Impact of Different Greenspace Metrics on Cardiovascular Disease Incidence in Urban Settings: A Comparative Analysis

Abstract

Cardiovascular diseases (CVDs) are the leading cause of global mortality, and urban greenspace can reduce CVDs risk. However, the evidence relating various greenspace metrics to CVDs risk is inconclusive. To enhance the understanding of the correlation between greenspace and CVDs, we compared three greenspace indicators – Street View-based Greenspace (SVG), Normalized Difference Vegetation Index (NDVI), and Green Cover Rate (GCR). We used a large sample of 36,504 CVDs hospitalization records with precise residential addresses from 2017 to 2022 in Jingzhou, China. Employing the Geographically Weighted Regression (GWR) model, we investigated the association between greenspace and CVDs incidence at the population level. We found significant negative associations between NDVI/SVG and CVDs incidence (SVG: $\beta = -1.64$; 95% CI: [-2.12, -1.15]; NDVI: $\beta = -8.57$; 95% CI: [-9.81, -7.33]), with NDVI exhibiting a more substantial protective effect. However, no significant relationship was found in GCR ($p = 0.161$). The impacts varied by age, but not by gender, with younger individuals benefiting more than the elderly, and SVG showed no significant relationship with CVDs incidence in individuals over 65 years. Our findings suggested the importance of the presence of greenspace in CVDs prevention. Consequently, in urban greenspace planning, priority should be given to the vegetation quantity in residential areas over the size of greenspace facilities located distant from residences.

Keywords: Cardiovascular diseases; Greenspace; NDVI; Street view greenness; Green cover

1 Introduction

Cardiovascular diseases (CVDs) are the leading cause of mortality worldwide, accounting for over 18 million fatalities each year [1]. In China, both prevalence and mortality rates of CVDs are on the rise [2]. Therefore, making effective efforts to reduce CVDs incidence is of paramount importance. CVDs are widely recognized as the result of complex interplay between genetic predisposition and environmental factors. All personal, social, and natural domains of environment collectively affect CVDs risk [3]. Urban environment represents a modifiable determinant with a profound impact on CVDs, and thus its optimization serves as a cost-effective strategy to accrue widespread gains against CVDs. Researchers have shown a long-standing interest in the association between greenspace and human health [4,5]. "Green space", a specific concept of the built environment, usually refers to undeveloped open land covered with vegetation like grass and trees, and further includes parks, public spaces, and residential vegetation [6]. Urban greenspace encourages physical activity, and reduces air pollution, noise, and heat, all of which are well-known risk factors for CVDs [1].

Some natural experimental studies have indicated that residents of greener areas exhibit a lower risk of CVDs [7,8]. In addition, some epidemiological studies have found a negative correlation between greenspace quantity and CVDs risk [9,10]. These studies utilized land use or remote sensing data to measure greenspace, which reflected macro-level greenspace exposure. More recently, there have also been studies employing Street View Images (SVI) to investigate the impact of ground-level greenspace on CVDs, yielding positive results [11]. While many studies indicated a protective effect of greenspace on CVDs risk, some others reported invalid results [12–14]. Current evidence remains limited and inconclusive, and these discrepancies may stem from the lack of standard definitions and measurements of greenspace [15]. Normalized Difference Vegetation Index (NDVI), Green Cover Rate (GCR), and Street view-based greenness (SVG), are three mostly used greenspace indicators in studies, which are used in most of the studies mentioned before. Different indicators may reflect different aspects of greenspace, and there is a need to clarify the differential impacts of various greenspace indicators on CVDs incidence, and whether they influence human health. In addition, different demographic groups may have varying levels of access to greenspace and use space differently, and demographic factors could modify the relationship between greenspace and CVDs risks [16].

This study aimed to elucidate the associations between greenspace and CVDs incidence at the population level by applying three greenspace indicators (SVG, NDVI, and GCR) to measure greenspace. It aimed to refine the understanding of greenspace impacts on CVDs, thereby helping better reduce urban CVDs burden through greenspace planning efforts. To address this issue, our study is guided by the following questions: (1) To what extent do different greenspace indicators agree on the presence of greenspace? (2) Will the correlation between greenspace and CVDs differ across different indicators? (3) Are the associations modified by gender or age?

2 Methods and materials

2.1 Study settings

This study was conducted in Jingzhou District and Shashi District, located in the heart of the principal urban expanse of Jingzhou City, China (36°20′ N, 112°14′ E). We used a large sample of CVDs hospitalization data collected from local hospitals, which included the date of admission, primary diagnosis, sex, age, and residential address. The primary diagnosis was coded according to the International Statistical Classification of Diseases and Related Health Problems, 10th Revision (ICD-10). We extracted records with ICD-10 codes (I05-I52) from 2017 to 2021 as CVDs cases. Out of the 37640 records that had residential address information available; 1136 addresses could not be geocoded, leaving us with a final sample of 36,504 records. Personal information was treated confidentially in strict adherence to the Personal Information Protection Law of China.

There are unavoidable deviations in the geocoding of patient addresses given privacy concerns, the geocoding results utilized in this study are sufficiently detailed to ascertain accurate point density information for our analysis. We used the Kernel Density Estimation (KDE) method to estimate the CVDs incidence of each 500m grid to ensure spatial comparability across all other datasets. KDE is a widely used spatial interpolation technique that estimates the density of a specific variable across a continuous surface. This method is based on kernel smoothing, where a kernel function (typically Gaussian) assigns weights to observations within a defined radius, and can better avoid the mutation problem at boundaries as well as the homogenization problem inside the grid [17]. We obtained the population distribution grid map from WorldPop (www.worldpop.org), which provides high-resolution population estimates based on a combination of census data, satellite imagery, and various geospatial datasets. Combined with the population distribution grid map, CVDs incidence was expressed as ratio-based statistics and normalized to a population size of 100,000, the calculation formula for CVDs incidence is as follows:

$$Incidence(x, y) = \frac{1}{n \cdot Pop(x, y)} \sum_{i=1}^{n} K(x_i, y_i)$$

Where $Incidence(x, y)$ is the incidence at location (x, y); $Pop(x, y)$ represents the population at location (x, y); $K(x_i, y_i)$ is the kernel density estimation result of each point inside the grid of location(x, y). Fig. 1 shows the total workflow diagram of this study.

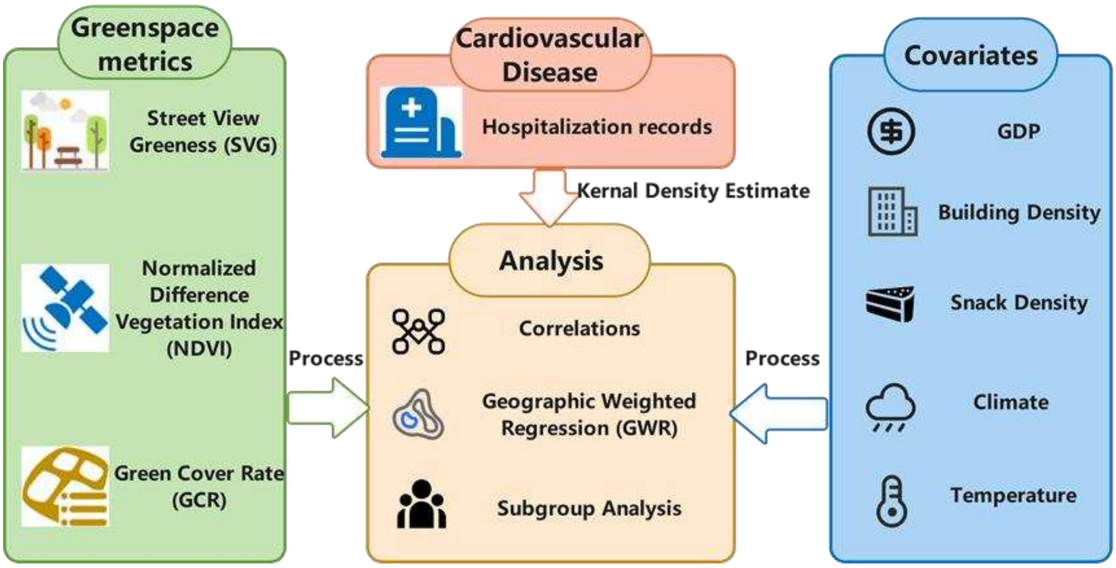

Fig. 1. Total workflow diagram of this study.

2.2 Greenspace indicators

We selected three frequently used greenspace indicators: SVG, NDVI, and GCR for analysis. Table 1 delineates the characteristics of these indicators.

Table 1 Characteristics of greenspace metrics.

	SVG	NDVI	GCR
Full Name	Street view-based greenspace	Normalized difference vegetation index	Green cover Rate
Description	Percentage of vegetation pixels of street view image	Using satellite images to calculate the vegetation index	Percentage of trees and flooded vegetation land cover
Type of Data	Primary data	Secondary data	Secondary data
Data Source	Street view image	Landsat satellite	Landcover dataset
Characteristic	On-the-ground perspective for greenspace, capturing people's perception of greenspace more accurately	Quantifies the density of photosynthetically active greenspace, without biophysical meaning	Quantifies the extent of vegetation, yet could not reflect the density of vegetation.
Raw Resolution	single images	30 meters	10 meters

We extracted SVG from street view images, in line with methods used in previous studies [18,19]. First, we sampled points at 100m intervals along the road network obtained from the Open Street Map, and created a 500m grid over the main urban area of Jingzhou, with four uniformly distributed points per grid. For each point, we obtained a street panorama from the Baidu Map API, then applied the DeeplabV3 model [20], which was pre-trained on the cityscapes dataset [21], to segment images and calculate vegetation pixels percentage as the SVG value, ranging from 0 to 1. The mean SVG of four points represented the grid's greenness. Since street view images lack full historical records, contemporaneous data were used for all greenspace metrics and covariates to ensure consistency and comparability.

NDVI is a satellite-derived vegetation index indicating the density of vegetation, based on the surface reflectance at visible red and near-infrared (NIR) wavelengths. It ranges from -1 to 1, with higher values indicating a higher density of greenness, and has been approved by WHO as an indicator for greenspace availability measurement. We obtained the maximum NDVI each year from the National Ecosystem Science Data Center, National Science & Technology Infrastructure of China [22]. It's derived from Landsat 5/7/8/9 at 30m × 30m resolution, and the average value represented the grid's NDVI value.

GCR represents the size of land covered by plants, rather than the amount of vegetation on the green land. The ESRI Sentinel-2 10m-resolution Land Cover dataset was the third source of greenspace. It provides land cover derived from ESA Sentinel-2 imagery from 2017 to 2021, classifying land cover into 10 categories: water, trees, flooded vegetation, crops, built area, bare ground, snow/ice, clouds, and rangeland. The dataset was generated from Impact Observatory's AI model, trained by a dataset of massive human-labeled pixels. We calculated the percentage of trees in each 500m grid as the Green Cover Rate.

2.3 Covariates

Multiple factors have been proven to contribute to CVDs including socioeconomic status, built environment, diets, humidity, temperature, etc. [6] These factors can be summarized as social and natural environments. Following previous studies, we added the following covariates to adjust the model: Gross Domestic Product (GDP), building density, snack bar and dessert shop density, precipitation, annual lowest temperature, and annual highest temperature. Due to the lack of neighborhood-level socioeconomic status data in the study area, we used the spatial distribution of GDP as a proxy indicator to reflect the general economic conditions. We followed the method using nightlight images, population distribution, and regional statistics to estimate the neighborhood-level GDP, which was interpolated to a 500m × 500m grid, consistent with study units. Specifically, we utilized NPP-VIRS nightlight images, population distribution raster from WorldPop, and regional statics from the Chinese City Statistical Yearbook [23,24]. Building density refers to the percentage of built area in the grid, and snack bar and dessert shop density is estimated using the KDE method. Temperature and precipitation datasets from 2017-2021 were sourced from the National Tibetan Plateau / Third Pole Environment Data Center (https://data.tpdc.ac.cn), with a spatial resolution of 1 km [25–27]. All raster data was transformed and resampled to a uniform 500m resolution using ArcGIS 10.8.

2.4 Statistical analysis

Pearson correlation coefficients (*r*) were calculated to investigate the differences and relationships among three greenspace indicators and CVDs incidence. Subsequently, we used the Lagrange Multiplier (LM) test to detect the spatial effect. The results of Moran's I and LM were significantly positive at the 1% significance level (Table 2), indicating a spatial effect in this study. The inclusion of spatial model is critical due to spatial autocorrelation and non-independence of the data, necessitating their inclusion for accurate analysis. We compared Ordinary Least Squares (OLS) and 3 spatial models: the Spatial Lagged Model (SLM), Spatial Error Model (SEM), and Geographically Weighted Regression (GWR). GWR turned out to be the best choice (Table 3), thus we employed the GWR model to investigate the correlation between greenspace and CVDs incidence.

GWR is a regression model tailored to address spatial heterogeneities in the "response to predictor variable" relationships [28]. Residents are influenced not only by environmental factors within their grid, but also by those in surrounding areas. By accounting for the influence of neighboring areas, GWR enhances the interpretability and validity of the results.

Table 2 Result of the LM test

Test	Statistic	df	p-value
Spatial error:			
Moran's I	27.10***	1	0
Lagrange multiplier	673.06***	1	0
Robust Lagrange multiplier	19.13***	1	0
Spatial lag:			
Lagrange multiplier	724.72***	1	0
Robust Lagrange multiplier	70.79***	1	0

Table 3 Model comparison results

Model	R-squared	RMSE (Sigma)	Log Likelihood	AIC
OLS	0.217	70.95	-6720.7	13463.4
SLM	0.364	63.65	-6597.7	13221.5
SEM	0.093	63.42	-6593.4	13212.7
GWR	0.796	40.824	-5925.6	12371.3

Note: OLS: ordinary least squares; SLM: spatial lagged model; SEM: spatial error model; GWR: geographically weighted regression.

3 Results

3.1 Descriptive statistics

Table 4 presents the characteristics of CVDs cases and the greenspace indicators. The mean annual incidence of CVDs is 47.17 (per 100,000 population). Males constitute the majority of cases (58.99%). Approximately half of the cases are found in the age group above 65 years old (50.15%), slightly fewer cases are between 15 and 65 years old (36.81%), and 0-15 years old cases only account for 13.04%.

Fig. 2 (a) shows the spatial distribution of CVDs incidence. Hotspots of CVDs cases are mainly distributed in the north and the south-west, and there is also a significant concentration of incidence in the central area. The mean SVG, NDIV, and GCR levels are 0.158, 0.445, and 0.038 respectively. Fig. 2 (b, c, d) illustrates spatial differences between greenspace measurements. The map shows an agreement between NDVI and GCR, but GCR indicates a lower level of greenspace. NDVI and GCR show higher levels in the periphery, whereas SVG value is higher in the center.

Table 4 Descriptive statistics of the study

Variable	Mean (SD) / Numbers (%)
CVDs cases:	
All cases	36504 (100)
Male	21533 (58.99)
Female	14917 (41.01)
<15 years old	4760 (13.04)
15-65 years old	13438 (36.81)
>65 years old	18306 (50.15)
NDVI	0.445 (0.101)
SVG	0.158 (0.109)
GCR (%)	0.038 (0.104)
GDP (million yuan)	206.244 (308.406)
Building density (%)	0.878 (0.191)
Snack bar and dessert density	4.498 (2.307)
Precipitation (mm)	916.879 (119.183)
Temperature minimal (℃)	17.766 (12.147)
Temperature maximal (℃)	339.220 (4.724)
CVDs incidence (per 100,000)	47.17 (79.798)

Note: Categorical variables are presented as count (%) and continuous variables as mean (standard deviation, SD). NDVI refers to Normalized Difference Vegetation Index, SVG refers to Street View-based Greenness, and GCR is Green Cover Rate.

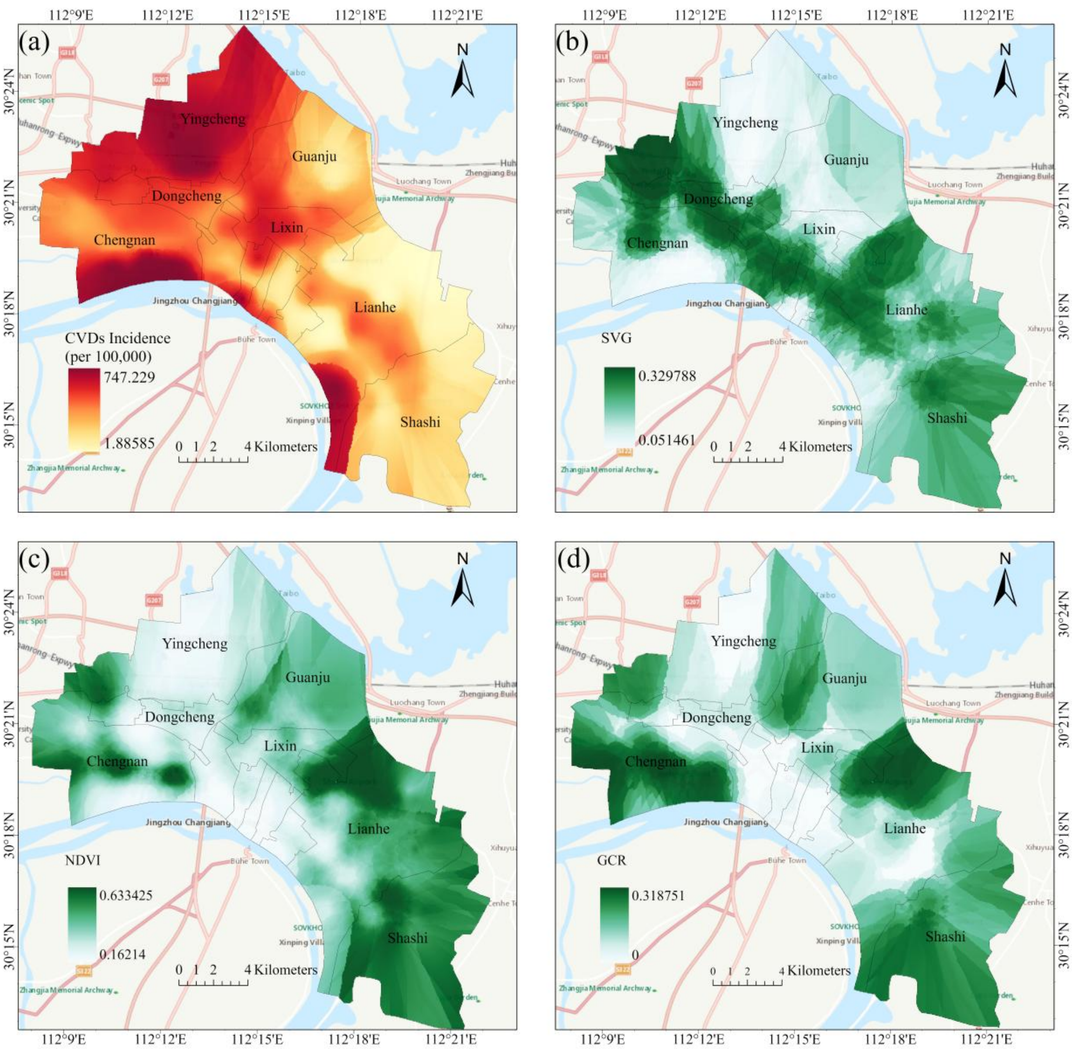

Fig. 2. Spatial distribution of average cardiovascular diseases (CVDs) incidence, SVG (Street View-based Greenness), NDVI (Normalized Difference Vegetation Index), and GCR (Green Cover Rate) in Jingzhou, China, during the study period.

3.2 Correlations

Fig. 3 presents the correlations between all variables and CVDs incidence. NDVI and GCR show a moderate correlation ($\alpha = 0.49$, $p < 0.01$). No significant correlations are observed between SVG and NDVI ($\alpha = 0.02$, $p = 0.44$) or GCR ($\alpha = -0.04$, $p = 0.16$). Both NDVI and SVG present significant negative correlations with CVDs incidence, with NDVI showing a stronger correlation (NDVI: $\alpha = -0.16$, $p < 0.01$; SVG: $\alpha = -0.08$, $p < 0.01$). GCR is not correlated with CVDs incidence ($p = 0.57$). Furthermore, all variables have Variance Inflation Factors (VIFs) below 5, indicating no multicollinearity in this study. Therefore, we included all these variables in the regression models to assess the effect of three greenspace indicators on CVDs incidence.

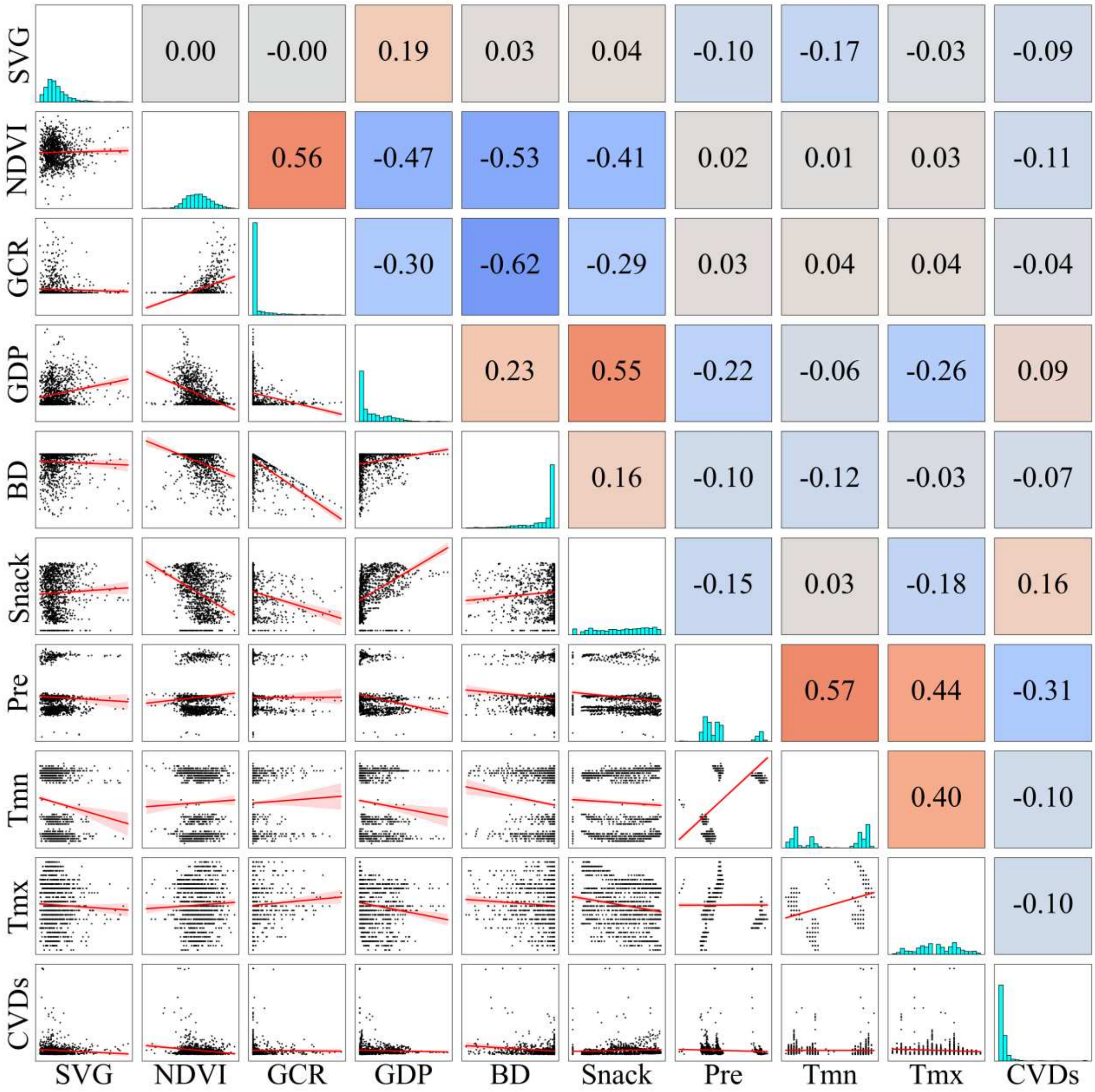

Fig. 3. Association between control variables for the incidence and greenspace exposure indicators.

Note: *p < 0.10, **p < 0.05, ***p < 0.01.

Covariates: Gross Domestic Product (GDP), Building Density (BD), Snack and Dessert shop Density (Snack), Precipitation (Pre), Temperature Minimum (Tmn), Temperature Maximum (Tmx)

3.3 Relations between greenspace indicators and CVDs incidence

Table 5 presents the estimates for three greenspace indicators in association with CVDs incidence. The adjustments were accomplished through four models: Model 1 was unadjusted, Model 2 adjusted for socioeconomic factors, Model 3 additionally adjusted for natural environmental factors, and Model 4 included both socioeconomic and natural environmental covariates for full adjustment. Unadjusted analysis (Model 1) shows a consistent inverse association of SVG and NDVI with CVDs incidence. A 1% increase in SVG and NDVI are respectively related to a 5.46% (95% CI: [-6.19, -4.72]) and 8.45% (95% CI: [-10.12, 6.79]) average decrease in CVDs incidence. Conversely, GCR shows a positive but less significant association with CVDs incidence ($p = 0.015$). After being adjusted by social environmental covariates (Model 2), the association between SVG and CVDs incidence weakened ($\beta = -0.28$; 95% CI: [-0.67, 0.11]), while that of NDVI strengthened ($\beta = -10.79$; 95%CI: [-12.35, -8.62]). The correlation between GCR and CVDs incidence also weakened, but with lower significance ($\beta = 2.12$; $p = 0.024$). Model 3 is adjusted for the natural environment variables, and it suggests a weaker negative effect of SVG and NDVI on CVDs incidence than Model 1 (SVG: $\beta = -3.63$; 95%CI: [-4.17, -3.09]; NDVI: $\beta = -5.45$; 95%CI: [-6.69, -4.22]). The correlation between GCR and CVDs incidence remains positive in Model 3, and is at a low significance level ($\beta = 6.94$; $p= 0.061$). In the fully adjusted model (Model 4), the inverse correlations of SVG and NDVI with CVDs incidence persist (SVG: $\beta = -1.64$; 95% CI: [-2.12, -1.15]; NDVI: $\beta = -8.57$; 95% CI: [-9.81, -7.33]). The effect of SVG on CVDs incidence becomes much weaker and less significant ($p = 0.079$), while the effect of NDVI remains largely consistent and highly significant ($p < 0.01$). Additionally, GCR shows no significant association with CVDs incidence after being fully adjusted ($p = 0.161$).

The fully adjusted model (Model 4) performed the best in terms of model evaluation criteria such as AIC and Log Likelihood. Therefore, we conducted further in-depth research using all covariates. The results of the fully adjusted GWR model are listed in Table 6, which explains 79.6% of the prevalence of CVDs in the grid ($R^2 = 0.796$). NDVI has a more beneficial effect on alleviating CVDs compared to SVG, while the effect of GCR is insignificant. As for covariates, an increase in GDP, building density, and precipitation resulted in less CVDs incidence in the region, and the rising density of snack and dessert shops and maximum temperature would increase CVDs incidence. Additionally, no significant relationship between annual minimum temperature and CVDs incidence is observed.

Table 5 Cross-sectional associations of greenspace indicator and CVDs incidence

	Model 1		**Model 2**		**Model 3**		**Model 4**	
	Estimate (95% CI)	p value	Estimate (95% CI)	p value	Estimate (95% CI)	p value	Estimate (95% CI)	p value
SVG	-5.46 (-6.19, -4.72)	<0.01	-0.28 (-0.67, 0.11)	0.013	-3.63 (-4.17, -3.09)	0.074	-1.64 (-2.12, -1.15)	0.079
NDVI	-8.45 (-10.12, -6.79)	<0.01	-10.79 (-12.35, -8.62)	<0.01	-5.45 (-6.69, -4.22)	<0.01	-8.57 (-9.81, -7.33)	<0.01
GCR	9.53 (5.47, 13.59)	0.015	2.12 (-2.73, 6.98)	0.024	6.94 (2.26, 11.61)	0.061	2.84 (-2.57, 8.19)	0.161
AIC	13018.22		12717.36		12554.15		12371.3	
Log Likelihood	-6398.71		-6194.65		-6070.01		-5925.64	
RMSE	56.478		48.769		44.852		40.824	
R-square	0.545		0.678		0.739		0.796	

Model 1: Unadjusted model.

Model 2: Adjusted for social covariates (GDP, Building density, Snack shop density).

Model 3: Adjusted for natural environment covariates (Precipitation, Min/Max Temperature).

Model 4: Adjusted for all covariates above.

Table 6 Adjusted estimates from the GWR model predicting CVDs incidence

Variable	Coefficient	95% CI [low, high]	p-value	VIF
SVG	-1.64*	[-2.12, -1.15]	0.079	1.086
NDVI	-8.57***	[-9.81, -7.73]	0	1.663
GCR	2.84	[-2.52, 8.19]	0.161	1.865
GDP	-40.03***	[-42.99, -37.07]	0	1.487
BD	-8.98***	[-10.26, -7.70]	0	1.704
Snack	13.92***	[11.63, 16.20]	0	1.653
Pre	-8.77***	[-10.07, -7.46]	0	2.3
Tmn	-3.68	[-4.71, -2.65]	0.217	2.381
Tmx	8.22***	[5.63, 10.81]	0	4.324

Note: *p < 0.10, **p < 0.05, ***p < 0.01.

3.4 Relations in subgroups

Fig. 4 presents the associations between environmental variables and CVDs incidence stratified for gender. We do not observe notable sex differences in the impact of NDVI and SVG on CVDs incidence in the region. The effect of SVG in reducing incidence in female cases is slightly stronger than in male cases (Female: $\beta = -0.967$; 95% CI: [-1.29, -0.64]; Male: $\beta = -0.78$; 95% CI: [-1.23, -0.44]). For both genders, the effect of NDVI is stronger than SVG (Female: $\beta = -9.07$; 95% CI: [-10.44, -7.70]; Male: $\beta = -9.25$; 95% CI: [-10.54, -7.95]), while GCR exhibits no significant relationship with CVDs incidence (Female: $p = 0.974$; Male: $p = 0.616$). All covariates, except for minimum temperature, show a significant correlation with CVDs incidence, with minimal difference across gender strata. The snack and dessert shop density has a stronger positive relationship with the male CVDs incidence, while the increase in maximum temperature is observed to be more associated with CVDs incidence in females.

In the age-stratified analyses, we observed a stronger association between SVG/NDVI and CVDs incidence in the 0-15 age group compared to other age groups, as shown in Fig. 5. The effect of SVG in reducing CVDs incidence in the 0-15 age group ($\beta = -6.21$; 95% CI: [-7.84, -4.58]) is much stronger than in the 15-65 age group ($\beta = -2.33$; 95% CI: [-2.94, -1.73]), but it does not show a clear effect on CVDs incidence in those over 65 (95% CI: [-4.16, 0.17]). NDVI shows significant inverse associations with CVDs incidence in all age groups, with the smallest associations in cases over 65 (0-15: $\beta = -15.59$; 95% CI: [-19.08, -12.10]; 15-65: $\beta = -13.16$; 95% CI: [-15.43, -10.90]; over 65: $\beta = -8.34$; 95% CI: [-9.49, -7.18]). There is still no significant correlation between GCR and CVDs incidence among all age groups (0-15: $p = 0.733$; 15-65: $p = 0.659$; over 65: $p = 0.404$). Notable differences in covariates are also observed across age groups. The inverse association between GDP and CVDs incidence is statistically significant for cases under 65, but not for those over 65. The density of snack and dessert shops has a much smaller effect on CVDs incidence in the 15-65 age group than others. Notably, the correlation between the minimum temperature and CVDs incidence is significant only in the 0-15 age group, albeit at a low significant level.

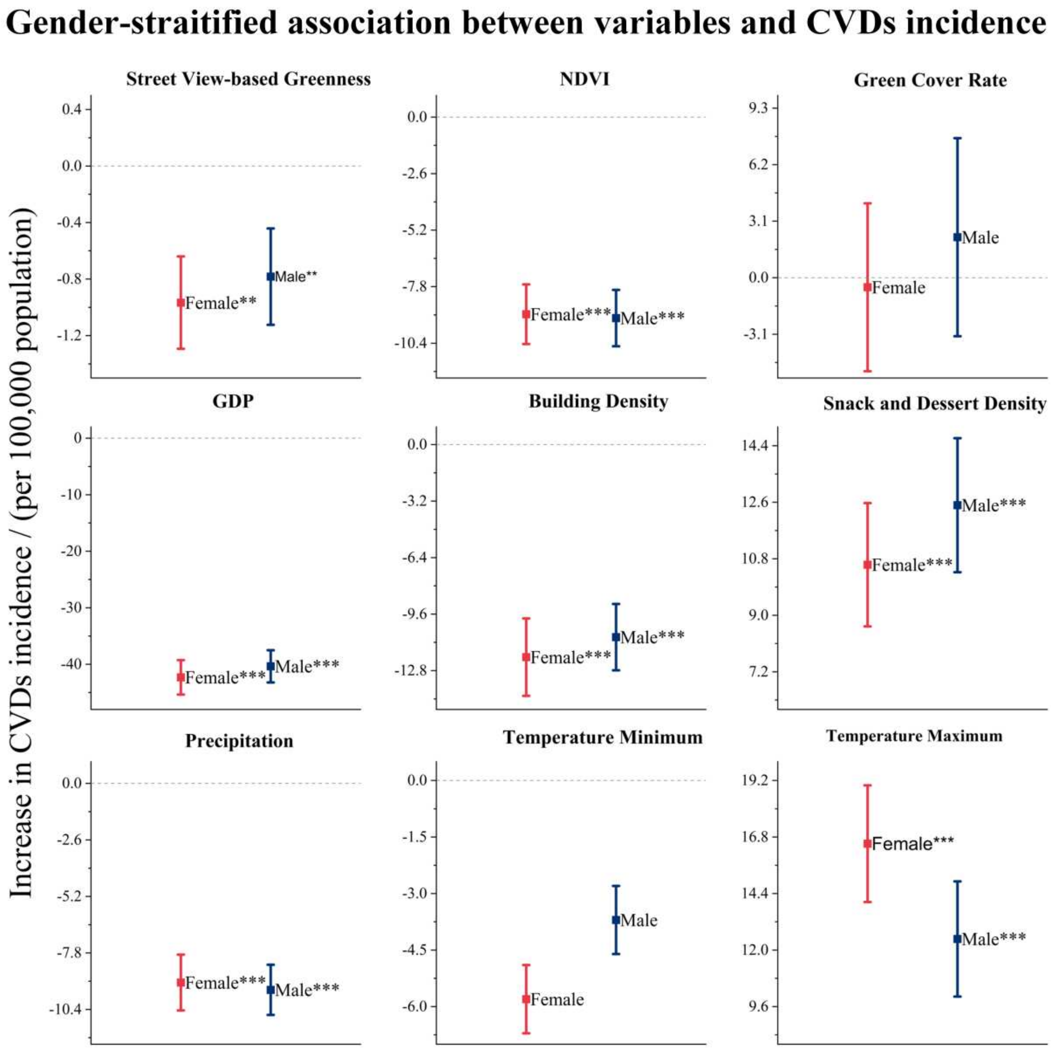

Fig. 4. Gender-stratified associations between variables and CVDs incidence. The red points and bars represent associations for females, while the blue points and bars represent associations for males. Error bars denote 95% confidence intervals.

Note: *p < 0.10, **p < 0.05, ***p < 0.01.

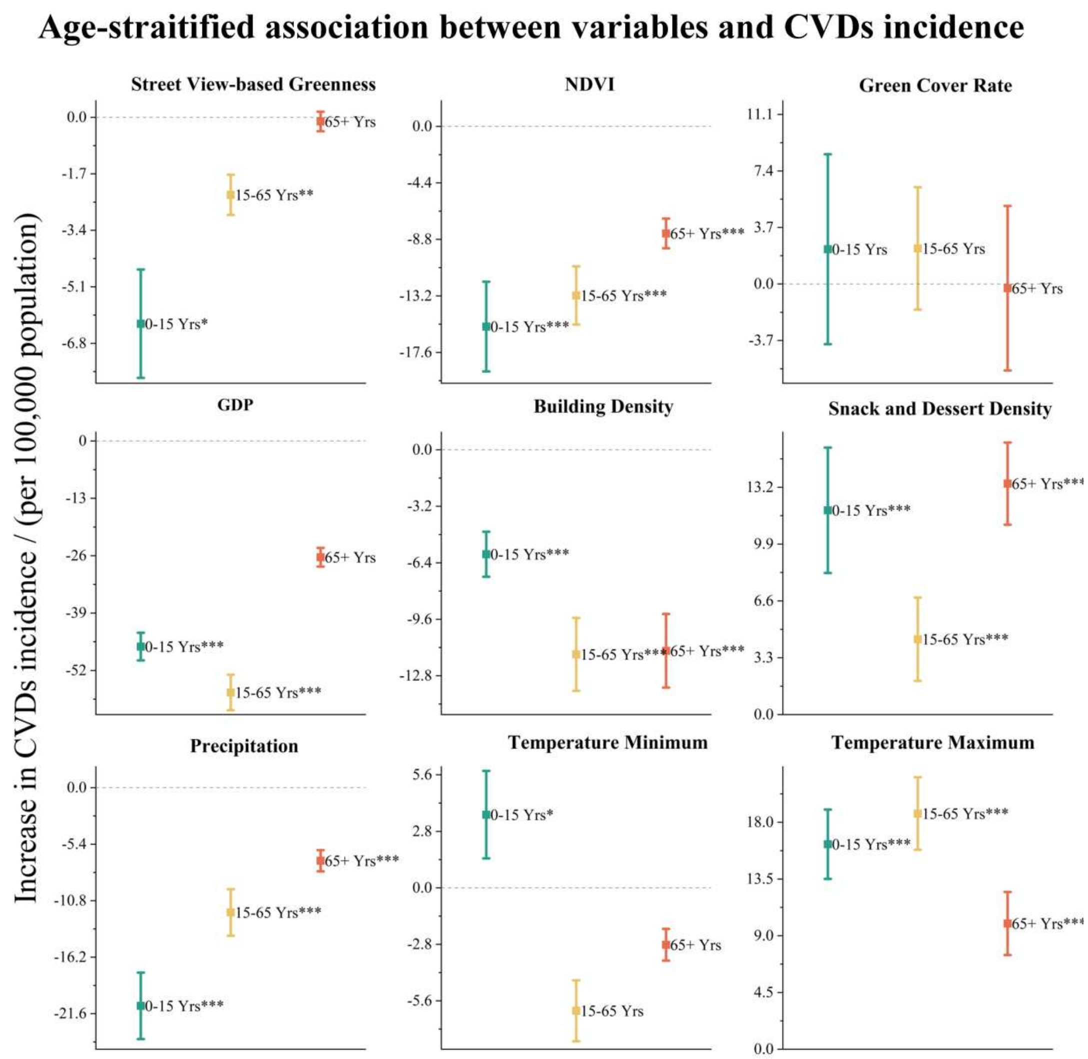

Fig. 5. Age-stratified associations between variables and CVDs incidence. The green points and bars represent associations for the 0–15 years group, the orange points and bars represent the 15–65 years group, and the red points and bars represent the 65+ years group. Error bars denote 95% confidence intervals.

Note: *p < 0.10, **p < 0.05, ***p < 0.01.

4 Discussion

This study intended to assess the consistency of three greenspace indicators measured from different aspects, and to investigate their different effects on regional CVDs incidence using a spatial model (GWR). The results indicated that higher values of SVG and NDVI are associated with less CVDs incidence, but no such relationship was found in GCR. The association did not vary by sex, but we observed notable differences across various age groups.

4.1 Comparison among greenspace indicators

Three indicators measured different aspects of greenspace in this study. The most commonly used greenspace metrics in health research are greenspace coverage and vegetation level [29], which are represented by GCR and NDVI in this study. While both metrics are useful for assessing the overall amount of greenspace, they do not distinguish between different forms and public availability. NDVI is a satellite-derived vegetation index measuring greenspace from a top-down perspective. It calculates the level of greenspace based on the different reflection capabilities of plants for NIR and red light, indicating the density of vegetation. However, it lacks specific concrete biophysical meaning. GCR also measures top-down greenspace and has actual physical significance, representing the size of land covered by plants, rather than the amount of vegetation on the green land. Although over-head greenspace has been proven to be important for health, eye-level greenspace may better reflect people's perceptions of greenness on the ground. The combination of street-view images and deep learning provides a unique approach to estimating natural features from a ground perspective. SVG measures human-scale greenspace, mainly street plants at eye level. Compared to the other two indicators, SVG offers a more subjective measurement of greenspace, reflecting people's perceptions of greenspace [30].

We found that SVG levels in the inner city were slightly higher compared to the suburbs. Conversely, NDVI was relatively more abundant in the suburbs and less in the inner city, which is consistent with previous research conducted in the United States [31,32]. Similarly, previous studies suggested that there is no evidence that NDVI is related to street-level greenness [33]. A possible explanation is that the inner city of China is dominated by commercial and residential areas, with few large green facilities. Due to the limited space, urban greenspaces mainly consist of scattered street plants like street trees and flower beds, which can be more easily perceived by pedestrians [34]. NDVI measures greenspace from the top down, and it does not reflect street plants. This results in an overall lower vegetation density in the inner city, but a slightly higher level of visible greenspace. The trend of GCR was consistent with NDVI, but its value in the inner-city was far lower. This may be due to the inherent flaws in land cover data, as land cover measurement only allows for a single land use per pixel. Despite the relatively high resolution of the land cover data, there may still be multiple land uses within one pixel, and small greenspace would be overlooked. Urban greenspace is known to be heterogeneous and highly fragmented, characterized by a relatively small number of large green spaces and amounts of dispersed small patches of vegetation [35,36]. Medium-resolution data cannot detect most of these small patches, resulting in a significant underestimation of green cover. Additionally, land cover data has been proven to underestimate tree canopies, especially in developed areas [37].

To summarize, NDVI and GCR measure the quantity of vegetation, with NDVI emphasizing the vegetation density and GCR revealing the size of green land. Notably, when using land cover data with lower resolution to measure GCR, the level of greenspace could be underestimated, posing limitations in the study. On the other hand, SVG measures the greenspace exposure at eye level and has no significant correlation with the actual amount of vegetation. The three indicators capture different aspects of greenspace, and the optimal measurement depends on the research topic. Empirical research is needed to explore the relationship between three greenspace indicators and CVDs incidence.

4.2 Relationships between greenspace and CVDs

We observed protective associations of SVG and NDVI with CVDs incidence, while GCR did not show such effect. With further adjustments of social and natural environmental covariates, the protective effect and significance of SVG weakened, whereas the effect of NDVI remained almost unchanged and highly significant. This finding underscored the significance of appropriately addressing covariates in studies of greenspace and health, and inconsistencies in confounders may explain differences in previous studies [38]. In the fully adjusted model, NDVI was crucial for the reduction of CVDs incidence, SVG was marginally significantly associated with the decrease of CVDs incidence, while GCR showed no significant association.

Our study focused on the contemporaneous association between greenspace and CVD hospitalization rates. While chronic exposure to greenspace likely confers cumulative health benefits, our approach aimed to capture the immediate or short-term effects of the environment on acute health outcomes. This is particularly relevant given that hospitalization rates reflect acute events that are plausibly influenced by current environmental conditions. Similar approaches have been adopted in prior studies, providing precedent for using contemporaneous data to assess health impacts [11,39]. In our study, the effect of NDVI is more substantial than SVG, indicating that the actual quantity of vegetation may have a more pronounced impact than the visual presence of greenness in reducing CVDs incidence. Our findings lined up with previous studies that found associations between greenspace and reduced CVDs incidence. Most studies using NDVI as an exposure metric have found a significant association between greenspace and CVDs incidence [40–42], which is consistent with our findings. Few researchers used SVG to investigate the relationship between greenspace and CVDs incidence [11,39], all of which confirmed a significant protective effect of SVG on CVDs, supporting our findings. However, one research claimed that SVG had a greater beneficial effect on CVDs than objective measures of vegetative cover at the individual level, which conflicted with our results [39]. Our population-level study showed a weaker impact of SVG on CVDs incidence compared to NDVI, and it may lead to statistical bias from individual studies due to discrepancies in study units and scales [43,44]. The green cover rate has been widely used in studies of greenspace and CVDs, but there is still wide variation within these studies. Most ecological studies, whether using 30m, 10m, or 2m resolution land cover data, have not found a statistically significant association between GCR and CVDs [42,45,46]. However, most individual-level studies have found an association between GCR and reduced risk of CVDs [47,48]. The lack of correlation between GCR and CVDs may be attributed to the underestimation of greenspace and the ambiguity of the amount of vegetation. The differences caused by research units and scales are also worth further investigation. In addition, given that our study area experiences relatively stable greenspace throughout the year, the findings may not fully apply to regions with greater seasonal variability. Future studies should explore these effects in diverse climatic contexts.

4.3 Possible mechanisms

Different greenspace indicators may influence health through various pathways, which contributed to part of the variations in their effects on CVDs. NDVI and GCR reflect the greenspace that individuals are more automatically exposed to when spending time around home. Mechanistically, they provide myriad ecosystem services [49], such as regulating climate, alleviating urban heat island effect, improving air quality, conserving biodiversity, etc. And these mechanisms can be very effective at the population level. In urban environments, greenspace coverage also provides shielding and buffering effects. It alleviates physiological and psychological burdens by reducing environmental noise, traffic pollution, and heat stress [50]. In addition, the presence of greenspace around residences has been proven to have positive impacts on health through immune responses [6] and improved sleep [51]. These combined effects may help reduce allostatic load [52] and avoid mechanisms that increase the risk of CVDs, including macrovascular damage, elevated blood pressure, changes in heart rate variability and cardiac output, chronic low-grade inflammation, fat accumulation and redistribution, poor glycemic control and disturbances in lipid metabolism [53]. Greenspace coverage and vegetation levels are both useful indicators of the overall density of greenspace, but they fail to distinguish different forms and public availability and therefore have limited impact through promoting physical activities [54].

SVG primarily reflects people’s subjective exposure to greenspace, and has been shown to effectively alleviate stress and protect mental health [33]. Contact with nature is recognized as a basic human need, feelings in connection with nature contribute to higher well-being, and short-term exposure to greenness improves stress-related physiological indicators such as blood pressure and heart rate [55]. Stress reduction theory explains this mechanism. Greener surroundings would foster physiological recovery, manifested by reduced muscle tension, skin conductance, and lower pulse rate and blood pressure. Meanwhile, it evokes an emotional response that increases positive feelings and decreases negative thoughts [56]. An exploratory study in Scotland examining salivary cortisol secretion patterns as a biomarker of stress levels found a significant relationship between visiting or viewing greenspace and stress relief [57]. Furthermore, street greenspace is widely believed to be associated with promoting health-related physical activities, such as exercise [58] and exposure to sunlight [59]. Several studies suggested that streets are the most popular places for walking, cycling, and other leisure sports activities [60], which have been proven to increase endorphin levels and inhibit activation of the hypothalamic-pituitary-adrenal axis, thereby promoting physical and mental health [61]. Overall, mechanisms of greenspace visibility are more effective for mental health outcomes, but in terms of physical health, the mechanism of greenspace quantity may play a more important role. This may also explain our findings to some extent.

4.4 Stratified analysis

When the analyses were stratified by sex, we observed no differences in the association between greenspace and CVDs incidence, but we did find significant disparities across age groups. Our sex-stratified analyses showed that SVG and NDVI significantly reduced CVDs incidence both in male and female cases, with minimal difference in the effects. This finding aligns with some cross-sectional studies [8,48], and a study from Sweden also showed no difference in greenspace use between men and women [51]. However, there are studies suggesting that the protective effect is statistically significant only for men, but not for women [7,46]. Some researchers believe that this gender difference may be related to safety issues [62]. For example, studies from North America pointed out that areas with high tree density may be related to a higher risk of crime [63], and that women have less access to urban greenspace than men [16]. China maintains a relatively high level of public safety and mitigates such concerns, suggesting no gender disparities.

Our age-stratified analyses showed that NDVI had a significant reducing effect on CVDs incidence for all ages, with the greatest impact on the 0-15 age group, and the least on the elderly over 65 years. Additionally, although SVG showed significant negative associations with CVDs incidence in 0-15 and 15-65 age groups, there was no evidence to support such associations in the elderly over 65, which is in line with existing studies [8,39]. One of the main pathways through which street greenness improves health outcomes is by promoting physical activity, and the influence of individual characteristics on physical activity levels is greater than that of built environments [16]. Older people have lower activity levels than young people and therefore benefit less from street greenness. In addition, human basal metabolic levels generally decrease with age, especially after the age of 60 [64], making the elderly less likely to obtain physiological benefits from greenspace around their homes, such as microbes that benefit the immune system.

4.5 Strengths and limitations

Strengths of our study include a comprehensive comparison of greenspace indicators measured from the ground, over-head perspective, and land use assessments, enabling us to gain an in-depth understanding of multiple aspects of greenspace. Also, our study presented a comparative analysis of the relationships across populations with different demographic characteristics, allowing for a more precise evaluation of the impact of greenspace on CVDs outcomes. In addition, the large CVDs sample with accurate addresses allowed for zip code level measurement of environmental factors, thereby improving the accuracy of exposure measurement. Finally, spatial effects play a crucial role in environmental health studies, as the location of greenspaces and their proximity to individuals can significantly impact health outcomes. Traditional statistical models assume independence of observations, an assumption that is often violated when dealing with spatial data. Our study accounted for spatial effects and provided more accurate and reliable results.

Despite these contributions, several limitations should be noted. This study did not account for greenspace accessibility indicators, such as Euclidean distance and network distance to parks. Secondly, spatial analyses rely on spatial scales and units, which may lead to imperfect definitions of the environment. Furthermore, we only measured the greenspace around homes without taking human mobility into account, which may lead to a bias in actual exposure. As a regional study, our findings are meaningful at the population level, but cannot be transferred to individuals. The residual confounding by socioeconomic status (SES) may also be a potential limitation. While we adjusted for GDP as a proxy indicator of economic conditions, it may still result in incomplete adjustment for individual SES factors. Future research should prioritize the collection and inclusion of individual- or neighborhood-level SES data to better disentangle the relationship between greenspace and CVDs risk. More comprehensive suite of greenspace indicators should also be considered, including greenspace accessibility, for comparison. Future work should also incorporate longitudinal hospitalization data and long-term-health revisit data to better understand the temporal dynamics of greenspace-health associations.

5 Conclusion

This study contributes to the quantitative relationship between cardiovascular diseases (CVDs) and urban greenspace exposure. We found that higher levels of NDVI and SVG were associated with reduced CVDs incidence, but no such association was found in GCR. The protective effect of NDVI was stronger than that of SVG. This finding highlighted the importance of the mere greenspace presence in the living environment. In urban greenspace planning, priority should be given to increasing vegetation density in proximity to residents, rather than focusing only on large greenspace facilities away from residential areas. The impacts varied by age, but not by sex. The youngest demographic derives the most substantial benefit from greenspace.

This suggests that early exposure to greenspace may have enduring health advantages, underscoring the importance of integrating greenery into settings frequented by youth such as schools. Also, tailored strategies, such as the development of more accessible and safer green areas that cater to the physical capabilities of the older population, should be devised.

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