

MARITIME TRANSPORTATION RESEARCH AND EDUCATION CENTER  
TIER 1 UNIVERSITY TRANSPORTATION CENTER  
U.S. DEPARTMENT OF TRANSPORTATION



**Quantifying and Evaluating Community Resilience for Sustainable Cities**  
**10/01/2015 – 06/01/2018**

Brian Wolshon, Ph.D., P.E., P.T.O.E. (PI)

[brian@rsip.lsu.edu](mailto:brian@rsip.lsu.edu)

Louisiana State University

Scott Parr, Ph.D. (Co-PI)

[parrs1@erau.edu](mailto:parrs1@erau.edu)

Embry-Riddle Aeronautical University

Nafiseh Farhadi M.S.C.E

[nfarha1@lsu.edu](mailto:nfarha1@lsu.edu)

Louisiana State University

Kenneth Ned Mitchell, Ph.D.

[Kenneth.N.Mitchell@usace.army.mil](mailto:Kenneth.N.Mitchell@usace.army.mil)

US Army Engineer Research and Development Center

**August 31, 2018**

**FINAL RESEARCH REPORT**

**Prepared for:**

**Maritime Transportation Research and Education Center**

University of Arkansas  
4190 Bell Engineering Center  
Fayetteville, AR 72701  
479-575-6021

#### ACKNOWLEDGEMENT

*This material is based upon work supported by the U.S. Department of Transportation under Grant Award Number DTRT13-G-UTC50. The work was conducted through the Maritime Transportation Research and Education Center at the University of Arkansas.*

#### DISCLAIMER

*The contents of this report reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated under the sponsorship of the U.S. Department of Transportation's University Transportation Centers Program, in the interest of information exchange. The U.S. Government assumes no liability for the contents or use thereof.*

## **Abstract**

The United States Marine Transportation System (MTS) makes large contributions to the nation's economy, security, safety, and quality of life. Strategic investment, planning, administrative and operational decisions by government at all levels are necessary to maintain the marine transportation system performance at all times, which in turn requires a technical approach and professional leadership based on research. This study describes the approach and results of an ongoing research effort to assess the resiliency of port operations following major disasters and other disruptive events. The work presented in this research uses a set of archival data from the United States Coast Guard's Nationwide Automatic Identification System (NAIS) to quantify the state of resiliency by investigating the operation of coastal navigation systems before, during and after disruptive events.

To illustrate the ability of proposed methodology to assess the resiliency of a marine transportation system, two case studies representing two different types of infrastructure disruption are presented. The first case study involves the disruption that resulted from a collision in March 2014 in Texas in the Houston Ship Channel as a no-notice event. The second was a disruption caused by Superstorm Sandy in 2012 on the greater Port of New York/New Jersey as a pre-notice event. The results of this study revealed the importance of AIS data as a source of quantitative data when seeking post-disaster measures of resiliency. From an application perspective, the methods and results presented herein can be adapted and implemented to quantitatively evaluate the amount of port's service loss and the levels of port activity following disruptive events.

## 1. Introduction

The United States Marine Transportation System (MTS) is a complex network consisting of hundreds of deep-draft coastal ports connected to thousands of miles of inland river channels and other navigable waterways. As with most interdependent, dynamic networks, domestic and international supply chains are susceptible to disruptions, because even a single severe event can have cascading effects that can disrupt freight transportation throughout the overall system. Similar to traffic backups on interstate freeways, disruptions in navigation channels can also cause delays and congestion that propagates rapidly and widely throughout the broader MTS. This leads to concerns that even a single, isolated, disruptive event such as a storm, terrorist act, or shipping accident can have devastating system-wide impacts.

The threat of natural disasters and human-caused disruptions has driven the need for robust and objective performance evaluation methods to quantify the resiliency of maritime transportation systems (MTS). The term “resiliency,” as used in this research, refers to how system functionality is altered by a disruptive event and how the system recovers over time from a distressed state into normalcy (1). Previous work in this area found that, in general, measures of time, cost, capacity, and environmental impact should be included to evaluate overall MTS performance (2). However, the challenge has been in recognizing quantifiable and reliable parameters that are consistently collected and archived so that the initial disruptive impacts can be quantified and to allow analysis of the subsequent recovery characteristics of maritime systems for resiliency. The work presented here uses archival data from the U.S. Coast Guard’s nationwide automatic identification system (NAIS), which collects real-time traffic data on waterborne vessels that operate in U.S. territorial waters. Transceivers on board the vessels broadcast an AIS signal via very-high-frequency (VHF) radio waves, which relay their position, heading, speed, and other identifying information to shore-based towers with a reporting interval of only several seconds. In addition to providing a live picture of waterway traffic conditions, NAIS provides an archive of MTS activity covering several years of individual vessel position reports. This large archived data set allows rigorous, quantitative analysis of vessel patterns and waterway performance trends in both coastal and inland navigable waterways.

The research summarized in this paper adapted archival NAIS data for resilience analyses of coastal port operations following disruptive events. Archival vessel position reports were used to establish a baseline of navigation channel and port operations under routine nonevent conditions. Observed losses in system functionality following a major disruption were used to quantify the resiliency of the waterway through time-dependent performance analysis. This type of analysis is essential for investigations into the efficacy of the recovery process protocols and management strategies used in the days and weeks following a major disruptive event.

In the two presented case studies, the measurement of system resiliency is expressed as vessel dwell time and net vessel transit counts into and out of the port area, respectively. Recent disruptions experienced in critical, high-use commercial ports were analyzed: the closure of the Houston Ship Channel in Texas for 4 days in March 2014 following the collision of a bulk carrier with an underway barge tow, and the disruptions to the Port of New York and New Jersey after Superstorm Sandy in October 2012.

This research represents first steps toward a systematic, objective means of measuring commercial port resiliency. The developed methods can be used as a basis for future studies of postdisaster operations and protocols, such as evaluations of navigation channel and port operation protocols following disruptive events to gain an understanding of MTS characteristics that increase resiliency.

## **2. Research Background**

Much of the existing body of knowledge on disruptive events for infrastructure systems focuses on security policies such as protective action, prevention, and risk mitigation (3). This approach overlooks the need for systems that adapt to disruptive events while maintaining a desirable level of service (4). For a system to be better prepared for disruption, the likelihood of event occurrences should be mitigated, and system designs should be adaptive and robust for maintaining service during and after a disruptive event. To this end, Attoh-Okine et al. developed a resiliency index for urban infrastructure (5). Li and Lence used the ratio of the probability of failure and recovery as a measure within water resources systems to formulate a resiliency index (6).

For telecommunications networks, Omer et al. proposed a quantitative approach to measure resiliency with the ratio of “valued delivered” during and before a disruptive event (7). Reed et al. used power outages and restorations after Hurricane Katrina in 2005 to estimate the resiliency of interdependent systems after a natural disaster (8). These examples show that there is no consistent, quantitative approach to defining resiliency in the many fields and disciplines of infrastructure networks. To address this issue, Henry and Ramirez-Marquez proposed a fundamentally quantitative approach to estimating resilience that is applicable to various disciplines (1). They proposed resiliency as a time-dependent function, system deliverables being quantified for the duration encompassing before, during, and after a disruptive event. This approach was applied to stochastic systems in subsequent work (9, 10).

### **2.1 Potential Threats, Risks and Disruptions to MTS**

Sources of disruptions were categorized by Omer et al. into the following groups (11):

- Natural factors: disruptions due to damage caused by nature, such as hurricane
- Human factors: disruptions caused by humans operating or using the system, such as human errors or terrorist attacks
- Organizational factors: disruptions that occur due to events at organizational level, such as worker strikes
- Technical factors: failure in system components, such as faulty or outdated equipment

### **2.2 Resilience Marine Transportation System Network (MTSN)**

Concerning resiliency of the MTS, previous studies introduced techniques to reduce vulnerability and increase coping capacity. The vulnerability reduction strategies include the implementation of robustness, redundancy, diversity, modularity, and rapidity into the system network, whereas scenarios to increase the coping capacity of a system cover resourcefulness,

collaboration, preparedness, and cognition (11). MTS resiliency perhaps can best be measured in time, cost, capacity (loss), and environmental impact. By quantifying these measures both before and after a disruptive event, it is possible to measure the full impact of the disruption on serviceability and recovery.

NCHRP Report 732 evaluated the nation's major freight corridors and intermodal facilities to estimate the impact of interruptions and bottlenecks on the movement of goods. The report attempted to assess the full economic impact of disruptive events, including the economic impact of MTS closures. The report developed two approaches to estimating economic impact: (a) a high-level methodology for estimating the likely economic costs associated with any type of disruption and (b) a more detailed approach, requiring higher data input and a sophisticated analysis of supply chain dynamics (12).

### **2.3 Nationwide Automatic Identification System (NAIS) Data Applications**

The use of archival NAIS records as a remote-sensing technology to infer aspects of navigation system performance has become more frequent. Numerous studies have used archival AIS position reports to measure or estimate the environmental impacts of shipping, such as air emissions (13, 14) and whale strikes (15). Schwehr and McGillivray explored the use of AIS to track illegal oil releases from vessels and provide real-time monitoring of traffic to improve incident response times and management (16). Hatch et al. used AIS data to estimate the impact of large oceangoing vessels on noise levels near shipping lanes in a national marine sanctuary off the coast of Massachusetts (17). Dobbins and Langsdon used AIS data as a proof of concept for vessel trip generation to improve on existing data sources (e.g., U.S. Army Corps of Engineers waterborne commerce statistics and lock performance monitoring system) in the vicinity of Paducah, Kentucky, along the lower Ohio River (18). Shu et al. used Show Route software, developed by the Marine Research Institute, Rotterdam, Netherlands, to investigate forcing factors that affected ship path and speed (19). For its Atlantic coast port access route study, the U.S. Coast Guard used aggregated NAIS data to provide a detailed map of shipping lanes along the Atlantic coast (20). Calder and Schwehr investigated the use of NAIS data to inform risk management strategies across a variety of spatial and temporal domains (21). Mitchell and Scully used archival NAIS data to assess tidal influence on vessels that call at deep-draft coastal ports as well as to conduct waterway transit time analysis over a range of spatial and temporal domains (22).

## **3. Research Methodology**

This research proposes a new methodology to quantify MTS resilience by plotting time-dependent resiliency figures for commercial ports using archival AIS data. This paper shows how these figures can be used to develop time-dependent resiliency plots, first introduced by Henry and Ramirez-Marquez (1), showing time resiliency and port transit count resiliency.

### 3.1 Data Collection and Processing

AIS technology was developed primarily for improving marine safety and maritime domain awareness (23). The AIS technology uses the VHF radio spectrum to broadcast and receive (ship-to-ship, ship-to-shore, and shore-to-ship) real-time information concerning vessel identity, dimensions, position, speed, and headings, among other fields (<http://www.navcen.uscg.gov>). The Maritime Transportation Security Act of 2002 (46 USC §§70113, 70114) mandates an AIS carriage requirement by commercial vessels operating in or bound for U.S. waters. The U.S. Coast Guard has implemented this requirement through regulations in 33 CFR §164. The Coast Guard also enforces these and other equipment carriage requirements, is involved in developing standards for AIS message formatting, and has established an archive of historical AIS data as part of its NAIS program. The archival AIS data sets used in this study were obtained by the U.S. Army Corps of Engineers through a suite of NAIS web services, made available to the Corps of Engineers as part of a standing interagency service agreement. Manual real-time and archival data requests can be made to the Coast Guard's Navigation Center, pursuant to agency terms concerning requesting entity, intended use of the data, and disclosure to third parties. There are numerous commercial vendors of both real-time and archival AIS data, and transceiver units needed to broadcast and receive AIS messages are available for purchase by those seeking to collect their own data.

MTS travel time statistics for maintained navigable waterways can be compiled for classes of vessel and by direction (inbound or outbound, upstream or downstream) through a straightforward comparison of the time-stamped position reports as unique vessels move through the various geo-fenced watch areas of interest. Recent examples of archival AIS data applied in this fashion, as well as practical methods for dealing with some of the issues encountered with travel time outliers, are available in the literature (24–26). A similar treatment of AIS data can be applied to derive dwell time estimates for vessels within a defined bounded region (27): the time stamp of the first observed vessel position report within a defined area is compared with the time stamp of the subsequently first observed report outside the defined area. This approach can be applied at spatial scales from specific berthing terminals or waterway segments to entire port zones, although AIS data coverage in the area must be thorough and reliable.

### 3.2 Time-Dependent Resiliency Analysis

A generic time-dependent resiliency plot is shown in Figure 1 for an increasing service system and Figure 2 for a decreasing service system (10). In an increasing service system, network output is positively correlated with service; that is, as the output increases, so does the service provided. An example is a production process in which output in units built increases with the overall service of the production line. In a decreasing service system, the network output is negatively correlated with the service. An example is dwell times; in a system that is performing well, dwell times are minimized. In Figure 1 and 2, a system,  $S$ , is analyzed before, during, and after a disruptive event.  $S$  experiences three steady states, that is, the original state  $S_o$ , the disrupted state  $S_d$ , and the stable state  $S_f$ , and two transitional states—one where the system transitions between the steady state and the disrupted state and the other between the

disrupted state and the stable state. These transitions are marked by two events: the first event is the onset of the disruption ( $e_j$ ) and the second is a recovery event. The figure illustrates how the initial system, as measured by its output performance  $\phi(t)$ , initially exists in a steady state. Then, because of the onset of a disruptive event,  $e_j$ , it transitions to a disrupted state. Finally, after the start of a recovery event, the system transitions to a stable state. Using the time-dependent resiliency function, Henry and Ramirez-Marquez quantified resilience as the ratio of recovery to loss (1). Therefore, resiliency can be calculated at any time  $tr$  after event  $e_j$  with Equation 1:

$$\mathfrak{R}_F(t_i|e^j) = \frac{F(t_i) - F(t_d)}{F(t_0) - F(t_d)} \quad \forall e^j \in D \quad (1)$$

Where,

- $\mathfrak{R}_F(t_i|e^j)$  = the resiliency of system  $S$  at any time  $t_i$ , resulting from the disruptive event  $e^j$
- $F(t_i)$  = the performance of the system at time  $t_i$
- $F(t_d)$  = the performance of the system at time  $t_d$ , corresponding to the time of maximum system service loss
- $F(t_0)$  = the performance of the system at time  $t_0$ , corresponding to the original state
- $D$  = set of all disruptive events which could hinder service

Henry and Ramirez-Marquez made several important observations about the resiliency formulation: (a)  $\mathfrak{R}\phi(tr | e_j)$ : (1)  $\mathfrak{R}\phi(tr | e_j)$  indicates the proportion of service that has been recovered by time  $tr$ , keeping in line with the meaning and intent of resiliency; (b) the minimum value of  $\mathfrak{R}\phi(tr | e_j)$  is zero, indicating that the system has not recovered from its disrupted state; (c) when the value of  $\mathfrak{R}\phi(tr | e_j)$  is equal to one, the system has fully recovered at time  $tr$ ; and (d)  $\mathfrak{R}\phi(tr | e_j)$  is undefined when  $\phi(t_0 | e_j) = \phi(t_d | e_j)$ , indicating that no drop in performance was measured as a result of event  $e_j$  and therefore  $e_j$  is not an element of  $D$ .



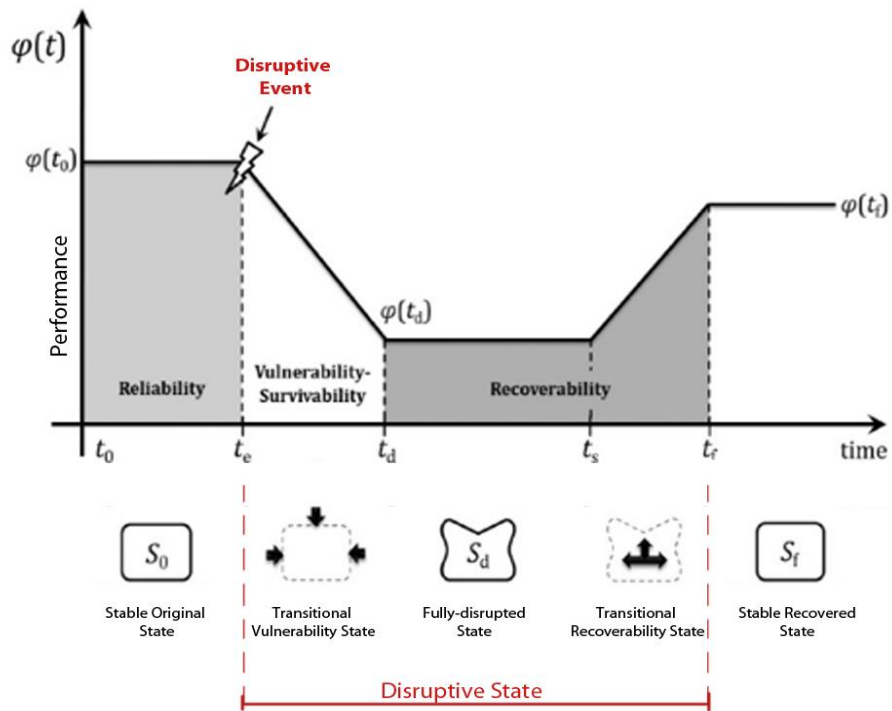


Figure 1: Increasing service system function (10)

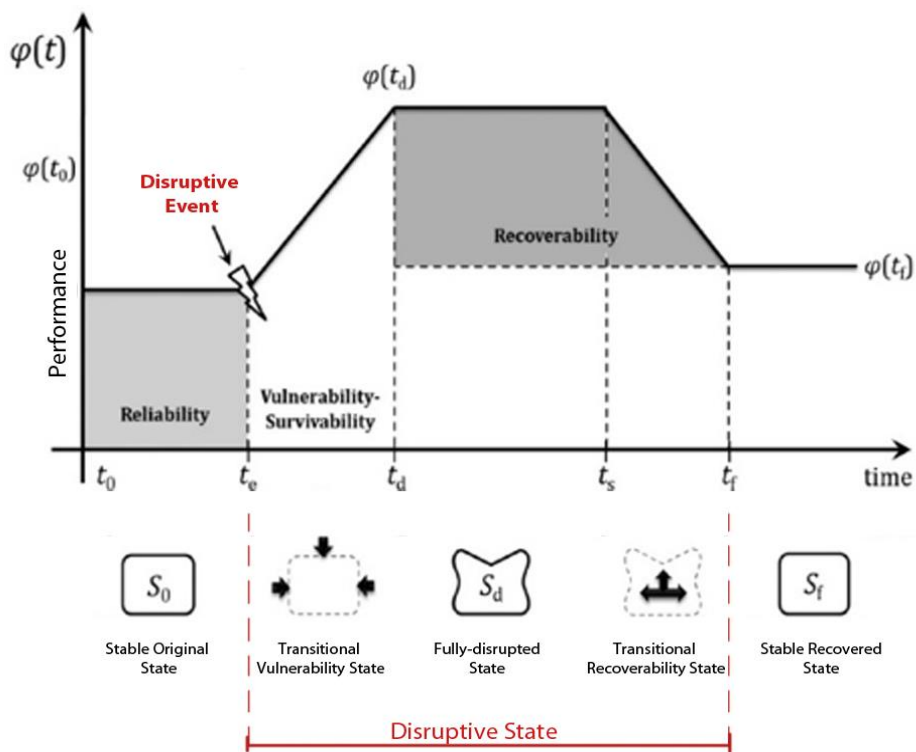


Figure 2: Decreasing service system function (10)

### 3.3. Resiliency Parameters

In this study, vessel location information from onboard AIS transceivers was used to generate two performance indicators: average vessel dwell time within the port areas of interest and net vessel transits into and out of the port areas of interest. Dwell time is the continuous length of time a vessel spends within the port area or associated regions such as offshore anchorages. In terms of freight throughput efficiency, dwell time indicates the “capability of the port to efficiently handle cargo flows at the terminals and beyond” (28). Decreases in port performance following a disruption tend to limit the rate at which vessels can be processed, extending the overall average vessel dwell time within the greater port area. The net number of vessels within a port area is obtained from a running tally of vessels both entering and departing the port area and surrounding zones. In the case of port terminals that handle cargo, this quantity can indicate relative rates of freight throughput (loading and unloading of vessels) at any point in time, whereas in the case of anchorages where vessels typically wait for berthing slots to open within the port area, this quantity can indicate backlogs and excessive delay caused by disruptions in port operations. Also, external factors can influence resiliency performance measures, such as use of anchorages by vessels for reasons (e.g., bunkering and lightering operations) unrelated to the MTS disruption. Here the two performance measures (average vessel dwell time and net vessel transits into and out of the port) provides general trends in the efficiency of overall port operations and the associated maintained waterways. With estimation and plotting of the resiliency for these two metrics for the days and weeks before and after major disruptive events, additional analysis can be conducted of the recovery efforts and their impact on overall port resiliency and performance.

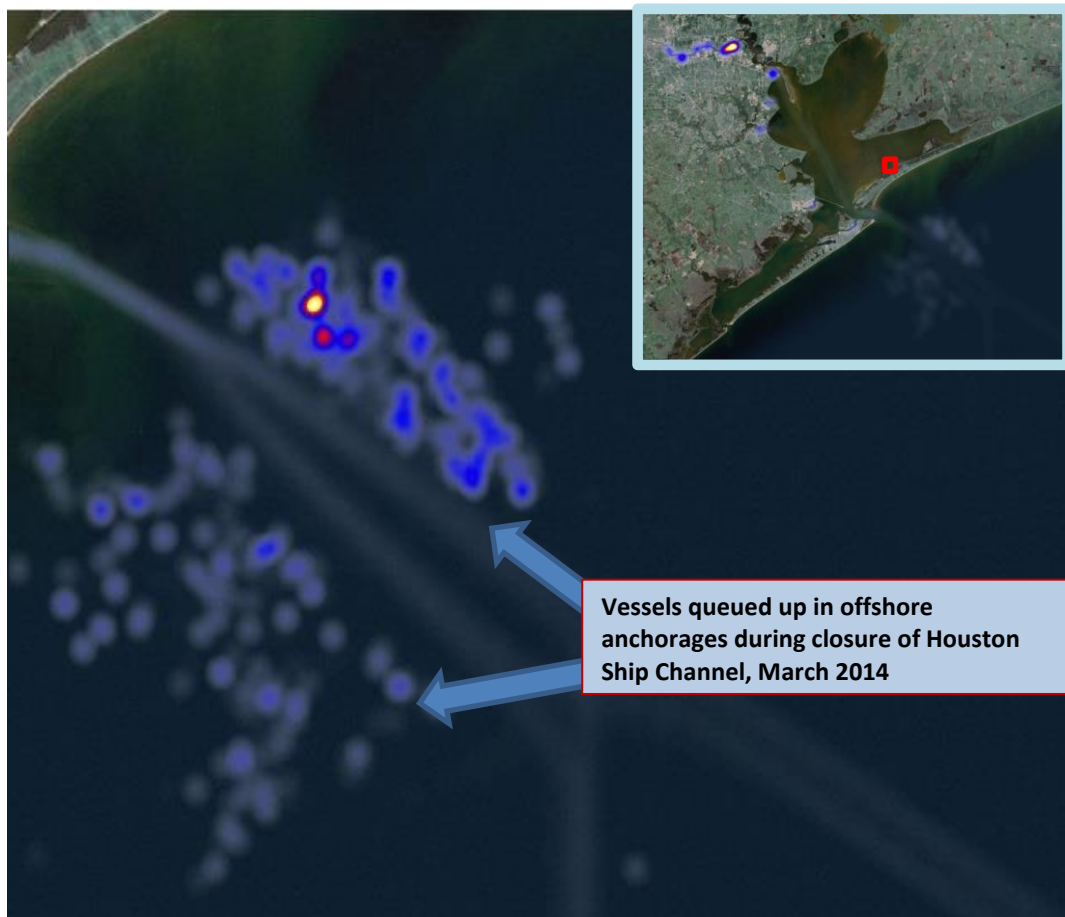
## 4. Empirical Application

To demonstrate the versatility of the proposed methodology, two empirical case studies are presented here. The first applies the methodology to a no-notice event (an event with no warning time) which was triggered by a collision between an oceangoing bulk carrier vessel and a tow of fuel barges in the Houston Ship Channel on March 22, 2014. The second case study demonstrates the methodology on a pre-notice event (warning time is greater than 24 hours), the closure of harbor operations in the greater Port of New York/New Jersey resulting from Superstorm Sandy on October 28, 2012.

### 4.1 Galveston Channel Closure

On March 22, 2014, the 607-foot long bulk carrier *Summer Wind* collided with a tank-barge being pushed by the *Miss Susan* near the end of the Texas City Dike in Lower Galveston Bay. The collision was caused primarily by heavy fog in the area, and it resulted in about 4,000 barrels (168,000 gallons) of fuel oil spilling into the waterway (29). During the ensuing channel closure for cleanup operations, pilot services were suspended and oceangoing vessels began queuing up in the various anchorage areas near the entrance to Galveston Bay. This study uses a set of NAIS data covering January-June 2014 for cargo and tankers transiting in the vicinity of the intersection of the Houston Ship Channel with the Gulf Intracoastal Waterway (GIWW). To

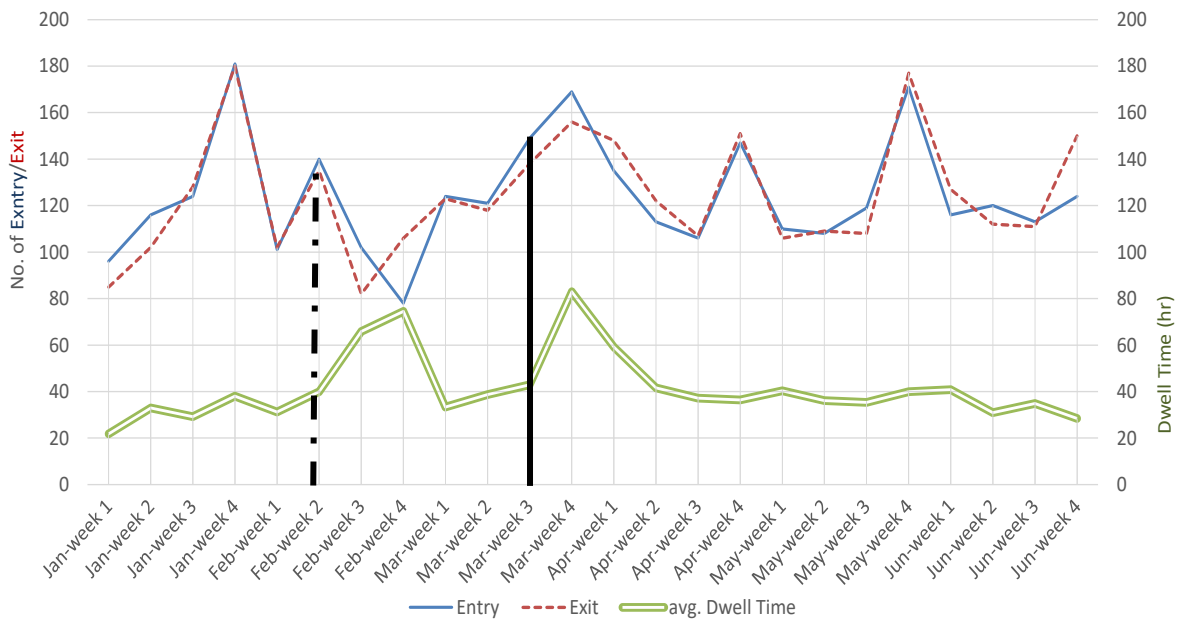
keep data file sizes and processing times manageable, the temporal sampling rates vary from 5 minutes to 1 hour, depending on the amount of time each vessel was within range of shore-based AIS towers. Figure 3 shows density plots of vessel traffic are shown for the overall Galveston Bay port area (inset) as well as the offshore anchorages where vessels queue up while waiting for pilots and/or berthing slots to open at the various port terminals in Galveston, Texas City, or Houston. The small box in the inset map shows the general location of the collision in March 2014. The density plots reflect the relative number of AIS position reports per unit area, but they do not necessarily indicate higher number of unique vessels. The inbound and outbound traffic fairways can also be seen bisecting the two offshore anchorage areas.



**Figure 3: AIS density plot of vessel traffic near Galveston entrance channel**

A large watch area encompassing both of the offshore anchorage areas seen in Figure 3 was used as the basis for AIS-derived dwell time observations and a rolling vessel entrance/exit tally during the 6-month study period. The dwell time observations are taken as the difference in the time stamps of vessel position reports when first appearing within and subsequently outside of the watch area. Some (manageable) dwell time error is introduced by the differing sampling rates used for unique vessels, which vary between 5 minutes and 1 hour for vessels within range of AIS receiving towers.

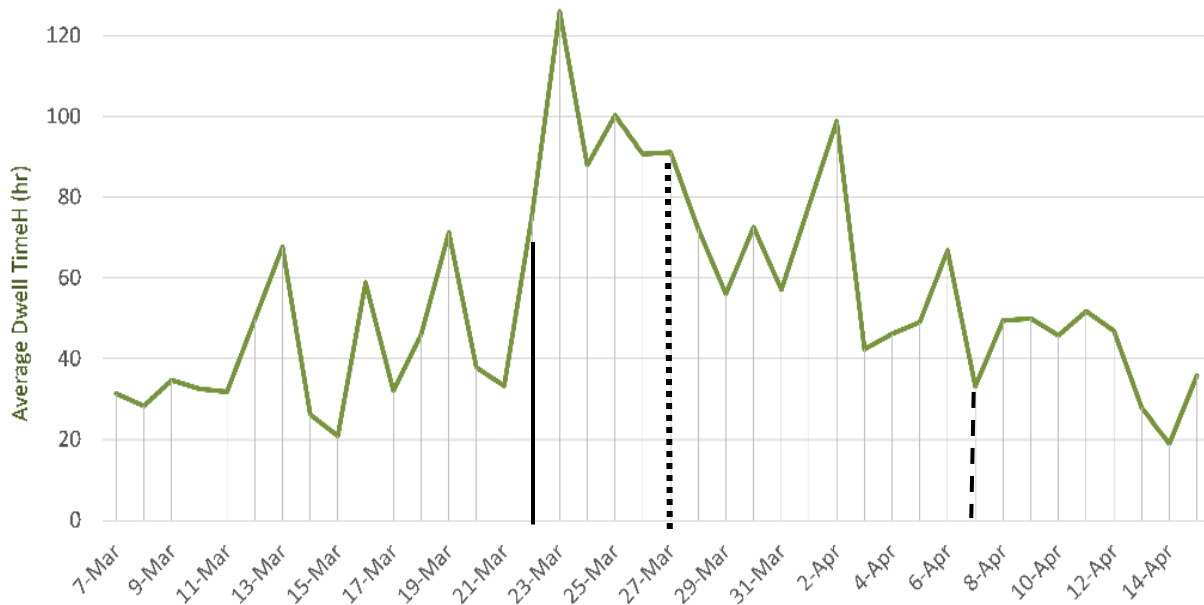
Figure 4 shows the weekly average vessel dwell times and the number of inbound and outbound vessels within the offshore watch area for the 6-month period encompassing the vessel collision. The disruptive event date (March 22, 2014) is indicated in the figure by the vertical solid line. This period coincided with an imbalance in the number of inbound and outbound vessels and subsequent increases in the average vessel dwell time. An unexpected finding was an earlier increase in average vessel dwell time (indicated by the vertical dot-dash line) 5 weeks before the collision event. Channel closure records obtained from officials with the Houston–Galveston Vessel Traffic Service showed that cumulative weekly closure durations were higher in February 2014, mostly because of fog, than they were in March 2014, even after the postcollision closure is taken into account. Some of the closure durations represent service disruptions in various parts of the greater Galveston Bay port area, and they do not necessarily represent closures of the entire waterway system. The postcollision disruption that is the focus of this study is indicated by the vertical solid line in the figure. Because this closure was continuous and affected the entrance to the entire Houston–Galveston–Texas City port zone, it was assumed to have led to the significant disruptions to overall vessel traffic shown by the average dwell time and net transit count increases in the outer anchorages. However, according to the dwell time resiliency results, the multiple closures during February (indicated by the vertical dashed line) also appear to have affected the performance of the overall port area.



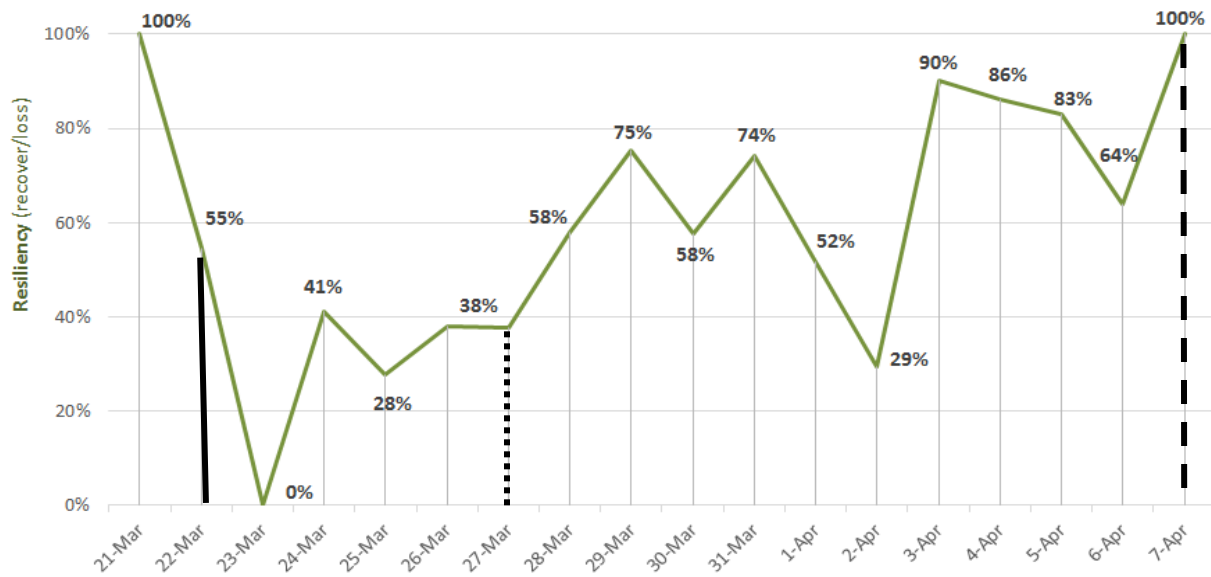
**Figure 4: Six-month vessel traffic summary for Galveston offshore anchorage area**

Figure 5 shows the daily average dwell times in the outer anchorages of the Galveston entrance from March 7 to April 14, 2014. The event date is shown by a solid vertical line and corresponds to the closure of the channel for 4 days. On March 27, 2014 (shown by a dotted vertical line), the channel was partially reopened, and it was finally fully opened on April 7, 2014 (shown by the dashed vertical line). The figure shows that before the event, the outer anchorage

area (the system  $S$ ) was in the original state condition. The system reached the full disrupted state starting March 23, 2014. On March 27, a recovery action was taken (the partial reopening of the channel), which began the transition between the disruptive state and the stable state. Finally, the system reached the stable state around April 7, 2014. Figure 6 shows the resiliency, as calculated from Equation 1, for each day after the disruptive event. This analysis demonstrates that the recovery action (vertical dotted line) was effective for increasing the resiliency of the system. Then, over the ensuing days, the resiliency of the system fluctuated until it again reached its stable state (vertical dashed line). For this demonstration, the original state was quantified as the average vessel dwell time the day before the incident. Future work will incorporate a more statistically robust measure of steady-state, predisruption port operations.



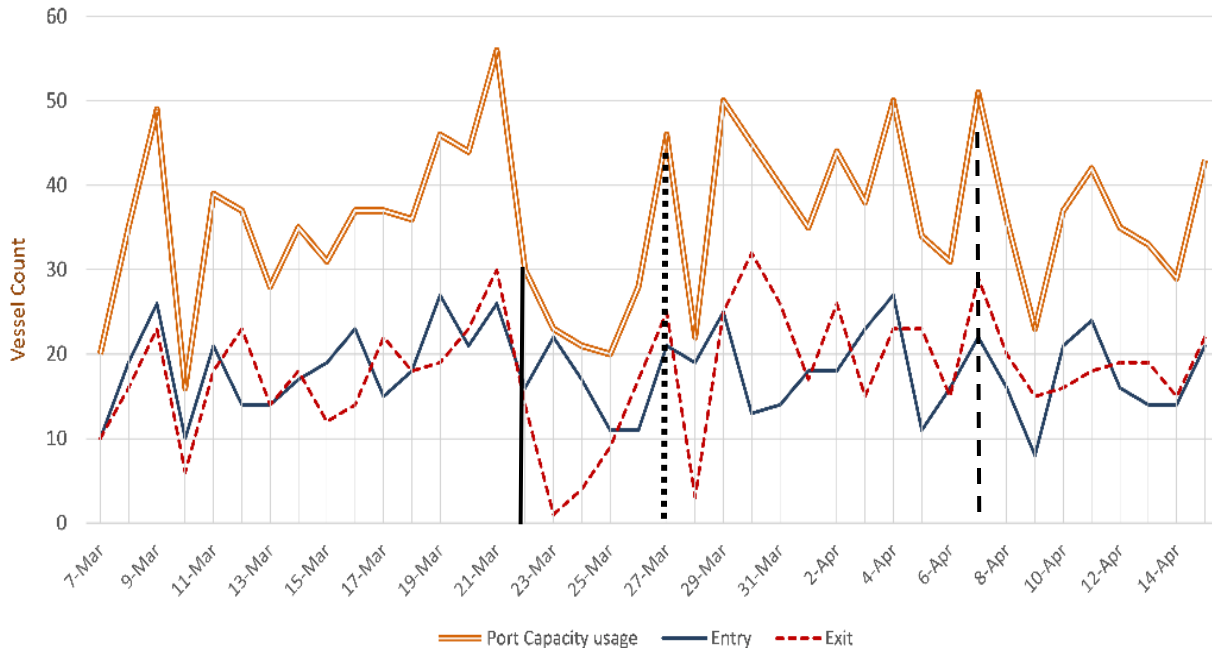
**Figure 5: Galveston Bay dwell times**



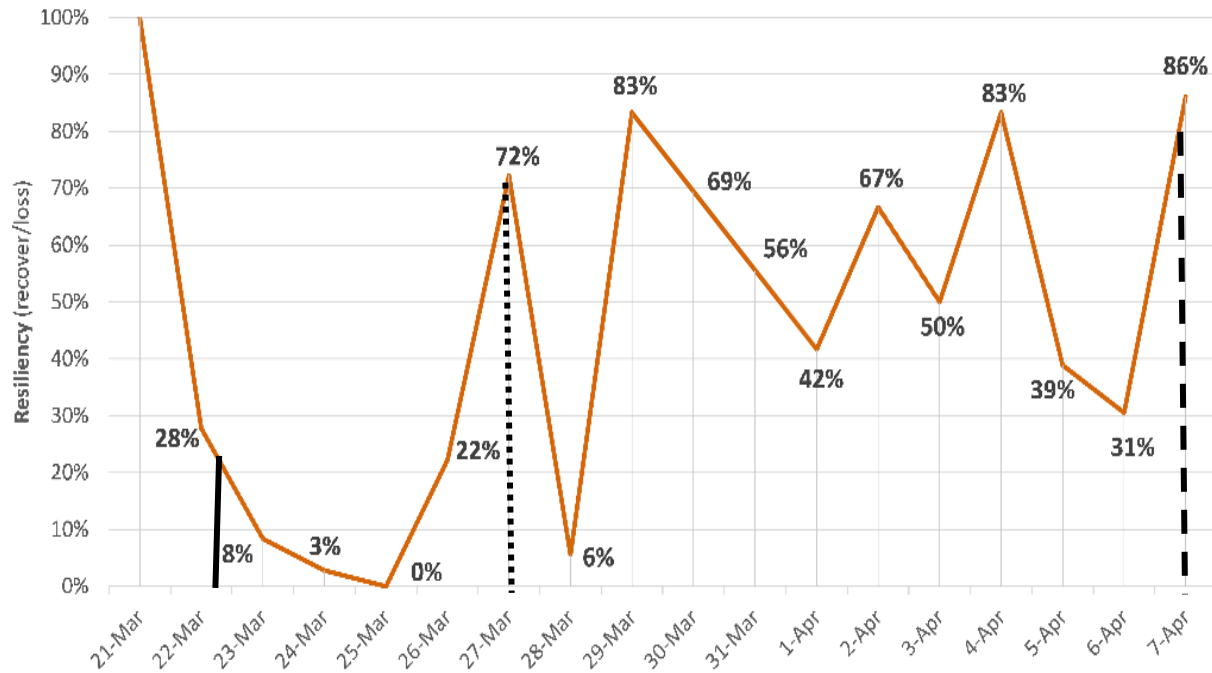
**Figure 6: Galveston Bay resiliency – dwell time**

Figure 7 shows the daily number of inbound and outbound vessels through the Galveston offshore anchorages for the same period. Also shown in the figure (solid, dotted, and dashed vertical lines) are the event day, partial reopening, and full opening of the channel. There was a sharp drop in cumulative inbound and outbound vessels on the incident day. This drop continued (marking the start of the transitional state) until March 25, 2014, when the system entered the disruptive state. The beginning and end of the disruptive state occurred on the same days as shown in Figure 5. After March 26, 2014, the system began transitioning, and by the time of the full reopening on April 7, 2014, the system was in its stable state.

Figure 8 displays the daily net vessel count resiliency for the Galveston Bay port area, as based on vessels entering and exiting the offshore anchorages. In general, the net transit count resiliency of the system performed similarly to the dwell time resiliency, with corresponding peaks and valleys. This finding was as expected, because of the relationship between dwell time and the total number of inbound and outbound vessels. The vessel collision in the Houston Ship Channel in March 2014 caused a decrease in overall port area performance. NAIS data were used to quantify the resiliency of the port area operations with two metrics: average anchorage area dwell time and net transit count into and out of the anchorage area.



**Figure 7: Galveston Net Vessel Transit Counts**



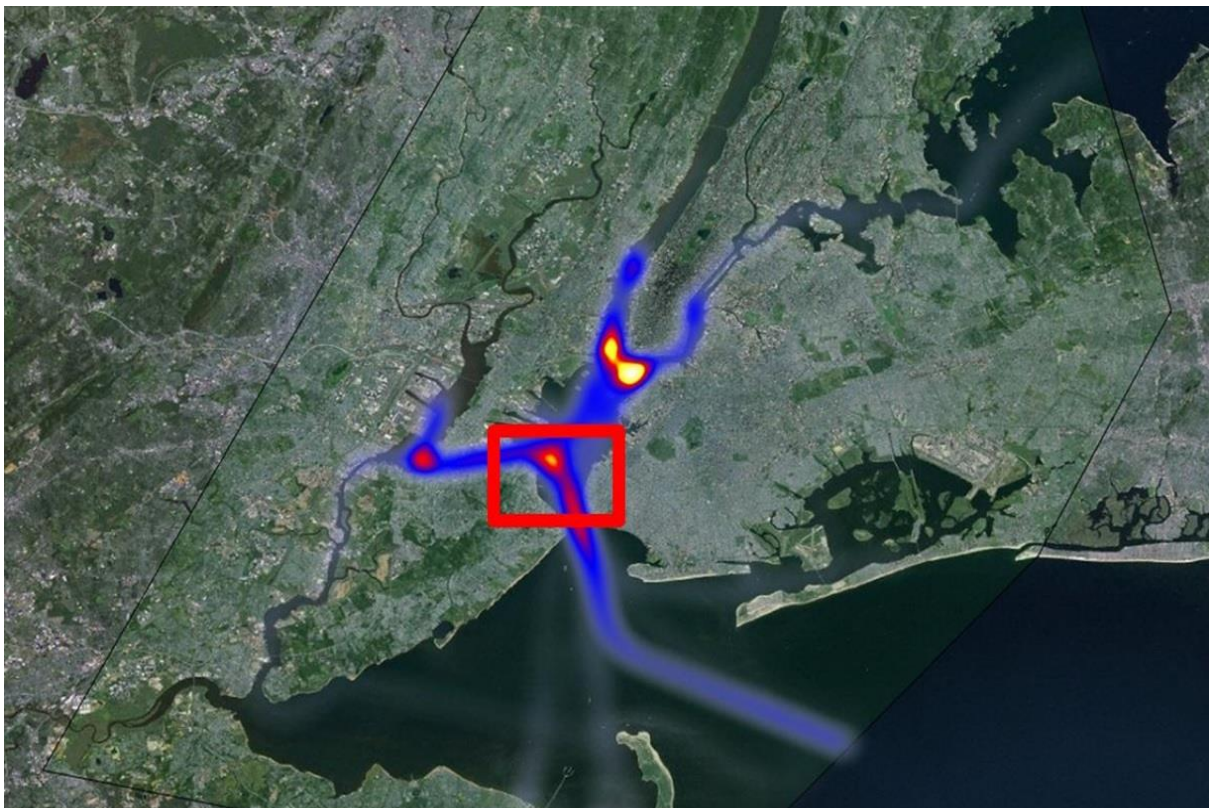
**Figure 8: Galveston Net Vessel Transit Count Resiliency**

#### 4.2 New York - New Jersey Channel Closure

The Port of New York and New Jersey, which spans both the New York and New Jersey sides of New York harbor, is the third largest port in the U.S. and the largest port on the Atlantic coast. In late October 2012, New York harbor was significantly disrupted and damaged by



Superstorm Sandy as that unusual extra-tropical system moved slowly up the U.S. eastern seaboard. In preparation for the storm, the port was shut down in the evening of October 28, 2012 and remained closed for almost 8 days. For the study reported here, NAIS data is used for cargo and tankers transiting the Arthur Kill area of New York Harbor during a 6-month period (August 2012 – January 2013) encompassing the landfall of Superstorm Sandy. The sampling rate for unique vessels ranged from 5-minutes to 15 minutes, depending on the amount of time each vessel was within range of AIS receiving towers. Figure 9 shows the AIS density plot of vessel traffic within the greater New York area based on the NAIS data obtained for this study. The small box near the center of the figure shows the area that was queried for NAIS archival data; all vessels transiting this box were tracked for the full 6-month study period. The larger bounded region indicated by the polygon encompassing the greater New York metropolitan area shows the larger port area that was used for the post-Superstorm Sandy resiliency analysis.

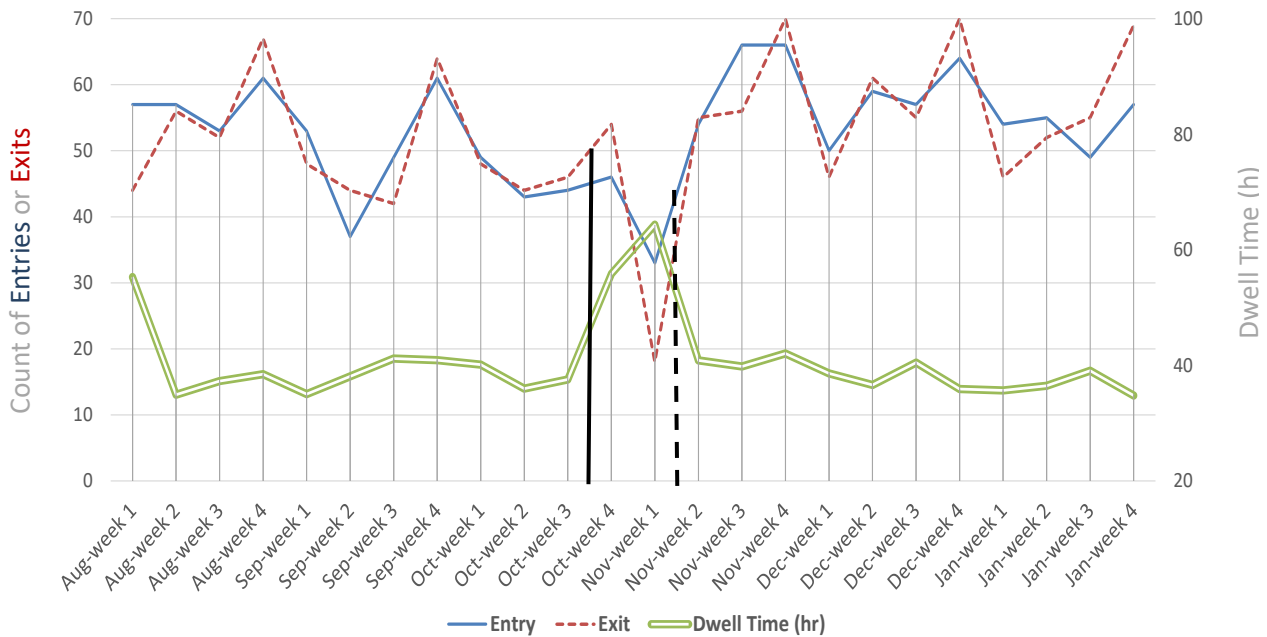


**Figure 9: Density plot of AIS position reports in greater New York Harbor**

Figure 10 shows the weekly average vessel dwell times and the number of inbound and outbound vessels for New York Harbor during the 6-month study period. The day of the closure (October 28, 2012) and the day the harbor was reopened (November 4, 2012) are shown with solid and dashed lines, respectively. In the week leading up to the closure, there was a drop in the number of vessels, likely due to vessels routing away from the harbor in advance of the storm. Also shown prior to the closure is an increase in vessel dwell time, also likely due to storm

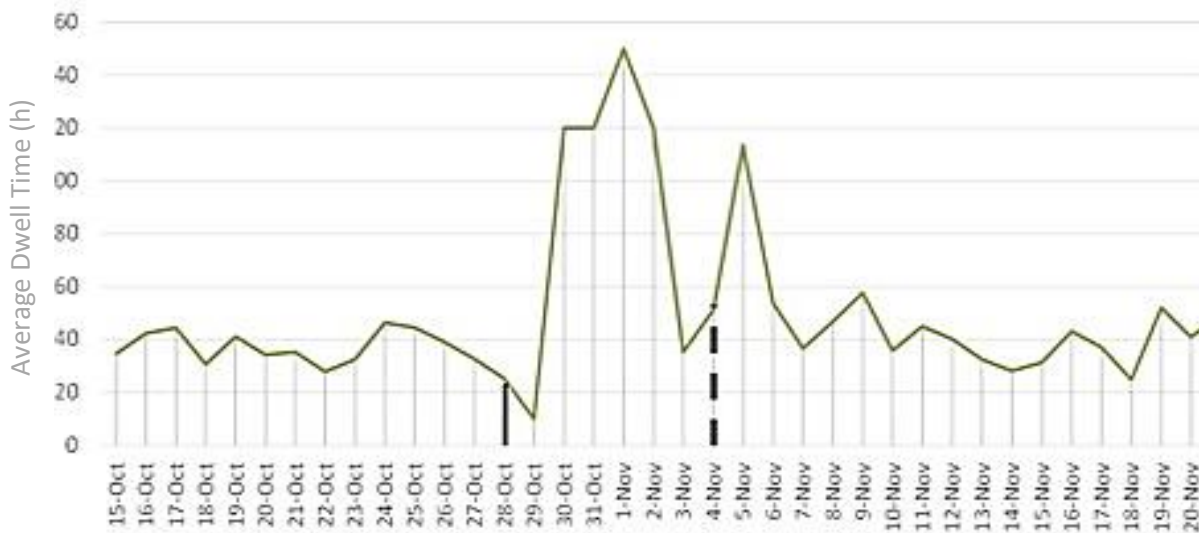


preparations. The figure shows that the port returns to normal operations by the third or fourth week in November.



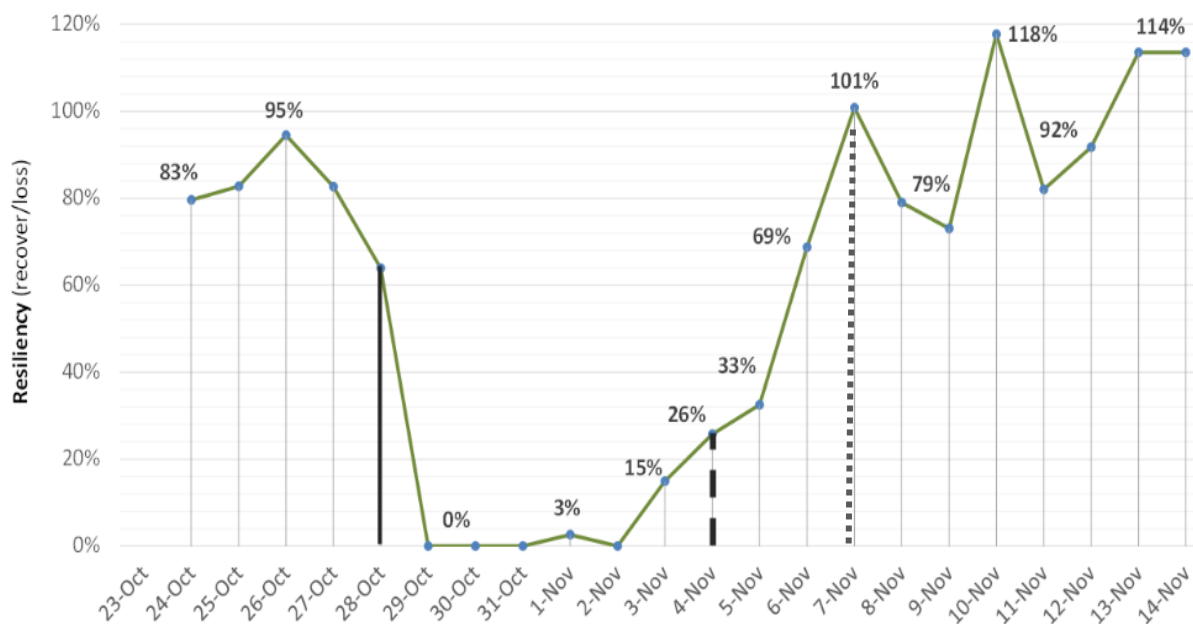
**Figure 10: Six-month vessel traffic summary for New York Harbor area**

Figure 11 shows New York Harbor average daily dwell times from October 15, 2012 to November 20, 2012. The closure of the harbor began on October 28 (shown with a solid vertical line), Superstorm Sandy made landfall the following day, October 29, and the port reopened on November 4 (shown on the figure with a dashed vertical line). The figure shows that vessel dwell times started to decrease a week prior to the incident and that the vessel average dwell times did not immediately increase following the closure. This is in contrast to the no-notice event which took place in Galveston Bay, where there was a drastic increase in dwell times immediately following that incident. However, in the ensuing days after Superstorm Sandy, average dwell times for the greater New York port area increased as vessels began to queue, waiting for the port operations to reopen. By November 9, the port area appeared to have returned to a stable dwell time performance.



**Figure 11: Greater New York Port Area Dwell Times**

Figure 12 shows the dwell time resiliency for each day after the harbor closure. The figure begins on October 24, 2012, a few days prior to the closure to provide a reference. The day of the closure, the reopening day of the port, and the day by which the port were fully recovered are shown in the figure with a solid, dashed, and dotted line, respectively. After the closure, the system transitioned to a disruptive state, reaching its maximum on October 31, 2012. The ultimate recovery event was the reopening of the harbor, after which the vessel activity began the transition into a stable state, and essentially normal operating daily average dwell times.



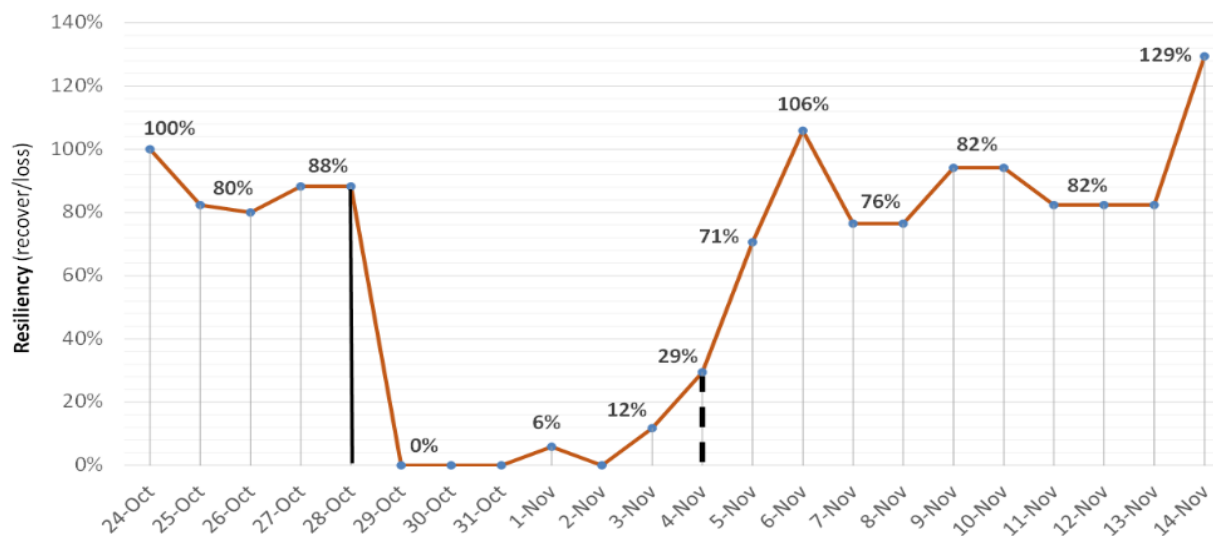
**Figure 12: Greater New York Port Area Dwell Time Resiliency**

Figure 13 shows the daily number of inbound and outbound vessels through the greater New York port area between October 15 and November 22, 2012. The figure shows the harbor closure and reopening with solid and dashed lines, respectively. A sharp drop is seen in the cumulative inbound and outbound number of vessels on the day of the closure.



**Figure 13: Greater New York Port Area Net Vessel Transit Counts**

Figure 14 shows the daily net vessel transit count resiliency (port serviceability resiliency) for New York Harbor as calculated from Equation 1. Again, as seen during the Galveston Bay disruption, the start and end dates of the various states in the resiliency process (original state, disruptive state, transitive state) are the same between the dwell time and net vessel count resiliency figures.



**Figure 14: Greater New York Port Area Net Vessel Transit Count Resiliency**

A comparison of these two events from a resiliency stand-point, shows several differences. First, in the days leading up to Superstorm Sandy, there was a gradual increase in the number of exiting vessels, showing that many of the large tankers and cargo ships evacuated before the arrival of the storm. No such evacuation was possible before the incident in Galveston Bay. Also, since the New York Harbor closure was scheduled in preparation for the storm, the drop-off in port performance was drastic. However, at Galveston Bay, vessels were able to access the anchorage areas offshore of the Galveston entrance channel both before and after the incident, which resulted in a more gradual drop-off in port system performance. Furthermore, approximately 48 to 72 h after New York Harbor was reopened, vessel traffic and dwell times returned to a pre-event levels. After the no-warning event in Galveston Bay, however, normal port operations did not resume until several days later.

## 5. Conclusions

Despite efforts to mitigate the risks and effects of catastrophic events, disruptions will continue to cause significant losses to maritime infrastructure and efficiency. For this reason, MTS stakeholders must continue making improvements to the design and operation of port and waterway facilities and their associated infrastructure to minimize losses and maintain functionality in cases of disruption and major disasters. A key aspect in improving system resiliency is the ability to identify robust and objective performance evaluation methods. The research presented here was developed from AIS data to create new methods and metrics for the assessment of resiliency in maritime systems. This methodology advances the field of disaster science by expanding on the concepts first proposed by Henry and Ramirez-Marquez (1) and Baroud et al. (10) and applying these methods to empirical observations.

In general, the results of the research show that an AIS is an excellent source of quantitative data on postdisaster measures of resiliency. The time-dependent performance models developed from these data show the cascading effects of disruptions and quantify the benefits gained by recovery efforts in a time-progressive series. One of the more interesting findings is the manner in which the data show, in quantifiable terms, reductions in performance resulting from incremental, less-publicized disruptions (February 2014 at Galveston Bay) and evidence, albeit limited, of the benefits of warning before a disruptive event. The proposed approach can also be applied to longer disruptions. The West Coast labor dispute and associated port slowdowns in late 2014 and early 2015 provide a prime example of the need for unbiased analysis and can be studied within the context of this research in future work.

These findings are first steps toward the development of standardized metrics for quantifying MTS operational resiliency. AIS data, collected from nearly all commercial vessels on a semicontinuous basis, are a rich source with many applications in disaster science. The methods developed and applied in this research incorporate an all-hazards approach to quantifying resiliency in navigable waters and can be applied across a range of temporal and spatial scales.

## 6. References

1. Henry, D., and J. E. Ramirez-Marquez. Generic Metrics and Quantitative Approaches for System Resilience as a Function of Time. *Reliability Engineering and System Safety*, Vol. 99, 2012, pp. 114–122.
2. Omer, M., A. Mostashari, and R. Nilchiani. Assessing Resilience in a Regional Road-Based Transportation Network. *International Journal of Industrial and Systems Engineering*, Vol. 13, No. 4, 2013, pp. 389–408.
3. *Critical Thinking: Moving from Infrastructure Protection to Infrastructure Resilience*. CIPP Discussion Paper Series, George Mason University, Arlington, Va., 2007.
4. Li, O., B. Sauser, and J. E. Ramirez-Marquez. Analyzing the Influence of Zeroth Responders on Resilience of the Maritime Port Enterprise. In *Proceedings of the IEEE International Systems Conference*, Montreal, Quebec, Canada, 2011, pp. 24–27.
5. Attoh-Okine, N. O., A. T. Cooper, and S. A. Mensah. Formulation of Resilience Index of Urban Infrastructure Using Belief Functions. *IEEE Systems Journal*, Vol. 3, No. 2, 2009, pp. 147–153.
6. Li, Y., and B. J. Lence. Estimating Resilience for Water Resources Systems. *Water Resources Research*, Vol. 43, No. 7, 2007.
7. Omer, M., R. Nilchiani, and A. Mostashari. Measuring the Resilience of the Trans-Oceanic Telecommunication Cable System. *IEEE Systems Journal*, Vol. 3, No. 3, 2009.
8. Reed, D. A., K. C. Kapur, and R. D. Christie. Methodology for Assessing the Resilience of Networked Infrastructure. *IEEE Systems Journal*, Vol. 3, No. 2, 2009, pp. 174–180.
9. Pant, R., K. Barker, and W. Zobel. Static and Dynamic Metrics of Economic Resilience for Interdependent Infrastructure and Industry Sectors. *Reliability Engineering and System Safety*, Vol. 125, 2014, pp. 92–102.
10. Baroud, H., K. Barker, J. E. Ramirez-Marquez, and C. M. Rocco. Inherent Costs and Interdependent Impacts of Infrastructure Network Resilience. *Risk Analysis*, Vol. 35, No. 4, 2014.
11. Omer, M., A. Mostashari, R. Nilchiani, and M. Mansouri. A Framework for Assessing Resiliency of Maritime Transportation Systems. *Maritime Policy and Management*, Vol. 39, No. 7, 2012, pp. 685–703.
12. Georgia Tech Research Corporation, Parsons Brinckerhoff, Inc., and A. Strauss-Wieder, Inc. *NCHRP Report 732: Methodologies to Estimate the Economic Impacts of Disruptions to the Goods Movement System*. Transportation Research Board of the National Academies, Washington, D.C., 2012.

13. Pitana, T., E. Kobayashi, and N. Wakabayashi. Estimation of Exhaust Emissions of Marine Traffic Using Automatic Identification System Data (Case Study: Madura Strait Area, Indonesia). In *Proceedings of OCEANS*, Sydney, Australia, IEEE, New York, 2010, pp. 1–6.
14. Charlton-Perez, C. L., M. J. Evans, J. H. Marsham, and J. G. Esler. The Impact of Resolution on Ship Plume Simulations with NO<sub>x</sub> Chemistry. *Atmospheric Chemistry and Physics*, Vol. 9, 2009, pp. 7505–7518.
15. Wiley, D. N., M. Thompson, R. M. Pace III, and J. Levenson. Modeling Speed Restrictions to Mitigate Lethal Collisions Between Ships and Whales in the Stellwagen Bank National Marine Sanctuary. *USA Biological Conservation*, Vol. 144, 2011, pp. 2377–2381.
16. Schwehr, K. D., and P. A. McGillivray. Marine Ship Automatic Identification System (AIS) for Enhanced Coastal Security Capabilities: An Oil Spill Tracking Application. In *Proceedings of OCEAN*, Vancouver, British Columbia, Canada, IEEE, New York, 2007, pp. 1–9.
17. Hatch, L., C. Clark, R. Merrick, S. Van Parijs, D. Ponirakis, K. Schwehr, M. A. Thompson, and D. N. Wiley. Characterizing the Relative Contributions of Large Vessels to Total Ocean Noise Fields: A Case Study Using the Gerry E. Studds Stellwagen Bank National Marine Sanctuary. *Environmental Management*, Vol. 42, 2008, pp. 735–752.
18. Dobbins, J. P., and L. C. Langsdon. Use of Data from Automatic Identification Systems to Generate Inland Waterway Trip Information. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 2330, Transportation Research Board of the National Academies, Washington, D.C., 2013, pp. 73–79.
19. Shu, Y., W. Daamen, H. Ligteringen, and S. Hoogendoorn. Vessel Speed, Course, and Path Analysis in the Botlek Area of Port of Rotterdam, Netherlands. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 2330, Transportation Research Board of the National Academies, Washington, D.C., 2013, pp. 63–72.
20. *Atlantic Coast Port Access Route Study Interim Report*. U.S. Coast Guard. [http://www.uscg.mil/-lantarea/ACPARS/docs/ACPARS\\_Interim\\_Report-Final\\_09AUG.pdf](http://www.uscg.mil/-lantarea/ACPARS/docs/ACPARS_Interim_Report-Final_09AUG.pdf). Accessed July 20, 2013.
21. Calder, B. R., and K. Schwehr. Traffic Analysis for the Calibration of Risk Assessment Methods. Presented at U.S. Hydrographic Conference, Norfolk, Va., 2009.
22. Mitchell, K. N., and B. Scully. Waterway Performance Monitoring with Automatic Identification System Data. In *Transportation Research Record: Journal of the Transportation Research Board*, No. 2426, Transportation Research Board of the National Academies, Washington, D.C., 2014, pp. 20–26.
23. Tetreault, B. J. Use of the Automatic Identification System (AIS) for Maritime Domain Awareness (MDA). In *Proceedings of OCEANS*, IEEE, New York, 2005, pp. 1590–1594.

24. DiJoseph, P. K., and K. N. Mitchell. Estimating Vessel Travel Time Statistics for Inland Waterways with Automatic Identification System Data. Presented at 94th Annual Meeting of the Transportation Research Board, Washington, D.C., 2015.
25. Riley, I. L., K. N. Mitchell, P. K. DiJoseph, R. W. Whalin, and F. Wang. Analysis of Vessel Travel Times and River Stages. Presented at 94th Annual Meeting of the Transportation Research Board, Washington, D.C., 2015.
26. DiJoseph, P., and K. N. Mitchell. Marine Transportation System Travel Time Analysis via Automatic Identification System Data. Presented at PIANC World Congress, San Francisco, Calif., 2014.
27. Turnbull, K. *Transportation Research Circular E-C187: Developing Freight Fluidity Performance Measures: Supply Chain Perspective on Freight System Performance*. Transportation Research Board of the National Academies, Washington, D.C., 2014.
28. International Transport Forum. <http://www.internationaltransportforum.org/>.
29. *Marine Accident Report*. NTSB/MAR-15/01. National Transportation Safety Board, June 9, 2015