AN EVALUATION OF TRANSPORTATION NETWORK ROBUSTNESS AGAINST EXTREME FLOODING: A GIS BASED APPROACH

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ABSTRACT

The main objective of this article is to study the robustness of road networks to extreme flooding events that can negatively affect entire regional systems in a relatively unpredictable way. Here, we adopt a deterministic approach to simulate extreme flooding events in two cities, New York City and Chicago, by removing entire sections of road systems using U.S. FEMA floodplains. We then measure changes in the number of real trips that can be completed (using travel demand data), Geographical Information Systems (GIS) properties, and network topological indicators. We notably measure and discuss how betweenness centrality is being redistributed after flooding. Broadly, robustness in spatial systems like road networks is dependent on many factors, including system size (number of nodes and links) and topological structure of the network. Expectedly, robustness also depends on geography, and cities that are naturally more at risk will tend to be less robust, and therefore the notion of robustness rapidly becomes sensitive to individual contexts.

Keywords: Robustness, Road Networks, Extreme Events, GIS Analysis, Network Science
INTRODUCTION

Today, more than half of the world population lives in coastal areas that are prone to flooding (1). As the world population keeps urbanizing, this proportion is likely to increase in the near future. While offering many benefits, coastal areas are under constant threats of flooding, not only because of sea-level rise, but also because of extreme weather events like hurricanes, storms and many other natural hazards that are predicted to increase both in number and intensity in the foreseeable future (2–4).

Past extreme events are mainly characterized by their intensity and frequency. Here, intensity is defined as a discrepancy from usual events (3), and extreme events are therefore characterized by high intensities. Focusing on intensity therefore shifts the emphasis of extreme event analysis by trying to estimate the impact of the damages after an extreme event instead of trying to determine when an extreme event is likely to occur. Nowadays, there is a rising awareness in city management about the necessity of risk mitigation and post-disaster recovery systems, which systematically couple “preparedness” and “prompt response” to extreme events. Within this context, the emerging concept of resilience has become a priority in many cities around the world. While not a novel concept (5), the realm of resilience and resilient design has spurred much interest in the academic literature in the past decade. For instance, it can refer to the ability of a system to spring back from a disruption or to the ability to withstand an excessive amount of stress before failing (6). Despite many positive and substantial initial efforts, much work remains to be done to design resilient cities in an era of climate change. This general endeavor also fits particularly well the increasing body of work on urban sustainability (7–9) and with the current proliferation of data (10, 11).

In this article, road infrastructure systems are analyzed as physical networks, composed of a set of nodes (intersections) and links (road segments). The general field of Network Science (12) is establishing itself as a particularly fitted field of study to tackle matters of system resilience. Indeed, networks have measurable properties that can directly and quantitatively assess resilience (13–17). Moreover, gaining a complete and holistic understanding of the network structural resilience and robustness of a road network is essential for traffic management and urban planners (18). In this study, we focus on measuring the robustness of roads networks to extreme flooding. The term robustness was chosen because the study does not include a time dimension and instead attempts to quantify and measure the impact of extreme flooding in cities (19).

Generally, the efficient movement of vehicles in normal conditions and fast return to normal conditions after a disruption are considered as attributes of a robust transportation system. In our study, robustness is defined as network structural and topological resistance of transportation infrastructure networks against extreme events. We therefore do not focus on service or demand, but solely on the presence of infrastructure. This work attempts to link the realm of extreme events and network robustness. To achieve this objective, we simulate extreme flooding events, apply them on the road networks in two metropolitan cities in the United States, Chicago and New York City, and measure their impacts. More specifically, we use 100-year floodplains by the Federal Emergency Management Agency (FEMA), which assumes a yearly 1% chance of experiencing a severe flood and is often used as a design criterion in engineering. Previously, a similar method has been used to quantify and visualize the robustness of road networks to random zonal disturbance, central disturbance, and targeted disturbance in cities (20). The simulation is performed in Geographic Information Systems (GIS) and the network properties are calculated in python using the igraph library (21).

In the next section, we first offer a general background of the importance to study matters of robustness and resilience to extreme events and the pertinence of network science as a method of choice. We then define our methodology to properly simulate extreme flooding events. We also introduce several metrics, namely trip variation metrics, GIS network metrics and topological indicators, and explain how we measure the robustness of road networks. We finally apply our methodology to the case studies of Chicago and New York City. The reason for selecting New York City and Chicago is that these two metropolitan cities are adjacent to great bodies of water. They have experienced severe flooding recently and this trend is likely to continue in the foreseeable future.
BACKGROUND
In the past two decades, the frequency and magnitude of extreme events have significantly increased all over the globe (22, 23). Society as a whole is not prepared for these extreme events and current urban infrastructure systems are not able to withstand them. Looking back at the recent patterns in climate variability, the issue of studying the impact of extreme events such as flood, tsunami, earthquake, severe storms and heavy snowfall to name a few, has become critical. Indeed, these extreme events can bring all of the vital interactions within an urban area to a complete standstill (24) and cause significant human and economic losses to a region (25). This is further accentuated by the fact that these natural extreme events are hard to predict and that the magnitude of the impacts are miscalculated in hindsight (e.g. 2011 Tōhoku tsunami in Japan, 1960 Great Chilean Earthquake). Sometimes referred to as Black Swans (26), these random extreme events are unprecedented and unpredictable. While their characterizing parameters may differ (e.g., time, location), their impacts are often similar, causing significant human and economic losses to a region. Moreover, considering the high degree of uncertainty and variability in the climate, it has become paramount to better prepare for these extreme events (27). Therefore, by simulating previous extreme events on a regional scale and by analyzing the responses, we can collect useful information that will help us prepare for future disasters, minimize their impacts and therefore increase the resilience of urban transportation systems.

In parallel, the field of Network Science is an emerging discipline that provides a new way of studying the topological structure and evolution of complex networks (26, 28). The importance of network infrastructure resilience is reliant on the location of its components; i.e., the location of its links and nodes, as well as on the connectivity between these components (29). Like all other complex systems, a road transportation system can be modeled as a network with nodes/vertices and links/edges (30). Studies on the relationship between network structure and functionality of a system have shown that topological structural diversity is a key factor to network resilience. Networks with greater levels of degree diversity are more vulnerable to targeted attacks on nodes with high degrees, but they are more resilient to random disruptions (31, 32). Jiang (33) compared structural characteristics of more than 40 cities using metrics from Network Science. Moreover specifically, a series of studies have been conducted on road transportation networks to investigate the concept of resilience in these networks. Many of these studies have investigated road network vulnerability using different methods that are classified in different categories. Murray et al. (34) put these methods into four evaluation methods: scenario-based, strategy-based, simulation-based, and mathematical model-based. Of relevance to our topic, Jenelius et al. (35) focused on finding vulnerable sections of road networks. Several studies emphasize on the general integrity of a network using node-based and link-based disruption strategies (36–39). Huang et al. (40) showed that the concept of robustness, or vulnerability to attack, relates to the decline of network performance due to the targeted removal of nodes or edges. Derrible and Kennedy (41) used a mathematical-based metric to study the robustness of worldwide metro networks.

To date, no research seems to have significantly studied road network vulnerability by combining scenario-based and simulation-based methods in real case studies of extreme flooding. To partially address this knowledge gap, this study attempts to bridge conventional transportation techniques with network science to quantify the impacts of extreme events on road systems using Geographical Information System (GIS) information. The ultimate goal here is to focus on new methods for resiliency studies in the road systems from another prospective which opens new fields of science for analyzing these systems.

DATA AND METHODOLOGY
Using geographical information systems (GIS) technology, the framework proposed in this study is to simulate the impacts of extreme events using FEMA data and assess and measure the robustness of a road transportation system by means of network topological indicators, Longitudinal Employer-Household Dynamics (LEHD) data and GIS network metrics.

The road networks data for Chicago and New York City were obtained from United States Census Bureau's TIGER database (42). We assimilate each road system as a graph $G$, with $V$ nodes/vertices and $E$ edges/links, $G=\{V, E\}$, where the nodes represent road intersections and the links represent road segments that connect the nodes. Moreover, we measure the total road length $L$ of the system.
**Extreme Flooding Event Simulation**

In this study, road networks are exposed to extreme flooding events. The reason for using flooding is that 100-year floodplains are nationally accepted standards provided by FEMA, and they are commonly used by insurance companies and municipalities. A 100-year floodplain essentially assumes a yearly 1% chance of experiencing a severe flood and is often used as a design criterion in engineering. FEMA produces these floodplains using peak flow data to estimate the streamflow related to a 100-year flood. From hydraulic models, it then determines the elevation profile of the flood along the length of the stream. To identify the inundated network elements, the floodplains are superposed to the road network and the elements within the flooded area (i.e., the nodes and links) are removed. From the modified network, we can then measure the impacts of the extreme flooding using various metrics that are discussed in this section. Although we could have used a stochastic approach by only removing some of the links present in the floodplains and run a set of scenario analyses, we preferred to adopt this deterministic approach as a “worst-case” scenario. Moreover, this approach is computationally inexpensive and more easily applicable and reproducible.

**Measuring Road Network Robustness**

*Overall Properties*

To measure the impact of flooding, the first properties that can be measured are the proportional losses in infrastructure, which include the number of vertices, $ΔV$, affected (i.e., loss of intersections), as well as the number of edges, $ΔE$, affected (i.e., loss of number of road segments), and the total length (in meters) of roads that have been affected, $ΔL$. These properties can help us determine the level of exposure of a city to an extreme event.

*Longitudinal Employer-Household Dynamics (LEHD) data*

In this study we used LEHD data set to measure variations in real trip distribution in the road networks after extreme flooding as an indicator of resiliency. LEHD data set is based on all the employer reports of quarterly earnings for the Unemployment Insurance (UI) program from the U.S. Census Bureau. Essentially, it provides us with an origin-destination (OD) matrix for the home-work trip. Here, we use LEHD Origin-Destination Employment Statistics (LODES) data for New York City and Chicago to observe commuting patterns between jobs to households. More specifically we look into trips generated from jobs with both workplace and residence within the cities and for all of types of jobs (Primary Jobs, All Private Jobs, Private Primary Jobs, All Federal Jobs, and Federal Primary Jobs) for a specific time period (i.e., year 2010) (43–45).

As the first step in our approach, we choose the trips for the census tract of the road network of the given city from the dataset of entire state. In the second step, we find the shortest path between every pair of census tracts in the normal pre-flooding conditions in that road network (e.g., finding the shortest path between an incident location and an emergency station). Here we assume that the route of trips from households to jobs are the shortest path between origins and destinations. Therefore, this process represents $T^{pre}$ trips, where $T^{pre}$ is the total number of trips completed before extreme flooding in a city (i.e., $T^{pre} =$ 2,686,918 for New York City and $T^{pre} =$ 212,989 for Chicago). The next step is to define a measure of the impact of extreme flooding events on these trips. We define the post-flooding number of trips $T^{post}$ as:

$$T^{post} = T^{post}_A + T^{post}_B + T^{post}_C + T^{post}_D$$  \hspace{1cm} (1)

where the total number of trips post-flooding essentially fall into four categories; $T^{post}_A$ are the completed trips that traveled the exact same path before and after the extreme flooding; $T^{post}_B$ are the completed trips that were forced to travel longer distances; $T^{post}_C$ are the trips that could not be completed after the extreme flooding because the trip origins/destinations are isolated and cannot be reached (e.g., failure of a bridge); and $T^{post}_D$ are the trips that could not be completed because a trip origin/destination is located in a floodplain. Using the results from Equation (1), we define five metrics (19), $τ_A$, $τ_B$, $τ_C$, $τ_D$, and $τ_{AB}$ that can
capture the impacts of the extreme events on the road networks (Equations (2)-(6)). $\tau_i$ is the proportion of trips that were not affected; $\tau_b$ is the proportion of trips that traveled longer distance; $\tau_c$ is the proportion of trips that could not be completed after the extreme event; $\tau_d$ is the proportion of trips that could not be completed due to removal of the origins/destinations; and $\tau_{ab}$ is the proportion of completed trips only that were forced to travel longer distances. The information that we obtain from these trip variation metrics can be used as a form of sensitivity analysis, and it can help develop emergency preparatory plans in response to disasters in parts of the city that require more resources for related emergency sites, hospitals, and access routes.

$$\tau_A = \frac{\tau_{A\text{post}}}{\tau_{A\text{pre}}}$$  
$$\tau_B = \frac{\tau_{B\text{post}}}{\tau_{B\text{pre}}}$$  
$$\tau_C = \frac{\tau_{C\text{post}}}{\tau_{C\text{pre}}}$$  
$$\tau_D = \frac{\tau_{D\text{post}}}{\tau_{D\text{pre}}}$$  
$$\tau_{AB} = \frac{\tau_{B\text{post}}}{\tau_{A\text{post}} + \tau_{B\text{post}}}$$  

GIS Network Metrics: Service area

In order to measure the robustness of a city, it is important to know how its road network will react to various impediments, where we define as ‘impediment’ as a restriction or obstacle that prevents movement within the network. In our case, impediments due to extreme flooding events are the floodplains that make the road network inoperable. Understanding the impacts of these impediments is not only important at the city level, but also at the service area level (defined below), which is where essential services like hospitals, fire stations, police stations, shelters, and so on and so forth, are located.

A service area is a region that contains all accessible streets that are within a specified distance. It is conceptually and mathematically close to accessibility, where only area is considered (as opposed to number of businesses for instance). Here, the service area of a specific location in the road networks would be the area that is in closest proximity to that location. It may also be referred to as the area that can be reached from that location within a specified time or distance. For this work, we use the community areas/districts established by the municipal governments as service areas. Moreover, here, we use another GIS feature to determine the percentage change in accessible areas around a specific location after the extreme flooding in New York City and Chicago. More specifically, we investigate percentage change in three service areas with distances of 1, 2 and 5 kilometers around the centroids of community areas/districts, as a place that all of human activities in these cities originates from, in New York City (with 71 community districts) and Chicago (with 77 community area). These changes in service areas can be defined as:

$$\Delta A_i = \frac{\sum A_i^{pre} - \sum A_i^{post}}{\sum A_i^{pre}}$$  

where $\sum A_i^{pre}$ is the total service area from the centroid of community areas/districts $i$ in pre-flooding conditions and $\sum A_i^{post}$ is the total service area from the centroid of community areas/districts $i$ in post-flooding conditions.

Robustness Topological Indicators

In order to assess the impact of extreme events on the topology of road networks, the concept of betweenness centrality is used, which essentially measures how likely a node or edge is to be used to link any given pair of nodes. This topological indicator can capture some aspects of a network structure. Overall, betweenness centrality is a structural importance indicator based on the global information of the
shortest paths connecting all pairs of nodes. A high betweenness of a node or edge indicates that there are
more shortest paths passing through that node or edge (46). A node or edge with betweenness much higher
than the average could play an important role in a network, and thus is a crucial part of a network in
disturbance situation, if alternative routes are not provided in the network. It is also often used as one of the
most representative indicators of network centrality (47).

Mathematically, node betweenness centrality is defined as (48):

\[ C_{Bv}(i) = \sum_{s \neq i \neq t \in V} \left( \frac{\sigma_{st}(i)}{\sigma_{st}} \right) \]  

where \( \sigma_{st} \) is the total number of shortest paths from node \( s \) to node \( t \) and \( \sigma_{st}(i) \) is the number of those paths
that pass through node \( i \). The definition of edge betweenness centrality is identical but applied to links as
opposed to nodes. We define the maximum node betweenness as \( C_{Bv}^{\text{max}} \), maximum edge betweenness as
\( C_{Be}^{\text{max}} \), average node betweenness as \( C_{Bv}^{\text{avg}} \), and average edge betweenness as \( C_{Be}^{\text{avg}} \).

Generally, we can say that node betweenness centrality helps us measure the volume of traffic
moving through each intersection and road segments (49) and it can also be used as a measure of the
influence that a node has over the spread of information throughout the network. Conceptually, it is
different from shortest path (i.e., the ‘distance’ between two nodes) that we have measured in route of trips
from households to jobs. Here, opposed to shortest path between jobs to households, lengths are not
considered and the number of hops between each pair of nodes is measured instead. Moreover, betweenness
centrality looks at all pairs of nodes as opposed specific origins and destinations. Also, the robustness of a
network is a function of how the network properties respond to disturbances. The overall assumption is that
the impact of removing of nodes/edges with high betweenness centralities is much larger than the impact of
removing nodes/edges with low betweenness centralities. Moreover, to evaluate the robustness in road
networks, we also measure how these network properties are being redistributed in a road network.

We can also see from Equation (8) that betweenness centrality is a simple sum and it is therefore
not standardized, and larger networks will simply have larger betweenness centralities. Comparing the
average betweenness centralities between two networks, pre- and post- extreme event, therefore offers one
measure of robustness, but we can also compare the difference between the maximum betweenness
centralities, pre- and post- extreme events.

RESULTS AND DISCUSSION

Using the results of extreme flooding events simulation, the responses of the road networks to the resulting
disruption are shown graphically to highlight the redistribution of edge betweenness centralities after
extreme flooding events (Figure 1).

Road Network Response to Simulated Extreme Flood

The main difference between the flood simulations in New York City and Chicago relates to the geography
of the floodplains in each city (Figure 1). Most notably, the Chicago road network is split by the 100-year
floodplain into three major sections, two of which are located on the north side and one is located in the
southern part of the city. In comparison, the floodplain in New York City cuts the road network into two
major, as well as several minor, parts. The New York City 100-year floodplain has many branches that
result in the separation of collateral parts of the road network, while keeping one main core intact in the
southern part (Brooklyn and Queens) of the city.

Figure 1 shows the edge betweenness centralities in road networks of New York City and Chicago
before and after the extreme flooding. We can naturally see that highways surrounding New York City have
high edge betweenness centralities (Figure 1 a.), and they are also located in the floodplains (Figure 1 b.).
From Table 1, this results in a 67% reduction in \( C_{Be}^{\text{max}} \) and 72% reduction in \( C_{Be}^{\text{avg}} \) in the road network after
the extreme flooding event. Moreover, because of extreme flooding, many important bridges are also
removed from the New York City’s road network. For example, the Verrazano Bridge (which has the
maximum edge betweenness centrality in the network) connects Richmond County to the other parts of the
city, has been impacted by the extreme flooding. The removal of such important road segments (e.g., major
bridges and highways) greatly impacts the resilience of a road system. Moreover, after flooding, there is a shift in concentration of roads with higher edge betweenness centralities from north and west to middle and southern parts of the road network. This central region, i.e., Brooklyn and Queens boroughs, of New York City road network plays an important role for transportation of vehicles under critical conditions that the city will encounter after the extreme flooding.

Similarly, Table 1 shows drastic drops in Chicago of 74% and 75% for $C_{Be}^{max}$ and $C_{Be}^{avg}$ respectively. Here again, the main cause of these significant drops is the separation of Chicago road network into three isolated parts by the floodplain.

**TABLE 1** New York City and Chicago Road Network Properties Before and After Flooding

<table>
<thead>
<tr>
<th>Network Property</th>
<th>New York City</th>
<th></th>
<th></th>
<th>Chicago</th>
<th></th>
<th>% Change</th>
<th></th>
<th>% Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>V</td>
<td>54,660</td>
<td>55,192</td>
<td>0.97</td>
<td>30,191</td>
<td>30,485</td>
<td>0.97</td>
<td></td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>91,327</td>
<td>87,542</td>
<td>-4.14</td>
<td>50,025</td>
<td>50,137</td>
<td>-0.22</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$L$ (m)</td>
<td>14,565,269</td>
<td>13,584,514</td>
<td>-6.73</td>
<td>7,098,036</td>
<td>7,075,199</td>
<td>-0.32</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C_{Be}^{max}$</td>
<td>434,871,345</td>
<td>144,111,217</td>
<td>-66.86</td>
<td>85,568,982</td>
<td>21,970,940</td>
<td>-74.32</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C_{Bv}^{max}$</td>
<td>434,873,687</td>
<td>150,056,039</td>
<td>-65.49</td>
<td>88,193,668</td>
<td>24,302,698</td>
<td>-72.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C_{Be}^{avg}$</td>
<td>1,709,246</td>
<td>480,642</td>
<td>-71.87</td>
<td>755,966</td>
<td>190,646</td>
<td>-74.87</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$C_{Bv}^{avg}$</td>
<td>2,828,658</td>
<td>753,385</td>
<td>-73.36</td>
<td>1,237,799</td>
<td>307,986</td>
<td>-75.11</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Despite the fact that Chicago only loses 0.3% (22.8 km) of the length of its road network during the flood, the decrease in $C_{Be}^{max}$ is around 7.5% higher than New York City, where 6.7% of the road length was impacted (981 km). These observations suggest that resilience is context specific, and that by nature of its topography, Chicago may simply be more impacted by extreme floods than New York City. In general, the analysis of node betweenness centrality results in similar observations since they capture the same property of a network. This can be seen from Table 1 in which the maximum/average node betweenness centralities, $C_{Be}^{max}$ and $C_{Be}^{avg}$, percentages of changes after the extreme flooding in New York City and Chicago road networks are almost similar to the percentages of changes in maximum/average edge betweenness centralities, $C_{Be}^{max}$ and $C_{Be}^{avg}$, in these cities.

**LEHD Trip Variation Metrics**

Table 2 shows the results of LEHD trips change in pre- and post-flooding conditions for the five trip variation metrics defined in Equations (2)-(6). We can see that the trips are impacted significantly by the extreme flooding events, though depending on the way each city is exposed to the aforementioned extreme events. As for the extreme flooding event in New York City, 6% of trips were not completed after the extreme flood (i.e., $\tau_D = 6.34\%$) because the origins/destinations become inaccessible. From the remaining accessible locations, 47% of the trips could not be completed (since they were isolated), after the removal of the affected links and nodes, and of the remaining, 17% were forced to travel longer distances. This significant decrease in the number of not completed trips, $\tau_{C +}^{D} = 53.26\%$, in New York City is a consequence of the rupture of the road network into many smaller parts. Despite that, New York City road network still offers 17% alternative routes for completed trips (i.e., $\tau_{AB} = 16.91\%$).
In Chicago, 20% of trips were not completed after the extreme flooding event because of the inaccessibility of origins/destinations. This drop in completed trips is more than three times higher than \( \tau_D \) of New York City. Similar to New York City, Chicago witnesses a significant drop of 30% in the number of completed trips after the extreme flood (i.e., \( \tau_c = 30.42\% \)) due to isolation of the origins/destinations. However, a large difference exists between the longer-traveled trips metrics between the two cities. After the flood, the Chicago road network keeps its functionality in three major intact sections that can be seen as signs of higher robustness in the road network, helping the trips to be completed along their shortest-possible paths within those sections. Thanks to this fact, only 4% of remaining completed trips are forced to travel longer distances (i.e., \( \tau_{AB} = 3.86\% \)).

**GIS Network Analysis**

As an example of service area change after extreme events, Figure 2 shows the changes in service area with accessibility of 5 km before and after extreme flooding in Chicago. Table 3 shows that the service areas with accessibility of 1, 2 and 5 kilometers around community districts in New York City have decreased by 9%, 12% and 26% respectively because of the extreme flooding.

<table>
<thead>
<tr>
<th>City</th>
<th>( \tau_A )</th>
<th>( \tau_B )</th>
<th>( \tau_C )</th>
<th>( \tau_D )</th>
<th>( \tau_{AB} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>New York City</td>
<td>38.84%</td>
<td>7.90%</td>
<td>46.92%</td>
<td>6.34%</td>
<td>16.91%</td>
</tr>
<tr>
<td>Chicago</td>
<td>47.38%</td>
<td>1.89%</td>
<td>30.42%</td>
<td>20.31%</td>
<td>3.86%</td>
</tr>
</tbody>
</table>

The percentage change in service areas in post-flooding for Chicago is much lower than New York City. In fact, this capability to keep the accessibility level same as normal condition after the extreme flooding event, originates from the way that floodplains segregate the road network of Chicago into three major parts. This kind of exposure to extreme flooding in Chicago, keeps short distance accessibility (i.e., 1 and 2 km) in normal condition. We can see that there are almost no changes in service area levels from the centroids of community areas to 1 and 2 kilometers around them after the extreme flood. This information can be used in emergency and risk management programs in Chicago with providing appropriate emergency facilities (e.g., hospitals, emergency medical centers and fire departments) in each of the three major sections in the city.

**CONCLUSION**

Transportation resiliency, and more specifically road robustness in our case, is a crucial factor in post-disaster management of cities. The unpredictable nature of extreme events such as floods can have a substantial impact on road systems. Our study indicates that this impact is mostly related to how the road...
network is subjected to these extreme events as well as to the inherent road network’s characteristics (i.e., size and topological structure of the network).

After simulating extreme flooding event, we initially calculated various topological indicators that showed that the Chicago road network would be more impacted than New York City’s. Although Chicago’s road network is not built on floodplains, the structural framework of its road network is vulnerable to extreme flooding events due to the geographical location of the 100-year floodplain in this city. The real trip distribution from LEHD data showed that in both cities, the trips will be highly impacted by extreme flooding; however there are still signs of robustness in road networks of both cities. This fact shows itself in New York City with alternative routes that exist in network for completing the trips and in Chicago with higher percentage of completed trips.

One of the main outcomes of this study is that different metrics can capture different properties of robustness of a system, which can be contrasted with results captured from the other metrics. The results of GIS network analyses for service areas showed no significant changes in accessibility levels for short distances after the extreme flooding in Chicago. Despite the previous metrics, especially topological indicators, this metric (i.e., service area) shows a sign of robustness in road network of Chicago.

Overall, we find that extreme events can have tremendous impacts on road networks. In an era when we observe an increase in the frequency and intensity of extreme events, cities must be equipped with robust transportation networks that can withstand large and unpredicted extreme events. This is, however, a challenging task that must not only be sensitive to the type of extreme events, but that must also take into account the presence of the current infrastructure. In this study, we offered a simple and freely reproducible approach to quantify the robustness of road networks to extreme flooding, but future work should include elements of land-surface topography to better account for surface runoffs. A stochastic approach may also be preferred although it would significantly increase the computational cost of the method.

Finally, we can conclude that the impact of any extreme event on any road network should be studied on its own, and general design recommendations cannot be made at this point. This fact and the results from various metrics that we investigate in this study, prevent us from reaching a failsafe conclusion to compare the resiliency of New York City’s road network and Chicago’s road network.
1. **FIGURE 1** Edge Betweenness Centrality in Road Networks Before and After Extreme Flood.
FIGURE 2  Service Area with Accessibility of 5 Kilometers in Chicago Road Network.
REFERENCES


