

Accessing Acute Care Hospitals in the San Francisco Bay Area after a Major Hayward Earthquake

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Abstract

Earthquakes can severely disrupt healthcare access, especially in dense cities. Here, we provide a comprehensive assessment of how a magnitude 7.25 earthquake on the Hayward Fault would impact access to acute care hospitals in the San Francisco Bay Area. By integrating seismic hazard with hospital and transportation infrastructure’s vulnerability and connectivity data, we analyze 76 hospitals (426 buildings with 16,639 beds) and 5,163 bridges within a vast network of ~ 1.5 million edges and ~ 0.5 million nodes. We leverage the rich data to formulate a coupled risk-network model to quantify simultaneous failures and cascading disruptions across the healthcare and transportation systems. Our results revealed that hospital bed capacity could drop to 51%, with Alameda County retaining only 20%. Widespread transportation failures further restrict access, increasing regional travel times by 177% and exceeding 1000% in parts of East Bay, potentially fully isolating hospitals and entire urban communities. These findings underscore the urgent need for resilient healthcare and transportation infrastructure to mitigate life-threatening disruptions following major earthquakes.

Earthquakes wield the power to severely disrupt healthcare, placing vulnerable populations at risk.¹ For example, the 2023 M 7.8 earthquake in Türkiye left tens of thousands without hospital services after damaging more than 50 hospitals.² In a mass-casualty earthquakes,^{3,4} such as those in 2005 Pakistan, 2010 Haiti, 2008 China, 2011 Japan, 2023 Türkiye,^{5–10} thousands of injured people can worsen their health, even up to deadly conditions, if they do not receive timely to medical care. Healthcare disruptions from earthquakes can persist for years,¹¹ as exemplified by the 2003 Bam earthquake in Iran, where communities lost access to essential treatments, such as dialysis, for up to five years.¹²

In the U.S., even moderate earthquakes have severely disrupted healthcare access. The 1971 M 6.6 San Fernando Earthquake severely damaged four major hospitals, resulting in forced evacuations, two structural collapses, and more than 40 fatalities.¹³ These tragedies prompted legislative action,

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notably the Alfred E. Alquist Hospital Seismic Safety Act of 1973, mandating stronger, more resilient hospital infrastructure. The law emphasizes that hospitals must be capable of protecting vulnerable patients and providing critical medical services immediately after disasters, highlighting the importance of resilience planning in disaster-prone regions.¹³

In 1994, the M 6.7 Northridge Earthquake severely disrupted healthcare services,¹⁴ forcing evacuations at eight acute care hospitals in Los Angeles County and causing around USD 3 billion in losses.¹⁵ Twelve hospital buildings constructed before the Alquist Act were deemed unsafe for occupancy. Post-Alquist Act buildings experienced less structural damage, but non-structural damage was still extensive.¹⁶ These disruptions prompted California Senate Bill 1953, mandating significant retrofits to acute care hospitals by 2030.^{17,18} Notably, many hospitals face financial barriers that may prevent them from meeting these critical resilience goals.¹⁹

Recognizing these vulnerabilities, this paper investigates the effects of future earthquakes on healthcare access in the entire San Francisco Bay Area, California. Previous research has largely focused on individual hospital vulnerability, using methods such as structural engineering analyses, performance-based assessments, and fault-tree evaluations to examine structural and non-structural damages within isolated facilities.^{20–23} Other studies evaluated patient treatment dynamics and medical resource demands through flow models and discrete event simulations in post-earthquake scenarios but are similarly limited to single-building analyses.^{24–27}

Yet, hospitals do not function in isolation—particularly in dense urban areas—as demonstrated by seismic events in Chile, New Zealand, and Japan.^{21,28–31} Failures in individual hospitals can trigger broader network impacts, overwhelming remaining facilities and forcing patients to travel greater distances for care, severely exacerbating health outcomes for critically injured individuals. Thus, understanding healthcare resilience requires examining interconnected failures across healthcare and transportation infrastructure.^{32–34}

Failures in transportation infrastructure significantly compound healthcare disruptions. Historical evidence from earthquakes, including those in China (2008), Haiti (2010), Japan (2011), and Türkiye (2023), demonstrates the severe consequences when transportation networks fail, impeding access to critical emergency medical care.^{5–8} In the U.S., the 1989 M 6.9 Loma Prieta earthquake also highlighted this vulnerability: 91 state highway bridges were damaged, resulting in 13 closures, severely disrupting hospital access. These interconnected disruptions underscore the urgent need to evaluate joint vulnerabilities within healthcare and transportation infrastructure, particularly in earthquake-prone regions like the San Francisco Bay Area.

Transportation and healthcare infrastructure are critical to disaster response, prompting extensive research on their vulnerability to natural hazards.^{11,35–37} Models applied to diverse urban areas such as Lima, Peru,^{35,38} and Butte County³⁶ and the San Francisco Bay Area^{39,40} in the U.S., have significantly improved our understanding of how disruptions in transportation^{39–41} or healthcare^{11,35,36} infrastructure individually affect emergency response. However, these studies typically treat the two systems independently, overlooking critical interactions between them. Addressing this interplay is essential since transportation failures can severely restrict access to functioning hospitals, yet integrating these systems remains challenging due to limited data and region-specific complexities.

To fill this critical gap, we investigate, for the first time, joint failures of healthcare and transportation networks across the San Francisco Bay Area after a major earthquake. By examining diverse urban communities near active seismic faults—often underrepresented in previous studies^{11,35–37}—this research provides valuable insights into post-earthquake healthcare access,

particularly relevant for earthquake-prone regions worldwide with diverse populations and similarly vulnerable hospitals and bridges, such as those in the U.S., Japan, and Türkiye.

Our Bay Area case study uniquely combines state-of-the-art seismic risk modeling with computationally efficient network analysis, enabling us to explore thousands of possible earthquake disruption scenarios (see Methods). Our results leverage unique information with granular categorizations of structural and non-structural vulnerabilities of 76 acute care hospitals’ 426 buildings to identify the facilities more likely to lose functionality after a M 7.25 earthquake on the Hayward Fault. We also leverage rich vulnerability information from 5,163 bridges and the Bay Area’s extensive transportation network data with ~ 1.5 million edges and ~ 0.5 million nodes. This research offers a foundational assessment that identifies communities likely to experience the most severe disruption in healthcare access, explicitly capturing the complex interactions between healthcare services and supporting transportation infrastructure.

Results

The Bay Area is home to more than 7M people in Northern California, and as a major city, it has a large demand for healthcare. The region’s 76 acute care hospitals provide critical inpatient care and specialized medical services for surgery, acute conditions, and injuries, making them essential for disaster response.

Much of the Bay Area’s healthcare infrastructure faces significant seismic risks due to proximity to major active faults. Most hospitals lie near the San Andreas and the Hayward Fault, where major earthquakes (> 7.0) can occur (Figure 1). The Laguna Honda Hospital and Rehabilitation Center and the University of California, San Francisco (UCSF) Medical Center are the largest facilities, with 780 and 580 beds. Both are located in San Francisco, less than 2 km from each other, highlighting the concentration of critical medical resources in geographically small areas. The three zip codes with the most beds are Palo Alto, San Francisco (where the two largest hospitals are), and San Jose, with 1410, 1360, and 932 beds, respectively.

Acute Care Vulnerability in the San Francisco Bay

We found that a significant part of the acute care portfolio is seismically vulnerable due to structural or non-structural deficiencies (Figure 1). To quantify these vulnerabilities, we compiled information from 426 buildings belonging to the 76 acute care hospitals in the Bay Area, including structural typologies, year of construction, number of stories, and seismic vulnerability ratings.^{18,42,43} Supplementary Note 1 and Supplementary Figure 1 describe and summarize the hospitals’ years of construction, structural typologies, and the number of stories. The Methods section establishes how to use this information to model seismic vulnerability, as these building features indicate buildings’ dynamic properties, strength, and ductility. Here, we describe the Structural Performance Categories (SPC) and Non-structural Performance Categories (NPC), established by California’s Department of Health Care Access and Information (HCAI) to characterize structural and non-structural deficiencies.⁴⁴ Each hospital building receives vulnerability ratings (SPC or NPC) ranging from 1 to 5, from the most to the least vulnerable. Supplementary Tables 1 and 2 fully describe SPC and NPC.

Structural vulnerabilities are pronounced across the portfolio. (Figure 1). Sixteen (4%) hospital buildings have an SPC of 1. All these buildings, constructed before 1974, face a higher collapse risk

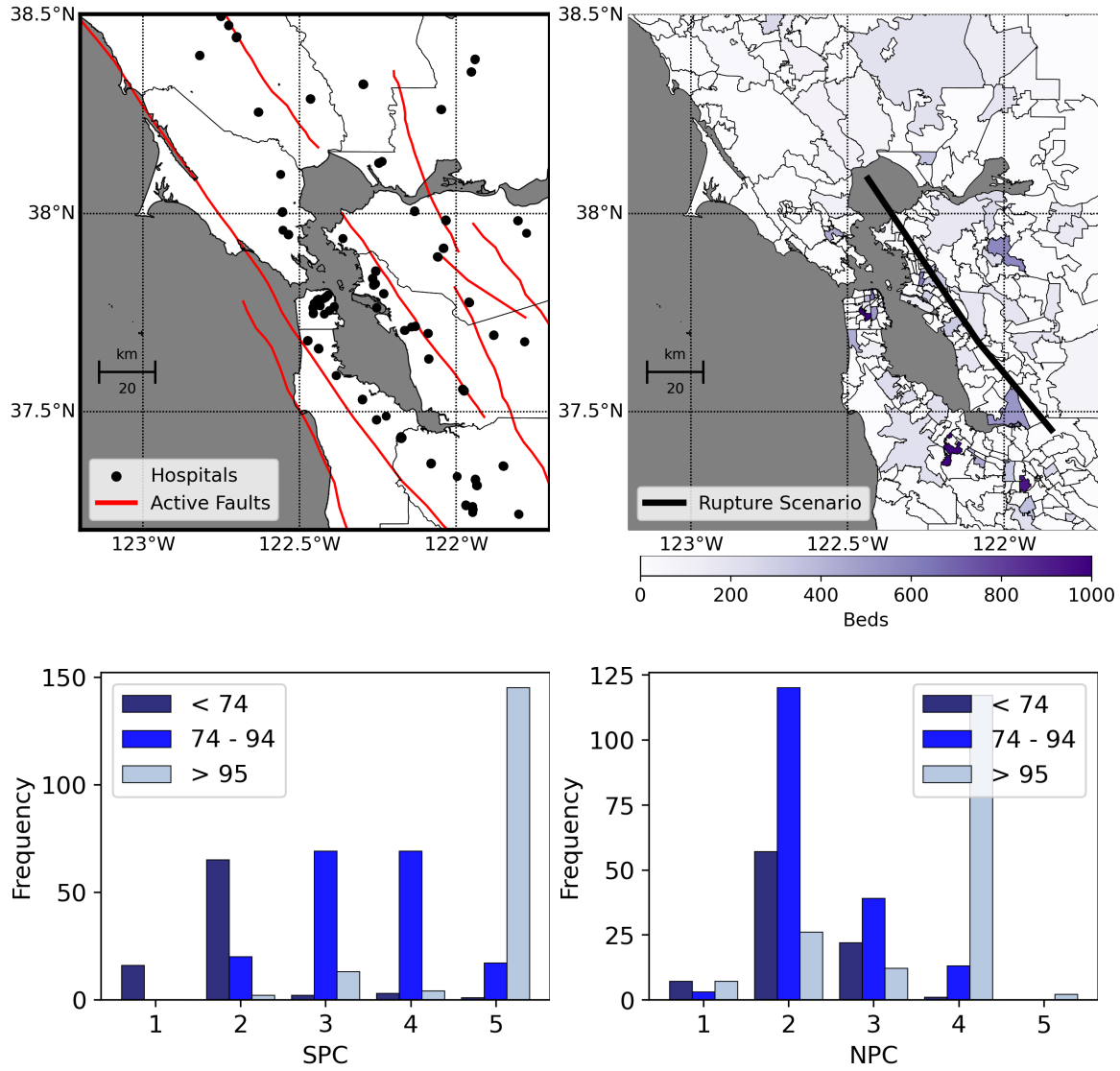


Figure 1: Seismic hazard and hospital exposure and vulnerability in the San Francisco Bay, California. Upper left: Acute care hospital inventory and all major active faults. Upper right: Bed count per zip code and M 7.25 rupture scenario on the Hayward Fault. Lower Left: Histogram of hospital buildings' structural performance category (SPC) and their years of construction. Lower right: Histogram of hospital buildings' non-structural performance category (NPC) and their years of construction.

due to earthquakes than regular modern buildings (e.g., those designed for life safety in 475-year return period events).⁴⁵ None of these buildings were supposed to provide acute care services by 2020. An additional 87 (20%) hospital buildings have an SPC of 2; of these, 65 were built before 1974 and 20 between 1974 and 1994. SPC-2 buildings meet pre-1973 standards for regular buildings but not those for hospitals, requiring upgrading by 2030.⁴⁶ Only buildings rated SPC-3 or above may operate as acute care facilities after this deadline. Only buildings rated SPC-3 or above may operate as acute care facilities after this deadline. Buildings with an SPC-5 rating—163 buildings (38%), predominantly constructed after 1994—meet essential-facility standards under modern codes;⁴⁵

these, they can remain operational immediately after 475-year return period events.

Non-structural vulnerabilities are even more widespread. Over half of the buildings (220, 52%) have an NPC rating of 2 or lower, with most constructed before 1994 (Figure 1). NPC-2 buildings have anchorage and bracing only for limited components, typically for basic building access, and were mandated to be upgraded by 2002 to support acute care services. Buildings rated NPC-4 (131 buildings, predominantly built after 1994) have comprehensive anchorage and bracing for all non-structural components, meeting the standard required for acute care facilities after 2030. Only two buildings currently meet the stringent NPC-5 criteria, requiring additional onsite provisions for continuous 72-hour acute care operations. Even facilities meeting modern structural codes may not attain an NPC-5 rating due to the presence of vulnerable external resources, such as water tanks, necessary for sustained hospital operations during emergencies.

Earthquake Scenario and Projected Building Damage

We studied an earthquake scenario of M 7.25 on the Hayward Fault in East Bay (Figure 2), a fault that has accumulated energy for over more than a century. Its last major earthquake (M 6.8, 1868) caused extensive damage across the region. Our selected scenario magnitude is based on an established reference case widely used in resilience policy-making for the Bay Area.⁴⁷

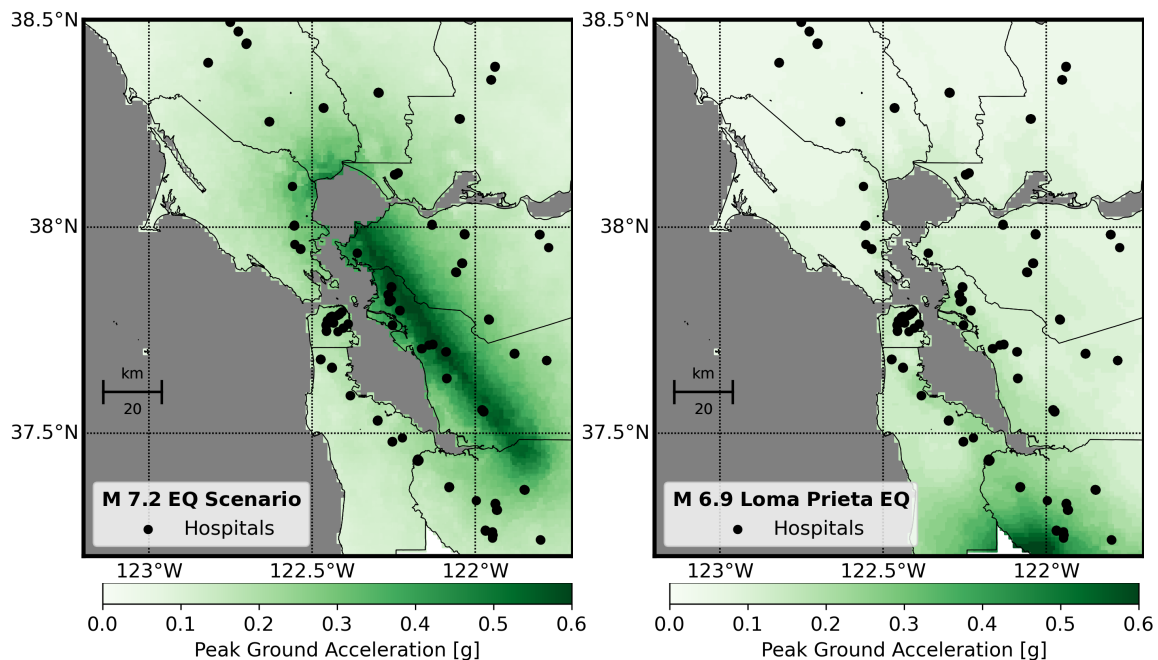


Figure 2: Earthquake ground motion simulations. Left: Median peak ground accelerations (PGAs) for the magnitude 7.25 Hayward Fault earthquake scenario analyzed in this study. Right: Median PGAs from the 1989 magnitude 6.9 Loma Prieta earthquake—the largest regional event in more than a century—highlighting that current infrastructure has not experienced shaking intensities projected for the Hayward scenario. We used 5,000 Monte Carlo simulations to conduct the analysis.

We modeled the rupture geometry (see Methods) and found that 10 acute care hospitals with 2167 beds (13% of the Bay’s total) are within just 5 km of the projected rupture. Our shaking intensity predictions show that many hospitals will experience violent ground shaking

at unprecedented levels in modern times (See Methods). On average, we predict 51 hospitals will experience peak ground accelerations above 0.2g (Figure 2). By comparison, the 1989 M 6.9 Loma Prieta Earthquake—previously the strongest since the devastating 1906 M 7.9 San Francisco Earthquake—subjected only 14 hospitals to similar shaking intensities (Figure 2). Supplementary Figure 2 further contextualizes these findings, illustrating how recent events such as the 2014 Napa Earthquake (M 6.0) exposed just three hospitals to significant shaking ($>0.2g$). In contrast, the historic 1906 earthquake exposed nearly the entire portfolio (72 out of 76 hospitals).

We then estimated structural and non-structural damage across all 426 acute care hospital buildings, as both types of damage critically disrupt continuous hospital operations. We employed damage thresholds as tipping points to model potential service interruptions at various levels of severity (see Methods). For simplicity, we refer to the probability of exceeding these thresholds as the “probability of damage” or “probability of failure.” Our findings reveal extensive potential damage: 214 buildings (50%) have greater than a 25% probability of structural damage, and 254 buildings (60%) exceed this threshold for non-structural components. Notably, 71% and 94% of these at-risk buildings lie within 20 km of the Hayward Fault or have low SPC/NPC ratings (Supplementary Figure 3, Supplementary Note 3).

Post-earthquake Hospital Capacity

Our risk analysis predicts a substantial loss of hospital capacity throughout the Bay Area following the earthquake scenario (see Methods). We estimate a loss of 8,165 hospital beds, resulting in only 51% of total acute care beds remaining functional (standard deviation: 21%). This significant reduction in capacity is highly uneven across the region (Figure 3, Table 1). Our baseline predictions assume hospitals lose functionality when structural or non-structural damage exceeds a threshold of slight damage—conditions historically shown to disrupt hospital services (see Methods).^{21,28–31} We also analyzed more optimistic scenarios with moderate (“favorable”) and extensive (“idealistic”) damage thresholds, resulting in increased overall functionality of 79% and 93%, respectively (Figure 3 and Supplementary Table 3). However, empirical evidence supports our baseline assumption, as hospitals often lose operations at early stages of damage.^{21,28–31}

Alameda County faces the most severe impacts due to its proximity to the Hayward Fault and the concentration of vulnerable hospitals (Table 1). Bed functionality there would drop dramatically, from 3,221 to only 651 functional beds (20%, standard deviation: 19%). As Alameda houses 1.6 million residents—making it the Bay Area’s second most populous county—this represents a critical healthcare disruption for numerous communities. Marin County, situated northward near the fault rupture, will be the second-most impacted, retaining only 45% of its original capacity. However, with a significantly smaller population (251,000 residents), Marin’s absolute impact is lower, further highlighting Alameda’s critical vulnerability.

Hospitals within 20 km of the fault retain, on average, only 25% functionality, compared to 51% at 20–40 km and 82% beyond 40 km (Supplementary Figure 4, Supplementary Note 4). Facilities with over half their buildings rated structurally poor ($SPC \leq 2$) have 14% lower functionality (40% vs. 54%), and those with predominantly poor non-structural ratings ($NPC \leq 3$) have 17% lower functionality (45% vs. 62%). Structural damage dominates near the fault, but non-structural damage remains critical at greater distances (64% structural vs. 70% non-structural damage within 20 km; 30% vs. 38% beyond 40 km).

Table 1: Predicted post-earthquake hospital bed capacities across Bay Area counties under a threshold of slight damage (baseline scenario). Numbers in parentheses represent the percentage relative to pre-earthquake capacities. Supplementary Table 3 presents results for thresholds of moderate (favorable scenario) and extensive (idealistic scenario) damage.

County	Pre-earthquake Beds	Post-earthquake Beds	
		Mean	Std. Dev.
Alameda	3,221	651 (20%)	621 (19%)
Contra Costa	1,749	878 (50%)	481 (28%)
Marin	627	280 (45%)	209 (33%)
Napa	351	248 (71%)	89 (25%)
San Francisco	3,618	2,284 (63%)	950 (26%)
San Mateo	1,444	944 (65%)	367 (25%)
Santa Clara	4,323	2,277 (53%)	1,069 (25%)
Solano	722	476 (66%)	179 (25%)
Sonoma	584	436 (75%)	124 (21%)
Total	16,639	8,474 (51%)	3,567 (21%)

Post-earthquake Bridge Functionality

Our risk analysis model predicts that 1,469 bridges out of 5,163 would be damaged due to the earthquake scenario (see Methods). Consequently, 3,693 bridges (72%, standard deviation: 17%) are expected to remain undamaged and fully operational (Figure 3). Some damaged bridges could continue operating, albeit at reduced capacities. Under our “baseline scenario”, where only bridges with at most slight damage remain operational, a total of 3,964 bridges (77%, standard deviation: 15%) would function. In a more optimistic “favorable scenario”, where bridges with at most moderate damage also remain partially operational, 4,069 bridges (79%, standard deviation: 14%) could provide service. In an idealistic scenario, which assumes that bridges even with extensive damage retain emergency functionality,⁴⁸ 4,527 bridges (88%, standard deviation: 11%) would remain operational.

Similar to hospitals, Alameda County faces the most severe transportation impacts (Figure 3, Table 2). Under the baseline scenario, Alameda retains only 44% functional bridges (from 642 down to 282). Marin County is second most impacted, retaining 64% (from 195 to 125 bridges). Additionally, estimates of reductions in bridge travel speeds⁴⁸ (see Methods)—calculated from their damage probabilities—highlight Alameda’s higher vulnerability due to proximity to the Hayward Fault rupture (Figure 3, Table 2).

Acute Care Accessibility

We predict that the earthquake scenario will radically change healthcare access in the Bay. We coupled the risk model for the hospital and bridge portfolio with a network model to assess the cascading effects of earthquakes on healthcare access across the Bay (see Methods).

We evaluated accessibility based on travel times to functioning hospitals. Across the Bay Area, average travel times to the nearest operational acute care hospital increase from 6.1 minutes

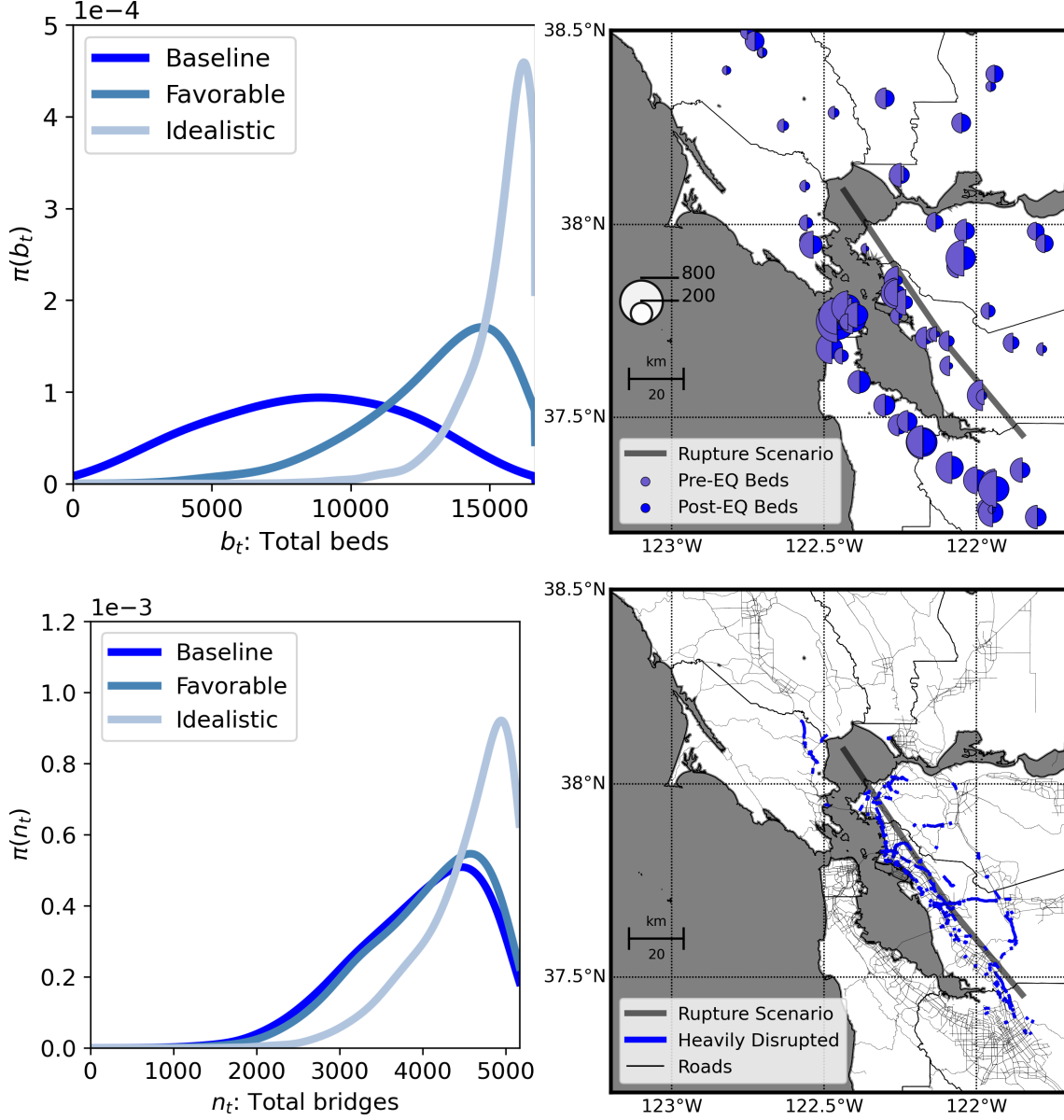


Figure 3: Post-earthquake functionality of hospitals and bridges across the Bay Area. Upper left: Probability distribution of functional acute care beds under baseline (slight), favorable (moderate), and idealistic (extensive) damage thresholds. Upper right: Spatial distribution of acute care beds before and after an earthquake scenario using the baseline (slight) damage threshold. Lower left: Probability distribution of fully functional bridges under baseline (slight), favorable (moderate), and idealistic (extensive) damage thresholds. Lower right: Spatial distribution highlighting bridges with post-earthquake travel capacities below 75%. Results generated from 5,000 Monte Carlo simulations.

pre-earthquake to 16.9 minutes post-earthquake—a 177% increase. However, this impact varies significantly by county. Alameda County, the second most populous (1.6M residents), experiences the most drastic increase of 407%, from 5.1 to 25.6 minutes (Table 3). Marin and Contra Costa counties follow, with increases of 314% and 147%, respectively, demonstrating widespread disruption

Table 2: Predicted post-earthquake functionality of bridges across Bay Area counties under the baseline scenario (bridges with at most slight damage remain functional). The expected capacity represents the average ratio of post-earthquake to pre-earthquake maximum speeds across all bridges in each county.

County	Pre-earthquake Bridges	Post-earthquake Bridges		Post-earthquake Capacity	
		Mean	Std. Dev.	Mean	Std. Dev.
Alameda	642	282 (44%)	147 (23%)	52%	23%
Contra Costa	604	407 (67%)	114 (19%)	73%	17%
Marin	195	125 (64%)	46 (23%)	71%	22%
Napa	158	135 (86%)	27 (17%)	89%	14%
San Francisco	126	102 (81%)	21 (17%)	84%	15%
San Mateo	346	280 (81%)	64 (19%)	85%	16%
Santa Clara	946	648 (69%)	215 (23%)	75%	20%
Solano	360	319 (89%)	49 (14%)	91%	11%
Sonoma	590	531 (90%)	74 (13%)	92%	10%

to healthcare access.

At a more detailed neighborhood scale, these disruptions are even more pronounced (Figure 4). We identified six densely populated zip codes (each exceeding 15,000 residents, labeled #1 to #6 in Figure 4) facing substantial reductions in healthcare access. The most severely impacted is Novato (#1, Marin County), where travel times increase nearly 25-fold, from 7.3 to 185.5 minutes, affecting approximately 18,000 residents. Similarly, a Fremont zip code (#6, Alameda County) with roughly 66,000 residents experiences an eightfold increase (from 8.4 to 42.2 minutes). Other significantly impacted zip codes in Richmond (#4), Oakland (#2 and #5, Alameda County), and San Jose (#3, Santa Clara County) face travel time increases of 10, 11, 9, and 11 times their pre-earthquake levels, respectively. These results underscore the dramatic reshaping of healthcare access throughout East Bay communities along the earthquake rupture.

Finally, we explored the relative contributions of hospital and transportation infrastructure disruptions through scenario analyses (Figure 4). We compared the baseline (None, no infrastructure disruptions) against scenarios modeling probabilistic damage only to transportation infrastructure (Transp., hospitals fully resilient), only to hospital infrastructure (Hosp., transportation fully resilient), and simultaneous probabilistic disruptions to both (Transp. & Hosp.). When considering disruptions only to transportation infrastructure (Transp.), average Bay Area travel times increase by 41% (from 6.1 to 8.6 minutes), notably less than the combined scenario (Transp. & Hosp., 177% increase). Conversely, modeling only hospital infrastructure disruptions (Hosp.) yields a 79% increase (from 6.1 to 10.9 minutes), highlighting greater relative fragility in hospital networks.

At localized urban scales, the compounding effects of simultaneous transportation and hospital infrastructure failures lead to disproportionately severe impacts (Figure 4). For example, as mentioned earlier, in the most severely impacted zip code (Novato, labeled #1 in Figure 4), travel times dramatically increase from 7.3 to 185.5 minutes under combined disruptions (Transp. & Hosp.), compared to only 14.1 minutes when transportation disruptions are excluded (Hosp. only). Similarly, for other highly affected zip codes (labeled #2 to #6 in Figure 4), travel-time ratios notably decrease—from 11, 11, 10, 9, and 8 under combined disruptions, to 6.4, 3.1, 6.1, 4.7,

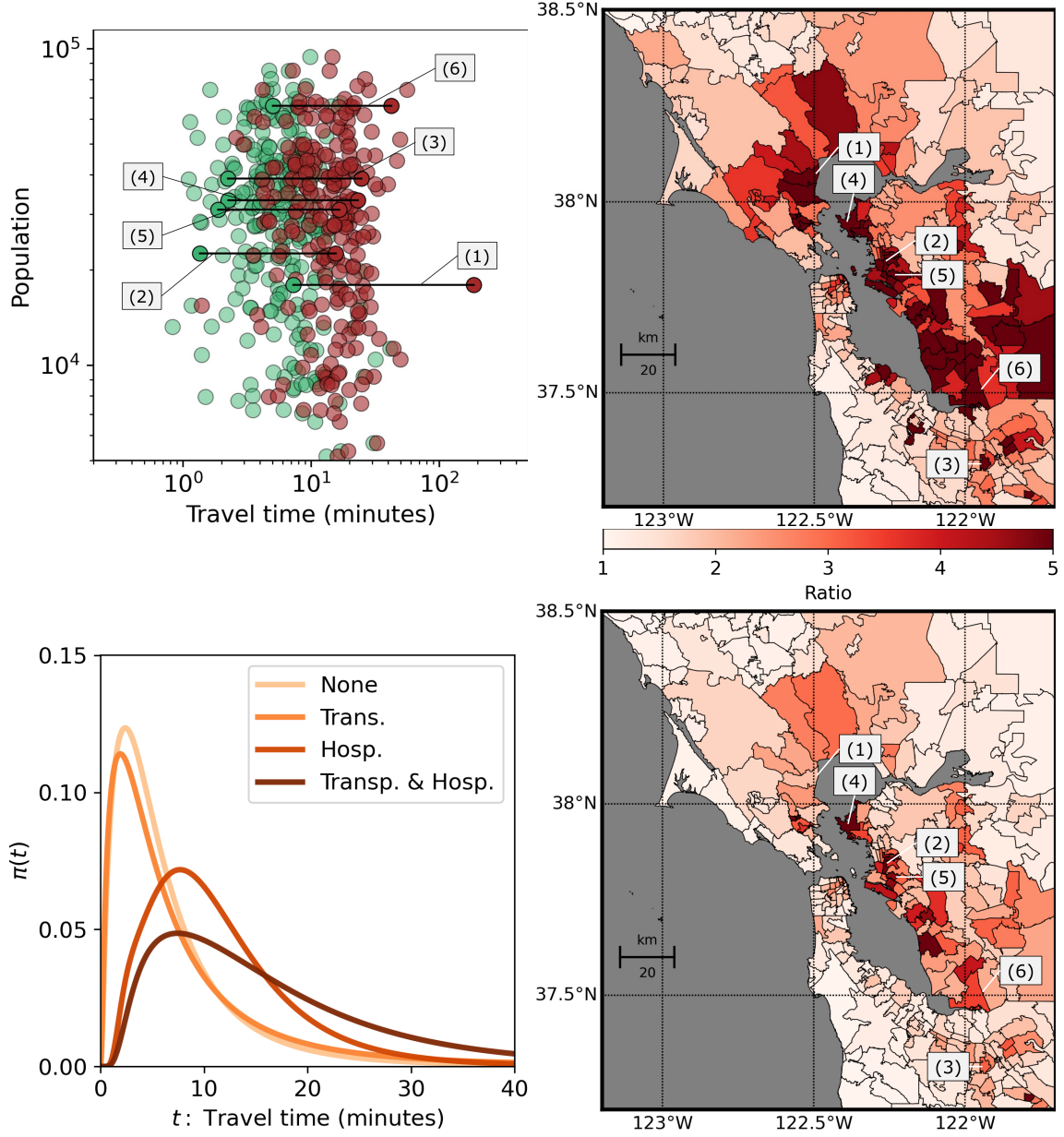


Figure 4: Access to functional acute care hospitals in the Bay Area after the earthquake. Upper left: Post-earthquake increases in travel time at the zip-code level, highlighting densely populated areas most severely impacted. Upper right: Ratios of post- to pre-earthquake travel times to the closest acute care hospitals. Lower right: Distribution of travel times per zip code under four scenarios: None (no infrastructure disruptions), Transp. (only transportation infrastructure is vulnerable), Hosp. (only hospital infrastructure is vulnerable), and Transp. & Hosp. (both transportation and hospital infrastructures are vulnerable). Lower left: Ratios of post- to pre-earthquake travel times when only hospital infrastructure (Hosp.) is vulnerable. Results generated from 5,000 Monte Carlo simulations.

and 3.4 when transportation disruptions are not considered—highlighting the critical influence of compounding infrastructure failures on healthcare access.

Table 3: Travel times (in minutes) to reach the closest functional acute care hospital before and after the earthquake for different Bay Area counties. Post-earthquake values include the mean and standard deviation, expressed as a percentage of pre-earthquake travel times (in parentheses).

County	Pre-earthquake	Post-earthquake		Population (thousands)
		Mean	Std. Dev.	
Alameda	5.1	25.6 (507%)	34.8 (688%)	1,682
Contra Costa	7.9	19.6 (247%)	27.7 (350%)	1,166
Marin	8.1	33.6 (414%)	47.7 (588%)	251
Napa	7.9	17.9 (228%)	27.8 (354%)	138
San Francisco	2.8	6.0 (215%)	24.0 (857%)	874
San Mateo	5.6	10.9 (195%)	25.6 (461%)	764
Santa Clara	6.1	13.8 (226%)	27.1 (442%)	1,936
Solano	7.3	13.9 (191%)	29.2 (401%)	453
Sonoma	9.5	15.5 (162%)	22.1 (231%)	489
Total	6.1	16.9 (277%)	23.9 (391%)	7,753

Isolated Hospitals and Communities

To understand the drivers behind the sharp increases in travel times observed earlier, we analyzed travel volumes to the closest acute care hospitals before and after the earthquake. Figure 5 shows pre-earthquake road usage, with line thickness representing travel volume. Roads in brown highlight those whose usage falls above the 90th percentile based on pre-earthquake conditions, emphasizing the most critical travel routes. As expected, the highest-usage roads prior to the earthquake were located near hospitals, especially in densely populated areas with fewer hospitals. For instance, communities in Fremont (#6 in Figures 4 and 5) are served by only two hospitals, while Richmond (#4) relies on just one.

Figure 5 also displays post-earthquake road usage, using the same pre-earthquake 90th percentile threshold to highlight heavily traveled roads. After the earthquake, patient travel patterns shift significantly, with many communities forced to travel longer distances along major corridors. For example, residents in Oakland (#2 and #5 in Figures 4 and 5), who previously relied on nearby hospitals, will now have to travel west to the San Francisco Peninsula or east to Walnut Creek due to simultaneous disruptions in both hospital and transportation infrastructure. These shifts help explain the steep increases in travel times observed in East Bay communities along the rupture zone.

Four major bridges connect the East and West Bay: the Richmond–San Rafael, Oakland–San Francisco Bay, San Mateo–Hayward, and Dumbarton bridges. Before the earthquake, no patients needed to cross these bridges to reach their nearest acute care hospital (Figure 5). After the earthquake, however, these bridges become critical, with travel volumes increasing to 3.6, 9.3, 6.3, and 13.6 times the pre-earthquake 90th percentile values—reflecting the large-scale redistribution of healthcare demand.

Our analysis also revealed a more complex post-disaster phenomenon: micro-scale isolation of hospitals and communities due to localized bridge failures. For example, the hospital serving the most severely impacted zip code in Novato (#1 in Figures 4 and 5), which has 64 beds, depends entirely on a single bridge for access. If this bridge fails, the hospital becomes inaccessible, increasing

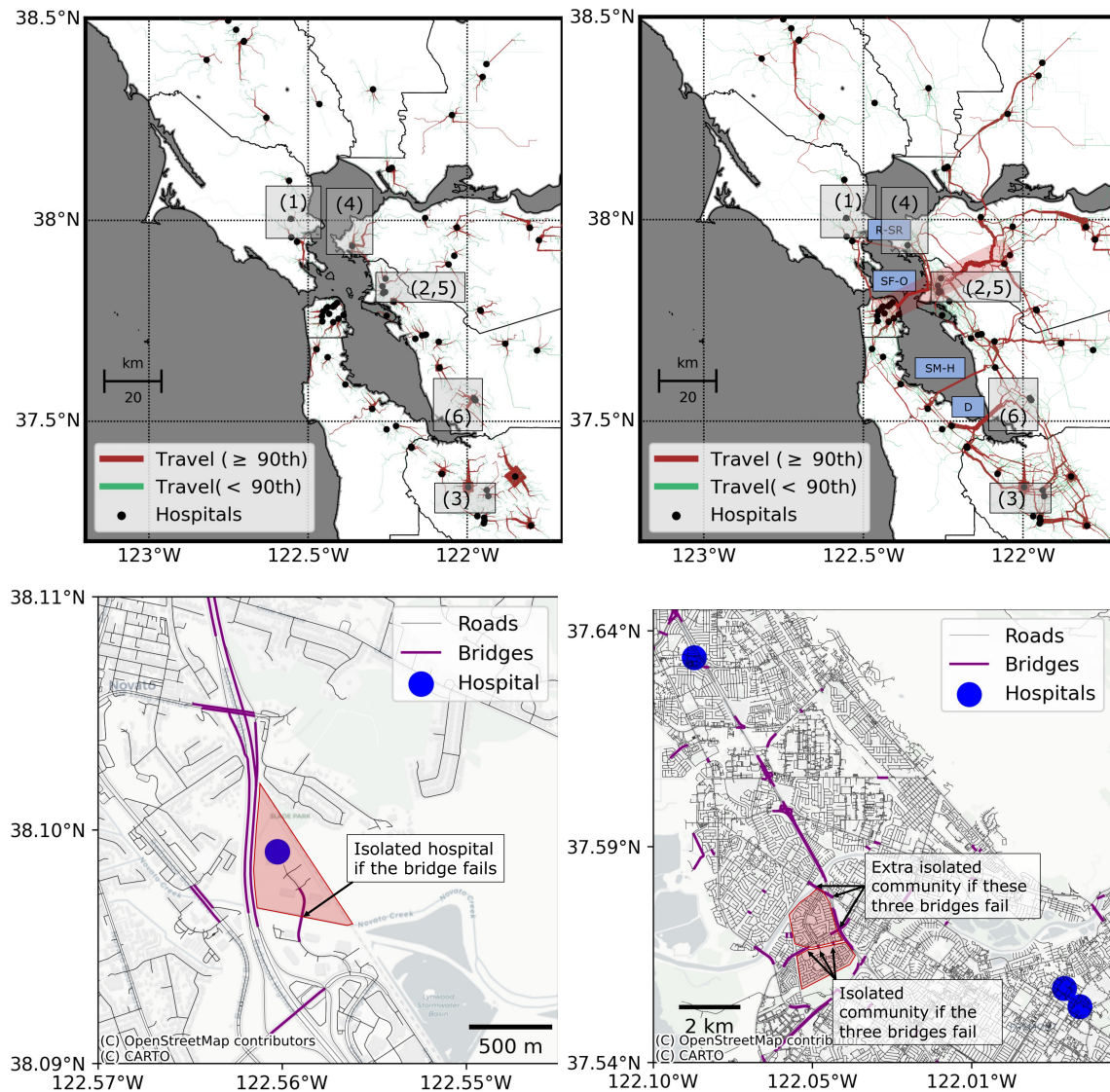


Figure 5: Mobility to reach the closest functional acute care hospital in the San Francisco Bay Area. Upper left: Pre-earthquake travel volumes to the closest acute care hospitals. Numbers 1 to 6 indicate the hospitals serving the dense zip codes with the highest post-earthquake increases in travel time. Upper Right: Projected travel volumes after the earthquake, showing major shifts in patient mobility. The red-shaded corridor illustrates how Oakland residents (#2 and #5) must travel west to the Peninsula or east to Walnut Creek due to hospital and transportation disruptions. Lower left: The hospital serving zip code #1 (Novato) relies entirely on a single bridge; if the bridge fails, all access to its 64 beds is lost. Lower right: Community near zip code #6 (Fremont), where the southern and northern sections become fully isolated if three different bridges fail in each area. Results are based on 5,000 Monte Carlo simulations of post-earthquake patient mobility.

travel times from 7.3 to 185.5 minutes for the surrounding population.

More concerning, we found that urban neighborhoods near Fremont (#6) could become fully isolated (Figure 5). In one area, failure of three bridges would trap one part of the neighborhood; in another, a different set of three bridge failures would isolate the remaining part. These communities

would lose access not only to hospitals but also to other essential services such as grocery stores and pharmacies—illustrating how cascading infrastructure failures can sever lifeline access in disaster scenarios.

Discussion

We present a modeling framework that integrates probabilistic risk analysis with network modeling to study disruptions to acute care access after earthquakes. Using detailed data on 76 hospitals (426 buildings) and 5,163 bridges, we assess infrastructure risks and interdependencies across Bay Area communities (see Methods).

First, we find that hospital services will face significant disruption. Nearly half of all acute care beds (49%) could be lost due to building damage, reducing regional capacity from 16,639 to 8,474 beds. In Alameda County, that figure drops to just 20% of pre-earthquake capacity (from 3,221 to 651 beds). These results point to the urgent need for preparedness. While structural damage may render many buildings unusable, past earthquakes show that medical staff can adapt. For instance, Christchurch Hospital in New Zealand moved triage to the parking lot after the 2011 earthquake.⁴⁹ Similarly, during the 2023 Türkiye earthquake, personnel at Mustafa Kemal University Hospital relocated operations from upper floors to the ground floor and later to outdoor spaces.⁵⁰ If hospitals in vulnerable counties like Alameda prepare in advance—e.g., securing water and power supply to exterior areas—they could partially recover functionality in an emergency. This rapid recovery can be lifesaving, especially for communities near the rupture that may see high numbers of severely injured patients.

Second, our findings underscore the need to retrofit both structural and non-structural components. While most retrofitting efforts have focused on structural safety, non-structural failures often drive hospital outages. In 2011, Christchurch Hospital remained structurally intact but lost ICU and radiology services due to generator damage.^{28,49} Similarly, 80% of hospitals surveyed after the 2016 Kumamoto Earthquake reported water system failures that disrupted dialysis and sterilization, despite minimal structural damage.^{30,31} California’s mandate to retrofit hospitals with $\text{SPC} \leq 2$ and $\text{NPC} \leq 3$ by 2030 is ambitious—and needed—but difficult to achieve. Currently, 24% of buildings fall below the SPC threshold and 69% below the NPC threshold.¹⁹ If the 2030 goal proves unrealistic, targeting retrofits for hospitals serving large or vulnerable populations could offer a more strategic path to resilience.

Third, access to acute care will become significantly more uneven. On average, travel time to the nearest functional hospital increases by 177%, from 6.1 to 16.9 minutes. Alameda County will see the sharpest increases—up 407% overall—with some zip codes experiencing 10 to 20 times longer travel times. These delays are critical. Patients with severe fractures or crush syndrome—a common injury in collapsed buildings—require immediate care, including x-rays, surgeries, or dialysis, all typically found in acute care hospitals. For many in Alameda, these services will be significantly harder to reach, which could have deadly consequences.

Fourth, the earthquake will reveal the deep interdependence between the hospital and transportation systems. Many communities will be forced to cross major bridges—such as the Richmond–San Rafael, Bay, San Mateo–Hayward, or Dumbarton—to access care, despite having relied on local hospitals pre-earthquake. Our analysis shows that hospital access hinges on the functionality of surrounding bridges. These critical connectors should be retrofitted to the same seismic standards as hospitals. In some cases, bridge failures could fully isolate neighborhoods—cutting off access

not only to hospitals but also to basic services like food. These findings highlight the need for a system-level approach to infrastructure planning—one that prioritizes interdependencies and regional importance rather than treating assets in isolation. Retrofitting the most critical bridges could greatly reduce the cascading effects of an earthquake on healthcare access.

Methods

Risk Formulation: From single to multiple infrastructure units

We utilize an extension of the performance-based earthquake engineering (PBEE) framework, initially established to assess earthquake consequences in an infrastructure unit, and analyze multiple hospital buildings.^{51–53} Under Markovian (conditional independency) assumptions described in canonical PBEE formulations,^{52,53} we find the probability distribution of an earthquake consequence, e.g., economic losses or fatalities, as

$$P_{DV,DS,IM}(dv, ds, im) = P_{DV|DS}(dv|ds)P_{DS|IM}(ds|im)P_{IM}(im), \quad (1)$$

where $P()$ is a probability distribution (or mass) function, and DV is a random variable representing an earthquake consequence (also called a decision variable). For example, DV can track repair costs in buildings. In this case, DV will be a positive number with an upper bound of dv_u , i.e., the total replacement cost of the building. In other applications, DV has a different variable space, e.g., $DV \in \mathbb{Z}$ for the number of injured people in a building.^{3,4} DS is an ordinal random variable that evaluates structural damage in an infrastructure unit, and typically $DS \in \{\text{None, Slight, Moderate, Extensive, Complete}\}$. Finally, IM is a random variable representing an intensity measure of shaking at the building site, and generally, $IM \in \mathbb{R}_{\geq 0}$. Note that earthquake shaking on the Earth’s crust has a physical upper bound, but such a bound is not generally modeled since extremely high shaking cannot produce a bigger DS than Complete, thus barely impacting seismic risk analysis. Frequently, DS and IM are marginalized from $P_{DV,DS,IM}(dv, ds, im)$ (e.g., through summation and integration) to find $P_{DV}(dv)$.^{51–53}

Lee and Kiredmjian⁵⁴ first formalized the extension of the PBEE formulation to multiple infrastructure units,^{55–57,57,58} focusing on transportation infrastructure. After finding marginal distributions of damage in single units, they formulate joint distributions of damage for all units by defining spatial correlations and their decay for distant sites. However, in the last two decades, empirical studies have better characterized spatial correlation on shaking (i.e., IM) rather than building damage.^{59–62} To account for it, Ceferino et al.³ first formulated an extension of regional PBEE incorporating earthquake shaking’s spatial correlation, defining fully the set of conditional independencies in state-of-the-art regional risk models and applications.^{63–66} Ceferino et al.³ defined the regional model for earthquake casualties in the residential building portfolio, and here we apply it to hospital and transportation infrastructure portfolios in a region.

We first formulate the model for hospital infrastructure. We redefine the traditional PBEE notation to keep the equations concise in the extension to a regional analysis with many buildings. We denote a random variable X ’s probability distribution $P_X(x) = \pi(x)$. Similarly, for a multi-variate vector $\mathbf{X}$, we denote its probability distribution $P_{\mathbf{X}}(\mathbf{x}) = \pi(\mathbf{x})$, where $\mathbf{x}$ is a specific realization of $\mathbf{X}$. Using this notation, we define the damage ordinal variable D , instead of DS , and call D_k^s and D_k^n the structural and non-structural damage of building k . Thus, we are interested in the damage vector $\mathbf{D} = \{D_1^s, D_1^n, \dots, D_m^s, D_m^n\}$, where m is the total number of buildings in the region. We also define

the shaking variable I , instead of IM , and call I_k^s and I_k^n the shaking measure affecting structural and non-structural damage of building k . For example, I_k^s can be the peak ground acceleration or spectral acceleration affecting the structural components of buildings, and I_k^n is the peak floor acceleration affecting acceleration-sensitive non-structural components, e.g., ceilings. Thus, we are interested in the shaking intensity vector $\mathbf{I} = \{I_1^s, I_1^n, \dots, I_m^s, I_m^n\}$, where m is the total number of buildings in the region. We extend the Markovian (or conditional independence) assumptions from single buildings^{52,53} to multiple buildings³ to estimate the joint probability distribution of damage and intensity vectors as

$$\pi(\mathbf{d}, \mathbf{i}) = \pi(\mathbf{d}|\mathbf{i})\pi(\mathbf{i}) \quad (2a)$$

$$\pi(\mathbf{d}|\mathbf{i}) = \prod_{k=1}^m \pi(d_k^s|i_k^s)\pi(d_k^n|i_k^n), \quad (2b)$$

where $\mathbf{d} = \{d_1^s, d_1^n, \dots, d_m^s, d_m^n\}$ and $\mathbf{i} = \{i_1^s, i_1^n, \dots, i_m^s, i_m^n\}$ are specific realizations of $\mathbf{D}$ and $\mathbf{I}$, respectively. Eq. 2b assumes damage is independent at different buildings conditioned on their respective shaking intensities; thus $\pi(\mathbf{d}|\mathbf{i})$ can be estimated as the product of probability distributions of damage in each building. However, unconditional damages will be correlated through the joint probability distribution of shaking in the region, $\pi(\mathbf{i})$. Similarly, we assume that structural and non-structural damage (D_k^s and D_k^n) within a building k are conditionally independent given their respective shaking intensities (I_k^s and I_k^n). Yet, these two random variables of damage will be correlated since these shaking intensities in the building are also correlated, e.g., peak ground acceleration and peak floor acceleration. Figure 6 illustrates and summarizes all conditional dependencies through a probabilistic graphical model for the hospital buildings.

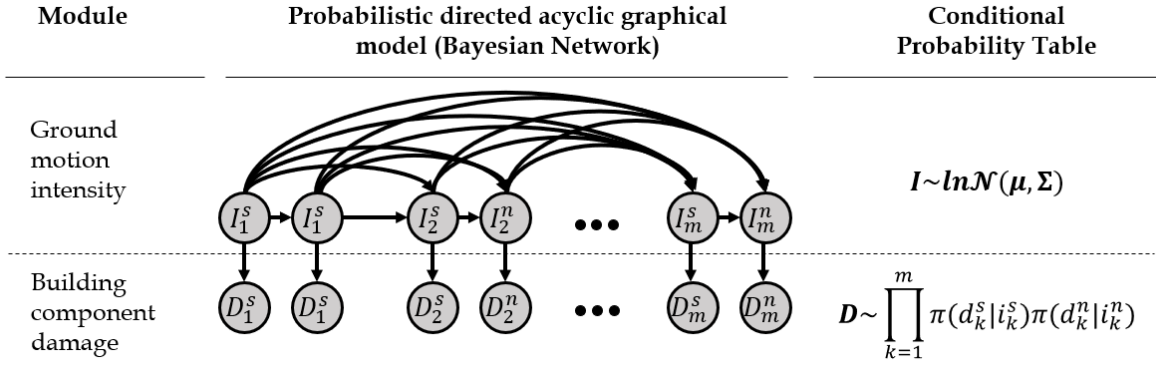


Figure 6: Probabilistic graphical model (Bayesian network) representing the joint distribution of the risk model to assess structural and non-structural damage from earthquake ground motion intensities.

We assess the building functionality vector $\mathbf{F} = \{F_1, \dots, F_m\}$, where F_m is a Bernoulli random variable that assesses whether the hospital building k will work ($F_k = 1$) after the earthquake. We model F_k as a deterministic function of the structural and non-structural damage of the building as an input. Thus, under a change of variables, Eq. 2 becomes

$$\pi(\mathbf{f}, \mathbf{i}) = \pi(\mathbf{f}|\mathbf{i})\pi(\mathbf{i}) \quad (3)$$

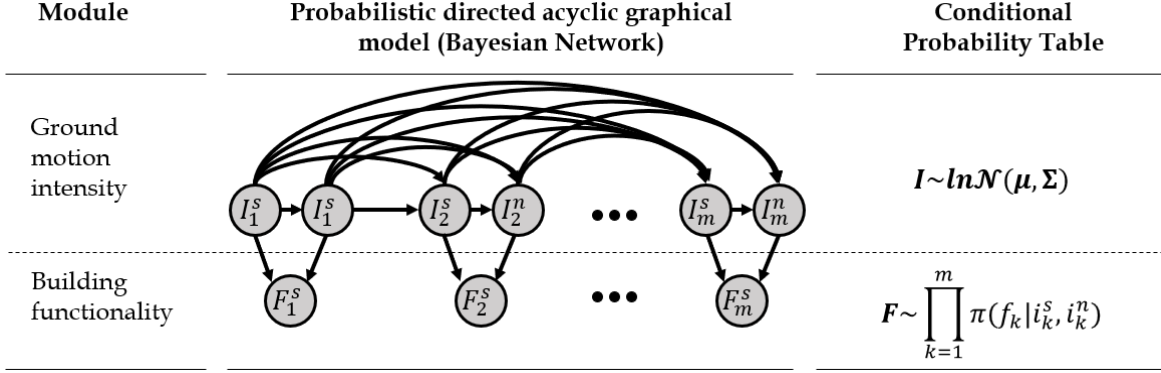


Figure 7: Probabilistic Graphical Model representing the joint distribution of the risk model to assess hospital functionality from earthquake ground motion intensities.

where $\mathbf{f} = \{f_1, \dots, f_m\}$ is a specific realization of $\mathbf{F}$. Figure 7 illustrates and summarizes all conditional dependencies through a probabilistic graphical model. Note that a probabilistic formulation that links damage to functionality could also be incorporated, introducing an additional term to Eq. 3, similar to Eq. 1. Thus, our approach admits such extensions.

Hospitals can rapidly lose functionality at early stages of structural and non-structural damage, as observed in the 2023 M 7.8 Kahramanmaraş Earthquake in Turkey,¹⁰ 2011 M 6.1 Christchurch Earthquake in New Zealand,²¹ and 2010 M 8.8 Maule Earthquake in Chile.⁶⁷ We consider that damage thresholds, d^s and d^n , for the structural and non-structural components trigger the disruption of hospital functionality, i.e., if either fails, the hospital loses functionality. We can estimate the probabilities of not exceeding these thresholds as $p_k^s = \pi(D_k^s \leq d^s | I_k^s = i_k^s)$ and $p_k^n = \pi(D_k^n \leq d^n | I_k^n = i_k^n)$, respectively, which can be evaluated with earthquake fragility functions. Thus, we can model functionality as the intersection of both random events, i.e., the structural and non-structural components work after the earthquake. Since D_k^s and D_k^n are conditionally independent, the F_k is a Bernoulli random variable with probability $p_k^s p_k^n$. Accordingly,

$$\pi(\mathbf{f} | \mathbf{d}) = \prod_{k=1}^m \left[p_k^s p_k^n \right]^{f_k} \left[1 - p_k^s p_k^n \right]^{1-f_k} \quad (4)$$

The functionality of the hospital relies on the structural and non-structural components as described in Eq. 4. The hospital portfolio has various levels of SPC and NPC that control the final functionality of the hospital.

We are also interested in the probability distribution of the total number of functional beds B_t in the region, which can be estimated as

$$B_t = \sum_{k=1}^m \beta_k F_k \quad (5)$$

where β_k is the number of beds (all functional before the earthquake) at the hospital building k . We are also interested in estimating the distributions of the total number of functional beds B_h in hospital h as each hospital can have multiple buildings with beds. Let $\mathbf{k}_h$ be the set containing all indexes of the buildings belonging to the hospital h . Thus,

$$B_h = \sum_{k \in \mathbf{k}_h} \beta_k F_k \quad (6)$$

In addition, we want to evaluate the contributions of structural and non-structural damage in buildings to the loss of functionality on the hospital campus. We can model the expected number of buildings with structural damage in a hospital campus given that the hospital only has a portion ϕ of functional beds as

$$\mathbb{E} \left(\sum_{k \in \mathbf{k}_h} 1\{D_k^s > d^s\} \middle| B_h < \phi \sum_{k \in \mathbf{k}_h} \beta_k \right) = \sum_{k \in \mathbf{k}_h} \frac{\pi(D_k^s > d^s \cap B_h < \phi \sum_{k \in \mathbf{k}_h} \beta_k)}{\pi(B_h < \phi \sum_{k \in \mathbf{k}_h} \beta_k)} \quad (7)$$

Similarly, we can evaluate the number of buildings with nonstructural damage in a hospital campus given that the hospital only has a portion ϕ of functional beds as

$$\mathbb{E} \left(\sum_{k \in \mathbf{k}_h} 1\{D_k^n > d^n\} \middle| B_h < \phi \sum_{k \in \mathbf{k}_h} \beta_k \right) = \sum_{k \in \mathbf{k}_h} \frac{\pi(D_k^n > d^n \cap B_h < \phi \sum_{k \in \mathbf{k}_h} \beta_k)}{\pi(B_h < \phi \sum_{k \in \mathbf{k}_h} \beta_k)} \quad (8)$$

We formulate the model for damage to the bridge infrastructure and its post-earthquake functionality following the state of the art in previous implementations.³⁹ As with buildings, we use fragility functions to estimate structural damage to bridges. Post-earthquake functionality is represented in terms of reduced maximum free-flow travel speed. We adopt deterministic relationships between damage levels and speed reductions based on previous research, as fully described later below.

Approaches for numerical solutions

Regional seismic risk analysis is a hyper-dimensional problem. $\pi(\mathbf{f}, \mathbf{i})$ in Eq. 3 can be analytically evaluated because $\pi(\mathbf{f}|\mathbf{i})$ and $\pi(\mathbf{i})$ have closed-form expressions.^{60–62,68} However, $\pi(\mathbf{f})$ cannot be analytically evaluated because it requires the marginalization of correlated random variables, i.e., in $\mathbf{i}$, which involves integration without closed-form solutions. Conducting marginalization operations through numerical integration (e.g., Reimann integration) also becomes computationally intractable, even for a few buildings.³ Thus, modern seismic risk analysis models are often solved using Monte Carlo to find regional earthquake consequences, such as $\pi(\mathbf{f})$.

Risk modelers also compute the distribution of aggregated earthquake consequences, such as total repair costs in regions. In our analysis, we seek to estimate the probability distribution $\pi(b_t)$, the sum of functional beds from different hospital buildings. $\pi(b_t)$ cannot be solved analytically, and numerical integration is computationally intractable even for a few buildings.³ Thus, we often solve these high-dimensional problems with Monte Carlo. Other techniques can also find $\pi(b_t)$ with high computational efficiency when the number of buildings is large enough through approximations of $\pi(b_t|\mathbf{i})$. Ceferino et al.^{3,4} utilized techniques arising from the Central Limit Theorem (CLT) to show both theoretically and empirically when and why these approximations can be accurate and computationally efficient. Later, Heresi and Miranda⁵⁸ empirically showed that similar approximations work under mild correlation conditions in seismic risk models.

Since hospitals have different numbers of buildings, from a few to many, this study uses Monte Carlo to solve our risk model instead of the approximations from CLT. We leveraged the Natural Hazards Engineering Research Infrastructure (NHERI) SimCenter's R2D tool^{69–71} to set up and

compute $\pi(\mathbf{i})$ and $\pi(\mathbf{d}, \mathbf{i})$ in Eq. 2. We used R2D to generate 5,000 realizations of $\mathbf{i}$ and $\mathbf{d}$ (for hospitals and bridges).

Earthquake Rupture and Shaking Modeling

We study an M 7.25 earthquake scenario on the Hayward Fault. Similar scenarios have been extensively studied to inform resilience policy-making in the Bay Area.⁴⁷ The rupture geometry was obtained from the Uniform California Earthquake Rupture Forecast (UCERF) 2.⁷² The earthquake ruptures the Hayward South and North sections over a total length of ~ 110 km.

Estimates of shallow shear wave velocities (averages at the top 30 m of soil) are utilized over the entire Bay Area.⁷³ With this information, we built the joint probability distribution of shaking intensities $\pi(\mathbf{i})$ in R2D. We utilized a state-of-the-art ground motion model⁷⁴ for shallow crustal earthquakes to estimate medians and logarithm standard deviations of $\mathbf{i}$. $\mathbf{i}$'s uncertainty is divided into two components.⁷⁵ The first component captures between-event uncertainty and affects the entire region equally, but it varies per intensity measure type, e.g., peak ground acceleration versus spectral acceleration. The first component captures correlation across different intensity measures.⁷⁶ The second component captures within-event uncertainty and affects the entire region and intensity measure types differently. This component captures spatial correlation and correlation across different intensity measure types. We use a computationally efficient method to account for the second component.^{62,77} As stated earlier, we sampled 5,000 realizations of $\mathbf{i}$ and show expected values $\mathbb{E}(\mathbf{i})$ for the entire region (Figure 1). Notice that for illustration purposes, we show $\mathbb{E}(\mathbf{i})$ for the entire Bay Area (+10,000 locations), but for the hospital network's risk analysis, we only need to quantify $\mathbf{i}$ at the 426 building locations and 5,163 bridge locations.

Hospital Vulnerability modeling

This paper utilized building-level lognormal fragility functions to determine damage to structural and non-structural components. For example, to determine the likelihood of not exceeding a structural damage threshold d^s in building k as a function of the shaking intensity measure, we use fragility functions like

$$\pi(D_k^s \leq d^s | I_k^s = i_k^s) = \Phi \left(\frac{\log(i_k^s) - \log(\alpha)}{\beta} \right) \quad (9)$$

where Φ is the standard normal cumulative distribution function.⁷⁸ The parameters α and β define the fragility function and vary according to the damage threshold d^s and the building's structural type and vulnerability (e.g., SPC rating) for building k . α equals the shaking intensity (e.g., PGA) that exposes the building to a 50% probability of damage of at least d^s . β is a normalizing factor that defines the width of the transition range between shaking with low and high damage probability, and it is a measure of aleatory uncertainty in the vulnerability analysis. In the limit, when $\beta \rightarrow 0$, Eq. 9 becomes equivalent to a deterministic assessment, where the building would fail after a fixed shaking threshold. An analogous equation is used for non-structural damage.

We assess structural damage for the variety of structural systems types and five levels of structural vulnerability (Figure 1 and Supplementary Figure 1). We used and adapted structural fragility functions developed in HAZUS,⁷⁹ also available in R2D,⁸⁰ to obtain this wide variety of fragility functions. Following the definitions of SPC ratings (Supplementary Table 1), we mapped SPC

1, and 2 to pre-code and moderate-code fragility functions for regular buildings from HAZUS,⁷⁹ i.e., we used those α and β values for Eq. 9. Note that SPC 1 and 2 category does not comply with the structural provisions of the Alquist Act. In contrast, SPC 3, 4, and 5 comply with the Alquist Act. Fragility functions for SPC 5 buildings are obtained by increasing all the α values for high-code structures by 50% higher PGAs. These adjustments were made to represent that hospitals designed to meet the Alquist Act (SPC 5) according to the ASCE7-16 building code are designed to withstand 50% higher seismic loads than regular buildings, i.e., an importance factor of 1.5.⁸¹ SPC 3 buildings are steel structures that comply with the Alquist Act but are pre-Northridge. We used regular building fragility functions to represent the vulnerability of SPC buildings as pre-Northridge’s non-ductile connections as it takes $\sim 30\%$ less seismic demands to make them reach moderate and extensive levels of damage,⁸² i.e., $0.7 \times 1.5\alpha = \sim \alpha$. Finally, we modeled SPC 4 buildings with 1.25α to represent that these buildings have lower performance than SPC 5 buildings (1.5α). SPC 4 buildings comply with the Alquist Act but can have some structural conditions that make them more prone to damage, e.g., lack of weak beam/strong column, presence of short captive columns.⁸³

We followed a similar approach for the fragility functions of buildings’ non-structural components (Supplementary Table 2). We mapped NPC 1, 2, and 3 to pre-code, moderate-code, and high-code fragility functions for acceleration-sensitive non-structural components from HAZUS.⁸⁴ For NPC 4 and 5, we adjusted the fragility functions of high-code fragility functions by increasing the median peak floor acceleration (PFA) to reach different damage states by 25% and 50%, respectively. Unlike structural components, we defined the same fragility functions for all building types because hospitals have similar non-structural components, e.g., equipment for acute care. However, as stated earlier, the input PFA for each hospital building differs and depends on the structural type.

After defining these fragility functions for the portfolio of hospital buildings, we computed realizations of building damage utilizing R2D.⁸⁵ As mentioned, we generated 5,000 samples of the buildings’ structural and non-structural damage for each ground-shaking simulation. As stated earlier, we initially tested multiple thresholds of damage, d^s and d^m (e.g., slight, moderate, extensive damage) to evaluate hospital disruptions (Figure 3). However, we used the slight damage threshold for most of the analysis later in the study since most hospitals lose functionality at quite early stages of damage.

At each building k , we used the Peak Ground Acceleration (PGA) as the shaking intensity random variable I_k^s to estimate structural damage. While spectral accelerations can also be used to improve damage predictability through the inclusion of structural properties, such as period of vibration,⁴ we did not follow this approach here since fragility spectral acceleration-based fragility functions are not available for the diversity of building typologies in the San Francisco Bay Area.

We used PFA as the shaking intensity random variable I_k^n to estimate non-structural damage at building k . Our focus on PFA stems from the fact that acceleration-sensitive non-structural components—such as ceilings, shelves, and mechanical or medical equipment—tend to fail at lower shaking levels than drift-sensitive components like partition walls. Furthermore, in hospitals, acceleration-sensitive components (e.g., x-ray machines) often play a more critical role in maintaining functionality after an earthquake.

PFA varies with height within a building, and total non-structural damage depends on how these components are distributed across different stories. However, detailed data on the story-by-story distribution of non-structural elements are rarely available. To address this limitation, we used a simplified proxy to approximate the variation of PFA across building height. Specifically, we

assumed a linear distribution of floor accelerations, with the base acceleration equal to the peak ground acceleration (PGA), and the roof acceleration equal to the spectral acceleration at a height corresponding to the effective height of a single-degree-of-freedom (SDOF) system representing the building’s dynamic properties. This effective height can be estimated for each structural type using information from the HAZUS database.⁷⁹ Further studies can enhance the fidelity of this analysis if higher-resolution information for non-structural components is available, e.g., on each floor.

Bridge Vulnerability modeling

This paper assesses highway bridge damage due to both ground shaking and soil liquefaction. To estimate shaking-induced damage, we adopt the methodology developed in HAZUS,⁷⁹ which defines 28 representative bridge archetypes. Each archetype is assigned a fragility function of the form in Eq. 9, using spectral acceleration at a 1-second period as the intensity measure (denoted as $\dot{u}$). To account for variations among individual bridges within each archetype, modification factors are applied to the fragility parameter α . These include a three-dimensional modification to capture deck arching effects in multi-span bridges and a skew factor to reflect reduced capacity at skewed deck-pier connections. Additionally, for estimating slight damage, a spectral shape modification converts the intensity measure to an equivalent 0.3-second spectral acceleration, acknowledging that bridges are typically elastic and sensitive to short-period ground motions.

To assess damage from ground failure, HAZUS⁸⁶ defines fragility curves that use permanent ground deformation (PGD) as the intensity measure. Given the high liquefaction susceptibility in the Bay Area, we adopt the HAZUS-recommended geologic model HAZUS⁸⁶ to estimate liquefaction-induced PGD at each bridge location. This model first uses empirical correlations between soil types (e.g., intertidal mud, Holocene and Pleistocene alluvium, rock) and liquefaction susceptibility. Liquefaction probability is then estimated based on peak ground acceleration (PGA), earthquake magnitude (to capture shaking duration), and groundwater depth (to reflect pore pressure effects). PGD is subsequently estimated using empirical relationships with the calculated liquefaction probability. We utilize the California statewide geologic map⁸⁷ and a global groundwater depth model(2010)⁸⁸ for this analysis. Once PGD is estimated, ground failure-induced bridge damage is determined using HAZUS fragility curves through the R2D software platform.

These fragility curves yield the probability of each bridge reaching damage states—slight, moderate, extensive, or complete—under a given ground motion realization. HAZUS defines the physical characteristics associated with each state (e.g., slight damage involves minor cracking at abutments, while complete damage corresponds to column collapse or loss of bearing support). To estimate post-earthquake traffic performance, we adopt the damage-capacity model from Guo et al. (2017),⁴⁸ which relates bridge damage to residual free-flow speed. Travel time is computed as road length divided by this speed under the assumption that emergency vehicles receive priority and travel at free-flow speed. More realistic travel times could incorporate background traffic using volume-delay relationships such as the Bureau of Public Roads (1964) curve,⁸⁹ though this requires post-disaster traffic data, which remains a key challenge in traffic simulations after major events.

Network Model: Acute Care Accessibility Modeling

We denote $G = (\mathbf{v}, \mathbf{e})$ a graph, where $\mathbf{v}$ is the set of $|\mathbf{v}|$ vertices and $\mathbf{e}$ the set of $|\mathbf{e}|$ edges. This graph will represent the infrastructure system of hospitals and roads supporting healthcare access in the Bay Area. Let $p \in \mathbf{p}$ be a vertex representing the location of a patient needing acute care

and $\mathbf{p}$ be the set of all patient vertices. Also, let $h \in \mathbf{h}$ be a vertex representing the location of an acute care hospital and $\mathbf{h}$ be the set of all hospital nodes. In this case, $\mathbf{p} \subseteq \mathbf{v}$, and $\mathbf{h} \subseteq \mathbf{v}$. $\mathbf{e} = \{(u, v) | u, v \in \mathbf{v}\}$ is the set of $|\mathbf{v}|$ edges representing different roads connecting different locations (vertices) in the region. We denote $\tau(u, v) \in \mathbb{R}_{\geq 0}$ the travel time between vertices u and v .

To analyze healthcare access, we evaluate the shortest travel times for a patient in node p to reach any hospital vertex in the set $\mathbf{h}$. We modeled hospital h as a source vertex and found the shortest paths to all vertices $p \in \mathbf{p}$ simultaneously, resulting in a shortest-path tree problem. This approach is faster than computing multiple shortest for each pair h and p , separately. Thus, for each vertex h , we find the shortest time to reach the patient:

$$t^*(h) = \min_{(u, v) \in \mathbf{e}} \sum \tau(u, v) x(u, v) \quad (10a)$$

$$\text{s.t.} \quad \sum_{v: (u, v) \in \mathbf{e}} x(u, v) - \sum_{v: (v, u) \in \mathbf{e}} x(v, u) = b_u, \quad \forall u \in \mathbf{v} \quad (10b)$$

$$b_u = |\mathbf{p}| \quad \text{for} \quad u = h \quad (10c)$$

$$b_p = -1 \quad \text{for} \quad u \in \mathbf{p} \quad (10d)$$

$$b_u = 0 \quad \text{for} \quad u \neq h, p \quad (10e)$$

$$x(u, v) \in \{0, 1\}, \forall (v, u) \in \mathbf{e} \quad (10f)$$

This optimization problem seeks to find the minimum travel time from vertex h to all vertices in $\mathbf{p}$ simultaneously. This optimization problem can also be interpreted as a special network flow problem where we seek to find a directed path with minimum cost from a source node h to multiple destinations. $\tau(u, v)$ can be interpreted as edge flow cost, and the shortest path problem can be seen as sending a flow unit to each destination $p \in \mathbf{p}$. We solve Eq. 10 to find the shortest travel time $t^*(h)$ from each node $p \in \mathbf{p}$ to each (hospital) vertex h (Figure 8). We can use multiple algorithms to solve Eq. 10, including Dijkstra and Bellman-Ford.⁹⁰ For reference, the computational complexity of the classical Dijkstra's algorithm is $\mathcal{O}(|\mathbf{v}|^2)$ and Bellman-Ford is $\mathcal{O}(|\mathbf{v}||\mathbf{e}|)$. Note that these algorithms will find the shortest paths to all vertices in $\mathbf{v}$, and not just on $\mathbf{p}$, at once.

After finding $t^*(h)$ from all $h \in \mathbf{h}$, we compute the minimum travel time $t^*(h)$ to any hospital by comparing the different options each patient p has. Thus,

$$T^* = \min_{h \in \mathbf{H}} t^*(h) \quad (11)$$

In the post-earthquake scenario, all hospitals will be functional. Then, Eq. 11 finds the shortest time to reach an acute care hospital p (Figure 8).

In an earthquake, we adjust Eq. 11 to

$$\overline{T^*} = \min_{h \in \overline{\mathbf{h}}} t^*(h) \quad (12)$$

where $\overline{\mathbf{h}} = \{h | B_h > 0.5\beta_h \quad \forall h \in \mathbf{h}\}$ to account for the reduction in hospital capacity. Thus, $\overline{\mathbf{h}}$ is a set with a random selection of elements, i.e., hospital vertices. This means that in this model, the tipping for receiving new patients in hospitals is to have at least 50% of their beds (β_h) functional. Studies on hospital disaster resilience during earthquakes suggest that a significant reduction in

functional bed availability can severely strain hospital operations, particularly in accommodating new patients in the emergency department.^{27,91}

We also further adjust the edge capacity and the network topology to solve Eq. 10. As mentioned earlier, the free-flow travel times τ are adjusted to post-earthquake conditions $\bar{\tau}$ according to the bridge damage level. Thus, we use $\bar{\tau}$ instead of τ to find $t^*(h)$ in Eq. 10. While in practice, fully collapsed bridges would have travel time $\tau = \infty$, we found it was more computationally efficient to remove these edges the network. Thus, we also used a slightly different edge $\bar{e} = \{(u, v) | \bar{\tau}(u, v) < \infty \ \forall (u, v) \in e\}$ for each simulation. Thus, $\bar{T}^*(p)$ is a random variable. We solve Eq. 12 5,000 times using the 5,000 Monte Carlo simulations obtained before.

Bay Area's Transportation System

We study the entire San Francisco Bay, where the transportation network is massive, with $|v| = 0.5$ million vertices and $|e| = 1.5$ million edges. The edges in the graph represent the roads in the transportation system, whose information was obtained from the San Francisco Region Roadways⁹² and OpenStreetMap (OSM).⁹³ We incorporated directional and travel time data into the network models using OSM's OSMnx library.⁹⁴ We couple the transportation network data to the hospital and the patient data. The 76 hospitals are embedded in the network models by identifying the network's vertices closest to the hospital locations, forming the set $\mathbf{h}$. In addition, we obtained population data at 1,613 zip codes. We assume the number of patients is proportional to the population. To form the set $\mathbf{p}$, we identify the network's vertices closest to the census tract's centroids (Figure 8).

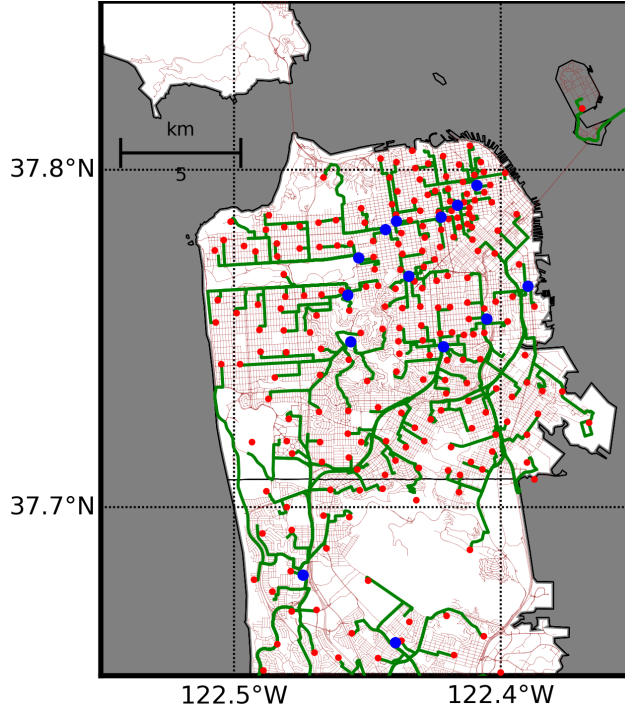


Figure 8: Shortest paths from patient vertices ($p \in \mathbf{p}$) to hospital vertices ($h \in \mathbf{h}$) before the earthquake in the San Francisco county. The transportation network is shown in brown lines, the shortest paths in green lines, hospital vertices in blue dots, and patient vertices in red dots.

Data Availability

The hospital data are publicly available in the California Department of Health Care Access and Information's Portal: <https://hcai.ca.gov/facilities/building-safety/facility-detail/>. The transportation data are publicly available in the San Francisco's Metropolitan Transportation Commission's Portal <https://opendata.mtc.ca.gov/>. In addition, we made the hospital disruption simulations and the pre-processed network data accessible in the following NSF's DesignSafe repository: <https://doi.org/10.17603/ds2-pc7z-7227>.

Code Availability

The risk model was run with NHERI SimCenter's R2D software, open and publicly available: <https://simcenter.designsafe-ci.org/research-tools/r2dtool/>. Also, we made the code to run the network model coupled to the risk model publicly available in the following NSF's DesignSafe repository: <https://doi.org/10.17603/ds2-pc7z-7227>.

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Competing Interests

The authors declare no competing interests.

Author’s contributions

L.C. conceived and formulated the risk-network model. C.K., D.M., X.L., J.W, and J.Z. compiled and pre-processed the hospital and transportation data. L.C., C.K., J.Z., and A.Z. run the risk-network simulations. L.C. drafted the manuscript with contributions and editing from all the authors.

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