An Equity-centered Approach to Prioritizing Flood Mitigation and Transportation Planning in Southeast Michigan

by

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Abstract

Transportation disruptions from flooding often reflect and exacerbate pre-existing socioeconomic disparities in an area. This study seeks to create an equity-centered model to assist with the prioritization of transportation and flood mitigation projects. Accessibility to life-sustaining core services was used as a proxy for community vulnerability. Through spatial analyses, two distinct methodologies were developed to formulate a novel vulnerability index. Vulnerability in both methods was defined as a function of sensitivity and adaptive capacity. While both methods used a combination of socioeconomic, transportation, and flood data, the way in which risk was defined differed among the methods. Method 1 utilized roads identified as highly susceptible to damage from flooding within its definition of sensitivity. Using a network analysis, Method 2 expanded the number of roads classified as 'high risk' by incorporating drivetimes to core services and how they may be impacted by a flood. A comparison of the methods demonstrates that differing definitions of risk and sensitivity to flooding can have significant impacts on vulnerability indices, where Method 2 yielded more areas of high vulnerability compared to Method 1. While this study focuses on a section of southeast Michigan, the methods used can be applied to other communities facing socioeconomic disparities in flood-prone areas.

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1. Introduction

Global climate change projections show that floods are increasing in frequency and severity, especially in urban areas where impervious surfaces can lead to increased runoff (Abenayake et al., 2022; Atta-ur-Rahman et al., 2016; Huong & Pathirana, 2013; Rubinato et al., 2019). Automobile transit is a sector that is particularly impacted by the effects of flooding (Abenayake et al., 2022). Flooded roads, for example, can greatly limit a community's access to life-sustaining resources such as food, income, education, and healthcare. Further, damage and recovery in communities can vary dramatically depending a variety of factors including income, housing conditions, and access to resources (Atta-ur-Rahman et al., 2016; Chakraborty et al., 2020). Inequitable impacts from flooding, such as damages, repair costs, and accessibility to resources, often stem from existing socioeconomic disparities (Burton & Cutter, 2008; Collins et al., 2013; Pallathadka et al., 2022). Similar to the projected increase in the number and severity of floods, the number and connectivity of transportation networks is also on the rise (Feng & Gauthier, 2021; Hamidi & Ewing, 2014). Urban sprawl can be a double-edge sword as increasing the connectivity of cities can allow for more accessible resources, but the increase in impermeable surfaces can contribute to more flooding (Dayaratne & Perera, 2008; Greiner et al., 2020; Rubinato et al., 2019). As more and more people become dependent on road networks, it is crucial to plan for how these networks will be impacted by flooding.

Modeling the susceptibility of infrastructure to floods is a commonly employed tool in transportation planning. A spatial assessment of areas facing the greatest risk of flooding overlayed with road infrastructure data can assist planners in prioritizing transportation projects (Dong et al., 2020; Duy et al., 2019; Johnson et al., 2007; Kalantari et al., 2019; Lin et al., 2019). One such tool is the Flood Risk Dashboard developed by the Southeast Michigan Council of Governance (SEMCOG), which will be discussed in depth in later sections. This tool combines topological, historical flooding, and infrastructure data over the seven-county SEMCOG area to assign a risk score to transportation assets such as roads and bridges (*SEMCOG Flooding Risk Tool Dashboard*, 2023). Tools such as the Flood Risk Dashboard provide decision support for planners looking to assess the urgency of completing certain projects based on their risk score. However, models like the Flood Risk Tool can be improved by addressing the possible inequities of flooding. Identifying where those potential inequities occur and which communities are impacted by them is the objective of this research.

An equity-centered approach to flood mitigation and transportation planning requires defining 'vulnerability' in a way that incorporates both infrastructure and socioeconomic variables into the analysis. Several definitions exist within the field of flood management and these existing definitions range their specificity. The International Panel of Climate Change (IPCC) defines vulnerability as the extent to which a community is incapable of managing sea-level rise and climate change effects (Nasiri et al., 2016). Alternatively, the United Nations (UN) defines vulnerability as the degree of damage to certain objects, where zero indicates no damage and one indicates full damage (Nasiri et al., 2016). Aspects from both the IPCC and the UN definitions can be valuable in this study as the IPCC incorporates community impacts and the UN introduces a way to quantify vulnerability. Models that overlap equity and transportation or equity and flooding are not uncommon; there are few models that integrate all three factors (Abenayake et al., 2022; Albano et al., 2015; Chakraborty et al., 2020, 2022; Evers et al., 2016). Previous studies on levee failures in California, for example, found that there is a disproportionate impact on minority communities and communities of lower income in flood prone areas (Burton & Cutter, 2008). In addition, there are several studies that demonstrate that green infrastructure (GI) is a viable method for reducing impervious surface area and therefore, flood risk, but GI is often built only in affluent cities (Greiner et al., 2020; Pallathadka et al., 2022). These cases highlight the linkages between infrastructure and climate injustice, but can be expanded to investigate the connection to transportation networks. Community-centric variables, such as demographic information, can have a tremendous impact on the applicability of previously mentioned models and studies. These factors should not only be incorporated into risk assessments, but they should be held at the same level of importance as hydrologic and infrastructure data (Borowski et al., 2021; Collins et al., 2018; Gutschow et al., 2021; Johnson et al., 2007). While previous studies provide groundwork for equity-centered modeling, there is a need for methodologies that place equity at the center of transportation and flood planning.

This project seeks to fill a gap in knowledge by assessing the potential for using equity-centered spatial analysis methodologies to assist with the prioritization of flood mitigation and transportation projects. Using two separate geospatial analyses, a novel vulnerability index was created that is specific to relevant socioeconomic, flooding, and transportation data for a subsection of Southeast Michigan in Wayne County. This index uses a community's access to life-sustaining services as a factor in the definition of vulnerability. Previous studies have shown that transportation interruptions to such services can have a detrimental effect on community members (Collins et al., 2018; Feng & Gauthier, 2021; Lin et al., 2019). Accessibility can be used as a proxy for vulnerability as the indirect effects of flooding can have damages as serious as those caused by the floods themselves (Borowski et al., 2021; Collins et al., 2018; Gutschow et al., 2021). The aftermath of Hurricane Katrina exemplified how socially marginalized communities often lack sufficient mitigation capacities for flooding. For example, accessibility issues from flooding resulted in the inability to return to work, difficulty evacuating dangerous areas, and delays in reaching health and childcare services (Collins et al., 2018). A high-risk of disruptions to accessing critical services, especially in marginalized communities, has been connected to higher levels of chronic stress and trauma (Gutschow et al., 2021). Based on available data for the study area, the core services used in this study were schools, grocery stores, and hospitals. Accessibility to these services was investigated since ability to obtain an education, food, and heath care as central to a community's wellbeing (Gutschow et al., 2021).

2. Background

2.1. Equity, Vulnerability, and Flooding

In addition to a growing number of severe flood events globally, planners must consider underlying socioeconomic disparities and how they may be perpetuated by flooding. The Executive Order on Further Advancing Racial Equity and Support for Underserved Communities Through the Federal Government defines equity as the "consistent and systematic fair, just, and impartial treatment of all individuals," (House, 2023). Equity can be categorized into several classifications. Most relevant to this study are social equity and geographic equity. Social equity is the distribution of impacts across population groups including race, income, social class, and mobility. Geographic equity refers to the distribution of impacts spatially and how that aligns with social inequities. (Bosisio & Moreno-Jiménez, 2022; Iseki, 2016). For this study, vulnerability is directly linked to the intersection of geographic and social equity and is defined as a function of sensitivity and adaptive capacity. Within this definition, sensitivity refers to the susceptibility to flooding and adaptive capacity refers to the ability of a community to prepare for and recover from flooding events (Balica et al., 2013). Variables describing accessibility to core services, such as community demographics and average driving time, are incorporated into the measurements of sensitivity and adaptive capacity. In determining vulnerability, it is important to identify areas where geographic inequities align with social inequities. Social factors can contribute to the overall vulnerability of geographically flood-prone areas by influencing the extent to which communities can mitigate potential flood damages(Iseki, 2016). For example, low-income, public transit-dependent households that are in flood zones may face more difficulties recovering from a flood than high-income households with private automobiles in the same area. Further, communities of high vulnerability and inequity from flooding tend to be in urban areas (Moulds et al., 2021; Wennink & Krapp, 2020).

Urbanization can increase the likelihood of flooding from altered drainage systems, higher surface runoff levels, and an increase in impervious services (Bosisio & Moreno-Jiménez, 2022; Dayaratne & Perera, 2008). In highly urbanized areas, flooding disproportionately affects people of lower income (Chakraborty et al., 2020; Moulds et al., 2021; Oliver-Smith et al., 2017). The American Planning Association found that communities of color and low income are more likely to be historically disadvantaged and excluded from transportation planning processes (Wennink & Krapp, 2020). Discriminatory housing practices and suburban sprawl further contribute to accessibility issues in urban areas as personal vehicles are typically purchased by white, wealthy people in urban areas (Wennink & Krapp, 2020). Inequities in flood impacts and vulnerability may be a result of lower income, minority, and historically disadvantaged communities being built in flood-prone areas, a lack of sufficient infrastructure, and an absence of policy that addresses social inequities (Moulds et al., 2021; Wennink & Krapp, 2020). Communities with overlapping social inequities and geographical inequities should be considered highly vulnerable, and therefore be prioritized in planning decisions, instead of being excluded from the planning process. Methodologies developed in this study aim to identify these communities so that their needs are better met by planners.

2.2. Equity in Current Transportation Policy

This study is guided by the principles and foundations of current, climate justice U.S. policies regarding equity and transportation. President Biden's Executive Order 14008, "Tackling the Climate Crisis at Home and Abroad," has resulted in many government agencies revamping their frameworks regarding equity and the development of numerous related initiatives in the form of task forces, decision support tool development, and monetary commitments (House, 2021). Specific to transportation, many local planning organizations and Departments of Transportation (DOT) at the state and federal level have created task forces and invested heavily into transit projects that address environmental justice and promote increasing equity. Across multiple government agencies and policies, the goal of creating equitable solutions to climate injustice is being pursued with more intensity than before (*FHWA - FAPG 23 CFR 200, Title VI Program and Related Statutes - Implementation and Review Procedures*, 1964; House, 2021, 2023). Guided by this objective, an equity-lens was applied to the spatial analyses completed in this study.

The signing of Executive Order 14008 led to the implementation of the Justice40 Initiative. The program, initiated in January 2021, aims to allot forty percent of Federal investments to programs that will benefit disadvantaged communities impacted by pollution. Categories of investments that align with the executive order include climate change mitigations, clean energy, and sustainable transit (House, 2021). The USDOT has stated that through this initiative, they will commit to the prioritization of projects aimed at increasing the affordability, equity, and safety of transportation for all communities. In addition, the department plans to evaluate and address the consequences of transportation construction and the extent to which community members are involved in project development. Objectives from the USDOT are summarized in the USDOT Equity Plan, with four focus areas. The area of Wealth Creation seeks to provide technical assistance to small, disadvantaged businesses. Power of Community addresses inequities in grants, goods, and services given to communities. Through Interventions, DOT aims to provide direct support for local planning, projects, and grant applications. The final focus area of Expanding Access seeks to create a measure for transit cost burden at a national level. An Equity Leadership Team has been established to oversee these goals. The team is divided into six groups - Data and Assessment, Workforce Equity and Economic Justice, Mobility Justice, Interagency and Stakeholder Engagement, Technology and Innovation, and Budget (*U.S. Department of Transportation Equity Action Plan | US Department of Transportation*, 2022). The methodologies in this study relate to the goals of several groups within the Equity Leadership Team. Specifically, accessibility data produced from this study can provide insights into workforce equity, economic justice, and mobility justice. The potential of planners using these methods to identify vulnerable communities is reflective of the goals of the Technology and Innovation group.

Within the USDOT, the Federal Highway Administration (FHWA) has also implemented an equity program. The program includes a planning guide directed at state DOTs, metropolitan planning organizations (MPOs), and public transit providers on how to integrate equity into transportation project development. The FHWA has traditionally used Title VI of the Civil Rights Act to identify equity instead of equity factors themselves (Rufat et al., 2015). In transportation planning, this statute requires all programs, services, and projects to be completed without discrimination “on the ground of race, color, national origin, sex, or disabilities,” (*FHWA - FAPG 23 CFR 200, Title VI Program and Related Statutes - Implementation and Review Procedures*, 1964). Further, the organization has developed a Screening Tool for Equity Analysis of Project (STEAP).

Similar to the USDOT, MDOT is in charge of project planning, construction, and maintenance of transportation, but at the state level. A draft of their next Five-Year Transportation Program (2023-2027) was released in 2022. This draft integrates equity in two focus areas - Equity and Inclusion and Transportation Resilience. Broadly, the goals of Equity and Inclusion are to reduce negative impacts on health and related environmental effects in historically disadvantaged communities, increase involvement of said communities in policy, and to minimize barriers of benefits reaching minority and low-income populations. Projects focused on Transportation Resilience seek to increase safety and sustainability, while reducing the vulnerability of transit assets through projects that can adapt and recover rapidly from climate related hazards (*Five-Year Transportation Program*, n.d.). Results from this study could provide insights into the resilience of transportation specific to communities in Southeast Michigan. Further, these insights can directly influence the prioritization process of transit asset projects by placing more emphasis on social vulnerability.

A leading challenge in measuring social vulnerability to hazards is for output metrics to better reflect the context in which vulnerability occurs. Through a meta-analysis of 67 flood disaster case studies (1997–2013), the leading drivers of social vulnerability to floods are profiled (Rufat et al., 2015). The results identify demographic characteristics, socioeconomic status, and health as the leading empirical drivers of social vulnerability to damaging flood events. Risk perception and coping capacity were also featured prominently in the case studies, yet these factors tend to be poorly reflected in many social vulnerability indicators. The influence of social vulnerability drivers varied considerably by disaster stage and national setting, highlighting the importance of context in understanding social vulnerability precursors, processes, and outcomes. To help tailor quantitative indicators of social vulnerability to flood contexts, the article concludes with recommendations that temporal context, measurability, and indicator interrelationships be incorporated in measuring vulnerability within policy (Rufat et al., 2015).

2.3. Review of Existing Equity and Transportation Tools

Several screening tools exist in the realms of transportation, flooding risk, and/or environmental justice. These tools allow users to quickly filter data to identify areas relevant to the problem they are trying to solve. The capabilities and spatial range of these tools are heavily dependent on who created them, the purpose for which they were created, and the available data. Most flood risk tools used by Transportation Planning Organizations (TPOs) have a local focus (Albano et al., 2015; Antwi-Agyakwa et al., 2023; Evers et al., 2016; Hagemeier-Klose & Wagner, 2009). Generally, environmental justice and equity tools have a broader geographic area as large, publicly available datasets like census data can be used. However, the extent to which these tools overlap transportation, flood, and equity data vary extensively, with only a few integrating variables from all three sectors. Creating a model that effectively utilizes an equity lens for flood planning requires an understanding of transportation system vulnerabilities and the ability to relate these to socio-economic factors in a community. This section highlights four existing screening tools. These tools were developed with goals specific to equity, transportation, or flooding. However, similar spatial analysis techniques are used in each. This commonality shaped how methods in this study were developed and showcases how an equity-lens is applicable to transportation and flooding models.

Developed by the Council on Environmental Quality for Justice40, the Climate and Economic Justice Screening Tool (CJEST) functions as a screening tool that identifies disadvantaged communities. It utilizes census tract data to evaluate twenty-two socioeconomic and environmental indicators to classify tracts into several categories of different types of disadvantages. The categories of disadvantage include climate change, clean energy and energy efficiency, clean transit, affordable and sustainable housing, reduction and remediation of legacy pollution, critical clean water and wastewater infrastructure, health burdens, and training and workforce development. If a census tract is at or above the 90th percentile for one or more environmental indicators and it is at or above category dependent thresholds for any socioeconomic indicators, then it is considered disadvantaged in that category (*Methodology & Data - Climate & Economic Justice Screening Tool*, 2022).

Like with this study, the USDOT developed a Transportation Disadvantaged Census Tract screening tool using the mapping software, ArcGIS. The tool displays a map of census tracts and highlights tracts that are considered disadvantaged in at least four of the following categories (Fig. 1), including historically disadvantaged, transportation access disadvantaged, health disadvantaged, economy disadvantaged, equity disadvantaged, resilience disadvantaged and environmental disadvantaged. A percentile method similar to that used in CJEST was employed in this model, with the difference of using averages for tracts calculated and assigned a score based on 50th and 75th percentiles. (*Transportation Disadvantaged Census Tracts (Historically Disadvantaged Communities) Interim Definition Methodology | US Department of Transportation*, 2023). As described further in the methods section below, I adopt this percentile approach to calculate a vulnerability index that integrates environmental, socioeconomic, and transportation indicators. Data from the Social Vulnerability Index, the Environmental Protection Agency, the Housing and Urban Development Location Affordability Index, and the Federal Emergency Management Agency is aggregated into a final indicator of one or zero (yes or no) for each category. This allows for planners to gain better locational context when deciding where projects and funds should be allocated.

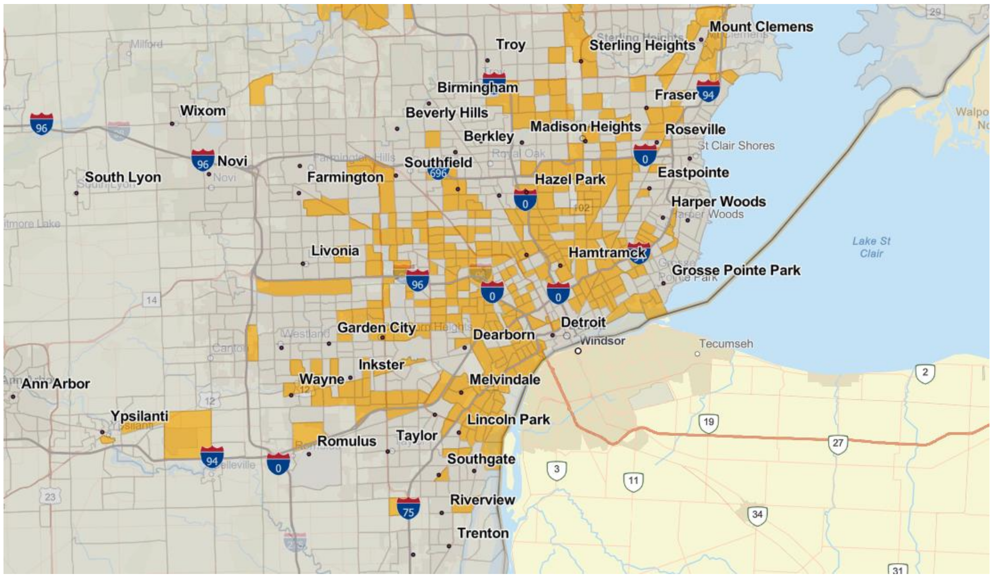

Fig.1. This image is a screenshot of the USDOT Transportation Disadvantaged Census Tract screening tool that zoomed in on southeast Michigan. Census tracts are color-coded to represent whether the tract is considered disadvantaged for transportation. Gray indicates that the tract is not disadvantaged and yellow indicates the tract is disadvantaged (*Transportation Disadvantaged Census Tracts*, 2023).

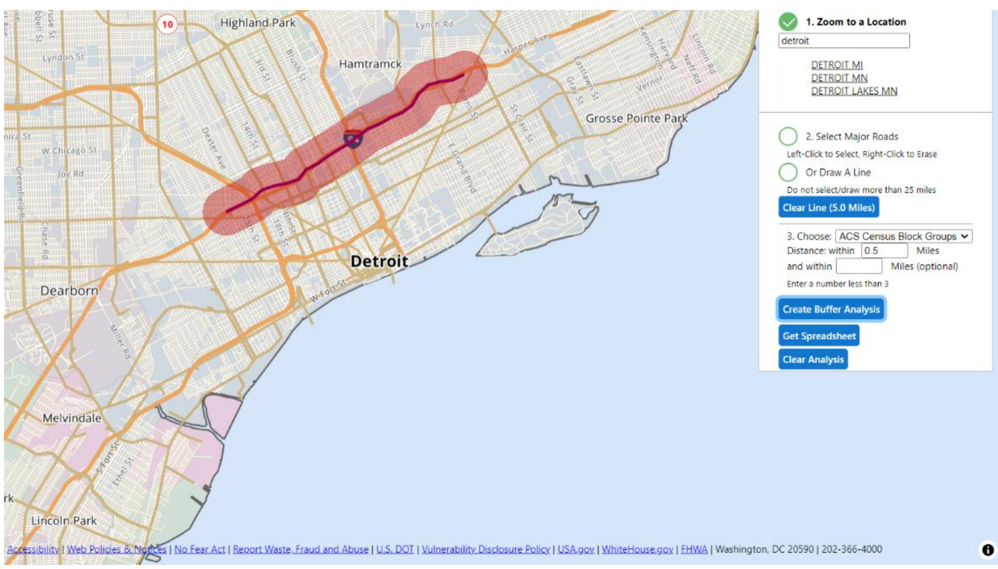

Fig. 2. This image is a screenshot from the STEAP tool. In this example, a line was drawn (dark red) to represent a potential transportation project. A .5 mile buffer was applied and data regarding the socioeconomic statistics of the communities within the buffer are later calculated (*HEPGIS Title VI Tool*, 2023).

As previously mentioned, the FHWA has created STEAP, an equity screening tool. The tool allows users to either select highways or draw lines that represent hypothetical transportation projects (Fig. 2). A buffer analysis is then performed to provide an estimate of the socio-economic data within the chosen buffer limit. Summarized data is taken from Title VI and various environmental justice related variables from the American Community Survey 2015-2019 Five Year report (*Introducing the Equity Analysis Radius Map Tool*, 2023). Users are able to adjust the project locations and buffer sizes to better conceptualize what communities may be impacted by a transportation project there.

The University of South Florida Center for Urban Transportation Research (CUTR) has developed a toolkit featuring several guidelines, forms, and assessments related to integrating equity into transportation planning. Within the toolkit, a policy brief provides a framework for local governments and TPOs to evaluate their communities' specific areas of need. The Transportation Equity Audit Tool outlines a survey for agencies and community members to use in identifying transportation needs and demographics of a location. The questions have a strong emphasis on accessibility, safety, and equity. The Transportation Equity Scorecard Tool assists with the prioritization of projects by allowing planners to rank the potential project’s impact on access to opportunity, health and environment, safety and emergency evacuation, affordability, mobility, and burdens (Allen, 2021).

Justice40 has propelled a series of subsequent policies and tools aimed at addressing environmental justice. Although many transportation, equity, and flood risk tools exist, there is still a need for a tool that thoroughly evaluates the factors from each sector. This study seeks to develop a model framework that places equity at the center of its analysis. Integrating socio-economic indicators at the forefront of the model will allow for a more holistic approach to project prioritization and the identification of vulnerable areas.

3. Data

3.1. SEMCOG Flood Risk Data

While components of this study build upon principles of the aforementioned tools, data from SEMCOG's Flood Risk Tool will be used directly in the creation of a new methodology for this project. The Flood Risk Tool was created as a part of the SEMCOG and MDOT 2020 Climate Resiliency and Flood Mitigation Study (*Climate Resilience*, 2020). The tool assigns a risk score to all transportation assets including road segments, bridges, culverts, and pump stations over the SEMCOG region. Assets are then scored on a scale of one to four, with four being the highest level of risk. Risk is defined as a function of criticality and vulnerability (Fig. 3). Criticality is the importance of an asset to the transportation system and SEMCOG region and is measured independent of vulnerability.

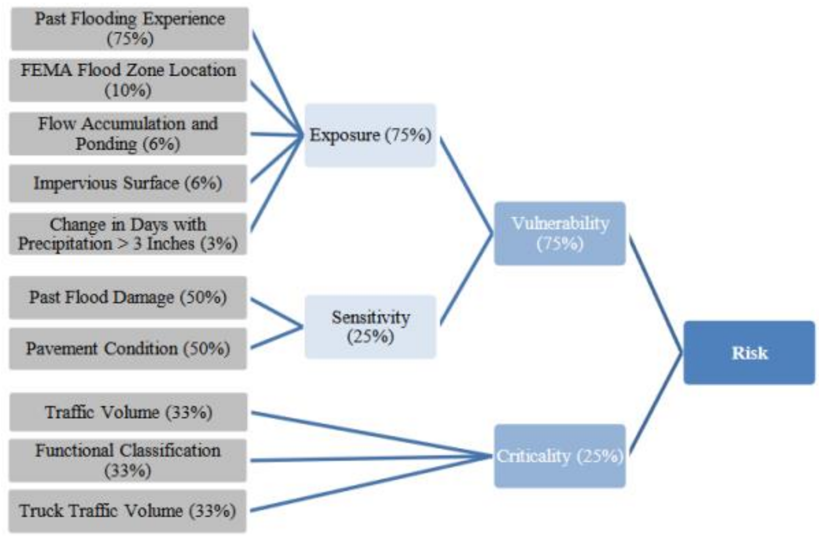

Fig. 3. Schematic representation of model used by SEMCOG in their Flood Risk Tool to determine risk scores for road segments. The percentages by the factors represent the weight given in the subsequent (from left to right) factor (*Climate Resilience*, 2020). The current study uses the final risk scores from the tool for each road to calculate a new vulnerability index.

Variables for determining each factor in the Flood Risk tool differ for each asset. This study only uses data associated with road segments (Fig. 4). Examples of variables included in road vulnerability measures are past flooding experience, FEMA flood zone location, traffic volume and pavement condition (*Climate Resilience*, 2020). SEMCOG derives vulnerability from exposure and sensitivity and defines it as the likelihood that an asset will experience impacts from flooding (*Climate Resilience*, 2020)In this study, vulnerability is derived from sensitivity and adaptive capacity. Although there is a difference in terminology, the methods used in this study directly use

SEMCOG's risk scores (which includes the vulnerability measure) to create a new definition of vulnerability.

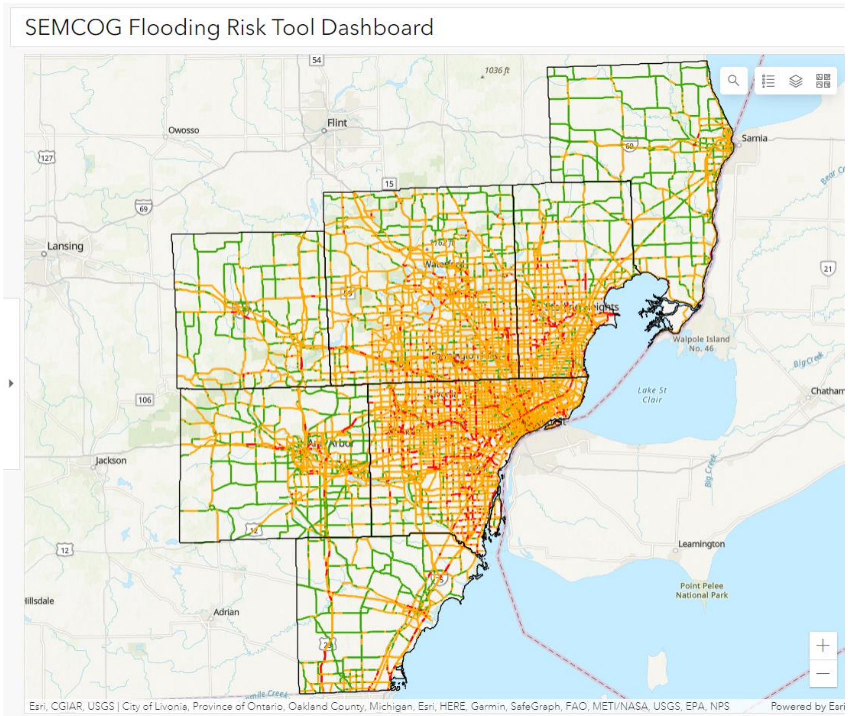

Fig. 4. Screenshot from SEMCOG's Flood Risk Tool Dashboard. The colored lines represent road segments and their corresponding risk scores indicating how susceptible the segment is to flooding (green = low, orange = medium, red = high)(*SEMCOG Flooding Risk Tool Dashboard*, 2023).

3.2. SEMCOG Equity Emphasis Data

Additionally, SEMCOG has developed their own Equity Emphasis Areas screening tool. Like with the Flood Risk data, a subsection of the Equity Emphasis Areas data will be used in this study. The tool allows users to summarize available demographic variables of their choosing at the regional, county, community, and census tract level. For example, the default selected variables are older adults, minority, youth, persons in poverty, and transit dependent households. Selecting the default variables color codes a corresponding map and assigns each geographic unit a number associated with vulnerability (Fig. 5). Numbers range from zero to four with zero being a low concentration and four being a high concentration of the selected factors (Fig. 6) (*SEMCOG Equity Emphasis Areas*, 2023). As described in greater detail in the methodology section, this study will use the equity data and census demographics used in the Equity Emphasis Areas tool.

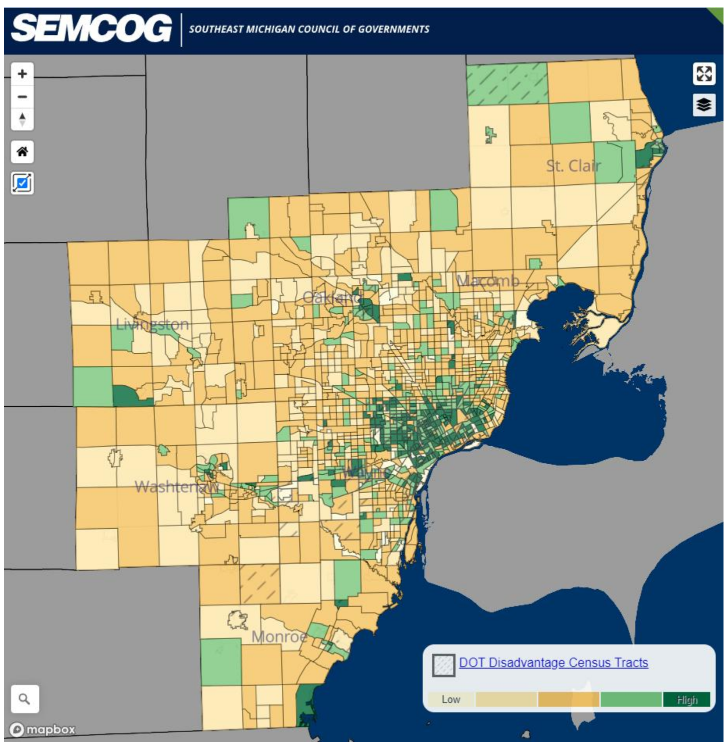

Fig. 5. Screenshot from SEMCOG's Equity Emphasis Tool. The area depicted is the seven-county region of SEMCOG at the census tract level. The variables selected in this example were older adults, persons in poverty, youth, and transit dependent households and a total score of 2.00 was given. The colors of the tracts represent the concentration of selected factors present (yellow = low, orange = medium, green = high) (*SEMCOG Equity Emphasis Areas*, 2023).

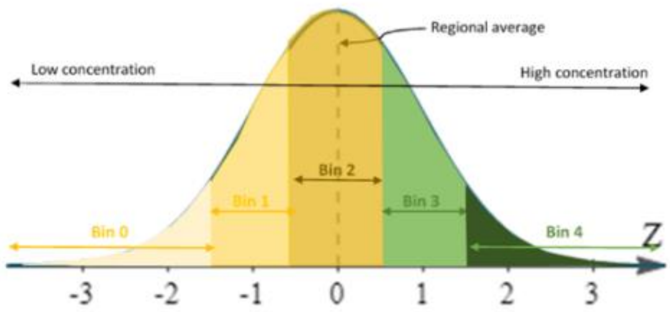

Fig. 6. Scoring system developed by SEMCOG for their Equity Emphasis tool. Scores are determined by calculating bins relative to a regional average (bin two). Bins below bin two have a low concentration and those above two have a high concentration. Concentration refers to the extent to which the selected variables are present in the area of analysis (*SEMCOG Equity Emphasis Areas*, 2023).

4. Methodology

4.1. Unit of Analysis

The units of analysis used for this study were Transportation Analysis Zones (TAZs). TAZs are the standard unit used by many transportation planning organizations and local governments when using transit models and evaluating transit data (Chen et al., 2019; Levashev et al., 2023). How TAZs are determined can vary across different planning organizations and transportation departments. Generally, TAZs are relatively similar to census tracts, but their boundaries are often defined by major transportation variables (i.e. highways, roads frequently used) (Levashev et al., 2023). Each TAZ contains approximately 3,000 people, but routes, origin, and destination points are much more heavily weighted than population when determining the size. Census block and tract information is typically aggregated to populate TAZs with socioeconomic data. TAZ data is typically created by regional transportation planning organizations and is mostly used internally by the organization. TAZ data for this study was provided by the transportation team at SEMCOG. In SEMCOG, there are roughly 2,800 TAZs.

4.2. Study Area

The study area chosen for this analysis includes seventy-four TAZs in Wayne County between the cities of Plymouth and Canton, MI (Fig. 7). An urban area was chosen as its transportation systems (e.g. roads, highways) may face greater impacts from flooding (Dayaratne & Perera, 2008; Greiner et al., 2020; Rubinato et al., 2019). Further, this area straddles a major highway, I-275. The study area encapsulates a range of socioeconomic conditions and contains a moderate number of high-risk roads identified through the SEMCOG Flood Risk Tool dataset. This study will be evaluating accessibility to core services (schools, hospitals, grocery stores), and the study area contains at least one of each core service being assessed.

Fig. 7. The study area used is highlighted in red. The area of analysis contains 74 TAZs within Wayne County in Southeast Michigan. The gray-highlighted area represents the seven counties within SEMCOG.

4.3 Vulnerability

Two different geospatial analysis methods were used to create distinct vulnerability maps at the TAZ level. Each map assigned a vulnerability score of one (low), two (moderate), or three (high) to each TAZ polygon. The data sources used to determine vulnerability (SEMCOG's Flood Risk Tool, Equity Emphasis Areas, and Fernleaf Interactive's drivetime data) were also consistent throughout the methods. The distinction lies in how sensitivity and adaptive capacity were defined; different variables and methods of integrating variables from flood, transportation, and socioeconomic data were used for each map. Specifically, Method 1 used the proportion of high-risk roads in each TAZ in its sensitivity measure, while Method 2 used the change in drivetime after a flood.

4.4. Accessibility and Calculating Drive Time

Core services investigated in this study were defined as hospitals, schools, and grocery stores. To quantify accessibility, drivetimes were calculated using an algorithm developed by Fernleaf Interactive that was inputted into ArcGIS. This was done for each road segment in the road network of the study area. A drivetime indicates the number of minutes an automobile would take to reach the nearest core service, assuming the vehicle is driving at the speed limit. Road segments were deemed either accessible or inaccessible based on drive time thresholds established by SEMCOG in their 2016 *Access to Core Services* study (Rabhi, 2016). A ten-minute threshold was used to define accessibility to hospitals, schools, and grocery stores. Road segments with a drivetime of ten minutes or less were considered accessible and road segments with a drivetime of more than ten minutes were labeled inaccessible for this study.

Data needed for the calculations included the TAZ boundaries of the study area, a road network, and point locations of the core services. Point locations for the core services were limited to those within the study area. To account for locations on or near the border of the study area, a 4,000-yard buffer was added. The road network used was taken from OpenStreetMaps and clipped in ArcGIS Pro to fit the study area. It contains 61,463 road segments classified as either highways, service, or residential. A baseline drive time was first established to distinguish between underlying accessibility issues and accessibility issues stemming from flooding. Each core service category was evaluated separately. Without the presence of a flood, 77.76% of the roads for hospitals, .68% for schools, and 5.46% for grocery stores were outside of the ten-minute threshold (Fig. 8).

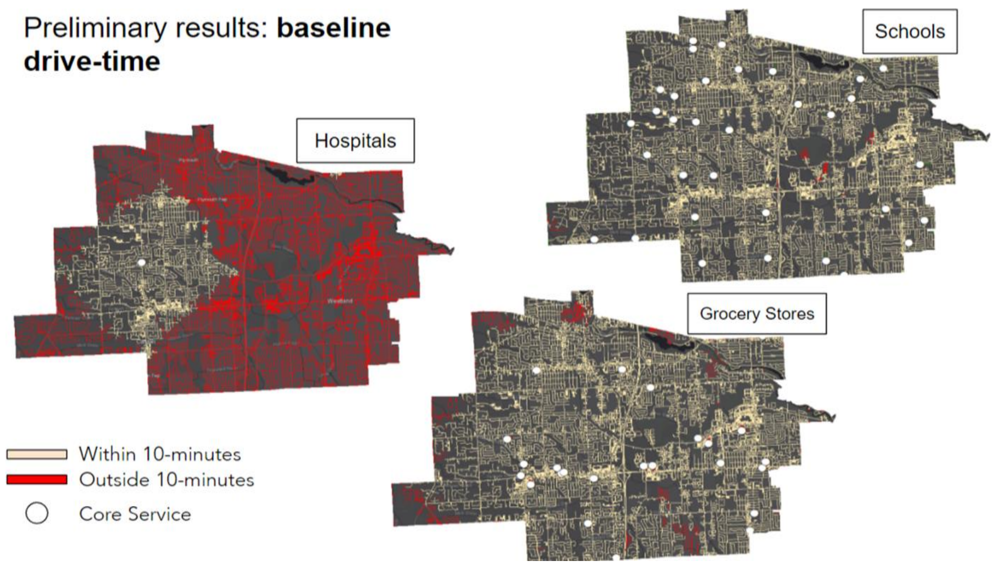

Fig. 8. Baseline drive time results for accessibility to core service. Road segments highlighted in beige are deemed accessible because they are within a ten-minute drive time to each corresponding core service. The inaccessible roads are highlighted in red and the core services are represented by a white dot. These maps were developed by Fernleaf Interactive.

Once a baseline drivetime map for each core service category was established, corresponding maps including the impacts of floods were created by Fernleaf. The same data and methods from the baseline analysis were used to do so, with the addition of barriers in the road network. Barriers in the analysis were defined as any road segment that had a flood risk score of three or higher from the Flood Risk Tool data (*SEMCOG Flooding Risk Tool Dashboard*, 2023). These road segments were recognized as complete obstructions, indicating that a vehicle cannot drive through or around the road during a flood event. Vehicles were then rerouted to alternate paths without high-risk segments present. With the flood data integrated, the number of inaccessible road segments for hospitals increased by 5.92%, 5.12% for schools, and 9.74% for grocery stores (Fig. 9).

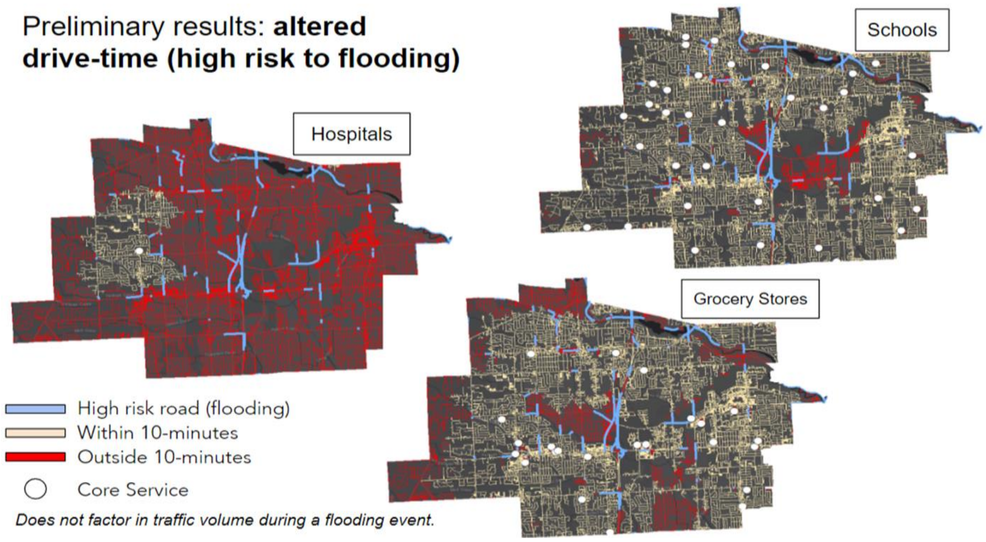

Fig. 9. Flood-impacted drive times to core services. Accessible (under a ten-minute drivetime) roads are colored beige, inaccessible (greater than a ten-minute drivetime) are colored red, and the high-risk roads from flooding (score of three or higher from the Flood Risk Tool) are colored blue. These maps were developed by Fernleaf Interactive.

4.5. Method 1: High Risk Roads

The first method used to calculate vulnerability utilized socioeconomic indicators and high-risk roads to assign vulnerability score to each TAZ. The data used for Method 1 of the analysis was taken from SEMCOG's TAZ demographics dataset, their Flood Risk dashboard, and the drivetime data previously calculated (*SEMCOG Equity Emphasis Areas*, 2023; *SEMCOG Flooding Risk Tool Dashboard*, 2023). Like the drivetime calculations, each core service category was evaluated individually. Socioeconomic indicators used to define sensitivity were chosen to reflect groups that would be most dependent on the core service being analyzed. For hospitals, these indicators were households with children and households with elderly people (Fig. 10). Schools used the number of households with children and the number of households with people who work in education in its analysis (Fig. 11). Finally, sensitivity for grocery stores was impacted the proportion of the TAZ that was in a food desert (Fig.12). To identify food desert locations, a one-mile buffer was applied to all grocery stores in the study area. This radius was based on the USDA distance benchmark for food deserts in urban areas (*USDA ERS - Documentation*, 2022). In addition to socioeconomic factors that were specific to each given core service, all analysis on Method 1 used the proportion of high-risk roads in a TAZ as another factor in the sensitivity score.

The proportion of high-risk roads was found by dividing the number of high-risk road segments (road segments with a score of three or higher) intersecting the TAZ by the total number of road segments in that TAZ. To find the number of high-risk road segments for each TAZ, a selection by attribute was done in ArcGIS Pro. After the proportion of high-risk roads was calculated, percentile averages for the entire SEMCOG region were used to rank the socioeconomic and high-risk road proportions for each TAZ. Sensitivity scores ranged from one to three, with one being low sensitivity, two being moderate sensitivity, and three being high sensitivity. If a TAZ's combined sensitivity indicators fell below twenty-five percent, it would be assigned a one. If its indicators fell between the twenty-fifth and seventy-fifth percentiles, a two would be assigned. Lastly, a three would be assigned if the indicators were above the seventy-fifth percentile.

Adaptive capacity was found using the indicators of the number of low-income households in a TAZ and the number of households without access to a car. As with the sensitivity scores, the adaptive capacity scores used percentile averages from the seven counties in SEMCOG to score the TAZs. Adaptive capacity scores reversed the order from sensitivity scores, so that one would indicate high adaptive capacity, two represented moderate adaptive capacity, and three indicates low adaptive capacity. Sensitivity and adaptive capacity scores for each TAZ were combined following a matrix, through which low vulnerability is represented by a one, moderate vulnerability is represented by a two, and high vulnerability is represented by a three (Fig. 13). Layers were created in ArcGIS Pro for each core service category that contained all demographic information, drivetime data, sensitivity scores, adaptive capacity scores, and vulnerability scores.

Drivetime data was used to create an additional layer that depicts roads that have a higher chance of facing accessibility issues than others. Another selection by attribute was conducted in ArcGIS Pro to capture any road segments that had a drivetime greater than ten minutes to any of the core services in either the baseline or flood scenarios. To investigate the magnitude of impact a flood event could have on the roads, roads with a change in drivetime greater than or equal to five minutes were selected. The selected road segments for both attributes were saved in a separate layer and overlaid with the vulnerability maps.

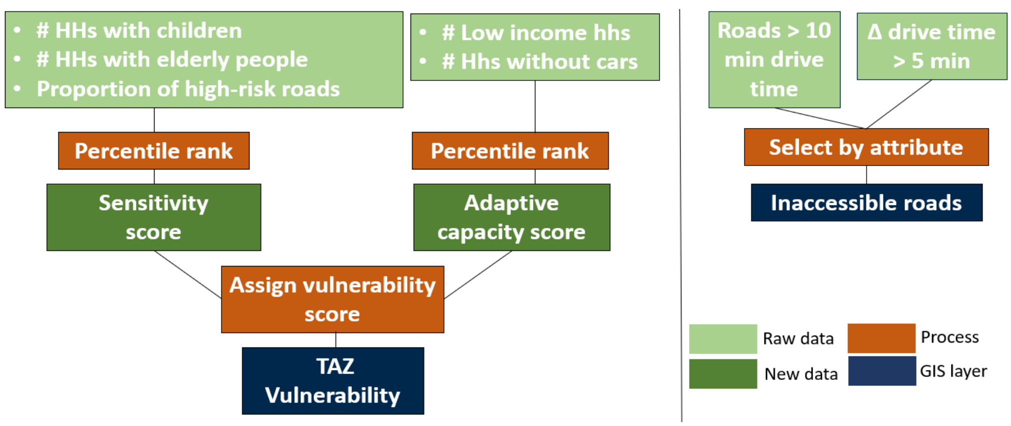

Fig. 10. Workflow representing Method 1 for calculating a vulnerability index for access to hospitals. Percentile rankings were used to assign sensitivity and adaptive capacity scores, then they were combined to calculate a final vulnerability score. The schematic to the right represents the workflow for identifying inaccessible roads that can be overlaid on the vulnerability map.

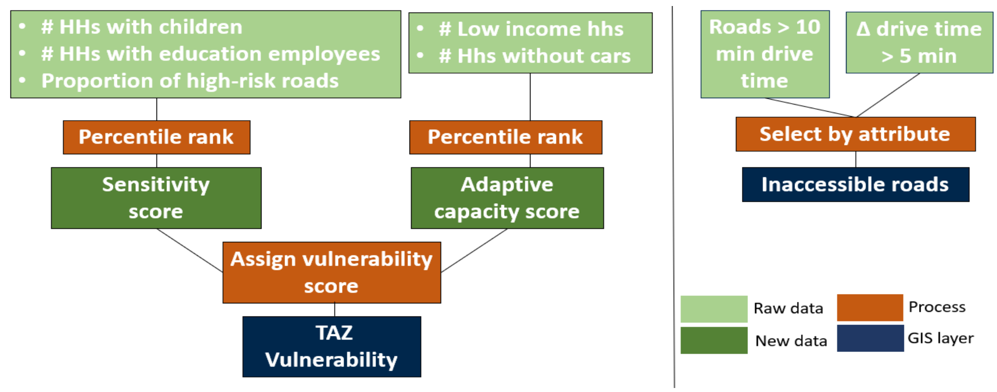

Fig. 11. Workflow representing Method 1 for calculating a vulnerability index for access to schools. Percentile rankings were used to assign sensitivity and adaptive capacity scores, then they were combined to calculate a final vulnerability score. The schematic to the right represents the workflow for identifying inaccessible roads that can be overlaid on the vulnerability map.

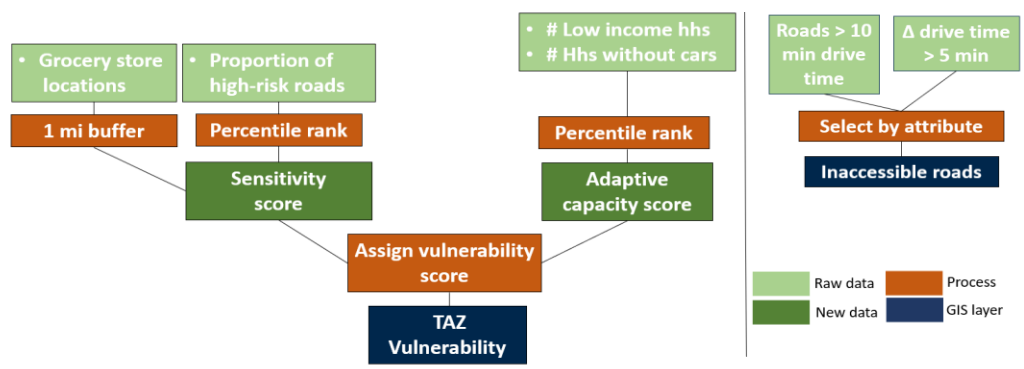

Fig. 12. Workflow representing Method 1 for calculating a vulnerability index for access to grocery stores. Percentile ranking was used to assign sensitivity scores. Adaptive capacity scores were based on the proximity of a road to the nearest grocery store. The scores were combined for the final vulnerability index. The schematic to the right represents the workflow for identifying inaccessible roads that can be overlaid on the vulnerability map.

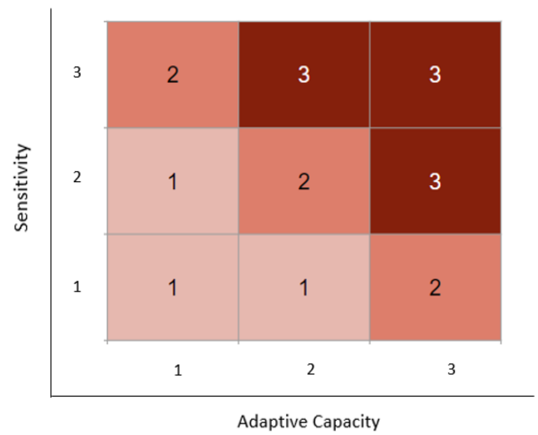

Fig. 13. Matrix used to combine sensitivity and adaptive capacity scores to calculate a final vulnerability score for both Method 1 and Method 2.

4.6. Method 2: High Risk Road Network

The major difference between Method 1 and Method 2 is that Method 2 expands on the number of roads considered to be at high-risk from Method 1 (Fig. 14). Specifically, Method 1 used the high-risk roads from SEMCOG's Flood Risk Tool in the sensitivity score (*SEMCOG Flooding Risk Tool Dashboard*, 2023). In addition to these road segments, Method 2 also includes the drivetime data in the calculations for sensitivity. In Method 1, drivetime data is included as a separate layer to overlay on top of the vulnerability map, but it is not used in the index itself. Socioeconomic variables from the first method were also included in the sensitivity measurements. The proportion of high-risk roads was replaced with the average change in drivetime from a flood event. The average baseline drivetime was subtracted from the average flood impacted drivetime to calculate the average change in drivetime for each TAZ.

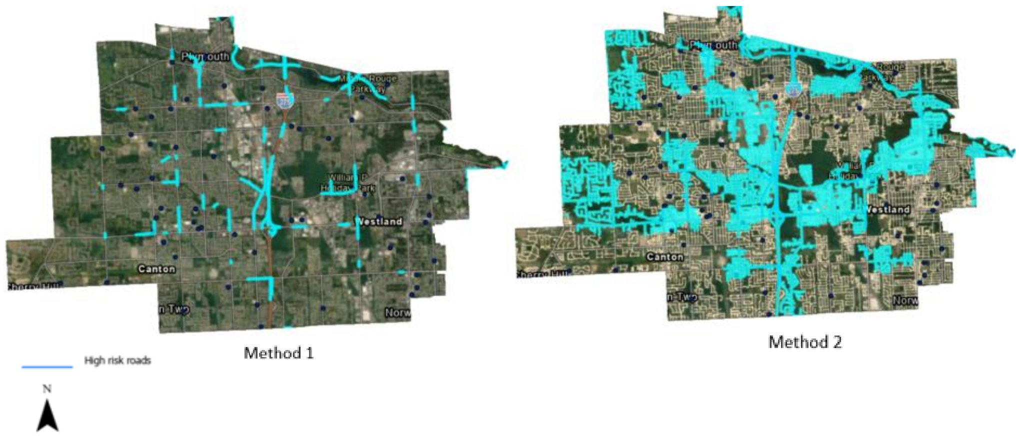

Fig. 14. Maps highlight the road segments used in the calculations for sensitivity to flooding in Method 1 (left) and Method 2 (right).

When the drivetime algorithm assigned a road segment a drivetime in a flood-impacted scenario, some segments were given a time of zero minutes. In averaging roads at the TAZ level and then finding the change in drivetime, these values resulted in a negative change for some TAZs. An assignment of zero minutes for a road segment in this case does not indicate a drivetime less than one minute, but rather that driving on the road is not possible. Because of this, the change in drivetime was evaluated in relation to zero minutes, as the algorithm used to determine time recognized high-risk roads as complete obstructions. TAZs with a change in drive time equivalent to zero were deemed as low sensitivity. A change in drivetime greater than zero minutes was assigned as moderately sensitive, as these TAZs on average face a delay in travel time. TAZs with a change in drivetime less than zero minutes were labeled as highly sensitive, since a flood event would make rerouting transit extremely near impossible. The average change in drivetime was combined with the same socioeconomic indicators in Method 1 for each core service (Figs. 15-16).

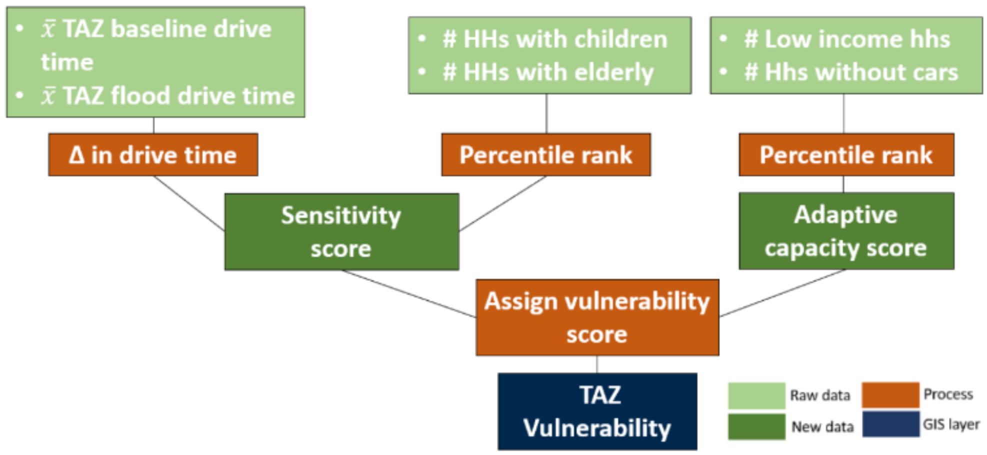

Fig. 15. Workflow representing Method 2 for calculating a vulnerability index for access to hospitals. Percentile rankings were used to assign sensitivity (based on the average change in drivetime for the area) and adaptive capacity scores, then they were combined to calculate a final vulnerability score.

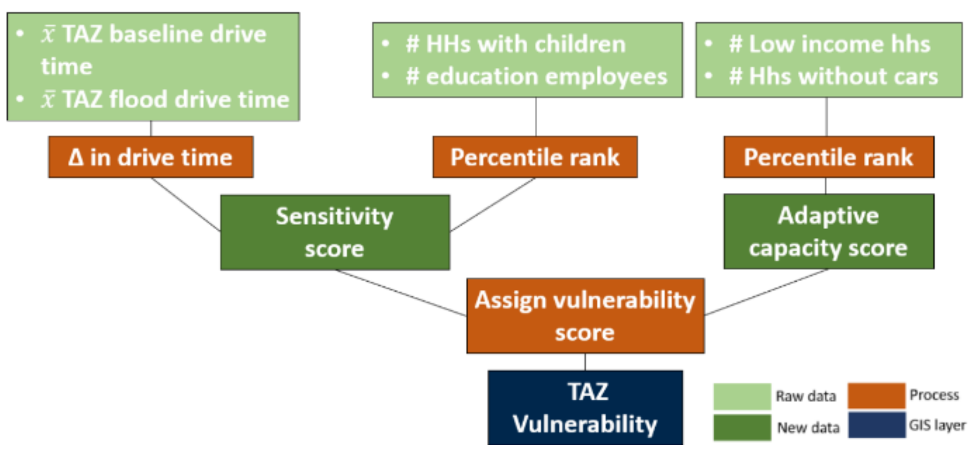

Fig. 16. Workflow representing Method 2 for calculating a vulnerability index for access to schools. Percentile rankings were used to assign sensitivity (based on the average change in drivetime for the area) and adaptive capacity scores, then they were combined to calculate a final vulnerability score.

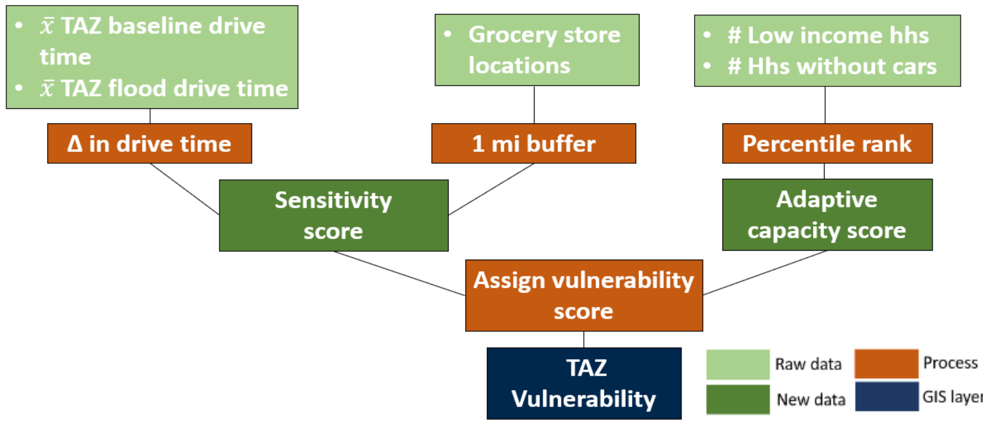

Fig. 17. Workflow representing Method 2 for calculating a vulnerability index for access to grocery stores. A percentile ranking based on the average change in drivetime was used to assign a sensitivity score. Adaptive capacity scores were based on the proximity of a road to the nearest grocery store. The scores were combined to calculate a final vulnerability score.

5. Results

5.1 General Trends

A comparison of results from both methods of evaluating vulnerability to transportation disruptions show that while the general spatial distribution of vulnerability scores is similar, Method 2 tends to have a greater number of highly vulnerable TAZs across all core service analyses (Figs. 18-22). On average, Method 2 assigned a high vulnerability score (three) to more TAZs than Method 1 (8.11% or approximately 5.67 TAZs) across all core services. TAZs with high vulnerability were concentrated on the eastern side of I-275 for both methods. The majority of the western side of the highway is moderately vulnerable, with a concentration of low vulnerability in the southern half. Results for hospitals and schools between the two methods display similar trends in vulnerability scores. Comparatively, the maps for grocery stores have a higher number of low vulnerability TAZs than the other core services. Figure 20 displays maps for each core service and highlights TAZs that have consistent scores between the methods. Figure 21 shows the TAZs that have consistent scores for all core services for each method. Two TAZs from Method 1 and six TAZs from Method 2 were identified as having high vulnerability for all core services. Method 1 had 20 TAZs that were low vulnerability and ten that were moderate, while Method 2 had 17 TAZs for low and ten for moderate.

5.2 Hospitals

Method 1 for evaluating vulnerability regarding accessibility to hospitals resulted in 18 highly vulnerable TAZs, compared to Method 2 resulting in 21 TAZs. Method 1 had 23 TAZs with low vulnerability and 33 with moderate vulnerability. Method 2 had 23 TAZs with low vulnerability and 30 with moderate vulnerability. The first map in Fig. 20 depicts TAZs that have identical scores from Method 1 and 2 for the hospital analysis. Between the two methods, there were 16 TAZs that were ranked highly vulnerable in both methods, 27 that were ranked moderately vulnerable, and 22 that were ranked low vulnerability. Nine TAZs had different scores from the methods for hospitals.

5.3 Schools

When evaluating the vulnerability of transportation disruptions in relation to schools, Method 1 returned 15 highly vulnerable TAZs and Method 2 returned 22. For moderate and low vulnerability, Method 1 had 36 and 23 TAZs, and Method 2 had 30 and 22 TAZs, respectively. When comparing the results from both methods, there were 13 TAZs identified as highly vulnerable in both, 26 identified as moderately vulnerable, and 21 identified as low vulnerability (Fig. 20). 14 TAZs had different scores for the school analyses between the methods.

5.4 Grocery Stores

For transportation vulnerabilities related to grocery stores, there were seven highly vulnerable TAZs from Method 1 and 14 from Method 2. TAZs with low vulnerability amounted to 39 in Method 1 and 33 in Method 2. For moderate vulnerability, Method 1 had 28 TAZs and Method 2 had 27. The total number of TAZs with equivalent scores from Methods 1 and 2 were six for high vulnerability, 17 for moderate vulnerability, and 30 for low vulnerability (Fig. 20). 21 TAZs had differing vulnerability scores from the two methods.

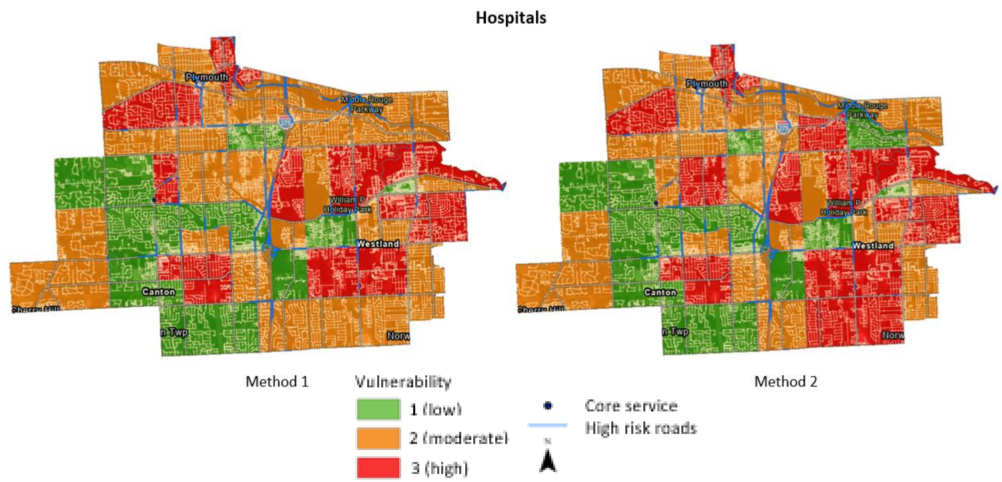

Fig. 18. Vulnerability maps using Methods 1 (left) and 2 (right) for accessibility to hospitals. A hospital is represented by a black dot. High-risk road segments (roads with a score of three or greater from SEMCOG's Flood Risk Tool) are highlighted in blue. TAZs in green have low vulnerability, orange TAZs are moderately vulnerable, red TAZs have high vulnerability.

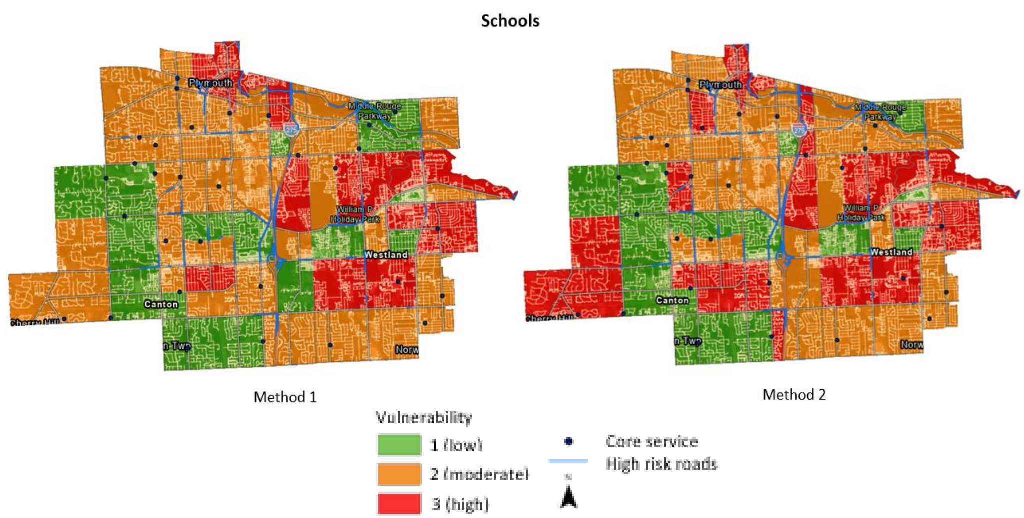

Fig. 19. Vulnerability maps using Methods 1 (left) and 2 (right) for accessibility to schools. Schools are represented by a black dot. High-risk road segments (roads with a score of three or greater from SEMCOG's Flood Risk Tool) are highlighted in blue. TAZs in green are considered to have low vulnerability, orange TAZs are moderately vulnerable, red TAZs have high vulnerability.

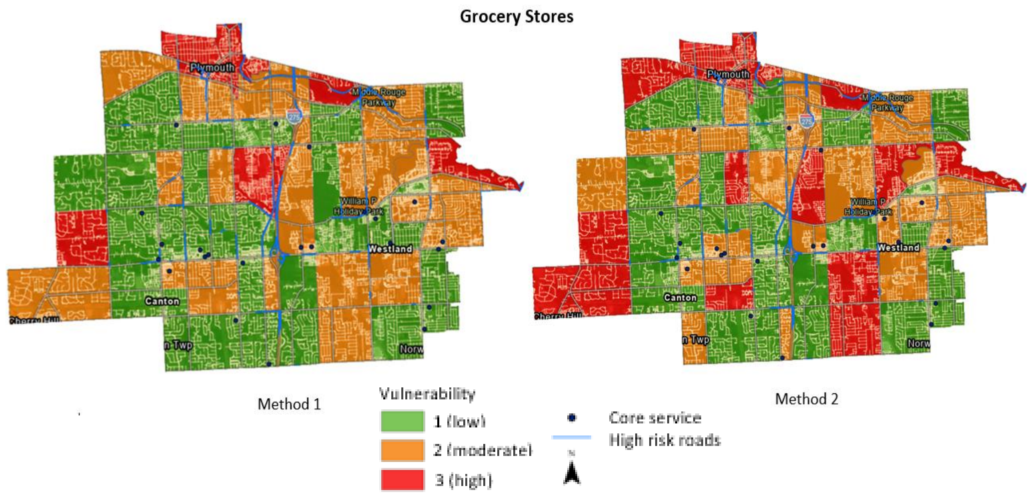

Fig. 20. Vulnerability maps using Methods 1 (left) and 2 (right) for accessibility to grocery stores. Stores are represented by a black dot. High-risk road segments (roads with a score of three or greater from SEMCOG's Flood Risk Tool) are highlighted in blue. TAZs in green are considered to have low vulnerability, orange TAZs are moderately vulnerable, red TAZs have high vulnerability.

Fig. 21. Maps (from left to right) for hospitals, schools, and grocery store analyses in which the scores for both methods are equivalent. Core services are represented by black dots and the high-risk roads are blue. TAZs with a low vulnerability from both methods are in green, TAZs with a moderate vulnerability from both methods are orange, and TAZs with high vulnerability from both methods are red.

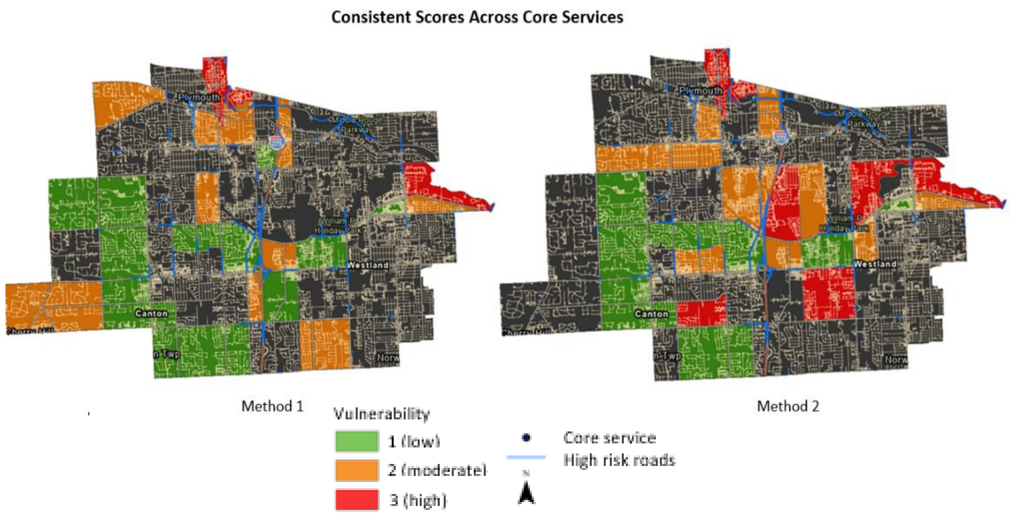

Fig. 22. Maps for Method 1 (left) and Method 2 (right) depict TAZs that have consistent scores across all core services. TAZs with low vulnerability in accessibility to hospitals, schools, and grocery stores are green, moderately vulnerable TAZs for all services are orange, and highly vulnerable TAZs for all services are red.

6. Discussion

6.1 Comparison of Methods

The difference between Methods 1 and 2 lies within how vulnerability is defined. Specifically, the variables used to assess transportation and flooding were evaluated differently in the sensitivity component of vulnerability. Both methods held the same variables constant for adaptive capacity and the same socioeconomic variables relevant to the core service being analyzed. Method 1 incorporates transportation and flooding data by using the proportion of high-risk roads as a measure of sensitivity, along with the socio-economic variables. Method 2 utilizes the change in drivetime between baseline and flood scenarios instead of the proportion of high-risk roads directly. The proportion of high-risk roads is still accounted for in this method, as it was used as a barrier in network analysis to calculate the drivetime. The preliminary results of drivetime data indicated that there were areas facing accessibility issues at the baseline level. This was especially true for hospitals, in which the majority of the study area had road segments outside of the ten-minute threshold. After running both methods, the maps for hospitals and schools appeared to share the same spatial patterns for vulnerability. Moreover, the high amount of accessibility inequities in the preliminary results for hospitals was not reflected to the same extent in the vulnerability maps. A possible explanation for this discrepancy and the similarity to the school vulnerability scores is that both core services used the number of households with children as a variable for sensitivity.

Method 2 consistently identified more TAZs as highly vulnerable than Method 1 throughout the analyses for all core services. One explanation for this is that by using the average change in drivetime for each TAZ, outliers skewed the sensitivity score and consequently, the overall vulnerability score. Additionally, using the average change in drivetime did not account for the differences in road length. While Method 1 uses a proportion to attempt to normalize the data, road length is still not addressed. The vast number of road segments in each TAZ compared to the relatively small number of high-risk roads may have led to this factor having a smaller impact on the sensitivity score compared to the change in drivetime used in Method 2. In future iterations of this project, it may be worthwhile to obtain road length and lane miles per road to better normalize the data.

A potential benefit to using Method 2 is that it may capture a more accurate picture of the impacts of flooding to a transportation network as a whole. Only using high-risk road segments in Method 1 may overlook the routes directly connected. The high-risk roads represent a small portion of a larger path. Incorporating drivetime into the vulnerability measure allows the connectivity of flooded roadways to be analyzed. This connectivity is extremely important in planning for transportation projects and flood mitigation as evaluates accessibility in a more realistic way. Evaluating the routes to core services in their entirety (using changes in drivetime), aligns more with origin-destination frameworks used in transportation modeling (Aerde et al., 2003; Bera & Rao, 2011).

To further investigate the differences between Method 1 and Method 2, paired t-tests were conducted. T-tests were conducted comparing the vulnerability scores of the two methods for each core service separately (see Appendix A). The results from the t-test for hospitals indicated that there is no significant difference between Method 1 and Method 2 for evaluating the vulnerability for accessibility to hospitals, as it had a p-value of .3206. The p-value for the schools t-test was .0315, indicating there is a significant difference between Methods 1 and 2 in determining vulnerability for accessibility to schools. The results for grocery stores were also significant at a p-value of .0039.

6.2 Use of Methods to Prioritize Transportation Projects

The methods developed in this study could be used to improve existing tools and models relating to transportation and flood planning. By applying an explicit equity-lens in both methods, these analyses align with the objectives outlined in Justice40. The Department of Transportation has approached Justice40 with the goal of identifying and prioritizing projects that would improve the lives of disadvantaged communities (House, 2021). Additionally, SEMCOG is planning to complete a major update to their Flood Risk Tool. The organization also has goals to interconnect their existing data from different departments. This section will provide an example of how elements from both methods from this study can be used to achieve these various goals. The example was completed in ArcGIS Pro.

If a transportation planner had funds to allot to transportation projects and was seeking an equitable way to prioritize where the funds were rewarded, they could use approaches from Methods 1 and 2 to do so. Since this is an equity-centered approach, the practitioner would first select for vulnerability. The vulnerability index from Method 2 is used here. In Figure 23, the TAZs highlighted are TAZs that have consistent scores across all core services. Planners with specific goals can filter further to meet the needs of their community. For example, if a planner knew their community had accessibility issues specific to food, they could choose to view only highly vulnerable TAZs within the category of grocery store accessibility. This example will look at TAZs with high vulnerability in accessibility to all core services.

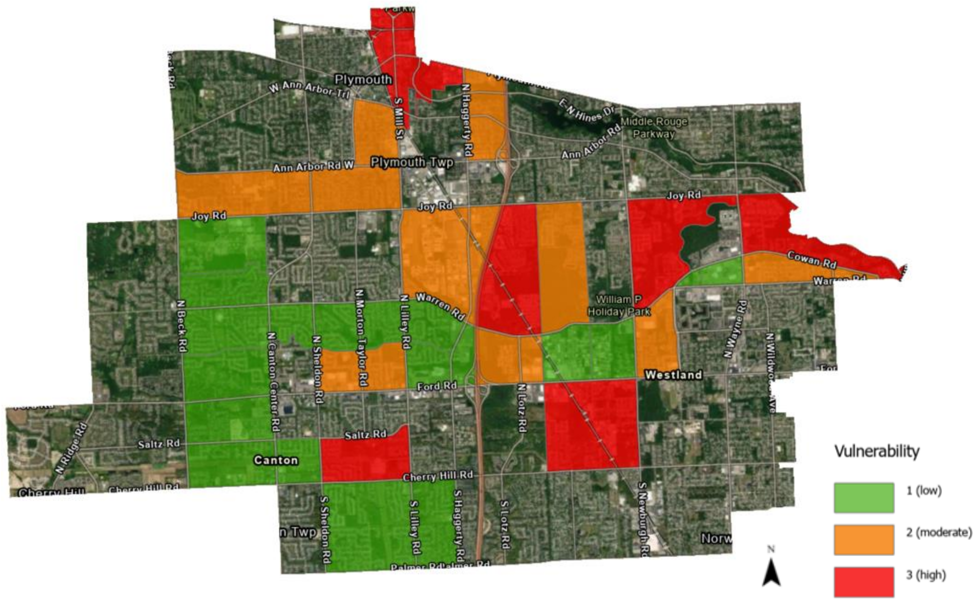

Fig. 23. Map of study area filtered to show vulnerability scores that are consistent across all core services for Method 2. The red TAZs will be the areas of highest concern as they have high vulnerability in accessibility to hospitals, grocery stores, and schools.

Next, the high-risk roads layer can be applied to view road segments that are highly susceptible to damages from flooding. To include issues that may arise from connectivity to these high-risk roads, the roads that were deemed inaccessible in Method 1 can be added. These road segments are highlighted in bright blue (Fig. 24).

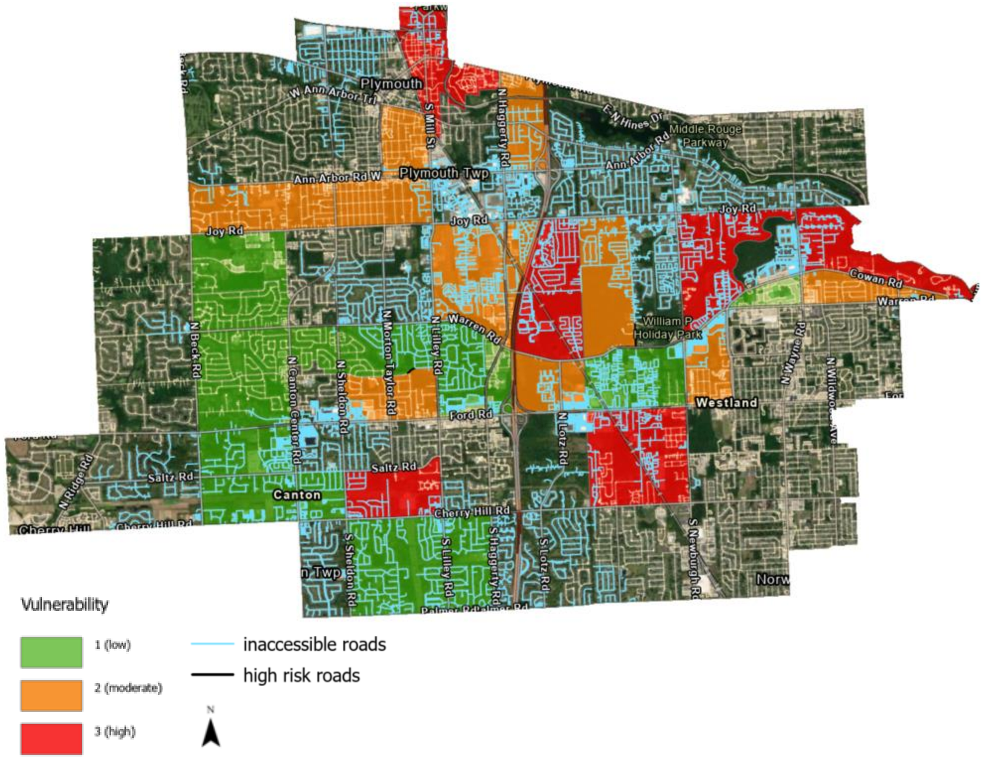

Fig. 24. Map of study area filtered to show vulnerability scores that are consistent across all core services for Method 2 and the inaccessible roads layer from Method 1.

Planners can then zoom into an area they believe needs to be prioritized. Using an equity-lens and the available socioeconomic, transportation, and flooding data, this would be areas in a red TAZ (highly vulnerable TAZ), near/intersecting a black line (high-risk road segment), and near/intersecting a blue line (inaccessible road segment). Figure 25 is a TAZ in which these statements are all true. This TAZ is also a viable choice because it is located near the busy highway of I-275.

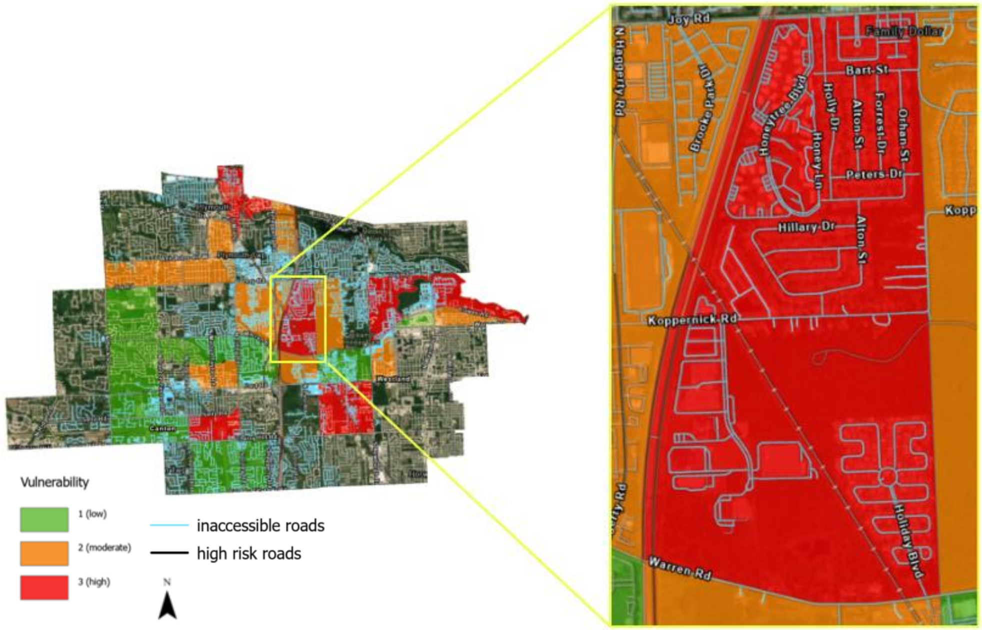

Fig. 25. A close-up of the selected TAZ. This TAZ is highly vulnerable in accessibility to all core services, contains a high proportion of high-risk roads, and a high proportion of inaccessible roads.

To select a specific road project to prioritize, planners should focus on identifying roads that are high-risk, inaccessible, and intersecting a highly vulnerable TAZ. Zooming in further and temporarily removing geographic labels allows better visibility to identify such areas. Figure 26 shows three points that fit the previous description. Figure 27 replaces the geographic labels to allow for identification of road names. From this, planners with the goal of equitably prioritizing projects can conclude that the points on Joy Road and Koppernick Road should be prioritized.

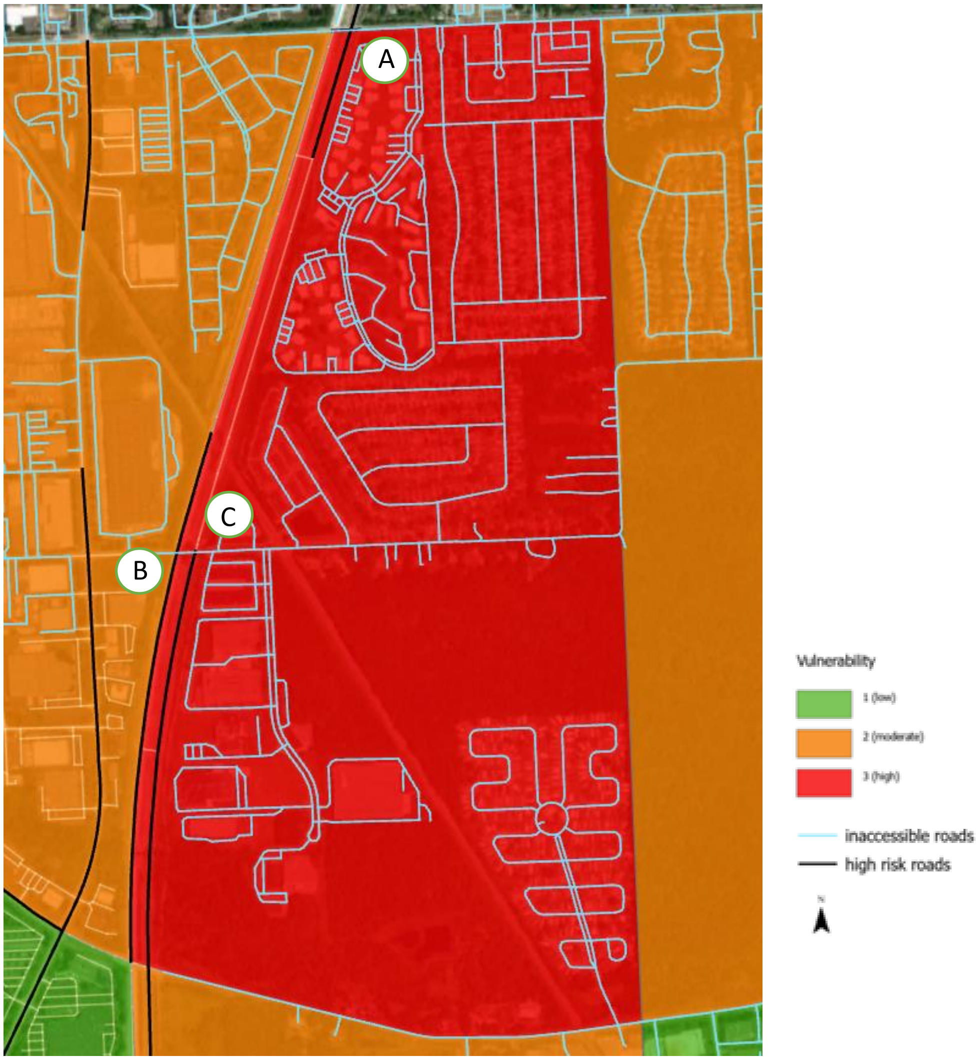

Fig. 26. Map showing the selected TAZ. Points of intersection between the highly vulnerable TAZ, high-risk roads, and inaccessible roads are labeled as A, B, and C.

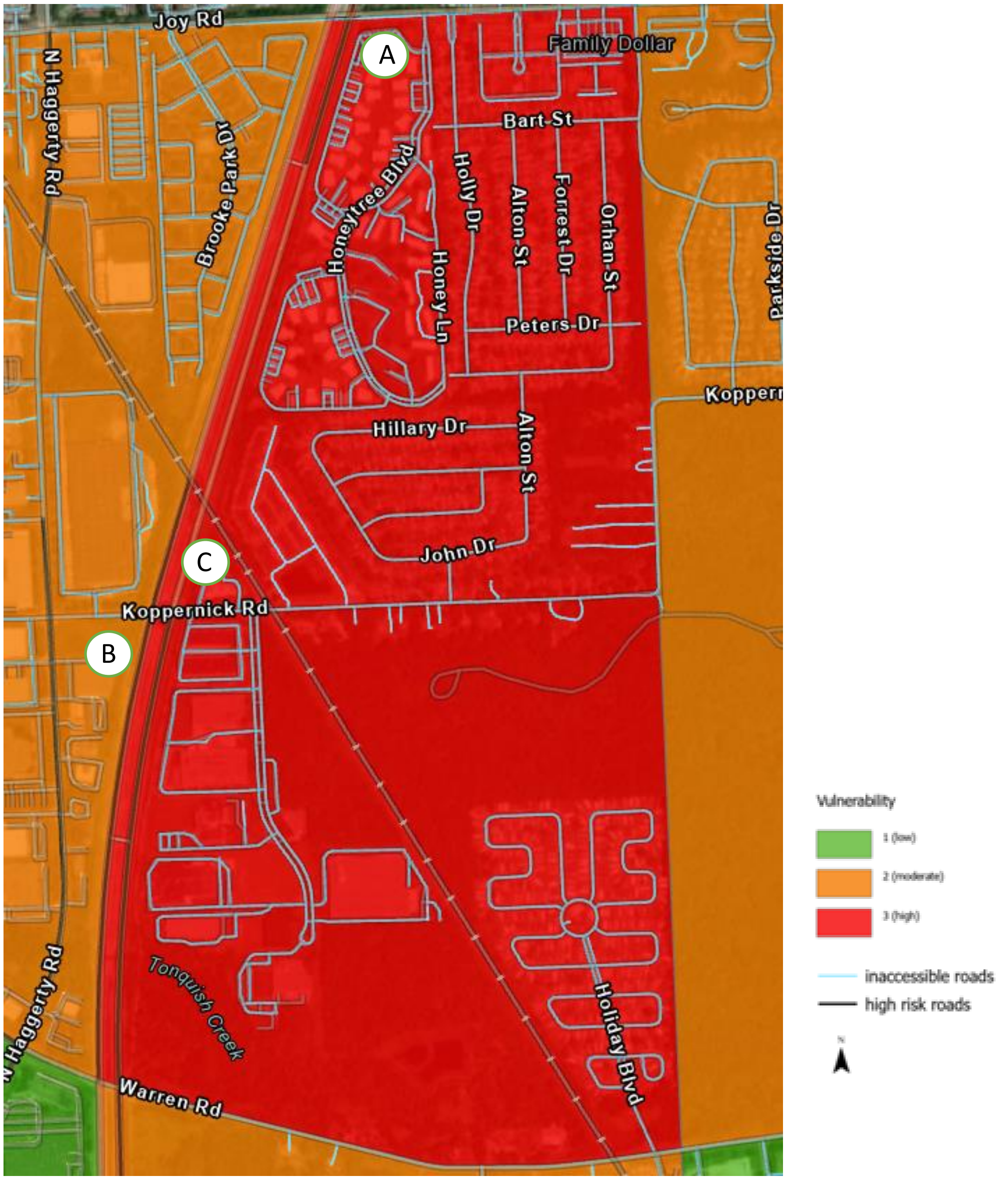

Fig. 27. Map showing the selected TAZ. Points of intersection between the highly vulnerable TAZ, high-risk roads, and inaccessible roads are labeled as A, B, and C. These areas of concern are along Joy Road and Koppernick Road.

Selecting the points of intersection along Joy and Koppernick Road allows the planner to view specific road data, vulnerability data, and flooding data (Fig. 28). Some of the relevant information that can be viewed includes the Flood Risk Tool risk score, traffic volume, the vulnerability score of the intersecting TAZ, average income, and the drivetimes associated with accessibility to core services at a baseline and flood-impacted level. These factors can be helpful understanding why the selected area is vulnerable and allows the practitioner to better form a strategic approach to the planning process.

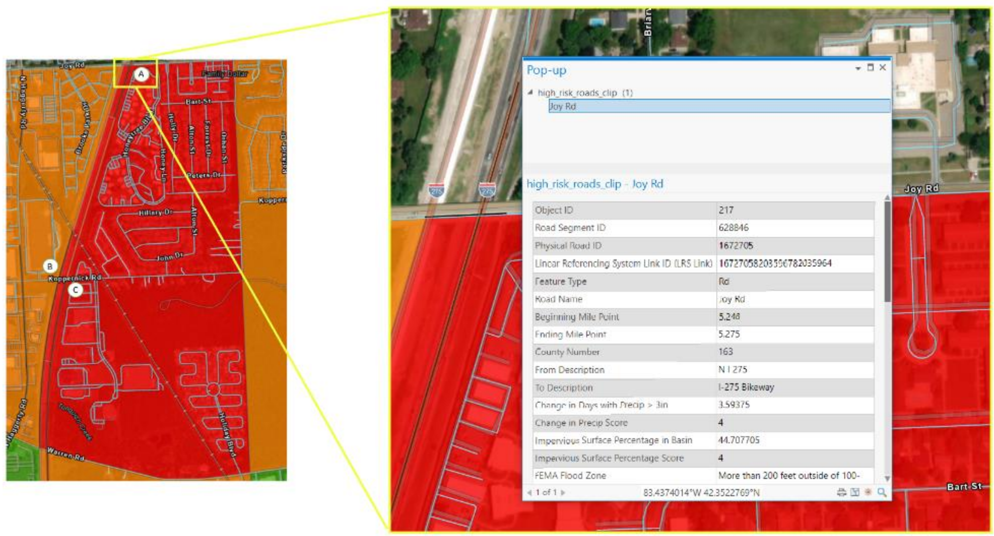

Fig. 28. Close-up of selected road segment. Selecting the road segment allows the user to view specific transportation data, vulnerability data, and flooding data.

6.3 Additional Analyses

As previously mentioned, future iterations of this study should include road data in a more precise manner. This could be done by using road length or lane miles in addition to the number of roads in a TAZ. Another improvement would be to expand the definition of a core service. Locations such as community centers and churches that can be used as shelter during a flood event may be included. Expanding the list of grocery store locations to include non-traditional food sources such as farmers markets, dollar stores, and gas stations could also give insight into accessibility inequities (Dong et al., 2020). Perhaps the most valuable expansion of this study would be to complete a similar analysis for pedestrian and public transportation, as access to a private automobile is an equity issue within itself (Litman, 2022; Sandt et al., 2016; Zuo et al., 2020). Public transportation is often a central method of transportation in historically disadvantaged areas and for community members who are of low income and/or who are minorities (Litman, 2022). Further, walkability and the ability to bike to public transit stations needs to be considered in expanding the definition of accessibility (Zuo et al., 2020).

7. Conclusion

The simultaneous increase in the severity and frequency of floods and the rise of urban sprawl has created a need for models and tools to assist in flood mitigation and transportation planning. Spatial models can allow planners to better understand how flood events disrupt accessibility to core services. Identifying where these disruptions take place and the communities that experience them can give insight into why inequities exist in relation to flooding. However, if the objective is to minimize inequity and work towards climate justice, variables reflective of socioeconomic conditions need to be at the center of models and tools. Transportation, flood, and equity data should be weighed equally in the frameworks created. Employing an equity-lens allows planners to explicitly address disparities and begin to strategize ways to minimize them.

Methods used in this study seek to reflect an equity-centered framework. Both methods approach vulnerability through an equity-lens by using accessibility to core services as proxy. Variables chosen for each analysis were directly relevant to the core service being analyzed by identifying groups most dependent on the service. The vulnerability index can be broken down to explore how vulnerability manifests in communities. For example, in an area with high vulnerability of accessibility to schools, it could be useful to examine how many people in the area work hourly education jobs. A flood event could be detrimental to such employees as they could face delays or complete impediments to earning their income. Having this type of data integrated and available in transportation and flood planning gives planners a greater opportunity to create solutions that best meet the specific needs of their communities.

The difference between Methods 1 and 2 demonstrates that the way the integration occurs, and the order of operations matters. Comparisons of the methods show that Method 2 tends to identify more TAZs as highly vulnerable than Method 1. This is likely because the way transportation data is evaluated in Method 2 recognizes the connectivity of road networks and how segments along a route can have a cascading impact on one another. Despite the statistically significant difference between Methods 1 and 2 for schools and grocery stores, elements from both methods can be used to in the prioritization process of transportation projects. As demonstrated in the practitioner example, overlaying the inaccessible roads layer from Method 1 on the vulnerability layers from Method 2 allows planners to precisely pinpoint areas of concern in terms of equity, transportation, and susceptibility to flooding.

The methods created in this study provide an equitable approach to flood mitigation and transportation planning. Possible iterations of this project could include expanding the modes of transportation to include public and pedestrian transit, expanding the area of study, broadening the definition of a ‘core service’, and developing a model that assigns demographic data to the road segments themselves rather than aggregated at the TAZ scale. This model and its many related predecessors clearly show that climate injustice exists. In improving models and tools, it is crucial to consider how their results can either compound inequities or help to minimize them. Intentionally placing equity at the center of analyses can help ensure that the latter occurs. Research should be expanded to explicitly assess transportation networks disparities in relation to flooding.

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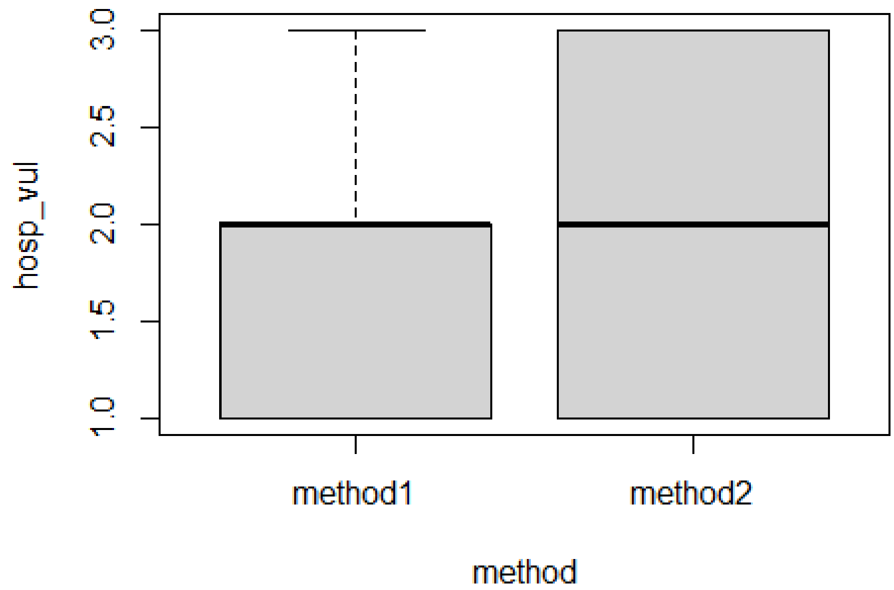
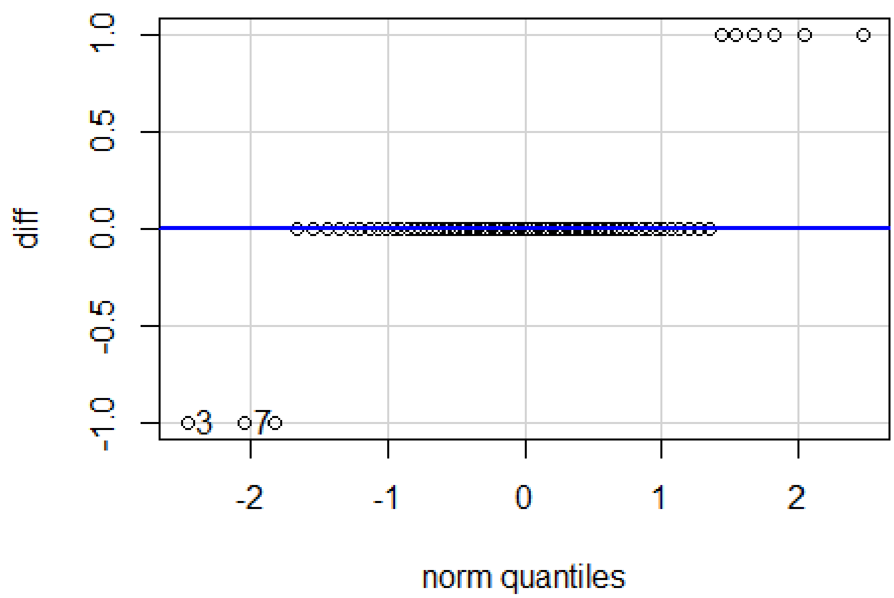
Appendix: T-Test Code Comparing Method 1 and Method 2

Code for Hospital T-test

```
## Hospitals

#Null: Methods 1 and 2 are not different in determining vulner
ability in accessibility to hospitals.
#Alt: Methods 1 and 2 are different in determining vulnerabili
ty in accessibility to hospitals.

# Read in Data
hosp_t <- read.csv("/Users/19526/Downloads/thesis_ttest1.csv")
head(hosp_t)

##    method hosp_vul sch_vul groc_vul
## 1 method1        3       2        1
## 2 method1        2       1        2
## 3 method1        2       1        2
## 4 method1        2       2        1
## 5 method1        3       3        2
## 6 method1        2       2        2

# Subset
hosp_test <- hosp_t[1:2]
head(hosp_test)

##    method hosp_vul
## 1 method1        3
## 2 method1        2
## 3 method1        2
## 4 method1        2
## 5 method1        3
## 6 method1        2

boxplot(hosp_vul~method, data=hosp_test)
```



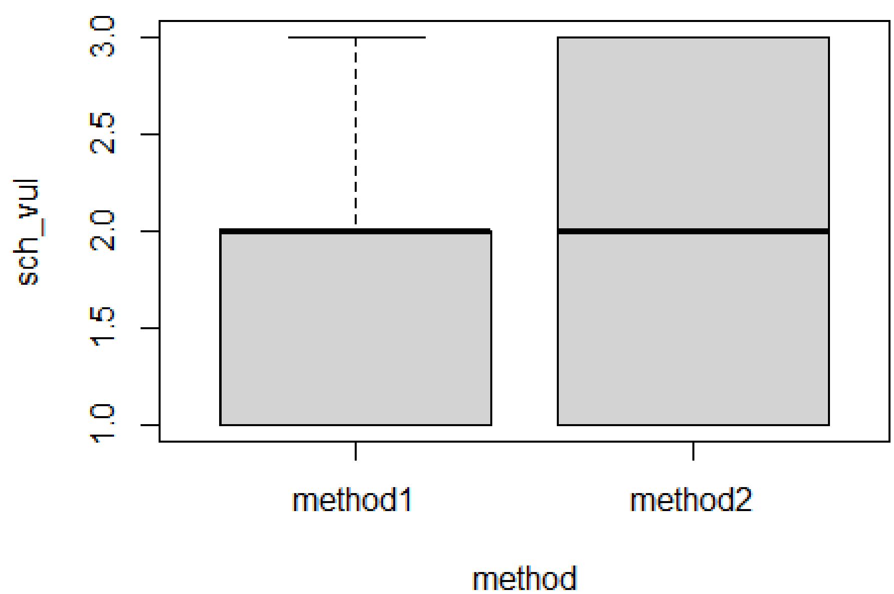

```
# Normality Test
method1 <- subset(hosp_test,method=='method1')
method2 <- subset(hosp_test,method=='method2')
diff <- method2$hosp_vul - method1$hosp_vul
shapiro.test(diff)

##
##  Shapiro-Wilk normality test
##
## data:  diff
## W = 0.47247, p-value = 7.303e-15

library(car)

## Loading required package: carData

qqPlot(diff)
```




```
## [1] 3 7

t.test(hosp_vul~method, data=hosp_test, paired = TRUE)

##
##  Paired t-test
##
## data:  hosp_vul by method
## t = -1, df = 73, p-value = 0.3206
## alternative hypothesis: true difference in means is not equ
al to 0
## 95 percent confidence interval:
##  -0.12133772  0.04025664
## sample estimates:
## mean of the differences
##             -0.04054054

# Accept null hypothesis (p-val >.05) at a 95% confidence leve
l.The mean vulnerability score for hospital accessibility for
Method 2 is lower than Method 1 by .04.
```

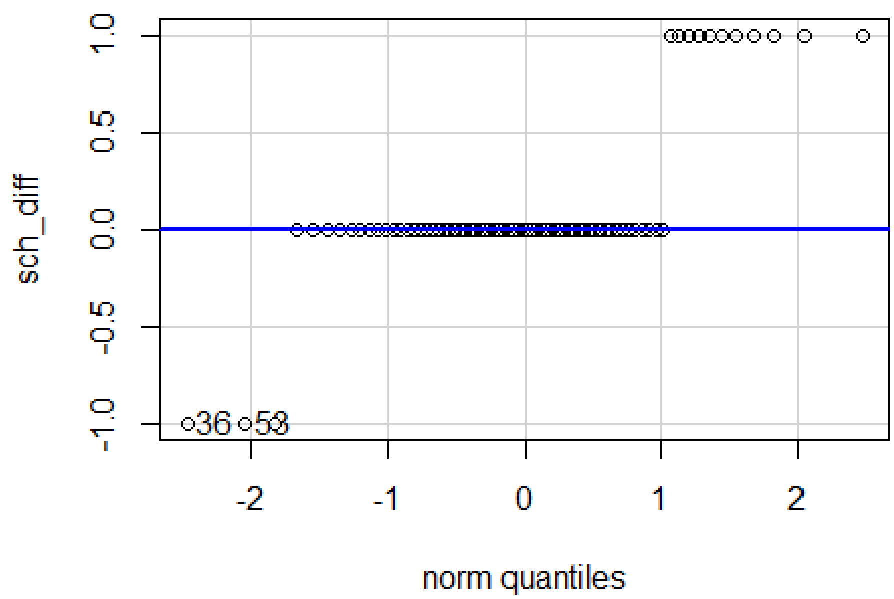
Code for School T-test

```
# Schools
#Null: Methods 1 and 2 are not different in determining vulner
ability in accessibility to schools.
#Alt: Methods 1 and 2 are different in determining vulnerabili
ty in accessibility to schools.

# Subset
sch_t <- hosp_t[c(1,3)]
head(sch_t)

##    method sch_vul
## 1 method1       2
## 2 method1       1
## 3 method1       1
## 4 method1       2
## 5 method1       3
## 6 method1       2

boxplot(sch_vul~method, data=sch_t)
```




```
# Normality Test
sch_method1 <- subset(sch_t,method=='method1')
sch_method2 <- subset(sch_t,method=='method2')
sch_diff <- sch_method2$sch_vul - sch_method1$sch_vul
shapiro.test(sch_diff)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  sch_diff
## W = 0.57499, p-value = 2.608e-13

qqPlot(sch_diff)
```

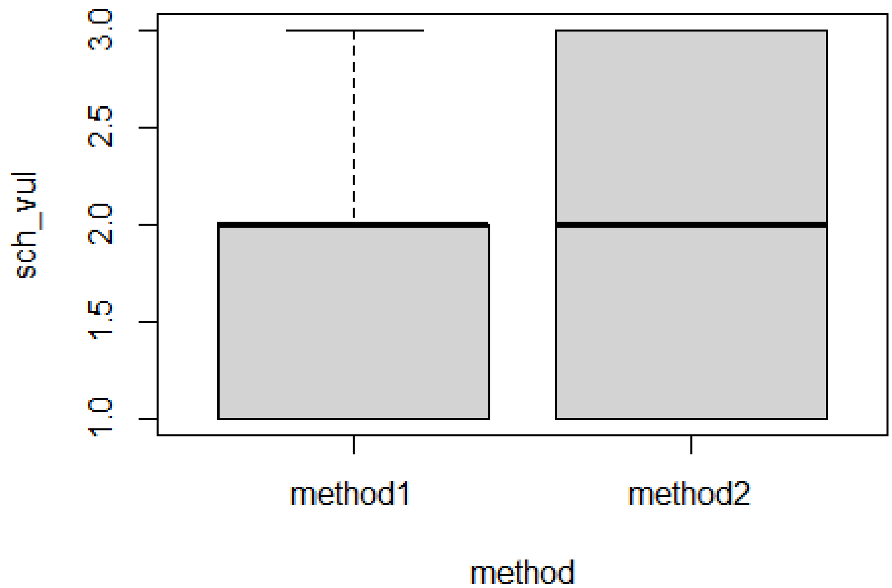



```
## [1] 36 53

t.test(sch_vul~method, data=sch_t, paired = TRUE)

##
##  Paired t-test
##
## data:  sch_vul by method
## t = -2.1924, df = 73, p-value = 0.03154
## alternative hypothesis: true difference in means is not equu
al to 0
## 95 percent confidence interval:
##  -0.206383923 -0.009832293
## sample estimates:
## mean of the differences
##               -0.1081081
```

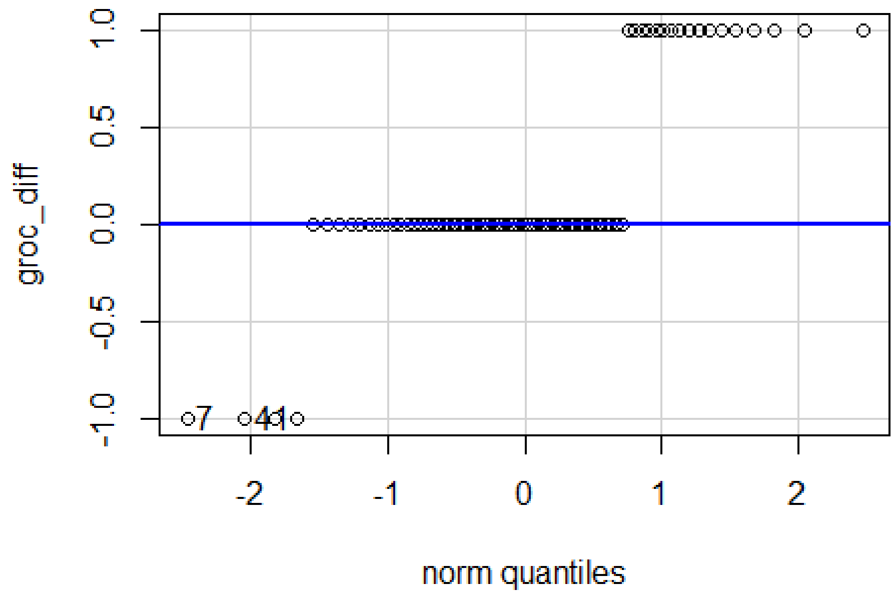
```
# Reject null hypothesis (p-val <.05) at a 95% confidence leve
l. The mean vulnerability score for school accessibility for M
ethod 2 is lower than Method 1 by .11.
```

Code for Hospital T-test

```
# Grocery Stores
#Null: Methods 1 and 2 are not different in determining vulner
ability in accessibility to grocery stores.
#Alt: Methods 1 and 2 are different in determining vulnerabili
ty in accessibility to grocery stores.

# Subset
groc_t <- hosp_t[c(1,4)]
head(groc_t)

##    method groc_vul
## 1 method1        1
## 2 method1        2
## 3 method1        2
## 4 method1        1
## 5 method1        2
## 6 method1        2

boxplot(sch_vul~method, data=sch_t)
```




```
# Normality Test
groc_method1 <- subset(groc_t,method=='method1')
groc_method2 <- subset(groc_t,method=='method2')
groc_diff <- groc_method2$groc_vul - groc_method1$groc_vul
shapiro.test(groc_diff)

##
##  Shapiro-Wilk normality test
##
## data:  groc_diff
## W = 0.67622, p-value = 1.724e-11

qqPlot(groc_diff)
```




```
## [1]  7 41

t.test(groc_vul~method, data=groc_t, paired = TRUE)

##
##  Paired t-test
##
## data:  groc_vul by method
## t = -2.9846, df = 73, p-value = 0.003861
## alternative hypothesis: true difference in means is not equ
al to 0
## 95 percent confidence interval:
##  -0.29298659 -0.05836476
## sample estimates:
## mean of the differences
##               -0.1756757

# Reject null hypothesis (p-val <.05) at a 95% confidence leve
l. The mean vulnerability score for school accessibility for M
ethod 2 is lower than Method 1 by .18
```