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A stochastic optimization model for patient evacuation from health care facilities during hurricanes

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ABSTRACT

We propose a rigorous modeling and methodological effort that integrates statistical implementation of hydrology models in predicting inland and coastal flood scenarios due to hurricanes and a scenario-based stochastic integer programming model which suggests resource and staging area decisions in the first stage and the evacuation decisions in the second stage. This novel study combines physics-based flood prediction models and stochastic optimization for large-scale multi-facility coordination of hospital and nursing home evacuations before impending hurricanes. The optimization model considers scenario-dependent evacuation demand, transport vehicles with varying capacities, and both critical and non-critical patients. Utilizing Hurricane Harvey of 2017 as a case study and actual healthcare facility locations in southeast Texas, we explore various evacuation policies, demonstrating the impact of routing strategies, staging area decisions, flood thresholds, and receiving facility capacities on evacuation outcomes. One of the findings is that choosing staging area(s) and deploying evacuation vehicles optimally considering the uncertainty of the hurricane's path at the time of decision making could have significant effect on the total cost of the operation and evacuation time experienced by the evacuees. We also show the non-negligible value of the scenario-based staging and routing solution conservatively calculated in relation to a single scenario solution using the concept of value of stochastic solution.

1. Introduction

Since 1980, the U.S. has sustained 263 weather and climate disasters where the overall damage costs reached or exceeded $1 billion, with a total cost exceeding $1.7 trillion. In particular, the years 2017, 2018, and 2019 alone accounted for 44 events with a total cost of $460 billion, with major hurricanes contributed more than 85% of the total bill [1]. Such hurricanes obviously have varying destructive capabilities, with the primary issue being catastrophic flooding. Hurricane Harvey in 2017, which was the most significant tropical cyclone rainfall event in U.S. history, caused catastrophic flooding in Harris and Galveston counties in Texas [2]. Similarly, Hurricane Maria in 2017 devastated Puerto Rico, resulting in widespread power outages and infrastructure damage [3]. The most notable hurricane with catastrophic damage by storm surge was Hurricane Katrina in 2005. During Katrina, storm surge-induced flooding up to 28 ft above normal tide levels caused most of the deaths in Louisiana and its miserable aftermath in the New Orleans area [4]. Given these disastrous events, federal, state, and local agencies engage in joint efforts to prepare for future hurricanes and other disasters. Especially for decisions like mobilizing resources and prepositioning supplies for rescue and recovery missions, which take place before an imminent but forecasted disaster such as a hurricane, the agencies have relied on

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weather forecasts, hurricane track and intensity models and flood prediction tools, all developed to support preparedness decision making.

Typically, preparedness decision making require plans for resource mobilization involving the safety of millions of citizens. These activities include prepositioning emergency supplies, making evacuation plans if necessary, opening and operating shelters, rescuing stranded people and animals, and of course rebuilding in the aftermath. In this paper, we focus our attention on the *patient evacuation problem*, which is a challenge to be tackled in almost every major hurricane event. At a high level, the problem deals with coordinating activities, allocating resources, and actually moving patients from hospitals and nursing homes in an area expected to be affected by the disaster to hospitals and other facilities outside the affected area. Although our focus, examples, and terminology use hurricanes as the unfortunate looming disaster, the underlying model can be used with some modification in other events such as fires and floods (not necessarily due to hurricanes). The main characteristic of the event under consideration for our focus is that it is predictable, such as a hurricane.

A review of the relevant literature (summarized in Section 2) indicates that most patient evacuation studies have focused on single hospital evacuations and have only considered one decision making point in time. Typically this point is the latest time the patients can be safely moved, just before the predicted landfall. We consider the large scale, multi-facility version of the problem, from the point of view of a state or federal agency, such as South East Texas Regional Advisory Council (SETRAC), which is the agency motivating our case study later in Section 4. Specifically, the agency must site and allocate patient evacuation resources (mainly vehicles and medical personnel), coordinate patient evacuation from multiple affected hospitals/nursing homes to multiple receiving facilities, and evaluate the costs and timing of these decisions carefully.

With the motivation above in mind, we propose a rigorous modeling and methodological effort that integrates statistical implementation of hydrology models in predicting inland and coastal flood scenarios due to hurricanes and a scenario-based integer programming model. First, we rely on a novel approach to generate comprehensive flood scenarios for hurricane-prone areas. By simulating hurricane landfall locations to generate multiple meteorological inputs, we run the hydrological models that are intended to predict water heights from different sources (inland precipitation and coastal storm surge), generate multiple scenarios, and suggest a technique to marry the outputs of the two models [5]. Consequently, we incorporate both inland flooding and storm surge (coastal flooding) into our scenarios. Using these scenarios, we introduce a stochastic integer programming model which produces resource and staging area decisions in the first stage and evacuation decisions in the second stage. The optimization model deals with pre-hazard evacuation. It considers scenario-dependent evacuation demand, transport vehicles with varying capacities, and both critical and non-critical patients. It is important to note that our methodology can be generalized to different regions and events.

The paper is organized as follows. Section 2 reviews the literature focusing on the evacuation of patients from health care facilities during hurricanes and explores the methodologies applied in modeling patient evacuation. In Section 3, we introduce the two-stage stochastic optimization model. Data from the Hurricane Harvey case study with actual health care facilities in southeast Texas region is described in Section 4. We present a comprehensive sensitivity analysis and discuss results and insights of this analysis in Section 5. We conclude and outline several future research directions in Section 6.

2. Literature review

Evacuation operations modeling has predominantly focused on general population evacuations, employing network flow models and simulation modeling to understand and plan for evacuation operations in several settings [6–10]. Early network flow models aim to move people efficiently from source to sink nodes, assuming homogeneous human behavior. To address time-dependent evacuations, dynamic network flow models are introduced, including seminal work by Ford and Fulkerson [6]. Studies like the quickest path problem and quickest flow problem contribute to the field by optimizing flow rates along single or multiple paths [7,8]. A relatively dated review of this literature is Hamacher and Tjandra [9]. Additionally, both Bayram and Yaman [11] and Hasan et al. [12] develop models for mass evacuations, addressing various aspects such as evacuation strategies, resource allocation, and zoning. In contrast to mass evacuations, the evacuation of individuals with special needs, particularly from healthcare facilities, presents unique challenges as they involve patients at greater risk during transport, emphasizing the need for decision support in the form of mathematical or simulation modeling [13,14]. Our study underscores the importance of addressing these complexities.

An important part of the evacuation problem, for either general or special populations, involves careful preparation and staging of resources before the evacuations take place. Regarding this phase of decision making, Balcik et al. [15] survey inventory management models in both predisaster and postdisaster phases, highlighting concerns like multi-item management, capacitated facilities, variable lead times, and diverse cost elements that merit further exploration. Sabbaghtorkan et al. [16] provide a more recent literature review on prepositioning relief supplies. Additionally, Bera et al. [17] develop a framework for selecting emergency evacuation shelter locations for multi-disaster impact planning, encompassing floods and landslides, utilizing P-median and maximal covering location problem methodologies. Bayram [18] provides a comprehensive review of evacuation planning literature, encompassing static/dynamic, deterministic/stochastic/robust evacuation modeling with a focus on network and traffic assignment methods. Noting the extensive work on general population evacuation, this review advocates targeted research for evacuating individuals with special needs, utilizing centrally controlled transportation means. Yazdani et al. [19,20] have two recent reviews of the studies focusing on hospital evacuation operations. For single hospital evacuations, Tayfur and Taaffe [21] propose a deterministic mixed-integer linear programming model for staff and vehicle resource allocation, minimizing costs while meeting predefined evacuation time constraints. They also employ a simulation-based approach to estimate evacuation times from hospitals.

Tayfur and Taaffe [22] introduce a stochastic hospital evacuation model that combines simulation and optimization techniques to address the probabilistic nature of disasters, optimizing transport requirements while minimizing costs within predefined evacuation time constraints. Paul and MacDonald [23] present a stochastic framework for determining the location and capacities of distribution centers for emergency stockpiles, utilizing an evolutionary optimization heuristic. Bish et al. [24] propose an integer programming model to minimize expected threat and transportation risks in evacuating a single hospital, considering patient criticality, care requirements, receiving hospital capacities, and vehicle and medical capabilities. Additionally, Aubrion et al. [25] introduce a simulation-based method for single hospital evacuation, when there is imminent risk.

Several studies [26–28] explicitly consider hurricane forecasts updated as the hurricane gets closer to landfall, not for patient evacuation, but for positioning relief supplies in preparation of recovery during aftermath. Some papers utilize stochastic optimization [29,30] and distributionally robust optimization [31] to preposition emergency supplies for disasters in which there is time to prepare for an impending threat but the scope or location of the threat is uncertain. Yazdani et al. [32] address uncertainties associated with hospital evacuation during a flood, proposing a robust possibilistic programming optimization model. Their focus is only on evacuation missions. They also have a separate paper focusing on evacuating the elderly population in the face of flood uncertainty [33]. On the other hand, our study aims to identify optimal staging area locations and allocate emergency vehicles/resources by considering an approaching hurricane, its potential landfall locations, the impact of rainfall and storm surge at these locations, and the subsequent evacuation plans of flooded facilities.

While the location and the capacity of distribution centers for emergency supplies, and the evacuation of patients from multiple hospitals under uncertain events are considered in different studies as highlighted above, to the best of our knowledge, no studies have considered providing a model and solution approach combining staging and patient evacuation for uncertain impacts of hurricane-induced floods. A review of the relevant literature indicates that most patient evacuation studies have focused on single hospital evacuations and have only considered one decision making point in time [21,25,34–36]. Typically this point is the latest time the patients can be safely moved, just before the predicted landfall. Rabbani et al. [37] contribute to the limited research on multiple facility evacuations by employing a bi-objective integer programming model to minimize the total evacuation time and the number of unevacuated patients over multiple periods, considering uncertainties in input data in a single decision making stage. We note that almost all the reviewed papers, including the work of Rabbani et al. [37], rely on fictitious networks or geographies and consider hypothetical scenarios of events that trigger evacuations (if they consider uncertainty or scenarios at all).

We consider the large-scale multi-facility patient evacuation problem under uncertainty. We study impending hurricanes as the event that triggers such evacuations and capture uncertainty surrounding the hurricane's track. We generate scenarios to model this uncertainty to inform two-stage decision making modeled as a stochastic integer program. We motivate the specific formulation from the point of view of a state or federal agency such as SETRAC. Specifically, the agency must site and allocate evacuation resources, coordinate patient evacuation from multiple affected hospitals/nursing homes to multiple receiving facilities, and evaluate the costs and timing of these decisions carefully. We further distinguish our work by utilizing scenarios generated by using the state-of-the-art hurricane forecasting and flood simulation models (one for inland and another for storm-surge flooding [5]) to provide a more pragmatic solution to the problem. We further create a compelling case study using an event that actually triggered large-scale patient evacuations in the Houston-Galveston area in 2017 (Hurricane Harvey). Floodwaters from Hurricane Harvey inundated 23 out of 25 southeast Texas counties covered by SETRAC's Regional Healthcare Preparedness Coalition. As part of the Catastrophic Medical Operations Center (CMOC) activated in response to Harvey, SETRAC evacuated more than 1500 patients from 44 facilities [38,39]. We now discuss in more detail how SETRAC conducts patient evacuation missions in both the preparation (staging) and operational (evacuation) stages to motivate our specific two-stage stochastic optimization formulation.

3. Model

3.1. Overview

Every major hurricane causes flooding with different characteristics. Hurricane Harvey, which was a Category 4 storm in 2017, was the second-most damaging in the U.S. history because of the enormous amount of rainfall that caused flooding in inland locations near Houston. On the other hand, the deadly flooding by Hurricane Sandy was primarily due to the heavy coastal storm surge, resulting in the catastrophic impact to the residents and health care facilities on the Atlantic coast. These examples motivate us to develop comprehensive flood scenarios which consider both inland and coastal flooding when modeling patient evacuation operations.

Pre-event evacuation can result in two major consequences: under-evacuation, where we do not evacuate enough patients, and over-evacuation, in which unnecessary evacuation occurs. It is difficult to quantify and connect the risks and monetary values of these consequences, particularly of under-evacuation, which can harm patients in disastrous ways. Therefore, in this study, we assume that a health care facility is fully evacuated if the location is expected to be flooded above a given threshold level. Each facility has different built-in resilience for flooding and it is known that proportion of nursing homes in FEMA's flood hazard zones is higher than that of hospitals [40], potentially presenting greater danger to residents in nursing homes. Our model is flexible so that we can apply different flooding threshold levels for different facility types (hospitals versus nursing homes) and individual facilities.

To ensure a successful evacuation operation prior to an emerging hurricane, SETRAC determines the candidate staging area locations for emergency medical service (EMS) vehicles and medical personnel. It then decides destinations (receiving hospitals and nursing homes with capacities to accept evacuees) for patients and residents being evacuated from hospitals and nursing homes forecast to be affected from the hurricane. The evacuation operation takes place before the storm makes landfall, and with the latest available hurricane forecasts, SETRAC strives to make the best staging area and then routing decisions. To make all these decisions, SETRAC needs to know which healthcare facilities are going to be impacted. However there is still uncertainty in the hurricane path at the time of decision-making. Fig. 6 illustrates a 5-day Forecast Track and Watch/Warning Graphic advisory, depicting the forecasted track of the storm center and its associated coastal areas. By utilizing the most recent National Hurricane Center (NHC) advisory, potential landfall locations are determined. Subsequently, for each potential landfall location, predicted intensity, direction, and weather data, inland and storm surge hydrological models are employed to determine flood level forecasts at healthcare facilities in the possibly impacted regions. Each predicted landfall location of the storm serves as a scenario within our model. We provide further details on scenario generation in Section 3.2. Given the unique characteristics of hurricane flooding and patient evacuation operations, our evacuation model is a two-stage stochastic program with recourse with an objective of minimizing the expected total evacuation cost across all potential hurricane scenarios. In the first stage, the model determines the staging area locations to house related resources (particularly EMS vehicles) until they are mobilized for evacuations. When a staging area is selected or "opened", the resources can be staged at that location. In our modeling approach, we also consider the number, location, and types of EMS vehicles allocated to staging areas as our first stage decisions. In our stochastic program, these first stage decisions must satisfy the second stage constraints in all scenarios. Then, the second stage decisions route the vehicles first from staging areas to sending hospitals and nursing homes to pick up patients or residents, then transport them to receiving facilities, and finally return to a staging area with the goal of completing the evacuations with minimum time-based and monetary costs.

3.2. Model inputs

In this section, we introduce additional modeling assumptions and parameters used in the flood scenarios and the stochastic programming model. In our application, SETRAC decision makers try to organize the evacuation missions about 48 h before the time of hurricane landfall. The 48-h window reduces the risks of having EMS vehicles being inoperable due to high-speed winds and congested roads. Hence, we assume that the travel time of the emergency medical service vehicles is unaffected by weather related factors and is constant throughout all scenarios for a given origin and destination pair (e.g., from a specific sending hospital to a specific receiving hospital). While the 48-h period preceding the landfall may initially appear sufficient for conducting multiple trips, the time window to even complete such short trips without risking the safety of patients, medical personnel, and vehicles is very short—indeed, well before the landfall. The main issue is that high wind speeds over land start making high-profile vehicles (such as ambulance and AMBUSes used in patient evacuation) transportation unsafe before the hurricane's landfall. There is also a need to return the medical personnel and EMS vehicles to safety (to a staging area) before there is elevated risk. Given that the lives of patients and medical personnel are at risk and there is still uncertainty in hurricane development, evacuation planning is typically carried out conservatively with a significant cushion of time. Therefore, in our model, we utilize single trip (per vehicle) evacuations for each second-stage scenario. We note that making more than one trip could be necessary, particularly when the number of vehicles that can be acquired is less than the evacuation demand (number of patients to be moved). We leave the multi-trip version of the problem for a future study.

For the potential flooding scenarios, S, we use the scenarios generated in Kim et al. [5]. They generate hurricane flood scenarios by sampling from a Gaussian distribution along the Texas coastline. This distribution is based on the National Hurricane Center's (NHC) forecast for Hurricane Harvey made two days before the predicted landfall. They also perturb the atmospheric inputs in accordance with the shifts from their original to the sampled locations. The scenarios are simulated using NHC's storm surge prediction model (SLOSH) for coastal flooding and National Water Center's (NWC) streamflow prediction model (WRF-Hydro) for fluvial inland flooding. Fig. 1 displays 25 landfall locations sampled and we refer to the work of Kim et al. [5] for the details of the scenario generation methodology.

For the two-stage stochastic optimization model, a set I of candidate staging area locations with large paved parking spaces to accommodate vehicles and personnel that are necessary for evacuation operations is chosen. The candidate staging areas are assumed to be chosen such that they are unaffected by any of the hurricane scenarios. The evacuating hospitals and nursing homes (called sending facilities), J, are the health care facility locations that are predicted to suffer from flooding. We assume that the location and availability of potential receiving hospitals and nursing homes, K, are known. The available bed capacities in potential receiving hospitals are determined just before evacuation, and assumed to be known and fixed for the purpose of evacuation operation. This also implies that the available bed capacities remain essentially unchanged from the time that data is obtained to the point of reserving beds for evacuees in the receiving facilities, due to the short period of time. We also assume that the receiving hospitals are safe from the hurricane and cannot be damaged or closed under any of the hurricane scenarios.

The set P represents the two patient types we consider explicitly for evacuation purpose: critical, C, and non-critical, N, $P = \{C, N\}$. Among all the patients, critical patients are those who need special or individual care, and the remaining patients are defined as non-critical. (The model is flexible to handle more patient criticality levels. For the purpose of multi-facility evacuation, the two levels of criticality is sufficient, especially given that we have two major EMS vehicle types, ambulances and AMBUSes.) To transport critical patients, EMS vehicles need to be equipped with special equipment, and in general both ambulances and AMBUSes can transport this type of patient. In large-scale, multi-facility patient evacuation situations, ambulances usually transport both critical and non-critical patients while AMBUSes handle non-critical patients. Although AMBUSes can carry both critical and non-critical patients in general, considering that the limited vehicle personnel cannot handle AMBUSes carrying critical patients, we limit the usage of AMBUSes to non-critical patients only. A regular ambulance, a type A vehicle, is defined to have capacity of 1 patient. An AMBUS, a type B vehicle, that Texas operates has a capacity of 20. We introduce an index v that indicates the vehicle utilization levels in solutions to the optimization problem. If a vehicle of utilization 5 ($v = 5$) is used, this is a vehicle that transports

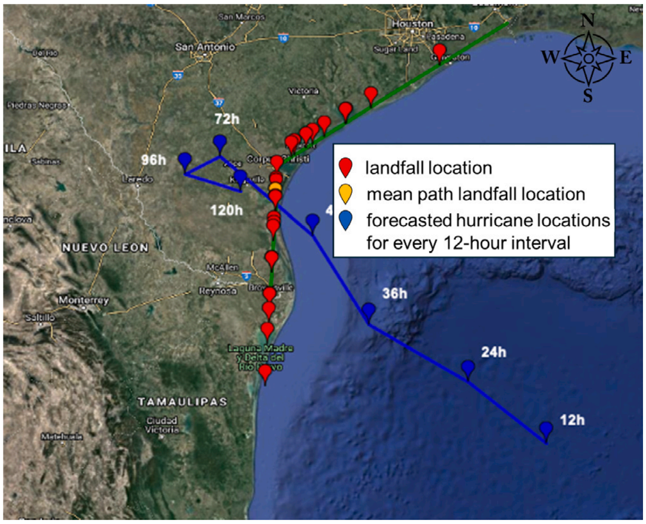

Fig. 1. 25 landfall locations (red drop pins) sampled along the Texas coastline based on Hurricane Harvey's forecast (the blue line shows the track) made by NHC two days before the predicted landfall. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

5 patients. In total, we have 20 utilization levels for AMBUSes and 1 utilization level for ambulances. The sets of vehicle utilization levels are denoted by $V_A = \{1\}$ and $V_B = \{1, \dots, 20\}$, respectively.

Some parameters used in the model can be differentiated by facility type (hospitals, denoted by H, and nursing homes, denoted by N). We incorporate this aspect by defining partitions J_H, J_N of the sending facility set J and partitions K_H, K_N of the receiving facility set K. In our base model, we consider a "restrictive routing" strategy, meaning that patient transports occur only between the same type of sending and receiving facilities. That is, hospital patients, $j \in J_H$ are restricted to evacuation destinations in hospitals, $k \in K_H$, and nursing home patients, $j \in J_N$ are limited to nursing homes, $k \in K_N$, reflecting real-world evacuation practices. We summarize the sets and indices as follows:

I	Set of candidate staging areas, indexed by i
J	Set of potential sending hospitals (J_H) and nursing homes (J_N), indexed by j
K	Set of potential receiving hospitals (K_H) and nursing homes (K_N), indexed by k
F	Set of facility types: hospital and nursing home; $\{H, N\}$, indexed by f
T	Set of vehicle types (ambulance A, and AMBUS B), indexed by t
V_t	Set of ambulance utilizations (V_A) and AMBUS utilizations (V_B), indexed by v
P	Set of patient types (critical C, and non-critical N), indexed by p
S	Set of scenarios, indexed by s

A potential evacuating facility j has certain level of "demand" for patient type p in scenario s, denoted by D_j^{ps}. The evacuation demand of a location (i.e., the number of patients to be evacuated) depends on whether the location is flooded in a given scenario. If the location is expected to experience flood above a threshold level in a scenario, the demand at that location is incurred. Otherwise, the demand is zero. Each receiving location, k, is capable of providing care to a certain number of type p patients. This capacity, denoted by B_k^p, is assumed to be unaffected by the scenario. The capacity of each receiving facility is pre-processed based on three factors: the capacity utilization rate, the proportion of occupied beds, and the proportion of beds for critical and non-critical patients, all at the receiving location. The occupancy rate is defined as the target occupancy (number of filled or occupied beds) after evacuation, calculated as the number of beds occupied after evacuation (the number at the facility before evacuation plus the newly received patients) divided by the total bed count of the receiving facility.

The vehicle utilization index v is a coefficient used to convert the vehicle type decision to the actual number of patients transported. The maximum number of AMBUSes that can be used in the overall evacuation mission is $O_{\max}$. These parameters are summarized as follows:

Constraint Parameters

D_j^{ps}	Demand of facility j for patient type p in scenario s
B_k^p	Total beds available for patient type p at receiving location k
$O_{\max}$	The number of AMBUSes available for evacuation
M	A big number, used in constraints needing big-M

Table 1
Variables in the two-stage stochastic programming formulation.

Symbol	Description
$z_i \in \{0,1\}$	1 if a staging area is opened at location i; 0 otherwise
$q_i^{tv} \in \mathbb{Z}^+$	Number of type t vehicles with utilization v stationed at staging area i
$x_{ij}^{ts} \in \mathbb{Z}^+$	Number of type t vehicles routed along arc ij in scenario s
$x_{jk}^{tvps} \in \mathbb{Z}^+$	Number of type t vehicles with utilization v routed along arc jk with patient type p in scenario s
$x_{ki}^{ts} \in \mathbb{Z}^+$	Number of type t vehicles routed along arc ki in scenario s

In addition, we define the operating costs of EMS vehicles along three types of "arcs", representing the origin and destination pairs that EMS vehicles visit. With the corresponding costs denoted by c_{ij}^t, c_{jk}^{tv} and c_{ki}^t for the three arc types, we calculate them by multiplying the distance of the arc (ij, jk, ki respectively) with per-mile operating cost of vehicle type t. Arc ij represents movement of a vehicle from staging area i to evacuating location j. Arc jk represents a movement of a vehicle from evacuating location j to receiving location k. After vehicles make evacuation trips to receiving hospitals and nursing homes, they return to a staging area i, which is represented by an arc ki. All operating costs depend on the vehicle type t. We also incorporate the variability in vehicle capacity utilization, denoted by v in c_{jk}^{tv}. Furthermore, we assume that the costs associated with higher patient intake at receiving facilities, such as increased staffing, are constant. However, a future research direction would be to investigate potential variations in these costs between different types of receiving facilities, such as nursing homes and hospitals, not just among specific facilities.

We now discuss the remainder of the model parameters. The probability of each scenario is given by p^s. The fixed cost f_i for opening a staging area is a scenario-independent first-stage cost. The total expected transportation cost is computed from the arc costs $c_{ij}^t, c_{jk}^{tv}, c_{ki}^t$ by multiplying the cost per vehicle with the number of vehicles making the specific arc trips. The following summarizes the objective function parameters:

Objective function parameters

f_i	Cost of opening staging area at candidate location i
p^s	Probability of scenario s
c_{ij}^t	Cost of routing a vehicle of type t along an arc ij
c_{jk}^{tv}	Cost of routing a vehicle of type t with utilization v along an arc jk
c_{ki}^t	Cost of routing a vehicle of type t along an arc ki.

3.3. Optimization model

We now provide the formulation for the patient evacuation problem as a two-stage stochastic program. We assume that an agency such as SETRAC makes resource allocation decisions, such as staging areas, at the latest possible time for safety, using the most accurate (latest) forecasts of hurricane development. Although incorporating more than two stages in decision making with evolving hurricane forecasts might be of use in other applications, in our time-sensitive problem, the two-stage model that incorporates the latest forecasts at the safe implementation time of decisions is reasonable representation of the decision process, according to our discussions with practitioners. Therefore, we utilize a two-stage stochastic program. The formulation decides types and number of vehicles assigned to arcs (i.e., making the following trips): (1) from staging areas to sending locations (ij), (2) from sending locations to receiving locations (jk), and (3) finally, from receiving locations back to staging areas (ki). Returning to the staging area is crucial for evacuation vehicles and medical personnel because they are not meant to be on the move. Moreover, it is critical for their safety that they shelter in place. The decision variables used are listed in Table 1. Decision variables x_{jk}^{tvps} determine the number of type t vehicles with utilization v making trips with patient type p in scenario s along arc jk, while $x_{..}^{ts}$ (without the patient type and vehicle utilization indices) determine the number of vehicles along the two types of arcs, ij and ki. Decision variables x_{jk}^{tvps} are only defined for certain jk arcs according to a "restrictive routing" strategy. When the sending facility j is a hospital in J_H, the receiving facility k can only be a hospital in K_H, and the same holds true for nursing homes.

The objective function of the patient evacuation model minimizes the expected total costs. In the literature that discusses optimization of logistics and resource allocation in the disaster preparedness stage, the minimization of cost or expected cost is commonly used. Some papers minimize the makespan of evacuation routes or risks [24] in evacuation procedures. For our stochastic programming model, we choose to minimize an expected cost which takes into account both set up and evacuation costs. In turn, the evacuation costs are dependent on spatial elements (distances) of our evacuation decisions. We do not model risks involved in evacuation explicitly. Our assumptions regarding the operational window, i.e., an undisturbed road network and scenario-independent receiving hospital capacities, ensure that patients are safely transported to receiving locations under any scenario. The risk of over-evacuation is not considered because the cost of under-evacuation is assumed extremely high compared to that of over-evacuation due to the imminent dangers a flooded health care facility presents to patient health. Therefore, all facilities predicted to be flooded above a certain threshold are assumed to be evacuated. We later present experiments that analyze the sensitivity of the results to this threshold.

We now provide the two-stage stochastic patient evacuation formulation:

$$\text{Minimize} \quad \sum_{i\in I} f_i z_i + \sum_{s\in S} p^s \left[\sum_{i\in I, j\in J, t\in T} c_{ij}^t x_{ij}^{ts} + \sum_{\substack{j\in J, k\in K, t\in T,\\ v\in V_t, p\in P}} c_{jk}^{tv} x_{jk}^{tvps} + \sum_{k\in K, i\in I, t\in T} c_{ki}^t x_{ki}^{ts} \right] \tag{1a}$$

Subject to

$$\sum_{k\in K_H} x_{jk}^{A,1,C,s} = D_j^{C,s} \qquad \forall j \in J_H, s \in S, \tag{1b}$$

$$\sum_{\substack{t\in T\\ v\in V_t,k\in K_f}} v x_{jk}^{t,v,N,s} = D_j^{N,s} \qquad \forall f \in F, j \in J_f, s \in S, \tag{1c}$$

$$\sum_{\substack{j\in J_f\\ t\in T,v\in V_t}} v x_{jk}^{tvps} \leq B_k^p \qquad \forall f \in F, k \in K_f, p \in P, s \in S \tag{1d}$$

$$\sum_{j\in J} x_{ij}^{ts} \leq q_i^{tv} \qquad \forall i \in I, t \in T, v \in V_t, s \in S, \tag{1e}$$

$$\sum_{\substack{j\in J\\ k\in K,p\in P}} x_{jk}^{tvps} \leq \sum_{i\in I} q_i^{tv} \qquad \forall t \in T, v \in V_t, s \in S, \tag{1f}$$

$$\sum_{i\in I} x_{ij}^{ts} = \sum_{k\in K,p\in P,v\in V_t} x_{jk}^{tvps} \qquad \forall j \in J, t \in T, s \in S \tag{1g}$$

$$\sum_{i\in I} x_{ki}^{ts} = \sum_{j\in J,p\in P,v\in V_t} x_{jk}^{tvps} \qquad \forall k \in K, t \in T, s \in S \tag{1h}$$

$$\sum_{i\in I,v\in V_B} q_i^{B,v} \leq O_{\max} \tag{1i}$$

$$x_{ij}^{ts} \leq M z_i \qquad \forall i \in I, j \in J, t \in T, s \in S \tag{1j}$$

$$x_{ki}^{ts} \leq M z_i \qquad \forall i \in I, k \in K, t \in T, s \in S \tag{1k}$$

$$q_i^{tv} \leq M z_i \qquad \forall i \in I, t \in T, v \in V_t. \tag{1l}$$

The objective (1a) minimizes the total expected evacuation costs from vehicle trips and the fixed cost from setting up one or more staging areas. Constraints (1b)–(1c) ensure that critical and non-critical patient demand from evacuating facilities are met by satisfying the "restrictive routing" strategy (hospitals evacuate to hospitals and nursing homes evacuate to nursing homes). In particular, constraints (1b) ensure that the evacuation of critical patients are carried out by ambulances only. We assume nursing homes do not have critical patients. The total number of patients evacuated to receiving facility k cannot exceed the available beds of the receiving facility for patient type p, which is stated in constraints (1d). The number of EMS vehicles, q_i^{tv}, in constraints (1e)–(1f) determines the number, type (t) and utilization (v) of EMS vehicles stationed at staging area locations, i. Notice that this variable is a first-stage variable which satisfies the demand requirements of all scenarios and restricts the number of vehicles leaving the staging area to conduct evacuation missions. The flow balance in evacuating (j) and receiving (k) facilities is imposed in constraints (1g)–(1h). The number of AMBUSes used is restricted by the maximum number available in constraint (1i). Constraints (1j)–(1k) ensure that a staging area is opened if there is a vehicle flow in or out of the staging area. By constraint (1l), vehicles cannot be stationed at a staging area if it is not opened. The domain and integrality requirements of the decision variables are provided in Table 1.

4. Case study data

4.1. Location data

In this section, we provide data on patient evacuation operations of hospitals and nursing homes in the southeast Texas region, primarily served by SETRAC. For the facilities served by SETRAC during disasters, we utilize hospital and nursing home data sets from the Homeland Infrastructure Foundation Level-Data (HIFLD).[1] From the data sets, we filter out the locations outside of the organization's service region, and select the locations that are operational (labeled as "open"). We also remove the locations with no bed count information. After filtering, we obtain 176 hospitals and 716 nursing homes in our region of interest. There are 6 hospitals and 14 nursing homes that are located outside the catchment areas of the rivers, meaning that the flood model is not applicable [41,42]. Therefore, we remove those locations from the data sets and are left with 170 hospitals and 702 nursing home locations. Fig. 2 shows the health care facility locations in the region that are input to the evacuation model.

To determine potential evacuating locations among the filtered hospitals and nursing homes, we determine whether a location is forecasted to be flooded in any of the 25 hurricane scenarios. Among the locations that are expected to be flooded in at least one scenario, we set locations with fewer than 300 beds as potential evacuating (sending) locations with the assumption that larger facilities (mainly hospitals) will handle their own evacuations because they typically have the staff, resources, and infrastructure necessary to manage emergencies internally, often serving as regional healthcare hubs. In contrast, smaller facilities lack these resources and are the primary evacuating locations in the event of flooding, needing resources and coordination from agencies such as SETRAC.

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

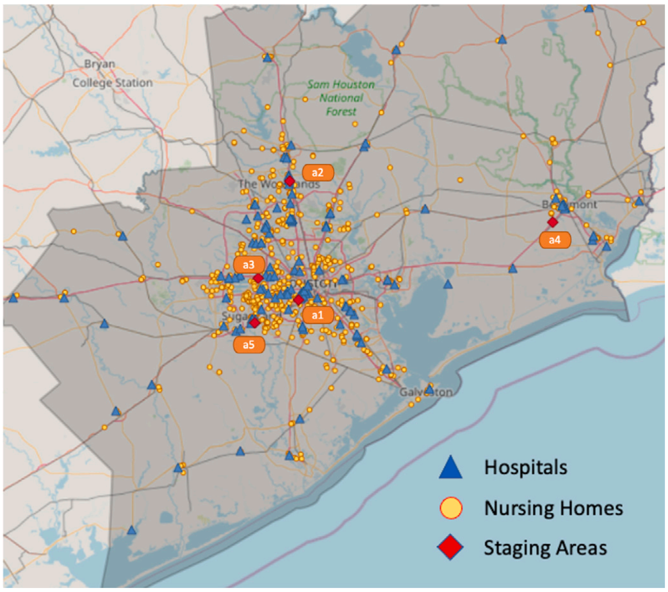

Fig. 2. Hospitals, nursing homes and staging areas with orange labels from a1 to a5 in the SETRAC region. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 2
Description of the evacuation network.

Candidate staging areas	Evacuating locations (Hospital, Nursing home)	Receiving locations (Hospital, Nursing home)
5	313 (55, 258)	559 (115, 444)

Regarding the potential receiving locations, we note that the Houston-Galveston Area Council has defined the hurricane evacuation zip zone maps for Brazoria, Chambers, Galveston, Harris and Matagorda counties for general population evacuation guidelines [43]. The evacuation zones are divided into four groups by zip code: Coastal, A, B, and C. The evacuation is carried out from the regions near the coastline. Although the zones are defined for general population evacuations, we assume that no locations in these zones can be receiving facilities since these four zones are subject to evacuation during hurricanes. Further, if a location outside these zones does not experience any flooding in any of the scenarios, it is considered as a potential receiving facility. Finally, with the assumption that large facilities would withstand flooding better due to the assumption that they are flood-resilient, equipped with features like flood doors, generators, and ample food and medicine supplies, if a facility has a bed count greater than 300, it is considered as a potential receiving location regardless of what flood scenarios predict for that location. There are 10 such large facilities (9 hospitals and 1 nursing home) that are assumed to be resilient against any flooding and in turn serve as potential receiving locations.

In the end, there are 313 locations (55 hospitals and 258 nursing homes) as potential evacuating facilities and 559 locations (115 hospitals and 444 nursing homes) as potential receiving facilities. The number of each kind of receiving location is determined so that they can provide shelters for the maximum demand realized in the worst case (i.e., the highest demand) scenario. Table 2 describes the network size.

For the study, we determine five candidate staging areas labeled as a1 to a5, one of which is Darrell Tully Stadium (a3) in Houston, which served as a staging area during Hurricane Harvey. NRG Stadium (a1), also in Houston, was one of the largest shelter locations that received thousands of evacuees from flooding during Harvey. The other three locations that are chosen as staging areas across the southeast Texas region satisfy similar conditions: Woodforest Bank Stadium (a2) in Shenandoah, Ford Park Entertainment Complex (a4) in Beaumont, and Edward Mercer Stadium (a5) in Sugar Land. Fig. 2 shows the locations of the candidate staging areas relative to hospital and nursing home locations. FEMA staged relief supplies and vehicles at the Joint Base San Antonio-Randolph to coordinate relief missions to respond to and mitigate the damages from Harvey. This location was designed to provide support during and after the impact of the hurricane. However, the location is too far to be utilized as a potential staging area to support patient evacuation missions during the short operation window before hurricanes, so it is not considered as a potential staging area for our model. The fixed cost f_i of opening staging area i is set at $1,000,000 for any i mainly to encourage the model to open fewer staging areas (as a way to reduce potential issues from coordinating a large number of staging areas). We later experiment with the number and locations of open staging areas to see the effect.

Table 3
Input parameters related to bed counts.

Patient type	Proportion of beds (π^p)		Occupancy rates (ρ^p)	
	Hospital	Nursing home	Hospital	Nursing home
Non-critical	0.16	1	0.65	0.68
Critical	0.84	0	0.68	0

4.2. Demand and capacity data

To calculate evacuation demands and receiving facility capacities, we use the bed count data (B_j for sending facility j and B_k for receiving facility k) from the HIFLD dataset. Typically, nursing homes have a higher occupancy rate than hospitals. According to 2012 data from the U.S. Centers for Medicare and Medicaid Services, Healthcare Cost Report Information System (HCRIS),[2] the proportion of intensive care unit (ICU) beds to total beds is 16.2%. The hospital occupancy rates for general hospital and ICU beds are 65% and 68%, respectively. We assume that the capacity of receiving hospitals and nursing homes (B_k^p for patient type p at receiving facility k) is determined by each facility's total bed count B_k, the proportion of beds for different patient types π^p, the current occupancy rate parameter ρ^p for patient type p, and the capacity utilization rate γ. Using these rates, we set the product of the four parameters, $\gamma B_k \pi^p (1-\rho^p)$, as the capacity of receiving facility k, producing B_k^p. The 2017 data from the Centers for Disease Control and Prevention[3] lists occupancy rates of nursing homes by state. For Texas, the occupancy rate is approximately 68%. Therefore, to calculate the available beds in Texas nursing homes to receive evacuation patients, we multiply each nursing home's bed count by 0.32. Additionally, the capacity utilization rate γ is set to 1, meaning that the receiving facilities allow evacuation patients to fill up to 100% of their available capacities. We vary this rate in the computational study. The calculated numbers are rounded down to the nearest integer. We similarly assume that the evacuation demand of sending hospitals and nursing homes (D_j^{ps} for patient type p at evacuating facility j in scenario s) is determined by each facility's total bed count B_j, the proportion of beds for different patient types π^p and the occupancy rate parameter ρ^p. The product of the three parameters, $B_j \pi^p \rho^p$, serves as the demand of sending location j, D_j^{ps}. Table 3 shows the rates used to calculate demands and capacities of facilities.

Another assumption on patient demand is that there are no critical patients requiring intensive care in nursing homes. This assumption arises because, although nursing homes typically serve individuals with varying levels of care needs, including those with chronic conditions or disabilities, it is assumed that their infrastructure and staffing may not be equipped to handle critical medical situations that necessitate intensive care interventions. Similarly, receiving nursing homes cannot be used as a receiving facility for critical patients. When residents from nursing homes are evacuated, there are reports that some residents experience deteriorating health conditions during the evacuation process and then require intensive care [44]. In our model, such a case can be considered as a non-critical patient from a nursing home becoming a critical patient who needs to be evacuated to a hospital instead of a nursing home. We do not model such cases in the scope of our model, but extending the model to include this possibility is a potential topic for future research. We use the default flood threshold level as 0 ft which we later change as part of a sensitivity analysis.

4.3. Vehicle data

In our case study, we consider two types of EMS vehicles: A, ambulances capable of carrying both critical and non-critical patients with capacity of 1, $v \in V_A = \{1\}$, and B, AMBUSes with room up to 20 non-critical patients, $v \in V_B = \{1, \dots, 20\}$.

The costs $c_{ij}^t, c_{jk}^{tv}, c_{ki}^t$ for vehicle type t are calculated by multiplying the per-mile cost by the distance between a given origin and destination pair, ij, jk and ki. In addition to that, c_{jk}^{tv} includes a labor cost of crew members working an 8-h shift. The number of crew members changes with vehicle utilization v. The mean hourly wage of medical technicians and paramedics is \$18.67 based on the 2019 data of U.S. Bureau of Labor Statistics.[4] The cost for ambulance $v = 1$ is calculated with the minimum required crew of 2, whereas the cost for AMBUS utilization $v = 20$ is calculated with the maximum crew of 6. The inflation adjusted total labor costs of 6 crew members operating the vehicle, \$896. When the AMBUS utilization is changed, we differentiate the resource costs of these vehicle types. For example, for $v = 1, 5, 10, 15, 20$, $h^{B,v}$ is set to \$296, \$596, \$696, \$796 \$896, respectively. Additionally, we use the per-mile cost of EMS/ambulance service as \$15, using a \$14.59 figure defined by the City of Houston[5] in 2019. The per-mile cost of AMBUSes is harder to estimate from data. Considering the additional hours required for providing care to multiple patients in a much larger vehicle, we set the per-mile cost of AMBUSes (\$29) by doubling the per-mile cost of the ambulances.

The Texas Emergency Medical Task Force has 16 AMBUSes in total pre-positioned and distributed across Texas. Since disasters such as hurricanes require state-wide support in emergency medical resources and assets, we assume that all 16 AMBUSes are available to support patient evacuation operations. The number of ambulances available to the network is assumed to be unlimited. This is justified given that our model needs to find an evacuation plan for all the patients needing evacuation from flooded facilities in any scenario. Table 4 summarizes characteristics and rates of the vehicles.

2 https://www.sccm.org/Communications/Critical-Care-Statistics
3 https://www.cdc.gov/nchs/data/hus/2017/092.pdf
4 https://www.bls.gov/oes/current/oes292040.htm
5 https://cohweb.houstontx.gov/FIN_FeeSchedule

Table 4
Vehicle characteristics and rates.

Vehicle type	Number available	Capacity	Per-mile cost
A, Ambulance	N/A	1	15
B, AMBUS with $\upsilon = 20$	16	20	29

Table 5
Demand in 25 scenarios with base level of occupancy rates in hospitals and nursing homes for critical (C) and non-critical (N) patient types.

Scenario	Hospital		Nursing home	Total		
	C	N	N	C	N	Total
n01	83	468	688	83	1,156	1,239
n02	84	478	829	84	1,307	1,391
n03	84	478	853	84	1,331	1,415
n04	93	536	1,286	93	1,822	1,915
n05	93	536	1,286	93	1,822	1,915
n06	128	763	3,186	128	3,949	4,077
n07	128	763	3,186	128	3,949	4,077
n08	266	1,563	3,936	266	5,499	5,765
n09	277	1,626	4,087	277	5,713	5,990
n10	277	1,626	4,170	277	5,796	6,073
n11	310	1,841	4,501	310	6,342	6,652
n12	320	1,901	4,501	320	6,402	6,722
n13	307	1,824	4,340	307	6,164	6,471
n14	286	1,692	4,429	286	6,121	6,407
n15	270	1,601	4,575	270	6,176	6,446
n16	150	908	4,234	150	5,142	5,292
n17	120	706	2,571	120	3,277	3,397
n18	120	706	2,362	120	3,068	3,188
n19	111	639	2,089	111	2,728	2,839
n20	111	639	1,863	111	2,502	2,613
n21	109	622	1,793	109	2,415	2,524
n22	102	579	1,531	102	2,110	2,212
n23	102	579	1,531	102	2,110	2,212
n24	104	600	2,017	104	2,617	2,721
n25	102	577	1,366	102	1,943	2,045

5. Computational study

5.1. Flood scenarios and evacuation demand

In this section, we show the changes in demands across the flood scenarios. There are two types of patients, critical (C) and non-critical (N). As mentioned, we assume that there are no critical patients needing intensive care in nursing homes. Table 5 summarizes the demands in 25 scenarios.

The highest-demand scenario is $n12$, where the sum of the hospital and nursing home demand is 6722. Scenario $n12$ could be viewed as the mean-path scenario as its track is the closest to the track forecasted by NHC that defines the mid-point of the cone of uncertainty. In Scenario $n01$, the total demand is 1239 which is about one fifth (0.18%) of the total demand in $n12$. Some of the scenarios are expected to have the same demand ($n04$ and $n05$, $n06$ and $n07$, $n22$ and $n23$) because the simulated landfall locations are too close to each other to generate different inland and coastal flooding events. We highlight three scenarios $n01$, $n12$ and $n25$ by showing their demand in the SETRAC region in Fig. 3. The demand level is represented by the size of the circle, and red circles denote hospitals, and orange circles denote nursing homes. Comparing the three scenarios, we observe that large coastal hospitals are under flood risk and most flooded nursing homes are inland in scenarios $n01$ and $n25$. Given the extent of flooding, both inland and coastal hospitals and nursing homes of varying sizes are expected to flood in scenario $n12$.

5.2. Baseline case

In this section, we solve the different instances of the populated evacuation model with the Gurobi Solver in Python on an Intel Core i5-6360U CPU @ 2.00 GHz, 16 GB RAM. The Gurobi integer programming solver is used with a default MIP optimality gap of 0.1%.

In the baseline case, a single type of AMBUS with utilization of 20 patients (υ = 20) is assumed, meaning when an AMBUS is used, it is used to evacuate 20 patients. This configuration represents a scenario where AMBUSes are fully utilized.

To assess the evacuation results, in addition to the total expected cost of the evacuation missions (the objective function value of the solutions suggested by the model), we report on the average evacuation time per patient (AET) in scenario 12 to gauge

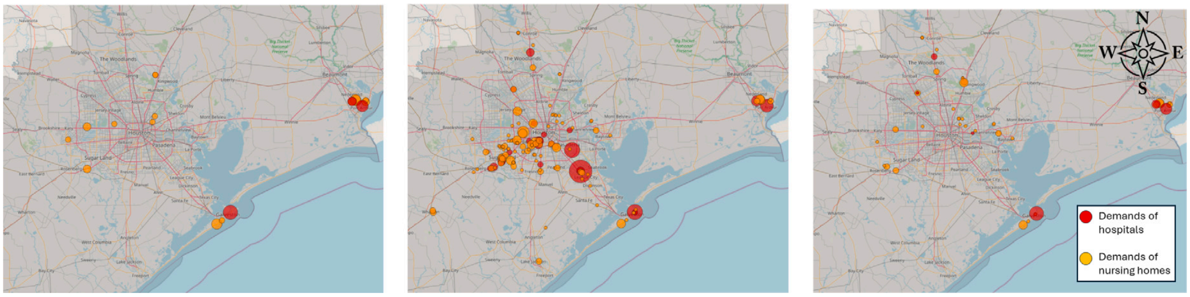

Fig. 3. Demands of hospitals (red) and nursing homes (orange) in Scenario $n01$, $n12$, and $n25$, from left to right. Larger circles indicate higher demand. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 6
Comparison of objective cost and evacuation times.

Routing strategy	AMBUS utilizations	Objective value	EET (h)	AET(n12) (h)	Number of staging areas
Restrictive	5,10,15,20	4,081,145	1.56	1.22	2
Relaxed	5,10,15,20	3,923,567	1.51	1.14	2
Restrictive	20	4,081,652	1.56	1.22	2
Relaxed	20	3,916,589	1.51	1.14	2

performance under the highest demand scenario, which coincides with the mean path scenario (n12). The AET of scenario s is calculated using the formula:

$$\psi^s = \sum_{j,t} \left(\sum_i \Delta^t_{ij} x^{ts}_{ij} \alpha^t + \sum_{k,p} \Delta^t_{jk} x^{t,\alpha^t,p,s}_{jk} \alpha^t \right) / \sum_{j,p} D^{ps}_j,$$

where Δ^t_{ij} and Δ^t_{jk} are the times it takes to travel arcs ij and jk, respectively, connecting a staging area i, sending facility j and receiving facility k by vehicle type t. x^{ts}_{ij} and x^{tvps}_{jk} are the number of vehicles using the suggested routes in the model's solution. α^t is the number of patients carried by vehicle t. For ambulances, α^A, is set to 1. For AMBUSes, α^B is the utilization v. In the baseline case, $\alpha^B = 20$ since the full utilization of AMBUSes is assumed. The denominator is the total evacuation demand in scenario s. Thus, ψ^s represents the average evacuation time per evacuee if the evacuation operation is executed based on scenario s. Then, ψ^{n12} is equivalent to the average evacuation time of the mean path (or equivalently, the highest demand) scenario $n12$, AET(n12). The EET is the average evacuation time per evacuee over all scenarios. It is calculated by summing over all scenarios in both the numerator and denominator of the AET formulation; $\sum_{s,j,t} \left(\sum_i \Delta^t_{ij} x^{ts}_{ij} \alpha^t + \sum_{k,p} \Delta^t_{jk} x^{t,\alpha^t,p,s}_{jk} \alpha^t \right) / \sum_{s,j,p} D^{ps}_j$.

We note that the evacuation time using ambulances only includes the travel time from a staging area to a sending facility, and then to a receiving location. The evacuation time for AMBUSes includes the aforementioned travel times as well as the loading time of additional patients calculated in the parameter pre-processing. In both cases, both AET and EET are evacuee centric, meaning additional time needed for preparing resources, unloading patients, or returning to staging areas after evacuations is not considered.

The results of the baseline case reveal an objective value of $4,081,652, representing total expected evacuation costs. The computation time for this instance is within one hour. The expected evacuation time per patient (EET) is 1.56 h, with an average evacuation time in scenario 12 (AET(n12)) of 1.22 h. Two staging areas, located at a1 and a4, are operational.

The baseline case, characterized by the restrictive routing strategy and by the full utilization of AMBUSes, sets the benchmark for evaluating the impact of strategic choices on the evacuation operation. These baseline results serve as a foundation for comparing the efficiency of alternative configurations in the subsequent sensitivity analysis.

5.3. Patient routing strategies and AMBUS configurations

In contrast to the established "restrictive routing" strategy, we introduce an alternative approach, which we refer to as the "relaxed routing" strategy. This strategy aims to test a more flexible patient routing framework, allowing nursing home patients to be evacuated to hospitals and thus expanding the range of potential destinations.

To further explore the impact of different strategies, we adjust the number of vehicle utilizations in the model. Instead of defining all 20 utilization levels for AMBUSes ($v = 1 \ldots 20$) that may or may not be used, we assume 4 utilizations, and set these levels to 5, 10, 15, and 20 out of maximum of 20 patients, i.e., $v \in V_B = \{5, 10, 15, 20\}$.

Table 6 provides a comprehensive summary of how the two distinct routing strategies and the varying number of AMBUS types impact both the total expected cost and the evacuation time experienced by patients. We observe that the restrictive strategy induces both a higher objective value and a longer average evacuation time. The computation time decreases more than 50% when the number of AMBUS types is reduced from 4 to 1. The results from the instances with 4 AMBUS utilization levels only use full

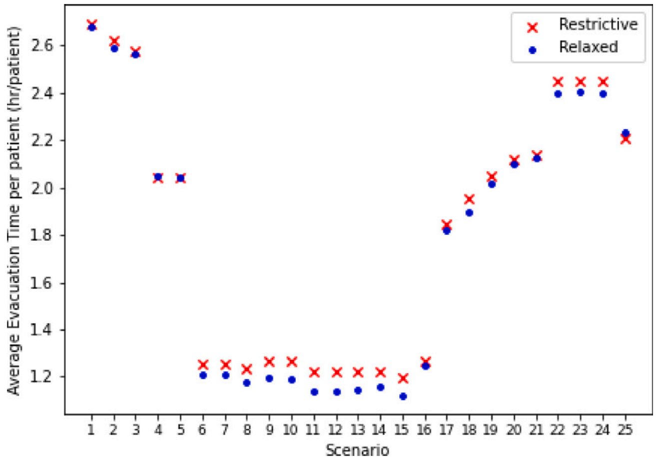

Fig. 4. Average evacuation time per patient in 25 scenarios.

capacity AMBUS (υ = 20), suggesting that AMBUSes should be utilized up to their maximum capacity. If we have a high enough demand at sending facilities and high enough capacity at individual receiving facilities, then it is optimal to use the fully utilized AMBUSes. If there were fewer than 20 evacuees at a facility and/or fewer available beds at a receiving facility, then an AMBUS could have been utilized under its capacity, but this is not observed in our instances due to the high evacuation demands and large receiving capacities. Therefore, evacuation demand, evacuee types, capacity of receiving facilities, and number of AMBUSes play a role on the utilization of AMBUSes. Additionally, in the optimal solution, the same two staging area locations are operational in all cases, a1 and a4.

The evacuation demand is the greatest in the mean scenario but the results show that the EETs are greater than the AET of $n12$. In other words, when the hurricane is expected to cause greater impact in the study region, the evacuation time for each patient is smaller although the demand is greater in the mean scenario. This is due to the proximity of flooded facilities to the receiving facilities in the mean scenario. Since the hurricane trajectory of the mean scenario is expected to hit the Houston area with the largest accumulated rainfall forecast in the study region, patients from flooded hospitals in and around the Houston area benefit from the nearby large-capacity receiving facilities in this scenario. Another reason is that there is no limit on resources in terms of the number of ambulances. With a constrained number of ambulances and relaxing the requirement of evacuating all patients, we would expect greater evacuation time in the mean scenario with a potential shortage in ambulances causing unsatisfied demand at some flooded hospitals.

Next, we compare the AET per patient in various scenarios. Fig. 4 shows the distributions of AETs in the last two settings from Table 6, with a υ = 20 type of AMBUS for the two routing strategies. From Scenarios 8 to 15, the AETs of the relaxed strategy are smaller, while in the other scenarios, the evacuation times are similar with both strategies. This indicates that the more flexible strategy is beneficial only in the scenarios with high demand.

5.4. Staging area decisions

The results from Table 6 suggest that the decision makers should conduct patient evacuation operations with two staging areas in a1 and a4 to respond to the flood risks of the generated 25 Harvey scenarios on hospitals and nursing homes in the region. However, during Hurricane Harvey, one staging area, a3, which is not among the staging areas chosen in the optimal solution, served as a staging area. In the next set of experiments, we study how the total cost and evacuation times change with respect to the number and locations of staging areas. We have five candidate locations for staging areas. Three locations (a1, a3 and a5) are in areas where potential evacuating hospitals and nursing homes are concentrated. Location a2 near the Woodlands suburb is in the north of Houston and a4 in Beaumont is to west of Houston and is home to a few hospitals and nursing homes. (Recall Fig. 2 for the staging area locations.) If the Beaumont location (a4) is opened as in the optimal solution to the baseline case, we expect it to serve the nearby demand. Forcing that location to be the only staging area to serve all evacuation missions increases both the costs and evacuation times significantly. We compare the total cost objective and EET with the solutions found by opening one staging area location among the potential locations in Table 7. All solutions are obtained fixing the routing strategy as restrictive.

Compared to the optimal solution (the first row of Table 7), the experiments with a one staging area restriction result in increase in objective value ranging from 7.48% (staging area at location a1) to 103% (a4). The EET per patient is significantly greater with the new solutions with one staging area. In most cases, the EETs are doubled compared to the EET of the optimal solution. According to these results, if the staging areas during Harvey were opened at a1 and a4, the total cost and EET would have been reduced by 16% and 70%, respectively, compared to the only staging area actually used at a3.

Table 7
Comparison of staging area decisions with restrictive routing strategy.

Number of staging areas	Objective value	Difference (%)	EET	Location
2	4,081,652	–	1.56	a1, a4
1	4,386,960	+7.48	2.37	a1
1	4,737,795	+16.08	2.65	a3
1	4,901,103	+20.08	2.57	a5
1	6,146,617	+50.59	3.01	a2
1	8,285,595	+103.00	2.90	a4

Table 8
Objective values with different flood threshold heights.

Threshold	Number of evacuating locations		Exp. number of evacuees	Objective	EET
level (ft)	Hospital (Mean, Min, Max)	NH (Mean, Min, Max)	(Hospital, NH)	value	(h)
0	15, 3, 31	71, 15, 127	3,823 (1,135, 2,688)	4,081,652	1.56
1	10, 1, 19	55, 7, 106	2,730 (657, 2,073)	3,834,515	2.06
2	7, 1, 14	41, 3, 83	1,995 (384, 1,611)	2,512,075	1.84
3	6, 1, 13	29, 0, 59	1,409 (314, 1,095)	2,216,399	1.74
4	5, 1, 10	22, 0, 43	1,127 (279, 848)	1,624,387	1.69

5.5. Flood threshold heights

We use a default flood threshold level of 0 ft in our experiments so far. Here, we define five different threshold heights (0, 1, 2, 3, and 4 ft) for flooding to determine the classification of a facility as needing evacuation. When the predicted flood level of a facility in a scenario is greater than the defined threshold level, the location needs evacuation. For this set of experiments, we set the patient routing strategy as restrictive and the AMBUS utilization as $\upsilon = 20$ only.

Table 8 shows the results of these experiments. As expected, with a higher threshold level, the predicted number of facilities requiring evacuation, both for hospitals and nursing homes, decreases as well as does the objective value. The saving from raising the threshold level from 0 to 1 foot generates approximately $250 thousand whereas the EET per patient is increased from 1.56 to 2.06. Increasing the threshold level to 2 ft would save approximately another $1.5 million and have a relatively positive impact on EET per patient. Fewer evacuees cause longer trips in general. This is because the evacuating facilities that suffer from more severe flooding are spread out geographically, resulting in longer distances to reach sending and receiving facilities.

From the patient's perspective, the shorter EET per patient generally implies a less risky evacuation. The analysis on the impact of threshold level on total expected cost and EET provides important insights to evacuation decision makers on how to choose a target flood threshold level and to spend savings from increasing the threshold level. Choosing a target flood threshold level directly influences the selection of evacuating facilities. The increased flood threshold means fewer facilities to evacuate and lower evacuation demand as shown in the table, resulting in significant cost savings. One strategy could be that the savings from raising the flood threshold level are spent on installing preventative measures or on deploying flood barriers to protect the facilities that experience lower flood levels and would have been evacuated with lower threshold levels.

5.6. Receiving facility capacities

In the baseline dataset, we define 65% and 68% as the receiving hospital's occupancy rates for non-critical and critical patients (ρ^p for patient type p), respectively. We also use 68% as the occupancy rate for receiving nursing homes. See Table 3 for details. Using these rates, the receiving locations may take evacuees up to 100% of their capacities. Unlike other industries, what constitutes an "optimum" or "socially desirable" utilization rate of healthcare facilities depends on a complex set of factors [45]. The literature suggests that 85%–90% is the ideal range for hospital bed occupancy in order to avoid the danger of overcrowding [46].

In this section, we vary the allowed "capacity" of each receiving facility k and each patient type p, B_k^p, by changing the capacity utilization rate γ. When $\gamma = 1$, receiving facilities utilize 100% of their capacities for evacuation patients. Therefore, we update the available capacity for each facility (hospital and nursing home) and patient type (critical and non-critical), B_k^p by varying γ. We analyze the impact of γ in evacuation cost, evacuation times and routing decisions. Additionally, we introduce the mean number of receivers, which is defined as the expected number of distinct receiving destinations for a sending facility.

Table 9 shows that the overall objective value, the EET, and AET of mean scenario $n12$ are all smaller when using the relaxed routing strategy rather than the restrictive strategy for each of the tested capacity utilization rate values. Again, this confirms the advantage of adopting the more flexible routing strategy. It is also clear that decreasing the occupancy rate increases the total costs as well as the evacuation times for a given routing strategy. However, these two-factor (capacity utilization rate and routing strategy) experiments reveal that if one is forced to bear higher costs and evacuation times due to a lower occupancy rate at receiving facilities, using the relaxed routing strategy could provide a relief in terms of evacuation costs and times. For example, the relaxed routing strategy with 90% occupancy produces total costs very close to 100% occupancy with restrictive routing. Overall, within a routing strategy, decreasing the occupancy rate means the use of more receiving facilities, resulting in larger mean number of

Table 9
Objective values with different capacity utilization rates γ.

Strategy	γ	Objective value	EET	AET(n12)	Mean number of receivers
Restrictive	1.00	4,081,652	1.56	1.22	2.94
Restrictive	0.95	4,174,629	1.58	1.26	3.33
Restrictive	0.90	4,341,173	1.63	1.33	3.87
Relaxed	1.00	3,916,589	1.49	1.14	2.71
Relaxed	0.95	3,991,180	1.50	1.17	2.85
Relaxed	0.90	4,133,515	1.54	1.23	3.34

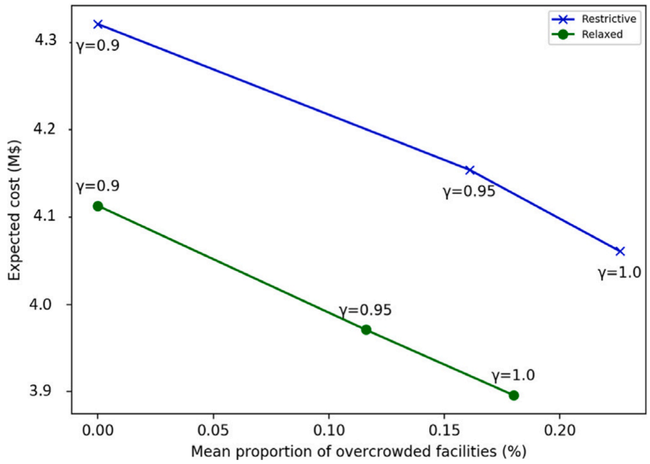

Fig. 5. Expected cost decreases as the overcrowded facilities increases.

receivers per sending facility. In general, the impact on all the metrics due to varying occupancy rate is bigger when the routing strategy is restrictive. For example, when we compare the EETs, we observe that the range of the EET per patient is larger in the restrictive strategy. This is also true for the mean number of receivers per sending facility: 2.94–3.87 for restrictive vs. 2.71–3.34 for relaxed. In the stricter routing strategy, the capacity utilization rate impacts receiving location decisions and forces some sending facilities to route their patients to locations further away.

We define a receiving facility to be overcrowded when the ratio of total patients to total beds, at the end of the evacuation process, is greater than 0.9. The trade-off between the expected costs and the proportion of overcrowded facilities among all facilities in the two routing strategies is plotted in Fig. 5. When $\gamma = 0.9$, it is obvious that there are no overcrowded receiving facilities. The percentage of overcrowded facilities increases to 22.6% and 18% for the restrictive and the relaxed strategies, respectively, when γ is increased to 1.0. The cause of the greater increase in the percentage is due to the more strict routing strategy where we expect more facilities to be “full” due to the fewer options in choosing receiving facilities. The drop in expected costs from $\gamma = 0.9$ to $\gamma = 1.0$ in both routing strategies seem similar (approximately 1.5%) but the increases in the percentage of overcrowded facilities are significant in both strategies. With a smaller number of overcrowded receiving facilities, the health care network should in general be more capable of providing services to public, especially when patient admissions after a hurricane are highly likely. As Table 9 indicates, when the capacity utilization rate is lowered from 1 to 0.9, approximately one additional receiving location is necessary to house patients from an evacuating location. Although it is not measured in this case study, simplicity in patient evacuation routing benefits decision makers in coordinating the evacuation missions. In other words, a lower number of receivers per sender could be preferable in terms of organizing the evacuation missions. The decision of setting a target capacity utilization rate has to consider the trade-off between the increase in the mean number of receivers and the increase in evacuation time and overcrowded facilities.

5.7. Value of stochastic solution

In this section, we study the value of the scenario-based flood modeling, i.e., the value of stochastic solution (VSS), for planning patient evacuation operations [47]. Typically, the VSS is the difference between the value of the optimal solution to the scenario-based stochastic program and the value of a deterministic, single scenario solution evaluated over the same set of scenarios. Normally, the expected values of the random elements (flood heights or demand levels in our problem setting) across scenarios would serve as the single scenario for comparison. However, given that our problem formulation requires full evacuation of all flooded facilities in all scenarios, such a single scenario problem will not be feasible. This is mainly due to the common first stage solution z_i and q_i^{tv} that must satisfy the constraints of all 25 scenarios, including the scenario-dependent evacuation demands.

Table 10
Value of stochastic solution of 5 instances with two routing strategies.

Routing strategy	Type	Occupancy parameter, ρ^p				
		Base	0.8	0.9	1.0	1.1
Restrictive	SP	4,081,652	4,553,909	5,064,412	5,772,928	6,220,760
	EMD	4,154,018	4,639,743	5,149,436	5,817,279	6,258,392
	VSS	72,366	85,834	85,023	44,351	37,632
	(+)	1.77%	1.88%	1.68%	0.77%	0.60%
Relaxed	SP	3,916,589	4,331,883	4,803,998	5,464,253	5,844,253
	EMD	3,985,687	4,413,705	4,889,182	5,556,389	5,926,352
	VSS	69,098	81,822	85,184	92,136	82,098
	(+)	1.76%	1.89%	1.77%	1.69%	1.40%

Therefore, a more logical choice in our problem is to use the scenario with maximum demand. In our case study, this is scenario $n12$ (see 5). Coincidentally, in our case study, this turns out to be the "mean path" scenario, meaning the scenario that matches the center track inside the cone of uncertainty in the NHC forecast. Thus, we use $n12$ as a deterministic input and determine the first stage solution z_i and q_i^{tv}. Then we solve the optimization problem for each scenario with the given first stage solution and take the expectation of the 25 objective values. We call this the EMD, meaning the Expected value of the Maximum-Demand scenario solution. Then, the VSS is the difference between the value of the stochastic program (denoted by SP in the Table 10) and the EMD. Note that the mean path scenario need not be the highest demand scenario in other evacuation problems or other hurricane forecasting situations. In fact, the mean-path solution would be infeasible for our problem if it did not have the highest demand. To test the changes in VSS with respect to patient routing strategies and level of demand, we create five demand levels with two patient routing decisions (restrictive and relaxed). The "Base" demand level is defined with the default occupancy rate parameters in Table 3. We vary the occupancy parameter, ρ^p, setting it to 0.8, 0.9, 1.0 and 1.1 for both non-critical ($p = N$) and critical patients ($p = C$). For example, when $\rho^p = 1.0$, the evacuation demand for a patient of type p at an evacuating location is equal to its total bed count. The result of the VSS study are presented in Table 10.

The VSS percentage of the base case is approximately 1.77% in both the restrictive and the relaxed routing strategies. As the occupancy rate ρ in evacuating facilities increases, indicating a rise in demand at each evacuating facility, the VSS decreases. This decline is more pronounced in the restrictive routing strategy. The difference in VSS between the two strategies is attributed to the inherent flexibility in patient routing within the relaxed strategy. Taking advantage of the flexible routing, the optimal solutions in the relaxed strategy allocate vehicles in different staging areas. Consequently, the VSS percentage decreases to 1.40% in the overcrowded case ($\rho = 1.1$) in the relaxed strategy, while it remains below 1% in the restrictive strategy. With less than 100% capacity utilization ($\rho < 1$), the VSS is consistently observed to be approximately 1.5% and above. We note that the VSS as a percentage seems small as it is a function of the scale of the objective function, which depends on the cost figures, particularly the assumed fixed costs of opening staging areas. Given that the fixed costs of staging areas are very high relative to the rest of the objective function and make up $2 M of the total costs in all optimal solutions, the true, arguably more practical, value of the stochastic solution is higher. The stochastic solution not only decreases the cost of evacuation but also reduces the expected evacuation time by positioning vehicles, while considering uncertain landfall locations of the hurricane and the corresponding uncertain flood potential.

6. Conclusion

This paper introduces a new framework addressing patient evacuation problems by integrating hurricane scenario generation and stochastic integer optimization modeling. We combine the outputs of hydrological models for inland flooding and storm surge, both involving probabilistic hurricane tracks. These scenarios are input to our two-stage stochastic optimization model that makes staging area and resource allocation decisions as well as the scenario-dependent patient evacuation and routing decisions. We use Hurricane Harvey as a case study, actual hospital and nursing home locations from the southeast Texas region, and a variety of parameter settings and options to obtain insights into the recommended solutions.

We present extensive experimental results on different evacuation policies. We discuss the impact of routing strategies, staging area decisions, flood threshold levels, and receiving facility capacities on the objective value and total evacuation time. A relaxed routing strategy by allowing nursing home residents to be evacuated to hospitals outperforms the restrictive version in terms of cost and evacuation time. Moreover, the strategic choice of a flood threshold level directly impacts the selection of evacuation facilities, with potential cost savings from raising the threshold, which can be achieved by deploying preventive measures for facilities initially considered for evacuation at lower thresholds. Additionally, lowering the capacity utilization of receiving facilities from 100% to 90% necessitates approximately one additional receiving location per sending facility to accommodate all evacuation patients. Another important finding is that optimally opening two staging areas during another event like Hurricane Harvey can lead to a nonnegligible reduction of 4% in total cost and an impressive 54% decrease in evacuation time.

To enhance hurricane preparedness, agencies like SETRAC can utilize the research findings in several key ways. First, they can adopt relaxed routing strategies, which allow nursing home residents to be evacuated to hospitals rather than restricting evacuations within similar facility types, in order to increases efficiency. By expanding evacuation options for each facility type,

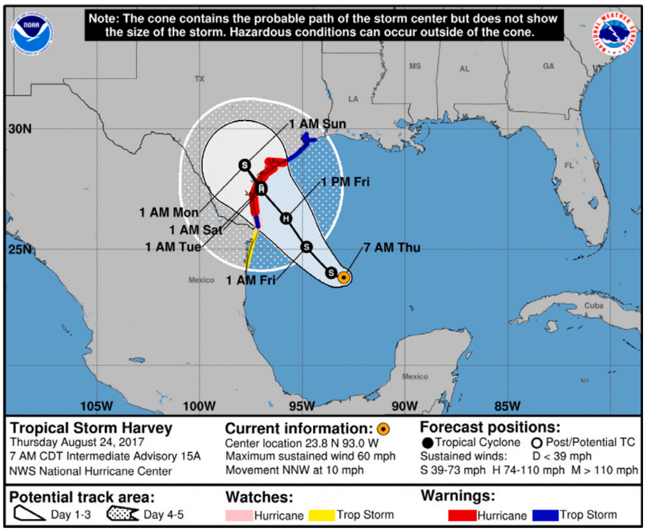

Fig. 6. An example of 5-day forecast track and watch/warning graphic.

agencies facilitate expedited evacuations while minimizing costs. Second, instead of relying on a single staging area for positioning vehicles and medical personnel, agencies should consider opening multiple staging areas, focusing on areas of concentration of potential evacuation demand to decrease total evacuation cost and time. Third, the choice of flood threshold levels significantly impacts evacuation facility selection and overall demand. By deploying preventive measures before hurricanes that will allow higher threshold levels for evacuation, agencies can optimize cost allocation and lower evacuation time — an aspect only partially addressed in the literature [48] and considered as an extension to this study for future research. Finally, compared to expected value of the Maximum-Demand scenario (EMD) solution, the scenario-based (SP) solution should not only decrease the expected cost of evacuation but also reduce the expected evacuation time by positioning vehicles while considering uncertain landfall locations of the hurricane and the corresponding uncertain flood potential. These measures, informed by research findings, can significantly enhance an agency's readiness for patient evacuations.

A limitation in our study is the difficulty in comparing model-generated evacuation strategies with the actual events during Hurricane Harvey due to challenges in collecting comprehensive healthcare facility evacuation data. Future work aims to secure more access to such data for further model calibration. Additionally, in optimizing patient evacuation, it is crucial to test the model under diverse resource and time constraints. One of the assumptions of the patient evacuation model is that there are sufficient vehicles to evacuate patients. With the goal of evacuating everyone under flood risk, this assumption might be valid but the availability of the resources may depend on time. Introducing the time element into resource constraints could highlight the prioritization in patient routing. In addition, if there is a limit to the number of vehicles that can be acquired, and this limit is below the evacuation demand (the number of patients to be moved), the available vehicles could make multiple trips. Currently, we do not consider the leasing cost of vehicles as a fixed cost in the objective function because the number of vehicles needed to satisfy the demand is constant for a given set of scenarios due to the current formulation with a single trip per vehicle setup. However, selectively allowing vehicles to make multiple trips, and measuring the relevant performances (say, evacuation time, etc.), particularly as a function of the number of leased vehicles, would be an interesting extension of the current paper. There is also a potential for higher value in the form of VSS when multiple trips or multiple time periods with trips are allowed. We consider these multi-trip assignments per vehicle and quantifying the higher VSS potential as a future study.

Another important future research direction is to introduce network congestion. Although the evacuation missions are conducted before hurricanes make landfall, the road network may become more congested due to potential evacuation of the general population and flooded roads, as well as reduced speed due to winds. Incorporating the transportation network into future research may provide valuable insights. Therefore, another important topic is to explore the timing of patient evacuation under different hurricane characteristics. Lastly, in our case study, we applied our model to the Texas coast and Hurricane Harvey. However, states like Florida, Louisiana and those in the Mid-Atlantic region are also prone to hurricanes and subsequent flooding. Since the flood forecasting models used in our study can easily be adapted to generate flood forecasts to those regions, by generating a set of landfall locations from a new hurricane event and running the stochastic optimization model, we should be able to generate flood scenarios and determine optimal patient evacuation strategies in other regions.

CRediT authorship contribution statement

Kyoung Yoon Kim: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Formal analysis, Data curation, Conceptualization. **Gizem Toplu-Tutay:** Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Erhan Kutanoglu:** Writing – review & editing, Supervision, Methodology, Investigation, Funding acquisition, Conceptualization. **John J. Hasenbein:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

https://github.com/gizemtt/Patient_Evacuation_during_Hurricanes.

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Appendix A. Weather forecast

See Fig. 6.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.ijdrr.2024.104518.

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