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A Generalized Model for Including Equity in the Siting of Emergency Services

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Research Article

Keywords: equity, logistic regression, maximal covering location problem, emergency rooms, location decision support

Posted Date: February 2nd, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1321825/v1

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Abstract

We propose a method to identify inequity in access to emergency services using logistic regression and present a model to address inequity by siting additional facilities, recommending both quantity and location. We classify emergencies by the median income bracket of their Zip code tabulation areas. We use logisitic regression to determine whether the probability of emergency responses classified by income bracket are within the average response, defined by time or distance, and quantify overall equity using mean absolute deviation. To address inequity, we iterate a bounded maximal covering location problem over coverage distance and additional facilities to provide a set of possible solutions. We evaluate the mean absolute deviation of each solution and identify the tradeoff of adding facilities and minimizing deviation.

We use 2019 data from the United States Internal Revenue Service and San Francisco Fire Department as an example case for our model. In this example, we find the distribution of emergency rooms leave the low income population of San Francisco significantly underserviced and recommend to decision makers additional locations that reduce the average distance to an emergency room while minimizing mean absolute deviation—providing more equitable access to emergency rooms across income groups in San Francisco.

Highlights

- We use logistic regression to identify inequity in access to emergency services.
- We present a model to site additional facilities with increasing equity as the goal.
- In our example, we find the distribution of emergency rooms leave the low income population of San Francisco significantly underserviced.
- We recommend five additional locations that reduce the average distance to an emergency room while minimizing mean absolute deviation

1. Introduction

Inequity in healthcare, defined as systematic disparities between more or less advantaged social groups, presents an ethical challenge within a community. Examining equity (often called fairness synonymously) considers disparities between groups based on heirarchies of wealth, power, and/or prestige. This differs from examining equality, which generally considers differences among individuals and not how disparties are distributed socially. [1] As the World Health Organization reported [2], it is necessary to assess community healthcare not simply by average levels but also by distribution. This paper, therefore, offers a model to assess differences in access to emergency services between social groups—in this case defined by income levels—providing a yardstick to evaluate health equity within a community.

Municipalities establish fire departments to protect citizens and property from fires, but firefighters are often also trained to perform emergency medical services [3] . As a result, fire departments provide a significant contribution to community access to emergency healthcare. The publicly available data of many fire departments, then, offer opportunities to assess a community's demand for emergency medical services (EMS).

Similarly, emergency rooms play a critical role in community healthcare, as they provide continuous access to care regardless of time or day. Increased mortality is tied closely with increased waiting time for interventions at an emergency department [4] . As distance and time are correlated in the case of medical emergencies, distance from emergency care is also positively correlated with mortality [5] .

While municipalities set their own standards for response times, EMS responses under five minutes reduce mortality risk [6] . Several studies demonstrate increased mortality with increased distance from hospital emergency departments [7, 8] and Jarman, et al. [9], show the highest odds of death exists for patients from low-income communities farthest from level 1 or 2 trauma centers. Specific to their study, the odds of death increased by 8.0% every five miles from a trauma center [9]. As such, the distribution of both emergency medical services—often through the fire department—and emergency departments in a community has significant potential to impact health equity.

Many researchers have proposed models to optimally site emergency services around a given city. The spatial nature of these models often applies set radii, whether in terms of time or distance, around each of a set of locations to ensure adequate protection and service to a population. [3] Discrete optimization models like the maximal covering location problem (MCLP) have supported planning and decision-making for the locations of public services for decades. The MCLP seeks to maximize coverage of demand within a set standard by locating a fixed number of facilities [10]. Using the MCLP to optimally site emergency services follows the literature, which has applied the MCLP to fire stations [3, 11], hospitals, ambulances, blood banks [12] and disaster relief facilities [13].

Models exist that consider equity in facility location, but these often include equity as a constraint of the problem rather than a component of the objective [14, 15, 16]. There are many examples of equity metrics available to include in these models, as this research has attempted to address this issue earnestly for decades [16, 17]. Barbati and Bruno [18], however, demonstrated that many of these measures yield similar results when considering the addition of multiple facilities. The evaluation of each of these metrics is outside of the scope of this paper. We therefore use mean absolute deviation to evaluate equity for its simple and intuitive nature and its continued use in evaluating equity within a community [17, 19, 20].

Our work differs from previous work balancing health equity with efficiency in that it focuses on access to public services instead of outcomes [15, 21, 22, 23] and that optimizing the equity metric is the objective function rather than the constraint [14, 15]. In writing this, we appreciate the findings of Drezner, et al. [24], that suggest the most equitable way to site a facility is to ensure poor service for everyone, and the work of Burkey, et al, [25] which finds the MCLP increases access and equity at the expense of efficiency when relocating facilities. Our method, however, starts by examining the current state of equitable access in a community and recommends additional facilities to address the inequity of that current state. Adding, versus relocating, facilities can only improve the aggregate level of service, and because our goal is to improve equitable access, it is appropriate that we keep equity in our objective function.

We propose a simple, general model to quantitatively evaluate equitable access to emergency services using logistic regression. We then offer an approach to site new facilities to address inequity through optimizing the resulting equity metric from a set of MCLP solutions. Finally, we provide an example of this model using data from San Francisco Fire Department (SFFD) and the Internal Revenue Service (IRS).

To address the effects of suburban sprawl on a fire department, Lambert, et al. [26] classified emergencies using median income in a ZIP code tabulation area (ZCTA) as a predictor of mean response time. Lian, et al. [27] estimated fire department response times based on call type, the time the call was received, and the ZCTA of the call in their regression model to address mortality in San Francisco, a dense city with limited parking and notorious traffic. Our model uses the median income in a ZCTA as the predictor in a simple logistic regression for the probability that a community receives the average response or access with both EMS and emergency departments. Although we focus on income, this idea could be generalized to other factors such as race, ethnicity, disability, or citizenship with sufficient data. Additionally, by categorizing emergencies using the respective median income brackets of their ZCTAs, we attempt to avoid unnecessary surveillance of individuals within a community—demanding less data from individual recipients of emergency services [28].

We used data from San Francisco in our example to capitalize on its dense, diverse, urban environment coupled with its publicly available fire department data to estimate the geographic distribution of its emergency services. Because the Paramedic Division of the San Francisco Department of Public Health merged with the SFFD in 1997, enlisting and certifying firefighters to handle life basic and advanced or life-threatening EMS calls, the dataset provides a detailed picture of a broad swath of emergency services in the city [27].

As of April 2020, San Francisco had a population of 873,965 people and a land area of 46.87 square miles [29]. Additionally, California and San Francisco have demonstrated an interest not only in aggregated impact of policies on community health but also on the distribution of the impact across socio-economic classes in its community [30, 31]. San Francisco has used equity metrics from the Healthy Places Index to capture areas including economics, housing, transportation, and healthcare, but the only indicator noted for access to healthcare was the number of insured adults [32].

For our example, we examined SFFD emergency responses using the median income of its ZCTAs as a predictor to estimate equitable access to services via logistic regression, defining the mean time or distance as a threshold or standard of service. In this example, we noted a significant disparity in distance to emergency rooms between the lowest income ZCTAs and the rest of the city and, applying our model to determine a set of optimal locations, recommended ZCTAs in which decision makers could consider building emergency departments to address this inequity.

2. Method

Our methodology follows five steps:

i. Categorize each ZCTA by its median income bracket.
ii. Determine a “fair” service threshold using the aggregate mean (time or distance) of all responses.
iii. Evaluate equity using logistic regression with publicly available data—specifically using median income brackets of emergencies’ ZCTAs as predictors for whether an emergency service can meet the determined threshold (average response). Additionally, evaluate equity with mean absolute deviation.
iv. In the event one finds inequity, iteratively apply the MCLP for a set of solutions used to site facilities that increase coverage addressing this inequity.
v. Minimize mean absolute deviation across this set of MCLP solutions to recommend locations for a set of additional facilities.

With a threshold of the average time or distance, logistic regression offers a simple method to evaluate health equity. Logistic regression provides probabilities of whether a threshold is met, and averages as thresholds provide insights into differences in service across groups compared to the overall service level. The United States Internal Revenue Service (IRS) classifies each household statement of income annually using the six brackets shown in Table 1, providing the ZIP code for every statement. Using these publicly available data, we can find the median income bracket of each ZCTA and categorize each emergency by this bracket.

Table 1. IRS Income Brackets [33]

Bracket	Annual Income Range
1	$1 - $25,000
2	$25,000 - $50,000
3	$50,000 - $75,000
4	$75,000 - $100,000
5	100,000 - $200,000
6	$200,000 or more

2.1 Logistic Regression

Using logistic regression, with the logit model in Eq. 1, we determine the probabilities that responses (time or distance) to emergencies—categorized by the median income bracket of their ZCTAs—meet the average response for the community. With equitable access to emergency care, large disparities in these probabilities should not exist between emergencies defined by their income bracket. Similarly, the median income bracket of a ZCTA should not be a significant predictor of whether emergency services meet the average response time or distance to an emergency in that ZCTA.

$$Prob\{X \leq avg\} = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\beta_2 x_2+\beta_3 x_3+\beta_4 x_4+\beta_5 x_5)}} \qquad \text{(Eq. 1)}$$

where

$$x_1 = \begin{cases} 1 & \text{if ZIP median income is \$25,000-\$50,000} \\ 0 & \text{otherwise} \end{cases}$$

$$x_2 = \begin{cases} 1 & \text{if ZIP median income is \$50,000-\$75,000} \\ 0 & \text{otherwise} \end{cases}$$

$$x_3 = \begin{cases} 1 & \text{if ZIP median income is \$75,000-\$100,000} \\ 0 & \text{otherwise} \end{cases}$$

$$x_4 = \begin{cases} 1 & \text{if ZIP median income is \$100,000-\$200,000} \\ 0 & \text{otherwise} \end{cases}$$

$$x_5 = \begin{cases} 1 & \text{if ZIP median income is more than \$200,000} \\ 0 & \text{otherwise} \end{cases}$$

We evaluate our regression model using the Hosmer-Lemeshow goodness-of-fit test and use these probabilities—and their differences—to draw conclusions regarding equitable access.

2.2 Mean Absolute Deviation

The aggregated probability of meeting the average response time or distance for the entire community provides a measuring stick for the probabilities determined for each group of ZCTAs defined by their median income brackets. If the probability of a group or groups to meet the average response time or distance falls well below the aggregated probability of meeting this threshold, this suggests inequity in access. Mean absolute deviation (MAD) using the probabilities found with logistic regression reveals the scaled total burden (distance or response time) above what would allow each group equitable access to emergency services (Eq. 2) [19]. MAD, however, is not a normalized measure, and one should not compare between municipalities.

$$MAD = \sum_{i=1}^{n} |P_i - \bar{P}| \qquad \text{(Eq. 2)}$$

where

n = number of groups

P_i = Probability that response for group $i \leq$ average response

$\bar{P}$ = Probability that all responses $\leq$ average response

2.3 Maximal Covering Location Problem (MCLP)

By applying the MCLP, we seek to maximize additional coverage beyond the existing facilities by adding a fixed number from the proposed locations—the ZCTA geographic centroids—given a fixed service distance. We iterate the MCLP in (Eq. 3), accounting for existing locations, in two dimensions: number of additional facilities, *p*, and the threshold distance for adequate coverage, *S*. Because the goal is to maximize the number of additional responses within the average response, we use the current average response as an upper bound on *S*. Assuming we have the locations of all emergencies, we treat each emergency as an individual demand node. As the goal of this analysis is equitable distribution, we weight the value of each emergency location, y_i, equally, $a_i = 1$.

$$\begin{aligned} &maximize\ z = \textstyle\sum_i a_i y_i \qquad \text{(Eq. 3)} \\ &subject\ to \sum_{j \in N_i} x_j - y_i \geq 0, i = 1, \dots, m \\ &\sum_{j=1}^{n} x_j = p \\ &x_j \in \{0,1\} \\ &y_i \in \{0,1\} \end{aligned}$$

where

$$x_j = \begin{cases} 1, \text{if facility is located at location } j \\ 0, \text{otherwise} \end{cases}$$

$$y_i = \begin{cases} 1, \text{if demand node } i \text{ is suitably covered } (\leq S) \text{ by one or more sited facilities} \\ 0, \text{otherwise} \end{cases}$$

a_i = population to be served at node i

p = number of additional facilities to site

N_i = set of potential facilities that suitably cover $(\leq S)$demand node i

S = service distance or time standard $(0 < S \leq$ average response with no additional facilities$)$

2.4 Model Formulation

We evaluate the fairness of each new distribution of additional locations by observing the MCLP solution where yields the minimum mean absolute deviation given we add facilities. Because additional facilities reduce average distances, we re-evaluate the aggregated probability of meeting the new average response. The new aggregated probability serves as the new measuring stick for the group probabilities. Whereas we can assume perfect equitable access will occur when every medical emergency has its own emergency room, an untenable solution, our model takes advantage of local minima within a reasonable range of additional facilities according to the decision maker. Further, because we reevaluate equity with each iteration, we continue to add facilities, *p*, incrementally, we provide the marginal utility (in terms of equity) to decision makers. This yields the final formulation in Eq. 4.

$$\min_{z \in Z} MAD(p) \qquad \text{(Eq. 4)}$$

$$z(p, S) = \text{MCLP solution}$$

$$Z = \text{set of MCLP solutions } z(p, S)$$

$$\min_{z \in Z} MAD(p) = \text{ minimum mean absolute deviation of } z(p, S) \text{ given p}$$

$$p = \text{number of additional facilities to site} = \{1, 2, \dots\}$$

$$S = \text{service distance or time standard } (0 < S \leq \text{average response with no additional facilities})$$

While we intended to provide a bounded set of solutions with this model, other constraints (fiscal, land use, etc.) may not permit optimally equitable distribution of service locations. Even though our model recommends a specific number of additional facilities, the set of MCLP solutions provides options to decision makers to address inequity with quantifiable impacts. It is reasonable that decision makers would elect the number of additional facilities where the relative percent change gained with an additional facility is sufficiently small rather than the local minimum across the domain of potential additional facilities. Further, by using the geographic centroids of each ZCTA for potential additional locations in the SCP and MCLP, these solutions offer general areas where municipal planners and decision makers can focus development efforts.

3. San Francisco Example – Data

The City of San Francisco reports all emergency calls since 01 January 2003 in a publicly available dataset [34]. As of 23 December 2021, the dataset noted 39 unique five-digit ZCTAs. While San Francisco County has only 28 standard ZCTAs including the San Francisco International Airport, SFFD does occasionally have activity in neighboring San Mateo (to the South), Marin (to the North), and Alameda (to the East) counties [35].

Tax Year 2019 ZIP code data from the IRS included data on the number and adjusted gross income of tax filings in each ZCTA [33] . The IRS had income data for 37 of the 39 ZCTAs in the dataset and classified each statement of income into one of six brackets (Table 1). 2010 US Census data included population and household information for each of the 39 ZCTAs [36]. The only ZCTAs in the dataset missing income data were 94128, associated with San Francisco International Airport, and 94037 in San Mateo County. As noted above, the IRS used six distinct brackets, but we only needed four of these brackets to classify San Francisco all ZCTAs by median income, as no ZCTA had median income in the highest (more than $200,000/year) or lowest brackets (less than $25,000/year). We graphically show the 2019 median income brackets for all ZCTAs in the dataset in Figure 1a and in San Francisco in Figure 1b.

San Francisco has 48 fire stations (Figure 2a), including three stations at the San Francisco International Airport [37] . We derived latitude and longitude of each fire station from their street addresses with an online tool at Get-Direction.com. Additionally, we determined the addresses of the 14 major emergency rooms around San Francisco from an area search in Google Maps and converted these addresses to latitude and longitude, shown in Figure 2b.

As of 12 December 2021, the San Francisco dataset constituted a total of 576,256 unique calls [34] . These data included alarm times, arrival times of emergency responders, locations of each call (both as addresses with ZCTA and as latitude/longitude coordinates), the station responsible for the area of each call, the primary situation, and actions taken. We removed incidents where SFFD actions were to only investigate, inform, or standby; calls canceled enroute; and calls with no location; leaving a dataset of 234,353 calls. We further narrowed our analysis by using only calls from 2019—the year of the most recent IRS data—for only 15,079 calls. For our analysis of emergency room distances, we considered only calls categorized by SFFD as medical emergencies—66,836 calls from the entire dataset (since 2003) and 4,315 calls in 2019 (Figure 3). Notably, the only ZCTA from 2019 in the dataset with a medical emergency

not in San Francisco was 94005, associated with Brisbane—just to the south in San Mateo County. Table 2 shows the distribution of emergencies in the dataset according to the median income brackets of the emergencies' ZCTAs.

Table 2. Distribution of emergencies in San Francisco Fire Department dataset classified by the median income bracket of each emergency's ZCTA, shown both from 2003 - 2021 and from only 2019

Median Income Bracket	Number of ZCTAs	Population	All Emergencies		Medical Emergencies	
	2019	*2019*	*Entire Dataset*	*2019*	*Entire Dataset*	*2019*
$25,000 - $50,000	5	197,040 (19.5%)	36,888 (15.7%)	2,177 (14.4%)	10,631 (15.9%)	716 (16.6%)
$50,000 - $75,000	16	500,230 (49.6%)	96,554 (41.2%)	6,736 (44.7%)	27,615 (41.3%)	1,955 (45.3%)
$75,000 - $100,000	6	134,720 (13.6%)	49,787 (21.2%)	3,017 (20.0%)	14,105 (21.1%)	823 (19.1%)
$100,000 - $200,000	10	177,040 (17.5%)	50,593 (21.6%)	3,116 (20.7%)	14,306 (21.4%)	821 (19.0%)
No Income Data	2	0	531 (0.2%)	33 (0.2%)	179 (0.3%)	0
Aggregated	39	1,009,030 (100%)	234,353 (100%)	15,079 (100%)	66,836 (100%)	4,315 (100%)

We determined 2019 was a representative year within the dataset. As shown in Table 3 the average response values for 2019 closely align with the average values for the entire dataset. The largest difference in these values is in the response time from a fire station (from alarm/notification to responders arrival at the emergency), a difference of 37 seconds. This was likely a result of noise in the data, evidenced by the significantly reduced range in these values when focused only on 2019. We used the average metrics for 2019 as the thresholds in our initial logisitic regression.

Table 3. Comparison of summary statistics from SFFD responses both from the entire dataset (2003-2021) and the year 2019.

	Average		**Standard Error**		**Range**	
	Entire Dataset	*2019*	*Entire Dataset*	*2019*	*Entire Dataset*	*2019*
Response Time from Fire Station	327 seconds	290 seconds*	1.09 seconds	1.61 seconds	0 – 83,515 seconds	0 – 6,838 seconds
Distance from Fire Station	0.61 km	0.62 km*	0.00068 km	0.0027 km	0.0014 – 18.20 km	0.0018 – 4.39 km
Distance to Emergency Room	1.61 km	1.65 km*	0.0067 km	0.018 km	0.0025 – 8.08 km	0.043 – 6.88 km

* used as thresholds for logistic regression

4. San Francisco Example – Calculations And Recommendations

4.1 Logistic Regression

We used logistic regression on the 2019 data, with the median income bracket of an emergency's ZCTA as the predictor of the probability a response time or distance would be less than or equal to the average for the dataset. We applied this to evaluate equity in emergency response times, distances from a fire station to an emergency, and distances from an emergency site to an emergency room. We calculated Euclidean distances based on the latitude/longitude pairs given. The regression models yielded the probabilities in Table 4. Using the Hosmer-Lemeshow Goodness of Fit Test, all three models had a *p*-value of 1.0 suggesting very good fits of each logistic regression model.

Table 4. Probabilities from logistic regression on 2019 SFFD responses.

Median Income Bracket	Number of ZCTAs	Incidents	Prob. Response ≤ 290 sec	Prob. Distance ≤ 0.62 km	Emergency Medical Incidents	Prob. Distance to ER ≤ 1.65 km
$25,000 - $50,000	5	2177	0.509	0.464	716	0.165
$50,000 - $75,000	16	6735	0.620	0.484	1955	0.744
$75,000 - $100,000	6	3017	0.732	0.700	823	0.818
$100,000 - $200,000	10	3116	0.616	0.568	821	0.731
Aggregated	37	15045	0.626	0.541	4315	0.659
Mean Absolute Deviation	—	—	0.239	0.320	—	0.809

While it is noteworthy that emergencies in ZCTAs with a median income in the lowest income bracket ($25,000-$50,000 annually) had the lowest in probabilities of response times and distances from fire stations meeting the average, a significant disparity in the probability of average distance to an emergency room for medical emergencies from these same ZCTAs—0.165 vs. 0.659—resulted in the largest mean absolute deviation. This signals inequity, made more apparent by the histograms in Figure 4, as Figure 4c shows a bimodal distribution with a second mode near 4 km. More than this, observing the locations of the existing emergency rooms overlaid on the medical emergencies of 2019 in Figure 5, ERs do not appear well-distributed to service emergencies in the lower income ZCTAs.

4.2 Applying the Model to Address Inequity in Access to Emergency Rooms

With the most notable inequity in the distribution of emergency rooms, we applied our model focused on addressing this issue. The MCLP provided a two-dimensional solution set, with both the number of new facilities and the distance threshold as variables for this analysis. We developed the set of potential ER locations for the MCLP with i) the 14 existing ERs in the and ii) the geographic centroids of all 39 ZCTAs in the dataset as reported in the 2010 U.S. Census [36]. In total, this set included 53 locations.

We found solutions iteratively, increasing suitable coverage distance from 0 to 1.65 km (the average distance to an emergency room without any additional facilities). We repeated this analysis calculating mean absolute deviation and increasing the additional facilities from one to ten for demonstration. We found the minimum mean absolute deviation

of this set with five additional emergency rooms. Table 5 summarizes the recommended additional locations across the iterations of the MCLP and Figure 6 shows the locations of the recommended additional emergency rooms.

Table 5. Summary of effects on mean absolute deviation and average distance to an emergency room by adding locations according to MCLP solutions. Mean absolute deviation minimized at five additional facilities at the recommended locations.

Additional Facilities	Mean Absolute Deviation	Marginal Decrease in Mean Absolute Deviation	Relative Marginal Decrease	Average Distance to an Emergency Room (km)	Recommended Locations
0	0.809	—	—	1.65	—
1	0.459	0.350	1	1.46	94112
2	0.296	0.163	0.318	1.33	94112, 94124
3	0.266	0.030	0.055	1.31	94112, 94124, 94134
4	0.258	0.008	0.015	1.26	94112, 94123, 94124, 94134
5*	**0.211**	**0.046**	**0.077**	**1.19**	**94103, 94112, 94123, 94124, 94134**
6	0.222	-0.010	-0.017	1.12	94103, 94112, 94123, 94124, 94127, 94134
7	0.256	-0.034	-0.062	1.04	94103, 94104, 94112, 94123, 94124, 94132, 94134
8	0.269	-0.013	-0.024	1.02	94103, 94104, 94112, 94123, 94124, 94127, 94132, 94134
9	0.287	-0.018	-0.034	0.98	94103, 94104, 94112, 94122, 94123, 94124, 94127, 94132, 94134
10	0.302	-0.016	-0.031	0.95	94103, 94104, 94112, 94122, 94123, 94124, 94127, 94129, 94132, 94134

*Recommended solution

5. Results And Discussion

Including the five recommended locations, we recalculated the probabilities that a medical emergency would be within the average distance to an emergency room. These updated probabilities in Table 6 show that not only does the new distribution reduce the average distance to an emergency room, but in doing so it significantly increases the probability that emergencies from ZCTAs with a median income in the lowest bracket are within this average distance. Further, it does so while bringing the probabilities of emergencies from ZCTAs across median income brackets closer together as demonstrated with the reduced mean absolute deviation. The histograms in Figure 7 also show the bimodal distribution of distances to an ER noted in the current state (Figure 7a) is not present with the recommended facilities added (Figure 7b).

Table 6. Comparison of probabilities stance from an ER with additional locations from MCLP solution

Median Income Bracket	Number of ZCTAs	Medical Emergencies	Prob. Distance to ER ≤ 1.65 km	Prob. Distance to ER ≤ 1.65 km (with five new locations)	Prob. Distance to ER ≤ 1.19 km (with five new locations)
$25,000 - $50,000	5	716	0.165	0.873	0.573
$50,000 - $75,000	16	1955	0.744	0.776	0.657
$75,000 - $100,000	6	823	0.818	0.859	0.738
$100,000 - $200,000	10	821	0.731	0.864	0.610
Aggregated	37	4315	0.659	0.825	0.649
Mean Absolute Deviation	—	—	0.809	0.169	0.211

We further show the impact on equity of additional facilities in Figure 8, with additional facilities decreasing mean absolute deviation as well as the average distance to an emergency room. It is notable, that these curves are not convex as this is a discrete model using real world data. Further, we know that mean absolute deviation could continue to decrease as the number of additional facilities approaches the number of emergencies. Even so, we found a local minimum across our set of one to ten additional facilities for our recommendation. When considering the strategic planning, oversight, and resources required to site a new emergency room [38], it seems naïve to expect multiple construction projects to occur simultaneously, so the gradient of these curves is also likely informative to decision makers as they work to address inequity in access to emergency care.

6. Conclusions

We proposed examining equity in access to emergency services using logistic regression and an equity metric of mean absolute deviation. We then offered a model to site additional locations to address any inequity found by minimizing mean absolute deviation informed by locations recommended in solving the MCLP. If a municipality intends to improve equitable access by adding facilities, it is appropriate to consider minimizing an equity metric as the objective. Our method bounds this optimization with the MCLP, a method shown to improve access [25, 10].

Applying our model to 2019 data from the San Francisco fire department, we found ZCTAs with the lowest median income bracket ($25,000 - $50,000) had the lowest probabilities to meet the average SFFD response thresholds whether in time or distance, and the probability of medical emergencies in these low income ZCTAs being within the city's average distance to an emergency room was significantly less than any higher income ZCTAs in 2019.

While the mean absolute deviation of distances to emergency rooms suggested an inequitable distribution, the context provided by the probabilities demonstrated this distribution underserviced the lowest income population of the city. The number of insured adults seems an insufficient measure of health equity for California and San Francisco to solely consider. The distribution of emergency rooms in San Francisco appears inequitable, with lower-income populations underserviced.

By minimizing mean absolute deviation informed by solutions of the MCLP (to maximize the number of emergencies within the average distance), we recommended five additional locations that significantly increase the access to

emergency rooms for low income ZCTAs while reducing overall average distance to an emergency room and the mean absolute deviation.

There are several limitations to this study. We only examined the relationship of an area's median income bracket with the response times and distances to emergency services via simple logistic regression, and did not control for any potentially confounding factors. There are clearly other factors we did not examine in this paper like race, ethnicity, disability, citizenship, etc., where disparities raise concern. While we used actual response times, we only used closest distances and did not control for capacity at any location. While using ZCTAs as the set of potential locations worked well for siting emergency rooms, doing so with siting fire stations would likely have yielded inadequate results. Given that there are already more fire stations in San Francisco than ZCTAs (48 vs. 28), solving the MCLP would require a much more granular set of potential locations. Finally, this study was purely quantitative, using publicly available data. Any actions by decision makers should be informed by qualitative studies as well in order to triangulate the most appropriate method to address health equity [39, 40, 41].

We recommend further research, as we treated facility costs and demand weights equally and did not account for facility capacities. Multi-criteria optimization models that account for cost and distance would further inform decision makers as they invest in equitable access to healthcare.

Declarations

7. Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

8. Declarations of Interest

None.

9. Data Ethics

All data was publicly available government-generated data, and ethics approval was not required.

10. CRediT authorship contribution statement

Robert Newton: Conceptualization, Formal analysis, Methodology, Software, Visualization, Writing - Original Draft.

Soundar Kumara: Conceptualization, Formal analysis, Methodology, Writing – Review & Editing.

Jose Ventura: Conceptualization, Formal analysis, Methodology, Writing – Review & Editing.

Paul Griffin: Methodology, Writing – Review & Editing.

Statements and Declarations

The authors have no competing interests to declare that are relevant to the content of this article.

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Figures

Figure 1

(left to right) Location and median income bracket for each ZCTA (a) in the SFFD dataset and (b) in San Francisco County

Figure 2

(left to right) Locations of (a) SFFD fire stations, and (b) emergency rooms in the San Francisco area.

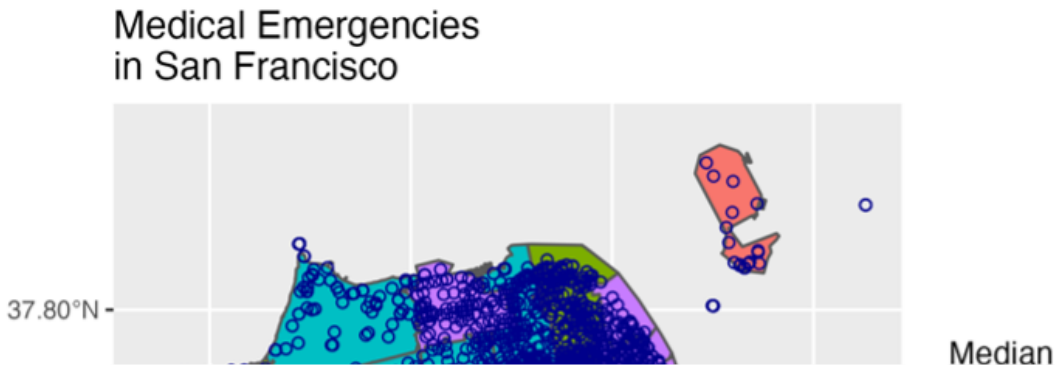

Figure 3

Locations of medical emergencies in SFFD dataset from 2019 overlaid on median income brackets of each ZCTA.

Figure 4

(left to right) Using 2019 data (a) Histogram of SFFD response times, (b) Histogram of distances from SFFD stations, (c) Histogram of distances from emergency rooms.

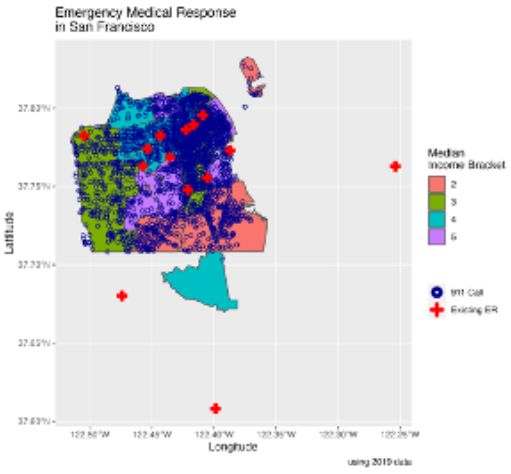

Figure 5

Locations of existing emergency rooms overlaid on the locations of 2019 medical emergencies.

Figure 6

Locations of existing and recommended five additional emergency rooms to minimize mean absolute deviation overlaid on locations of 2019 medical emergencies.

Figure 7

(left to right) Using 2019 data, histograms of distances from medical emergencies to the closest emergency room with (a) the existing 14 emergency rooms, and (b) including the five recommended additional locations.

Figure 8

(left to right) Effects on mean absolute deviation by (a) additional facilities and (b) reduced average distance to an emergency room as a result of adding facilities