Transportation Consortium of South-Central States

Tran-SET

Solving Emerging Transportation Resiliency, Sustainability, and Economic Challenges through the Use of Innovative Materials and Construction Methods: From Research to Implementation

Network Analysis to Identify Critical Links for Relief Activities During Extreme Weather Events

Project No. 20PUTA28

Lead University: University of Texas at Arlington

Final Report
August 2021

Disclaimer

Acknowledgements

The authors gratefully acknowledge the support provided by the Project Review Committee, Loyd Smith, Bill Wheeler, and Dr. Haizhong Wang.

TECHNICAL DOCUMENTATION PAGE

1. Project No.	2. Government Accession No.	3. Recipient's Catalog No.
20PUTA28		

4. Title and Subtitle	5. Report Date
Network Analysis to Identify Critical Links for Relief Activities During Extreme Weather Events	Aug. 2021
	6. Performing Organization Code

7. Author(s)

PI: Kate Kyung Hyun https://orcid.org/0000-0001-7432-8058
Co-PI: Stephen Mattingly https://orcid.org/0000-0001-6515-6813
GRA: Mehrdad Arabi https://orcid.org/0000-0003-3267-1362

8. Performing Organization Report No.

9. Performing Organization Name and Address	10. Work Unit No. (TRAIS)
Transportation Consortium of South-Central States (Tran-SET) University Transportation Center for Region 6 3319 Patrick F. Taylor Hall, Louisiana State University, Baton Rouge, LA 70803	**11. Contract or Grant No.**

12. Sponsoring Agency Name and Address	13. Type of Report and Period Covered
United States of America Department of Transportation Research and Innovative Technology Administration	Final Research Report Aug. 2020 – Aug. 2021
	14. Sponsoring Agency Code

15. Supplementary Notes

Report uploaded and accessible at Tran-SET's website (http://transet.lsu.edu/).

16. Abstract

As one of the principal lifeline systems, transportation networks are crucial for evacuation and delivering essential resources and services during the response and recovery phases of extreme weather events and must remain intact to enhance regional resiliency. The conventional evaluation measures that estimate the vulnerability or criticality of road network based on travel time or link volumes do not capture the community impacts due to disruptions. This study seeks to develop a framework to evaluate road network infrastructure criticality during extreme weather events by introducing measures that evaluate the vulnerability of roads users, rather than the physical aspects of link importance. The research develops an innovative approach that integrates three important concepts including hurricane evacuation behavior, community impacts, and road criticality to identify the critical links. Results show that the critical links for vulnerable populations during evacuation do not always align with conventional link-based measures. This highlights the importance of using a performance measure that takes the social vulnerability of road users into consideration when identifying the criticality of a road network and planning for fortification of links to avoid irreversible consequences for vulnerable population groups. Furthermore, decision-making that considers the risks to different communities may lead to a more effective distribution of resources and help support a timely and safe evacuation from disaster events by strengthening the preservation of critical infrastructure links.

17. Key Words	18. Distribution Statement
Hurricane Evacuation, Critical links, Vulnerability, Performance Measure, Natural Disaster	No restrictions. This document is available through the National Technical Information Service, Springfield, VA 22161.

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	57	

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized.**

SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

ACRONYMS, ABBREVIATIONS, AND SYMBOLS

ATSDR	Agency for Toxic Substances and Disease Registry
CDC	Centers for Disease Control
CT	Census Tracts
ECV	Economic Vulnerability
ENV	Environmental Vulnerability
FEMA	Federal Emergency Management Agency
FHWA	Federal Highway Administration
HDS	Hurricane Disruption Spatial Data
MEOW	Maximum Envelopes of Water
MOMs	Maximum of MEOWs
NHC	National Hurricane Center
NOAA	National Oceanic and Atmospheric Administration
OD	Origin-Destination
OSM	Open Street Map
SES	Socioeconomic Status
SLOSH	sea, lake, and overland surges from Hurricanes
SNAP	Supplemental Nutrition Assistance Program
SOV	Social Vulnerability
SVI	Social Vulnerability Index
TxDOT	Texas Department of Transportation
USGS	United States Geological Survey

EXECUTIVE SUMMARY

In 2017, the Texas Department of Transportation (TxDOT) closed over 530 disrupted road sections in the Houston area during Hurricane Harvey. Ground transportation for evacuation, motor carriers transporting humanitarian aid, and first responders entering the flooded areas had to be rerouted or rescheduled due to the road closures. To repair the damaged road infrastructure, the Federal Highway Administration (FHWA) allocated $25 million of federal funds to TxDOT for emergency repair activities such as removing debris, inspecting bridges and replacing traffic lights.

In general, network links that carry higher traffic volume and those that ensure connectivity to isolated subnetworks represent critical links because disruptions on the links would impact more vehicles with a greater magnitude of travel time increase from rerouting or rescheduling. However, the individuals and communities that use the infrastructure determines the importance of the road links for community resiliency during the response and recovery phases of extreme weather events varies based on their economic stability and social networks. If a certain link serves at-risk communities (i.e., lower income or older population) for evacuation or humanitarian aid, the link should be considered as a critical link regardless of its total traffic volume. These links must be resilient to save lives within the neighborhood and strengthen the region's overall resiliency.

The proposed research identifies the criticality of network links by identifying the community impacts from network disruption. In particular, this study focuses on developing a network index to determine the critical network links of the communities in a Hurricane-prone area. The outcome of this study will answer the following important questions for disaster planning, management, and recovery.

- What are the impacts of network disruptions on communities?
- Which road links should be given a higher priority for disaster restoration during the response and recovery phases of extreme weather events?

Results show that the user-based and conventional link-based measures do not always result in capturing the same critical links and the study demonstrates the differences between these two sets of measures. In fact, the critical links used by vulnerable users do not necessarily result in a significant impact on the general evacuee's throughput due to the geographical locations of the vulnerable populations. The study also highlights how the critical links for the vulnerable population may differ based on the vulnerability types defined in this study.

This study provides a useful comparison framework among different vulnerability and criticality measures so that decision makers can determine the critical links to prioritize retrofitting and protection strategies for evacuation. This helps to not only find the criticality of links based on their impacts on travel time and the number of evacuees they serve but also consider the variations caused by differences in the demographic, economic and land use characteristics of risk zones.

1. INTRODUCTION

Hurricanes and severe tropical storms are major disruptive events that have struck coastal cities with higher frequency and intensity during the past few decades and caused considerable local and global consequences. Research results on global warming and hurricanes by National Oceanic and Atmospheric Administration's (NOAA) geophysical fluid dynamics laboratory indicate that tropical cyclone intensities and rainfall rates will increase in the future and the proportion of tropical cyclones that reach intense (Category 4 and 5) levels will likely increase due to anthropogenic warming over the 21st century (1). Tracking the adverse weather events in the past few years after hurricane Harvey year indicate an increased number of named storms and hurricanes from 17 named storms and 10 hurricanes in 2017 to 23 named storms and 10 hurricanes in 2020. Since 2015, the Atlantic hurricane season may be growing because a named storm formed before the official start of the hurricane season on June 1. Figure 1 shows the paths of hurricane and tropical storms from 1980 to 2017.

The National Hurricane Center issues regular tropical weather outlooks during the hurricane Atlantic season, which generally lasts from June to November; tropical storms turn to major hurricanes (category 3 or greater) especially during a 2-month period after mid-August. Coastal cities that lack preventive strategies may fail to protect critical transportation infrastructure and face consecutive road disruptions. Preparation and regular evaluation of transportation network vulnerability and resilience can help reduce the impacts of the network disruptions. Furthermore, highway and bridge operations and resiliency represent one of the largest investments in Texas, the region, and the US. State and national agencies should ensure the sustainable operation of the transportation system during natural disasters for all residents, but the consequences for particularly at-risk communities including older adults, people with disabilities, and people with low income may require greater emphasis.

During the last major hurricane event in the Houston area in 2017, the Texas Department of Transportation (TxDOT) closed over 530 disrupted road sections. Ground transportation for evacuation, motor carriers transporting humanitarian aid, and first responders entering the flooded areas had to be rerouted or rescheduled due to the road closures. For some of the roads, the closure was prolonged, and many remained flooded or closed due to storm damage. Even the links that were dry a few days after the hurricane had to be inspected for possible damage before they reopened. According to officials, while the interstate highways were open soon, more than 100 other roadways remained closed and even in some cases, the roads remained closed for several weeks because of high floodwaters and ongoing releases of water from reservoirs into overflowing rivers and bayous. Furthermore, many of the infrastructures such as traffic signals were disrupted and not functional for weeks. To repair the damaged road infrastructure, the Federal Highway Administration (FHWA) allocated $25 million of federal funds to TxDOT for emergency repair activities such as removing debris, inspecting bridges and replacing traffic lights. Figure 2 shows samples of road closure and flooding after Hurricane Harvey.

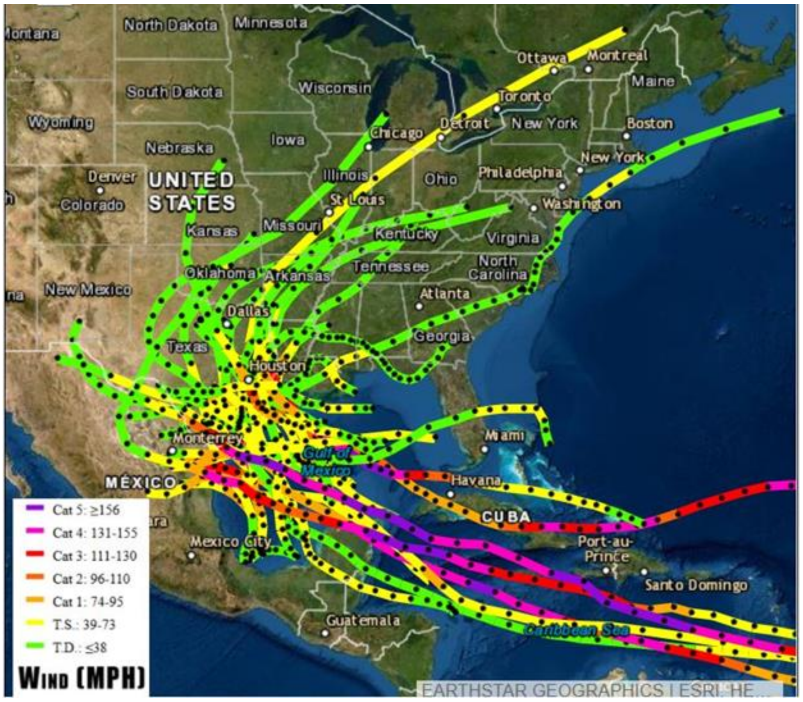

Figure 1. Hurricane and Tropical Storm paths (1980-2017) (Source: weather.org).

Figure 2. Roads closures after Hurricane Harvey in 2017.

Increased risk of severe weather events, especially in coastal cities, raises the frequency of government-issued evacuation orders or optional evacuation by a proportion of population. This highlights the importance of studies on optimization of evacuation, understanding evacuation behavior, and evacuation timing (2–4). The efficiency of different strategies to facilitate and improve the evacuation outcomes, such as contraflow, has also been investigated in evacuation research (5,6). The transportation network represents the most crucial infrastructure component of evacuation and in order to have an effective and timely evacuation, different transportation constituents must function properly. This motivates researchers to explore the vulnerability and resilience of various transportation infrastructures during different stages before and after natural disasters (7,8). Models developed based on real evacuation behavior obtained by surveys in areas affected by major hurricanes provide a foundation for evaluating the performance of strategies and infrastructure during evacuation and afterwards.

In general, network links that carry higher traffic volumes and those that ensure connectivity to isolated subnetworks represent critical links for evacuation because disruptions on the links would impact more vehicles with a greater magnitude of travel time increase from rerouting or rescheduling. However, the individuals and communities that use the infrastructure may also determine the importance of the road links because community resiliency during the evacuation phases of extreme weather events vary based on their social and economic stability. If a certain link serves at-risk communities (i.e., lower income or older population) for evacuation, the link should be considered as a critical link regardless of its total traffic volume. These links must be resilient to save lives within the neighborhood and strengthen the region's overall resiliency. This mainly occurs because a lack of transportation options for evacuation and food supply will significantly affect their survival during the extreme weather event. The geography of Texas presents particularly significant risks for these vulnerable populations along the Gulf coast. Although achieving community resiliency remains a priority of the region, scant research has been conducted to develop strategies that minimize societal impacts along with enhancing infrastructure reliability.

The importance of this research draws attention to the mobility challenges of vulnerable populations. Another issue is the limited resources available for these vulnerable groups including lack of financial resources, knowledge, education and technology; all of these affect evacuation during hurricane disasters. Furthermore, highly vulnerable and isolated communities encounter higher threats during different phases of disasters, mostly because of their inability to evacuate, significant damages from disaster effects such as flooding, and a lack of access to disaster relief measures.

The study identifies the criticality of zones (i.e., communities) and evacuation network links that serve the zones by identifying the vulnerability of communities and their impacts from network disruption. In particular, this study focuses on developing network criticality measures to determine the important evacuation network links in a Hurricane-prone area based on communities' social, economic, and environmental vulnerabilities. The traditional four-step evacuation demand modeling will capture the regional evacuation behaviors and evacuation network loading. Overall, the outcome of this study will answer the following important questions for disaster planning and management.

- What are the impacts of network disruptions on communities based on the evacuation behavioral and spatial distributions?

- Which road links should be given a higher priority for disaster preparation to support timely and safe evacuation for vulnerable communities?

The strategic plans obtained from the study will maximize the efficiency of disaster evacuation while considering the equity and need of communities with varying degrees of resilience and vulnerability. Decision-making that considers the risks to different communities may lead to a more effective distribution of resources and lead to a timely and safe evacuation from disaster events by strengthening the preservation of critical infrastructure links. The findings will strongly support short- and long-term transportation and infrastructure planning for policy makers and planners especially when optimizing maintenance and operation resources for future strategies while considering budget and time constraints to achieve maximum efficiency in disaster preparation.

2. OBJECTIVES

As one of the principal lifeline systems, transportation networks deliver essential resources and services during the response and recovery phases of extreme weather events and must remain intact to enhance regional resiliency. Since Hurricane Harvey in 2017, agencies and elected officials have placed an increasing emphasis on preserving regional infrastructure by prioritizing investments on transportation network infrastructure and operations to promote a fast and sustainable recovery and enhance community resiliency. The project directly addresses the regional focus of preserving and enhancing transportation infrastructure resiliency by understanding the current transportation network and identifying the most critical and impactful network links. The project evaluates network resiliency with an understanding of not only the transportation infrastructure system itself but also risks (consequences) associated with the system failure. Developing a strategy that prioritizes infrastructure resiliency investments based on the social and economic risks represents a critical strategy for maximizing the effectiveness of resiliency investments.

Maintaining the transportation network system remains critical for disaster relief activities and emergency responders during the response and recovery periods. The proposed research will enhance the resiliency of the transportation infrastructure in the event of extreme weather events because it focuses on the acute resiliency and risks associated with extreme weather events like Gulf of Mexico-based tropical storms. Given the size and scope of disaster events, the resources for road repair and restoration need to be strategically allocated during the response and recovery phases. Historically, stakeholders prioritize transportation network links that carry higher demand (volume) to minimize total system costs. However, this study emphasizes the need and vulnerability of the actual users of the infrastructure and their recovery from the event because the transportation network must serve these users during and after the disaster event for their survival and recovery.

This study seeks to develop a framework to evaluate road network infrastructure criticality during extreme weather events by considering the user characteristics of the transportation network. The team evaluates the risk and vulnerability of road network components and quantifies the impact on the primary road users' mobility and access during the evacuation phase of an extreme weather event. The study uses three criteria for network infrastructure criticality: if transportation links provide (i) access to evacuation routes and safe locations for socially vulnerable population who are at higher risk of long impacts in post-disaster period (Social Vulnerability) (ii) access to the residents of zones which will inflict significant economic losses if not properly evacuated or do not receive disaster relief measures during and after disasters (Economic Vulnerability), and (iii) mobility for populations and communities who are at considerably higher risk of getting impacted by disaster consequences such as flooding (Environmental Vulnerability).

This project meticulously reviews the literature on hurricane evacuation behavior to understand important factors that affect the evacuation decisions by households in different risk zones. It examines models and survey results based on real evacuation behavior data or stated preferences for population with various demographic and socioeconomic characteristics so that the study methodology and results reflect the most probable conditions as much as possible. The study incorporates valid models and parameters obtained from existing hurricane evacuation research, specifically those determined for hurricane experiences in Texas coastal areas. Such an approach estimates the traffic link data with more realistic and practical assumptions.

3. LITERATURE REVIEW

Evacuation demands and predictions

Establishing strategies and policies that maximize the efficiency of responses before, during and after hurricanes requires understanding evacuation behavior. An extensive body of research aims at identifying factors that potentially impact household evacuation decisions (9–11). The evacuation behavior for hurricanes differs from other types of emergency evacuation because numerous variables influence not only the decision to evacuate but also the modality and timing of evacuation. These variables range from risk perception (12), information sources and their reliability (13,14), social cohesion (15) and many demographic and social factors (16–19). The studies on this topic target the residents of hurricane-prone zones to investigate the role that different factors play in the household evacuation decision or to determine factors influencing the hurricane evacuation order compliance rate. Most of the research relies on survey results to model the evacuation behavior and decision. The models seek to predict the future behavior using observed behavior of respondents in after-event studies, and investigate hypothetical scenarios using respondents' stated preferences (20). The model findings in previous studies do not agree over a strong association between socioeconomic and demographic characteristics because of the uncertainties and complexities involved in hurricane evacuation decisions. However, several variables like age and presence of children in a household (19,21); storm intensity and housing condition (18,22); gender, perceived storm characteristics, official warnings, hurricane experience, and house ownership status (9,23–25); race and education level (25,26) exhibit important relationships with actual evacuation behavior.

The literature also investigates the issues related to hurricane evacuation and behavioral responses during different phases of pre- and post-disaster. Many of the studies examine how people respond to warning messages, and their various precautionary actions when dealing with potentially dangerous weather events. Understanding who evacuates and who does not evacuate has been a cornerstone of research in the area of disaster mitigation. The characteristics of warning messages represent an important part of this field. For example, research indicates that more specific warnings make people more likely to adopt adaptive responses, and if warnings are believed, then evacuation would be initiated (27). Other research aims at understanding how warning characteristics can trigger evacuation. Mileti and O'Brien (28) discuss that public responses to risk information depend on how they perceive the risk and how warning messages are constructed in terms of their clarity, accuracy, consistency, and frequency, and the personal characteristics of the person who receives the warning.

To better understand how people respond to disasters, a protective action decision model (PADM) has been used to examine the impacts of several decision-making factors including environmental cues and social information about a hazard as well as previous experience on perceived risk (29). Lindell and Hwang (30) extend the model to consider the effects of environmental proximity and personal experience, in addition to confirming the crucial role of perceived risk. The perceived risk represents an important factor that can significantly alter the households' decisions and how they react when facing a natural hazard. Lindell and Hwang (30) emphasize the effect of disaster experience, gender, income, and hazard proximity on the perceived risk. The perceived risk remains especially critical to impact evacuation behavior, facilitate and optimize evacuation, and develop disaster relief strategies. These study outcomes show that the interactions among warning, risk perception, and evacuation are determinative in understanding the evacuation decision making.

As more data about individual decisions on disaster responses have become available, researchers have tried to develop models to investigate the actual and expected behaviors. Besides, a number of surveys that have been conducted right after hurricanes provide generalized factors and variations in decisions among individuals during the threats of disasters. Baker (31) uses data and suggests five major variables that account for variation in decisions including:

- Risk level in the impacted area
- Actions adopted by authorities
- Housing conditions of the residents
- Previous personal risk perception
- Threat factors associated with the storm

As discussed earlier, inconsistencies appear in previous research around the significance of independent variables in predicting the evacuation decision. Using Hurricane Bonnie's household data in North Carolina, Whitehead et al. (18) assesses the role of storm intensity on evacuation behavior, and more specifically, destination patterns. They determine that a household's perceived risk of flooding rather than the perceived risk of wind primarily influences their evacuation decisions. The likelihood of evacuation for those who live in mobile homes appears higher than other groups. Their results also confirm that non-white households and those with higher levels of education seem more likely to evacuate to family or friends' homes.

The evacuation decisions directly impact the travel demand and network loading during the evacuation periods. Fu and Wilmot (32) discuss that the evacuation decision should be considered as a series of binary choices over time to estimate the probability of households' evacuation in different time periods based on their socioeconomic characteristics, intensity of hurricane and authority decisions before the hurricane landfall. In order to understand the reliance on different information sources, Lindell et al. (33) examine five hypotheses supported by previous hurricane evacuation research using the evacuation data from Hurricane Lili. These hypotheses included:

- Residents of risk zones rely on some information sources more than other sources; they trust local news media the most and the Internet the least.
- Residents of risk zones are more concerned about some information types than others; environmental cues concern them the most and evacuation impediments concern them the least.
- Coastal proximity, housing structure type, information sources, and evacuation difficulties predict evacuation decisions during hurricane events.
- The same variables mentioned as predictors of evacuation decisions, as well as time of day predict the timing of the hurricane evacuation decisions.
- The preparation time for evacuation is defined by the time it takes to prepare and travel from work to home, gather all family members, pack required items, to carry out property protection measures and reach the evacuation routes and this time ranges from 60 to 450 minutes.

Testing these hypotheses confirmed the previous findings about information courses, concerns and evacuation decision timings and showed that households' characteristics and evacuation decision and preparation time are not correlated.

An evacuee's destination played a major role in determining evacuation plans and the distribution of network loadings. Several studies investigate the significant variables influencing the determination of destination during an evacuation and developed models using observed behavior data. Mesa-Arango et al. (34) used a nested logit model considering houses of friends and relatives, hotels, public shelters, and churches as discrete destination choices and found the impact of factors such as hurricane position at evacuation time, household location, race, income, and evacuation notices on this decision. Sadri et al. (35) also employed a nested logit model to explain the destination choice behavior of Miami Beach residents in a hypothetical hurricane focusing on the needs of transit users. Jiang et al. (36) investigated the association between social factors (i.e., social distance) and evacuation destination choice using an integrated gravity model. Cheng et al. (37) investigated the socioeconomic and demographic characteristics of destinations on destination choice behavior using a multinomial logit model using two alternatives of relatives or friends' houses and hotels. Other studies proposed various models including the intervening opportunity model (38,39), agent-based model (40), and spatially correlated logit model (41). Cheng et al. (42) used a static gravity model for an estimation of dynamic OD matrices using a combined impedance function followed by a calibration using a dynamic gravity model. The destination choice model directly impacted the route choice models because the sparse rural networks often required significant travel time increases when drivers were forced to alternate routes.

Route choice represents another important decision that directly influences the identification of critical links during evacuation. Evacuees often prefer to take familiar routes or follow the evacuation routes recommended by officials. Sadri et al. (43) use household survey results after Hurricane Ivan in Alabama and evaluate the combined effect of different variables on evacuation route choice behavior using a mixed logit model. Their study shows that the majority of evacuees use the routes they consider as the shortest path rather than the recommended routes. Robinson and Khattak (44) investigate the effectiveness of advanced traveler information systems in route choice decisions by evacuees during hurricane evacuations. A study on hurricane evacuation logistics during Hurricanes Katrina and Rita shows that the evacuees mostly rely on their previous routing experience (45). Lindell et al. (46) evaluate the responses of evacuees during Hurricane Lili and determine that familiarity with the roads and evacuee's expectations about the evacuation time, safety and convenience appear the major contributors of route choices . Other studies show that the evacuation route choice significantly depends on previous experiences and the policies adopted by officials such as contraflow and information systems (47,48).

Performance Metrics to evaluate Network Criticality

The abovementioned evacuation decision making elements directly impact the susceptibility, vulnerability, and criticality of road segments. The literature extensively investigates road network vulnerability using indices such as change in travel cost (49), traffic volume (50), flow (51), accessibility (49,52), network efficiency measure (53), importance (54), and robustness index (55). Hurricane and natural disaster evacuation research only measures the vulnerability of the road network in terms of accessibility, clearance time, and connectivity (56–59). A few studies investigate the criticality of road links for evacuation purposes. Helderop and Grubesic (60) assess the road network criticality during flood evacuation using a modified grid-based centrality measure as a "high-fidelity" alternative for traditional centrality measures. Sullivan et al. (61) propose a methodology to rank the most critical links for short-term disruptive events using a link-based capacity disruption approach. Stamos et al. (62) develop a framework for criticality assessment in evacuation using a travel time minimization approach. All of these studies focus on physical characteristics of the infrastructure and try to investigate topological measures such as connectivity and accessibility of the network.

Vulnerability of transportation infrastructure has been quantitatively assessed, especially after natural and man-made disasters in the last few decades. However, the operational measures used to evaluate vulnerability or reliability depend on the context and the definition provided by the research. Some of these definitions include sensitivity to threats (63), susceptibility for big risks (64), "the non-operability of the network under certain circumstances" (65), and "society's risk of transport system disruptions and degradations" (66). The criticality of a link or node in the road network is often associated with the probability of that component failing and the resulting consequence for the whole system (54). This means that if the occurrence of an indicant is high and a link or node is weak and results in considerable consequences if disrupted or lost, they are considered critical. The consequences are mostly measures using traditional metrics such as change in travel cost.

Other recent studies assess the vulnerability of different communities during evacuation and the role their socioeconomic characteristics play in the impact of a disruptive event. Cutter et al. (67) assess the spatial vulnerability of people and places using biophysical and social vulnerability measures and show that these two measures do not lead to identifying the same vulnerable locations. Chakraborty et al. (68) use a geophysical risk index and social vulnerability index to understand the spatial patterns of evacuation assistance needs and find that each index can result in a different pattern.

Overall, summarizing the research in this field reveals that the performance measures used to assess the vulnerability of the road network during evacuation and post-disaster phases fall into four major categories related to link, node, flow, and threats. Figure 3 shows an example of some of the measures associated with each of these categories. Obviously, some of the metrics can be indirectly related to another category depending on how they are used to measure the vulnerability, resilience or criticality of a network or a series of links.

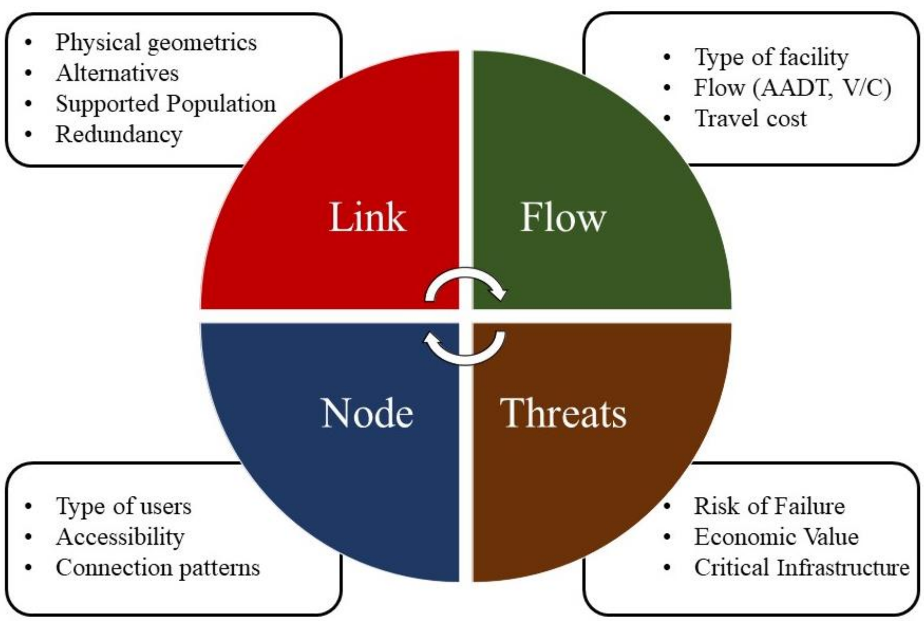

Figure 3. Performance metrics measuring network vulnerability classified in four major categories

The results of these studies indicate the crucial importance of taking the population or road users into consideration during hurricane evacuation analysis. Yet, despite the observed importance, a gap in the assessment of road user vulnerabilities and related indicators for identification of critical links in the road network during evacuation remains. This study aims at filling the existing gap by incorporating the effects of considering the socially, economically, and environmentally vulnerable communities in measuring and identifying the most critical links during hurricane evacuation.

4. METHODOLOGY

This study develops a multi-tiered framework to integrate various models and performance metrics to identify critical zones and evacuation links. The following sections present the details of each method and approach used in the framework.

4.1. Critical Zone Identification Using Three Vulnerability Criteria

The first step in the framework identifies the more vulnerable zones that appear critical for decision makers to facilitate evacuation during an emergency. This study develops three different criteria to evaluate the criticality of zones based on their unique and distinct vulnerability to a hurricane event.

The first criterion indicates users' social vulnerability to determine critical zones. The Social Vulnerability Index (SVI) developed by the Centers for Disease Control (CDC) is a comprehensive indicator of a community's resilience to assess community response during different phases of a disaster. This index ranks the census tracts (CTs) on 15 social factors based on socioeconomic status, household composition and disability, minority status and language, and housing type and transportation (69). The socially vulnerable areas based on the SVI index represent at-risk communities that a hurricane may disproportionately affect due to a lack of essential resources to withstand a disaster event. Their safe and fast evacuation means saving more lives; therefore, the transportation network that serves socially vulnerable communities must be prioritized.

The second criterion provides a measure of environmental vulnerability. This criterion determines locations with a higher danger of flooding during a hurricane based on the Federal Emergency Management Agency (FEMA) 100-year floodplain map, which defines varying levels of flood risk and more vulnerable areas. Residents who live close to stream channels and floodplains bear higher vulnerability as their impact and damages could be more likely and intense. Therefore, residents living in these flooding-prone areas have a greater need to evacuate, and the transportation network must ensure their access to evacuation routes.

The third criterion uses economic vulnerability from the decision-makers' perspective to determine critical zones. During an emergency, locations with higher economic values may need more attention because their failed evacuation could lead to more considerable losses affecting the local economy and political leverage, from the perspectives of politicians and decision-makers. A property appraisal provides an estimation of the economic liability of a natural disaster on different districts and households. The critical zones selected by property value conversely represent the locations of greatest economic vulnerability from the decision maker's standpoint. This index also appears important since it may identify different locations from the other two criteria due to the nature of the vulnerable assessment standpoint, which provides more inclusive and comprehensive research outcomes and critical links for decision-makers.

If considered together, these criteria represent a sustainable approach to hurricane preparedness that emphasizes the most vulnerable community along the three sustainability areas of economic, social, and environmental well-being. This paper represents an initial effort to distinguish the differences in priorities that may arise from over reliance on one of the sustainability thrusts and the benefits of trying to consider all of the sustainability components.

4.2. Four-Step Travel Demand Model

In the framework, the four-step demand model provides an estimation of the number of evacuating vehicles in different risk zones, the destination choices of households, and routes selected to reach their destination. Evacuation behaviors inherently involve uncertainties especially during an emergency since the risk perception of individuals and households change based on the level and type of the disaster event. However, the evacuation prediction results must determine critical network links with stability because these important links should always be prioritized to support evacuation activities. This study assumes a 'worst-case' scenario where all of the households in a flooding impact area evacuate with a very short lead time after an evacuation order. This assumption allows the vehicle loading on each network to reach at maximum, which warrants a less sensitive prioritization depending on the evacuation demand estimations.

4.2.1. Trip generation

The trip generation step estimates the number of vehicles evacuating from different zones impacted by the disaster using household characteristics such as household size and number of available vehicles. Previous studies use various models including a fixed evacuation rate (70), logistic regression (71) or advanced machine-learning neural network models (71) to estimate trips generated for evacuation. They typically use resident household trips as an evacuation unit since trips of non-residents or transient populations are negligible during an evacuation. This study adopts a well-known study by Lindell and Prater (72) with the following model to estimate the number of evacuating vehicles based on hurricane category:

$$EV_{zsc} = \left(\frac{P_{zs}}{PHH}\right) D_{zc}(1 - TD)(EVHH + ETHH)(1 - S)U_{zs} \tag{1}$$

Where EV_{zsc} = the number of evacuating vehicles from Sector *s* of Risk Zone *z* during Hurricane Category c;
P_{zs} = population of Sector *s* in Risk Zone *z*;
PHH = number of persons per household;
D_{zc} = the proportion of households in Risk Zone *z* deciding to evacuate in Hurricane Category *c*;
TD= proportion of transit dependent households;
$EVHH$ = average number of evacuating vehicles for each household;
$ETHH$ = average number of evacuating trailers for each household;
S = the proportion of early evacuees;
U_{zs} = the proportion of households in Sector *s* of Risk Zone *z* who use the primary evacuation routes.

The location of a residence (e.g., risk zones) and intensity of a hurricane represent the most important decision factors impacting the evacuation decision. Lindell and Prater (72) use these two determinants to regress the evacuation rate based on a storm category and smooth out the rates using linear and quadratic terms. The risk areas range from 1 to 5 (1 being the highest risk) and increases as the hurricane category rises. The study adopts this approach and defines the coastal zone as risk area 1 and the central and north areas of Harris County as risk area 5. The authors divide the central and northern parts of Harris County into the 5S and 5N zones and compute the rate for the northern part using interpolation. Thus, the evacuation rate for zones 1 to 6 represent 98.2% 88.2%, 83.4%, 80.5%, 78.8%, and 75%, respectively.

Those who rely on transit for evacuation include the disabled and older adults as well as individuals with low socioeconomic status (SES) ((73), (74)). Many studies estimate the transit dependent population by applying a fixed ratio for all the study areas with an assumption of a fixed proportion of transit dependent population across the region; however, this method can result in significant bias in the areas with higher or lower SES. Therefore, this study uses the percentage of the population who are disabled and received Food Stamps/SNAP in the past 12 months as a proxy for transit dependence. This measure represents the population who commonly lack financial resources and highly correlate to vehicle ownership.

Finally, in order to simulate the worst-case scenario, the study sets the proportion of early evacuees at zero. By applying these ratios and assumptions in equation 1, the authors estimate the trips generated in each census tract.

4.2.2. Trip distribution

The destination choice by the evacuees appears to be difficult to formulate as it is highly dependent on personal preferences. However, previous studies reveal that most evacuees prefer the homes of friends/relatives and hotels in safe areas (34), which provides a logical foundation for an assumption that urban areas attract more population. Using a gravity model, which determines the patterns of trips from origins based on the relative attractiveness of destinations and the difficulties of making trips to destinations, this study distributes the evacuating vehicles from origins in the risk zones to destinations in safe zones particularly urban areas. A production-constrained gravity model estimates the number of trips from each origin zone to destination zones using the following equation:

$$T_{ij} = P_i \frac{A_j \gamma_{ij}}{\sum_{j=1}^{N} A_j \gamma_{ij}} \tag{2}$$

Where:

T_{ij} = the number of trips produced in zone i and attracted to zone j
P_i = the total number of trips produced in zone i,
A_i = the total number of trips attracted to zone j,
γ_{ij} = impedance of travel between zones i and j,
N = total number of destination zones.

Impedance measures the trip difficulty. Evacuees tend to travel to places not threatened by hurricane impacts; however, the number of trips to a specific destination is inversely proportional to the length of trip since the evacuation is an involuntary trip. To accommodate these two terms, Cheng et al. (42) used two widely accepted functions including negative exponential and Rayleigh function as shown by equations 3 and 4, respectively.

$$f(c_{ij}) = e^{-\alpha c_{ij}} \tag{3}$$

$$f(d_j) = \frac{d_j}{\beta^2} e^{-0.5(\frac{d_j}{\beta})^2} \tag{4}$$

Where, c_{ij} is the travel cost, d_j is distance between risk zone and destination, and α and β are parameters. The parameters can be estimated based on real hurricane evacuation behavior data. Using OD data from evacuation during Hurricane Floyd, a category 4 Hurricane, Cheng et al (42) estimated α and β through a chi-square minimization process. The study uses their estimated value of α=0.006 and β=1.9 for the static gravity model.

4.2.3. Modal split

Public transit serves households for local evacuation (e.g., those who evacuate to local shelter). This study does not include trips to local shelters; therefore, it assumes 100 percent auto-trips in the modal choice step as a worst-case loading.

4.2.4. Traffic assignment

Traffic assignment during evacuation is a complex process affected by various factors such as drivers' acquaintance with routes, management of evacuation routes, and preference of drivers to use the shortest path or familiar roads. The majority of evacuees tend to be more familiar with and feel safe on major roads and interstate highways (75), which federal and state agencies also designate as evacuation routes. During an emergency, evacuees do not detour unless a shortest path is not available due to flooding or incidents. This study uses evacuation routes consisting of major arterials and interstate highways as a baseline network and applies the shortest path algorithm to estimate route choices.

The study uses critical zones selected based on the vulnerability criteria as the origin of evacuation. The shortest path analysis for vehicles travelling from evacuation zones to destinations determine the links expected to be used during evacuation. In addition to the baseline network loading, this study needs to estimate the impact of link disruptions to identify the critical links over the network. To simulate a link disruption, the authors remove a link of the evacuation routes by creating a barrier. If the study area includes too many links, they can be reduced by identifying the links more likely to experience a disruption such as links disrupted or flooded during previous hurricanes. After identifying a limited number of links for each set of evacuation ODs, the final link criticality estimation uses a set of performance measures described in the following section.

4.3. Identifying Critical Links

A network link assesses its criticality based on a set of performance measures that capture the impacts of a link disruption. While conventional measures focus on the traffic volumes or travel times served by network links, this study develops new performance measures that take the characteristics of the actual users into consideration, since different locations pose social, environmental, and financial vulnerabilities for evacuation. Table 1 lists the conventional link-based performance measures that estimate the impact of disruption by relying on V/C ratio or changes in travel time from a disruption. However, the new user-based performance measures identify the critical links by understanding the impact of disruption on the corresponding road users. For example, the Social Vulnerability (SOV) measure indicates the average value of SVI for the zones, therefore a link that has a high SOV value serves socially vulnerable communities. On the other hand, Economic Vulnerability (ECV) shows the average property values of the zones impacted by a link disruption. Therefore, a link that has a high ECV serves more affluent communities with higher property values. Links with higher Environmental Vulnerability (ENV) serve communities that have higher flooding impacts. Overall, these user-based measures integrate the characteristics of the link users to understand where the disruption consequences occur.

Table 1. Performance measures used to determine the criticality of road links.

Type	Performance measure	Definition
Conventional Link Based Measures	Length	The length of a link
	Volume	The number of vehicles expected to use a link
	Change in travel time	The increase in evacuation time due to a link disruption
New User Based Measures	Social Vulnerability (SOV)	Average value of social vulnerability index of zones expected to use the link during evacuation
	Economic Vulnerability (ECV)	Average value of appraisal values of zones expected to use the link during evacuation
	Environmental Vulnerability (ENV)	Average value of flood risk expected to use the link during evacuation

5. DATA COLLECTION AND PROCESSING

This study requires extensive data on population, network, land value, and disruption-related maps for critical zone and link development and travel demand modeling. The study area is limited to the counties in the greater Houston area likely impacted by a major category 4 hurricane in Texas and the residents would likely evacuate. The study area includes Harris, Galveston, Brazoria, Chambers, Fort Bend, and Matagorda counties as shown in Figure 4.

The locations of safe zones or evacuation destinations were selected by evaluating the counties within a reasonable distance from the hurricane impact area or areas that can potentially be considered as an evacuation destination. The research team merged smaller and less populated counties. The study uses 26 destination areas with the boundaries for these locations shown in Figure 5. This figure shows the names of the highly populated counties. As shown, the northern part of Harris County represents a destination zone since it is far from high-risk areas in coastal zones. Jefferson County is not within the risk zone map used in this study. Since this county is one of the most susceptible areas during a major hurricane event, it would be unsafe, or evacuees and the study considers the number of trips to this county to be zero.

The socioeconomic and demographic data are obtained from the 2018 U.S. Census estimate. The team obtains the Social Vulnerability Index data (SVI) from the Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry (CDC/ATSDR) at the Census Tract level as shown in Figure 6 (76). The study uses the road network from Open Street Map (OSM). The network includes motorway, primary, and secondary roads with direction, speed, and number of lanes data and covers the area from Dallas in the North, Austin and San Antonio to the west, Corpus Christi to the south and the Texas boundary with Louisiana to the east.

As shown in Figure 7, the study obtains the parcel dataset from the Texas Natural Resources Information System, which provides property information such as property owner, land use, value, and location attributes (77). The data highlights the higher market value (including land value and improvement value) of properties in the central areas of Houston and some parts of coastal areas in Galveston County. The research team uses this dataset to estimate economic vulnerability metrics.

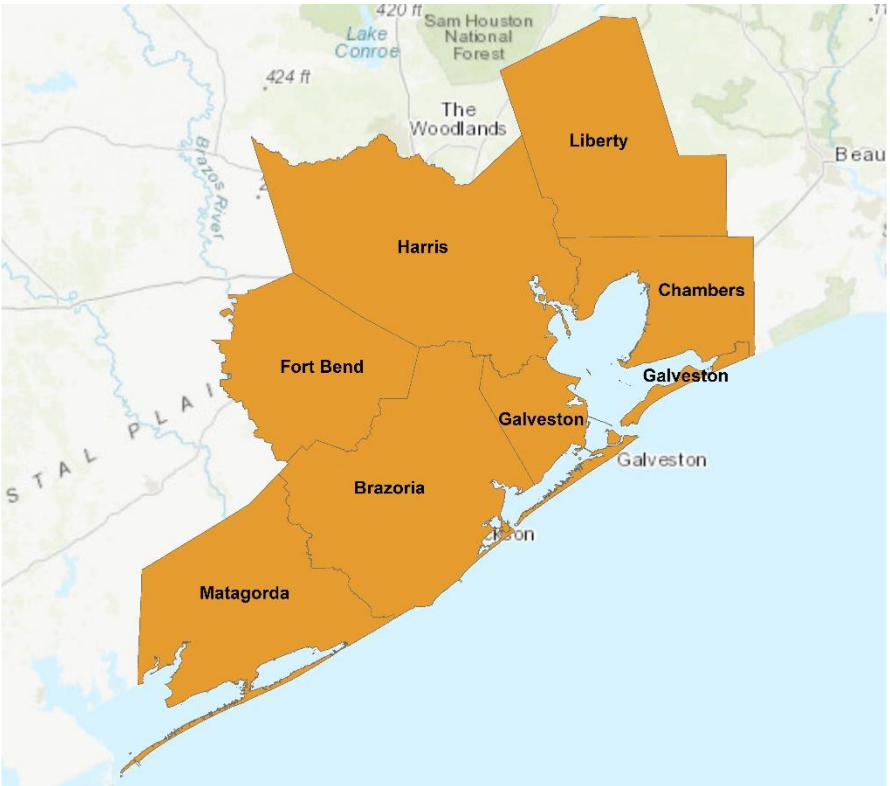

Figure 4. Hurricane evacuation study area.

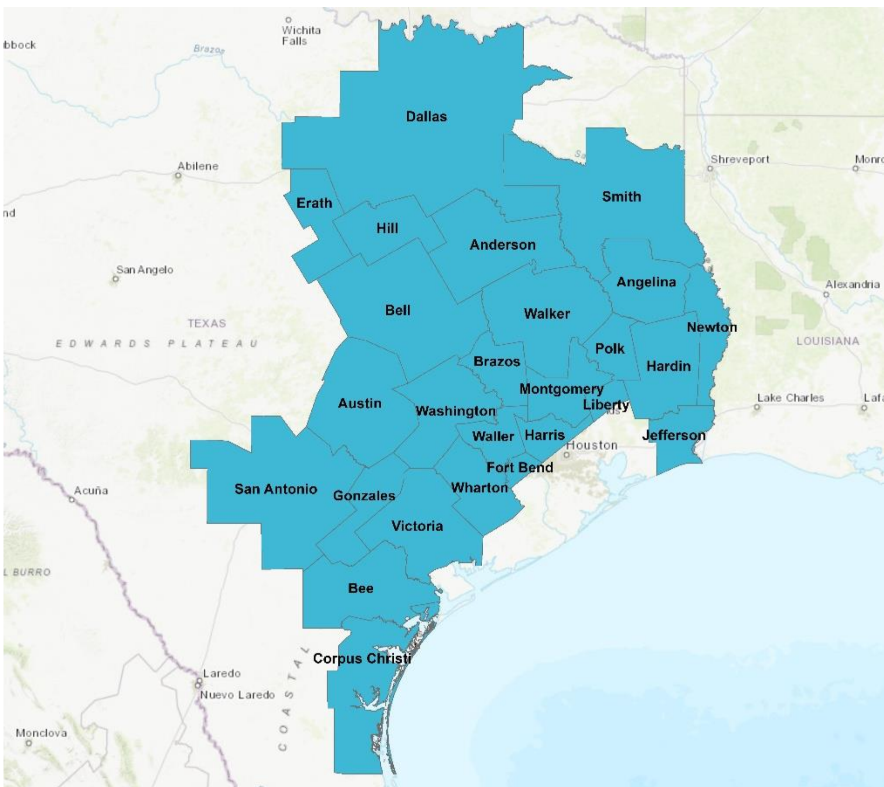

Figure 5. Boundaries for the location of hurricane evacuation destinations.

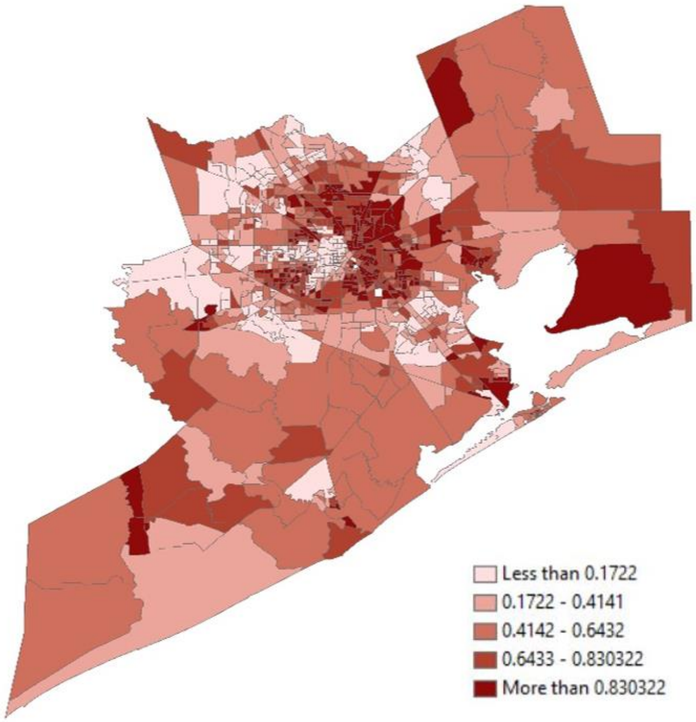

Figure 6. Distribution of Social Vulnerability Index in the study area.

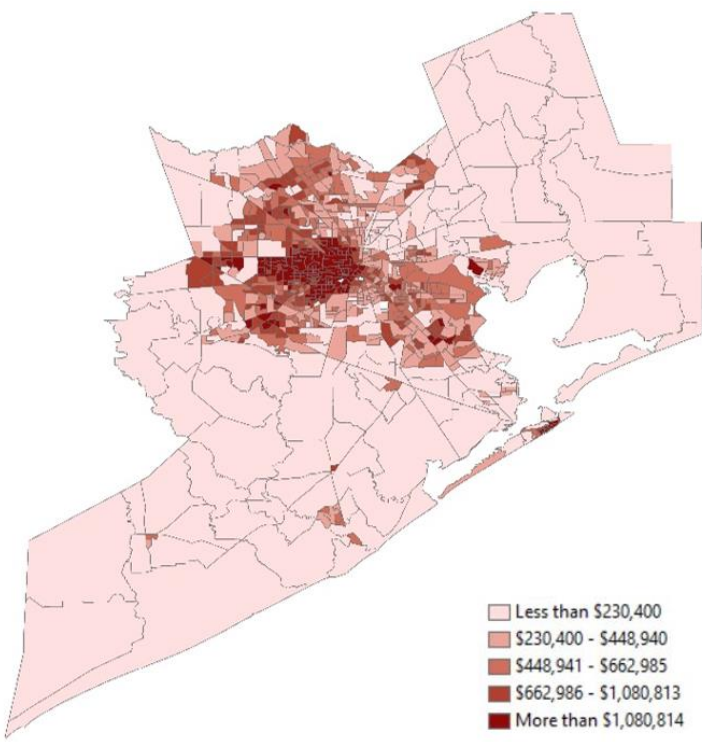

Figure 7. Distribution of property value in the study area.

The (FEMA) database published in 2018 provides the 100-year flood plain maps. According to FEMA, this map can help to identify any place with at least a 1% chance of experiencing flood during a year, and those areas have at least a one-in-four chance of flooding during a 30-year mortgage. The flood zones designated in the map (Figure 8) are geographical areas that FEMA defines based on varying levels of flood risk. These zones are depicted on a community's flood insurance rate map or flood hazard boundary map. Each zone in the map reflects the severity of the type of flooding in the area. This study selects high risk areas to determine the flood risk in the study area. These zones are labeled as A, AE, AH, AR, and VE zones and FEMA describes them as follows:

Zone A: Areas with a 1% annual chance of flooding and a 26% chance of flooding over the life of a 30-year mortgage.

Zone AE: The base floodplain where base flood elevations are provided.

Zone AH: Areas with a 1% annual chance of shallow flooding, usually in the form of a pond, with an average depth ranging from 1 to 3 feet. These areas have a 26% chance of flooding over the life of a 30-year mortgage.

Zone AR: Areas with a temporarily increased flood risk due to the building or restoration of a flood control system (such as a levee or a dam).

Zone VE: Coastal areas with a 1% or greater chance of flooding and an additional hazard associated with storm waves.

The flood risk map is used to develop the environmental vulnerability measure by calculating the proportion of each census tract with high flood risk and the results are shown in Figure 9.

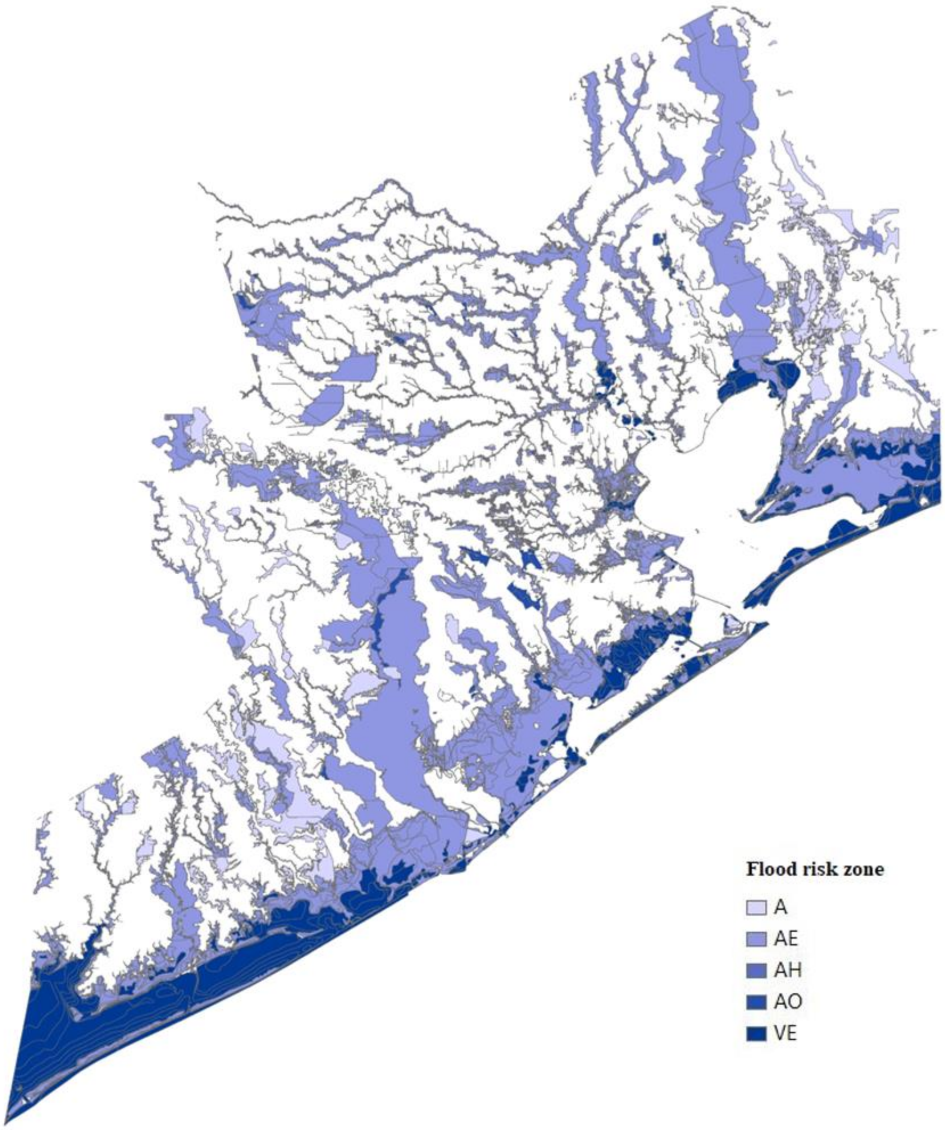

Figure 8. FEMA 100-year flood zones in the study area.

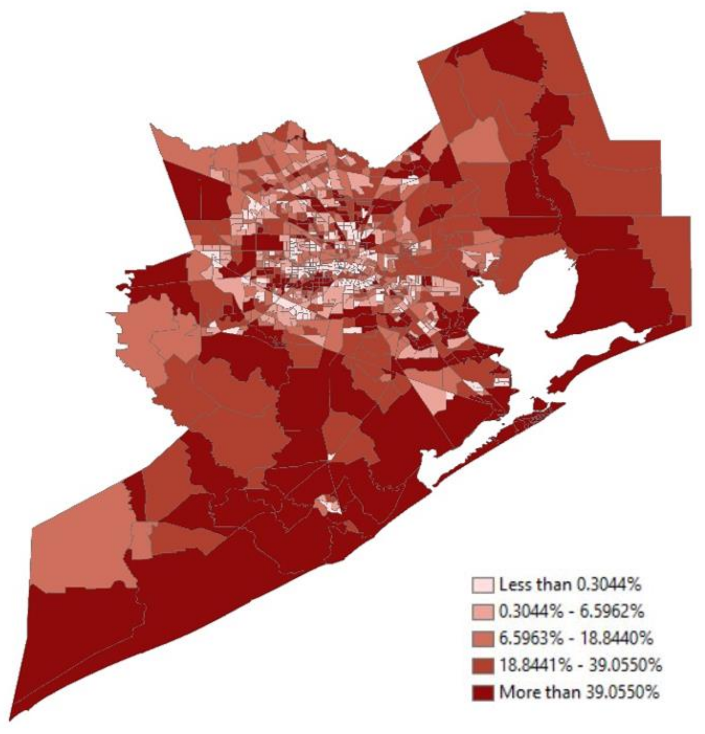

Figure 9. Distribution of percent of the census tract with high flood risk in the study area.

In addition, the National Hurricane Center (NHC) and Central Pacific Hurricane Center database provides the storm surge hazard map for different coastal zones including Texas to Maine (78). Storm surge is defined as the abnormal rise of water generated by a storm, over and above the predicted astronomical tides. Flooding from storm surge depends on many factors, such as the track, intensity, size, and forward speed of the hurricane and the characteristics of the coastline where it comes ashore or passes nearby. Storm surges from tropical cyclones are simulated by utilizing the hydrodynamic sea, lake, and overland surges from the Hurricanes (SLOSH) model. The NHC provides two products based on hypothetical hurricanes including Maximum Envelopes of Water (MEOWs) and Maximum of MEOWs (MOMs). MEOWs are created by computing the maximum storm surge resulting from up to 100,000 hypothetical storms simulated through each SLOSH grid of varying forward speed, radius of maximum wind, intensity (Categories 1-5), landfall location, tide level, and storm direction. MOMs are created for each storm category by retaining the maximum storm surge value in each grid cell for all the MEOWs, regardless of the forward speed, storm trajectory, or landfall location. The storm surge hazard map for category 4 hurricanes is used to calculate the distance between destinations and the hurricane-induced storm surge. The storm surge map is shown in Figure 10.

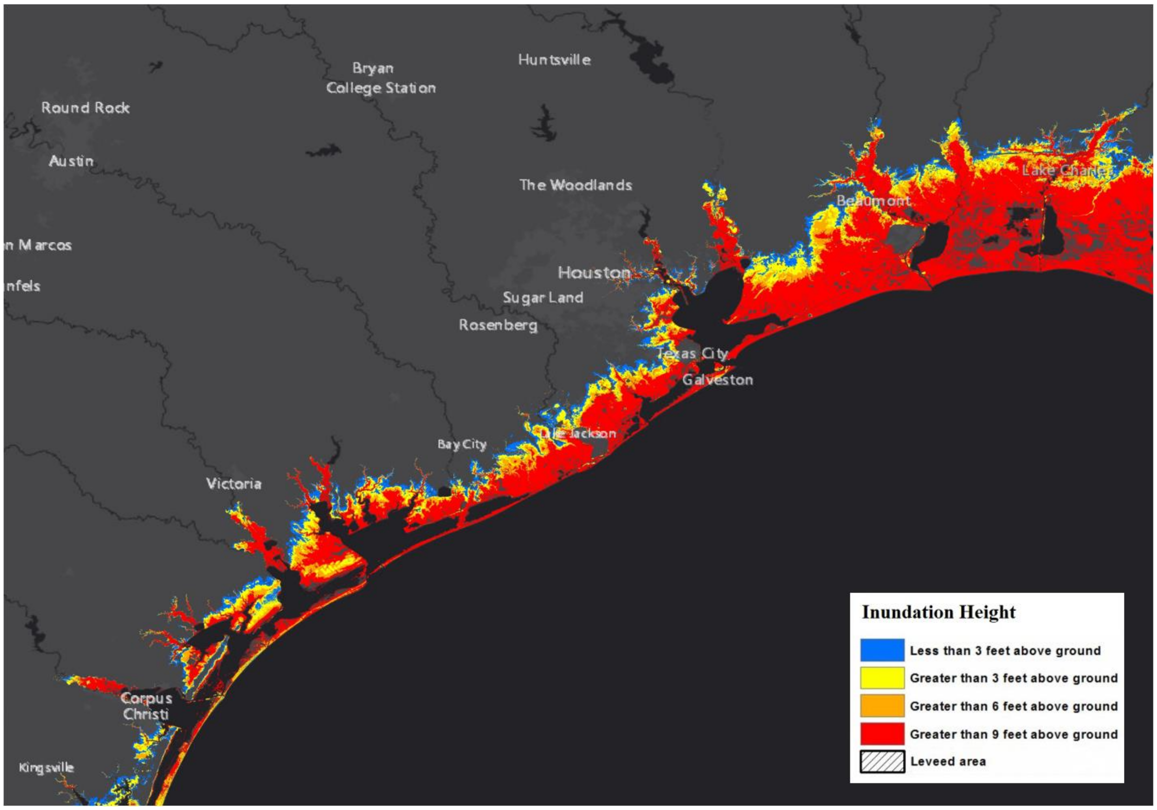

Figure 10. Storm surge hazard map for a category 4 hurricane for Texas to Maine region.

The study uses the Hurricane Disruption Spatial Data (HDS) from the Hurricane Harvey Flood Data Collections database to develop high risk network links. The HDS includes information on flood depths, flood extents, high water marks, streamflow and damages recorded from national agencies such as NOAA, USGS, FEMA, and Civil Air Patrol (79). This dataset can help to find the locations which are more susceptible to flooding due to hurricanes. The probability of link disruption of these locations could be higher due to their high water in a hurricane event. Figure 11 presents the location of previously impacted areas in hurricane Harvey.

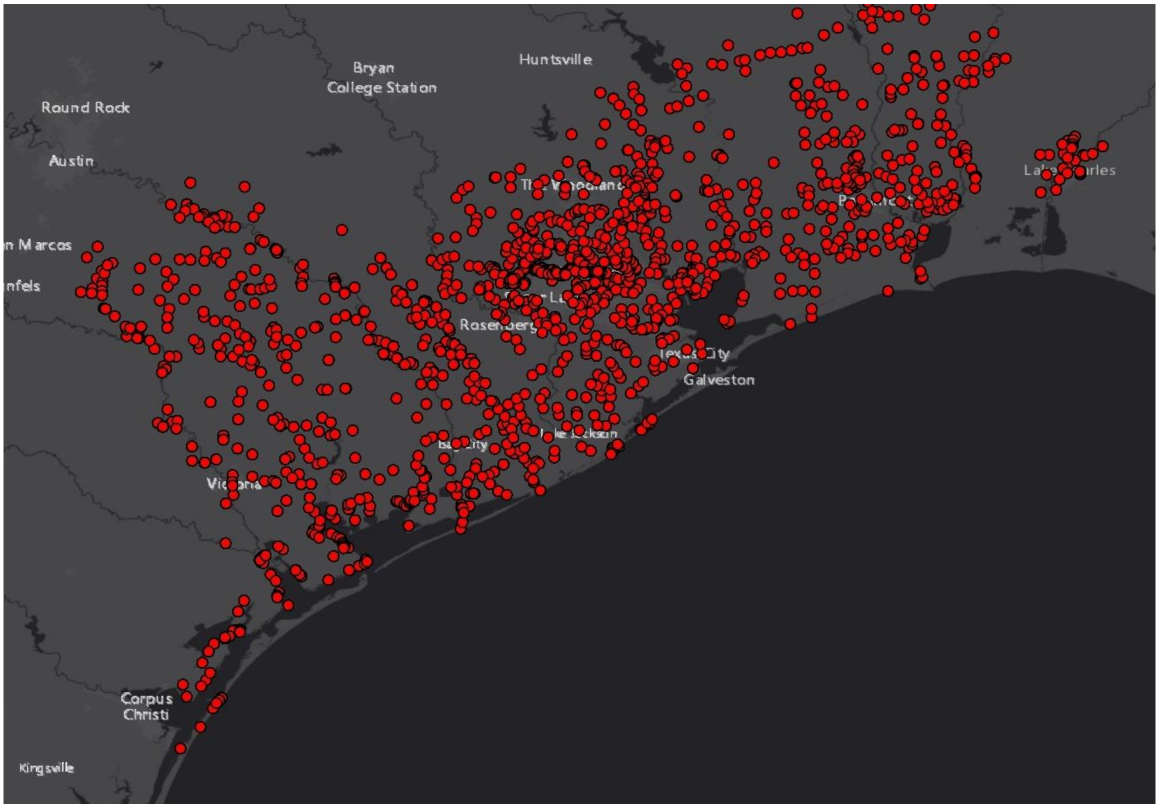

Figure 11. High water marks and flooded locations during and after Hurricane Harvey.

Finally, the road network dataset is extracted from OpenStreetMap which includes the direction of travel, speed and number lanes. The team interpolates the missing data of speed and number of lanes considering the type of road and the existing data for neighboring links. Figure 12 shows the road network covering the area between evacuation origins and expected evacuation destinations in Texas.

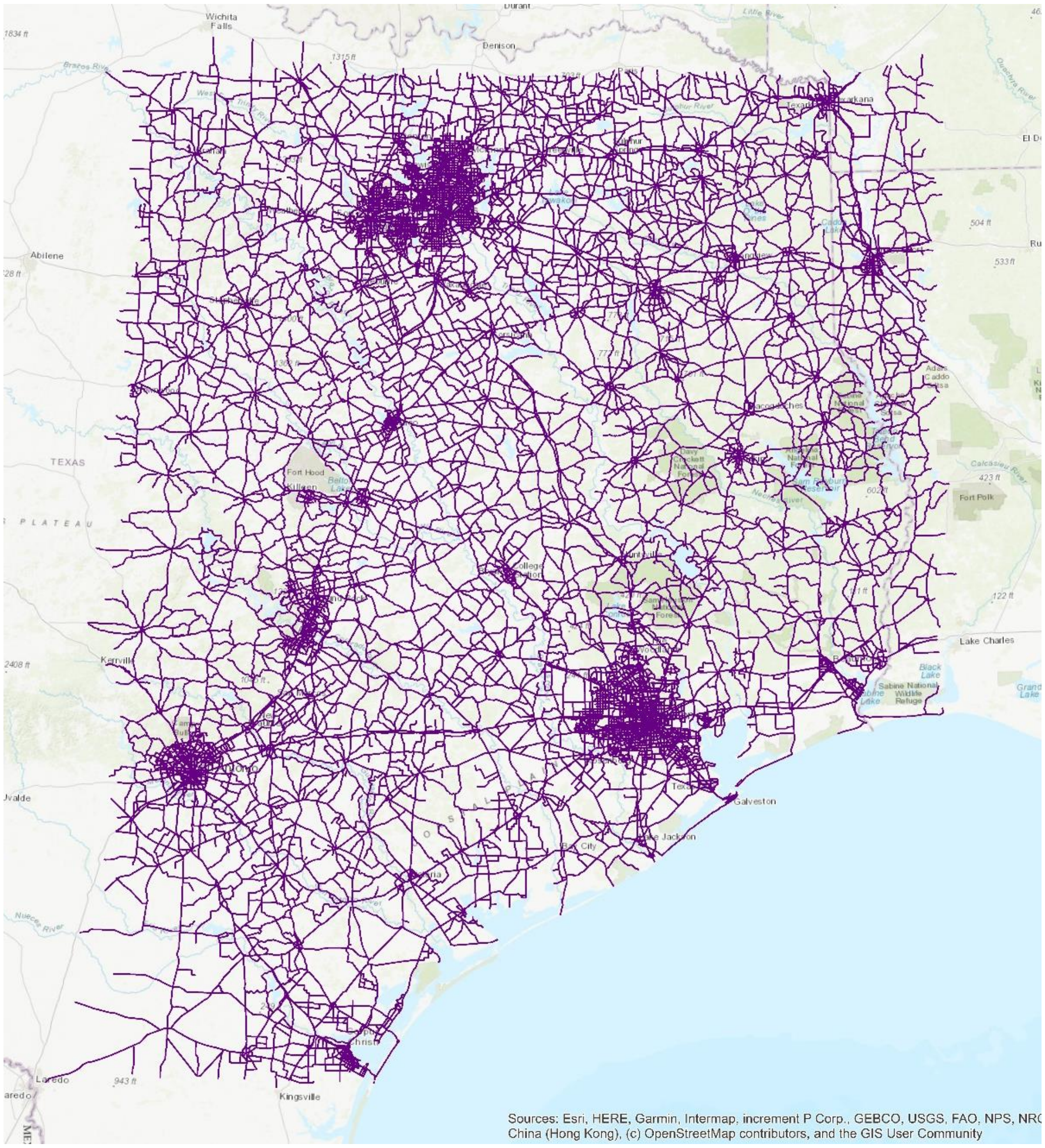

Figure 12. Road network from in the area between evacuation origins and destinations.

6. RESULTS

6.1. Critical Zone Identification

Figure 13 shows the most critical zones selected by the three vulnerability criteria for the risk areas 1 to 5S/N. Even though any number of Census Tracts (CTs) could represent the critical zones, this study uses 17 CTs since they comprise the top quartile (25%) of the entire CTs for risk area 1. Therefore, 102 zones (=17CTs * 6 Risk areas) are selected as the most critical zones for each vulnerability criteria from each of the six risk areas. Expectedly, a proportion of these 102 zones share two or three criteria, since socially vulnerable zones could also be environmentally vulnerable as an example. Six zones are selected as the critical zones using all three vulnerability criteria. This seems counterintuitive since social vulnerability and high property value (which determines the economic vulnerability from the decision-maker's standpoint) might not be compatible, however SVI (that determines the social vulnerability) relies on a combination of various social, demographic, and economic features. Therefore, a specific zone might be characterized as socially vulnerable (based on non-economic variables such as age) but economically high valued.

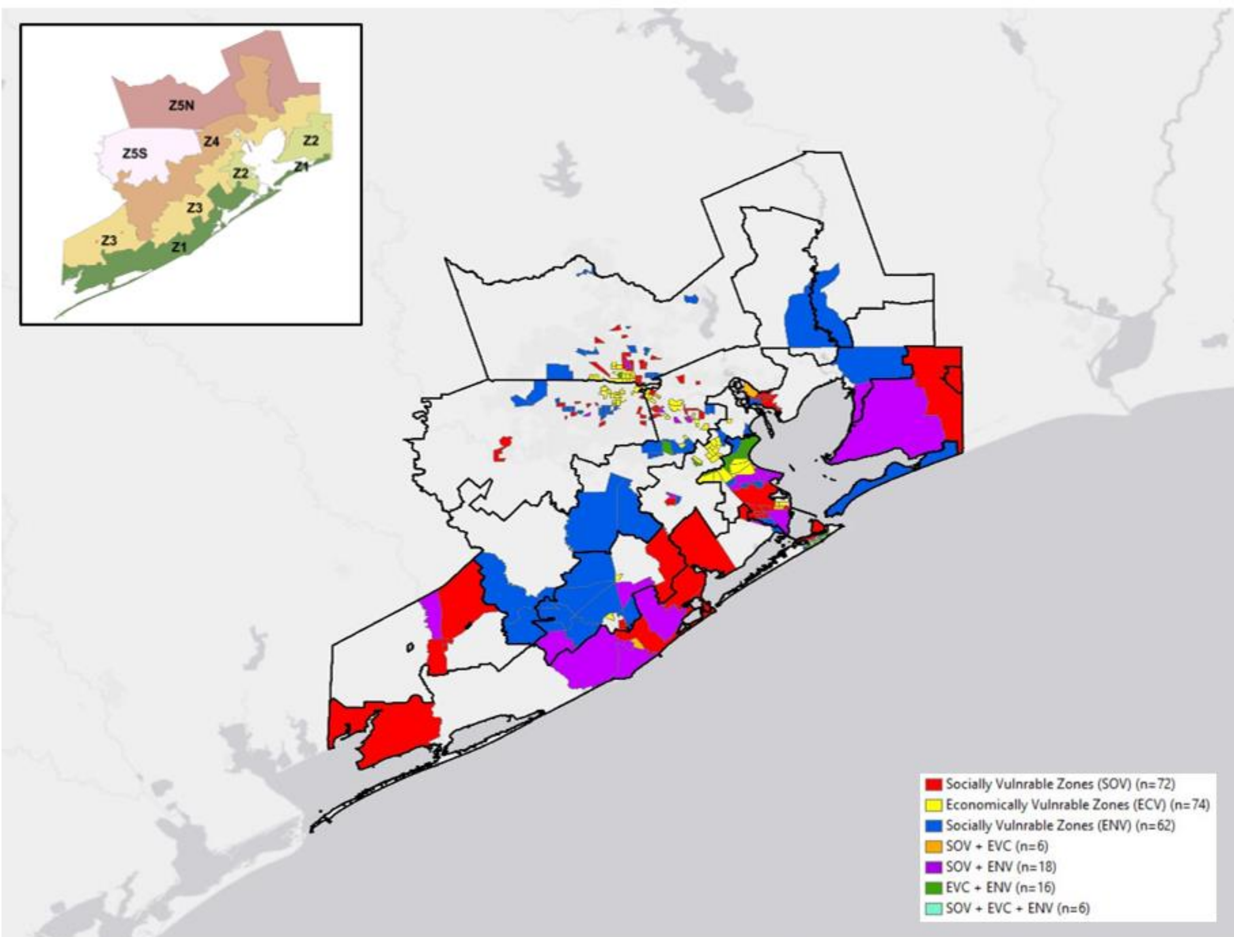

Figure 13. Critical zones in six risk areas.

6.2. Trip Generation and Distribution

Table 2 shows the trips generated from all 1,004 CTs located in the six risk areas. The trip generation model uses the given proportion of transit dependent population based on the percentage of the population who are disabled and received Food Stamps/SNAP in the past 12 months. Risk zones 1 and 2 show a higher rate of transit dependent population and consequent risk of isolation if evacuation transportation is not provided. The total number of evacuees, specifically for Zones 5S and 5N are high due to their high population density near the city of Houston. The gravity model calculates the destination choice for the evacuees and shows the highest proportion of evacuees travelling to the Dallas region, which is the largest and most populated area with the safest distance from the hurricane impact area.

Table 2. Trip Generation and Distribution Results.

	Trip Generation		Trip Distribution (vehicles)					
Risk Area	% Transit Dependent Population	Total Evacuating Vehicles	Austin Region	Dallas Region	San Antonio Region	Bell Region	Smith Region	Other Region
Area 1	7.95	44,701	4,454	30,162	5,107	1,925	1,616	3,666
Area 2	8.22	98,113	9,178	62,259	10,523	3,959	3,318	7,234
Area 3	4.33	157,797	16,089	109,030	18,445	6,944	5,820	12,899
Area 4	5.95	326,669	31,361	212,636	35,946	13,531	11,343	25,007
Area 5S	4.32	713,911	67,728	458,716	77,652	29,218	24,440	53,833
Area 5N	5.56	727,132	69,169	468,849	79,184	29,843	24,987	55,129

6.3. Trip Assignment

The shortest path algorithm in GIS for each set of ODs results in 442 routes from 17 origins to 26 destinations for six risk areas. Overall, this study obtains 1,155,883 links used by 102 socially vulnerable zones, 1,203,139 links by economically vulnerable zones, and 1,170,907 links by environmentally vulnerable zones as shown in Figure 14(a). In link disruption scenarios, a barrier is created on each link, and the shortest path identifies new routes. Figure 14(b) compares the outputs of the shortest path analysis with a link disruption. The network shows the routes taken by evacuees. If the grey link is disrupted, whole orange links remain unused due to the changed shortest paths of the disrupted link users.

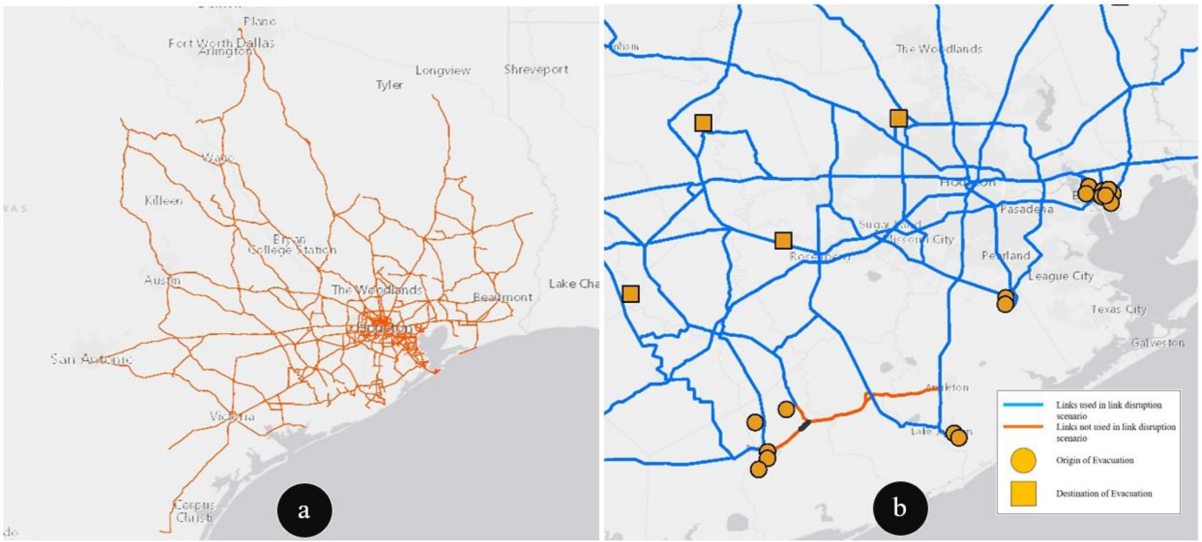

Figure 14. (a) Traversed edges by all OD trips (b) An example of a link disruption output.

Overall, this study assesses over 3.4 million links in the Gulf coast and Houston area, which creates a significant computational burden to simulate a link disruption and estimate changes in link volumes. The authors identify the most vulnerable links that are prone to flood using a geographic proximity to the past disruption. This study selects links that are within 400 feet of disruptions during Hurricane Harvey and assume they have a high likelihood of flooding or high-water damage in a future event. As a result, Table 3 shows the total number of links used for the further analysis categorized by risk areas and critical zones.

Table 3. Total number of evacuation links by zone and criterion.

Risk Area	Critical Zones		
	Socially Vulnerable Zones (High SVI Index)	Economically Vulnerable Zones (High Property Value)	Environmentally Vulnerable Zones (High Flood Risk)
Area 1 (Highest)	69	43	82
Area 2	57	44	65
Area 3	73	72	98
Area 4	42	46	77
Area 5S	45	53	50
Area 5N (Lowest)	40	54	82

6.4. Critical Links

Altogether, the study identifies 173 links used by socially vulnerable critical zones, 163 links by economically vulnerable critical zones, and 222 links by environmentally vulnerable critical zones. These numbers differ from the subtotal of each criterion shown in Table 3 because many of the links are selected by multiple critical zones.

In order to understand how the links differently serve critical zones, the study identifies the most critical links based on conventional and user-based performance measures. Links selected by each performance measure are classified into 3 groups referring to as the most critical, moderately critical, and less critical links, and the most critical links are only used for the comparisons. In this comparative analysis, the links selected by a particular performance measure (e.g., link length) by each critical zone (e.g., socially vulnerable zones) are compared to the links selected by other measures (e.g., traffic volume, travel time, user-based) in the same zones.

Table 4 compares the link shares selected by different performance measures. For each critical zone, the most critical links selected by conventional performance measures (e.g., traffic volume) are compared with other conventional measures (e.g., length and travel time) and the user-based measure. For example, among the links serving socially vulnerable zones, the most critical links selected based on the traffic volume measure share 51% of their links with a link set selected by the travel time measure. However, the same set of links selected by the traffic volume share only 18% of links with the user-based measure. This indicates that the critical links carrying high evacuation traffic may not connect socially vulnerable communities; therefore, prioritizing resources to such high-volume links may disproportionately affect socially vulnerable communities. Similarly, among the links selected based on economic vulnerability, the only 37.5% common links occur between the travel time-based and user-based set of links. Finally, among the links selected based on environmental vulnerability, the percentage of shared links remains less than 30% between those selected by link-based measures and environmentally vulnerable users.

Table 4. Percentage of links selected by different performance measures.

Critical Zones	Performance Measure		Link-based		User-based		
			Volume	Travel Time	Social Vulnerability	Economic Vulnerability	Environmental Vulnerability
Socially Vulnerable Zones	Link-based	Link Length	31.6%	47.4%	18%	-	-
		Traffic Volume	-	51%	24.6%	-	-
		Travel Time	-	-	3.6%	-	-
Economically Vulnerable Zones	Link-based	Link Length	33.3%	48.1%	-	25.9%	-
		Traffic Volume	-	41.7%	-	37.5%	-
		Travel Time	-	-	-	29.4%	-
Environmentally Vulnerable Zones	Link-based	Link Length	29.3%	46.7%	-	-	29.3%
		Traffic Volume	-	47.9%	-	-	27.4%
		Travel Time	-	-	-	-	27.8%

The study also compares the most critical links identified the user-based measures with one another since the performance measures within the thrust of vulnerabilities could select different links as the most critical ones to serve different vulnerable communities. This study identifies that that 21% of links serving socially vulnerable zones also serve economically vulnerable or environmentally vulnerable zones; however, economically and environmentally vulnerable zones only share 9% of their links.

Figure 15 compares the most critical links identified by user-based measures (Figure 15(a)) and a link-based measure, i.e., change in travel time, (Figure 15(b)) identified for all socially, economically, and environmentally vulnerable zones. The link-based measures select the links more sparsely and mostly on major highways while the user-based measures identify links in denser areas where more vulnerable populations will use them.

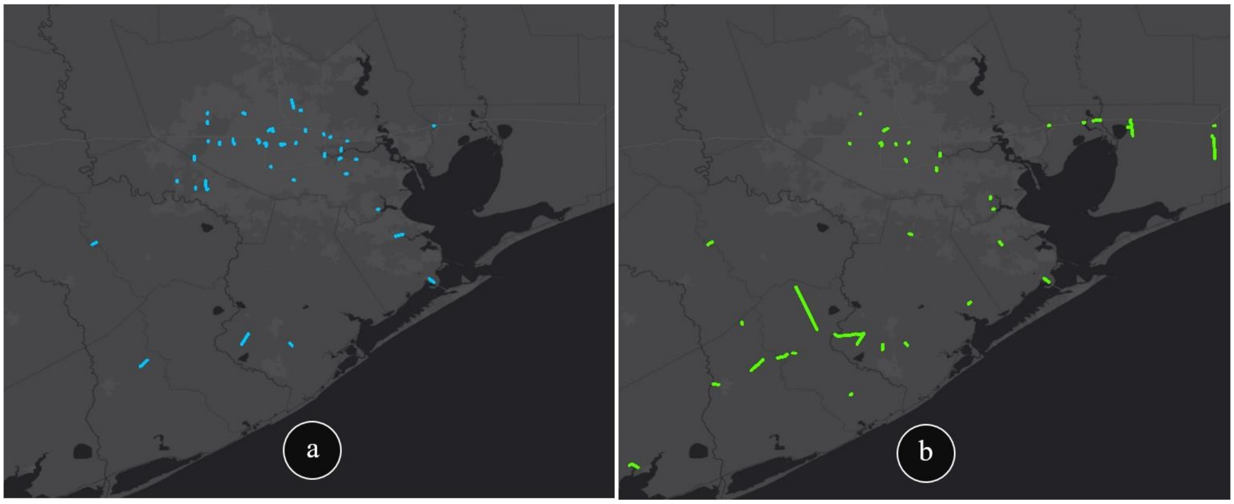

Figure 15. Most critical links identified by: (a) user-based measures; (b) link-based measures.

Figure 16 presents the spatial distribution of critical links from all risk zones selected by the three vulnerability criteria. Many links in risk zones 1 and 2 share the same links regardless of the vulnerability criteria because their evacuees use a limited number of links to reach major evacuation routes due to the sparse network. For other zones, however, the three vulnerability criteria select different links. For Zone 1, road segments of the major highways I-45, Beltway 8, SH 288, SH 35, and SH 36 are identified critical by all criteria, while long segments of FM 2004 are critical to serve socially vulnerable zones. For Zone 2, critical links are mostly found east of Houston such as I-10 eastbound and I-610 northbound, even though each vulnerability criterion selects different links in this region. Zone 3 shows the links selected by most diverse criteria combinations, which select many links on I-10 and I-610. However, links in the inner city of Houston are selected by all criteria since the Houston network mainly connects local origins to outer destination areas. On the other hand, Zone 4 shows the most links selected by a single criterion including long segments on SH 36 and FM 1301 used by environmentally vulnerable zones. A noticeable link is the segment of SH 36 which mainly serves environmental vulnerable zones in risk area 4 while it serves all three critical zones for risk areas 1 and 3. For Zones 5S and 5N, most of critical links are located in the inner city except a few link segments on I-10 which appear to serve all critical zones that connect to the Beaumont region.

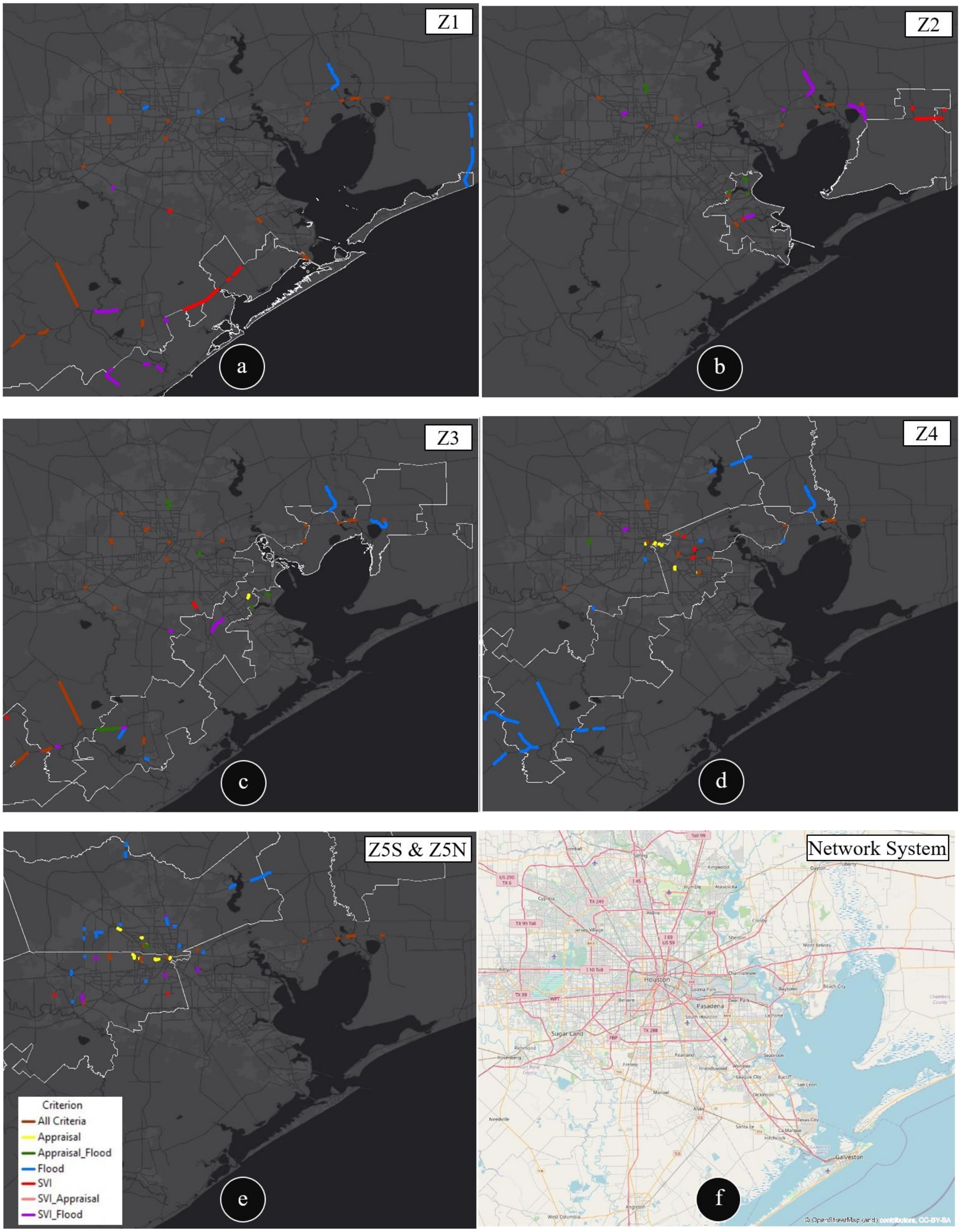

Figure 16. Critical Links Selected by Vulnerability Criteria (a-e) and Network System (f).

6.5. Interactive GIS Map

The final outputs of this study are presented in an online GIS map where the users can find the critical links and the associated attributes of each link such as the criticality value measured by different metrics. This interactive visualization also includes other layers and data used throughout this study, e.g., evacuation zones, evacuation destinations, and trip distribution results. Any future updates and changes will be applied to this map. The developed online GIS map and a brief summary of the research can be accessed by using this link: https://uta-arcgis.maps.arcgis.com/apps/webappviewer/index.html?id=ff6b75f6238843af956e238cf3724aa3

7. CONCLUSION

Historically, critical links for disaster responses rely on measures that capture the overall performance of a link disruption on the network. The links that their disruption causes higher travel cost and increases travel time or reduces throughput appear to have a higher priority for protection or restoration during an emergency. The performance measures that represent the clearance time and travel length for evacuees remain important to achieve system efficiencies in evacuation. However, the most important performance measure for evacuation from natural disasters such as major hurricanes is lives saved; therefore, the impacts of link disruptions that could result in more devastating consequences for some communities, especially for socially or economically vulnerable ones require special attention. These vulnerable populations lack the resources to withstand a hurricane if isolated; therefore, a failed evacuation could result in significant (life-threatening) consequences.

This study proposes a methodology to identify the critical evacuation links by integrating the vulnerability measures of communities. Three vulnerability measures including social, economic, and environmental vulnerability create critical zones to provide more attention and priorities to vulnerable communities for evacuation. A travel demand model integrates the findings from important evacuation behavior analysis studies based on real-data and calculates the trips generated from selected critical zones and distributed to safe destinations. A pool of evacuation links more susceptible to flooding based on recent tropical storm experiences identify the critical zones.

The results show that the critical links selected by the user-based measures do not always remain critical when applying conventional link-based measures. The critical links used by vulnerable users do not necessarily result in a significant impact on the general evacuee's throughput due to the geographical locations of the vulnerable populations. Even the critical links selected by the vulnerable users differ as only 49% of the links are shared by all three vulnerable communities, which raises an important question for decision-makers to determine critical links to prioritize restoration and protection for evacuation. Differences between demographic, economic, and land use characteristics of different risk zones creates variations in the criticality of the links.

The framework developed in this study can be used to identify the routes serving the highly vulnerable population during evacuation and disaster relief phase. This study finds those communities at higher risk to suffer from longer-term consequences, which would potentially result in higher mortality rate if not evacuated or impose higher economic impacts. Therefore, the location of disaster relief points can be assessed, or new locations added, if required, by considering the criticality of roads serving the vulnerable population who might require various emergency and relief help during different disaster stages.

The findings of this research provide a fundamental insight into the role of network infrastructure for evacuation. The network links achieve the overall system efficiencies like higher throughput and shortest travel time to equally serve all communities may exist. However, when applying a lens of equity, those links may not save the lives of vulnerable populations. The selection of critical links can vary depending on what criteria decision-makers prioritize. For evacuation planning and hurricane preparedness, the vulnerability of road users must be incorporated into the formula that selects the critical links.

Using the suggested framework, a more comprehensive study can compare the critical links identified by user-based measures and link-based measures such as change in travel cost of evacuees at a larger-scale network. This can help to better understand the difference between these two measures and develop a framework that can identify the critical links by using an index that captures both measures and ranks the most critical links. Future study will also expand the work and develop operational strategies that enhance network resilience and community survivability based on the critical links that serve vulnerable road users. The framework may also be expanded to prioritize links during the recovery process.

REFERENCES

1. Global warming and hurricanes: An overview of current research results. Geophysical Fluid Dynamics Laboratory. 2020.

2. Yi W, Nozick L, Davidson R, Blanton B, Colle B. Optimization of the issuance of evacuation orders under evolving hurricane conditions. Transportation Research Part B: Methodological. 2017 Jan 1;95:285–304.

3. Apivatanagul P, Davidson RA, Nozick LK. Bi-level optimization for risk-based regional hurricane evacuation planning. Natural hazards. 2012;60(2):567–88.

4. Han LD, Yuan F, Urbanik T. What is an effective evacuation operation? Journal of urban planning and development. 2007;133(1):3–8.

5. Tuydes H, Ziliaskopoulos A. Tabu-based heuristic approach for optimization of network evacuation contraflow. Transportation Research Record. 2006;1964(1):157–68.

6. Xie C, Turnquist MA. Lane-based evacuation network optimization: An integrated Lagrangian relaxation and tabu search approach. Transportation Research Part C: Emerging Technologies. 2011 Feb 1;19(1):40–63.

7. Freckleton D, Heaslip K, Louisell W, Collura J. Evaluation of resiliency of transportation networks after disasters. Transportation research record. 2012;2284(1):109–16.

8. Arabi M, Hyun K, Mattingly SP. Adaptable Resilience Assessment Framework to Evaluate an Impact of a Disruptive Event on Freight Operations. 2021.

9. Huang S-K, Lindell MK, Prater CS, Wu H-C, Siebeneck LK. Household Evacuation Decision Making in Response to Hurricane Ike. Natural Hazards Review [Internet]. 2012 Nov 1 [cited 2021 Jul 28];13(4):283–96. Available from: https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29NH.1527-6996.0000074

10. Basolo V, Steinberg LJ, Gant S. Hurricane threat in Florida: examining household perceptions, beliefs, and actions. Environmental Hazards. 2017;16(3):253–75.

11. Perry RW, Lindell MK, Tierney KJ. Facing the unexpected: Disaster preparedness and response in the United States. Joseph Henry Press; 2001.

12. Burnside R, Miller DS, Rivera JD. The impact of information and risk perception on the hurricane evacuation decision-making of greater New Orleans residents. Sociological Spectrum. 2007;27(6):727–40.

13. Sadri AM, Ukkusuri S V, Gladwin H. The role of social networks and information sources on hurricane evacuation decision making. Natural Hazards Review. 2017;18(3):4017005.

14. Burnside R. Leaving the big easy: An examination of the hurricane evacuation behavior of New Orleans residents before Hurricane Katrina. Journal of Public Management and Social Policy. 2006;12(2):49–61.

15. Horney JA. Hurricane evacuation failure: The role of social cohesion, social capital, and social control. The University of North Carolina at Chapel Hill; 2009.

16. DeYoung SE, Wachtendorf T, Davidson RA, Xu K, Nozick L, Farmer AK, et al. A mixed method study of hurricane evacuation: Demographic predictors for stated compliance to voluntary and mandatory orders. Environmental hazards. 2016;15(2):95–112.

17. Bowser G. Determining the differences in hurricane perception and evacuation behavior in the elderly of South Carolina. University of South Carolina; 2013.

18. Whitehead JC, Edwards B, Van Willigen M, Maiolo JR, Wilson K, Smith KT. Heading for higher ground: Factors affecting real and hypothetical hurricane evacuation behavior. Global Environmental Change Part B: Environmental Hazards. 2000;2(4):133–42.

19. Goodie AS, Sankar AR, Doshi P. Experience, risk, warnings, and demographics: Predictors of evacuation decisions in Hurricanes Harvey and Irma. International Journal of Disaster Risk Reduction. 2019 Dec 1;41:101320.

20. Yang H, Morgul EF, Ozbay K, Xie K. Modeling evacuation behavior under hurricane conditions. Transportation research record. 2016;2599(1):63–9.

21. Smith SK, McCarty C. Fleeing the storm(s): an examination of evacuation behavior during florida's 2004 hurricane season. Demography 2009 46:1 [Internet]. 2009 [cited 2021 Jul 28];46(1):127–45. Available from: https://link.springer.com/article/10.1353/dem.0.0048

22. Solis D, Thomas M, Letson D. An empirical evaluation of the determinants of household hurricane evacuation choice. Journal of Development and Agricultural Economics [Internet]. 2010 May 31 [cited 2021 Jul 28];2(5):188–96. Available from: https://academicjournals.org/journal/JDAE/article-abstract/77CFEAB1645

23. Hasan S, Ukkusuri S, Gladwin H, Murray-Tuite P. Behavioral Model to Understand Household-Level Hurricane Evacuation Decision Making. Journal of Transportation Engineering [Internet]. 2010 Sep 23 [cited 2021 Jul 28];137(5):341–8. Available from: https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29TE.1943-5436.0000223

24. Morss RE, Demuth JL, Lazo JK, Dickinson K, Lazrus H, Morrow BH. Understanding Public Hurricane Evacuation Decisions and Responses to Forecast and Warning Messages. Weather and Forecasting [Internet]. 2016 Apr 1 [cited 2021 Jul 28];31(2):395–417. Available from: https://journals.ametsoc.org/view/journals/wefo/31/2/waf-d-15-0066_1.xml

25. Meyer MA, Mitchell B, Purdum JC, Breen K, Iles RL. Previous hurricane evacuation decisions and future evacuation intentions among residents of southeast Louisiana. International Journal of Disaster Risk Reduction. 2018 Oct 1;31:1231–44.

26. Thiede BC, Brown DL. Hurricane Katrina: Who Stayed and Why? Population Research and Policy Review 2013 32:6 [Internet]. 2013 Sep 5 [cited 2021 Jul 28];32(6):803–24. Available from: https://link.springer.com/article/10.1007/s11113-013-9302-9

27. Mileti DS, Drabek TE, Haas JE. Human systems in extreme environments: A sociological perspective. Institute of Behavioral Science, University of Colorado; 1975.

28. Mileti DS, O'Brien PW. Warnings during disaster: Normalizing communicated risk. Social problems. 1992;39(1):40–57.

29. Lindell MK, Perry RW. Communicating environmental risk in multiethnic communities. Sage Publications; 2003.

30. Lindell MK, Hwang SN. Households' perceived personal risk and responses in a multihazard environment. Risk Analysis: An International Journal. 2008;28(2):539–56.

31. Baker EJ. Hurricane evacuation behavior. International journal of mass emergencies and disasters. 1991;9(2):287–310.

32. Fu H, Wilmot CG. Sequential logit dynamic travel demand model for hurricane evacuation. Transportation Research Record. 2004;1882(1):19–26.

33. Lindell MK, Lu J-C, Prater CS. Household decision making and evacuation in response to Hurricane Lili. Natural hazards review. 2005;6(4):171–9.

34. Mesa-Arango R, Hasan S, Ukkusuri S V, Murray-Tuite P. Household-level model for hurricane evacuation destination type choice using hurricane Ivan data. Natural hazards review. 2013;14(1):11–20.

35. Sadri AM, Ukkusuri S V., Murray-Tuite P, Gladwin H. Analysis of hurricane evacuee mode choice behavior. Transportation Research Part C: Emerging Technologies. 2014 Nov 1;48:37–46.

36. Jiang Y, Li Z, Cutter SL. Social distance integrated gravity model for evacuation destination choice. International Journal of Digital Earth. 2021;1–15.

37. Cheng G, Wilmot CG, Baker EJ. A destination choice model for hurricane evacuation. In: Proceedings of the 87th Annual Meeting Transportation Research Board, Washington, DC, USA. 2008. p. 13–7.

38. Wilmot CG, Modali N, Chen B, others. Modeling Hurricane Evacuation Traffic: Testing the Gravity and Intervening Opportunity Models as Models of Destination Choice in Hurricane Evacuation [Report]. 2006.

39. Chen B. Modeling destination choice in hurricane evacuation with an intervening opportunity model. 2005;

40. Yin W, Murray-Tuite P, Ukkusuri S V., Gladwin H. An agent-based modeling system for travel demand simulation for hurricane evacuation. Transportation Research Part C: Emerging Technologies. 2014 May 1;42:44–59.

41. Parady GT, Hato E. Accounting for spatial correlation in tsunami evacuation destination choice: a case study of the Great East Japan Earthquake. Natural Hazards. 2016;84(2):797–807.

42. Cheng G, Wilmot CG, Baker EJ. Dynamic gravity model for hurricane evacuation planning. Transportation Research Record. 2011;2234(1):125–34.

43. Sadri AM, Ukkusuri S V, Murray-Tuite P, Gladwin H. How to evacuate: model for understanding the routing strategies during hurricane evacuation. Journal of transportation engineering. 2014;140(1):61–9.

44. Robinson RM, Khattak A. Evacuee route choice decisions in a dynamic hurricane

evacuation context. Transportation research record. 2012;2312(1):141–9.

45. Wu HC, Lindell MK, Prater CS. Logistics of hurricane evacuation in Hurricanes Katrina and Rita. Transportation Research Part F: Traffic Psychology and Behaviour. 2012 Jul 1;15(4):445–61.

46. Lindell MK, Kang JE, Prater CS. The logistics of household hurricane evacuation. Natural hazards. 2011;58(3):1093–109.

47. Kim S, Shekhar S, Min M. Contraflow transportation network reconfiguration for evacuation route planning. IEEE transactions on Knowledge and Data Engineering. 2008;20(8):1115–29.

48. Banipal K. Strategic approach to disaster management: lessons learned from Hurricane Katrina. Disaster Prevention and Management: An International Journal. 2006;

49. Taylor MAP, Sekhar SVC, D'Este GM. Application of accessibility based methods for vulnerability analysis of strategic road networks. Networks and Spatial Economics. 2006;6(3):267–91.

50. Berdica K, Mattsson L-G. Vulnerability: a model-based case study of the road network in Stockholm. In: Critical infrastructure. Springer; 2007. p. 81–106.

51. Kim S, Yeo H. A Flow-based Vulnerability Measure for the Resilience of Urban Road Network. Procedia - Social and Behavioral Sciences. 2016 May 9;218:13–23.

52. Lu Q-C, Peng Z-R, Zhang J. Identification and prioritization of critical transportation infrastructure: Case study of coastal flooding. Journal of Transportation Engineering. 2015;141(3):4014082.

53. Nagurney A, Qiang Q. A transportation network efficiency measure that captures flows, behavior, and costs with applications to network component importance identification and vulnerability. In: Proceedings of the POMS 18th Annual Conference, Dallas, Texas, USA, MAY. 2007.

54. Jenelius E, Petersen T, Mattsson LG. Importance and exposure in road network vulnerability analysis. Transportation Research Part A: Policy and Practice. 2006 Aug 1;40(7):537–60.

55. Scott DM, Novak DC, Aultman-Hall L, Guo F. Network Robustness Index: A new method for identifying critical links and evaluating the performance of transportation networks. Journal of Transport Geography. 2006 May 1;14(3):215–27.

56. Zhu YJ, Hu Y, Collins JM. Estimating road network accessibility during a hurricane evacuation: A case study of hurricane Irma in Florida. Transportation Research Part D: Transport and Environment. 2020 Jun 1;83:102334.

57. Chen X, Li Q. Modeling road network vulnerability for evacuees and first responders in no-notice evacuation. Journal of advanced transportation. 2017;2017.

58. Mitchell SW, Radwan E. Heuristic priority ranking of emergency evacuation staging to reduce clearance time. Transportation research record. 2006;1964(1):219–28.

59. Rupi F, Bernardi S, Rossi G, Danesi A. The evaluation of road network vulnerability in mountainous areas: a case study. Networks and Spatial Economics. 2015;15(2):397–411.

60. Helderop E, Grubesic TH. Flood evacuation and rescue: The identification of critical road segments using whole-landscape features. Transportation Research Interdisciplinary Perspectives. 2019 Dec 1;3:100022.

61. Sullivan JL, Novak DC, Aultman-Hall L, Scott DM. Identifying critical road segments and measuring system-wide robustness in transportation networks with isolating links: A link-based capacity-reduction approach. Transportation Research Part A: Policy and Practice. 2010 Jun 1;44(5):323–36.

62. Stamos I, Grau JMS, Mitsakis E, Aifadopoulou G, Chiu Y-C. On criticality assessment based evacuation modeling: empirical findings. Journal of Traffic and Logistics Engineering. 2013;1(2):148–52.

63. Holmgren Å. Vulnerability analysis of electric power delivery networks. Citeseer; 2004.

64. Berdica K. An introduction to road vulnerability: what has been done, is done and should be done. Transport Policy. 2002 Apr 1;9(2):117–27.

65. Husdal J, others. Reliability/vulnerability versus cost/benefit. Nicholson AJ, Dante, A. 2004;

66. Jenelius E, Mattsson LG. Road network vulnerability analysis: Conceptualization, implementation and application. Computers, Environment and Urban Systems. 2015 Jan 1;49:136–47.

67. Cutter SL, Mitchell JT, Scott MS. Revealing the vulnerability of people and places: A case study of Georgetown County, South Carolina. Annals of the association of American Geographers. 2000;90(4):713–37.

68. Chakraborty J, Tobin GA, Montz BE. Population evacuation: assessing spatial variability in geophysical risk and social vulnerability to natural hazards. Natural Hazards Review. 2005;6(1):23–33.

69. E. F, W. G, J H, L. H, Brian L. A Social Vulnerability Index for Disaster Management. Journal of Homeland Security and Emergency Management. 2011;

70. Lim GJ, Baharnemati MR, Zangeneh S, Parsaei HR. A network flow based optimization approach for hurricane evacuation planning. Proc ICOVACS. 2009;

71. Wilmot CG, Mei B. Comparison of Alternative Trip Generation Models for Hurricane Evacuation. Natural Hazards Review [Internet]. 2004 Nov 1 [cited 2021 Jul 5];5(4):170–8. Available from: https://ascelibrary.org/doi/abs/10.1061/%28ASCE%291527-6988%282004%295%3A4%28170%29

72. Lindell MK, Prater CS. Critical Behavioral Assumptions in Evacuation Time Estimate Analysis for Private Vehicles: Examples from Hurricane Research and Planning. Journal of Urban Planning and Development. 2007 Mar;133(1):18–29.

73. Bish DR. Planning for a bus-based evacuation. OR Spectrum. 2011;

74. Kaisar EI, Hess L, Palomo ABP. An emergency evacuation planning model for special needs populations using public transit systems. Journal of Public Transportation. 2012;

75. Dow K, Cutter SL. Emerging Hurricane Evacuation Issues: Hurricane Floyd and South Carolina. Natural Hazards Review. 2002;

76. Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry/ Geospatial Research, Analysis, and Services Program. CDC/ATSDR Social Vulnerability Index [2018] Database [Texas] [Internet]. [cited 2021 May 23]. Available from: https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html

77. Strategic Mapping Program (StratMap). Land Parcels, 2019-03-01.

78. Zachry BC, Booth WJ, Rhome JR, Sharon TM. A national view of storm surge risk and inundation. Weather, climate, and society. 2015;7(2):109–17.

79. Harvey Flood Data Collections | CUAHSI HydroShare [Internet]. [cited 2021 May 23]. Available from: https://www.hydroshare.org/resource/12e69ee668124fdf833b29b5167e03c3/

APPENDIX A. CRITICAL LINKS IDENTIFIED BY DIFFERENT USER-BASED CRITICALITY MEASURES

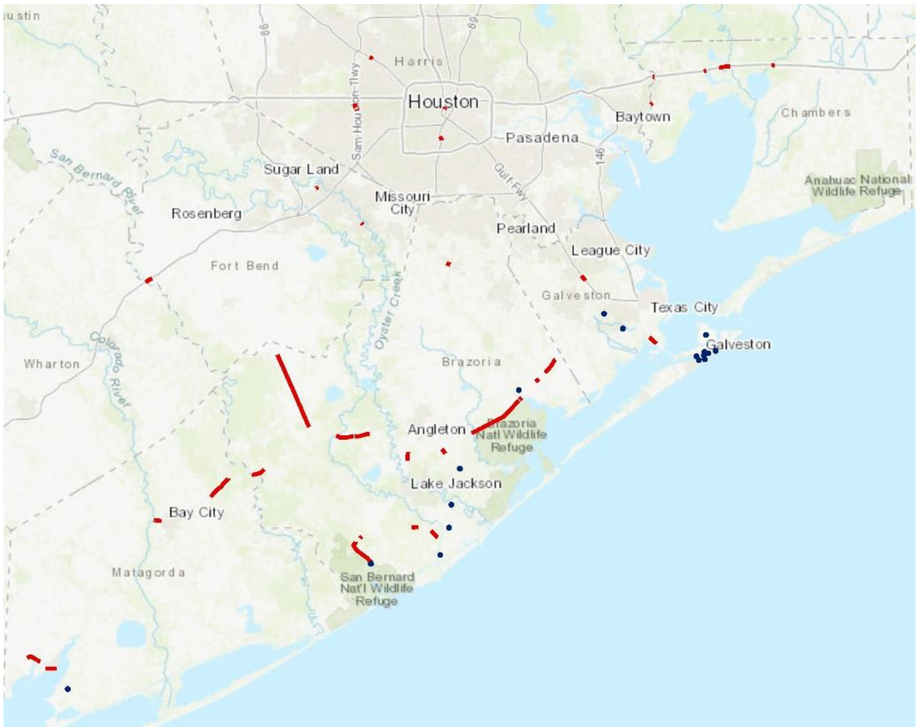

Figure A.1. Critical links identified for socially vulnerable CTs in Zone 1.

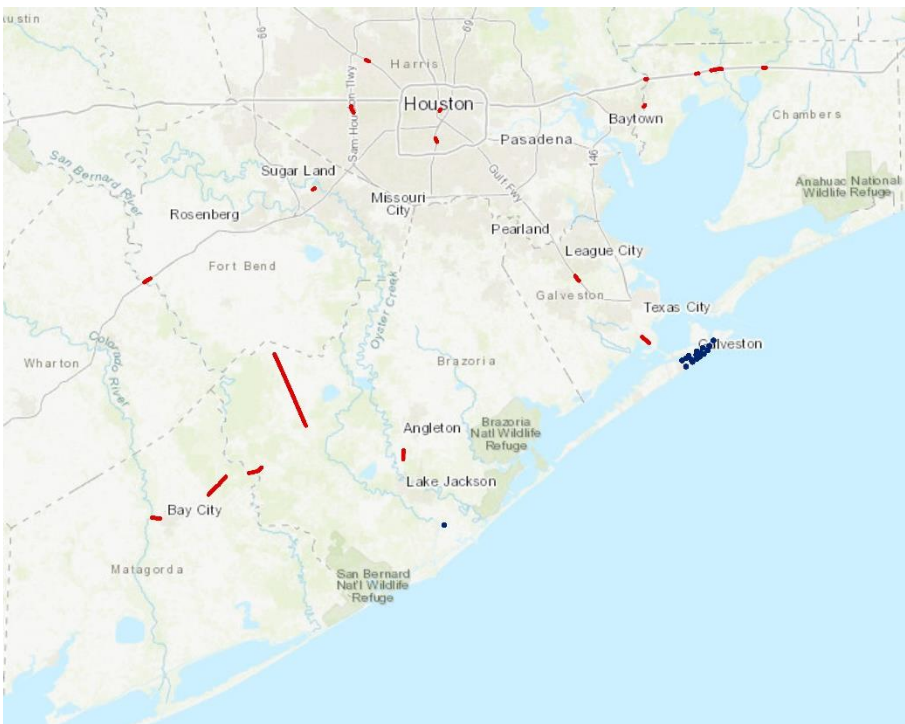

Figure A.2. Critical links identified for economically vulnerable CTs in Zone 1.

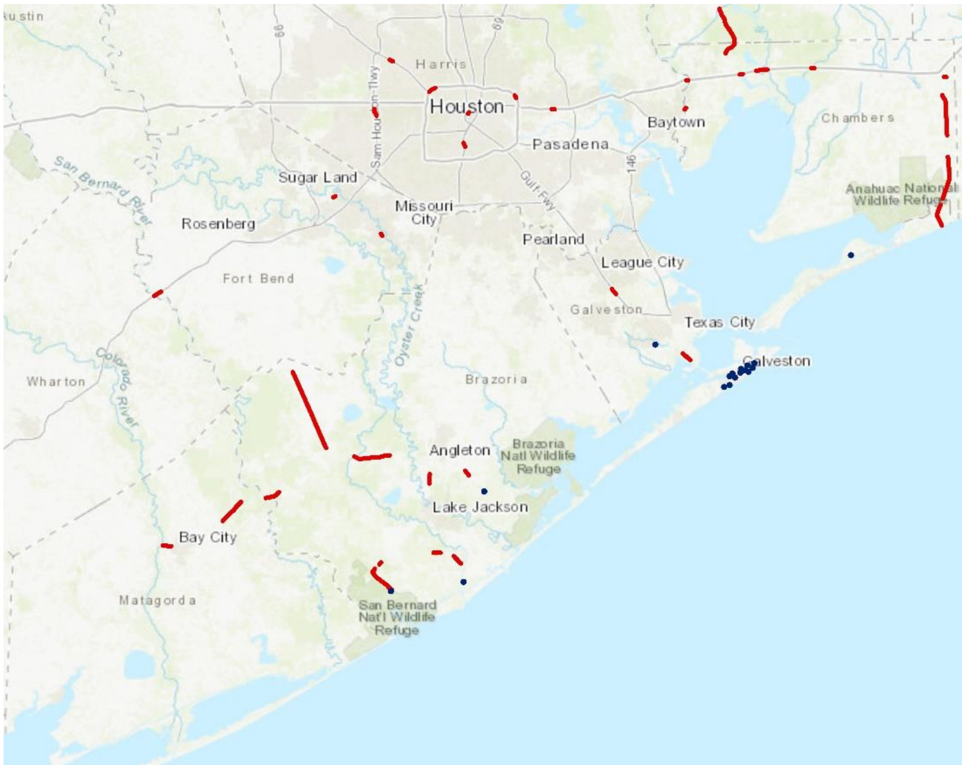

Figure A.3. Critical links identified for environmentally vulnerable CTs in Zone 1.

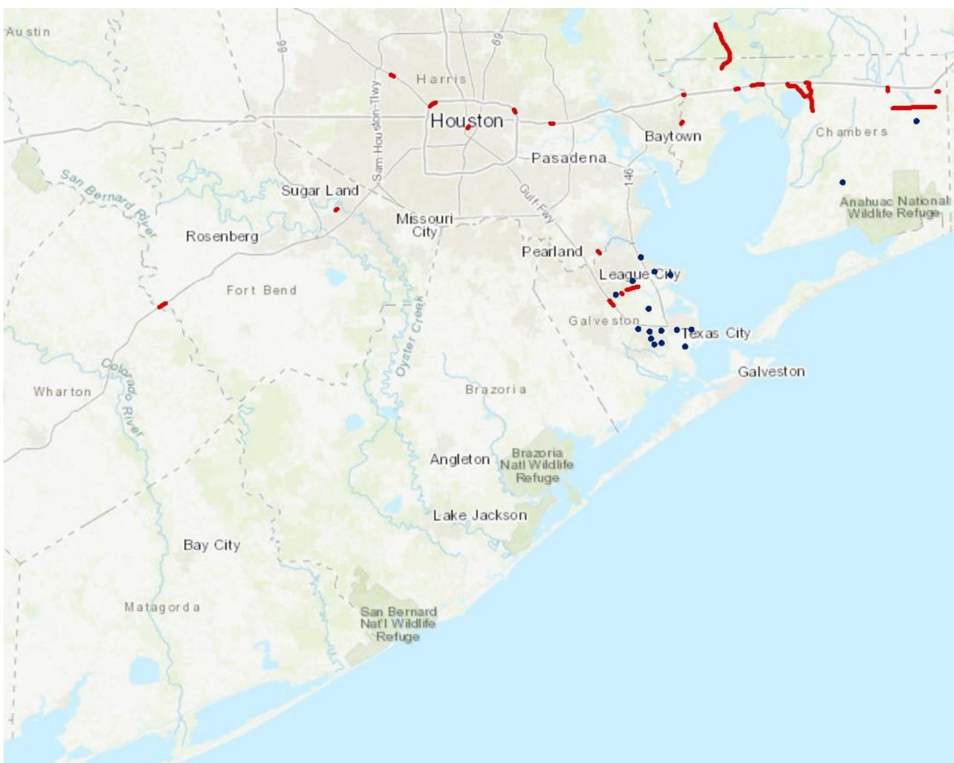

Figure A.4. Critical links identified for socially vulnerable CTs in Zone 2.

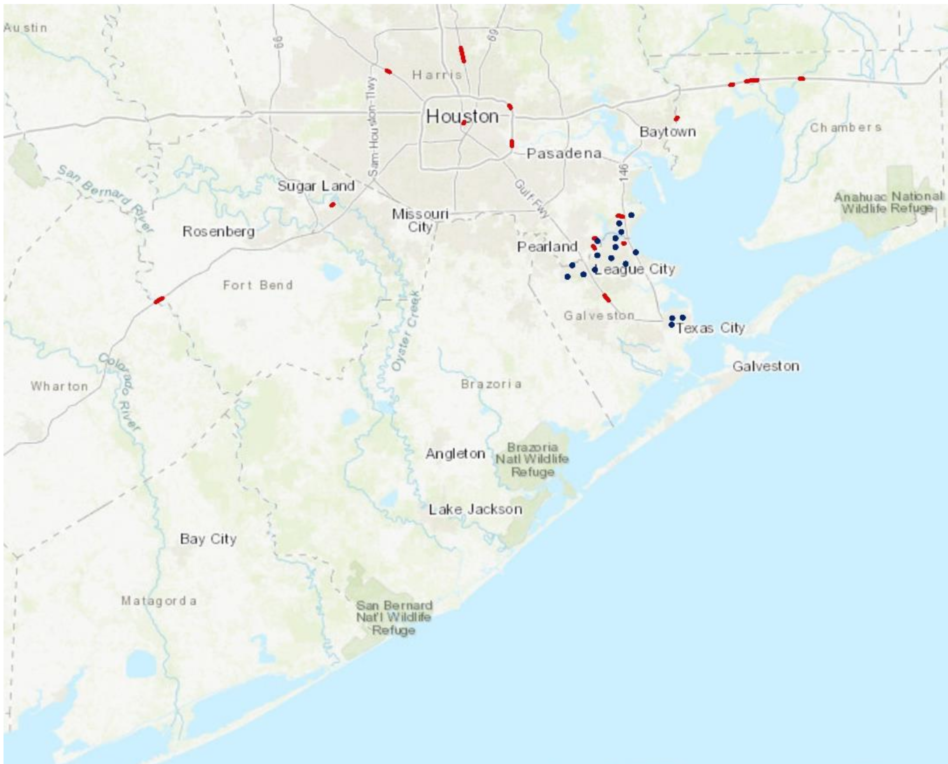

Figure A.5. Critical links identified for economically vulnerable CTs in Zone 2.

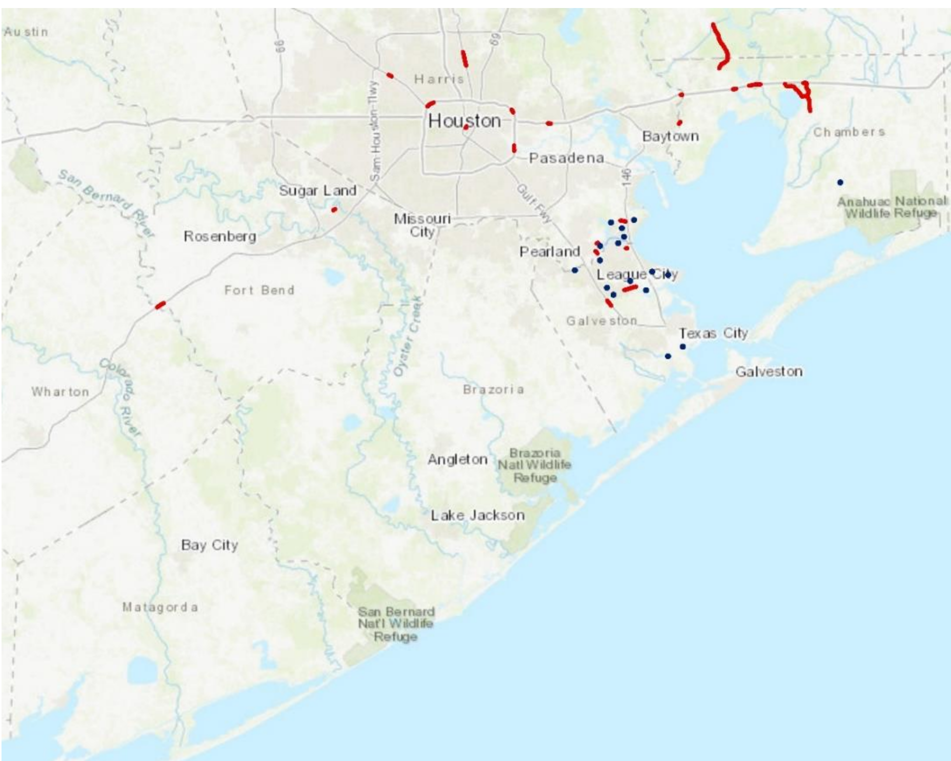

Figure A.6. Critical links identified for environmentally vulnerable CTs in Zone 2.

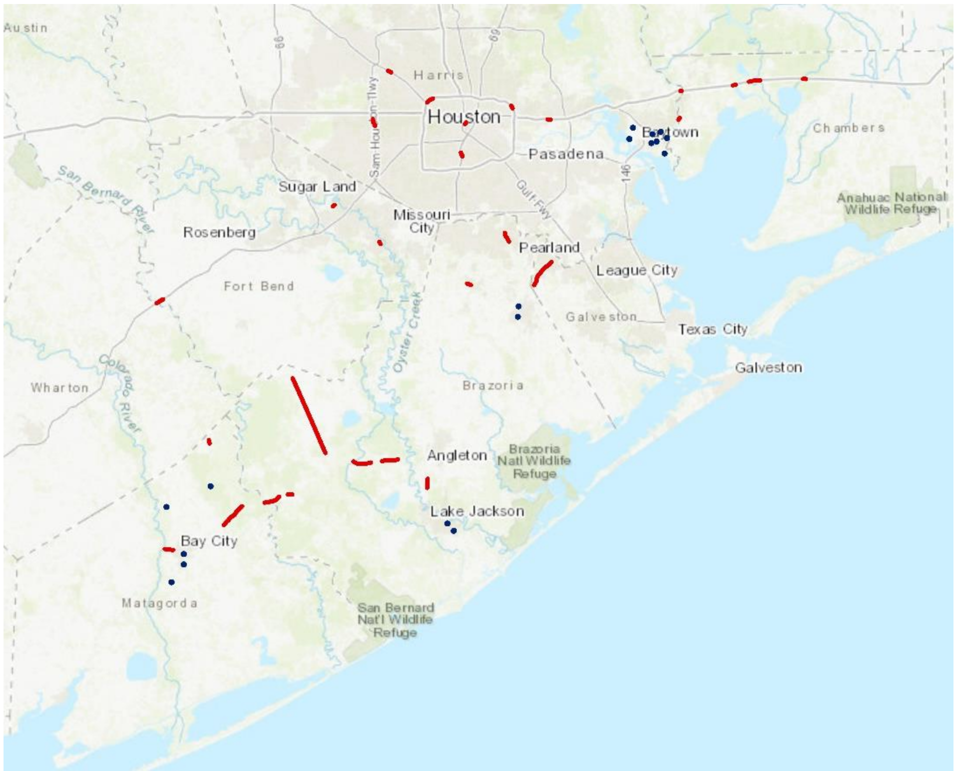

Figure A.7. Critical links identified for socially vulnerable CTs in Zone 3.

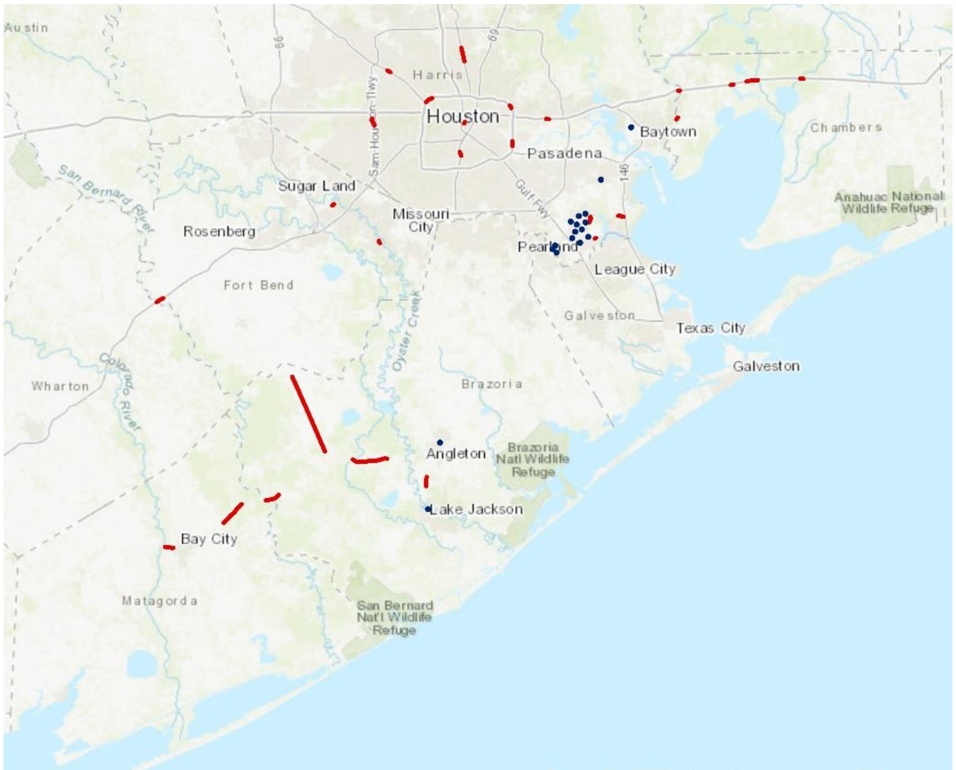

Figure A.8. Critical links identified for economically vulnerable CTs in Zone 3.

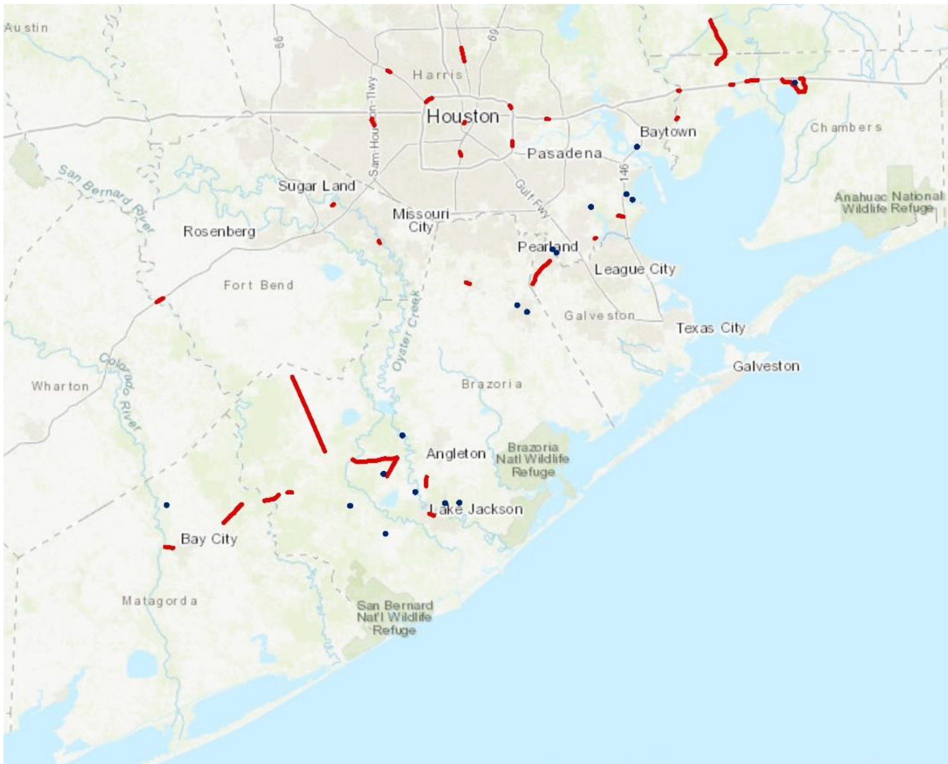

Figure A.9. Critical links identified for environmentally vulnerable CTs in Zone 3.

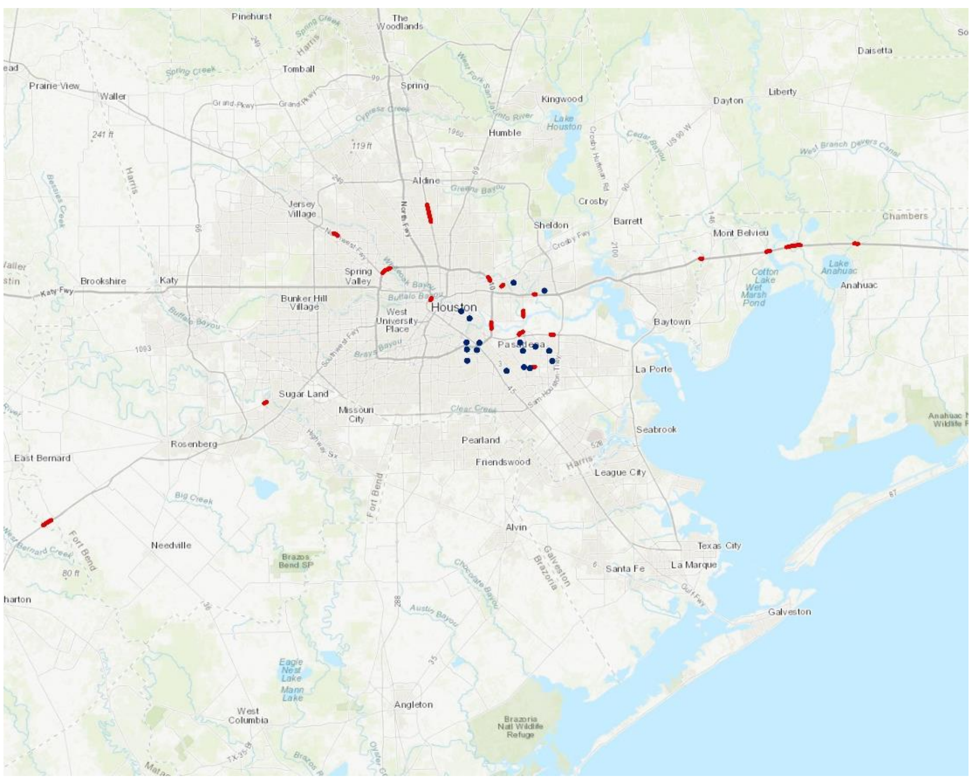

Figure A.10. Critical links identified for socially vulnerable CTs in Zone 4.

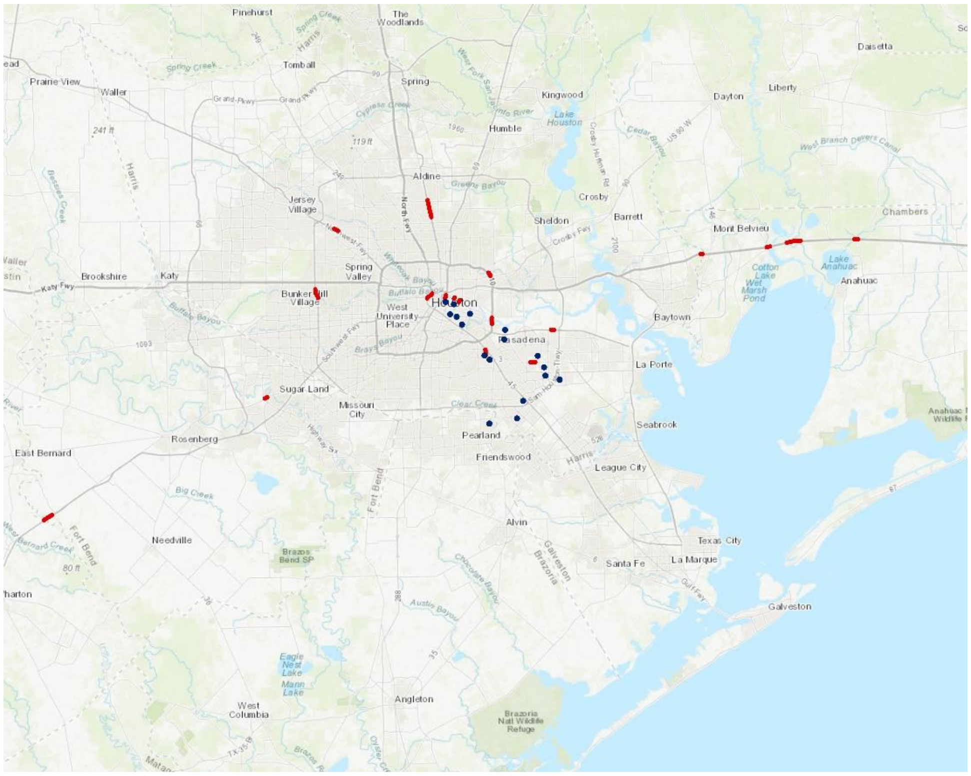

Figure A.11. Critical links identified for economically vulnerable CTs in Zone 4.

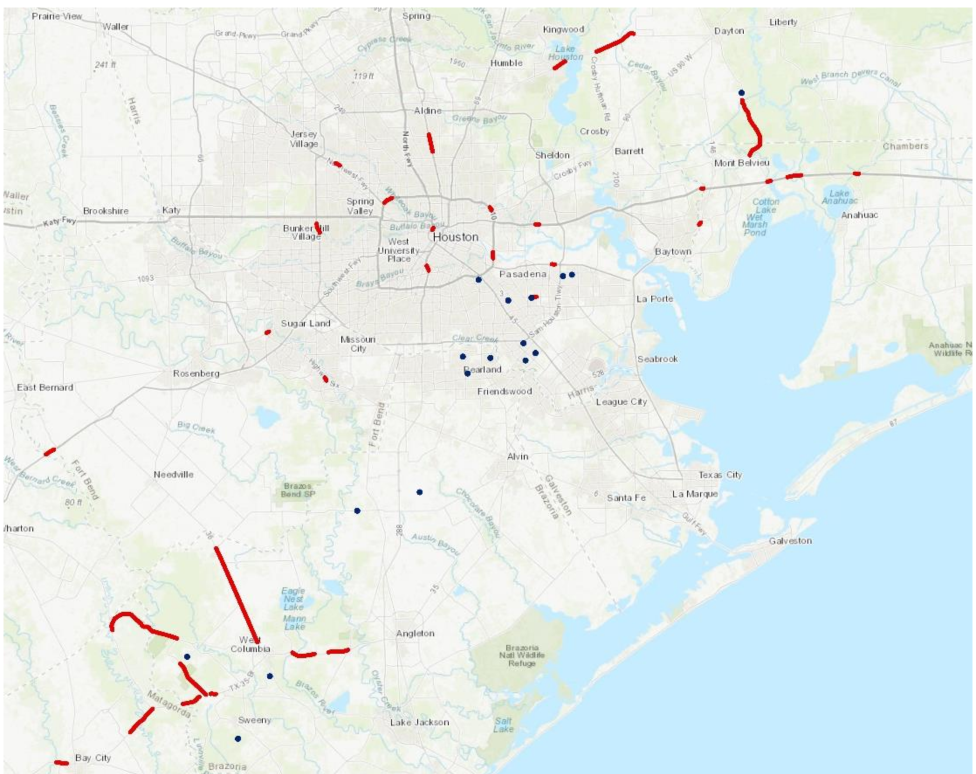

Figure A.12. Critical links identified for environmentally vulnerable CTs in Zone 4.

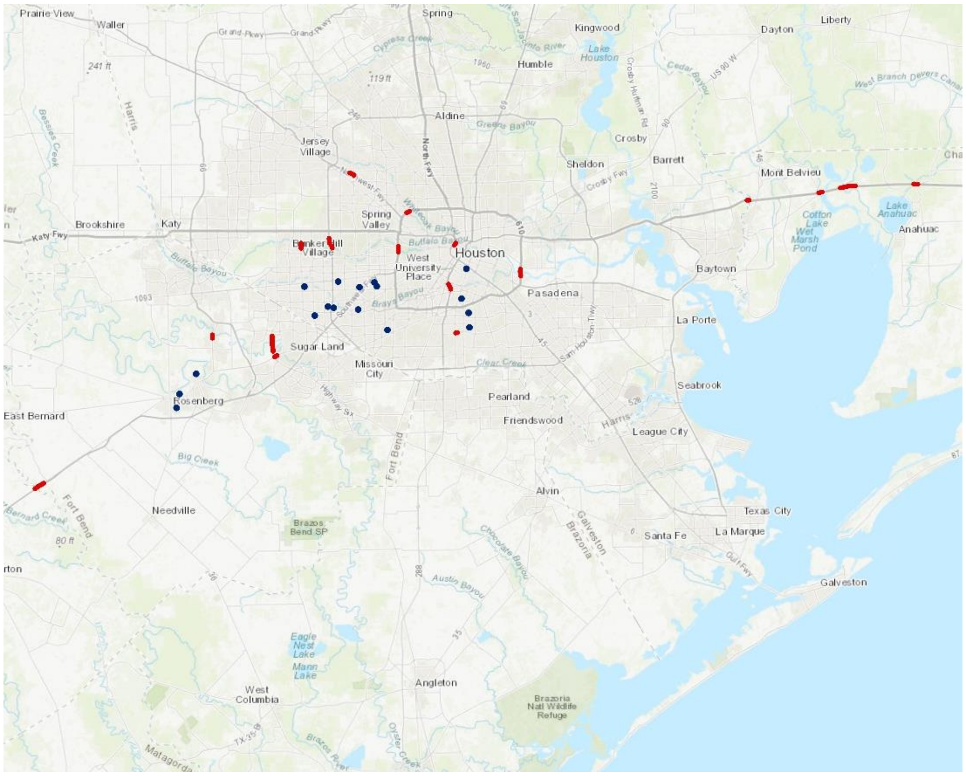

Figure A.13. Critical links identified for socially vulnerable CTs in Zone 5S.

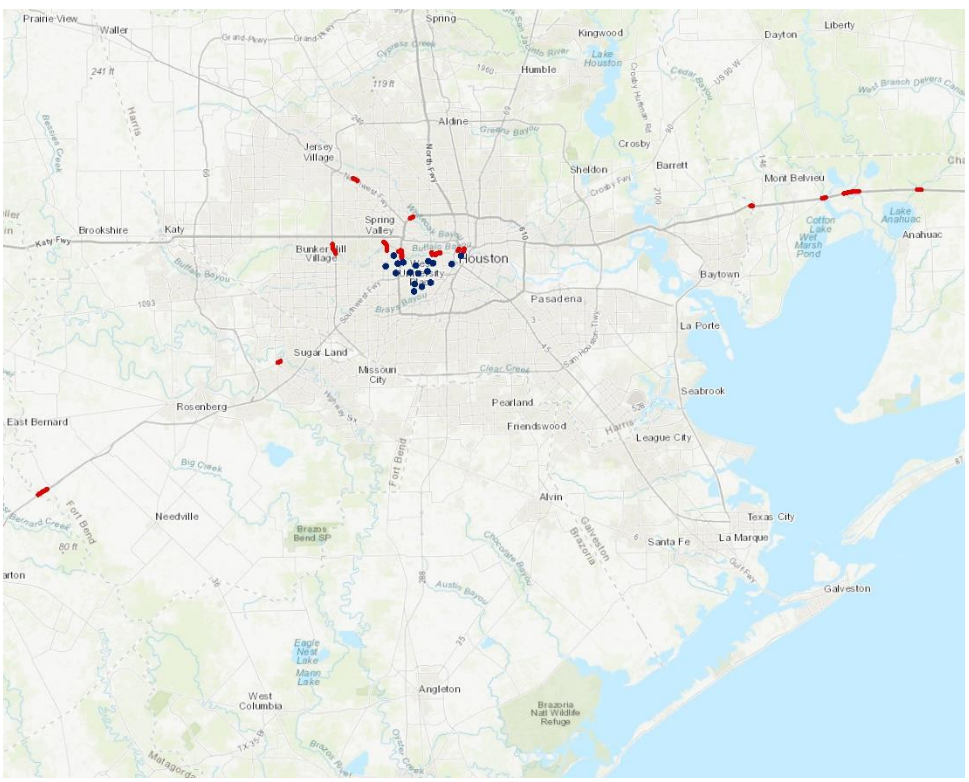

Figure A.14. Critical links identified for economically vulnerable CTs in Zone 5S.

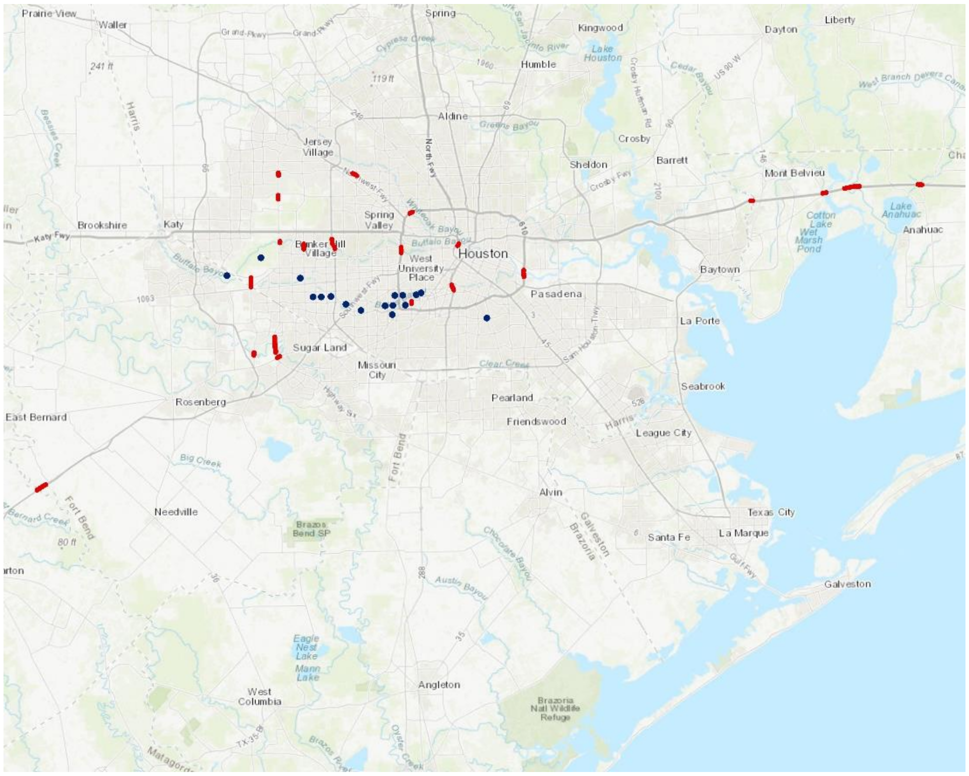

Figure A.15. Critical links identified for environmentally vulnerable CTs in Zone 5S.

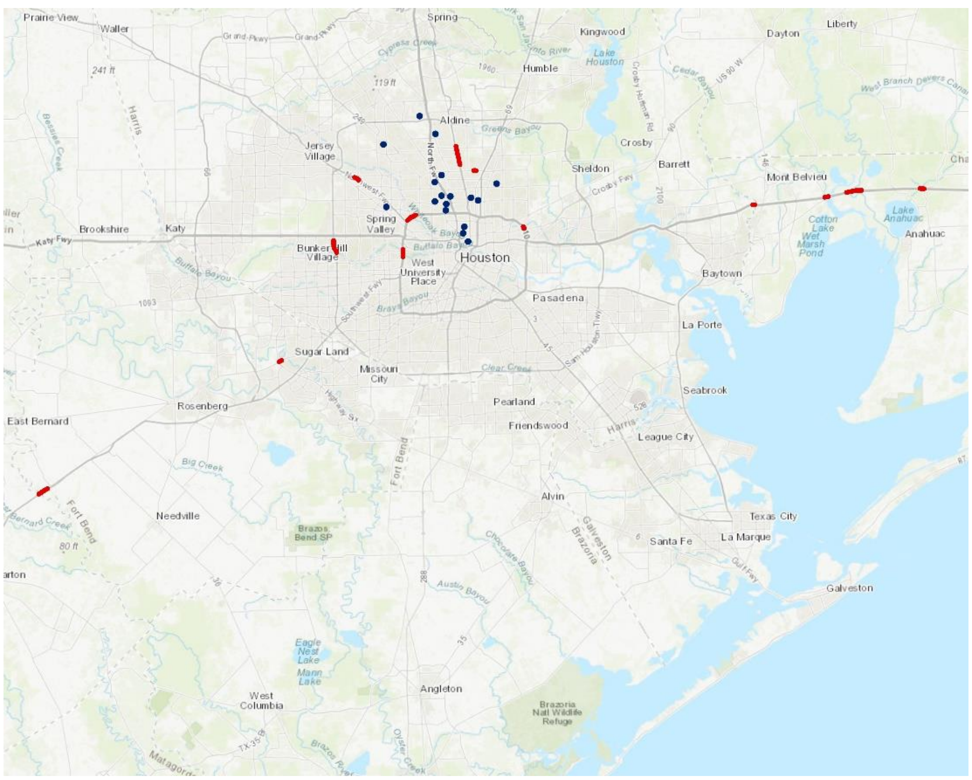

Figure A.16. Critical links identified for socially vulnerable CTs in Zone 5N.

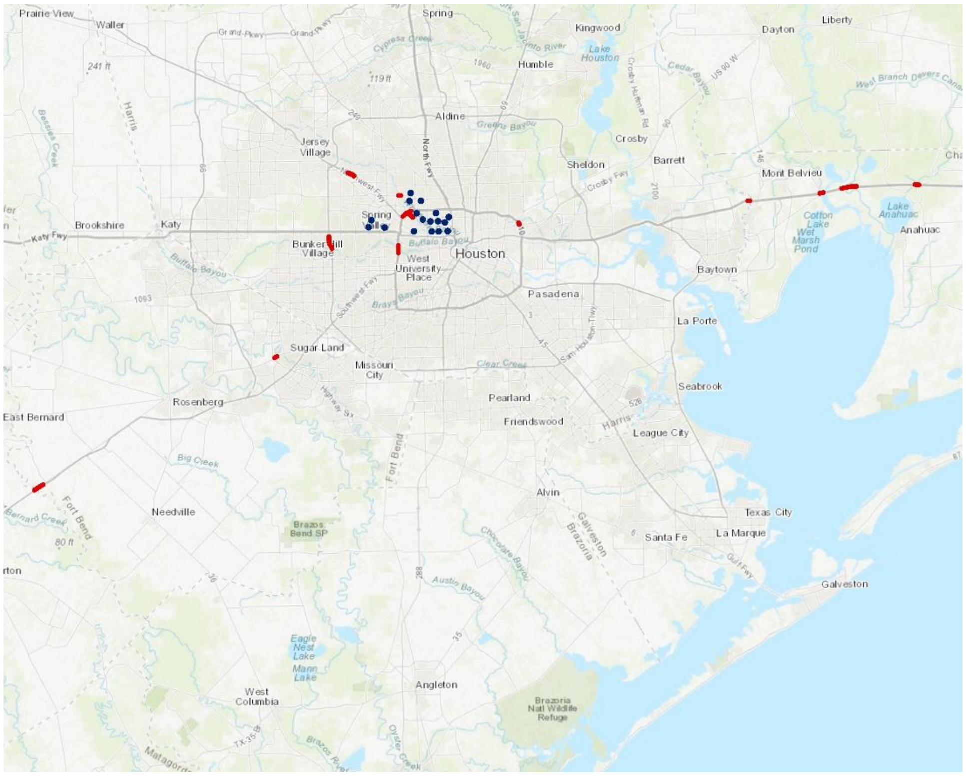

Figure A.17. Critical links identified for economically vulnerable CTs in Zone 5N.

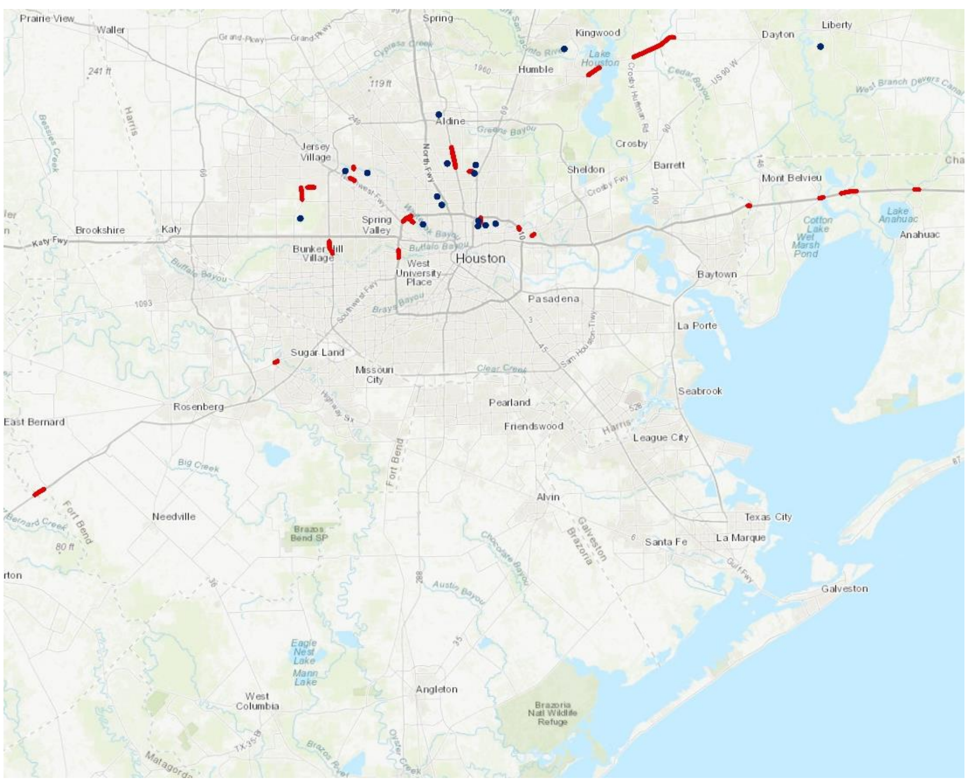

Figure A.18. Critical links identified for environmentally vulnerable CTs in Zone 5N.

APPENDIX B. MOST CRITICAL LINKS IDENTIFIED BY DIFFERENT USER-BASED AND LINK-BASED CRITICALITY MEASURES

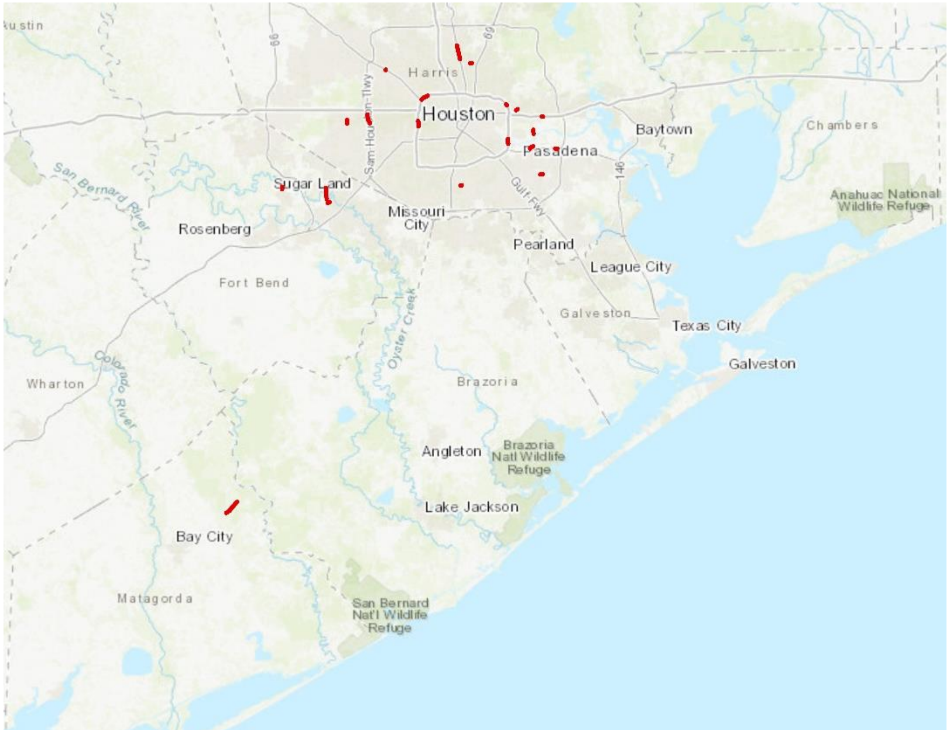

Figure B.1. Most critical links identified for socially vulnerable CTs ranked by average SVI.

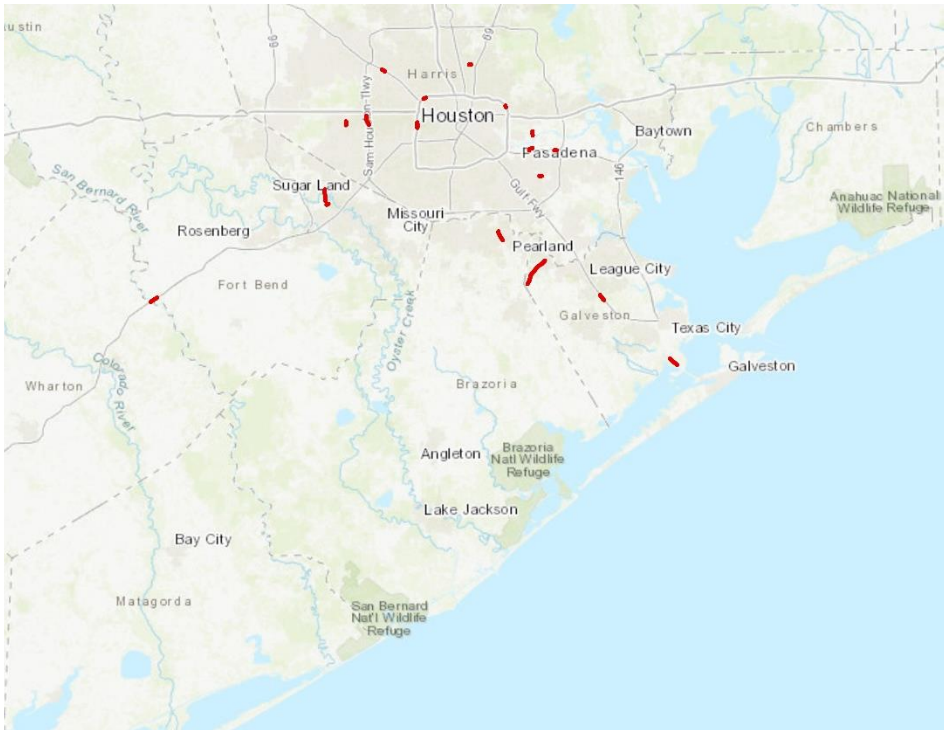

Figure B.2. Most critical links identified for socially vulnerable CTs ranked by average economic vulnerability.

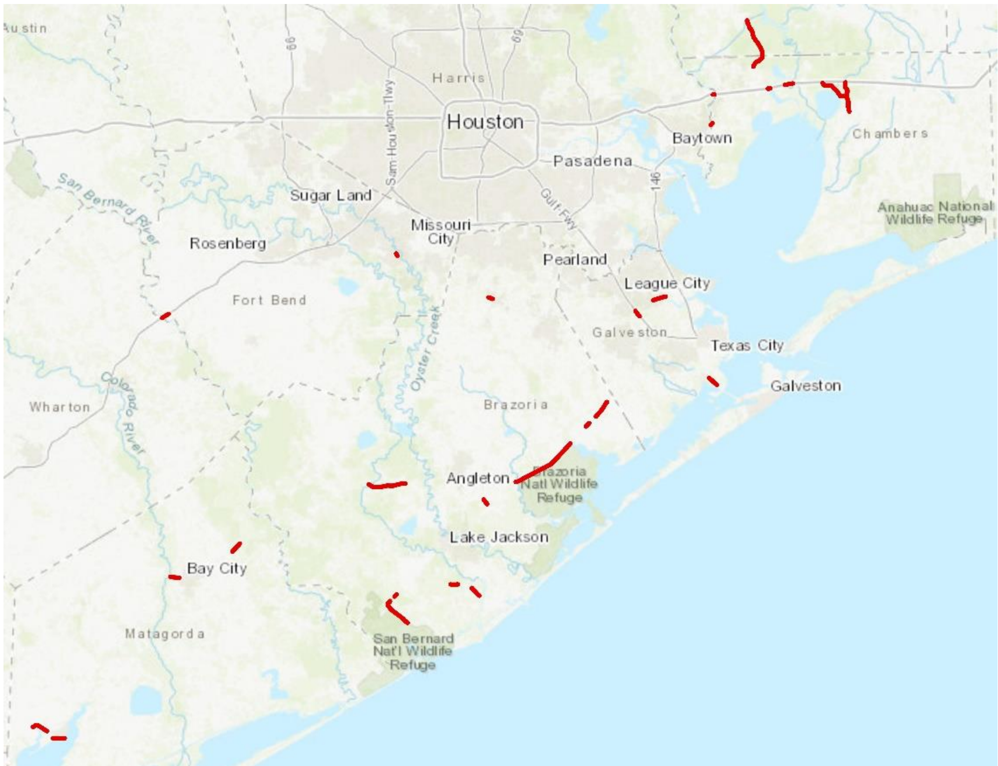

Figure B.3. Most critical links identified for socially vulnerable CTs ranked by average environmental vulnerability.

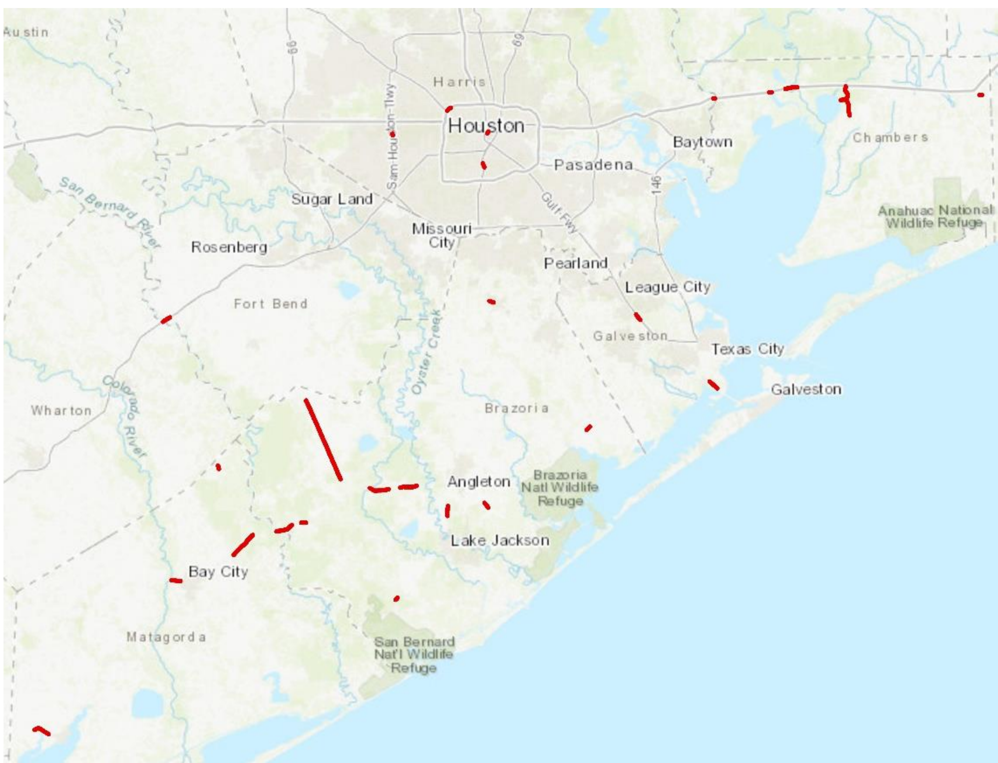

Figure B.4. Most critical links identified for socially vulnerable CTs ranked by change in travel time.

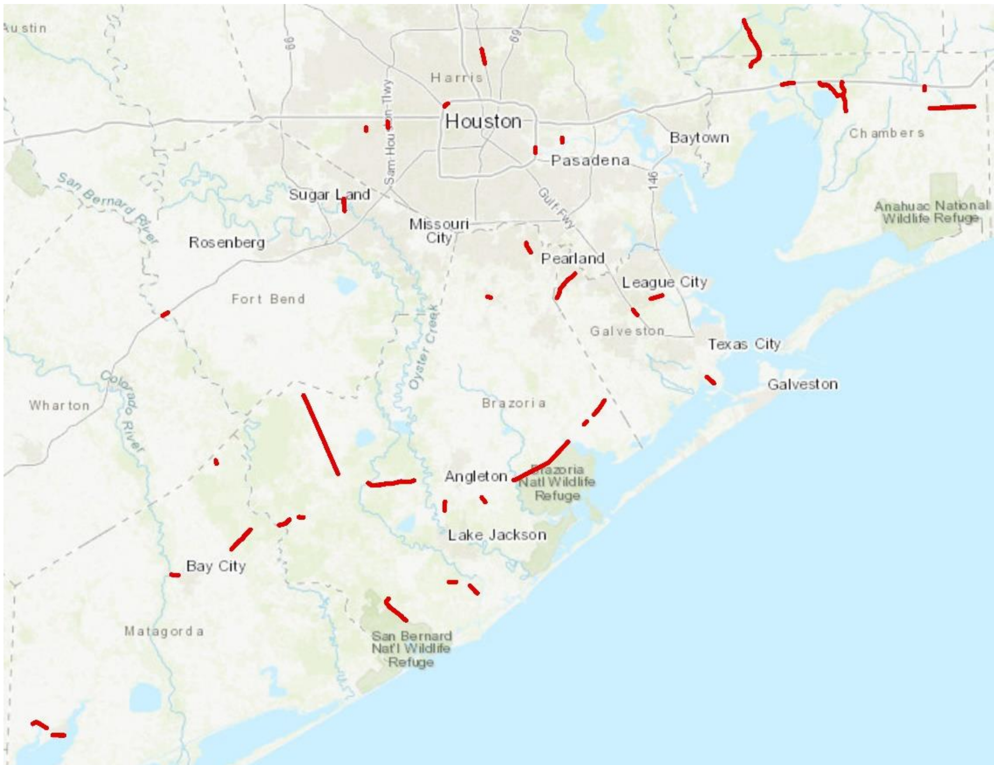

Figure B.5. Most critical links identified for socially vulnerable CTs ranked by link length.

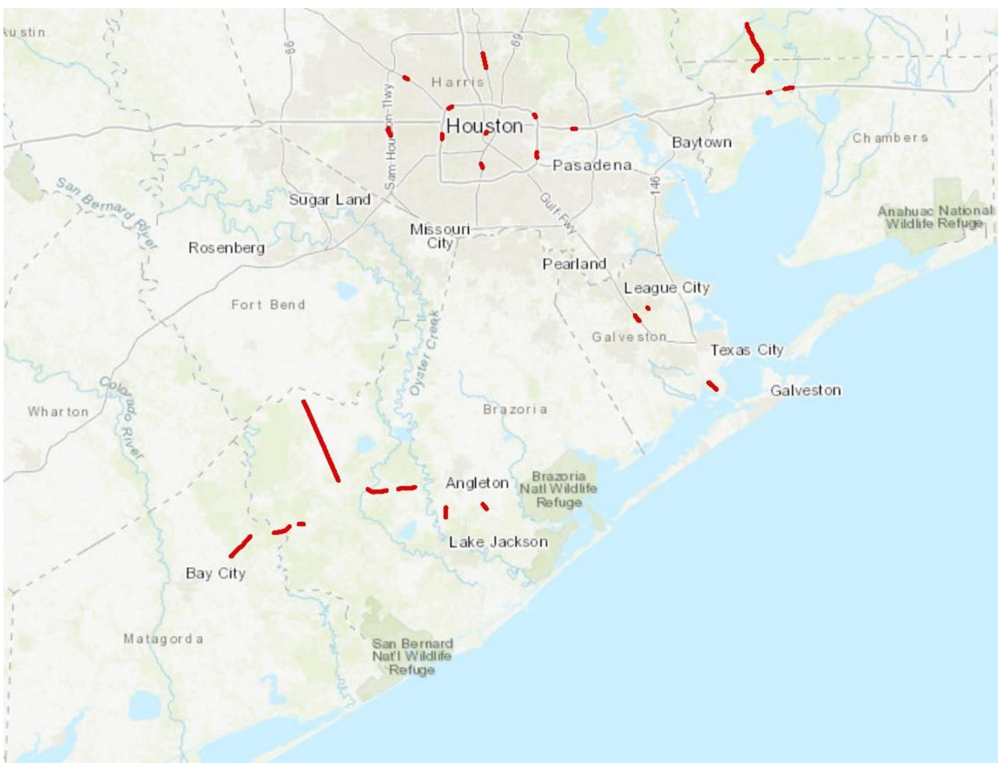

Figure B.6. Most critical links identified for socially vulnerable CTs ranked by link volume.

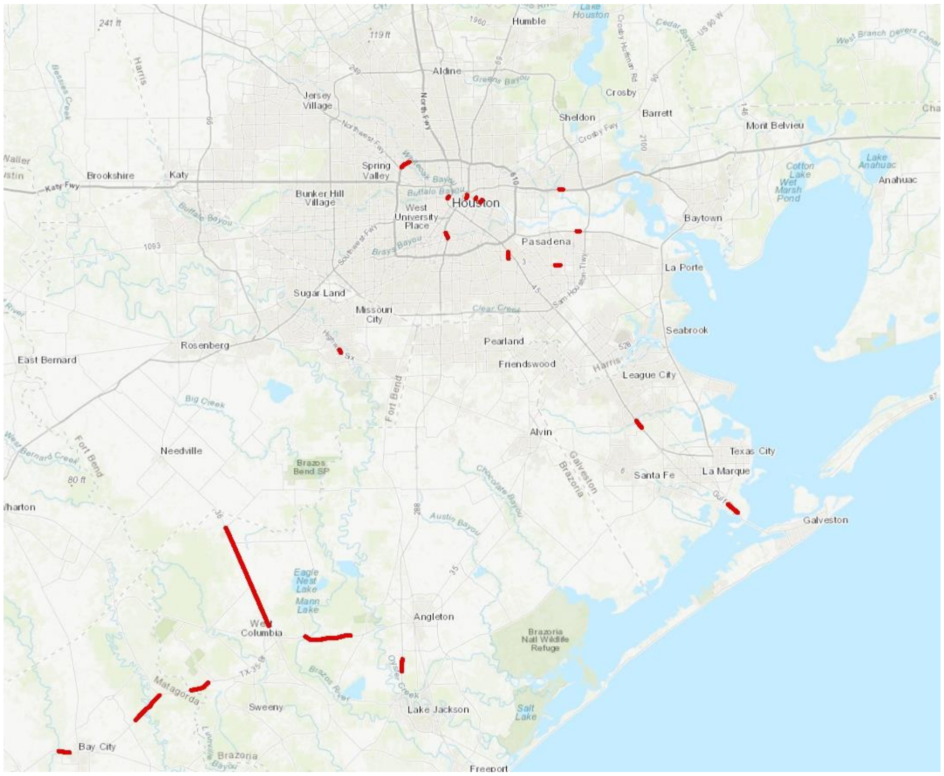

Figure B.7. Most critical links identified for economically vulnerable CTs ranked by average SVI.

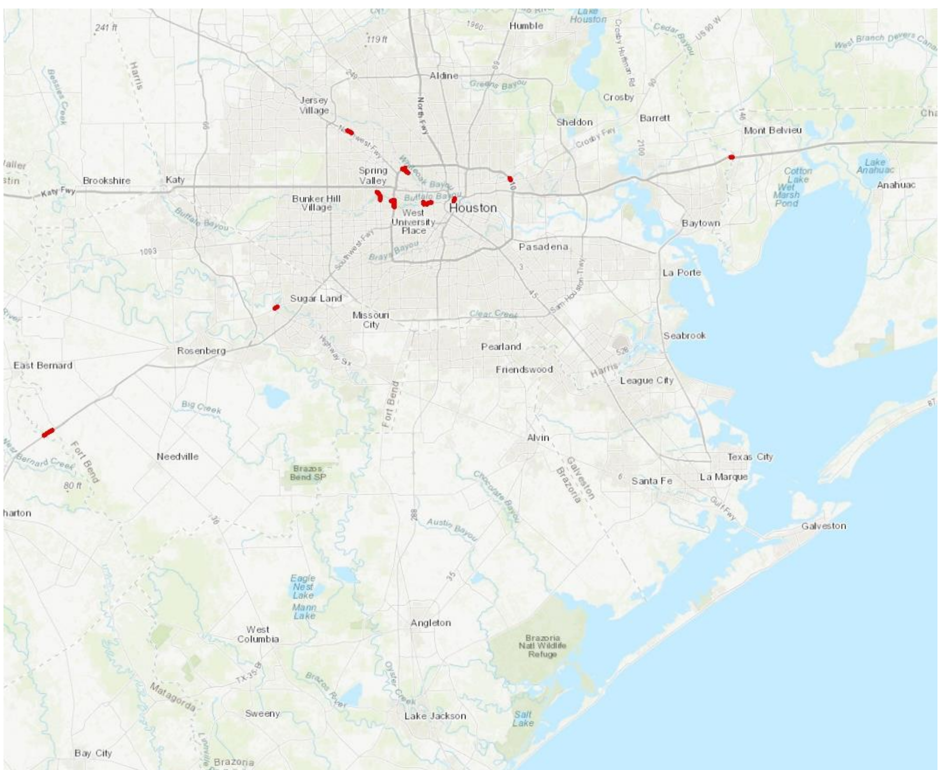

Figure B.8. Most critical links identified for economically vulnerable CTs ranked by average economic vulnerability.

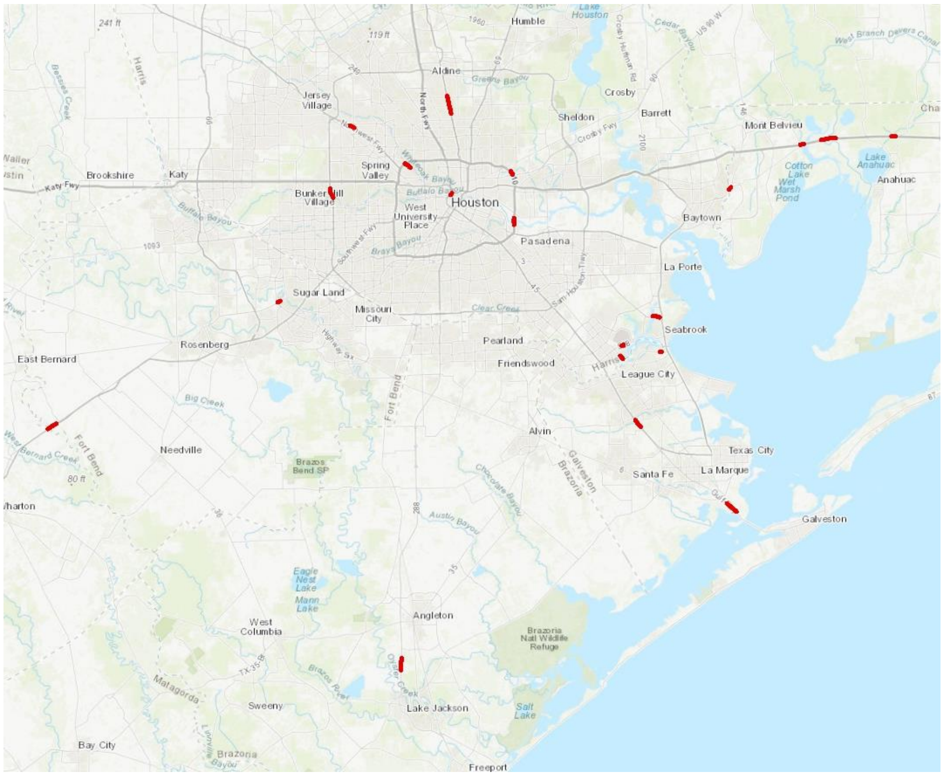

Figure B.9. Most critical links identified for economically vulnerable CTs ranked by average environmental vulnerability.

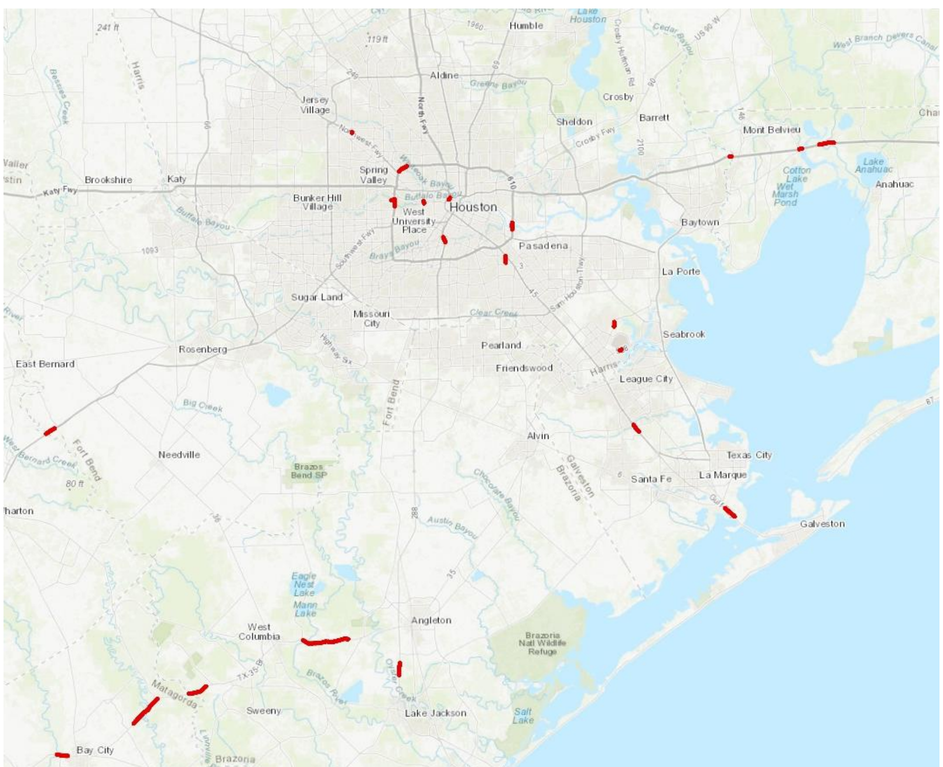

Figure B.10. Most critical links identified for economically vulnerable CTs ranked by change in travel time.

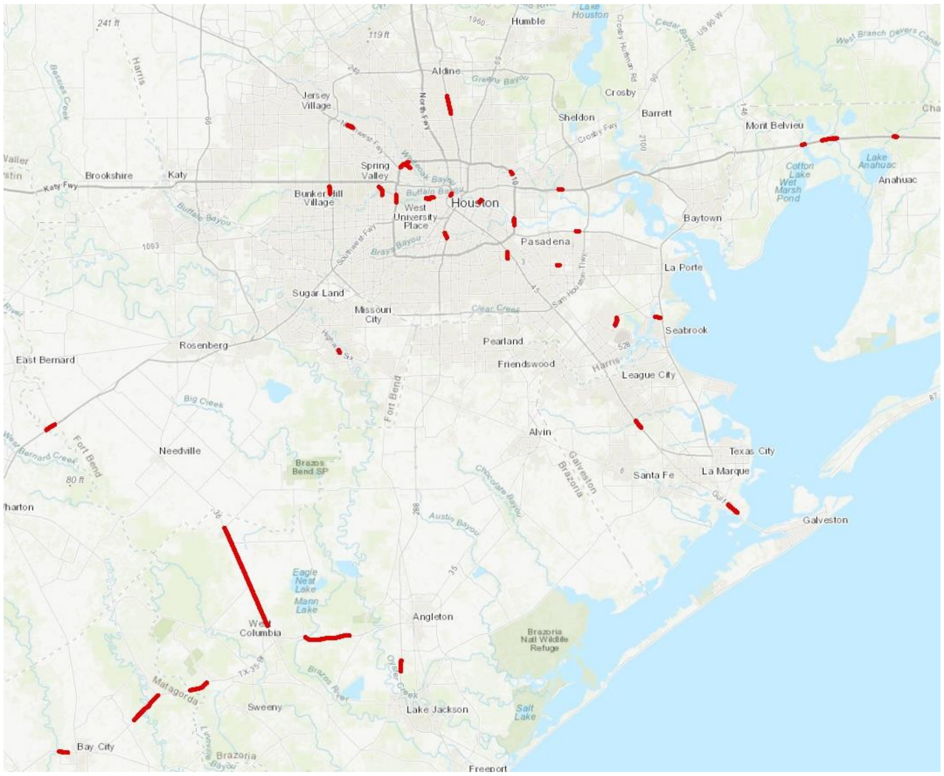

Figure B.11. Most critical links identified for economically vulnerable CTs ranked by link length.

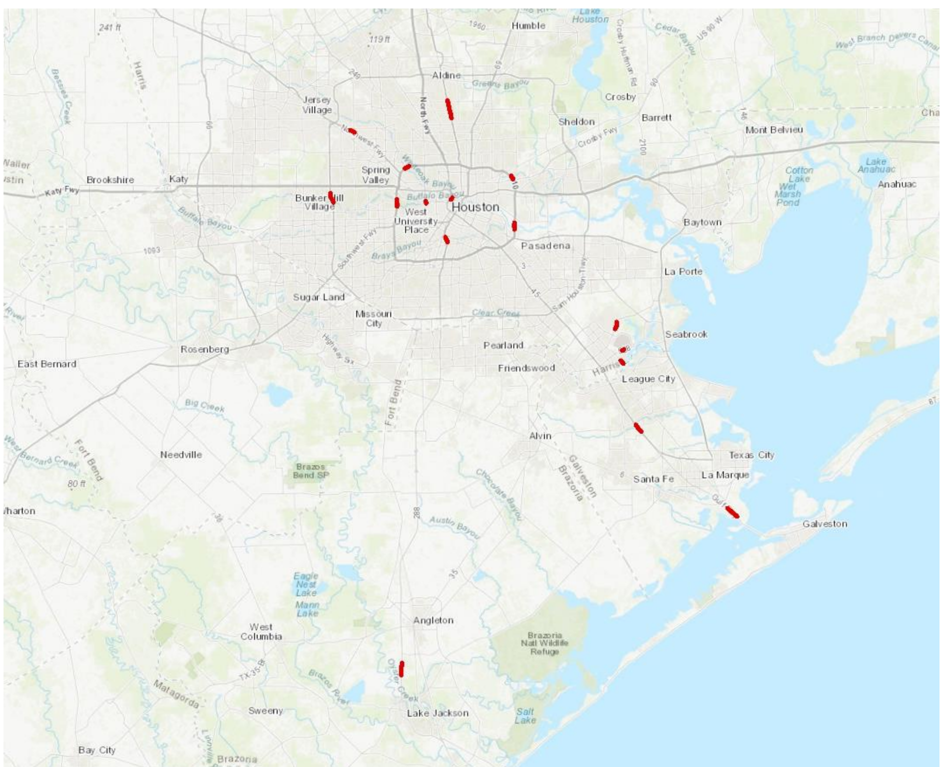

Figure B.12. Most critical links identified for economically vulnerable CTs ranked by link volume.

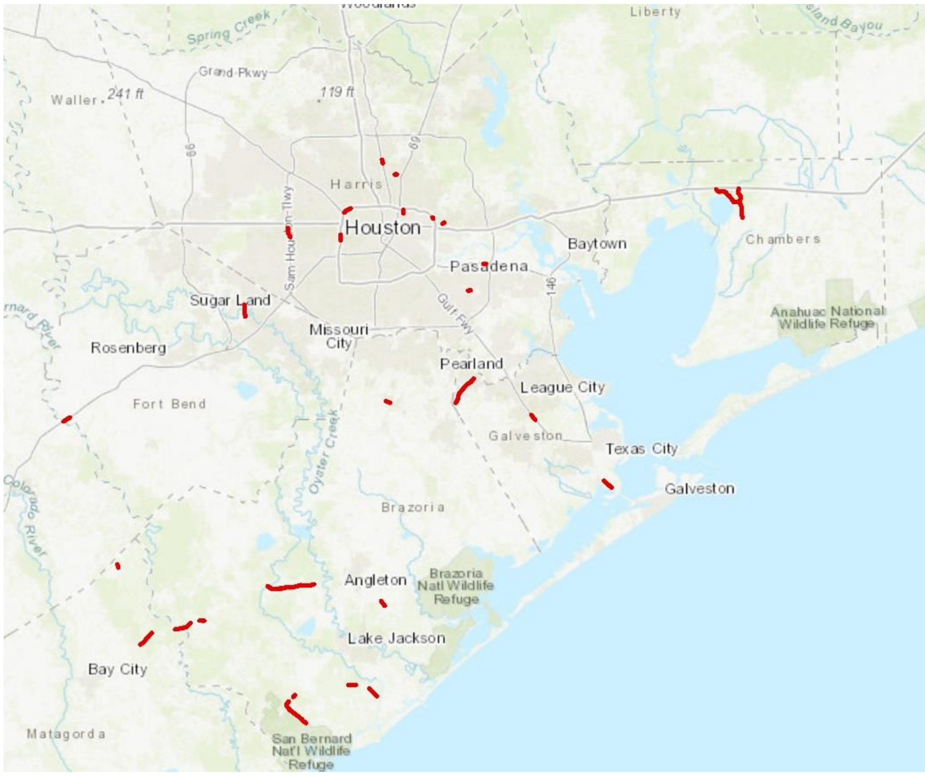

Figure B.13. Most critical links identified for environmentally vulnerable CTs ranked by average SVI.

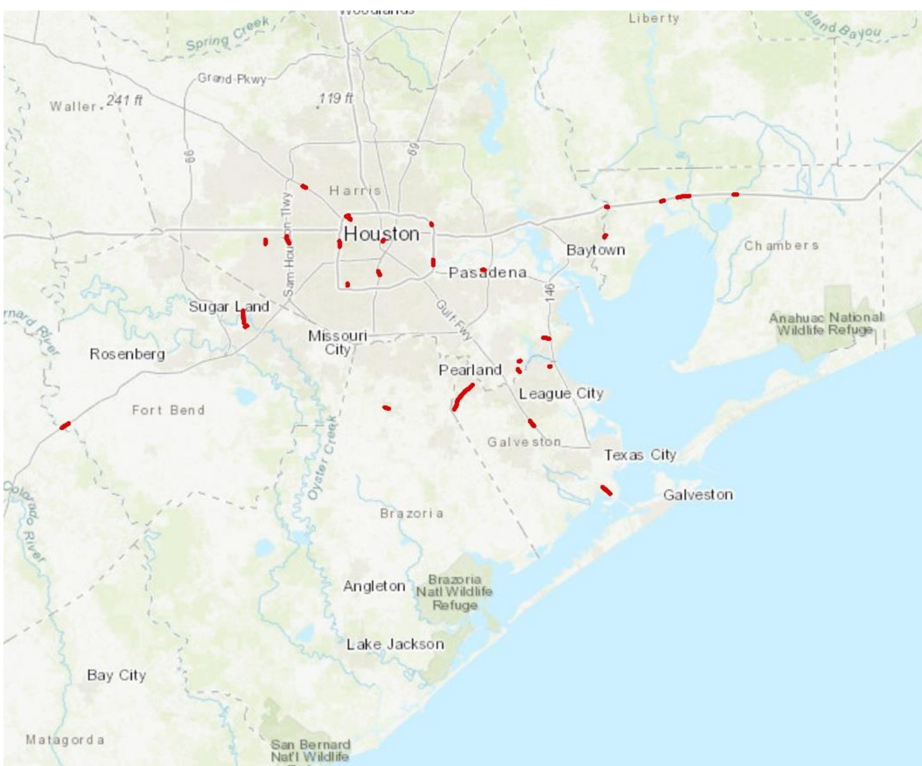

Figure B.14. Most critical links identified for environmentally vulnerable CTs ranked by average economic vulnerability.

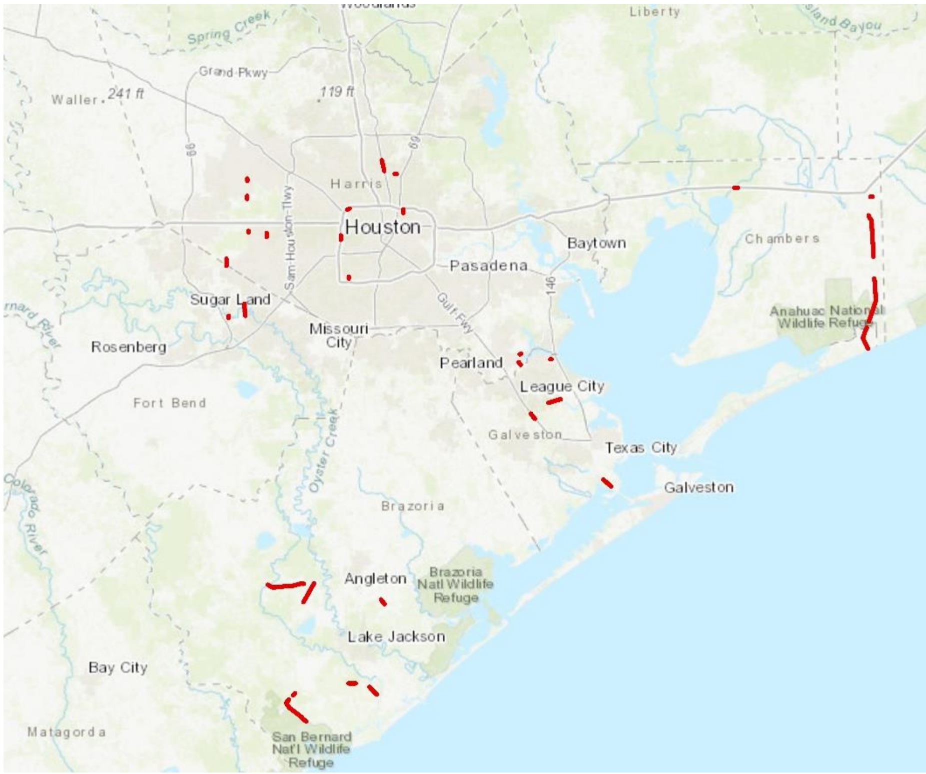

Figure B.15. Most critical links identified for environmentally vulnerable CTs ranked by average environmental vulnerability.

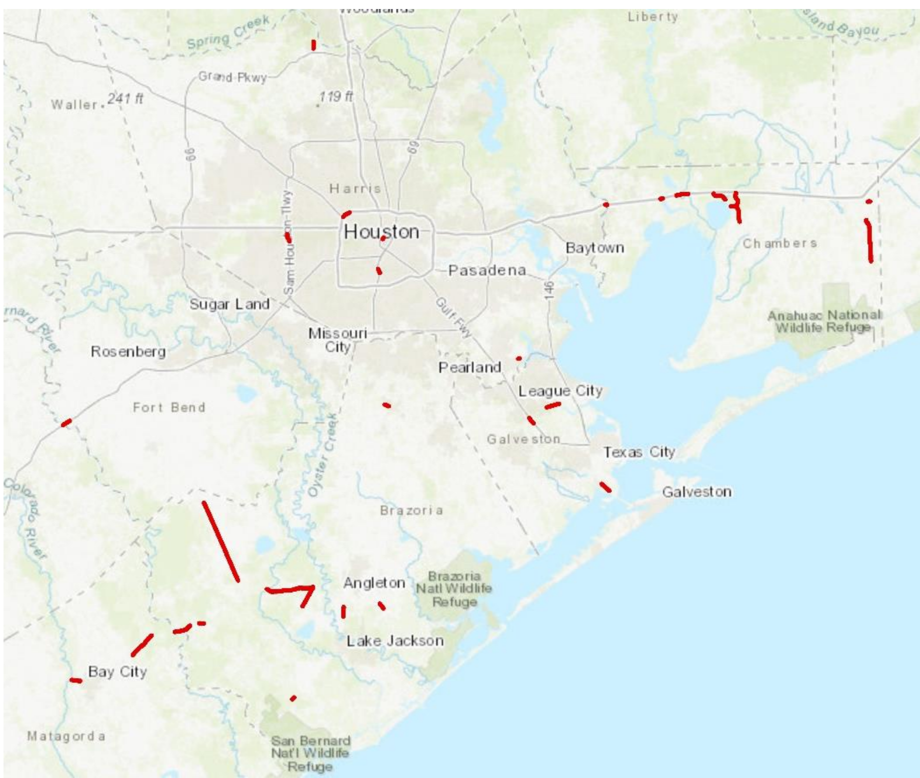

Figure B.16. Most critical links identified for environmentally vulnerable CTs ranked by change in travel time.

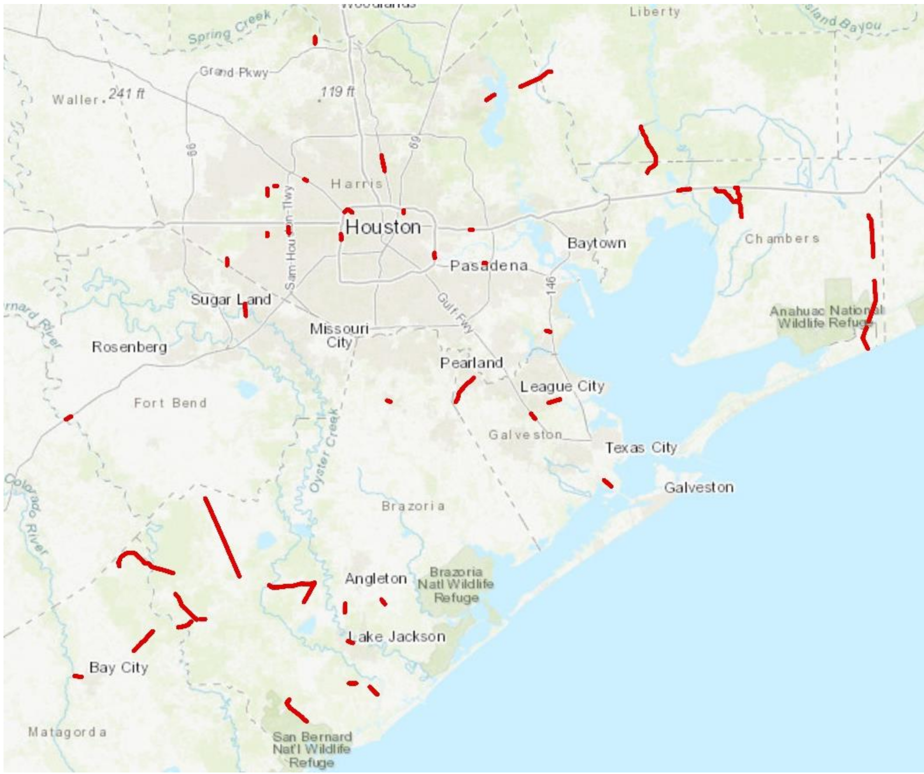

Figure B.17. Most critical links identified for environmentally vulnerable CTs ranked by link length.

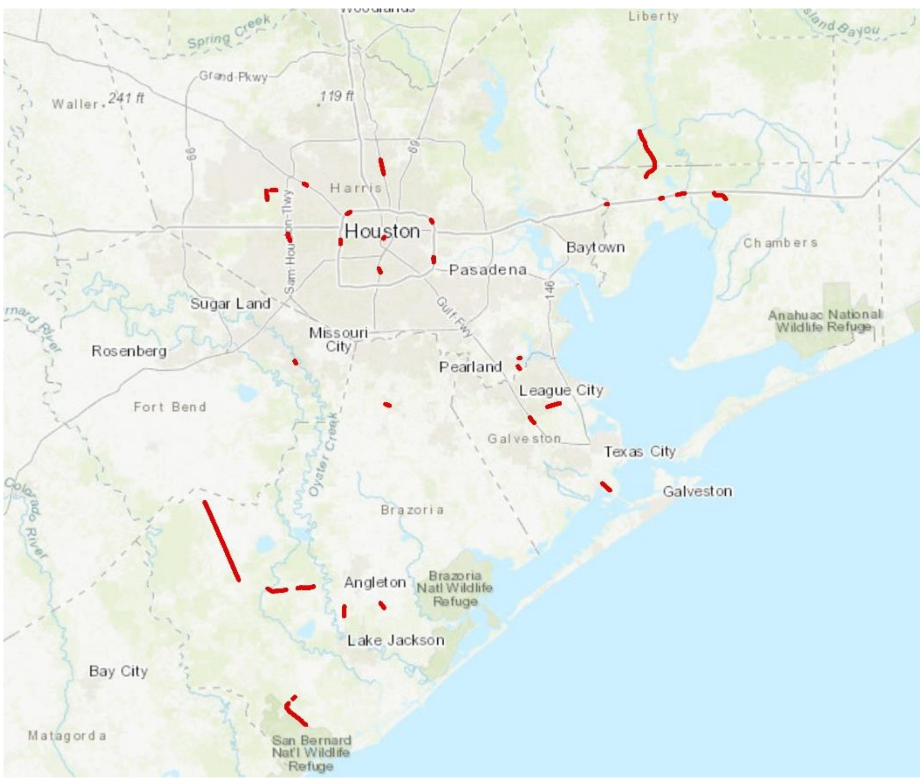

Figure B.18. Most critical links identified for environmentally vulnerable CTs ranked by link volume.