Cascading Effects of Mass Gatherings on COVID-19 Infections from a Multi-hazard Perspective: A Case Study of New York City

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ABSTRACT

The devastating economic and societal impacts of COVID-19 can be substantially compounded by other secondary events that increase individuals' exposure through mass gatherings such as protests or sheltering due to a natural disaster. Based on the Crichton's Risk Triangle model, this paper proposes a Markov Chain Monte Carlo (MCMC) simulation framework to estimate the impact of mass gatherings on COVID-19 infections by adjusting levels of exposure and vulnerability. To this end, a case study of New York City is considered, at which the impact of mass gathering at public shelters due to a hypothetical hurricane will be studied. The simulation results will be discussed in the context of determining effective policies for reducing the impact of multi-hazard generalizability of our approach to other secondary events that can cause mass gatherings during a pandemic will also be discussed.

Keywords

COVID-19 pandemic, mass gatherings, multi-hazard, vulnerability.

INTRODUCTION

The world is experiencing a widespread biological hazard – the COVID-19 pandemic – which has presented a severe threat to global health. By the end of January 2021, the total number of confirmed COVID-19 cases exceeded 26 million worldwide, with more than 440,000 deaths in the U.S. alone (John Hopkins University and Medicine, n.d.). Many countries have declared restrictive orders to prevent the spread of the virus, including travel bans, stay-at-home orders, social distancing, and face-covering practices. Scientific evidence suggests that mass gatherings play a significant role in COVID-19 spread, especially during the early phase of the pandemic (Ebrahim & Memish, 2020; World Health Organization, 2020). As a result, many mass gathering events were canceled or postponed by authorities worldwide, such as the Euro 2020 football championship, the Hajj in Saudi Arabia, and the Mobile World Congress in Barcelona (McCloskey et al., 2020).

Some mass gatherings caused by certain extreme events such as natural disasters (e.g., earthquakes, hurricanes, or floods) or other complex emergencies (e.g., protests or military movements) are inevitable or unpredictable (Aitsi-Selmi et al., 2016; Hariri-Ardebili, 2020). These mass gatherings may have cascading effects on the COVID-19 infections. In addition to the COVID-19 pandemic's devastating social and economic impacts, the magnified consequences of intersecting natural and biological disasters have already become apparent: communities have been obliged to mobilize due to natural disasters and other emergencies, which challenged policymakers to impose social distancing rules particularly in crowded shelter locations within the affected areas (Sarkar-Swaisgood & Srivastava, 2020). The massive winter storm in Texas in February 2021 was an example of an unexpected extreme event during COVID-19 pandemic that resulted in over 170 million displaced people, left millions of people without electricity and caused at least 111 fatalities by March 26 (Whelan, 2021). Many emergency and homeless shelters and warming stations in Texas served not only homeless people but also the people that do not have heating or electricity with increased health precautions and reduced capacities due to the necessity of social distancing (Garnham, 2021).

Global mass protests were also held throughout the COVID-19 pandemic, which raises the question of whether those mass gatherings may have led to more COVID-19 cases (Karan & Katz, 2020). The killing of George Floyd on May 25, 2020, sparked nationwide Black Live Matter (BLM) protests against racism, which resulted in what may have been the largest movement in U.S. history: four polls suggested that between 15 and 26 million people have participated in the BLM protests in the United States (Buchanan, Bui, & Patel, 2020; Hoover & Lim, 2020).

The combined impact of the COVID-19 pandemic, natural disaster(s), and the social justice crisis can impede the common mitigation measures used to control pandemic spread. Additionally, the inevitable mass gatherings during both disaster response and social justice demonstrations may have cascading effects on the number of COVID infections, especially considering the inferred increase in exposure and vulnerability. This paper first analyzes the potential impacts of mass gatherings due to secondary events (e.g., a natural disaster, a social crisis) on the COVID-19 pandemic. Considering New York City as a case study, this paper proposes a Markov Chain Monte Carlo (MCMC) simulation framework based on Crichton's Risk Triangle model (Crichton, 1999) to estimate COVID-19 infection by adjusting levels of exposure and vulnerability in the context of mass gathering due to a hypothetical hurricane. We conclude with a discussion of what policies could be effective in the multi-hazards context based on the simulation results, along with a discussion on the generalizability of our approach to any events causing mass gatherings, such as protests, during a pandemic.

LITERATURE REVIEW

Recent incidents remind us that the simultaneous occurrence of a pandemic and other extreme events is quite likely and poses significant threats to communities' well-being. Adverse consequences dramatically increase if the authorities are not well prepared to enforce necessary actions to prevent infection spread, or the individuals do not entirely practice restrictions. For example, in May 2020, 11000 people were forced to evacuate due to the Michigan dam failures during the COVID-19 pandemic (Hariri-Ardebili, 2020). In their response, local authorities tried to encourage evacuees to take precautions to prevent the virus's transmission (Graber, 2020). Additionally, during Cyclone Amphan in 2020, Eastern Indian and Bangladeshi evacuees found that many evacuation centers had already been converted to quarantine shelters, resulting in inadequate space for social distancing and limited hospital capacities (Sarkar-Swaisgood & Srivastava, 2020).

In addition to natural disasters, health care providers and governments have been challenged with an increased risk of infection spread due to mass gatherings. World Health Organization (WHO) (2016) defines a mass gathering as a spontaneous or planned event that gathers a significant number of participants who may overstretch the region's health planning and response capacities. Protests and major sporting, religious, and cultural events are examples of mass gatherings. Historical events such as the Festival of Pacific Arts and the Micronesian games in 2016 or the Rio de Janeiro Olympics and Paralympics in 2016 reveal that mass gathering events can cause serious public health challenges and potentially cause the global spread of infectious diseases (Memish et al., 2019).

Researchers have recently studied the multi-hazard perspective of pandemics, considering the likelihood of simultaneous disasters during an ongoing pandemic, potential consequences, and preparedness for such extreme scenarios. For example, Little et al. (2021) examine how a community's recovery time from a hurricane could be affected due to an ongoing pandemic, including the potential consequences of this multiple-disaster scenario. Silva and Paul (2020) study the coincidence of earthquakes with epidemics and analyze the impact on the affected regions' infection rate. Hariri-Ardebili (2020) explores multiple hazard scenarios considering natural disasters (e.g., earthquakes or floods) and complex emergencies (e.g., mass protests) during the COVID-19 pandemic.

Sarkar-Swaisgood and Srivastava (2020) point out the challenges in incorporating a multi-hazard perspective in disaster preparedness during the COVID-19 pandemic and discuss key priorities for governments to build resilient infrastructure from the current crisis.

Although the BLM protests raised concerns among some government officials and public health professionals on the potential health consequences of mass gatherings, many scholars argue that anti-racism protests are understandable or reasonable during the COVID-19 pandemic (Kampmark, 2020). Karan and Katz (2020) argue that while large crowds may lead to more COVID-19 cases, anti-racism protests are understandable because racism is also a public health problem, as demonstrated by higher rates of COVID-19 among Black and Hispanic populations (Vahidy et al., 2020). Dave et al. (2020) use SafeGraph cell phone data to determine that outdoor BLM protests did not reignite community-level COVID-19 growth, thanks to the risk-avoiding responses (e.g., wearing masks) taken by many protesters. Currently, there is no evidence showing a direct causal relationship between protests and the growth of COVID-19 infections.

Given the public health restrictions put in place to slow the spread of infections during a pandemic, Hariri-Ardebili (2020) emphasizes that it becomes even more challenging to manage the displacement of a large number of people when an additional extreme event occurs. Any event that mobilizes crowds exacerbates the impact by constraining the pandemic response plans. Prior studies emphasize the increased infection risk at evacuation centers during a pandemic (Okada et al., 2014). Although simulation models for mass evacuations due to natural disasters are well-established in the literature (Pidd et al., 1996; Kimms & Maassen, 2011; Goto et al., 2012; Bernardini et al., 2014), little research examines the impact of mass gatherings during a pandemic (Lant et al., 2008; Araz et al., 2011; Okada et al., 2014). In this study, we investigate how simultaneous events that mobilize people may affect the spread of COVID-19 infections.

CONCEPTUAL MODEL

In the following section, we summarize the state-of-the-art knowledge on concepts of hazard, vulnerability, and exposure, which relies on Crichton's Risk Triangle (Crichton, 1999) (Figure1) and the modifications applied to evaluate mass gathering impact on these components.

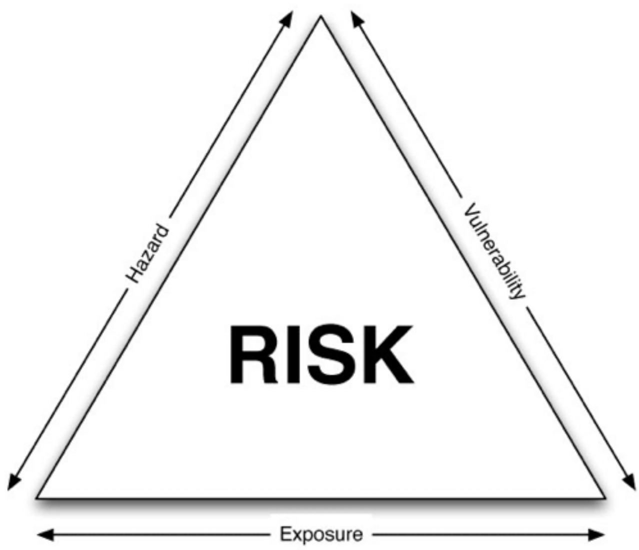

Figure 1. Crichton's Risk Triangle (Crichton, 1999)

A hazard can be defined as "a physical event, a phenomenon caused naturally or technologically, and/or human activity that potentially causes loss of life or injury, damage to property, disruption in social and economic activities, or environmental degradation" (Schneiderbauer, 2006). Although single event hazards are generally studied more extensively, hazards can also be "sequential or combined" in their origin and effects. Also, Middlemann (2007, Chapter 3) explains that hazards are characterized by a certain magnitude or likelihood of occurrence. For the purpose of our study, we are considering multiple hazards like meteorological (storm surge) and biological (COVID-19 pandemic) hazards happening either at the same time or in close succession. We aim to use the triangle model to study the combined impact of multi-hazards on COVID-19 cases and subsequent management of disasters like sheltering and evacuation.

Vulnerability is more commonly defined as "the characteristics of a person or a group in terms of their capacity to anticipate, cope with, resist and recover from the impact of a natural or man-made disaster - noting that vulnerability is made up of many political-institutional, economic and socio-cultural factors" (Schneiderbauer, 2004). Therefore, in regards to sequential multi-hazards of different categories like meteorological and biological hazards, vulnerabilities will be quantified differently. However, these categories can be linked together to identify the population most vulnerable to a combination of hazards. For instance, the Social Vulnerability Index (SoVI) (Cutter et al., 2003), a widely recognized vulnerability measure for natural hazards, is comprised of eleven factors, while the COVID-19 Pandemic Vulnerability Index (Marvel et al., 2021) consists of twelve factors that are distinct but could also be used for defining vulnerability in different contexts, as shown in Table 1. It should be noted that another Social Vulnerability Index (SVI) was developed by the Centers for Disease Control and Prevention (CDC) to help emergency managers identify and help communities before, during, and after disasters (CDC, 2015) (Table 1). Unlike Cutter et al.'s SoVI calculation, CDC follows a ranking-based approach in social vulnerability quantification (*SVI 2016 Documentation CDC*, 2016).

Table 1. List of variables used to measure different kinds of vulnerability

Theme	COVID-19 Pandemic Vulnerability Index	Social Vulnerability Indices	
	(Marvel et al., 2021)	(CDC, 2015)	(Cutter et al. 2003)
Socioeconomic Status	Population Demographics	Below Poverty Unemployed Income No High School diploma	Personal Wealth Occupation Single-Sector economic dependence
Household Composition and Disability	Age Distribution Health Disparities Co-morbidities	Age 65 or older Age 17 or younger Older than 5 with a disability Single parent households	Age
Built Environment (Housing & Transportation)	Air pollution Hospital Beds Population Mobility Residential Density	Multi-unit structures Mobile homes Crowding No Vehicle Group Quarters	Density of built Environment Housing Stock and tenancy Infrastructure dependence
Minority Status and Language		Minority Speak English "less than well"	Race-Asian Ethnicity- Native American Ethnicity-Hispanic Race-African American
Infection Rate and Intervention	Testing Social Distancing Transmissible Cases Disease Spread		

Concepts and measures of vulnerability change with respect to the kind of hazard considered and whether and which type of vulnerability index is utilized. Chakraborty et al. (2005) found that considering spatial variability in social vulnerability along with geophysical risk is crucial for successful evacuation management. The authors also found that different measures of social vulnerability and social component selection can affect evacuation strategies. For instance, Ng et al. (2014) studied the difference in evacuation behavior and needs of medically fragile people over the general population. Therefore, in the context of determining sheltering needs amidst COVID-19 and a natural hazard, it might be essential to consider factors relevant to sheltering needs for individuals with different vulnerabilities.

Middlemann (2007, Chapter 3) mentions that the elements (structures, people, environment, etc.) which are the subject of the impact of a specific hazard make the component 'exposure' of the Crichton's Risk Triangle. Exposures vary for each hazard, meaning that exposure in a multi-hazard environment might be dynamic and change with each hazard considered. Our proposed framework will implement time-dependent probabilistic models to account for the varying nature of exposure due to multi-hazard sequence.

CASE STUDY & DATA SELECTION

Case Study: New York City

We selected New York City as our case study for three key reasons. First, New York City (NYC) was considered an epicenter of the COVID-19 outbreak in the United States during spring 2020. From March 1 to June 1 in 2020, NYC reported a total of 203,792 COVID-19 cases, which has the highest overall cumulative COVID-19 incidence among all jurisdictions in the United States (Bialek et al., 2020; Thompson et al., 2020). As of February 9, 2021, there are 551,982 confirmed cases and 22,819 confirmed deaths in NYC, according to the NYC Health Department (2021). Second, besides the COVID-19 pandemic, NYC has also experienced multiple natural disasters in the past 20 years, including Hurricane Sandy, which provides prior data on multi-hazard occurrence. As one of the most densely populated cities in the United States, NYC is highly vulnerable to multiple hazards such as terrorism and hurricane storm surge in the future (Harrigan & Martin, 2002; Lin et al., 2010; Depietri, & McPhearson, 2018). Third, NYC has witnessed large BLM and other mass protests, enabling us to study the impact of mass gatherings. Thousands of BLM demonstrators in New York City marched in public every day in June following George Floyd's death (Robinson, 2020).

In summary, NYC was an early epicenter of the COVID-19 pandemic in the United States. We can anticipate that it will also be systematically affected by future natural hazards, such as heatwaves, hurricanes, and social crises, like terrorism and civil unrest, in the long term. Combining the real-time data of the pandemic and historical data about other hazards, the multi-risk context of NYC can help us better understand the potential impacts of multiple disruptive events during the COVID-19 pandemic.

COVID-19 Data Source

The New York Department of Health disseminated COVID-19 data through a public repository (NYC Health, n.d.) starting from February 29, 2020 (date of the first laboratory-confirmed case in New York). Citywide daily counts of confirmed cases, hospitalizations, and deaths are included in this dataset. In addition, the dataset provides a 7-day average of daily confirmed cases to address variations in diagnosed patients.

Protest Data Source

The mass protest data in NYC during the COVID-19 pandemic is available through Crowd Counting Consortium (Crowd Counting Consortium, 2021). This online crowdsourcing platform covers data on dissent and collective action arising during the COVID-19 pandemic in the United States. In addition to general civil unrest activities during the COVID-19 pandemic, this dataset also includes a separate part which focuses on anti-racism movements, including BLM. The data source includes the location, date, estimated number of participants, the actors and their claims, event type, and other details for each event.

Hurricane Sandy Data Sources

The U.S. Department of Housing and Urban Development (HUD) provides open access to Hurricane Sandy damage estimates by block groups, which was used to determine eligibility for FEMA Individual Assistance (HUD Open Data, 2014). Additionally, the New York City Office of Emergency Management provided a list of consolidated, operating evacuation centers following Hurricane Sandy (NYC Office of Emergency Management, 2012).

SafeGraph Data Source

SafeGraph COVID-19 data consortium provides free access to aggregated and anonymized datasets on social distancing and foot traffic to businesses in the United States for researchers interested in investigating the mobilization during the COVID-19 pandemic (SafeGraph, 2020). We will use this dataset to identify mass gatherings in NYC during the pandemic and observe changes in community behavior with respect to changes in the number of infections.

MODELING FRAMEWORK

The epidemic's transmissibility is often characterized by the average number of new infections from a single infected person at time t, referred to as effective reproduction number (R_t). Following Fraser (2007), the number of new COVID-19 cases are represented using a Poisson distribution as follows:

$$I_t \sim Pois\ (R_t \textstyle\sum_{s=0}^{t} I_{t-s} w_s) \qquad (1)$$

where I_t is the number of new cases, w_s is the transmissibility profile of each infected case, and R_t is the COVID-19 effective reproduction number. It is assumed that w_s can be characterized as the time interval between symptoms onset for primary and secondary cases (Cori et al., 2013; Silva and Paul, 2020), which for COVID-19 follows a Gamma distribution with a mean of 6.5 days and standard deviation of 3.8 days (Fergusen et al., 2020).

A Markov Chain Monte Carlo (MCMC) (e.g., Speagle, 2019) model is then used to evaluate the impact of a secondary hazard (i.e., hurricane) on COVID-19 transmission. MCMC is a numerical approach combining Monte Carlo simulation with Markov Chains' properties to introduce uncertainties in modeling parameters (e.g., in R_t parameter of Equation 1) using a sequence of random samples. The Monte Carlo method approximates complex probability distributions (e.g., I_t) by drawing a large number of random samples from the target distribution, whereas Markov chains generate sequences of samples that are probabilistically dependent on the immediate prior values (e.g., each new COVID-19 cases sample is only dependent on the number of cases at the previous iteration of the algorithm). In the context of the current problem, at each iteration, R_t is sampled from a distribution and new cases are introduced into the sampling scheme (Silva and Paul, 2020).

To evaluate the impact of the secondary hazard, it is assumed that only the evacuated population will be more vulnerable to COVID-19 due to presumably poorer health situations at shelters (e.g., congested area, lack of personal protective equipment, etc.). The increased vulnerability is introduced as an increase in R_t factor (R_t^{adj}), and a new number of cases due to the secondary event will be obtained as follows (Silva and Paul, 2020):

$$I_t \sim Pois\ (R_t \textstyle\sum_{s=0}^{t} I_{t-s} w_s)\ (1 - p_e)\ + Pois\ ({R_t}^{adj} \textstyle\sum_{s=0}^{t} I_{t-s} w_s)\ (p_e) \qquad (2)$$

Where p_e is the probability of attending a mass gathering. For the case study, p_e equals the probability of each given individual going to the shelter due to the hurricane; however, this parameter can account for other types of mass gatherings such as the probability of an individual participating in the BLM protest. Based on Mileti et al. (1991), it is expected that a maximum of 20% of the population go to shelters due to the hurricane, hence p_e is taken as 0.2 in this study. Regarding R_t^{adj}, several scenarios can be implemented such as a constant increase from pre-event R_t to a peak R_t value in the studied timeframe (worst-case scenario), or an increase-decrease model (an optimistic scenario). Additional sensitivity assessment on the impact of P_e and R_t^{adj} can be carried out in the performed MCMC. We aim to use MCMC results to discuss the interaction of sheltering activities and health policy enforced at shelters.

Application of the conceptual model

R_t^{adj} is proposed to be determined using the "vulnerability" component of the conceptual model. With multiple hazards occurring at the same time, we anticipate the vulnerability indicators will be different. Therefore, a zonal study is required to identify those populations that are vulnerable to multiple disasters. Hence, R_t^{adj} will be determined using expert judgment and indexing methods. The distribution of the R_t^{adj} will be characterized either through sampling approaches (i.e., fitting an empirical distribution) or possible literature. We assume that exposure will be dynamic through time and space and will be impacted with increased cases of COVID-19 and a second event, which necessitates attending a mass gathering (e.g. evacuating to a shelter). Exposure in our study will be defined by the number of people affected by multi-hazards.

Considering the potential data sources we present in this paper, we will create a hypothetical hurricane scenario that coincides with the COVID-19 pandemic. Based on the historical data sources available for Hurricane Sandy (in 2012), we plan to identify areas that are more likely to be affected by a hurricane and are, thus, likely to order evacuation to shelters. Additionally, protests data sources and the SafeGraph dataset will provide information about mass gatherings in NYC during the ongoing pandemic. With the actual infection rates provided by the New York Department of Health, we can also assess the impact of mass gatherings during the BLM protests. In this way, we aim to adjust and validate the model parameters using the aforementioned data sources. We will build an MCMC model to estimate the impacts of a hypothetical hurricane on COVID-19 infections, which will be generalizable to other secondary events that cause mass gatherings. Although the proposed numerical study will explore a hypothetical scenario at which real data does not exist, the probabilistic model parameters will be estimated from collected data described in the previous section. Therefore, the numerical analysis will be grounded on accurate representation of COVID cases, mobility and sheltering data.

FUTURE WORK

The COVID-19 pandemic is continuing globally and its impacts remain uncertain in the long-term. As President Biden announced in January 2021 in the *National Strategy for the COVID-19 Response and Pandemic Preparedness*, "the honest truth is we are still in a dark winter of this pandemic; it will get worse before it gets better" (White House Office, 2021). The social unrest and related gatherings are also not over; in addition to the ongoing BLM protests, the U.S. Capitol Riots in January 2021 caused a new round of policing crises (Alexander, 2021). As for natural disasters, the 2020 Atlantic hurricane season generated 30 named storms, which is the highest on record (NOAA, 2020), and coastal communities will continue to be threatened by storms in the coming hurricane season. It is very likely that the multi-hazard situation will become a "new normal" in the U.S.

Therefore, we would like to estimate the impacts of different disruptive events on the COVID-19 infection from a multi-hazard perspective. Existing research on COVID-19 pandemic infections rarely takes into account the multiple disasters scenario, and we aim to fill this gap. In this paper, we developed a preliminary conceptual model based on Crichton's Risk Triangle to clarify the key elements affecting the infection risks. We emphasized the changes in mobility caused by natural disasters or social unrest, and paid special attention to the potential effects of mass gatherings on the number of COVID-19 infections. Taking New York City as a case study, a Markov Chain Monte Carlo framework is a promising approach for projecting how changes in exposure and vulnerability levels will affect the COVID-19 infections in different multi-hazard scenarios.

We expect the results can help decision-makers and experts in emergency management to better understand risks in the multi-hazard context, and to make effective pandemic response plans. For example, suppose the simulation results show that the COVID infection rate has increased significantly due to NYC residents gathering in shelters during a hurricane. In that case, the emergency management department should give priority to improving the quality of shelters, such as increasing the stock of masks, disinfectants and other personal protective equipment (PPE) in the shelters. This can help decision-makers to more effectively distribute resources, which is especially important given that local resources are generally limited in multi-hazard situations.

There are several limitations in the approach proposed herein. First, it is difficult to identify specific vulnerability indicators and obtain the corresponding data. Different population groups have varied vulnerability levels towards different hazards, and more importantly, the research on vulnerability during the pandemic is far from perfect. What is more, some data, such as protesters' demographic characteristics, are difficult to observe. Second, our MCMC framework currently considers only hurricane and BLM protests, other disruptive events such as earthquakes, heat waves, or terrorist attacks may affect COVID-19 infections in different ways. Last but not least, this research only addresses the impact of mass gathering on COVID-19 infections, and we do not address how the pandemic affects human behaviors in other crises. This may cause some bias. For example, non-protesters may be worried about being infected with COVID-19, so the more vulnerable elderly are less likely to participate in the BLM protests.

In the near future, we seek to improve the conceptual model and find more empirical evidence to support the development of a vulnerability index in a multi-hazard context. If possible, we would like to obtain more first-hand data by conducting surveys and interviews. Our future work will also discuss characteristics of mass gatherings in other disruptive events, and demonstrate how the analysis method and framework can be applied in different situations. Finally, we desire to conduct an extensive sensitivity analysis to address the effect of each parameter on the model outcomes and a robust test to reduce potential biases on the simulation results.

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