LAF | https://doi.org/10.15302/J-LAF-2026-0009
Volume 14 / Issue 1 / 260009 / 2026
Received Date | 2025-06-03 Accepted Date | 2025-10-30

Equity Assessment of Emergency Shelter Spatial Distribution in High-Density Urban Areas Under Population Aging

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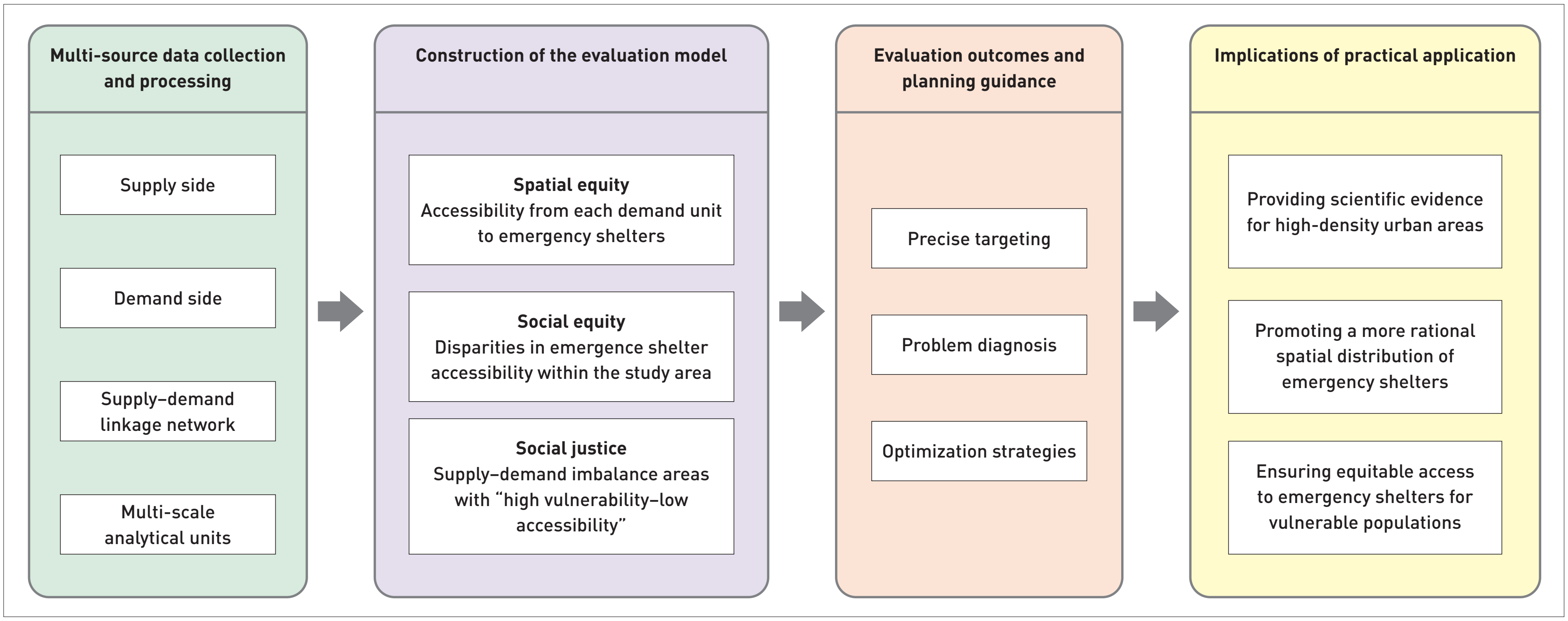
GRAPHICAL ABSTRACT



ABSTRACT

Population aging has increased the need for safety protection among vulnerable groups. In high-density urban areas, mismatches between emergency shelter supply and demand limit equitable access to these services. This study examines three high-density districts in Guangzhou—Yuexiu, Liwan, and Haizhu—to identify areas requiring planning intervention. An evaluation model is proposed that assesses emergency shelter distribution from three perspectives: spatial equity, social equity, and social justice. Combining a multi catchment sizes Gaussian 2SFCA (MC-GA2SFCA) method with the Gini coefficient, Lorenz curves, factor analysis, and bivariate spatial autocorrelation analysis, this study measures emergency shelter accessibility and reveals its spatial relationships with population distribution and social vulnerability. Results indicate that Haizhu and Liwan districts have insufficient emergency shelter coverage, with significant within-district disparities in accessibility. Four supply–demand imbalance areas exhibit high social vulnerability yet with low accessibility. These areas contain large concentrations of older adults and other vulnerable populations but lack adequate shelter coverage and effective sheltering areas. The study further proposes optimization strategies for increasing quantity, improving quality, strengthening governance, and supporting vulnerable groups. This evaluation model provides a basis for planning decisions on urban emergency shelter distribution.

KEYWORDS

Emergency Shelter; Spatial Distribution; Accessibility; Spatial Equity; Social Equity; Social Justice; High-density Urban Area; Social Vulnerability

HIGHLIGHTS

- Examines relationships among emergency shelter distribution, population characteristics, and socio-economic factors
- Develops a fine-grained equity assessment model for emergency shelter spatial distribution
- Uses multi-scale analysis to identify global equity patterns and local inequitable areas
- Provides evidence-based guidance for equitable emergency shelter allocation

RESEARCH FUND

Open Research Fund of the Key Laboratory of Ecology and Energy Saving of Dense Habitat, Ministry of Education (Grant No. 20230106)

1 Introduction

Emergency shelters constitute a critical component of urban public safety systems, and their equitable spatial distribution directly affects disaster response effectiveness and social stability[1]. High-density urban areas exhibit pronounced social vulnerability and spatial constraints due to concentrated populations, significant aging trends, and complex built environments. Limited land resources result in an unbalanced distribution of shelter and inadequate service provision[2]. Traditional disaster prevention planning evaluations focus primarily on facility quantity and spatial coverage, failing to reflect the disparity in service access across social groups[3–4]. Internationally, current planning has shifted from emphasizing spatial accessibility to prioritizing social equity, with particular attention to safeguarding vulnerable populations[5–6]. Population aging has intensified the need for safety protection[7], and high-density urban areas with large concentrations of these populations demonstrate elevated shelter demand but lack corresponding disaster resilience[8]. This situation requires planners to identify socially vulnerable areas and establish demand-oriented resource allocation mechanisms.

However, existing research exhibits three limitations. First, systematic equity evaluation of emergency shelter spatial distribution in high-density urban areas remains insufficient. Although some studies address disaster prevention planning in high-density contexts[9–11], they primarily focus on disaster-prevention spatial design and emergency evacuation simulation. The complexity and urgency of equity in emergency shelter distribution in high-density areas, given their distinct population structures, spatial forms, and resource constraints, necessitate targeted research.

Second, evaluation dimensions remain narrow. Social vulnerability significantly influences shelter demand in aging contexts, yet few studies systematically incorporate social vulnerability indicators into equity evaluation frameworks. Existing research primarily assesses shelter service capacity from the supply side, focusing on service coverage and accessibility[12–15], with limited attention to whether resources are directed toward socially vulnerable areas.

Third, evaluation methods lack precision. Current accessibility measurements typically employ single service radius settings, failing to account for differences in service capacity across emergency shelter levels[16–17]. Additionally, evaluations predominantly use administrative units such as townships or communities[18–19], which cannot reveal internal variations. Advances in multi-source data and GIS technology enable fine-grained grid-based evaluation[20], yet their application to the equity analysis of emergency shelters remains limited.

From a landscape architecture perspective, emergency shelters are typically located in public spaces like parks and plazas, making equitable distribution relevant to social justice in accessing urban public space services. To address these research gaps, this study integrates theories and methods from urban planning, transport geography, and disaster prevention to examine relationships among emergency shelter distribution, population characteristics, and socio-economic factors. The evaluation model proposed in this study provides a reference for scientific planning of emergency shelter distribution.

2 Literature Review

2.1 Paradigm Shift in Disaster Prevention Planning and International Experience

Disaster prevention planning has transitioned from traditional physical defense approaches toward social equity-oriented frameworks. Early planning focused primarily on engineering measures and physical protection capacity, employing technical means to reduce disaster risk. However, disasters such as Hurricane Katrina in 2005 revealed the limitations of relying solely on physical defenses[21]. Research has demonstrated that social inequities result in significantly different disaster impacts on social groups within the same area[22–23].

This conceptual shift is reflected in disaster prevention planning practices internationally. Japan's disaster prevention planning has evolved from facility-centered to community-centered approaches, expanding from disaster prevention park construction to comprehensive disaster-prevention living zones and welfare-oriented shelters, while establishing a multi-stakeholder disaster prevention model involving government, communities, and individuals[24–25]. In the USA, the 2022–2026 FEMA Strategic Plan① explicitly identifies "equity" as one of three core objectives, emphasizing that emergency management must prioritize vulnerable populations[26]. These international experiences indicate that emergency shelter planning should address not only physical accessibility but also priority protection for specific areas and populations. China's disaster prevention planning exhibits distinct characteristics in spatial form, social institutions, and data conditions (e.g., type, availability) due to its unique social spatial patterns derived primarily from strong institutional and policy interventions (including spatial concentration of specific groups, urban–rural dualism, household registration systems, and residential segregation), which influence urban–rural development, population mobility, and resource allocation in ways that are relatively uncommon globally[27]. This necessitates developing evaluation frameworks suited to China's specific context.

2.2 Development of Social Vulnerability Theory and Its Application in Equity Assessment

Social vulnerability research provides an important theoretical framework for understanding social differences in disaster impacts. In 1976, geographer Phil O'Keefe introduced the concept of "social vulnerability," arguing that socioeconomic conditions constitute key determinants of natural disaster losses[28]. American geographer Susan L. Cutter's hazards-of-place model revealed the critical role of socioeconomic factors in disaster response. The Social Vulnerability Index (*SoVI*) developed from this model provides a scientific basis for identifying socially vulnerable areas susceptible to disasters[22] and has been widely adopted in planning practice. The USA's Centers for Disease Control and Prevention (CDC) developed the *SoVI* map using 16 census variables to create a scientific framework for identifying vulnerable communities[29]. Chinese scholars have identified key factors affecting social vulnerability—including demographic characteristics, household structure, education background, housing, and related public facilities—and developed localized assessment frameworks adapted to China's context[30–32].

Social vulnerability is intrinsically linked to equity assessment. Under human-centered and sustainable development principles, scholars have recognized that public service facility planning should aim not merely for geographic equity but for distributional equity among different social groups[33]. Public service facility distribution is shifting from "place-based indicator allocation" toward "user-oriented supply–demand balance," emphasizing demand differences resulting from social spatial differentiation[34]. Therefore, evaluating the spatial distribution equity of emergency shelters requires not only analyzing facility–population spatial matching but also identifying whether high-vulnerability areas receive corresponding service provision. Social vulnerability provides a scientific basis for identifying socially disadvantaged areas and promoting refined urban governance. However, most existing research focuses on analyzing spatial patterns of social vulnerability, with limited integration of social vulnerability into emergency shelter equity evaluation. This gap hinders precise identification of "high vulnerability–low accessibility" areas in planning practice, constraining the development of differentiated resource allocation strategies.

3 Research Method

3.1 Study Area

This study examined three districts in Guangzhou—Yuexiu, Liwan, and Haizhu—encompassing 58 subdistrict-level census units. These three districts were selected based on three representative characteristics.

1) They exhibit high-density characteristics. According to the Seventh National Population Census of China (SNPCC), the study area has 4.09 million residents (22% of the city's total population)

① FEMA stands for the Federal Emergency Management Agency of the USA.

across 183.3 km^2 (2.4% of the city's total area).

2) They demonstrate significant population aging. While the population aged 60 and above in Guangzhou accounts for 11.4%, the selected districts show substantially higher proportions: 19.81% in Liwan, 22.25% in Yuexiu, and 17.06% in Haizhu[35].

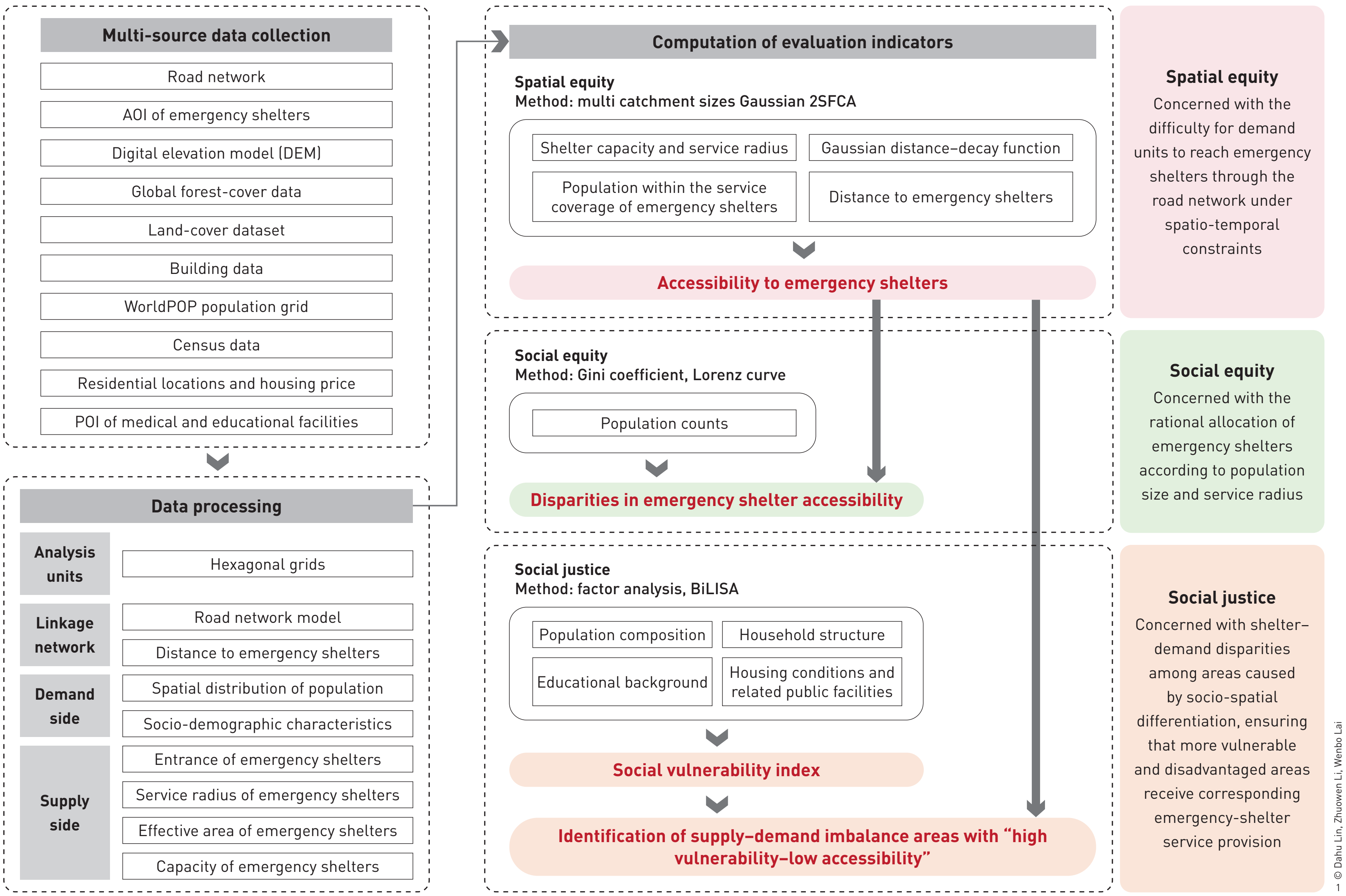
3) They face urgent needs for improved emergency shelter distribution. These districts have experienced frequent disasters, and the per capita emergency shelter area in Haizhu and Liwan districts (less than 2 m^2 per person) falls below the standard in the urban health assessment indicator system established by the Ministry of Housing and Urban–Rural Development[36].

The supply–demand imbalance of emergency shelters represents a common challenge for high-density urban areas experiencing population aging. Therefore, this empirical study of Guangzhou's high-density districts can provide practical guidance for improving the equitable distribution of emergency shelters.

3.2 Analytical Framework

This study employed a three-stage analytical framework: data collection and processing, evaluation model construction, and empirical analysis. First, multi-source data were collected to establish a fine-grained spatial database. Second, an evaluation model was developed based on three dimensions—spatial equity, social equity, and social justice—integrating factors, indicators, and methods relevant to emergency shelter distribution equity (Fig. 1). Finally, inequity areas were identified and their underlying

Fig. 1 Equity evaluation model for the spatial distribution of emergency shelters.



causes analyzed.

Referring to existing research[37–39], the spatial equity dimension applied the multi catchment sizes Gaussian two-step floating catchment area (MC-GA2SFCA) method[40] to measure emergency shelter accessibility at the subdistrict-unit level. The social equity dimension emphasized the equal access to basic public services for all residents, with resource allocation based on population size[4,41]. Gini coefficients and Lorenz curves were employed to measure within-area accessibility disparities. The social justice dimension emphasized the preferential allocation of public services to socially vulnerable groups[20,34,42]. Factor analysis was used to measure social vulnerability, and bivariate Local Indicator of Spatial Association (BiLISA) analysis identified supply–demand imbalance areas characterized by high vulnerability and low accessibility.

These three dimensions formed a progressive relationship. Spatial equity addressed whether emergency shelters can be reached, social equity addressed whether distribution matches population, and social justice addressed whether resources favor vulnerable populations. This multi-dimensional approach overcame the limitations of single-dimensional evaluation and provides more precise guidance for policy development.

3.3 Data Collection and Processing

In this study, multi-source data were collected to provide reliable support for evaluating the equity of emergency shelter distribution (Table 1). Official emergency shelter directories, high-precision open data (i.e., WorldPOP, ALOS-DEM, SinoLC-1, JRC Global Forest Cover), and web mapping services (i.e., Baidu Maps, Amap) were integrated to calculate effective shelter area, capacity, and accessibility. Additionally, residential population data from the SNPCC, residential area and housing price data from Anjuke, and points of interest (POI) were collected for social vulnerability analysis.

Transportation networks, population distribution, and facility service capacity are critical factors that affect accessibility measurement and equity evaluation[14]. Therefore, data processing was conducted systematically across four aspects: analysis unit, linkage network, demand-side, and supply-side.

First, the study area was divided into 3,495 regular hexagonal grids (side length of each grid is 125 m, area of each grid is 4 hm^2). Grid-based division provides higher spatial resolution and better reveals spatial variation of indicator scores within census areas[20]. Second, road centerlines were extracted using Feature Manipulation Engine (FME) tools to create a road network model for calculating walking distances from analysis units to emergency shelters. Third, on the demand side, WorldPOP data provide high-precision residential population distribution. The data used in this study were adjusted based on the SNPCC, following established methods[43]. Fourth, on the supply side, emergency shelter service capacity—determined by effective shelter area, per capita effective area, and service radius—is critical for measuring accessibility. Shelter classification and requirements (Table 2) were determined according to Guangzhou's local standard *Design Specification for Emergency Shelter* (DB4401/T 158-2022), national standard *Code for Design of Disasters Mitigation Emergency Congregate Shelter* (GB 51143-2015), and relevant literature[18]. Specifically, based on regulatory definitions of effective shelter area, unsuitable areas—including forests, water bodies, steep slopes, and building collapse zones—were identified through land cover, elevation, and building data.

Table 1: Data sources for the evaluation of spatial distribution equity of emergency shelters

Data	Source	Year
Emergency shelter	Guangzhou Emergency Management Bureau, Baidu Maps AOI	2023
Medical facility	Amap	2023
Educational facility	Amap	2023
Road network	Amap	2023
Population count	WorldPOP	2020
Residential population	*Guangzhou Population Census Yearbook 2020*	2020
Land cover data (SinoLC-1)	National Tibetan Plateau Data Center (TPDC)	2023
Global forest cover	JRC, European Commission	2020
Building	Baidu Map	2020
Residential area and housing price	Anjuke	2023
DEM	Advanced Land Observing Satellite (ALOS)	—

Table 2: Classification and requirements for emergency shelters

Type	Effective shelter area	Per capita effective area	Service radius
Long-term emergency shelter	≥ 5.0 hm^2	4.5 m^2/person	3,000 m
Mid-term emergency shelter	≥ 1.0 hm^2	3.0 m^2/person	1,500 m
Short-term emergency shelter	≥ 0.2 hm^2	2.0 m^2/person	1,000 m
Temporary emergency shelter	≥ 0.2 hm^2	1.0 m^2/person	500 m

3.4 Evaluation Methods

3.4.1 Spatial Equity Dimension

Emergency shelter accessibility serves as the analytical indicator for the spatial equity dimension, measured using the MC-GA2SFCA, involving two steps.

The first step calculates the supply–demand ratio for each emergency shelter. Based on catchment areas (i.e., the service range in this study) formed by population grids within the shelter service radius, a Gaussian distance–decay function weights population quantities in all grids within the radius. Weighted population quantities are then summed to obtain potential shelter demand for each shelter site. This demand is combined with shelter capacity to calculate the supply–demand ratio:

$$R_j^i = \frac{C_j^i}{\sum_{k\in\left\{d_{kj}^i \le r_0^i\right\}} G\left(d_{kj}^i, d_0^i\right) P_k} \; ; \; d_0^i = \begin{cases} \le 500 \ \text{ m, if } i = \text{Temporary} \\ \le 1000 \text{ m, if } i = \text{Short-term} \\ \le 1500 \text{ m, if } i = \text{Mid-term} \\ \le 3000 \text{ m, if } i = \text{Long-term} \end{cases} , \quad (1)$$

where R_j^i represents the supply–demand ratio of shelter j of type i; C_j^i represents the capacity of shelter j of type i; P_k represents the population of grid k within the service coverage of shelter j of type i; d_{kj}^i represents the distance cost from the center of grid k to the entrance of shelter j of type i; and d_0^i represents the service radius of type i shelter. $G(d_{kj}^i, d_0^i)$ represents the Gaussian distance–decay function:

$$G\left(d_{kj}^i, d_0^i\right) = \begin{cases} \dfrac{e^{-\left(\frac{1}{2}\right)\times\left(\frac{d_{kj}^i}{d_0^i}\right)^2} - e^{-\left(\frac{1}{2}\right)}}{1 - e^{-\left(\frac{1}{2}\right)}}, & \text{if } d_{kj}^i \le d_0^i \\ 0, & \text{if } d_{kj}^i > d_0^i \end{cases} . \quad (2)$$

The second step calculates the accessibility for each demand unit. Based on catchment areas formed by shelters accessible within the search threshold from each grid, the Gaussian distance–decay function weights shelter supply–demand ratios. Weighted ratios are summed to obtain the accessibility for each demand unit:

$$A_k = \sum A_k^i ; \; A_k^i = \sum_{j\in\left\{d_{kj}^i \le d_0^i\right\}} G\left(d_{kj}^i, d_0^i\right) R_j^i , \quad (3)$$

where A_k represents the accessibility of grid k; A_k^i represents the accessibility of grid k to type i shelter; R_j^i represents the supply–demand ratio of shelter j of type i; and $G(d_{kj}^i, d_0^i)$ represents the Gaussian distance–decay function.

Finally, ArcGIS was employed for visualization and hot spot analysis of the spatial distribution of accessibility scores. By calculating the population size in areas lacking shelter service coverage, the population coverage gap can be determined.

3.4.2 Social Equity Dimension

Disparities in accessibility among residents within the study area serve as the analytical indicator for the social equity dimension, measured using the Gini coefficient which ranges from 0 to 1, with higher values indicating greater inequality. The formula is:

$$G^m = 1 - \sum_i (P_k - P_{k-1})(A_k + A_{k-1}), \quad (4)$$

where G^m represents the Gini coefficient, P_k represents the cumulative percentage of population in demand units, and A_k represents the cumulative percentage of accessibility shared by demand units.

3.4.3 Social Justice Dimension

The spatial correlation between *SoVI* and emergency shelter accessibility serves as the analytical indicator for the social justice dimension. BiLISA analysis reveals the spatial distribution patterns of these two variables. The analytical process comprises four steps.

Step 1: indicator selection. Referring to relevant research adapted to China's context[32], social vulnerability variables were selected across four aspects: demographic characteristics, household structure, educational background, and housing and related public facilities (Table 3).

Step 2: indicator standardization and transformation. Prior to factor analysis, all indicators were standardized. social vulnerability increases as the value of positive indicator (+) increases, which decreases as the value of negative indicator (−) decreases. The standardization formulas are:

Table 3: Indicators for social vulnerability measurement

Variable	Explanation	Directionality
Demographic characteristics		
Elderly proportion	Population aged ≥ 60 (%)	+
Children proportion	Population aged ≤ 14 (%)	+
Female proportion	Female population (%)	+
Population density	Population per unit area (persons/km^2)	+
Household structure		
Elderly household	Households with members aged ≥ 60 (%)	+
Empty-nest household	Households with elderly aged ≥ 60 without children (%)	+
Dependency ratio	Non-working age to working age population ratio (%)	+
Average household size	Average persons per household	+
Educational background		
Low education	Population with middle school education or below (%)	+
Higher education	Population with college degree or above (%)	–
Illiteracy rate	Illiterate population (%)	+
Housing and related public facilities		
Crowded household	Households with living area < 16 m^2 (%)	+
Per capita housing area	Average residential area per person (m^2/person)	–
Average household area	Average residential area per household (m^2/household)	–
Housing price	Average housing price (yuan/m^2)	–
Medical facility coverage	Population served by medical facilities at the township level (%)	–
Educational facility coverage	Population served by educational facilities at the township level (%)	–

$$\text{Positive indicators: } s_{ij} = \frac{X_{ij} - X_{\min}}{X_{\max} - X_{\min}}, \tag{5}$$

$$\text{Negative indicators: } s_{ij} = \frac{X_{\max} - X_{ij}}{X_{\max} - X_{\min}}. \tag{6}$$

Step 3: social vulnerability index calculation. Factor analysis was performed on the standardized data matrix using IBM SPSS Statistics 26.0 to extract principal factors. Factor analysis is widely used for social vulnerability assessment, as it condenses information-rich original variables into fewer factors with minimal information loss while maintaining strong interpretability. A weighted sum method using each factor's variance contribution rate as the weight was employed to calculate the social vulnerability score:

$$SoVI = \sum_{i=1}^{n} w_i \times F_i, \tag{7}$$

where *SoVI* represents the social vulnerability score, w_i represents the variance contribution rate of factor *i* (factor weight), and F_i represents the score of factor *i*.

Step 4: spatial statistical analysis. Hot spot analysis (Getis-Ord Gi*) was performed using ArcGIS to display the spatial distribution characteristics of *SoVI* scores. Hot spot analysis is a commonly used spatial cluster analysis method that identifies statistically significant spatial clusters of high values (hot spots) and low values (cold spots) by comparing the mean score of each geographic unit and its neighbors with mean score of the overall study area:

$$G_i^* = \frac{\sum_j W_{ij} \times X_j}{\sum_j X_j}, \tag{8}$$

where X_j represents the social vulnerability score of grid *j*, and W_{ij} represents the spatial weight between grids *i* and *j*.

Finally, BiLISA analysis was conducted using GeoDa software to calculate Moran's *I* and measure the BiLISA indicators between social vulnerability and emergency shelter accessibility, thereby identifying supply–demand imbalance areas characterized by "high vulnerability–low accessibility":

$$I_{S,A} = \frac{\sum_i \left(\sum_i W_{ij} Z_j^A \times Z_i^S \right)}{\sum_i \left(Z_i^S \right)^2}, \tag{9}$$

$$I'_{S,A} = Z_i^S \sum_j W_{ij} Z_j^A, \tag{10}$$

where $I_{S,A}$ represents the global Moran's *I*, $I'_{S,A}$ represents the local Moran's *I*, W_{ij} represents the spatial weight between grids *i* and *j*, Z_i^S

represents the standardized value of variable S (social vulnerability) for grid i, and Z_j^A represents the standardized value of variable AI (emergency shelter accessibility) for grid j.

4 Research Results

4.1 Spatial Equity Dimension

4.1.1 Spatial Distribution Characteristics of Emergency Shelters

Based on the emergency shelter directory provided by the Guangzhou Emergency Management Bureau and AOI data, 74 emergency shelters with effective area exceeding 2,000 m^2 were identified, including urban parks, plazas, and schools (Table 4, Fig. 2). In the figure, District A stands for Yuexiu, District B stands for Liwan, and District C stands for Haizhu. The spatial distribution exhibits pronounced imbalance: Yuexiu District contains the most shelters (N = 28), concentrated primarily in the old city center; Liwan District has 34 shelters with relatively dispersed distribution, while Haizhu District has the fewest (N = 12).

Table 4: Emergency shelter classification within the study area

Type	Quantity	Effective shelter area
Long-term emergency shelter	11	122.8 hm^2
Mid-term emergency shelter	24	58.4 hm^2
Short-term emergency shelter	22	10.4 hm^2
Temporary emergency shelter	17	7.4 hm^2
Total	74	199 hm^2

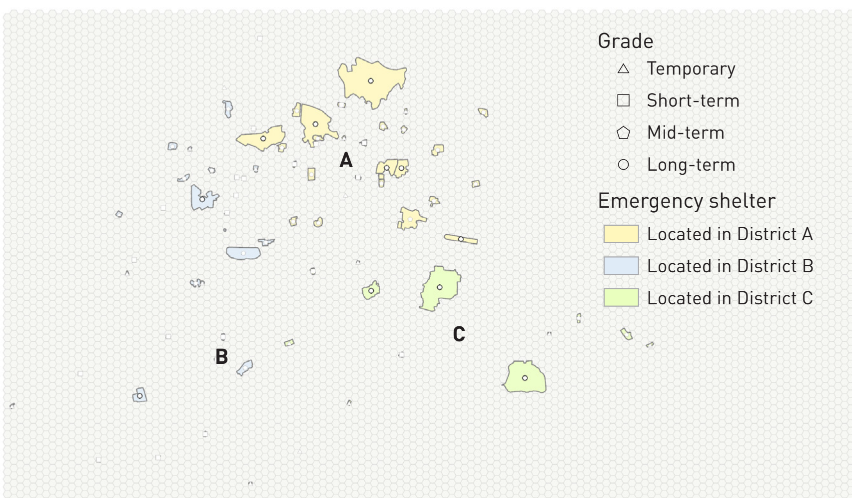


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Fig. 2 Spatial distribution of emergency shelters.

4.1.2 Emergency Shelter Accessibility

Accessibility scores for each grid were calculated using the MC-GA2SFCA method. High-accessibility clusters are concentrated primarily in the northern Yuexiu District and the southern Liwan District, where large-scale, long-term emergency shelters such as Luhu Park, Yuexiu Park, and Liuhuahu Park provide relatively high service levels. Low-accessibility clusters are concentrated in the western, southern, and eastern Haizhu District, and in the eastern and western Liwan District. These areas experience supply–demand imbalances due to small shelter sizes and large populations within service coverage areas (Fig. 3).

Analysis of population distribution across districts reveals significant coverage gaps. Both Haizhu and Liwan districts exhibit substantial population coverage deficits (Fig. 4). The former shows the largest gap, with 440,000 residents (24% of the district population) lacking access, while 180,000 residents (14% of the district population) for the latter. These gap areas, located in the periphery of the old city center, contain high concentrations of old factories and villages, characterized by dense population and limited construction land.

4.2 Social Equity Dimension

4.2.1 Gini Coefficient

The overall Gini coefficient of 0.67 indicates severe social inequity in the spatial distribution of emergency shelters (Fig. 5). A total of 21 subdistricts exhibit Gini coefficients exceeding 0.5, classified as “highly disparate,” primarily distributed in Liwan and Haizhu districts (Table 5). In contrast, Yuexiu District (Gini = 0.49) demonstrates relatively balanced accessibility among residents.

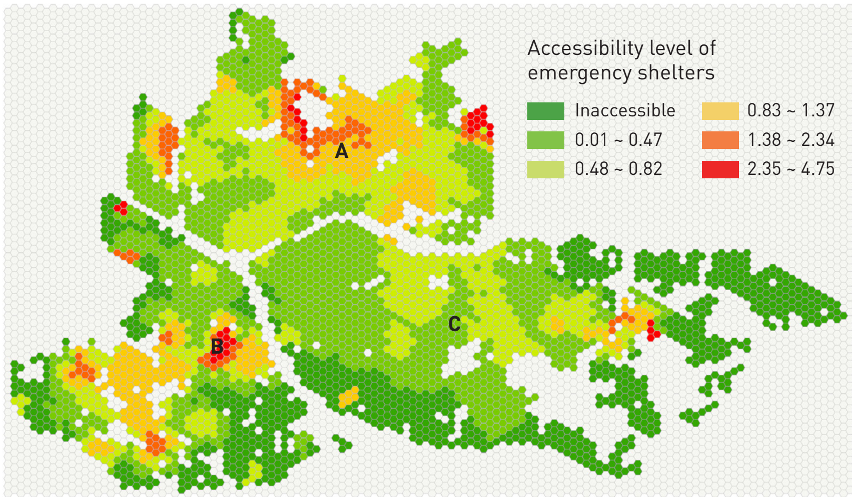
4.2.2 Lorenz Curve

The Lorenz curve further illustrates the specific manifestations of distributional inequity (Fig. 5). In Liwan and Haizhu districts, 80% of the population enjoys only approximately 25% and 30% of the area’s accessibility, respectively, indicating that a small proportion of residents have substantially higher accessibility.

4.3 Social Justice Dimension Evaluation Results

4.3.1 Social Vulnerability

Factor analysis was conducted to reduce the dimensionality of highly correlated variables and calculate social vulnerability (Table 6). The KMO value of 0.763 and significant Bartlett’s test of



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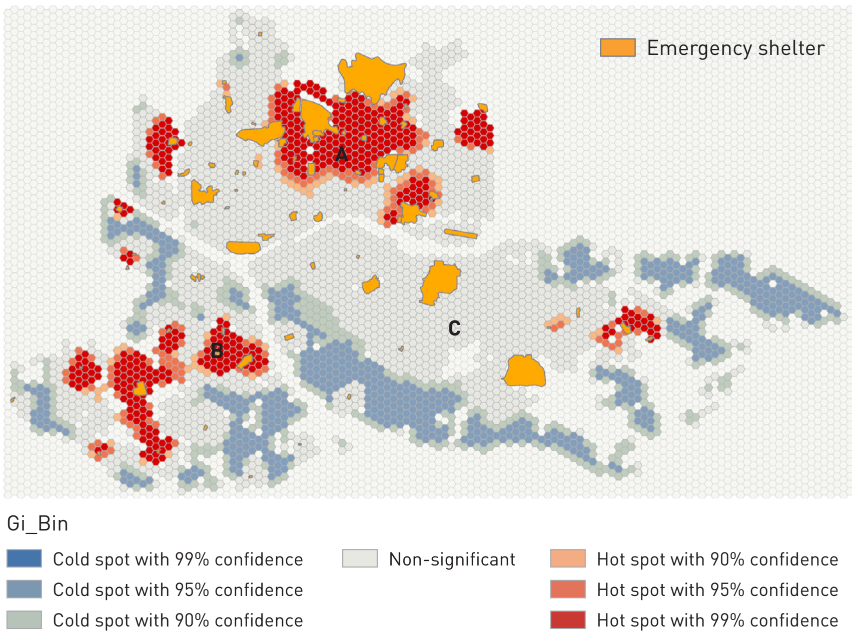

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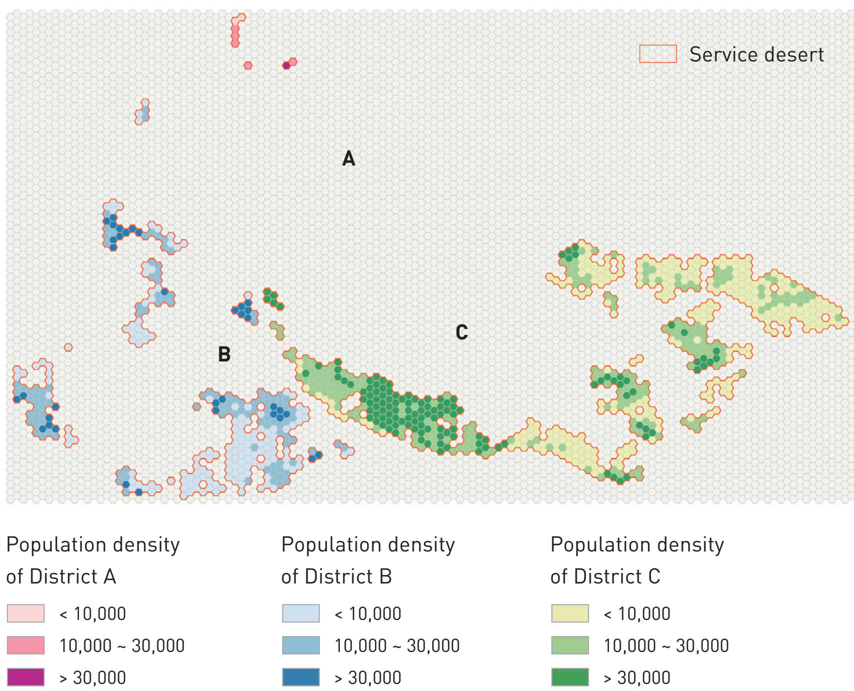

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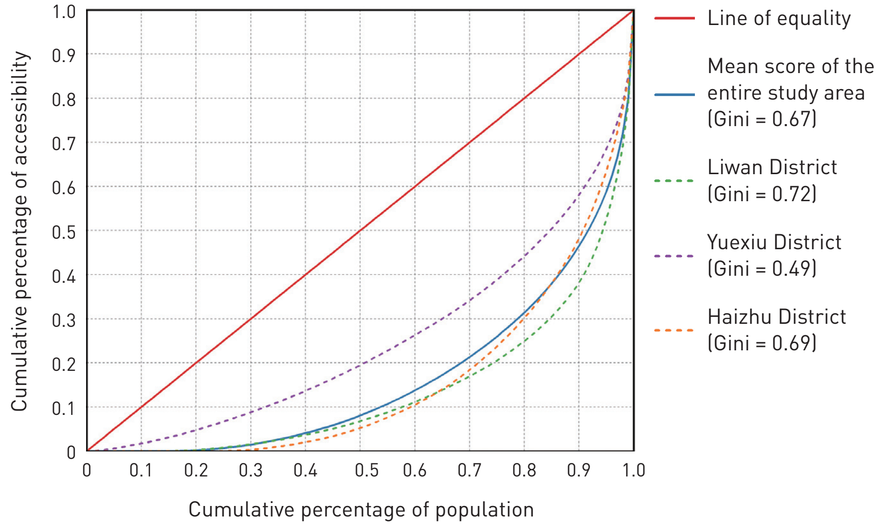

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Fig. 3 Spatial distribution and clustering of accessibility to emergency shelters.
Fig. 4 Areas lacking emergency shelter service.
Fig. 5 Lorenz curves.

Table 5: Gini coefficient classification and distribution

Gini coefficient	Classification	Number of subdistrict	Distribution
< 0.2	Highly equal	4 (7%)	· Liwan District: Shamian, Lingnan, and Hualin · Yuexiu District: Nonglin Neighborhood
0.2 ~ 0.3	Relatively equal	16 (28%)	Northeastern Liwan District and most subdistricts of Yuexiu District
0.3 ~ 0.4	Relatively reasonable	9 (15%)	Most subdistricts of Yuexiu District
0.4 ~ 0.5	Relatively disparate	8 (14%)	Northern Haizhu District
> 0.5	Highly disparate	21 (36%)	Most subdistricts in Liwan and Haizhu districts

NOTE
Percentages represent the proportion of total subdistricts in the study area.

sphericity indicate that the selected variables are suitable for factor analysis. Four factors extracted from 16 variables with loadings greater than 0.5 account for 87.170% of the total variance.

Hot spot analysis reveals the spatial distribution of high-value (red) and low-value (blue) social vulnerability clusters

Table 6: Factors of social vulnerability

Component	Variance (%)	Cumulative (%)	Variable	Loading	Component score coefficient
Factor 1: aging and household structure	35.961	35.961	Empty-nest households	0.945	0.214
			Elderly proportion	0.960	0.212
			Elderly households	0.960	0.208
			Dependency ratio	0.895	0.175
			Population density	0.645	0.140
			Average household size	0.739	0.137
			Female proportion	0.748	0.109
Factor 2: housing conditions and education	28.100	64.061	Per capita housing area*	0.945	0.292
			Crowded households	0.923	0.277
			Average household area*	0.926	0.239
			Higher education level*	0.756	0.136
			Lower education level	0.684	0.108
Factor 3: public service accessibility	11.706	75.766	Medical facility coverage*	0.880	0.583
			Educational facility coverage*	0.866	0.571
Factor 4: literacy and economic development	11.403	87.170	Illiteracy rate	0.922	0.601
			Housing price*	0.635	0.330

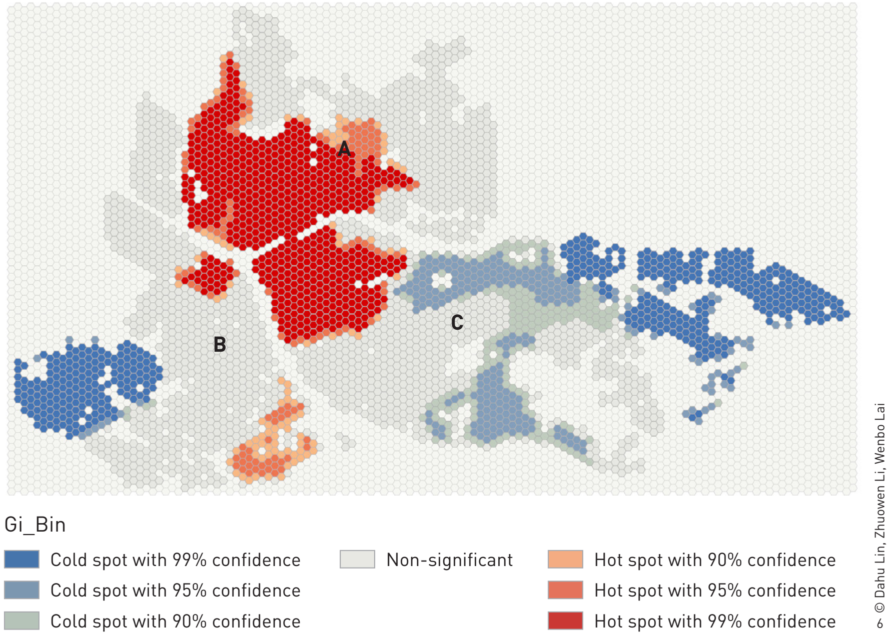
NOTES

1. Rotation method: Varimax with Kaiser normalization; rotation converged in 5 iterations.
2. Extraction method: principal component analysis; * indicates variables with negative influence directionality that were transformed to positive directionality.

(Fig. 6). Social vulnerability exhibits a "high center, low periphery" pattern, with high-vulnerability clusters concentrated primarily at the intersection of Yuexiu, Liwan, and Haizhu districts. Notably, given the study area's spatial structure, most high-vulnerability clusters are located in the old city center, where scientific planning and spatial quality improvements for emergency shelters are particularly needed.

4.3.2 Supply–Demand Imbalance Areas With "High Vulnerability–Low Accessibility"

Using *SoVI* as the first variable and emergency shelter accessibility (AI) as the second variable, four spatial clustering patterns were identified and color-coded (Fig. 7), including Taigucang Wharf–Nanshitou cluster (Area 1), Huatai–Tuhua–Xiaozhou Community cluster (Area 2), Wuyanqiao–Huadi River–Huadi Bay–Julong Bay cluster (Area 3), and Dongsha cluster (Area 4). Red grids represent areas exhibiting high social vulnerability but inadequate emergency shelter accessibility, classified as the supply–demand imbalance areas. Yuexiu District demonstrates a relative supply–demand balance, with high social vulnerability units enjoying correspondingly high accessibility. In contrast, Haizhu and Liwan districts exhibit pronounced inequity,



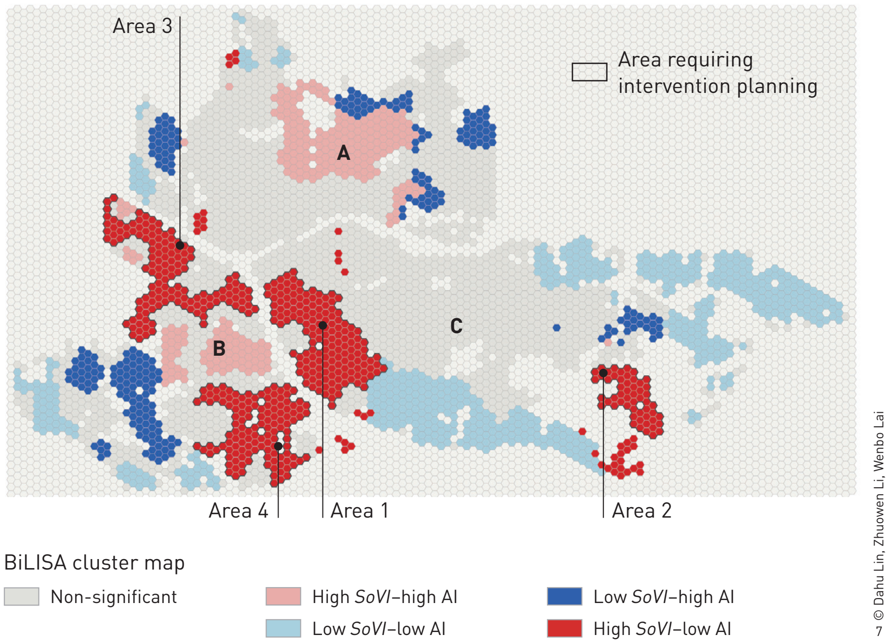


Fig. 6 Spatial clusters of social vulnerability scores.
Fig. 7 BiLISA between social vulnerability and emergency shelter accessibility.

with four large-scale supply–demand imbalance areas identified (Table 7, Fig. 7).

5 Discussion

Following a progressive research logic of problem identification–strategic response–methodological reflection, this study analyzed the overall spatial distribution patterns of emergency shelters

Table 7: Causes of inequity in several examples of supply–demand imbalance areas

Area No.	Causes of high social vulnerability	Causes of low accessibility
1	Aging population; high population density	Insufficient effective shelter area
2	High proportion of lower-educated groups and crowded households; low coverage of educational and medical facilities	Lack of emergency shelters
3	Aging population; high proportion of lower-educated groups and crowded households; low housing prices; high illiteracy rate; high population density	Insufficient effective shelter area
4	High proportion of lower-educated groups and crowded households; low coverage of educational and medical facilities; low housing prices; high illiteracy rate	Lack of emergency shelters

in high-density urban areas, and identified and examined typical characteristics and formation mechanisms of inequitable areas, with particular attention to challenges posed by population aging. In the following chapters, targeted optimization strategies are proposed and methodological limitations are reflected upon to guide future research.

5.1 Spatial Distribution Patterns of Emergency Shelters in High-Density Urban Areas

The case study reveals a pronounced "core–periphery" differentiation pattern in emergency shelter distribution. The old city center, despite high population density and significant aging, maintains adequate shelter numbers and high accessibility due to well-established public facilities such as parks and schools, resulting in a relatively equitable distribution. However, peripheral areas beyond the old city center face uneven distribution, insufficient numbers, and inadequate scale of emergency shelters, leading to pronounced supply–demand imbalances. This differentiation pattern reflects the profound impact of unbalanced regional development on the equitable spatial distribution of emergency shelters.

5.2 Typical Characteristics of Inequitable Areas

Based on the Guangzhou Urban Renewal Plan (2021–2035) and field surveys, these inequitable areas exhibit typical spatial characteristics of high concentrations of old factories and urban villages. The underlying causes operate at three levels.

5.2.1 Historical Development Factors

During rapid urbanization, these areas remained at the urban periphery. Guangzhou's urban construction has been intensified in Yuexiu and Tianhe districts, while western Liwan and southern Haizhu developed more slowly. Lacking comprehensive and systematic planning guidance, public service facility construction lagged significantly behind population growth. For example, Huazhou and Guanzhou subdistricts in southern Haizhu District were predominantly agricultural during early urbanization with low public service standards, while Dongsha and Shiweitan subdistricts in Liwan District were traditional industrial areas with high industrial land use but insufficient supporting facilities.

5.2.2 Planning Constraints

The complexity of land ownership and planning control requirements in the region impose dual constraints. On the one hand, old village areas contain substantial collectively-owned construction land involving multiple property rights holders, making unified planning difficult and renovation costly, particularly given the numerous urban villages in the study area. On the other hand, some areas have cultural heritage protection requirements. For instance, Liwan's Julongwan area preserves typical Lingnan settlement characteristics, while Haizhu's Xiaozhou Village retains historical "oyster-shell houses," requiring a balance between heritage protection and disaster prevention needs and constraining emergency shelter construction.

5.2.3 Socioeconomic Characteristics

These areas provide low-cost residential spaces, forming distinctive population concentration patterns. Relatively low rents and living costs attract large numbers of migrant workers, low-income groups, and migrant populations. Simultaneously, low coverage of educational and medical facilities creates severe mismatches between public service provision and population size. These overlapping factors produce spatial mismatches characterized by high population density and strong social vulnerability but inadequate public service provision.

5.3 Special Challenges Under Population Aging

Population aging imposes higher requirements on emergency shelter planning. Elderly populations face difficulties during emergency evacuations due to declining physical function, including slower mobility and shorter evacuation distances, requiring stricter accessibility standards. However, the results indicate that some areas with high levels of aging do not have correspondingly higher emergency shelter accessibility. This phenomenon reveals the limitations of traditional planning methods: resource allocation approaches that rely on per capita indicators and service coverage rates cannot address differentiated needs across social groups or meet the precise regulatory and demand-based allocation requirements in the new urbanization era. By recognizing these mismatches, this study provides a new technical pathway for precisely identifying priority planning areas under population aging.

5.4 Recommendations of Optimization Strategies

Based on evaluation results combined with field surveys and case experience, this study proposes phased equity optimization strategies for short-, medium-, and long-term priorities, including increasing quantity, improving quality, strengthening governance, and supporting vulnerable groups. These strategies particularly address special needs under population aging, aiming to provide safer, more accessible shelter services for the elderly and other vulnerable populations.

1) Short-term priority should be given to increasing quantity through systematic suitability assessment of the renovation potential of public spaces such as schools, parks, and plazas. The site selection model can be constructed using optimization algorithms, such as ant colony and particle swarm optimization, to determine optimal layouts scientifically. Subsequently, emergency shelters at the selected locations can be upgraded through urban regeneration projects to meet the corresponding requirements[18]. Site selection should prioritize areas with severe aging, ensuring the service radius of new shelters cover high social vulnerability areas and reduce evacuation distances for elderly populations.

2) Medium-term emphasis should advance quality improvement and governance strategies, systematically enhancing built environment resilience through renovation projects of rundown towns, disused factories, and old villages, and improving emergency signage systems. Special attention should be given to elderly visual perception needs by optimizing the font size, color contrast, and information clarity of the shelter signage system, and by adding clear directional guidance at key evacuation route nodes. Simultaneously, disaster prevention living circles and the "self-help + mutual-assistance + public-support " disaster prevention model should be established using schools as basic units[24] (Fig. 8), emphasizing subdistrict mutual assistance network construction and establishing "one-to-one" or "many-to-one" elderly evacuation assistance

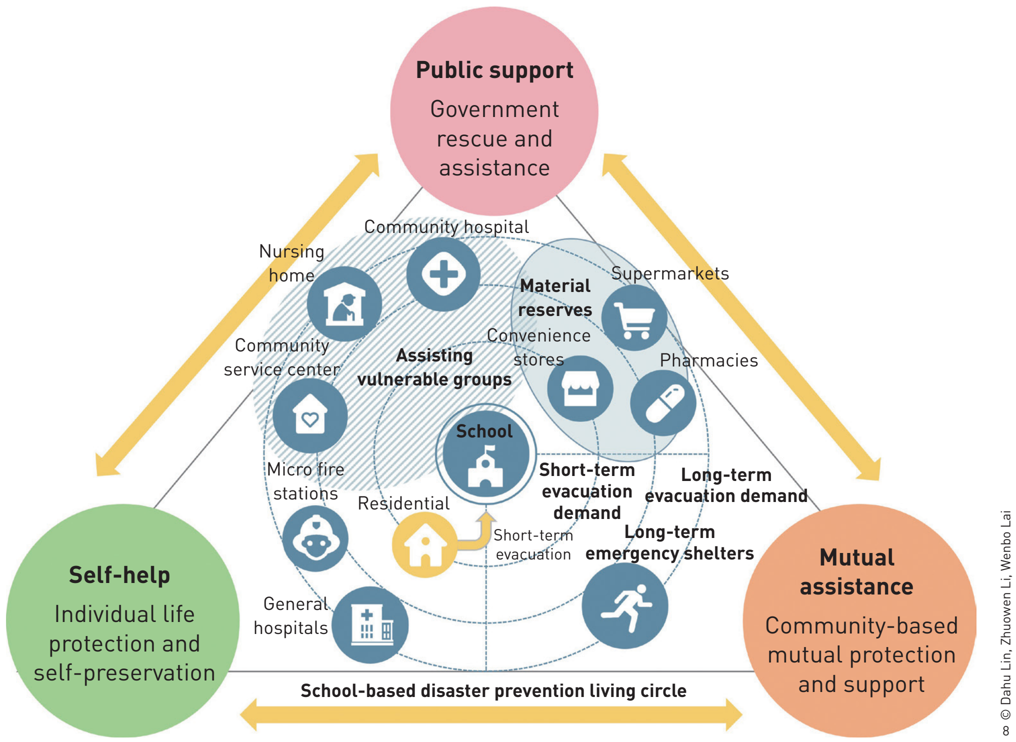


Fig. 8 Diagram of disaster prevention living circle and "self-help + mutual-assistance + public-support" disaster prevention model.

mechanisms to ensure timely, effective assistance for mobility-impaired elderly during disasters.

3) Long-term efforts should improve support strategies for vulnerable groups, constructing welfare-oriented emergency shelters in socially disadvantaged areas to provide refined service guarantees for the elderly and other vulnerable populations[7,25].

5.5 Limitations and Prospects

The multi-dimensional evaluation framework demonstrates strong applicability and scientific validity: multi-radius settings reflect service differences across shelter levels, grid-scale analysis improves evaluation precision, and social vulnerability indicators fill gaps in traditional research that overlooks vulnerable group needs. However, limitations exist. First, due to the uncertainty and difficulty of predicting natural disasters, differences in disaster risk exposure across areas were not incorporated. Second, cities vary in geographic environment, disaster characteristics, and socioeconomic conditions, potentially affecting evaluation parameters including service radius, effective shelter area, and capacity. Future research should conduct empirical studies across varied city types to validate and improve model universality. Third, based on behavioral geography theory[44], elderly populations exhibit behavioral characteristics during evacuation including preference for familiar routes and slower walking speeds, directly affecting evacuation efficiency. Fourth, framework application to other cities requires systematic parameter calibration and methodological optimization based on local conditions. For instance, for medium and small cities with lower population density, parameters including shelter service radius and per capita effective area require adjustment according to local standards; for mountainous cities, terrain significantly affects accessibility calculations, requiring consideration on slope factors and elevation data in distance–cost calculations and emphasizing geological disaster risk constraints on shelter site selection.

Future research should be deepened in four directions. First, incorporate age-friendly indicators, including evacuation route gradient, barrier-free facility coverage, signage clarity, and rest facility density, to establish elderly-specific accessibility evaluation models. Second, adjust distance–decay function parameters based on empirical data on elderly activity radius and security needs to more accurately reflect their sensitivity to shelter distance. Third, employ virtual simulation technology to construct realistic evacuation scenarios that incorporate elderly mobility differences, evacuation route preferences, and environmental obstacles, and to optimize emergency shelter distribution through multi-scenario simulation to improve accessibility measurement and precision in equity evaluation under aging contexts. Last, conduct comparative studies across cities with different geographic environments and scales to establish guidelines for parameter adjustment, enhancing model adaptability across urban environments.

6 Conclusions

This study examined three typical high-density urban districts in Guangzhou—Yuexiu, Liwan, and Haizhu—and revealed inequities in the spatial distribution of emergency shelters using a multi-dimensional evaluation model. Three core findings are: 1) regarding spatial equity, Haizhu and Liwan districts exhibit insufficient emergency shelter coverage (with population coverage gaps of 440,000 and 180,000 residents, representing 24% and 14% of district populations, respectively), while Yuexiu District demonstrates adequate coverage; 2) regarding social equity, significant disparities exist in accessibility among residents (in Liwan and Haizhu districts, 80% of the population have only approximately 30% of accessibility); 3) regarding social justice, four large-scale supply–demand imbalance areas (characterized by "high vulnerability–low accessibility") contain large concentrations of disaster-vulnerable populations, including the elderly, yet suffer from inadequate shelter service provision. Overall, the spatial distribution of emergency shelters exhibits a pronounced "core–periphery" differentiation, highlighting the urgency of improving rational emergency shelter distribution amid population aging.

To identify inequitable areas requiring urgent planning intervention, this study achieves three advances. First, the MC-GA2SFCA method comprehensively accounts for complex interactions among shelter service radius and capacity, population distribution, and road networks, more accurately reflecting accessibility. Second, incorporating social vulnerability indicators combined with BiLISA analysis enables a deeper examination of equity in shelter service access for socially disadvantaged areas, precisely identifying supply–demand imbalance areas and addressing gaps in existing research on the social justice dimension. Third, multi-source data collection and grid-based division methods capture finer spatial variations. This comprehensive evaluation model supports multi-dimensional equity assessment, providing guidance for refined emergency shelter allocation under the new urbanization era.

Competing interests | The authors declare that they have no competing interests.

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LAF https://doi.org/10.15302/J-LAF-2026-0009 收稿日期 | 2025-06-03 录用日期 | 2025-10-30
第14卷 / 第1期 / 260009 / 2026 中图分类号 | TU984 文献标识码 | A

老龄化背景下高密度城区应急避难场所空间布局公平性评价

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摘要

老龄化的加剧使弱势群体的安全保障需求日益凸显。高密度城区应急避难场所供需矛盾突出，制约了居民获得避难服务的公平性。为了识别亟需规划干预的不公平区域，本研究选取广州市越秀区、荔湾区、海珠区三个高密度城区作为研究区域，构建涵盖空间公平、社会公平和社会正义三个维度的应急避难场所空间布局公平性评价模型。研究综合运用多级半径－高斯两步移动搜索法、基尼系数、洛伦兹曲线、因子分析与双变量空间自相关分析等方法，在衡量应急避难场所可达性的基础上，揭示其与人口、社会脆弱性的空间关系。评价结果显示，海珠区和荔湾区的应急避难场所服务覆盖不足，区内居民享有的可达性水平差距悬殊，并且存在四个“高脆弱性－低可达性”的供需失衡区域。这些区域集中了大量老年人口和其他脆弱群体，但存在避难场所覆盖不足和有效避难面积匮乏等问题。根据评价结果与现状分析，研究提出旨在“增量、提质、治理、扶弱”的公平性优化策略。本研究提出的评估模型能够为城市应急避难场所空间布局的规划决策提供科学依据。

关键词

应急避难场所；空间布局；可达性；空间公平；社会公平；社会正义；高密度城区；社会脆弱性

文章亮点

- 探究了应急避难场所空间布局、人口特征与社会经济因素的关系
- 构建精细化的应急避难场所空间布局公平性评价模型
- 采用多尺度分析方法识别整体公平性和局部不公平区域
- 为存量规划下应急避难场所的公平配置提供科学依据

基金项目

高密度人居环境生态与节能教育部重点实验室开放课题（编号：20230106）