Calling 311: evaluating the performance of municipal services after disasters

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ABSTRACT

As part of a movement towards enabling smart cities, a growing number of urban areas in the USA, such as New York City, Boston, and Houston, have established 311 call centers to receive service requests from their citizens through a variety of platforms. In this paper, for the first time, we propose to leverage the large amount of data provided by these non-emergency service centers to help characterize their operational performance in the context of a natural disaster event. We subsequently develop a metric based on the number of open service requests, which can serve as the basis for comparing the relative performance of different departments across different disasters and in different geographic locations within a given urban area. We then test the applicability and usefulness of the approach using service request data collected from New York City's 311 service center.

KEYWORDS

Resilience, Municipal Departments, 311 Service Center, Disaster, Critical Infrastructure

INTRODUCTION

Modern societies increasingly rely on systems that provide basic services to them, such as electric power systems, water supply systems, healthcare, transportation, and communication systems. These interdependent critical infrastructure systems serve as the backbone of a nation's security, economy, and health (Department of Homeland Security, 2016). The 2003 Northeast blackout event highlights the devastating effects that the failure of one critical infrastructure can have on society, and it emphasizes the importance of being prepared to face such natural and manmade disasters: "The outage stopped trains, elevators and the normal flow of traffic and life…water supplies [also] were affected because water is distributed through electric pumps…" (CNN, 2003). A number of different industries, including the automotive, airline, and telecommunications sectors, also were disrupted by the outage (WSJ, 2003).

According to the U.S. National Academies, disaster resilience is the ability to prepare and plan for, absorb, recover from, and more successfully adapt to the disruptive event (National Academies, 2012). This definition of disaster resilience can be applied at different levels of a society, from an individual, to a community, to an entire metropolitan area, and even to an entire nation. Efforts to improve societal resilience have gained a lot of attention over the past few decades, particularly after recent tragedies such as Hurricane Katrina in 2005, the Japanese earthquake and tsunami in 2011, and Hurricane Sandy in 2012 (Cutter, 2016).

In spite of growing research about the concept of disaster resilience, however, there are still few rigorous quantitative methods available for evaluating the resiliency of systems against disasters at different levels of a society. Such methods have the potential to provide valuable information about how the system reacts and responds to the occurrence of a disaster and thus support decision makers in comparing different approaches for improving resilience. In an attempt to contribute to this important area of research, this current study focuses on quantitatively evaluating the disaster resilience of one of the most important service providers after disasters, i.e. ***municipalities***.

Providing and maintaining an appropriate level of public services is the primary responsibility of a municipality to its citizens. Some of these services, such as maintaining roadways and providing access to water and sewer systems, become even more important after disasters, and it is critical that a municipality have access to accurate and up-to-date information about the demand for such services. This has become much easier with advances in information and communication technologies that allow citizens to make requests of municipal service providers directly, such as by calling 311 or by accessing a dedicated website (such as http://www1.nyc.gov/311/).

The following discussion seeks to leverage the increasing availability of such municipal service data by exploring the number of open service requests as a measure of performance of a municipal service provider, both before and after a disaster event. This new measure will allow us to compare the relative performance of different departments across different disasters and in different geographic locations within a given urban area. A growing number of big cities have established 311 call centers to receive such service requests and our first goal in this paper is to demonstrate the potential of using the large amount of data generated from these centers to characterize the disaster resilience of a municipality.

In the following sections, we begin by briefly summarizing related studies about evaluating disaster resilience. We then introduce the dataset upon which our analysis is based: the complete set of municipal service calls received by New York City's 311 call center between 2004 and 2015. We then apply the methodology to the task of evaluating the resiliency of one of NYC's municipal departments, in response to several different disaster events occurring between 2010 and 2012. We conclude the discussion with a summary of the current findings and a statement of future work.

LITERATURE REVIEW

Disaster resilience has received a lot of attention from both policymakers and academics in recent years. For example, in 2009, a new program called the Regional Resiliency Assessment Program (RRAP) was launched by the U.S. Department of Homeland Security (Department of Homeland Security, 2015). The aim of the new program was to assess resiliency of U.S. critical infrastructure within defined geographic areas, in order to address resilience issues that could have significant consequences.

Even with increased attention on resilience, however, there still are few rigorous quantitative methods available for evaluating the level of disaster resilience that is inherent in or exhibited by different levels of a society. In an attempt to address this gap, some researchers adopt a stationary view of resilience and construct social and economic indicators, such as the percentage of educated population within a community, demographics, and average annual income, as component measures of a society's disaster resilience (see for example, Norris et al., 2008 and Cutter et al., 2008). Although these indicators provide an overview of a society's capacities to deal with disaster events, they do not capture the dynamic aspects of the resilience concept. Other researchers thus adopt a more active systems viewpoint to quantify disaster resilience (Zobel, 2014; Pant et al., 2014; MacKenzie and Zobel, 2016). In this study, we consider municipalities as a type of complex system and adapt this systems resilience viewpoint to evaluate their resilience performance against disaster events.

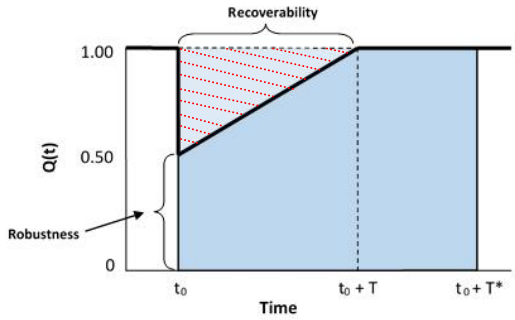

Figure 1. Predicted resilience (adapted from Zobel, 2011)

As one of the first attempts to analyze a system's ability to face a disruptive event, Bruneau et al. (2003) proposed examining a response curve that provides changes in a system's performance over time. Figure 1 shows an example of such a response curve for a system that experiences a disruption at time t_0, where $Q(t)$ shows the system's functionality at time t. Bruneau et al. (2003) proposed to use the area above the response curve (for example, the red shaded area in Figure 1) to measure the *loss of resilience* in the system due to the disruption. They named the shaded area the *resilience triangle* and argued that when the resilience triangle is smaller, the system is more resilient.

Zobel (2010, 2011) revisited this original concept and introduced a new measure of resilience, known as *predicted resilience* (R), which can evaluate a system's resilience directly instead of indirectly. He defined the predicted resilience as the area beneath the response curve after it is normalized by the corresponding area that would have been realized if there had been no disruption. For example, considering a sudden-onset disruption and linear recovery as shown in Figure 1, the predicted resilience can be calculated using the following formula:

$$R = 1 - \frac{XT}{2T^*} \tag{1}$$

where X is equal to the loss suffered at time t_0 and T^* is a user-defined upper bound on the recovery time.

Zobel (2014) further argued, however, that the sudden-onset disruption and linear recovery do not always match the reality of a disruption profile, and he developed a general predicted resilience function that is applicable for different types of disruptive events and recovery functions, a version of which is shown in formula 2.

$$R = \frac{\int_{t=t_0}^{t=t_0+T^*} Q(t)dt}{T^*} \tag{2}$$

Subsequently, this measure of resilience and its extensions have been widely applied to measure the resilience of systems in different contexts, such as interdependent infrastructure and industry sectors (Pant et al., 2014; Baghersad and Zobel, 2015), supply chains (Spiegler et al., 2012; Torabi et al., 2015), and transportation systems (Adjetey-Bahun et al., 2016). In this paper, we will adapt this generalized predicted resilience formula to calculate the resilience of *municipalities* against different disaster events. This process is described in the analysis section of the paper.

NEW YORK CITY SERVICE REQUEST DATASET

New York City, like several other big cities such as Boston and Houston, has created a specific call center to receive nonemergency city service requests, named NYC311. The main mission of the NYC311 service is "*to efficiently respond to inquiries and requests from residents, businesses, and visitors by providing reliable information and accurately processing requests for city services 24 hours a day, 7 days a week*" (NYC global partners, 2011). This center allows New Yorkers to request all variety of nonemergency city services through a number of different platforms: an easy-to-remember phone number (311), an online site, a smartphone app, social media, text messaging, video relay services, and TTY/text telephone service. The NYC311 service was launched in 2003, and it has served as a significant step towards New York City's goal of becoming a smart city. Over 120 million calls had been received by the center by 2012, and these service requests have been made publically available through New York City's Open Data initiative (https://nycopendata.socrata.com/).

As the basis for our analysis of municipal services, we collected all available 311 service requests recorded on the NYC Open Data website for the period covering years 2004 – 2015: the dataset includes a total of 23.5 million

Table 1. Selected 311 service request attributes

Attribute name	Description
Created Date	Date and time the record was created
Closed Date	Date and time the record was closed
Agency Name	Specific agency name
Complaint Type	Category of complaint type
Descriptor	Detailed description of complaint
Incident Zip	Zip code of incident location
Incident Address	Street address of incident location
City	City of incident location
Borough	Borough of incident location
Due Date	Date and time the request is due
Resolution Description	Description of call resolution update
Latitude	Latitude of incident location
Longitude	Longitude of incident location

Table 2. Top six agencies based on number of service requests in 2012

Agency	Agency name	No. of calls in 2012	Top five complaint types
HPD	Department of Housing Preservation and Development	562,761	Heating, General Construction, Plumbing, Paint – Plaster, Non Construction
NYPD	New York City Police Department	294,053	Noise – Residential, Blocked Driveway, Illegal Parking, Noise – Commercial, Noise - Street/Sidewalk
DOT	Department of Transportation	256,972	Street Light Condition, Street Condition, Traffic Signal Condition, Broken Muni Meter, Sidewalk Condition
DEP	Department of Environmental Protection	147,084	Water System, Sewer, Noise, Air Quality, Hazardous Materials
DSNY	Department of Sanitation	112,008	Dirty Conditions, Sanitation Condition, Graffiti, Missed Collection, Sanitation Condition
DPR	Department of Parks and Recreation	106,055	Damaged Tree, Overgrown Tree/Branches, Root/Sewer/Sidewalk Condition, New Tree Request, Maintenance or Facility

unique service requests. Each unique service request includes characteristics of the service request such as the time and date of the request, the agency called, the complaint type, the street address, the borough, how and if the request was resolved, the resolution date, and the latitude and longitude of the incident, as shown in Table 1.

These service requests include a variety of service types (more than 130 types) from different municipal departments. Table 2 shows the top six agencies that received service requests, along with each one's top five complaint types, in terms of the number of service requests received in 2012. The Department of Housing Preservation and Development (HPD), the New York City Police Department (NYCPD), the Department of Transportation (DOT), and the Department of Environmental Protection (DEP) received the most service requests during this time period. The top 12 complaint types overall (based on number of service requests) for this same year are also reported in Table 3. The last column of Table 3 shows the ratio of the number of service requests related to each complaint type to all service requests received by the agency in 2012. This indicates that Heating and General Construction complaints include more than half of the complaints received by HPD. Table 3 also shows that *Damaged Tree* complaints, in the Department of Parks and Recreation (DPR), have the highest ratio across all departments in 2012.

Table 3. Top 12 complaint types in 2012

Rank	Complaint type	Agency	N. of calls in 2012	% of overall services
1	Heating	HPD	182,974	32.51
2	Noise - Residential	NYPD	127,524	43.37
3	General Construction	HPD	112,436	19.98
4	Street Light Condition	DOT	93,866	36.53
5	Plumbing	HPD	91,192	16.20
6	Paint - Plaster	HPD	77,287	13.73
7	Street Condition	DOT	67,050	26.09
8	Non Construction	HPD	60,055	10.67
9	Water System	DEP	57,600	39.16
10	Blocked Driveway	NYPD	50,645	17.22
11	Damaged Tree	DPR	50,394	47.52
12	Traffic Signal Condition	DOT	47,484	18.48

Table 4. The seven disaster events from 2010 to 2012

Event ID	Event description	Date of Event
Event 1	2010 Nor'Easter	13-14 Mar. 2010
Event 2	Brooklyn / Queens tornadoes	16 Sep. 2010
Event 3	N. American Blizzard	25-27 Dec. 2010
Event 4	Hurricane Irene	28 Aug. 2011
Event 5	Major Snowstorm	31 Oct. 2011
Event 6	Hurricane Sandy	29 Oct. 2012
Event 7	2012 Nor'Easter	7 Nov. 2012

ANALYSIS

We start our analysis by focusing on the number of service requests received both during and after several major natural disasters in New York City from 2010 to 2012. We found a total of seven major disaster events reported during this time period; some of these disaster events were localized, like the tornadoes that hit Brooklyn and the Bronx in 2010, and some of them, like Hurricanes Irene and Sandy, impacted the entire New York City metropolitan area. Table 4 shows these seven events and date of their occurrence. Our discussion focuses on calls related to the *Damaged Tree* category of complaints, which exhibits some interesting behaviors in response to the different disasters. As mentioned above, this category of calls also includes almost half of the service requests received by DPR and therefore it is a reasonable proxy of that agency's overall performance.

Figure 2 shows the daily number of service requests related to the *Damaged Tree* complaint type between 2010 and 2012. It is easy to see that number of calls associated with every event, except for Event 3, the North American Blizzard of December 2010, increases in conjunction with that event. Specifically, Figure 2 implies that Hurricane Sandy (event 6), Hurricane Irene (event 4), and the 2012 Nor'Easter (event 7) had the most impacts on the number of service requests related to the *Damaged Tree* complaint type.

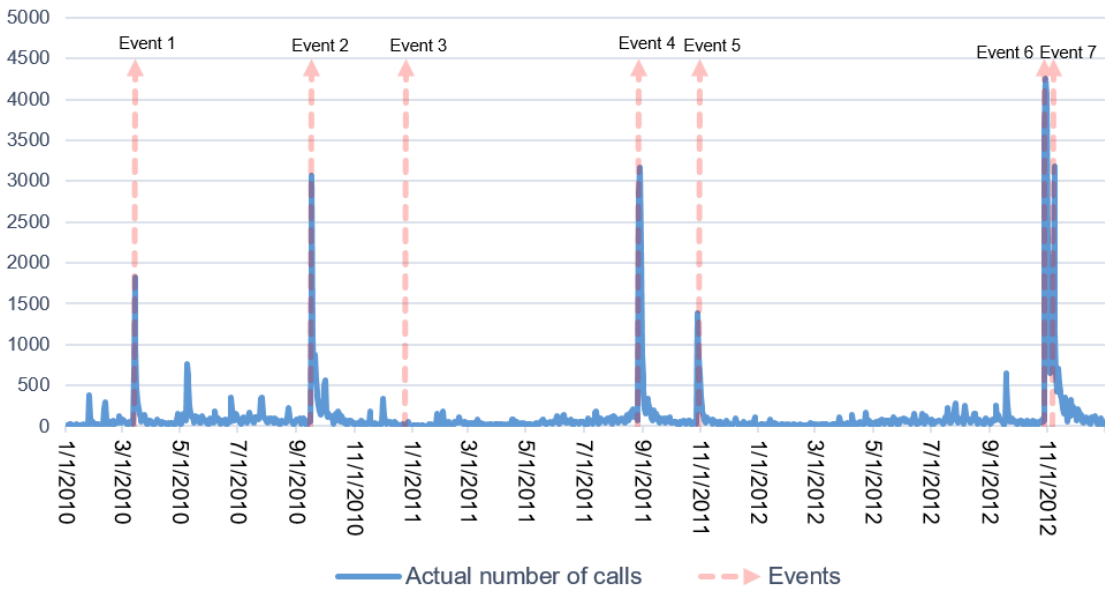

Figure 2. Number of *Damaged Tree* service requests

This measure of the number of service requests over time describes the effect of disasters on the community, in terms of how citizens are reacting to changes in their physical environment. However, it does not directly provide any information about the related operational performance of the municipal departments during and after those same events. In order to analyze the performance of these agencies, therefore, we introduce a new measure: the number of open service requests per day, which is the number of prior service requests that are still in process on the day in question. This measure is calculated using the created date and closed date attributes of the individual service requests, and it indicates the ability of the respective department to deal with service requests over time.

Figure 3 illustrates the new measure by showing the number of open service requests per day for the *Damaged Tree* complaint type. It is straightforward not only to see that six out of seven events have a significant impact on the number of open service requests but also to see that the different events had different amounts and types of impacts on the agency's ability to address its open workload.

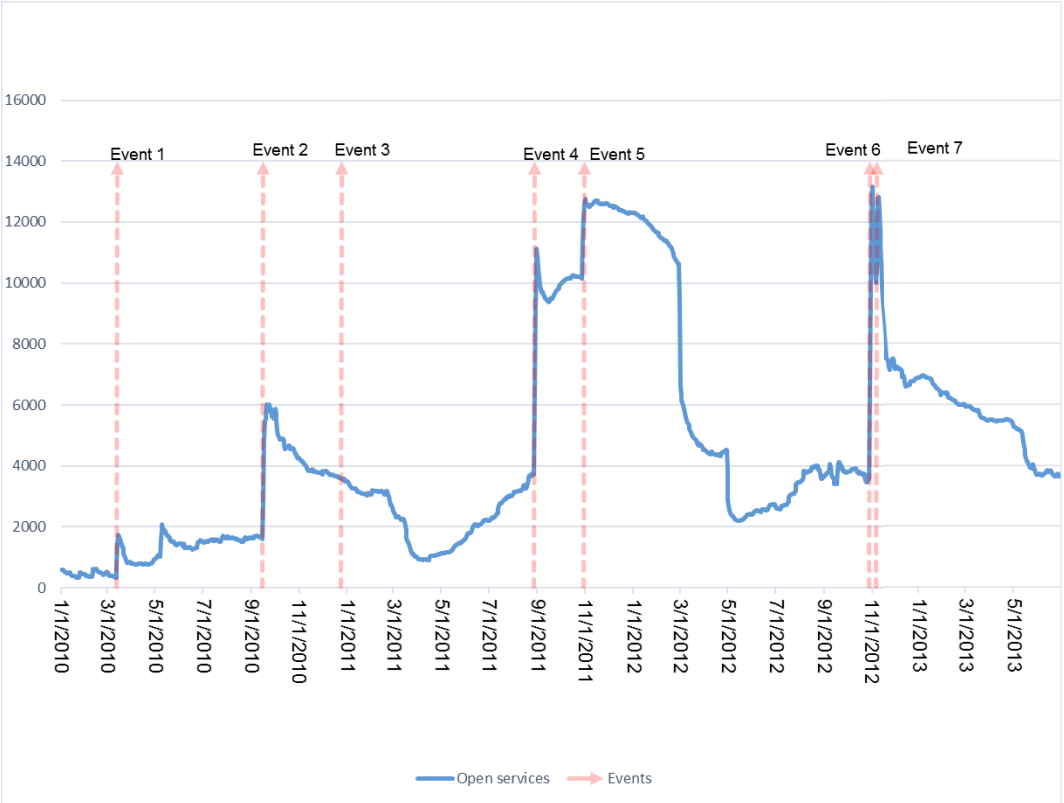

Figure 3. Number of open service requests for damaged tree complaint type

In order to create a quantitative measure by which the agency's performance can be compared across the seven events, we calculate the relative ability of the system to resist and then quickly recover from the impact of each event, or its resilience. Specifically, we adapt the notion of predicted resilience, as proposed by Zobel (2010), and measure the relative loss in performance level over a pre-specified time interval (in this case, two months). We consider that the system has recovered from a given event if it is able to return to the number of open calls that existed immediately before that event occurred. If the number of open service calls does not come back to its original level after two months, however, then we simply calculate the total amount of loss over time during those two months. As an example of this, the total loss of performance over time for event 2 is highlighted in Figure 4. The two month time frame was chosen so that there was enough time elapsed to capture the system response. A longer time period might capture the longer term effects of a given disaster, yet it could also lead to more frequent occurrences of multiple events occurring during the same interval. Regardless of the time frame, however, as long as the resilience values are interpreted with respect to that specific interval, the implications of the results will be consistent with previous research.

To calculate the relative amount of resilience reflected in the system response during the chosen time period, the area of loss (A_i) for event i is therefore divided by the maximum observed loss in performance (relative to the initial number of open calls) and the length of the chosen time interval (T^* = 2 months) in order to normalize the results. The resulting ratio is then subtracted from one:

$$R(i) = 1 - \frac{A_i}{X_{max}T^*} \qquad (3)$$

This provides an analogous result to the formulation of the predicted resilience function that was given in equation (2). Furthermore, it extends the previous work of Zobel (2014) by capturing loss as a positive (rather than negative) deviation from the default performance curve.

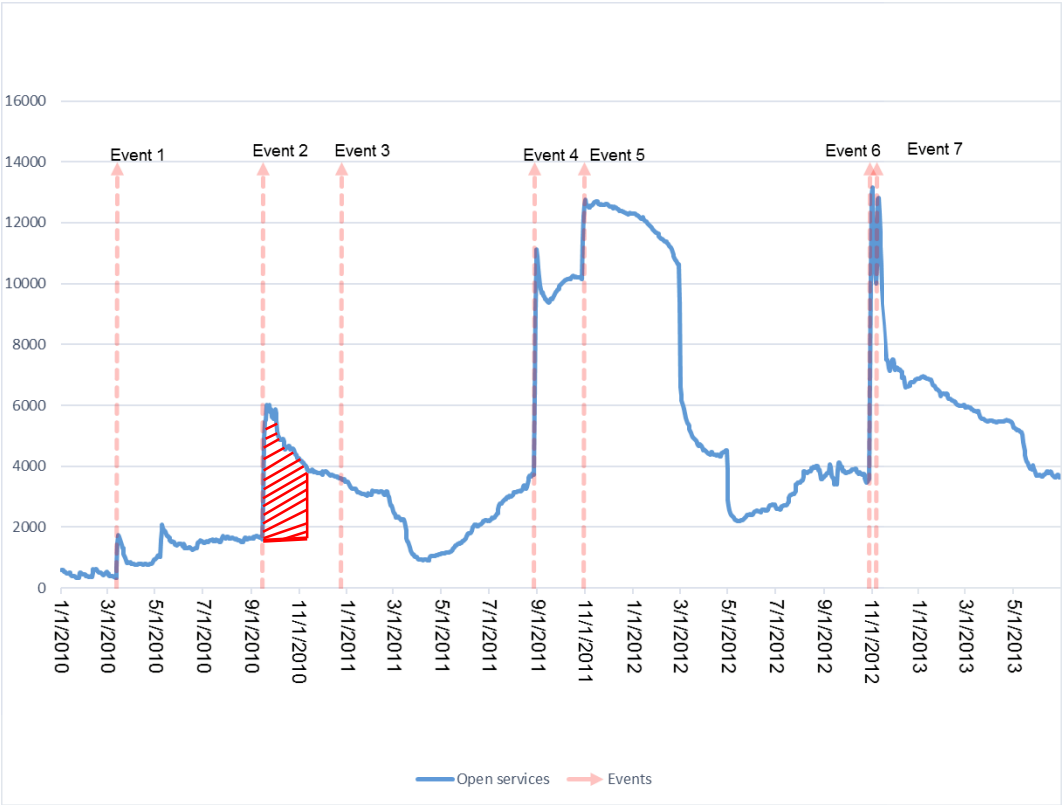

Figure 4. Example of loss of performance area

Table 5 shows the resulting resilience values related to the *Damaged Tree* complaint type for the seven different disaster events, given the chosen two month time window. The results indicate that the resilience values were lowest for Hurricane Irene (event 4), Hurricane Sandy (event 6), and the 2010 tornadoes (event 2), respectively.

Comparing these results with those obtained from the number of incoming service requests (Figure 1) gives us some insights about operational performance of the municipal department. For example, although the number of service requests was highest for Hurricane Sandy, this event did not actually have the largest impact on the number of open service requests. Instead, the worst resilience value is related to Hurricane Irene, which had the second highest increase in number of service requests. The cause of this big change in performance from Hurricane Irene to Hurricane Sandy easily could be due to gaining experience from the first hurricane or it could be due to other operational factors that may require further review by managers.

Table 5. Resilience value with respect to *Damaged Tree* open calls

Event ID	Event description	Resilience value (%)
Event 1	2010 Nor'Easter	92.89
Event 2	Brooklyn / Queens tornadoes	67.93
Event 3	N. American Blizzard	100.00
Event 4	Hurricane Irene	37.37
Event 5	Major Snowstorm	96.91
Event 6	Hurricane Sandy	51.51
Event 7	2012 Nor'Easter	98.01

CONCLUSIONS AND FUTURE WORK

Municipalities are responsible for providing an appropriate level of public services to their citizens. Some of these services, such as maintaining roadways and providing access to water and sewer systems, become even more

important after disasters. A growing number of big cities have established 311 call centers to receive service requests from their citizens, and the data generated through some of these non-emergency service centers are available for public use. In this paper, we propose that using this data to analyze the performance of municipal departments during and after disaster events can provide valuable information to a municipality's decision makers, and thus help to improve its resilience.

As the first step towards realizing this goal, we developed a new metric based on the number of open service requests to measure the performance of a municipal service provider both before and after a disaster event. This new measure allows us to compare the relative performance of different departments across different disasters and in different geographic locations within a given urban area. We tested the applicability and usefulness of the measure by using real data collected from New York City's 311 service center, and specifically analyzed characteristics of the *Damaged Tree* complaints, within the Department of Parks and Recreation, during seven major disaster events during 2010 to 2012. These initial analyses revealed several interesting insights. For example, we found that although Hurricane Sandy had the most impact on the number of new service requests received, it did not have the worst overall impact on operational performance. The results instead indicate that Hurricane Irene had the worst impact on operational performance, even though its associated impact on the number of new service requests was not as high.

There are a number of possible extensions to the work presented here. For example, an alternative performance measure that might have interesting characteristics would be the ratio of the number of open service requests to the number of new service requests. By incorporating the number of new service requests, this new measure would eliminate any possible biases due to large numbers of new service requests associated with some disaster events. This paper also only considers a single measure of resilience. Zobel (2010, 2012) argued that a single measure cannot capture the resilience behavior of a system completely, and proposed expanding the characterization of resilience to include the system's robustness and recoverability as explicit sub-measures. Another extension of this research, therefore, could be to define robustness and recoverability measures in this current context and to evaluate municipal performance across different events with respect to these sub-measures. Finally, our analysis was limited only to the *Damaged Tree* complaint type, as received from all boroughs across New York City. Since the 311 dataset also includes the geographic location of service requests, another interesting extension would be to consider the relative performance of different boroughs of New York City, i.e. Manhattan, the Bronx, Queens, Brooklyn, and Staten Island, in dealing with disaster events.

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