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Spatial analysis of the impact of urban built environment on cardiovascular diseases: a case study in Xixiangtang, China

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Abstract

Background The built environment, as a critical factor influencing residents' cardiovascular health, has a significant potential impact on the incidence of cardiovascular diseases (CVDs).

Methods Taking Xixiangtang District in Nanning City, Guangxi Zhuang Autonomous Region of China as a case study, we utilized the geographic location information of CVD patients, detailed road network data, and urban points of interest (POI) data. Kernel density estimation (KDE) and spatial autocorrelation analysis were specifically employed to identify the spatial distribution patterns, spatial clustering, and spatial correlations of built environment elements and diseases. The GeoDetector method (GDM) was used to assess the impact of environmental factors on diseases, and geographically weighted regression (GWR) analysis was adopted to reveal the spatial heterogeneity effect of environmental factors on CVD risk.

Results The results indicate that the built environment elements and CVDs samples exhibit significant clustering characteristics in their spatial distribution, with a positive correlation between the distribution density of environmental elements and the incidence of CVDs (Moran's I > 0, $p < 0.01$). Further factor detection revealed that the distribution of healthcare facilities had the most significant impact on CVDs ($q = 0.532$, $p < 0.01$), followed by shopping and consumption ($q = 0.493$, $p < 0.01$), dining ($q = 0.433$, $p < 0.01$), and transportation facilities ($q = 0.423$, $p < 0.01$), while the impact of parks and squares ($q = 0.174$, $p < 0.01$) and road networks ($q = 0.159$, $p < 0.01$) was relatively smaller. Additionally, the interaction between different built environment elements exhibited a bi-factor enhancement effect on CVDs. In the local analysis, the spatial heterogeneity of different built environment elements on CVDs further revealed the regional differences and complexities.

Conclusions The spatial distribution of built environment elements is significantly correlated with CVDs to varying degrees and impacts differently across regions, underscoring the importance of the built environment on cardiovascular health. When planning and improving urban environments, elements and areas that have a more significant impact on CVDs should be given priority consideration.

Keyword Built environment, CVDs, Impact mechanism, Spatial analysis

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Background

Cardiovascular diseases (CVDs) have become one of the most common lethal diseases worldwide, with both the number of affected individuals and the mortality rate continuously rising over the past two decades. Statistical data reveal that from 1990 to 2019, the number of individuals with CVDs globally increased from 271 to 523 million, while deaths climbed from 12.1 million to 18.6 million, accounting for approximately one-third of the total annual global deaths [1]. The severity of CVDs poses not only a global health challenge but also exerts immense pressure on the healthcare system and the economy [2]. According to the World Heart Federation, global medical costs for CVDs are projected to rise from approximately 863 billion US dollars in 2010 to 1044 billion US dollars by 2030 [3]. Thus, it is particularly important to deeply explore the mechanisms that influence CVDs and to develop effective and sustainable strategies to reduce risk and prevent these diseases.

The urban built environment refers to the comprehensive physical structure and man-made surroundings of an urban area, including buildings, transportation systems, infrastructure, land use planning, and elements of natural and artificial spaces [4]. Numerous studies have focused on the close connection between the built environment and human health, particularly with respect to cardiovascular health. Research indicates that the impact of the built environment on cardiovascular health is a process network structure with various influencing factors, including but not limited to factors contributing to CVDs such as obesity, diabetes, high blood pressure [5–10], environmental issues like traffic noise and air pollution [11, 12], as well as aspects of physical exercise, psychological stress, and lifestyle [13–17], all of which collectively affect the pathogenesis of CVDs [18–20]. Studies show that optimizing urban design, such as rational land allocation and planning street layouts, can guide people to access more life services, cultivate proactive attitudes and healthy bodies, thereby reducing the risk of CVDs [21, 22]. Urban spatially compact development models can encourage physical activity, reducing the risk of cardiovascular and metabolic issues [23]. In contrast, long commutes and high traffic density may lead to chronic stress and lack of exercise, increasing the risk of obesity and hypertension. Conversely, appropriate intersection density, land-use diversity, destination convenience, and accessibility might encourage walking, improve health, and reduce the risk of obesity, diabetes, hypertension, and dyslipidemia, which are cardiovascular-related problems [24–26]. The density and accessibility of supermarkets have a direct impact on the dietary habits of community residents, wherein excessive density may increase the risk of obesity and diabetes and correlate with blood pressure levels [27]. Urban green spaces and outdoor recreational areas have a positive effect on cardiovascular health; green spaces not only offer places for exercise and relaxation but also help alleviate stress, improve mental states, and enhance air quality, thus mitigating the harm caused by air pollution and protecting cardiac and vascular health [28]. Research also indicates that individuals residing in areas with high greenery rates are more likely to enjoy opportunities that promote physical activity, mental health, and healthy lifestyles, thereby minimizing CVD risks [29, 30]. In summary, scientific and rational urban planning, such as diversified land use, appropriate building density, good street connectivity, convenient destinations, short-distance commuting, and beautiful environments, are key factors in promoting overall health and preventing CVDs.

Although numerous studies have focused on exploring the relationship between the built environment and CVDs, the specific mechanisms underlying this relationship remain unclear. This knowledge gap is mainly due to the complexity of the built environment itself and the multifactorial pathogenesis of CVDs. Current research mostly concentrates on individual aspects of the built environment, such as noise, air pollution, green spaces, and transportation [31], lacking consideration for the overall complexity of the built environment. Many elements of the built environment are interactive; for instance, pedestrian-friendly urban design may enhance physical activity and social interaction, yet it could also be counteracted by air and noise pollution caused by urban traffic [32]. Therefore, the same element of the built environment might have different effects in different contexts, adding complexity to the study of the built environment. Furthermore, while existing research has exhibited considerable depth and breadth in exploring the complex and dynamic relationship between the built environment and CVDs, many areas still require further improvement and deepening. Traditional linear correlation analyses, such as OLS and logistic regression models, have been widely used to assess the significance level between built environment characteristics and CVDs mortality rates, and to investigate factors such as intersection density, slope, greening, and commercial density [33, 34]. However, these methods fall short in addressing the complexity and non-linear characteristics of spatial data.

Therefore, from a geographical perspective, it is particularly important to adopt more appropriate methods to capture the non-stationarity and heterogeneity of spatial data and to explore the spatial correlation characteristics between the built environment and CVDs. However, current research utilizing spatial models has mainly focused on macro-level perspectives, such as national or provincial levels. For example, ŞENER et al. employed spatial autocorrelation models and hot spot analysis models to assess the spatiotemporal variation characteristics of CVD mortality across multiple provincial administrative regions [35]. Baptista et al. analyzed the impact of factors such as per capita GDP, urbanization rate, education, and cigarette consumption on the growth trends of CVD incidence using spatial lag and spatial error models across different countries or regions [36]. Eun et al. used Bayesian spatial multilevel models to measure built environment variables in 546 administrative districts of Gyeonggi Province, South Korea, and evaluated the impact of the built environment on CVDs [37]. While these studies have, to some extent, revealed the spatial distribution characteristics of CVDs and their spatial relationships with environmental features, the scope of these studies is often large, and they tend to overlook the heterogeneity at the micro-level within cities and its specific impact on residents' health. As a result, it is challenging to accurately capture the differential effects of the built environment on CVD incidence across different areas within a city, and many critical environmental factors at the micro-geographical scale, which are directly related to the daily lives and health of residents, may be obscured.

Given this, we focus on Xixiangtang District in Nanning City, China, and construct a research framework centered on multi-source data, including the distribution of CVDs, road networks, and urban POI data. By employing KDE to reveal hotspot areas, spatial autocorrelation analysis to explore spatial dependence, the GDM to dissect key factors, and GWR to capture the spatial heterogeneity effects, we deeply analyze the complex mechanisms by which the urban built environment influences the incidence of CVDs. Our study aims to answer: Is there a significant spatial association between urban built environment elements and the incidence rate of CVDs? To what extent do different built environment elements impact CVDs? And, what are the regional differences in the impact of built environment elements on CVDs in different areas?

Method

Study area

This study focuses on Xixiangtang District in Nanning City (Fig. 1), an important administrative district located in the northwest of Nanning City, covering an area of approximately 1,276 square kilometers with a permanent population of over one million. As an exemplary early-developed area of Nanning City, the built environment of Xixiangtang not only carries a rich historical and cultural heritage but also witnesses the transformation from a traditional old town to a modern emerging area, forming a unique urban–rural transitional zone. However, with the acceleration of urbanization, Xixiangtang District also faces numerous environmental challenges, such as declining air quality, congested traffic networks, increasing noise pollution, and continuously rising population density, all of which may pose potential threats to residents' cardiovascular health. Therefore, choosing the built environment of Xixiangtang as the core area of this study is not only due to its representativeness but also because the issues faced by this area are of profound practical significance for exploring the health impacts of urbanization and formulating effective environmental improvement strategies.

Data

The CVD case data is sourced from the cardiovascular department's medical records at Guangxi National Hospital. Located in the southeastern core area of Xixiangtang District, near metro stations and densely populated areas, the hospital's superior geographical location and convenient transportation conditions greatly facilitate patient visits, especially for those seeking high-level cardiovascular medical services. Although spatial distance is an important consideration for patients when choosing a medical facility, our study on the spatial distribution patterns of CVDs also takes into account various influencing factors, including socioeconomic status, environmental factors, patient health conditions, and healthcare-seeking behaviors, ensuring the depth and accuracy of the results. Additionally, Guangxi National Hospital is one of the few top-tier (tertiary A) comprehensive hospitals in Xixiangtang District, with its cardiovascular department being a key specialty. The department's outstanding reputation and wide influence, combined with its advantages in equipment, technology, and healthcare costs compared to other non-specialized cardiovascular departments in the region, make it particularly attractive to patients in Xixiangtang, thus rendering the data relatively representative. To ensure the fairness of our study results, we have implemented multiple verification measures, including comprehensive data collection, independent evaluation of medical standards, rigorous statistical analysis, and consideration of healthcare costs.

With authorization from Guangxi National Hospital, we obtained and analyzed the cardiovascular department's data records. Our study adheres to ethical principles and does not involve any operations that have a substantial impact on patients. The cardiovascular data records include basic patient information (such as age, gender, address, etc.), diagnostic information (disease type, diagnosis date, etc.), and treatment records. We focused on CVD patients diagnosed between January 1, 2020, and December 31, 2022. Through systematic

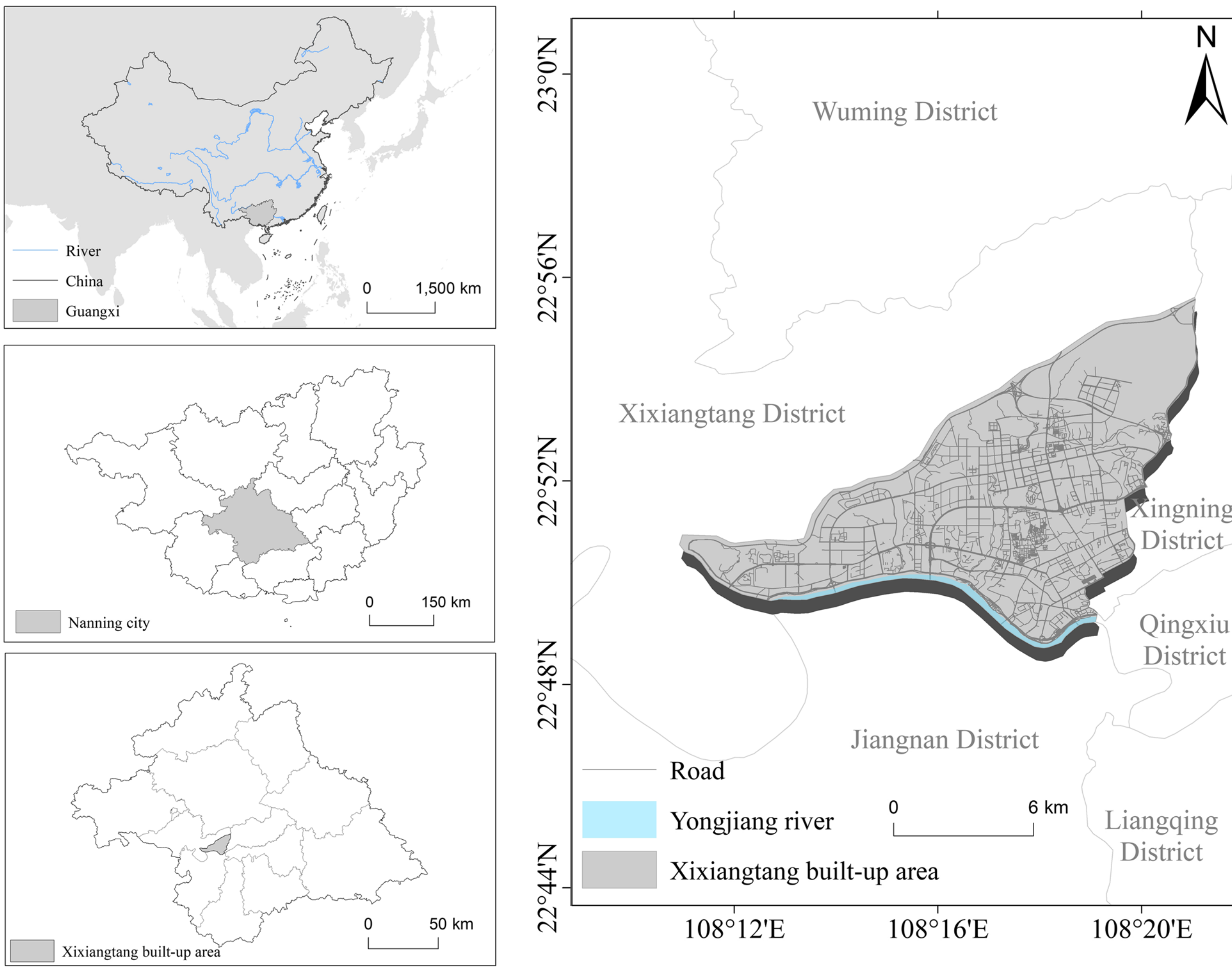

Fig. 1 Location of study area

screening and organization, we constructed a database of CVD patients during this period. During the data processing procedure, we implemented a rigorous data cleaning process, identifying and excluding incomplete, duplicate, or abnormal data records. This included checking for missing data, logical errors (such as extremely large or small ages), and consistency in diagnostic codes, ensuring the quality and reliability of the data. After data cleaning, we selected 3,472 valid samples, which are representative in terms of disease types, patient characteristics, and geographic distribution. Considering the study involves geographic location analysis, we used a text-to-coordinate tool developed based on the Amap (Gaode) API to convert patient address information into precise geographic coordinates. Finally, using ArcGIS 10.8 software, we visualized the processed case data on a map.

As a multidimensional and comprehensive conceptual framework, the built environment encompasses a vast and intricate system of elements. Given the accessibility, completeness of data, and the robust foundation in current research domains, we have centered our in-depth analysis on two core components: the urban road system and urban POIs. Road data is primarily sourced from OpenStreetMap (OSM) and processed using ArcGIS 10.8 to filter and handle incomplete records. We ultimately selected five types of roads for analysis: highways, expressways, arterial roads, secondary roads, and local roads [38]. Urban POI data was selected based on existing research and obtained through Amap. Amap is a leading map service provider in China, known for its vast user data, precise geocoding system, and advanced intelligent analysis technology, which accurately captures and presents the spatial distribution and attribute characteristics of various urban facilities. We used Amap's API interface and offline map data package to obtain the coordinates and basic attributes of POIs in the study area, including six key environment elements: dining [39], parks [40], transportation [20], shopping [41], sports [42], and healthcare [43] (Table 1). These elements significantly reflect the distribution status of the urban

Table 1 Description of indicators of built environmental factors

Environmental indicators	Source	Quantity (unit)	Indicator description
Road network	OSM	692 (lines)	Including the distribution of five main types of roads: expressways, express roads, trunk roads, secondary roads and branch roads
Catering and food	Amap	9905 (individuals)	Including the distribution of Chinese food, foreign food, fast food restaurants, snack shops, milk tea shops, etc
Parks and squares		191 (individuals)	Including the distribution of parks, squares, attractions, zoos, botanical gardens, etc
Shopping and consumption		14,851 (individuals)	Including the distribution of department stores, shopping centers, convenience stores, commercial streets, markets, etc
Transportation facilities		2659 (individuals)	Transportation facilities include the distribution of bus stops, parking lots, subway entrances, toll stations, bus stations, etc
Sports and fitness		442 (individuals)	Including the distribution of fitness centers, basketball courts, badminton courts, swimming pools, gymnasiums, etc
Medical care		2092 (individuals)	Including the distribution of emergency centers, clinics, specialty hospitals, general hospitals, pharmacies, etc

built environment. This comprehensive and detailed data provides a solid foundation for further exploring the relationship between the built environment and cardiovascular health.

Spatial analysis

Based on existing research findings, we have identified key built environment factors that influence the occurrence of cardiovascular diseases (CVDs) and meticulously processed the data sourced from [34, 35, 44]. The preprocessed data was then subjected to spatial analysis utilizing software tools such as ArcGIS 10.8, Geoda, and the Geographic Detector. Through various methods including KDE, spatial autocorrelation analysis (encompassing both univariate and bivariate analyses), factor detection and interaction detection using the Geographic Detector, as well as GWR, we aimed to explore the potential links between the urban built environment and CVDs (Fig. 2).

Kernel Density Estimation (KDE)

Before delving into the complex relationship between the built environment and CVDs, it is crucial to accurately depict the spatial distribution of these key elements within the study area. Given this need, KDE, an advanced non-parametric statistical technique, was introduced as our core analytical tool. KDE is a non-parametric method used to estimate the probability density function of a random variable, and we implemented it using ArcGIS 10.8 software. Compared to other density estimation methods, such as simple counting or histograms, KDE more accurately reflects the true distribution of spatial elements, helping us identify hotspots and cold spots in the city with greater precision. The core of this method lies in assigning a smooth kernel function to each observation point, which describes the influence range of the observation point on its surrounding space, known as bandwidth. The density distribution map of the entire area is then obtained by overlaying the kernel functions of all observation point [45–47]. In parameter settings, we set the cell size to 100 m, based on a comprehensive consideration of the study area's scope, the distribution characteristics of geographic phenomena, and computational resource limitations. This aimed to maintain sufficient precision while avoiding excessive computational burden and amplification of data noise. To further refine the analysis and visually present the continuous spatial distribution of CVDs, we used the natural breaks method to classify the KDE results into five levels. KDE visually displays the continuous spatial distribution of CVDs, identifying high-risk and low-risk areas, and provides foundational data support for subsequent spatial analyses.

Spatial autocorrelation analysis

Spatial autocorrelation analysis is a statistical method used to assess the similarity or correlation between observed values in geographic space. We derived the point attribute values from the kernel density transformation and conducted univariate global spatial autocorrelation analysis, as well as bivariate global spatial autocorrelation analysis between built environment factors and CVDs using Geoda software. Univariate global spatial autocorrelation analysis was used to study the spatial distribution characteristics of the overall dataset, using Moran's I to evaluate whether the dataset exhibits spatial autocorrelation, indicating clustering or dispersion trends [48, 49]. Bivariate global spatial autocorrelation further analyzed the spatial correlation between different indicators [50, 51]. Spatial autocorrelation analysis helps verify whether the spatial clustering in KDE results is significant and preliminarily explores whether

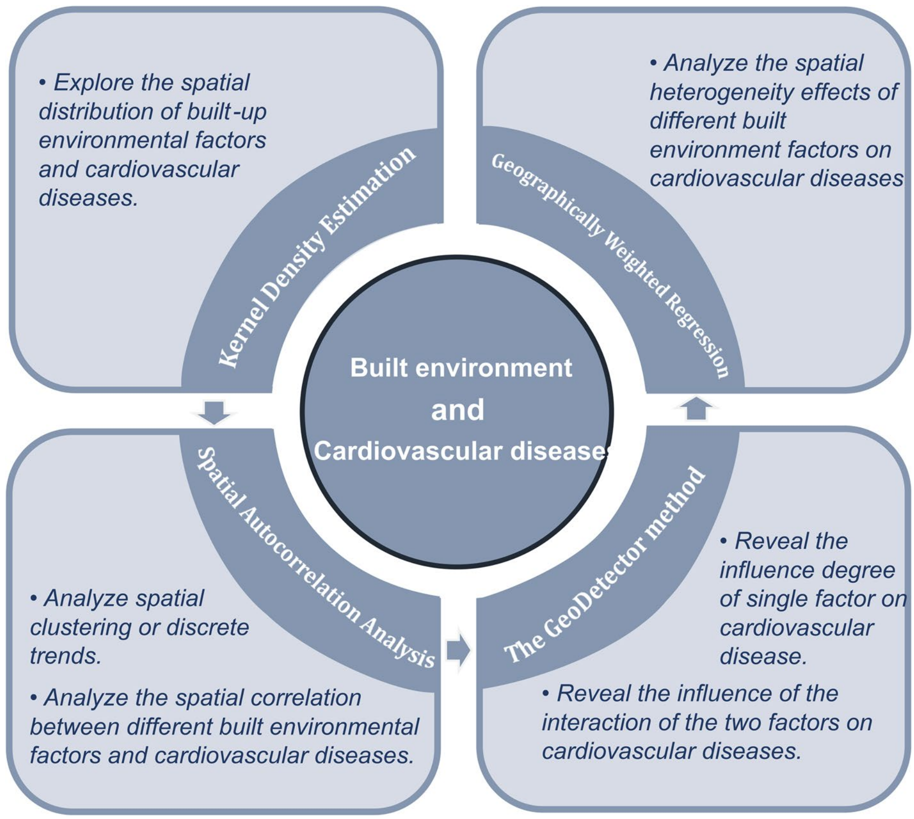

Fig. 2 Research framework

there is spatial interdependence between environmental factors and CVDs.

The results of spatial autocorrelation analysis include the Moran's I index, which directly reflects the strength and direction of spatial autocorrelation, as well as key indicators such as p values and Z values, together constructing a comprehensive quantitative system for evaluating spatial autocorrelation. In the results of spatial autocorrelation analysis, when the p-value is less than 0.01, the confidence level reaches 99%, and the Z value is greater than 2.58, the null hypothesis can be rejected, indicating that the research results are highly reliable. The degree of spatial clustering of variables is measured by Moran's I. The range of Moran's I is [-1, 1]; if Moran's $I > 0$, it indicates positive correlation, with higher values indicating stronger clustering; if Moran's $I < 0$, it indicates negative correlation, with lower values indicating stronger clustering; and if Moran's $I = 0$, the variables are not clustered and show a dispersed distribution, with the correlation weakening as the value approaches 0 [52].

The GeoDetector method (GDM)

We analyzed the processed kernel density attribute data using the GDM to parse the influence of the built environment on CVDs and uncover the underlying driving factors. The geographic detector tool was developed by a team led by Researcher Jinfeng Wang at the Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences [53]. The GDM mainly includes factor detection, interaction detection, risk area detection, and ecological detection, and it has been widely applied in multiple fields. We used the factor detection function to evaluate the impact of environmental factors on the distribution of CVDs and utilized the interaction detection function to analyze the interaction between different environmental factors [54, 55]. The purpose of the factor detector is to detect the extent to which independent variables explain the spatial differentiation of the dependent variable. It quantifies the influence of independent variables on the spatial distribution of the dependent variable to reveal which factors are the main contributors to the spatial distribution differences of the dependent variable. However, the impact of built environment elements on CVDs may not be determined by a single factor but rather by the synergistic effect of multiple built environment factors. Therefore, through the means of interaction detection, we further analyzed the synergistic impact of pairs of built environment elements on the spatial distribution of CVDs.

In this analysis, the q value was used as a quantitative indicator of the influence of environmental factors on CVDs, with values ranging between [0,1]. A higher q value indicates a more significant influence of the environmental factor, whereas a lower q value indicates a smaller influence. Additionally, a significance level of $p < 0.01$ further emphasizes the reliability of these factors' significant impact on the distribution of CVD samples.

Geographically Weighted Regression (GWR)

However, while the GDM can reveal the overall impact of built environment elements on CVDs, its limitation lies in its difficulty to finely characterize the specific differences and dynamic changes of these impacts within different geographic spatial units. To address this shortcoming, we introduced the GWR model through the spatial analysis tools of ArcGIS 10.8 software for local analysis. This model dynamically maps the distribution and variation trajectory of regression coefficients in geographic space, incorporating the key variable of spatial location into the regression analysis. In this way, the GWR model can reveal the spatial heterogeneity of parameters at different geographic locations, accurately capturing the relationships between local variables, thus overcoming the limitations of traditional global regression models in handling spatial non-stationarity [56, 57]. Compared to traditional global regression models, the GWR model excels in reducing model residuals and improving fitting accuracy.

When interpreting the results of the GWR model, it is necessary to consider the regression coefficients, R^2 (coefficient of determination), and adjusted R^2 comprehensively. The dynamic changes in regression coefficients in space reveal the complex relationships between independent and dependent variables at different geographic locations, with their sign and magnitude directly reflecting the nature and intensity of the impact. Although the R^2 value, as an indicator of the model's goodness of fit, focuses more on local effects in the GWR, its variation still helps to assess the explanatory power of the model in each area. These comprehensive indicators together form a thorough evaluation of the GWR model's performance. Through a comprehensive evaluation of the GWR model results, we can more precisely capture the relationships between local variables, revealing the specific impact of environmental factors on CVD risk within different regions.

Results

Kernel density distribution characteristics

By applying kernel density analysis, the spatial distribution pattern of CVD samples and various built environment elements was detailed, effectively capturing their spatial density characteristics. The obtained kernel density levels were divided into five tiers using the natural breaks method and arranged in descending order, as shown in Fig. 3. Analysis results indicate that high-density areas of elements such as shopping, dining, transportation facilities, and medical care are mainly focused in the southeastern part of the city, i.e., the city center. The high-density areas of the road network extend along the southern Yonjiang belt and appear patchy in the city center. Dense areas of parks are mostly near the southern riverside areas, while high-density distributions of sports facilities extend in the southeastern and central regions. Overall, the distribution pattern of these environmental factors reveals that Xixiangtang District's development trend mainly extends from southeast to northwest, indicating that the northeastern part of the region is relatively underdeveloped, with a sparse population and a lack of various infrastructure layouts. Additionally, kernel density distribution characteristics show that high-incidence areas of CVDs are concentrated in the southeast, highly coinciding with the high-density areas of most built environment elements.

Spatial Autocorrelation Characteristics

To explore the spatial relationship between urban built environment elements and the distribution of CVDs, spatial autocorrelation analysis was performed using Geoda software [58]. The study involved univariate and bivariate global spatial autocorrelation analyses (Table 2). The results of the analysis passed the significance level test at 0.01, with p values below 0.01 and Z values exceeding 2.58, achieving a 99% confidence level. This reinforces the reliability of the spatial autocorrelation results.

Univariate analysis is used to evaluate the clustering or dispersion status of feature points in space. In univariate analysis, the Moran's I value of the road network was 0.957, which significantly indicates a clustering trend in its spatial distribution. Moran's I values for other built environment elements, such as parks, transportation facilities, sports and fitness, and medical care, all exceeded 0.9, while the Moran's I values for shopping and dining also surpassed 0.8. By comparison, the Moran's I value for CVD samples was 0.697, approaching 0.7, revealing significant aggregation. Overall, the clustering nature of the built environment elements and CVD samples in Xixiangtang District implies that these elements are not randomly deployed but follow some patterns of hierarchical assembly.

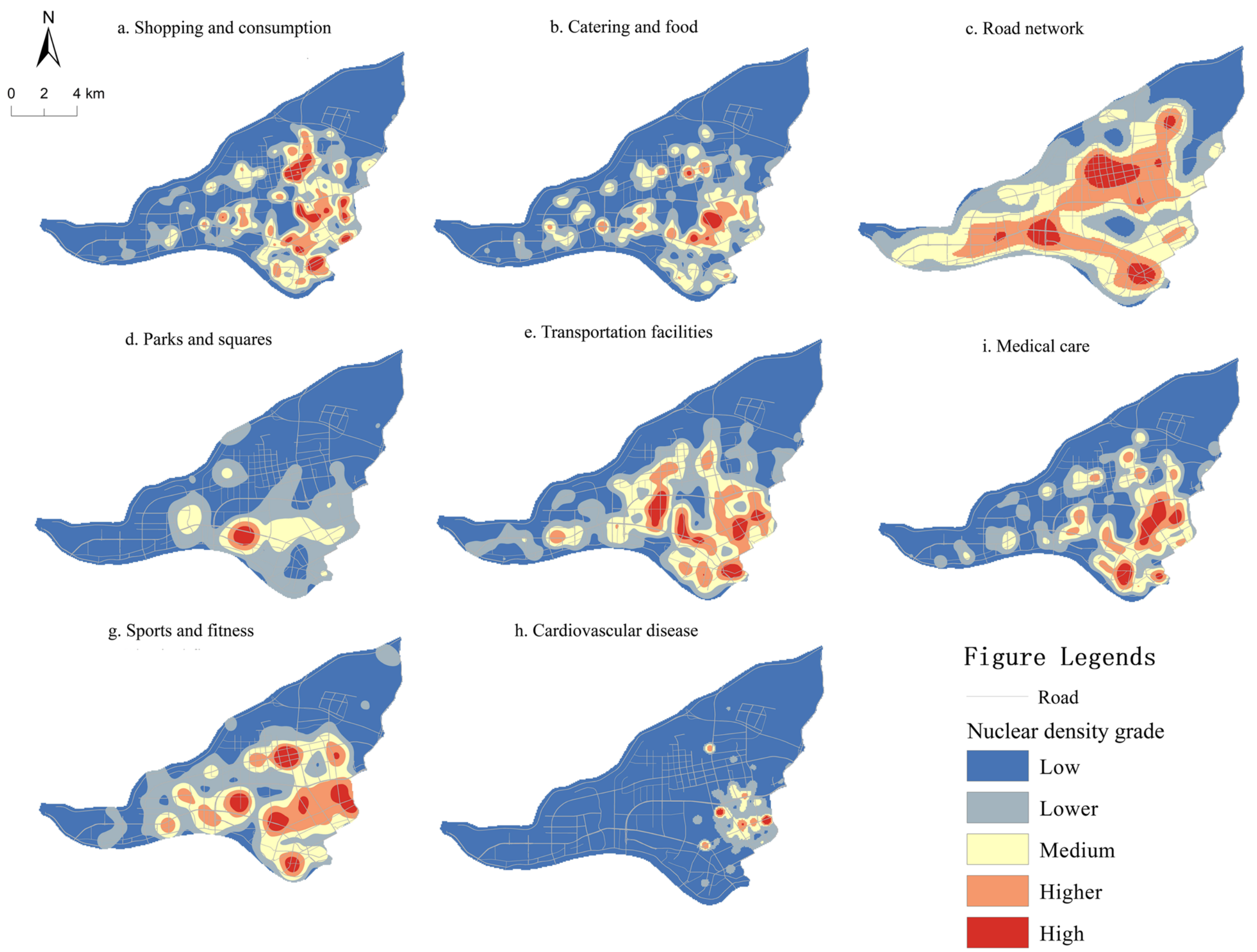

Fig. 3 Distribution of nuclear density of each element in the study area

Table 2 Spatial autocorrelation results of each element in the study area

Element	Univariate			Bivariate		
	Z Value	*p* Value	Moran's I	*Z* Value	*p* Value	Moran's I
Shopping and consumption	81.98	0.001	0.847	45.178	0.001	0.364
Catering and food	81.855	0.001	0.838	47.976	0.001	0.391
Road network	91.06	0.001	0.957	11.693	0.001	0.088
Parks and squares	94.931	0.001	0.945	17.371	0.001	0.131
Transportation facilities	86.863	0.001	0.917	47.677	0.001	0.389
Sports fitness	90.687	0.001	0.944	44.84	0.001	0.355
Medical care	86.698	0.001	0.908	52.82	0.001	0.431
Cardiovascular disease	68.837	0.001	0.697			

Bivariate analysis, on the other hand, is used to evaluate the spatial correlation between different environmental factors and CVDs. Bivariate analysis further revealed the spatial interaction between environmental factors and CVDs. The results show that all considered environmental elements exhibited significant positive correlation with CVDs. The spatial association between medical care elements and CVDs was the strongest, with a Moran's I value of 0.431, surpassing the significant threshold of 0.4. Additionally, the Moran's I values for dining, transportation facilities, shopping, and sports and fitness were all over 0.3. Road networks and parks, on the other hand, showed relatively weaker correlations with CVDs, with Moran's I values around 0.1, indicating that in that region, the spatial connection between these built environment elements and CVDs is comparably weak.

Geodetector results analysis

A detailed analysis of the impact of various environmental factors on CVDs was achieved through the factor detection model of the GDM. According to the factor detection results shown in Table 3, significant differences in the impact of environmental factors on the distribution of CVD samples were observed. The analysis results indicate that the environmental factors influencing the distribution of CVDs, in descending order of impact, are: healthcare services > shopping > dining > transportation facilities > sports and fitness > parks and squares > road networks. Specifically, healthcare services lead with a q value of 0.532, indicating that the spatial distribution of healthcare services has the most significant impact on the spatial distribution of CVDs. This highlights the importance of a high-density layout of healthcare facilities in the prevention and treatment of CVDs and suggests that individuals at risk for CVDs tend to prefer living in areas with convenient access to medical services [59].

Subsequently, shopping, dining, and transportation facilities all have q values exceeding 0.4, reflecting their significant effects on the urban built environment's clustering characteristics and regional commercial vitality. The concentration of human traffic brought about by these factors may, while increasing residents' lifestyle choices, also lead to certain psychological burdens and declining air quality, thereby indirectly placing a burden on the cardiovascular system. In contrast, parks and squares and road networks have relatively low q values (both less than 0.2), suggesting that the incidence of CVDs is lower in areas concentrated with these environmental elements, likely related to their ecological and transportation benefits.

Subsequently, interaction detection was used to analyze the synergistic impact of pairs of built environment elements on the spatial distribution of CVDs. From the results shown in Table 4, it is evident that any two built environment elements exhibit a bi-factor enhancement effect on CVDs, suggesting that the combined influence of two built environment elements exceeds the effect of a single element. Among these, the interaction between healthcare services and shopping has the greatest impact on CVDs, with a value of 0.571. This indicates that CVDs patients or high-risk individuals tend to prefer living in areas rich in healthcare resources and convenient for shopping, as they can more easily access health services and daily necessities. Conversely, the interaction between road networks and parks and squares has the weakest impact on CVDs, with a value of 0.313. This suggests that their combined effect in reducing CVD risk is relatively limited, possibly due to the negative impacts of road networks, such as traffic congestion and air pollution, which may offset some of the health benefits provided by parks and squares. This result further validates an important point: the impact of the built environment on CVDs is not driven by a single element but by the synergistic effects of multiple environmental factors working together.

Table 3 Geographical detector factor detection results

Environmental indicators	*q* Value	*P* Value
Catering and food	0.433	0.001
Road network	0.159	0.001
Parks and squares	0.174	0.001
Shopping and consumption	0.493	0.001
Transportation facilities	0.423	0.001
Sports and fitness	0.355	0.001
Medical care	0.532	0.001

Table 4 Geographic detector interactive detection result

Environmental indicators	Catering and food	Road network	Parks and squares	Shopping and consumption	Transportation facilities	Sports and fitness	Medical care
Catering and food	0.433						
Road network	0.460	0.159					
Parks and squares	0.473	0.313	0.174				
Shopping and consumption	0.522	0.513	0.533	0.493			
Transportation facilities	0.486	0.445	0.477	0.544	0.423		
Sports and fitness	0.474	0.437	0.392	0.533	0.465	0.355	
Medical care	0.540	0.552	0.568	0.571	0.547	0.548	0.532

Geographically weighted regression analysis

The GDM revealed the influence of built environment factors on CVDs. To further uncover the spatial heterogeneity effects of built environment elements on CVDs in different regions, we employed the GWR model. To ensure the rigor of the analysis, we conducted multicollinearity detection for all built environment elements before establishing the model. We confirmed that the Variance Inflation Factor (VIF) values for all elements did not exceed the conventional threshold of 5, effectively avoiding multicollinearity issues and ensuring the robustness of the model results. The GWR model results showed that the model's coefficient of determination R^2 was 0.596, and the adjusted R^2 was 0.575, indicating that the model could adequately explain the relationships between variables in the study. The analysis results also highlighted the spatial non-stationarity of the effects of built environment elements, manifested by different degrees of variation and fluctuation characteristics, as shown by the coefficient magnitudes and their dynamic changes in spatial distribution in Table 5.

Looking more closely at the details, as demonstrated in Fig. 4, the regression coefficients of the dining elements fluctuated relatively little, ranging from -0.372 to 0.471, reflecting a relatively balanced spatial effect. Moreover, although this factor's impact in the Xixiangtang District showed both positive and negative aspects in different areas, more than half of the analysis units indicated positive values, especially in the southern and northeastern parts of the Xixiangtang District. In contrast, the high-incidence areas of CVDs in the eastern part and areas in the north showed negative correlations.

The GWR coefficients and their fluctuations for parks were significant, ranging from -69.757 to 35.43, indicating significant spatial differences in their impact on the distribution of CVDs. Specifically, the spatial distribution of positive and negative impacts was nearly 1:1, revealing the complexity of its effects. In high-incidence areas of CVDs, the distribution of parks showed a significantly negative correlation with disease distribution, while a significant increase in positive correlation was observed north of the significantly negative regions. This implies the presence of other moderating factors influencing the direction of the impact of parks on CVDs.

The regression coefficients and fluctuations for shopping were the smallest among the seven environmental factors, confined to a range of -0.093 to 0.219, suggesting a high consistency in its spatial effects. In the Xixiangtang built-up area, nearly two-thirds of the spatial units yielded positive impacts. Particularly in the northern, northeastern, southern, and southeastern regions, the positive impacts of shopping were especially pronounced.

The regression coefficients and fluctuations for transportation facilities were relatively large, ranging from -0.487 to 7.363. For the Xixiangtang District, nearly three-quarters of the analysis units displayed positive spatial impacts, with the largest positive value areas concentrated in the southeastern part. However, areas with negative impacts from transportation facilities were relatively fewer, suggesting a clear positive correlation with the distribution of CVDs.

The fluctuation range for sports and fitness regression coefficients was also broad, from -10.578 to 33.256. The analysis indicated that only a quarter of the analysis units in the Xixiangtang District had a positive correlation. The most significant positive values were located near the high-density areas for CVDs, suggesting that sports and fitness facilities might have a positive correlation with the disease distribution in these areas. Meanwhile, the intensity of the negative correlation increased north of the areas with significant positive values, potentially pointing to other factors' potential moderating effects on the relationship between sports and CVDs.

The regression coefficients and their fluctuations for healthcare were relatively small, ranging from -1.235 to 3.352. In the Xixiangtang District, the vast majority of analysis units showed a positive correlation, especially in the northern regions. The southern areas exhibited negative correlations, highlighting potential differences in medical resources in that region.

Table 5 GWR operation result

Environmental indicators	Mean	Minimum	Upper quartile	Median	Lower quartile	Maximum
Catering and food	0.002	-0.372	0.086	-0.002	-0.079	0.471
Parks and squares	-5.434	-69.757	0.532	-0.509	-6.958	35.430
Shopping and consumption	0.010	-0.093	0.031	0.008	-0.010	0.219
Transportation facilities	0.871	-0.487	0.703	0.135	0.040	7.363
Sports and fitness	0.492	-10.578	0.037	-0.329	-1.010	33.256
Medical care	0.590	-1.235	1.032	0.109	-0.029	3.352
Road network	-426.409	-7905.743	10.468	-28.629	-238.995	411.617

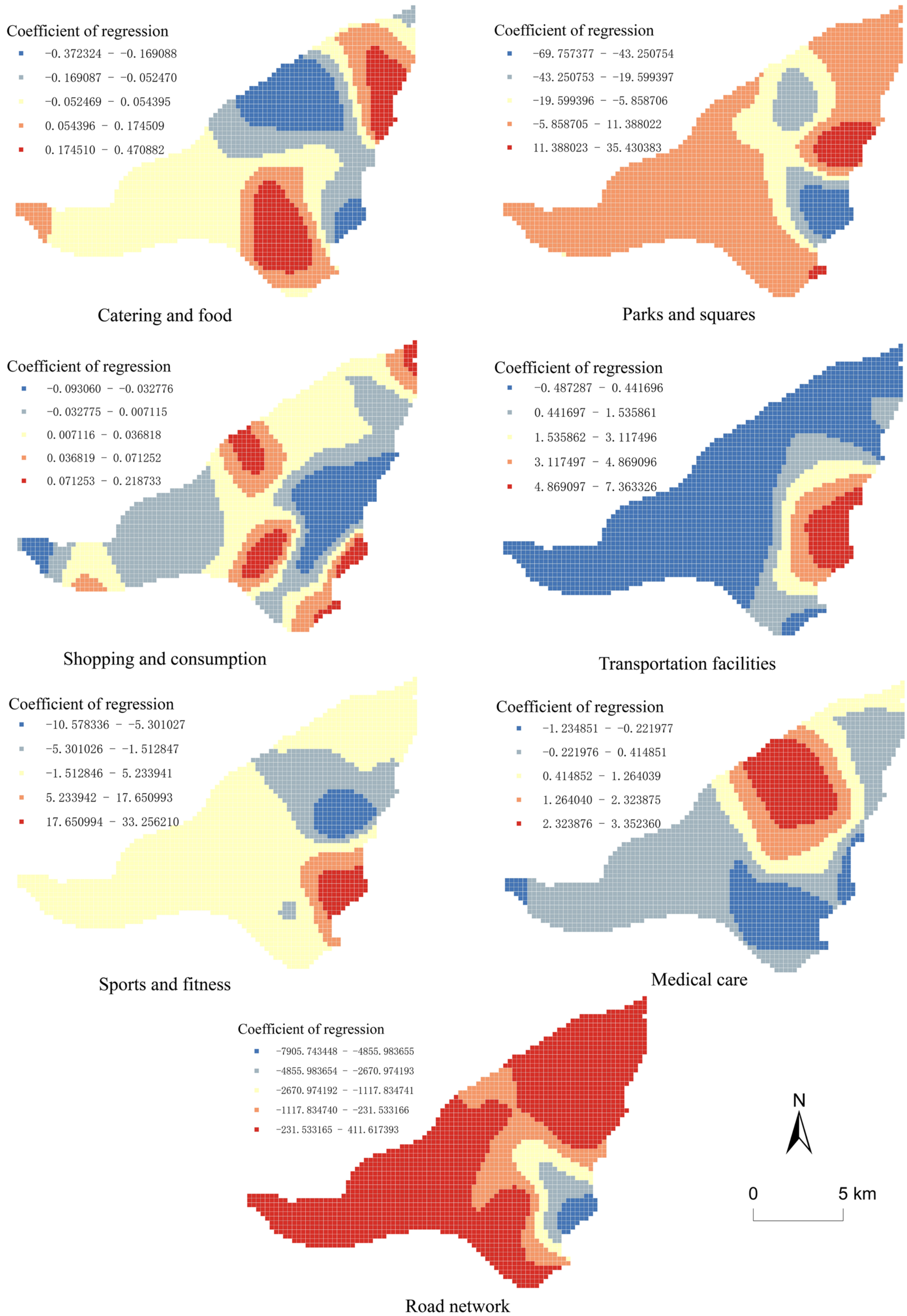

Fig. 4 Spatial distribution of regression coefficient of built-up environmental factors

Of all the built environment elements, road networks had the largest range of regression coefficients and fluctuations, swinging from -7905.743 to 411.617, demonstrating extremely strong spatial variability. Only a small portion of the spatial units in the Xixiangtang District showed positive correlations, while the significantly negative regions were mostly concentrated in high-incidence areas for CVDs. This phenomenon was similar to the negative correlation distribution trend of parks, pointing to a significantly negative correlation between park distribution and the distribution of CVDs. Notably, the effect of road networks was opposite to transportation facilities, which could be related to the connectivity of the road network and traffic congestion conditions, factors that could influence the incidence of CVDs.

Discussion

This study reveals a high-density aggregation of CVDs and various built environment elements in the southeastern part of the study area, i.e., the urban central area. Through spatial statistical analysis, all examined environmental elements and CVDs showed high Moran's I values, indicating significant clustering in their spatial distribution. Furthermore, the positive spatial correlation between these environmental elements and CVDs corroborates the deep connection between the urban built environment and the incidence of CVDs.

Geodetector analysis reveals significant differences in the impact of different built environment elements on CVDs. Healthcare facilities had the most influence, followed by shopping, dining, and transportation facilities, while parks and road networks had relatively weaker impacts. Notably, the occurrence of CVDs is not only related to individual built environment elements but likely results from the combined effects of multiple elements. Further interaction detection analysis confirmed this hypothesis, finding that the joint impact of any two environmental elements was stronger than any individual element, showing a clear dual-factor enhancement effect. Specifically, the interaction between healthcare and shopping had the most significant impact on the distribution of CVDs, while the combined effect of road networks and parks was the least. By delving into individual factors and their interaction effects, this study reveals a comprehensive view of the impact of the built environment on CVDs, highlighting the complex relationships and differences between environmental elements and the occurrence of diseases.

The GWR model was used to analyze in detail how built environment elements affect CVDs in different regions, aiming to gain a deep understanding of the local effects of the built environment. The research results showed the regression coefficients of built environment elements and their range of variation. Specifically, the regression coefficients for dining exhibited relatively stable trends in spatial distribution. Although the overall impact was moderate, slight fluctuations revealed a slightly enhanced positive correlation in specific areas such as densely commercial or culturally vibrant dining regions. Particularly in the southern and northeastern parts, the combination of diverse dining options and frequent dining consumption patterns showed a slight positive correlation with CVD risk. This reflects the complex impact of dietary habits, food composition, and intake levels on cardiovascular health [60, 61].

The regression coefficients for parks and squares showed relatively large fluctuations in spatial distribution, indicating significant regional heterogeneity. This is mainly due to factors such as differences in regional population density and per capita park and square area. In our study, the southeastern region, which is a high-incidence area for CVDs, exhibited negative regression coefficients for parks and squares. This is because this region is the central urban area with a high population density, leading to a significant shortage of per capita green space, thus showing a negative correlation. Conversely, in the northern region, where population distribution is more balanced and parks and squares are more abundant, the per capita green space is relatively sufficient. Therefore, CVD patients have more access to green spaces and exercise areas, showing a positive correlation [29].

The regression coefficients for shopping consumption showed the smallest fluctuations in spatial distribution. The positive and negative effects were not significantly different, with the positive effects being notably concentrated in the northern, northeastern, and southern commercial thriving areas. Compared to other regions, these areas might have relatively well-developed commercial facilities or superior shopping environments. This could indirectly affect CVD risk through various dimensions, such as physical exertion from walking or cycling during shopping and the regulation of psychological states like satisfaction and pleasure after shopping [44].

The regression coefficients for transportation facilities showed a significant positive correlation in high-incidence areas of CVDs, with notable fluctuations. This deeply reveals the direct and important impact of traffic conditions, especially congestion and pollution, on cardiovascular health across different regions. In traffic-dense areas such as city centers and transportation hubs, high traffic volume, severe congestion, and increased noise and air pollution collectively pose major threats to residents' cardiovascular health. This not only directly harms the cardiovascular system through accumulated psychological stress and exposure to air pollution but also further exacerbates the risk due to a lack of exercise opportunities [62].

The regression coefficients for sports and fitness facilities exhibited a high degree of heterogeneity in spatial distribution, showing a significant positive correlation in the southeastern high-incidence area for CVDs, which gradually shifts to a negative correlation towards the outer regions. This deeply reflects the regional differences in the allocation of sports and fitness facilities, residents' exercise habits, and participation rates. In areas with well-developed urban facilities and strong resident awareness of physical activity, the positive effects of sports and fitness activities on cardiovascular health are particularly significant. These activities effectively reduce CVD risk by enhancing physical activity, optimizing cardiopulmonary function, and lowering body fat percentage. However, in areas with relatively scarce sports facilities and poor exercise habits among residents, negative impacts may be observed, highlighting the potential threats to public health due to uneven distribution of sports resources and a lack of exercise culture [63].

The regression coefficients for healthcare services showed regional differences in spatial distribution. In the northern region, due to the lower population density, the abundance and superior quality of per capita healthcare resources have a significant positive effect on residents' cardiovascular health. In contrast, the southern region, with relatively scarce resources or limited service quality, fails to fully realize the potential benefits of healthcare services. This disparity not only reveals the current uneven distribution of healthcare resources but also emphasizes the importance of enhancing the equalization of healthcare services [64]. The positive impact of healthcare on CVDs is primarily achieved through efficient prevention, precise diagnosis, and timely treatment. Its effectiveness is influenced by multiple factors, including the sufficiency of medical resources, service quality, residents' healthcare-seeking behavior, medical policies, and technological advancements.

The road network and transportation facilities together constitute the urban transportation system. In the process of transportation planning, we advocate for the continuous optimization of the road network layout, reserving space for future traffic growth, and utilizing intelligent technology to optimize traffic signal management to alleviate congestion. Meanwhile, in the densely populated eastern and southeastern areas, we emphasize enhancing the convenience of public transportation by adding routes and optimizing station locations, making it the preferred mode of travel for residents. Additionally, measures such as the construction of sound barriers and green belts are implemented to effectively reduce noise and air pollution caused by public transportation. Furthermore, we actively promote green travel methods such as cycling and walking by building a comprehensive network of bike lanes and pedestrian paths, thereby promoting public health and environmental protection [20].

These findings provide a more comprehensive understanding of the complex interactions between built environment elements and CVDs. Therefore, it is essential to balance the integrated impact of these factors in urban planning and public health interventions. Based on a comprehensive analysis of existing research and our study's results, we propose the following viewpoints.

Firstly, healthcare is the primary factor influencing the distribution of CVDs. Living near medical institutions offers substantial benefits to cardiovascular patients, not only enhancing the accessibility of medical services but also helping to quickly respond to emergency medical situations, providing a sense of security for patients. We suggest establishing additional medical centers in the densely populated southeastern region to ensure that community members can easily access high-quality medical services [65].

Secondly, shopping and dining are the next most important factors affecting the spatial distribution of CVDs. Although the spatial variation of these factors is not significant, their long-term cumulative impact should not be overlooked. We recommend that future urban renewal or renovation efforts reasonably control and plan the density of commercial areas, especially in the eastern region. This requires ensuring that residents can enjoy convenient shopping services to meet their daily needs while avoiding the increased living costs and stress caused by excessive commercial concentration. Additionally, it is necessary to strengthen the management of dining environments, including encouraging dining establishments to offer more healthy food options, such as low-sugar, low-fat, and high-fiber dishes. It is also important to increase the availability of healthy dining options by establishing healthy restaurants and vegetarian eateries, while reasonably controlling and optimizing the layout and number of high-sugar and high-fat food outlets within communities to reduce health risks induced by frequent exposure to such foods [66].

Road networks and transportation facilities together form the city's transportation system. In transportation planning, we advocate for the continuous optimization of road network layouts, reserving space for future traffic growth, and leveraging intelligent technology to optimize traffic signal management to alleviate congestion. Additionally, enhancing the convenience of public transportation by adding routes and optimizing stops can make it the preferred mode of travel for residents. Complementing this with the construction of sound barriers and green belts can effectively reduce noise and air pollution caused by public transportation. Furthermore, promoting green travel methods such as cycling and walking by building a comprehensive network of cycling lanes and walking paths can foster both health and environmental benefits [20].

Sports and fitness facilities, along with parks and squares, are essential for improving residents' quality of life and promoting healthy lifestyles. During planning, sports and fitness facilities should be reasonably distributed, especially in the northern part of the study area, to ensure that all communities have convenient access to exercise amenities. Diverse fitness facilities catering to different age groups and exercise needs, such as basketball courts, soccer fields, and fitness equipment zones, should be provided to meet the varied exercise requirements of different groups. Additionally, parks and squares, as crucial spaces for residents' leisure and entertainment, should be planned with a harmonious balance of ecology and landscape. In densely populated and space-constrained southeastern areas, small green spaces, leisure seating, and children's play facilities can be added to provide residents with a pleasant environment for relaxation and nature interaction [67].

We have explored the mechanisms by which environmental elements impact CVDs and proposed suggestions for optimizing the urban built environment, but this paper still has certain limitations. The impact of the environment on health and disease is complex, and due to time and resource constraints, it was not possible to consider and analyze all potential variables comprehensively, which may have some impact on the research results. To further deepen the study of the relationship between the built environment and cardiovascular health, future research could consider the following aspects: first, expand the scope of research, collecting and analyzing data from different cities and regions to better understand geographical differences in the impact of the built environment on cardiovascular health; second, enhance the scientific nature of the research methods, using more objective and precise methods for data collection and analysis to improve the reliability and accuracy of the research; and finally, deepen the study of the mechanisms between the built environment and cardiovascular health, exploring biological and psychological mechanisms to better understand their relationship.

Conclusion

Focusing on the built-up area of Xixiangtang in Nanning City as the research area, this study delves into the intrinsic connection between the urban built environment and CVDs, uncovering several findings. Utilizing hospital cardiovascular data and urban POI data, and employing spatial analysis techniques such as KDE, spatial autocorrelation analysis, geodetectors, and GWR, we systematically assessed the extent and mechanisms through which various built environment elements impact CVDs. The results show a significant positive correlation between the urban built environment and CVDs. Particularly, healthcare facilities, shopping venues, restaurants, and transportation facilities have significant effects on the incidence and distribution of CVDs. The spatial aggregation of these elements and the dense distribution of CVDs demonstrate significant consistency, further confirming the close link between the built environment and CVDs. Simultaneously, we discovered spatial heterogeneity in the impact of different built environment elements on CVDs. This indicates that in planning and improving the urban environment, elements and areas with a greater impact on CVDs should be considered specifically.

Abbreviations

CVD	Cardiovascular Disease
GWR	Geographically weighted regression
MGWR	Multiscale geographically weighted regression
GDM	The GeoDetector method
OSM	OpenStreetMap
KDE	Kernel Density Estimation
POI	Points of Interest
VIF	Variance Inflation Factor
API	Application Programming Interface
VIF	Variance Inflation Factor

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Authors' contributions

D.S. Provides research topics, conceptual guidance, translation, paper revision and financial support; L.J. Conceived the framework and wrote the original draft; P.Y. Manuscript checking, chart optimization; L.W. Provided suggestions for revision, and reviewed and edited them; S.J. Is responsible for data acquisition and editing; Z.S. Edits the visual map.

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Availability of data and materials

The datasets used or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

Our study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki, as well as relevant national and institutional guidelines for human research. The study received approval from the Medical Ethics Committee of Guangxi Zhuang Autonomous Region Nationality Hospital (Approval No.: 2024–65). The de-identified data records from the cardiovascular department that we accessed and analyzed were authorized by Guangxi Nationality Hospital. These data were collected and maintained in compliance with the hospital's patient data management policies and procedures. Given that our study involved only a retrospective analysis of existing medical records, with no direct interaction with patients and no potential for causing any substantial harm, the Medical Ethics Committee of Guangxi Zhuang

Autonomous Region Nationality Hospital determined that individual patient informed consent was not required. Nonetheless, we have ensured that all data used in the study were fully anonymized and protected, adhering to the highest standards of confidentiality and privacy.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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