Research Report

A Model of the Spread of the COVID-19 Pandemic During a Hurricane in Virginia

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Preface

The study underlying this report was conducted during the coronavirus disease 2019 pandemic to provide analysis of the implications of a hurricane during a pandemic for the Commonwealth of Virginia. The intent is that this analysis can be used to inform planning well in advance of a hurricane threatening Virginia and also in response to a specific storm with an estimated track through Virginia.

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Summary

As of August 24, 2020, the coronavirus disease 2019 (COVID-19) pandemic had resulted in the deaths of approximately 2,500 Virginians. The 2020 hurricane season began June 1 and is considered to be extremely active. The threat of a hurricane increases the complexity of risk management decisions related to the pandemic—and the effects of the pandemic increase the complexity of planning for a hurricane. In this report, we study the implications that a hurricane during the COVID-19 pandemic would have for the Commonwealth of Virginia. This analysis should help inform advance planning for the hurricane season in general and could be used in response to a specific storm with an estimated track through Virginia. We focus on the combined impacts of COVID-19 and a hurricane on morbidity and mortality; we do not examine other effects, such as effects on infrastructure, social networks, and the economy.

A conceptual framework for assessing risk is foundational for developing a model of the risks associated with the intersection of hurricanes and COVID-19. We adopt the Department of Homeland Security Risk Lexicon definition of risk as “potential for an adverse outcome assessed as a function of threats, vulnerabilities, and consequences associated with an incident, event, or occurrence” (U.S. Department of Homeland Security, Risk Steering Committee, 2010). Using this definition, we separate risk into the categories of threat, vulnerability, and consequence, as seen in Figure S.1.

In this report, we examine two threats: a hurricane and COVID-19. The vulnerability involved is the susceptibility to these threats and can be thought of in terms of storm, health, and socioeconomic vulnerabilities. Storm vulnerability is related to parts of the physical environment that would be adversely affected by a hurricane exposure, such as homes in a storm surge area, homes without floodproofing, and areas where roads are likely to be flooded. Health vulnerability is related to characteristics that make a person more susceptible to health threats, such as age and comorbidities. Socioeconomic vulnerability includes a lack of resources to evacuate in case of inclement weather; limited access to consistent, high-quality health care; and the inability to access social services because of barriers associated with language or other characteristics.

In this report, we focus on how these vulnerabilities affect consequences: hurricane-associated COVID-19 spread, death from COVID-19 or a hurricane, and other health and safety effects.
Using this risk framework, we assessed consequences using data from a variety of sources on the prevalence of COVID-19 across Virginia,\(^1\) the frequency and severity of hurricanes in Virginia, health vulnerability, vulnerability to storm effects, and socioeconomic vulnerability (including poverty, household composition, and access to transportation). We considered three primary responses for an individual who is facing a hurricane. *Sheltering in place* involves staying in a potentially affected area in one’s own home or in the home of a friend or family member. *Communal shelters* in the community provide a second option. *Self-evacuation* involves leaving the area completely to go to a safe place.

We then developed a decision tree to identify how individuals should respond to a hurricane during the COVID-19 pandemic, based on their composite risk (see Figure S.2). The decision tree offers the options of sheltering in place, going to a communal shelter, and self-evacuation.

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\(^1\) Because COVID-19 data generally do not capture asymptomatic carriers and because of a general lack of testing, we use a figure of five times Virginia’s reported COVID-19 rate as a baseline.
Our model has four modules. The first module predicts the number of people displaced by a hurricane, providing an estimate of the extent and geographic distribution of required evacuations caused by environmental exposure. This information is then provided to the three modules representing each of the response options we consider. Each module provides a rough estimate of the outcome of each response option in terms of deaths and COVID-19 infections. In general, the decision to self-evacuate or evacuate to a communal shelter should depend on the relative safety of the self-evacuation options. If there is a low risk for COVID-19 at the destination, self-evacuation is likely the preferred option. Otherwise, a communal shelter may be safer, particularly if appropriate precautions are taken.

We modeled the consequences of each option by considering the following hazards and using the following models:

- For people who **self-evacuate**, the primary hazard is COVID-19, as they could either spread the virus or be exposed to it in their evacuation location. We used the Federal Emergency Management Agency Hazus model to estimate the number of households displaced by a storm. We then used data about the ambient level of COVID-19 cases in starting and destination locations to estimate the likelihood that an individual would spread or catch COVID-19.
- For people who **shelter in place**, the primary hazard is the hurricane. For this population, we used the Hazus estimates of deaths.
- Finally, for the **communal shelter** population, we used the ambient COVID-19 case level data and shelter characteristics (e.g., size of the shelter, anti–COVID-19 precautions) to estimate potential virus spread among those in the shelter.

The outputs from these models differ based on the estimated hurricane track, the characteristics of the potentially affected population, and other factors. In addition, although we can estimate people’s sheltering decisions in response to a hurricane during a pandemic, substantial
uncertainty still exists. We have built sensitivity testing into the models that allows us to more thoroughly explore the variety of plausible outcomes.

Trade-offs will have to be made between these three options. Using the historic track of Hurricane Isabel as an example, Hazus indicates that the full population sheltering in place for a comparable hurricane would result in fewer than 20 deaths. This is largely because Hurricane Isabel made landfall in North Carolina; the direct deaths caused by winds and storm surge would be relatively low. More deaths could occur if vital services were disrupted for a significant period of time after the hurricane; however, the recovery period is beyond the scope of this report.

The trade-offs between using communal shelters or self-evacuating to a safer location very much depend on the size of the available shelters and the ambient rate of COVID-19 in the immediate community versus the likely evacuation destinations. Smaller shelters increase the attractiveness of communal sheltering in terms of avoiding COVID-19. If community COVID-19 case levels are high, individuals in the area are more likely to spread the disease during the evacuation process or in communal shelters. Alternatively, if community COVID-19 case levels are low, the risk of individuals spreading the disease by evacuation or in communal shelters is low. Ultimately, outcomes will depend on both storm characteristics and the spatial distribution of COVID-19 case levels. Lower levels of COVID-19 greatly reduce the overall risk from all outcomes.

The models used and developed for this effort produce information specific to a storm track that can inform the immediate response and the eventual recovery from the hurricane. In addition, the following lessons learned from the construction of the models and analysis of model outcomes under different scenarios can provide insights for decisionmakers:

- Individuals need information from trusted sources to know how to safely react to a hurricane based on their personal risk.
- Self-evacuations could be a major source of COVID-19 spread.
- Because COVID-19 might make more people shelter in place, the hurricane recovery phase might need to be accelerated.
- Communal shelter characteristics, such as capacity and social distancing, will determine the COVID-19 risk of particular shelters.
This project would not have been possible with the input of many people. We would like to thank the Virginia Department of Emergency Management for its sponsorship of this research. In particular, Curtis Brown and Dillon Taylor provided guidance on the focus of the analysis. We also would like to thank our reviewers, Aaron Clark-Ginsberg, Bryan Lewis, and Jodi Liu, for their thoughtful comments on this work.

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Abbreviations

ACS  American Community Survey
CCVI  COVID-19 Community Vulnerability Index
COVID-19  coronavirus disease 2019
FEMA  Federal Emergency Management Agency
Hazus-MH  Hazards U.S. Multi-Hazard
SLOSH  Sea, Lake, and Overland Surges from Hurricanes
1. Introduction

The coronavirus disease 2019 (COVID-19) pandemic has led to dramatic changes in day-to-day activities. People have changed their patterns of life to avoid crowds and stay at home because of the risk posed by COVID-19.

However, hurricanes create a different set of risks that require a different set of responses. People in the path of a hurricane might need to evacuate to either a communal shelter or to a hotel or the home of a friend or relative outside the path of the storm.

Because the responses to COVID-19 and to hurricanes are, to an extent, contradictory, it is important to consider the risk dynamics and how policymakers should prepare for and respond to a potential hurricane during the COVID-19 pandemic. This document presents a risk framework and corresponding models to understand the implications of such scenarios.

Virginia first announced the presence of a COVID-19 case on March 7, 2020 (COVID Tracking Project, 2020). As of August 24, 2020, the Virginia Department of Health had reported 113,630 cases, 2 9,207 total hospitalizations, 3 and 2,471 deaths. The state had experienced 793 individual outbreaks (at least two laboratory-confirmed cases from a single setting; Virginia Department of Health, undated).

In May 2020, the National Oceanic and Atmospheric Administration’s forecasts indicated that the 2020 Atlantic hurricane season (June 1 to November 30) was likely to be particularly active (National Oceanic and Atmospheric Administration, 2020). Because of its position on the mid-Atlantic coast, Virginia is occasionally directly hit by hurricanes that make landfall in the southeast of the commonwealth; more frequently, Virginia is indirectly affected by hurricanes and tropical storms that make landfall in North Carolina or states further south. Hurricanes and tropical storms, such as Hurricane Isabel in 2003, have caused billions of dollars in damage and have been associated with dozens of deaths in Virginia alone.

Hurricanes and COVID-19 may create a combined threat that is greater than the sum of its parts. Hurricanes can change patterns of mobility and expand the spread of COVID-19. For example, communal shelters could become outbreak sites. On the other hand, fear of COVID-19 could cause people who might otherwise evacuate to shelter in place, 4 causing more deaths from a hurricane than otherwise expected. The adverse economic impacts from COVID-19 (e.g.,

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2 The total number of cases includes both confirmed cases (19,357) and probable cases (899); probable cases were symptomatic and had known exposure.

3 This value is the number of hospitalizations that the Virginia Department of Health has investigated; it is likely an underestimate.

4 There are other potential options. For instance, after a norovirus outbreak in communal shelters after a California wildfire, evacuees responded with alternative approaches, such as camping (Karmarkar, 2020). Similar behavioral responses could result in additional decisions. For the purposes of this study, we assume that people will choose between the three options as described.
unemployment) also might force more people to seek communal shelters rather than face the expense of evacuating to a hotel. Furthermore, the damage to the economy done by COVID-19 might also slow the long-term recovery from a hurricane. Modeling the combined effects of a hurricane and COVID-19 can help policymakers understand how these threats may interact.

Policymakers seeking to minimize mortality associated with COVID-19 and a hurricane should consider how different interventions might influence these outcomes. To that end, a model capable of comparing the effects of individual responses to the hurricane will be necessary, because those individual decisions determine how many people are in harm’s way from both the hurricane and COVID-19. In a previous report, we assessed suitable modeling of COVID-19 for policymaking (Price and Propp, 2020). With that report in mind, we subsequently constructed a set of models to inform policies related to hurricane responses. Specifically, we developed models to simulate the risks of sheltering in place, self-evacuating, and using communal shelters, based on data about the prevalence of COVID, potential hurricane paths, and other factors.

In this study, we sought to provide information suitable for answering the following policy questions:

- How might behavior change during a hurricane because of the presence of COVID-19?
- How would these behavioral changes increase the risk of death because of the hurricane and the risk of the spread of COVID-19?
- Are there policy interventions that can be implemented in advance of a hurricane to prepare?
- How should response and recovery activities related to a hurricane change because of COVID-19?

The model we developed to answer these questions consists of four modules. The first module predicts the number of people displaced by a hurricane, providing an estimate of the extent and geographic distribution of required evacuations caused by environmental exposure. This information is then provided to the three modules representing each of the response options we consider: sheltering in place, evacuation to a communal shelter, or self-evacuation to another safe location. Each module provides a rough estimate of the outcome of each response option in terms of deaths and COVID-19 infections.

The model used in this report is useful for answering these questions but should be periodically updated to incorporate the most-recent data available. This analysis is focused on health outcomes and hurricane effects during the disaster, response, and early recovery phases. Most of our analysis used county-level data because this level of data provides enough geographic specificity to produce useful estimates without burdening decisionmakers with excessive detail.

In Chapter 2, we introduce the framework that we used to understand the risk associated with a hurricane during the COVID-19 pandemic. In Chapter 3, we describe the data and models that we developed to explore the risk components. Chapter 4 contains an example of the risk model
that we built using the data from Hurricane Isabel. In Chapter 5, we discuss the policy implications of this work and offer some concluding remarks.
2. Risk Framework

A conceptual framework for assessing risk is a critical first step for developing a model of the risks associated with the intersection of hurricanes and COVID-19. One common approach to assessing risk is to consider the components of that risk. We define risk as “potential for an adverse outcome assessed as a function of threats, vulnerabilities, and consequences associated with an incident, event, or occurrence” (U.S. Department of Homeland Security, Risk Steering Committee, 2010). Using this definition, we separate risk into the categories of threat, vulnerability, and consequence (see Figure 2.1).

For this analysis, we are interested in the intersection of two threats: a hurricane and COVID-19. Vulnerability is the susceptibility to these threats (a combination of exposure to a threat and the potential for harm when exposed); we define these in terms of storm, health, and socioeconomic vulnerabilities. Storm vulnerability is related to the physical characteristics that would be adversely affected by exposure to a hurricane, such as homes in a storm surge area or areas where roads are likely to be flooded. Health vulnerability is related to characteristics that make a person more susceptible to health threats, such as age and comorbidities. Socioeconomic vulnerability includes a lack of resources to evacuate in case of inclement weather; limited access to consistent, high-quality health care; and inability to access social services because of barriers associated with language or other characteristics. In this report, we focus on how these vulnerabilities affect the consequences: hurricane-associated COVID-19 spread, death from COVID-19 or the hurricane, and other health and safety effects.

The following sections explore how we assess each of these components of risk.
Threat

The threat associated with either a hurricane or COVID-19 is understood to some degree. We have historical data on hurricanes, and meteorology has some predictive capability for hurricane evolution. Similarly, epidemiologists and other researchers have some understanding of how COVID-19 spreads and its effects on a population. However, when these two threats are combined, new considerations emerge. For example, a hurricane might alter the behavior patterns that drive the spread of COVID-19, and fear of COVID-19 may change the responses to a hurricane. Therefore, it is important to consider the intersection of these threats.

Hurricanes

Hurricanes bring rains that can lead to flash floods, storm surges that can lead to severe coastal damage, and damaging winds that can knock down trees and power lines and destroy houses. Since 1852, 117 hurricanes, tropical cyclones, and tropical depressions have passed through Virginia (National Oceanic and Atmospheric Administration, undated). Researchers have found that the average time between hurricane landfalls in Virginia is 13 to 15 years; Category 3 and above hurricanes can be expected to make landfall in Virginia about every 58 to 66 years.

It is important to consider historical data in addition to model predictions. Since the advent of satellite data in the late 1970s, the ability to determine hurricane wind speed has improved. From 1980 through 2020, 37 hurricanes, tropical cyclones, or tropical depressions passed through Virginia (National Oceanic and Atmospheric Administration, undated). Of these 37 events, the following three were Category 1 hurricanes or above when their track entered Virginia:

1. Hurricane Fran (1996), which made landfall in North Carolina. When the hurricane’s eye entered the middle of Virginia, Hurricane Fran was still a Category 1 hurricane. However, it was downgraded to a tropical storm as it passed through most of the state (National Oceanic and Atmospheric Administration, undated).
2. Hurricane Floyd (1999), which swiped the coast as a Category 1 hurricane (National Oceanic and Atmospheric Administration, undated).
3. Hurricane Isabel (2003), which made landfall in North Carolina as a Category 2 hurricane, hit the middle of Virginia as a Category 2 hurricane, and downgraded to a Category 1 hurricane as it passed through most of the state in a northwesterly direction (National Oceanic and Atmospheric Administration, undated). Hurricane Isabel was one of the most damaging hurricanes on record, causing $1.9 billion in total damages, ten direct deaths, and 22 indirect deaths in Virginia (Beden and Cobb, 2014). We do not have the specific causes of death for these indirect deaths; indirect deaths during hurricanes are typically deaths from heart attacks, house fires, electrocution during repairs, or car accidents (Stobbe, 2018).

The 2020 hurricane season has been one of the most active Atlantic hurricane seasons on record, with 20 named tropical cyclones at the time of writing. Although global tropical cyclone intensity is predicted to increase in the coming years (Geophysical Fluid Dynamics Laboratory,
2020), Virginia rarely receives a direct hit from major hurricanes. Tropical cyclones typically enter Virginia from the south and move north across the state; direction can greatly affect storm surge, whereas winds and precipitation are less affected by the storm track. Hurricane Isabel can be thought of as close to an upper bound on what is likely to be seen in the near future; although a direct hit from a major hurricane (Category 3 or above) is plausible, it is highly unlikely.

COVID-19

COVID-19 is more infectious and virulent than seasonal influenza is. Because it spreads easily, particularly in confined spaces, COVID-19 poses a threat to the health and well-being of Virginians during a hurricane, when they might need to evacuate from their residence to a communal shelter, to the home of a friend or relative, or to a hotel or some other facility. The evacuating population might spread COVID-19 to their evacuation locations, or they could catch COVID-19 at their destinations and return with the virus after the storm.

COVID-19 was first detected in Virginia in early March 2020. As seen in Figure 2.2, the initial wave peaked at 14 cases per 100,000 residents per day at the end of May; this was likely an underestimate of the actual incidence because the testing was not sufficiently widespread at that point in time (COVID Tracking Project, undated). The initial wave subsided briefly, before a second wave plateaued in early August, again at roughly 12 cases per 100,000 residents per day. There were more than 2,900 deaths attributed to COVID-19 in Virginia as of September 16, 2020 (Virginia Department of Health, undated).

Figure 2.2. Seven-Day Rolling Average for Confirmed COVID-19 Cases per 100,000 Residents of Virginia

SOURCE: Virginia Department of Health, undated.
Figure 2.3 is a county-level map of new COVID-19 cases across Virginia from September 10 to September 16, 2020. Southern counties—particularly those in the southeast—have had disproportionately higher case levels. Therefore, the areas most likely to be directly affected by a hurricane also have had the highest levels of COVID-19 cases, indicating that these threats are, in practice, likely to compound one another.

Figure 2.3. Seven-Day Average of Cases per 100,000 Residents by County, September 10–16, 2020

Vulnerability

As discussed earlier, storm, health, and socioeconomic factors are relevant in the consequences of both hurricanes and COVID-19.

Storm

We consider storm vulnerability to be the vulnerability of infrastructure, including homes and property, to the storm (as opposed to the vulnerability of the people to the storm, which is discussed in the health and socioeconomic sections).

During a hurricane, infrastructure can be damaged by wind or water. The geographic locations that are typically hardest hit are areas where storm surge or flooding is common.¹

¹ In the Northern Hemisphere, the storm surge typically arises on the right side of the hurricane (relative to its forward travel track) because of a combination of the hurricane’s central pressure, its rotation, and the local
Figure 2.4 shows the maximum amount of inundation caused by a Category 2 hurricane storm surge making landfall in Virginia, and Figure 2.5 shows the maximum plausible flooding. Both these maps are important in determining which buildings will be damaged. In addition, flooded roads render travel very difficult, and therefore floodplain maps are important for evacuation decisionmaking. (Note that although these maps are similar, there are differences, partially because storm surge comes from ocean water flooding, but flooding is caused by rainwater falling on land and draining to the sea.)

Infrastructure data can be obtained from public records (e.g., U.S. Department of Homeland Security Infrastructure Foundation-Level Data, census data) and then combined in Geographical Information System mapping with hazard intensity information to determine where and what infrastructure might be affected. As we discuss in Chapter 3, infrastructure data are included in the Federal Emergency Management Agency (FEMA) catastrophe model known as Hazards U.S. Multi-Hazard (Hazus-MH, or Hazus). Hazus uses this data, along with hazard data (in this case, a storm track), as inputs and calculates predicted effects (as discussed in the Data and Methods section).

Figure 2.4. Category 2 Storm Surge, Maximum Envelope of Open Water

SOURCE: National Hurricane Center and Central Pacific Hurricane Center, undated.
NOTE: Hurricane Isabel’s effects would have been similar to the effects depicted in this map if the hurricane had hit the Chesapeake Bay directly.

topography and bathymetry. Areas susceptible to storm surge and flood are also often affected by wind. Storm surge areas are often (in absence of mitigation or hardening infrastructure) hardest hit.
Health

Comorbidities and age are significant risk factors for adverse outcomes from a COVID-19 infection. The Surgo Foundation has compiled a series of health risk factors to produce a COVID-19 health vulnerability measure by state, county, and census-tract level for the United States that includes “underlying conditions (cardiovascular, respiratory, immunocompromised, obesity, diabetes), high flu and pneumonia mortality, or high population density” (Surgo Foundation, undated). Figure 2.6 shows the Surgo Foundation’s county-level health vulnerability
index for Virginia. Note that the southeastern counties (which a hurricane would first affect) have a disproportionately high degree of vulnerability to COVID-19.²

Figure 2.6. Health Vulnerability by County Level

SOURCE: Surgo Foundation, undated.

Socioeconomic

In addition to health vulnerability, the Surgo Foundation drew upon additional socioeconomic factors to produce a measure of community vulnerability to COVID-19. The Surgo Foundation produced the COVID-19 Community Vulnerability Index (CCVI), based in part on the Centers for Disease Control and Prevention’s Social Vulnerability Index. The CCVI is a composite score of factors expected to make accessing COVID-19 resources more difficult. It incorporates the following six factors relevant to the current pandemic:

1. **socioeconomic status**: individuals with low income, low educational attainment, and no occupation
2. **household composition and disability**: single-parent households or households with elderly (over 65), young (under 17), or disabled members
3. **minority status and language**: racially marginalized groups or those with limited English proficiency
4. **housing type and transportation**: dwellings with multiple units; mobile, group, or crowded living arrangements; and households without access to transport

² Note that county-level data can disguise pockets of vulnerability. This is particularly a problem in heterogeneous locations—for instance, homeless people in an affluent area or minority neighborhoods within a majority-White city.
5. **epidemiological factors**: high-risk COVID-19 populations with underlying conditions (cardiovascular conditions, respiratory conditions, immunocompromising conditions, obesity, diabetes), high flu and pneumonia mortality, or high population density

6. **health care system factors**: poor health system capacity, strength, and preparedness.

Figure 2.7 is a county-level map of the CCVI. As with the other vulnerability measures, southern counties are the most vulnerable.

**Figure 2.7. COVID-19 Community Vulnerability**

Before the emergence of COVID-19, the Virginia Department of Emergency Management had identified different evacuation zones to be used in case of a hurricane (see the “Know Your Zone” maps in Figure 2.8). Residents should know their zones ahead of time and evacuate by zone in the event of a hurricane.
Figure 2.8. “Know Your Zone” Maps

We were unable to determine the methodology used to define the evacuation zones, but it is likely that their differing levels of vulnerability were determined by known evacuation routes and traffic models, likely flooding infrastructure damages, and knowledge of which communities have special needs for evacuation.

SOURCE: Adapted from Virginia Department of Emergency Management, undated b.
However, this system does not inherently account for COVID-19. The presence of COVID-19 in a community increases the risk from interactions outside the home, particularly for older individuals and those with comorbidities.

Consequences

The final component of risk is the consequence of the interaction between threat and vulnerabilities. There are three primary consequences from a hurricane in the midst of the COVID-19 pandemic:

1. increased COVID-19 spread and resulting deaths for and as a result of the population evacuating by car
2. COVID-19 spread within communal shelters
3. additional deaths from sheltering in place that occur because people fear exposure to the virus if they leave their homes.

The first two of the above consequences stem from COVID-19, and the third can be attributed to the hurricane. To estimate the range of values for each of these consequences, we developed a series of relevant models and data tools, which we discuss in the next chapter.
3. Data and Methods

We use Hurricane Isabel as an example of the potential effect that a hurricane could have on Virginia for modeling purposes. When Hurricane Isabel made landfall in North Carolina, it had diminished in strength to a Category 2 (National Weather Service, undated). In preparation for Hurricane Isabel, approximately 160,000 residents in southeastern Virginia were told to evacuate (“States in Isabel’s Path Prepare,” 2003). However, compliance rates were relatively low (Post, Buckley, Schuh, and Jernigan, 2005):

- Hampton: 31 percent compliance
- Norfolk: 22 percent compliance
- Northern Neck: 41 percent compliance
- Surry County: 9 percent compliance
- Eastern Shore: 30 percent compliance.

For those who evacuated, the destinations varied: 64 percent evacuated to the house of a friend or a relative, 24 percent evacuated to a hotel or motel, and 12 percent evacuated elsewhere (i.e., to a communal shelter). At least 6,000 and potentially over 16,000 people ultimately evacuated to one of at least 67 communal shelters, for an average of up to 240 people per shelter (Post, Buckley, Schuh, and Jernigan, 2005; Franke and Simpson, 2004; “States in Isabel’s Path Prepare,” 2003).

The risk of COVID-19 increases with interaction, which should increase the likelihood that individuals would choose to shelter in place. However, the magnitude of this effect will depend on COVID-19 prevalence, perceptions about dangers of the storm, and individuals’ perceptions of risk from COVID-19, including such vulnerabilities as age and comorbidities. Although this analysis contains a great deal of uncertainty, consider the confluence of hurricane vulnerabilities (the combination of the storm and socioeconomic vulnerabilities as a function of location within the hurricane path, as discussed in the previous chapter) and COVID-19 vulnerabilities (health and socioeconomic vulnerabilities). Assuming low, medium, and high levels of vulnerability for each, we can assign a county to one of nine categories based on its level of vulnerability to the hurricane (i.e., location within a storm surge or high wind area) and vulnerability to COVID-19 (based on the CCVI) (see Figure 3.1). This type of analysis can support preparations for evacuations and sheltering in the event of a hurricane.
### Figure 3.1. Composite Risk

<table>
<thead>
<tr>
<th>COVID-19 Risk</th>
<th>Low: Young and no comorbidities</th>
<th>Medium: Middle-aged or young with comorbidity</th>
<th>High: Older or middle-aged with comorbidity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hurricane Risk</td>
<td>Evacuation</td>
<td>Evacuation required, may need assistance</td>
<td>Evacuation required, may need assistance</td>
</tr>
<tr>
<td>High:</td>
<td>In storm surge area</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medium:</td>
<td>In storm surge area</td>
<td>Consider evacuation if safe</td>
<td>Consider sheltering in place if safe</td>
</tr>
<tr>
<td>High winds or near storm surge area</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low:</td>
<td></td>
<td>Sheltering in place</td>
<td></td>
</tr>
<tr>
<td>Outside storm and high winds area</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**NOTE:** *Evacuation* could entail either self-evacuation or evacuation to a communal shelter. Green = a generally low risk of adverse consequences; yellow = an elevated risk for adverse consequences; red = a significant risk of adverse consequences.

### Decision Tree

The set of behavioral responses to COVID-19 is a primary factor driving the spread of the disease. Similarly, behavioral responses to a hurricane will dictate the number of casualties. People respond to a hurricane in one of three ways: sheltering in place, self-evacuating by car to a safe location outside the affected area, or going to a local communal shelter. Communal shelters could be a high school gymnasium, a public auditorium, or some other public location. People could walk, take public transportation, or travel via car to a shelter.

Figure 3.2 illustrates the decisions that would lead someone to choose one of these responses over the others. Although this decision tree would apply to any hurricane, the specific factors considered at each decision point are influenced by the current state of the COVID-19 pandemic.
The outcome of the above decision tree is determined by an individual or household’s responses to the following questions:

1. **Do you know whether an evacuation order has been given for where you live?**
   Ideally, emergency communications efforts succeed in alerting most, if not all, of the population in an area under an evacuation order.

2. **Is it necessary to follow the order?** Individuals will decide whether or not it is necessary to follow the order based on their trust in government, among other factors. If individuals believe that the government is excessively risk adverse or has overused evacuation orders in the past, they might be less inclined to follow the orders.

3. **Does staying pose a risk to you/your family/your pets/your business?** Individuals will make personal risk assessments based on their perceived vulnerability in determining whether it is safe to shelter in place. This decision will include such factors as age, medical conditions, number and type of dependents, housing situation, and storm conditions.

4. **Can you self-evacuate?** If individuals have determined that it is necessary to follow an evacuation order or that it is likely to be unsafe to shelter at home, they must assess whether they can self-evacuate. They must consider whether they have access to a vehicle (a car or public transport), have money for travel expenses (e.g., food, gas, bus tickets, a hotel room), and can realistically reach a safe destination.
5. **Is it safe to reach this place?** If individuals have determined that it is feasible to self-evacuate, whether they are driving or using public transportation, they must then determine if it is safe to do so. In normal times, this would be based on the distance and travel conditions. However, during the COVID-19 pandemic, the individual must also assess whether there is a substantially higher COVID-19 risk in the new location. This assessment will be based on perceptions about disease prevalence in the alternate location and perceptions of the risk of contracting COVID-19. Individuals who determine the alternate location to be safe should self-evacuate by automobile.

6. **Are you safer in a communal shelter?** Individuals who cannot safely evacuate by automobile to a safer location will then assess whether they will be safer in a mass shelter than at home. This will depend on local shelter conditions, gender, living status, medical needs, and perceived COVID-19 risk. Individuals who determine that the shelters pose too great a risk will shelter in place.

### Data

Our model required data from multiple sources (see Table 3.1).

<table>
<thead>
<tr>
<th>Data Source</th>
<th>Metrics Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACS</td>
<td>• Population</td>
</tr>
<tr>
<td></td>
<td>• Number of households</td>
</tr>
<tr>
<td></td>
<td>• Number of households with a car</td>
</tr>
<tr>
<td>Virginia Department of Health</td>
<td>COVID-19 prevalence</td>
</tr>
<tr>
<td>Surgo Foundation</td>
<td>CCVI</td>
</tr>
<tr>
<td>Homeland Infrastructure Foundation,</td>
<td>Shelter capacity</td>
</tr>
<tr>
<td>National Shelter System Facilities</td>
<td></td>
</tr>
<tr>
<td>Hazus (equations and input data)</td>
<td>• Environmental vulnerability level (i.e., storm</td>
</tr>
<tr>
<td></td>
<td>surge area, high wind area)</td>
</tr>
<tr>
<td></td>
<td>• Number of evacuees</td>
</tr>
<tr>
<td>National Oceanic and Atmospheric Administration</td>
<td>Data on historic hurricane tracts (wind speeds,</td>
</tr>
<tr>
<td></td>
<td>locations, etc.)</td>
</tr>
</tbody>
</table>

We obtained county-level demographic information, such as population size, number of households, and number of households with access to a vehicle, from the U.S. Census Bureau American Community Survey (ACS; Ruggles et al., 2020). To inform our understanding of the COVID-19 risk across Virginia, we used COVID-19 county-level case numbers from the Virginia Department of Health. For information about communal shelters, we obtained a database of public shelters with capacity and location information from the Homeland Infrastructure Foundation (U.S. Department of Homeland Security, undated). Finally, we used Hazus (FEMA, 2020), using historical hurricane tracks provided by the National Oceanic and Atmospheric Administration and fictional hurricane tracks to estimate numbers of potential evacuees.
We conducted our analysis at the county level because the COVID-19 prevalence data from the Virginia Department of Health are currently available only at the county level. We acknowledge that county-level data can disguise pockets of vulnerability for specific groups, such as homeless people or people living in minority or low-income neighborhoods within otherwise nonminority or high-income areas. This limitation could be addressed in future iterations of the analysis.

Models

We sought to construct a model that can help policymakers understand the potential for immediate health-related impacts of a hurricane making landfall in Virginia during the COVID-19 pandemic, considering both death and COVID-19 transmission. We did not consider the broader impacts—such as economic damages, social disruptions, injury, or psychological health effects—of either hazard.

Our model consists of four modules. The first module predicts displacement, providing an estimate of the extent and geographic distribution of required evacuations caused by environmental exposure. This information is then provided to the three modules representing each of the response options (sheltering in place, self-evacuating to a safe location, or evacuating to a communal shelter). Each module provides a rough estimate of the outcome of each response option in terms of deaths and COVID-19 infections.

In reality, each individual or household would select one of the three response options following the decision processes depicted in Figure 3.2. However, the model described here does not attempt to predict the choices made by households and individuals. Rather, we consider historic and hypothetical scenarios and explore potential outcomes in the context of COVID-19. Thus, the models here involve general assumptions and order-of-magnitude estimates and are evaluated based on their sensitivity to a range of parameter values.

Displacement Module

To assess the response to storms, we used historic data to determine how many people sheltered in place, how many evacuated by car, and how many went to a mass shelter during past hurricanes. We used that information to create a model to predict responses for fictional hurricanes.

The Hazus model can be used to determine hurricane effects (FEMA, 2020). The Hazus software, which is available for download from FEMA’s website, takes hurricane scenarios as input and produces a threat assessment for each geographic region. A historic hurricane scenario can be loaded from a data file, or the user can define the parameters of the hurricane, choosing the maximum wind speed, translation speed, radius to maximum winds, and central pressure for a set of specified latitudes and longitudes. Using these input parameters, Hazus outputs the predicted wind speeds at the county or census tract level. Figure 3.3 shows peak wind gust from
Hurricane Isabel in 2003 as calculated by Hazus. These wind speed maps inform other Hazus outputs and are used in later steps of our model to predict relevant outcomes, but they may also be useful to decisionmakers designing evacuation protocols.

The Hazus model can be interfaced with other disaster models to provide additional details, such as flooding from rainfall. For example, by combining Hazus with a known storm surge model (for example, the National Hurricane Center’s Sea, Lake, and Overland Surges from Hurricanes [SLOSH] model, which determines the maximum envelope of open water; see Figure 2.4), we can determine the geographic distribution of related hazards. Although the Hazus hurricane model does not directly predict the number of deaths, Hazus has distinct models for wind speed, flood level, and infrastructure data that make it possible to probabilistically determine deaths.

**Figure 3.3. Hazus Model Output for Peak Gust Speed for Hurricane Isabel**

![Image of Hazus Model Output for Peak Gust Speed for Hurricane Isabel]


Given a set of hurricane specifications, resulting wind speed predictions, and demographic data (i.e., population size, age distribution, income, ethnicity, home ownership), Hazus can predict the number of displaced households and short-term shelter needs by region (see Figure 3.4 for a sample output of households displaced by Hurricane Isabel).
Figure 3.4. Households Displaced by Hurricane Isabel

Note that the output based on historical wind scenarios for Hurricane Isabel drastically underestimates figures for evacuation and sheltering: Hurricane Isabel prompted the evacuation of 24 counties (hundreds of thousands of individuals) and the sheltering of between 6,000 and 16,000 individuals in Virginia, but this is not reflected in the Hazus output shown in Figure 3.4. Hazus underestimates these numbers because its calculations of the number of displaced households and short-term shelter needs are informed by historical data about actual needs after a storm has passed. In reality, evacuations are ordered before the precise track of a hurricane is known. Therefore, Hazus output does not directly correspond to the number of prelandfall evacuees and short-term shelter needs, although it can help inform evacuation decisions by providing information about the likely extent and geographic distribution of damage and displacement.

To determine actual evacuation needs, it would be necessary to use Hazus to model multiple tracks within the cone of uncertainty. This allows the identification of a potential worst-case
scenario and provides a broader understanding of prehurricane evacuation needs. Using Hazus, one can run a number of hurricanes within the cone of uncertainty to find the worst-case hurricane for Virginia and identify all regions that are likely to be affected; in practice, this would typically involve adjusting the hurricane track to make landfall directly on Virginia (such as the hypothetical hurricane track in Figure 3.5; Hypothetical Hurricanes, undated).

Figure 3.5. Hazus Output for Peak Windspeed for a Hypothetical Direct-Hit Scenario

![Figure 3.5. Hazus Output for Peak Windspeed for a Hypothetical Direct-Hit Scenario](source)

NOTE: This is a hypothetical hurricane track.

Further note that Hazus does not directly include information related to evacuation or percent compliance, although these could be supplied by other models, such as those provided in the appendix. Running these models has the potential to further improve model fidelity.

Deaths from Increased Sheltering in Place

We used the decision tree to estimate how people might change their response to a hurricane because of COVID-19. We then based estimates of the increase in hurricane fatalities on the Hazus casualty estimates (with values scaled by the change in population in an area). We recognize that we could underestimate fatality rates because COVID-19 could cause large rises from the historic rates of sheltering in place, and these additional people sheltering in place might include people who are in more-dangerous geographic areas or have additional

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1 Note that we need to run only Hazus’s wind model; there is no need to run the Hazus storm surge model for evacuation predictions. This is because the storm surge occurs slightly to the right of the hurricane track, which would already be experiencing very high wind speeds and therefore have a high evacuation need. If a decisionmaker were interested in Hazus’s other model outputs, such as damages to infrastructure, the storm surge model would need to be run.
comorbidities that put them at higher risk. Given the large amount of uncertainty in the behavioral response, we use sensitivity testing to produce a variety of possible outcomes.

We explored ways to refine these estimates to the extent possible. Because high-intensity hurricanes are so uncommon in Virginia, there is very little historic data on deaths from sheltering in place. We combined existing data for sheltering-in-place death rates from a historic high-intensity hurricane (such as from Hurricane Isabel) with a model to estimate the death rates for those who choose to shelter in place. For example, we compared Hurricane Isabel’s known direct deaths and evacuation compliance rates (which also indicated the rates of sheltering in place) with the Hazus model to determine rates for other hurricanes. In the case of an actual hurricane hitting Virginia, we could also provide an uncertainty range on deaths from sheltering in place by considering a variety of evacuation compliance rates.

Spread in Mass Shelters

Evacuees might have a higher risk of catching COVID-19 in a shelter, depending on shelter capacity and conditions. Hurricane shelters are inherently enclosed, indoor spaces, as they must protect their inhabitants from high winds, flying debris, heavy rain, surge inundation, rainfall flooding, hazardous materials, and damaged infrastructure. For efficiency and to meet demand, shelters are commonly set up in schools, religious centers, arenas, recreation centers, and other public gathering spaces that meet the American Red Cross design standards (American Red Cross, undated). Shelters often suffer from overcrowding, supply shortages, and difficulties caring for elderly individuals or those with medical conditions (Post, Buckley, Schuh, and Jernigan, 2005). Based on the pattern of COVID-19 spread indoors and typical mass shelter conditions, hurricane shelters may pose a high risk of COVID-19 transmission.

We modeled the spread of COVID-19 within mass shelters using demographic data, COVID-19 case rates, and the Virginia public shelter database. Conceptually, this model is very similar to the approach used by Fox, Lachmann, and Meyers (2020), although their context was a school environment. We assumed that an individual’s COVID-19 infection status is drawn from a binomial distribution, in which each individual’s probability of carrying COVID-19 is equivalent to the prevalence of COVID-19 in that county. To estimate COVID-19 prevalence, we used the reported case rate and inflated it by five times to account for asymptomatic cases and general undercounting of the infection rate (Oran and Topol, 2020; Havers et al., 2020). The reported case rate was calculated by dividing the number of cases per county by the county population, as obtained from the Virginia Department of Health and the ACS, respectively. Assuming independent sorting, larger shelters are more likely than smaller shelters to host at least one infected individual. The expected number of infected individuals entering the shelter is the product of the shelter size and the probability that a given individual is infected with COVID-19, as shown in Equation 1:

\[ E(I_0) = N_s p_c. \]  

(Eq. 1)
$I_0$ is the number of infected individuals at time period 0, or at the time of entrance into the shelter; $N_S$ is the number of people sheltering in shelter $S$; and $p_C$ is the COVID-19 prevalence in county $C$.

As a baseline, we assume that minimal COVID-19 precautions are enacted within the communal shelters—in other words, proper social distancing is impossible. The literature on the secondary attack rate for COVID-19, or the likelihood of infection from contact with an infected individual, suggests rates from 0.7 percent to 16.3 percent, with household contacts on the upper end of the spectrum (Cheng et al., 2020; Kwok et al., 2020; Wei et al., 2020; Bi et al., 2020). We follow Bhatia and Klausner (2020) in assuming a rate of 10 percent as a baseline probability of transmission ($p_T$), but we also tested 40 percent as an upper limit because of the unusually long exposure time expected in a communal hurricane shelter.\(^2\) Ideally, the model should have included a temporal aspect to account for exposure duration in determining the likelihood and extent of transmission. However, the literature lacks strong consensus on how to parameterize this effect. We assumed that, on average, sheltering duration will be less than the incubation period of COVID-19 (approximately 5 days), and we tested a wide range of values for $p_T$ to account for the uncertainty.

We tested two different models for infection. In the simple model (Equation 2), we assumed that $p_T$ gives the proportion of susceptible individuals who are subsequently infected in any shelter with at least one initially infected individual (where $E(I_0) \geq 1$). Letting $I_0$ represent the infected individuals at time of entrance, $I_1$ represent the number of secondary infections, and $p_T$ represent the transmission probability ($p_T = 0.1$ or $p_T = 0.4$, as above), then

$$I_1 = (N_S - E(I_0)) \times p_T. \quad (\text{Eq. 2})$$

A slightly more nuanced model accounts for the number of expected interactions between individuals in the shelter. Assuming that the shelter is well-mixed, a given interaction between an infected individual and a susceptible individual has probability of $p_T$ of transferring infection. This allows calculation of the escape probability—the probability that a susceptible individual avoids infection in each expected interaction and emerges without COVID-19. The escape probability for a susceptible individual is calculated in Equation 3:

$$P(e) = (1 - p_T)^{E(I_0)}. \quad (\text{Eq. 3})$$

To calculate the number of secondary infections, we use Equation 4:

\(^2\) If the length of stay in a shelter is shorter than three to five days or appropriate precautions are taken (such as mandatory mask usage), the 10- to 40-percent range may still overestimate the likelihood of infection.
\[ I_1 = (N_S - I_0) \times (1 - P(e)) = (N_S - I_0) \times (1 - (1 - p_T)^{E(t_0)}). \]  
(Eq. 4)

Again, this model would be improved by a temporal aspect, as the number of interactions between individuals will be related to the duration of stay in the communal shelter.

In the context of the COVID-19 pandemic, it is reasonable to assume that most individuals would opt to shelter in place or self-evacuate by car rather than take refuge in a communal shelter. The ACS provides data on the number of households with vehicles available, which we compared with the Hazus estimate of the number of displaced households to estimate the number of individuals who might reasonably seek refuge in a mass shelter. As a baseline, we assumed that the proportion of individuals who need to evacuate and have access to a vehicle is equivalent to the overall proportion of individuals with access to a vehicle, by county. The remaining proportion we assigned to a communal shelter, representing what might happen in a severe hurricane when sheltering in place is not possible. This does not account for the possibility that the need to evacuate and access to a vehicle might be inversely related, but it provides a reasonable benchmark.

**COVID-19 Spread and Deaths Caused by Evacuations**

Because of the high COVID-19 risk inherent in evacuating to a communal shelter, we expect that a large number of individuals in the path of the storm and in areas with high storm vulnerability would opt to evacuate by car (if possible) if they determine that sheltering in place poses too great a risk. Therefore, in the case of a severe hurricane, the COVID-19 pandemic might lead an even greater number of individuals to evacuate by car than under nonpandemic conditions. Individuals self-evacuating by car face two major threats: COVID-19 infection and traffic accidents.

**COVID-19 Spread and Deaths Caused by Evacuations**

There are many factors relevant to the spread of COVID-19 in the context of evacuation. Evacuees might bring COVID-19 to an area (to an extent related to the prevalence in the origin location). In addition, evacuees are exposed to COVID-19 at a rate determined by COVID-19 prevalence in the destination location; prevalence might be lower, higher, or similar to that of their origin location.

We assumed that the likelihood that individuals who evacuate by car contract COVID-19 is a factor of their increased mobility and the ambient level of COVID-19 in the destination area. We assume that the relationship between mobility and the spread of COVID-19 found in Glaeser, Gorback, and Redding (2020)—in which a 10-percent decrease in mobility leads to a 17- to 27-percent decrease in COVID-19 spread—also applies in reverse. This is a potential limitation of our approach; although Glaeser, Gorback, and Redding suggest that movement might cause COVID-19 spread, movement can also be correlated with other behaviors that increase the risk of COVID-19 transmission, such as failing to wear a mask or observe social distancing. People
evacuating from a hurricane might or might not increase behaviors that spread COVID-19, so increased mobility might not have the same effects on COVID-19 transmission. However, it can still provide a useful reference for policymakers seeking to understand the variety of possible outcomes stemming from evacuation.

We assumed that individuals evacuate to regions of Virginia that are predicted to be unaffected by the hurricane (based on the Hazus output). Individuals could evacuate to neighboring states or even farther away. These details should not affect the mechanism by which evacuation leads to an increase in the spread of COVID-19. It should nevertheless be noted that evacuees might disperse more widely than we assumed, so the resulting increase in mobility in the destination regions may be less drastic than estimated.

We evaluated a theoretical worst-case scenario in which all individuals in a surge or high-wind region are ordered to evacuate. For a given compliance rate, we divided the number of evacuees by the population of the remaining regions in Virginia to produce a crude estimate of the increase in mobility in those regions. This assumes that mobility is directly tied to population and population density; although the relationship is more nuanced in reality, this provides a useful upper bound for our estimates. We then applied the adapted figures from Glaeser et al. (2020), (a 17- to 27-percent increase in the COVID-19 rate of spread for every 10-percent increase in mobility).

Historically, compliance with evacuation orders has been low, depending on the perceived exposure of the region and severity of the storm. The expected effect of COVID-19 on compliance is uncertain; individuals could be discouraged from evacuating because of the health risks involved, but they might be more likely to evacuate to avoid entering a mass shelter later on if the storm proves to be stronger than anticipated. To account for these possibilities, we consider the full range of possible compliance rates (0 to 100 percent).

Traffic Deaths Because of Evacuations

Detailed analysis of evacuation routes is out of scope for the current study. However, because traffic deaths caused by evacuations are often several orders of magnitude higher than deaths from sheltering in place, we include these data in the model. Estimates of traffic deaths are highly uncertain; they are very much a function of the decisionmakers’ choices concerning evacuations. Emergency managers might have access to such models as HURREVAC, which, by predicting traffic patterns, can help decisionmakers optimize evacuation orders for safety and efficiency (HURREVAC, undated). To give a rough estimate of expected traffic deaths without access to models of this nature, we considered the reported number of indirect deaths that were caused by traffic accidents for a historical hurricane and assumed that the number of deaths scales with evacuation compliance rates. This allowed us to provide a range of likely traffic deaths at each level of evacuation compliance.
Limitations

As with any model, the estimates are only as accurate as the available data. For COVID-19 case rates, the quality of the data is dependent on testing. If testing rates are adequate, estimates for the likely rate of spread will be more accurate. If alternative testing strategies become available (such as a low-cost test that is widely available in large volumes), estimates could further improve. Alternatively, if the testing rate declines, the accuracy of those estimates could be off by a substantial margin and the model results might underestimate the associated risk of COVID-19.

Similarly, hurricane tracks begin with wide uncertainty bands that narrow as the storm nears landfall. Therefore, estimates for the size and geographic distribution of the population affected by a hurricane will improve as the hurricane approaches Virginia. Although the estimates of the likely path of a hurricane should improve in accuracy over the duration of the storm, the ability to respond to that information diminishes over time; evacuation protocols and shelter preparations that might be feasible with a week’s notice might be impossible with only one to two days’ notice. There is a trade-off between precision of information and the ability to respond to that information.

A second key limitation comes from our ability to understand the distribution of behavioral responses (Lindell and Perry, 2012). Recent literature has highlighted that risk perceptions substantially drive behavior and activities in ways that influence the overall spread of COVID-19 (Glaeser et al, 2020). If people view COVID-19 as a minor concern relative to the hurricane, their response to the hurricane is more likely to reflect general historical trends. Alternatively, if they view COVID-19 as a serious concern, their response to the hurricane could be significantly different. Similarly, the behavioral response to a hurricane will depend on the perception of the likely severity of the storm; perceptions are partly socially determined, and vulnerable and marginalized populations might be particularly at risk of false perceptions (Clark-Ginsburg and Petrun Sayers, 2020). We can estimate actual risks, but if perceptions of those risks are different from what is expected, the model will be biased accordingly.

Finally, the policy and socioeconomic landscape might change in the future. For example, if unemployment benefits increase, more people might feel comfortable with the costs self-evacuation. If neighboring states impose quarantine requirements for Virginians, individuals might change their evacuation behavior.

We conducted sensitivity testing to constrain the effects of these limitations. Further, we have taken steps to appropriately convey the limitations and their effects in the results.
4. Results and Sensitivity

In this chapter, we provide the results of our analysis as conducted with the modeling described in Chapter 3. Our model is intended to be used with the predicted track of a hurricane and information on the current number of people infected with COVID-19 in the area likely to be affected. In this report, we present modeling results for both a historical and for a hypothetical hurricane. We used data from Hurricane Isabel to inform our estimates of deaths from sheltering in place and traffic accidents, as these outcomes are most likely to resemble those of historic events. Hazus output from a fictional, worst-case scenario was used to inform our estimates of how many people may ultimately evacuate and how COVID-19 might spread as a result (both within communal shelters and in regions receiving evacuees from highly exposed areas).

Recall that Hazus, which we use to estimate the number and geographic distribution of hurricane evacuees, is limited to predicting the effects of a specific hurricane scenario. It does not account for the uncertainty that policymakers face when establishing evacuation guidelines days before the storm’s landfall. Therefore, the results obtained from historical hurricane tracks, such as that of Hurricane Isabel, do not provide a reasonable basis for estimates of the number of evacuees to be expected in the event of a predicted direct- or near–direct hit scenario.

Ultimately, we find that the projected number of deaths from increased sheltering in place is orders of magnitude lower than the number that would be expected to be caused by self-evacuation (through both accidents and COVID-19 spread) and COVID-19 spread in communal shelters. Our results incorporate a high level of uncertainty, but we find that the risk of COVID-19 is likely to outweigh the risk of exposure to hurricane conditions for most hurricane scenarios that Virginia is likely to experience.

Deaths from Increased Sheltering in Place

When residents shelter in place in response to a Category 1 or 2 hurricane, some deaths are expected. Hurricane Isabel, one of the worst hurricanes to hit Virginia, caused ten direct deaths and 22 indirect deaths in the state (Virginia Department of Emergency Management, undated a). Recall that indirect deaths are typically not related to sheltering in place (they are typically deaths from heart attacks, house fires, electrocution during repairs, or car accidents; Stobbe, 2018). We assumed that all ten direct deaths could be attributed to Hurricane Isabel, assuming historic sheltering-in-place rates.\(^1\) Using historic sheltering-in-place rates of similar to those in

\(^1\) We find that this upper bound condition still results in several orders of magnitude fewer deaths than those from evacuation by car or evacuation to a mass shelter, and therefore we consider this to be a sufficient test for this case. If a very strong hurricane (such as a Category 5) were to make landfall in Virginia, we would need to revisit this assumption.
Northern Neck (59 percent) and Surry County (91 percent), we estimate the range of deaths that Hurricane Isabel might have caused as a function of sheltering-in-place rates at zero to 18 deaths (see Figure 4.1). Because Hurricane Isabel was a Category 1 hurricane for much of its transit across Virginia, a similar ratio (as a function of geographic spread of damages) could be assumed for other Category 1 hurricanes. As we show in later sections, deaths predicted because of sheltering in place are orders of magnitude lower than those predicted because of the other responses to a hurricane that involve increased risk of COVID-19 infection.

If a higher category of hurricane were expected, the number of deaths could greatly increase. For example, Hurricane Maria (a Category 5 hurricane) is estimated to have led to approximately 3,000 deaths in Puerto Rico, some of which were related to sheltering in place (Milken Institute School of Public Health, George Washington University, 2018). We could use Hazus to estimate the number of deaths by calculating the number of those sheltering in place, controlling for systematic biases, and taking the ratio. A Category 5 hurricane making landfall in Virginia would certainly be catastrophic, but such an event is highly unlikely (such a hurricane has not made landfall in Virginia in recorded history). First-order estimates suggest that deaths from evacuation by car and communal sheltering would far outweigh those related to sheltering in place (except in a historically extreme hurricane).

### Spread in Shelters

To evaluate the risk of COVID-19 spread in shelters, we ran Hazus for a plausible worst-case scenario: a Category 1 hurricane making direct landfall on Virginia. We use a hypothetical storm track to analyze potential shelter and evacuation needs. (Note that evacuation models based on
historical wind scenarios alone likely underestimate numbers for evacuation and sheltering, as evacuations are typically ordered before the precise track of the storm is known.

The predicted displacements for Virginia totaled 190,580 individuals. We estimated that 14,863 of these individuals might reasonably need access to a communal shelter, based on the proportion of individuals without access to a car, by county. These figures are not far from the actual figures for displacement and shelter needs for Hurricane Isabel (approximately 160,000 people evacuated and up to 16,000 were housed in shelters) (Post, Buckley, Schuh, and Jernigan, 2005; Franke and Simpson, 2004; “States in Isabel’s Path Prepare,” 2003).

Using our simple model of transmission, we calculated that 1,000 to 4,400 individuals might be expected to contract COVID-19 in a shelter. Using the interaction-based model of transmission (assuming that each contact between an infected and susceptible individual has a fixed probability of transmission), between 2,800 and 8,300 individuals might be expected to contract COVID-19 in a shelter, assuming the same transmission probabilities. The case-fatality ratio for COVID-19 is currently estimated to be 2 to 3 percent;\(^2\) therefore, the direct death toll of COVID-19 from the use of mass shelters could vary from 20 to 250 individuals (not including subsequent waves of infection). Although these estimates vary greatly, the results do indicate that the risk of COVID-19 spread in a communal shelter is at least as great and likely much greater than the risk of death from sheltering in place.\(^3\)

As expected, the differences between models and the effect of such parameters as the assumed transmission probability are more apparent for larger shelters (as spread is lower in smaller shelters and differences are harder to distinguish). As Figure 4.2 illustrates, all models produce a strong correlation between shelter size and the number of secondary COVID-19 infections.

\(^2\) The observed case-fatality ratio for the United States was estimated at 3 percent as of September 16, 2020 (Johns Hopkins University of Medicine Coronavirus Resource Center, undated). In Virginia, the mean observed case-fatality ratio was 2.4 percent as of July 2020, calculated using Virginia Department of Health, undated.

\(^3\) Note that this is the risk as calculated absent of people’s risk perceptions. People may choose very different options based on any number of cognitive heuristics. A decisionmaker needs to be very careful to differentiate between risk and perceived risk.
The uncertainty in these estimates reflects uncertainty in how COVID-19 spreads between individuals in various scenarios and uncertainty in the extent to which social distancing, sanitization, mask-wearing, and other precautions can be enacted within a communal shelter. It is clear, however, that refinements to the transmission model are essential to improve model fidelity. A temporal aspect of the model will likely be necessary to adequately capture the additional risk posed by longer stays in a shelter. Given that the need for long-term shelters is heavily dependent on the damage to infrastructure, the risk for longer durations in shelters is best estimated once an initial damage assessment is available.

Spread Caused by Evacuations

Evacuation to nearby locations can increase the rate of COVID-19 spread by increasing mobility and population density in the regions receiving evacuees. The combined effects of thousands of people leaving home, stopping at gas stations, staying with friends and relatives or at hotels, grocery shopping, and attending restaurants, parks, and other public spaces increases the number of interactions within the community, leading to higher rates of spread.

To estimate the spread of COVID-19 caused by evacuation for our worst-case scenario analysis, we assume that all individuals within a storm surge or high wind area are ordered to evacuate. A large source of uncertainty in this analysis is the predicted compliance rate; typically, only a fraction of those instructed to evacuate actually do so. For this reason, we
produced upper- and lower-bound estimates for infections across a range of compliance rates. Figure 4.3 shows the estimated COVID-19 infections resulting from evacuation by car, assuming a 17- to 27-percent increase in the infection rate per 10-percent increase in mobility.\footnote{We used the infection rates for the expected destinations of the evacuating populations.} Even at low compliance rates, estimated infection rates number in the thousands.

**Figure 4.3. Estimated COVID-19 Infections for Worst-Case Direct-Hit Scenario Caused by Evacuation by Car**

Evacuation by car can also lead to traffic accident deaths. This is of particular concern during severe hurricanes, and the risk could be exacerbated if fewer people feel comfortable opting for a communal shelter. Decisionmakers will likely want to carefully consider evacuation routing and timing (although this is outside the scope of this analysis). In absence of access to HURREVAC, we consider the range of deaths caused by traffic accidents to be a function of compliance rate (see Figure 4.4 for a sample range for Hurricane Isabel). Assuming a case-fatality ratio for COVID-19 of 2 to 3 percent, the number of traffic deaths is roughly on the same order of magnitude as (although somewhat higher than) the number of predicted COVID-19 deaths. However, if a hurricane limited hospitals’ ability to provide care to COVID-19 patients, the case-fatality rate could rise above that range.
In the case of Hurricane Isabel, Hazus indicates that the full population sheltering in place would result in fewer than 20 deaths. This is largely because Hurricane Isabel made landfall in North Carolina, so direct deaths caused by wind and storm surge in Virginia were relatively low. Depending on the degree of the damage following the storm, more deaths could occur if vital services are disrupted for significant periods of time. However, the recovery period is beyond the scope of this report.

The trade-offs between sheltering in communal shelters or self-evacuating to a safer location will very much depend on the size of the available shelters and the ambient rate of COVID-19 in the immediate community versus in the range of likely evacuation destinations. Smaller shelters increase the attractiveness of communal sheltering relative to evacuating in terms of avoiding COVID-19. On one hand, if community COVID-19 case levels are high, individuals in the area are more likely to spread the disease elsewhere during an evacuation and in communal shelters. Alternatively, if community COVID-19 case levels are low, the risk of individuals spreading the disease during evacuation or in communal shelters is low. Ultimately, the outcomes will depend on both the storm characteristics and the spatial distribution of COVID-19 case levels. Lower levels of COVID-19 greatly reduce the overall risk from all outcomes.
5. Conclusions

We have presented an approach to framing the risk associated with a hurricane during the COVID-19 pandemic and a set of models to assess the risk posed by a particular storm. The risk of deaths from the storm will depend not only on hurricane characteristics, such as the strength of the storm and its path, but also on the level of COVID-19 in areas being evacuated and areas receiving evacuees. We have described a set of models to explore the implications of both the storm and disease risks. This modeling points to a few policy interventions for decisionmakers to consider in advance of a hurricane. In the absence of other changes, we expect that people will be more likely to prefer sheltering in place than evacuating to a communal shelter or some other location, but the exact levels will depend on the perceived risk of the different options.

**Individuals need information from trusted sources to know how to safely react to a hurricane based on their personal risk.** The risks of COVID-19 and a hurricane will vary based on an individual’s characteristics, and their responses should vary accordingly. In particular, clear and consistent risk communication will be vital to inform the population about the safest options for their family. This communication must be population-specific, because different groups will have access to and prefer different communication modes. Given the potential nuances in personal and household risk, this communication should begin as soon as possible; it should be targeted to the most-vulnerable populations, and the messaging should not be so complex as to risk confusion. Furthermore, to the extent that people can act earlier, the risk of traffic deaths caused by poor road conditions will be reduced.

**Shelter characteristics, such as capacity and social distancing measures, will determine the risk associated with using communal shelters.** To the extent possible, smaller methods of shelter should be used to prevent spread of COVID-19. For example, empty hotel rooms could be used in lieu of communal shelters. Because of large uncertainty in shelter demand, it might be more cost-effective to find alternatives to reserving large blocks of hotel rooms. Possible alternatives include distributing hotel vouchers to individuals evacuating, prioritizing high-risk populations if hotel room availability is limited, or structuring variable quantity contracts that have a low marginal cost. Deaths from COVID-19 spread caused by communal shelters could be quite high if there are outbreaks, particularly because of the conditions that often follow in the aftermath of hurricanes and other disasters. Overwhelmed health care facilities, damaged infrastructure, and the type of activity required to rebuild or reconstitute households and communities might lead to a second, larger wave of infections.
The Virginia Department of Emergency Management should also consider whether a hub-and-spoke method of sheltering is preferred or whether there is an alternative method of allocation and transportation to shelters that minimizes the number of people in any one shelter. If leaders anticipate that large numbers of people will use shelters, it would be prudent to prepare plans, COVID-19 cleaning equipment, and masks ahead of time. The biggest shelters (e.g., St. Paul Elementary School, which has a reported capacity of more than 8,000 evacuees) should have these plans.

Because more people may shelter in place, the response phase will need to be accelerated. A strong hurricane could cause electrical power to fail for multiple weeks in some areas. To mitigate this risk, Virginia might wish to be prepared to enact mutual aid for utilities and hospitals more quickly than under normal circumstances so as not to exacerbate the health consequences for those with COVID-19 and other conditions who sheltered in place.

Self-evacuations by car could be a major source of spread for COVID-19. COVID-19 risks caused by self-evacuation will depend on the case rates in the evacuation destinations and the precautions taken by travelers. Evacuees should be informed of best practices for safe travel and the risks associated with various destinations. In addition, there will be a lag between the hurricane evacuation and any resulting spike in COVID-19 cases. Extensive testing of evacuees throughout hurricane season, particularly prior to hurricane landfall, can better inform policymakers of the risks. If there appears to be a spike in cases, it may be important to both hospitals and emergency first responders (who will have to accept COVID-19 risk in order to check on residents) for a spike in cases.

Policymakers can take certain steps now, such as ensuring an adequate stockpile of COVID-19 tests and protective personal equipment and making plans for the use of low-capacity shelters. Other policy considerations may require more-extensive planning. In the event of a hurricane, decisionmakers at the local, state, and federal levels will need to closely coordinate across both the health and emergency response domains to effectively execute these plans. Planning and preparation will be important to ensure that the coordination and execution are effective.

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1 A hub-and-spoke method is a networking approach similar to a metaphorical wheel with hubs and spokes. Nodes are linked to centralized hubs so that traffic from the outlying nodes moves along spokes to the hub and then out along other spokes to the final destination.
Appendix. Select Models in Use by Emergency Managers

U.S. Department of Homeland Security (2019) describes the following resources for emergency managers to aid in decisionmaking on evacuation and shelter in place for such hazards as hurricanes:

- **Hazus-MH (HAZards US Multi-Hazards), or Hazus**, is a FEMA model (FEMA, 2020). In Hazus, threat assessment comes from hurricane track data. Hazus uses inputs of storm characteristics (e.g., hurricane tracks, maximum wind speed, radius to maximum winds) to produce wind speeds at the census tract level. Hazus models can be interfaced with other disaster models to provide additional details, such as flooding from rainfall.

- **Sea, Lake, and Overland Surges from Hurricanes (SLOSH)** is a National Hurricane Center model that predicts storm surge heights on coastal lands (National Hurricane Center and Central Pacific Hurricane Center, undated). This can be used as an input to Hazus. We provide a sample Hazus output using SLOSH data in Figure A.1.

- **HURREVAC** provides evacuation timing estimates (based on wind speeds, perhaps flooding, and traffic modeling). It appears to be available to emergency managers only (HURREVAC, undated). We provide a sample output in Figure A.2.

- **Real Time Evacuation Planning Model (RtePM, or Route–P-M)** is hosted by Old Dominion University and partially funded by the U.S. Department of Homeland Security and the Virginia Department of Emergency Management (Old Dominion University, undated). It estimates the time required for evacuating vehicles as a function of the evacuation scenario and multiple other user-defined parameters.

- **National Oceanic Atmospheric Administration Hurricane Evacuation Studies** contain data and lessons learned for historic evacuations (National Oceanic and Atmospheric Administration, Office for Coastal Management, undated). (The most recent Virginia study is from 1963 and was not used for this report.)

- **State departments of transportation, state and jurisdictional evacuation plans, and other related plans.**
In addition, an older resource on hurricane evacuations (U.S. Department of Transportation and U.S. Department of Homeland Security, 2006) suggests the following additional models. The first, Evacuation Traffic Information Systems (ETIS), appears to still be in operation; we were unable to get data suggesting that the other models are currently in use.

- ETIS is available to emergency managers. It provides “the evacuation participation rate and type (i.e., voluntary or mandatory evacuation), expected congestion levels on primary

- Consequence Assessment Tool Set/Joint Assessment of Catastrophic Events (CATS/JACE) appears to be an old model, mainly for chemical, biological, radiological, and nuclear threats, created by SAIC in the 1990s (Kaul, undated; Goddard Space Flight Center, 2009).
- Network Emergency Evacuation (NETVAC)
- Mass Evacuation (MASSVAC)
- Oak Ridge Evacuation Modeling System (OREMS).
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