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

MarTREC

Maritime Transportation Research & Education Center

Interdependency of port clusters during regional disasters

Project start and end dates

Scott Parr, Ph.D.
Embry-Riddle Aeronautical University
Parrs1@erau.edu

Brian Wolshon, Ph.D., PE., PTOE
Louisiana State University
Brian@rsip.lsu.edu

Student Authors:
Hannah Russell
Embry-Riddle Aeronautical University
Thomash6@my.erau.edu

Emily Jannace
Embry-Riddle Aeronautical University
Emilyj19@vt.edu

Fanny Kristiansson
Embry-Riddle Aeronautical University
KRISTIAF@my.erau.edu

FINAL RESEARCH REPORT
Prepared for:
Maritime Transportation Research and Education Center

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

Please use the first page as your report cover

ACKNOWLEDGEMENT

This material is based upon work supported by the U.S. Department of Transportation under Grant Award Number 69A3551747130. The work was conducted through the Maritime Transportation Research and Education Center at the University of Arkansas.

DISCLAIMER

ABSTRACT

Ports play a vital role in the economy of nations and provide a critical link in the supply chain. Ports form the gateway by which essential goods are received within large geographic regions. Because of their function, ports are exposed to substantial risk of flooding, storm events, sea-level-rise, and climate change. The resiliency of ports is essential for the economy, the people, and national readiness. The contribution of this research work is in providing a methodology to quantify port resiliency that is applicable at the individual port level and regionally. The research approach first defines a quantifiable measure of systematic resiliency. Then applies this measure to quantify the resiliency of six ports located in the Southeast US impacted my Hurricane Matthew (2016). Based on the analysis of these individual ports, a regional resiliency assessment is then applied to quantify the regional resiliency of the impacted area. In general, the results showed that regionally, ports are more resilient to disruptive events than the individual ports that make up the region. This was likely because as one port enters the disrupted state, another may be entering the recovery state providing regional continuity. This may suggest that port clusters rely upon each other during disruptive events to increase the overall resiliency of waterborne commerce. In general, the study ports struggled to absorb the impact of the storm and subsequent closures, whereas adaptability and recovery were significantly higher.

1. INTRODUCTION

The need to enhance resiliency within the transportation systems and their management capabilities is vital toward providing safe, reliable mobility. Traditionally, civil infrastructure has included design limits that anticipate the reality of continually changing conditions. When these design limits are reached, the resulting disruption often has a significant impact on system performance. Minor disruptions to the transportation systems have generally been tolerated by the public as routine. Flight cancelations, delayed shipments, lane closures, and power outages are tolerated as everyday occurrences to be expected with the movement of people and goods. Global climate change and an increase tendency toward urbanization are likely to increase the rate of disruptions within the transportation system.

Ports are a vital piece of infrastructure for many nations. In 2014, seaports contributed to 26 percent of the United States' $17.4 trillion economy. Ports help to deliver essential goods including food and gasoline to major distribution hubs to be sent throughout the country. Ports employ 23.1 million people and contribute $1.1 trillion to personal wages and local consumption [1]. In the United States, there are 29 ports on the West Coast and 16 between the East Coast and Gulf of Mexico [2]. Ten metropolitan ports across the country account for 60 percent of international goods arriving in the country by sea, air, and road [3].

Ports are also vulnerable to disruptive events. In the last 26 years, sea levels have risen 2.6 inches [4]. With rising sea levels, major hurricanes (category three or higher) in the Atlantic have increased 74 percent [5]. The increase in major storms has made the need for resilient marine transportation systems even more vital. The proximity of ports to other major bodies is affected by storm surge and changing currents and tides. In addition to the economic impact of port disruptions, the environmental effects that could occur within the waters also threaten the ecosystem. Furthermore, as elements of an interconnected system of channels and waterways, ports play a critical role in supply-chain.

Hurricanes, oil spills, and labor disputes can all be sources of port disruptions. Hurricane Sandy in October 2012 closed the Port of New York/New Jersey for over a week from full operations. The hurricane caused flooding, loss of power, and damages to the port that prevented the ports from reopening immediately. It was estimated by the Port Authority of New York and New Jersey (PANYNJ) that the port closure cost $170 million [6]. Between the time the port partially reopened (three days after landfall) and the time the port returned to full operation (eight days after landfall), dwell times of vessels trying to enter the port climbed as high as 50 hours **Error! Reference source not found.**. The overall impact of a disruption on a port is a function of vulnerability of the port and the severity of the disruption. The resiliency of ports and inland waterways is critical for maintaining the flow of essential goods throughout the United States and is critical to national security and defense readiness.

The goal of this research is to investigate regional disruptions to port clusters, areas of the country with multiple ports servicing the same region. The contribution of this research is to empirically show how port clusters rely upon each other during disruptive events to increase the overall resiliency of waterborne commerce. The National Science Foundation's (NSF) definition of resilience as "*the ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events"* [8]. This definition of resiliency is intuitive, succinct, and comprehensive. It signifies the ability to "bounce back" after a disruptive event. However, it lacks any quantitative reference. Given the NSF definition, there is no way to measure resiliency, as it is a combination of several, often abstract, concepts. However, when assessing the operations of real systems, the measured loss in functionality resulting from a disruption can be quantified. Furthermore, the system's ability to absorb, recover, and adapt can also be measured. There is a need for methods and practices that can quantify the resiliency of ports by unifying the concepts of absorption, adaption, and recovery and that also reflect the impact of planning and preparation efforts. This research presents a novel approach to quantifying regional port resiliency by addressing the quantification shortcoming.

2. LITERATURE REVIEW

Broadly, the literature review exams four general areas of research. The first section presents prior work attempting to quantify port resiliency. The second section investigates the modeling of port operations and the third section focuses on estimating port performance and assessment. The final section explores prior work conducted using automatic identify system (AIS) data. Each of these topics are described in detail in the sections that follow.

2.1 Quantifying Resiliency

In the United Kingdom, 95 percent of supplies come by sea, including over one third of the UK's food supply, making continuous port operations a necessity for the sustainability of supply chains, economy, and port business. The resilience of UK ports relies on multiple, interdependent stakeholders. Kamal Achuthan (2011), has created a methodology for assessing resilience of seaports (MARS). Assessing the resilience of seaports is necessary for stakeholders to improve the resilience of ports by assessing and developing contingency plans. MARS is capable of modeling both wet-side and dry-side operations before, during, and after a disaster. It is based on existing data already collected for port operations management. The user must input downtimes or port resources affected and tolerable limits for the complete port system and individual stakeholders. MARS will model the delays and queues in operations and the stakeholders must determine if the delays and queue lengths are acceptable for their system. Assessing the delays and queues allows the user to alter downtime inputs, until recovery time objectives can be me.

According to Morris et al. (2016), a Resilience Index is an indicator of a Port organization's ability to reach and maintain an acceptable level of functioning and structure after a disaster. The Ports Resiliency Index (PRI) is a self-assessment tool for determining if Ports and the regional marine transportation sector are prepared to maintain operations during and after disasters. This assessment is to be completed with a group of internal and external Port stakeholders. The PRI is capable of identifying strengths and weaknesses in management and operations, assessing the overall resilience of the port industry, and identifying action items the industry should work towards to address system vulnerabilities and maintain long-term viability. It is recommended that the PRI be revisited every 1-2 years. The method in which the PRI was developed consisted of a checklist of possible indicators of resilience for ports taken from the American Association of Port Authorities 2006 Emergency Best Practices Manual, the NOAA Port Resilience Planning Tool, and academic sources. Leaders in the ports and marine transportation industry were also asked to identify measures of resiliency. These indicators were written in the form of ‘yes’ or ‘no’ questions and grouped into broad categories. The Port Resiliency Index is determined using a percentage system. The Resilience Index is identified as LOW, MEDIUM, or HIGH in different categories. A high Resilience Index indicates a Port is well prepared for a disaster and will likely reopen with few difficulties [10].

The community self-assessment Resilience Index by Seimpier et al. (2010), provides community leaders a simple method of predicting if their community will reach and maintain an acceptable level of functioning after a disaster. This assessment does not claim to replace a detailed study. When this self-assessment is completed, a Resilience Index will be assigned to determine how long it may take a community to provide basic services and reoccupy homes and businesses after a disaster. These indexes are defined as LOW, MEDIUM, or HIGH [11]. Seaports and their intermodal connectors support the global supply chain and provide regional economic activity. According to Wakeman et al. (2015), climate change and the disruption of major weather events bring a need for enhanced coastal resilience. They define disaster resilience “the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events,” and that “enhanced resiliency allows better anticipation of disasters and better planning to reduce disaster losses – rather than waiting for an event to occur and paying for it afterward” [12]. The objective of the Resiliency Assessment and Planning Tool is to create a standardized framework for resilience in transportation systems that integrates physical infrastructure and social systems. This was done by gaining information from stakeholder interviews and workshops to create flow charts that show links between social and infrastructural assets that provide rapid recovery on the coast after major events. The Resiliency Assessment and Planning Tool determines a numerical value for resilience that is determined by functionality and not infrastructure [12].

The Department of Homeland Security along with its partners, has developed a scorecard method for quantifying resiliency using spatial evaluation. The goal of this scorecard method is to help communities identify conflicting policies in respect to disaster protocol for different departments in the community. Physical and social vulnerability areas should be mapped by each department and compared to reveal vulnerability hotspots. Each disaster plan is scored and the community as a whole receives a score for resilience. This method utilizes spatial mapping to generate a resilience values [13].

The United States Army Corps of Engineers has created a three tier approach for quantifying resiliency. They assessed multiple quantification methods already in use, and modified them to fit their needs. Their resilience matrix consists of 16 cells that cover the preparation, absorption, recovery, and adaptation of a system within physical, information, cognitive, and social domains. A percentage value is then assigned to each cell and the rating of “poor”, “moderate”, or “good” is assigned. This method of quantification differs from the Resiliency Assessment and Planning Tool as it does not output a numerical resiliency index value for the system and the inputs are based off stakeholder feedback [14].

2.2 Port Modeling

The planning and management of port terminals can be modeled with social, economic, environmental, and institutional variables using Bayesian Networks. Bayesian Networks are used to make optimal decisions by introducing possible actions and the utility of their results. This method developed by Molina Serrano et al. (2018), allows for estimating the probability of unknown variables, based on their relationship with known values. The method used generates more than 40 port variables classified as social, economic, environmental, and institutional, and creates a non-cyclic conducted graph. This allows for port variable parent-child relationships to be known. Economic variables represent the parent role in most cases as they are the cause of the rest of the variable typologies. The Bayesian Network allows uncertainty to be modeled in a probabilistic way based on variable relationships [15].

The national freight transportation system represents about 9.5 percent of GDP in the United States and is responsible for about 8 percent of greenhouse gas emissions. Efficient design and operation of the national freight transportation system is critical to the stability of the United States. Wang et al. (2018), developed a mathematical model to estimate international and domestic freight flows across the ocean, rail, and truck routes. This mathematical model can be used to study the impacts of changes in the infrastructure of the United States, as well as the results of new user fees and changes in operating policies. The model develops a solution that is demonstrated on a large scale for all intercity freight and U.S. export/import containerized freight. Flow volumes are then compared to the model's results. In this study, Wang et al. applies the mathematical model to two case studies: (1) a disruption from an earthquake at the seaports of Los Angeles and Long Beach; and (2) the implementation of new user fees at the ports in California [16].

A comprehensive traffic network model within a port city has been modeled by Bela et al. (2018), to estimate emissions of trucks and passenger cars. The model generates, distributes, and assigns trucks and passenger cars to a traffic network within the port city of Halifax, Canada. Unique data sources are used to determine truck trip generation and distributions within the network. It was found that 48% of total truck trips occur during the mid-day peak period and emissions are significantly affected by the truck volume of the entire network. This paper also examines emissions within Traffic Analysis Zones in the hopes of determining policy direction for future emission reduction strategies [17].

2.3 Quantifying Port Performance

The performance of maritime ports is often measured with indicators such as container throughput and facility productivity. A quantitative measure of port performance is of great importance for models of port operations. Chen et al. (2016), proposes to derive port performance indicators from vessel GPS traces and maritime open data. Port performance indicators include ship traffic, container throughput, berth utilization, and terminal productivity. These indicators are directly related to vessel counts and the amount of containers handled. The authors propose the container-handling events at terminals are the basis of a quantified port performance measurement. Strengths and weaknesses of different terminals are compared to benefit terminal productivity, linear schedule optimization, and regional economic development planning. The methodology for this study consists of large-scale, real-world GPS traces of containerships at major container ports. Variation of data from ports throughout the world, from different times of year, and from various maritime open data sources validate the study. The authors found that the proposed framework can accurately estimate port performance indicators and compare port performance rankings and regional port performance rankings [18].

Efficient cargo transfers are critical to port performance. There are many diverse ways to measure port performance and efficiency, Ducruet et al. (2014), proposes a method that is based on turnaround time. This study hypothesizes that turnaround time efficiency of individual ports may exhibit certain commonalities functionally and/or regionally outside of individual situations. An overview of time efficiency in world container ports is analyzed for 1996, 2006, and 2011 to identify possible determinants of time efficiency, such as the volume of traffic and size of vessels [19].

The capacity utilization of a seaport can be found using well-known standard queuing models following the methodology proposed by Layaa et al. (2014). The authors of this study used the seaport of Dar es Salaam (Tanzania) as a case study. Historical data on Dar es Salaam terminal performance for the general cargo and the container terminal has been analyzed to validate the model. Using standard queuing models, this study found that the Dar es Salaam terminal capacity was underutilized and vessels were subjected to lengthy queues. While a standard queuing model can be used to quickly evaluate seaport terminal capacity, actual ship arrivals and service time distributions require further analysis [20].

2.4 Utilization of Automatic Identification Systems (AIS) data

Automatic Identification System technology can provide commercial vessel trajectory data that is valuable for research. Zhao et al. (2018), presents an algorithm that can be used to compress this data from its large, inefficient, initial form. The improved Douglas-Peucker algorithm takes vessel trajectory data and makes it easier to store, query, and process. A case study of AIS data gathered over the duration of a month in the Chinese Zhou Shan Islands proves that the Douglas Peucker algorithm can effectively compress ship trajectory information [21]. AIS data has also been used to help prevent vessel collisions. Altan et al. (2018), found a solution to distribute vessels in congested waterways to avoid collision [22].

Automatic Identification System receivers collect vessel movement information that can be used to classify vessel motion patterns. A study by Chen et al. (2018), presents a method to aid in automatic vessel motion pattern classification in inland waterways. The first step is to use the Least-squares Cubic Spline Curves Approximation technique, followed by a traditional classification model based on Lp-norm sparse representation, and the Matching Pursuit-Fletcher Reeves method. The model created was validated with two AIS datasets from the Yangtze River. Following the previously stated methodology, the proposed model was found to effectively classify vessel motion patterns in inland waterways [23].

Data from Automatic Identification System technology is critical in collision avoidance, risk evaluation, and navigation behavior study. However, raw AIS data contains outliers and errors that can result in erroneous conclusions. Zhang et al. (2018), proposes a three step process to produce a valid multi-regime vessel trajectory reconstruction model. The first step is outlier removal, followed by ship navigational state estimation, and vessel trajectory fitting for different navigation states, namely hoteling, maneuvering, and normal-speed sailing. This proposed model was validated with a large AIS dataset containing movements of more than 500 ships in Singapore Port. The created model was then compared with three other popular trajectory reconstruction models based on the same dataset. The authors found that their proposed model performed significantly better than the popular linear regression model, polynomial regression model, and weighted regression model [24].

3. METHODOLOGY

The research approach first defines a quantifiable measure of systematic resiliency. Then applies this measure to quantify the resiliency of six ports located in the Southeast US impacted my Hurricane Matthew (2016). Based on the analysis of these individual ports, a regional resiliency assessment is then applied to quantify the regional resiliency of the impacted area. The research methodology first describes the resiliency quantification process. This is followed by a description of the port data collection and processing for the generation of resiliency plots.

3.1 Resiliency Quantification

NSF's definition of resiliency calls for a means of measuring the system's ability to absorb, adapt, and recover. Figure 1 provides insight into how this can be accomplished. Let function $\omega(t)$ represent a direct measure of system output at any time t. System *S* will undergo five distinctive states. Prior to event *E* ($t < t_E$), the system is operating in stable, pre-event conditions. After event *E*, output decreases as the system absorbs the impact of the disruption. Eventually, the system will stabilize as the effect of the disruption reaches its maximum impact on functionality. Therefore, for $t_E < t \leq t_A$, the system is in the absorption state. While system performance is no longer decreasing, system output is still reduced from the pre-event conditions $\omega(t_A) \cong \omega(t_{A+1}) < \omega(t_{E-1})$. The system will remain in this disrupted state until a recovery action is taken $t_A < t < t_D$. The system begins to recover as functionality is restored, $\omega(t_{D+1}) > \omega(t_D)$. This recovery continues until the system reaches a stable recovery at $t = t_R$.

Figure 1: Time Dependent Resiliency Plot

The system functionality between t_E and t_A can be used as a direct measure of absorption. In particular, the angle created between in the functionality plot for $W(t_{E)} < W(t) \leq W(t_A)$.

Figure 2 shows this angle as $\theta_{\overline{EA}}$ and is calculated in equation 1. As formulated, $\theta_{\overline{EA}}$ has a maximum value of 90 degrees ($\frac{\pi}{2}$ radians) and a minimum value of zero degrees (zero radians). Therefore, the angle $\theta_{\overline{EA}}$ can be normalized as a value between 1 and zero by dividing Equation 1 by 90 degrees ($\frac{\pi}{2}$ radians). This results in the function taking a value closer to one when the loss in functionality is greatest and a value closer to zero when the functionality loss is the lowest. By subtracting this function from one, this is reversed, resulting in values closer to one representing a more gradual loss in functionality and a better ability to absorb the impact of the disruption. Equation 2 formulates the system's absorption as R_A.

Figure 2: Absorption State Diagram

$$\tan^{-1}(\theta_{\overline{AE}}) = \frac{\Delta Y}{\Delta t} \qquad \text{Equation 1}$$

$$R_A = 1 - \left| \frac{2tan^{-1}(\frac{\Delta Y}{\Delta t})}{\pi} \right| \qquad \text{Equation 2}$$

The disrupted state spans the period between the absorption state and the recovery state ($t_A < t < t_D$. Ideally, the disrupted state is as short as possible. The length of the disrupted state is calculated as $t_D - t_A$. This value can be normalized as the ratio of time disrupted and the total time of the disruptive event. Figure 3 shows the disrupted state diagram, labeling these two periods. Equation 3 defines R_D as the systems resiliency during the disrupted state. In the formulation, the ratio of time within the disruptive state to the overall duration of the event, is subtracted from one. This allows the formulation to take a value of one when $t_A = t_D$. This is the ideal situation because it suggests recovery begins immediately following the absorption state (i.e. there is no measureable disrupted state). Longer periods of disruption result in a disrupted state resiliency value closer to zero.

Figure 3: Disrupted State Diagram

$$R_d = 1 - \frac{t_o - t_a}{t_r - t_e} \qquad \text{Equation 3}$$

The recovery state begins only after a recovery action has been taken and the system begins to increase in functionality. Similar, to the absorption state, the recovery state can be quantified as a function of the angle generated by the functionality curve as the system transitions between the disrupted state and the stable recovered state. This angle is defined as $\theta_{\overline{DR}}$ in Equation 1 and shown in the recovery state diagram (Figure 4). Again, the angle must be normalized by dividing the function by 90 degrees ($\frac{\pi}{2}$ radians). Equation 5 provides the formulation for the resiliency of the recovery state. Values closer to one, represent a more rapid transition to the stable recovered state whereas lower values are indicative of a more gradual system response.

$$\theta_{\overline{DR}} = \tan^{-1}\left(\frac{\Delta Y}{\Delta t}\right) \qquad \text{Equation 4}$$

$$R_R = \left|\frac{2tan^{-1}\left(\frac{\Delta Y}{\Delta t}\right)}{\pi}\right| \qquad \text{Equation 5}$$

Figure 4: Recovery State Diagram

The NSF defines a system’s resiliency as a function of its ability to absorb, adapt, and recover. This inherently suggests that a system unable to absorb, adapt, or recover is decidedly, not resilient. Therefore, a quantification for resiliency needs to reflect these three characteristics. Equation 6 provides such a formulation for system resiliency that is in line with NSF’s definition and fundamental to any generic system with measureable output.

$$R = R_A * R_D * R_R \qquad \text{Equation 6}$$

This formulation of resiliency suggests that if the system is unable to absorb or adapt or recover, it is, effectively not resilient, $R = 0$. Furthermore, this approach also allows for the quantification of robustness, which is defined by NSF as “the loss of service that is induced by a disturbance”[1]. The fractional area of system functionality between the disruption and recovery is therefore a direct measure of the robustness of the system and provided in Equation 7.

$$\rho = \frac{2\int_{t_E}^{t_R} \omega(t)\, dt}{[\omega(t_R) - \omega(t_E)](t_R - t_E)} \qquad \text{Equation 7}$$

3.2 Data Collection and Processing

AIS data of vessel arrivals and departures was purchased from marinetraffic.com for six ports located in the Southeast US. The data purchased consisted of vessel information from January 1st to December 31st, 2016 for the ports of Miami, Everglades, Palm Beach, Jacksonville, Savannah and Charleston. Vessels were separated into four main categories: container vessels, non-containerized cargo vessels, tanker vessels, and passenger ships. The container vessel category consisted of container ships, cargo/container, vehicle carriers, and ro-ro cargo vessels. The non-containerized cargo vessel category contained general cargo, cargo, pallet carriers, cement carriers, heavy lift vessels, barge carriers, bulk carriers, and heavy load carriers. The tanker vessel category contained oil/chemical tankers, oil product tankers, tankers, crude oil tankers, asphalt/bitumen tankers, and chemical tankers. The passenger vessel category consisted of passenger ships, ro-ro/passenger ships, and high speed craft containing more than 50 passengers. The AIS database provided vessel arrival and departure times at the various ports.

Two measures were used to assess the performance of the ports before, during, and after the Hurricane Matthew event: daily vessel arrivals and average daily dwell times. The cumulative number of vessel arrivals was calculated for each vessel class at the study ports on a daily basis. Vessel dwell times were calculated as the difference between the arrival and departure times. Average daily dwell times were calculated for each vessel class. Both measures were used to generate functionality plots for each port. Regional totals and averages were also calculated for the resiliency analysis.

4. RESULTS

The results focus on containerized cargo vessel arrivals and dwell times because only this vessel class was pervasive at all six ports. The results first present functionality plots generated from the AIS data for each of the six ports. Then, resiliency measures were calculated for individual ports and the region as a whole. Daily containerized cargo vessel arrivals and average daily dwell times were used as the performance functionality measures.

4.1 Daily Arrivals

Figure 5 shows the daily arrivals for containerized vessels at each of the study ports and regionally. The x-axis shows the date and the y-axis provides the number of containerized cargo vessels arriving. Also shown on the figure is the landfall date of 10/8/2016. In the days leading up to landfall, the storm threatened nearly the entire eastern coast of the Southeast US, ultimately coming ashore in South Carolina. The dates corresponding to the event (t_E), the end of the absorption state (t_A), the end of the disruptive state (t_O), and the end of the recovery state (t_R), are also provided for the regional impact. These dates, however, were not universal between the six ports. Some ports felt the impact of the storm earlier or later and were disrupted for different periods of time. Their recoveries were also individualized. Ports further to the south, were generally, less disrupted than ports to the north. However, each of the study ports showed a measurable impact from the storm.

Figure 5: Containerized Cargo Vessel Daily Arrivals

Table 1 shows the resiliency results calculated for each port and the region as a whole. In general, closures issued by managers significantly hindered each of the port's ability to absorb the impact of the storm. The average absorption was only 0.243, with the regional absorption calculated at 0.161. The Port of Jacksonville showed the strongest absorption at 0.5 whereas the Port of West Palm Beach was the weakest at 0.126. The poor performance of the absorption was expected because closures tend to bring a sudden halt to operations. With no vessels arriving, a rapid drop in vessel arrivals was expected. In general, many of the ports in the study reopened relatively quickly, following the passage of the storm resulting in high disruption state values. This was expected, as many of the ports did not suffer significant damage and were able to resume receiving containerized cargo vessels. Recovery was also relatively high, with an average port recovery value of 0.859 and a regional recovery value of 0.900. This suggest that not only were the ports able to reopen quickly after the storm, they were accommodating as many vessels, or in some cases even more vessels, than prior to the storms passing. Overall, the resiliency of each port was limited by its ability to absorb the impact of the event. The regional resiliency was 0.145 with the Port of Jacksonville having the largest resiliency value of 0.211. This was unexpected because of Jacksonville's proximity to landfall. Ports Canaveral and Charleston showed the lowest resiliency values of 0.110. Charleston's resiliency was limited by its ability to adapt (i.e. end the disrupted state). This was likely because Charleston was closest to landfall, possibly suffering infrastructure damage.

Table 1: Containerized Cargo Vessel Arrivals Resiliency Results

PORT OF CALL	ABSORPTION	DISRUPTION	RECOVERY	RESILIENCE
MIAMI	0.156	1.000	0.874	0.136
EVERGLADES	0.177	0.800	0.861	0.122
W. PALM BEACH	0.126	1.000	0.874	0.110
JACKSONVILLE	0.500	0.600	0.705	0.211
SAVANNAH	0.295	0.500	0.942	0.139
CHARLESTON	0.205	0.600	0.895	0.110
AVERAGE	0.243	0.75	0.859	0.138
REGIONAL	0.161	1.000	0.90	0.145

4.2 Average Daily Dwell Times

Figure 1 provides the average daily dwell times for the study ports and the region. The x-axis provides the date and the primary y-axis shows the average daily dwell times for the six study ports. The secondary y-axis shows the average daily dwell time for the region, as a whole. Hurricane Matthew began impacting regional dwell times on October 4, 2016. This was evident in a sharp spike in average daily dwell times. Diminished dwell times continued until landfall, corresponding with port closures. However, as the ports reopened, dwell times began their accent to normalcy, signifying a brief disrupted state on a regional level. By October 11, 2016 regional dwell times generally returned to their pre-storm levels.

Figure 6: Containerized Cargo Vessel Average Daily Dwell Times

Table 2 provides the resiliency results for containerized cargo vessel average daily dwell times. In general, the study ports struggled to absorb the impact of the storm and subsequent closures. However regionally, the absorption value was significantly higher than five of the six study ports. The Port of West Palm Beach was the only individual port able to absorb the impact of the disruptive event at a higher level than the region as a whole. The disruptive state at individual ports was in general, longer for average daily dwell times and for vessel arrivals. This may suggest that while ports may be able to receive vessels, their ability to handle cargo may still be inhibited. Interestingly, the regional dwell time showed no disruptive state, i.e. recovery coincided with the end of the absorption state. This was likely because while ports to the south were impacted by the storm first, they reopened sooner initiating a recovery while northern ports were still in the disrupted state. The resiliency at individual ports was generally lower for average daily dwell times when compared to vessel arrivals. However, the regional resiliencies were much closer in magnitude.

Table 2: Containerized Cargo Vessel Average Daily Dwell Time Resiliency Results

PORT OF CALL	ABSORPTION	DISRUPTION	RECOVERY	RESILIENCE
MIAMI	0.058	0.250	0.994	0.014
EVERGLADES	0.049	0.750	0.935	0.034
W. PALM BEACH	0.283	1.000	0.931	0.264
JACKSONVILLE	0.038	0.400	0.965	0.015
SAVANNAH	0.032	0.286	0.969	0.009
CHARLESTON	0.050	0.667	0.921	0.030
AVERAGE	0.085	0.559	0.953	0.061
REGIONAL	0.151	1.000	0.885	0.134

5. CONCLUSION

Ports play a vital role in the economy of nations and provide a critical link in the supply chain. Often times, ports form the gateway by which essential goods are received within large geographic regions. Because of their function, ports are exposed to substantial risk of flooding, storm events, sea-level-rise, and climate change. The resiliency of ports is essential for the economy, the people, and national readiness. The long term contribution of this research work is in providing a methodology to quantify port resiliency that is applicable at the individual port level and regionally.

In general, the results showed that regionally, ports are more resilient to disruptive events than the individual ports that make up the region. This was likely because as one port enters the disrupted state, another may be entering the recovery state or stable recovered state. An example of this was illustrated by the low resiliency values of individual ports and the significantly higher resiliency values for the region. This was an expected finding, because it was anticipated that port clusters rely upon each other during disruptive events to increase the overall resiliency of waterborne commerce.

Based on the findings of this research it is expected the proposed resiliency quantification methodology can be expanded to other systems and areas of science. Future researchers will be able to build upon this work by identifying a level-of-resiliency measure based on the quantification methodology described here. This could enable a level-of-resiliency rating between A and F similar to the level-of-service analysis for highway systems provided in the Highway Capacity Manual [25]. From an application perspective, it is apparent that a coordinated effort is needed to maintain the resiliency of waterborne commerce during disruptive events. For example, during a hurricane similar to Matthew containerized cargo vessels could be routed away from southern ports early as the storm threatens the southern region. As the event progresses, cargo deliveries bound for northern ports could be sent southward. A coordinated effort could bring about greater resiliency and an ease of transaction during times of unrest and uncertainty.

6. REFERENCES

[1] American Association of Port Authorities. (2015, April 21). Retrieved from https://www.aapa-ports.org/advocating/PRDetail.aspx?ItemNumber=20424

[2] Welshans, Krissa. (2015, June 1). "East coast ports gaining ground: supply chain users look to diversify to East Coast and Gulf ports after long-lasting labor dispute at West Coast ports." *Feedstuffs*. *Business Insights: Essentials*.

[3] Tomer, A., & Kane, J. (2015, July 1). The top 10 metropolitan port complexes in the U.S. Retrieved from https://www.brookings.edu/blog/the-avenue/2015/07/01/the-top-10-metropolitan-port-complexes-in-the-u-s/#cancelNOAA. (2008, October 27). Is sea level rising? Retrieved from https://oceanservice.noaa.gov/facts/sealevel.html

[4] NOAA. (2008, October 27). Is sea level rising? Retrieved from https://oceanservice.noaa.gov/facts/sealevel.html

[5] NOAA. (2015, June 1). Frequently Asked Questions. Retrieved from http://www.aoml.noaa.gov/hrd/tcfaq/E11.html

[6] Smythe, T. C., PhD. (2013, May 31). Assessing the Impacts of Hurricane Sandy on the Port of New York and New Jersey's Maritime Responders and Response Infrastructure. *Quick Response Report No. 238 to the University of Colorado Natural Hazards Center*. Retrieved from https://rucore.libraries.rutgers.edu/rutgers-lib/43635/PDF/1/play/.

[7] Farhadi, N., Parr, S. A., Mitchell, K. N., & Wolshon, B. (2016). Use of Nationwide Automatic Identification System Data to Quantify Resiliency of Marine Transportation Systems. Transportation Research Record: Journal of the Transportation Research Board, 2549(1), 9–18. https://doi.org/10.3141/2549-02

[8] National Science Foundation (NSF). (2016). Critical Resilient Interdependent Infrastructure Systems and Processes. Retrieved from https://www.nsf.gov/pubs/2016/nsf16618/nsf16618.htm

[9] Achuthan, Kamal. Improving Port Resilience: MARS. 2011, pp 1-2

[10] Morris, Lauren L., Tracie Sempier, Ports Resilience Expert Committee 2016. Ports Resilience Index: A Port Management Self-Assessment. GOMSG-H-16-001

[11] Seimpier, T.T., D.L. Swann, R. Emmer, S.H. Sempier, and M. Schneider. 2010. Costal Community Resilience Index: A Community Self-Assessment. MASGP-08-014.

[12] Wakeman III, Thomas; Miller, Jon; Python, Grace. Port Resilience: Overcoming Threats to Maritime Infrastructure and Operations From Climate Change. University Transportation Research Center-Region 2, 2015, pp i

[13] The Department of Homeland Security. Plan Integration for Resilience Scorecard. 2017, pp 1-2

[14] Rosati, Julie & Touzinsky, Katherine & Jeff Lillycrop, W. Quantifying coastal system resilience for the US Army Corps of Engineers. Environment Systems and Decisions. 2015, pp 2-14

[15] Molina Serrano, Beatriz; González-Cancelas, Nicoleta; Soler-Flores, Francisco; Camarero-Orive, Alberto. Classification and prediction of port variables using Bayesian Networks. Transport Policy, Volume 67, Issue 0, 2018, pp 57-66

[16] Wang, Hao; Nozick, Linda; Xu, Ningxiong; Gearhart, Jared. Modeling Ocean, Rail, and Truck Transportation Flows to Support Policy Analysis. Maritime Economics & Logistics, Volume 20, Issue 3, 2018, pp 327-357

[17] Bela, Pauline Laila; Habib, Muhammad Ahsanul. Urban Freight Network and Emission Modeling for Port City Halifax, Canada: A Spatial and Temporal Evaluation of Commercial Vehicles Movement. Transportation Research Board 97th Annual Meeting, 2018, 18p

[18] Chen, Longbiao; Zhang, Daqing ; Ma, Xiaojuan; Wang, Leye; Li, Shijian ; Wu, Zhaohui; Pan, Gang . Container Port Performance Measurement and Comparison Leveraging Ship GPS Traces and Maritime Open Data. IEEE Transactions on Intelligent Transportation Systems, Volume 17, Issue 5, 2016, pp 1227-1242

[19] Ducruet, César; Itoh, Hidekazu; Merk, Olaf. Time Efficiency at World Container Ports. International Transport Forum Discussion Papers, Issue 2014-08, 2014, 32p

[20] Layaa, John; Dullaert, Wout. Measuring and Analysing Terminal Capacity in East Africa: The Case of the Seaport of Dar es Salaam. Maritime Economics & Logistics, Volume 16, Issue 2, 2014, pp 141-164

[21] Zhao, Liangbin; Shi, Guoyou. A method for simplifying ship trajectory based on improved Douglas–Peucker algorithm. Ocean Engineering, Volume 166, Issue 0, 2018, pp 37-46

[22] Altan, Yigit C; Otay, Emre N. Spatial mapping of encounter probability in congested waterways using AIS. Ocean Engineering, Volume 164, Issue 0, 2018, pp 263-271

[23] Chen, Zhijun; Xue, Jie; Wu, Chaozhong; Qin, Lingqiao; Liu, Liqun; Cheng, Xiaozhao. Classification of vessel motion pattern in inland waterways based on Automatic Identification System. Ocean Engineering, Volume 161, 2018, pp 69-76

[24] Zhang, L., Meng, Q., Xiao, Z., & Fu, X. (2018). A Multi-Regime Vessel Trajectory Reconstruction Model for Ships in Port Waters Using AIS Data. Transportation Research Board 97th Annual Meeting Compendium of Papers. Retrieved from https://trid.trb.org/view/1496102

[25] Transportation Research Board. “HCM 2010 Highway Capacity Manual.” National Research Council, Washington D.C., 2010.