SUPPLEMENTAL MATERIALS

ASCE *Journal of Infrastructure Systems*

Investigating Social Vulnerability, Exposure, and Transport Network Disruption in the Mid-Atlantic Region

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DOI: 10.1061/JITSE4.ISENG-2258

Supplementary Material

Detailed Methods

Table S-1: Data Source Details

Data Source	Use	Variables	Reference
Freight Analysis Framework V4	Model Highway Network	Shape file of highway network, Roads	1
Freight Analysis Framework V4	Modified county to county freight flow to only estimate truck freight, not other modes	Percentage of each SCTG class in each state transported by truck, see table A-2 below.	1
County Scale Commodity Flow	O-D flows between counties	Volume of freight flow between each county, by SCTG class	2
N-CAST	Truck average travel time	Truck average travel time	3
Google Maps	Truck average travel time	Truck average travel time	4
2019 5 Year American Community Survey	Demographic information for SoVI	% Black or African American, % Hispanic or Latino, % of Alaska Native and American Indian Population, % of population <18, % of population >65, % females, % female-headed households, % female-headed households, with children <18, % male-headed households, with children <18, % female-headed households, living alone, % male-headed households, living alone, % population with no high school diploma, % of civilian noninstitutionalized population with a disability, % living in poverty, % of mobile home housing units, % multi-family housing units, % of housing units built up to 1989	5

The County Tonnage Flow Data from Lin et al.[2] utilized did not include the transportation mode, however based on these percentages provided by FAF v4[1], we multiplied the county to county flows from Lin et al by the percentages of truck-transported goods for each SCTG class to produce our final flow volumes.

Table **S-2**:FAF4 Agricultural/food Standard Classification of Transported Goods (SCTG) Flow Data[1]

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%

Theoretical Justification of 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.[6–12] 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 food, water, and energy resources as easily as non-Hispanic, white households.[9,13,14] Note that citizenship status[15,16] 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.[6–8,17–19] Low-income households are also likely to have poor preparation behavior in relation to food, water, energy infrastructure service disruptions,[8] which could theoretically decrease the household's ability to respond to critical infrastructure 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.[7] Revelations of these sorts highlight the disparities that are felt by food-insecure households and that could be exacerbated in a food, water, energy, critical infrastructure disruption where access might become not only limited but economically impractical. For our 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[20] 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.[21]

Household Composition

Households comprised of older adults (65 and older),[9] children (under 18),[7,11] single men and women with children,[7] men or women living alone,[7] females,[22] lower educational attainment,[8,11,22] and disabled members[8] have been shown to have increased trends for household food, energy, and/or water insecurity. Overall, disruptions to the food, water, energy 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.[17,18] 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.[9] Renters are also found to have poorer quality housing with less energy-efficient systems and weatherization.[23] Energy insecure household types are also typically built before the 1980/1990's and are multi-family units.[6,9] Note, that due to multicollinearity issues with multi-family housing units, the renter variable was eliminated from the SoVI model.

Disruption details

We assume that when a node or edge is disrupted, all paths and flows that travel through that node are no longer accessible as a result of the disruption. We simulate impact scenarios where nodes and edges in the network are disrupted, and as a result of this perturbation, 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:

$$PSPI(i) = 100 * \frac{TSPI(i)}{TSP}$$

where *PSPI(i)* represents the percent of shortest paths impacted as a result of removal of node *i*, *TSP* is the total number of shortest paths between all nodes in the network, and *TSPI(i)* is the total number of shortest paths affected due to of removal of node *i*.

The impact of a potential disruption can also be quantified by the magnitude of the flow affected.[24] If the path(s) between an origin and destination are impacted, then the connectivity and food flow between that pair of nodes are lost. For this work, the impact on food flows after a node disruption is calculated as follows:

$$PFFI(i) = 100 * \frac{TFFI(i)}{TFF}$$

Where *PFFI* represents the percent of food flows impacted as a result of removal of node *i*, *TFF* is the total food-flow volume between all nodes in the network, and *TFFI(i)* as the total food-flow volume affected due to the removal of node *i*.

Table **S-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)

Extended Results

Network Disruption(s) and Vulnerability Analysis

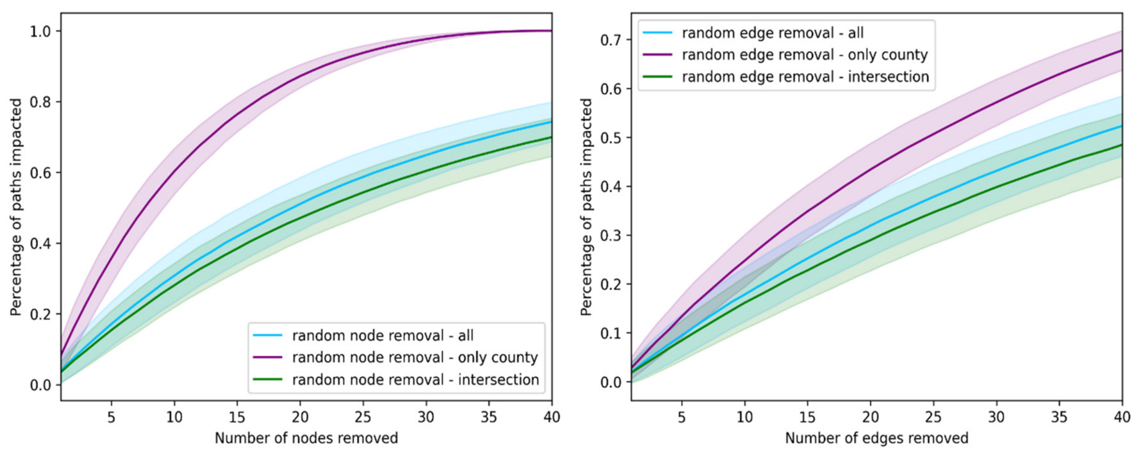

Figure **S-1**: Percentage of shortest paths impacted for a varying random node disruptions scenarios (all, only county, intersection).

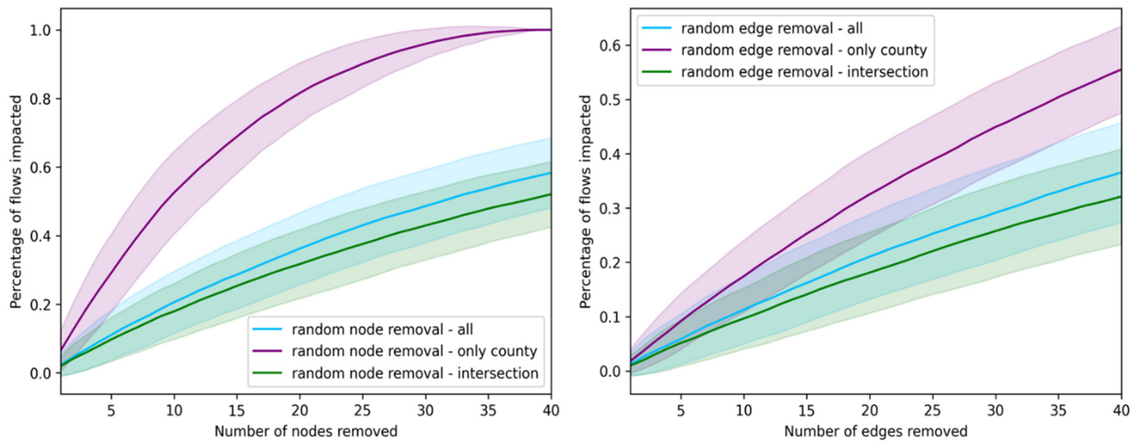

Figure **S-2**: Percentage of food flows impacted for a varying random node disruptions scenarios (all, only county, intersection).

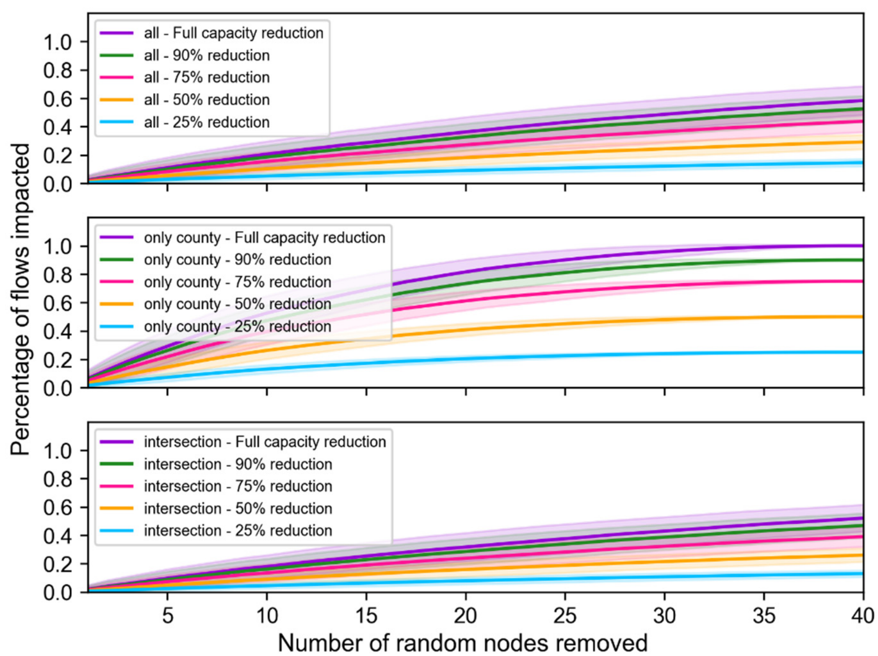

Figure **S-3**: Percent of foods flows impacted with different capacity reduction scenarios due to random disruption scenarios (Full, 90%, 75%, 50, and 25% node reduction).

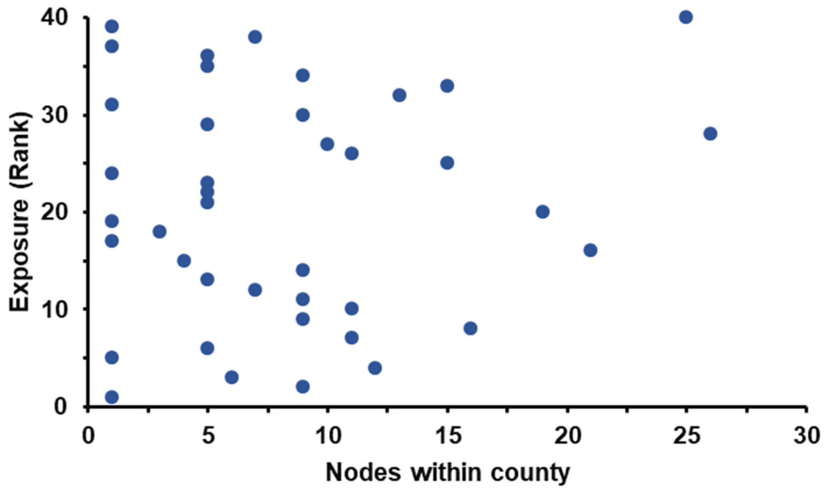

Figure **S-10**: Scatter plot for food-weighted exposure ranking v. amount of network nodes that fall within county

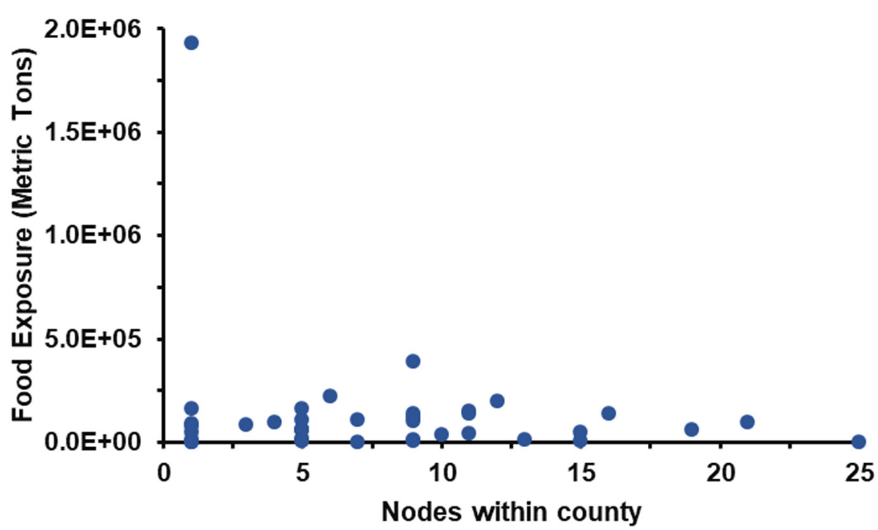

Figure **S-11**: Scatter plot for food-weighted exposure v. amount of network nodes that fall within county

Social Vulnerability Index By Components

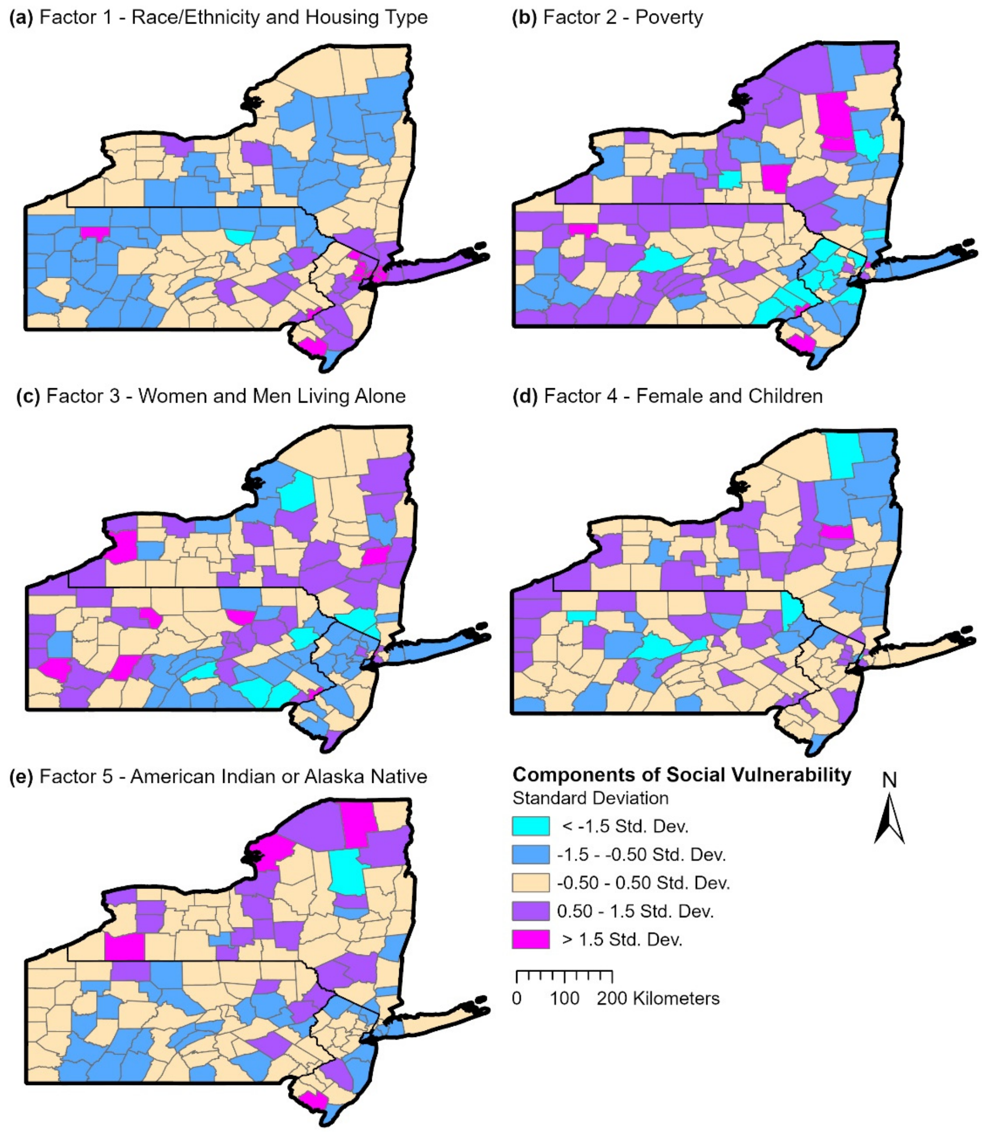

Figure **S-14**:.Five main groupings of social vulnerability Index: (a) Race/Ethnicity and Housing Type, (b) Poverty, (c) Women and Men Living Alone, (d) Female and Children, (e) American Indian or Alaska Native.

Supplemental References

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