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AN EXPLORATION OF SOCIAL VULNERABILITY, EXPOSURE, AND FREIGHT TRANSPORT NETWORK DISRUPTION IN THE MID-ATLANTIC REGION

A Thesis in

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by

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ABSTRACT

Freight transportation infrastructure is crucial to economic prosperity and the functioning of modern society, but unanticipated events (e.g. weather-induced hazards), human-caused accidents, and/or malicious attacks can disable or reduce the capacity of components of the system (e.g. bridges & roads/highways segments). To ensure movement and access of agricultural/food commodities, there has been an increasing interest to assess the impact of failures on transportation networks. While transportation vulnerability and disaster risk management assessments often provide probable impacts of disruptions, very few planners and researchers consider societal equity dimensions that inform unequal impacts on communities. Impacts of disruptions can differ between urban and rural areas, hence, to promote equity and regional development, an integrated analysis approach that considers both physical transportation network and social vulnerability to perturbations is proposed. This framework will help us discover critical locations that influence disruption to food-flow commodities due to road network perturbations, and identify communities that are socially intolerant to access loss to food, water, and energy resources. Discovering the most vulnerable communities may inform emergency response planning by prioritizing those areas for resource allocations to reduce the societal impact of the loss of accessibility.

Knowledge of the vulnerability of freight transportation networks allows us to assess transport behaviors, identify critical components, and devise contingency plans for future resilience. Utilizing datasets that describe county-scale commodity flow and freight mobility performance, we built and examined a roadway network in the Mid-Atlantic region of the United States and associated flows that could be subject to disruptions. To quantify vulnerability to commodity flow disruptions, we constructed a social vulnerability index (SoVI) whose objective is to understand the spatial variability of household food, energy, and water insecurity in New York, New Jersey, and Pennsylvania. We determined the communities that are most exposed to risk from

failures and compared their importance with SoVI measures to describe consequences with ethical implications.

The results of the network's performance of vulnerability impact and exposure against various disruption scenarios indicate that it is robust against random failures but vulnerable to deliberate attacks (e.g. nodes/edges that transport the highest/maximum total amount of food flow). Overall SoVI scores denote that the most vulnerable counties are located in Philadelphia County (Philadelphia), PA, and Essex County (Newark), NJ. By integrating the counties' scores and rankings for both network vulnerability and SoVI, we identified the most vulnerable communities (High exposure-High SoVI). Discovering the most vulnerable communities may inform emergency response planning by prioritizing those areas for resource allocations to reduce the societal impact of the loss of accessibility.

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Chapter 1

Introduction

Background and Problem Statement

Freight transportation infrastructure is crucial to economic prosperity and the functioning of modern society, but unanticipated events (e.g., weather-induced hazards), human-caused accidents, and/or malicious attacks can disable or reduce the capacity of components of the system (e.g., bridges & roads/highways segments). Agricultural/food freight movement is heavily reliant on roads and highways (McCoy et al., 2020), and these distribution systems are vital in ensuring food security and feeding the U.S. population (Schipanski et al., 2016; Seekell et al., 2017). To ensure movement and access of these goods, there has been an increasing interest to assess the impact of failures on transportation networks, and making these systems more resilient (Faturechi and Miller-Hooks, 2015; Mattson and Jenelius, 2015; Miller-Hooks et al., 2012; Reggiani et al., 2015). While transportation vulnerability and disaster risk management assessments often provide probable impacts of disruptions, very few planners and researchers consider societal equity dimensions that inform unequal impacts on communities. A sustainable and equitable supply and demand transportation network is one "whose costs are paid by those who benefit and does not disproportionately favor or deny transportation improvements to certain demographic populations" (Ahmed et al., 2008). Concerns relating to equity and justice are themes of great interest in the transportation research domain, and the need to balance efficiency with equity and vulnerability considerations is widely acknowledged (Ahmed et al., 2008; Manaugh et al., 2015; Novak et al., 2020; Pereira et al., 2017; Sánchez et al., 2003).

Network-based approaches have been used previously in transportation risk assessments to capture the *short* and *long-term* consequences of disruptions in freight transportation (e.g., He et al., 2020; Jansuwan et al., 2021; Miller-Hooks et al., 2009; Park et al., 2011). Traditionally, transport network vulnerability analyses evaluate the overall impact of the network's performance after a perturbation and the importance of each component (e.g., based on contribution to network performance). The outcomes from the assessments are often used to prioritize interventions, such as strategic disinvestment of road infrastructure (Novak et al., 2020), climate-related resilient transport interventions (Demirel et al., 2015; Espinet et al., 2016; Ortega et al., 2020; Papilloud et al., 2020), and (post-) disaster transport infrastructure reparation (Aydin et al., 2019; Merschman et al., 2020; Nelson et al., 2019; Zhu et al., 2020). A societal vulnerability network analysis that is not often considered in such work is the identification of transport users' (including users in rural, low-density, low-income, and disadvantaged communities) *exposure* to disruptions. Jenelius et al. (2006) introduced the concept of user *exposure* in a case study of the Swedish road network and defined the exposure of a specific user to a particular reduction in system performance as the reduction in user service that follows from the performance reduction. Authors deduced that most exposed regions are explained by the network structure and the average user travel cost in the area and that this concept could be used to study and compare the situation for different groups of individuals that could be particularly severely impacted due to disruptions.

Transportation infrastructure vulnerability/risk reduction assessments should be consistent with the principles of society's sustainable development goals (Gudmundsson and Höjer, 1996), where no group should be impacted too severely, and the inequity between communities shouldn't be too considerable. Authorities and policymakers are responsible for the significance of this concern since they manage how to direct investments and actions to strengthen the network's accessibility against potential threats (Gilbert, 2003; Taylor, 2017). Recent federal policies have recognized the importance of ensuring equal support for underserved communities and sought to address this by instituting an executive order requiring agencies to assess equity concerning race, ethnicity, religion, income, geography, gender identity, sexual orientation, and disability (The White House, 2021). With regard to emergency management, FEMA has instituted several initiatives to increase opportunities so that all populations get help when they need it (FEMA, 2022).

Impacts of disruptions can differ between urban and rural areas, hence, to promote equity and regional development, an integrated analysis approach that considers both physical transportation infrastructure and social vulnerabilities to perturbations is proposed.

Equity and Justice in Transportation and Social Considerations

Transportation *equity* refers to the fairness of the dissemination of impacts (benefits and burdens), and the degree to which that distribution is regarded as fair and appropriate (Litman, 2017). Consideration of equity in freight transportation becomes convoluted since there's no standard process to describe injustice and analyze consequences (Behbahabi et al., 2019, Litman, 2017; Martens et al., 2012; Mercier, 2009). For instance, it is necessary to identify the equity "of what" (i.e., what good is being distributed), "for whom," and "how much" (e.g., Karner 2016; Karner and Niemeier 2013; Manaugh and El-Geneidy 2012). Besides, the interpretation of what is an appropriate distribution and by what moral, legal, or ethical basis this decision can be made has long been argued in the literature (e.g., Hunold and Young 1998; Young 2011). Nevertheless, equity-based transport studies have emerged in recent years to explicitly reflect on the *distributive consequences (*e.g., distribution of impacts among individuals*)* of transport policies (Beyazit, 2011; Di Ciommo and Shiftan, 2017; Lee et al., 2017; Van Wee, 2011), transport network design and planning (Behbahabi et al., 2019; France-Mensah et al., 2019; Mollanejad and Zhang, 2014; Shang et al., 2018), and transport vulnerability analysis (Jafino, 2021; Jenelius, 2010; Tahmasbi et al., 2021). Typically, these studies enhance travel demand models to include new indicators that increase equity or distributional considerations. The drawback of this current underlying equity perspective is that it centers on a *reformative* change (i.e. reforming processes and fine-tuning distributions). The scope of this work is to not only advocate for a reformative change but for a *transformative* approach with a broader consideration of transportation *justice* and society that can address community resilience and highlight social concerns related to transportation network vulnerability.

Assessing the *distributional* effects of physical perturbations on a transportation network can highlight priorities to reroute commodity flows after a disruptive event, or to repair/maintain critical network components. However, insecurity at the local-scale is most prominent to disasters, impacting substantial burdens on the socially and economically disadvantaged population. The capacity of local communities to endure these unanticipated events depends on various social and economic factors. As a result, understanding the broader societal consequences of physical disruption is critical when determining the allocation of resources to reduce community vulnerability. The term *social vulnerability* specifies how societal characteristics of individuals, groups, or communities impact their ability to anticipate, cope with and recover from hazards, and/or unprecedented events (Blaikie et al., 1994; Cutter, 2017). Generally, social vulnerability studies show that the most vulnerable communities are those with *limited resources* to withstand the effects of disruptive events (Paton et al., 2006). Similarly, Cutter et al., 2003, assert that the main cause of social vulnerability is *inequality* (e.g., inaccessibility to resources, income, age, physical limitations, etc.) which reduces the *capacity* of certain subpopulations to cope with and recover from hazards. Social vulnerability indicators have been developed and employed to demonstrate how sub-populations experience these impacts/hardships distinctively, and to address the vulnerabilities that arise due to the surrounding social environment (Morrow, 1999; Cutter et al. 2003; Tierney, 2009). The consideration of this social dimension is particularly critical for disaster preparedness efforts and humanitarian supply chain management (Gralla et al., 2014; Huang et al., 2012). For example, it can readjust the relief efforts and allocation of resources based on the varying vulnerability, expectations, and social demographics of the different communities (Arnette and Zobel 2019; Zolfaghari and Peyghaleh 2015).

To be able to deliver key and helpful information in the decision-making process, a performance analysis should appropriately represent community needs and impacts. In infrastructure modeling, the majority of literature that account for societal aspects in the context of physical infrastructure disruptions do so in very general and qualitative terms or remain largely conceptual without practical or solution-oriented research outcomes (Garschagen et al., 2018). Cutter et al. (2003) proposed a Social Vulnerability Index (SoVI) using principal component analysis (PCA) to combine a large number of factors into a single composite score at the county level. This indicator is not based on specific hazard risks but instead focuses on the general demographic characteristics that make a community more vulnerable to any hazard. Integrating this method could uncover disruptive impacts on transportation networks and their dependent communities, which can have benefits in supporting climate adaptation, and risk mitigation and planning. Recent studies have successfully incorporated a measure of social vulnerability (e.g., SoVI) to highlight the risk disparities to households due to physical-infrastructure disruptions (e.g., Balakrishnan and Zhang, 2018; Boyle et al., 2021; Dong et al., 2020; Eid and El-adaway, 2017; Karakoc et al., 2020; Lobban et al., 2021). However, in the context of transportation, Mattsson and Jenelius (2015) indicated the limited attention that has been given to how changes in a transportation network, due to failures, impact different travelers in different locations. Unlike the few recent network analysis that focuses on preventing social inequitable changes (e.g. Jafino, 2021; Jenelius, 2010; Tahmasbi et al., 2021), this research proposes an integrative approach that calls and addresses current inequalities. This framework accounts for community needs, builds community knowledge, and increases community buy-in of results.

Research Questions

Building upon previous gaps, this work seeks to leverage network science, transportation theory, and social vulnerability studies to showcase opportunities for incorporating equity and justice into disruption planning. Currently, there is limited work that targets how freight transportation network disruption may have impacts on different parts of the society, thus, integrating these concepts and creating a framework that can evaluate the risks to communities can signal to stakeholders their needs, and be instructive for emergency response. The research questions I seek to address are:

1) How does a physical freight transportation network in the Mid-Atlantic Region behave under different failure scenarios, and which communities are most exposed to disruption?
2) Who is socially vulnerable in the Mid-Atlantic Region?
3) How can we understand the potential ethical implications of freight transportation disruption by combining the two previous research questions?

The first research question will help us discover critical locations that influence disruption to food-flow commodities due to road network perturbations. These areas could be prioritized for transportation planning so that the critical routes, roads, and/or intersections are prioritized for hazard mitigation and protection. Identification of communities that are socially intolerant to access loss to food, water, and energy resources could allow managers to promote the inclusion of people's needs in the relief and resource allocation sitting decision-making. Discovering the most vulnerable communities may inform emergency response planning by prioritizing those areas for resource allocations to reduce the societal impact of the loss of accessibility.

Chapter 2

Materials and Methods

To analyze the physical consequences of disruptive events on the transportation of food commodities by truck, we modeled a physical roadway network that incorporates existing freight transportation databases. The proposed framework for this work is illustrated in Fig 2-1.

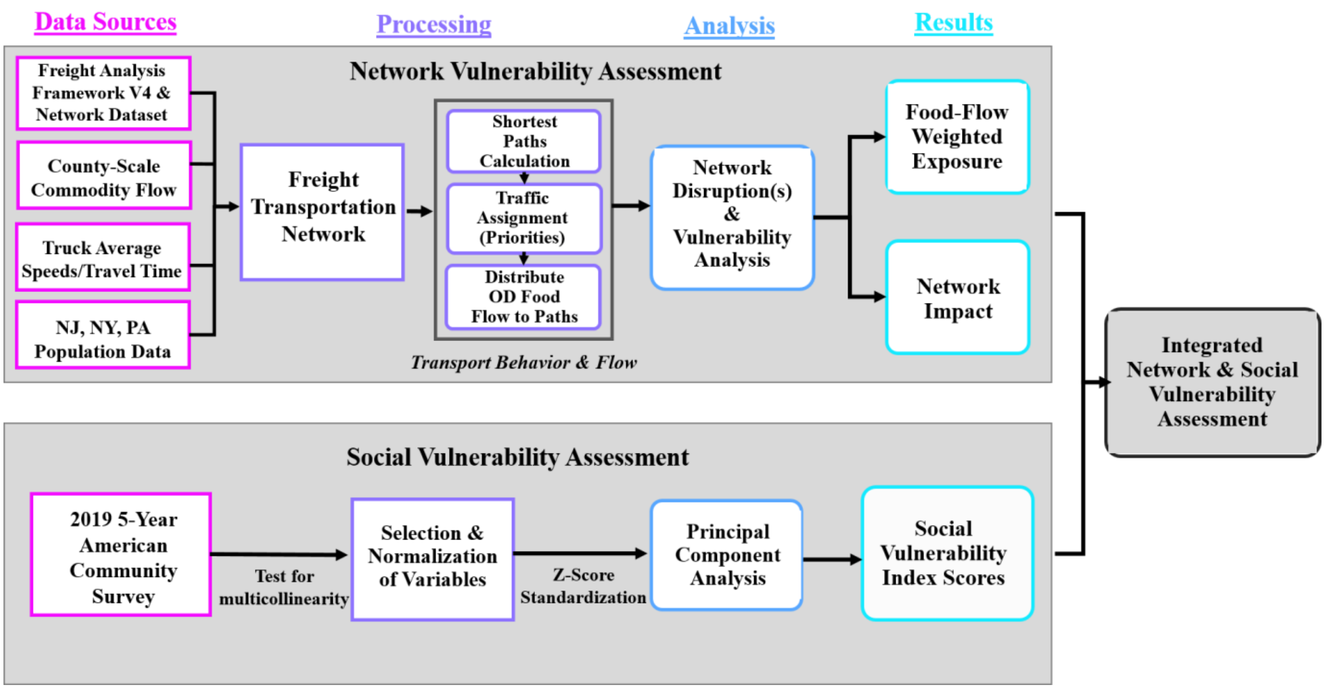

Figure **2-1**: Integrated transportation network & social vulnerability assessment framework

Commodity Flow Database and Network Model

The main source of data on inter-regional freight activity for all modes takes the form of commodity flows. The limited data about freight traffic patterns is a barrier to help and understand how commodities move through roads. The Federal Highway Administration's (FHWA) *Freight*

Analysis Framework (**FAF**) generated from a variety of data sources (including the Commodity Flow Survey (CFS)), is the leading data source for freight commodity-based modeling (Freight Analysis Framework, 2022). FAF4 is the fourth database of its kind for the 2012 base year. It represents both domestic and foreign trade shipments which include shipment origin and destination commodity flows among 132 domestic FAF zones, 43 commodity classes (7 agricultural-food categories), and 8 modal categories for 2 metrics—annual tons and annual dollar values (U.S. Department of Transportation Federal Highway Administration, 2012.). The origin-destination FAF4 flow is restricted at a coarse spatial resolution scale, but it's now possible to generate a data-driven freight transportation network that can assign commodity food flow volume at a refined sub-national scale (Lin et al., 2019).

I adapted and assigned the county-to-county tonnage flow from Lin et al. 2019, to build our network. Since this dataset does not include the mode of transportation for flows, we used statistics from FAF4 based on each SCTG class (standard classification of transported goods). From Table A-1 in Appendix A, we notice that the primary mode of transportation for selected agricultural/food commodities within this region for domestic flow was by **truck** therefore for our assessment we assumed single modal transportation for our study. Along with the estimates of commodity movements, the FHWA provides the *FAF4 network database and flow assignment*. This network model is used to disaggregate flows from the OD database into flows by truck between localities and to assign these flows to individual highways (either using average payloads per truck and truck counts on individual highway segments). FAF4 network database doesn't include freight mobility performance estimates (e.g., truck average speed during peak hours). The American Transportation Research Institute (ATRI) and FHWA *National Corridors Analysis and Speed Tool* (N-CAST) network dataset, provides average operating speeds from January through June 2012 for trucks that travel on interstate highways and other segments of the National Highway System (NHS) (ATRI FHWA: N-CAST, 2012). N-CAST dataset was utilized to obtain truck average travel speed, highway distances, and travel time. Additional details on network construction, as well as, network processing/transport behavior and assignment flow to be discussed in the next chapter.

Network Vulnerability Assessment

Physical transportation vulnerability is depicted as the network's "susceptibility to unusual incidents that can result in considerable reductions in system serviceability" (Berdica, 2002). This concept can also be interpreted as the unusual sensitivity of the network to internal or external disruptive scenarios, which decrease the system's capacity – reduce accessibility (connectivity), and increase travel costs (Pan et al., 2021). The concept of vulnerability can be separated into two approaches, one evaluates the impact of a disruption(s) to the transportation network, and the other contains the nature and degree to which a system, user, or location/place, is exposed to significant variations (Demirel et al., 2015). In other words, *exposure* can represent the decrease of accessibility of individual or grouped network nodes (e.g., municipalities) under a particular disruption scenario (Jenelius et al., 2006). So for instance, a county/city node is vulnerable ''if loss (or substantial degradation) of a small number of network components significantly diminishes the *accessibility* of the node" (D'Este and Taylor, 2003). The concept behind the exposure is to understand and compare the situation for different groups depending on the socio-economic, demographic, and geographic variables of interest, making it possible to study the *distribution* of impacts among users and identify communities that would be particularly severely affected by a certain scenario (Jenelius and Mattsson, 2015).

For this study, I will analyze the two mentioned vulnerability analysis approaches. (1) The first will evaluate overall performance impact under random and deterministic/targeted attacks. Here, connectivity (shortest paths) and traffic-flow (food-flow demand) loss due to disruptions will be determined. (2) The second will rank how much disruption would counties experience. These network-based metrics for describing and quantifying vulnerability have been useful to analyze the risk of disruptions across transportation networks. To date, however, these techniques have not adequately addressed community inequalities.

Network Impact Measure

When a node or edge is disabled, all incident paths and flows are therefore no longer accessible as a result of the disruption. I simulate scenarios where nodes (i) and edges (j) in the network are disrupted and as a result of this perturbation, the OD shortest paths and food flows traversing that node (edge) are no longer functional. For this work, the shortest paths connectivity will be tested to investigate our network's functionality as follows:

$$PSPI(i) = 100 * \frac{TSPI(i)}{TP}, i = 1,2,3 \tag{1}$$

where PSPI represents the percent of shortest paths (between OD pairs) impacted, TSPI as the total number of shortest paths between OD impacted due to removal of a network component (i), and TP is the total number of shortest paths between all OD pairs.

The impact of a potential disruption can also be determined by the magnitude of the flow affected (Matisziw et al., 2009). If the path(s) between an origin and destination post-disruption are impacted, then connectivity and flow for that O-D pair are lost. For this work, how much food flow (volume) was affected (percentage) is calculated as follows:

$$PFFI(i) = 100 * \frac{TFFI(i)}{TFF}, i = 1,2,3 \tag{2}$$

where PFFI represents the percent of food flows (between OD pairs) impacted, TFFI as the total food-flow volume between OD impacted due to removal of a network component (i), and TP is the total food-flow volume between OD pairs.

Network Disruption(s) Scenarios

I simulated two types of scenarios for the network impact analysis. The first scenario is aimed at simulating **random** disruptions of nodes or edges in the network. In this random impact scenario, I select one node (edge) at random and remove it from the network and then I measure the impact on shortest paths and food flows. We repeat this process in the random impact scenario and each iteration, we add one more node at random to the list of removed nodes. We repeat this process until a selected amount of nodes (edges) are removed at random. To assess the average importance of different types of nodes (edges) we assess three cases: i) removing **any** node (edge) in the list, ii) removing only **county** nodes (edges), and iii) removing only **intersection** nodes (edges). We argue that more important nodes (edges) will have a higher measured impact on the entire network when disrupted. Further, to account for the uncertainty in the selection of the node to be removed we run 1000 realizations of this node removal process with different random nodes being removed in each realization.

The second scenario focuses on simulating **deterministic** (i.e. targeted) disruptions of nodes (edges) in the network. I select a set of deterministic-based elements using centrality-based indices that have been used in previous studies that measured the network structure due to changes (López et al., 2017; Mattsson and Jenelius, 2015; Zhang et al., 2015). Table A-2 in the Appendix, summarizes the centrality measures and their respective formulation and description. Prior literature has highlighted the value of accounting for functional vulnerability (i.e. considering supply and demand; flow characteristics measures) as oppositely focusing solely on traditional topological-based (connectivity) assessments (e.g., Matisziw et al., 2009; Nicholson et al., 2016; Ouyang et al., 2014). Only considering structural metrics cannot effectively characterize the impact of disruptions, thus, I considered an operational/functional indicator (e.g., the magnitude of the interaction between the county pairs can vary in changes of demand) that can help better understand the freight transportation network. This flow-based metric, which is referred to as 'Max total flow', will find the nodes (edges) that transport the highest/maximum total amount of food flow. I then simulate the impact in shortest paths and flows for each deterministic attack scenario similar to the random scenario.

Disruption Exposure

I employ an approach similar to Jenelius et al. (2006) and Rodriguez-Nunez et al., (2014) to calculate the exposure of counties to food flow access due to disruptive events. The standard indicator of accessibility (for the user) is the cost of travel (either weighted by demand or not). For this calculation, I employ the indicator to take into account the travel time $\overline{tt}$ between OD pairs as the generalized cost of travel, and either the total food-inflow TI or food-outflow TO volume of each OD pair as the significant weight. The first step is to calculate the exposure of the county nodes by obtaining the average increase in travel time for trips with origin (destination) in the county i (j) when a randomly chosen node n in the set of all nodes N_n is disrupted. Since the function of the network is accessibility, I considered the exposure of destination county nodes (as opposed to a serviceability/operability function that focuses on the supply). The value from the change in the cost of travel is multiplied by the respective county node total food-inflow weight. This measure is defined as *food-flow weighted exposure* (FFWE), and the formulation is given below:

$$\mathrm{FFWE_j} = \frac{\sum_{\mathrm{n \in N_n}} (\overline{\mathrm{tt}}_{\mathrm{(n)j}} - \overline{\mathrm{tt}}_{\mathrm{j}})}{\mathrm{N_n}} * TI_j \tag{3}$$

Social Vulnerability Assessment

To quantify vulnerability to commodity flow disruptions we developed a social vulnerability index (SoVI) whose objective is to understand the spatial variability of household food, energy, and water insecurity in New York, New Jersey, and Pennsylvania, and determine the role of social vulnerability has amid commodity flow transportation disruptions.

Social Vulnerability Index (SoVI) and SoVI Creation

The 2019 5-Year American Community Survey provided by the U.S. Census Bureau (U.S. Census, 2019) was used to construct the social vulnerability index. The county spatial scale was utilized as this allows us to correlate county food flow data to social vulnerability. The SoVI is comprised of 17 variables spanning four domains of race and ethnicity, economic status, housing composition, and housing type (Table 3-1). For the components of the SoVI & the variable selection see Appendix A.

Table **2-1**: Input variables for the social vulnerability index

Domains	No.	Description
Race and Ethnicity	1	Percent Black or African American
	2	Percent Hispanic or Latino
	3	Percentage of Alaska Native and American Indian Population
Household Composition	4	Percent of population under 18 years old
	5	Percent of population over 65 years old
	6	Percent females
	7	Percent female-headed households, no spouse present

	8	Percent female-headed households, no spouse present, with children under 18 years
	9	Percent male-headed households, no spouse/partner present, with children under 18 years
	10	Percent female-headed households, no spouse present, living alone
	11	Percent male-headed households, no spouse present, living alone
	12	Percent of population with no high school diploma, 25 years and over
	13	Percent of civilian noninstitutionalized population with a disability
Economic Status	14	Percent living in poverty (≤ 200 % of the poverty level)
Household Type	15	Percent of mobile home housing units
	16	Percent multi-family housing units (5 or more units)
	17	Percent of housing units built up to 1989

The Social Vulnerability Index (SoVI®) model created by Cutter et al., 2003 served as the blueprint for the development of the social vulnerability index for this study (The SoVI, 2016). We began by testing for multicollinearity among the initial identified 19 variables, resulting in 17 variables. Then we normalized the select variables regarding the total population and/or households of the respective county. The input variables were scaled and centered using z-score standardization by subtracting by the mean and dividing by the standard deviation. Principal component analysis (PCA) was employed to calculate the social vulnerability scores and determine the dominant social factors. After performing the PCA, five principal components (PCs) were identified based on the Kaiser selection criterion which indicates an eigenvalue greater than 1. Overall, the five PCs describe approximately 79.3% of the variance. From the determination of the PCs, Varimax rotation was implemented to understand the dominant social factors of the PCA output. The social factors were assigned factor names based on the theme of the principal variables, which were selected if the correlation was greater than (±) 0.50 (Table 2-2).

Table **2-2**: Dimension of social vulnerability (Components, Principal Variables, and Direction of Influence)

Component Name	Percent Variance Explained	Principal Variables (+/- Correlation)	Cardinality (Effect of SoVI)
1. Ethnicity, Race, and Multi-Family Housing	27.5	Hispanic or Latino (+0.88) Black or African American (+0.87) Multi-Family Housing (+0.76) Single-Female with Children Under 18 Years Old (+0.75) Older Adults (Over 65 Years Old) (-0.74) Female-Headed Households, No Spouse Present (+0.70) Mobile Home Housing (-0.60)	+
2. Education and Low-Income	17.9	Education (No High School Diploma) (+0.90) Income (≤ 200% Poverty Level) (+0.81) Civilian noninstitutionalized population with a disability (+0.76)	+
3. Men and Women Living Alone	15.3	Single-Female Living Alone (+0.92) Single-Male Living Alone (+0.70) Housing Built Before the Year 1989 (+0.50)	+
4. Female and Children	10.8	Female (+0.82) Children (Under 18 Years Old) (+0.65)	+
5. American Indian and Alaska Native (AIAN)	7.71	American Indian and Alaska Native (+0.88) Single-Men with Children Under 18 Years Old (+0.58)	+

The five factor scores were then placed in an additive model to produce the composite social vulnerability score (Eq. X). The factors were provided equal weighting given no defensible method for a weighting scheme (Cutter et al., 2003b). Additionally, in SoVI construction, it is important to identify directionality with the principal variables (+, -). All variables increase vulnerability and are therefore added together. The summed Overall SoVI factor scores were then spatially mapped into five divergent classes based on the standard deviation from the mean to highlight the most and least vulnerable BGs, ranging from -1.5 (lower vulnerability) to +1.5 (higher vulnerability).

$$\text{Overall SoVI Score} = \text{Factor 1} + \text{Factor 2} + \text{Factor 3} + \text{Factor 4} + \text{Factor 5} \qquad (4)$$

Chapter 3

Case Study

While the data generation and analysis from the previous section cover commodity flows into and across the United States, management decisions tend to occur on a much smaller scale. For this case study, the Mid-Atlantic region of the United States will serve as an exploratory area of investigation. Three states are primarily considered are New Jersey (NJ), New York (NY), and Pennsylvania (PA). These states are home to 40.9 million people (U.S. Census, 2019), which is about 13% of the U.S. population. Also, this region is highly susceptible to sea-level rise (Little et al., 2015; Fitzgerald et al., 2008; Gornitz, 1990), and includes thousands of miles of key bridges, railroads, highways, and tunnels critical to the movement of goods and people countrywide.

Freight Transportation Network and Simplifications

To analyze the physical consequences of disruptive events on the transportation of food commodities by truck, we modeled a physical road network that incorporates existing freight and truck transportation data sources. I established the base roadway network using the formerly mentioned national highway network dataset of the Freight Analysis Framework. By generating *geographical centroids,* I was able to combine the mentioned commodity county-to-county tonnage flow data from Lin et al. 2019, with the base roadway network. Narrowing and selecting the most populous cities (origins/destinations) between the states served as the center-point for food commodity transportation in and out of the county (additional selection process/details in Appendix A). The total city/county selection was 40 cities/county pairs, 9 in NJ, 15 in NY, and 16 in PA.

I confined the base network database and the commodity flow assignment to our targeted region and simplified it to capture the main important routes between our counties of interest. To reduce computational burdens but still retain sufficient redundancy, we took several steps to simplify the network. First, we selected major highways and local roads with a particular truck volume (20 truck/road segment/day). Based on this selection, we aggregated the N-CAST travel time dataset to the designated pathways. Also, disjointed road network segments were extended, and the network was planarized (adding nodes for intersections of crossing segments) and cleaned (removed unnecessary/dangling paths). To have a more continuous network that could more realistically represent re-routing during disruptions, we extended road segments near the boundaries of states to the closest intersection out of state. Roads that may be used for rerouting/deviation were included if the detour took less than 2 hours, and additional intersections were included in the states of Ohio, West Virginia, Maryland, and Delaware. Google Maps data was used for these road segments with missing travel time attributes.

Network Configuration and Properties

A traditional transportation planning representation to assign traffic flows was considered (discrete model). This step of the process is the assignment of food flow on each of the network's edges based on specific input (i.e., assumptions, origin-destination traffic demand, and associated edge performance (impedance) functions). Typically, traffic assignment models assign flow based on one of the following criteria: (1) assignment of all trips between an origin and a destination to a unique optimum (i.e., minimum cost) route (all-or-nothing assignment), or (2) assignment to multiple cost routes (i.e., other routes in addition to the minimum cost route). In a detailed highway network, there may be several paths between a pair of centroids that are very close to that of the minimum path. To consider more realism for this analysis, a multipath assignment (Dial's algorithm) is used. For this model, the shortest paths between OD pairs were selected based on origin and destination commodity flows (i.e. only OD pairs with commodify flow movements), and five feasible routes were selected between any OD pair. For more details on the logit-type formula that defines the probability of choosing a route as a proportion of the whole choice set, and other criteria (shortest paths sensitivity) see Figures B-1 and B-2 in the Appendix.

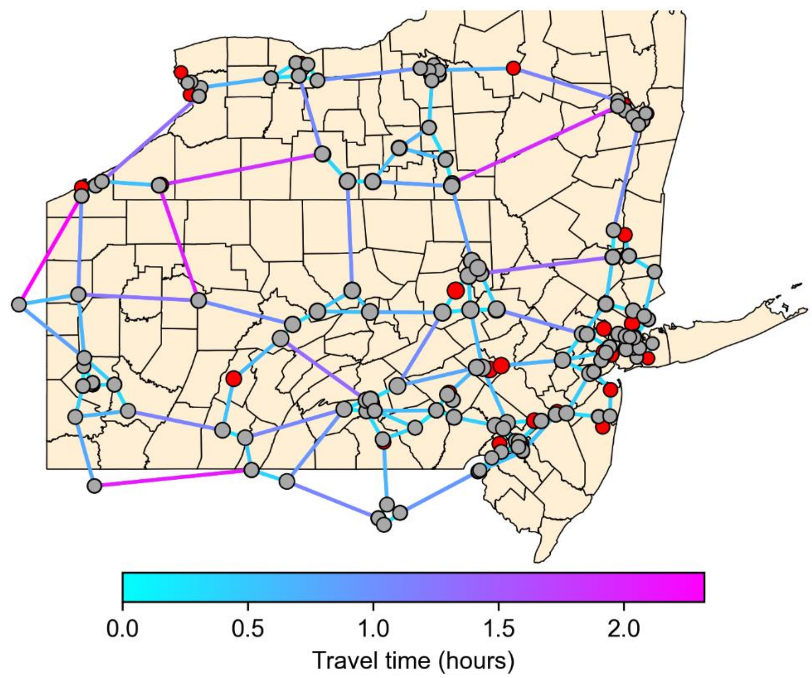

Figure **3-1**: Mid-Atlantic transportation network is represented by a weighted directed graph with a set of nodes and a set of connecting edges. Nodes symbolize highway intersections and the city/county pair locations (red), and the edges represent the weighted highway routes (attributes: length (miles), avg. speed (mph), and travel time (hours)).

The final weighted and directed freight transportation network is illustrated in Figure 3-1. The Mid-Atlantic Freight transport network consists of 509 Nodes (40 centroid/county nodes), 906 weighted edges (attributes: length (miles), avg. speed (mph), and travel time (hours)), and 478 OD shortest paths.

Chapter 4

Results and Discussion

First, the performance of vulnerability impact and exposure are investigated in the freight transportation network illustrated in the previous section. Consequently, the vulnerability spatial analysis of the Mid-Atlantic region is investigated and discussed. Finally, both concepts are integrated and analyzed to highlight freight transport-related inequalities/injustices.

Network Vulnerability Analysis

Network Disruption(s) and Impact Analysis

To analyze the impact of network performance, I evaluate the connectivity and system flow due to several disruptive scenarios. For the *three* cases of **random** impact analysis ('any', 'only county, and 'only intersection'), a node or edge was removed at random until a total of 40 nodes (edges) were removed. Figures B-3 to B-6 in Appendix show the shortest paths and food flow impacts from the different random cases, where the average impact and standard deviation (bounds) are shown in the plots. From this analysis, the main takeaways are that *county* nodes are more important in the network as removing this type of node causes a higher impact on food flows and shortest paths. This behavior is observed even when a few nodes are removed but the difference in importance between county nodes and other types of nodes is stronger after the removal of ~5 nodes. This same behavior is not observed for the edge removal analysis which shows that the difference in importance between county edges (i.e. any edge connected to a county node) and the other 2 types is not as marked. After removing ~23 edges the impact of removing county edges falls outside the confidence bounds of removing all nodes. Across all types of nodes and edges, removing nodes is more important than removing edges. This is expected as removing a node involves removing all the edges connected to the node which are usually more than 1.

Figure 4-1, compares the ‘any’ random disruption scenario with the impacts from deterministic attacks (centrality-based and total flow-based). In this figure, we can see differences between the percentage of shortest paths and food flows impacted as both nodes and edges are removed from the network. The upper panels show how connectivity is impacted as nodes (left) and edges (right) are removed from the network. When removing the first 10 notes, *closeness* and *max flow* are within the random range, then max flow exceeds random between 10 and 20 node removal and again falls within the random range after that. The betweenness line is within random the whole time, and the closeness is within the random except after the ~25 node removal. The percentage of shortest paths impacted by edge attacks is within the range or less than the *random* edge scenario.

It is also critical to investigate network flow-demand patterns as it is key to potential disruption risks. Hence, the bottom panels from Fig 4-1, illustrate how food flows are impacted as both nodes (left) and edges (right) are removed from the network. In both the node and edge removal cases, the food flows are notably more vulnerable to *max-total flow* attacks than any of the other scenarios. As mentioned before, county nodes are more important in the network as removing this type of node causes a higher impact on food flows. Thus, the majority of the top 40 *max-total flow* nodes represent county nodes. Additional deterministic and sensitivity scenarios (e.g., capacity reduction) are analyzed in Appendix, Figure B-7 to B-9.

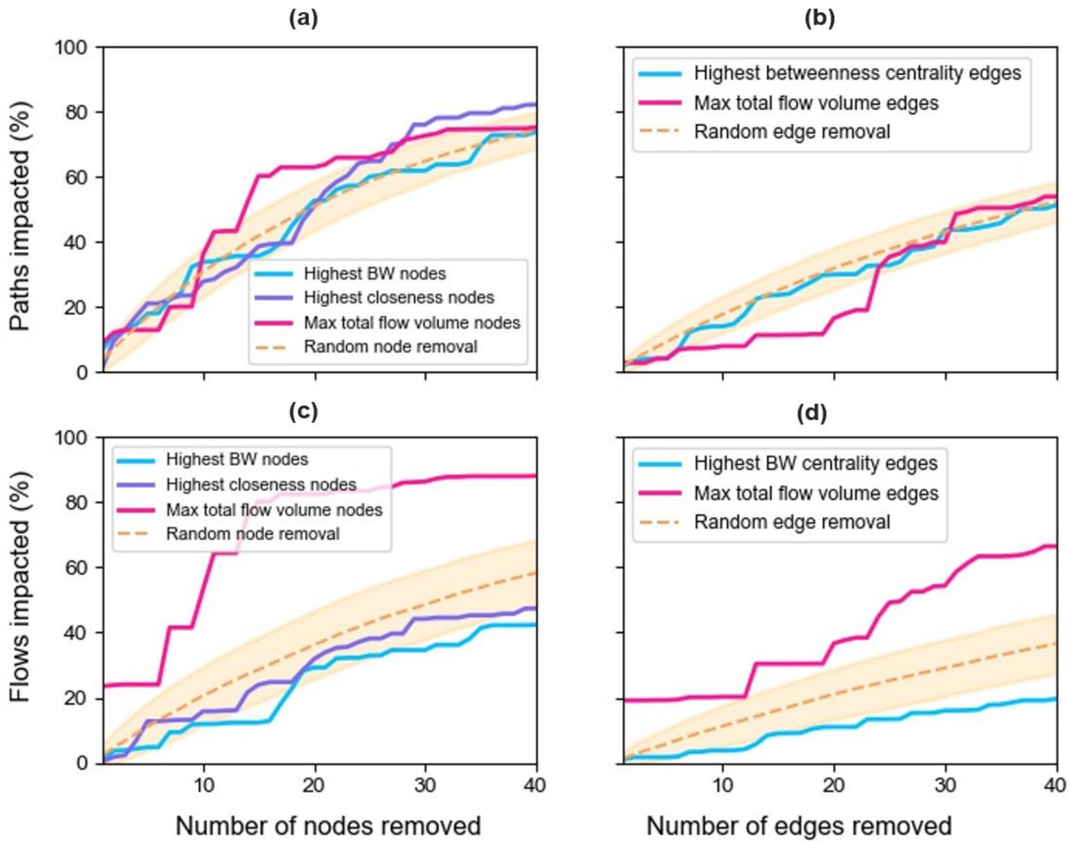

Figure **4-1**: Impact Vulnerability Analysis: Upper panels - percent of shortest paths impacted due to removal of random ('any' scenario) and deterministic components: (a) node removal and (b) edge removal. Bottom panels – percent of food-flows impacted due to removal of random ('any' scenario) and deterministic components: (c) node removal and (d) edge removal

Analysis of the disruptive scenarios reveals that the impact is much greater in the *max-total flow* targeted attack than in the other *centrality-based* and *random* attacks. As previous authors have mentioned, the flow-based aspects of network performance are often overlooked in the literature or are misrepresented through the use of weak approximations (Matisziw et al., 2009, Hines et al., 2010, Ouyang et al., 2014). While it is intuitive that connectivity is an important concern when assessing network risk, this assessment confirms that actual network flow is also a critical component of risk assessment.

Food-Weighted Exposure

Food-weighted exposure ranking was calculated by the average increase in travel time and the food-flow weight. To rank the exposure of county nodes, and be able to compare them with the social vulnerability assessment (next section), the county nodes were ranked from 1 to 40, where 1 is the most vulnerable and 40 is the least vulnerable. For this network, the most exposed counties are generally in the southeastern of the region (Fig. 4-2). In this localized area, a large part of the exposure is due to the high food-inflow demand (Fig. 4-4). The highest exposed county is Erie County (Buffalo), NY located in the northwestern region. Here, this peripheral county node suffers from both the smaller number of edges in the proximity of the connection to the rest of the network and the high total amount of inflow demand (Figure 4-4). The less exposed counties located in the western region of Pennsylvania, can maintain service and accessibility at levels approaching the original. Hence, when nodes or edges are removed or not functioning in the network, the county food-flow exposure to disruptions may not be critical in areas where more alternative routes are available and less food demand is accessible. From Fig. B-10 and B-11 in the Appendix, we find that there’s no significant relationship between county exposure and the amount of network nodes within the county.

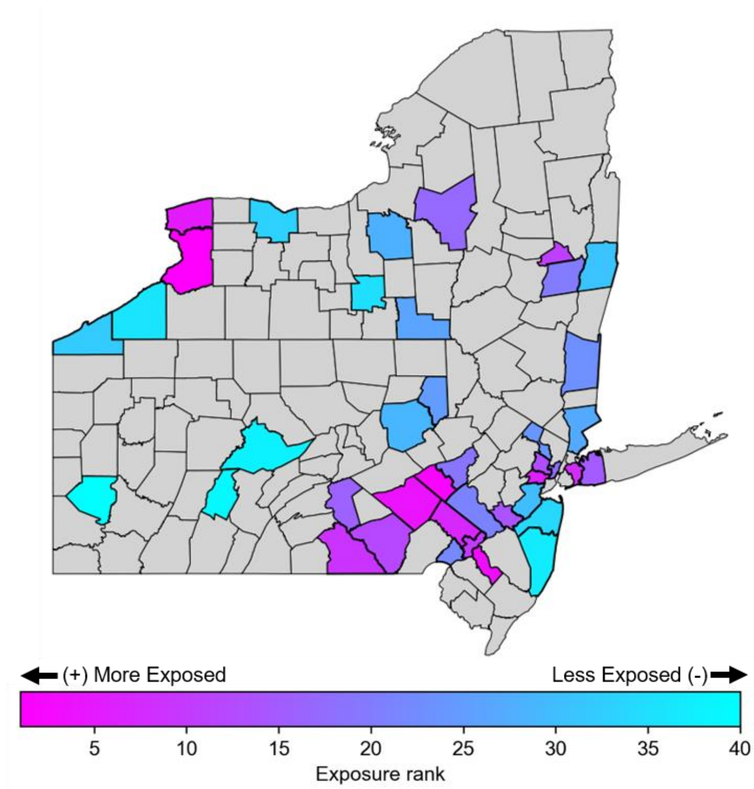

Figure **4-2**: Food-flow weighted exposure ranking for the 40 network-defined counties. From most vulnerable to least vulnerable county (1 to 40).

Social Vulnerability Analysis

The estimated overall SoVI scores for counties in the Mid-Atlantic region is shown in Figure 4-3. Analyzing the spatial distribution of SoVI scores, it is evident the degree of difference across communities. The map demonstrates that 4% of the total counties have a lower vulnerability (< -1.5 standard deviation), 27% of the counties have a moderate to lower vulnerability (-1.5 to -0.5 std. dev.), 42% of the counties have a moderate vulnerability (-0.5 to 0.5 std. dev.), 22% have a moderate to higher vulnerability (0.5 to 1.5 std. dev.), and 5% a have higher vulnerability (> 1.5 std. dev.). From the counties selected in the previous network section, Philadelphia County, PA, and Essex County, NJ, have a high overall social vulnerability. Additionally, these counties were ranked based on the SoVI scores (from 1 to 40, where 1 is the most vulnerable and 40 is the least vulnerable), and compared with network analysis results (Exposure v. SoVI – next section).

While these results represent the overall SoVI factor scores, it is also important to note that certain counties are especially vulnerable with respect to some factors/variables and not to others, suggesting that considering only one variable may not provide a sufficient perspective. See Fig. B-14 in Appendix for additional SoVI factor maps.

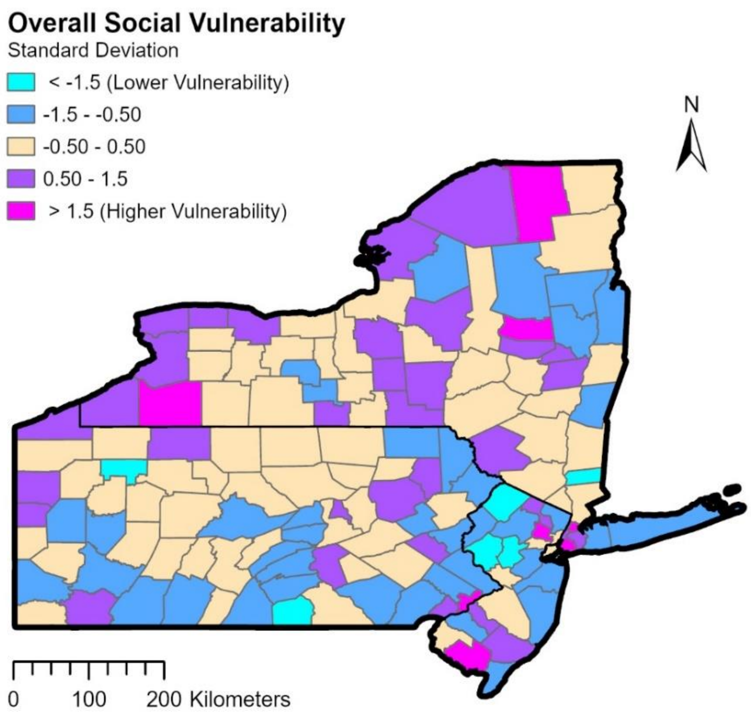

Figure **4-3**: Overall Social Vulnerability Index Scores for all counties in the Mid-Atlantic Region.

Network Vulnerability and SoVI Integration

The total food inflow and outflow for the 40 counties that were selected for the network analysis, and their respective SoVI score are depicted in Figure 4-4 and Figure 4-5, respectively. For the total county food flow plots, we see some variability among the county's total flow and social vulnerability index score (i.e. flow doesn't have an impact on SoVI value and vice-versa). Nonetheless, Fig. 4-4 demonstrates that Erie County, NY has a substantially greater inflow value (~4.1E+06 Metric Tons/Yr) and a moderate to high social vulnerability (0.5 - 1.5 std. dev.). From Fig. 4-5, Niagara County, NY has the most outflow (~3.9E+06 Metric Tons/Yr) and a moderate to high social vulnerability (0.5 - 1.5 std. dev). Lehigh County follows with a total inflow of ~1.4E+06 Metric Tons/Yr and with a moderate social vulnerability, and Lancaster County, PA with a total outflow of ~2.4E+06 Metric Tons/Yr and low to moderate vulnerability (-1.5 - -0.5 std. dev.). The most socially vulnerable counties (> 1.5 std. dev.), Philadelphia County, PA, and Essex County, NJ, have total inflow values of ~1.0E+06 and ~9.6E+05, respectively (Outflows: ~9.95E+05 and ~1.17E+06 Metric Tons/YR).

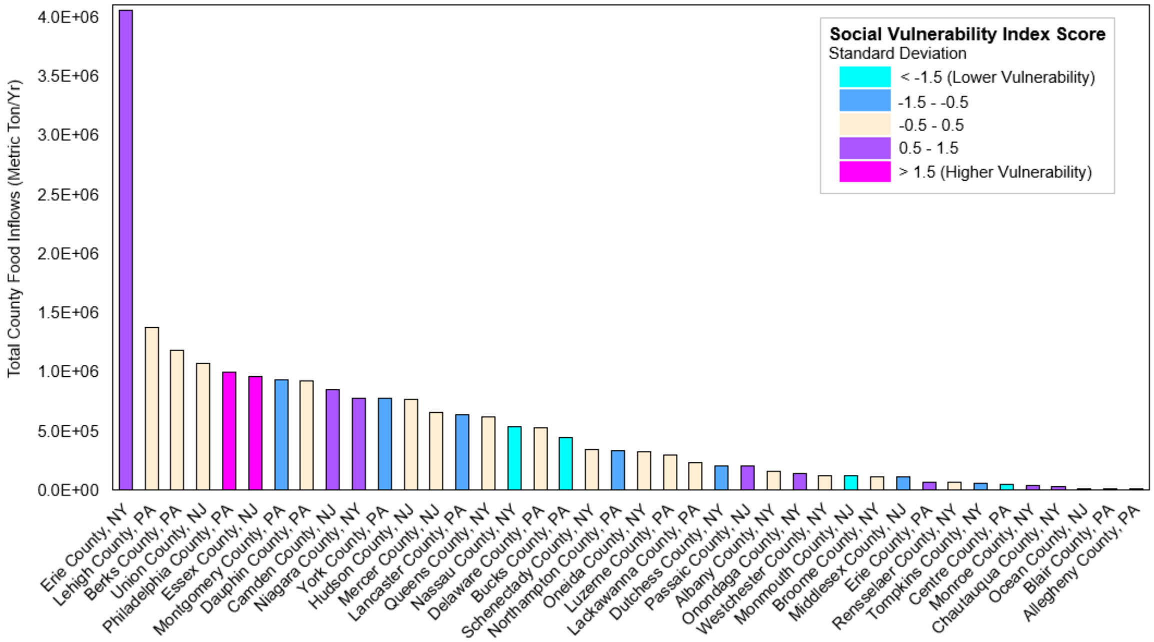

Figure **4-4**: The total county food inflow & SoVI Score for the 40 network-defined counties.

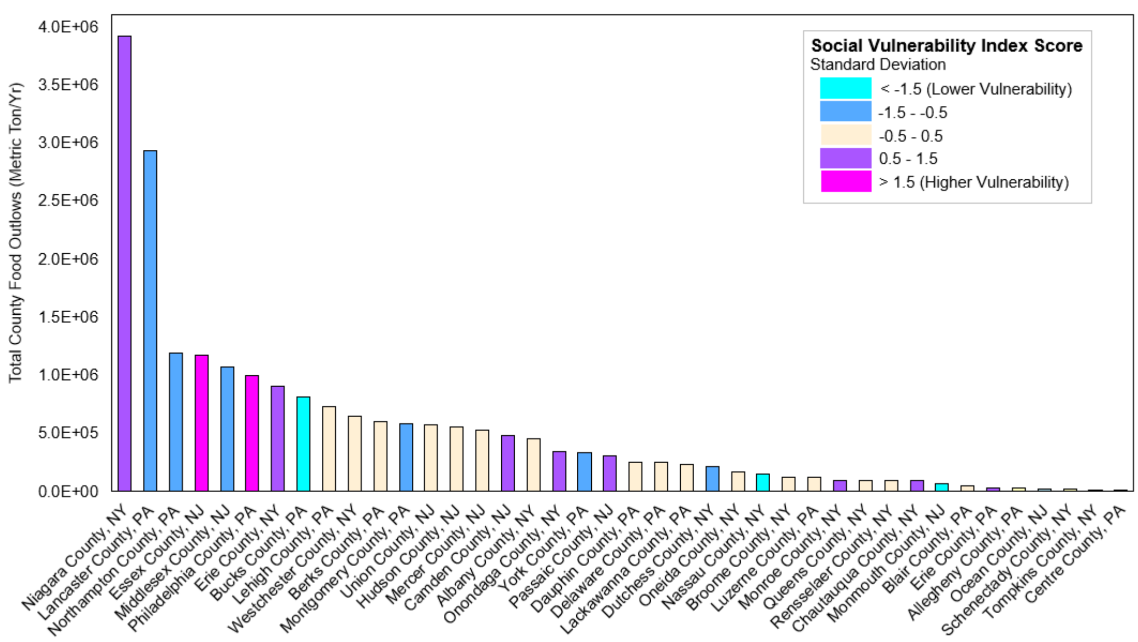

Figure **4-5**: The total county food outflow & SoVI Score for the 40 network-defined counties.

Vulnerability to disruptions is not only determined by the potential physical network failures but also by the capability of communities to withstand unprecedented events. Continuing testing for relationships, the scatter plot of Food-weighted exposure v. SoVI *ranking* for the 40 network-defined counties is observed in Fig. 4-6. The High exposure-High SoVI category is defined as the counties that have a food-flow weighted exposure and a SoVI ranking of less than 20. High exposure-Low SoVI is grouped as counties with an exposure rank less than 20 and a SoVI rank greater than 20. Low exposure-High is categorized as counties with an exposure rank greater than 20 and a SoVI rank less than 20. Lastly, Low exposure-Low SoVI is classified as counties with a food-flow exposure and SoVI ranking greater than 20. The scatter plots suggest no significant linear correlation but can still highlight vulnerable regions where additional resources might be necessary. Counties with high exposure-high SoVI include Essex County, NJ, Camden County, NJ, Erie County, NY, Niagara County, NY, Queens, NY, and Philadelphia County, PA. These areas could indicate that the planning practices and current policy settings have neglected the urgency of planning for vulnerability reduction in socially vulnerable regions, which consequently led to the clustering of urban areas that are vulnerable both physically and socially. Counties with low exposure-low SoVI include Monmouth County, NJ, Ocean County, NJ, Tompkins County, NY, Allegheny County, PA, and Centre County, PA.

Examining food-weighted exposure and SoVI in more detail, Fig 4-7 compares standard score values for the 40 network-defined counties. From this scatter plot we can see how counties are now grouped close together, and recognize the gap between vulnerability categories. Additionally, we can spot a few outliers that set apart from the rest, for example, Erie County, NY, Philadelphia County, PA, and Essex County, NJ. See Fig. B-12 and B-13 in Appendix for additional scatter plots with SoVI factors integrated with exposure scores and rankings.

Integrating and comparing the counties for both network exposure and SoVI, provides a transformative framework that corrects/mitigates social inequalities. This framework can be applied to other/larger areas and scenarios, and outcomes can provide great insights into policy-making, by allowing decision-makers to identify critical communities for road retrofitting and protection, and prioritize the emergency response concerning the access to essential commodities.

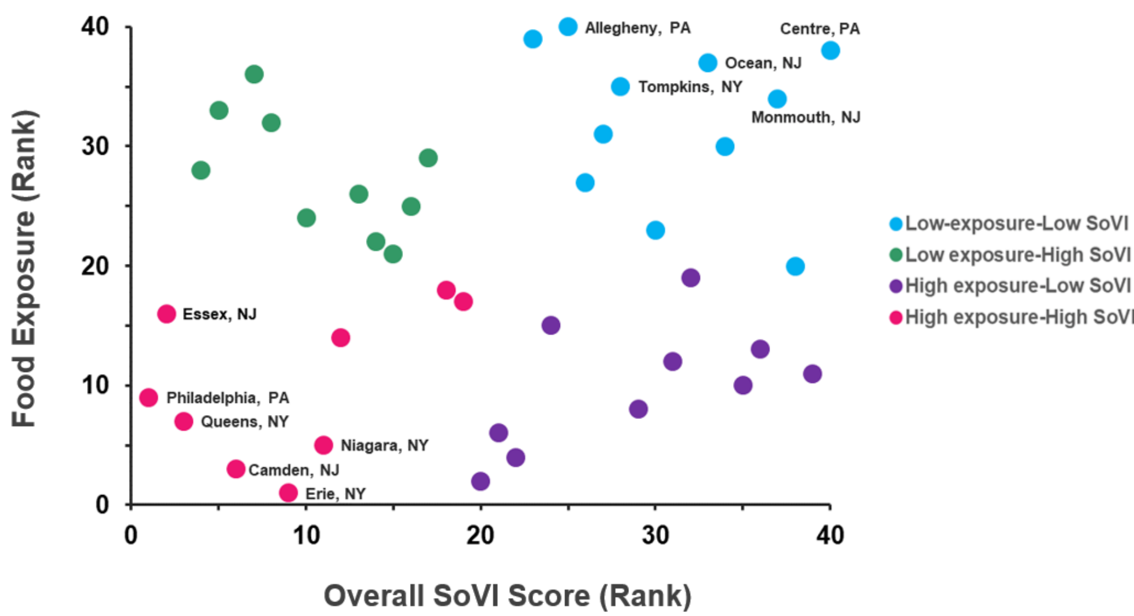

Figure **4-6**: Scatter plot with Food-flow weighted Exposure and SoVI Ranking for the 40 network-defined counties.

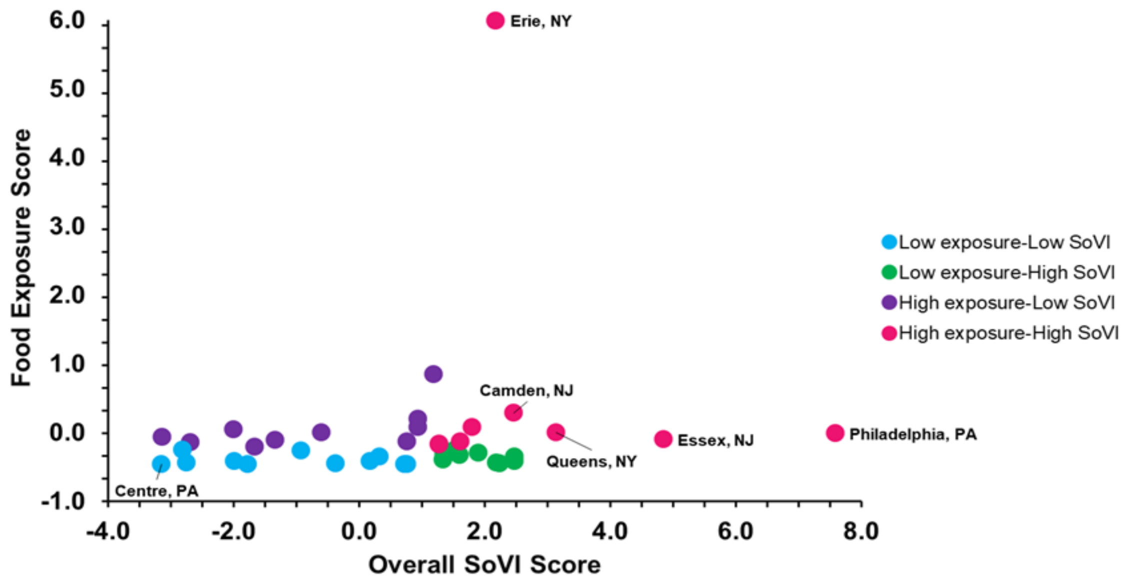

Figure **4-7**: Scatter plot with food-weighted exposure and SoVI standard scores for the 40 network-defined counties.

Chapter 5

Conclusions

Summary, Limitation and Future Work

Understanding who is impacted by disruption is an essential factor in analyzing the sustainability and equity of infrastructure systems. This study incorporated the community-level social vulnerability assessment into the transportation network analysis to help understand the impact of disruption and make decisions that ensure reasonable assistance/resources for the most vulnerable areas. This work was able to discover the overall network impacts due to disruptions, and the most exposed counties that are physically prone to access to food-flow commodities due to road network perturbations. Driven by a social vulnerability index, this assessment was able to demonstrate how communities experience hardships distinctively, and highlight areas where reasonable assistance/resources are necessary. Lastly, incorporating and comparing the counties' scores and rankings for both network vulnerability and SoVI can identify the most vulnerable communities, and can inform the emergency response planning by prioritizing those areas for resource allocations to reduce the societal impact of the loss of accessibility.

There were a few concerns that limited this study, data availability being the main one. In the network development, we were bounded to the spatial scale available for the commodity flow OD pairs. Having smaller geographical units for a community is key for disruption analysis and transport planning. Additionally, where using yearly commodity flow data. Thus, the amounts of food flow disrupted are for theoretical comparisons only since disruption most often occurs on a much smaller timescale. Despite these limitations, the purpose of this exploratory research was to investigate theoretical interconnections and address ethical implications in transport disruption analysis.

An organic future step is to expand the road to include all US counties. Automating the network construction will speed up the process and reduce errors. Also, incorporate other freight commodities, such as industrial commodities. But, to do so, we must acquire datasets at a finer spatial scale. Further, we must expand network disruption analysis by including different infrastructure types in a multilayer framework. For example, other infrastructure types to consider could include other modes of transportation (e.g., rail, fluvial, air), agricultural and industrial products processing plants, retailers, electricity generation infrastructure, and water treatment plants. This critical infrastructure network could be simulated more real-world disturbances such as floods, drought, and hurricanes. Also, potential ethical analysis of decision-making and resilience planning could be carried out.

To conclude, integrating social equity dimensions into transportation planning is only one step of the process. To guarantee a transformative change, will depend on the development of trusting and collaborative relationships between researchers, advocates, and planners.

References

Ahmed, Q.I., Lu, H. and Ye, S., 2008. Urban transportation and equity: A case study of Beijing and Karachi. Transportation Research Part A: Policy and Practice, 42(1), pp.125-139.

Aydin, N.Y., Casali, Y., Sebnem Duzgun, H. and Heinimann, H.R., 2019, July. Identifying changes in critical locations for transportation networks using centrality. In International Conference on Computers in Urban Planning and Urban Management (pp. 405-423). Springer, Cham.

Balakrishnan, S. and Zhang, Z., 2018. Developing priority index for managing utility disruptions in urban areas with focus on cascading and interdependent effects. Transportation research record, 2672(1), pp.101-112.

Behbahani, H., Nazari, S., Kang, M.J. and Litman, T., 2019. A conceptual framework to formulate transportation network design problem considering social equity criteria. Transportation research part A: policy and practice, 125, pp.171-183.

Berdica, K., 2002. An introduction to road vulnerability: what has been done, is done and should be done. Transport policy, 9(2), pp.117-127.

Berry, C., Hronis, C., Woodward, M., 2018. One in three U.S. households faces a challenge in meeting energy needs - Today in Energy - U.S. Energy Information Administration (EIA) [WWW Document]. eia.gov. URL https://www.eia.gov/todayinenergy/detail.php?id=37072 (accessed 5.11.21).

Beyazit, E., 2011. Evaluating social justice in transport: lessons to be learned from the capability approach. Transport Rev. 31 (1), 117–134. https://doi.org/10.1080/01441647.2010.504900.

Bird, S., Hernández, D., 2012. Policy options for the split incentive: Increasing energy efficiency for low-income renters. Energy Policy 48, 506–514. https://doi.org/10.1016/j.enpol.2012.05.053

Blaikie, P., T. Cannon, I. Davis and B. Wisner. 1994. At Risk: Natural Hazards, People's-Vulnerability and Disasters. Routledge.

Bohr, J., McCreery, A.C., 2020. Do Energy Burdens Contribute to Economic Poverty in the United States? A Panel Analysis. Soc. Forces 99, 155–177. https://doi.org/10.1093/sf/soz131

Boyle, E., Inanlouganji, A., Carvalhaes, T., Jevtic, P., Pedrielli, G. and Reddy, T.A., 2021. Social Vulnerability and Power Loss Mitigation: A Case Study of Puerto Rico. Available at SSRN 3838896.

Brandes, U., 2001. A faster algorithm for betweenness centrality. Journal of mathematical sociology, 25(2), pp.163-177.

Burke, M.P., Jones, S.J., Frongillo, E.A., Fram, M.S., Blake, C.E., Freedman, D.A., 2018. Severity of household food insecurity and lifetime racial discrimination among African-American households in South Carolina. Ethn. Health 23, 276–292. https://doi.org/10.1080/13557858.2016.1263286

Chen, Y., Bouferguene, A., Shen, Y. and Al-Hussein, M., 2019. Assessing accessibility-based service effectiveness (ABSEV) and social equity for urban bus transit: A sustainability perspective. Sustainable Cities and Society, 44, pp.499-510.

Coleman-Jensen, A., 2020. Household Food Security in the United States in 2019 47.

Cutter, S.L., 2017. The Perilous Nature of Food Supplies: Natural Hazards, Social Vulnerability, and Disaster Resilience. Environ. Sci. Policy Sustain. Dev. 59, 4–15. https://doi.org/10.1080/00139157.2017.1252603

Cutter, S.L., Boruff, B.J., Shirley, W.L., 2003. Social Vulnerability to Environmental Hazards*. Soc. Sci. Q. 84, 242–261. https://doi.org/10.1111/1540-6237.8402002

Dargin, J., Berk, A., Mostafavi, A., 2020. Assessment of household-level food-energy-water nexus vulnerability during disasters. Sustain. Cities Soc. 62, 102366. https://doi.org/10.1016/j.scs.2020.102366

Deitz, S., Meehan, K., 2019. Plumbing Poverty: Mapping Hot Spots of Racial and Geographic Inequality in U.S. Household Water Insecurity. Ann. Am. Assoc. Geogr. 109, 1–18. https://doi.org/10.1080/24694452.2018.1530587

Demirel, H., Kompil, M. and Nemry, F., 2015. A framework to analyze the vulnerability of European road networks due to Sea-Level Rise (SLR) and sea storm surges. Transportation Research Part A: Policy and Practice, 81, pp.62-76.

D'Este, G.M., Taylor, M.A.P., 2003. Network vulnerability: an approach to reliability analysis at the level of national strategic transport networks. In: Bell, M.G.H., Iida, Y. (Eds.), The Network Reliability of Transport. Proceedings of the 1st International Symposium on-Transportation Network Reliability (INSTR). Pergamon, Oxford, England, pp. 23–44.

Di Ciommo, F., Shiftan, Y., 2017. Transport equity analysis. Transp. Rev. 37 (2), 139–151. https://doi.org/10.1080/01441647.2017.1278647.

Ding-Mastera, J., 2016. Adaptive Route Choice in Stochastic Time-Dependent Networks: Routing Algorithms and Choice Modeling.

Dong, S., Esmalian, A., Farahmand, H. and Mostafavi, A., 2020. An integrated physical-social analysis of disrupted access to critical facilities and community service-loss tolerance in urban flooding. Computers, Environment and Urban Systems, 80, p.101443.

Drehobl, A., Ross, L., Ayala, R., 2020. An Assessment of National and Metropolitan Energy Burden across the United States 80.

Eid, M.S. and El-Adaway, I.H., 2017. Integrating the social vulnerability of host communities and the objective functions of associated stakeholders during disaster recovery processes using agent-based modeling. Journal of Computing in Civil Engineering, 31(5), p.04017030.

Espinet, X., Rozenberg, J., 2018. Prioritization of climate change adaptation interventions in a road network combining spatial socio-economic data, network criticality analysis, and flood risk assessments. Transp. Res. Rec. 2672 (2), 44–53. https://doi.org/10.1177/0361198118794043.

Executive Order On Advancing Racial Equity and Support for Underserved Communities Through the Federal Government [WWW Document], 2021. . White House. URL https://www.whitehouse.gov/briefing-room/presidential-actions/2021/01/20/executive-order-advancing-racial-equity-and-support-for-underserved-communities-through-the-federal-government/ (accessed 5.11.22).

FAF3 Network Database and Flow Assignment: 2007 and 2040 - FHWA Freight Management and Operations [WWW Document], n.d. URL

Faturechi, R., Miller-Hooks, E., 2015. Measuring the Performance of Transportation Infrastructure Systems in Disasters: A Comprehensive Review. J. Infrastruct. Syst. 21, 04014025. https://doi.org/10.1061/(ASCE)IS.1943-555X.0000212

FEMA, Equity. Available at: https://www.fema.gov/emergency-managers/national-preparedness/equity [Accessed May 19, 2022].

FitzGerald, D.M., Fenster, M.S., Argow, B.A. and Buynevich, I.V., 2008. Coastal impacts due to sea-level rise. Annu. Rev. Earth Planet. Sci., 36, pp.601-647.

France-Mensah, J., Kothari, C., O'Brien, W.J., Jiao, J., 2019. Integrating social equity in highway maintenance and rehabilitation programming: A quantitative approach. Sustain. Cities Soc. 48, 101526 https://doi.org/10.1016/j.scs.2019.101526.

Freeman, L., 1979. Centrality in networks: I. conceptual clarifications. social networks. Social Network.

Freight Analysis Framework - FHWA Freight Management and Operations [WWW Document], n.d. URL https://ops.fhwa.dot.gov/freight/freight_analysis/faf/ (accessed 3.22.22).

Freight Disruptions: Impacts on Freight Movement from Natural and Man-Made Events - FHWA Freight Management and Operations [WWW Document], n.d. URL https://ops.fhwa.dot.gov/freight/freight_analysis/fd/index.htm (accessed 3.22.22).

Garschagen, M. and Sandholz, S., 2018. The role of minimum supply and social vulnerability assessment for governing critical infrastructure failure: current gaps and future agenda. Natural Hazards and Earth System Sciences, 18(4), pp.1233-1246.

Gilbert, P.H., Isenberg, J., Baecher, G.B., Papay, L.T., Spielvogel, L.G., Woodard, J.B. and Badolato, E.V., 2003. Infrastructure issues for cities—Countering terrorist threat. Journal of infrastructure systems, 9(1), pp.44-54.

Gornitz, V., 1990. Vulnerability of the East Coast, USA to future sea level rise. Journal of Coastal research, pp.201-237.

Gralla, E., Goentzel, J. and Fine, C., 2014. Assessing trade-offs among multiple objectives for humanitarian aid delivery using expert preferences. Production and Operations Management, 23(6), pp.978-989.

Gudmundsson, H. and Höjer, M., 1996. Sustainable development principles and their implications for transport. Ecological economics, 19(3), pp.269-282.

Harker Steele, A.J., Bergstrom, J.C., 2021. "Brr! It's cold in here" measures of household energy insecurity for the United States. Energy Res. Soc. Sci. 72, 101863. https://doi.org/10.1016/j.erss.2020.101863

He, Z., Navneet, K., van Dam, W. and Van Mieghem, P., 2021. Robustness assessment of multimodal freight transport networks. Reliability Engineering & System Safety, 207, p.107315.

Hernández, D., Siegel, E., 2019. Energy insecurity and its ill health effects: A community perspective on the energy-health nexus in New York City. Energy Res. Soc. Sci. 47, 78–83. https://doi.org/10.1016/j.erss.2018.08.011

Huang, M., Smilowitz, K. and Balcik, B., 2012. Models for relief routing: Equity, efficiency and efficacy. Transportation research part E: logistics and transportation review, 48(1), pp.2-18.

Hunold, Christian, and Iris Marion Young. 1998. "Justice, Democracy, and Hazardous Siting." Political Studies 46 (1): 82–95. doi: 10.1111/1467-9248.00131.

Jafino, B.A., 2021. An equity-based transport network criticality analysis. Transportation Research Part A: Policy and Practice, 144, pp.204-221.

Jansuwan, S., Chen, A. and Xu, X., 2021. Analysis of freight transportation network redundancy: An application to Utah's bi-modal network for transporting coal. Transportation Research Part A: Policy and Practice, 151, pp.154-171.

Jenelius, E., 2010. User inequity implications of road network vulnerability. Journal of Transport and Land Use, 2(3/4), pp.57-73.

Jenelius, E. and Mattsson, L.G., 2015. Road network vulnerability analysis: Conceptualization, implementation and application. Computers, environment and urban systems, 49, pp.136-147.

Jenelius, E., Petersen, T., Mattsson, L.-G., 2006. Importance and exposure in road network vulnerability analysis. Transp. Res. Part Policy Pract. 40, 537–560. https://doi.org/10.1016/j.tra.2005.11.003

Jernigan, V.B.B., Huyser, K.R., Valdes, J., Simonds, V.W., 2017. Food Insecurity among American Indians and Alaska Natives: A National Profile using the Current Population Survey-Food Security Supplement. J. Hunger Environ. Nutr. 12, 1–10. https://doi.org/10.1080/19320248.2016.1227750

Karakoc, D.B., Barker, K., Zobel, C.W. and Almoghathawi, Y., 2020. Social vulnerability and equity perspectives on interdependent infrastructure network component importance. Sustainable Cities and Society, 57, p.102072.

Karner, Alex, and Deb Niemeier. 2013. "Civil Rights Guidance andEquity Analysis Methods for Regional Transportation Plans: ACritical Review of Literature and Practice." Journal of Transport Geography 33 (December): 126–34. doi: 10.1016/j.jtrangeo.2013. 09.017.

Karner, Alex, Dana Rowangould, and Jonathan London. 2016. We Can Get There from Here: New Perspectives on Transportation Equity. Davis, CA: National Center for Sustainable Transportation.

Lee, R.J., Sener, I.N., Jones, S.N., 2017. Understanding the role of equity in active transportation planning in the United States. Transport Rev. 37 (2), 211–226.
https://doi.org/10.1080/01441647.2016.1239660.

Liese, A.D., Sharpe, P.A., Bell, B.A., Hutto, B., Stucker, J., Wilcox, S., 2021. Persistence and transience of food insecurity and predictors among residents of two disadvantaged communities in South Carolina. Appetite 161, 105128. https://doi.org/10.1016/j.appet.2021.105128

Litman, todd., 2017. Evaluating Transportation Equity: Guidance for Incorporating Distributional Impacts in Transportation Planning,
VTPI.

Little, C.M., Horton, R.M., Kopp, R.E., Oppenheimer, M., Vecchi, G.A. and Villarini, G., 2015.Joint projections of US East Coast sea level and storm surge. Nature Climate Change, 5(12), pp.1114-1120.

Lobban, H., Almoghathawi, Y., Morshedlou, N. and Barker, K., 2021. Community vulnerability perspective on robust protection planning in interdependent infrastructure networks. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 235(5), pp.798-813.

López, F.A., Páez, A., Carrasco, J.A., Ruminot, N.A., 2017. Vulnerability of nodes under controlled network topology and flow autocorrelation conditions. J. Transp. Geogr. 59, 77–87. https://doi.org/10.1016/j.jtrangeo.2017.02.002

Manaugh, Kevin, and Ahmed El-Geneidy. 2012. "Who Benefits from New Transportation Infrastructure? Using Accessibility Measures to Evaluate Social Equity in Public Transport Provision." In Accessibility Analysis and Transport Planning, edited by Karst Geurs, Kevin K. Krizek, and Aura Reggiani, 211–27. Cheltenham, UK: Edward Elgar.

Map the Meal Gap 2020 Technical Appendix (2018 data) [WWW Document], 2020. . feeding america.org. URL https://www.feedingamerica.org/research/map-the-meal-gap/overall-executive-summary?s_src=WXXX1MTMG&_ga=2.162863804.121602475.1623709731-1424534739.1621533405 (accessed 6.15.21).

Martens, K., Golub, A. and Robinson, G., 2012. A justice-theoretic approach to the distribution of transportation benefits: Implications for transportation planning practice in the United States. Transportation research part A: policy and practice, 46(4), pp.684-695.

Matisziw, T.C., Murray, A.T., Grubesic, T.H., 2009. Exploring the vulnerability of network infrastructure to disruption. Ann. Reg. Sci. 43, 307–321. https://doi.org/10.1007/s00168-008-0235-x

Mattsson, L.-G., Jenelius, E., 2015. Vulnerability and resilience of transport systems – A discussion of recent research. Transp. Res. Part Policy Pract. 81, 16–34. https://doi.org/10.1016/j.tra.2015.06.002

McCoy, K., Peirce, S., Baker, G., Andorf, R., Foreman, C., Galton, R., Gilmore, M.M., Kittredge, D., Mahavier, K., Mason, D.J. and Pace, D., 2020. The Importance of Highways to US Agriculture (No. DOT-VNTSC-USDA-21-01). United States. Dept. of Agriculture..

Meehan, K., Jurjevich, J.R., Chun, N.M.J.W., Sherrill, J., 2020. Geographies of insecure water access and the housing-water nexus in US cities. Proc. Natl. Acad. Sci. U. S. A. 117, 28700–28707. https://doi.org/10.1073/pnas.2007361117

Memmott, T., Carley, S., Graff, M., Konisky, D.M., 2021. Sociodemographic disparities in energy insecurity among low-income households before and during the COVID-19 pandemic. Nat. Energy 6, 186–193. https://doi.org/10.1038/s41560-020-00763-9

Mercier, J., 2009. Equity, social justice, and sustainable urban transportation in the twenty-first century. Administrative theory & praxis, 31(2), pp.145-163.

Merschman, E., Doustmohammadi, M., Salman, A.M., Anderson, M., 2020. Postdisaster decision framework for bridge repair prioritization to improve road network resilience. Transp. Res. Rec. 0361198120908870 https://doi.org/10.1177/0361198120908870.

Miller-Hooks, E., Chen, L., Nair, R. and Mahmassani, H.S., 2009. Security and mobility of intermodal freight networks: Evaluation framework for simulation and assignment. Transportation research record, 2137(1), pp.109-117.

Miller-Hooks, E., Zhang, X. and Faturechi, R., 2012. Measuring and maximizing resilience of freight transportation networks. Computers & Operations Research, 39(7), pp.1633-1643

Modesti, P. and Sciomachen, A., 1998. A utility measure for finding multi-objective shortest paths in urban multimodal transportation networks. European Journal of Operational Research, 111(3), pp.495-508.

Mollanejad, M., Zhang, L., 2014. Incorporating spatial equity into interurban road network design. J. Transp. Geogr. 39, 156–164. https://doi.org/10.1016/j. jtrangeo.2014.06.023.

Morrow, B.H., 1999. Identifying and mapping community vulnerability. Disasters, 23(1), pp.1-18.

National Corridors Analysis and Speed Tool (N-CAST) [WWW Document], 2012. . TruckingResearch.org. URL https://truckingresearch.org/n-cast/ (accessed 6.19.21).

Nelson, A., Lindbergh, S., Stephenson, L., Halpern, J., Arroyo, F.A., Espinet, X., Gonz´alez, M.C., 2019. Coupling natural hazard estimates with road network analysis to assess vulnerability and risk: case study of freetown (sierra leone). Transp. Res. Rec. 2673 (8), 11–24. https://doi.org/10.1177/0361198118822272.

Newman, M.E.J., 2010.Networks: An Introduction. Oxford University Press, USA, pp. 169.

Nicholson, C.D., Barker, K., Ramirez-Marquez, J.E., 2016. Flow-based vulnerability measures for network component importance: Experimentation with preparedness planning. Reliab. Eng. Syst. Saf. 145, 62–73. https://doi.org/10.1016/j.ress.2015.08.014

Novak, D.C., Sullivan, J.F., Sentoff, K. and Dowds, J., 2020. A framework to guide strategic disinvestment in roadway infrastructure considering social vulnerability. Transportation Research Part A: Policy and Practice, 132, pp.436-451.

Ortega, E., Martín, B., Aparicio, ´A., 2020. Identification of critical sections of the Spanish transport system due to climate scenarios, 102691 J. Transp. Geogr. 84. https://doi.org/10.1016/j.jtrangeo.2020.102691.

Ouyang, M., Zhao, L., Hong, L., Pan, Z., 2014. Comparisons of complex network based models and real train flow model to analyze Chinese railway vulnerability. Reliab. Eng. Syst. Saf. 123, 38–46. https://doi.org/10.1016/j.ress.2013.10.003

Pan, S., Yan, H., He, J., He, Z., 2021. Vulnerability and resilience of transportation systems: A recent literature review. Phys. Stat. Mech. Its Appl. 581, 126235. https://doi.org/10.1016/j.physa.2021.126235

Papilloud, T., R¨othlisberger, V., Loreti, S., Keiler, M., 2020. Flood exposure analysis of road infrastructure – Comparison of different methods at national level. Int. J. Disaster Risk Reduct. 101548 https://doi.org/10.1016/j.ijdrr.2020.101548.

Park, J., Cho, J., Gordon, P., Moore II, J.E., Richardson, H.W. and Yoon, S., 2011. Adding a freight network to a national interstate input–output model: a TransNIEMO application for California. Journal of Transport Geography, 19(6), pp.1410-1422.

Paton, D., McClure, J. and Bürgelt, P.T., 2006. Natural hazard resilience: The role of individual and household preparedness. Disaster resilience: An integrated approach, 105, p.27.

Pereira, R.H., Schwanen, T. and Banister, D., 2017. Distributive justice and equity in transportation. Transport reviews, 37(2), pp.170-191.

Reggiani, A., Nijkamp, P. and Lanzi, D., 2015. Transport resilience and vulnerability: The role of connectivity. Transportation research part A: policy and practice, 81, pp.4-15.

Rodríguez-Núñez, E. and García-Palomares, J.C., 2014. Measuring the vulnerability of public transport networks. Journal of transport geography, 35, pp.50-63.

Schipanski, M.E., MacDonald, G.K., Rosenzweig, S., Chappell, M.J., Bennett, E.M., Kerr, R.B., Blesh, J., Crews, T., Drinkwater, L., Lundgren, J.G. and Schnarr, C., 2016. Realizing resilient food systems. BioScience, 66(7), pp.600-610.

Seekell, D., Carr, J., Dell'Angelo, J., D'Odorico, P., Fader, M., Gephart, J., Kummu, M., Magliocca, N., Porkka, M., Puma, M. and Ratajczak, Z., 2017. Resilience in the global food system. Environmental Research Letters, 12(2), p.025010.

Shang, P., Li, R., Liu, Z., Yang, L., Wang, Y., 2018. Equity-oriented skip-stopping schedule optimization in an oversaturated urban rail transit network. Transp. Res. Part C: Emerging Technol. 89, 321–343. https://doi.org/10.1016/j.trc.2018.02.016.

Southworth, F., 2018. Freight flow modeling in the United States. Applied Spatial Analysis and Policy, 11(4), pp.669-691.

Tahmasbi, B., Haghshenas, H. and Birzhandi, S., 2021. Network vulnerability analysis based on the overall and inequity impacts of the distribution of the added travel time to the network users. European Journal of Transport and Infrastructure Research, 21(1), pp.94 114.

Taylor, M., 2017. Vulnerability analysis for transportation networks. Elsevier.

The Importance of Highways to U.S. Agriculture, n.d. 154.

The SoVI® Recipe | Hazards & Vulnerability Research Institute, 2016. . Univ. S. C.

Tierney, K., 2009. Disaster response: Research findings and their implications for resilience measures (Vol. 6). Oak Ridge, TN: CARRI research report.

Van Wee, B., 2011. Transport and ethics: ethics and the evaluation of transport policies and projects. Edward Elgar Publishing.

Young, Iris Marion. 2011. Justice and the Politics of Difference. Princeton, NJ: Princeton University Press.

Zhang, X., Miller-Hooks, E., Denny, K., 2015. Assessing the role of network topology in transportation network resilience. J. Transp. Geogr. 46, 35–45. https://doi.org/10.1016/j.jtrangeo.2015.05.006

Zhu, Y.-J., Hu, Y., Collins, J.M., 2020. Estimating road network accessibility during a hurricane evacuation: A case study of hurricane Irma in Florida. Transp. Res. Part D: Transport Environ. 102334 https://doi.org/10.1016/j.trd.2020.102334.

Zolfaghari, M.R. and Peyghaleh, E., 2015. Implementation of equity in resource allocation for regional earthquake risk mitigation using two-stage stochastic programming. Risk analysis, 35(3), pp.434-458.

Appendix A

Detailed Methods

Table **A-1**:FAF4 Agricultural/food Standard Classification of Transported Goods (SCTG) Flow Data

FAF4 Data Transportation Statistics[1]	SCTG 1 Live Animals and Fish	SCTG 2 Cereal Grains	SCTG 3 Other Agricultural Products	SCTG 4 Animal Feed	SCTG 5 Meat and Seafood	SCTG 6 Milled Grain Products	SCTG 7 Other Foods
% Truck AVG. NJ Exports	100.0%	97.2%	100.0%	98.9%	99.8%	99.9%	97.8%
% Truck AVG. NY Exports	100.0%	100.0%	99.9%	100.0%	100.0%	98.6%	99.7%
% Truck AVG. PA Exports	100.0%	100.0%	100.0%	99.8%	100.0%	99.9%	99.9%

Table **A-2**: Selected Centrality-based Measures

Index - Centrality	Expression	Description
Betweenness	$x_i = \sum_{OD} \frac{g_{OD}^i}{g_{OD}}$	Number of shortest paths passing by the given element (node/edge) (Brandes, 2001)
Closeness	$c_i = \frac{N-1}{\sum_{i=1}^{N-1} d(i,j)}$	The accessibility of a node in the network; the more central a node is, the closer it is to all other nodes (Freeman, 1979)
Eigenvector	$Ax = \lambda x$	The centrality for a node based on the centrality of its neighbors (Newman, 2010)

Data Selection Process

I started by narrowing the counties (origins/destinations) between these states, we began by selecting the top 20 cities based on population using US Census Data (U.S. Census Bureau, 2018). We used these cities as the center-point for food commodity transportation in and out of the county. Then taking those combined 60 most populous cities, we reduced them given the multiple city and county pairings prevalent in the data. When multiple cities were located in one county, the selected pairing was based on greatest population (e.g. Newark, NJ (pop. 282,011), and East Orange, NJ (pop. 64,367), in Essex County). Similarly, when one city covered multiple counties, the county was chosen based on which county had the most land area in the city (e.g. Lehigh, PA (345.17 mi2), and Northampton (369.67 mi2), in Bethlehem County). We ended up with 40 total cities county pairs, 9 in NJ, 15 in NY, 16 in PA.

Static Traffic Assignment

Five pre-determined routes (shortest paths) between counties (OD) pairs: **R** is the number of routes between a given OD pair and r = {1, 2, … , R} be an index for each route.

The utility of a given route (i.e., how likely it is to be used):

$$U_r = \beta \times tt_r$$

where tt_r is the travel time on route r and β is the time coefficient (Setting β = -1; Modesti and Sciomachen, 1998; Ding-Mastera, 2016).

The logit-type formula (see below) defines the probability of choosing a route p_r as a share (proportion) of the whole choice set:

$$p_r = \frac{\exp(U_r)}{\sum_r^R \exp(U_r)}$$

Components of the SoVI & Variable Selection

Race and Ethnicity

Present literature has identified an increased statistical likelihood for households headed by people of color, namely Black, Hispanic, and American Indian or Alaska Natives (AIAN), as being disproportionately affected by food, energy, or water insecurity (Berry et al., 2018; Coleman-Jensen, 2020; Dargin et al., 2020; Deitz and Meehan, 2019; Drehobl et al., 2020; Harker Steele and Bergstrom, 2021; Hernández and Siegel, 2019; Jernigan et al., 2017; Meehan et al., 2020; Memmott et al., 2021). Systematic policies and practices are embedded in systems in the U.S. for economic, social, and/or political exclusions, which prevent these communities from accessing the same basic household FEW resources as easily as non-Hispanic, white households (Burke et al., 2018; Cutter et al., 2003b; Drehobl et al., 2020). Note that citizenship status (Jepson and Vandewalle, 2016) was excluded from the SoVI model due to multicollinearity issues (e.g., citizenship status with Hispanic variable).

Economic

Low-income households are a predictor of household food, energy, and water insecurity (Berry et al., 2018; Coleman-Jensen, 2020; Dargin et al., 2020; Deitz and Meehan, 2019; Meehan et al., 2020; Memmott et al., 2021). Low-income households are also likely to have poor preparation behavior in relation to FEW infrastructure service disruptions (Dargin et al., 2020), which could theoretically decrease the household’s ability to respond to CI disruptions safely and effectively. For example, of the 5.3 million food-insecure households in the U.S., the majority fear that they do not have the necessary financial resources and income to supply food for their household (Coleman-Jensen, 2020). Revelations of these sorts highlight the disparities that are felt by food-insecure households and that could be exacerbated in a FEW-CI disruption where access might become not only limited but economically impractical. For this study, households at ≤ 200% of the Federal Poverty Level (FPL) will be considered based on (1) food-based federal assistance program's FPL requirements such as Supplemental Nutrition Assistance Program (SNAP), Women, Infants and Children (WIC), and the National School Lunch Program (NSLP) in the states of NJ, NY, and PA ("Map the Meal Gap 2020 Technical Appendix (2018 data)," 2020) and (2) energy-based federal assistance programs such as the Low-Income Home Energy Assistance Program (LIHEAP) use 150% to 200% as the qualification FPL (Bohr and McCreery, 2020).

Household Composition

Households comprised of older adults (65 and older) (Drehobl et al., 2020), children (under 18) (Coleman-Jensen, 2020; Hernández and Siegel, 2019), single men and women with children (Coleman-Jensen, 2020), men or women living alone (Coleman-Jensen, 2020), females (Liese et al., 2021), lower educational attainment (Dargin et al., 2020; Hernández and Siegel, 2019; Liese et al., 2021), and disabled members (Dargin et al., 2020) have been shown to have increased trends for household food, energy, and/or water insecurity. Overall, disruptions to the FEW nexus resources may be more impactful for these identified population groups.

Household Type

Housing type and tenure have a strong correlation with household water and energy insecurity. Characteristics associated with household water and energy insecurity include renters, multi-family units (5+ units), mobile homes, and households built before 1980/1990s. On the national scale, many unplumbed households are renter-occupied housing and mobile home occupants (Deitz and Meehan, 2019; Meehan et al., 2020). Amid a CI disruption, the households lacking complete plumbing may have different and variable incoming water sources and types and could encounter challenges in attaining a safe and reliable water source, especially during a disruption. Furthermore, regionally renters and low-income multi-family housing also face disproportionately higher energy burden costs, where energy burden is the relative cost of household energy to household income (Drehobl et al., 2020). Renters are also found to have poorer quality housing with less energy-efficient systems and weatherization (Bird and Hernández, 2012). Energy insecure household types are also typically built before the 1980/1990's and are multi-family units (Berry et al., 2018; Drehobl et al., 2020). Note, that due to multicollinearity issues with multi-family housing units, the renter variable was eliminated from the SoVI model.

Appendix B

Extended Results

Network Disruption(s) and Vulnerability Analysis

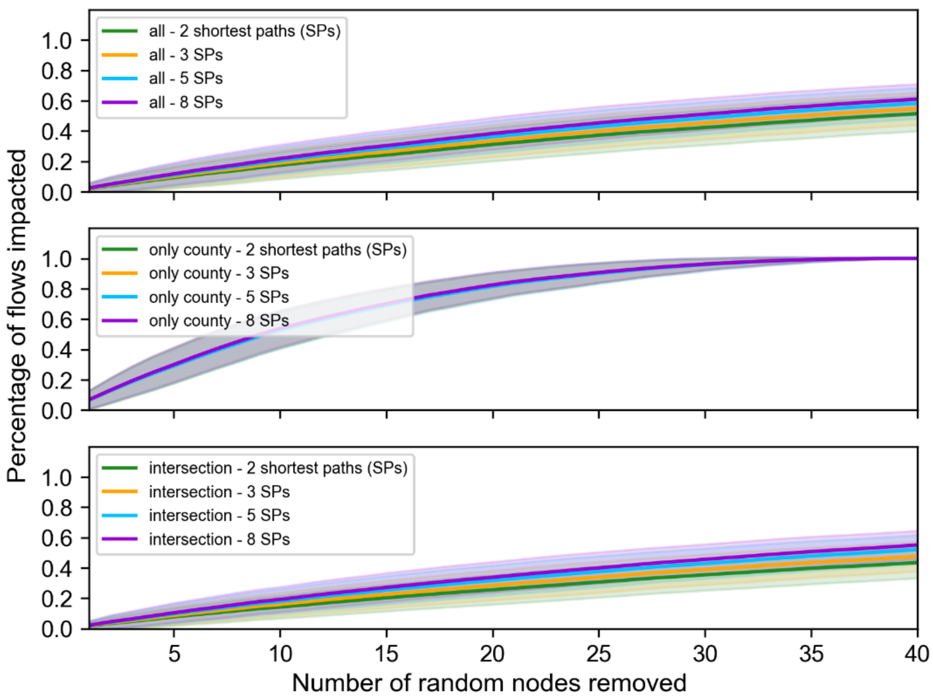

Figure **B-1**: Percentage of food flows impacted for a varying number of shortest paths due to random disruptions scenarios (all, only county, intersection).

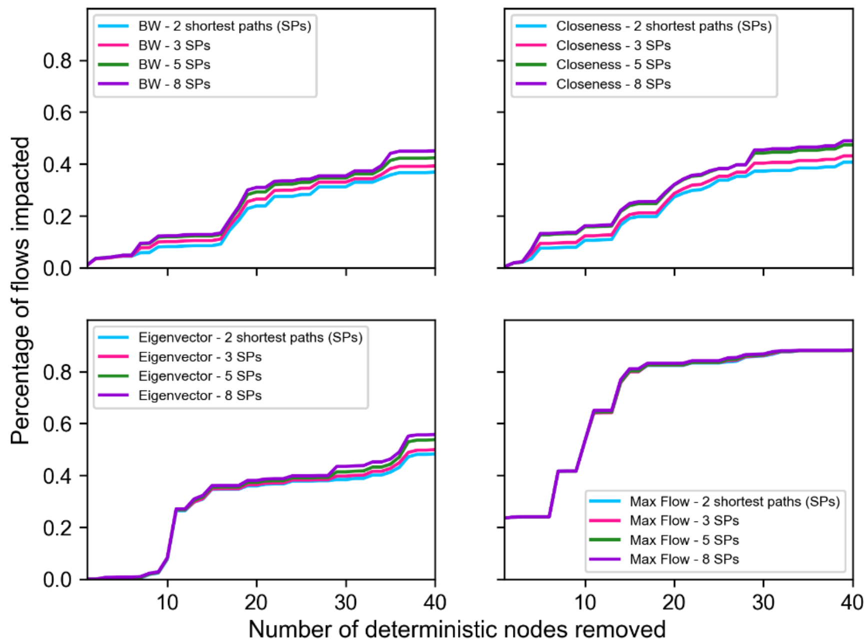

Figure **B-2**: Percentage of food flows impacted for different number of shortest paths due to deterministic disruption scenarios (Betweenness (BW), Closeness, and Eigenvector Centrality and Max total flow.

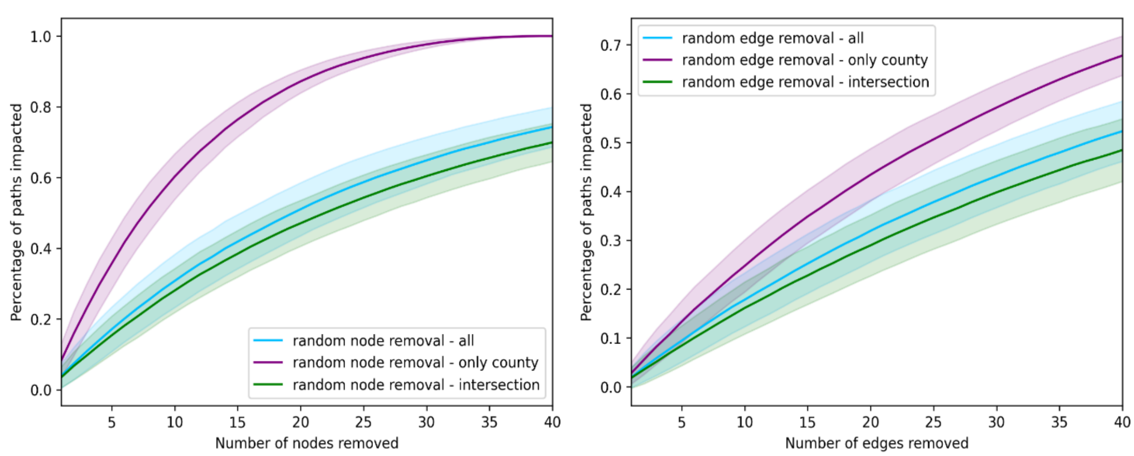

Figure **B-3**: Percentage of shortest paths impacted for a varying random node disruptions scenarios (all, only county, intersection).

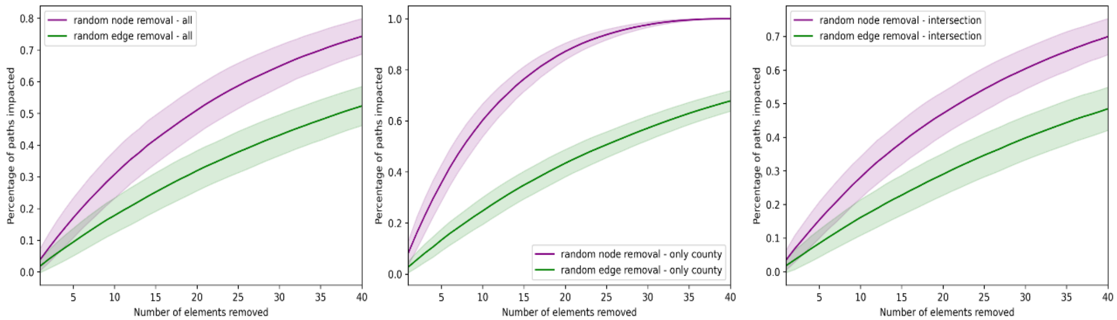

Figure **B-4:** Percentage of shortest paths impacted for a varying random edge disruptions scenarios (all, only county, intersection).

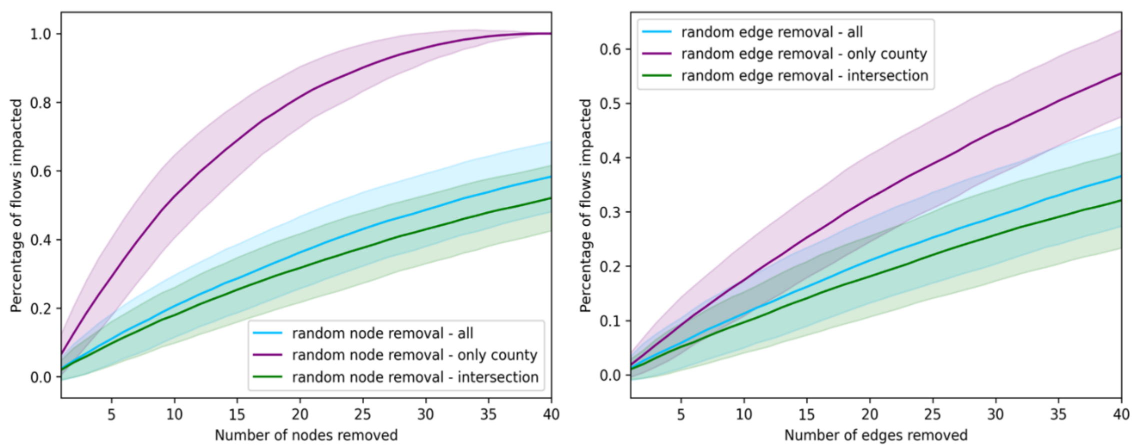

Figure **B-5**: Percentage of food flows impacted for a varying random node disruptions scenarios (all, only county, intersection).

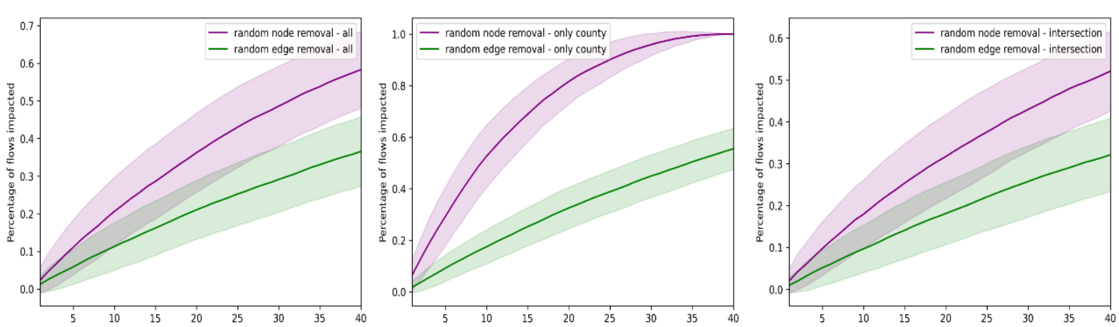

Figure **B-6**: Percentage of shortest paths impacted for a varying random edge disruptions scenarios (all, only county, intersection).

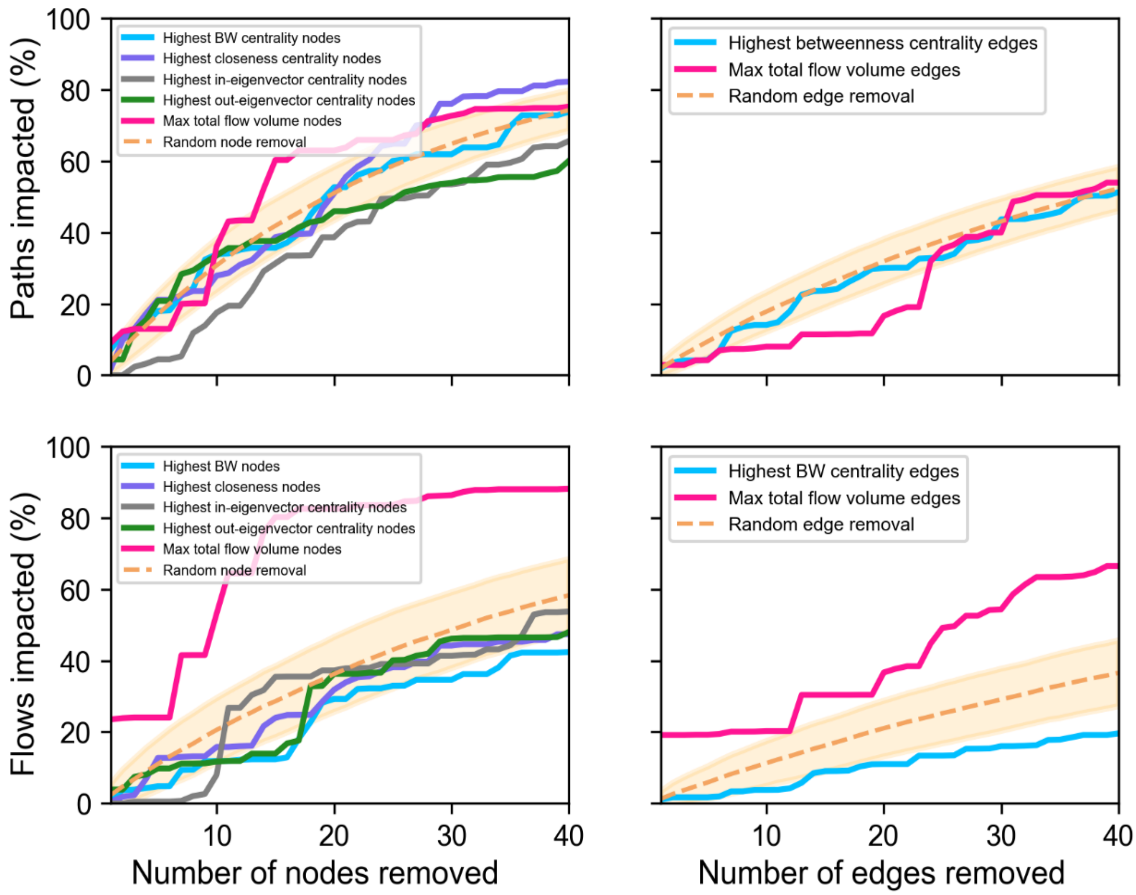

Figure **B-7**: Impact Analysis including *eigenvector* centrality measure scenario.

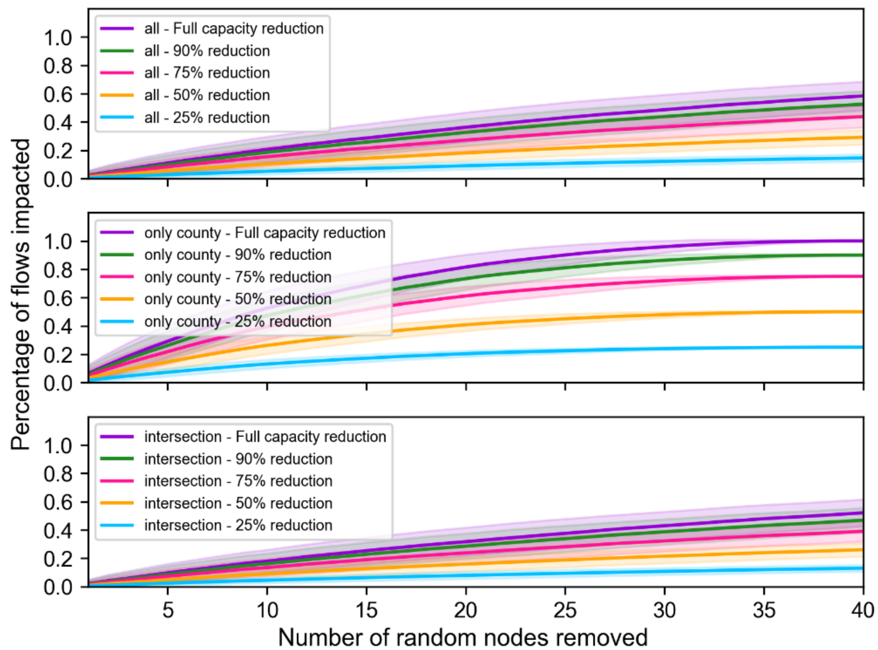

Figure **B-8**: Percent of foods flows impacted with different capacity reduction scenarios due to random disruption scenarios (Full, 90%, 75%, 50, and 25% node reduction).

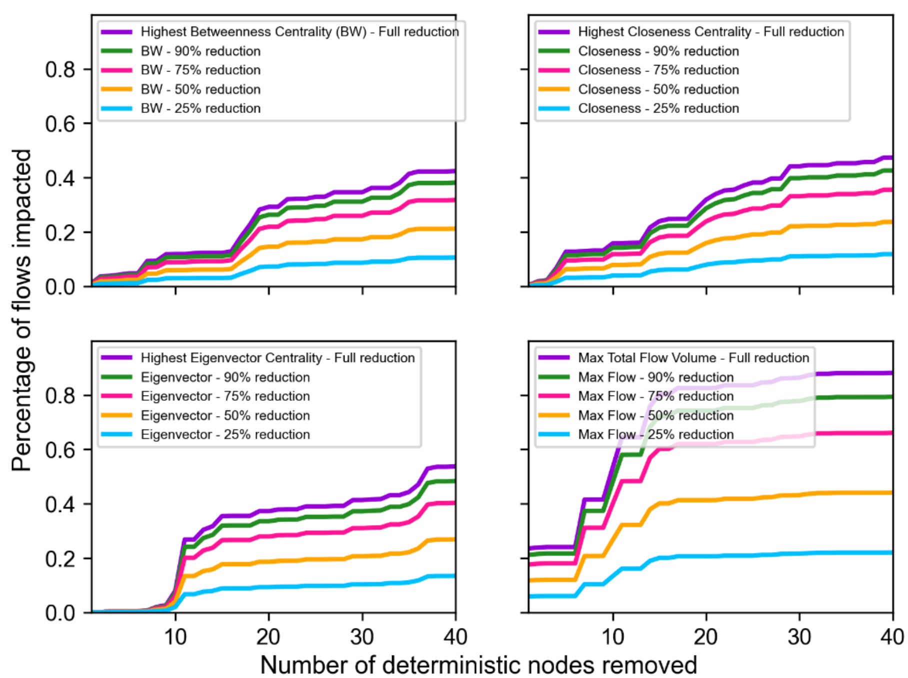

Figure **B-9**: Percent of foods flows impacted with different capacity reduction scenarios due to deterministic disruption scenarios (Full, 90%, 75%, 50, and 25% node reduction).

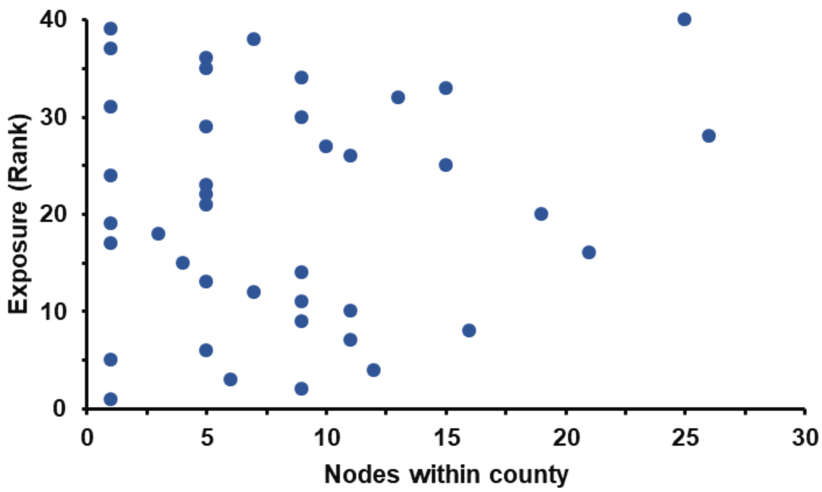

Figure **B-10**: Scatter plot for food-weighted exposure ranking v. amount of network nodes that fall within county

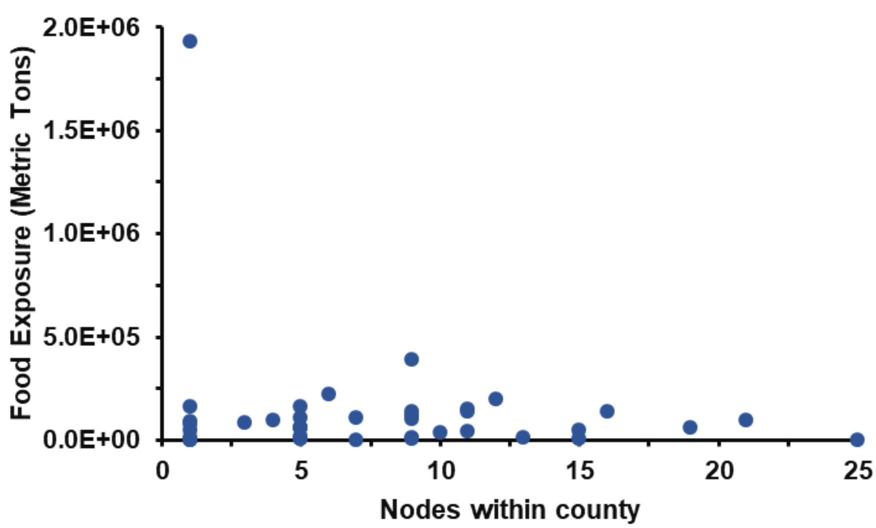

Figure **B-11**: Scatter plot for food-weighted exposure v. amount of network nodes that fall within county

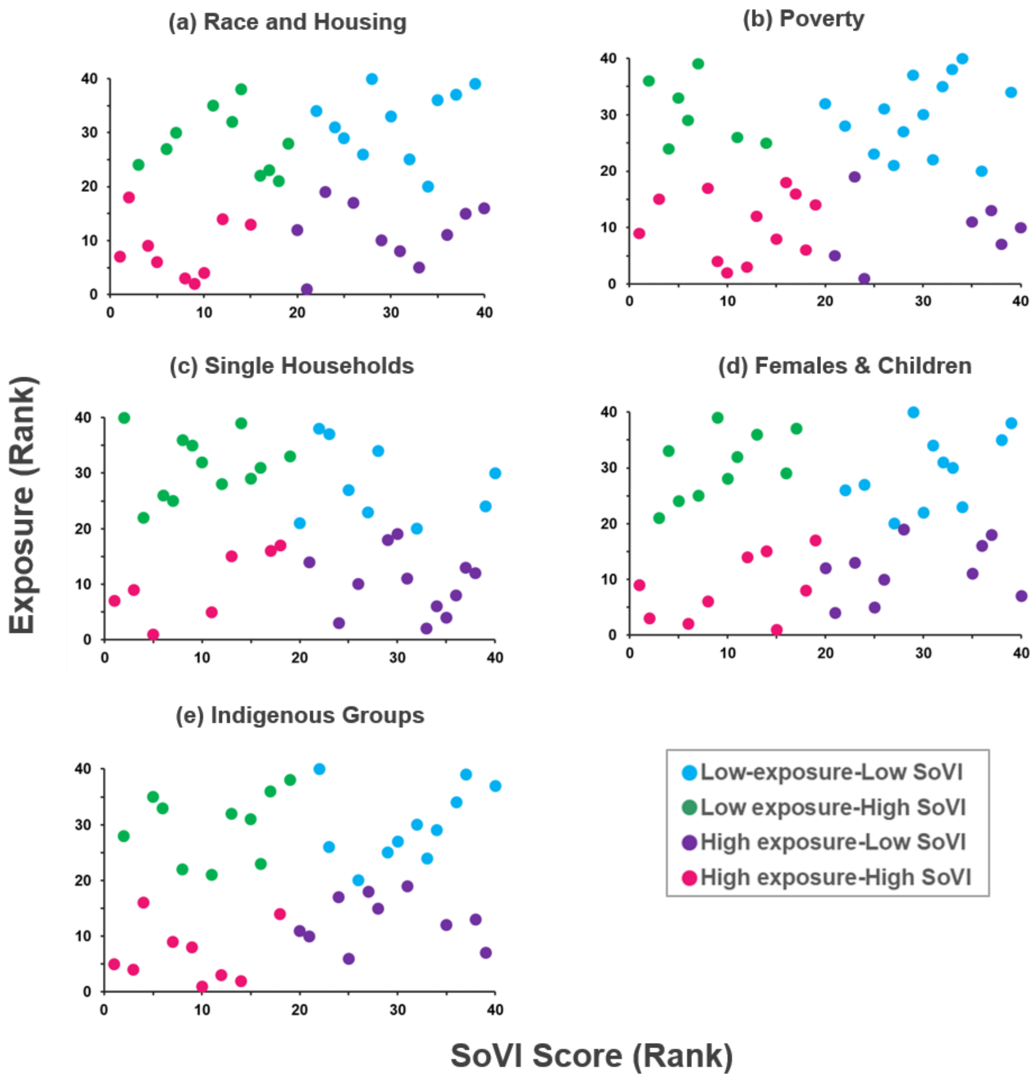

Figure **B-12**: Scatter plots for food weighted exposure v. SoVI ranking for five main groupings: (a) Race/Ethnicity and Housing Type, (b) Poverty, (c) Women and Men Living Alone, (d) Female and Children, (e) American Indian or Alaska Native.

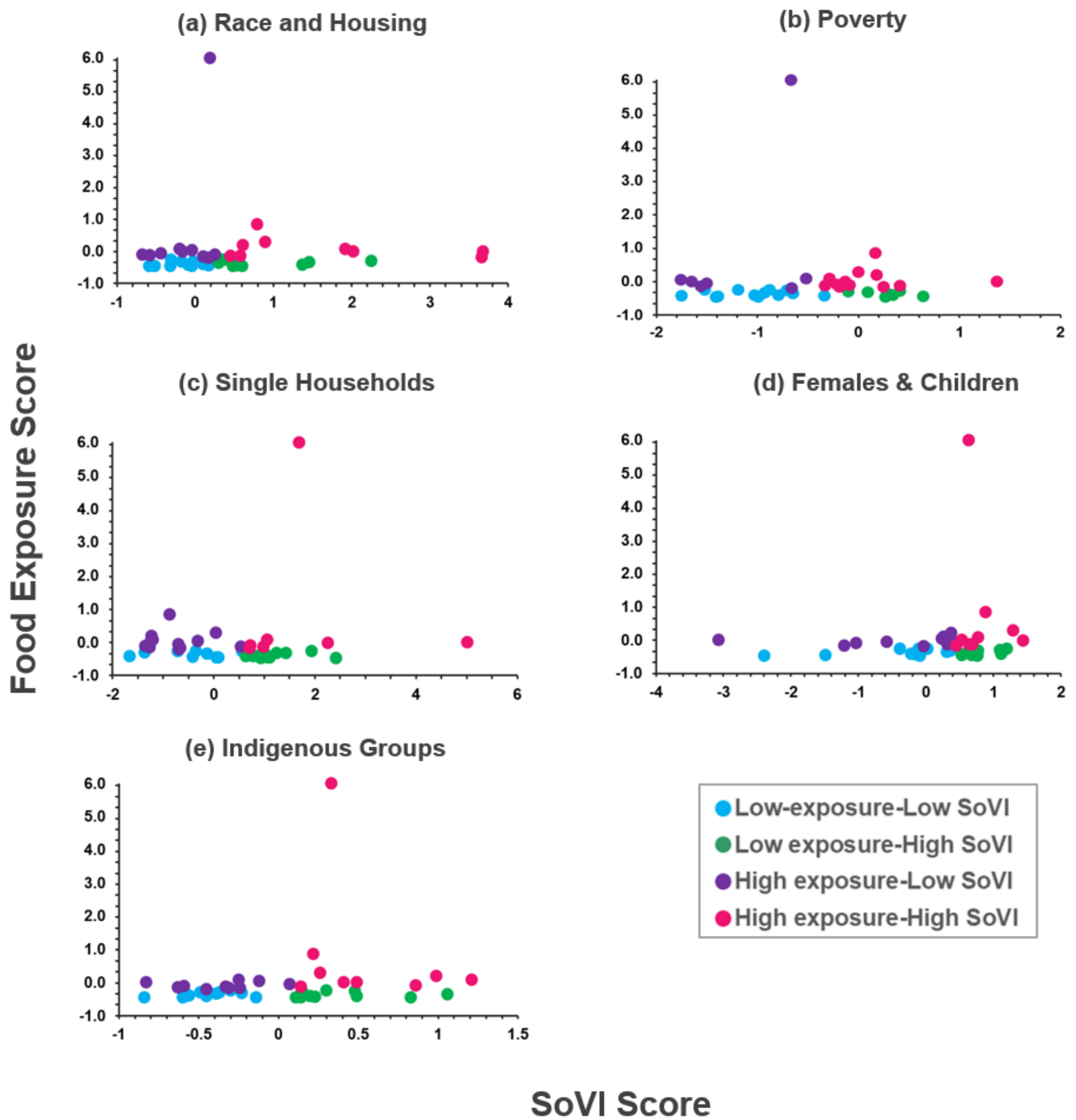

Figure **B-13**: Scatter plots for food-weighted exposure v. SoVI standard scores for five main groupings: (a) Race/Ethnicity and Housing Type, (b) Poverty, (c) Women and Men Living Alone, (d) Female and Children, (e) American Indian or Alaska Native.

Social Vulnerability Index

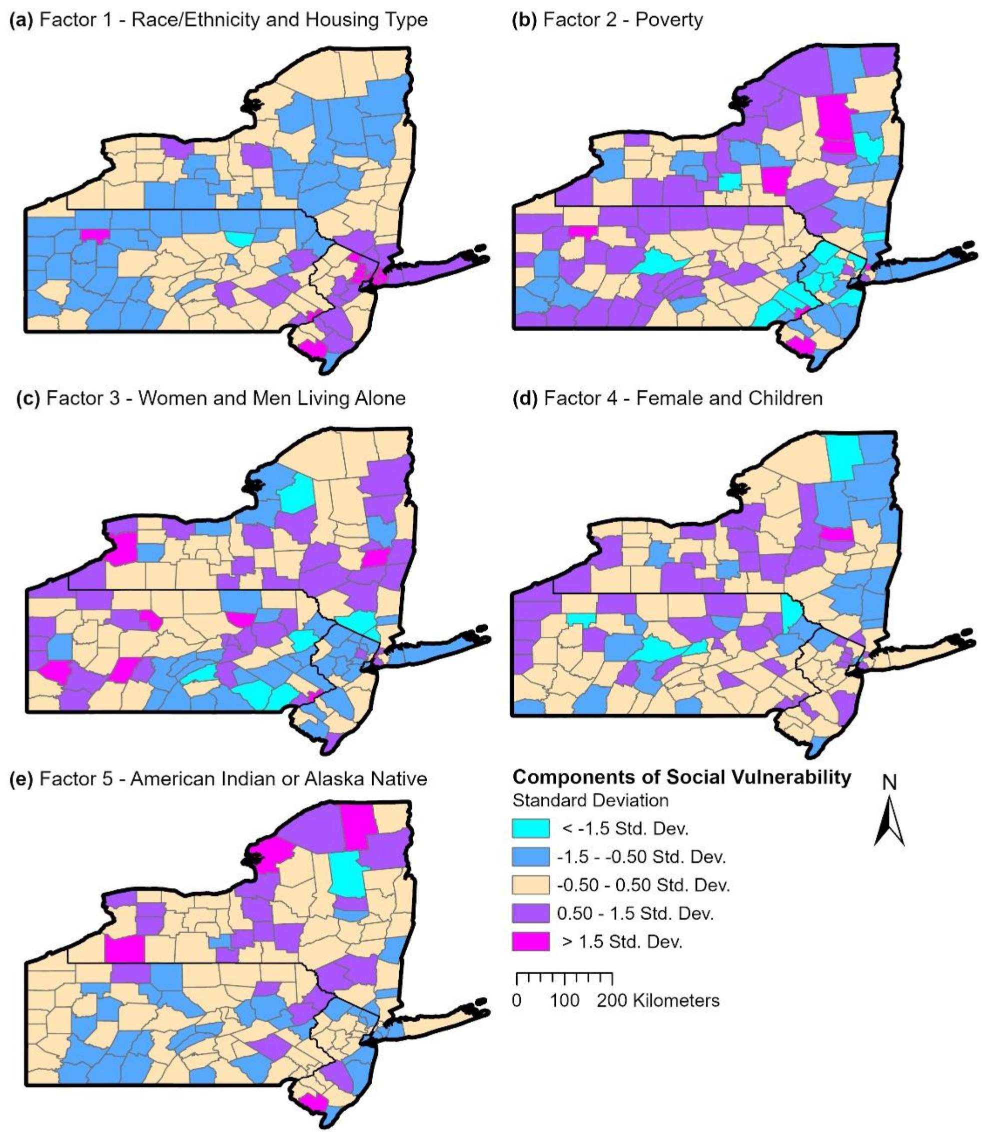

Figure **B-14**:.Five main groupings of social vulnerability Index: (a) Race/Ethnicity and Housing Type, (b) Poverty, (c) Women and Men Living Alone, (d) Female and Children, (e) American Indian or Alaska Native.