Integrate Socioeconomic Vulnerability for Resilient Transportation Infrastructure Planning

Final Report

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by

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for

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| 16. Abstract  This research project develops a novel methodology for assessing transportation network vulnerability and resilience, with a particular focus on incorporating social vulnerability into the analysis. The study addresses a critical gap in existing research by integrating socioeconomic vulnerability indicators into the evaluation of transportation infrastructure vulnerabilities for areas facing multi-hazards, using the Portland metropolitan area as a case study.  The methodology combines spatial analysis, network modeling, and social vulnerability indices to identify critical links in the transportation system. It assesses the impact of potential disruptions on accessibility to essential services such as hospitals, emergency shelters, schools, and community centers. The study considers multiple natural hazards, including earthquakes, floods, and landslides, providing a comprehensive risk assessment.  Key innovations include the integration of social vulnerability measures to highlight differential impacts on various population groups, ensuring equity considerations in resilience planning. The research reveals that some links, while not critical for the overall network, can have substantial localized impacts on specific communities, particularly those with high social vulnerability.  The findings provide valuable insights for policymakers and transportation planners in prioritizing infrastructure investments for retrofit, repair, and reconstruction. The methodology developed can be used for scenario planning, allowing stakeholders to evaluate different mitigation strategies and their potential impacts on network resilience and social equity.  While the study focuses on the Portland area, the approach is designed to be adaptable to other urban areas, contributing to broader efforts in transportation resilience planning. The research also identifies limitations and areas for future investigation, including the need to consider multi-modal transportation, incorporate business vulnerability, and address data uncertainties. | | | | | |
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# excutive Summary

Transportation networks are a vital lifeline essential to the functionality of modern society (Platt 1995). Disruption to transportation networks can interrupt economic production and severely impact people’s daily lives (Miller 2003). Transportation infrastructure is vulnerable to the impact of natural disasters, such as earthquakes, floods, landslides, and severe weather (Jenelius and Mattsson 2015). The restoration of damaged transportation infrastructure can take months or even years after disasters (Chang 2000). Therefore, it is critical to prepare transportation infrastructure for potential disasters. To do that, it is imperative to understand the vulnerability of transportation networks and the potential consequences of disruption.

Developing quantitative indices for measuring transportation vulnerability is important because they allow comparison of various threats and trade-offs among potential mitigation and response measures (Chen et al. 2007). These indices help identify the links that are most vulnerable to the impact of disasters, most critical in terms of their contribution to network accessibility, and most impactful in terms of the induced socioeconomic consequences due to their interruptions. This information is crucial for pre-disaster mitigation planning and post-disaster recovery planning. It can be used to rank the importance of transportation infrastructure in retrofitting, repairs, and reconstruction.

There has been recent progress in building transportation vulnerability models, many of which center on accessibility, a fundamental concept in transportation analysis and planning. For example, Chen et al. (2007) developed network-based accessibility measures for assessing transportation network vulnerability due to disruption. Based on a hypothetical network structure, they demonstrated how to calculate the increase in network travel time or generalized travel cost associated with one or more link failures. Sohn (2006) proposed an accessibility index and applied it to calculate the loss of accessibility due to hypothetical disruption of transportation network links within the floodplain in Maryland. This modeling framework allows the identification of priority links (with high percentages of potential accessibility loss) for retrofit to prevent disruption to road networks. Jenelius and Mattsson (2015) considered both single-link disruptions and area-covering network disruptions. The latter represent spatial correlation among adjacent links/nodes. They calculated disrupted travel times in the worst-case plausible scenario for the Swedish road network.

Berdica (2002) pointed out that both probabilities and consequences should be considered in risk evaluation. The increases in travel time cause social consequences such as loss of income, reduced accessibility to societal services, and reduced welfare (Jenelius and Mattsson 2015). Some existing models consider socioeconomic measures such as population and employment sizes in the calculation of consequences (Jenelius, Petersen, and Mattsson 2006; Lu et al. 2014; Sohn 2006). However, they treat all populations and/or employment as uniform entities and have not differentiated the varying levels of social vulnerabilities among individuals.

The concept of social vulnerability is well-established in social sciences and has been applied in disaster management (Cutter, Boruff, and Shirley 2003; Flanagan et al. 2011; Tate 2012). Due to social and place inequalities, certain groups of people, such as those with low income, minorities, seniors, etc., could suffer higher levels of adverse impacts from disruptions. Thus, the end-users of the transportation system differ in their abilities to cope with transportation disruption. For equity and social justice purposes, we should consider social vulnerability in consequence measures in studies of transportation vulnerability. However, to our knowledge, no existing research has incorporated socioeconomic vulnerability in planning for resilient transportation infrastructure.

In summary, previous research and current practice heavily focus on the vulnerability of the transportation infrastructure alone and largely ignore the socioeconomic vulnerability of the communities dependent on the infrastructure. In this research, we will integrate socioeconomic vulnerability indicators into the vulnerability assessment of transportation systems. We will consider both the vulnerabilities of individuals and households (for equality consideration) and community businesses (for economic impact).

This project contributes to the NITC theme of improving mobility of people and goods to build strong communities by ensuring the mobility for vulnerable populations so that their access to critical services and opportunities will not be hampered extensively in case of a hazard. It also develops data, models, and tools for resilience planning.

The project aims to improve mobility for all people, particularly socially vulnerable populations, through enhancing the resilience of transportation networks in case of disasters, which is a hallmark of strong communities. By integrating the social vulnerability concept into the assessment of the resilience of transportation networks, we pay special attention to the connections between transportation, land use, and the spatial distribution of people and businesses. Our research will identify the barriers to mobility and accessibility in case of a transportation network failure due to disasters for the general population and businesses, and for more vulnerable groups. Our methodology allows us to identify the links in the transportation network that are most vulnerable to the impact of disasters, most critical in terms of their contribution to mobility and accessibility, and most impactful in terms of the induced socioeconomic consequences due to their interruptions. This information can help policy-makers prioritize investments in infrastructure improvements in preparation for disasters, prioritize repairs and reconstruction after a disaster to overcome these barriers, and improve accessibility and equity. We believe this is a critical element of the NITC theme of improving mobility of people and goods to build strong communities.

The data, models, and tools we developed for this project can be adopted by others for resilient transportation planning. We collected and integrated four major types of data, including data on hazard exposure (i.e., earthquake, landslides, floods, etc.), social vulnerability, transportation networks, and essential services.

We then developed accessibility measures and conducted travel modeling for the purpose of resilient transportation planning. Finally, we assessed the impacts on mobility and the loss of accessibility for transportation links that are most exposed to hazards. Besides the data we collected and our methodology documented in papers and conference presentations, the final products also include a decision support tool that can help cities, regions, and states prioritize disaster preparation, repairs and reconstruction, and optimize the use of the transportation system in case of a disaster. We use the Portland metropolitan area as a case study, but our methods and tools can be easily applied to other regions. The data, models, and tools have been made available to researchers, practitioners, and the general public according to our data management plan.

# INTRODUCTION

The resilience of transportation networks is crucial for the functionality of modern society, particularly in the face of natural disasters. The Portland metropolitan area, like many urban regions, faces multiple hazard risks, including a high risk of earthquakes and medium risks of landslides, wildfires, and floods. This research project develops a new methodology that incorporates community social vulnerability in the evaluation of transportation infrastructure vulnerabilities for areas facing multi-hazards.

Transportation networks are vital lifelines that, when disrupted, can severely impact economic production and people’s daily lives (Miller 2003; Jenelius and Mattsson 2015). The restoration of damaged transportation infrastructure can be a lengthy process, often taking months or even years after disasters (Chang 2000). Therefore, it is critical to prepare transportation infrastructure for potential disasters, which requires a thorough understanding of the vulnerability of transportation networks and the potential consequences of disruption.

Recent developments in transportation resilience and social vulnerability assessment have paved the way for more comprehensive approaches to disaster preparedness. For instance, the City of Portland has developed an all-hazards transportation recovery plan, funded by the Federal Transit Administration. This plan provides an integrated process for transitioning from emergency response to mobility recovery strategies. Building on this, Oregon Metro and the Regional Disaster Preparedness Organization (RDPO) have revised regional emergency transportation routes and conducted a Social Vulnerability Tools Project (Oregon Metro 2021). These efforts have established a common operating profile of people in the region who are most likely to experience barriers to disaster preparedness services and programs.

Furthermore, in support of the Portland All-Hazards Transportation Recovery Plan, MacArthur and Siwek (2020) developed a Portland Transportation Recovery Alternatives Prioritization Tool using Microsoft Excel. This tool allows for the ranking of transportation links based on their usage, access, and equity indicators. However, while these developments are significant, there remains a need for a more integrated approach that considers both the physical vulnerabilities of the transportation network and the socioeconomic vulnerabilities of the communities it serves.

Our research project synthesizes these efforts and advance the techniques by evaluating the importance of links in the transportation network, taking into consideration:

* Their exposure to hazard risks
* The direct and indirect impacts over the entire network
* The socioeconomic vulnerability of the populations affected

This comprehensive approach allows us to assess not just the physical resilience of the network, but also its role in maintaining accessibility and equity for all community members, especially those most vulnerable to disruptions. Specifically, our research addresses the following key questions:

1. Which areas and links are the most susceptible to disruptions in the transportation system?
2. Which links are the most critical to the operation of the transportation system as a whole and to specific areas?
3. Considering the socioeconomic vulnerabilities of people, which links are most impactful to socioeconomically vulnerable populations in a disaster?

To answer these questions, we employ a methodology that includes:

* Spatial analysis overlaying transportation networks and hazard maps
* Network analysis and modeling to rank the criticality of links in the transportation networks
* Construction and application of social vulnerability indices
* Integration of multiple data sources, including hazard exposure data, social vulnerability data, transportation network data, and essential services location data

Our approach goes beyond traditional methods by considering not just the physical aspects of the transportation network, but also the social and economic contexts in which it operates. This allows for a better understanding of resilience, one that accounts for the differential impacts of disasters on various population groups and considers equity in disaster preparedness and response.

The outcomes of this research have significant implications for policy and practice in transportation planning and disaster preparedness. By identifying the most critical and vulnerable links in the transportation network, and understanding their importance to different community groups, we can provide valuable insights for:

* Prioritizing infrastructure investments for retrofit, repair, and reconstruction
* Enhancing overall network resilience
* Developing more equitable disaster preparedness and response strategies
* Improving accessibility and mobility for all community members, particularly those most vulnerable to disruptions

While our case study focuses on the Portland metropolitan area, the methodology and tools developed in this project are designed to be adaptable to other regions facing similar multi-hazard risks. This research contributes to the broader field of transportation resilience planning and aligns with the National Institute for Transportation and Communities (NITC) theme of improving mobility to build strong communities.

By integrating physical infrastructure vulnerability assessment with social vulnerability considerations, this project provides a more comprehensive and equitable approach to creating resilient transportation systems in the face of natural disasters.

# Methodology

This project integrates methods from distinct academic fields and proposes an approach for assessing the resilience of transportation systems and service provision for the general public and vulnerable populations specifically.

Building on existing research on social vulnerability and accessibility, we develop our method to answer these three research questions laid out in the previous chapter:

1. Which areas and links are the most susceptible to disruptions in the transportation system?
2. Which links are the most critical to the function of the transportation system as a whole and to specific areas?
3. Considering the socioeconomic vulnerabilities of people, which links are most impactful to socioeconomically vulnerable populations in a disaster?

To answer the first research question, we rely on spatial analysis overlaying transportation networks and hazard maps. The City of Portland and Oregon Department of Geology and Mineral Industries (DOGAMI) release and maintain maps of geographic locations, propensity, and possible intensities of various hazards, including earthquakes, flooding, and landslides, for the Portland metropolitan area. We use GIS (Geographical Information System) to overlay the transportation networks and hazard maps to identify areas and links in the transportation system that are most susceptible to these hazards.

For the second research question, we apply network analysis and modeling to rank the criticality of links in the transportation networks. For links identified in the first research question, we compute and model their impact on mobility and accessibility to critical services (emergency medical facilities, potential shelter sites, etc.) and essential necessities (grocery stores, restaurants, and retail) assuming these links fail. Compared with the method prioritizing the current usage of links (traffic volume) used in the Portland Transportation Recovery Alternatives Prioritization Tool, network analysis and travel modeling allow us to take into account the connectivity and capacity of the transportation networks. On one hand, our method can identify links whose usage may not be high, but their failure would disconnect a substantial area (by population counts or by geographical size) from critical services; on the other hand, some of the normally busiest links may have feasible alternatives when these links fail in a disaster. This method allows us to compare the criticality of all links susceptible to hazards in the transportation network and find out the most critical links in terms of mobility and accessibility.

To answer the third research question, we construct a social vulnerability index and apply it as weights to the criticality calculation in the previous step. We use block group level data from the American Community Survey (ACS) to identify the spatial distribution of population (i.e., users of the transportation networks) and, particularly, socioeconomically vulnerable populations. Built on previous research, the socioeconomic characteristics of individuals and households, such as income, age, education, and minority status, are used to construct the social vulnerability index, which allows us to identify the spatial distribution of the most vulnerable population.

Finally, we combine results from these steps to show the links that are the most susceptible to the impact of disasters, most critical in terms of their contribution to mobility and accessibility, and most impactful in terms of the induced socioeconomic consequences due to their interruptions.

These steps are implemented as scripts written in the statistical programming language R. They are released as open-source software and can be used by other researchers or practitioners to conduct similar analyses for their region. The tool can also be used in scenario planning, for example, to study scenarios for retrofit and/or repairs to find the optimal mitigation and recovery strategy that can achieve the best efficiency and equality in terms of transportation accessibility in a disaster.

## Suspectability of Disasters

Like Portland, many metropolitan areas are susceptible to heightened risk of various natural disasters, such as earthquakes, floods, and landslides. While transportation networks are a lifeline for recovery from these disasters, they themselves are also vulnerable to damage and disruptions from these disasters. Risk, including disaster risk, is commonly operationalized as the product of two components: probability or susceptibility Pr(X) and consequence C(X), (Jenelius, Petersen, and Mattsson 2006). Assessing the probability of natural hazards is out of the scope of this project, and we instead rely on institutions specialized in assessing these probabilities. For our purpose, the consequence of disasters is the disruption to mobility and accessibility to essential services, which is covered in the next section.

In the state of Oregon, the Department of Geology and Mineral Industries (DOGAMI) conducts research and analysis on natural hazards in Oregon and publishes the information through Oregon HazVu: Statewide Geohazards Viewer (Bauer, Burns, and Madin 2018). Following the method used by Regional Disaster Preparedness Organization (RDPO) and Oregon Metro in their Regional Emergency Transportation Routes (RETR) project, we focus on earthquakes, landslides, and floods (Pyrch and Tu 2021). For each type of hazard, DOGAMI classifies the risk of each disaster. For example, for earthquakes, DOGAMI provides GIS files showing the perceived shaking (Figure 2.1) and potential damage for the Oregon Metro area.

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| A map of the state of california  Description automatically generated  Figure .: Perceived Shaking Intensity due to Earthquake (Source: Oregon DOGAMI) |

## Accessibility to Essential Services

In the transportation context, the term accessibility has two related but distinct definitions:

The first definition focuses on the ability of individuals with disabilities to use transportation systems and services (Litman 2019). The second refers to the ease with which people can reach desired destinations or services using available transportation options (Geurs and Wee 2004). While both definitions are relevant for planning for disasters, this report primarily focuses on the second definition, as the implications of the first are mostly at the facility and service level, while the second is more at the system level, corresponding to the focus of this project.

To measure accessibility, researchers typically employ cumulative opportunity measures or gravity-based models. These methods consider factors such as travel time, distance, and the spatial distribution of destinations or services (Handy and Niemeier 1997). Common metrics include the number of opportunities (e.g., jobs, healthcare facilities, or schools) reachable within a specified time threshold, or a weighted sum of opportunities adjusted for travel impedance (Levinson and Wu 2020).

For this project, we use travel distance by automobile to the nearest services as the primary metric of accessibility. One may argue that the road network, thus driving, is the most fragile and the most susceptible to damage and disruption in a disaster; walking and biking are likely more robust in such a situation. We choose the accessibility metric based on the driving mode for several reasons:

1. In most of the US, driving is the predominant mode of transportation and critical services are only accessible by driving for the majority of the population.
2. Not all travelers can walk or bike long distances amid a disaster. The young, old, and injured may not be able to walk or bike to reach critical services, but rely on driving or someone else driving them. Similarly, delivery of critical services such as medical assistance and rescue is most efficient using motor vehicles.
3. When the road network for driving is disrupted in a major disaster, transit service will likely be disrupted as well and cannot be relied upon.
4. Since driving is the most susceptible to disruption, metrics based on driving provide the worst-case measurement in a disaster.

We use travel distance by driving, that is, travel distance along the road network, instead of travel time, to essential services as the primary accessibility measure, because travel speed is less predictable in a disaster, as the road condition (and thus capacity) and traffic volume are unknown. Despite these unknowns, driving distance is a reasonable measure for accessibility to essential services, as being closer to these services is preferred, regardless of travel speed or mode.

To assess changes to accessibility due to disruption of the transportation network by disasters, we create hypothetical scenarios in which links in areas with high disaster risk are assumed damaged (i.e., removed from the network) and re-calculate the travel distance to nearest services for each scenario.

To compute the travel distance between origin and destination points, we need an efficient algorithm and software to route the large number of origin-destination pairs. dodgr, an R package for efficient flow aggregation over millions of routes within a network, provides such a solution (Padgham 2019). Even so, we are still constrained by computational speed, as the number of scenarios we need to evaluate is extremely large, and we limit ourselves to only evaluating links in high-risk areas.

## Social Vulnerability Index

Social vulnerability is defined as “the characteristics of a person or group in terms of their capacity to anticipate, cope with, resist and recover from the impacts of a natural hazard.” (Wisner et al. 2003) It is often used to understand how the broader conditions in which people are born, live, work, and age can worsen the impact of an unfortunate event like a natural disaster (Mah et al. 2023). The concept of social vulnerability is well-established in social science and has been applied in disaster management and planning, environmental science, and health science (Bauer, Burns, and Madin 2018; Cutter, Boruff, and Shirley 2003; Flanagan et al. 2011; Tate 2012). Due to social inequalities and place inequalities, certain groups of people, such as those with low income, minorities, seniors, and car-less households, could suffer higher levels of adverse impacts from disruptions. Thus, the end-users of the transportation system differ in their abilities to cope with transportation disruption. For equity and social justice purposes, we should consider social vulnerability in consequence measures for transportation vulnerability studies.

Social Vulnerability Indices (SVIs) are essential tools for assessing community resilience in the face of environmental and public health threats (Flanagan et al. 2011). These indices integrate multiple socioeconomic and demographic factors, such as poverty rates, access to transportation, and housing conditions, to create a comprehensive measure of vulnerability (Cutter, Boruff, and Shirley 2003; Van Zandt et al. 2012). In the United States, the Centers for Disease Control and Prevention (CDC) has developed a widely-used SVI that employs ACS data to rank census tracts based on 15 social factors grouped into four themes: socioeconomic status, household composition and disability, minority status, and housing type and transportation (Centers for Disease Control and Prevention (CDC) 2018). By aggregating these factors, SVIs provide emergency planners and public health officials with data-driven insights into which communities may require additional support during crises. This information is crucial for developing targeted interventions, allocating resources efficiently, and mitigating the impact of hazards on the most vulnerable populations (Bakkensen et al. 2017). The use of SVIs has become increasingly important in disaster preparedness and response planning, as well as in addressing health disparities and environmental justice issues (Bergstrand et al. 2015). Moreover, SVIs have been applied to enhance housing and neighborhood resilience, highlighting the interconnections between social vulnerability and the built environment (Van Zandt et al. 2012).

The SVIs in this project are drawn from Centers for Disease Control and Prevention (CDC) (2018) and Van Zandt et al. (2012). Figure 2.2 shows the variables used in CDC’s Overall Social Vulnerability Index (Centers for Disease Control and Prevention (CDC) 2018), while Table 2.1 shows the SVIs used by Van Zandt et al. (2012) in their assessment of housing and neighborhood resilience post natural disasters like Hurricane Katrina.

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| A diagram of a social status  Description automatically generated with medium confidence  Figure .: CDC’s Overall Social Vulnerability Indices (Source: CDC) |

|  |
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| **Table 2.1: van Zandt et al’s Social Vulnerability Indicators for Housing and Neighborhood Resilience**  A table of information  Description automatically generated with medium confidence |

Source: van Zandt et al, 2012.

Since the focus of this project is on short- and intermediate-term disruptions to the transportation network, we select the following SVIs, considering data availability and the relevancy to short- and intermediate-term travel needs in a disaster (Table 2.2):

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 2.2: Variables Used as Social Vulnerability Measures**   | Variables | | --- | | Percentage of population 5 or below | | Percentage of population 65 or above | | Percentage of population below 150% poverty line | | Percentage of population in group quarters | | Percentage of non-white population | | Percentage of population above 25 with less than high school education | | Percentage of population above 5 that speak English not well or not at all | | Percentage of population with Disability | | Percentage of occupied housing units without a vehicle | |

## Assess Link Vulnerability

While it may be desirable to identify links impacting the accessibility of each individual block group, the amount of information can be overwhelming. The impact can be aggregated by comparing the travel distance to each essential service destination weighted by population, either total population or socially vulnerable populations:

For a given type of destination (Hospitals, Shelters, Schools, and Community Centers):

, Equation 1

where is the shortest travel distance from block group to the nearest destination, while is the population (total or vulnerable populations).

The steps to calculate the changes in accessibility are:

1. Identify links with high risk of disruption,
2. Loop through high risk links , for each link :
   1. Remove or mask in the transportation network,
   2. Loop through each type of essential services, for each type of destination,
      1. Compute the travel distance to the nearest destination from each block group centroid
      2. Compute the travel distance weighted by total population or vulnerable populations
3. Identify link(s) with the largest impact on travel distance of individual block group, or weighted travel distance by populations.

# Data Sources

Considering the generalizability of our method, we draw from four sources of data that are widely available in the US:

1. Susceptibility to natural hazards
2. Transportation networks
3. American Community Survey
4. Location of essential services

## Susceptibility to Natural Hazards

As discussed in section [Section 2.1](#sec-prob-of-disasters), we rely on specialized agencies for information on susceptibility to natural hazards in the study area. Nationwide, the Federal Emergency Management Agency (FEMA) provides maps and geospatial data of flood risk (Federal Emergency Management Agency (FEMA) 2024) and earthquake risk (Federal Emergency Management Agency (FEMA) 2020). In the Portland case study, we rely on the hazard susceptibility data compiled for the Regional Emergency Transportation Routes (RETR) project (Pyrch and Tu 2021), which were originally created by the Oregon Department of Geology and Mineral Industries (DOGAMI). Figure 3.1 shows the risk of liquefaction, landslide, and flood in the Portland area.

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| A collage of maps of different regions  Description automatically generated  Figure .: Risk of Liquefaction, Landslides and Floods in the Portland Area |

## Transportation Networks

We use transportation networks to assess where they are more likely to be damaged in disasters and how these damages would impact the mobility and accessibility of residents, including socially vulnerable populations. The data need to include spatial network geometry with nodes and edges representing intersections/interchanges and links, respectively. The attribute table should also contain information, such as number of lanes and speed limit, necessary for routing (Ortúzar and Willumsen 2011). Besides road networks, other transportation networks include public transit networks, bicycle networks, and pedestrian networks. As discussed in section [Section 2.2](#sec-access-to-essential-services), this project focuses on road networks.

Transportation network data is commonly available from local, regional, and state transportation agencies. Other sources of network data include OpenStreetMap (Open Street Map n.d.). For the Portland case study, the road network data is obtained from Oregon Metro’s Regional Land Information System (Figure 3.2).

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| --- |
| A map of a city  Description automatically generated  Figure .: Transportation Network in the Portland Area |

### Links Susceptible to Disasters

By overlaying the transportation network (Figure 3.2) with areas of high risk of disasters (Figure 3.1), we identify the links in the network with high susceptibility to various disasters. Figure 3.3 shows links susceptible to the three types of disasters.

|  |
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| A map of a disaster  Description automatically generated  Figure .: Links in Transportation Network Suspectable to Disasters in the Portland Area |

## American Community Survey

Since Social Vulnerability Indices (SVIs) rely on US Census data as inputs, the selection of Census geographies for SVIs involves a trade-off between spatial resolution and information richness. Census tracts, block groups, and blocks represent progressively smaller geographic units, each offering advantages and limitations. While Census tracts offer rich data to measure social vulnerability, they are generally too large to be useful for assessing accessibility impact due to disruption to the transportation network. Blocks, on the other hand, have the finest spatial resolution but lack many variables of interest in measuring social vulnerability. Block groups offer a reasonable compromise in data availability and spatial scale (Van Zandt et al. 2012) and are used in this project. Van Zandt et al. (2012) also concludes that block groups are the viable compromise when considering rich social and economic data and homogeneous areas of socially vulnerable populations.

Figure 3.4 shows block group population for the Portland area.

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| --- |
| A map of a group of people  Description automatically generated  Figure .: Block Group Population Count (2015-2019 ACS) |

## Location of Essential Services

To determine the impact of disasters on accessibility, we need to have the location of essential services in GIS format. We focus on three types of essential services:

* 1. Hospitals and emergency medical services
  2. Potential sites for emergency services, including community centers and schools
  3. Shelter sites

To our knowledge, there are no public data sources providing these location data for the entire US. OpenStreetMap (Open Street Map n.d.) provides Points of Interest (POIs) data that include essential services, but since the data is collected by volunteers, the data quality is uneven and not always up-to-date. Other proprietary data sources, such as Google Places and InfoUSA, have better data quality but can only provide limited access without a paid subscription. The Longitudinal Employer-Household Dynamics (LEHD) is a public data source providing aggregated employment count by sector (NAICS) at the Census block level. It can be used to roughly approximate the location of essential services.

For the Portland case study, RDPO and Metro provide locational information of essential services (Figure 3.5).

When applying our method to areas for which location data is not available, we recommend looking into OpenStreetMap POI and LEHD data.

|  |
| --- |
| A collage of maps of different states  Description automatically generated  Figure .: Location of Essential Services in the Portland Area |

# Baseline Conditions

Before evaluating the vulnerability and resilience of the transportation network in the Portland area, we document the current conditions of social vulnerability and accessibility as our baseline.

## Social Vulnerability Indices

For this project, we build on the two sets of SVIs developed by Centers for Disease Control and Prevention (CDC) (2018) and Van Zandt et al. (2012). As discussed in Section [Section 2.3](#sec-method-svi) and [Section 3.3](#sec-data-acs), we choose the Census Block Group as the geography level for our SVI, balancing information richness and usefulness for accessibility analysis.

Below, we map the geographic distribution of each SVI and highlight the location of the top 30 block groups for each measure.

### Percentage of Population 5 or Below

Young children and older adults are more likely to be mobility constrained and in need of medical care and other services. In 5-year ACS data, variables B01001\_003 and B01001\_027 provide counts of young children (5 years or below) at the block group level (Figure 4.1).

|  |
| --- |
| A screenshot of a map  Description automatically generated  Figure .: Percentage of Population Below 5 by Block Group |

### Percentage of Population 65 or Above

[Figure 4.2](#fig-bg-g65) shows Block Group population 65 or above based on variable C21007\_017.

|  |
| --- |
| A screenshot of a map  Description automatically generated  Figure .: Percentage of Population 65 or Above by Block Group |

### Percentage of Occupied Housing Units without a Vehicle

Households without a vehicle are less likely to evacuate before a disaster Van Zandt et al. (2012) and are more dependent on public transit and other means of transportation. [Figure 4.3](#fig-bg-veh0) shows the percentage of occupied housing units without a vehicle based on block group variables B25044\_003 and B25044\_010.

|  |
| --- |
| A screenshot of a map  Description automatically generated  Figure .: Percentage of Occupied Housing Units Without a Vehicle by Block Group |

### Percentage of Non-white Population

According to Van Zandt et al. (2012), households in poverty and non-white households experienced lower evacuation rates. [Figure 4.4](#fig-bg-nonwh) shows the Percentage of Non-White Population by Block Group.

|  |
| --- |
| A map of white and blue regions  Description automatically generated with medium confidence  Figure .: Percentage of Non-White Population by Block Group |

### Percentage of Population in Group Quarters

People living in group quarters are more likely to have temporary shelter and housing recovery needs Van Zandt et al. (2012). However, as seen in [Figure 4.5](#fig-bg-gq), none of the block groups in the Portland area has a valid group quarter population value from the 2015-2019 5-year ACS data. For this reason, we exclude this SVI in further analysis.

|  |
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| A black and grey outline of a map  Description automatically generated  Figure .: Percentage of Population in Group Quarters by Block Group |

### Persons in Poverty

Households in poverty are less likely to evacuate before disasters. They have fewer resources to prepare and thus are more vulnerable in disasters Van Zandt et al. (2012). [Figure 4.6](#fig-bg-pov) shows the percentage of population in poverty based on block group variables C17002\_002 and C17002\_003 in the 5-year ACS.

|  |
| --- |
| A collage of maps of poverty  Description automatically generated  Figure .: Percentage of Population in Poverty by Block Group |

### Percentage of Population above 25 with Less than High School Education

Research by Van Zandt et al. (2012) shows that neighborhoods with higher proportions of low-education households have a greater proportion of homeowners without home insurance or unable to make emergency repairs to their homes. [Figure 4.7](#fig-bg-lhs) shows the percentage of population with less than high school education.

|  |
| --- |
| A screenshot of a map  Description automatically generated  Figure .: Percentage of Population with Less Than Highschool Education by Block Group |

### Percentage of Population above 5 that Speak English Not Well or Not at All

Population that speaks English not well or not at all may have difficulty receiving information or communicating their needs. They are more likely to need assistance in a disaster. [Figure 4.8](#fig-bg-eng) shows the percentage of population speaking English not well or not at all.

|  |
| --- |
| A screenshot of a map  Description automatically generated  Figure .: Percentage of Population Speaking English Not Well or Not At All by Block Group |

### Percentage of 20-64 Years Population with a Disability

Finally, population with a disability likely faces more challenges in a disaster and is more likely to need assistance with mobility and access to essential services.

Ideally, we would want to get population with a disability for all age groups, but some of the variables (C18130\_003, C18130\_010, and C18130\_017) are not available at the block group level. Therefore, we have narrowed the age range to 20-64 ([Figure 4.9](#fig-bg-disab)).

|  |
| --- |
| A screenshot of a map  Description automatically generated  Figure .: Percentage of 20-64 Years Population with a disability |

## Accessibility to Essential Services

As discussed in [Section 2.2](#sec-access-to-essential-services), we use travel distance to the nearest essential services as the accessibility measure. For the baseline condition, we preserve all links in the existing transportation network. [Figure 4.10](#fig-accessibility-baseline) shows the travel distance to the nearest destination by type of service.

|  |
| --- |
| A group of maps of different colors  Description automatically generated  Figure .: Driving Distance (kilometers) to the Nearest Service Location by Block Group |

# Assess Link Vulnerability

As discussed in Section [Section 2.2](#sec-access-to-essential-services), to assess the vulnerability of the transportation network in the Portland area, we evaluate the effect of susceptible links on accessibility to essential services by assessing the change in accessibility when one susceptible link is removed at a time. The change in travel distance due to the removal of susceptible links may be weighted by block group population or socially vulnerable populations identified by the SVIs in Section [Section 4.1](#sec-base-svis).

[Table 5.1](#tbl-agg-links) shows a list of the links with the highest aggregated impact on accessibility by type of essential services and population weights, and [Figure 5.1](#fig-map-high-impact-links) maps the location of these links.

A map with numbers and a number on it

Description automatically generated

Figure .: Links with the Highest Impact on Aggregated Accessibility

**Table 5.1: Links with the Highest Impact on Aggregated Accessibility by Type of Destination and Population Weights (Travel Distance to the Nearest Destination in meters)**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Link ID | Destination Type | Overall | Disability | Poverty | Non-White | ESL | <5 | 65+ | 0 Vehicle |
| 2844 | Community Centers |  |  |  |  | 98.9 |  |  |  |
| 3003 | Community Centers |  |  |  |  | 98.9 |  |  |  |
| 7729 | Community Centers | 141.9 |  | 105.9 | 250.5 | 141.4 | 163.2 | 111.9 | 96.6 |
| 7767 | Community Centers |  |  |  | 90.6 |  |  |  |  |
| 7826 | Community Centers |  |  |  | 92.2 |  |  |  |  |
| 7832 | Community Centers |  |  |  | 92.2 |  |  |  |  |
| 9410 | Community Centers |  | 228.2 |  |  |  |  |  |  |
| 9552 | Community Centers |  | 228.2 |  |  |  |  |  |  |
| 9555 | Community Centers |  | 228.2 |  |  |  |  |  |  |
| 9556 | Community Centers |  | 228.2 |  |  |  |  |  |  |
| 9597 | Community Centers |  | 228.2 |  |  |  |  |  |  |
| 2080 | Hospitals | 124.4 |  | 93.6 |  |  | 117.3 | 153.1 |  |
| 2130 | Hospitals | 124.4 |  | 93.6 |  |  | 117.3 | 153.1 |  |
| 2142 | Hospitals |  | 94.3 |  |  |  |  |  |  |
| 2310 | Hospitals |  | 99.3 |  |  |  |  |  |  |
| 2312 | Hospitals |  | 99.3 |  |  |  |  |  |  |
| 2398 | Hospitals |  | 94.3 |  |  |  |  |  |  |
| 2553 | Hospitals |  | 99.3 |  |  |  |  |  |  |
| 2557 | Hospitals |  | 94.3 |  |  |  |  |  |  |
| 2562 | Hospitals |  | 99.3 |  |  |  |  |  |  |
| 2572 | Hospitals |  | 94.3 |  |  |  |  |  |  |
| 2731 | Hospitals |  | 171 |  |  |  |  |  |  |
| 2732 | Hospitals |  | 171 |  |  |  |  |  |  |
| 2733 | Hospitals |  | 171 |  |  |  |  |  |  |
| 2734 | Hospitals |  | 171 |  |  |  |  |  |  |
| 2769 | Hospitals |  | 171 |  |  |  |  |  |  |
| 2844 | Hospitals |  |  |  |  | 99.7 |  |  |  |
| 2882 | Hospitals |  | 171 |  |  |  |  |  |  |
| 3003 | Hospitals |  |  |  |  | 99.7 |  |  |  |
| 3006 | Hospitals |  | 171 |  |  |  |  |  |  |
| 3823 | Hospitals |  |  |  | 94.6 | 177 |  |  |  |
| 3856 | Hospitals |  |  | 137.6 | 137.1 | 235.5 |  |  |  |
| 3857 | Hospitals |  |  |  | 94.6 | 177 |  |  |  |
| 3896 | Hospitals |  |  | 137.6 | 137.1 | 235.5 |  |  |  |
| 9410 | Hospitals |  | 256.2 |  |  |  |  |  |  |
| 9425 | Hospitals |  | 97.6 |  |  |  |  |  |  |
| 9552 | Hospitals |  | 256.2 |  |  |  |  |  |  |
| 9555 | Hospitals |  | 256.2 |  |  |  |  |  |  |
| 9556 | Hospitals |  | 256.2 |  |  |  |  |  |  |
| 9597 | Hospitals |  | 256.2 |  |  |  |  |  |  |
| 9678 | Hospitals |  | 97.6 |  |  |  |  |  |  |
| 11869 | Hospitals |  | 97.6 |  |  |  |  |  |  |
| 12233 | Hospitals |  | 94.3 |  |  |  |  |  |  |
| 12242 | Hospitals |  | 94.3 |  |  |  |  |  |  |
| 2844 | Shelters |  |  |  |  |  |  |  |  |
| 3003 | Shelters |  |  |  |  |  |  |  |  |
| 3856 | Shelters |  |  |  |  | 96 |  |  |  |
| 3896 | Shelters |  |  |  |  | 96 |  |  |  |
| 9555 | Shelters |  | 225.5 |  |  |  |  |  |  |
| 9556 | Shelters |  | 225.5 |  |  |  |  |  |  |

For the overall population, links 2080 and 2130 have the biggest impact on access to hospitals, lengthening the travel distance by 124.4 meters on average, while link 7729 lengthens the travel distance to the closest community centers by 141.9 meters on average. All other links change the weighted travel distance by no more than 100 meters.

For the population with disability (ACS definition), several links have a large impact: links 9410, 9552, 9555, 9556, and 9597 increase the weighted average travel distance by 256.21 meters and 228.24 meters to hospitals and community centers, respectively. Links 2731-2734, 2769, 2882, and 3006 all increase the weighted travel distance to hospitals by 171.05 meters.

For the population in poverty, links 3856 and 3896 increase their access to hospitals by 137.58 meters on average, and link 7729 increases their travel distance to community centers by 105.90 meters on average.

For the non-white population, link 7729 increases their travel distance to community centers by 250.46 meters on average, while links 3856 and 3896 both increase the travel distance to hospitals by 137.06 meters on average.

For people speaking English not well or not at all, link 7729 increases their travel distance to community centers by 141.36 meters on average. Links 3856, 3896, 3823, and 3856 increase the travel distance to hospitals by more than 171 meters on average.

For young children and older adults, link 7729 increases travel distance to community centers by 163.19 and 111.89 meters, respectively, on average. Links 2080 and 2130 lengthen their travel distance to the closest hospitals by 117.31 and 153.14 meters, respectively, on average.

No link increases the average travel distance for households without a vehicle to any essential service destination by more than 100 meters.

We didn’t perform the analysis on the group quarter population because there is no valid group quarter data at the block group level.

It is worth noting that weighted impacts differ for each vulnerable population group and from the overall population. A few links substantially affect more than one group of vulnerable populations: links 7729, 2080, 2130, 3856, and 3896.

While the aggregated measures presented above are helpful in digesting the results, many details are lost in the aggregation. To address this, our method allows us to examine the impact on travel distance for each individual block group (origin) by each susceptible link.

[Table 5.2](#tbl-indiv-link) shows the links that have the largest increase in travel distance for individual block groups by type of destinations. Similarly, [Figure 5.2](#fig-map-indiv-link) shows the location of these links.

While the number of links is too large to enumerate one by one, we highlight a few of the links here. Links 7804, 7818, 8993, or 8994, when either of them is disrupted, would increase the travel distance to community centers for block group 410670336001 by 27 kilometers (km) from 5 km to 32 km. According to 2015-2019 ACS, this block group has a population of 784 in 2019, including 25 in poverty, 75 non-white, 11 young children and 169 older adults, as well as 17 households without a vehicle.

For hospitals, disrupting links 7804, 7818, 8993, or 8994 would increase the travel distance for block group 410670336001 by 28 km to 34 km from 6 km.

For schools, the change in travel distance is relatively small since schools are distributed more widely, with the largest increase being for links 9259, 9260, 11219, and 2992, all at about 9 km from 2 km. Even though the increase is relatively small, it can still make a significant difference - potentially making the distance no longer accessible by walking.

For shelters, links 7804, 7818, 8993, and 8994 all increase the travel distance for block group 410670336001 by 20.69 km from 2.59 km, again making the distance no longer accessible by walking.

|  |
| --- |
| A map with numbers and a black text  Description automatically generated  Figure .: ID of Links with the Highest Impact on Individual Block Group |

**Table 5.2: Links Increasing Travel Distance the Most for Individual Block Group by Type of Destination**

|  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Link ID | Destination Type | Block Group GEOID | Distance w/o link (km) | Baseline Distance (km) | Δ Distance (km) | Population (2019) | Poverty | Non-White | ESL | <5 | 65+ | 0 Vehicle |
| 7804 | Community Centers | 410670336001 | 32.5 | 5.1 | 27.4 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 7818 | Community Centers | 410670336001 | 32.5 | 5.1 | 27.4 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 8993 | Community Centers | 410670336001 | 32.5 | 5.1 | 27.4 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 8994 | Community Centers | 410670336001 | 32.5 | 5.1 | 27.4 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 2844 | Community Centers | 410670325011 | 20.4 | 1.6 | 18.9 | 2309 | 465 | 591 | 170 | 103 | 317 | 151 |
| 3003 | Community Centers | 410670325011 | 20.4 | 1.6 | 18.9 | 2309 | 465 | 591 | 170 | 103 | 317 | 151 |
| 4925 | Community Centers | 410050223022 | 19.8 | 5 | 14.8 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 4929 | Community Centers | 410050223022 | 19.8 | 5 | 14.8 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 4930 | Community Centers | 410050223022 | 19.8 | 5 | 14.8 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 4931 | Community Centers | 410050223022 | 19.8 | 5 | 14.8 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 5202 | Community Centers | 410050223022 | 19.8 | 5 | 14.8 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 9411 | Community Centers | 410510099073 | 18.3 | 3.6 | 14.7 | 3370 | 305 | 452 | 14 | 265 | 703 | 18 |
| 9429 | Community Centers | 410510099073 | 18.3 | 3.6 | 14.7 | 3370 | 305 | 452 | 14 | 265 | 703 | 18 |
| 9690 | Community Centers | 410510099073 | 18.3 | 3.6 | 14.7 | 3370 | 305 | 452 | 14 | 265 | 703 | 18 |
| 12218 | Community Centers | 410510099073 | 18.3 | 3.6 | 14.7 | 3370 | 305 | 452 | 14 | 265 | 703 | 18 |
| 4925 | Community Centers | 410050223021 | 19.4 | 5.5 | 14 | 1960 | 18 | 71 | 50 | 200 | 224 | 25 |
| 4929 | Community Centers | 410050223021 | 19.4 | 5.5 | 14 | 1960 | 18 | 71 | 50 | 200 | 224 | 25 |
| 4930 | Community Centers | 410050223021 | 19.4 | 5.5 | 14 | 1960 | 18 | 71 | 50 | 200 | 224 | 25 |
| 4931 | Community Centers | 410050223021 | 19.4 | 5.5 | 14 | 1960 | 18 | 71 | 50 | 200 | 224 | 25 |
| 5202 | Community Centers | 410050223021 | 19.4 | 5.5 | 14 | 1960 | 18 | 71 | 50 | 200 | 224 | 25 |
| 9566 | Community Centers | 410510104071 | 16.4 | 3 | 13.5 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9583 | Community Centers | 410510104071 | 16.4 | 3 | 13.5 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9587 | Community Centers | 410510104071 | 16.4 | 3 | 13.5 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9588 | Community Centers | 410510104071 | 16.4 | 3 | 13.5 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9635 | Community Centers | 410510104071 | 16.4 | 3 | 13.5 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9647 | Community Centers | 410510104071 | 16.4 | 3 | 13.5 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9566 | Community Centers | 410510104091 | 16.4 | 3 | 13.5 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 9583 | Community Centers | 410510104091 | 16.4 | 3 | 13.5 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 9587 | Community Centers | 410510104091 | 16.4 | 3 | 13.5 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 9588 | Community Centers | 410510104091 | 16.4 | 3 | 13.5 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 9635 | Community Centers | 410510104091 | 16.4 | 3 | 13.5 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 9647 | Community Centers | 410510104091 | 16.4 | 3 | 13.5 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 7804 | Hospitals | 410670336001 | 34.6 | 6.1 | 28.5 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 7818 | Hospitals | 410670336001 | 34.6 | 6.1 | 28.5 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 8993 | Hospitals | 410670336001 | 34.6 | 6.1 | 28.5 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 8994 | Hospitals | 410670336001 | 34.6 | 6.1 | 28.5 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 2844 | Hospitals | 410670325011 | 20.8 | 1.9 | 19 | 2309 | 465 | 591 | 170 | 103 | 317 | 151 |
| 3003 | Hospitals | 410670325011 | 20.8 | 1.9 | 19 | 2309 | 465 | 591 | 170 | 103 | 317 | 151 |
| 4925 | Hospitals | 410050223022 | 19.4 | 2.9 | 16.4 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 4929 | Hospitals | 410050223022 | 19.4 | 2.9 | 16.4 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 4930 | Hospitals | 410050223022 | 19.4 | 2.9 | 16.4 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 4931 | Hospitals | 410050223022 | 19.4 | 2.9 | 16.4 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 5202 | Hospitals | 410050223022 | 19.4 | 2.9 | 16.4 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 4925 | Hospitals | 410050223021 | 18.9 | 3.4 | 15.6 | 1960 | 18 | 71 | 50 | 200 | 224 | 25 |
| 4929 | Hospitals | 410050223021 | 18.9 | 3.4 | 15.6 | 1960 | 18 | 71 | 50 | 200 | 224 | 25 |
| 4930 | Hospitals | 410050223021 | 18.9 | 3.4 | 15.6 | 1960 | 18 | 71 | 50 | 200 | 224 | 25 |
| 4931 | Hospitals | 410050223021 | 18.9 | 3.4 | 15.6 | 1960 | 18 | 71 | 50 | 200 | 224 | 25 |
| 5202 | Hospitals | 410050223021 | 18.9 | 3.4 | 15.6 | 1960 | 18 | 71 | 50 | 200 | 224 | 25 |
| 3965 | Hospitals | 410510072011 | 18.2 | 4.6 | 13.6 | 1226 | 145 | 218 | 0 | 0 | 270 | 33 |
| 9566 | Hospitals | 410510104071 | 18.3 | 4.7 | 13.6 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9583 | Hospitals | 410510104071 | 18.3 | 4.7 | 13.6 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9587 | Hospitals | 410510104071 | 18.3 | 4.7 | 13.6 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9588 | Hospitals | 410510104071 | 18.3 | 4.7 | 13.6 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9635 | Hospitals | 410510104071 | 18.3 | 4.7 | 13.6 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9647 | Hospitals | 410510104071 | 18.3 | 4.7 | 13.6 | 2750 | 199 | 262 | 0 | 54 | 326 | 0 |
| 9566 | Hospitals | 410510104091 | 18.3 | 4.7 | 13.6 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 9583 | Hospitals | 410510104091 | 18.3 | 4.7 | 13.6 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 9587 | Hospitals | 410510104091 | 18.3 | 4.7 | 13.6 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 9588 | Hospitals | 410510104091 | 18.3 | 4.7 | 13.6 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 9635 | Hospitals | 410510104091 | 18.3 | 4.7 | 13.6 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 9647 | Hospitals | 410510104091 | 18.3 | 4.7 | 13.6 | 4680 | 324 | 673 | 147 | 325 | 394 | 79 |
| 9259 | Schools | 410670322002 | 11.1 | 2.1 | 9 | 916 | 74 | 0 | 4 | 20 | 166 | 0 |
| 9260 | Schools | 410670322002 | 11.1 | 2.1 | 9 | 916 | 74 | 0 | 4 | 20 | 166 | 0 |
| 11219 | Schools | 410670322002 | 11.1 | 2.1 | 9 | 916 | 74 | 0 | 4 | 20 | 166 | 0 |
| 2992 | Schools | 410670330003 | 11.1 | 2.1 | 8.9 | 1542 | 76 | 254 | 63 | 35 | 237 | 0 |
| 7746 | Schools | 410670336002 | 11.9 | 3.5 | 8.4 | 693 | 88 | 48 | 0 | 23 | 177 | 0 |
| 7747 | Schools | 410670336002 | 11.9 | 3.5 | 8.4 | 693 | 88 | 48 | 0 | 23 | 177 | 0 |
| 7748 | Schools | 410670336002 | 11.9 | 3.5 | 8.4 | 693 | 88 | 48 | 0 | 23 | 177 | 0 |
| 7756 | Schools | 410670336002 | 11.9 | 3.5 | 8.4 | 693 | 88 | 48 | 0 | 23 | 177 | 0 |
| 7761 | Schools | 410670336002 | 11.9 | 3.5 | 8.4 | 693 | 88 | 48 | 0 | 23 | 177 | 0 |
| 10807 | Schools | 410670321033 | 9.8 | 1.5 | 8.4 | 3931 | 123 | 372 | 0 | 348 | 332 | 61 |
| 10968 | Schools | 410670333022 | 11.7 | 3.7 | 8 | 3903 | 91 | 314 | 12 | 193 | 722 | 0 |
| 10969 | Schools | 410670333022 | 11.7 | 3.7 | 8 | 3903 | 91 | 314 | 12 | 193 | 722 | 0 |
| 10970 | Schools | 410670333022 | 11.7 | 3.7 | 8 | 3903 | 91 | 314 | 12 | 193 | 722 | 0 |
| 9261 | Schools | 410670322002 | 9.8 | 2.1 | 7.6 | 916 | 74 | 0 | 4 | 20 | 166 | 0 |
| 7746 | Schools | 410670335001 | 19.3 | 11.9 | 7.4 | 960 | 126 | 103 | 0 | 0 | 202 | 0 |
| 7747 | Schools | 410670335001 | 19.3 | 11.9 | 7.4 | 960 | 126 | 103 | 0 | 0 | 202 | 0 |
| 7748 | Schools | 410670335001 | 19.3 | 11.9 | 7.4 | 960 | 126 | 103 | 0 | 0 | 202 | 0 |
| 7756 | Schools | 410670335001 | 19.3 | 11.9 | 7.4 | 960 | 126 | 103 | 0 | 0 | 202 | 0 |
| 7761 | Schools | 410670335001 | 19.3 | 11.9 | 7.4 | 960 | 126 | 103 | 0 | 0 | 202 | 0 |
| 9245 | Schools | 410670335001 | 19.3 | 11.9 | 7.4 | 960 | 126 | 103 | 0 | 0 | 202 | 0 |
| 9246 | Schools | 410670335001 | 19.3 | 11.9 | 7.4 | 960 | 126 | 103 | 0 | 0 | 202 | 0 |
| 10951 | Schools | 410670335001 | 19.3 | 11.9 | 7.4 | 960 | 126 | 103 | 0 | 0 | 202 | 0 |
| 7746 | Schools | 410670336003 | 26.4 | 19 | 7.4 | 883 | 29 | 38 | 0 | 39 | 175 | 0 |
| 7747 | Schools | 410670336003 | 26.4 | 19 | 7.4 | 883 | 29 | 38 | 0 | 39 | 175 | 0 |
| 7748 | Schools | 410670336003 | 26.4 | 19 | 7.4 | 883 | 29 | 38 | 0 | 39 | 175 | 0 |
| 7756 | Schools | 410670336003 | 26.4 | 19 | 7.4 | 883 | 29 | 38 | 0 | 39 | 175 | 0 |
| 7761 | Schools | 410670336003 | 26.4 | 19 | 7.4 | 883 | 29 | 38 | 0 | 39 | 175 | 0 |
| 9245 | Schools | 410670336003 | 26.4 | 19 | 7.4 | 883 | 29 | 38 | 0 | 39 | 175 | 0 |
| 9246 | Schools | 410670336003 | 26.4 | 19 | 7.4 | 883 | 29 | 38 | 0 | 39 | 175 | 0 |
| 10951 | Schools | 410670336003 | 26.4 | 19 | 7.4 | 883 | 29 | 38 | 0 | 39 | 175 | 0 |
| 7804 | Shelters | 410670336001 | 23.3 | 2.6 | 20.7 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 7818 | Shelters | 410670336001 | 23.3 | 2.6 | 20.7 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 8993 | Shelters | 410670336001 | 23.3 | 2.6 | 20.7 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 8994 | Shelters | 410670336001 | 23.3 | 2.6 | 20.7 | 784 | 25 | 75 | 0 | 11 | 169 | 17 |
| 10968 | Shelters | 410670333022 | 22.1 | 3.8 | 18.3 | 3903 | 91 | 314 | 12 | 193 | 722 | 0 |
| 10969 | Shelters | 410670333022 | 22.1 | 3.8 | 18.3 | 3903 | 91 | 314 | 12 | 193 | 722 | 0 |
| 10970 | Shelters | 410670333022 | 22.1 | 3.8 | 18.3 | 3903 | 91 | 314 | 12 | 193 | 722 | 0 |
| 2844 | Shelters | 410670325011 | 17.9 | 1.1 | 16.9 | 2309 | 465 | 591 | 170 | 103 | 317 | 151 |
| 3003 | Shelters | 410670325011 | 17.9 | 1.1 | 16.9 | 2309 | 465 | 591 | 170 | 103 | 317 | 151 |
| 10968 | Shelters | 410670335002 | 21.3 | 4.5 | 16.8 | 3351 | 45 | 368 | 14 | 226 | 297 | 18 |
| 10966 | Shelters | 410670335002 | 21.3 | 4.5 | 16.8 | 3351 | 45 | 368 | 14 | 226 | 297 | 18 |
| 10969 | Shelters | 410670335002 | 21.3 | 4.5 | 16.8 | 3351 | 45 | 368 | 14 | 226 | 297 | 18 |
| 10970 | Shelters | 410670335002 | 21.3 | 4.5 | 16.8 | 3351 | 45 | 368 | 14 | 226 | 297 | 18 |
| 4925 | Shelters | 410050223022 | 16.1 | 4.3 | 11.8 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 4929 | Shelters | 410050223022 | 16.1 | 4.3 | 11.8 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 4930 | Shelters | 410050223022 | 16.1 | 4.3 | 11.8 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 4931 | Shelters | 410050223022 | 16.1 | 4.3 | 11.8 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 5202 | Shelters | 410050223022 | 16.1 | 4.3 | 11.8 | 1610 | 165 | 196 | 0 | 43 | 422 | 0 |
| 9411 | Shelters | 410510099073 | 14 | 2.6 | 11.4 | 3370 | 305 | 452 | 14 | 265 | 703 | 18 |
| 9429 | Shelters | 410510099073 | 14 | 2.6 | 11.4 | 3370 | 305 | 452 | 14 | 265 | 703 | 18 |
| 9690 | Shelters | 410510099073 | 14 | 2.6 | 11.4 | 3370 | 305 | 452 | 14 | 265 | 703 | 18 |
| 12218 | Shelters | 410510099073 | 14 | 2.6 | 11.4 | 3370 | 305 | 452 | 14 | 265 | 703 | 18 |
| 5819 | Shelters | 410510104092 | 11.8 | 0.6 | 11.2 | 2391 | 38 | 218 | 0 | 119 | 242 | 0 |
| 5829 | Shelters | 410510104092 | 11.8 | 0.6 | 11.2 | 2391 | 38 | 218 | 0 | 119 | 242 | 0 |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Table 5.3: Frequency of Links Increasing the Travel Distance the Most for Individual Block Group by Type of Destination (Travel Distance to the Nearest Destination in kilometers)**   | Link ID | Unique block groups | Σ(Δ Distance) | | --- | --- | --- | | 7804 | 1 | 76.6 | | 7818 | 1 | 76.6 | | 8993 | 1 | 76.6 | | 8994 | 1 | 76.6 | | 4925 | 2 | 72.5 | | 4929 | 2 | 72.5 | | 4930 | 2 | 72.5 | | 4931 | 2 | 72.5 | | 5202 | 2 | 72.5 | | 2844 | 1 | 54.7 | | 3003 | 1 | 54.7 | | 9566 | 2 | 54.1 | | 9583 | 2 | 54.1 | | 9587 | 2 | 54.1 | | 9588 | 2 | 54.1 | | 9635 | 2 | 54.1 | | 9647 | 2 | 54.1 | | 10968 | 2 | 43.2 | | 10969 | 2 | 43.2 | | 10970 | 2 | 43.2 | | 9411 | 1 | 26.1 | | 9429 | 1 | 26.1 | | 9690 | 1 | 26.1 | | 12218 | 1 | 26.1 | | 7746 | 3 | 23.2 | | 7747 | 3 | 23.2 | | 7748 | 3 | 23.2 | | 7756 | 3 | 23.2 | | 7761 | 3 | 23.2 | | 10966 | 1 | 16.8 | | 9245 | 2 | 14.8 | | 9246 | 2 | 14.8 | | 10951 | 2 | 14.8 | | 3965 | 1 | 13.6 | | 5819 | 1 | 11.2 | | 5829 | 1 | 11.2 | | 9259 | 1 | 9.0 | | 9260 | 1 | 9.0 | | 11219 | 1 | 9.0 | | 2992 | 1 | 8.9 | | 10807 | 1 | 8.4 | | 9261 | 1 | 7.6 | |

[Table 5.3](#tbl-freq-indv-link) shows the frequency with which each link appears in [Table 5.2](#tbl-indiv-link) and how many unique block groups they affect. These are the links that increase the travel distance the most for some of the block groups when disrupted. Unlike the links in [Table 5.1](#tbl-agg-links), they do not necessarily affect travel distance substantially in aggregate, but their impact on access to essential services is concentrated on localized block groups. While it is important to pay attention to links in [Table 5.1](#tbl-agg-links), links in [Table 5.3](#tbl-freq-indv-link) also need attention in pre-disaster preparation and post-disaster restoration.

# Conclusion and Future Research

This research project has developed and demonstrated a novel methodology for assessing transportation network vulnerability and resilience, with a particular focus on incorporating social vulnerability into the analysis. By integrating multiple data sources and analytical techniques, we have provided a comprehensive framework for identifying critical transportation links and evaluating their importance in the context of disaster preparedness and response.

Our analysis of the Portland metropolitan area considered multiple natural hazards, including earthquakes, floods, and landslides, providing a more realistic assessment of the risks faced by transportation networks in disaster-prone regions. Through network analysis and accessibility modeling, we identified the most critical links in the transportation system – those which, if disrupted, would have the most significant impact on overall network performance and accessibility to essential services.

A key innovation of our approach is the integration of social vulnerability indices into the assessment, highlighting the differential impacts of network disruptions on various population groups. This ensures that equity considerations are central to resilience planning efforts. Our methodology focused on accessibility to critical services such as hospitals, emergency shelters, schools, and community centers, providing valuable insights for emergency planning and resource allocation during disaster response.

Interestingly, the research revealed that some links, while not necessarily critical for the overall network, can have substantial localized impacts on specific communities, particularly those with high social vulnerability. This finding underscores the importance of considering both system-wide and localized effects in resilience planning.

The implications of this research for policy and practice are significant. Our findings can guide policymakers and transportation planners in prioritizing infrastructure investments for retrofit, repair, and reconstruction to enhance overall network resilience. By highlighting the links most critical to socially vulnerable populations, this research supports more equitable disaster preparedness and response strategies. Furthermore, the methodology we’ve developed can be used for scenario planning, allowing stakeholders to evaluate different mitigation strategies and their potential impacts on network resilience and social equity.

Our approach demonstrates the power of data-driven decision-making in resilience planning. By integrating multiple data sources – hazard maps, transportation networks, census data, and essential service locations – we’ve shown how data-driven analyses can inform more effective and equitable planning decisions.

## 6.1 Limitations and Future Research

While our study provides valuable insights, it’s important to acknowledge its limitations and identify areas for future research:

1. **Limited Disaster Types**: We considered only three types of disasters likely to occur in Portland: earthquakes, floods, and landslides. Future studies could expand to include other disaster types such as pandemics, wildfires, severe air quality events, and heat waves. While our methodology can be adapted to some extent, each disaster type impacts travel differently and requires specific consideration.
2. **Temporal Scope**: Our analysis primarily addresses pre-disaster preparation and immediate post-disaster recovery. Future research could explore intermediate- and long-term disruption scenarios, which might involve different strategies such as population relocation, creation of new facilities or service locations, or construction of alternative road links.
3. **Correlated and Unknown Risk**: To manage computational constraints, we assessed the impact of damaged links individually. However, real disasters often damage multiple links simultaneously, potentially amplifying accessibility impacts. Future studies could explore methods to efficiently analyze these complex, multi-link failure scenarios. Additionally, our focus on high-risk areas meant that potentially impactful failures in lower-risk areas were not assessed, presenting another avenue for future investigation. It further adds to the complexity of the problem that links outside areas susceptible to high risk of disaster may be brought down and have an outsized impact on accessibility.
4. **Social Vulnerability of Businesses**: While there is substantial research on population social vulnerability, less is known about business vulnerability. Due to data limitations, our project focused on residents. Future research could develop frameworks and gather data to incorporate business vulnerability into resilience assessments.
5. **Multi-modal Transportation**: This study primarily focused on road networks. Future work could expand to include public transit, pedestrian, and bicycle networks for a more comprehensive assessment of transportation resilience, particularly important for vulnerable populations who may rely more heavily on these alternative modes.
6. **Data Uncertainty**: Some data sources, particularly the American Community Survey (ACS), have high degrees of uncertainty. Variables used in our Social Vulnerability Indices (SVIs) often have high margins of error at the block group level. Future research could incorporate these uncertainty measures into the analysis, potentially using probabilistic methods to provide more robust results.
7. **Validation and Calibration**: As with any modeling approach, validation with real-world data from past disasters would strengthen the methodology’s reliability and applicability. Future studies could focus on comparing model predictions with actual disaster impacts and recovery patterns.
8. **Scalability and Transferability**: While demonstrated in the Portland area, further research could explore the applicability of this methodology to other urban areas with different geographic, demographic, and hazard profiles. This could lead to the development of more generalized tools and frameworks for resilience planning.

By addressing these limitations and pursuing these research directions, future studies can build upon our work to create more comprehensive, accurate, and widely applicable methodologies for assessing and enhancing transportation network resilience and accessibility in the face of diverse disaster scenarios.

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**Appendix A Source Code**

The source code for the project is available on Github <https://github.com/cities-lab/network-resilience>. Here we include the main functions implemented in R for completeness.

library(tigris)

library(sf)

library(dplyr)

library(sf)

library(tmap)

library(tidyr)

library(stringr)

library(glue)

library(dodgr)

road\_sf <- st\_read("data/RETR/v107/etr\_master\_layers\_ftp.gdb",

query = "select \* from MotorVehicleSystem\_RLIS",

quiet = TRUE

)

# road\_sf <- st\_transform(road\_sf, crs\_pdx\_bg)

## Weighting network will lose "geometry"

network <- st\_cast(road\_sf, "LINESTRING") |>

st\_set\_geometry("geometry") |>

mutate(id = 1:n()) # since LOCALID is not unique

links\_disrupted <- function(gdb\_layer, condition\_query, network, disaster\_type, buffer = 100) {

# 100 ft buffer

disaster\_sf <- st\_read("./data/RETR/v107/etr\_master\_layers\_ftp.gdb",

# layer = "Landslides\_poly",

query = glue("select \* from {gdb\_layer} where {condition\_query}"),

quiet = TRUE

)

# buffer <- 100 # unit: feet

## Identify the disaster polygons nearby the road network

disaster\_nearby <- st\_intersection(

disaster\_sf,

st\_buffer(network, buffer)

)

links\_ <- network[st\_buffer(disaster\_nearby, buffer), ]

links\_[["disaster\_type"]] <- disaster\_type

links\_ |> st\_drop\_geometry()

}

calculate\_tt <- function(network, broken\_link\_ids, origin\_coords, dest\_coords) {

# flag broken links as MOTORCODE 99

network\_ <- network %>%

mutate(

MOTORCODE =

ifelse(id %in% broken\_link\_ids, 99, MOTORCODE)

) |>

st\_transform(crs\_pdx\_bg) # lonlat

way <- sort(unique(network\_[["MOTORCODE"]]))

weights <- rep(1, length(way))

broken\_weight <- 0.0001

if (99 %in% way) {

weights[way == 99] <- broken\_weight

} else {

way <- c(way, 99)

weights <- c(weights, broken\_weight)

}

wts <- data.frame(

name = "custom",

way = way,

value = weights[1:length(way)]

)

wt\_network <- weight\_streetnet(network\_,

wt\_profile = wts,

type\_col = "MOTORCODE",

id\_col = "id"

)

wt\_network <- wt\_network[wt\_network$component == 1, ]

tt\_mtx <- dodgr\_dists(wt\_network,

from = origin\_coords,

to = dest\_coords

)

apply(tt\_mtx, 1, min)

}

library(purrr)

library(furrr)

library(future)

library(progressr)

links\_susp\_df <- links\_susp |>

select(id, disaster\_type) |>

distinct(id, .keep\_all = TRUE)

plan(multisession, workers = 8)

parallel\_fn <- function(ids, dest\_coords\_) {

p <- progressor(steps = length(ids))

future\_map(ids, ~ {

p()

calculate\_tt(network, c(.x), origin\_coords, dest\_coords\_)

}, .options = furrr\_options(seed = T))

}

tt\_output\_file <- "output/intermediate/tt\_df.rds"

if (!file.exists(tt\_output\_file)) {

ids <- links\_susp\_df |> pull(id)

ids <- c(-1, ids) # -1 enables full network as ids are all > 0

tt\_df <- NULL

for (dest in names(dest\_coords\_ls)) {

print(dest)

with\_progress({

tt\_ <- parallel\_fn(ids, dest\_coords\_ls[[dest]])

})

df\_ <- tibble(id = ids, tt = tt\_, dest\_type = rep(dest, length(ids)))

# this works for first iteration when tt\_df is NULL too

tt\_df <- bind\_rows(tt\_df, df\_)

}

saveRDS(tt\_df, file = tt\_output\_file)

} else {

tt\_df <- readRDS(file = tt\_output\_file)

}

library(tidyr)

x\_df\_file <- "output/intermediate/x\_df.rds"

x\_gdf\_file <- "output/intermediate/x\_gdf.rds"

if (!file.exists(x\_df\_file) | !file.exists(x\_gdf\_file)) {

joined\_ldf\_file <- "output/intermediate/joined\_ldf.rds"

if (!file.exists(joined\_ldf\_file)) {

pdx\_bg\_ldf <- pdx\_bg |>

st\_drop\_geometry() |>

select(-moe19, -gq) |>

pivot\_longer(pop19:eng, names\_to = "variable")

geoids <- pdx\_bg |>

st\_drop\_geometry() |>

pull(GEOID)

tt\_df$GEOID <- list(geoids)

tt\_ldf <- tt\_df |> unnest(c(GEOID, tt))

joined\_ldf <- pdx\_bg\_ldf |>

left\_join(tt\_ldf, by = "GEOID", relationship = "many-to-many")

saveRDS(joined\_ldf, joined\_ldf\_file)

} else {

joined\_ldf <- readRDS(joined\_ldf\_file)

}

}

#x\_df\_file <- "output/intermediate/x\_df.rds"

if (!file.exists(x\_df\_file)) {

base0\_df <- joined\_ldf |>

# ungroup() |>

filter(id == -1) |>

select(-id, -value, tt0 = tt)

x\_df <- joined\_ldf |>

# ungroup() |>

filter(id != -1) |>

left\_join(base0\_df, by = c("GEOID", "dest\_type", "variable")) |>

mutate(delta\_tt = tt - tt0) |>

group\_by(dest\_type) |>

slice\_max(delta\_tt, n = 200)

saveRDS(x\_df, file = x\_df\_file)

} else {

x\_df <- readRDS(x\_df\_file)

}

#x\_gdf\_file <- "output/intermediate/x\_gdf.rds"

if (!file.exists(x\_gdf\_file)) {

summary\_gdf <- joined\_ldf |>

group\_by(id, dest\_type, variable) |>

summarize(wt\_tt = sum(value \* tt, na.rm = T) / sum(value, na.rm = T)) |>

ungroup()

base0\_gdf <- summary\_gdf |>

# ungroup() |>

filter(id == -1) |>

select(-id, wt\_tt0 = wt\_tt)

x\_gdf <- summary\_gdf |>

# ungroup() |>

filter(id != -1) |>

left\_join(base0\_gdf, by = c("dest\_type", "variable")) |>

mutate(delta\_wt\_tt = wt\_tt - wt\_tt0) |>

group\_by(variable, dest\_type) |>

slice\_max(delta\_wt\_tt, n = 30)

saveRDS(x\_gdf, x\_gdf\_file)

} else {

x\_gdf <- readRDS(x\_gdf\_file)

}