Using a Geographic Information System (GIS) to Assess Pediatric Surge Potential After an Earthquake

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ABSTRACT

Geographic information systems (GIS) and geospatial technology (GT) can help hospitals improve plans for postdisaster surge by assessing numbers of potential patients in a catchment area and providing estimates of special needs populations, such as pediatrics. In this study, census-derived variables are computed for blockgroups within a 3-mile radius from Children's Hospital Los Angeles (CHLA) and from Los Angeles County–University of Southern California (LAC–USC) Medical Center. Landslide and liquefaction zones are overlaid on US Census Bureau blockgroups. Units that intersect with the hazard zones are selected for computation of pediatric surge potential in case of an earthquake. In addition, cartographic visualization and cluster analysis are performed on the entire 3-mile study area to identify hot spots of socially vulnerable populations. The results suggest the need for locally specified vulnerability models for pediatric populations. GIS and GT have untapped potential to contribute local specificity to planning for surge potential after a disaster. Although this case focuses on an earthquake hazard, the methodology is appropriate for an all-hazards approach. With the advent of Google Earth, GIS output can now be easily shared with medical personnel for broader application and improvement in planning.

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Key Words: geographic information systems (GIS), geospatial technologies (GT), vulnerability, pediatric, surge

The events following Hurricane Katrina have reaffirmed how quickly any social support system can be stretched to its breaking point. In an extreme event, especially a catastrophe that affects an entire city, any facility that is part of the response must be as fully prepared as possible. Part of being prepared is having accurate estimates of surge potential. This report uses commonly available sources of population data, including counts, density, and demographic characteristics, to show how a surge of one vulnerable population sector, pediatric patients in this case, can be calculated for a hospital. Also discussed are new methods of data dissemination, whereby surge predictions can be easily distributed to maximize situation awareness of decisionmakers. Finally, new approaches are described that could improve on surge prediction based on other available data, particularly geographically targeted survey approaches that lend local specificity to the accuracy of estimates.

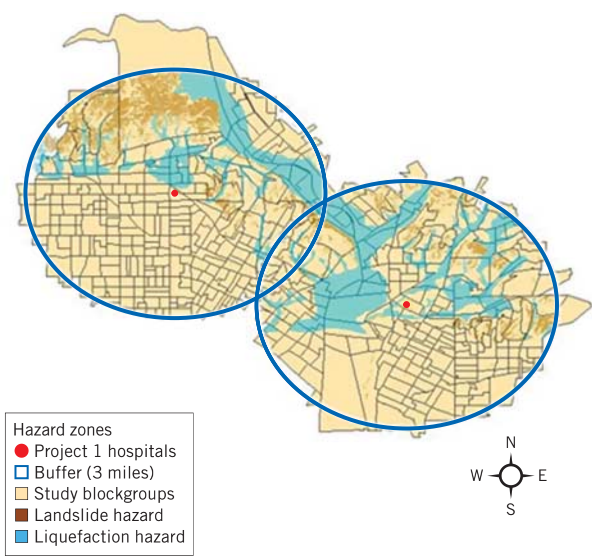
Geographic information systems (GIS) and geospatial technology (GT) are gaining widespread recognition for their utility in emergency management (EM).[1-3] However, their full potential has yet to be realized.[4-7] One area that could benefit from GIS/GT and emerging user-friendly dissemination formats, such as Google Earth, is planning for patient surge in hospitals in the aftermath of an extreme event. Outlined here is a methodology for using variables based on US Census Bureau data to derive vulnerability maps for hospital catchment areas.

The Los Angeles (LA) basin contains multiple faults, as well as areas at risk for landslide and liquefaction (Figure 1). This biophysical vulnerability is one component of the region's multihazard landscape or hazardscape.[8] The LA basin is also at risk for wildfire, and human/technological threats from terrorist attacks to chemical spills to transportation accidents. This unique hazardscape places a responsibility on local hospitals to be prepared to respond to a variety of events. In particular, hospitals should be able to determine (1) how many people they will serve, (2) what type of people they will serve, and (3) for what types of injuries they must be prepared. Although the question about injuries has already been addressed for various types of disasters,[9,10] the first two questions have received scant attention. This dearth of research is a critical gap in planning for a postevent surge, especially considering its implications for highly vulnerable populations such as children.

Children pose challenging care problems to facilities that do not normally treat this population. Under routine operations many hospitals only have limited pediatric supplies in their emergency departments.[11] The most challenging issue facing hospitals is the range in physiology that pediatric patients present to nurses and physicians in these settings. For instance, a newborn may have a normal heart rate that is over three times as rapid as an adults'. Another challenge to an adult hospital's plans for children is the lack of child-sized equipment.

FIGURE 1

Landslide Zones and Liquefaction Zones in CHLA and LAC–USC Study Area, Los Angeles, California.



In some emergencies, physicians must place intravenous or airway devices in patients to save their lives. It is obvious that in small children these devices will vary according to the child's age and size. Most hospitals may not have some of the smallest devices for small children. This situation argues for the importance of planning for pediatric surge in emergency departments, particularly taking into account the types of hazards that may be encountered, the resulting population needing care in these events, and the hospital resources required to meet these needs.

In addition, plans should take into account the time frame in which a surge will likely occur, as this is a factor in the number of pediatric patients that will use the hospital resources. It should be remembered that the common time frame for self-sufficiency before federal help arrives is 72 hours, and that reports from past events indicate that most earthquake victims seek medical attention within the first five days post-earthquake.[10] It is, therefore, important for a health care facility to have detailed scenario plans based on likely events. These plans can be made with the use of GIS/GT and census data, and can be further refined for specific hospital catchment areas and for specific events (such as earthquake vs chemical spill). However, these incidents should not be addressed only as individual cases, but should be imagined in multihazard scenarios,[12,13] which takes into account both biophysical and social vulnerability.

Although biophysical vulnerability is composed of measurable factors surrounding an extreme event, which in this case includes proximity to landslide zones and liquefaction zones, social vulnerability is a more complex concept. The blend of components that create social vulnerability vary from place to place and include characteristics such as age, gender, income, ethnicity, and race.[14,15] Several existing studies have found that factors related to these types of vulnerability, in addition to built environment characteristics,[16-19] are linked to earthquake injuries. For example, Peek-Asa and others have found that age and disability were factors for hospitalization after the 1994 Northridge earthquake.[20] Indeed, they noted, "earthquake injuries have complex causal pathways which include many variables, both behavioural and environmental." In addition, Fawcett and Olveira contend that attractiveness of hospital resources and proximity of the hospital are factors that influence where patients will seek care in the aftermath of an earthquake.[13] Based on these existing studies, the approach described in this report maps socially vulnerable populations and biophysically vulnerable populations in the context of their distance from the hospitals under investigation.

METHODS

Several assumptions have been made in this report. First, data are derived from the US Census 2000 and are now more than 10 years old. Therefore, although these data were the most currently available during the study period, the resulting maps and tabulated risk assessments are dated and subject to revision in light of more recent data when planning for surge. Second, in relation to hospital surge, these numbers are based on location of residence; this approach assumes that the earthquake occurs outside of work and school hours.

Data

Data from the US Census 2000 Summary File 1 and Summary File 3 were mapped by blockgroup for the two study areas. Landslide and liquefaction zones were overlaid on this surface, and blockgroups that intersected the hazard zones were selected for further investigation based on the assumption that they are likely locations of injuries in an earthquake. The Table displays census variables that are used to calculate social vulnerability for this study. These were chosen based on their common acceptance as indicators in the literature[15] and are used here not to provide a comprehensive view of social vulnerability but rather to serve as examples of the types of census data that can be visualized and analyzed in a GIS.

Visualization and Analysis

The most common means of displaying spatial information, such as numbers of pediatric patients in a hospital catchment area, is in a graduated color map. The simplest form of these maps would comprise administrative boundaries, for example by census tract or blockgroup. A GIS allows the manipulation of these data into more appropriate geographies in relation to a hazard. For example, buffer zones can be used to create an area of impact around a key feature—either a hazard location or facility expecting surge after a disaster. The population living or working in this buffer zone can be identified as "at risk" for a specific event (earthquake) or ongoing exposure (particulate matter).

A different GIS approach involves "overlaying" data, which, in effect, means stacking spatial information in the search for common intersections. For example, overlaying demographic information on a highway network might be used to show that higher levels of poverty spatially correlate with close proximity to highways, which, in turn, might be used to prove a thesis on environmental justice where impoverished cohorts suffer disproportionately from particulate matter exposure. For a study considering disaster-related surge potential in a hospital, the simplest form of analysis would involve extending zones of impact (buffers) outward from the facility, and extracting (overlaying) the census-derived vulnerability found within. This general approach can be specified based on a particular event. As this study is focused on post-earthquake surge potential, the relevant inputs are individual/demographic, biophysical, and built environment.[16,18,19] Given this report's focus on developing a widely applicable and easily replicated methodology, built environment data are not included in the two basic approaches used to demonstrate the utility of GIS in assessing pediatric surge potential: (1) visual or cartographic analysis, and (2) spatial analysis. Due to primary and/or proprietary nature of built environment data, they are discussed as a future direction.

Cartographic analysis comprises looking at spatial layers to identify areas where they align or correlate, such as blockgroups that have high values for low educational attainment, high single-parent households, and high numbers of families for whom English is not the first language. This apparent correlation of social vulnerability characteristics suggests the need for further investigation. A next step would be to perform a spatial analytic technique to test the apparent relationship. Then, if this area is identified as a hot spot of multiple vulnerability characteristics, it should be prioritized for updated pediatric population counts, as children in these places are likely more at risk.

In addition to visual analysis, data can also be investigated for statistically significant clusters or hot spots. These are areas of elevated data values that are adjacent to or within a defined proximity of one another. For this report, hot spots of social vulnerability associated with surge potential are identified using a univariate local indicator of spatial autocorrelation (LISA).[21] In this case, LISA is calculated through the program GeoDa.[22]

The values are calculated as a Moran's I statistic, which is a weighted correlation coefficient used to detect departures from spatial randomness. When rates in nearby areas are similar, Moran's I will be large (near 1) and positive. Values are then converted to spatially weighted rates, and GeoDa uses these data to identify hot spots, cold spots, and spatial outliers. The mapped output of LISA shows statistical clusters as a diverging color scheme map, with clusters of high positive (red) and high negative (blue) values. This output is easily interpreted as showing where areas of concern (for example, a vulnerable cohort) are found in the general area of impact from which the surge is expected.

TABLE

Example of Census Variables Indicating Social Vulnerability.

Variable	Description
P001001	Total Population
P012003	Population - Male <5 y
P012004	Population - Male 5-9 y
P012005	Population - Male 10-14 y
P012027	Population - Female <5 y
P012028	Population - Female 5-9 y
P012029	Population - Female 10-14 y
P012A003	Population (White Alone) - Male <5 y
P012A004	Population (White Alone) - Male 5-9 y
P012A005	Population (White Alone) - Male 10-14 y
P012A027	Population (White Alone) - Female <5 y
P012A028	Population (White Alone) - Female 5-9 y
P012A029	Population (White Alone) - Female 10-14 y
P018001	Total Households from Summary File 1
P018012	Male Householder - No wife present - with own children <18 y
P018015	Female Householder - No husband present - with own children <18 y
P053001	Households: Median household income in 1999 (SF3)
P020001	Total Households from Summary File 3
P020002	Households: English
P037001	Population ≥ 25 y: Total
P037011	Population ≥ 25 y: Male; High school graduate (includes equivalency)
P037012	Population ≥ 25 y: Male; Some college; <1 y
P037013	Population ≥ 25 y: Male; Some college; ≥ 1 y; no degree
P037014	Population ≥ 25 y: Male; Associate degree
P037015	Population ≥ 25 y: Male; Bachelor's degree
P037016	Population ≥ 25 y: Male; Master's degree
P037017	Population ≥ 25 y: Male; Professional school degree
P037018	Population ≥ 25 y: Male; Doctorate degree
P037028	Population ≥ 25 y: Female; High school graduate (includes equivalency)
P037029	Population ≥ 25 y: Female; Some college; <1 y
P037030	Population ≥ 25 y: Female; Some college; ≥ 1 y; no degree
P037031	Population ≥ 25 y: Female; Associate degree
P037032	Population ≥ 25 y: Female; Bachelor's degree
P037033	Population ≥ 25 y: Female; Master's degree
P037034	Population ≥ 25 y: Female; Professional school degree
P037035	Population ≥ 25 y: Female; Doctorate degree
PEDS	Total Population ≤ 14 y
WH_PEDS	White population ≤ 14 y
NW_PEDS	Non-white population ≤ 14 y
SING	Households with a single householder with own children $<$ under 18 y in the home
ED	Population ≥ 25 y with at least a high school diploma or equivalent
NO_ED	Population ≥ 25 y without at least a high school diploma or equivalent
LANG	Households that do not report English as their first language

RESULTS

Descriptive Analysis: CHLA

According to Census 2000 Summary File 1 data, 93 862 children, aged 14 years or younger, reside within a 3-mile buffer zone around the hospital. Of these, 61 066 (65.06%) are nonwhite. In addition, 171 232 households reside in this area; 17 657 of these are single-parent households with children younger than 18 years of age. Drawing data from Census 2000 Summary File 3, of the more than 171 000 households assessed, 119 169 (approximately 70%) do not report English as their first language. Finally, of the population 25 years and older, 112 789 (38.05%) report not having a high school diploma or its equivalent. The

FIGURE 2

Three-Dimensional Visualization of Selected Social Vulnerability Indicators.

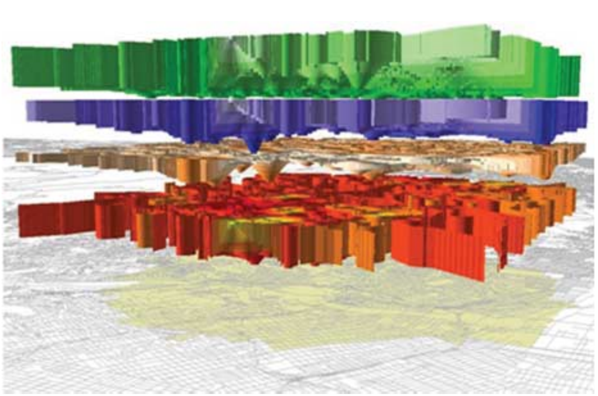
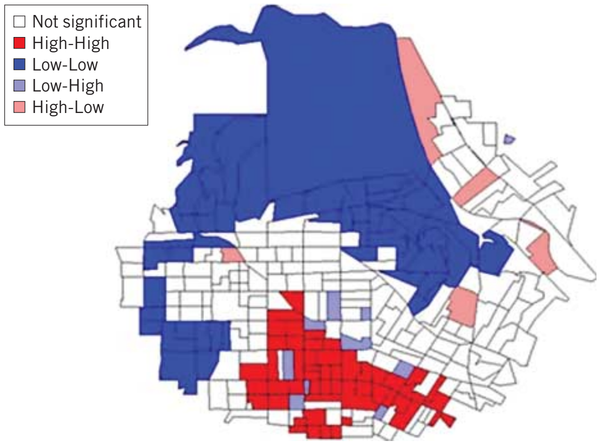


FIGURE 3

Local Indicator of Spatial Autocorrelation (LISA): Cluster Analysis of Non-white Pediatric Population.



median household income ranges from $10 938 to $200 001, with a mean of $33 709 and a median of $25 926.

Descriptive Analysis: LAC–USC

According to Census 2000 Summary File 1 data, 79 009 children aged 14 years or younger reside within a 3-mile buffer zone around the hospital. Of these, 52 834 (66.87%) are non-white. In addition, 84 343 households reside in this area; 11 052 of these are single-parent households with children younger than 18 years. Drawing data from Census 2000 Summary File 3, of the over 84 000 households sampled, 69 924 (approximately 83%) do not report English as the language spoken at home. Finally, of the population 25 years and older, 106 880 (58.20%) report not having a high school diploma or its equivalent. The median household income ranges from $6250 to $120 339, with a mean of $27 949 and a median of $27 153.

Results from both study areas indicate the presence of socially vulnerable pediatric populations. However, they are not necessarily distributed evenly across the three-mile buffer zone nor do they necessarily share the same biophysical vulnerability. Maps and spatial analysis are essential to understanding the geography of pediatric vulnerability and for using this understanding to plan for post-event surge potential.

Visual/Cartographic Analysis

A basic example of buffer analysis is demonstrated in the selection of study areas for this project. A 3-mile buffer zone was extended from both CHLA and LAC–USC. This distance was selected due to its practicality as a “walkable” distance. The rationale was that, in an earthquake, it could be assumed that transportation routes are damaged, and therefore injured people will walk or be carried to a proximate hospital. To add geophysical detail to the potential number of pediatric patients needing care in an earthquake, the landslide and liquefaction zones were identified within these buffer zones (Figure 1). Therefore, the pediatric population is calculated in two ways: first for the total surge area (3 miles) and second for those blockgroups that intersect with known hazard zones.

In this study, overlay analysis was used to investigate the relationship between several commonly accepted indicators of social vulnerability. In Figure 2, green represents language isolation, blue represents educational level, orange represents single-parent households, and red represents minority pediatric population. Rather than display these indicators in a flat and semitransparent format, they have been rendered as contours of their values, inverted, and then displayed in three dimensions floating over the study area. Two benefits of the approach[23] used to create this three-dimensional view are that the surface can be manipulated both above and below a horizontal axis, and it can be viewed from any direction. These features increase the potential insight a user can gain. The vortexes extending down from each layer identify areas of high language isolation, low educational achievement, high numbers of single-parent households, and high concentrations of minority pediatric population.

Spatial Analysis

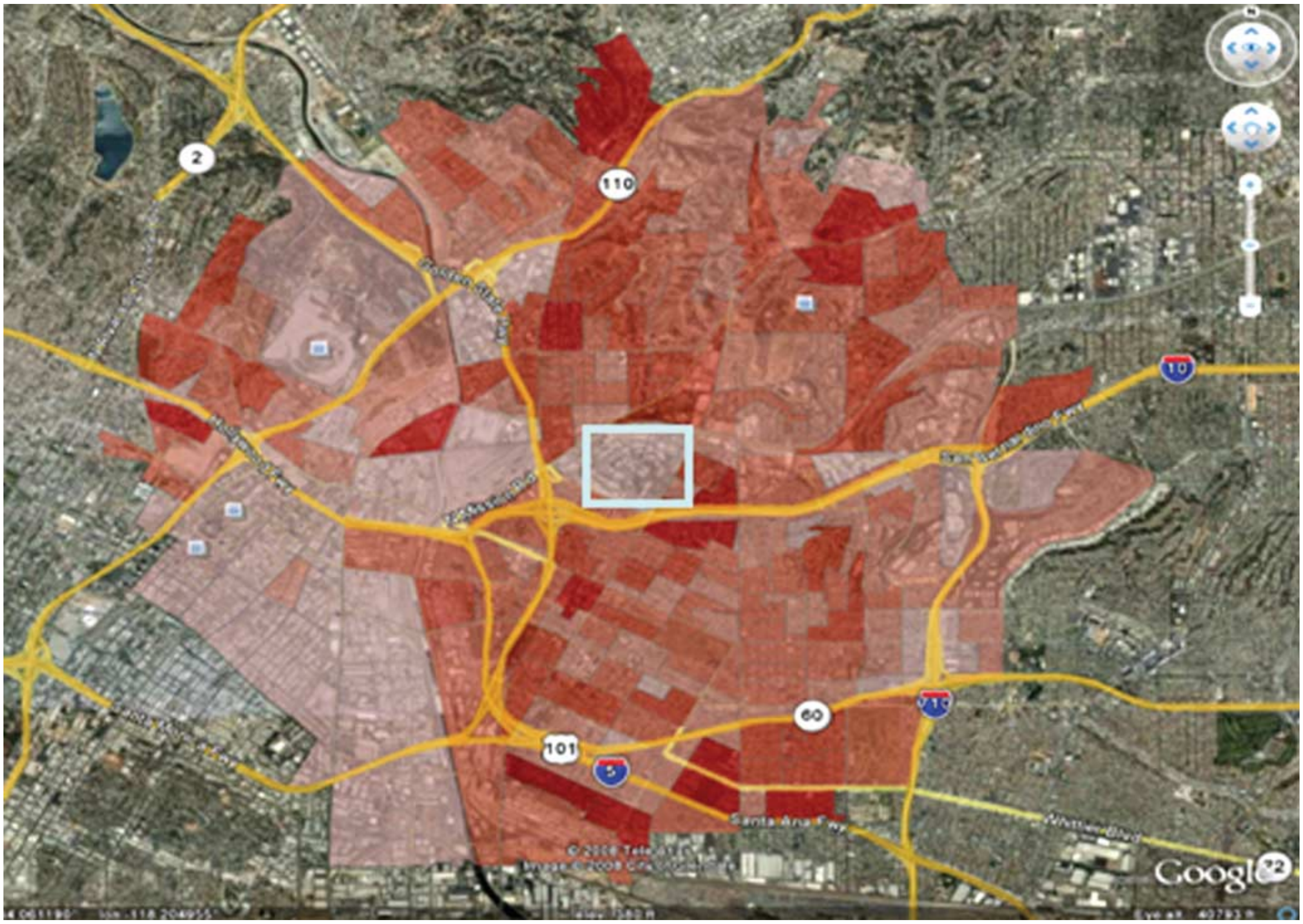
The combination of the mapped outputs, from traditional graduated displays, through three-dimensional overlay surfaces, to LISA hot spots, reveals the following patterns. First, physical vulnerability (proximity to landslide and liquefaction zones) is limited to the northern and eastern sectors of the CHLA study area. Second, these areas of potential physical impact do not coincide with geographies of social vulnerability, which are located to the south of the hospital. Clusters of non-white pediatric population (cf, Figure 3), single-parent households, low educational attainment, and language isolation are located to the south of CHLA.

The result is that much of the physical vulnerability is in an area with minimal population, Griffith Park (the large blockgroup in the northernmost part of the study area), or in areas where the population is affluent with a structurally sound built environment. Initially, this may be interpreted as a more favorable situation, as socially vulnerable people are not residing in the physically vulnerable areas. However, landslide and liquefaction are only two of a number of events that could affect this population in an earthquake. For example, the degree of shaking and resulting injuries is not only a function of the physical environment, but also of the built environment.[20] However, built environment data are usually either proprietary or require primary collection. As the focus of this report is on widely accessible data and an easily replicable methodology, built environment data layers are not specifically included. Rather, social vulnerability characteristics are used due to the spatial association between populations with limited resources and substandard housing. Given the clusters of socially vulnerable populations to the south of CHLA, a major earthquake is still likely to generate a considerable surge in pediatric cases from traditionally vulnerable populations. In this case, the findings are similar to those reported by Cutter and others, in that areas of high social vulnerability do not necessarily coincide with areas of high biophysical vulnerability.[8] This finding is important because these areas may not be included in postdisaster plans due to distance from physical threats, but this is a mistake. These areas may not face the same biophysical vulnerability, but injuries may nonetheless occur.

Alternatively, in the LAC–USC study area, social vulnerability characteristics are more evenly distributed than they are around CHLA. Once again, differing exposures to physical hazards will affect the resulting pediatric surge potential. The built environment in this area is also of concern, as residential land use is mixed with commercial and industrial uses and is intersected by major transportation corridors, which increase the potential of secondary events emanating from an earthquake. Figure 4 displays one of the social vulnerability indicators (nonwhite pediatric population) in Google Earth Keyhole Markup Language (KML) format. Converting GIS data into Google

FIGURE 4

Google Earth Keyhole Markup Language (KML) Overlay of Non-white Pediatric Population in the LAC–USC Study Area.



Earth allows medical personnel to take advantage of the power of GIS for planning surge potential, without the requirement of learning the software. This approach also allows a general assessment of the surrounding built environment, including local facilities that might pose additional threat to the surrounding population, as is the case in the LAC–USC study area.

COMMENT

The surge prediction approach employed in this report provides a quick glance of surge potential; however, there is room for greater specificity. The approach can be dramatically improved to gain a more accurate understanding of the population needing help after a disaster. Improvement can be made in three general areas: refining the buffer zone, using existing data sets, and employing primary data collection for targeted areas at risk. Each of these approaches is discussed in the following sections.

First, for this report, a circular buffer zone was used. However, a more accurate manipulation of space would involve a buffer shape that matched transportation corridors. If the rationale of using a circular buffer is to approximate walking distance, then actual corridors along which one can walk should be included. Barriers such as the Los Angeles River would limit surge potential from certain directions. Similarly, depending on the event, it would be reasonable to assume that under certain conditions the transportation system would remain intact. This would mean that the zones should be elongated along major arterials, such as Interstate 5, which runs close to LAC–USC. A further improvement would be the addition of all competing destination facilities. For this report, the assumption was made that all people residing inside the surge buffer zones would choose the hospital under investigation. Alternative clinics and hospitals might reduce the reported surge to both of the hospitals mentioned.

The second major improvement would involve using actual data to estimate the geography of surge location. It is relatively easy to combine spatial data sets in a GIS, and adding current patient home addresses onto the surge surface could help refine predicted numbers. Questions can be asked, such as how many current patients come from within and outside the buffer zone? How many current patients originate from the areas of high vulnerability as identified using the LISA analysis? These actual data can be further improved by using pseudosurge data, as is sometimes used to test syndromic surveillance methods.[24,25] The most obvious example would be the mapping of pediatric surge during past influenza seasons.[26]

The third major improvement would be in collecting more accurate information from the vulnerable population falling inside the buffer zones. A simple survey could be targeted to the population residing inside the LISA hot spots (as well as to a small control population outside the buffer zone) to ascertain answers to simple questions such as where would you go in the event of a disaster? Alternatively, a survey can be conducted of the neighborhood built environment to capture both physical and social characteristics.[27] However, all of these approaches require the involvement of expert personnel in emergency management, geography, and GIS, who are not usually found within a hospital environment. Therefore, effective implementation of such strategies must occur through collaboration. Hospitals should seek out the involvement of these academic and government professionals for projects that focus on planning for disaster.

In summary, the census is a useful data source for assessing potential pediatric surge after an earthquake or other extreme events. It is the only geographically comprehensive data set containing social vulnerability data for every place in the United States. For this reason alone, the approach described here can be applied anywhere in the country. However, these data can also be augmented with individual-level surveys designed on a spatial sample to focus on areas proximate to the hospital. In essence, combining census-based data with GIS provides a unique way of planning for surge potential. GIS is becoming a commonly used tool in all aspects of emergency management. Its use for assessing pediatric surge potential is in its infancy, however, and needs further development in directions such as those cited here.

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