USING BIG DATA TO STUDY RESILIENCE OF TAXI AND SUBWAY TRIPS FOR HURRICANES SANDY AND IRENE

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ABSTRACT

Hurricanes Irene and Sandy had significant impact on New York City, resulting in devastating damage to its transportation systems which took days, even months to recover. This study explores post-hurricane recovery process by analyzing travel patterns of the roadway and subway systems of New York City based on taxi trip data from Taxi and Limousine Commission (TLC) and subway turnstile ridership data from Metropolitan Transportation Authority (MTA). Both these datasets are examples of big data with millions of individual ridership records per month. The study investigates spatio-temporal variations of transportation system recovery behavior using Neighborhood Tabulation Areas (NTAs) as units of analysis. Recovery curves are estimated for each evacuation zone category to model time-dependent recovery patterns of the roadway and transit systems. The recovery rate for Hurricane Sandy is found to be lower than that of Hurricane Irene. Moreover, the results indicate higher resilience of the road network compared to the subway network. The methodology proposed in this study can be used to evaluate the resilience of transportation systems to natural disasters and the findings can provide government agencies with useful insights into emergency management.

Keywords: Emergency management, hurricane, recovery curve, evacuation zone, taxi and subway data
INTRODUCTION

New York City (NYC) is a city vulnerable to hurricanes. In the last 120 years, 13 hurricanes impacted coastal areas of NYC (1). Two of most recent ones, Hurricanes Irene and Sandy caused significant devastation to NYC. Hurricane Irene, which made landfall at Coney Island, NY in the morning of August 28th, 2011, led to inland flooding to NYC. Irene didn’t impact most of subway infrastructure, and subway system returned to normal one day after the landfall. Fifteen months later, Hurricane Sandy, which landed in New Jersey in the evening of October 29th, 2012, made recorded surges which was 14 ft higher than average tide (2). Sandy made NYC one of the most severely impacted areas in United States, resulting in excessive damage to subway tunnels and roadways(3). Several subway stations and tubes were filled with salt water after Sandy’s landfall, which jeopardized normal operation of subway system (4). Because of flooded stations and tunnels and power outage for entire lower Manhattan, all subway service between Manhattan and Brooklyn was suspended until November 4. Major service restoration started on November 5 to deal with first rush hour after the storm. On November 7, half of subway lines were back to service under normal schedules, while the other half were running partial service under special schedules (5). The roadway system of NYC was also disrupted in Hurricane Sandy. The storm caused major flooding at Hugh Carey Tunnel and Queens Midtown Tunnel, and severe water damage to the Marine Parkway and Cross Bay bridges. Other major bridges and tunnels also suffered damage of varying degrees (6).

Considering that hurricane events brought devastating disruption to transportation systems of NYC, the main objective of this study is to evaluate the resilience of roadway and transit systems after the impacts of hurricanes using very large and unique taxi and transit ridership datasets. The period we focus on is from two days before to 13 days after each hurricane’s landfall. Neighborhood Tabulation Areas (NTA) in NYC are used as units of analysis. Taxi trip data and subway turnstile ridership data of study periods are used in this approach.

LITERATURE REVIEW

Concept and Framework of Resilience

In recent years, scholars have shown increasing interest in system resilience under and after extreme conditions, such as hurricanes, earthquakes etc. The concept of resilience was introduced to the transportation area in recent years. According to Heaslip et al. (7), resilience is defined as “the ability for the system to maintain its demonstrated level of service or to restore itself to that level of service in a specified timeframe”. Bruneau et al. (8) established a conceptual framework that can identify and quantify the extent of seismic resilience. They have set up a four-dimensional framework, which is measured by technical, organizational, social and economic factors. They point out to three critical issues to evaluate a resilient system. First one is the possibility of failure due to an incident, second is severity of the outcome of an incident, then the duration of recovery. They utilize a triangular representation shown in Figure 1 to illustrate these issues. The size of community resilience loss is quantified as the area of the triangle. Mathematically, shown as:

\[ R = \int_{t_0}^{t_1} [100 - Q(t)] dt \]  

(1)

Where R is the loss of resilience and Q(t) is the quality of infrastructure (8). It can be seen that the size of the triangle is determined by the depth of the breakdown and the slope of recovery curve, which is consistent with the three abovementioned issues.
Bruneau et al. (8) introduced the concept of “resilience cycle”, a four-step framework shown on Figure 2 that illustrates nature of resilience. The steps of this approach are:

- Normality: The system is fully-functioning (7).
- Breakdown: Disruption and reduction of system performance.
- Self-annealing: Users of system attempt to find alternative route or travel modes.
- Recovery: Restoration of system infrastructure and service.

According to Pant (9) degradation and response profiles differ in regions within the resiliency cycle, and length of time from the beginning of "Self-Annealing Stage" and the completion of "Recovery Stage" is crucial to determine resilience of system.

Resilience Studies of Roadway and Subway Systems

Recently there have been few studies focusing on resilience of the road network utilizing GPS probe data. Donovan and Work (11) utilized taxi data set to measure roadway resilience of
NYC during Hurricane Sandy by measuring the deviation of normalized travel times between four different regions of the city, including three Manhattan regions and one Queens region. Their result shows minor delays for the evacuation period before hurricane landfall, while significant network deterioration after the hurricane impact, and the disruption took more than five days to recover. D’Lima and Medda (12) utilized a mean-reverting stochastic model to explore daily fluctuations of London Underground in terms of subway lines. They used passenger counts to measure recovery speed from shock for each line and thereafter determine the line resilience.

Evacuation Response Curves

Evacuation response and system recovery are two areas where resilience studies focused on. Normally evacuation and recovery processes all follow similar patterns. That is, the rates of evacuation or restoration follow an S-shape (see (13)). Such behavior can be modeled using a logistic function. The curve describing logistic function is called Sigmoid Curve (S-Curve). In 1985, Lewis (14) introduced the concept of S-Curve to represent evacuation rate. Fu et al. (15) improved this curve so that it can reflect intensity of a hurricane, time-of-day, and evacuation order time. Besides Sigmoid curves, researchers also attempted to use other types of curves to represent evacuation demand, including Rayleigh Curve by Tweedie et al. (16) and Poisson Distribution by Cova and Johnson (17). Li and Ozbay (13) built an empirical response curve based on traffic data of Cape May County, New Jersey based during Hurricane Irene, and compared it with different types of S-shape curves. Their result show better fit to logistic and Rayleigh functions compared to Poisson distribution.

In this paper, these previous studies related to evacuation response curves mentioned above will be extended to building recovery curves of two different transportation systems namely, roadway and transit networks in New York City in the aftermath of Hurricanes Irene and Sandy. Big data sets of taxi trips and turnstile ridership data from NYC subway will be used to study spatio-temporal resilience characteristics of NYC roadway and subway systems, respectively.

BIG DATA AND TRAVEL PATTERNS

In this study, two types of data from different agencies were used. First is New York City taxi trips, which is made available to public by NYC Taxi & Limousine Commission (TLC) (11, 18). The dataset includes taxi trips from years 2010 to 2013 and it contains pick-up and drop-off time and location information. The data is organized by each month and stored as csv files (18). The other is subway ridership data, which was obtained from turnstile dataset from Metropolitan Transportation Authority (MTA). This dataset includes subway turnstile information since May, 2010 and is updated every week. The data is stored in txt format and available on through an official data feed (19). The data is organized by weeks, remote units (stations) and control areas (turnstiles). Each station can have multiple control areas, and for each turnstile, there are two increment counters used to record numbers of entries and exits. In each weekly file, a row contains one read of entry and exit counters, time of the read, station and turnstile IDs. Typically counter readings of each turnstile is recorded every four hours, but each station may have a different time of reading. In order to obtain daily ridership of each station, first we need to convert values of counters to turnstile ridership by subtracting last reading and first reading of day, and then calculate sum of all turnstiles.
The processed datasets were then incorporated into Neighborhood Tabulation Areas (NTA). NTA is a set of polygons created by New York City Department of City Planning, and used for presenting data from Census and American Community Survey (20). There are overall 195 NTAs in NYC and each NTA corresponds to one Neighborhood with unique ID and name. There are two reasons for selecting NTAs. First, the sizes of NTAs are appropriate for analysis, especially for subway data. These areas are neither too big that may cover more than one category of evacuation zones, nor too small that may not include even one subway station. Second, as mentioned above, unlike Traffic Analysis Zones (TAZs) or Census Tracts, each NTA also has a familiar name, so it’s much easier to follow the travel patterns based on these names. Data for our study periods were extracted from taxi and subway datasets, and for each trip, NTA attributes are associated with each trip’s origin and destination using an R script and rgdal geoprocessing package (21).

As mentioned above, taxi trips and subway ridership data during the study period is compared with data for the same period of the previous year. Since traffic in NYC has significant day-of-the-week pattern, we find days closest to days of week in the study period, instead of the exact same days in previous years. For road networks, we calculates daily taxi trips whose destinations belong to same NTA. For transit networks, daily ridership for each NTA is obtained as sum of ridership for all stations located in the NTA. For both hurricanes, we choose the days before evacuation orders as the start days of study, and duration are 15 days. Study periods of hurricanes and normal conditions are shown in Table 1.

There are several important issues in processing taxi and subway turnstile data. First issue is the filtering noisy or erroneous data. For taxi trips, according to (11), there are significant amounts of error in taxi dataset, including missing or unrealistic coordinates (e.g. coordinate point is in the sea), impossible travel times or speeds. For subway trips, errors including extremely low or high ridership values, which is caused by counter reset due to maintenance need to be filtered out. Besides, for normal days, daily subway entrance and exit counts are close. However in first two days of November 2012, entrance counts are significantly lower than exit counts. That is due to the fact that fare was not collected in the initial recovery period of the system, and entry data was not recorded at all (5). So for the comparison purpose, ridership in terms of exit data only is used.

<table>
<thead>
<tr>
<th>Cases</th>
<th>Start Date (Day 1)</th>
<th>Evacuation Order</th>
<th>Hurricane Landfall</th>
<th>End Date (Day 15)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hurricane Irene</td>
<td>Aug 25, 2011 (Thu)</td>
<td>Aug 26, 2011 (Fri)</td>
<td>Aug 28, 2011 (Sun)</td>
<td>Sep 8, 2011 (Thu)</td>
</tr>
<tr>
<td>Reference Irene</td>
<td>Aug 26, 2010 (Thu)</td>
<td>-</td>
<td>-</td>
<td>Sep 7, 2010 (Thu)</td>
</tr>
<tr>
<td>Reference Sandy</td>
<td>Oct 29, 2011 (Sat)</td>
<td>-</td>
<td>-</td>
<td>Nov 8, 2011 (Sat)</td>
</tr>
</tbody>
</table>

Table 1 Study period of the empirical taxi and subway data

Figure 3 shows summary of citywide traffic and transit counts, and comparison with the previous year data. It can be seen that the total number of daily taxi trips is between 400,000 and 500,000 on weekdays, and the number drops on weekends, including Labor Day holidays as shown on day 10-12 of (a) and (b). Based on (a), the number of taxi trips before Irene evacuation and after the hurricane is slightly higher (less than 10%) than the total number a year ago while
subway ridership remains nearly identical. For Hurricane Sandy, trip counts before evacuation are also close to the ones in the previous year. Taxi trips have fallen down to half after the landfall and gradually recovered to previous levels nearly in a week but subway recovery took even longer.

For both hurricanes as well as both modes, there are significant decreases from the day of evacuations, however the recovery speeds of two storms are quite different from each other. After the Hurricane Irene, both taxi and subway trips have been restored to normal levels in two days, while recovery took much longer after the Hurricane Sandy. There are multiple reasons for these differences. First, Hurricane Sandy caused more damage to the road network and the transit infrastructure, resulting a suspension of the entire subway network for three days. It took nearly ten additional days for the ridership to return to normal.

Apart from showing basic patterns of travel during hurricane periods, these results imply that the travel demand in NYC is stable without weather the impact when compared to previous years. In addition, in years prior to Hurricanes Irene and Sandy, there were no severe disruptive events. Therefore we can utilize data from previous years as reliable benchmarks to quantify the degree of recovery in the aftermath of both Hurricanes.

Besides in volume, comparison are also made in terms of recovery rates. The rate of recovery is defined as the quotient of trips during a certain hurricane period divided by trips during a corresponding normal (control) period. In this study, the recovery rates for each NTA in NYC is calculated. Results of recovery rates in 50 NTAs of highest volumes are selected out of 195 NTA’s for the purposes of visualization. The reason for selection based on volumes is that characteristics of most critical zones, and criticality for different NTAs are directly related to the volumes of the area. If the recovery rate reached 100%, we assume the area is fully recovered and keep the rate at 100%. For modeling purposes, this assumption is also applied to our methodology of recovery curve modeling, which will be discussed later.

Figure 3 Comparison of trips during hurricane periods with those during normal conditions
Figure 4 illustrates the recovery rates for both hurricanes and modes for 50 neighborhoods, ordered by the number of daily taxi trips for normal conditions. These heatmaps mainly focus on general patterns of the city, and also characteristics of most critical zones. It’s shown that neighborhoods with highest taxi activities are located in the south and middle sections Manhattan Midtown being the busiest area. It can be seen from Figure 4 (a) that taxi trips were affected for only three days for most areas during Hurricane Irene study period. The tip rate dropped down to its lowest level on Day 4, the day when hurricane made the landfall, then returned to normal before Day 6. Spatial-temporal patterns of taxi trips are observed to be quite different during Sandy study period, as seen on Figure 4 (c). Taxi trips for major Manhattan NTAs started to fall on Day 2 (evacuation order). On Day 3, taxi trips for most NTAs reached their lowest levels. Recovery of taxi trips in Manhattan took about one week after the Hurricane Sandy until Day 10 (Monday Nov 5, 2012). In addition, recovery of Midtown is observed to be faster than Downtown Manhattan, which can be seen from the colors map for specific NTAs. Unlike Manhattan, taxi trips for inland Brooklyn, Queens and Bronx neighborhoods were restored after three days.

Several reasons account for much slower recovery rate of taxi trips in Manhattan. Manhattan, especially downtown suffered more severe infrastructure damage, causing closure of many interborough corridors. Also, power-outage in lower Manhattan lasted for several days resulting in, lower travel demands for residential and commercial activities. Moreover, HOV enforcement is implemented between November 1 and November 5 for all Manhattan bound taxis (22, 23). Naturally, carpooling reduced overall taxi trips.
Figure 4 (b) and (d) visually shows rates for the NYC subway system. Unlike taxi trips, subway ridership is seen to have less resiliency because it heavily depends on service status of transit infrastructure. It can be seen from Figure 4 (b) that during Hurricane Irene, ridership of the subway system in most NTAs start to drop on day 3, since the system shut down at noon. On day 4, Irene made landfall in the morning and subway system remained closed for another day. Then the subway ridership quickly returned to the levels before the hurricane for most areas. Moreover, on Days 10 to 12, recovery rates for Washington Height North dropped to 30%. That is because all subway stations in Washington Height North are Line 1 stations, and during the Labor Day holiday, ridership reduced due to the service change caused by the construction work on Subway Line 1 (24).

Recovery patterns of subway system during Hurricane Sandy is shown in Figure 4 (d). It’s evident that Hurricane Sandy caused far more serious disruption to the subway operations than Hurricane Irene. The ridership decreased one Day 2 and subway stations remained closed until Day 6 of the study period, when initial recovery began for upper sections of Manhattan. However
the recovery rate is relatively small. This is because number of lines that were in service was quite limited. Moreover, the subway connection between Queens, Manhattan and Brooklyn were still not operational. On Day 8, interborough subway connection is partially restored, and recovery rates for more than half of NTAs came back to at least 50% of the original while other areas include Lower Manhattan, Southern Brooklyn and Williamsburg. On Day 10, there is a major increase in ridership for most areas, since it was the first Monday after Sandy, and multiple lines were back into service (25). Due to extensive damage to the system infrastructure, post-Sandy rehabilitation for stations in specific NTAs took longer than the time covered by the study period, especially Whitehall Street and South Ferry Station for Lower Manhattan and Far Rockaway Stations (25).

METHODOLOGY

The main objective of this section is to propose a practical yet robust method to calculate recovery curves based on evacuation zones of NYC, and build a multi-layer model represented by individual zonal recovery curves. The evacuation zone category corresponds to the vulnerability to hurricanes, so it is likely that the resilience of transportation systems in the same zone category share similarity.

Although Figure 4 clearly shows the spatio-temporal variations during the study period, two problems arose. First, it’s still very hard to see the patterns of recovery merely based on NTAs. Moreover, mathematical models are needed to quantify recovery performance, which is essential in determining the resilience of each region. In the following section, construction and comparison of recovery is based on evacuation zones, since evacuation zones can generalize regional evacuation patterns better than neighborhoods.

NYC categorized evacuation zones based on vulnerability to the storm surge. Currently, the evacuation zoning system include six evacuation zones (26). All other areas are considered to be in the safe zone. As part of the data processing effort, TAZ attribute is added to each taxi trip and subway station. We have also slightly adjusted evacuation zone related data by associating evacuation zone information with each individual TAZ. The adjusted evacuation zones are shown on Figure 5, which is nearly overlapped with original ones.
Figure 5 Evacuation zones based on TAZs

Logistic Function

The logistic function was introduced by Belgian mathematician Pierre Francois Verhulst in 1838, for the purpose of analyzing growth of population in Belgium (27). He discovered this curve can represent the nature of natural growth. High growth rate (shown as slope of curve) are fast at first, because supply is greater than demand, then rate becomes steady. At the end, the rate slows down and stops growing because demand is greater than supply. These characteristics resemble evacuation and recovery activities, which are shown to follow an s-shape. In recent years, logistic function are applied in evacuation modeling of various studies, such as modeling tools named MASSVAC (28) and TEDSS (29), demand generation approach by Ozbay and Yazici (30), and modeling of hurricane evacuation in Louisiana by Fuet al. (15). Basic logistic function is shown in equation (2):

\[
P_t = \frac{1}{1 + e^{-\alpha (t - H)}}
\]

In modeling evacuation response curve, \( P_t \) is percentage of evacuees leave the risk area by time \( t \), and this function has two parameters: \( \alpha \) and \( H \), which stand for slope and duration of evacuation. Similarly, we use the logistic function to represent recovery rate of the system.

In our recovery model, \( P_t \) represents zonal recovery rate by time \( t \), \( \alpha \) is the factor affecting slope of the recovery rate, \( H \) is half recovery time, in other words the time when half of the lost service capacity is restored. According to Yazici and Ozbay (31), \( \alpha \) can be regarded as the parameter that controls behavior of evacuees whereas \( H \) controls total clearance time (2\( H \)). So \( \alpha \)

and $H$ together can also be used to determine two abovementioned factors of resilience namely, severity of outcome and time for recovery. The range of the logistic function is between 0 and 1, which means worst service status and full recovery of the service. In practice, the lowest point of the recovery curve can be greater than 0 (Partial disruption of system), and the peak maybe lower than 1 at the end of the analysis period (system not fully recovered during the study period). Also, once the system is fully recovered, the rate will stay at 1 even there are some other reductions in subsequent days, since reductions caused by other events are not taken into count for the specific analysis. Also, study period of the recovery curve modeling is set as 12 days from Day 4 to Day 15 of the overall analysis period, which covers most of recovery periods while ignoring the evacuation period.

Model Calibration

Nonlinear Least Square Error (LSE) method shown on equation (3) is used to fit the model by comparing difference of modeled function and empirical data points.

\[ S = \sum_{t=0}^{11} (y_t - P_t)^2 \]  

(3)

Where $y_t$ is the observed recovery rate of day $t$, $P_t$ is logistic function (equation (2)). The objective is to minimize $S$, the difference between observed and estimated recovery rates. For each zone, distinct pairs of model parameters ($\alpha$ and $H$) are calibrated to minimize $S$.

Loss of Zonal Resilience (LoR)

Based on calibrated recovery curves from the previous section, the resilience lost due to hurricane can be calculated using Recovery model based on the equation (1) (8). In this case, the equation can be written as:

\[ LoR = \int_0^\infty \left[ 1 - \frac{1}{1 + e^{-\alpha(t-H)}} \right] dt \]

(4)

Where $LoR$ is the loss of resilience from the time original hurricane impact, which is the area enclosed by the logistic function, $y$ axis and line $x=1$ (100%), which is shown in Figure 1.

RESULTS AND DISCUSSIONS

In order to clearly describe characteristics of the recovery curves, the results are presented in two distinct forms. Table 2 and Table 3 show parameters, errors and LoRs for each travel mode namely roadway and subway. Empirical and model based curves are visualized in Figure 6. The recovery curves and modeling results are presented for six evacuation and safe zones in NYC. For the subplot of each zone category, Hurricane Irene results are on the left side of the subplot while Hurricane Sandy results are on the right side. Each plot includes model based and empirical curves for both travel modes for the same storm incident. X axis of each plot range from 0 to 11, which stands for the days elapsed from hurricane impact to the end of the study period. For Hurricanes Irene and Sandy, starting days are August 28, 2011 and October 30, 2012, respectively.
As shown in Table 2, parameters $\alpha$ and $H$ for roadways Hurricane Irene study period differ from those of the subway. Factor $\alpha$, as previously described, stands for slope and represents behavior of the overall response (31). For all zones and citywide, $\alpha$ values of roadways based on the taxi data are more stable than those of subways, since $\alpha$ values for roadways are between 4 to 7, while for subways, these values range between 2 to 8. $H$ values for roadways are lower than those of subways, and spatial patterns of parameter $H$ are not significant for roadways, since most of $H$ values are around 0.5. For subways, $H$ values are decreased from 0.932 for Zone 1 to 0.733 for Zone 6 (except for Zone 2), however this difference is negligible. These differences of parameters can also be presented to illustrate the shape of recovery curves as shown in Figure 6. It’s observed that the curves for roadway recovery reached one in two days for nearly all zones. Full recovery of the subway system took longer than the roadway system for most zones. Trip for both modes of all studied zones reached pre-hurricane levels in three days.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Roadway</th>
<th>Subway</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Alpha</td>
<td>$H$</td>
</tr>
<tr>
<td>Zone 1</td>
<td>5.413</td>
<td>0.503</td>
</tr>
<tr>
<td>Zone 2</td>
<td>5.104</td>
<td>0.469</td>
</tr>
<tr>
<td>Zone 3</td>
<td>6.588</td>
<td>0.398</td>
</tr>
<tr>
<td>Zone 4</td>
<td>5.277</td>
<td>0.459</td>
</tr>
<tr>
<td>Zone 5</td>
<td>4.595</td>
<td>0.505</td>
</tr>
<tr>
<td>Zone 6</td>
<td>4.732</td>
<td>0.509</td>
</tr>
<tr>
<td>Safe Zone</td>
<td>4.338</td>
<td>0.569</td>
</tr>
<tr>
<td>NYC</td>
<td>4.529</td>
<td>0.546</td>
</tr>
</tbody>
</table>

Table 2 Model parameters, LSE and LoR for Hurricane Irene

Model results for Hurricane Sandy are seen on Table 2. Compared to Irene, $\alpha$ values for Hurricane Sandy are significantly lower. Also, side-by-side comparison of $\alpha$ values show that subway system has higher values than Irene. Parameter $\alpha$ in Zone 1 is the smallest. For subsequent evacuation zone categories, $\alpha$ parameter increases. Maximum $\alpha$ value of 0.552 has been found for safe zones. Zonal variations for the subway system follow similar pattern for the roadway system as well. In contrast to $\alpha$, $H$ values of Hurricane Sandy are significantly higher compared with $H$ values for Irene for both modes. $H$ values for the Hurricane Sandy study period also exhibit trend of growth with risk of storm surge, since $H$ value for roadways in Zone 1 is the highest. Moreover, for each zone, $H$ value for the subway system is considerably higher for the corresponding roadway system. The half-loading time for the subway system is three times higher than the roadway system in Zone 1. Sandy recovery curves are shown in Figure 6. Compared with Hurricane Irene, Sandy recovery for both modes required much longer recovery time with a slower recovery speed. Subway system recovery in the case of Sandy is also slower than roadway system, since all of the estimated recovery curves for the subway are below the roadway curves. Spatial patterns are also shown in Figure 6. Roadway curves were not fully recovered at the end of study period for Zones 1 to 4. For Zone 5, roadway system recovered on Day 10, Zone 6 and Safe Zone recovered on Days 6 and 5, respectively. Subway recovery curves remain flat for high-risk zones. With decreasing rates of zonal vulnerability, subway curves become steeper. For Zone 1, only 25% of subway recovery was completed on Day 11. Patterns for all other zones are similar, and subway ridership recovered on Day 10 or 11. Moreover, fluctuations are observed for empirical curves during Sandy, and the reasons will be discussed later.
The LSE values are low for both Hurricanes Irene and Sandy, both showing satisfactory fit with empirical data. Due to peaks-and-valleys for the Subway system that is shown in Figure 6, LSE values for the subway system recovery of Zone 3 are highest for both hurricane scenarios.

The LoR values are direct indicators of the impact of the storm surge caused by the travel modes. LoR results are consistent with actual conditions. Resilience lost due to Hurricane Irene is significant but small, while major reduction in the transportation system resilience was caused by Hurricane Sandy. Also, for Hurricane Sandy, zones with higher risk also have greater LoR unlike Hurricane Irene. For both hurricane scenarios, LoR values for the subway system is found to be higher than roadway system.

<table>
<thead>
<tr>
<th>Zone</th>
<th>Roadway</th>
<th>Subway</th>
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<tbody>
<tr>
<td></td>
<td>Alpha</td>
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<td>Zone 1</td>
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<td>0.459</td>
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<td>Zone 6</td>
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<td>NYC</td>
<td>0.396</td>
<td>0.791</td>
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Table 3 Model parameters, LSE and LoR for Hurricane Sandy
Figure 6 Empirical and modeled recovery curves
As seen from results shown above, the process of multi-mode post-hurricane recovery can be captured in multiple S-shaped curves for different evacuation zones. The parameter estimates of these recovery curves can be used to measure recovery performance of both roadway and subway systems in NYC.

Moreover, unlike Hurricane Irene scenario, both empirical curves of roadway and subway systems exhibit significant fluctuations during post-Sandy recovery time period, which can be seen from the recovery curves Figure 6. The reason for the fluctuations is a secondary weather impact. On November 7, 2012, a nor’easter hit NYC and brought large amount of early season snow, which extended the post-hurricane restoration process (32). The storm lasted for four days and affected the recovery by either descend the initial recovery rate and slowing down the recovery operations (e.g. Subway system for Zone 2 and Zone 4).

The modeled curves are found to clearly describe restoration patterns of evacuation zones. The initial recovery rate of zones which are prone to hurricane-related risk such as zone 1 is lower than those of others, and full recovery of such zones took a longer time. Road network shows better resilience than subway network, according to parameters $H$, LoR in Table 3 and recovery curves in Figure 6. Subway recovery has later initial starting point, lower initial percentage and longer recovery period for the Hurricane Sandy. That is because availability of various road network alternatives, while subway service is significantly dependent on the operation of certain stations and lines. Also, failure of one single subway station/line always influences the entire system, whereas this is not the case for the roadway system due to far more alternative routes. Although subway recovery for the severer storm is slower, its instantaneous recovery speed may be higher than roadway system once the subway service is restored (e.g. Zone 3, Zone 6 and Safe Zone).

Since each parameter set uniquely defines recovery time, speed and starting percentage of recovery curve of a specific zone under certain hurricane condition, it should be careful to apply those parameters to other zones, modes and types of emergency events. The non-transferability of the sequential logistic model estimated for evacuation demand estimation under the threat of hurricanes is also stated in Li and Ozbay (13).

CONCLUSION

This paper investigates ridership recovery patterns of roadway and subway systems in NYC after the impact of Hurricanes Irene and Sandy. By exploring big datasets of the subway and taxi ridership, recovery performance is found to vary spatially and temporally. For each evacuation zone category, recovery curves are estimated using logistic function, and resilience performance measure is computed. The proposed recovery curves can be a good representation of the actual system recovery behavior, and effective way to quantify resilience of various evacuation zones and travel modes. The recovery rate for Hurricane Sandy is found to be lower than that of Hurricane Irene. Moreover, the results indicate higher resilience of road network compared to subway in both hurricanes. However, it’s not yet enough to reach the conclusion that overall resilience of the road network higher than the subway network in any extreme events or anywhere else in the world, since these results are based on specific data and events. Particularly, NYC is quite a unique city in the United States due to its location, land use and extensive and aged roadway and subway infrastructure. As such, the results in this study are difficult to be generalized to other study areas and should be considered with the understanding that they are location and event specific.

This study proposes a novel big data driven approach to evaluate the resilience of the transportation systems to natural disasters. The proposed approach can further be utilized to
determine how the transportation system within a specific region can be improved to increase its resilience especially in hurricane prone zones. The findings can provide government agencies useful insights into emergency management.

However, it should be noted that the conclusions of this study might not be easily generalized, considering the datasets of only two hurricanes are used in this study. To predict recovery performance for hurricanes with different intensities, additional data from a variety of hurricane scenarios is needed. Moreover, recovery models can be improved by incorporating well-calibrated regional multi-modal simulation models that can be used to generate synthetic network performance data. Moreover, the methodology of logistic modeling can be applied to smaller zones, such as TAZ or NTAs, or even particular subway line. Exploring resilience of more detailed zones will be continuation of this study.

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REFERENCES

6. metropolitan Transportation Authority, MTA Bridges & Tunnels continues work to repair and strengthen vital inter-borough vehicle links, available online at: http://web.mta.info/sandy/bandt.htm.


