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Evaluation and Spatial Optimization Model of Urban Medical Resource Distribution Considering Equity and Efficiency

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ABSTRACT

The rapidly increasing demand for medical resources in accelerating urbanization countries is facing the challenge of unequal resource distribution. Despite numerous studies on the siting of medical resources aimed at improving public accessibility and efficiency to these resources, there is comparatively less research focusing on the equity of access to medical resources. This study establishes a framework that optimizes the distribution of medical resources by considering both equity and efficiency. We introduce an optimization allocation model for both equity and efficiency based on the location set coverage problem (LSCP). The model combines region growing algorithm and genetic algorithm to optimize site selection for hospitals. Taking Wuhan as the study area, the results demonstrate that the optimized service coverage increases by 21.2%, and the number of people served has reached 87.3%. The hospital bed utilization rate in downtown areas reaches 92.89%, while it exceeds 99% at suburban hospitals. The optimized site selection significantly enhances medical resource utilization efficiency, effectively addressing the resource distribution inequity between urban and rural areas. This study offers a novel approach to optimizing medical resource allocation, effectively balancing equity and efficiency, and providing valuable theoretical underpinnings for enhancing medical service systems in emerging urban areas.

1 | Introduction

Ensuring sufficient and equitably distributed medical facility resources is crucial for enhancing public health, improving living conditions, and promoting social equity (Zhao et al. 2021). In some developing countries, particularly China, there is rapid social and urban development, including the swift expansion of medical resources. However, these countries also face severe challenges in the uneven distribution of medical resources (Wang 2018). These distribution issues hinder the public's ability to access high-quality medical services to some extent (Li et al. 2022), thereby affecting patient satisfaction (Mouratidis 2021). Thus, optimizing the strategy for distributing medical resources, ensuring their effective utilization and equitable access, becomes a key factor in improving the overall quality of medical services.

As the highest level medical institutions within China's healthcare system, tertiary hospitals possess comprehensive medical services and advanced equipment, attracting patients from both local and distant areas (Wang et al. 2021). Nevertheless, constrained investment in labor and material resources has led to the clustering of hospitals primarily in urban centers, limiting convenient access for residents in emerging and remote regions (Jin et al. 2022). Therefore, investigating the spatial distribution and accessibility of urban medical facilities is valuable, as it can help assess the spatial equity of healthcare resources and optimize the spatial organization of medical services.

Equity is an important component of social justice, referring to whether the distribution of various resources and opportunities among different populations is reasonable under specific conditions (Braveman and Gruskin 2003; Richardson et al. 2022). The definition of equity is quite diverse and can generally be divided into several aspects, including horizontal equity and vertical equity (Whitehead et al. 2019). In this study, we primarily explore the spatial equity of healthcare resources, which refers to the equality of access to medical services, resources, and opportunities among different locations or communities within a region, falling under the category of horizontal equity (Lian et al. 2024).

Numerous studies have been dedicated to investigating the equity of healthcare services. However, previous studies primarily focus on traditional statistical perspectives or measurements of accessibility. For instance, Chen et al. (2018) utilized the Gini coefficient and agglomeration measures to assess the evolving equity trends in health resource allocation. H. Yu et al. (2021) employed the Gini coefficient and Theil index, analyzing the equity of existing physician distribution across 31 provincial-level administrative regions in China from the perspectives of population distribution and service area distribution. Zhou (2024) employed the Lorenz curve, Gini coefficient, and health resource density index to evaluate the equity of health resource allocation within township health centers. Nevertheless, these methods fail to account for spatial characteristics when assessing the comprehensive allocation impact of multiple medical resources. These evaluation methods lack a unified standard and only consider a single dimension of evaluation, thereby inadequately reflecting the spatial distribution features of medical resources.

Spatial accessibility measures play a pivotal role in underpinning spatial equity assessments (Rong et al. 2020; Li et al. 2022). In recent years, an increasing number of scholars have turned to spatial accessibility as a tool for evaluating the equity of medical resource distribution. For instance, Kanuganti et al. (2016) conducted a quantitative analysis of healthcare resource accessibility in rural areas, identifying regions with insufficient healthcare resources in conjunction with topographical considerations. Tao et al. (2020) introduced a hierarchical facility spatial accessibility measure to evaluate the healthcare resource supply capacity of healthcare organizations in Shenzhen. Xu et al. (2022) leveraged spatial accessibility metrics to assess the response time, delivery time, and waiting time in various neighborhoods of Xi'an City during emergencies, integrating data from a web map Application Programming Interface (API) service to pinpoint areas with vulnerable access to emergency healthcare resources. In general, current research on the equity of medical services often relies on data from regional statistical yearbooks and analyzes administrative divisions, streets, or larger spatial units. This level of analysis lacks the necessary granularity to accurately reflect the spatial distribution characteristics of medical resources at a microscale. Moreover, existing studies frequently evaluate the equity of medical resources from a singular perspective, leading to a lack of unified evaluation standards and an inability to comprehensively reflect the distribution of medical resources.

The above studies evaluated the distributional equity of urban healthcare facilities, which provides a foundation for optimizing the layout of facilities (Tao et al. 2023). To scientifically determine the optimal layout of facilities, domestic and foreign researchers in geography, operations research, and other disciplines have proposed a series of location-allocation models. For instance, the P-median model aims to minimize the average travel distance to the nearest facility (Metais et al. 2022). The maximum coverage model (MCLP) aims to cover the largest population demand (Xu et al. 2022) and the location-set covering model (LSCP) aims to fulfill population requirements with the fewest facilities necessary (Wolf 2022). In recent years, an increasing number of scholars have applied these models to address optimal allocation challenges. Wang et al. (2016) utilized quadratic programming to minimize the inequitable accessibility index. Li et al. (2017) proposed a two-step approach integrating location and capacity optimization to achieve equitable accessibility as a singular objective. Yao et al. (2019) utilized the P-median model and the LSCP model to integrate maximized coverage and median objectives in service for demand areas, thereby enabling the identification of alternative fire station location proposals. Moreover, Taiwo (2021) employed the MCLP model to extend the coverage of government areas, identifying university teaching and research hospitals for epidemiological testing. These studies have made some progress in enhancing the optimization of public resource allocation in urban areas, but they tend to focus on the coverage or equity of healthcare resources and have not sufficiently considered the dual demands for both equity and efficiency in the optimization process of healthcare resources.

Medical resource allocation goes beyond mere spatial distribution, necessitating a focus on the structural rationality and equity of resource allocation while maximizing efficiency (Debie et al. 2022; Moeeni et al. 2023). Cho (1998) used weight summing to optimize equity (healthcare provider revenue and resident cost of care) and efficiency (per capita transportation cost). Luo et al. (2017) and Li et al. (2022) adopted a two-step optimization approach, sequentially optimizing efficiency (weighted travel time from residents to hospitals) and equity (standard deviation of accessibility) to address the unequal distribution of healthcare resources. However, the two-step optimization method struggles to achieve collaborative optimization of equity and efficiency, which may result in suboptimal outcomes and lacks in-depth exploration of the trade-off relationship between the two. Furthermore, The World Health Organization (WHO) clearly identifies the Bed Occupancy Rate as a key indicator for evaluating the efficiency of healthcare systems in its "2018 Global Reference List of 100 Core Health Indicators (plus health-related SDGs)." The current healthcare system in China has not maximized the utilization of medical resources due to existing technological and management limitations, resulting in overall inefficiency and resource waste (Zhao and Zheng 2023).

To address the challenges above, this study develops a comprehensive healthcare service equity evaluation framework to assess the accessibility and equality of medical resources, thereby shedding light on the distribution of tertiary hospitals. Building upon this evaluation, the study formulates a hospital site selection optimization model grounded in the LSCP, which integrates considerations of both medical resource utilization efficiency and equity. This model involves partitioning the hospital service population range and conducting site selection optimization through a combined approach utilizing the region growing algorithm and genetic algorithm.

2 | Study Area and Dataset

2.1 | Study Area

Wuhan, situated in Hubei Province, China, holds the distinction of being a national central city, a mega-city, and a central urban hub in central China. Encompassing a total area of 8569.15 km^2, the city recorded a resident population of 13.739 million and a gross regional product of 1886.643 billion yuan by the conclusion of 2022 (Wuhan Municipal Bureau of Statistics Official Website). Wuhan boasts a unique tripartite urban layout comprising the towns of Hankou, Wuchang, and Hanyang, embodying the characteristics of a typical multicenter city. Administratively, Wuhan is divided into central districts including Jiangan, Jianghan, Qiaokou, Hanyang, Wuchang, Hongshan, Qingshan, and suburban districts encompassing Dongxihu, Caidian, Jiangxia, Huangpi, Xinzhou, and Hannan, totaling 13 districts.

2.2 | Dataset

2.2.1 | Medical Data

Hospitals serve as pivotal nodes for delivering essential medical services to residents. In this study, data pertaining to medical facilities, encompassing addresses and the bed capacities of 65 graded tertiary specialized and general hospitals (excluding branch districts), were systematically gathered from the Wuhan Municipal Commission of Health, official hospital websites, and the Hubei Provincial Commission of Health in December 2020. Subsequently, the collected data were standardized and converted into geographic coordinates using the Tianmap Address Coding Application Programming Interface (API) to facilitate spatial analysis and mapping.

2.2.2 | OpenStreetMap (OSM) Road Network Data

The transportation road network plays a crucial role in determining the spatial movement and accessibility of supply and demand points within a given area. In the context of this study, OSM road network data from 2020 was acquired to analyze healthcare facility accessibility. OSM is a collaborative open-source mapping platform maintained by volunteers, offering a comprehensive database of global road network information (Biljecki et al. 2023). This data encompasses a wide array of details on roads, streets, bridges, and signage, providing extensive geographic location information (Justiniano et al. 2022) that can be leveraged for route planning and research concerning healthcare facility locations (Das and Alam 2014).

2.2.3 | Population Data

The demand for hospital services is primarily driven by population size, with both the size and distribution of the population playing a significant role in shaping hospital facility layout (Falchetta et al. 2020). In this study, data from the 2020 Wuhan Statistical Yearbook, street-level resident population data obtained from the seventh population census, and real-time Tencent user density data in Wuhan were gathered. The population density data encompassed variations for a typical working day, a day of rest, and a holiday in Wuhan for the year 2019. These datasets were collected with a spatial resolution of 1000 m and a temporal resolution of 1 h.

3 | Methodology

As illustrated in Figure S1, the methodology of this study comprises three steps: (1) Preprocessing of research data to prepare data for subsequent experiments; (2) Development of a framework for assessing the equity of medical resources, examination of the accessibility patterns of existing tertiary hospitals, and analysis of the equality in the distribution of medical resources within the research area from the standpoint of supply and demand; (3) Creation of a hospital site optimization model integrating the region growing algorithm and genetic algorithm. The region growing algorithm is applied to delineate the population coverage of hospital services, while the genetic algorithm is utilized to address the optimization challenge.

3.1 | Data Preprocessing

The initial phase involved processing data on the supply points for residents to access medical services. Information regarding tertiary hospitals lacking spatial details was obtained from the Wuhan Municipal Health Commission. Utilizing the Tianmap address coding Application Programming Interface (API), structured addresses were systematically converted to WGS-84 latitude and longitude coordinates. Concurrently, bed data for each hospital was compiled from the official websites of the hospitals and the Hubei Provincial Health Commission. Subsequently, the transportation road network, a critical factor influencing travel times between supply and demand points, was analyzed. Fundamental transportation road network data for Wuhan was sourced from OSM, encompassing 13 road types such as highways, primary roads, secondary roads, tertiary roads, and sidewalks. Following this, data processing focused on the demand points for medical services. Population data from the 2020 Wuhan Statistical Yearbook, street-level resident population data from the seventh census, and real-time Tencent user density data were refined and extrapolated to the community level. The community center of gravity served as the designated demand point for medical services. To facilitate the delineation of hospital service populations in the subsequent hospital site optimization model, the processed temporal population data was interpolated into a raster grid with a resolution of 500 m by 500 m, representing healthcare demand. At the same time, the area of Wuhan, excluding water bodies, was divided into a grid of 100 m by 100 m, with the center points of these grids serving as the candidate hospital locations. Using the Geospatial Data Abstraction Library (GDAL), the candidate hospital locations were matched with the population distribution raster data to be input into the hospital site selection optimization model for accurately delineating the service areas of hospitals.

3.2 | A Framework for Evaluating the Equity of Medical Resources Based on Ga-2SFCA and Spatial Clustering

Exploring the spatial distribution pattern of medical resources can provide spatial references for optimizing the selection of healthcare facility locations. In this study, a framework for evaluating the equity of medical resources is proposed, leveraging the Gaussian two-step floating catchment area method (Ga-2SFCA) integrated with spatial clustering analysis. Initially, Ga-2SFCA is employed to analyze the accessibility distribution of medical resources. At the same time, spatial autocorrelation analysis is utilized to depict the spatial clustering of medical resource accessibility, enabling an assessment of resource accessibility. Subsequently, the Gini coefficient and Lorenz curve are employed to evaluate the overall equality of medical resources.

3.2.1 | Methodology for Assessing the Accessibility of Medical Resources

The Two-step Floating Catchment Area (2SFCA) method is an effective tool for assessing spatial accessibility, known for its comprehensive factor consideration and straightforward calculations, but neglecting accessibility variations within the search area (Wang 2012). To address this limitation, numerous studies have proposed enhancements by integrating diverse distance decay functions (Dai 2010; Tao and Cheng 2016). In this study, the Ga-2SFCA method, which incorporates a Gaussian-type distance decay function, is employed. In the Gaussian distance decay function, the rate of accessibility decay accelerates initially and then slows down as distance increases. This pattern is similar to people's expectations for choosing medical facilities, which change with increased travel distance or time, allowing for a more realistic simulation of actual decision-making conditions. In addition, the Gaussian function requires only one parameter, which reduces subjectivity and uncertainty compared to other methods with more complex parameter settings (Tao et al. 2020). The Ga-2SFCA method operates in two primary steps: Initially, based on the size of demand points and the distance decay function, the resources of each facility are allocated to the demand points within the search area. Subsequently, the accessibility value of each demand point can be determined by aggregating the resources accessible from facilities within its search area. The formula for this method is as follows:

$$A_i = \sum_{j \in \{d_j \in D_0\}} \frac{S_j f(d_{ij}, D_0)}{\sum_{k \in \{d_{ij} \in D_0\}} P_k f(d_{ij}, D_0)} \tag{1}$$

In the formula, A_i represents the accessibility value of demand point i. S_j denotes the service capacity of facility j, specifically the number of beds. P_K signifies the demand at demand point k, corresponding to the total resident population. d_{ij} represent the transportation costs between the demand point and the facility. D_0 stands for the radius of the facility's search area. Additionally, f indicates a Gaussian-type distance decay function, which can be mathematically expressed as:

$$f(d_{ij}, D_0) = \begin{cases} \dfrac{e^{-1/2 \times (d_{ij}/D_0)^2} - e^{-1/2}}{1 - e^{-1/2}} & d_{ij} \le D_0 \\ 0 & d_{ij} > D_0 \end{cases} \tag{2}$$

In this study, we examined the spatial distribution of healthcare resource accessibility through the computation of the global Moran's I index and the Local Indicators of Spatial Association (LISA) (Getis 2009). Spatial autocorrelation analysis was utilized to investigate the spatial patterns and regional disparities in healthcare resource accessibility (Huang et al. 2020). The global Moran's I index, as presented in Formula (3) (Waldhör 1996), is a global autocorrelation index used to measure the degree of autocorrelation in an entire spatial dataset. LISA is an indicator used for local autocorrelation analysis, aimed at identifying local spatial clustering patterns of variables within specific areas. Unlike global Moran's I, LISA provides localized information about spatial clustering (Anselin 1995).

$$\mathrm{I} = \frac{\Sigma_j W_{ij} \cdot Z_i \cdot Z_j / s}{\Sigma_i z_i^2 / n} \tag{3}$$

In the equations, Z_i and Z_j represent the deviations of attributes i and j from their respective mean values. s signifies the sum of all spatial weights within the set, W_{ij} indicates the spatial relationships between i and j. The variable n denotes the total number of elements considered in the analysis.

3.2.2 | Methodology for Assessing the Equality of Medical Resources

The Gini coefficient is a fundamental index for assessing income inequality and is widely used in various domains such as income, education, and environmental equity (Malakar and Mishra 2017). As a relative indicator, the Gini coefficient offers distinct advantages, including anonymity, chi-square properties, population independence, transferability, strong Lorenz consistency, and standardization. Ranging from 0 to 1, values closer to 0 signify greater equality, while values closer to 1 indicate heightened inequality. In economic terms, a Gini coefficient up to 0.3 suggests a relatively equal distribution, with values exceeding 0.3 pointing toward increasing inequality, and a threshold of caution is typically recognized at 0.4 (Gu et al. 2022).

3.3 | Optimization Model for Hospital Site Selection by Coupling Region Growing Algorithm and Genetic Algorithm

3.3.1 | Region Growing Algorithm-Based Population Scoping for Hospital Services

Delineating the hospital service areas is essential for optimizing hospital locations. According to the “15-Minute Living Circle” concept in the “Standards for Urban Residential Area Planning and Design” issued by the Ministry of Housing and Urban–Rural Development of the People's Republic of China, as well as the principles of the urban “15-Minute Community Health Service Circle” and rural “30-Minute Medical and Health Service Circle” mentioned in the “Health Wuhan 2035” plan, residents choose medical treatment locations based on proximity. In this study, we use the region growing algorithm to allocate each hospital's service area based on the population distribution raster. Region growing is defined as starting from a specific cell, gradually adding neighboring cells based on set criteria, and terminating the region growing once certain conditions are met.

The procedure for delineating the hospital service area involves the following steps: Initially, the nearest medical demand point to the hospital is identified as the seed point. Subsequently, the neighboring eight medical demand points around the seed point are assessed to determine if they meet the region growing criteria, and if so, they are included. Finally, the distance between the hospital and the medical demand points is calculated, and the medical demand points are assigned to the hospital from near to far. The region growing algorithm incorporates two conditions for region expansion: (1) The distance between the resident's point of care need and the hospital does not exceed the hospital's service radius. (2) The demand at the resident's point is within the maximum bed capacity of the hospital.

3.3.2 | Optimization Model of Hospital Site Selection in Different Scenarios Based on Genetic Algorithm

Upon completion of the hospital service area delineation, the hospital location should be optimized based on the LSCP and genetic algorithm, including mathematical model construction and optimization model solving. In mathematical model construction, the LSCP aims to cover all service demand points in a given area using the fewest possible facilities. Models based on the LSCP have been widely applied in the optimal location of emergency facilities such as fire stations and ambulances (W. Yu et al. 2021).

Given China's population growth, increasing healthcare demand, unequal resource distribution, and limited beds availability resulting in healthcare service oversupply, the primary objective is to “maximize resident access to beds (equity) and enhance hospital bed utilization efficiency (efficiency).” The LSCP effectively reduces infrastructure and operational costs while maximizing bed utilization efficiency by minimizing the number of hospitals and ensuring full coverage of all demand points within a specified distance. Additionally, the LSCP ensures that all demand points are covered within the specified range, which is crucial for achieving the goal of maximizing the number of accessible beds for residents. Based on this, a hospital site selection model founded on the LSCP was devised.

In this study, the number of resident-accessible beds is computed as the ratio of beds allocated to the residents' demand point to the total number of residents requiring medical care. Similarly, the hospital bed utilization rate is defined as the ratio of beds actually provided by the hospital to the total number of hospital beds. The objective function and constraints are presented in Formulas (4–9).

Objective function:

$$F(x) = \mathrm{Max}\left(W_{\text{equity}} * \text{equity} + W_{\text{efficiency}} * \text{efficiency}\right) \tag{4}$$

$$\text{equity} = \frac{\sum B_i Y_i}{P} \tag{5}$$

$$\text{efficiency} = \frac{\sum \frac{N_j X_j}{\mathrm{M}_j}}{H} \tag{6}$$

Constraints on variables:

$$N_j \le \mathrm{M}_j \tag{7}$$

$$d_{ij} \le R \tag{8}$$

$$W_{\text{equity}} + W_{\text{efficiency}} = 1 \tag{9}$$

In the formula above, equity refers to the number of beds accessible to residents, reflecting equity, while efficiency denotes the hospital bed utilization rate, representing efficiency. The symbols associated with the formulas are shown in Table 1.

Constraint (7) ensures the provision of medical resources at the point of demand based on a specified number of hospital beds, thereby preventing an oversupply of beds. Constraint (8) serves to restrict the distance between the hospital and the point of demand for medical care for residents to be within the maximum service radius of the hospital. Additionally, Constraint (9) ensures that the combined weight of equity and efficiency is equal to 1.

Based on the current restrictions on the population size, traffic conditions, and construction cost of tertiary hospitals in the downtown and suburban areas of the city, this study combined with the principles of the urban “15-Minute Community Health Service Circle” and the rural “30-Minute Medical Service Circle” as outlined in the “Healthy Wuhan 2035” plan, and conducted hierarchical optimization for the downtown and suburban areas, respectively. For the downtown areas, the hospital service radius R is set at 7.5 km (15 min driving distance). For the suburbs, the hospital service radius R is 15 km (30 min driving distance).

TABLE 1 | The definition of symbols in formulas.

Symbols	Definition
i	Index of residents' demand points
j	Index of potential hospitals locations
X_j	If potential hospital j is sited, $X_j = 1$; otherwise, $X_j = 0$
Y_i	If demand i is served, $Y_i = 1$; otherwise, $Y_i = 0$
B_i	The number of beds obtained by the residents' demand point i
P	The number of residents at the residents' demand point
H	The total number of selected hospitals
N_j	The actual number of beds allocated by the hospital j
M_j	The maximum bed capacity of hospital j
d_{ij}	The distance between demand point i and the hospital j
R	The maximum service radius of the hospital
W_{equity}	Weight of equity, $0 \leq W_{\text{equity}} \leq 1$
$W_{\text{efficiency}}$	Weight of efficiency, $0 \leq W_{\text{efficiency}} \leq 1$

Upon formulating the optimization model, the subsequent step involves solving the optimization problem. Selecting P optimal hospital locations from N candidates to maximize resident-accessible beds and hospital bed utilization efficiency represents an NP-hard challenge. Prior research has demonstrated that heuristic algorithms are adept at addressing NP-hard problems (Seyhan et al. 2018), among which genetic algorithms have exhibited effectiveness in tackling optimization problems (Comber et al. 2011) and have delivered favorable outcomes in various pertinent studies (Kaveh et al. 2020; H. Yu et al. 2021), thus warranting their selection for implementation in this study.

The optimization model of hospital site selection utilizes the genetic algorithm to identify the optimal hospital location. To ensure the algorithm converges to the global optimal solution, parameter tuning is performed. The parameters subject to tuning through the genetic algorithm include the number of iterations, population size, and chromosome length. Optimal parameter values are determined by assessing the accuracy of results obtained by varying parameter values within predefined ranges.

4 | Results

4.1 | Evaluation of the Equity of Medical Resources

4.1.1 | Results of the Accessibility Assessment of Original Medical Resources

In this study, the evaluation of the accessibility of original tertiary hospitals in Wuhan was conducted using the Ga-2SFCA method based on the OSM road network and existing hospital locations. The resulting distribution map of accessibility for the original tertiary hospitals in Wuhan (Figure 1) reveals noticeable spatial disparities in accessibility, indicating a pronounced polarization issue. Accessibility to medical services is generally higher in the downtown areas, gradually contracting toward the core region, with clusters of high accessibility values observed. In contrast, suburban areas, excluding the central district, exhibit significantly low accessibility levels, with up to 57.18% of the area lacking access to medical services.

Figure S2 showcases the accessibility levels across Wuhan's administrative districts; specifically, there is an unequal distribution of medical resource allocation between the downtown area and suburban regions. The analysis reveals an unequal distribution of healthcare resources, with a higher proportion of residents in central urban areas such as Jiangan, Jianghan, Qiaokou, Hanyang, and Wuchang districts enjoying good accessibility rates exceeding 88%. In contrast, residents in suburban districts like Caidian, Hannan, and Huangpi districts experience lower accessibility rates, with less than 40% of residents benefiting from good accessibility of medical services.

Based on the accessibility of medical services, the calculation of the global Moran's I index for medical service accessibility in Wuhan yielded a value of 0.208 ($p = 0.00$, z-score 90.71), indicating a notably strong positive spatial correlation in the distribution of medical services across the city. This finding underscores a distinct spatial clustering pattern among demand points with similar accessibility levels. The calculated z-scores highlight the substantial spatial inequity in the provision of medical services in Wuhan. On this basis, the results of the local autocorrelation analysis of medical service accessibility in Wuhan obtained based on the local Moran's I index are shown in Figure 2. Most of the communities with heightened clustering of medical service accessibility are concentrated in the downtown areas, totaling 1001 (28.8%). Communities with low value clustering of healthcare service accessibility are distributed in the periphery of the city's suburban centers, totaling 1654 (47.7%).

4.1.2 | Results of the Equality Assessment of the Original Medical Resources

The equality of the overall medical resources in Wuhan is assessed using the Gini coefficient and Lorenz curve, as depicted in Figure 3. The calculated Gini coefficient value for Wuhan's overall medical resources is 0.38, surpassing the threshold of 0.3 (Gu et al. 2022), indicating a slight tendency toward inequality in the distribution of medical resources. Furthermore, the Gini coefficient for the suburban areas is reported as 0.13, showcasing a notable disparity compared to the downtown areas.

4.2 | Multi-Scenario Optimization of Site Selection Results

4.2.1 | Optimizing Site Selection Results Considering Only Equity Scenario

Based on the results of the equity evaluation of the original medical resources in 4.1, spatial optimization is conducted utilizing

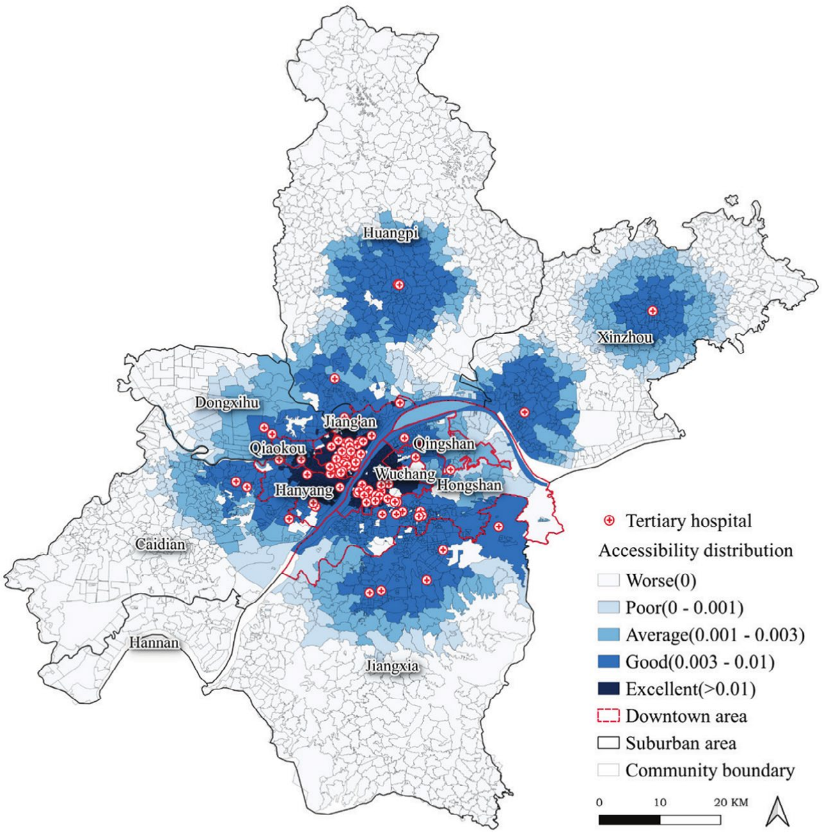

FIGURE 1 | Original tertiary hospital accessibility distribution.

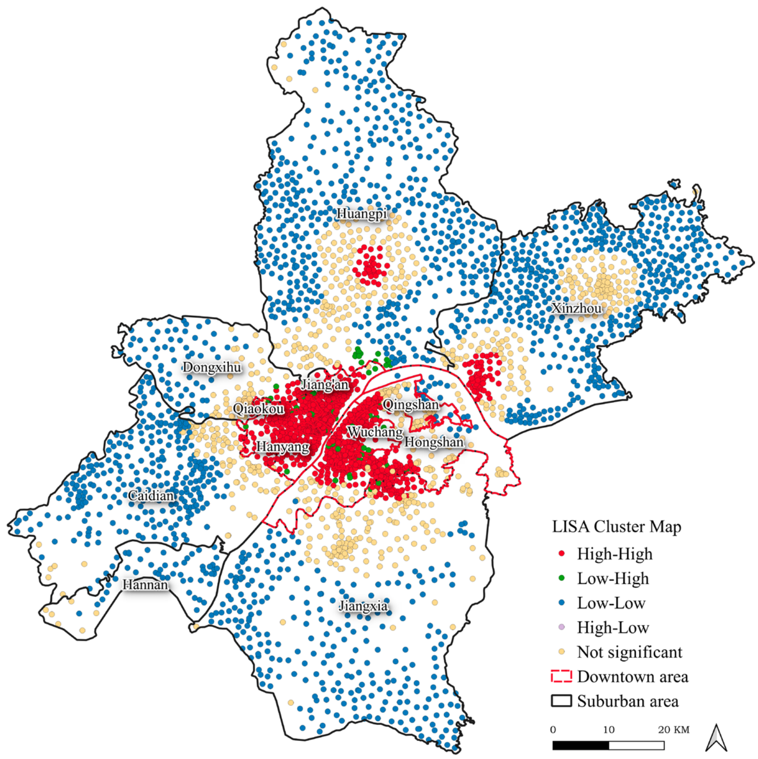

FIGURE 2 | Original tertiary hospital LISA distribution.

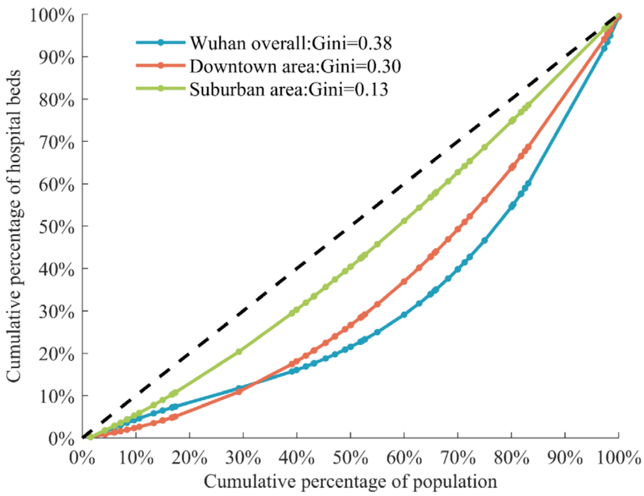

FIGURE 3 | Wuhan medical resources Lorenz curve.

the site selection optimization model. In the equity-only scenario, with equity weight $W_{equity} = 1$ and efficiency weight $W_{efficiency} = 0$, the distribution of medical service accessibility in Wuhan is analyzed, as depicted in Supp 3 (Figure S3 and Table S1).

4.2.2 | Optimizing Site Selection Results Considering Only Efficiency Scenario

In the efficiency-only scenario, with efficiency weight $W_{efficiency} = 1$ and equity weight $W_{equity} = 0$, the distribution of medical service accessibility in Wuhan is analyzed, as illustrated in Supp 4 (Figure S4 and Table S2).

4.2.3 | Parametric Sensitivity Analysis of Equity and Efficiency Weights

To investigate the optimal balance between equity and efficiency in maximizing healthcare services, a parameter sensitivity analysis was conducted for equity weight and efficiency weights in hierarchical optimal siting experiments within Wuhan's downtown areas and suburban regions. The range of variation for equity weight W_{equity} was set from 0.0 to 1.0, while the range for efficiency weight $W_{efficiency}$ was set from 1.0 to 0.0 (Liu et al. 2025), as detailed in Tables 2 and 3.

In the scenario prioritizing efficiency in the optimization strategy, with W_{equity} ranging from 0.0 to 0.5 and $W_{efficiency}$ ranging from 1.0 to 0.5, the optimization process for the downtown areas yielded notable outcomes. Specifically, when both equity and efficiency weight parameters were set at 0.5, as outlined in Table 2, the bed utilization efficiency reached 92.89%, surpassing levels observed in other scenarios. Simultaneously, the number of accessible beds per 1000 individuals improved significantly. In the suburban areas of the city, the optimization process, detailed in Table 3, resulted in a bed utilization efficiency of 99.29%, slightly lower than other scenarios. However, the number of accessible beds per 1000 individuals stood at 6.02, higher than other scenarios, signifying an enhancement in the equity of medical resources.

TABLE 2 | Changes in equity and efficiency parameters in Wuhan's downtown area (The selected optimal parameters are highlighted in bold).

Parameter setting		Number of hospitals	Bed utilization rates	Accessible beds (beds/1000 persons)
W_{equity}	$W_{efficiency}$	(size)	(%)	
0.0	1.0	44	90.93	4.86
0.1	0.9	48	90.45	5.22
0.2	0.8	50	89.19	5.36
0.3	0.7	50	89.15	5.27
0.4	0.6	51	90.16	5.53
0.5	**0.5**	**47**	**92.89**	**5.30**
0.6	0.4	53	89.44	5.70
0.7	0.3	54	89.96	5.83
0.8	0.2	54	89.95	5.83
0.9	0.1	54	89.95	5.84
1.0	0.0	54	89.95	5.84

TABLE 3 | Changes in equity and efficiency parameters in Wuhan's suburban areas (The selected optimal parameters are highlighted in bold).

Parameter setting		Number of hospitals (size)	Bed utilization rates (%)	Accessible beds (beds/1000 persons)
W_{equity}	$W_{efficiency}$			
0.0	1.0	14	99.34	3.51
0.1	0.9	14	99.48	3.52
0.2	0.8	15	99.63	3.78
0.3	0.7	19	99.31	4.77
0.4	0.6	23	99.53	5.78
0.5	**0.5**	**24**	**99.29**	**6.02**
0.6	0.4	26	99.22	6.52
0.7	0.3	29	99.05	7.26
0.8	0.2	34	99.12	8.82
0.9	0.1	41	98.97	10.26
1.0	0.0	40	98.81	9.99

As seen from the results above, when W_{equity} and $W_{efficiency}$ are both set to 0.5, a harmonious balance between equity and efficiency is achieved, resulting in improved medical resource allocation. This optimal scenario showcases enhancements in equity alongside the maintenance of high efficiency, demonstrating a superior effect on medical resource distribution. Overall, the optimization effect achieved through the balance of equity and efficiency surpasses that of other scenarios, proving to be more effective in both the downtown and suburban areas.

4.3 | Optimizing Site Selection Results Considering Both Equity and Efficiency Scenario

4.3.1 | Results of the Accessibility Assessment of the Optimized Medical Resource

The optimization parameter weight settings derived from the results of 4.2.3 consider both equity and efficiency, with $W_{\text{efficiency}} = 0.5$ and $W_{\text{equity}} = 0.5$, and the outcomes of the optimized site selection as depicted in Figure 4 and Table 4. Following the optimization process, the count of tertiary hospitals in Wuhan stands at 71, reflecting a reduction of 29.9% tertiary hospitals in the downtown area and an increase of 50% tertiary hospitals in the suburban regions. The refined allocation of medical resources within Wuhan has notably enhanced utilization efficiency and eased the inequity in resource distribution between urban and rural locales. Specifically, post-optimization, the coverage of tertiary hospitals has risen to 63.9%, marking a 21.2% increase from pre-optimization levels. Moreover, the downtown area witnessed a 7.08% surge in hospital bed utilization rates, while the suburban areas now offer 2.1 more accessible beds per 1000 residents. This augmentation not only bolsters bed utilization efficiency but also fosters greater equity in medical resource accessibility for urban and rural

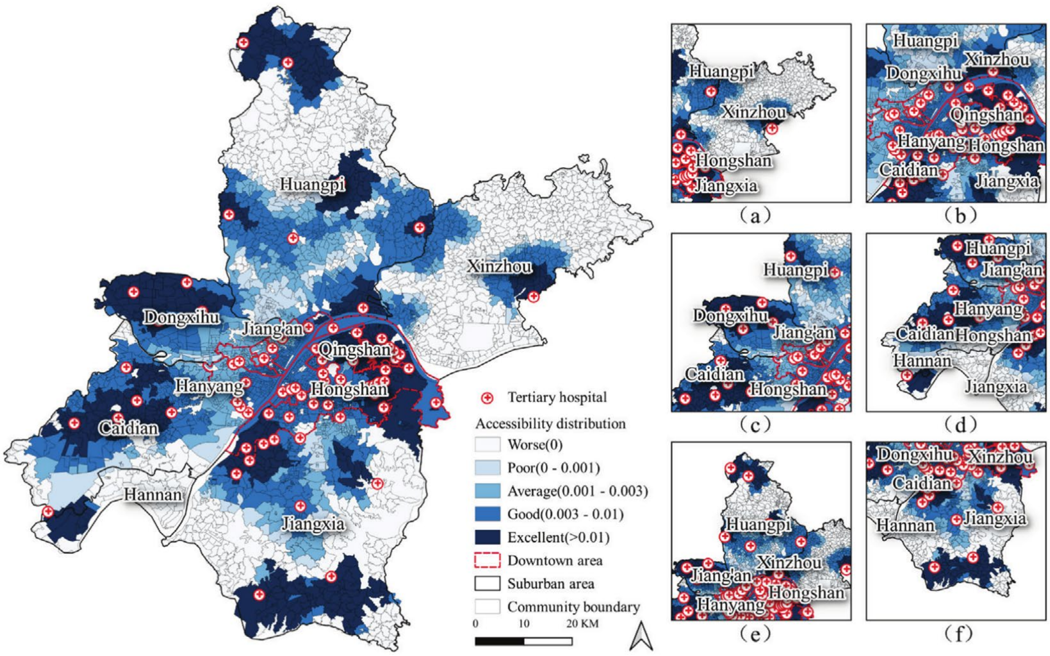

FIGURE 4 | Optimized site selection results under the scenarios of equity and efficiency: (a) Xinzhou district, (b) central city, (c) Dongxihu district, (d) Caidian and Hannan districts, (e) Huangpi district, and (f) Jiangxia district.

TABLE 4 | Comparison of optimized site selection results in equity and efficiency scenarios.

Area	Number of hospitals (size)	Variation value (%)	Accessible beds (beds/1000 persons)	Variation value (beds/1000 persons)	Utilization rate (%)	Variation value (%)
Wuhan						
Original	83	−14.5	6.4	−0.8	97.23	+0.62
Post-optimization	71		5.6		97.85	
Downtown areas						
Original	67	−29.9	6.9	−1.6	85.81	+7.08
Post-optimization	47		5.3		92.89	
Suburban areas						
Original	16	+50	3.9	+2.1	98.04	+1.24
Post-optimization	24		6.0		99.28	

inhabitants. The post-optimization scenario reveals a substantial enhancement in the equity of medical resource distribution between urban and rural areas, with a notable reduction in the gaps between accessible beds per resident and utilization rates. Specifically, the gap in accessible beds per resident decreased from 3 per 1000 to 0.7, while the utilization rate disparity dwindled from 12.23% to 6.39%, effectively narrowing the inequity chasm between urban and rural regions.

A comparative analysis of the accessibility distribution between the original hospital layout and the optimized site selection outcome, considering both equity and efficiency scenarios, is depicted in Figure 5. The newly identified hospital locations are predominantly situated in the eastern region of New High-Tech Development Zone (Hongshan District), industrial park (Dongxihu District), aggregation area of tourist scenic spots (Huangpi District), and Sino-French Eco-New City (Caidian District). Post-optimization, the downtown area of Wuhan exhibits a decrease in accessible beds per 1000 residents to 5.3, marking a reduction of 1.6 beds compared to the pre-optimization phase. At the same time, the utilization rate climbs to 92.89%. Conversely, in the suburban areas, the number of accessible beds per 1000 residents has increased post-optimization, while the utilization rate of beds has been raised to over 99%. Specifically, the number of beds per 1000 residents in Dongxihu District, Huangpi District, Caidian District, and Jiangxia District increased by 2.1, 0.8, 2.6, and 1.3 respectively.

Figure S5 illustrates the distribution of tertiary hospitals before and after optimization. The results of the nearest neighbor analysis for the tertiary hospitals before and after optimization are shown in Figures S6 and S7. In the suburban areas where medical resources are scarce, the optimized tertiary hospitals are evenly distributed in a circular pattern around the original tertiary hospitals, providing broader coverage for the residents in the suburbs. In contrast, for the downtown areas where medical resources are concentrated (Figure S7), the optimized tertiary hospitals are mostly located near the midpoints of the lines connecting multiple existing tertiary hospitals, which helps to reduce resource redundancy caused by an overly concentrated distribution of hospitals.

Figure S8 depicts the distribution of healthcare resource accessibility levels across the administrative districts of Wuhan following optimization considering both equity and efficiency scenarios. Notably, the equity in healthcare resource allocation within Wuhan has experienced a significant enhancement, leading to a more equitable accessibility landscape between urban and rural regions and a reduction in accessibility differentials compared to the pre-optimization scenario. In more than half of the administrative districts, the proportion of residents with good accessibility level is above 60%.

4.3.2 | Results of the Equality Assessment of the Optimized Medical Resource

The assessment of the equality of medical resource distribution in Wuhan post-optimization utilizes the Gini coefficient and Lorenz curve, as depicted in Figure 6a. The calculated Gini coefficient for the overall medical resources in Wuhan stands at 0.292, indicating a state of equality in the distribution of medical resources. Furthermore, the Gini coefficients for both downtown and suburban areas are below 0.3, signifying an equal distribution within these regions. A comparison before and after optimization, as depicted in Figure 6b, reveals a decrease in the Gini coefficient of medical resources in Wuhan from 0.38 to 0.29, representing a decline of 0.09. This transformation signifies a shift from an inequality state to an equality state, demonstrating a substantial enhancement in the equity of medical resource allocation in Wuhan.

5 | Discussion

In the current analysis of medical service equity, the prevailing methodologies employ mathematical statistics and individual accessibility measures to gauge the equity of medical resource allocation. However, these methods are relatively simplistic. In addition, the spatial optimization model of medical resources is mostly single-objective optimization, which fails to balance equity and efficiency. In view of this, this study introduces a framework for assessing the equity of healthcare resources,

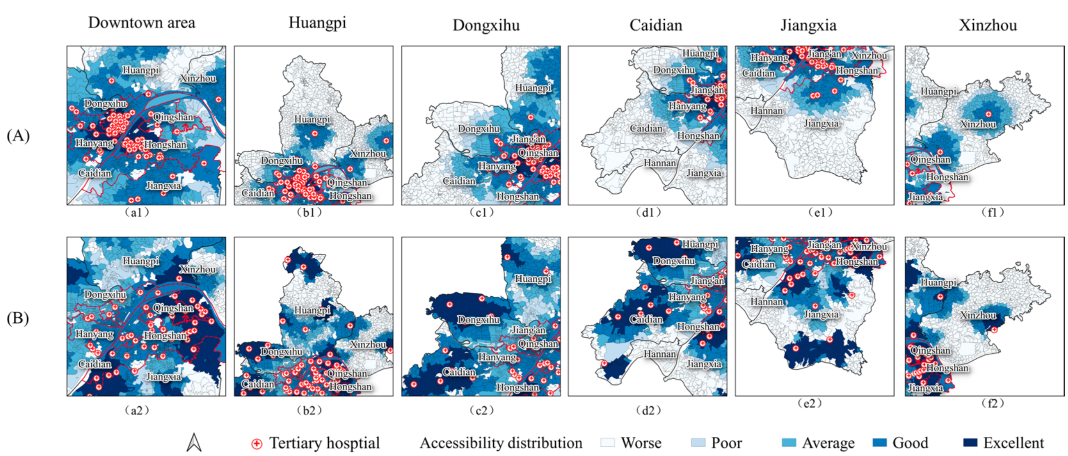

FIGURE 5 | Comparison of optimized site selection results before and after optimization: (A) original hospital distribution, (B) optimized site selection results under the scenario of balancing equity and efficiency.

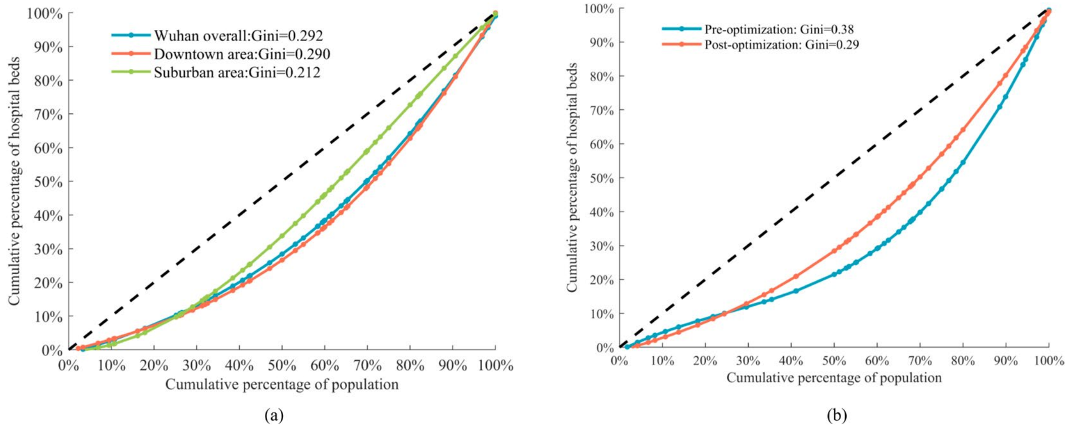

FIGURE 6 | Lorenz curve of medical resources in Wuhan: (a) Lorenz curve under the scenario of balancing equity and efficiency, (b) comparison of the Lorenz curve of medical resources before and after optimization.

utilizing detailed community demographic data and integrating healthcare accessibility and equality for quantitative evaluation. Furthermore, a novel hospital site selection optimization model based on the LSCP is developed, with the objective of balancing healthcare resource utilization efficiency and equity. The model ensures an adequate and equitable distribution of hospital beds while aiming to maximize bed utilization rates. To optimize hospital site selection, the region growing algorithm is combined with a genetic algorithm to define the population catchment area of the hospital service. This approach not only enhances the efficiency of hospital bed utilization significantly but also addresses the disparity in resource allocation between urban and rural areas.

5.1 | Interpretation of the Findings

This study integrates medical service accessibility and equality for quantitative analysis, establishing a framework for evaluating medical resources equity and elucidating the spatial distribution characteristics of existing tertiary hospitals in China's megacity. This study calculates that the global Moran'I index of medical resource accessibility is 0.208, the z score is 90.71, and the Gini coefficient value of the overall medical resource is 0.38, all of which reflect the spatial inequity of the medical service level.

The findings reveal a spatial autocorrelation in the accessibility of original tertiary hospitals, while the demand points with similar accessibility exhibit strong spatial clustering characteristics. Additionally, the original tertiary hospital medical service accessibility demonstrates a continuous circular distribution pattern characterized by inequality, with pronounced core circle polarization and a decline in accessibility from the city center toward the outskirts. These outcomes offer theoretical substantiation for the identified phenomena of delayed urban facilities development and the mismatch between the urbanization of physical space and population urbanization, as proposed by Mao et al. (2019).

In the downtown areas, accessibility exhibits notable aggregation of high values, primarily attributed to the concentrated allocation of medical resources and the well-developed transportation network within the urban core. Conversely, in the suburban regions beyond the downtown areas, the sparse presence of medical institutions and relatively inadequate transportation infrastructure contribute to a phenomenon of low-low aggregation in medical care accessibility. This comprehensive framework enables a more precise identification of inequity in medical resource distribution and serves as a foundation for equitable allocation of healthcare resources.

This study introduces an innovative hospital site selection optimization model based on the LSCP, which considers both the efficiency and equity of medical resource utilization. Compared with recent hospital siting models proposed by Taiwo (2021) and Tao et al. (2023), this model takes the utilization efficiency of hospital beds and the accessibility of beds to residents as site selection optimization objectives. By coupling region growing algorithm and genetic algorithm, the service population range of the hospital is more finely divided and the location optimization is carried out. Through parameter sensitivity analysis experiments, optimal equity weight ($W_{\text{equity}} = 0.5$) and efficiency weight ($W_{\text{efficiency}} = 0.5$) are determined. The optimization outcomes have the potential to address challenges related to urban medical resource constraints and underutilization of beds, offering insights into the optimal allocation of medical resources in emerging urban areas. The study finds that the service coverage increases by 21.2% after optimization, with the number of people served reaching 87.3%. The utilization rate of hospital beds in the central urban area increases to 92.89%, and in suburban areas, it rises to more than 99%. The incorporation of equity and efficiency considerations in the optimization model leads to a substantial enhancement in utilization efficiency and a notable reduction in the disparity of resource distribution between urban and rural areas compared to current distributions. It offers a novel approach to achieving an optimal balance between equity and efficiency in the strategic siting of medical resources.

Furthermore, the model offers a scientific basis for guiding the strategic planning of medical resources in emerging urban areas. This guidance can assist in addressing the challenges associated with hospital location optimization in new urban settings, mitigating the pressures stemming from irrational hospital distribution, and effectively meeting the fundamental healthcare requirements of urban inhabitants.

5.2 | Policy Implications

Based on the findings above, this study offers the following two policy recommendations. Initially, attention should be directed toward addressing the issue of unequal medical resource allocation in suburban regions. The traffic constraints and the unequal distribution of medical facilities between the downtown areas and suburban locales often result in inadequate access to healthcare services for residents in suburban areas. Concurrently, inefficiencies in bed utilization and redundant medical resources are prevalent in the downtown areas. Therefore, achieving a more equitable distribution of medical resources between urban and rural areas, enhancing bed utilization rates in the downtown areas, and elevating the quality of medical services in suburban areas hold significant importance for urban development planning.

Furthermore, in the optimization of medical resource allocation, it is recommended to prioritize the establishment of comprehensive hospitals in regions characterized by developed educational, commercial, and tourist landscapes. These areas typically experience high population mobility coupled with relatively low accessibility to medical resources. Accordingly, efforts should be concentrated on enhancing the service quality of healthcare resources in these regions to elevate the public's healthcare service experience, thereby bolstering the equity and efficiency of healthcare resource allocation.

5.3 | Limitation and Future Works

This study is subject to certain limitations that warrant consideration. Initially, when exploring the distribution of healthcare resource accessibility, accurate and comprehensive data were not available. The diverse healthcare needs of various demographic groups, such as the elderly, children, pregnant women, and other specialized populations, are not taken into account. The second limitation of this study is that, in constructing the medical resource optimization model, specific cities and municipalities are used as samples to evaluate and optimize the allocation of urban medical resources. Furthermore, affected by the objective data conditions and for the convenience of modeling, it fails to take into account the flow of patients between cities in the evaluation and optimization. In future investigations, the studies intend to examine the correlation between socioeconomic attributes and accessibility to assess the group-specific equity of medical resources in Wuhan across different populations. Additionally, future studies aim to incorporate resident health metrics and patient mobility dynamics to facilitate a more objective evaluation, enhancing the model's adaptability and generalizability.

6 | Conclusion

This study introduces a comprehensive framework for evaluating the equity of medical resources in response to the rapid urbanization trends in China, addressing the challenges posed by the mismatch between the availability of medical resources and the pace of urban development, as well as the spatial disparities in medical resource allocation. The framework quantitatively assesses medical resource accessibility and equality, shedding light on the spatial distribution patterns of tertiary hospitals in China's megacity. Building upon this analysis, the study proposes a novel hospital site selection optimization model based on the LSCP, which leverages the region growing algorithm and genetic algorithm to optimize the placement of tertiary hospitals. The optimization results reveal strong spatial autocorrelation and a continuous circular distribution of medical resource accessibility characterized by inequality in the original distribution. The application of the optimization model effectively mitigates urban medical resource supply constraints and enhances bed utilization rate, which is particularly beneficial for optimizing medical resource allocation in emerging urban areas. Post-optimization, a notable improvement in utilization efficiency is observed compared to the existing distribution, significantly reducing the disparity in resource distribution between urban and rural areas. This study offers a fresh perspective on the optimal allocation of medical resources, successfully balancing considerations of equity and efficiency, and provides valuable insights for regional health planning and optimal resource allocation amidst the ongoing construction of new urban areas.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The medical-related data can be accessed upon request to the corresponding authors for privacy protection purposes. The OSM data and population data used in this study are openly accessible and available online.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.