors which make a population particularly susceptible or less able to cope with these exposures. The social and economic indicators examined in this study were obtained from the U.S. Census American Community Survey (2012 5-year estimates) which is the best available data for the year (U.S. Census Bureau, 2016). All variables used in this study were obtained at the county level for the United States. These variables make it possible to evaluate the characteristics of communities with and without prisons and LULUs as well as to analyze the factors that influence health outcomes. As such, these variables are used in the regression analyses to understand the complex social, economic, and physical characteristics impacting risk of toxin exposure.

Average income (income), percent of the population that is employed (employment), and percent of the population achieving less than a high school diploma (education) describe the available financial capital a community can employ for any purpose. Areas with greater affluence and disposable income have more potential opportunities to influence the landscape of their community. More affluent communities are better able to influence the placement of

LULUs within the area than lower-income areas and this collective siting minimizes the overall burden of facility placement (Al-Kohlani and Campbell, 2016). Demographic data including the percent of the population reporting as white only (white) and the percent of the population that is male (male) assist in describing the composition of the communities and assessing the impact of race and gender on air quality and the LULU landscape. The percent of housing that is renter occupied (renter) and percent of housing that is mobile homes (mobile homes) are used as proxy variables for population transience.

3.1.2: Locations of LULUs

Prison location data (prison) was provided by Dr. Kerbs and Dr. Jolley through manual geocoding of facilities into a GIS compatible format. Additionally, prison location data was also obtained through publicly available department of corrections (DOC) websites. This data provided the location of inmate population centers. The data was obtained for the year 2012 making the information compatible with other data sources examined in this study.

Land use data (LULU area) was obtained from the United States Geologic Survey (USGS) United States Conterminous Wall-to-Wall Anthropogenic Land Use Trends (NWALT) 1974 – 2012 dataset (Falcone, 2015). The 2012 dataset is continuous for the 48 contiguous states within the United States but excludes Alaska and Hawaii. NWALT data is provided in the form of a continuous raster dataset containing 60-meter squared raster cells with 19 discrete classifications. The continuous nature of the NWALT raster dataset permits a more general characterization of the anthropogenic landscape within each county. For the purpose of this study, LULUs were defined as cells classified as Commercial/Service (class 22), Industrial/Military (class 23), and Mining/Extraction (class 41). The percent land area classified as LULUs was then calculated using the total land area for each county and the net land area from classes 22, 23, and 41.

TRI facility locations (LULUs) were used as another source of LULU data as well as the direct source of emissions data in this study. The TRI sites are industrial and extraction facilities that report emissions estimated to the U.S. EPA on an annual basis. For this study, the TRI database was obtained from the EPA online repository for the year 2012 (U.S. Environmental Protection Agency, 2016h). The emissions data from these sites is a proxy for all BTEX point source emissions within the study areas. The TRI facilities data are used in both the regression and plume analysis as the direct source of toxins.

3.1.3: Emissions Variables

Emissions are quantified using the LULUs data obtained from the TRI data set. VOCs, and more specifically BTEX, were selected for this study because of their status as precursors to surficial ozone and their direct medical effects on the respiratory system. Ozone is an unstable and uncommon byproduct of manufacturing and industry, however, the interaction between BTEX and exhaust fumes with exposure to sunlight produces ozone at the surface level. BTEX chemicals are also commonly emitted during numerous industrial processes including hydraulic fracturing (fracking), petroleum extraction, and all aspects of petroleum refinement and production of daughter materials. VOCs were defined exclusively as BTEX for this study due to limitations in the reported emissions data. BTEX chemicals are potentially carcinogenic (Sigma-Aldrich, 2016; 2017a; 2017b; 2017c) at long term and high-volume exposure. Common symptoms of exposure include headaches, respiratory irritation, and aggravation of asthma symptoms (Adegate et al., 2014). Ozone levels are not modeled or examined in this study due to the limited availability of ozone emissions and monitored ozone concentration data.

The target emissions for this study were BTEX chemicals which serve as ozone precursors under surface level atmospheric conditions. Data used for this section was obtained from the EPA's TRI public database. The TRI database is a collection of reported emissions from industrial sources exceeding regulatory requirements. BTEX chemicals are not persistent bioaccumulative toxins (PBTs), non-metals, and non-dioxin or dioxin-like compounds. Being categorized as such, BTEX chemical emissions must be reported if either greater than 25,000 pounds of the chemical is used as an input for industrial processes or greater than 10,000 pounds of the chemical is produced as a byproduct of production methods. These values can be determined as either measured emissions or by mass balance calculation for the industrial process (U.S. Environmental Protection Agency, 2018). The requirement for self-reporting by industry places certain limitations on the data during analysis. Based on requirements, it must be assumed that annual concentrations are reported as calculated estimates rather than measured emissions.

This study is concerned with air quality and exposure to airborne toxins. For this reason, stack emissions and fugitive air emissions were selected as representative variables for BTEX emissions into the environment. Emissions through other media would contribute in a minor way to airborne exposure, however the airborne component of soil or water borne emissions would be negligible at the scale of analysis employed in this study. The annual emissions for this study are calculated as the sum of fugitive air emissions and stack emissions for BTEX chemicals at each facility.

3.1.4: Health Outcome Indicators

Percent of Medicare expenses related to asthma and COPD for the year of 2012 were selected as proxy data for prevalence of those conditions in each county. Medicare expenses were selected rather than emergency department visits or other incident reports because it is publicly available for all counties in the contiguous United States. Air quality, both indoor and outdoor, impact the prevalence of symptoms for both conditions, and exposure to BTEX chemicals and ozone directly impact the prevalence of symptoms for both conditions (Sigma-Aldrich, 2016; 2017a; 2017b; 2017c; U.S. Department of Labor, 2018). The percent of population with health insurance is representative of the potential preventative or treatment care available in each county. A higher percent of the population with medical insurance is likely to have a lower percent of Medicare expense attributed to asthma and COPD due to the availability of preventative treatments. In the case of inmate health, asthma and COPD are prevalent conditions due to lifestyles prior to incarceration and the poor ventilation and overcrowding prevalent in state prison systems.

3.1.5: Air Quality and Risk Data

The U.S. EPA's Air Quality Index (AQI) values were selected to represent risk of exposure to toxins for each county. The data was downloaded for the 2012 reporting year and was treated as the dependent variable for this study (mapped in Appendix A). The U.S. EPA calculates and reports AQI values on annual, monthly, and daily scales at the county level for the United States. The AQI is a calculated metric accounting for the concentration of particulate matter ($PM_{2.5}$ and PM_{10}), nitrogen dioxide, sulfur dioxide, ozone, and carbon monoxide reported daily. Automatic air quality monitoring is used for the reported concentrations and processed to generate an AQI value (U.S. Environmental Protection Agency, 2016a; 2016b). The AQI is reported as a daily value and an annual summary report; for this study, the annual 90th percentile AQI value was used as the metric for risk of exposure. The AQI value represents the physical impact pollution levels have on the population with respect to the concentrations of carbon monoxide, sulfur dioxide, nitrogen dioxide, ozone, and particulate matter in the air. The 90th percentile value was selected because it represents the incidence of high risk but prevents the use of outliers from extreme events in analysis.

The AQI value is reported on a scale of 0 (good) – 500 (hazardous) based on the relative concentrations of each previously mentioned pollutant (U.S. Environmental Protection Agency, 2016b). The scale also corresponds to the anticipated health outcomes related to changes in air quality for the general population and those with greater sensitivity to airborne contaminants. A discrete color ramp for each level of contamination is provided by the EPA to standardize representation of air quality information (U.S. Environmental Protection Agency, 2016b). This color ramp is used on all AQI and regression maps in this study. Table 3.1 presents the AQI scale, color ramp, and predicted health impacts.

Table 3.1: U.S. Environmental Protection Agency AQI reference scale and recommended classification system (U.S. Environmental Protection Agency, 2016b)

Air Quality Index Levels of Health Concern	Numerical Value	Meaning
Good	0 to 50	Air quality is considered satisfactory, and air pollution poses little or no risk.
Moderate	51 to 100	Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.
Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is not likely to be affected.
Unhealthy	151 to 200	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects.
Very Unhealthy	201 to 300	Health alert: everyone may experience more serious health effects.
Hazardous	301 to 500	Health warnings of emergency conditions. The entire population is more likely to be affected.

3.1.6: Variable Selection and Data Processing

Initial selection of socioeconomic variables was guided by the available scholarly literature and the available prison location data. Tables 3.2 through 3.6 present the descriptive statistics for each dataset being examined, Appendix B presents details related to application and data source for each variable. All variables used for location and specific site selection analysis in this study were obtained through publicly available records with the exception of the prison location data which was obtained through both publicly available DOC data and the private database provided by Dr. Kerbs and Dr. Jolley. The use of data from multiple agencies required data formats to be modified to ensure that there was no loss of information due to formatting or misalignment. All data files were converted to comma separated (csv) format to minimize storage space and also reduce the risk of corruption. Preprocessing of data was performed using a combination of Esri ArcGIS, Microsoft Excel, and R opensource software.

The AQI data obtained from the U.S. Environmental Protection Agency, sociodemographic data obtained from the U.S. Census, and health outcomes data obtained from the Medicare records were directly imported into R because they were published in csv format with data aggregated for the county level. All socioeconomic variables that were reported as counts were normalized into a percent to prevent a bias against lower population areas. Prison locations and TRI locations were intersected with county polygon files in ArcGIS to obtain a count for each facility type for all counties in the United States. NWALT land use data was available in raster format, and the raster was separated by U.S. county using ArcGIS to ensure that all land uses were accurately attributed to the correct county. Each class of land use was then summed to give a total land area in each land use classification within each county. The sum of classes 22, 23, and 41 was calculated to determine the net LULU land area in each county and the percent LULU land use was calculated using the previous sum divided by the total land area for each county. The resulting attributes tables were then exported to csv format and entered in the R models as representative of the prison, TRI, and land use variables.

Table 3.2: Descriptive statistics for site selection calibration dataset

Short Name	Calibration Set					
	N	Mean	Standard Deviation	Median	Range	Skew
Income	144	26040.05	5680.964	25133	32375	1.192159
Education	144	16.66944	6.894766	16.5	34.3	0.346765
Male	144	49.69042	1.437183	49.42097	9.607972	1.594898
White	144	84.92396	11.6922	88.81686	57.87313	-1.23054
Uninsured	144	13.58819	4.778704	13.6	26.9	0.333591
Employed	144	37.04028	6.817894	36.65	34.4	0.36431
Renter	144	29.28815	7.616306	28.45736	54.20988	1.377458
Mobile Homes	144	9.535417	7.231356	8.65	30.6	0.873031
LULU area	144	2.080773	2.963201	0.95257	19.44345	3.058086
LULUs	144	0.548611	1.210848	0	8	3.208238
Prison	144	0.805556	1.415586	0	8	2.487794
AQI/IAQ[1]	144	68.54861	18.14812	67	113	0.033384
Asthma	144	4.419444	1.156029	4.3	5.6	0.553441
COPD	144	11.19375	3.123948	10.95	18.8	0.445346

[1] Influence on Air Quality (IAQ) is the site selection model output based on the AQI.

Table 3.3: Descriptive statistics for the collective three state dataset

Short Name	Three Target States					
	N	**Mean**	**Standard Deviation**	**Median**	**Range**	**Skew**
Income	134	22743.91	4803.388	22018.5	29793	0.674753
Education	134	21.8694	10.27354	20.75	62.3	1.045077
Male	134	50.14843	2.485995	49.49333	18.01489	2.73545
White	134	82.19778	14.04374	86.62693	68.18571	-1.37978
Uninsured	134	18.87463	6.003366	19.3	33.7	0.229323
Employed	134	41.44254	7.156997	41.15	42.3	0.567759
Renter	134	27.95803	7.468523	27.27006	42.02969	0.572589
Mobile Homes	134	14.18657	8.709141	12.55	38.4	0.527562
LULU area	134	1.917126	3.999376	0.678085	30.49358	4.535423
LULUs	134	0.708955	2.929817	0	31	8.52503
Prison	134	0.768657	1.746809	0	16	5.612044
AQI/IAQ	45	70.6	14.11865	71	64	0.266
Asthma	134	4.552985	1.076802	4.4	7.6	1.490655
COPD	134	11.95373	2.685233	11.75	14.4	0.444439

Table 3.4: Descriptive statistics for the Pennsylvania dataset

Short Name	Pennsylvania					
	N	Mean	Standard Deviation	Median	Range	Skew
Income	65	24922.78	4653.971	23586	27529	1.631745
Education	65	14.96769	5.005563	14.9	24	0.61497
Male	65	49.70722	2.452466	49.14807	19.05064	4.831537
White	65	91.71344	8.736087	94.34387	56.91004	-3.28817
Uninsured	65	10.09077	2.038897	9.8	10	0.43986
Employed	65	39.74154	5.783973	39.9	38.3	1.818479
Renter	65	25.79243	5.203174	25.42508	31.34078	1.101554
Mobile Homes	65	7.481538	4.268924	7.5	17.6	0.31658
LULU area	65	2.867075	4.494472	1.498198	30.42046	4.031129
LULUs	65	0.492308	0.95399	0	5	2.413759
Prison	65	1.030769	2.249786	0	16	4.825985
AQI/IAQ	38	74.76316	12.16649	76.5	58	0.176415
Asthma	65	4.606154	1.068129	4.5	6.7	1.574937
COPD	65	11.87538	1.549297	11.9	7.7	0.35451

Table 3.5: Descriptive statistics for the North Carolina dataset

Short Name	North Carolina					
	N	Mean	Standard Deviation	Median	Range	Skew
Income	99	22083.51	3943.037	21289	18387	0.935939
Education	99	20.81818	6.788035	21.2	37.8	-0.03497
Male	99	49.13312	1.606452	48.93038	8.124216	1.58149
White	99	71.94092	17.77575	75.88768	66.30164	-0.39875
Uninsured	99	17.08081	2.97838	16.7	19.2	0.637061
Employed	99	40.67273	5.812194	40.2	25.5	-0.1027
Renter	99	28.90196	6.908952	27.76207	31.07555	0.364262
Mobile Homes	99	19.96061	7.902219	20	37.1	-0.26944
LULU area	99	1.727152	2.369129	0.901781	15.87647	3.156762
LULUs	99	0.252525	0.849291	0	6	4.548591
Prison	99	0.636364	0.801205	0	4	1.441323
AQI/IAQ	45	60.48889	11.87745	59	68	-0.88379
Asthma	99	4.677778	0.886124	4.6	6	1.64542
COPD	99	11.88788	2.200894	11.8	10.2	-0.19552

Table 3.6: Descriptive statistics for the Texas dataset

Short Name	Texas					
	N	**Mean**	**Standard Deviation**	**Median**	**Range**	**Skew**
Income	237	22195.44	4599.853	21895	26260	0.535754
Education	237	23.83629	10.55448	21.8	79.2	1.2267
Male	237	50.65064	3.034534	49.60582	22.20973	2.492343
White	237	84.73426	8.419016	86.22353	45.20315	-0.89575
Uninsured	237	22.28143	4.832507	21.5	28.8	0.790152
Employed	237	41.89367	7.552421	41.4	42.3	0.614748
Renter	237	27.10593	6.938962	26.56634	43.35262	0.531282
Mobile Homes	237	14.36414	7.567584	13.7	36	0.484775
LULU area	237	1.014779	2.339538	0.33538	20.35667	5.571768
LULUs	237	0.476793	2.295096	0	31	10.4605
Prison	237	0.468354	1.05568	0	7	3.267546
AQI/IAQ	41	70.41463	14.4758	71	60	0.340871
Asthma	237	4.410549	1.147923	4.3	9.6	0.838648
COPD	237	12.18439	2.98578	11.9	20.2	0.052462

Once all variables were uniformly formatted in csv files, a combination of string and numeric R scripts was used to merge the data files and subset only the target variable fields. Values of NA in the prison and TRI fields were replaced with 0 because the lack of a reported point feature (prison or TRI facility) in a county indicates that no facilities were present rather than missing data. In all other fields, the NA values were retained to reflect data gaps. Initial variable selection provided 13 independent variables to be analyzed relative to the dependent variable, AQI. These variables were highly colinear upon initial testing and required refinement to determine which were the most meaningful for analysis. Rigorous screening of the variables was performed in R using a combination of data refining functions. The *ggpairs* pairwise testing (Emerson et al., 2012) and base-R *step regression* (Hastie and Pregibon, 1992; Venables and Ripley, 2002) were employed to ensure only the most meaningful variables were retained during analysis. During pairwise analysis, a correlation coefficient of 0.25 was used as the threshold value for maximum correlation between variables. Variable pairs with a correlation value less than or equal to 0.25 were retained for secondary screening while those with a coefficient greater than 0.25 were discarded. This removed three variables from the initial list (percent of mobile homes, percent of population achieving less than a high school diploma, and percent of population that is uninsured). Following the pairwise test, a step regression was performed on the variables to ensure that screening was rigorous and thorough; only variables in the best-fit stepwise equation were retained for linear regression analysis. The stepwise regression reduced the variable list to six independent variables with significance (Table 3.7).

Table 3.7: Final variables determined for the specific site selection model and their significance as determined by pairwise and stepwise analysis (Pairwise screening results in Appendix C).

Variable	p
Income	0.12324
Employed***	0.00098
Renter*	0.01495
Asthma*	0.01805
LULUs*	0.03625

Note: * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$

3.1.7: Calibration Data Selection

Using the processed data, a calibration dataset (Appendix D) was selected to fit the specific site selection (linear) model. The calibration dataset was determined by randomly selecting three counties from each of the 48 contiguous states. Counties with a value of NA in any field were excluded from selection as curve fitting without a complete set of variables would produce poor results with greater error. The selection process was not forced to choose an even number of both prison and non-prison counties as this would introduce another level of bias and error to the model. The selection process also did not control for the variety of AQI values represented by the dataset. For this reason, it is possible that the calibration curve does not reach the maximum and minimum AQI within the dataset. The resulting 144 counties were then exported into a separate dataset to be used for calibration of both the location analysis and specific site selection.

3.2: Location Analysis

The first research question examines the relationship between prisons, other LULUs, and the socioeconomic indicators which may contribute to their coexistence. To address this question, a combination of logistic regression models and Poisson probability distributions were employed using multiple scales of analysis. The Poisson distributions were used to assess the relationship between the number of prisons present in each county and the number of other

LULUs present within the county. The *polr* (Agresti, 2002; Venables and Ripley, 2002) logistic regression model was selected to complete the location analysis and address the relationship between the presence of prisons, the presence of other LULUs, and the associated socioeconomic influence on their presence.

The Poisson analysis addressed the relationship between prisons and other LULUs at the county level without regard for potential socioeconomic influences. A Poisson probability distribution was performed on the full dataset for the contiguous United States with the division of data into counties with prisons and counties without prisons. The distribution analyzed the probability of each observed number of LULUs being present in counties with and without prison facilities. The Poisson distribution was used to compare the observed to predicted presence of TRI facilities relative to prison facilities.

The location analysis model was completed for each individual state as well as all three study states collectively to assess the varied impact variables have with changing scales. The initial model run used the same four socioeconomic variables considered in the linear regression model. This model run assessed if the site selection variables were also representative of the socioeconomic influences on LULU coexistence. The second model run incorporated a stepwise regression component to determine which of the original socioeconomic variables are most indicative of LULU development at the county level.

3.3: Specific Site Selection

Linear regression analysis was employed in this study to assess the relationship between prisons, LULUs, socioeconomic characteristics, and their influence on air quality (IAQ). Linear regression analysis was used to perform an unbiased site selection for counties with and without prisons accounting for the inherent physical contributions of the AQI as well as the health and socioeconomic variables selected previously. While the Poisson distribution and location analysis models examine the spatial distribution of LULUs and socioeconomic influences on their presence, the site selection model examines the relationship between LULUs, socioeconomic variables and the air quality at the county level.

Linear regression was used for a site selection model to ensure that no human bias influenced the choice of study areas and that each variable was given appropriate weight in determining target counties in each state. A linear least squares fit was performed using the base-R *linear model* (*lm*) function (Wilkinson and Rogers, 1973; Chambers, 1992; R Core Team, 2016) to assess the relationship between air quality and the previously determined socioeconomic variables. Least squares analysis was selected because a fit that minimizes the sum of the squares for each calibration point ensures a best fit line with the strongest correlation available for linear data. The dependent variable was the calculated IAQ, which addresses the relationship between LULUs, socioeconomic influences, and physical influences on air quality. AQI values were used in model calibration because it allowed the model to examine the influence of socioeconomic factors and LULUs on the physical air quality at the county level. After calibration was completed, the resulting equation was used to determine the IAQ for each county (Chambers, 1992). Counties were grouped as either prison or non-prison and the location with the greatest IAQ in each group and state was selected for plume analysis.

3.4: Plume Analysis

Plume analysis was performed using the ALOHA emergency management dispersion model, using annual level data based on the availability of annual level TRI data. The hourly emissions were determined based on a 24-hour continuous working schedule prevalent in petroleum and chemical industries (Northrup et al., 1979). Stack height was estimated at 65 meters which is the EPA minimum for air emissions (U.S. Environmental Protection Agency, 1985). Wind speed and direction were determined by the annual average for 2012 and sites were assigned the atmospheric data for the nearest Automated Surface Observing System (ASOS) site within the county (when more than one site is present in the county) (ASOS sites are listed in Appendix E). Because the ALOHA system cannot perform with wind speeds lower than 1.95 knots, the analysis rounded the annual wind speed up to this threshold at all sites (National Climatic Data Center, 2013). The annual average temperature was used for the region based on the National Climatic Data Center (NCDC) U.S. climatological division (map of divisions is in Appendix F) containing the target site. Source elevation was extracted from the 2011 National Elevation Dataset (U.S. Geological Survey, 1999) for each TRI facility (Appendix G shows the DEMs by county).

Plume boundaries were assigned using the EPA Acute Exposure Guidelines Levels (AEGL) for airborne chemicals. The 8-hour exposure limit was used for each of the three defined levels published by the EPA for each of the BTEX toxins. The AEGL categories correlate to: 1) notable discomfort or irritation with reversible effects, 2) irreversible or serious lasting adverse health effects, and 3) life-threatening levels of exposure (U.S. Environmental Protection Agency, 2016c). These levels are defined for the BTEX chemicals in Table 3.8.

Table 3.8: Tabulated 8-hour AEGL exposure limits for BTEX chemicals (U.S. Environmental Protection Agency, 2016d; 2016e; 2016f; 2016g)

Chemical	AEGL Level Concentration (ppm)		
	1	2	3
Benzene	9.0	200	910
Toluene	67	250	1400
Ethylbenzene	33	580	910
Xylene	130	400	1000

The dispersion model was run for the annual average for all facilities with emissions values greater than 1.0 pounds per hour due to model accuracy limitations. The model has the ability to perform Gaussian and heavy gas plume models; for this study, the model was allowed to determine the most effective dispersion method for the given data. Based on the molecular weight of the target chemicals, the model performed a heavy gas dispersion model for all BTEX facilities (Table 3.9). Emissions below this threshold yielded warnings that plume accuracy is limited over short distances and reported the same output regardless of emissions levels. For the highest emissions value in each study site, an extreme case scenario run was also performed using the highest reported wind speed for the year to assess the most extreme potential implications. Plumes that were successfully generated were imported into ArcGIS to compare with the locations of prisons and other facilities.

Table 3.9: Molecular weight of each target chemical and oxygen gas

Chemical	Mass
Oxygen Gas	32 g/mol
Benzene	78 g/mol
Toluene	87 g/mol
Ethylbenzene	106 g/mol
Xylene	106 g/mol

CHAPTER 4: LOCATION ANALYSIS, SITE SELECTION RESULTS AND DISCUSSION

The location and site selection analyses address the relationships between 1) prisons and other LULUs; 2) prisons, LULUs, and socioeconomic influences on their distribution; 3) prisons, LULUs, socioeconomic variables, and the relationship with respiratory health; and 4) prisons, LULUs, socioeconomic variables and their influence on air quality. Location analysis assessed the relationship between prisons, other LULUs, socioeconomic factors, and health outcomes for each state individually and collectively. The linear regression analysis provided an unbiased site selection methodology based on the socioeconomic, environmental, and physical components of the study. This allows all contributing factors to be considered without making assumptions regarding the optimal study sites and limiting bias related to perception of socioeconomic influences.

Location analysis, using Poisson probability analysis and logistic regression, addressed the first three relationships listed above while the site selection model addressed the relationship between prisons, LULUs, socioeconomic variables and air quality. The location analysis was performed twice, once using the same four socioeconomic variables selected for linear regression and a second time using a stepwise function on all variables, for each state and for all three states collectively. Calibration used a randomly selected dataset from each state and from the collective three states.

4.1: Prisons and Other LULUs

Current literature indicates that the presence of LULUs leads to the development of additional LULUs based on perceived socioeconomic impacts (Hoyman and Weinberg, 2006; Eason, 2010; Stewart et al., 2014; Al-Kohlani and Campbell, 2016; Moore, 2017). The Poisson probability analyses address this relationship exclusively, examining the influence the presence of prison facilities has on the predicted number of LULUs in a particular county and was completed for each state individually and collectively. The following equations were used to calculate the Poisson distribution for LULUs in counties with and without prisons:

$$z = (N/F) \quad (1)$$

Equation 1: Calculation of z value for Poisson probability distribution where N is the total number of counties and F is the total number of facilities.

$$Probability = (x^z/e^z)*x! \quad (2)$$

Equation 2: Poisson probability equation where x is the number of counties and z is the ratio of N:F

Using the above equations and data for all three states, the following z and probability are anticipated for counties containing a prison but no other LULUs (Appendix H):

$$z = 0/7445$$

$$Probability = 0.4750$$

In contrast to the 47.5% probability that a county containing a prison will not contain additional LULUs, counties without a prison experience a 77.29% probability that no other LULUs will be present. This relationship, at the scale of multiple states, indicates that the presence of at least one prison increases the probability that additional LULUs will be co-located.

These results indicate a greater disparity between counties with and without prisons than is observed at the scale of individual states. However, in both Pennsylvania and Texas, counties with prisons have a higher probability of other LULUs being co-located than those without prisons. In Pennsylvania the probability of counties with prisons being without other LULUs is 51.94% while those without prisons have a 69.69% probability of having no other LULUs. In Texas the probability of having a prison but no LULU is 30.12% and having neither prisons nor LULUs is 79.32%. These predicted probabilities are consistent with the current literature, indicating that LULUs tend to be clustered in similar locations. It is likely that the probability is skewed due to Harris County containing 31 LULUs and a prison which encompasses approximately 51% of LULUs present in counties with prisons.

In North Carolina the opposite relationship is observed between the presence of prisons and the probability of other LULUs being present. The probability of having neither a prison nor a LULU is 75.99% while that of having a prison but no LULU was 79.52%. This probability relationship is opposite of the findings of current literature and indicates that the presence of a prison decreases the probability that other LULUs will be co-located in North Carolina; however, the probabilities are much closer than in the other three test cases. One potential explanation for this relationship is that in North Carolina, unlike Pennsylvania or Texas, the number of counties with and without prisons is approximately equal (48 counties with prisons and 51 without).

4.2: Prisons, LULUs, and Socioeconomic Influences

The spatial relationship between prisons and other LULUs indicates that the presence of prisons increases the probability of other LULUs also being present. The influences of socioeconomic factors on this relationship is also relevant in understanding the factors contributing to LULU coexistence. The location analysis models assess the relationship between prisons, LULUs, and the socioeconomic influences on their coexistence. These models also assess whether the variables linked to air quality are also indicative of prison and LULU coexistence at the county scale. A logistic regression methodology is useful in that it addresses the relationship between the presence of prisons and/or other LULUs and the socioeconomic factors that influence their coexistence. The first set of location analyses evaluated the relationship of the site selection variables (indicative of influences on air quality) to the presence of prisons and other LULUs while the second set used a stepwise variable refinement method to determine which socioeconomic characteristics were most influential on the presence of prisons and other LULUs. The location analysis model results are listed in Table 4.1 including coefficients and summary statistics and applied using equations 3 through 10.

Examination of the location model coefficients provides insight into the positive or negative relationship between each variable and the presence of prisons and/or other LULUs. Based upon this analysis, the variables that are most influential on air quality are not consistently the most influential on the presence of LULUs within the county. Error analysis for each location model is reported in Appendix J including evaluation of each category as well as the model overall. While there were variations in accuracy between each model, no model accurately identified counties with no prisons but one or more other LULUs. This could be a result of the small portion of counties containing only other LULUs and without a prison, In all cases, however, important relationships can be inferred from the location analysis results.

$$Y = 1.326*10^{-4} (A) + 0.092 (B) + 0.1163 (C) + 0.3020 (D) \quad (3)$$

Equation 3: Location analysis equation using the site selection variables for all three states

$$Y = 1.127*10^{-4} (A) 0.1288 (C) + 0.2793 (D) + 0.1699 (E) + 0.2334 (F) \quad (4)$$

Equation 4: Location analysis equation using stepwise selected variables for all three states

$$Y = 2.116*10^{-4} (A) + 0.0726 (B) + 0.1465 (C) - 0.2192 (D) \quad (5)$$

Equation 5: Location analysis equation using the site selection variables for Pennsylvania only

$$Y = 1.971*10^{-4} (A) +0.1701 (C) + 0.1699 (E) + 0.2429 (F) \quad (6)$$

Equation 6: Location analysis equation using stepwise selected variables for Pennsylvania only

$$Y = 2.093*10^{-5} (A) - 0.0180 (B) + 0.0481 (C) + 0.2393 (D) \quad (7)$$

Equation 7: Location analysis equation using site selection variables for North Carolina only

$$Y = 1.976*10^{-4}\,(A) + 0.2901\,(E) + 0.1884\,(F) - 0.0504\,(G) \quad (8)$$

Equation 8: Location analysis equation using stepwise selected variables for North Carolina only

$$Y = 1.086*10^{-4}\,(A) + 0.0729\,(B) + 0.1403\,(C) + 0.3197\,(D) \quad (9)$$

Equation 9: Location analysis equation using site selection variables for Texas only

$$Y = 9.636*10^{-5}\,(A) + 0.0800\,(C) + 0.3233\,(D) + 0.1711\,(F) - 0.1125\,(G) \quad (10)$$

Equation 10: Location analysis equation using stepwise selected variables for Texas only

Table 4.1: Coefficient and intercept values for location analysis. Air Quality indicates that the model employed variables selected for the site selection model. Stepwise indicates that the variables were selected using stepwise regression from the original socioeconomic and health variables.

	Category		3-state		PA		NC		TX	
	Call	Variable	Air Quality^	Stepwise^	Air Quality^	Stepwise^	Air Quality	Stepwise	Air Quality^	Stepwise
Coefficients	A	Income	1.326E-04	1.127E-04	2.116E-04	1.971E-04	2.093E-05	1.976E-04	1.086E-04	9.636E-05
	B	Employed	0.0902		0.0726		-0.0180*		0.0729	
	C	Renter	0.1163	0.1288	0.1465	0.1701	0.0481**		0.1403	0.0800
	D	Asthma	0.3020	0.2793	-0.2192		0.2393		0.3197	0.3233***
	E	COPD		0.1699				0.2901***		
	F	Male		0.2334		0.2429		0.1884		0.1711
	G	White						-0.0504		-0.1125
Category	Call	Description								
	0|1	No Prison/LULU | Prison Only	11.6259	21.46732	10.58945	20.9923	2.070345	13.30368	11.47117	5.735335
	1|3	Prison Only | LULU Only	13.1555	23.08771	12.0244	22.47209	4.174052	15.53458	12.70664	7.171969
	3|4	LULU Only | Both Prison and LULU	14.19197	24.15582	12.84453	23.31229	4.733515	16.10498	13.70834	8.377759

Note: ^ indicates Hessians contain NAs and summary statistics could not be generated

Note: * indicates p < 0.05, ** indicates p < 0.01, *** indicates p < 0.001

Note: Shaded cells indicate a variable that was not retained for analysis

In each model run, income was identified as a positive influence on the presence of LULUs within a county, indicating that a higher annual income correlates with a higher number of LULUs. The response is small; however, this is potentially a result of the disparity between values for annual income and the much smaller percentages and counts representing other variables. Income can also be indicative of employment within each county in that the presence of more LULUs is likely proportional to the presence of more jobs within the county. With a greater number of people working within a county, the average income will increase because there will be a smaller contribution by the population earning zero income (unemployed or under age groups). Employment was excluded by the stepwise function for all target states, however, it was evaluated in the second model run (using site selection variables). In the overall analysis of all states, as well as in Pennsylvania and Texas, income represented a small positive influence on the presence of LULUs. This is consistent with the possibility that increasing the number of LULUs increases the number of available jobs. In contrast, in North Carolina income was identified as a negative influence on the presence of LULUs and was identified as significant at the 95% confidence interval. This indicates that higher employment correlates with a lower number of LULUs (not higher, as was found in the other states and the overall analysis). The findings in North Carolina are consistent with the available literature where LULUs tend to be placed in less affluent areas.

Renter occupancy of housing also correlated positively the presence of LULUs in all cases, though analysis of North Carolina excluded renter occupancy in the stepwise method. Renter occupancy is, based on the literature, an indicator of lower income housing and transience within the county. In this case it could indicate that the counties were using the development of LULUs to increase employment and promote other forms of development within the area, as suggested by (Hoyman and Weinberg, 2006). Another potential implication is the influence of urban counties outweighing that of lower density counties. In an urban environment, rental housing is frequently the most readily available due to population density.

The demographics of each county also represent a minor influence on the presence of LULUs at the county level. In both North Carolina and Texas, the percent of the population that is white correlates negatively to the presence of LULUs within the county. This supports the findings in the literature that LULUs tend to be placed in minority communities. In all study areas, the percent of the population that is male correlated positively with the presence of LULUs. This is potentially because historically men are the working member of the family whether or not the female family member also works. Therefore, the relationship between LULUs and male population is likely related to the relationship between employment and LULUs.

4.3: Prisons, LULUs, Socioeconomic Variables, and Air Quality

The relationship between prisons, LULUs, socioeconomic variables and air quality provided the foundation for the site selection model in this study. The model was calibrated using the AQI values reported by the U.S. EPA. These values are representative of physical air quality and their impact on health outcomes. This analysis evaluated the impacts of prisons, LULUs, and socioeconomic influences on air quality and provided an unbiased site selection model for the plume analysis.

The site selection model results were grouped by state and by the presence or absence of prison facilities to allow for comparable sites to be picked in each study region. To determine the optimal county for each state (PA, NC, TX), the county with the highest modeled AQI was selected for the group with prisons and the group without prisons in each state. This method was designed to compare all factors associated with the social, economic, health, and LULU landscape variables and ensure that the sites are comparable in terms of impact. Table 4.3 provides variable definitions and significance of the coefficients for the site selection model. The IAQ was calculated using equation 11 with a sample calculation using data for Guilford, NC:

$$IAQ = -4.703E\text{-}04(A) - 1.134(B) - 0.5302(C) + 2.558(D) + 3.255(E) - 0.3472(F) + 124 \quad (11)$$

Equation 11: Site selection model results. This model was calibrated using 144 randomly selected counties and applied to all counties within the study states.

$$IAQ = 83.80$$

Table 4.2: Definition and coefficients for site selection model variables

Name	Variable	Coefficient
A	Income	-4.703×10^{-4}
B	Employed	-1.134***
C	Renter	-0.5302*
D	LULUs	2.558*
E	Asthma	3.255*
F	Prisons	-0.3472
b	y-intercept	124.0

Note: * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$

The above variables were determined using pairwise and stepwise screening, as described earlier. These variables, which were evaluated in both the location analysis model and the site selection model, are most representative of air quality at the county level based upon the calibration dataset. The results of these analyses indicate that the influences on air quality do not behave the same with regard to the presence of LULUs. While these variables are representative of the air quality at the county level, they do not describe the LULU landscape equally well.

Figure 4.1 presents the modeled AQI for all counties within Pennsylvania, North Carolina, and Texas. While the pattern appears spatially uniform with the exception of one county reaching an unhealthy level for sensitive population groups, there are variations in AQI within each classification. The classification levels encompass a large range of values (each class represents an AQI range of 50 or greater increments on the scale). For example, the “moderate” AQI class represents AQI’s ranging from 51 to 100 while “hazardous” ranges from 301 to 500.

The influence on the variables in Table 4.2 was evaluated for both air quality and the presence of LULUs within a county. These results, however, do not necessarily indicate the same conclusions. IAQ values increase with decreasing air quality; therefore, in the site selection model, a negative correlation represents a positive contribution to air quality. The presence of LULUs, as anticipated, correlated positively with the modeled IAQ. This suggests that the presence of LULUs negatively influences the air quality of the county. This is consistent with the prediction that industrial LULUs produce toxins which negatively influence air quality in the surrounding area. In contrast, prisons correlate negatively with IAQ suggesting a positive influence on air quality in counties where prisons are present. This result is inconsistent with the literature in that LULUs tend to be located together to minimize negative impacts on other populations.

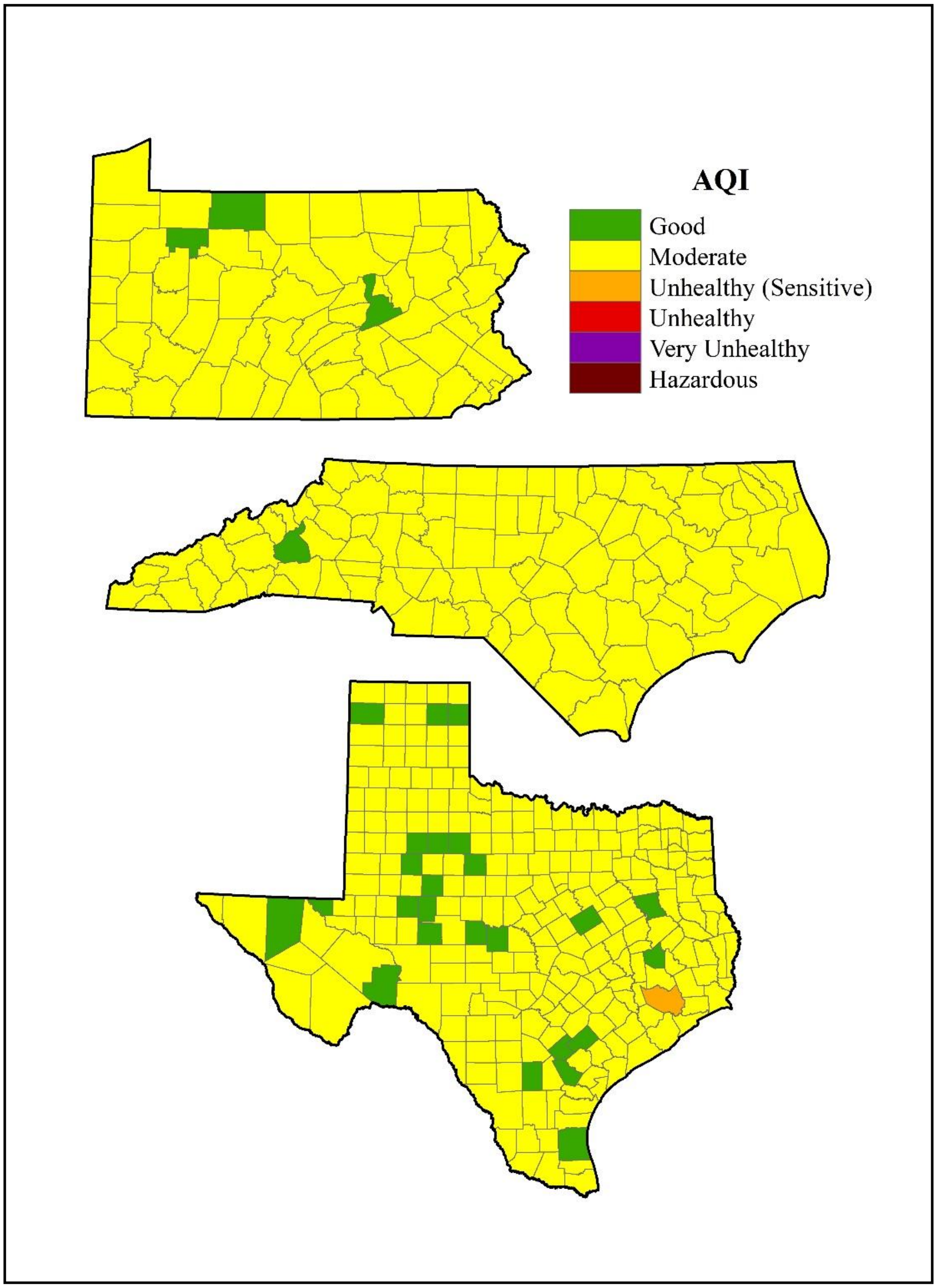

Figure 4.1: Modeled IAQ values for all counties in Pennsylvania, North Carolina, and Texas. A detailed explanation of the classification system is provided in Table 3.1. (U.S. Environmental Protection Agency, 2016b).

Income, employment, and renter occupancy all correlate negatively with the modeled IAQ values. This result indicates that all of these variables contribute to air quality in a positive way. These results are opposite what is anticipated from the location analysis because the number of LULUs correlates positively with AQI and these socioeconomic variables correlate positively with the presence of LULUs. The contradictory nature of these results is likely the result of the scale of analysis. Examining the variables at the county level presents the macro influences on air quality and LULU location, however, this scale is likely too large to observe the more subtle and localized impacts of these influences.

4.4: Prisons, LULUs, Socioeconomic Variables, and Respiratory Health

The influence of prisons, LULUs, and socioeconomic influences on respiratory health is more consistent among analyses in this study. The relationship between LULUs and respiratory health variables in all models, except the air quality variables location model for Pennsylvania, suggests a positive correlation between the two. In Pennsylvania, asthma correlated negatively with LULUs in one model. The relationship only being present in the site selection variables suggests that it could be an artifact of poorly suited variables. The positive correlation between respiratory health and LULUs is supported by the selection of industrial LULUs to represent all non-prison LULUs in the study areas. Similarly, asthma correlated positively with the modeled IAQ value. This indicates that asthma correlates with poor air quality. This also supports the validity of the model in that the AQI values used for calibration are indicative of health impacts on sensitive (specifically targeted to asthmatic) groups based on the measured air quality. These results agree with the prediction that LULUs negatively impact the respiratory health of the surrounding population.

4.5: The Specific Study Sites

Counties were selected only on the criteria of modeled IAQ values as this value accounts for social, health, and economic indicators collectively as well as the LULU landscape of each county. The list of counties is shown in Table 4.3 and their locations in Figure 4.2. Both Rutherford and Gaston counties in North Carolina were included as a control measure where Rutherford, NC has a prison but no TRI facilities and Gaston, NC contains both a prison and TRI facilities. In North Carolina, the selected counties are concentrated in the western half of the state rather than the coastal regions while in Texas the two target sites are in the eastern half of the state

Table 4.3: Target counties in Pennsylvania, North Carolina, and Texas (including modeled AQI value and determination of prison and LULU presence)

State	County	Prison	TRI	Predicted AQI
North Carolina	Gaston	Yes	Yes	75.84
North Carolina	Rutherford	Yes	No	78.00
North Carolina	Guilford	No	Yes	83.80
Pennsylvania	Berks	Yes	Yes	81.23
Pennsylvania	Bucks	No	Yes	82.66
Texas	Harris	Yes	Yes	146.96
Texas	Tarrant	No	Yes	97.39

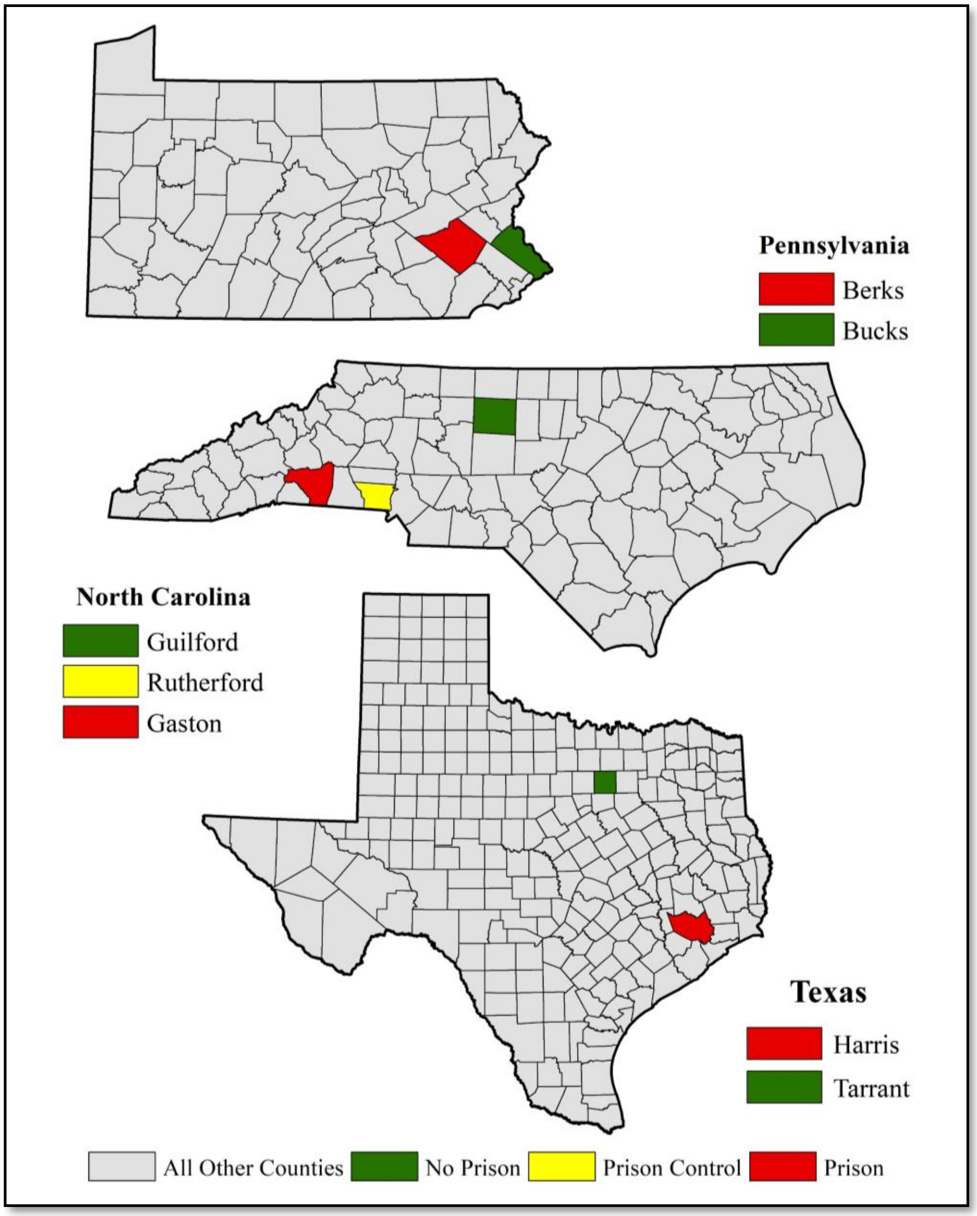

Figure 4.2: Target counties in Pennsylvania, North Carolina, and Texas

Linear regression analysis assists in understanding the relationship between prisons, their LULU landscape, and the air quality within the counties. Based on the modeled air quality, Texas has a positive relationship between the presence of prison facilities and predicted air quality. However, in both North Carolina and Pennsylvania, the counties without prison facilities have higher modeled IAQ values. While these IAQ values are representative of the model employed for specific site selection, the IAQs are not aligned well with the reported total emissions for each county. Figure 4.3 displays the number of prisons, the number of TRI facilities, and the reported annual emissions for the 2012 reporting year for each target county (U.S. Environmental Protection Agency, 2016h).

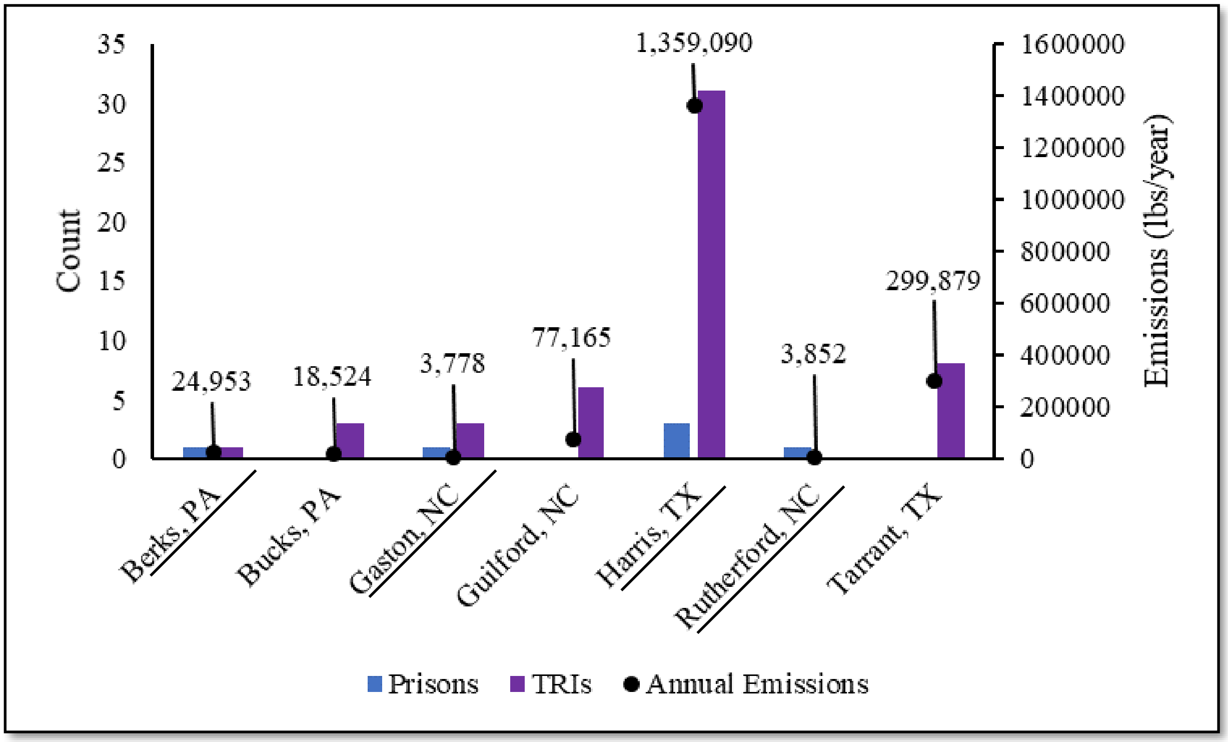

Figure 4.3: Annual air emissions (lbs/year) number of prisons, and number of LULUs for study sites (U.S. Environmental Protection Agency, 2016h).
Note: Underline indicates a prison county.

While the modeled IAQ values are not consistently higher for counties with prisons, in both Pennsylvania and Texas the total reported annual emissions are greater for counties with prisons than those without. This relationship is not present in North Carolina; however, the counties in North Carolina also have a greater range of urban development between counties than do Pennsylvania or Texas. While measures were taken to account for the urban-rural divide within the United States in this study, the results indicate that when a diverse group of land uses is present, urban influences are still dominant on the air quality. The presence of prisons in counties has a negative correlation with the IAQ value. This contradicts the predicted results because it shows that as the number of prisons increases the air quality improves. The positive relationship between the IAQ and both the number of LULUs and asthma expenses is not unanticipated as BTEX emissions are respiratory irritants and the IAQ was designed to describe respiratory impacts of airborne toxins.

The contributions of the categorical analysis and the probability analysis directly address the relationship between prisons and their LULU landscape and provide insight into the general conclusions drawn from the site selection model. Income related variables (income, renter occupied housing, and employment) represent a positive relationship with the location of LULUs; however, they have a negative relationship to the IAQ which also indicates that air quality is improved as these variables are increased. These results are not as expected. They show that while air quality is better in more affluent areas consistent with the studies by Hoyman and Weinberg (2006) and Russell (2017), the positive relationship between the presence of LULUs and income is contrary to their results. The analysis of socioeconomic, land use, and health outcomes provides a holistic approach to air quality analysis. Land use varies greatly between the counties and between the states examined in this study (Table 4.4). Rutherford, NC is the most rural location examined in this study while Tarrant, TX is the most urbanized county. The land uses for the three target counties in North Carolina are shown in Figures 4.4 and 4.5 while Figure 4.6 presents the land use for target counties in Pennsylvania, and Figure 4.7 presents land use for the target sites in Texas.

Table 4.4: Tabulated land use percentages for the seven target counties.

County Land Use	Bucks, PA	**Berks, PA**	Guilford, NC	**Gaston, NC**	**Rutherford, NC**	Tarrant, TX	**Harris, TX**
11 - Water	2.3797	0.9879	1.6393	1.7947	0.5021	4.4775	3.2008
12 - Wetlands	1.4058	0.4813	0.5825	0.5062	0.2734	0.1340	0.7603
21 - Major Transportation	2.8683	2.0450	3.4137	1.8397	1.2349	4.9309	4.0515
22 - Commercial/Service	5.0973	2.1309	5.7252	3.9650	0.7799	9.1544	14.9428
23 - Industrial/Military	2.3741	1.1888	2.4038	2.0737	0.3810	5.4121	5.2859
24 - Parks/Recreation	1.7122	0.9733	1.7247	0.8735	0.1837	3.9502	3.1812
25 - High Density Residential	4.8315	2.1784	5.0596	1.5667	0.0010	18.0093	17.9542
26 - Low Density Residential	15.8168	6.5144	13.3616	16.6317	3.8205	15.3674	14.0104
27 - Other Developed Uses	0.2951	0.5801	0.5540	0.3951	0.7755	1.3545	1.0085
31 - High Urban Interface	5.3676	1.1407	2.0240	5.6237	0.0005	7.0801	6.7690
32 - Low/Medium Urban Interface	22.1221	18.8951	24.8420	37.3197	16.1117	9.8222	8.5503
33 - Other Anthropogenic Interface	0.0034	0.0204	0.0093	0.0187	0.0368	0.0721	0.0056
41 - Mining	0.4421	0.2033	0.0290	0.0275	0.0290	0.0763	0.1329
43 - Cropland	11.0774	18.3455	0.5958	0.2027	0.0447	1.3218	2.7188
44 - Pasture/Hay	13.1463	22.3202	23.0329	16.8650	14.8307	4.3142	11.8099
45 - Grazing Potential	0.5626	0.4947	0.8296	0.6288	0.6900	6.0545	0.8633
50 - Low Usage	10.4973	21.5001	14.1728	9.6677	59.8107	8.4686	4.7545
60 - Conservation	0.0004	0.0000	0.0000	0.0000	0.4938	0.0000	0.0000
LULUs	7.9135	3.5229	8.1580	6.0662	1.1899	14.6427	20.3617

Note: Counties in bold print are prison counties.

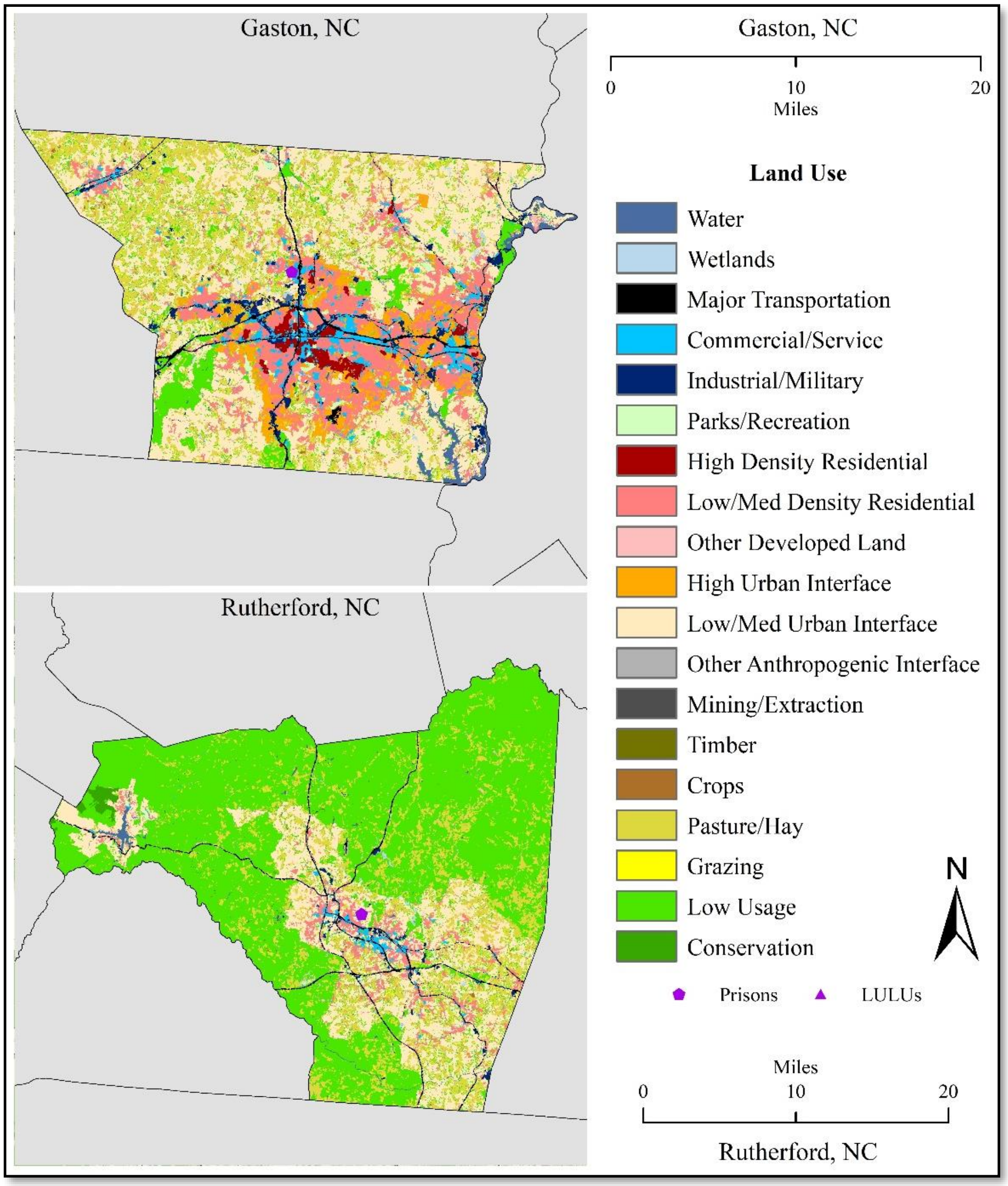

Figure 4.4: Land use maps of Gaston and Rutherford Counties in North Carolina. These counties are the prison sites for North Carolina.

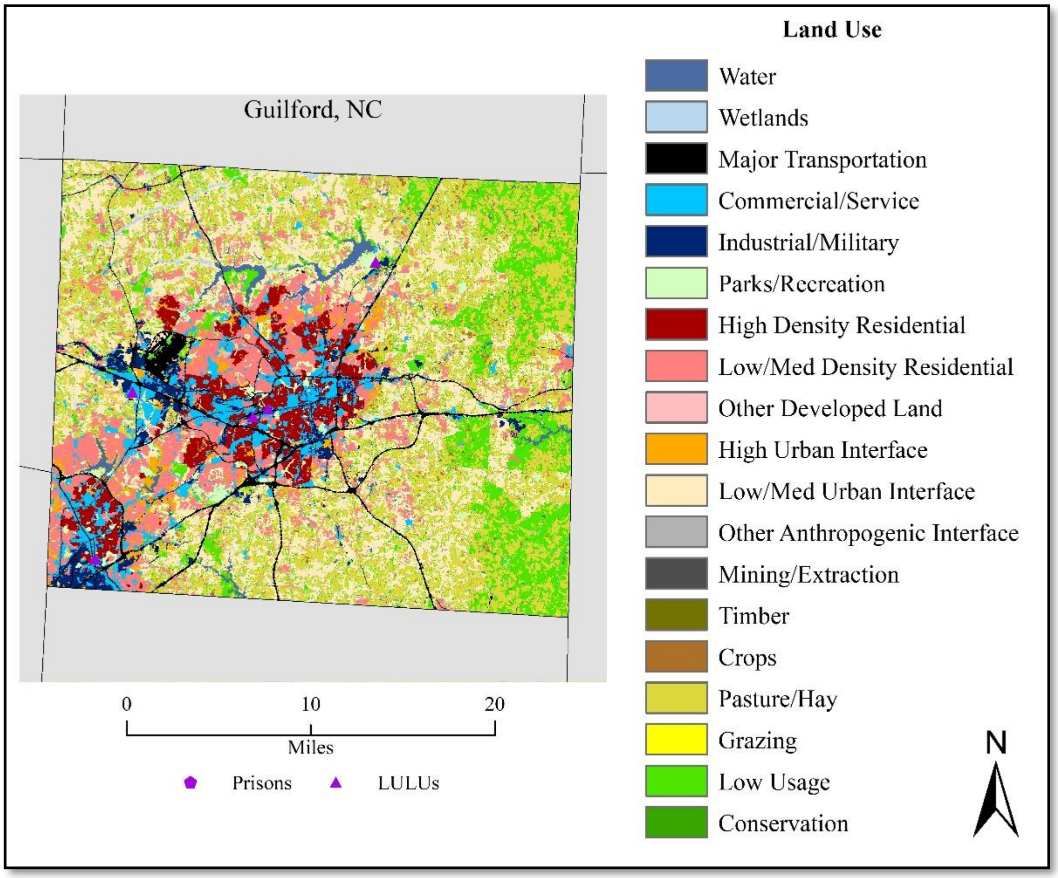

Figure 4.5: Land use map of Guilford, NC. Guildford County is the non-prison site in North Carolina.

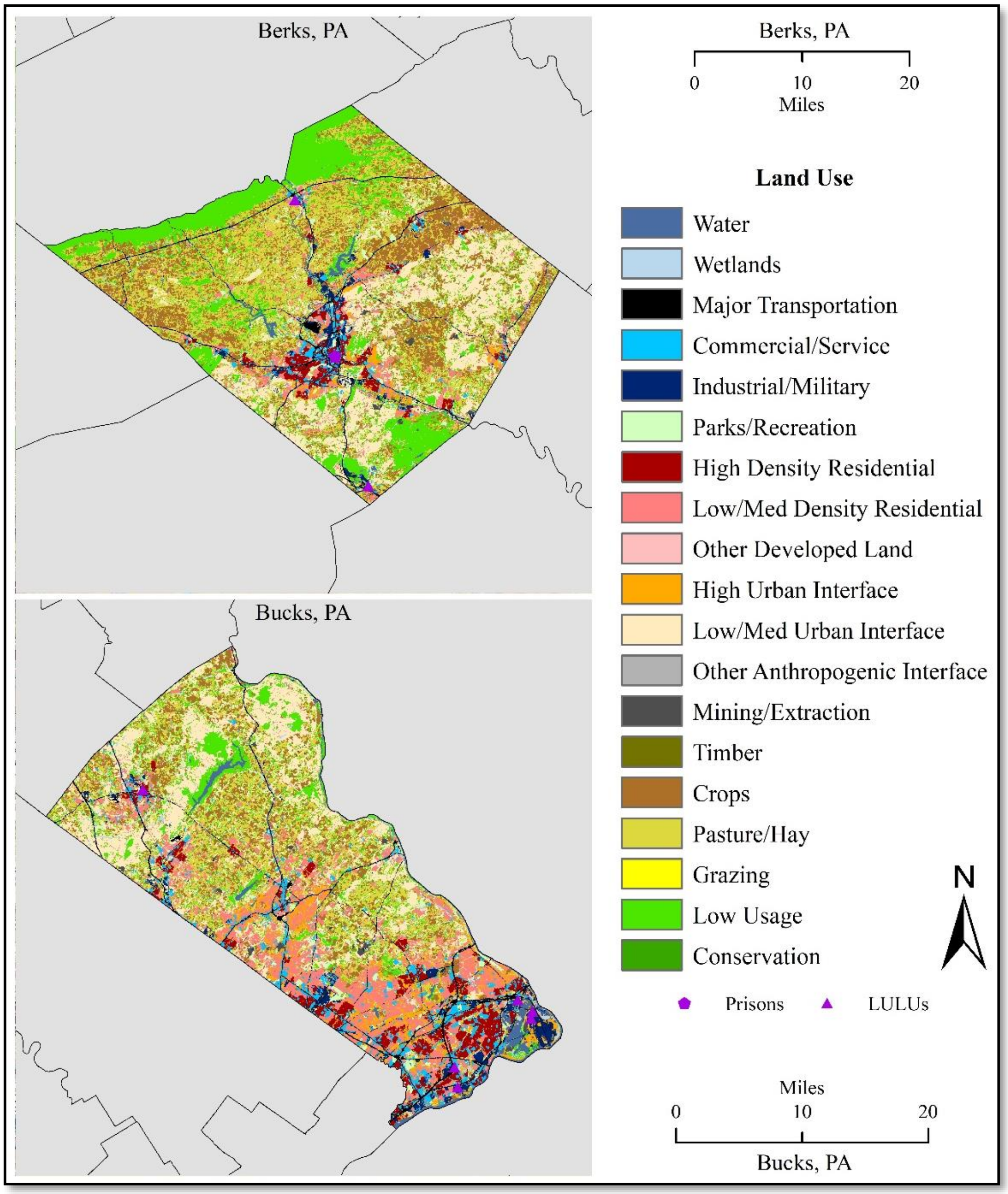

Figure 4.6: Land use maps of Berks and Bucks Counties in Pennsylvania. Berks is the prison site and Bucks is the non-prison site.

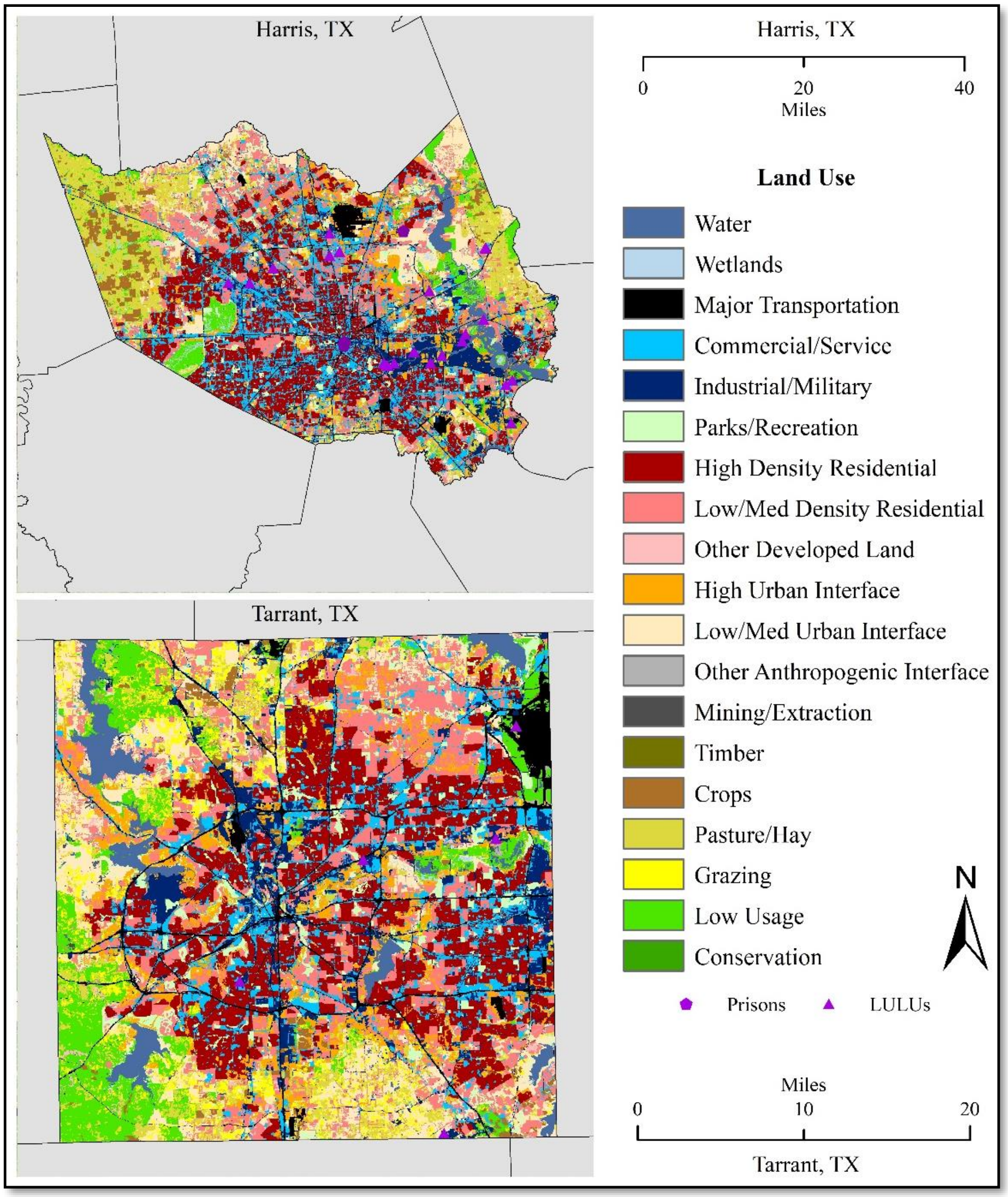

Figure 4.7: Land use maps of Harris and Tarrant Counties in Texas. Harris is the prison site and Tarrant is the non-prison site in Texas.

Land uses in the target study sites vary greatly, with counties ranging from rural to urban and several that are somewhere between the two extremes. In North Carolina, Guilford County does not contain a prison and it represents the highest predicted IAQ values. This is likely a result of the more urban development pattern seen in Figure 4.5. BTEX chemicals and ozone are more prevalent in urban environments at the surface level due to their presence in automotive exhaust. Gaston County contains less area devoted to high density development and a larger percentage of the land devoted to pastureland. Rutherford County represents the most rural study site examined, with the majority of its land devoted to low intensity use or pasture purposes indicating that exhaust and other transportation and population density pollution sources will have a much smaller influence on the air quality. Table 4.5 presents the total reported BTEX emissions for the 2012 reporting year in each study site.

Table 4.5: 2012 reported annual stack, fugitive, and net BTEX air emissions for study sites. Data is rounded to the nearest pound per year (U.S. Environmental Protection Agency, 2016h).

County	Fugitive (lbs/y)	Stack (lbs/y)	Total (lbs/y)
Harris, TX	559948	799142	1359090
Tarrant, TX	89876	210003	299879
Guilford, NC	18582	58583	77165
Berks, PA	4711	20242	24953
Bucks, PA	3033	15492	18524
Rutherford, NC	371	3481	3852
Gaston, NC	750	3028	3778

Berks County in Pennsylvania represents a less urban county than Bucks, however, both represent counties with high density population areas and a small percentage of land devoted to low intensity uses and conservation zones. This makes these counties more susceptible to urban influences on air quality. Berks, PA represents a lower modeled IAQ than in Bucks County, however, the total reported annual air emissions in Berks County are greater than Bucks County (Table 4.5). This indicates that while the population density is influential in the modeled air quality, it is not completely representative of the total air quality within a county.

Harris and Tarrant counties in Texas are the most urban counties examined in this study with both counties having a majority of their land devoted to high density residential development. These counties also represent the highest modeled IAQ values among the study areas, likely a combination of the increased urban influences and the higher number of TRI facilities present in both counties. Harris County (a prison county) represents an IAQ approximately 50 points higher than Tarrant County and exceeds Tarrant County in both number of TRI facilities and total reported emissions for 2012 (Table 4.5).

The socioeconomic environment in each county also varies greatly. Figure 4.8 represents the four sociodemographic characteristics considered by both linear and multinomial regression analyses in this study. Bucks County has the highest mean annual income per capita within the study areas while Rutherford County has the lowest. The income difference encompassed by these study areas is $17,628 but does not reflect the employment patterns observed in them. Counties with prisons have a lower mean income than the corresponding counties without prisons, suggesting that income may have an influence on the placement of prisons and other LULUs. The reported percent asthma expenses do not vary greatly between counties whether prison or non-prison counties. Renter occupied housing also reflects the rural or urban development of each county to a greater extent than the presence of prisons or other LULUs in each county. Outside of North Carolina, the percent of renter occupied housing is higher in prison counties than the corresponding non-prison counties. In North Carolina, the renter occupied housing likely reflects the rural/urban divide between Rutherford County and Guilford County rather than the presence or absence of prison facilities in each county.

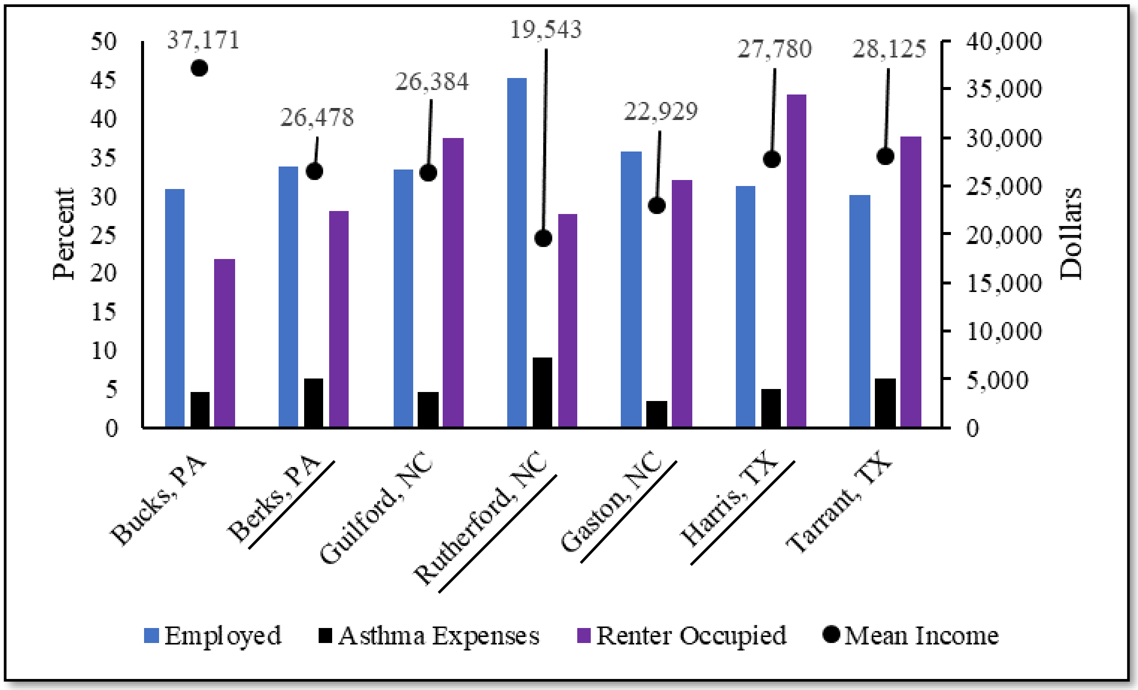

Figure 4.8 Socioeconomic variables which contributed to the location analysis and site selection analysis (U.S. Census Bureau, 2016).
Note: Underline indicates a prison county

CHAPTER 5: PLUME ANALYSIS RESULTS AND DISCUSSION

The site selection model provides a general analysis of the air quality and socioeconomic influences in each county. Building from those results, plume analysis begins to address the role of LULUs on the health and environment in these counties. Plume analysis provides an approximate spatial distribution of emissions data using available environmental and toxin criteria.

5.1: Method Validation

The plume model validation for this study was performed using sites in Harris County, Texas. These sites were analyzed using the methodology described in previous chapters to assess the ability of ALOHA to generate plumes from the available emissions data. Table 5.1 provides the generated dispersion information for the initial sites being considered with annually averaged atmospheric data. These results indicate that the model is viable for emissions sources with large hourly discharges. However, below approximately 1.0 pound per hour, the model reaches its tolerance for BTEX chemicals, and all outputs provide errors related to model accuracy over short dispersion distances. Examination of the initial runs indicates that low concentrations and low wind conditions are likely preventing the model from running effectively. Based on these results, model runs were completed for the annual averaged wind speed using all TRI sources exceeding 1.0 pounds per hour of emissions while a second scenario was performed using the source with the greatest emission and the highest reported wind speed for the associated ASOS site in each county.

Table 5.1: BTEX dispersion distances for sample data in Harris County, Texas. AEGL headings indicate the distance over which the AEGL level is met or exceeded, and nd indicates concentrations were below the mode's limit of quantification.

Toxin	Hourly Emissions (lbs/hour)	AEGL 1 (yards)	AEGL 2 (yards)	AEGL 3 (yards)	Plume Generated?
ETHYLBENZENE	6.692922	13	13	30	No
BENZENE	3.652968	13	13	59	Yes
TOLUENE	2.648402	13	13	13	No
TOLUENE	2.617466	10.9	12	16	No
BENZENE	2.078082	10.9	12	51	No
ETHYLBENZENE	1.180489	13	13	13	No
BENZENE	0.707763	13	13	13	No
ETHYLBENZENE	0.428425	13	13	13	No
BENZENE	0.269064	13	13	13	No
TOLUENE	0.105959	13	13	13	No
ETHYLBENZENE	0.074429	13	13	13	No
O-XYLENE	0.06603	10.9	10.9	11	No
ETHYLBENZENE	0.057078	13	13	13	No
TOLUENE	0.057078	nd	10.9	10.9	No
O-XYLENE	0.052489	10.9	10.9	11	No
XYLENE (MIXED ISOMERS)	0.037785	13	13	13	No
ETHYLBENZENE	0.02911	13	13	13	No
ETHYLBENZENE	0.02911	13	13	13	No
ETHYLBENZENE	0.020947	13	13	13	No
ETHYLBENZENE	0.020091	13	13	13	No
ETHYLBENZENE	0.007192	nd	nd	nd	No
ETHYLBENZENE	0.00411	nd	nd	nd	No
ETHYLBENZENE	0.003995	nd	nd	nd	No
XYLENE (MIXED ISOMERS)	0.002797	13	13	13	No
ETHYLBENZENE	0.001319	nd	nd	nd	No
BENZENE	0.000228	nd	nd	nd	No
ETHYLBENZENE	0.000228	nd	nd	nd	No
ETHYLBENZENE	0.000137	nd	nd	nd	No

5.2: Results Using the Annual Averaged Wind Speed

The annual averaged wind speed represents a worst-case scenario for gas dispersion. Due to decreased wind speeds, the gas spends a greater amount of in the area rather than dispersing quickly and over a larger distance. The high molecular weights of BTEX chemicals also lead to a smaller dispersion radius due to the higher density. Because the gases are much heavier than oxygen, they sink, rather than rise, in the atmosphere and reach the surface sooner. This characteristic of BTEX chemicals is likely an influence on the short distance over which it is dispersed (Tables 5.2 and 5.3). Based on the average annual wind speed only one facility, located in Harris County, produced a plume through the ALOHA model (Figure 5.1). The plume length was approximately 59 yards indicating that while it was quantifiable, it is unlikely to have a significant impact on the surrounding community. Examining the single plume generated, the emissions only impact industrial areas and are only hazardous at approximately a 59-yard radius. The ALOHA model was unable to produce a plume for any other facilities in this analysis.

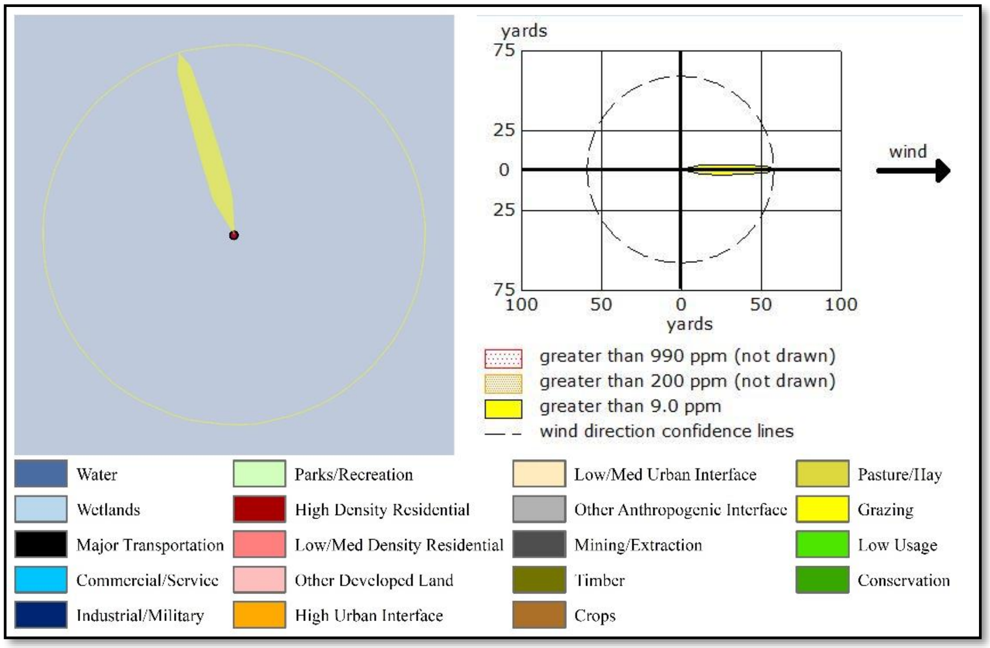

Figure 5.1: Plume generated for a Benzene emitting facility in Harris, County TX. The plume is presented on a land use map (left) to indicate that it is not impacting any residential areas and on a Cartesian grid (right) to indicate the small radius that it impacts.

Table 5.2: Tabulated plume radii for sites emitting greater than 1 pound per hour in Harris County, Texas. * indicates that a plume was generated by ALOHA rather than a simple dispersion radius, nd indicates that the value was below the model's limit of quantification.

County	X°	X'	Y°	Y'	Chemical	Elevation (m)	Emissions (lbs)	Hourly (lbs/hr)	T (°F)	Wind Speed (knots)	Wind Direction (°)	AEGL 1 (yards)	AEGL 2 (yards)	AEGL 3 (yards)
Harris	29	49.0	-95	-6.5	Ethylbenzene	10.12	58630.0	6.69	71.5	0.222	166.05	13	13	30
Harris*	29	44.4	-95	-0.4	Benzene	6.66	32000.0	3.65	71.5	0.222	166.05	13	13	59
Harris	29	37.0	-95	-3.1	Toluene	3.08	23200.0	2.65	71.5	0.222	166.05	13	13	13
Harris	29	44.6	-95	-10.3	Toluene	2.88	22929.0	2.62	71.5	0.222	166.05	11	12	16
Harris	29	44.1	-95	-1.4	Toluene	4.58	21000.0	2.40	71.5	0.222	166.05	13	13	13
Harris	29	43.4	-95	-16.5	Xylene	5.22	19000.0	2.17	71.5	0.222	166.05	13	13	13
Harris	29	43.9	-95	-9.3	Benzene	7.28	18204.0	2.08	71.5	0.222	166.05	11	12	51
Harris	29	42.0	-95	-2.2	Toluene	7.62	16084.0	1.84	71.5	0.222	166.05	13	13	13
Harris	29	45.4	-95	-0.8	Toluene	7.03	11400.0	1.30	71.5	0.222	166.05	nd	11	12
Harris	29	43.4	-95	-12.5	Ethylbenzene	5.14	10341.1	1.18	71.5	0.222	166.05	13	13	13
Harris	29	47.9	-95	-17.8	Xylene	12.68	10228.0	1.17	71.5	0.222	166.05	13	13	13
Harris	29	38.6	-95	-15.2	Xylene	11.04	10200.0	1.16	71.5	0.222	166.05	13	13	13
Harris	29	40.4	-95	-1.5	Xylene	5.46	9719.6	1.11	71.5	0.222	166.05	13	13	13
Harris	29	52.7	-95	-32.7	Xylene	30.13	19261.0	2.20	71.5	0.397	174.20	13	13	13
Harris	29	52.1	-95	-36.5	Xylene	35.42	17153.0	1.96	71.5	0.397	174.20	12	12	13
Harris	29	52.8	-95	-35.3	Xylene	34.61	11845.9	1.35	71.5	0.397	174.20	13	13	13
Harris	29	51.8	-95	-36.4	Xylene	34.72	11583.0	1.32	71.5	0.397	174.20	13	13	13
Harris	29	54.5	-95	-31.7	Xylene	39.26	10075.5	1.15	71.5	0.397	174.20	13	13	13
Harris	29	55.2	-95	-31.5	Toluene	33.91	9250.0	1.06	71.5	0.397	174.20	13	13	13

5.3: Results Using the Maximum Wind Speed

Using the same procedure as the annual averaged wind speed, the ALOHA model was also used to generate the dispersion pattern using the maximum recorded wind speed for the year 2012 at the site with the highest emissions level in each county. This analysis revealed that at high wind speeds, airborne toxins disperse more efficiently and do not produce any zones where adverse health impacts would be anticipated. Table 5.4 shows the plume radii using the highest wind speed detected; no other variables were changed to ensure only the influence of wind speed was evaluated. These results show that in windier conditions the plumes will disperse more quickly than at lower wind speeds resulting in safer living conditions for the population.

5.4: Limitations

This analysis has several limitations that can significantly alter the results. The atmospheric data was obtained using the nearest in-county ASOS station, meaning that the model was performed under the condition that weather was uniform across the entire county. The annual averages of temperature, wind speed, and wind direction also significantly influence the dispersion patterns as variations in wind speed alter the rate at which the chemicals are dispersed. The model also does not account for the influence of land cover or elevation (beyond the physical elevation of the source and stack height), both of which significantly influence the dispersion pattern of the chemical plume. Nonetheless, the results provide a means of evaluating the potential risk to residents downwind of TRI facilities.

Table 5.3: Tabulated plume radii for sites emitting greater than 1.0 pound per hour or the highest amount of BTEX chemicals within the county for Tarrant, Guilford, Gaston, Bucks, and Berks Counties. No plumes were generated based on the emissions from these counties.

County	X°	X'	Y°	Y'	Chemical	Elevation (m)	Emissions (lbs)	Hourly (lbs/hr)	T (°F)	Wind Speed (knots)	Wind Direction (°)	AEGL 1 (yards)	AEGL 2 (yards)	AEGL 3 (yards)
Tarrant	32	45.0	-97	-2.5	Toluene	168.25	10000.0	1.14	67.6	0.152	181.92	13	13	13
Tarrant	32	37.6	-97	-19.1	Xylene	216.52	9973.0	1.14	67.6	0.208	178.48	13	13	13
Guilford	36	3.7	-79	-50.0	Toluene	260.10	11835.0	1.35	59.9	0.488	200.89	12	12	13
Guilford	35	56.6	-80	0.0	Toluene	270.54	8150.0	0.93	59.9	0.488	200.89	12	12	13
Gaston	35	13.9	-81	-19.1	Toluene	262.57	3740.0	0.43	62.1	0.434	168.55	11	12	12
Berks	40	9.8	-75	-52.5	Toluene	171.52	6610.0	0.75	55.2	0.301	215.50	13	13	13
Bucks	40	11.6	-74	-47.2	Toluene	12.74	5109.0	0.58	55.2	0.280	191.92	13	13	13

Table 5.4: Tabulated results for the extreme wind case scenario analysis. Plume radii for sites emitting greater than 1.0 pound per hour or the highest amount of BTEX chemicals within the county for all target counties. No plumes or exposure radii were generated during this analysis. nd indicates that the concentration were below the models limit of quantification.

County	X°	X'	Y°	Y'	Chemical	Elevation (m)	Emissions (lbs)	Hourly (lbs/hr)	T (°F)	Wind Speed (knots)	Wind Direction (°)	AEGL 1 (yards)	AEGL 2 (yards)	AEGL 3 (yards)
Harris	29	49.0	-95	-6.5	Ethylbenzene	10.12	58630.0	6.69	71.5	39.250	166.05	nd	nd	nd
Harris	29	44.4	-95	-0.4	Benzene	6.66	32000.0	3.65	71.5	39.250	166.05	nd	nd	nd
Tarrant	32	45.0	-97	-2.5	Toluene	168.25	10000.0	1.14	67.6	51.200	181.92	nd	nd	nd
Guilford	36	3.7	-79	-50.0	Toluene	260.10	11835.0	1.35	59.9	40.230	200.89	nd	nd	nd
Gaston	35	-59.8	-81	-19.1	Toluene	262.57	3740.0	0.43	62.1	58.540	168.55	nd	nd	nd
Berks	40	9.8	-75	-52.5	Toluene	171.52	6610.0	0.75	55.2	73.430	215.50	nd	nd	nd
Bucks	40	11.6	-74	-47.2	Toluene	12.74	5109.0	0.58	55.2	34.140	191.92	nd	nd	nd

CHAPTER 6: CONCLUSIONS

The goal of this study was to address the relationship between prisons, other LULUs, and air quality in the surrounding communities using interdisciplinary techniques including plume dispersion analysis, linear and multinomial regression, and geographic information sciences. Using a combination of socioeconomic, health outcome, and environmental variables examined in this study, several models were produced to address the socioeconomic and environmental relationships between prisons, LULUs, and the air quality in the surrounding community. The spatial patterns were addressed at three scales, each informing the development of the next.

Location analysis was performed at the national level, using the socioeconomic and Medicare indicators to examine the large-scale spatial trends between prisons and BTEX emitting TRI facilities (the metric LULU in this study). The multinomial regression model produced results that were successful in identifying counties with neither a prison nor a TRI; however, the model yielded poor accuracy when identifying the counties with prisons and/or TRI facilities. The multinomial regression did show that income has a positive relationship with the presence of prisons and TRI facilities, indicating that higher income correlates with the presence of prisons and LULUs at the county level. Examining the location analysis model in combination with the Poisson distribution indicates a positive relationship between the presence of prison facilities and the presence of one or more TRI facilities in the same county. Both components of the location analysis indicate that TRI facilities are placed in a very small portion of the counties within the United States, a finding that is consistent with Moore's (2017) study examining the implications of Executive Order 12898. The distribution appears to be scattered throughout the nation, but the specific placement of facilities falls within a small subset of the overall counties.

The relationship between income and the presence of these facilities is positive in both multinomial regression models (equations 3 – 10). This indicates that the presence of prisons and LULUs is correlated with higher incomes rather than lower income levels as suggested by Hoyman and Weinberg (2006), Eason (2010), Al-Kohlani and Campbell (2016), and Stewart et al. (2017) where the findings indicate that prisons are sited in disadvantaged communities. The location analysis, therefore, indicates that while income does not present the anticipated relationship with LULUs, there is a relationship between the placement of prisons and the placement of other LULUs within the same county. This confirms the initial hypothesis that the presence of one type of LULU begets other. The negative relationship between income and IAQ is consistent with studies such as Hoyman and Weinberg (2006) and Eason (2010) in that a lower IAQ indicates higher air quality in the area.

The negative correlation between prisons and IAQ is opposite the anticipated results, however, other LULUs remain positively correlated with IAQ based on equation 11. This suggests that while prisons contribute positively to air quality, other LULUs negatively impact predicted air quality. IAQ is negatively related to air quality in that a higher IAQ is indicative of a more hazardous level of airborne toxins; for this reason, this study suggests that risk of exposure to airborne toxins is increased when prisons or LULUs are present in a county. This analysis is consistent with the findings of Al-Kohlani and Campbell (2016) and Stewart et al (2014) which suggest that environmental burdens are associated with less affluent populations, while the relationship with income is not consistent, the incarcerated prisoners are neither affluent nor capable of influencing their environment. Based on these results, site selection analysis indicates that while income can be correlated with a larger number of LULUs, the presence of non-prison LULUs is correlated with decreased air quality. These results highlight a contradiction between the location and site selection analysis. While income correlates with increased air quality and the presence of LULUs, the presence of LULUs correlates negatively with air quality.

The relationship between prisons and LULUs, air quality, and respiratory health is positive for both the location and site selection analyses. This suggests that higher asthma expenses correlate with decreasing air quality as well as with the presence of prisons and other LULUs. All equations except the location analysis using IAQ variables for Pennsylvania (equation 5) suggest a negative relationship between asthma and LULUs The variation in this equation is likely an artifact of poor suitability rather than the influence of the variables in Pennsylvania. The positive relationship with IAQ is not unexpected as the Air Quality Index (used in model calibration) is an index designed to communicate risk of adverse respiratory health impacts to the populations due to air quality measurements.

Plume analysis of the TRI facilities within each study area was successfully performed using the ALOHA model. However, the results indicate that it is unlikely that the BTEX TRIs considered in the study contribute to the respiratory health impacts. Only one plume was generated using ALOHA; the other sites produced radii that did not meet the model's internal quality assurance standards. The plume (and radii) produced using the BTEX emissions indicate that the airborne toxins do not travel more than approximately 60 yards from the facility under ideal dispersion conditions. The annual wind speed averages yielded extremely low wind speeds for the model, resulting in very little dispersion of the chemicals; however, using the maximum reported wind speed for the year yielded concentrations below the ALOHA model's limit of quantification. This indicates that at low wind speeds, the toxins are not dispersed in a way that will adversely impact the local population and, under very strong winds, the chemicals are dispersed very quickly resulting in little accumulation in any single area.

Based on the plume analysis, the higher asthma related expenses in prison counties is unlikely to be related to the emissions from the BTEX facilities being examined. With the exception of North Carolina, emissions are higher in prison counties than in the associated non-prison county. Despite the increase in emissions, the exposure predicted around each facility is insignificant at either extreme of the atmospheric conditions examined. It can therefore be concluded that the increase in asthma related expenses is not related to the modeled exposure to BTEX chemical emissions. These results are not comprehensive of all methods of exposure within the United States, however they indicate that the chemicals being examined in this study are unlikely to influence the respiratory health of the target populations.

6.1: Limitations

The study does have several limitations, particularly with regard to the plume dispersion model. The use of single atmospheric data sources for all emissions points within each county limits the accuracy of any plume directions that are produced because the wind was not accounted for at the local level. The ALOHA model, unlike the regulatory model AERMOD, also does not account for the impacts of terrain and land cover surrounding the facility which can significantly influence the distance and concentration of chemical dispersion. The AERMOD preprocessor AERMET is also capable of using hourly ASOS data for the entire year to produce a meaningful wind surface at each location. Due to technical failures in the AERMOD system, it became necessary to use the ALOHA model its place. ALOHA does not process the 1-minute observations and so it was necessary to use the annual averages at point locations as representative of the counties' atmospheric conditions. In future studies, it would be preferable to use the AERMOD model. The ALOHA model is viable for single source analysis and for its intended purpose as an emergency management model, but it is not ideal for multiple continuous emissions sources.

The examination of BTEX chemicals in this study was designed based on the health impacts of these toxins. This approach could be improved by using the chemical emitted at the greatest amount for each facility rather than predetermining the chemicals. This approach would be consistent with the approaches by Chakraborty and Armstrong (1997) and Chakraborty (2001). The analyses in these studies yielded plume dispersions for each facility by examining the chemical being released in the largest quantity; this ensured that the most impactful toxin at each location was being modeled.

The exposure levels modeled indicate that communities with prisons are not likely to be exposed to higher levels of BTEX chemicals than comparable non-prison communities. However, despite the similarity in exposure, the relationship between prison communities and respiratory health indicators suggests that residents of prison counties are more likely to experience asthma related medical conditions that require treatment. It is also important to note that the positive relationship with asthma related Medicare expenses does not account for the portion of the population using private medical insurance.

Additionally, the scale of analysis likely influenced the findings, despite being the only suitable level based on available data. The county scale represents the only available level at which health data is available publicly. However, the influences of the examined toxins and sociodemographic variables are likely more prominent at a finer scale of analysis. It would have been beneficial for this study to examine the variables at the zipcode or census tract level in data was available.

6.2: Extending the Research

The results of this research set a foundation for future work. First, an examination of the relationship between prisons, TRIs, and asthma related expenses at a finer scale (such as zipcodes or census tracts) would allow for assessment of more nuanced local relationships between the factors considered here. It would also be useful to compare the asthma related expenses outside of prison facilities to those of inmates in the facility to assess the differences in air quality impacts between the two different groups of residents. Second, repetition of plume analysis using a seasonal or monthly approach would also likely foster understanding of exposure at each location as it would account for seasonal influences on the chemical dispersion. Finally, evaluation of other airborne industrial toxins may provide an opportunity to understand the range of potential risks to the populations in an area. Chakraborty and Armstrong (1997) and Chakraborty (2001) used the ALOHA model to evaluate the toxins released from TRI facilities with a successful plume generation. The approach used in these studies, however, involved examining the toxin released at the greatest volume rather than a particular toxin (or set of toxins) (Chakraborty and Armstrong, 1997; Chakraborty, 2001). In this way, the studies examined the chemical most likely to impact the surrounding area without assumptions about the role of each toxin.

6.3: Contributions of this work

The conclusions of this study suggest that counties with prisons are more likely to also contain other LULUs; in this case industrial LULUs emitting BTEX chemical were specifically examined. These facilities also tend to emit chemicals in greater quantity than in counties without a prison (the exception being North Carolina). Prison counties and counties with other LULUs also experience higher asthma related expenses than non-prison counties indicating that the respiratory health of counties with prisons is being impacted by their presence. In this way, it suggests that the outdoor air quality at prison facilities is worse than outside of the facilities. It also suggests a further need to study outdoor air quality at prison facilities in a similar way to the indoor air quality. Current literature suggests comprehensive studies of the indoor air quality in prison facilities (March et al., 2000; Ofungwu, 2005; Binswanger et al., 2009; Vinkels Melchers et al., 2013; Urrego et al., 2015; Reis et al., 2016), yet there are no outdoor air quality studies to compare this work to. Many of these indoor air quality studies also suggest that indoor conditions decrease the respiratory health of inmates. However, these results indicate that the outdoor air quality is also likely to contribute to their health outcomes.

The positive relationship between income and LULU presence is contradictory to much of the current research (Hoyman and Weinberg, 2006; Eason, 2010; Stewart et al., 2014; Al-Kohlani and Campbell, 2016). Based on this relationship, and its contradiction of current literature, it would be beneficial to examine the context of each site in greater detail than previously heretofore undertaken. The increased consideration given to context at each location would provide a more complete understanding of factors influencing the placement of LULU facilities (beyond the role of economic affluence).

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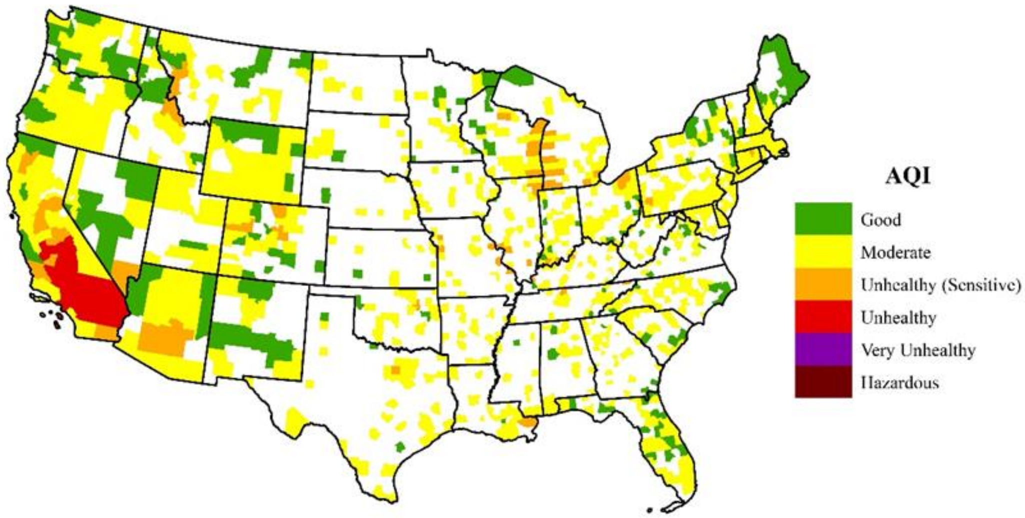
APPENDIX A

Mapped AQI values reported by the EPA for 2012.



APPENDIX B

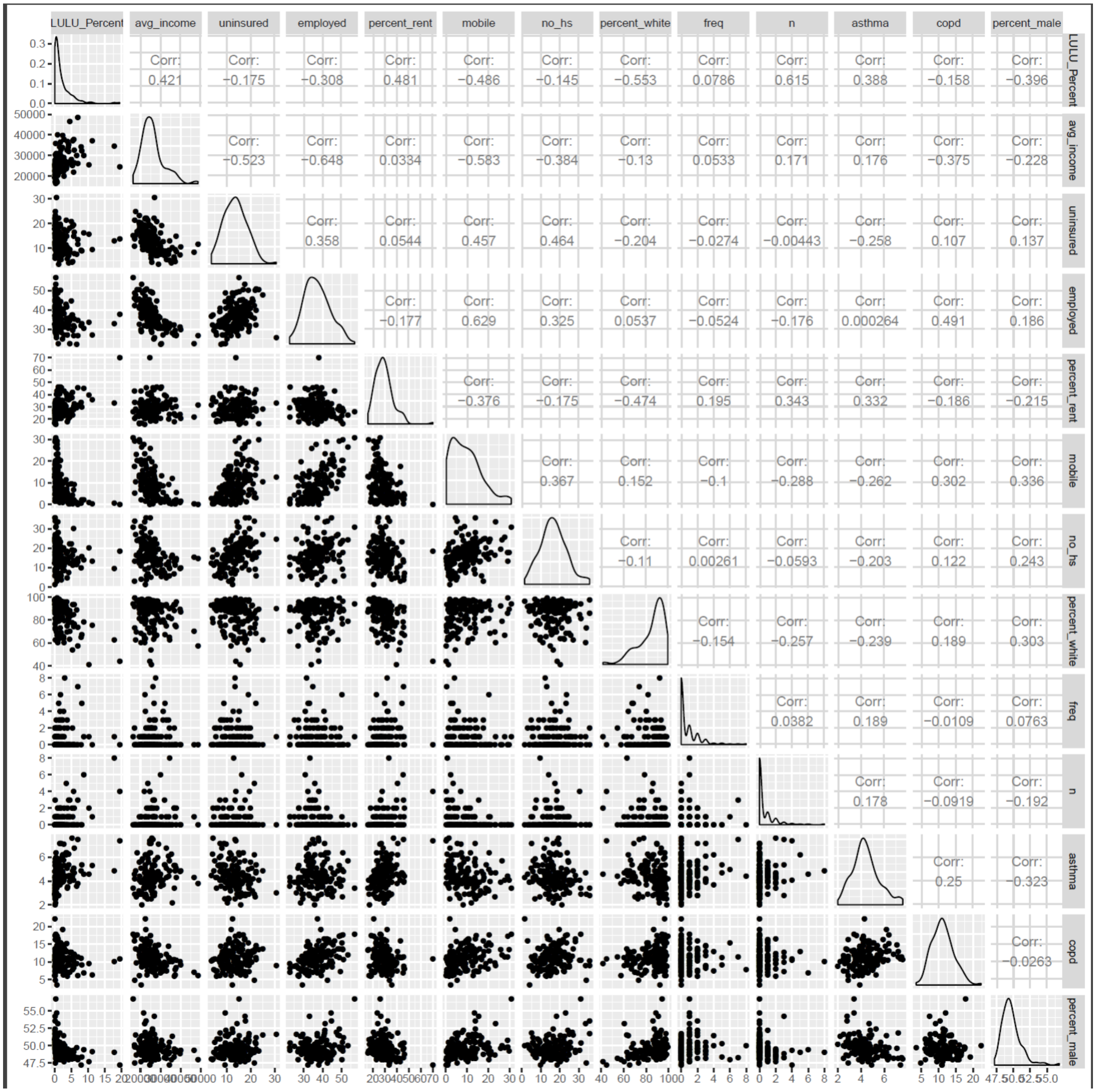
Descriptive information about data sources, application, and type for model variables and outputs.

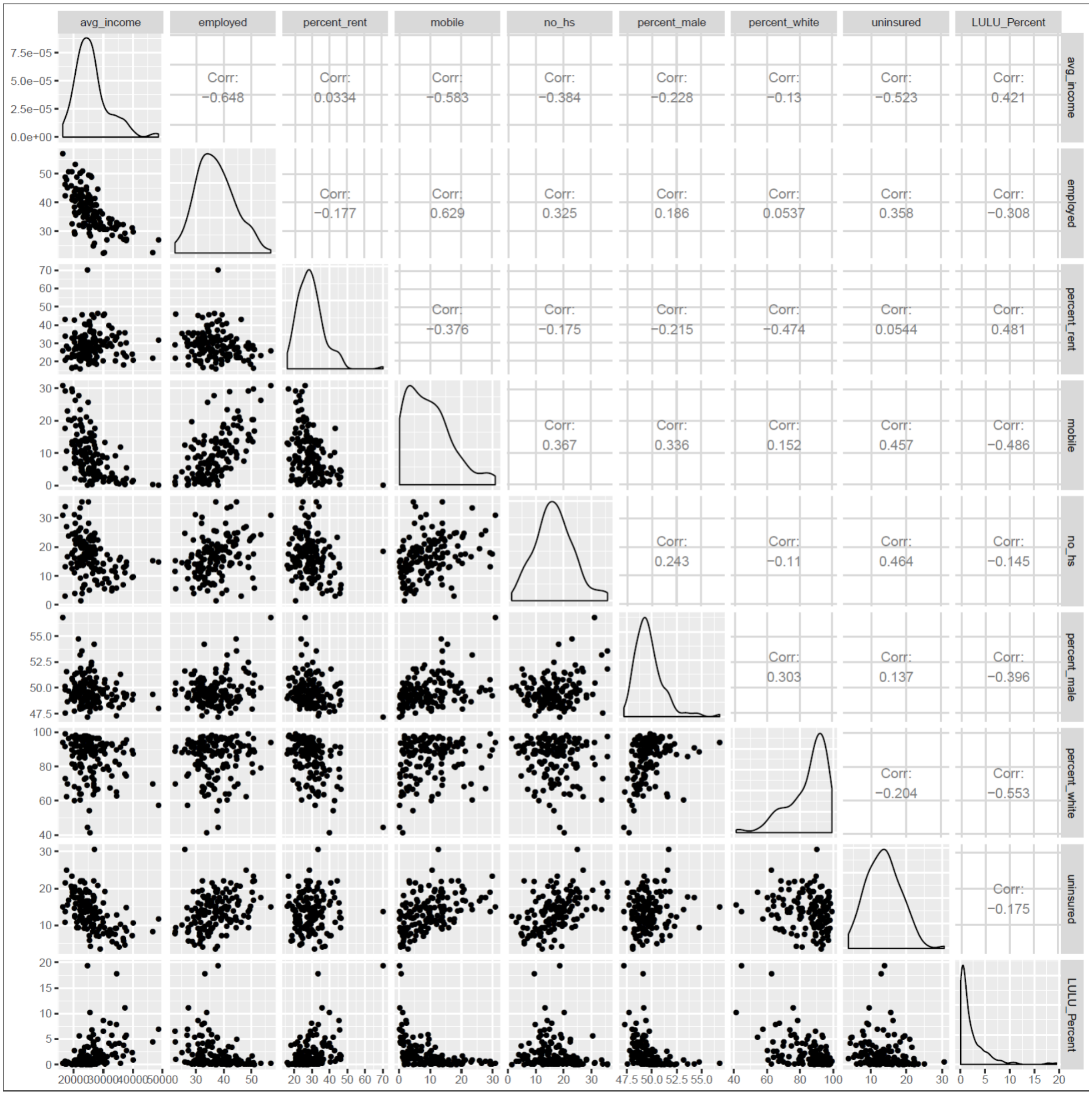
Short Name	Description	Source	Analysis Type
Income	Mean Income Per Capita	US Census (2012 5-Year Estimates)	Site Selection, Location Analysis
Education	Percent of Population Achieving Less Than a High School Diploma	US Census (2012 5-Year Estimates)	Site Selection, Location Analysis
Male	Percent of Population that is Male^	US Census (2012 5-Year Estimates)	Site Selection, Location Analysis
White	Percent of Population White Only^	US Census (2012 5-Year Estimates)	Site Selection, Location Analysis
Uninsured	Percent of Population Uninsured	US Census (2012 5-Year Estimates)	Site Selection, Location Analysis
Employed	Percent of Population Employed	US Census (2012 5-Year Estimates)	Site Selection, Location Analysis
Renter	Percent of Housing That is Renter Occupied^	US Census (2012 5-Year Estimates)	Site Selection, Location Analysis
Mobile Homes	Percent of Housing That is Mobile Homes^	US Census (2012 5-Year Estimates)	Site Selection, Location Analysis
Total Pop	Total Population	US Census (2012 5-Year Estimates)	Data Normalization
Total Housing	Total Occupied Housing	US Census (2012 5-Year Estimates)	Data Normalization
LULU area	Percent Land Use That is Industrial/Military, Commercial/Service, and Mining/ Extraction	USGS	Site Selection, Location Analysis
LULUs	BTEX TRI Location Data	US EPA	Plume Model, Site Selection, Location Analysis

Short Name	Description	Source	Analysis Type
Prison	Prison Location Data	John Kerbs and Jennifer Jolley, Publicly Available DOC Data	Plume Model, Site Selection, Location Analysis
AQI/IAQ	Air Quality Index (calibration) or Influence on Air Quality as Output	US EPA/Modeled	Site Selection, Location Analysis
Asthma	Asthma Percent (Medicare)	US Medicare Database	Site Selection, Location Analysis
COPD	COPD Percent (Medicare)	US Medicare Database	Site Selection, Location Analysis
0	No Prisons or LULUs	Modeled	Location Analysis
1	Prison Only	Modeled	Location Analysis
3	LULUs Only	Modeled	Location Analysis
4	Both Prisons and LULUs	Modeled	Location Analysis

APPENDIX C

Pairwise variable screening results. Correlations greater than 0.25 were excluded from analysis.

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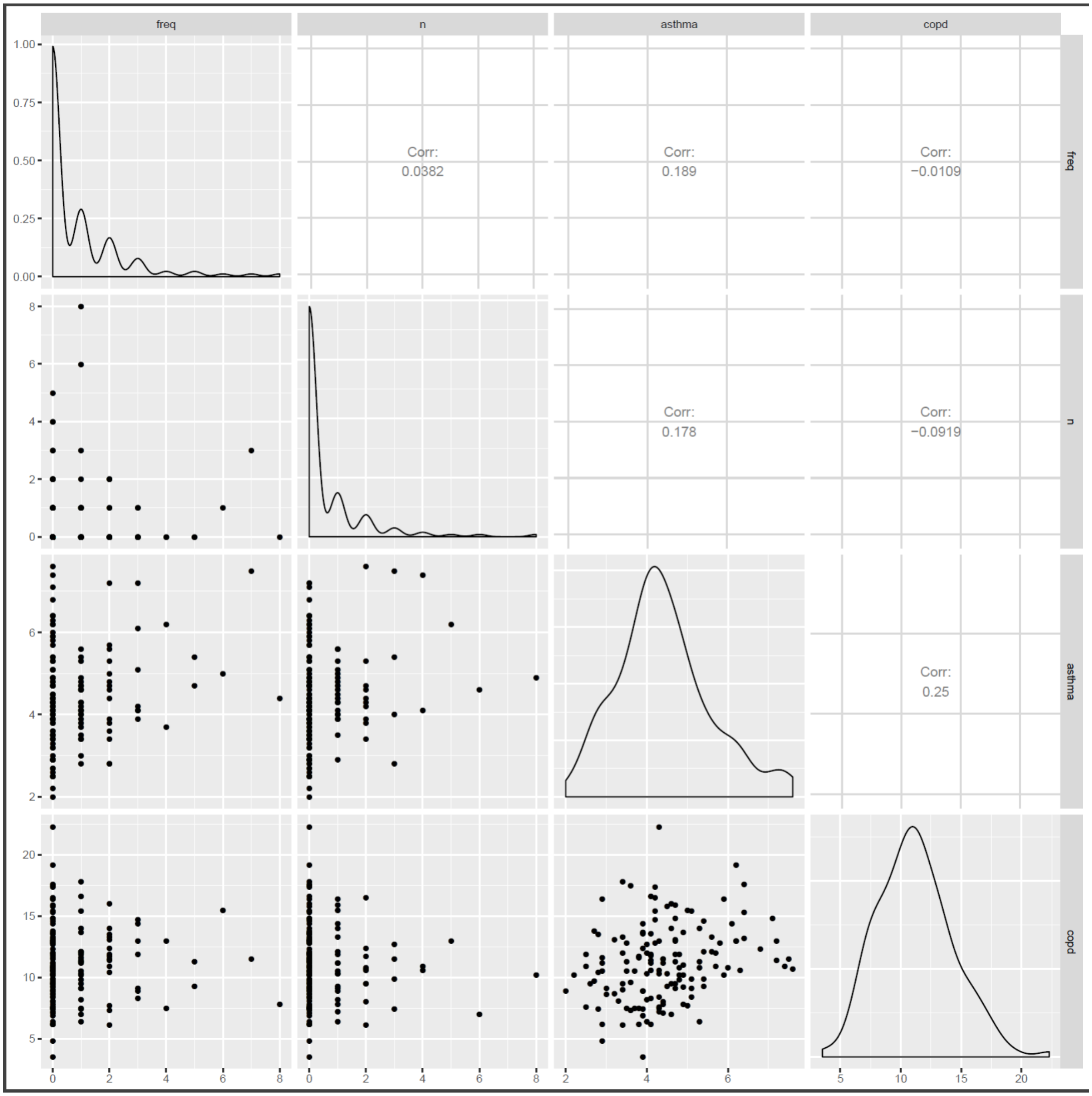
employed
percent_rent
mobile
no_hs
percent_male
percent_white
uninsured
LULU_Percent
Corr: −0.648
Corr: 0.0334
Corr: −0.583
Corr: −0.384
Corr: −0.228
Corr: −0.13
Corr: −0.523
Corr: 0.421
Corr: −0.177
Corr: 0.629
Corr: 0.325
Corr: 0.186
Corr: 0.0537
Corr: 0.358
Corr: −0.308
Corr: −0.376
Corr: −0.175
Corr: −0.215
Corr: −0.474
Corr: 0.0544
Corr: 0.481
Corr: 0.367
Corr: 0.336
Corr: 0.152
Corr: 0.457
Corr: −0.486
Corr: 0.243
Corr: −0.11
Corr: 0.464
Corr: −0.145
Corr: 0.303
Corr: 0.137
Corr: −0.396
Corr: −0.204
Corr: −0.553
Corr: −0.175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copd
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Corr:
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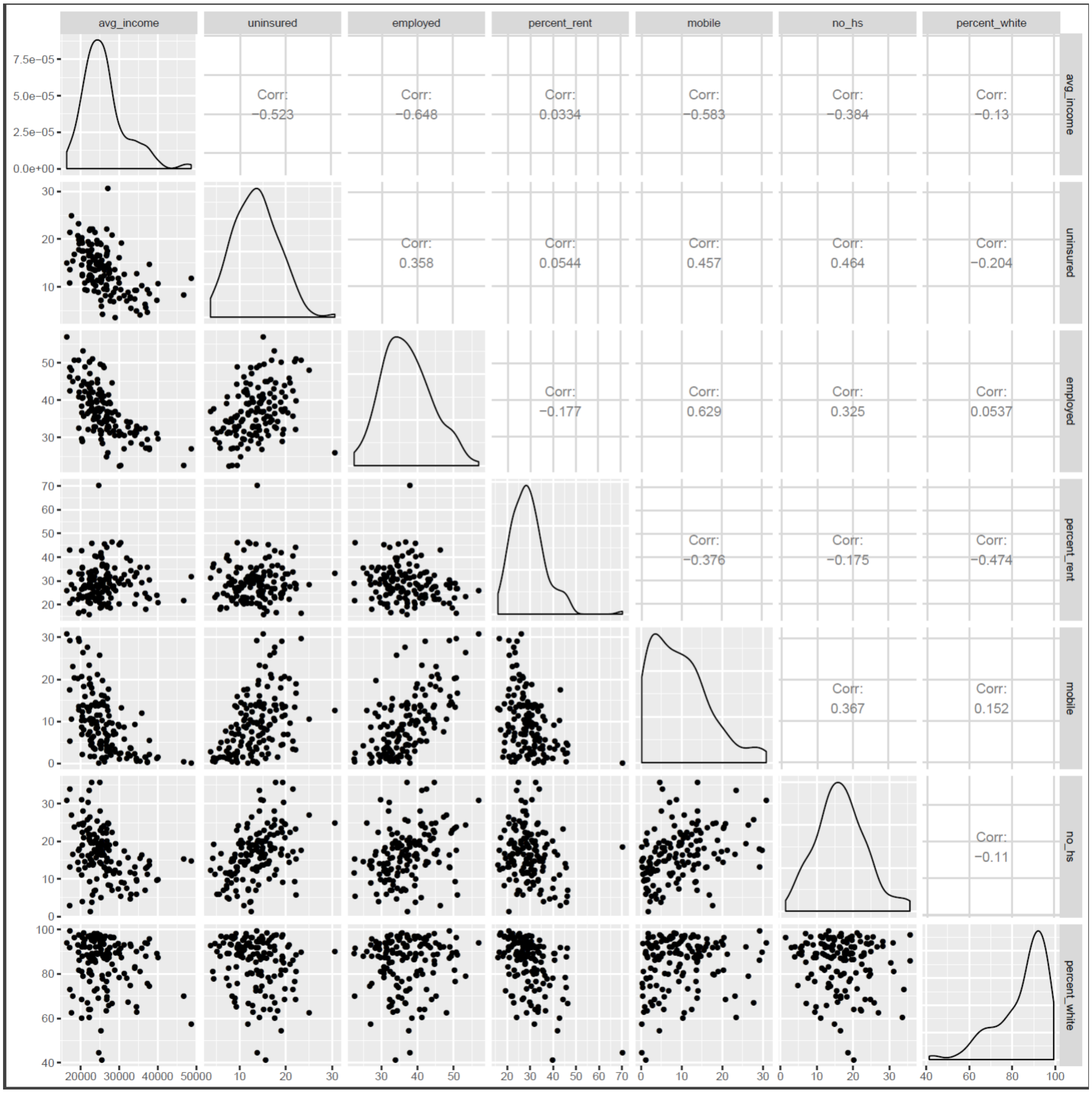
−0.0919
Corr:
0.25


avg_income
uninsured
employed
percent_rent
mobile
no_hs
percent_white
Corr:
−0.523
Corr:
−0.648
Corr:
0.0334
Corr:
−0.583
Corr:
−0.384
Corr:
−0.13
Corr:
0.358
Corr:
0.0544
Corr:
0.457
Corr:
0.464
Corr:
−0.204
Corr:
−0.177
Corr:
0.629
Corr:
0.325
Corr:
0.0537
Corr:
−0.376
Corr:
−0.175
Corr:
−0.474
Corr:
0.367
Corr:
0.152
Corr:
−0.11

APPENDIX D

Counties used to calibrate the site selection model based on random selection. Three counties were selected in each of the 48 conterminous states.

Calibration Counties

Baldwin, AL
Colbert, AL
Shelby, AL
Polk, AR
Faulkner, AR
Arkansas, AR
Santa Cruz, AZ
Gila, AZ
Pima, AZ
Trinity, CA
Tuolumne, CA
Yolo, CA
El Paso, CO
Garfield, CO
La Plata, CO
Middlesex, CT
New London, CT
Tolland, CT
Sussex, DE
Kent, DE
New Castle, DE
Marion, FL
Santa Rosa, FL
Lee, FL
Pike, GA
Chatham, GA
Walker, GA
Pottawattamie, IA
Van Buren, IA
Palo Alto, IA
Twin Falls, ID

Ada, ID
Benewah, ID
Randolph, IL
Tazewell, IL
Madison, IL
Shelby, IN
Monroe, IN
Elkhart, IN
Trego, KS
Sumner, KS
Ford, KS
Trigg, KY
Morgan, KY
Henderson, KY
Jefferson, LA
Rapides, LA
Livingston, LA
Essex, MA
Berkshire, MA
Hampden, MA
Baltimore, MD
Cecil, MD
Montgomery, MD
Aroostook, ME
Oxford, ME
York, ME
Wexford, MI
Manistee, MI
Washtenaw, MI
Washington, MN
Hennepin, MN
Lake, MN
Stoddard, MO
Callaway, MO
Iron, MO
Jones, MS
Forrest, MS
Jackson, MS
Cascade, MT
Fergus, MT
Silver Bow, MT
Franklin, NC
Graham, NC

Granville, NC
Burleigh, ND
Williams, ND
Cass, ND
Garden, NE
Dawson, NE
Sarpy, NE
Grafton, NH
Coos, NH
Rockingham, NH
Atlantic, NJ
Middlesex, NJ
Cumberland, NJ
Chaves, NM
Sandoval, NM
Bernalillo, NM
Clark, NV
White Pine, NV
Mineral, NV
Kings, NY
Albany, NY
Essex, NY
Washington, OH
Clark, OH
Athens, OH
Creek, OK
Caddo, OK
Cleveland, OK
Multnomah, OR
Lane, OR
Crook, OR
Greene, PA
Lebanon, PA
Centre, PA
Kent, RI
Providence, RI
Washington, RI
Oconee, SC
Abbeville, SC
Greenville, SC
Meade, SD
Minnehaha, SD
Custer, SD

Union, TN
Shelby, TN
Anderson, TN
Nueces, TX
Hunt, TX
Collin, TX
Cache, UT
Weber, UT
Wayne, UT
Fauquier, VA
Loudoun, VA
Frederick, VA
Rutland, VT
Bennington, VT
Chittenden, VT
Lewis, WA
Snohomish, WA
Clallam, WA
Kewaunee, WI
Waukesha, WI
Monroe, WI
Kanawha, WV
Hancock, WV
Marshall, WV
Uinta, WY
Platte, WY
Carbon, WY

APPENDIX E

Table of ASOS monitoring sites used to obtain annual average and maximum wind speed and direction for plume analysis.

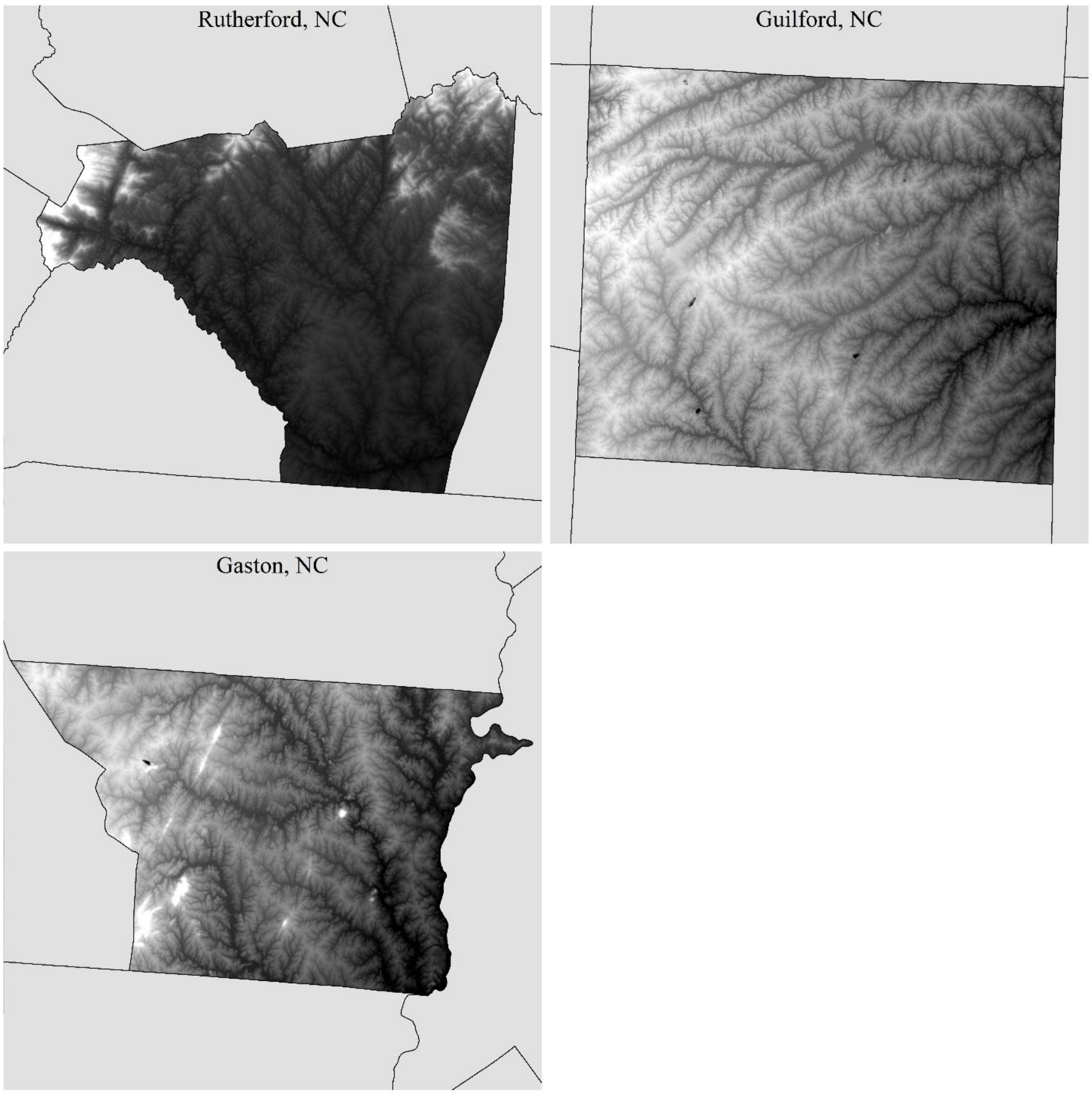
State	County	Prison	4 Digit Code	Location
Pennsylvania	Berks	Yes	KRDG	Reading
Pennsylvania	Bucks	No	KDYL	Doylestown
North Carolina	Gaston	Yes	KAKH	Gastonia
North Carolina	Guilford	No	KGSO	Greensboro
Texas	Harris	Yes	KIAH	Houston-Bush Intercontinental
Texas	Harris	Yes	KDWH	Davie-Wayne Hooks
Texas	Harris	Yes	KHOU	William P. Hobby
Texas	Tarrant	No	KGKY	Arlington
Texas	Tarrant	No	KAFW	Fort Worth Alliance
Texas	Tarrant	No	KFWS	Fort Worth Meacham

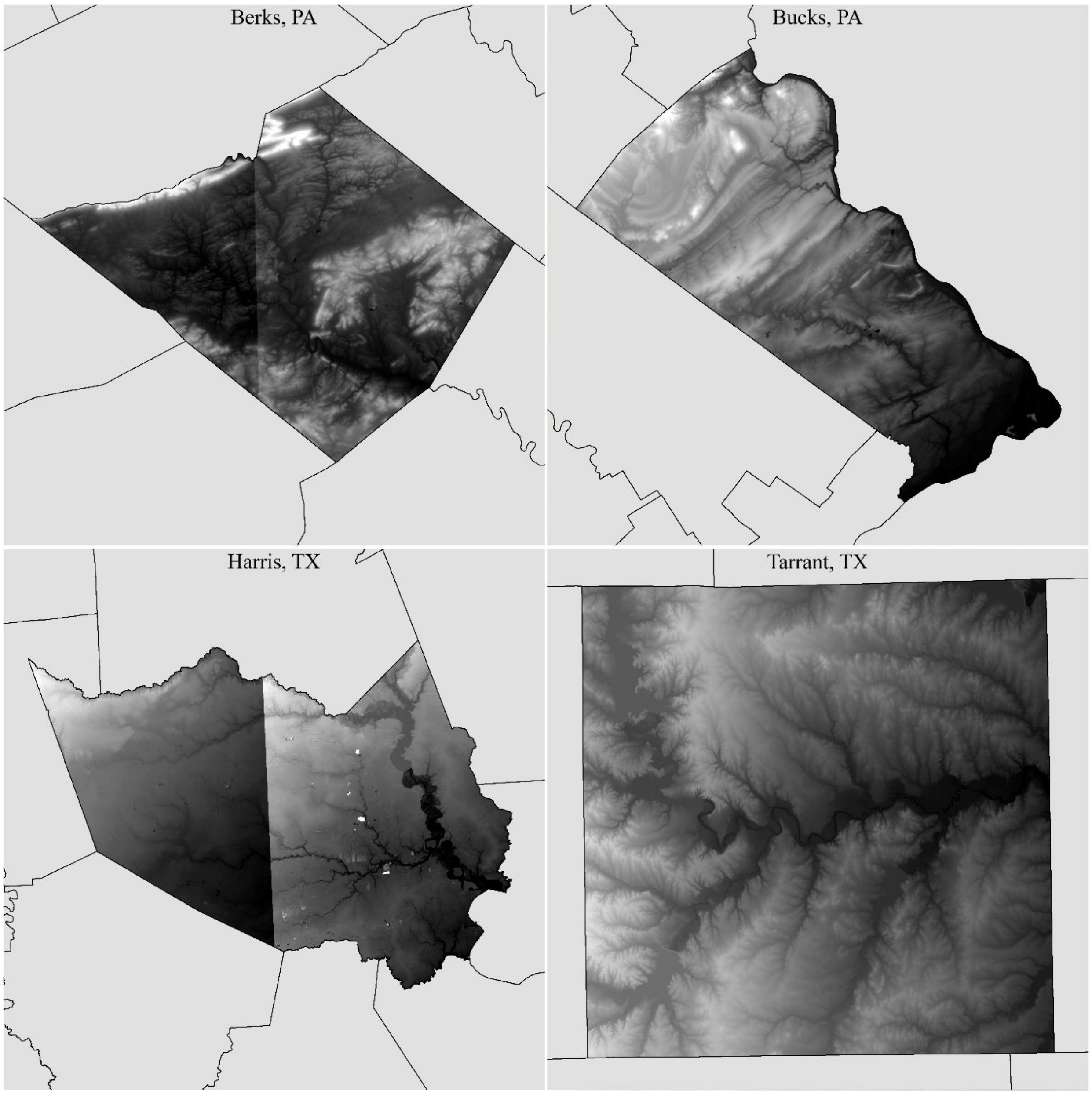
APPENDIX F

Map of the U.S. climatological divisions used to obtain average annual temperature
(National Oceanic and Atmospheric Administration, n.d.)

APPENDIX G

Digital elevation models for all study sites examined in this study. Data was extracted to source points and imported directly into ALOHA for this model and the models were not directly considered in analysis.




Berks, PA
Bucks, PA
Harris, TX
Tarrant, TX

APPENDIX H

Poisson probability tables calculated during location analysis.

Three State Counties With Prisons					
Number of LULUs	Number of Counties	Total LULUs	Observed Probability	Poisson Probability	Expected Number of LULUs
0	102	102	0.7445	0.4750	65
1	19	19	0.1387	0.3536	48
2	7	14	0.1022	0.1316	18
3	3	9	0.0657	0.0327	4
4	1	4	0.0292	0.0061	1
5	2	10	0.0730	0.0009	0
6	1	6	0.0438	0.0001	0
9	1	9	0.0657	0.0000	0
31	1	31	0.2263	0.0000	0
Grand Total	137	102			
N	137				
F	102				
e	2.72				
z	0.7445				

Three State Counties Without Prisons					
Number of LULUs	Number of Counties	Total LULUs	Observed Probability	Poisson Probability	Expected Number of LULUs
0	232	232	0.8788	0.7729	204
1	15	15	0.0568	0.1991	53
2	10	20	0.0379	0.0256	7
3	2	6	0.0076	0.0022	1
4	2	8	0.0076	0.0001	0
5	1	5	0.0038	0.0000	0
6	1	6	0.0038	0.0000	0
8	1	8	0.0038	0.0000	0
Grand Total	264	68			
N	264				
F	68				
e	2.72				
z	0.2576				

Pennsylvania Counties With Prisons					
Number of LULUs	Number of Counties	Total LULUs	Observed Probability	Poisson Probability	Expected Number of LULUs
0	18	18	0.6207	0.5194	15
1	7	7	0.2414	0.3403	10
2	2	4	0.1379	0.1115	3
3	1	3	0.1034	0.0243	1
5	1	5	0.1724	0.0005	0
Grand Total	29	19			
N	29				
F	19				
e	2.72				
z	0.6552				

Pennsylvania Counties Without Prisons					
Number of LULUs	Number of Counties	Total LULUs	Observed Probability	Poisson Probability	Expected Number of LULUs
0	28	28	0.7778	0.6969	25
1	4	4	0.1111	0.2517	9
2	3	6	0.0833	0.0454	2
3	1	3	0.0278	0.0055	0
Grand Total	36	13			
N	36				
F	13				
e	2.72				
z	0.3611				

North Carolina Counties With Prisons					
Number of LULUs	Number of Counties	Total LULUs	Observed Probability	Poisson Probability	Expected Number of LULUs
0	40	40	0.8333	0.7952	38
1	6	6	0.1250	0.1822	9
2	1	2	0.0417	0.0209	1
3	1	3	0.0625	0.0016	0
Grand Total	48	11			
N	48				
F	11				
e	2.72				
z	0.2292				

North Carolina Counties Without Prisons					
Number of LULUs	Number of Counties	Total LULUs	Observed Probability	Poisson Probability	Expected Number of LULUs
0	46	46	0.9020	0.7599	39
1	2	2	0.0392	0.2086	11
2	1	2	0.0196	0.0286	1
4	1	4	0.0196	0.0002	0
6	1	6	0.0196	0.0000	0
Grand Total	51	14			
N	51				
F	14				
e	2.72				
z	0.2745				

Texas Counties With Prisons					
Number of LULUs	Number of Counties	Total LULUs	Observed Probability	Poisson Probability	Expected Number of LULUs
0	44	44	0.7333	0.3012	18
1	6	6	0.1000	0.3614	22
2	4	8	0.1333	0.2169	13
3	1	3	0.0500	0.0867	5
4	1	4	0.0667	0.0260	2
5	1	5	0.0833	0.0062	0
6	1	6	0.1000	0.0012	0
9	1	9	0.1500	0.0000	0
31	1	31	0.5167	0.0000	0
Grand Total	60	72			
N	60				
F	72				
e	2.72				
z	1.2000				

Texas Counties Without Prisons					
Number of LULUs	Number of Counties	Total LULUs	Observed Probability	Poisson Probability	Expected Number of LULUs
0	158	158	0.8927	0.7932	140
1	9	9	0.0508	0.1837	33
2	6	12	0.0339	0.0213	4
3	1	3	0.0056	0.0016	0
4	1	4	0.0056	0.0001	0
5	1	5	0.0056	0.0000	0
8	1	8	0.0056	0.0000	0
Grand Total	177	41			
N	177				
F	41				
e	2.72				
z	0.2316				

APPENDIX I

Hessian matrices for location analysis models. Matrices containing NA values resulted in a failure to produce summary statistics for the associated model.

Three States Model Using Site Selection Variables

	Income	Employed	Renter	Asthma	0|1	1|3	3|4
Income	NA	NA	NA	NA	NA	NA	NA
Employed	NA	57583.2187	39180.8529	6334.52226	-1367.411234	-672.430871	-135.447002
Renter	NA	39180.8529	29549.1563	4507.55321	-965.03043	-563.2109	-127.844989
Asthma	NA	6334.5223	4507.5532	747.22774	-153.985207	-84.003616	-18.681499
0|1	NA	-1367.4112	-965.0304	-153.98521	33.442809	17.467399	3.806657
1|3	NA	-672.4309	-563.2109	-84.00362	17.467399	54.840094	5.537705
3|4	NA	-135.447	-127.845	-18.6815	3.806657	5.537705	15.465852

North Carolina Model Using Site Selection Variables

	Income	Employed	Renter	Asthma	0|1	1|3	3|4
Income	1.58E+09	1.32E+07	9482334.549	1.54E+06	-3.29E+05	-182034.4296	-9994.678278
Employed	1.32E+07	4.52E+04	30964.97709	5.17E+03	-1.09E+03	-524.91786	-24.4924071
Renter	9.48E+06	3.10E+04	23188.88266	3.66E+03	-7.69E+02	-414.09144	-22.5656071
Asthma	1.54E+06	5.17E+03	3659.07016	6.19E+02	-1.26E+02	-65.36103	-3.116143
0|1	-3.29E+05	-1.09E+03	-768.83566	-1.26E+02	2.68E+01	13.38051	0.6587423
1|3	-1.82E+05	-5.25E+02	-414.09144	-6.54E+01	1.34E+01	56.16534	1.3858
3|4	-9.99E+03	-2.45E+01	-22.56561	-3.12E+00	6.59E-01	1.3858	5.2400581

Pennsylvania Model Using Site Selection Variables

	Income	Employed	Renter	Asthma	0|1	1|3	3|4
Income	NA	NA	NA	NA	NA	NA	NA
Employed	NA	28424.91025	17932.26504	3118.86095	-696.170193	-412.928085	-80.667885
Renter	NA	17932.26504	12185.27234	2066.39766	-451.72314	-304.449066	-64.084475
Asthma	NA	3118.86095	2066.39766	369.16552	-78.436137	-49.552632	-10.543876
0|1	NA	-696.17019	-451.72314	-78.43614	17.415663	10.871736	2.287262
1|3	NA	-412.92809	-304.44907	-49.55263	10.871736	30.805542	3.282106
3|4	NA	-80.66789	-64.08447	-10.54388	2.287262	3.282106	9.442197

Texas Model Using Site Selection Variables

	Income	Employed	Renter	Asthma	0|1	1|3	3|4
Income	NA	NA	NA	NA	NA	NA	NA
Employed	NA	90760.4104	58667.6284	9450.1994	-2071.340477	-608.112011	-136.138906
Renter	NA	58667.6284	42662.5873	6468.29217	-1406.7624	-492.059056	-136.656782
Asthma	NA	9450.1994	6468.2922	1092.20678	-223.615373	-73.645147	-19.297614
0|1	NA	-2071.3405	-1406.7624	-223.61537	48.901635	14.815191	3.705603
1|3	NA	-608.112	-492.0591	-73.64515	14.815191	57.109576	4.578158
3|4	NA	-136.1389	-136.6568	-19.29761	3.705603	4.578158	21.199833

Three States Model Using Stepwise Variables

	Income	Renter	Asthma	Male	White	0|1	1|3	3|4
Income	NA	NA	NA	NA	NA	NA	NA	NA
Renter	NA	27895.9373	4268.62759	45570.6581	70723.7647	-903.149543	-620.668467	-130.11
Asthma	NA	4268.6276	711.35009	7290.7897	11407.2438	-144.762297	-93.035143	-19.355
Male	NA	45570.6581	7290.7897	79235.9387	124968.9082	-1567.482304	-970.833696	-193.56
White	NA	70723.7647	11407.24376	124968.9082	204299.9378	-2477.859338	-1390.511383	-274.02
0|1	NA	-903.1495	-144.7623	-1567.4823	-2477.8593	31.10102	19.261847	3.91185
1|3	NA	-620.6685	-93.03514	-970.8337	-1390.5114	19.261847	59.778462	6.44233
3|4	NA	-130.1121	-19.35501	-193.5648	-274.0173	3.911854	6.442333	15.7204

North Carolina Model Using Stepwise Variables

	Income	COPD	Male	White	0|1	1|3	3|4
Income	1582042041	3.74E+06	1.56E+07	2.25E+07	-3.16E+05	-2.03E+05	-11102.62526
COPD	3735729.85	3.78E+03	1.51E+04	2.16E+04	-3.06E+02	-1.82E+02	-8.466675
Male	15566677.28	1.51E+04	6.21E+04	8.82E+04	-1.26E+03	-7.50E+02	-35.950827
White	22543970.56	2.16E+04	8.82E+04	1.33E+05	-1.79E+03	-9.65E+02	-45.972772
0|1	-316346.82	-3.06E+02	-1.26E+03	-1.79E+03	2.55E+01	1.52E+01	0.740641
1|3	-202513.51	-1.82E+02	-7.50E+02	-9.65E+02	1.52E+01	6.02E+01	1.652294
3|4	-11102.63	-8.47E+00	-3.60E+01	-4.60E+01	7.41E-01	1.65E+00	5.259213

Pennsylvania Model Using Stepwise Selected Variables

	Income	Renter	Male	0|1	1|3	3|4
Income	NA	NA	NA	NA	NA	NA
Renter	NA	11739.92145	21854.0899	-440.715341	-300.44445	-66.607921
Male	NA	21854.08988	42874.8442	-856.773071	-539.42191	-115.783847
0|1	NA	-440.71534	-856.7731	17.179601	10.88738	2.373341
1|3	NA	-300.44445	-539.4219	10.887381	31.15363	3.51204
3|4	NA	-66.60792	-115.7838	2.373341	3.51204	9.532529

Texas Model Using Stepwise Selected Variables

	Income	Renter	Asthma	Male	White	0|1	1|3	3|4
Income	3297648658	15931867.86	2554021.606	28550447.76	46283581.04	-5.60E+05	-2.34E+05	-71080
Renter	15931867.86	38254.4132	5836.77067	64698.6174	103357.8916	-1.26E+03	-5.75E+02	-170.07
Asthma	2554021.61	5836.7707	994.65887	10358.2736	16649.2754	-2.03E+02	-8.61E+01	-24.513
Male	28550447.76	64698.6174	10358.27364	116602.0461	186178.4304	-2.26E+03	-9.23E+02	-246.79
White	46283581.04	103357.8916	16649.27535	186178.4304	301679.5736	-3.63E+03	-1.36E+03	-344.51
0|1	-560047.42	-1264.0513	-202.65522	-2263.0162	-3631.9294	4.41E+01	1.78E+01	4.87398
1|3	-233566.39	-575.1033	-86.09491	-922.6169	-1364.3514	1.78E+01	6.27E+01	7.00212
3|4	-71079.51	-170.0663	-24.51317	-246.7905	-344.5124	4.87E+00	7.00E+00	22.7331

APPENDIX J

Percent error tables for location analysis results.

Three State Site Selection Variables				
Category	Observed	Expected	Error	Percent
No Prison/No LULU	216	232	0.06897	6.89655
Prison/No LULU	17	102	0.83333	83.3333
No Prison/LULU	0	32	1	100
Prison/LULU	7	35	0.8	80
Overall	240	401	0.4015	40.1496

Three State Stepwise Selected Variables				
Category	Observed	Expected	Error	Percent
No Prison/No LULU	205	232	0.11638	11.6379
Prison/No LULU	30	102	0.70588	70.5882
No Prison/LULU	0	32	1.0000	100.0000
Prison/LULU	11	35	0.68571	68.5714
Overall	246	401	0.38653	38.6534

Pennsylvania Site Selection Variables				
Category	Observed	Expected	Error	Percent
No Prison/No LULU	26	28	0.07143	7.14286
Prison/No LULU	1	18	0.94444	94.4444
No Prison/LULU	0	8	1.0000	100.0000
Prison/LULU	4	11	0.63636	63.6364
Overall	31	65	0.52308	52.3077

Pennsylvania Stepwise Selected Variables				
Category	Observed	Expected	Error	Percent
No Prison/No LULU	26	28	0.07143	7.14286
Prison/No LULU	2	18	0.88889	88.8889
No Prison/LULU	0	8	1.0000	100.0000
Prison/LULU	3	11	0.72727	72.7273
Overall	31	65	0.52308	52.3077

North Carolina Site Selection Variables				
Category	Observed	Expected	Error	Percent
No Prison/No LULU	34	46	0.2609	26.0870
Prison/No LULU	15	40	0.6250	62.5000
No Prison/LULU	0	5	1.0000	100.0000
Prison/LULU	0	8	1.0000	100.0000
Overall	49	99	0.5051	50.5051

North Carolina Stepwise Selected Variables				
Category	Observed	Expected	Error	Percent
No Prison/No LULU	27	46	0.4130	41.3043
Prison/No LULU	24	40	0.4000	40.0000
No Prison/LULU	0	5	1.0000	100.0000
Prison/LULU	0	8	1.0000	100.0000
Overall	51	99	0.4848	48.4848

Texas Site Selection Variables				
Category	Observed	Expected	Error	Percent
No Prison/No LULU	156	158	0.0127	1.2658
Prison/No LULU	0	44	1.0000	100.0000
No Prison/LULU	0	19	1.0000	100.0000
Prison/LULU	4	16	0.7500	75.0000
Overall	160	237	0.3249	32.4895

Texas Stepwise Selected Variables				
Category	Observed	Expected	Error	Percent
No Prison/No LULU	152	158	0.0380	3.7975
Prison/No LULU	5	44	0.8864	88.6364
No Prison/LULU	0	19	1.0000	100.0000
Prison/LULU	7	16	0.5625	56.2500
Overall	164	237	0.3080	30.8017