Healthcare Analytics 4 (2023) 100268

Contents lists available at ScienceDirect

Healthcare Analytics

journal homepage: www.elsevier.com/locate/health

An equitable patient reallocation optimization and temporary facility placement model for maximizing critical care system resilience in disasters

Chia-Fu Liu *, Ali Mostafavi

Zachry Department of Civil and Environmental Engineering, Texas A&M University, 199 Spence St., College Station, TX, 77843-3136, USA

A R T I C L E I N F O

Handling editor Madijd Tavana

Keywords:
Patient reallocation optimization
Healthcare network resilience
Disaster response management
Facility placement
Simulation

A B S T R A C T

Medical infrastructure disruptions during disasters pose a major threat to critically ill patients with advanced chronic kidney disease or end-stage renal disease. There is a need to assess the potential threat to critical care facilities from hazardous events to improve patient access to dialysis treatment. We propose optimization models for patient reallocation and temporary medical facility placement to equitably improve critical care system resilience. We leverage human mobility data in Texas to assess patient access to critical care facilities and dialysis centers under the simulated hazard impacts. The optimization model was formulated as an integer programming and solved by COIN-OR Branch-and-Cut (CBC) solver. The results show (1) the capability of the optimization model in efficient patient reallocation to alleviate disrupted access to dialysis facilities; (2) the importance of large facilities in maintaining the system functionality. The critical care system, particularly the network of dialysis centers, is heavily reliant on a few larger facilities, characteristic of scale-free networks, making it susceptible to targeted disruption, such as capacity failures. (3) Considering equity in the optimization model formulation reduces access loss for vulnerable populations in the simulated scenarios. (4) The proposed temporary facilities placement could improve access for the vulnerable population, thereby improving the equity of access to critical care facilities in disaster. The proposed patient reallocation optimization model and temporary facilities placement offer a data-driven and analytics-based decision support tool tailored to the needs of healthcare organizations across private and public sectors to proactively mitigate the potential loss of access to critical care facilities during disasters.

1. Introduction

Healthcare systems have been under enormous pressure caused by various types of disasters, including natural disasters and man-made disasters [1]. Such disasters have triggered a surge in demands for medical services and exacerbated the shortage of healthcare resources in the affected regions. The objective of this study was to create an equitable optimization framework for patient reallocation and temporary facility placement to maximize the resilience of critical care facilities network, with a focus on dialysis centers. In this study, the term resilience was used to refer to healthcare resilience, defined as the ability of the healthcare system to reduce the potential impact of a disaster and meet the needs of the population [2]. Critical healthcare facilities like dialysis centers are crucial in safeguarding the wellbeing of patients with heightened vulnerability. The disruption of these services due to disasters can lead to perilous kidney failure in patients reliant on dialysis treatments [3]. Patient risk is especially elevated during severe weather incidents, such as hurricanes, floods, or harsh cold conditions, when widespread kidney failure can result from interrupted access to these critical care facilities due to their forced closure [4]. Lempert & Kopp [5] describe such a predicament as a “kidney failure disaster”, an event that exposes a large number of patients, either on maintenance dialysis or recently diagnosed with acute kidney injury (AKI), at serious risk due to the unavailability of dialysis services. Historical data points to such health disasters, for instance, during Hurricane Katrina in 2005 [6–8] and Hurricane Gustav in 2008 [9]. For instance, the effects of Hurricane Sandy in 2012 were the major cause of kidney failure issues in the New York metropolitan area. Dialysis services were closed in anticipation of the storm or due to flooding, power outages, and structural damage caused by the storm [5]. The closure of dialysis services in some severely flooded areas forced surrounding hospitals to house the evacuated patients, who were often admitted to emergency rooms with hyperkalemia. Despite the rapid response from renal communities, some patients are at increased health risk, and some may have suffered

* Corresponding author.
E-mail addresses: joeyliu0324@tamu.edu (C.-F. Liu), amostafavi@civil.tamu.edu (A. Mostafavi).

https://doi.org/10.1016/j.health.2023.100268
Received 13 June 2023; Received in revised form 9 September 2023; Accepted 26 September 2023
Available online 27 September 2023

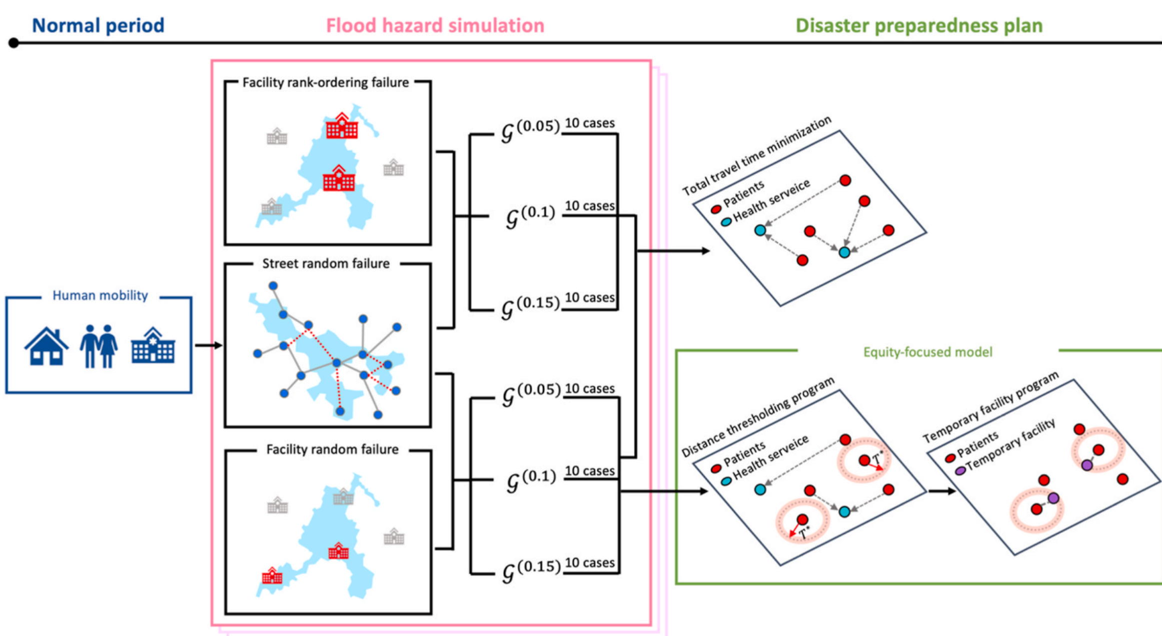


Fig. 1. Conceptual framework of optimizing healthcare system resilience. The initial phase involves estimating the dialysis patient demand during the normal period (i.e., pre-disaster period). The subsequent flood-hazard simulation section examines 30 random failure scenarios which consist of facility random failure and street random failure, as well as 30 rank-ordering failure scenarios, which consist of facility rank-ordering failure and street random failure. Finally, the analysis includes total travel time minimization for both random failure and rank-ordering scenarios, while the equity-focused model is specifically applied to the random failure scenarios.

significant health consequences from missed dialysis sessions. The uncertainty and disruption caused by hazardous events may have resulted in acute and long-term mental health implications for maintenance dialysis patients.

In addition, the transportation network acts as the backbone of healthcare, connecting individuals to critical care facilities. Ensuring access to essential facilities becomes even more crucial during and post-disasters, as it directly influences the community's overall welfare [10]. However, this access is often hampered by disturbances from natural hazards [11]. A prominent example is the extensive flooding caused by Hurricane Harvey in 2017, which severed road connections to various key facilities and posed significant threats to public safety, especially for those already in vulnerable conditions [12]. Neglecting public access to critical care services after disasters can hinder community recovery. To build the resilience of the community of people with functional needs, it is important to establish a predetermined communication system to inform this population where they can receive dialysis treatment [13]. It is important to recognize that the disruption to routine dialysis sessions can have ripple effects, including an influx of patients to other dialysis centers, an increased strain on facilities caring for more dialysis-dependent patients, and more emergency department visits [14, 15]. Furthermore, redundant communication methods and transport plans should be established to ensure uninterrupted access to critical care facilities.

The examination of disaster-induced disruption to vital dialysis centers remains an under-researched area within healthcare services and medical center studies. One of the rare investigations in this field, conducted by Kaiser et al. [16], evaluated the flooding impact on dialysis centers in Harris County, Texas, during Hurricane Harvey, utilizing the flood maps from that weather incident. This study made use of flood zone categorizations provided by the Federal Emergency Management Agency (FEMA) to measure and classify dialysis centers based on their proximity to flood areas. However, focusing solely on the flood exposure of dialysis centers does not provide a comprehensive view of the potential threats to patients in the region arising from compromised access to these centers. Flooding can lead to multifaceted disruptions in accessing dialysis services, such as road inundation preventing patient travel [17]; closures or malfunctions of dialysis centers due to facility flooding [16]; and disturbances in the communities where dialysis-dependent patients reside [18].

Two strategies in dealing with patients' disrupted access to critical care facilities, such as dialysis centers, include reallocation of patients across the network of facilities in a region and setting up temporary facilities to meet the demand [19]. Different optimization methods have been proposed in the literature to solve patient and medical resource allocation problems [20–27]. For the pandemic cases, Tsai et al. [24] applied linear programming models to optimize the allocation of patients during the dengue fever epidemic. In the study, the objective function was to minimize the total travel distance of all patients. Ma & Demeulemeester [27] developed an integer linear programming (ILP) model with the aim of efficiently allocating existing beds while optimizing the hospital's financial situation. The model takes various constraints into account, including bed capacity and occupancy. Sun et al. [23] addressed patient and resource allocation between hospitals in a healthcare network during the pandemic influenza pandemic. The mathematical models take into account two objectives related to patients' cost of accessing healthcare services: (1) minimizing the total travel distance, and (2) minimizing the maximum distance a patient travels to a hospital. Ye et al. [25] constructed a patient allocation model during major epidemics that considered the severity of patients' conditions by applying a multi-objective planning method. Mosallanezhad et al. [28] devised a multi-objective model to address personal protection during the COVID-19 pandemic. This multi-objective, multi-product, and multi-period framework aims to satisfy the demand for personal protection equipment while optimizing the objective of minimizing total cost.

For the disaster response cases, Minciardi et al. [21] developed a mathematical model to assist decision makers in optimal resource allocation before and during a natural hazard emergency. Revelle & Snyder [22] addressed emergency room location issues while respecting the maximum demand met. Fiedrich et al. [20] investigated the allocation of available resources to the operational area to minimize the total death toll during the initial search and rescue phase after a major earthquake. Yi & Özdamar [26] built an integrated location-distribution model to study the selection of temporary emergency centers that would result in maximum coverage of post-disaster medical needs in the affected area and optimal distribution of medical staff across both the temporary and permanent emergency response units. Gulzari & Tarakci [29] addressed the problem of strategically locating temporary health facilities, allocating health professionals to these facilities, and incorporating telemedicine into an earthquake response phase. The studied objective was to develop an optimal solution that minimizes unmet healthcare demand by efficiently allocating health professionals to the demand points.

Although past studies have implemented mathematical models in solving the problem of patient reallocation and resource allocation, limited attention has been paid to healthcare network optimization considering the possible infrastructure disruption in the aftermath of hazard events. Conversely, most studies make the assumption that existing facilities will not be affected by the disaster [30–32]. This presumption, however, could be unrealistic, since the infrastructure, such as transportation facilities and medical facilities, could be severely damaged by a large-scale hazard event and remain inoperable for a period of time. Very few studies in the literature consider possible damage exclusively for the medical centers or the aid depots [33–35].

Recognizing the gap, we propose a framework for disaster preparedness and response in healthcare networks considering infrastructure disruptions in the post-disaster period. Specifically, we focus on addressing the following research questions. (1) To what extent is the critical care facility network vulnerable to various infrastructure failure scenarios? (2) What is the optimized patient reallocation plan for dialysis patients whose access is disrupted due to hazardous events? and (3) Where is a potential site for housing temporary medical facilities to improve access for socially vulnerable patients in an equitable manner? Accordingly, there are three objectives in the proposed model: the highest allocation effectiveness, the lowest transportation distance, and the equity of access to treatment for patients in each stricken area. The remainder of this paper is organized as follows. In the next section, we present the examined material and the formulation of the optimization models. In Section 3, numerical results of the studied case are presented to show how the model could help decision makers in determining patient allocation and the potential temporary facility placement in the healthcare system. In Section 4, the analysis and discussion based on the optimization results are presented. Section 5 contains concluding remarks. Fig. 1 presents the conceptual framework of this study.

2. Materials and methods

2.1. Population-facility visitation network and demand setting

This study uses the aggregated human mobility data to capture the dynamic visiting pattern of dialysis patients in the Houston metropolitan area. The human mobility dataset of stops at points-of-interest (dialysis centers in this study) from mobile devices, was collected from a mobility data provider. Each stay point (home location) has been aggregated at the Census Block Group (CBG) level, thus forming the CBG-to-center visit. Dialysis demand exists in 2010 CBGs out of a total of 2144 CBGs in Harris County within which the Houston metro area is located. A total of 142 dialysis centers were included in the study. We used the two-week study period from August 1, 2017, to August 14, 2017, to estimate the number of patients in each CBG. A total of 5308 visits were included in the two-week time window. These visits represent a sample of the actual number of visits. Since obtaining the actual number of visits is not feasible, we assume that these visits represent a fraction of the total visits. We discuss this assumption in the following section where we present the characteristics of facilities and their capacity.

Table 1
Notations used in the paper.

General subscripts and sets	
i, i'	Index of census block groups
j	Index of medical centers
l	Number of road segments
m	Number of Census Block Groups
n	Number of studied medical facility
$\mathscr{G}$	Street topology network
$\mathscr{G}^{(\delta)}$	Flooded street topology network with flooding coefficient δ
S_r	Set of road segments, $S_r = \{1, \ldots, l\}$
S_r^{100}, S_r^{500}	Set of road segments intersects with 100- and 500-year floodplains accordingly, $S_r^{100}, S_r^{500} \subseteq S_r$
S_c	Set of Census Block Groups, $S_c = \{1, \ldots, m\}$
S_c'	Set of socio-vulnerable Census Block Groups, $S_c' \subseteq S_c$
S_f	Set of medical facilities, $S_f = \{1, \ldots, n+1\}$
S_f^{100}, S_f^{500}	Set of dialysis cares intersect with 100- and 500-year floodplains accordingly, $S_f^{100}, S_f^{500} \subseteq S_f$
Parameters	
δ	Flooding coefficient, $\delta \in [0, 1]$
T_{ij}^f	Shortest travel time for trips from Census Block Group i to facility j, $i \in S_c$, $j \in S_f$
$T_{ii'}^c$	Shortest travel time for trips from Census Block Group i to Census Block Group i', $i, i' \in S_c$
T^*	Threshold value for shortest travel time
p_i	Lost-access patient in Census Block Group i, $i \in S_c$
p_i^{dt}	Lost-access patient after distance thresholding program in Census Block Group i, $i \in S_c$
c_j	Remaining capacity in medical facility j, $j \in S_f$
ρ	Median household income poverty line
Variables	
x_{ij}	Relocated patient from Census Block Group i to facility j, $i \in S_c$, $j \in S_f$
P	Total number of relocated patient
T	Total travel time for all lost-access patients

2.2. Topological datasets

To model the accessibility of the transport network to patients, we collect spatial data from OpenStreetMap, a collaborative mapping project that provides a free and publicly editable map. We imported the street network GIS data along with additional attributes (such as street type, street length, and speed limit) and then created the Harris County topological street network using the OSMnx package [36]. The road network, denoted by $\mathscr{G}$, characterizes intersections as nodes and road segments as edges in Harris County. To propose a proactive patient relocation plan considering the potential hazard event, we used the National Flood Hazard Layer (NFHL) to simulate flood hazards. As part of its National Flood Insurance Program, FEMA creates NFHL, consisting of digitized information for delineating floodplains in large geographic areas. The NFHL identifies not-at-risk zone as areas within the 500- or 100-year floodplains, as well as specially designated zones (e.g., coastal hazard zones). We extract the detailed floodplain boundary for our study case in Harris County.

2.3. Flood simulation

To simulate the impact of flooding on the Harris County dialysis healthcare network, we design two failure scenarios. We first identify the vulnerable zone based on the topological characteristics of the road network and the location of the medical facility. We identify the road segments overlaid with 100- and 500-year floodplains, denoted S_r^{100} and S_r^{500}, respectively. In the same way, we identify the medical facility in the 100- and 500-year floodplain, denoted as S_f^{100} and S_f^{500}. In the first scenario, the random failure scenario, we perform random removal of both road segments and medical facilities according to the flooding coefficient, δ, defined as the percentage of flooded road segments in S_r^{100} and the percentage of flooded facilities in S_f^{100}. For each setting of the flooding coefficient, $\mathscr{G}^{(\delta)}$, δ% road segments in S_r^{100} and $0.2 \times \delta$% road segments in S_r^{500} would be randomly selected as flooded and thus inaccessible. In the same way, δ% medical facilities in S_f^{100} and $0.2\times\delta$% medical facilities in S_f^{500} are randomly selected as flooded and closed. In the second scenario, the capacity rank-ordering failure scenario, we perform the same random removal of the road segments but alternate the medical facility failure to capacity rank-ordering removal, where the medical facility on the floodplain, both S_f^{100} and S_f^{500}, with the highest 10% capacity will be identified as flooded and therefore closed.

2.4. Notations

All relevant notations used in the formulations are listed in Table 1.

2.5. Optimization formulation

2.5.1. Total travel time minimization model

In this study, we propose two optimization models to improve the dialysis healthcare network in the face of natural disasters. The first is the model of minimizing total travel time. The goal is to minimize the travel time T for patients with lost access, which is expressed as follows

$$Min \quad T = \sum_{i=1}^{m}\sum_{j=1}^{n+1} T_{ij}^{f} \bullet x_{ij} \tag{1}$$

in flood scenarios, disruption to road segments and medical facilities will result in some patients losing access while others may retain accessibility without regard to travel time. We assume that patients who still have access will continue their treatment at the same facility, while patients who loses access will be transferred to the nearby facility based on the shortest travel time. We calculate the patient's shortest travel time to the medical facility, T_{ij}^{f}, based on the flooded street graph, $\mathscr{G}^{(\delta)}$, in each simulated scenario. The travel time for the entire route was calculated taking into account the free-flow travel speed and the travel length of each road segment. In addition, the model uses a dummy facility $n+1$ to receive the unsatisfied demand. Assigning patients to the dummy facility results in a prohibitively long travel time, $T_{i(n+1)}^{f}$, to the objective function. There are three constraints in the model of minimizing total travel time. First, the patient demand constraints for each CBG are

$$\sum_{j=1}^{n+1} x_{ij} = p_i \forall i \in S_c \tag{2}$$

where, x_{ij} is the relocated number from CBG i to facility j and p_i is the number of lost-access patients in CBG i. Also, the number of relocated patients should not exceed the remaining capacity of facility j. The facility capacity constraints are

$$\sum_{i=1}^{n} x_{ij} \le c_j \forall j \in S_f \tag{3}$$

where, c_j is the remaining capacity in medical facility j. Finally, the relocation number is a non-negative integer variable.

$$x_{ij} \in \mathbb{Z}^{+} \forall i \in S_c, \forall j \in S_f \tag{4}$$

2.5.2. Equity-focused model

The second model proposed in this study consists of two optimization programs, the distance thresholding program and the temporary facility program, which form an equity-focused model. The primary goal of the equity-focused model is to prioritize socially vulnerable (e.g., low-income and minority) patients. In large-scale disasters, the impact is particularly severe for minority communities, the elderly, the economically disadvantaged, and those with chronic illnesses. This demographic pattern is consistent with the population living with end-stage renal disease. Financial constraints and being in disaster-prone areas make economically disadvantaged people more vulnerable to disasters. Relocating dialysis treatment facilities places a significant burden on these patients, particularly those who rely heavily on public transport. To reduce this burden, when planning temporary post-disaster medical facilities, it is important to prioritize locations that are more accessible for these patients. This equity-focused model is geared towards setting up temporary medical facilities close to socio-vulnerable patients, thereby minimizing the need to travel long distances on public transport to travel to relocated facilities.

2.5.2.1. Distance thresholding program. We implement the equity-focused model for the random failure scenario. In the first part of the equity-focused model, we perform the distance thresholding program that has the same objective function in the total travel time minimization model as shown in Eq. (1). The program adds an additional constraint along with Eqs. (2)–(4) which is

$$x_{ij} = 0 \forall T_{ij}^{f} > T^{*}, \forall i \in S_c^{'}, \forall j \in S_f \backslash \{n+1\} \tag{5}$$

The additional constraint makes moving a socio-vulnerable patient to a facility with a travel time, T_{ij}^{f}, above the threshold, T^{*}, an infeasible solution. We have defined the socio-vulnerable population as patients residing on the CBG with a median household income below the poverty line, ρ. Therefore, following the relocation of the distance thresholding program, most non-vulnerable patients will be reassigned to the available medical facility, while the majority of socio-vulnerable patients who are far from the relocated facility will enter the second part of the equity-based model.

2.5.2.2. Temporary facility program. In the second part of the equity-focused model, select the locations for temporary medical facilities. We specify the possible locations for temporary facilities at the centroid of all CBGs. The program was designed as a multi-objective optimization problem. The first objective is to maximize the number of relocated patients, which is expressed as follows:

$$Max \quad P = \sum_{i \neq i^{'}} x_{ii^{'}} \tag{6}$$

The second objective function is to minimize the total travel time from the lost-access patients to the temporary facilities located in the centroid of CBGs. The objective is defined by:

$$Min \quad T = \sum_{\substack{i=1 \\ i \neq i^{'}}}^{m} \sum_{\substack{i^{'}=1 \\ i \neq i^{'}}}^{m} T_{ii^{'}}^{c} \bullet x_{ii^{'}} \tag{7}$$

where, $T_{ii^{'}}^{c}$ is the shortest travel time for trips from Census Block Group i to Census Block Group $i^{'}$. For each CBG, the relocated number should not exceed the remaining patients with lost access after the distance thresholding program indicated by p_i^{dt}. The demand constraint is shown in Eq. (8).

$$\sum_{j=1}^{m} x_{ii^{'}} \le p_i^{dt} \forall i \in S_c \tag{8}$$

Also, the non-negative integer constraint still applies to the relocating variables.

$$x_{ii^{'}} \in \mathbb{Z}^{+} \forall i, i^{'} \in S_c \tag{9}$$

in this study, we addressed the solution of ILP models by implementing an open-source optimization solver called Coin-OR Branch and Cut (CBC). Developed by the Computational Infrastructure for Operations Research (COIN-OR) community, this solver was applied in Python using the PuLP package. The branch-and-cut technique, a tree-search

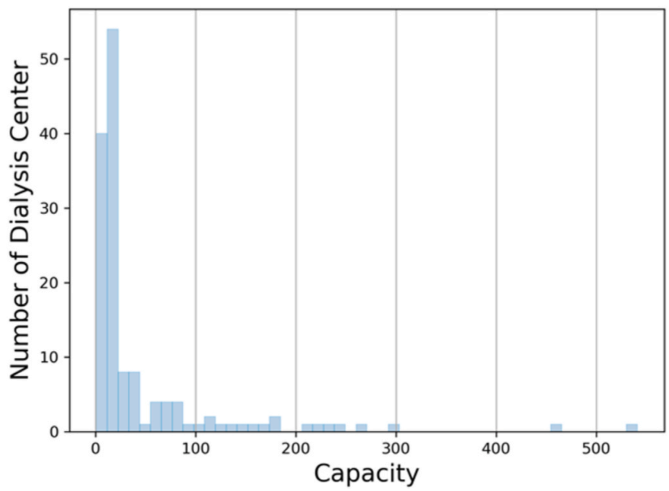


Fig. 2. The distribution of estimated service capacity for the 142 dialysis centers in Harris County, Texas.

method, has been used to address (mixed) integer linear programs and has found diverse applications ranging from solving hub location routing problems [37–39] and scheduling problems [40–42] to addressing energy and environmental modeling [43–45]. This exact algorithm combines elements of the branch-and-bound approach with a cutting plane method. The methodology revolves around solving a sequence of linear programming relaxations of the ILP problem. Branch-and-bound algorithms solve the problem through a sophisticated divide-and-conquer strategy while cutting plane methods improve the relaxation of the problem to more closely approximate the integer programming problem.

3. Results

3.1. Impacts of simulated flood hazard

To build the Harris County dialysis facility network and the demand for facilities, we first estimate the capacity of each dialysis center based on the assumption that the two-week demand accounts for 90% of each facility's total capacity. This assumption is mainly due to the infeasibility of obtaining actual demand and capacity data. The distribution of

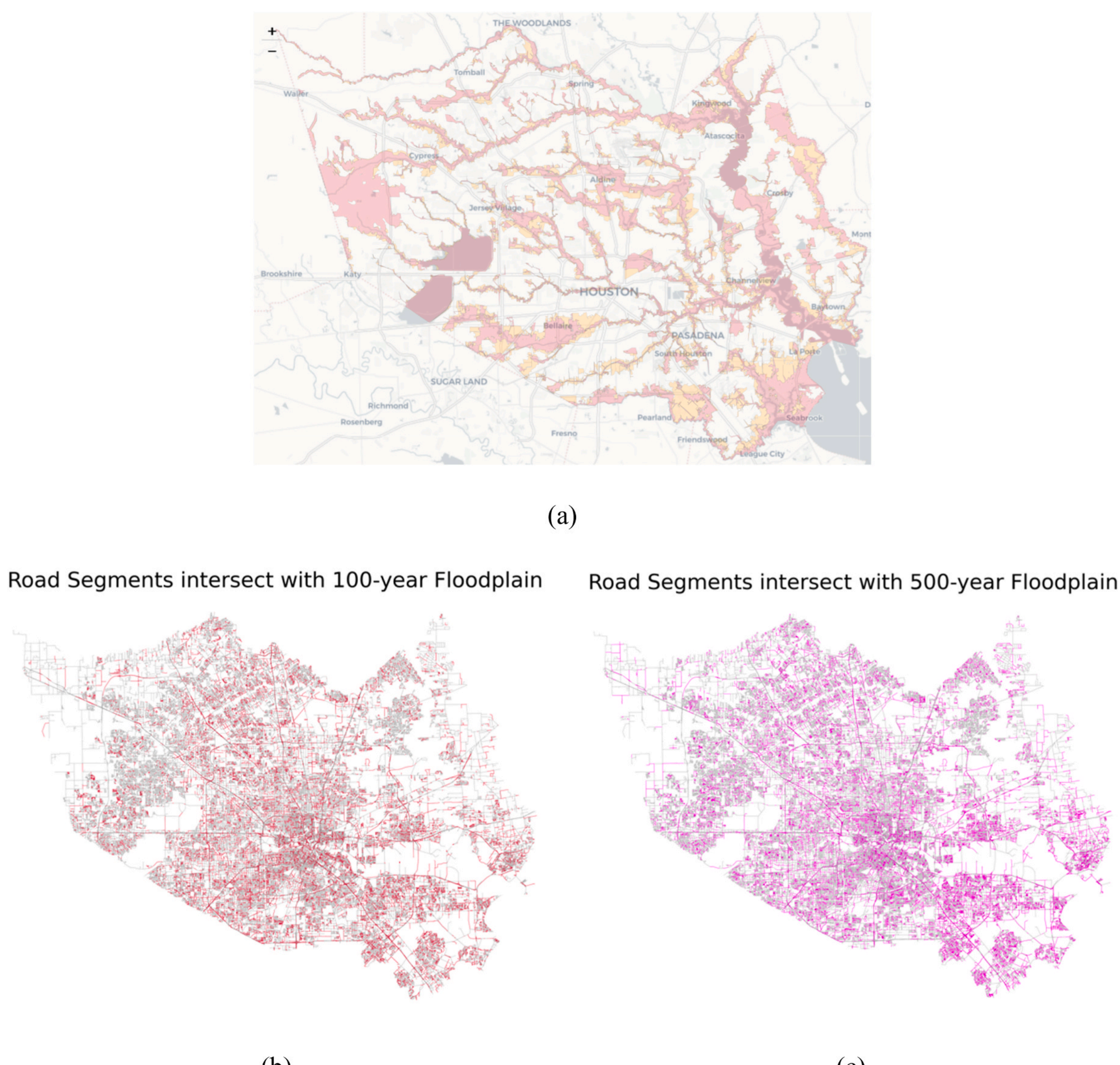


Fig. 3. (a) 100-year and 500-year floodplains in Harris County, Texas. (b) The geographic topology of the road segments intersects with the 100-year floodplain. (c) The geographic topology of the road segments intersects with the 500-year floodplain.

Table 2
The average flooded road segment and flooded medical facility in random failure scenario under different δ settings.

Flood coefficient (δ)	0.05	0.1	0.15
Road segment	3328.6	6644	9942.8
Medical center	1	3	5

the estimated capacity for the dialysis center is shown in Fig. 2. The capacities of the dialysis centers follow a long-tail distribution with a small number of facilities having the largest capacity and greatest demand.

Second, we perform geospatial processing on the road network and the floodplain to classify the road segment. Of the 354,546 total road segments in Harris County, Texas, 54,084 segments denoted as S_r^{100}, that intersect with the 100-year floodplain, while 63,170 segments denoted as S_r^{500} intersect with the 500-year floodplain. The geographic topology of S_r^{100} and S_r^{500} is shown in Fig. 3. In addition, of the 142 total Harris County medical facilities examined, there are 25 medical facilities, S_f^{100}, at the 100-year floodplain and 27 facilities, S_f^{500}, at the 500-year floodplain.

In the random failure scenario, we generated flooded street topology networks $\mathscr{G}^{(\delta)}$ by setting δ equals 0.05, 0.1, and 0.15 to simulate both road failure and medical facility failure. In this scenario, δ% of S_r^{100} and S_f^{100} are randomly selected as flooded and $0.2 \times \delta$% of S_r^{500} and S_f^{500} are randomly selected as flooded. We simulated 10 cases for each δ setting.

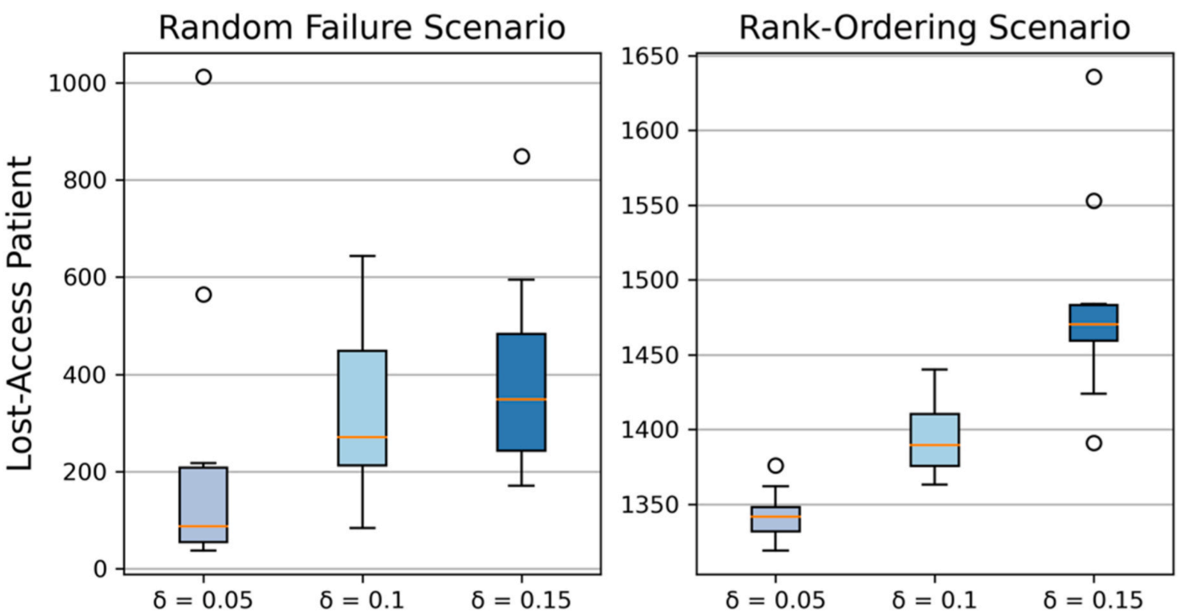


Fig. 4. The distribution of patients losing access to facilities in random failure and capacity rank-ordering failure scenario.

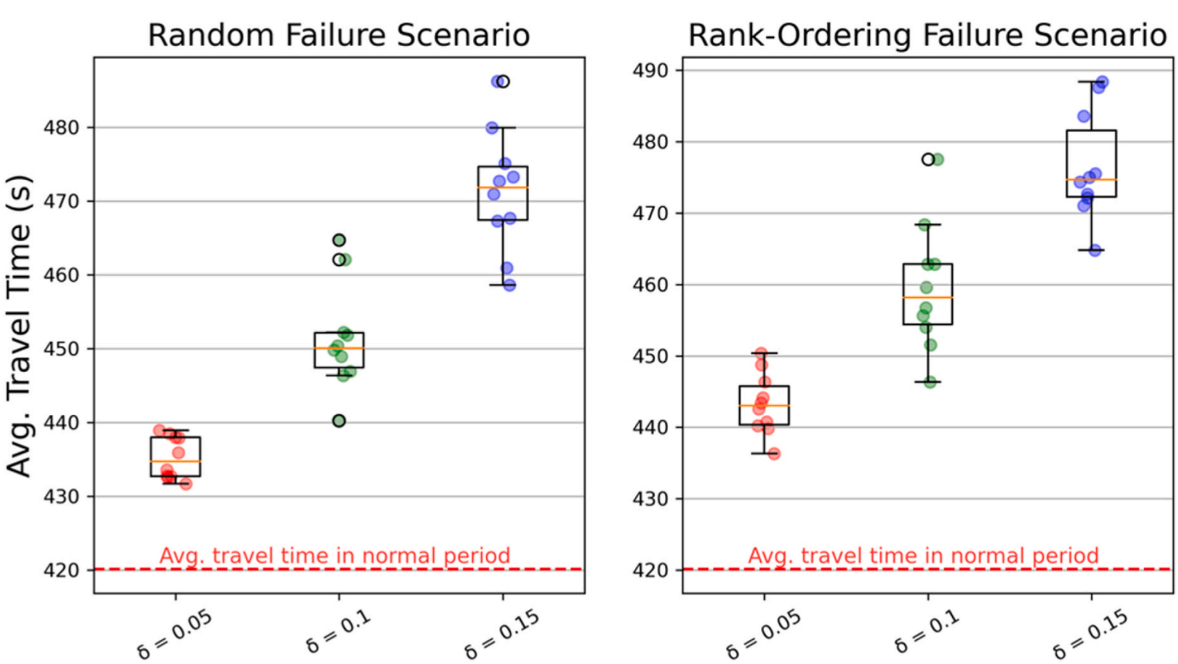


Fig. 5. The distribution of average travel time with three flooding coefficients in random failure scenario and capacity rank-ordering capacity. The red dashed line with a value of 420.19 (seconds) indicates the average travel time in the normal period.

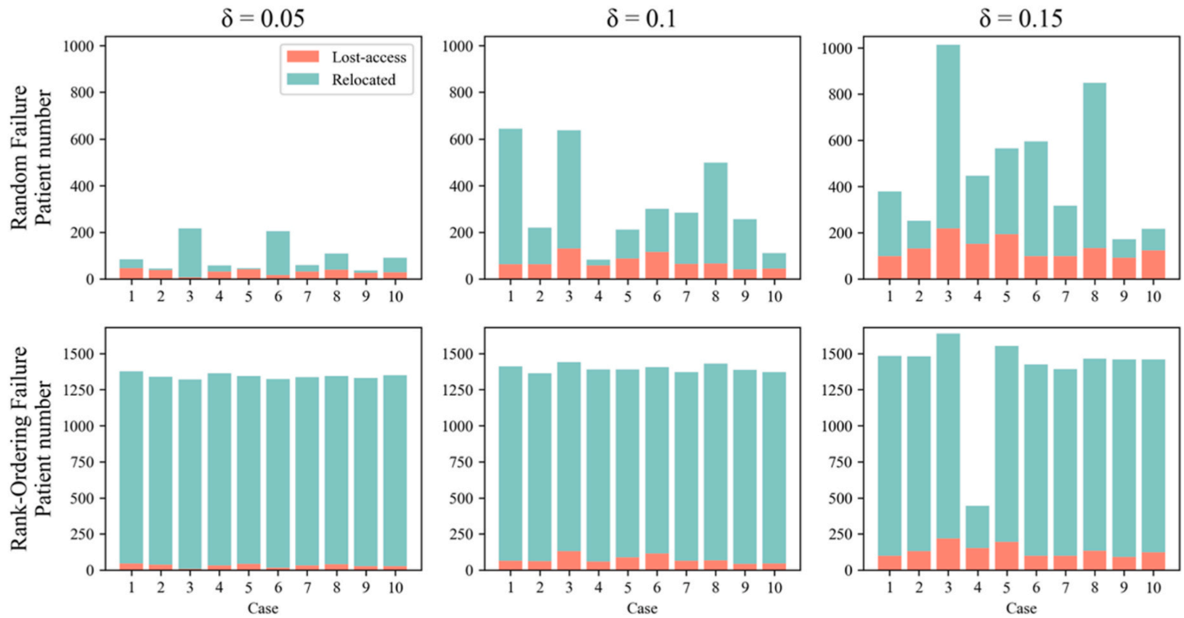


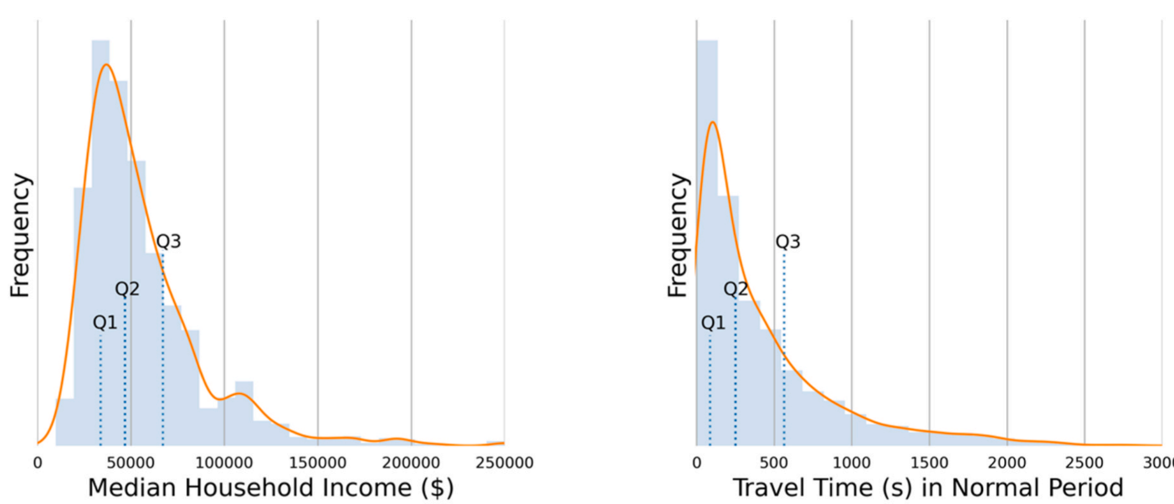
Fig. 6. The optimization result of the total travel time minimization model under random failure scenario and capacity rank-ordering scenarios. The green area represents the patients who were reallocated to nearby dialysis centers. The red area represents patients who still did not have access according to the total travel time minimization model.

The average flooded road segment and medical facility in each δ setting is shown in Table 2.

In the capacity rank-ordering failure scenario, the identification of the flooded road segment follows the same procedure as in the random failure scenario, resulting in an identical $\mathscr{G}^{(\delta)}$. However, for the medical facility failure, we select facilities in the floodplain with the largest 10% capacity, which is 5 of 52 facilities to be flooded. The goal of the capacity rank-ordering failure scenario is to stress test the system and assess the level of dependency of the Harris County dialysis community on these major dialysis centers. Similarly, to assess the potential impact on the dialysis healthcare system in Harris County, we generate ten cases for each flooded street network $\mathscr{G}^{(\delta)}$, giving a total of 60 flooding cases.

We run the flooding simulations; the results show that in the random failure scenario, the average access-lost patient under three flooding coefficient settings is 95 ($\mathscr{G}^{(0.05)}$), 324 ($\mathscr{G}^{(0.1)}$), and 480 ($\mathscr{G}^{(0.15)}$). Meanwhile, in the capacity rank-ordering failure scenario, the average loss of access for patients under three flooding coefficient settings is 1342 ($\mathscr{G}^{(0.05)}$), 1396 ($\mathscr{G}^{(0.01)}$), and 1483 ($\mathscr{G}^{(0.15)}$). The distributions of lost-access distributions are shown in Fig. 4. Lost access means the patients would not be able to access any facility in the region since all facilities are out of capacity or out of service. Disrupted access, on the other hand, means patients need to take longer travel to access facilities.

In the random failure scenario, the average travel time (in seconds) of patients still able to access their medical facility under the impact of flooding is 435.27 ($\mathscr{G}^{(0.05)}$), 451.35 ($\mathscr{G}^{(0.1)}$), and 471.26 ($\mathscr{G}^{(0.15)}$). Meanwhile, in the capacity rank-ordering failure scenario, the average travel time of patients who still have access to their medical facility despite the flood impact is 443.26 ($\mathscr{G}^{(0.05)}$), 459.53 ($\mathscr{G}^{(0.1)}$), and 476.5 ($\mathscr{G}^{(0.15)}$). The distribution of the average travel time at different flooding coefficients in each flood scenario is shown in Fig. 5.



(a) (b)

Fig. 7. (a) The distribution of dialysis patients' median household income distribution. (b) The distribution of travel time of all patients during the normal period.

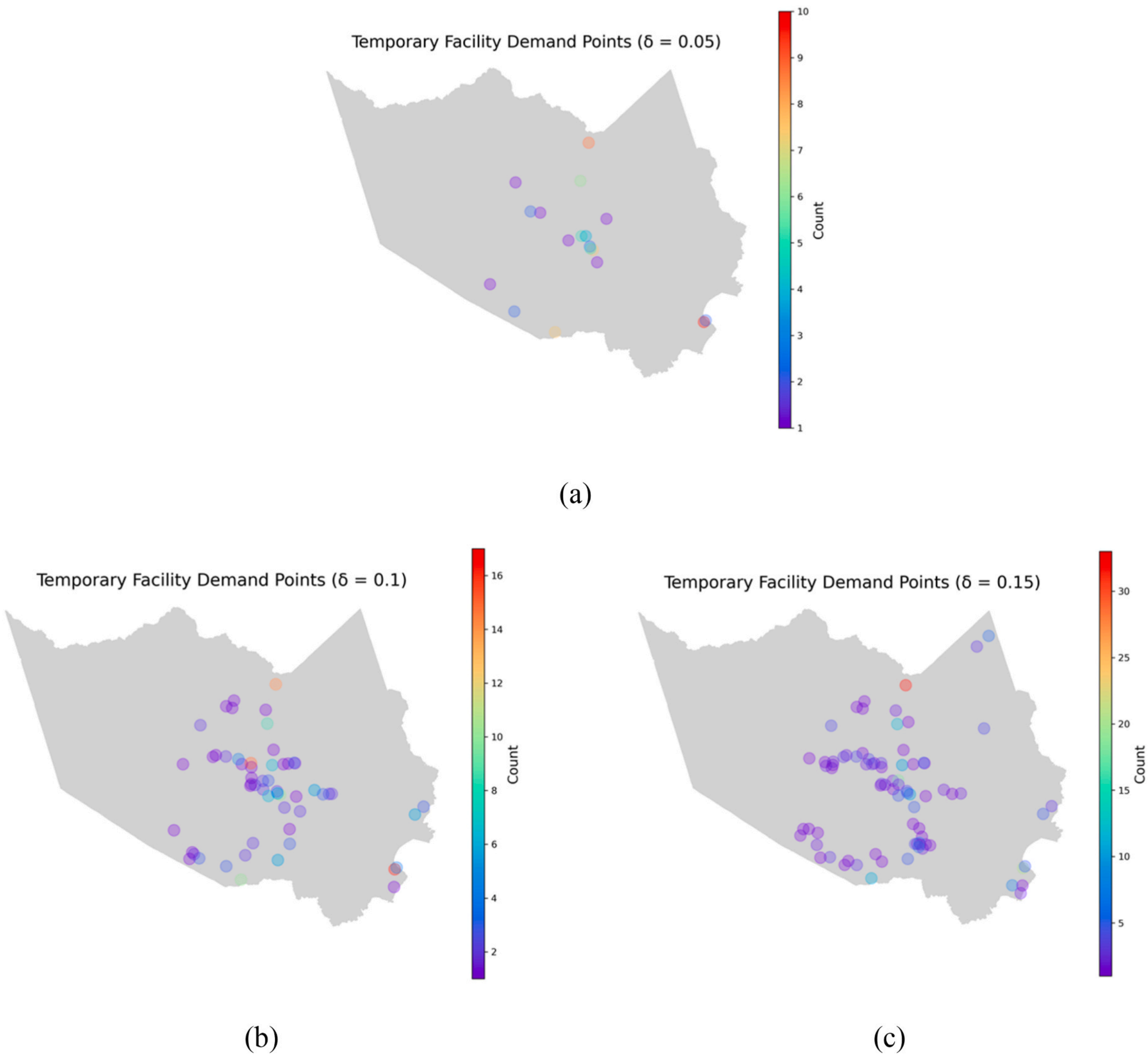


Fig. 8. The geographic distribution of demand points for temporary medical facilities under three flooding coefficients with their ten-case aggregate demand.

3.2. Total travel time minimization model

In Fig. 6, we present the optimization result for minimizing the total travel time under random failure and facility capacity rank-ordering scenarios.

3.3. Equity-focused model

In this study, we set the poverty line, ρ, as the first quartile of the median household income of all patients, which is \$33,956.75. Patients in the CBG with a median household income of less than ρ are classified as a socio-vulnerable population. We also set the travel time threshold, T^*, for the socio-vulnerable population as the median travel time of all patients in the normal period, which is 251.4 s. The relocation of socio-vulnerable patients with a travel time greater than T^* is identified as an infeasible solution under the distance thresholding program. Fig. 7 shows the distribution of median house income for CBGs in Harris County and the distribution of travel time for all patients over the normal period.

We aggregate the ten cases in each flooding coefficient setting to represent the points of need for temporary facilities that could provide the shortest travel time for the nearby patients losing access. In the flooded road topology network $\mathscr{G}^{(0.05)}$, there are 18 temporary facility demand points with a total demand of 59. In addition, in the flooded street topology network $\mathscr{G}^{(0.1)}$, there are 56 temporary facility demand points with a total demand of 183. Finally, in flooded street topology network $\mathscr{G}^{(0.15)}$, there are 80 temporary facility demand points with a total demand of 281. Fig. 8 shows the geographic distribution of the aggregated temporary facility demand point with ten cases under different flooding coefficients.

4. Analysis and discussion

In this study, we designed two failure scenarios to assess the extent to which the examined healthcare network is dependent on large medical facilities. As shown in Fig. 2, there are only 18 medical facilities with an estimated capacity greater than 100, which means that 87.32% of medical care has a capacity less than 100. The result shows that the dialysis healthcare network relies heavily on a few medical centers with large capacities. As shown in Fig. 9, the critical care facility capacity rank-ordering results in a higher average travel time (green) than in the random failure scenario (red). This shows that the accessibility of dialysis is highly dependent on the operation of these large medical centers. This means that once these large medical facilities are perturbed, patients will find it difficult to find an alternate facility nearby to continue their maintenance dialysis. In other words, the critical care facility network has a scale-free structure and is vulnerable to targeted attacks on hub nodes (i.e., large facilities).

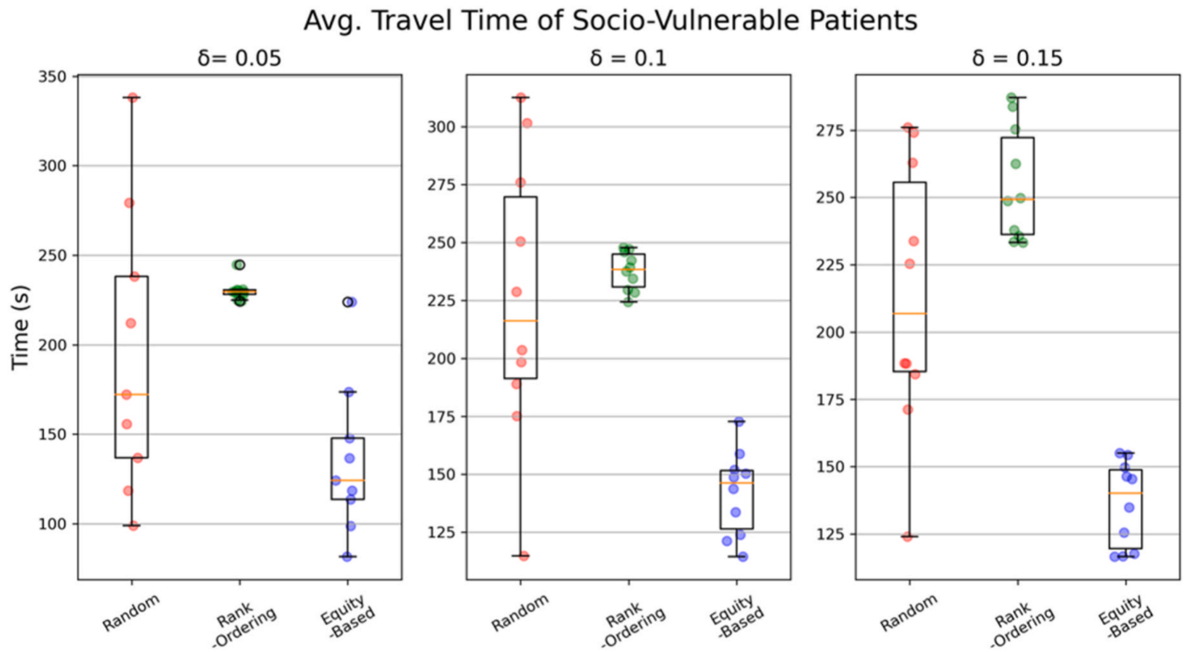


Fig. 9. The average travel time with the travel minimization model (red and green) and the equity-based model (blue) under three flooding coefficients.

Although the capacity rank-ordering medical facility failure results in many more patients losing access (red plus green area) as shown in the second row of Fig. 6, the total travel time minimization model could reallocate most of the patients (green) and achieve the same level of performance, in terms of the number of remaining patients with lost access (red), as in the random failure scenario.

In addition, as shown in Fig. 9, the model for minimizing total travel time will reallocate the socio-vulnerable patient with a longer average travel time, particularly with less variance in the rank-ordering failure scenario (green) than in the random failure scenario (red). By formulating the equity-focused model, we can greatly reduce the average travel time (blue) of socially vulnerable patients in all flooding coefficient settings, thus improving the equity of accessibility of dialysis patients when the facility network is perturbed.

From Fig. 8 we can observe that in the central part of Harris County, there is a strip of demand points in all three flooding coefficient settings, regardless of its demand magnitude. This could be an indicator of high patient demand and an alarm signal that the central-area road segment is highly vulnerable to simulated flooding. In addition, although there are some large demand points in the northern periphery, particularly under $\mathscr{G}^{(0.15)}$ setting, it could be a false positive signal, in particular considering we have excluded the possible medical center north of the border of Harris County. The boundary of the study region is the limits of Harris County. Patients living in the boundary regions of the county might visit facilities in the neighboring county. Hence, demand points identified in the periphery of the county should be further examined in light of proximity of facilities in the neighboring county. Also, the facilities in neighboring counties are likely to be impacted by the flood event as well. Hence, not considering the neighboring county's facilities does not undermine the results of the optimization model.

5. Concluding remarks

This study proposed an equity-focused optimization framework to assess the critical care facility network resilience in disasters. The study and its outcomes have multiple important contributions. First, the proposed optimization framework is among the first efforts to characterize and improve the resilience of regional critical care facility networks in disasters. The framework proposed in this study can serve as a decision support tool to inform emergency managers and public health officials to better understand, prepare, and respond to the effects of disasters on dialysis centers by optimizing patient reallocation and temporary facility placement. Second, this study incorporates equity in the optimization model formulation which is mostly ignored in prior studies [20–22,26,29]. Disasters are known to disproportionately impact vulnerable populations [46,47]; if decision support models (such as the optimization model presented in this paper) do not consider equity aspects, the impacts on vulnerable populations will be exacerbated. Third, this study developed the optimization model of population-facility network based on observational location-based data that would provide a more realistic representation of patients' dependence on different facilities.

Specifically, we simulated the disruption of the road network and the closure of dialysis facilities based on different levels of flood severity. The results show that: (1) the critical care facility network is highly dependent on certain large dialysis centers, which means that the system has the characteristics of scale-free networks and is vulnerable to targeted disruption such as capacity rank-ordering failure. (2) In addition, by assessing the geographic distribution of temporary facility demand points, we also identified the areas of the dialysis patient community that are vulnerable to critical facility failures. A possible solution is to develop a distributed dialysis healthcare system in the study area. While a centralized healthcare system can leverage economies of scale to provide healthcare services more cost-efficiently, especially in areas with large populations, a distributed healthcare system could allow better access to patients. By providing dialysis care closer to where patients live, a distributed healthcare system can reduce travel time and costs and make healthcare more accessible. In addition, a distributed critical care system can be more flexible and responsive to local needs and conditions, enabling providers to adapt to changing patient demands when facing hazardous events. Still, distributed facilities can be more complex to manage and may require greater investment in infrastructure. (3) Furthermore, this study identified potential sites for temporary medical facilities that could be deployed to enhance the healthcare system in the context of disaster resilience, with a particular focus on the socioeconomically vulnerable population. Given socioeconomically vulnerable patients' transportation barriers to reach their relocated dialysis treatment, the increased travel time caused by relocation could pose a significant burden. Therefore, to promote an equitable healthcare network, when designing temporary medical facilities, the dialysis community should consider prioritizing locations that are more accessible to these socioeconomically vulnerable patients.

Incorporating data-driven methods into disaster risk management has transformative potential to mitigate the adverse impacts of hazards on communities, particularly the most vulnerable. This study represents a breakthrough approach by using location-based datasets, critical care facility information, road networks, and hazard exposure data to create and validate an optimization model. This model effectively redistributes dialysis patients during disruptive weather events, a challenge that requires for proactive solutions. Traditionally, responses to access disruptions have been reactive and suboptimal, potentially compromising patient care. In contrast, our data-driven optimization model empowers public health officials and emergency managers to anticipate and strategize. They can assess different scenarios of road inundations and facility closures to pinpoint at-risk areas, optimize patient distribution, and increase the redundancy of care networks. Such insights could inform plans to reduce the impact of disrupted access by increasing the capacity of facilities in critical areas during extreme weather events and building new facilities in vulnerable zones. By integrating data-driven foresight, we are able to prevent catastrophic incidents of kidney failure during extreme weather events. Furthermore, the method and dataset presented here have broader applicability, extending to the optimization of various critical care facilities beyond dialysis centers. The synergistic fusion of data-driven innovation, strategic forethought, and healthcare resilience heralds a paradigm shift in disaster preparedness and response. With this holistic approach, we can work to protect communities, save lives, and strengthen the integrity of critical healthcare systems.

Code availability

The code that supports the findings of this study is available from the corresponding author upon request.

Author contributions

C.F.L. and A.M. conceived the idea. C.F.L collected the data and carried out the analyses. C.F.L. and A.M. wrote the manuscript.

Declaration of competing interest

The authors declare no competing interests.

Data availability

The authors do not have permission to share data.

Acknowledgments

This material is based in part upon work supported by the National Science Foundation under Grant CMMI-1846069 (CAREER). Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

[1] P. Yi, S.K. George, J.A. Paul, L. Lin, Hospital capacity planning for disaster emergency management, Socioecon. Plann. Sci. 44 (3) (2010) 151–160, https://doi.org/10.1016/j.seps.2009.11.002.
[2] S. Crowe, et al., Examining the feasibility of using a modelling tool to assess resilience across a health-care system and assist with decisions concerning service reconfiguration, J. Oper. Res. Soc. 65 (10) (2014) 1522–1532, https://doi.org/10.1057/jors.2013.102.
[3] R.S. Smith, R.J. Zucker, R. Frasso, Natural disasters in the americas, dialysis patients, and implications for emergency planning: a systematic review, Prev. Chronic Dis. 17 (2020) E42, https://doi.org/10.5888/pcd17.190430.
[4] D. Howard, R. Zhang, Y. Huang, N. Kutner, Hospitalization rates among dialysis patients during hurricane Katrina, Prehospital Disaster Med. 27 (4) (2012) 325–329, https://doi.org/10.1017/S1049023X12000945.
[5] K.D. Lempert, J.B. Kopp, Hurricane Sandy as a kidney failure disaster, Am. J. Kidney Dis. 61 (6) (2013) 865–868, https://doi.org/10.1053/j.ajkd.2013.03.017.
[6] M. Bonomini, S. Stuard, A. Dal Canton, "Dialysis practice and patient outcome in the aftermath of the earthquake at L'Aquila, Italy, Nephrol. Dial. Transplant. 26 (8) (2009) 2595–2603, https://doi.org/10.1093/ndt/gfq783.
[7] J.B. Kopp, et al., Kidney patient care in disasters: emergency planning for patients and dialysis facilities, Clin. J. Am. Soc. Nephrol. 2 (4) (2007) 825, https://doi.org/10.2215/CJN.01220307.
[8] R.C. Vanholder, W.A. Van Biesen, M.S. Sever, "Hurricane Katrina and chronic dialysis patients: better tidings than originally feared?,", Kidney Int. 76 (7) (2009) 687–689.
[9] M.A. Kleinpeter, Disaster preparedness of dialysis patients for hurricanes Gustav and ike 2008, Adv. Perit. Dial. Conf. Perit. Dial. 25 (2009) 62–67.
[10] T.M. Logan, S.D. Guikema, Reframing resilience: equitable access to essential services, Risk Anal. 40 (8) (2020) 1538–1553, https://doi.org/10.1111/risa.13492.
[11] S.A. Argyroudis, S.A. Mitoulis, M.G. Winter, A.M. Kaynia, Fragility of transport assets exposed to multiple hazards: state-of-the-art review toward infrastructural resilience, Reliab. Eng. Syst. Saf. 191 (2019), 106567, https://doi.org/10.1016/j.ress.2019.106567.
[12] K.A. Chambers, et al., Impact of hurricane Harvey on healthcare utilization and emergency department operations, West. J. Emerg. Med. 21 (3) (2020) 586–594, https://doi.org/10.5811/westjem.2020.1.41055.
[13] L.R. Lukowsky, A. Dobalian, D.S. Goldfarb, K. Kalantar-Zadeh, C. Der-Martirosian, Access to care for VA dialysis patients during superstorm Sandy, J. Prim. Care Community Health 10 (2019), 2150132719863599, https://doi.org/10.1177/2150132719863599.
[14] C.I. Obialo, W.C. Hunt, K. Bashir, P.G. Zager, Relationship of missed and shortened hemodialysis treatments to hospitalization and mortality: observations from a US dialysis network, Clin. Kidney J. 5 (4) (2012) 315–319, https://doi.org/10.1093/ckj/sfs071.
[15] R. Saran, et al., Nonadherence in hemodialysis: associations with mortality, hospitalization, and practice patterns in the DOPPS, Kidney Int. 64 (1) (2003) 254–262, https://doi.org/10.1046/j.1523-1755.2003.00064.x.
[16] R. Kaiser, I. Karaye, T. Olokunlade, T. Hammond, D. Goldberg, J. Horney, Hemodialysis clinics in flood zones: a case study of hurricane Harvey, Prehospital Disaster Med. 36 (2021) 1–20, https://doi.org/10.1017/S1049023X21000042.
[17] I. Redlener, M.J. Reilly, Lessons from Sandy — preparing health systems for future disasters, N. Engl. J. Med. 367 (24) (2012) 2269–2271, https://doi.org/10.1056/NEJMp1213486.
[18] J. Du, et al., Assessing the effects of urbanization on annual runoff and flood events using an integrated hydrological modeling system for Qinhuai River basin, China, J. Hydrol. 464 (465) (2012) 127–139, https://doi.org/10.1016/j.jhydrol.2012.06.057.
[19] N. Murakami, H.B. Siktel, D. Lucido, J.F. Winchester, N.B. Harbord, Disaster preparedness and awareness of patients on hemodialysis after hurricane Sandy, Clin. J. Am. Soc. Nephrol. 10 (8) (2015) 1389, https://doi.org/10.2215/CJN.10181014.
[20] F. Fiedrich, F. Gehbauer, U. Rickers, Optimized resource allocation for emergency response after earthquake disasters, Saf. Sci. 35 (1) (2000) 41–57, https://doi.org/10.1016/S0925-7535(00)00021-7.
[21] R. Minciardi, R. Sacile, E. Trasforini, Resource allocation in integrated preoperational and operational management of natural hazards, Risk Anal. 29 (1) (2009) 62–75, https://doi.org/10.1111/j.1539-6924.2008.01154.x.
[22] C. Revelle, S. Snyder, Integrated fire and ambulance siting: a deterministic model, Socioecon. Plann. Sci. 29 (4) (1995) 261–271, https://doi.org/10.1016/0038-0121(95)00014-3.
[23] L. Sun, G.W. DePuy, G.W. Evans, Multi-objective optimization models for patient allocation during a pandemic influenza outbreak, Comput. Oper. Res. 51 (2014) 350–359, https://doi.org/10.1016/j.cor.2013.12.001.
[24] J.-F. Tsai, T.-L. Chu, E.H. Cuevas Brun, M.-H. Lin, Solving patient allocation problem during an epidemic dengue fever outbreak by mathematical modelling, Healthcare 10 (1) (2022), https://doi.org/10.3390/healthcare10010163. Art. no. 1.
[25] Y. Ye, L. Huang, J. Wang, Y.-C. Chuang, L. Pan, Patient allocation method in major epidemics under the situation of hierarchical diagnosis and treatment, BMC Med. Inf. Decis. Making 22 (1) (2022) 331, https://doi.org/10.1186/s12911-022-02074-3.
[26] W. Yi, L. Özdamar, A dynamic logistics coordination model for evacuation and support in disaster response activities, Eur. J. Oper. Res. 179 (3) (2007) 1177–1193, https://doi.org/10.1016/j.ejor.2005.03.077.
[27] G. Ma, E. Demeulemeester, A multilevel integrative approach to hospital case mix and capacity planning, Comput. Oper. Res. 40 (9) (2013) 2198–2207, https://doi.org/10.1016/j.cor.2012.01.013.
[28] B. Mosallanezhad, V.K. Chouhan, M.M. Paydar, M. Hajiaghaei-Keshteli, Disaster relief supply chain design for personal protection equipment during the COVID-19 pandemic, Appl. Soft Comput. 112 (2021), 107809, https://doi.org/10.1016/j.asoc.2021.107809.

[29] A. Gulzari, H. Tarakci, A healthcare location-allocation model with an application of telemedicine for an earthquake response phase, Int. J. Disaster Risk Reduc. 55 (2021), 102100, https://doi.org/10.1016/j.ijdrr.2021.102100.
[30] H.O. Mete, Z.B. Zabinsky, Stochastic optimization of medical supply location and distribution in disaster management, Int. J. Prod. Econ. 126 (1) (2010) 76–84, https://doi.org/10.1016/j.ijpe.2009.10.004.
[31] R. Mohammadi, S.M.T.F. Ghomi, F. Jolai, Prepositioning emergency earthquake response supplies: a new multi-objective particle swarm optimization algorithm, Appl. Math. Model. 40 (9) (2016) 5183–5199, https://doi.org/10.1016/j.apm.2015.10.022.
[32] M. Rabbani, H.R. Soufi, S.A. Torabi, Developing a two-step fuzzy cost–benefit analysis for strategies to continuity management and disaster recovery, Saf. Sci. 85 (2016) 9–22, https://doi.org/10.1016/j.ssci.2015.12.025.
[33] G. Galindo, R. Batta, Prepositioning of supplies in preparation for a hurricane under potential destruction of prepositioned supplies, Socioecon. Plann. Sci. 47 (1) (2013) 20–37, https://doi.org/10.1016/j.seps.2012.11.002.
[34] R. Huang, S. Kim, M.B.C. Menezes, Facility location for large-scale emergencies, Ann. Oper. Res. 181 (1) (2010) 271–286, https://doi.org/10.1007/s10479-010-0736-8.
[35] J.A. Paul, L. MacDonald, Location and capacity allocations decisions to mitigate the impacts of unexpected disasters, Eur. J. Oper. Res. 251 (1) (2016) 252–263, https://doi.org/10.1016/j.ejor.2015.10.028.
[36] G. Boeing, OSMnx: new methods for acquiring, constructing, analyzing, and visualizing complex street networks, Comput. Environ. Urban Syst. 65 (2017) 126–139, https://doi.org/10.1016/j.compenvurbsys.2017.05.004.
[37] J. Skålnes, S.T. Vadseth, H. Andersson, M. Stålhane, A branch-and-cut embedded matheuristic for the inventory routing problem, Comput. Oper. Res. 159 (2023), 106353, https://doi.org/10.1016/j.cor.2023.106353.
[38] I. Espejo, A. Marín, J.M. Muñoz-Ocaña, A.M. Rodríguez-Chía, A new formulation and branch-and-cut method for single-allocation hub location problems, Comput. Oper. Res. 155 (2023), 106241, https://doi.org/10.1016/j.cor.2023.106241.
[39] Y. Wu, A.G. Qureshi, T. Yamada, S. Yu, Branch-and-price-and-cut algorithm for the capacitated single allocation hub location routeing problem, J. Oper. Res. Soc. 0 (0) (2023) 1–13, https://doi.org/10.1080/01605682.2023.2197933.
[40] M. Avci, M.G. Avci, A. Hamzadayı, A branch-and-cut approach for the distributed no-wait flowshop scheduling problem, Comput. Oper. Res. 148 (2022), 106009, https://doi.org/10.1016/j.cor.2022.106009.
[41] N. Bianchessi, On optimally solving sub-tree scheduling for wireless sensor networks with partial coverage: a branch-and-cut algorithm, Networks 81 (4) (2023) 499–513, https://doi.org/10.1002/net.22145.
[42] A.V. Mittal, A. Sharanappa, K. Bagchi, S.P. Ramalingam, P.K. Shanmugam, Electric vehicle charging scheduling using branch and cut algorithm, in: International Conference on Advanced Research in Computing, ICARC), 2023, pp. 166–171, https://doi.org/10.1109/ICARC57651.2023.10145685.
[43] B. Yan, M. Di Somma, G. Graditi, P.B. Luh, Markovian-based stochastic operation optimization of multiple distributed energy systems with renewables in a local energy community, Electr. Power Syst. Res. 186 (2020), 106364, https://doi.org/10.1016/j.epsr.2020.106364.
[44] Y. Yu, Y. Chen, J. Jiang, Y. Li, Low-carbon scheduling of integrated hydrogen transport and energy system, Int. J. Hydrog. Energy, Apr. (2023), https://doi.org/10.1016/j.ijhydene.2023.04.064.
[45] P. Zhao, H. Guan, P. Wang, H. Yan, Evaluation of environmental benefits caused by reservation-based shared parking: a case study of Beijing, China, IEEE Access 9 (2021) 3744–3751, https://doi.org/10.1109/ACCESS.2020.3039437.
[46] O.E. Adepoju, et al., Health disparities and climate change: the intersection of three disaster events on vulnerable communities in Houston, Texas, Int. J. Environ. Res. Publ. Health 19 (1) (2022), https://doi.org/10.3390/ijerph19010035. Art. no. 1.
[47] G.S. Smith, E. Anjum, C. Francis, L. Deanes, C. Acey, Climate change, environmental disasters, and health inequities: the underlying role of structural inequalities, Curr. Environ. Health Rep. 9 (1) (2022) 80–89, https://doi.org/10.1007/s40572-022-00336-w.