Hospital-system functionality quantification based on supply–demand relationship under earthquake

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Abstract
The hospital system is one of the most critical systems in the city and plays an irreplaceable role in the whole process of earthquake disasters. This paper presents a method that considers the medical supply–demand relationship to quantify the functionality and functional loss of a hospital system under earthquake conditions, which is different from the current quantitative method that only considers internal factors of the hospital system. This method provides a “finest granularity” method for the division of quantitative evaluation units of hospital system functionality based on GIS overlay. Secondly, the functionality of the hospital system considering the medical supply–demand relationship and the quantitative metric, substitution capacity of medical resources (SCMR), is constructed. Then, we propose a quantification method of SCMR by combining the spatial and network analysis methods. Finally, a hospital system in eastern China is considered as an illustrative example. The impact of changes in the medical supply and demand at different times of the day on the hospital system functionality is analyzed. The results show that the medical supply and demand can impact hospital system functionality. The loss of medical supply causes a decline of hospital system functionality, while changes in the spatial aggregation of medical demand positively affect the loss of hospital system functionality. This paper can use the proposed method to quantify the hospital system functionality and reflect the balance of the medical supply–demand relationship before and after the earthquake. It can help decision-maker develop scientific post-earthquake emergency plans and enhance hospital system resilience.

Keywords Hospital system · Functionality quantification · Supply–demand relationship · GIS

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1 Introduction

In human social development, many cities have been continuously damaged by natural disasters, which have caused severe casualties and economic losses (Gencer 2013). The hospital system is one of the most critical systems in a city, and its ability to provide services after an earthquake is an essential factor affecting the recovery of urban areas. Hospital system organization and external infrastructure systems generally sustain varying degrees of damage, which may compromise the supply capacity of the hospital system (Fang et al. 2017). Furthermore, the increase in medical demand after the earthquake will exacerbate the imbalance between medical supply and demand, resulting in more serious casualties and losses. Therefore, it is meaningful to study the relationship between changes in medical supply and demand after the earthquake and analyze the impact of changes in medical demand on hospital system functionality.

Medical supply capacity can be understood as the performance of the hospital system in daily and disaster situations, and the measures of the hospital system functionality are classified into two aspects: qualitative and quantitative.

In qualitative evaluation, some scholars consider hospital system functionality as the performance of hospital system services after an earthquake. World Health Organization (2015) proposed a guideline for evaluating safe hospitals to ensure that hospitals provide sustainable performance after adverse events. This guideline suggests that hospitals can be evaluated in terms of structural safety, non-structural safety, and emergency and disaster management. Achour and Miyajima (2020) considered the hospital performance in the post-earthquake period related to building integrity, lifeline damage, medical equipment, post-earthquake medical services, and generic information on medical facilities. Besides, the hospital functionality is also affected by external networks (telecommunication and road networks) that generally do not prevent hospitals from working, but affect the quality of healthcare services (Achour 2015). At the same time, more and more scholars have begun to study the hospital performance after earthquakes from the perspective of resilience. Post-earthquake functional recovery is widely regarded as a critical index for analyzing the functionality of healthcare. For instance, Zhong et al. (2014a, b) adopted four indicators to evaluate hospital disaster resilience, including emergency medical response capability, disaster management mechanisms, hospital infrastructural safety, and disaster resources. From the perspective of emergency management, cooperation and training management, resources and equipment capability, structure, and organizational operating procedures, were selected by Cimellaro et al. (2018). Fallah-Aliabadi et al. (2020) designed resilience evaluation indicators of medical system from three dimensions: constructive, infrastructural, and administrative. In addition, Qing-xue et al. (2019) proposed a framework for the quantitative assessment of hospital system resilience based on total probability theory. In summary, the evaluation methods of hospital system functions can be roughly classified into structural, non-structural, and post-earthquake emergency response and management. Although methods have gradually matured, subjective factors and limitations have become more and more prominent.

In quantitative evaluation, Cimellaro et al. (2010a) defined the functionality of medical facilities according to their service quality (such as waiting time). Yavari et al. (2010) and Mitrani-Reiser et al. (2012) defined the functionality of medical facilities according to the availability of services of the medical facilities. Jacques et al. (2014) linked the functionality of medical facilities with the available space in the hospital to define the functionality of the medical facilities. Bruneau and Reinhorn (2007) used the ratio of the actual number
of patients received per day to the number of patients as a functional quantification index and evaluated the state of the hospital system using a value in the range of 0–1. The above approaches focused on the ability of hospitals to cope with medical demand. However, the impact of real medical demand after the earthquake on the functionality of the hospital system was not considered.

In addition to the internal factors mentioned above, the external network (telecommunication and road networks) has a strong influence on hospital system functionality (Tari-verdi et al. 2019). The WHO guidelines for evaluating safe hospitals mention that the prerequisite for a hospital to operate is access to the hospital. However, even if the hospital is not affected by the earthquake, damage to the external network may limit the operation of hospital system (Kuwata and Takada 2004). In the Great Hanshin Earthquake in Japan, urban transportation system was severely damaged, which brought great difficulties to the post-earthquake emergency rescue of critical infrastructures such as hospitals and firefighting (Tsujie 2001). In the Taiwan Jiji earthquake, many roads and bridges were blocked, causing disorder in the transportation system. In this case, the difficulty of emergency rescue, which can only be implemented by helicopter or on foot, is significantly increased (Ke and Hsu 2022). Due to road interruptions or closures, the ability of hospital systems to receive patients after a disaster has plummeted. Therefore, the impact of external transportation networks on infrastructure in an earthquake is critical. Many scholars have studied the impact of external transportation networks on the functionality of hospital systems. For example, Dong and Frangopol (2017) analyzed the impact of road damage on hospital capacity, using the bridge network as the main external factor. Tamima and Chouinard (2017) identified the accumulation of road debris due to structural damage as a significant obstacle to evacuation and emergency rescue, affecting the function of emergency facilities during an earthquake.

To improve the resilience of hospital systems, establishing a rational emergency management policy is also essential. Achour (2015) argued that hospitals can cooperate with other emergency services according to specific needs. In addition, scientific emergency management plans have been established, such as road repair plan (Li and Teo 2019) and medical evacuation plans (Bish et al. 2014). In this paper, the functionality of hospital system refers to the ability to provide pre-hospital emergency services during an earthquake, as indicated by the probability of the injured seeking medical care after the earthquake, which is greatly influenced by the external transportation network. Therefore, this study focuses on the impact of the external transportation network on the hospital system functionality and aims to enhance the hospital system resilience.

Post-earthquake medical demand plays a crucial role in the functional analysis of hospital systems. After a devastating earthquake, the medical supply cannot meet post-disaster medical demand, resulting in a serious imbalance between medical supply and demand and exacerbating casualties. Meanwhile, dynamic changes in medical demand can also affect the functionality and losses of hospital systems (Cimellaro et al. 2010b). At present, few studies consider both medical supply and demand factors when assessing hospital system functionality. It is urgent to sort out the dynamic changes of supply and demand in the hospital system and analyze its impact on the functionality of the hospital system. Therefore, this paper presents a method to quantify the hospital system functionality while considering the medical supply–demand relationship. The remainder of this paper is organized as follows: Sect. 2 introduces the quantification methods of hospital system functionality and functionality loss. In Sect. 3, a case study applying the method to a hospital system located in northeastern China, is presented. Section 4 analyzes the results and provides some suggestions for decision-makers. Section 5 is the conclusions of this study.
2 Methodology

2.1 Overview

This study presents a functionality quantification method for medical systems based on the medical supply–demand relationship that comprises three steps, as shown in Fig. 1. Firstly, we propose the method of “finest granularity” evaluation unit based on GIS overlay analysis to address the limitations of current research methods. Secondly, a quantitative metric of hospital system functionality, substitution capacity of medical resources (SCMR), which refers to medical supply and demand factors, is provided. The SCMR introduces the supply and demand coefficient based on the cumulative opportunity method, and considers the influence of hospital diversity. Meanwhile, the quantification of medical demand metrics adopts Baidu maps and image processing techniques, which aims to obtain urban population distribution data. Accordingly, an improved earthquake hazard prediction model is
used to quantify medical demand after an earthquake. The quantification of medical supply metrics is achieved by using network analysis of GIS, which can calculate the maximum service range of the hospital and combine it with the number of beds in the hospital. In addition, to improve the accuracy of functionality quantification, we used a Gaussian function and proposed a functionality attenuation coefficient to reflect the variation of hospital functionality with distance. Finally, a weighted summation of the SCMR is used to quantify hospital system function before and after the earthquake. In this study, the post-earthquake functional loss of the hospital system takes into account the impact of the loss of medical supply capacity.

2.2 Functionality quantification of urban hospital system

2.2.1 Division of evaluation units

The study area is divided at the finest granularity, results in multiple irregular evaluation units. In urban-scale evaluation research, the division of evaluation units is a crucial step. The amount of data increases with the refinement of the unit division. Therefore, to simplify the calculation process, many scholars express the evaluation unit as a community or administrative region (Cimellaro et al. 2019; Zhou et al. 2020). However, urban grid management has high requirements on the accuracy of urban information scale, and the unit division method can no longer meet the current needs. Therefore, this paper presents a process of dividing the evaluation units at the finest granularity: considering a series of indivisible evaluation units according to the distribution of medical demand and medical supply. The schematic of the division is presented in Fig. 2, where $u_i$ is the distribution of medical demand, $v_j$ represents the distribution of medical supply, $u_i v_j$ represent the evaluation unit after segmentation, which corresponds to a unique medical demand and supply.

2.2.2 Substitution capacity of medical resources (SCMR)

The SCMR is the main quantitative indicator for calculating the functionality of a hospital system. It evaluates the amount of medical resources available to the injured within a limited range and ensures that the hospital system meets post-earthquake medical demands in the event of disruption or loss of hospital functionality, also known as medical resource redundancy. Studies on medical resource redundancy have mainly focused on calculating the number of subjects by the cumulative opportunity. However, this paper adds the supply and demand coefficient to analyze the differences among different hospitals, which reflects

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**Fig. 2** Schematic of evaluation unit division
the relationship between medical supply and demand. A functionality attenuation coefficient is introduced to show the objective law of supply capacity. The equation for calculating the SCMR is as follows.

\[ A_{it} = \sum_{j=1}^{n} w_{ij} \cdot \alpha_{ij} \]  

(1)

\[ w_{ij} = 1 - \frac{M_i}{N_j} \]  

(2)

where \( A_{it} \) represents the SCMR of the evaluation unit \( i \) at time \( t \), \( w_{ij} \) and \( \alpha_{ij} \) represents the supply–demand coefficient and functionality attenuation coefficient of hospital \( j \) for the evaluation unit \( i \). \( n \) represents the number of times the evaluation unit is covered by the hospital. \( M_i \) represents the number of injured in the evaluation unit \( i \), \( N_j \) indicates the number of beds available in the evaluation unit, which is the sum of the number of available beds in the nearby hospitals.

2.2.3 Functionality of urban hospital system

In existing studies, the functionality of a hospital system can be assessed in terms of the percentage of healthy population, patient waiting time during a disaster, or the number of reception of patients (Bruneau and Reinhorn 2007; Cimellaro et al. 2010a). Most of studies focus on the hospital system supply capacity and study its seismic performance based on constant demand (Cimellaro and Pique 2016; Khanmohammadi et al. 2018). However, few scholars combined the temporal and spatial characteristics of medical demand with the supply of the hospital system. Therefore, this study considers both medical demand and supply and is characterized by the extent of available medical resources in each evaluation unit to quantify the functionality of urban hospital system. The calculation equation is as follows.

\[ Q(t) = \sum_{i=1}^{m} A_{it} \cdot \beta_i \]  

(3)

where \( Q(t) \) represents the service capacity of the hospital system as a function of time \( t \); \( A_{it} \) is the SCMR of evaluation unit \( i \) at time \( t \); \( \beta_i \) is the rate of the total population in the evaluation unit to the total population, which performs the population share of the evaluation unit; and \( m \) is the number of evaluation units within a hospital system.

2.3 Medical demand metrics

2.3.1 Earthquake injury rate

In earthquake damage research, earthquake casualty prediction models are mainly categorized into two types: empirical evaluation methods based on historical data, casualty rate evaluation methods based on building vulnerability. The advantages of the first method are that input variables are fewer and no detailed data are required. However, owing to the limited availability of historical disaster data in various places, the established models are usually a global or national scale, which are not suitable for urban-scale casualty population.
prediction (Yin 1991; Li et al. 2015). The second method considers the state of building structures in the earthquake, and the calculated result is closer to the actual value (Coburn et al. 1992; So and Spence 2013). However, the second method requires many primary data and a long computation time. Therefore, a semi-empirical method combining empirical and structural analysis is generated to supplement the earthquake prediction suggested by experts, which is more suitable for situations where the primary data are insufficient. Therefore, we choose the semi-empirical method for earthquake damage prediction.

We introduced the seismic vulnerability matrix of the structure based on the empirical model to form the semi-empirical model for this study. The number of earthquakes in China is very large worldwide, and earthquakes cause a lot of casualties and property losses every year. There are sufficient empirical data in Chinese cases and studies to derive formulas for building type damage probability matrices (DPMs) (Yuan et al. 2019). Therefore, we select the casualty prediction model proposed by Ma and Xie (2000) with population density, building collapse rate, earthquake occurrence time, and earthquake intensity as influencing factors. The equation for earthquake casualty prediction is as follows:

\[
\log_{10} RD = 9.0 \cdot RB^{0.1} - 10.07
\]

where \( RD \) is the mortality rate of the population, \( ND \) is an estimate of the number of deaths, \( RB \) is the probability of building collapse (\( RB = \) collapsed building area/total building area), and \( M \) is the total population of the area. \( f_p \) represents the correction factor for population density, and \( f_t \) denotes the correction factor for the time of earthquake occurrence in the region, which only considers day and night.

To address the shortcomings of the above model, this paper improves the population density, earthquake occurrence time and building collapse rate to calculate the injury rate.

\[
\log_{10} RD = 9.0 \cdot RB'^{0.1} - 10.07
\]

\[
RI = 3RD
\]

\[
ND = RD \cdot M'
\]

\[
NI = 3ND
\]

where \( RB' \) denotes the improved earthquake building collapse rate, \( RD \) and \( RI \) are the mortality rate and injury rate of earthquake population, respectively. \( M' \) denotes the total population of the evaluation unit considering the population density correction factor and the time factor, and \( NI \) is the number of injuries in the evaluation unit. In this model, the number of injured is assumed to be three times the number of deaths (Phalkey et al. 2011). The improvements are as follows.

(1) Building collapse rate

In this paper, we take \( 500 \times 500 \text{ m}^2 \) as a grid and calculate the seismic building collapse rate for each grid under an intensity earthquake. The method for gridding the building collapse rate provides more accurate and spatially distributed model results (Yuan et al. 2019). Studies have shown that masonry structures are more likely to collapse in earthquakes
than other structures (Bayraktar et al. 2016). Therefore, this paper adopts conservative results and only considers the collapse of masonry structures. The collapse probability of a masonry structure in an earthquake is determined based on the vulnerability matrix (Sun and Zhang 2011), as shown in Table 1.

(2) Population density and Earthquake occurrence time

The population distribution better characterizes by the population density distribution than the population density correction factor. Thus, we use the population prediction model based on Baidu heat map data (Li et al. 2019; Peng et al. 2021), which used the correspondence between heat map color and population density to calculate the population share to obtain the distribution of urban population density. The Baidu Maps heat map has been widely used for urban population distribution research (Ye et al. 2016; Cao et al. 2019). Based on the data of 200 million Baidu Maps users, it collects population density and population flow information in real-time through regional statistics, and uses visualization technology to display the population aggregation state map with "heat index" (Tan et al. 2016). Meanwhile, the real-time update of the heat map data provides more options for the seismic time of the model and increases the timeliness of the model.

2.3.2 Number of people injured in the earthquake

Equation (10) is a method for calculating the number of people injured in an earthquake, where $N_{I,t,\text{tol}}$ is the number of injured people at time $t$ in the earthquake, $M'_{jt}$ is the number of people in the $j$ evaluation unit at time $t$, and $k$ is the total number of evaluation units.

$$N_{I,t,\text{tol}} = \sum_{j=1}^{k} 3\text{RD} \cdot M'_{jt}$$

(10)

2.4 Medical supply metrics

In this study, medical supply was considered as the number of beds available for injured people in the evaluation unit, expressed in terms of hospital service coverage and number of beds. The number of beds considers the hospital level and how different hospitals are combined.

| Seismic intensity | VI  | VII | VIII | IX  | X   | XI  |
|-------------------|-----|-----|------|-----|-----|-----|
| Almost intact     | 0.00/20 | 28.68/43.47 | 9.52/22.13 | 6.28/9.8 | 9.8/32.18 | 7.25/22.37 |
| Slight damage     | 33.33/0.00 | 32.45/35.26 | 25/25.78 | 7.11/16.25 | 19.61/25.29 | 10.14/22.37 |
| Moderate damage   | 0.00/60 | 25.28/16.26 | 20.83/27.87 | 19.25/29.97 | 13.73/25.29 | 8.7/9.21 |
| Serious damage    | 66.67/20.00 | 11.70/4.56 | 34.52/22.82 | 56.49/35.29 | 31.37/13.79 | 31.88/34.21 |
| Damage            | 0.00 | 1.89/0.46 | 10.12/1.39 | 10.88/8.68 | 25.49/3.45 | 42.03/1.30 |

The left side of the oblique presents the seismic damage matrix of the non-seismic designed masonry structures, and the right side is the seismic damage matrix of seismic designed masonry structures. This paper argues that there is no seismic design for buildings before 1978.
At the same time, considering that the infrastructure service functionality attenuates with the increase of service distance, the functionality attenuation coefficient is proposed to improve the authenticity of the model. In this paper, we first predict the scope of hospital services and then quantify the medical supply metrics corresponding to the evaluation units.

### 2.4.1 Service range and number of beds

Expressing medical supply based on the service range is a criterion for accessibility analysis research (Owen et al. 2010; Verma and Dash 2020). There are two methods to present the medical supply capacity: a circular area with a certain distance as a radius (buffer analysis method) and a polygonal area with a certain topological distance as an endpoint (network analysis method). The first method has a low accuracy rate and cannot accurately reflect the limitation of the road to the service range. In contrast, the second method can better reflect the fundamental laws of human travel. Thus, the second method is selected to determine the topological distance of medical services in each hospital, as shown in Table 2 (Qi et al. 2014; Halder et al. 2020).

The construction of a network dataset for the road capacity is the basis for quantifying medical supply. The network dataset comprises the capacity of roads, such as number of roads, length, travel time, and travel speed. Based on the field investigation in the study area, the average speed of vehicles on the roads was set to 25 km/h, and the walking speed was set to 1.5 m/s, while the road capacity was expressed by the calculated road traffic time for each section. Finally, we used network analysis to quantify medical supply according to Table 2.

### 2.4.2 Functionality attenuation coefficient

The Gaussian function reveals the law of hospital service functionality attenuation with distance (Luo et al. 2018). The Gaussian function $g(t_j)$ is defined as the attenuation coefficient that varies with the rescue time $t$, as shown in Eq. (11). In addition, to reduce the difference in the functionality attenuation coefficient within the same time threshold, this study divides the total service time with a time step of 1 min, as shown in Table 3.

$$
g(t_j) = \begin{cases} 
\frac{e^{-1/2(t_j/t_0)^2} - e^{-1/2}}{1 - e^{-1/2}}, & t \leq t_0 \\
0, & t > t_0
\end{cases}
$$

### 2.5 Functionality loss

Loss of functionality is considered to be an instantaneous change in functionality before and after an earthquake. This functional change can be understood as a loss of functionality

| Table 2  | Medical service distance |
|----------|-------------------------|
| Hospital level | Maximum service distance (time) |
| Community health center | 0.5 km (5-min walk) |
| Primary hospital | 1.5 km (3.6 min drive) |
| Secondary hospital | 2.5 km (6 min drive) |
| Tertiary hospital | 3 km (7.2 min drive) |
that ultimately due to building collapse affecting traffic capacity, thereby reducing medical supply while medical demand remains constant. This paper uses ArcGIS buffer analysis to simulate the impact range of building collapse. According to previous studies on the distribution of post-earthquake debris, it can be found that the impact range of debris distribution after the collapse of various buildings generally does not exceed half of its height. Therefore, this paper takes a conservative value, which is $\frac{2}{3}$ of the building height (Wang et al. 2020). Then, according to the simulation results, the impact of the collapse on road capacity is analyzed. Finally, based on the medical supply quantification method and road impact analysis, a road capacity reduction coefficient $\alpha$ is applied to reduce the traffic speed of roads in the network dataset to decrease the medical supply. The road capacity reduction coefficient is shown in Table 4. Therefore, the calculation of the functionality loss of hospital system is shown in Eq. (12).

$$L = Q(t_0) - Q(t'_0)$$  \hspace{1cm} (12)

where $L$ represents the functionality loss of the hospital system and $Q(t_0)$ and $Q(t'_0)$ represent the functionality of the hospital system before and after an earthquake, respectively.

### 3 Case study

The research object of this paper is a city with a seismic fortification intensity of 7 degrees in eastern China. The case in this paper selects an earthquake with an intensity of 8 as the seismic input to quantify the functionality of the hospital system. The city covers an area of 48.32 square kilometers and has a population of approximately 700,000. As of 2021, the district has ten general hospitals (including four tertiary hospitals, two secondary hospitals, and three primary hospitals) and 18 community health service centers with 9584 beds. There are 352 roads and more than 20,000 buildings, which includes 6053 masonry buildings, as shown in Fig. 3. The above data are all from the local urban construction bureau.
3.1 Spatial distribution of injured populations

Figure 4 presents the distribution of population density at six time points within a working day. It can be observed that there are differences in the distribution of population density at different times. At 2.00 am population distribution is mainly concentrated in the east. From 6.00 to 10.00 am, the population begins to spread continuously, and the distribution status remained until 2.00 pm. At 6.00 pm, the population is most active and widely distributed. At 10.00 pm, the population gradually concentrates eastward, which is the same as the population distribution characteristics at 2.00 am. It can be seen that the characteristics of the population distribution change over time with significant differences.

Figure 5 shows the earthquake population injury rate calculated by the improved semi-empirical model. It can be observed that the earthquake population injury rates in the southwest, central, and northeast regions of this area are relatively high, which is consistent with the density distribution trend of masonry structures in this area.

We can obtain the distribution of medical demand after the earthquake, as shown in Fig. 6. Overall, the southwest, central, and northeast regions have higher density of injured populations. In terms of time, the number of injured people in different time of the earthquake occurrence presents significant differences, as shown in Fig. 7. When an MS 8.0 earthquake occurred in the study area, the highest medical demand was (7522 people) at 10.00 pm and the lowest was (7213 people) at 2.00 pm.

3.2 Spatial distribution of medical services

The hospital service range is used to represent the medical supply. The data in Table 2 are considered as the time cost of ArcGIS network analysis. The medical supply before and after the earthquake is then quantified based on the network dataset, as shown in Fig. 8. The network dataset of some roads after the earthquake is shown in Table 5, and the road capacity reduction coefficient is added. Similarly, according to Table 3, the distribution of the functionality attenuation coefficients of the hospital system before and

Fig. 3 Study area medical system
after the earthquake was predicted by using network analysis of ArcGIS, as shown in Fig. 9. It can be observed that medical resources in this area before the earthquake were sufficient. However, the service range of hospital system will be highly reduced after the earthquake. The higher the level of the hospital, the more serious the damage will be.
3.3 Functionality and loss of functionality of urban hospital system

Figures 10 and 11 present the distribution of SCMR before and after the earthquake. The SCMR distributions are similar when earthquakes occur at different times. From the spatial
dimension, the SCMR in urban centers is generally high, which suggests that before and after the earthquake, the injured in urban centers had more hospital options or access to hospitals with more beds than other areas. However, in the aftermath of the earthquake, it can be observed that the damage of the system has a more significant impact on SCMR. The eastern region has a higher redundancy of medical resources, so SCMR remained high after the earthquake. However, SCMR in all other regions fell by more than 50%.

Table 5  Road capacity reduction coefficient

| Road number | Road grade | Length (m) | Speed (m/min) | Transit time (min) | Reduction coefficient | Reduction of transit time (min) |
|-------------|------------|------------|---------------|--------------------|-----------------------|-------------------------------|
| 1           | Secondary  | 443.61     | 416.67        | 1.06               | 0.25                  | 4.26                          |
| 2           | Branch     | 280.57     | 416.67        | 0.67               | 1.00                  | 0.67                          |
| 3           | Branch     | 342.36     | 416.67        | 0.82               | 0.25                  | 3.28                          |
| 4           | Main       | 158.25     | 416.67        | 0.38               | 1.00                  | 0.38                          |
| 5           | Branch     | 389.12     | 416.67        | 0.93               | 0.25                  | 3.73                          |
| 6           | Branch     | 131.29     | 416.67        | 0.31               | 0.58                  | 0.54                          |
| 7           | Branch     | 103.96     | 416.67        | 0.25               | 0.25                  | 0.99                          |
| 8           | Branch     | 177.34     | 416.67        | 0.42               | 0.25                  | 1.70                          |
| 9           | Secondary  | 209.28     | 416.67        | 0.50               | 0.25                  | 2.01                          |
| 10          | Branch     | 106.42     | 416.67        | 0.25               | 0.58                  | 0.44                          |
| 11          | Branch     | 415.60     | 416.67        | 0.99               | 0.25                  | 3.99                          |
| 12          | Branch     | 223.62     | 416.67        | 0.54               | 0.25                  | 2.15                          |
| 13          | Branch     | 54.64      | 416.67        | 0.13               | 0.25                  | 0.52                          |
| 14          | Branch     | 189.47     | 416.67        | 0.45               | 0.25                  | 1.82                          |
| 15          | Branch     | 168.97     | 416.67        | 0.40               | 0.25                  | 1.62                          |

Fig. 8 The service range of hospital system before and after the earthquake
According to Eq. (3), the functionality of the hospital system after earthquake was calculated for each earthquake occurrence time. The calculation results were presented in Fig. 12. It can be observed that, before the earthquake, the functionality of the hospital system was lower than after the earthquake.
system at different earthquake occurrence times was different, which indicated that changes in medical demand can affect the functionality of the hospital system. At 10:00 am, the hospital had a maximum functionality of 0.8148. At 2:00 am, the hospital has a minimum function of 0.7740.

Figure 13 presents the functionality loss at each earthquake occurrence time. In terms of the spatial dimension, changes in demand had a great influence on the functionality loss of the hospital system. The largest loss of functionality was at 2.00 am (0.5140), followed by 10.00 pm (0.5061) and 6.00 am (0.4989). In contrast, the losses at 2.00 pm (0.4775), 6.00 pm (0.4919), and 10.00 am (0.4948) were relatively low. Overall, the functionality loss after the earthquake is generally high, with an average loss of 49.72%.

### 4 Discussion

In this paper, we propose a method to quantify the functionality of the hospital system by considering the relationship between medical supply and demand and analyzing the impact of supply and demand changes on the hospital system functionality. We found that reducing medical supply may lead to serious loss of hospital system functionality while medical demand remains constant. Taking 2:00 am as an example, we selected the southwest area, where red represented the service range of medical supply, and yellow represented the density of injured population, as shown in Fig. 14. It can be seen that a reduction in medical supply leads to a decrease in the functionality of the hospital system. The above situation is
due to the decline of hospital services, so that fewer casualties can be treated with the same number of beds, and many patients cannot be rescued in time after the earthquake. It can be understood that the decline in medical supply makes the number of beds in the evaluation unit not covered by the hospital service range to 0, resulting in the $A_{it}$ of the evaluation unit being 0, so the hospital system functionality declines. As a result, we can increase post-earthquake emergency medical facilities and beds in areas with severely undersupplied medical supply, such as the central, southwest, and northeast of cities, both before and during the disaster. In addition, it can help administrators implement medical resource allocation programs, thereby increasing the redundancy of medical resources.

As shown in Fig. 12, when medical supply remains constant and medical demand changes, population mobility causes the population density distribution to change and the number of injuries that can be treated in the hospital service area changes, resulting in changes in the supply and demand coefficients and affecting the functionality of the medical system. In this paper, we conducted a global spatial autocorrelation analysis on the hospital demand distribution to analyze the impact of demand aggregation on hospital system functionality. Figure 15 shows the Moran index of medical demand at each time point. After comparison, it was found that the global Moran index was positively correlated with the functionality loss of the hospital system after the earthquake. The higher the Moran index, the greater the functionality loss of the hospital system. As shown in Fig. 16, the Moran indexes had high aggregation of medical demand at 2.00 am and 22.00 pm, with the greatest functionality loss of hospital system. The Moran indexes had a low medical demand aggregation at 10.00 am and 14.00 pm, and the functionality loss of
hospital system were the smallest. Therefore, this paper suggests establishing emergency rescue plans for different earthquake times to improve the accuracy of rescue. For example, the medical rescue emergency plan will change with the earthquake time, and the rescue deployment will be carried out according to dynamic demand, and the emergency medical resources will be reasonably allocated.

5 Conclusion

In this paper, we investigate existing methods for quantifying the functionality of hospital systems. It can be found that these methods aim to evaluate the impact of internal factors on hospital systems without considering the impact of medical demand. The accuracy of such city-scale evaluations must also improve. Therefore, this paper proposes a method to quantify hospital system function by considering the relationship between medical supply and demand. Finally, a case study is conducted with a hospital system in a local area of a city in eastern China as the research object. The results show that imbalance between medical supply and demand and demand aggregation both lead to the loss of hospital system functionality. The stronger the aggregation of medical demand, the more significant the loss of hospital system functionality.

The quantitative method presented in this paper has important timeliness. It can not only quantify the functional loss of the hospital system according to the earthquake time, but also display the service status of the system functionality according to the distribution of the SCMR. It is convenient for hospitals to reserve resources and increase medical facilities before an earthquake. They can also assist emergency management departments to formulate pre-earthquake emergency plans, and provide a basis for post-earthquake emergency rescue decisions. However, there are still some limitations that need to be addressed. Firstly, this paper only considered the influence of medical supply and demand and medical demand on the functionality of the hospital system and did not consider other influencing factors. We will add internal influencing factors of the hospital system in subsequent studies, such as damage to structural components, damage to non-structural components, and functional coupling of departments within the hospital. We will also add external influencing factors, such as emergency management decisions, rescue strategies, and critical infrastructure systems. Secondly, this study proposed a functionality quantification method.
Fig. 15  Moran index of the injured population
for hospital systems, adding several limitations. Such as only considering masonry collapse when calculating building collapse rates and building collapse simulations and did not analyze buildings of other structural types. The building collapse range in this paper did not consider the actual collapse of the structure, which used two-thirds of the height as the building collapse influence distance. We will improve the quantification method in further research to improve the accuracy of the method. Finally, this study only analyzed the functionality quantification method of the hospital system through a hypothetical case and did not validate it with actual earthquake disaster data. We will improve and validate the method in subsequent research.

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Declarations

Conflict of interest The authors declare no conflict of interest.

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