Modelling the recovery of critical commercial services and their interdependencies on civil infrastructures

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Abstract: When an extreme event occurs in a specific area, the mere recovery of civil infrastructures is not enough to help recover local communities due to the cascading disruptions that can occur to supply chains of critical commercial services, whose operation and restoration is highly dependent on infrastructures. We build single-period, multi-commodity disruption models to examine the interdependencies between infrastructures and critical commercial services and predict the outages experienced by local communities after extreme events. We further build multi-period restoration models to select and schedule the restoration tasks after disruptive events with an objective to maximise the aggregated flows of utilities and commodities. We simulate scenarios of Categories 2, 3, 4 hurricanes and apply the models to a dataset of an artificial county with a population of half a million. We find that coordinated infrastructure restoration decisions with critical commercial services help improve community resilience, especially under relatively severe extreme events.

Keywords: infrastructure restoration; interdependencies; critical commercial services; community resilience; cascading failures; supply chain disruption.

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1 Introduction

In this paper, we examine the contribution of critical commercial services to community resilience when there are disruptions to local civil infrastructure systems caused by extreme events. Residents' quality of life is supported by multiple kinds of services including: utilities from civil infrastructure systems and critical commercial services, i.e., pharmaceuticals, food, cash, and fuel, from supply chains. When an extreme event occurs in a specific area, the disruption of essential services such as power, water and telecommunications due to damage to these infrastructures not only impacts the well-being of local residents but also interrupts the flow of critical commodities such as food, fuel, and pharmaceuticals, which may further degrade the situation within the community. Therefore, in order to better understand and improve community resilience, it is necessary to model the cascading disruptions to the systems responsible for delivering critical commercial services to the community and how their recovery depends on the civil infrastructure restoration process.

For example, in September 2017, Hurricane Maria caused widespread utility outages as well as critical commercial service shortages in Puerto Rico. However, one week after it struck Puerto Rico, at least 10,000 containers of vital supplies were reported as sitting at the San Juan port, still waiting to be delivered, due to blocked roads and lack of drivers (Gillespie et al., 2017). Blocked roads impacted the flow of goods from terminals (or warehouses) to local distribution points (such as convenience stores or pharmacies). Further, the failure of cell towers in the telecommunication infrastructure made it difficult to coordinate the movement of goods; for example, only 20% of truck drivers were able to be contacted one week after the hurricane. Therefore, it is of the utmost importance to take the interdependencies between civil infrastructure systems and these critical commercial services into consideration when making restoration decisions to help the impacted communities recover from the extreme event.

In our research, we model two sets of networks, civil infrastructure systems and critical commercial services. Civil infrastructure systems include power, telecommunication, water, wastewater, and transportation and utilise dedicated facilities to deliver service to consumers. For example, electricity is transmitted from its point of production over the power grid and ultimately delivered to the customers. Critical commercial services, on the other hand, are provided by private enterprises and, although they may use dedicated vehicles to deliver their products, they share the same transportation system. The second area where critical commercial services differ from civil infrastructure systems is that multiple commodities may be obtained from the same retailer. For example, convenience stores usually offer a basic selection of food, fuel, and cash at the same location and, therefore, act as a delivery hub for a set of commercial services. Additionally, the same commodity will be available from multiple suppliers. For example, people may obtain some food items from convenience stores (e.g., Stewarts' which operates in the northeast of the US), which are operated locally as well as supermarkets operated by national businesses (e.g., Walmart or Safeway, which operate all over the US). The third feature is that utility services are provided directly to the consumers, critical commercial services are sent to retailers (e.g., convenience stores, and pharmacies) to which customers must travel to purchase the items they need. Therefore, it is necessary to separately model the 'wholesaling flow' of critical commercial services from the supply nodes to these retailers (e.g., which model the interactions between the companies responsible for the logistics of these commodities and those responsible for selling them to consumers) and the 'retailing flow' from retailers to demand nodes (e.g., commodities purchased by customers from retailers).

While traditional research tends to view the two systems independently, one innovation of our research is to recognise the interdependencies that exist between them. Interdependencies not only exist between civil infrastructures (e.g., wastewater treatment facilities need power to operate) but also between civil infrastructures and the provision of critical commercial services (e.g., pharmacies need power to operate and telecommunications to order prescription drugs from distribution centres and/or fill prescriptions). The reliance of pharmacies on both power and telecommunications is an important type of interdependency to consider when examining community resilience. The widespread interdependencies between the two sets of interlinked networks require us to aggregate the networks and, should we be interested in overall community recovery, we must optimise infrastructure restoration decisions in terms of the joint benefits to them and reduced unmet demand. For instance, when the telecommunication restoration teams make the restoration plan independently, they may focus on the restoration of services to points with a larger demand, such as local neighbourhoods. In contrast, a coordinated restoration plan may emphasise the efficient restoration of telecommunication service to hospitals and pharmacies where services are necessary for efficient and accurate delivery of drugs. One important contribution of the computational analysis from our modelling efforts is to show that there is a 'breaking point' in terms of the size of disruptions where coordination between infrastructures and critical commercial services can greatly benefit the restoration of disrupted critical commercial services.

In our model, we examine the routing problem of local supply chains delivering critical commercial services within an area under disrupted transportation systems. Pharmaceutical companies usually hire a secondary drug logistics company that operates local warehouses and specific vehicles to deliver pharmaceuticals to respective pharmacies. Instead of delivering pharmaceuticals to every single retailer by themselves, vehicles of the pharmaceutical companies visit the local warehouse on a fixed schedule and then let the secondary drug logistics company finish the so-called 'last mile' of the supply chain distribution within the area. Similarly, local businesses such as convenience stores also send vehicles to deliver basic food and daily necessities from local warehouse to retailers. Thus the efficiency and robustness of the local supply chains is vital to the community resilience in terms of the pharmaceutical and basic food supply. During disruptions, the routes selected by vehicles of local supply chains are heavily impacted by the restoration decisions of the transportation system since local supply chains are flexible enough to change their routes according to the updated road conditions during the restoration process. Therefore, we model the routing problem of these vehicles during the restoration process and aim to select the best feasible route for them. The post-event performance of local supply chains can serve as a reliable measurement of the restoration of the transportation system and is an important contributor to the resilience of a community.

In addition to the routing problem of local supply chains, another aspect that can impact the critical commercial services is the placement of inventory, in the form of safety stocks, throughout the supply chain. Generally, the size of a business will dictate its operating strategy and the extent to which it will centralise its supply chains. National business chains usually maintain higher inventory levels and large warehouses to service retailers in the entire region due to the large quantities they are shipping and the distances they need to cover. Regional or local businesses generally have more options when deciding how best to supply their retail locations. They may prefer to have a low inventory level at local warehouses and maintain higher inventory levels at their retailers, thus, reducing the shipping cost from warehouses to retailers. They may also choose to have larger warehouses with lower inventory levels at their retailers, thus, hedging risks from demand fluctuation through the risk-pooling effect of centralised inventory. The different supply chain structures not only influence their performance during normal operations, but also strongly impact the post-event supply of critical commercial services to local communities. On one hand, since the disruptive event may seriously damage civil infrastructure systems and force many retailers to shut down due to lack of necessary services, higher inventory levels may be useless since they are still not available to local residents. On the other hand, the disruptive event may also badly damage the transportation system, thus diminishing the capacity or availability of the road network. This means that inventory at local warehouses could be more important. Therefore, we will investigate the post-event performance of local businesses with different supply chain structures and their impact on community resilience.

In our research, we simulate Categories 2, 3, and 4 hurricanes and build single-period, multi-commodity disruption models to examine the impacts on both infrastructures and critical commercial services. Our particular case study is an artificial county with a population of half a million people. We also build multi-period restoration models to select and schedule the restoration efforts of the civil infrastructure systems after disruptive events with an objective to maximise the aggregated performance of the set of considered networks (as measured through flows of utilities and commodities). Different weights are placed on different utilities and commodities to reflect the specific demands of the community. Further, the weights on demand nodes also vary to reflect the priority of specific demand nodes. For instance, during extreme events, facilities providing emergency medical services, such as hospitals, usually have a higher priority than retailers, such as convenience stores. However, hospitals often have on-site generators and emergency supplies of diesel fuel and, therefore, may be able to withstand a certain period without power. Therefore, the decision to restore power at either a hospital or convenience store will depend on the timing of this restoration (e.g., will the hospital run out of fuel prior to its restoration) and the amount of communication between the power company and the hospital. Note, though, we should ensure power to hospitals (either through the grid or back-up generators) as early as possible. The contributions of our research are:

1 a greater understanding of the impact of disruptions to the supply chains for critical commercial services on infrastructure restoration decisions and further, on community resilience

2 the routing problem of local supply chains during the restoration periods

3 the impact of inventory decisions of local businesses on their post-event performance.

Furthermore, our research can provide quantitative metrics for community resilience in addition to existing metrics such as NIST (2018).

The rest of the paper is organised as follows: Section 2 presents a summary of related literature, Section 3 presents a high-level summary of the disruption and restoration models, and Section 4 introduces the dataset and discusses numerical findings from our computational tests. Section 5 concludes the paper by discussing managerial implications of the research and the limitations of our models.

2 Literature review

The focus of this literature review is to demonstrate a number of issues related to interdependent infrastructures and critical commercial services during extreme events and discuss how our work contributes to this area. We begin by summarising literature on damage assessment of infrastructures during extreme events and definitions of resilience. We then examine network models of interdependent infrastructures and related problems. We further discuss the literature on the interdependencies between civil infrastructure networks and social networks and network restoration literature.

We first examine damage assessment models of extreme events. Various methodologies are applied to measure the damage on physical structures from natural disasters such as hurricanes, earthquakes and floods. Unanwa et al. (2000) propose the idea of a damage band prediction methodology to estimate hurricane wind damage while Vickery et al. (2009) present a summary of hurricane simulation models to forecast hurricane wind speeds. Merwade et al. (2008) present a probabilistic flood inundation map with assorted inherent uncertain variables into consideration. Nadal et al. (2010) describe the vulnerability assessment of buildings against various flood actions in terms of floodwater hydrodynamics. In addition to physical structures, societal factors, such as demographic information and socioeconomic status, are also included to give a better prediction of damage on infrastructures from extreme events, especially in the field of community resilience. Burton (2010) describes the relationships between social parameters and hurricane impacts. Dawson (2007) proposes a framework to analyse the vulnerability of civil and social systems in urban areas facing environmental changes. Godschalk (2003) defines a resilient city and suggests hazard mitigation practices. Bruneau et al. (2003) defines a quantitative framework to measure seismic resilience of communities and Cutter et al. (2003) design an index to measure social vulnerability to environmental hazards on a county level. More definitions of resilience and approaches to measure it can be found in Hosseini et al. (2016). Our research not only predicts the detailed damage on infrastructures based on HAZUS-MH®, a vulnerability analysis tool for various disasters designed for FEMA Mitigation Division (2017), but also calculates the outages experienced by local communities from damage during extreme events. Furthermore, we also take the cascading failures on emergency services and critical commercial services into consideration since they may further degrade the situation. The comprehensive description of post-event performance of civil infrastructures and critical lifeline networks is a unique contribution of our research in community resilience.

The operations of civil infrastructure systems (e.g., power, telecommunication, water, wastewater, and transportation) depend on each other, thus disruptions in one system may radiate to other systems and cause cascading failures. Lee et al. (2007) build an interdependent layered network model to explicitly capture the operation interdependence of interconnected infrastructures. Ouyang (2014) offers a review of research in interdependent infrastructures and categorise modelling approaches into six groups. Our research falls into the network-based approaches. Loggins and Wallace (2015) build models to determine the outages of interdependent infrastructures from the cascading impact of hurricane damage. In this paper, we extend the approach of Loggins and Wallace (2015) to determine outages in both civil infrastructure systems and critical commercial supply chains. In order to accomplish this, it is necessary to appropriately model the relationships between the infrastructures and the critical commercial supply chains. Sharkey et al. (2015a) demonstrate that a variety of interdependencies not only exist during normal operations, but also exist during post-event restoration efforts. When an extreme event occurs in a specific area, the mere recovery of civil infrastructures is not enough to help recover local communities. The recovery of social services (e.g., medical emergency services, police, and supply chains of critical commercial services) is also of great importance to improve community resilience against extreme events. Furthermore, the operation and restoration of these ‘social infrastructures’ is also highly dependent on civil infrastructures. Gong et al. (2014) examine the dependencies of a supply chain on a set of infrastructures after a disruption and encourage the cooperation between supply chain managers and infrastructure managers to mitigate the impact from disruptions on the supply chain. However, Gong et al. (2014) only consider the interdependency between a single supply chain and supporting infrastructures, which is inadequate when considering the resilience of a community. Loggins et al. (2018a, 2018b) model the relationships between the interdependent infrastructures and various emergency and critical commercial services, including firefighters, police, emergency medical service, cash availability and fuel flow within a county during extreme events, and discuss the preparedness and restoration strategies to optimise the post-event performance of multiple networks. Based on Loggins et al. (2018a), we bring two more critical commercial services into consideration, basic food and pharmaceuticals, and further look into the routing subproblem of delivering critical commercial services to local communities under conditions of degraded infrastructures. We also study the supply chains of critical commercial services in much more detail, with more realistic features of respective supply chains added to the model. These improved features include modelling the flows within these supply chains, modelling the closed loop of cash flow within the county and modelling different dependencies on telecommunication of transactions in cash or credit card.

We now review the literature on network restoration from disruptive events. This literature tends to concentrate on either problems with reduction in independent network performance in each time period (e.g., we find the maximum flow in the network in each time period) or on problems regarding the time which each demand node is reconnected to a supply node. Kim et al. (2008) and Coffrin et al. (2011) examine infrastructure network restoration problems that focus on scheduling the repair operations within the network but do not consider the problem of selecting which components to repair. Nurre et al. (2012) and Nurre and Sharkey (2014) examine so-called integrated network design and scheduling (INDS) problems that focus on selecting a set of components to install into a network and then scheduling them on a set of machines in order to optimise the performance of the network over time. Xu et al. (2007), Averbakh (2012), Averbakh and Pereira (2012, 2015), Çelik et al. (2015) and Berktaş et al. (2016) consider problems that focus on the connectivity over time between supply nodes and demand nodes. For example, Averbakh (2012) and Averbakh and Pereira (2012, 2015) optimise the *recovery times* of the nodes, where this time for a node is the earliest time it is connected to a supply node. Morshedlou et al. (2018) examine issues around work crew routing it restore infrastructure networks. Our research looks into the cumulative restoration performance of the infrastructure networks as well as the supply chains of critical commercial services throughout the restoration horizon, which offers a better measurement of their contribution to the resilience of local communities against extreme events.

In terms of the restoration of interdependent infrastructure networks, Cavdaroglu et al. (2013) and Sharkey et al. (2015b) examine INDS problems that focus on interdependent infrastructure networks that are linked both through their operations and restoration efforts and measure the cumulative post-event performance during the restoration horizon. González et al. (2016) look into the interdependent network design problem and build a mixed integer programming model to determine the selection and ordering of reconstruction tasks. They are able to show that INDP-based approaches converge to quasi-optimal solutions in all of their studied configurations. While there are many other types of interdependencies among infrastructures during both normal operations (e.g., Katina et al., 2014) and disrupted operations (e.g., Chang et al., 2005; McDaniels et al., 2007, 2009), the interdependencies discussed in our research fall into three classes of interdependencies summarised in Rinaldi et al. (2001): physical, cyber and geographic. Further, our research focus on the interdependency between infrastructures and critical commercial services and the respective infrastructure restoration decisions.

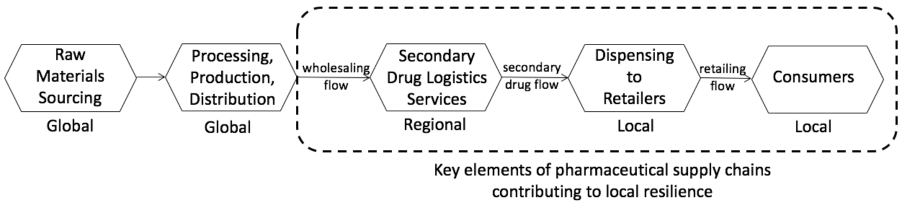
3 Model formulations

In this section, we will provide a brief overview of the disruption and restoration models. Detailed notation and model formulations can be found in Appendix. In order to model the community resilience of a specific area against extreme events, we consider five infrastructures (e.g., power, water, wastewater, telecommunication, and transportation systems), three emergency services (e.g., police, firefighters, and emergency medical services), and four critical commercial services (e.g., cash, fuel, pharmaceuticals, and basic food). The interdependent networks of infrastructures, emergency services, and critical commercial supply chains work together to satisfy the basic needs of local communities.

The network of each infrastructure is composed of supply nodes, demand nodes, transshipment nodes and exclusive arcs delivering the specific service. However, the transportation system does not have supply nodes and demand nodes since the transportation system itself does not offer any service during the recovery period from the disruptive event. Instead, emergency services and critical commercial services flow through transportation arcs, and transportation nodes serve as transshipment nodes of these services. The network of emergency services is composed of supply nodes (e.g., fire stations and police stations), demand nodes (e.g., residential areas) and the transportation arcs delivering these services (based upon the transportation infrastructure).

The supply chain network of each of the critical commercial services is composed of supply nodes (e.g., warehouses and distribution centres), distribution points (e.g., retailers) and demand nodes (e.g., residential areas). Similar to emergency services, critical commercial services depend on transportation arcs to deliver services to customers. Commodities are first shipped in bulk from supply nodes to distribution points by vehicles and then purchased by customers in small amounts at the distribution points. We model the flow of goods from the distribution point to a demand node as flowing along a path of arcs in the network (note that although 'flow' moves from the distribution point to the demand node, the actual interaction involves customers picking up their goods from the distribution point). In order to distinguish these two types of flows, we call the flow from supply nodes to distribution points the 'wholesaling flow' and the flow from distribution points to demand nodes as the 'retailing flow'. We model these two flows of critical commercial services separately and they interact at the distribution points. While the distribution networks of the four critical commercial services are similar, there are two features of pharmaceuticals and basic food worth further discussion. First, since pharmaceutical companies typically use local secondary drug logistics services to fulfill the delivery in a specific area, there will be one more type of pharmaceuticals flow, the secondary drug logistics flow, in addition to the wholesaling flow and the retailing flow. As illustrated in Figure 1, the secondary drug logistics service is responsible for receiving wholesaling flow from the distribution centres of the pharmaceutical companies and then delivering the secondary drug logistics flow to respective pharmacies. Secondly, in terms of basic food, we can get supply from two sources: large national chains such as Walmart or Safeway and local businesses (e.g., convenience stores). We model supply from these two sources as two separate distribution networks for basic food, which allows us to compare their respective contribution to community resilience against extreme events. In the basic food distribution network of national businesses, there are distribution centres outside of the area which serve as supply nodes and plazas act as the distribution points. In the network of local businesses, there are local warehouses that act as supply nodes and convenience stores as distribution points. These two networks (national and local) share the same set of basic food demand nodes.

Figure 1 Pharmaceutical supply chains



3.1 Disruption model

In this subsection, we will present an overview of the single-period multi-commodity disruption model. The objective of the disruption model is to minimise the summation of outages of demand nodes in the infrastructures, the network of emergency services and the critical commercial supply chain networks after extreme events. Mathematically, our objective is:

$$\sum_{s\in S}\sum_{i\in V^{s-}} w_i^s * O_i^s + \sum_{m\in M\setminus\{trans\}}\sum_{i\in V^{m-}} w_i^m * O_i^m + \sum_{e\in\mathcal{E}}\sum_{i\in V^{e-}} w_i^e * O_i^e$$

where $w_i^m/w_i^e/w_i^s$ is the weight on each demand node i of infrastructure m/ emergency service e/ critical commercial service s. $O_i^m/O_i^e/O_i^s$ are the binary variables representing outages at demand node i of infrastructure m/ emergency service e/ critical commercial service s.

The constraints of the disruption model consist of ten parts, describing the following aspects: the operations of the non-transportation infrastructures [constraints (1) to (8) in Appendix], the operations of the emergency services [constraints (9) to (11)], the flow of critical commercial services on damaged transportation arcs and nodes [constraints (12) to (14)], the operations of the retailing flow [constraints (15) to (27)], the operations of the wholesaling flow [constraints (28) to (51)], the details of the cash flow [constraints (52)], the details of pharmaceuticals flow to hospitals [constraints (53) to (55)], local logistics [constraints (56) to (63)], interdependencies relationships [constraints (64) to (69)], and those determining whether outages occur within the networks [constraints (70) to (74)].

Now we will explain some specific constraints of our disruption model. In terms of damage on arcs and nodes, we consider two levels: partial damage and full damage. For most infrastructures, the flow on both partially damaged and fully damaged arcs and nodes will be reduced to zero, though partial damage requires a shorter time to repair the damaged component. The only exception is the transportation arc. We allow traffic through partially damaged roads with a longer traveling time [constraint (60)]. In terms of the cash flow, we assume that customers have a certain amount of cash on hand and the rest deposited in banks. So therefore customers can only buy commodities with cash if they have cash on hand or they take cash from their bank deposits [constraints (18) to (20)]. Furthermore, people can get cash from free-standing ATMs in convenience stores. We assume these free-standing ATMs cooperate with one local bank and can only get replenished with cash from this specific bank [constraint (52)]. We consider two payment methods in our model: cash and credit cards. Although retailers (e.g., convenience stores and supermarket plazas) can still operate without telecommunication during extreme events, transactions by credit (and debit) cards will be unavailable without telecommunication. So therefore if there is a telecommunication outage at a retailer, customers can only purchase commodities by cash [constraints (68) to (69)] at this retailer. Furthermore, since pharmacies need telecommunication to check customers' prescriptions, once there is no telecommunication, no transaction for pharmaceuticals will be allowed at that retailer. In terms of the pharmaceuticals, we assume hospitals keep a high inventory of pharmaceuticals and can serve as supply nodes of pharmaceuticals only when all pharmacies are down [constraints (53) to (55)].

3.2 Restoration model

In this subsection, we will present the multi-period multi-commodity restoration model. Our focus is to maximise the cumulative percentage of overall met demand throughout the restoration horizon with the selection and scheduling of restoration tasks. Please note that critical commercial services include fuel (shown as 'f' in the following), cash (shown as 'ca' in the following), pharmaceuticals (shown as 'ph' in the following), basic food from national businesses (shown as 'bp' in the following), basic food from local businesses (shown as 'bl' in the following). Our objective is:

$$maximise \sum_t W_t * \left(\sum_{m \in M \setminus \{trans\}} \varpi_m * \mathcal{P}_t^m + \sum_{e \in \mathcal{E}} \varpi_e * \mathcal{P}_t^e + \sum_{s \in S} \varpi_s * \mathcal{P}_t^s \right)$$

where

$$\mathcal{P}_t^m = \frac{\sum_{i \in V^{m-}} (w_i * \sum_{(j,i) \in E^m} X_{j,i,t})}{\sum_{i \in V^{m-}} (w_i * d_{it}^m)} \qquad \forall m \in M \setminus \{trans\}$$

$$\mathcal{P}_t^e = \frac{\sum_{i \in V^{e-}} (w_i * \sum_{(j,i) \in E^{trans}} X_{j,i,t})}{\sum_{i \in V^{e-}} (w_i * d_{it}^e)} \qquad \forall e \in \mathcal{E}$$

$$\mathcal{P}_t^s = \frac{\sum_{i \in V^{s-}} (w_i * \sum_{(j,i) \in E^{trans}} \sum_{a \in V^{s\sim}} x_{a,j,i,t})}{\sum_{i \in V^{s-}} (w_i * d_{it}^s)} \qquad \forall s \in \{ca, ph\}$$

$$\mathcal{P}_t^s = \frac{\sum_{i \in V^{s-}} (w_i * \sum_{(j,i) \in E^{trans}} \sum_{a \in V^{s\sim}} \sum_{p \in \{1,2\}} x_{a,j,i,p,t})}{\sum_{i \in V^{s-}} (w_i * d_{it}^s)} \qquad \forall s \in \{bl, bp, f\}$$

$\mathcal{P}_t^m/\mathcal{P}_t^e/\mathcal{P}_t^s$ is the percentage of overall met demand of infrastructure m/emergency service e/critical commercial service s, which is calculated as dividing the weighted flow into all demand nodes by the weighted required demand of all demand nodes. And $\sum_{i \in V^{m-}} (w_i * d_{it}^m)/\sum_{i \in V^{e-}} (w_i * d_{it}^e)/\sum_{i \in V^{s-}} (w_i * d_{it}^s)$ is the overall weighted demand of the infrastructure m/emergency service e/critical commercial service s, which is a constant parameter. $\varpi_m/\varpi_e/\varpi_s$ is the general weight of the infrastructure m/emergency service e/critical commercial service s and W_t is the weight of flow in time period t.

The constraints of the restoration model are very similar to those of the disruption model. One of the main differences is that we have restoration constraints instead of outage constraints. Another difference is that we examine the unmet demand instead of the outages at the demand nodes in order to better measure the effects of restoration efforts in detail. In particular, this will allow us to backlog unmet demand in future time periods. The restoration efforts (e.g., repairing damaged components) gradually recover the damaged networks, damaged arcs and nodes can be used as usual in period t if they are restored on period t [e.g., constraints (76) to (81) and constraints (105) to (107)]. Since the restoration model consists of multiple periods, most constraints in the disruption model are expanded with one more dimension, time period t. However, some features of the multi-period model require further modifications. For example, unmet demand in the critical commercial services can be carried over to the next period and satisfied in later periods [constraints (82) to (84)]. Similarly, we also have inventory at distribution points that can be carried over to the next period, thus cumulative flow until period t is considered instead of the single flow in period t [constraints (88) to (99)].

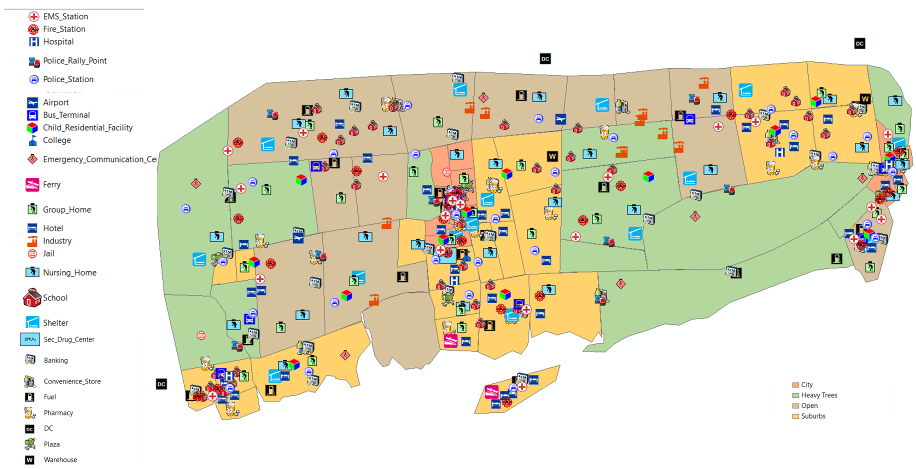
4 Computational results and analysis

4.1 Dataset

The dataset is similar to the one used in Loggins et al. (2018b) with more retailers of critical commercial services included. CLARC is an artificial county with a population of half a million, covering 1,065 square miles. Figure 2 illustrates all facilities in CLARC, including retailers in the distribution networks of critical commercial services and many other facilities such as schools and nursing homes, which act as demand nodes of infrastructures, emergency services and critical commercial services.

Now we will discuss the retailers in CLARC in detail. These retailers are key components in distribution networks of critical commercial services. In comparison with the dataset used in Loggins et al. (2018b), our dataset includes more retailers and represents more realistic, but more complicated, networks of critical commercial services. In particular, Loggins et al. (2018b) only consider the distribution points of the cash and fuel networks whereas our research examines the entire distribution network required to move flow from supply points to these points of distribution. Further, we bring two more critical commercial services into consideration, basic food and pharmaceuticals, which are of equal importance as cash and fuel for communities after extreme events. Further, retailers are where the networks of critical commercial services overlap with each other. As we explained earlier, each retailer may provide multiple commodities while each commodity may be available at multiple retailers. Figure 3 demonstrates all the retailers in CLARC and Table 1 illustrates all the retailers in CLARC and commodities available at them. In adding the more detailed characteristics of the distribution networks for critical commercial services, we have increased the computational difficulty of obtaining solutions to the disruption and restoration models. In order to provide insights to this problem, we have chosen to examine retailers at an aggregate level (e.g., all retailers of a company located within a small geographic area rather than each individual retailer). Therefore, at first glance, the number of retailers in Table 1 is relatively small for a population of half a million; however, we have scaled their capacity/demand appropriately to ensure that all demand can be met by the retailers. Further, we believe that all retailers within an aggregation are likely to experience similar situations during the extreme event (e.g., similar power outages), which means that we are not losing fidelity in modelling the cascading disruptions and can thus still provide insights into the reliance of critical commercial services on civil infrastructures and their impact on community resilience.

Figure 2 Facilities in CLARC (see online version for colours)



The disruption model is a single-period model while the restoration model includes ten periods where each period represents 12 hours, leading to five days in total. The demand for critical commercial services in one period at each residential area is proportional to its population. In terms of the amount of cash in CLARC, we use US money supply M1 in August 2017 (Board of Governors of the Federal Reserve System, 2017) as a reference to estimate the cash in hand of residents and deposited in banks by local communities. We assume three banks operate in CLARC and the deposits from local communities are split equally among them. In each of the eight convenience stores in CLARC, there is a free-standing ATM, which is owned by one company. This company only works with one bank, thus replenishing its free-standing ATMs with the cash from the specific bank. We assume all ATMs, including the eight free-standing ATMs have identical cash inventory as well as identical cash capacity, which is equal to five times the level of initial inventory. Furthermore, customers can purchase commodities by cash and retailers will deposit the cash they receive from transactions to nearby banks at the end of every period. We then need to convert the transactions over commodities into cash flow within the county. We assume the price of basic food is 7.5 US dollars per kilogram and the price of fuel is 2.3 US dollars per gallon. We further assume that the cash is equally deposited back to the three banks, and banks will send the cash to their ATMs, thus forming a closed cash loop within the county.

Figure 3 Retailers in CLARC (see online version for colours)

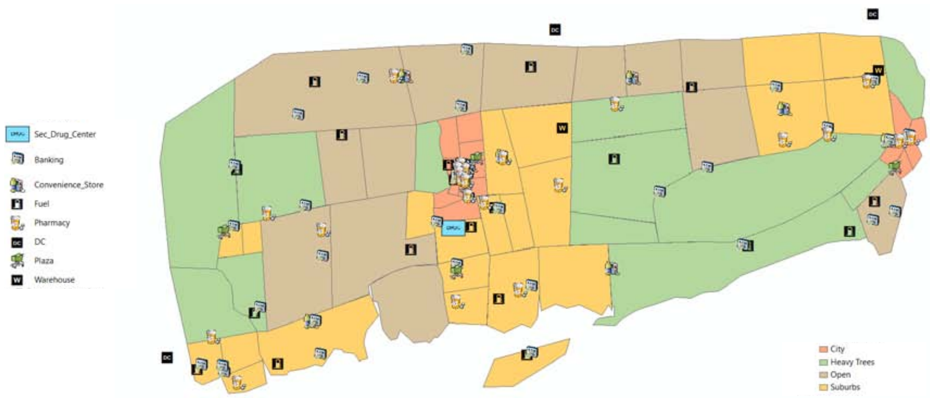


Table 1 Summary of retailers and critical commercial services available at them

Retailers	*Total number of retailers in CLARC*	*Cash*	*Fuel*	*Pharmaceuticals*	*Basic food*
ATMs	34 of 3 banks	x			
Convenience stores	8 of 2 companies	x	x		x
Supermarket plazas	6	x		x	x
Pharmacies	23 of 3 companies			x	
Gas stations	18		x		
Hospitals	6			x	

In terms of fuel, we use the daily gasoline consumption in the US Energy Information Administration (2018) as a reference to estimate the total demand of fuel according to the population of CLARC. Unlike other commodities, in addition to residential areas, demand nodes such as bus terminals and airports, also have demand for fuel. We assume that the demand of fuel at residential areas is proportional to their populations while the demand of fuel at other demand nodes are identical. We assume there is unlimited supply of fuel at two fuel terminals (supply nodes of the fuel network) since the underground gasoline pipes are rarely damaged and are able to continuously send fuel to terminals. All convenience stores and gas stations (distribution points of fuel network) have identical inventory level and capacity level. We further assume each of the tanks at the fuel terminals follow a fixed schedule, visiting every convenience store and gas station once every three periods. Since the disruption model only considers a single period, we randomly select a subset of convenience stores and gas stations that are able to receive fuel from terminals while the rest only have fuel inventory stored at them without replenishment from terminals.

In terms of basic food, we estimate the food demand according to Holguín-Veras et al. (2012). Since there are two sources of basic food, national businesses (e.g., supermarket plazas) and local businesses (e.g., convenience stores), we assume during normal operations, one quarter of the total basic food demand is met by local convenience stores while three quarters of the total demand is met by national businesses. Further, national businesses have distribution centres outside of CLARC (supply nodes in the basic food network of national businesses) with uninterrupted supply of basic food. All six supermarket plazas (distribution points in the basic food network of national businesses) have identical inventory levels with the total inventory equal to twice the met demand at them during normal operations. The capacity of supermarket plazas is equal to three times this inventory level. Eight convenience stores (distribution points in the basic food network of local businesses) are run by two companies and we assume that they are responsible for an equal amount of demand during normal operations. Each of the companies that operate convenience stores has a local warehouse (supply nodes in the basic food network of local businesses) in CLARC, which keeps inventory an amount equal to ten periods of their stores' demand. Please note we will vary this initial inventory level when we study the inventory policy of local businesses.

In terms of pharmaceuticals, we take the prescription drug use in 2011–2014 in the US as a reference (National Center for Health Statistics, 2017) to estimate the demand at each residential area. Pharmacies in CLARC belong to three pharmaceutical companies and we assume that each has an equal market share (i.e., demand for pharmaceuticals is split evenly across the companies). Every pharmaceutical company has a distribution centre outside of the county (supply nodes in the pharmaceutical network) with an unlimited supply of pharmaceuticals. Since every pharmaceutical distribution centre needs to cover all pharmacies in a large region, their delivery vehicles run on a fixed schedule. Similar to the tankers of fuel terminals, each delivery vehicle of pharmaceutical companies visits the warehouse of the secondary drug logistics service once every three periods. The total inventory stored at pharmacies is equal to the total demand. Since a person usually purchase pharmaceuticals at the same pharmacy for each replenishment, we customise the inventory level at a pharmacy to be proportional to the met demand at it during normal operations, as opposed to setting a uniform inventory level across pharmacies. Since pharmaceutical companies are allowed to store inventory at the warehouse of the secondary drug logistics service temporarily during the restoration horizon, the capacity at the warehouse assigned to each company is large enough to cover the total demand for five periods. In addition to pharmacies, there are also six hospitals serving as a complimentary source of pharmaceuticals. We assume customers will turn to hospitals when the pharmacies they usually choose during normal operations are unaccessible. For example, When Hurricane Matthew hit North Carolina in October 2016, hospitals received increased requests of pharmaceuticals from displaced individuals separated from their pharmaceuticals because of evacuation (Moore and Kenworthy, 2017). Hospitals start with a high inventory level of pharmaceuticals, with the total inventory equal to half of the total demand. However, we do not consider any replenishments to hospitals during the restoration periods.

In terms of the delivery vehicles, we assume each supply node of critical commercial services has one vehicle and will be stored at the node, waiting to deliver commodities. Since we are tracking the routes of the delivery vehicles of the local logistics (e.g., local businesses and secondary drug logistics services), we assume that the vehicles are traveling at an average speed of 50 miles per hour and we collect the length of each road in CLARC to guarantee that the delivery cannot exceed the time limit of 12 hours in each period. The delivery vehicles also have a capacity which is the maximum amount of commodities they can carry with them. The capacity of the vehicles is relatively large since supply is often the bottleneck when missing demand for commercial services.

In terms of the retailing flow of the four critical commercial services, these flows are carried by customers who typically make purchases at nearby retailers. We assume the longest distance customers are willing to cover to make a purchase is 17 miles, especially when the road conditions are degraded by the extreme event. Please note that all parameters introduced in this subsection can be adjusted according to user's estimates for a specific county.

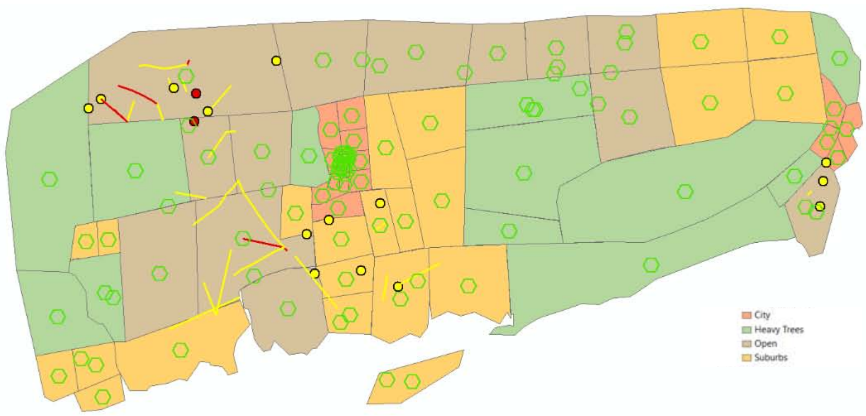
We now describe the damage from potential extreme events. The following computational analysis will focus on damage caused by hurricanes. For example, it is unlikely that our damage will include damage to underground arcs (e.g., water pipes and sewage pipes) and will not include damage to telecommunication arcs (e.g., signals). However, as a comprehensive dataset, CLARC is capable of simulating any kind of extreme events, such as floods and earthquakes, and our disruption and restoration models are also able to calculate outages and suggest restoration plans for different extreme events. Due to the scarcity of Category 5 hurricanes, we will only consider Categories 2, 3 and 4 hurricanes in the following analysis. Note that Category 1 hurricanes do not cause enough damage to disrupt normal operations. Our models can be expanded to analyse Category 5 hurricanes but likely would require advances to the solution methodologies to attack these problems due to the large number of decision variables involved in the restoration efforts of a Category 5 hurricane. We generate five scenarios for each category of hurricanes, leading to 15 scenarios in total.

We implement the model in OPL, using CPLEX 12.8.0.0 as the integer programming solver and ArcMap as the GIS visualisation tool. We run the disruption model without any damage to get customers' choice over all retailers within the county. We take the flow out of each retailer as the demand met by it during normal operations. As we discussed earlier, the met demand serves as a reference to determine the inventory level at retailers. In the following analysis, we will examine the computational results of disruption model in Subsection 4.2 and the results of restoration model in Subsection 4.3.

4.2 Results of disruption model

We are able to solve the single-period multi-commodity disruption model within ten minutes with a MIP gap tolerance of 0.25% and provide a detailed prediction on the respective service outages across infrastructures and critical commercial services within CLARC for each of the 15 scenarios. We first show the damage and resulting outages here with Scenario 4 of Category 2 hurricane as an example. We calculate the respective outages on the four infrastructures, three emergency services and four critical commercial services with the disruption model. We use basic food outages here as an example. Figure 4 illustrates the simulated damage on arcs and nodes in networks of five infrastructures within CLARC from a Category 2 hurricane as well as the basic food outages. The red/yellow dots in the figure represent fully/partially damaged nodes while the red/yellow lines in the figure represent fully/partially damaged arcs. The green hexagons represent demand nodes without an outage in the basic food network while the red hexagons represent those with an outage in the basic food network.

Figure 4 Damage on five infrastructure systems and the resulting basic food outages under a Category 2 hurricane (see online version for colours)



As we can see from Figure 4, although there are multiple damaged nodes and arcs in CLARC, there are no outages in the basic food network among demand nodes (e.g., all hexagons are green in CLARC), which indicates the delivery of basic food in CLARC is not immediately impacted by damage in five infrastructure systems. Thus, damage to infrastructure systems may not necessarily lead to immediate outages of critical commercial services due to the redundancy of resources in CLARC. For example, delivery vehicles can select a path without damaged arcs to deliver basic food and retailers of basic food not impacted by the damage to infrastructures can help supply customers who belong to those retailers whose infrastructure services were disrupted.

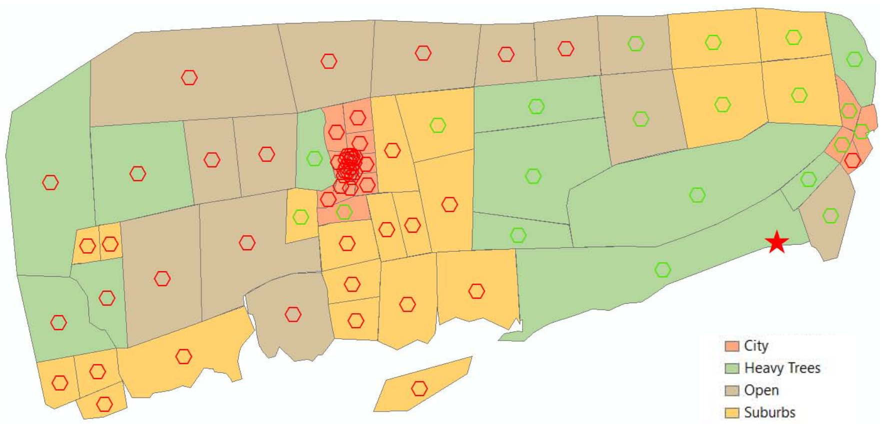
One feature of the basic food supply from local businesses is that they have complete control over the supply nodes (warehouses within the county) as well as retailers within the county. In comparison with other critical commercial services, which typically receive a stable supply from distribution centres (or refineries in the case of fuel) outside of the county, basic food supply from local businesses have more flexibility in adjusting their inventory levels through changing the assignment of inventory at warehouses and retailers. Thus, it is easier for local communities to negotiate with local businesses about inventory policies in order to better serve communities after extreme events. We are interested in understanding whether this inventory will impact the basic food outages and further help improve community resilience against extreme events. In order to examine the extent to which the inventory level at retailers of local businesses would impact the post-event performance of basic food supply chains, we consider three inventory levels at the convenience stores while the total basic food supply from local businesses remains the same (e.g., increasing the inventory level at convenience stores will result in decreasing the inventory level at warehouses). The low inventory level at convenience stores refers to a small value close to zero (e.g., four units stored at each convenience store and 1,282 units at each local warehouse). The medium inventory level is the initial value we set in the model (e.g., 54 units at each convenience store and 1,082 units at each local warehouse). The high inventory level refers to a large value close to the capacity of convenience stores (e.g., 135 units at each convenience store and 758 units at each local warehouse). In the disruption model, we calculate the overall weighted outages at demand nodes. Among all demand nodes of critical commercial services, there are 77 demand nodes of basic food and they all have weight equal to one. When we adjust the inventory level at convenience stores, we can expect that any changes in the objective value come from the outages of basic food. There may be minor impacts on other critical commercial services since they are competing over diminished utility supply from infrastructures during extreme events. Table 2 shows the food outages of three levels in 15 scenarios.

Table 2 Basic food outages under different inventory levels at convenience stores

Scenario	*Low inventory*	*Medium inventory*	*High inventory*
Category 2 hurricane Scenario 1	0	0	0
Category 2 hurricane Scenario 2	0	0	0
Category 2 hurricane Scenario 3	0	0	0
Category 2 hurricane Scenario 4	0	0	0
Category 2 hurricane Scenario 5	0	0	0
Category 3 hurricane Scenario 1	56	40	21
Category 3 hurricane Scenario 2	56	40	21
Category 3 hurricane Scenario 3	56	44	13
Category 3 hurricane Scenario 4	58	52	43
Category 3 hurricane Scenario 5	56	35	13
Category 4 hurricane Scenario 1	77	77	77
Category 4 hurricane Scenario 2	61	56	49
Category 4 hurricane Scenario 3	77	77	77
Category 4 hurricane Scenario 4	77	77	77
Category 4 hurricane Scenario 5	77	77	77

From Table 2, we can see that under the Categories 2 and 4 hurricanes, the differences in the basic food outages of the three inventory levels are almost always zero. However, the differences under Category 3 hurricanes are relatively prominent in most scenarios. One possible reason is that Categories 2 and 4 hurricanes are relatively extreme in comparison with Category 3 hurricanes. Category 2 hurricanes are too weak to challenge infrastructures and services in CLARC (e.g., there are very few outages in any network), thus adjusting the inventory level at convenience stores will not make a difference under Category 2 hurricanes. Similarly, Category 4 hurricanes are so severe that most infrastructures and services are badly damaged (e.g., there are widespread outages across infrastructure networks), thus any adjustment in inventory level fails to impact outages of basic food since other infrastructure services are out to the convenience store. In comparison, under Category 3 hurricanes, we observe that the highest objective value is always achieved when the inventory level is high at the convenience stores. The advantage of reserving more inventory at convenience stores is obvious; it avoids issues in sending commodities from warehouses to retailers, thus, reducing the probability of being impacted by the damaged transportation system during extreme events. However, a high inventory level at retailers may increase the holding cost during normal operations. Therefore, we suggest increasing the inventory level at retailers of local businesses temporarily when there is forecast showing that a medium-scale extreme event (e.g., Category 3 hurricanes) is imminent.

Figure 5 Basic food outages in Scenario 2 of Category 4 hurricane and the location of 9003 (see online version for colours)



Further, although local businesses only account for a relatively small percentage (one quarter) of food supply within CLARC during normal operations, we can observe that in most scenarios of Category 3 hurricanes in Table 2, the changes in basic food outages under three inventory levels exceed 50%, which demonstrates the significant impact from local businesses on the basic food supply chains during extreme events. We take Scenario 1 of Category 3 hurricane as an example. When we keep a medium inventory level at the convenience stores of the local business, national businesses meet 43.9% of satisfied demand while local business meet 66.1% of demand for basic food. When we keep a high inventory level at retailers of local businesses, national business only account for 23.9% of satisfied demand while local businesses meet 76.1% of demand. Since the distribution centres of national businesses are located outside of the county and their wholesaling flow needs to cover a long distance to deliver the commodities to supermarket plazas (retailers of national businesses), the possibility of being disrupted due to the damaged transportation system is also higher. In addition, in spite of high inventory at supermarket plazas, supermarket plazas are not as widespread as convenience stores, thus leaving their inventory less accessible to customers during extreme events. Thus, cooperation with local businesses is of great importance in improving the resilience of a community.

We now discuss the interesting Scenario 2 of the Category 4 hurricane in Table 2, whose outages are much less severe than the other scenarios (for example, for basic food, we have 100% outages for the other scenarios but between 63% and 79% outages for Scenario 2). After carefully examining the scenarios, we find a key node is not damaged in this scenario. In particular, the node '9003' is a wastewater treatment plant which is not damaged by the hurricane in this scenario. Figure 5 shows the basic food outages of this scenario. The red star is where '9003' is located. We can see that all basic food demand nodes whose demand is satisfied (e.g., green hexagons) are located in the eastern part of the county, where '9003' is in charge of the wastewater supply. We observe the same distribution of met demand nodes not only in the four critical commercial services, but also in other three infrastructures. However, when we manually turn off '9003', the eastern area has widespread outages. Given the impact of this single node on outages across infrastructure networks, we view '9003' as a good example of the importance of examining interdependencies within infrastructures as well as that between infrastructures and critical commercial services in exploring community resilience. The contribution of '9003' is also corroborated by the results of our restoration analysis in Subsection 4.3, where '9003' is always the first wastewater node to be restored.

4.3 Results of restoration model

In this section, we will examine whether the coordination between infrastructures and critical commercial supply chains will lead to better overall post-event performance of all infrastructures and services, and thus improving community resilience against extreme events. Before looking into the computational tests, we first discuss the specific parameters required for the restoration model that are utilised in this section. The objective function of the restoration model (see Subsection 3.2) is to maximise the weighted summation of the cumulative percentage of overall met demand across the networks. In determining the weights placed on each network (e.g., the $\varpi_m/\varpi_e/\varpi_s$ in the objective function), we will view each infrastructure, critical commercial service network, and the network of emergency services equally and place a weight of one to each network. In terms of the time periods in the restoration model, we place a decreasing weight on them (in particular, $W_t = 10 - t + 1$) in order to encourage early fulfillment of demand for services across infrastructures and critical commercial services. Note that these restoration-related parameters can be adjusted according to the preferences of the decision-makers.

In terms of modelling the restoration process, we assume there are two repair teams for each of the five infrastructures (e.g., power, water, wastewater, telecommunication, and transportation), one for damaged nodes and the other for damaged arcs. They can only repair components in their own infrastructure network. We assume a non-preemptive setting implying that a restoration task must be processed without interruption. We focus on damage to infrastructure systems and, therefore, our focus is on infrastructure restoration decisions. The restoration of infrastructures will help to restore the critical commercial services that were disrupted due to their dependencies on the disrupted infrastructures.

The number of decision variables in the restoration model grows rapidly as the restoration horizon grows and, therefore, the optimisation problem takes longer to solve. One of the main difficulties is modelling the routing decisions involved in the basic food and pharmaceuticals networks. In order to keep the problem tractable, we will allow each vehicle of the local logistics to take five tours around the county in each period (e.g., the vehicle is allowed to leave the warehouse five times each period). Further, in order to reduce the number of potential tours, we divide all retailers of pharmaceuticals into five districts in terms of their geographical locations and the vehicles are allowed to visit one district at a time. In reality, it is quite normal that the vehicles will visit nearby retailers together, so the assumption should make the calculations easier without a loss of generality or applicability.

We are able to solve the multi-period multi-commodity restoration model with a MIP gap tolerance of 0.25% within three hours for most scenarios of Categories 2 and 3 hurricanes. However, the Category 4 restoration problem cannot be optimised within three hours. Despite the relatively large MIP gap for Category 4 restoration problems, we are still able to gain insights into restoration plans, including an idea of how important it is for the infrastructure networks to coordinate with the providers of critical commercial services.

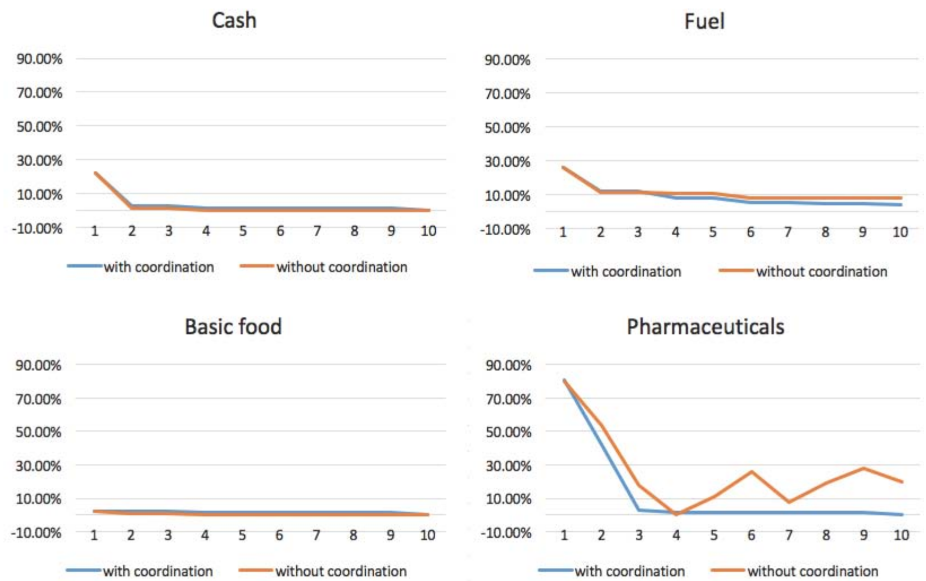
Table 3 Objective value with and without coordination (four critical commercial services included)

Scenario	*Without coordination*	*With coordination*
Category 2 hurricane Scenario 1	487.13	487.13
Category 2 hurricane Scenario 2	479.46	478.72
Category 2 hurricane Scenario 3	490.33	490.92
Category 2 hurricane Scenario 4	486.74	486.55
Category 2 hurricane Scenario 5	486.94	487.41
Category 3 hurricane Scenario 1	415.52	416.21
Category 3 hurricane Scenario 2	408.70	417.10 (with a MIP gap of 1.17% after three hours)
Category 3 hurricane Scenario 3	401.35	401.58 (with a MIP gap of 1.28% after three hours)
Category 3 hurricane Scenario 4	406.08	406.08 (with a MIP gap of 2.8% after three hours)
Category 3 hurricane Scenario 5	374.29	374.29 (with a MIP gap of 5.1% after three hours)

We are particularly interested in how taking critical commercial services into consideration when making infrastructure restoration decisions will alter these decisions. This will, therefore, provide an understanding of the importance between coordinating the infrastructure restoration decisions and the priorities of the community in ensuring the flow of critical commercial services into the area. In order to analyse this impact, we first run the restoration model where the objective only focuses on infrastructures and emergency services (i.e., the weights of the critical commercial services are zero). We view this as the benchmark and can determine the flows of the critical commercial services *based upon* these restoration decisions. We then compare the objective of this restoration plan with one where we place weights on all networks (recall that the three emergency services are viewed as a single network) and have optimised the overall restoration plan. In this way, we examine the post-event performance of all services if there is no coordination between the infrastructures and the critical commercial services. Table 3 compares the objective values of scenarios under Categories 2 and 3 hurricanes with and without the coordination for the entire set of critical commercial services. As we can see in the objective function of Subsection 3.2, when there is no disruption, the weighted flow into all demand nodes should be equal to the overall weighted demand. Therefore, the maximum objective value we can get is 495 [e.g., nine infrastructure/service networks times 55 (e.g., the summation of weights on ten periods for each of them)].

The benchmark restoration decisions will always be a feasible solution to the problem of restoring the infrastructures and critical commercial services with coordination. Therefore, we should always see an improvement (although it can potentially be small) by implementing the restoration plan created by considering all networks. This improvement will come from an improved performance in the critical commercial service networks. Note that it is possible that two sets of restoration decisions may lead to the same, or very close objective values (whose difference is smaller than 0.25%), thus, we may have multiple optimal solutions for our problems under the MIP gap tolerance of 0.25%. From Table 3, we can see in all scenarios of Category 2 hurricanes, there is no difference (or negligible difference lower than 0.25%) between the objective values of the two situations, which means coordination between infrastructures and supply chains does not help to improve the post-performance of all networks in a specific area under Category 2 hurricanes.

Figure 6 Percentage of cumulative unmet demand of four critical commercial services in Scenario 2 of Category 3 hurricane (see online version for colours)



We can observe a similar phenomenon in most scenarios of Category 3 hurricanes in Table 3. Although the problem for Category 3 hurricanes becomes harder to solve, leading to larger MIP gap, we can still have the same objective values under two situations. The only exception is Scenario 2 of the Category 3 hurricane. Coordination leads to an increase of about 2% in the objective value (e.g., from 408.7 to 417.1). We look into the restoration plan of this scenario in detail and find that while the restoration decisions on the other four infrastructures remain the same, the restoration decisions on transportation system are completely different. When there is no coordination with supply chains, the only need for restoration on transportation system is for the network of emergency services. However, once critical commercial supply chains are brought into consideration, their specific requirements on transportation system may change the restoration decisions on which transportation node and arc to select and when to restore.

Figure 6 illustrates the benefits of the coordination for each critical commercial service by comparing the percentage of cumulative unmet demand of the service throughout the restoration horizon. This percentage is calculated as dividing the weighted overall cumulative unmet demand of all demand nodes by the weighted overall cumulative demand over time. As we can see in the figure, in Scenario 2 of Category 3 hurricane, the critical commercial supply chains with coordination outperform that without coordination (e.g., blue lines overlap with orange lines in 'cash' and 'basic food', indicating similar performance and the blue lines are lower than orange lines in 'fuel' and 'pharmaceuticals', indicating less unmet demand and better post-event performance).

We can also examine the impact of coordination for each critical commercial service individually. We apply the same method as previously discussed except we only place a weight of one on the service under consideration. In this case, the maximum objective value we can get is 330. We achieve results in accordance with Table 3. There is no difference (or negligible difference lower than 0.25%) in objective value from coordination for any critical commercial service in all scenarios of Categories 2 and 3 hurricanes except Scenario 2 of Category 3 hurricane. Table 4 demonstrates the objective value concerning each critical commercial service individually in Scenario 2 of a Category 3 hurricane. We observe that coordination helps improve the post-event performance of the fuel and pharmaceuticals supply chains, where the pharmaceuticals supply chain seems to benefit the most from the coordination. Although the benefit of the coordinated restoration decisions is not significant under most scenarios of Categories 2 and 3 hurricanes, we do see significant improvement in certain scenarios. Categories 2 and 3 hurricanes may not be severe enough to accentuate the benefits of coordination between infrastructures and supply chains. However, we expect that as the severity of the hurricane increases, the impact of the coordinated restoration decisions will become more important. We, therefore, turn our attention to analysis on Category 4 hurricanes.

Table 4 Objective value with and without coordination (individual critical commercial service) in Scenario 2 of Category 3 hurricane

Scenario	*Without coordination*	*With coordination*
Category 3 hurricane Scenario 2 (cash)	259.23	259.74
Category 3 hurricane Scenario 2 (fuel)	255.15	258.37
Category 3 hurricane Scenario 2 (basic food)	260.00	260.00
Category 3 hurricane Scenario 2 (pharmaceuticals)	249.28	257.89

The size of the integer program significantly increases with Category 4 hurricanes since the larger number of damaged components requires more decisions to model the restoration process. The problem with benchmark restoration decisions can still be optimised within ten minutes, which serves as a warm start for the problem with coordination (which is much harder to solve computationally). Table 5 shows the best integer solution we can find in three hours for the problem with coordination for the situation where we consider each service *individually*. Please note that due to the large MIP gap (e.g., higher than 50% after three hours) when we include all four critical commercial services into consideration, we only demonstrate the results of restoration problems with one critical commercial service included. Although we do not solve most problems to optimality, the best integer solutions we can find already show a significant increase from the objective value without coordination. Further, note that the MIP gap is still over 20% in most cases, demonstrating that there could be potentially even greater increases.

Table 5 Objective value with and without coordination in Scenarios of Category 4 hurricane

Scenario	*Without coordination*	*With coordination (best integer solution within 3 hours)*	*Minimum increase from coordination*
Category 4 hurricane Scenario 1 (cash)	109.14	110.10	0.88%
Category 4 hurricane Scenario 1 (fuel)	110.19	113.14	2.68%
Category 4 hurricane Scenario 1 (basic food)	111.02	113.62	2.34%
Category 4 hurricane Scenario 1 (pharmaceuticals)	79.87	98.51	23.34%
Category 4 hurricane Scenario 2 (cash)	120.93	120.93	0%
Category 4 hurricane Scenario 2 (fuel)	140.20	141.26	0.76%
Category 4 hurricane Scenario 2 (basic food)	113.20	151.71	34.02%
Category 4 hurricane Scenario 2 (pharmaceuticals)	109.02	109.02	0%
Category 4 hurricane Scenario 3 (cash)	86.93	86.93	0%
Category 4 hurricane Scenario 3 (fuel)	76.90	77.39	0.64%
Category 4 hurricane Scenario 3 (basic food)	101.76	107.07	5.22%
Category 4 hurricane Scenario 3 (pharmaceuticals)	67.45	72.98	8.20%
Category 4 hurricane Scenario 4 (cash)	104.65	105.05	0.38%
Category 4 hurricane Scenario 4 (fuel)	87.28	113.74	30.32%
Category 4 hurricane Scenario 4 (basic food)	122.94	123.44	0.41%
Category 4 hurricane Scenario 4 (pharmaceuticals)	79.54	83.57	5.07%
Category 4 hurricane Scenario 5 (cash)	70.03	70.03	0%
Category 4 hurricane Scenario 5 (fuel)	69.85	92.64	32.63%
Category 4 hurricane Scenario 5 (basic food)	101.11	102.19	1.07%
Category 4 hurricane Scenario 5 (pharmaceuticals)	70.98	71.29	0.44%

In Table 5, the last column shows the minimum increase of the best integer solution found from coordination. As we can see, 16 out of 20 scenarios indicate an increase higher than 0.25% (the MIP gap tolerance), when comparing the best computed solution with coordination to a solution without coordination, which means the coordination leads to a better set of infrastructure restoration decisions with higher overall performance of all networks included. There also exists the potential for even better sets of restoration decisions for the coordinated efforts due to the significant MIP gaps after three hours (around 20% gaps). The increase demonstrates the potential gains in community resilience brought by coordination between infrastructures and critical commercial supply chains. In conclusion, the coordinated restoration decisions do help to improve community resilience, especially when the extreme events are more severe (e.g., Categories 4 and 5 hurricanes).

One assumption in our analysis of the restoration model is that there is no backup emergency equipment at retailers. However, medical facilities, such as hospitals, usually have on-site generators and emergency supplies of diesel fuel to mitigate the impact from extreme events so that they may be able to withstand a certain period without power from the grid (although they will tend not to perform non-critical surgeries). In order to examine how backup emergency equipment will alter the infrastructure restoration decisions, we allow on-site generators at six hospitals in CLARC that enable hospitals to operate four periods (e.g., two days) without a supply of power from the grid. We run the restoration model with on-site generators included under Categories 3 and 4 hurricanes. However, we achieve the same objective values (or objective values with negligible differences lower than the MIP gap tolerance) with all critical commercial services included in all scenarios of the Category 3 hurricanes. Further, we also achieve very close objective values with pharmaceuticals included in all scenarios of Category 4 hurricanes. Since we still have a relatively large MIP gap in all scenarios of Category 4 hurricanes, we cannot conclude that the appearance of generators at hospitals will or will not change the infrastructure restoration decisions. We then increase the time that generators can allow hospitals to operate without power supply from the grid to eight periods (e.g., four days) , the result holds in all scenarios of Category 3 hurricanes. So, while backup emergency equipment at hospitals helps to guarantee the timely medical services for patients, it has a trivial impact on the infrastructure restoration decisions and we should still ensure power to hospitals (either through the grid or back-up generators) as early as possible.

5 Conclusions

In this paper, we design a single-period, multi-commodity disruption model and a multi-period, multi-commodity restoration model to measure the contribution of critical commercial services to community resilience. We examine multiple interdependent networks to model five infrastructures (e.g., power, water, wastewater, telecommunication, and transportation), three emergency (e.g., emergency medical services, police, and firefighters) and four critical commercial services (e.g., cash, fuel, basic food, and pharmaceuticals). We consider the features of critical commercial services such as the availability of the same commodity from multiple retailers and logistics of delivering commodities through the transportation system. We especially consider the contribution of local businesses to community resilience in terms of basic food supply. We simulate five scenarios for Categories 2, 3, and 4 hurricanes on an artificial county with a population of half a million people. With the disruption model, we can calculate the outages based on simulated damage to the county after extreme events across the interdependent infrastructures and critical commercial service networks. With the restoration model, we select which damaged nodes/arcs to restore and schedule when to complete these restoration tasks in order to maximise the overall flow of services into demand nodes across infrastructures. Our models and insights are applicable to interdependencies between infrastructures and supply chains that need to distribute goods within an area impacted by the event and may not be appropriate for other classes of interdependencies between systems.

In our computational analysis on the disruption model, we find that damage may not necessarily lead to outages due to redundancy in the networks. We also locate a key node, '9003', whose failure to function can cause widespread outages of all services in the entire eastern region of the county. As a node in the wastewater network, its impact on all other networks in a certain area is an example of the nature of interdependencies within infrastructures and critical commercial supply chains. Further, we find that while local businesses only account for a relatively small percentage of basic food supply within the county, their inventory policy has a significant impact on basic food supply after certain extreme events. In particular, reserving a higher inventory level at their retailers as preparation for medium-size extreme events may help improve the community resilience when immediate outages are an important concern. In the computational analysis of the restoration model, we demonstrate that coordinated infrastructure restoration decisions can improve the overall post-event performance of all infrastructures and services (e.g., meeting demand earlier, less unmet demand and backordering), especially when the extreme event is more severe (e.g., Categories 4 and 5 hurricanes).

There are limitations in our models that are worth studying in future research. First, as we discuss in Subsection 4.3, the restoration model in many scenarios becomes hard to solve. Although we can still gain meaningful insights from the best integer solutions, better algorithms are needed to solve the problem to optimality. Second, there may be interdependencies within critical commercial services, e.g., vehicles need fuel to deliver other commodities and outages in fuel may lead to disrupted supply chains of other critical commercial services. Third, we design the demand at each residential area according to its population. However, we can include more demographic features of each residential area to give a better estimate of its demand of a certain commodity. For example, a residential area with a high percentage of senior citizens may have a higher demand of pharmaceuticals. Fourth, the analysis in this paper is based on hurricane damage. Analysis of other extreme events can be conducted to find the common preparations and specific preparations for each kind of extreme event in order to better improve the community resilience against all kinds of extreme events.

Appendices/Supplementary materials are available on request by emailing the corresponding author or can be obtained under https://homepages.rpi.edu/~sharkt/Appendix_IJCI.pdf.

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