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Highlights:

- The distribution of medical facilities in Guangzhou is clearly imbalanced. They are concentrated in the city centre. There are fewer facilities in the suburbs.
- Basic medical resources are well distributed and meet residents' daily healthcare needs, but there is a lack of secondary and tertiary healthcare resources in outlying areas.
- The distribution of access to healthcare facilities is highly correlated with topography and road network density.

Keywords:
Medical Facility
POI Data
Gaussian-2SFCA
Spatial Accessibility
Matching Supply and Demand

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Accessibility Analysis of Healthcare Facilities in Guangzhou Using the Gaussian Two-Step Floating Catchment Area Method (Ga2SFCA)

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Abstract The Spatial accessibility to healthcare resources is a key indicator for measuring the fair and impartial of public services in cities and assessing equity in residents' access to healthcare. The traditional two-step Floating Catchment algorithm (2SFCA) overlooks the effect of distance attenuation, making it difficult to capture the objective pattern whereby demand for healthcare gradually diminishes as travel costs increase. This study takes the entire city of Guangzhou as its research area, using the number of people in medical institutions at all levels to represent supply capacity and the population within a grid system as the demand base. It employs the Gaussian two-step Floating Catchment algorithm (Ga2SFCA), combined with travel time resistance derived from the road network, to construct a model of healthcare resource accessibility. By comprehensively utilising Kernel Density Estimation, global spatial autocorrelation (Moran's I) and hotspot analysis, the study identifies the spatial differentiation patterns and agglomeration characteristics of healthcare resource accessibility in Guangzhou. The results indicate that: (1) The spatial distribution of medical facilities in Guangzhou exhibits an unbalanced pattern characterised by 'high concentration in the city centre, uneven distribution in the inner suburbs, and a shortage in the outer suburbs'; (2) Accessibility to healthcare resources in Guangzhou exhibits a decreasing pattern from the core to the periphery, with high levels of accessibility concentrated in central urban districts such as Yuexiu, Tianhe and Haizhu, whilst peripheral areas such as Conghua, northern Zengcheng and western Nansha exhibit significantly lower levels of accessibility; (3) The accessibility index exhibits significant positive spatial autocorrelation, with high-high clusters concentrated in the old urban areas, whilst low-low clusters are distributed across the northern mountainous regions and the outlying suburbs. The findings of this study can provide spatial decision-making support for the optimisation of healthcare facility layout in Guangzhou, the implementation of tiered medical care, and the balanced allocation of public health resources.

1. Introduction

Spatial accessibility to healthcare resources is a key tool for characterising spatial equity in public services. It enables a quantitative characterisation of the interrelationship between healthcare supply capacity, population demand

and transport costs, and serves as a vital basis for identifying areas with inadequate healthcare provision, supporting healthcare planning and advancing the implementation of tiered medical care (Chen, B. et al. 2024; Bai, J. et al. 2026; Cao, Y. et al. 2022). Guangzhou is a core megacity in South China with a robust foundation of healthcare resources, hosting a large number of Grade A3 general hospitals, specialist hospitals and primary community healthcare institutions (Jin, M et al. 2019; Ni, J et al. 2019). However, influenced by factors such as the city's historical development, topographical conditions and the phasing of new district development, the uneven spatial distribution of healthcare resources remains a prominent issue: healthcare facilities are concentrated in the central urban areas, where high-quality healthcare provision is abundant (Chao, R. et al.2024; Yu, M. et al.2023); conversely, large general hospitals are scarce in the outlying suburbs (Li, J. et al. 2022), whilst the development of healthcare infrastructure in some rapidly growing near-suburban areas has lagged behind. Consequently, residents face high time costs when seeking medical care across different regions, and the imbalance between supply and demand is particularly pronounced (Chen, X. et al.2026). The "Guangzhou Healthcare Facilities Layout Plan (2021–2035)" (Website,2024.) explicitly sets out the tasks of addressing healthcare shortcomings in outlying areas, allocating healthcare resources according to tier, and improving access to healthcare services. This requires a quantitative evaluation method that takes into account travel time costs and distinguishes between different tiers of healthcare institutions, in order to conduct a detailed assessment of healthcare accessibility across the entire city.

The accessibility of facilities is a core component of evaluating equity in public services (Chen, B. et al. 2024; Dai, S. 2025; Dong, J. et al. 2022; Kang, S. et al. 2025; Mao, K. et al. 2023; Sun, Y. 2025; Xu, C., & Sun, Y.2026). It aims to quantify the relationship between the supply of facilities, population demand and spatial barriers, thereby providing a basis for the optimal spatial allocation of public resources (Yu, Y. et al.2023; Zhang, K. et al. 2025). With the continuous development of GIS spatial analysis techniques, accessibility models have gradually evolved from early simple ratio methods (Salonen, M., & Toivonen, T. 2013; Zhao, F. et al.2003), buffer zone methods (Malekzadeh, A., & Chung, E. 2020) and gravity models (Ergen, M. 2020; Cheng, M.et al. 2021) towards search-based models; the Two-Step Flow Computation Approach (2SFCA) and its extended series of models (Dong, J. et al. 2022; Liu, S. et al. 2020; Cao, Y. et al. 2022; Zhang, S. et al. 2021) have become the mainstream tools for research into the accessibility of public service facilities in China.

The 2SFCA method, which is essentially a special case of the gravity model (Luo, W., & Wang, F.2003). This method takes into account both the scale of facility supply and the demand population, and achieves supply-demand matching by setting a fixed search threshold (Kang, S., & Lee, G.2025). It overcomes the shortcomings of traditional gravity models—namely, the difficulty in interpreting their parameters and the ambiguity of their thresholds—and has been widely applied in the evaluation of public services such as healthcare (Kang, S., & Lee, G.2025; Li, F. et al. 2024), sports (Xu, C., & Sun, Y. 2026), parks (Mao, K. et al. 2023; Cao, Y. et al. 2022) and green spaces (Sun, Y.2025; Zhang, K., & Chen, M.2024), elderly care (Gu, M. et al. 2025; Jin, M. et al. 2023; Zhang, K. et al. 2025) and education (Chen, B. et al. 2024; Zhou, T. et al. 2025). However, its inherent limitations have gradually been highlighted by the academic community: it assigns equal weights to all demand points within the search threshold range, making no distinction based on distance (Liao, Y., & Furuya, K. 2024); it ignores the fact that residents' willingness to use public services diminishes as travel costs rise; and it exhibits significant deviations from actual travel behaviour (Liang, Y. et al. 2023; Song, Q. et al. 2026). To address this shortcoming, scholars have successively introduced various forms of decay functions, giving rise to multiple extended 2SFCA models (Liang, Y. et al. 2023; Song, Q. et al. 2026; Mao, K. et al.2023, Li, J., & Yan, H.2020; Liao, Y., & Furuya, K.2024; Jin, M. et al.2023), including the exponential 2SFCA, kernel density 2SFCA, and the Ga2SFCA. Among these, the Ga2SFCA employs a continuous, smooth Gaussian decay function, whereby weights decrease gradually from near to far within the threshold and drop to zero once the threshold is exceeded. The decay curve more closely aligns with the psychological patterns of residents' behaviour regarding medical care (Yang, X. et al.2025), recreation and other activities (Dong, J. et al2022.); the model is highly stable and has the widest range of applications. In the healthcare sector, a large number of domestic scholars have utilised the Ga2SFCA (Chao, R. et al.2024; Chen, X. et al.2026; Liang, Y. et al.2023; Song, Q. et al.2026) to evaluate medical resources in provincial capitals and megacities, with research focusing on the distribution of medical facilities in central urban areas, the accessibility of emergency medical services, and the assessment of primary community healthcare service zones.

Existing studies (Ngui, A. et al.2011; Sui, J. et al.2023; Long,H. et al.2025; Kang, S., & Lee, G.2025) predominantly characterise healthcare demand using the total permanent resident population, implicitly assuming that 'demand is of equal intensity across different age groups'. This runs counter to the consensus in health services research that age is a key determining factor, and also makes it difficult for measures of accessibility to identify the actual supply-demand mismatches arising from differences in population structure. This article refers to the existing research experience and achievements (Yu, P. et al.2021; Sui, J. et al.2023), the age structure of the population is incorporated into the demand side, with the 15–64 age group set as the baseline 1.0; with the relative demand weights for the 0–14 age group and the 65 and over age group set at 1.2 and 2.5, respectively. This means that the healthcare demand of one person in the 0–14 age group is equivalent to that of 1.2 people in the 15–64 age group, and equivalent to that of 2.5 people in the 15–64 age group. This transforms the demand metric from population size to demand intensity, thereby completing the logical loop of 'demographic structure – service utilization – spatial accessibility', and providing quantifiable and comparable criteria for 'age-friendly' and 'spatial justice'. This drives the allocation of healthcare resources away from a 'per capita' approach towards one based on 'weighted demand'. It provides a quantitative basis for prioritising the expansion and refurbishment of healthcare facilities (Ngui, A. et al.2011; Long,H. et al.2025), whilst also offering assessment criteria for primary-care networks that more closely reflect actual usage within the context of tiered diagnosis and treatment.

This study took the 11 administrative districts of Guangzhou as its study area and utilised travel time via the road network as a measure of spatial impedance. Using the two-step Gaussian moving search method, differentiated time thresholds were set for healthcare facilities of different levels; combined with population data on a 1 km × 1 km grid, the study comprehensively assessed the accessibility of healthcare facilities at various levels under different modes of travel. Utilising methods including kernel density estimation, global spatial autocorrelation and Getis-Ord Gi* hotspot analysis (Kamara, et al. 2026), a quantitative analysis of the spatial distribution and accessibility patterns of healthcare facilities was conducted. This study revealed the spatial disparities and clustering characteristics of healthcare accessibility in Guangzhou and identified areas with insufficient healthcare resources. It aims to provide a scientific basis for healthcare spatial planning, the development of healthcare alliances and the realisation of equitable public services in Guangzhou.

2. Materials and Methods

2.1. Study Area

Guangzhou is situated at the heart of the Pearl River Delta and comprises four core urban districts—Yuexiu, Liwan, Haizhu and Tianhe—three near-suburban districts—Baiyun, Huangpu and Panyu—and four far-suburban districts—Huadu, Nansha, Conghua and Zengcheng, with a total area of 7,434.4 km^2 (e.g., Figure 1.). In 2020, the city's permanent resident population reached 18.7403 million, making it a typical megacity. Guangzhou has a vast population and a distinct stratification of urban zones: the core districts are well-developed and concentrated with medical resources; the near-suburban areas are experiencing rapid population growth; whilst the far-suburban areas are vast, with a dispersed population and a shortage of large-scale medical facilities. The disparity between the supply and demand for healthcare resources is striking. The 'Guangzhou Healthcare Facilities Layout Plan (2021–2035)' (Website,2024.) sets out the objectives of balancing the distribution of healthcare resources, enhancing primary healthcare service capacity, and advancing the development of 15-minute healthcare access zones (Zhou, T. et al.2025). It highlights the practical need for an assessment of healthcare resource accessibility. Consequently, conducting a spatial accessibility analysis of Guangzhou's healthcare resources is of great significance for optimising the allocation of healthcare resources and enhancing equity in healthcare services.

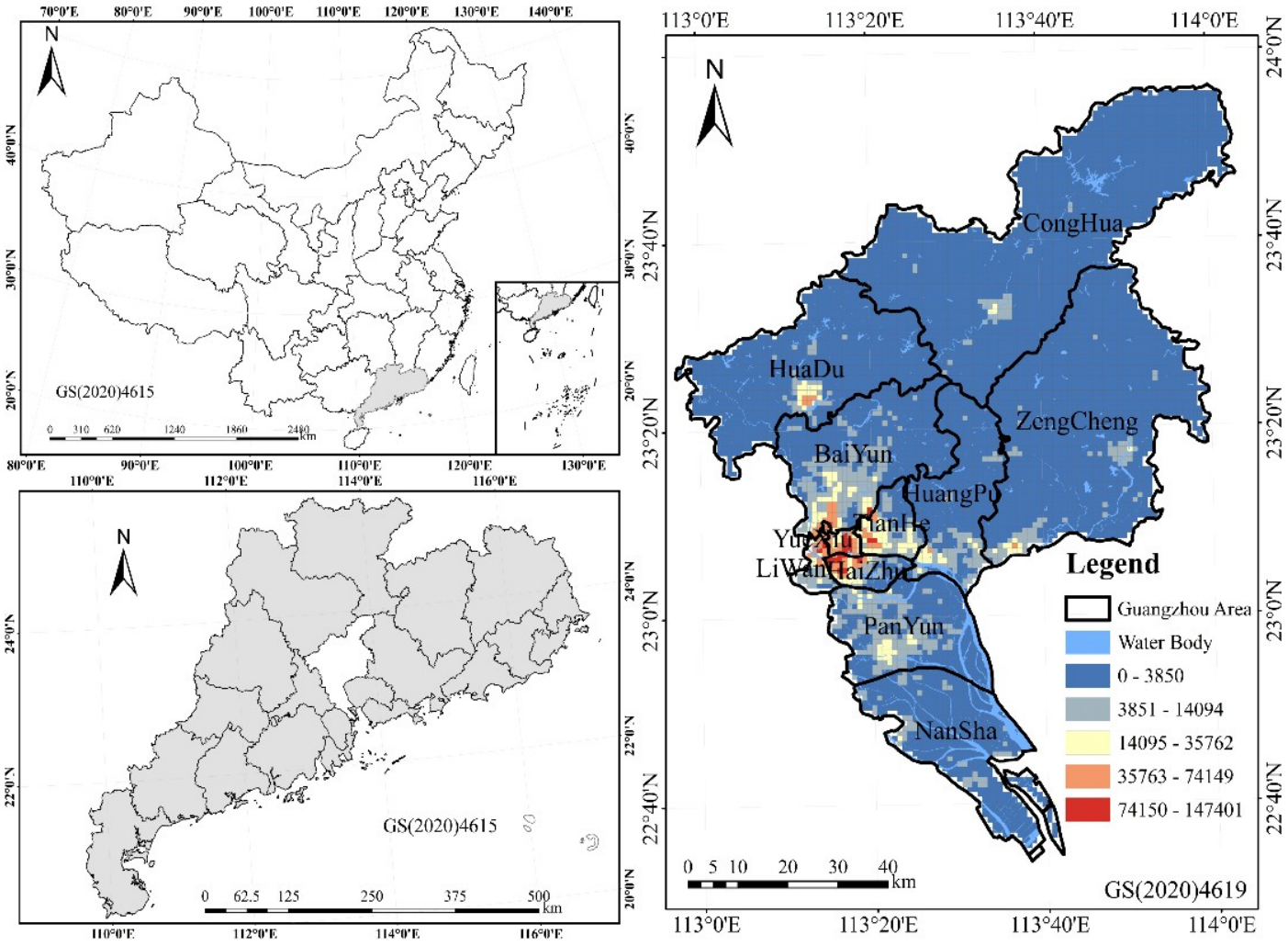

Fig. 1 Study area

2.2. Data Sources and Preprocessing

(1) Healthcare POI data: Sourced from the Amap Open Platform, 876 raw healthcare locations were collected via web scraping. Following deduplication, error correction, filtering and the removal of invalid locations, 656 valid healthcare POIs were retained. In accordance with the national standards for the classification of medical institutions and the requirements of the tiered diagnosis and treatment system, the data was categorised into three types (Li, F. et al,2024; Liu, L. et al, 2023): 56 tertiary-level medical institutions, 259 Secondary healthcare institutions, and 341 primary-level medical institutions, to align with differentiated service capabilities and search thresholds.

Table 1. Classification of Public Healthcare Facilities in Guangzhou

Level	*Hospital Category Names*	*Travel time(minutes)*
Primary healthcare institutions	Community health service posts, Community health service centres, Clinics and Township health centres	15
Secondary healthcare institutions	Specialist hospitals, Dental hospitals, District general hospitals, District traditional Chinese medicine hospitals, and Branch hospitals of affiliated hospitals	20
Tertiary-level medical institutions	Grade 3A hospitals, General hospitals, and University Affiliated hospitals	30

* The distances for walking 15 minutes, 20 minutes and 30 minutes are set as 1 km, 1.5 km and 2 km respectively. After cycling for 15 minutes, 20 minutes, and 30 minutes, the distances covered were 4 km, 5 km, and 6 km respectively.

Table 2. Statistics on healthcare facilities of different grades across the districts of Guangzhou

Districts	*Primary healthcare institutions*	*Secondary healthcare institutions*	*Tertiary-level medical institutions*
Liwan	33	21	8
Yuexiu	20	21	14
Tianhe	33	35	7
Haizhu	36	22	11
Baiyun	52	50	3
Huangpu	44	19	4
Panyu	65	24	3
Huadu	16	14	4
Conghua	23	16	1
Zengcheng	9	20	1
Nansha	10	17	0

(2) Demand-side population data: The 2020 population data for Guangzhou from the WorldPop dataset was resampled into 1km × 1km grids using the results of the Seventh National Population Census. the population aged 0–14 group, the population aged 15–64 group, and the population aged 65 and over group. This was done in order to accurately characterise the spatial distribution of the population at the micro-scale, thereby avoiding errors caused by the averaging of traditional street-level population data and improving the accessibility calculations accuracy (Ni J, et al. 2019; Song Q, et al. 2026). The study area consisted of a total of 6786 grids, with 310 located in the main urban area, 1615 in the near-suburban areas 4861 in the far-suburban areas.

(3) Auxiliary spatial data: A topological check was carried out on the road network data using Guangzhou's administrative division vector data (GS (2020)4619, sourced from the National Geographic Information Public Service Platform) and city-wide road transport network data, a topological check was carried out on the road network data to ensure its accuracy. Driving speed parameters were also set in accordance with the road network hierarchy specified in Table 3.

To ensure consistency and accuracy in the spatial analysis, all the data were converted to the same projected coordinate system.

Table 3. The driving speed parameters of the road network in Guangzhou have been set to specific values

No.	*Level*	*Driving Speed (km/h)*
1	High Speed Road	80
2	Urban expressway	60
3	Main city roads	60
4	Secondary urban roads	30
5	Urban side streets	30

2.3. Methodology

2.3.1. Kernel Density Estimation

Kernel density estimation (KDE) identifies changes in facility density to characterize the spatial distribution and clustering of healthcare facilities (Kamara, D. et al.2026; Spencer, J., & Angeles, G.2007). By calculating the spatial density at each facility location, it provides a visual representation of the spatial concentration patterns and hot and cold spots of public service facilities; higher density values indicate a more concentrated distribution of facilities, enabling the precise identification of areas with high concentrations and those with gaps in provision.

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} k(\frac{x-x_i}{h}) \quad (1)$$

In the formula (1): f(x) represents the estimated kernel density; n is the number of measurement points for medical facilities; h is the search bandwidth; k is the kernel function; and $x - x_i$ is the difference in distances between measurement points. The higher the kernel density value, the greater the concentration of events, and the denser the layout of medical facilities.

2.3.2. Gaussian Two-Step Floating Catchment Area Method (Ga2SFCA)

The Two-Step Floating Catchment Area Method (2SFCA) is a classic method for assessing spatial accessibility and is widely used to calculate the accessibility of various types of public service facilities. Its core principle involves calculating the spatial interaction between demand points and supply points through a two-step search process. The Gaussian Two-Step Flow Computation Algorithm (Ga2SFCA) is an improved version of the 2SFCA; The advantage of the Gaussian decay function lies in its ability to reflect the smooth decline in access to healthcare services as distance increases; the further away residents are, the less likely they are to use the facility, although it is not entirely inaccessible, which better reflects actual healthcare-seeking behavior. It introduces a Gaussian distance attenuation function based on the traditional Two-Step Flow Computation Algorithm (Song, Q. et al.2026), enabling it to more accurately reflect the continuous attenuation characteristics of healthcare resources as distance varies. The core calculations of the Ga2SFCA method are divided into two steps:

Step 1: Calculate the supply-to-demand ratio for each level healthcare facilities at R_j

In the first step, centred on healthcare facility j and using the threshold time as the search radius, the supply-demand ratio is calculated for all demand points k (the central points of the population grid) within the search range, as shown in Equation (2): within the search time threshold set for this type of healthcare facility, all residential points k that are likely to use this type of facility are identified. Weigh the population demand of settlement k using a Gaussian distance attenuation function, and calculate the supply-to-demand ratio for facility j, denoted by R_j.

$$R_j = \frac{S_j}{\sum_{k\in\{t_{kj}\le t_0\}} G(t_{kj},t_0)D_k} \quad (2)$$

S_j: The service capacity of healthcare facilities (number of healthcare staff); D_k: The population demand of the settlement (weighted);$G(t_{kj}, t_0)$: Gaussian distance attenuation function.

$$G(t_{kj}, t_0) = \begin{cases} \frac{e^{-\frac{1}{2}\left(\frac{t_{kj}}{t_0}\right)^2} - e^{-\frac{1}{2}}}{1-e^{-\frac{1}{2}}}, & t_{kj} \le t_0 \\ 0, & t_{kj} > t_0 \end{cases} \quad (3)$$

t_{kj}: The travel time via the road network from settlement k to healthcare facility j; t_0: The search time threshold for this type of healthcare facility.

Step 2: calculate settlement of the accessibility index A_k

In the second step, taking settlement k. as the centre, within the specified travel time threshold (e.g.,Table 2), aggregate the supply-to-demand ratio (denoted by R_j) for each medical point is summed based on the Gaussian decay function to obtain the distance-based accessibility and calculate the accessibility index (denoted by A_k) for settlement k.

$$A_k = \sum_{j\in\{t_{kj}\le t_0\}} G\left(t_{kj}, t_0\right) R_j \quad (4)$$

Where: Uppercase A_k: the medical facilities accessibility index for settlement k; a higher value indicates a more abundant supply of medical facilities accessibility at that location.

According to this equation, the key factors used to measure access to healthcare services via the Gaussian 2FSCA method include the service capacity of healthcare facilities, the resident population, and the time (distance) costs of the road network. Among these, the number of healthcare professionals is a commonly used key indicator reflecting the service level of healthcare facilities. The resident population is determined using the grid-level population data obtained in the previous step. The Gaussian distance decay function gradually reduces the weights assigned to individual residential locations and facilities as travel time (distance) within the road network of the service area increases.

The comprehensive accessibility of healthcare facilities at each level can be set according to the strength of preference for different modes of transport (Zhu, R., & Liu, X.2026; Ni, J., et al.2019). Finally, by setting parameters in accordance with existing research (Zhu, R., & Liu, X.2026; Xu, H., et al.2023) and assigning weights to healthcare accessibility at each level (e.g.,Table 4). These weightings reflect the relative contributions of the three tiers of care to the overall healthcare system, taking into account differences in their scope of services, functional complexity and the types of healthcare needs they address.

The total medical services function is obtained through the index superposition method, and the specific expression is as follows:

$$T_A = \sum_{k=1}^{3}\sum_{l=1}^{3} n_{kl} \times A_{kl} \quad (5)$$

Here, T_A represents the overall accessibility of healthcare services accessibility, and A_{kl} denotes the accessibility of k-level healthcare facilities via the lth mode of transport. n_{kl} is the weighting coefficient for the accessibility of k −level healthcare facilities via the lth mode of transport (e.g.,Table 4).

Table 4. Setting of accessibility-weighted parameters for medical facilities of various grades under different travel modes

Level	*Walking*	*Biking*	*Driving*	*Total*
Primary healthcare institutions	0.51	0.24	0.25	0.15
Secondary healthcare institutions	0.2	0.37	0.43	0.35
Tertiary-level medical institutions	0.05	0.15	0.8	0.50

2.3.3. Global Spatial autocorrelation

Global spatial autocorrelation analysis is used to describe the spatial correlation and difference level of medical facilities accessibility in the entire study area. The global Moran's I test (Kamara, D. et al.2026; Khan, M.et al.2023; Liu, S.2019) was employed to analyse the overall spatial autocorrelation characteristics of medical facilities accessibility

in Guangzhou; This study used ArcGIS pro 3.4.0 software to calculate the global Moran's I to quantify the overall spatial correlation degree of the medical facilities accessibility. The calculation formula is as follows:

$$I = \frac{\sum_{x=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{j=1}^{n}\sum_{k=1}^{n} W_{ij}\sum_{j=1}^{n}(x_i - \bar{x})^2} \quad (6)$$

In formula (6), I is the global Moran's I; n represents the total number of grid cells. x_i and x_j denote each level medical facilities accessibilities values of grid cells i and j, respectively. $\bar{x}$ is the mean accessibility value across all grid cells. W_{ij} is the spatial weight matrix, defining the spatial relationship between units i and j. The value range of global Moran's I is [−1,1]. If $I > 0$ and passes the significance test, it indicates a positive correlation between the medical facilities accessibility; if $I < 0$ and passes the significance test, the medical facilities accessibilities are negatively correlated; and if $I = 0$ and passes the significance test, the spatial distribution of the medical facilities accessibility has randomness. In addition, a standardized Z-statistic test method is needed to determine whether the global Moran's I is significant.

2.3.4. Getis-Ord Gi* hotspot analysis

Getis-Ord Gi* analysis (hot spot analysis) can also identify the spatial difference in the overall accessibility of medical facilities within the study area (Shen, Y., & Tao, Y.2019; Kamara, D. et al.2026; Khan, M.et al.2023; Liu, S.2019). The results of which can supplement that of cluster and outlier analysis. Comparisons can be made accordingly. GIS provides the hot spot analysis tool to calculate Getis-Ord Gi* statistics for each level medical facilities in the dataset to identify spatial clusters of statistically significant hot spots (with high values of Gi*) and cold spots (with low values of Gi*). It also presents the locations where hot and cold spot elements cluster in space. An element should have a high (low) value and be surrounded by other elements that also have high (low) values to be a hot (cold) spot. The formula is as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j}x_j - \bar{X}\sum_{j=1}^{n} w_{i,j}}{S\sqrt{\frac{\left[\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}^2\right)^2\right]}{n-1}}} \quad (7)$$

where G_i^* is the Getis-Ord local statistic that is a z-score; x_j is the spatial accessibility for population grid j; n is the total number of population grids; and w_i,j is the spatial weight between population grid i and j.

A distance-threshold weighting scheme was applied to the spatial weight matrix, with calculations and visualisation carried out in ArcGIS.

3. Results and Discussion

3.1. Spatial Distribution Patterns of Healthcare Facilities

In terms of primary healthcare facilities (e.g., Table 1.), Baiyun, Huangpu and Panyu Districts have the highest numbers; the central urban districts of Haizhu, Yuexiu and Liwan have the Second highest numbers, whilst the outlying districts of Huadu, Zengcheng and Nansha have the fewest; the distribution of Secondary healthcare medical institutions is relatively even, with the highest numbers in central urban districts such as Baiyun and Tianhe, whilst other areas show little variation, with around 20 institutions each Tertiary-level medical institutions. Yuexiu, Liwan, Tianhe and Haizhu have a relatively high number, whilst the distribution in the near-suburban areas of Baiyun, Huangpu, Panyu and Huadu is next highest, with Conghua, Zengcheng and Nansha having the fewest.

Nuclear density analysis was used to illustrate the spatial layout characteristics of healthcare facilities at various levels, as shown in Figure 2.

Analysis of primary healthcare facilities and their density (e.g., Figure 2(a).) reveals a concentrated distribution in core urban areas such as Liwan, Yuexiu, western Haizhu and western Tianhe, whilst a slight concentration is evident in

the near-suburbs of southern Baiyun, southern Huangpu and central Panyu. In the outlying suburbs—including Nansha, Zengcheng, Conghua and Huadu—no such pattern of concentration was observed.

Secondary healthcare facilities exhibit (e.g., Figure 2(b).) a highly concentrated distribution pattern in the north-western parts of Yuexiu, Liwan and Haizhu, the western part of Tianhe, and the southern part of Baiyun; a slightly concentrated pattern is observed in the central part of Panyu, the southern part of Huangpu, the central part of Conghua and the southern part of Huadu; whilst no such concentration is evident in the outlying districts of Nansha, Zengcheng, the northern part of Conghua and the northern part of Huadu.

Tertiary healthcare institutions (e.g., Figure 2(c).) are highly concentrated in the central urban areas of districts such as Liwan and Yuexiu in the northwestern Haizhu, with a relatively limited geographical spread; whilst in central Tianhe and Huangpu, southern Baiyun and southern Huadu, they exhibit a slight concentration, with no such concentration observed in other areas.

Medical institutions of all levels are very high concentrated in core urban districts such as Yuexiu, Liwan, Haizhu and Tianhe, with a relatively wide geographical distribution; and in the near suburbs—namely the southern Baiyun, southern Huangpu and the central part of Panyu—the concentration is high; whilst in the outlying suburbs of Conghua, Huadu, Zengcheng and Nansha, no pattern of concentration is evident (e.g., Figure 2(d).).

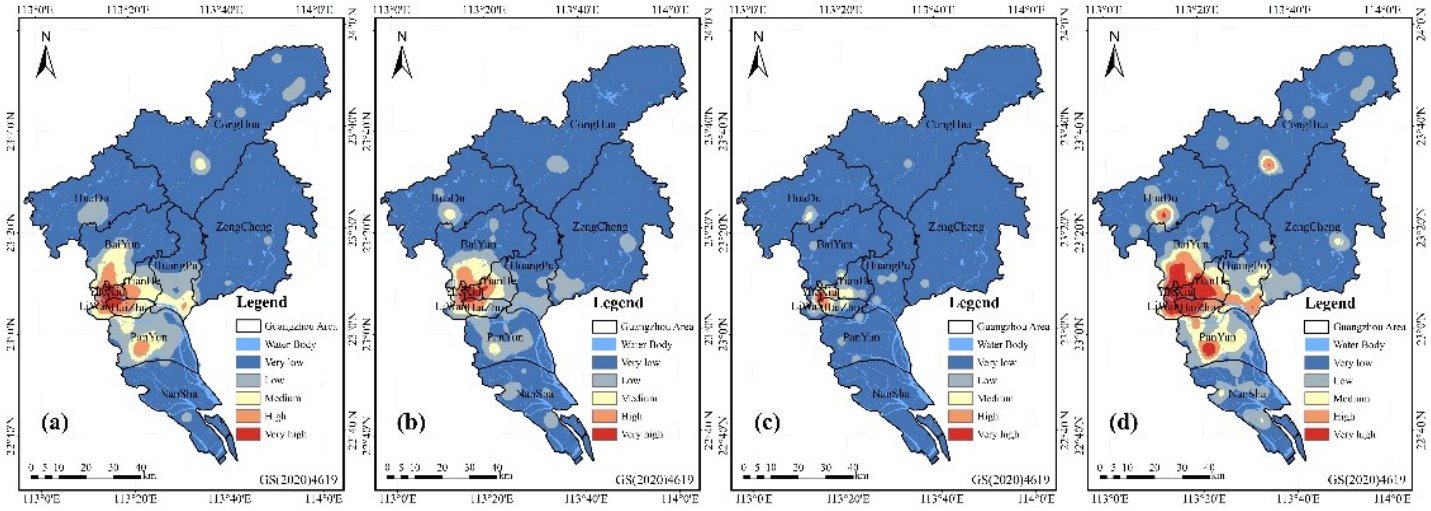

Fig. 2 Results of the point-by-point density analysis of medical facilities. (a) Results of the analysis of the density of primary healthcare facilities, and (b) Analysis of point-of-care density for secondary healthcare facilities, and (c) Analysis of the density of tertiary healthcare facilities, and (d) Analysis of nuclear density at healthcare facilities of all grades.

3.2. Spatial Distribution of Service Areas for Healthcare Facilities by Travel Time Thresholds in the Road Network.

Using ArcGIS Pro 3.4.0 software, a road network dataset was created by speed setting from Table 2. Using the travel time thresholds for healthcare facilities of different grades shown in Table 1, the service areas for each grade of healthcare facility by different modes of travel were generated as shown in Figure 3. The distance parameters for different time thresholds under the walking, cycling and driving modes are set as shown in Table 1, whilst the specific service distances for the driving mode were calculated by converting the speeds given in Table 2.

In order to better illustrate the scientific rigour and thoroughness of the service coverage provided by primary healthcare institutions in Guangzhou (Zhu, R., & Liu, X.2026; Ni, J., et al.2019), a 15-minute travel time threshold was set for each level of healthcare facility for three modes of transport—walking, cycling and driving (with distances set at

1,000 m and 4,000 m respectively)—thereby defining the catchment areas of primary healthcare facilities within the road network for each mode of transport (e.g., Figure 3(a).).

The coverage of walking-accessible primary healthcare services is relatively limited, extending only within a 1,500-metre radius of healthcare facilities. It covers most of the central urban area, whilst in the near-suburban areas—central Panyu, southern Huangpu, southern Baiyun and southern Huadu—it is scattered. In terms of the coverage area of primary healthcare facilities, the area served within a 15-minute walking is 343.016 km^2, which is merely 4.75 % of Guangzhou's total area and this accounts for 37.98 per cent of Guangzhou's population. The service area for primary healthcare facilities within a 15-minute cycling is 1459.523 km^2, accounting for 20.19 % of Guangzhou area and this accounts for 40.94 % of Guangzhou's population. Meanwhile, the service area for primary healthcare facilities within a 15-minute drive reaches 4,905.591 km^2, accounting for 67.88 % of Guangzhou's total area and this covers 97.49 % of Guangzhou's population.

The catchment areas for secondary healthcare facilities are defined as the accessibility zones within the road network that can be reached within a 20-minute walk, a 20-minute cycle ride or a 20-minute drive (e.g., Figure 3(b).). The coverage of walking-accessible service area for secondary-level healthcare facilities covers 486.760 km^2, accounting for approximately 6.73 % of Guangzhou area and this accounts for 47.69% of Guangzhou's population. The coverage of cycling-accessible service area for secondary-level healthcare facilities covers 1893.714 km^2, accounting for approximately 26.20 % of Guangzhou area and this accounts for 39.41% of Guangzhou's population. The coverage of cycling-accessible service area for secondary-level healthcare facilities covers 5697.852 km^2, accounting for approximately 78.84 % of Guangzhou area and this accounts for 98.49% of Guangzhou's population.

The service area for tertiary healthcare facilities, defined as the accessibility zones within the road network that can be reached within a 30-minute walk, a 30-minute cycle ride or a 30-minute drive (e.g., Figure 3(c).). The coverage of walking-accessible service area for tertiary healthcare facilities covers an area of 188.354 km^2, accounting for approximately 2.61 per cent of Guangzhou area and this accounts for20.94% of Guangzhou's population. The coverage of cycling-accessible service area for tertiary healthcare facilities covers an area of 552.776 km^2, accounting for approximately 7.65% of Guangzhou area and this accounts for 33.69% of Guangzhou's population. The coverage of driving-accessible service area for tertiary healthcare facilities covers an area of 4501.362 km^2, accounting for approximately 62.82 per cent of Guangzhou area and this accounts for 96.38% of Guangzhou's population. The cover encompasses the city's central urban areas and immediate suburbs. However, the southern Nansha, the northern Zengcheng, the north-western outskirts of Huadu, and the northern Conghua are not effectively covered.

The superposition of the maximum coverage areas for different modes of transport across healthcare facilities of various levels, is shown in the Figure 3(d). It covers an area of 5726.662 km^2, accounting for approximately 79.24 % of Guangzhou area and this accounts for 98.52% of Guangzhou's population, with the exception of Conghua, the northeastern part of Zengcheng and the northwestern part of Huadu, which are not effectively covered.

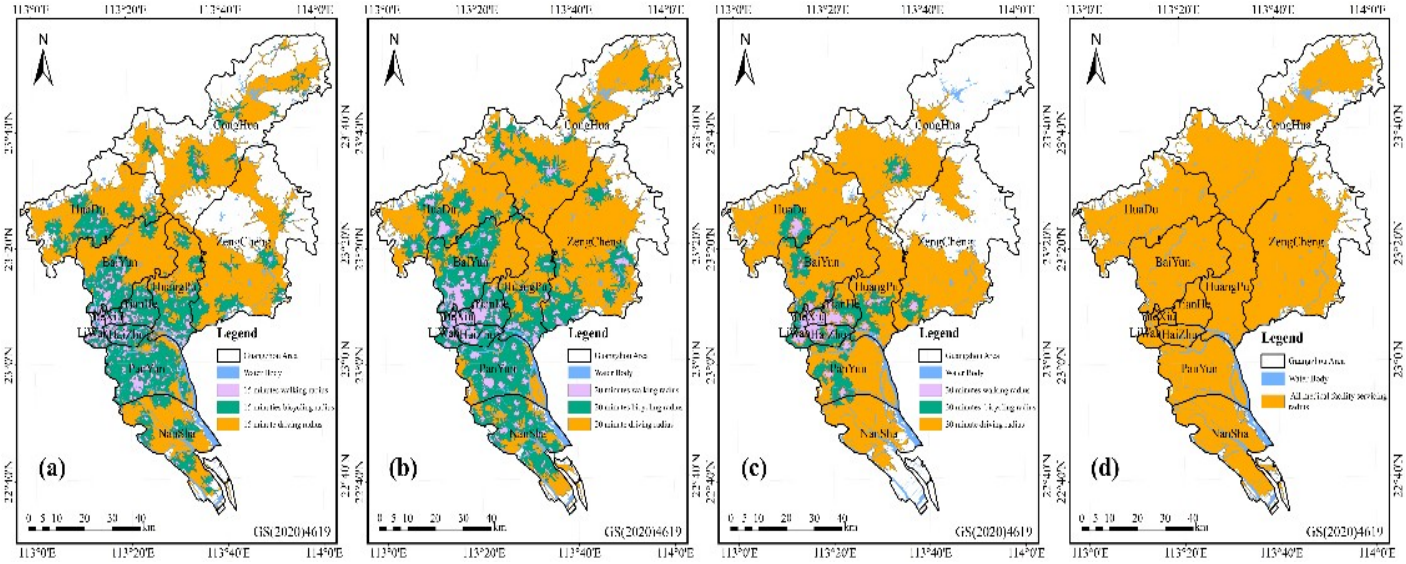

Fig. 3 Scope of services provided by healthcare facilities of different levels. (a) Service coverage of primary healthcare facilities within a 15-minute travel time threshold by walking, cycling and driving on the road network, and (b) Service coverage area of secondary healthcare facilities within a 20-minute time threshold by walking, cycling and driving on the road network, and (c) Service coverage of tertiary healthcare facilities within a 30-minute time threshold by walking, cycling and driving on the road network, and (d) Maximum catchment areas for healthcare facilities of different grades at different time thresholds.

3.3. Spatial Variations in Access to Healthcare Resources using Ga2SFCA

Calculations were carried out using a Ga2SFCA to assess the accessibility of healthcare facilities of various levels in Guangzhou, which was then classified into five levels using the natural breakpoint method: very low, low, medium, high and very high accessibility zones. The cumulative accessibility of each grid cell was determined under scenarios where the travel time threshold for primary healthcare facilities was set at 15 minutes (e.g., Figure 4(a~c).), for secondary healthcare facilities at 20 minutes (e.g., Figure 4(d~f).), and for tertiary healthcare facilities at 30 minutes (e.g., Figure 4(g~i).).

The accessibility classification map for primary healthcare facilities shows that walkable accessibility is relatively high, but coverage is limited, with access spreading only sporadically around individual primary healthcare facilities (e.g., Figure 4(a)). In contrast, the distribution of accessibility by bicycle expands the coverage area compared to walking whilst reducing intensity (e.g., Figure 4(b)). Spatially, distribution is relatively balanced in the central urban area, but intensity is lower in the northern Baiyun and the central and northern Huangpu in the near suburbs, as well as in the southern Zengcheng, the southern Huadu and the central Conghua in the far suburbs. Primary healthcare facilities are sparsely distributed in these areas, but the population served is small; consequently, they exhibit high accessibility values. Under the driving mode (e.g., Figure 4(c).), the accessibility values for primary healthcare facilities further decreased whilst the coverage area expanded and the population served is large; in the central urban area, coverage was widespread, whilst in the near-suburbs—namely southern and northern Huangpu, central Panyu, as well as southern and northern Baiyun, southern Huadu and most of Conghua—coverage was extensive and exhibited a patchy distribution. An anomalous area with high accessibility values appeared in northern Conghua.

A marked stratification was observed in terms of population access to secondary healthcare facilities. Under the walking mode, a pattern emerged characterised by a small coverage area centred on healthcare facilities, yet with high accessibility values; the reasons for this are similar to those observed for primary healthcare facilities under the walking mode (e.g., Figure 4(d).). Compared with the walking mode, the reachability coverage area for the cycling mode increased significantly, exhibiting a patchy distribution pattern (e.g., Figure 4(e).); however, reachability values

weakened somewhat as the population covered increased. Coverage was observed in most areas of the central urban district and in some parts of the near suburbs, whilst in the distant suburbs—specifically central Huadu, south-central Conghua, southern Zengcheng and central Nansha—a patchy distribution pattern was evident. Under the driving mode (e.g., Figure 4(f).), compared with the cycling mode, the reach of accessibility spreads further, showing full coverage in the central urban area and coverage in most of the near-suburban areas, whilst most areas in the far-suburbs—such as Conghua, Huadu, Zengcheng and Nansha—are also covered. However, the intensity of accessibility is further reduced compared to the cycling mode. This is because, given equivalent medical facilities, as the coverage area expands, the number of people served increases significantly, leading to a marked reduction in per capita accessibility to medical facilities. Nevertheless, moderate accessibility is still observed in the central urban area, whilst clusters of high accessibility values appear in central Nansha, south-eastern Zengcheng and central Conghua.

There are significant spatial disparities in the accessibility of tertiary healthcare facilities. When travel walking model (e.g., Figure 4(g).), the coverage area is relatively small but accessibility scores are high; these facilities are primarily concentrated in the central urban districts, with scattered locations in the near and far suburbs. When travelling by bicycle, the coverage area for healthcare facilities shows a marked expansion (e.g., Figure 4(h).), with the central urban area, southern Huangpu and southern Zengcheng exhibiting a distinct band-like distribution, whilst western Panyu, southern Huadu and central Conghua display a scattered, diffuse distribution, resulting in a trend towards reduced accessibility values. When travelling by driving (e.g., Figure 4(i).), the distribution of healthcare facility accessibility exhibits a typical pattern of significant diffusion and gradual decline from the centre outwards. High accessibility values are concentrated in the central urban area, whilst the near-suburbs surrounding the central urban area exhibit a ring-shaped distribution characterised by clusters of moderate accessibility values. In the outlying suburbs, only the southern parts of Zengcheng, and the central-southern parts of Huadu and Conghua, show extensive coverage of low-value areas; accessibility is extremely low in all other areas.

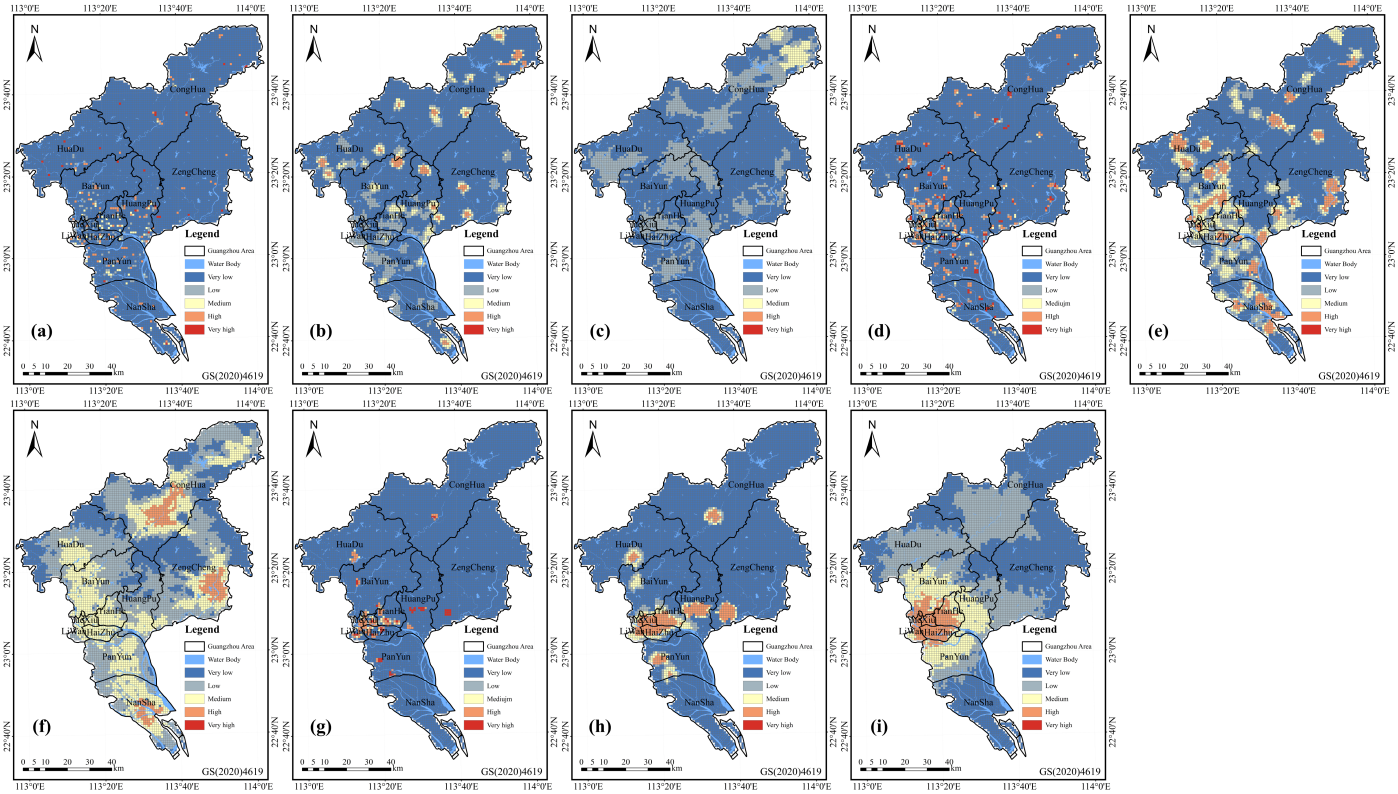

Fig. 4 Spatial distribution of accessibility to healthcare facilities of various levels by mode of transport. Spatial distribution of accessibility to primary healthcare facilities by walking (a), cycling (b) and driving (c); Spatial distribution of accessibility to secondary healthcare facilities by walking (d), cycling (e) and driving (f); Spatial distribution of accessibility to tertiary healthcare facilities by walking (g), cycling (h) and driving (i).

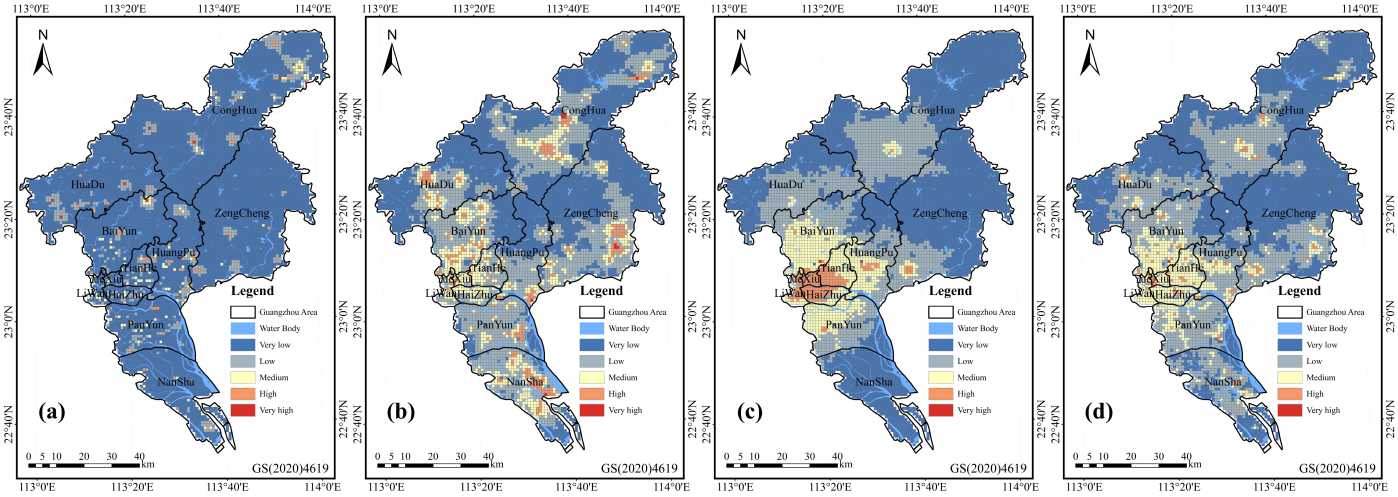

Fig. 5 Spatial Distribution of Accessibility to each Levels Medical Facility at Population Grid (a~c) and weighted comprehensive accessibility of various levels of medical facilities.

A weighted aggregate calculation of the accessibility of healthcare facilities at each level under different travel modes was performed to derive the comprehensive accessibility distribution for healthcare facilities at each level. The weighted average provides a more accurate reflection of the actual accessibility of healthcare facilities in everyday life. Primary healthcare facilities (e.g., Figure 5(a).) have a relatively small reach, exhibiting a scattered distribution that expands radially from the facilities themselves; they are characterised by high accessibility values but a limited coverage area. Similarly, the comprehensive distribution characteristics of secondary healthcare facilities (e.g., Figure 5(b).) show full coverage of the central urban area and coverage of most areas in the near-suburban districts. In the core urban area, spatial clusters with high accessibility values appear in southern Panyu, central Nansha, southern Huangpu, eastern Zengcheng, central Conghua, central Huadu and western Baiyun; whereas in northern Huangpu, northern Zengcheng, northern and southern Conghua, and northern and western Huadu, an irregular distribution with extremely low accessibility values is observed.

The overall distribution pattern of tertiary healthcare facilities (e.g., Figure 5(c).) exhibits a radial pattern, characterised by strong coverage in the central urban area, moderate coverage in the immediate suburbs, and weak coverage in the outlying suburbs; High accessibility values are observed across the entire central urban area and cover the majority of the near-suburban areas; moderate accessibility values are found in northern Panyu, southern Huangpu, southern Baiyun, southern Zengcheng, central Conghua and southern Huadu; whilst extremely low accessibility values are observed in the far-suburban areas of Nansha, northern Zengcheng, northern Conghua, and western and northern Huadu. The weighted composite accessibility of all healthcare facilities (e.g., Figure 5(d).) shows that moderate accessibility covers the entire central urban area, whilst in the suburbs, moderate accessibility is found in south-central Panyu, southern Huangpu, southern Zengcheng, southern Huadu and central Conghua; the remaining areas exhibit extremely low accessibility.

3.4. Spatial autocorrelation and hotspot analysis of accessibility

The Moran's index for the spatial distribution of accessibility to each level healthcare facilities indicating positive spatial autocorrelation. In other words, the positive correlation with accessibility is weakest for primary healthcare facilities (e.g., Figure 6(a).), gradually strengthens for second-tier healthcare facilities (e.g., Figure 6(b).), and is strongest for third-tier healthcare facilities (e.g., Figure 6(c).), with the weighted composite accessibility for all healthcare facilities reaching a maximum positive correlation of (e.g., Figure 6(d).). As can be seen from the changes in the Z-values, with the exception of primary healthcare facilities, where the Z-value was 26.76, the Z-values for all other tiers and for the weighted composite accessibility all exceeded 100 (e.g., Figure 6(b~d).), indicating a pattern of significant clustering.

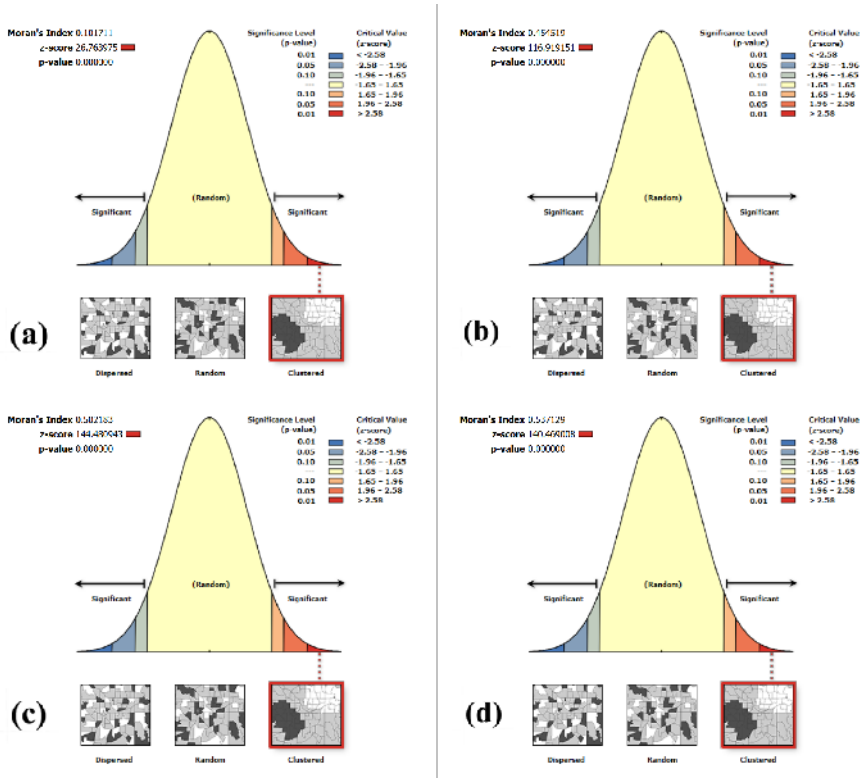

Fig. 6 Report on the Moran Index for the Spatial Distribution of Accessibility to Healthcare Facilities of Various Levels.

The results (e.g., Figure 7(a).) of the spatial distribution analysis of access to primary healthcare facilities indicate significant clusters of low values in areas such as northern Conghua, southern Huadu and northern Huangpu, accounting for approximately 9.24 % of Guangzhou. Clusters of low values were observed in areas such as northern Zengcheng and northern Huadu, accounting for approximately 18.33 % of Guangzhou.

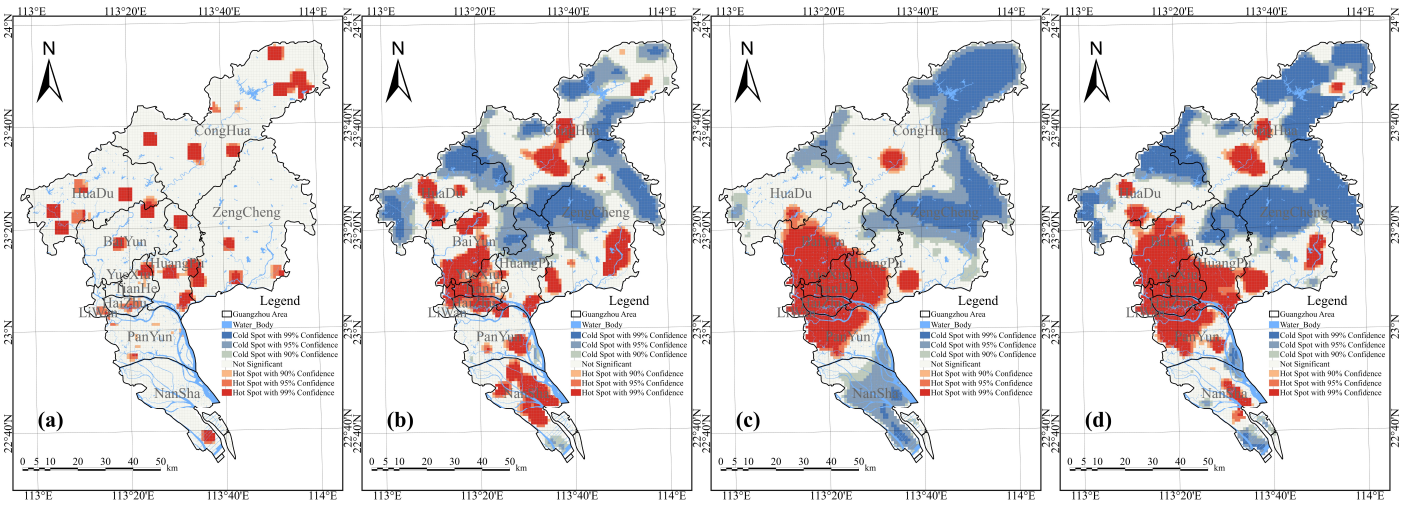

Fig. 7 Analysis of Accessibility to Healthcare Facilities of Various Levels: Spatial Distribution and Hotspot Analysis. (a) Analysis of Hotspots and Coldspots in the Spatial Distribution of Primary Healthcare Facilities Based on Population Grid Cell Accessibility, and (b) Analysis of Hotspots and Coldspots in the Spatial Distribution of Secondary-Level Healthcare Facilities Based on Population Grid Cell Accessibility, and (c) Analysis of Hotspots and Coldspots in the Spatial Distribution of tertiary healthcare facilities Based on Population Grid Cell Accessibility, and (d) Analysis of hotspots and coldspots in the spatial distribution of population grid-based weighted accessibility to healthcare facilities of all levels.

The spatial distribution of accessibility to secondary-level healthcare facilities exhibits greater heterogeneity (e.g., Figure 7(b).), with the central urban area and In the south-western part of Baiyun and the southern part of Huadu, for example, a distinct banded pattern of high-density clustering is evident; in the southern part of Huangpu, the eastern part of Panyu and the northern part of Nansha, a zoned distribution characterised by high-density clustering is observed; high-density clustering is also present in the eastern Zengcheng and the southern Conghua , accounting for approximately 30.07 % of Guangzhou; whilst in the peripheral areas of Conghua, the northern and western Zengcheng, the northern Huangpu, the northern Baiyun and the northern Huadu, a banded distribution characterised by low-density clustering is evident, accounting for approximately 38.11 % of Guangzhou.

The distribution of accessibility to tertiary healthcare facilities (e.g., Figure 7(c).), shows a banded pattern of high-accessibility clusters along the central urban area, northern Panyu, southern Huangpu, most of Yunda and southern Huadu, covering an area accounting for approximately 22.09 per cent of Guangzhou; whilst in southern Nansha, northern Zengcheng and the Conghua area, a pattern of low-accessibility clusters is observed, accounting for approximately 54.36 % of Guangzhou;

The results (e.g., Figure 7(d).), of the spatial hot-spot and cold-spot analysis of weighted accessibility to healthcare facilities of various levels show that extensive clusters of high accessibility have formed in the Xincheng District, as well as in northern Panyu, southern Huangpu, southern Baiyun and southern Conghua. At the same time, a smaller area of high-value clustering has formed in northern Conghua, covering approximately 23.47 per cent of Guangzhou's total area, whilst low-value clustering zones have emerged in eastern Panyu, southern Nansha, northern Zengcheng, the outskirts of Conghua, northern Huangpu and northern Huadu. These areas account for approximately 40.85 per cent of Guangzhou's total area.

4. Discussion

4.1. Uncertainty in the results arising from the ambiguity of the data and the subjective nature of model parameter settings

This study assumed 1 km × 1 km population grid cells as the demand points for the accessibility analysis, rather than actual residential estates, and conducted an accessibility analysis of healthcare facilities at all levels. Consequently, uncertainties in the data may affect the accuracy of the accessibility analysis results; furthermore, during the construction of the accessibility model, whilst young and middle-aged adults were taken as the reference group, the demand weights for healthcare resources were recalibrated for the population aged 0~14 group and 56 and over group. Due to a lack of data on morbidity rates and frequency of visits, the demand for healthcare facilities based on age structure was not considered in terms of morbidity rates or frequency of visits, resulting in deviations from the actual situation.

Certain parameter settings used in the study may affect the results. Firstly, the thresholds for travel times to primary, secondary and tertiary healthcare facilities were all determined by reference to relevant literature; in terms of travel, the impact of public transport (Zhu, R., & Liu, X.2026; Xu, H., et al.2023) —particularly the underground—on travel times to healthcare facilities of various levels was not taken into account, which may differ from the actual situation. Furthermore, when aggregating population figures for each grid cell, no account was taken of the varying demand for healthcare facilities resulting from demographic characteristics such as age and gender distribution. This may affect the results of the spatial layout analysis regarding the accessibility of healthcare facilities across different categories.

4.2. Analysis of Factors Influencing the Results of Accessibility Analyses for Healthcare Facilities

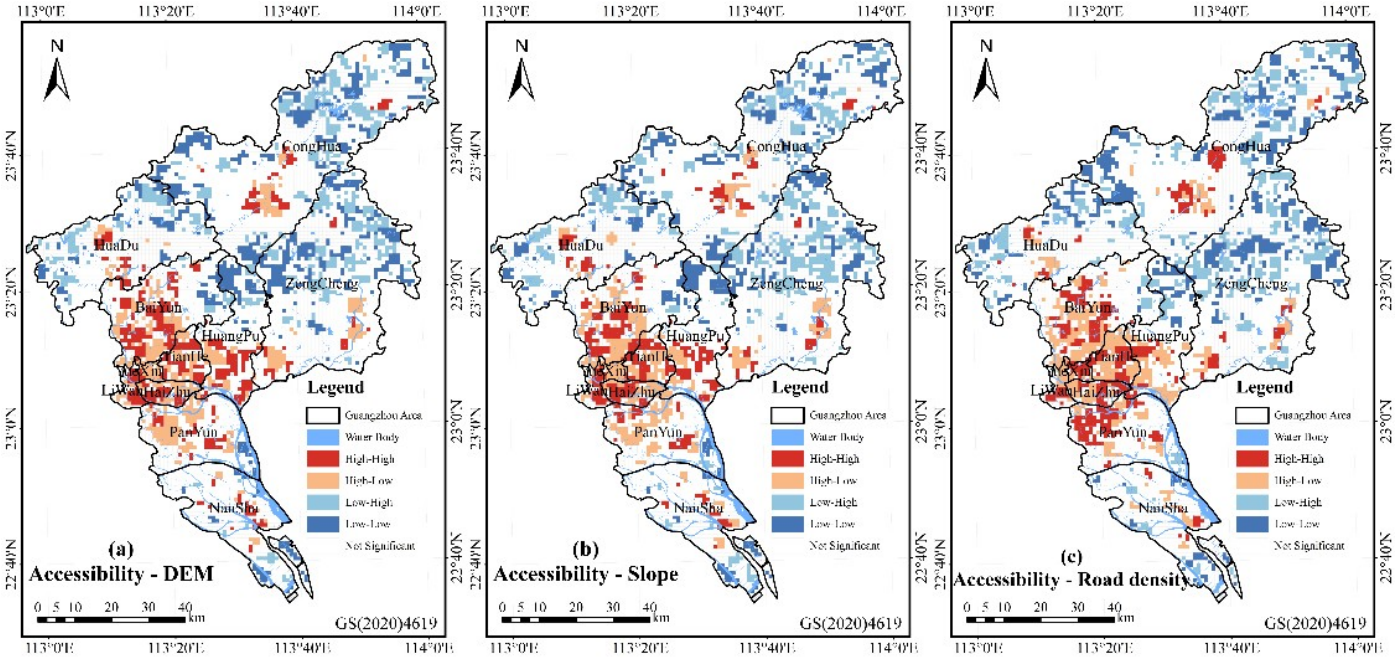

Fig. 8 The results of the Bivariate Spatial Association (Lee's L) between the weighted comprehensive accessibility and factors such as DEM (a), Slope (b) and road density (c).

In order to investigate the correlation between the spatial distribution of accessibility for healthcare facilities and factors such as topography and road network density, the 'bivariate spatial correlation coefficient (Lee's L)' was employed to measure the 'spatial covariation/co-aggregation patterns' between accessibility and these factors.

The results of the bivariate spatial correlation between the spatial distribution of accessibility to healthcare facilities and topographical factors (Figures 8(a–b)) indicate that areas in the central part of Panyu, southern Huangpu and southern Baiyun—all located in the central urban area and its immediate suburbs—exhibit an HH/HL distribution, whilst areas in the central part of Conghua, central Huadu, southern and eastern Zengcheng, and central Nansha—all situated in the outlying suburbs—exhibit HH and HL distributions. Furthermore, the results regarding the correlation between the spatial distribution of healthcare facility accessibility and road network density are consistent with those for topographical factors. The spatial distribution characteristics of healthcare facility accessibility are primarily influenced by factors such as topography and road network density; this also explains why relatively high values of healthcare facility accessibility were observed in eastern Conghua.

5. Conclusion

Based on 2020 Amap POI data, street-level population data from the Seventh National Population Census, and Guangzhou's transport network data, and utilising a combination of kernel density estimation, the two-step moving search algorithm and spatial autocorrelation analysis, this study has reached the following key conclusions:

Significant spatial imbalance: Guangzhou's public healthcare resources generally exhibit a spatial distribution characterised by 'high concentration in the core and a gradual decline towards the periphery', with resource density decreasing progressively from the central urban areas to the outlying districts. There are significant differences in the distribution characteristics of healthcare resources across different tiers: primary healthcare facilities are distributed relatively evenly, providing a network of facilities based on the population of each subdistrict; secondary-level healthcare facilities follow a 'multi-core' layout along urban transport routes; whilst tertiary healthcare facilities are highly concentrated in the core urban districts of Yuexiu, Liwan and southern Tianhe, with the concentration of high-quality resources far exceeding that in the outlying districts.

The level of accessibility to healthcare resources exhibits a typical 'core–periphery' pattern of differentiation. Overall, access to primary healthcare facilities generally aligns with population distribution and largely meets residents' day-to-day healthcare needs; however, coverage of secondary healthcare facilities is insufficient in some remote townships; regional disparities in tertiary healthcare facilities are most pronounced, with residents in remote urban areas facing extremely high out-of-pocket costs when accessing advanced medical services.

This study conducted a systematic analysis of the accessibility of healthcare facilities in Guangzhou using the Ga2SFCA method, revealing the uneven spatial distribution of healthcare resources and providing a scientific basis for optimising the allocation of such resources. Future research could further incorporate factors such as population growth and ageing trends to develop a long-term predictive model for healthcare resource accessibility, thereby providing more comprehensive support for healthcare resource planning in Guangzhou.

Author Contribution

Junchao Wu: Software, Visualization, Writing —original draft; **Xiaolan Zhang:** Formal analysis, Writing—review & editing; **Xuelei Zhang:** Formal analysis, Writing—review & editing; **Jiaqi Zhou:** Data curation, Visualization and Investigation;**Zhaozhong Gao:** Data curation, Visualization and Investigation.

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Conflict of Interests

The authors declare no conflicts of interest.

Data Availability

Data will be made available on request.

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