GeoHealth

RESEARCH ARTICLE
10.1029/2022GH000651

A. T. Tarabochia-Gast and D. R. Michanowicz contributed equally to this work.

Key Points:

- A total 25 of 78 metropolitan statistical areas (MSAs) on the U.S. Atlantic and Gulf Coasts have half or more of their hospitals at risk of flooding from relatively weak hurricanes
- 0.82 m of sea level rise expected within this century from climate change increases the odds of hospital flooding 22%
- In 18 MSAs, at least half of the roads within 1.6 km of hospitals were at risk of flooding from a category 2 cyclone

Supporting Information:
Supporting Information may be found in the online version of this article.

Correspondence to:
A. S. Bernstein,
aaron_bernstein@hms.harvard.edu

Citation:
Tarabochia-Gast, A. T., Michanowicz, D. R., & Bernstein, A. S. (2022). Flood risk to hospitals on the United States Atlantic and Gulf Coasts from hurricanes and sea level rise. *GeoHealth*, *6*, e2022GH000651. https://doi.org/10.1029/2022GH000651

Received 7 MAY 2022
Accepted 5 SEP 2022

Author Contributions:
Conceptualization: A. T. Tarabochia-Gast, A. S. Bernstein
Data curation: A. T. Tarabochia-Gast, D. R. Michanowicz, A. S. Bernstein
Formal analysis: D. R. Michanowicz, A. S. Bernstein

Flood Risk to Hospitals on the United States Atlantic and Gulf Coasts From Hurricanes and Sea Level Rise

A. T. Tarabochia-Gast[1,2], D. R. Michanowicz[1,3], and A. S. Bernstein[1,4]

[1]Center for Climate, Health and the Global Environment, Harvard T.H. Chan School of Public Health, Boston, MA, USA, [2]Department of Family Medicine, Boston University School of Medicine, Boston, MA, USA, [3]Physicians, Scientists, and Engineers for Healthy Energy, Oakland, CA, USA, [4]Boston Children's Hospital, Boston, MA, USA

Abstract Hurricanes have caused major healthcare system disruptions. No systematic assessment of hurricane risk to United States hospital-based healthcare delivery has been performed. Here, we show that 25 of 78 metropolitan statistical areas (MSAs) on the United States Atlantic and Gulf Coasts have half or more of their hospitals at risk of flooding from relatively weak hurricanes. 0.82 m of sea level rise expected within this century from climate change increases the odds of hospital flooding 22%. Furthermore, in 18 MSAs at least half of the roads within 1.6 km of hospitals were at risk of flooding from a category 2 storm. These findings identify previously undescribed risks to hospital-based care delivery in Atlantic and Gulf Coast communities. They suggest that lower intensity hurricanes can have outsized impacts on healthcare access, particularly in places where per capita bed availability is low.

Plain Language Summary Hurricanes often incapacitate hospitals, a critical component of healthcare delivery. Climate change is contributing to more intense hurricanes and sea level rise that increase flood risk. Flooding can curtail operations of and limit access to hospitals. We analyzed how hurricane landfalls affect flooding risks to hospitals that serve highly populated cities on the Atlantic and Gulf Coasts of the United States. We find that even relatively weak hurricanes can flood most of the hospitals in urban coastal areas and that sea level rise expected within this century due to climate change significantly increases flooding risk.

1. Introduction

1.1. Effects of Hurricanes on Hospitals

Despite substantial preparations for hurricanes, including medical supply reserves, redundant communication and documentation systems, back-up power supplies, and on-call personnel, hurricanes often incapacitate hospitals, a critical component of healthcare delivery. Hurricane Sandy, for instance, cut off electricity to 40% of hospitals in the declared disaster area. Back-up generators failed at more than a third of these hospitals (Levinson, 2015). When utilities failures forced hospitals to evacuate after initially sheltering in place, they encountered several challenges including flooded roadways, inoperable elevators, insufficient ambulances, a lack of regional coordination, and a shortage of hospital, and particularly specialty, beds (Levinson, 2015). After a hurricane, flooded roads interfere with hospital access when demand for healthcare services may be heightened. Following Sandy, one-third of hospitals in the declared disaster area suffered from staffing shortages despite the declaration of a state of emergency 2 days before the storm made landfall (Levinson, 2015).

Interruptions in care after hurricanes prevent patients from obtaining necessary medical care. Lack of access to dialysis centers, substance use treatment facilities, pharmacies, ambulatory care centers, and reliable electricity in patients' homes leads to higher rates of complications and exacerbations of chronic medical problems such as diabetes, asthma, and chronic kidney disease (Baum et al., 2019; Dominianni et al., 2018; Kelman et al., 2015; Melin & Rodríguez-Díaz, 2018; Shuler et al., 2017). Having a hurricane disaster declared during radiation therapy for patients with non-small cell lung cancer is associated with worse overall survival (Nogueira et al., 2019). These impacts from care disruption have been shown to persist well after the storm has passed (Baum et al., 2019; Quast & Feng, 2019).

Investigation: A. T. Tarabochia-Gast, D. R. Michanowicz, A. S. Bernstein
Methodology: D. R. Michanowicz, A. S. Bernstein
Supervision: A. S. Bernstein
Validation: D. R. Michanowicz
Visualization: D. R. Michanowicz
Writing – original draft: A. T. Tarabochia-Gast, D. R. Michanowicz, A. S. Bernstein
Writing – review & editing: A. T. Tarabochia-Gast, D. R. Michanowicz, A. S. Bernstein

1.2. Effects of Climate Change on Hurricane Intensity and Sea Level

The most recent U.S. National Climate Assessment asserted that stronger hurricanes are more likely in a warmer world (Hayhoe et al., 2018). Devastating "gray swan" hurricanes with high storm surge, such as Hurricane Katrina which delivered the greatest storm surge in United States' history at nearly 8.5 m (28 feet) above sea level, may also be more common with climate change (Hayhoe et al., 2018; Lin & Emmanuel, 2016). The odds of a hurricane with a storm surge of 6 m (~20 feet) striking and submerging Tampa, Florida are about 1 in 10,000 today and may increase to about 1 in 700 by the end of this century (Lin & Emmanuel, 2016). Along with increasing the frequency of severe hurricanes, climate change is expected to cause sea levels to rise between 0.3 and 1.3 m (1–4.3 feet) or more by 2100 relative to 2000 (Hayhoe et al., 2018; Horton et al., 2020; Sweet, Horton, et al.,).

As hurricanes intensify and sea levels rise (Hayhoe et al., 2018), the populations that depend on healthcare systems vulnerable to hurricanes in the United States are large and growing. More than half of the United States population lives in coastal counties, and, by mid-century, millions more may move to coastal cities (National Oceanic and Atmospheric Administration, 2013).

Given the growing likelihood of more destructive Atlantic hurricanes due to climate change and the history of hospital system failures after extreme storms, we assess how hurricane storm surge and sea level rise may compromise care delivery at and access to acute care hospitals that serve communities on the United States' Atlantic and Gulf Coasts.

2. Materials and Methods

2.1. The Sea, Lake and Overland Surges From Hurricanes Model

We utilized storm surge hazard maps from the composite model output of the validated Sea, Lake and Overland Surges from Hurricanes (SLOSH) model from the National Weather Service of the National Oceanic and Atmospheric Association. SLOSH is the operational storm surge model of the U.S. National Hurricane Center.

SLOSH predicts storm surge inundation based upon several thousand hurricane simulations in each hurricane basin with varying intensities, sizes and landfall locations and includes bridges, roads, levees, and other physical features. In validation studies, the SLOSH model has been found to have an error of ±20% (Glahn et al., 2009).

SLOSH can provide storm surge heights associated with hurricanes based on probabilistic or deterministic inputs, or a composite of both (Glahn et al., 2009). For our analysis, we rely upon composite model outputs to assess storm surge inundation extent and sea level rise based on Maloney and Preston (2014). Composite model outputs represent maximum storm surge surface water elevations based upon several thousand simulated hurricanes at various strengths at high tide. The SLOSH model as applied in Maloney and Preston (2014) and used here has a horizontal resolution is 1 arc second (~27 m at 30° latitude) and a vertical resolution of 2.44 m (based on root mean square error).

2.2. Sea Level Rise

We consider sea level rise of 0.82 m (2.69 feet) based upon recent expert consensus of expected sea level rise given limited greenhouse gas mitigation by 2100 (Horton et al., 2020). We note that this may be a substantial underestimate and that rates of sea level rise vary greatly across the Atlantic and Gulf Coasts (Sallenger et al., 2012; Sweet, Kopp, et al., 2017). For comparison, and to evaluate more near-term risk, we also present findings from a 0.5 m (1.64 ft) sea level rise (Data Set S1, https://doi.org/10.7910/DVN/TYOHSF, Hospital-level tab).

2.3. Assessment of Inundation Status

For all combinations of predicted storm surge and sea level rise, the geospatial hazard layers effectively represent a new coastline that was then compared to hospital locations to determine inundation. Inundation analyses were performed for individual hospitals and for roadways surrounding hospitals using 12 hazard layers for each combination of hurricane category (1–4) with current sea level or with 0.50 m or 0.82 m of sea level rise. Hospital locations were geographically represented by a circular area with an ~161 m (0.1 mile) radius centered on the hospital complex's footprint (Figure S1 in Supporting Information S1). A hospital was deemed inundated if any portion of its 161m radial buffer area intersected with any portion of the storm surge hazard layer as predicted by SLOSH model output. When deemed inundated, all associated beds within that hospital were also considered as "beds at risk." Hospital and bed data were also aggregated to their respective metropolitan statistical areas (MSAs) along the Gulf and Atlantic coasts.

2.4. Sensitivity Analyses

We performed a sensitivity test on the representativeness of the 161 m hospital buffer by comparing inundation at the 161 m radius versus inundation at the centroid of the hospital building footprint. We assessed the impact of sea level rise on hospital inundation using logistic regression. The analysis was carried out using the glm function in RStudio version 1.3 (RStudio Team, 2020).

2.5. Road Inundation

Flooding of roads around hospitals were assessed at 1.6 km (1 mile) radii search areas (Figure S1 in Supporting Information S1). The choice of a 1.6 km buffer radius was made for illustrative purposes. Roadway lengths were calculated and summed for each hospital to represent the potential roadway inundation denominator. A similar clip and length summation procedure was performed for each roadway that intersected a hazard layer. Hospital roadway flooding percent equals the summed length of inundated roadways divided by the total roadway length within 1.6 km. Roadway data were obtained from the United States and Canada Detailed Streets data set (Esri, 2012). Prior to calculating impacted roadways, all bridge-trafficked roadway segments within 1.6 km of hospitals were removed. All geospatial analyses were performed using ArcGIS 10.4.1 (Redlands, CA).

2.6. Regional Flooding Analysis

To estimate regional impacts, we utilized 2018 population estimates from the United States Census to calculate hospital beds per capita by MSA and populations at risk from compromised healthcare facilities (United States Census Bureau, 2018). We identified 661 hospitals located within the geographic boundaries of 78 MSAs in which an estimated 84,939,609 people live. Twenty-one hospitals within 16 km (10 miles) of a coastline were not located within an MSA and therefore were not included in MSA-level analyses but were included in individual hospital analyses. Some coastal MSAs (e.g., Tallahassee, FL) do not contain hospitals within 16 km of the coastline and were omitted from MSA analyses. Hospital beds per capita were calculated by summing all hospital beds in each MSA then dividing by total MSA population. Per capita estimates were then multiplied by 1,000 to aid interpretability. To address differing risks based upon per capita bed availability, we divided the beds at risk from a category 2 hurricane by MSA per capita beds.

2.7. Hurricane Landfall Probability

To predict the likelihood of a hurricane making landfall, we used the statistical/deterministic hurricane model developed by Emanuel et al. (2008) to generate 6,000 synthetic hurricane tracks based upon the historical climate of the twentieth century. Annual probabilities of hurricane-force winds were determined by the annual exceedance frequencies of maximum wind speeds predicted to occur anywhere within a defined circular buffer area at 30-m above ground level. These probabilities were then used to calculate a relative risk of hurricane impact for each MSA by dividing each probability by the lowest probability of a category 2 hurricane anywhere in the United States. Maximum wind speeds were set to Saffir-Simpson categories to produce hurricane category strength probabilities. Circular buffer areas were defined for each MSA based upon by the maximum geographic extent between the hospital bed-weighted centroid boundary and the boundary of the MSA, referred to as a hurricane impact zone (Figure S1 in Supporting Information S1). The hospital bed-weighted centroid does not coincide with any one specific hospital location but was numerically weighted by bed counts to a geometric mean location that is contained within an MSA. All hurricane model simulations were performed using MATLAB Version 9.6 ("MATLAB," 2019).

3. Data

3.1. Hospital and Bed Identification

We identified acute care hospitals located within 16 km (10 miles) of the United States Atlantic and Gulf Coasts using hospital GIS coordinates obtained from the Oak Ridge National Laboratory Geographic Infor-

Table 1
Metropolitan Statistical Area (MSA) Population-Weighted Impact From Category 2 Hurricane

Rank	MSA	Total hospitals//beds	Beds per 1,000 people	Hospitals at risk (%)	Beds at risk (%)	RR hurricane strike[a]
1	Miami-Fort Lauderdale-West Palm Beach, FL	49//18,089	2.9	38 (77.6)	12,904 (71.3)	183.6
2	New York-Newark-Jersey City, NY-NJ-PA	128//49,114	2.5	25 (19.5)	9,271 (18.9)	15.4
3	Boston-Cambridge-Newton, MA-NH	40//9,279	1.9	6 (15.0)	2,240 (24.1)	9.6
4	Orlando-Kissimmee-Sanford, FL	3//491	0.2	1 (33.3)	221 (45.0)	136.5
5	New Orleans-Metairie, LA	19//4,240	3.3	15 (78.9)	3,471 (81.9)	137.7
6	Tampa-St. Petersburg-Clearwater, FL	28//8,381	2.7	8 (28.6)	2,507 (29.9)	89.3
7	North Port-Sarasota-Bradenton, FL	7//2,176	2.6	6 (85.7)	2,056 (94.5)	69.4
8	Jacksonville, FL	14/4,187	2.7	6 (42.9)	2,004 (47.9)	75.0
9	Cape Coral-Fort Myers, FL	5//1,630	2.2	4 (80.0)	1,542 (94.6)	44.3
10	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	49//15,195	2.5	5 (10.2)	1,639 (10.8)	3.2

[a]The relative risk of hurricane impact for each MSA was obtained by dividing the MSA's probability of a category 2 hurricane strike by the lowest probability of a category 2 hurricane anywhere in the United States.

mation Science and Technology Group and the National Geospatial-Intelligence Agency Homeland Security Infrastructure Program Vector Team (Oak Ridge National Laboratory Geographic Information Science and Technology Group, 2016). Inpatient licensed medical and surgical bed counts were obtained either from state agencies and hospital associations ($n = 597$) (see Text S1 in Supporting Information S1 for bed sources) or secondarily from the latest Homeland Infrastructure Foundation-Level Data ($n = 79$) (U.S. Department of Homeland Security, 2019). The remaining hospital bed counts were obtained directly from hospitals ($n = 6$).

4. Results

We identified 682 acute care hospitals located within 16 km (10 miles) of the Atlantic and Gulf Coasts of the United States. In aggregate, these hospitals operate in 78 MSAs with a total population of just under 85 million people. They have an estimated 192,821 medical and surgical inpatient beds, hereafter referred to as beds (median 229 beds, standard deviation 215.17).

4.1. Hospitals and Beds Risk From Hurricane Storm Surge

Just over one half ($n = 40$) of all MSAs are predicted to contain flooded hospitals if struck by a category 1 storm, whereas two-thirds ($n = 51$) and nearly 80% ($n = 62$) of MSAs contain hospitals at risk from a category 2 or 4 storm, respectively (Data Set S1, https://doi.org/10.7910/DVN/TYOHSF, MSA-level tab). An estimated 147 hospitals (22.2% of total hospitals) with 41,493 beds (21.6% of total beds) may be at risk of inundation from a category 1 storm while 306 hospitals (46.2%) containing 84,842 beds (44.2%) may be at risk with a category 4 storm (Data Set S1, https://doi.org/10.7910/DVN/TYOHSF, Hospital-level tab). In 25 of 78, or nearly 1 in 3 MSAs, a category 2 storm risks flooding half or more of their hospitals (Data Set S1, https://doi.org/10.7910/DVN/TYOHSF, MSA-level tab).

Differences between the buffer and centroid were statistically insignificant for all hurricane categories (Table S1 in Supporting Information S1). We tested the validity of the SLOSH model hazard layers for predicting hospital inundation by comparing SLOSH model predictions with flooding observed in Hurricane Sandy within New York City (Text S2, Table S2, and Figure S2 in Supporting Information S1). The SLOSH model hazard layers had a sensitivity of 80.0% (95% CI 28.4–99.5) and specificity of 97.8% (95% CI 88.2%–99.9%)

Risk was also explored based on the population served by these hospitals. As bed availability within MSAs varied from less than 1 to nearly 6 beds per 1,000 residents, we ranked MSAs based upon the quotient of beds at risk from a category 2 storm divided by beds per 1,000 MSA residents to better represent risk to healthcare access due to flooding. Table 1 lists the 10 MSAs with the greatest risk to inpatient hospital beds from a category 2 hurricane using this quotient. Category 2 is shown for illustrative purposes (category 2 storms are the median intensity of all storms making landfall between 1851 and 2004) (Blake et al., 2005); category 5 storms were excluded given

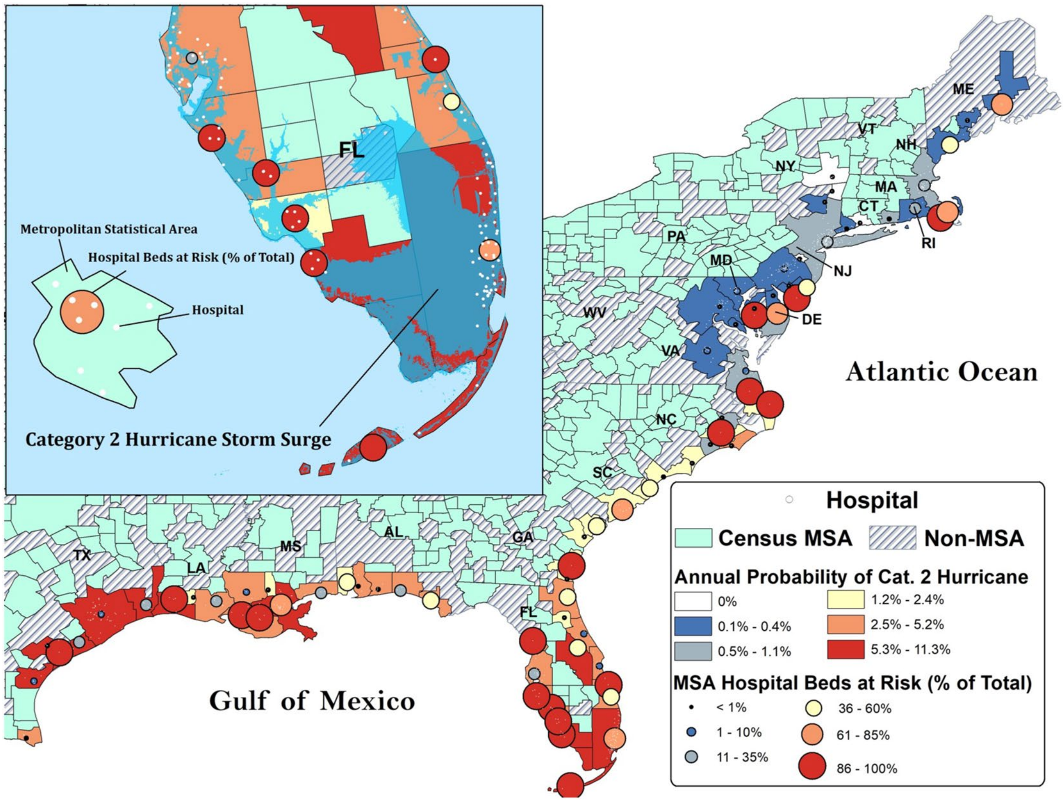

Figure 1. Annual predicted probability of storm landfall and percentage of beds at risk. Map of metropolitan statistical areas (MSAs) on the United States Atlantic and Gulf Coasts at risk of hurricane landfall. Shading indicates probability of landfall. Circles represent percent of beds at risk from a category 2 hurricane. Inset depicts focused area of Florida peninsula with hospital locations (white markers) and Sea, Lake and Overland Surges from Hurricane model predicted flooding area in blue.

their rarity. Table 1 also contains percentages of hospitals and beds predicted to be inundated and the relative risk of a category 2 hurricane making landfall within each MSA.

Florida has populous MSAs with some of the highest percentages of facilities and beds at risk as well as with the greatest probabilities of hurricane landfall. Despite having lower percentages of beds and hospitals at risk and less frequent landfalls, hurricanes that strike further north, including New York-Newark-Jersey City, Boston-Cambridge-Newton, and Philadelphia-Camden-Wilmington, also put healthcare access for substantial numbers of people at risk.

4.2. Storm Surge Flood Risk and Hurricane Landfall Probability

The vulnerability of an MSA to hurricane-induced disruptions in healthcare delivery is determined by both how far inland storm surge reaches and the likelihood that a hurricane strike occurs in the MSA. Based on SLOSH model outputs, Figure 1 illustrates the percentage of beds at risk from a category 2 hurricane within each MSA superimposed on the annual probability of a category 2 hurricane making landfall in that region. The inset map of Florida depicts the extent of flooding due to storm surge relative to individual hospitals to highlight the extensive impact hurricanes may have in this state.

4.3. Hospitals at Risk From Storm Surge and Sea Level Rise

Climate change is raising sea levels, which may put more hospitals at risk from hurricane induced storm surge. Sea level rise of 0.82 m (2.69 feet) increases the odds of hospital flooding from any strength (category 1–4) hurricane (odds ratio 1.22 95% CI 1.087, 1.361). It puts hospitals and beds in 6 MSAs (Easton, MD; Hammond, LA; Pensacola-Ferry Pass-Brent, FL; Savannah, GA; Washington, NC; and Washington-Arlington-Alexandria, DC-VA-MD-WV) at risk that would otherwise be unaffected by a category 2 storm without sea level rise and increases beds at risk by over 50% in 7 MSAs (Baton Rouge, LA; Beaumont-Port Arthur, TX;

Table 2
Flooded Roads Within 1.6 km (1 Mile) of a Hospital From Category 2 Storm Surge by Metropolitan Statistical Area (MSA)

Rank	MSA	Hospitals flooded//total	Total roads in meters	Flooded roads in meters (%)
1	Punta Gorda, FL	3//3	283,457	283,348 (100.0%)
2	Naples-Immokalee-Marco Island, FL	4//4	275,425	272,997 (99.1%)
3	Houma-Thibodaux, LA	5//5	290,730	253,332 (87.1%)
4	North Port-Sarasota-Bradenton, FL	6//7	566,377	455,422 (80.4%)
5	Miami-Fort Lauderdale-West Palm Beach, FL	38//49	4,808,450	3,480,949 (72.4%)
6	Charleston-North Charleston, SC	5//7	536,112	365,331 (68.1%)
7	New Orleans-Metairie, LA	15//19	1,977,409	997,003 (50.4%)
8	Tampa-St. Petersburg-Clearwater, FL	8//28	2,497,280	553,397 (22.2%)
9	New York-Newark-Jersey City, NY-NJ-PA	25//128	13,665,203	2,037,666 (14.9%)
10	Boston-Cambridge-Newton, MA-NH	6//40	4,051,925	574,926 (14.2%)

Boston-Cambridge-Newton, MA-NH; Corpus Christi, TX; Deltona-Daytona Beach-Ormond Beach, FL; Philadelphia-Camden-Wilmington, PA-NJ-DE-MD; and Virginia Beach-Norfolk-Newport News, VA-NC) from a category 2 storm (Table S3 in Supporting Information S1). The MSAs most susceptible to sea level rise were not the same as those most at risk under present-day sea level conditions. In particular, the Baton Rouge, Virginia Beach, Corpus Christi, Philadelphia, and Boston MSAs all had over 90% increases in the number of beds at risk of flooding from a category 2 storm with 0.82 m of sea level rise. Baton Rouge and Virginia Beach were particularly vulnerable to sea level rise, having roughly 10-fold greater beds at risk with a category 2 storm when compared to current sea level. (See Data Set S1, https://doi.org/10.7910/DVN/TYOHSF, hospital-level tab, for hospitals at risk with 0.5 m of seal level rise.)

4.4. Hurricane Storm Surge and Road Inundation

Table 2 shows the 10 MSAs with the highest percent of roadways within 1.6 km (1 mile) of a hospital at risk of inundation. (For comparison, percent of road inundation by SA using a 0.8 km buffer can be found in Data Set S1, https://doi.org/10.7910/DVN/TYOHSF, MSA-level tab.) Seven MSAs had 50% or more of roads within 1.6 km (1 mile) of hospitals at risk of flooding from a category 2 storm (Data Set S1, https://doi.org/10.7910/DVN/TYOHSF, MSA-level tab). MSAs at greatest risk of road inundation around hospitals are similar to MSAs that contain the most hospitals at risk, with many MSAs in Florida as well as major MSAs further north in New York and Massachusetts having relatively high percentages of roadways at risk.

We further analyzed the extent to which non-inundated (or "dry") hospitals may have nearby roads flooded. In general, dry hospitals are unlikely to have substantial lengths of roadways within 1.6 km (1 mile) that are at risk of flooding. The exceptions to this are the: (a) Boston-Cambridge-Newton, (b) Miami-Fort Lauderdale-West Palm beach, (c) New York-Jersey City, and (d) Tampa-St-Petersburg-Clearwater MSAs in which 10 of 34, 7 of 11, 18 of 103, and 7 of 20 dry hospitals had between 10% and 30% of nearby roads flooded, respectively (Tables S4 and S5 in Supporting Information S1).

5. Conclusions

To our knowledge, this study is the first to systematically investigate flooding risk from hurricanes to hospital care provision in Atlantic and Gulf Coast communities in the United States. Our results, which join models for storm surge and hurricane paths, provide a more robust and precise assessment of risk to hospital-based care for communities along the Gulf and Atlantic Coasts than has previously been available. Our results suggest that storms of lower intensity may have substantial impacts on healthcare delivery and access. This holds where category 2 landfall is relatively more likely (e.g., 2.5%–11.3% in parts of Florida, Alabama, Mississippi, Louisiana, and Texas), as well as less likely (e.g., <1.2% in states north of North Carolina). Additionally, our analysis finds that large populations may have limited care access even when relatively small fractions (e.g., 10%–20%) of beds are at risk due to low per capita bed availability.

MSAs with greater risk of hospitals flooding from hurricanes were also more likely to have road inundation, such as the Miami and New Orleans MSAs. However, some MSAs with lower risk of hospital inundation have a relatively high percentage of nearby flooded roads. Two of these, Boston-Cambridge-Newton, and New York-Newark-Jersey City, are in regions with relatively less experience in managing hurricane impacts.

Our results are subject to several limitations. First, the SLOSH models do not account for wave height on top of storm surge, flooding from river overflow or precipitation, or changes in coastal geomorphology associated with storms. The lack of these elements may lead to misestimation of the extent of inundation. The SLOSH model also used high water tide conditions which will not reflect flooding outcomes from lower tide levels.

Second, the synthetic hurricane events generated by the Emanuel et al. model are based on historical conditions, which may change with climate change. Recent research suggests that climate change may be shifting hurricane tracks northward. As a result, the relative risks calculated for a category 2 landfall in northern MSAs may be underestimates (Baldini et al., 2016; Kossin et al., 2014). Additionally, sea level rise is happening faster on the East Coast, especially between Cape Hatteras and Cape Cod where rates of rise have been far higher than global averages. Leaving this factor out of the model may result in underestimation of risk for MSAs in that region (National Oceanic and Atmospheric Administration, 2009; Sallenger et al., 2012). The effects of sea level rise on flooding risk may be greatest in more northern states whereas states further south, and particularly Gulf Coast states, are at higher risk from hurricane storm surge (Marsooli et al., 2019). We also note that of the 6,000 hurricanes in the model, only 230 strike the New England area, thus limiting the statistical fidelity of the hurricane probabilities in this region, although this incidence is consistent with current observed rates of landfall (National Oceanic and Atmospheric Administration, n.d.).

Third, we analyzed hospital beds in aggregate and did not separately look at the numbers of medical-surgical, step-down, and intensive care unit beds. Flooding may have disparate effects on access to hospitals with more beds dedicated to higher acuity care. Future work can investigate this possibility as well as flooding risk to other healthcare facilities including, as examples, ambulatory clinics, pharmacies, dialysis centers, substance use treatment facilities, and nursing homes.

Finally, our findings do not account for actions that buffer flooding risk. Many hospitals have begun to construct protections against storm surge and sea level rise. For example, the new Southeast Louisiana Veterans Health Care Center, which replaced the VA Hospital and Charity Hospital in New Orleans after Hurricane Katrina, was designed to remain operational for 7 days even if city utilities and infrastructure are compromised. The hospital features back-up fuel supplies, on-site sewage treatment facilities, and sufficient accommodations for up to 1,000 staff and patients to shelter in place. Critical mechanical and electrical equipment as well as patient care areas are located at least 20 feet above the 100 years floodplain (Guenther & Balbus, 2014).

Hospital preparedness extends beyond securing individual buildings. After Hurricane Sandy, hospitals had difficulty absorbing post-storm patient surge, which in part resulted from patient transfers from closed facilities (Adalja et al., 2014). Roadway flooding can prevent staff, patients and supplies from getting to hospitals. While supply stockpiling and inter-institutional coordination of staff and supplies may address these challenges, limits in storage capacity, insurance portability, access to medical records, and faculty credentialing may all still impair care access and delivery (Adalja et al., 2014).

Many cities and healthcare systems in the United States are shoring up resilience to extreme events, but more work is needed. After Hurricane Harvey, even though improvements in hospital infrastructure and collaboration among community organizations and government agencies lessened the storms devastation, staff burnout, roadway flooding, and patient evacuation and transportation all remained problematic (Hines & Reid, 2021).

Hospital emergency managers and administrators have attributed their ability to prepare to past experience with hurricanes. The prospect of more probable and severe hurricane strikes in regions lesser experience with hurricanes, such as the Northeast, underscores the importance of sharing best practices and standardized approaches to hurricane preparedness and response. Annual hospital vulnerability analyses required by the Joint Commission afford one means to do so (Runkle et al., 2018).

This paper finds that relatively weak hurricanes may flood many hospitals that care for roughly 1 in 4 Americans and that sea level rise stands to increase risk. This study highlights that while innovation and investments to protect hospital buildings and operations are necessary to ensure care delivery during hurricanes, finding ways to improve patient and staff access to care may also be needed. With prospects of more intense hurricanes making landfall atop higher seas owing to climate change, greater resilience to hurricanes will be necessary to ensure that healthcare remains viable when it is needed most.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

All data generated or analyzed during this study are included in this published article and available in the Harvard Dataverse https://doi.org/10.7910/DVN/TYOHSF via creative commons license 1.0 (Michanowicz et al., 2022).

Acknowledgments
The authors thank Kerry Emmanuel for providing us technical assistance in assessing hurricane landfall probabilities and Mark Schuster for helping conceive of this paper.

References

Adalja, A. A., Watson, M., Bouri, N., Minton, K., Morhard, R. C., & Toner, E. S. (2014). Absorbing citywide patient surge during hurricane sandy: A case study in accommodating multiple hospital evacuations. *Annals of Emergency Medicine*, *64*(1), 66–73. https://doi.org/10.1016/j.annemergmed.2013.12.010

Baldini, L. M., Baldini, J. U. L., McElwaine, J. N., Frappier, A. B., Asmerom, Y., Liu, K., et al. (2016). Persistent northward North Atlantic tropical cyclone track migration over the past five centuries. *Scientific Reports*, *6*(1), 37522. https://doi.org/10.1038/srep37522

Baum, A., Barnett, M. L., Wisnivesky, J., & Schwartz, M. D. (2019). Association between a temporary reduction in access to health care and long-term changes in hypertension control among veterans after a natural disaster. *JAMA Network Open*, *2*(11), e1915111. https://doi.org/10.1001/jamanetworkopen.2019.15111

Blake, E. S., Jarrell, J. D., Rappaport, E. N., & Landsea, C. W. (2005). The deadliest, costliest, and most intense United States hurricanes from 1851 to 2004 (and other frequently requested hurricane facts) (NOAA Technical Memorandum NWS TPC-4). Retrieved from https://www.nhc.noaa.gov/pdf/NWS-TPC-4.pdf

Dominianni, C., Lane, K., Johnson, S., Ito, K., & Matte, T. (2018). Health impacts of citywide and localized power outages in New York City. *Environmental Health Perspectives*, *126*(6), 067003. https://doi.org/10.1289/EHP2154

Emanuel, K., Sundararajan, R., & Williams, J. (2008). Hurricanes and global warming: Results from downscaling IPCC AR4 simulations. *Bulletin of the American Meteorological Society*, *89*(3), 347–367. https://doi.org/10.1175/BAMS-89-3-347

Esri. (2012). North American Streets v. 10.1. Retrieved from https://www.arcgis.com/home/item.html?id=f38b87cc295541fb88513d1ed7cec9fd

Glahn, B., Taylor, A., Kurkowski, N., & Shaffer, W. A. (2009). The role of the SLOSH model in National Weather Service storm surge forecasting. *National Weather Digest*, 1–12. Retrieved from http://www.nws.noaa.gov/mdl/pubs/Documents/Papers/Role_of_SLOSH_Model_August2009.pdf

Guenther, R., & Balbus, J. M. (2014). Primary protection: Enhancing health care resilience for a changing climate. Retrieved from https://toolkit.climate.gov/sites/default/files/SCRHCFIBestPracticesReportfinal22014Web.pdf

Hayhoe, K., Wuebbles, D. J., Easterling, D. R., Fahey, D. W., Doherty, S., Kossin, J. P., et al. (2018). Chapter 2: Our changing climate. Impacts, risks, and adaptation in the United States: The Fourth National Climate Assessment, volume II. https://doi.org/10.7930/NCA4.2018.CH2

Hines, E., & Reid, C. E. (2021). Hospital preparedness, mitigation, and response to Hurricane Harvey in Harris County, Texas. *Disaster Medicine and Public Health Preparedness*, 1–7. https://doi.org/10.1017/DMP.2021.146

Horton, B. P., Khan, N. S., Cahill, N., Lee, J. S. H., Shaw, T. A., Garner, A. J., et al. (2020). Estimating global mean sea-level rise and its uncertainties by 2100 and 2300 from an expert survey. *Npj Climate and Atmospheric Science*, *3*(1), 18. https://doi.org/10.1038/s41612-020-0121-5

Kelman, J., Finne, K., Bogdanov, A., Worrall, C., Margolis, G., Rising, K., et al. (2015). Dialysis care and death following hurricane sandy. *American Journal of Kidney Diseases*, *65*(1), 109–115. https://doi.org/10.1053/j.ajkd.2014.07.005

Kossin, J. P., Emanuel, K. A., & Vecchi, G. A. (2014). The poleward migration of the location of tropical cyclone maximum intensity. *Nature*, *509*(7500), 349–352. https://doi.org/10.1038/nature13278

Levinson, D. R. (2015). Hospital emergency preparedness and response during Superstorm Sandy. *Journal of Healthcare Protection Management: Publication of the International Association for Hospital Security*, *31*(1), 31–50. Retrieved from https://oig.hhs.gov/oei/reports/oei-06-13-00260.pdf

Lin, N., & Emmanuel, K. (2016). Grey swan tropical cyclones. *Nature Climate Change*, *6*(1), 106–111. https://doi.org/10.1038/nclimate2777

Maloney, M. C., & Preston, B. L. (2014). A geospatial dataset for U.S. hurricane storm surge and sea-level rise vulnerability: Development and case study applications. *Climate Risk Management*, *2*, 26–41. https://doi.org/10.1016/j.crm.2014.02.004

Marsooli, R., Lin, N., Emanuel, K., & Feng, K. (2019). Climate change exacerbates hurricane flood hazards along US Atlantic and Gulf Coasts in spatially varying patterns. *Nature Communications*, *10*(1), 1–9. https://doi.org/10.1038/s41467-019-11755-z

MATLAB. (2019). MATLAB (version 9.6) [Software]. The Mathworks, Inc. Retrieved from https://www.mathworks.com/products/matlab.html

Melin, K., & Rodríguez-Díaz, C. E. (2018). Community pharmacy response in the aftermath of natural disasters: Time-sensitive opportunity for research and evaluation. *Journal of Primary Care and Community Health*, *9*, 215013271881349. https://doi.org/10.1177/2150132718813494

Michanowicz, D., Tarabochia-Gast, A., & Bernstein, A. (2022). Hospital and road inundation risk data [Dataset]. https://doi.org/10.7910/DVN/TYOHSF

National Oceanic and Atmospheric Administration. (2009). Sea level variation of the United States, 1854–2006 (Technical Report NOS CO-OPS 053). Retrieved from https://tidesandcurrents.noaa.gov/publications/Tech_rpt_53.pdf

National Oceanic and Atmospheric Administration. (2013). National coastal population report population trends from 1970 to 2020. Retrieved from https://aambpublicoceanservice.blob.core.windows.net/oceanserviceprod/facts/coastal-population-report.pdf

National Oceanic and Atmospheric Administration. (n.d.). Historical hurricane data. Retrieved from https://coast.noaa.gov/hurricanes/

Nogueira, L. M., Sahar, L., Efstathiou, J. A., Jemal, A., & Yabroff, K. R. (2019). Association between declared hurricane disasters and survival of patients with lung cancer undergoing radiation treatment. *JAMA, the Journal of the American Medical Association*, *322*(3), 269. https://doi.org/10.1001/jama.2019.7657

Oak Ridge National Laboratory Geographic Information Science and Technology Group. (2016). Homeland infrastructure foundation-level data (HIFLD) database [Dataset]. Retrieved from https://gii.dhs.gov/HIFLD

Quast, T., & Feng, L. (2019). Long-term effects of disasters on health care utilization: Hurricane Katrina and older individuals with diabetes. *Disaster Medicine and Public Health Preparedness*, *13*(4), 724–731. https://doi.org/10.1017/dmp.2018.128

RStudio Team. (2020). RStudio: Integrated development environment for R (Version 1.3) [Dataset]. Retrieved from https://rstudio.com

Runkle, J., Svendsen, E. R., Hamann, M., Kwok, R. K., & Pearce, J. (2018). Population health adaptation approaches to the increasing severity and frequency of weather-related disasters resulting from our changing climate: A literature review and application to Charleston, South Carolina. *Current Environmental Health Reports*, *5*(4), 439–452. https://doi.org/10.1007/s40572-018-0223-y

Sallenger, A. H., Doran, K. S., & Howd, P. A. (2012). Hotspot of accelerated sea-level rise on the Atlantic coast of North America. *Nature Climate Change*, *2*(12), 884–888. https://doi.org/10.1038/nclimate1597

Shuler, M., Suzuki, S., Podesta, A., Qualls-Hampton, R., & Wallington, S. F. (2017). A post-hurricane Katrina examination of substance abuse treatment discharges with co-occurring psychiatric and substance use disorders. *Journal of Dual Diagnosis*, *13*(2), 144–156. https://doi.org/10.1080/15504263.2016.1277816

Sweet, W. V., Horton, R., Kopp, R. E., LeGrande, A.N., & Romanou, A. (2017). Sea level rise. In D. J. Wuebbles, et al. *Climate Science Special Report: Fourth National Climate Assessment, Volume I* (pp. 333–363). U.S. Global Change Research Program. https://doi.org/10.7930/J0VM49F2

Sweet, W. V., Kopp, R. E., Weaver, C. P., Obeysekera, J., Horton, R. M., Thieler, E. R., & Zervas, C. (2017). Global and regional sea level rise scenarios for the United States.

United States Census Bureau. (2018). Metropolitan and micropolitan statistical areas population totals and components of change: 2010–2019. Retrieved from https://www.census.gov/data/datasets/time-series/demo/popest/2010s-total-metro-and-micro-statistical-areas.html

U.S. Department of Homeland Security. (2019). Homeland infrastructure foundation-level data (HIFLD). Retrieved from https://hifld-geoplatform.opendata.arcgis.com/datasets/hospitals

References From the Supporting Information

City of New York. (n.d.). Sandy inundation zone. Retrieved from https://data.cityofnewyork.us/Environment/Sandy-Inundation-Zone/uyj8-7rv5

NYC Special Initiative for Rebuilding and Recovery. (2013). A stronger more resilient New York. Retrieved from https://www1.nyc.gov/site/sirr/report/report.page