Extreme Weather Events and Critical Infrastructure Resilience: Lessons from Hurricane Irma in Florida

Shahnawaz Rafi[1], Joost Santos[2], Sisi Meng[3] and Pallab Mozumder[4]

Abstract

[1] Department of Economics, Department of Earth and Environment and Institute of Environment, Florida International University, Miami, Florida, USA. Corresponding author. Email: srafi004@fiu.edu. ORCID ID: https://orcid.org/0000-0002-3482-9728.
[2] Engineering Management & Systems Engineering, George Washington University, Washington DC, USA. Email: joost@gwu.edu. ORCID ID: https://orcid.org/0000-0001-5092-543X.
[3] Keough School of Global Affairs, University of Notre Dame, Notre Dame, Indiana, USA. Email: smeng@nd.edu. ORCID ID: https://orcid.org/0000-0003-0677-2717.
[4] Department of Earth & Environment, Department of Economics and Institute of Environment, Florida International University, Miami, Florida, USA. Email:mozumder@fiu.edu. ORCID ID: https://orcid.org/0000-0001-9675-6176.

Severe weather events like hurricanes can severely impact the local economy. They disrupt vital services such as power, communication, and transportation. This study evaluated business sector operation loss in Florida due to disruption in seven critical infrastructure systems following Hurricane Irma's landfall in 2017. These sectors included disruptions in electricity, water, phone, internet, transportation, workplace, and grocery access. A household survey of Florida residents across 14 Metropolitan Statistical Areas (MSAs) provided the extent of disruption in each infrastructure system. Then, the household survey responses (percentage of respondents experienced the specific type of disruption and average days of that disruption) were incorporated into the Dynamic Inoperability Input-Output Model (DIIM) to assess the impact of these disruptions on Florida's 71 interconnected business sectors. The total estimated projected business sector loss from the DIIM ranges from $3.66 to $5.30 billion depending on the assumption made with respect to the number of working days. This study highlights the business sector recovery and resilience due to critical infrastructure system failure and provides insights regarding the resilience of each sector and their inherent interdependencies. The findings can be valuable to policymakers for disaster preparedness and recovery planning for future extreme weather events.

Keywords: Resilience, Inoperability, Input-output Model, Infrastructure, Utility Disruption.

JEL Classification: Q50, Q54. R11, R12, R15

1. Introduction

On September 10, Hurricane Irma landed in the Florida Keys as a Category 4 Hurricane. The storm passed north toward central Florida. It brought winds exceeding 130 mph and 10-15 feet of surge and flooding (Charlie, 2017). The hurricane caused widespread damage across South Florida. Over three-quarters of electric power customers in Florida experienced power outages for about a week, and the western areas faced the heaviest impacts, such as infrastructure damage and flooding (National Weather Service, 2018). The resulting monetary loss from the hurricane's impact on the State of Florida was estimated to be around $50 billion (NOAA NCEI, 2020).

Recently, extreme weather events and their repercussions on the economy have increased. For example, prolonged and widespread power outages, as seen during the 2017 Atlantic hurricane season, are notable examples of recent extreme weather events (Larsen et al., 2020). These events result in widespread infrastructure damage, inefficiency of utility systems (electricity, water, phone, etc.), and cascading economic impacts. These extensive power outages and consequential disruptions in critical infrastructure can hinder the recovery of households and communities by limiting access to vital facilities and services (Mitsova et al., 2021). Urban safety management relies on the resilience of Critical Infrastructures (CIs), which are vital components of urban technological systems, especially during crises or disasters (Yang et al., 2023). Hence, evaluating the well-being of households affected by the disruption of critical infrastructure and utility services due to Hurricane Irma is of utmost importance.

Infrastructure systems are essential to maintain sustainable development, especially ensuring optimal operation under uncertainty, focusing on maximizing availability, safety, and cost efficiency (Sánchez-Silva et al., 2016). Efficient operational infrastructure is vital for the economy, impacting regional industries, as critical infrastructures are interconnected physically, functionally, economically, geographically, or logically (Rafi et al., 2024; J. Santos et al., 2023).

Interdependencies within critical infrastructure, such as electric power, transportation, and energy systems, can intensify the risk of catastrophic consequences; a local failure due to extreme weather events quickly proliferates across the entire network, aggravating the vulnerability of the whole system (Gong et al., 2023). Modeling and evaluating infrastructure operations can analytically assess the consequence of losing infrastructure components, promoting operational resilience (Alderson et al., 2015). Therefore, judging the resilience of CIs is crucial for effective adaptation strategies, evaluating costs and benefits for informed resource allocation decisions, and understanding CIs vulnerabilities and capacities after extreme weather events (Amer et al., 2023).

Hurricane Irma caused considerable economic damage to the State of Florida's economy. One of the factors that caused that damage was the prolonged disruption of the utility system in the post-Irma period. There is also a significant distinction between the definitions of damage and loss. Damage is a comprehensive measure of loss, including infrastructure, buildings, and housing. Meanwhile, loss related to utility disruption directly impacts the productive sectors of the economy that depend on them.

This study emphasizes the need to incorporate household experience of utility disruption into regional impact models such as the Input-Output Model (IOM). It highlights the need to implement effective measures and policies to mitigate the consequences of prolonged utility system outages in vulnerable areas. The research attempts to analyze the impact of utility outages on interconnected critical infrastructure systems and estimate the resulting cascading economic losses using Hurricane Irma in this empirical study.

The data for this study came from a household survey of Hurricane Irma-affected households in Florida.[5] The survey collected information on the proportion and duration of utility system outages. In any regional GDP component, the sector is an industry that produces certain goods or services. In this study, the individual GDP sector measures the impact of Hurricane Irma on the Florida economy. We collected the Florida sectoral GDP data from the Bureau of Economic Analysis (BEA) to calculate that impact. The proportion and duration of disruption were incorporated as micro information into the Dynamic Inoperability Input-Output Model (DIIM), a macroeconomic model, to measure inoperability (inefficiency) and economic loss at the sector level of GDP. The survey information is a link to examine the macroeconomic repercussions of household hurricane-induced utility disruption experience from an inoperability-based IOM.

The paper proceeds as follows. Section 2 discusses literature related to research and methods of analyzing utility disruption damage. Section 3 investigates the motivation of this study, discusses survey details, and describes the DIIM. Section 4 describes descriptive statistics of the survey sample, integrated simulation results, and sensitivity analysis between 252 days (i.e., weekends excluded) and 365 days per year of economic loss assessment. Section 5 presents a discussion of the key findings of our research. Section 6 concludes the paper.

2. Literature review

Utility disruptions after a major hurricane can jeopardize the regular operation of critical infrastructure systems at a location, which further delays recovery efforts in the affected areas. Critical infrastructure systems are susceptible to future weather extremes and climate change due to high costs and increased frequency of extreme weather events, as evidenced by recent

[5] In 2020 the household survey was collected under the National Science Foundation (NSF) funded Organizing Decentralized Resilience in Critical Interdependent Infrastructure Systems and Processes (ORDER-CRISP) project.

disasters (Brody et al., 2019). Hence, studying post-disaster recovery shows that factors like property damage, infrastructure disruption (electric power, communication services), insurance coverage, disaster assistance, and income loss can significantly predict recovery outcomes (Mitsova et al., 2019).

Several methods have been used to assess utility disruption's impact on the local economy. Over the years, there have been methodological developments for measuring the damage and impact of utility disruption after extreme weather events. In general, impact assessment models are categorized as either 'retrospective,' which analyzes economic data post-disaster to identify impacts, or 'prospective,' which simulates consequences by describing the 'normal' economic situation and utilizing disaster data to model hypothetical events (Jahn, 2015; Rose, 2004). Under the prospective category, Computable General Equilibrium (CGE) models and Input-Output Models (IOMs) have been widely used to predict the cascading impact of utility disruption damage.

A CGE model can assess the impact of utility disruptions on various sectors, including industries that rely on a consistent power supply, potentially causing a ripple effect. CGE models have been used in the past to predict economic damages due to extreme weather event disruption on utility systems such as electricity (Baik et al., 2021; Rose & Guha, 2004; Wing & Rose, 2020), water (Rose & Liao, 2005), transportation networks (Z. Chen & Rose, 2018; Tatano & Tsuchiya, 2008; Wei et al., 2022), telecommunications (Sue Wing et al., 2022), and supply chains (Tokunaga et al., 2013). In contrast, IOM uses industry-specific fixed coefficients to measure the cascading effect of utility system disruptions. Hence, IOMs could not capture substitution behavior (time dimension), and they neglected prices and factor market adjustments

(Wing & Rose, 2020). Therefore, IOMs have limitations in the regional impact measurement due to an exogenous shock.

To tackle the limitations of IOMs for regional impact modeling, Santos and Haimes (2004) developed the Inoperability Input-Output Model (IIM). This model, which characterizes economic interdependence, has been spatially extended using an interregional model instead of the traditional single-region model (Koks et al., 2016). IIMs are based on Leontief's IOM, which characterizes economic interdependence and analyzes the resulting ripple effects based on initial disruptions to sectors (Haimes et al., 2005a). At the same time, the Dynamic Inoperability Input-Output Model (DIIM) applies similar principles by portraying the temporal behavior of economic impacts linked to disruptive events and ranking the affected systems by economic loss and inoperability (Santos, 2006).

The DIIM is extensively utilized to assess the economic repercussions of infrastructure system disruptions, particularly in extreme weather events. Electricity disruptions, as exemplified by H. Chen et al. (2022) can lead to substantial business interruption costs, with losses estimated at 1.44 billion yuan in China's provincial outage event. Furthermore, extensions of DIIM have been applied to evaluate water supply disruptions, such as droughts, as seen in the work of Pagsuyoin & Santos (2021), who found significant economic losses in the utility and real estate sectors. Workforce disruptions due to pandemics and extreme weather events have also been scrutinized using DIIM, revealing higher losses in sectors dependent on physical workforce presence, as shown by studies like El Haimar & Santos (2014) and Santos et al. (2022). For instance, in a simulated low-intensity hurricane scenario, workforce absenteeism led to an estimated economic loss of approximately $410 million across various industry sectors in Virginia (Akhtar & Santos, 2013). Thus, DIIM has emerged as a robust methodology for quantifying the economic impacts of critical infrastructure disruptions caused by extreme weather events.

3. A Case Study of Hurricane Irma

3.1. Motivation

Hurricane Irma, a category 4 hurricane, made dual landfalls on September 10, 2017, in the Florida Keys and Marco Island. It marked Florida's first major hurricane landfall since Hurricane Wilma in 2005, and the storm's northward track brought significant statewide impacts from the winds, rain, or storm surge (Wang, 2018). The storm had maximum sustained winds of 132 mph and surges of up to 8 feet in the hardest-hit areas in the Lower and Middle Keys (Hurricane Irma Recovery, 2018).

The storm left trails of destruction across its track in Florida. Around 65% of homes in the Florida Keys sustained major damage, with 25% destroyed and a potential 15-foot surge flooding projected along the Southwest coast of Florida (Monnette, 2017). Irma was the fifth-costliest US mainland hurricane, causing $50 billion in damage, 6 million Floridians evacuated, and 129 deaths (Huber, 2018).

The cascading impacts of Hurricane damage affected household access to essential utility services. The forefront of household distress was the electricity outage. Hurricane Irma, on the day of landfall, left 6.7 million electricity customers without power, impacting 64% of all customer accounts in the State (Hodge & Lee, 2017). The transmission system across Florida suffered significant damage, and the restoration of electricity needed time. The electricity companies had to hire workers to expedite the restoration process. About 12,000 utility technicians worked in Florida to restore power, some coming from as far away as Canada and the West Coast (Griffin & Johnston, 2017). Despite outsourcing technicians, Duke Energy Florida and Florida Power Light (FPL) predicted to restore power to most customers by Sunday, a week after Irma's first landfall in Florida (Sullivan et al., 2017).[6]

Irma's path covered a large portion of the State, affecting cities such as Miami, Naples, and Tampa. The Florida Keys, a chain of islands, were particularly hard-hit, significantly damaging infrastructure and homes. The storm surge and heavy rains led to extensive flooding in various regions, exacerbating the overall impact. The power supply is essential for post-hurricane recovery and rebuilding initiatives. Hurricane Irma left 1.3 million Florida residents without power during the first four hours after landfall (Monnette, 2017). Over 70 percent of the State lost electricity due to heavy rains and wind, resulting in an estimated $50 billion in wind and water damage (Teamcomplete, 2020).

The supply chain system was abruptly damaged due to property damage and road closures, further impeding the gas station's functionality and fuel supply. Feito & Ballard (2022) pointed out that the aftermath of Hurricane Irma distress intensified; over 43% of Florida gas stations were dry or out of service, particularly 60 percent of gas stations in cities like Gainesville and Miami-Fort-Lauderdale faced supply shortages.

Hurricane Irma caused power failure in Florida, which led to water contamination. Power loss at water treatment facilities leads to sewage problems, with over 300,000 gallons of partially treated effluent released in Clearwater Creek and 30,000 gallons of raw sewage in Miami-Dade County parks (Phoslab, 2018). Hence, it prompted the Department of Health to issue boiling water notices and water advisories due to elevated Enterococci bacteria levels, highlighting the potential health impact of widespread sewage leaks (Krimsky, 2017).

[6] Duke Energy Florida, formerly known as Florida Power, provides electricity to central and north Florida. Meanwhile, FPL supplies electricity to areas along the east coast of Florida, excluding Jacksonville and four other cities that have municipal electric systems.

Hurricane Irma posed an unprecedented challenge for Florida's local government, requiring the largest evacuation in the State's history with 6.5 million people and approximately 4 million vehicles, leading to widespread traffic jams across the entire State. Feng & Lin (2021) analyzed smartphone data-based traffic flow across all Florida highways during Irma and found catastrophic congestion throughout the State peak evacuation flows from Tampa and Miami in the Orlando region. Traffic congestion increased a surge in fuel demand. Subsequent infrastructure challenges, exacerbated by the storm's impacts on ports, roads, and power, led to difficulties in Florida's fuel distribution and supply chain resilience (FDOT, 2018).

Communication services are vital for managing evacuation, recovery, and resilience, especially in the coastal areas of the US. The operation of the internet and phone is dependent upon the power supply. In Florida, 24.6 percent of cell sites were out of service on September 11; despite the pitfall, providers such as Comcast, AT&T, Charter, CenturyLink, and Frontier worked to maintain connectivity in Hurricane Irma-affected areas (Brodkin, 2017). The Federal Communications Commission reported over 7 million subscribers without Internet, TV, or phone service in Alabama, Florida, and Georgia, and three counties (Collier, Hendry, and Monroe) had 50% or greater of cell sites out (FCC, 2017)

Given the utility system outages and ensuing economic challenges in Florida, we aim to analyze the scale of Hurricane Irma-induced utility disruptions. This identification process allows for a thorough examination of the impacts of these disruptions, shedding light on their consequences for the GDP of various business sectors and the subsequent economic losses incurred.

3.2. Survey Data

This study data was collected from a household survey in Florida. The survey gathered data on household utility disruption and recovery. This paper aims to measure the impact of utility system disruption on the business sectors, using survey information collected at the household level. In September 2020, the online data management company Qualtrics XM conducted the survey in Florida after we received the Institutional Review Board (IRB) approval from Florida International University (FIU). The Qualtrics team maintained the integrity of the data collection processes by dropping responses with erroneous or incomplete household information.

The study sample comprises 780 randomly selected households affected by Hurricane Irma in Florida. We resorted to associating the sample at the Metropolitan Statistical Area (MSA) level. MSAs usually comprise a core city with a large population and its surrounding region, including several adjacent counties typically marked by significant social and economic interaction (GANTI et al., 2022). The sample from 14 MSAs along the Hurricane Irma track was chosen to ensure it accurately represents the state population.

The 14 MSAs were selected based on shared boundaries with each other. We geolocated the respondents into 14 MSAs using longitude and latitude information from the survey. Hence, we determined a representative sample size of 588 survey respondents from the fourteen MSAs, as shown in Table 5. We computed the proportions and average utility disruption days from the Hurricane Irma household survey. Figure 1 depicts the distribution of the selected household units in Florida.

Survey data can provide important information for analyzing the effects of natural disasters on households, regions, and the nation. Although challenging to implement, survey data provide precise details on how extreme weather events affect households, thereby enhancing the impact modeling capacity. By incorporating information from the Florida household survey into the DIIM model, we can better assess the economic effects of utility service disruptions caused by extreme weather. This assessment covers the immediate impacts on households and the ripple effects on businesses and the economy. It is essential to systematically document the diverse experiences of sub-populations within a community resulting from infrastructure disruptions to emphasize household needs and disparities (Dargin & Mostafavi, 2020). Furthermore, community factors offer crucial insights into vulnerability to service disruptions, guiding infrastructure prioritization and emergency responses to mitigate societal impacts on vulnerable populations (Coleman et al., 2020).

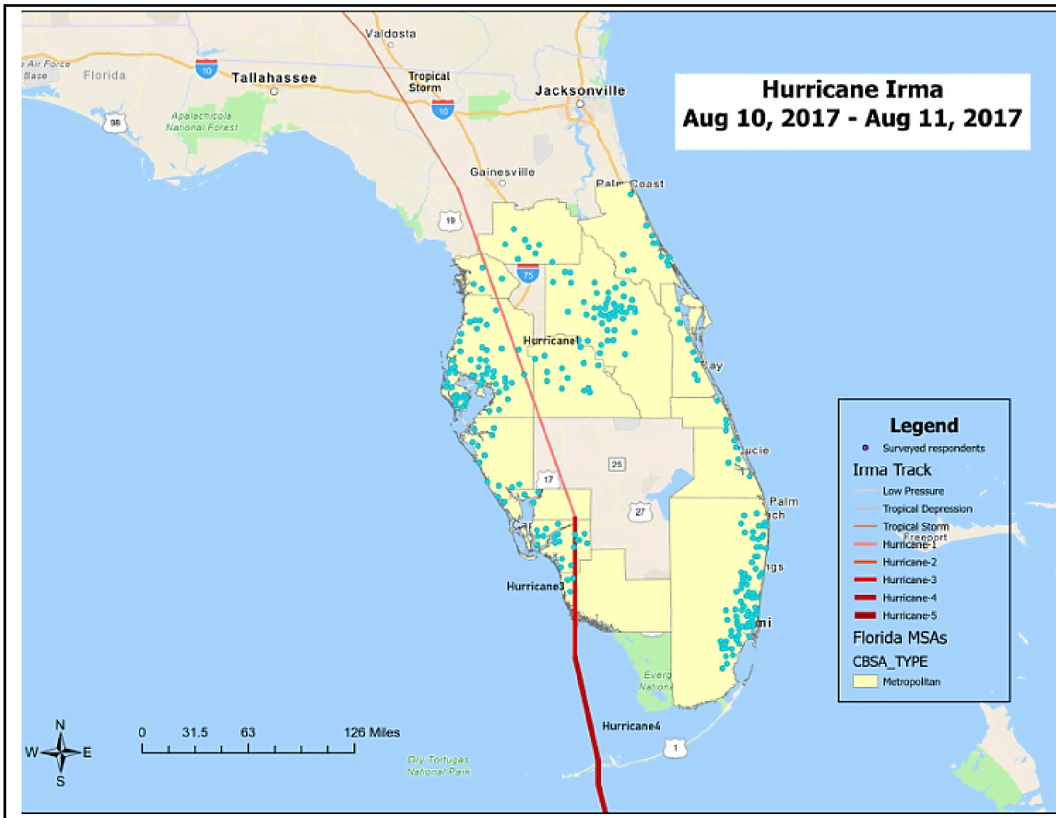

Fig. 1. Distribution of household units from the Hurricane Irma household survey.

The survey-DIIM data integration can also capture the heterogeneity of household disruptions and be utilized in policy frameworks for extreme weather risk mitigation. The heterogeneity of household utility disruption behavior can vary in income, preferences, behavioral rules, or social position (Castro et al., 2020). The survey-DIIM model can analyze individual household behaviors and the interaction of heterogeneous agents at the micro-level, providing valuable insights into the global climate of utility disruption. (Rai & Henry, 2016).

Thus, our DIIM incorporates details of utility disruption from various household groups based on location and socio-economic factors to simulate and quantify economic ripple effects. This micro-level approach to connect the broader financial landscape helps understand how utility disruptions impact diverse economic sectors.

3.3. Inoperable Input-Output Model

Leontief's (1936) IOM helps researchers understand how different parts of an economy are connected. The linear IOM was generalized into a generic risk (with the dynamics of risk of inoperability) model by Haimes & Jiang (2001) to predict how a change in one segment of the economy will affect another. This extension of IOM is known as the Inoperability Input-Output Model (IIM). The subsequent development of IIM by Haimes et al. (2005b) can analyze initial disruptions to a set of interdependent sectors and the resulting ripple effects. Santos and Haimes (2005) then updated the "inoperability" metric in IIM to quantify a sector's production deviation from the desired level. This metric facilitates and visualizes a multi-criterion ranking of industries based on economic loss and inoperability.

This paper measured the economic resiliency of interconnected sectors in Florida after Hurricane Irma. It used a household survey integrated with the DIIM framework developed by Santos et al. (2023). The goal was to understand the sectoral ripple effects. A similar methodology was used by Rafi et al. (2024) to measure the intersectoral cascading impact in Houston, Texas, due to Hurricane Harvey's landfall in 2017. Hence, this household-survey-DIIM survey integration model is a new addition to the DIIM literature to measure the ripple effects of extreme weather events on interdependent and interconnected sectors.

The central idea of DIIM is based on the concept of inoperability. Inoperability is defined as the industry sector's loss of production normalized with respect to its pre-disaster level due to disasters. It is measured on a scale from 0 to 1. A value of 0 means an industry sector is operating on "business as usual" levels, while one implies complete failure. The generalized equation of the DIIM model is as follows,

$$q(t+1) = q(t) + K\left[A^{*}q(t) + C^{*}(t) - q(t)\right] \text{..................}(1)$$

Equation (1) has four components: ***q(t+1)*** is the inoperability vector at time *t+1*, ***q(t)*** is the inoperability vector at time *t*, ***K*** is the sectoral resilience matrix, and ***A**** is the interdependency matrix between sectors. ***C*(t)*** represents the demand fluctuation at time *t*.

The data integration process combined BEA input-output tables with Florida Household survey data. This process provided insights into the proportion and duration of utility disruptions after Hurricane Irma. The survey focused on affected areas and used probability-based sampling. This integration thus helps us understand the impact of the hurricane on regional economic activity and how it affected Florida households. It connects industry-level flow with household-level disruptions.

We combined these statistics to study the impact of business sector disruptions on households. We can also analyze post-disruption duration and recovery patterns and assess the local economy's resilience. This technique helps us find which sectors are most at risk and which can affect policy decisions. Balancing the demand and supply when recalculating a supply-use table for the Florida economy is vital in DIIM analysis. We did this by iteratively updating the values, starting with the commodity or industry with the most significant difference between supply and demand. We keep the table's original structure while recalculating the supply-use table.

We considered the location quotient (LQ) in the supply use table calculation to accurately reflect regional economies' industrial specialization. LQ compares the concentration of an industry within a specific area to the concentration of that industry nationwide (Wise, 2022). An LQ value of 1 denotes the industry's local area concentration aligning with the national average, while an LQ greater than 1 indicates a higher local concentration than the national average. For example, the LQ value for housing in our DIIM was 1. Rental and leasing services and lessors of intangible assets were 0.93. Hence, they align their industrial concentration with the national average.

Now, we can compute the base inoperability. $q_i(t)$, by estimating the dependency per unit of output ratio $\left(\frac{w_i}{x_i}\right)$, multiplied with the time-varying demand disruption factor $d_k(t)$. Where w is the weight of the expenditure of each industry, and x is the output of each sector. After the simplification process, the following equation denotes the matrix-vector formulation of the base inoperability ***q***,

$$q = d_k(t) * (diag(x))^{-1} w \text{..............(2)}$$

Where $(diag(x))^{-1}$ is the diagonal of the output vector of all sectors.

The household survey gave us the proportion and duration of utility system disruption. Specifically, $d_k(t)$ comes from the proportion of disruption, and K comes from the duration. We replace the pre-hurricane inoperability in equation (1) with the inoperability from equation (2). Equation (3) then calculates the inter-sector interdependent inoperability at time $t+1$.

$$q_1 = d_k(t) * (diag(x))^{-1} w + K\left[A^* d_k(t) * (diag(x))^{-1} w + C^*(t) - d_k(t) * (diag(x))^{-1} w\right] \text{......(3)}$$

We acquired Florida 14 MSA GDP data with 92 sectors from the BEA. Adapting it to the 71 sectors of the DIIM model for Hurricane impact analysis, we converted the data to 2017 dollars. Due to missing sectoral GDP data in some MSAs, we substituted it with standardized Florida GDP data. The process involved recalculating the proportions of 71 sectors in Florida's GDP compared to the US sectoral GDP in 2017 dollars, then multiplying these proportions by the total GDP of 14 MSAs in 2017 dollars to address the gaps.

The DIIM model has a Graphical User Interface (GUI) feature. The GUI needs two parameters per disruption: proportion of household affected and duration. These parameters come from survey data. Adjusting the parameters of seven utility systems in the GUI creates plots that show inoperability and economic losses over time. Detailed calculations using equations (1)-(3) make the plots and a summary of each sector's economic loss and inoperability. Integrating household-level data of utility systems improves the accuracy of regional impact modeling.

This study analyzes integrated disruptions in Florida's seven utility sectors. The DIIM model in this study compares recovery periods for standard five-day (252 days per year) and extended seven-day work (365 days per year) weeks. The DIIM model's graphical interface estimates and ranks sectors by the highest dollar amount of loss using disruption duration and proportion. The study only focuses on business interruption losses and does not include costs for property damage or property values like housing and buildings.

4. Results

4.1. Results from the Household Survey Data

This study surveyed households affected by Hurricane Irma in Florida. A total of 780 households participated in the survey. The survey gathered detailed information about the damage caused by the hurricane, people who evacuated, and people who experienced utility disruptions. For this paper, we chose 588 people from the 14 MSAs in Florida. They make up 75 percent of the total survey participants.

The survey data shows that respondents in Florida come from a wide range of demographic backgrounds. These people included different ages, genders, marital statuses, ethnicities, education levels, political affiliations, employment statuses, income brackets, homeownership, and housing types. Table 6 shows the demographic profile of survey participants in Florida. It provides an overview of the main characteristics of the respondents. The age distribution among participants is diverse. Most participants are between 30 and 44 years old (40.14%). The second largest group comprises those aged 60 and above (22.62%). The average age of the surveyed population is 44 years.

Regarding gender, the survey shows that slightly more females participated, making up 56.46% of the respondents. Males accounted for 43.31%. When it comes to marital status, the participants were diverse. 50.34% identified as married, 24.32% as single, and 25.34% fell into other categories. Most of the surveyed population in Florida is White and non-Hispanic (76.87%). Hispanic participants comprised 11.39%, Black participants comprised 7.99%, and a smaller percentage fell into the "Others" category (3.75%).

The survey results represented various educational backgrounds; 45.95% have a bachelor's degree or higher. 18.03% have completed high school or its equivalent. 28.23% have some college education but no degree. 5.44% fall into the "Others" category and 2.55% fall into less than high school. The survey also includes diverse political affiliations; 37.25% identify as independent. Among those with clear political leanings, 21.43% consider themselves liberal, 9.69% highly liberal, 20.92% conservative, and 10.71% very conservative.

The survey also shows the breakdown of employed (54.93%) and unemployed (45.07%) participants. Income varies with different brackets. While some participants (24.15%) reported no income, the median income ranges from $60,000 to $63,000. Other income brackets include participants earning less than $17,999 (22.11%), $18,000 - $35,999 (22.96%), $36,000 - $77,999 (21.26%), $78,000 - $119,999 (9.52%), and more than $120,000 (22.11%). Most participants (70.26%) are homeowners, and the rest (29.74%) are renters. As for housing type, the majority (57.14%) live in attached single-family homes, followed by detached single-family homes (25%). The remaining 17.86% fall into the "Others" category.

From the household survey, we collected information on seven types of utility disruptions: electricity, water, phone, internet, public transportation, workplace, and grocery stores. We gathered data on each disruption's proportion (percentage) and duration (mean). The proportion of disruption in each utility system is computed by multiplying the frequency of disruption experiences in each MSA by the respective MSA GDP weight (Table 7). Furthermore, we estimated the duration of each disruption by multiplying the MSA GDP weight with the mean value of the number of disruption days (by MSA).

Table 1. Summary of Utility Services Disruptions.

Service Systems	**Disruption (percent)**	**Duration (days)**
1. Electricity	77	5
2. Water	43	5
3. Phone/Cell phone	47	6
4. Internet	69	6
5. Public transportation	48	6
6. Workplace	60	7
7. Grocery stores	61	6

The proportion and duration of each utility disruption acted as the initial inoperability and recovery parameters in our DIIM model. The duration of each utility disruption was vital for the household recovery period. Our analysis then identified the top ten critically affected industries based on their economic loss and interoperability. Table 1 provides baseline information on utility disruptions: inoperability (proportion) and duration (recovery parameter).

Table 1 shows the proportion and duration of the disruption of seven impacted sectors. We incorporated this information in the DIIM simulation module. The DIIM's built-in graphical user interface (GUI) then calculated and ranked the top ten industries that suffered the most loss and those that were the least efficient. The GUI also generated plots that showed how inoperability and economic loss changed over time during the recovery period. The economic losses for Florida were valued using 2017 dollars to align with the year that Hurricane Irma occurred. In the following subsection, we discussed results from the integrated sectors.

4.2. Results from Integrated Sector Analysis

The integrated systems analysis is a DIIM simulation that assumes Hurricane Irma simultaneously impacted interdependent infrastructure and utility systems. The simulation process computes each business sector's loss and inoperability with the availability of data from the household survey, the proportion of utility disruption (base inoperability), and the duration of the disruption. The built-in graphical tool GUI then creates graphs of loss and inoperability based on a preset recovery period. The recovery window period was set at 365 days a year to predict performances in the top ten sectors' loss and inoperability. Table 2 shows the integrated sector analysis for the loss and inoperability of the top ten industries.

Table 2 shows the top ten industry losses and sectors that cannot operate at the pre-hurricane level after the landfall. The predicted 71-integrated business sectors' loss was \$3.66 billion. Our analysis found that individual insurance carriers and related activities topped the economic impact list with \$339 million, followed by miscellaneous professional, scientific, and technical services (\$326 million). The combined total predicted loss of the federal government enterprise and Federal Reserve banks, credit intermediation, and related activities was $359 million.

Table 2. Top Ten Inoperable Sectors and High-impacted Industries.

Top ten sectors based on inoperability	**Inoperability score (10^{-3})**	**Top ten sectors based on economic loss**	**Economics Loss ($ million)**
Administrative and support services	6.39	Insurance carriers and related activities	339
Forestry, fishing, and related activities	5.71	Miscellaneous professional, scientific, and technical services	326
Warehousing and storage	5.43	Legal services	230
Primary metals	4.99	Federal government enterprises	214
Management of companies and enterprises	4.64	Chemical products	196
Other transportation and support activities	4.61	Computer systems design and related services	145
Miscellaneous professional, scientific, and technical services	4.38	Federal Reserve banks, credit intermediation, and related activities	145
Insurance carriers and related activities	4.06	Food and beverage stores	96
Computer systems design and related services	3.90	Broadcasting and telecommunications	88
Apparel and leather and allied products	3.85	Waste management and remediation services	83
		Total Loss (includes top 10 + remaining 61 sectors)	**3,656**

The legal service industry had a predicted loss of $230 million and was the third from the top of the loss. Hurricane Irma considerably impacted grocery stores' access, primarily related to food purchases. Hence, simulation results from the DIIM showed that disruption to grocery stores, such as Food and beverage stores, had suffered a $96 million loss. Telecommunications are vital for post-disaster recovery initiatives. The total business sector in-operation loss of the Broadcasting and telecommunications sector is $88 million, which indicates that the recovery process was compromised.

Other industries within the top ten include Chemical products ($196 million), Computer systems design and related services ($145 million), and Waste management and remediation services ($88 million). The chemical sector is the only manufacturing sector in the top ten list. Eight out of the top ten impacted business sectors were service sectors, accounting for 43% ($1570 million) of the total 71 business sector losses. The dominance of the service sector loss in the top ten list compels us to analyze the service and manufacturing sectors in-depth. We separated the business and service sectors and created two Tables, 8 and 9, for manufacturing and service sector loss performance in post-Hurricane Irma time. The projected service sector loss was $2079.36 million. The combined manufacturing sector loss is $678.55 million. The service sector loss was 3 times bigger than the manufacturing sectors. Furthermore, out of the total loss ($3656 million) of 71 industries, the service sector alone accounted for 57 percent. Hence, Hurricane Irma had a dominant impact on the service sector, leading to substantial business sector loss.

Table 2 also highlighted the top ten inoperable sectors four days after Hurricane Irma's landfall. We observed that the inoperability scores ranged between 0.39 to 0.64 percent, which indicated the magnitude of post-hurricane efficiency loss in each industry. Administrative and support services had the highest inoperability (0.64%), which means this sector was most vulnerable to Hurricane Irma's impact. On the other hand, the apparel and leather and allied products had the lowest inoperability (0.39%), indicating they are relatively more resilient to withstand the hurricane shock.

Out of the top ten sectors of inoperability, only two sectors (the primary metals, apparel and leather, and allied products) represent the manufacturing sector, and the rest are service sectors. This pattern suggests that the service sectors may suffer substantially due to the disruption of critical utility systems. We separately tabulated the manufacturing and service sectors' inoperability in Tables 10 and 11 to assess their dominancy. We found that 23 manufacturing industries were inoperable, constituting 32% of the impacted industries. In contrast, 27 service sector industries were inoperable, comprising 38% of the affected sectors. We also analyzed the progression of inoperability across manufacturing and service sectors over the 365-day recovery period, as presented in Tables 10 and 11. In the manufacturing sector, inoperability ranges from 0.06 to 0.499 percent, while in the service sector, it varies between 0.020 and 0.639 percent. Upon closer examination of the manufacturing table, we observed that one industry was impacted at 0.4 percent and above, 14 industries between 0.20 and 0.40 percent, four industries between 0.10 and 0.20 percent, with the rest being less than 0.01 percent.

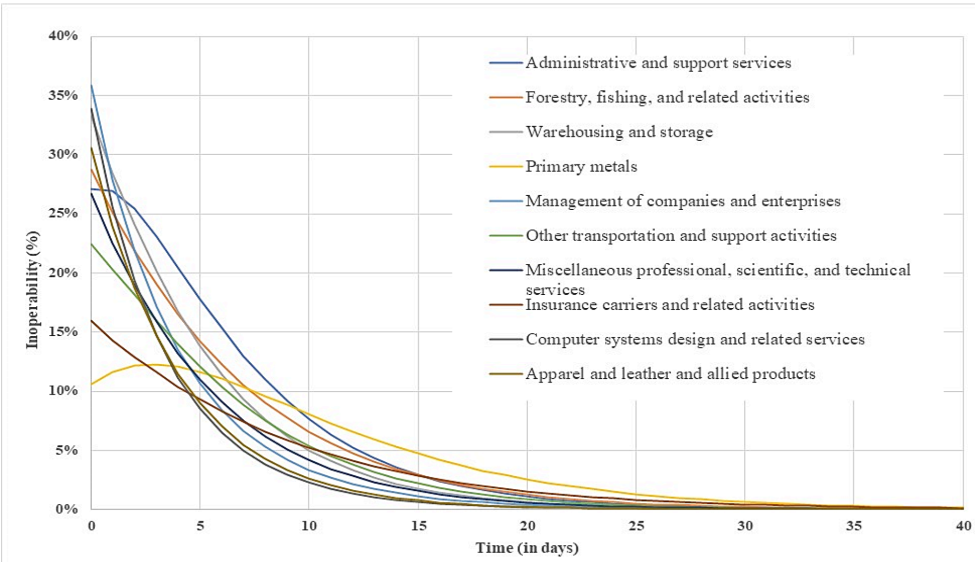

Fig. 2a. Florida's top ten inoperable sectors after Hurricane Irma's landfall.

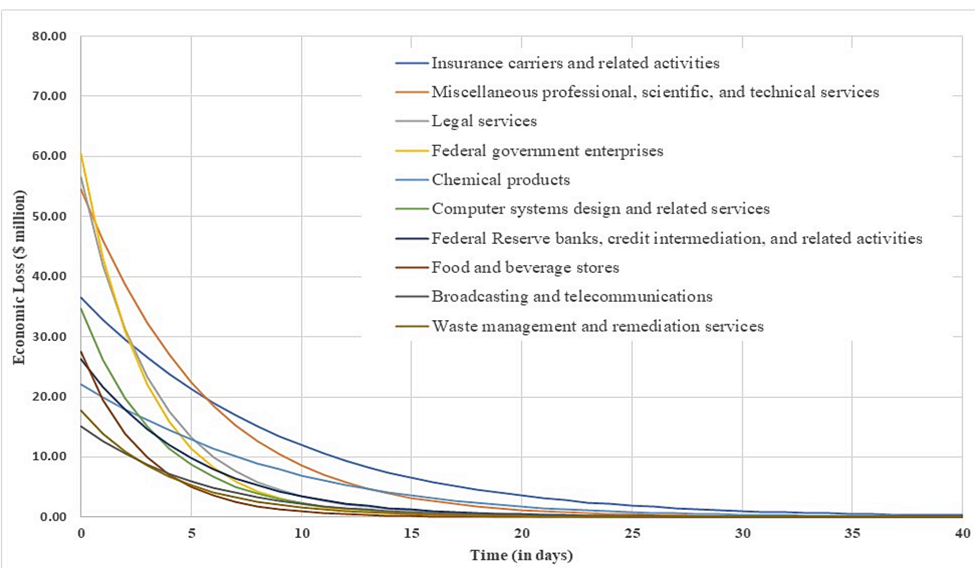

Fig. 2b. Florida's top ten sectors' loss after Hurricane Irma's landfall.

Fig. 2. Florida's top ten inoperable sectors and top ten impact sectors loss after Hurricane Irma's landfall.

In contrast, in the service sector table, five industries were above 0.40 percent, 23 industries between 0.20 and 0.40 percent, and two industries between 0.10 and 0.20 percent. Consequently, although the manufacturing sector's impact was smaller, it was less affected than the service sector. This analysis further supports the notion that Hurricane Irma predominantly affected service sectors, explaining why our total predicted business sector loss was approximately $3.66 billion. Figure 2a and Figure 2b illustrate the transition of inoperability and economic losses over the 365-day recovery period following Hurricane Irma's landfall. We readjusted the diagrams to a 40-day recovery period to reflect better predictive analysis. In Figure 2a, the top ten sectors unable to operate post-hurricane are listed, with percentages ranging from 10% (Primary metals) to 40% (Management of companies and enterprises). However, 30 days after Hurricane Irma's landfall in Florida, the operational capabilities of these sectors improved. Figure 2b presents a similar scenario for the top ten industries experiencing losses, showing a significant decrease after 20 days. These findings highlight the importance of disaster planning and the need for prompt support during extreme weather events.

4.3. Results from the Comparative Analysis of 365- vs. 252-day Recovery Windows

In this subsection, we conduct a sensitivity analysis comparing sectoral economics loss and inoperability across different recovery periods. For this comparative analysis, our DIIM simulation included the additional assumption of a five-day week or 252-day-a-year recovery window. This shorter recovery window allowed us to compare the performance of 71 sectors to a 365-day recovery period. This comparative scenario would help find whether there will be any changes in the distribution of sectoral performance.

Table 12 shows the comparison of inoperability between the two recovery periods. We observed similar inoperability patterns in both 252- and 365-day recovery periods. Furthermore, the inoperability value ranged between 0.39 and 0.64 percent in both periods. Again, the trajectory of inoperability shown in Figure 3 exhibits a similar reduction rate across Florida. A notable finding from this study is that, under the DIIM model, the value of inoperability appears to be independent of the recovery period in a region. This conclusion depends on comparing DIIM scenarios across different locations, making it challenging to ascertain the intra-regional variations outside the current study's scope. Therefore, further research is required to compare the inoperability patterns in each location in contrast to the aggregation of the 14 MSAs.

Table 3. Comparison of Top Ten Sector Losses in a 252- and 365-day Recovery Window.

365-day recovery window		**252-day recovery window**		
Top ten industries with economic loss	**($ million)**	**Top ten industries with economic loss**	**($ million)**	**Difference ($ million)**
Insurance carriers and related activities	339	Insurance carriers and related activities	491	152
Miscellaneous professional, scientific, and technical services	326	Miscellaneous professional, scientific, and technical services	473	147
Legal services	230	Legal services	333	103
Federal government enterprises	214	Federal government enterprises	309	95
Chemical products	196	Chemical products	284	88
Computer systems design and related services	145	Computer systems design and related services	211	66
Federal Reserve banks, credit intermediation, and related activities	145	Federal Reserve banks, credit intermediation, and related activities	211	66
Food and beverage stores	96	Food and beverage stores	138	42
Broadcasting and telecommunications	88	Broadcasting and telecommunications	127	39
Waste management and remediation services	83	Waste management and remediation services	120	37
Total Loss (includes top 10 + remaining 61 sectors)	**3,656**	**Total Loss (includes top 10 + remaining 61 sectors)**	**5,296**	1,640

Table 3 compares economic losses in the top ten industries between two recovery periods: 252 and 365 days a year. The selection of two different recovery periods does not change the ranking of the affected industries. We ran an additional simulation using a five-day week recovery window. We observed every single industry's economic loss value went up. For example, the Insurance carriers and related activities sector suffered a $339 million loss in the longer window, which increased to $491 million in the shorter window. The other sectors also experienced an increase in economic damage.

In the 252-day-a-year work window, the total economic impact is $5,296 million. This loss is $1,640 million higher than the total $3,656 million in the 365-day scenario. The top ten sectors alone contributed $835 million of the differences. The shorter work window may reduce operational time, potentially causing higher economic losses across industries. This difference demonstrates the importance of the length of the work window in disaster planning and risk management. These findings highlight how complicated the economic effects are during extreme events.

In Figure 4, we compared the economic loss pattern of the top ten sectors over recovery windows of 252 and 365 days. On both occasions, the top ten industries recuperated within the 30 days of Hurricane Irma's landfall. Furthermore, the economic loss ranking of the top ten sectors remained the same regardless of the recovery window. The apparent differences in $1640 million losses may be due to the slow recovery process across the 14 MSAs in Florida. Finally, we believe Hurricane Irma caused significant economic damage to Florida's economy. Based on our simulation, the loss in Florida ranged between approximately $3.66 billion and $5.30 billion.

5. Discussion and Policy Implications

The DIIM analysis in this paper examines the repercussions of Hurricane Irma-led utility systems disruption on the interconnected business sector in the Florida economy. The research uses an integrated DIIM simulation to predict losses and inefficiencies in business sectors. The simulation considers post-Irma base inoperability and disruption duration in the utility system disruption. The study reveals several key findings. The State of Florida is well known for insurance companies that have left the industry or been declared bankrupt due to Hurricanes. The

State is also famous for its tourism industry, with the Central Florida region generating $87.6 billion in impact on the state economy (VisitOrlando, 2023). Hence, we will justify the rationale for highlighting Florida's insurance and tourism sectors in our discussion section and validate the estimated dollar value of these sectors' losses with published results. These results will open a conversation on disaster planning tactics, economic resilience, and recovery strategies.

Florida's GDP amounted to $1.015 trillion in 2017, with the insurance sector contributing approximately 3% (BEA, 2023). Koch & Blake (2023) found a $27 billion loss for the insurance industry due to Hurricane Irma, which is 2.66 percent of the GDP. Our integrated DIIM simulation found that the insurance carriers and related activities sector incurred the highest damages, $339 and $494 million in the 365- and 252-day recovery period, approximately 9.27% of the total loss projections.

This 9.27% is the business sector loss of the insurance industry due to the interruption caused by the failure in the utility system. Whereas published results worth $13.1 billion (Cederburg et al., 2021), $35-55 billion (Külle & Gibson, 2018), and $20-$40 billion (Walsh, 2017) were the reported housing insurance damage claims. Hence, our estimated result is smaller than the published results. Note that the estimated losses from the DIIM only include business interruption losses, and most of the estimates published in the literature include property damage (i.e., physical damage to buildings and infrastructure and associated insurance claims).

The State of Florida is famous for its tourism industry: warm weather, beaches, national parks, and wildlife. In 2016, 113 million tourists (domestic & international) visited Florida (DINEEN, 2017), and the total revenue from tourism was $112 billion (Tampa Bay Times, 2018). This thriving tourism industry faced a significant setback after Hurricane Irma's landfall in 2017. Against this backdrop, 6.8 million people evacuated, the largest in US history, and took shelter in hotels (Feito & Ballard, 2022). In Table 4, we project the loss of business interruption in the tourism industry from our DIIM simulation results. To validate it with the published loss figures.

Table 4. Tourism Industries' Business Operations Only Losses (365-day Recovery Window)

Sectors	**Rank**	**Loss ($million)**
Food and beverage stores	8	95.60
Amusements, gambling, and recreation industries	11	75.25
Accommodation	12	73.18
Food services and drinking places	20	57.34
Performing arts, spectator sports, museums, and related activities	25	49.16
Rental and leasing services and lessors of intangible assets	28	41.15
General merchandise stores	32	33.22
Rail transportation	41	25.00
Forestry, fishing, and related activities	44	22.12
Air transportation	60	7.90
Other retail	63	5.29
Water transportation	65	4.36
Total projected loss ($ million)		**489.58**

Table 4 compiled the sectors closely associated with the tourism industry. It shows the estimated loss of $490 million in the tourism sector's business operations after Hurricane Irma's landfall. Publicly available data show that Hurricane Irma cost Florida 1.8 million out-of-state visitors in 2017, resulting in a $1.5 billion loss in spending and a $882 million loss in September 2017 alone (VISIT FLORIDA, 2018). We believe our projection reasonably approximated the loss, amounting to only three times less than the published report from VISIT Florida. Our justification stands on the fact that our estimate of tourism sector loss is solely based on simulated results derived from household survey data specific to residents of Florida. While our loss figures may represent the decline in tourism revenue from domestic travelers, they may not capture the full extent of losses incurred by out-of-state visitors. The projected total loss from our DIIM results ranges between $3.66 to $5.30 billion.

In contrast, Hurricane Irma's estimated cost varies by estimation techniques and sources, such as $50 billion (NOAA NCEI, 2020) and $43-65 billion (Peebles, 2017). These publicly available loss estimation processes included property damage (buildings and physical assets). Whereas our calculation is based on utility systems disruption's impact on business interruptions, excluding property damage. The exclusions of property damage in DIIM methodology typically lead to smaller loss figures than broader estimates available in the literature (Rafi et al., 2024). Hence, our reported utility disruption loss estimate is notably smaller than the published comprehensive loss or damage estimate.

6. Conclusion

This study is based on a methodology developed to connect household survey information to the Dynamic Inoperability Input-Output Model (DIIM). Our main goal was to understand how Hurricane Irma affected critical infrastructure and utility systems would impact business sectors in Florida. After Hurricane Irma landed in Florida, we collected data on utility disruptions in 14 MSAs within the State. We specifically studied seven systems: electricity, water, workforce, transportation, phone, internet, and grocery. For each scenario, we collected data on the proportion and duration of disruption.

We incorporated the proportion and duration information into the DIIM. The DIIM has a built-in GUI tool that processes the proportion and duration of distribution data along the 71 economic sector categories. Then, we performed an integrated system disruption simulation in DIIM. Using the GUI, the simulation predicts the performance of each sector. Additionally, the GUI ranked and listed the top ten inoperable sectors and ten sectors with the highest monetary loss.

The DIIM analysis of integrated utility systems in Florida estimated a total business interruption loss of $3.66 billion, conducted within the 365-day recovery window. The most vulnerable sector listed in the result will help policymakers make decisions and take action to protect communities and critical infrastructures during extreme weather events. The top ten sectors in terms of inoperability are as follows: (1) Administrative and support services, (2) Forestry, fishing, and related activities, (3) Warehousing and storage, (4) Primary metals, (5) Management of companies and enterprises, (6) Other transportation and support activities, (7) Miscellaneous professional, scientific, and technical services, (8) Insurance carriers and related activities, (9) Computer systems design and related services, and (10) Apparel and leather and allied products. The top ten sectors based on economic losses ($ millions) are (1) Insurance carriers and related activities, (2) Miscellaneous professional, scientific, and technical services, (3) Legal services, (4) Federal government enterprises, (5) Chemical products, (6) Computer systems design and related services, (7) Federal Reserve banks, credit intermediation, and related activities, (8) Food and beverage stores, (9) Broadcasting and telecommunications, and (10) Waste management and remediation services. Hurricane Irma significantly impacted Florida's business sectors. The service sector experienced a three times larger loss than the manufacturing loss. The service sector accounted for 57 percent of the total loss among 71 industries and was the most affected. This analysis shows that the service sector is vulnerable to disruptions in utility systems.

We conducted a sensitivity analysis between 365- and 252-day recovery period. Our findings identified consistent patterns in inoperability and economic loss caused by Hurricane Irma in Florida. The disruption led to utility system losses ranging from $3.66 billion to $5.30 billion. Our findings demonstrated that disaster preparedness and having response strategies at both the state and local levels are essential. By adopting proactive measures, Florida can mitigate substantial economic losses during extreme weather events, such as Hurricane Irma. This underscores the necessity of comprehensive disaster preparedness and response planning.

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CRediT authorship contribution statement

Shahnawaz Rafi: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Visualization, Writing – original draft, Writing – review & editing, Visualization. **Joost Santos:** Conceptualization, Writing – review & editing. **Sisi Meng:** Writing – review & editing. **Pallab Mozumder:** Conceptualization, Writing – review & editing.

All authors read and approved the final manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendices

Table 5. Tabulation of MSAs in FL.

NAME	Freq.	Percent	Cum.
Cape Coral-Fort Myers, FL	19	3.23	3.23
Deltona-Daytona Beach-Ormond Beach, FL	28	4.76	7.99
Homosassa Springs, FL	5	0.85	8.84
Lakeland-Winter Haven, FL	29	4.93	13.78
Miami-Fort Lauderdale-Pompano Beach, FL	154	26.19	39.97
Naples-Marco Island, FL	7	1.19	41.16
North Port-Sarasota-Bradenton, FL	21	3.57	44.73
Ocala, FL	23	3.91	48.64
Orlando-Kissimmee-Sanford, FL	140	23.81	72.45
Palm Bay-Melbourne-Titusville, FL	18	3.06	75.51
Port St. Lucie, FL	16	2.72	78.23
Punta Gorda, FL	8	1.36	79.59
Sebastian-Vero Beach, FL	7	1.19	80.78
Tampa-St. Petersburg-Clearwater, FL	113	19.22	100.00
Total	588	100.00	

Table 6. Demographic Profile of Survey Participants in Florida.

Variables	Percent	Variables	Percent
Age (mean = 44)		**Political affiliation**	
18-29 years old	20.07	Liberal	21.43
30-44 years old	40.14	Highly very liberal	9.69
45-59 years old	17.18	Conservative	20.92
60+ years old	22.62	Very Conservative	10.71
Gender		Independent	37.25
Male	43.37	**Employment**	
Female	56.46	Employed	54.93
Marital status		Unemployed	45.07
Married	50.34	**Income** (median= $60,000 – $63,000)	
Single	24.32	No income	24.15
Other	25.34	Less than $17, 999	22.11
Ethnicity		$18,000 - $35,999	22.96
White, non-Hispanic	76.87	$36,000 - $77,999	21.26
Black, non-Hispanic	7.99	$78,000 - $119,999	9.52
Hispanic	11.39	More than $120, 000	22.11
Others	3.75	**Homeownership**	
Education		Owner	70.26
Less than high school	2.55	Renter	29.74
High school or equivalent	18.03	**Housing type**	
Some college, no degree	28.23	Single-family detached	25
Bachelor's degree or higher	45.95	Single-family attached	57.14
Others	5.44	Others	17.86

Table 7. Current GDP by MSA and Related Weight in Florida.

MSA Name	GDP ($, 000)	GDP weight
Cape Coral-Fort Myers, FL	31306862	0.038
Deltona-Daytona Beach-Ormond Beach, FL	20505609	0.025
Homosassa Springs, FL	3755067	0.005
Lakeland-Winter Haven, FL	25548811	0.031
Miami-Fort Lauderdale-Pompano Beach, FL	340676214	0.414
Naples-Marco Island, FL	18596230	0.023
North Port-Sarasota-Bradenton, FL	34343636	0.042
Ocala, FL	9805167	0.012
Orlando-Kissimmee-Sanford, FL	133740648	0.163
Palm Bay-Melbourne-Titusville, FL	24334883	0.030
Port St. Lucie, FL	16768834	0.020
Punta Gorda, FL	5243098	0.006
Sebastian-Vero Beach, FL	6469489	0.008
Tampa-St. Petersburg-Clearwater, FL	151021798	0.184
14 MSA Total GDP (thousands of current dollars)	**822116346**	**1**

Table 8. List of Manufacturing Sectors in Florida's Economy and Associated Loss ($ million).

Industries	Rank	Loss ($ million)
1. Chemical products	5	195.79
2. Natural gas distribution	16	65.53
3. Fabricated metal products	19	58.73
4. Primary metals	27	43.54
5. Nonmetallic mineral products	30	35.12
6. Paper products	31	33.54
7. Furniture and related products	33	32.89
8. Plastics and rubber products	36	31.94
9. Wood products	37	31.63
10. Textile mills and textile product mills	43	22.69
11. Electrical equipment, appliances, and components	45	21.83
12. Computer and electronic products	49	18.24
13. Apparel and leather and allied products	50	16.34
14. Construction	51	15.55
15. Oil and gas extraction	56	10.33
16. Machinery	57	10.24
17. Mining, except oil and gas	58	8.99
18. Farms	59	8.80
19. Petroleum and coal products	61	7.41
20. Miscellaneous manufacturing	64	4.44
21. Motor vehicles, bodies and trailers, and parts	68	2.66
22. Housing	69	1.29
23. Food and beverage and tobacco products	70	1.03
23 manufacturing sectors' total loss ($M)	5	**678.55**

Table 9. List Of Service Sectors in Florida's Economy and Associated Loss ($ million).

Industries	Rank	Loss ($ million)
1. Insurance carriers and related activities	1	339.07
2. Miscellaneous professional, scientific, and technical services	2	326.46
3. Legal services	3	229.57
4. Computer systems design and related services	6	145.40
5. Federal Reserve banks, credit intermediation, and related activities	7	145.36

6. Waste management and remediation services	10	82.65
7. Amusements, gambling, and recreation industries	11	75.25
8. Accommodation	12	73.18
9. Educational services	13	69.91
10. Other real estate	17	64.02
11. Administrative and support services	18	61.84
12. Food services and drinking places	20	57.34
13. Printing and related support activities	21	55.71
14. Other services, except government	22	54.41
15. Data processing, internet publishing, and other information services	24	50.32
16. Other transportation and support activities	26	44.19
17. Rental and leasing services and lessors of intangible assets	28	41.15
18. Nursing and residential care facilities	34	32.09
19. Management of companies and enterprises	39	26.82
20. Social assistance	42	24.06
21. Ambulatory health care services	46	20.64
22. Funds, trusts, and other financial vehicles	47	20.41
23. Motor vehicle and parts dealers	48	18.67
24. Hospitals	55	11.18
25. Other retail	63	5.29
26. Securities, commodity contracts, and investments	66	3.44
27. Support activities for mining	71	0.95
27 service sectors' total loss ($M)		**2079.36**

Table 10. List of Manufacturing Sectors in Florida's Economy and Associated Inoperability.

Industry	**Rank**	**Inoperability (percent)**
1. Primary metals	4	0.499
2. Apparel and leather and allied products	10	0.385
3. Fabricated metal products	11	0.384
4. Textile mills and textile product mills	18	0.325

5. Electrical equipment, appliances, and components	21	0.311
6. Plastics and rubber products	24	0.296
7. Wood products	30	0.267
8. Computer and electronic products	31	0.259
9. Nonmetallic mineral products	37	0.233
10. Chemical products	43	0.226
11. Mining, except oil and gas	45	0.221
12. Furniture and related products	46	0.220
13. Miscellaneous manufacturing	50	0.208
14. Construction	51	0.207
15. Paper products	53	0.201
16. Machinery	57	0.185
17. Motor vehicles, bodies and trailers, and parts	63	0.146
18. Natural gas distribution	65	0.117
19. Food and beverage and tobacco products	66	0.110
20. Petroleum and coal products	67	0.094
21. Farms	68	0.091
22. Oil and gas extraction	69	0.075
23. Housing	71	0.006

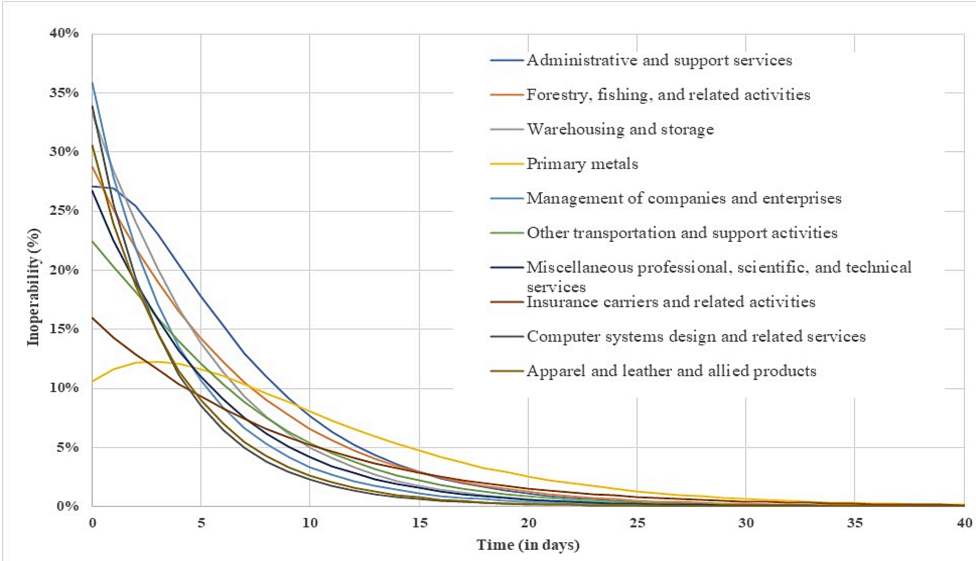
Table 11. List of Service Sectors in Florida's Economy and Associated Inoperability.

Industry	**Rank**	**Inoperability (percent)**
1. Administrative and support services	1	0.639
2. Management of companies and enterprises	5	0.464
3. Other transportation and support activities	6	0.461
4. Miscellaneous professional, scientific, and technical services	7	0.438
5. Insurance carriers and related activities	8	0.406
6. Computer systems design and related services	9	0.390
7. Food services and drinking places	12	0.375
8. Securities, commodity contracts, and investments	14	0.368
9. Other services, except government	15	0.357
10. Educational services	16	0.342
11. Nursing and residential care facilities	19	0.318
12. Ambulatory health care services	22	0.300
13. Social assistance	23	0.297

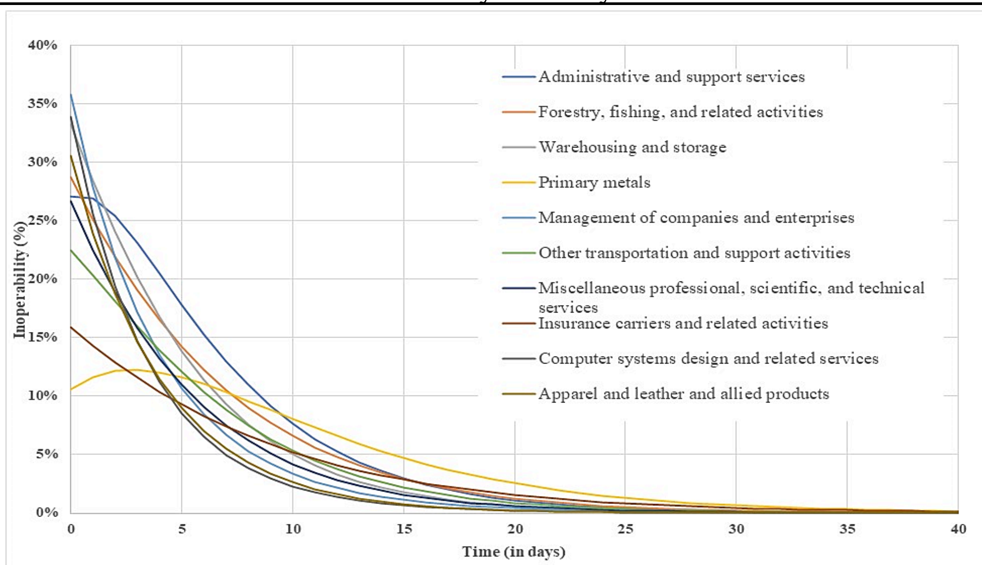
14. Data processing, internet publishing, and other information services	26	0.285
15. Hospitals	28	0.278
16. Other real estate	29	0.278
17. Legal services	32	0.257
18. Federal Reserve banks, credit intermediation, and related activities	36	0.238
19. Printing and related support activities	38	0.230
20. Motor vehicle and parts dealers	39	0.229
21. Accommodation	41	0.228
22. Amusements, gambling, and recreation industries	47	0.220
23. Waste management and remediation services	49	0.210
24. Rental and leasing services and lessors of intangible assets	54	0.201
25. Other retail	56	0.191
26. Support activities for mining	60	0.166
27. Funds, trusts, and other financial vehicles	70	0.020

Table 12. Top Ten Sectors' Inoperability Comparison in 365- and 252-day Recovery Window.

365-day recovery window		**252-day recovery window**	
Top ten inoperable industries	**Inoperability score (10^{-3})**	**Top ten inoperable industries**	**Inoperability score (10^{-3})**
Administrative and support services	6.39	Administrative and support services	6.39
Forestry, fishing, and related activities	5.71	Forestry, fishing, and related activities	5.71
Warehousing and storage	5.43	Warehousing and storage	5.43
Primary metals	4.99	Primary metals	4.99
Management of companies and enterprises	4.64	Management of companies and enterprises	4.64
Other transportation and support activities	4.61	Other transportation and support activities	4.61
Miscellaneous professional, scientific, and technical services	4.38	Miscellaneous professional, scientific, and technical services	4.38
Insurance carriers and related activities	4.06	Insurance carriers and related activities	4.06
Computer systems design and related services	3.90	Computer systems design and related services	3.90
Apparel and leather and allied products	3.85	Apparel and leather and allied products	3.85

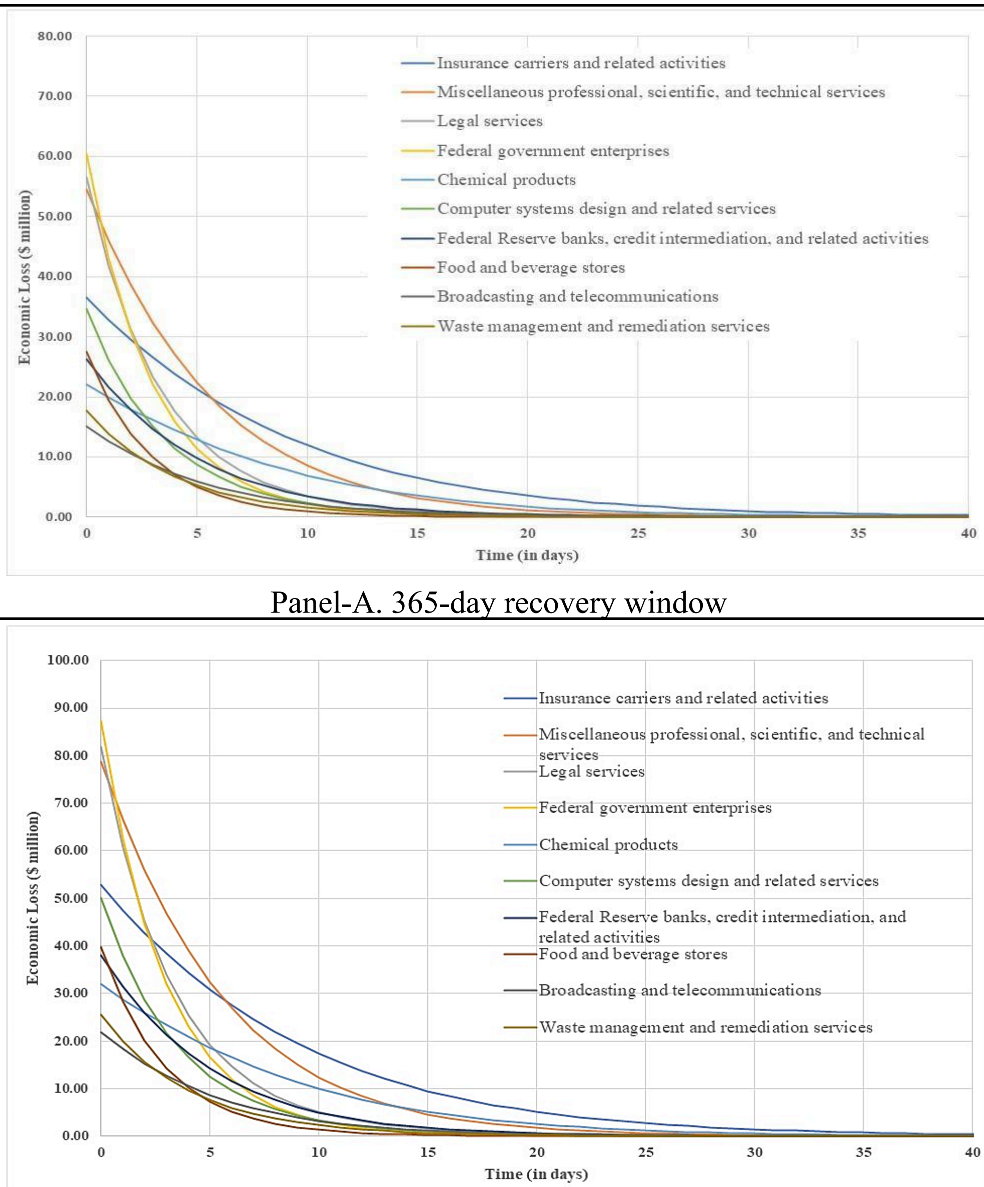


Panel-A. 365-day recovery window



Panel-B. 252-day recovery window.

Fig. 3. Inoperability reduction pattern between the 365-day (panel-A) and 252-day (panel-B) recovery window.



Panel-A. 365-day recovery window

Panel-B. 252-day recovery window

Fig. 4. Economic loss reduction pattern between the 365-day (panel-A) and 252-day (panel-B) recovery window.

Data availability

Data will be made available at a reasonable request, subject to compliance with the Institutional Review Board (IRB) guidelines.

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