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31 January 2024

Weighted and Fuzzy Multi Criteria Decision Analysis: Free Standing Emergency Department Site Suitability

Introduction

Availability and accessibility of emergency medical services is vital to ensuring positive patient outcomes. Though San Francisco's healthcare system has gone against the statewide trend of decreasing emergency room and ICU bed capacity, the ongoing impacts of COVID-19 and respiratory illnesses such as RSV and influenza over the past two years have strained the city's emergency medical response, increasing wait times at emergency departments (Guverich, 2023; Baustin, 2023).

Some emergency room overcrowding is caused by medical emergencies that could be handled without the full resources of a general acute care hospital. Free-standing emergency departments (FSED), most commonly seen in rural settings, are one option to provide patients with emergency medical care while relieving hospital ER overcrowding (Williams & Pfeffer, 2009). FSEDs can provide the same emergency medical services as a hospital emergency department and, if a patient in a FSED requires more intensive care, such as those necessitating a trauma center, they can often be stabilized and supervised by emergency medical personnel before being transferred to a general acute care hospital staffed with additional specialists. Additionally, FSEDs are significantly smaller than hospitals, and could thus extend the resources of existing hospital or medical systems without the same level of intensive capital investment required by typical hospital campus expansions.

The goal of this site suitability analysis is to identify where within the City and County of San Francisco (excluding Terminal Island) a free-standing emergency department should be sited — both which neighborhoods within the city should be prioritized, as well as potential empty parcels that could be developed into an FSED. The primary objectives of this FSED are to serve low-income San Francisco residents who face inequities in healthcare access and availability and to relieve hospital emergency department overcrowding. To perform this site suitability analysis, a weighted overlay and fuzzy overlay were produced as part of a spatial multi-criteria decision analysis (MCDA).

Study Area

San Francisco is located on a peninsula between the San Francisco Bay and the Pacific Ocean full of sloped hills and warm California weather. Despite the complaints of high rates of homelessness and high costs of living, it is still known to be a very attractive and distinctive place to live (Conrad, 2024). However, like much of California, it has struggled with emergency room capacity (Baustin, 2023). The study area is shown below (Figure 1); the islands will not be included in the analysis.

Figure 1. Study area map

Methods

The overall analysis followed the general steps shown below in Figure 1: determining decision making criteria, acquiring the relevant data, cleaning and preparing the data, performing weighted and fuzzy overlays, performing sensitivity analysis, and analyzing the overlays to provide recommendations.

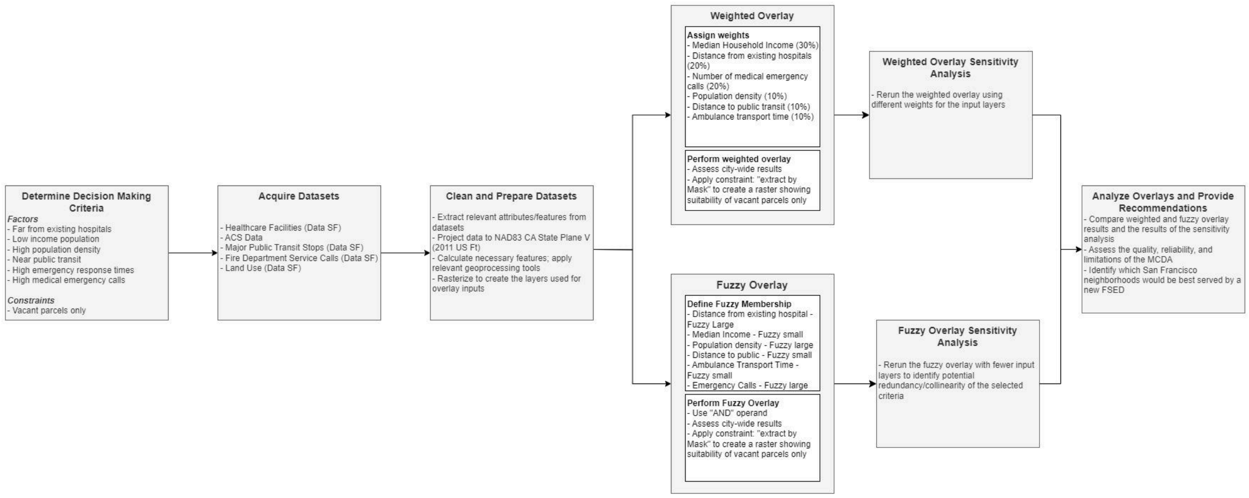


Figure 2. MCDA workflow diagram for FSED site suitability.

Criteria and Constraints

As previously stated, the primary goals for siting an FSED were to reduce hospital emergency room congestion and to improve emergency healthcare accessibility for low-income San Francisco residents (excluding Terminal Island). With this in mind, six criteria were selected:

(*1*) distance from existing San Francisco hospitals, because a new FSED should be sited far from existing hospitals in order to maximize emergency service accessibility throughout the city;

(*2*) median household income, because locating a new FSED in a lower income area would reduce disparities in distance from medical care associated with income (Newton et al., 2022)

(*3*) population density, a commonly used criteria for healthcare (and specifically hospital) spatial MCDAs because higher population densities maximize accessibility for a population (Soltani & Marandi, 2011);

(*4)* hospital accessibility, split into two sub-criteria which provide measures of accessibility for two modes of transportation (though we acknowledge taking public transit is less likely during a medical emergency):

(*4a*) distance to public transit and

(*4b*) mean ambulance transit time; and

(*5*) demand for emergency medical services as measured by 911 calls resulting in transport to a hospital, because high-volume call areas indicate a greater need for emergency care in the area and are most likely to contribute more to hospital emergency room congestion.

The datasets used to represent each of these criteria were, respectively: (*1*) Locations of general acute hospitals; (*2* and *3*) American community survey data for median household income and population; (*4a*) Major public transit stops from the Association of Bay Area Governments Metropolitan Transportation Commission; and (*4b* and *5*) San Francisco Fire Department Calls for Service. Additionally, the San Francisco land use polygon layer was transformed into a raster and used as the snap layer, and the layer used to apply the constraint—vacant parcels only. The table below (Table 1) summarizes the data sources used in the analysis, the relevant criteria, process steps, and how it relates to suitability.

Table 1. Data table

Note: Within the data table, "NAD 1983" refers to "NAD 1983 (2011) StatePlane California III FIPS 0403 (US Feet)."

Criteria	**Reasoning**	**Data Source**	**Data Preparation**	**Suitability**
Distance from Existing Hospitals		Healthcare Facilities. Point data (DataSF)	- Filter to only include general acute hospitals - Calculate Euclidean distance from hospitals	Higher distances from preexisting hospitals are more suitable
Population Density		Population Estimate by Census Block Group. NAD 1983 (American Community Survey)	- Calculate population density - Rasterize	Higher population densities are more suitable
Income		Median Income by Census Block Group. NAD 1983 (American Community Survey 2022)	- Rasterize	Lower median incomes are more suitable
Proximity to nearest major public transit stop	Proxy for transit accessibility	MTA Association of Bay Area Governments Major Transit Stops WGS 1984	- Calculate euclidean distance from stops	Lower distances from major public transit stops are more suitable

Ambulance Transport to Hospital Time	Availability of emergency medical services	Fire Department Calls for Service (DataSF)	- Select only Code 2 and Code 3 (emergency) transports to a hospital in 2022 - Calculate emergency transport time (Hospital arrival datetime - Transport datetime) for each call - Calculate average time per census block group - Use IDW to interpolate missing average transport times	Higher times are more suitable
Fire Department Emergency Calls	Number of emergency calls per block group that end up going to hospital	Fire Department Calls for Service (DataSF)	- Calculate number of calls per block group in 2022	Higher number of calls is more suitable
Land Use	Constraint: Vacant parcels only	San Francisco Land Use - 2020 (DataSF)	- Rasterize	

Data preparation

The snap raster we chose was the San Francisco land use raster, which we rasterized and with a cell size of 180 feet (polygon to raster with cell size of 180 feet and cell assignment max area). This is an appropriate cell size given FSEDs within the U.S. often range from 5,000-20,000 ft^2, with additional square footage required for an ambulance bay and parking (New York State Department of Health, 2013). This was the scale of analysis for all raster overlay inputs, but the ACS data (income and population) and the San Francisco Fire Department Emergency Response data (ambulance transport time and number of medical emergency calls) was originally aggregated to the census block-group level; thus, results at the sub-block group level, though necessary for identifying individual vacant parcels, are artifactual.

The first step for data preparation was to add all of the data onto the map and project to NAD 1983 (2011) StatePlane California III FIPS 0403 (US Feet). Using the hospital csv as well as emergency response times csv, 2 Python scripts were run to extract the coordinates. The scripts used python and the *regex* and *pandas* modules to extract the correct numbers from the strings in the coordinates column. For the emergency response times, the datetime module was used to get the seconds from ambulance departure time at the scene to the arrival at the hospital. Using x y table to point, the coordinates were put onto the table in the WGS 1984 projection (uses degrees as default), and reprojected to NAD 1983. Once the map was added and projected, an extract features was run to get the type of hospitals that were desired. For the emergency response times a spatial join was used to get the count per block group as well as the average time (Sf_block_groups). A feature to points was then run and finally an inverse distance weighting with the z value of time. This raster layer was then clipped to the block groups. A euclidean distance was run on the transit stop points as well as the hospital points. This yielded the distance from hospitals and transit stops. A polygon to raster was run on the block groups data to get the household median income for the past year. To get population density, a new field was created in the block groups and was calculated by taking the total population and dividing by the area of land added to the area of water (for each block group). A polygon to raster was then run with cell assignment max area and size 180 feet.

To inform variable weighting, a random forest model for prediction of the current hospital locations was run.

Unfortunately, not much was done to combat edge effects. The hospital dataset was limited to San Francisco, so areas towards the edges might have a misleading suitability score.

Random Forest

Random forest is a supervised machine learning algorithm, so there must be some sort of labeling of the input raster data. This was achieved by creating a buffer around the hospital locations, intersecting with the SF boundary, erasing the buffer from the boundary, adding an attribute to the hospital buffer called hospital and giving it a value of 1. A union was then run on the hospital buffer along with the hospital erase and a polygon to raster was then run. This yields a raster where the buffer around the hospitals has a value of 1 and everything outside has a value of 0 (our labeled data). Using the calls per block group, emergency response time, income, distance from transit and population density as explanatory training rasters, the forest regression model was created. Other parameters included compensation for sparse categories, 20% training data reserved for validation, 2 validation runs and the creation of a variable importance table. The variable importance table was used in conjunction with background research to help guide the weighting of the criteria in the weighted overlay.

Weighted overlay

As previously mentioned, weighting for the weighted overlay was determined based on a combination of the results of the random forest and literature review. A table showing exact cutoffs for classification and the weighting scheme for each criteria is below (Table 2). Low income population was weighted the highest, at 30%, given both the stated goal of the suitability analysis to target low income populations and due to research by Newton et al. (2022), showing that lower-income populations in San Francisco have lower access to emergency medical service. Classification cutoffs chosen for income from most to least suitable were: ≤ federal poverty line, ≤ the 2022 HUD very low income limit (50% AMI) in San Francisco, ≤ the 2022 HUD low income limit (80% AMI) in San Francisco, ≤ San Francisco median income, and > San Francisco median income (Fukumori & Robbennolt, 2023).

A related but distinct criteria "far from existing hospitals" was weighted at 20%; as previously mentioned by Newton et al. (2022), hospitals within the city are not evenly spatially distributed, and locating the FSED farther from existing hospitals would maximize the benefits. Because "far from a hospital" is context and city dependent, natural breaks were used as classification cutoffs, which provided roughly equal interval classes except for the 5th class.

The cutoffs for population density were also determined using natural breaks for similar reasons of lack of pre-defined cutoffs; quantiles were considered, but ultimately too uneven of a distribution. For this criteria, higher population densities were more favorable, so higher population densities were assigned higher classifications. Due to the importance of this criteria in other hospital MCDA studies, it was weighted highly at 20% (Soltani & Marandi, 2011).

Hospital accessibility by two modes of transportation, ambulance and public transit, were weighted 10 percent each to reflect the overall importance of hospital accessibility using different methods while recognizing potential collinearity or overlap between the two, given the robustness of San Francisco's transit system. Distance from transit was classified by the widely agreed upon "walkable" distance of 400m, or 13,399 ft, in the United States (El-Geneidy et al., 2013); A very good walkability (classified as a 5) was within 400 m, with each increasingly unfavorable classification increasing by 400 m. Because of a lack of predefined standards in the literature within the study area, ambulance transport time cutoffs were also determined using natural breaks, with higher times receiving higher classifications.

Finally, emergency medical calls by block group were also classified by natural breaks. This was due to, again, a lack of predefined standards for what qualified as a high number of emergency calls and the large differences in values (ArcGIS, 2024).

Table 2. Weighted overlay classification scale cutoffs and weighting

Objectives	Criteria	1 (very poor)	2	3	4	5 (very good)	Weighting Score
Low income population (federal poverty line and)	Income using HUD cutoffs	>137.7k+	137,700	114,500	71,600	27,750	30
Far from	Distance	<3,513	6536	9,967	13,399	>13,399	20

existing hospitals	to hospital						
Number of people served (natural jenks)	Population density (people per 10000/sq ft)	0-150	151-300	301-450	451-600	601+	10
Hospital access by transit (walking distance 5 minute increments)	Distance to public transit	>5.2k ft	3.9k-5.2k	2.6k-3.9k	1.3-2.6k	<1.3k	10
Ambulance Transport Time (natural jenks)	Ambulance Departure to Hospital Arrival	<1500 s	1501-2000 s	2001-2500 s	2501-3000	3000+	10
Number of emergencies	Calls per block group	97	215	371	806	>806	20

Following the initial weighted overlay, another weighted overlay was run for sensitivity analysis where the income was given 40% and the EMS response time was eliminated.

Fuzzy overlay

The fuzzy reclassification was performed using the Fuzzy Membership tool in ArcGIS Pro using the parameters found below (Table 3). For the population density layer, the chosen midpoint is the median of population density within the study area, which was used to represent the "typical" population density; large membership type was chosen because higher population densities are more suitable. For income, the midpoint was set equal to median household income in the city; small membership type was chosen because higher incomes are less suitable. For ambulance time, the chosen midpoint is the median ambulance transport time, representing the "typical" response time; large membership was chosen because locations with higher transport times are more suitable. For distance from transit, the midpoint was set equal to 5000 ft, slightly over double the “walkable” distance (approximately half a mile); small membership type was chosen because locations closer to transit are more suitable. Finally, the chosen midpoint for calls per block group was the median number of calls, again representing a typical number of calls; large membership type was chosen because higher numbers of calls are more suitable (indicating greater need for nearby emergency medical services). The “AND” operator was used as it resulted in the most conservative suitability assessment, which was necessary given the potentially high degree of collinearity in factors (ArcGIS, 2023). Initially, an exploratory overlay using the “SUM” operator resulted in much higher suitability overall, to the point it would not have aided in decision making.

Table 3. Fuzzy overlay parameters

Raster Layer	Midpoint	Membership Type
Population density	58	Large
Income	137,700	Small
Distance to Hospitals	5000 ft from hospital	Large
Ambulance Time to Hospital	2317.55615 (Median)	Large
Distance from Transit	3000	Small
Calls per Block Group	109 (median)	Large

Due to concerns about potential redundancy/collinearity of factors, sensitivity analysis was performed by rerunning the fuzzy overlay using five criteria (income, population density, ambulance transport time, number of emergency medical calls, and distance from hospital) and using four criteria (income, population density, ambulance transport time, and number of emergency medical calls).

Results

The results from the forest regression model showed income and population density to be the top predictors of a hospital. Although predicting where hospitals will be and trying to find a suitable place for a new hospital are not exactly the same, it still has potential to lend meaningful insight. We had previously decided that income would be our highest weighted factor, which this variable importance model validated. Although population density was ranked next highest, we decided to split the weight between that and calls per block group, since those were of similar importance given the overall goal of addressing emergency room overcrowding. This indicates that there is some multicollinearity, but we did not decide to run any dimensionality reduction such as principal component analysis or variable inflation factor.

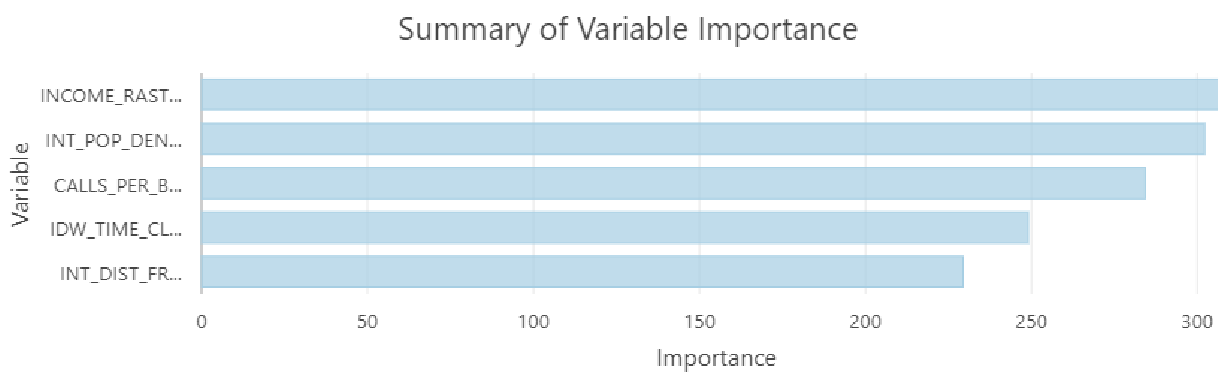


Figure 3. Results of the random forest analysis

The Northern areas of the study area had a plethora of hospitals, and in the weighted overlay we can see that there are very few spots of high suitability in these regions. Although it was found during exploratory data analysis, that there were many regions of low income in this area, much of it is eliminated due to our criteria of being on vacant land.

The results of the weighted overlay show highest suitability in the south western region near TPC Harding Park. There are also scattered spots in the southeast near Bayview. Along the waterfront in the northeast there are a few connected spots with medium high suitability. Along the freeway there is a large amount of low and medium low suitability.

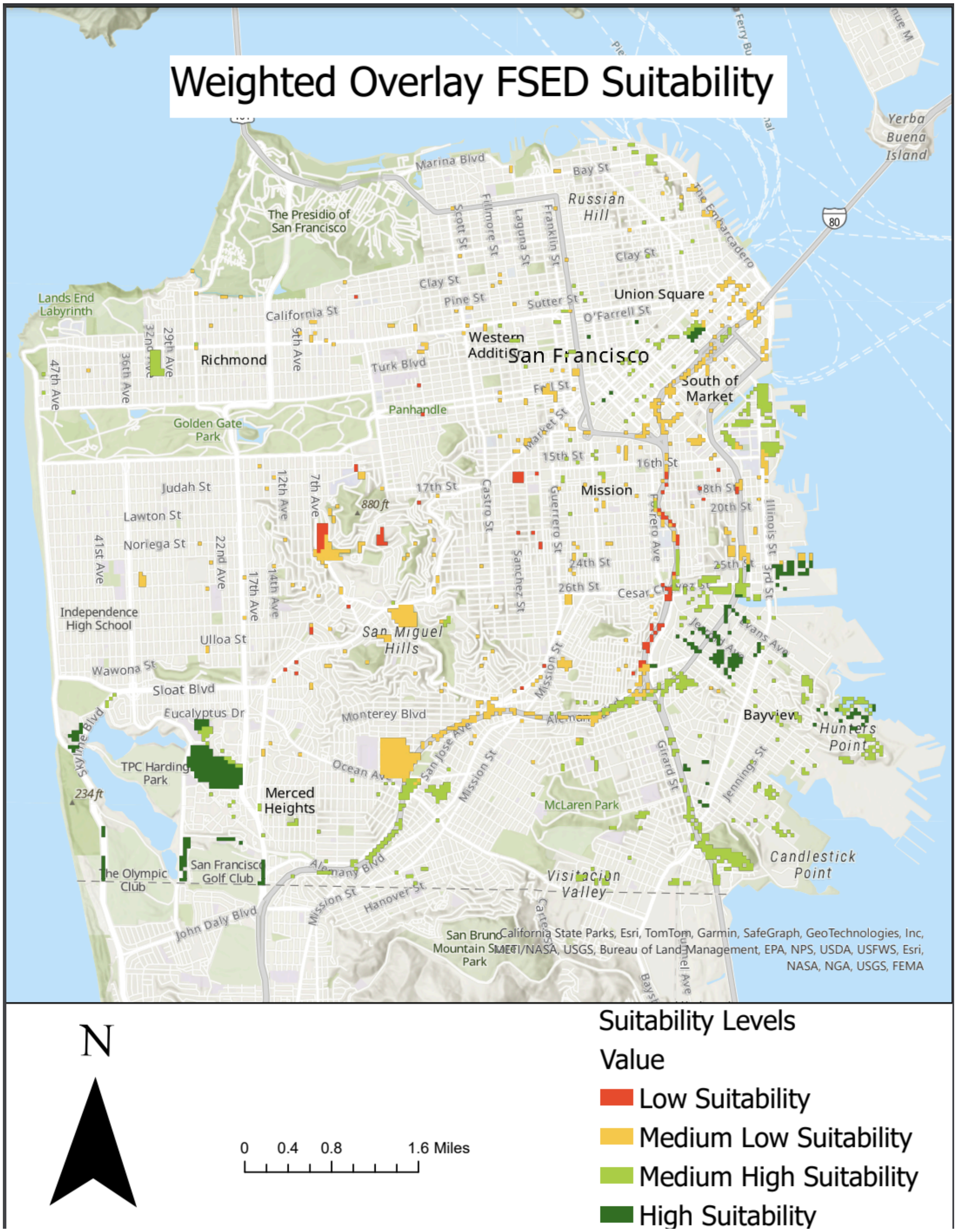


Figure. 4 Weighted Overlay Suitability Analysis of Vacant Parcels

The results of the fuzzy overlay (Figure 4, below) were show fewer suitable parcels overall; many parcels that were moderately suitable (symbolized in yellow) in the weighted overlay were assessed as unsuitable in the fuzzy overlay (in particular, the suitable areas in the southwest of the city by TCP Harding park were determined to have lower suitability, as were Hunters' Point and Candlestick Point.

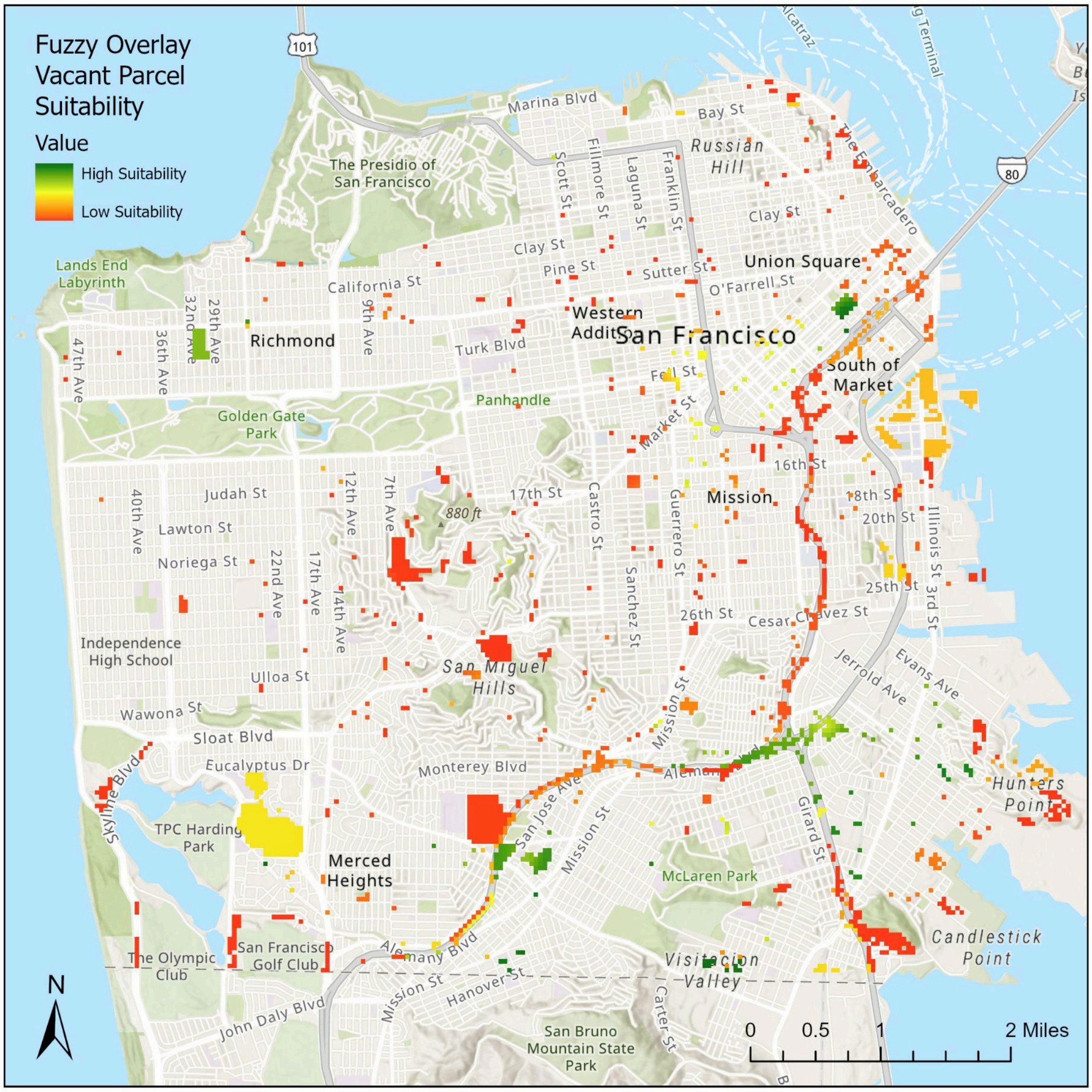
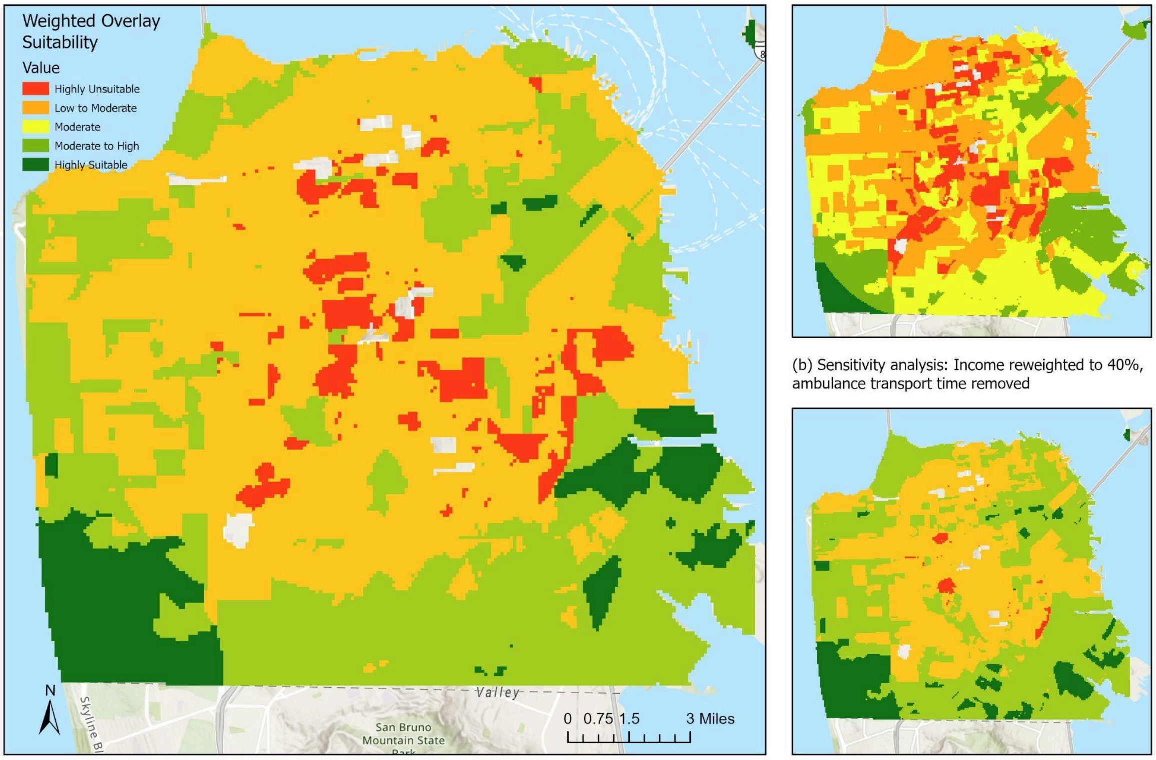


Figure 5. Fuzzy overlay suitability analysis of vacant parcels

Following the initial weighted and fuzzy overlays, sensitivity analyses were performed (Figures 6 and 7). The weighted overlay was first rerun with income reweighted to 40% and ambulance transport time removed as a factor. A third weighted overlay was run removing distance to public transit stops as a factor, and reweighting all remaining factors equally.



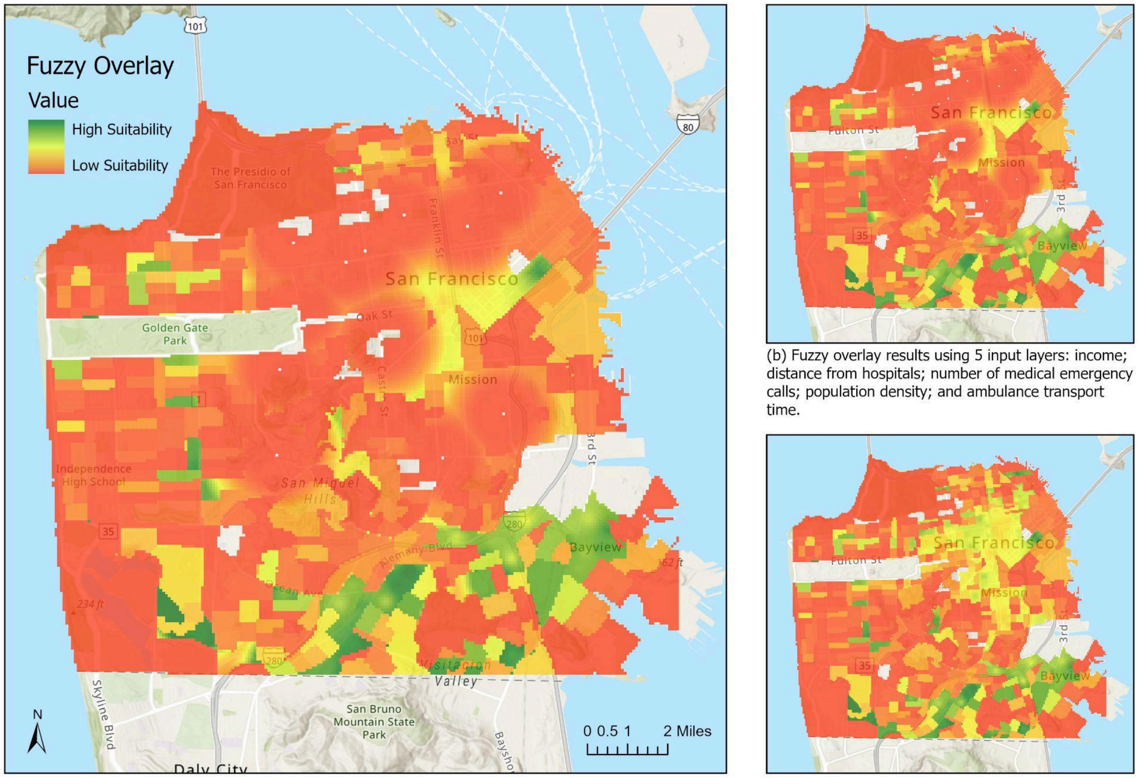
(a) Original weighted overlay (see weighted overlay table for more details).

(b) Sensitivity analysis: Income reweighted to 40%, ambulance transport time removed

(c) Sensitivity analysis: Distance from transit removed as a factor; all 5 remaining factors weighted equally

Figure 6. Weighted overlay and sensitivity analyses (all parcels)

The original weighted overlay and the overlay with five factors and equal weighting are relatively similar; the primary difference is the reduced number of "highly unsuitable" parcels, which in the original analysis were heavily clustered toward the center of the city. The overlay which reweighted income to 40% and removed ambulance transport time retained the higher levels of unsuitability toward the center of the city and reduced suitability around the edges of the city from moderate-to-high suitability to moderate suitability. In other words, while some areas were consistently assessed with the same level of suitability despite changing parameters, there was a relatively high degree of instability revealed by the sensitivity analysis.



(a) Fuzzy overlay results from the original 6 input layers: income; distance from hospitals; number of medical emergency calls; population density; ambulance transport time; and distance to public transit.

(b) Fuzzy overlay results using 5 input layers: income; distance from hospitals; number of medical emergency calls; population density; and ambulance transport time.

(c) Fuzzy overlay results using 4 input layers: income; number of medical emergency calls; population density; and ambulance transport time.

Figure 7. Fuzzy overlay results and sensitivity analysis (all parcels)

The sensitivity analysis for the fuzzy overlay garnered a generally more stable result. The overlay result from using the original six input layers compared to just five (removing distance from public transport) showed almost identical results. Removing two of the six inputs (distance from public transport and distance from hospitals), much of the overlay remained the same, with the main change being a slight increase in suitability (from highly unsuitably to low-to-moderate unsuitability) near Union Square (in the north east quadrant of the city).

Despite the discrepancies between the weighted and fuzzy overlays and their sensitivity analyses, there is still general agreement among the overlay results showing the southern portion of the city to be more suitable for an FSED. Additionally, there are a few blocks in the Richmond District (northwest quadrant of the city) that were consistently scored as suitable by multiple overlays.

Further investigation into high suitability vacant parcels revealed data quality issues that prevented candidate parcels from being identified, as initially intended. The majority of the "vacant" parcels were not actually vacant or undeveloped lots and are currently in use by institutions such as schools.

Discussion

The results of the FSED suitability analysis performed here suggest that multiple neighborhoods adjacent to the southern boundary of the city would be an ideal location for a FSED which would serve low-income residents, improve emergency medical service accessibility, and reduce hospital emergency room overcrowding. Though similar analyses exist for full hospitals, none have attempted to site a FSED, which has slightly different requirements and considerations than a hospital. Still, this recommendation comes with a number of limitations.

Despite moderate agreement between the weighted and fuzzy overlays, the analysis was limited by data quality issues such as incorrectly identified vacant parcels and potential edge effect issues, which will be discussed further below. The moderate degree of instability with regard to the weighted overlay sensitivity analysis suggests that the model could be refined more and made more robust, but further sensitivity analysis would need to be conducted to determine which part of the model is contributing to the lack of stability. The fuzzy overlay sensitivity analysis suggested a far more robust model, but it is also important to note that fewer parameters were changed. Unlike the weighted overlay, where factors were reweighted and adjusted, the only factors were removed for the fuzzy overlay sensitivity analysis. Midpoints and spreads were not adjusted. Further sensitivity analysis for the fuzzy overlay is recommended, particularly with regard to fuzzy membership parameters, in order to further validate the model.

As previously mentioned, upon closer examination, the vacant parcels layer does not appear to be very accurate. Our main areas that we chose to have the FSED are located on properties that have already been developed, including a still operational convention center, mall, and college campus. Future analyses should reconsider land use constraints and, if not, must acquire more accurate data regarding parcel vacancy.

Additionally, due to the lack of coverage on the datasets, there are some issues with edge effects. Some of the southern areas may have artificially higher suitability scores due to the distance to hospitals. Although it may seem like there are not any hospitals in the area, there could be some right to the south of the border. This may cause an apparent need for hospitals when in fact people have accessibility to them. Future analysis would incorporate hospitals in the region below San Francisco. There does not appear to be a need to deal with edge effects to the north, east and west since San Francisco is surrounded by water so there would not be any hospitals or need for any hospitals. The other dataset that would be affected by edge effects would be the emergency response time.

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