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Spatiotemporal effects of urban micro-scale built environment on cardiovascular diseases

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Cardiovascular disease (CVD) has become a significant threat to the health of urban populations, and the urban built environment, as a key determinant of cardiovascular health, affects residents through various dimensions including physical activity, urban pollution, mental health, and dietary habits. However, existing research predominantly focuses on macro-level geographic scales, with limited exploration of the potential impact of intra-urban microenvironments on CVD. This study focuses on the central area of Nanning, China, as the case study area, employing methods such as global spatial autocorrelation analysis, emerging spatiotemporal hotspot analysis, and spatiotemporal geographically weighted regression (GTWR) analysis to comprehensively examine the spatiotemporal associations between CVD and built environment elements. The results reveal that CVD and built environment elements exhibit significant spatial clustering and correlations, with all variables demonstrating spatial clustering patterns. Six built environment factors—parks and squares, transportation facilities, life services, sports and leisure, medical care, and Catering and food—are spatially associated with disease incidence. The influence of built environment factors on CVD varies and exhibits pronounced spatiotemporal heterogeneity, with the greatest coefficient fluctuation observed for parks and squares, and the smallest for catering services. Parks and squares generally contribute positively to cardiovascular health by lowering disease risk across most areas, although in the central zone, dense population and heavy traffic lead to a positive association with disease incidence. Fortunately, this adverse impact has been gradually mitigated through ongoing improvements in urban green space planning; transportation facilities increases disease risk due to associated noise and air pollution, with particularly strong effects observed in the central region. However, the implementation of green transportation initiatives has effectively mitigated this negative impact; life services show a positive association with CVD, but their diverse types and spatially balanced distribution render their impact relatively minor; sports and leisure are associated with reduced disease risk in the central part of the study area, but in the northeast and northwest, they exhibit a positive association due to population dispersion. As residents' usage habits become more consistent, the associated impacts are gradually stabilizing; medical care help reduce disease risk in the central and eastern regions, but show a positive correlation in the northern area due to patient overflow and referral patterns. With the more equitable distribution of healthcare resources, this relationship is gradually stabilizing; catering and food are positively associated with CVD, but the effect is relatively small and spatially balanced, likely due to their widespread and uniform distribution. These findings offer valuable case-based evidence for urban planning and public health policymaking, thereby contributing to the construction and advancement of healthy cities.

Keywords Built environment, Cardiovascular diseases, Spatiotemporal evolution, Spatiotemporal epidemiology

Cardiovascular disease (CVD), encompassing conditions like coronary heart disease, stroke, and heart failure, represent one of the most prevalent fatal disease categories globally, with both incidence and mortality rates rising each year[1]. Statistics indicate that the number of global CVD patients rose sharply from 271 million in 1990 to 523 million in 2019, with deaths from CVD increasing from 12.1 million to 18.6 million, underscoring the severe threat to global health[2,3]. Research indicates that, beyond demographic factors (e.g., aging)[4,5],

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socioeconomic conditions (e.g., education, income, and poverty)[6–8], and behavioral patterns (e.g., tobacco use, sedentary lifestyle, and unhealthy diet)[9,10], the urban built environment is also a key factor affecting the incidence and mortality of CVD[11].

The urban built environment, comprising the constructed spaces and infrastructure of a city, not only accommodates the daily activities of residents, but also exerts complex and significant impacts on cardiovascular health amid accelerating urbanization[12]. Research indicates that street connectivity and design significantly influence residents' travel behaviors and walkability, which in turn impacts cardiovascular health[13,14]. In a U.S.-based community study, researchers assessed walkability among 70,123 individuals across census tracts, revealing significant correlations between walkability and the prevalence of coronary artery CAD, hypertension, hypercholesterolemia, and obesity, with walkability directly accounting for 9% of CAD outcomes, and additional mediation by cardiovascular risk factors[15]. Green spaces and parks contribute to cardiovascular health by improving air quality, regulating microclimates, and alleviating psychological stress, thereby offering protective cardiovascular benefits, although such benefits may be constrained by spatial configuration and accessibility[11,16,17]. For instance, a 25-year prospective cohort study in the U.S. investigated coronary artery calcification (CAC) in relation to green space changes, analyzing its associations with the percentage of green space and proximity to major parks. Results revealed that every 10% increase in green space coverage was associated with a significantly lower likelihood of CAC among Black participants and individuals from low-income communities[18]. The diversity and accessibility of recreational facilities foster social interaction, supporting both physical and psychological well-being, and subsequently benefiting cardiovascular health[19,20]; a Canadian study highlighted regional disparities in access to physical activity infrastructure, finding that 28.7% of rural residents experienced barriers to accessing free or affordable recreational facilities, compared to just 8.9% of urban dwellers[21]. Echoing this, a recent review by the American Heart Association (AHA) further elaborated on how limited access to recreational facilities contributes to lower levels of physical activity, which is closely linked to poorer cardiovascular outcomes, thus advocating for equitable access to physical activity infrastructure across regions, to enhance cardiovascular health[22]. The layout of commercial and food environments shapes residents' dietary choices, and thoughtful spatial planning can mitigate CVD risk, though the convenience of obtaining unhealthy food remains a significant concern[23,24]. For example, a geospatial study in South Asia analyzed the distribution of fast-food outlets within 100 m and its relation to residents' health, and found that residents living in areas with high fast-food outlet density faced a 19% higher risk of diabetes, illustrating that excessive clustering of unhealthy food outlets, which facilitates easy access to high-fat, high-sugar fast foods, can pose substantial risks to public health[25]. Overall, the urban built environment exerts a profound influence on cardiovascular health via pathways including physical activity, air quality, mental well-being, and dietary behaviors, shaping long-term cardiovascular health outcomes among residents, highlighting the critical role of optimizing built environments in the prevention of CVD[26–30].

Spatiotemporal epidemiological research on CVD incorporates temporal and spatial dimensions into traditional cardiovascular epidemiology, aiming to investigate the spatiotemporal distribution, evolution, and interaction of CVD incidence with associated risk factors[31]. At present, related case studies utilize a range of analytical techniques, including spatial autocorrelation[32], spatiotemporal kriging[33], Bayesian spatiotemporal analysis[34], and geographic information systems (GIS)[35], which deeply integrate statistical and epidemiological principles to conduct in-depth investigations into the occurrence, progression, and diffusion patterns of diseases within specific temporal and spatial contexts. For example, a study in China applied ordinary kriging to estimate spatiotemporal variations in coronary heart disease (CHD) and stroke mortality rates across all counties from 1991 to 2009[36]. In a study of major metropolitan regions in North America, researchers applied GIS and spatial autocorrelation analysis to uncover strong spatiotemporal associations between concentrations of air pollutants (especially PM2.5 and O_3) and the rate of cardiovascular emergency visits. The study not only confirmed the immediate health effects of pollutant exposure, but also revealed the cumulative effects of long-term exposure on CVD incidence through the construction of a spatiotemporal lag model[37]. Another spatiotemporal clustering analysis conducted in Manitoba, Canada, focused on the spatiotemporal patterns of ischemic heart disease (IHD) and their interaction with socioeconomic determinants, in which researchers employed a Bayesian spatial statistical model, integrating regional socioeconomic indicators and population density data, to identify high-risk clusters of IHD, and revealed that these areas were marked by high population concentrations and significant socioeconomic deprivation[38].

Overall, existing studies have integrated spatial analysis, statistics, and epidemiology to enable an in-depth analysis of CVD within complex spatiotemporal environments, providing support for uncovering disease patterns and developing effective prevention and control strategies[34,39,40]. However, current studies still have limitations, as they mostly concentrate on macro geographic scales, such as national, provincial, or municipal levels, using large-scale data analyses to illustrate the spatiotemporal distribution of CVD[41–43]. This macro perspective cannot reveal the potential influence of urban micro-built environments on CVD incidence, neglecting the unique spatiotemporal mechanisms by which differences in built environment elements affect residents' cardiovascular health. Moreover, current studies primarily focus on the spatiotemporal distribution characteristics of CVD and their relationships with macro-level variables, such as socioeconomic factors and air pollution. Although these studies offer insights into the external drivers of CVD, research is limited when it comes to analyzing the disease mechanisms from the perspective of urbanization and the spatiotemporal evolution of the built environment[44]. During urbanization, factors such as land use changes, green space reduction, and traffic congestion may profoundly impact residents' cardiovascular health, yet these factors are seldom mentioned in current research. In light of this, to achieve a more comprehensive understanding of CVD incidence patterns in urban environments, this study takes a micro-level approach, employing multiple analytical methods to uncover the potential impact of urban built environments on the spatiotemporal evolution of CVD.

We selected the central urban area of Nanning, China—within a 3 km radius of Guangxi National Hospital—as the case study area to analyze how built environment factors affect the spatiotemporal evolution of CVD. Unlike previous research, this study concentrates on the intra-urban scale, examining the spatial associations between urban built environment factors and CVD within the study area, to reveal how the spatiotemporal dynamics of built environments influence CVD incidence at a fine scale. We comprehensively employ global spatial autocorrelation analysis, emerging spatiotemporal hotspot analysis, and spatiotemporal geographically weighted regression (GTWR) to investigate the clustering patterns and spatial associations between built environment features and CVD, analyze spatiotemporal hotspots between 2013 and 2022, and reveal the micro-scale spatiotemporal evolution patterns linking built environments and CVD, providing a robust scientific foundation for urban planning and public health policymaking to promote the construction and advancement of healthy cities.

Materials and methods

Study area

This study focuses on the central area of Nanning, located in southwestern China (107°45′E–108°51′E, 22°13′–23°32′N), the capital of Guangxi Zhuang Autonomous Region and a regional hub for politics, economy, and culture, as well as a microcosm of regional development and social transformation. Over the past decade, the city has undergone rapid development, with urbanization, a complex social structure, and a diverse environment offering a robust context and population base for studying the impact of urbanization on residents' health. Guangxi National Hospital, the primary data source for CVD in this study, is one of Nanning's major healthcare institutions, located in the city center, with surrounding areas embodying the city's developmental history while showcasing the evolving landscape of modern urban life. The 3-kilometer buffer zone was selected based on two primary considerations. First, cardiovascular patients are predominantly elderly, for whom regular follow-ups demand proximity and transport convenience[45,46]; second, this radius aligns with the 3–5 km emergency medical service range defined by China's National Health and Family Planning Commission, and thus holds strategic value in medical resource planning, especially in facilitating cardiovascular and cerebrovascular emergency response, and for optimizing the configuration of priority healthcare areas[47–49]. Patients typically prefer nearby medical facilities to minimize transportation expenses and avoid the physical and psychological burden associated with long commutes, particularly for elderly populations[50]. Thus, the study area was defined as a 3-kilometer radius around Guangxi National Hospital, reflecting both scientific rigor and practical feasibility. Using ArcGIS 10.8 software, we divided the study area into 733 fishnet grids at 200 m × 200 m resolution (Fig. 1), and collected sample points related to CVD and built environment features, with point counts assigned to each grid cell for subsequent spatial analysis.

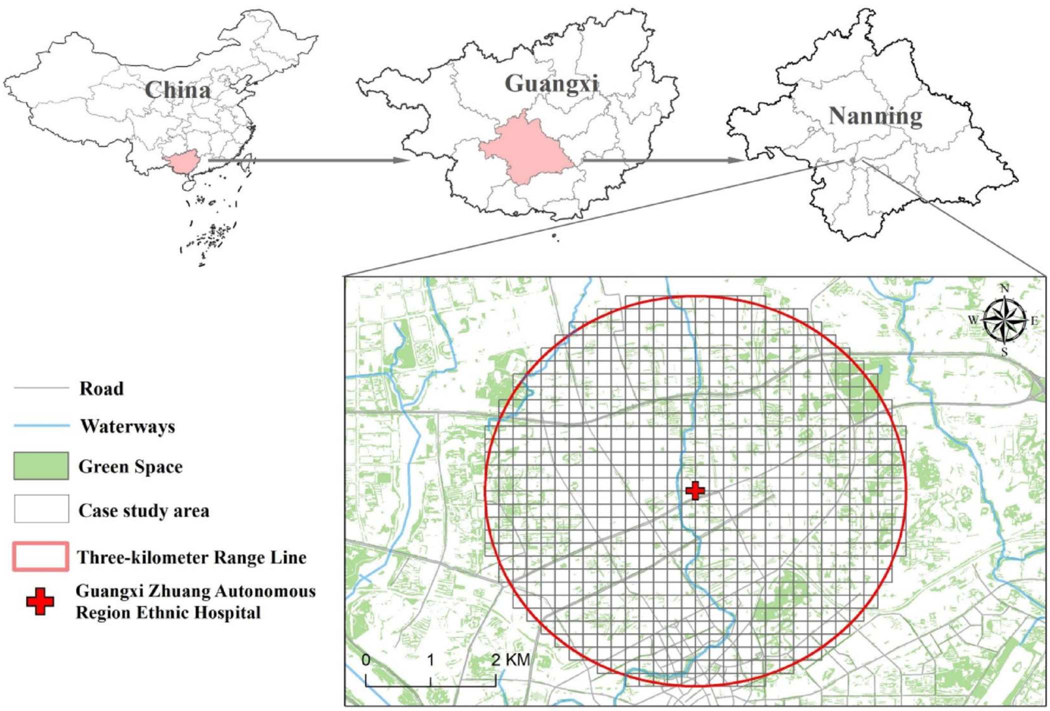


Fig. 1. Location of the study area in China.

Study data

CVD data

The CVD dataset was obtained from the cardiology department records at Guangxi National Hospital between 2013 and 2022, including patient gender, age, address, and medical expenditure, serving as a core data source for the spatiotemporal analysis of CVD. Guangxi National Hospital is situated in the central district of Nanning, where its prime location and convenient transport greatly enhance healthcare accessibility. As a renowned Class A tertiary hospital in the region, its cardiology department is highly trusted for its superior clinical capacity, advanced medical equipment, and cost-effective care, which enhances the representativeness and reliability of the dataset. During data processing, all patient-identifiable information was removed, ensuring ethical compliance. We employed a text-to-coordinate geocoding tool using the Amap (Gaode) Maps API to convert patient address information into geographic coordinates, which were then mapped using ArcGIS 10.8. After data cleaning, 19,024 valid samples within the study area were retained.

We conducted a statistical summary of CVD cases (Table 1). In terms of gender, female patients accounted for 48.5%, slightly fewer than their male counterparts, indicating no significant gender disparity. With respect to age, individuals over 61 constituted the main affected group, accounting for a substantial 71%, underscoring the high prevalence of CVD in older populations. Actual treatment costs revealed that CVD care tends to be costly, with the highest proportion of patients (42.4%) incurring expenses between 5,001 and 10,000 yuan, while those spending 10,000–20,000 yuan and above 20,001 yuan represented 29.8% and 15.9%, respectively, collectively accounting for more than 88.1% of cases, reflecting the considerable financial burden placed on patients and their families. Moreover, from a temporal perspective, the number of CVD cases has shown a fluctuating upward trend over the past decade, rising from 1,627 cases in 2013 to 1,956 in 2022, demonstrating an overall increasing pattern with some fluctuation.

Built environment data

The built environment is a multidimensional, highly integrated concept, encompassing all man-made physical spaces and their interrelations within a city or region that influence human activities[1]. Given the availability, completeness, and robust foundation of existing research in the field[51], this study adopts urban road networks and Points of Interest (POI) data as the core analytical variables (Table 2).

In the context of the built environment, the road network functions as the structural backbone linking different city zones, with its configuration, hierarchy, and traffic flow patterns directly affecting accessibility, traffic efficiency, and environmental quality. The extent to which the road system is optimized directly influences daily mobility, transportation safety, and air quality[52]. Thus, incorporating road networks as a key dimension of analysis helps us better understand how urban spatial structures shape different aspects of residents' lives. We retrieved road network data from 2013 to 2022 using the OpenStreetMap (OSM) platform. Using OSM data download tools, we specified the geographic boundary of the study area (a 3-kilometer buffer around Guangxi National Hospital) and set a precise data download range to ensure that only road data within this area was retrieved. The annual raw data were then processed and cleaned using ArcGIS 10.8, based on OSM attribute fields, eliminating duplicate entries, mislabels, and fragmented road segments. We further conducted topological

Name	Option	Frequency	Percentage (%)	Cumulative Percentage (%)
Gender	Female	9230	48.5	48.5
	Male	9794	51.5	100
Age	Above 61 years old	13,508	71.0	71.0
	36 to 60 years old	5150	27.1	98.1
	19 to 35 years old	334	1.7	99.8
	Below 18 years old	32	0.2	100
Actual Receipt Amounts	Above 20,001	3023	15.9	15.9
	10,000 to 20,000	5662	29.8	45.7
	5001 to 10,000	8059	42.4	88.1
	1001 to 5000	2209	11.5	99.6
	Below 1000	71	0.4	100
Time	2013	1627	8.6	8.6
	2014	1756	9.2	17.8
	2015	1990	10.5	28.3
	2016	1965	10.3	38.6
	2017	1954	10.3	48.9
	2018	1955	10.3	59.2
	2019	2070	10.9	70.1
	2020	1845	9.7	79.8
	2021	1906	10.0	89.8
	2022	1956	10.2	100

Table 1. Statistical results of CVD patients in the study area.

Environmental indicators	Source	Relationship with cardiovascular system	Subtype
Road network	OSM	A well - developed and well - connected road network can improve traffic efficiency, reducing the time spent in traffic congestion. Prolonged traffic congestion is associated with increased stress levels, elevated blood pressure, and potential impacts on heart rate variability, all of which can affect the cardiovascular system. Additionally, a good road network can facilitate access to healthcare facilities for cardiovascular patients. On the contrary, a complex or congested road network may lead to increased air pollution in local areas, with pollutants such as particulate matter having a negative impact on cardiovascular health.	Expressway, expressway, main road, secondary road and branch road.
Catering and food	Amap	The distribution of different types of Catering and food can influence residents' dietary choices. For example, a high density of fast - food restaurants may be associated with an increased intake of high - fat, high - salt, and high - sugar foods, which can contribute to obesity, high blood pressure, and elevated cholesterol levels, all risk factors for CVD.	Chinese food, western food, fast food restaurant, snack bar, tea shop, etc.
Parks and squares		Parks and squares provide spaces for physical activity, which is beneficial for cardiovascular health. Regular physical activity in these areas can improve cardiovascular function, increase heart strength, and lower the risk of developing CVD. Moreover, the greenery in parks can also improve air quality, reducing the inhalation of harmful pollutants that can damage the cardiovascular system.	Parks, squares, scenic spots, zoos, botanical gardens, etc.
Shopping and consumption		Easy access to shopping areas can impact lifestyle. If residents can easily reach stores to buy fresh produce and healthy groceries, it can support a heart - healthy diet. However, the presence of large shopping centers with long - distance travel requirements may lead to more sedentary behavior if people rely on cars for transportation, increasing the risk of cardiovascular problems.	Distribution of department stores, shopping centers, convenience stores, commercial streets, markets, etc.
Transportation facilities		Adequate and well - located transportation facilities, such as subway entrances and bus stops in close proximity to residential areas, can encourage active transportation like walking to and from stops, which is beneficial for cardiovascular health. On the other hand, areas with a high density of toll stations or congested transportation hubs may cause stress due to traffic delays, potentially affecting the cardiovascular system.	Bus station, parking lot, subway entrance, toll station, bus station, etc.
Sports and fitness		The availability of sports and fitness facilities within the community encourages regular exercise. Regular physical activity in fitness centers, on basketball courts, or in swimming pools can enhance cardiovascular endurance, lower blood pressure, and improve lipid profiles, all of which are positive for cardiovascular health.	Fitness center, basketball court, badminton court, swimming pool, gym, etc.
Medical care		Proximity to medical care facilities, such as emergency centers, clinics, and hospitals, is crucial for cardiovascular patients. Quick access to medical services in case of emergencies can save lives and improve the prognosis of CVDs. Additionally, the availability of pharmacies nearby can ensure patients' compliance with medication regimens, which is essential for managing cardiovascular conditions.	Distribution of emergency centers, clinics, specialized hospitals, general hospitals, pharmacies, etc.

Table 2. Description of indicators of built environmental factors.

checks to ensure spatial connectivity and consistency, filling missing connections and correcting topological issues. Following this rigorous data processing procedure, we obtained a complete and accurate road network dataset for each year. Analyzing this time-series dataset al.lows us to examine the evolution, optimization, and changing trends in the urban road system.

Urban POI data serve as important carriers of urban spatial information, recording the locations, types, and attributes of various city facilities. With rapid updating and easy accessibility, POI data reflect the latest trends in urban development in a timely manner[53]. POI data elements encompass various aspects of daily life, including dining, shopping, healthcare, and entertainment, directly showcasing the diversity of urban functions. Analyzing the spatial distribution and trends of POI data allows us to capture changes in the built environment, such as functional layout, facility density, and accessibility, and to assess the potential impacts of these changes on residents' cardiovascular health. For this study, we used the API provided by Amap, a leading map service provider in China, to obtain urban POI data from 2013 to 2022. Amap's extensive user data and geocoding system enable us to capture the spatial distribution and attribute characteristics of elements such as catering and food[54], transportation facilities[55], parks and squares[56], sports and leisure[57], life services[58], Shopping and consumption[59], and medical care[60] and track their changes over the decade. Comparative analysis of POI data across different years reveals dynamic changes in the urban built environment in terms of functional layout, facility diversity, and accessibility, enabling exploration of the potential impacts of these changes on residents' lifestyles and cardiovascular health[61].

Analysis method

Global Spatial autocorrelation analysis

(1) Univariate global spatial autocorrelation.

We employed global spatial autocorrelation to examine the spatial heterogeneity of CVD and built environment distribution, using Geoda software to evaluate the spatial clustering of CVD and various built environment elements across different years[62]. Global spatial autocorrelation analysis can reveal the spatial distribution characteristics of variables, specifically focusing on the clustering or dispersal phenomena of CVD incidence or specific built environment element values[63,64]. In global spatial autocorrelation analysis, Moran's I is the primary indicator of spatial autocorrelation, comprehensively reflecting the spatial clustering of CVD or a specific built environment element across the study area. Through significance testing (p-value < 0.01, confidence level up to 99%, and $|z|$-value significantly above the critical value of 2.58), we can confirm the validity of Moran's I, indicating whether significant spatial clustering or dispersal is present in the variable[65]. The formula is:

$$I = \frac{n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \sum_{i=1}^{n} \left(x_i - \bar{x}\right)^2} \tag{1}$$

Here, I denotes the Moran's I statistic, n indicates the number of spatial units within the study area, x_i represents the incidence rate of CVD or the value of a built environment variable in the ith spatial unit, $\bar{x}$ is the average value of CVD incidence, and *wij* represents the spatial weight between spatial units i and j, reflecting the spatial relationships among geographic units. To ensure analytical robustness and scientific validity, Moran's I is typically subjected to statistical significance testing ($p < 0.01$, confidence level of 99%, and $z > 2.58$) to confirm its validity. When Moran's I is significantly greater than zero, it indicates a spatially positive correlation of the variable (e.g., CVD incidence or a built environment value), where high-value areas tend to be surrounded by other high-value areas, and low-value areas by other low-value areas, indicating significant spatial clustering. Conversely, when Moran's I is significantly negative, it indicates a spatial negative correlation, where high-value areas are adjacent to low-value areas, forming a distinct spatial dispersion pattern. In this study, the 10-year cardiovascular case counts and the average values of built environment features were computed for each grid cell, and univariate global spatial autocorrelation analysis was conducted using GeoDa software.

(2)Bivariate global spatial autocorrelation.

Correlation analysis is a widely used method to assess the relationship between variables and serves as a preliminary step for regression modeling. Traditional Pearson correlation tests focus primarily on detecting linear associations but are ineffective when spatial autocorrelation is present among variables. Moreover, conventional tests cannot capture the spatial co-patterning of two variables, even though co-patterning is a crucial aspect of spatial relationships[66]. To overcome this limitation, we applied bivariate global spatial autocorrelation analysis using the GeoDa software to assess the spatial correlation between CVD and built environment features, and the formula is as follows:

$$I_{x,y} = \frac{\sum_i (\tilde{x}_i - \bar{x})(\tilde{y}_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2}\sqrt{\sum_i (y_i - \bar{y})^2}} \tag{2}$$

Here, I denotes the Moran's I value, x denotes the first variable, and y denotes the second variable. Variables marked with a tilde $(\sim)$ represent the spatially weighted average of neighboring values. All neighborhood weights are standardized such that their sum equals 1. Variables denoted with a bar $(-)$ indicate the unweighted average across all n input features. The subscript i refers to an individual input feature. All summations in the formula refer to summing across all spatial units. The Moran's I value typically ranges between −1 and 1. When Moran's I is significantly greater than 0, it suggests that CVD and the corresponding built environment factor exhibit a spatially positive correlation. Conversely, when Moran's I is significantly less than 0, it indicates a spatially negative correlation between CVD and the built environment feature. The significance criteria are consistent with those used in univariate global spatial autocorrelation, i.e., $p < 0.01$ and $|z| > 2.58$. We conducted bivariate global spatial autocorrelation analysis using GeoDa based on 10-year average values of CVD and built environment variables, and selected variables with statistically significant correlations for further analysis.

Emerging Spatiotemporal hotspot analysis

Although spatial autocorrelation reveals the overall clustering of elements, it cannot capture the spatiotemporal evolution of clustering characteristics. To capture this feature, we introduced the emerging spatiotemporal hotspot analysis method. This method integrates temporal scan statistics with spatial hotspot analysis, effectively identifying and quantifying abnormal clustering of variables across time and space[67]. We utilized ArcGIS 10.8 software and applied the FDR (False Discovery Rate) corrected Getis-Ord Gi statistic to assess whether the CVD incidence and built environment elements at each location were significantly higher or lower than their surrounding areas over time. This statistic calculates the spatial clustering intensity of cases within a local area and provides Z-scores and P-values to quantify the statistical significance of hotspots and cold spots. Specifically, we designated hotspots with Z-scores exceeding 1.96 (P-value < 0.05) as statistically significant regions, typically exhibiting high clustering intensity. Using the Mann-Kendall trend test, we further analyze the temporal trends of these hotspots and cold spots. The Mann-Kendall statistic detects monotonic trends in non-parametric time series data, encompassing both linear and non-linear trends. Each time interval's trend is expressed using a z-score (positive values indicate increasing trends, negative values indicate decreasing trends), with p-values used to determine statistical significance[68]. Through this method, we were able to detect changing trends of different elements across multiple temporal scales, including eight distinct hotspot or cold spot categories[69]—new, consecutive, intensifying, persistent, diminishing, sporadic, oscillating, and historical—as illustrated by the results shown in Table 3.

Geographically and temporally weighted regression

To delve deeper into the complex effects of the built environment on CVD incidence and its dynamic changes over time and space, we introduced the geographically and temporally weighted regression (GTWR) model for analysis. This model extends the traditional geographically weighted regression (GWR) by incorporating a temporal dimension[70]. The GWR model, a spatial statistical method, establishes local regression equations for each geographic location and uses a spatial weight matrix and kernel function to reflect spatial relationships between observations, capturing the local effects between variables[71]. The formula is:

$$y_i = \beta_0(u_i, v_i) + \sum_{K=1}^{K} \beta_k(u_i, v_i) \times x_{ik} + \epsilon_i \tag{3}$$

Here, y_i denotes the observed value of the dependent variable at observation point i; (u_i, v_i) represents the spatial coordinates of observation point i; $\beta_0(u_i, v_i)$is the intercept term at that location; $\beta_k(u_i, v_i)$ is the regression coefficient for the k-th independent variable at location (u_i, v_i), which varies by spatial position;

Type	Is the final time step hot?	Have > 90% of time steps been hot?	Has there been significant change in how hot?	Has location ever been a cold spot?
New	Yes	No	not applicable	not applicable
Consecutive	Yes	No	not applicable	not applicable
Intensifying	Yes	Yes	Yes, increasing	not applicable
Persistent	not applicable	Yes	No	not applicable
Diminishing	Yes	Yes	Yes, decreasing	not applicable
Sporadic	not applicable	No	not applicable	No
Oscillating	Yes	No	not applicable	Yes
Historical	No	Yes	not applicable	not applicable

Table 3. Types of Spatio-temporal hotspot distribution mode.

	Univariate global spatial autocorrelation			Bivariate global spatial autocorrelation		
	z	*p*	Moran's I	z	*p*	Moran's I
Parks and squares	12.798	0.001	0.236	−2.961	0.002	−0.039
Shopping and consumption	21.504	0.001	0.398	−1.454	0.070	−0.019
Transportation facilities	20.836	0.001	0.386	17.714	0.001	0.235
Life services	22.002	0.001	0.413	11.101	0.001	0.145
Sports and leisure	15.643	0.001	0.300	12.035	0.001	0.156
Medical care	20.401	0.001	0.396	17.918	0.001	0.278
Catering and food	21.753	0.001	0.413	9.719	0.001	0.128
Road network	17.951	0.001	0.337	−1.076	0.141	−0.014
CVD	18.052	0.001	0.342			

Table 4. Global Spatial autocorrelation analysis.

x_{ik} is the observed value of the k-th independent variable at observation point i; k represents the total number of independent variables, and ϵ_i is the random error term.

However, when dealing with data characterized by significant spatiotemporal heterogeneity, spatial weighting alone is insufficient to fully capture the dynamic variation in the data. Therefore, we further introduced the GTWR model in this study. In the GTWR model, spatial weights are determined based on geographic distance and are standardized using a Gaussian kernel function, such that the total spatial weights sum to 1, thereby ensuring comparability across regions. Temporal weights are assigned based on the relative importance of time intervals within the study period, with more recent observations assigned higher weights, and temporal weights are normalized accordingly. We implemented the GTWR model using the plugin developed by Huang et al., which was integrated into ArcGIS 10.8[72], enhancing the traditional GWR model by incorporating a temporal dimension, thereby enabling regression coefficients to vary dynamically across both space and time.

In the practical application of the GTWR plugin, we enabled the "Export local model stats result" option under the "Environ" settings to evaluate the statistical significance (*p*-values) of each grid cell at different time intervals. For bandwidth selection, we adopted the Akaike Information Criterion (AIC) as the primary selection criterion. AIC accounts for both model goodness-of-fit and complexity, and iteratively calculates AIC values across different bandwidth settings, selecting the bandwidth that yields the lowest AIC. This optimal bandwidth achieves the best trade-off between model fit and parsimony, effectively preventing overfitting and excessive sensitivity to local noise, and also avoiding underfitting, which would limit the model's ability to capture spatiotemporal heterogeneity[73]. The formula is:

$$y_i = \beta_0(u_i, v_i, t_i) + \sum_{K=1}^{K} \beta_k(u_i, v_i, t_i) \times x_{ik}(t_i) + \epsilon_i \quad (4)$$

Here, t_i represents the temporal coordinate of observation point i; $\beta_0(u_i, v_i, t_i)$ and $\beta_k(u_i, v_i, t_i)$ are the intercept term and the regression coefficient of the k-th independent variable at location (u_i, v_i) and time t_i, respectively, both of which vary with spatial location and time; $x_{ik}(t_i)$ denotes the observed value of the k-th independent variable at observation point i and time t_i.

Results

Global Spatial autocorrelation

We performed both univariate and bivariate global spatial autocorrelation analyses to explore the spatial distribution characteristics and associations between CVD and various built environment factors. The results presented in Table 4 show that, in the univariate global spatial autocorrelation tests, all variables—including parks and squares, shopping and consumption, transportation facilities, life services, sports and leisure, medical care, catering and food, road network, and CVD—passed the statistical significance test ($p < 0.001$ and $z > 2.58$), confirming the robustness of the Moran's I results. All Moran's I values were positive, clearly revealing significant spatial clustering in the distribution of parks and squares, shopping and consumption, transportation facilities, life services, sports and leisure, medical care, catering and food, road network, and CVD. Specifically, parks and squares had a Moran's I value of 0.236, reflecting relatively weaker spatial clustering among the variables; whereas shopping and consumption (0.398), transportation facilities (0.386), life services (0.413), and catering and food (0.413) showed stronger spatial clustering patterns, indicating relatively higher spatial autocorrelation.

In the bivariate global spatial autocorrelation analysis, the relationships between shopping and consumption ($z = -1.454$, $p = 0.070$, Moran's I $= -0.019$) and CVD, as well as between road network ($z = -1.076$, $p = 0.141$, Moran's I $= -0.014$) and CVD, also failed to meet the significance criteria ($p < 0.01$ and $z > 2.58$), suggesting that these bivariate relationships were not statistically significant and were therefore excluded from subsequent analyses. Among the remaining bivariate combinations with CVD, transportation facilities and CVD ($z = 17.714$, $p < 0.001$, Moran's I $= 0.235$), life services and CVD ($z = 11.101$, $p < 0.001$, Moran's I $= 0.145$), sports and leisure and CVD ($z = 12.035$, $p < 0.001$, Moran's I $= 0.156$), medical care and CVD ($z = 17.918$, $p < 0.001$, Moran's I $= 0.278$), catering and food and CVD ($z = 9.719$, $p < 0.001$, Moran's I $= 0.128$) all showed z-values exceeding 2.58 and p-values below 0.001, with positive Moran's I values, indicating significant positive spatial correlations between these built environment features and CVD, suggesting that they follow similar spatial distribution patterns. Conversely, parks and squares and CVD ($z = -2.961$, $p = 0.002$, Moran's I $= -0.039$) showed a negative z-score and a negative Moran's I value, indicating a negative spatial association between parks and squares and CVD, suggesting an opposite spatial trend in their distribution patterns.

The emerging Spatiotemporal hotspot analysis

Based on the point distribution data of CVD cases and built environment elements from 2012 to 2022, a 200 m × 200 m space-time cube was constructed to conduct spatiotemporal hotspot analysis (Fig. 2). CVD hotspots were concentrated in the central and northwestern parts of the study area, with persistent and intensifying hotspots in the central area, scattered hotspots along the periphery, emerging hotspots in the west-central region, and cold spots concentrated in marginal areas. These findings imply that the central and northwestern parts of the study area may harbor potential factors contributing to CVD, such as elevated environmental stress due to high population density or psychological tension induced by a fast-paced lifestyle. The persistence of the central region as a hotspot suggests the presence of stable and enduring influencing factors, while the newly emerged hotspot in the west-central region may be associated with recent urbanization, lifestyle transitions, or environmental changes.

Regarding built environment elements, parks and squares exhibited hotspots in the southeast and northeast, and cold spots in the north, northwest, and southwest. These hotspots may reflect inclusion in designated urban ecological zones, resulting in a higher concentration of such facilities, supporting outdoor activities and promoting both physical and mental health. In contrast, the cold spot regions in the north, northwest, and southwest likely reflect insufficient investment in recreational infrastructure during urban development. Transportation facilities hotspots were found in the central and southern regions, with cold spots in the north and west. The central and southern areas, characterized by dense populations and high commercial activity,

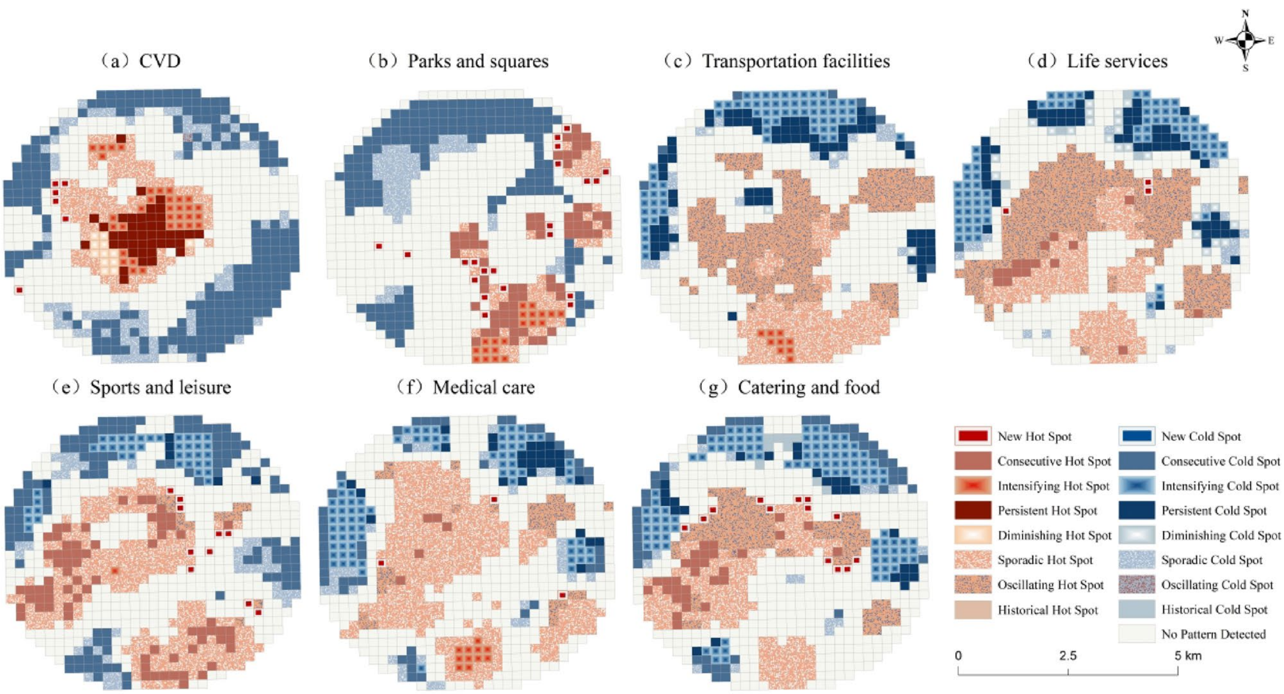


Fig. 2. Spatio-temporal Hotspot Distribution.

Variable	VIF
Parks and squares	1.047
Transportation facilities	1.401
Life services	2.440
Sports and leisure	1.518
Medical care	1.668
Catering and food	1.854

Table 5. Multiple collinearity test.

Model	*R*-squared	Adjusted *R*-squared	AICc
OLS	0.028	0.027	47064.124
GWR	0.222	0.221	45619.300
GTWR	0.240	0.239	45558.500

Table 6. Comparison of model results for OLS, GWR, and GTWR.

have strong demand for transport infrastructure, which drives ongoing development, whereas the north and west may be less developed, resulting in lower transportation demand. Life service hotspots were distributed across the central, southern, southwestern, and southeastern regions, while cold spots appeared in the north and west. This reflects relatively high population density in these areas, with strong resident demand for services such as housekeeping, maintenance, and retail, which has attracted a concentration of related service facilities. Conversely, the cold spots in the north and west suggest that these areas have relatively low population densities and limited demand, making it difficult to sustain large numbers of service facilities. Sports and leisure hotspots were observed in the central, southeastern, and southwestern areas, while cold spots were present in the north, east, and west. This implies that more sports venues and fitness facilities are likely available in the central, southeastern, and southwestern regions, with higher levels of participation in physical activity among residents; whereas the north, east, and west may suffer from facility scarcity or low population density, leading to a less active recreational environment. Medical care hotspots appeared in the central, southern, southeastern, and southwestern regions, with cold spots in the north, east, and west. This indicates that the central, southern, southeastern, and southwestern regions are well equipped with medical resources, allowing better access to medical care for residents; whereas the northern, eastern, and western areas are relatively underserved. Catering and food hotspots were observed in the central, southern, and southwestern regions, while cold spots occurred in the north, east, and west. This indicates high consumer activity in the central, southern, and southwestern regions, where diverse dining demands among residents have fostered a thriving food service industry; whereas food markets in the north, east, and west remain relatively underdeveloped.

Overall, hotspots of various built environment elements tend to converge in the central part of the study area, where hotspots of CVD and life services, among others, are concentrated, suggesting strong urban vitality in this region. In contrast, cold spots are primarily located in the northern area, where resources such as parks and squares, and medical care are notably lacking, reflecting lagging development and inadequate infrastructure in the north.

Spatiotemporal geographically weighted regression

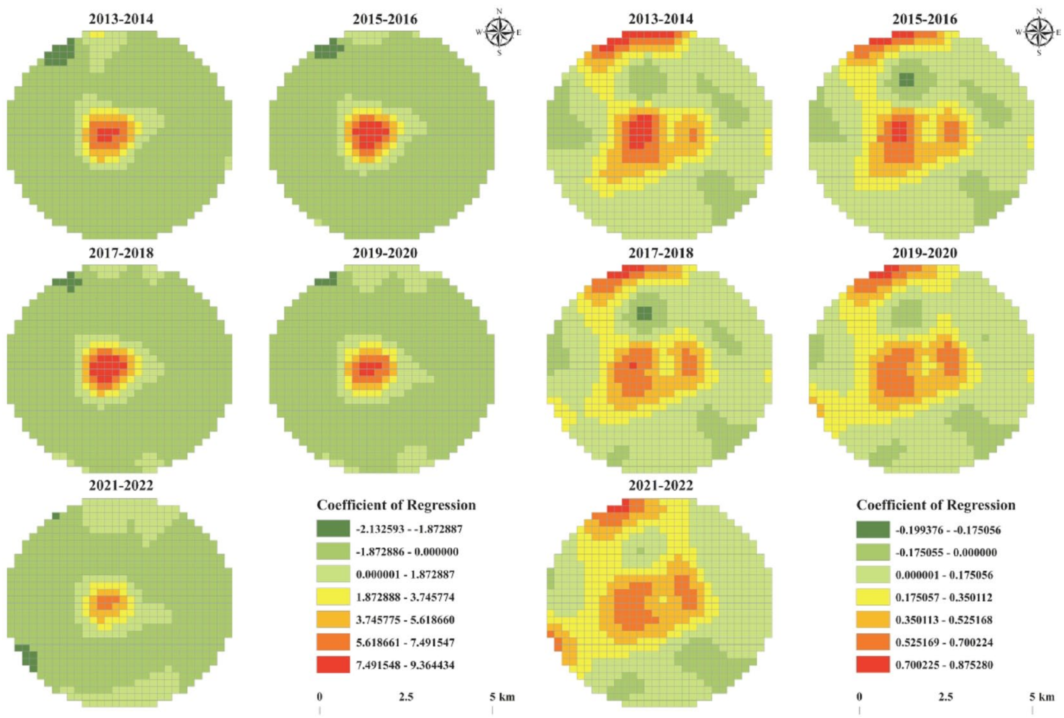
In examining the impact of the built environment on CVD, we first performed a collinearity diagnostic using IBM SPSS Statistics 24.0 to ensure the robustness of the results. The variance inflation factor (VIF) test confirmed that all variables had VIF values below 10, indicating that the dataset did not exhibit significant multicollinearity (Table 5). We then implemented three regression models—OLS, GWR, and GTWR—using IBM SPSS Statistics 24.0 and ArcGIS 10.8 to compare their performance (Table 6). The results showed that the OLS model had an R-squared of just 0.028 and an adjusted R-squared of 0.027, with a relatively high AICc value of 47064.124, indicating that it performed poorly in capturing the relationships among variables. In contrast, the GWR model showed improved R-squared and adjusted R-squared values of 0.222 and 0.221, respectively, with the AICc decreasing to 45619.300, demonstrating a better model fit. The GTWR model further increased the R-squared and adjusted R-squared to 0.240 and 0.239, respectively, and achieved an even lower AICc value of 45558.500, outperforming the GWR model. These findings provide strong evidence of the GTWR model's superiority in capturing the complex relationships between the built environment and CVD, as it accounts for variation across both spatial and temporal dimensions, thereby offering a more accurate representation of their dynamic associations.

Table 7 reports coefficient statistics from GTWR model, highlighting the spatially dynamic patterns of how various environmental factors influence cardiovascular health. Notably, parks and squares, along with medical care, exhibited the most pronounced extremes in their effects, while life services demonstrated the most stable influence, albeit with limited marginal benefits, and other factors exhibited diverse spatially varying associations.

The data revealed that parks and squares (mean = − 0.018) exhibited a marked polarization in their impact, with coefficient values ranging from − 3.79 to 9.438 (standard deviation = 1.504), suggesting strong spatial

Variable	Mean	Min	Median	Max	Standard deviation
Parks and squares	−0.018	−3.79	−0.268	9.438	1.504
Transportation facilities	0.176	−0.215	0.110	0.966	0.195
Life services	0.028	−0.246	0.017	0.225	0.061
Sports and leisure	0.051	−0.855	0.016	1.110	0.244
Medical care	0.175	−0.383	0.106	1.619	0.298
Catering and food	−0.028	−0.270	−0.016	0.074	0.051

Table 7. Statistics of GTWR regression coefficients.



(a) Parks and squares (b) Transportation facilities

Fig. 3. Regression coefficient distribution of parks and squares and transportationfacilities.

heterogeneity in the health effects of green space—where high-quality parks may considerably reduce disease risk, whereas poorly designed or inaccessible green spaces may lead to adverse impacts. Medical care had a coefficient range of 2.0 (−0.383 to 1.619), where the positive extreme (1.619) reveals health disparities in areas with limited access to medical services, and the negative extreme (−0.383) underscores the protective effect of high-quality medical facilities. In contrast, life services exhibited the smallest coefficient variation (−0.246 to 0.225, SD = 0.061), reflecting their role as universally accessible basic services; though their low mean (0.028) and median (0.017) values suggest limited marginal effects. Sports and leisure demonstrated asymmetric polarization (range = − 0.855 to 1.11), indicating a threshold effect, where intensifying facility coverage may be necessary to trigger significant health benefits. Transportation facilities exhibited a strong positive effect overall (with 75% of regions showing coefficients > 0.28), although the minimum value (−0.215) indicates elevated risk in extremely underserved areas. For catering and food, 90% of coefficient values were below 0.1 (range = − 0.27 to 0.074), and the left-skewed distribution supports the notion of chronic cumulative risk in areas densely packed with fast food outlets.

In the GTWR analysis results, all grid-level p-values across the study area were below 0.05, successfully passing the threshold for statistical significance and confirming the robustness of the model outputs. We then visualized the GTWR coefficients using ArcGIS, classifying them into seven intervals. To compare the spatiotemporal effects of different built environment features on CVD, we partitioned the data from 2013 to 2022 into five discrete time intervals. For each period, we calculated the average coefficients and conducted comparative analyses, as illustrated in the results.

As shown in Fig. 3, in terms of parks and squares, over 70% of spatial grid cells exhibited negative regression coefficients, indicating a predominantly suppressive effect, albeit with strong variation and notable spatial heterogeneity. The central hotspot region displayed significant positive effects, likely influenced by usage behaviors and social context, whereas smaller zones in the northwest were dominated by negative effects, potentially linked to local environmental characteristics. Temporally, from 2013 to 2018, the number of maximum-value grids in the central region increased, suggesting growing positive effects, possibly resulting from changes in surrounding environment or utilization patterns; from 2018 to 2022, these peak values declined and overall coefficients approached neutrality, reflecting a weakening and stabilization of impact intensity, likely attributable to improved urban planning and heightened public health awareness.

Regarding transportation facilities, more than 90% of spatial grid coefficients were positive, suggesting that transport infrastructure tends to promote CVD incidence in most areas. The central and northern hotspot zones exhibited strong positive impacts, likely attributable to high traffic volumes and severe pollution; whereas some intermediate areas between them showed negative effects, possibly reflecting well-planned traffic systems. Between 2013 and 2022, the variation in regression coefficients gradually decreased, with a reduction in peak grid counts in the central and northern regions, suggesting weakening transportation-related impacts; while increasing positive values in the southwest hinted at the formation of a new hotspot cluster, likely driven by accelerated economic activity and escalating traffic congestion in the region.

As shown in Fig. 4, regarding life services, over 60% of the spatial grid cells exhibited positive regression coefficients, with central and northern regions displaying strong positive associations due to high facility density and fast-paced urban lifestyles, indicating significant positive correlations with CVD. Temporally, the distribution of coefficients evolved from a U-shaped pattern (2013–2014) to an H-shaped pattern by 2021–2022, reflecting transformations in urban development and lifestyle behaviors. In the northwest, the number of negative extreme-value grids declined, indicating a weakening of the protective effect; while the southwest emerged as a center of negative values, potentially due to the integration of health-promoting design in emerging facilities. Overall, the influence tended toward neutral (zero) values, likely due to optimized urban planning and rising health consciousness among residents.

For sports and leisure facilities, positive and negative coefficients were almost evenly distributed, indicating strong spatial divergence, with prominent positive extremes in the northeast and northwest. Over time, positive-effect areas in the northwest initially expanded due to urban development, then contracted as health awareness rose and facility optimization occurred. In the northeast, the area of positive coefficients shifted westward and diminished, influenced by shifting population density and infrastructure development. In the central region, the number of negative grids decreased, likely due to the occupation of recreational spaces; and in the southwest, some grid cells exhibited increasing positive values, potentially linked to facility construction or use-related issues. Overall, the effects trended toward neutrality, likely due to recent improvements in the planning and management of public recreational infrastructure.

As shown in Fig. 5, in the context of medical care, more than 60% of spatial grid cells exhibited positive regression coefficients, with the northern region showing significant positive associations, likely due to intensive patient mobility. In contrast, small zones between the central and eastern regions showed negative effects, likely owing to a robust primary healthcare network. Temporally, from 2013 to 2022, the variability in regression

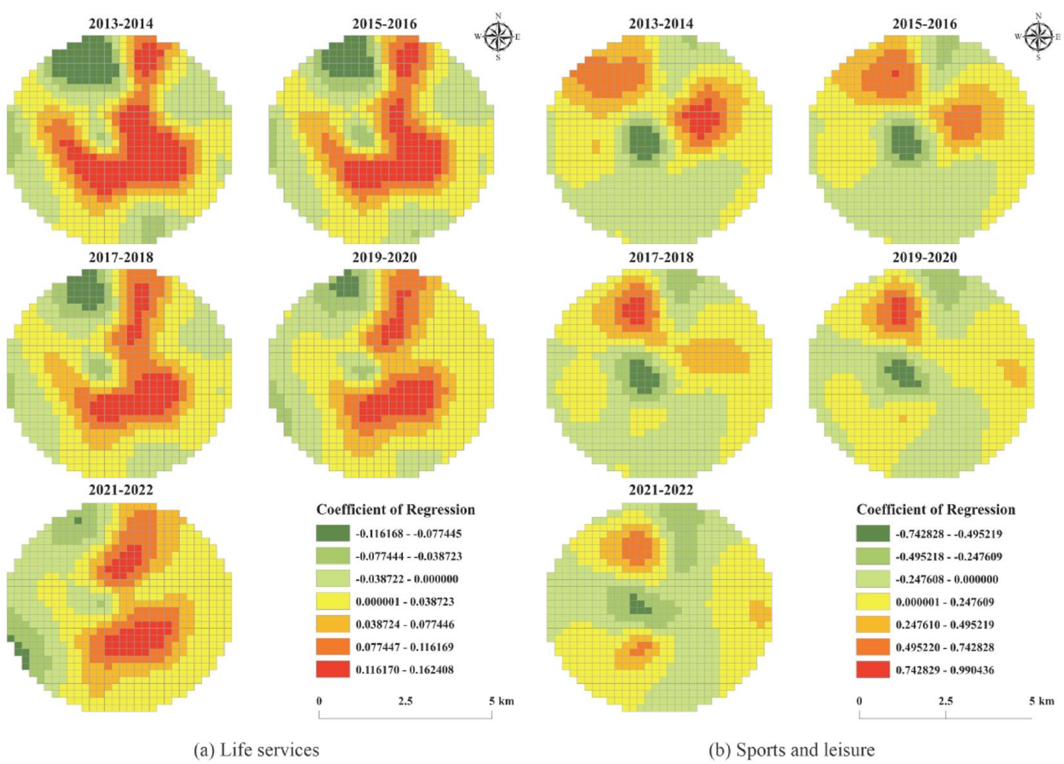


Fig. 4. Regression coefficient distribution between life services and sports and leisure.

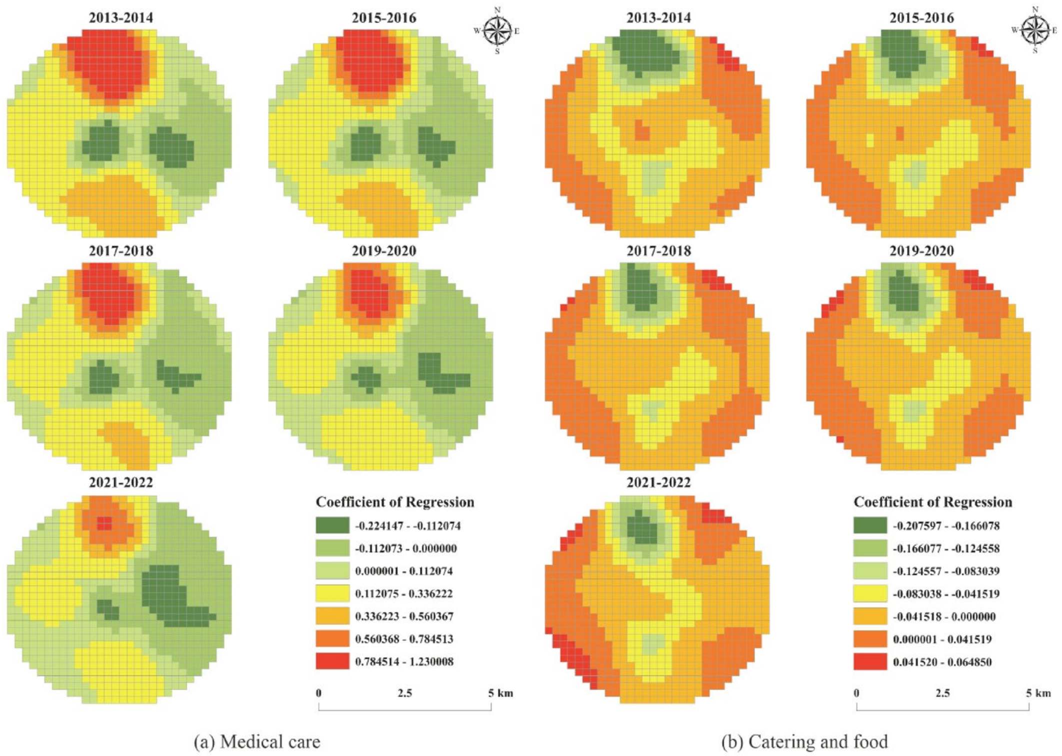


Fig. 5. Regression coefficient distribution of medical care and catering and food.

coefficients decreased. Positive extreme-value grids in the north declined, attributed to optimized spatial allocation of healthcare resources, while a downgrading of large positive-value zones in the south highlighted improvements in healthcare infrastructure. Negative-value clusters were primarily concentrated in the central and eastern regions. In the central region, land-use reallocation weakened service capacity and reduced negative-value grids; in the eastern area, they first declined with service restructuring and then increased after subsequent improvements. Overall, the spatial trend shifted toward negative effects, driven by increased investment, layout optimization, enhanced primary care services, and improved disease prevention efforts.

For catering and food facilities, over 60% of spatial grids exhibited negative coefficients, with a predominance of healthy dining in the north that was associated with reduced CVD risk. In contrast, the southeast, northeast, southwest, and northwest all exhibited positive associations with CVD. Between 2013 and 2022, positive extreme values gradually increased in the four peripheral regions, while the magnitude of negative values in the north diminished. Overall, the spatial trend shifted toward more positive associations, attributed to rapid urban expansion, changing dietary behaviors, and the growing restaurant industry, with fast food culture and the rise of food delivery significantly reshaping residents' dietary patterns, which may adversely impact cardiovascular health.

Discussion

We examined the spatiotemporal dynamics of CVD cases in the central area of Nanning from a micro-scale perspective and investigated their intrinsic associations with the urban built environment. Through a comprehensive analysis of CVD incidence data from 2013 to 2022 in the study area, integrated with multiple built environment elements, we gained new insights into the mechanisms driving CVD incidence.

In the overall distribution of patients, gender differences in the total number of cases were minor, with female cases slightly fewer than male. In contrast, age differences were pronounced, with individuals aged 61 and above constituting the predominant group affected by CVD. Epidemiological studies have shown that metabolic risk factors typically increase with age, a trend that is largely unavoidable[74,75]. Interestingly, some studies have shown that male mortality from heart disease is higher at relatively younger ages, while the mortality rate for women rises sharply after the age of 60, suggesting that gender differences in CVD incidence and mortality are age-dependent[76]. In terms of diagnosis and treatment, 88.1% of patients spent more than 5,000 RMB, which represents a substantial financial burden for local residents, particularly for elderly individuals who are already in retirement, as such expenses may equal or exceed their average monthly pension. During the observation period from 2013 to 2022, the number of CVD cases in the study area showed a generally rising trend with fluctuations, peaking in 2019, highlighting the growing urgency and severity of CVD prevention and control efforts.

We employed global spatial autocorrelation analysis, emerging spatiotemporal hotspot analysis, and GTWR analysis to reveal the spatial distribution, correlation patterns, and spatiotemporal influence characteristics between the built environment and CVD in the study area. The findings demonstrated that both CVD and built environment elements exhibited significant spatial clustering, indicating non-uniform distributions and distinct spatial heterogeneity. Furthermore, CVD displayed spatial correlations with six built environment elements: parks and squares, transportation facilities, life services, sports and leisure, medical care, and catering and food. The spatiotemporal impacts of these built environment elements on CVD varied under different temporal and spatial conditions.

Regarding parks and squares, green spaces represented by parks and squares generally exhibited heterogeneous effects on CVD. In most regions, parks and squares showed a significant negative association with CVD, consistent with prior studies concluding that green spaces have protective and risk-reducing effects on CVD[77]. However, in the central area of the study region, an opposite trend emerged: parks and squares positively influenced CVD hotspot areas, where increased park and square density correlated with higher CVD case numbers—a finding contradictory to conventional research. This anomaly may stem from the central area's inherent transportation convenience, which already attracts a higher baseline population of patients. The addition of parks and squares may amplify this clustering effect due to their accessibility, drawing even larger crowds. The resultant population density increase reduces per capita green space availability[78], while heightened traffic flows exacerbate environmental pollution and noise. These adverse factors likely negate the protective benefits of green spaces, leading to the observed positive association in the central area. Over time, however, this effect gradually weakened, potentially due to improved urban green space planning that enhanced per capita green space ratios.

For transportation facilities, spatial autocorrelation with CVD was positive, aligning with existing evidence that transportation-related noise and air pollution indirectly promote CVD risk[79,80]. On one hand, increased vehicular emissions elevate particulate matter (PM), particularly PM2.5, worsening air quality. Long-term exposure to such pollution raises the risk of cardiovascular conditions, including atherosclerosis[81]. On the other hand, prolonged exposure to traffic noise activates the sympathetic nervous system, elevating blood pressure and heart rate, thereby increasing CVD susceptibility. A systematic review corroborates this, reporting that every 10 dB increase in traffic noise elevates ischemic heart disease (IHD) incidence by 8% (RR: 1.08, CI: 1.01–1.15)[82]. In the central study area—a preexisting CVD hotspot—transportation facilities exhibited a pronounced positive influence, with facility density strongly correlating with CVD case numbers. In recent years, however, urban planning initiatives promoting green transportation have gradually mitigated this effect, suggesting that strategic transportation policies can alleviate negative health impacts.

Concerning life services amenities, spatial autocorrelation with CVD was positive, indicating that increased density of such facilities may promote CVD risk. This effect was concentrated in the central study area, where daily service facilities significantly correlated with CVD hotspot intensity. However, regression coefficients revealed a relatively weak influence, likely because the central area's service facilities are diverse and evenly distributed, meeting residents' needs without excessively exacerbating environmental pressures.

With respect to sports and leisure facilities, spatial autocorrelation with CVD appeared generally positive, which seems somewhat inconsistent with most prior research concluding that physical activity has a positive effect on cardiovascular health. Prior studies have indicated that the availability of sports and recreational facilities facilitates physical activity and helps improve cardiovascular function[22,83]. However, the overall positive correlation observed in this study may be due to a combination of complex underlying factors. Specifically, when examining the distribution of regression coefficients, in the central area of the study region, sports and recreational facilities exhibited a negative effect on CVD hotspots, where increased facility numbers were significantly associated with reduced cardiovascular case counts—aligning with the well-established view that physical activity and recreation help reduce cardiovascular risk[84]. The growth of recreational and fitness infrastructure in the central region has provided residents with greater access to physical activity. Regular exercise supports cardiopulmonary function, lowers blood pressure, and improves lipid metabolism, thereby reducing the likelihood of developing and progressing CVD. However, in the northeastern and northwestern areas, regression coefficients were strongly positive, likely because the addition of recreational amenities in these areas diverted physical activity participation from the central region, which had traditionally served as the core activity hub, attracting a large number of residents, including CVD patients. The new facilities attracted portions of this population away from the center, including those with CVD, thereby relieving usage pressure in the center. Meanwhile, changes in user demographics in the northeast and northwest, especially the localized aggregation of CVD patients, contributed to the observed positive association between recreational facilities and CVD. Over time, usage of recreational facilities by residents became more stable across regions, and population distribution and activity patterns gradually adapted to the new facility landscape, leading to a flattening of regression coefficients—indicating that the relationship between sports and recreational infrastructure and CVD has moved toward a dynamic balance.

Regarding medical care infrastructure, the overall spatial autocorrelation with CVD was positive, which contrasts with the widely accepted notion that improved access to medical care can effectively reduce CVD risk[85]. Typically, a comprehensive healthcare system should contribute to lowering CVD risk. However, in our study, the overall spatial association was found to be positive, suggesting that in most areas, increased healthcare facility density was associated with higher CVD consultation rates. In contrast, in the central and eastern areas of the study region, the pattern differed, as healthcare infrastructure exhibited a negative association with CVD hotspots, and the growth in healthcare facilities was significantly linked to reductions in CVD incidence. This aligns with findings from a South African case study suggesting that improved access to and utilization of medical care can alleviate cardiovascular risk[86] In the central and eastern subregions, the availability of ample healthcare resources enabled patients to access timely diagnosis, treatment, and rehabilitation guidance. However, in the northern region, regression coefficients showed a significantly positive relationship. This could be attributed to the fact that following the addition of new healthcare facilities in this region, the patient load on central healthcare facilities was reduced—which mirrors the redistribution mechanism observed with recreational facilities. The newly established healthcare resources in the north drew some of the patient population from the center, thereby altering the patient composition in the northern region, with a relatively higher proportion of CVD cases emerging, resulting in a positive correlation between medical care and CVD in the north. Over time, healthcare resources became more equitably distributed across the study area, and patients' healthcare-seeking behaviors became more rational and diverse, with population mobility and service usage patterns gradually stabilizing, resulting in a flattening of regression coefficients—indicating that the relationship between healthcare infrastructure and CVD has reached a new equilibrium through dynamic redistribution.

Regarding catering and food, the number of dining establishments exhibited a positive spatial autocorrelation with CVD, which aligns with conclusions drawn from certain prior studies—such as a study conducted across counties in the state of Maine, USA, which found that low density of full-service restaurants at the county level was positively associated with obesity and poor cardiovascular health scores[87]. It is noteworthy that based on regression coefficients, the impact of food-related facilities was relatively minor compared with other environmental factors, resembling the influence pattern observed with life services. This could be attributed to the fact that food establishments serve essential daily needs and are widely and evenly distributed across regions, making it unlikely for their influence to result in significant spatial clustering or dispersion. Most residents in the study area have easy access to diverse dining services, so spatial variation in restaurant availability is unlikely to cause substantial changes in CVD risk.

Limitations and prospects

This study has several limitations that warrant further investigation in future research. Geographically, the analysis was confined to a specific area in the central district of Nanning, and the findings may be shaped by local environmental and cultural conditions. As diverse geographic environments, urban development models, and lifestyle patterns in other regions may result in heterogeneous relationships between built environments and CVD, future research should therefore extend beyond the current geographic scope and incorporate multi-city comparative case studies to better capture contextual differences across geographic and cultural settings, and thereby deepen the understanding of their complex interactions. From a variable perspective, the current study primarily emphasized physical elements of the built environment in relation to CVD, although the pathogenesis of CVD is multifactorial, with socioeconomic conditions and individual behavioral patterns also playing critical roles. Future studies should consider incorporating these factors as mediating variables for deeper exploration, to build a more integrated theoretical framework, which can serve as a basis for more targeted disease prevention and intervention strategies.

Conclusion

This study focused on the central district of Nanning, providing an in-depth analysis of the relationship between CVD and the built environment from 2013 to 2022, and revealed significant spatial clustering and associations between them. The effects of various built environment elements on CVD differed and exhibited marked spatiotemporal heterogeneity. Parks and squares were associated with reduced disease risk in most areas, but demonstrated a positive correlation in the central region, likely due to specific contextual factors—and this effect diminished over time with improved urban green space planning. Transportation facilities elevated disease risk through noise and air pollution, with the central region showing the strongest positive effects, though green transport initiatives have helped to alleviate these impacts. Life services showed a positive spatial correlation with CVD, but the overall influence was relatively minor due to their wide availability and functional diversity. Sports and recreational facilities lowered CVD risk in the central region, but showed a positive correlation in the northeast and northwest due to the redistribution of users, and as user habits stabilized, the effect moved toward a balanced state. Healthcare infrastructure reduced CVD risk in the central and eastern regions, but showed a positive correlation in the north due to patient inflow from other regions, with this relationship gradually stabilizing as healthcare resources became more evenly distributed. Food-related facilities showed a small but consistent positive association with CVD, likely due to their broad and uniform spatial distribution. These findings suggest that Nanning has made tangible progress in its pursuit of a healthy city, with the overall influence of the built environment on cardiovascular health becoming more balanced, and increasingly evolving in a direction that supports cardiovascular health. These findings offer valuable evidence to support urban planning and public health policy, contributing to the advancement of healthy city initiatives and the enhancement of population health.

Data availability

The datasets used and/or analyzed in this study are available from the corresponding author upon reasonable request.

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References

1. Lai, K. Y., Webster, C., Gallacher, J. E. & Sarkar, C. Associations of urban built environment with cardiovascular risks and mortality: a systematic review. *J. Urb. Health*. **100**, 745–787. https://doi.org/10.1253/circj.CJ-19-0323 (2023).
2. Roth, G. A., Mensah, G. A. & Fuster, V. Vol. 76 2980–2981 (American College of Cardiology Foundation Washington DC, (2020).
3. Masaebi, F. et al. Trend analysis of disability adjusted life years due to cardiovascular diseases: results from the global burden of disease study 2019. *BMC Public. Health*. **21**, 1–13. https://doi.org/10.1186/s12889-021-11348-w (2021).

4. North, B. J. & Sinclair, D. A. The intersection between aging and cardiovascular disease. *Circul. Res.* **110**, 1097–1108. https://doi.org/10.1161/CIRCRESAHA.111.246876 (2012).
5. Kollia, N., Tragaki, A., Syngelakis, A. I. & Panagiotakos, D. Trends of cardiovascular disease mortality in relation to population aging in Greece (1956–2015). *open. Cardiovasc. Med. J.* **12**, 71. https://doi.org/10.2174/1874192401812010071 (2018).
6. Wu, Y., Benjamin, E. J. & MacMahon, S. Prevention and control of cardiovascular disease in the rapidly changing economy of China. *Circulation* **133**, 2545–2560. https://doi.org/10.1161/CIRCULATIONAHA.115.008728 (2016).
7. Spiteri, J. & von Brockdorff, P. Economic development and health outcomes: evidence from cardiovascular disease mortality in Europe. *Soc. Sci. Med.* **224**, 37–44. https://doi.org/10.1016/j.socscimed.2019.01.050 (2019).
8. Khaing, W., Vallibhakara, S. A., Attia, J., McEvoy, M. & Thakkinstian, A. Effects of education and income on cardiovascular outcomes: a systematic review and meta-analysis. *Eur. J. Prev. Cardiol.* **24**, 1032–1042. https://doi.org/10.1177/2047487317705916 (2017).
9. Kondo, T., Nakano, Y., Adachi, S. & Murohara, T. Effects of tobacco smoking on cardiovascular disease. *Circ. J.* **83**, 1980–1985. https://doi.org/10.1253/circj.CJ-19-0323 (2019).
10. Jingjie, W. et al. Sedentary time and its association with risk of cardiovascular diseases in adults: an updated systematic review and meta-analysis of observational studies. *BMC Public. Health*. **22**, 286. https://doi.org/10.1186/s12889-022-12728-6 (2022).
11. Malambo, P., Kengne, A. P., De Villiers, A., Lambert, E. V. & Puoane, T. Built environment, selected risk factors and major cardiovascular disease outcomes: a systematic review. *PloS One*. **11**, e0166846. https://doi.org/10.1371/journal.pone.0166846 (2016).
12. Bloom, D. E. et al. Program on the Global Demography of Aging,. The global economic burden of noncommunicable diseases. (2012).
13. Hartig, T., Evans, G. W., Jamner, L. D., Davis, D. S. & Gärling, T. Tracking restoration in natural and urban field settings. *J. Environ. Psychol.* **23**, 109–123. https://doi.org/10.1016/S0272-4944(02)00109-3 (2003).
14. Levy, L. Dietary strategies, policy and cardiovascular disease risk reduction in England. *Proc. Nutr. Soc.* **72**, 386–389. https://doi.org/10.1017/S0029665113001328 (2013).
15. Makhlouf, M. H. et al. Neighborhood walkability and cardiovascular risk in the united States. *Curr. Probl. Cardiol.* **48**, 101533. https://doi.org/10.1016/j.cpcardiol.2022.101533 (2023).
16. Seo, S., Choi, S., Kim, K., Kim, S. M. & Park, S. M. Association between urban green space and the risk of cardiovascular disease: A longitudinal study in seven Korean metropolitan areas. *Environ. Int.* **125**, 51–57. https://doi.org/10.1016/j.envint.2019.01.038 (2019).
17. Yeager, R. A., Smith, T. R. & Bhatnagar, A. Green environments and cardiovascular health. *Trends Cardiovasc. Med.* **30**, 241–246. https://doi.org/10.1016/j.tcm.2019.06.005 (2020).
18. Kim, K. et al. Associations of urban blue and green spaces with coronary artery calcification in black individuals and disadvantaged neighborhoods. *Circulation* **150**, 203–214. https://doi.org/10.1161/CIRCULATIONAHA.123.067992 (2024).
19. Chandrabose, M. et al. Built environment and cardio-metabolic health: systematic review and meta-analysis of longitudinal studies. *Obes. Rev.* **20**, 41–54. https://doi.org/10.1111/obr.12759 (2019).
20. Loo, C. J., Greiver, M., Aliarzadeh, B. & Lewis, D. Association between neighbourhood walkability and metabolic risk factors influenced by physical activity: a cross-sectional study of adults in Toronto, Canada. *BMJ Open.* **7**, e013889. https://doi.org/10.1136/bmjopen-2016-013889 (2017).
21. Pelletier, C. A., White, N., Duchesne, A. & Sluggett, L. Barriers to physical activity for adults in rural and urban Canada: a cross-sectional comparison. *SSM-Population Health*. **16**, 100964. https://doi.org/10.1016/j.ssmph.2021.100964 (2021).
22. Jerome, G. J. et al. Increasing equity of physical activity promotion for optimal cardiovascular health in adults: a scientific statement from the American heart association. *Circulation* **147**, 1951–1962. https://doi.org/10.1161/CIR.0000000000001148 (2023).
23. Dendup, T., Feng, X., Clingan, S. & Astell-Burt, T. Environmental risk factors for developing type 2 diabetes mellitus: a systematic review. *Int. J. Environ. Res. Public Health*. **15**, 78. https://doi.org/10.3390/ijerph15010078 (2018).
24. Sarkar, C., Webster, C. & Gallacher, J. Are exposures to ready-to-eat food environments associated with type 2 diabetes? A cross-sectional study of 347 551 UK biobank adult participants. *Lancet Planet. Health*. **2**, e438–e450. https://doi.org/10.1016/S2542-5196(18)30208-0 (2018).
25. Kusuma, D. et al. Food environment and diabetes mellitus in South Asia: A Geospatial analysis of health outcome data. *PLoS Med.* **19**, e1003970. https://doi.org/10.1371/journal.pmed.1003970 (2022).
26. Xu, J. et al. Spatial scale analysis for the relationships between the built environment and cardiovascular disease based on multi-source data. *Health Place*. **83**, 103048. https://doi.org/10.1016/j.healthplace.2023.103048 (2023).
27. Grazuleviciene, R., Andrusaityte, S., Gražulevičius, T. & Dėdelė, A. Neighborhood social and built environment and disparities in the risk of hypertension: A cross-sectional study. *Int. J. Environ. Res. Public Health*. **17**, 7696. https://doi.org/10.3390/ijerph17207696 (2020).
28. Ghosh-Dastidar, B. et al. Distance to store, food prices, and obesity in urban food deserts. *Am. J. Prev. Med.* **47**, 587–595. https://doi.org/10.1016/j.amepre.2014.07.005 (2014).
29. Braun, L. M. et al. Walkability and cardiometabolic risk factors: cross-sectional and longitudinal associations from the multi-ethnic study of atherosclerosis. *Health Place*. **39**, 9–17. https://doi.org/10.1016/j.healthplace.2016.02.006 (2016).
30. Anza-Ramirez, C. et al. The urban built environment and adult BMI, obesity, and diabetes in Latin American cities. *Nat. Commun.* **13**, 7977. https://doi.org/10.1038/s41467-022-35648-w (2022).
31. Meliker, J. R. & Sloan, C. D. Spatio-temporal epidemiology: principles and opportunities. *Spat. spatio-temporal Epidemiol.* **2**, 1–9. https://doi.org/10.1016/j.sste.2010.10.001 (2011).
32. Baptista, E. A. & Queiroz, B. L. Spatial analysis of cardiovascular mortality and associated factors around the world. *BMC Public. Health*. **22**, 1556. https://doi.org/10.1186/s12889-022-13955-7 (2022).
33. Dabass, A. et al. Using spatio-temporal modeling for exposure assessment in an investigation of fine particulate air pollution and cardiovascular mortality. *Environ. Res.* **151**, 564–572 (2016).
34. Liu, Y. et al. Analysis of short-term effects of air pollution on cardiovascular disease using bayesian spatio-temporal models. *Int. J. Environ. Res. Public Health*. **17**, 879. https://doi.org/10.3390/ijerph17030879 (2020).
35. ŞENER, R. & Türk, T. Spatiotemporal analysis of cardiovascular disease mortality with geographical information systems. *Appl. Spat. Anal. Policy*. **14**, 929–945. https://doi.org/10.1007/s12061-021-09382-7 (2021).
36. Ren, H., Wan, X., Wei, C. & Yang, G. Spatiotemporal variations in cardiovascular disease mortality in China from 1991 to 2009. *BMC Cardiovasc. Disord.* **19**, 1–10. https://doi.org/10.1186/s12872-019-1128-x (2019).
37. Yoo, E. H., Brown, P. & Eum, Y. Ambient air quality and spatio-temporal patterns of cardiovascular emergency department visits. *Int. J. Health Geogr.* **17**, 1–16. https://doi.org/10.1186/s12942-018-0138-8 (2018).
38. Dyck, J., Tate, R., Uhanova, J. & Torabi, M. Social determinants and spatio-temporal variation of ischemic heart disease in Manitoba. *BMC Public. Health*. **21**, 1–15. https://doi.org/10.1186/s12889-021-12369-1 (2021).
39. Huang, H., Xin, D., Hailin, Y., Xinhui, Z. & Qi, J. Spatio-temporal mechanism underlying the effect of urban heat Island on cardiovascular diseases. *Iran. J. Public. Health*. **49**, 1455. https://doi.org/10.18502/ijph.v49i8.3889 (2020).
40. Baptista, E. A. Cardiovascular diseases mortality in Mexican municipalities: A Spatio-Temporal approach. *Appl. Spat. Anal. Policy*. **17**, 637–650. https://doi.org/10.1007/s12061-023-09562-7 (2024).
41. He, M. Z. et al. Short-term PM 2.5 and cardiovascular admissions in NY State: assessing sensitivity to exposure model choice. *Environ. Health*. **20**, 1–11. https://doi.org/10.1186/s12940-021-00782-3 (2021).

42. Wang, W. et al. Spatiotemporal trends and ecological determinants of cardiovascular mortality among 2844 counties in Mainland China, 2006–2020: a bayesian modeling study of National mortality registries. *BMC Med.* **20**, 467. https://doi.org/10.1186/s12916-022-02613-9 (2022).
43. Wang, W. et al. Mortality and years of life lost of cardiovascular diseases in China, 2005–2020: empirical evidence from National mortality surveillance system. *Int. J. Cardiol.* **340**, 105–112. https://doi.org/10.1016/j.ijcard.2021.08.034 (2021).
44. Liu, M. et al. The built environment and cardiovascular disease: an umbrella review and meta-meta-analysis. *Eur. J. Prev. Cardiol.* **30**, 1801–1827. https://doi.org/10.1093/eurjpc/zwad241 (2023).
45. Yamashita, T. & Kunkel, S. R. The association between heart disease mortality and geographic access to hospitals: County level comparisons in Ohio, USA. *Soc. Sci. Med.* **70**, 1211–1218. https://doi.org/10.1016/j.socscimed.2009.12.028 (2010).
46. Murata, A. & Matsuda, S. Association between ambulance distance to hospitals and mortality from acute diseases in Japan: National database analysis. *J. Public. Health Manage. Pract.* **19** https://doi.org/10.1097/PHH.0b013e31828b7150 (2013). E23-E28; doi.
47. Yan, K. et al. The equity of China's emergency medical services from 2010–2014. *Int. J. Equity Health*. **16**, 1–8. https://doi.org/10.1186/s12939-016-0507-5 (2017).
48. Wei, L. et al. Impact on mortality following first acute myocardial infarction of distance between home and hospital: cohort study. *Heart* **94**, 1141–1146. https://doi.org/10.1136/hrt.2007.123612 (2008).
49. Nutsford, D., Pearson, A. L. & Kingham, S. An ecological study investigating the association between access to urban green space and mental health. *Public. Health*. **127**, 1005–1011. https://doi.org/10.1016/j.puhe.2013.08.016 (2013).
50. Du, M., Cheng, L., Li, X. & Yang, J. Factors affecting the travel mode choice of the urban elderly in healthcare activity: comparison between core area and suburban area. *Sustainable Cities Soc.* **52**, 101868. https://doi.org/10.1016/j.scs.2019.101868 (2020).
51. Noorali, A. A. et al. Built environment and cardiovascular Diseases–Insights from a global review. *Curr. Atheroscler. Rep.* **27**, 1–12. https://doi.org/10.1007/s11883-025-01282-2 (2025).
52. Pourabdollah, A., Morley, J., Feldman, S. & Jackson, M. Towards an authoritative openstreetmap: conflating OSM and OS opendata National maps' road network. *ISPRS Int. J. Geo-Information*. **2**, 704–728. https://doi.org/10.3390/ijgi2030704 (2013).
53. Liu, K., Yin, L., Lu, F. & Mou, N. Visualizing and exploring POI configurations of urban regions on POI-type semantic space. *Cities* **99**, 102610. https://doi.org/10.1016/j.cities.2020.102610 (2020).
54. Mazidi, M. & Speakman, J. R. Association of Fast-Food and Full-Service restaurant densities with mortality from cardiovascular disease and stroke, and the prevalence of diabetes mellitus. *J. Am. Heart Association*. **7**, e007651. https://doi.org/10.1161/JAHA.117.007651 (2018).
55. Nieuwenhuijsen, M. J. Influence of urban and transport planning and the City environment on cardiovascular disease. *Nat. Reviews Cardiol.* **15**, 432–438. https://doi.org/10.1038/s41569-018-0003-2 (2018).
56. Grazuleviciene, R. et al. The effect of park and urban environments on coronary artery disease patients: a randomized trial. *Biomed. Res. Int.* **2015** (403012). https://doi.org/10.1155/2015/403012 (2015).
57. Hoevenaar-Blom, M. P., Wendel-Vos, G. W., Spijkerman, A. M., Kromhout, D. & Verschuren, W. M. Cycling and sports, but not walking, are associated with 10-year cardiovascular disease incidence: the MORGEN study. *Eur. J. Prev. Cardiol.* **18**, 41–47. https://doi.org/10.1097/HJR.0b013e32833bfc87 (2011).
58. Kweon, S. et al. Quality of life and awareness of cardiac rehabilitation program in people with cardiovascular diseases. *Annals Rehabilitation Med.* **41**, 248–256. https://doi.org/10.5535/arm.2017.41.2.248 (2017).
59. Haralson, M. K., Sargent, R. G. & Schluchter, M. The relationship between knowledge of cardiovascular dietary risk and food shopping behaviors. *Am. J. Prev. Med.* **6**, 318–322 (1990).
60. Sepehrvand, N. et al. Ambulance use, distance and outcomes in patients with suspected cardiovascular disease: a registry-based geographic information system study. *Eur. Heart Journal: Acute Cardiovasc. Care*. **9**, 45–58. https://doi.org/10.1177/2048872618769872 (2020).
61. Deng, S. et al. Spatial analysis of the impact of urban built environment on cardiovascular diseases: a case study in Xixiangtang, China. *BMC Public. Health*. **24**, 2368. https://doi.org/10.1186/s12889-024-19884-x (2024).
62. Chen, Y. Development and method improvement of Spatial autocorrelation theory based on Moran statistics. *Geographical Res.* **28**, 1449–1463 (2009).
63. Pang, R., Teng, F. & Wei, Y. A gwr-based study on dynamic mechanism of population urbanization in JIlin Province. *Sci. Geogr. Sin.* **34**, 1210–1217. https://doi.org/10.13249/j.cnki.sgs.2014.010.1210 (2014).
64. Anselin, L. & (GeoDa Press, L. L. C. (2014).
65. Zhang, Z., Shan, B., Lin, Q., Chen, Y. & Yu, X. Influence of the Spatial distribution pattern of buildings on the distribution of PM2. 5 concentration. *Stoch. Env. Res. Risk Assess.* 1–13. https://doi.org/10.1007/s00477-021-02118-6 (2022).
66. Lee, S. I. Developing a bivariate Spatial association measure: an integration of Pearson's R and Moran's I. *J. Geogr. Syst.* **3**, 369–385. https://doi.org/10.1007/s101090100064 (2001).
67. Zhao, H. et al. Interpretation of hot spots in Wuhan new town development and analysis of influencing factors based on Spatio-Temporal pattern mining. *ISPRS Int. J. Geo-Information*. **13**, 186. https://doi.org/10.3390/ijgi13060186 (2024).
68. Singh, M. & Yan, S. Spatial–temporal variations in deforestation hotspots in Sumatra and Kalimantan from 2001–2018. *Ecol. Evol.* **11**, 7302–7314. https://doi.org/10.1002/ece3.7562 (2021).
69. Cuba, N. et al. Emerging hot spot analysis to indicate forest conservation priorities and efficacy on regional to continental scales: a study of forest change in Selva Maya 2000–2020. *Environ. Res. Commun.* **4**, 071004. https://doi.org/10.1088/2515-7620/ac82de (2022).
70. Guo, B. et al. Identifying the Spatiotemporal dynamic of PM2. 5 concentrations at multiple scales using geographically and temporally weighted regression model across China during 2015–2018. *Sci. Total Environ.* **751**, 141765. https://doi.org/10.1016/j.scitotenv.2020.141765 (2021).
71. Hu, J., Zhang, J. & Li, Y. Exploring the Spatial and Temporal driving mechanisms of landscape patterns on habitat quality in a City undergoing rapid urbanization based on GTWR and MGWR: the case of Nanjing, China. *Ecol. Ind.* **143**, 109333. https://doi.org/10.1016/j.ecolind.2022.109333 (2022).
72. Huang, B. & Wu, S. *In Spatiotemporal Analytics*145–173 (CRC, 2023).
73. Liu, N., Zou, B., Li, S., Zhang, H. & Qin, K. Prediction of PM2. 5 concentrations at unsampled points using multiscale geographically and temporally weighted regression. *Environ. Pollut.* **284**, 117116. https://doi.org/10.1016/j.envpol.2021.117116 (2021).
74. Tuomilehto, J. Impact of age on cardiovascular risk: implications for cardiovascular disease management. *Atherosclerosis Supplements*. **5**, 9–17. https://doi.org/10.1016/j.atherosclerosissup.2004.03.006 (2004).
75. Sniderman, A. D. & Furberg, C. D. Age as a modifiable risk factor for cardiovascular disease. *Lancet* **371**, 1547–1549. https://doi.org/10.1016/S0140-6736(08)60313-X (2008).
76. Mikkola, T. S., Gissler, M., Merikukka, M., Tuomikoski, P. & Ylikorkala, O. Sex differences in age-related cardiovascular mortality. *PloS One*. **8**, e63347. https://doi.org/10.1371/journal.pone.0063347 (2013).
77. Liu, X. X. et al. Green space and cardiovascular disease: a systematic review with meta-analysis. *Environ. Pollut.* **301**, 118990. https://doi.org/10.1016/j.envpol.2022.118990 (2022).
78. Rahnama, M. R. & Shaddel, L. Urban green space is Spatially associated with cardiovascular disease occurrence in women of Mashhad: a Spatial analysis of influential factors on their presence in urban green spaces. *J. Urb. Health*. **96**, 653–668. https://doi.org/10.1007/s11524-019-00373-1 (2019).

79. Kupcikova, Z., Fecht, D., Ramakrishnan, R., Clark, C. & Cai, Y. S. Road traffic noise and cardiovascular disease risk factors in UK biobank. *Eur. Heart J.* **42**, 2072–2084. https://doi.org/10.1093/eurheartj/ehab121 (2021).
80. Franchini, M. & Mannucci, P. M. Short-term effects of air pollution on cardiovascular diseases: outcomes and mechanisms. *J. Thromb. Haemost.* **5**, 2169–2174. https://doi.org/10.1111/j.1538-7836.2007.02750.x (2007).
81. Middleton, N. et al. A 10-year time-series analysis of respiratory and cardiovascular morbidity in Nicosia, Cyprus: the effect of short-term changes in air pollution and dust storms. *Environ. Health.* **7**, 1–16. https://doi.org/10.1186/1476-069X-7-39 (2008).
82. Van Kempen, E., Casas, M., Pershagen, G. & Foraster, M. WHO environmental noise guidelines for the European region: a systematic review on environmental noise and cardiovascular and metabolic effects: a summary. *Int. J. Environ. Res. Public Health.* **15**, 379. https://doi.org/10.3390/ijerph15020379 (2018).
83. Jasiura, A., Lipczyńska, W., Warchoł, K. & Gorzel, M. Access to public sports infrastructure in Poland as a preventive factor for cardiovascular diseases. *J. Educ. Health Sport*. **21**, 115–122. https://doi.org/10.12775/JEHS.2023.21.01.012 (2023).
84. Bassuk, S. S. & Manson, J. E. Physical activity and the prevention of cardiovascular disease. *Curr. Atheroscler. Rep.* **5**, 299–307. https://doi.org/10.1007/s11883-003-0053-7 (2003).
85. Byiringiro, S., Nyirimanzi, N., Mucumbitsi, J., Kamanzi, E. R. & Swain, J. Cardiac surgery: increasing access in low-and middle-income countries. *Curr. Cardiol. Rep.* **22**, 1–7. https://doi.org/10.1007/s11886-020-01290-5 (2020).
86. Kapwata, T. & Manda, S. Geographic assessment of access to health care in patients with cardiovascular disease in South Africa. *BMC Health Serv. Res.* **18**, 1–10. https://doi.org/10.1186/s12913-018-3006-0 (2018).
87. Briggs, A. C., Black, A. W., Lucas, F. L., Siewers, A. E. & Fairfield, K. M. Association between the food and physical activity environment, obesity, and cardiovascular health across Maine counties. *BMC Public. Health.* **19**, 1–9. https://doi.org/10.1186/s12889-019-6684-6 (2019).

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Author contributions
Jinlong Liang: Conceived the framework and drafted the manuscript; Shuguang Deng: Provided the research topic, conceptual guidance, translation, manuscript revision, and funding support; Heping Yang: Responsible for data provision, manuscript proofreading, and provided revision suggestions; Shuyan Zhu: Edited the visual maps; Rui Zheng: Responsible for data processing.

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Declarations

Competing interests
The authors declare no competing interests.

Ethical 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. Ethical approval was granted by the Medical Ethics Committee of Guangxi Ethnic Hospital (Approval No.: 2024-65). We accessed and analyzed de-identified cardiovascular department records with authorization from Guangxi Ethnic Hospital. These data were collected and maintained in accordance with the hospital's patient data management policies and procedures. As this study involves only a retrospective analysis of existing medical records, without any direct patient interaction or risk of substantial harm, the Medical Ethics Committee of Guangxi Ethnic Hospital determined that individual patient consent was waived. Nonetheless, we ensured that all data used in the study were fully anonymized and protected, adhering to the highest standards of confidentiality and privacy.

Additional information
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