Disaster Supply Chains: Moving from Situational Awareness to Actionable Analysis

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List of Acronyms

AHC	All Hazards Consortium
CART	Classification and regression tree
CII	Critical Infrastructure Information Act
CIPSEA	Confidential Information Protection and Statistical Efficiency Act
CISA	US Cybersecurity and Infrastructure Security Agency
CSA	County Staging Area
DC	Distribution center
DHS	US Department of Homeland Security
DOTs	Departments of Transportation
DSD	Direct store delivery
EEI	Essential Elements of Information
EIA	US Energy Information Agency
EOC	Emergency Operations Center
ERP	Enterprise resource planning
FEMA	Federal Emergency Management Agency
FSA	Federal Staging Area
GIS	Geographic information system
GPU	Graphics processing unit
ISB	Incident Support Base
LSTM	Long short-term memory
NGO	Non-governmental organization
NICC	National Infrastructure Coordinating Center
NISC	National Information Sharing Consortium
PADDs	Petroleum Administration for Defense Districts
POD	Point of Distribution
SABER	Single Automated Business Exchange for Reporting
SNAP	Supplemental Nutrition Assistance Program
SSA	State Staging Area
USDA	US Department of Agriculture
USVI	US Virgin Islands
VMI	Vendor managed inventory

Key Takeaways

The following bullets summarize the key takeaways and learnings from this report.

1. Achieving situational awareness is insufficient when it comes to restoring private sector supply chains. More important than being aware of the current situation is correctly understanding interdependent supply chains, forecasting resources and flows, and knowing where and how to intervene with government assistance.

2. Private sector organizations achieve supply chain visibility with enterprise resource systems. Achieving the same visibility across competing and decentralized private sector organizations will require a shift in how the emergency management community approaches cooperation and data aggregation.

3. Accurate, timely, and representative data feeds are required for explanatory, forecasting, and prescriptive tools that should be used dynamically during disasters, not afterwards. Successful data aggregation strategies will require a mix of connecting to pre-existing data feeds and collecting information directly through creation of voluntary trusted spaces and mandatory reporting requirements.

4. Complex models that leverage optimization and machine learning can provide emergency managers with a better understanding of the causes and remedies of supply chain disruption. Models will take time and effort to develop and employ. Models should support, not replace, current information sources to enable better decision making.

5. Improved communication between government and the private sector is critical for improved disaster response. Collaboration between public and private sector actors will contribute to better information flow and help prioritize recovery efforts.

1 Introduction

The 2017 Atlantic hurricane season was the most catastrophic in U.S. history, causing over $275 billion in damages. The season's three major storms impacted three distinct regions: Harvey set a rainfall record that caused wide-spread flooding around Houston, Texas; Irma forced South Florida to conduct the largest evacuation in U.S. history; and Maria devastated the power grid in Puerto Rico, leaving most of the island without power for almost three months and delaying full power restoration until late 2018. Overall, these storms impacted more than 48 million people and prompted 5 million homes to register for government assistance [6].

Within the US Department of Homeland Security (DHS), the Federal Emergency Management Agency (FEMA) is tasked with *providing support for people before, during, and after disasters*. Before disasters, FEMA focuses on building relationships with private sector stakeholder's and emergency management partners to better understand their unique challenges and requirements. During and after disasters, FEMA provides on-the-ground support for state and local governments in the form of funding, specialized response teams, and the provision of essential commodities such as food, water, fuel, and healthcare. For example, FEMA deployed over 17,000 personnel and provided survivors with more than $2 billion in essential commodities during the 2017 hurricane season [6].

> *Improving supply chain resiliency – the ability to continuously anticipate and adapt to changes – is critical for effective disaster response.*

The timely provision of essential commodities during and after a hurricane is a core component of FEMA's response efforts. When called upon by states, FEMA's primary role is to fill gaps and supplement supply chain networks that have been disrupted by a storm. To do this, FEMA must first know where essential commodities are needed and then decide how to best get them there. FEMA transports commodities through operational supply chain collaborations with private industry, non-government organizations, and other federal agencies. However, supply chain performance can be significantly disrupted by hurricanes, thereby impacting the ability to provide essential commodities in a timely manner. For example, the 2017 hurricanes severely damaged distribution and transportation infrastructure such as highways, airports, and shipping ports. Infrastructure disruptions during disasters are often confounded by the fact that supply chains are optimized to maximize efficiency during normal times, leaving minimal slack to adapt to changes.

Improving supply chain resiliency – the ability to continuously anticipate and adapt to changes – is critical for effective disaster response. Operating a resilient supply chain typically requires a real-time data stream that allows managers to monitor performance and identify disruptions. However, real-time data collection is prohibitively difficult during disasters in part due to frequent communication outages. For example, widespread communication outages during the 2017 hurricane season meant that many companies were blind to the status of their facilities or networks, and therefore unable to place orders to replenish depleted resources. Furthermore, identifying disruptions in real-time may not provide enough lead time for managers to make effective adaptations.

In this report, we conceptualize analytical tools that can be employed by FEMA to improve post-hurricane supply chain resiliency and adaptability in preparation for future hurricane seasons. To do this, we leverage the idea of sentinel surveillance from public health and epidemiology [15]. In epidemiology, sentinel surveillance comprises specific nodes in a health network – sentinel indicators – that are continuously monitored to enable the early identification of an impending outbreak. We adapt the idea of sentinel surveillance to monitor a collection of supply chain components that enable early identification of changes that may cause pervasive disruptions in the access and availability of key commodities. To do this, we focus on three types of tools:

1. *Descriptive:* used to describe current supply chain health and provide situational awareness. We highlight popular tools such as GIS systems, daily situation reports, and information sharing platforms.

2. *Predictive:* used to explain and forecast future supply chain health. We highlight spatial-temporal statistical models that can be used to explain the effect of various supply chain metrics and measurements on overall supply chain health. We then discuss advanced machine learning models that can be used to predict future supply chain health at fine spatial and temporal resolutions. The ability to predict supply chain disruptions before, during, and after hurricanes, will help FEMA understand where essential commodities are needed in advance.

3. *Prescriptive:* used to identify sentinel indicators and prescribe solutions to restore supply chain health. We develop optimization models that can be used to determine the best usage of limited resources (e.g., generators), how to prioritize disaster response efforts, and understand the most vulnerable components of the supply chain. We then develop centrality metrics that can be used to identify the most critical components of the supply chain.

These tools are developed using a generalized network approach that integrates interdependencies among multi-party supply chains and the essential resources of product, people, power, and communications. While these essential resources may further rely on different supply chains, such as maintenance parts, we choose to characterize them by spatial-temporal resource availability. We characterize this system as a network of nodes and arcs through which materials flow. The aim following a disaster is to maximize the flow of critical commodities subject to constraints on nodes and arcs derived directly from operational capacity of supply chain actors and from spatial-temporal pools for the essential resources of people, power, and communications. These constraints may be represented by a "recipe" of resources required for flow, e.g. fuel, power, payment communications, and employee at a fuel station.

> *We paint a picture of what actionable situational awareness can look like, if the right relationships, technologies, processes, incentives, and legal environments are in place.*

Following the development of these approaches, we analyze the actual supply chain performance of diesel fuel and bottled water during the 2017 hurricane season:

1. *Diesel fuel:* Access and availability of diesel fuel is critical for effective disaster response. Diesel fuel is necessary for last mile supply chains, emergency response vehicles, and backup generators. Fuel comprises one component of the DHS/FEMA community lifeline for Energy (Power & Fuel). This report looks at four of the Essential Elements of Information (EEI) identified by FEMA for fuel: status of commercial fuel stations, responder fuel availability, status of critical fuel facilities, and status of the fuel supply line.

2. *Bottled water:* Clean drinking water is a fundamental need during disaster response. Although water is used in disaster settings for purposes of cooking, hygiene, health care, and sanitation, this analysis is solely focused on drinking water, often called potable water. During disasters, bottled water is the main source of drinking water for emergency response crews, shelters, and impacted households. Potable water also comprises one component of the DHS/FEMA community lifeline for Food, Water, and Sheltering. This report looks at one of the EEIs identified by FEMA for potable water: impacts to the food supply chain.

By gathering information above and beyond what emergency managers had access to in the moment, we paint a picture of what actionable situational awareness can look like, if the right relationships, technologies, processes, incentives, and legal environments are in place. At the end of this report, we discuss approaches for implementing concrete and fundamental changes that can improve how emergency managers view and analyze supply chains. We outline different strategies that are already being employed (voluntary and mandatory data collection, using pre-existing proxy data, targeted data collection), and we identify some of the key factors needed to realize better supply chain visibility.

To be successful, this report will not be placed on a shelf. It will be utilized by leaders in the emergency management community who want to move past situational awareness when it comes to private sector supply chains. This report is meant to begin the conversation of a roadmap that provides emergency managers with actionable analysis on how to effectively understand and support private sector supply chains.

2 Data

In this section, we provide background and describe our data collection for diesel fuel (Section 2.1) and bottled water (Section 2.2) supply chains. We then outline the challenges faced during our data collection efforts (Section 2.3). Lastly, we outline key data points and potential sentinel indicators for both diesel fuel and bottled water (Section 2.4).

2.1 Diesel fuel data collection

Diesel fuel is a critical component of disaster response and recovery for three key reasons:

1. *Supply chain function:* Tractor units (i.e., transport trucks) rely on diesel fuel and are used for "last mile" delivery in almost all supply chains. Tractor units are needed to maintain normal supply chain function and to replenish key commodities (e.g., fuel, bottled water, food, medicine, etc.) as part of post-disaster recovery.

2. *Emergency response vehicles:* Ambulances, fire engines, and other emergency response vehicles typically rely on diesel fuel and are essential during disaster response and recovery.

3. *Generators:* Diesel generators provide temporary power for critical infrastructure (e.g., hospitals) during disasters. Generators are also used by fuel retailers to supplement lost power and maintain operations. In many states, legislation requires fuel retailers on emergency evacuation routes to have generator connection capabilities.

The diesel fuel supply chain is a complex system ranging from crude oil extractors to fuel retailers. Figure 1 provides a graphical illustration of the diesel fuel supply chain. The United States Energy Information Administration (EIA) is responsible for monitoring the fuel supply chain and partitions the country into five distinct Petroleum Administration for Defense Districts (PADDs) as shown in Figure 2. We focus on PADD3: Gulf Coast and PADD1C: Lower Atlantic because these two districts are the most vulnerable to hurricanes due to their geographical location and large coastline.

We analyze the diesel fuel supply chain during the 2017 hurricane season, with a particular focus on Hurricanes Harvey and Irma. To do this, we obtained publicly available data from multiple sources including EIA, the Florida Department of Transportation, the United States Census Bureau, and fuel retailer websites. We also obtained daily sales volume data (diesel and regular) for 12 retail locations distributed along Florida's major transportation corridors (e.g., I-95, I-75, I-10) during August and September 2017. These data were provided by private sector fuel retailer partner(s).

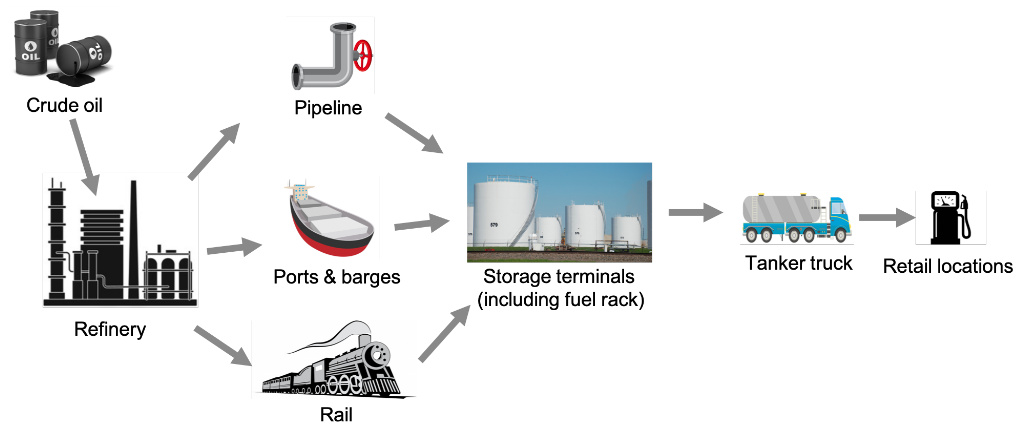

Figure 1: A graphical illustration of the diesel fuel supply chain. Source: MIT analysis.

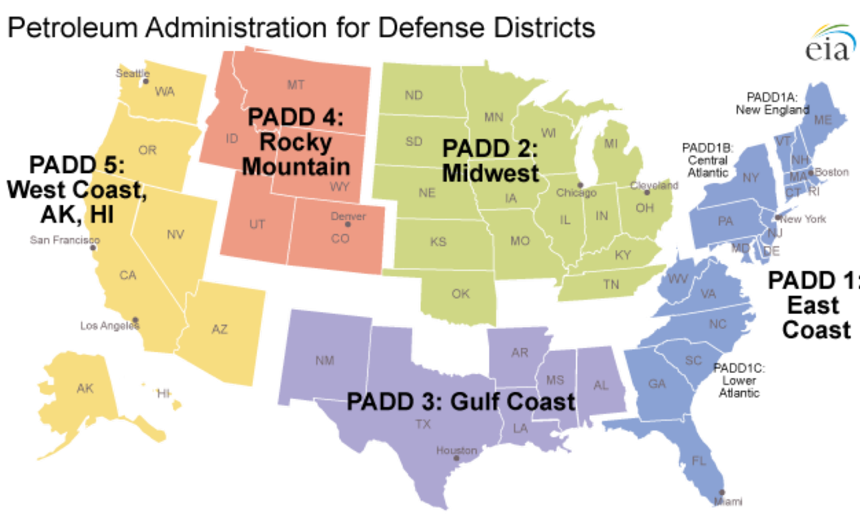

Figure 2: Petroleum Administration for Defense Districts (PADDs) as defined by the United States Energy Information Administration. Source: EIA.

2.2 Bottled water data collection

In the United States, roughly 60% of drinking water volume comes from tap water and roughly 40% comes from bottled water [5, 13]. In total in 2017, the United States consumed 13.7 billion gallons of bottled water. During disaster times, the localized demand for bottled water increases [4]. This can be driven by a number of factors including:

- Outages or lower output by municipal water systems, due to disaster damage or electricity outages.
- A spike in pre-disaster demand at retail locations due to people "stocking up".
- High numbers of people evacuating or in congregate shelters with limited access to tap water.
- New demand from first responders, including those brought in from outside the area.
- Increased physical activity by individuals across the disaster area.

In disaster impacted areas, we have categorized three major sources of demand on bottled water:

1. *Points of Distribution (POD):* Local and state governments identify centralized locations where those in need can obtain life sustaining commodities following a declared emergency or disaster. This represents a large portion of demand.
2. *On the spot consumption:* Bottled water may get delivered, via government channels, to shelters, responder support camps, or other government locations in need (e.g., fire stations). These bottled water deliveries are generally for the consumption of the responders or disaster survivors on site, though some POD-like activities may occur. This represents a small portion of total demand.
3. *Retail sales:* Stores that have reopened will resume regular sales of food, bottled water, and other goods to those impacted by disasters. Retail supply chains exist parallel to government supply chains. This represents a large portion of demand.

In the United States, an estimated 63% of bottled water is made using municipal tap water [4]. Regardless of the source of the water in bottled water, 100% of the supply of bottled water starts with bottlers. Retailers operate a year-round supply chain with highly predictable demand. Local, state, and federal emergency managers operate a parallel supply chain with less predictable demand. Private sector actors orient their supply chain network to reduce costs by increasing the velocity of items through their network. Although the private sector prefers to have no more than needed at any location, they strive to have enough for predictable demand plus a small buffer. On the other hand, emergency managers maintain a large inventory of bottled water to ensure they enough on-hand to meet immediate needs after major disasters. See Figure 3 which details America's bottled water network. Note that we used the following simplifying assumptions to keep the Figure 3 flow chart understandable:

- Excluded FEMA Incident Support Bases (ISBs) as interim waypoints
- Excluded FEMA Responder Support Camps and Joint Field Offices as consumption points of small quantities of bottled water for responder use
- Merged State Staging Areas (SSAs) and County Staging Areas (CSAs)
- Excluded federal bottled water acquisition from the Defense Logistics Agency, which was minimal for 2017 hurricane season
- Assumed all public sector shipments to shelters go through SSAs/CSAs

To understand the nature of these parallel supply chains, we assembled and analyzed public and private sector bottled water shipment information from Hurricanes Harvey, Irma and Maria. This includes interviews, shipment logs, and resource requests across impacted states. In total, tens of thousands of FEMA bottled water shipments and tens of thousands of private sector bottled water shipments informed our analysis. Our end goal was to:

1. Identify overall trends and interactions between public sector and private sector bottled water movements.
2. Suggest actions to monitor and improve these parallel yet interdependent supply chains for future disasters.

While our analysis is limited to notice events, takeaways can similarly apply to no-notice events. A note on units of measurement: FEMA measures in liters; the private sector tends to measure in cases; the State of Texas measures in pallets. When practical, we convert and list all figures in pallets.

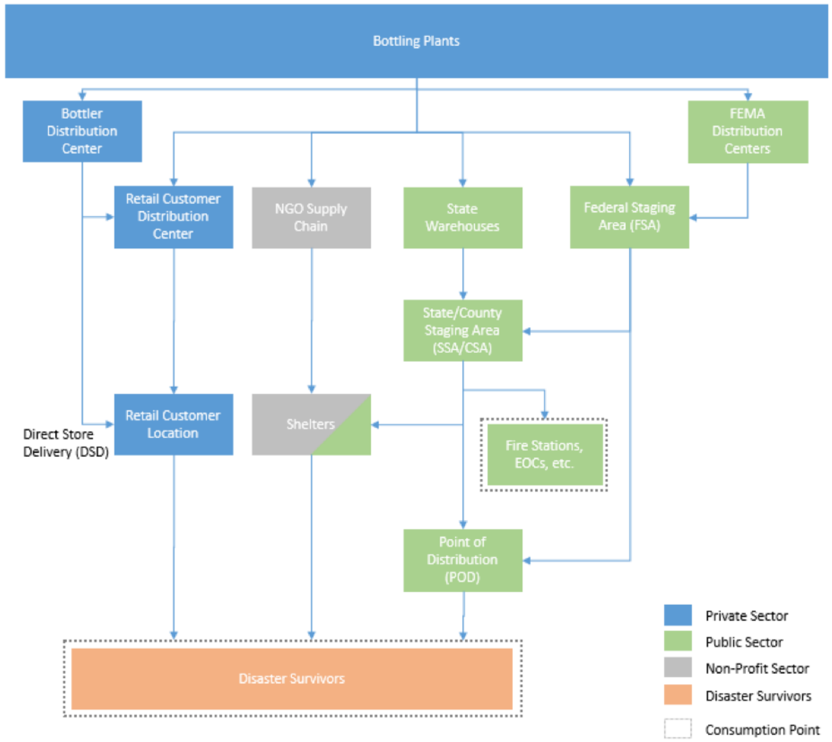

Figure 3: A conceptual visualization of America's bottled water supply chain network. Source: MIT analysis.

2.3 Data collection challenges

The analysis in this report leveraged data on public and private sector supply chains. The data was difficult to collect and compile, and that difficulty reflects the need for a cultural change and a reorientation of how emergency managers interact with private sector supply chains. This section details some of the challenges we faced in collecting data for this report.

There were many strengths that we were able to capitalize upon when gathering data for this report. For example:

- Working in an official capacity in support of a National Academies of Science, Engineering, and Medicine committee study,
- Having FEMA staff members directly connect us with supply chain experts at key private sector organizations,
- Building upon established relationships within the emergency management community at the local, state, and federal level,

- Accessing the corporate partner network of MIT's Center for Transportation and Logistics, and
- Focusing on the universally accepted topic of disaster response.

During the course of our effort, we reached out to:

- 9 government agencies at the local, state, or federal level
- 7 experts in the diesel and fuel industry
- 6 of the largest bottling companies in the United States
- 9 of the largest grocery store retail chains in the United States

In the most unusual case, we successfully connected with a total of 13 employees at a single organization. The contacts we interacted with came from various offices within the company: Chief Sustainability Officer, Chief Supply Chain Officer, corporate foundation, community affairs, and even local warehouse managers from impacted states. After dozens of follow-ups, and impressive referrals, we were still unable to get any usable data to further our disaster supply chain analysis.

In total, we were only able to leverage a very small percentage of the data we know to be available. Of all those connections described above, the vast majority of our analysis in this report was completed utilizing the data of five organizations, one of which is FEMA.

> *As much as data collection challenged our team during this analysis, the challenges are even greater for emergency managers to conduct real-time, cross-sector analysis of the supply chains necessary for the stabilization of community lifelines.*

We believe that the main obstacles to leveraging private sector supply chain data to be more than just competitive reasons. Although companies are hesitant to share information that may reveal trade secrets, many companies lacked publicly available automated data feeds, even for disaster relief purposes. In the absence of this automation, companies were unwilling or unable to do the work to provide us with information on their supply chain performance during the 2017 hurricane season.

In addition to automated data feeds, another major obstacle to real-time analysis during large-scale disasters is the lack of standardization of data. For example, emergency management agencies at local, state, and federal levels often use some form of cloud-based virtual emergency operations center (EOC). These EOC platforms managed their data in incompatible formats that prevented us from capturing the handoff of bottled water from FEMA to state and local government. Opportunities around data standardization for emergency managers can leverage the expertise of organizations like the US Department of Commerce's National Institute for Standards and Technology.

As much as data collection challenged our team during this analysis, the challenges are even greater for emergency managers to conduct real-time, cross-sector analysis of the supply chains necessary for the stabilization of community lifelines.

2.4 Sentinel indicators

Adequately monitoring private sector supply chains to optimize disaster response and recovery efforts will require fundamental changes in the collection, anonymization, and sharing of key data points. We focused on fuel and bottled water to identify the following sentinel indicators along each supply chain that may help identify supply chain issues before, during, and after disasters.

Adequately monitoring private sector supply chains to optimize disaster response and recovery efforts will require fundamental changes in the collection, anonymization, and sharing of key data points.

To the best of our knowledge, Tables 1 and 2 catalog and categorize relevant data points for fuel and water supply chains, respectively. We utilize the following definitions:

- Data is said to be "collected" if we know there to be recurring automated reporting mechanisms internal to a company where this information is accessible to authorized parties on an as needed basis via either push or pull methods.
- "Aggregation" is said to occur if we know there to be a mechanism where data is gathered from across various individual operators/owners/companies by a trusted source.
- Data is used by emergency management for "situational awareness" purposes if we believe it is information that would likely be shared in regular sitreps if emergency management agencies had the information available to them.
- Data is used by emergency management for "forecasting" purposes if we know that these data points are combined with logic, historical experience, or rigorous analysis to make calculated estimates of future disaster needs or lifeline status. This category does not reflect whether or

not this data point can be forecasted. This category reflects whether or not this data point is used to forecast other things.

- Data is used by emergency management for "actionable intervention" purposes if we understand there to be specific actions that emergency managers can take (including providing support to other private sector organizations) as a direct result of understanding the current status of this data point.

Table 1: Sentinel indicators for the fuel supply chain. Source: MIT analysis.

Data point	Collection		Aggregation		Current Emergency Management Uses		
	Yes/No	Party	Yes/No	Party	Situational Awareness	Forecasting	Actionable Interventions
Refinery count	Yes	Owner	Yes	EIA, CISA	Yes	No	Yes
Refinery status	Yes	Owner	Yes	EIA, CISA	Yes	No	Yes
Pipeline status	Yes	Owner	Yes	EIA, CISA	Yes	No	Yes
Pipeline inventory	Yes	Owner	Yes	EIA, CISA	Yes	No	Yes
Pipeline throughput	Yes	Owner	No	-	Yes	No	Yes
Terminal status - power	Unknown	-	No	-	Yes	No	Yes
Terminal status - personnel	No	-	No	-	No	No	No
Terminal status - inventory	Yes	Owner	Yes	EIA	Yes	No	Yes
Terminal racks - throughput	Yes	Owner	No	-	Yes	No	Yes
Terminal racks - count	Yes	Owner	No	-	No	No	No
Terminal racks - wait times	No	-	No	-	Yes	No	No
Fuel tanker fleet - operating %	Yes	Owner	No	-	Yes	No	Yes
Fuel tanker fleet - route choices	Yes	Owner	No	-	Yes	No	No
Retailer status - power	Yes	Owner	Yes	GasBuddy	Yes	No	Yes
Retailer status - personnel	Unknown	-	No	-	No	No	No
Retailer inventory - diesel	Yes	Owner	Yes	GasBuddy	Yes	No	No
Retailer inventory - regular	Yes	Owner	Yes	GasBuddy	Yes	No	No
Retailer sales - diesel	Yes	Owner	No	-	Yes	No	No
Retailer sales - regular	Yes	Owner	No	-	Yes	No	No
Retailer generator - connection	Yes	Owner	Partial	Unknown	Yes	No	Yes
Retailer generator - on site	Yes	Owner	No	-	Yes	No	Yes
Road, highway, bridge status	Partial	DOT	Partial	DOT	Yes	No	Yes

The parties listed in Table 1 can be described as follows:

- *The Cybersecurity and Infrastructure Security Agency (CISA):* an agency within DHS who's mission is to "partner with industry and government to understand and manage risk to our Nation's critical infrastructure." Within CISA sits the National Infrastructure Coordinating Center (NICC), an organization with functions including Situational Awareness, Information Sharing and Collaboration, Critical Infrastructure Assessment, Decision Support, and Future Operations. CISA, and the NICC, are a natural place for private sector infrastructure aggregation responsibilities. Two subsectors of the Transportation Systems Sector include pipeline systems and highway and motor carrier. CISA has a strong focus on the upstream supply chain of fuel but has less visibility over aggregating information from and managing risk to the downstream fuel supply chain. Note that MIT has an incomplete understanding of CISA's data access due to the confidentiality of their work.

- *State Departments of Transportation (DOTs):* an agency that manages roadway infrastructure including roads, highways, bridges, and tunnels. State DOTs work with local authorities as well as the US Department of Transportation.

- *The US Energy Information Agency (EIA):* an agency within the US Department of Energy which serves as the nation's premier source of energy information. With roots in the 1970s, the EIA has had decades to refine its processes of collecting, anonymizing, analyzing, and disseminating energy information. The EIA has a strong focus on short-term (13 to 24 months) and long-term (multi-year) trends and information. The EIA has little to no practice forecasting short-term fuel flows to retailers.

- *GasBuddy:* a private company that manages a database of real-time fuel price information and retailer status (e.g., power) for more than 150,000 gas station convenience stores. During disasters, GasBuddy information can be used to identify the open/close status of individual gas stations.

- *Owners:* individual companies in the fuel sector own their piece of the fuel sector pipeline which can extend from refineries to gas stations. Many of the key portions of the fuel supply chain (e.g., fuel tanker fleets) are heavily decentralized with many actors. Owners have a wide range of information technology capabilities and many owners may be unable to regularly share detailed information during disasters.

The aggregators in Table 9 exclude for-profit organizations (such as OPUS) that aggregate disaster supply chain data from both public and non-public sources primarily for paying customers.

Table 2: Sentinel indicators for the bottled water supply chain. Source: MIT analysis.

Data point	Collection		Aggregation		Current Emergency Management Uses		
	Yes/No	Party	Yes/No	Party	Situational Awareness	Forecasting	Actionable Interventions
Municipal Water Systems – status	Yes	Utility Operator, Regulator	Yes	Utility Operator, Regulator	Yes	No	Yes
Bottling plant – status	Yes	Owner	Unknown	CISA	No	No	Yes
Bottling plant – inventory	Yes	Owner	No	-	No	No	No
Bottling plant - wait times	Unknown	Owner	No	-	No	No	No
Bottler DC – status	Yes	Owner	No	-	No	No	No
Bottler DC – inventory	Yes	Owner	No	-	No	No	No
Bottler DC - wait times	Unknown	-	No	-	No	No	No
Retailer DC – status	Yes	Owner	No	-	No	No	No
Retailer DC – inventory	Yes	Owner	No	-	No	No	No
Retailer DC - wait times	Unknown	-	No	-	No	No	No
Retailer status – overall	Yes	Owner	Partial	SABER	Yes	No	Yes
Retailer status – power	Yes	Utility Operator, Regulator	Partial	Utility Operator, Regulator	Yes	No	Yes
Retailer status – personnel	Unknown	-	No	-	No	No	No
Retailer inventory	Yes	Owner	No	-	No	No	No
Retailer sales	Yes	Owner	Partial	USDA, Electronic Payment Provider	No	No	No
Retailer generator – connection	Yes	Owner	Unknown	-	Yes	No	Yes
Retailer generator - on site	Yes	Owner	Unknown	-	Yes	No	Yes

The parties listed in Table 2 can be described as follows:

- *Electronic Payment Provider:* Companies like VISA, Mastercard, American Express, and Discover facilitate the payment of goods or services by customers utilizing debit or credit cards. The networks maintained by these organizations can indicate activity level per retail location which can be reflective of the store's operating status. Note that stores may be operating on a cash only basis, in which case these organizations are unable to indicate any activity.

- *Owners:* The bottled water production industry in the United States is moderately concentrated with a relatively small number of very large players. For example, a March 2019 IBISWorld report indicates that the top four players are expected to generate 60% of revenue in 2019 [1]. Bottled water producers typically maintain both bottling plants as well as distribution centers. Retailers typically maintain their own distribution centers, or if they are small, work with wholesalers who maintain distribution centers. Bottlers and wholesalers likely have robust information technology capabilities that could potentially allow them to regularly share detailed information during disasters.

- *SABER:* The Single Automated Business Exchange for Reporting (SABER) is a non-profit founded in 2014 with the goal of "influencing government recovery priorities and enable business-to-business brokering by providing accurate and timely business status information to get businesses back in business faster." Individual companies can opt-in to providing automated or manual reporting of business location status. Emergency management agencies then have access to consolidated information across a number of different private sector actors. SABER is one example of data aggregation platforms that help users understand overall business restoration status.

- *US Department of Agriculture (USDA):* The agency that operates the Supplemental Nutrition Assistance Program (SNAP), which is a federal program that provides nutrition benefits to low-income individuals and families that are used at stores to purchase food. The presence or absence of SNAP related purchases at the individual retail store level can be indicative of a community's overall business restoration status.

- *Utility Operator / Regulator:* Individual utility operators (i.e., water authorities) provide information on the status of water processing and treatment capabilities after a disaster. Many different factors can contribute to decreased integrity of municipal water systems after a disaster. Utility operators may choose to issue boil water notices or other indications that there is a recommendation not to drink tap water. Similarly, individual power companies provide information on the number of customers without power over a geographic area following a disaster. Water status and electricity status can reflect the demand and supply of bottled water during disaster response and recovery. Utility regulators may oversee multiple utility companies and may further aggregate, validate, and communicate information across a disaster area.

In the next three sections, we outline three classes of analytical tools that can be leveraged by emergency managers to describe the current state (Section 3), predict the future state (Section 4), and prescribe priority actions for supply chain repair (Section 5). The emergency management community frequently uses tools to describe the current state, but rarely uses tools to either predict the future state or prescribe actions for supply chain repair.

3 Descriptive tools

In this section, we outline the benefits and discuss the limitations associated with analytical tools that can be (and often are) leveraged by emergency managers to describe the current state of supply chains. Achieving more complete situational awareness has been an ongoing goal of the emergency management community. Tools that have been developed to achieve better situational awareness and unity of effort include:

- Communications interoperability,
- GIS systems,
- Conference calls and video teleconferences,
- Daily situation reports, and
- Planning cells within the Incident Command System.

To describe the status of private sector supply chains, the emergency management community has tends to rely on the existing set of situational awareness tools, and has minimally developed and adopted new tools specific to monitoring supply chains. These existing tools do a good job monitoring individual nodes or paths in a supply chain, but do not adequately capture the overall picture of supply chain health. For example:

- Knowing the open/close status of retail locations in an impacted area does not describe which goods may be unavailable at locations across the impacted area.
- Knowing that a key bridge or highway may be impassable does not describe how much additional time will be required for goods to arrive from a different distribution center.

Tools currently used to describe supply chain health after disasters generally fail to combine pictures of node status, path status, and implications on overall supply chain performance. Consumers of situational awareness reports are left to put the anecdotal puzzle pieces together, usually with information from the most vocal subset of the private sector. This can result in reactive measures (i..e, putting out fires as they come up), rather than using data driven methods to intervene in strategic places that are known to have outsized benefits.

Figures 4 and 5 show descriptive tools highlighting open/close status of a subset of retail establishments in a disaster area. Figure 4 illustrates the open/close status of various retailers, big box stores, fuel locations, pharmacies, and hotels during Hurricane Harvey. Similarly, Figure 5 illustrates outages of big box stores, pharmacies, hotels, fuel stations, restaurants, and department stores for Hurricane Irma.

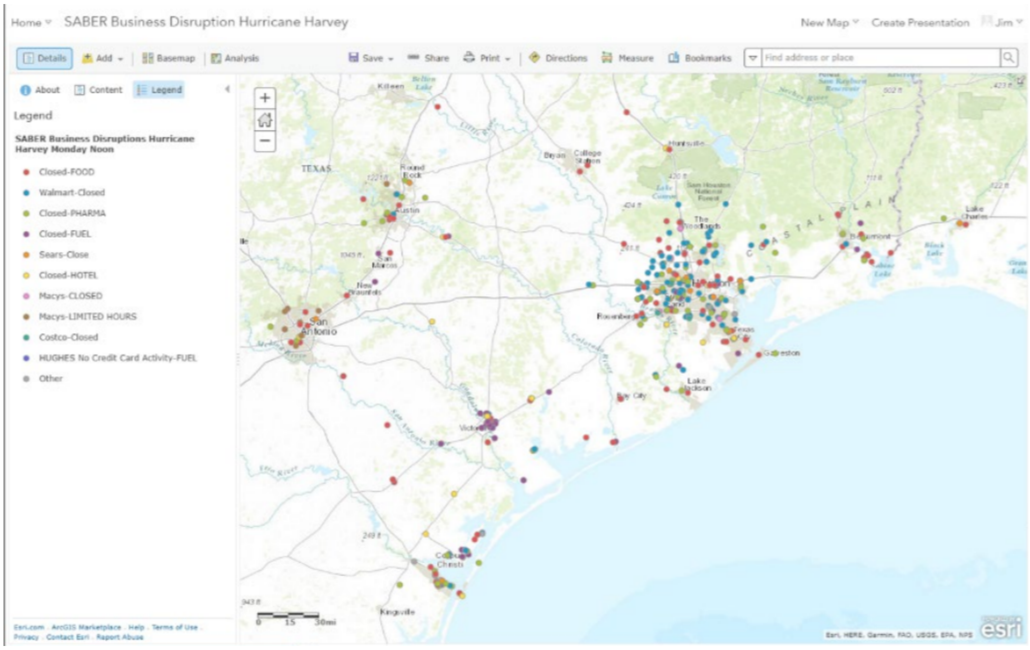

Figure 4: Business disruptions during Hurricane Harvey (August 28, 2017). Source: SABER, National Information Sharing Consortium.

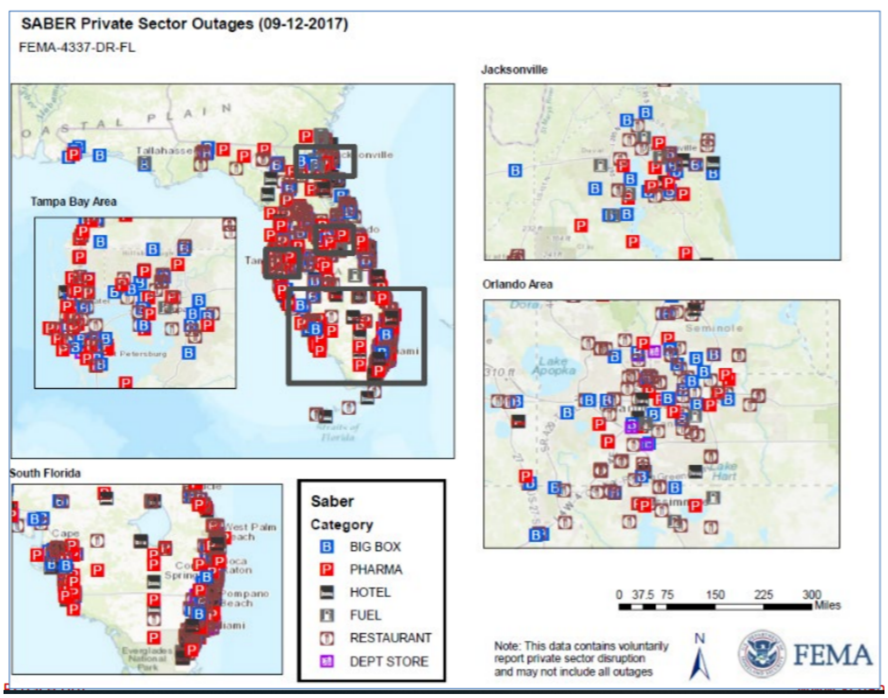

Figure 5: Business disruptions during Hurricane Irma (September 12, 2017). Source: SABER, National Information Sharing Consortium.

Figure 6 displays the outages of fuel retailers during Hurricane Irma. The cause of the outage is not known (e.g., lack of supply, lack of power, etc.). Although this information can be useful for consumers and real-time situational awareness, it cannot be used for proactive planning purposes or detailed retrospective analysis (because we not do know the outage cause). The ability to forecast the most likely outage locations could allow emergency managers to proactively plan routes and preposition aid (e.g., generators).

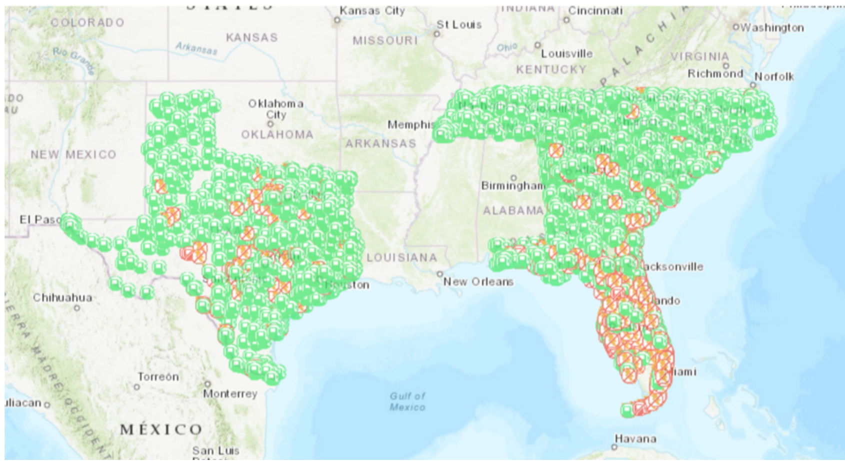

Figure 6: Gas retailer disruptions during Hurricane Irma (September 11, 2017). Source: ArcGIS, GasBuddy.

Figure 7 provides a slightly different picture on business restoration after disasters. Consumers of this information can easily see if business closures remain a problem (are staying constant) or are improving (decreasing in number over time). If desired, consumers of this information can compare the speed of restoration to other similar disaster events to benchmark restoration performance as a proxy for supply chain health. While past performance is an indicator of future performance, current data is unable to provide the information needed to estimate unmet needs at the initial onset of a disaster.

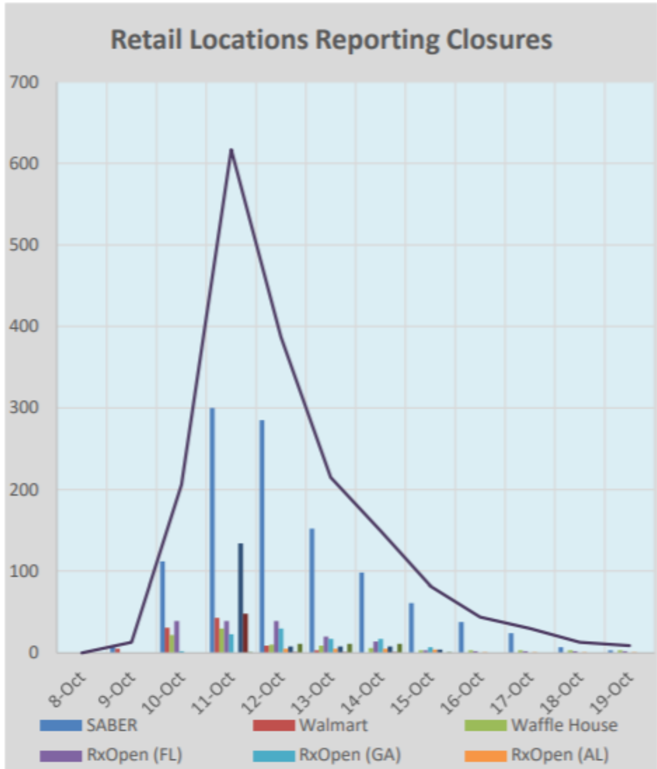

Figure 7: Business disruptions during Hurricane Michael (October 2018). Source: SABER, National Information Sharing Consortium.

During a disaster, emergency managers have fairly good situational awareness of the status of major transportation networks as shown in Figure 8. If 100% of routes into an area are disrupted, it is reasonable to conclude that 100% of supply chains feeding into the community are inoperable. Knowing which portion of infrastructure may be up or down can help drive prioritization of road repair crews, can help when making decisions about shipment routing, and can inform decisions about re-entry access by families who were evacuated. Transportation status alone cannot indicate what percent of critical goods and services might be delayed, or the size of the gap in a community's critical lifelines.

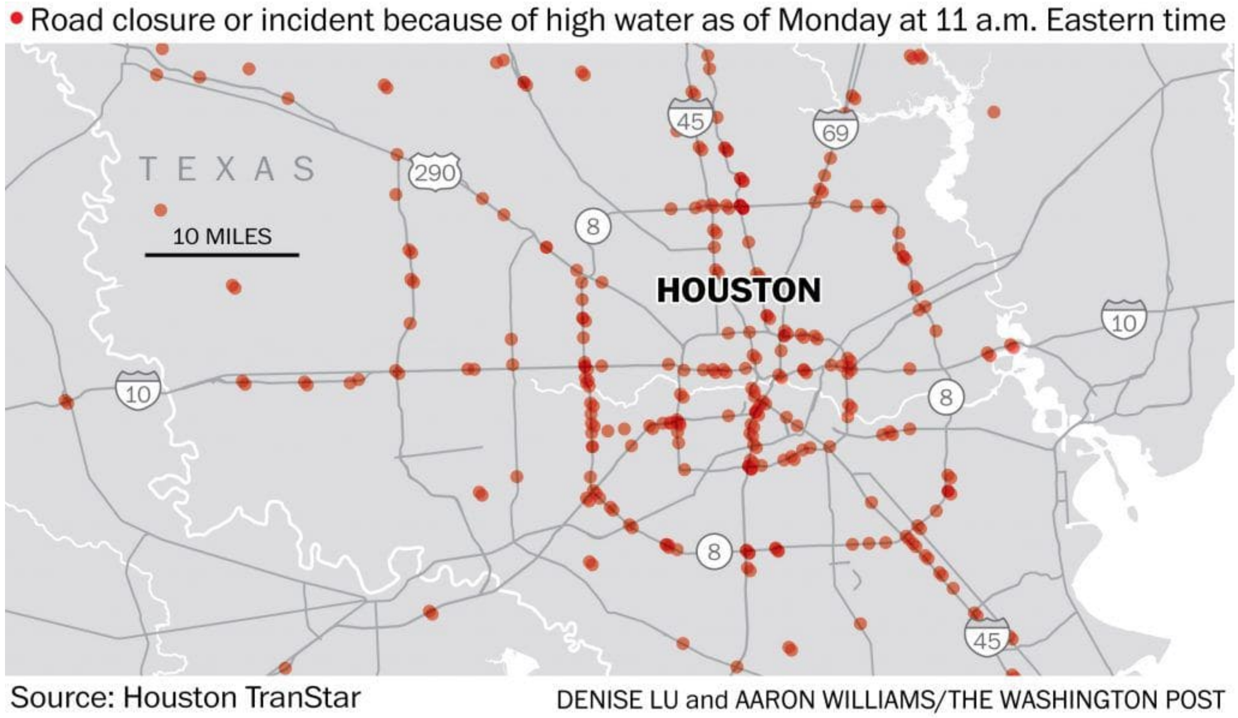

Figure 8: Road closure status during Hurricane Harvey (August 28, 2017). Source: Houston TranStar & Washington Post.

Knowing the current status of retail locations as well as transportation infrastructure is critical for immediate response activities. However, current status information alone is insufficient to understand a community's current supply chain capabilities and operational status. Emergency managers who know the current status of select nodes in a supply chain remain unable to properly plan for anticipated needs or the ongoing restoration of community lifelines. In other words, *descriptive tools are not enough.*

4 Predictive tools

Moving past tools that describe the current state of affairs requires more rigorous approaches and methods. In this section, we introduce data-driven predictive tools that can be used to explain and forecast the spatial-temporal access and availability of a particular commodity (e.g., diesel fuel). Predictive tools aim to understand and model the impact that proximate and relevant factors have on the outcomes of interest. This additional insight allows us to identify the drivers of the current state and anticipate the future state. To do this, we conceptualize two distinct types of data-driven tools:

- *Explanatory:* used to explain (and quantify) the factors that influence access and availability
- *Forecasting:* used to forecast future access and availability

Mathematically, we represent the access and availability of a particular commodity as a binary variable:

$$a_{r,t} = \begin{cases} 1, & \text{if the commodity is accessible and available at retailer location } r \text{ at time } t, \\ 0, & \text{otherwise.} \end{cases}$$

This variable, $a_{r,t}$, has both spatial and temporal components encoded by the retailer location (r) and the time (t). We treat $a_{r,t}$ as the target (dependent variable) and seek to determine the features (independent variables) that best explain and predict its value.

4.1 Explanatory tools

Explanatory models, such as spatial-temporal statistical models, can be used to explain the effect of various features on the target. A precise understanding of the features that impact $a_{r,t}$ allows us to determine the effect of various supply chain metrics and measurements on the access and availability of a commodity. A variety of features including inventory levels, throughput, shipment data, storm characteristics, and geographic location should be evaluated. Conceptually, we can represent the regression as (with some minor abuse of notation):

$$a \sim \beta_R \mathbf{x}_R + \beta_H \mathbf{x}_H + s + \tau + \epsilon,$$

where $\mathbf{x}_R$ represents retailer-based features (e.g., number of diesel lanes, distance to fuel terminal, etc.), $\mathbf{x}_H$ represents hurricane based features (e.g., wind speed, rainfall, etc.), s captures the spatial effect (e.g., similarities between nearby retailers), τ is the temporal effect (e.g., time-series lags/dependencies), and ϵ represents the independent error. Note that due to the binary nature of $a_{r,t}$ we will need to use a Logit or Probit link function to guarantee that our inferences lie in the interval $[0, 1]$. The regression equation above has been left purposefully vague because the exact type of model used ultimately depends on the data available. Ideally, multiple approaches should be considered and compared. See [16] for a thorough treatment of spatial-temporal statistical models.

4.2 Forecasting tools

Machine learning models can be used to forecast future values for $a_{r,t}$. In particular, random forest and long-short term memory (LSTM) neural networks have demonstrated effectiveness for spatial-temporal prediction problems [7, 9]. These models allow decision makers to forecast the access and availability at each retail location some number of days in the future. To do this, we can combine various features (e.g., inventory levels, throughput, shipment data, storm characteristics, geographic location, etc.) to predict access and availability disruptions before, during, and after hurricanes. These forecasts allow us to determine, in advance, where FEMA should supplement essential commodities.

Random forest is a type of *ensemble learner* [3]. The general idea is to train many classification and regression tree (CART) models and combine their individual predictions. Furthermore, random forest models are easy (and fast) to train and implement. LSTM networks are a type of recurrent neural network that has feedback loops [8]. The feedback loops allow LSTM networks to model complex dependencies and lags, including those found in time-series data. LSTMs are arguably the most powerful, versatile, and commercially viable networks (at least, right now). For example, Uber has developed an LSTM network that can accurately predict spatial-temporal ride requests during extreme events, such as holidays, major events, and inclement weather [9].

Both random forest and LSTM networks can handle a large number of features and include internal feature selection methods, removing the need for manual pre-processing, feature selection, and feature engineering. Although LSTM networks require far more data than random forest, they can typically achieve better prediction accuracy. LSTM networks are also much harder to train and require significant expertise due to the large number and high sensitivity to hyper-parameter choices.

4.3 Application areas

These models are particularly well-suited to three key application areas:

1. *Fuel retailers:* forecasting and explaining the access and availability of fuel is critical for supply chain function. GasBuddy collects detailed spatial-temporal data on both fuel availability (i.e., supply) and accessibility (i.e., ability to pump).

2. *Food retailers:* forecasting and explaining the access and availability of food retailers (e.g., grocery stores) is critical for understanding where essential commodities need to be delivered. The Supplemental Nutrition and Assistance Program (SNAP) collects detailed spatial-temporal data on retailer availability.

3. *Healthcare facilities:* forecasting and explaining the access and availability of healthcare facilities (e.g., hospitals, pharmacies) is critical for disaster response and recovery. Healthcare Ready (through RxOpen) collects detailed spatial-temporal data on pharmacy availability and is looking to expand into hospitals.

The three aforementioned application areas are very similar in the type of data produced. A single LSTM architecture may be applicable to all three problems, removing the need to develop multiple approaches. Most importantly, different organizations (e.g., GasBuddy, SNAP, etc.) currently collect data on $a_{r,t}$ for different commodities, suggesting that there are viable opportunities to apply these techniques in practice to the three aforementioned industries.

4.4 Implementation considerations

Although there exists data on $a_{r,t}$, there are still significant challenges associated with obtaining feature data and building both explanatory and forecasting tools. We highlight the following key considerations for emergency managers:

- Both approaches require large amounts of data. For $a_{r,t}$, we require data for multiple retailer locations across a large area and large time period that (ideally) includes multiple storms. Obtaining this data is challenging.

- Feature data must be collected and processed on an ongoing basis. In order to use these models on an on-going basis, a data collection pipeline is required to obtain and process the relevant features (e.g., storm information). Setting up the infrastructure to do this will take time and resources.

- Significant computational resources are required. All the aforementioned models (especially LSTMs) require large amounts of computational resources. Graphics processing units (GPUs) have demonstrated effectiveness for improving computational time (and ultimately accuracy) [12].

- Machine learning and statistical expertise is required to train the models. LSTMs are notoriously difficult to train and build, and require careful oversight during the training process.

5 Prescriptive tools

In this section, we develop prescriptive tools for identifying sentinel indicators and critical supply chain components. Section 5.1 outlines our generalized network-based framework for disaster supply chains, Section 5.2 develops an optimization model based on the framework, and Section 5.3 develops a centrality metric that can be efficiently computed.

5.1 Generalized framework

Tools aiming to represent dynamics and prescribe solutions in critical supply chains must consider the broader, more complex system in which they operate. We propose a generalized framework for this system that represents important interdependencies across various supply chains. The conceptual modeling construct for this framework is a network because it facilitates interdependency linkages and spatial-temporal representation.

Supply chains are comprised of independently operated companies connected via business relationships to enable the flow of materials. Few companies own or directly control all extraction, manufacturing, storage, transportation, distribution, and retail assets required to transform raw materials into finished goods and deliver them to consumers. Companies guide operations for segments of the supply chain and typically outsource some of the activities to third-party service providers. For example, many companies choose to outsource transportation to third parties rather than directly operate assets. It is cost effective for them to rely on third party assets to handle the peaks and valleys in material flows.

Supply chains are often characterized by three flows: material, financial, and information. Material does not move without the finances to pay for goods and the information to coordinate order and delivery. The modern digital financial and information flows are dependent on power grids and communication networks. Vulnerabilities in the critical power and communication infrastructure exposed during disaster as outages will inhibit material flows. Thus, supply chains that deliver essential goods during disaster are dependent on power and communications networks.

Finally, in addition to operational assets and the enabling environment of power and communication, supply chains rely on people to operate, e.g., drivers, site operators, repair technicians. Supply chains operating in disaster-affected regions are constrained when critical employees cannot return to work while they address urgent needs in the disaster-affected community. These needs may be difficult to meet while supply chains are constrained, leading to a coupling of human and operational systems. Without drivers, critical commodities like food and water cannot be distributed. And yet, without food and water, critical employees such as drivers across the supply chain may need to address family needs before resuming their role in transporting goods.

Therefore, our generalized approach must integrate interdependencies among multi-party supply chains and the essential resources of people, power, and communications. While these essential resources may further rely on different supply chains, such as maintenance parts, we choose to characterize them by spatial-temporal resource availability. More complex modeling is required to further incorporate these extended supply chains.

We characterize this system as a network of nodes and arcs through which materials flow. The aim following a disaster is to maximize the flow of critical commodities subject to constraints on nodes and arcs derived directly from operational capacity of supply chain actors and from spatial-temporal pools for the essential resources of people, power, and communications. These constraints may be represented by a "recipe" of resources required for flow, e.g. fuel, power, payment communications, and employee at a fuel station.

Figure 9 shows the generalized network for the diesel fuel supply chain. The aim is to maximize fuel sales at a retail location. The material flow requires raw material supply of oil, production capacity at the refinery, bulk transportation by various modes (e.g., pipeline, maritime, rail) to a distribution terminal, last mile transportation by tanker truck, and retail operations for fuel transactions. Enabling resources are only partially represented in the figure. Human resources are shown as a general employee pool, which could be required for various nodes and arcs, and only one specialized resource pool for certified drivers that are required for last mile transportation. Only the truck equipment is represented as an operational asset pool. Power and communications resource pools are represented generally and could apply to various nodes and arcs. The concept of a resource recipe can be seen with last mile fuel transport. It requires a blend of upstream fuel supply at the terminal, power for terminal rack pumps, and resource pools of equipment, certified driver, retail location employee, and communications to enable terminal and retail transactions.

In order to maximize flow, we develop models to prescribe solutions that address potential bottlenecks in the supply chain. These bottlenecks likely shift dynamically across the generalized network following a disaster. System resilience relies on the ability to monitor each potential bottleneck and rapidly deploy solutions to address resource constraints. We develop models to identify potential bottlenecks in order to monitor them as sentinel indicators. We also develop models to prescribe solutions that could be prioritized for rapid deployment.

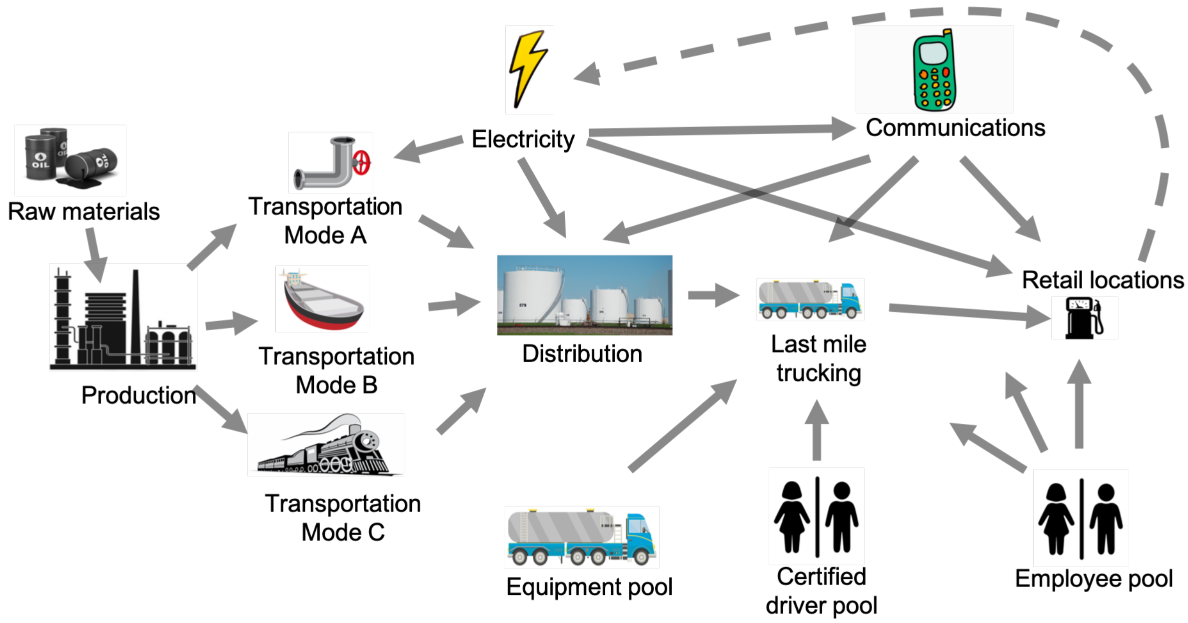

Figure 9: A graphical illustration of the generalized diesel fuel supply chain. Source: MIT analysis.

5.2 Optimization models

In this section, we use the generalized framework outlined in Section 5.1 to develop three optimization models:

1. *Baseline model (Section 5.2.1):* The baseline model determines how to satisfy consumer demand. The model solution provides optimal route choices from the supply nodes (e.g., fuel terminals, distribution centers, neighborhoods) to retail locations (e.g., gas stations, grocery stores). Given a limited budget of product (e.g., fuel), people (e.g., available employees), and power (e.g., mobile generators), the model can be used to determine the best usage of these resources (i.e., when and where should they be sent). The model can be solved during normal operating conditions or during a disaster with outages as input parameters (e.g., road closures, power disruptions, etc).

2. *Disaster response model (Section 5.2.2):* The disaster response model determines how to restore supply chain function by prioritizing disaster response efforts. The model builds upon the baseline model and as a result, also prescribes solutions for how to satisfy consumer demand under disaster conditions. The model can be used during a disaster by inputting road and power outages determined from real-time descriptive tools. The model can also be used to plan

for various disaster scenarios by simulating or creating specific disaster conditions and outages (e.g., using Hazus).

3. *Interdiction model (Section 5.2.3):* The interdiction model determines the most critical components of the supply chain. The model leverages a game-theoretic approach (interdiction) where an agent strategically destroys components of the supply chain. Note that the agent is not mean to represent a storm. Instead, the solutions allow emergency mangers to understand various worst-case scenarios by elucidating the most vulnerable and critical components of the supply chain.

Note that the disaster response model and interdiction model independently build upon the baseline model.

Before introducing the models, we need to define our notation and parameters. Let the road network be represented by a graph $G = (N, E)$. The node set N is comprised of five disjoint subsets: N_S indicates the set of supply nodes (i.e., fuel terminals, distribution centers), N_D indicates the set of demand nodes (i.e., retail locations), N_H represents the set of personnel supply nodes (i.e., housing neighborhoods), N_P indicates the set of power supply nodes (in our work we assume, $|N_P| = 1$), and N_N represents the set of nodes that do not belong to any of the previously defined sets. The edge set E is comprised of all roads and $|N_p| * |N_D \cup N_S|$ dummy edges that directly connect the power supply node p to all nodes $n \in N_S \cup N_D$. We make this simplifying assumption to remove the need to model the entire power network and the implication of this assumption is that the power supply of each node $n \in N_S \cup N_D$ is independent of each other node. Lastly, we assume that the planning horizon is divided into a set of discrete time periods indicated by T. Table 3 defines our input parameters and decision variables.

Table 3: Summary of all decision variables and input parameters.

Decision variables	
d_j^t	Demand satisfied at node $j \in N_D$ during period $t \in T$
ud_j^t	Remaining unsatisfied demand at node $j \in N_D$ at the start of period $t \in T$
nd_j^t	New demand arising at node $j \in N_D$ during period $t \in T$
s_i^t	Supply used at node $i \in N_S$ during period $t \in T$
rs_i^t	Remaining supply at node $i \in N_S$ at the start of period $t \in T$
ns_i^t	New supply arriving at node $i \in N_S$ during period $t \in T$
f_{ij}^t	Flow along edge $(i,j) \in E$ during period $t \in T$
ϕ_{pj}^t	Binary variable that is equal to one if node $j \in N_s \cup N_D$ is receiving power from node $p \in N_p$
ω_{ij}^t	Flow of personnel along edge $(i,j) \in E$ during period $t \in T$
Input parameters	
b^t	Utility accrued from satisfying one unit of demand during period $t \in T$
Φ_p^t	Total power available at node $p \in N_p$ during period $t \in T$
Ω_h^t	Total number of personnel available at node $h \in N_H$ during period $t \in T$

5.2.1 Baseline model

The baseline model determines how to best satisfy consumer demand. As noted above, the model solution provides optimal route choices from the supply nodes (e.g., fuel terminals, distribution centers, neighborhoods) to retail locations (e.g., gas stations, grocery stores). The model solutions can be validated via prospective data collection or industry collaboration to determine if the suggested routes match with those used in reality. This information can then be used by emergency managers to understand the flow of product, people, and power throughout the supply chain network during normal operating conditions.

The model can also be used to determine the best usage of limited product, people, and power resources during a disaster (i.e., when and where should they be sent). Outages (e.g., road closures, power disruptions, etc) can be input to the model and new solutions (i.e., route choices and resource allocation) that account for outages can be prescribed. Note that the model allows for each time period to be weighted differently, allowing us to model the *Golden Hour*, which suggests that demand should be satisfied as quickly as possible (i.e., early periods receive a higher weight). We formulate the model as follows:

$$\underset{\omega,\phi,d,ud,nd,d,rs,ns,s,f}{\text{maximize}} \quad \sum_{t\in T} b^t \sum_{j\in N_D} d_j^t \left(\sum_{p\in N_P} \phi_{pj}^t\right)\left(\sum_{(i,j)\in E} \omega_{ij}^t\right), \tag{1a}$$

$$\text{subject to} \quad ud_j^{t+1} = ud_j^t - d_j^t\Big(\sum_{p\in N_P} \phi_{pj}^t\Big)\Big(\sum_{(i,j)\in E} \omega_{ij}^t\Big) + nd_j^t, \qquad \forall j \in N_D, t \in T, \tag{1b}$$

$$rs_i^{t+1} = rs_i^t - s_i^t\Big(\sum_{p\in N_P} \phi_{pi}^t\Big)\Big(\sum_{(j,i)\in E} \omega_{ji}^t\Big) + ns_i^t, \qquad \forall i \in N_S, t \in T, \tag{1c}$$

$$\sum_{(j,i)\in E} f_{ji}^t - \sum_{(i,j)\in E} f_{ij}^t = (d_i^t - s_i^t)\Big(\sum_{p\in N_P} \phi_{pi}^t\Big)\Big(\sum_{(j,i)\in E} \omega_{ji}^t\Big), \qquad \forall i \in N_D \cup N_S, t \in T, \tag{1d}$$

$$\sum_{(j,i)\in E} f_{ji}^t - \sum_{(i,j)\in E} f_{ij}^t = 0, \qquad \forall i \in N_N, t \in T, \tag{1e}$$

$$\sum_{(j,i)\in E} \omega_{ji}^t - \sum_{(i,j)\in E} \omega_{ij}^t = 0, \qquad \forall i \in N_N, t \in T, \tag{1f}$$

$$\sum_{j\in N_D\cup N_S} \phi_{pj}^t \le \Phi_p^t, \qquad \forall p \in N_P, t \in T, \tag{1g}$$

$$\sum_{(h,j)\in E} \omega_{hj}^t \le \Omega_h^t, \qquad \forall h \in N_H, t \in T, \tag{1h}$$

$$\omega_{ij}^t \in \{0,1\}, \qquad \forall (i,j) \in E, t \in T, \tag{1i}$$

$$\phi_{pj}^t \in \{0,1\}, \qquad \forall p \in N_p, j \in N_S \cup N_D, t \in T, \tag{1j}$$

$$f_{ij}^t \ge 0, \qquad \forall (i,j) \in E, t \in T, \tag{1k}$$

$$d_j^t,\ ud_j^t,\ nd_j^t \ge 0 \qquad \forall j \in N_D, t \in T, \tag{1l}$$

$$s_i^t,\ rs_i^t,\ ns_i^t \ge 0 \qquad \forall i \in N_S, t \in T. \tag{1m}$$

The objective function (1a) maximizes the total utility accrued from satisfying demand over time. In our model, demand can only be satisfied if it is available (i.e., there is supply at the demand location) and accessible (i.e., there is power and personnel at the demand location). Similarly, supply is only available if the supply node has power and personnel. Constraint (1b) determines the unmet demand at node j at the start of period $t+1$ by accounting for unmet demand at the start of period t, the demand met during period t, and any new demand arising during period t. Constraint (1c) similarly determines the remaining supply at node i at the start of period $t+1$. Constraints (1d) and (1e) ensure that the flow of product is conserved, while constraint (1f) ensures that the flow of personnel is conserved. Constraint (1g) limits the total power available and constraint (1h) limits the total supply of personnel available at each housing node $h \in N_H$.

Formulation (1) was inspired by the model in [14] with two key differences: 1) we consider the availability of power and personnel as critical factors for satisfying demand (and providing supply), and 2) we allow new demand and supply to arrive during the time horizon. In the following two sections, we provide tactical and strategic extensions to the baseline model.

5.2.2 Disaster response model

The disaster response model determines how to restore supply chain function by prioritizing disaster response efforts. The model prescribes solutions for restoring supply chain function by prioritizing outage restoration on edges in the network. To do this, the model requires road and power outages as input, which can be obtained from real-time descriptive tools allowing the model to be solved and prescribe disaster response solutions that can be immediately implemented. Outages can also be simulated or created using validated software tools (e.g., Hazus) allowing emergency managers to plan and prepare for potential disasters in advance.

The disaster response model builds upon the baseline model by including additional variables and constraints. Intuitively, these additional constraints model restoration efforts by emergency responders. Each edge requires a predetermined level of restoration based on the scale of the outage. For example, a collapsed bridge requires more restoration effort than debris (e.g., trees) blocking the road. In each period, there is a limited budget of restoration effort and the model determines how to prioritize these limited resources so that supply chain function is restored as quickly as possible (and demand can be satisfied). To model restoration, we follow the general approach of [14] to add the following constraints to the baseline model:

$$
\begin{aligned}
& f_{ij}^t \leq M v_{ij}^t, \qquad \forall (i,j) \in E, t \in T, \\
& \omega_{ij}^t \leq M v_{ij}^t, \qquad \forall (i,j) \in E, t \in T, \\
& A_{ij}^t + y_{ij}^t = A_{ij}^{t+1}, \qquad \forall (i,j) \in E, t \in T, \\
& W_{ij} - A_{ij}^t \leq (1 - v_{ij}^t) W_{ij}, \qquad \forall (i,j) \in E, t \in T, \\
& W_{ij} - A_{ij}^t \geq (1 - v_{ij}^t), \qquad \forall (i,j) \in E, t \in T, \\
& \phi_{pj}^t \leq M z_{pj}^t, \qquad \forall p \in N_P, j \in N_D \cup N_S, t \in T, \\
& A_{pj}^t + y_{pj}^t = A_{pj}^{t+1}, \qquad \forall p \in N_P, j \in N_D \cup N_S, t \in T, \\
& W_{pj} - A_{pj}^t \leq (1 - z_{pj}^t) W_{ij}, \qquad \forall p \in N_P, j \in N_D \cup N_S, t \in T, \\
& W_{pj} - A_{pj}^t \geq (1 - z_{pj}^t), \qquad \forall p \in N_P, j \in N_D \cup N_S, t \in T, \\
& \sum_{(i,j) \in E} v_{ij}^t + \sum_{p \in N_P} \sum_{j \in N_D \cup N_S} z_{pj}^t \leq \Xi^t, \qquad \forall t \in T, \\
& v_{ij}^t,\ z_{ij}^t \in \{0, 1\}, \qquad \forall (i,j) \in E, t \in T,
\end{aligned}
$$

where A_{ij}^t denotes the total restoration performed on edge (i, j) up to the start of period t, y_{ij}^t represents the amount of restoration done on edge (i, j) during period t, and W_{ij} represents the total amount of restoration required on edge (i, j). Note that v and z are dummy binary variables.

5.2.3 Interdiction model

The interdiction model determines the most vulnerable and critical components of the supply chain network. To do this, the model leverages a game-theoretic approach, called interdiction [17]. Interdiction models typically employ an agent that strategically destroys or adds outages to various components of the supply chain. In our case, the agent has a limited budget of disruption that can be applied to various edges in the networks to disrupt the flow of product, people, and power. The amount of outage added to a particular link corresponds to the restoration effort required to clear the outage. For example, the agent may choose to add small disruptions to some links (e.g., debris) and large disruptions to other links (e.g., floods). It is important to note that the agent is not meant to represent a storm because storms do not act strategically. Instead, the strategic agent allows Emergency Mangers to understand various worst-case scenarios by elucidating the most vulnerable and critical components of the supply chain.

We formulate this problem using a two-stage maximin formulation with the following inner minimization problem (and the baseline model as the out maximization problem):

$$\begin{aligned}
\underset{v,w,z}{\text{minimize}} \quad & \sum_{t\in T} b^t \sum_{j\in N_D} d_j^t \left(\sum_{p\in N_P} \phi_{pj}^t\right)\left(\sum_{(i,j)\in E} \omega_{ij}^t\right), && \text{(2a)}\\
\text{subject to} \quad & f_{ij}^t \le M - v_{ij}^t, \qquad \forall (i,j)\in E, t\in T, && \text{(2b)}\\
& \omega_{ij}^t \le M - w_{ij}^t, \qquad \forall (i,j)\in E, t\in T, && \text{(2c)}\\
& \phi_{ij}^t \le M - z_{ij}^t, \qquad \forall (i,j)\in E, t\in T, && \text{(2d)}\\
& \sum_{(i,j)\in E} v_{ij}^t + w_{ij}^t + z_{ij}^t \le \Xi^t, \qquad \forall t\in T, && \text{(2e)}\\
& v_{ij}^t,\ w_{ij}^t,\ z_{ij}^t \ge 0, \qquad \forall (i,j)\in E, t\in T. && \text{(2f)}
\end{aligned}$$

We combine Formulation 1 and 2 to obtain the complete interdiction model:

$$
\begin{aligned}
\underset{\omega,\phi,d,ud,nd,d,rs,ns,s,f}{\text{maximize}} \quad \underset{v,w,z}{\text{minimize}} \quad & \sum_{t\in T} b^t \sum_{j\in N_D} d_j^t \left(\sum_{p\in N_P} \phi_{pj}^t \right) \left(\sum_{(i,j)\in E} \omega_{ij}^t \right), \\
\text{subject to} \quad & ud_j^{t+1} = ud_j^t - d_j^t \Big(\sum_{p\in N_P} \phi_{pj}^t \Big) \Big(\sum_{(i,j)\in E} \omega_{ij}^t \Big) + nd_j^t, \qquad \forall j \in N_D, t\in T, \\
& rs_i^{t+1} = rs_i^t - s_i^t \Big(\sum_{p\in N_P} \phi_{pi}^t \Big) \Big(\sum_{(j,i)\in E} \omega_{ji}^t \Big) + ns_i^t, \qquad \forall i \in N_S, t\in T, \\
& \sum_{(j,i)\in E} f_{ji}^t - \sum_{(i,j)\in E} f_{ij}^t = (d_i^t - s_i^t) \Big(\sum_{p\in N_P} \phi_{pi}^t \Big) \Big(\sum_{(j,i)\in E} \omega_{ji}^t \Big), \qquad \forall i \in N_D \cup N_S, t\in T, \\
& \sum_{(j,i)\in E} f_{ji}^t - \sum_{(i,j)\in E} f_{ij}^t = 0, \qquad \forall i \in N_N, t \in T, \\
& \sum_{(j,i)\in E} \omega_{ji}^t - \sum_{(i,j)\in E} \omega_{ij}^t = 0, \qquad \forall i \in N_N, t \in T, \\
& \sum_{j\in N_D \cup N_S} \phi_{pj}^t \le \Phi_p^t, \qquad \forall p \in N_P, t\in T, \\
& \sum_{(h,j)\in E} \omega_{hj}^t \le \Omega_h^t, \qquad \forall h \in N_H, t\in T, \\
& f_{ij}^t \le M - v_{ij}^t, \qquad \forall (i,j)\in E, t\in T, \\
& \omega_{ij}^t \le M - w_{ij}^t, \qquad \forall (i,j)\in E, t\in T, \\
& \phi_{ij}^t \le M - z_{ij}^t, \qquad \forall (i,j)\in E, t\in T, \\
& \sum_{(i,j)\in E} v_{ij}^t + w_{ij}^t + z_{ij}^t \le \Xi^t, \qquad \forall t\in T, \\
& v_{ij}^t,\ w_{ij}^t,\ z_{ij}^t \ge 0, \qquad \forall (i,j)\in E, t\in T, \\
& \omega_{ij}^t \in \{0,1\}, \qquad \forall (i,j)\in E, t\in T, \\
& \phi_{pj}^t \in \{0,1\}, \qquad \forall p \in N_p, j\in N_S \cup N_D, t\in T, \\
& f_{ij}^t \ge 0, \qquad \forall (i,j)\in E, t\in T, \\
& d_j^t,\ ud_j^t,\ nd_j^t \ge 0 \qquad \forall j\in N_D, t\in T, \\
& s_i^t,\ rs_i^t,\ ns_i^t \ge 0 \qquad \forall i\in N_S, t\in T.
\end{aligned} \tag{3}
$$

Note that M represents a large number (i.e., "Big M"). To solve this problem, we need to take the dual of the inner minimization and combine with the outer maximization problem. At first glance, it appears as though this approach will result in a bilinear formulation that may be difficult to solve. Note that all our models are mixed integer linear programming problems and can be shown to be NP-hard. Further theoretical research is needed to better understand how to solve these models efficiently.

It is likely that for large scale problems representative of real world disasters, a heuristic (approximate) solution algorithm will be needed. The next section investigates an alternative approach (centrality) that can be used in lieu of additional theoretical research and the development of custom solution algorithms.

5.3 Centrality metrics

In this section, use the generalized framework outlined in Section 5.1 to develop centrality metrics that can be used as an alternative to our optimization models. Centrality is used to identify the most important vertices in a graph and there are many different types of centrality metrics depending on how "most important" is defined. We develop a modified version of the betweenness centrality measurement introduced in [14]. Intuitively, betweenness centrality measures how often a node belongs to the shortest path between two other nodes (i.e., fuel terminal and fuel retailer). Nodes with a high betweenness centrality measurement are a part of many shortest paths implying that if these nodes were removed there will be significant disruption to the system (i.e., many routes will need to find detours).

In the next two sections, we develop separate metrics for product (Section 5.3.1) and personnel (Section 5.3.2). It is possible to develop a separate metric for power that explicitly models the power grid, which we do not explore here.

5.3.1 Product centrality

The product centrality metric determines the most important nodes for shipping product from supply locations (e.g., fuel terminals, bottled water distribution centers) to demand locations (e.g., retailers).

To do this, we first find the number of shortest paths (denoted by $\bar{g}_{ij}$) between each supply node $i \in N_S$ and each demand node $j \in N_D$ and the length of those paths (denoted by $|\bar{g}_{ij}|$). We then count the number of shortest paths between $i \in N_S$ and $j \in N_D$ that pass through $k \in N$ (denoted by $\bar{g}^k_{ij}$). Lastly, we weight the metric using the average daily demand arriving at $j \in N_D$ (nd^T_j) times the daily average supply available at $i \in N_S$ (ns^t_j). Putting this together, we obtain the following metric for each node

$$C_k = \sum_{i \in N_S} \sum_{j \in N_D} \frac{\bar{g}^k_{ij}}{\bar{g}_{ij}} \frac{\sum_{t \in T}(nd^t_j * ns^t_j)}{|T| * |\bar{g}_{ij}|}.$$

To obtain edge importance, we add the metrics for both nodes that are adjacent to the given edge:

$$\hat{C}_{ij} = \hat{C}_i + \hat{C}_j.$$

5.3.2 Personnel centrality

The personnel centrality metric determines the most important nodes for employees to travel from their home to their work location (either a supply or demand node). Recall that Ω_h^t denotes the supply of personnel at node $h \in N_H$ at time $t \in T$. We define the following function

$$\psi(j) = \begin{cases} \sum_{t \in T} nd_j^t, & \text{if } j \in N_D, \\ \sum_{t \in T} ns_j^t, & \text{if } j \in N_S, \end{cases}$$

which is used to weight the metric according to the supply (or demand) at the each persons employment node. Combing this information, we obtain the following metric for personnel:

$$L_k = \sum_{i \in N_H} \sum_{j \in N_D \cup N_S} \frac{\bar{g}_{ij}^k}{\bar{g}_{ij}} \frac{\sum_{t \in T} \Omega_h^t \psi(j)}{|T| * |\bar{g}_{ij}|}.$$

Similar to the product metric, we can add nodes metrics to obtain edge scores. We can also sum the product and personnel metrics to obtain an overall score for each node and edge.

6 Diesel fuel analysis

In this section, we analyze the diesel fuel supply chain during the 2017 hurricane season to provide insights using real data (Section 6.1 and 6.2) and demonstrate the application of product centrality (Section 6.3). Most of the data in this section was obtained from publicly available sources at EIA.

6.1 Upstream fuel supply chain analysis

There are 32 diesel refineries in PADD3 and they produce roughly 60% of all diesel fuel in the United States. The majority of the crude oil used in these refineries is supplied via sub-sea pipeline from off-shore sites in the Gulf of Mexico. Due to their location, the off-shore extraction sites are highly vulnerable to hurricanes and during Hurricane Harvey, many off-shore extraction sites were temporarily closed, limiting the overall supply of crude oil to the refineries. Refineries without a constant supply of crude oil may be forced to cease operations, which is both a dangerous and costly event. As a result, the Strategic Petroleum Reserve – the world's largest emergency store of crude oil – was used to supply 5.2 million barrels of crude oil to the impacted refineries.

Although the Strategic Petroleum Reserve was used to maintain operations at some refineries, a total of 15 refineries (47%) were closed during Hurricane Harvey, primarily due to lack of supply, flooding, power outages, and lack of personnel. Table 4 compares refinery utilization rates during Hurricane Harvey and the previous 5-years. Note that utilization and capacity are not equivalent - 100% utilization refers to the standard utilization, factoring in maintenance and other temporary production issues. The refineries along the Texas Gulf Coast were significantly impacted, but the remaining regions were able to ramp up production and mitigate the impact of the closures.

Table 4: PADD3 refinery utilization. Source: EIA.

PADD3 district	5-year average utilization (2012-2017)	September 2017 utilization
Texas Gulf Coast	90%	58%
Louisiana Gulf Coast	93%	99%
Texas Inland	94%	95%
Northern Louisiana/Arkansas	80%	86%
New Mexico	96%	112%

After refining, diesel fuel is transported to fuel terminals at the final destination via pipeline and barge. Table 5 breaks down the transportation and final destination for the diesel fuel produced in PADD3. Hurricane Harvey disrupted the transportation of diesel fuel due to both pipeline and port closures. The Colonial pipeline (the largest in the US) closed both lines between Houston, TX and Lake Charles, LA for five days due to a lack of supply from refiners and power outages. Service was intermittent east of Lake Charles, primarily due to supply restrictions. The Plantation pipeline (the second largest) was not impacted and remained operational. Although the PADD3 pipeline stocks decreased temporarily due to these closures, aggregate pipeline stocks were not significantly affected. Figure 10 displays the aggregate pipeline stocks in PADD1 and PADD3. Note that PADD3 and PADD1 stocks increased significantly in October, November, and December, likely to replenish stocks used during the closures.

The damage from Hurricane Harvey also closed six major ports in Texas (Houston, Galveston, Corpus Christi, Texas City, Freeport, and Brownsville) and one major port in Louisiana (Lake Charles). The Port of Houston was closed for seven days and dozens of ships were stranded off the cost or diverted to other locations. The impact on the ports persisted for months due to sediment shoaling and buildup, which prevented larger ships from accessing the port. Significant time and resources were required to dredge the ports back to their original depth.

Table 5: PADD3 diesel transportation and final destination. Source: EIA.

Primary transportation method	Final destination	Amount of total production
Pipeline	Canada	44%
Pipeline	PADD1	25%
Pipeline	PADD2	4%
Pipeline	PADD3	21%
Pipeline	PADD5	1%
Barge	Florida	6%

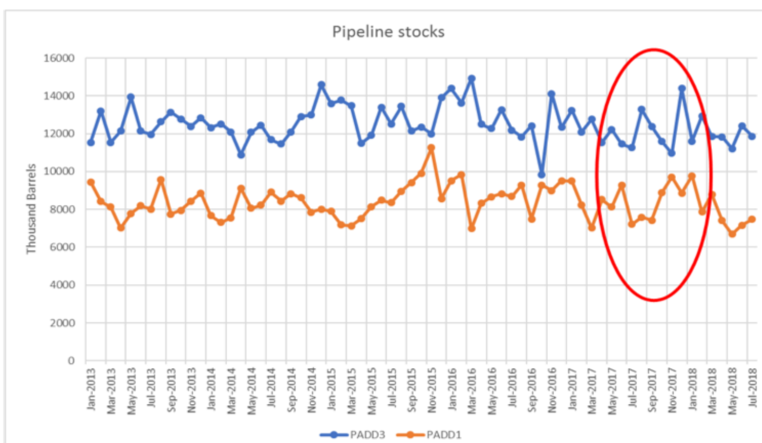

Figure 10: Aggregate pipeline stocks in PADD1 and PADD3. Source: EIA.

In addition to port and pipeline closures, Hurricane Harvey also impacted the bulk terminals used to store and transfer fuel from pipelines and barges to tanker trucks for delivery to retail locations. Figure 11 displays the aggregate bulk terminal stocks in PADD1 and PADD3. Many terminals in Corpus Christi, Freeport, Houston, Galveston, and Beaumont were closed due to power outages. Between July and October 2017, terminal stocks fell by 15% in PADD1 and 38% in PADD3, primarily due to supply restrictions. Although these represent significant decreases in supply, total stocks did not reach critically low levels. Lack of data and visibility into individual terminal stocks is a major challenge for understanding the precise spatial-temporal impact. For example, although the aggregate stocks did not reach critically low levels, individual terminals may have.

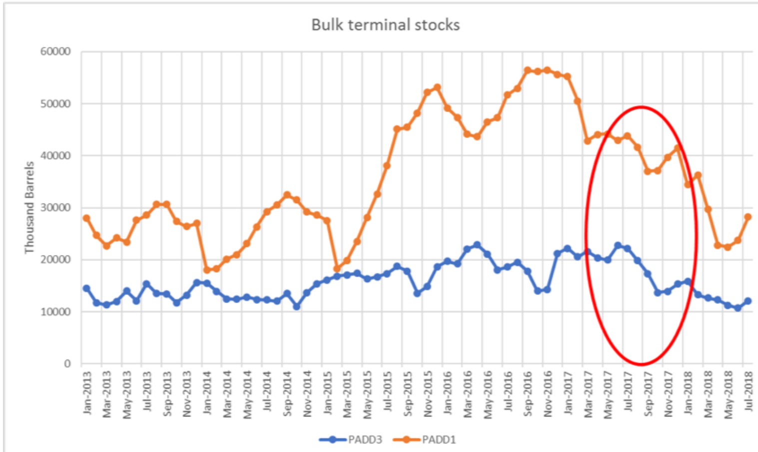

Figure 11: Aggregate bulk terminal stocks in PADD1 and PADD3. Source: EIA.

Thus far, our analysis indicates that the upstream supply of fuel was resilient. Although Hurricane Harvey caused significant damage to production and transportation, terminal stocks did not reach critically low levels. In other words, fuel was available for transport from terminals to retailers. As a result, we focus on the downstream fuel supply chain – the transportation of fuel from terminals to retailers and the access and availability of fuel at the retailers. In contrast to the upstream fuel supply chain, which is closely monitored by EIA, there is no centralized monitoring or data collection for the distribution and sale of fuel at the retail level. This leads to several challenges associated with analyzing the performance and resilience of the system.

6.2 Downstream fuel supply chain analysis

The downstream fuel supply chain includes three key components:

1. *Fuel racks:* used to distribute fuel from the terminal to the tankers. Each terminal has a limited number of racks and location-specific licenses are required to access them.

2. *Fuel tankers:* used to transport fuel from the terminal to the retail location.

3. *Retail locations:* used to sell fuel to the public.

As noted above, there is no centralized monitoring agency or database of the downstream fuel supply chain. This leads to significant challenges associated with data collection and analysis. As a result, our analysis of the downstream fuel supply chain primarily focuses on Hurricane Irma's impact on Florida. We focus on Florida for three main reasons:

1. We obtained daily sales volume data (diesel and regular) for 13 retail locations along the major transportation corridors (e.g., I-95, I-75, I-10) during August and September 2017.

2. Florida experiences a large number of hurricanes.

3. Florida's fuel supply chain is particularly vulnerable to disruption during hurricanes because the majority of the fuel arrives at the major ports via barge. Florida is not directly connected to any major pipelines (e.g., Colonial or Plantation), but there are smaller pipelines that connect the ports to the inland airports (e.g., Tampa to Orlando).

Our analysis found that 12/13 stores suffered outages, defined as days with no sales of either diesel or regular fuel. All outages occurred between September 9 and September 17, 2017. Figure 12 displays the number of stores with various outage lengths. The only store without an outage was located on the I-10, just outside of Tallahassee. Although Tallahassee was impacted by Irma, the damage was not severe, primarily because the storm had begun to decrease in severity (e.g., Tallahassee's maximum sustained wind was only 35mph as compared to >100mph in South Florida). The two stores with outages of seven (Ocala) and nine (Fort Myers) days were located directly along Hurricane Irma's path. Although there were other stores located directly along the storm path, these two stores were the farthest from a fuel terminal. It is difficult to conclude that distance from fuel terminal was a key factor due to the small sample size. However, we believe this is worth exploring in future analysis and distance to nearest fuel terminal may serve as a strong predictive variable for access and availability of fuel.

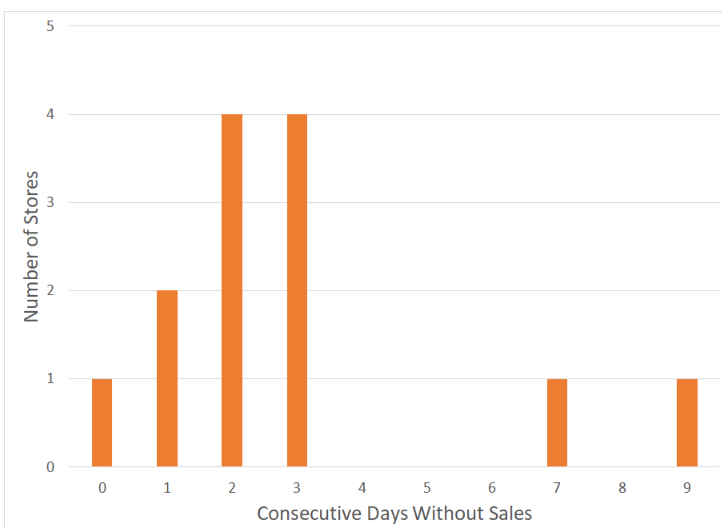

Figure 12: Fuel retail outages for our 13 store sample. Source: Retailer(s), MIT analysis.

Figure 14 displays diesel fuel sales volume for 13 stores and Figure 13 displays regular fuel sales volume for 12 stores in Florida during August and September 2017 (store 13 was missing regular fuel sales). Note that a State of Emergency was declared on September 4, evacuation took place between September 7-9, and Hurricane Irma made landfall on September 10. Diesel sales volume was 4.5 times larger on weekdays and 2 times larger on weekends as compared to regular fuel. The exact sales volume amounts (the y-axis) are removed for confidentiality reasons.

We observe a significant spike in regular fuel sales between September 4 and September 9, likely due to residents stocking up and/or evacuating. There is also a major secondary spike after the storm from September 12-14, likely due to residents returning home from evacuation locations. The same effect is not observed for diesel, suggesting that the total volume of tractor units had not increased due to the emergency.

We also found that diesel fuel sales follow a cyclical nature, with low sales volumes on Saturday, Sunday, and holidays (e.g., Labor Day). By contrast, regular fuel sales do not appear to follow the same cyclical nature. Note that the majority of the observed outages occurred on September 9 (Saturday) and 10 (Sunday), low days for diesel sales. Had the storm resulted in mid-week outages, the impact on the supply chain may have been more severe. Further research (and data) is required to fully investigate this hypothesis.

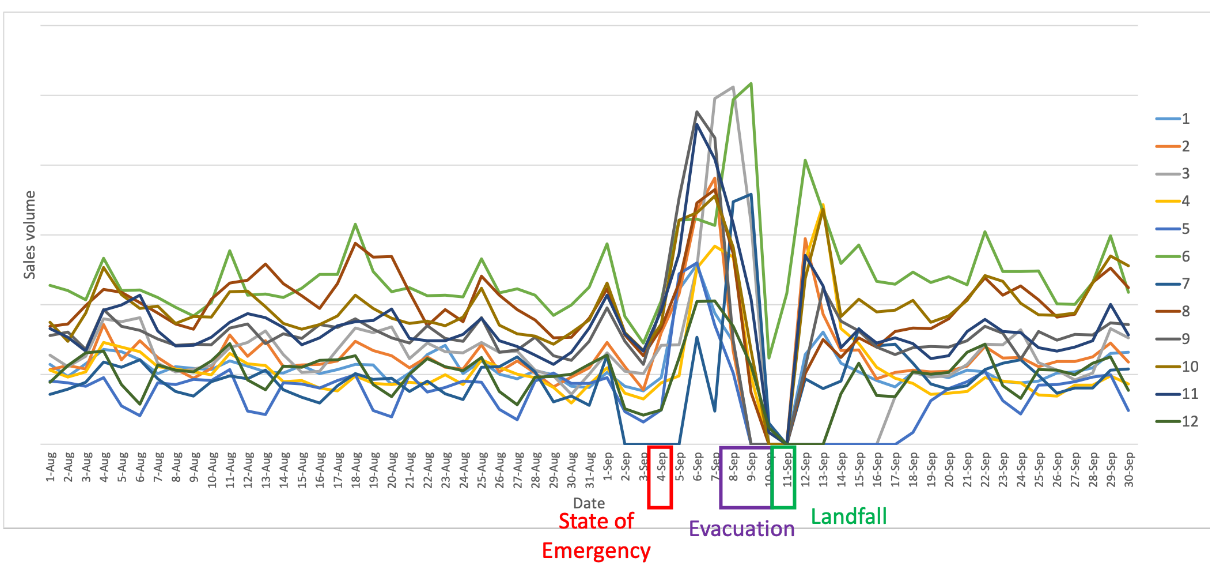

Figure 13: Regular fuel sales volume for 12 retailer locations in Florida during August and September 2017. Source: Retailer(s), MIT analysis.

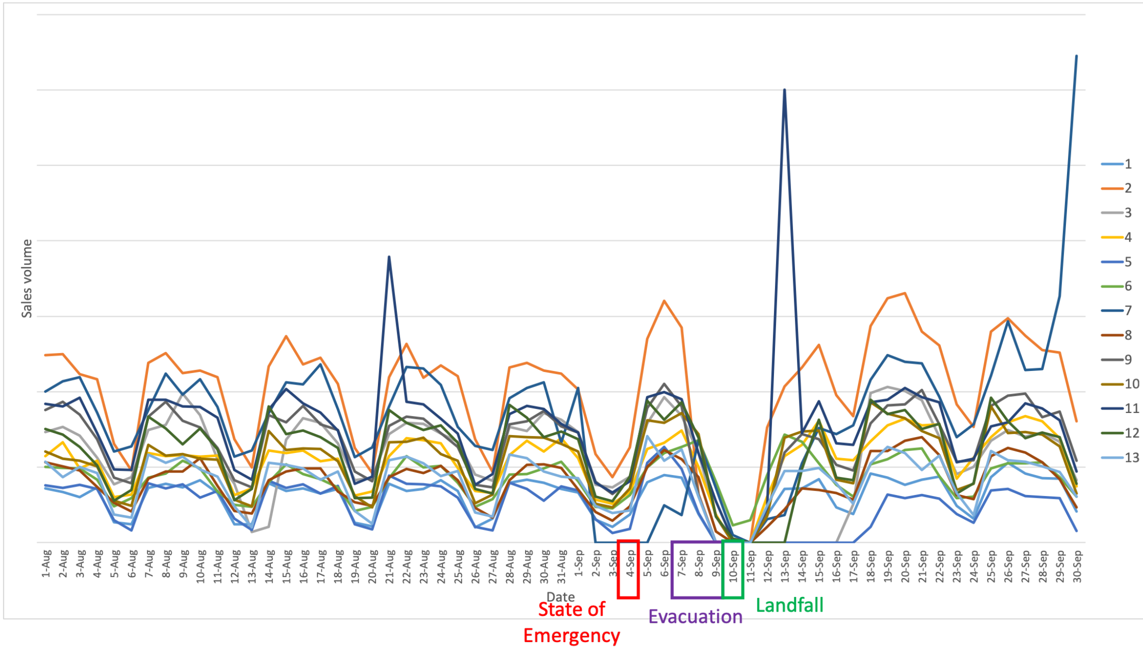

Figure 14: Diesel fuel sales volume for 13 retailer locations in Florida during August and September 2017. Source: Retailer(s), MIT analysis.

6.3 Application of product centrality to diesel fuel

In this section, we apply the product centrality metric to the diesel fuel supply chain in Florida. To do this, we obtained the location of all major fuel terminals (supply nodes, N_S) and major diesel fuel retailers (demand nodes, N_D). Due to lack of data availability, we use terminal capacity as a proxy for supply (ns_j^t) and we use the number of diesel lanes at each retailer as a proxy for demand (nd_j^t). We consider a single time period ($T = \{1\}$) because the number of diesel lanes and terminal capacity is fixed. Lastly, we obtained the Strategic Intermodal Road Network from the Florida Department of Transportation. Figure 15 displays the road network with major intersections, fuel terminals, and fuel retailers.

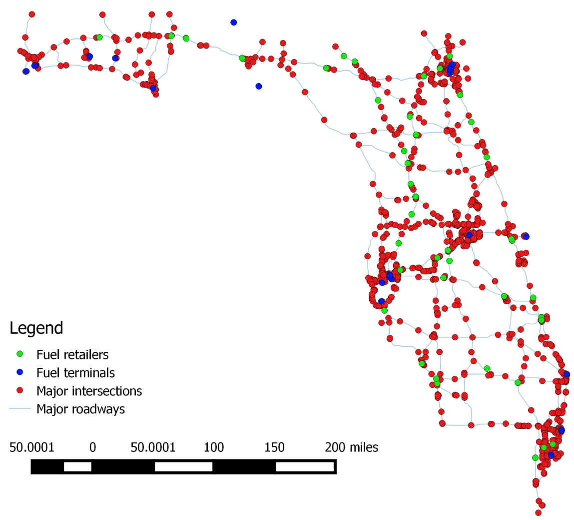

Figure 15: Visualization of the Florida road network with major intersections, fuel terminals, and fuel retailers. Source: MIT analysis.

We compute the product centrality metric for all road network nodes (i.e., intersections). Figure 16 displays the ten most critical nodes in red (i.e., the largest centrality metric). We find that all the critical nodes are located on the west coast of Florida near Tampa Bay. Most of the critical nodes are near or on the I-75, which is one of two major north-south highways. Furthermore, the Tampa Bay area has a large collection of fuel terminals and the Port of Tampa receives large amounts of fuel via barge from the Gulf Coast refineries. Also note that the only major pipeline in Florida connects the Port of Tampa to the city of Orlando. Lastly we highlight the concentration of fuel retailers along the I-75, north of Tampa (towards Ocala), which are likely to receive their fuel from the Port of Tampa terminals. Note that our fuel retailer sales analysis found that the retailers with the largest outages were located in this area.

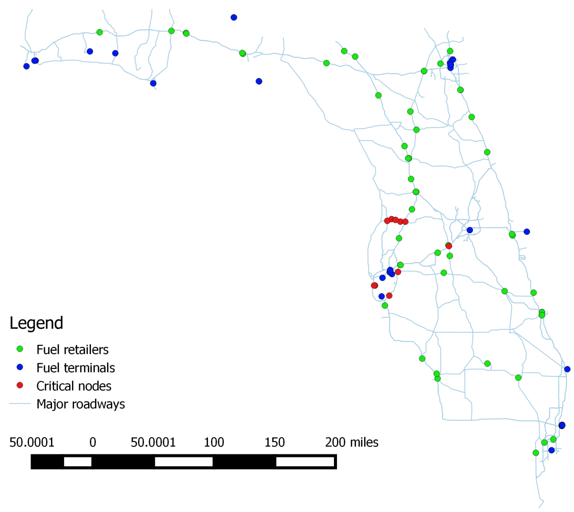

Figure 16: Visualization of the Florida road with with major fuel terminals, fuel retailers, and critical nodes identified by the centrality metric. Source: MIT analysis.

This analysis can be improved with better data, including real demand and supply over time. Furthermore, if retailers and fuel terminals are aware of the home location of their employees, then the personnel metric can be used to further understand critical nodes (we did not have access to this data).

7 Bottled water analysis

In this section, we analyze the bottled water supply chain during the 2017 hurricane season. The analysis illustrates how data and descriptive analysis can be used to tell a story, complementing anecdotal information. We aim to demonstrate how data can be used to understand the interaction between government and private sector actors.

7.1 Bottled water production

Annual consumption of bottled water in the United States totals 13.7 billion gallons [4]. This is effectively 100% produced by the private sector, and the vast majority is produced from domestic bottlers. The largest and fastest bottled water production facilities in the United States may:

- Produce in excess of 1,500 bottles per minute.

- Turn out millions of bottles per day.
- Produce only bottled water, or produce bottled water alongside other beverages.

Bottled water production plants from different private sector actors may be co-located near the same readily available water sources. Bottle water packaging is an important consideration when determining what locations have capacity to increase production. Annually, about 70% of bottled water is in single-serve bottles from a case, 9% are bulk containers (2 gallon and 5 gallon) from retail locations, 11% is home office delivery, and 7% is vending machine sales. See Figure 17 for more information. Production may not be possible for all the various segments of bottled water (e.g., 24 oz cases and 5 gallon containers) at each location. In situations where water production is reduced because of the impacts of a disaster event, it is important to realize that different water plants may require different sets of inputs (e.g., plastic for bottle caps as opposed to lids for 5 gallon containers).

Following Hurricane Maria in Puerto Rico, local bottled water production was severely limited. One limiting factor was that the materials to make bottle caps were stuck at the port. The tax/treasury inspectors at the port did not understand what that product was, so they held this "private good" at the port.

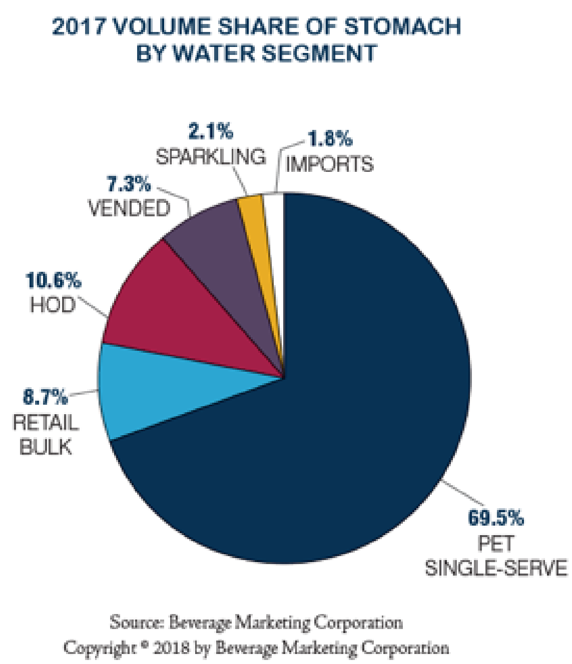

Figure 17: US bottled water market share by category. Source: Beverage Marketing Corporation.

7.2 Private sector bottled water supply chain

Retail demand for bottled water fluctuates predictably with the season. In warmer months like July, August, and September, more bottled water is consumed, and thus produced. This somewhat aligns with the annual Atlantic Hurricane Season (June 1 to November 30). This alignment often leads to a combined inventory build for the dual purposes of increased summer demand and safety stock from notice events like hurricanes and tropical storms.

Private sector actors (both producers and retailers) generally develop an inventory strategy using a number of factors including measurements and assumptions in the following categories:

- Demand histories
- Percent growth assumptions
- Safety stock targets
- Hurricane buffer assumptions

Ultimately both producers and retailers are seeking to have enough inventory on hand to meet the demands of their customers. However, the actual timing of the inventory build up itself is likely different across producers and retailers. Producers typically begin ramping up production in February, reach peak production in July/August, and begin scaling back production in the fall. This allows for sufficient inventory on-hand for both peak summer demand and peak hurricane demand. See Figure 18 for a figurative illustration. An estimated four inventory-weeks of surplus bottled water inventory is held at private sector bottler distribution centers during hurricane season in the relevant parts of the continental United States.

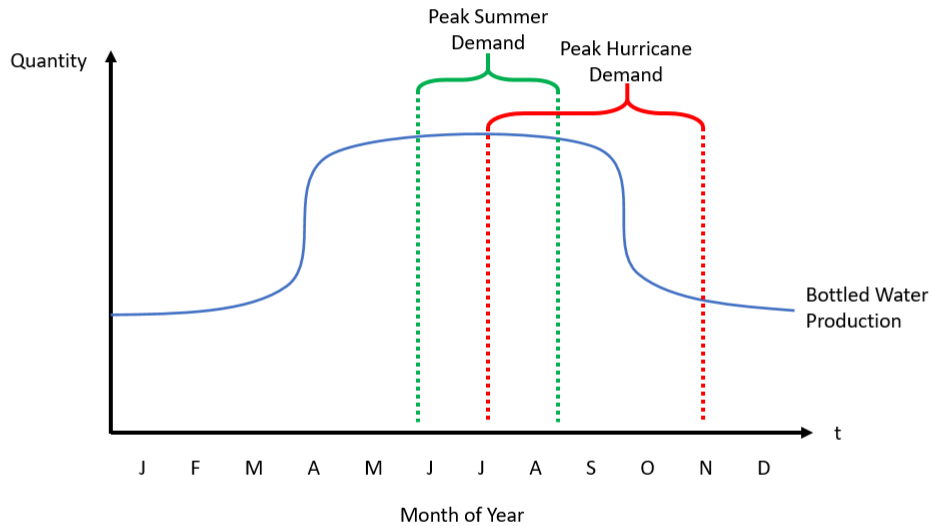

Figure 18: Figurative illustration of bottled water production trends. Source: Bottler(s), MIT analysis.

Because lead times for bottled water production exceed lead times for purchase or shipment of bottled water to a retailer, producers have to build up more inventory than retailers (as a percentage of each organization's current sales). Retailers have more flexibility to put in large orders once a notice event like a hurricane is actually on the horizon. Excess inventory at a producer's DC can more easily be routed to a different region than excess inventory at a retailer's DC.

Retailers have faster velocity of bottled water through their supply network during months with higher demand such as summer months. The retailers we spoke with indicated that they did not materially increase their inventory holdings of bottled water at their distribution centers for the purposes of higher demand in the summer months. However, these retailers did increase their inventory holdings of bottled water at their DCs in preparation for an incoming hurricane.

While we did not conduct deep research into public sector inventory strategies for this analysis, in select cases, based on funding levels and anticipated disaster activity, various public sector entities (emergency management and otherwise) at all levels of government (federal, state, local, etc.) have the capability to store bottled water in a number of appropriate locations throughout their jurisdiction.

7.3 FEMA bottled water supply chain

FEMA sources its bottled water from one of three sources:

- FEMA Distribution Centers

- Private Sector Vendors
- Government Partner Agencies (US Army Corps, Defense Logistics Agency, etc.)

We define FEMA's relief supply chain network to represent all goods that have been purchased or assigned for current disaster activity. This happens once it is en route to a location that is not a FEMA DC. Purchases to backfill FEMA's DCs, and inventory standing at FEMA's DCs, are both excluded from our definition.

At the initial onset of a disaster, and in preparation for a notice event, FEMA deploys its bottled water inventory from DCs. As the extent of disaster damage becomes evident, and as a commodity pipeline gets built going into Federal Staging Areas, FEMA switches from leveraging its DC inventory towards making purchases directly from private sector partners. Shipments from FEMA DCs ramp down at the same time that purchases from private sector partners ramps up. Figure 19 illustrates this by categorizing shipments of water into impacted and nearby states (TX and LA for Harvey; AL, GA, and FL for Irma) by procurement source. Note that this graph only captures shipments entering into FEMA's relief network which is largely made up by Federal Staging Areas, Incident Support Bases, and State Staging Areas. Shipments within FEMA's relief network and shipments from one disaster to another disaster are excluded.

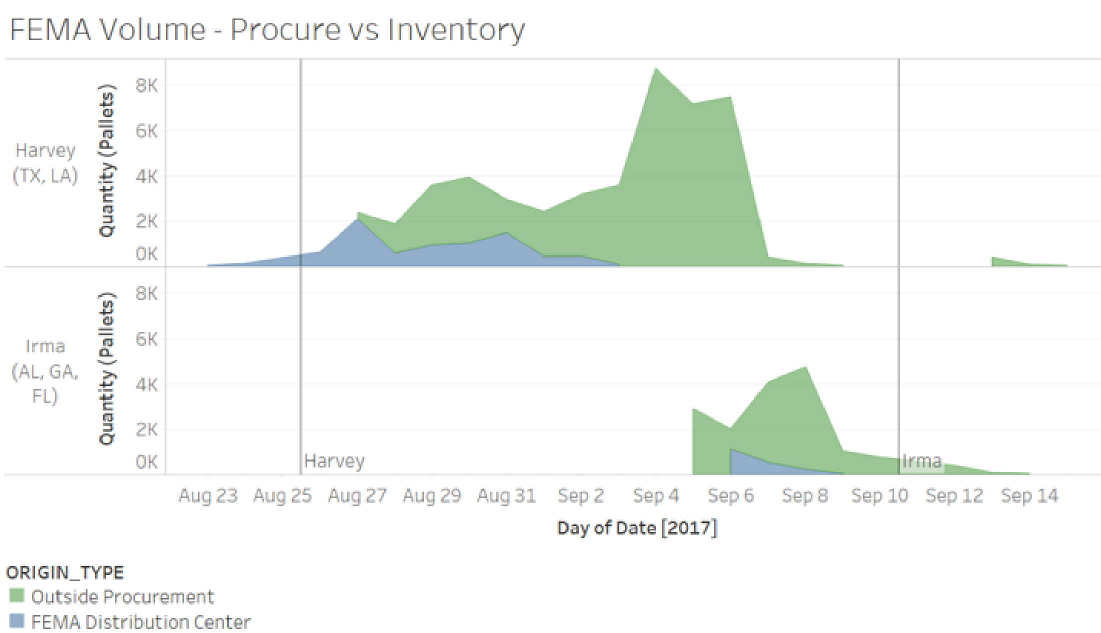

Figure 19: FEMA bottled water sourcing for Harvey and Irma by source and by state, over time. Source: FEMA, MIT analysis.

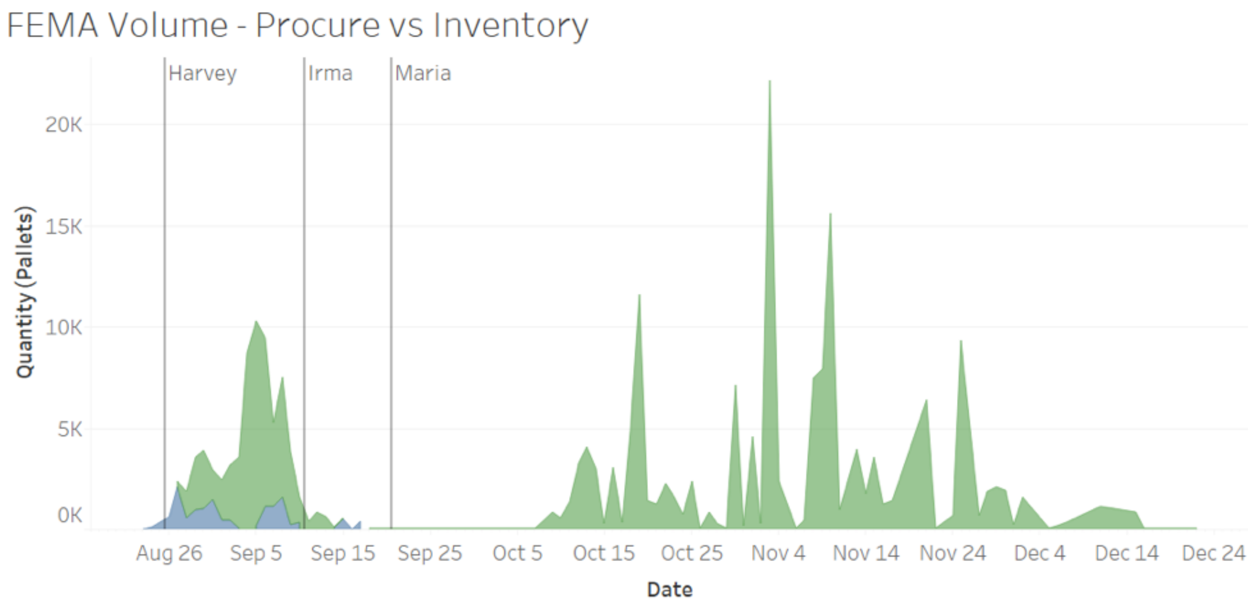

Figure 20: FEMA bottled water sourcing for Harvey, Irma, and Maria by source and by state, over time. Source: FEMA, MIT analysis.

By looking at the same information (bottled water coming into FEMA's relief network from its DCs and from private vendors), and looking through December 31, Figure 20 includes all the activity for Hurricane Maria in Puerto Rico and the US Virgin Islands (USVI). Across this entire period (8/23/17 to 12/31/17), we estimate that bottled water inside FEMA's relief network for Harvey, Irma and Maria is 6% from their safety stock at DCs, and 94% from private sector purchases. See Table 6.

Table 6: FEMA bottled water sourcing for Harvey, Irma, and Maria, by source, 8/23/2017 – 12/31/2017. Source: FEMA, MIT analysis.

Bottled Water Source	Volume
FEMA Distribution Center	13,500 Pallets (6%)
Outside Procurement	214,000 Pallets (94%)
Partner Government Agencies	Negligible (0%)

In Figure 20, we suspect that the gap of bottled water coming into the FEMA relief network (for Harvey, Irma and Maria) from mid September to early October can be explained by:

- FEMA moved excess water that it had procured for Harvey, out of Texas and towards Florida, to meet the initial needs for Irma and Maria.
- FEMA moved excess water that it had after Irma, via air bridge and sea bridge, to meet initial bottled water needs in Puerto Rico and the USVI.
- We have limited visibility into bottled water transfers from the FEMA DCs in Puerto Rico and the US Virgin Islands. Because of the short duration between Irma and Maria, we believe that bottled water assigned from FEMA DCs in Puerto Rico and USVI prior to Irma was used to meet immediate needs following Maria which impacted the same geographies.

To be clear, the gap in bottled water procurement between mid September and early October is likely because FEMA was moving bottled water within its network, rather than bringing in bottled water from outside its network. The total FEMA purchase of bottled water for Harvey, Irma, and Maria from 8/23/17 to 12/31/2017 represents a draw of just 0.3% of the total volume of bottled water consumed by Americans each year.

7.4 Shipment of bottled water

Bottled water cases are palletized and shrink wrapped at bottled water production facilities. Note that we are ignoring bulk containers (e.g., 2.5 gallons). The vast majority of bottled water transportation happens in 53 foot tractor trailers. When the government purchases bottled water from suppliers, commercial haulers bring the product into the relief supply chain network via deliveries at a Federal Staging Area or State Staging Area (or other government locations). When bottled water is moved within the relief supply chain network, the vast majority of transportation happens, once more, with commercial haulers. Specialized government vehicles are generally only utilized for last-mile delivery of bottled water to hard-to-reach locations. This may happen via high water vehicles, helicopters, etc.

FEMA's reliance on commercial carriers to move disaster relief supplies is frequently discussed as a significant demand spike that alters the commercial over-the-road shipping market. Contract rates for shipping generally do not change in response to a disaster, however the ability for vendors to fulfill their contracts may change. The spot market for trucking loads regularly changes after a disaster. Factors further impacting localized spot market rates can be geography-specific, based on a relative balance of inbound and outbound loads. Changes in fuel prices may further impact the costs of shipments.

Bottled water shipments represent a portion of the disaster shipments taking place, but any overall increase in spot market rates is driven by the overall increase in demand for loads for the purposes of disaster relief – not bottled water loads specifically. The increase in demand for loads into a disaster area can be made up of FEMA loads, grocery stores resupplying their locations, utility companies bringing in telephone poles and wiring to rebuild electric grids, building materials for reconstruction, and others. The cause, extent and predictability of spot market rate increases is an area deserving of further study. Currently available information suggests that regional spot market rates increase dramatically (e.g., 50% would not be unheard of) and that national spot market rates increase less substantially (e.g., 10% would not be unheard of).

7.5 Bottled water lifeline during Hurricane Harvey

In this section, we use descriptive tools to analyze the bottled water supply chain during Hurricane Harvey.

7.5.1 Blue sky bottled water capabilities

Nationwide, FEMA maintains readiness (via contracts, partnerships with other federal agencies, and inventory held at their distributions centers) to ensure food and water needs following disasters. FEMA recommends that all residents maintain a three day supply of food and water in their disaster kits. One FEMA Distribution Center (DC) is in the state of Texas and it has a standing inventory target/average of ∼3,600 pallets (∼2.3M liters) of bottled water. This DC serves disaster needs all across the United States, as do all other FEMA DCs. On an average week (baseline is 8/1 to 10/31) we estimate the private sector moves some ∼17,500 pallets of bottled water "into market" in the state of Texas. See Table 7 for a summary.

Table 7: Approximate steady state / blue sky bottled water capabilities, within Texas and Nationwide. Source: Beverage Marketing Corporation, FEMA, MIT analysis.

	Within Texas	Nationwide
Private Sector Sales	∼17,500 pallets sold each week (∼11.2 million liters)	∼13.7 billion gallons sold each year (∼81.3 million pallets; ∼51.9 billion liters)
FEMA Owned Inventory Targets	∼3,600 pallets (∼2.3 million liters)	∼11,500 pallets (∼7.3 million liters)
FEMA Contracts and Partner Agencies	N/A	Indefinite delivery / indefinite quantity

Note that the private sector orients supply chains around transportation networks, not state boundaries. Thus, water facilities in Texas may also serve Oklahoma, and vice versa. We define "into market" to be the distribution of water to retail locations, or into retail markets (i.e., excluding from a bottling location to a distribution center.) This terminology ignores the state where the bottled water was produced. Inventory targets in Table 7 are as of 2014. Inventory on-hand totaled across the DC network is as high as 170% of total inventory target. Nationwide total combines DCs inside and outside the continental US.

7.5.2 Pre-landfall and post-landfall shipments by actor

Prior to forecasted landfall of any hurricane, the nature of pre-landfall demand and pre-landfall shipments vary significantly, and predictably, across the parties. Pre-landfall, private sector demand will spike due to people stocking up (and also as a result of downstream nodes in the supply chain increasing orders in anticipation of future post-landfall demand); state inventory will be optimally located within the state based on long-term planning assumptions; and FEMA will move inventory closer to likely impact areas. Disaster uncertainty can cause FEMA to pre-position inventory across a multi-state area in anticipation of potential impact in a wide area. Table 8 details demand surges and water movements prior to landfall.

Table 8: Water demand and shipments, prior to Hurricane Harvey's 8/25/17 landfall. Source: Bottler(s), FEMA, MIT analysis, State of Texas.

H minus 48 (2 days pre-landfall)	Bottlers had above average deliveries of bottled water beginning on 8/23/2017. Estimated demand was approximately 5x its normal level. FEMA made its first movement of bottled water on 8/23/2017. It was within the state of Texas from its DC in the Dallas / Fort Worth area to a Federal Staging Area (FSA) in the Austin / San Antonio area.
H minus 24 (1 day pre-landfall)	Retail locations within the state executed the final steps in their hurricane water pre-positioning plans by 8/24/2017. The State of Texas made its first movements of bottled water on 8/24/2017. The destinations were Bexar County (near San Antonio) and Nueces County (near Corpus Christi).

A clear sequencing of bottled water shipments can be seen by looking at shipments, by actor, to the state of Texas, over the days immediately preceding and after Hurricane Harvey made landfall.

As Figure 21 illustrates, bottlers had peak activity prior to landfall with a smaller peak following landfall, state deliveries peaked soon after landfall, and FEMA deliveries peaked soon after that. The observed sequence validates the principle that state (and local) government respond to disasters first, seeking federal support as their capabilities get exhausted over the course of a response.

Please note that these are all shipments with a destination in the state of Texas, so water moved from San Antonio to Houston is shown here. Water moved from one part of Houston to another part of Houston is also shown here. This activity does not necessarily reflect bottled water inventory or demand.

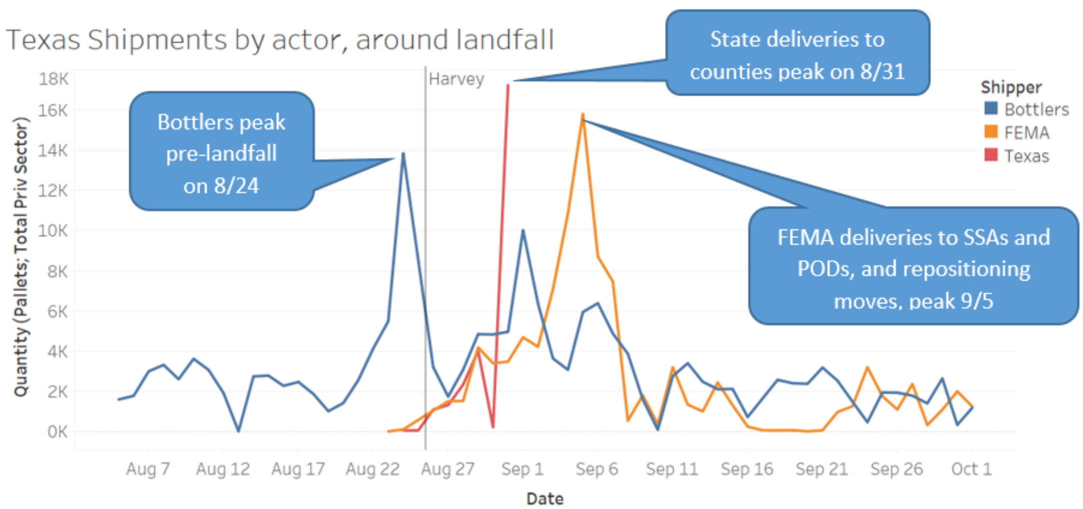

Figure 21: Shipments to destinations within Texas, by actor. Source: Bottler(s), FEMA, MIT analysis, State of Texas.

7.5.3 Sequence of bottled water shipments and grocery store closures in the greater Houston area

Though Harvey made landfall on 8/25/17 near Corpus Christi, the majority of its impact on population occurred several days later and 200 miles northeast in the greater Houston area. Locations in the Houston area received anywhere from 30 to 60 inches of rainfall from Harvey, which became the wettest tropical cyclone on record in the United States.

To understand local supply chain dynamics for bottled water, we looked at the greater Houston area, which we define to be Harris, Fort Bend, Galveston, and Waller counties. Figure 22 illustrates volume of shipments, by actor, for shipments with destinations in the greater Houston area.

Note that these are all shipments with a destination in the four named counties, so water moved from Bexar County to Harris County is shown here. Water moved from one part of Houston to another part of Houston is also shown here. This does not necessarily reflect bottled water inventory or demand. This data likely does not capture shuttle shipments or other shipments to "last mile" locations. And finally, FEMA shipments get transferred to the state, either at state staging areas or at a delivery site such as a POD. That transfer process is not fully reflected in this data.

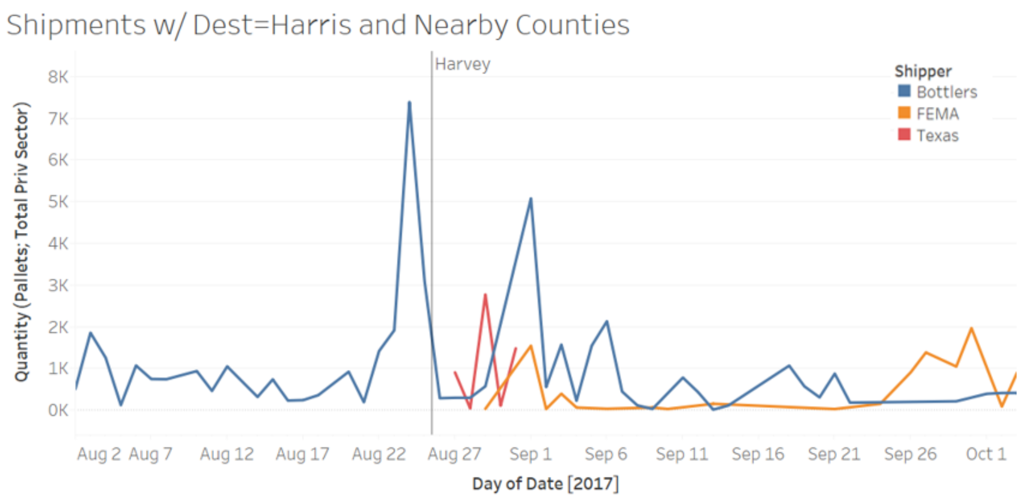

Figure 22: Shipments to destinations within the Houston area, by actor. Source: Bottler(s), FEMA, MIT analysis, State of Texas.

Once more, the observed sequence of shipments to the disaster impacted area reflects the principle that state (and local) government responds to disasters first, seeking federal support as their capabilities get exhausted over the course of a response. Additionally:

- Demand from "stocking up" occurs pre-landfall.
- The private sector halts shipments during times with the highest potential for disaster impact.
- The state of Texas meets initial needs, followed by FEMA which continues deliveries for much longer.
- The private sector has a period of back-filling before returning to normal.
- Overall, total private sector volume is much higher than either state or FEMA bottled water shipments.

Within the greater Houston area we can observe the relative timing of private sector shipments alongside grocery store openings and closures. As a proxy for county-wide grocery store closures, we use operating status amongst businesses that accept SNAP. Figure 23 shows an analysis of store openings and bottled water shipments. Using this figure, we can conclude:

- Private sector shipment activity drastically decreased to near-zero levels from 8/26 to 8/29.
- Grocery stores were at their highest level of closures on 8/27.
- In general, grocery store reopening preceded bottled water replenishment shipments from private sector sources.
- Beginning 8/30, private sector bottled water shipments resumed in earnest, with a spike in activity likely to fill the surplus of backlogged orders.
- Shipments were back to normal levels by 9/2.

There is a period of time immediately after landfall when grocery store are reopening faster than the ramp up of private sector bottled water deliveries. During this *Window of Temporary Shortage*, it is likely that many grocery stores will have reduced inventory due to high demand prior to the closing of the grocery store and the inability to transport goods in and out of the affected area due to road closures, flooding, and other distribution challenges.

The difficulty emergency managers face is seeing this demand signal and not overcorrecting by ordering too much bottled water. Such actions can result in unnecessary surplus inventory on hand in a community, crowding out local businesses. An area's supply chain can be further squeezed by diverting both bottled water manufacturing capacity, as well as shipping capacity, to a commodity that is not needed.

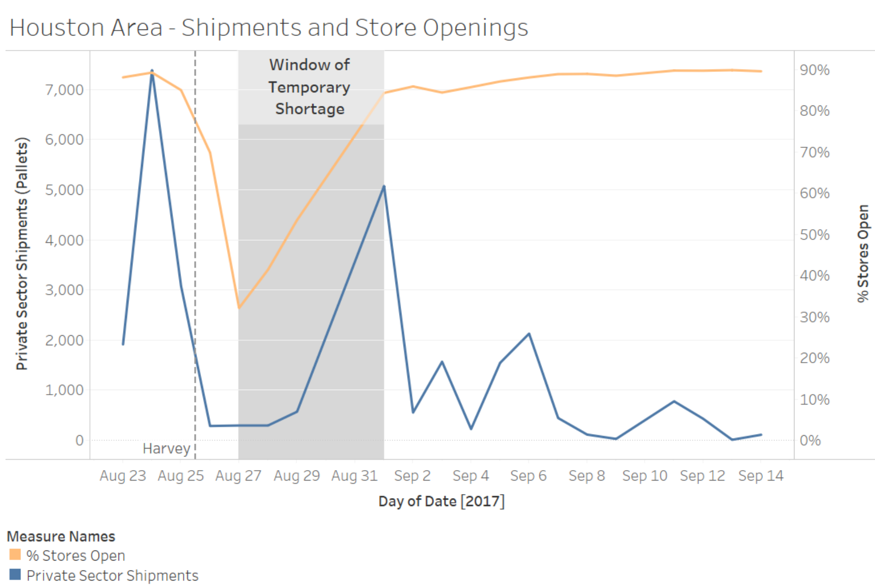

Figure 23: Private sector shipments and grocery store open status, within the Houston area. Source: Bottler(s), MIT analysis, USDA.

7.6 Impact of surplus bottled water purchases by FEMA

FEMA faces a recurring problem of needing to build up bottled water inventory once an area has been impacted by disaster, without knowing the total volume demanded. Rather than risk stocking-out of bottled water inventory, FEMA will default to building up excess bottled water in disaster zones. As a provider of last resort, if FEMA runs out of bottled water when it is needed, there is a significant negative human impact. FEMA's priority is to avoid the high service penalty of under-ordering, and accept potentially high financial costs of over-ordering.

FEMA usually has the option of shipping unused bottled water from Federal Staging Areas near disaster zones back to FEMA's DCs, incurring additional transportation costs along the way. To mitigate overall costs from purchasing, storing, and transporting excessive quantities of bottled water, FEMA can employ a number of strategies including:

1. Shipping water from one disaster to another adjacent disaster, rather than making new purchases.
2. Transferring water inventory to non-profits and food-banks in the community, via states, for ongoing post-disaster needs.

During the 2017 hurricane season, FEMA purchased a large quantity of bottled water for response efforts in Texas. As supply on-hand exceeded demand, and as the impact of Irma and then Maria became apparent, FEMA moved bottled water eastward from the Texas/Louisiana area, to impact areas for Irma and Maria. Figure 24 reflects bottled water shipments (measured in pallets) originating in Texas or Louisiana, with a destination of Texas, Alabama, Florida, the US Virgin Islands, and Puerto Rico.

> *Utilizing strategies like transferring bottled water to future disasters and local agencies, FEMA returned just 1.2% of their total water procurement back into stock in its distribution centers.*

Soon after Hurricane Irma made landfall, FEMA moved a large quantity of bottled water from Texas and Louisiana to Alabama, which was a staging area for Irma response and recovery efforts in Florida. After Hurricane Maria made landfall, FEMA moved additional bottled water from Texas and Louisiana to Florida, the US Virgin Islands, and Puerto Rico.

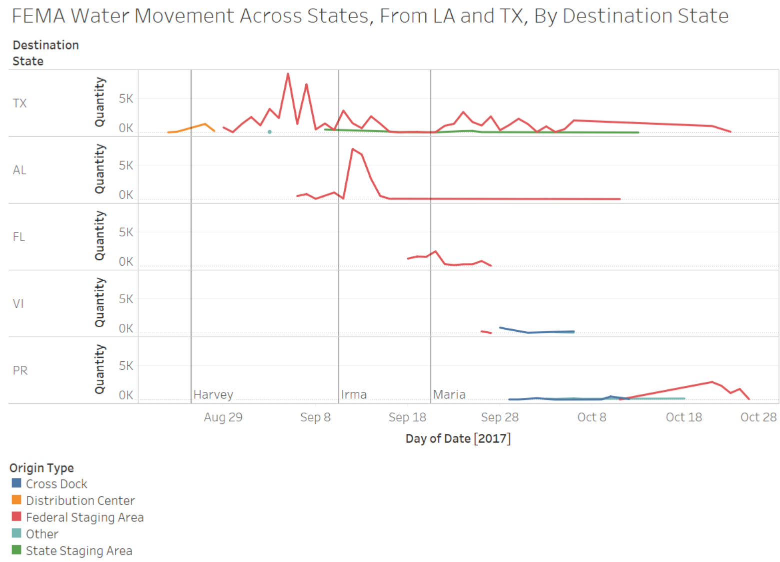

Figure 24: FEMA water movements from Louisiana and Texas, by destination state. Source: FEMA, MIT analysis.

Note that this analysis does not necessarily reflect bottled water inventory or demand. Water moved from a Texas origin to a Texas destination is shown here, while water moved from a Florida origin to a Florida destination (or from a Florida origin to a Puerto Rico destination) is not shown here. Additionally, this analysis does not reflect bottled water transfers to the state or to local non-profits and food banks in excess of their usable demand. For example, excess bottled water was transferred to state (in this case, commonwealth) and local officials and accumulated in areas of Puerto Rico long-after initial Maria response efforts. This transfer of ownership was in part due to the high cost of shipping bottled water back to FEMA DCs from Puerto Rico.

Of the nearly 230,000 pallets of water procured by FEMA for Harvey, Irma and Maria, a total of 2,749 pallets were sent back to FEMA DCs at various times during the response. This backfilling was used to reduce excess at locations like FSAs. Utilizing strategies like transferring bottled water to subsequent disasters as well as local agencies, FEMA returned just 1.2% of their total water procurement back into stock at distribution centers.

By these metrics, it can be argued that over the course of the 2017 hurricane season, FEMA did not over-order bottled water. Unfortunately, it is difficult to understand and measure the impact that short term excess bottled water purchases have on strained private sector supply chains.

FEMA should seek to decrease larger than necessary orders not because of the high financial cost, or the increased difficulty in managing large quantities of inventory;

FEMA should work to shave excess purchases because of the negative spillover effects these FEMA orders may have on private sector supply chains.

Looking only at Hurricane Harvey, we can see that FEMA brought ∼49,000 pallets into its relief network. Subsequently, FEMA shifted ∼39,000 pallets from Texas and Louisiana to Alabama, Florida, USVI, and Puerto Rico. By this metric, it appears that over the course of the Hurricane Harvey response, FEMA significantly over-ordered bottled water.

Large bottled water orders within a focused period of time have the potential to strain private sector supply chains causing long wait times at bottling plants and a tightening in the shipping market. During the immediate post-disaster time when disaster shipments are at their highest, FEMA is also likely to over-order needed commodities at the expense of the private sector.

FEMA should seek to decrease larger than necessary orders not because of the high financial cost, or the increased difficulty in managing large quantities of inventory; FEMA should work to shave excess purchases because of the negative spillover effects these FEMA orders may have on private sector supply chains.

7.7 Alternatives to Bottled Water

Most of this analysis has focused strictly on bottled water. It is also worthwhile discussing alternatives to bottled water based on the disaster circumstances that caused a need for water support. For example, in communities that have functioning water treatment facilities but non-functional distribution methods, emergency managers may have the option of choosing to conduct water distribution via water tanker trucks, also called “water buffalos”. Effective use of water tanker trucks has the potential to decrease overall demand on bottled water in a disaster area, freeing up shipment capacity for other relief shipments.

In emergency plans, water tanker trucks are often considered as a strategy alongside bottled water distribution. For example, the California Governor’s Office of Emergency Services has, since the 1994 Northridge Earthquake, maintained a state-wide plan for emergency drinking water procurement and distribution [10]. This plan considers bottled water alongside non-bottled packaged water (e.g. sachet water, bagged water, pouch water) and bulk water deliveries. The plan also references the California Department of Public Health’s list of 186 licensed water haulers (as of August 2018) [11]. Further, in 2011 the US Environmental Protection Agency commissioned a series of workshops about emergency drinking water, and the resulting summary detailed considerations for bulk water distribution alongside pre-packaged water distribution [2].

The success of emergency managers in leveraging bulk water to meet emergency water needs depends in part on the public perception of bulk water deliveries. Bulk deliveries have the potential to meet the following internationally recognized Sphere Standards:

- Distance from any household to the nearest waterpoint is less than 500 meters.
- Queuing time at water sources is less than 30 minutes.

But in spite of the functionality of bulk water distribution in disaster times, survivor preferences may continue to emphasize bottled water. As Figure 25 illustrates, Americans have been steadily consuming more and more bottled water for the last several decades. This causes bottled water distribution to remain an important consideration for emergency managers.

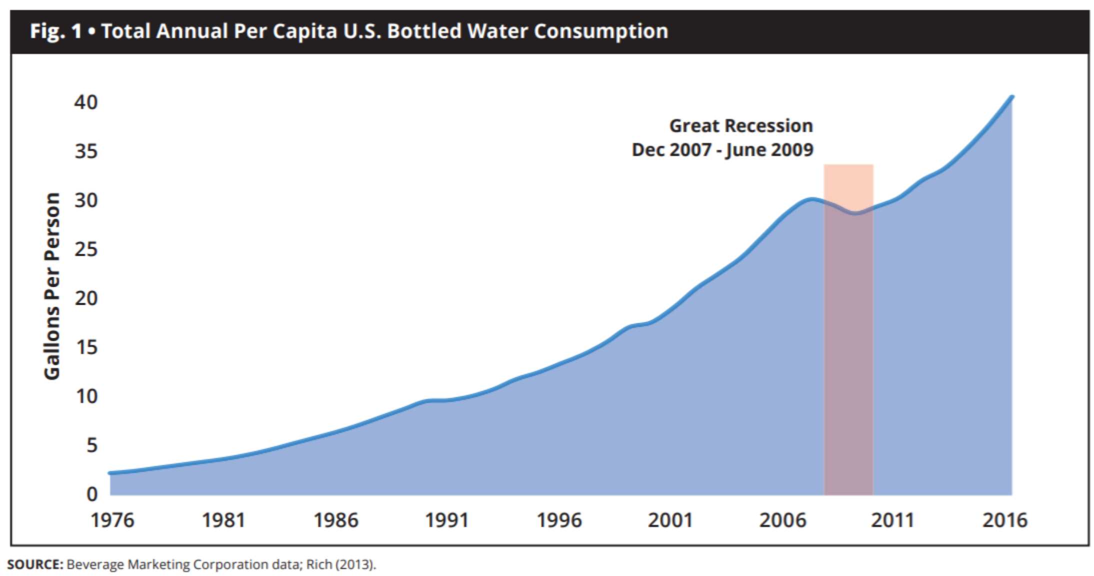

Figure 25: Annual per capita US bottled water consumption. Source: Food and Water Watch, Beverage Marketing Corporation.

8 Discussion and Conclusion

8.1 Implementation Strategies

Recognizing the importance of situational awareness after disasters, the emergency management community has been seeking out resources for better decision making and more strategic supply chain monitoring.

In the private sector, it is relatively easy for a single organization to achieve the goal of full visibility within their own network. Enterprise resource planning (ERP) software systems integrate a company's supply chain, operations, manufacturing, and reporting functions (among others).

> *"If one [of our] DCs goes down, it takes 1 hour for our system to reorient. For example, new DCs prepare to make deliveries to existing stores. Inbound deliveries to [our offline] DC get redirected to different DCs based on what product is needed to support the specific stores being picked up by other DCs."*
>
> – Executive Vice President for Logistics for a major retail chain, speaking at an MIT Center for Transportation and Logistics event in 2017

Across multiple private sector organizations, vendor managed inventory (VMI) is a business model where a supplier has responsibility for determining order sizes for a customer, with the goals of reducing the chance of having a product go out of stock, and reducing the cost of holding too much inventory of a single product.

These two concepts, ERP and VMI, represent models that work in the private sector because of unified control or collaboration for mutual gains. Competitive interests amongst private sector actors inhibits broad information sharing during non-disaster times, and these interests are not completely set aside after a disaster. To facilitate better information sharing, multiple actors have tried to create an environment more conducive to information sharing. Table 9 summarizes some of the strategies that have been implemented in the emergency management space.

Table 9: Disaster information aggregation strategies. Source: MIT analysis.

Strategy	Real world examples
Leverage pre-existing automated data feeds as proxy data	*Healthcare Ready's RX Open* platform leverages billing information from the last 12 hours on a pharmacy by pharmacy basis to infer open/close status of individual pharmacies. The *USDA* leverages billing status of SNAP to infer open/close status of individual food retailers. Payment processors *(VISA/MasterCard/American Express/Discover)* have the ability to leverage electronic payment processing status to infer electronic billing of individual retailers.
Loop the private sector actors out of the picture and collect the information directly.	*GasBuddy* is a for-profit entity that operates a free website and app compiling crowdsourced information on gas prices as well as open/close status of gas stations during disasters. Gas retail chains can also submit open/close status information directly to GasBuddy.
Create voluntary trusted spaces where private sector actors can opt-in to information sharing. Private sector actors can choose what information (not) to share.	*The Single Automated Business Exchange for Reporting (SABER)* aggregates open/-close status based on data provided by major retail chains. *The National Information Sharing Consortium (NISC)* is a voluntary consortium across the emergency management space designed to facilitate greater sharing of technology, data processes, and best practices. NISC activities are oriented around long-term capacity building. *The All Hazards Consortium (AHC)* is a voluntary consortium across the emergency management space designed to reinvent emergency response and information sharing for industry and government. AHC working groups, including a working group focused on a Sensitive Information Sharing Environment, are oriented around long-term capacity building. *The National Business Emergency Operations Center (NBEOC)* is a voluntary virtual clearing house for two way-information sharing during disasters. The NBEOC gives emergency management actors non-automated visibility into private sector requests, offers, and information. *The US Department of Homeland Security (DHS)* facilitates and supports several forums for voluntary information sharing for cybersecurity and critical infrastructure. A portion of information collected by DHS falls under the Critical Infrastructure Information Act (CII) which provides assurances that information will be held in confidence and will be used only for homeland security purposes.
Create mandatory trusted spaces where private sector actors are required by law to report information. To be a trusted space, private sector actors must have a reasonable expectation that business sensitive information will remain secure.	*The US Energy Information Agency (EIA)* regularly collects detailed information on gasoline, diesel, and electricity stocks and prices from actors across the private sector. Most information collected by EIA falls under the Confidential Information Protection and Statistical Efficiency Act (CIPSEA) which provides assurances that information will be held in confidence and will be used only for statistical purposes.

The real world examples in Table 9 exclude for-profit organizations (such as Resilinc, DHL 360, Riskpulse, and Freightwaves) which aggregate disaster supply chain data from both public and non-public sources primarily for paying customers. While not an inclusive list, the strategies outlined in Table 9 are possible routes to achieve better access to necessary data for advanced supply chain analysis. Table 10 illustrates how specific data points can feed into tools for both diesel fuel and bottled water.

Table 10: Example Diesel Fuel and Bottled Water Tools with Data Requirements from Tables 1 and 2. Source: MIT analysis.

	Diesel Fuel	Bottled Water
Necessary Data Groups	Terminals, Terminal Racks, Fuel Tankers, Retailers, Transportation Network	Bottling Plants, Bottler DCs, Retailer DCs, Retailers
Descriptive Questions	Where is diesel fuel available? Is there a shortage?	How much water has been moved?
Predictive Questions	When will a shortage resolve itself? What areas are most likely to experience shortages?	What communities will be requesting more bottled water? How much?
Prescriptive Questions	What intervention does the most to rebuild the diesel fuel supply chain?	What intervention does the most to reduce the need for bottled water shipments?

With more advanced data visibility and better understanding of the impacts of emergency managers decisions on private sector supply chains, we believe that the emergency management community can move well past "do no harm" towards providing strategic support to the private sector in the way they need it the most.

> *If emergency managers can develop an understanding of fundamental network behaviors, they can help avoid unintentionally suppressing supply chain resilience, with the ultimate goal of ensuring emergency managers "do no harm" to surviving capacity.*
>
> – FEMA Supply Chain Resilience Guide, April 2019

8.2 Key takeaways

The following bullets summarize the key takeaways and learnings from this report.

1. Achieving situational awareness is insufficient when it comes to restoring private sector supply chains. More important than being aware of the current situation is correctly understanding interdependent supply chains, forecasting resources and flows, and knowing where and how to intervene with government assistance.

2. Private sector organizations achieve supply chain visibility with enterprise resource systems. Achieving the same visibility across competing and decentralized private sector organizations will require a shift in how the emergency management community approaches cooperation and data aggregation.

3. Accurate, timely, and representative data feeds are required for explanatory, forecasting, and prescriptive tools that should be used dynamically during disasters, not afterwards. Successful data aggregation strategies will require a mix of connecting to pre-existing data feeds and collecting information directly through creation of voluntary trusted spaces and mandatory reporting requirements.

4. Complex models that leverage optimization and machine learning can provide emergency managers with a better understanding of the causes and remedies of supply chain disruption. Models will take time and effort to develop and employ. Models should support, not replace, current information sources to enable better decision making.

5. Improved communication between government and the private sector is critical for improved disaster response. Collaboration between public and private sector actors will contribute to better information flow and help prioritize recovery efforts.

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