ABSTRACT

ASSESSING THE HEALTH EFFECTS OF CLIMATE CHANGE, SOCIAL VULNERABILITY, AND ENVIRONMENTAL INJUSTICE IN CAMDEN COUNTY, NEW JERSEY

by
Daniil Ivanov

Climate change negatively impacts health, while socially vulnerable and overburdened communities disproportionately experience climate change and negative health determinants. Camden County is used as a case study for analyzing environment, socioeconomics, and health. Environmental variables—PM2.5 and land cover of impervious surfaces, floodplains, and forests—were compared to the CDC Social Vulnerability Index (SVI) at the census tract level, finding significant correlations between land cover, air quality, and the SVI. The overburdened communities defined by the NJ Environmental Justice Law experienced a significantly higher incidence of emergency department visitation for respiratory, circulatory, and mental illnesses than non-overburdened communities. Health outcomes were compared to the CDC SVI and environmental factors, finding positive and significant correlation between the SVI, environment, and emergency department visitation for respiratory, circulatory, and mental illnesses. Data suggests that climate change will impact the health of all, while having magnified effects on the socially vulnerable and overburdened communities.

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by
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A Thesis
Submitted to the Faculty of
New Jersey Institute of Technology
in Partial Fulfillment of the Requirements for the Degree of
Master of Science in Environmental Science

Department of Chemistry and Environmental Science

December 2022

APPROVAL PAGE

ASSESSING THE HEALTH EFFECTS OF CLIMATE CHANGE, SOCIAL VULNERABILITY, AND ENVIRONMENTAL JUSTICE IN CAMDEN COUNTY, NEW JERSEY

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ACKNOWLEDGEMENT

Thank you to everyone who has given me guidance, assistance, and inspiration during this challenging task of researching and completing my thesis research and attaining my Master's degree. I hold especial gratitude toward Dr. Zeyuan Qiu, who began to influence me before I was even aware of it. Dr. Qiu was one of my first introductions into the study of environmental science when he taught my Society, Technology, and Environment course during my undergraduate studies. This was an introduction into the history of environmental issues and regulations, and he made clear the influence of humanity on our environment and our responsibility to it. After continuing to explore interests within the environmental field, our paths crossed again in my senior year as I searched for an advisor for undergraduate research, and he quickly took me on. Dr. Qiu introduced me to work that was interesting and impactful, as we worked with community members in Princeton to calculate ecosystem services and save forests. He continued my growth in environmental science, and is the reason for me choosing this Master's degree and writing this thesis. I thank Dr. Qiu for his persistence and patience with me as he has spent the last two years teaching me the scientific process while engaging me to see the importance of the work we do. Dr. Qiu has been an important figure in my life, especially in this past year, and I have benefited significantly from his universal dedication to teaching.

I would like to thank Dr. Omowunmi Sadik for her support of me throughout my graduate studies. I have had the opportunity to learn from Dr. Sadik in my graduate coursework and more so in the many questions she has answered for me along the way. Our conversations have always given way to more questions and more ideas, leaving me with a deep sense of personal growth in academia. I am thankful to have her as a committee member.

I would also like to thank Dr. Mei Fu for her support and professional insight on this thesis. This project was made possible by the health outcome data provided by her and her team. Her work has been greatly beneficial to my understanding, and I thank her for being a valuable committee member.

I also owe gratitude to my friend Birju Dhaduk, who volunteered his service to me to assist in coding my data analysis and interpretation. I have never been accused of being a great coder or a mathematician, but thankfully Birju took all of my calls to answer what must have seemed to him like the most trivial questions.

I would also like to thank my girlfriend Katherine for endlessly supporting me. Despite being busy herself in medical school, she has always found time to give love and support that has carried me through this experience.

Lastly, I would like to thank my family. My personal, professional, and academic work have only been possible because of the opportunities afforded by their hard work. My parents packed up two children and left for the unknown to plant roots in a country where hard work pays off. They taught me the values of persistence and sacrifice, as their own persistence and sacrifices have given myself and my siblings opportunities to pave our own way.

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CHAPTER 1

BACKGROUND AND INTRODUCTION

1.1 Climate Change

Climate change has been established as a major threat to humanity, the environment, and the future. The 2022 Intergovernmental Panel on Climate Change (IPCC, 2022) report finds that the anthropogenic changes to climate have and will continue to have increasingly harmful impacts on ecosystems, biodiversity, and human systems. According to the IPCC (2022), an approximately 1°C increase in average global surface temperature from the 1850-1900 baseline has impacted global systems via increased frequency and intensity of weather events such as heat waves, floods, droughts, and fires; increased sea levels due to melting polar ice causing increased intensity of tropical cyclones and regional drought; and an unprecedented rate of species extinction and ecosystem destruction. Extreme heat events, food and water-borne diseases from floods, zoonotic illnesses from the expansion of warm climates, and diminished air quality have taken tolls on human life in both mortality and quality of life (IPCC, 2022).

The increase in temperatures has also implicated the acceleration of natural tropospheric chemistry: transformation of methane, carbon dioxide, and nitrogen dioxides to ozone and carbon dioxide have been shown to increase with air temperature, thus increasing ambient ozone concentrations on hot days (Lu et al., 2019; Pusede et al., 2015). At the same time, increased temperatures increase natural biogenic emissions (Giorgi & Meleux, 2007).

Meanwhile, as a response to an increasingly more hostile and extreme climate, developed countries are predicted to increase the use of climate control systems (air conditioning and home heating) which are also often pollutant forming and energy intensive (Nazaroff, 2013). An expected result is that such indoor systems will be controlled via efficiency measures that prevent the escape of indoor pollutants while the further increased concentration of outdoor pollutants may still infiltrate the home, thus causing stagnant and harmful indoor air quality in a feedback loop of energy-intensive greenhouse gas emitting measures to react to greenhouse gas mediated climate change (Nazaroff, 2013).

Adding to the atmospheric pollution is the issue of droughts resulting from climate change. Such droughts create dry conditions that are conducive to wildfires as well as forming fine, dry soil that can be easily aerosolized while at the same time lacking precipitation—both processes that induce the accumulation of particulate matter in the atmosphere (Ebi et al., 2021; Giorgi & Meleux, 2007).

1.2 Health Effects of Climate Change

Health implications of climate change have been found to be numerous and systemic. Table 1.1 summarizes the current understanding of the health impacts of climate change. While some impacts are well understood, many impacts are not.

Exposure to extreme high temperatures, for example, has negative impacts on the respiratory system. High temperatures are correlated with emergency department admission for chronic obstructive pulmonary disorder (COPD) and asthma (Sangkharat et al., 2020; O'Lenick et al., 2017). Extended exposure to high temperatures in heat waves is linked with increased emergency department visits for respiratory diseases, and heat waves are also associated with higher incidence of COPD (Sohail et al., 2020; Cheng et al., 2019; Xu et al., 2019; Sherbakov et al., 2018). Higher carbon dioxide levels, which are intrinsically linked to climate change, trigger arboreal blooms which in turn cause an increase in seasonal pollen release and allergic rhinitis (Ray & Ming, 2020). Similarly, allergic rhinitis consultations were found to increase in frequency inversely to rainfall suggesting a heightened impact from future drought conditions (Todkill et al., 2020). Exposure to high ozone concentrations has been linked with pneumonia, asthma, and other respiratory issues (Gu et al., 2020; Tian et al., 2020; To et al., 2020; Yu et al., 2020; Anenberg et al., 2018; Malley et al., 2017; Ierodiakonou et al., 2016; Larrieu et al., 2009). Particulate matter 10µm or smaller specifically is shown to increase incidence of respiratory disease, while particulate matter 2.5µm or smaller has been connected to asthma (Anenberg et al., 2018; Gu et al., 2020; Yu et al., 2020; Malley et al., 2017; (Larrieu et al., 2009). Furthermore, particulate matter (PM) from wildfires has led to asthma, pneumonia, bronchitis, and upper respiratory infection diagnoses even beyond the exposure period of the fire suggesting that the alterations to the atmospheric composition can persist (Hutchinson et al., 2018).

Further impacts of climate change are manifested in the cardiovascular system. Exposure to high temperatures has been correlated with emergency department admissions for strokes and myocardial infarctions (Sun et al., 2021; Sangkharat et al., 2020; Thu Dang et al., 2019; Sherbakov et al., 2018). Extended heat exposure under heat waves has also been linked with increased emergency department visits for myocardial infarctions, as well as an association with increased ischemic heart disease, stroke, and heart failure (Sohail et al., 2020; Cheng et al., 2019; Xu et al., 2019). The release of small particulate pollution imposes worrying health effects as well. PM has been shown to penetrate the lungs, with PM2.5 (particles 2.5μm or smaller) penetrating as far as the alveolar region and passing into the bloodstream to cause plaques in the arteries (Spickett et al., 2021). PM2.5 is thus logically associated with increased risk of stroke (Wolf et al., 2021). PM10 (particles 10μm or smaller) is also shown to increase incidence of cardiovascular death and ischemic stroke (Dong et al., 2018). Exposure to particulate matter specifically originating from wildfires is also known to increase all-cause hospitalizations as well as cardiorespiratory hospitalizations (Ye et al., 2021). Nitrogen dioxide and other NOx derivatives in the atmosphere have been associated with ischemic strokes and coronary heart disease (Gao et al., 2022; Wolf et al., 2021; Tsai et al., 2019; Dong et al., 2018.) Sulfur dioxide is also correlated with a rise in ischemic stroke (Dong et al., 2018).

Pregnancies are impacted by climate change, as exposure to extreme heat during pregnancy is associated with decreases in birth weight and gestational length promoting preterm births, and with increases in the incidence of stillborn children and neonatal mortality (Hajdu & Hajdu, 2021; Mathew et al., 2021; Kuehn & McCormick, 2017). PM2.5 concentrations were also linked to increases in preterm births (Malley et al., 2017).

The renal system is affected since exposure to high temperatures has been correlated with emergency department admission for kidney injury and renal disease, dehydration, heat related illness, and urinary stones (Xu et al., 2020; Malig et al., 2019; Sherbakov et al., 2018). Longer term heat exposure in heat waves has also been linked with increased emergency department visits for renal failure and dehydration (Sherbakov et al., 2018).

Similarly, the endocrine system is implicated as heat waves are linked to increased emergency department visits for diabetes and other endocrine issues, (Xu et al., 2019; Sherbakov et al., 2018). PM2.5 has also been associated with exacerbation of endocrine and metabolic diseases (Gu et al., 2020).

Mental illnesses have been correlated to exposure to high temperature with higher rates of emergency department admission for psychiatric emergencies and mental health problems on hotter days (Yoo et al., 2021; Carlsen et al., 2019; Sherbakov et al., 2018). Heat waves have also been linked with increased emergency department visits for mental health issues (Liu et al., 2019; Xu et al., 2019). PM2.5 levels are similarly correlated to higher rates of mental and behavioral illness (Gu et al., 2020).

Yet another affected system is the skin, with heat waves having been linked with increased emergency department visits for integumentary system issues (Xu et al., 2019). Exposure to high ozone concentrations has been correlated with skin rashes and eczema (To et al., 2020; Fuks et al., 2019; Szyszkowicz et al., 2016; Larrieu et al., 2009). PM10 is shown to increase incidence of rashes and conjunctivitis (Larrieu et al., 2009).

Increasing temperatures have made the climatic conditions of higher latitudes more tolerable for disease vectors—with milder winters, earlier springs, increased moisture in the spring, and overall, more temperate conditions—which has increased the vectorial capacity for ticks, mosquitos, and other such species (Lillepold et al., 2019; Liu-Helmersson et al., 2014; Moore et al., 2014). Increases in rainfall in some areas further adds to the magnification of the vectorial capacity (M'Bra et al., 2018). As a result, higher incidence of infectious diseases such as malaria, yellow fever, dengue, Zika, and Lyme have recently been noted in areas with previously unremarkable rates (Lubinda et al., 2021;

Lillepold et al., 2019; Caminade et al., 2017; Short et al., 2017; Liu-Helmersson et al., 2014; Moore et al., 2014). Other notable vectors affected in the same way are triatomine insects carrying Chagas disease, the tsetse fly carrying human African Trypanosomiasis, and sand flies carrying leishmaniasis—all of three of which are carriers for protist pathogens (Short et al., 2017). The increases in temperature and humidity as well as increases in extreme floods and storms are also favorable to the spread and growth of fungi, with increases in fungal infections as a result (Nnadi & Carter, 2021; Rickerts, 2019). Infectious diseases have also been associated with heat waves, high ozone levels, and PM2.5 (Gu et al., 2020; Tsai et al., 2019; Xu et al., 2019).

As climate indicators are tied to a number of body systems, it should come as no surprise that climate change is also linked to mortality. Increases in ambient temperature, nighttime temperature, and temperature extremes in general have been tied to the elevated risk of death (Roye et al., 2021; Zhang et al., 2020; Zhang et al., 2018). Specifically, excess heat has been associated with increased risk of cardiovascular and respiratory mortality (Iniguez et al., 2021). Heat waves are also associated with increased cardiovascular and respiratory mortality (Cheng et al., 2019). Mortality and morbidity under heatwave conditions is especially high for patients with preexisting diabetes mellitus as well as increased lethality in women and the elderly (Li et al., 2021; Moon, 2021). Exposure to high ozone concentrations has been linked with mortality due to oxidative stress and inflammatory response mechanisms from the radical species. (Malley et al., 2017; Bell et al., 2014;). Furthermore, pairing the exacerbated biological heat stress response with the inflammatory response from increased tropospheric ozone concentration results in even higher positive correlations with cardiovascular and respiratory mortality than between mortality and heat or ozone alone (Shi et al., 2020; Analtis et al., 2018; Spickett et al., 2011).

Table 1.1 Summary of Literature on Health Effects and Climatological Etiology

System of Health Effects	Cause of Health Effects: High Ambient Temperature	Heat Waves	Drought	Increased Rainfall and Flooding	Air Pollutants
Respiratory	Sangkharat et al., 2021; O'Lenick et al., 2017, Iniguez et al., 2018	Cheng et al., 2019; Sohail et al., 2020; Xu et al., 2019; Sherbakov et al., 2018			Ye et al., 2021; Gu et al., 2020; Ray & Ming, 2020; Shi et al., 2020; Tian et al., 2020; To et al., 2020; Todkill et al., 2020; Yu et al., 2020; Anenberg et al., 2018; Hutchinson et al., 2018; Malley et al., 2017; Ierodiakonou et al., 2016; Spickett et al., 2011; Larrieu et al., 2009
Cardiovascular	Sangkharat et al., 2021; Sun et al., 2021; Thu Dang et al., 2019; Iniguez et al., 2018; Sherbakov et al., 2018	Sohail et al., 2020; Cheng et al., 2019; Xu et al., 2019	Berman et al., 2017		Wolf et al., 2021; Ye et al., 2021; Gu et al., 2020; Shi et al., 2020; Contiero et al., 2019; Dong et al., 2018; Spickett et al., 2011
Obstetric	Hajdu & Hajdu, 2021; Mathew et al., 2021; Kuehn & McCormick, 2017				Malley et al., 2017
Renal	Xu et al., 2020; Malig et al., 2019; Sherbakov et al., 2018	Sherbakov et al., 2018			Chu et al., 2021; Gu et al., 2020
Endocrine		Moon, 2021; Xu et al., 2019; Sherbakov et al., 2018			Gu et al., 2020
Mental	Yoo et al., 2021; Carlsen et al., 2019; Sherbakov et al., 2018	Liu et al., 2019; Xu et al., 2019			Gu et al., 2020
Skin		Xu et al., 2019			Gu et al., 2020; To et al., 2020; Fuks et al., 2019; Szyszkowicz et al., 2016; Larrieu et al., 2009
Infectious Disease	Lubinda et al., 2021; Wang et al., 2021; Lillepold et al., 2019; Caminade et al., 2017; Short et al., 2017; Liu-Helmersson et al., 2014; Moore et al., 2014	Xu et al., 2019		Lubinda et al., 2021; Nnadi & Carter, 2021; Lillepold et al., 2019; Rickerts, 2019; M'Bra et al., 2018; Caminade et al., 2017; Short et al., 2017; Liu-Helmersson et al., 2014; Moore et al., 2014	Gu et al., 2020; Tsai et al., 2019
Death	Roye et al., 2021; Zhang et al., 2020; Iniguez et al., 2018; Zhang et al., 2018	Li et al., 2021; Moon, 2021; Cheng et al., 2019	Berman et al., 2017		Gao et al., 2022; Shi et al., 2020; Analtis et al., 2018; Malley et al., 2017; Bell et al., 2014; Spickett et al., 2011

1.3 Social Vulnerability

Social vulnerability is a measure of adaptability to changes, and socially vulnerable individuals are those who are not afforded the capacity to adapt to changes in conditions from environmental issues or disasters (Benevolenza & DeRigne, 2018). One system for measuring such vulnerability in communities is the CDC Social Vulnerability Index (SVI), which is a biennial ranking at the census tract level of a set of factors that influence the vulnerability status of residents who live in a community (CDC SVI, 2018). SVI is a composite index that is made of a set of categorical indices on socioeconomic status, household composition, minority status, English language ability, housing type, and access to transportation (CDC SVI, 2018). Socioeconomic status is the first theme, and is determined by metrics on poverty, employment, income, and achievement of a high school diploma (CDC SVI, 2018). Theme 2 is household composition, which is based on number of single parent households, disability status within homes, number of persons aged 17 or under, and number of persons in a household aged 65 or over (CDC SVI, 2018). Theme 3 is composed of minority status, entailing racial or ethnic makeup that is not white non-Hispanic, and English language ability (CDC SVI, 2018). Finally, theme 4 encompasses access to a vehicle for personal transportation and housing status, which is measured by the number of individuals which reside in a multi-unit dwelling, mobile home, or group quarters (such as barracks, dorms, or intermittent homeless sheltering) and the occurrence of overcrowding within a home (having more people in a home than rooms) (CDC SVI, 2018). Communities in the higher percentile ranks for the four themes are considered to be socially vulnerable (CDC SVI, 2018).

The impacts of social vulnerability on health are well-documented, but still poorly understood. External stressors, such as natural disasters or environmental pollutants, have disproportionate effects on socioeconomically disadvantaged persons, with vulnerability being attributable to a poverty-induced lack of available options when facing susceptibility or exposure to hazards (Diderichsen et al., 2019). The impacts are further magnified by lack of access to regular healthcare as higher social vulnerability is shown to create difficulties in getting care stemming from availability of providers, costs, or transportation issues, with these factors manifested in the high rates of Emergency Room usage for primary care (Haggerty et al., 2020). In addition, the combination of multiple risk factors in an individual have been shown to amplify the negative health effects of social vulnerabilities (Haggerty et al., 2020). This can be seen in the health inequities of the homeless and vulnerably housed populations, which tend to have overlaps in vulnerabilities, as they have been noted to exhibit avoidance of care, stigmatization, and unmet healthcare needs from inflexibility of the primary care system (Purkey & MacKenzie, 2019). Epigenetics has also recently been considered as a function within the healthcare-social vulnerability dilemma, as early life poverty and even generational poverty can create conditions of differential methylation of gene promoter regions that can impact inflammatory reactions within the body (Diderichsen et al., 2019).

Health effects of social vulnerability are more evident in urban areas, where a large proportion of the socially vulnerable populations live. The 2022 IPCC report notes that increased heatwaves have intensified the most in urban areas, thus having the highest intensity of impact on temperature, air pollutant evolution, and infrastructure disruption such as transport, water, and sanitation. This phenomenon of increased heat in urban areas is well-documented and established as the urban heat island effect, which is caused by a lack of trees causing a lack of evapotranspiration, a lack of bodies of water within cities, thermally polluting industrial activities, and higher rates of solar energy absorption by the large proportion of impervious surfaces (Leal Filho et al., 2018).

As a result of the interactions between the urban heat island effect and social vulnerability, a 10% increase in Social Vulnerability Index value of a census tract has been shown to result in an 18% increase in heat-related Emergency Room visits and 31% higher mortality rates (Lehnert et al., 2021). This can be attributed to various factors within the index: a low English language proficiency is a strong indicator of vulnerability in a heat emergency, suggesting that language is a barrier in understanding of warnings issued by authorities and availability of resources; low economic status or housing type may influence the accessibility to air conditioning in extreme heat whether it be from the unit cost, electricity cost, or not having control over building maintenance or systems; age of a household is important as small children and geriatric populations are more susceptible to health effects from heat; and a lack of transportation can prevent one from accessing a public cooling area, especially the elderly who have a lower driving participation rate and are more likely to live away from their family (Leal Filho et al., 2018; Nayak et al., 2018).

As stated previously, another factor that has associated health outcomes with social vulnerability in urban environments is air quality, with urban areas releasing higher levels of air pollutants from industrial sites, a higher vehicle density emitting criteria air pollutants from combustion engines, and warmer temperatures in cities allowing for the higher evolution of air pollutants in the area (IPCC, 2022). Atmospheric pollution has shown to have cardiorespiratory risks, especially in children, and has been linked with racial and spatial disparities as exposure risk ties in heavily with discrimination in economic development, social disadvantage, and health inequity (Kane, 2022; Spickett, 2011).

Finally, increases in extreme weather events due to climate change will impact the socially vulnerable population more. After exposure to fires, individuals with a lower socioeconomic status have been shown to have higher incidence of general anxiety disorder, major depressive disorder, and post-traumatic stress disorder (Silviera et al., 2021). Similarly, the impact of Hurricane Harvey in 2017 resulted in a higher rate of post-traumatic stress disorder for minorities (Fitzpatrick, 2021). This is often the case, as the socially vulnerable are often hit the hardest by natural disasters because economic circumstances lead them to residing in the most disaster-prone neighborhoods as well as ones that have limited social and psychological resources (Fitzpatrick, 2021). Such disasters also tend to increase contamination in surface waters, well water, untreated water, and sanitation facilities—especially to cholera—and socially vulnerable communities may not be afforded the opportunity for alternate sources of water (Jones et al., 2020).

1.4 Environmental Justice

As defined by the United States Environmental Protection Agency (U.S. EPA), environmental justice is "the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income, with respect to the development, implementation, and enforcement of environmental laws, regulations, and policies" (U.S. EPA). The goal of environmental justice is to provide "protection from environmental and health hazards" and to offer "equal access to the decision-making process" (U.S. EPA).

Environmental justice is closely tied to social vulnerability as the socially vulnerable communities are often subject to a systematic impact of environmental pollution.

The inequalities and lack of protection that environmental justice aims to address stem from several factors. Many pollutant-emitting facilities have historically been built in socially vulnerable communities due to prior racial injustices, lower fees associated with placement of the facilities, and lower political participation (Banzhaf et al., 2019). Historically, legal penalties have been lower on environmental nuisances endured by socially vulnerable communities; and there is often a lack of participation in the decision making of facility siting by those who are to be endure the highest costs of pollution (Banzhaf et al., 2019). Additionally, political participation tends to be lower by those in environmental justice communities, and even when participation is high the elected officials tend to not be representative of affected community (Kronenberg et al., 2020; Banzhaf et al., 2019).

Another aspect of environmental justice is that socioeconomically vulnerable communities, regardless of their participation in the democratic process, are forced to prioritize basic needs such as food, water, shelter, and healthcare—while being mindful of the costs—which in turn means that urban greening is not a priority (Kronenberg et al., 2020). What this leads to is the process of sorting, where regardless of the diligence in city planning for a pollutant source, affluent individuals are more socially mobile and thus tend to relocate outside of an environmental justice community anyway, gentrify their new community, and cause the disadvantaged to occupy the new environmental justice community (Banzhaf et al., 2019).

This rearrangement of wealth and resources causes the rift in green spaces that is seen across the country. Affluent cities, which tend to have a higher proportion of white inhabitants, typically have a higher proportion of green spaces and have more acres of parks compared to low-income ethnic minority cities (Rigolon et al., 2018). The land value and tourism implications of having urban green space and parkland means that wealthier cities tend to see parks as a worthy investment, while impoverished cities do not have the capital on hand to pursue similar improvements (Rigolon et al., 2018). As a result, a lack of parks keeps residents from enjoying the benefits of access to green space, such as higher perception of health status, better integration into social networks, and better mental health outcomes (Enssle & Kabisch, 2020).

1.5 Climate Change and Health Impacts on Socially Vulnerable Communities

As discussed in detail up to this point, literature has been written extensively on the health impacts of climate change, the health impacts of social vulnerability, and the climatological hardships that impact socially vulnerable communities. Figure 1.1 summarizes the key finding from the literature review of these relationships. However, the literature is not as thorough on the intersection of climate change, socio-economic status, and health outcomes. This thesis intends to approach all three of these areas of study holistically to further understand the interplay between them.

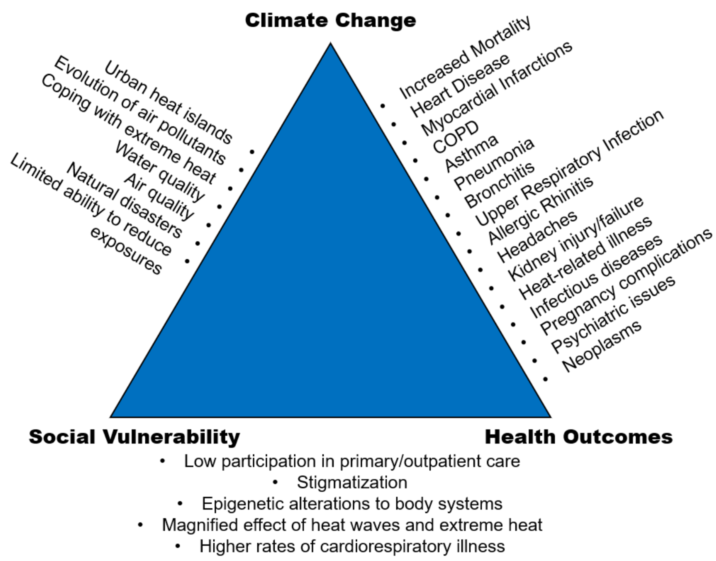


Figure 1.1 Key findings of the review of impacts of climate on health, climate on social vulnerabilities, and social vulnerability on health.

1.6 Study Area

Camden County, New Jersey was chosen as the study area for further evaluation of the interactions between health outcomes, social vulnerability, and climate change. The county is on the south-western side of the state of New Jersey, in the northeastern United States. The county occupies 221 square miles. In the 2020 Census, the county had a population of 523,485 with a median household income of $70,451 while having a poverty rate of 12.4% (U.S. Census Bureau, 2021). The median household income was above the national median of $67,521 and the poverty rate was 1% higher than the national rate of 11.4% (Shrider et al., 2021). Summary statistics are presented in table 1.2.

Table 1.2 Summary Statistics of Camden County

Area	221 square miles
Population (2020 Census)	523,485
Population Density	2,368 people per square mile
Median Household Income (2020 Census)	$70,451
Poverty Rate (2020 Census)	12.4%

Camden County is an ideal study area for such research in that it has a very wide range in social vulnerability. In 2018, the most current year that is available for the Social Vulnerability Index, the summation of all 4 themes within the index ranged from the 0.25th percentile in the state (tract 607504 in Voorhees) to the 99.9th percentile (tract 600400 in the city of Camden).

1.7 Research Question

Climate change, through intermediate factors, will affect all people. From review of prior literature, it is evident that health outcomes are negatively affected by climate factors such as excessive heat, heat waves, and air pollutants. It also becomes evident that vulnerable populations are limited in their responses to disasters and climate variability.

This thesis uses Camden County, New Jersey as a case study to analyze the variability in social vulnerability and environmental factors of various communities. This thesis further uses the gradients in social and environmental factors to compare them to data for health outcomes. The research done here aims to determine the connections between social and environmental determinants, and how they impact health.

CHAPTER 2

DATA

2.1 Environmental Data

2.1.1 Weather Data

Weather data on temperature was gathered from January 1, 2014 to December 31, 2017 via the National Oceanic and Atmospheric Administration (NOAA) NCEI database found at https://www.ncei.noaa.gov/cdo-web/search?datasetid=GHCND.

Data was acquired from stations at the Philadelphia International Airport, Millville Municipal Airport, and South Jersey Regional Airport as these weather stations surround Camden County. Linear distance from the center of each census tract to each weather station was then determined and applied as a factor to estimate a weighted average for temperature and precipitation at the tract level. The average weather data for the county was then extrapolated from this dataset.

Day-to-day temperature averaged across the county is seen in Figure 2.1. The cycle is as expected, with peaks in temperature in the warmer summer months and lower temperatures in the winter months. Temperature remained fairly consisted on a year-to-year basis.

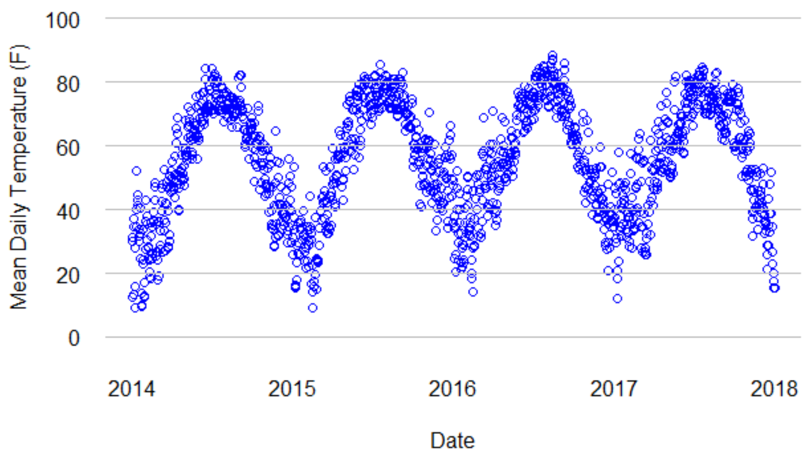


Figure 2.1 Average daily temperature (°F) in Camden County from 2014-2018.

Average daily precipitation for Camden County is plotted in Figure 2.2. The thick blue line across the bottom indicates that most days either had no rain or were mostly dry for the count. Most days that did have precipitation had one inch or fewer. Only 8 days over the 4-year period exceeded two inches of precipitation. Overall, no drastic differences or trends were noted on a year-to-year basis.

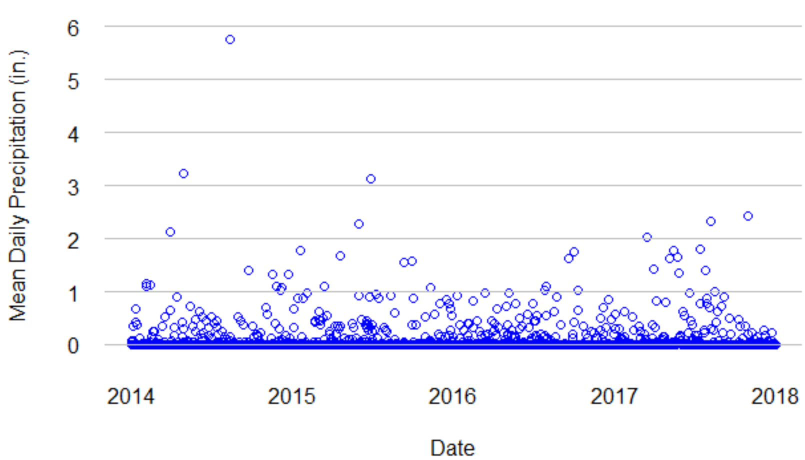


Figure 2.2 Average daily precipitation (in.) in Camden County from 2014-2018.

2.1.2 Particulate Matter

Tract-level Particulate Matter of 2.5µm or smaller (PM2.5) data is available in the CDC database through the year 2016. This data was retrieved from the CDC database, with 2011-2015 data and 2016 data available at the following websites, respectively:

- https://data.cdc.gov/Environmental-Health-Toxicology/Daily-Census-Tract-Level-PM2-5-Concentrations-2011/qjxm-7fny
- https://data.cdc.gov/Environmental-Health-Toxicology/Daily-Census-Tract-Level-PM2-5-Concentrations-2016/7vu4-ngxx

These datasets capture estimated daily averages of PM2.5 per census tract. As the period for this research is between 2014-2018, PM2.5 concentrations were analyzed from 2014 to the latest data in 2016. The 95th percentile of these values was determined, then the number of days per tract that the PM2.5 concentration exceeded the 95th percentile was tabulated. Subsequently, the average PM2.5 concentration for the days exceeding the 95th percentile was determined for each tract.

The Camden County mean PM2.5 concentration for the time period was 10.116 micrograms per cubic meter, while the state had the lower mean concentration of 9.099 mcg/m^3. Similarly, the median PM2.5 concentration for Camden County was 8.895 mcg/m^3, while the state had a median concentration of 8.030 mcg/m^3. The 95th percentile of PM2.5 for the county was determined to be 19.351 mcg/m^3, while the statewide 95th percentile was only 18.018 mcg/m^3.

The number of days in this period that a tract in Camden County exceeded the 95th percentile marker for the county ranged from 32 days to 65 days. These values were mapped to their tracts in ArcGIS and can be seen in Figure 2.3.

Higher 95th percentile of PM2.5 exceedance days are noted in the northwestern section of the county and further north in general in comparison to the southern portions of the county. This correlates with the more urbanized areas of the county, especially the city of Camden.

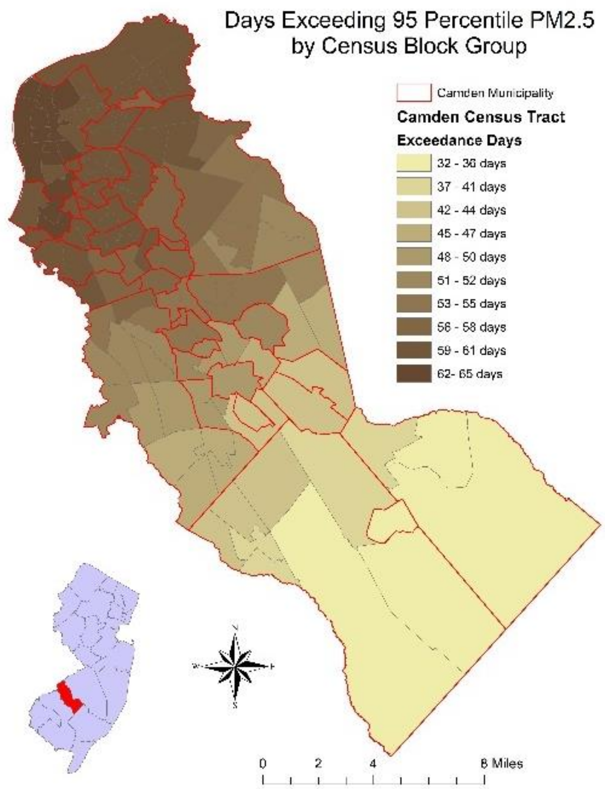


Figure 2.3 Days exceeding the 95th percentile of PM2.5 per census tract.

2.1.3 Land Cover

Land cover is an environmental variable that refers to the percentage of land that is impervious surface or forest cover. Either the lack or abundance of greenspace affects the urban heat island effect and can indirectly be used to assess heat effects. Impervious surfaces are also related to flooding within the community due to a lack of natural drainage, and this could potentially contribute to some health outcomes as well.

The percentage of forest cover and impervious surfaces for each tract in Camden County were derived from the 2015 Land Use/Land Cover of New Jersey map developed and maintained by the NJDEP. This map can be found at the following website:

https://gisdata-njdep.opendata.arcgis.com/documents/6f76b90deda34cc98aec255e2defdb45/about

For each land use polygon in Camden County, a land use/land cover type and a specific percentage of impervious surfaces were estimated. The percentage of forest cover in a tract is equal to total forest area time 100 divided by tract area, excluding water. Similarly, the percentage of impervious surface is equal to the area weighted impervious surface rate without water. Water was excluded from these rates in order to eliminate the impacts of the presence of water on community health outcomes, which could dilute the impacts of impervious surfaces or forest cover.

Instead, water impacts were measured via floodplain coverage. The percentage of floodplain in each tract was based on the FEMA National Flood Hazard Layer data for Camden County, released August 16, 2016, from the following website:

https://www.floodmaps.fema.gov/NFHL/status.shtml

The 100-year and 500-year flood hazard and flood waterways were combined as one floodplain layer. Then, the floodplain coverage was calculated as the area of the floodplain within a tract times 100 divided by the total area of the tract.

Land distribution for the county had a higher percentage of impervious surfaces in the urban northwest, with a higher rate of forest cover for the southern portion of the county as noted in Figure 2.4. The flood plains of the county are noted in the north following the tributaries of the Delaware River and in the south from a series of rivers within the Winslow Fish and Wildlife Management Area, noted in Figure 2.5. Forest cover, floodplain, and impervious surface values were attributed as a percentage of coverage for each tract.

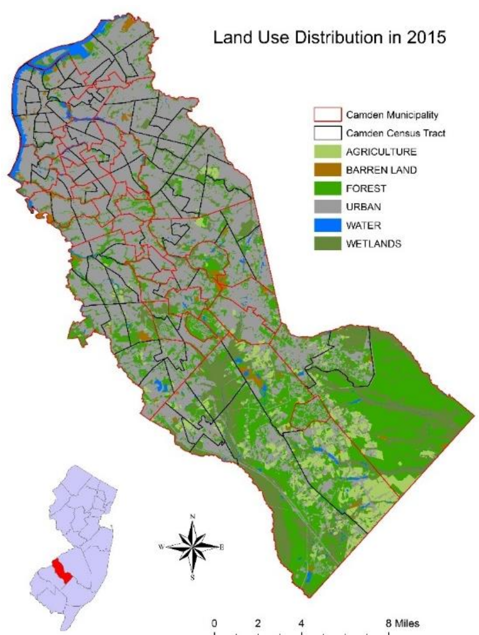


Figure 2.4 Camden County land distribution, 2015.

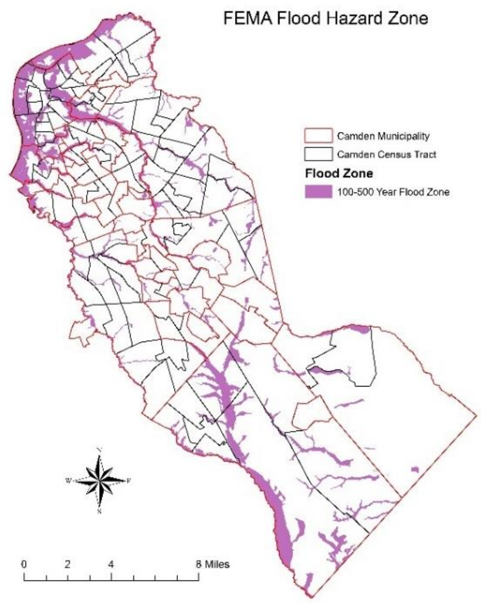


Figure 2.5 Camden County FEMA flood zone map.

Summary statistics for land cover in the county are displayed in Table 2.1. The median impervious surface coverage was 43.28% with a high of 83.08% and a low of 1.94%. This indicates, as seen in the land distribution map, that there is a wide range of urban and non-urban land within the county. This is significantly higher than the land use for the state reported by the NJDEP, with only 27% of the land use being urban ("Environmental Trends Report, 2020"). Likewise, the median forest cover for Camden County is 7.60% with a mean of 10.73%. The range in numbers is also vast, as some tracts have no forest cover whatsoever while the maximum forest cover is 58.94%. Camden

County has considerably less forest cover than the state as a whole, which has a 26% forest cover ("NJDEP, 2020").

Furthermore, the flood plain percentages show that the median flood plain coverage is 7.95% showing that most of the county is not flood prone. However, the maximum is 87.51 indicating that some select areas, as previously indicated in the flood zone map, are highly flood prone as they are neighboring major waterways.

Table 2.1 Summary Statistics of Land Cover in Camden County

	Impervious Surfaces	**Forest Cover**	**Flood Plain**
Minimum	1.94%	0%	0%
First Quartile	31.13%	2.81%	2.86%
Median	43.28%	7.60%	7.95%
Mean	42.78%	10.73%	15.37%
Third Quartile	52.70%	14.88%	18.91%
Maximum	83.08%	58.94%	87.51%

2.2 Social Vulnerability Index

Socioeconomic data was retrieved from the CDC Social Vulnerability Index (SVI). This is a ranking system that is released by the CDC every two years and categorizes census tracts by vulnerability in four themes. Theme 1 is a metric of socioeconomic status (poverty, employment, income, and high school graduation status). Theme 2 is household composition (number of parents, disability status, and number of pediatric or geriatric occupants). Theme 3 is minority status and English language ability. Theme 4 is transportation and housing (access to a vehicle, residence in a multi-unit dwelling such as a shelter or barracks, and occurrence of overcrowding in a household). Finally, a percentile ranking is also available for the sum of the themes in order to depict a holistic view of the vulnerability of a community. Communities with a higher ranking in either one or multiple themes is considered socially vulnerable, as their situation prevents them from ease of adaptation to abrupt changes in their local environment. The database also provides estimates of the tract-level population for the time.

Data was retrieved for the years 2014 and 2016 from the CDC Database at this website: https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html.

Figure 2.6 is a collection of maps from the 2018 CDC SVI for tracts in Camden County. The four themes do not overlap exactly, though several spots do overlap to form a higher ranking in the overall SVI. These appear to be centered in the urban north of the county near the city of Camden as well as in the center of the county. This would indicate that these areas are the most socially vulnerable.

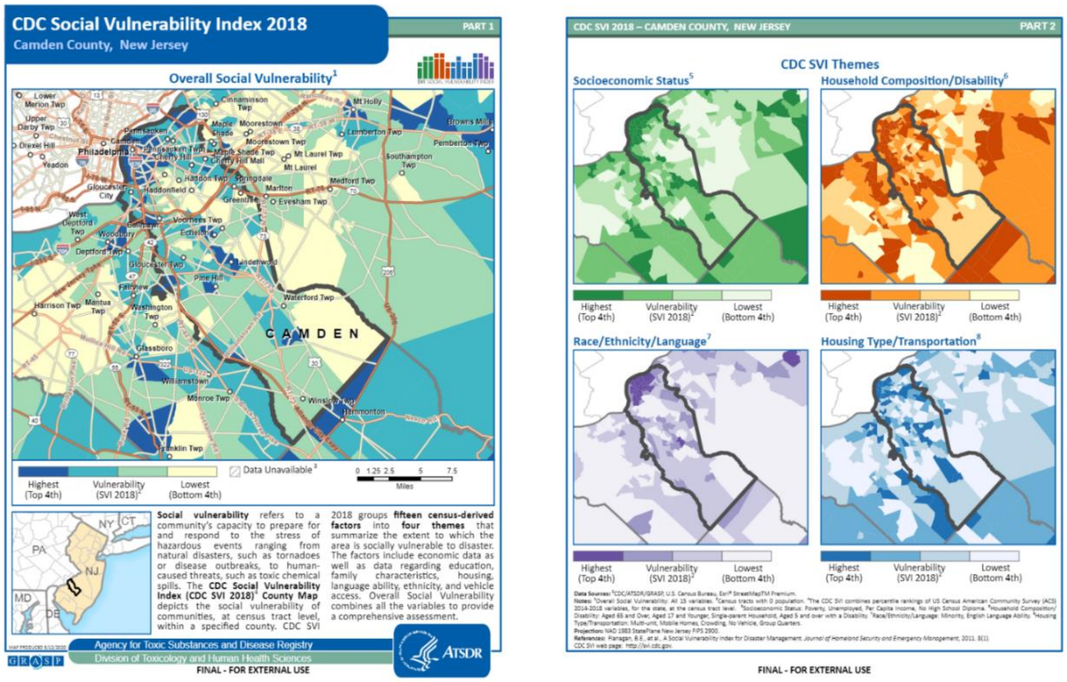


Figure 2.6 CDC Social Vulnerability Index maps of Camden County, New Jersey.

2.3 Overburdened Communities

According to the New Jersey Environmental Justice Law, an "Overburdened community" is any census block group, as determined by the most recent census data, in which: (1) at least 35% of the households qualify as low-income households (L); at least 40% of the residents identify as a minority or as members of a State recognized tribal community (M); or (3) at least 40% of the households have limited English proficiency (E). Section 3 of the New Jersey Environmental Justice Law N.J.S.A. 13:1D-159 requires the NJIDEP to "notify a municipality if any part of the municipality has been designated an overburdened community pursuant to this act."

Since this study uses the Census tract as the basis spatial unit, we assign the EJ Community status for each tract based on the overburdened community data using the following criteria (EJCode2):

- The community status was assigned to the community with the highest percentage of land area, which is applicable to most non-EJ community tracts and some EJ community tracts.
- If EJ communities occupy a significant amount of the land surface in a tract (at least 40%), the tract will be assigned as an EJ community that has higher percentage of land surface.

The final designation of EJ communities in 129 tracts are M for Minority, L for Low Income, LM for Low Income and Minority, LME for Low Income and Minority and limited English Proficiency, and N for non-EJ community. These designations were mapped to the appropriate tracts in figure 2.7. The urban northwest portion of the county as well as a small portion in the center of the county has blocks that are low income, minority, and of limited English-speaking ability. The northwestern portion also takes most of the overlap of low income and minority communities, with several blocks otherwise spread out among the county. Several communities adjacent to those that overlap also contain blocks with only minorities or only low-income households. Much of the Overburdened Communities map overlaps with the results found in the Social Vulnerability Index in figure 2.6.

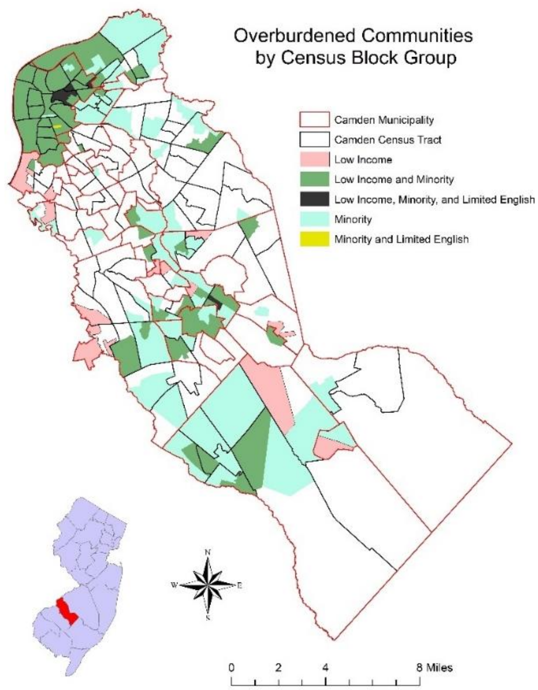


Figure 2.7 New Jersey overburdened communities map, Camden County.

2.4 Health Outcomes

Health outcome data on an annual basis from January 1, 2014 to December 31, 2017 were analyzed in this study. Such data were detailed for four categories: emergency department visits, emergency department unique patient counts, inpatient care visits, and inpatient unique patient counts. Data for the year 2018 was available but was incomplete, thus it was excluded from this study.

CCS (Clinical Classification Software) codes were used for health data stratification. CCS codes are a tool for the simplified analysis of healthcare diagnosis codes. As opposed to the full International Classification of Diseases (ICD) code system, which has over 14,000 codes, the CCS system modifies these into a multi-level numerical category system that can be used at a wider or more narrow scope (CCS, 2012).

As such, health data was stratified by year, CCS code for chief complaint, and by census tract of the patient's primary residence. Data was provided at the yearly sum level for each census tract and CCS code for each year.

Analysis was conducted for multi-level CCS codes based on similarity of illnesses: neoplasms (Multilevel Code 2, Single Level Codes 11-47); endocrine, nutritional, and metabolic diseases and immunity disorders (Multilevel Code 3, Single Level Codes 48-58); mental illness (Multilevel Code 5, Single Level Codes 650-663, 670); circulatory system disease (Multilevel Code 7, Single Level Codes 96-121); and respiratory disease (Multilevel Code 8, Single Level Codes 122-134). Specific illnesses related to their CCS codes can be found in Appendix A.

Health outcome data was first normalized to be representative of population within the census tract. As the CDC SVI has tract-level population data, this was used to convert ED visits, ED patients, inpatient visits, and inpatient patients to a ratio of visit frequency to tract population. First, tract numbers were aligned in between datasets. Here, it was noted that tracts 603201 and 603202 for health data were representative of data in tract 603200 in the SVI dataset. Similarly, health data tracts 609206 and 609207 were representative of tract 609203 in the SVI dataset. As such, the health data tracts were merged to fit the tract numbers of the SVI datasets.

Health outcome datasets were then divided by population tract population size from the SVI, with health outcomes from 2014-2015 being divided by the 2014 SVI tract populations, and the 2016-2017 health outcomes divided by the 2016 SVI tract populations.

Figure 2.8 presents the data for the 5 disease categories and 4 data sets for 4 years. Those values represent the incidence rate per 100,000 people. ED visits were higher than

ED patients for each category, and Inpatient visits were higher than Inpatient patients. This implies that a significant number of patients return for inpatient or emergency treatment within a year. Average values were greater for inpatient patients and inpatient visits than for ED patients and ED visits. Rates for ED patients and ED visits generally increased for the 4-year period. No obvious year-to-year trends were noted for inpatient patients or inpatient visits.

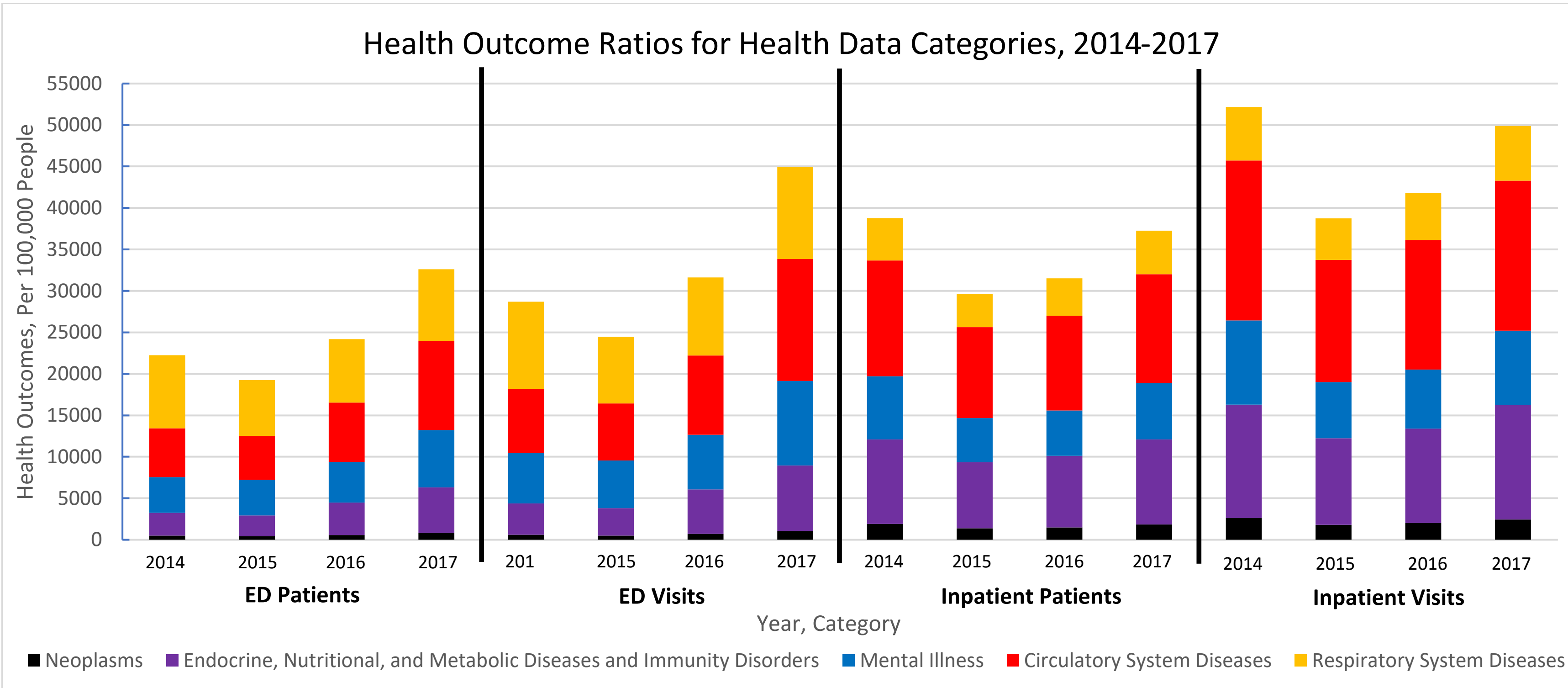


Figure 2.8 Yearly health outcomes for all health data groups and disease categories (per 100,000 people).

CHAPTER 3

METHODOLOGY

3.1 Social Vulnerability and Environmental Factors

Data sets were imported to R Studio for analysis, including Impervious Surface Percentage, Forest Cover Percentage, Floodplain Coverage Percentage, and 5 Social Vulnerability datasets (SVI Themes 1-4 and the overall percentile for all themes). The ggplot function in R Studio was used to form plots and visually compare datasets. These were formed using the following code, with the comparison of forest cover against percentile ranks for SVI themes 1-4 being used as an example:

```
jpeg(Forest Cover vs SVI.jpg)
ggplot(data = data0, mapping = aes(x = RPL_THEMES, y
        = fcover)) + geom_point() + labs(x = "SVI Percentile", y
        = "Forest Cover Percentage", title
        = "Forest Cover vs Social Vulnerability Index"
dev.off()
```

The correlation between the two variables was determined via the correlation function, with the forest cover against SVI percentile example being used here:

```
cor(data0$fcover, data0$RPL_THEMES)
```

Further analysis of the correlation values was determined per established literature guidelines for correlation interpretation (Hinkle et al., 2003).

Table 3.1 Guideline for Interpretation of Correlation Values

Value	Designation
+/- 0.9-1.0	Very High Correlation
+/- 0.7-0.9	High Correlation
+/- 0.5-0.7	Moderate Correlation
+/- 0.3-0.5	Low Correlation
+/- 0.0-0.3	Negligible Correlation

Following this, further analysis of the significance of values was also performed using the glm function. The glm function evaluates the data as a generalized linear model, then providing a summary of statistical information such as the significance of the relationship between two variables. In order optimize data analysis, just the coefficients were retrieved in order to quickly extract p-values from the dataset. A p-value of 0.05 or less is considered significant. An example code is shown, analyzing the generalized linear model between the aggregate of SVI themes and forest cover:

$$glm.mod0 <- glm(fcover \sim RPL\_THEMES, family = binomial(link = "logit"), data = data0)$$

$$coef(summary(glm.mod0))$$

3.2 Overburdened Communities and Health Outcomes

Data were uploaded for health outcomes in 4 data sets (ED visits, ED patients, Inpatient visits, and Inpatient patients) and EJ code classifications for overburdened communities. Health outcomes are numerical values presented as the ratio of incidence to census tract population. EJ code classifications are instead letter values assigned to each tract to signify a mix of socioeconomic variables. As such, a comparison of the correlation of values is not possible.

Instead, figures were formed that plotted data points of incidence-to-population ratios along the y-axis for EJ codes along the x-axis. These EJ codes included L for low income, M for minority, LM for low income AND minority, and LME for low income AND minority AND limited English proficiency. Also included was N for no EJ codes assigned. A t-test was utilized to compare the health outcomes of overburdened census tracts to those with no assigned EJ codes. This test would find if there was a significant difference in health outcomes between overburdened communities and non-overburdened communities. The results were also compared to themselves to see if communities with more than one EJ code, thus facing multiple socioeconomic issues, had a more significant difference in health outcomes than non-overburdened communities.

The function dummyVars was utilized in this scenario, creating a variable arbitrarily named Alpha out of the EJCode dataset. The following line creates the arbitrarily named variable Beta, which splits the dataset to group the tracts by their assigned EJ Code. Then, the same generalized linear model code is used, with this example showing the comparison of emergency department visits for respiratory complaints. The result in calling for a summary function is the p-values of the comparisons of tracts labeled L, M, LM, and LME each compared to tracts with no EJ Code assigned.

$$dummyVars('{\sim}EJcode1', data = data0) -> \ Alpha$$

$$\begin{aligned} Beta <- cbind(&data0[, !(colnames(data0)\ \%in\%\ c(\text{"}EJcode1\text{"}))], \\ &predict(Alpha, newdata\ =\ data0)) \end{aligned}$$

$$\begin{aligned} glm.mod0\ <- glm(&Respiratory\_ED\_Visits \sim EJcode1.L + EJcode1.LM \\ &+ EJcode1.M + EJcode1.LME, family\ = binomial(link \\ &= \text{"}logit\text{"}), data\ =\ Beta) \end{aligned}$$

$$coef(summary(glm.mod0))$$

3.3 Social Vulnerability, Land Cover, and Health Outcomes

Health data, land cover data, and SVI data were uploaded. Each health outcome (neoplasms, respiratory, cardiovascular, mental, and metabolic/endocrine/immune) for each health category (ED visits, ED patients, Inpatient visits, and Inpatient patients) was compared to the 4 SVI themes, the aggregate of themes, and environmental indicators (PM2.5, impervious surfaces, floodplain coverage, and forest cover).

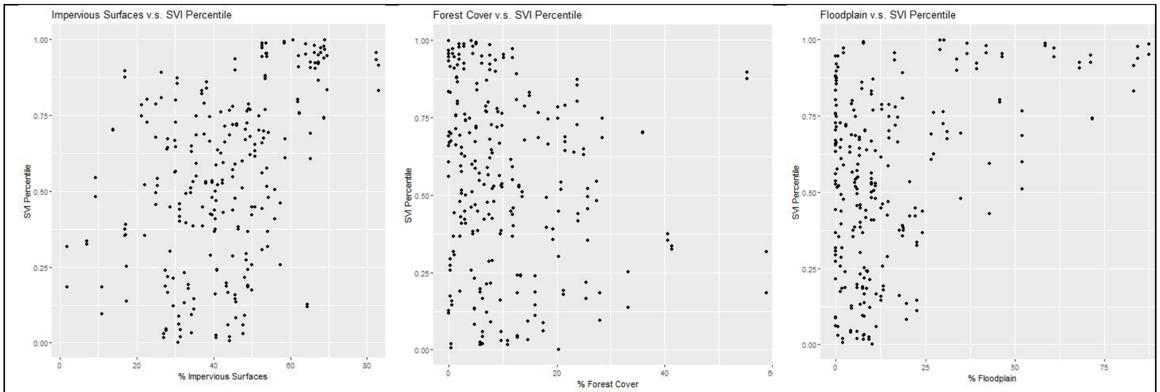
The ggplot function was used to create plots as demonstrated in 3.1. In visual analysis of the comparisons of variables, it was noted that several of these comparisons appeared to display a clear logarithmic relation. The health outcomes were graphically converted to a logarithmic form via the function "$scale\_y\_log10()\ +$" within the ggplot function and logarithmic forms of the graphs were included.

The cor function and glm function were used to determine the correlation and significance of the correlation, respectively, as described in 3.1.

CHAPTER 4

RESULTS

4.1 Social Vulnerability and Environmental Factors



Correlation = 0.442, p=0.000 Correlation = -0.163, p=0.036 Correlation = 0.408, p =0.000

Figure 4.1 Land cover and social vulnerability.

Figure 4.1 compares the aggregate of the 4 categories of the Social Vulnerability Index against impervious surfaces, forest cover, and floodplain coverage. The aggregate of SVI percentile had a low positive correlation of with impervious surface coverage, and it is at a high statistical significance. This is a generally positive trend with an especially dense cluster in the high SVI region and 70% impervious surface coverage. This suggests support of the trend of urban and highly developed living conditions for the most socially vulnerable.

Contrary to impervious surfaces, forest cover and social vulnerability have a negative correlation, though a negligible one. The p-value indicates statistical significance. Although high SVI percentile tends to accompany urban living conditions, the presence of socially vulnerable rural communities could explain a very high forest cover while also having limited social mobility. This suggests that urbanization is not necessary for social vulnerability.

Social vulnerability and floodplains were shown to have a low positive correlation that is statistically significant. The graph indicates that not only is a positive correlation present, but the non-floodplain areas (left) encompass all levels of social vulnerability, but flood prone areas (right) are exclusively occupied by the socially vulnerable households. This can be attributed to factors such as a lack of mobility and a willingness to accept occasional flooding in exchange for affordable housing.

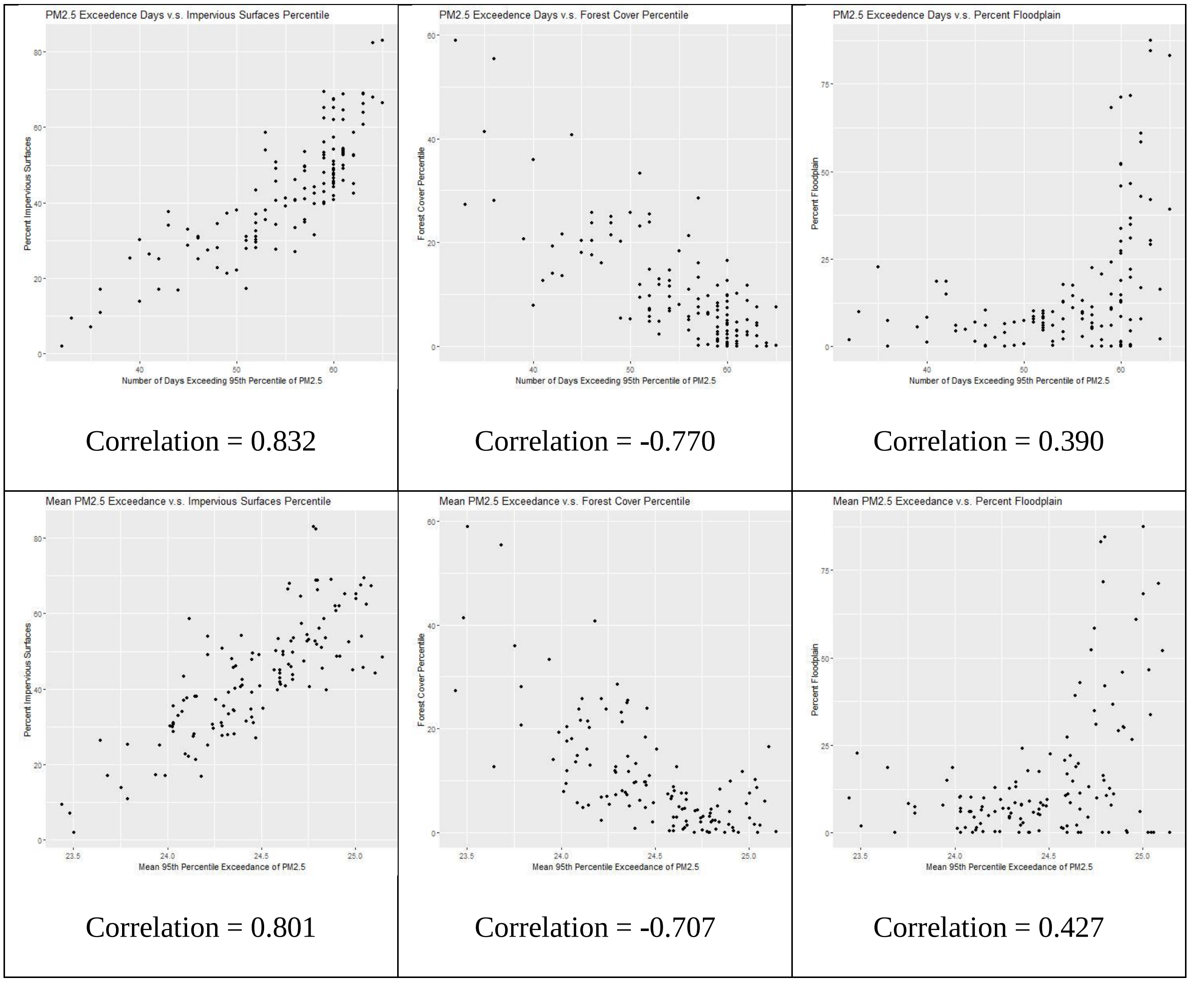
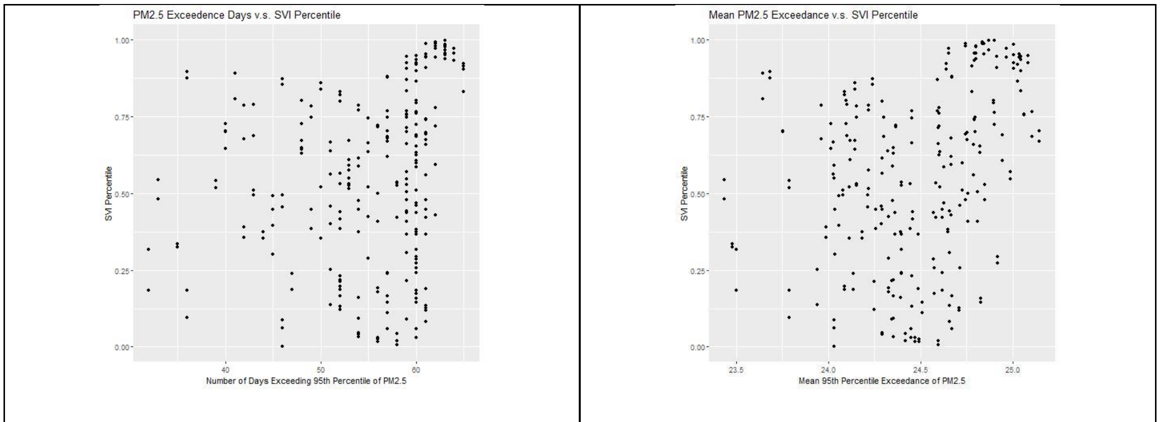


Figure 4.2 Land cover and PM2.5.

Figure 4.2 compares aerosolized particulate matter against impervious surfaces, forest cover, and floodplain coverage. The correlation between impervious surfaces and days exceeding the 95th percentile of PM2.5 and mean PM2.5 exceedance is high. This is indicative of the issues of air quality in urban environments, as those who live in areas with high impervious surfaces suffer from the worst air quality. This can be attributed to a number of factors, as was covered in Section 1.3, such as urban environments being more exposed to vehicular traffic, which comes with a slew of emissions, as well as industrial emissions. These factors, accompanied by the lack of trees and water bodies to hold particulate matter from reentering the air means that the air stays polluted for longer. Air chemistry is also accelerated by excess heat in these urban environments from a lack of evapotranspiration by trees and absorption of heat by roads and buildings.

Opposite to the correlation between PM2.5 and impervious surfaces is the high negative correlation between forest cover and days exceeding the 95th percentile of PM2.5 and mean PM2.5 exceedance. As stated previously, the evapotranspiration efforts of trees decrease temperature while also doing a better job of stabilizing and holding particulate matter out of the atmosphere. Also, the presence of forests takes away from the amount of impervious surface land cover and in turn is contrary to the effects of urbanization.

Floodplains showed a low positive correlation to the presence of PM2.5, especially when floodplain coverage exceeds 25%. Part of this phenomenon in Camden County can possibly be attributed to the fact that the urban center of the county, the city of Camden, is found on the Delaware River and within its floodplain. Though no literature suggested that these factors are inherently related, it can be supposed that industrial areas would have historically been built around major waterways for ease of shipment, thus urban environments may be historically linked to floodplains.



Correlation = 0.215, p = 0.006	Correlation = 0.322, p = 0.000

Figure 4.3 PM2.5 and social vulnerability.

Figure 4.3 compares particulate matter in the air to the aggregate of SVI themes. The correlation between particulate matter exceedance days and social vulnerability is negligible, though the correlation with mean PM2.5 and social vulnerability is a low positive correlation with high significance. This data corresponds with Figures 4.1. and 4.2., which find a correlation with SVI and urbanization as well as urbanization and air pollution. Here it is made clear that poor air quality impacts socially vulnerable communities at the highest rate, supporting the idea that low social and economic mobility induces higher exposures to the risks carried by air pollution.

4.2 Overburdened Communities and Health Outcomes

Health outcomes were compared amongst Camden county's overburdened communities. This was done by assessing the health outcome ratios for census groups with no assigned environmental justice codes (N for none) and comparing them to those with environmental justice codes (L for low income, M for minority, LM for low income and minority, LME for low income and minority with limited English ability). Examples are shown in figures 4.4 and 4.5. In 4.4, the rates of respiratory ED patients in the low income and minority group were significantly higher than the null group, and the LME group was also substantially higher than the null group. Minority status alone also tended to have higher respiratory effects than those communities which had no EJ codes assigned to them while low-income status alone had a modest and near negligible effect. Conversely, figure 4.2 shows that the null group had no significant difference from EJ communities in respiratory inpatient visits. All graphs are available in Appendix B.

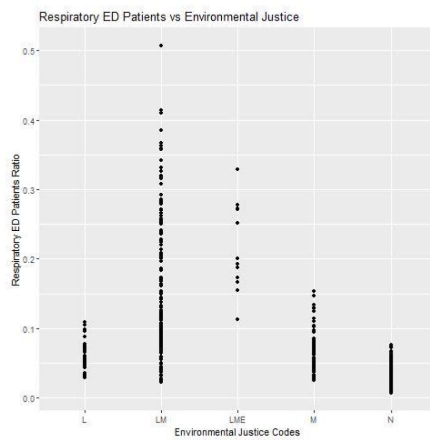


Figure 4.4 Environmental justice codes and respiratory ED patient ratios.

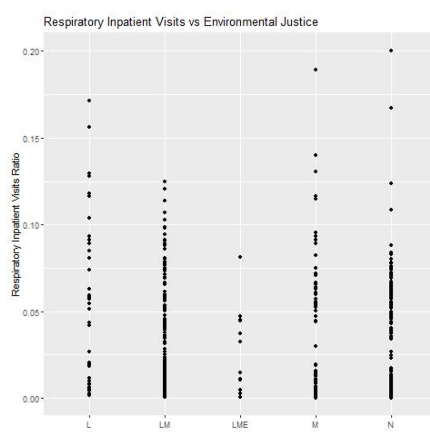


Figure 4.5 Environmental justice codes and respiratory inpatient visits ratios.

No significant differences from the null group were noted in any health outcome in inpatient visits. The only mildly significant difference within inpatient patients was for psychiatric patients, as seen in figure 4.6, where a low number of instances of higher risk was found in low income and minority and low-income alone communities.

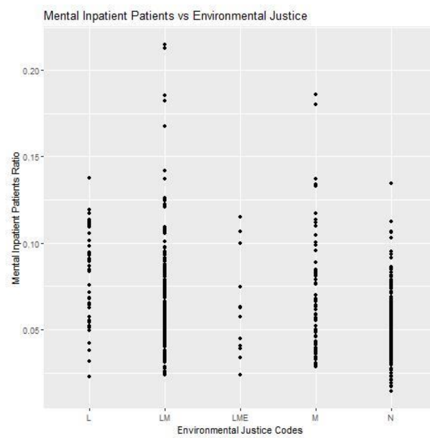


Figure 4.6 Environmental justice codes and psychiatric inpatient patient ratios.

Tables 4.1, 4.3, 4.5, and 4.7 depict the median health outcome ratio for each health outcome for each EJ community and non-EJ communities. Based on the comparisons between null tracts and tracts with one or more EJ Codes, significance of data was then determined. Tables 4.2, 4.4, 4.6, and 4.8 depict the p-values of the comparisons of tracts with assigned EJ Codes to those with no EJ Codes assigned. Neither inpatient visits (Table 4.6) nor inpatient patients (Table 4.8) showed any level of significant differences (where p is less than 0.05) between EJ Codes tracts and null tracts.

For both ED visits and ED patients, neither minority status nor low income alone showed significant enough difference from the null tracts in any system. However, the combination of low income and minority status showed significance in ED visits for circulatory and psychiatric complaints, with very high significance (p less than 0.001) in respiratory patients. In the few tracts that met the criteria for low income, minority, and limited English status, high significance remained for respiratory ED visits.

Significance in circulatory and psychiatric effects did not carry over to ED patients, however. The only significant values seen for ED patients were in respiratory cases for tracts with the combination of low income and minority, and tracts that combine low income, minority, and limited English status.

Table 4.1 Median Ratio of Health Outcomes in EJ Communities for ED Visits

	ED Visits				
	Respiratory	Circulatory	Neoplasms	Psychiatric	E/I/M
Non-EJ	**0.035**	**0.055**	**0.005**	**0.039**	**0.026**
Low Income	0.065	0.098	0.008	0.057	0.042
Minority	0.070	0.076	0.007	0.049	0.042
Low Income and Minority	0.142	0.123	0.007	0.080	0.066
Low Income, Minority, and Limited English Ability	0.247	0.150	0.008	0.147	0.083

Table 4.2 Significance of Difference in Health Outcomes Between EJ Communities and Non-EJ Communities for ED Visits

	ED Visits				
	Respiratory	Circulatory	Neoplasms	Psychiatric	E/I/M
Low Income	0.355	0.415	0.875	0.520	0.511
Minority	0.192	0.287	0.881	0.504	0.385
Low Income and Minority	***0.000	*0.011	0.819	*0.011	0.058
Low Income, Minority, and Limited English Ability	**0.002	0.144	0.892	0.116	0.205

* when $p < 0.05$
** when $p < 0.005$
*** when $p<0.001$

Table 4.3 Median Ratio of Health Outcomes in EJ Communities for ED Patients

	ED Patients				
	Respiratory	Circulatory	Neoplasms	Psychiatric	E/I/M
Non-EJ	**0.031**	**0.046**	**0.004**	**0.030**	**0.022**
Low Income	0.055	0.077	0.007	0.045	0.034
Minority	0.058	0.060	0.005	0.037	0.031
Low Income and Minority	0.113	0.088	0.006	0.059	0.046
Low Income, Minority, and Limited English Ability	0.196	0.105	0.006	0.096	0.057

Table 4.4 Significance of Difference in Health Outcomes Between EJ Communities and non-EJ Communities for ED Patients

	ED Patients				
	Respiratory	Circulatory	Neoplasms	Psychiatric	E/I/M
Low Income	0.376	0.516	0.861	0.585	0.606
Minority	0.234	0.409	0.870	0.636	0.513
Low Income and Minority	***0.000	0.068	0.822	0.058	0.176
Low Income, Minority, and Limited English Ability	*0.009	0.294	0.896	0.233	0.373

* when $p < 0.05$
** when $p < 0.005$
*** when $p<0.001$

Table 4.5 Median Ratio of Health Outcomes in EJ Communities for Inpatient Visits

	Inpatient Visits				
	Respiratory	Circulatory	Neoplasms	Psychiatric	E/I/M
Non-EJ	**0.026**	**0.026**	**0.020**	**0.073**	**0.018**
Low Income	0.041	0.036	0.035	0.106	0.037
Minority	0.026	0.026	0.025	0.093	0.022
Low Income and Minority	0.026	0.027	0.027	0.106	0.026
Low Income, Minority, and Limited English Ability	0.023	0.024	0.024	0.096	0.028

Table 4.6 Significance of Difference in Health Outcomes Between EJ Communities and Non-EJ Communities for Inpatient Visits

	Inpatient Visits				
	Respiratory	Circulatory	Neoplasms	Psychiatric	E/I/M
Low Income	0.629	0.366	0.333	0.345	0.579
Minority	0.790	0.578	0.541	0.499	0.741
Low Income and Minority	0.952	0.629	0.590	0.391	0.764
Low Income, Minority, and Limited English Ability	0.913	0.943	0.979	0.858	0.982

* when $p < 0.05$
** when $p < 0.005$
*** when $p<0.001$

Table 4.7 Median Ratio of Health Outcomes in EJ Communities for Inpatient Patients

	Inpatient Patients				
	Respiratory	Circulatory	Neoplasms	Psychiatric	E/I/M
Non-EJ	**0.037**	**0.108**	**0.016**	**0.049**	**0.078**
Low Income	0.060	0.159	0.023	0.088	0.123
Minority	0.048	0.122	0.018	0.058	0.094
Low Income and Minority	0.051	0.120	0.015	0.066	0.096
Low Income, Minority, and Limited English Ability	0.047	0.100	0.010	0.060	0.083

Table 4.8 Significance of Difference in Health Outcomes Between EJ Communities and Non-EJ Communities for Inpatient Patients

	Inpatient Patients				
	Respiratory	Circulatory	Neoplasms	Psychiatric	E/I/M
Low Income	0.489	0.352	0.800	0.442	0.436
Minority	0.654	0.564	0.905	0.636	0.585
Low Income and Minority	0.591	0.793	0.937	0.436	0.660
Low Income, Minority, and Limited English Ability	0.929	0.863	0.873	0.868	0.977

* when $p < 0.05$
** when $p < 0.005$
*** when $p<0.001$

4.3 Social Vulnerability, Land Cover, and Health Outcomes

Health outcomes were compared to the social vulnerability index scores for each SVI theme, the average of all SVI themes, aerosolized particulate matter concentrations and exceedance days, and land cover values. This was achieved by analysis of correlation values between the variables and subsequent assignment of significance values. All plots for these comparisons and their correlations values are available in Appendix C. Analysis of correlation values was done per established literature guidelines (Hinkle et al., 2003). Table 4.9 establishes the color coordination of correlation values for tables 4.10 and 4.11.

Values for inpatient patients and inpatient visits had negligible correlation and no significance. As such, these values are excluded from this analysis, though they are available within Appendix C. Correlation values and significance are shown in tables 4.10 and 4.11 for ED patients and ED visits, respectively.

The category that showed the highest levels of significance and correlation was respiratory health effects. SVI themes for ED patients showed high significance and even higher significance in ED visits. This was matched with high correlation values for theme 1 and 3 for ED patients and theme 1 for ED visits. Low correlations were found for environmental factors in both groups including particulate matter, impervious surfaces, and flood plain coverage. The correlations were also all significant.

Mental illness was the next most significant category. Moderate correlations with significance were noted for themes 1 and 3 as well as the aggregate of themes for both groups. Low correlations for themes 2 and 4 were also significant in ED visits. A low correlation was significant for impervious surfaces in ED patients, though further environmental factors were significant for ED visits: low correlations were significant for mean PM2.5 exceedance concentration, impervious surface coverage, and flood plain coverage.

Effects on the circulatory system were primarily tied to socioeconomic factors. Themes 1 and 3 and the SVI themes aggregate had moderate correlations that were significant in ED patients. This expanded in ED visits to also include significant low correlations for themes 2 and 4. A significant low correlation was also observed between ED visits and impervious surface coverage.

The endocrine/immune/metabolic category was significant for themes 1 and 3 and the aggregate of SVI themes only in ED visits. These had a moderate correlation. Otherwise, all other correlations were insignificant for this health category.

Finally, neoplasms showed no significant connection to any social or environmental category. Neoplasms only showed a low correlation for theme 1 and the aggregate of SVI themes in ED patients, though this was insignificant, and otherwise had negligible correlation values.

Notably, forest cover had negligible correlation throughout all health outcomes, with all values being statistically insignificant.

Results were also compared to logarithmic forms. Plots are available in Appendix C. For the most part, significance and correlation had minor increases when looked at on a logarithmic scale, though correlation values were much lower for environmental effects compared to social vulnerability measures. This may suggest that social vulnerability and health outcomes have a logarithmic relationship.

Table 4.9 Key for Significance of Correlation Values

Value	Designation	Color
+/- 0.9-1.0	Very High Correlation	
+/- 0.7-0.9	High Correlation	
+/- 0.5-0.7	Moderate Correlation	
+/- 0.3-0.5	Low Correlation	
+/- 0.0-0.3	Negligible Correlation	

Table 4.10 Correlation Values and Significance of ED Health Outcomes

	ED Patients				
	Respiratory	Circulatory	Neoplasms	Mental	E/I/M
Theme 1	0.715***	0.591*	0.361	0.625*	0.586
Theme 2	0.512**	0.439		0.453	0.437
Theme 3	0.707***	0.546*		0.552*	0.556
Theme 4	0.461**	0.420		0.445	0.432
SVI Themes 1-4	0.689***	0.588*	0.369	0.603*	0.592
PM2.5 95th Exceedance Days	0.339*			0.336	
Mean PM2.5 Exceedance	0.411*			0.373	
Impervious Surfaces	0.485**	0.364		0.490*	0.361
Forest Cover					
Flood Plain	0.421*	0.320		0.439	0.313

* when p < 0.05
** when p < 0.005
*** when p<0.001

Table 4.11 Correlation Values and Significance of ED Visit Outcomes

	ED Visits				
	Respiratory	Circulatory	Neoplasms	Mental	E/I/M
Theme 1	0.702***	0.589**		0.582***	0.584*
Theme 2	0.501***	0.437*		0.424*	0.431
Theme 3	0.692***	0.556**		0.523**	0.562*
Theme 4	0.453***	0.422*		0.420*	0.432
SVI Themes 1-4	0.675***	0.586**		0.565**	0.588*
PM2.5 95th Exceedance Days	0.346*			0.314	
Mean PM2.5 Exceedance	0.409**	0.304		0.342*	
Impervious Surfaces	0.488***	0.381*		0.465*	0.382
Forest Cover					
Flood Plain	0.416**	0.345		0.410*	0.333

* when p < 0.05
** when p < 0.005
*** when p<0.00

CHAPTER 5

DISCUSSION

5.1 Socioeconomics and Environment

Assessment of social and environmental factors in Camden County found results consistent with prior literature review. The social vulnerability index was used as a marker for social status within the county at a tract level, and it was found that high social vulnerability was correlated with worse environmental conditions.

Positive correlations were made between the SVI and impervious surfaces and floodplain coverage, seen in figure 4.1. This is indicative of a process referred to as sorting, which describes the tendency affluent individuals to relocate out of poor environmental conditions and to gentrify their new community thus economically barring socially vulnerable individuals from leaving poor environmental conditions (Banzhaf et al., 2019). This correlation of impervious surfaces to socioeconomic status is further seen in the development of green spaces and parkland in affluent communities, as these are capital improvements that are not high priorities for struggling communities (Rigolon et al., 2018). It is a common thread that environmental justice concerns in vulnerable communities are not priorities as funds are instead diverted to basic needs such as food, water, shelter, and healthcare (Kronenberg et al., 2020).

Furthermore, high positive correlations were drawn between aerosolized particulate matter and impervious surface coverage (figure 4.2), with a high negative correlation found between PM2.5 and forest cover (figure 4.2). A positive correlation between PM2.5 and floodplain coverage is also noted. This data supports the logic that urban environments tend to have worse air quality.

Given that associations between SVI and land coverage were established for Camden County, and strong associations between land use and particulate matter were established, it is evident that social vulnerability and particulate matter would also correlate. In fact, a positive correlation with high significance was made between SVI percentile and mean PM2.5 exceedance values (figure 4.3). This corresponds with the IPCC reporting that urban areas tend to have higher air pollutant concentrations due to industrial sites, higher vehicle density, and warmer temperatures in cities allowing for the higher evolution of air pollutants in the area (2022).

5.2 Social Effects on Health

Assessment of the effects of social and economic factors on health found significant effects in the number of emergency department visits and individual patients. This aligns with prior research that stressors have disproportionate effects on socioeconomically vulnerable populations, induced by a lack of alternatives when exposed to hazards due to poverty (Diderichsen et al., 2019). This is especially true of unhoused and vulnerably housed populations, which often have several social vulnerabilities and experience stigmatization and unmet healthcare needs (Purkey & MacKenzie, 2019).

In the ED patients group, circulatory and mental health impacts were significant in relation to themes 1 and 3, which are socioeconomic status and minority status respectively. Respiratory effects were the most universal, with all 4 SVI themes impacted. This includes theme 2, household composition, and theme 4, transportation and housing.

These effects expanded in the ED visits group, with all 4 SVI themes having a significant impact on respiratory, circulatory, and mental health effects. In the ED visits group, significant impact was also seen for themes 1 and 3 for the endocrine, immune, and metabolic illnesses.

Additionally, accumulation of risk factors was shown to cause negative health effects. In ED patients, reaching the overburdened community definition for low income or minority community was not enough to have a statistically significant increase in any particular health outcome, though communities that were low income and minority had increased rates of respiratory disease. The same was found for communities with low income, minority status, and limited English ability. Similar results were noted for ED visits, with no significant increases for low income or minority communities, but the overlap of these factors led to significant increases in respiratory, circulatory, and psychiatric health outcomes. Negative respiratory health outcomes in ED visits were also noted for communities with low income, minority status, and limited English ability. These results are in line with previous studies that found that the overlap of multiple risk factors amplify the health effects of social vulnerabilities (Haggerty et al., 2020).

5.3 Environmental Effects on Health

Health impacts were also noted based on environmental factors, such as particulate matter in the air, levels of impervious surface coverage, and levels of floodplain coverage.

Impervious surfaces had a large effect in the study. Higher levels of impervious surfaces meant a lower amount of forest, grassland, and green spaces. Previous research has found that green spaces afford benefits such as better perception of health status, better socialization, and overall better mental health (Enssle & Kabisch, 2020). This study agreed with prior findings, as higher levels of impervious surfaces had significant increases in negative mental health outcomes for both ED patients and ED visits.

High levels of impervious surfaces are also directly responsible for the urban heat island effect, which intensifies effects of heat waves and increases evolution of air pollutants (IPCC, 2022; Leal Filho et al., 2018). The relation between air pollutants and impervious surfaces has also been established in Camden County (figure 4.2). Particulate pollution is worrisome as prior literature has found PM to have a number of health damages due to penetration into the alveoli of the lungs and formation of arterial plaques (Spickett et al., 2021). Along with many other conditions, particulate matter has been associated with negative cardiovascular, respiratory, and mental health outcomes (Wolf et al., 2021; Gu et al., 2020; Yu et al., 2020; Tsai et al., 2019; Analtis et al., 2018; Anenberg et al., 2018; Dong et al., 2018; Malley et al., 2017; Szyszkowicz et al., 2016, Larrieu et al., 2009). Concurrently, this study found significant correlation between respiratory illness and particulate matter and impervious surfaces in ED patients. Moreso, significant correlation was also found in ED visits between impervious surfaces and particulate matter and respiratory and mental illness. A significant correlation in ED visits was made between cardiovascular health and impervious surfaces, but not with particulate matter.

Floodplain coverage was also found to be significant, having increases in respiratory health effects for ED patients and respiratory, circulatory, and mental health effects in ED visits.

5.4 Limitations

One of the major limitations within this study was the lack of measurement capabilities at a local scale for factors such as temperature, rainfall, and air quality. Such measurements would require a larger number of monitoring stations to precisely capture phenomenon such as the urban heat island effect or to determine the local concentration of particulate matter more accurately along with other key pollutants. Since the monitoring stations for Camden County are few and surround the county instead of existing throughout the county, attempts to determine environmental factors in the interior of the county based on distance from measuring stations would be inaccurate. As a result, land use was used as an indirect measurement of the effects of heat and precipitation. Though this comparison is useful, and the connection between urbanization and excess heat is established in literature, further and more accurate analysis could be performed if more data was available.

Another limitation is the interpretation of the health data. Although some of the correlations between social vulnerability and health effects were very strong, they presented in visitation to the Emergency Department. Likewise, significant correlations were absent for inpatient patient and inpatient visit values. It is established that people of low socioeconomic status, which are represented within the SVI, have higher rates of ED utilization with lower rates of primary care utilization due to costs and transportation issues (Haggerty et al., 2020). This variable was not accounted for, and the extent to which a high utilization of emergency services accounts for health effects of social vulnerability cannot be determined.

CHAPTER 6

CONCLUSION

Investigation of the effects of climate and socioeconomics on health outcomes proved to offer insight into the complex interactions between the processes while opening the door for further investigation.

It was found that the risk of negative health impacts was most significantly correlated with social vulnerability. However, low to moderate effects were also noted for a number of the environmental factors evaluated, such as aerosolized particulate matter and impervious surface coverage. This would indicate that future interventions in the community might focus on environmental justice with a stronger focus on social factors.

Health risks were also increased and compounded when several social and economic variables were added, as seen in Tables 4.2 and 4.4. Such phenomenon had previously been observed, and have been confirmed for this test area. This would indicate that further research and intervention should have a focus on multi-risk communities.

Health impacts were seen in ED visits and ED patients, but were insignificant in inpatient visits and inpatient patients. ED visits also exceeded ED patients in correlation and significance values. At face value, this would indicate that health impacts tend to be more emergent, but not severe to the extent that patients are brought in for inpatient treatment. However, this can also be reflective of higher levels of ED usage and lower levels of preventative care by socially vulnerable patients. Much higher ED visit values also reflect this point, as this indicates that much of the volume of patients is coming from repeat patients who are generally more sick and more likely to utilize the emergency system.

The highest health impacts were found on the respiratory system, with the most associated factors, highest significance, and highest correlation values. Negative effects were also noted for cardiovascular and mental health to a significant degree, with some effects also found in endocrine, immune, and metabolic diseases. No significant findings were found in relation to neoplasms. Further research should look further into the categories to find specific illnesses of concern. With significant effects in cardiovascular and respiratory health, a better understanding of mechanisms and appropriate countermeasures can be attained with closer examination. Questions for further research can also be found in the subjectivity of mental health evaluations, as diagnosis of conditions is not as straightforward as other illnesses. As these diagnoses are subject to clinician discretion and a level of subjectivity in how patients present, additional research on mental health impacts is also appropriate. Finally, neoplasms were insignificant as a group. However, this category is wide ranging in etiology and presents in populations over a larger time scale than was evaluated in this study. The possibility of a connection between neoplasms and environmental factors should not be dismissed, and further research would be appropriate.

APPENDIX A:

CCS CODES AND LABELS USED IN ANALYSIS

Table A1 CCS Codes Used in the Analysis of Health Outcomes, and Their Corresponding Disorders

CCS Level 1	Level 1 Label	CCS Category	CCS Category Label
2	Neoplasms	11	Cancer of head and neck
2	Neoplasms	12	Cancer of esophagus
2	Neoplasms	13	Cancer of stomach
2	Neoplasms	14	Cancer of colon
2	Neoplasms	15	Cancer of rectum and anus
2	Neoplasms	16	Cancer of liver and intrahepatic bile duct
2	Neoplasms	17	Cancer of pancreas
2	Neoplasms	18	Cancer of other GI organs; peritoneum
2	Neoplasms	19	Cancer of bronchus; lung
2	Neoplasms	20	Cancer; other respiratory and intrathoracic
2	Neoplasms	21	Cancer of bone and connective tissue
2	Neoplasms	22	Melanomas of skin
2	Neoplasms	23	Other non-epithelial cancer of skin
2	Neoplasms	24	Cancer of breast
2	Neoplasms	25	Cancer of uterus
2	Neoplasms	26	Cancer of cervix
2	Neoplasms	27	Cancer of ovary
2	Neoplasms	28	Cancer of other female genital organs
2	Neoplasms	29	Cancer of prostate
2	Neoplasms	30	Cancer of testis
2	Neoplasms	31	Cancer of other male genital organs
2	Neoplasms	32	Cancer of bladder
2	Neoplasms	33	Cancer of kidney and renal pelvis
2	Neoplasms	34	Cancer of other urinary organs
2	Neoplasms	35	Cancer of brain and nervous system

CCS Level 1	Level 1 Label	CCS Category	CCS Category Label
2	Neoplasms	36	Cancer of thyroid
2	Neoplasms	37	Hodgkin's disease
2	Neoplasms	38	Non-Hodgkin's lymphoma
2	Neoplasms	39	Leukemias
2	Neoplasms	40	Multiple myeloma
2	Neoplasms	41	Cancer; other and unspecified primary
2	Neoplasms	42	Secondary malignancies
2	Neoplasms	43	Malignant neoplasm without specification of site
2	Neoplasms	44	Neoplasms of unspecified nature or uncertain behavior
2	Neoplasms	45	Maintenance chemotherapy; radiotherapy
2	Neoplasms	46	Benign neoplasm of uterus
2	Neoplasms	47	Other and unspecified benign neoplasm
3	Endocrine; nutritional; and metabolic diseases and immunity disorders	48	Thyroid disorders
3	Endocrine; nutritional; and metabolic diseases and immunity disorders	49	Diabetes mellitus without complication
3	Endocrine; nutritional; and metabolic diseases and immunity disorders	50	Diabetes mellitus with complications
3	Endocrine; nutritional; and metabolic diseases and immunity disorders	51	Other endocrine disorders
3	Endocrine; nutritional; and metabolic diseases and immunity disorders	52	Nutritional deficiencies

CCS Level 1	Level 1 Label	CCS Category	CCS Category Label
3	Endocrine; nutritional; and metabolic diseases and immunity disorders	53	Disorders of lipid metabolism
3	Endocrine; nutritional; and metabolic diseases and immunity disorders	54	Gout and other crystal arthropathies
3	Endocrine; nutritional; and metabolic diseases and immunity disorders	55	Fluid and electrolyte disorders
3	Endocrine; nutritional; and metabolic diseases and immunity disorders	56	Cystic fibrosis
3	Endocrine; nutritional; and metabolic diseases and immunity disorders	57	Immunity disorders
3	Endocrine; nutritional; and metabolic diseases and immunity disorders	58	Other nutritional; endocrine; and metabolic disorders
5	Mental Illness	650	Adjustment disorders
5	Mental Illness	651	Anxiety disorders
5	Mental Illness	652	Attention-deficit conduct and disruptive behavior disorders
5	Mental Illness	653	Delirium dementia and amnestic and other cognitive disorders
5	Mental Illness	654	Developmental disorders
5	Mental Illness	655	Disorders usually diagnosed in infancy childhood or adolescence
5	Mental Illness	656	Impulse control disorders NEC

CCS Level 1	Level 1 Label	CCS Category	CCS Category Label
5	Mental Illness	657	Mood disorders
5	Mental Illness	658	Personality disorders
5	Mental Illness	659	Schizophrenia and other psychotic disorders
5	Mental Illness	660	Alcohol-related disorders
5	Mental Illness	661	Substance-related disorders
5	Mental Illness	662	Suicide and intentional self-inflicted injury
5	Mental Illness	663	Screening and history of mental health and substance abuse codes
5	Mental Illness	670	Miscellaneous mental health disorders
7	Diseases of the circulatory system	96	Heart valve disorders
7	Diseases of the circulatory system	97	Peri-; endo-; and myocarditis; cardiomyopathy (except that caused by tuberculosis or sexually transmitted disease)
7	Diseases of the circulatory system	98	Essential hypertension
7	Diseases of the circulatory system	99	Hypertension with complications and secondary hypertension
7	Diseases of the circulatory system	100	Acute myocardial infarction
7	Diseases of the circulatory system	101	Coronary atherosclerosis and other heart disease
7	Diseases of the circulatory system	102	Nonspecific chest pain
7	Diseases of the circulatory system	103	Pulmonary heart disease
7	Diseases of the circulatory system	104	Other and ill-defined heart disease
7	Diseases of the circulatory system	105	Conduction disorders
7	Diseases of the circulatory system	106	Cardiac dysrhythmias

CCS Level 1	Level 1 Label	CCS Category	CCS Category Label
7	Diseases of the circulatory system	107	Cardiac arrest and ventricular fibrillation
7	Diseases of the circulatory system	108	Congestive heart failure; nonhypertensive
7	Diseases of the circulatory system	109	Acute cerebrovascular disease
7	Diseases of the circulatory system	110	Occlusion or stenosis of precerebral arteries
7	Diseases of the circulatory system	111	Other and ill-defined cerebrovascular disease
7	Diseases of the circulatory system	112	Transient cerebral ischemia
7	Diseases of the circulatory system	113	Late effects of cerebrovascular disease
7	Diseases of the circulatory system	114	Peripheral and visceral atherosclerosis
7	Diseases of the circulatory system	115	Aortic; peripheral; and visceral artery aneurysms
7	Diseases of the circulatory system	116	Aortic and peripheral arterial embolism or thrombosis
7	Diseases of the circulatory system	117	Other circulatory disease
7	Diseases of the circulatory system	118	Phlebitis; thrombophlebitis and thromboembolism
7	Diseases of the circulatory system	119	Varicose veins of lower extremity
7	Diseases of the circulatory system	120	Hemorrhoids
7	Diseases of the circulatory system	121	Other diseases of veins and lymphatics

CCS Level 1	Level 1 Label	CCS Category	CCS Category Label
8	Diseases of the respiratory system	122	Pneumonia (except that caused by tuberculosis or sexually transmitted disease)
8	Diseases of the respiratory system	123	Influenza
8	Diseases of the respiratory system	124	Acute and chronic tonsillitis
8	Diseases of the respiratory system	125	Acute bronchitis
8	Diseases of the respiratory system	126	Other upper respiratory infections
8	Diseases of the respiratory system	127	Chronic obstructive pulmonary disease and bronchiectasis
8	Diseases of the respiratory system	128	Asthma
8	Diseases of the respiratory system	129	Aspiration pneumonitis; food/vomitus
8	Diseases of the respiratory system	130	Pleurisy; pneumothorax; pulmonary collapse
8	Diseases of the respiratory system	131	Respiratory failure; insufficiency; arrest (adult)
8	Diseases of the respiratory system	132	Lung disease due to external agents
8	Diseases of the respiratory system	133	Other lower respiratory disease
8	Diseases of the respiratory system	134	Other upper respiratory disease

APPENDIX B

GRAPHS OF EJ CODES FOR OVERBURDENED COMMUNITIES AND HEALTH OUTCOMES

Codes for overburdened communities were assigned for each census tract per the New Jersey Environmental Justice Law. Low income communities are labeled L, minority communities are labeled M, low income AND minority communities are labeled LM, and low income AND minority AND limited English ability communities are labeled LME. Health outcomes were compared to non-overburdened communities, labeled N.

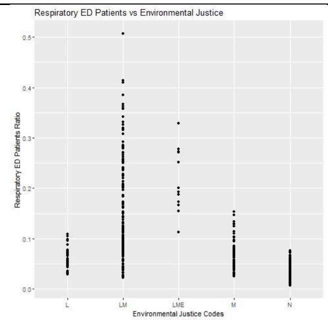
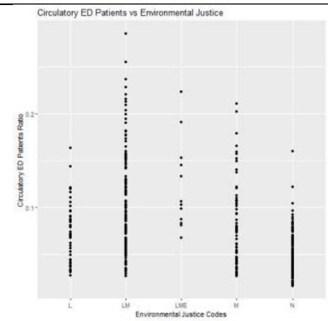
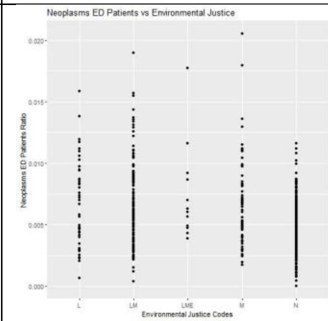
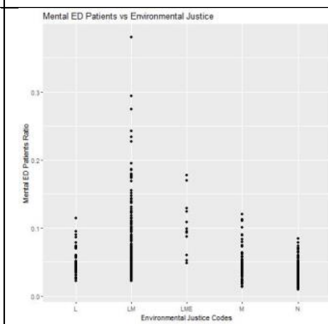
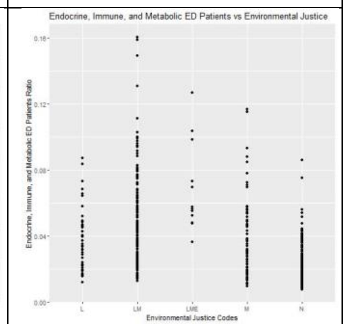
<table>
<tr><td></td><td>Respiratory</td><td>Circulatory</td><td>Neoplasms</td><td>Psychiatric</td><td>Endocrine, Immune, and Metabolic</td></tr>
<tr><td>Graph</td><td>
</td><td>
</td><td>
</td><td>
</td><td>
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Figure B1 EJ codes vs. ED patients.

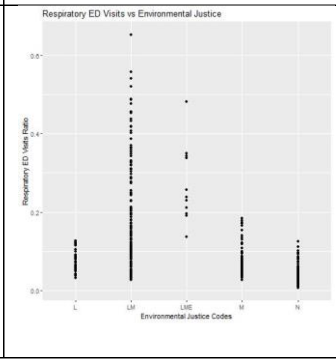
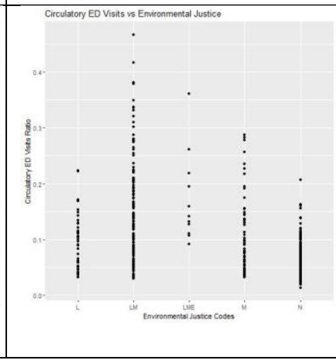
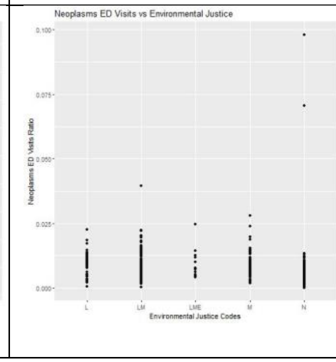
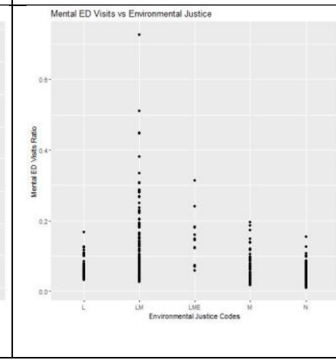
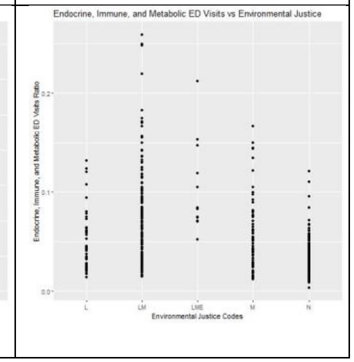
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					

Figure B2 EJ codes vs. ED visits.

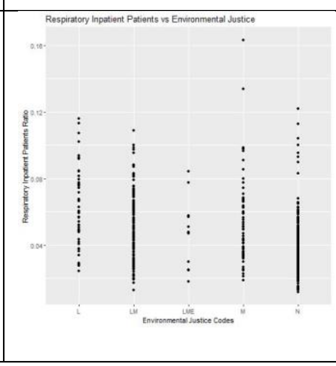
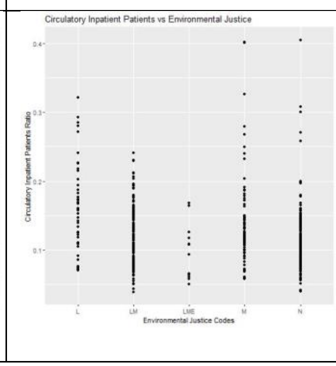
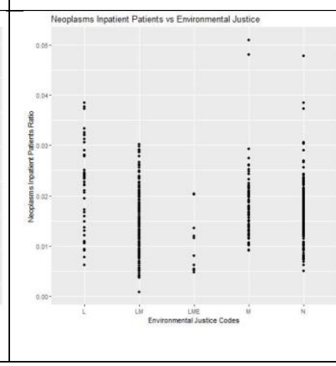
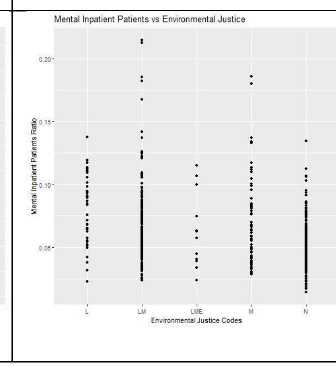
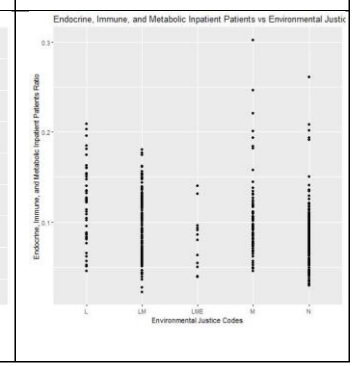
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					

Figure B3 EJ codes vs. inpatient patients.

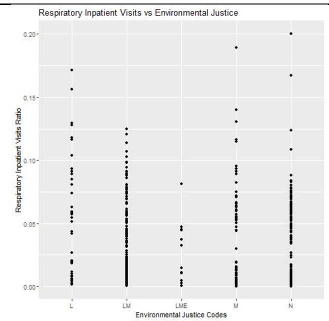
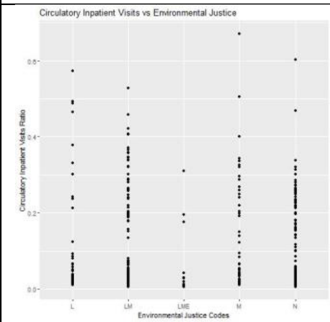
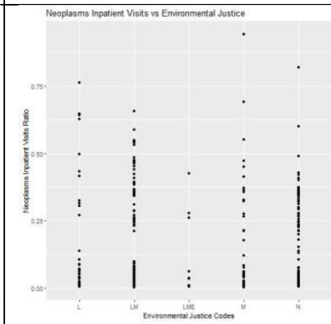
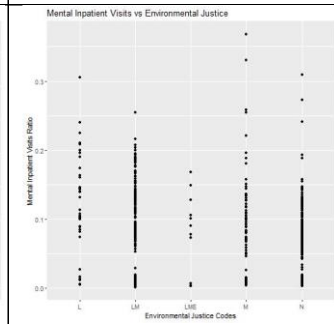
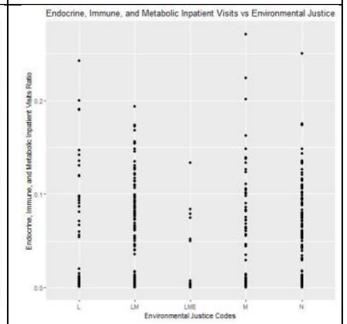
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					

Figure B4 EJ codes vs. inpatient visits.

APPENDIX C

GRAPHS OF CORRELATIONS BETWEEN SOCIAL AND ENVIRONMENTAL FACTORS AND HEALTH OUTCOMES

Health outcomes were compared to the CDC Social Vulnerability Index and environmental factors (impervious surface coverage, forest cover, floodplain coverage, Days exceeding the 95th percentile of PM2.5 in Camden County, and mean concentration of values exceeding the 95th percentile). It was noted that some of these comparisons and correlations appeared to exhibit a logarithmic correlation. As such, a logarithmic model was also run for each comparison.

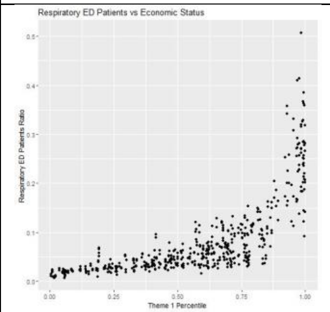
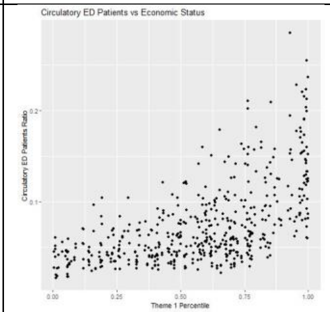
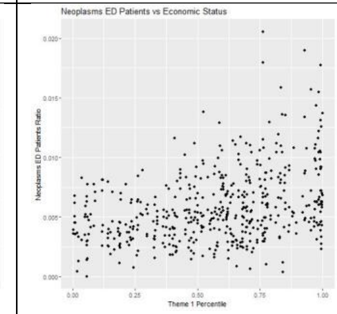
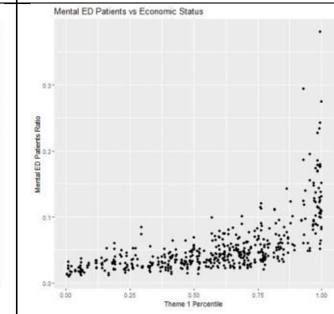
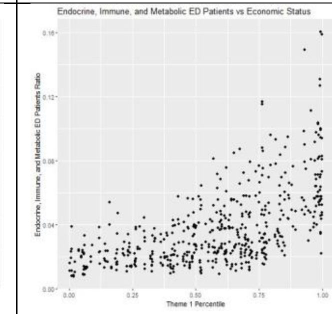
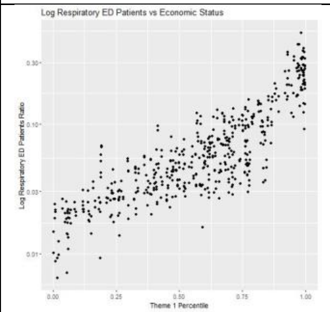
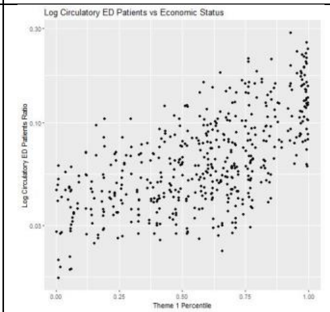
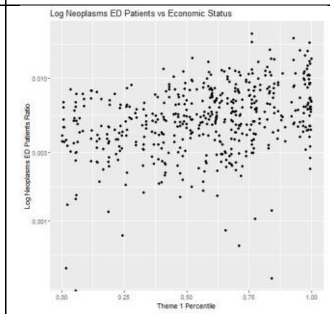
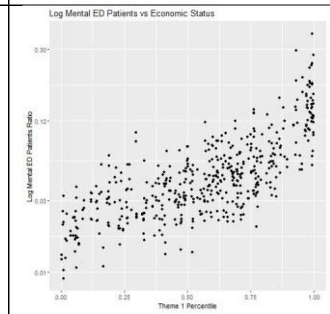
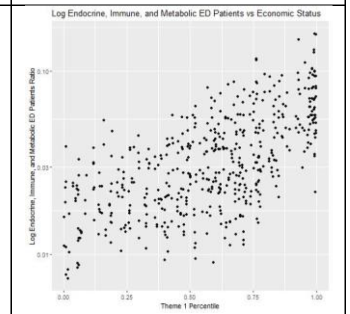
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.715086	0.590888	0.360511	0.624583	0.586475
Graph of Log Relation					
Cor. of Log	0.851277	0.623785	-	0.742545	0.622196

Figure C1 Theme 1 vs. ED patients.

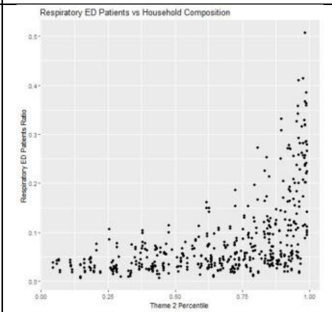
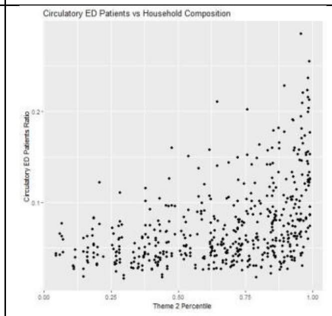
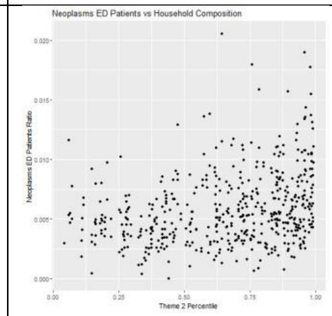
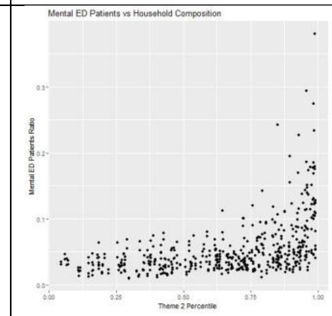
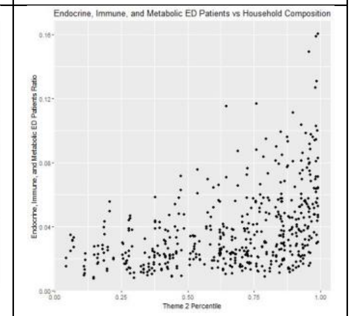
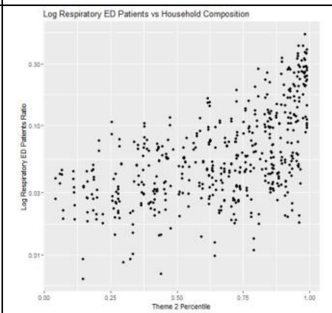
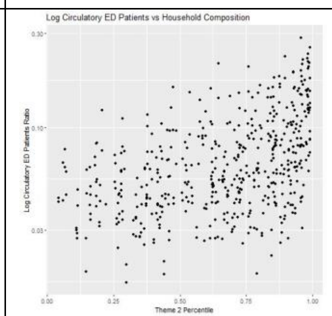
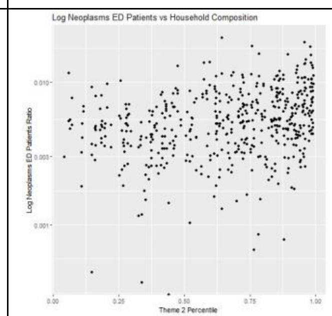
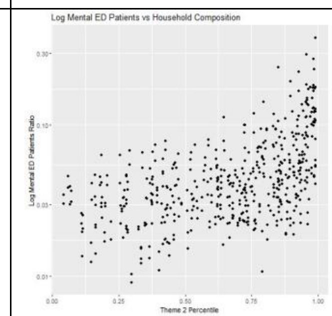
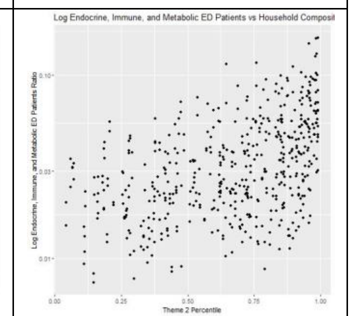
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.512318	0.439045	0.279524	0.452744	0.436867
Graph of Log Relation					
Cor. of Log	0.559016	0.450252	-	0.509687	0.453905

Figure C2 Theme 2 vs. ED patients.

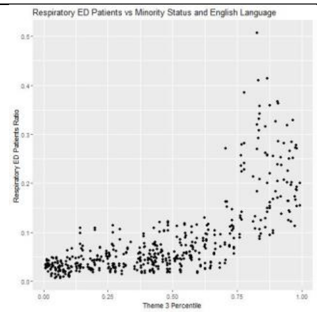
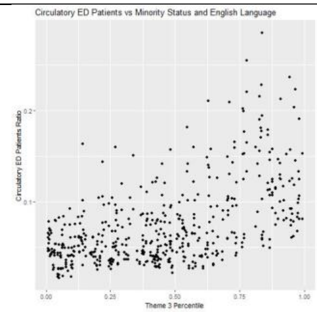
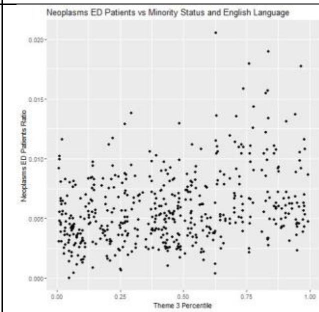
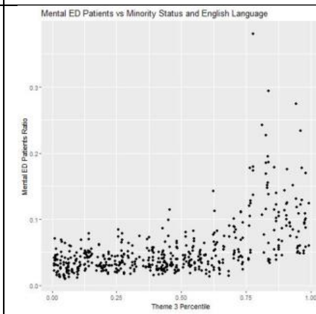
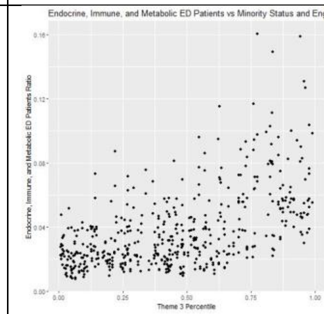
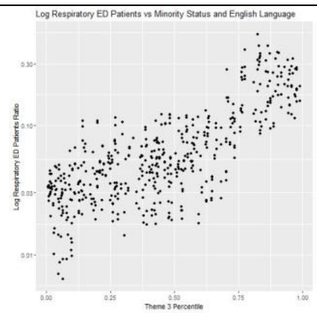
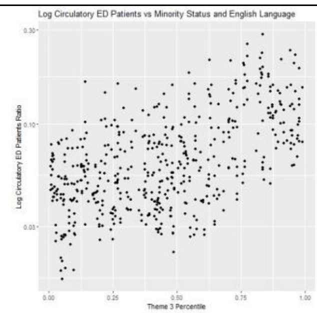
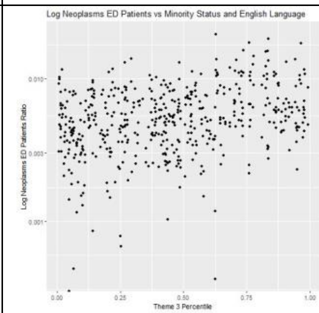
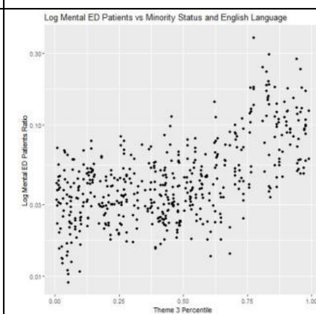
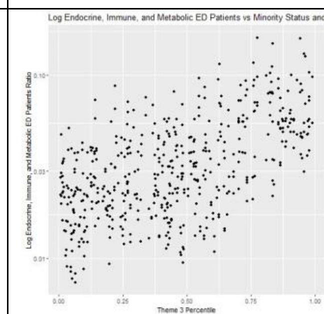
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.706979	0.545965	0.295553	0.552431	0.556177
Graph of Log Relation					
Cor. of Log	0.759943	0.550274	-	0.591589	0.565724

Figure C3 Theme 3 vs. ED patients.

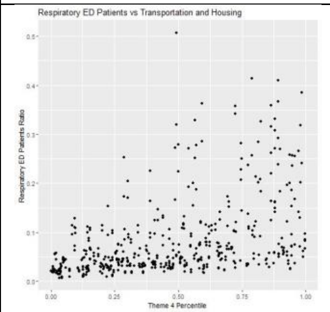
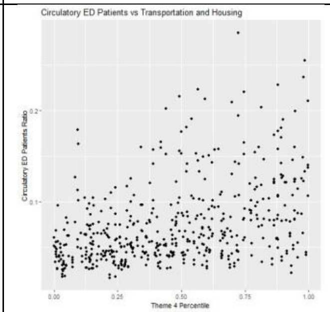
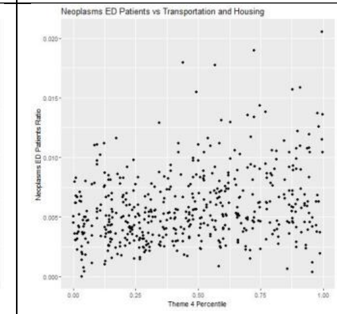
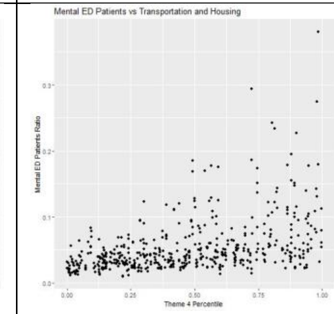
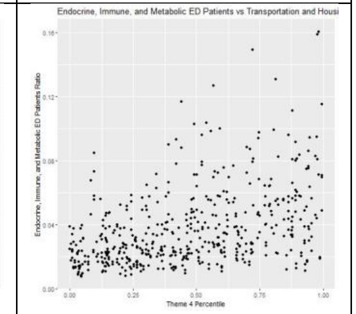
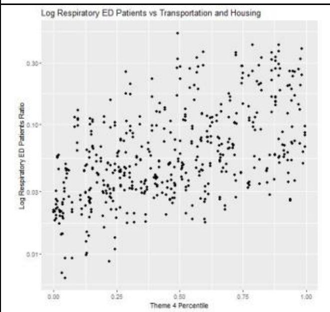
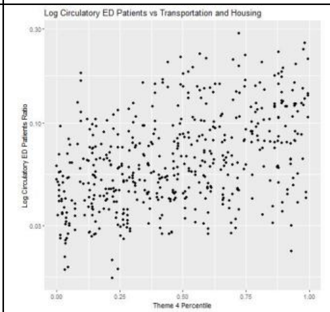
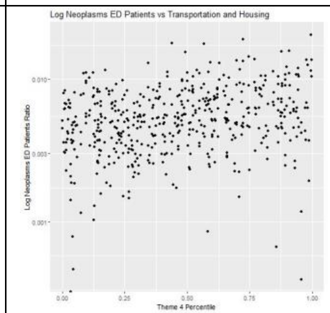
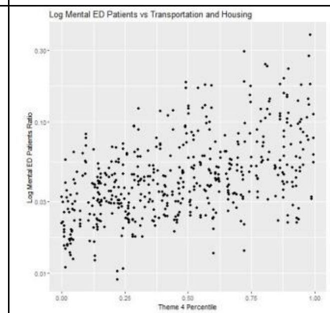
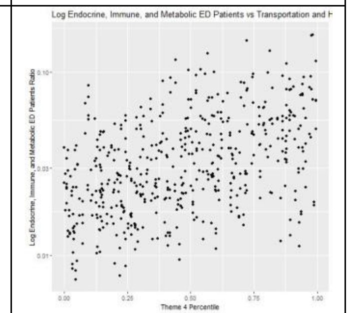
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.460557	0.419795	0.287797	0.444577	0.432159
Graph of Log Relation					
Cor. of Log	0.533937	0.439249	-	0.510052	0.451587

Figure C4 Theme 4 vs. ED patients.

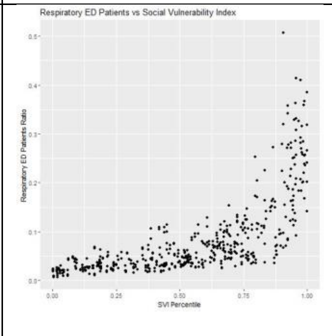
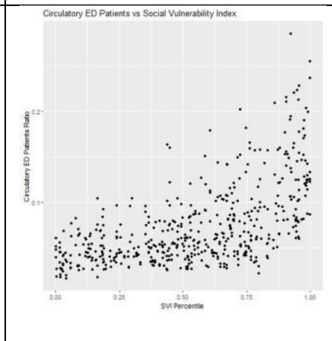
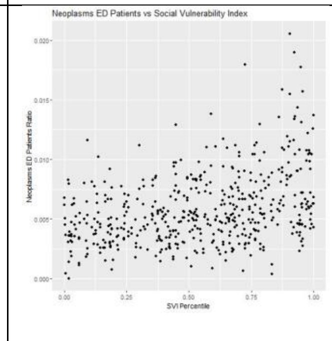
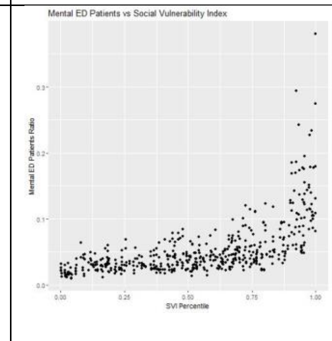
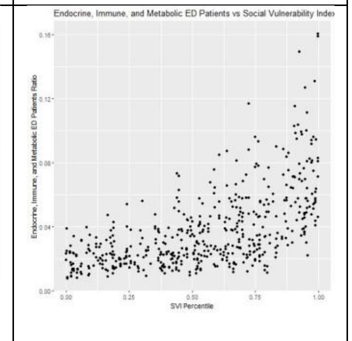
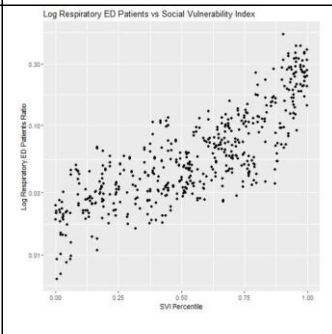
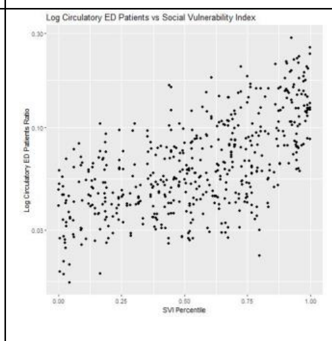
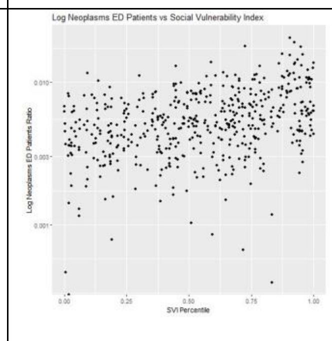
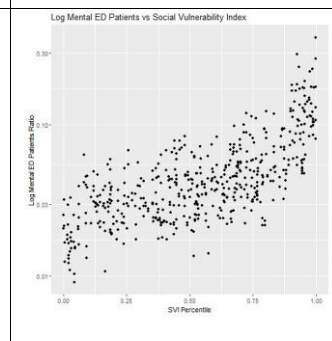
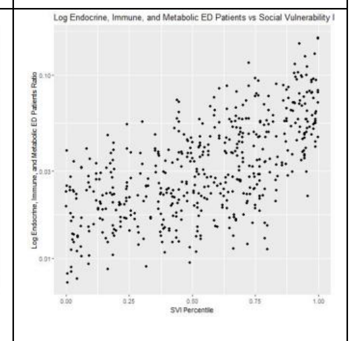
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.68873	0.58807	0.369084	0.602652	0.592479
Graph of Log Relation					
Cor. of Log	0.806812	0.615094	-	0.704247	0.624541

Figure C5 All SVI themes vs. ED patients.

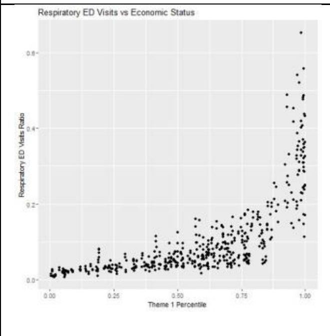
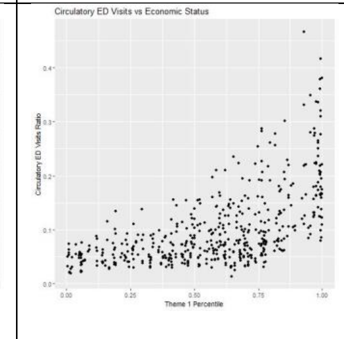
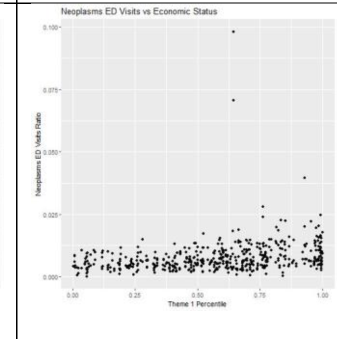
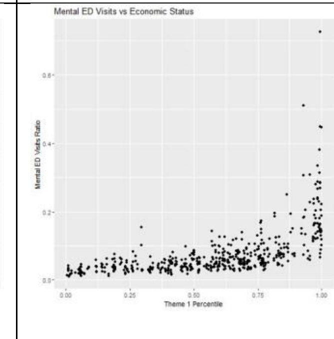
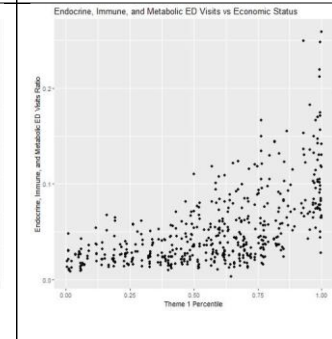
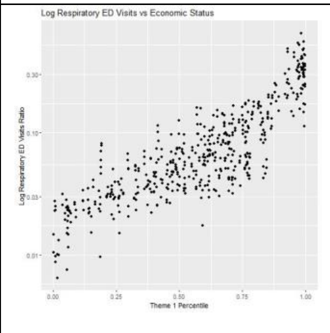
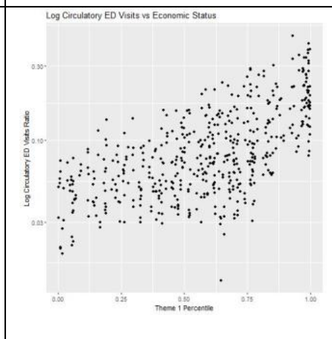
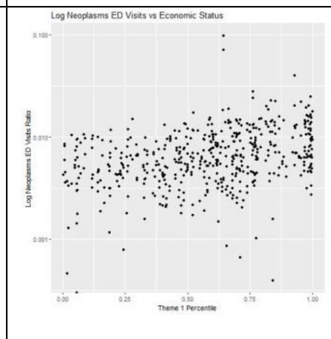
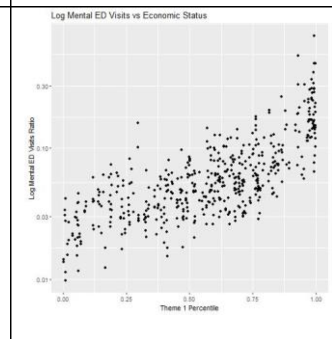
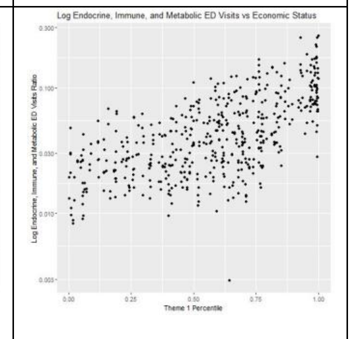
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.701516	0.588501	0.248921	0.581848	0.583985
Graph of Log Relation					
Cor. of Log	0.848215	0.620861	-	0.732314	0.604765

Figure C6 Theme 1 vs. ED visits.

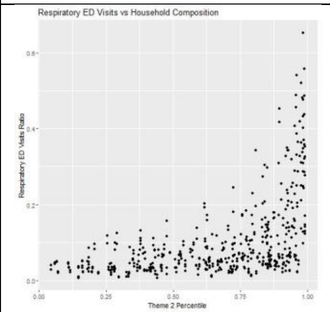
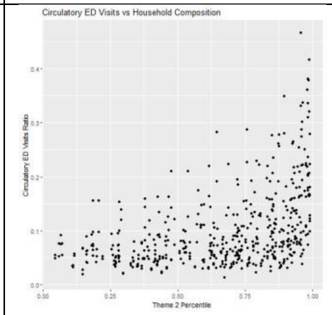
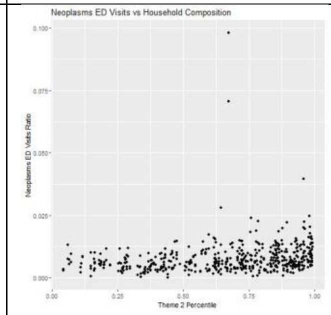
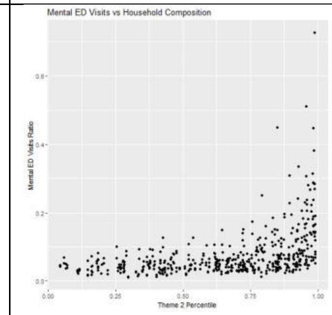
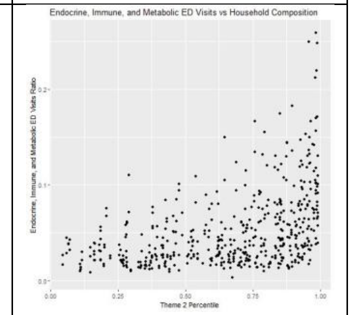
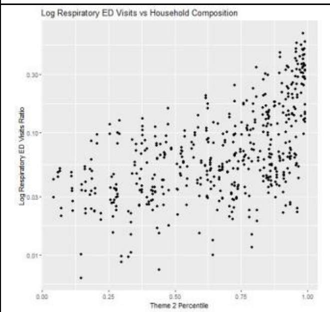
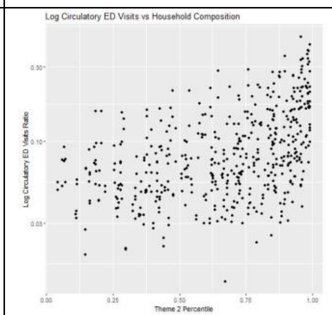
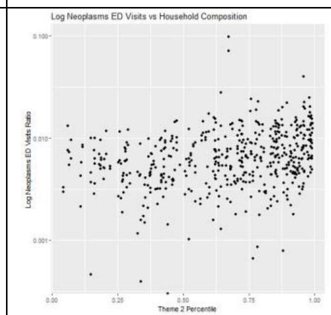
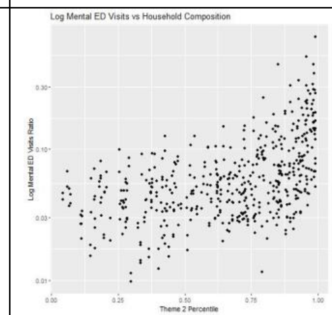
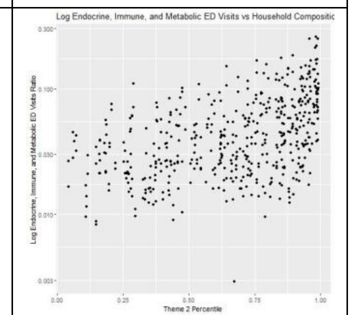
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.501429	0.436772	0.192335	0.423544	0.43086
Graph of Log Relation					
Cor. of Log	0.552488	0.449446	-	0.498895	0.441127

Figure C7 Theme 2 vs. ED visits.

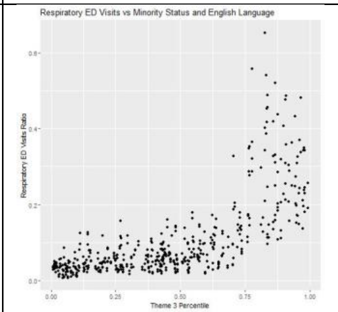
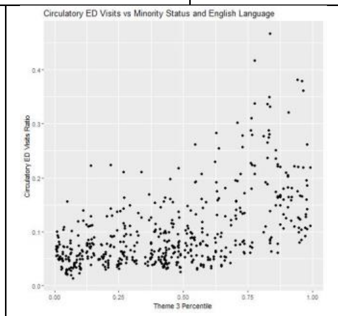
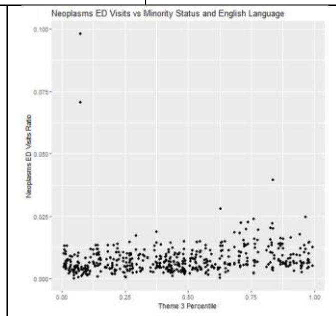
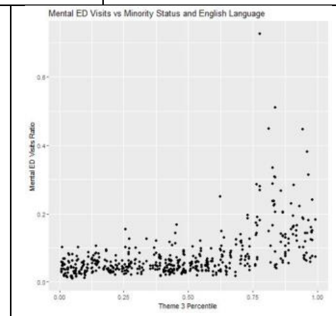
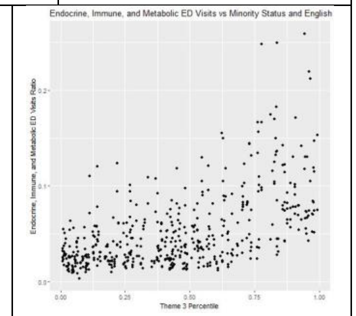
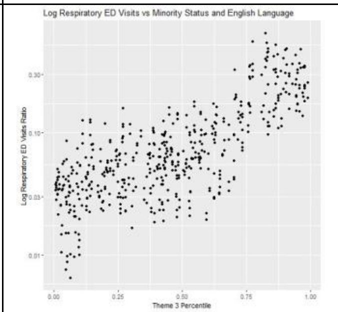
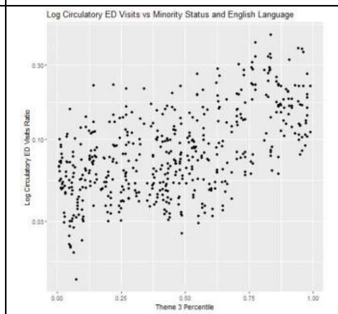
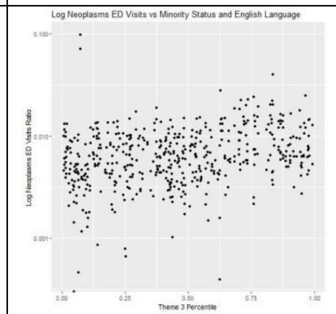
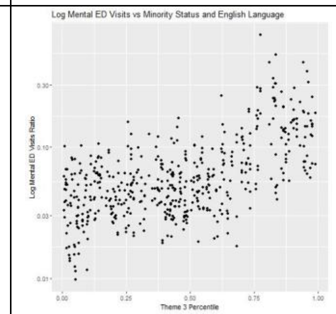
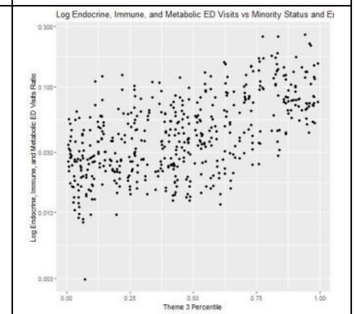
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.691839	0.55568	0.145324	0.523151	0.561681
Graph of Log Relation					
Cor. of Log	0.755111	0.572883	-	0.597531	0.578219

Figure C8 Theme 3 vs. ED visits**.**

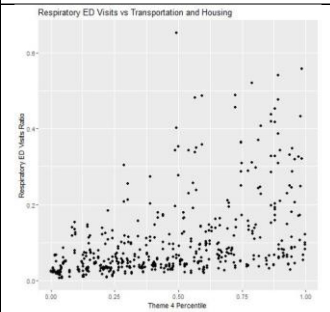
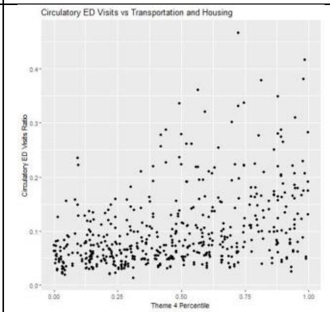
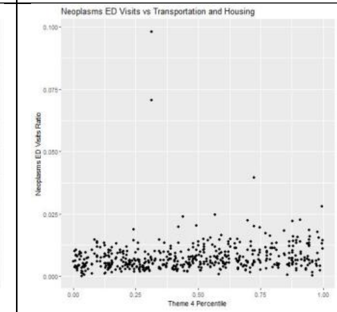
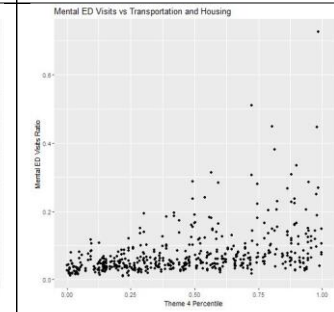
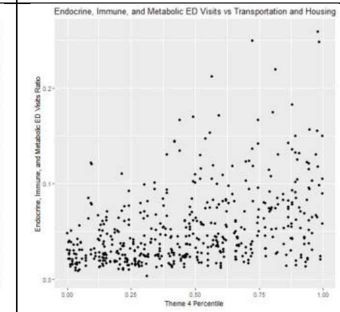
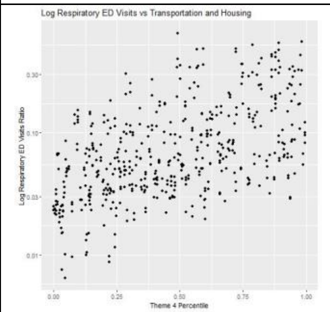
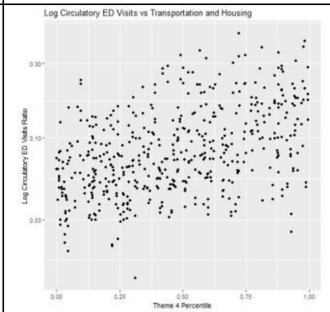
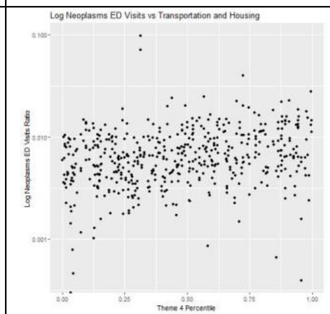
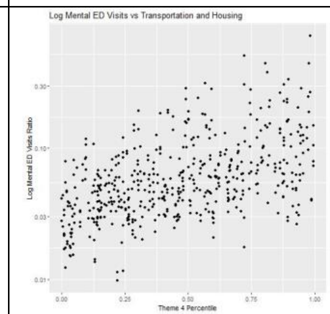
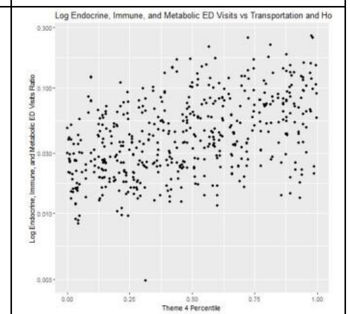
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.452522	0.422189	0.157592	0.419699	0.432278
Graph of Log Relation					
Cor. of Log	0.52975	0.447647	-	0.513416	0.451954

Figure C9 Theme 4 vs. ED visits.

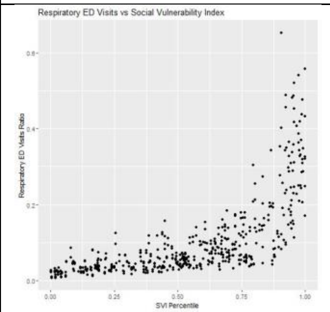
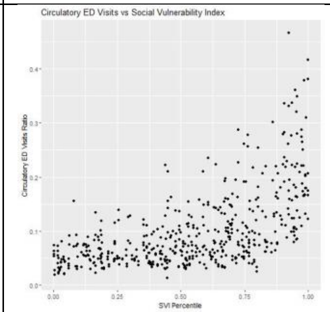
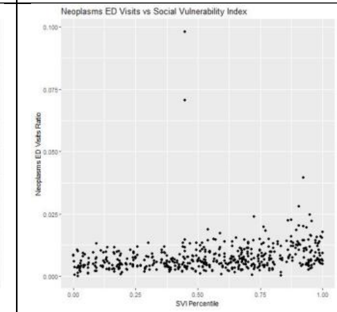
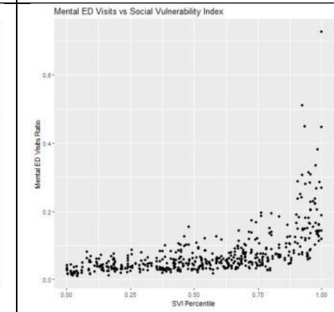
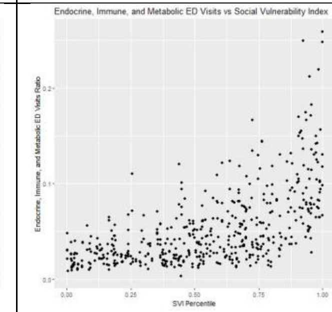
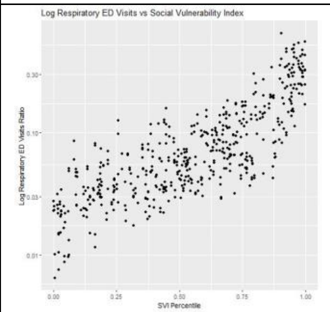
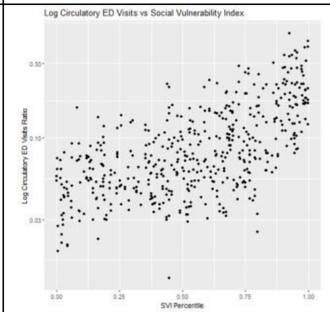
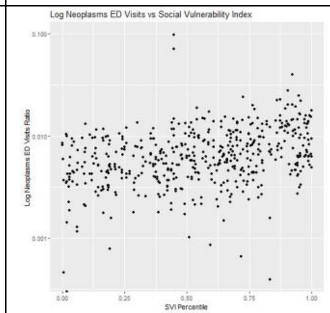
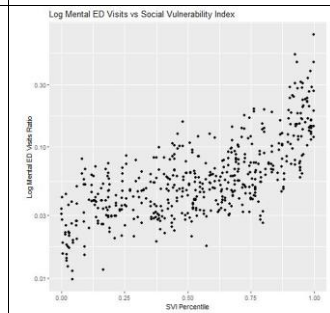
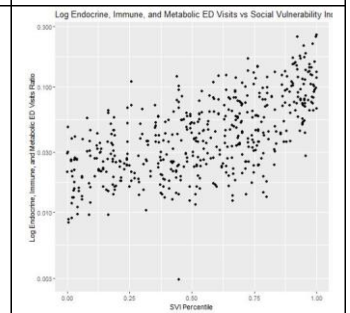
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.6746	0.586249	0.22804	0.564824	0.587959
Graph of Log Relation					
Cor. of Log	0.801983	0.619179	-	0.702204	0.615533

Figure C10 All SVI themes vs. ED visits.

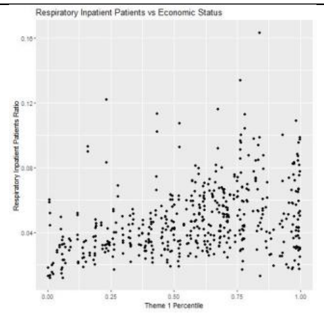
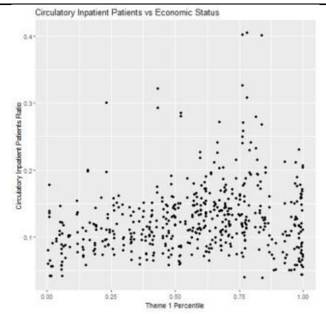
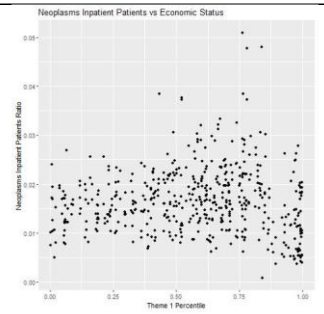
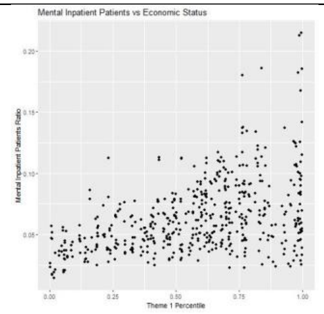
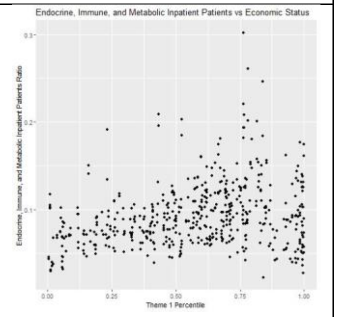
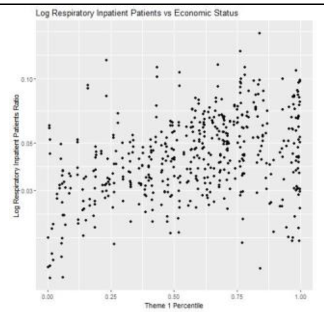
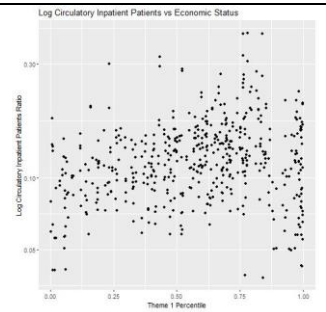
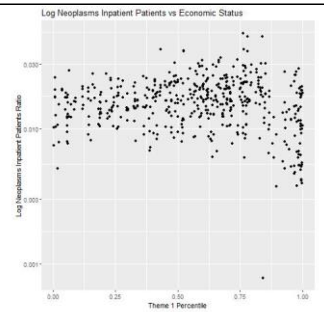
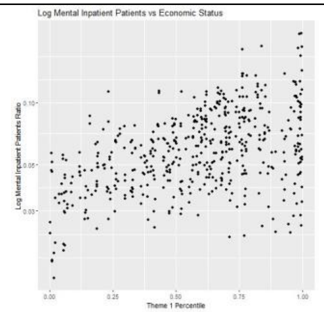
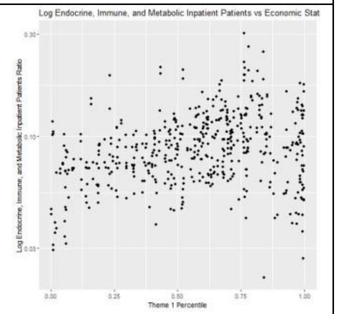
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.35818	0.190323	-0.01608	0.448342	0.257668
Graph of Log Relation					
Cor. of Log	0.383406	0.178262	-0.10774	0.463069	0.249558

Figure C11 Theme 1 vs. inpatient patients.

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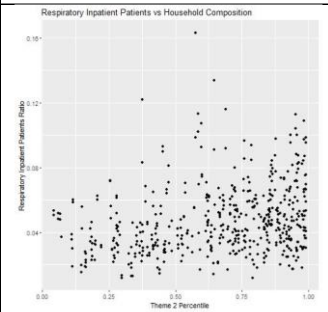
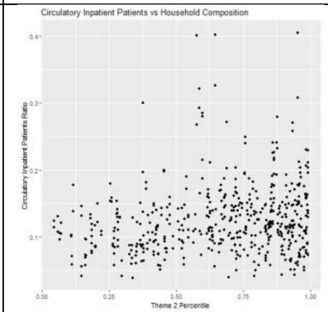
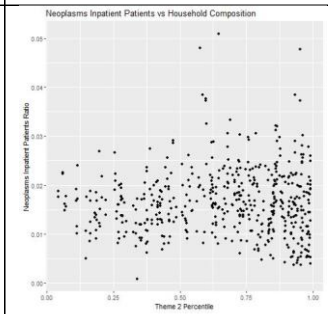
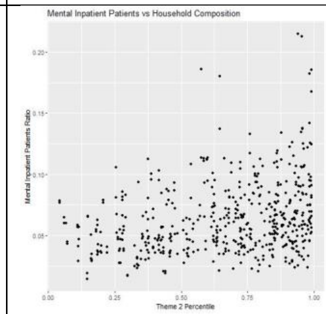
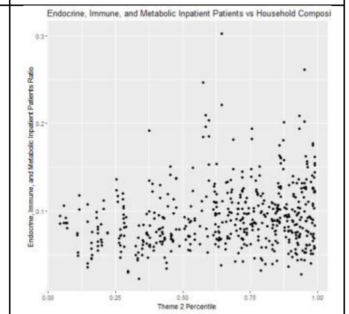
<tr><td>Graph</td><td></td><td></td><td></td><td></td><td></td></tr>
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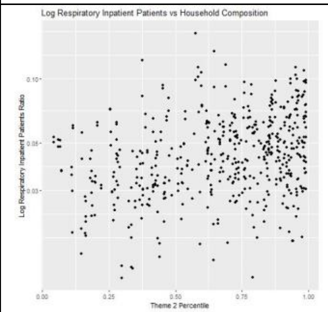
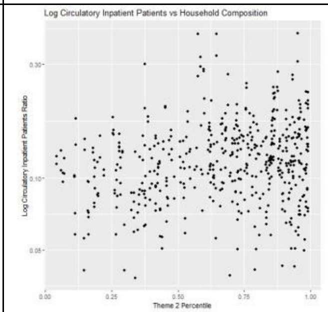
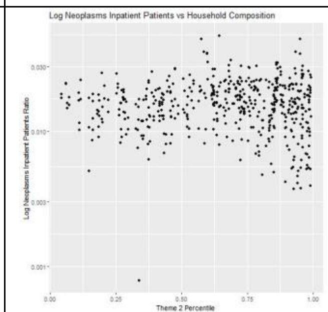
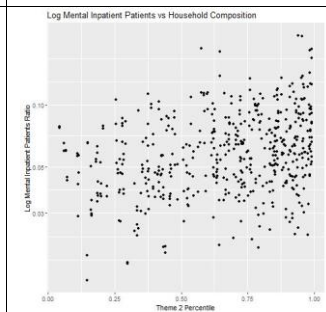
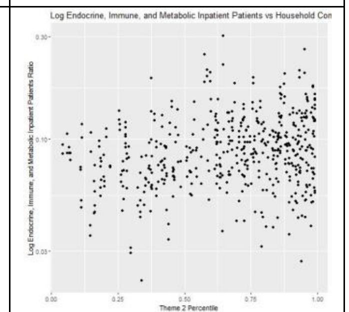
<tr><td>Graph of Log Relation</td><td></td><td></td><td></td><td></td><td></td></tr>
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Figure C12 Theme 2 vs. inpatient patients.

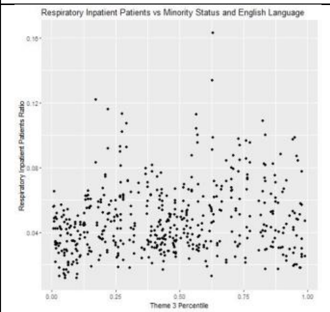
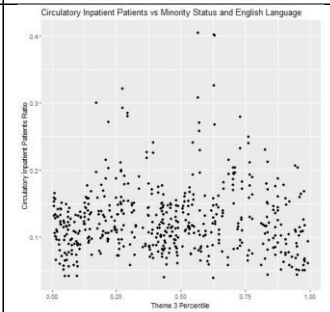
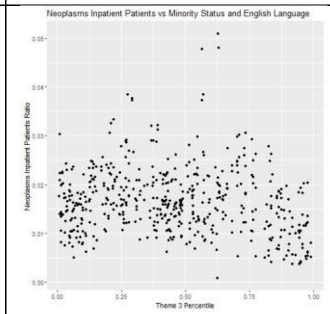
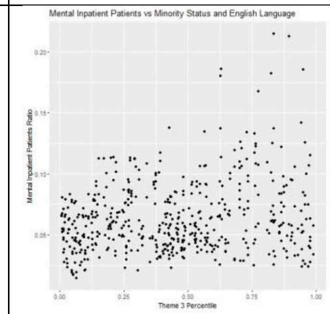
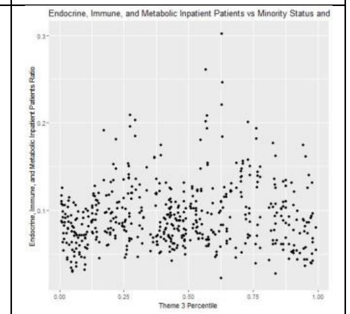
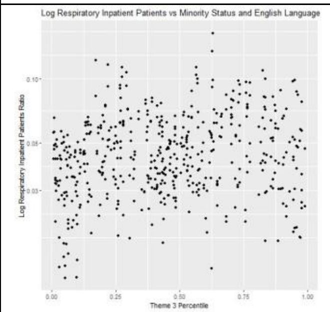
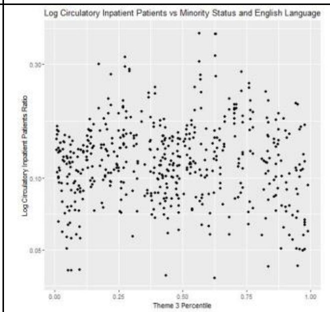
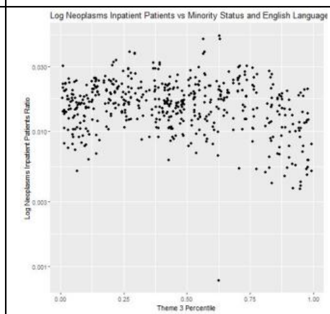
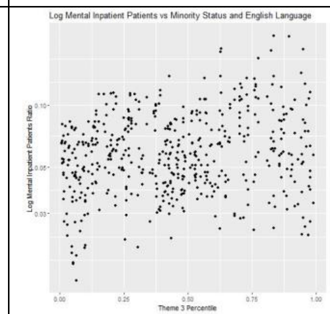
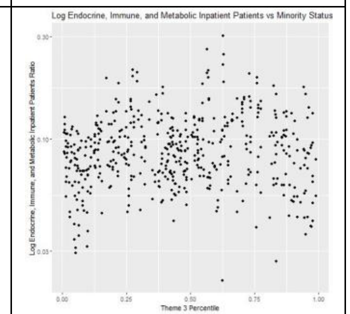
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.181041	0.030481	-0.15641	0.222433	0.093837
Graph of Log Relation					
Cor. of Log	0.173782	-0.00954	-0.22512	0.192763	0.067647

Figure C13 Theme 3 vs. inpatient patients.

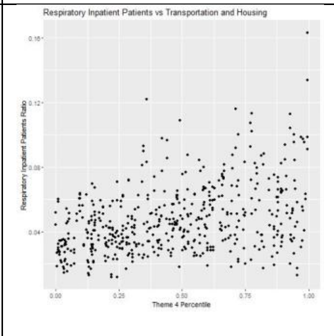
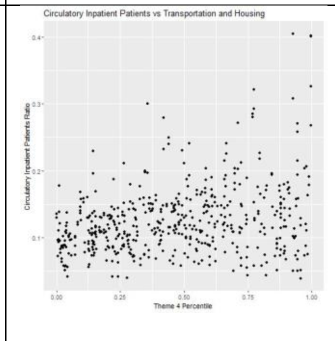
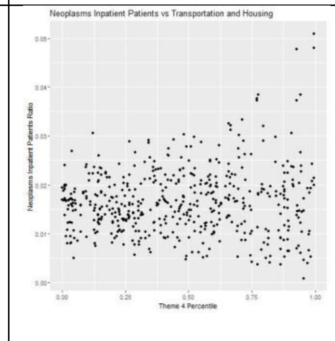
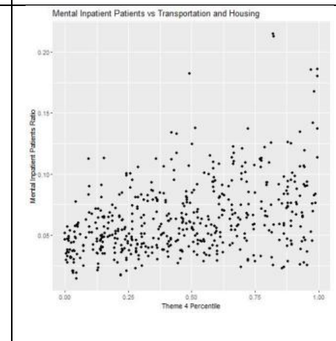
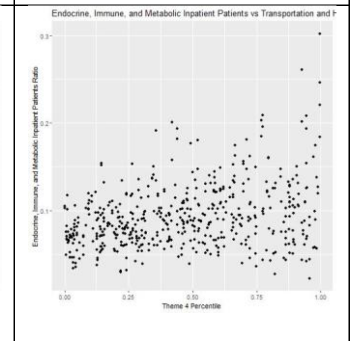
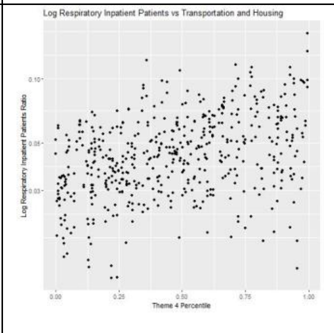
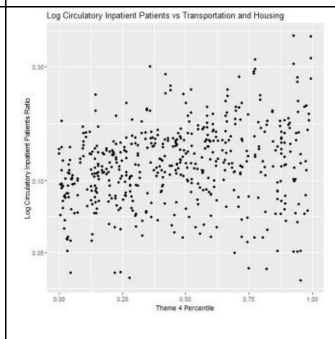
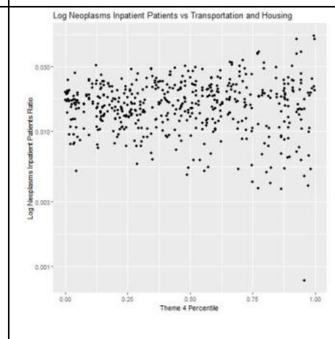
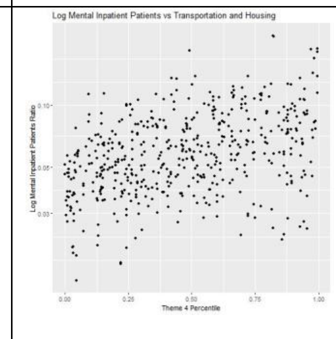
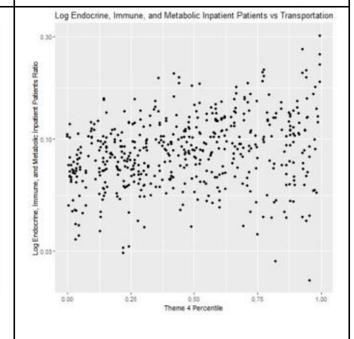
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.397633	0.294703	0.10656	0.407212	0.316809
Graph of Log Relation					
Cor. of Log	0.378862	0.244385	-0.00575	0.397228	0.271739

Figure C14 Theme 4 vs. inpatient patients.

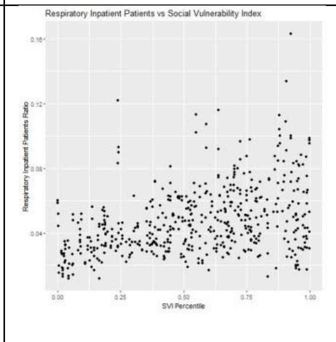
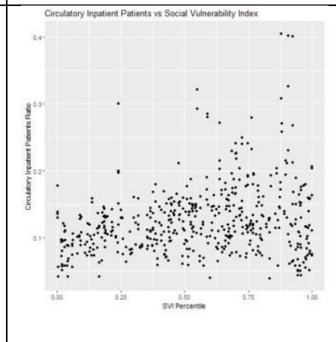
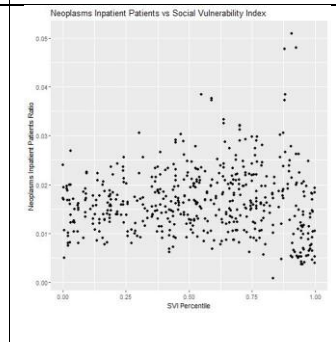
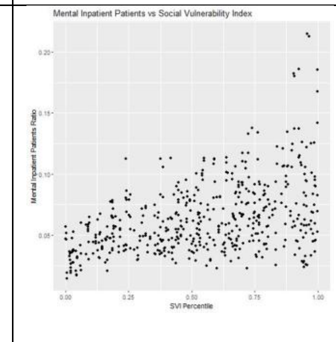
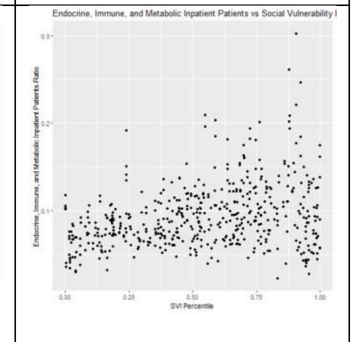
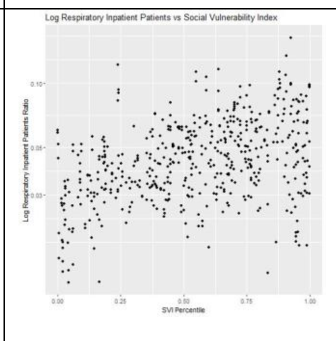
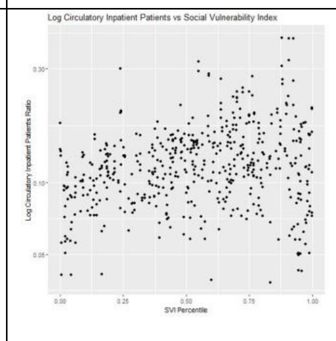
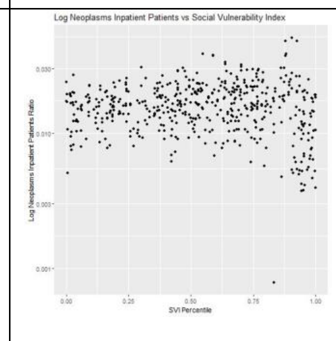
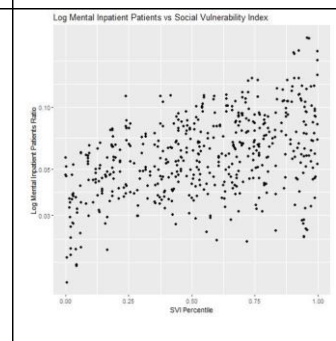
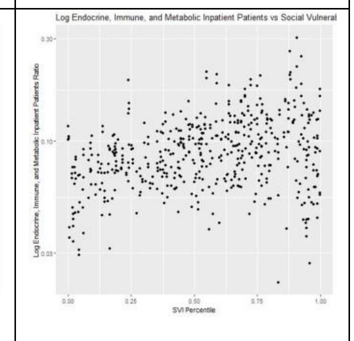
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.3941	0.246245	0.021448	0.438731	0.301041
Graph of Log Relation					
Cor. of Log	0.402906	0.215155	-0.08088	0.43949	0.276527

Figure C15 All SVI themes vs. inpatient patients.

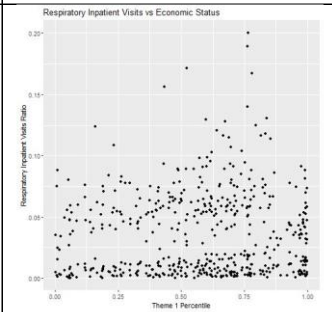
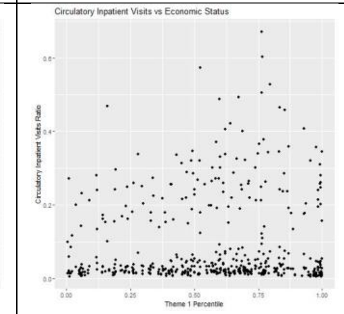
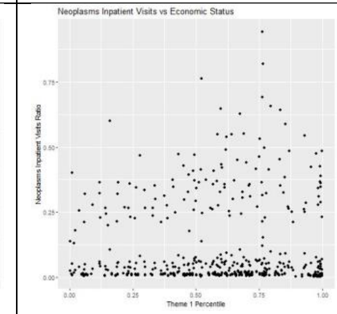
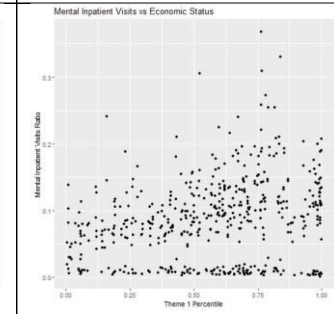
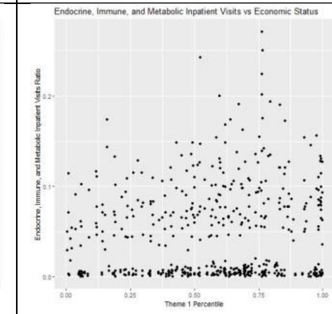
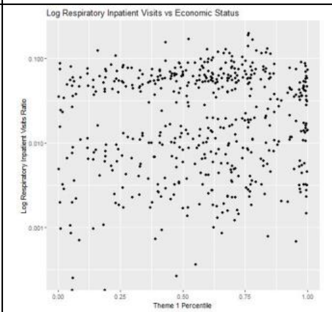
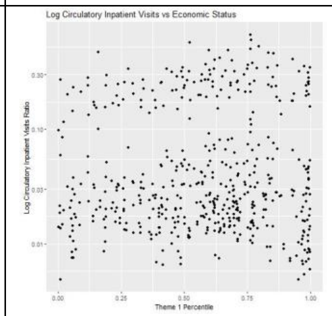
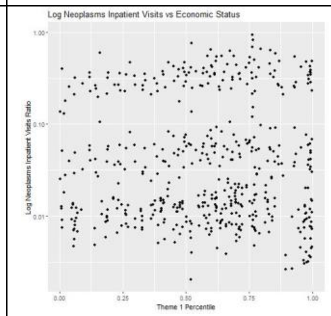
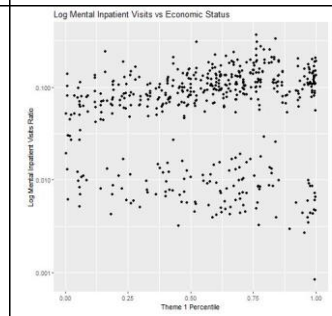
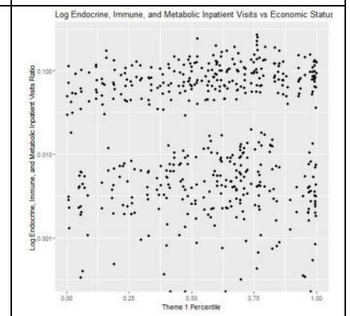
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.053749	0.062967	0.010421	0.233352	0.086644
Graph of Log Relation					
Cor. of Log	-	0.015867	0.010421	0.094161	-

Figure C16 Theme 1 vs. inpatient visits.

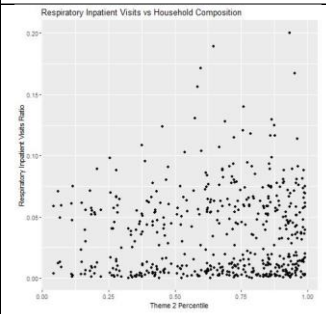
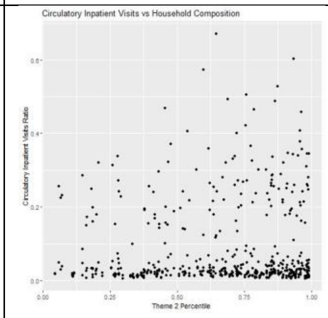
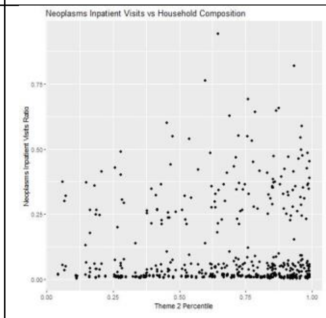
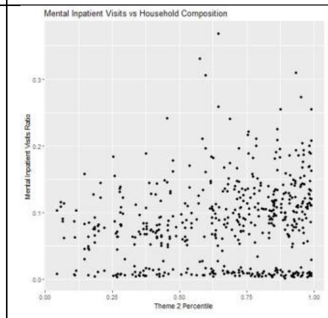
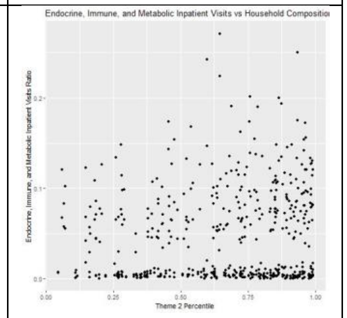
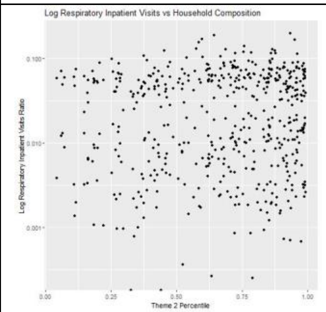
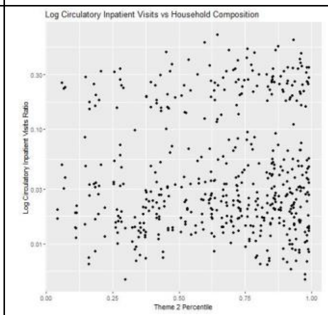
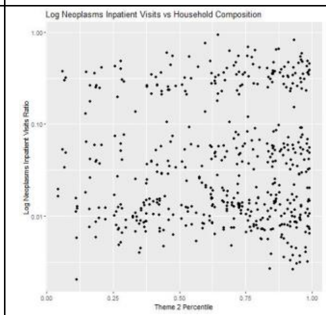
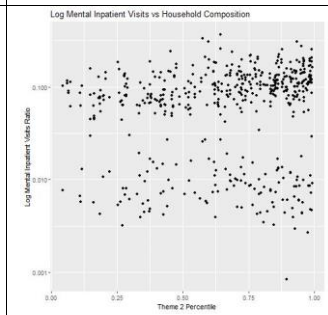
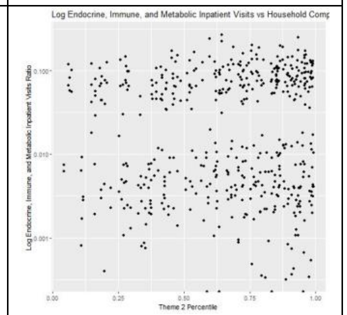
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.063595	0.070537	0.065565	0.184163	0.099396
Graph of Log Relation					
Cor. of Log	-	0.049992	0.038271	0.095368	-

Figure C17 Theme 2 vs. inpatient visits.

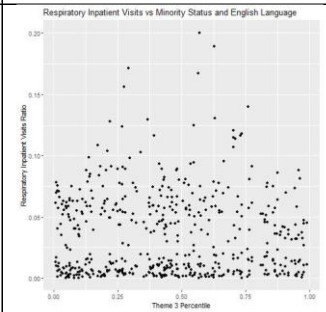
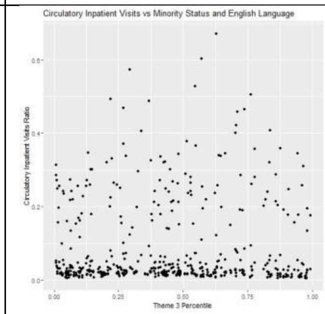
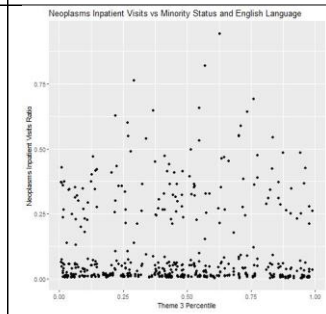
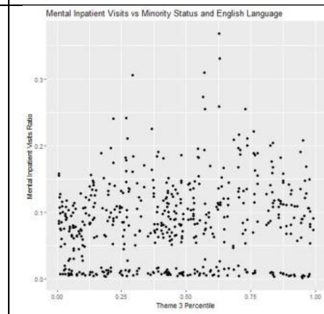
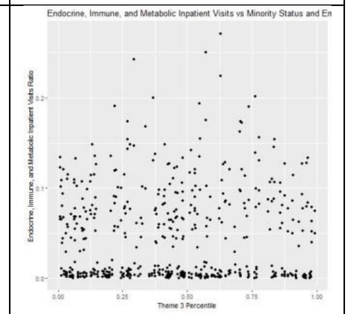
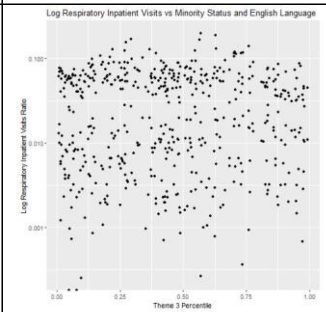
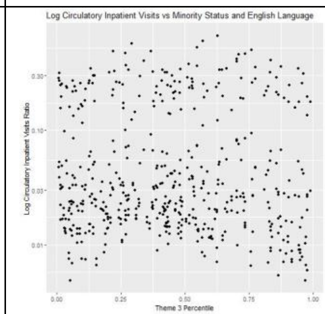
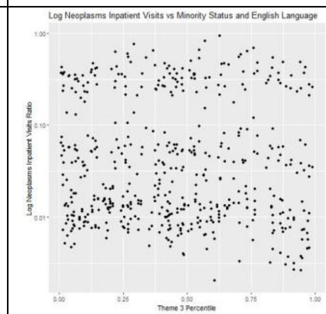
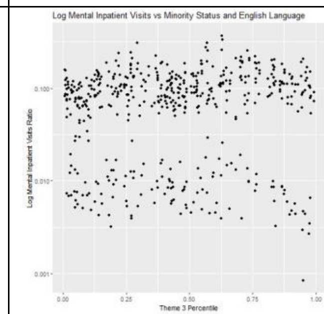
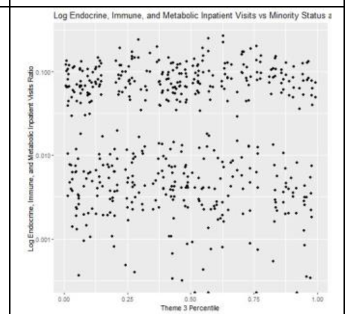
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	-0.01014	0.023765	0.023331	0.131491	0.031266
Graph of Log Relation					
Cor. of Log	-	-0.02942	-0.0327	0.042216	-

Figure C18 Theme 3 vs. inpatient visits.

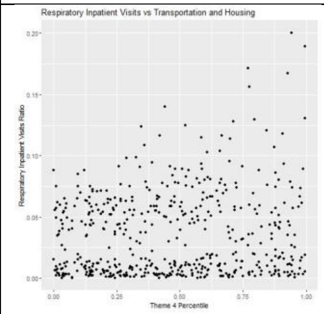
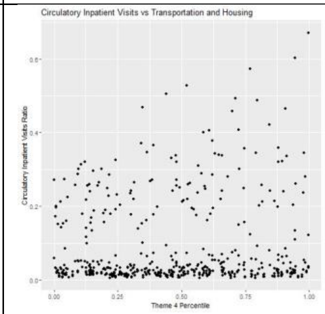
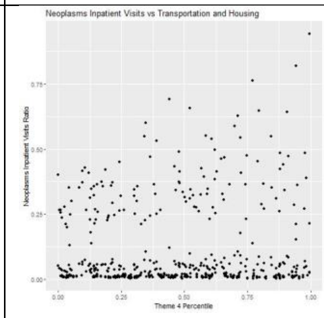
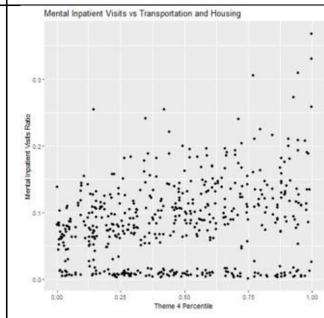
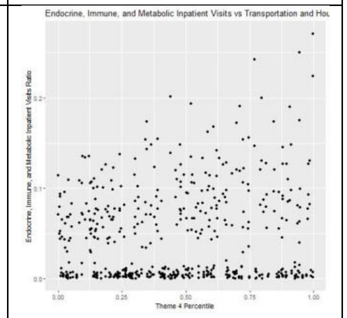
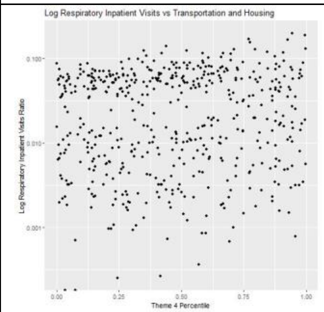
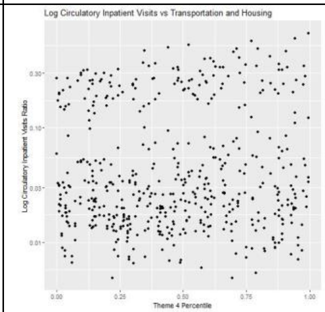
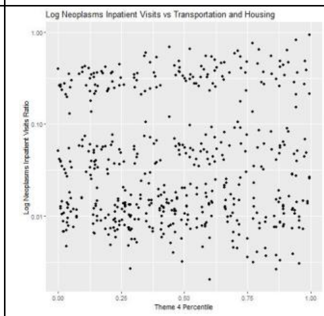
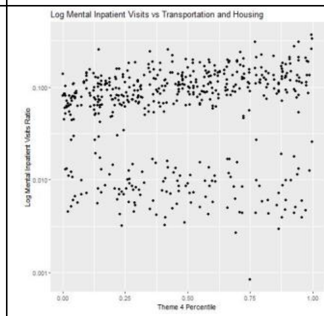
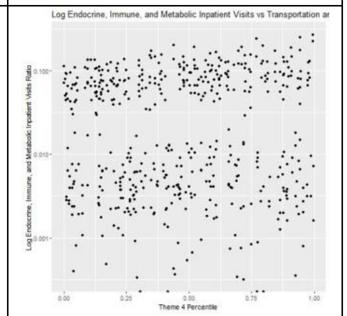
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.119032	0.093036	0.083542	0.254044	0.115292
Graph of Log Relation					
Cor. of Log	-	0.045745	0.020809	0.09531	-

Figure C19 Theme 4 vs. inpatient visits.

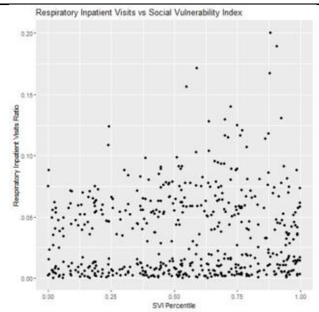
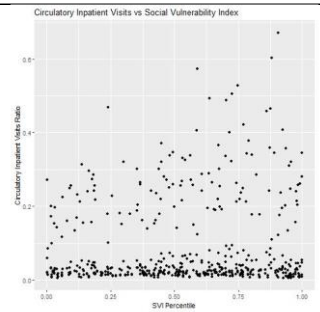
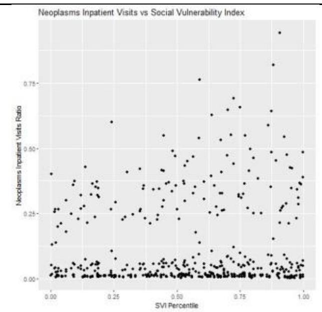
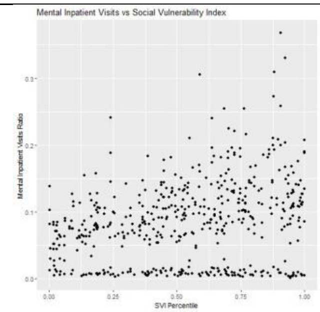
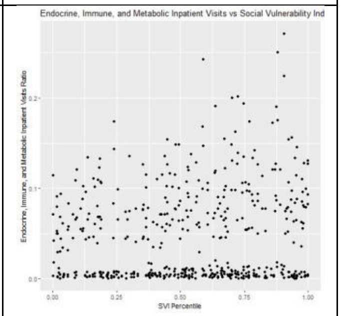
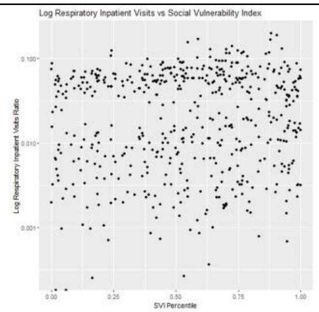
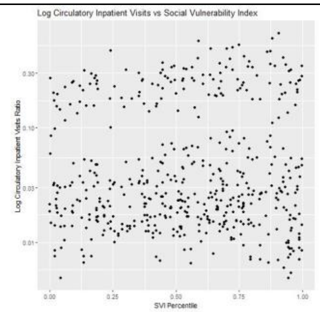
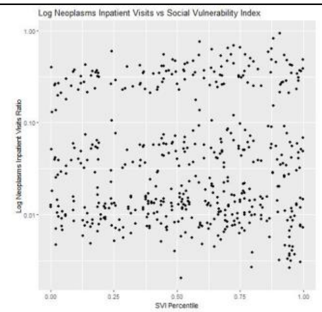
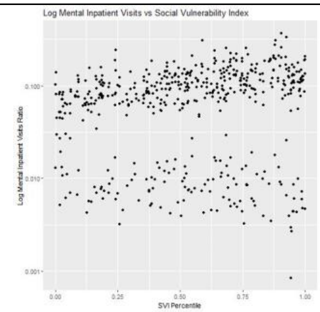
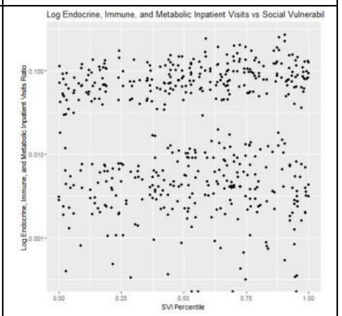
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.083068	0.080285	0.073767	0.258716	0.103592
Graph of Log Relation					
Cor. of Log	-	0.029197	0.012654	0.104962	-

Figure C20 All SVI themes vs. inpatient visits.

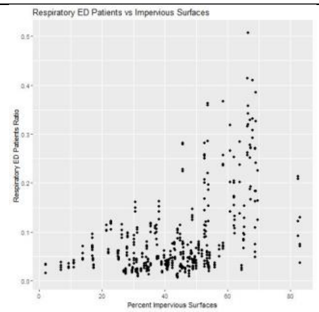
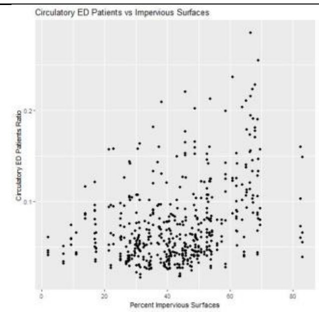
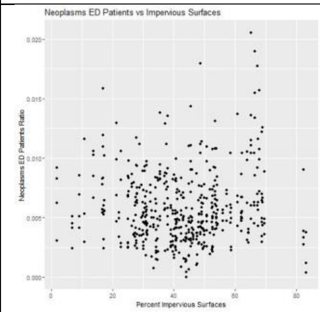
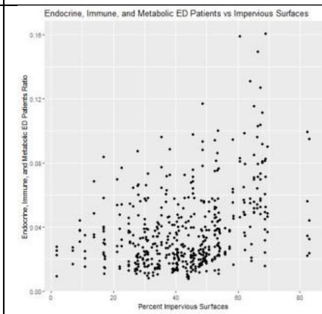
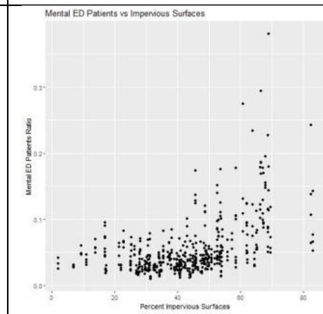
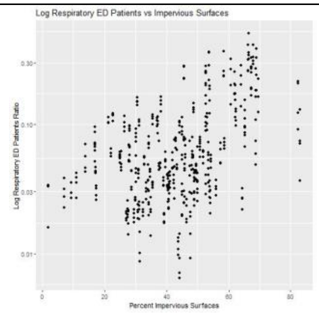
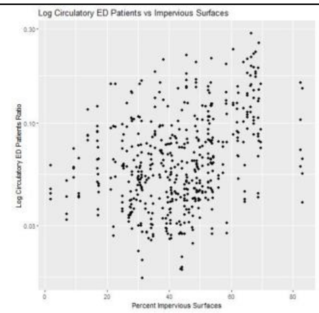
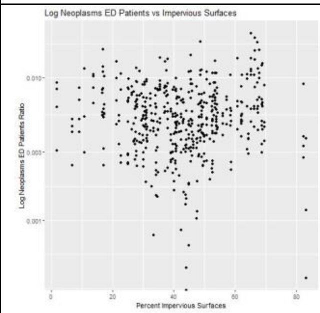
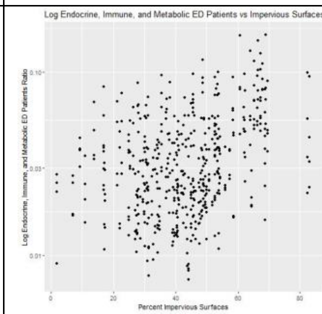
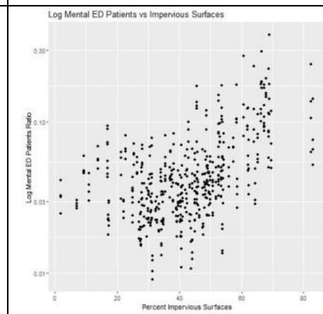
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.485011	0.363779	0.056815	0.489686	0.360572
Graph of Log Relation					
Cor. of Log	0.444923	0.340778	-	0.488208	0.335886

Figure C21 ED patients vs. impervious surfaces.

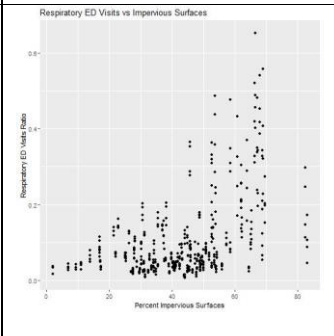
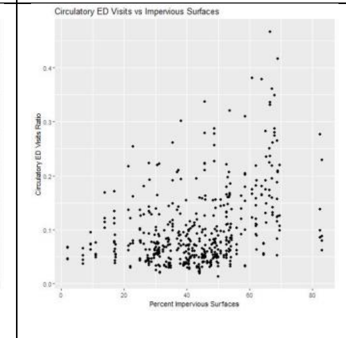
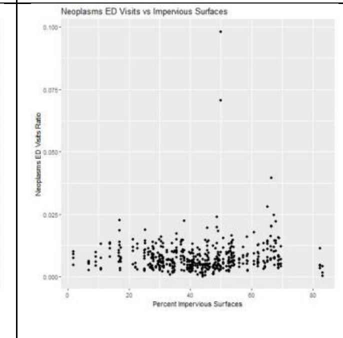
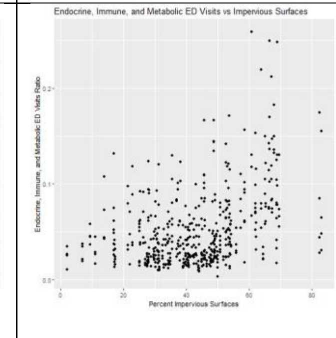
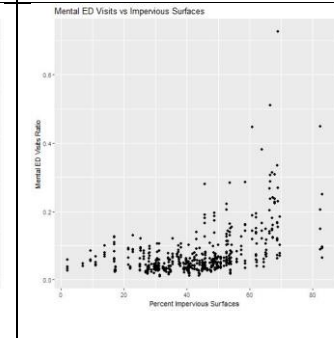
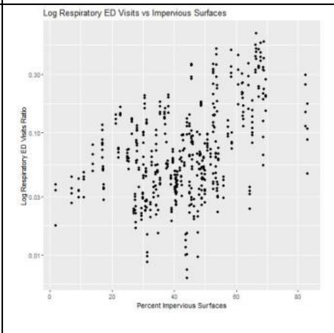
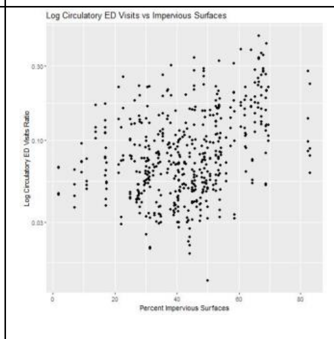
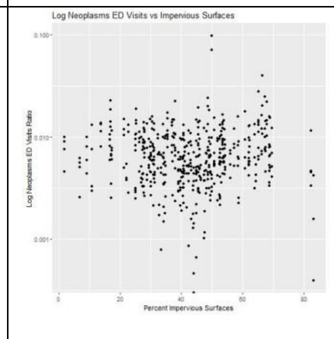
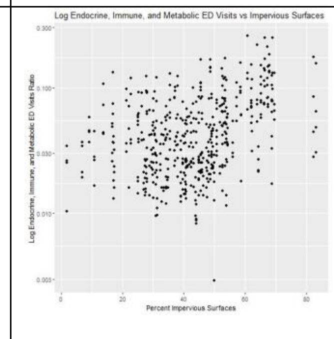
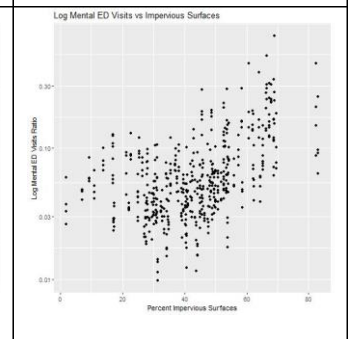
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.487575	0.38051	0.060182	0.465359	0.38156
Graph of Log Relation					
Cor. of Log	0.453043	0.355955	-	0.476282	0.341692

Figure C22 ED visits vs. impervious surfaces.

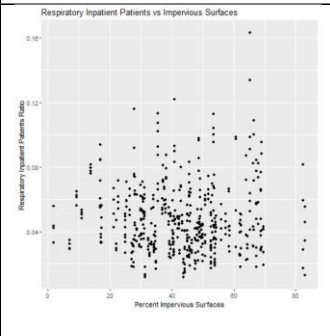
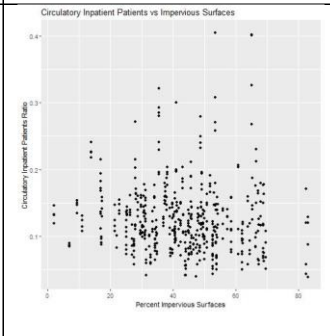
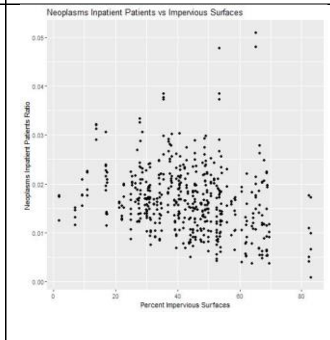
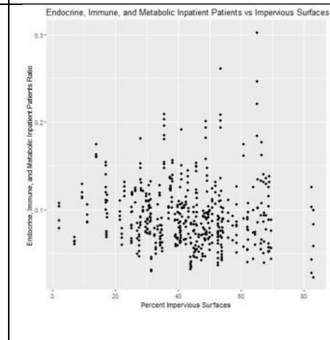
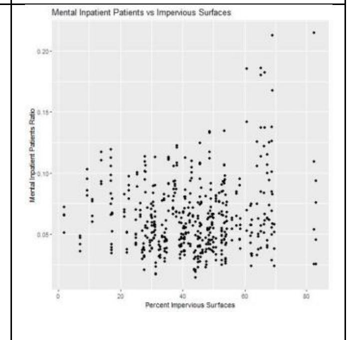
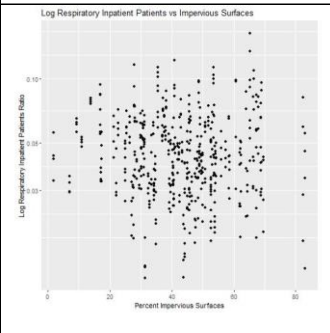
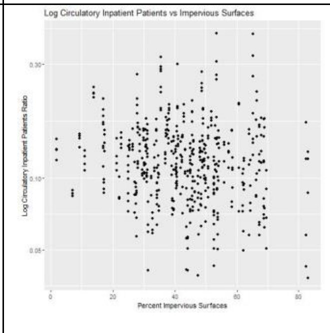
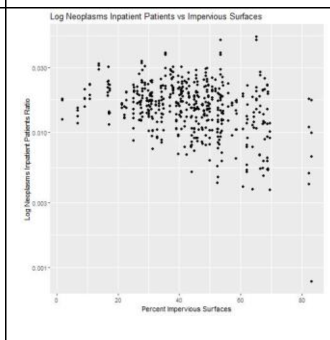
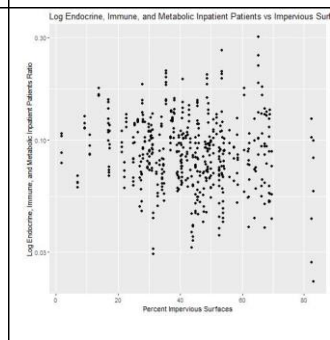
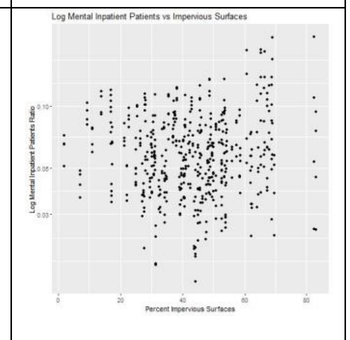
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	-0.00221	-0.05929	-0.24683	0.099181	-0.08329
Graph of Log Relation					
Cor. of Log	-0.04354	-0.11977	-0.3389	0.042466	-0.14044

Figure C23 Inpatient patients vs. impervious surfaces.

<table>
<tr><th></th><th>Respiratory</th><th>Circulatory</th><th>Neoplasms</th><th>Psychiatric</th><th>Endocrine, Immune, and Metabolic</th></tr>
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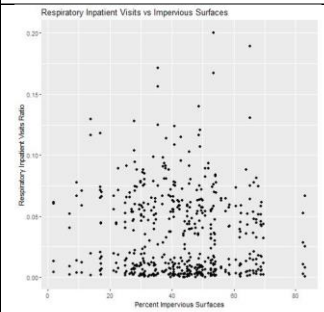
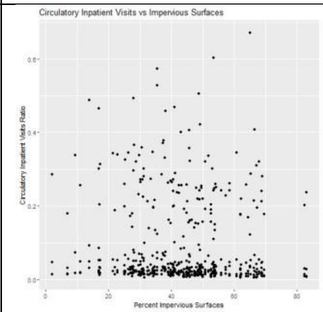
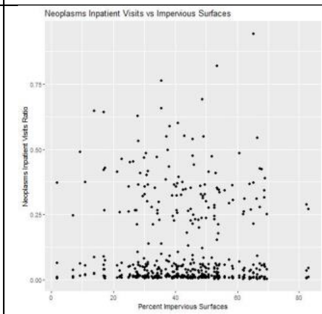
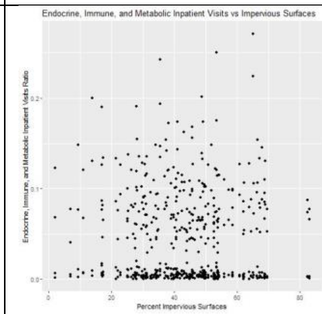
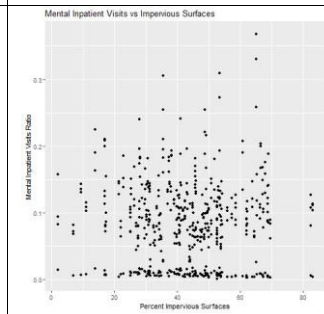
<td></td>
<td></td>
<td></td>
<td></td>
<td></td></tr>
<tr><td>Cor.</td><td>-0.05951</td><td>-0.04389</td><td>-0.02703</td><td>-0.00212</td><td>-0.01697</td></tr>
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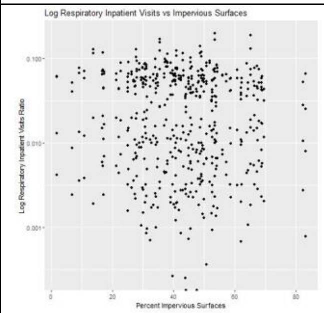
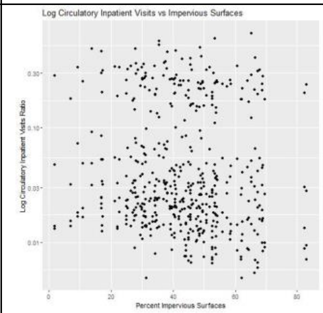
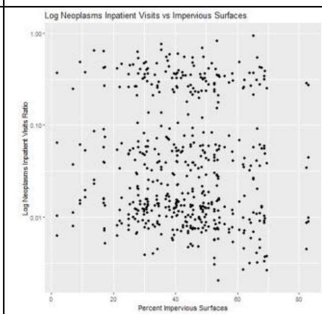
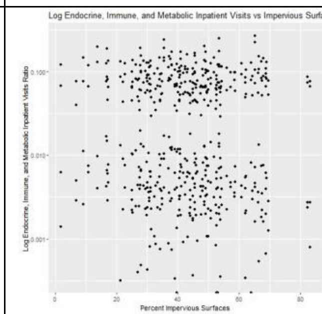
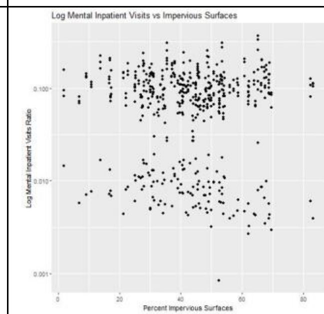
<td></td>
<td></td>
<td></td>
<td></td>
<td></td></tr>
<tr><td>Cor. of Log</td><td>-</td><td>-0.0892</td><td>-0.05575</td><td>-0.03573</td><td>-</td></tr>
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Figure C24 Inpatient visits vs. impervious surfaces.

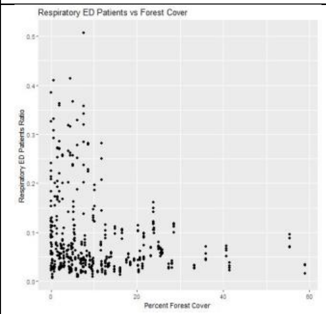
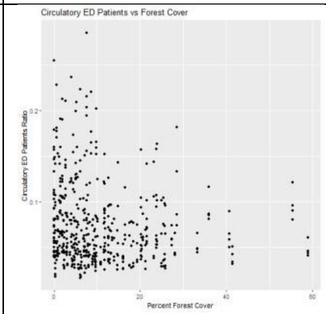
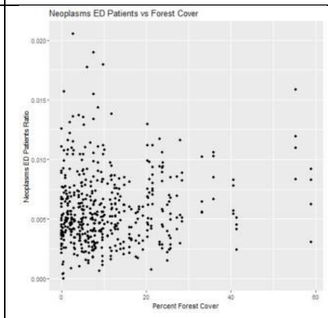
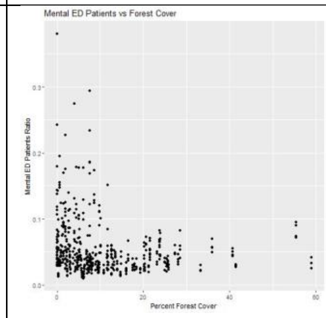
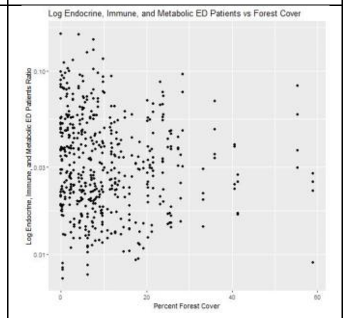
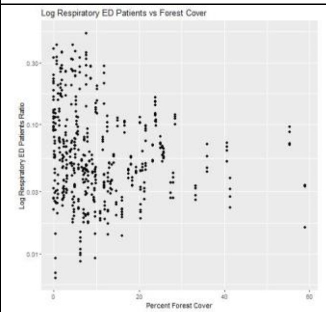
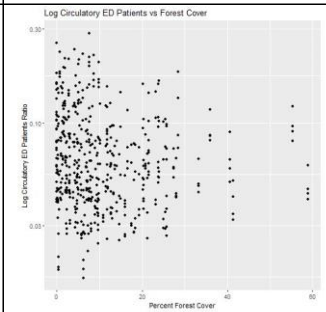
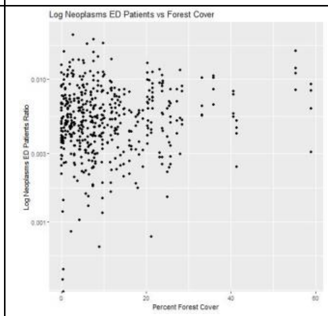
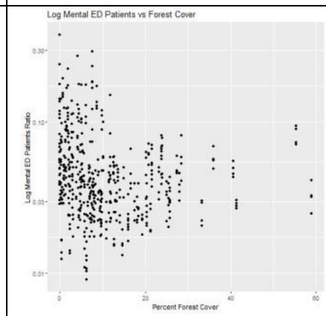
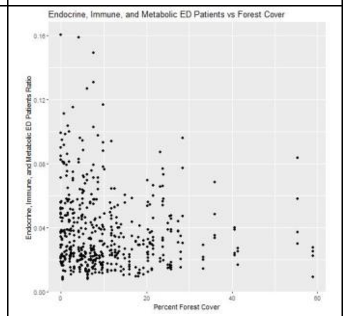
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	-0.19571	-0.11838	0.105018	-0.18865	-0.11262
Graph of Log Relation					
Cor. of Log	-0.13172	-0.08774	-	-0.15722	-0.08705

Figure C25 ED patients vs. forest cover.

<table>
<tr><th></th><th>Respiratory</th><th>Circulatory</th><th>Neoplasms</th><th>Psychiatric</th><th>Endocrine, Immune, and Metabolic</th></tr>
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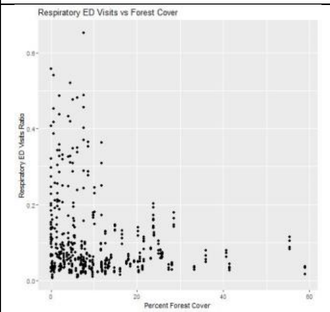
<td>
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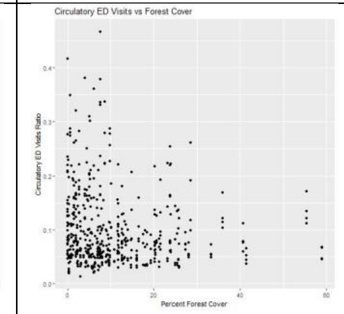
<td>
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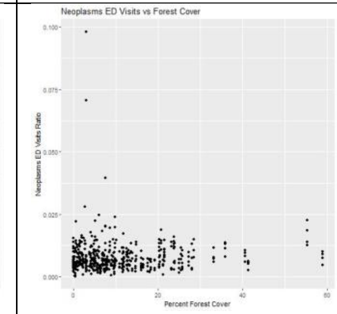
<td>
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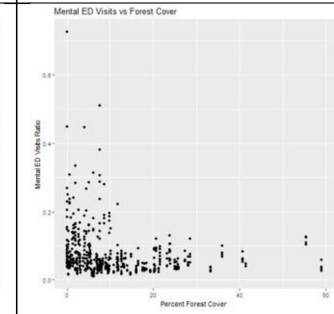
<td>
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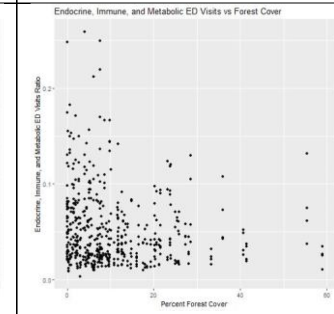
<td>
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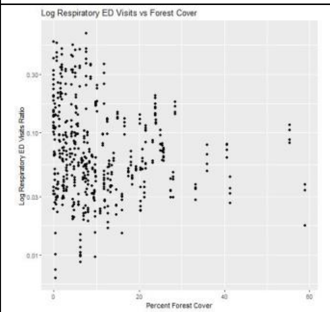
<tr><td>Cor.</td><td>-0.19878</td><td>-0.12547</td><td>0.043482</td><td>-0.17996</td><td>-0.12421</td></tr>
<tr><td>Graph of Log Relation</td>
<td>
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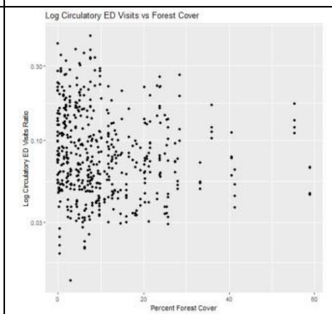
<td>
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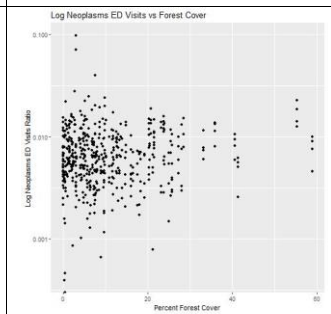
<td>
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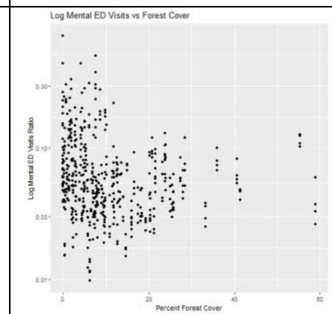
<td>
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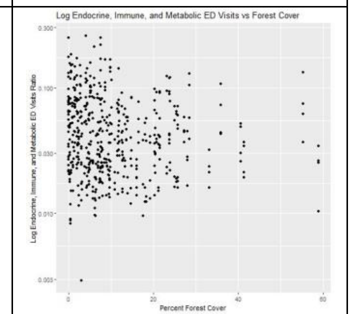
<td>
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<tr><td>Cor. of Log</td><td>-0.13878</td><td>-0.09404</td><td>-</td><td>-0.15108</td><td>-0.08917</td></tr>
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Figure C26 ED visits vs. forest cover.

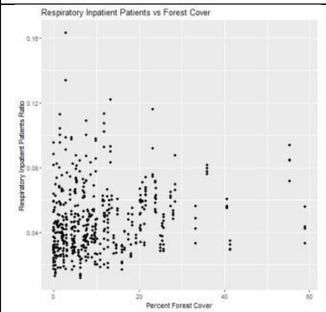
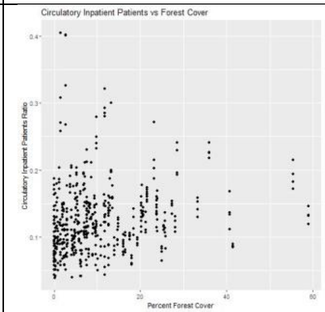
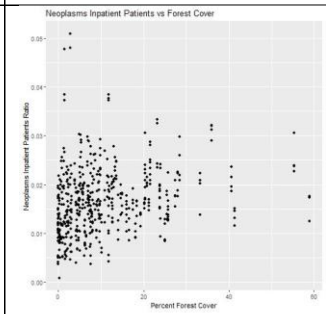
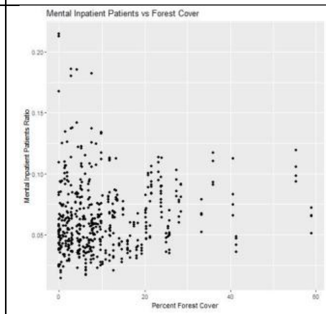
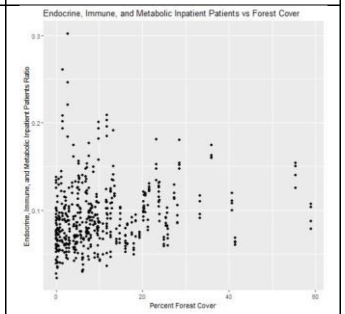
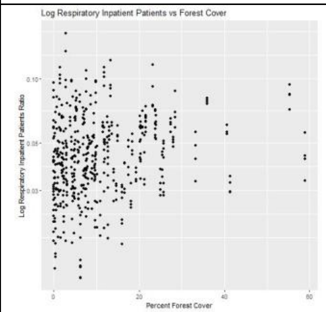
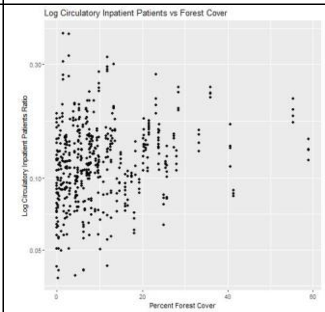
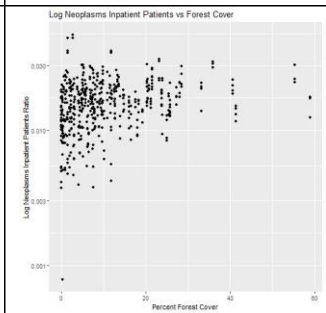
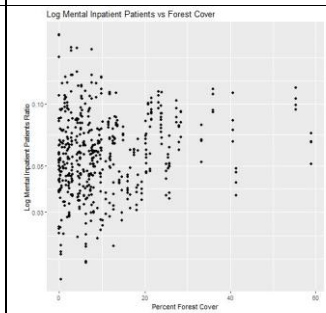
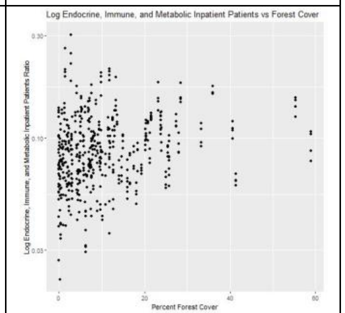
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.156885	0.153691	0.228587	0.104651	0.184696
Graph of Log Relation					
Cor. of Log	0.194562	0.198179	0.265411	0.156696	0.225782

Figure C27 Inpatient patients vs. forest cover.

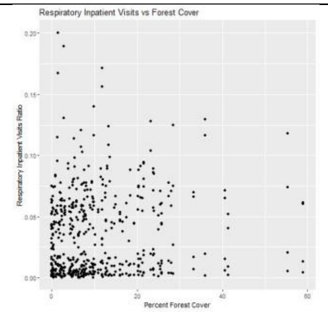
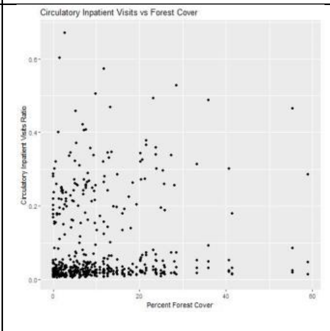
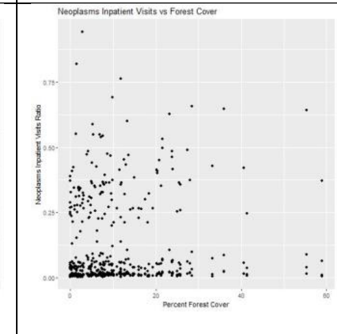
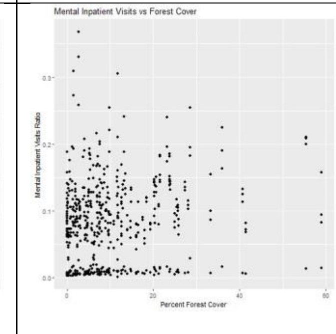
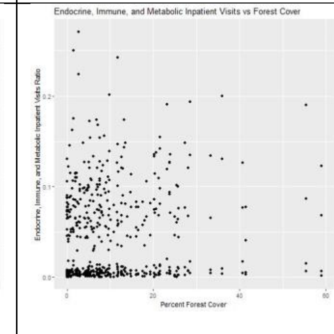
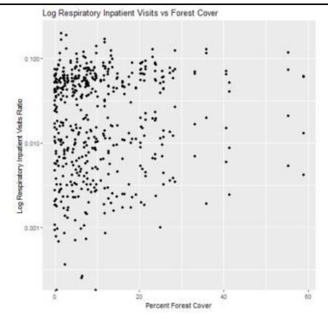
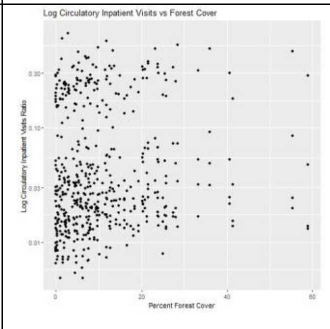
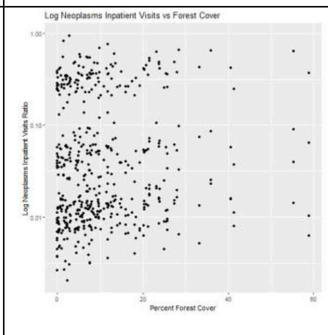
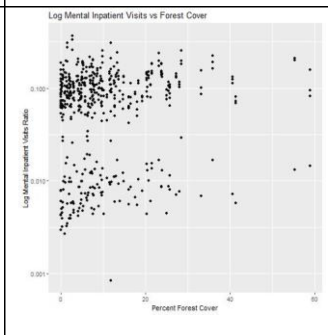
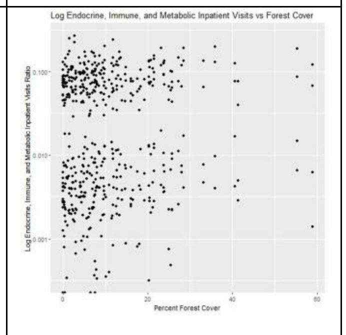
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.080875	0.075417	0.059099	0.112706	0.066832
Graph of Log Relation					
Cor. of Log	-	0.095514	0.066042	0.084002	-

Figure C28 Inpatient visits vs. forest cover.

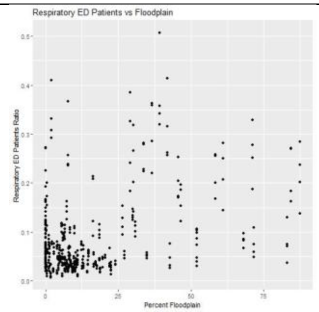
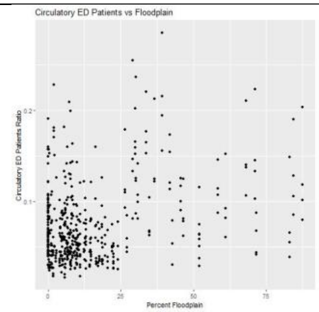
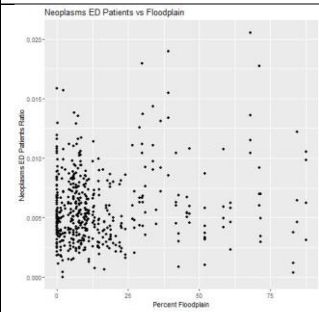
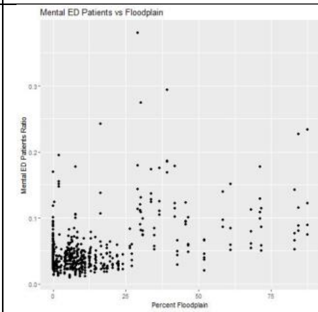
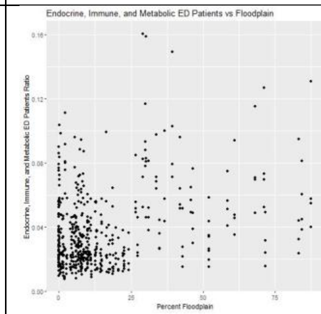
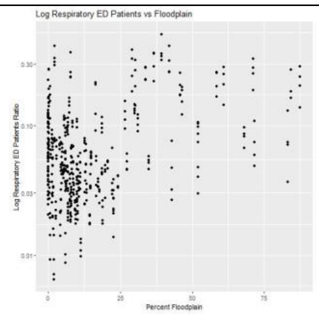
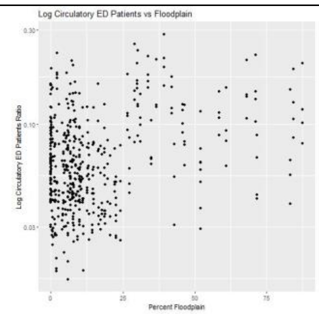
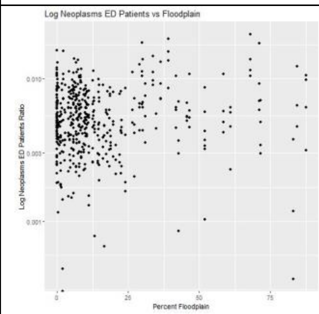
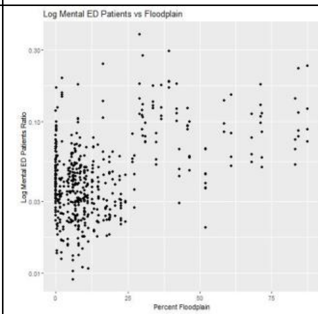
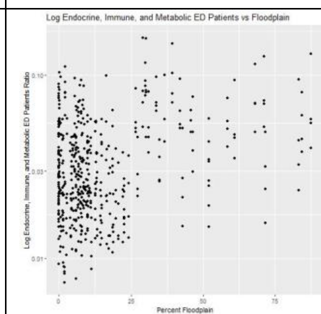
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.421391	0.319986	0.123028	0.438724	0.31268
Graph of Log Relation					
Cor. of Log	0.395171	0.307566	-	0.447964	0.298167

Figure C29 ED patients vs. floodplain coverage.

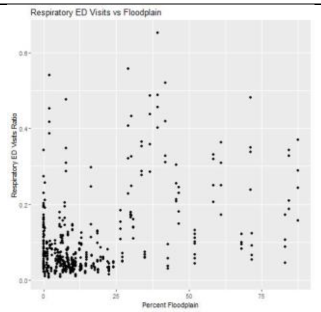
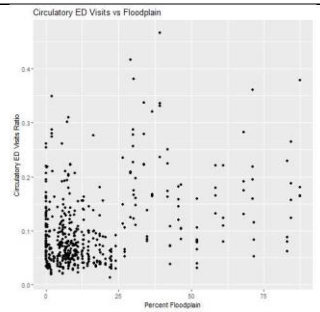
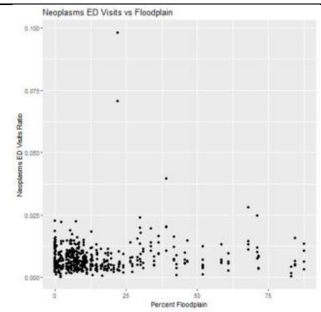
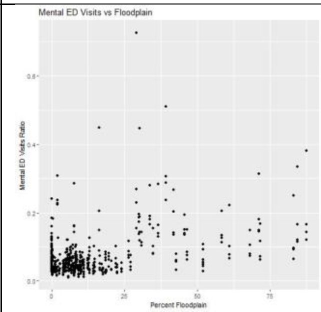
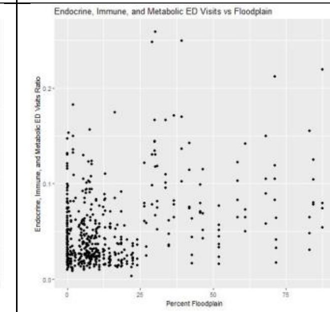
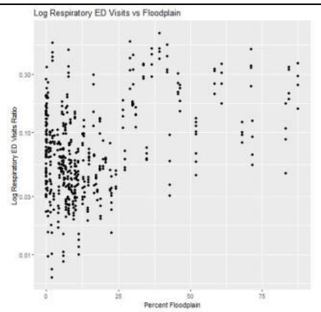
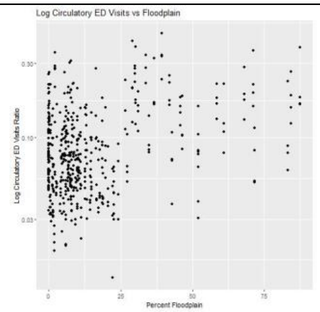
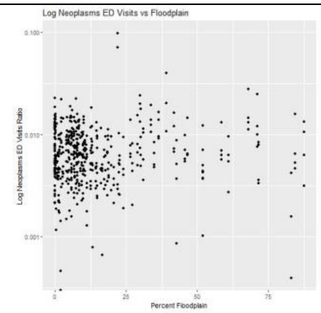
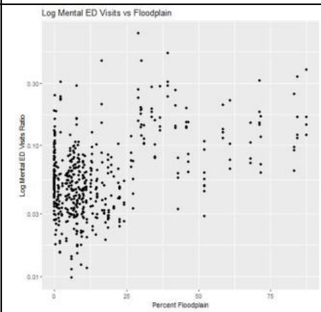
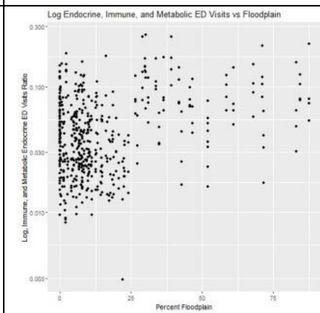
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.416294	0.345252	0.086582	0.409665	0.333283
Graph of Log Relation					
Cor. of Log	0.398216	0.327611	-	0.437037	0.304891

Figure C30 ED visits vs. floodplain coverage.

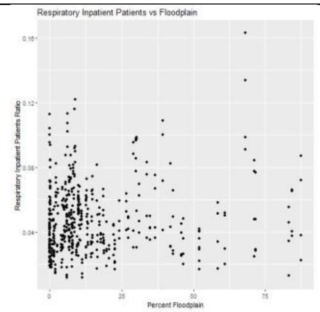
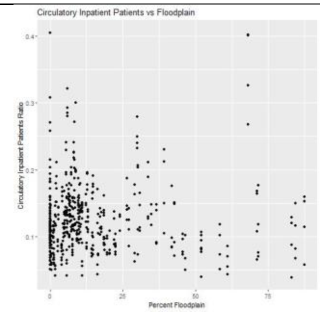
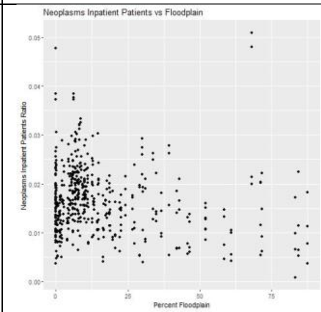
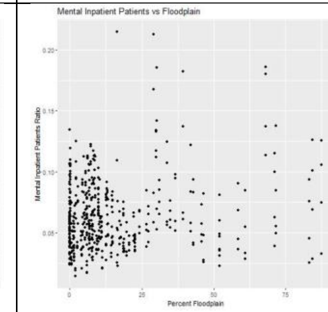
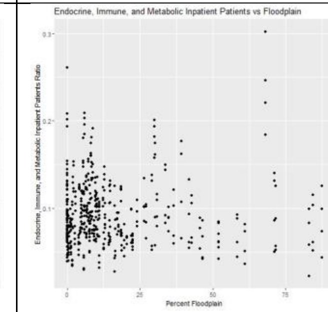
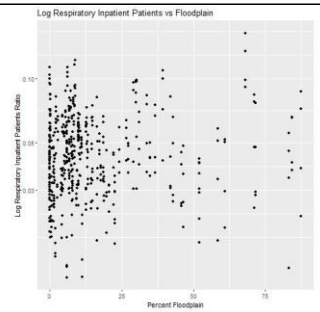
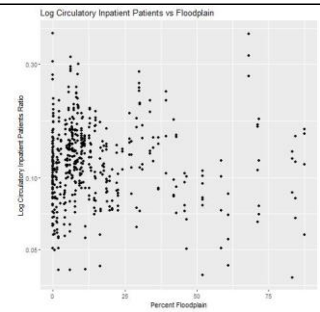
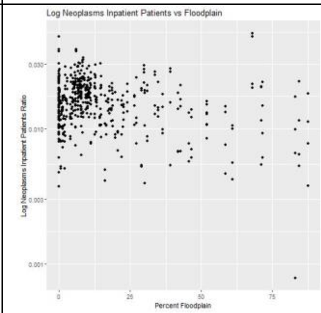
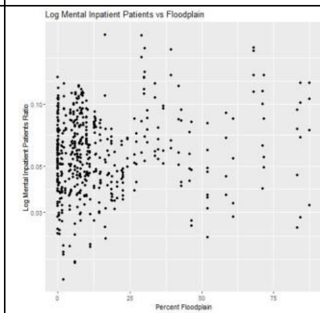
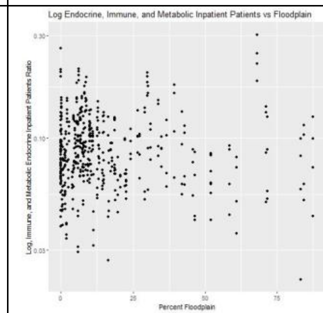
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.08259	-0.00321	-0.1868	0.171865	-0.00404
Graph of Log Relation					
Cor. of Log	0.045245	-0.05917	-0.27909	0.130359	-0.05376

Figure C31 Inpatient patients vs. floodplain coverage.

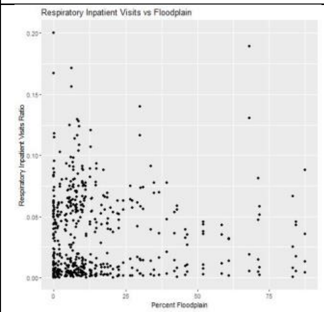
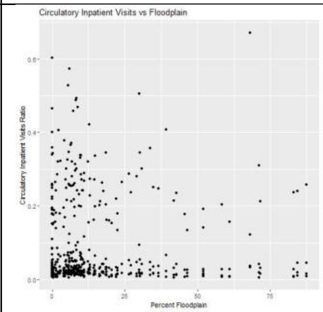
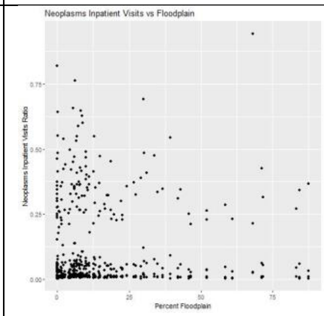
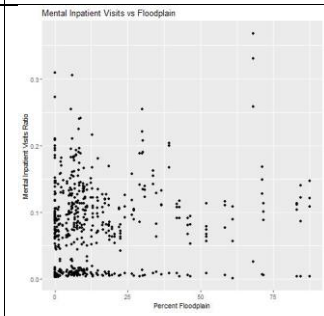
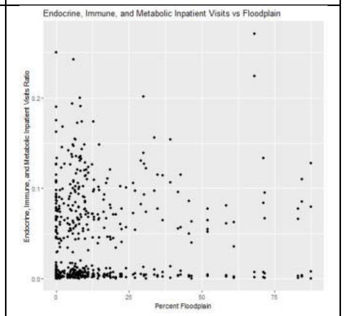
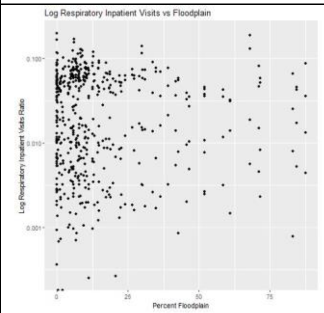
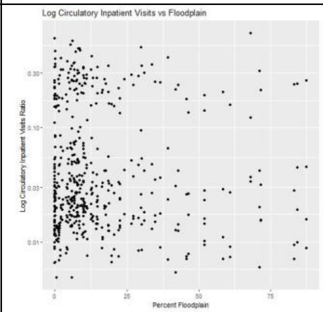
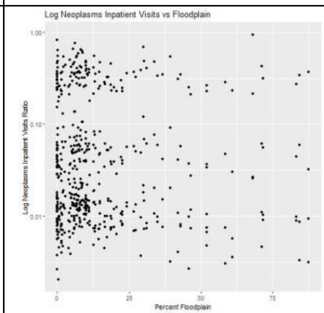
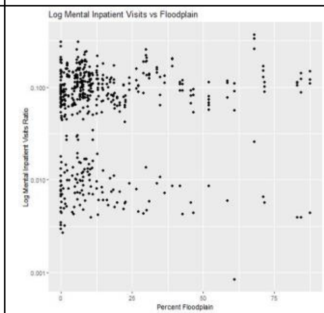
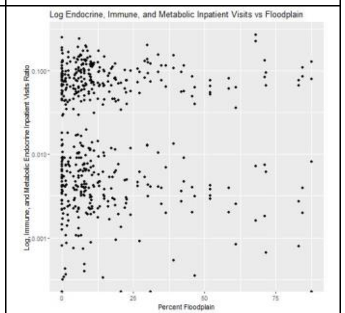
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	-0.03541	-0.0117	0.001357	0.05705	0.01457
Graph of Log Relation					
Cor. of Log	-	-0.04944	-0.03361	0.002238	-

Figure C32 Inpatient visits vs. floodplain coverage.

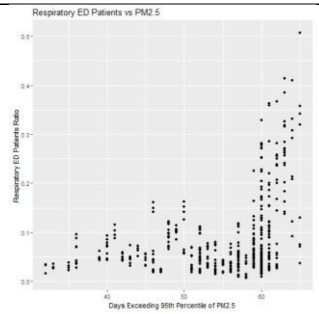
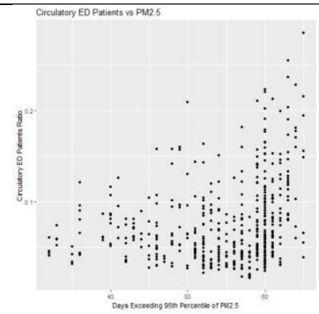
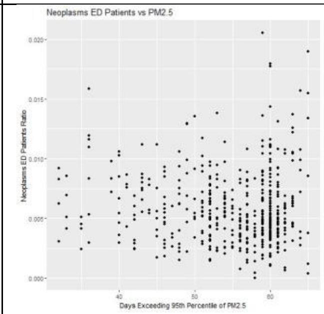
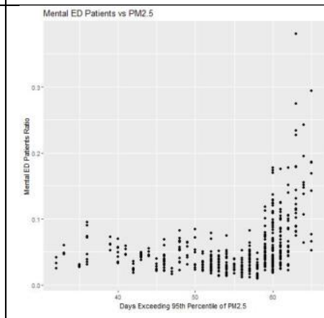
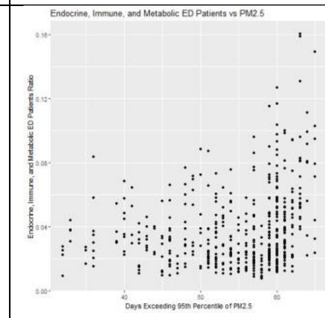
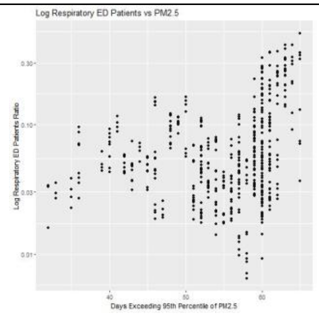
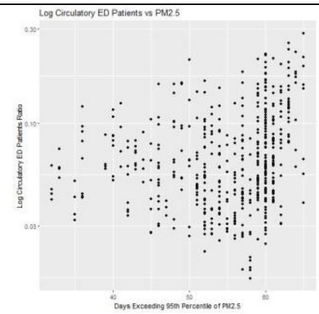
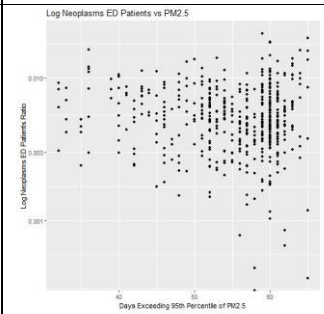
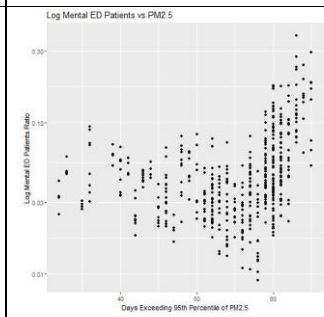
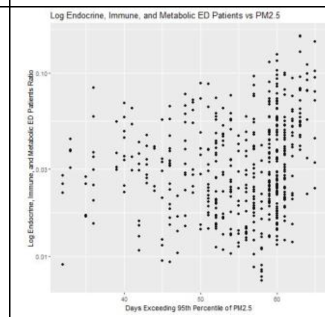
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.338999	0.230632	-0.04484	0.336359	0.214839
Graph of Log Relation					
Cor. of Log	0.248978	0.183596	-	0.297683	0.168213

Figure C33 ED patients vs. PM2.5 exceedance days.

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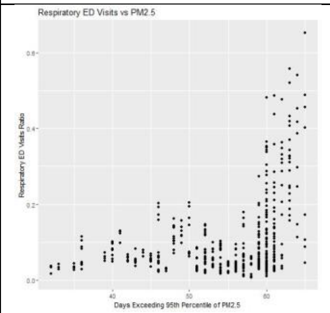
<td>
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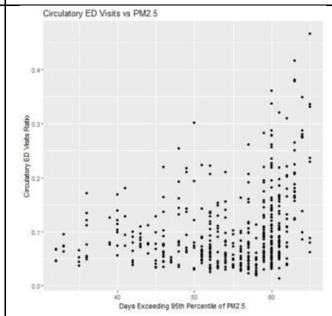
<td>
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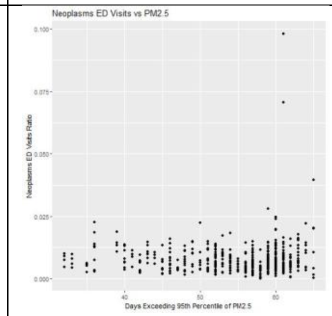
<td>
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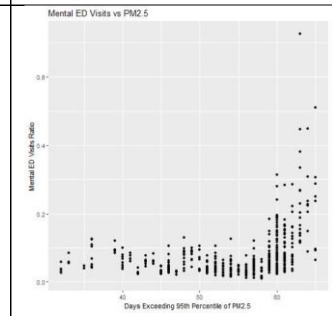
<td>
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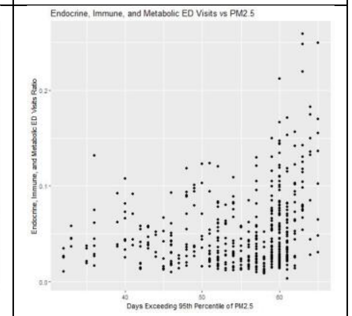
<td>
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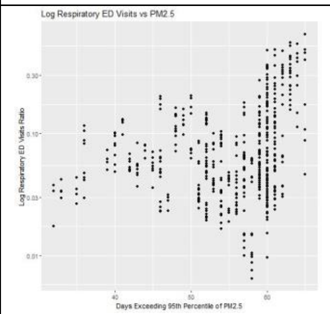
<tr><td>Cor.</td><td>0.346069</td><td>0.249096</td><td>0.006186</td><td>0.313589</td><td>0.231841</td></tr>
<tr><td>Graph of Log Relation</td>
<td>
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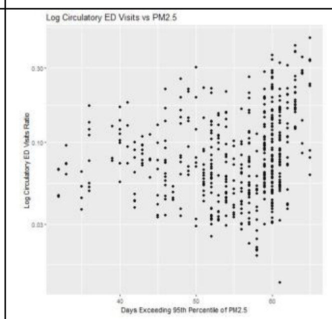
<td>
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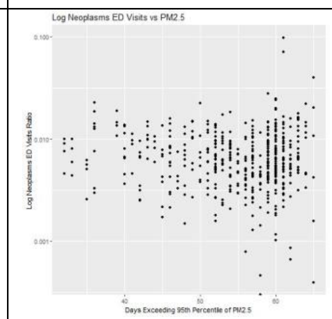
<td>
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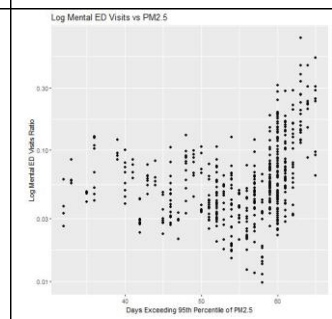
<td>
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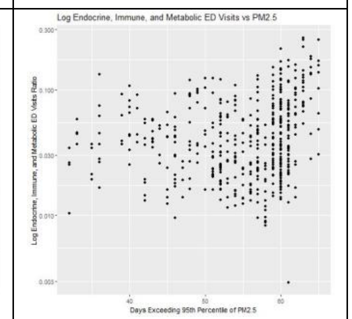
<td>
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<tr><td>Cor. of Log</td><td>0.258353</td><td>0.193703</td><td>-</td><td>0.27552</td><td>0.165318</td></tr>
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Figure C34 ED visits vs. PM2.5 exceedance days.

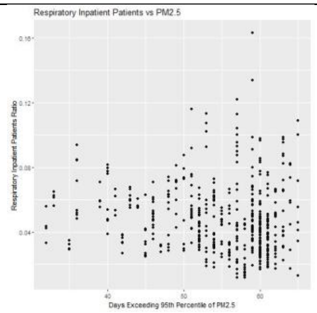
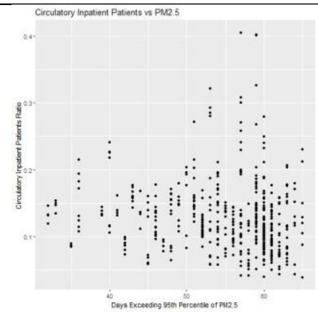
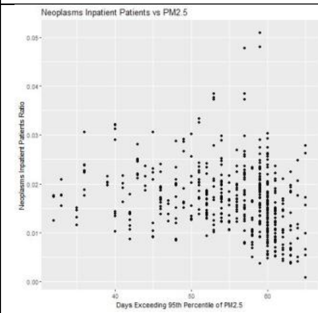
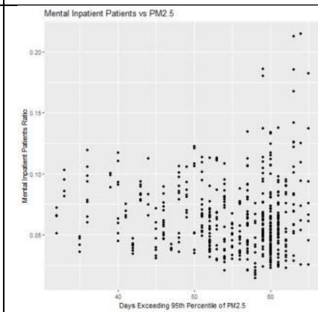
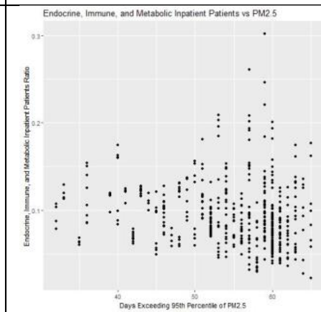
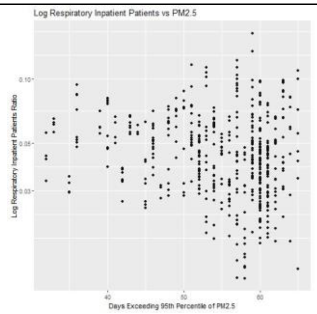
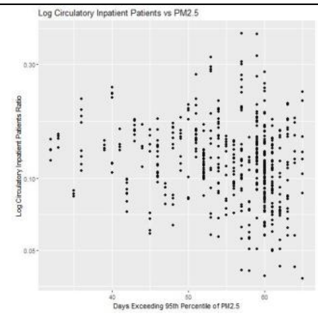
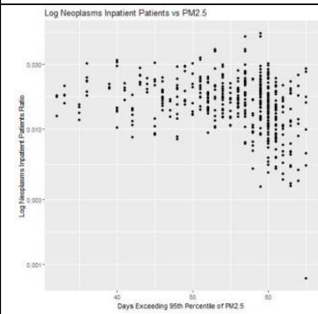
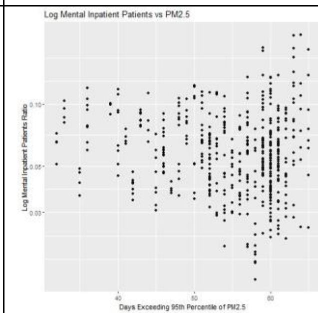
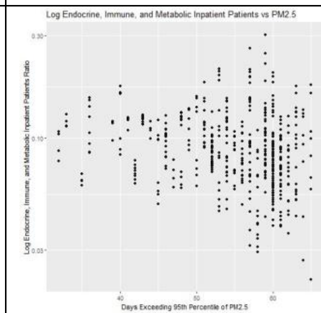
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	-0.11988	-0.12042	-0.02623	-0.05026	-0.17315
Graph of Log Relation					
Cor. of Log	-0.16882	-0.17305	-0.31562	-0.10935	-0.22425

Figure C35 Inpatient patients vs. PM2.5 exceedance days.

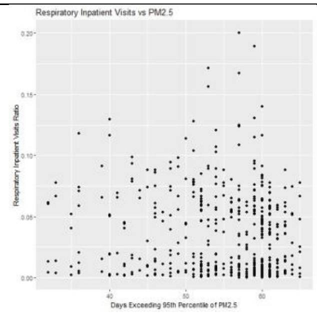
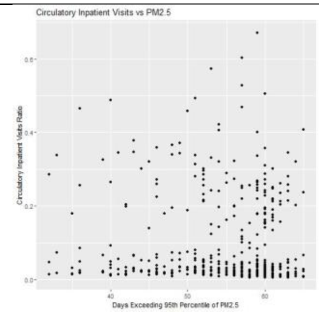
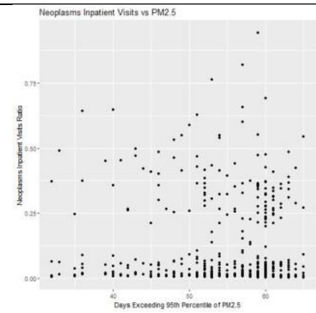
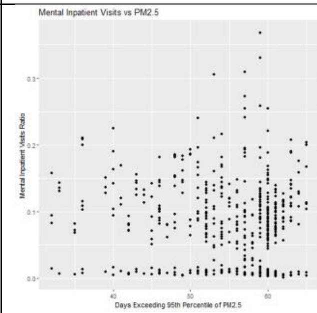
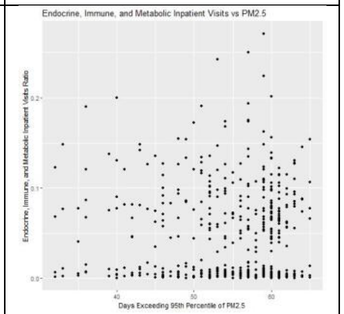
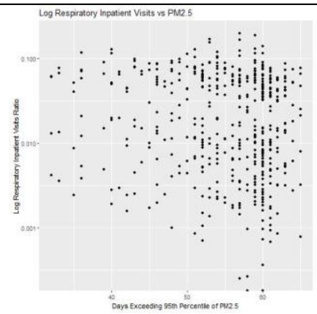
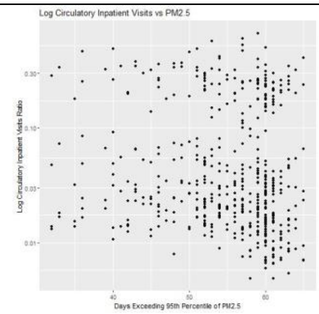
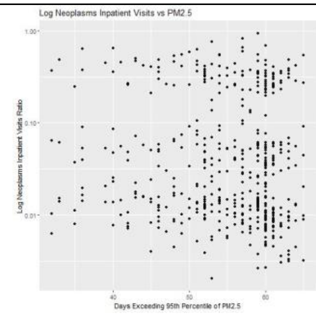
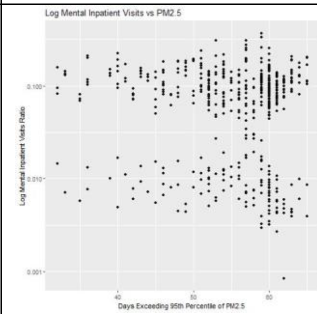
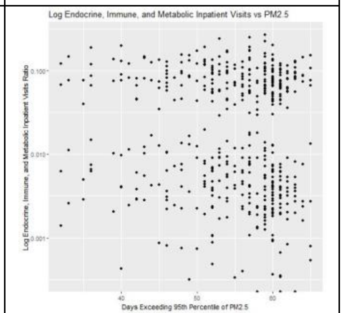
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	-0.0855	-0.07028	-0.05103	-0.07508	-0.04898
Graph of Log Relation					
Cor. of Log	-	-0.10674	-0.06455	-0.067	-

Figure C36 Inpatient visits vs. PM2.5 exceedance days.

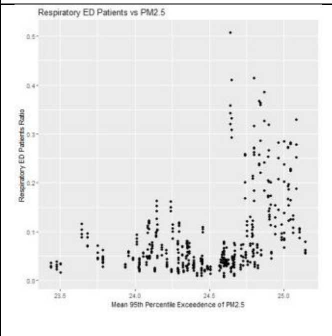
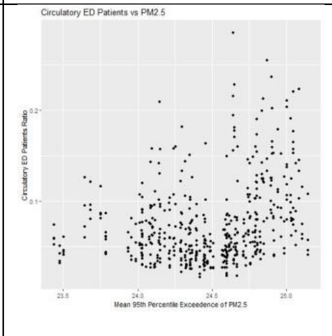
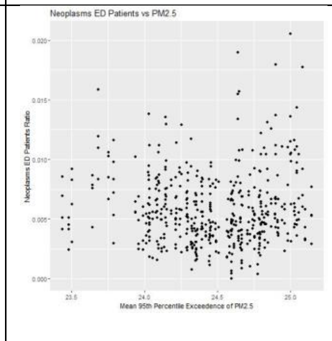
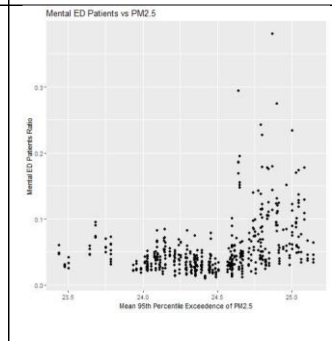
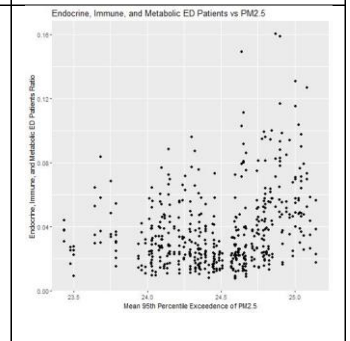
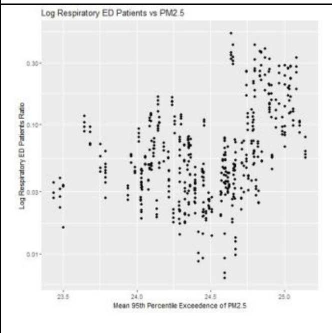
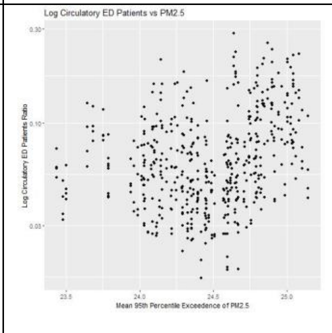
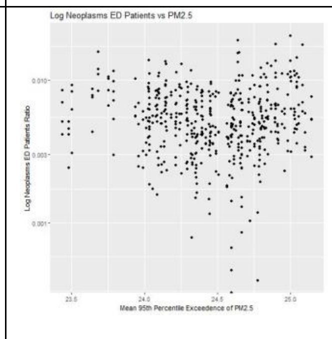
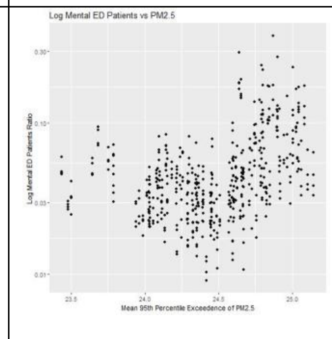
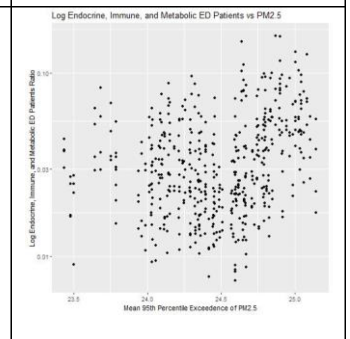
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.411087	0.294271	0.0154	0.372501	0.285625
Graph of Log Relation					
Cor. of Log	0.37805	0.267598	-	0.375187	0.253829

Figure C37 ED patients vs. mean PM2.5 exceedance.

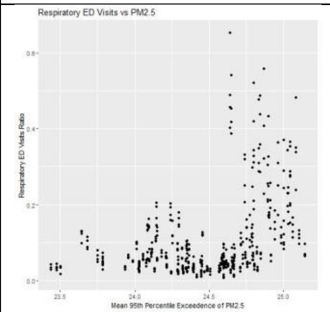
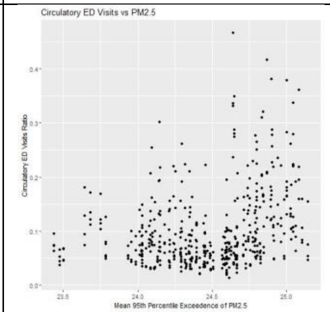
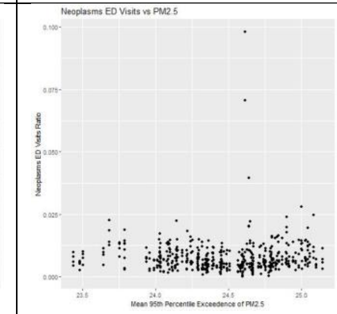
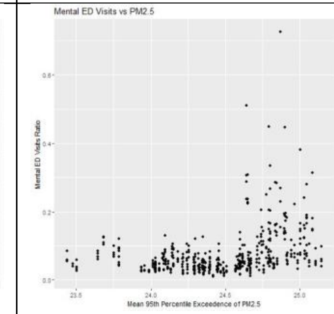
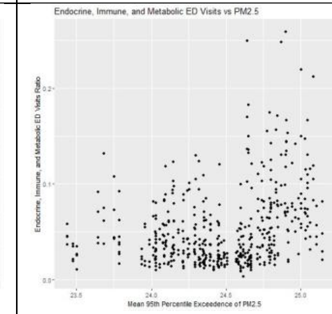
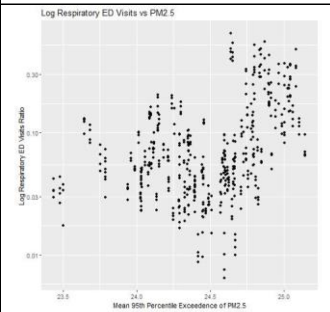
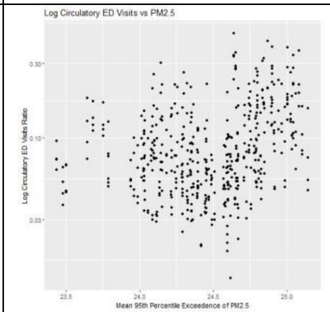
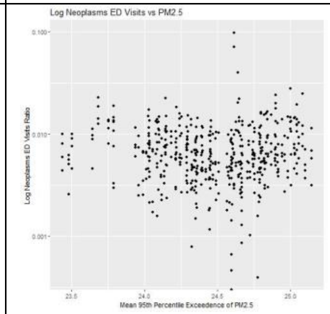
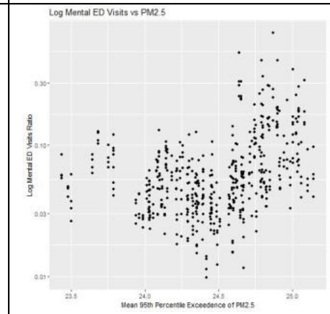
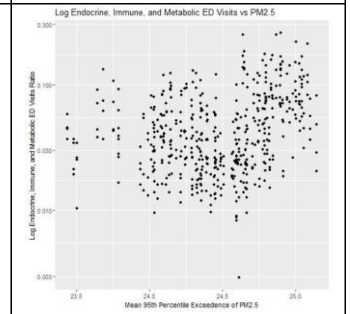
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	0.40856	0.303514	0.017914	0.341642	0.297438
Graph of Log Relation					
Cor. of Log	0.381714	0.276179	-	0.350644	0.255202

Figure C38 ED visits vs. mean PM2.5 exceedance.

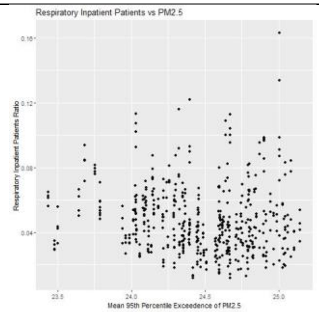
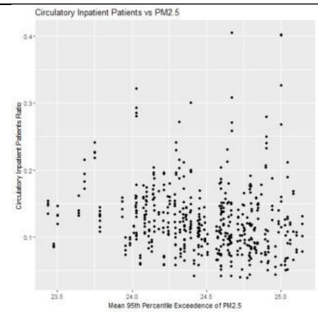
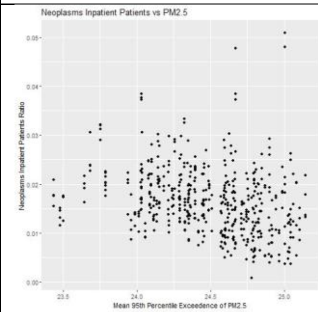
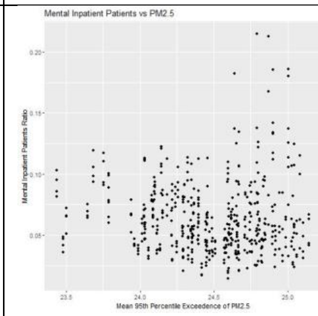
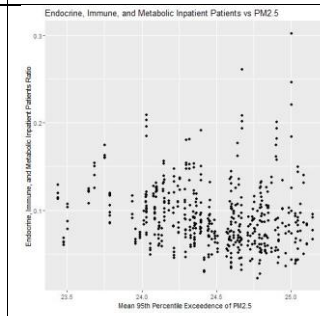
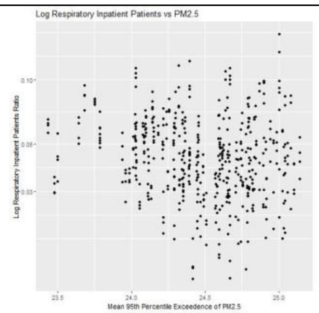
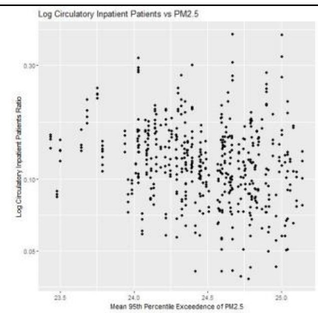
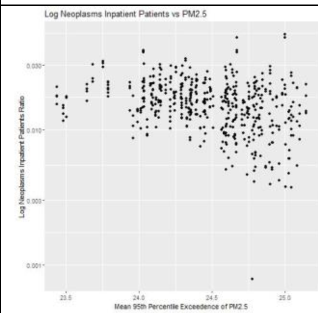
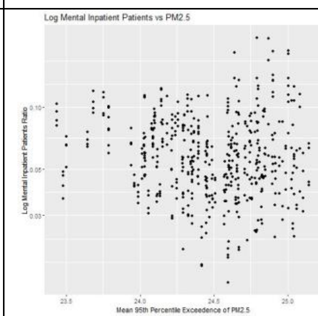
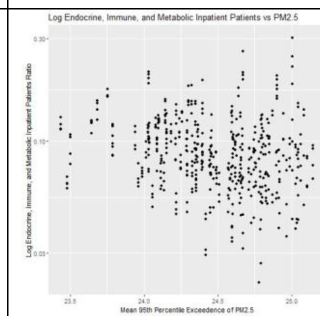
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	-0.10086	-0.13022	-0.27753	-0.04137	-0.16114
Graph of Log Relation					
Cor. of Log	-0.14529	-0.1911	-0.33308	-0.10096	-0.21242

Figure C39 Inpatient patients vs. mean PM2.5 exceedance.

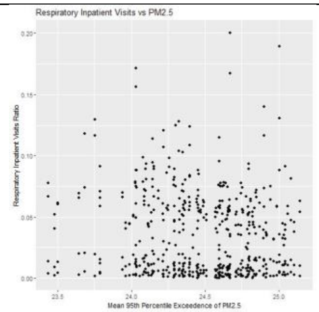
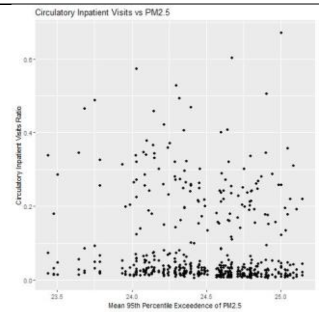
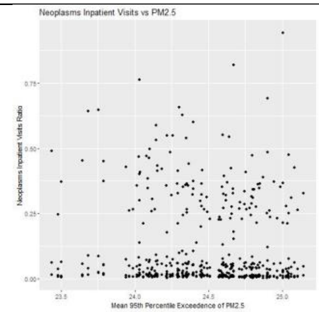
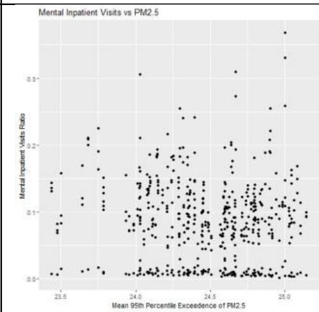
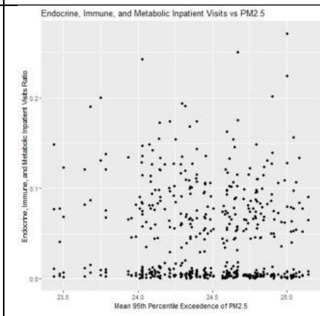
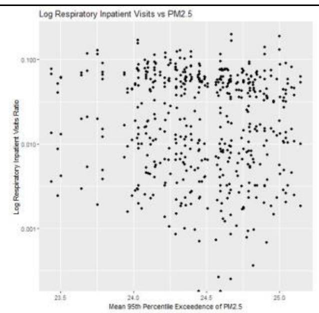
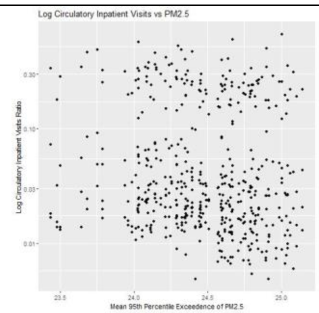
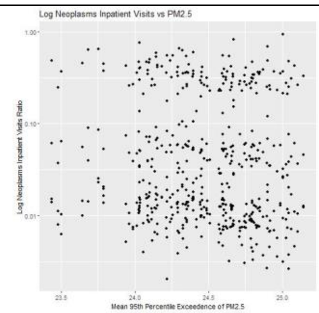
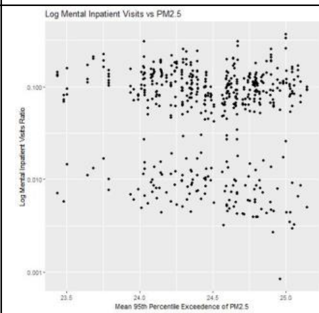
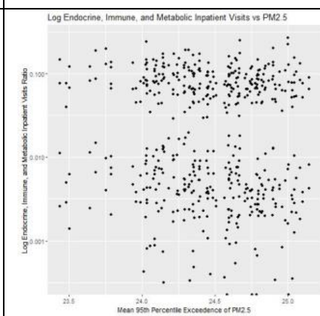
	Respiratory	Circulatory	Neoplasms	Psychiatric	Endocrine, Immune, and Metabolic
Graph					
Cor.	-0.09265	-0.07267	-0.04904	-0.06483	-0.0491
Graph of Log Relation					
Cor. of Log	-	-0.11222	-0.06575	-0.06699	-

Figure C40 Inpatient visits vs. mean PM2.5 exceedance.

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