CHARACTERIZATION OF ROAD NETWORK RESILIENCE AGAINST CASCADING FAILURES USING DYNAMIC NETWORK APPROACHES

A Dissertation

by

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ABSTRACT

Transportation infrastructure is subject to many disruptive events, and the economic, social, or environmental consequences of these disruptions on these systems are becoming increasingly dire. While actual disruptions and disasters in transportation network breakdown can provide important learning opportunities, these lessons are prohibitively expensive in economic, social, and environmental terms. Re-creating these disruptions in laboratory settings is impossible, and real-world data on the performance profile of the critical infrastructure systems during disruptions are extremely challenging to get. Therefore, using simulation-based approaches for (1) studying the transportation systems' disaster response; (2) examining its performance profile during a wide-spectrum of disruptions; (3) identifying factors contributing to the transportation systems' resilience are becoming increasingly imminent. This study aims to make transportation systems, more specifically, road networks, more resilient to disruptions. To that end, this research has four interwoven objectives. First, this research examined the validity and relevance of robustness metrics proposed in the literature in the context of road networks and characterize the road network robustness under many disruptive events. It has been found that the performance profiles of the road networks under different disruptions scenarios are significantly different. This study also proposed a new measure, called expected robustness, to assess road networks' connectivity considering disruptions' uncertain nature. Second, this study modeled the cascading failures in the road network using dynamic network approaches and characterize the road network's performance profile under the different types of cascading failures. The study under this objective concluded that the variance in the road network's performance profiles under cascading failures depends on the magnitude and locations of disruptions. Third, this study proposed a way to quantify the interdependence among critical sectors and characterize the building blocks' sensitivity of accessibility on the other features of the interdependent critical infrastructure systems. Findings from this objective include (1) locations of the fire stations that are critical for accessibility of households; (2) the extent of colocation interdependency between flood control and transportation network plays an important role in ensuring the accessibility. Fourth, this study proposed a framework that could be used to measure the holistic impact of a certain type of change on the transportation infrastructure. This research has concluded that a transition matrix-based approach could be used to measure the overall implications of changes or shifts in the configuration of the system operations. Contributions of this study could be summarized from theoretical, methodological, and practical perspectives. On the theoretical side, this study examined the performance profile of the road network using graph-theory-based approaches. It reduced the gap between findings between theoretical graphs and real-world networks by characterizing the vulnerability of the road networks to disruptions of various types and magnitudes. On the methodological side, this study proposed ways to model and measure cascading failures in the road network on the methodological aspect. On the practical side, this study demonstrated the applicability of the proposed method in actual settings by case studies that include Houston emergency service network, flood control network, and the Texas freight network, the importance of inter-sector collaborations and more active type of management of critical infrastructure systems has been demonstrated. These results, insights, and findings could have important policy implications for reducing transportation networks' vulnerability.

DEDICATION

The list of people or things I would like to dedicate this work to is too long, as I dedicate this work to every being (everyone or everything) that helped me so far in one way or another. Especially, I dedicate this work to: (1) My parents, father Abdulla, my mother, Maryam; (2) My two siblings, Marhaba and Nasrulla. The Chinese regime cut off all direct communications with my family members since early 2017, and therefore I don't know if they are still alive or not. Needless to say, I do not know their well-being. I am the only one who received education beyond middle school in my family. Therefore, if I had been able to share the news of my Ph. D. degree program's successful completion, that would have been one of the happiest and proudest moments in family members' lives. Unfortunately, this was not the case. Like dozens of thousands of Uyghur people living abroad, my immediate family members and I suffered from immense emotional and psychological torments due to inhumane treatment of our Uyghur people by the Chinese regime, which is described by then U.S.-Secretary of State Mike Pompeo as the "stain of the century."

I also dedicate this work to my immediate and extended family, including my wife, Nurbiye, and two sons, Mohammed and Ibrahim (I wish there was a way I can list their names at the same time, and I hope they don't fight due to the order in which their names appear here), without whom I would not have been able to endure torments inflicted by the loss of contacts with my parents and other family members back home.

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1. INTRODUCTION

1.1. Research Problem

Disruptions to critical infrastructure systems, both natural or human-made, could negatively impact lives' and businesses' normalcy. Every year substantial economic, social, or environmental losses occur due to disruptions in critical infrastructure systems, and these losses are becoming increasingly expensive. There are many reasons for failure in critical infrastructure systems that are getting increasingly costly. First of all, growing interdependence among sectors renders cascading failures among sectors more likely. With the help of improving communication and computation technologies, interdependencies among different human-made systems have been consistently growing. Consequently, interconnection and interdependence between critical infrastructure systems are also increasing over time. Growing independence also brings an increased level of uncertainty and complexity associated with critical infrastructure systems' performance. Growing uncertainty makes it even more challenging to forecast or estimate both the failure probabilities and magnitudes of breakdowns. Uncertainty from other sources, like disruptive technologies and political situations, could make an accurate assessment of the impacts of critical infrastructure failures even more challenging. Recent developments surrounding Covid-19 and 2021 Texas Power Outage highlighted the importance of preparing for uncertain disruptions, and we had been repeatedly made aware of the dire consequences of doing otherwise. In recent decades, floods and flood-induced problems have become common worldwide, leading to considerable loss of life and assets, including direct damage to critical infrastructure systems (Singh, Sinha, Vijhani, & Pahuja, 2018). One of the immediate impacts of these flooding events is the crippling of the transportation systems, including (and especially) road networks. Most of the real-world critical infrastructure systems, including transportation systems, are spatially embedded, therefore, spatially constrained, which leads to a heterogeneous exposure to disruptive events among systems components. There is a relationship between these spatial constraints and transportation systems' resilience, as the network configuration could impact the road network's resilience against flooding events (Leu, Abbass, & Curtis, 2010). Spatial constraints for transportation networks include many designs, topological and collocation independence aspects of the transportation systems (Benedetto & Chiavari, 2010). It is of great significance to study and understand the relationship between these spatial constraints and transportation systems' resilience. However, in order to study resilience, there is a need to specify the disruption type, as the resilience of transportation systems could be assessed against numerous disruptions, both human-made and natural. Transportation systems could exhibit unique resilience profiles under different disruptions types and different disruption magnitudes. This research examines and characterizes the impact of the topological (physical network) characteristics of road networks on the resilience of transportation systems under the flood induced by heavy rainfalls. Resilience is defined as transportation systems' ability to keep their normal functionality or return to normalcy once being disrupted. To be more precise, one of the purposes of the proposed study is to test the hypothesis that the road networks' topological and network characteristics have significant impacts on their flood resilience. This research will examine the impact of theoretical network measures/features on the road networks' resilience profile by controlling factors like flood magnitude, flood type, flood timing (month of the year), flood duration, structural features of roadway systems and road network size. This research's ultimate objective is to inform planning and policy-making decisions pertaining to improving road networks' resilience towards fluvial flooding. In order to achieve this objective, this research examines and characterizes the relationship between the resilience profile of the road networks during floods and topological features of the road network, which will enhance our understanding of the mechanism with which fluvial flood propagates within the road network. To be more specific, this study contributes to the scientific community in the following five aspects: (1) this study proposed a new method to assess the connectivity levels in the road network under uncertain disruptive events, which could be generalized to other types of networks and disruptive events; (2) this study modeled the propagation of floodwater in the road systems using network percolation and network diffusion approaches; (3) this study evaluated the validity of the existing network robustness measures for assessing the flood vulnerability of the road networks; (4) this study assessed the accessibility of residential buildings to and from critical facilities during a flooding event using the proposed network diffusion and percolation approaches; (5) this study proposed an approach that could be used to assess the impacts of changes (both positive or negative) holistically. Findings from this research have important implications for predicting road closures and changes in the accessibility levels during flooding events and informing the planning, designing or operating decisions related to road networks to optimize their resilience.

1.2. Research Objectives

The main goals of this research could be summarized with the below points:

- Quantify the interdependencies among the road and flood control networks and assess the impacts of the level of interdependency on the connectivity of road networks during flooding events;
- Model the stochastic and dynamic nature of the flood propagation on the road networks and assess the impacts of flood-induced disruptions and random-type of disruptions on the road network connectivity;

- Model and capture the flood-induced dynamic and cascading failures in the road network using network diffusion models and characterize the impacts of disruptions stemming from different locations in the road networks;
- Quantify and assess the impacts of the different types of disruptions on the accessibility of the critical service providers (fire stations);
- Quantify the impacts of disruptive events or hardening options on the performance-critical infrastructure systems using the transition matrix-based approach.

1.3. Research Assumptions

This section provides a brief discussion of the epistemological, ontological orientation of this research, as well as major assumptions this research has made. A research paradigm is defined as "the set of common beliefs and agreements shared between scientists about how problems should be understood and addressed" (Thomas, 1962). According to Guba (1990), it is possible to characterize a research paradigm by its ontology, epistemology, and methodology. This section provides a high-level view of the main epistemology, ontology, and methodology of this research. After the proposed main research question was broken down into several sub-questions, these research sub-questions are suitable for addressing with objectivist research paradigm, which entails assuming that there is a single reality or truth and this reality can be measured or modeled with reliable and valid tools. These types of questions should be answered using experimental approaches using a quantitative research methodology. However, some other sub-questions require the research paradigm to be more constructivism (or interpretivism) oriented, which entails assumptions that there is no single reality or truth and reality needs to be interpreted. Reality can be used to discover the underlying meaning of events (epistemology). These types of questions are answerable with qualitative/empirical research approaches. From an epistemological point of view, the statements listed below are already "known." These statements are used as tools (or information) for conducting this research and are the main theoretical and knowledge building blocks for this research. Below concepts are from the independent variable side, and this research is constructed upon this knowledge base:

- Complex network theory is a theory that originated from mathematical graph theory. It is a popular method used for the abstraction and modeling of many real-world systems. The definition of a graph, its relevant properties, and the nodes' centrality measures are well-accepted scientific approaches. These concepts were used to construct the foundation for this research.
- Network robustness measures are standard measures used in the literature to assess the vulnerability of both real-life and theoretical networks;
- Topological characteristics of the road networks could be measured and captured by network centrality measures

Below concepts are the form of the dependent variable (resilience profile of road networks) aspect of the research problem, and this research is constructed upon this knowledge base:

- The vulnerability of critical infrastructure in the face of certain disruption could be measured with the resilience triangle concept. Vulnerability is measured with the resilience profile of the road network.
- Resilience profile can be quantified using the magnitude of lost functionality and the time it takes to return to normalcy

This research uses computation algorithms and machine learning tools to simulate and re-create reality. This process uses standard simulation tools and methods. This research can also be traced back to physics because it models and captures the dynamic percolation and diffusion process in the road network during a fluvial flooding event by borrowing the percolation and diffusion process in physics. Modeling a complex infrastructure system's topology and performance like a transportation network during a flooding event and quantitatively assessing its resilience towards a natural disruption inevitably entails making several assumptions. The main assumptions this research has made during the modeling and simulation process are:

(1) Road network could be modeled as graphs

This research's central assumption is that the land transportation system under consideration could be modeled as networks made up of nodes and links. This assumption is at the core of this research because using a network model enables one to apply system-modeling techniques like network flow analysis to predict the system's behavior under different circumstances.

(2) Impacts of flood on road network topology could be reliably measured

This study assumes that the impact of disruptions on the transportation networks' major performance indicators is measurable and quantifiable. This assumption is needed to monitor (or predict) the system performance before, during, and after the disruptions. To be more specific, this research will measure the impact of the flood on road network topology by introducing an intermediate variable called flood depth. Flood-depth of different levels could be used to categorize the nodes or edges in the road network. These different categories of nodes will be further used to model the connectivity of the overall road network.

(3) Other impacts of the flood on road network structure are negligible

The impact of floods on transportation systems is quite multifaceted. It could cause roads to be closed, weaken the foundation structure, or cause erosion. Except for the commonly understood reason that accumulation of the excessive amount of water on the surface of roads will render them nonfunctional, there could be numerous other reasons for the road network to be closed, which can be caused by, among many others, collapsed bridges, blocked tunnels, accumulation of debris on roadway premise, various construction and maintenance activities, traffic control, exposure to hazardous materials and road accidents. For the sake of convenience in modeling and analysis, this study neglects other causes of closure. It assumes that the road network's closure is only caused by the accumulation of the excessive amount of water on the surface of roadway systems.

1.4. Research Methodology

This research aims at improving the safety of the people and assets in flood-prone areas. The methodology employed in examining the network performance is a dynamic network modeling approach, including network percolation and network diffusion methods. This research methodology has been conceived by the many different conditions (factors) becoming increasingly imminent in recent decades.

1. Increasing interdependence between different sectors and different fields due to breakneck–speed development in information and telecommunications technologies has made it increasingly evident that studying complex systems like critical infrastructure systems using the reductionist approach is no longer enough. As there are intricate interdependencies and communication among the critical infrastructure systems, studying each component in isolation will not paint a comprehensive picture. Furthermore, to operate more optimally, infrastructure sectors need input from many different sectors, which leads to an increasing interdependence within and between other sectors.
2. Due to the increasing data availability and improving computational power, advancements in science and technology, collecting, storing, and processing mass data have become increasingly viable. Therefore, in the context of interdependent critical infrastructure systems, making use of big data has become an increasingly imminent issue.

3. With recent advances in statistical physics that studies theoretical and real-world networks, network theory's advantages in its ability to abstract and deal with large and complex systems have been proven in many fields.

It is also important to point out that the suitable method for studying the impact of extreme weather events (like flooding) on transportation networks is the simulation approach. Collecting real-time data about these events at the necessary temporal and spatial scale or resolution is almost infeasible. Besides, it does not make practical sense or is infeasible to (simulate) conduct a disruption experiment on a neighborhood or city scale. What's more, it is not possible to re-create these events and scenarios in a laboratory setting. Due to the nature of the research questions, this research will use a quantitative approach. In other words, the author will employ an objectivist approach to find answers to the research questions. This research will focus mainly on empirical approaches, which are reflected in the below ways: (1) Survey to collect data about experienced hardships during flooding events; (2) Statistical inference method;(3) Simulations using Python and other programming languages. The nature of the research problem proposed in this research requires applying both objectivism and interpretivism research methodology.

1.5. Dissertation Outline

The contents of this dissertation are presented in eight chapters. A brief overview of each of the chapters is introduced as follows: The first chapter chiefly presents an introduction, the motivation, the assumptions, and the methodology overview of the proposed work. The second chapter presents a discussion and a survey of the relevant work in the literature. This will lead to the identification of gaps in the literature as well as specific research objectives this dissertation aims to achieve. The third chapter introduces the overall research framework and a brief introduction of the research objectives and corresponding research tasks. This chapter also presents an overview of the case studies, data source, and integrative methodological justification for the following four chapters. Each of the subsequent four chapters is based on corresponding research objectives. The fourth chapter will provide an empirical study aiming to validate the network robustness index proposed in the literature. Based on this study's findings, an index for road network robustness will be presented and used across this dissertation. The fifth chapter introduced the framework to model the percolation phenomena in the road network. There will be a detailed introduction to each step of the methodology. There will be a demonstration of the proposed methods on the road networks and the super neighborhoods in Houston during Hurricane Harvey, which happened in August 2017. This chapter also introduces a network diffusion method for modeling the flood propagation network. To be more specific, this paper will calibrate the diffusion model using granular flood depth data. The sixth chapter will discuss a methodology to model the co-location interdependency between the road network and the flood control infrastructure. This chapter also includes a study that used a machine-learning approach to identify flood-prone areas in the road network. In addition, this chapter also presents the real-world application of the framework from previous chapters. To be more specific, this chapter will assess the impacts of the road closure on the accessibility to and from emergency service providers. The seventh chapter presents the transition matrix-based framework, which is demonstrated using the Texas freight network performance under the influence of truck platooning and automation. The last chapter, chapter eight, provides detailed discussions on the summary, integrative results and conclusions, and the possible future avenues for further research and improvements.

2. LITERATURE REVIEW

This research is based on the existing knowledge in the field of infrastructure resilience modeling using networks. However, it advances the understanding of transportation network resilience by several theoretical, methodological, and practical contributions that revolve around examining the percolation behavior in real-life critical infrastructure networks under major flooding events. Failures in critical infrastructure systems are becoming prohibitively costly, mainly due to the possible cascading failures initiated from one sector and subsequently cause a series of failures in other dependent sectors. Thus, the resilience of interdependent critical infrastructure (ICI) systems is one of the grand challenges facing engineers and policy-makers in the 21st century (Heller, 2002; O'Rourke, 2007; van Laere et al., 2017). Over the past two decades, the body of knowledge on ICI resilience has advanced in the domains of modeling, simulation methods, and theoretical frameworks. Despite the growing literature (Dueñas-Osorio, Craig, Goodno, & Bostrom, 2007; Haimes & Jiang, 2001; Reed, Kapur, & Christie, 2009) on ICI resilience, our understanding of the dynamics and mechanisms of disruptions in ICI systems that shape resilience patterns in these complex networks is somewhat limited. This lack of understanding is particularly evident in urban areas where transportation systems are frequently affected by weather-related hazards.

2.1. Graph-based Approach for Transportation Network Vulnerability

Due to transportation networks' planar nature, they tend to lend themselves readily to being represented as graphs. Therefore graph theory-based approaches have been common tools to study the vulnerability in transportation systems (Tamvakis & Xenidis, 2013). Graph theory reduces a road network to a mathematical matrix where the vertices (nodes) represent road intersections, and the edges are the road sections between these nodes (Leu et al., 2010). This type of matrix abstraction of road networks facilitates the accessibility and connectivity analysis and helps identify critical locations using available graph-theoretic centrality measures. However, there are two crucial challenges in network modeling of transportation networks. On the one hand, transportation networks, similar to many other critical infrastructure networks, are spatially embedded (Bashan, Berezin, Buldyrev, & Havlin, 2013), and the environment's configurations in which network elements (nodes or edges) operate are inherently heterogeneous. When coupled with the possible spatial or temporal variance of the magnitude of the disruptive events, this fact makes failure probabilities significantly variable from node to node. On the other hand, the most critical infrastructure network topology is intrinsically dynamic and evolving, especially during disruptive events. Understanding the patterns for temporal shifts in critical infrastructure networks' functional topology during disastrous events is crucial in devising efficient plans to reduce their vulnerabilities. However, the almost complete absence of the time dimension in such problem definitions is a problem that can be attributed to (1) the graph theory ancestry of the field and (2) the limited number of dynamic data sources available when the area of complex networks analysis emerged (Rossetti et al., 2018).

Therefore, topological approaches have been widely used to describe the system's behavior due mainly to the fact that they require significantly less data and computation time than physics-based methods. For example, using network theory to assess infrastructure systems' robustness does not require many physical details about the system but rather a simple mathematical description of the linkage relationship between network components (LaRocca, Johansson, Hassel, & Guikema, 2015). Other examples of topological approaches include (Demšar, Špatenková, & Virrantaus, 2008; Ip & Wang, 2011; King, Shalaby, & Eng, 2016; Leu et al., 2010; Mattsson &

Jenelius, 2015). Most graph-theory-based approaches used network centrality-based measures to identify critical or vulnerable locations in the network. While it is important to identify nodes crucial to network integrity and ensure their normal functionality, examining the failure of nodes exposed to hazards is critical for improving transportation network resilience. This is important because centrality-based, theoretically important nodes are not necessarily exposed to hazards, and centrality-based vulnerability analysis may not always be practical.

2.2. Assessing the Vulnerability of Transportation Networks to Flooding

Flood hazard is a severe problem in many coastal urban regions due to the ever-growing urban population and increasingly frequent flooding events. Flooding due to various reasons has been a significant cause of disruption to our lives and has been causing substantial economic, social, and environmental losses in recent decades (Hammond, Chen, Djordjević, Butler, & Mark, 2015). There are multiple ways of categorizing damage caused by floods (Meyer et al., 2013; Smith & Ward, 1998). Hammond et al. (2015) classified the losses caused by flooding disasters into four categories: (1) direct tangible impacts, (2) business interruption and indirect tangible impacts, (3) impacts on infrastructure, and (4) intangible impacts. It is worthy to note that these categorizations of damage are neither exclusive nor exhaustive. Besides, it is hard to define, without introducing a certain level of subjectivity, a clear-cut system boundary, both spatial and temporal, for the flood-damage analysis. In the meantime, some of the flood-induced losses are difficult to quantify in monetary terms. Flood-induced disruptions to the critical infrastructure systems, like transportation, telecommunication, power supply, emergency medical service (EMS), food supply chain, and healthcare, could have serious negative implications. Damages to critical infrastructure take up significant portions of total damage caused by the flooding disasters. For example, in the 2007 summer flood in the United Kingdom, out of the total estimated economic loss of £4bn, about

£670m was credited to the damage caused to the critical infrastructure systems (Chatterton, Viavattene, Morris, Penning-Rowsell, & Tapsell, 2010).

In recent decades, a growing volume of research examines transportation vulnerability in the face of flooding events. Pregnolato et al. (2017) examined the relationship between safe vehicle speed and depth of inundation on the road surface during a flooding event using both empirical data and existing research studies. They derived a quadratic function that models the relationship between the two variables. The authors also studied the relationship between the two variables for different vehicle types. This study is one of the growing numbers of studies that move forward from the traditional binary consideration of flooding. Choo et al. (2020) studied the flood's impact on the road network in much finer detail. The authors used the Spatial Runoff Assessment Tool (S-RAT) and Flood Inundation model (FLO-2D model) to estimate the extent of flooding in urban areas caused by rainfall. The authors also presented rainfall-flood depth curves were that describe the distribution of flood depth under given rainfall events. Mukherjee and Singh (2019) identified flood-prone areas by integrating nine flood conditioning factors such as slope, elevation, soil type, rainfall intensity, flow accumulation, LULC, NDVI, and distance from river and distance from the road. Then, the authors combined the factors using the weighted overlay method in ArcGIS to map the areas in Harris County that are prone to flooding. Finally, they overlayed the 2017 FEMA flood hazard map on the weighted overlay flood hazard map. In work by Vanolya and Niaraki (2019), the flood hazard map of Mazandaran province is assessed using subjective-objective weights in an Ordered Weighted Averaging-based GIS analysis. Flood hazard maps are produced based on the two types of weights, along the scale ranging from the pessimistic to optimistic decision strategies.

2.3. Dynamic Network Approaches for Modelling Disruptions

Network percolation is an approach that is capable of modeling the changes in the topology of a generic network due to disruptions using a parameter called occupation probability(Newman, 2018). Occupation probability is usually used to capture the stochastic nature of the failure locations on the network. It is denoted using φ, which represents the probability of a certain node to be functional at a given time (or under a given scenario). As the level of exposure for the nodes in the road network to a given type of disruption usually tends to be heterogeneous, a set of occupation probabilities for the network nodes could be assigned to reflect the spatio-temporal variation of the failure probabilities. The values for φ range from 0 to 1, both inclusive. A higher φ value denotes the nodes are less prone to be removed from the network, while a low φ value means the node is less prone to be disabled. Once disastrous events disrupt the road network, one or more nodes in the network would be disabled due to the disruptions, leading to fragmentation of the road network. Schneider et al. (Schneider, Moreira, Andrade, Havlin, & Herrmann, 2011) have proposed an index that could be used to measure the robustness or integrity of a generic network. It can also be characterized by the largest connected component's integrated size throughout the entire percolation process. They introduced the robustness measure R.

$$R = \frac{1}{N} \sum_{Q=1}^{N} s(Q)$$

Where: N is the total number of the nodes in the network, and $s(Q)$ is the fraction of nodes in the largest connected component after removing $Q = N(1 - \varphi)$ nodes. The 1/N normalizes the result so that the results can be compared. R ranges from 1/N (star graph) and 0.5 (fully connected network).

Flooding, especially ones due to excessive and intense rainfall precipitation, has been the predominant cause of weather-related disruptions to the transportation infrastructure (Pregnolato et al., 2017). Such events could undermine the vital functionality of transportation systems, especially road networks. Many studies have shown that roads are among the major causes of deaths in cities during flooding; this is mainly due to the vehicles being driven through flooded roadways (Ashley & Ashley, 2008; Drobot, Benight, & Gruntfest, 2007; FitzGerald, Du, Jamal, Clark, & Hou, 2010; Kreibich et al., 2009). Locations, such as Texas, where road mobility through cars is the primary mode of passenger transportation, are especially vulnerable to the impact of flooding (Blackburn, 2017). The advantage, in this case, of having the largest road network in the U.S. could become a curse when the majority of the roads are closed due to flooding, and there are few other alternatives to go around the city, as was the case during Hurricane Harvey in 2017 (ASCE, 2017). Besides, during disastrous events, the road network functions as a lifeline system for rescuing people and assets and plays a vital role in repairing and restoring other infrastructure systems when they are disrupted. In order to cope with disruptions efficiently and take active precautionary measures, it is critical to understand the mechanisms and patterns with which the disruptions unfold in the transportation network. Flooding in urban roadways is a process that presents both of the challenges mentioned above. Relevant studies in the literature that are aimed at tackling the flood vulnerability of critical infrastructure networks could be categorized into two main types: (1) graph-theory based topological approaches that focus on topological integrity of the network; and (2) hydrological approaches that model the flood propagation process in (or around) critical infrastructure in urban areas (Singh et al., 2018). Each of these methods considers the flood vulnerability problem from different angles; consequently, each approach only reflects some parts of the whole picture. Most of the studies attempted to apply dynamic network modeling approaches focused on complete or random graphs to demonstrate their applicability in real-world network failure problems. However, transportation networks are neither random nor complete. They have a unique configuration manifested in a relatively small range of node-degrees and spatial constraints that are not observed in other types of networks. The aforementioned historic decoupling between the two types of methods could largely be attributed to the lack of granular flood data that could be input to network models.

In this context, the process of spreading the floodwater around the road network could be assumed as a diffusion process, which is analogous to the spread of contagious diseases among human beings. The origin of diffusion modeling could be traced back to the spread of epidemics, and mathematical modeling of epidemics predates most of the studies on networks by many years (Newman, 2010). The traditional diffusion modeling approaches avoid discussing contact networks by making use of fully mixed or mass-action approximation, in which it is assumed that every individual (node in the network) has an equal chance, per unit of time, of coming into contact with every other node (Newman, 2018). Based on the assumptions of this approach, nodes (people) mingle and meet completely at random, which is not a realistic representation of most real-world networks. This un-realistic representation is because nodes in real-world networks are spatially embedded and have a heterogeneous exposure to diffusion mechanisms (the reader is referred to Shakarian et al. (2015) for a comprehensive review of network diffusion).

2.4. Interdependence Among Critical Sectors

Allocating resources effectively in terms of how to equip the facilities, where to position the fire stations, and what transportation tools to use under certain flood scenarios is the decision that emergency personnel has to make in a fast-evolving and intense environment. Available scientific research on the topic of emergency management is quite multidisciplinary, as examples can be seen in psychology (Mileti & Peek, 2000), computer science (Latonero & Shklovski, 2011; Rathore, Ahmad, Paul, Wan, & Zhang, 2016), telecommunications (Bergstrand, Landgren, & Nuldén, 2016), medicine (Veenema, 2018), atmospheric science (Albano et al., 2016), and social science (Houston et al., 2015). This fact alone could reiterate the research topic's clear interdisciplinarity and the need for collaborations among people from various fields. Due to the limitations in terms of the focus and space, this paper primarily surveys the research works conducted in the context of flooding events within the domain of transportation. Impacts of various types of flooding on transportation networks have been a favorite area of study among civil engineering researchers. A comparison between the impacts of the random events and targeted events could lead to insights on choosing appropriate coping strategies for these events under various resource constraints. A survey of the relevant literature revealed that, given the abundance of granular data and availability of the necessary simulation tools, few studies have looked into the accessibility during the flooding events at a household level (Coles, Yu, Wilby, Green, & Herring, 2017; Jie Yin, Yu, Yin, Liu, & He, 2016). Most of the studies focused only on the vulnerability of road network against flooding events, while some researchers have proposed depth-disruption models by examing the relationship between the depth of accumulated floodwater on the streets and safe vehicular speed for different vehicle types (Choo et al., 2020; Pregnolato et al., 2017). Using the results from the above depth-disruption models, some other researchers characterized the impacts of fluvial flooding on road network connectivity with the help of the SIS network diffusion model and simulation techniques that could capture the temporal shift in connectivity in road networks during a flooding event(Abdulla, Kiaghadi, Rifai, & Birgisson, 2020a). Authors also characterized road networks' vulnerability to flooding using a network percolation approach (Abdulla & Birgisson, 2020c) or machine learning classification methods

(Abdulla & Birgisson, 2020d). This study conducted a detailed survey of the literature on the impact of flooding on the accessibility of emergency service providers. A review of the flood emergency plans used in the county of Cumbria (in northern England) during the 2009 flooding found that emergency responders particularly value tools that help them evaluate the vulnerability of critical infrastructure (such as roads, electricity substations, and care homes) during the response phase of a flood emergency (Lumbroso & Vinet, 2012). A study by (McCarthy, 2007) found that models used to estimate the breach locations and inundation extent levels on the road network were considered useful by emergency responders in the Thamesmead area of London for decisions about evacuations or allocate of scarce resources. In a study by Coles et al (Coles et al., 2017), accessibility was quantified using two metrics: (1) the area coverage from emergency response stations within legally required timeframes (for example, in the UK, it is 8-min for the Ambulance Services and 10-min for Fire & Rescue Services); (2) the shortest time it takes from an emergency response node to vulnerable populations, which is evaluated against the legislated targets. They employed the service area method to map the spatial coverage of the emergency services within the specified response timeframes. Another study by (Green et al., 2017) proposed a somewhat similar approach as above for accessibility assessment. This study also found that surface water flooding tends to cause more disruption to emergency responders operating within the city due to its widespread and spatially distributed footprint compared to fluvial flood events of comparable magnitude. Other recent and relevant studies on the topic include works by Arrighi et al. (Arrighi, Pregnolato, Dawson, & Castelli, 2019), Abdan et al. (Janius, Abdan, & Zulkaflli, 2017), and Mejia-Argueta et al. (Mejia‐Argueta, Gaytán, Caballero, Molina, & Vitoriano, 2018). The relevant literature review concluded that few studies focused on assessing the accessibility during flooding events at a more granular level (like individual building blocks), regardless of the increasing availability of some relevant data and improved computational power. Motivated by this observation and based on the recent development of simulation techniques, this research looked into the reduction in accessibility (measured by the percentage decrease in the buildings accessible by the fire station personnel) due to the road closure under different flooding levels events.

2.5. Assessment of Holistic Impacts of Stressors

There has been a growing focus among the infrastructure resilience research community on developing techniques and frameworks to assess transportation infrastructure systems' resilience or vulnerability in recent decades. It is possible to categorize the critical infrastructure resilience assessment methods into several main categories, analytical, probabilistic, graph-based, and fuzzy inference systems, among others (Tamvakis & Xenidis, 2013). In another context, some combinations of several related concepts like vulnerability, robustness, recovery, survivability, response and mitigation have been used to measure the resilience and approaches for measuring the resilience could fall into one of the below categories: data-driven approach, topological approach, simulation approach and optimization approach (Bešinović, 2020). While it is essential to have an accurate estimate of the vulnerability for improving resilience and reducing the disruptive events' negative implications, assessing physical vulnerability is merely one of the many preliminary steps for achieving the intended final goal. To translate the results and findings of resilience assessment methods into specific and actionable policies, comprehensive frameworks that take different dimenstions of the resilience into account are needed. A search on the topic resulted in some variations of traditional project evaluation methods like life-cycle-assessment (LCA)(Saxe & Kasraian, 2020) and cost-benefit-analysis (CBA)(Räikkönen et al., 2016). Other researchers have proposed systems analysis methods to holistically investigate the resilience of critical infrastructure systems (Alfaqiri et al., 2019). Even though the has been some progress on holistic impacts assessment methods, not enough research attention has been contributed to the even more crucial step: applying these frameworks and achieving the intended resilience objective. To this end, this research proposes a framework based on the transition matrix to quantify the impacts of changes on the critical infrastructure systems.

2.6. Research Gaps and Hypothesis

The majority of research in network vulnerability is focused on theoretical networks; relatively fewer published research papers are focused on the networks of real-world systems. Due to their unique topological structure and configuration, road networks represent one of the common types of real-world networks. Understanding, characterizing, and conceptualizing these networks could bridge the gap between advancement in the field of theoretical networks and real-world networks. In summary, below major research gaps have been identified through the literature review.

- There is a need to examine and validate the theoretical network robustness measures in the context of real-life networks;

To this end, after reviewing relevant literature on the topic, this study proposed and tested two interwoven research hypotheses.

H1-1: In a road network, the overall network-level robustness measures are not dependent on networks sizes and positively correlated with average node-level centrality measures;

H1-2: Ceteris paribus, the more robust the road network, the lower the average mobility hardship experienced by the road users;

- There is a need for the application of dynamic network approaches to model and study cascading failure patterns in the road networks;

Under this research objective, three relevant research hypothesis has been tested:

H2-1: In a road network, the failure profile (measured with average connectivity levels) of road networks exhibits a power-law pattern. i.e., it takes a small percentage of nodes to be removed from the road network in order to cause a large reduction in the overall-network connectivity;

H2-2: In a road network, the relative locations of the nodes where cascading failures start to have a significant impact on the connectivity profile of the road networks and failures start from nodes with high centrality-measures cause a faster decrease in the connectivity;

H2-3: On average, road networks are more vulnerable to disruptions that are random in nature than disruptions that are induced by flooding events;

- An adequate understanding of the interdependence among critical sectors are necessary for achieving better resilience;

Under this research objective, two research hypothesis that is closely related have been tested:

H3-1: The extent of co-location between flood-control and transportation road networks is positively correlated with road networks' flood exposure and vulnerability. In addition, the extent of the impacts of the flooding in the road networks is significantly correlated with the alignment between edge-bearings of the road and flood control networks;

H3-2: Relative locations of fire stations have crucial implications for ensuring accessibility of the road networks during flooding events;

- A holistic performance measuring tool is essential for the adoption and dissemination of the resilience assessment framework;

A system-level and comprehensive performance evaluation technique are essential for capitalizing on the recent advancements in vulnerability/resilience assessment for critical infrastructure systems. Under this objective, the central research hypothesis:

H4: The magnitude of the overall impacts of disruptions (interventions) on a system could be measured using the corresponding transition matrix's average eigenvalues, and overall impacts are negatively correlated with the average eigenvalue of the transition matrix.

3. OVERARCHING RESEARCH FRAMEWORK

3.1. Introduction

The methodology chapter introduces the proposed framework called "Characterization of Road Network Resilience Against Cascading Failures" for systematically assessing and characterizing transportation networks' resilience under various disruptions. This framework is made up of four main modules that could be broken down into eight specific tasks. This chapter first demonstrates the main integrative framework. Then there are further elaborations of each of the stages and steps in the framework. This dissertation presents the research methodology in a constructively aligned manner. The intellectual journey from the high-level research objective to specific research questions and then to the research results and analysis are presented in a gradual and constructive manner.

The overarching research framework revolves around achieving four interwoven research objectives, as shown in Figure 1. First, this study aims to characterize road networks' topological vulnerability by examining topological factors (centrality measures) that contribute to road network vulnerability. This objective also examines the performance of road networks under generic (random) disruptive events. Second, partly based on the first objective findings, this study proposes dynamic network approaches like network percolation and network diffusion to model the road network's cascading failures during flooding events. Third, this study characterizes coupled flood control, road, and emergency service networks under flooding events. Fourth, this study proposes a novel approach to quantify and assess the impacts of natural or human-induced changes (disruptions, hardening options) on system performance holistically.

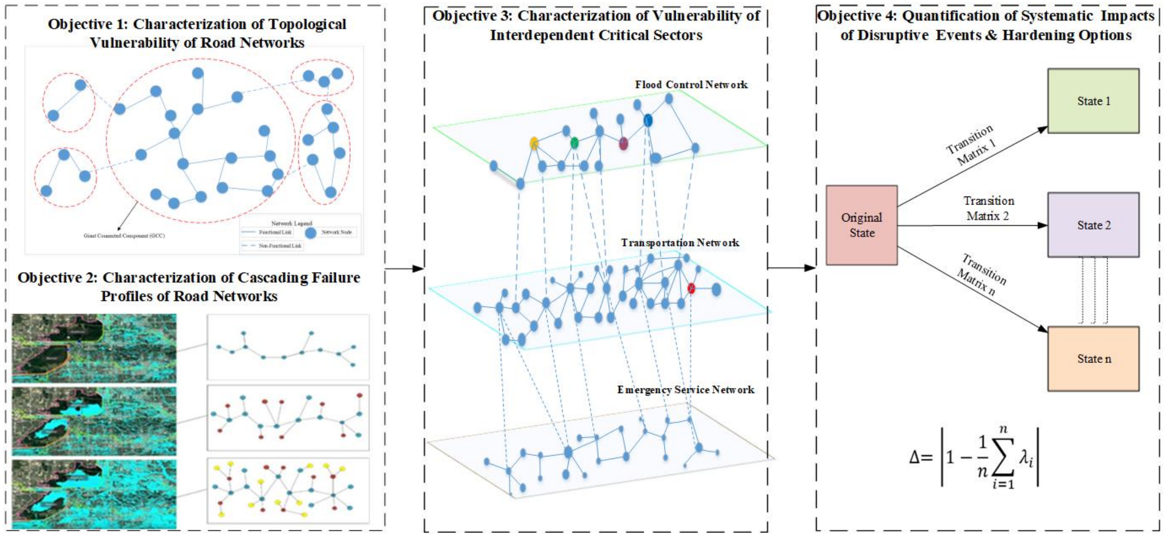

Figure 1 Schematic view of research objectives

3.2. Objective One: Characterization of Topological Vulnerability of Road Networks using Graph-based Approaches

In order to improve the resilience and decrease the vulnerability of transportation systems, aka, to make the critical infrastructure system disaster-proof, it is essential to understand the mechanisms with which disruptive event unfolds during the disruptive events. Since collecting detailed data about the failure of critical infrastructure systems, is both challenging and mostly infeasible, simulating the critical infrastructure systems' performance in the face of disruptive events is a viable way to study their performance. This study aims to characterize the topological vulnerability of road networks using network-based methods. In order to test the hypothesis mentioned above, the below research tasks have been undertaken:

Step1: A comprehensive literature review mainly on: (i) transportation system resilience assessment methods and its main components; (ii) graph theory and identification of measures for network performance; (iii) dynamic network modeling approaches and current gaps in the literature;

Step 2: Retrieval, cleaning, processing, and analyzing of topological data for the road networks in the case study area;

Step 3: Analyze and characterize the road network's robustness using other networks' topological network features.

3.3. Objective Two: Characterization of Cascading Failure Profiles of Road Networks during Flooding Events

Most of the available graph-based approaches either use static graph measures to assess the static topographical network vulnerability or focus on transportation vulnerability under a single disruption event. It is also noted that there is abundant literature on theoretical resilience or vulnerability measures, which is demonstrated mostly in test (theoretical) networks while examination of the vulnerability of existing transportation networks under various disruptions left relatively under-researched. Achieving this objective is considered as one of the main contributions of this dissertation to the body of knowledge on road network resilience and vulnerability. There are three main steps under this objective that respectively resulted in three manuscripts. These three research steps (tasks) are:

Step 1: Modelling the percolation process in road networks during fluvial flooding events using the Bayesian update approach and its impact on the network connectivity;

Step 2: Characterizing the impacts of hypothetical random disruptions and flood-induced disruptions on the connectivity of road networks using network percolation approach;

Step 3: Characterization of road networks' vulnerability to fluvial flooding using the SIS network diffusion model.

3.4. Objective Three: Characterization of Vulnerability of Interdependent Critical Sectors

As transportation systems have close interactions with many other systems (land use, demographics, social, natural, economy, environment, etc.), most of the external disruptions to normal operations are realized via one or more of these interactions with the external environment. To better understand how these external systems interact with an urban transportation system, it's important to understand the interdependencies among different sectors. For example, when natural disasters (like earthquakes) hit transportation systems, the infrastructure layer tends to be the one that suffers most. When there is a deliberate or unexpected disruption to the transportation systems' operations, the agency layer tends to have to recover the situation. In contrast, the other two layers remain relatively unaffected. Under this research objective, interdependencies among three main sectors, namely flood control, road, and emergency service networks, are examined. Research task under this research objective has been conducted in the below steps:

Step 1: Examination of the factors that could contribute to the flood vulnerability of road networks using machine learning methods;

Step 2: Modeling co-evolution of the road and flood control network during flood event using network percolation approaches;

Step 3: Comparison of households' vulnerability by emergency service providers under different types of disruptive events on road networks.

3.5. Objective Four: Quantification of Systematic Impacts of Disruptive Events using Transition Matrix-based Approach

The roadway system's network abstraction facilitated identifying different vulnerability levels for the network components (nodes and edges). However, analysis in previous research tasks could be of limited use if their results are not incorporated with other analyses or not considered inputs for policy-making regarding improving road networks' vulnerability. As this study adopts a high-level and macro-scale view of the critical infrastructure systems, a comprehensive scenario analysis tool is needed to assess the impacts of potentially disruptive events or would-be hardening options on the system performance. To that end, with the help of corresponding models that capture the temporal changes of the main system performance indicators for the transportation network, the temporal evolution of system performance is modeled using a new transition matrix method. This approach was able to quantify the network-level changes.

Step1: Identification of the main dimensions of system resilience and corresponding performance indicators for each dimension;

Step 2: Collection of data about the identified system performance indicators both before and after the occurring of a disruptive event or implementation of a hypothetical hardening option;

Step 3: Estimate the transition matrix and estimate the magnitude of system performance impacts using eigenvalue-based metrics.

3.6. Data and Case Study

The data or the other information used to demonstrate, test, or validate the proposed methods or frameworks are mostly from case studies in Houston or Harris County road networks under the influence of flooding caused by Hurricane Harvey. In order to demonstrate the methodology used to achieve the last research objective, a case study of the Texas freight network was used. Figure 2 shows the flow and progression of research ideas and topics for research tasks in this dissertation.

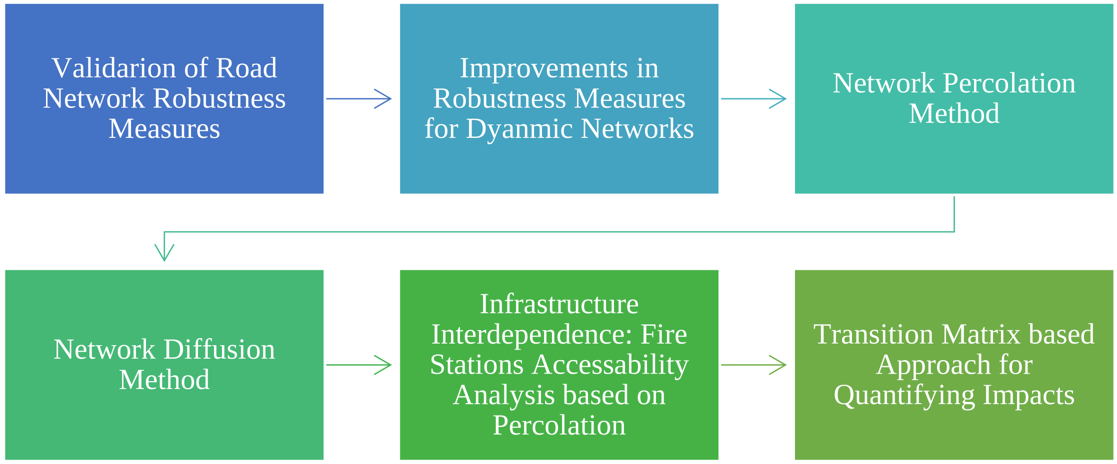

Figure 2 Workflow diagram for main research tasks

4. CHARACTERIZATION OF TOPOLOGICAL VULNERABILITY OF ROAD NETWORKS USING GRAPH-BASED APPROACHES

4.1. Chapter Introduction

This chapter presents the research tasks conducted under the first research objective. There are three main research tasks conducted under this objective. (1) Study of the performance profile of the road networks under random disruptions and the flood-induced disruptions; (2) Study the performance profile of different types of road networks used for walking, biking, driving, service, and private roadways; (3) The impacts of the disruption locations on the robustness of the road networks are also examined.

4.2. Flood-Zone based Network Percolation for Road Network Vulnerability Assessment

4.2.1. Introduction

The objective of this study is to quantify and characterize the vulnerability of road networks to flooding. Security of critical infrastructure systems like transportation in the face of disastrous events has always been a critical area of study. There has been a growing sense of uncertainty and complexity inherent in critical infrastructure systems in recent decades, making it even more important to understand and characterize the impacts of a wider spectrum of disruptive events on the critical infrastructure systems. Only with enough understanding of the mechanism with which the disruptions unfold is it possible to make the critical infrastructure systems more robust and resilient. This paper's objective is twofold: (1) proposes a method to estimate the vulnerability of the road network based on the flood zone type of the locations where roads are located; (2) compare and characterizes the vulnerability of the road network under different disruption scenarios. To that end, this study first models road networks as planar primal graphs where nodes represent the road intersections or endpoints on the road network. Second, this using the Federal Emergency Management Agency (FEMA) flood zone categories, nodes in the road network are categorized into three-four broad categories, representing different exposure levels for the flood hazards. Third, using the network percolation method, disruptions due to flooding hazards and other disruptions are simulated. The percolation process in the road network is modeled by assigning different removal probabilities to the road network. Fourth, using the ratio of connected largest component and original network size, the impacts of the disruptions on the road network are compared and characterized. It is found that road networks are more vulnerable to the disruptions caused by flooding events than random events of similar magnitude. The relationship between the magnitude of flood-induced disruption and the impact of flooding on road network connectivity is not linear. The impact of network size doesn't significantly impact network robustness. Results and findings of this study could inform decisions pertaining to flood-impact reduction, designing, and planning road networks. A similar framework and approaches could be extended to assessing road network vulnerability under other types of disruptions or vulnerability of other types of critical infrastructure systems, which could be modeled as networks.

Disruptions, both natural or human-made, to critical infrastructure systems could cause serious negative impacts on lives and businesses' normalcy. Every year, substantial economic, social, or environmental losses occur due to disruptions in critical infrastructure systems, and these losses are becoming increasingly expensive. There are many reasons for failure in critical infrastructure systems being more costly. First of all, growing interdependence among sectors renders the cascading failures among sectors more likely. With the help of improving communication and computation technologies, interdependencies among different things have been consistently growing. Similarly, interconnection and interdependence between critical infrastructure systems are also increasing over time. In fact, the call to study the critical infrastructure systems in each other's context has been growing. This is partly because failure in critical infrastructure is becoming increasingly costly due to the cascading failures. Growing independence also brings an increased level of uncertainty and complexity associated with critical infrastructure systems' performance. Growing uncertainty makes it even more challenging to forecast or estimate both the failure probabilities and magnitudes of breakdowns. Uncertainty from other sources, like disruptive technologies and political situations, could also make an accurate assessment of the impacts of failure in critical infrastructure even more challenging. Recent developments surrounding Covid-19 reinstated the importance of preparing for uncertain disruptions, and we had been made aware of the dire consequence of doing otherwise.

Flood hazard is one of the severe problems in many coastal urban regions due to the ever-growing urban population and increasingly frequent flooding events. Flooding due to various reasons has been a major cause of disruption to our lives and has been causing substantial economic, social, and environmental losses in recent decades (Hammond et al., 2015). There are multiple ways of categorizing damages caused by floods (Meyer et al., 2013; Smith & Ward, 1998). Hammond et al. (2015) classified the losses caused by flooding disasters into four categories(1) direct tangible impacts, (2) business interruption and indirect tangible impacts, (3) impacts on infrastructure, and (4) intangible impacts. It is worthy to note that these categorizations of damages are neither exclusive nor exhaustive. Besides, it is hard to define, without introducing a certain subjectivity level, a clear-cut system boundary, both spatial and temporal, for the flood-damage analysis. In the meantime, some of the flood-induced losses are difficult to quantify in monetary terms.

Flood-induced disruptions to the critical infrastructure systems, like transportation, telecommunication, power supply, emergency medical service (EMS), food supply chain, and healthcare, could have serious negative implications. Damages to the critical infrastructure take up significant portions of the total damage caused by the flooding disasters. For example, in the 2007 summer flood in the United Kingdom, out of the total estimated economic loss of £4bn, about £670m was credited to the damage caused to the critical infrastructure systems (Chatterton et al., 2010). As an important lifeline system, the transportation network plays a particularly important role during a disruptive event like flooding. These roles include but not limited to, facilitating necessary evacuations, providing access to critical services like healthcare, food, or emergency medical services. What makes the transportation system even more critical during disastrous events is that fixing the failures in many other sectors (like a power outage or responding to traffic accidents) depends on a functioning transportations system. Therefore, the resilience of transportation systems in the face of flooding events are of crucial importance. Thus, vulnerability or the road transportation network's resilience has been popular a popular research topic among civil engineering researchers, especially in recent decades. Transportation engineering and transportation planning could be viewed as the nexus of different fields, material science, mathematics, structure, hydraulics, among many other disciplines. Therefore, the topic could be approached from many areas of scientific investigation.

In recent decades, there is a growing volume of research that examined transportation vulnerability in the face of flooding events. Pregnolato et al. (2017) examined the relationship between safe vehicle speed and depth of inundation on the road surface during a flooding event using both empirical data and existing research studies. They derived a quadratic function that models the relationship between the two variables. The authors also studied the relationship between the two variables for different vehicle types. This study is one of the growing numbers of studies that move forward from the traditional binary consideration of flooding. Based on the findings of Pregnolato et al. (2017), Abdulla et al. (2020a) used the diffusion SIS model to capture the dynamic propagation of floodwater in the road network. Threshold flood depth values were chosen for different types of vehicles. Stochastic propagation of a fluvial flood on a road network was modeled using probabilistic "open" and "closure" status for each node at a given time. Abdulla et al. (2019) used a network percolation method to characterize road network vulnerability under the influence of fluvial flooding events. In this paper, the framework's focus was to capture the temporal profile of the road network connectivity under the influence of fluvial flooding. Abdulla and Birgisson (2020d) use machine learning classifiers to identify factors that contribute to the flood vulnerability of a node in the road network, which is measured using the cumulative inundation depth of a node during the entire process of a flooding event. They demonstrated the method using the road network in the Memorial neighborhood of Houston. Abdulla and Birgisson (2020b) claimed a high level of uncertainty in the formation of the giant connected component (GCC) when disruption occurs in a network. Consequently, the author used the level of co-location (proximity) between the road networks and flood control infrastructure as a proxy for the distribution of the giant connected component. They then proposed using the expected values of the giant component of a network under the influence of the diasters event, considering the inherent uncertainty in the formation of the giant component. The authors demonstrated their study using the road network in Houston. Choo et al. (2020) studied the flood's impact on the road network in much finer detail. The authors used the Spatial Runoff Assessment Tool (S-RAT) and Flood Inundation model (FLO-2D model) to estimate the extent of flooding in urban areas caused by rainfall. The authors also presented rainfall-flood depth curves were that describe the distribution of flood depth under given rainfall events. Mukherjee and Singh (2019) identified flood-prone areas by integrating nine flood conditioning factors such as slope, elevation, soil type, rainfall intensity, flow accumulation, LULC, NDVI, and distance from river and distance from the road. Then, the authors combined the factors using the weighted overlay method in ArcGIS to map the areas in Harris County prone to flooding. Finally, they overlayed the 2017 FEMA flood hazard map on the weighted overlay flood hazard map. In work by Vanolya and Niaraki (2019), the flood hazard map of Mazandaran province is assessed using subjective-objective weights in an Ordered Weighted Averaging-based GIS analysis. Flood hazard maps are produced based on the two types of weights, along the scale ranging from the pessimistic to optimistic decision strategies.

Road systems take the form of planar networks, and they lend themselves readily to the study of complex networks. The resilience analysis of the road network using graph theory, therefore, provides a basis for future extensive work that can be conducted to assess the capability of the transportation network. The results could help problems like how to handle potential disasters and what measures can be taken in advance of these disasters so that the network maintains its functionality. Therefore, topological approaches have been widely used to describe the system's behavior because they require significantly less data and computation time than physics-based methods. For example, using network theory to assess infrastructure systems' robustness does not require many physical details about the system but rather a simple mathematical description of the linkage relationship between network components (LaRocca et al., 2015). Other topological approaches include (Demšar et al., 2008; Ip & Wang, 2011; King et al., 2016; Leu et al., 2010; Mattsson & Jenelius, 2015). Most graph-theory-based approaches used network centrality-based measures to identify critical or vulnerable locations in the network. While it is important to identify nodes crucial to network integrity and ensure their normal functionality, examining the failure of nodes exposed to hazards is critical for improving transportation network resilience. This is important because centrality-based, theoretically important nodes are not necessarily exposed to hazards, and centrality-based vulnerability analysis may not always be practical. This study uses a network percolation method to assess the vulnerability of road networks to flooding events. Network percolation is an approach that is capable of modeling the changes in the topology of a generic network due to disruptions using a parameter called occupation probability(Newman, 2018). Occupation probability is usually used to capture the stochastic nature of the failure locations on the network, and it is denoted using φ, which represents the probability of a certain node to be functional at a given time (or under a given scenario). As the level of exposure for the nodes in the road network to a given type of disruption usually tends to be heterogeneous, a set of occupation probabilities for the nodes in the network—the values for φ range from 0 to 1, both inclusive. A higher φ value denotes the nodes are less prone to be removed from the network, while a low φ value means the node is less prone to be disabled. Once disastrous events disrupt the road network, one or more nodes in the network would be disabled due to the disruptions, leading to the fragmentation of the road network. Schneider et al. (Schneider et al., 2011) have proposed an index that could be used to measure the robustness or integrity of a generic network. It can also be characterized by integrating the largest connected component's sizes throughout the entire percolation process. They introduced the robustness measure R.

$$R = \frac{1}{N}\sum_{Q=1}^{N} s(Q)$$

Where N is the total number of the nodes in the network, and $s(Q)$ is the fraction of nodes in the largest connected component (see Figure 3) after removing $Q = N(1-\varphi)$ nodes. The 1/N normalizes the result so that the results can be compared. R ranges from 1/N (star graph) and 0.5

(fully connected network). The road network connectivity could be assessed using the size of the giant connected component (Figure 3).

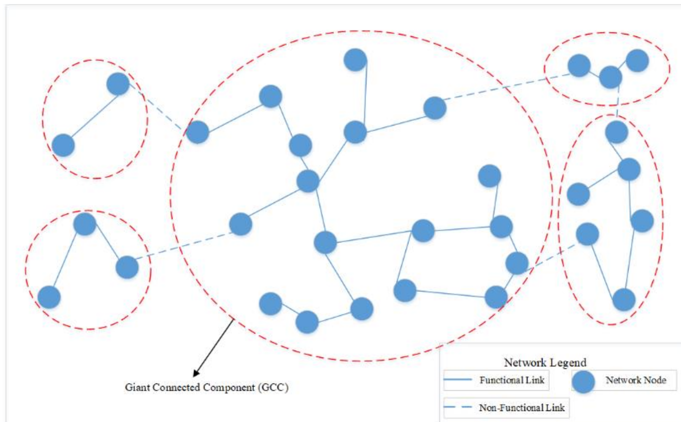

Figure 3 Giant connected component (GCC) of a network, reprinted from Abdulla & Birgisson (2020b)

In summary, the resilience of transportation systems is a topic that attracting growing attention from researchers. Graph-theory-based approaches are one of the popular methods to study the vulnerability of critical infrastructure systems, including road networks. However, most of the graph-based approaches are based on the node or network centrality measures, which are derived from theoretical mathematics. These measures could not necessarily reflect the actual exposure of the network towards certain disastrous events. This study proposes a network percolation-based framework to assess the vulnerability of road networks to flooding by using floodplain type as a proxy for the level of hazard-exposure for the nodes in the network. The impacts of each level of flood-induced failures are compared with that of random failures. The rest of the study is presented in the following order. First, the methodology is presented with a detailed introduction of the major steps used. Then, the impacts of the two types of percolation at different failure extents on the road network connectivity are presented under the results section. In the end, conclusions, interpretation, and implications of the results are provided, followed by discussions on possible avenues for future research.

4.2.2. Methodology

This study proposed a framework to assess road networks' vulnerability to flooding events based on flood plain information. At any given time, the exposure level of each of the locations on the road network has heterogeneous. It is essential to recognize heterogeneity among the road network locations, which renders the failure probability of each location different. This study does this by assigning different removal probabilities to the road network located at different flood zones summary of the methodology used in this study presented in Figure 4. The first road network is modeled as a primal graph where nodes represent the interactions and edges represent the road sections. Then, based on the FEMA flood zone categorization, nodes in the road network are divided into several categories, representing the level of exposure to flood hazards. The impact of different types of flooding on road network connectivity is assessed using a network percolation approach. In the end, road network vulnerability to flooding events and random events are compared, which leads to the categorization of the vulnerability so the road network against these two types of disruptive events.

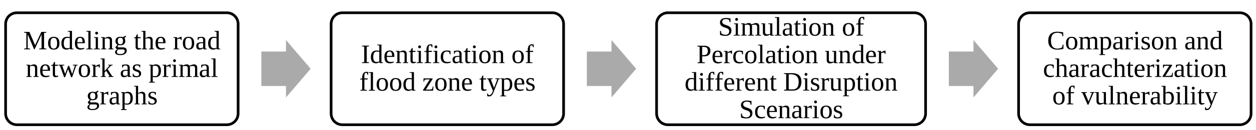

Figure 4 Main steps in methodology

When a hydraulic event (often a severe rainfall for an extended period) happens, there is sequential order in which the nodes in the road network get flooded. In the first place, road sections (nodes or edges in the network) in the floodway are inundated as floodwater usually takes its course into the flood control infrastructure like bayous, channels, stormwater systems, as well as drainage network. These systems are usually the first defense line for most of the minor rainfalls or stormwater surge events. The road closures do not go beyond these areas. Suppose the flood control systems' capacity is reached, and there are still is excess water that can not be channeled to the drainage system on time. In that case, the water gradually creeps into the immediate surroundings. This causes that parts in the 100-year flood zones are flooded and are closed consequently. If the rainfall continues or is flooding more severe, the flooding propagates into the less flood-prone areas, like 500-year flood zones. Figure 5 graphically and symbolically demonstrates this process during hurricane Harvey in the Energy Corridor region located west Houston. Different node colors in the network could represent the types of nodes located respectively in different flood zones, which suffer from different levels of flood-exposure (in terms of both magnitude and probability).

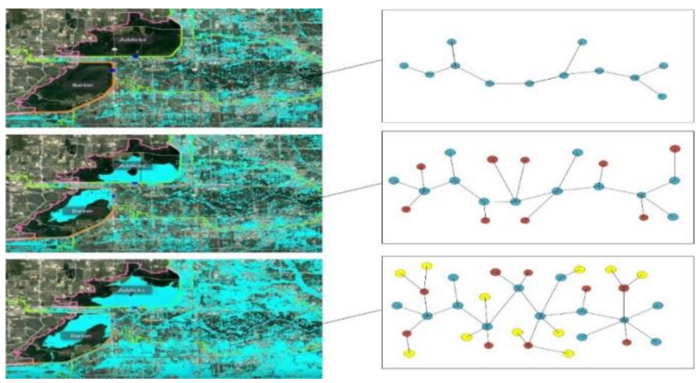

Figure 5 Propagation of floodwater from highly flood-prone areas to lower flood-prone areas

1. Modeling of Road Networks

This study used the primal graph to abstract the road network where nodes represent the intersections and edges represent the road sections. Network data for the road networks are retrieved from OpenStreetMap using OSMnx, a Python package developed by Boeing (2017).

2. Identification of flood zone types

The categorization of the nodes in the road network based on the flood zone type is based on the FEMA proposed flood-map. There are three broad categories of flood zones: floodway, 100-

year, and 500-year flood zones. Areas outside of these regions are called areas with minimum flood hazards. See Table 1 for details.

Table 1 Flood zones and their descriptions (reprinted from FEMA (2020))

Flood Plain Type		Description
High Flood Risk	A	100-year Floodplain, areas with a 1% annual chance of flooding.
	AE	100-year Floodplain. The base floodplain where base flood elevations are provided.
	AH	100-year Floodplain, 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. Flood elevations derived from detailed analyses are shown at selected intervals within these zones.
	AO	AO 100-year Floodplain, river or stream flood hazard areas, and areas with a 1% or greater chance of shallow flooding each year, usually in the form of sheet flow, with an average depth ranging from 1 to 3 feet.
	AR	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).
	A99	A99 100-year floodplain, areas with a 1% annual chance of flooding that will be protected by a Federal flood control system where construction has reached specified legal requirements.
Low Flood Risk	B and X	Between the limits of the 100-year and 500-year Floodplain, area with a 0.2% (or 1 in 500 chance) annual chance of flooding.
	C and X	500-year Floodplain, area of minimal flood hazard

First, the authors overlapped the road network in the FEMA floodplain map. Nodes that lie on different types of flood plains are identified. Road networks are modeled as a primal graph where intersections are modeled as nodes and road sections as edges (links). The network percolation method was used to simulate the impacts of disruptions on the road network. Node percolation in the road network could be modeled by assigning certain removal probability to the nodes based on the level of exposure to the road network. This study compared the connectivity of the road network under different scenarios and characterized the vulnerability of the road network

i. Simulating the percolation of the road network under varying levels of flooding

The impact of flooding on the road network was modeled by removing nodes in a certain category with a certain removal-probability. For example, when the flooding extent is mild (only nodes in the floodway were removed from the road network), the remaining network's connectivity level was computed. When a more severe flood occurs (nodes located in floodways and nodes located at lesser flood-prone areas, i.e., 500-year floodplain, are removed from the road network), corresponding connectivity is computed. First, only nodes located in the corresponding floodplains are removed from the road network to model the only flooding of that type on the road network. Second, To model the impacts of severe floods in the road network, higher removal probabilities were assigned to flood-prone nodes. Lower removal probability was assigned to the nodes located in less flood-prone areas. Multiple simulations were conducted, and both mean connectivity for each super neighborhood and variance of the connectivity were computed. It is also possible for the flood to happen for other reasons like blockage of the sewage systems, accumulation of debris, failure of bridges, and the pipeline networks explosion. This being said, road networks that are located outside of the FEMA-designated flood zones could also be disrupted. Therefore, simulation of the road network's performance under a severe rainfall event requires the consideration of the impacts of non-flood zone factors. This study achieves this by assigning relatively smaller removal-probabilities to the nodes located at less-flood-prone areas.

ii. Simulating the percolation of the road network under different level of random disruptions

An equivalent magnitude (the same fraction of node removal) random disruption on the road network was simulated, corresponding to two levels of a flooding event. In order to reduce the impact of random sampling, multiple (50 in total) simulations are repeated for each φ value of the percolation. The mean and variance of the results are reported. After the simulation of the percolation under two scenarios, namely flood-induced and hypothetical random disruptions, the results of these disruptions on the network connectivity are compared. Both spatial comparisons and comparisons among different scenarios are conducted. This study also computed the super neighborhood-level road networks' robustness in multiple cities and examined its relationship with other network features like network size and average node-degree networks.

4.2.3. Results and Discussions

Results on Network Robustness

First of all, road network robustness results under the influence of random disruptions are computed for different spatial locations (super neighborhoods as spatial units). It was found that the robustness of the road network does not significantly vary with the size of the road network. The super neighborhoods in central Houston are significantly larger than the robustness of those in the periphery of Houston. Though the robustness values don't change significantly with the network size, it does seem to have a significant correlation with the relative location of the super neighborhoods in the city (see Figure 6 and Figure 7, respectively, for the road network in Houston and Dallas). An examination of the robustness values and average node degrees of the road network in the super neighborhoods shows that the robustness values are positively correlated with the road network's average node degree (Figure 8). The correlation coefficient between robustness and other network features was calculated. For the network size, the correlation coefficient is not significant for the examined cities; however, for the average node degree of Houston road networks, the correlation coefficient is 0.57. A similar analysis was also conducted for other cities in Texas (Table 2). The positive correlation between network robustness and average node-degree persists in all city road networks. The implications of these findings include: when allocating resources to improve the neighborhoods' robustness, it is important to allocate them according to how exposed the network to that type of disruption. For example, in random disruptions, roads in the center of Houston city don't need as many resources as those in Houston's periphery.

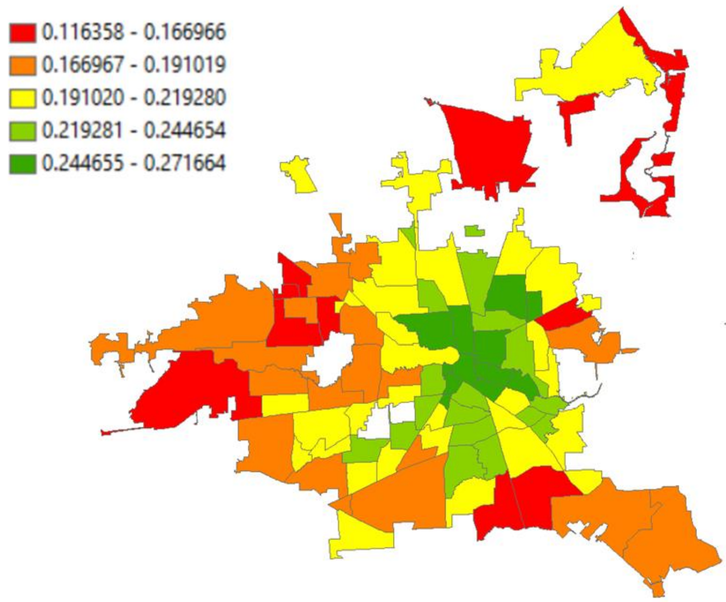

Figure 6 Robustness of road networks in Houston (92) super neighborhoods

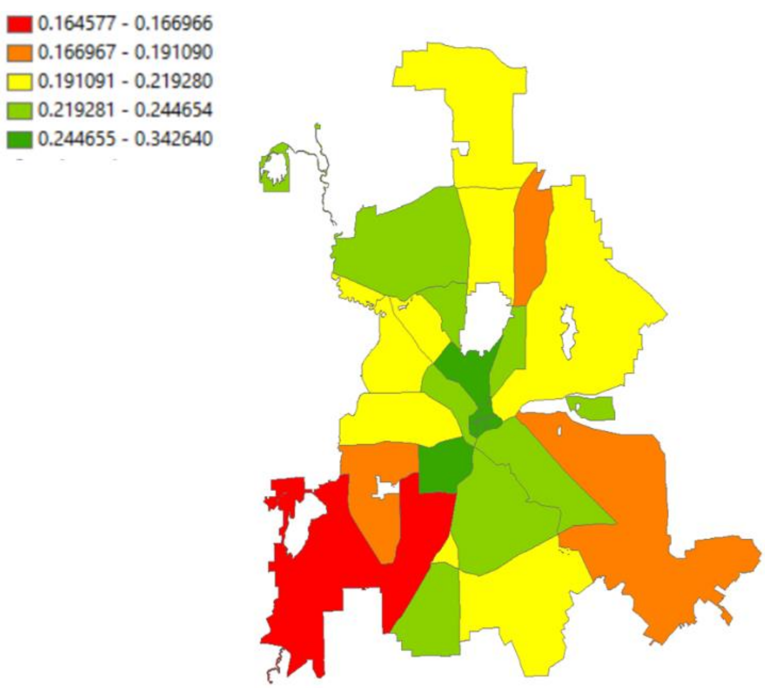

Figure 7 Robustness of road networks in Dallas (36) super neighborhoods

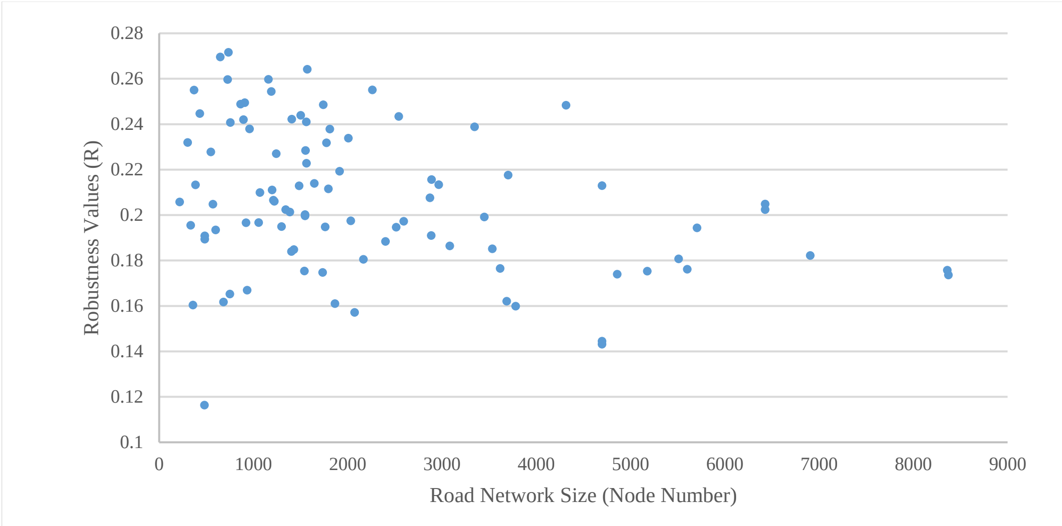

Figure 8 Scatterplot of network robustness and network size and average node degree

Table 2 Correlation between network robustness and average node-degree

City	Number of Neighborhoods	Correlation (R and k_avg)
Houston	92	0.570
Waco	23	0.461
El Paso	55	0.383
Lubbock	40	0.518
Austin	66	0.742
Dallas	34	0.343

Results on Network Disruptions

The performance of nodes in three categories (floodway, 100-year, and 500-year flood zones) are modeled separately and compared with the corresponding random disruption with the same magnitude. The impact of the flooding on the road network connectivity was assessed for 92 super neighborhoods in Houston.

1. Disruption due to Nodes being on the Floodway

Figure 9 shows the comparison between the minimal flooding in the areas located in the floodways and that of random disruptions. As can be seen in Figure 9, random disruption tends to cause less disruption when the magnitude of perturbations is small. Figure 10 shows the spatial locations of the impact during the flooding. A neighborhood in southwest Houston, namely

Braeswood Place, is particularly vulnerable for a minor flood type that occurs only in the floodways. Road networks in two other neighborhoods named Greater Inwood and Langwood are also susceptible to this type of minor flooding.

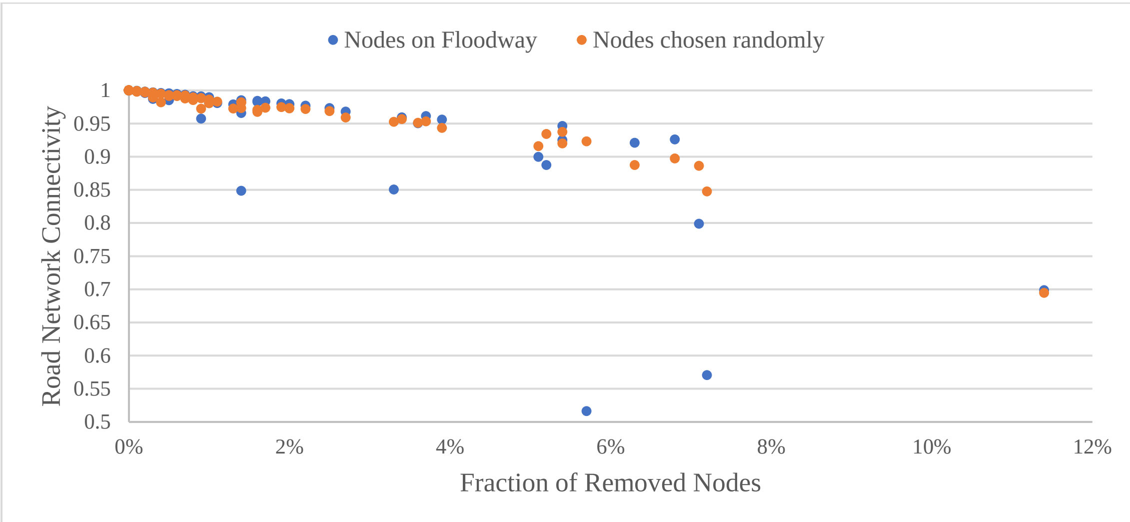

Figure 9 Scatterplot of network connectivity and node removal due to floodway

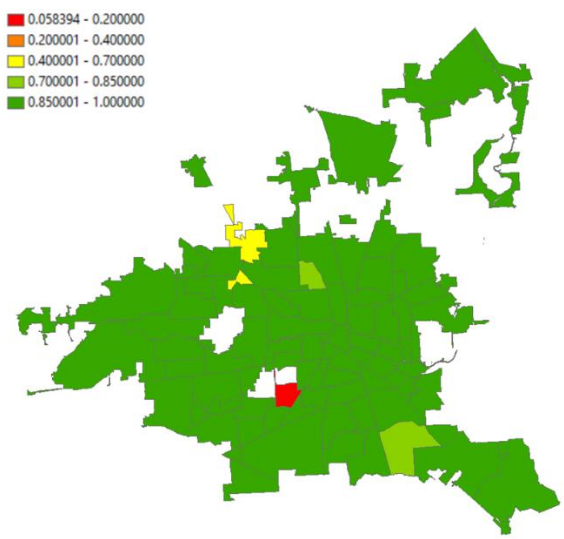

Figure 10 Road network connectivity when nodes in floodway disrupted

2. Disruption due to Nodes being on a 100-year floodplain

Similarly, the impacts of the percolation of nodes in the 100-year zone are also computed for the 92 neighborhoods in Houston. A comparison is made with a similar magnitude random disruption (see Figure 11). Under this scenario, a random disruption tends to cause more severe damage to the network connectivity than an equivalent flooding event.

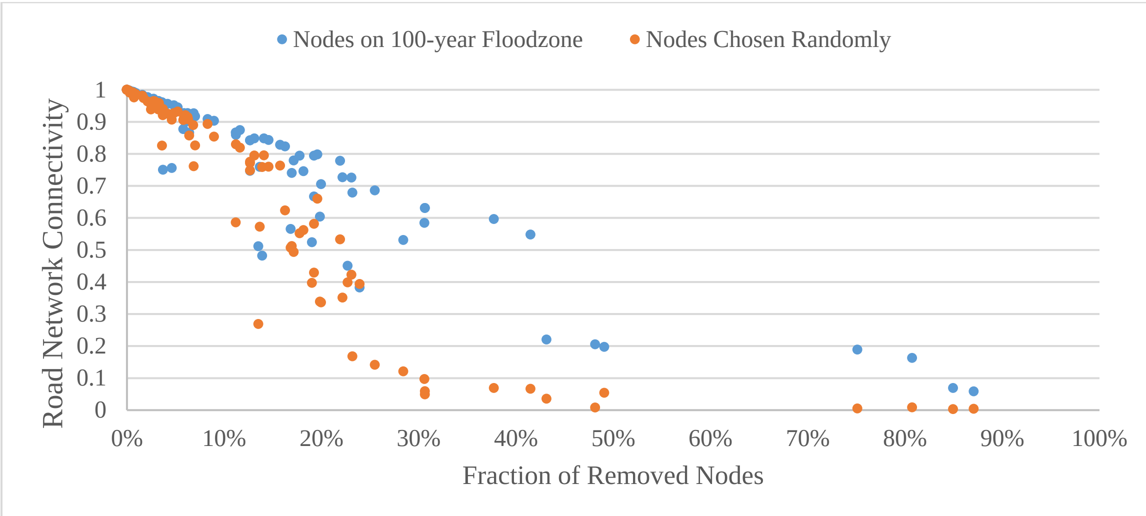

Figure 11 Scatterplot of network connectivity and node removal due to 100-year flood zone

The spatial distribution of the flood-induced and random disruption is shown in Figure 12 and Figure 13. The more severe impact of random disruption can be seen in Figure 12, comparing the number of red and brown neighborhoods. Several neighborhoods that are not impacted heavily by floodway type of disruptions become more fragmented under a 100-year type of flooding disruption.

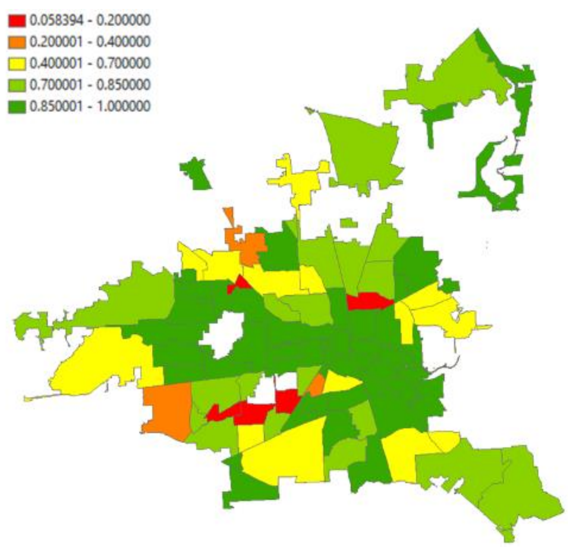

Figure 12 Road network connectivity when nodes in 100-year zone removed

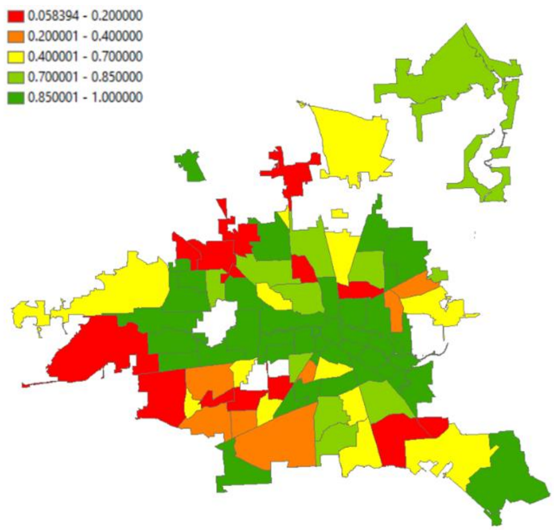

Figure 13 Road network connectivity when the same number of nodes as 100-year zone randomly removed

3. Disruption due to Nodes being on a 500-year flood zone

The results of these simulations are shown for the impacts of the percolation of nodes in the 500-year zone, which is computed for the 92 neighborhoods in Houston. Similar to the 100-year zone hazard, the impacts of random disruptions are more severe to network connectivity (see Figure 14) when the level of disruptions is higher. Figure 15 and Figure 16 show the spatial distribution of the impacts of two types of hazards. Interestingly, under the influence of an equivalent random disruption scenario, road network connectivity is less impacted in the areas that are located in downtown Houston.

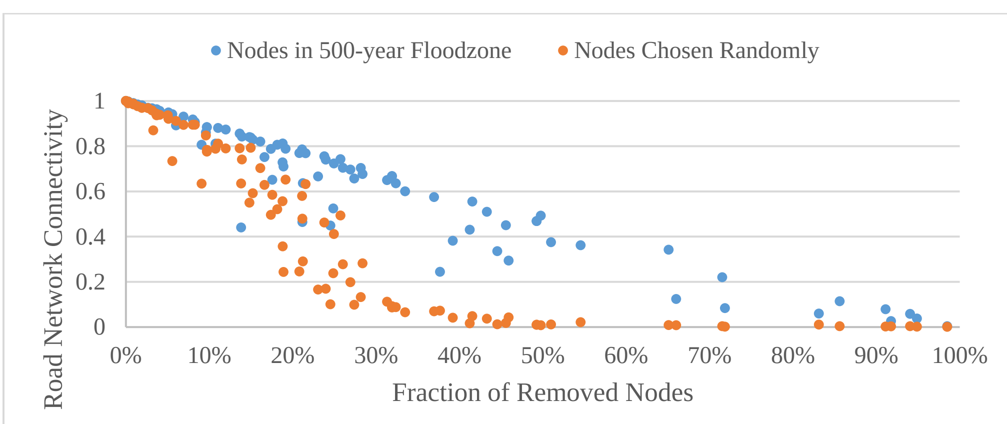

Figure 14 Scatterplot of network connectivity and node removal due to 500-year flood zone

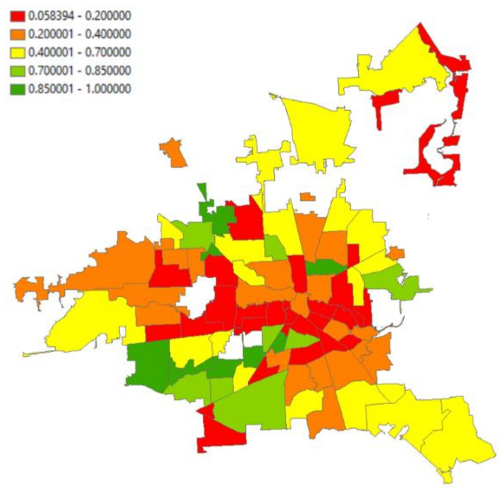

Figure 15 Road network connectivity when nodes in 500-year zone removed

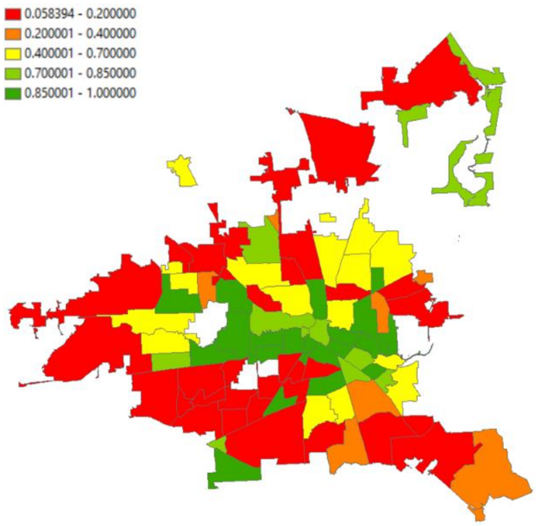

Figure 16 Road network connectivity when same number of nodes as 500-year zone randomly removed

To quantify the impact of the flooding escalating from a 100-year to a 500-year flood, the difference in the road network's connectivities under these two types of flooding events is computed and presented in Figure 17.

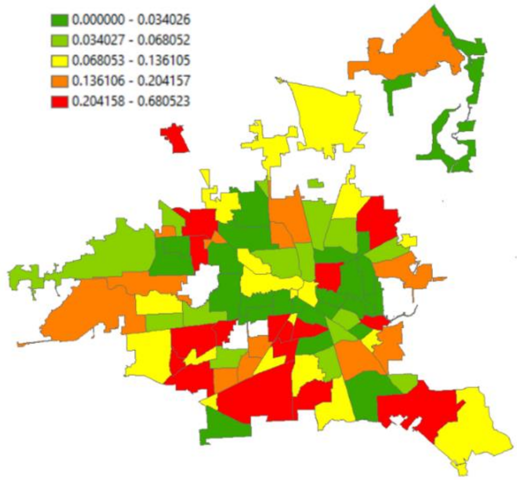

Figure 17 Level of reduction in connectivity when flooding changes from 100-year to 500-year zone

A node's location into a specific type of flooding (100-year or 500-year) zone doesn't necessarily mean flooding only occurs in those corresponding flood zone locations in the road network. While flood zone variable is a significant reason for a certain location to be flooding, the roads' closure is a function of many factors, like the functionality of the flood control infrastructure, proximity with flood control infrastructure, sewage network, and street grade (Abdulla et al., 2019). It is possible for the road closure to occur in each part of the road network but with different probabilities. This study used a list of probabilities for modeling this type of flooding scenario with network percolation, and corresponding node-removal probabilities for nodes located at different floodplain types are shown in Table 3.

Table 3 Mixed percolation scenario (flooding at all node types)

Flood Zone Types of Node Location	Removal Probability
Floodway and 100-year zone	0.9
500-year flood zone	0.6
Areas with minimal flood risk	0.1

For this simulation, the same magnitude (500-year flood zone) of disruption is considered across all super neighborhoods, and results are graphically presented in Figure 18.

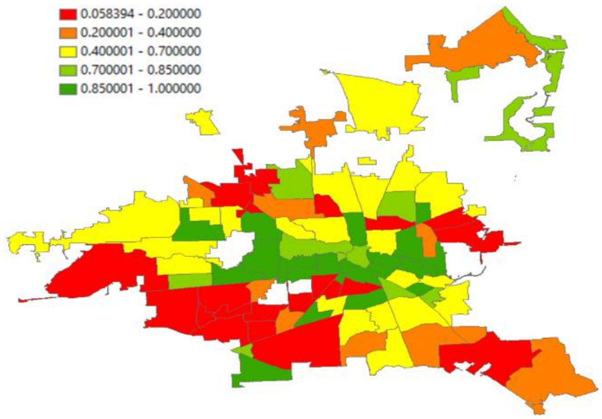

Figure 18 Road network connectivity under mixed flooding

The same analysis was also conducted for the entire Harris County and City of Houston road networks. About 15% of the Houston and Harris county nodes lie within the 100-year flood zone, while twice as many nodes are located within a 500-year flood zone. For both road networks, connectivities are reduced by about 20% when nodes within 100-year flood zones are disabled. The summary of the network features and results of the connectivity analysis is presented in Table 4. However, disruption caused by a 500-year flood has a significantly larger impact on Houston's road network as its connectivity is reduced by 37%. In comparison, the road network for Harris county sees a reduction of 29%. Compared to disruptions caused by flooding on the road network, both networks are much more vulnerable to more random disruptions. As shown in Table 4, the level of reduction in road network connectivity is much more severe under the equivalent random (same fraction of nodes being disabled) disruptions. Especially random disruptions equivalent to a 500-year flood (about 30% node failure), could cause the loss of 90% connectivity. A random disruption comparable to the disruptions caused by a 100-year flood also causes more loss to the road network connectivity than a 100-year flood.

Table 4 Vulnerability of road network in Houston city and Harris county

Road Network	**Network Size (**Node number and Edge Number)	A fraction of nodes in 100 zones and 500 zone	Connectivity under 100-year flood disruption	Connectivity under 500-year flood disruption	Connectivity under random disruption equivalent to a 100-year flood	Connectivity under random disruption equivalent to a 500-year flood
Harris County	375111 959531	14.7% 29.4%	0.82	0.71	0.66	0.11
Houston City	179533 461629	15.6% 29.6%	0.79	0.63	0.69	0.09

4.2.4. Summary and Conclusions

The significant results of this study could be summarized in the below points.

(1) The robustness of the road network, measured with the connected giant component (GCC), is not variable with the network's size but is positively correlated with the road network's average node-degree. It was also found that road network in the central regions of an urban area tends to be more robust compared to those in the periphery of the city.

(2) The reduction of the road network's connectivity is not necessarily positively correlated with the magnitude of disruption (i.e., the fraction of disabled nodes). The location of the disruption does matter, as there are clear differences in the impacts by flood-induced and random disruptions on the network connectivity; Impacts of random disruptions tend to be more severe compared to that of random disruptions;

(3) The shift in the disruption's magnitude could cause quite a heterogeneous impact on the road network connectivity. As observed from the cross-comparison among the impacts under 100-year and 500-year flood zones, some localities see a drastic decrease in the network connectivity.

(4) Larger road networks (at a city or county level) are particularly vulnerable to severe disruptions that are random compared to flooding-induced disruptions.

The methodology proposed in this study could be applied anywhere in the world where network topological and floodplain data (or flood probability data) are available for different localities. This study proposed a methodology to assess the impact of flooding events on road network connectivity. Impacts of flooding events with different magnitude were examined and compared with that of random events. When the magnitude of the flooding is small, the difference between the impacts of the random and flood-induced disruptions is small. However, when the magnitude of disruptions grows, the difference between the impacts of two types of disruptions (with the same magnitude) becomes more protruding. Especially in larger networks, network connectivity is more sensitive to random disruptive events than flood-induced disruptions. For example, in the road network of Harris county, when nodes in the 100-year and 500-year zone are disabled through a flood of the corresponding magnitude, the network only loses, respectively, about 20% and 30% of its connectivity. In comparison, an equal number of randomly chosen nodes would result in nearly 35% and a 90% reduction in connectivity. There are important implications of these results on improving the vulnerability of the road network. For example, in the face of disruptive events whose spatial distribution is relatively hard to predict, it is essential to actively adopt hardening strategies to keep network integrity at the need threshold level. The results of this study could also assist network centrality-based vulnerability analysis in order to have a more comprehensive assessment of the vulnerability of the road network to flood-induced disruptions. For example, one may compute the fraction of nodes with high betweenness centrality in a corresponding floodplain and measure flood exposure. In addition, road network robustness is positively correlated with the average node-degree in the road network. It is worth mentioning that this study's results may not necessarily apply to other areas (other cities or regions) because the relative locations of the nodes in the network that are located within the flood zones are the deciding factor for the impacts of flooding on connectivity. There is a need for a more accurate and refined categorization of the nodes' exposure to flooding hazards. The 100-year and 500-year zone categorization was intended for a broad categorization of the localities based on the flood hazard exposure. In reality, flood hazard is much more complex and heterogeneous than simply categorizing them into 100-year and 500-year zones. First of all, the probability of flood hazard exposure in the same flood zone could vary significantly, as there could be other levels of exposure like a 200-year zone. Therefore, there is a need to classify the location further based on the exposure levels, making it possible to classify the nodes further and assign a more diverse occupation probability for the nodes in the road network for the percolation due to flooding. Second, flooding status is not a binary term. There are both duration and depth components that need to be considered for a more accurate assessment of the impact of flood hazards. This is because the same depth of flooding could have different ramifications to different types of vehicles, and the impact of a flooding event that lasts for only a few hours is not the same one that lasts for a couple of weeks.

4.3. Relationship Between the Theoretical Road Network Robustness Measures and User Experienced Mobility Hardship during Flooding Events

4.3.1. Introduction

This study has two interwoven objectives. First, it investigates the robustness profile of different types of road networks in the face of disruptive events. Second, it examines the relationship between theoretical network robustness measures and subjective mobility hardships experienced during a disastrous event, like flooding due to a hurricane. Various types of network robustness measures have been proposed in the literature and have been used to assess road networks' vulnerabilities or resilience in the face of disruptions. Some of these measures have been devised to measure the global network characteristics when faced with disruptive events, while others have been used to identify individual nodes or edges critical to network connectivity. Given the wide-spread application of graph-theory-originated network resilience or robustness indices to assess the topological vulnerabilities of transportation networks (primarily of road networks), in most of the studies on the topic, few distinctions have been made on the types of road network studied or little research focus has been allocated to examining the possible relationship between different topological features of road networks and mobility hardship experienced during a disruptive or emergency event. Road networks used by different modes of transportation (i.e., walking, cycling, or driving) tends to have different topological features. As road network topology measures are important proxies for land use patterns and travel behavior, it is of great significance to understand their relationship with mobility impedance experienced during the disastrous event. This paper addresses this intriguing question using the road in the context of disruptions due to significant flooding during Hurricane Harvey. This study first reviewed the literature to identify commonly used road network robustness measures. Then, based on a survey conducted in the immediate aftermath of Hurricane Harvey, it estimated the average level of mobility hardships experienced during the hurricane flooding. After accounting for the impacts of other main factors, like the level of road closures in each road network, it studied the correlation between levels of mobility hardship and network robustness. Results indicate that (1) Different types of road networks exhibit different levels of robustness in the face of disruptions and, compared to other types of road networks, road networks for driving is relatively more robust to disruptions.; (2) Residents, who are using road networks with a higher level of robustness measures, ceteris paribus, experience lower levels of mobility hardship during the disruptive events caused by flooding. This study's results and conclusions could inform other studies that aim to identify those locations with the most pressing needs and faced with the highest level of hardships.

In the first two decades of this century, the world has experienced serious and large-scale disruptions, both natural and human-made, which usually are sudden and disastrous. Examples of these include the 2004 South Asian Tsunami and Haiti's earthquake in 2010, with over 220,000 casualties each. In all these events, transportation systems played very important (if not the most important) roles in the process of preparing for, coping with and recovering from the disasters (Serulle, 2015). Disruptions to transportation systems can be caused by a wide variety of factors, which can be classified as either internal or external. Internal disturbances include accidents caused by staff or users, system failures, the breakdown of components, overload, and faults in construction. External disturbances, which are usually initiated by the failure of other sectors upon which certain component(s) of transportation system relies, can be linked to naturally occurring phenomena, which include severe weather conditions and natural disasters. Intentional external disturbances could also occur due to hostile actions ranging from pranks to acts of war (Mattsson

& Jenelius, 2015). Some natural disasters could induce both internal and external disruptions simultaneously and could cause huge economic, social and environmental losses. Few other disasters have caused more losses of lives and property than floods, in one form or another. There are plenty of mechanisms with which flooding can cause these losses. For example, it could destroy plants, causes bridges to collapse, ruin vehicles, and it could even drown people. One of the common mechanisms by which various losses (both direct and indirect) could be caused is its disruption to the transportation network by disabling the normal functionality of one or more components of the transportation systems, as it could effectively cut off access to and from the critical necessities of normal life and business, which could paralyze the essential supply chain. The transportation sector's role becomes even more crucial during disasters due to its prominent role in pre-disaster evacuation and post-disaster recovery. Therefore, assessing the transportation network's vulnerability and identifying system weakness is a critical precondition for effective hardening measures. However, assessing the vulnerability of transportation systems in the face of flooding is a challenging task as the vulnerability of transportation systems is dependent not only on structural factors(road pavements, bridge foundations, topological network characteristics), but also on non-structural factors like it's co-location with flood control infrastructure and social demographic characteristics of the neighborhood the transportation network located. There is plenty of literature that has studied the empirical relationship between causalities and social vulnerabilities. It has been found that the higher the vulnerabilities, the higher the casualties, in the face of the same level of disaster (Serulle, 2015). Most of the casualties tend to happen due to the fact that there are limited options for the people to seek evacuation or having access to necessities that are essential to their lives. In other words, high casualties are partly due to socially vulnerable people experience more hardships in the face of disruptions, as their option for mobility tends to be relatively limited before, during and after the disaster event. To better inform planning, policy, as well as design decisions pertaining to the road network, it is crucial to identify factors that contribute to the mobility challenges during a disruptive event, which is the main motivation for this study. Network approaches have been widely used to assess the vulnerability of road networks in the face of disruptions. While these approaches could throw some lights into the topological characteristics of the transportation network, graph-based topological measures are borrowed from the field of network science, and their application in the field of transportation network has not been validated, and there is a big conceptual-leap in translating theoretical topological vulnerabilities into perceived vulnerabilities of the transportation network. Our study aims to help determine vulnerable sections in urban road infrastructure systems (in terms of the hardship level experienced) and distinguish them from those that are able to withstand crisis events. This paper is organized as below. In the next section, a survey of the related works in the literature will be provided, which also includes the discussion of the gaps in the present state of knowledge in the field. Then it discusses the data source and case study region. Two main components of the methodology: robustness analysis of the road network and multinomial logistics regression analysis on the variables, will be discussed in detail. A detailed description of the findings accompanies the results of each analysis. Finally, the manuscript was concluded with discussions about the study results and the interpretation of these results.

4.3.2. Literature Review

A city's road network provides spatial access to its different areas through an overlapping hierarchy, ranging from highways to local access streets. This form of network organization has resulted in increased susceptibility to vulnerability, exposing parts of the city to severe reductions in accessibility when blockages in traffic ensue at junctions or on the main links. Since road systems take the form of networks, they lend themselves readily to the study of complex networks. The resilience analysis of the road network using graph theory will, therefore, provide a basis for future extensive work that can be conducted to assess the capability of the transportation network to handle potential disasters and what measures can be taken in advance of these disasters so that the network maintains its functionality. Therefore, topological approaches have been widely used to describe the behavior of the system due mainly to the fact that they require significantly less data and computation time than physically-based methods. For example, using network theory to assess infrastructure systems' robustness does not require many physical details about the system but rather a simple mathematical description of the linkage relationship between network components (LaRocca et al., 2015). However, the empirical literature on street networks suffers from some limitations, as discussed by Boeing (2017). There is limited work that studied the relationship between network topological characteristics and empirical road user experience.

Various graph-theoretical metrics have been proposed to quantify a network's topological properties both at the global and the local levels (please see (Bullmore & Sporns, 2009)for a detailed and comprehensive explanation of these metrics). Graph theory in transportation is commonly used to study issues related to routing and networks (Monteiro, Robertson, & Atkinson, 2012). With the use of graph theory, researchers have tried to analyze networks' resilience by performing statistical studies of different topological measures within the graphs' structure. Albert, Jeong, & Barabási (2000) exhibited that many large-scale networked systems share a similar statistical characteristic, power-law distribution of node degree, which gives them increased tolerance to random failures of nodes and very low tolerance to targeted attacks on highly connected nodes. Callaway, Newman, Strogatz, & Watts (2000) used the concept of node failure and introduced a generalized concept of percolation, through which resilience is calculated for any type of graph based on the size of the giant component (largest connected cluster) after the arbitrary failure of a node or set of nodes. These studies generally fall under two categories (Mattsson & Jenelius, 2015): (1) Topological vulnerability analysis: the transportation system is represented as an abstract network (graph), which comprises nodes and edges, which could be directed or directed, and weighted or unweighted. Depending on the application of each study, the nodes and edges could represent different parts of the real transportation network; (2) System-based vulnerability analysis: the transportation system is represented as an abstract network, but the nodes and edges typically correspond to intersections and links in the real network, and the links are usually weighted with weights corresponding to lengths, travel times, costs or a generalized combination of them all. In work by Demšar, Špatenková, & Virrantaus (2008), the Helsinki Metropolitan Area's urban street network was studied and analyzed as an undirected and unweighted network. Porta, Crucitti, & Latora (2006) also studied graphs of urban street networks using centrality measures, in addition to the typical properties of degree distribution and average path length. Their conclusions included the suggestion that road networks should be studied as weighted networks, with the weights assigned in their study being related to the length of the edges. Erath, Löchl, & Axhausen (2009) suggested that road networks should be approached as multiple weighted networks; in addition to the length of links being significant to studies, the travel demands and travel times should also be given sufficient consideration. Leu, Abbass, & Curtis (2010) measure the physical layer of resilience in a transportation system. They represent the transportation network as an undirected graph. Centrality measures for nodes were calculated, such as degree, betweenness, and clustering. Their approach allows for both the determination of critical nodes within the transportation network and the associated spatial damage (increased travel distance required) incurred upon a node's failure through the distance gap measure's utilization. Ip

& Wang (2011) propose an approach to quantify the resilience of transportation networks, where resilience is linked to the concept of friability. Identifying the critical cities or routes is determined by calculating the total reduction in the network's resilience upon removing a node or edge. A recent example of resilience analysis of transportation networks was conducted by King, Shalaby, & Eng (2016). In this work, the Toronto public transit network's resilience was analyzed using network science and graph theory, coupled with simulations of the transit network's behavior and its users. More recent works on the topic include works by Abdulla et al. (Abdulla & Birgisson, 2020a, 2020c, 2020b, 2020d; Abdulla et al., 2020a, 2019) that combined graph-theory-based analysis with methods like network percolation, network diffusion, uncertainty analysis, and machine learning classification.

In summary, while these existing graph-based works have tried to analyze the resilience of transportation networks using a certain type of centrality measures of the individual node or the whole network, each of them has used certain topological characteristics of the network to assess its vulnerability holistically. It is found that few studies that examined the vulnerabilities of the road network have specified the type of road network they focused on. It is also found that no studies have attempted to understand or address the possible relationship between the form (topological features) of the road networks and the mobility hardship the road user could experience while the connectivity of the road network is compromised.

4.3.3. Methodology

The methodology this study used to assess and validate the road network robustness measures using empirical data could be summarized in Figure 19. First, a survey of the literature about the available network robustness measures was conducted, and network robustness measures were identified. Then vulnerability profile of different types of road networks was examined and characterized. After that, based on the results of the survey, which was conducted in the aftermath of the hurricane, the level of mobility hardship experienced by the residents 138 zip codes in Houston was estimated.

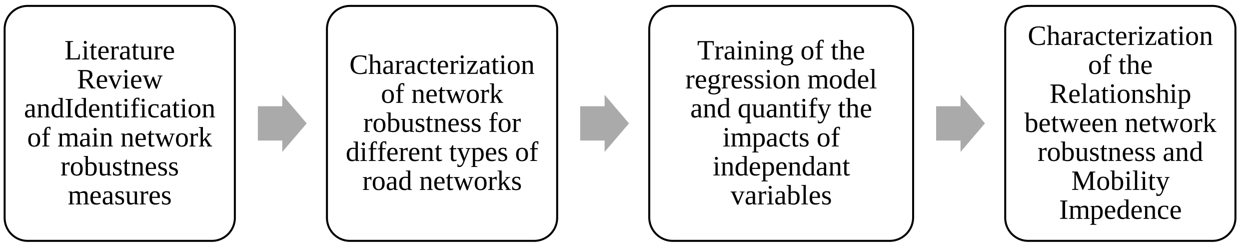

Figure 19 Main steps in methodology

Identification of Dependent and Independent Variables

1. Average Mobility Hardship Level

A research survey has collected data from people in more than 138 zip codes about the transportation hardships people experienced during the disaster, and it is used as the measure of the vulnerability index. This is the question asked from the respondents: "What was the extent of overall hardship that your household experienced due to road closures and access disruptions posed by Hurricane Harvey?" This measure is assumed to be a proxy to the resilience of the transportations network within each super neighborhood.

$$AH_j = \frac{1}{n}\sum_{i}^{n} MH_i$$

$where, AH_j: the\ average\ level\ of\ hardship\ experienced\ by\ residents\ in\ \ zip\ code\ j,$

$n: number\ of\ respondednts\ in\ Zip\ code\ j,$

$MH_i: the\ reported\ level\ of\ hardship\ by\ respondent\ i$

It is worth mentioning that many factors could contribute to the level of hardship, as even the people in the same zip code level, which tend to have the same level of service by the transportation systems, still report very different levels of hardships. This is inherently due to the social aspects of the respondent.

Identification of Independent Variables

2. Extent of Road Closure

Road flood extent (FE) is a measure of the seriousness of the road closure in each network of analysis during the hurricane. It is estimated using the cumulative closed portion of the roads within a certain zip-code. Details about FE are as below:

$$FE_j = \frac{CL_j}{TL_j}$$

Where:

FE_j: flooding extent of the road network within certain (j) zip-code;

CL_j: $cumulative\ length\ of\ closed\ portion\ of total\ road\ in\ Zip - Code\ j$;

TL_j: $the\ total\ length\ of\ the\ road\ network\ in\ certain\ zip - code\ j$;

As could be seen from the definition of the FE variable, it could take values from 0 to 1.

3. Network Topological Characteristics Variables

A search for the network level of robustness measures for road networks resulted in the below list of variables.

(1) Global Efficiency (GE)

Global efficiency is a measure of the exchange of information within the network (Crucitti, Latora, Marchiori, & Rapisarda, 2003). If Z_{st} is the length of the shortest path between nodes s and t, then the global efficiency of the network is calculated as follows:

$$GE = \frac{1}{N(N-1)} \sum_{s \neq t} \frac{1}{Z_{st}}$$

$where\ GE$: $global\ efficiency$;

N: $number\ of\ nodes$;

Z_{st}: the length of the shortest path between nodes s and t.

The higher the global efficiency of the network, the more redundant the network is considered to be, making it more resilient to disruptions.

(2) Average Distance (AD)

The average distance is a measure of the exchange of information within the network. If d_{st} is the length of the shortest path between nodes s and t, then the average distance of the network is calculated as follows:

$$AD = \frac{1}{N(N-1)} \sum_{s \neq t} d_{st}$$

$where\ AD$: $gaverage\ distance$;

N: $number\ of\ nodes$;

Z_{st}: the length of the shortest path between nodes s and t.

(3) Percolation Limit

According to Cohen, Erez, Ben-Avraham, & Havlin (2000), the percolation limit of a network returns the critical fraction of nodes that need to be removed before the network disintegrates (disconnects). Here p is the fraction of the nodes (vertices) and their connections (edges) of a graph/network that is (randomly) removed. Here, we calculate the threshold p_c which means that if p > p_c the network disintegrates into smaller, disconnected parts

$$p_c = 1 - \frac{1}{\frac{\langle k_0^2 \rangle}{\langle k_0 \rangle} - 1}$$

Where:

$\langle k_0 \rangle = \frac{\sum_1^n \delta_i}{n}$; $\langle k_0^2 \rangle = \frac{\sum_1^n \delta_i^2}{n}$

(n is the number of nodes in the network, δ_i is the degree of node i in the network).

Boeing (2018) has proposed two metrics: average node connectivity and maximum betweenness centrality as the network resilience measures.

(4) Average Node Connectivity

The average connectivity of a graph is defined to be the average, over all pairs of vertices, of the maximum number of internally disjoint paths connecting these vertices.

$$ANC = \frac{1}{n}\sum_{i}^{n} NC$$

(5) Maximum Betweenness Centrality

The minimum betweenness centrality is a measure of centrality in a graph based on the number of shortest paths passes through a certain node.

$$MBC = argmaxBC$$

$Where\ BC: the\ set\ of\ betweennes\ centrality\ of\ the\ nodes\ within\ the\ network$

(6) Network Robustness Index

Schneider et al. (2011) have proposed an index that could be used to measure a network's robustness. It can also be characterized by the integrated size of the largest connected component throughout the entire percolation process. They introduced the robustness measure R.

$$R = \frac{1}{N}\sum_{Q=1}^{N} s(Q)$$

Where N is the total number of the nodes in the network, and $s(Q)$ is the fraction of nodes in the largest connected component after removing $Q = N(1 - \varphi)$ nodes. The 1/N normalizes the result so that the results can be compared. R ranges from 1/N (star graph) and 0.5 (fully connected network).

Case Study and Data

The above methodology has been applied to all the zip-codes (138) located in Houston, Texas. The data for this project has been obtained from multiple sources. The mass flooding and closure of roads occurred in Houston during and after Hurricane Harvey, which happened between late August and early September of 2017. It is easy to notice some clusters in the road closure to be more severe in the Energy Corridor region and downtown (central) Houston. These two closures--clusters were formed mainly because, despite the floodwater from the record-breaking heavy rain, the energy corridor region is located in the immediate downstream of the dams/reservoirs (the Addicks and Barker) from which water had been released during the hurricane Harvey and these areas have relatively lower elevation, which is one of the aspects makes this study unique as most of the other studies look only into the flooding due to heavy rainfall. The main reason for a large road closure in central Houston is its relatively lower elevation compared to the regions located in the north and west.

- Characterization of Road Network Robustness Measure

When discussing road networks, the first thing that comes to mind is the road network that is used for driving. However, mobility happens in many forms and modes. There are other types of mobility modes like walking, cycling, cars, bus, transit, among others. What's more important, mobility in some cities has more focus on driving while others concentrate more on cycling or walking. Disruptions to the drive-only road might not cause a big loss to accessibility. Similarly, when most of the roads used for walking are closed, roads used for driving might stay almost intact. Therefore, when studying the vulnerability or resilience of road networks, it is essential to distinguish the types of road networks studied. This study examined the six different types of road networks for cities around the world. Which are all_private, all, walk, bike, drive service, and drive type of networks. This study has analyzed the major cities' performance in the US, New York, Los Angeles, Chicago, Houston. It was found that the same pattern is true in all of these cities. For example, Chicago and New York is more cycling friend than Houston. All private, which means all road networks including private road network, all, which is a road network excluding private roads, drive service, which is roads that are used for public driving and service roads. The drive is the only road that is used for passenger driving. These six networks for a location have differing sizes. During the disruptive events, the closure of any of the roads could cause inconvenience to the residents. The underlying assumption is the road network that is used for driving is directly related to the mobility hardship in a city like Houston, where driving is the main mode of transportation. Other networks that include roads used for biking or walking are not as impacted as those used for driving. Therefore, this study made the assumption that mobility hardship is more related to the robustness of the road network consisted of sections used for driving. It is anticipated that drive type networks have the largest correlation coefficients with mobility hardship. The connectivity profile of a road network was simulated in the below method:

1) The network was retrieved from OpenStreetMap using OSMnx python package;
2) An incremental value of $\varphi = 0.01$ was used for the percolation of the nodes in the road network. At under all scenarios, when the road network suffers from failure in about 40% of nodes, connectivity in the road network drops down to near-zero values. Therefore, this study only simulated the performance up to 50% loss in nodes;
3) For each φ value, a random sample of 25 was repeated and the mean value of the $\frac{S_{GCC}}{N}$ was computed for each φ value;
4) R-value was computed for each of the super neighborhoods under three different types of network.

First, this study simulated the performance of Houston road networks under different levels of random disruptive events. The connectivity profiles of different network configurations are presented in Figure 20 (details about Houston's network sizes, please refer to Table 5). As seen from Figure 20, the drive type network is more tolerant to disruptions than the drive service type of network. For example, as could be seen from their profiles, under a 20% node loss, connectivity of bike or walk type network is reduced to less than 50% of original while that of drive type network is about 70% of the original. Road networks that are all-private, all, or drive-service are relatively less vulnerable.

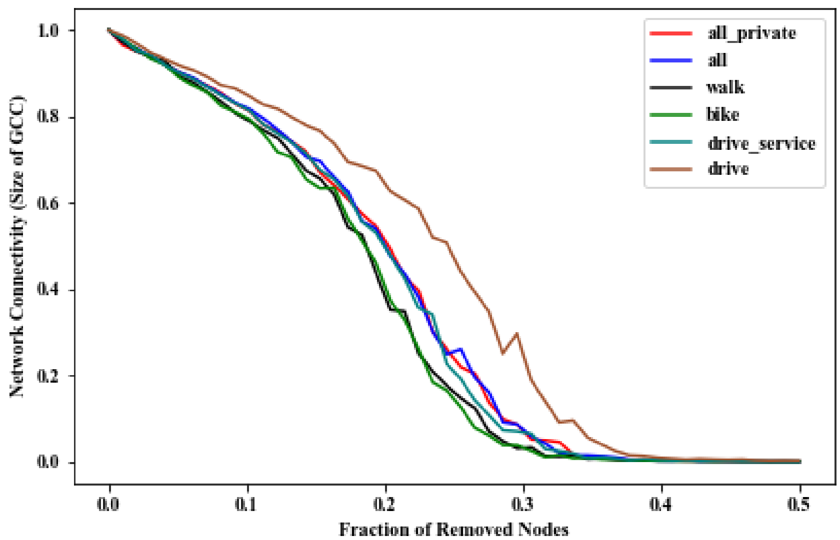

Figure 20 Vulnerability of different types of road network in Houston to random disruption

This study also examined the performance profile of road networks in major cities in the world, mainly the ones in the US (see Table 5). It was found that the performance profile of the road networks of different types in the same region is significantly different. For most US cities examined, passenger-driver-only road networks are substantially more robust to random disruptions than other types of road networks.

Table 5 Summary of road network sizes in different cities

	Road Network Type					
City	drive	drive_service	bike	walk	all	all_private
Houston	59235	147559	160626	178121	181819	196540
Austin	25799	52632	67680	75217	78848	83738
Dallas	36122	79050	84137	102164	104494	115495
Waco	5454	7501	8861	9636	9888	10165
Fayetteville	8434	14320	18166	19213	19368	19552
Amsterdam	11513	15251	25944	31717	43398	44948
Portland	20300	37752	46135	54970	56153	61671
Montreal	19610	31116	38635	47944	50614	51263
Los Angeles	50799	94376	106668	135125	140631	163868
New York	55316	82414	76930	125755	153520	160101
Chicago	28520	88365	100426	117914	119824	122923
Phoenix	48107	85957	121130	129233	132968	149553

In order to examine the possible impact of network size on the theoretical network connectivity measure and facilitate the comparison among different road networks more feasible, all network types are normalized using the size of the smallest network (passenger drive only network), see Figure 21. It is observed that the ratio of network size is quite different across cities, though the gradual increase in network size persists (from drive type to all_private type). It appears that network size is not the main contributing factor for the difference in the performance profiles.

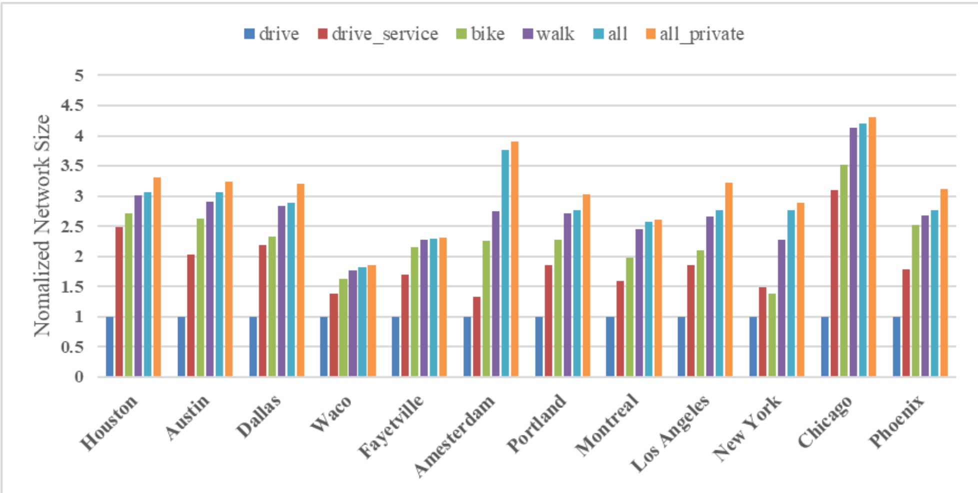

Figure 21 Normalized network size for cities

- Performance Profile of Different Type of Road Networks

The performance profile of the road networks of different types for some cities in Texas, the USA, and other parts of the world, are presented respectively in Figure 22, Figure 23, and Figure 24. When faced with the same type of disruptions in a similar magnitude that is random, roads that have extensive walkways (like roads in Amsterdam, Portland, or New York) fair better than those who have mostly drive-only roads(like Houston, Los Angeles).

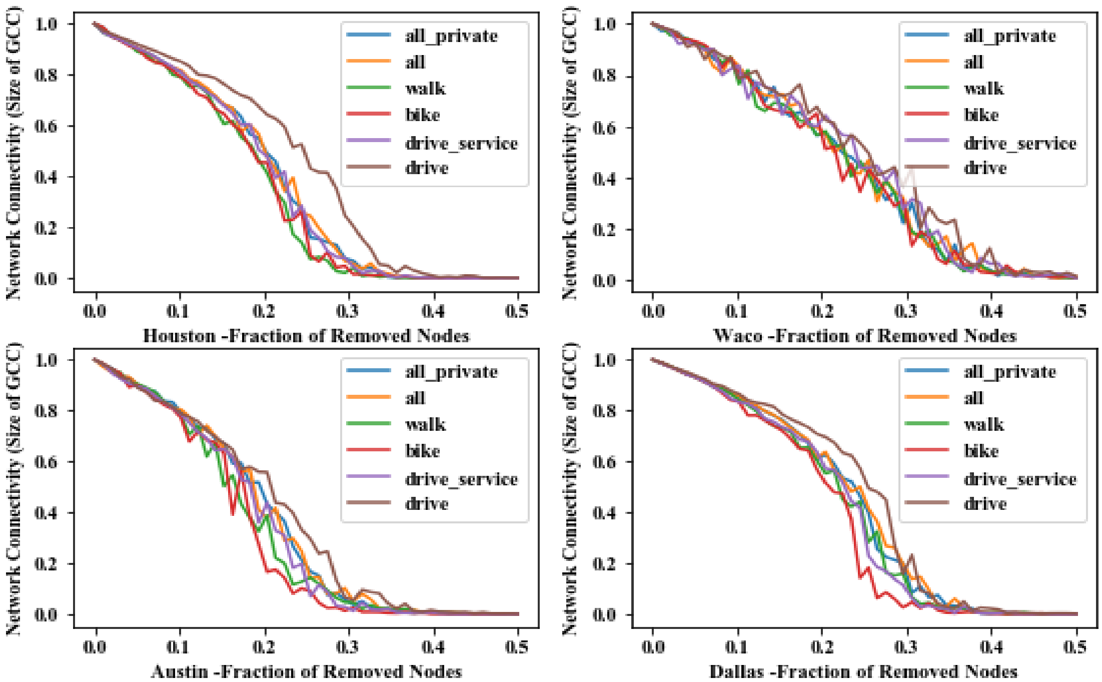

Figure 22 Vulnerability of different types of road networks cities in Texas to random disruption

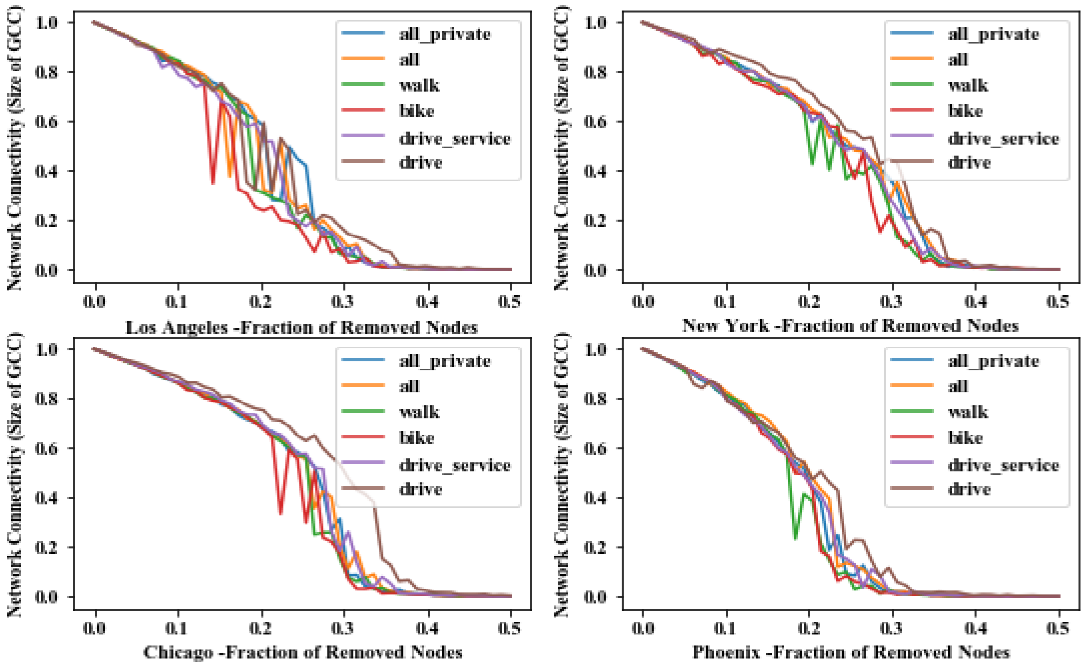

Figure 23 Vulnerability of different types of road networks some cities in US to random disruption

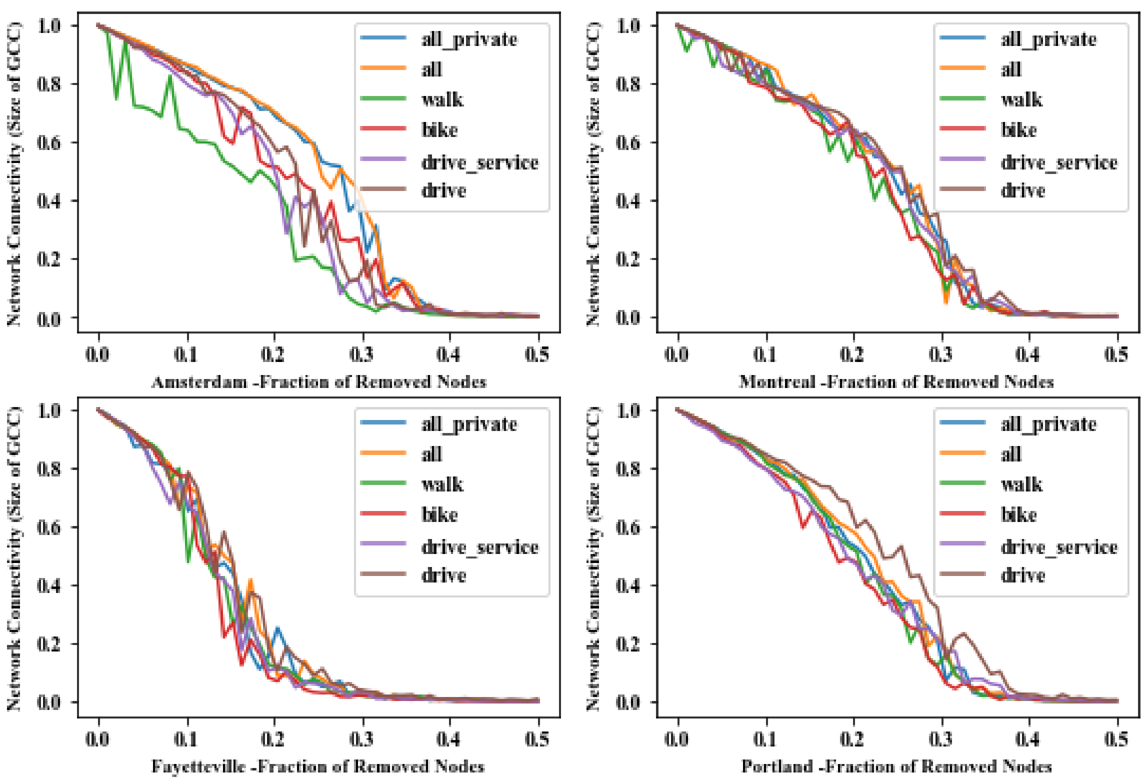

Figure 24 Vulnerability of different types of road networks in some cities in the world to random disruption

All the cities examined, except from Amsterdam and Los Angeles, drive type of network exhibit more tolerance to disruptions, and its connectivity is reduced at a much slower rate than other types of road networks. In order to compare the overall performances of different types of road networks, the average connectivity values (for $\varphi = 0.01$ to $\varphi = 0.50$) are computed for each network. Then the averages of each network type are calculated. The results are presented in Figure 25. As expected, the drive type road network has the highest average connectivity while walk, bike type of road network have the smallest average connectivity. These results agree with the above observation that these two types of road networks (walk and bike) suffer from a sudden decrease in connectivity under random disruptions.

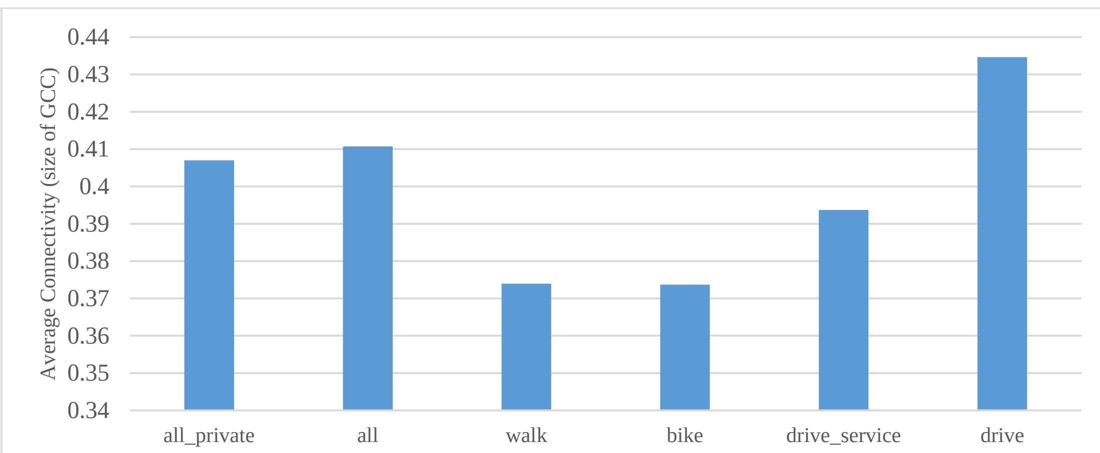

Figure 25 Average connectivity of different types of road networks

In order to examine the factors that cause the obvious differences in the average connectivity of different types of road networks, the correlation coefficient between the average network connectivity for each type of network and the average node-degree in the corresponding network is calculated. The results are presented in Figure 26. For most of the network types, the correlation coefficient is positive, which means the larger the average node-degree, the greater the average network connectivity. However, the magnitude of positive correlation differs quite significantly among different network types. The walk type of network has the greatest correlation coefficient.

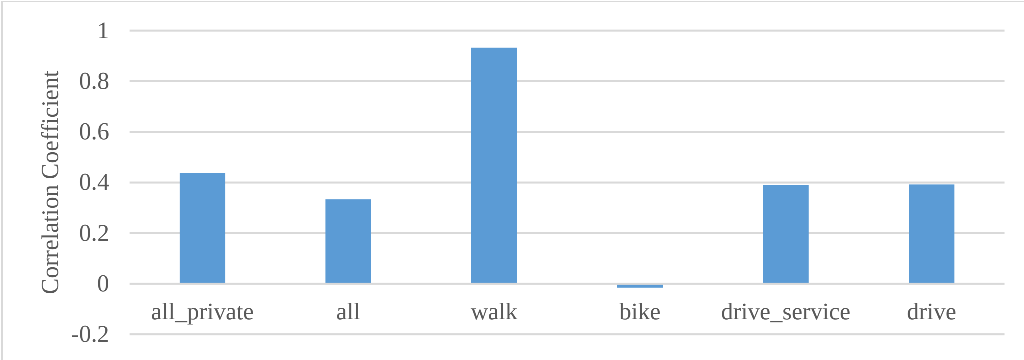

Figure 26 Correlation between average network connectivity and average node degree for different network types

It is worth noting that the different types of networks are not independent networks used exclusively for walking, biking, and for their purposes. The size and nature of the road network are incremental. The network size grows based on a smaller-sized network like a drive-network.

Comparison Among Different Locations

The performance profiles of different types of road networks were compared among the cities. The results are presented in Figure 27. This study examined the correlations among the average network connectivity for the same region's road networks and corresponding average node-degrees. It was found that road networks in the same region, the average network connectivity, and average node-degree are negatively correlated. The larger the average node-degree, the less robust the network is to the random type of disruptions that disables its nodes (Figure 28).

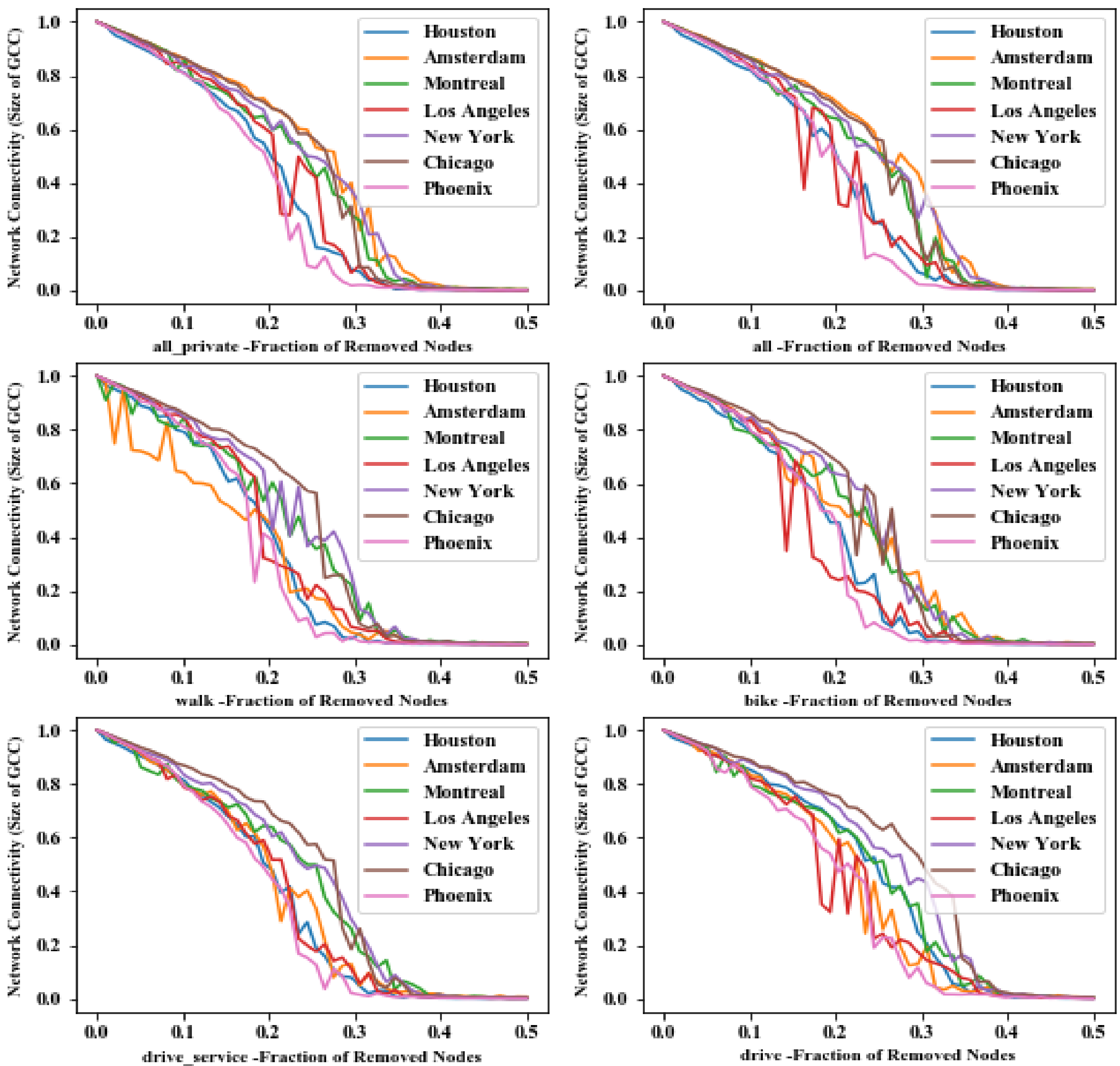

Figure 27 Comparison of different types of road networks among different cities

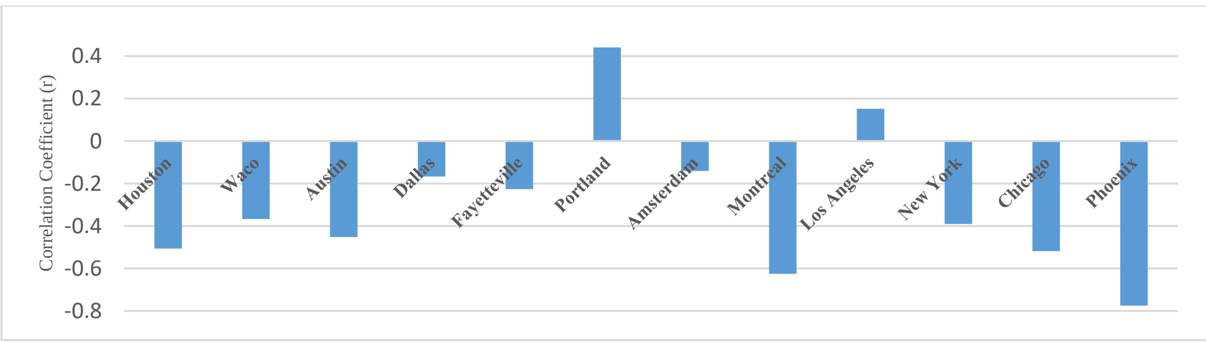

Figure 28 Correlation between average network connectivity and average node degree for road networks in different locations

Multinomial Logistics Regression Model

As the dependent variable is categorical (with discrete values), the multinomial (ordinal) logistics regression was used to model the relationship between the dependent variable, which is the perceived mobility hardship, and independent variables, which are network configuration or topological features, social vulnerability and level of the road closure.

$$y^* = X^T\beta + k$$

Where,

y* is the dependent variable is the hardship experienced by the residents; possible values are 1,2,3,4, and 5. X is the vector of independent variables (independent variables are network robustness, the extent of the road closure, and social vulnerability measures), k is the intercept term and β is the vector of regression coefficients.

- Network Robustness Measures

Network robustness measures, average distance (AD), global efficiency (GE), maximum betweenness centrality (MBC), average node connectivity (ANC), percolation limit (PL), and network robustness (NR) identified in the earlier sections are analyzed. Due to the high correlations among the network robustness measures, only two were chosen for the analysis, which are network robustness (NR), global efficiency (GE), and average distance (AD) measures. One of the measures, network robustness (NR) was presented in Figure 29 (the maximum value is 0.257, and the minimum is 0.119). The zip codes are divided into five categories based on robustness values. The deep green values represent the most robust networks, while the red colors represent the least robust networks. As could be seen, there is a pattern in the level of robustness the road networks possess: ones located in the central region are relatively more robust than those who are located in the periphery of the region of study (Harris County, Texas).

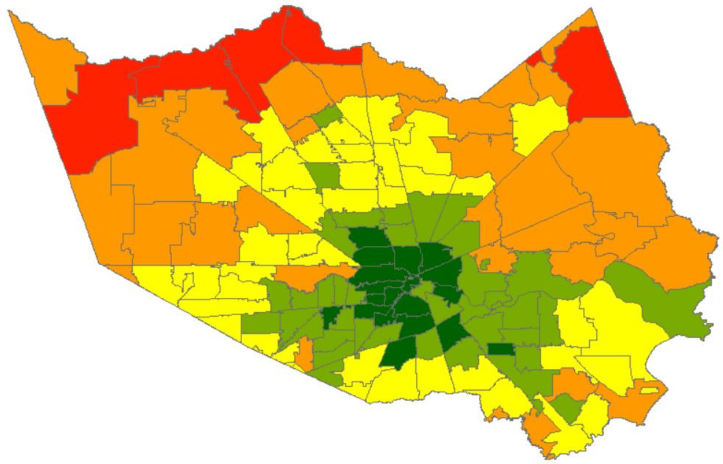

Figure 29 Spatial distribution of network robustness values for Harris county

- Road Closure Status

The level of road closure during the case study event, Hurricane Harvey, was obtained from TxDOT, and the extent of road closure for a given region is calculated based on a fraction of the number of edges that are closed at any given time during the span of the flooding event. Road network closure status is presented in Figure 30.

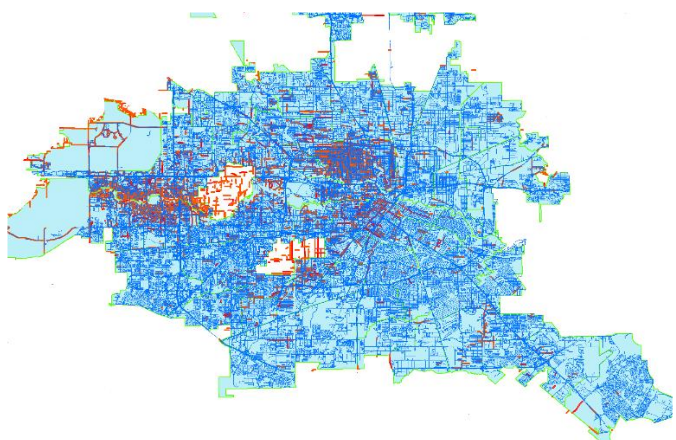

Figure 30 Houston road closure during Hurricane Harvey (created using data from TxDOT)

- Social Vulnerability

This study used the CDC developed a social vulnerability index for the year 2014. The housing and transportation vulnerability index was used for the analysis in this study (see Figure 31).

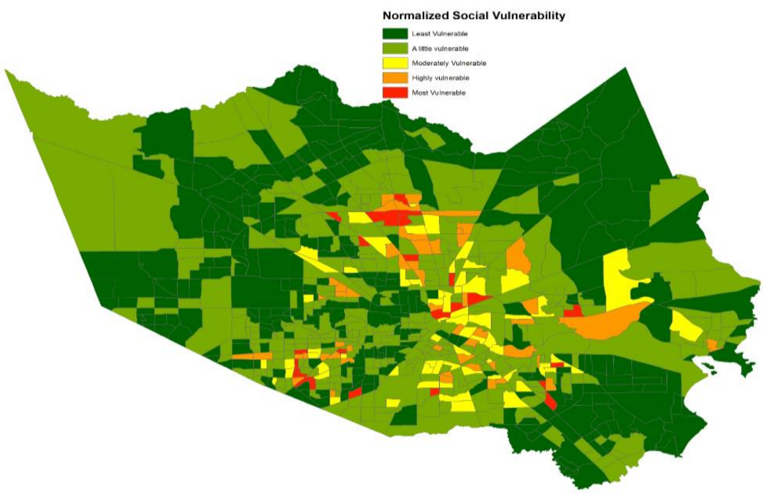

Figure 31 Census tract-level social vulnerability index for Harris county

Mobility Hardship

Based on the survey conducted among Houston residents in the immediate aftermath of Hurricane Harvey, mobility hardships experienced by different zip-codes were mapped. As could be seen in Figure 32, different locations have experienced a different level of mobility hardships during Harvey. Albeit subjective, it could cast insights into the level of mobility challenges faced by residents in other geographical locations.

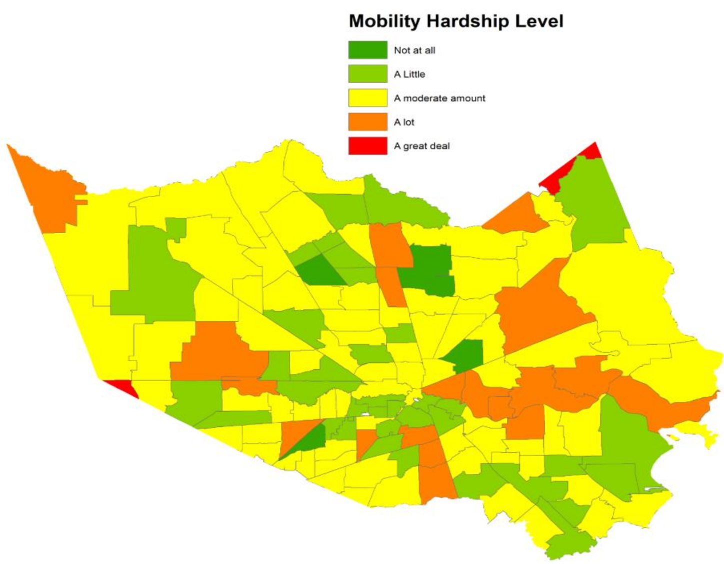

Figure 32 Perceived mobility hardship during Hurricane Harvey

4.3.4. Results and Discussions

The multinomial logistic regression analysis was conducted at two spatial scales, zip code level and super neighborhood levels. The reason for this choice is to examine if the choice of the spatial unit could impact the results of the model. The spatial unit for the perceived mobility hardship could be different depending on where the person resides and where the mobility impedance was experienced. A resident may not necessarily travel within a zip code, and it is possible that a larger spatial unit (like the super neighborhood) could result in different results. The results based on the zip code level analysis are presented in Table 6. In total, 139 zip codes were analyzed. About 85% of the data was used to train the multinomial regression analysis, and the rest was used to test the accuracy. The zip code level analysis produced an accuracy rate of about 60%. As could be seen, the impact of road closure and SVI is the greatest for category 1. All network robustness measures negatively contribute to the mobility hardship experienced by the residents. The results of the super neighborhood-level analysis are presented in Table 7. In total, 23 neighborhoods were analyzed, and 18 were used to train the model, while the rest (5) was used to test the prediction accuracy.

Table 6 Results of zip code level analysis

Mobility Hardship Class	Coefficient Vector					Intercept
	SVI	Road Closure	AD	BC	NR	
1	0.467987	0.81572	-0.00699	-0.02744	-0.0181	-0.6611
2	-0.37188	-0.50602	0.011197	0.005968	0.114643	1.629927
3	0.151767	-0.33665	0.006456	0.028857	-0.08836	0.074305
4	-0.24787	0.026949	-0.01066	-0.00739	-0.00819	-1.04313

This analysis produced an 80% accuracy for prediction. Similar to the zip-code level analysis results, the impacts of the SVI and road closure contribute positively to the mobility hardship experienced by the residents. The mobility hardship negatively impacts network robustness measures like average distance and network robustness during flooding events. In addition to the above analysis, the relationship between network size and average distance is examined. It was noted that there is a positive relationship between AD and network size until network size approaches around 4000 nodes, after which network size doesn't seem to have an impact on the connectivity measure (AD).

Table 7 Results of neighborhood-level analysis

Class	Coefficient Vector					Intercept
	SVI	Road Closure	AD	BC	NR	
1	0.21932	0.03594	0.01867	-0.03317	0.17224	1.20486
2	0.36501	0.01646	-0.01538	-0.37402	-0.16872	11.60996
3	-0.50853	0.03481	-0.00284	-0.28369	-0.01911	8.31954
4	-0.07580	-0.08721	-0.00045	0.69088	0.01559	-18.72465

This study found that network connectivity increases under a certain threshold (about 4000 nodes) as network size increases. Exceeding this threshold doesn't have a significant impact on network connectivity (AD). The relationship between the hardship level and the road closure index is an attempt to characterize people's difficulties from different geographical locations. The extent of road closure and network robustness indices cannot fully explain the experienced mobility hardship variability. Therefore, this study examined the possible impact of the social vulnerability index in the case study region on mobility hardship. The correlation between the flood vulnerability (especially road vulnerability) and mobility hardship is significantly higher in the road sections, which are considered major roads (an example being I10, highway 290, highway 9). This could be because these road sections are used very heavily by different types of users, and the closure of these roads renders them particularly inconvenient for them to meet their mobility needs. The results also indicate that there is a significant positive correlation between the subjective hardship level and social vulnerabilities. In addition, there is a particularly high correlation between the geographical locations which are located on or near the major roadways.

4.3.5. Conclusions

This study set out to examine the robustness of road networks with different configurations, and it was found that, on average, based on the areas studied, the drive-network has the highest level of robustness, which is followed by the drive_service type road network. It was found that the walk type road network has the smallest average robustness compared to other types of road networks. It was also found that the robustness of the road network at different localities is negatively correlated with the average node-degrees in the road networks. This study found some local differences in the flood preparedness and hardship levels experienced by different geographical locations. This study also found certain clusters in terms of the hardship levels experienced by different groups of people. As the western part of Houston tends to experience a higher level of hardship compared to their western counterparts, which coincides with the relatively lower social vulnerabilities. This study also found that network connectivity is a function of network size until network size reaches a certain threshold. The higher closure rate for the roads doesn't mean that people have experienced a higher level of mobility hardships (the level of mobility hardship experienced by each of the super neighborhoods). Last but not least, for a different level of mobility hardship experienced by road users, the major contributing factors vary. In most cases, road network robustness is negatively correlated with the hardship experienced by the residents during a disruptive event. Future works are needed to improve the proposed method further, using more accurate data and making the method more applicable in different circumstances. For example, a unified and specifically defined method for measuring the residents' mobility hardship level could be beneficial. Another area that could be improved is a number of independent variables, which could be considered as the independent variable for the hardship levels. More data from different disaster events would help provide a more generalized critical infrastructure vulnerability analysis system.

5. CHARACTERIZATION OF CASCADING FAILURE PROFILES OF ROAD NETWORKS DURING FLOODING[1]

5.1. Chapter Introduction

This chapter presents the methodology this study proposed to model the cascading failures in the road networks: network diffusion and network percolation. This study applied these dynamic network approaches to examine the impacts of the road networks' profile during cascading failures. This chapter presents the research tasks conducted under the second research objective. In the following sections of this chapter, two main types of dynamic network approaches, network percolation and network diffusion, will be presented. For the diffusion analysis, the road network for a neighborhood in western Houston called Memorial was used to train the diffusion model's parameters. Road network in all 88 super neighborhoods in Houston was used to characterize the vulnerability of road networks. For the percolation analysis, the road network in the entire Houston and road network in central Houston was studied.

5.2. Characterization of Vulnerability of Road Networks to Random and Non-random Disruptions

5.2.1. Introduction

This paper examines road networks' vulnerability to two types of disruptions by modeling the percolation dynamics in road networks under different disruption scenarios. The objective of this paper is threefold: (1) to examine if the theoretical network robustness measure proposed in the

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[1] Chapter 5 is reprinted with permission from two journal papers: (1) "Characterization of Vulnerability of Road Networks to Random and Nonrandom Disruptions Using Network Percolation Approach" by Abdulla, B., & Birgisson, B. (2021). *Journal of Computing in Civil Engineering, 35(1), 04020054; (2)* "Characterization of vulnerability of road networks to fluvial flooding using SIS network diffusion model." By Abdulla, B., Kiaghadi, A., Rifai, H. S., & Birgisson, B. (2020a). Journal of Infrastructure Preservation and Resilience, 1(1), 6. https://doi.org/10.1186/s43065-020-00004-z

literature is applicable for measuring the integrity of road networks during disruptions; (2) to unveil the impacts of network size on the overall vulnerability of road networks; (3) to compare the performance profile of road networks to random and non-random types of disruptions. To that end, this study first modeled the road system in a community as a planar graph. Then, the percolation dynamic in the road network during the flood is captured by assigning different removal probabilities to nodes in the road network according to Bayesian rules that take floodplain types, node-elevation, and street-grade as inputs. In the end, an overall road network robustness measure and its temporal changes were obtained and for random and non-random scenarios, using road networks of different sizes. The results were compared in order to characterize the vulnerability of road networks under different scenarios. The proposed method was applied to the road network in central Houston during Hurricane Harvey. The results show that: (1) The theoretical network robustness measure is applicable to assess the road network robustness. (2) Compared to the random percolation model, the probability (Bayesian-rule) based percolation could lead to a greater decrease in the network robustness. (3)The percolation profiles of the road networks with different sizes are not significantly different. This study's findings could inform the stakeholders' resilience-enhancing decisions and serve as a foundation for future vulnerability-related research.

Transportation systems are of fundamental importance to the normal functioning of societies in developed and developing countries alike. A system is a set of interacting components with well-defined forms and well-defined functions (De Weck, Roos, & Magee, 2011). In order for a system to be able to deliver its intended functionality, all system components have to be present and be able to deliver their designated roles, which is a process that requires delicate interactions among systems components. A transportation network is to an urban area as the circulatory system is to a human body. The circulatory system in the human body transports oxygen and nutrients to numerous cells to ensure various organs' health. The transportation system transfers people, goods and services to ensure the economy's health between all the different parts of a city (Galadari, 2008). In the meantime, an urban transportation system is characterized by numerous complex and nonlinear interdependencies among or between its internal and external components (Sussman, 2000), which renders the delicate functional mechanism of the urban transportation systems vulnerable to a wide range of disruptions. It is essential to characterize the vulnerability of urban critical infrastructure systems in the face of various disruptions and devise strategies accordingly to improve their resilience. This is important because disruptions to the system are becoming increasingly costly and frequent due to three major reasons. First, our modern critical infrastructure systems are becoming increasingly interdependent due to the rise of information and telecommunication technology, so they should no longer be treated as isolated objects in designing and modeling. Breakdown of failure in an independent system could cause a chain reaction, which could severely cripple the transportation systems. Second, as urban areas around the globe continue to grow, the stress posed by the influx of population to critical infrastructure systems in the cities cannot be ignored. Finally, the change in the climate, possible terrorist attacks, and other crisis events have increased in frequency and unpredictability. All of these lead to the conclusion that since disruptions to transportation systems are becoming increasingly frequent and unpredictable, it is important to understand the transportation systems' performance profiles in a wide range of disastrous scenarios.

As an integral part of transportation systems, during disastrous events, the road system functions as a life-line system for rescuing people and assets and plays a vital role in repairing and restoring other infrastructure systems when they are disrupted. However, road networks are vulnerable to natural and human-made disasters, which could undermine their vital functionality. To cope with disruptions efficiently and take active preventive measures, it is critical to understand the mechanisms with which the disruptions unfold in the transportation network. Due to road systems' planar nature, they tend to lend themselves readily to being represented as graphs. Graph theory reduces a road network to a mathematical matrix, where the vertices (nodes) represent road intersections, and the edges are the road sections between these nodes, which could facilitate the accessibility and connectivity analysis within the road network using available graph-theoretic measures. However, the topology of most of the critical infrastructure networks is intrinsically dynamic and evolving over time and especially so during disastrous events. Therefore, many network topological and centrality measures devised to measure the static features of a graph could be of limited use for modeling the change in the network. Callaway et al. (2000) introduced a generalized concept of percolation. Percolation is a term used to describe a continuous phase transition in physics, and it is described with low-dimensional lattices. There are two types of percolation: site percolation and bond percolation (Stauffer & Aharony, 2014). The existence of a particular site or a bond between the sites is modeled with probability p, when $p=1$, it means all of the sites (or bonds) are present or functional, and when $p=0$, it means none of the sites or bonds are functional or present (Stauffer & Aharony, 2014). In networks, these two percolation types correspond to the node and edge percolation (Newman, 2010). Therefore, the dynamic changes in the transportation network's topology during a certain disruptive event could be captured by a corresponding set of probabilities for the nodes in the network. Since most infrastructure networks, including transportation networks, are spatially embedded (Bashan et al., 2013) and level of exposure by individual nodes to different types of disruptions could be different, which leads to different failure probabilities for nodes in the network. When this heterogeneity among nodes is considered, a simulation-based framework could be used to capture the dynamic propagation of the impacts of disruptions in road networks, which enables characterization of the performance profile of the transportation network under the impacts of various types of disruptions. The remaining sections of this paper are presented in the below order. First, a review of the literature on the concept of transportation resilience, graph theory's application in modeling transportation vulnerability and road network disruption, was presented. Second, the overall methodological framework used in this paper is presented constructively. A detailed description of the simulation process of a certain type of non-random disruption due to fluvial flooding was provided. Then this method is used to estimate the topological performance profiles of road networks, which is measured with a network robustness measure based on the size of the giant connected component. In the end, the results of the two types of simulations and the findings and implications based on these results are presented.

5.2.2. Literature Review

In recent years, the topic of resilience or vulnerability of transportation systems has been attracting growing attention from researchers around the world. Many definitions of resilience exist in the literature (Serulle, 2015) and one definition of resilience is provided by Heaslip et al. (2009) as "the ability of the system to maintain its demonstrated level of service or to restore itself to that level of service in a specified time frame." Murray-Tuite (2006) summarized the properties of resilience found in the literature with ten indicators: diversity, efficiency, autonomous components, redundancy, strength, adaptability, collaboration, mobility, safety, and the ability to recover quickly. Mohammad et al. (2006) have also proposed different parameters for evaluating network resilience, which includes density (e.g., number of nodes), mobility (e.g., speed), channel (e.g., capacity), node resources, network traffic, and derived properties (e.g., connectivity, delay).

Battelle (2007a), however, related the concept of resilience to redundancy. According to Battelle, redundancy depends on excess capacity, inter-modality, vulnerabilities (e.g., bottlenecks in the system), stochastic behavior of the network's users, and the effects of network management techniques. Based on a review of available works, four major types of methods are used to evaluate transportation resilience in the literature: probabilistic methods, fuzzy inference systems methods, analytical methods, and graph (network) theory approach (Tamvakis & Xenidis, 2013). Below is a more detailed introduction of these five methods: (1) ***The probabilistic methods*** try to model the system's performance during disruptive events using a probabilistic performance function and assumes that the level of resilience is the expected value of the total loss due to the disruptive events. The paper by Decò et al. (2013) is an example of an application of this approach. To a large extent, this approach only considers single dimensions (technical dimensions, especially) of the resilience due to the methodology's limitation. (2) ***Analytical methods*** attempt to quantitatively measure resilience by dividing the concept into different dimensions, such as technical, organizational, social and economic (Mayunga, 2007). This has been done by analyzing resilience-related system properties like robustness, redundancy, rapidity, and resourcefulness in order to achieve the resilience objective (Bruneau et al., 2003). Except being relatively qualitative, this method has the disadvantage of not being able to integrate the organizational and social aspects with the economic and technical ones in terms of both data quality and availability, and modeling requirements, as can be seen in the study conducted by (Chang & Shinozuka, 2004); (3) ***The fuzzy inference*** method tries to overcome the shortcomings of the previous two methods by introducing two main concepts: 1)The resilience cycle, which represents a system condition flow under a disruptive event in four phases, namely normalcy, breakdown, self-annealing, and recovery; 2) The system performance hierarchy, a structure that defines and ranks performance levels according to the hierarchy schema introduced by Maslow in his theory for the hierarchy of human needs (Freckleton, Heaslip, Louisell, & Collura, 2012; Urena Serulle, 2010). Although the fuzzy inference method has its own advantages in terms of treating data of different types (qualitative and quantitative) and aggregation of different dimensions, a complete fuzzy inference system (FIS) should include a great number of fuzzy rules, which is dependent on the number of the variables; the more analytic the insight on the system is, in terms of describing its performance levels through several variables, the more complicated and computationally unaffordable the FIS becomes (Tamvakis & Xenidis, 2013). (4) ***Graph theory*** is an approach that has been used to assess the resilience of a variety of real-life networks. A graph's resilience concerning property measures how much one has to change the graph to destroy the specific property (Sudakov & Vu, 2008). With the use of graph theory, researchers have tried to analyze networks' resilience by performing statistical studies of different topological measures within the structure of the graphs. Ip and Wang (2011) have claimed that if the transportation network is assumed to be an undirected graph with cities as nodes and the edges as traffic rode, the resilience of a city node could be measured by the weighted average number of reliable, independent passageways between the city and all other cities. The network resilience could be measured by the weighted sum of the resilience of all nodes. Pant (2012) has proposed a novel approach to evaluate the resilience of transportation networks by looking into some major widely-accepted performance measures of the transportation network, such as robustness and redundancy, to evaluate the resilience of a test network commonly used in literature (1984). Leu et al. (2010) measured the physical layer of resilience in a transportation system. They represent the transportation network as an undirected graph. Centrality measures for nodes were calculated, such as degree, betweenness, and clustering. Çetinkaya et al. (2015) have proposed a method which is based on graph theory to analyze the resilience of transportation and communication networks. In a study by King et al. (2016), the resilience of the Toronto public transit network was analyzed using graph theory, coupled with simulations of the behavior of the transit network and its users.

Levenberg et al. (2017) proposed a framework for assessing the resilience of networked infrastructure considering the temporal changes in the condition. Applegate and Tien (2019) proposed a Bayesian-Network (BN) based framework to assess interdependent infrastructure systems' resilience. They used the condition of infrastructure components to estimate corresponding failure probabilities. El-Anwar et al. (2016) proposed an optimization scheme for post-disaster reconstruction plans for transportation networks based on mixed-integer linear programming (MILP). Nourzad and Pradhan (2016) used a multivariate approach that considers both structure and dynamic attributes of the road network to evaluate the alternatives in the face of disruptions. Dong et al. (2020) proposed a network-of-networks (NoN) framework to model the impacts of probabilistic cascading failures on interdependent infrastructure systems. The framework was demonstrated in the contest of co-located road-sewer networks. Abdulla et al. (Abdulla, Kiaghadi, Rifai, & Birgisson, 2020b) used the SIS network diffusion model to capture the propagation of fluvial flooding impacts in the road network by considering the flood depth. Xu et al. (2018) proposed a graph-based approach to evaluate the redundancy in the road networks from both travel alternative diversity and network spare capacity perspectives. Wang et al. (2020) examined the spatiotemporal patterns in transportation network resilience in the face of extreme weather events using end to end deep learning framework. Xu et al. 2017 (2017) proposed an optimization approach used to estimate the lower and upper bounds of a transportation network vulnerability when multiple link combinations are simultaneously removed from the network. The method was demonstrated in a small-sized test network. Zhou et al. (2019) proposed a mathematical framework to assess the post-earthquake connectivity of road networks both at global and local levels. In their study, the author used the percolation theory to model the impacts of both random and localized disruptions in the road networks. Dunn and Wilkinson (2016) used a graph-based approach to compare adaptive and fixed resilience strategies and concluded that an adaptive reconfiguration strategy performs better than a fixed re-routing solution. Other examples that used graph theory to model the transportation system vulnerability include (Ganin et al., 2017; Shang, Han, Ochieng, & Angeloudis, 2017; Shiyan, Zhenfu, ZHONG, & Daqing, 2019). Some studies examined transportation networks' resilience, considering the interdependency with other sectors (Yang, Ng, Zhou, Xu, & Li, 2019). Some other studies proposed new measures for the resilience or reliability of transportation networks (Gu, Fu, Liu, Xu, & Chen, 2019; Z. Xu, Ramirez-Marquez, Liu, & Xiahou, 2020). While all of these works are valuable contributions to the transportation resilience literature, they proposed a new framework or a new measure for the transportation network vulnerability and tested the methodologies in a test network. It is believed that a lack of studies examine actual real-life transportation networks' performance profile under different disruption scenarios and characterize their resilience. Comparatively, in theoretical graph theory, there have been many advances in terms of dynamic network modeling and network resilience. An example is given by Callaway et al. (2000), in which they use the concept of node failure and introduce a generalized concept of percolation, through which resilience is calculated for any type of graph based on the size of the giant connected component after the arbitrary failure of a node or set of nodes. Another example is a work by Gao et al. (2016). They exhibit that many large-scale networked systems share a similar statistical characteristic, power-law distribution of node degree, which gives them increased tolerance to random failures of and very low tolerance to targeted attacks on highly connected nodes. There has been growing interest in the infrastructure resilience community for applying or validating the findings from the theoretical graph theory domain in the context of real-life networks (G. Dong et al., 2013). A survey of transportation vulnerability research is conducted while focusing on methods that used graph theory to assess the transportation system's resilience. Graph theory-based approaches have their intrinsic advantage of achieving the necessary level of abstraction and granularity at the same time when studying the transportation network topography. Most of the available graph-based approaches either use static graph measures to assess the static topographical network vulnerability or focus on transportation vulnerability under a single disruption event. It is also noted that there is abundant literature on theoretical resilience or vulnerability measures, which is demonstrated mostly in test (theoretical) networks while examination of the vulnerability of actual transportation network under various disruptions left relatively un-researched. Very few studies have examined the vulnerability of transportation systems under different broad types of disruptions or within the context of its other dependent sectors by considering the possible interdependence. Bešinović (2020) stated that an increased number of disruptions from a wide spectrum of sources could be expected to interrupt the normal functionality of transportations systems in the future. Therefore it is critical to categorize the disruptions and characterize their impacts on transportation systems. This paper aims at narrowing the gaps in existing studies in the following aspects. First, this study examined the suitability of a network connectivity metric in the literature for assessing the robustness in road networks. Second, more importantly, instead of using specific node centrality measures to identify "vulnerable" areas in the network to random disruptions, this study considers the compromise of the road network topology due to two types of disruptions as a dynamic process. Third, the performance profile of the road network is compared under random and flood-induced non-random scenarios. The incorporation of flood plain types reflected the interdependency between flood control infrastructure and road networks into the percolation analysis.

5.2.3. Methodology

The main steps in the methodology used in this paper are as follows. After modeling road networks as planar primal graphs, the propagation of the disruption during a non-random disruption (fluvial flooding) is modeled using Bayes-rules. Then, performance profiles of the road network under random and non-random scenarios were examined. Network vulnerability patterns under different scenarios and in networks of various sizes are analyzed and compared, which leads to the characterization of the vulnerability of road networks under given types of disruptions.

Modeling the Road Network

In this study, the road network is modeled as a directed primal graph, where nodes in the network represent intersections in the roadway systems, while directed edges represent actual travelable road sections. Road network topology and network-related information like node elevations, street grades are obtained from OpenStreetMap using the OSMnx, a Python package developed by Boeing (2017). It is also worth mentioning that, in order to assess the connectivity of road network during disruption for the general users, this study chose to focus on the roads which could be used for driving passenger vehicles on, as opposed to more detailed road networks with bikeways, walkways and service ways included, which also are available through OSMnx package.

Modeling the Network Percolation Dynamics

The closure sequences of roads due to fluvial flooding in an area are primarily affected by factors like the types of floodplain and relative elevation of the nodes in the road network. Therefore, this paper uses this information as the proxy for the likelihood of a node being an initiation point for the flood, flood-prone areas (located in a 100-year flood plain) with lower elevation having a higher chance of being removed first. It is also noteworthy that, to a certain extent, fluvial flood in the road network also spreads in a way that an infectious disease does, as flooding of an adjacent node could lead to the flooding of certain road nodes. Therefore, this study estimates the prior probability of nodes being flooded based on the adjacent nodes' flooding status and grade level between nodes, which be used to update the initial flood plain and the elevation-based probability of nodes being removed. Since numerous factors could cause the road network to be flooded, there is uncertainty about what areas get flooded first (i.e., places on the road network where the flooding originates). In order to identify where the flood initiates, a fuzzy inference method is used. Two groups of variables (See Table 8 for variables and their possible values) are introduced to estimate the initial removal probability (See Table 9 for an example). The rationale is if a certain node in the road network is located in a highly flood-prone area and its elevation is low, there is a high chance for it being removed from the road network first. The elevation data for the nodes in the road network is retrieved using Google API on OSMnx.

Table 8 Variables and possible values

Variables	Possible Values		
	Low Probability	Medium Probability	High Probability
Flood Plain (Flood Control Infrastructure) Variable	Non-floodplain	500-year flood plain	100-year flood plain
Elevation Variable	Fourth quartile	Third quartile	First & Second Quartile

Table 9 An example of fuzzy rule for initial probability for node removal

IF	Flood Plain Type	AND	Elevation	THEN	Probability P(A)
If	100 year	And	First & Second quartile	Then	Very high
	100 year		Third quartile		High
	100 year		Fourth quartile		Medium

As to the estimation of the prior probability, which intends to models the possible propagation trends (directions) for the flood in the road network, two variables are used as input for the fuzzy inference model and they are the status of the adjacent nodes and the type of grade between the adjacent node and the node in question. Two possible values are considered for the first variable: (1) there is at least one adjacent node that has already been flooded;(2) there is no adjacent node that has already been flooded. Similarly, binary values (positive or negative) are considered to the street-grade variable. For example, if the slope for the road section which is connecting one of the flooded adjacent nodes and the grade of the road section is negative, then there is a high chance for that node to be removed next (See Table 10 for an example). The data for grade types between every two adjacent nodes in the road network is retrieved using Google API using the OSMnx tool in Python. Using Bayesian rule in the below equation on this page, the posterior probability ($P(A|B)$) of a particular node being removed is obtained by updating the initial probability after each removal phase. Further details of this methodology could be seen in another work by the author (Abdulla et al., 2019).

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$Where$: $P(A \cap B)$: $the\ initial\ probability$; $P(B)$: $the\ prior\ probability$

Table 10 Example of fuzzy rule for prior probability for node removal

IF	An Adjacent Node	AND	Street Grade	THEN	P(B)
If	Flooded	And	Negative	Then	High
	Not flooded		Positive		Low

Assessing the Change in Connectivity

This study uses a network connectivity measure proposed by Schneider et al. (2011) and recently used by other researchers to assess transportation networks' vulnerability (S. Dong et al., 2020). It can be characterized by integrating the size of the largest connected component throughout the entire percolation process. The robustness measure R is calculated using the equation:

$$R = \frac{1}{N}\sum_{Q=1}^{N} s(Q)$$

Where: N: the total number of the nodes in the network; Q: number of removed nodes from the network; $s(Q)$: the fraction of nodes in the largest connected component after removing Q number of nodes. The normalization of the result by $1/N$ could facilitate comparison across the networks of different sizes. The theoretical values of R range from $1/N$ (star graph) to 0.5 (fully connected network).

5.2.4. Comparison and Characterization

Many studies have proposed using the giant connected components of the network as the proxy for the robustness of the various networks, and this measure is an indeed useful measure of integrity for some networks, like the internet and power supply networks, as the largest connected components indicate how functional the network is after a disruption and the remaining portion of the network (nodes and links which are not part of the giant connected components) is of relatively little significance to the overall functionality of the reaming network (Buldyrev, Parshani, Paul, Stanley, & Havlin, 2010). The giant-component-based measure of robustness could also be of special interest to road networks during the disruptions since the larger the connected components of a road network on average, the better the overall connectivity in the road network. However, little or no investigation had been conducted to check the validity of this theoretical measure as a proxy for road network robustness, because considering only the largest component might not be a true measure of the connectivity if there are other sub-graphs in the network whose sizes are large enough and comparable to the "giant component." This is because road networks are not as coupled and nested as some other networks. The remaining portion (non-giant components) of the network could be independently useful as they were before the disruptive event, which motivated this paper to investigate the size of those portion of the road networks which are not considered as giant components (GC) and therefore not be considered as part of the road network robustness analysis. As can be seen from the histogram (Figure 33) of the sizes of sub-networks formed by a disruptive event of different magnitudes, there is one connected giant component in the road network when the level of disruption is lower (percentage of the nodes removed due to the interruption is lower, at and below 25%). However, this is no longer the case once the level of disruption exceeds certain thresholds (about 30% of the nodes being removed), as could be seen from below Figure 34. As could be observed from the histogram, networks that are large enough and with comparable sizes with the giant component started to emerge as the level of disruption escalates. This could be observed from the visualization of the networks when a different fraction of total nodes removed from the network. The corresponding original intact network is shown in Figure 35 (A).

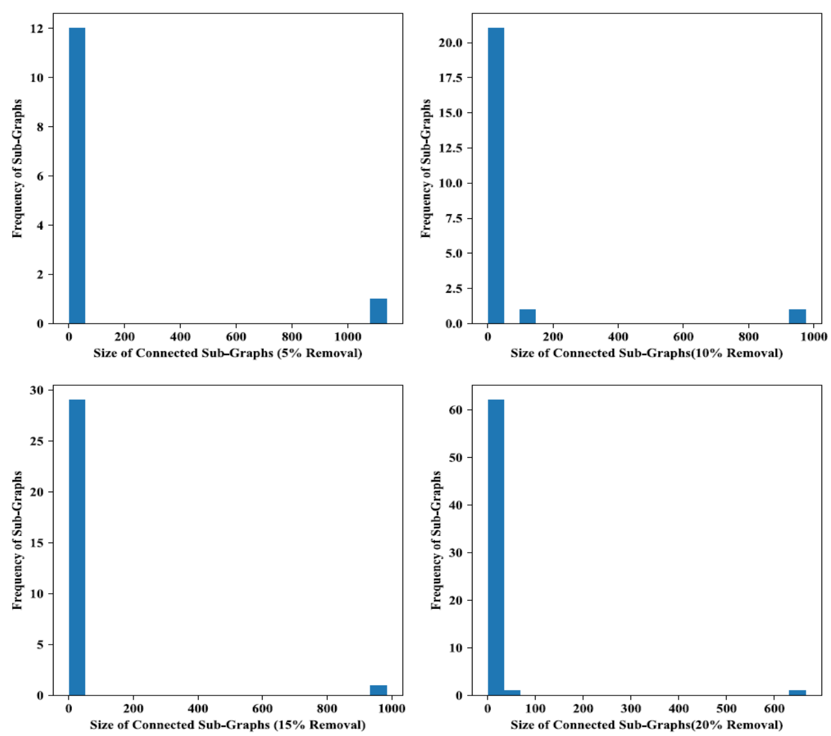


Figure 33 Histogram of connected components under lower levels of disruptions

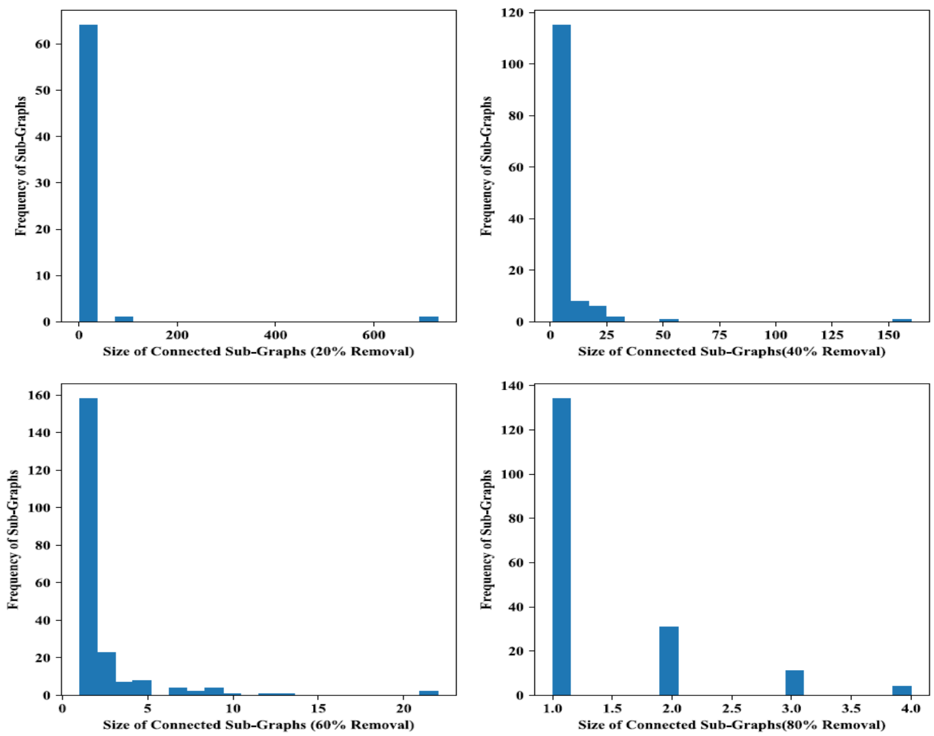


Figure 34 Histogram of connected components under higher levels of disruptions

It is worth noting that only sub-graphs that have two or more nodes are shown in the graph. Below is a detailed analysis of the percolation process in a road network (Figure 35) under a hypothetical random disruptive event. The road network in Figure 35 has R=0.24368. As could be seen from Figure 35 (B), the size of the giant component of the network decreases with an increasing rate as the removed number of nodes from the network increases until about 40% of the nodes are removed from the network. After about half of the nodes are removed from the network, it becomes fragmented and there is no significantly large enough "giant component" in the network. Similar-to-above analysis (the profile of the network's giant components under different levels of disruptions) has been conducted with road networks with different sizes (about 0.5, 1.5, 2.5, and 4 times larger than the original network). It turned out that, due to the fractal characteristics of the road network (Kalapala, Sanwalani, Clauset, & Moore, 2006), the R-value for the road network of different sizes tends to be approximately the same (See Table 11).

Table 11 Robustness of network with different sizes

Network Size (number of nodes)	R-Value under Random Percolation
635	0.257
1073	0.244
1456	0.243
2689	0.241
4231	0.245

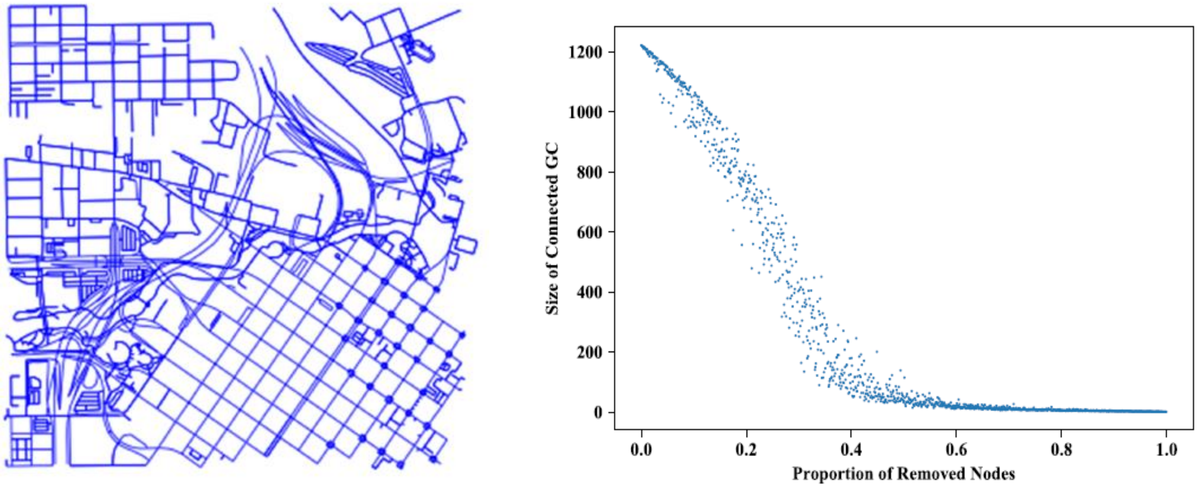
A statistical significance analysis (a two-tailed t-test) for the differences of the R values of networks with different sizes shows that R values do not change significantly as network sizes vary (a very large t value was observed for the mean-subtracted R values for networks of different sizes). It is also observed that the histogram of the sizes of the sub-networks also exhibits a similar pattern as the network in Figure 35 does. This finding has an important implication for the robustness analysis of road networks with different sizes, as it enables the cross-comparison between the robustness of the networks with different sizes, which is not the case with many other centrality measures like global efficiency and average distance (Zanin, Sun, & Wandelt, 2018).

5.2.5. Case Study and Results

The proposed methodology has been applied to the road network in central Houston (Figure 35), which is one of the areas that suffered from heavy road closure during the hurricane Harvey and the impact of the fluvial flooding is the primary cause of the road closure, unlike Energy corridor region which also suffered from heavy road closure, but the impact of the reservoir release is significant. The areas influenced by the fluvial flooding are chosen because the proposed non-random percolation scheme is intended to model the road closure due to the fluvial flooding, as the removal scheme is mainly based on the relative elevation of the nodes within the road network. Networks (centering around a point whose geographic coordinate is latitude=29.764708, longitude=-95.366896) of varying sizes have been retrieved and analyzed. The network which has been predominantly discussed within this paper is a network (depicted in Figure 35) of size 1073 nodes, 2558 edges, and an average node degree of 2.384. Figure 36 shows the topological integrity of the road network under various disruption levels. Nodes in the network have heterogenic elevations levels, as can be seen from Figure 37 (maximum elevation is about 17 meters while the minimum is about 0 meters). There are a few nodes with relatively low elevation, and despite the large variance in the elevations, only about 20% of the nodes have elevations less than about 10m. Due to the lack of accurate GIS data, approximations were made for the boundaries of the flood plains. The simulated node removal is compared with the observed temporal closure of the road in this neighborhood, and the visual comparison of the results showed that the proposed method is capable of capturing the approximate order to node failure in the road network. This simulated result corresponds to the road closure in this neighborhood, which started on Aug 25, 2017, and peaked (about 60% of the roads closed) on Aug 29, 2017.

Scenario One: Road Network Vulnerability Under Random Failure

This section presents the result of the simulated performance of a road network under hypothetical random failures. Even though most of the failures and disruptions in the road networks tend to be non-random in nature, there indeed are some disruptions whose locations, magnitude or occurrence probability are challenging to estimate. For example, road network failure due to earthquakes, flash floods, snowstorms, an explosion of sewage pipelines, vehicular accidents, and even construction/maintenance could be considered random failures.



(a) (b)

Figure 35 (a) Original road network; (b) Performance profile of road network at different levels of random disruptions

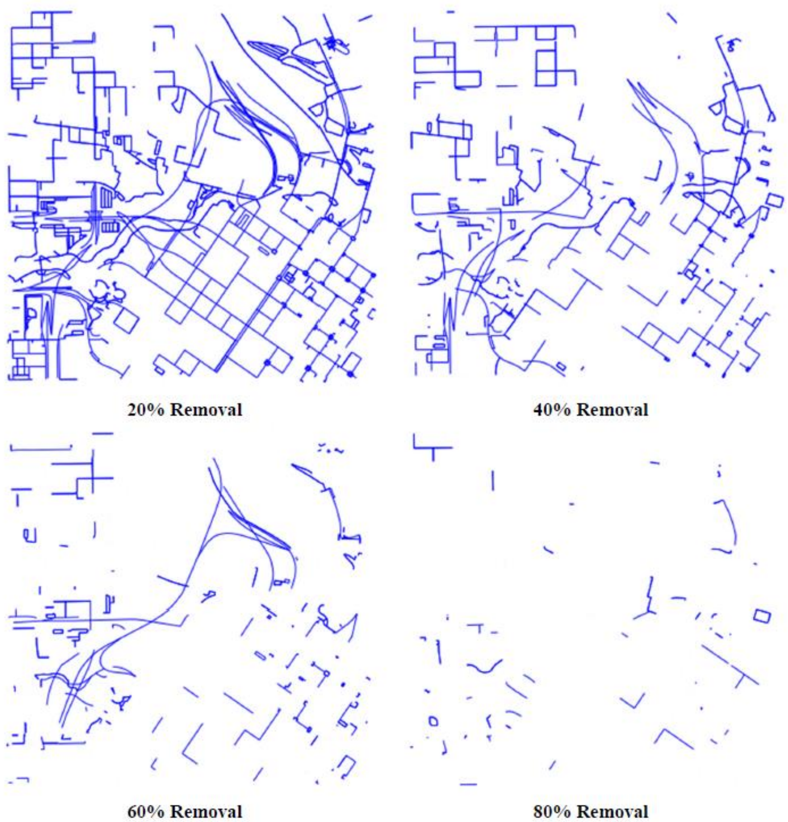


Figure 36 Road networks under different levels of disruptions

Analyzing the road network's robustness profile under random percolation could be a good benchmark for other non-random percolations, which internal and external factors could cause. Percolation profiles of the road network with different sizes (about 0.5, 1,2, and 4 times larger than the original network) have been obtained by simulating the road network's random removal. In order to reduce the possible impact of sampling, at each step (every increment in the number of removed nodes), 5 simulations were conducted, and the average size of the giant components was taken. The results of the simulation are presented in Figure 38. There is a sharp decrease in the network's giant component when the nodes' removal percentage is beneath about 40%. The giant component decrease at a slower rate when the removal percentage is between 40%-60%. After losing about 60% of the nodes, the network becomes fragmented, and no distinct large component exists in the network. The network has an overall R-value of about 0.245. In order to check the impact of the scale on the percolation profile, similar simulations were conducted on the road networks of different sizes. Networks with differing sizes also exhibit a similar percolation profile under random disruptions. Their corresponding R values are given in Table 11, and there are no significant differences among the overall robustness index of differing sized networks under random percolation.

Scenario Two: Road Network Vulnerability Under Fluvial Flooding

Using the Baye-rules-based percolation scheme proposed in the paper's methodology section, road network percolation is simulated for the same network (as could be seen from Figure 39). It turned out that the pattern for the road network percolation (the magnitude of reduction in the size of the giant component in the road network, the speed of decline as the node-removal proceeds) is approximately the same as those in the random percolation. However, one significant difference seems to the less "bumpy" and more "smooth" shape of the fitted curve for the targeted percolation.

Another point worthy to note is that under this targeted node-removal scheme, the network has an overall R-value of about 0.235, which amounts to about 5% less robustness index than the random node-removal scheme. This corroborates the common belief among transportation researchers that road networks are more resilient to random failures than targeted failure modes. A closer comparison of the two curves (see Figure 39 and Figure 40) could show that: (1) In the initial phases of the percolation, when removal percentage is between 0 and 15%, the impact of the two types of node-removal have on the network robustness (giant component) is roughly the same; (2) when the node-removal is between 15%-50%, the random percolation tend to lead to larger giant component than the probability-based percolation; (3) Once more than half of the nodes removed from the network, there is slightly higher network robustness under the probability-based percolation scheme, as the curve tends to be always above the curve representing the random percolation. The simulation results on the different sized networks were also compared (see Figure 41 as an example). Due to the exponential increase in the simulation time for the larger networks, in order to save time, fewer observations were collected (less simulation at each node-removal iteration, and only up to 60% node-removal). While there seem to be some variations in the curves' exact shapes, the pattern with which these two curves evolve as node removal continues remains the same. They start with about the same rate and exhibit a similar pattern until node removal reaches about 15-20%, after which the random percolation exhibits relatively greater robustness until it comes below the curve representing the targeted failure mode when about 40% of the nodes are removed from the network.

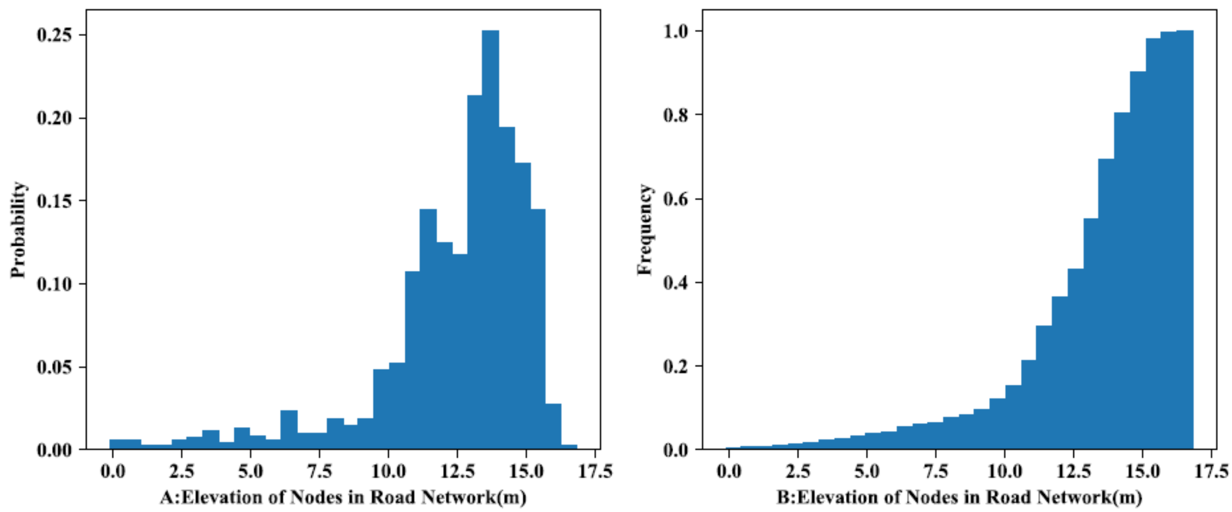


Figure 37 A: Histogram; and (B) Cumulative distribution function (CDF) of node elevation

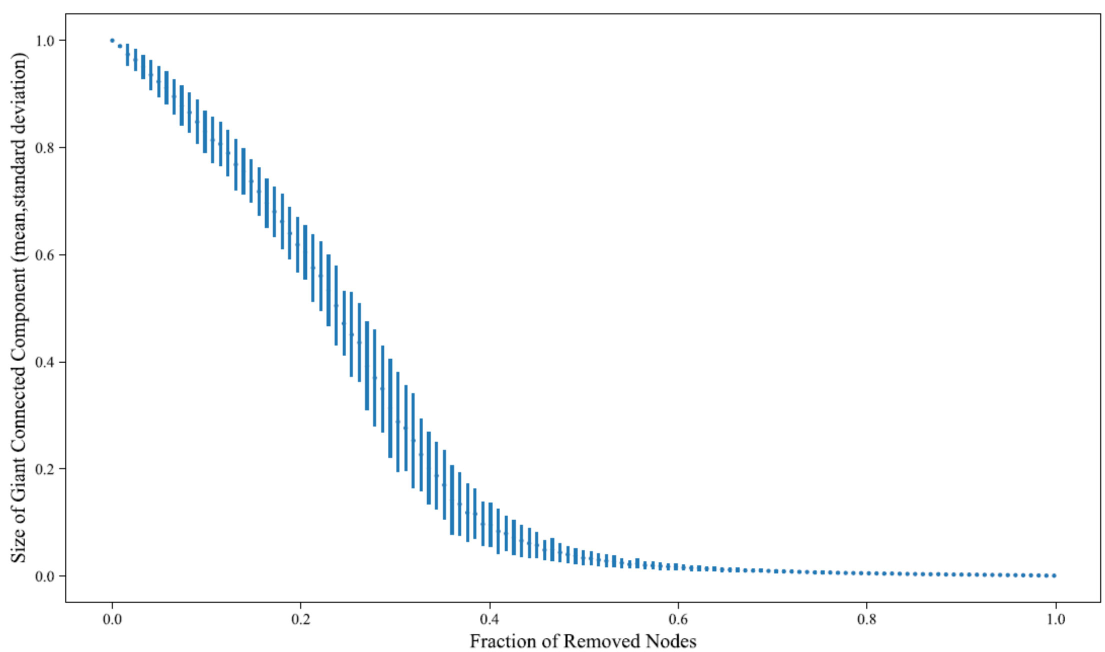


Figure 38 Percolation profile of road network under random disruption

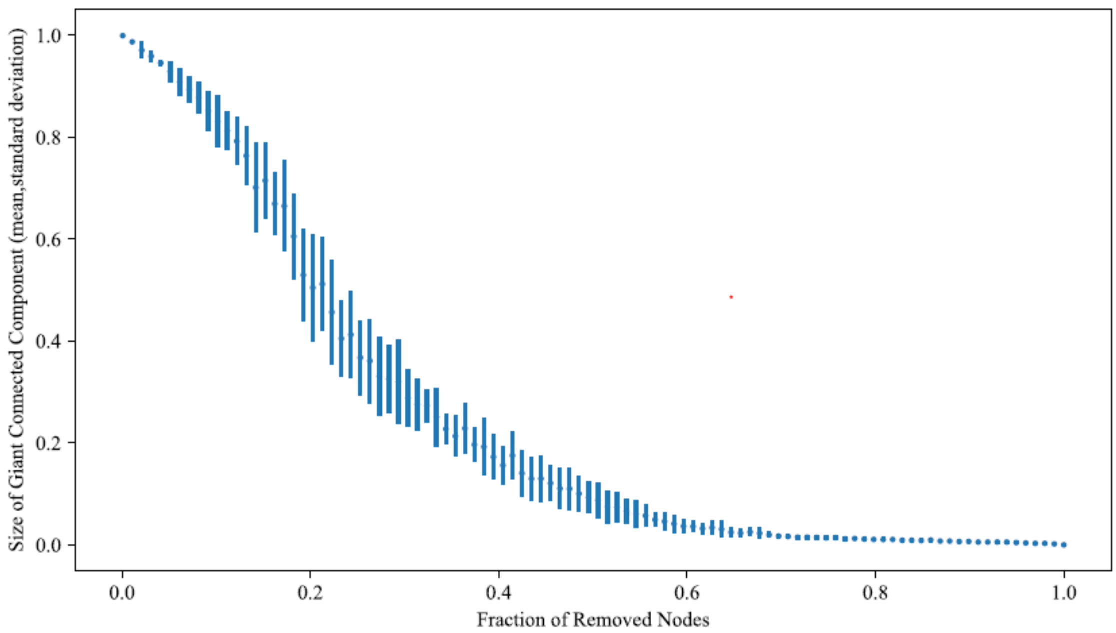


Figure 39 Percolation profile of road network under targeted disruption

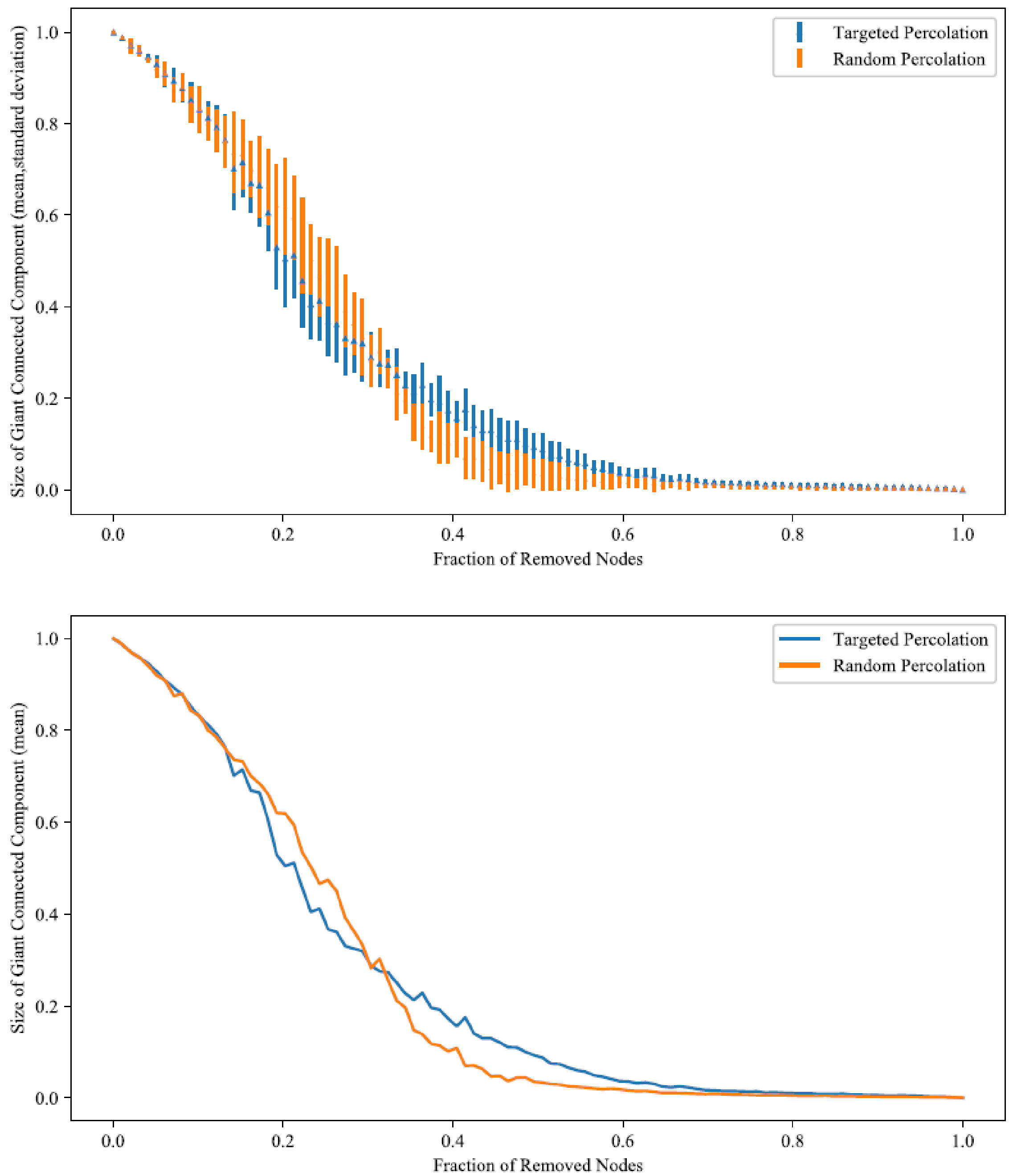


Figure 40 Comparison of the percolation under targeted and random disruption scenarios (top figure: error plots results; bottom figure: plot of mean values of GCC)

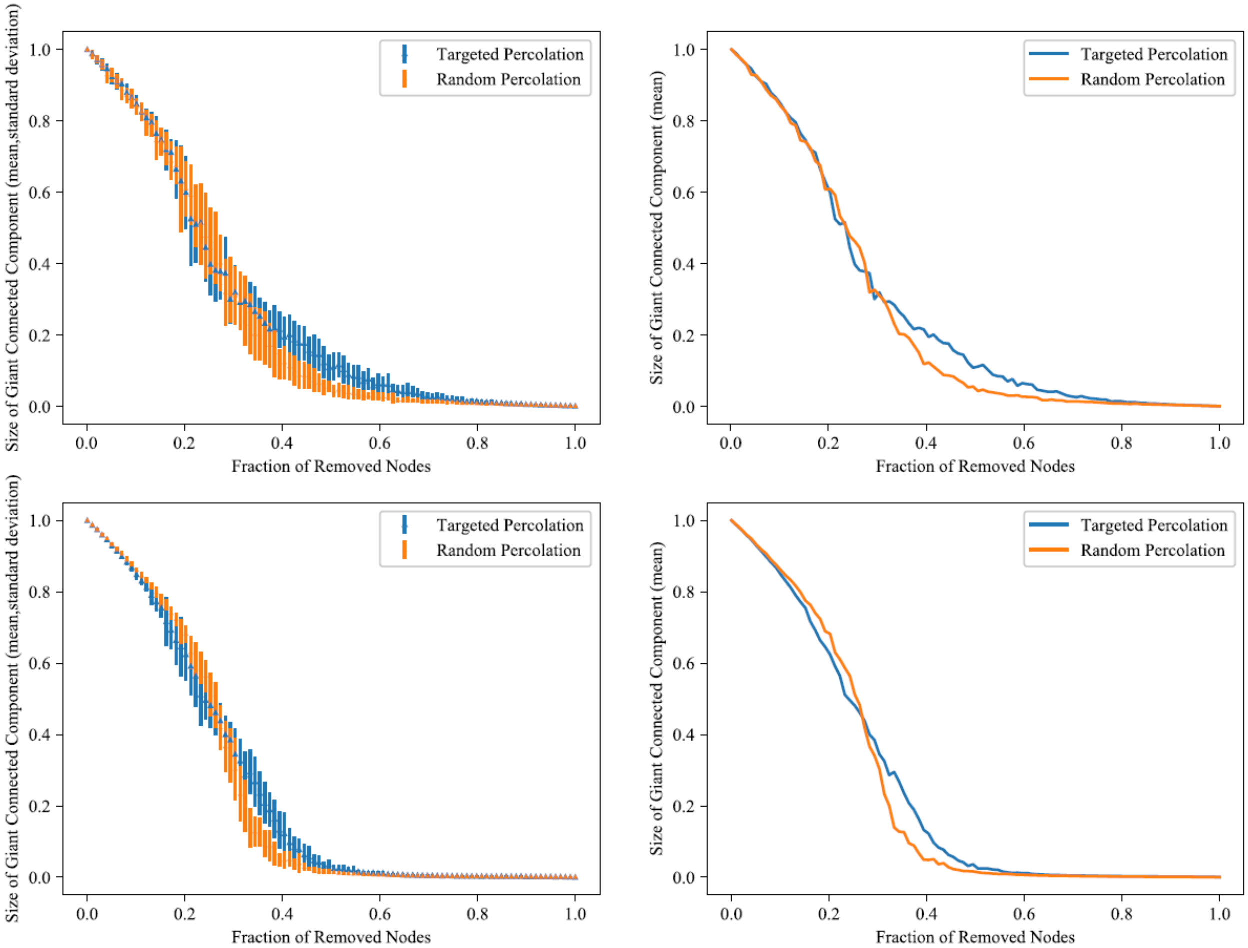


Figure 41 Comparison of percolation profiles of networks with different sizes: (upper graph) network with 622 nodes; and (lower graph) network with 4,801 nodes

5.2.6. Discussions and Conclusion

An investigation was conducted to the histogram of the sub-graphs' size created by the network percolation. The robustness measure based on the giant connected component is suitable for the road network, as there tends to be a large enough disparity between the size of the giant component of the graph and other subgraphs created by the network percolation. This is especially true for the road network percolation scenarios where the removal percentage of nodes is less than 30%, as these cases consistently show the existence of a significantly large giant component. The road network percolation under two scenarios exhibits roughly the same patterns. The giant component's size decreases at an increased rate until the removal proportion reaches about forty percent. This is true in the road networks of different sizes (from about 100 nodes to 4500 nodes). However, there are two important observations: (1) under the probability-based percolation scenario, when the node-removal percentage is between about 20% and 50%, the size of the giant components tend to be smaller than that of the random percolation; (2) under the non-random scenario, when the removal portion of the nodes exceeds 40%, the sizes of the giant components are slightly larger than those of the random percolation. If aggregated over the entire period of percolation, the robustness values under the non-random percolation scenario are slightly less than that of the random scenario. This has two important implications. First, contrary to the common belief, disruptions due to fluvial flooding tend to occur in clusters, and its impact on the overall connectivity of the road network (measured by the R-value used in this study) tends to be "contagious." Second, when the level of disruptions is not too high (below about 15%), the percolation patterns exhibited by the road network under two types of scenarios are the same, which could mean the impact of the road closures due to fluvial flooding (to a certain extent) could be treated as one with random failure.

This study first examined the suitability of a theoretical network robustness measure in the context of road networks by examining the histogram of the sizes of the sub-networks created by random disruptions. It is observed that there is a distinct heterogeneity in the size of the sub-graphs, indicating that the giant connected component (GCC) based robustness measure is suitable for use in road networks. This study also compared the robustness of the road network with different sizes and found that there are no significant differences among the normalized robustness measures in road networks with different sizes, which enables cross-comparison of the robustness measure of networks with varying sizes. Last but not least, this study used a probability-based simulation framework to model the percolation process in the road networks during fluvial flooding.

Percolation profiles and the overall vulnerability of the road networks under random and non-random (fluvial flooding) failures were compared, and some important observations were made. Another important novelty of this study is its utilization of the publicly available big data (like retrieving the topological network data on OpenStreetMaps, node elevation, and street grade data on Google Maps using Google API) about the road network. Findings and observations made in this study could inform the resilience-enhancing decisions pertaining to road networks under different disruption scenarios. For example, under both types of disruptions, the size of the GCC is reduced in a nonlinear manner, at a noticeably faster rate after about 20% of nodes rendered non-functional until the removal ratio reaches about 40%. As disruptions to critical infrastructure systems are expected to grow both in frequency and magnitude, there is an increasing need for efficient tools or frameworks to study critical infrastructure systems' performance profiles under a broader spectrum of disruptions. This is especially true for the transportation network. Characterizing the transportation system's resilience in the face of various stressors and warehousing corresponding response strategies are essential preconditions for active disaster management. The fact that the operation of other critical sectors (like search and rescue, emergency medical services, and food supply) are dependant on functional transportation systems makes such initiative even more important. The approach proposed in this study could be used to assess the loss in the accessibility of households or critical facilities during disruptive events. This study, together with other growing bodies of knowledge in the field, responds to the growing need in the field to assist decision-making pertaining to the resilience of critical infrastructure by effective use of increasingly available big data and improving computational power. Using a similar approach, it is also possible to compare the road networks' performance profiles under a broader range of disruptions if an appropriate methodology is available to model the percolation process in the road network under a given non-random disruption. In addition, the proposed framework could also be used to examine the topological integrity of other networked critical infrastructure systems (pipeline network, railway network, power supply network, supply chain network, telecommunication network, air traffic network) in the face of various disruptions, using appropriate percolation scheme. Many avenues of future research could either improve this study's prediction results or complement its findings. For example, this study only considered and modeled the fluvial flooding that is due to the overflow of the flood control infrastructure, while there could be multiple types of flooding that could coincide during a hurricane. More variables and parameters could be introduced to paint a more comprehensive picture of the disruptions caused by floods on the road networks. Constructing a weighted graph of road networks by taking other operation and demand characteristics (i.e., traffic demand) could facilitate a more realistic computation of the giant connected component. It is also possible to relate the depth of flooding in the road network with the travel speed to develop a more accurate model about the impact of the flooding on the traffic flow.

5.3. Characterization of Vulnerability of Road Networks to Fluvial Flooding using SIS Network Diffusion Model

5.3.1. Introduction

This study aims to characterize the vulnerability of road networks to fluvial flooding using a network diffusion-based method. Various network diffusion models have been applied widely to model the spreading of contagious diseases or capture opinion dynamics in social networks. By comparison, their application in the context of physical infrastructure networks has just started to gain some momentum, although physical infrastructure networks also exhibit diffusion-like phenomena under certain stressors. This study applies a susceptible-impacted-susceptible (SIS) diffusion model to capture the impact of flooding on road network connectivity. To that end, this paper undertook the following four steps. First, the road network was modeled as primal graphs and nodes that were flood-prone (or the origins of the fluvial flood) were identified. Second, temporal changes in the flood depth within the road network during a flooding event were obtained using a data-driven geospatial model. Third, based on the relationship between vehicle speed and flood depth on road networks, at each time step, the road network nodes were divided into two discrete categories, namely functional and closed, standing for Susceptible and Impacted in the SIS diffusion model, respectively. Then, two parameters of the SIS model, average transition probabilities between states, were estimated using the hydraulic simulation results. Fourth, the robustness of the road network under various SIS diffusion scenarios was estimated, which was used to test the statistical significance of the difference between the robustness of the road network against diffusions started from the randomly chosen nodes and nodes with different high centrality measures. The methodology was demonstrated using the road network in the Memorial super neighborhood in Houston. The results show that diffusive disruptions that start from nodes with high centrality values do not necessarily cause more significant loss to the road network's connectivity. The proposed method has important implications for applying link predictions on road networks. It casts significant insights into the mechanism by which cascading disruptions spread from flood control infrastructure to road networks and the diffusion process in the road networks.

Changes in the earth's climate, potential global warming, and unprecedented and ever-increasing urbanization, coupled with the increased interdependence among different sectors, are putting critical infrastructure systems under increasing pressure (Rodin, 2014). In the meantime, failures in critical infrastructure systems are becoming prohibitively costly, mainly due to the possible cascading failures that are initiated from one sector and subsequently cause a series of failures in other dependent sectors. Thus, the resilience of interdependent critical infrastructure (ICI) systems is one of the grand challenges facing engineers and policy-makers in the 21st century (Heller, 2002; O'Rourke, 2007; van Laere et al., 2017). Over the past two decades, the body of knowledge on ICI resilience has advanced in modeling, simulation methods, and theoretical frameworks. Despite the growing literature (Dueñas-Osorio et al., 2007; Haimes & Jiang, 2001; Reed et al., 2009) on ICI resilience, our understanding of the dynamics and mechanisms of disruptions in ICI systems that shape resilience patterns in these complex networks is somewhat limited. This lack of understanding is particularly evident in urban areas where transportation systems are frequently affected by weather-related hazards. Flooding, especially ones due to excessive and intense rainfall precipitation, has been the predominant cause of weather-related disruptions to the transportation infrastructure (Pregnolato et al., 2017). Such events could undermine the vital functionality of transportation systems, especially road networks. Many studies have shown that roads are among the major causes of deaths in cities during flooding; this is mainly due to the vehicles being driven through flooded roadways (Ashley & Ashley, 2008; Drobot et al., 2007; FitzGerald et al., 2010; Kreibich et al., 2009). Locations, such as Texas, where road mobility through cars is the primary mode of passenger transportation, are especially vulnerable to the impact of flooding (Blackburn, 2017). The advantage of having one of the largest road networks in the U.S. could become a curse when the majority of the roads are closed due to flooding and there are few other alternatives to go around the city, as was the case during Hurricane Harvey in 2017 (ASCE, 2017). In addition, during disastrous events, the road network functions as a lifeline system for rescuing people and assets and plays a vital role in repairing and restoring other infrastructure systems when they are disrupted. In order to cope with disruptions efficiently and take active precautionary measures, it is critical to understand the mechanisms and patterns with which the disruptions unfold in the transportation network. Due to the planar nature of transportation networks, they tend to lend themselves readily to being represented as graphs, and therefore graph theory-based approaches have been one of the standard tools to study the vulnerability in transportation systems (Tamvakis & Xenidis, 2013). Graph theory reduces a road network to a mathematical matrix where the vertices (nodes) represent road intersections and the edges are the road sections between these nodes (Leu et al., 2010). This type of matrix abstraction of road networks not only facilitates the accessibility and connectivity analysis but also assists in the identification of critical locations using available graph-theoretic centrality measures. However, there are two crucial challenges in network modeling of transportation networks. On the one hand, transportation networks, similar to many other critical infrastructure networks, are spatially embedded (Bashan et al., 2013) and the configurations of the environment in which network elements (nodes or edges) operate are inherently heterogeneous. This fact, when coupled with the possible spatial or temporal variance of the magnitude of the disruptive events, makes failure probabilities significantly variable from node to node. On the other hand, the topology of most critical infrastructure networks is intrinsically dynamic and evolving, especially during disruptive events. Understanding the patterns for temporal shifts in the functional topology of critical infrastructure networks during disastrous events is a crucial step in devising efficient plans to reduce their vulnerabilities. However, the almost complete absence of the time dimension in such problem definitions is a problem that can be attributed to (1) the graph theory ancestry of the field, and (2) the limited number of dynamic data sources available when the area of complex networks analysis emerged (Rossetti et al., 2018).

Flooding in urban roadways is a process that presents both of the challenges mentioned above. The flood-induced disruption to road network is realized by rendering certain components of roadway system non-functional. For example, certain road sections or intersections could suffer from high water levels and be forced to be closed. Another important disruption mechanism of floods to road network is scouring of bridges (Briaud et al., 1999; Melville & Coleman, 2000; C. Wang, Yu, & Liang, 2017), which can cause both short-term or long-term damage to road network connectivity. Relevant studies in the literature that are aimed at tackling the flood vulnerability of critical infrastructure networks could be categorized into two main types: (1) graph-theory based topological approaches that focus on topological integrity of the network; and (2) hydrological approaches that model the flood propagation process in (or around) critical infrastructure in urban areas (Singh et al., 2018). Each of these methods considers the flood vulnerability problem from different angles; consequently, each approach only reflects some parts of the whole picture. Most of the studies attempted to apply dynamic network modeling approaches focused on complete or random graphs to demonstrate their applicability in real-world network failure problems. However, transportation networks are neither random nor complete. They have a unique configuration manifested in a relatively small range of node-degrees and spatial constraints that are not observed in other types of networks. The aforementioned historic decoupling between the two types of methods could largely be attributed to the lack of granular flood data that could be input to network models. Recently, for identifying the probability of flooding in a road network, the coupling of remotely sensed data with hydrodynamic models has been used. Such an approach was used to identify the most critical and vulnerable nodes (intersections) in a transportation network. Sadler et al. (2017) combined storm surge levels associated with different return periods, provided by the Federal Emergency Management Administration (FEMA), with High-resolution Digital Elevation Models (DEMs), compiled from data collected by Light Detection and Ranging (LiDAR). The authors then compared the surge elevations with the road elevations to assess different scenarios and reported the most vulnerable roadway segments based on the frequency of flooding. In another study, Kalantari et al. (2017) developed a LiDAR-based data-driven model to quantify the risk of flooding and sediment transport at different roadway intersections in Sweden. While these efforts are essential to study the impacts of the most severe inundation scenarios, they do not provide enough information on how the system's internal components behave during a flood event. This limitation is mainly due to the use of only one snapshot of the flood rather than a time series of water depth. In contrast, other researchers have coupled the results of hydrodynamic models with remotely sensed elevation data to estimate the probability of heavy inundation during flooding events. Courty et al. (2017), Lagmay et al. (2017), and Pyatkova et al. (2019) coupled the results of MIKE FLOOD, LISFLOOD-FP, and FLO-2D GDS PRO, respectively, to LiDAR elevations and reported the risk of inundation for roads during flooding events. Though more accurate hydrodynamic models are useful tools in storm surge and flood simulation/prediction, they are costly because of lengthy computational time, expensive equipment, and the need for skilled users.

In addition, an extensive calibration of the model using observed data is required to enhance model reliability. In summary, existing methods are either focused on a single point in the duration of the disastrous event, and there is a lack of understanding about the internal mechanism of the disruptive events on road networks or are computationally or operationally too expensive.

This study aims to bridge the gaps mentioned above between these two closely related fields. Furthermore, given the improved computational powers and relatively wide availability of the data, the condition is mature enough to do a more granular and detailed temporal analysis on the road network. This study is motivated by these factors; in the study, a simple methodology was developed to have both the reliability of using field measured data directly and the advantage of using time series water depth instead of one snapshot. To be more specific, the measured high-water marks (HWMs) after a flooding event were combined with the observed pattern in water surface elevation (WSE) of nearby rivers recorded by United States Geological Survey (USGS) to create a WSE time series at the location of the HWMs. Each time series was then compared with LiDAR elevations to calculate the water depth at any given point. When it comes to analyzing the effect of flooding on network vulnerability, it is important to know how a phenomenon spreads through a network. Based on authors' interviews with stakeholders of critical infrastructure systems in Houston, after runoff conveyance infrastructure systems (bayous, channels, creeks, and stormwater systems) reach their capacity under an excessive rainfall, road networks become part of the conveyance system and play the role of moving excessive water into lower elevation areas and/or releasing water into other storm-water drainage systems. In this context, the process of spreading the floodwater around the road network could be assumed as a diffusion process, which is analogous to the spread of contagious diseases among human beings. The origin of diffusion modeling could be traced back to the spread of epidemics and mathematical modeling of epidemics predates most of the studies on networks by many years (Newman, 2010). The traditional diffusion modeling approaches avoid discussing contact networks by making use of fully mixed or mass-action approximation, in which it is assumed that every individual (node in the network) has an equal chance, per unit of time, of coming into contact with every other node (Newman, 2018). Based on the assumptions of this approach, nodes (people) mingle and meet completely at random, which is not a realistic representation of most real-world networks. This un-realistic representation is because nodes in real-world networks are spatially embedded and have a heterogeneous exposure to diffusion mechanisms (the reader is referred to Shakarian et al. (2015) for a comprehensive review of network diffusion). In summary, most of the research in the field of network vulnerability is focused on theoretical networks; fewer published research papers are focused on real-world networks. Due to their unique topological structure and configuration, road networks represent one unique type of real-world network. Understanding, characterizing, and conceptualizing these networks could bridge the gap between advancement in the field of theoretical networks and real-world networks. The proposed method facilitates the assessment of the vulnerability of the road network to flooding which contributes to the advancement of network science in the realm of real-life networks. Given that flooding and inundation of road networks frequently occur all around the globe, the findings from this research are directly applicable to other road networks and of interest to many.

5.3.2. Methodology

A summary of the methodology used in the study is presented in Figure 42. The first step was modeling the road systems as the primal graph, which is followed by a simulation of the hydraulic process in the areas where roads are located in order to obtain the granular (node-level) flood depth data. A diffusion model that is commonly used to study the spread of communicable disease, Susceptible-Impacted-Susceptible (SIS Model), is proposed to model the propagation of the flood in road networks. Parameters of the SIS model were estimated using the temporal flood depth for the road network nodes. Finally, the impact of both the number and locations of the seed nodes on the connectivity of the road networks during diffusion was evaluated.

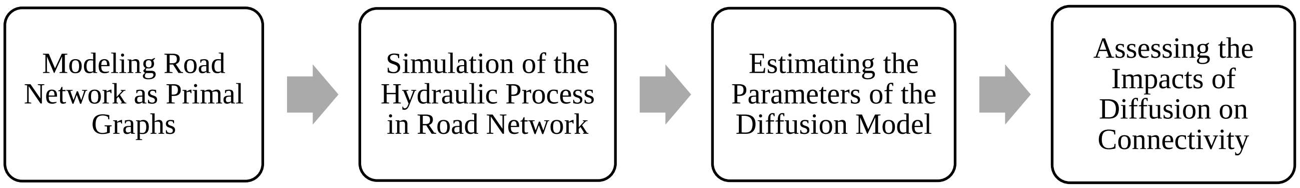


Figure 42 Main steps in research methodology

Road Network Modelling

The road network was modeled as a non-planar primal graph, where nodes represent the intersections in the road network while edges represent the actual road sections. As a proxy for flood vulnerability, the elevation of each node in the road network was also retrieved using Google Application Programming Interfaces (API). Road network topological data and other auxiliary information were obtained from OpenStreetMap using the OSMnx python package (Boeing, 2017). As the vulnerability of roads used for vehicular travel is the primary focus of this study, we chose to focus on road types used for passenger and service vehicles and didn’t include the roadways intended for biking or walking also available through OSMnx.

Simulation of the Hydraulic Process

In this study, the depth of flooding at nodes within the road network was used as a proxy for their functional status. Therefore, obtaining the granular temporal flood depth information in the road network during the case study event- Hurricane Harvey, was crucial. During Harvey, flooding in the study started at 20:00:00 on August 26, 2017. The temporal changes in the flood depth at the node location in the road network was obtained for a temporal scale of 17 days. Observations are in hourly intervals, from 12 AM, 25 August 2017 to 11 PM, 10 September 2017. This study looked into the time between 22:00:00 on August 26, 2017, and above peak period, which is 11:00:00 on August 30, 2017. The methodology applied in this study to calculate the water depth at each node of the road network is similar to what Kiaghadi et al. (2019) developed. In brief, a geospatial model was developed in ArcMap using the many existing tools, including Feature to Polygon, Intersect, Topo to Raster, Extract by Mask, Mosaic to New Raster, Resample, and Raster Calculator. Catchment shapefiles and HWMs points were used in the developed mode as inputs to generate a continuous WSE raster at 1 m by 1 m resolution were generated. The land elevation represented by the LiDAR DEM raster was then subtracted from the continuous WSE raster to develop the inundation raster with depth information at the desired resolution. To isolate the effect of flooding, existing waterbodies were eliminated from the generated inundation raster. The final product was used as a static snapshot of the event that represents the worst-case flooding scenario. The main difference was converting the observed HWMs (one snapshot of the flood representing the maximum WSE) into a time series. In other words, in the current study, a water surface elevation over the time of the flooding event (i.e. Hurricane Harvey) was used instead of a static snapshot of the event. Due to a smaller study area, all calculations were undertaken at the catchment level and only HWMs within the catchments covering the study area were used. Catchment boundaries were extracted from the watershed delineation in the Tropical Storm Allison Recovery Project (TSARP). Figure 43 shows the catchments and associated HWMs used in the study. A total of 11 HWMs were used.

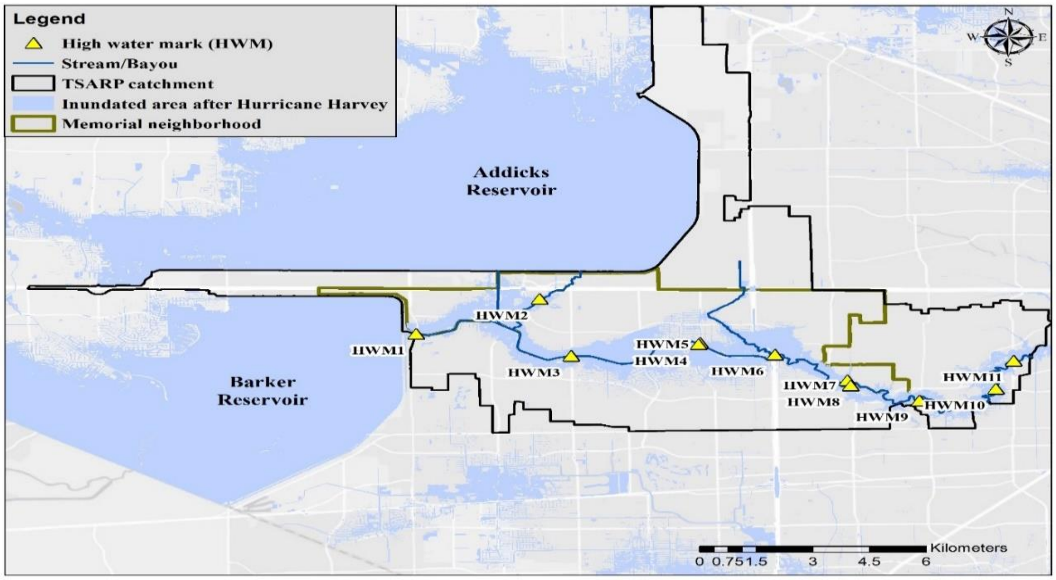


Figure 43 Study area and location of High-Water Marks (HWMs) used in the study

To convert the single measured HWM values into a WSE time series, the observed temporal pattern in the WSE at the closest USGS gage was used. Since the majority of the HWMs were measured close to the banks of rivers and were caused by the river overtopping its banks, it was assumed that the WSE time series at the location of the HWM was similar to the river behavior. The HWM represents the highest level of water observed at the specific location that is equivalent to the peak of the WSE time-series recorded by USGS. For the period of simulation and for each USGS gage, the ratio between the WSE at each time step and the peak were calculated and multiplied by the reported values of nearby HWMs to generate the WSE time series at the location of each HWM. For HWMs located on the tributaries (see HWM2 in Figure 43), the pattern observed in the difference between recorded discharges from two USGS gages (one upstream and one downstream) was applied to the HWMs. Here, it was assumed that the discharge rates' difference was solely caused by the input from the tributary and not by direct runoff from the drainage areas between the two USGS gages. To automate the process of generating a WSE at each time step (one hour), a model was built in ArcMap. Several existing tools in ArcMap were applied to (1) Convert the HWMs within the catchments into a WSE raster with a resolution of 1 m by 1 m for each time step; (2) Subtract the surface elevation raster (LiDAR DEM) from the WSE raster to calculate the water depth at time steps; (3) Extract the water depths at the locations of specific nodes (intersections) for each time step; (4) Filter the depths to only consider nodes with a positive depth. A negative value indicates that the river water is contained within the original river bank; (5) Export the excel file containing the locations and associated water depths. A MATLAB code was developed to combine all the excel files and create a metafile with the nodes and water depth locations at each time step over the length of the simulation.

Estimation of the Parameters of the SIS Network Diffusion Model

It was hypothesized that the propagation of the flooding impacts in the road network could be modeled using the SIS diffusion approach. Based on a separate study in which the author proposed a Bayes-rule-based percolation approach for the road network during flooding (Abdulla et al., 2019), highly flood-prone areas tend to be inundated first due to overflow of flood control infrastructure. The disruption propagates to adjacent areas based on relative elevation, drainage condition, terrain, level and type of vegetation, soil type, intensity, and rainfall duration, among many others. Due to the complex and stochastic nature of the propagation of floods, a probability-based approach should be used to model its disruptions on the road network. At the propagation stage, due mainly to gravity, a node is more likely to be inundated because of the existence of an inundated adjacent node. The same above factors might also cause the receding of the flood at a certain location, which makes that particular node functional again. The binary transitions between the nodes' functional or non-functional statuses in the road network could be captured using a basic diffusion model called SIS diffusion. There are two types of nodes (Susceptible and Infected) in SIS diffusion, and the rate of change between these two statuses is characterized by two parameters labeled beta and gamma (See Figure 44). The main reason to focus on the nodes instead of links is that once a node is flooded enough to be removed from the network, the edges connected to that node will be rendered as nonfunctional and will no longer be part of the connected network component.

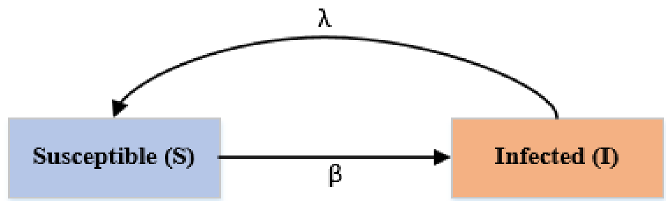


Figure 44 Schematic representation of the SIS diffusion model

The first task in developing the SIS diffusion model is to categorize the study population (nodes in this context) into different classes using certain criteria defined by the user. In the context of the current study, it is appropriate to categorize the nodes in the road network into functional or closed categories. During a flooding event, the closed or functional status of the road network is a binary value, but the flooding (depth) status in different parts of the road network is a continuous variable. It is possible to relate the flood depth to roads' closed or functional status via safety vehicle speed. Researchers have studied the relationship between the depth of the flooding and the speed of the vehicles driving on the roads during the flooding event. Pregnolato et al. (2017) have estimated the relationship between the depth of standing water and the speed of different types of vehicles as:

$$v(w) = 0.0009w^2 - 0.5529w + 86.9448$$

$where$:

v(w)is the vehicle speed $\left({}^{km}/_{h}\right)$, and w is the depth of the floodwater on the road(in mm).

Using above equation about depth-disrution model, nodes in the road network were divided into two categories based on the vehicle speed at any given point in time. (1) Susceptible Nodes

(S): The susceptible group is a node in the network that is either intact at a given point or the flood depth in the node location is less than $140mm$. On such types of nodes, the passenger vehicle speed is more than or equal to $20km/h$. (2) Infected Nodes (I): The Impacted group is the nodes that have been heavily impacted by the flood and are rendered non-functional. The speed of vehicles on these types of nodes is less than $20km/h$. The next step in SIS diffusion modeling is to identify the seed nodes, the portion of the nodes in the network that were already impacted when diffusion started. During a fluvial (or riverine) flooding event, the flood-prone areas' nodes initiate a flood-induced diffusion phenomenon in the road network. Estimating the flood-proneness of the nodes can be based on the floodplain type, proximity to flood control infrastructure and relative elevation of the nodes (Abdulla et al., 2019). The last step is to estimate the other two essential parameters of the SIS diffusion, β ,and γ. Parameters of the diffusion model are solved for using two equations from Newman (2018):

$$\frac{dS}{dt} = \gamma x - \beta s x$$

$$x(t) = x_0 \frac{(\beta - \gamma)e^{(\beta-\gamma)t}}{\beta - \gamma + \beta x_0 e(\beta - \gamma)t}$$

$where$:

β and γ: transition parameters of diffusion; S: number of susceptible individuals (nodes) at a given point in time; I: number of infected individuals (nodes) at a given point in time; $x(t)$: the fraction of infected nodes at a given point in time; x_0: the fraction of susceptible nodes at the beginning of diffusion.

Assessing the Diffusion Profile and Connectivity under Different Scenarios

The connectivity profile of the road network under two types of disruptions were studied. (1) The impacts of the flood-induced network diffusion that started at different locations on the connectivity profile of the same road network; (2) The impact of diffusion on the overall connectivity of the road network during the flood propagation process in the road network by studying the road network in all 88 neighborhoods in the case study area.

Connectivity Profile

This study first estimated the parameters of SIS diffusion under different thresholds: 150 mm represents the maximum flood depth in which sedan cars can travel on the road, while 300 mm represents the depth for SUV vehicles, whereas 600 mm represents the threshold flood depth for the fire trucks. Using the SIS diffusion parameters under the 150 mm threshold, the road network's connectivity profile under different scenarios was examined. The diffusion scenario which starts from randomly selected seed nodes, was considered as a baseline scenario. Due to diverse colocation patterns between road networks and flood control infrastructure networks, it is possible for fluvial flooding to occur at any road network location. Because of the road networks' unique topography and layout, nodes with high centrality measures represent unique locations on the road networks. The impacts of diffusion on road networks were quantified using the relative (to original network size) size of the connected giant component (GCC) (Schneider et al., 2011)in the road network. Five considered scenarios include: (1) diffusion is initiated from a certain number of randomly selected nodes; (2) diffusion started from a certain number of nodes with the highest betweenness centrality (BC); (3) diffusion started from a certain number of nodes with the highest degree centrality (DC); (4) diffusion started from a certain number of nodes with highest closeness centrality (CC); (5) diffusion started from a certain number of nodes with highest eigenvector centrality. For this analysis, the Memorial super neighborhood's road network was used in the analysis (Figure 45). A super neighborhood in the case study region is a geographically designated area in which different stakeholders work collectively to address the community's needs and concerns.

Overall Connectivity

While the connectivity profile could cast some insights into the sensitivity of diffusion at different levels on the road network's connectivity, it is not an aggregate measure of the overall impact of flooding on road connectivity. Therefore, a measure called overall connectivity (OC) is introduced to assess the network's connectivity during the diffusive disruptive events. The connectivity changes due to diffusive disruptions are quite uneven under different scenarios. In order to make the magnitude of the impacts of different diffusions on road networks comparable, the area under the performance curve was calculated. OC is defined using the equation:

$$OC = \int_{t_0}^{t_1} GC(t)\, dt$$

where:

t_0 − the starting time for the disruptive event;

t_1 − the time the disruptive event ends;

$GC(t)$ − the relative size of the connected giant component in the road network.

In order to examine the impacts of the location of the initial diffusive set seeds on the vulnerability of the road network, a two-sample significance test was conducted. The working hypothesis was that the road network is more vulnerable to the contagious disruptions that start from the significant nodes (with high centrality measures). This vulnerability is because removing the significant nodes alone usually caused a greater magnitude of loss to the network's connectivity. If we classify road networks under the disruptions of random diffusive failures as group 1, road networks under the targeted diffusive failures (failures originating from those nodes which are considered significant, i.e. high degree centrality, high betweenness, nodes with low closeness centrality and nodes with high Eigenvector centrality) would be classified as group 2. Overall connectivity of the network in the two groups was studied in this research using the OC values for each of the 88 super neighborhoods in the study area.

5.3.3. Results and discussion

Road Network and Hydraulic Process

The road network in the Memorial super neighborhood has 4,073 nodes and 9,762 edges, with an average node degree of 2.397. A snapshot of the road network when the most severe flooding occurred can be seen in Figure 45, which happened at 11:00:00 on August 30th, 2017, when the maximum number of nodes (937 nodes out of 4073) flooded in the network. A flood depth observation for each node in the road network, at the hourly interval, was made for 408 hours. A temporal change in the fraction of flooded nodes (as long as a node is under non-zero flood water, it was considered as flooded) can be seen in Figure 45. In Using the size of the giant connected component in the network as a measure of overall connectivity, the temporal change in the performance of the network during the flooding, under different closure thresholds for node-removal (a condition that corresponds to road closure for different types of vehicles,140 mm-sedan cars, 300 mm-SUVs, and 600 mm-common fire trucks) was presented in Figure 46. As could be seen in Figure 46, the vulnerability of the road network connectivity under different thresholds is quite different. Understanding the mechanism behind the sudden drop in the relative size of giant connected components at the 140 mm threshold has important implications for improving road network resilience to flooding events.

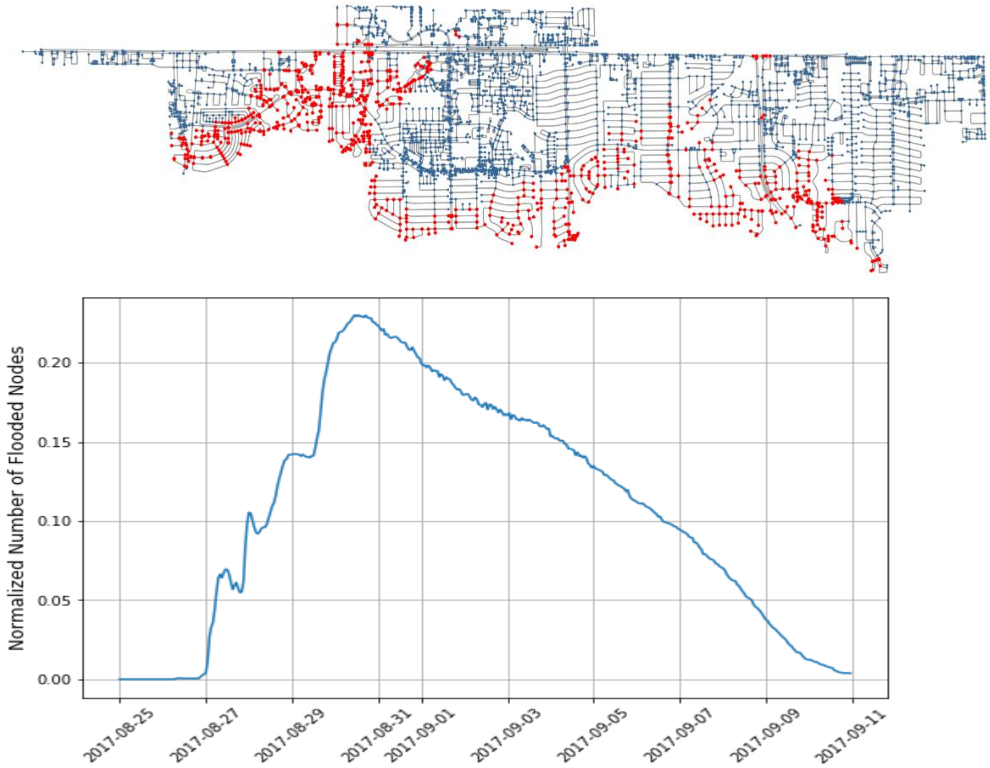


Figure 45 Road network under maximum flooding (top); Temporal change in the normalized number of inundated nodes in the Memorial road network (bottom)

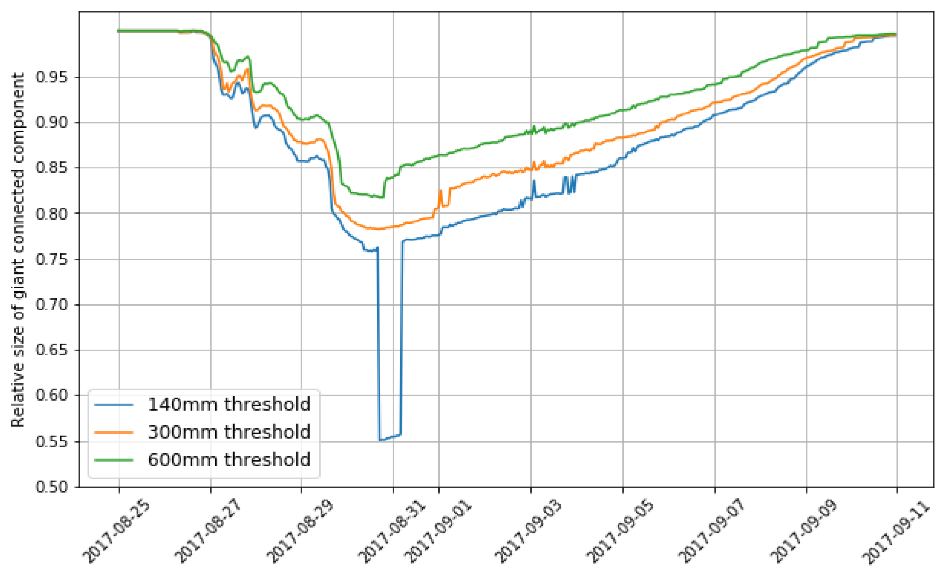


Figure 46 Size of GCC in road network under different closure thresholds

Obtaining the Network Diffusion Parameters

Three parameters were estimated for the SIS diffusion model. The initially impacted parameter was estimated based on the number of nodes within a certain flood plain type. The transition rate parameters (β and γ) were estimated by minimizing the squares method's residual sum. In other words, the sum of squares of the difference between predicted and observed node numbers in each category is minimized. Table 12 presents a summary of the parameter estimation for the SIS model under the four different flood threshold scenarios that correspond to the maximum threshold for the flood depth for certain types of vehicles, as discussed in the paper's methodology section

Table 12 Summary of diffusion parameters under different diffusion threshold

Diffusion Threshold (in mm)	Beta (β)	Gamma (γ)	Initially Impacted (% of nodes)
0	0.025	0.02	1
150	0.02	0.013	0.8
300	0.03	0.024	0.5
600	0.02	0.015	0.4

In order to characterize the vulnerability of road networks to various diffusive disruptions, two types of simulation experiments were conducted, as discussed in the methodology section.

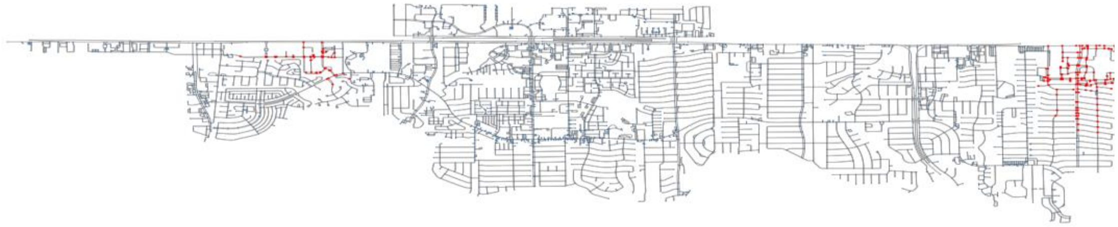
Experiment One: Assessing the Impact of Diffusion on Connectivity Profile

This study first estimated the SIS diffusion parameters based on the actual hydraulic process in the road network, which facilitated simulations of the road network diffusion under various hypothetical fluvial flooding events. A better understanding of the impact of parameters of the SIS diffusion model on the diffusion profile of the road networks is crucial as different combinations of β and γ values represent a different flooding profile, like the intensity of precipitation, runoff, the capacity of the flood control infrastructure or drainage systems. Furthermore, once an estimate of the values for the SIS diffusion parameters, Beta (β) and Gamma (γ), are obtained, it is possible to conduct scenario analysis by initiating the diffusion from different locations in the road network, which represents areas fluvial flooding most likely starts. Figure 47 (highlighted in red) shows a set of randomly chosen nodes that serve as the seed nodes for the diffusion. In order to facilitate a comparison between different scenarios, 5% of the total node number was selected for all the scenarios and diffusions are simulated in the same network in Memorial Super Neighborhood. Figure 48 depicts the road network's connectivity profile in the case study area under different diffusion scenarios, where diffusions are initiated from nodes with high centrality measures. The extent of diffusion was simulated until about 20% of the nodes were removed from the road network. In order to facilitate a comparison between the impacts of diffusive disruption and targeted disruptions on road network connectivity, the author simulated five intentional disruptions. Figure 49 shows the road network's connectivity profile when the nodes in the network are intentionally removed at a decreasing order of corresponding node centrality measure.

A: Randomly chosen seeds

B: High betweenness centrality seeds

C: High degree centrality seeds



D: High Eigenvalue centrality seeds

E: High closeness centrality seeds

Figure 47 Locations of seed nodes in road network

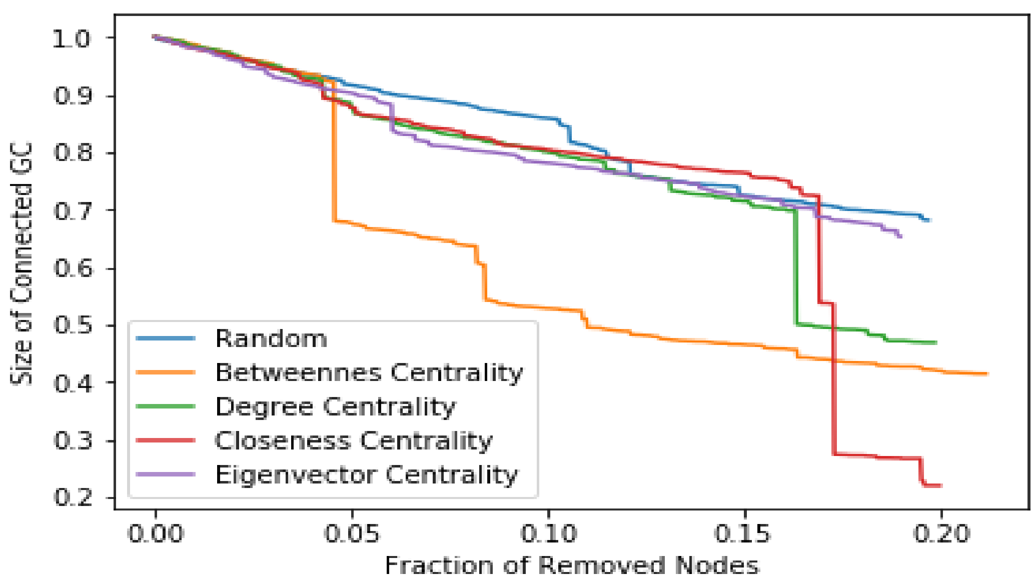


Figure 48 Connectivity profile of road network under diffusion with different seed locations

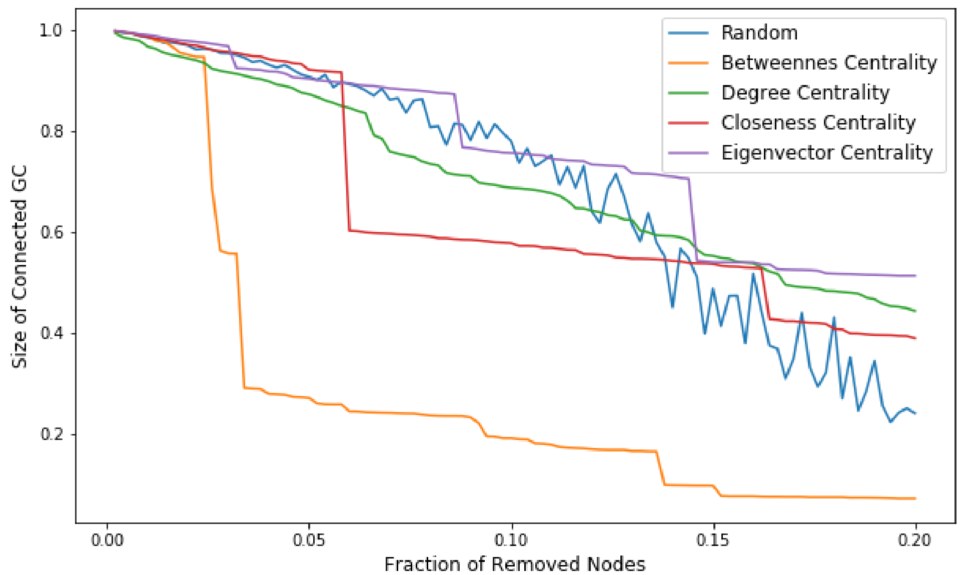


Figure 49 Connectivity profile of road network under different targeted disruption scenarios

As could be seen from Figure 48, the rate at which the connectivity of the road network is reduced under different diffusion scenarios varies significantly. There is an apparent non-linear pattern of reduction in road networks' connectivity when diffusion in the road network is initiated from nodes with high betweenness, degree and closeness centralities. The connectivity of road networks is particularly vulnerable to the diffusion initiated from nodes with high betweenness centrality (BC) . The removal of less than 5% of nodes from the network reduced the size of the GCC to less than 70% of the original size. When a fraction of removed nodes reaches 10%, the size of GCC becomes less than half of its original size. However, under this scenario, the impact of disruption on connectivity becomes less severe as the fraction of removed nodes increases. This is probably due to the fact that, once the significant nodes (with high BC values) are removed and disruption propagates into less significant nodes, further removal of nodes doesn’t cause a sharp reduction on the network connectivity, which is validated by the quick reduction of connectivity under high BC scenario in Figure 48. At different magnitudes of disruption (as the fraction of removed nodes varies in the x-axis), the overall reduction of the road network's connectivity also different. The area under the high-BC curve is significantly smaller than the areas under any other scenario. The particularly severe impact of nodes with high betweenness centrality on road network connectivity could be observed from both Figure Figure 48 and Figure 49.

Experiment Two: Characterization of Road Network Vulnerability to Diffusive Disruptions

A separate simulation of diffusion on the road network was conducted for each of the scenarios (random, BE, DC, CC, and EC). The working hypothesis is that a diffusion that starts from nodes with high centrality values will cause greater connectivity loss. According to this hypothesis, the average connectivity of the road network under these scenarios (μ_{AD} , μ_{BC}, μ_{CC}, μ_{EC}) is less than the connectivity of the road network under a diffusive failure, starting from a set of randomly chosen nodes. The parameters of the diffusion are initially impacted seed size α (α =1%, 5% and10%), $\beta = 0.04,\ \gamma = 0.02$. This process was conducted for 88 super neighborhoods in Houston in order to get a sample of the road network connectivity under these scenarios. Independence between samples was assumed, as the number of samples is more than 30, the z-test was used for testing the hypothesis. Table 13 presents a summary of the hypothesis testing when the seed size parameter is $\alpha = 10\%$. When larger seed size values (1% and 5%) are used, the results for tall high centrality scenarios (high DC, EC, CC and BC) centrality scenarios are not significantly different from the diffusion initiated from randomly chosen seeds.

Table 13 Results of the hypothesis tests (on the different networks)

Initial Seed Type	Working Hypothesis	z-statistics	Conclusion (at $\boldsymbol{\alpha = 0.1}$)
high DC	$\mu_{AD} < \mu_{random}$	0.214921	Fail to reject the Null
high BC	$\mu_{BC} < \mu_{random}$	2.078136	Reject the Null
high CC	$\mu_{CC} < \mu_{random}$	0.677877	Fail to reject the Null
high EC	$\mu_{EC} < \mu_{random}$	1.780124	Reject the Null

As could be inferred from the results in Table 13, contrary to the initial belief, diffusion started from high significance nodes does not cause the expected greater decrease in the network connectivity. Diffusion, which originates from seeds of nodes that have high betweenness and high eigenvector centrality, causes greater loss to the connectivity loss when the seed size is large, compared to ones that started from randomly selected nodes. In contrast, a diffusion that originates from seeds of nodes with high closeness centrality seems to cause less loss to the network's connectivity than a diffusion started from the randomly chosen nodes.

Average connectivities in road networks (for the above-mentioned five cases) under different seed-size scenarios were also studied (see Figure 50). Diffusion, which originates from seeds of nodes with high eigenvector and betweenness centrality, seems to cause a more significant loss to the connectivity loss when the seed sizes are 2% and 4%. It is also observed that if diffusion starts from a larger number of nodes (above 7% of total nodes) with high betweenness centrality, the impacts on the network connectivity would be higher than that of diffusion originated from the randomly chosen nodes with the same size.

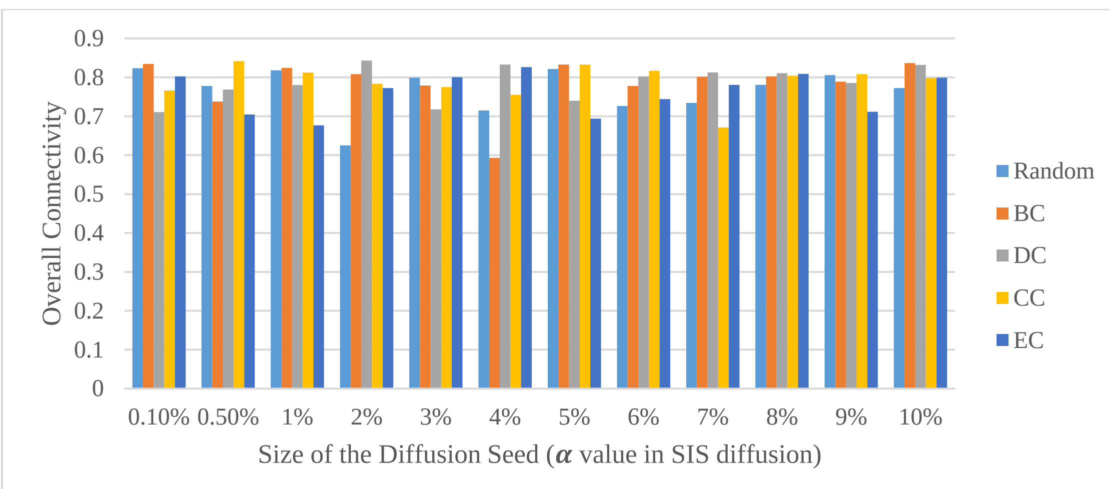


Figure 50 Average network connectivity under different diffusion scenarios

The above findings have important implications for flood management. The results indicate that to ensure the connectivity of the graph or the transportation network, it is crucial to maintain the functionality of a number of critical nodes in the network. This paper illustrates that the SIS diffusion model can be used to identify critical nodes in transportation road networks. This paper also presented a sensitivity analysis of the impact of the number of initially flooded nodes. The second application of the finding is that network size increase may not necessarily result in improved robustness in the network. This also means that adding extra lanes to the roadways may not improve the road network's flood resilience. Instead, working on ensuring the functionality of a few nodes in road networks is critical to the road network's robustness.

5.3.4. Conclusions

This paper presented the use of the SIS diffusion model to study diffusion phenomena in the road network under the influence of fluvial flooding during heavy rainfall. The results show that there is significant variability in the sensitivity of the road network connectivity to the diffusive disruptions initiated from different locations. The results indicate that the road network is particularly vulnerable to disruptions that occur at nodes with high betweenness centrality. Both the diffusion-based disruptions and intentional disruptions show the variance on the impacts of disruptions at different locations. It was found that a road network does have critical threshold values for a fraction of removed nodes, being above, which could lead to the loss of most of the connectivity in the road network. Ensuring the fraction of removed nodes under a certain threshold could lead to disproportionate benefits in terms of communities' social and economic well-being, whose mobility depends on the network. It has been observed that the sensitivity of the robustness of the road network is different for the intentional disruptions and diffusive disruptions. It has been observed that, in general, the rate of the reduction in the connectivity is faster under the intentionally targeted disruptions than the SIS diffusive phenomenon. In summary, if we can predict the configuration of the road network under a given flooding scenario, we would be able to predict various types of accessibilities. There is also a threshold value for the node removal portion for the robustness decrease, while the change in the robustness (measured in terms of the size of the largest connected component) under the random percolation is relatively moderate. The critical threshold value for the removal fraction of the nodes under the diffusion phenomenon is about 25%. This has two critical implications on road network resilience. The first marginal utility of the investment in improving the road network's vulnerability is different at different disruption levels. In terms of ensuring the connectivity of the road network, the dividend, on investing to avoid the node-removal, is particularly high for the nodes with high betweenness centrality.

Even though this study aims to bridge the gaps between findings in the realms of theoretical networks and performance of real-life networks. There are several areas that need further study to render the findings and conclusions in this study even more realistic. For example, even though the depth of the standing floodwater in the road network is an important indicator for it's safe to travel or not, there could be numerous other factors that also should be taken into account for predicting safe travel speed. These factors could include vehicle conditions (tire pressure, roadworthiness, etc.), condition of the pavement, visibility and aptitude and behavior of the driver during the flooding events because all of these could contribute to whether a road network is being “closed” or not. In terms of the granularity of the data, this study has used the hourly flood depth data as input for the diffusion. Based on the rainfall intensity and other factors, less or more granular data could be needed in order to predict the transitions between node statuses. This process is not captured in the $S \rightarrow \boldsymbol{I} \rightarrow \boldsymbol{S}$ transition process. It is also possible to train diffusion models using the data for multiple super neighborhoods or under multiple types of flooding scenarios, enabling the identification of the diffusion model that is best able to model the floodwater diffusion in road networks during a given flooding event.

6. CHARACTERIZATION OF VULNERABILITY OF INTERDEPENDENT CRITICAL SECTORS DURING FLOODING[2]

This chapter presents works conducted under objective three: Characterization of Vulnerability of Interdependent Critical Sectors. Under this chapter, there are three main work packages: (1) assessing the impacts of flooding on the accessibility of building blocks at fire district levels; (2) quantifying the interdependence between road networks and flood control network and assess the impacts of this interdependence on the road network connectivity; (3) apply machine learning classification algorithms to identify the sections of the road network that are significantly exposed to flooding risk. The first section of the dissertation presents a study that examines the impacts of the flooding events on the accessibility of the fire stations and households. The idea is to clarify the possible relationship between road network percolation and accessibility. The second section presents a method this study proposed to quantify the colocation interdependence among the road networks and flood control infrastructure. In the third section, a machine learning classification-based approach is presented. In which, we used algorithms to identify locations that are vulnerable to flooding events.

6.1. Characterization of Accessibility Loss by Emergency Services under Different Disruptions Scenarios

6.1.1. Introduction

This study aims to characterize the impacts of disruptions in road networks on the accessibility of emergency service providers. To this end, this paper proposes a framework to investigate the

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[2] Parts of Chapter 6 is reprinted with permission from two sources: (1) "Characterization of Resilience of Networks to Uncertain Disruptions: A Case Study of Houston Road Network during Hurricane Harvey." by Abdulla, B., & Birgisson, B. (2020). ASCE International Conference on Transportation & Development (ICTD 2020). https://doi.org/10.1061/9780784483169.004 ; (2) "Predicting Road Network Vulnerability to Fluvial Flooding Using Machine Learning Classifiers: Case Study of Houston during Hurricane Harvey" by Abdulla, B., & Birgisson, B. (2020). Construction Research Congress 2020, 38–47. https://doi.org/10.1061/9780784482865.005

integrity of the coupled emergency services and road network under two districts types of disruption scenarios: (1) random disruptions, which is modeled by removing randomly sampled nodes in the road network, and (2) disruptions induced by fluvial flood, which is modeled by removing nodes based on probabilities estimated by fuzzy Bayesian rules. Then, the accessibility of the building blocks by fire stations is estimated based on a graph-based metric. The proposed methodology was demonstrated using the road network and fire districts in Houston, and the fluvial flooding scenario considered was the one caused by Hurricane Harvey. Results show that (1) The impacts of the two disruption scenarios on accessibility are significantly different; (2) location of disruptions matter and severity of the flood doesn't directly translate into the loss of accessibility in the fire districts; (3) the locations of the fire stations are critical for maintaining accessibility and artificially elevating the fire stations is not effective to render them functional during the flooding events. This study's results can inform the fire departments' decision-making on resource allocations like optimizing fire stations' locations, placing the fireboats and firetrucks when and where they could be put into the best use and rescue prioritization for flood protection.

Changes in the earth's climate(Marshall & Plumb, 2016), potential global warming, unprecedented and ever-increasing urbanization, and increased interdependence among different sectors put the critical infrastructure systems under increasing pressure(Rodin, 2014). This is particularly evident in urban areas when transport systems are affected by weather-related hazards. During disastrous events, the road system usually functions as a life-line system for rescuing people and assets and plays a vital role in repairing and restoring other infrastructure systems when they are disrupted. However, transportation networks, especially road networks, are vulnerable to natural and human-made disasters, which could undermine their vital functionality. Flooding, especially ones due to excessive and intense rainfall precipitation, has been the predominant cause of weather-related disruptions to the transportation infrastructure (Pregnolato et al., 2017). According to a report by the International Federation of Red Cross and Red Crescent Societies, floods are one of the most significant natural hazards, affecting 116 million people globally, causing approximately 7000 deaths and damages in the region of USD 7.5 billion annually (IFRC, 2010). Furthermore, a study by Serulle (2015) found that natural hazards tend to cause more serious death and injury among those situated in the lower rungs of the social ladder. Many critical infrastructure systems, such as utility services, pharmacy and clinics, emergency service stations (police, ambulance, and fire and rescue stations), and the transportation networks that facilitate access among these services are also susceptible to flooding (Douglas et al., 2010; Stålhult & Andersson, 2014). One of the mechanisms to cope with sudden and disruptive events is the emergency service provision systems at a community, district, city, county, state, and country level. In most cases, before the occurrence of catastrophic events, emergency service provision mechanisms would be activated, and plans for search and rescue operations would be put into place. In some of these cases, however, the emergency service provision systems themselves are susceptible to the very disastrous disruptions they intend to save people from. In the face of flooding, access by emergency service personnel to those who need help could be effectively cut off by the closure of the roads. Allocating resources effectively in terms of how to equip the facilities, where to position the fire stations, and what transportation tools to use under certain flood scenarios is the decision that emergency personnel has to make in a fast-evolving and intense environment. Available scientific research on the topic of emergency management is quite multidisciplinary, as examples can be seen in psychology (Mileti & Peek, 2000), computer science (Latonero & Shklovski, 2011; Rathore et al., 2016), telecommunications (Bergstrand et al., 2016), medicine (Veenema, 2018), atmospheric science (Albano et al., 2016), and social science (Houston et al., 2015). This fact alone could reiterate the clear interdisciplinarity of the research topic and the need for collaborations among people from various fields. Due to the limitations in terms of the focus and space, this paper primarily surveys the research works which have been conducted in the context of flooding events within the domain of transportation. Impacts of various types of flooding on transportation networks have been a favorite area of study among civil engineering researchers.

There is a long list of disruptive events, which could undermine urban critical infrastructure systems' normal functionality. Due to the relatively random nature of the locations where disruptions occur, the impacts of some disruptive events, like snow, earthquakes, the explosion of sewage pipelines, occasional tornados, as well as traffic accidents and construction, on the connectivity of the road network could be considered as random. Impacts by some other disasters, like fluvial flooding and landslides, cannot be considered as random events as different locations tend to have clearly different levels of exposure to disruptive events. It is important to understand the spatial distribution of the impacts of these types of non-random events. It is equally important to know how these types of events affect the accessibility of the households by reducing the functionality of the road networks. A comparison between the impacts of the random events and targeted events could lead to insights on the types of coping strategies for these events under various resource constraints. A survey of the relevant literature revealed that, given the abundance of granular data and availability of the necessary simulation tools, few studies have looked into the accessibility during the flooding events at a household level (Coles et al., 2017; Jie Yin et al., 2016). Most of the studies focused only on the vulnerability of road network against flooding events, while some researchers have proposed depth-disruption models by examing the relationship between the depth of accumulated flood-water on the streets and safe vehicular speed for different vehicle types (Choo et al., 2020; Pregnolato et al., 2017). Using the results from the above depth-disruption models, some other researchers characterized the impacts of fluvial flooding on road network connectivity with the help of the SIS network diffusion model and simulation techniques that could capture the temporal shift in connectivity in road networks during a flooding event(Abdulla et al., 2020a). The author also characterized road networks' vulnerability to flooding using a network percolation approach (Abdulla & Birgisson, 2020c) or machine learning classification methods (Abdulla & Birgisson, 2020d). This study conducted a detailed survey of the literature on the impact of flooding on the accessibility of emergency service providers.

A review of the flood emergency plans used in the county of Cumbria (in northern England) during the 2009 flooding found that emergency responders particularly value tools that help them evaluate the vulnerability of critical infrastructure (such as roads, electricity substations, and care homes) during the response phase of a flood emergency (Lumbroso & Vinet, 2012). A study by (McCarthy, 2007) found that models used to estimate the breach locations and inundation extent levels on the road network were considered useful by emergency responders in London's Thamesmead area for decisions about evacuations or allocation of scarce resources. Individual street-level, higher resolution flood footprints obtained using numerical models could enable detailed evaluation of flood impacts on urban transport networks that, in turn, determines accessibility during flooding. This is not limited to fluvial flooding and enables surface water flood and impacts modeling (J Yin, Yu, Environment, & 2016, n.d.). In a study by Coles et al (Coles et al., 2017), accessibility was quantified using two metrics: (1) the area coverage from emergency response stations within legally required timeframes (for example, in the UK, it is 8-min for the Ambulance Services and 10-min for Fire & Rescue Services); (2) the shortest time it takes from an emergency response node to vulnerable populations, which is evaluated against the legislated targets. They employed the service area method to map the emergency services' spatial coverage within the specified response timeframes. Another study by (Green et al., 2017) proposed a somewhat similar approach as above for accessibility assessment. This study also found that surface water flooding tends to cause more disruption to emergency responders operating within the city due to its widespread and spatially distributed footprint when compared to fluvial flood events of comparable magnitude. Other recent and relevant studies on the topic include works by Arrighi et al. (Arrighi et al., 2019), Abdan et al. (Janius et al., 2017), and Mejia-Argueta et al. (Mejia-Argueta et al., 2018). The review of the relevant literature concluded that few studies focused on assessing the accessibility during flooding events at a more granular level (like individual building blocks), regardless of the increasing availability of some relevant data and improved computational power. Motivated by this observation and based on the recent development of simulation techniques, this paper looked into the reduction in accessibility (measured by the percentage decrease in the buildings accessible by the fire station personnel) due to the road closure under different flooding levels events. This study demonstrated the application of the proposed methodology using the fire districts and road networks in Houston. The remaining sections of the paper are structured as below: First, the proposed methodology that is used for simulating the change in accessibility is introduced in detail. Under each step of the proposed methodology, its corresponding application is also demonstrated. Then, the case study area, as well as data requirements, are presented. An estimate of Hurricane Harvey's impacts on the accessibility of the fire districts in the entire Houston area is conducted using the proposed probability-based mechanism. In the end, the results of the analysis and their implications are presented.

6.1.2. Methodology

The following section provides a synopsis of each of the steps undertaken in this study's methodology section. This study treats each fire district as a unit of analysis and models the road networks within it as primal graphs. After identifying the fire stations' numbers and locations and building blocks in each fire district, disruption scenarios in each fire district are simulated. Further analysis is conducted to assess the reduction in accessibility to building blocks for fire stations. The main objective of the first three steps is to characterize the reduction in the accessibility of the building blocks in each fire district for fire station personnel during a flooding event by examining the different features of the fire districts.

Modeling the Road Network and Building Blocks

Modeling Road Networks

The road network is modeled using the primal approach, which assumes the road sections as the links (edges) and intersections (junctions) of the road sections as the nodes. The OSMnx tool was used to retrieve the road network from the OpenStreetMap website (Figure 51). It is worth noting that OSMnx models the road networks as non-planar graphs that could accommodate non-planar structures like tunnels and bridges in the network. The directionality of the lanes is also retained the graph-based representation of the road network. Other information regarding the road networks (elevations of nodes and street grade) was retrieved from Google Maps using the appropriate API.

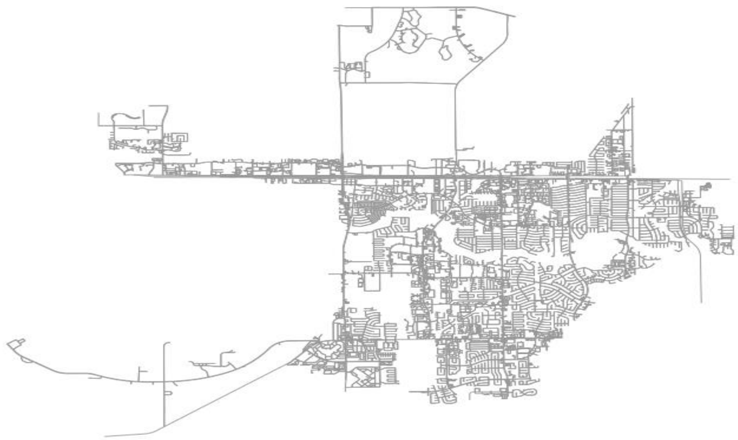
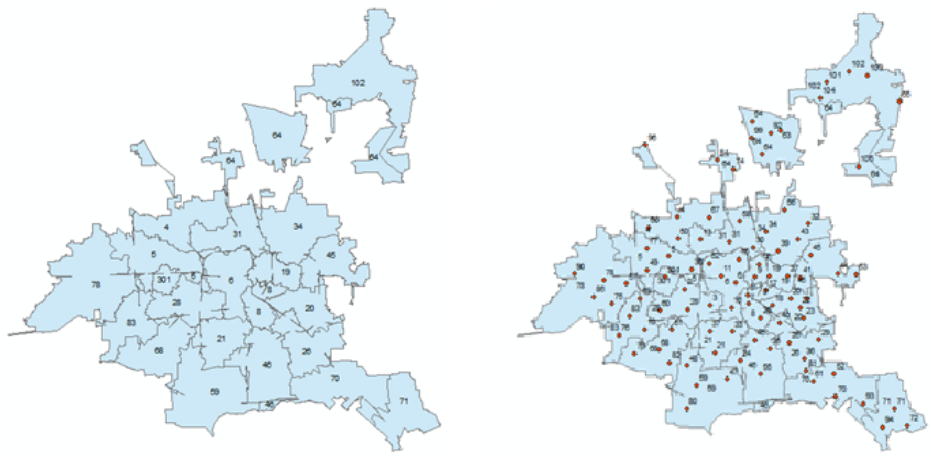


Figure 51 Road network in fire district 78 in Houston

Modeling the Building Blocks

According to the information provided by the Houston Fire Department, each of the fire districts (see Figure 52) operates mostly independently and only outsources their rescue effort when instructed to do so. Therefore, this study assumed that fire stations within each of the fire districts collaborate and work together, and accessibility of the building blocks was analyzed as a fire district is an independent unit. The building block footprint was retrieved from OpenStreetMap using OSMnx. It is noted that there are three ways to abstract a "building" in OpenStreetMap, which are node, way, and multi-polygons, which respectively represent different types of building structures with varying sizes. To check the generality of pattern in the ratios of different building types, an analysis is conducted among all of the 20 fire districts in Houston. It is noted that there is a similar pattern (in terms of a ratio of the three different types of buildings). This study has chosen to focus on those building blocks represented with a "node," which accounts for about 90% of the total building blocks across all fire districts (see Figure 54 for distribution of building block types in FD-78). This choice is due to two reasons: (1) "node" type represent the overwhelming majority of the buildings in a certain area; (2) accessibility analysis is relatively more straightforward for node type building blocks as a single nearest node in the road network could be identified, as opposed to "way" and "polygon" type building blocks, both of which could have multiple accessible "nearest" nodes and accessibility analysis to these types of structures is challenging to abstract with network models.



A B

Figure 52 Spatial location of fire districts (A) and fire stations in Houston (B)

Modeling the Percolation in the Road Networks

This study analyzed the change of accessibility in the road network under two scenarios: random disruptions and non-random disruptions caused by fluvial floods. The performance of the road network under these scenarios was modeled using network percolation. Percolation is a term used to describe a continuous phase transition in physics, and it is described with low-dimensional lattices, and there are two types of percolation: site percolation and bond percolation (Stauffer & Aharony, 2014). The existence of a particular site or a bond between the sites is modeled with probability p, when p=1, it means all of the sites (or bonds) are present or functional, and when p=0, it means none of the sites or bonds are functional or present (Stauffer & Aharony, 2014). In the context of networks, these two percolation types correspond to the node and edge percolation (Newman, 2010). Therefore, the dynamic changes in the topology of the transportation network during a certain disruptive event could be captured by a corresponding set of probabilities for the nodes in the network.

The impacts of random disruptions on the road network are modeled by randomly choosing a fraction of nodes ($\emptyset$) and removing them from the original network. Each value of $\emptyset$ represents a corresponding network performance in terms of connectivity.

The impacts of non-random disruptions on the road network were modeled by assigning removal probability using a Bayes-rule. Using a Bayesian rule, the posterior probability ($P(A|B)$) of a particular node being removed is obtained by updating the initial probability after each removal phase.

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$Where: P(A): the\ initial\ probability\ ;\ P(B): the\ prior\ probability$

The rationale behind this percolation method is, during the fluvial flooding, the removal of the nodes in the network is not only impacted by geographical factors like elevation and being located within certain floodplains (which is represented by the $p(A)$) but also the flooding status of the all the neighboring nodes (which is represented by $p(B)$). A more detailed introduction of the road network percolation method can be found in another study by author (Abdulla et al., 2019).

Assessing the Reduction in Accessibility

In order to quantify the impact of disruptions on the road network (Figure 51), that could cause a reduction in the accessibility of building blocks (Figure 53, Figure 54) for fire stations Figure 52, an index called lost accessibility (LA) is proposed, which is defined as:

$$LA = 1 - \frac{N_D}{N}$$

Where:

LA: $Lost$ accessibility ;

N_D: accessibility under disruption, $measured\ by\ the\ number\ of\ buildings\ accessable\ by\ at\ least\ one\ fire\ \ stations\ \ within\ the\ fire\ district\ under\ certain\ adisruptive\ event$;

N: $total\ number\ of\ buildings\ \ within\ the\ fire\ district.$

The underlying assumption in the assessment of the accessibility is that, at the time of the rescue, the fire station crew has all the information about the open/closure status of all the roads within their district. At each stage of the disruption, first, the nearest node on the road network is identified for both the fire stations (origin node) and the building blocks (destination node). Then, for each destination node, a path is searched in the network from each origin node. As long as there is at least one fire station with access to the destination node, it is assumed that this node is accessible for the fire station crew under that specific disaster scenario.

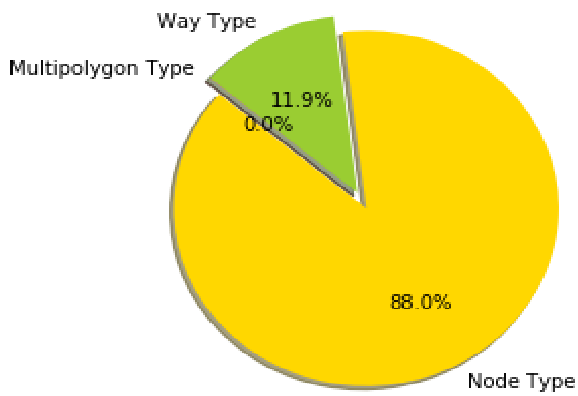


Figure 53 Breakdown of building type in fire district 78

6.1.3. Characterization of the Reduction in Accessibility

This study's overarching objective is to identify factors or features that make the fire districts less vulnerable to disruptive scenarios. By comparing the performance profile of fire districts under two different disruption scenarios, this study will identify disruptive events that are more destructive to the accessibility by fire stations. Furthermore, by conducting cross-comparison among different fire districts based on factors like the number of fire stations, network edge-bearings and overall edge length ratio, this study identifies factors that make fire districts more robust in the face of disruptions caused by fluvial flooding.

Data Requirements and Case Applications

This study makes use of data from various sources. There are three main types of data used in this paper. The first one is the data about the road network (its network topology, the elevation of the nodes and street grade), as well as data about the spatial location of the fire stations. This information was retrieved from the OpenStreetMap website using the OSMnx toolbox in Python. Second, the shapefile of the fire districts and fire stations in Houston were obtained from the City of Houston Geographic Information System website. Third, the data about the floodplains and their geographic boundaries were obtained from the Federal Emergency Management Agency (FEMA)website. For the simulation of both random and probability-based disruption on the road network, the programming language Python was used. The proposed method was first applied to the 20 fire districts (including Fire District 78 (FD-78, Figure 52), one of which is located in west Houston and one of the areas that suffered from heavy flooding. There are more than 53000 building blocks (see Figure 54) and five fire stations serving these building blocks. The five fire stations are as below: Station 57, Station 75, Station 78, Station 86, and Station 90. There are, on average, about 10000 buildings for each of the fire stations. In the following section, the accessibility profile of building blocks under two types of disruptions will be compared and characterized.

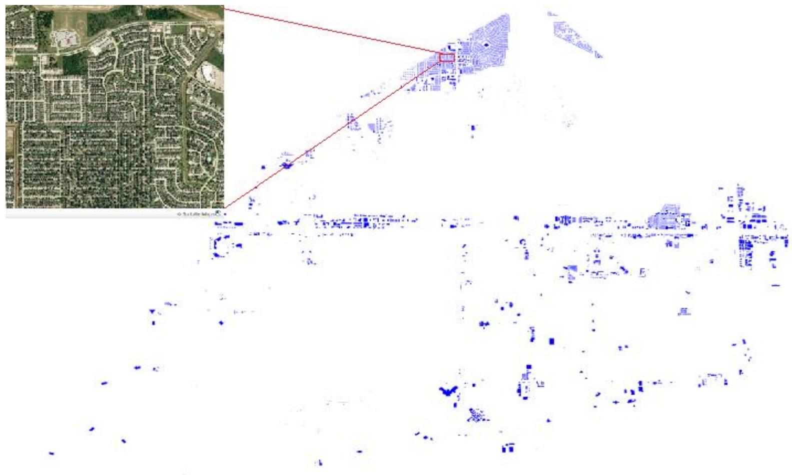


Figure 54 Geospatial location of building blocks in fire district 78

6.1.4. Results and Discussions

This section presents the performance profile of the coupled road and emergency network under two disruption scenarios. The normalized number of accessible buildings as the disruption deteriorates in the network was used for comparison. After that, a cross-comparison of the performance among different fire districts was conducted.

Accessibility Reduction Profile under Random Failures

Figure 55 shows the results of the simulation under the random removal of the nodes in the network. For the percolation of the network under a random disruption scenario, an incremental value of $\phi = 0.01$ is used for the node-removal and the simulation is repeated 120 times for each of the ϕ value and the mean value of the three observations was taken. As can be seen from Figure 55, the accessibility of building blocks by fire stations is highly susceptible to the removal of the nodes in the road network. In the beginning phase ($\emptyset < 0.05$) of the random-disruption, the reduction in the normalized number of accessible buildings is relatively slow. Accessibility decreases at a high rate as the removal of nodes becomes more serious until about 20% of the nodes are removed from the road network when more than 80% of the buildings lose accessibility by fire stations.

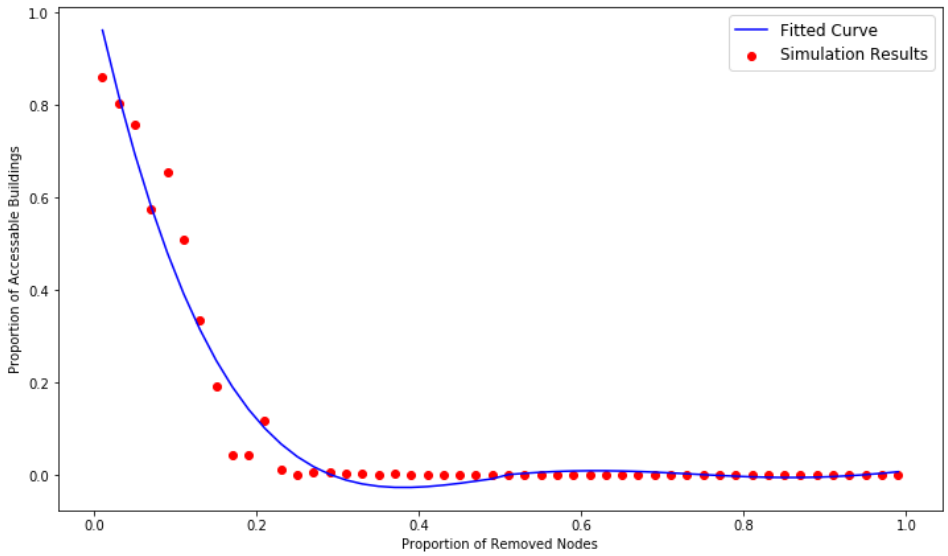


Figure 55 Lost accessibility under random failure of road networks (FD78)

Results under Flood-induced Non-random Failures

According to the probability-based scheme, simulation of the percolation process in the road network in FD-78 is conducted in the same way as above, the only difference being, the removal of the nodes in the road network no longer random, as there is a high probability of removal for the nodes which are located in the lower elevations area and located in the flood-prone areas. The incremental value of $\phi = 0.01$ is used for the simulation. Only one observation for each removal percentage is collected. The results are presented below in Figure 56. The shape of the graph shows that the accessibility is relatively less sensitive to the node removal, as the accessibility diminishes at a slower rate compared to the random scenario, and it is not until the removal percentage reaches 40%, the majority of the buildings' accessibility is lost. This could be due to the fact that under food-induced non-random disruptions, the percolation mechanism is relatively more "infectious" than that of random percolation. The removal tends to start from a certain part of the network (nodes with lower elevations and closer to high probability floodplains) and extends to the neighboring parts of the network. Under this scenario, the accessibility of the buildings in this FD-78 by the fire stations is relatively more resilient to flood-induced road closures. An assessment of the impacts of the observed road closure on the overall accessibility of the buildings is also presented below.

Characterization of Accessibility loss in Flood-Induced Disruptions

Figure 56 shows the extent of the road networks' closures within the entire Harris County region, which includes Houston. These images are based on the overall flooding extent in each of the fire districts from two different sources, namely the Texas Department of Transportation and Google. For example, in district 78, about 70% of the roads were closed, while in district 45 about 5% of the roads were closed.

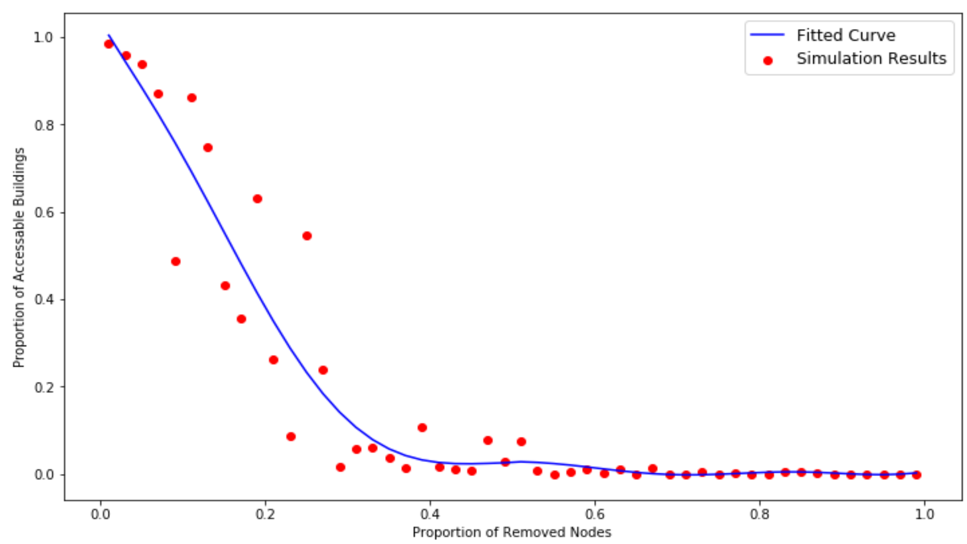


Figure 56 Accessibility of buildings under targeted percolation of the road network (FD-45)

In Table 14, an estimation of the impact of Harvey on the accessibility of the buildings in each of the fire districts is provided. In order to examine if the relative density of the flood control network within the fire district, for each fire district ratio of the total length of links in the two networks is obtained(Figure 57).

Table 14 Fire districts in Houston and level of accessibility loss during Hurricane Harvey

Fire District Number	Number of Fire Stations	Number of Buildings	Estimated Edges Closed in the Road Network	Buildings Accessible after Disruption	Percentage of Buildings lost accessibility
Fire District 5	4	46162	10%	45774	0.84%
Fire District 6	5	79291	65%	66254	16.44%
Fire District 8	4	86917	40%	73630	15.29%
Fire District 19	4	11709	30%	9920	15.28%
Fire District 20	5	122078	12%	98189	19.57%
Fire District 21	3	17906	35%	15661	12.54%
Fire District 26	4	124234	30%	98781	20.49%
Fire District 28	4	17153	30%	15152	11.67%
Fire District 31	4	13398	15%	11156	16.73%
Fire District 34	5	5207	5%	4575	12.14%
Fire District 45	4	3053	5%	2817	7.73%
Fire District 46	4	9699	5%	8092	16.57%
Fire District 59	4	2369	10%	2072	12.54%
Fire District 64	8	20033	20%	17379	13.25%
Fire District 68	4	9709	20%	8513	12.32%
Fire District 70	5	6191	15%	5413	12.57%
Fire District 71	3	2741	2%	2433	11.24%
Fire District 78	5	53725	70%	38241	28.82%
Fire District 83	4	7683	30%	6446	16.10%

It turned out that the density of the flood control infrastructure is a better indicator of the severity of the loss in accessibility than the level of similarity of bearings of the edges in two networks. In order to examine the impacts of the edge bearings and density of the flood control infrastructure network on the flood exposure of the building blocks in each fire district, a relationship between edge bearing of two types of networks (Figure 58) was studied. Bearings of the links (edges) in a network are meant to measure the overall configuration of the orientation of the links in a network. This study compared the edge bearings of the road network and flood control network. The idea and rationale are when excessive rainfall happens to trigger fluvial flooding, flood control infrastructure exceeds its capacity, and excess water starts to spill laterally (sideways), which makes the flooding even worse. Therefore, its underlying hypothesis is that if the edge bearings of the two networks more heterogeneous, the more severe the flooding in the road network.

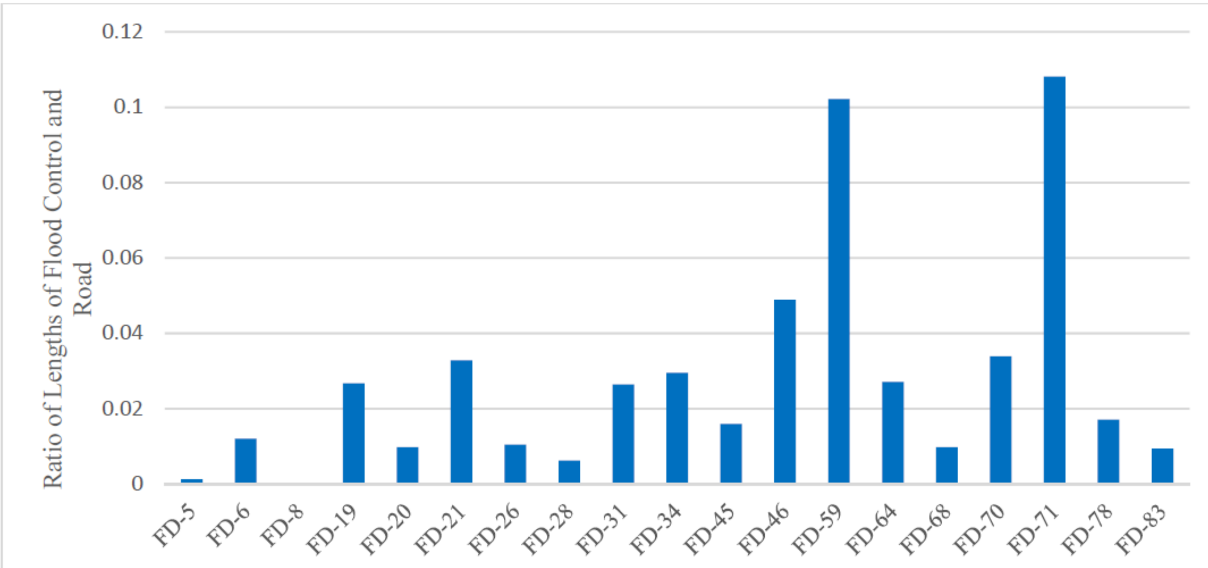


Figure 57 Ratio of flood control and flood control network across fire districts

Two observations could be made from the above results. First, the impact of the extent of the road closure on the accessibility of the building blocks is not necessarily the same across different fire districts, even though the same fraction of the edges are closed in the road network. As could be seen from the FD-5 and FD-59, the number of building blocks in the former is about 20 times greater than those in the latter and its fire stations are located within areas that are less prone to flooding, which make the FD-5 relatively more resilient. Second, the location of the fire stations within the network matters when it comes to their level of accessibility to buildings under road closure scenarios caused by fluvial flooding, as could be seen from the results of FD-45 and FD-46. For example, in the FD-71, only two percent of the edges are removed from the road network. However, because these 2% nodes include the nodes of the road network, which are close to the fire stations, the impact of this mere two percent on the overall accessibility of the buildings is highly disproportional, as about 12% of the buildings rendered inaccessible. Three fire districts, namely FD4, FD102 and FD 301, are excluded from the analysis as the irregular shape of the first two renders extraction of the road network and retrieval of building footprint geographical data files quite challenging. The latitude and longitude data for fire station numbered 301 was not found.

It is also worthy to note that, as only one observation was made under each of the simulated percolation scenarios above, there is a certain level of randomness in the results, which could be improved by collecting more observations under each scenario. Accessibility of the buildings (houses) to the fire station workers through roads is quantified and assessed under a different type of disastrous events to the roads:

- **Under Random Failure of Road Networks:** It was found that the road network is relatively more vulnerable to random failures in the road networks. Removal of just under 20% of the nodes in the road network could result in the loss of nearly all of the accessibility of the buildings by the fire stations.
- **Under Non-random Failure of Road Networks:** The susceptibility of the accessibility of the buildings to the non-random disruptions (presumably due to the fluvial flooding) is less than that of the random perturbations, as the decrease in the accessibility is less drastic compared to a random scenario.

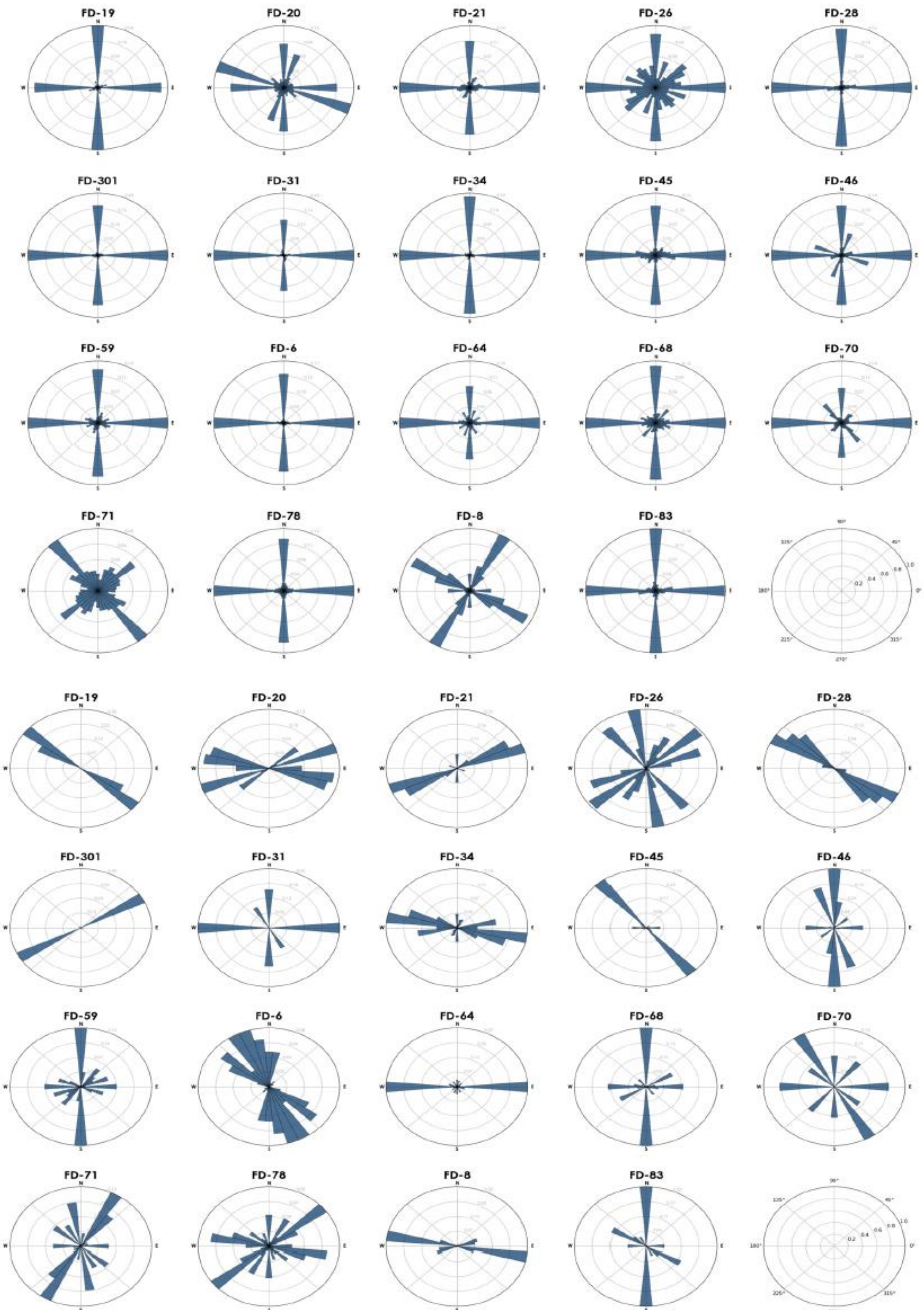


Figure 58 Comparison of edge bearings in two types of networks

- **Overall Accessibility of the Households under Fluvial Flood Scenario:** A comparison of the impacts of the road closure across different geographical areas reiterated the importance of having the right (enough) number fire stations at the right (not-flood prone) locations, as having the fire stations located within the flood-prone areas could have devastating impacts on the resultant accessibility level due to road closures. However, as the location of the fire stations is a decision governed by many different factors, for those fire stations, which, for one reason or another, had to be located within the areas that are prone to flooding, other considerations, like equipping them with boats or even helicopters, have to be made. The results also cast some doubts to the significance of artificially elevating the fire stations in order to avoid them being flooded, as neighboring nodes (edges) which rendered unusable by the flooding could "trap" the fire stations and could make them of limited use when it comes to accessing the buildings nearby.

6.1.5. Conclusions

This section set out to examine the relationship between the extent of the different types of disruptions to the road network and the accessibility of the buildings to fire stations. It turned out that the sensitivity of the accessibility to different types of disruptions are significantly different, as the random failures cause more dramatic reductions in the number of buildings accessible to the emergency service providers, while the probability-based failures (presumably due to fluvial flooding) cause a slower reduction in the amount of accessibility as the disaster worsens. In addition, in this paper, the accessibility of the households (building blocks) within each fire district to the emergency service providers (namely fire stations) was quantified by simulating the percolation within the transportation network. It turned out that the flood exposure (vulnerability) of the different fire districts under the same level of flooding is different. These findings have important implications for optimizing the allocation of limited resources during and after flooding events. This study has three main advantages: (1) For the accessibility analysis of the households, it made use of the publicly available data for the road network and other critical facilities, both of which are of high resolution; (2) It effectively avoided the data-intensive transportation demand modeling by making use of the available features of the network theory, as the model is able to capture the directed and non-planar nature of the road network and could assess the existence of the path between any two given nodes; (3) Compared to some existing studies which assessed the accessibility in a more aggregated level (i.e., community and census tract), this study examined the accessibility at an individual building level, which could be more accurate and tends to be more realistic, as there could be road failures within the census tract. It is possible to extend this work by (1) conducting scenario analysis for the location of the fire stations at certain given types and magnitudes of disasters to optimize the locations of the fire stations; (2) considering more types of disruptive events and conducting a comparison between their impacts on the accessibility of the houses; (3) as most of the emergency search and rescue operations are time-sensitive, instead of treating the accessibility of households a binary variable, introducing the time dimension by considering the speed and route length could draw a relatively more accurate picture of the overall accessibility.

6.2. Characterization of Resilience of Road Networks to Uncertain Disruptions

6.2.1. Introduction

Existing research that focused on dynamic changes in the networks either studied the phenomenon on theoretical random networks or assumed the disruptions or failures in the real-life networks are completely random, which is hardly the case. Motivated by this observation, this paper has two interwoven objectives: On one hand, the vulnerability of road network under different types of targeted disruptions is characterized; on the other hand, a vulnerability measure based on the expected size of the giant components of the network under an uncertain disruptive event has been proposed. In order to achieve these objectives, first, the road network is represented as planar graphs and targeted disruption percolation patterns were simulated based on the values of the node -significance metrics. Second, the probability distribution of the giant component under uncertain disruptive events is modeled using the co-location index of the road network with flood control infrastructure. Third, percolations at different extents are simulated in order to estimate the giant components of the network under disruptions of different magnitudes, which, together with the probability estimated in the above step, is used to estimate the expected size of the giant connected component of the road network. The proposed method was applied to super neighborhoods in Houston during Hurricane Harvey. Comparisons are made among the vulnerabilities of different geographical locations, which lead to the identification of disaster-prone areas. It is found that the proposed method is capable of identifying areas that would have a lower level of connectivity as a result of a possible flooding event.

A transportation network is a representation of a spatial network, describing the infrastructure through which the flow of vehicles or commodities is facilitated. In addition to people's everyday movements and transport of merchandise, the road system functions as a life-line system for rescuing people and assets of economic values and plays a vital role in repairing and restoring other infrastructure systems when they are disrupted (Mattsson & Jenelius, 2015). However, transportation networks, including road networks, are vulnerable to natural and manmade disasters, which could disrupt their vital functionality. Achieving sustainability for these systems requires, primarily, the strengthening of their resilience, i.e., their capacity to preserve their modus operandi against the effects of any unexpected events that may challenge their operational performance and continuity during their life cycle. Disruptions to transportation systems can be caused by a variety of different factors, which can be classed as either internal or external. Internal disturbances can include accidents caused by staff or users, system failures, the breakdown of components, overload, and faults in construction. External disturbances can be linked to naturally occurring phenomena, which include severe weather conditions and natural disasters. Intentional external disturbances could also occur due to hostile actions ranging from pranks to acts of war (Mattsson & Jenelius, 2015). The role of the transportation sector becomes even more crucial during disasters due to its prominent role in pre-disaster evacuation as well as post-disaster recovery. For example, the snow disaster in the winter of 2008 destroyed a key railway of the Guangzhou to Beijing Line, which prevented millions of people from returning home for the Chinese Lunar New Year. Half a million passengers crowded in front of Guangzhou Railway Station and caused a serious stampede (Ip & Wang, 2011). Vulnerability analysis of transport networks is dealt with quite extensively in the literature in comparison to resilience. Berdica (2002) provides a definition of the vulnerability of road networks that is widely cited in the literature: "Vulnerability in the road transportation system is susceptibility to incidents that can result in considerable reductions in road network serviceability." To result in a more resilient system, vulnerability analysis, monitoring, responding and learning must all interact (Hollnagel, 2011).

Vulnerability analysis assists with the anticipation of what might befall the system, which is an essential prerequisite for sufficient proactive actions. A city's road network provides spatial access to its different areas through an overlapping hierarchy, which ranges from highways to local access streets. This form of network organization has resulted in increased susceptibility to vulnerability, exposing parts of the city to severe reductions in accessibility when blockages in traffic ensue at junctions or on the main links. The very ability of transportation systems to retain their performance during and after disruptions with little or no loss of functionality, as well as their ability to return to the normal state of operation quickly after disasters, defines their level of resilience. Resiliency analysis of transportation networks helps in the identification of specific weaknesses within these networks, which facilitates decision-making processes for the proper prioritization of investments and improvement projects. In order to achieve this ultimate objective, there is a need for reasonably realistic modeling of the impacts of the different disruptions with varying types and magnitudes. However, theoretical networks, rather than real-life networks like transportation, have been the subjects of most of the dynamic network modeling approaches, which renders the findings from these studies of limited use in real-life networks. This gap in the literature motivates this study to characterize the vulnerabilities of the road network under different types of targeted disruptions and proposing a measure for assessing the connectivity of the road networks under an uncertain disruption. The remaining sections of the paper are organized as follows: a survey of the literature pertaining to systems vulnerabilities and transportation network resilience will be provided; then, the proposed methodology will be presented, which is followed by the demonstration of its application on the Houston road networks; in the end, discussion of the results, their practical implications, paper conclusion, as well as the possible areas for future research, are presented.

6.2.2. Literature review

Graph theory is an approach that has been used to assess the resilience of a variety of real-life networks. The resilience of a graph with respect to a specific property measure how much one has to change the graph to destroy the specific property. The global resilience of a graph is defined more specifically as the minimum number of edges that must be removed so that the graph no longer possesses a specific property (Sudakov & Vu, 2008). Graph theory in transportation is commonly used to study issues related to routing and networks (Monteiro et al., 2012). With the use of graph theory, researchers have tried to analyze networks' resilience by performing statistical studies of different topological measures within the structure of the graphs. Albert et al. (2000) exhibited that many large-scale networked systems share a similar statistical characteristic, power-law distribution of node degree, which gives them increased tolerance to random failures of nodes and very low tolerance to targeted disruptions on highly connected nodes. Callaway et al. (2000) used the concept of node failure and introduced a generalized concept of percolation, through which resilience is calculated for any type of graph based on the size of the giant component (largest connected cluster) after the arbitrary failure of a node or set of nodes. Studies on the vulnerability of transport systems using graph theory have increased in the past decades. In the work by Demšar (2008), the urban street network of the Helsinki Metropolitan Area in Finland was studied and analyzed as an undirected and unweighted network. Their argument is that if a link in the network is cut (which means a link is removed and the network is divided into two non-connected sub-networks), links with a high value of betweenness centrality are the critical components in the road network. In real-world transportation networks, links have important properties such as length, capacity as well as operation and maintenance cost. Porta (2006) also studied graphs of urban street networks using measures of centrality, in addition to the typical properties of degree distribution and average path length. Their conclusions included the suggestion that road networks should be studied as weighted networks, with the weights assigned in their study being related to the length of the edges. Erath (2009) suggested that road networks should be approached as multiple weighted networks; in addition to the length of links being significant to studies, the travel demands and travel times should also be given sufficient consideration. Leu et al. (2010) measure the physical layer of resilience in a transportation system. They represent the transportation network as an undirected graph. Centrality measures, such as degree, betweenness and clustering, for nodes were calculated. They note that nodes with a higher betweenness than average may act as bottleneck nodes and would represent a high structural value within a network. They utilize the clustering coefficient to confirm the existence of bottlenecks so as not to rely on the betweenness centrality measure alone. They proceed then to analyze the road, train and tram networks in the city of Melbourne by removing nodes and determining topological integrity and the distance gap. The probability that the removal of a certain node results in the formation of a number n of sub-graphs is determined and a corresponding probability density function is generated. The analysis approach allows for both the determination of critical nodes within the Melbourne ground transportation network and the associated spatial damage (increased travel distance required) incurred upon the failure of a node, through the utilization of the distance gap measure. Ip and Wang (2011) propose an approach to quantify the resilience of transportation networks, where resilience is linked to the concept of friability. They represent the network as an undirected graph, with the nodes being the cities and the edges the traffic roads between them. They evaluate the resilience of a node by the weighted average number of independent reliable passageways with all other nodes in the network. The resilience of the network is then calculated as a weighted sum of the resilience of all nodes. Another example of resilience analysis of transportation networks was conducted by King et al (2016); the resilience of the Toronto public transit network was analyzed using network science and graph theory, coupled with simulations of the behavior of the transit network and its users. The nodes of the generated multidirectional graph represent surface transit stops and metro stations, while the edges represent the connecting roads or underground tunnels which join the stops and subway stations respectively. The main novelty of this work is that additional travel time is included in the quantification of resilience, so as not to rely only on the network's topological characteristics.

Schneider et al (Schneider et al., 2011) have proposed a network robustness measure based on the size of the giant connected component of the network after being disrupted. This work has been used by many researchers to estimate the robustness of both theoretical and real-world networks (Abdulla et al., 2020b; Song, Luo, & Wood, 2019; Tishby, Biham, Kühn, & Katzav, 2018; S. Wang & Liu, 2019). However, these giant-component based methods in the literature for assessing the robustness of networks fall short of considering the stochastic nature of the impacts of the disruptions on the networks. In summary, while existing works all have tried to analyze the resilience of transportation networks using a certain type of centrality measures of the individual node or the whole network, our understanding of the behavior of the real-life networks like road network under different disruptions scenarios is still limited. Furthermore, there is a need to distinguish the methods which are suitable for studying theoretical networks and actual real-life networks. Thus this study intends to characterize the vulnerability of road networks under different disruptions schemes and proposes a new measure that is able to consider the uncertain nature of the configuration of the road network after a given disruption.

6.2.3. Methodology

In the literature(Schneider et al., 2011), the overall resilience of a network is obtained through averaging the giant components of the network after randomly removing nodes incrementally, as can be seen from the equation below on this page. This measure (R) is capable of measuring the topological integrity of any network. However, all giant connected components (GCC) sizes, S(Q), are given equal weight, and the overall robustness is obtained by taking the algebraic average of the sizes of all possible giant components. Therefore, this measure is only applicable to theoretical networks as it idealizes the scenarios of removing a different fraction of the nodes from the network as an equal probability event. As seen in Figure 59, if we assume the original intact network comprised of 32 nodes and 33 functional edges. A certain disruption occurs and renders 5 of the edges nonfunctional. Consequently, the original network is broken into 5 sub-networks, the largest connected of which has 18 nodes. Thus the relative size of the GCC under this given disruption scenario would be $18/32 = 0.5625$.

$$R = \frac{1}{N}\sum_{Q=1}^{N} S(Q)$$

$where$: R: network robustness measure; N: $total\ number\ of\ nodes\ in\ the\ network$;
Q: $number\ of\ nodes\ removed$; (Q): normalized $giant\ component\ after\ removing\ Q\ nodes,$ which is the ratio of the number of nodes in the giant connected component after the original network fragmented and original network size. S(Q) takes the values between 0 to 1.

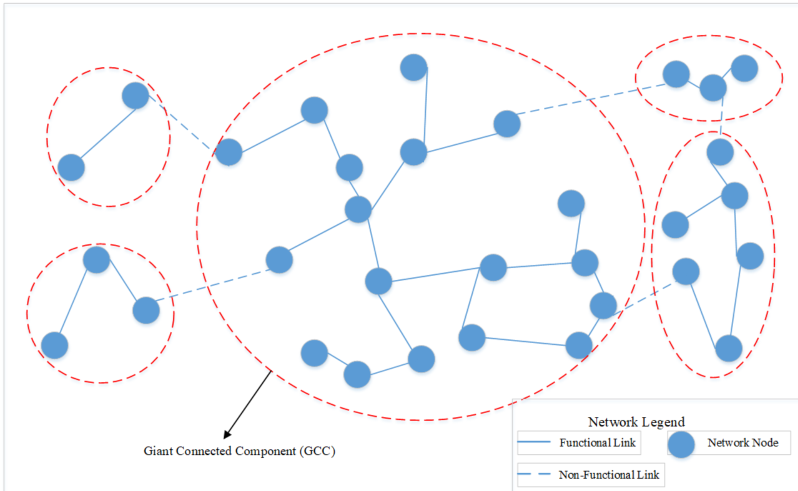


Figure 59 Schematic explanation of connected giant component (GCC)

In real life networks (like road networks), however, the formation process of each S(Q) represents a unique disruption portfolio to the network. Due to the unique topology of the real-life networks, removal of the same number of nodes with different topological features could lead to S(Q) value of varying sizes. There is a need to consider the heterogeneity in the node failure sequence (NFS) and the likelihood of the formation of giant components of different sizes. In order to address the latter, an expected resilience (ER) measure, measured using the sum of probability-weighted giant-connected components, is proposed. Mathematically, this can be expressed as in equation:

$$ER = \frac{1}{N}\sum_{Q=1}^{N} S(Q) \cdot \mathrm{P}_Q$$

where,

ER: *expected resilience*; Q: *number of nodes removed*;

P_Q: *probability of removing Q nodes*;

S(Q): normalized *giant component after removing Q nodes*

The formation of a giant connected component in the road network during or after a disruptive event is a process governed simultaneously by numerous endogenous and exogenous factors. Suppose we assume the underlying disruption is a fluvial flood caused by heavy rainfall. In that case, endogenous factors could include various hydraulic features of roadway systems, for example, availability and functional capacity of drainage systems, type of flood plain in the areas roadway system located, slope, alignment, elevation, proximity to flood control infrastructure, to name a few. Exogenous factors could include the time of the year, the intensity of the rainfall, the temporal and spatial distribution of the rainfall, and the availability of buffering green space on the roadways' sides. Therefore, in order to estimate the probability distribution of the giant component size, in theory, historical data about the size of the giant component under flooding of various intensity could be collected for a certain area, which could be used to forecast the future probability distribution of the size of the giant components for the road network within certain area. For example, there have been at least 70 tropical or subtropical cyclones that affected the state of Texas and most of them brought heavy rainfall (Roth, 2010). There is a certain pattern in these events, as about three happens every four years and they most probably happen in the month of September. Due to the lack of access to the historical data about the sizes of the giant components in the road networks at the peak of the flooding caused by rainfalls, furthermore, the main objective of this study is to demonstrate the application of the proposed method rather than forecasting the distribution of the size of the giant components on the road network. This study made several important assumptions about the type of distribution model and the parameters of the model. A triangular distribution is assumed for the distribution of the size of the giant components formed in the road network after its being disrupted by the fluvial floodings. A triangular distribution that features three parameters $(l, m\, and\, r)$ could be written as below (Samuel, 2004).

$$P(x; l, m, r) = \begin{cases} \dfrac{2(x-l)}{(x-l)(m-l)} & for\ l \leq x \leq m, \\ \dfrac{2(r-x)}{(r-l)(r-m)} & for\ \ m \leq x \leq r \end{cases}$$

As the size of the giant component in a certain network could only be between 0 and 1, the maximum and minimum values for the giant component are respectively 0 and 1. Thus, the l and r values in the triangular distribution, respectively 0 and 1. The simplified triangular distribution could be written as:

$$P(x; 0, m, 1) = \begin{cases} \dfrac{2(x)}{xm} & for\ 0 \leq x \leq m, \\ \dfrac{2(1-x)}{r(1-m)} & for\ \ m \leq x \leq r \end{cases}$$

The mode (m) for the triangular distribution is estimated using the normalized proximity index proposed by Abdulla et al (Abdulla et al., 2019). The higher the proximity index, the smaller the mode of the triangular distribution, which means there is a higher probability that giant components are smaller. The relationship could be written as*:*

$$m_i = 1 - \frac{CI_x - \min[CI]}{\max[CI] - \min[CI]}$$

Where: CI_x: *the colocation index for super neighborhood x*;

$\min[CI], \max[CI]$: *respectively minimum and maximum colocation index*

6.2.4. Results

The data for the road network is retrieved from OpenStreetMap via the OSMnx python package. The spatial distribution of the flood control infrastructure and their GIS map is provided by Harris County Flood Control District (HCFCD) and super Neighborhood shapefiles are obtained from the City of Houston Open Data Portal. Programming language Python is used for the simulation. Analysis has been conducted at two spatial scales, super neighborhood scale and city scale. Among 88 super neighborhoods in Houston, this study has focused on 26 located in and around energy corridor regions in west Houston. The road network for one of the super neighborhoods, named Memorial, is presented with the city scale road network in Figure 60. The Houston road network has more than 20,600 miles' length of roadway, with 153818 nodes and 397116 edges, average node degree being 2.58, while Memorial road network has a node number of 4073, edge number of 9762 and average in and out the degree of about 2.4.

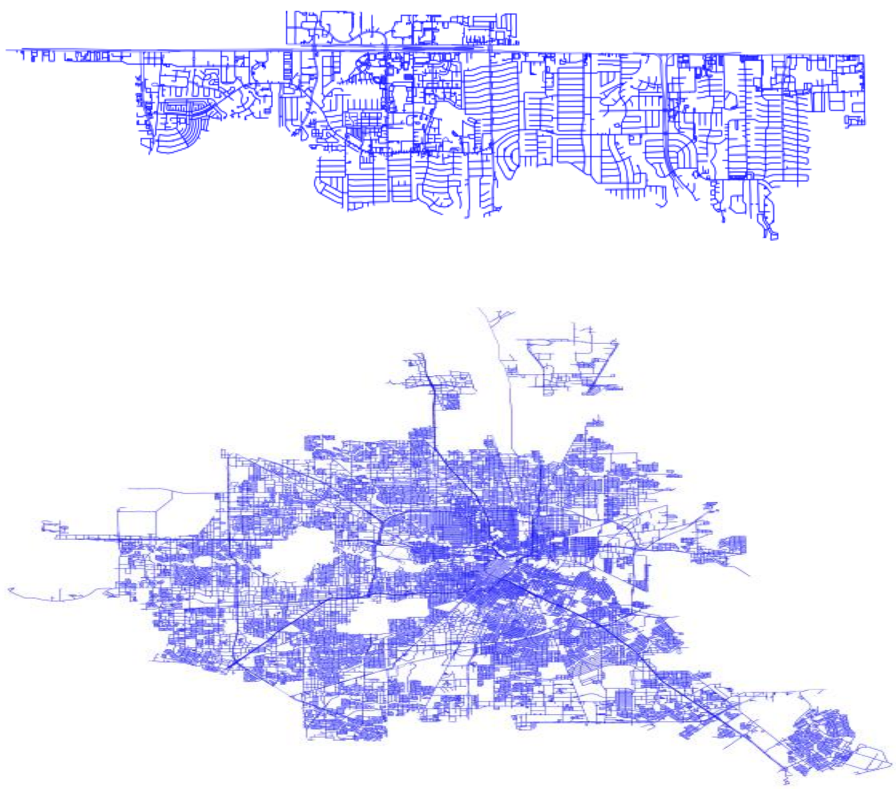


Figure 60 Road network in Memorial super neighborhood (top); city of Houston (bottom)

Percolation under Different Removal Sequences

To check the sensitivity of the connected giant connected component on different removal sequences, the relationship between different types of removal patterns and change in giant component sizes is studied. The simulation is conducted on the 26 super neighborhoods located near the energy corridor region of West Houston. Nodes with a higher degree, betweenness, Eigen-vector, and closeness centrality are considered to be more important for maintaining the network's overall connectivity. These four centrality measures of all the nodes network are calculated and nodes are ranked based on their respective centrality measures (with nodes with the highest values ranking first). Then nodes are removed from the network based on their ranks, nodes with higher centrality measures being removed from the network first. Results on percolation on road network on super neighborhood level are presented in the below Figure 61. Invariably, the targeted disruptions based on the value of betweenness centrality of the nodes are the most "efficient" for reducing the road network's connectivity. In order to check the impact of scale on the above result, simulation on the entire road network in Houston is conducted and results are presented in Figure 61. Betweenness centrality-based node-removal brings connectivity down faster than other types of disruptions.

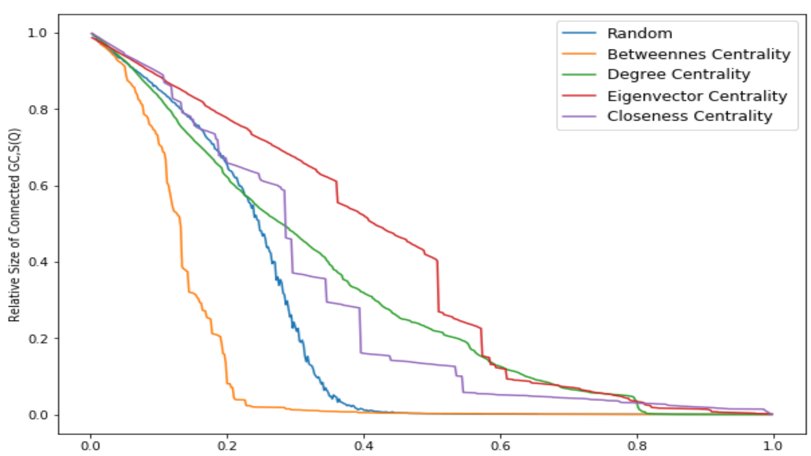


Figure 61 Percolation in Houston road network under different sequence of disruptions

The robustness of the network under different removal schemes (in descending order) differs widely and the below relationship is observed.

$$R_{BC} < R_{DC} < R_{Ran} < R_{CC} < R_{EC}$$

Percolation with Different Removal Probabilities

In order to demonstrate the application of the expected resilience (ER) measure, the colocation index (CI), which is defined by Abdulle et al (2019), is estimated for 26 super neighborhoods by overlaying the spatial distribution of the flood control infrastructure on the super neighborhood shapefiles, which can be seen in Figure 62. The cumulative values for the colocation index (CI) for the super neighborhoods are presented in Table 15.

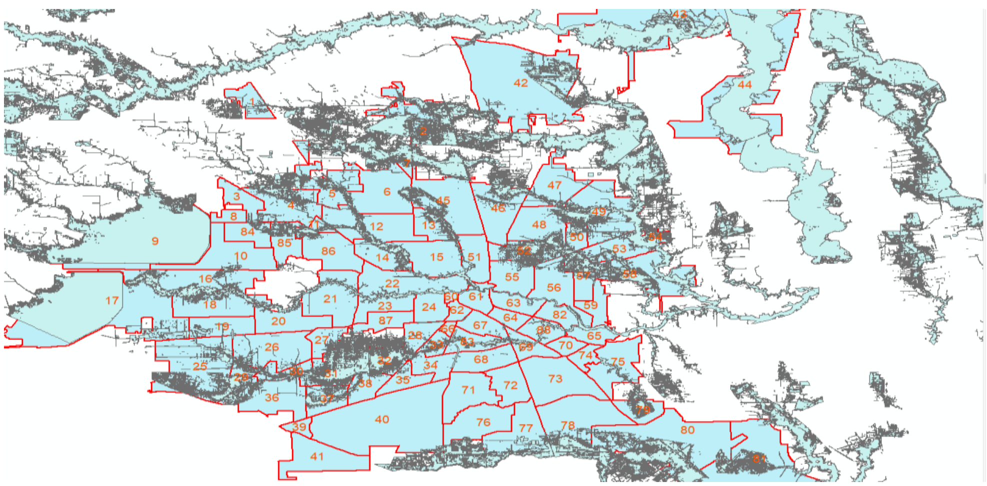


Figure 62 Colocation of flood control infrastructure and super neighborhoods in Houston

For each of the super neighborhoods, the mode of the triangular distribution is obtained. Using corresponding distribution, the expected robustness based on the giant component size distribution is obtained for each of the super neighborhoods. A comparison was made between the robustness values of the road networks under uniform-probability percolation and expected resilience values obtained using the proposed method, as shown in Figure 63.

Table 15 Colocation index (CI) of super neighborhoods

Super Neighborhoods	Colocation Index (CI)	Super Neighborhoods	Colocation Index (CI)
Carverdale	3	Eldridge - West Oaks	9
Fairbanks - Northwest Crossing	3	Briarforest Area	4
Greater Inwood	5	Westchase	4
Acres Home	3	Woodlake - Briarmeadow	3
Westbranch	2	Greater Uptown	5
Addicks Park Ten	8	Washington Avenue Coalition - Memorial Park	5
Spring Branch West	6	Afton Oaks - River Oaks Area	3
Langwood	3	Neartown - Montrose	2
Oak Forest - Garden Oaks	3	Gulfton	8
Independence Heights	2	Spring Branch Central	4
Lazy Brook - Timbergrove	4	Spring Branch North	3
Greater Heights	6	Spring Branch East	4
Memorial	8	Greenway - Upper Kirby Area	2

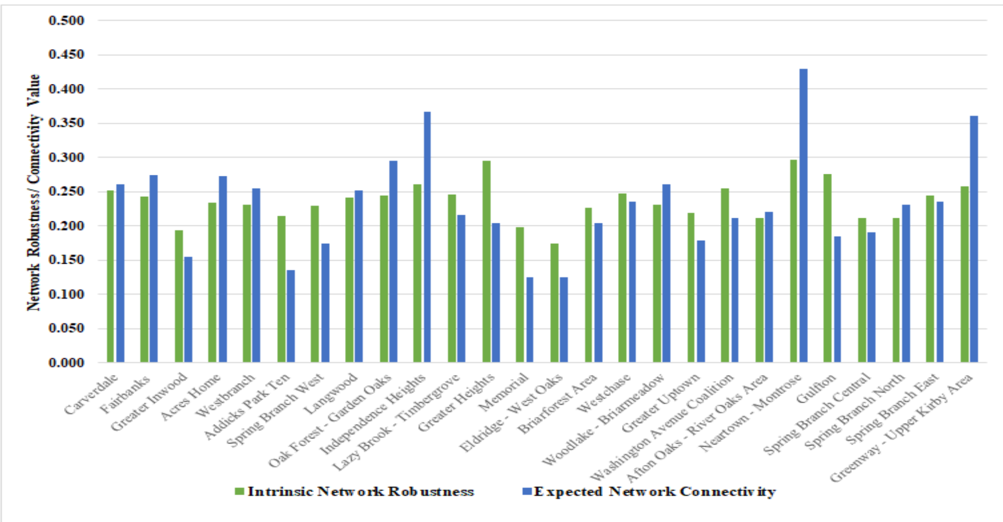


Figure 63 Comparison of intrinsic robustness and expected robustness

6.2.5. Discussion and conclusions

Results on different spatial scales and geographical locations invariably revealed that nodes with higher betweenness centrality will cause the greatest damage to the connectivity in the network. As it turned out that if the node removals are conducted in a way the betweenness centrality of the nodes is descending, the size of the GCC in the road network will drop faster compared to random percolation as well as other types of targeted percolation. In order to identify these high-risk nodes, a road network in the Memorial neighborhood is visualized based on the values of the betweenness centrality of the nodes (see Figure 64). It turned out that most of the high-stake nodes tend to be on the major arterial roads (I-10), Sam Houston Tollway, Highway 6 and Memorial Drive, which corroborates the finding of the other researchers in the field that keeping major arterial roads functional is of great significance for ensuring the connectivity in the neighborhood.

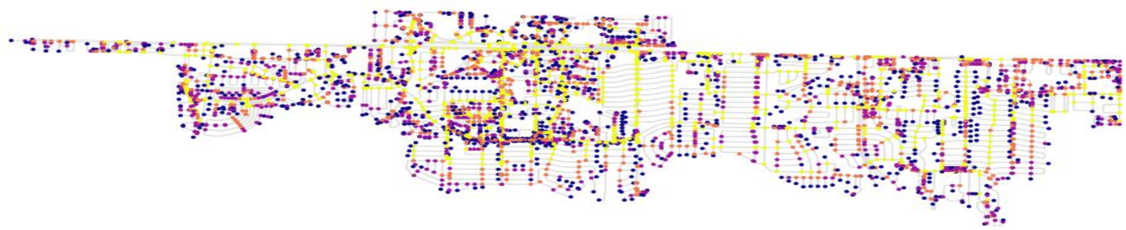


Figure 64 Visualization of nodes in Memorial neighborhood based on betweenness centrality (yellow is high, violet is low)

Figure 64 shows the highlighted critical portion of the nodes in the road network in order to maintain road network connectivity. Based on this finding, it is possible to propose a measure to assess the vulnerability of road networks to flooding events by looking at the ratio of high betweenness-centrality nodes within the flood plain. If this ratio is high, the road network is particularly vulnerable to flooding. On the other hand, if this ratio is low, the road network is less vulnerable to the disruption caused by flooding. As to the expected resilience (ER) measure, the results (in Figure 64) show areas located within the immediate vicinity of the flood control infrastructure tend to have smaller expected connectivity, while road networks in areas with less flood control infrastructure have higher expected connectivity. This is a generalized method that could be applied to assess any type of network's robustness under any disruption, given a distribution of the GCC sizes could be estimated. This proposed method can also measure the robustness of the network under multiple or different disruptions, as it is possible to estimate the joint probability of the GCC of the network under different disruptions. As a part of a separate study, when examining the correlation between the proposed expected network resilience metric and the empirical hardship experienced by road users in different super neighborhoods, it was discovered that proposed expected robustness has a higher negative correlation with the level of mobility hardship experienced by residents within that neighborhood than the intrinsic robustness index. This indirect validation of the proposed method could be further used to estimate the mobility hardship experienced by different geographical locations.

The contributions of this paper to the infrastructure resilience community could be summarized in two points. The first one is the characterization of the vulnerability of the road network against the targeted disruptions based on commonly used centrality measures of nodes. It turned out that the betweenness centrality-based removal scheme results in the most destructive impact on network connectivity. The second contribution of the proposed expected network connectivity measure is that it could capture both intrinsic network robustness as well as disaster exposure of the road networks. The method and results presented in this study could inform the resilience-enhancing decisions for the road networks in the face of fluvial flooding. The methodology proposed in this study could be applied to other types of infrastructure or disruptions with an appropriate method to estimate the probability distribution of the giant components' sizes. The methodology could serve as a theoretical foundation for recommendations on how to overcome the identified weaknesses and further increase the road network's capability to handle disasters.

6.3. Predicting Road Network Vulnerability Using Machine Learning Classifiers

6.3.1. Introduction

This study aims to identify vulnerable sections in the transportation network with the help of machine learning classifiers. Many network-theory-based frameworks have been proposed to assess transportation networks' vulnerability using network centrality-based measures; however, those measures can not be directly translated into the actual vulnerability of transportation networks as many studies seem to proclaim. This is because there are clear heterogeneities in disaster-exposure levels of the individual nodes due to the spatially embedded nature of transportation networks. It is possible to study and characterize this heterogeneity with the help of classification tools in machine learning. First, the road network at a super neighborhood level is modeled as a primal graph. Then, a new measure for flood exposure of the nodes in a road network was proposed and treated as the dependent variable. Two independent variables, namely elevation and the shortest distance from flood control infrastructure, were identified for each individual node. A classification algorithm was trained and tested in order to predict the flood exposure of individual nodes in the road network. In the end, connectivity of the road network was estimated after removing nodes (which are predicted using the best performing classification algorithm) that are particularly vulnerable to fluvial flooding. The results indicated that the K-means clustering algorithm had the highest prediction accuracy. The proposed methodology was then applied to assess the vulnerability of other super neighborhoods in Houston during Hurricane Harvey. The proposed framework expands the scope of traditional vulnerability assessment analysis for road networks by effectively making use of machine learning tools, as well as publicly available big data. Results from this study could be used to inform resilience enhancement decisions.

Critical infrastructure resilience against various disruptions is important but is less-known for parts of the city's development and maintenance. The importance and criticality of these systems are usually felt, especially during disaster scenarios when their functionality is compromised. By using models and theories to determine what aspects of the city could stay functional during potential crisis events like hurricanes and storm surge events, we can better create a first-response network that will be prepared for when the city faces a real crisis event. Our study aims to determine vulnerable sections in urban critical infrastructure systems and distinguish them from those that are able to withstand crisis events using the power of machine learning classifiers. This is important for three major reasons. First, our modern critical infrastructure systems are becoming increasingly interdependent due to the rise of digital technology, so they should no longer be treated as isolated objects in designs and models. Second, as urban areas worldwide continue to grow, the influx of population poses stress to the city's infrastructure that cannot be ignored. Third, climate change, terrorist attacks, and other crisis events have increased in frequency and unpredictability. Therefore, failures in critical infrastructure systems are becoming prohibitively costly due mainly to the possible cascading failures. Thus, the resilience of interdependent critical infrastructure (ICI) systems is one of the grand challenges facing engineers and policy-makers in the 21st century (Heller, 2002; O'Rourke, 2007).

Various types of flooding are one of the critical challenges faced by many urban areas. Flooding, especially ones due to excessive and intense rainfall precipitation, has been the predominant cause of the weather-related disruptions to the transportation infrastructure (Pregnolato et al., 2017). Such events could undermine the vital functionality of transportation systems, especially road networks. Many studies have shown that roads are among the major causes of deaths in cities during flooding; this is mainly due to the vehicles being driven through flooded roadways (Ashley & Ashley, 2008; Drobot et al., 2007; FitzGerald et al., 2010; Kreibich et al., 2009). Locations like Texas, where road mobility through cars is the primary mode of passenger transportation, are especially vulnerable to the impact of flooding. The very advantage of having one of the best road networks in the country could become a serious disadvantage when the majority of the road networks are closed due to flooding events, and there are few other alternatives to go around the city, as was the case during the Hurricane Harvey. In addition, during the disastrous events, the transportation system functions as a life-line system for rescuing people and assets and plays a vital role in repairing and restoring other infrastructure systems when they are disrupted, which makes it crucial to identify the vulnerable (with a high level of exposure) locations and assess their impacts on the overall connectivity of the network. Vulnerability analysis of transport networks is dealt with quite extensively in the literature in comparison to resilience. Berdica (2002) provides a definition of the vulnerability of road networks that is widely cited in the literature: "Vulnerability in the road transportation system is susceptibility to incidents that can result in considerable reductions in road network serviceability." Four major types of methods are used to evaluate resilience identified in the literature: probabilistic methods, fuzzy inference systems method, analytical methods, and graph theory-based methods (Tamvakis & Xenidis, 2013). Graph theory in transportation is commonly used to study routing and networks issues (Monteiro et al., 2012). With the use of graph theory, researchers have tried to analyze networks' resilience by performing statistical studies of different topological measures within the structure of the graphs. Porta (2006) studied graphs of urban street networks using measures of centrality, in addition to the typical properties of degree distribution and average path length. Their conclusions included the suggestion that road networks should be studied as weighted networks, with the weights assigned in their study being related to the length of the edges. Erath (2009) suggested that road networks should be approached as multiple weighted networks; in addition to the length of links being significant to studies, the travel demands and travel times should also be given sufficient consideration. Leu et al. (2010) studied the physical layer of resilience in a transportation system. They represent the transportation network as an undirected graph. Centrality measures, such as degree, betweenness, and clustering, for nodes were calculated. They note that nodes with a higher betweenness than average may act as bottleneck nodes and would represent a high structural value within a network. They utilize the clustering coefficient to confirm the existence of bottlenecks so as not to rely on the betweenness centrality measure alone. Ip and Wang (2011) propose an approach to quantify the resilience of transportation networks, where resilience is linked to the concept of friability. They represent the network as an undirected graph, with the nodes being the cities and the edges the traffic roads between them. The resilience of the network is then calculated as a weighted sum of the resilience of all nodes. Most of the infrastructure networks, including transportation networks, are spatially embedded (Bashan et al., 2013) and failure probabilities for individual nodes within these networks are inherently different. This heterogeneity renders the findings from many graph-based methods of limited use for resilience-improvement decisions, as they tend to consider only the possible consequences of failures but not the probability. With the advent of improving computational power and data collection methods, various machine learning techniques have been used in a wide spectrum of fields. While some machine learning methods have been applied to assess critical infrastructure risk analysis (Bui, Ho, Revhaug, Pradhan, & Nguyen, 2014; Mojaddadi, Pradhan, Nampak, Ahmad, & Ghazali, 2017; Tehrany, Pradhan, & Jebur, 2014), the field as a whole has not yet explored the breadth of machine learning tools in the analysis of risk to critical infrastructure. There has been some limited use of classification algorithms in order to analyze critical infrastructure. Rather than this holistic approach, we intend to examine these qualitative features using a quantitative analysis involving machine learning algorithms that classify areas as flood-prone or not flood-prone.

6.3.2. Methodology

This study first proposed a new measure for the flood vulnerability of a node in the road networks and used machine learning classifiers to identify nodes with a high level of exposure to the flooding. Using the results obtained from a super neighborhood, the vulnerable nodes in all other super neighborhoods in Houston were identified. An analysis of the overall connectivity of the individual road networks was conducted after the removal of the highly vulnerable nodes. The steps undertaken in this study could be summarized with the four steps in Figure 65.

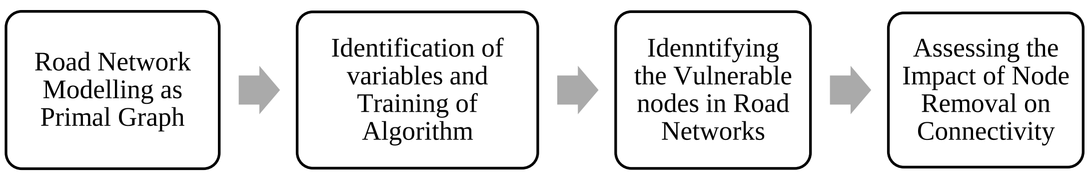


Figure 65 Steps in proposed methodology

Abdulla, Mostafavi, & Birgisson (2019) have applied a dynamic network approach to model the propagation of the fluvial flood in the road networks. As an indicator of the inherent fluvial flood vulnerability, the author used node elevation and colocation index with flood control infrastructure to predict the probability of a certain node being removed from the network. This study uses these two main features of a node in a road network as the independent variable. As for the dependent variable, which intends to capture the flood exposure of the nodes in the road network, this study departs from the existing measures proposed in the literature. Pregnolato et al. (2017) studied the relationship between vehicle speed and flood depth on road networks. While the depth of inundation at a certain location on the road network does provide some insights into the severity of disruption to the traffic flow at a certain point in time, the clear temporal variation in the flood depth is not reflected in this depth-disruption model. Based on this observation, this study proposed a new measure called Cumulative Inundation (CI) to assess the overall flood vulnerability of a certain node in the network during a particular flooding event. The rationale behind this new measure is

$$CI = \int_{t=0}^{T} FD(t)\, dt$$

$Where$:

CI: $Cumulative\ inundation\ (in\ feet)$; T: $An\ entire\ duration\ of\ the\ flooding\ event$;

$FD(t)$: $flood\ depth\ at\ time\ t\ (in\ feet)$

After obtaining the temporal flood depth data for the individual nodes in the road network at hourly intervals, the linear interpolation method was used to obtain the nodes' cumulative inundation level during the flooding event. In this study, a water surface elevation over the flooding event duration (i.e. Hurricane Harvey) was used instead of a static snapshot of the event. For every node, hourly observations were made between 00:00:00, on 8/25/2017 and 23:00:00, on 9/10/2017. Thus, there are 408 flood depth observations for each individual node. The maximum CI values for the study area nodes were 6840 (hour. feet) and the minimum is 0. The mean CI value was about 120 (hour. feet), and the standard deviation was about 389 (hour. feet). The data for both the node elevation and colocation with the flood control infrastructure was obtained from the OpenStreetMaps website using Google API with the help of a Python package called OSMnx (Boeing, 2017). The elevation of the individual nodes is measured in meters (m), while the distance between nodes of fthe lood control network and road network is measured in kilometers (km). For the proximity to the flood control infrastructure (bayou, channel or creek) variable, the average of the two distances between a particular node in the road networks and two closest nodes in the flood control infrastructure network was used. For example, suppose a node $\boldsymbol{A}$ in a road network is respectively 0.5km and 0.7km away from the two nearest nodes (node B and C) in the flood control infrastructure. In that case, the value of the flood control network proximity variable for node $\boldsymbol{A}$ is 0.6km. Due to the relatively high computational cost for obtaining the high resolution (both temporal and spatial) inundation data at an individual node level, classification algorithms were trained using a road network node in one super neighborhood. Then results were applied to identify the vulnerable nodes in another road network. Below is a step-by-step explanation of the methodology in this paper.

Step One: Road Network Modeling as Primal Graphs

Road networks are modeled as primal graphs. Figure 66 depicts the road network in the Memorial super neighborhood in Houston. Classification algorithms were trained using the nodes in this network. As this study is primarily interested in assessing the impact of the flooding on vehicular traffic, only roads used for traversing passenger and service vehicles are extracted. Roads used primarily for walking and cycling were omitted. There are 4073 nodes in this network, and the average node degree is about 4.74.

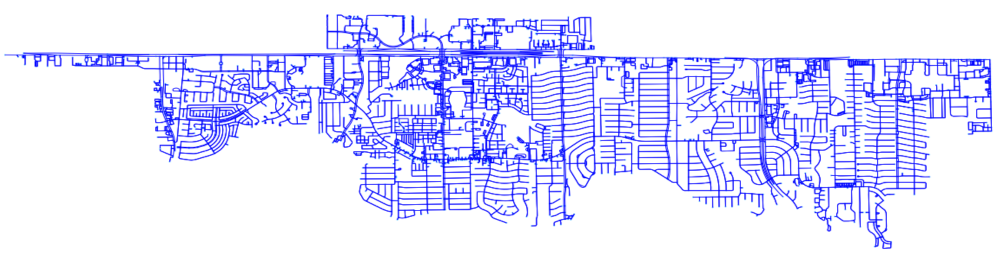


Figure 66 Road network in Memorial neighborhood in Houston

Step Two: Application of Classification Algorithms

After implementing filtering algorithms and discretizing the independent and dependent variables' values, different classification algorithms (k Nearest Neighbor, Multilayer Perceptron, Random Forest, Logistic Regression, and Naive Bayes) were trained with the data for the case study region. In these classification methods, the output variable was the cumulative inundation of the network nodes (Figure 67). Nodes are classified into three types based on the cumulative inundation value: Highly vulnerable, moderately vulnerable and not vulnerable.

Figure 67 Color map for the cumulative inundation values of nodes (yellow represents high values; purple represents low values)

The input variables for the classification algorithm are: (1) Node elevation (Figure 68), the maximum value for the node elevation was about 36*m* while the minimum was about 24*m*, and the standard deviation is about 2*m*; (2) Node proximity from the flood control infrastructure (see Figure 69 for flood control network in Memorial neighborhood), the maximum distance was more than 18*km* while the minimum was only about 0.4*km*.

Figure 68 Elevation of nodes in Memorial duper neighborhood road network (blue represent high values; yellow represents low values)

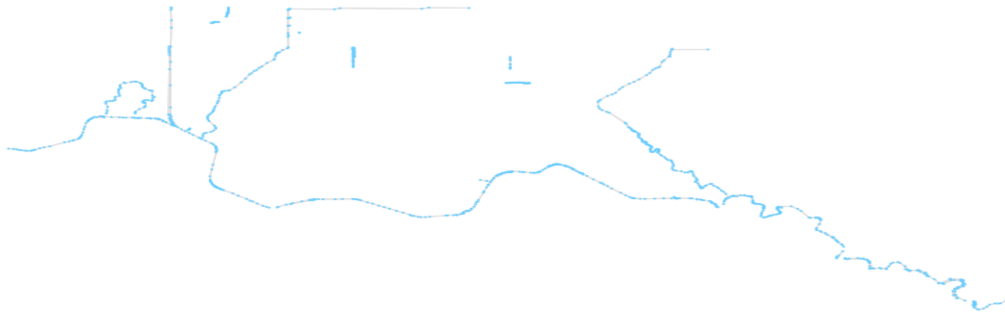


Figure 69 Spatial distribution of flood control infrastructure in Memorial neighborhood

Cross-validation was used to improve the prediction accuracy of the prediction algorithms. As the kNN algorithm has provided the highest prediction accuracy, it was used to predict the vulnerable nodes in the road networks in Houston's remaining super neighborhoods. When k=5, the algorithm has the highest prediction accuracy (results for the Memorial neighborhood are visualized in Figure 70).

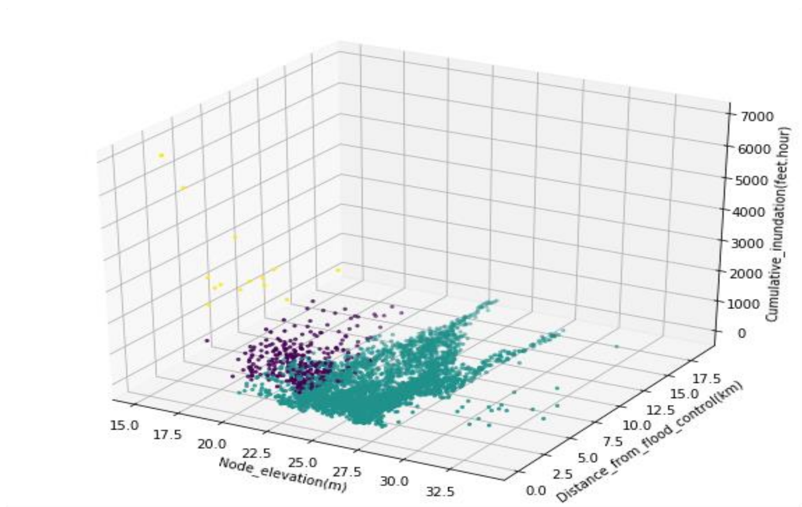


Figure 70 Classification of nodes in Memorial super neighborhood

Step Three: Identification of Vulnerable Nodes in Road Network

Using the proposed method, vulnerable nodes in the road network are identified using the two independent variables' values, namely node elevation and the shortest distance from the flood control infrastructure. A visualized (highlighted in red) road network with vulnerable nodes is presented in Figure 71. As could be seen from the maps in Figure 71 , both the node elevation and node distance from flood control infrastructure play important roles in the vulnerability of the nodes, while the role of node elevation is more evident for the highly vulnerable nodes and proximity with flood control infrastructure is more evident for the moderately vulnerable nodes. This could be due to the possible fact that, in lower elevation areas, nodes tend to be inundated for a longer period of time while in areas that are in close proximity with flood control but relatively high elevation could suffer from deeper inundation but could recover relatively quickly.

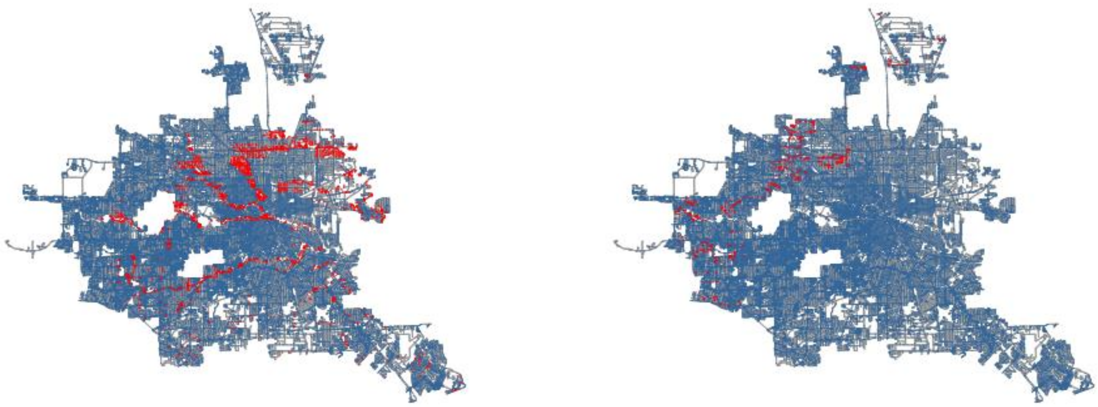


Figure 71 Highly vulnerable (left) and moderately vulnerable (right) nodes in Houston road network

Step Four: Assessment of Connectivity of Road Network

Schneider et al. (Schneider et al., 2011) proposed using the normalized cumulative sizes of the connected giant components in a graph when its nodes are being gradually removed as a measure of the integrity of a given network. This study assessed the connectivity of the road network using the ratio of the sizes of respectively the giant connected components in the network after highly vulnerable nodes are removed and the network's original size.

$$CON = \frac{S_{GC}}{S_o}$$

Where:

CON: $connectivity\ level\ in\ certain\ road\ network;$

S_{GC}: $size\ of\ the\ connected\ giant\ component\ after\ certain\ nodes\ are\ removed$

S_o: $the\ original\ number\ nodes\ in\ the\ uninterrupted\ network$

Using the previous section results, nodes identified to have high cumulative inundation levels were removed from the network. This is because these network nodes represent parts on the road network rendered non-functional by either extended time they are inundated or the flood's depth is too high. Results of the impacts of the removal of highly vulnerable nodes in each of the individual road networks were visualized in a color map in Figure 72.

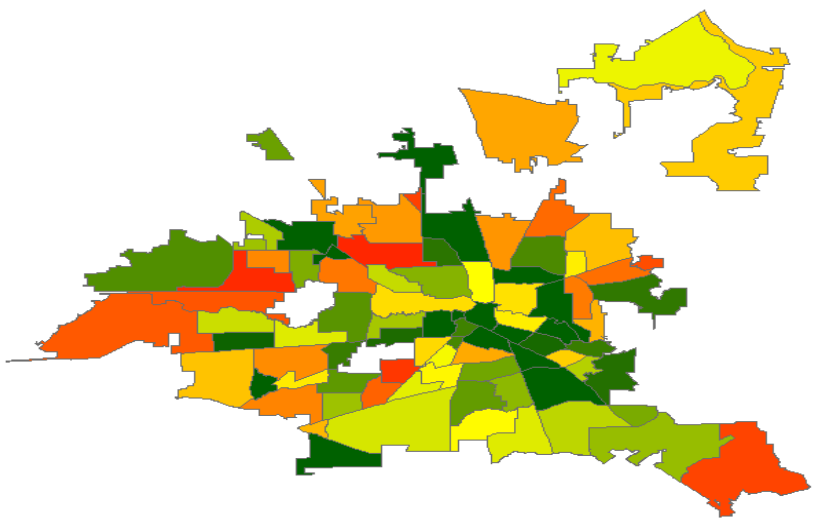


Figure 72 Connectivity levels in road networks in Houston during Hurricane Harvey (red represents severe loss; dark green represents impacted)

6.3.3. Results and discussion

As previously mentioned, a number of different classifiers were trained using the available data and one with the highest prediction accuracy was the kNN algorithm. We also looked into the K-Nearest Neighbor classifier's accuracy as we tune the hyperparameter (in this case, the value of K) and the highest accuracy was achieved with a K value of 5. As the value of K was further changed, we noticed that accuracy decreased, likely due to overfitting. From the connectivity analysis on the road networks in individual super neighborhoods after removing the vulnerable nodes from the network, it is also observed that the severity of node removal and severity of accessibility loss is not necessarily a one-to-one relationship. Areas in the west and north Houston suffered from particularly high accessibility loss, probably due to the fact that the identified vulnerable nodes tend to be high centrality nodes. This could have important implications for resource allocation decisions.

6.3.4. Conclusions

This study aimed at applying machine learning classifiers to identify features that contributes to the fluvial flood exposure of the road network. As shown in the previous section, the results found that the kNN classifier combined with the two features gives the highest prediction accuracy for road network vulnerability. It was also observed that the severity of the flood (measured with the number of nodes impacted) is not directly correlated with the severity of the loss in connectivity in the road network. Another noteworthy contribution of this study is the measure proposed to assess the road network's flood exposure, which comprehensively captures the severity and duration of the flood. Findings from this study could be used to inform resilience enhancement decisions pertaining to road networks susceptible to fluvial floods. It is possible to improve the accuracy and precision of the vulnerable areas' prediction by considering observation from larger spatial or temporal scales or including more features into the analysis. Similar data-based machine learning methods could also be applied to identify factors that contribute to the road network's vulnerability under other types of disruptions. Additionally, with an appropriate set of feature variables, extending the proposed method to identify and assess the vulnerabilities of other types of critical infrastructure systems is also possible.

7. QUANTIFICATION OF SYSTEMATIC IMPACT OF DISRUPTIVE EVENTS OR HARDENING OPTIONS USING A TRANSITION MATRIX-BASED APPROACH[3]

7.1. Introduction

There has been a growing interest among the infrastructure resilience research community in developing techniques and frameworks to assess transportation infrastructure systems' resilience or vulnerability in recent decades. It is possible to categorize the critical infrastructure resilience assessment methods into several main categories, analytical, probabilistic, graph-based, and fuzzy inference systems, among others (Tamvakis & Xenidis, 2013). In contexts, some combinations of several related concepts like vulnerability, robustness, recovery, survivability, response, and mitigation have been used to measure the resilience, and approaches for measuring the resilience could fall into one of the below categories: data-driven approach, topological approach, simulation approach and optimization approach (Szymula & Bešinović, 2020). While it is essential to have an accurate estimate of the vulnerability for improving resilience and reducing the disruptive events' negative implications, assessing physical vulnerability is merely one of the many preliminary steps for achieving the intended final goal. In addition, translating the findings of these types of studies into actionable policy recommendations still needs some research, as most of the vulnerability assessments tackle the issue purely from the technical or structural aspect. In reality, improving vulnerability is a quite multidisciplinary topic that spans the realms of social, economic, technical, and environmental domains. There is a need for a framework that could take

[3] Some parts of Chapter 7 is printed with persmission from the Chapter 8 of the report for TxDOT Project 0-6984 “Evaluate Potential Impacts, Benefits, Impediments, and Solutions of Automated Trucks and Truck Platooning on Texas Highway Infrastructure: Technical Report”,by Birgisson, B., Morgan, C. A., Yarnold, M., Warner, J., Glover, B., Steadman, M. P., ... & Lee, D. (2020). (No. FHWA/TX-21/0-6984-R1).

the inputs from multiple sources and convert them into a single holistic measure. To translate the results and findings of resilience assessment methods into specific and actionable policies, comprehensive frameworks that take different dimensions of resilience into account are needed. A search on the topic resulted in some variations of traditional project evaluation methods like life-cycle-assessment (LCA) (Saxe & Kasraian, 2020) and cost-benefit-analysis (CBA) (Räikkönen et al., 2016). Others proposed systems analysis methods to holistically investigate critical infrastructure systems' resilience (Alfaqiri et al., 2019). Even though the has been some progress on holistic impacts assessment methods, not enough research attention has been contributed to the even more crucial step: applying these frameworks and achieving the intended resilience objective. This section of the dissertation presents a method to comprehensively and systematically assess the impacts of the resilience-enhancing projects on the projects/system's overall performance using the transition matrix's eigenvalue.

7.2. Methodology

In the following sections of this chapter, research objectives and corresponding completed research, and brief information about the produced manuscripts under these research tasks are presented in a constructive manner. This chapter introduced methodology in the below steps:

Step One is the identification of the main dimensions of system resilience and corresponding performance indicators for each dimension. In order to apply this framework to assess the resilience of critical infrastructure, the dimension of the resilience from multiple domains has been identified for the given spatial/organizational/temporal/ operational unit of analysis (Figure 73). The directed graph's eigenvalue could be used to assess the impacts of the disruptions on the critical infrastructure systems. Roads are represented as a network (graph), which has nodes (N) and edges (E). nodes and edges in the network are weighted based on their features. There is a clear hierarchical relationship between the road sections.

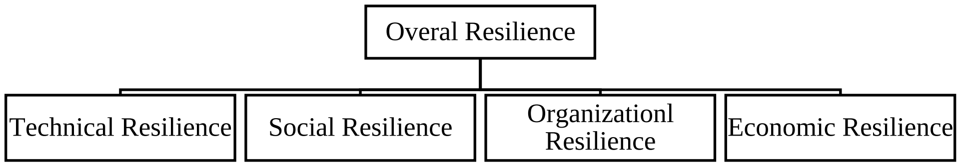


Figure 73 Main dimensions of resilience

Step two is the collection of data about system performance indicators both before and after the occurring of a disruptive event or implementation of a hypothetical hardening option. The condition of the system in question before and after a certain disruptive event (or hardening options) are respectively C_i and C_{i+1}. If we assume, there are m performance indicators and n units of analysis under a given scenario. The matrix as T_i, then this equation holds true: $C_i T_i = C_{i+1}$, which can be written as:

$$\begin{bmatrix} c_{11} & \cdots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nm} \end{bmatrix}_i \begin{bmatrix} t_{11} & \cdots & t_{1m} \\ \vdots & \ddots & \vdots \\ t_{m1} & \cdots & t_{mm} \end{bmatrix} = \begin{bmatrix} c_{11} & \cdots & c_{1m} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nm} \end{bmatrix}_{i+1}$$

where,

C_i: system $condition\ at\ a\ given\ time$; T_i: $transition\ matrix\ at\ a\ given\ time$; C_{i+1}: $system\ condition\ at\ the\ aftermathc\ of\ disruption\ or\ hardening\ options$

Step three is the estimation of the transition matrix and subsequent quantification of the magnitude of impacts on system performance using eigenvalue-based metrics. Using the above equation, we can solve for transition matrix:

$$T = [C_i^T C_i]^{-1} \left[{C_i}^T C_{i+1} \right]$$

By definition, if we assume λ and E as the eigenvalues and eigenvectors of the above transition matrix, by definition below equation should hold true. $\lambda E = ET$. Eigenvalues (λ) of the matrix could be calculated by setting the characteristic polynomial equation to zero.

$$\det(T - \lambda I_n) = 0$$

where: I_n is the identity matrix. The above equation would be used to calculate the eigenvalues and eigenvectors of the transition matrix. Then, arithmetic and geometric averages of the eigenvalues could be used to assess the magnitude of change.

$$\bar{\lambda}_{arithmatic} = \frac{1}{n}\sum_{i=1}^{n} \lambda_i$$

$$\bar{\lambda}_{geometric} = (\prod_{i=1}^{n} \lambda_i)^{\frac{1}{n}}$$

Alternatively, it is possible to calculate the sum and product of the eigenvalues using the below properties of the eigenvalues. (Herstein, 1964):

$$\bar{\lambda}_{arithmatic} = \frac{1}{n}\sum_{i=1}^{n} \lambda_i = \frac{tr(T)}{n}$$

$$\bar{\lambda}_{geometric} = \left(\prod_{i=1}^{n} \lambda_i\right)^{\frac{1}{n}} = \det\ (T)^{\frac{1}{n}}$$

The above relationship between eigenvalues and a matrix's trace and determinants could be used to estimate the arithmetic and geometric means of the eigenvalues conveniently. In the context of this study, a transition matrix is a unique matrix where the cells in the transition matrix are scaler-values for the original performance measures. For example, if no change ever happens to any performance measures, then all of the diagonal elements of the transition matrix would be a value of 1. Depending on the specific performance indicator, the values either go up or down.

The overall magnitude (impacts) of the disruptions on the system performance could be quantified using the average deviation from original values:

$$\Delta = \left| 1 - \frac{1}{n}\sum_{i=1}^{n} \lambda_i \right|$$

Eigenvalues of a matrix could be used to measure the impact changes in the measurement indicators if there are significant changes in the indicators. Eigenvalues and eigenvectors of a matrix could be used to measure the variance profile of the matrix cells. Certain eigenvector projects the transition matrix into a one-dimensional line and corresponding eigenvalues denote the corresponding dimensions' variance level. After normalizing the eigenvalues, the eigenvalues represent the portion of the variance that is projected into a certain dimension. The average value of the eigenvalues represents the magnitude of the changes in the corresponding scenario. The higher the average eigenvalues, the greater the magnitude of the change in the scenario. The transition matrix approach can be used to model and monitor the performance of any given network asset temporally and under different scenarios. Its application is demonstrated separately for modeling the performance of pavements and bridges. The eigenvalues and eigenvectors of the transition matrix are essential since they help identify and quantify the sources of asset changes under different scenarios. For example, by ranking the transition matrix's eigenvalues, it is possible to identify the performance indicator with the most significant change in asset performance, which can quantify the impacts on the individual performance indicator. If comparing scenarios, the average of the eigenvalues corresponding to the respective scenarios can reveal the scenario in which the performance indicator is highly impacted.

7.3. Case Study

The proposed method was demonstrated by conducting a vulnerability analysis on Bridges on Texas Freight Network. In the National Bridge Inventory (NBI) database, there are more than

55,000 bridges in Texas highway network. Out of that, 20,922 bridges are a part of the Texas highway freight network and have a span length of at least 45 feet, which is the minimum length needed to accommodate two trucks in a platoon. A further 591 bridges are excluded because they fall outside the assumptions of the analysis. In total, 20,331 bridges are considered in this report (Figure 74).

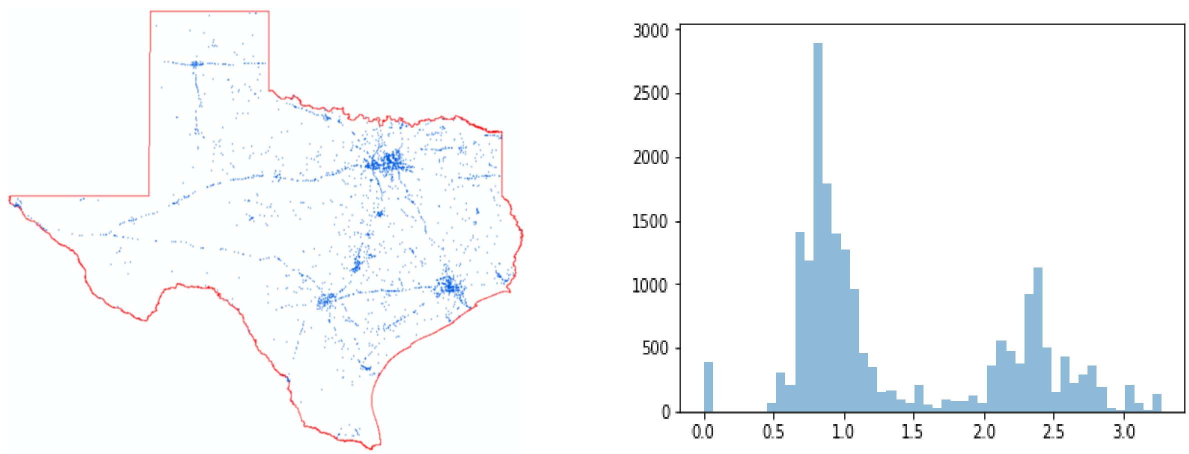


Figure 74 Locations of bridges and priority rating under a platooning scenario (2 3S2 truck at 50ft)

Two common types of five-axle trucks were considered for truck platooning. They are 3S2 and C5. The differences between these truck configurations are that the C5 trucks had closer axle spacing than the 3S2 trucks, resulting in more severe bridge loading conditions on bridges with longer span lengths. As for the number of trucks in the platoon, two and three truck scenarios were considered since these are most likely cases. For the spacing (S_a) between the platooned trucks in a single platoon, two scenarios, 30 ft and 50 ft, were considered. Thus there are eight scenarios in total (Table 16). Since the two 3S2 truck platooning at 50 ft scenario is closest to the "business as usual scenario," we considered it as the base-case scenario, thus allowing us to obtain a corresponding transition matrix for each of the seven other transition scenarios.

Table 16 Possible transition scenarios for bridges in Texas freight network

Transition from	Transition to
Base case scenario	2 3S2 30ft spacing
Base case scenario	2 C5 30ft spacing
Base case scenario	2 C5 50ft spacing
Base case scenario	3 3S2 30ft spacing
Base case scenario	3 3S2 50ft spacing
Base case scenario	3 C5 30ft spacing
Base case scenario	3 C5 50ft spacing

Three performance indicators were chosen for the bridges: operator rating, load resistance factor rating (LRFR), and net rating. For 20,331 bridges in the Texas freight network, a 20,331$\times$ 3 matrix exists for every truck platooning scenario. In order to compare results under the normalized and raw-data scenario, in one category, the data were normalized using the:

$$NCi = \ Ci/\,max(Ci)$$

NCi: $normalized\ condition\ rating$

$Ci\ is\ the\ original\ condition\ rating\ for\ the\ bridges$

$Max(Ci)\ is\ the\ maximum\ value\ in\ the\ data\ for\ the\ bridge\ rating$

7.4. Results and Conclusion

As we consider the two 3S2 truck platooning at 50ft scenario as the base-case scenario, each scenario's transition matrix is estimated using estimated values for the three performance indicators for each of the 20,331 bridges (see Table 17). Similarly, the transition matrix for temporal changes in the performance indicators could be collected, and a transition matrix for each bridge or pavement section could be constructed under a given scenario. The magnitude of an eigenvalue corresponding to certain performance indicators reflects the extent of the network performance change concerning that performance indicator. Thus, a low eigenvalue corresponding to a certain performance indicator means a relatively greater impact. The average value of all eigenvalues can be used to measure truck platooning's overall impact on the whole network's performance. This study used the difference between eigenvalues of 1 (indicating no change in performance) and the average of eigenvalues to quantify truck platooning's overall impact.

Table 17 Transition matrix under different platooning scenarios

Comparison with	Transition Matrix (original raw values)	Eigen Values	Average Eigen Value
2 3S2 30ft spacing	[[0.907 -0.020 -0.015] [0.032 0.962 0.009] [0.010 0.009 0.956]]	[0.928 0.957 0.950]	0.94
2 C5 30ft spacing	[[0.754 -0.023 -0.016] [0.030 0.811 -0.002] [0.018 0.014 0.822]]	[0.776 0.799 0.811]	0.79
2 C5 50ft spacing	[[0.854 0.0001 0.001] [-0.010 0.844 -0.116] [0.011 0.008 0 0.865]]	[0.858 0.852 0.853]	0.85
3 3S2 30ft distance	[[0.880 -0.005 -0.003] [0.028 0.910 -0.002] [-0.016 -0.012 0.900]]	[0.910 0.887 0.894]	0.89
3 3S2 50ft spacing	[[1.004 0.009 0.007] [-0.023 0.972 -0.008] [0.004 0.003 0.986]]	[0.994 0.985 0.983]	0.98
3 C5 30ft spacing	[[0.710 -0.015 -0.012] [0.025 0.752 0.006] [0.009 0.008 0.750]]	[0.725 0.742 0.745]	0.74
3 C5 50ft spacing	[[0.852 0.019 0.013] [-0.058 0.779 -0.016] [0.025 0.0195 0.819]]	[0.832 0.816 0.802]	0.82

The impact of truck platooning was assessed using two methods: the average eigenvalues of the transition matrix (Figure 75). It is worth noting that Figure 76 shows the impact under the two 3S2 trucks at the 50ft spacing scenario is zero. As mentioned earlier, the author assumed that this scenario (two 3S2 trucks at 50 ft spacing) is the base case, and each of the possible scenarios (including itself) is compared to this scenario. The other method used to estimate truck platooning impacts is using a performance indicator (called priority rating, PR) for the bridges (Figure 76).

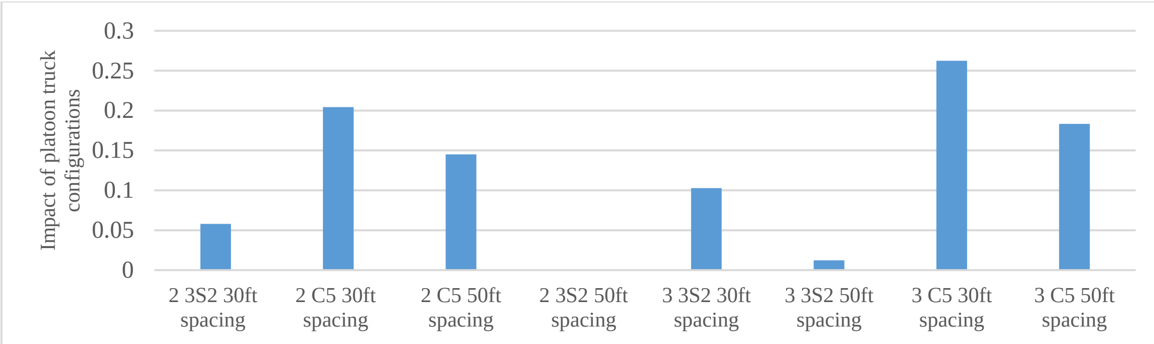


Figure 75 Overall impact of truck platooning on bridges (based on eigenvalues)

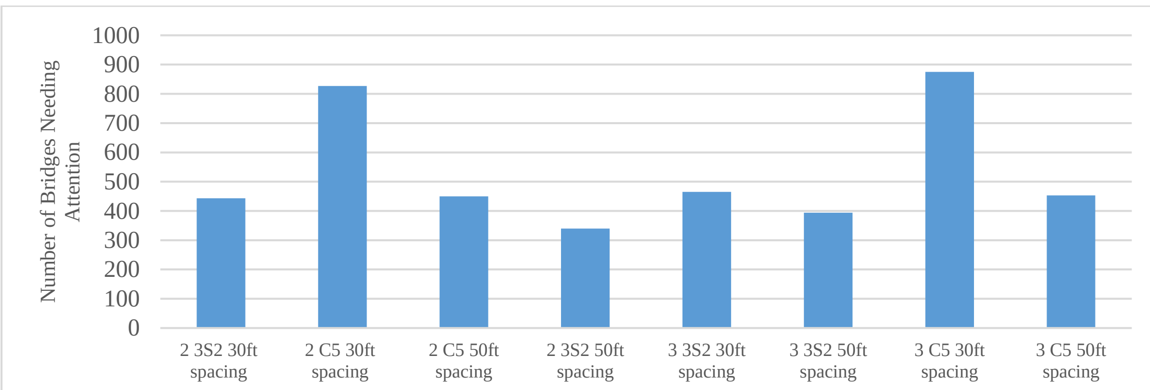


Figure 76 Number of bridges needing attention after full truck platoon (based on PR)

This method enables a more comprehensive evaluation of the truck-platooning impacts on the freight network bridges. It uses the performance indicators of the entire bridge population as model inputs. For example, when three C5 30ft spacing scenario is used,

$$\bar{\lambda}_{arithmatic} = \frac{1}{n}\sum_{i=1}^{n} \lambda_i = \frac{1}{3}(0.725 + 0.742 + 0.745) = 0.74 ,$$

$$\Delta_{ar} = \left|1 - \bar{\lambda}_{arithmatic}\right| = 0.26$$

Similarly,

$$\bar{\lambda}_{geometric} = \left(\prod_{i=1}^{n} \lambda_i\right)^{\frac{1}{n}} = (0.725 \times 0.742 \times 0.745)^{\frac{1}{3}} \approx 0.1336$$

$$\Delta_{geo} = \left|1 - \bar{\lambda}_{geometric}\right| \approx 0.866$$

As could be seen from the results of the geometric and algebraic means of the eigenvalues for the transition matrix, the changes' overall magnitude is 1 or 0.82, respectively. In summary, the research team has proposed a comprehensive index called Priority Rating (PR) to quantify a bridge's ability to support truck platoons. Second, a Microsoft Excel tool was developed for conveniently identifying bridges that need attention at different spatial scales. Finally, the impact of platooning has been assessed using two different methods: (1) using key performance indicators (PR) for the bridges; (2) Using full Texas Freight network-level analysis. The bridge vulnerability study's main findings include: (1) Truck gap spacing has a moderate impact on bridge vulnerability. For example, there is a 33% increase in the number of high-priority bridges when truck spacing reduction from 40 to 30 feet; (2) The number of trucks in a platoon has a minor impact. Policy or investment implications of bridge vulnerability analysis include: (1) Some truck-platoon configurations (for example, 3 C5 Truck at 30ft spacing) have a higher impact on bridges than others; (2) Introducing guidelines for platoon truck weight distributions could be a way to reduce the impact; (3) network-level analysis tool can be used to assess future platooning configuration policies holistically.

8. CONCLUSION

8.1. Integrative Summary of Results

This dissertation intended to undertake the challenging task of characterizing the resilience and vulnerability of transportation networks. As stated at the beginning, it is inevitable to introduce certain proxies as the performance indicators for the quantitative measurement of performance in various transportation network dimensions. The reason for choosing network science as the primary research methodology is that it can, up to a certain extent, capture the dynamics of the systems without losing the mainframe and structural integrity of the system. Main results include: (1) a measure for assessing the connectivity of road network under uncertain disruptions; (2) dynamic network approach (percolation and diffusion) for capturing the cascading failure modes in the road networks; (3) metric for measuring the interdependence among critical sectors (transportation and flood control) and its impact on the road network vulnerability; measure for assessing the accessibility of building blocks; (4) a holistic framework that could quantify the impacts of changes on system performance.

8.2. Contributions

This research's contribution could be summarized from three angles: theoretical, methodological, and practical. This dissertation proposed novel approaches to model profound cascading failures in road networks. It also examined road networks' performance profile under various disruptions, including flood-induced disruptions and random types of destruction disruptions. This dissertation went on to examine key performance profiles independent critical infrastructure systems. This was achieved by first quantifying interdependence among critical sectors then analyzing the impact of interdependence on vulnerability. The final chapter presented a new framework used to assess the overall impact of any changes on critical infrastructure systems' performance. The magnitude of the impact was quantified by the average eigenvalues of the transition matrix. The contributions of this research can be categorized into three aspects: first, theoretical contribution. The study helps bridge the gap between the resilience of theoretical networks and real-life networks. Second, methodological contribution, this study proposed methods to model cascading failures on road networks or the network in general, using dynamic network approaches like percolation and network diffusion. Third, practical contributions. This study has demonstrated the applicability of a holistic methodology that could be used to assess and quantify the impacts of disruptions or changes in real-world settings.

8.2.1. Theoretical Contributions

This research pushed the boundaries of the infrastructure resilience field in the below two aspects. First, in the domains of characterizing the transportation network resilience, it extended the scope of analysis into other important dimensions like social characteristics and infrastructure interdependency, instead of focusing only on the graph metrics of transportation networks, which is both an interdisciplinary approach and a critical way to validate the traditional graph-based resilience assessment frameworks. Second, this research examined the network behaviors and performance of a network of networks instead of studying critical infrastructure networks in isolation. This will facilitate the identifications of the interdependence between infrastructure systems and advance the theory and science behind the super networks (the network of networks).

8.2.2. Methodological and Modeling Contributions

This research proposed methods to model flood propagation in the road network using dynamic network approaches. This study also examined the performance profile of the road network under various types of disruptions scenarios. This network method to explore the road networks' performance profile could also provide a basis for applying other types of critical infrastructure systems or systems that could be modeled using networks could be studied using this type of methodology.

8.2.3. Practical Contributions

The proposed research will address pressing societal challenges in three critical ways. First, it will facilitate the building of more resilient critical infrastructure systems in the face of flooding, especially due to climate change and sea-level rise, which is one of humanity's grand challenges in the 21st century. Results of this study could facilitate dialogue among stakeholders. For example, the research will identify the functional and physical interdependence between different sectors and facilitate dialogue and collaboration among decision-makers of various sectors by educating them about resiliency science and theory. By identifying the factors that lead to mobility hardships during the flooding, this research could help map the dynamic shift of transportation challenges over space and time. This type of live information could help the public, especially those socially vulnerable and underrepresented groups of people, who oftentimes suffer from a disproportionally higher number of casualties during sudden disasters, better cope with disruptions by making the transportation network and emergency service systems more resilient.

Even though this research primarily focuses on modeling and analyzing the transportation and flood control infrastructure sectors, the dynamic network type phenomenon is ubiquitous among other infrastructure sectors (communication, power supply, supply chain, etc.), which could be subject to (respective) other types of disruption. The behavior of these sectors could also be modeled with a similar approach.

8.3. Limitations and Future Work

Future works are needed to validate the proposed method further using more accurate data and make the method more applicable under different circumstances. Possible future work or further research could be suggested for each of the research objectives. For example, under objective one, a unified and specifically defined method for measuring the residents' hardship level during disasters could facilitate comparing the impacts of different types of disruptive events. It is also possible that people of different social backgrounds tend to express their vulnerability in different ways. Those who are less vulnerable tend to consider more aspects when answering the questions and tend to enlarge the extent to which they face the hardships. Additional room for expansion includes applying our results to different domains such as terrorist attacks, using a mix of classifiers, and using a deep neural network instead of a simple neural network. Graph theory has found its application in both theoretical and practical domains. However, compared to the advancements in the theoretical fields, its practical application can be considered as in its infancy. Straightforward direction for future research would include:

1. The inclusion of other transportation modes' network models into the road network analysis could facilitate a more comprehensive vulnerability assessment. This is because there is high independence between different modes of the transportation network. They have to be compatible in terms of, among other factors, their accessibility, capacity, scheduling, and other operational aspects. This is necessary because a transportation network operates and functions as a whole, and there is intricate interdependency between the modes. A percolation analysis on the multi-layer network would assist in drawing a complete picture in the face of the flooding disruptions.

2. This study has predominantly used the largest connected component in the road network as a proxy for network robustness. Inclusion of other factors like transportation network demand, road network capacity, and allowed speed in each section of the road network in assessing the network vulnerability will provide more realistic insights into the network's performance. This is because robustness measured with the topological network centrality measures may not reflect the actual functionality (bottlenecks, critical nodes) of the network models' systems. As is the case with any other essential systems of infrastructure-related networks, the functionality of nodes and edges in the transportation network are highly heterogeneous.

3. The third improvement could be the inclusion of different kinds of disruptions into the vulnerability assessment. There is a need to understand the collective level of preparedness within the system towards multiple disruptive events. For example, this study only focused on pluvial flooding; however, the road network will suffer from disruptions caused by nothing pluvial flooding in rare cases. Other flooding types could occur concurrently, like coastal flooding, pluvial flooding, and surface water flooding. The mechanism for road closure due to other types of flooding could be different. For example, under coastal flooding, the road network closure tends to start from one side of the network. It gradually propagates to older parts of the network, which is different from the pattern this study mainly researched. It is also possible to model the impacts of disruptions caused by other natural disasters and human-made calamities on the road network using similar network-based approaches.

4. The fourth type of improvement could be modeling the destruction caused by accidents. Under these scenarios, even though the road network is not structurally damaged (in other words, closed as in the sense of flooding), traffic flow could still be at a standstill. The network

could be, at least, temporarily rendered non-functional. This reduction in the speed could propagate to neighboring nodes, which is a phenomenon that could propagate and the same fashion into the adjacent nodes. The rate at which this impact propagates within the network is impacted by the roadway types (one-way or two-way), the number of available lanes, and the number of closed roads.

5. It is possible to study or examine the emergent correlation between road networks' topological features and the road network's flood vulnerability. This could be an important arena for future study because cascading failures and emergent interdependencies could not be observed during the infrastructure systems' normal operations. However, like the crashing of the stock market, the crash of the stocks in one sector often-times results in a series of chain reactions, which results in the crash of some other relevant sector, which continues until the whole market crashes. Similar emergent properties in the failure of the critical infrastructure could also be observed during disastrous events.

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