Wayfinding and Accessibility Analysis for Critical Amenities in Iowa During Flood Events

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Abstract

Transportation infrastructure plays an essential role in flood response and recovery. However, flooding may disturb road functionality and generate direct and indirect adverse impacts, including the loss of access to essential services. This paper presents a comprehensive analysis of flood impacts on road network topology and accessibility to amenities for major communities in the State of Iowa using graph-theoretic methods, including single-source shortest path analyses. We assessed the disruption of transportation networks on the accessibility to critical amenities (e.g., hospitals) under 100 and 500-year flood scenarios. Our analysis methodology leads toward the development of an integrated real-time decision support system that will allow decision-makers to explore "what if" flood scenarios to identify vulnerable areas and population in their authority. Due to locations and effects on road topology under flood events, the results show differential impacts in access to critical services.

Introduction

The effects of flooding can be devastating in terms of scope and effect, including loss of lives, adverse economic and financial impacts, and increased uncertainty regarding the normal function of communities. In the U.S., no place is immune to flooding, and about 99% of U.S. counties have been impacted by flooding (FEMA, 2020). Due to climate change, population growth, and urban development, flooding will continue to occur more often with severe consequences (Sadler et al., 2017). According to the National Weather Service, in the United States, the average annual effects of flooding lead to approximately 100 deaths and $8 billion in flood-related damages. The State of Iowa has experienced many flood disasters that have affected its people, infrastructure, and agriculture over the last two decades (Yildirim & Demir, 2019). For example, the 2008 flood affected more than 40,000 people and caused over $10 billion in estimated damage across the State (Zogg, 2014). Recently, Iowa experienced a flood event in 2019 along the Missouri River and elsewhere across the state with estimated damage of $1.6 Billion (Iowa.gov, 2019). Change in native tallgrass to agricultural production is contributing to the scope and magnitude of flood effects (Gilles et al., 2012). These changes increase water flow on the surface, and existing drainage channels may not be able to hold the increased flow. In addition, soil conditions and topography contribute to flooding by increasing runoff velocity and decreasing infiltration.

Floods can significantly impact a community and prevent critical facilities such as police stations and fire departments from providing services (FEMA, 2015). During flood events, people requiring treatment may have to travel to hospitals or outpatient services. Therefore, it is crucial to determine the critical facilities at risk of flooding and how changing conditions alter their accessibility. Floods can prevent hospitals from operating efficiently and consistently. For example, during the 2008 flood in Iowa, the Mercy Medical Center in Cedar Rapids was submerged, and 183 patients were evacuated (Ware, 2013). Moreover, to have an effective response to flooding, it is important to study the accessibility of emergency vehicles (e.g., ambulance) to residential areas before and after a flood event. Some people are more concerned about their properties during floods while ignoring the importance of road operation (Ensor, 2019). When a road is flooded, the effects of its closure can cascade throughout the network system and affect people, businesses, emergency response, and traffic capacity. For example, a school bus may not be able to access an area because of inundated roads. Also, flooded roads may prevent people from obtaining essential supplies (e.g., food) or reaching their work. This may cause emotional distress and losses in work hours and GDP (Botzen et al., 2019). In addition, disruption of road networks may make emergency evacuation impossible. It is critical for flood disaster management to assess transportation networks under dynamic disaster conditions in real-time using information technologies.

Flood risk management and disaster mitigation have been studied extensively in recent years using real-time and integrated information frameworks. These cyber systems can benefit from automated (Sermet et al., 2020) and structured data integration (Sermet & Demir, 2019b; Demir

& Szczepanek, 2017), and volunteer computing infrastructures (Agliamzanov et al., 2020). Transportation analysis under flood conditions is a critical component of such information and decision support systems to support the public and decision-makers on flood-related planning and mitigation. Information and knowledge generated through data-driven models (Sit & Demir, 2019; Xiang et al., 2020) can be communicated to end-users via visualization systems (Seo et al., 2019; Sermet & Demir, 2019a) for flooding.

In our study, we analyzed the vulnerability of all road classes during a 100 year and 500-year flood events in Iowa and the effects of flooding on road network topology and accessibility to essential services provided by hospitals, police, and fire departments. Our research focuses on relative travel distances to amenities under no flood, 100-year, and 500-year flood scenarios. This analytical method provides an overall assessment of the road system, including potential improvements on road design to respond to flood events and enhancing flood risk management. We used an increase in travel distances due to flood-related road closures as the comparison metric to evaluate the impact of flood conditions on the road network.

The paper is divided into four sections. Section 1 provides a review of studies related to flood impacts on routing systems and emergency services. The research methodology for integrating transportation networks and flood models to assess and analyze the road vulnerability and accessibility for cities in Iowa, including bridge operation conditions, is presented under section 2. Section 3 presents the results and effects of flood damage analysis on transportation networks. Discussions and conclusions follow these sections.

1. Background

Floods can severely impact infrastructure in rural and urban environments. Urbanization, heavy rains, and river or stream overflow can lead to flooding (Zhang et al., 2018). Also, soil conditions and topography of an area contribute to increased flood risk (Cunha et al., 2011). Floods can occur as a result of human-made causes. For example, poor infrastructure design increases the probability of experiencing a devastating flood event. Even though flooding can happen whenever and in any zone, some areas and seasons are associated with an increased likelihood of flooding (Ruslan et al.,2014). It is necessary to develop plans for mitigating the adverse impacts of flooding through preparation and changes to infrastructure.

Flood impacts can be addressed through structural and non-structural techniques (Tingsanchali, 2012). Structural methods such as water management systems (e.g., dams) contribute to control and manage floodwater movement. However, these may introduce other issues, including changes to water flow and increased biodiversity losses (Wu et al., 2004). On the other hand, moving people from the flooded area to a safe shelter is an example of non-structural mitigation (Tingsanchali, 2012). These methods can also introduce issues due to equity and cost concerns. The need for sustainable flood mitigation management practices is essential to protect people, infrastructure, economy, transportation, and agriculture. Previous research has contributed to flood mitigation including role of homeowners(e.g., constructing floodwalls on the property) (Laska, 1986), adaption and mitigation techniques for agriculture (Arbuckle et al., 2013), preventing power system blackouts exposed to extreme weather (Dou et al., 2015), strategies to improve floodwater quality (Nicholson et al., 2012), and decision support systems with serious gaming (Carson et al., 2018; Xu et al., 2020; Sermet et al., 2020).

Transportation networks are one of the essential infrastructures for the functioning of a society and economy (Guze, 2014). These networks may experience adverse impacts, including floods, earthquakes, and terrorist attacks affecting their performance, efficiency, and accessibility (Dehghani et al., 2014; Xu et al., 2019). Decisions about the placement of shelters, temporary services, and potential evacuation routes must be made within the context of current and predicted flood extents and scopes. Research on route-finding and navigation during dynamic events has approached these issues in many ways. Researchers have published studies related to optimal evacuation strategies, such as determining safe evacuee routes (Campos et al., 2012; Goerigk et al., 2014), reaching the shelters from flood inundated areas using a legislative time (Borowska-Stefańska et al., 2017), determining evacuation routes that minimize the evacuation time (Bayram and Yaman, 2017; Zhao et al., 2016), and location-allocation of shelters (Kongsomsaksakul et al., 2005). Other researchers focus on routing systems for emergency services (e.g., police and deliveries of essential goods) during emergency situations (Jotshi et al., 2009; Campbell et al., 2008; Mali et al., 2012; Özdamar & Demir, 2012). In addition, planning evacuation routes are a challenge during a disaster, as evacuees often exceed the route's capacity. Kim et al. (2007) suggest the use of heuristics for major highway networks to overcome the network's capacity constraints during evacuation using a macroscopic traffic simulation model.

Road infrastructure is designed to enhance movement within urban and rural settings. These features have a significant role in fostering or hindering economic growth (Arrighi et al., 2019). Increased urbanization, however, increases the pressure on transportation networks, especially at regional and local levels. Therefore, there is a need to assess road network resilience, particularly road components under various disaster scenarios. A resilient transportation network has the ability to maintain its functionality during and after extreme events (Pregnolato et al., 2016). During disasters, road networks provide a valuable infrastructure that can be changed or functionally non-existent in unexpected ways.

Researchers have explored and studied the adverse effects of a flood event on transport infrastructure from a variety of perspectives. These include graph theoretic methods such as the betweenness centrality measure (Kermanshah & Derrible, 2017; Mount et al., 2019), accessibility indices (Sohn, 2006), damage indices (Setunge et al., 2014), and geographical information system (GIS) approaches (Dawod et al., 2012; Yin et al.,2016). However, not all research can provide methods that can be readily utilized. For example, Kermanshah & Derrible

(2017) compared the impacts of extreme weather on the road network between Chicago and New York City. Their method seems to increase the likelihood of returning ineffective results since the city boundary restricts their study. In Iowa, research on the integration of flood depth models with routing analysis has been limited in scope in the literature. Iowa DOT (2017) evaluates the I-80 and identifies areas that at risk of flooding. Also, Zhang & Alipour (2019) investigate the adverse impact of flooding on the road network in Iowa, however, they focus only on the primary road system.

2. Methods

Data Preparation: In this paper, we selected hospitals, fire departments, and police stations as critical amenities to evaluate in major communities in Iowa. We used ArcGIS Business Analyst data, licensed from Infogroup, to determine amenity locations. During flood events, each of these may provide unique and essential services, so we consider potentially changing travel distances and routes from, and to, these facilities to be essential knowledge for service providers and users. Data from the OpenStreetMap (OSM) project is used to build a graph-based representation of road networks. The representation allows for the exploration of the network system using spatial and graph-theoretic methods. It includes a spatially and topologically-explicit road network model used in GIS to explore the relations (i.e., connectedness and adjacency) of graph data structure (i.e., nodes and edges). Locations of bridges and culvert are extracted from the Iowa Department of Transportation (Iowa DOT) database and represented on the road network topology. We generated bridge deck heights using Light Detection and Ranging (LIDAR) data from the GeoInformatics Training Research Education and Extension (GeoTREE) Center. A 3m bare-earth digital elevation model (DEM) from Iowa Geodata provides base elevations for the research areas. Based on stream gage, topographical data, and other hydraulic properties of the drainage networks, Iowa Flood Center has created flood inundation maps that provide the extent and depth of flooding for different return periods (Gilles et al., 2012). A 100-year flood probability has a 1-percent chance of occurring each year at the given flood extent on the landscape. A 500-year flood probability is a 0.2-percent chance of occurring at a given flood extent. FEMA considers the 100-year floodplain as high-risk areas to experience flood damage. Different flood scenarios have been observed over the State of Iowa, including 100-year and 500-year flood events (Tate et al., 2016). Even though the probability of a 500-year flood extent is low, it has been seen, so properties located between the 100- and 500-year floodplain are not risk-free.

Bridge Closure Determination: Bridge closures are particularly important to the analysis. Simple two-dimensional intersections of flood extents and bridges are inadequate to determine if a bridge will be overtopped and closed. Therefore, we have extended this to a three-dimensional analysis to account for bridge design features. We used bridge point locations to determine if a bridge is closed under various flood scenarios. The bridge deck height can indicate the highest elevation on the lidar-derived DEM (not including columns and support mechanisms). The lowest elevation will be on the bare-earth DEM. The value of flood depth plus the bare-earth DEM will be compared with the height of the bridge deck (Equation 1). Once the difference between those elevations returns negative values, the bridge deck is overtopped and closed (Figure 1).

$$B_i = H_i - (E_i + F_i) \qquad \text{Eq. (1)}$$

$B_i < 0$ (bridge is close), else (bridge is open)

Where B_i is the bridge condition, H_i deck height, E_i bare earth elevation, and F_i flood depth

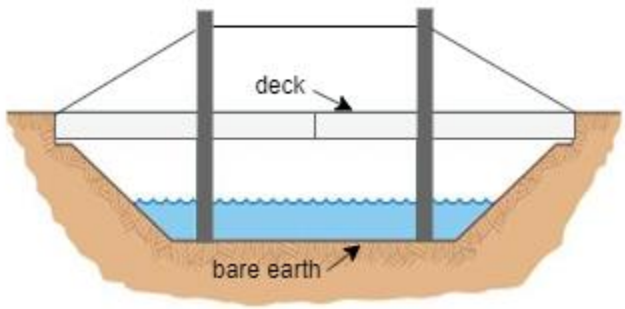

Figure 1. A side view of a bridge above a water body.

Vulnerability Analysis: Graph theory can help understand, design, analyze, and solve complex problems for transportation systems (Guze, 2014). A graph G represents a set of vertices, nodes, or points V(G) connected by edges or lines E(G) (Dickson, 2006). Each edge in the graph can have a weight or cost associated with it. A graph is represented by drawing a point for each node and an edge for connecting between nodes. When each edge in a graph is assigned a direction and an ordered pair of nodes, the graph is called a digraph. In this research, accessibility is analyzed on a digraph by evaluating the alternative routes to reach the amenities under flood conditions.

A resilient and reliable road system requires studying the system's vulnerability under several flooding scenarios (Rogelis, 2015). The vulnerability of transportation networks can be defined as the potential disruption parts of the road structure for an incident and how those affect society. Once a node or edge is inundated, they become impassable and dangerous to traverse. In addition, a critical facility may be vulnerable to flooding if it is located within inundated areas. In our paper, overlapping 100- and 500-year flood maps on road networks generates vulnerable intersections, edges, and critical facilities. Understanding the vulnerability contributes to developing strategic plans to increase the road network's reliability and efficiency and improve the readiness of emergency interventions.

The network graph's initial topological structure is determined using graph-theoretic methods. These methods are used to compute the number of nodes and edges within the graph before and after flooding. During varying flood events, inundated edges and nodes of the graph will be removed so the original topology may alter. People and emergency providers will be affected as a result of the disruption of the road network. These impacts may include an increase in driving time or distances for certain sites within the study area and may be worse by creating “island” or isolated populations that cannot access other parts of the road network and, potentially, essential services. We also analyzed road networks under baseline conditions, 100-year and 500-year flood return periods using all-pairs and single-source shortest path analyses to understand the road network's topological structure. These analyses help us find the shortest path length of all the nodes from a single source node. Running the shortest path algorithm under flood scenarios can determine route vulnerability. The shortest path can assess overall effects on node and edge disruption on the road network.

In this research, we used multiple Python libraries; OSMnx for obtaining OSM data (Boeing, 2017), (GeoPandas, 2019) for geoprocessing data, and (Networkx, 2019) for graph operations and analyses. Also, a QGIS tool (QNEAT3, 2018) was applied for network-based analysis. Networkx contains many methods for calculating shortest-paths, but we use their version of Dijkstra’s algorithm (Xiao-Yan & Yan-Li, 2010) to find the shortest path from a specified location (node) to all other nodes in the graph. Dijkstra’s algorithm sets a specific node as a source and generates the shortest path from the source to all nodes. In this research, we used optimal shortest paths to assess the difficulty of reaching the road network's locations. We realize that people use preferred set choices that may not consider optimal routing. However, without ancillary information, we cannot infer personal set choices, so we use optimal shortest paths as a substitute for additional information. After generating the shortest path, each node has a minimum traveling cost from the source (Figure 2). This is calculated from all amenities to all nodes resulting in k-shortest paths assigned to each node. K-shortest path algorithm calculates not only the shortest path, but also the next $k-1$ shortest paths. The travel cost for each edge can be represented as time or distance, but we use edge length as we don’t have ancillary data on travel time. The sparsity of the network, representation of the network in the computer code, and the way of calculating edge weights influence the Dijkstra’s algorithm results (Golden, 1976). In this research, accessibility is evaluated on a digraph by analyzing the ability (alternative routes) to reach the amenities (hospital, fire department, and police station) under 100-year and 500-year flood return periods as well as the assessment of the difficulty (an increase of shortest distance) of reaching the amenities in the network.

Data Challenges: In this study, we experienced many challenges with respect to geospatial data. We extracted some road networks from OSM data that had misplaced or incomplete regions in varying quality. However, we conclude that it is essential to use freely available data, as many communities cannot afford expensive network data resources. This research required extensive data processing to align LIDAR, flood, and DEM models into the same spatial scale. As this research focuses on the effects of accessibility of services within populated places in Iowa, we selected cities of a certain size with required data appropriate for our analyses. We found that the flood depth models had missing regions or had unconnected river networks. Unfortunately, some cities had to be eliminated from the analysis due to issues with the flood depth models. Also, although business data were released in 2019, we observed inaccurate locations and counts of some amenities for certain cities.

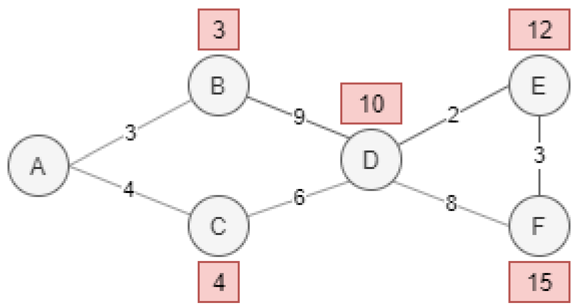

Figure 2. An example of generating shortest path from a source (A) to all nodes. The shortest path from A to F is A-C-D-E-F.

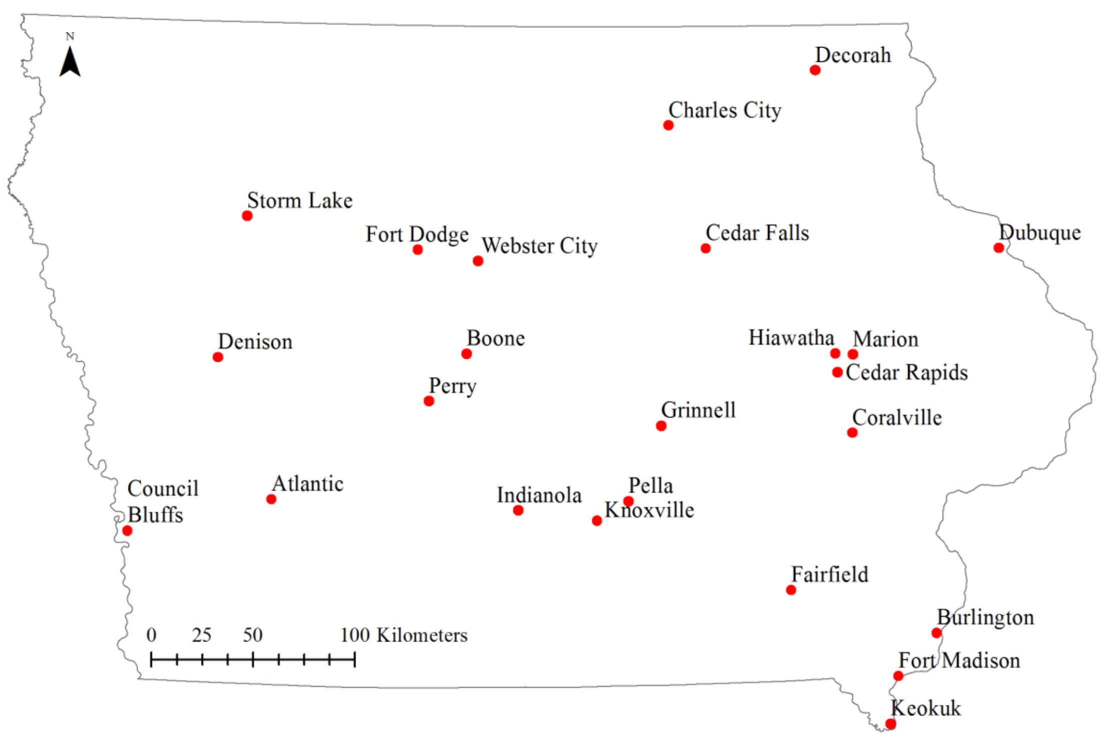

Figure 3. Locations of cities that are analyzed.

Case Study: We analyzed 59 populated places out of 1009 total populated places in the State of Iowa, including only those over 7000 population. Our analysis requires cities to have critical amenities. We observed a natural break in the presence of amenities between those over and under 7000. Due to data issues for some cities, mostly related to the flood depth models, only 24 out of 59 cities are presented here (Figure 3). We examine each city using a boundary envelope of the city plus 3 miles. We refer this to a city+ extent and did this to address edge boundary effects, which caused amenities and nodes/edges to become disconnected and, therefore, not reachable from other edges and nodes.

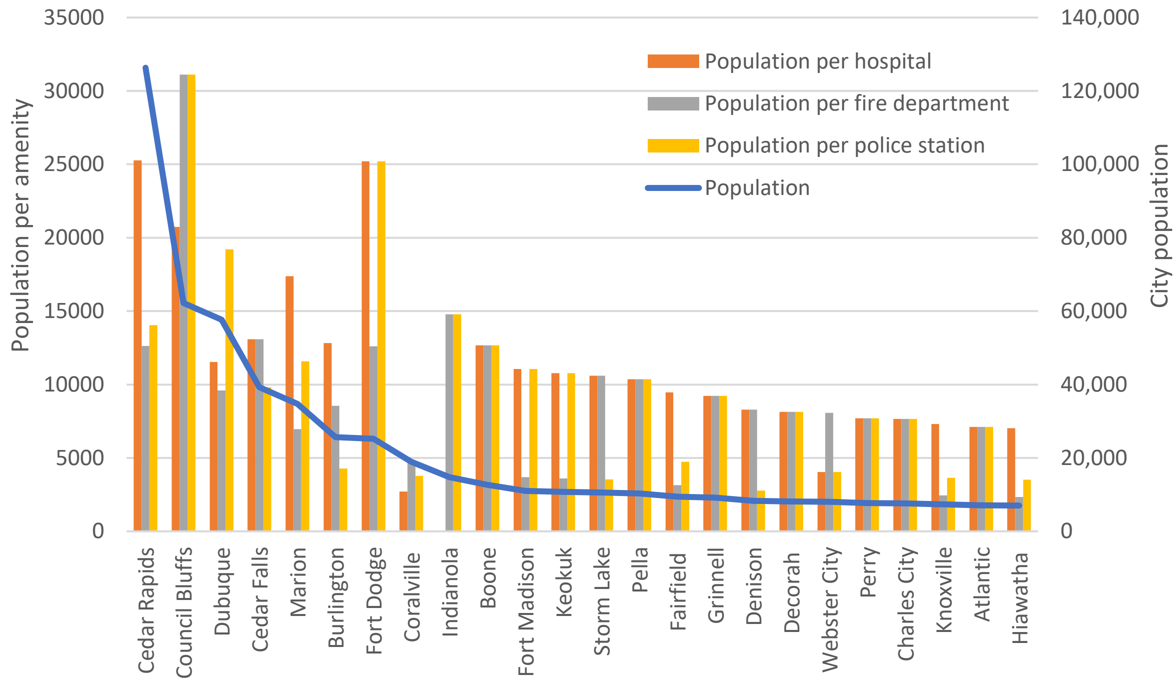

Figure 4. Distribution of amenities per population sorted by population.

Table 1 shows the population, according to the 2010 U.S Census Bureau, and the number of nodes, edges, and critical amenities for each city in the study. Figure 4 shows the number of people served by listed amenities in each city. By comparing the results, we noticed that cities such as Coralville have a good number of services to accommodate their people. There is a hospital per 2700 persons in Coralville, while a hospital in Cedar Rapids serves about 25,200 people. In addition, Fort Dodge has a population and area almost the same as Burlington. However, Fort Dodge hospital and police stations support more people. In some cities, there is just one amenity that can serve its people, which may not be able to respond if it is placed in the floodplain. Also, some areas require people to travel to other cities to utilize services. This may increase the time and distance, as well as the pressure on the service providers.

3. Results and Discussion

Once water overtops a road, the road is considered closed. As expected, road network topologies are differentially vulnerable to the two flood scenarios. Figure 5 shows the percentage of the inundated nodes and edges under 100- and 500-year flood return periods. Some cities have a significant loss for the road network under the two scenarios, and others have little impact. For example, Cedar Rapids, the largest city in our analysis since Des Moines was missing essential data, will lose about 3 percent of its nodes under a 100-year flood event and about 5 percent under a 500-year flood extent. Also, about 4 percent and 7 percent of its edges are affected by 100- and 500-year flood events, respectively. Even though the percentage may appear small, it may reflect severe indirect damages. For example, people may not be able to move out of the flooded area if all surrounding roads are inundated. Council Bluffs, on the state's border in southwest Iowa, shows major flood impacts in terms of node and edge losses.

Table 1. Population, road network topology, and amenities for each city.

City	**Population**	**# of Node**	**# of Edge**	**# of Hospital**	**# of Fire Department**	**# of Police Station**
Cedar Rapids	126,326	8,403	22,385	5	10	7
Council Bluffs	62,230	10,152	28,493	3	2	2
Dubuque	57,637	4,231	10,495	5	6	3
Cedar Falls	39,260	3,716	10,220	3	3	4
Marion	34,768	4,244	11,578	2	5	3
Burlington	25,663	2,168	5,795	2	3	6
Fort Dodge	25,206	1,688	4,752	1	2	1
Coralville	18,907	3,841	9,610	7	4	5
Indianola	14,782	823	2,208	0	1	1
Boone	12,661	1,078	3,233	1	1	1
Fort Madison	11,051	1,363	3,712	1	3	1
Keokuk	10,780	1,527	4,367	1	3	1
Storm Lake	10,600	682	2,052	1	1	3
Pella	10,352	694	1,836	1	1	1
Fairfield	9,464	931	2,570	1	3	2
Grinnell	9,218	525	1,502	1	1	1
Denison	8,298	623	1,678	1	1	3
Decorah	8,127	862	2,208	1	1	1
Webster City	8,070	497	1,423	2	1	2
Perry	7,702	604	1,757	1	1	1
Charles City	7,652	926	2,588	1	1	1
Knoxville	7,313	619	1,752	1	3	2
Atlantic	7,112	579	1,744	1	1	1
Hiawatha	7,024	2,793	7,163	1	3	2

Flood impacts are particularized to cities and their individual situation, including factors like the city layout, environmental setting, recent rainfall, and stage conditions. Flooding is an interesting problem because it is inherently a spatiotemporal issue. In addition, not only large cities but also some small cities show severe losses in its road network topology. For example, about 15.5 and 18 percent of Charles City's edges will be vulnerable to 100- and 500-year flood scenarios, respectively. On the other hand, Keokuk's transportation network, located along the Mississippi River in the southeast corner of Iowa, seems to be resilient to flooding compared with Fort Madison, which has almost the same location and road structure. Closed edges lead to make areas inaccessible and increase travel time and distance as well as an increase of traffic capacity on other opened roads.

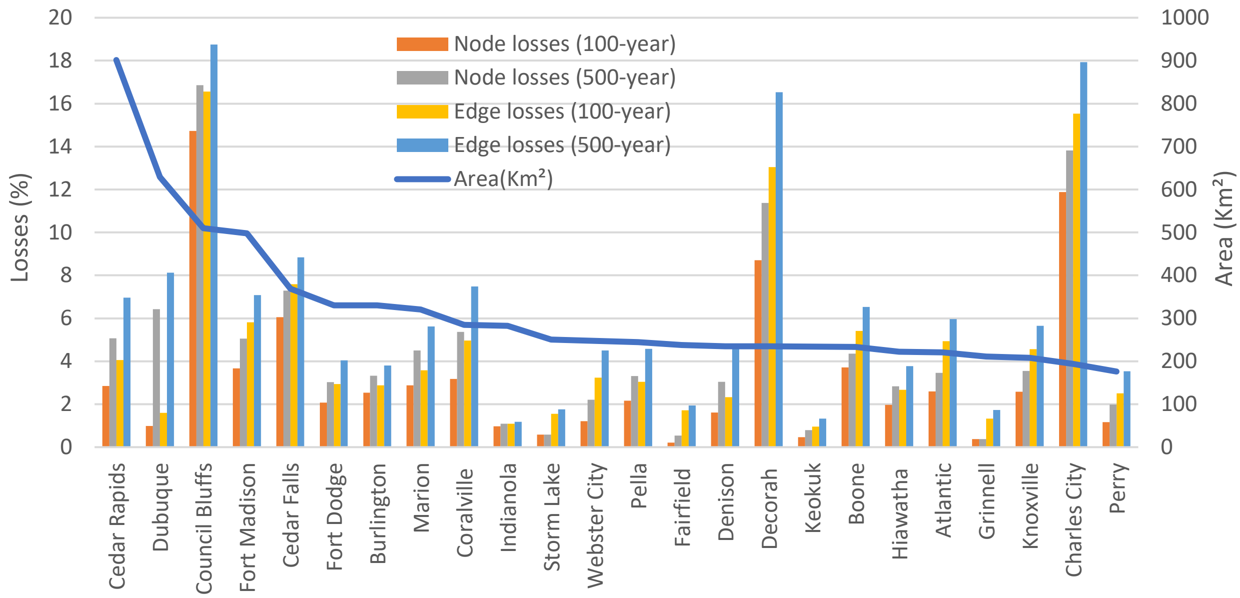

Figure 5. The losses of nodes and edges for each city under 100-yr and 500-yr return periods sorted by the area of each city

Each network consists of different road classes. Motorway, trunk, and primary classes are major highways normally with two or more running lanes. Secondary class is a highway usually linking large towns, but it is not part of a major highway. If a route connects minor streets to major roads, it is called tertiary. Residential class streets refer to routes that surround houses while unclassified class is a minor road (not residential) serving as a public access road. It has been observed that residential roads are the most affected type within the study area (Figure 6). This gives an indicator that flooding is a significant threat to residential areas, and it may disrupt people's movement. Therefore, it is necessary for emergency organizations to identify flooded roads to make plans and be ready for intervention in terms of providing services and emergency evacuation.

Bridge Operation under Flooding:

A bridge plays a vital role in connecting areas that may be separated by rivers, streams, or valleys. Due to the high cost of building bridges, they are usually limited in number and often serve as network constraints. Under flood conditions, evacuation for some areas may be impossible because of bridge insecurity. To mitigate flood impacts on transportation networks, it is essential to ensure all bridges during a flood event are open. However, the likelihood of a bridge that is built above a water body (e.g., river) to be flooded is high. In our analysis, although Cedar Rapids has the largest number of bridges, its bridges appear less vulnerable to flooding compared to Council Bluffs, Dubuque, Cedar Falls, and Coralville. Also, small cities such as Keokuk, Storm Lake, Denison, and Perry show that most of their decks are resistant to flooding (Table 2).

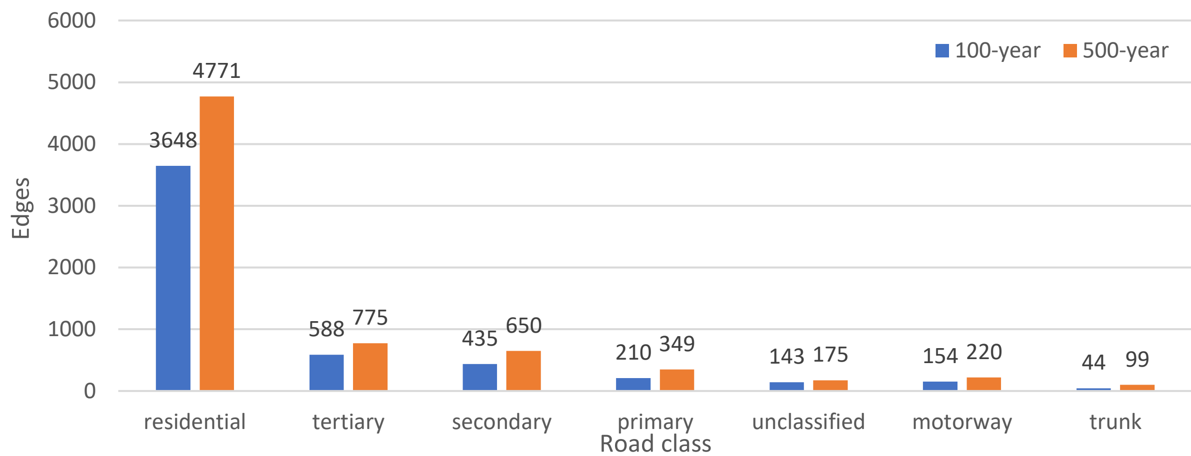

Figure 6. Closed edge classes for all cities.

Table 1. Percentage and number of available bridges before and after the 100- and 500-year floodplain.

City	No flood	100 Year		500 Year	
	Available	Available	% Accessible	Available	% Accessible
Cedar Rapids	300	290	96	272	90
Cedar Falls	164	145	88	132	80
Council Bluffs	161	135	83	128	79
Dubuque	155	130	83	117	75
Coralville	125	104	83	95	76
Marion	110	104	94	89	80
Hiawatha	85	82	96	75	88
Fort Madison	74	66	89	64	86
Decorah	73	68	93	66	90
Burlington	67	63	94	63	94
Fort Dodge	63	55	87	50	79
Fairfield	49	45	91	43	87
Denison	46	45	97	43	93
Atlantic	44	43	97	40	90
Grinnell	44	35	79	33	75
Webster City	41	39	95	38	92
Knoxville	39	21	53	20	51

Indianola	36	34	94	34	94
Pella	32	28	87	25	78
Charles City	31	26	83	23	74
Perry	27	26	96	26	96
Storm Lake	21	21	100	19	90
Keokuk	18	18	100	16	88
Boone	18	16	88	15	83

In these locations, transportation planning accounted for flood scenarios during the design phase, or they may have adjusted their bridges overtime after experiencing flood events. On the other hand, about half of Knoxville's bridges will fail to operate during the 100 and 500-year flood events, while Indianola, which has almost the same land topography and number of bridges, will lose nearly 5 percent of its bridges under the two flood scenarios (Figure 7). Moreover, under the 500-year flooding scenario, we observed some cities such as Marion that will have vulnerable bridges more than double of the 100-year flood event. That may be a result of a long-time construction, poor design, or a lack of financial support. Based on the analysis for bridge closure determination and bridge data used in this research, we noticed across study areas that not only old bridges are vulnerable to overtopping under 100- and 500-year flood return periods but also an increasing number of bridges built or reconstructed in the last ten years (Figure 8).

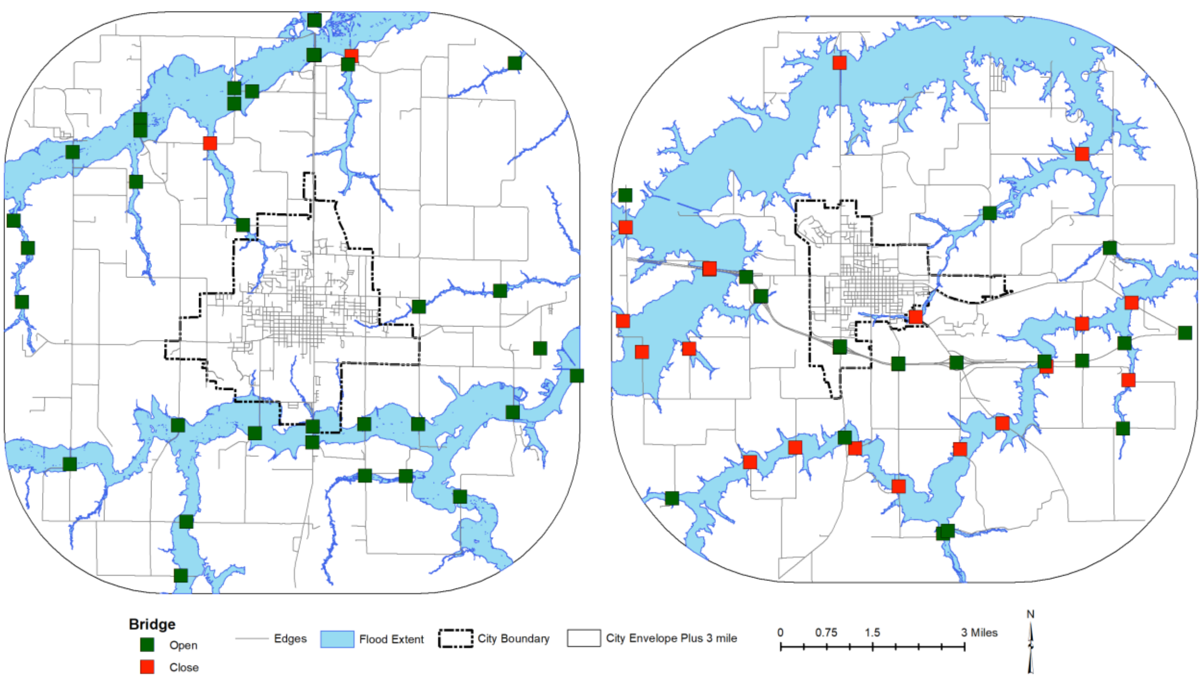

Figure 7. Bridge condition under the 500-year flood extent for Indianola (left) and Knoxville (right).

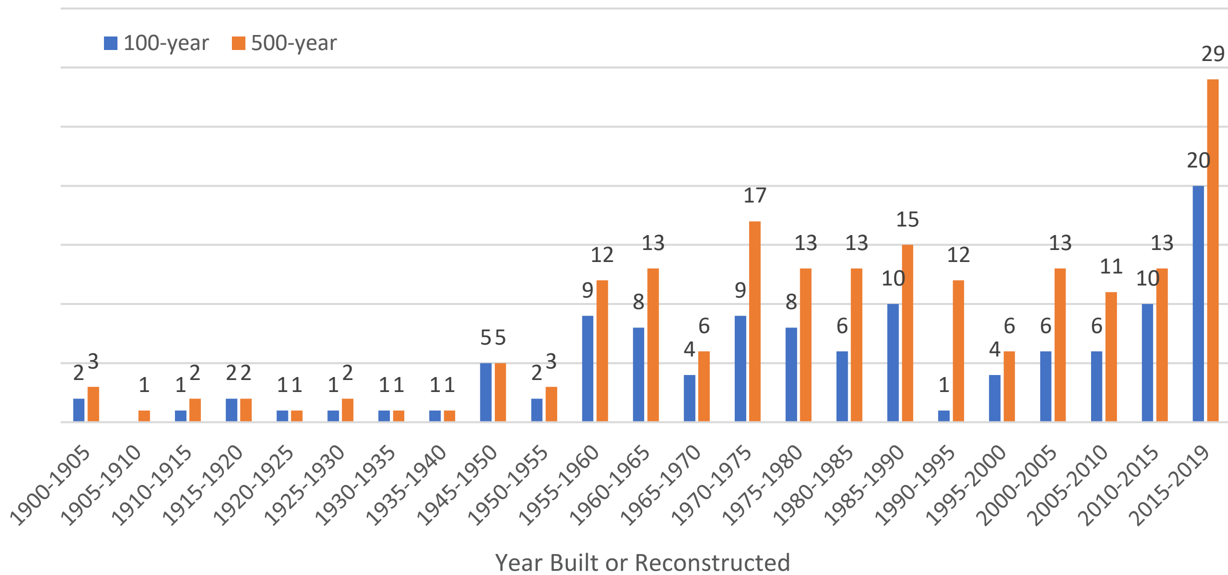

Figure 8. Number of vulnerable bridges to flooding.

Residential edges are also the most affected bridge edge class under the two flood scenarios, and tertiary and secondary classes come in second and third order in terms of the most affected-bridge edges, respectively (Figure 9). In contrast, the trunk class seems to be resistant to 100 and 500-year flood events. Based on these analyses, we can say that most residential bridges seemed to be designed for lower flood return periods. Readjusting bridges, especially in residential areas to withstand under extreme flooding scenarios, can enhance effective response and recovery during flooding.

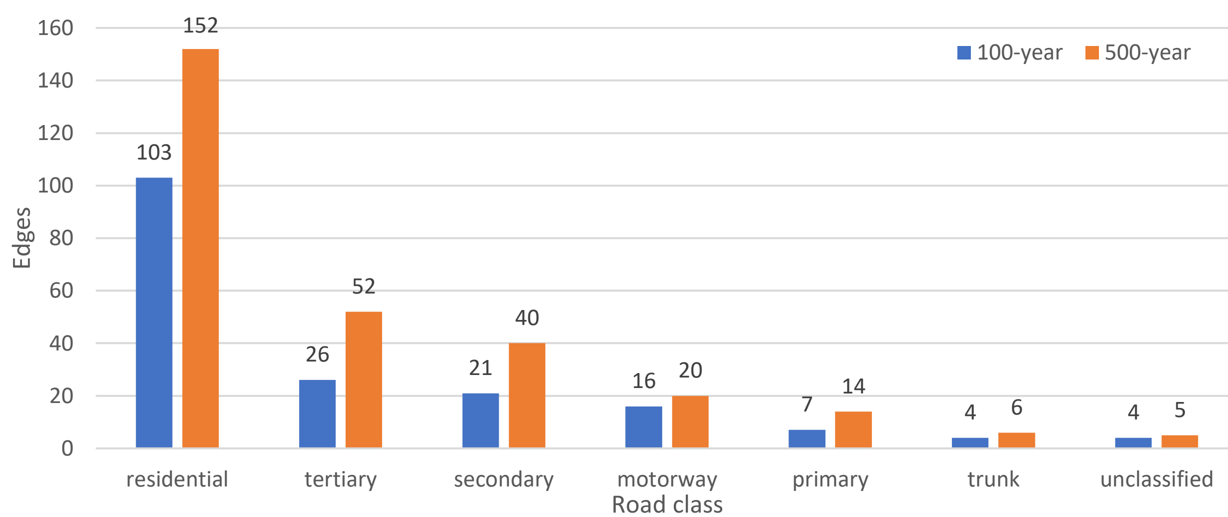

Figure 9. Closed bridge edge classes for all cities.

Community Analysis

Cedar Rapids is analyzed in detail as one of the largest cities in Iowa and also experienced a severe flood event in 2008, impacting 5,390 houses and 310 city facilities, and displaced more than 18,000 residents (Cedar Rapids, 2020). The Cedar Rapids road network consists of 8,403 nodes and 22,385 edges for our city extent framework. Figure 10 illustrates the distribution of amenities and the closed edges and bridges in Cedar Rapids. The total length of the edges is 2,659 km. For the city envelope plus 3 miles, the total length of the closed road during a 100-year return period is 152 km while under a 500-year flood period, the total closed road length is 241 km.

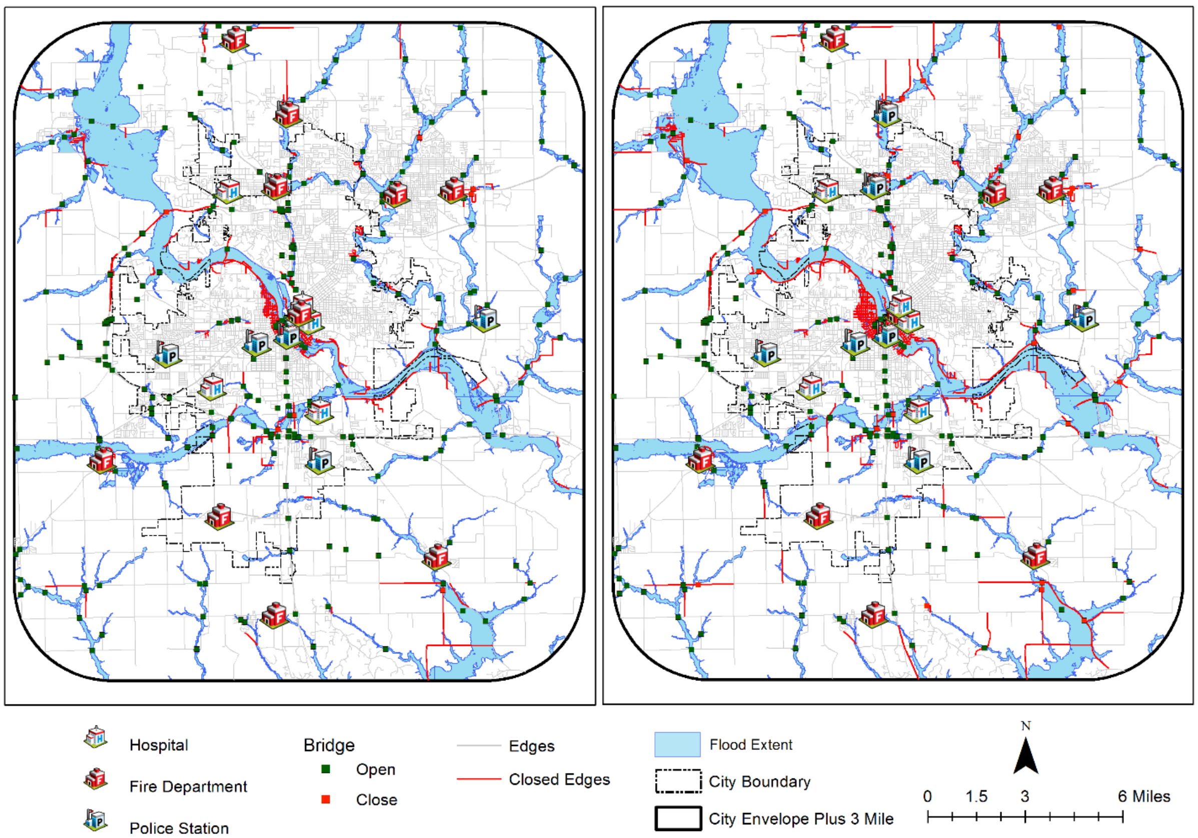

Figure 10. The distribution of amenities and the impact of the 100-year (left) and 500-year (right) flood extent on the road network.

Table 3 shows the total length of each closed road class under baseline condition and the 100 year and 500-year flood scenarios. People and emergency organizations will encounter challenges since the largest closed class is residential. In contrast, Cedar Rapids trunk roads are resilient to flooding. Also, it has been noticed that 127 and 373 of the closed road segments are fully inundated with a total length of 13.6 km and 40 km under 100- and 500-year flood extents, respectively. Figure 11 illustrates the impact of flooding in the city center of Cedar Rapids. It is obvious that some roads are partially flooded under the 100-year flood extent while they will be fully inundated during the 500-year flood. Also, it shows that most of the center locations inaccessible.

Table 2. The number of segments for each scenario, total length (km) before flooding and the total number of closed edges after flooding for each road class.

Road Class	**No flood**		**100 year**		**500 year**	
	# of Segments	**Total Length**	**# of affected Segments**	**Total Length**	**# of affected Segments**	**Total Length**
Residential	8,580	1,717	337	99	582	155
Tertiary	1,188	289	45	18	75	34
Secondary	1,074	270	64	13	125	24
Motorway	335	196	17	11	21	13
Unclassified	111	23	7	8	12	9
Primary	400	71	12	3	24	6
Trunk	132	93	0	0	0	0

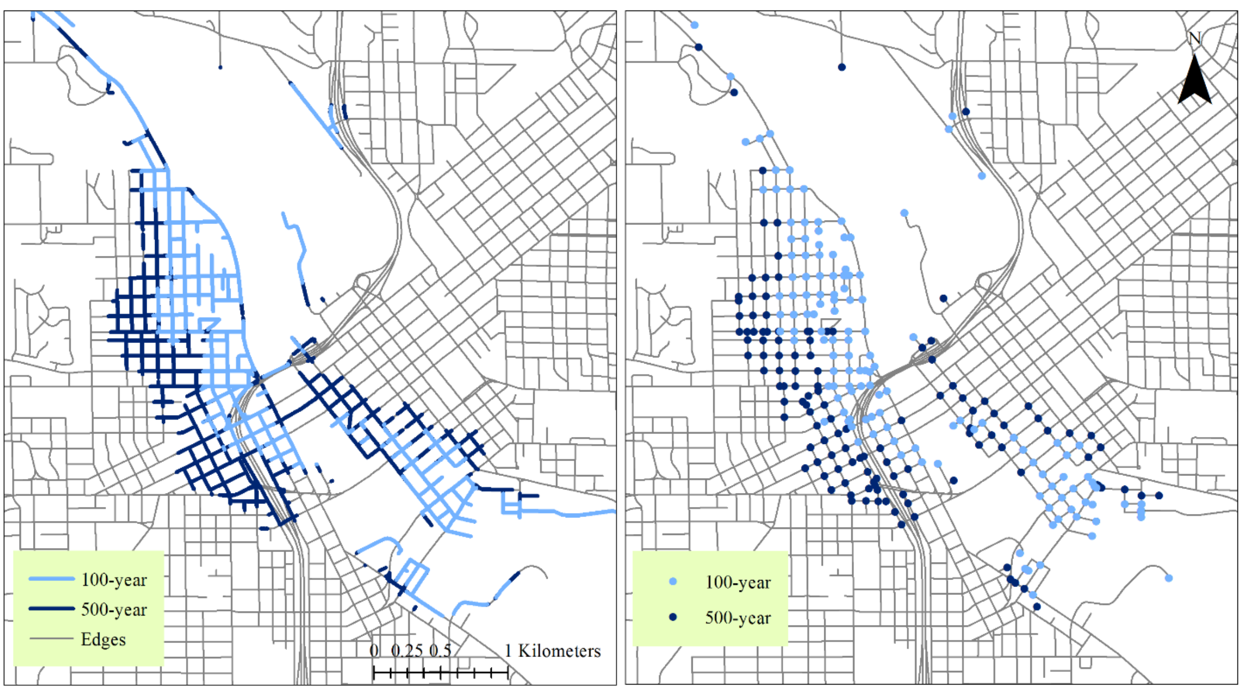

Figure 11. The affected road edges segments (left) and nodes (right) under two flood scenarios.

When nodes and edges are removed, they affect road structure and well-known paths for population. We run k-shortest path analyses from the amenities to all nodes to explore the overall effects of those changes. We look from an institutional support perspective to better understand the real impacts of edge removal. Accessibility is assessed in terms of travel distance changes, and whether these critical amenities can be reached at all. When a flood hits a community, some services (e.g., hospitals) require people to travel to facility locations to access those services. Others (e.g., fire, police) require service providers to reach people located across the city in order to provide services. Ambulances, not included in the analysis here, must be able to reach a destination and then potentially return a person to a medical center

The greater the distance that a person must travel; the greater the difficulty is in receiving vital services. As expected, our results show changes in the distance required to reach amenities/nodes under 100- and 500-year flood scenarios, and some nodes are inaccessible. We calculate the shortest path length from each amenity to all nodes. For every amenity, we calculate the short path length to all nodes. Therefore, if there are five police stations in a city, we calculate the shortest path length from each station to all other nodes. After that, we sort the shortest path lengths to determine each amenity order relative to all other nodes. We then find the closest amenity to each node, the next closest amenity, and so on by network distance.

Table 4 provides an example showing how path length changes under the various flood scenarios for Cedar Rapids. The example shows that people at the given nodes (node field) will be required to travel additional distances to the closest and second closest hospitals, fire departments, and police stations. This example assumes the location of the nearest amenities under flooding inconsistent. Each amenity has three fields; NF (No flood), 100 Year, and 500 Year. Under the baseline condition, NF represents the shortest path distance to the closest amenity. 100 Year and 500 Year fields show the shortest distance from a node to the facility under the 100-year and 500-year flood extents.

Table 3. The path length to the first and second closest hospital, fire department, and police station before (NF) flooding and after 100 and 500-year flood events (in km) for select nodes.

	1st			**2nd**			**1st**			**2nd**			**1st**			**2nd**		
	Hospital						**Fire Department**						**Police Station**					
Node	**NF**	**100 yr**	**500 yr**	**NF**	**100 yr**	**500 yr**	**NF**	**100 yr**	**500 yr**	**NF**	**100 yr**	**500 yr**	**NF**	**100 yr**	**500 yr**	**NF**	**100 yr**	**500 yr**
A	2.3	4.2	4.2	6.8	7.4	7.4	7.2	8.4	10.2	8.4	8.4	10.2	7.0	7.0	7.0	11.4	15.5	17.0
B	2.4	4.9	4.9	3.7	5.6	5.7	4.1	11.0	11.0	10.5	12.7	12.8	3.9	3.9	3.9	8.3	19.4	19.4
C	1.0	6.0	6.5	1.8	6.5	6.7	1.4	12.1	12.8	8.5	12.8	13.4	2.1	2.0	3.8	6.0	20.6	21.6
D	3.5	x	x	6.6	x	x	1.2	x	x	5.3	x	x	1.1	x	x	2.9	x	x

A person at Node A must travel 2.3 km to reach the closest hospital and 6.8 km to the second closest under a no-flood scenario. This is the baseline distance to hospitals for a person at a particular location. Under a 100-year flood scenario, a person much travel almost twice (1.8 times) as far to reach the closest hospital (4.2 km vs. 2.3 km originally). For node B, the Fire department will need twice no-flood distance to reach the node. Also, this node illustrates a significant change in distance after flooding for the second nearest police station. A more extreme case can be seen in the last row of Table 4. During the 100-year and 500-year flood model, a person at this node would not be able to reach the hospital due to either their location becoming disconnected or isolated. In addition, rescue operations and police services will encounter a challenge to reach this node. The path length from each node to an amenity can also increase to the extent where the closest hospital may "flip" to other order hospitals (i.e., second or higher-order) (Figure 12). As can be seen for the hospital, located in the lower-left corner, we noticed that the closest hospital for some nodes has changed under flooding scenarios. Therefore, road and node losses due to flooding can affect the distance and the order to reach the closest amenity.

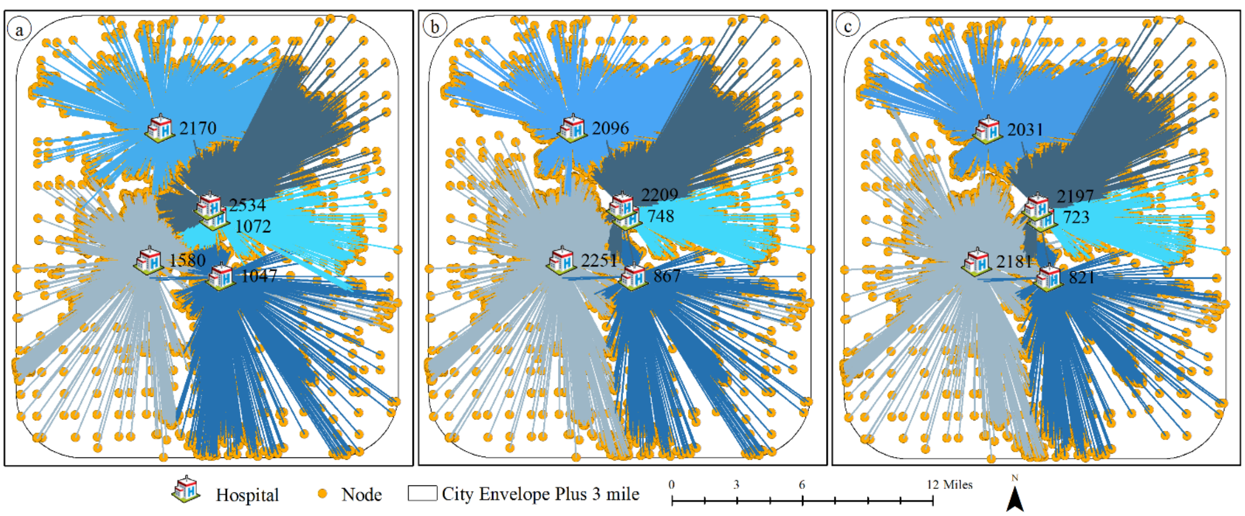

Figure 12. Number of shortest path length from each node to the closest hospital under no flood (a), 100 year-flood (b), and 500-year flood (c) scenarios.

In addition, a node (ID #160380928), is located in the city center, has been selected for the accessibility examination and visualization to the closest three hospitals, fire departments, and police stations (Figure 13). We examine the three closest amenities under the two flooding scenarios based on the baseline order. It has been observed that this node is accessible by the police under flooding. However, we noticed that the third order of the closest fire department and hospital under the baseline scenario becomes the first order under 100- and 500-year floodplain. In addition, the distance of the first closest fire department and hospital to this node under the two flooding scenarios will be increased about three times from the baseline distance. During flooding, people who want to reach the hospital may not be realized the change in the length, which will affect their time, distance, and fuels. Also, providing this valuable information to the emergency organization can enhance emergency plans' effectiveness during flooding.

Charles City is another example that shows us significant impacts of flooding on its road network topology and its accessibility to amenities. Cedar River flows the middle of the city and divides the city into two parts. Figure 14 shows the city topology after the 100 and 500-yr flood scenarios. Yellow edges indicate that the edge will be closed under a 100-yr flood extent while the red edges are 500-yr closed edges. Flood events affect not only distance but also the spatial distribution of the city’s critical amenities. Under 100-yr and 500-yr flood extents, the fire department will be inundated. This will make the response to emergency cases hard and maybe impossible. Even though there will be an open bridge connecting the east side of the city with the west side under the 500-yr flood scenario, people on the east side cannot reach the hospital because of the inundated edges surrounded the open bridge. In addition, the police station, on the east side of the Cedar River, will be inundated according to the flood models used in this research.

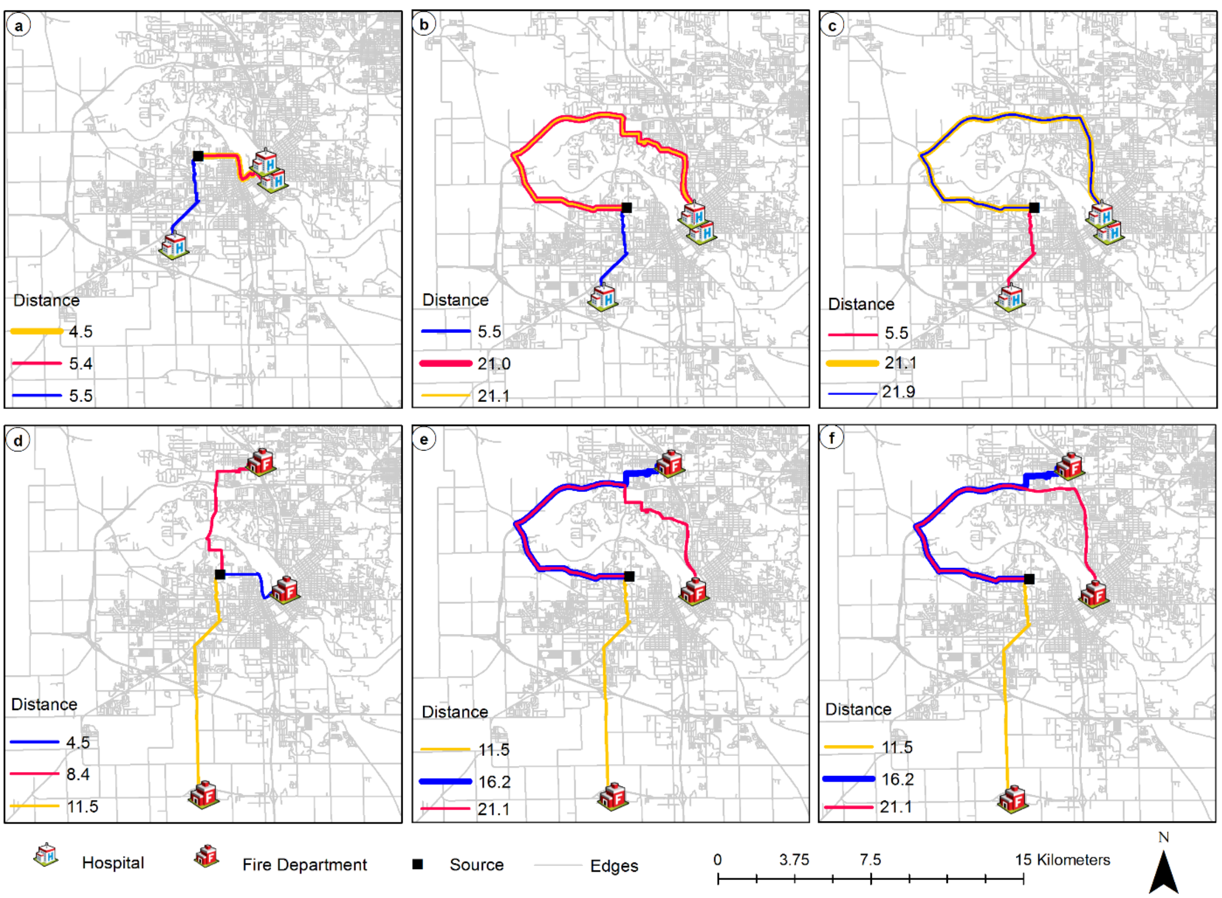

Figure 13. Distance (km) to reach the closest hospital under no flood (a) 100-year flood extent (b) and 500-year flood extent (c) and the closet fire department under no flood (d), 100-year flood extent (e), and 500-year flood extent (f).

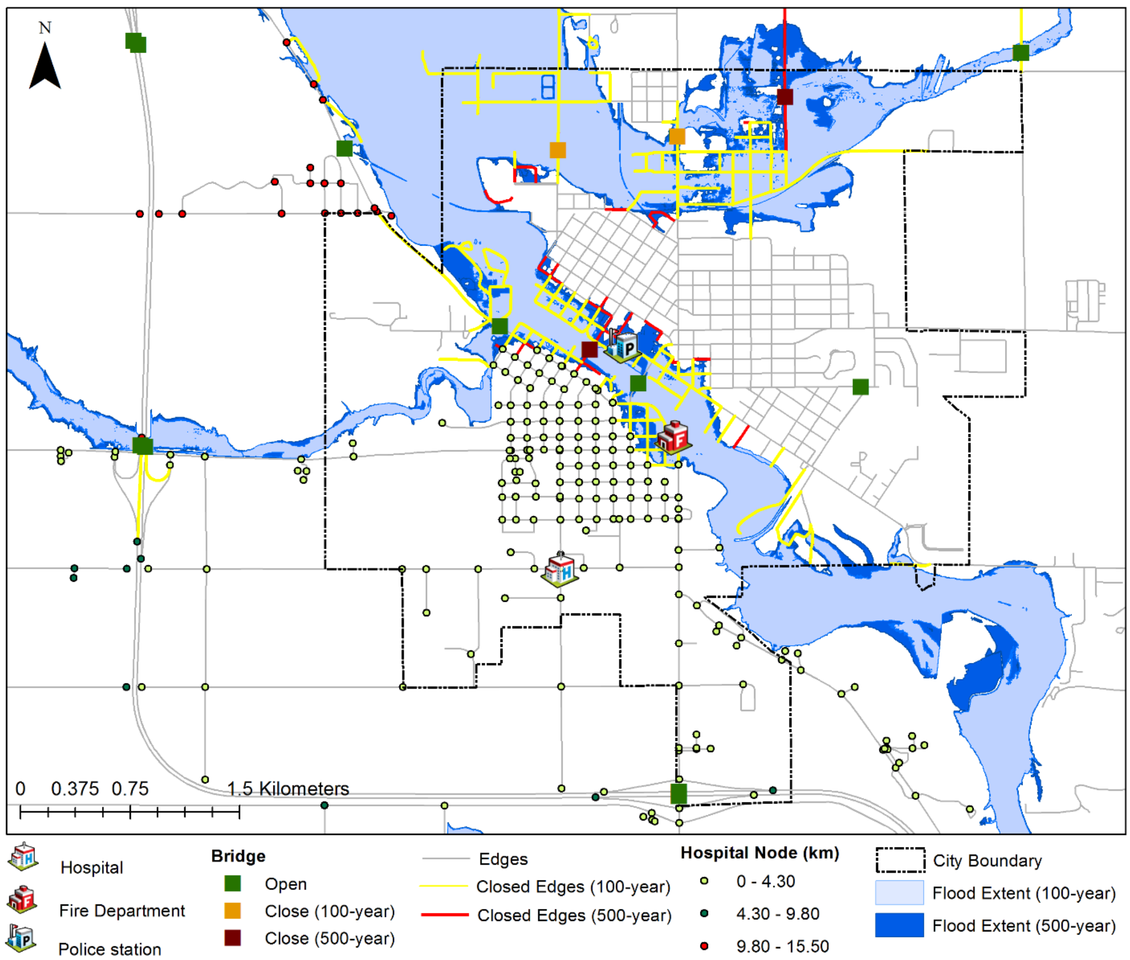

Figure 14. The impact of the 100- and 500-year flood extent on Charles City including, bridge condition, closed edges, spatial distribution of amenities, and distance to reach hospital during the 500-year floodplain.

4. Conclusions and Future Work

This research provides a methodology for an analytical framework to explore the resiliency of road systems during flood events and how flooding affects accessibility to essential services provided by hospitals, police, and fire departments. Based on the unique environmental conditions for populated places in Iowa and the flood risk model used in the analysis, we note that road networks are differentially affected by floods. We evaluate and demonstrate the vulnerability and accessibility of road systems of urban communities using graph theoretic methods and how natural disasters affect those systems. It is evident that flooding threatens Iowa cities in terms of network topology and accessibility to critical amenities or emergency services. Facilities themselves can be affected directly by flooding, as seen in the Charles City case study. Vulnerable areas can be made more resilient to flooding by adjusting the locations or increasing the elevation of important roads or bridges, changing water flow patterns, or changing the locations of essential infrastructure, including water treatment facilities, hospitals, and power production plants. Our detailed accessibility analysis for road systems during flooding enhances preparation for future flood events. Considering flood scenarios in the infrastructure-design phase contributes to decreasing community vulnerability.

In further research, our work can be extended to explore the relative importance of edges and nodes within the road network, considering additional factors such as the distribution of population, households, and traffic density within a city. Because flooding is a dynamic process, it is important to provide the ability to predict flooding effects on road networks. As part of the coupled natural and built environments, floods will continue to change as those systems change. The analyses presented here could be used to highlight potential improvements for infrastructure that could make communities more resilient to natural disasters. Future work for this project may include real-time dynamic routing capabilities based on current or expected flood conditions, the addition of social media to identify flooded or closed network edges, and an interactive web environment to explore how network failures cascade throughout the system.

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