Effective Plans for Hospital System Response to Earthquake Emergencies

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Abstract

Hospital systems play a critical role in treating injuries and preventing additional deaths during disaster emergency response. Natural disasters hinder the ability of hospital systems to operate at full capacity. Therefore, it is important for cities to develop policies and standards that enable hospitals' continuous operations to provide patients with timely treatment and ensure urban resilience. Here, we present a methodology to evaluate emergency response based on a probabilistic model that assesses the loss of hospital functions and quantifies multiseverity injuries as a result of earthquake damage. The proposed methodology is able to design effective plans for patient transferal and allocation of medical resources using an optimization formulation. This methodology is applied to Lima, Peru, subjected to a disaster scenario based on the M 8.0 earthquake that occurred there in 1940. Our results show that the spatial distribution of health service demands mismatches the post-earthquake capacities of hospitals, leaving large zones on the periphery of Lima significantly underserved. This study demonstrates how emergency plans that leverage hospital-system coordination can address this demand-capacity mismatch, enabling effective patient transfers, ambulance usage, and deployment of emergency medical teams.

Hospital systems are at the core of disaster resilience because they must provide timely critical healthcare services to communities during and after an emergency response.[1] Because cities are becoming larger and more densely populated, natural disasters are impacting public health on a larger scale. A database including the most 21,000 devastating disasters worldwide since 1900 indicates that 50% of disasters with the largest number of injuries occurred only during the last 20 years.[2] Natural disasters such as earthquakes, landslides, floods, typhoons put heavy demands on hospital systems because these disasters can cause thousands or even tens of thousands of injuries in a short timespan (Figure 1). At the same time, natural disasters cause massive disruptions to hospital systems by damaging their supporting infrastructure. For example, the M 7.6 1999 Turkey

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earthquake caused around 50,000 injuries in Izmit and disrupted 10 major hospitals, which required relocation of most patients from these hospitals.[3]

Because hospital systems are so critical, the World Health Organization (WHO) and Pan-American Health Organization (PAHO) urge countries to institute policies to strengthen hospital capacities and enhance coordination in the hospital system to make efficient use of resources at national and regional levels during emergency response.[4,5] To effectively develop measures for capacity-enhancing prioritization and resource sharing and allocation, national and regional governments require information based on robust methodologies that can characterize hospitals' emergency response as an interconnected system on a large urban scale.

However, most previous studies have primarily focused on modeling emergency response only at single-hospital scale as opposed to characterizing the response of hospital systems on a large urban scale. Some of these studies relied on disaster analytics to evaluate post-disaster functionality of the supporting infrastructure in the individual hospitals.[6–9] Other studies used emergency medicine modeling tools, such as discrete event simulation (DES) and flow models, to characterize emergency response and evaluate post-disaster resource allocation but also at a single-hospital scale.[10–13] Lack of methods and high-resolution disaster risk data have hindered the extension of single-hospital scale analyses to system-level analyses on an urban scale. As a result, regional emergency response policies have not effectively addressed capacity-enhancing prioritization and resource sharing and allocation in hospital systems, especially in large and complex urban centers.

Here, we present findings from a methodology that characterizes the disaster emergency response of hospital systems on a large urban scale. Our integrative methodology combines models of multiseverity earthquake casualty estimation[14,15] and post-earthquake hospital functionality with a proposed network flow model for hospital systems. We focus on seismic hazard because earthquakes are the natural disasters that have caused the largest number of injuries in most countries (Figure 1). The methodology is applied to Lima, Peru, based on a M 8.0 earthquake and includes an evaluation of effective emergency plans for allocation of hospital resources and patient transfers. We selected Lima because it has a high seismic risk and it has recently built a unique dataset containing high-resolution hospital vulnerability. We use citywide data on the seismic vulnerability of more than 1.5 M buildings in Lima to estimate casualties and data including the seismic vulnerability of 41 public hospital campuses (composed of +700 buildings) and their respective operating rooms and ambulance resources.[9,16,17]

We propose a metric based on patient waiting times and effective use of ambulance patient transfers as a performance measure for developing emergency response plans. Our focus is on high-severity injuries that require surgical procedures. We evaluate the spatial distributions of high-severity injuries in the city at a higher spatial resolution (i.e., 1kmx1km) than other widely used methods.[18] Then, we compare the spatial distribution of casualties with the distribution of functional operating rooms in the hospital system, identifying the zones more likely to be underserved during the emergency response. Combining the network flow model with an optimization formulation, we assess the performance of four alternative emergency response plans to treat the patients in the city.

The first and second emergency plans are baseline strategies with limited levels of coordination. In both strategies, hospitals without available operating resources will use their own ambulances to transfer patients, but in the first strategy, patients will only be sent to the closest working hospital, whereas in the second strategy, patients will be sent to the hospital with the largest number of functional operating rooms.

The third and fourth emergency plans are strategies with higher levels of coordination that use the optimization formulation on the system performance metric. In both strategies, all hospitals will share ambulance resources across the system to transfer patients according to post-earthquake needs, but in the third strategy, the system only uses the residual operating room capacities in the hospitals, whereas in the fourth strategy, emergency medical teams (EMTs) supply the system with additional mobile operating rooms in key locations in the city. Through the Action Plan for Humanitarian Assistance, the WHO and PAHO require countries to elaborate policies for deploying ETMs to assist people affected by emergencies and disasters,[19,20] thus, this study aims to directly inform policies for EMT deployment in countries with high seismic risk.

We analyze the behavior and performance of these four plans during the emergency response and discuss their implications in terms of patient treatment times, ambulance usage, and patient transfers. We utilize traffic data to show the most important roads for patient transfers from localized zones with lower hospital capacity to zones with higher capacity in the city. This research represents a first-cut assessment on the effectiveness of emergency response policies to inform city-scale decision-making that leads to more effective treatment of patients during an emergency response to a major earthquake.

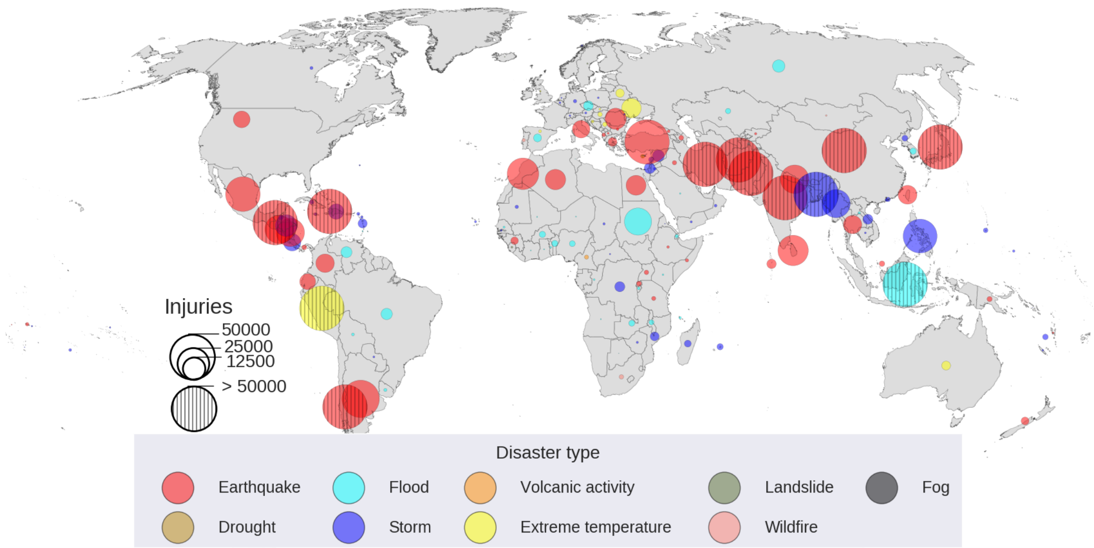


Figure 1: Per-country distribution of disasters with the highest number of injuries since 1900. The sizes of the circles indicate the relative number of injuries and the colors indicate the natural disaster type. Since 1900, 117 countries that experienced at least one natural disaster with more than 100 injuries. Earthquakes were the natural disaster with largest injury tolls in 45 of these countries, followed by storms in 38 of these countries. Earthquake events can cause large number of injuries suddenly. For example, the 2008 Great Sichuan earthquake injured more than 368k people in only two minutes. Data from EM-DAT.[2]

1 Results

We applied our methodology to Lima, a large city with a population close to 10 million people,[21] where previous large earthquakes have caused large numbers of casualties.[22,23] Because the last large earthquake in the region occurred more than 40 years ago, studies indicate that the city is currently exposed to high hazard of large-magnitude earthquakes.[24,25] Using our proposed methodology, we characterize the emergency response and evaluate response plans to effectively to treat patients in Lima after an earthquake scenario of large magnitude occurring in the near future. This earthquake scenario was simulated according to the seismotectonics of the 1940 M 8.0 earthquake, which occurred in close proximity to Lima.[26] Figure 2 shows the estimated rupture area of the 1940 earthquake and its proximity to the city. Our methodology estimates the impact of this disaster scenario on the demands on healthcare by quantifying earthquake casualties and on the capacity of healthcare by quantifying the post-earthquake reduction in functionality in the hospital system. The results of applying our methodology are discussed here and the details of the methodology formulation, workflow and required data are described in the Methods section.

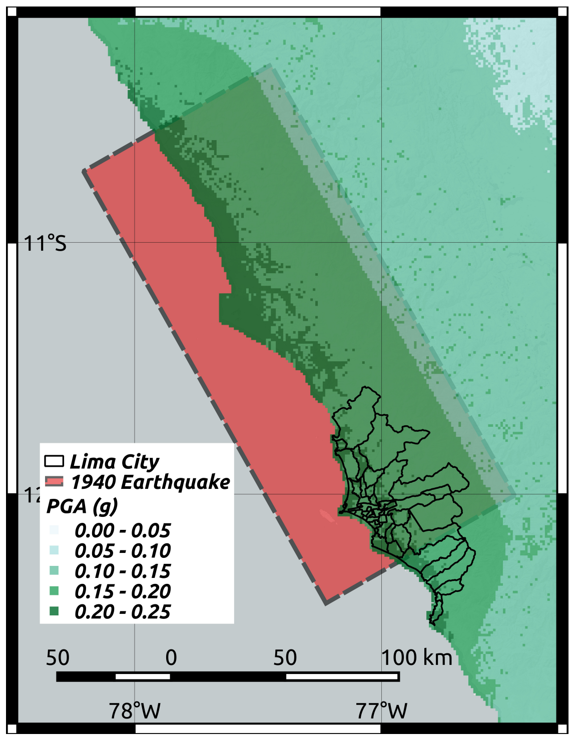
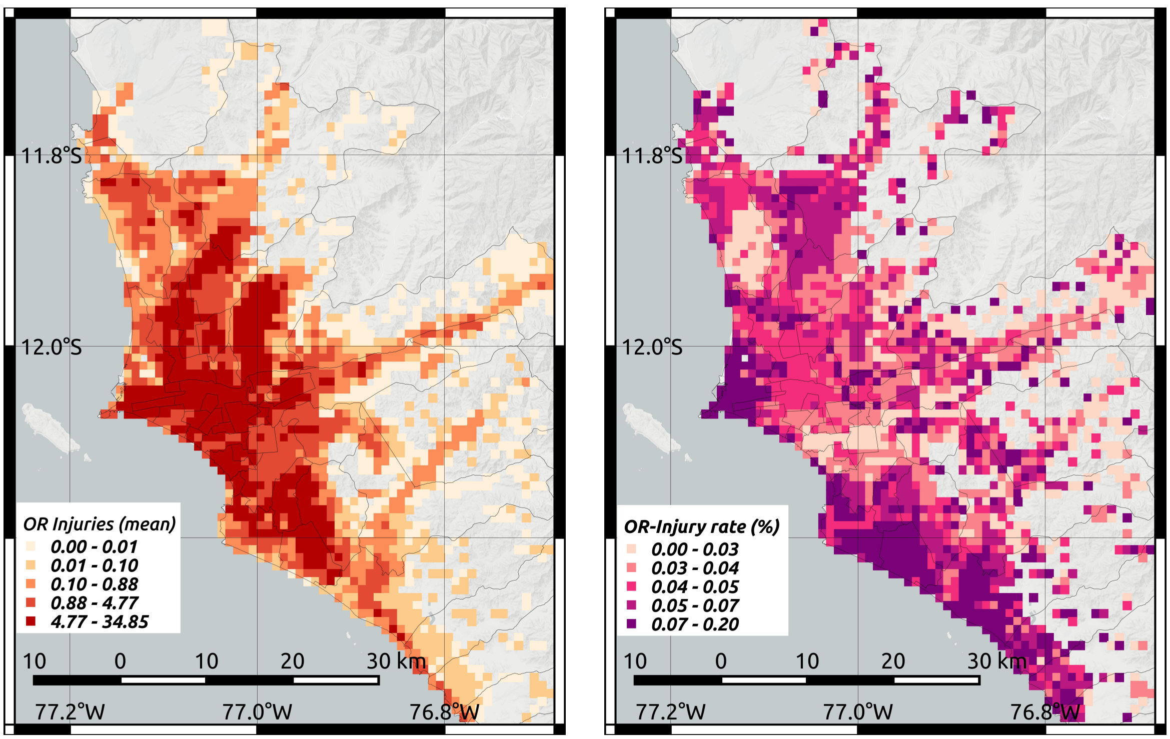


Figure 2: Earthquake scenario representing the M 8.0 1940 earthquake in Lima. The earthquake occurred in the subduction fault in the coast of Lima and caused widespread damage to the city.[22,27] The estimated area of fault rupture is shown in red. The edge dimensions were estimated with empirical formulas.[28] The fault plane dips 15°, where the edge underneath the coast is deeper than the edge under the ocean. The median peak ground acceleration (PGA) is also estimated with empirical formulas.[29] The shaking attenuates for regions further away from the rupture in the fault plane. Lima city and its districts are delimited by the black shapes.

1.1 Earthquake Casualties

We found that on average close to 4.7k people will require surgical procedures in operating rooms after the M 8.0 earthquake. This estimate results from applying a probabilistic model that utilizes high-resolution building seismic vulnerability data, population distribution and soil conditions to evaluate multiseverity earthquake casualties caused by widespread building damage[14,15] (see Methods). Earthquake injuries can have different severity degrees, ranging from small bruises to more serious spinal cord injuries.[30–34] The 4.7k patients requiring surgical procedures will have high severity injuries such us compound bone fractures, punctured organs or crush syndrome with open wounds, thus they require timely interventions for stabilization and treatment.

Our results are designed for a nighttime scenario, when most people are inside residential buildings, because residential infrastructure is particularly vulnerable in Lima. Predominantly the city's periphery has vulnerable residential infrastructure as a result of poor construction practices and lack of seismic code enforcement.[35,36] Figure 3a shows the spatial distribution of the average number of patients that will require the surgical procedures. A comparison with the spatial distribution of nighttime population density in Lima (Figure 9) indicates that most of these patients are located in high-density zones. However, the ratio between the number of injured people and the total number of people follows a different pattern (Figure 3b). The spatial distribution of this ratio reflects the uneven distribution of ground shaking intensities and seismic vulnerabilities of buildings in the city. It shows that people living closer to the coastline and in the city's peripheral zones have higher earthquake injury risk as a result of higher ground shaking (Figure 2) and more vulnerable buildings, respectively.



(a) **(b)**

Figure 3: Casualty scenario for M 8.0 earthquake occurring at nighttime in Lima. (a) Spatial distribution in km^2 of earthquake injuries requiring surgical procedures after the M 8.0 seismic event. (b) Spatial distribution of earthquake injury ratios, i.e., number of injuries as a percentage of the population per km^2. The intervals in the two plots represent quintiles (5-quantile) on the spatial data.

1.2 Post-earthquake Hospital Capacity

We found that on average only 93 of 182 total hospital operating rooms (51%) will be functional after the M 8.0 earthquake. This estimate results from performing a probabilistic earthquake simulation on a high-resolution dataset (see Methods). The dataset includes the structural vulnerabilities of +700 buildings belonging to 41 healthcare campuses,[16] the operating room resources, and "Hospital Safety Index" (HSI) of each campus. HSI is a metric created by WHO to measure post-disaster functionality potential due to multiple factors such as backup water, power, medical resources and hospital accessibility.[37] This unique dataset in combination with the earthquake simulation enables us to capture the residual hospital functionality on a large urban scale.

Figure 5a shows the spatial distribution of both the operating rooms in the dataset and the average predictions of operating rooms after the earthquake. Both spatial distributions are heavily uneven across the city. In the dataset, 95 operating rooms (52%) are concentrated in only four centric districts, Lima, Breña, La Victoria and Jesús María, whose summed areas represent less than 2% than the total area of the city. The earthquake slightly worsens such a resource centralization due to the non-uniform spatial distribution of earthquake shaking and the variations in the vulnerabilities of hospitals' buildings according to their construction age and standards or structural types (Figure 11). As a result, we estimate that these four districts will have 55 functional operating rooms, 59% of the total functional operating rooms, in the emergency response.

Additionally, addressing the centralization issue can become even more critical because the number of injuries needing surgical procedures and the functional operating rooms are negatively correlated. Our findings show a strong correlation (-0.49) between the simulations of earthquake injuries and functional operating rooms across the system in the city (Figure 4). Such a large correlation indicates that an earthquake that injures a larger amount of people will likely be very destructive; thus, that scenario will also cause a heavier disruption to the hospital system.

1.3 Demand-capacity Mismatch of Health Services

We analyzed patient arrivals to the hospitals and found that patient distribution significantly mismatches the distribution of residual hospital resources after the earthquake. We assumed that search and rescue (SAR) teams, relatives, friends and neighbors will initially transport patients to the triage areas in the closest hospitals as it occurred after previous earthquakes.[38] Figure 5b shows the distribution of the total arrivals of the patients who will need surgical procedures in each hospital. In contrast to the distribution of functional operating rooms, injuries are mainly located in the periphery. Only 596 patients would arrive at the hospitals in the four centric districts highlighted in Figure 5b. Those patients represent only 13% of the total demand for surgical procedures. However, as described earlier, these four districts will concentrate 59% of the functional operating rooms available.

Such a mismatch in the distribution of demands and capacities creates localized health service imbalances leading to long patient waiting times, with particularly severe effects in the periphery. Emergency plans can play a key role in addressing this mismatch and improve the treatment effectiveness in the city if they either mobilize patients from lower-capacity zones to higher-capacity zones or supply lower-capacity zones with additional resources. We tested four emergency plans. Two of them are baseline strategies that only require limited coordination in the system, whereas the other two are strategies that require higher coordination at the system level. To evaluate their performance during the emergency response, we used a system metric based on city-wide patient

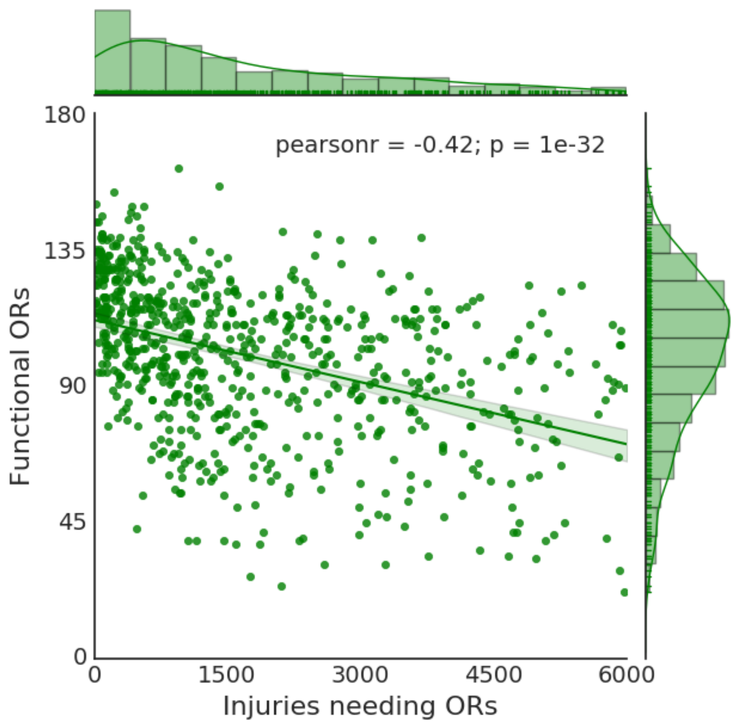
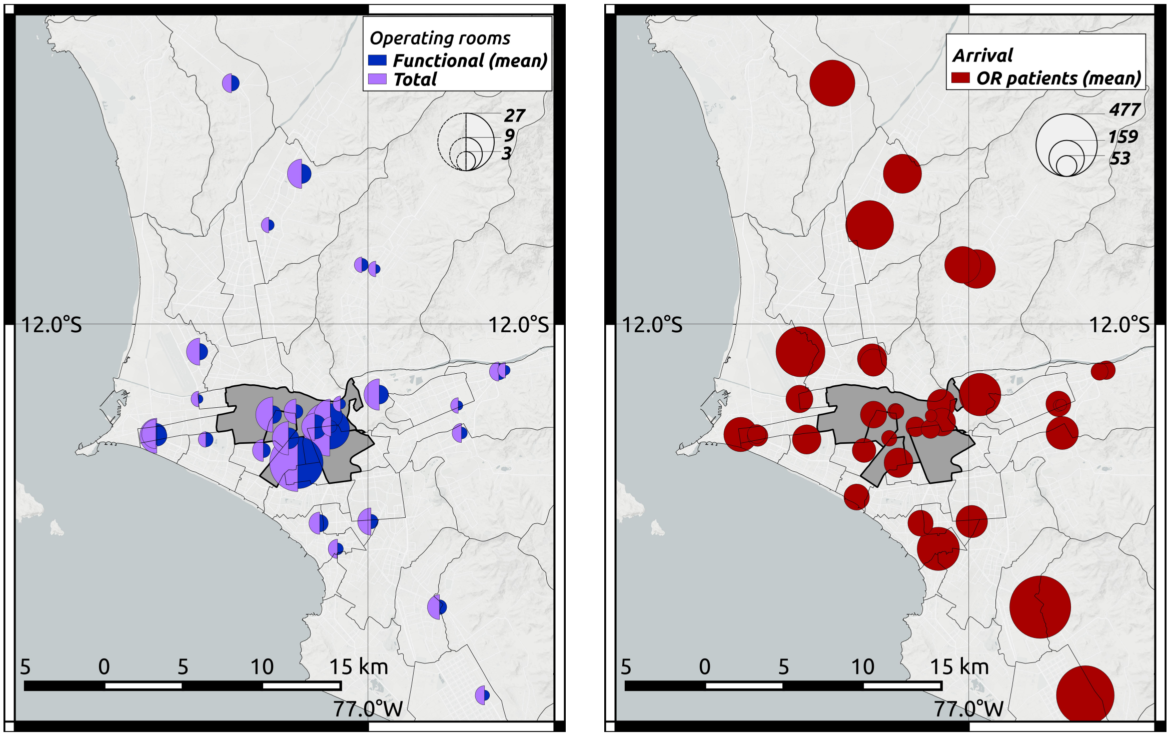


Figure 4: 1,000 simulations of number of casualties needing surgical procedures in operating rooms (ORs) and number of functional operating rooms after the earthquake for the M 8.0 earthquake. The simulations result from probabilistic earthquake modeling (see Methods) and capture uncertainty in ground shaking, building damage, injury occurrence and hospital functionality. The linear trend indicates a negative correlation between the functional ORs and the number of injuries in the simulations.

waiting times and effective use of ambulance resources (see Methods). Waiting times are a key metric to establish necessary patient stabilization procedures until there is an available operating room in the queue, and the use of ambulances is a complementary measure to ensure that patient transfers occur effectively. Combining simulations on post-earthquake demand-capacity with data including the available ambulances at each campus and regular traffic conditions in Lima from Google Maps API, we conducted a probabilistic evaluation of the system metric performance for the four emergency plans.

1.4 Baseline Strategies with Limited Coordination

In the first strategy, hospitals send patients to the closest hospital with functional operating rooms only if all their operating rooms are non-functional after the earthquake. In this strategy, hospitals use their own ambulance resources to transfer their patients. This strategy only requires limited coordination between pairs of hospitals located relatively close to each other, representing an emergency response where the system becomes a set of islands composed of districts or neighborhoods that treat injuries independently of each other. With this strategy, our mean estimates indicate that the average waiting time will be 30 days to receive treatment in operating rooms (Figure 6). In some worst-case scenarios, this metric could even increase up to 76 days, as indicated by the 90th-percentile of this distribution. The 1988 Armenia[39] and the 1991 Costa Rica[38] earth-



(a) (b)

Figure 5: Distribution of operating rooms in Lima. The circle size represents the relative number of operating rooms. (a) Current number of operating rooms in hospital locations[16] and mean estimates of functional operating rooms after the M 8.0 earthquake. (b) Mean estimates of total arrivals of patients who will need surgical procedures after the earthquake.

quakes showed that delayed surgical treatment can worsen the patients' health to life-threatening conditions, for example, those who need resuscitative surgery, e.g., intra-abdominal hemorrhage or emergency amputation. Thus, such long waiting times in Lima can result in many additional deaths.

For the first strategy, Figure 7a shows the mean estimates of the spatial distribution of treated patients at each hospital and the patient transfers between hospital pairs. Though this strategy can offload demands in critical zones, it does not effectively mobilize patients from the lower-capacity zones to higher-capacity zones. Hospitals with more functional operating rooms treat a similar number of patients as hospitals with fewer operating rooms. Hospitals in the four centric districts highlighted previously only treat 1.3k patients, which represents 28% of the demand for operating rooms, despite having 59% of the total capacity. Additionally, because hospitals do not share ambulance resources, we find that ambulances are the bottleneck of the system in the periphery. Hospitals with limited ambulances have to transfer large numbers of patients to offload the high demand for operating rooms. Thus, if they do not have sufficient ambulance resources, their patients will lose the opportunity to be treated more promptly in other less crowded hospitals.

In the second strategy, hospitals send patients to the hospital with the largest number of functional operating rooms. In this strategy, hospitals send patients only if all their operating rooms are non-functional and use their own ambulance resources. With this strategy, the mean and the 90th

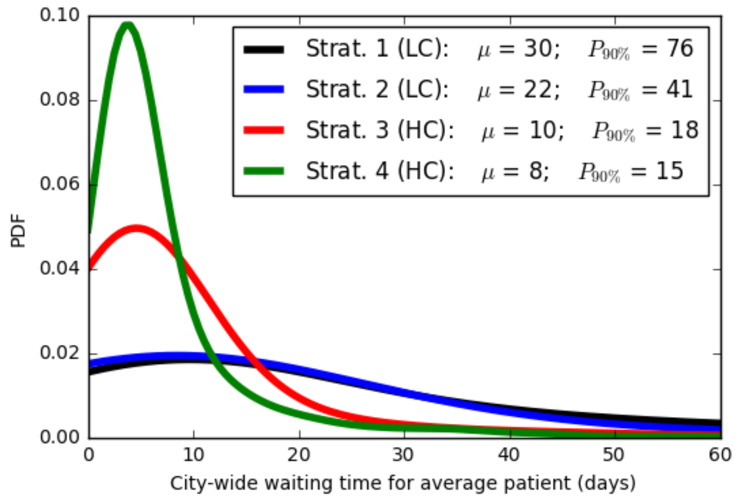


Figure 6: Distribution of city-wide average waiting time for treatment after the earthquake according to four emergency response plans, highlighting mean (μ) and 90th-percentile values ($P_{90\%}$). The time is measured from when the patient is injured by the earthquake until he or she is treated in an operating room. Strategies 1 and 2 are baselines with limited coordination (LC) capacities, whereas strategies 3 and 4 introduce higher coordination (HC) capacities across the whole system level for resource allocation and patient transfers. The ambulance usage and the treatment spatial distribution are show in Figure 7 for each plan.

percentile estimates of city-wide waiting time are 22 and 41 days, respectively, outperforming the first baseline strategy, but not significantly (Figure 6). With this strategy, the system mostly relies on the largest two hospitals, located in the highlighted centric districts, to meet the demands of surgical procedures. Figure 7b shows the corresponding distributions of treated patients and transfers. The two largest hospitals treat 2.8k patients, 60% of the total demand, though their functional operating rooms only constitute 44% of the total. Because multiple hospitals with non-functional operating rooms send patients to the same large hospitals under this strategy, their operating rooms overflow. Moreover, such an strategy leads to heavy use of roads from the periphery to the city center. For example, our mean estimates indicate that 231 patients would have to be transported from the southernmost hospital alone to the largest hospital, nearly twice as many as the maximum number of transfers between any hospital pair in the first baseline strategy.

1.5 Strategy 3: Sharing Ambulances

In the third strategy for effective emergency response, hospitals transfer patients across the system (see Methods). In addition, they share their ambulance resources across the system. This strategy represents an emergency plan that requires high coordination at the system level. During the emergency response following the next big earthquake in Lima, emergency managers could deploy this policy as soon as they collect information on the actual status of the operating rooms in hospitals and the actual distributions of injuries, which often takes a few days after the disaster depending on its magnitude.[40–43] Using this strategy, the mean and 90-th percentile estimates of city-wide waiting time are 10 and 19 days, respectively, significantly outperforming the first and second strategies by factors of 3 and 2.2 in the mean estimates, respectively (Figure 6). Because

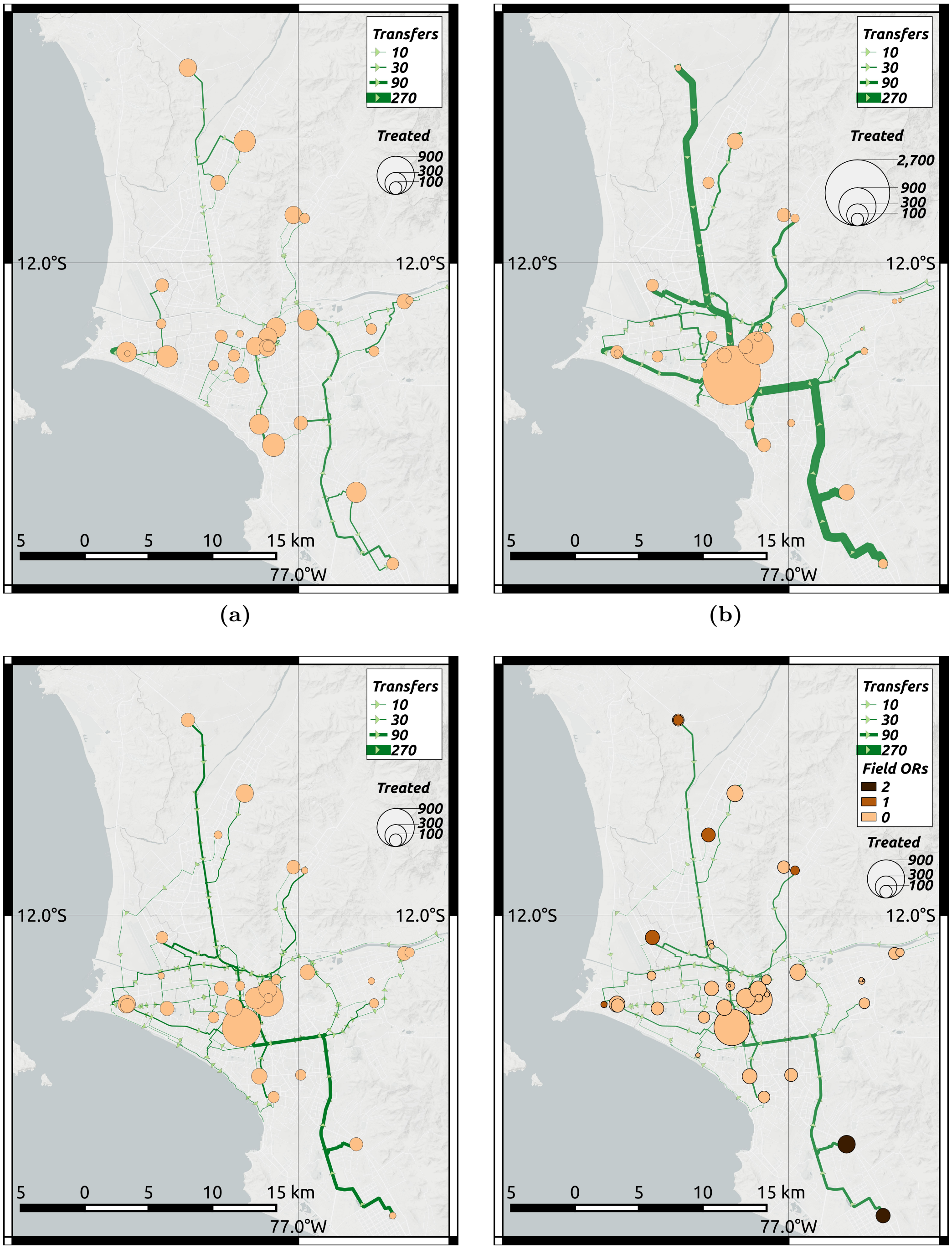


Figure 7: Spatial distribution of patient treatment and transfers. These values represent the average transfers and treated people according to the uncertain distribution of earthquake casualties and residual capacities in the hospital system. (a) Strategy 1: hospitals with unavailable operating rooms can transfer patients to the closest working hospital. (b) Strategy 2: hospitals with unavailable operating rooms can transfer patients to the largest working hospital. (c) Strategy 3: ambulances are shared in the hospital system. (d) Strategy 4: EMTs deploy 15 additional mobile operating rooms during the emergency response. The figure only shows roads between hospital pairs that transferred at least 5 patients.

an optimization formulation is used at the system level under this policy, patient transfers are effective at transporting patients from lower-capacity zones to higher-capacity zones, leading to a more effective use of the functional operating rooms across the city.

The distribution of treated patients matches the distribution of the residual operating room capacity in the system (Figure 7c). 2.6k people are treated in the hospitals in the four highlighted centric districts, which represents 56% of the total patients in the city and closely approaches the residual capacities in this zone, 59% of the total functional operating rooms. Unlike the second strategy, this strategy does not overload the capacities in the two largest hospitals by sending most patients to them, instead it distributes patients across the system according to the residual capacities of each hospital. Additionally, unlike with the first strategy, ambulance capacities do not bottleneck the system with this policy. Because hospitals share all ambulances in the system, the ambulances will work where they are most needed, from the periphery to the city center. An emergency plan that implements such a strategy will lead to a more balanced use of ambulances through the city and thus it offloads critical roads. With this strategy, close to 90 patients would have to be transported from the southernmost hospital to the largest hospital, less than half the number with the second baseline strategy.

1.6 Strategy 4: Deployment of Additional Operating Rooms by EMTs

In the fourth policy for effective emergency response, EMTs will deploy 15 additional mobile operating rooms to alleviate high demand-capacity gaps across the system (see Methods). We assume that the additional operating rooms will be functioning three days after the earthquake. This strategy deploys the operating rooms in close proximity to existing hospitals to leverage their triage areas and additional resources such as personnel, power generators or backup water. As with the third strategy, hospitals are also able to share ambulance capacities across the city. Because an optimization formulation is also used, the additional operating rooms are effectively deployed in locations and quantities that are critical to improve the performance of the emergency response. Using this policy, the mean and 90-th percentile estimates of city-wide waiting times are 8 and 15 days, respectively (Figure 6). As expected, these estimates outperform the response with the first policy due to the additional operating rooms in the system.

Our analysis strategically locates the additional operating rooms in the periphery, mainly in the southernmost and northernmost zones (Figure 7d). By deploying field hospitals in the periphery, more patients can be treated there, offloading the hospitals in the center. With this policy, 2.3k people, representing 48% of the total patients, are treated in the four previously highlighted centric districts, 16% fewer patients than with the first policy. As a result, fewer patients have to be transported from the periphery to the city center, offloading critical roads even more. In this case, the southernmost hospital will only have to transfer 76 patients to the largest hospital, a 17% reduction than with the first policy. If the EMTs deploy more field hospitals using this methodology, then treatment times will be further reduced, the periphery will be better supplied with needed resources, and the usage of ambulances and critical roads will be further offloaded in the city.

2 Discussion

We present a methodology for characterizing the emergency response of hospital systems after earthquakes and designing policies to treat patients effectively. Our methodology establishes the groundwork for assessing the value of hospital system coordination through a metric that measures the performance of high-coordination emergency policies in terms of waiting times and effective use of hospital resources. Because our methodology considers hospitals in a large urban center behave as a system, emergency managers and resilience officers can apply our methodology to a whole large city and evaluate optimal patient transfer strategies between hospitals, effectively allocate ambulances in the system, and guide the deployment of field hospitals.

We found that a M 8.0 earthquake in Lima will cause a spatial distribution of casualties that does not match the post-earthquake capacities of the hospital system (Figure 5). The zones with higher post-earthquake capacity are located in the city center, in clear contrast with the zones with higher post-earthquake demands of health services. Large numbers of patients are located in the periphery, where, unlike the city center, deficient construction practices have rapidly increased the seismic vulnerabilities of the housing infrastructure.[44] The neighborhoods in the periphery tend to be populated by families with less income and wealth, so the disparities in disaster risk overlap with the economic disparities.[45] This overlap will exacerbate the critical conditions in the periphery because these families will have less resources to obtain treatment and medicine from private hospitals, relying mostly on public hospitals. During an emergency response, this uneven vulnerability profile in the housing sector exacerbates the resource centralization problem of hospitals in the city, thus leaving the neighborhoods in the periphery predominately underserved during an emergency response. Because in many cities, neighborhoods in peripheral zones have precarious access to health services[46] and high concentration of seismic vulnerabilities,[47] these observations in Lima can be extrapolated to multiple urban centers in Latin America and even in developed countries.

Emergency planners who aim to treat patients in the city effectively must address these disparities by either transporting patients from lower-capacity to higher-capacity zones or supplying the lower-capacity zones with additional resources to meet demands of health services. Though emergency managers can elaborate multiple reasonable strategies to implement such emergency response measures, our findings shows that strategies based on deeper coordination between hospitals prove to be significantly more effective than the ones with less ability to coordinate (Figure 6).

Turning to the two baseline strategies with reduced coordination, both of them have similar low performance even though the system behavior differs fundamentally. Because in the first strategy hospitals transfer patients to the next closest working hospital only when they do not have available operating rooms, ambulance capacities are the bottleneck in some hospitals, whereas they are not even used in other ones. Additionally, the first strategy distributes the number of people treated at each hospital roughly evenly (Figure 7a). Such a treatment distribution results in hospitals with fewer resources treating similar patient numbers as hospitals with more resources, making the system inefficient and increasing waiting times.

The second strategy is also a baseline that enables hospitals to transfer patients only to the hospital with the largest number of functional operating rooms in the city. Contrary to the first strategy, the second one distributes the number of treated patients highly unevenly (Figure 7b). Because multiple hospitals often end up transferring patients to the two largest hospitals in the city, these two hospitals largely overflow their capacities. In addition, the second strategy requires heavy use of ambulance resources to transfer patients from the periphery to the city center, where these two largest hospitals are located.

In contrast, the third and fourth strategies that have deeper coordination significantly improve the emergency response performance because under these policies, hospitals share resources and leverage strategic system-level information. Because ambulances are shared across the system, they do not bottleneck the system as in first baseline strategy and start to be effectively used in critical zones. Patients are also strategically transferred across the entire hospital system, leading the spatial distribution of treated people matches the post-earthquake capacities of the hospital system (Figure 7c). As a result, the citywide-average waiting times to treat patients decrease quite significantly compared to the previous baseline strategies that only allowed reduced pairwise coordination by factors larger than 2 (Figure 6).

In practice, emergency managers will need a few days after the next large earthquake to collect necessary system-level information including both casualties and the residual functionality.[40–43] However, they can use the trends shown in Figure 7c to establish more informed policies for pragmatic implementation. Emergency planners should use this type of assessment to create earthquake preparedness plans. These plans may include implementing reliable communication lines between hospitals more likely to transfer large number of patients. Additionally, preparedness plans may include a usage prioritization of critical emergency corridors that are more likely to be heavily used by ambulances or an identification of alternative roads in case these corridors have known seismic vulnerabilities.

Another advantage of policies with deeper coordination the strategic deployment of EMTs and their additional mobile operating rooms. Besides decreasing waiting times, EMTs that supply operating rooms to the most underserved zones also achieve a more efficient use of ambulances because fewer transfers are needed. EMTs might find it practical to locate these additional operating rooms at the city center, where equipment mobilization is easier and availability of doctors and nurses is higher. However, such a plan may lessen the ability of the hospital system to treat patients because more patients would have to be transferred from the periphery to the center, overloading the roads and potentially overflowing ambulance capacities. Thus, robust earthquake preparedness plans should be developed based on a thorough understanding of the uneven distribution of capacity and demand of health services in an earthquake aftermath. Effective plans will capitalize on the methodology and information provided here to better prepare cities facing high significant risk from future large earthquakes.

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3 Methods

3.1 Network Flow Model and Optimization Formulation

We model the post-earthquake hospital treatment process as a minimum cost time-varying network flow (MCTVNF) problem.[48,49] In our MCTVNF formulation, a directed graph $G = (N, E)$ represents the hospital system, where $n = |N|$ is the number of graph nodes, and $e = |E|$ is the number of graph edges. We use a discrete time model with a finite time horizon t_f with time-steps dt, thus the time $t \in T : \{0, dt, 2dt, \ldots, t_f\}$. At each time t, each hospital has two nodes: one triage node where patients are received into the hospitals, and one discharge node where patients go after they complete their treatment. Each graph node is associated to an index i and a time t, where hospitals' triage areas have indexes $i \in \Gamma : \{1, 2, \ldots, n_h\}$, and the discharge areas have indexes $i \in \Lambda : \{n_h + 1, n_h + 2, \ldots, 2n_h\}$, where n_h is the number of hospitals in the system. To define a one-to-one correspondence within the indices of a hospital, if its triage index is $i \in \Gamma$, then its discharge index is $i + n_h \in \Lambda$. Figure 8 shows an example of a network representation at time t for a system with three hospitals, where the triage nodes are in red and the discharge nodes in blue. In this model, the decision variables are both the flows through the edges and the patient queues in thee triage nodes. These variables will track how many patients will stay in triage, be treated or be transferred to other hospitals.

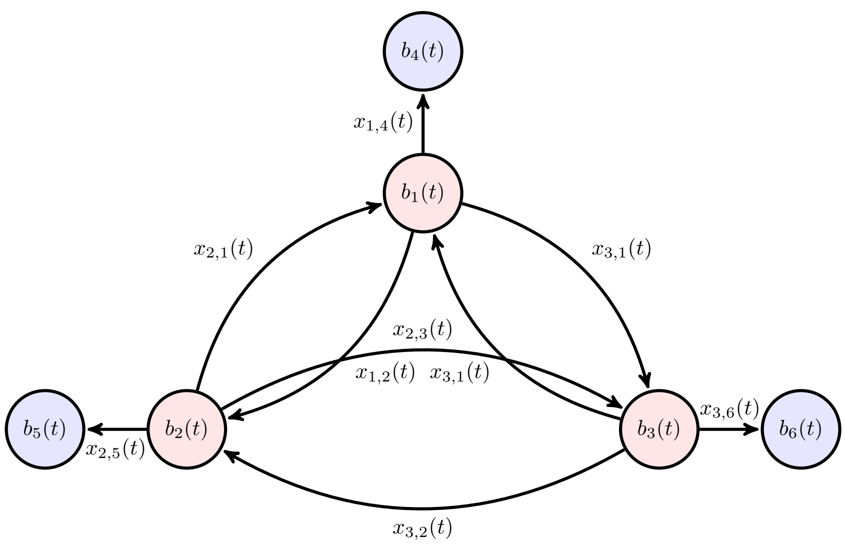


Figure 8: System model with three hospitals at time t as a directed graph. The system model used for the application to Lima has 41 hospitals, i.e., 41 triage and 41 discharge nodes.

Each graph node is associated to a time-variant demand-supply variable $b_i(t)$. In triage nodes, $b_i(t)$ represents the number of people arriving to hospital, thus they are analyzed as source nodes with nonnegative flows: $b_i(t) >= 0, \forall i \in \Gamma$. In the discharge nodes, $b_i(t)$ represent the number of patients who finish their treatment and exit the hospital at time t, thus they are analyzed as sink nodes with nonpositive flows: $b_i(t) <= 0, \forall i \in \Lambda$. We assume that patients who finish the treatment process and exit the hospital do not to return to the hospital system during the time horizon t_f.

Each graph edge is associated to a flow of patients $x_{i,j}(t)$ that leaves node i at time t to go to node j. In this formulation, edges fully connect the triage nodes to allow hospitals to redistribute their patient loads to potentially any other hospital within the system according to their available ambulances. Additionally, each triage node is connected to its respective discharge node to represent the patient treatment process within a hospital. Figure 8 shows the edges and respective flows between triage nodes from different hospitals and between triage and discharge nodes within same hospitals for the system with three hospitals. At each time t, the flow $x_{i,j}(t)$ has a maximum bound $u_{i,j}(t)$ and a travel time $\tau_{i,j}(t)$. In this discrete formulation, it is considered that the flow $x_{i,j}(t)$ leaves the node i at time t and reaches the node j at time $t + \tau_{i,j}(t)$.

For the edges connecting triage areas, $u_{i,j}(t)$ represents the maximum number of patients who can be transported from triage i to triage j in a different hospital according to the available transportation resources (e.g., ambulances available in the hospital), and $\tau_{i,j}(t)$ is the transportation time of the patients from triage i to triage j. For the application to Lima, $u_{i,j}(t)$ and $\tau_{i,j}(t)$ in these edges were defined according to the ambulance capacities in each hospital and the travel times from pre-earthquake traffic conditions, respectively. When vulnerability data for the transportation system in Lima is available, our model will be able to leverage existing risk models for transportation systems[50, 51] to adjust travel times to post-earthquake traffic conditions.

For the edges connecting triage nodes i with their respective discharge nodes $j = i+n_h$, $u_{i,i+n_h}(t)$ represents the maximum number of patients who can be treated according to the available medical resources for the type and severity of the patients' injuries, and $\tau_{i,i+n_h}(t)$ is the treatment time. For the application to Lima, $u_{i,j}(t)$ and $\tau_{i,j}(t)$ in these edges were defined according to the functional operating rooms in each hospital and average treatment times in operating rooms in previous earthquakes.[52]

Additionally, we define $y_i(t)$ as a storage variable at each triage node to represent the patients who wait in the hospital queue to either be treated within the hospital or be transported to another hospital with more available resources.

3.1.1 Optimization of Performance Metric

We evaluate both waiting times and effective use of ambulances as the system performance metric, thus the metric includes two objective functions. The first objective function $C_1(X)$ measures waiting time across the city as the average time that a patient would take since the earthquake until completing treatment in the operating room.

$$C_1(X) = \frac{\sum_{t\in T} \sum_{\substack{i\in\Gamma, \\ j=i+n_h}} \{t + \tau_{i,j}\} \times x_{i,j}(t) \times dt}{\sum_{t\in T} \sum_{i\in\Gamma} b_i(t)} \tag{1}$$

X represents a vector containing all the decision variables of flow $x_{i,j}(t)$ in edges and the storage $y_i(t)$ in the triage nodes. The numerator of $C_1(X)$ represents the total number of patients passing through the operating rooms (from each triage node $i \in \Gamma$ to the corresponding discharge node $j = i+n_h \in \Lambda$) multiplied by their respective times to complete treatment, whereas the denominator is the total number of patients arriving to the triage areas. The time horizon t_f is carefully chosen to have enough modeling time to treat the patients. However, in few simulations with significant number of patients and not many functional operating rooms, a couple of terms are added to the numerator, one with the remainder patients in the triage areas, $t_f \times \sum_{i\in\Gamma} y_i(t_f) \times dt$, and another with the remainder patients in the ambulances, $t_f \times \sum_{i\in\Gamma} x_{i,i+n_h}(t_f) \times dt$, in order to properly incorporate the unmet demands at the end of the simulation into $C_1(X)$.

The second objective function measures ambulance usage as the total number of patients transported in ambulances. The objective function $C_2(X)$ is normalized by the total number of patients analogously to $C_1(X)$.

$$C_2(X) = \frac{\sum_{t\in T}\sum_{i\in\Gamma}\sum_{j\in\Gamma} x_{i,j}(t) \times dt}{\sum_{t\in T}\sum_{i\in\Gamma} b_i(t)} \tag{2}$$

We define a system cost $C(X)$ as a weighted sum of $C_1(X)$ and $C_2(X)$ to find a Pareto-optimal solution.

$$C(X) = \alpha_1 \times C_1(X) + \alpha_2 \times C_2(X) \tag{3}$$

After assessing multiple α_1 and α_2 values, we minimized $C(X)$ using values of 0.90 and 0.1, respectively. Smaller α_2 values resulted in inefficient ambulance usage with small reductions in waiting times, requiring some patients to be transferred multiple times in ambulances before being treated. Larger α_2 significantly increased waiting times, thus these α_2 values do not appropriately represent that the priority in the formulation is to minimize waiting times over to use ambulances with efficiency. We find the best set of decisions $\hat{X}$, vector that contains the values of flow variables $x_{i,j}(t)$ and storage variables $y_i(t)$ which minimize $C(X)$.

$$\hat{X} = \mathrm{argmin}_{x_{i,j}(t);y_i(t)} \quad C(X) \tag{4}$$

The decision variables are subject to the constraints in Equations 5, 6, 7, and 8. Equation 5 represents patient flow conservation, which guarantees that all the patients coming into the hospital system stay within the system until they leave through the discharge nodes.

$$x_{i,i+n_h} + \sum_{j\in\Gamma} x_{i,j}(t) - \sum_{j\in\Gamma} x_{j,i}(t - \tau_{i,j}(t)) + y_i(t+dt) - y_i(t) = b(i), \quad \forall i \in \Gamma, t \in T \tag{5}$$

Equations 6 and 7 represent flow capacity constraints. Equation 6 ensures that the people in the operating rooms do not exceed the unitary capacities $u_{i,i+n_h}$, where $u_{i,i+n_h}$ is estimated as the number of functional operating rooms in the hospital i over the number of surgeries per day. We assumed that each surgery takes 4 hours, and that hospitals will be functional 24 hours during the emergency response using multiple personnel shifts. Such treatment rate equals the rates in foreign field hospitals after the 2004 Indonesia earthquake/tsunami.[52]

$$0 \leq \frac{x_{i,i+n_h}(t)}{u_{i,i+n_h}} \leq 1, \quad \forall i \in \Gamma, t \in T \tag{6}$$

Equation 7 ensures that the patient transfers do not exceed the total unitary transportation capacities in a hospital, where $u_{i,j}$ is the unitary capacity if all ambulances of a hospital were only transferring patients from triage i to j. $u_{i,j}$ equals the number of ambulances in the hospital times the number of patients transported per ambulance trip over the number of round trips that the an ambulance can make from triage node i to j. We retrieved travel time information from Google Maps API to estimate the round trip numbers and assumed that each ambulance trip can take up to two patients.

$$0 \leq \sum_{j\in\Gamma} \frac{x_{i,j}(t)}{u_{i,j}} \leq 1, \quad \forall i \in \Gamma, t \in T \tag{7}$$

Equation 8 ensures that the number of patients waiting in the hospitals' triage queues are properly represented by a non-negative number.

$$0 \leq y_i(t), \quad \forall i \in \Gamma, t \in T \tag{8}$$

Equations 6, 7 and 8 introduce a model relaxation. Whereas the number of patients who are treated, transported or waiting in the queue can only be non-negative integers, the formulation expands the variables' domain to include real numbers. This relaxation ensures that the formulation is tractable. Thus, because the cost and the constraint functions are linear combinations of the decision variables, we solve this minimization as a linear programming problem using the simplex algorithm in GLPK of the cvxopt implementation in Python.[53,54]

3.1.2 Model Adaptation for Baseline Strategies 1 and 2

Both baseline strategies have limited coordination capacity and only allow each hospital to transfer patients to only one single hospital with functional operating rooms instead of multiple ones. Thus, to represent these strategies, the model ignores multiple transfer edges in the flow model, reducing the elements of the edge set E. In the first baseline strategy, only the edges going from hospitals without functional operating rooms to the closest hospitals are activated. In the second baseline strategy, only the edges going from hospitals without functional operating rooms to the hospital with the are largest number of functional operating rooms are activated.

Because the model is solved multiple times according to the number of patients and functional operating rooms in the earthquake simulation, then the edge connectivity varies from simulation to simulation. With strategies 1 and 2, the number of edges in the model is significantly reduced, thus we modeled larger time horizons. We selected a time horizon T_f of 100 days, which is sufficiently long period to treat treat all earthquake patients in most simulations, and a time step dt of 1 day.

3.1.3 Model Adaptation for Strategy 3: Sharing Ambulances

Strategy 3 does not need to disconnect edges in the model. Yet, it modifies the transportation edges' capacity constraints to enable hospitals to share ambulance resources. Thus, the constraint in Equation 7 is relaxed as follows.

$$0 \leq \sum_{i \in \Gamma} a_i \sum_{j \in \Gamma} \frac{x_{i,j}(t)}{p_{i,j}} \leq \sum_{i \in \Gamma} a_i, \quad \forall t \in T \tag{9}$$

Equation 9 ensures that unitary transportation capacities are not exceeded at a system level at each time step, where a_i represents the number of ambulances of hospital i. All the other constraints remain the same. Because modeling this policy requires higher edge connectivity than the baseline strategies and thus has more computational demands, the time horizon t_f was reduced to 40 days. It was verified that such a variation did not affect the optimization because less modeling time was needed as a result of shorter optimal waiting times with the strategies 3 and 4 (Figure 6). The time step dt was kept equal to 1 day.

3.1.4 Model Adaptation for Strategy 4: Deployment of Additional Operating Rooms by EMTs

Strategy 4 requires an additional modification to the constraint on the operating room capacity in Equation 6. This strategy allows EMTS to increase hospital capacities by introducing additional mobile operating rooms in close proximity to them as follows.

$$0 \leq \frac{x_{i,j}(t) - q_i}{u_i} \leq 1, \quad \forall i \in \Gamma, j = i + n_h \in \Lambda, t \in T - \{0, dt, \ldots, t_s\} \tag{10}$$

Equation 10 ensures that hospitals can increase their unitary operation room capacities by q_i after the time t_s at which the operating rooms in the field hospitals are deployed in the city. In addition the sum of the additional resources distributed across the system cannot exceed the total capacity Q supplied by all the field hospitals in the region as follows.

$$0 \leq \sum_{i \in \Gamma} q_i \leq Q \tag{11}$$

All the other constraints remain the same. These modifications barely change the optimization complexity. Thus, we kept the time horizon equal to 40 days and the time step equal to 1 day.

3.2 Earthquake Casualty Modeling

We utilize an earthquake multiseverity casualty model previously developed by the authors[15] to evaluate the spatial distribution of injuries requiring surgical treatment after the M 8.0 earthquake. The model is probabilistic and uses ground shaking estimates to propagate the earthquake intensity to building damage according to the building seismic vulnerability[55] and the site-specific soil conditions in Lima.[56] Next, the model uses information on building occupancy to provide probabilistic estimates of the spatial distribution of injuries and fatalities in the city. The validity of the model results was verified[14] by comparing the casualties and fatality levels in the city to empirical formulas[18] and with fatality-to-collapse building data from the 2005 Pakistan earthquake.[57]

The model categorizes injuries into three severities. The second- and third-degree severity require specialized medical attention and hospitalization, however, unlike the second degree, the third one requires immediate rescue and treatment to avoid death.[58–60] We considered that 100% of the patients with third-degree injuries, for example, having punctured organs or crush syndrome with exposed wounds, plus 10% of patients with second-degree injuries, for example, having compound bone fractures, will require surgical treatment in operating rooms. We considered that patients arrive to the closest hospital during a period of 4 days after the earthquake in accordance to the evidence from previous earthquakes.[39,61] Thus, in the flow model the demand-supply variable $b_i(t)$ is larger than 0 in the triage nodes during the first four days after the earthquake. We considered that patients wait in triage zones to until an operating room is available in the hospital or until they are transferred to other hospitals.

3.3 Seismic Analysis for hospital functionality

We utilize earthquake simulation to model the functionality of operating rooms during the emergency response.[62] Hospitals are complex infrastructure, whose post-earthquake functionality depends on multiple components: structural damage; damage in mechanical, electrical components and medical equipment; utility failure; shortage of medical supplies (i.e., oxygen, blood), and shortage of medical personnel.[7,8,13,63] Hospitals with slight structural damage can lose partial or total functionality as a result of damage and loss of the other components of hospitals.[64]

To capture these effects, we analyzed that the structural vulnerability[55] of the +700 buildings belonging to the 41 healthcare campuses in the city according to the earthquake shaking intensity and the soil conditions on site. Then, we used a Bernoulli distribution to model loss of functionality that can occur due to failure of components different to the hospitals' structure according the "Hospital Safety Index" (HSI). HSI is based on a qualitative evaluation of multiple hospital components including buildings' nonstructural elements such as equipment and backup medical resources, and technical and organization capacities in the hospitals' personnel.[37] HSI has three categories: "A", "B" and "C", ranging from the best to the lowest performance. We used a different Bernoulli distribution for each HSI category. We considered that operating rooms in buildings with no structural damage have 1, 0.75, and 0.5 of functionality probability for categories "A", "B" and "C", respectively, whereas that in buildings with slight structural damage, operating rooms have 0.6, 0.45, and 0.3 of functionality probability. Operating rooms in buildings with larger damage levels were considered completely nonfunctional.

The 41 campuses in the dataset are part of the public healthcare system led by the Peruvian Health Ministry (MINSA) and the Social Security (Essalud). Even though there is a growing private healthcare system, most of the health care services are provided by the public system in Lima.[65] Physicians who work full time in the public healthcare system often work part-time in the private system,[66] thus, in an emergency, they would aim to provide services in the public system rather than in the private one. We consider that studying the response of the public sector represents a robust starting point to characterize the earthquake emergency response of the hospital system in Lima.

We supplemented the hospitals' building information with the number of ambulance in each hospitals. Because, a few hospitals have no ambulances, we considered that during the emergency response the local government or private institutions will supply one ambulance to each of these hospitals so that each hospital is able to mobilize patients.

3.4 Earthquake Shaking

We studied the tectonics of the M 8.0 1940 earthquake and located the rupture area in the region delimited by the earthquake aftershock zone.[26] We defined the rupture dimensions along the fault strike and dip directions using an empirical function based on subduction zone earthquake data.[28]

Next, we evaluated the ground shaking in a grid of 1kmx1km using site-specific lognormal distriutions. We evaluated three ground shaking intensity measures, Peak ground acceleration, PGA, spectral acceleration at 0.3s, $Sa(0.3)$, and spectral acceleration at 1s, $Sa(1.0s)$. We selected these intensity measures to better capture the response of multiple typologies of buildings in the inventory according to their predominant period of vibration. The log-mean and log-standard-deviation values of the intensity measures were extracted from empirical formulas that relate magnitude, site distance, and soil conditions to the ground shaking.[29] We included within-[67] and between-[68]event correlations in the intensity measures. The between-event correlations introduce spatial correlations to the ground shaking.

3.5 Data Availability

All the data to reproduce the findings of the paper can be found at `https://purl.stanford.edu/dp530wq8437`.

3.6 Code Availability

All the computer code to reproduce the findings of the paper can also be found at `https://purl.stanford.edu/dp530wq8437`.

4 Supplementary Information

Lima is a fast-growing megacity with a population close to 10 million people.[21] Though the center of the city is denser, the peripheral areas of the city have become heavily populated over the last few decades. Currently, close to three million people live in peripheral zones in slums,[69] where families are low-income, who often start constructing their homes with precarious materials, e.g., wooden shacks, and then upgrade them to confined-masonry buildings over timespans ranging from a few years to decades.[70] Figure 9 shows how heavily populated the peripheries are. The population distribution in this plot represents the average number of people over 24 hours in grids of 1 km^2. Population density is dynamic, but often people spend most time at their residential buildings, mainly during nighttime. Thus, we considered that this average distribution is a reasonable representation of nighttime population densities.

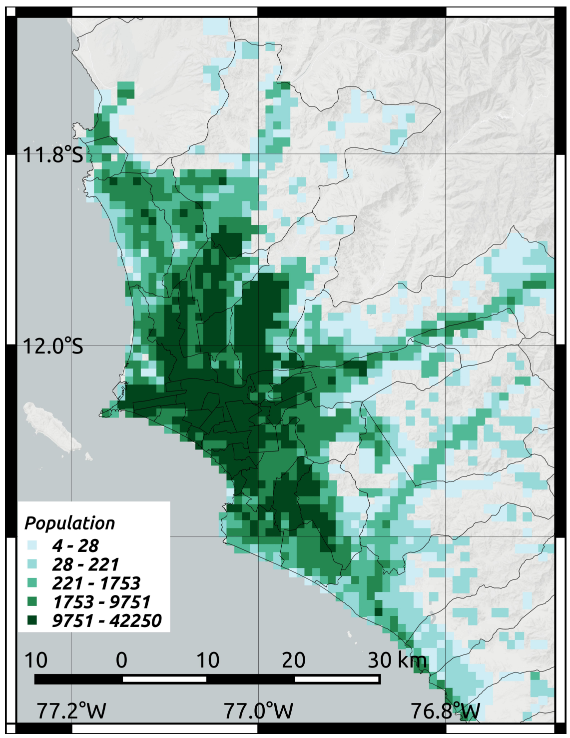
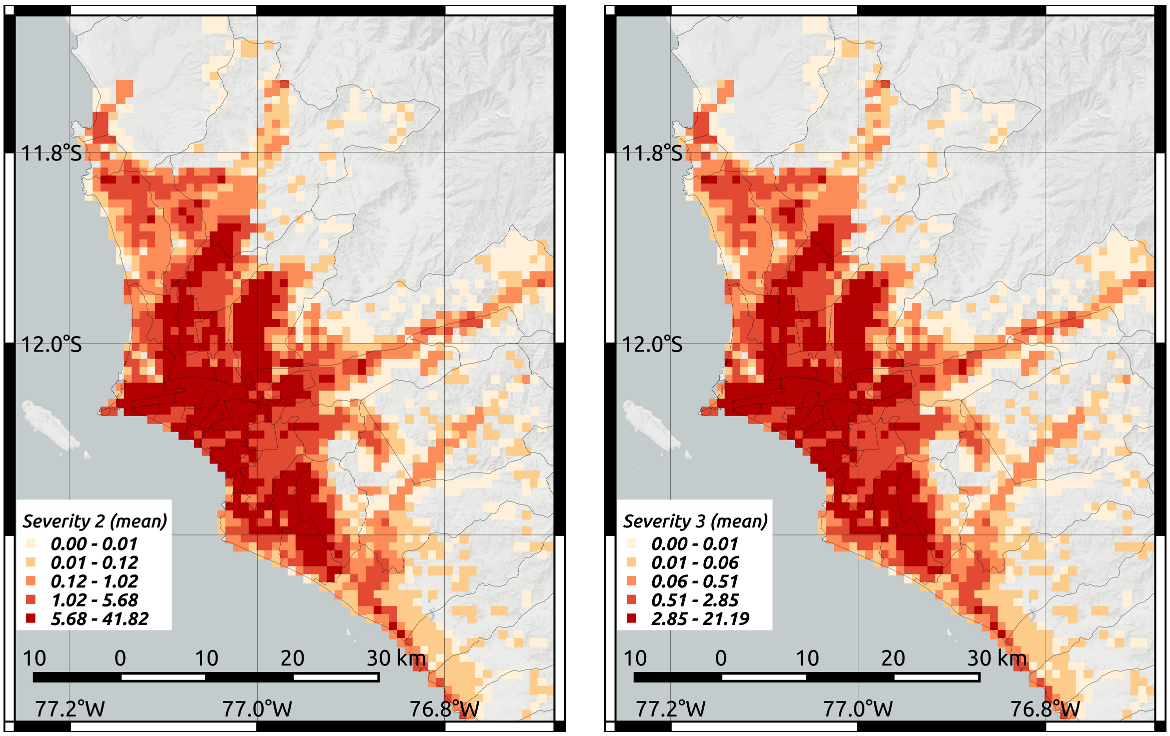


Figure 9: Spatial distribution of population density in Lima per km^2. Data obtained from LandScan.[71] The intervals in the two plots represent quintiles on the spatial data.

The seismic analysis included the assessment of the the number of fatalities and injured people with three types of severities caused by an M 8.0 earthquake occurring at nighttime in Lima, when people are often within their houses. As observed in previous earthquakes, the model considers that most casualties are caused by earthquake damage to buildings in the city. Our mean estimates indicate that the M 8.0 earthquake will cause 60.3k people with injuries of severity 1, 18.9k of severity 2, 2.8k of severity 3, and 5.6k immediate fatalities. People with injuries of severity 1 will require basic medical aid and no hospitalization. People with injuries of severity 2 will require hospital treatment, but the injuries are not life-threatening in the short term, and people with severity 3 will require immediate hospitalization otherwise injuries become life-threatening.[14,60]

Figures 10a and 10b show the mean spatial distributions of injured people with severity 2 and 3 in the city. Because in the model, casualties are result of building damage, the spatial distribution of patients with severity 2 and 3 are heavily cross-correlated and particularly concentrated in areas with large number of buildings that collapse.



(a) **(b)**

Figure 10: Spatial distribution of patients with a) injuries of severity 2 and b) injuries with severity 3. The intervals in the two plots represent quintiles on the spatial data.

The seismic analysis also included the assessment of the ability of hospitals to function after the earthquake. Figure 11 shows the mean functionality ratio of operating rooms in the 41 healthcare campuses that were analyzed. The ratio represents how likely are operating rooms to function after the M 8.0 earthquake considering their structural vulnerabilities, their "HSI" score, and their proneness to experience large shaking intensities as a result of the proximity to the earthquake fault or the soil conditions. Though the absolute number of functional operating rooms was higher at the center of the city, the spatial patterns of of functionality ratios did show a strong prevalence of high ratios in particular zones of the city. Instead of geographical location, construction year was a better indicator of the hospitals' ability to function, as most newer hospitals showed higher functionality ratios.

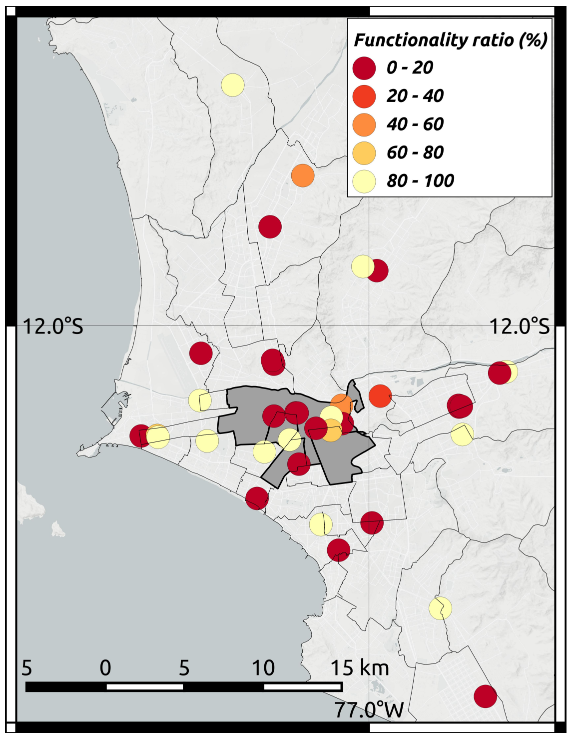


Figure 11: Spatial distribution post-earthquake functionality ratio. Newer hospitals, some of the located in the city center, tend to perform better than the older ones. Few hospitals that did not have operating room capacities under normal conditions were assigned 0% functionality ratio.

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