Analyzing the Flood Risk of Buried Streams in Wayne County, Michigan

By

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Abstract

Wayne County, Michigan, faces significant urban flooding challenges due to socio-economic disparities, historical urban development, and aging infrastructure. With a population of 1,793,561 (U.S. Census Bureau, 2020) and covering 673 square miles, including 61 square miles of water, the county remains vulnerable to flood hazards. Severe flooding events, such as the 2021 disaster causing over $1 billion in damage and affecting more than 20,000 homes, highlight the need for comprehensive flood risk assessment. This study integrates Social Vulnerability Index (SVI) data, Flood Factor data from the First Street Foundation, and environmental variables such as vegetation cover and proximity to current and historic streams. Using ArcGIS Pro, the study identifies flood-prone areas based on low vegetation (NDVI values), proximity to current and ghost streams digitized from an 1860 map, and Flood Factor scores ≥ 5. A 100-meter buffer around streams captures potential overflow zones. Bivariate mapping and scatter plots analyze the spatial relationship between social vulnerability and flood risk across Wayne County census tracts. The results show that most census tracts fall into the High-Low category, meaning high social vulnerability but low flood risk. Only one tract (5245) shows a Mid-High relationship. Even in areas with moderate or low overall flood risk, buried streams increase local flood vulnerability, as seen in Tracts 5245 and 5133. Scatter plot analyses reveal weak correlations, with R^2 values of 0.0024 for low flood risk (Flood Factor ≤ 2) and 0.00045 for major flood risk (Flood Factor ≥ 5). These findings suggest that social vulnerability alone does not strongly predict flood risk in Wayne County. Changes in historical stream networks due to urbanization increase surface runoff and reduce groundwater recharge, elevating flood risks. Urban areas with low vegetation, especially in Detroit, face higher flood vulnerability. This study emphasizes the need for more comprehensive analyses, combining environmental, social, and infrastructural factors to improve equitable flood risk mitigation and urban planning strategies.

Chapter One: Introduction

A flood occurs when water spills over onto land that is usually dry. It involves the submergence of typically dry areas due to rising water levels in existing waterways, such as rivers, streams, or drainage channels (Green et al., 2000). According to the Federal Emergency Management Agency (FEMA), flooding is a temporary and widespread condition where two or more acres of normally dry land or at least two properties become partially or completely submerged. This can occur due to various causes, including the overflow of inland or tidal waters, rapid accumulation of surface water runoff triggered by flooding, which resemble a river of flowing mud. Additionally, flooding can result from the collapse or subsidence of land along lake shores or similar bodies of water, caused by erosion or undermining from waves or currents exceeding expected levels.

Flooding occurs in different types: fluvial, pluvial, and coastal. Fluvial flooding happens around rivers, streams, or lakes, either as overbank flooding when water rises above banks or as flash flooding with rapid water flow through riverbeds mentioned below (Nasr et al., 2021).

1. Fluvial (River) Flooding:

- Heavy rainfall leading to river overflow
- Rapid snowmelt increasing river volume
- Ice jams blocking river flow
- Dam or levee failure releasing large water volumes (Abdrabo et al., 2022)

2. Pluvial (Surface Water) Flooding:

- Intense rainfall overwhelming drainage systems
- Poor urban drainage and impermeable surfaces (e.g., concrete)
- Saturated soil unable to absorb more water Localized flash flooding from sudden downpours (Abdrabo et al., 2022)

3. Coastal Flooding:

- Storm surges caused by hurricanes or strong storms
- High tides or king tides inundating coastal areas

- Tsunamis triggered by underwater earthquakes or landslides
- Sea level rise increasing flood risk over time (Abdrabo et al., 2022)

In 2024, the world experienced several extreme flooding events. Kazakhstan faced spring floods due to rapid snowmelt, leading to widespread displacement and property damage. In Southeast Asia the Philippines and neighboring countries were hit by Typhoons Gaemi and Yagi, which brought heavy rains and caused severe flooding, affecting millions of residents. India and Bangladesh experienced recurring floods during the monsoon season, exacerbating humanitarian challenges and impacting agriculture and infrastructure. In Central Europe countries like Germany, Austria, and the Czech Republic suffered from intense rainfall leading to river overflows and urban flooding, resulting in significant economic losses (Lewek, 2024).

The U.S. faced multiple billion-dollar weather and climate disasters, including severe storms and inland flooding, contributing to substantial economic damage. Flooding in the U.S. during 2024 led to catastrophic losses, particularly in the wake of major hurricanes like Helene and Milton. These events unleashed historic rainfall, storm surges, and widespread inundation, causing severe damage to infrastructure, homes, and agricultural areas. Communities in Florida, North Carolina, and surrounding states were among the hardest hit, with damages from Hurricane Helene alone totaling $79.6 billion, the costliest flood-related disaster of the year. The impacts extended beyond property damage to disrupt critical systems, including transportation, electricity, and water supplies. In western North Carolina, historic flooding from Hurricane Helene destroyed roads, bridges, and communication systems, with rainfall levels statistically exceeding a once-in-1,000-years event. These floods caused long-term economic challenges for affected regions, highlighting the increasing vulnerability to extreme weather (Smith, 2025).

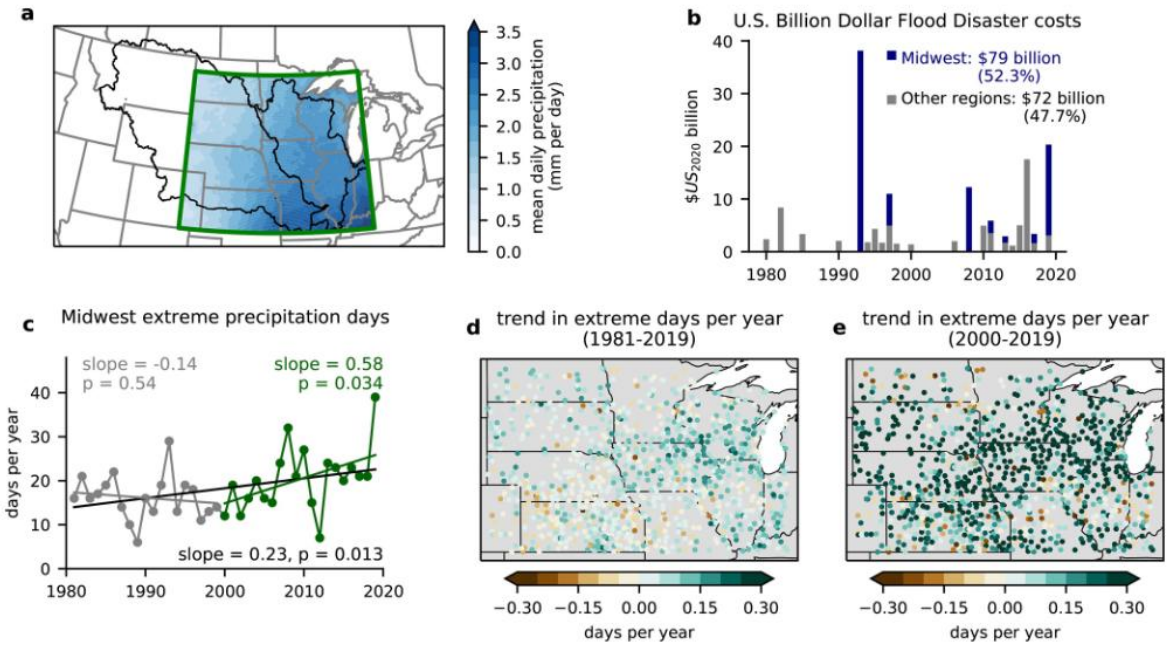


Figure 1: (a) Average daily precipitation within the designated study area (outlined in green). (b) Annual financial losses due to U.S. Billion Dollar Disaster floods, with damages from floods impacting the Midwest highlighted in blue. (c) Linear trend depicting the number of extreme precipitation days per year in the Midwest, shown for the entire period (black), early period (gray), and late period (green), with individual years represented by points. (d) Linear trend of extreme precipitation days per year recorded at Global Historical Climatology Network (GHCN) stations. (e) Same as (d), but specifically for the late period (2000–2019) (Diffenbaugh, 2021).

Research has evaluated future flood risks by analyzing historical trends using global climate models (Xu, 2019). Over the past century, annual precipitation in the U.S. has increased, primarily driven by more frequent and intense rainfall events. This trend is projected to continue in the future (Pryor, 2014). Since the 1920s, the Midwest has seen a significant rise in extreme precipitation events, likely influenced by spatial and temporal variations in sea surface temperatures (Angel, 1997). Studies using historical precipitation data (1961–1990) and projections for 2000–2099 suggest that 24-hour and 7-day extreme rainfall events will double by the end of the next century in the Midwest (Wuebbles, 2004). Furthermore, more than half of the damages from U.S. billion dollar disasters are attributed to flooding in the Midwest (Figure 1a.; Smith, 2021). These damages, shaped by both physical and socio-economic factors, are closely tied to the increasing frequency of extreme precipitation events in the region (Figure 1) (Diffenbaugh, 2021).

Urban flood risk is further exacerbated by the historical practice of burying streams and reorganizing surface water, particularly to facilitate residential development. In many U.S. cities, streams and wetlands were initially altered to support agricultural activities on the outskirts of urban areas (Julian et al., 2015). Over time, these regions transitioned to industrial and residential use, replacing natural water systems with impervious surfaces, such as concrete and asphalt. This transformation created urban areas devoid of visible waterways, despite the hidden remnants of these features beneath the developed landscape (Napieralski et al., 2015). Although these natural water features no longer exist, homes constructed over buried stream valleys are likely to face a higher risk of flooding. This increased risk is often excluded from standard floodplain maps. Additionally, the burial and displacement of streams were shaped by income and race disparities, tied to discriminatory housing policies from the 1930s and 1940s (Napieralski et al., 2024).

Another main cause of the increased risk of flooding in urban areas is the decrease in vegetation density. Urban greenery is essential for improving air quality, lowering storm water runoff, and raising urban dwellers' standard of living. However, societal inequities are often reflected in its uneven distribution (Endsley et al., 2018). Flood frequency and peak discharge can be increased by increased rainfall runoff into neighboring streams caused by reduced plant cover and land removal. Additionally, streams that have been buried by urban expansion are less able to control floodwaters, which increases the risk of flooding. Consequently, the increasing frequency of urban flooding is directly associated with vegetation loss, which reduces infiltration and makes water management more difficult (Zúñiga et al., 2020). Floods disproportionately affect socio-economic conditions, with poor households in low-lying, flood-prone areas suffering the most due to their limited income, poor living conditions, and reliance on labor-intensive livelihoods. Severe floods exacerbate economic disparities, with losses for poor households being higher than those of non-poor households, even during minor floods. Vulnerable housing locations, lack of urban planning, and inadequate financial resources further increase risks for the poor, while geographic factors and housing types also influence flood damage among non-poor households (De Silva & Kawasaki, 2020).

Flood risk in homes is strongly influenced by the age of the home and the condition of its infrastructure. Older homes, especially those built before 1910, are at the highest risk of flooding, while homes built between 1910 and 1958 tend to have lower risk. However, flood risk rises again for homes constructed in the late 20th and early 21st centuries, showing a parabolic trend. Infrastructure issues such as poor roof quality, cracks in basement walls, and

unfinished basements increase vulnerability to flooding. Rental properties are generally more at risk than owner-occupied homes, likely due to differences in maintenance. Signs of structural problems—such as mold, disrepair in basements, uncapped sewer outlets, and past sewer backups—further elevate flood risk. Well-maintained roofs and updated infrastructure can help reduce this vulnerability. These findings emphasize the need to address aging infrastructure and improve housing conditions to mitigate household flood risk (Larson et al., 2021).

Some studies examine flood conditions, their causes, and their impact on society. A study conducted across the United States highlights the geographic patterns of social vulnerability and flood exposure, identifying high-risk clusters in both rural and urban areas. The study found that rural areas in the South exhibited high-social vulnerability (high-high clusters), while urban and suburban areas showed higher wealth and lower social vulnerability (high-low clusters). These findings underscore the significant disparities in flood risk, emphasizing the need for targeted interventions in high-risk regions based on demographic, economic, and housing characteristics (Tate et al., 2021). By 2050, flood hazards are projected to intensify along the Eastern seaboard and in the Western states, while remaining relatively stable or showing minimal change in the central and southwestern regions (Bates et al., 2021). A study revealed that redlined areas in Detroit, Michigan (USA) reveals that flood risk is disproportionately higher in C and D graded neighborhoods compared to A and B, with coastal areas near the Detroit River and Lake St. Clair experienced significantly greater risk regardless of Home Owners' Loan Corporation (HOLC) grade. Historical factors like buried streams and wetlands further exacerbate flood vulnerability in D graded neighborhoods, highlighting the enduring impact of past discriminatory housing policies on flood risk distribution (Napieralski et al., 2024). These studies focus on the spatial patterns and disparities in flood risk exposure, with a particular emphasis on how social vulnerability, buried streams, and geographic location contribute to varying levels of flood risk. They explore broader patterns, but not the detailed connection between socio-economic conditions and specific flood risks in census tract level.

In the U.S., the Centers for Disease Control and Prevention (CDC), in collaboration with the Agency for Toxic Substances and Disease Registry (ATSDR), developed the Social Vulnerability Index (SVI), reflecting on demographic, economic, and social conditions. It focuses on the social vulnerability of populations in the event of a natural disaster, public health emergency, or other stressors. It evaluates the resilience of communities helping to identify areas that may be more at risk. It offers a detailed, census tract-level analysis (Gay et al., 2016). On the other hand, The First Street Foundation has developed a flood risk model, Flood Factor,

to provide accurate, property-level flood risk data in the U.S. This probabilistic model estimates flood risks from rain, rivers, tides, and storm surges, considering factors like elevation, climate, and proximity to water. It creates hazard layers based on flood probabilities (e.g., 0.2%, 1%, 10%) and assigns a Flood Factor score from 1 (minimal risk) to 10 (extreme risk) (Wing et al., 2018). By combining the SVI, and Flood Factor points, along with data on buried streams and vegetation cover, the detailed relationship between socio-economic conditions and specific flood risks at the census tract level can be explored. This detailed, localized approach allows for the identification of community-specific patterns, providing more accurate insights into flood risk disparities driven by socio-economic factors, geographic location, and urbanization.

Wayne County, Michigan, exemplifies the challenges of urban flooding in the United States, with its unique socio-economic landscape and historical urban development patterns contributing to heightened flood risk. The county has experienced significant flooding events in recent years, driven by factors such as increasing rainfall intensities, aging infrastructure, and urbanization. Notably, the region suffered extensive damage during the 2021 flooding caused by severe storms, with FEMA declaring multiple disaster areas within the county. Over 20,000 homes were impacted, resulting in damages exceeding $1 billion (Detroit Free Press, 2021). Wayne County's flood vulnerability is further exacerbated by buried streams and wetlands, which were historically altered to accommodate industrial and residential development. Studies have shown that areas with buried waterways often experience higher flood risks due to reduced drainage capacity (Napieralski et al., 2024). Additionally, the county's socio-economic disparities create unequal flood impacts, as lower-income households in historically redlined neighborhoods face greater exposure to flood hazards due to inadequate infrastructure and poor housing conditions. Despite these challenges, there is a lack of detailed, localized analyses connecting socio-economic conditions with flood risks within Wayne County.

Cities like Detroit, MI, characterized by relatively flat topography and aging infrastructure, face heightened risks, necessitating comprehensive flood risk assessment and management strategies (Larson et al., 2021; Khosravi et al., 2016). These challenges emphasize the critical importance of accurate flood risk assessment and mitigation strategies, particularly in areas prone to severe flooding events like Michigan. Historical flood events in the state, between 1986 and 2014, have caused substantial damages, underlining the urgency of implementing robust flood management measures (National Weather Service; United States Flood Loss Report). Additionally, recent floods in June 2021 have further highlighted vulnerabilities,

particularly in regions like Dearborn, emphasizing the need for enhanced stormwater management in vulnerable watersheds (City of Dearborn). The significant number of populations residing within flood-prone areas, reinforcing the necessity of proactive flood risk assessment and mitigation efforts (Wing et al., 2018). Existing flood risk assessments often focus on broad regional trends, neglecting the intricate relationship between social vulnerability and environmental factors at the census tract level. Tools such as the Social Vulnerability Index (SVI) and Flood Factor provide valuable insights but have not been comprehensively applied to explore flood disparities in Wayne County. This study focuses on Wayne County to address this gap by combining SVI, Flood Factor data, and environmental variables such as vegetation cover and buried streams.

Chapter Two: Literature Review

Urbanization, driven by the need to accommodate growing populations, land use, and expand infrastructure, alters land and water flow patterns. This process often involves the burial of streams and the obstruction of natural water pathways. Concurrently, global climate change is intensifying weather events such as cyclones and storms, leading to rising temperatures, increased precipitation, and elevated sea levels. These factors collectively heighten the risk of flooding. Many cities and counties in the U.S. are experiencing increased flood risks due to historical practices of stream burial and extensive urbanization. This study focuses on Wayne County, which has a significant portion of the Rouge River watershed; to illustrate how early 20th-century stream burial practices have exacerbated flood risks. Numerous studies have documented flood events in southeast Michigan, particularly in Detroit and surrounding areas, which predominantly affect low-income, Black American communities. These past flood events have had devastating impacts, and projections indicate that future floods could worsen the situation. Therefore, it is imperative to develop effective planning and policies to mitigate flood risks.

2.1 Stream Burial and Flood Risk

Rapid urbanization is a complex problem as cities and populations grow quickly (UN PD, 2014). This process changes the natural landscape by replacing green spaces and water bodies with roads, buildings, and other infrastructure. As cities expand, streams are modified or buried, leaving many areas without natural waterways. This large-scale burial of urban streams disrupts the hydrological system. Urban stream deserts are areas where streams have likely been buried (Napieralski and Carvalhaes, 2015). Urbanization, driven by rising population density, has changed landscapes in North America and is expected to have a major global impact by 2050 (UN Department of Economic and Social Affairs, Population Division, 2011; U.S. Census Bureau, 2014). Open land, rivers, grasslands, and forests are converted into infrastructure, reducing water availability and quality (Steele et al., 2014). Wetlands, rivers, and lakes are often modified by deepening, straightening, and channelizing them (Hammer,

1972; Booth, 1990, 2005; Trimble, 1997; Leopold, Huppman, and Miller, 2005; Wheeler, Angermeier, and Rosenberger, 2005).

Stream burial is common in cities like Detroit, Michigan, and increases flood risks by removing natural drainage systems (Napieralski et al., 2024). About 85% of Detroit's urban streams have disappeared since 1905, making the city more vulnerable to flooding (Napieralski et al., 2015; Napieralski and Welsh, 2016). When streams are buried, the land absorbs less water, which leads to flooding and property damage (Gao et al., 2020). The Rouge River watershed in southeast Michigan faces these challenges due to large areas covered by pavement and a highly altered stream system (EPA, Rouge River AOC).

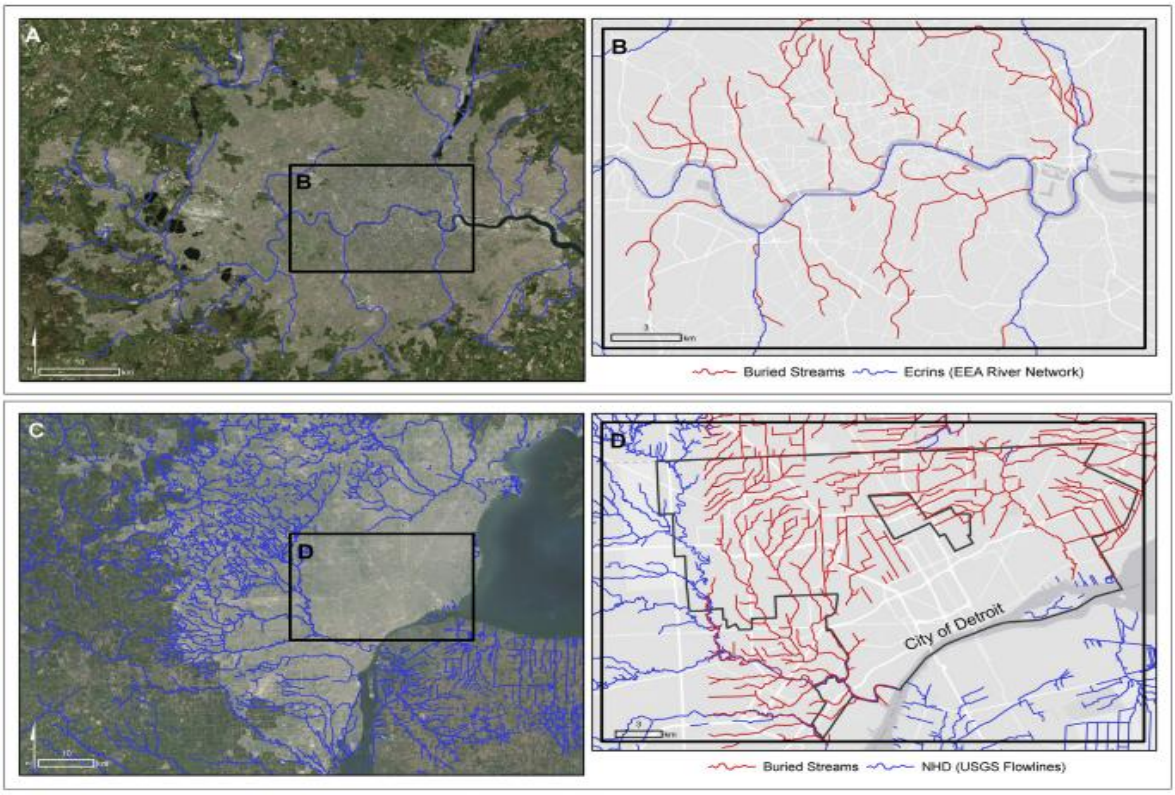


Figure 2: Both the Greater London (UK) and Detroit, Michigan (US) urban areas exhibit a noticeable reduction in stream density, as shown by the overlay of flowlines and buried stream channels (Figures A and C). The data from the European catchments and rivers network system (Ecrins) for London and the National Hydrography Dataset (NHD) flowlines for Detroit reveal significant alterations to the stream networks due to urbanization (Figures B and D). These images emphasize the extensive impact of urban development on stream systems, highlighting the necessity for effective management strategies to address the consequences of stream burial (Napieralski & Carvalhaes, 2016).

Detroit's rapid industrial growth, led by Henry Ford's factories, caused urbanization to spread after 1950 (U.S. Census Bureau, 2014). Western Detroit and Dearborn were among the first areas to urbanize, leading to stream burial. Other places along U.S. Route 12 changed from farms and forests to cities (U.S. Census Bureau, 2014). Aerial photos from 1949 to 1997 show

how human activity changed the Rouge River watershed (Detroit Edison Energy; Napieralski et al., 2015). Mapping old streams and wetlands helps us understand flood risks, especially in historically redlined and yellow-lined communities that suffer more from flooding (Chung, 2016). Knowing about hidden waterways and historical factors can help communities prepare for future floods (Napieralski et al., 2016).

Flood risks in U.S. cities are worse because streams and wetlands were buried to make space for homes and industries (Julian et al., 2015). This practice, which started for farming and later supported industrialization, increased the amount of pavement, making floods worse (Napieralski et al., 2015). Light Detection and Ranging (LiDAR) elevation models show the remains of buried streams, revealing flood risks that do not appear in official floodplain maps. Housing policies from the 1930s and 1940s contributed to these risks by placing marginalized communities in flood-prone areas (Napieralski et al., 2024). Climate change, heavy rain, aging drainage systems, and social inequalities make urban flooding worse, especially in coastal cities (Field, 2012; Rosenzweig et al., 2018; Rentschler, 2022). Marginalized communities face the highest flood risks due to past segregation and poor infrastructure (Bodenreider et al., 2019).

Detroit is mostly flat, with only a 33-meter difference between its highest and lowest points. Its drainage system includes the Rouge River and the Detroit River where most small streams were buried before the 1960s. The City has a combined sewer system, which treats stormwater and sewage together. During heavy rain, it overflows, sending untreated sewage into the rivers and eventually into Lake Erie. Rainfall has increased in the Midwest (Dai et al., 2016), putting more pressure on Detroit's stormwater system. In 2018, the Great Lakes Water Authority released 7,275 million liters of untreated sewage and 51,568 million liters of treated sewage, showing the need for better water management (Michigan EGLE, 2018). When storms are too strong, the system cannot handle the excess water, leading to sewage backups in homes (Steis Thorsby et al., 2020).

2.2 Flood Incidents in U.S.

Urban flooding incurs significant economic costs, making it the most frequent and economically burdensome natural disaster in the United States, with an average annual damage cost of $7.96 billion. These floods affect public health, local and regional economies, and the environment (Koen de Koning et al., 2019). In the U.S., floods have consistently disrupted

livelihoods for decades, and just one inch of water can cause up to $25,000 in damage to a home (DHS, 2020; NFIP, 2020).

Approximately 3% of the population lives in 100-year coastal floodplains, which have a 1% chance of flooding each year in the United States (Crowell et al., 2010). Moreover, 52% of people reside in counties intersecting coastal watersheds, and 39% live in counties along the shorelines of oceans, major estuaries, or the Great Lakes, where the risks of flooding are heightened due to sea-level rise and more frequent storms (NOAA, 2013). Nearly one million individuals in the U.S. are exposed to inland flooding from rivers and streams annually (Kundzewicz et al., 2014). Urbanization worsens flood hazards by increasing peak runoff and flood volumes, reducing the time to flood peaks, and altering the magnitude and frequency of storm events (National Research Council, 2012; Shepherd, 2013; Welty, 2009). These impacts

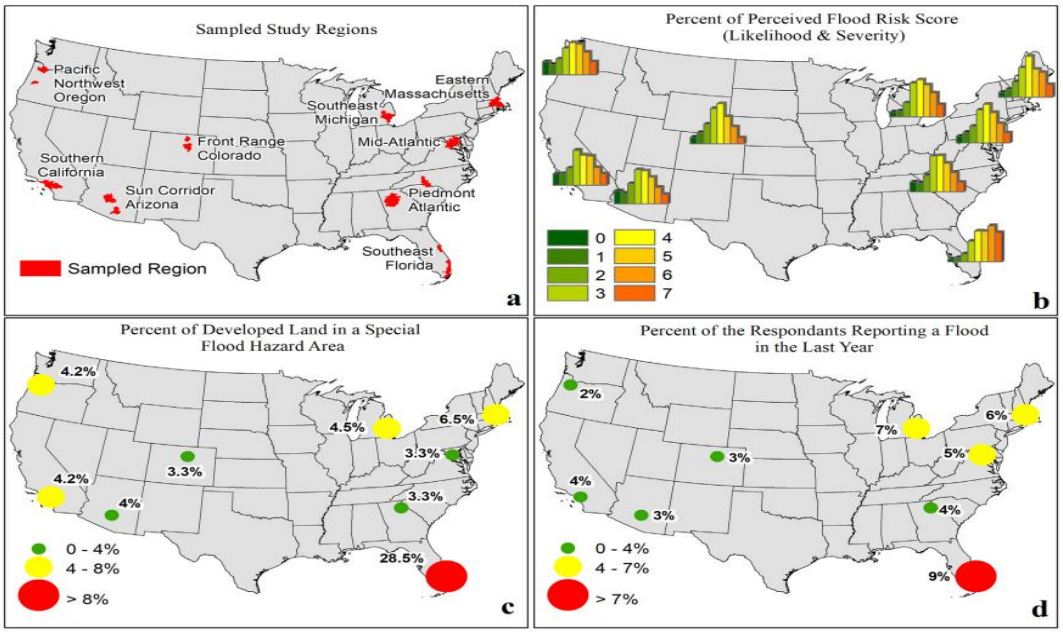


Figure 3: Regional summaries of flood risk (a) sampled study regions across the US, (b) distribution of perceived flood risk scores, (c) average percentage of developed land classified as special flood hazard areas (SFHA) and (d) the proportion of respondents who reported experiencing a local flood (Harlan et al., 2019).

are unevenly distributed, disproportionately affecting older adults, non-white and poorer communities, women, and those in poor health (Debbage, 2018).

Research by Rowe and Villarini (2013) highlights the role of historic cyclones and hurricanes, such as Lili (2002), Grace (2003), Matthew (2004), Rita (2005), Erin (2007), and Ike (2008), in contributing to severe rain events and substantial flooding in the Midwest, particularly in densely populated cities like Detroit, Michigan, and Chicago, Illinois. Tropical Storm Erin and Hurricane Ike were responsible for the most severe flood events in terms of both magnitude

and spatial extent, emphasizing the impact of these precipitation events (PREs) on urban flooding (Rowe and Villarini, 2013).

Survey data from the Center for Urban Studies, collected from 4,803 households between September 2012 and May 2020 in southeast Michigan, showed that 54.26% of respondents reported experiencing home flooding due to rainfall (Figure 2) (Larson et al., 2021).

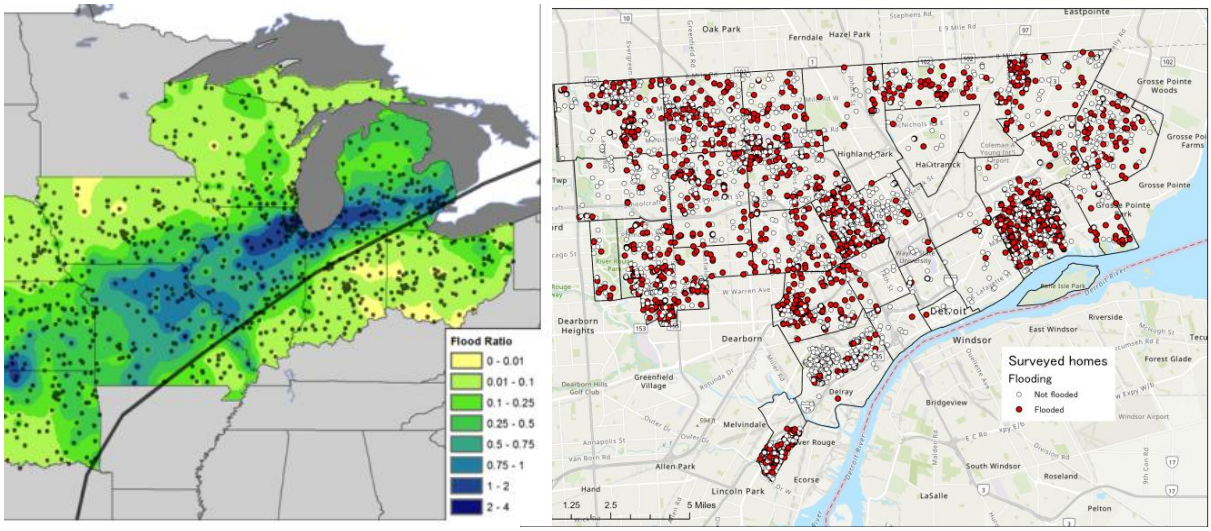


Figure 4. a) Flood ratio maps for (a) Lili (2002), (b) Grace (2003), (c) Matthew (2004), (d) Rita (2005), (e) Erin (2007), and (f) Ike (2008) depict the tracks of these cyclones with black lines. Circles indicate gauging stations where flood ratios were calculated, and interpolation was performed using the inverse distance weighting method (Rowe and Villarini, 2013). b) Locations of households that reported experiencing pluvial flooding are shown. Households that indicated no flooding are not displayed (Larson et al., 2021).

2.3 Recent Flood Events in Southeast Michigan

Michigan experienced one of its most severe flood disasters in September 1986, known as the "Great Flood of 1986," which brought rainfall averaging 6 to 12 inches in central and lower southeast regions. This event caused damage estimated to be $500 million (Deedler, 2016; FEMA, 1986; Kehoe, 1989). Another significant event, the "Metro Detroit Flood," occurred in August 2014, affecting Metro Detroit, Flint, and the Saginaw Valley areas. Wayne, Southern Oakland, and Macomb counties experienced the worst flooding, resulting in damages exceeding $1.8 billion, surpassing the 1986 floods, and affecting around 75,000 homes and businesses (Guin, 2023).

The June 2021 floods further underscored the vulnerability of areas like Dearborn, highlighting the importance of stormwater management for both public and private development in the Rouge River Watershed. A report by the City of Dearborn found that with an average of 6 inches of rainfall in 24 hours and some places like Dearborn receiving up to 7.5 inches, this

500-year flood event emphasized the need for regional cooperation and solutions. East Dearborn is especially susceptible to flooding due to its lower ground elevation and outdated sewer system (Guin, 2023).

2.4 Flood Risk and Social Vulnerability

Over the past fifty years, climate and rainfall patterns in the Midwest, including Detroit, have changed due to climate change (Angel et al., 2018; Dai et al., 2016). In cities like Detroit, aging infrastructure can be overwhelmed by changes in rainfall frequency and intensity, leading to stormwater issues (Sandink, 2016). These natural hazards worsen economic inequality and pose challenges for cities already facing economic and social disparities (Howell and Elliott, 2019). Moreover, the impact of flooding can harm both physical and mental health, with effects that can be short-term or long-lasting (Ramesh et al., 2021).

Detroit, a post-industrial city in Southeast Michigan, faces numerous challenges like demographic shifts and decades of financial and political neglect (Sugrue, 2014). Nearly 80% of Detroit's residents are African-American, and the city is one of the poorest large cities in the U.S., with a median household income of $31,000 lower than the state median of $72,000 (United States Census Bureau, 2020). The area struggles with poor public services and outdated infrastructure.

A study of 164 homes in northwest Detroit found that 64% experienced at least one flooding event in the past year, with many homes experiencing multiple events (Lichten et al., 2017). Interviews with residents confirmed widespread flooding, uneven resources for prevention and recovery, and extensive social, economic, and health implications (Sampson et al., 2019). The Detroit Office of Sustainability reported that residents frequently experience flooding: 13% reported it very often, 23% somewhat often, and 32% occasionally (Office of Sustainability, 2019). Major flooding events like the 2014 Detroit flood have significant acute impacts, but recurrent household flooding is likely an under-reported issue that may worsen with climate change (Festing et al., 2014). Survey data from the Center for Urban Studies, covering 4,803 households between September 2012 and May 2020, revealed that 54.26% of respondents experienced home flooding due to rainfall (Larson et al., 2021).

2.5 CDC/ATSDR Social Vulnerability Index (SVI)

Social vulnerability refers to the socioeconomic and demographic factors that affect community resilience, with vulnerable populations experiencing lower recovery rates and

higher mortality during disasters. Addressing social vulnerability reduces human suffering and economic losses from social services post-disasters. Disasters, both natural and anthropogenic, affect all U.S. regions, from large-scale events like hurricanes to localized incidents such as tornadoes. Even minor hazards can escalate into disasters, causing severe injuries, emotional distress, and extensive property damage. Understanding the specific impacts on socially vulnerable communities enhances resource allocation for disaster mitigation, preparedness, response, and recovery. The Social Vulnerability Index (SVI), developed by the Centers for Disease Control and Prevention (CDC) and the Agency for Toxic Substances and Disease Registry (ASTDR), aids disaster management officials in identifying and supporting these populations, ensuring safety and effective community-based disaster mitigation and preparation (Morrow, 1999; Juntunen, 2005; Cutter et al., 2012; Flanagan et al., 2011).

The CDC/ATSDR Social Vulnerability Index (SVI) uses U.S. Census data to assess the social vulnerability of every census tract, which are subdivisions of counties for statistical data collection. The SVI ranks each tract on 15 social factors grouped into four themes: Socioeconomic Status; Household Composition and Disability; Minority Status and Language; and Housing Type and Transportation. Higher SVI ranks means higher vulnerability whereas lower SVI implies lower vulnerability. Socioeconomic status includes variables like income, poverty, employment, and education, with economically disadvantaged populations disproportionately affected by disasters. Unemployed individuals and those with less education face greater challenges in disaster preparation and recovery (Morrow, 1999; Cutter et al., 2012; Tierney, 2006; Brodie et al., 2006). Household composition and disability factors, such as age, single parenting, and disability, influence vulnerability during disasters. Children, elders, and individuals with disabilities are particularly at risk, requiring additional support for financial needs, transportation, medical care, and daily activities (Ngo, 2001; Cutter et al., 2012; Martin et al., 2006; Morrow, 1999; Eidson et al., 1990; White et al., 2006; Rosenkoetter et al., 2007). Minority status and language, encompassing race, ethnicity, and English language proficiency, further complicate disaster vulnerability. Some racial and ethnic groups, including African Americans and Native Americans, and certain immigrant populations, face increased risks due to economic and social marginalization and communication barriers. Housing and transportation factors also play a critical role; poor housing quality and limited vehicle access heighten vulnerability during evacuations. Urban populations with lower rates of automobile ownership and those living in multi-unit housing face significant challenges during disasters, highlighting the need for targeted support and planning to ensure the safety and well-being of

socially vulnerable communities (Morrow, 1999; Cutter et al., 2003; Elliot and Pais, 2006; U.S. O'Hare, 2013; Eidson et al., 1990; Peek-Asa et al., 2003; Daley et al., 2005; Tierney, 2006; Pucher and Renne, 2004).

Different studies have summarized the link between health outcomes and flooding. Effect modification occurs when flooding impacts health outcomes differently among various population subgroups. For example, health impacts from flooding are generally more pronounced in populations over 65 years old (Collins et al., 2013; Zhang et al., 2019). Gender differences have also been observed: women experience higher rates of heat-related injuries, while men face increased rates of water-borne infections post-flooding, though fatalities show no gender differences (Jonkman et al., 2009). Research on socioeconomic status (SES) and educational attainment shows mixed results; some studies suggest adverse health impacts from flooding decrease with higher SES or education, others indicate increased impacts, and one well-controlled study found no effect (Flanagan et al., 2011).

Variations in flooding impacts by race or ethnicity have been noted. Some studies found increased impacts among Hispanic, Native American, or non-Hispanic Black individuals, while others found no significant differences across these categories (Collins et al., 2013). Hispanic populations with limited English proficiency experienced increased impacts following a 2006 flooding event in Texas, and higher food and emergency requests were reported after Hurricane Florence (Jonkman et al., 2009).

2.6 FEMA and First Street Flood Models of Flood Risk Assessment

The Federal Emergency Management Agency (FEMA) plays a crucial role in flood risk management in the United States by developing and maintaining Flood Insurance Rate Maps (FIRMs). These maps are vital for identifying flood risk zones and determining base flood elevations (BFEs), guiding design requirements and insurance pricing. However, while FEMA focuses extensively on coastal flood hazard areas, mapping for fluvial and pluvial flooding is incomplete nationwide, raising concerns about potential underestimation of flood risks (Wing, 2018).

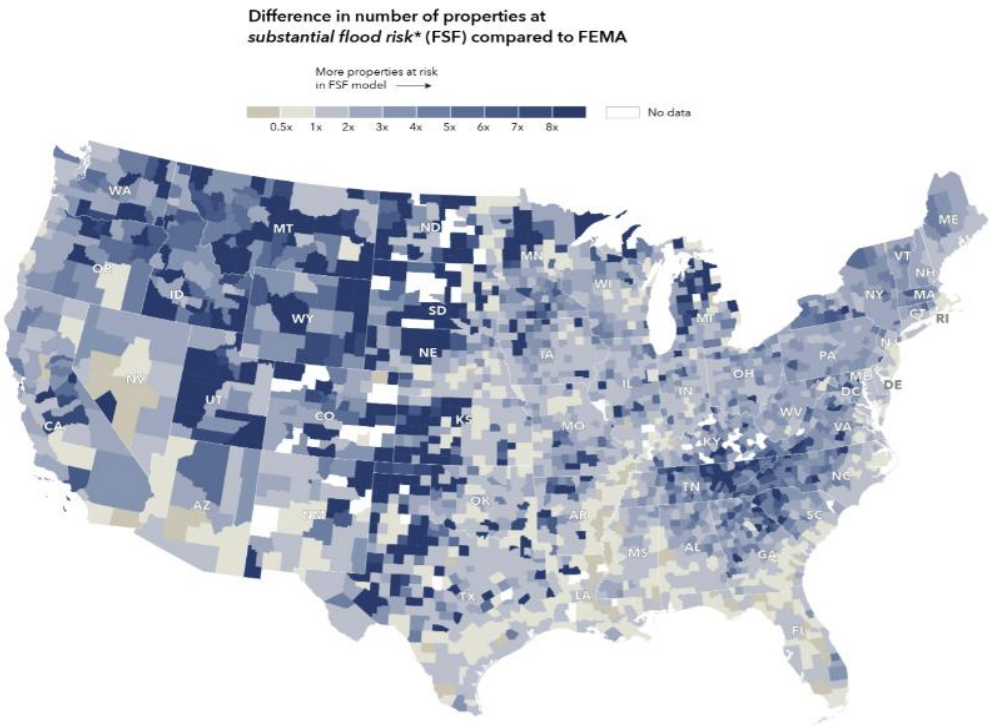


Figure 5: Difference in number of properties at substantial risk (analyzed by First Street Foundation) compared to FEMA

The Flood Factor model, introduced by the First Street Foundation, provides detailed flood risk assessments for individual properties, assigning a Flood Factor from 1 to 10. It utilizes federal elevation and rainfall data, along with hurricane-related estimates, to offer comprehensive evaluations. Compared to FEMA maps, the Flood Factor model often reveals higher risk levels, especially in areas with outdated FEMA mapping. Its extensive coverage and accurate assessments highlight a significant number of properties facing flood risks, exceeding FEMA's estimations. According to The First National Flood Risk Assessment, the Flood Factor model identifies around 1.7 times more properties at substantial risk than FEMA's designation of 1-in-100 Special Flood Hazard Areas. This underscores the importance of leveraging advanced tools like the Flood Factor model to improve flood risk management and awareness among property owners (Figure 5).

The Flood Factor model, developed by the First Street Foundation, provides a valuable tool for researchers, businesses, and government agencies to analyze flood risk, promote public safety, and address flood risk inequities (Flores, 2023; Porter, 2021; Porter, 2022). Its utilization extends to examining flood risk for various building types and assessing community-level flooding risks, covering areas that FEMA has not updated in decades and offering insights into flood risks that may otherwise go unnoticed (First Street Foundation, 2020).

Chapter Three: Methodology

3.1 Study Area

Wayne County, the most populous county in Michigan, serves as the primary focus of this study. As of the 2020 United States Census, the county had a population of 1,793,561, making it the 19th-most populous county in the nation. Detroit, the county seat, is a major urban center within the county. Wayne County was established in 1796 and formally organized in 1815, and it is part of the Detroit-Warren-Dearborn Metropolitan Statistical Area. The county is named after General Anthony Wayne, a prominent figure of the Revolutionary War era. Geographically, Wayne County spans a total area of 673 square miles (1,740 km²), of which 612 square miles (1,590 km²) is land and 61 square miles (160 km²), or 9%, is water. The water area includes sections of the Detroit River and Lake St. Clair (U.S. Census Bureau, 2020).

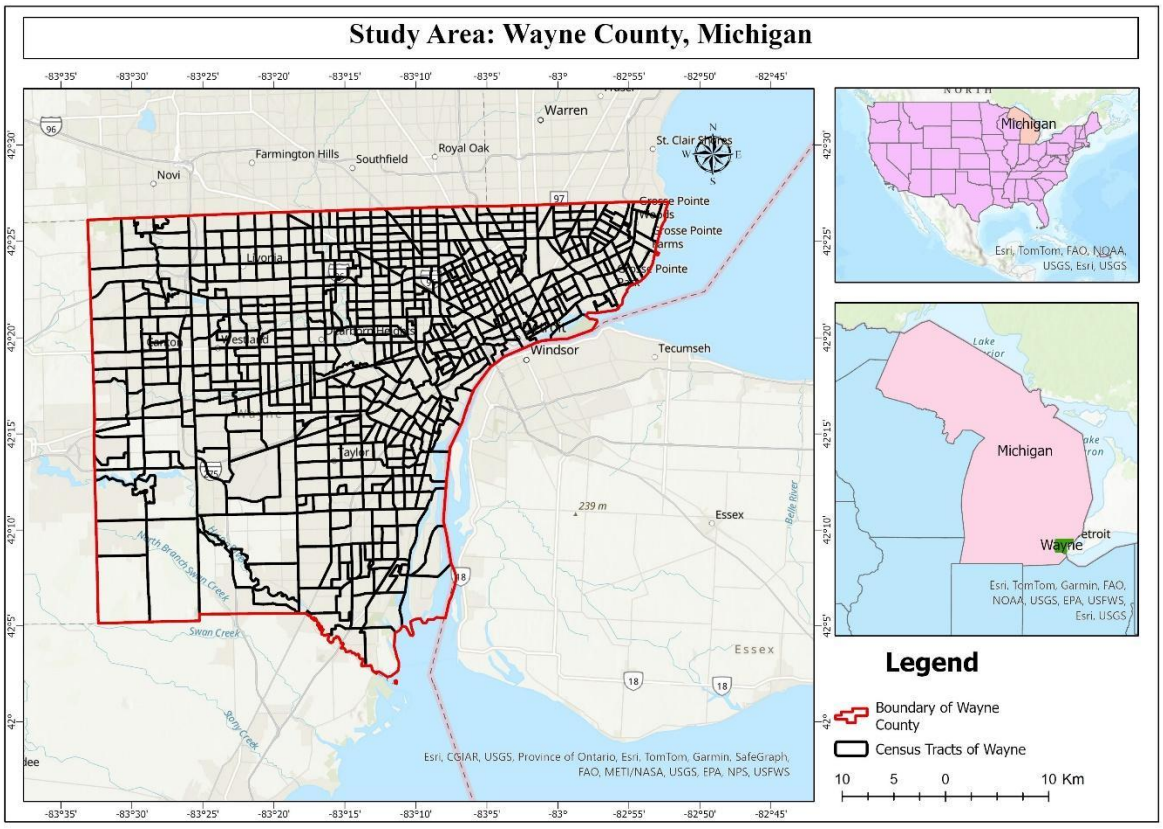


Figure 6: Study area map of Wayne County census showing tract

The country shares land borders with Oakland County and Macomb County to the north, Washtenaw County to the west, and Monroe County to the south. To the east, the Detroit River and Lake St. Clair form a natural water boundary with Essex County, Ontario, Canada. Automotive connectivity across the international border is facilitated by the Detroit-Windsor Tunnel and the Ambassador Bridge. Notably, due to the southwestern course of the Detroit River, portions of Essex County lie geographically south of Wayne County. Wayne County includes a variety of distinct geographic and cultural regions.

3.2 Social Vulnerability

The SVI is reliable because it is based on the regularly updated and methodologically rigorous American Community Survey. The SVI ranks census tracts based on their composite index scores, which are derived from the combined scores of the four themes. This ranking helps to identify and prioritize areas with higher levels of social vulnerability. By comparing these scores, it is possible to determine which communities may require more targeted interventions and support to mitigate their vulnerability and enhance their resilience to environmental hazards (Adger et al., 2005). To construct the SVI, 15 social factors are utilized, grouped into four main themes: Socioeconomic Status, Household Composition & Disability, Minority Status & Language, and Housing Type & Transportation. Each of these factors is standardized and scored to create theme-specific indices. These theme scores are then aggregated to produce a composite SVI score for each census tract. Higher scores indicate greater social vulnerability, reflecting a higher level of susceptibility to adverse impacts from environmental hazards (Agency for Toxic Substances and Disease Registry (ATSDR), 2024).

3.3 Flood Risk

Flood risk data were sourced from the First Street Foundation Flood Model (FSF-FM), which assigns Flood Factor scores ranging from 1 to 10. Flood Factor scores a property's risk of flooding over 30 years. The score is based on the likelihood of flooding from high tides, storm surges, overflowing rivers and streams, and high-intensity rainfall. Flood Factor data is used in this research to provide a comprehensive and standardized measure of property-level flood risk based on probability and severity (Napieralski et al., 2024; Zenodo, 2021). To integrate this data with Wayne County's census tracts, the Spatial Join tool in ArcGIS Pro was used to align flood risk data with the corresponding census tracts. The resulting attribute table was then exported to Excel, where a pivot table was utilized to organize the data for further analysis.

To calculate flood risk percentages, two measures were considered. First, for overall flood risk, flood factor scores from 2 to 10 were summed for each census tract to represent parcels with any level of flood risk. This sum was divided by the total Flood Factor points within the census tract to determine the percentage of parcels at risk of flooding. Second, for major to extreme flood risk, Flood Factor scores from 5 to 10 were summed and similarly divided by the total Flood Factor points within each census tract to assess the percentage of parcels facing significant flood risk. The parcel percentage values were joined with census tracts of Wayne to assess flood risk.

"Jenks Natural Breaks" is used to symbolize the percentage of parcels at any and major flood risk on both of the maps. It is a data classification method used in ArcGIS to create clear and meaningful choropleth maps. It identifies natural groupings within data by minimizing variance within each class and maximizing variance between classes. This helps highlight significant differences and patterns in the data, making the map easier to interpret.

3.4 Normalized Difference Vegetation Index (NDVI)

High-resolution 1 m imagery from the 2018 National Agriculture Imagery Program (NAIP) was obtained and processed to derive the Normalized Difference Vegetation Index (NDVI) using Google Earth Engine. The NDVI, a widely used vegetation index, is designed to highlight areas with healthy vegetation by comparing the reflection of near-infrared (NIR) and red light. The formula used to calculate NDVI is as follows:

$$NDVI = \frac{(NIR + Red)}{(NIR - Red)}$$

In the NDVI formula, NIR refers to near-infrared light, which is strongly reflected by healthy vegetation, indicating its vigor. Red light, on the other hand, is absorbed by chlorophyll in plants, making it a crucial component for photosynthesis. The contrast between these two wavelengths allows the NDVI to effectively assess vegetation health. The NDVI values range from -1 to +1, where higher values indicate healthier vegetation. A value of +1 represents dense, healthy vegetation, while values between 0 and +0.2 typically correspond to bare soil, rock, or urban areas. Values close to 0 suggest minimal or no vegetation. Negative NDVI values are generally associated with water, snow, or clouds, as these surfaces absorb near-infrared light differently than vegetation does (USGS, 2018). The NDVI values are classified into three categories: Sparse vegetation (NDVI 0–0.4), Moderate Vegetation (NDVI 0.4–0.6), and Dense Vegetation (NDVI 0.6–1) (*NDVI Mapping In Agriculture, Index Formula, And Uses*, 2023).

Given the extensive area of Wayne County, the NDVI was calculated using a coarser resolution of 15 x15 m to reduce data volume.

3.5.1 Active Stream Digitization

Active streams were digitized from 2025 Google satellite image, focusing on streams that are presently active within Wayne County. To identify these streams, digitization was performed on the satellite-derived stream data. Once the digitized active streams were established, a 100-meter buffer was generated around the identified streams to assess their potential flood risk (Figure 8).

3.5.2 Ghost Stream Digitization

Ghost streams were digitized from a historic 1860 map (Figure 7) of Wayne County, focusing on streams that existed during that time but have since been removed from the landscape. To identify these ghost streams, digitization was performed on the historic stream data within the county, and a visual comparison was made with the active streams. Once the digitized historical streams were established, any datasets representing active streams were eliminated, resulting in a database solely consisting of ghost streams. To further analyze the relationship between these ghost streams, wetlands, and flood risk, a dissolved buffer of 100 meters was generated around the identified ghost streams and wetlands. This distance was selected to encompass approximately one city block of parcels on both sides of the ghost stream, addressing potential mapping inaccuracies of the original channel and ensuring parcels within the relict stream valley, whether partially or fully, were included (Figure 8) (Napieralski et al., 2024).

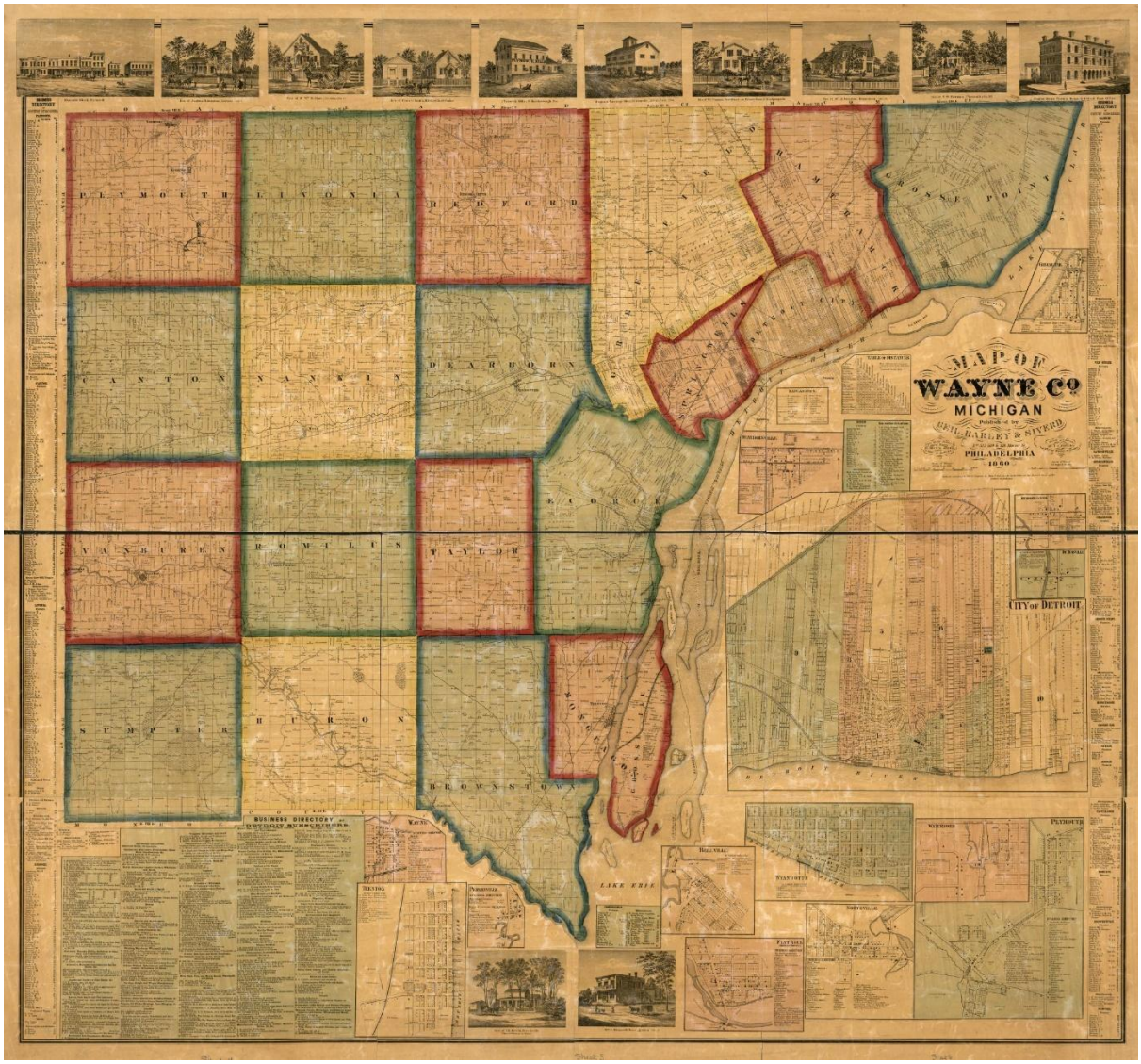


Figure 7: Topographic Map 1860 of Wayne County (Geil And Jones et al., 1860)

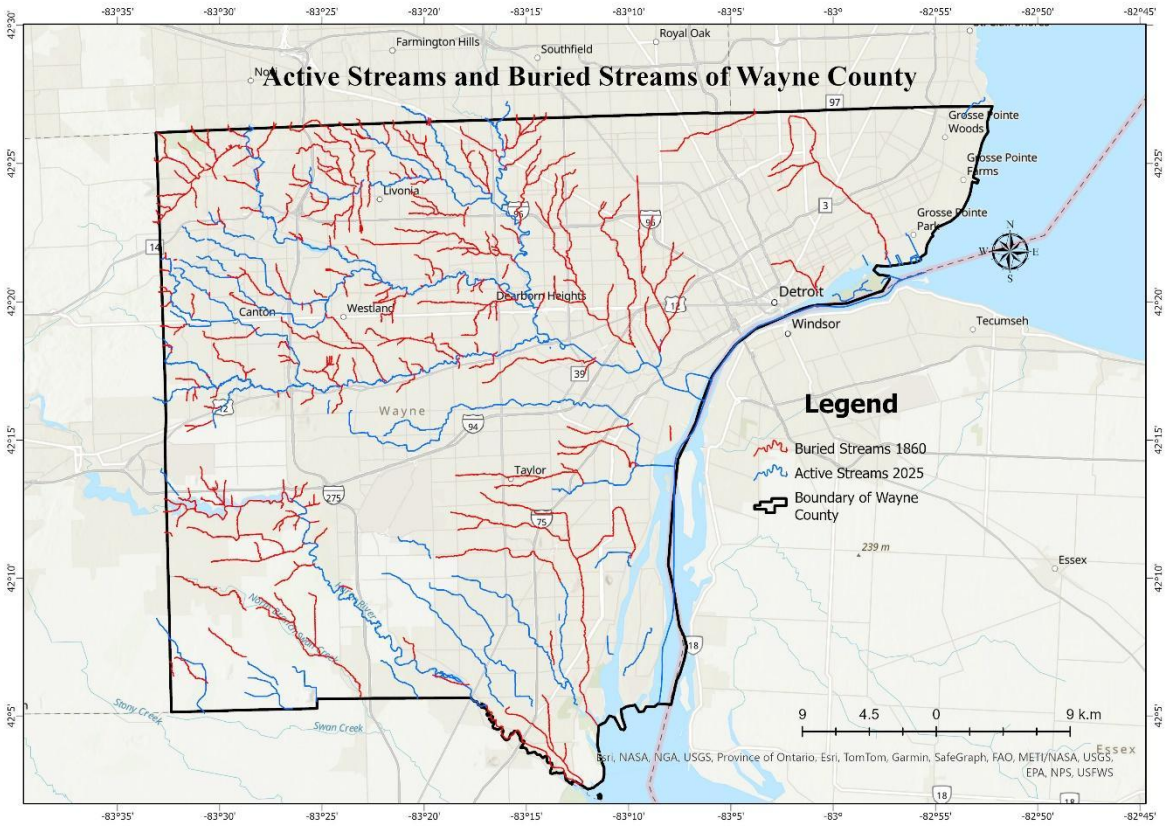


Figure 8: Active Streams vs Buried Streams

3.6 Flood Risk Property Identification

Flood risk properties were identified using four criteria to assess their susceptibility to flooding. The "Select by Location" tool was utilized to analyze spatial relationships between parcel data and flood risk factors. First, properties with sparse vegetation were selected, as they serve as strong indicators of flood vulnerability. Second, parcels located within a 100-meter buffer of active streams were identified as flood-prone due to potential overflow during flood events. Third, properties within a 100-meter buffer of buried streams from 1860 were considered at risk, as these areas historically existed in lowland regions. Finally, properties with a Flood Factor of 5 or higher were classified as high-risk, while those with lower values were designated as low-risk. Based on these criteria, properties were categorized into five flood risk levels in equal intervals: very low, low, moderate, high, and very high risk.

3.7 Correlation Between Socially Vulnerable and Flood-risk Areas

The SVI data, along with the flood risk areas, were analyzed in conjunction with the ghost streams, flood factor points, and NDVI values through a spatial join in ArcGIS Pro. This process allowed for the creation of a dataset that mapped social vulnerability and flood risk

property on a census tract basis. Subsequently, a scatter plot was generated to visualize the relationship between social vulnerability and flood risk, providing insights into how these factors interact across the study area. A scatter plot was created to examine the relationship between social vulnerability and flood risk in Wayne County.

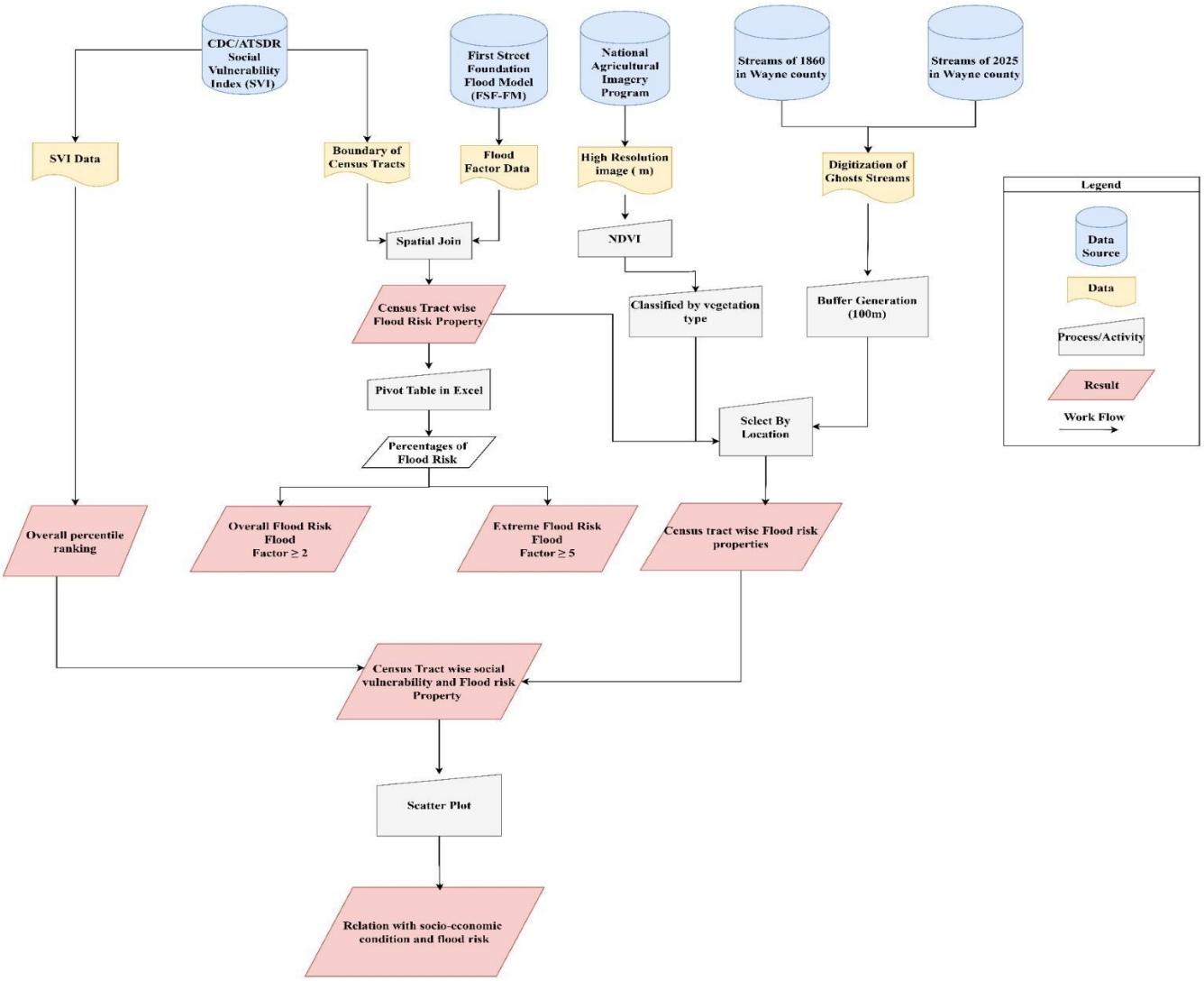


Figure 9: Methodological Framework

Chapter Four: Results

4.1 Social Vulnerability

The spatial distribution of social vulnerability across Wayne County census tracts using the CDC/ATSDR Social Vulnerability Index (SVI) rankings has been shown in Figure 10. Manual Classification Method was used to classify SVI RPL (Ranked Percentile) theme values as it ensures uniform classification across maps, making comparisons easier. Areas with higher SVI rankings, indicated by darker red shades, represent census tracts with greater social vulnerability. These regions, predominantly concentrated in the eastern and central parts of the county, exhibit heightened challenges related to socioeconomic status, household composition, minority status, and housing or transportation issues. These areas are likely to face increased difficulty in preparing for, responding to, and recovering from disasters or public health emergencies, necessitating targeted interventions to enhance resilience. Conversely, census tracts in the western parts of Wayne County, marked by lighter green shades, indicate lower social vulnerability and relatively better access to resources and infrastructure to mitigate disaster impacts. The map also highlights some areas classified as "Null," indicating census tracts where no SVI data is available.

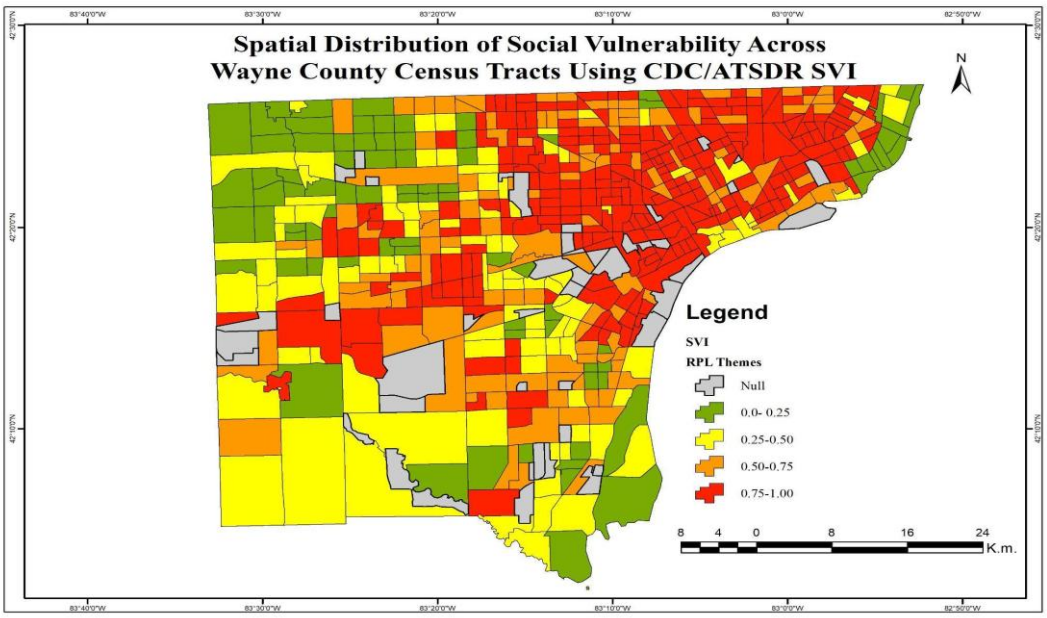


Figure10: Social Vulnerability Index assessment in Wayne County

4.2 Flood Factor Points

Two maps were created to visualize these flood risk percentages across Wayne County: one illustrating the percentage of parcels at any flood risk (Flood Factor ≥ 2) by census tract (Figure 11), and another showing the percentage of parcels at major to extreme flood risk (Flood Factor ≥ 5) by census tract (Figure 12). This analysis provides a clear representation of both general and severe flood risk, offering valuable insights for flood mitigation and planning efforts in Wayne County. Null data was ignored in this analysis.

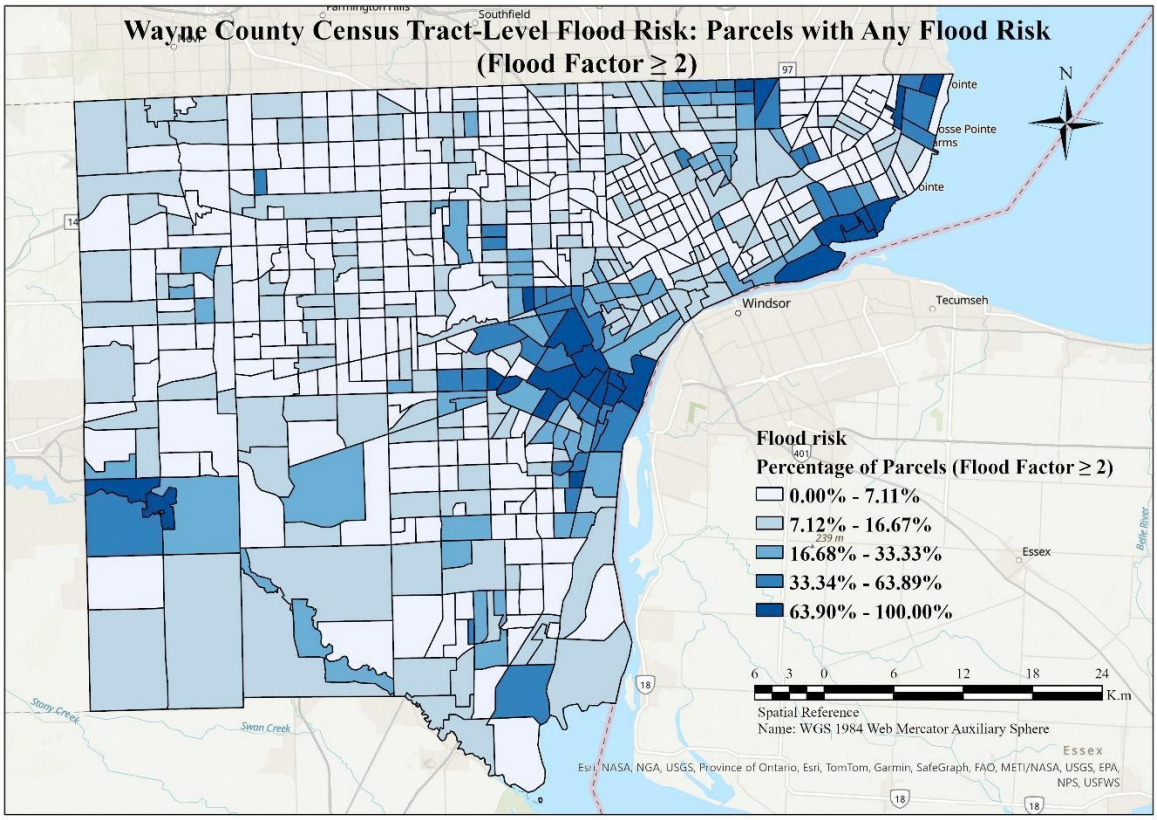


Figure 11: Parcel with any flood risk in Wayne County

Census tracts near the Detroit River, including 5245, 9856, 9838 (Annexure) etc. exhibit high flood risks in both categories. Similarly, tracts near Belleville Lake, such as 5883, 5870, 5882 (Annexure) etc. also display significant flood risks. These tracts have over 30% of their area classified as at risk of flooding, highlighting them as critical zones for flood mitigation efforts. Tracts near the Detroit River are naturally prone to flooding due to their location along a major watercourse, which is susceptible to overflow during periods of heavy rain or snowmelt. Census tracts near Belleville Lake face similar risks, as lakes and their surrounding lowlands often accumulate runoff from upstream watersheds (Figure 13).

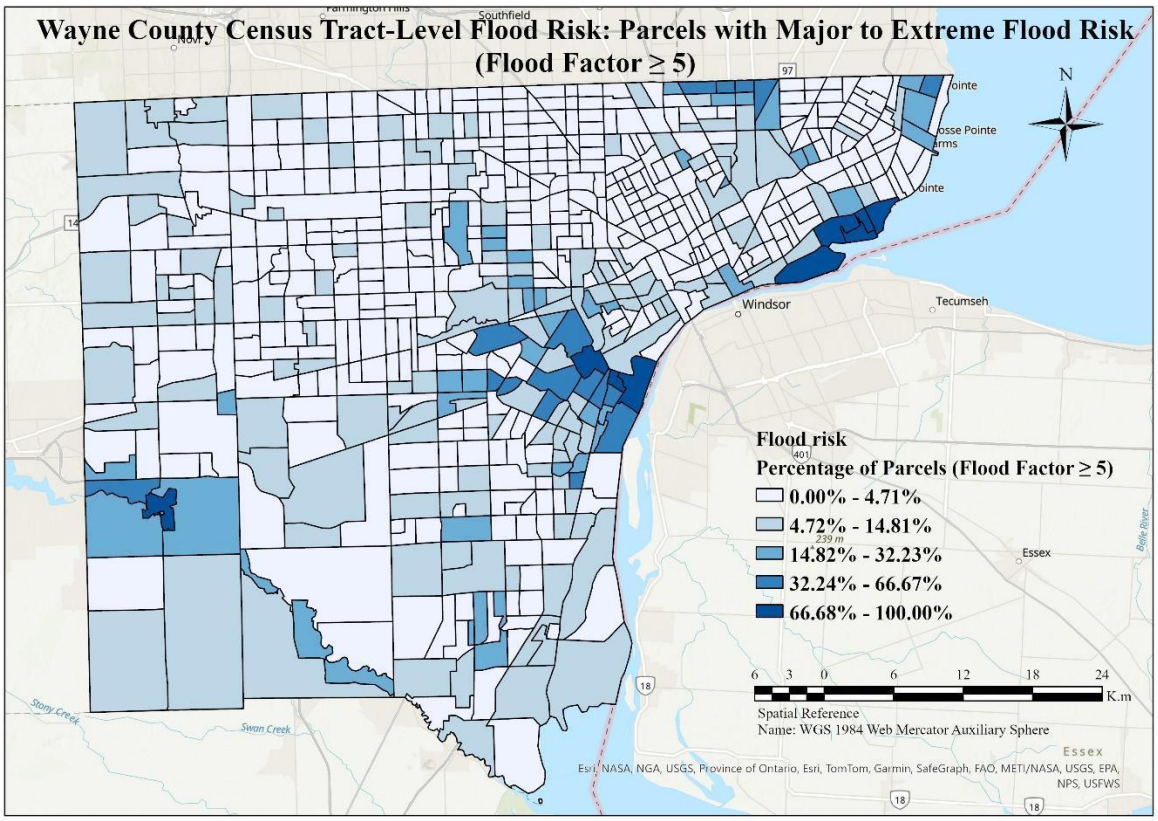


Figure 12: Parcel with Major to Extreme flood risk in Wayne County

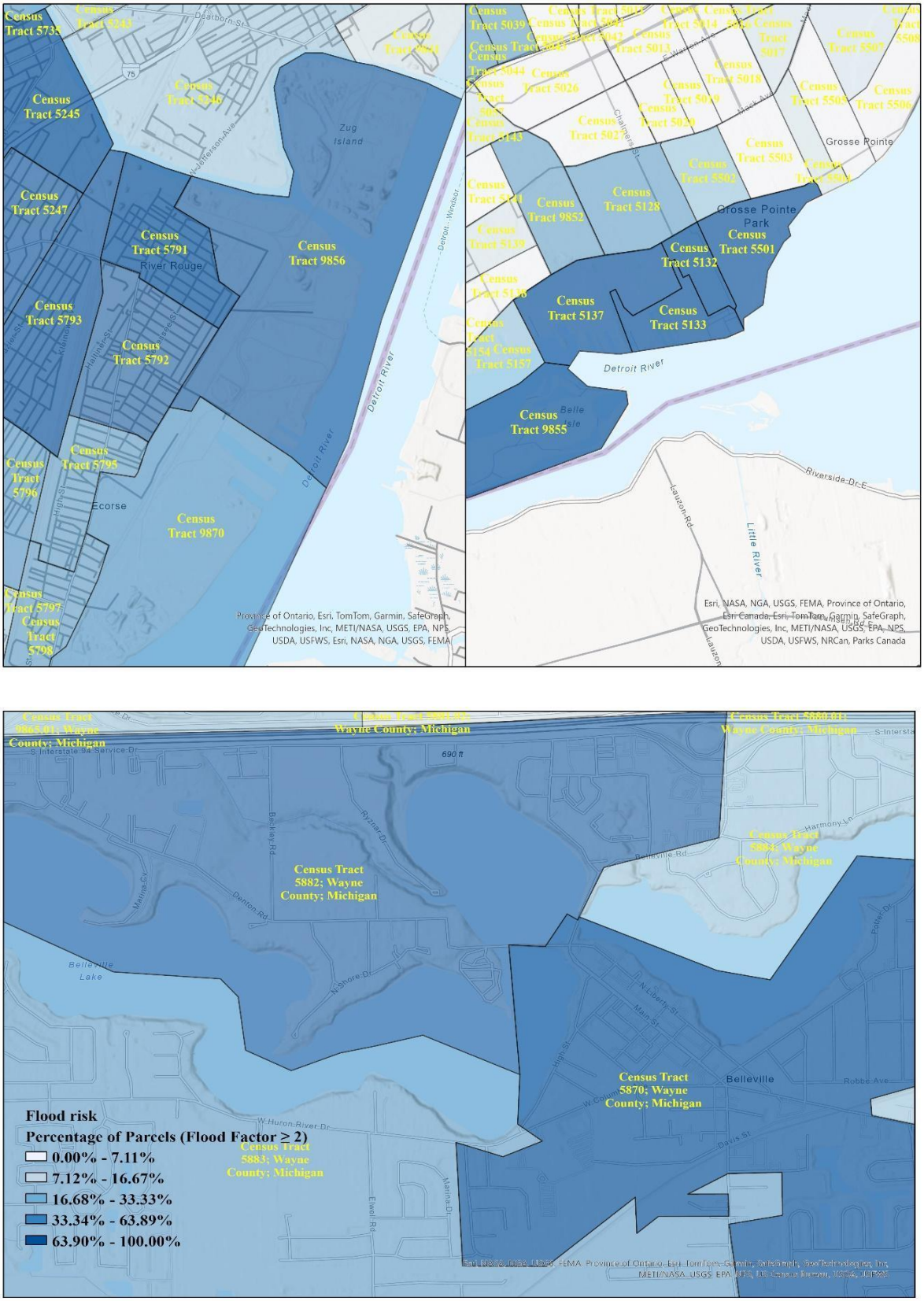


Figure 13: Flood risk near Belleville Lake and Detroit River

4.3 Comparison of Active and Buried Streams

A comparative analysis was conducted to examine changes in stream networks between 1860 and 2025. Digitized buried streams from 1860 were overlaid with active stream data to identify areas where stream paths have been altered or lost. The analysis revealed that many lower-order streams have disappeared due to urbanization, with former streambeds now occupied by parking lots, residential zones, recreational areas, or commercial developments. Additionally, significant modifications in river and stream paths were observed, including straightening, channelization, and rerouting, likely driven by urban expansion and flood control measures. These modifications have likely contributed to altered hydrological responses, including increased surface runoff, reduced groundwater recharge, and higher flood risks in urbanized areas.

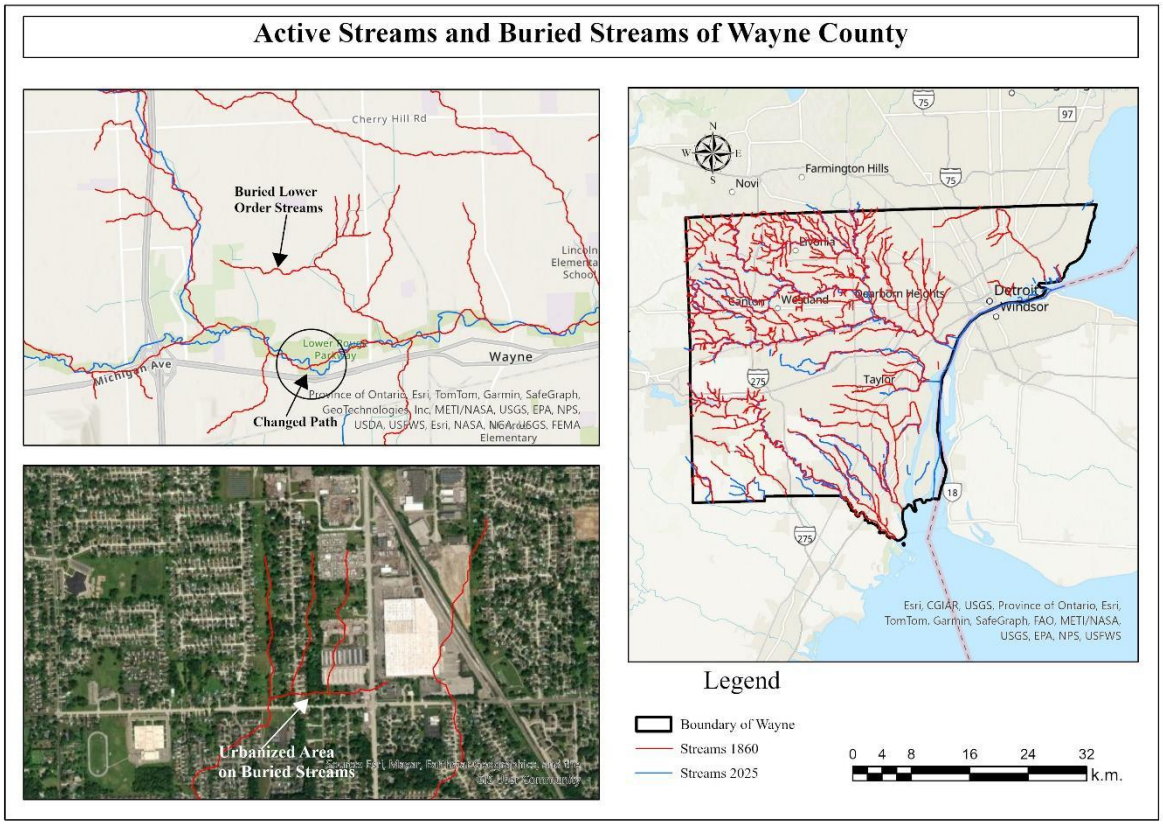


Figure 14: Comparison of Active and Streams of 1860 in Wayne County

4.4 Normalized Difference Vegetation Index (NDVI)

The NDVI data for Wayne County reveals valuable insights into the distribution of vegetation density. The total land area analyzed is 1,636.29 square kilometers, distributed among these vegetation classes. The largest portion of Wayne County, approximately 568.42 km^2 (54.7%),

falls under the sparse Vegetation category. This indicates that a significant part of the county has sparse vegetation, possibly due to agricultural land, grasslands, or degraded areas. The dense vegetation category, representing the healthiest plant cover, covers 496.94 km^2 (30.4%). This suggests that nearly one-third of the county has areas with robust vegetation, which are likely crucial for ecosystem services such as biodiversity conservation, water regulation, and carbon sequestration. Mid Vegetation areas, covering 244.37 km^2 (14.9%), are the smallest category, highlighting that regions with intermediate vegetation density are less prevalent.

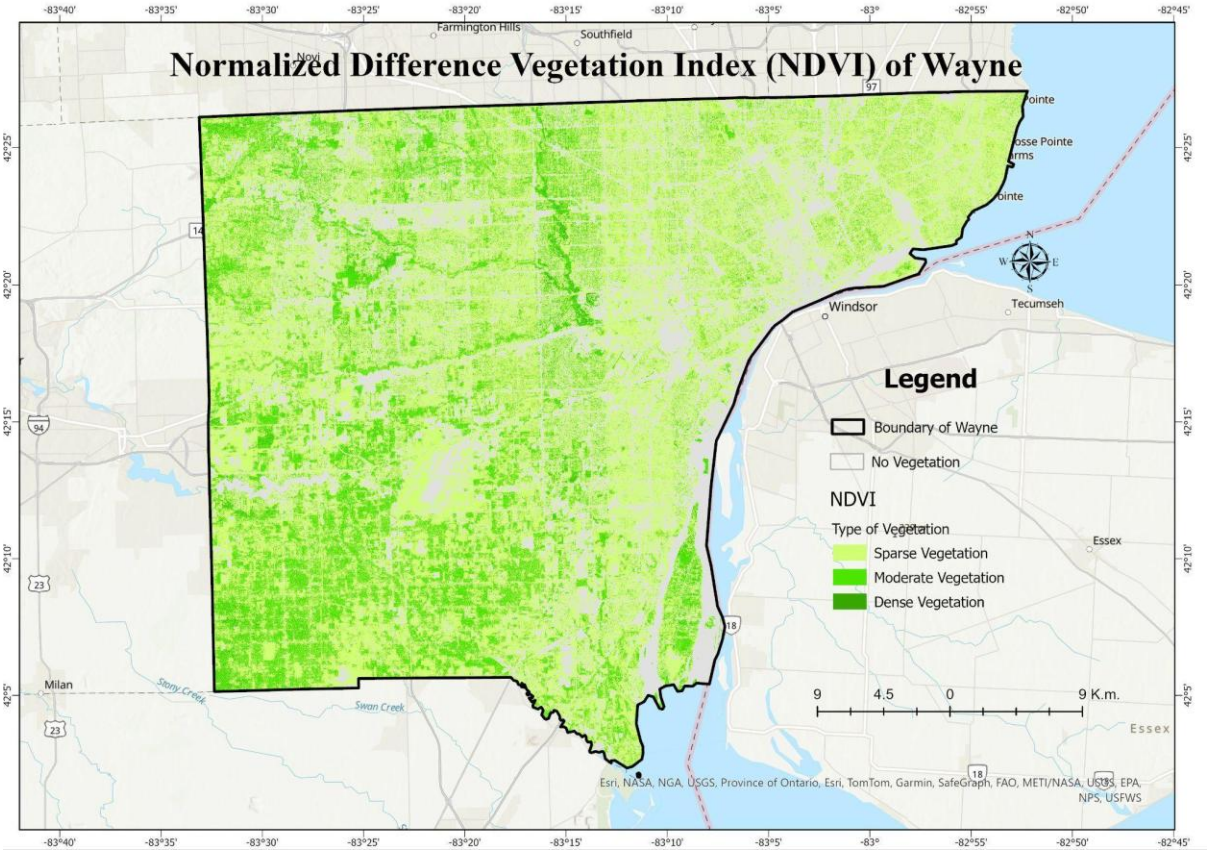


Figure 15: Normalized Difference Vegetation Index of Wayne County

The NDVI map of Wayne County highlights varying vegetation densities. Urbanized areas, particularly around Detroit and the northeast, show low to no vegetation (grey and light green), reflecting dense infrastructure. In contrast, rural and suburban areas, especially in the county's southern and western regions, display higher NDVI values (medium to dark green), indicating healthier vegetation and agricultural activity (Figure 15). Key green zones are evident near parks, farmlands, and along the outskirts, while the Detroit River area shows limited vegetation due to urban and industrial land use. These patterns emphasize the need for enhanced green spaces in urban areas to balance ecological health.

4.5 Identification of Flood Risk Properties

Flood risk properties in Wayne County were identified based on four key criteria: proximity to sparse vegetation area, location within a 100-meter buffer of active stream and buried streams, and a flood factor of 5 or higher. To assess overall risk at the census tract level, an average value of these criteria was calculated, representing the number of risk factors met by each tract. The analysis revealed that only two census tracts, 5245 and 5133 (Annexure), met three of the four risk criteria on average. Notably, no census tract fulfilled all four criteria. Among the 625 census tracts analyzed, 158 met two criteria on average, while the majority (465 tracts) fulfilled only one risk criterion. This means that most census tracts in Wayne County exhibit relatively lower flood risk based on the evaluated criteria. Since the majority (465 tracts) meet only one criterion on average, they have limited exposure to multiple risk factors. The fact that 158 census tracts meet two criteria suggests moderate susceptibility, but not extreme vulnerability. Only two census tracts (5245 and 5133) meet three risk criteria, indicating a higher potential for flooding (Figure 16).

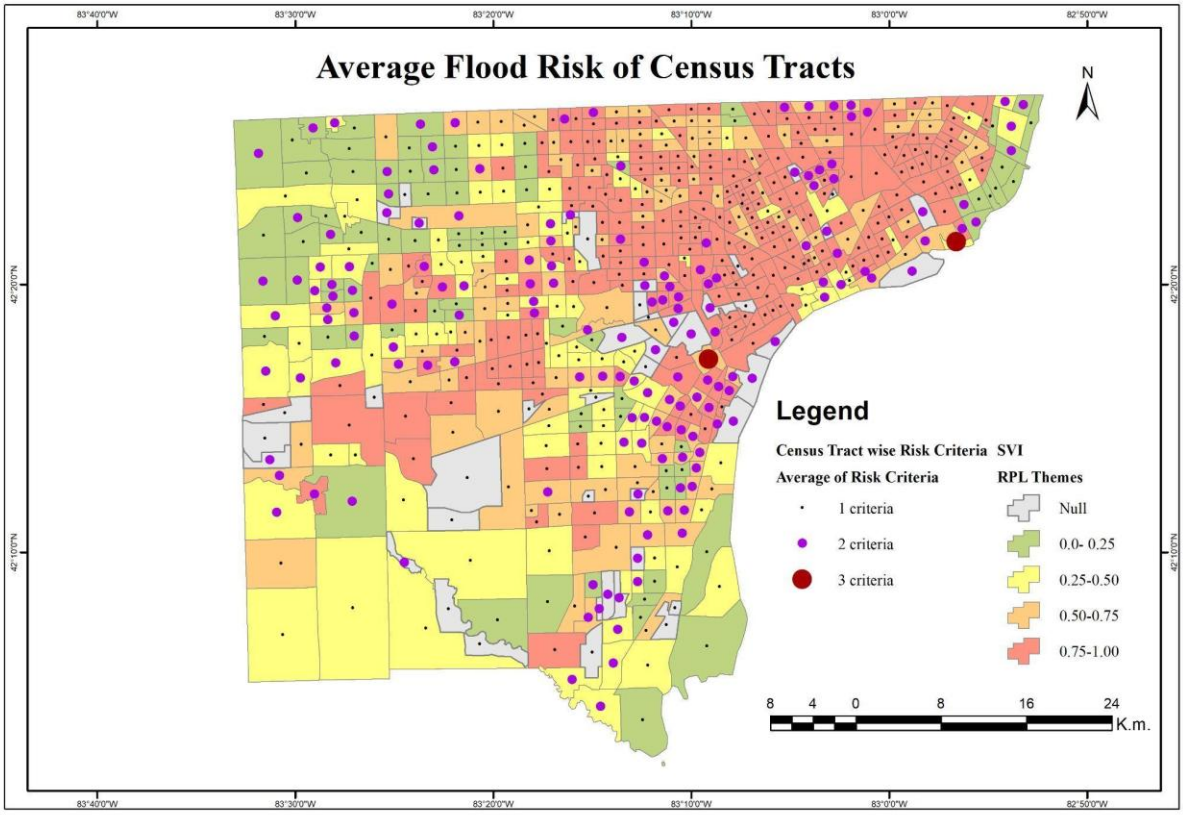


Figure 16: Average of risk criteria fulfilled by per census tract in Wayne county

Property specific analysis (Annexure) revealed that 185,776 properties were classified as very low risk, as they did not meet any of the flood risk criteria, such as proximity to streams or

sparse vegetation, nor did they have a high flood factor. 526,386 properties were categorized as low risk; these properties meet any one of the four criteria, suggesting a lesser likelihood of flooding. A total of 68,106 properties were deemed to have moderate risk, meeting two of the criteria for flood risk, but not reaching the threshold for high flood risk. 7,808 properties were identified as high risk, indicating a significant vulnerability to flooding. Finally, 926 properties were classified as very high risk, meeting all criteria for flood risk, sparse vegetation, proximity to streams, and a high flood factor highlighting them as the most vulnerable to flooding events.

The analysis of flood risk across Wayne County census tracts revealed that 100% of the properties within census tracts 5034, 5170, 5203, 5204, 5218, 5588, 9832, 9834, 9858, 981902, 982302, 983901, 986502, 5513, 5015, 5397, 5375, 5418, and 5304 were classified as having low flood risk. The properties within these census tracts exhibit sparse vegetation density, which can be an indicator of flood susceptibility; however, they do not meet other high-risk flood criteria. Specifically, they are not located within the 100-meter buffer of either current or buried streams, reducing their likelihood of flooding due to overflow or historical water pathways. Additionally, these properties have flood factor points below 5, meaning they are not classified as high-risk based on flood probability assessments. While these areas may still experience minor surface water accumulation due to limited vegetation, their overall flood risk remains low compared to other census tracts with higher flood factor values and proximity to water bodies. A total of 19 census tracts, including 9855, 5803, 5133, 5501, 5137, 5791, 9852, 5793, 5051, 5245, 5772 etc. have at least 50% of their properties classified under moderate flood risk.

A total of 29 census tracts has 15% to 53% of their properties classified as high flood risk. Notably, census tract 9856 has 53% of its properties at high risk. Several census tracts have a notable percentage of properties classified as very high flood risk. Among them, census tract 9864 has the highest proportion, with 26% of its properties at very high risk, followed by 5882 (23%), 9857 (20%), 986501 (19%), 5726 (18%), and 9838 (15%). These areas are particularly vulnerable to flooding due to their proximity to low-to-no vegetation areas, their location within a 100-meter buffer zone around current and buried streams, and a flood factor of 5 or higher for each property.

4.6 SVI and Flood Risk Area

A bivariate map is used in ArcGIS Pro to visualize the relationship between two variables SVI and Flood risk area simultaneously by using a combination of colors or symbols. It helps identify spatial patterns and correlations between two datasets across geographic regions. The classification is based on a legend that categorizes areas according to their levels of social vulnerability and flood risk:

- Dark purple signifies High-High, where both social vulnerability and flood risk are elevated.
- Pink represents High-Low, indicating high social vulnerability but low flood risk.
- Blue denotes Low-High, highlighting regions with low social vulnerability yet high flood risk.
- Ash corresponds to Low-Low, signifying areas with minimal social vulnerability and flood risk.
- Other categories include Light Blue (Low-Mid), Light Pink (Mid-Low), Purple (Mid-Mid), Dark Pink (High-Mid), and Dark Blue (Mid-High), representing varying degrees of SVI and flood risk.
-

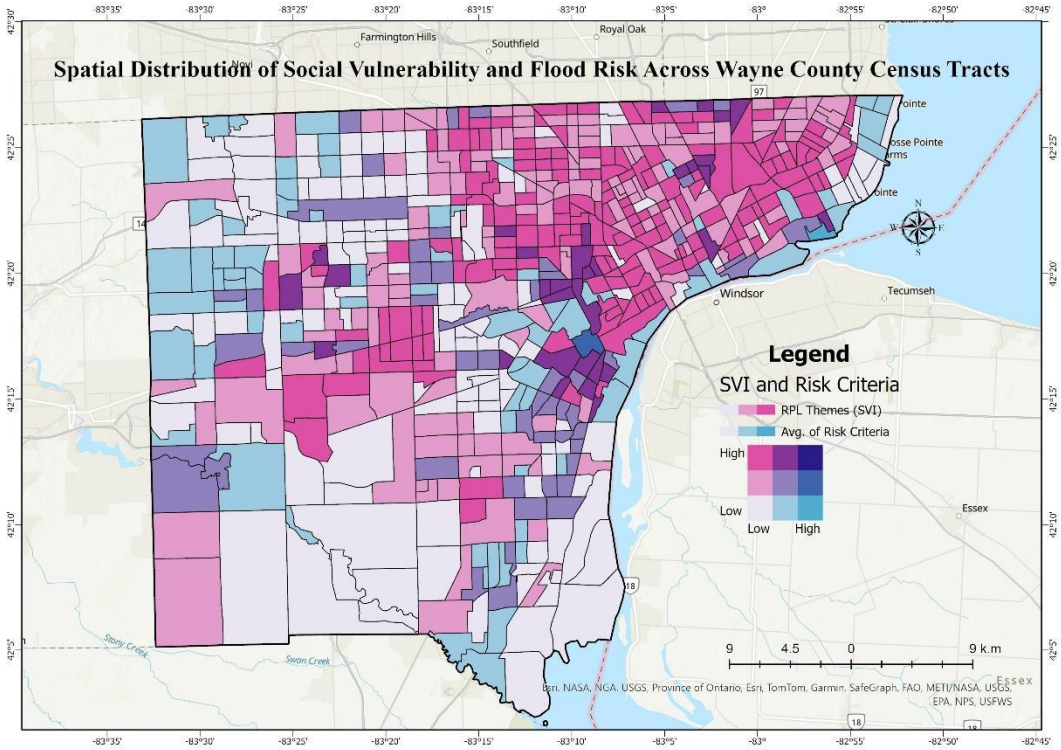


Figure 17: Comparing Bivariate Map of SVI with Flood Risk Criteria for Wayne County

The analysis of Wayne County's bivariate map suggests that no census tract simultaneously experiences both high social vulnerability and high flood risk. Instead, a predominant pattern of High-Low is observed across most census tracts, particularly in the northeastern part of the county. Additionally, census tracts along the Detroit River primarily exhibit a Mid-Mid

relationship, reflecting moderate levels of both social vulnerability and flood risk. Particularly, only one census tract (5245) shows the Mid-High category. Overall, the spatial distribution highlights that most census tracts in Wayne County fall into the High-Low category, emphasizing disparities in vulnerability and risk exposure (Figure 17).

4.7 Buried Stream and Flood Risk Area

Areas with high social vulnerability generally coincide with fewer buried streams, while areas with low social vulnerability tend to have more buried streams. However, a closer look at census tracts 5245 and 5133 both classified as having moderate flood risk reveals that properties situated along buried stream lines fall within moderate to very high risk categories. These two tracts stand out among the 625 census tracts analyzed, as no tracts were identified with high or very high risk. Apart from these, 158 census tracts fall under low flood risk, and the remaining 465 are categorized as very low flood risk (Figure 18).

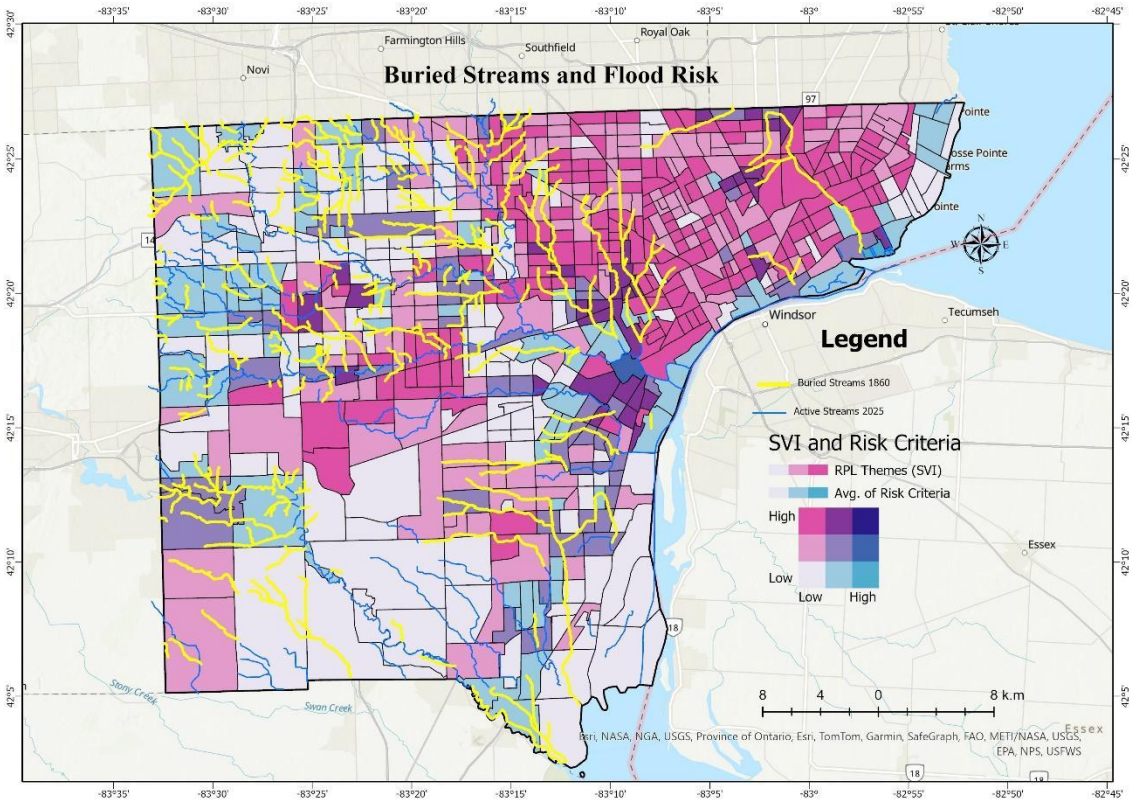


Figure 18: Impact of buried stream in Wayne County

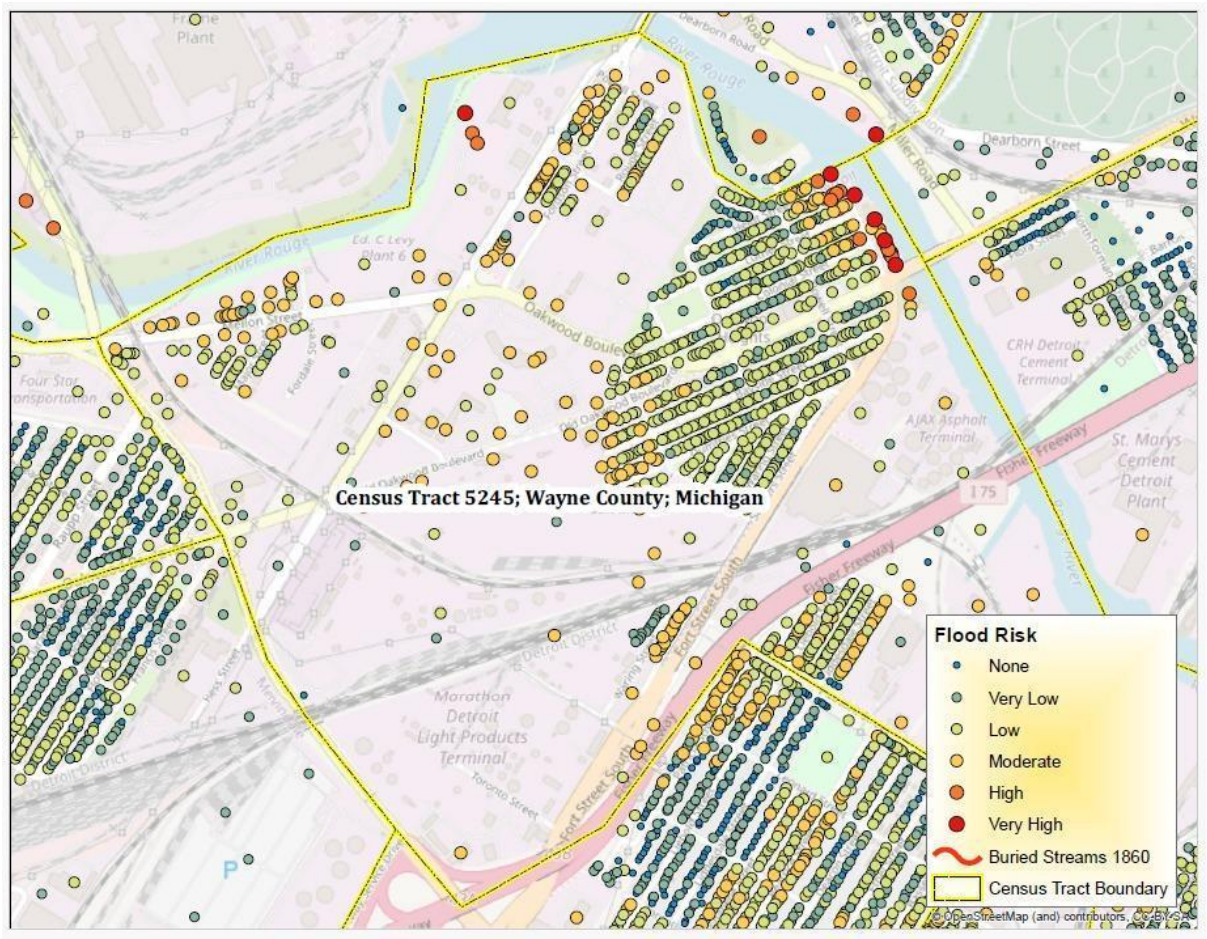


Figure 19: Influence of Active Streams on Property-Level Flood Risk in Census Tract 5245



Figure 20: Influence of Buried Streams on Property-Level Flood Risk in Census Tract 5133

In Census Tract 5245, the influence of active streams on flood risk is more evident at the local scale. Properties situated along these streamlines predominantly fall within the moderate to very high flood risk categories (Figure 19). In Census Tract 5133 of Wayne County, the influence of buried streams on flood risk is again noticeable when analyzed at a closer scale (Figure 20). A concentration of properties near the buried streamlines shows elevated flood risk levels ranging from moderate to very high. Most of the remaining areas, especially those further away from the buried streams, fall into low to very low flood risk categories, similar to what was observed in Census Tract 5245.

These findings underscore that while the overall flood risk classification of a census tract may be moderate or low, buried stream corridors present significant micro-scale flood vulnerabilities. In both Tract 5245 and Tract 5133, properties adjacent to buried streams may display higher flood risk levels, suggesting that these subsurface hydrological features might play a role in shaping flood exposure at the neighborhood level.

4.8 Correlation Between Socially Vulnerable and Flood Risk Area

In ArcGIS Pro, a scatter plot was created to examine the relationship between social vulnerability and flood risk in Wayne County. The data used for this analysis included the Social Vulnerability Index (SVI) overall percentile ranking (RPL Themes) and the percentage of parcels with Flood Factor scores ≥ 2, representing areas with any level of flood risk. On the scatter plot, the SVI percentile ranking was plotted on the x-axis, while the flood risk percentage was plotted on the y-axis.

The resulting scatter plot yielded an R^2 value of 0.0024, indicating a very weak correlation between the overall SVI percentile ranking and the percentage of parcels with low-level flood risk. This low R^2 value suggests that there is little to no linear relationship between the social vulnerability of a census tract and the proportion of parcels experiencing any flood risk (Figure 21). Consequently, it indicates that social vulnerability, as measured by the SVI, does not strongly correlate with the flood risk percentages in Wayne County's census tracts. This finding implies that factors other than social vulnerability might be more significant in determining flood risk.

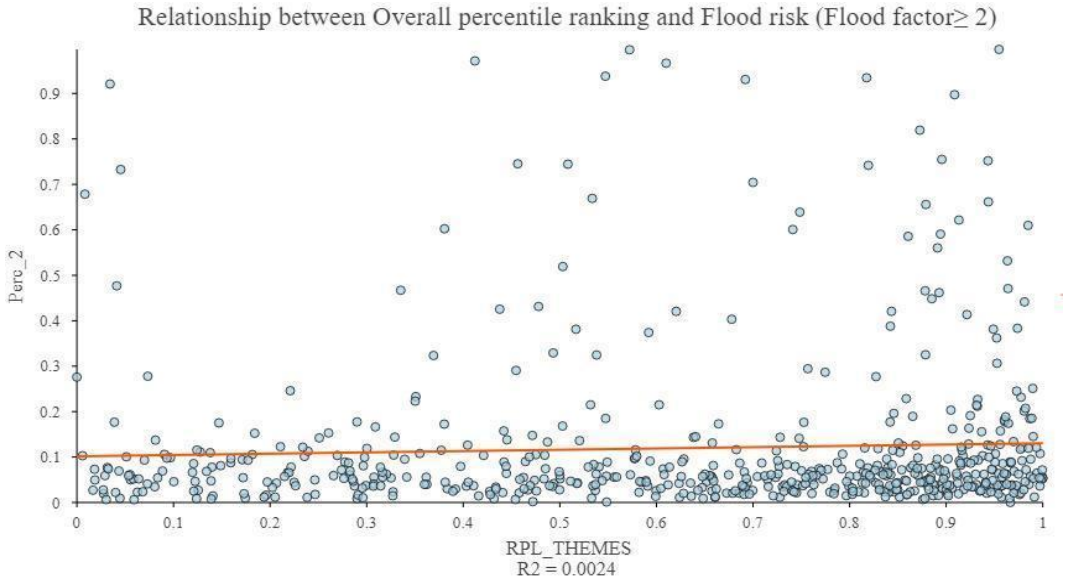


Figure 21: Relation between overall percentile ranking and flood risk (flood factor≥2)

Similarly, a scatter plot was created to analyze the relationship between social vulnerability and major flood risk in Wayne County. The analysis used the Social Vulnerability Index (SVI) overall percentile ranking (RPL_Themes) on the x-axis and the percentage of parcels with Flood Factor scores ≥ 5, indicating major to extreme flood risk, on the y-axis.

The scatter plot resulted in an R^2 value of 0.00045, which reflects an extremely weak correlation between the SVI percentile ranking and the percentage of parcels at major to extreme flood risk. This very low R^2 value suggests that there is virtually no linear relationship between social vulnerability and the proportion of parcels facing significant flood risk (Figure 22). The minimal correlation implies that social vulnerability, as measured by the SVI, does not appear to be a strong predictor of major flood risk in the census tracts of Wayne County. This finding indicates that other factors may be more influential in determining the extent of major flood risk, or that the relationship between social vulnerability and flood risk is not straightforward.

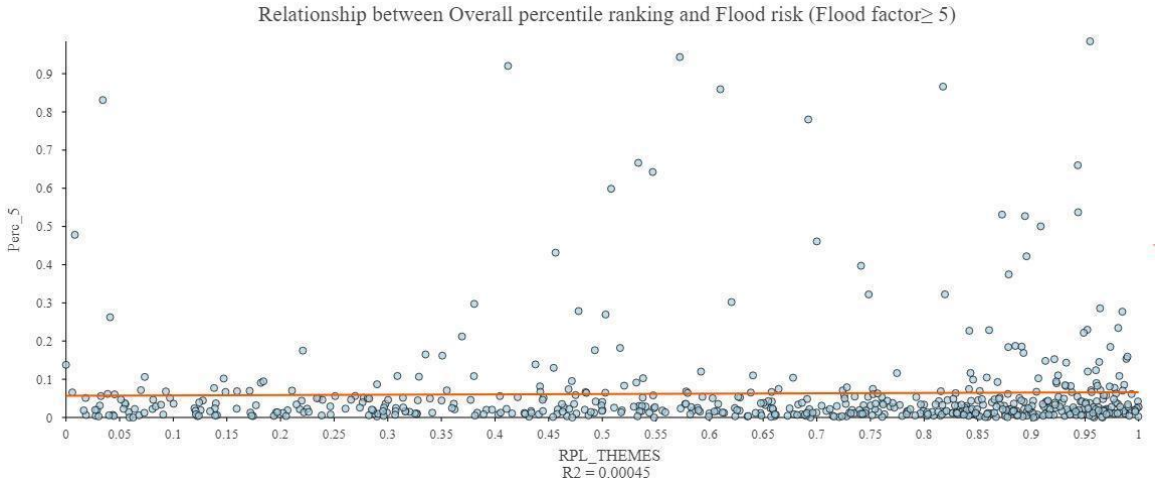


Figure 22: Relation between overall percentile ranking and flood risk (flood factor≥2)

A scatter plot was created to analyze the relationship between average risk criteria (AVG_RISK) and RPL Themes (RPL_THEMES) across census tracts. The x-axis represents the AVG_RISK, while the y-axis represents the RPL_THEMES. The scatter plot resulted in an R^2 value of 0.02, indicating an extremely weak negative correlation between average risk and RPL themes. This suggests that changes in average risk criteria have little to no linear effect on RPL themes (Figure 23). The minimal correlation implies that other factors may be more influential in determining RPL themes or that the relationship between these variables is not straightforward.

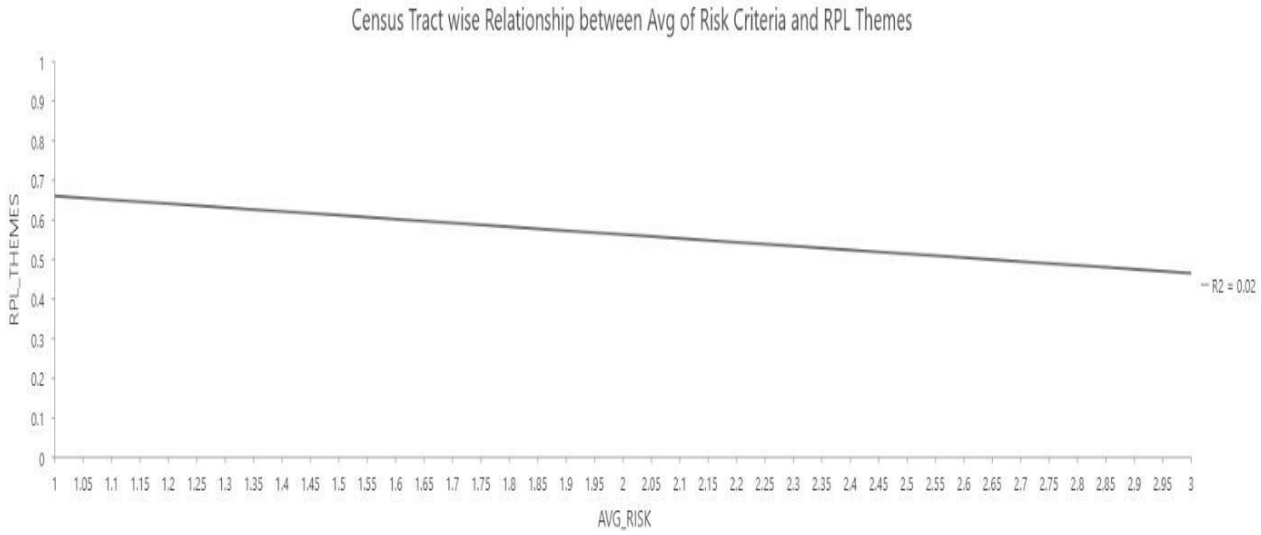


Figure 23: Relation between overall percentile ranking and flood risk (Avg. flood risk criteria)

Chapter Five: Discussion

The spatial analysis of social vulnerability in Wayne County unveils significant geographic disparities in community resilience, closely tied to socio-economic inequalities and environmental risks. Utilizing the CDC/ATSDR Social Vulnerability Index (SVI), the study highlights that census tracts in the eastern and central parts of the county, particularly around Detroit, exhibit the highest levels of vulnerability. These tracts depicted in dark red in Figure 10 are characterized by elevated poverty rates, high minority populations, limited access to transportation, and substandard housing conditions. Such socio-economic disadvantages hinder residents' capacity to prepare for, respond to, and recover from natural disasters and public health emergencies. The application of the Manual Classification Method for mapping SVI themes ensured consistency across different dimensions of vulnerability, thereby enhancing the robustness and interpretability of the spatial patterns observed.

Conversely, the western portion of Wayne County demonstrates comparatively lower social vulnerability, as shown by the green shades on the SVI map. These areas benefit from greater socio-economic stability, better infrastructure, and increased access to resources, which collectively strengthen community resilience to environmental hazards. Identifying these spatial disparities is vital for policymakers, emergency managers, and urban planners aiming to develop equitable disaster preparedness initiatives, targeted interventions, and long-term recovery frameworks that address the unique needs of high-risk populations.

Complementing the SVI analysis, flood risk mapping reveals that many communities particularly those near the Detroit River and Belleville Lake are highly exposed to hydrological hazards. Figures 11, 12 and 13 illustrate that specific census tracts, such as 5245, 9856, and 9838 near the Detroit River, as well as 5883, 5870, and 5882 near Belleville Lake, are among the most flood-prone areas, with over 30% of properties facing flood risk. These areas exhibit elevated vulnerability under both moderate (Flood Factor ≥ 2) and high flood risk categories (Flood Factor ≥ 5), underscoring the need for immediate mitigation efforts (Stets et al., 2025). Their proximity to major water bodies inherently increases susceptibility to flooding, especially during periods of intense precipitation, snowmelt, or watershed overflow.

By overlaying flood risk with SVI data, this study identifies areas where socio-economic and environmental vulnerabilities intersect, creating compounded risks. Communities experiencing both high social vulnerability and elevated flood exposure such as those located along the Detroit River are particularly at risk of experiencing disproportionate harm during flooding events. These findings advocate for an integrated disaster risk reduction (DRR) strategy that simultaneously addresses physical exposure and social fragility to build more resilient, adaptive communities.

The historical analysis of hydrological changes further contextualizes current flood vulnerability in Wayne County. By comparing digitized stream networks from 1860 with current hydrological data for 2025, the study reveals extensive modifications to the county's natural drainage systems. Numerous lower-order streams that once functioned as natural flood mitigators have been buried or transformed due to urbanization and infrastructural expansion. In many locations, these buried streams have been replaced by impervious surfaces, including roads, commercial buildings, parking lots, and residential developments, thereby diminishing natural infiltration and increasing surface runoff (Shuster et al., 2005). This urban transformation correlates strongly with increased flood risks in affected areas.

Moreover, alterations such as straightening, channelization, and rerouting of streams driven by regulatory efforts for flood control and urban development have significantly modified the region's hydrological responses. The disruption of historical flow paths and loss of permeable landscapes have likely reduced groundwater recharge and elevated localized flood hazards (Figure 14) (Ávila-Carrasco et al., 2023). The comparison of historical and modern stream networks not only highlights the extent of anthropogenic impact on natural water systems but also underscores the urgency of incorporating green infrastructure and sustainable water management strategies in urban planning efforts.

Taken together, the spatial analyses of social vulnerability, flood risk, and historical hydrological changes in Wayne County present a compelling case for holistic resilience planning. Integrating socio-economic and environmental data is essential for identifying at-risk communities, prioritizing intervention areas, and designing adaptive responses that address both human and ecological dimensions of flood vulnerability.

The Normalized Difference Vegetation Index (NDVI) analysis offers valuable insights into Wayne County's land cover composition, particularly regarding vegetation density and distribution. Of the county's total area (1,636.29 km^2), the largest proportion 568.42 km^2

(54.7%) falls within the sparse vegetation category, indicating a predominance of land with limited vegetative cover. This sparse classification likely encompasses agricultural zones, degraded landscapes, and low-density grasslands (USGS, 2023). Dense vegetation, which accounts for 496.94 km² (30.4%) of the area, represents regions with robust plant coverage that contribute to ecological stability, carbon sequestration, and microclimatic regulation. The remaining 244.37 km² (14.9%) is categorized as mid-density vegetation.

Spatially, NDVI mapping reveals pronounced differences between urban and rural zones. Urbanized regions, particularly around Detroit and its northeastern peripheries, exhibit the lowest vegetation densities, highlighted by grey and light green tones on the NDVI map. These areas likely reflect high impervious surface coverage due to dense industrial and residential development. In contrast, the southern and western parts of the county comprising more suburban and rural landscapes show higher vegetation density, denoted by medium to dark green hues. Additionally, the Detroit River corridor appears sparsely vegetated, suggesting high levels of urban and industrial land use. These spatial disparities highlight the importance of integrating green infrastructure in urban environments to mitigate environmental stressors and support urban resilience (Benedict & McMahon, 2006).

Complementing the NDVI findings, the integrated flood risk assessment provides a multi-layered understanding of spatial vulnerability across Wayne County census tracts. This analysis incorporates four key criteria: proximity to sparse vegetation, location within a 100-meter buffer of active and buried streams, and a Flood Factor rating of 5 or higher. Results reveal that 465 of the 625 census tracts meet only one criterion, indicating that while flood-related vulnerabilities are present, they are often isolated in nature. These tracts require continued monitoring but may not necessitate urgent intervention.

Moderate risk is observed in 158 census tracts that meet two criteria, suggesting more complex vulnerability profiles. Notably, only two tracts 5245 and 5133 meet three of the four criteria, signifying critical zones requiring prioritized mitigation strategies. No census tract met all four criteria, implying that extreme multi-factor flood risk is not widespread, although concentrated hotspots do exist.

The property-level analysis reinforces these findings. A substantial proportion of properties 185,776 are categorized as very low risk, while 526,386 fall into the low-risk group. Moderate risk is assigned to 68,106 properties, while 7,808 are considered high risk and 926 as very high risk, indicating exposure to three major flood-inducing factors. These figures reflect the

nuanced flood vulnerability across the county and underscore the need for differentiated risk management approaches (First Street Foundation, 2024).

Further disaggregation reveals distinct spatial trends in flood risk. Certain census tracts such as 5034, 5170, 5203, and 5204 contain 100% of properties under the low-risk category, largely due to their absence of major flood-contributing features like stream proximity or sparse vegetation. Conversely, 19 tracts including 9855, 5133, and 5245 have over 50% of properties classified at moderate risk, suggesting cumulative vulnerabilities that, while not extreme, warrant attention.

Particularly concerning the 29 tracts with high-risk properties ranging from 15% to 53%, with tract 9856 standing out for having the highest proportion of high-risk properties. Additionally, tracts such as 9864, 5882, and 9857 demonstrate elevated shares of very high-risk properties up to 26% underscoring the compounding effects of low vegetation, proximity to stream networks, and elevated flood susceptibility.

These spatial concentrations of high and very high-risk properties highlight the urgency for targeted mitigation strategies. With the increasing frequency of extreme weather events driven by climate change, such areas are especially vulnerable to precipitation surges and stormwater-related damages (IPCC, 2021). Local and regional planners must prioritize these zones for green infrastructure investment, stormwater management upgrades, and public awareness initiatives to enhance adaptive capacity and reduce long-term flood impacts.

The integration of social vulnerability into flood risk analysis through a bivariate mapping framework provides a deeper understanding of community-level risk by contextualizing environmental hazards within the broader socio-economic landscape. Using the CDC/ATSDR Social Vulnerability Index (SVI) alongside flood exposure data, the analysis presents a more comprehensive spatial risk profile across Wayne County (CDC/ATSDR, 2020). Notably, no census tracts fall into the High-High category, indicating areas of both elevated social vulnerability and severe flood risk. Instead, the most prevalent pattern is High-Low, particularly concentrated in the northeastern section of the county. This configuration suggests that while these communities may not reside in physically flood-prone areas, their heightened vulnerability could still impede emergency preparedness, response, and recovery (Flanagan et al., 2011).

Areas along the Detroit River are generally categorized as Mid-Mid, combining moderate levels of both social and environmental risk, while a single census tract 5245 falls into the Mid-

High classification. This tract represents a critical intersection between moderate social vulnerability and high flood exposure, signifying a priority zone for targeted intervention strategies. These spatial configurations highlight a mismatch between social vulnerability and physical flood exposure in Wayne County, underscoring the need for integrated risk management frameworks that address both dimensions simultaneously (Cutter et al., 2012). Identifying even limited zones where vulnerabilities overlap is vital for enhancing disaster preparedness and promoting equitable resource allocation.

A closer examination of buried stream networks in Wayne County reveals a significant micro-scale hydrological factor that traditional tract-level flood assessments may overlook. Spatial analysis shows a general inverse relationship between social vulnerability and the presence of buried streams—tracts with higher social vulnerability tend to contain fewer of these subsurface hydrological features, whereas less vulnerable tracts are more likely to intersect with buried stream corridors (UM Dearborn GIS Lab, 2025). While this may suggest lower direct hydrological risk for vulnerable populations, it also points to other forms of environmental exposure that may not be as easily observable.

More granular assessments of Census Tracts 5245 and 5133 challenge this broader trend and illustrate how buried streams can significantly intensify flood risk at the property level. Although both tracts are classified as moderate-risk areas when assessed at the census level, parcel-level data reveals that properties located directly along buried stream paths exhibit elevated flood vulnerability, ranging from moderate to very high risk. In Tract 5245, for instance, areas aligned with historic streambeds show markedly higher flood exposure compared to surrounding neighborhoods. This demonstrates how localized hydrological features often invisible in standard mapping can drive internal risk disparities within a tract.

A similar pattern emerges in Tract 5133, where clusters of moderate to very high-risk properties are concentrated around buried stream alignments. Outside these corridors, most properties fall into low or very low flood risk categories, reaffirming that buried streams continue to influence surface hydrology despite being obscured by urban development. These findings align with studies highlighting the persistent impact of historical stream alterations on urban drainage patterns and flood susceptibility (Walsh et al., 2005).

This internal variability in flood exposure within single tracts reinforces the importance of incorporating buried stream data into flood modeling and land-use planning. By identifying high-risk pockets embedded within moderate-risk zones, municipalities can enhance the

precision of their flood mitigation efforts and ensure more equitable protection for vulnerable properties. Given the complex urban drainage history of cities like Detroit, accounting for hidden hydrological features is essential to accurately assess risk and guide adaptation measures (Booth and Jackson, 1997).

To assess the spatial relationship between social vulnerability and flood exposure across Wayne County, a series of scatter plot analyses were conducted using the CDC/ATSDR Social Vulnerability Index (SVI) percentile rankings (RPL_THEMES) in conjunction with various flood risk indicators. These visualizations aimed to determine whether census tracts with elevated social vulnerability also experience higher levels of flood risk, an essential consideration for equitable climate resilience planning (Cutter et al., 2003; Flanagan et al., 2011).

The first analysis examined the relationship between the overall SVI percentile ranking and the proportion of parcels classified with any level of flood risk, defined as a Flood Factor score of ≥2. The resulting scatter plot yielded an R^2 value of 0.0024, indicating an extremely weak positive correlation between social vulnerability and general flood exposure. This suggests that socially vulnerable communities in Wayne County are not necessarily located in areas with a high prevalence of flood-prone parcels. These findings challenge common assumptions that environmental risks disproportionately burden socially disadvantaged populations and underscores the need to treat social vulnerability and environmental exposure as distinct yet occasionally overlapping dimensions (Cutter and Finch, 2008).

To further explore this dynamic, a second scatter plot assessed the relationship between SVI rankings and the percentage of parcels with major to extreme flood risk (Flood Factor ≥5). This analysis produced an R^2 value of just 0.00045, revealing an even weaker association. This near-absence of linear correlation suggests that major flood risk is not strongly linked to social vulnerability in Wayne County, and that patterns of high flood exposure may instead be influenced by land-use policies, zoning regulations, or the historical placement of flood control infrastructure, which could have shielded certain neighborhoods irrespective of socioeconomic status (Bakker, 2012; Smiley et al., 2020).

A third scatter plot was developed to explore the relationship between average flood risk scores calculated based on proximity to sparse vegetation, active or buried streams, and Flood Factor and SVI rankings. The plot revealed a similarly low R^2 value of 0.02, indicating a very weak negative correlation between social vulnerability and composite flood risk. This pattern

supports the previous findings and confirms that in Wayne County, there is no meaningful linear relationship between social and environmental vulnerability.

Together, these three analyses highlight a key insight: social vulnerability, as measured by the CDC/ATSDR SVI, is not a strong predictor of flood risk in Wayne County. This has important implications for flood risk management and environmental justice planning. It suggests that flood mitigation efforts should not rely solely on social vulnerability metrics but rather integrate them with spatially specific hydrological and land-use data. A multidimensional, data-informed approach is crucial to ensure that adaptation strategies address both human and environmental risk factors, particularly in complex urban systems where historical development patterns have contributed to uneven exposures (Morello-Frosch et al., 2011).

Chapter Six: Conclusion

6.1 Conclusion

Examining historical and active stream networks is revealing significant changes caused by urbanization. The removal of natural streambeds is increasing surface runoff and reducing groundwater recharge. This transformation is contributing to higher flood risks in urban areas like Detroit. The presence of buried streams is further complicating drainage and increasing the likelihood of flooding. Understanding these hydrological changes is becoming critical for improving flood mitigation strategies. Incorporating historical hydrology into planning supports better flood risk management.

Urban areas with low vegetation, especially in Detroit, are showing higher flood vulnerability. In contrast, suburban zones with better vegetation are displaying greater flood resilience. Vegetation is playing a crucial role in absorbing rainfall and reducing surface runoff. These findings emphasize the importance of preserving and increasing green spaces. Promoting urban greening initiatives is enhancing natural water regulation and flood protection.

Analyzing the relationship between social vulnerability and flood risk in Wayne County provides important insights into flood hazards. This study found a weak correlation between these two variables, suggesting that other factors are influencing flood risk. This pattern suggests that social vulnerability alone is not a strong predictor of flood risk. Other environmental and infrastructural factors appear to play a larger role. Expanding the analysis to include additional variables is improving the understanding of flood risk dynamics.

Recognizing the complexity of flood risk is encouraging a broader and more interdisciplinary approach. Combining environmental, social, and infrastructural data provides a more comprehensive picture. This integrated approach is helping policymakers design targeted interventions for flood-prone areas. Focusing on areas with both high social vulnerability and flood risk is promoting equitable solutions. Implementing community-based strategies is strengthening local flood resilience. Engaging stakeholders is fostering collaboration and improving long-term disaster preparedness.

Wayne County is continuing to face significant flood challenges due to urban development and aging infrastructure. Despite these challenges, regional planning and sustainability efforts are promoting resilience. Incorporating diverse data sources is informing more effective and equitable flood mitigation strategies. This study contributes valuable insights to guide future policy decisions and urban planning. Addressing both environmental and socio-economic factors is ensuring a holistic response to flood risks. Enhancing community engagement and cross-sector collaboration is building a more resilient Wayne County.

This study highlights the need for more comprehensive research to understand flood vulnerabilities fully. Addressing these gaps is becoming essential for effective disaster planning and equitable flood management. While social vulnerability is not a strong predictor of flood risk in the county, other factors, such as vegetation cover, proximity to buried and current streams, and urban infrastructure, play a more significant role in flood susceptibility. Incorporating land-use planning strategies that promote urban greening, such as increasing vegetation cover in highly urbanized areas like Detroit, can enhance natural water absorption and reduce surface runoff, improving flood resilience. Additionally, the preservation of natural hydrological features, including streams and wetlands, is essential for improving drainage capacity and reducing flood risks. Local governments and planners should focus on identifying and addressing flood-prone areas with limited green space and deteriorating infrastructure to promote more resilient urban environments. Moreover, prioritizing data-driven and community-centered approaches that engage local stakeholders in flood mitigation efforts will ensure that interventions are both equitable and effective in addressing the county's flood risk challenges.

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Annexure:

Table 1: Percentages of Properties at risk in different census tracts

Location	Very Low	Low	Moderate	High	Very High
Census Tract 9864; Wayne County; Michigan	0%	34%	23%	17%	26%
Census Tract 5882; Wayne County; Michigan	0%	31%	25%	21%	23%
Census Tract 9857; Wayne County; Michigan	0%	26%	30%	25%	20%
Census Tract 9865.01; Wayne County; Michigan	0%	35%	47%	0%	19%
Census Tract 5726; Wayne County; Michigan	0%	59%	11%	11%	18%
Census Tract 9838; Wayne County; Michigan	0%	46%	38%	0%	15%
Census Tract 9822; Wayne County; Michigan	0%	67%	10%	10%	13%
Census Tract 5780; Wayne County; Michigan	0%	39%	30%	20%	12%
Census Tract 5471; Wayne County; Michigan	0%	65%	14%	10%	11%
Census Tract 5735.01; Wayne County; Michigan	0%	66%	16%	8%	9%
Census Tract 5727; Wayne County; Michigan	0%	53%	26%	13%	8%
Census Tract 5640; Wayne County; Michigan	0%	58%	27%	7%	8%
Census Tract 5602.01; Wayne County; Michigan	0%	58%	34%	0%	8%
Census Tract 5870; Wayne County; Michigan	0%	14%	52%	27%	7%
Census Tract 5728; Wayne County; Michigan	0%	44%	36%	14%	6%
Census Tract 5601; Wayne County; Michigan	0%	54%	29%	11%	6%
Census Tract 5627; Wayne County; Michigan	0%	58%	25%	13%	5%
Census Tract 5623; Wayne County; Michigan	0%	57%	23%	15%	5%
Census Tract 5729; Wayne County; Michigan	0%	40%	41%	14%	5%
Census Tract 5770; Wayne County; Michigan	0%	80%	9%	7%	5%
Census Tract 5626; Wayne County; Michigan	0%	77%	9%	9%	5%
Census Tract 5561; Wayne County; Michigan	0%	64%	25%	6%	5%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5548; Wayne County; Michigan	0%	70%	18%	7%	4%
Census Tract 5802; Wayne County; Michigan	0%	43%	42%	11%	4%
Census Tract 5245; Wayne County; Michigan	0%	8%	56%	31%	4%
Census Tract 5467; Wayne County; Michigan	0%	47%	34%	15%	4%
Census Tract 5847; Wayne County; Michigan	0%	88%	4%	4%	4%
Census Tract 5644.01; Wayne County; Michigan	0%	52%	32%	13%	3%
Census Tract 5883; Wayne County; Michigan	0%	53%	34%	11%	3%
Census Tract 5439; Wayne County; Michigan	0%	70%	24%	3%	3%
Census Tract 9856; Wayne County; Michigan	0%	20%	25%	53%	3%
Census Tract 5645.04; Wayne County; Michigan	0%	62%	28%	7%	3%
Census Tract 5572; Wayne County; Michigan	0%	59%	28%	11%	3%
Census Tract 5624; Wayne County; Michigan	0%	65%	24%	9%	3%
Census Tract 5571; Wayne County; Michigan	0%	68%	22%	7%	3%
Census Tract 5636; Wayne County; Michigan	0%	58%	38%	2%	3%
Census Tract 5664; Wayne County; Michigan	0%	57%	29%	12%	2%
Census Tract 5915.01; Wayne County; Michigan	0%	86%	4%	7%	2%
Census Tract 5779; Wayne County; Michigan	0%	55%	35%	8%	2%
Census Tract 5666; Wayne County; Michigan	0%	76%	18%	4%	2%
Census Tract 5133; Wayne County; Michigan	0%	6%	68%	24%	2%
Census Tract 5455; Wayne County; Michigan	0%	57%	33%	8%	2%
Census Tract 5629; Wayne County; Michigan	0%	77%	9%	12%	2%
Census Tract 5639; Wayne County; Michigan	0%	66%	12%	20%	2%
Census Tract 5604; Wayne County; Michigan	0%	86%	10%	2%	2%
Census Tract 5543; Wayne County; Michigan	0%	62%	25%	11%	2%
Census Tract 5665; Wayne County; Michigan	0%	68%	25%	5%	2%
Census Tract 5619; Wayne County; Michigan	0%	73%	20%	6%	2%
Census Tract 5645.01; Wayne County; Michigan	0%	89%	7%	3%	2%
Census Tract 5670; Wayne County; Michigan	0%	91%	5%	2%	2%
Census Tract 5725; Wayne County; Michigan	0%	57%	32%	9%	2%
Census Tract 5648; Wayne County; Michigan	0%	70%	25%	3%	2%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5635; Wayne County; Michigan	0%	65%	27%	6%	2%
Census Tract 5616; Wayne County; Michigan	0%	77%	17%	5%	2%
Census Tract 5884; Wayne County; Michigan	0%	58%	32%	8%	2%
Census Tract 5625; Wayne County; Michigan	0%	90%	7%	2%	1%
Census Tract 5167; Wayne County; Michigan	0%	95%	4%	0%	1%
Census Tract 5906; Wayne County; Michigan	0%	75%	22%	2%	1%
Census Tract 5653.02; Wayne County; Michigan	0%	69%	30%	0%	1%
Census Tract 5855; Wayne County; Michigan	0%	70%	24%	5%	1%
Census Tract 5799; Wayne County; Michigan	0%	81%	14%	4%	1%
Census Tract 5650.01; Wayne County; Michigan	0%	82%	12%	5%	1%
Census Tract 5456; Wayne County; Michigan	0%	64%	19%	16%	1%
Census Tract 5569; Wayne County; Michigan	0%	67%	25%	6%	1%
Census Tract 5950; Wayne County; Michigan	0%	70%	20%	9%	1%
Census Tract 5894.02; Wayne County; Michigan	0%	79%	16%	3%	1%
Census Tract 5645.03; Wayne County; Michigan	0%	61%	30%	8%	1%
Census Tract 5573; Wayne County; Michigan	0%	71%	22%	6%	1%
Census Tract 5991; Wayne County; Michigan	0%	65%	31%	3%	1%
Census Tract 5057; Wayne County; Michigan	0%	82%	12%	4%	1%
Census Tract 5641; Wayne County; Michigan	0%	61%	24%	15%	1%
Census Tract 5564; Wayne County; Michigan	0%	48%	43%	9%	1%
Census Tract 5132; Wayne County; Michigan	0%	19%	51%	29%	1%
Census Tract 5545; Wayne County; Michigan	0%	60%	29%	10%	1%
Census Tract 5246; Wayne County; Michigan	0%	77%	21%	1%	1%
Census Tract 5565; Wayne County; Michigan	0%	77%	19%	4%	1%
Census Tract 5570; Wayne County; Michigan	0%	69%	24%	6%	1%
Census Tract 5613.02; Wayne County; Michigan	0%	84%	14%	1%	1%
Census Tract 5574; Wayne County; Michigan	0%	57%	34%	8%	1%
Census Tract 5460; Wayne County; Michigan	0%	64%	32%	4%	1%
Census Tract 5417; Wayne County; Michigan	0%	55%	32%	12%	1%
Census Tract 5776; Wayne County; Michigan	0%	55%	34%	10%	1%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5414; Wayne County; Michigan	0%	59%	34%	6%	1%
Census Tract 5637; Wayne County; Michigan	0%	79%	18%	2%	1%
Census Tract 5724; Wayne County; Michigan	0%	81%	17%	1%	1%
Census Tract 5443; Wayne County; Michigan	0%	58%	31%	11%	1%
Census Tract 5701; Wayne County; Michigan	0%	89%	9%	1%	1%
Census Tract 5603; Wayne County; Michigan	0%	78%	17%	4%	1%
Census Tract 5546; Wayne County; Michigan	0%	87%	9%	3%	1%
Census Tract 5916; Wayne County; Michigan	0%	70%	28%	2%	1%
Census Tract 5772; Wayne County; Michigan	0%	36%	55%	8%	1%
Census Tract 5990.01; Wayne County; Michigan	0%	75%	22%	3%	1%
Census Tract 5797; Wayne County; Michigan	0%	63%	26%	11%	1%
Census Tract 5056; Wayne County; Michigan	0%	64%	29%	6%	1%
Census Tract 5672.02; Wayne County; Michigan	0%	80%	17%	3%	1%
Census Tract 5863; Wayne County; Michigan	0%	88%	11%	0%	1%
Census Tract 5633; Wayne County; Michigan	0%	49%	43%	7%	0%
Census Tract 5915.02; Wayne County; Michigan	0%	86%	12%	1%	0%
Census Tract 5642; Wayne County; Michigan	0%	50%	46%	4%	0%
Census Tract 5704; Wayne County; Michigan	0%	70%	28%	2%	0%
Census Tract 5717; Wayne County; Michigan	0%	65%	34%	0%	0%
Census Tract 5547; Wayne County; Michigan	0%	66%	30%	3%	0%
Census Tract 5720; Wayne County; Michigan	0%	61%	31%	7%	0%
Census Tract 5904.01; Wayne County; Michigan	0%	82%	13%	4%	0%
Census Tract 5644.02; Wayne County; Michigan	0%	62%	27%	10%	0%
Census Tract 5584; Wayne County; Michigan	0%	98%	1%	0%	0%
Census Tract 5719; Wayne County; Michigan	0%	74%	25%	1%	0%
Census Tract 5651; Wayne County; Michigan	0%	63%	31%	5%	0%
Census Tract 5760.01; Wayne County; Michigan	0%	36%	48%	16%	0%
Census Tract 5718; Wayne County; Michigan	0%	97%	1%	1%	0%
Census Tract 5804; Wayne County; Michigan	0%	86%	13%	1%	0%
Census Tract 5748; Wayne County; Michigan	0%	87%	11%	1%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5980; Wayne County; Michigan	0%	72%	22%	5%	0%
Census Tract 5575; Wayne County; Michigan	0%	67%	32%	1%	0%
Census Tract 5771; Wayne County; Michigan	0%	61%	34%	4%	0%
Census Tract 5585; Wayne County; Michigan	0%	71%	28%	0%	0%
Census Tract 5673; Wayne County; Michigan	0%	89%	10%	1%	0%
Census Tract 5761; Wayne County; Michigan	0%	74%	23%	3%	0%
Census Tract 5970; Wayne County; Michigan	0%	73%	25%	2%	0%
Census Tract 5791; Wayne County; Michigan	0%	17%	63%	20%	0%
Census Tract 5796; Wayne County; Michigan	0%	58%	33%	8%	0%
Census Tract 5501; Wayne County; Michigan	0%	12%	66%	21%	0%
Census Tract 5786; Wayne County; Michigan	0%	41%	55%	4%	0%
Census Tract 5137; Wayne County; Michigan	0%	23%	64%	13%	0%
Census Tract 5128; Wayne County; Michigan	0%	69%	30%	1%	0%
Census Tract 5058; Wayne County; Michigan	0%	85%	12%	2%	0%
Census Tract 5792; Wayne County; Michigan	0%	30%	35%	35%	0%
Census Tract 9839.03; Wayne County; Michigan	0%	52%	15%	33%	0%
Census Tract 5061; Wayne County; Michigan	0%	23%	46%	32%	0%
Census Tract 9861; Wayne County; Michigan	0%	36%	36%	27%	0%
Census Tract 5068; Wayne County; Michigan	0%	35%	40%	26%	0%
Census Tract 9862; Wayne County; Michigan	0%	58%	17%	25%	0%
Census Tract 9870; Wayne County; Michigan	0%	35%	40%	25%	0%
Census Tract 5051; Wayne County; Michigan	0%	22%	57%	20%	0%
Census Tract 9819.01; Wayne County; Michigan	0%	38%	43%	20%	0%
Census Tract 5736; Wayne County; Michigan	0%	52%	31%	17%	0%
Census Tract 5247; Wayne County; Michigan	0%	36%	47%	17%	0%
Census Tract 5734; Wayne County; Michigan	0%	49%	36%	16%	0%
Census Tract 5638; Wayne County; Michigan	0%	58%	27%	15%	0%
Census Tract 5930.01; Wayne County; Michigan	0%	54%	31%	14%	0%
Census Tract 5517; Wayne County; Michigan	0%	36%	52%	12%	0%
Census Tract 5568; Wayne County; Michigan	0%	73%	17%	10%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5740; Wayne County; Michigan	0%	59%	32%	9%	0%
Census Tract 9837; Wayne County; Michigan	0%	64%	27%	9%	0%
Census Tract 5435; Wayne County; Michigan	0%	58%	33%	9%	0%
Census Tract 5576; Wayne County; Michigan	0%	58%	33%	9%	0%
Census Tract 5737.01; Wayne County; Michigan	0%	83%	9%	8%	0%
Census Tract 9820; Wayne County; Michigan	0%	70%	22%	8%	0%
Census Tract 5795.01; Wayne County; Michigan	0%	70%	22%	8%	0%
Census Tract 5741; Wayne County; Michigan	0%	67%	25%	8%	0%
Census Tract 5165; Wayne County; Michigan	0%	76%	17%	7%	0%
Census Tract 5351; Wayne County; Michigan	0%	61%	31%	7%	0%
Census Tract 5457; Wayne County; Michigan	0%	72%	21%	7%	0%
Census Tract 5448; Wayne County; Michigan	0%	65%	28%	7%	0%
Census Tract 5612; Wayne County; Michigan	0%	56%	37%	7%	0%
Census Tract 5410; Wayne County; Michigan	0%	58%	36%	6%	0%
Census Tract 5168; Wayne County; Michigan	0%	76%	18%	6%	0%
Census Tract 5080; Wayne County; Michigan	0%	61%	33%	6%	0%
Census Tract 5716; Wayne County; Michigan	0%	71%	23%	6%	0%
Census Tract 5743.01; Wayne County; Michigan	0%	51%	43%	6%	0%
Census Tract 5262; Wayne County; Michigan	0%	46%	49%	6%	0%
Census Tract 5067; Wayne County; Michigan	0%	43%	51%	6%	0%
Census Tract 9850; Wayne County; Michigan	0%	71%	23%	6%	0%
Census Tract 5248; Wayne County; Michigan	0%	55%	40%	6%	0%
Census Tract 5919; Wayne County; Michigan	0%	82%	12%	5%	0%
Census Tract 5694; Wayne County; Michigan	0%	51%	44%	5%	0%
Census Tract 5260; Wayne County; Michigan	0%	62%	33%	5%	0%
Census Tract 5441; Wayne County; Michigan	0%	79%	16%	5%	0%
Census Tract 5562; Wayne County; Michigan	0%	71%	24%	5%	0%
Census Tract 5846; Wayne County; Michigan	0%	68%	27%	5%	0%
Census Tract 5433; Wayne County; Michigan	0%	63%	32%	5%	0%
Census Tract 5932; Wayne County; Michigan	0%	71%	24%	5%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5933.01; Wayne County; Michigan	0%	89%	7%	5%	0%
Census Tract 5412; Wayne County; Michigan	0%	77%	18%	5%	0%
Census Tract 5842; Wayne County; Michigan	0%	71%	25%	4%	0%
Census Tract 5702; Wayne County; Michigan	0%	79%	17%	4%	0%
Census Tract 9836; Wayne County; Michigan	0%	54%	42%	4%	0%
Census Tract 5579.01; Wayne County; Michigan	0%	62%	34%	4%	0%
Census Tract 5586; Wayne County; Michigan	0%	88%	8%	4%	0%
Census Tract 5674; Wayne County; Michigan	0%	85%	11%	4%	0%
Census Tract 5793; Wayne County; Michigan	0%	38%	58%	4%	0%
Census Tract 5437; Wayne County; Michigan	0%	73%	23%	4%	0%
Census Tract 5905; Wayne County; Michigan	0%	79%	17%	4%	0%
Census Tract 5844; Wayne County; Michigan	0%	56%	40%	4%	0%
Census Tract 5190; Wayne County; Michigan	0%	76%	20%	4%	0%
Census Tract 5809; Wayne County; Michigan	0%	69%	27%	4%	0%
Census Tract 5411; Wayne County; Michigan	0%	55%	41%	4%	0%
Census Tract 9821.02; Wayne County; Michigan	0%	74%	22%	4%	0%
Census Tract 5845.01; Wayne County; Michigan	0%	67%	29%	4%	0%
Census Tract 5634; Wayne County; Michigan	0%	65%	31%	4%	0%
Census Tract 5265; Wayne County; Michigan	0%	67%	30%	3%	0%
Census Tract 5279; Wayne County; Michigan	0%	79%	18%	3%	0%
Census Tract 5777; Wayne County; Michigan	0%	86%	11%	3%	0%
Census Tract 5721; Wayne County; Michigan	0%	63%	34%	3%	0%
Census Tract 5917; Wayne County; Michigan	0%	75%	22%	3%	0%
Census Tract 5764; Wayne County; Michigan	0%	72%	25%	3%	0%
Census Tract 5553; Wayne County; Michigan	0%	57%	40%	3%	0%
Census Tract 5563; Wayne County; Michigan	0%	64%	33%	3%	0%
Census Tract 5567; Wayne County; Michigan	0%	52%	45%	3%	0%
Census Tract 5749; Wayne County; Michigan	0%	77%	20%	3%	0%
Census Tract 5075; Wayne County; Michigan	0%	55%	42%	3%	0%
Census Tract 5952.01; Wayne County; Michigan	0%	82%	15%	3%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5963; Wayne County; Michigan	0%	88%	9%	3%	0%
Census Tract 5613.01; Wayne County; Michigan	0%	78%	20%	3%	0%
Census Tract 5044; Wayne County; Michigan	0%	64%	33%	3%	0%
Census Tract 5308; Wayne County; Michigan	0%	82%	15%	3%	0%
Census Tract 5652; Wayne County; Michigan	0%	91%	6%	3%	0%
Census Tract 5542; Wayne County; Michigan	0%	81%	17%	3%	0%
Census Tract 5775; Wayne County; Michigan	0%	68%	29%	3%	0%
Census Tract 5669; Wayne County; Michigan	0%	78%	20%	3%	0%
Census Tract 5409; Wayne County; Michigan	0%	50%	47%	2%	0%
Census Tract 5350; Wayne County; Michigan	0%	68%	29%	2%	0%
Census Tract 5643; Wayne County; Michigan	0%	54%	44%	2%	0%
Census Tract 5657; Wayne County; Michigan	0%	57%	40%	2%	0%
Census Tract 5544; Wayne County; Michigan	0%	73%	25%	2%	0%
Census Tract 5413; Wayne County; Michigan	0%	58%	39%	2%	0%
Census Tract 5765; Wayne County; Michigan	0%	65%	33%	2%	0%
Census Tract 5774; Wayne County; Michigan	0%	69%	29%	2%	0%
Census Tract 5803; Wayne County; Michigan	0%	28%	70%	2%	0%
Census Tract 5524; Wayne County; Michigan	0%	86%	12%	2%	0%
Census Tract 5839; Wayne County; Michigan	0%	90%	8%	2%	0%
Census Tract 5459; Wayne County; Michigan	0%	75%	23%	2%	0%
Census Tract 5862.01; Wayne County; Michigan	0%	86%	12%	2%	0%
Census Tract 5472; Wayne County; Michigan	0%	84%	15%	2%	0%
Census Tract 5407; Wayne County; Michigan	0%	94%	4%	2%	0%
Census Tract 5241.01; Wayne County; Michigan	0%	88%	10%	2%	0%
Census Tract 5617; Wayne County; Michigan	0%	86%	12%	2%	0%
Census Tract 5432; Wayne County; Michigan	0%	58%	40%	2%	0%
Census Tract 5920; Wayne County; Michigan	0%	76%	22%	2%	0%
Census Tract 5805; Wayne County; Michigan	0%	66%	33%	2%	0%
Census Tract 5602.02; Wayne County; Michigan	0%	80%	18%	2%	0%
Census Tract 5338; Wayne County; Michigan	0%	59%	39%	2%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5440; Wayne County; Michigan	0%	89%	9%	2%	0%
Census Tract 5257; Wayne County; Michigan	0%	72%	27%	2%	0%
Census Tract 5742.03; Wayne County; Michigan	0%	85%	13%	2%	0%
Census Tract 5918; Wayne County; Michigan	0%	94%	4%	1%	0%
Census Tract 5520; Wayne County; Michigan	0%	94%	4%	1%	0%
Census Tract 5551; Wayne County; Michigan	0%	55%	44%	1%	0%
Census Tract 5838; Wayne County; Michigan	0%	75%	24%	1%	0%
Census Tract 5762; Wayne County; Michigan	0%	90%	9%	1%	0%
Census Tract 5164; Wayne County; Michigan	0%	77%	22%	1%	0%
Census Tract 5311; Wayne County; Michigan	0%	89%	9%	1%	0%
Census Tract 5372; Wayne County; Michigan	0%	67%	31%	1%	0%
Census Tract 5848.02; Wayne County; Michigan	0%	92%	7%	1%	0%
Census Tract 5541; Wayne County; Michigan	0%	80%	19%	1%	0%
Census Tract 5211; Wayne County; Michigan	0%	93%	6%	1%	0%
Census Tract 5747; Wayne County; Michigan	0%	79%	20%	1%	0%
Census Tract 5458; Wayne County; Michigan	0%	78%	21%	1%	0%
Census Tract 5798; Wayne County; Michigan	0%	62%	37%	1%	0%
Census Tract 5942; Wayne County; Michigan	0%	65%	34%	1%	0%
Census Tract 5583.01; Wayne County; Michigan	0%	69%	30%	1%	0%
Census Tract 5857; Wayne County; Michigan	0%	95%	4%	1%	0%
Census Tract 5231; Wayne County; Michigan	0%	80%	19%	1%	0%
Census Tract 5672.01; Wayne County; Michigan	0%	90%	9%	1%	0%
Census Tract 5364; Wayne County; Michigan	0%	83%	16%	1%	0%
Census Tract 5722; Wayne County; Michigan	0%	72%	27%	1%	0%
Census Tract 5421; Wayne County; Michigan	0%	74%	25%	1%	0%
Census Tract 5373; Wayne County; Michigan	0%	67%	32%	1%	0%
Census Tract 5695; Wayne County; Michigan	0%	78%	22%	1%	0%
Census Tract 5893; Wayne County; Michigan	0%	83%	16%	1%	0%
Census Tract 5766; Wayne County; Michigan	0%	74%	25%	1%	0%
Census Tract 5808; Wayne County; Michigan	0%	79%	20%	1%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5423; Wayne County; Michigan	0%	88%	11%	1%	0%
Census Tract 5347; Wayne County; Michigan	0%	60%	40%	1%	0%
Census Tract 5425; Wayne County; Michigan	0%	89%	10%	1%	0%
Census Tract 5951; Wayne County; Michigan	0%	82%	17%	1%	0%
Census Tract 5961; Wayne County; Michigan	0%	79%	20%	1%	0%
Census Tract 5582; Wayne County; Michigan	0%	60%	39%	1%	0%
Census Tract 5528.01; Wayne County; Michigan	0%	98%	1%	1%	0%
Census Tract 5647; Wayne County; Michigan	0%	81%	18%	1%	0%
Census Tract 5581; Wayne County; Michigan	0%	69%	30%	1%	0%
Census Tract 5430; Wayne County; Michigan	0%	57%	42%	1%	0%
Census Tract 5812; Wayne County; Michigan	0%	71%	28%	1%	0%
Census Tract 5027; Wayne County; Michigan	0%	96%	3%	1%	0%
Census Tract 5843; Wayne County; Michigan	0%	84%	15%	1%	0%
Census Tract 5113; Wayne County; Michigan	0%	65%	34%	1%	0%
Census Tract 5356; Wayne County; Michigan	0%	79%	21%	1%	0%
Census Tract 5879; Wayne County; Michigan	0%	95%	5%	1%	0%
Census Tract 5685; Wayne County; Michigan	0%	83%	16%	1%	0%
Census Tract 5696; Wayne County; Michigan	0%	67%	33%	1%	0%
Census Tract 5737.02; Wayne County; Michigan	0%	96%	3%	1%	0%
Census Tract 5678; Wayne County; Michigan	0%	77%	23%	1%	0%
Census Tract 5692; Wayne County; Michigan	0%	80%	20%	1%	0%
Census Tract 5940; Wayne County; Michigan	0%	91%	9%	1%	0%
Census Tract 5856; Wayne County; Michigan	0%	91%	8%	1%	0%
Census Tract 5587; Wayne County; Michigan	0%	76%	24%	1%	0%
Census Tract 5367; Wayne County; Michigan	0%	91%	8%	1%	0%
Census Tract 5043; Wayne County; Michigan	0%	71%	28%	1%	0%
Census Tract 5731; Wayne County; Michigan	0%	78%	22%	1%	0%
Census Tract 5062; Wayne County; Michigan	0%	61%	38%	0%	0%
Census Tract 5577; Wayne County; Michigan	0%	69%	30%	0%	0%
Census Tract 5555; Wayne County; Michigan	0%	70%	29%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5831.01; Wayne County; Michigan	0%	93%	6%	0%	0%
Census Tract 5785; Wayne County; Michigan	0%	89%	10%	0%	0%
Census Tract 5773; Wayne County; Michigan	0%	66%	34%	0%	0%
Census Tract 5659; Wayne County; Michigan	0%	87%	12%	0%	0%
Census Tract 5806; Wayne County; Michigan	0%	65%	35%	0%	0%
Census Tract 5090; Wayne County; Michigan	0%	91%	8%	0%	0%
Census Tract 5715; Wayne County; Michigan	0%	76%	24%	0%	0%
Census Tract 5074; Wayne County; Michigan	0%	72%	28%	0%	0%
Census Tract 5342; Wayne County; Michigan	0%	73%	27%	0%	0%
Census Tract 5693; Wayne County; Michigan	0%	85%	14%	0%	0%
Census Tract 5941; Wayne County; Michigan	0%	77%	23%	0%	0%
Census Tract 5682; Wayne County; Michigan	0%	72%	27%	0%	0%
Census Tract 5066; Wayne County; Michigan	0%	69%	31%	0%	0%
Census Tract 5738; Wayne County; Michigan	0%	92%	8%	0%	0%
Census Tract 5646; Wayne County; Michigan	0%	91%	9%	0%	0%
Census Tract 5353; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5591; Wayne County; Michigan	0%	79%	21%	0%	0%
Census Tract 5371; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5336; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5462.01; Wayne County; Michigan	0%	94%	5%	0%	0%
Census Tract 5645.02; Wayne County; Michigan	0%	85%	15%	0%	0%
Census Tract 5801; Wayne County; Michigan	0%	88%	12%	0%	0%
Census Tract 5344; Wayne County; Michigan	0%	71%	29%	0%	0%
Census Tract 5944.01; Wayne County; Michigan	0%	77%	23%	0%	0%
Census Tract 5318; Wayne County; Michigan	0%	94%	5%	0%	0%
Census Tract 5858; Wayne County; Michigan	0%	86%	14%	0%	0%
Census Tract 5859; Wayne County; Michigan	0%	93%	6%	0%	0%
Census Tract 5507; Wayne County; Michigan	0%	90%	10%	0%	0%
Census Tract 5840; Wayne County; Michigan	0%	89%	11%	0%	0%
Census Tract 5228; Wayne County; Michigan	0%	90%	10%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5554.01; Wayne County; Michigan	0%	75%	24%	0%	0%
Census Tract 5730; Wayne County; Michigan	0%	82%	18%	0%	0%
Census Tract 5945; Wayne County; Michigan	0%	86%	14%	0%	0%
Census Tract 5378; Wayne County; Michigan	0%	58%	42%	0%	0%
Census Tract 5683; Wayne County; Michigan	0%	71%	29%	0%	0%
Census Tract 5687; Wayne County; Michigan	0%	88%	12%	0%	0%
Census Tract 5384; Wayne County; Michigan	0%	81%	19%	0%	0%
Census Tract 5733; Wayne County; Michigan	0%	72%	28%	0%	0%
Census Tract 5830.01; Wayne County; Michigan	0%	67%	32%	0%	0%
Census Tract 5754.01; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5566; Wayne County; Michigan	0%	63%	36%	0%	0%
Census Tract 5052; Wayne County; Michigan	0%	78%	22%	0%	0%
Census Tract 5667; Wayne County; Michigan	0%	89%	10%	0%	0%
Census Tract 5962; Wayne County; Michigan	0%	88%	11%	0%	0%
Census Tract 5363; Wayne County; Michigan	0%	86%	14%	0%	0%
Census Tract 5081; Wayne County; Michigan	0%	78%	22%	0%	0%
Census Tract 5739; Wayne County; Michigan	0%	88%	12%	0%	0%
Census Tract 5063; Wayne County; Michigan	0%	64%	35%	0%	0%
Census Tract 5697; Wayne County; Michigan	0%	95%	4%	0%	0%
Census Tract 5752; Wayne County; Michigan	0%	74%	25%	0%	0%
Census Tract 5069; Wayne County; Michigan	0%	77%	23%	0%	0%
Census Tract 5750; Wayne County; Michigan	0%	73%	27%	0%	0%
Census Tract 5816; Wayne County; Michigan	0%	92%	8%	0%	0%
Census Tract 5348; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5518; Wayne County; Michigan	0%	55%	44%	0%	0%
Census Tract 5511; Wayne County; Michigan	0%	72%	28%	0%	0%
Census Tract 9855; Wayne County; Michigan	0%	0%	100%	0%	0%
Census Tract 9852; Wayne County; Michigan	0%	38%	62%	0%	0%
Census Tract 9841; Wayne County; Michigan	0%	47%	53%	0%	0%
Census Tract 5881.01; Wayne County; Michigan	0%	48%	52%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 9818; Wayne County; Michigan	0%	50%	50%	0%	0%
Census Tract 9821.01; Wayne County; Michigan	0%	53%	47%	0%	0%
Census Tract 5261; Wayne County; Michigan	0%	54%	46%	0%	0%
Census Tract 5429; Wayne County; Michigan	0%	57%	43%	0%	0%
Census Tract 5508; Wayne County; Michigan	0%	59%	41%	0%	0%
Census Tract 9831; Wayne County; Michigan	0%	60%	40%	0%	0%
Census Tract 9829; Wayne County; Michigan	0%	60%	40%	0%	0%
Census Tract 9817; Wayne County; Michigan	0%	61%	39%	0%	0%
Census Tract 5106; Wayne County; Michigan	0%	62%	38%	0%	0%
Census Tract 5767; Wayne County; Michigan	0%	66%	34%	0%	0%
Census Tract 9866; Wayne County; Michigan	0%	69%	31%	0%	0%
Census Tract 5258; Wayne County; Michigan	0%	71%	29%	0%	0%
Census Tract 5408; Wayne County; Michigan	0%	71%	29%	0%	0%
Census Tract 5172; Wayne County; Michigan	0%	72%	28%	0%	0%
Census Tract 9833.01; Wayne County; Michigan	0%	73%	27%	0%	0%
Census Tract 5263; Wayne County; Michigan	0%	75%	25%	0%	0%
Census Tract 5684; Wayne County; Michigan	0%	76%	24%	0%	0%
Census Tract 9854; Wayne County; Michigan	0%	76%	24%	0%	0%
Census Tract 5431; Wayne County; Michigan	0%	76%	24%	0%	0%
Census Tract 5452; Wayne County; Michigan	0%	76%	24%	0%	0%
Census Tract 5451; Wayne County; Michigan	0%	77%	23%	0%	0%
Census Tract 5751; Wayne County; Michigan	0%	77%	23%	0%	0%
Census Tract 5259; Wayne County; Michigan	0%	77%	23%	0%	0%
Census Tract 5671; Wayne County; Michigan	0%	77%	23%	0%	0%
Census Tract 9859; Wayne County; Michigan	0%	77%	23%	0%	0%
Census Tract 5943; Wayne County; Michigan	0%	78%	22%	0%	0%
Census Tract 5502; Wayne County; Michigan	0%	78%	22%	0%	0%
Census Tract 5679; Wayne County; Michigan	0%	79%	21%	0%	0%
Census Tract 5415; Wayne County; Michigan	0%	80%	20%	0%	0%
Census Tract 9851; Wayne County; Michigan	0%	81%	19%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5166; Wayne County; Michigan	0%	81%	19%	0%	0%
Census Tract 5590; Wayne County; Michigan	0%	82%	18%	0%	0%
Census Tract 5820; Wayne County; Michigan	0%	82%	18%	0%	0%
Census Tract 5592; Wayne County; Michigan	0%	83%	17%	0%	0%
Census Tract 5680; Wayne County; Michigan	0%	83%	17%	0%	0%
Census Tract 5841; Wayne County; Michigan	0%	83%	17%	0%	0%
Census Tract 5705; Wayne County; Michigan	0%	83%	17%	0%	0%
Census Tract 5405; Wayne County; Michigan	0%	83%	17%	0%	0%
Census Tract 9824; Wayne County; Michigan	0%	83%	17%	0%	0%
Census Tract 9827; Wayne County; Michigan	0%	84%	16%	0%	0%
Census Tract 5530; Wayne County; Michigan	0%	84%	16%	0%	0%
Census Tract 5848.01; Wayne County; Michigan	0%	84%	16%	0%	0%
Census Tract 9863; Wayne County; Michigan	0%	84%	16%	0%	0%
Census Tract 9823.01; Wayne County; Michigan	0%	85%	15%	0%	0%
Census Tract 5208; Wayne County; Michigan	0%	85%	15%	0%	0%
Census Tract 5649; Wayne County; Michigan	0%	85%	15%	0%	0%
Census Tract 5699; Wayne County; Michigan	0%	85%	15%	0%	0%
Census Tract 5366; Wayne County; Michigan	0%	85%	15%	0%	0%
Census Tract 5072; Wayne County; Michigan	0%	86%	14%	0%	0%
Census Tract 5422; Wayne County; Michigan	0%	86%	14%	0%	0%
Census Tract 5157; Wayne County; Michigan	0%	86%	14%	0%	0%
Census Tract 5243; Wayne County; Michigan	0%	86%	14%	0%	0%
Census Tract 5434; Wayne County; Michigan	0%	86%	14%	0%	0%
Census Tract 5521; Wayne County; Michigan	0%	86%	14%	0%	0%
Census Tract 5214; Wayne County; Michigan	0%	87%	13%	0%	0%
Census Tract 5343; Wayne County; Michigan	0%	87%	13%	0%	0%
Census Tract 5894.01; Wayne County; Michigan	0%	87%	13%	0%	0%
Census Tract 5832; Wayne County; Michigan	0%	87%	13%	0%	0%
Census Tract 5691; Wayne County; Michigan	0%	87%	13%	0%	0%
Census Tract 5653.01; Wayne County; Michigan	0%	87%	13%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5404; Wayne County; Michigan	0%	88%	12%	0%	0%
Census Tract 5207; Wayne County; Michigan	0%	88%	12%	0%	0%
Census Tract 5302; Wayne County; Michigan	0%	88%	12%	0%	0%
Census Tract 5143; Wayne County; Michigan	0%	88%	12%	0%	0%
Census Tract 5383; Wayne County; Michigan	0%	88%	12%	0%	0%
Census Tract 5064; Wayne County; Michigan	0%	88%	12%	0%	0%
Census Tract 5589; Wayne County; Michigan	0%	88%	12%	0%	0%
Census Tract 5512; Wayne County; Michigan	0%	88%	12%	0%	0%
Census Tract 5406; Wayne County; Michigan	0%	89%	11%	0%	0%
Census Tract 9839.02; Wayne County; Michigan	0%	89%	11%	0%	0%
Census Tract 9833.02; Wayne County; Michigan	0%	89%	11%	0%	0%
Census Tract 5233; Wayne County; Michigan	0%	89%	11%	0%	0%
Census Tract 5881.02; Wayne County; Michigan	0%	89%	11%	0%	0%
Census Tract 5763; Wayne County; Michigan	0%	89%	11%	0%	0%
Census Tract 5556; Wayne County; Michigan	0%	89%	11%	0%	0%
Census Tract 5220; Wayne County; Michigan	0%	89%	11%	0%	0%
Census Tract 5837; Wayne County; Michigan	0%	89%	11%	0%	0%
Census Tract 9826; Wayne County; Michigan	0%	89%	11%	0%	0%
Census Tract 5658; Wayne County; Michigan	0%	90%	10%	0%	0%
Census Tract 5365; Wayne County; Michigan	0%	90%	10%	0%	0%
Census Tract 5442; Wayne County; Michigan	0%	90%	10%	0%	0%
Census Tract 5234; Wayne County; Michigan	0%	90%	10%	0%	0%
Census Tract 5010; Wayne County; Michigan	0%	90%	10%	0%	0%
Census Tract 5362; Wayne County; Michigan	0%	90%	10%	0%	0%
Census Tract 5811.01; Wayne County; Michigan	0%	90%	10%	0%	0%
Census Tract 9825; Wayne County; Michigan	0%	90%	10%	0%	0%
Census Tract 5358; Wayne County; Michigan	0%	91%	9%	0%	0%
Census Tract 9853; Wayne County; Michigan	0%	91%	9%	0%	0%
Census Tract 5215; Wayne County; Michigan	0%	91%	9%	0%	0%
Census Tract 5264; Wayne County; Michigan	0%	91%	9%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5689; Wayne County; Michigan	0%	91%	9%	0%	0%
Census Tract 5746; Wayne County; Michigan	0%	91%	9%	0%	0%
Census Tract 5382; Wayne County; Michigan	0%	91%	9%	0%	0%
Census Tract 5193; Wayne County; Michigan	0%	91%	9%	0%	0%
Census Tract 5189; Wayne County; Michigan	0%	92%	8%	0%	0%
Census Tract 5240.01; Wayne County; Michigan	0%	92%	8%	0%	0%
Census Tract 5005; Wayne County; Michigan	0%	92%	8%	0%	0%
Census Tract 5303; Wayne County; Michigan	0%	92%	8%	0%	0%
Census Tract 5160; Wayne County; Michigan	0%	92%	8%	0%	0%
Census Tract 5463.01; Wayne County; Michigan	0%	92%	8%	0%	0%
Census Tract 5309; Wayne County; Michigan	0%	92%	8%	0%	0%
Census Tract 5381; Wayne County; Michigan	0%	92%	8%	0%	0%
Census Tract 5152; Wayne County; Michigan	0%	93%	7%	0%	0%
Census Tract 9842; Wayne County; Michigan	0%	93%	7%	0%	0%
Census Tract 5426; Wayne County; Michigan	0%	93%	7%	0%	0%
Census Tract 5238; Wayne County; Michigan	0%	93%	7%	0%	0%
Census Tract 5880.01; Wayne County; Michigan	0%	93%	7%	0%	0%
Census Tract 5334; Wayne County; Michigan	0%	93%	7%	0%	0%
Census Tract 5466; Wayne County; Michigan	0%	93%	7%	0%	0%
Census Tract 5710; Wayne County; Michigan	0%	93%	7%	0%	0%
Census Tract 5139; Wayne County; Michigan	0%	93%	7%	0%	0%
Census Tract 5833; Wayne County; Michigan	0%	93%	7%	0%	0%
Census Tract 5706; Wayne County; Michigan	0%	93%	7%	0%	0%
Census Tract 5522; Wayne County; Michigan	0%	94%	7%	0%	0%
Census Tract 5357; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5242; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5391; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5070; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5202; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5232; Wayne County; Michigan	0%	94%	6%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5531; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5091; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5225; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5331; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5836; Wayne County; Michigan	0%	94%	6%	0%	0%
Census Tract 5154; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5807; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5006; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5142; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5369; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5504; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5305; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5598; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5341; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5424; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5536.01; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5141; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5324; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5880.02; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5333; Wayne County; Michigan	0%	95%	5%	0%	0%
Census Tract 5191; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5073; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5114; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5301; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5173; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5254; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5138; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5003; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5395; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5171; Wayne County; Michigan	0%	96%	4%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5315.02; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5153; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5688; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5017; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5632; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5180; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5339; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5026; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5549; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5708; Wayne County; Michigan	0%	96%	4%	0%	0%
Census Tract 5009; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5040; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5112; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5401; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5119; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5628; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5370; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5071; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5041; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5223; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5330; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5656; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5332; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5470; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5392; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5834; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5385; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5313; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5709; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5668; Wayne County; Michigan	0%	97%	3%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5169; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5054; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5065; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5368; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5326; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5192; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5004; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5402; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5317; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5007; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5523; Wayne County; Michigan	0%	97%	3%	0%	0%
Census Tract 5019; Wayne County; Michigan	0%	98%	3%	0%	0%
Census Tract 5778; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5033; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5016; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5387; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5403; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5316; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5386; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5361; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5580; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5515; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5014; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5018; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5532; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5020; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5013; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5219; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5396; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5377; Wayne County; Michigan	0%	98%	2%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5821; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5314; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5039; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5031; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5319; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5538; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5461; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5835; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5753; Wayne County; Michigan	0%	98%	2%	0%	0%
Census Tract 5042; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5503; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5389; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5315.01; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5376; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5011; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5352; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5145; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5516; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5036; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5327; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5001; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5505; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5394; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5514; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5321; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5756; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5698; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5002; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5035; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5390; Wayne County; Michigan	0%	99%	1%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5032; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5506; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5175; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5819; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5815; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5388; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5755; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5008; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5224; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5509; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5012; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5312; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5393; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5818; Wayne County; Michigan	0%	99%	1%	0%	0%
Census Tract 5304; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 5418; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 5375; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 5397; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 5015; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 5513; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 9865.02; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 9839.01; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 9823.02; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 9819.02; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 9858; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 9834; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 9832; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 5588; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 5218; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 5204; Wayne County; Michigan	0%	100%	0%	0%	0%

Location	Very Low	Low	Moderate	High	Very High
Census Tract 5203; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 5170; Wayne County; Michigan	0%	100%	0%	0%	0%
Census Tract 5034; Wayne County; Michigan	0%	100%	0%	0%	0%