Empirical assessment of road network resilience in natural hazards using crowdsourced traffic data

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ABSTRACT
Climate change and natural hazards pose great threats to road transport systems which are ‘lifelines’ of human society. However, there is generally a lack of empirical data and approaches for assessing resilience of road networks in real hazard events. This study introduces an empirical approach to evaluate road network resilience using crowdsourced traffic data in Google Maps. Based on the conceptualization of resilience and the Hansen accessibility index, resilience of road network is measured from accumulated accessibility reduction over time during a hazard. The utility of this approach is demonstrated in a case study of the Cleveland metropolitan area (Ohio) in Winter Storm Harper. The results reveal strong spatial variations of the disturbance and recovery rate of road network performance during the hazard. The major findings of the case study are: (1) longer distance travels have higher increasing ratios of travel time during the hazard; (2) communities with low accessibility at the normal condition have lower road network resilience; (3) spatial clusters of low resilience are identified, including communities with low socio-economic capacities. The introduced approach provides ground-truth validation for existing quantitative models and supports disaster management and transportation planning to reduce hazard impacts on road network.

1. Introduction
Road transport systems are ‘lifeline’ systems providing fundamental support for national security, economy, public welfare and individuals’ daily activities. Disruptions of road transport systems can lead to significant socio-economic impacts. Due to the changing climate and increasing extreme weather events, much attention has been paid to the vulnerability and resilience of road transportation systems to the environmental stressors. Ample evidence shows that extreme weather events can cause significant disruptions to the performance of road networks (Koetse and Rietveld 2009), which affect people’s accessibility to employment, shopping, health care, and emergency services. For example, a winter storm can cause billions of dollars’ economic loss (National Oceanic and Atmospheric Administration (NOAA) 2018; Smith and Katz 2013), a large proportion of which is due to reduced performance of road networks (Fortune 2016). The impacts of hazards on road networks are various in space and time, depending on the physical...
properties of road networks and a variety of environmental and socio-economic factors. It is of crucial importance to understand the complex interplay among the various factors and develop actionable metrics of road network resilience to guide planning, mitigation and emergency management.

Despite the available studies on measuring vulnerability and resilience of transport systems (will be reviewed in Section 2), there is a general lack of empirical methods for measuring resilience of road network in hazardous weather conditions. This issue is largely attributed to the challenge of collecting real-time and location-based traffic data using traditional means (e.g. traffic sensors or counters installed on roads). With the advent of Web 2.0, interactive web-map services (e.g. Google Maps® and Bing Maps®) are becoming platforms where numerous travelers acquire and share information at any time in any place. In addition to providing routing services to travelers, these crowd-sourced data create unique opportunities to monitor dynamic performance of road network in hazardous weather events and to obtain empirical knowledge about road network resilience.

This study introduces an innovative approach that utilizes mobility data crowdsourced in Google Maps® to analyze resilience of road network. Using travel times collected at a sequence of times during a weather event, dynamics of accessibility to critical facilities can be calculated for specific locations. Based on a conceptual framework of resilience, a novel approach is introduced to assess resilience of road network from accumulated accessibility reduction during the hazard. The utility of this approach is demonstrated in a case study of winter storm. The introduced approach fills the critical gap of empirical assessments for road network resilience in real hazard events. It helps to reveal the spatial variance of accessibility disturbance and the recovery rate of road networks during the hazards. The location-based resilience metric can provide actionable information for disaster management and transportation planning to mitigate hazard impacts on road transport systems.

The rest of the article is organized as follows: Section 2 presents a literature review of related studies and points out the current research gaps. Section 3 refines the conceptual framework of resilience and introduce the measurement method for road network resilience. Section 4 describes the process of data collection using Google Maps APIs and the settings in the case study of Cleveland, OH in Winter Storm Harper. Section 5 presents the analysis results in the case study. Section 6 discusses the implications, limitations and future directions.

2. Related work

As reviewed by Koetse and Rietveld (2009), abundant studies have been conducted to understand the impacts of hazardous weather conditions on road transport systems. Abundant evidence shows precipitation events can cause reduction of traffic speed in road networks. According to a report by Federal Highway Administration (1977), traffic speed reduces by 22% in a wet road condition and the reduction can reach to 42% in a snowy condition. The impact of weather on traffic speed has been confirmed in a series of subsequent studies (Ibrahim and Hall 1994, Martin et al. 2000, Hranac et al. 2006, Maze et al. 2006). Furthermore, Sabir et al. (2008) estimated that rain may cause € 0.88 welfare loss per commuting trip in the Netherlands due to increased travel time on road. In

The concept of vulnerability was introduced to describe the susceptibility of road networks to incidents that can result in reduction in road network serviceability (Berdica 2002). Vulnerability of road networks is commonly measured by the reduction of accessibility due to hypothetical disruptions or failures in the network (e.g. Berdica and Eliasson 2004, Husdal 2004, Sohn 2006, Taylor et al. 2006, Chen et al. 2007). As the principal service provided by road transport systems, accessibility is defined as ‘the potential of opportunities for interaction’ (Hansen 1959) or ‘the ease with which any land-use activity can be reached from a location using a particular transport system’ (Dalvi and Martin 1976). Accessibility is a deep-seated concept in geography and urban planning, which plays a central role in studying the interactions among land use, transport systems and people (Kwan 2013, Neutens 2015). For vulnerability assessment, accessibility is often used as a proxy to estimate hazard impacts on transport serviceability and identify critical links the loss of which may lead to significant socio-economic consequences (Taylor and Susilawati 2012, Jenelius and Mattsson 2015).

Another related concept is resilience, which is sometimes considered the opposite of vulnerability. With an origin in ecological research, resilience expresses the capacity of systems to absorb disturbances and return to pre-disaster condition or a new equilibrium (Holling 1996, Adger et al. 2005). In the field of transportation, the definition of resilience includes the ability of resisting and absorbing disturbances (i.e. resistance) and the ability of adapting to disruptions, and returning to normal functionalities (i.e. recovery) (Faturechi and Miller-Hooks 2014a, Calvert and Snelder 2018). Resilience of road transport system is dependent on both the inherent capacity of the system in coping with disturbance and adaptive actions taken by humans that help the system to restore performance (Faturechi and Miller-Hooks 2014b). Despite the available studies of resilience in the broad area of transportation (e.g. Chen and Miller-Hooks 2011, Cox et al. 2011, Ishfaq 2012), quantitative assessment approaches for road network resilience are relatively rare. Noticeable contributions include the stochastic framework developed by Faturechi and Miller-Hooks (2014b), which can be used to quantify and optimize travel time resilience in roadway networks, and the Link Performance Index for Resilience by Calvert and Snelder (2018), which evaluates the resilience of individual road sections. Both of the frameworks are theory-driven, predicting resilience of road networks using mathematical models with presumed network properties and traffic conditions.

There are a few issues that have not been well addressed in current approaches for road network vulnerability and resilience. First, few empirical approaches are available for evaluating road network vulnerability or resilience in real disaster events. The existing approaches (e.g. Taylor et al. 2006, Miller-Hooks et al. 2012) are primarily based on simulation models, predicting the potential degradation of network performance in hypothetical hazardous conditions. However, the actual performance of road networks in real hazard events is dynamic and complex, dependent on not only physical network properties (e.g. topology, road type and capacity) (Hooper et al. 2013), but also environmental (e.g. weather and topography) (Pregnolato et al. 2017) and human factors (e.g. mitigation, emergency management and individuals’ travel behavior) (Zheng and Ling...
Empirical observations of road network performance are needed to validate the predictions of the theory-based models and unravel the complex interplays among the various factors. Second, most existing approaches provide a system-level assessment of the entire network (e.g. Cox et al. 2011) or sections of the network (Adams et al. 2011). Few studies provide location-specific metrics from a community’s or individual’s perspective. Resilience assessments at a fine spatial scale can provide more specific and actionable guidance for improving road network resilience and disaster management in different areas with diverse environmental and socio-economic conditions.

3. Measurement framework

According to the notion of resilience including resistance and recovery, resilience of road networks should be measured from both the reduction of performance due to disturbance and the speed of recovering to normal performance. Figure 1 illustrates four simplified scenarios of system performance during a hazard. Figure 1(a) can be ranked as low resilience due to both the large performance reduction (low resistance) and the slow recovery. In the other extreme, Figure 1(d) represent a high-resilience scenario where the system has a small performance reduction (high resistance) and fast recovery. However, the in-between situations are difficult to compare, as they are paired with either low resistance and faster recovery (e.g. Figure 1(b)) or high resistance and slow recovery (e.g. Figure 1(c)). The dynamics of road performance can be more complex than the scenarios in Figure 1 and include several reduction troughs or different recovery speeds at different phases. Such complex patterns cannot be measured by a simple combination of the maximum disturbance and average recovery speed.

In this study, the resilience of a road transport system is measured by the accumulated reduction of road network performance during a hazard process, which can be represented as the difference (gray area in Figure 1) between actual performance in the hazard and benchmark performance at the normal condition. The accumulated reduction is dependent on both the extent of performance reduction (indicating resistance) and the lasting time of the reduction (indicating recovery). Not only the extreme situations (e.g. Figure 1(a,d)), intermediate conditions (e.g. Figure 1(b,c)) and more complex patterns can be differentiated. Assuming road network performance during a hazard can be modelled as a function over time, resilience ($R$) can be calculated as the integral of the performance function $f(x)$ from the time when the performance decline below the normal condition.

![Figure 1. Possible scenarios of road network performance in a hazard. (a): a low-resilience scenario. (b-c): the intermediate resilience scenarios, (d): a high-resilience scenario.](image-url)
(t₁) to the time when the accessibility restores to the normal condition (t₂) (see Equation 1).

\[ R = \int_{t_1}^{t_2} f(x) \, dx \]  

(1)

The Hansen accessibility index (Hansen 1959) is used as the indicator of road network performance. This index provides an overall measure of the accessibility from one location to a number of destinations. The original equation of the Hansen accessibility index can be written as:

\[ A_i = \frac{\sum_j w_j f(c_{ij})}{\sum_j w_j} \]  

(2)

where \( f(c_{ij}) \) is the ease from location \( i \) to destination \( j \). \( f(c_{ij}) \) is negatively related with the travel cost (e.g., travel time) from \( i \) to \( j \), which is denoted as \( c_{ij} \). \( w_j \) is the attractiveness of destination \( j \). In the introduced approach, travel cost \( c_{ij} \) is calculated as the reciprocal of travel time \( x_{ij} \) from location \( i \) to a nearby facility \( j \). The attractiveness coefficients \( (w_j) \) is considered equal for all nearby facilities. Other weighting schemes can be applied when the relative importance among the facilities can be determined. Thus, the Hansen accessibility can be adapted as:

\[ A_i = \frac{1}{n} \sum_{j=1}^{n} \frac{1}{x_{ij}} \]  

(3)

where \( x_{ij} \) is the normalized travel time from Location \( i \) to Facility \( j \). \( n \) is the number of nearby facilities of Location \( i \). By comparing the actual Hansen index and benchmark Hansen index over time, the accumulated reduction of accessibility can be calculated as:

\[ RA_i = \int_{t_1}^{t_2} \left( \frac{(A'_{i}(t) - A_i(t))}{A'_{i}(t)} \right) \, dt \]  

(4)

where \( A_i(t) \) and \( A'_{i}(t) \) are the actual and benchmark Hansen index at Location \( i \) and Time \( t \). \( RA_i \) is the accumulated reduction ratio of the Hansen index from \( t_1 \) to \( t_2 \). Road network resilience \( (R_i) \) is negatively proportional to the normalized value of \( RA_i \), which is calculated as:

\[ R_i = 1 - \frac{RA_i}{(\max(RA) - \min(RA))} \]  

(5)

4. Data collection
The data collection includes the following steps. First, the nearby facilities of each location are acquired using the Search API of Google Maps. With the coordinates of a location and text keywords (e.g., 'hospital') in a request, the API returns 20 facilities near the search location, ranked by distance. \( n \) (\( 1 \leq n \leq 20 \)) of the 20 nearest facilities are selected to calculate accessibility. Next, in-traffic travel times from each location to the \( n \) nearest
facilities at different times are acquired using the Direction API of Google Maps (Google 2019a). At a specific time \( t \), two travel times are retrieved for each location-facility pair with two different settings. The first travel time is requested with the departure time set to a future time corresponding to \( t \). The retrieved travel time is an estimate based on the historical traffic condition at \( t \) on the same day of week. This travel time is considered as the benchmark reflecting the normal traffic condition. The second travel time is requested at exactly time \( t \) during the event, using ‘now’ as the departure time. This travel time indicates the actual traffic condition. Finally, travel times retrieved in the two settings are used to calculate the benchmark \( A_i(t) \) and actual Hansen accessibility index \( \bar{A}_i(t) \), respectively, at the time \( t \). With requests at multiple time points during the disaster, the accumulated accessibility reduction \( RA_i \) is calculated using Equation 4, which is then used to calculate the resilience index \( R_i \) using Equation 5.

Data for the case study were collected in the metropolitan area of Cleveland, Ohio during Winter Storm Harper on January 19th and 20th, 2019, which was a major storm system that brought heavy snow from coast to coast in the United States. In the case study, in-traffic travel times from the centroid of each census tract to nearby facilities were requested at four time points, including 01/19/2019 11:00am \( (t_1) \), 01/19/2019 17:00pm \( (t_1) \), 01/20/2019 11:00am \( (t_3) \), and 01/20/2019 17:00pm \( (t_4) \) Eastern Time. According to the weather record (National Oceanic and Atmospheric Administration (NOAA) 2019), \( t_1 \) was a time point before the storm impact arrived at Cleveland. Snow was the heaviest at \( t_2 \) and lasting until the midnight of the day. Snow fall stopped between \( t_2 \) and \( t_3 \). In addition, we defined 01/21/2019 0:00am \( (t_5) \), which is 22 h after the last hour with recorded snowfall, as the time point when the accessibility was no longer affected by the storm. We thus define the accessibility returns to the benchmark (i.e. reduction = 0) at \( t_5 \). An overall resilience score was calculated from the accumulated accessibility reduction from \( t_1 \) to \( t_5 \) for each census tract. In case the accessibility reduces later than \( t_1 \) or recovers to the benchmark earlier than \( t_5 \), only the negative part (i.e. the part below the benchmark) was counted in the calculation. Due to the small number of sampling times, linear interpolation was applied to estimate the accessibility reduction between the sampled time points. Other interpolation functions (e.g. polynomial functions) could be applied for a denser sampling frequency.

In the case study, the Hansen index was calculated using travel times to five types of facilities, including the center of the CBD, the nearest hospital, grocery store, police department and fire station. The CBD represents the concentration of employments, resources and services, which is often included in road accessibility and vulnerability assessments (Taylor et al. 2006, Taylor and Susilawati 2012). Grocery stores are places to obtain emergency supplies such as food, water, clothes and batteries for hazard preparation. Hospitals, police department and fire stations are critical facilities for emergency response (Federal Emergency Management Agency (FEMA) 2010). Locations of the nearby facilities around each tract were acquired using Google Search API. 41.505W and -81.686N was considered as the center of the CBD, which was returned from the Search API using ‘Downtown, Cleveland, OH’ as the keywords. The travel times were requested using the settings of ‘fastest route’ and ‘driving mode’. The method can be expanded to other travel modes (e.g. transit, bike and walk) and other route criteria (e.g. the shortest route, avoid toll charge).
Selecting only five facility types and four sampling time points are primarily due to the cost of API usage. In the case study, the data collection includes 2,540 requests (635 census tract \( \times \) 4 facility types excluding the CBD) to the Search API and 25,400 requests to the Direction API (635 census tract \( \times \) 5 facility types \( \times \) 4 time points \( \times \) 2 settings). A request to the Search and Direction API costs \$0.032 and \$0.01, respectively (Google 2019b). The total requests result in a cost of \$335.28 (2,540 \( \times \) \$0.032 + 25,400 \( \times \) \$0.01).

5. Analysis results

5.1. Travel time increase

Increases of travel time from census tracts to nearby facilities were identified during the winter storm. As illustrated in Figure 2, the average increasing ratio of travel times to the five types of facilities all peaked at \( t_2 \), when the snow fall was the heaviest. Particularly, the average travel time to the CBD increased by nearly 30% at \( t_2 \), while the average travel times to other facilities increased by less than 10%. Thus, \( t_2 \) can be considered the time when the disturbance of the overall network is maximum at the four sampled time points. At \( t_2 \), the increasing ratios of travel time are positively related to travel distances to most of the facilities (Figure 3), meaning that the storm impact is more severe for long-distance travels. The linear relations of the fire station, grocery store, police department, and hospital are all significant \((p < 0.05)\) (Table 1). However, the increase ratio of travel times to the CBD shows a different pattern: the ratio increases until around 28 km and then starts to decline beyond this distance. This indicates that the storm impact to the accessibility to the CBD maximizes at a distance around 28 km. Whether this peak distance exists or varies in other cities and in other storms needs to be analyzed in future studies.

5.2. Accessibility reduction

The accessibility index at the pre-event time point \((t_1)\) was slightly higher than the normal condition, possibly due to the higher traffic volume at \( t_1 \). To eliminate the bias of the different traffic volume, the benchmark accessibility at all the four times was adjusted by.

![Figure 2. Average increasing ratios of travel time to the five types of facilities (refer to the left axis) and precipitation (refer to the right axis).](image-url)
the difference between the actual and benchmark accessibility at \( t_1 \), so that the accessibility reduction at \( t_1 \) became zero. The average accessibility reduction of the census tracts at different time points are illustrated in Figure 4(a), showing that the accessibility had the highest reduction at \( t_2 \) and gradually restored towards the benchmark at \( t_3 \) and \( t_4 \). The accessibility reduction differs at different census tracts at different times (Figure 4(b)). Spatially speaking, census tracts near the CBD and along the east part of lake shore had less accessibility reduction at \( t_2 \) (Figure 5). However, at \( t_3 \) and \( t_4 \), the distant census tracts recovered more quickly than the census tracts near the CBD. The spatial variance of accessibility reduction can be potentially explained by the physical conditions (network

Figure 3. Relations between increasing ratios of travel time and travel distances. The relations of fire station, grocery stores, police department, and hospital are fitted in linear models. CBD is fitted in a generalized additive model. A summary of the regression models is reported in Table 1.

Table 1. Summary of the regression analyses. Scatter plots and regression lines can be found in Figures 3 and 8.

<table>
<thead>
<tr>
<th>Dependent variable ((y))</th>
<th>Independent variable ((x))</th>
<th>Coefficient ((\beta))</th>
<th>Residual ((\epsilon))</th>
<th>(p)</th>
<th>(R^2)</th>
<th>Degree of freedom</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio of travel time increase</td>
<td>Dist. to fire station</td>
<td>0.0061</td>
<td>0.0557</td>
<td>&lt; 0.001</td>
<td>0.0292</td>
<td>635</td>
</tr>
<tr>
<td></td>
<td>Dist. to grocery store</td>
<td>0.0082</td>
<td>0.0353</td>
<td>&lt; 0.001</td>
<td>0.0586</td>
<td>635</td>
</tr>
<tr>
<td></td>
<td>Dist. to hospital</td>
<td>0.0046</td>
<td>0.0468</td>
<td>&lt; 0.001</td>
<td>0.0948</td>
<td>635</td>
</tr>
<tr>
<td></td>
<td>Dist. to police department</td>
<td>0.0069</td>
<td>0.0480</td>
<td>&lt; 0.001</td>
<td>0.0593</td>
<td>635</td>
</tr>
<tr>
<td>Normal accessibility</td>
<td>Accessibility reduction at ( t_2 )</td>
<td>1.5785</td>
<td>0.7711</td>
<td>&lt; 0.001</td>
<td>0.3263</td>
<td>635</td>
</tr>
<tr>
<td>Normal accessibility</td>
<td>Resilience</td>
<td>0.3417</td>
<td>0.3925</td>
<td>&lt; 0.001</td>
<td>0.1334</td>
<td>635</td>
</tr>
<tr>
<td>Accessibility reduction at ( t_2 )</td>
<td>Mean income</td>
<td>(-2.25e-07)</td>
<td>(-0.0403)</td>
<td>&lt; 0.001</td>
<td>0.0578</td>
<td>632</td>
</tr>
<tr>
<td>Resilience</td>
<td>Mean income</td>
<td>(-2.49e-07)</td>
<td>0.8682</td>
<td>&lt; 0.001</td>
<td>0.0082</td>
<td>632</td>
</tr>
</tbody>
</table>
topology, road type and capacity) as well as human interventions (e.g. snowplow and adapted travel behaviors).

5.3. Resilience

As shown in Figure 6, the spatial distribution of overall resilience scores is uneven. Census tracts with a low-resilience score are colored in red to express an alarming signal in these places. In general, census tracts with a high-resilience score are mostly distributed along the lakeshore north in parallel with the I-90 interstate highway. Low-resilience scores are
scattered in the inland area to the south of the lakeshore. The Getis-Ord Gi* analysis (Getis and Ord 1992) was applied to detect local clusters of resilience that are statistically significant at different probability levels (see Figure 7). A high-resilience cluster (also called ‘hot spot’) refers to a contiguous area where high-resilience census tracts are located near each other, while a low-resilience cluster (cold spot) represents the opposite. The result of the Getis-Ord Gi* analysis (Figure 7) further confirms the visual observation in Figure 6: most of the high-resilience clusters are located along the I-90 highway near the lakeshore.

Figure 6. Spatial distribution of road network resilience in census tracts.

Figure 7. Hotspot analysis of road network resilience in census tracts.
5.4. Relations between variables

As shown in Figure 8(a,b), the accessibility reduction at $t_2$ (the time point of the maximum reduction) and the overall resilience are both positively related with the normal accessibility. These results indicate that census tracts that have longer travel times to the facilities at the normal condition experienced a higher level of disturbance and/or slower recovery in the storm. These results also confirm the analyses in Figure 3 where longer distance travels are associated with higher increases in travel time to the facilities. The accessibility reductions at $t_2$ (maximum disturbance) and resilience are negatively related with mean incomes (Figure 8(c,d)), indicating that the higher-income communities were more affected in the storm. These relations can be attributed to the demographic landscape in Cleveland: the low-income communities tend to be located near the CBD where the density of the selected facilities is high and so as the accessibility. Note, this study uses travel time by driving to measure accessibility, which assumes equal access to a vehicle. Future studies should consider the inequalities in vehicle ownership and access to other transportation systems (e.g. transit). Still, some low-income communities with low resilience of road network are noticeable. Figure 9 highlights the census tracts where the income and road network resilience are both at the lower quantiles (25% and 50%). As one of the most important indicators of social vulnerability and resilience (Cutter et al. 2003, 2010, Lam et al. 2015, Cai et al. 2018), income is often related with the capacity of communities and individuals to cope with and adapt to the adverse impacts of hazards.
Given the low resilience of road network and socio-economic capacities, more attention should be paid to these communities to minimize the adverse impacts of the storm.

6. Discussion

The study demonstrates the utility of the crowdsourced mobility data from Web 2.0 platforms for assessment of road network resilience. The introduced approach measures resilience of road networks using ground-truth data collected in real-disaster events. Other than Google Maps, the measurement approach is applicable to similar data services provided by Microsoft Bing Maps, ArcGIS for Developers, and Uber Movement. Compared with traditional data collection methods (e.g. installation of road sensors and field data collection), the crowdsourced data can be acquired at real-time and at a relatively low cost. Despite the simple settings (e.g. only the nearest facility and five time points) applied in the case study, the introduced assessment approach can be easily expanded to a larger region, a longer period, more facilities, and/or a higher sampling frequency (e.g. hourly sampling). Not limited to winter storms, the approach can be applied in other hazards such as hurricane, king tide, sea level rise, and land slide that may cause accessibility reduction in road networks. With applications in more hazard events and larger geographical areas, this approach can increase the knowledge about the complex factors of road network resilience. Such knowledge is generally lacking but crucial for building resilient and sustainable transportation systems. Additionally, this approach can be implemented in an interactive interface for emergency responders to monitor real-time accessibility at different locations and identify communities in urgent need for assistance and disaster relief.

The effectiveness of hazard mitigation and emergency management can be evaluated by comparing assessments in different case studies. Using the same approach, the preliminary results shows a more complex pattern of network performance in Seattle in

![Figure 9. Census tracts where the mean income and resilience are both in the lower 50% quantile and 25% quantile. Colors of the tracts correspond to the colored points in Figure 8 (b).](image-url)
Winter Storm Maya (see Figure 10): the average increase of travel times to the CBD peaked for a short period at the very beginning of the storm (at around 14:00pm on Friday, 02/08/2019), and then quickly declined and stayed at a lower level afterwards. In the normal rush hour on Fridays (16:00–17:00 according to TomTom 2016), the travel time has returned near the normal condition, although the snowfall continued. The short disturbance period may be attributed to the effective emergency response in Seattle, including the timely issuance of winter storm warnings and the early release of schools at noon on the day. In addition to the case-by-case findings, general lessons about effective mitigation and emergency management can be gained from applications of this approach in more hazard events and larger geographical areas.

Figure 10. Average increase ratio of travel time from the CBD to census tracts in the Seattle metropolitan area during Winter Storm Maya.

The case study is limited to the measurement of accessibility to a few selected facilities. A complete assessment of road network resilience should consider the disturbance of individuals’ maximum mobility in space and time. As a profound conceptual model in time-geography, the space-time prism (Hägerstråland 1970) represents individuals’ maximum travel extents or interaction potential in space and time as 3D prisms (Miller 2005, Neutens et al. 2008). A future extension of the introduced approach could be the integration with space-time prisms. The resilience of road network for an individual person can be measured from the accumulated shrink of a 3D prism which represents his maximum mobility in space and time. Such location- or individual-level assessments of road network resilience can support real-time decision-making in hazard events and improve humanized transportation planning. Example questions can be answered include: which communities are experiencing the greatest accessibility reduction during a hazard? Are the socially vulnerable communities located in areas with low network resilience? Are there communities or population groups systematically or disproportionately affected due to low resilience of road networks?
7. Conclusion

This study introduces an empirical approach to assess road network resilience using crowdsourced traffic data from Google Maps. Built on the conceptualization of resilience and the Hansen accessibility index, accumulated accessibility reduction over time is used to measure resilience of road network during natural hazards. The utility of this approach is demonstrated in a case study of the Cleveland metropolitan area (Ohio) in Winter Storm Harper. The results reveal strong spatial variations of the disturbance and recovery rate of road network performance during the hazard event. The findings in the case study are: (1) longer distance travels have higher increasing ratios of travel time during the hazard; (2) communities with low accessibility at the normal condition have lower resilience (great and long-lasting accessibility reduction) in the local road networks; (3) the spatial clusters of low network resilience are identified. The study also suggests that special assistance should be applied to the communities where both road network resilience and socio-economic capacities (e.g. low income) are lower than the average. Utilizing crowdsourced geospatial data, this study filled the void of empirical assessment of road network resilience at real-time and real-place. The assessment results can provide ground-truth validation for existing quantitative models to better predict road network resilience in extreme weather events. Integrated with the theoretical frameworks of time-geography, this approach can be further expanded to model the dynamic aspects of road network resilience and advance research about the social issues (i.e. environmental justice and social equalities) related to transportation planning.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Data and codes availability statement

The data and codes that support the findings of this study are available in figshare.com with the identifier(s) [doi.10.6084/m9.figshare.10279295.v1].

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References


Berdica, K., 2002. An introduction to road vulnerability: what has been done, is done and should be done. Transportation Policy, 9, 117–127. doi:10.1016/S0967-070X(02)00011-2


