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A Scenario-based Optimization Model for Long-term Healthcare Infrastructure Resilience against Flooding

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Abstract

The total cost for weather-related disasters in the US has been increasing. Storms and storm-induced flooding usually create the most damage. One way to minimize the impact of damages due to floods is to increase the resilience of lifeline infrastructures (power grids, transportation, healthcare, etc.) via proactive flood mitigation efforts. In this paper, we propose a stochastic optimization model that provides hospital and nursing home hardening decisions in preparation for a variety of flood scenarios. Scenarios are generated using the state-of-the-art physics-based flood models (WRF-Hydro and SLOSH) for two types of floods, inland river flooding, and storm surge, using historical and simulated storms. The model then identifies hospitals and nursing homes susceptible to flooding and considers the costs of evacuating facilities to inform the hardening decisions and apportion the budget spent on hardening vs recovery. The computational study focuses on Texas, with special emphasis on the coastal areas and the Southeast Texas region, considering the actual healthcare facility locations in the region.

Keywords
Mitigation vs Recovery, Flood Resilience, Scenario Generation, Stochastic Optimization, Healthcare Infrastructure

1. Introduction and Problem Description

The U.S. has sustained 308 weather and climate disasters since 1980 where overall damages/costs reached or exceeded \$1 billion, and the total cost of these 308 events exceeds \$2 trillion. Hurricanes and hurricane-induced inland and coastal floods have caused the most damage and have the highest average event cost (\$20.3 billion per event) [1]. In 2017, Hurricane Harvey hit Texas and caused record-breaking rainfall over a week, which induced catastrophic flooding over a large area of southeastern Texas. It is the deadliest hurricane to hit Texas since 1919, and the second-costliest U.S. tropical cyclone (\$125 billion) after Hurricane Katrina (\$161.3 billion in 2017 dollars) [2]. The 1980–2020 annual average for billion-dollar disasters is 7.1 events, while the annual average for the most recent 5 years (2016–2020) is 16.2 events, 12 of which are severe storms and tropical cyclones [1]. These figures and the increase in the frequency of these “rare” storms with aftermath costs of billions motivate planning for longer-term investments to mitigate the impacts of future disasters.

Mitigation, preparedness, response, and recovery are four phases of emergency management defined by the Federal Emergency Management Agency (FEMA) [3]. In this paper, we focus on mitigation phase investments to increase the resilience of healthcare facilities against storm-induced floods. In our context, building flood defenses including floodwalls, and specialized doors and windows, installing a backup generator, and always keeping a 3-day food supply are among mitigation efforts for hospitals and nursing homes. Relocating generators, electricity rooms, and medicine/food supplies to upper floors are other ways to increase the resilience of healthcare facilities during the mitigation phase. If an emerging storm is a major hurricane like Hurricane Harvey, Ike, or Rita, Regional Advisory Councils (non-profit governmental organizations) plan and coordinate all preparedness stage activities within the 48-hour period before the hurricane landfall. These activities include choosing staging areas, positioning emergency vehicles (e.g., ambulances), and planning and executing the evacuations. Any applicable activity which has not been performed as a permanent hardening during the mitigation phase can be done temporarily in the preparedness stage (e.g., moving medicine supplies to upper floors). Finally, response activities include search and rescue missions while recovery activities include rebuilding damaged structures and caring for patients during the disaster.

FEMA is involved in disaster management both to support facilities financially in their mitigation efforts and to help during and after the event with disaster relief packages for the damaged facilities. In this paper, we build a model that is beneficial to FEMA or other regional governmental organizations to prioritize healthcare facilities and their relative funding for permanent hardening investments to reduce future flood preparedness, response, and recovery costs. To achieve this, we propose a scenario-based optimization model that integrates physics-based flood models with decision making models to recommend optimal resilience planning for healthcare facilities.

Our paper is organized as follows: Section 2 reviews existing work in the literature while Section 3 introduces the notation and explains the mathematical model. Section 4 introduces the actual healthcare network from southeast Texas and flood scenarios generated from Hurricane Harvey along with the parameters used in the sensitivity analysis. We present the results of the sensitivity analysis with zero-budget and unlimited-budget benchmarks in Section 5. We also assess some properties of facilities chosen to be hardened in the optimal resilience plan. Finally, Section 6 presents conclusions and future research directions.

3. Related Research

Scenario-based optimization has been used in the literature to determine permanent hardening investments against extreme weather events like hurricanes [4, 5] and winter storms [6]. These studies mostly seek to increase power infrastructure resilience. However, in healthcare infrastructure, there is little research on enhancing nursing home and hospital resilience. Several studies focus on health system resilience by capacity planning and resource allocation to enhance response and recovery with the surge of patients after the disaster [7] whereas others study patient evacuations during the preparedness phase [8]. In terms of mitigation applications in healthcare facilities against hurricane-induced flooding, FEMA has best practice reports [9, 10]. Our methodology is similar to [4]. However, our lifeline infrastructure is healthcare facilities rather than the power grid and our future costs are patient evacuation and facility-recovery costs.

4. Methodology

We introduce the nomenclature for our formulation, starting with sets and parameters, followed by decision variables.

J	Set of hospitals (J_H) and nursing homes (J_N)
S	Set of flooding scenarios
C_j^G	Cost of emergency generator per kW
C^H	Cost of permanent hardening per bed count per level of hardening
C^E	Cost of evacuation and recovery per patient
k_j	Back-up power at facility j
b_j, d_j	Bed capacity and number of patients at facility j, respectively
τ	Expected number of storms per year
T	Investment horizon in years
B	Investment budget
r	Discount rate
p_s	Probability of scenario s
M	Very large number
β_{sj}	Flood level considering both inland flooding and storm surge at facility j, in scenario s
x_j	Binary variable - 1 if facility j is chosen for deployment/upgrade of a backup generator as the first step of permanent hardening
y_j	Integer variable indicating flood level to which the facility j is hardened
γ_{sj}	Binary variable - 1 if facility j is flooded in scenario s even if hardened

The modeling methodology is two-stage stochastic optimization that considers the costs of response and recovery in the individual flood scenarios in the second stage to inform permanent hardening decisions at each healthcare facility in the first stage. We consider nursing homes and hospitals as facilities. The overall model is as follows:

$$\min\left(\sum_{j\in J} C_j^G k_j x_j + C^H b_j y_j\right) + \frac{(1+r)^T - 1}{r(1+r)^{T-1}} \cdot \tau \sum_{s\in S} p_s \left(\sum_{j\in J} C^E d_j \gamma_{sj}\right) \tag{1}$$

subject to:

$$\sum_{j\in J} C_j^G k_j x_j + C^H b_j y_j \leq B \tag{2}$$

$$y_j \leq x_j M \qquad \forall j \in J, \tag{3}$$
$$\beta_{sj} \leq y_j + \gamma_{sj} M \qquad \forall s \in S, j \in J, \tag{4}$$
$$\beta_{sj} \geq y_j - (1 - \gamma_{sj}) M \qquad \forall s \in S, j \in J, \tag{5}$$
$$y_j \in Z^+ \qquad \forall j \in J, \tag{6}$$
$$x_j, \gamma_{sj} \in \{0,1\} \qquad \forall s \in S, j \in J. \tag{7}$$

Objective function (1) minimizes the total spending on permanent hardening and expected response and recovery expenditures due to flooding over a T-year horizon. We assume that we invest at time 0, and no more hardening is done later in the time horizon. The first term captures acquisition of emergency generators and structural hardening investments at time 0. When the term *hardened facility* is used in this paper, we mean that it has both a back-up generator and structural flood resilience to a certain level. We assume that hospitals already have a back-up power due to regulatory enforcement while nursing homes do not have one. With this assumption, C_j^G significantly lower for hospitals than that of nursing homes since nursing homes need to purchase the generator whereas hospitals only need to upgrade the generator or relocate it to upper floors. In the second term, $\tau \sum_s p_s \left(\sum_j C^E d_j \gamma_{sj}\right)$ is the expected annual evacuation and recovery (i.e., "damage fixing") cost of the facilities not hardened enough in the first stage. When multiplied by the coefficient in front of the sum, the second term turns into the discounted total expected cost.

Neither C^H in the first nor C^E in the second term differentiate in terms of hospital versus nursing home. They are constant. We multiply the former by the size, b_j, and the level of hardening, y_j, to calculate the structural hardening cost at facility j by assuming that the size of the facility is proportional to the bed count, and we multiply the latter by the demand, d_j, to get response and recovery cost for facility j.

There could be variable costs such as fuel or maintenance costs of the emergency generator before each hurricane season. However, we ignore them in the model since it is from the perspective of a governmental organization trying to allocate hazard mitigation funding rather than a perspective of an individual facility and its costs.

Constraint (2) stipulates the investment at time 0 to be lower than budget B. In constraint (3), the hardening level against flooding is set to zero if a facility does not have a generator. Even though we consider flood mitigation to a certain level (say via flood walls or doors) for a facility, it must evacuate because we have not installed a back-up generator. If patients shelter in place at those facilities, their health condition would deteriorate due to heat (loss of air conditioning). Thus, connecting structural hardening, y_j, to having backup generator, x_j, is essential. We also choose not to limit the level of hardening, y_j, with a tighter upper bound since we minimize it with the objective function. Additionally, constraint (4) forces binary variable γ to be 1 if the facility is inundated, ($\beta_{sj} - y_j$), even if it is hardened in the first stage to flood level y_j. Constraint (5) forces γ to be 0 if the facility is considered not flooded. Finally, constraints (6) and (7) stipulate variables to be either non-negative integer or binary.

5. Results

5.1. Case Study

We use hospital (J_H) and nursing home (J_N) data sets from the Homeland Infrastructure Foundation Level-Data (HIFLD)[1]. By filtering applicable locations in the southeast Texas region (i.e., Houston-Galveston area, including Harris County, which is the third largest in the U.S.), we obtain 170 hospitals and 702 nursing homes to apply and test our model. We utilize 25 flood scenarios generated by running hydrological models for both inland (WRF-Hydro) and coastal flooding (SLOSH Display) using Hurricane Harvey [11]. Using Hurricane Harvey as a test instance is important since it caused heavy flooding and patient evacuations in the region in 2017. With these test instances, without hardening, there are 215 facilities flooded in at least one of the scenarios, 45 of which are hospitals. **Figure 1.a** shows the impact of flood scenarios on the hospitals.

In the model, we install a back-up generator as a first step of permanent hardening. Acquisition, installation, and other related costs of it for nursing homes, C^G, is around \$300-450 per kW depending on the brand, and we set it at \$300 and \$450 in our parametric study. We assume that the cost is 10 times lower for hospitals since they only need upgrades

1 https://hifld-geoplatform.opendata.arcgis.com/datasets/hospitals

and reinstallations. Back-up power for facility j, k_j, converts bed count of facility j first into area (400 sq feet/bed)[2], then power to be enough for 92 hours (50 kW + 4 kW/bed $\cdot\, b_j$)[3].
After tropical Storm Allison hit Texas in 2001, the Texas Medical Center with 42 medical institutions, 19 of which are hospitals, incurred over \$2.03 billion in damage due to flooding [9]. We may consider this case as an extreme example for the aftermath cost. Given they have 9,200 patient beds, the recovery cost is almost \$200,000 per patient. Also, Lourdes Hospital in New York had a loss of \$20M during flooding due to Storm Lee in 2006 [10]. Given they have 197 patient beds, the recovery cost is almost \$100,000 per patient. These losses are high since they are comprehensive for a facility, but they include costs that may not be eligible for grant funding by either FEMA or state. That is why we decide to use a response and recovery cost, C^E as \$20,000 and \$40,000 per patient in our parametric study. The response (evacuation mission cost) comprises a small portion in this unit cost. For mass evacuations, the cost of evacuation including transportation, housing, and food was \$1,000 per person in the aftermath of Hurricane Harvey in Texas[4]. On the other hand, evacuation of people with special needs requires more resources. Depending on how spread-out evacuating facilities are, how many patients they have, and time left before hurricane landfall, the cost may change tremendously because emergency vehicles must perform single or multiple trips to transport patients to safe locations, which changes the quantity of vehicles, and in return alters the total evacuation cost.

Additionally, a \$7M mitigation project of Lourdes Hospital [10] included closure structures, interior drainage, passive flood gates, pumping stations, utility relocations, letter of map revision, and the development of an operation and maintenance plan. We use its permanent hardening investment ($C^H \approx \$3{,}000$ per bed count per hardening level (ft)) as a reference since Lourdes Hospital makes the building flood resilient from scratch. We also set C^H at \$4,500 because buildings would need more protection in the future with more intense disasters.

In the last 42 years, 84 storms hit the Texas coastline, 17 of which are the deadliest major hurricanes including Hurricane Harvey in 2017 and Ike in 2008. Given our model considers permanent hardening investment decisions against major hurricanes that cause catastrophic flooding and damage, we use the expected number of annual storms, $\tau = 0.4\ (17/4)$. We also test $\tau = 2\ (84/42)$ as an extreme case given the expectation of more intense and wet tropical cyclones due to climate change.

Finally, the discount rate[5], r = 7 % is used to adjust the future flood related costs since it is the rate suggested for government investment and regulatory analyses by the Office of Management and Budget (OMB). We use investment horizon as 10 yrs, and we assume the 25 flood scenarios are equiprobable.

5.2. Results

We use Python-based optimization tool, Pyomo, to implement the stochastic optimization model instantiated with the data from the previous section and use Gurobi to solve the model to optimality. We perform sensitivity analysis for the model without budget limit by permuting the following values of parameters: C_j^G= \$300, \$450; C^H= \$3,000, \$4,500; C^E= \$20,000, \$30,000, \$40,000; T= 5,10 years, and τ = 0.4, 2. From 48 unique settings of parameters, **Table 1** illustrates six of the settings (with T=10 and C_j^G=\$450) and their results facilitating insights into general trends common in all settings. In the table, the first three columns display the parameters (expected number of storms - τ, evacuation cost per patient - C^E, and permanent hardening cost – C^H) used in each setting. The next two columns show the properties of the chosen facilities to be hardened in the optimal solution. The column labeled “Quantity” shows the numbers of hospitals and nursing homes hardened, and their total, respectively. The column labeled “Level of Hardening” shows the highest and mean flood level hardening in feet across all hardened facilities. “Optimal Spending” columns display the objective value (Total) in millions of dollars and its allocation between “Hardening” and “Expected Recovery” cost. Finally, the last two columns show the total costs in millions of dollars obtained with zero facilities hardened (“None”) and all facilities hardened to their maximum level (“All”) to compare with the optimal objective value.

Before comparing different parameter settings, we present the results of setting 5 as our base case. With zero investment budget, the expected cost of future floods is \$342M. The optimal plan has a total cost of \$261M and

2 https://seniorcare.levinassociates.com/2017/07/03/paying-square-footage-skilled-nursing/

3 https://www.genpowerusa.com/blog/how-to-calculate-commercial-generator-size

4 https://law.utexas.edu/news/2018/09/14/the-cost-of-emergency-evacuation/

5 https://www.energy.gov/sites/default/files/2021-04/2021discountrates.pdf

suggests hardening 75 facilities out of 215 flooded locations in at least one scenario. The maximum level of hardening among those facilities is 5 feet while maximum flood level among all scenarios is 17 feet. In comparison, the optimal plan with budget \$50M has a total cost of \$272M and suggests hardening 46 facilities, with the maximum hardening level of 4 feet across facilities.

Table 1: Results of Sensitivity Analysis

	Settings			Hardened Facilities - Optimal		Optimal Spending \$M			Hardening \$M	
	τ	C^E	C^H	Quantity (H,N,Total)	Level of Hardening (Max,Mean)	Hardening	Expected Recovery	Total	None	All
1	0.4	\$20,000	\$3,000	(26,79,105)	(12,3)	\$100	\$123	\$223	\$342	\$321
2	0.4	\$40,000	\$3,000	(41,129,170)	(17,4)	\$226	\$69	\$295	\$683	\$321
3	2	\$20,000	\$3,000	(45,164,209)	(17,5)	\$316	\$4	\$320	\$1,708	\$321
4	2	\$40,000	\$3,000	(45,170,215)	(17,5)	\$321	\$0	\$321	\$3,415	\$321
5	0.4	\$20,000	\$4,500	(22,53,75)	(5,2)	\$102	\$159	\$261	\$342	\$470
6	0.4	\$40,000	\$4,500	(35,108,143)	(12,3)	\$219	\$154	\$373	\$683	\$470

As we expect more intense hurricanes like Harvey, the importance of mitigating flood risks grows tremendously because otherwise we must face its catastrophic consequences as in setting 3. Almost all facilities (97%) are hardened since leaving the facilities as is (without any hardening, "None") has a total cost almost six times that of the "All" hardened solution. We also observe that when the parameter settings are such that an optimal solution is close to the solution of "All", inducing more hardening by changing a parameter's value does not alter the results (setting 3→4). Furthermore, when the permanent hardening cost, C^H, increases (setting 2→6), the model hardens fewer facilities, by choosing facilities with lower flood levels.

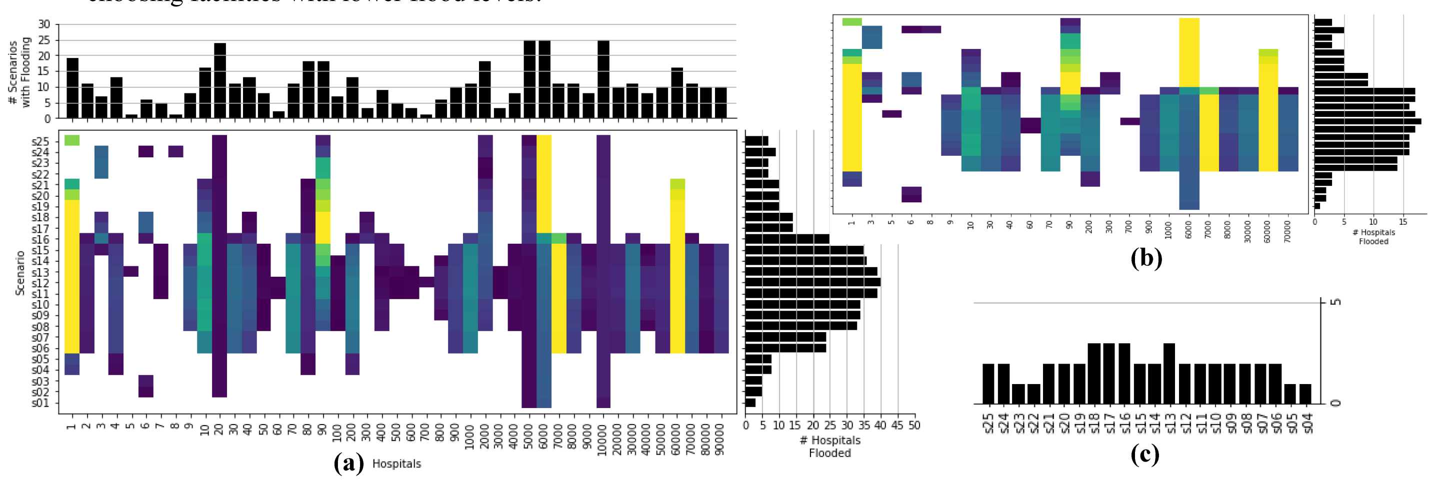

Figure 1: (a) Flooding in 45 Hospitals in each scenario **before** mitigation (hospitals are sorted by their size in ascending order from left to right). Colors represent flood level ranges. When it is dark blue, the flood level is very low (almost zero). As the flood level increases, the color is lighter until it is yellow, an indication of the highest flood level. The top bar chart shows the number of scenarios each facility gets inundated in. The right bar chart depicts the number of hospitals flooded in each scenario. **(b)** Flooded Hospitals **after** mitigation in setting 5. **(c)** The bar chart shows the number of hospitals flooded in each scenario **after** mitigation in setting 2.

Figure 1 depicts 3 figures about flooded hospitals at each scenario before and after mitigation. We only show hospitals in these figures rather than all flooded facilities, but the results do not change according to facility type. **Figure 1.a** shows flooded hospitals at each scenario before mitigation. We observe which scenarios each hospital gets inundated in, and flood levels in those scenarios by the color change. At the top, the bar chart demonstrates the number of scenarios in which a facility is inundated. At the right, the bar chart shows how many hospitals are flooded in each scenario. Whenever mitigation over recovery is more feasible, more facilities become resilient via hardening to even the worst scenarios (11, 12, and 13). Then, this bar chart is closer to uniform as in setting 2 shown in **Figure 1.c**. However, if the aftermath cost per patient, C^E, and the expected number of future hurricanes, $T \cdot \tau$ are low, in other words, if the model does not choose mitigation over recovery for most of the facilities as it is in setting 5, the number of hospitals flooded bar chart is not close to uniform, but similar to the one in **Figure 1.a**, but with fewer flooded hospitals in most of the scenarios. **Figure 1.b** demonstrates flooded hospitals after mitigation in setting 5. When we analyze hardened facilities and their resilience levels, we discover common features in those facilities chosen to be hardened: (1) they consistently get inundated to similar flood levels in many scenarios, (2) flood levels are below 5 feet, and (3) the hardened facilities mostly become resilient to all the flood scenarios. The ones not fully hardened have higher flood-levels in some of the scenarios compared to the others chosen to be fully hardened. If we look at the dark blue vertical lines in **Figure 1.a** (Hospitals 10000, 5000, 2000, 80, and 20), they consistently have very low flood levels throughout the scenarios. It means that if we do not apply permanent hardening, they will regularly experience flooding in the future. As expected, they are not part of **Figure 1.b** since they get fully hardened during the mitigation, and they are not flooded in any of the scenarios. On the other hand, although Hospital 5 has a low flood level (dark blue), it is not selected for mitigation since it is flooded only in scenario 13. Flooding to similar levels in many scenarios, the consistency, is an essential factor in decision making. It is indeed intuitive because if a facility is expected to be regularly inundated to a similar level, it is better to increase its resilience to endure those flood events.

An analysis of the optimal solutions reveals that when two facilities have identical flood profiles in each scenario, larger one is typically chosen for hardening. Therefore, the number of scenarios in which a facility is flooded, flood level consistency in those scenarios, and facility size are main drivers to choose a facility for hardening.

6. Conclusions

We propose a scenario-based optimization model to decide on resiliency planning of healthcare facilities and show how mitigation investments change with different parameter settings. An organization (e.g., FEMA) could utilize our model to prioritize the projects and find their optimal hardening level to allocate grant funds for mitigation by considering uncertainty of future costs. One limitation of our current study is generation of flood scenarios from historical data of Hurricane Harvey which we may consider as worst-case for Texas. However, when we consider climate change and population growth in big cities, a location that has never experienced flooding in the past would start getting inundated in the future. Increasing intensity or number of past flood events may be inadequate to consider future flood risks. Finally, flood events in general must be considered rather than simulating only hurricane-induced ones for future research.

References

[1] NOAA National Centers for Environmental Information (NCEI), "U.S. Billion-Dollar Weather and Climate Disasters," 2021, doi: 10.25921/stkw-7w73.

[2] B. S. Eric and Z. A. David, "National Hurricane Center Tropical Cyclone Report: Hurricane Harvey," National Hurricane Center, 2018.

[3] FEMA, "Unit Four : Emergency Management in the United States. https://training.fema.gov/emiweb/downloads/is111_unit%204.pdf."

[4] L. Souto *et al.*, "Power system resilience to floods: Modeling, impact assessment, and mid-term mitigation strategies," *International Journal of Electrical Power & Energy Systems*, vol. 135, p. 107545, 2022, doi: https://doi.org/10.1016/j.ijepes.2021.107545.

[5] A. Shukla, J. Hasenbein, and E. Kutanoglu, "A Scenario-based Optimization Approach for Electric Grid Substation Hardening Against Storm Surge Flooding," *IIE Annual Conference Proceedings*, pp. 1004–1009, 2021.

[6] B. Austgen, M. Garcia, B. Pierre, J. Hasenbein, and E. Kutanoglu, "Winter Storm Scenario Generation for Power Grids Based on Historical Generator Outages," 2022. *Working Paper.*

[7] A. H. Aghapour, M. Yazdani, F. Jolai, and M. Mojtahedi, "Capacity planning and reconfiguration for disaster-resilient health infrastructure," *Journal of Building Engineering*, vol. 26, p. 100853, 2019, doi: 10.1016/j.jobe.2019.100853.

[8] K. Y. Kim, E. Kutanoglu, J. Hasenbein, W.-Y. Wu, and Z.-L. Yang, "A Large-Scale Patient Evacuation Modeling Framework using Scenario Generation and Stochastic Optimization," *IIE Annual Conference. Proceedings*, pp. 67A-72A, 2020.

[9] FEMA, "Hospital Gears Up to Combat the Flood," Feb. 11, 2021. https://www.fema.gov/case-study/hospital-gears-combat-flood [Accessed Jan. 17, 2022].

[10] FEMA, "Advanced Mitigation Planning Allows Hospital to Stay Dry During Tropical Storm: Full Mitigation Best Practice Story," Aug. 2012.

[11] K. Y. Kim, W.-Y. Wu, E. Kutanoglu, J. J. Hasenbein, and Z.-L. Yang, "Hurricane Scenario Generation for Uncertainty Modeling of Coastal and Inland Flooding," *Frontiers in Climate*, vol. 3, (16 pages), 2021, doi: https://doi.org/10.3389/fclim.2021.610680.