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Assessment of Spatial Accessibility to Urban Park Green Spaces in Beijing: A Multi-scale Analysis and Influencing Factors Exploration

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Abstract

Urban Park green spaces are essential for ecosystem services and resident well-being in Beijing, yet rapid urbanization has exacerbated spatial inequities in accessibility. This study proposes a multi-scale spatial equity assessment framework integrating the Gaussian Two-Step Floating Catchment Area (Ga2SFCA) method, Geographic Detector, and Geographically Weighted Regression (GWR). Key findings include: (1) Significant polarization in accessibility, with suburban districts (*e.g.*, Miyun: 40.33) far outperforming central areas (e.g., Xicheng: 0.032); (2) Severe equity imbalance, with only 0.29% of the city achieving "balanced" accessibility, while 8.10%—mainly central districts—are "low-enjoyment high-density" zones, affecting 66.7% of residents; (3) Major influencing factors such as elevation (q=0.0224), relative humidity (q=0.0222), and residential density (q=0.0167) show spatial heterogeneity confirmed by GWR. Policy recommendations include: cost-effective central district renewal via vertical greening and vacant lot conversion (40% coverage increase at 60% lower cost), transit-oriented suburban access through BRT corridors (25% improvement for 4.3 million residents), and zoning restrictions on high-slope terrain (>15°, with 25–40% increased development cost). The study offers a data-driven framework for improving PGS equity in megacities, supporting Beijing's "livable city" goals, with methodological advances such as the hexagonal grid-based Ga2SFCA.

Keywords: Urban park green spaces; Spatial accessibility; Gaussian two-step mobile search method; Geographically weighted regression (GWR); Geographical detector.
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1. Introduction

1.1 Research background

Parks and green spaces are multifunctional cornerstones of sustainable urban development, delivering ecosystem services such as urban-heat-island mitigation, airborne-pollutant interception, storm-water retention, and even adjacent property-value appreciation.[1] Beyond ecological functions, they serve as critical social infrastructure: fostering community interaction in 15-minute livable neighborhoods, reducing mental health disparities through recreational access, and supporting physical activity—all of which enhance urban resilience and quality of life, directly aligning with Beijing's goal of building an "internationally first-class harmonious and livable city." They also underpin "15-minute livable neighborhood" agendas by fostering walkable recreational networks that strengthen social capital and active lifestyles.

As urbanization accelerates globally, it is crucial to ensure that these benefits are shared equitably across all neighborhoods. The equitable distribution and accessibility of these green spaces have become critical issues for urban planners and policymakers. Accordingly, ensuring that every resident can readily access such benefits has become a central equity concern in rapidly urbanizing metropolises. In China, the 19th National Congress of the Communist Party emphasized the need for balanced development and equitable resource allocation, highlighting the importance of fair access to public services, including park green spaces. Both the WHO (≥ 9 m² per-capita guideline) and China's "Healthy City"

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initiative explicitly list equitable green-space provision as a public-health priority.[2] Fair distribution is not merely a matter of policy rhetoric: in dense cities like Beijing, unequal access exacerbates health inequalities—residents in green-deficient areas face 32% higher heat stress risk and 18% higher rates of cardiovascular diseases, as documented in recent public health studies.[3,4] Such equity is not merely a policy goal but a public health necessity, as unequal access exacerbates disparities in heat stress, disease burden, and mental well-being.

The challenge is acute in Beijing, where relentless growth has produced pronounced spatial mismatches between population and greenery.[4] Its four core districts (Dongcheng, Xicheng, Chaoyang, and Haidian) accommodate ≈ 20,700 inhabitants km^{-2}—among the highest densities in Asia and nearly an order of magnitude above the city-wide mean.[5] Consequently, ensuring that every resident can readily access green-space services has shifted from a planning ideal to an urgent equity imperative. These disparities are already evident in Beijing, where unequal access correlates with higher rates of heat stress and cardiopulmonary morbidity.[6] Yet macro-level metrics—per-capita area or greening rate—mask neighborhood-scale service gaps, especially in dense inner-city grids.[7]

1.2 Research significance

The significance of this research lies in its theoretical and practical contributions to the field of urban green space planning and management. This study enriches the theoretical framework of spatial accessibility to park green space resources. Previous research has primarily focused on cities in China's eastern coastal regions and less developed western areas, with limited studies on international metropolises like Beijing.[8] By employing fine-grained hexagonal grids as research units, this study enhances the precision of spatial accessibility analysis and improves the methodological robustness of the analysis.[9] Practically, this research offers valuable insights for improving the distribution and utilization of park green spaces in Beijing. Using the Gaussian Two-Step Floating Catchment Area (Ga2SFCA) method,[10] the study evaluates the accessibility of park green spaces at multiple scales, including grids, districts, and townships. This approach helps identify areas with insufficient green space resources and provides a scientific basis for optimizing the layout of these spaces.[10] Moreover, the study explores the factors influencing park green space accessibility from a geographical perspective, using geographic detectors and geographically weighted regression models.[4,11] This analysis reveals the spatial heterogeneity of these factors and offers targeted suggestions for enhancing the accessibility and equitable distribution of green spaces.[12]

1.3 Current research status

1.3.1 Park green space accessibility research

The concept of accessibility was first introduced by Hansen in 1959 to measure the convenience of traveling from one point to another.[13] Accessibility can refer to the effort required to reach a destination, such as travel time or distance, or the number of services or resources accessible from a given location.[14] The accessibility of park green spaces is a key indicator of the fairness of their distribution, reflecting the willingness of residents to travel to these spaces.[15,16] Various methods have been developed to assess the accessibility of park green spaces, including the ratio method, buffer analysis, potential model, and the two-step floating catchment area method (2SFCA).[17] The 2SFCA method, proposed by Radke *et al*.,[18] and improved by Luo *et al*.,[19] is widely used due to its simplicity and effectiveness in capturing the supply-demand relationship of services. However, the original 2SFCA model has limitations,[12] such as its use of a binary distance decay function. This function assumes uniform accessibility within a search radius, but ignores the gradual decrease in demand with increasing distance.[20] To address this, enhanced versions of the 2SFCA method have been developed, including the Gaussian 2SFCA (Ga2SFCA) method, which incorporates a Gaussian decay function to more accurately model the relationship between distance and accessibility.[10]

1.3.2 Factors influencing accessibility

The gap between the demand for and supply of park green spaces is widening in urban areas, making it crucial to study the factors influencing their accessibility.[21] Previous research has identified various natural, social, and economic factors that affect the accessibility of park green spaces, such as elevation, slope, population density, road network density, and GDP.[22,23] These studies have primarily used regression models, including linear regression, spatial regression, and geographically weighted regression, to analyze the relationships between these factors and accessibility[20] However, existing studies have limitations. Most research has focused on cities in China's eastern coastal regions and less developed western areas, with limited studies on international metropolises like Beijing.[21] Additionally, many studies use larger administrative units such as counties or streets as research units, which have lower spatial resolution and may overlook detailed spatial differences within regions.[9] Finally, while most studies analyze the economic and statistical aspects of park green space accessibility, fewer studies have

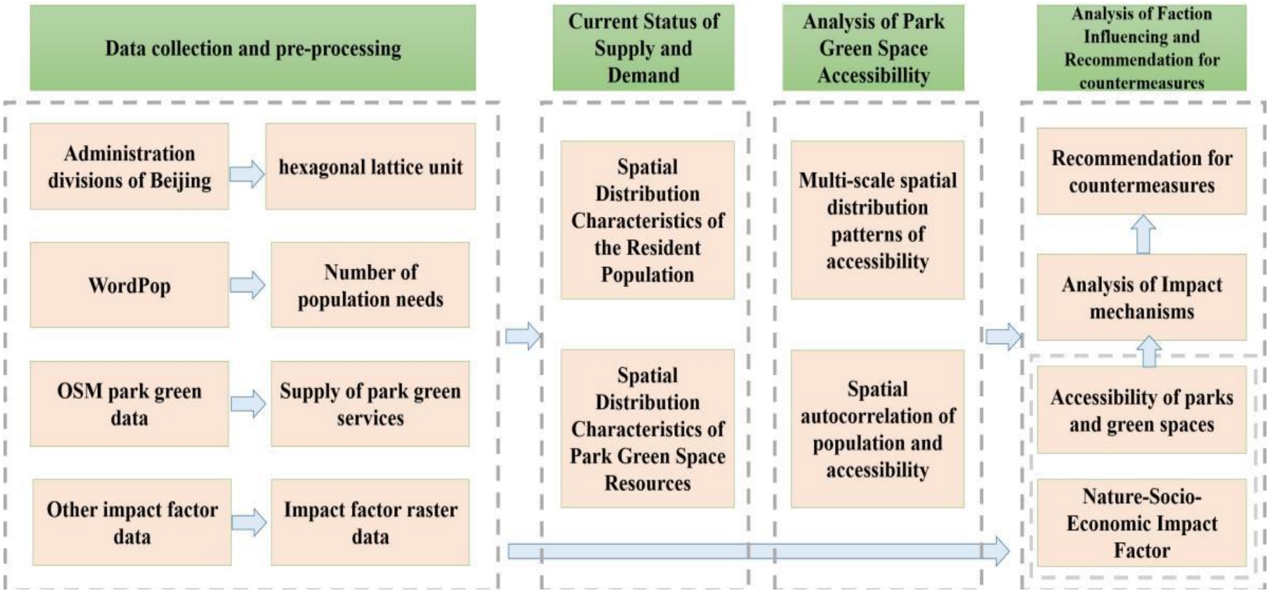

Fig. 1: Technical route.

explored the geographical mechanisms and spatial heterogeneity of these factors.[20] These studies have primarily used regression models, including linear regression, spatial regression, and geographically weighted regression, to analyze the relationships between these factors and accessibility. Recent scholarship also shows that the *geographical-potential-factor* concept is transferable across resource-allocation contexts; for example, Fauzi *et al*., applied a suite of geographical potential indices to locate cost-effective offshore-wind sites for remote Indonesian regions, thereby confirming the framework's robustness in decision-oriented spatial planning.[24]

1.4 Research objectives and structure

This study aims to address these gaps by conducting a comprehensive analysis of the spatial accessibility of park green spaces in Beijing using the Ga2SFCA method and exploring the factors influencing this accessibility using geographic detectors and geographically weighted regression models. The objectives of the research are: This study aims to conduct a comprehensive analysis of the current supply and demand of park green spaces in Beijing, evaluate their spatial accessibility across multiple scales, identify regions where park green space resources are insufficient, and assess the equity of resource distribution. Furthermore, the research seeks to explore the factors influencing the accessibility of park green spaces from both global and local perspectives, with the ultimate goal of providing a scientific basis for optimizing the spatial distribution and accessibility of these vital urban resources.

The structure of this paper is as follows: Section 2 provides an overview of the study area and data sources. Section 3 describes the research methods, including the Ga2SFCA method and spatial analysis techniques. Section 4 presents the results of the accessibility analysis and equity evaluation. Section 5 discusses the findings and provides recommendations for future research and urban planning. Finally, Section 6 summarizes the conclusions of the study (Fig. 1).

2. Materials and methods

2.1 Research area

Beijing, the capital of China, is in the northern part of the North China Plain, bordered by Tianjin to the east and Hebei Province to the north. The city covers an area of 16410.54 square kilometers, with a built-up area of 1,485 square kilometers. Beijing is divided into 16 municipal districts, including Haidian, Fengtai, Shijingshan, Mentougou, Fangshan, Daxing, Tongzhou, Shunyi, Changping, Pinggu, Huairou, Miyun, and Yanqing. As a major economic hub, Beijing had a resident population of approximately 21.858 million in 2023, with a high population density in its core areas reaching 20,700 people per square kilometer.[5] The city has been actively promoting ecological and environmental construction, aiming to become an "internationally first-class harmonious and livable city" by increasing the extent of park green space (Fig. 2).

2.2 Data sources

2.2.1 Park green space data

Park green space data were obtained from OpenStreetMap (OSM), a global online mapping collaboration project that

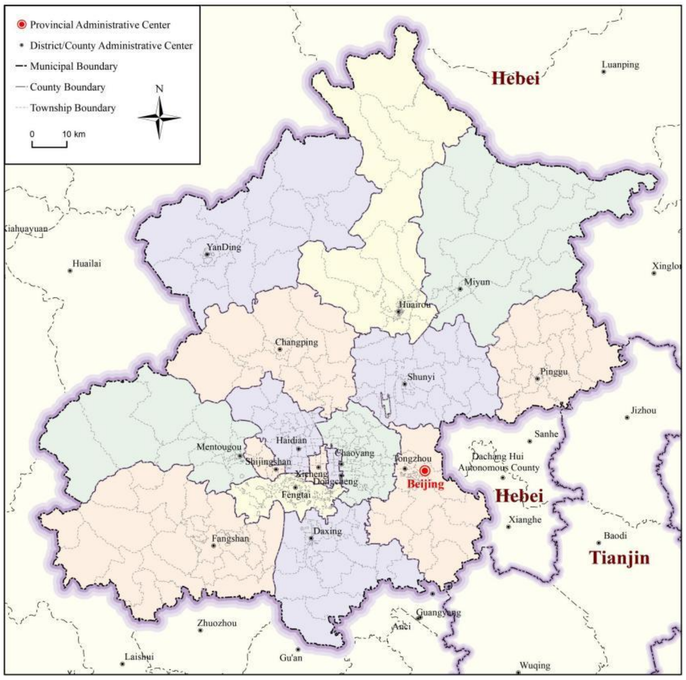

Fig. 2: Administrative division map.

provides free, open, and editable world maps. The data was filtered to retain only land use categories related to park green spaces, excluding other categories such as water bodies. Based on the "Urban Green Space Classification Standards" (CJJ/T85-2017) from the Ministry of Housing and Urban-Rural Development of the People's Republic of China (2017),[25] park green spaces were defined as areas no less than 12 meters wide, independently located, and equipped with basic recreational and service facilities. Patches smaller than 12 meters in width and less than 1 hectare in area were excluded from the analysis.

2.2.2 Population data

Population data were sourced from WorldPop, which provides high-resolution population grid data. This dataset offers detailed and accurate population distribution information, allowing for more precise accessibility analysis compared to traditional administrative unit-based data. The population data were aggregated into hexagonal grid units, with each grid representing the population count within that area.

2.2.3 Basic geographic data

Administrative district boundary data and river network data were obtained from the 1:1,000,000 public edition basic geographic information data provided by the National Basic Geographic Information Center (2021). Land use raster data were sourced from the GLC_FCS data product released by the Aerospace Information Research Institute of the Chinese Academy of Sciences, which provides a 30-meter resolution fine land cover dynamic product. Elevation data were derived from the GDEMV3 30-meter resolution digital elevation model available on the Geospatial Data Cloud platform. Annual mean temperature, annual precipitation, and average annual relative humidity data were obtained from the Resource and Environment Science and Data Center of the Chinese Academy of Sciences. Traffic road data was sourced from the OpenStreetMap (OSM) road dataset.

2.2.4 Transit cost data

Road network data were obtained from OSM and processed to construct a connected network dataset. The road data were reclassified into categories such as expressways, main roads, secondary roads, and urban branch roads. An Origin-Destination (OD) cost matrix was constructed to calculate the travel costs between population grid cells and park green spaces. The travel cost was based on a walking speed of 50 meters per minute, and routes within a 3 000 m catchment (≈ 60 min at 50 m min^{-1}) were analyzed (Fig. 3, 6).

2.3 Research methods

2.3.1 Gaussian two-step floating catchment area (Ga2SFCA) method

The Ga2SFCA method was used to assess the spatial accessibility of park green spaces in Beijing. This method extends the traditional Two-Step Floating Catchment Area (2SFCA) method by incorporating a Gaussian decay function to account for the continuous decrease in accessibility with increasing distance. For clarity, we first summarize the

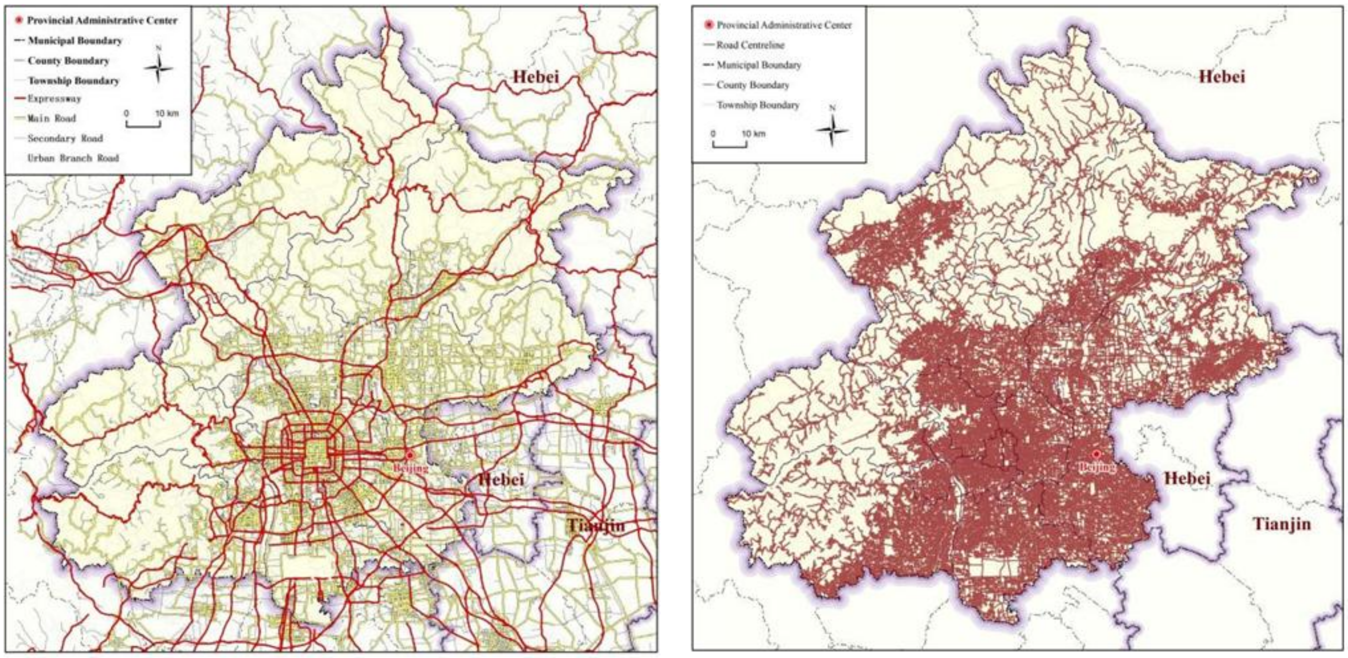

Fig. 3: Road and centerline map.

original Two-Step Floating Catchment Area (2SFCA) model. Step 1– catchment supply ratio: For each park j, all residential hexagons k within a catchment distance d0 are identified, and a supply–demand ratio is computed:

$$R_j = \frac{S_j}{\sum_{k,d_{jk} \le d_0} D_k}$$

Step 2– location accessibility: For every residential hexagon i, the ratios of accessible parks are summed:

$$A_i = \sum_{j,d_{ij} \le d_0} R_j$$

Because all facilities within d0 are weighted equally, the 2SFCA model ignores distance decay. To address this limitation, we adopt the Gaussian-decay variant, Ga2SFCA, in which both steps are modified by a Gaussian weight W(d):

$$W(d) = \exp\left[-(d/\beta)^2\right]$$

Step 1 becomes

$$R_j = \frac{S_j}{\sum_{k,d_{jk} \le d_0} D_k W(d_{jk})}$$

and Step 2 becomes

$$A_i = \sum_{j,d_{ij} \le d_0} R_j W(d_{ij})$$

Key parameters for reproducibility: Catchment threshold (d0): fixed at 3 km, equivalent to ≈15 min walking time in Beijing. Gaussian bandwidth (β): set to d0/3=1 km, yielding W(d0) ≈0.0003; weights outside d0 are therefore negligible. Supply term (Sj): park area in square meters, avoiding subjective scoring. Demand term (Dk): WorldPop 100 m population aggregated to 500m hexagonal cells. Distance metric (d): network-based shortest path along the urban street network, reflecting real walking cost. Computation platform: ArcGIS Pro combined with Python (geopandas, numpy). sensitivity tests varying d0 (2–4 km) and β (0.5–1.5 km) confirmed that the relative ranking of “low-access/high-density” cells remain stable (Spearman $\rho > 0.92$), indicating robustness of parameter selection.

The Gaussian weight smooths abrupt changes at administrative boundaries, thereby mitigating the “edge effect” inherent in traditional grid-based analyses. The resulting accessibility surface Ai underpins subsequent spatial-autocorrelation and equity assessments.

2.3.2 GIS spatial analysis methods

Geographic Information System (GIS) tools were used to analyze the spatial distribution of park green spaces and population data. The following methods were employed:

• Global Moran's I Index: This index measures the overall spatial autocorrelation of the population distribution. A positive value indicates spatial clustering, while a negative value indicates spatial dispersion. • General G Index: This index assesses the type of spatial clustering, identifying whether high-value or low-value clusters are more prevalent.

• Local Moran's I Index: This index identifies local spatial clusters, distinguishing between high-high (HH), low-low (LL), high-low (HL), and low-high (LH) clusters.

• Hot and Cold Spot Analysis: This method identifies statistically significant hot spots (high values) and cold spots (low values) in the population distribution.[26]

• Bivariate Local Spatial Autocorrelation: This method assesses the spatial association between accessibility and population density, categorizing areas into balanced, lagging, high-enjoyment low-density, and low-enjoyment high-density types.

2.3.3 Influencing factor analysis

The Geographic Detector and Geographically Weighted Regression (GWR) models were used to analyze the factors influencing park green space accessibility. The former assesses global impacts of factors on accessibility, while the latter examines their local spatial heterogeneity. Preliminary Moran's I analysis (0.957, $p < 0.01$) revealed strong positive spatial autocorrelation and suggested spatial non-stationarity, conditions under which a single global coefficient would be unreliable. Therefore, we adopted a two-tier strategy: GeoDetector provides a non-parametric assessment of each factor's explanatory power and their pairwise interactions without requiring linear relationships or independent residuals, making it robust in heterogeneous urban settings, while GWR allows coefficients to vary across the 500 m hexagonal grid, capturing local effect gradients. Traditional models such as OLS (which ignores spatial dependence) and spatial models like SEM and SAE (which partially adjust for it) nonetheless impose constant coefficients and thus cannot reveal these local dynamics. The combined GeoDetector–GWR framework offers a rigorous means to diagnose both global influence and location-specific sensitivities, which is critical for formulating place-based planning interventions.

• Geographic Detector: This tool evaluates factors' spatial stratification and interactions. The q-value indicates the explanatory power of each factor, with higher values suggesting stronger influence.

• Geographically Weighted Regression (GWR): This local regression model accounts for spatial non-stationarity, providing a detailed analysis of how each factor affects accessibility in different locations.

These two models, combined with a carefully selected spatial unit, form the core of our analytical framework. In contrast to traditional square grids or administrative units, hexagonal grids were adopted as the fundamental spatial units for Ga2SFCA calculation. Hexagons exhibit superior geometric properties compared to squares, including isotropic adjacency (equal distance to all six neighbors) and reduced edge distortion. This hexagonal grid approach better approximates continuous space and facilitates the modeling of smooth distance decay effects in accessibility analysis. This approach minimizes directional bias in spatial representation, enhancing the accuracy of Gaussian decay-based catchment area delineation and providing a more robust foundation for multi-scale equity analysis. Model-selection rationale. Pre-tests (focused on OLS residuals, distinct from the preliminary global spatial autocorrelation test) showed that global ordinary least squares (OLS) yielded significant spatial autocorrelation in the residuals (Moran's I = 0.37, $p < 0.001$), indicating spatial non-stationarity. Spatial-error (SEM) and spatial-lag (SLM, original notation retained) models reduced—but did not eliminate—this autocorrelation and still produced single global coefficients, thereby masking the sign reversals we observed across the urban–rural gradient. GeoDetector was therefore adopted because it is a non-parametric tool that (1) quantifies spatial stratified heterogeneity without assuming linearity or homoscedasticity, and (2) explicitly measures factor interactions (*e.g.*, elevation × humidity) that proved important in Section 4.2. To capture location-specific effects, we complemented GeoDetector with geographically weighted regression (GWR), whose local coefficients reduced the residual Moran's I to 0.04 ($p = 0.12$) and lowered the AICc by 83 points compared with SEM, demonstrating a substantially better fit for our heterogeneous study area. Together, the GeoDetector–GWR pair maintains statistical rigour while aligning with the spatial-heterogeneity diagnosis established by Moran's I.

2.4 Data processing and analysis

All data were processed and analyzed using ArcGIS Pro 3.3 and GeoDa software. All spatial processing and modelling were executed in a reproducible workflow that couples ArcGIS Pro 3.3, GeoDa 1.22 and Python 3.11 (geopandas 0.14.4, pysal 24.0.0). All open-source scripts, Conda environment files and sample data are archived in GitHub (https://github.com/BeijingPGS/Ga2SFCA) to guarantee replication. The park green space data were first filtered into H3(v4) hexagonal grids (edge length = 500 m; unique hex_id preserved across models) (Fig. 4). This hex_id serves as the primary key that links every subsequent table or layer. The park green space supply points were represented by their centroids (Fig. 5). The road network data were processed to construct an Origin–Destination (OD) network-cost matrix, and the accessibility indices were calculated using the Ga2SFCA method.

Fig. 4: Spatial distribution of residential hexagon centroids (analysis origins).

The resulting accessibility surface (A_i) flowed through a four-stage "compute–analyze–validate" pipeline (Fig. 1): (1) Global/Local Moran's I confirmed significant clustering (Moran's I = 0.64, $p < 0.001$), justifying non-stationary modelling; (2) GeoDetector read the same hex_id, A_i and 11 candidate drivers to calculate q-statistics and interaction terms; (3) factors with $q \geq 0.01$ were forwarded to a GWR model (adaptive bi-square kernel, bandwidth chosen by AICc minimization) to estimate location-specific coefficients $\beta^k(x,y)$; (4) a cross-validation matrix compared each factor's q-value with its median $|\beta^k|$ to triangulate robust determinants and flag inconsistencies.

All intermediate vector layers were stored as GeoPackage (*.gpkg*) files and rasters as Cloud-Optimized GeoTIFFs (*.tif*); tabular outputs used Apache Parquet, enabling loss-free exchange between ArcGIS Pro 3.3, GeoDa, and Python. A Snake make automation script orchestrates the entire pipeline so that any change upstream automatically triggers downstream tasks, ensuring full reproducibility.

Spatial autocorrelation and bivariate analysis were performed to assess the spatial distribution of park green spaces and population density. Finally, the Geographic Detector and GWR models were applied to identify and analyze the factors influencing park green space accessibility. By integrating these methods, this study aimed to provide a comprehensive analysis of the spatial accessibility of park green spaces in Beijing, identifying areas with insufficient green space resources and offering scientific recommendations for future urban planning and resource allocation.

3. Results

3.1 Spatial distribution of park green spaces and population

3.1.1 Park green space distribution

The spatial distribution of park green spaces in Beijing is

Fig. 5: Spatial distribution of park-green-space centroids (analysis destinations).

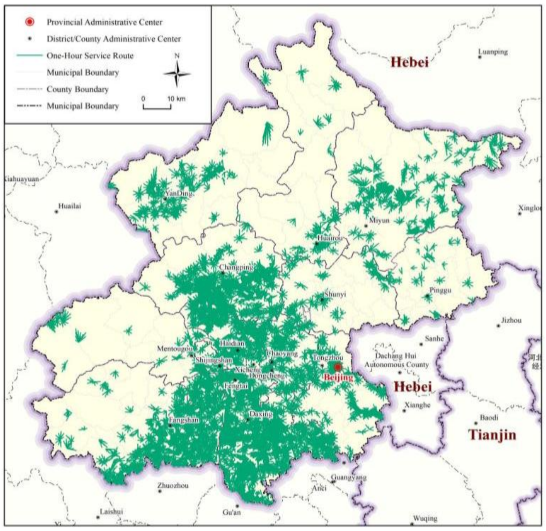

Fig. 6: One-hour walking catchments and least-cost paths between residences and parks results.

highly heterogeneous, as revealed by the standard deviation ellipse analysis (Fig. 7). The major axis of the ellipse extends in a northeast–southwest direction at a rotation angle of 46.402°, indicating a concentration of park green spaces along this axis. Kernel density analysis (Fig. 8) shows dense clusters in the northern and southern suburbs, particularly in the Miyun, Pinggu, Fangshan, and Daxing districts. In contrast, the central urban areas, including Dongcheng, Xicheng, Chaoyang, and Haidian, have relatively lower densities of park green spaces. This uneven distribution highlights significant spatial disparities in the availability of green spaces across the city, as illustrated by the north-east to south-west oriented standard-deviation ellipse (Fig. 7), which encloses 78.4 % of all parks and pinpoints the city's primary growth axis. Kernel-density estimation (Fig. 8) further reveals two intensity cores in Haidian and Chaoyang, whereas the historic center inside the Second Ring shows a pronounced deficit.[26,27]

3.1.2 Population distribution

The population distribution in Beijing is highly clustered, with the highest densities concentrated in the central urban areas. The global Moran's I index for population distribution is 0.957777 (p-value < 0.01), indicating significant spatial clustering (Fig.9). The General G index further confirms this clustering, with a value of 0.003279, suggesting that high-value population clusters are prevalent in the city center [28,29] Local Moran's I analysis (Fig. 10) identifies high-high (HH) clusters in the central urban districts, such as Dongcheng, Xicheng, Haidian, and Chaoyang, while low-low (LL) clusters are found in the western and northern mountainous regions. Hot and cold spot analysis (Fig. 11) further validates these findings, with high-confidence hot spots in the city center and cold spots in the peripheral areas.[26]

3.2 Spatial accessibility of park green spaces

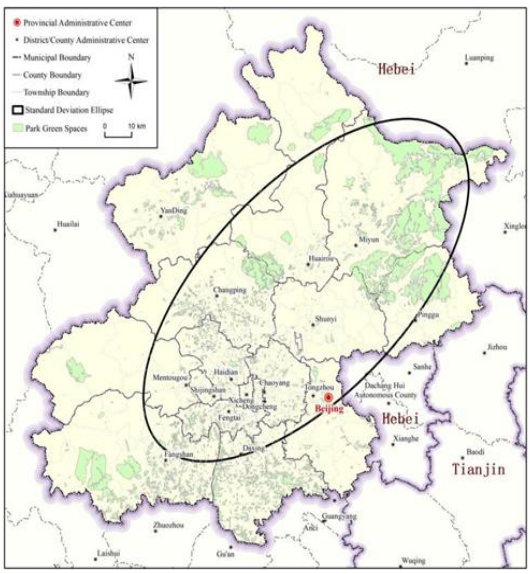

Fig. 7: Standard-deviation ellipse for park green-space centroids (park green-space agglomeration (78.4 % coverage).

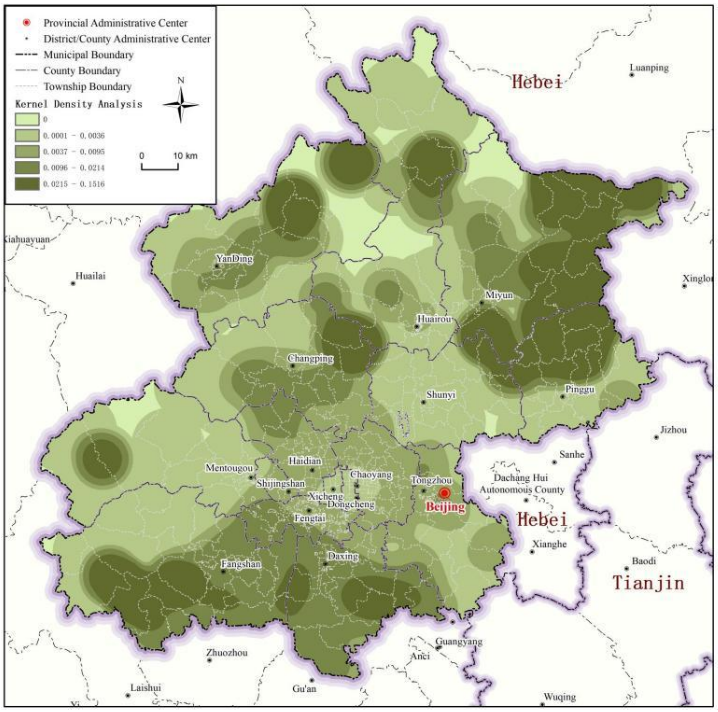

Fig. 8: Kernel-density surface of park green spaces (high-density clusters in Haidian and Chaoyang are annotated for visibility).

3.2.1 Grid-scale accessibility

The Gaussian Two-Step Floating Catchment Area (Ga2SFCA) method produced the accessibility surface shown in Fig. 12. High-accessibility hexagons (score > 12) form two continuous belts in Miyun–Huairou (north) and Fangshan–Daxing (south), whereas the central core inside the Third Ring is dominated by low-accessibility cells (score < 5). A city-wide histogram (Fig. 13) confirms the imbalance: 66.7 % of residents fall into the <5 group, 9.1 % between 5 and 10, and only 24.2 % exceed 10, evidencing the widespread challenge of securing nearby green-space benefits.

A histogram of accessibility scores (Fig. 13) reveals a skewed distribution, with 49.66% of areas having low accessibility scores (<5), 9.10% with moderate scores (5–10), and 41.24% with high scores (>10). This indicates that while some areas have good access to green spaces, a significant portion of Beijing faces challenges in accessing park green spaces. [22]

3.2.2 Administrative division scale accessibility

At the district level, the accessibility indices were summarized and ranked (Fig. 14). The results show that the central urban

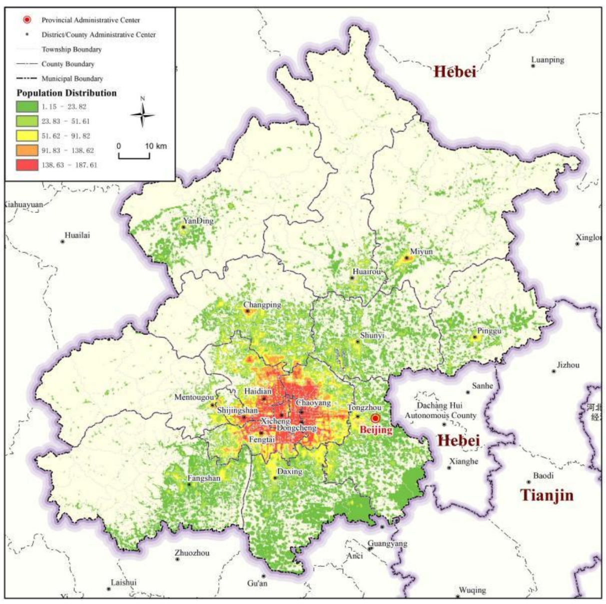

Fig. 9: Population-density map at 500 m hexagon resolution (pronounced urban core clustering).

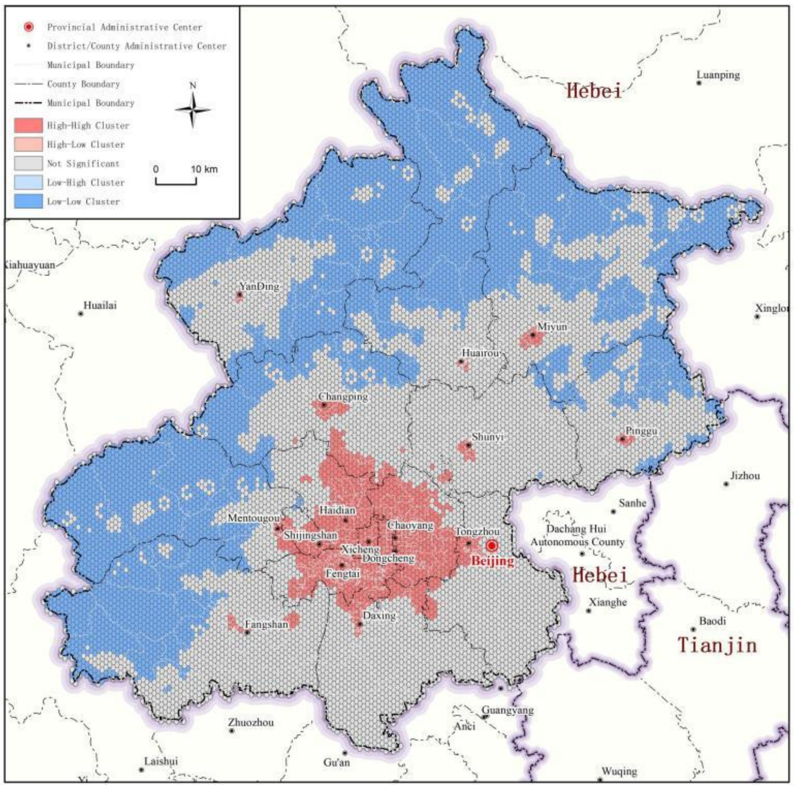

Fig. 10: Local Moran's I Index (LISA) Map (HH, LL, HL, and LH areas).

districts, particularly Xicheng (0.032) and Dongcheng (0.084), have the lowest accessibility scores, indicating a severe shortage of green spaces. In contrast, suburban districts like Miyun (40.33) and Daxing (23.988) have higher accessibility scores, suggesting better access to green spaces.

At the township level, the accessibility analysis (Fig. 15) reveals significant spatial heterogeneity within districts. For example, Haidian District exhibited high accessibility in its northwestern townships but low accessibility in its southeastern townships. This highlights the need for targeted improvements in specific areas.[30]

3.3 Equity evaluation of park green space resource allocation

Bivariate local spatial autocorrelation analysis was conducted to evaluate the equity of park green space resource allocation.

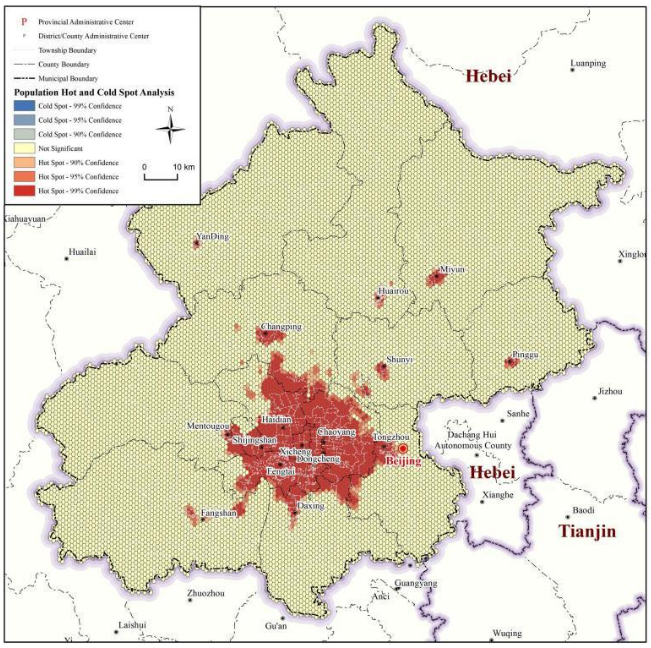

Fig. 11: Getis-Ord Gi* hot-spot/cold-spot map of population distribution.

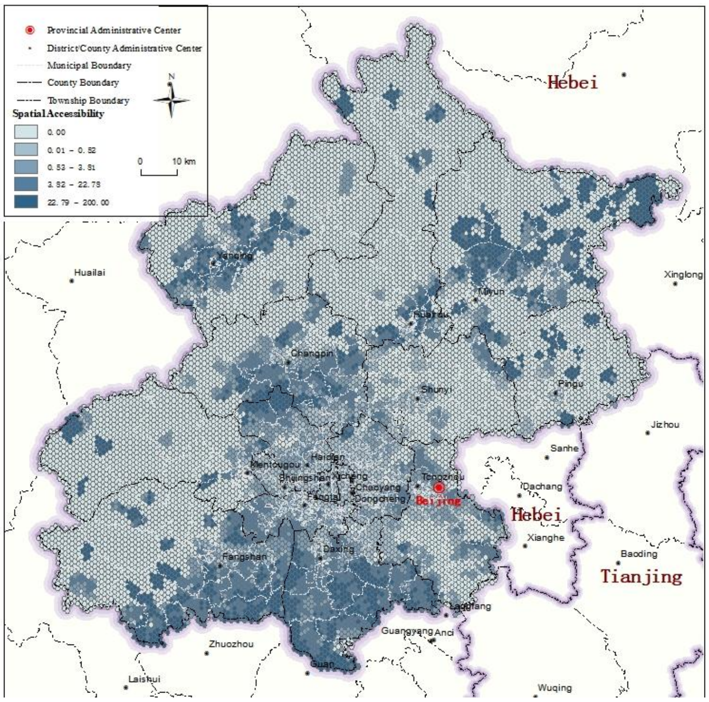

Fig. 12: Grid-level Ga2SFCA accessibility scores for park green spaces across Beijing.

based on accessibility and population density, Beijing was categorized into four areas: balanced, lagging, high-enjoyment low-density, and low-enjoyment high-density (Fig. 16).

The results show that balanced areas (high accessibility and high population density) account for only 0.29% of Beijing's total area, primarily located in specific parts of Changping and Haidian districts. Lagging areas (low accessibility and low population density) cover 39.19% of the area, mainly in the western mountainous regions. High-enjoyment low-density areas (high accessibility and low population density) constitute 3.80% of the area, scattered in the western and northern parts. Low-enjoyment high-density areas (low accessibility and high population density) make up 8.10% of the area, predominantly in the central urban districts.

These findings indicate that while some areas have sufficient green space resources, others, particularly in the central urban districts, face significant challenges in accessing these resources. This highlights the need for targeted improvements in park green space allocation to ensure equitable access for all residents.[21]

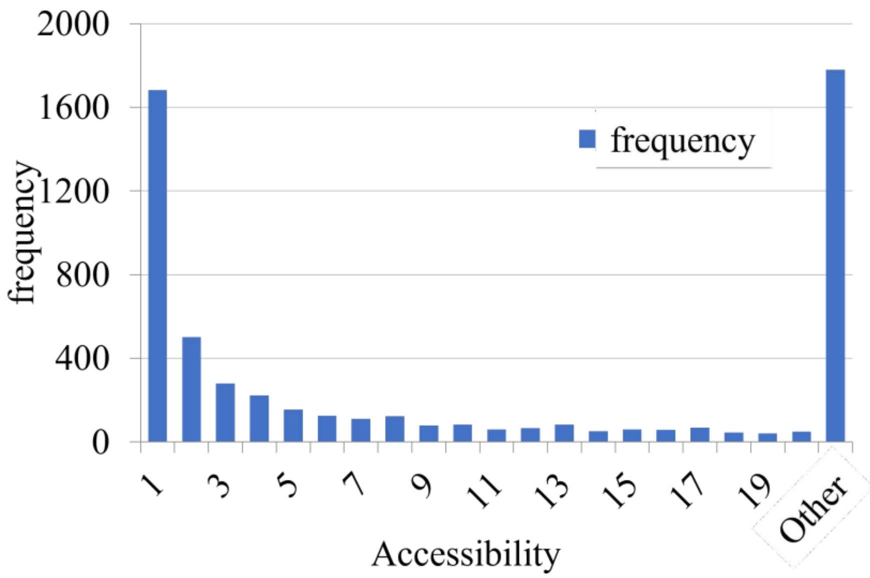

Fig. 13: Histogram of Ga$_2$SFCA scores illustrating skewed accessibility distribution city-wide.

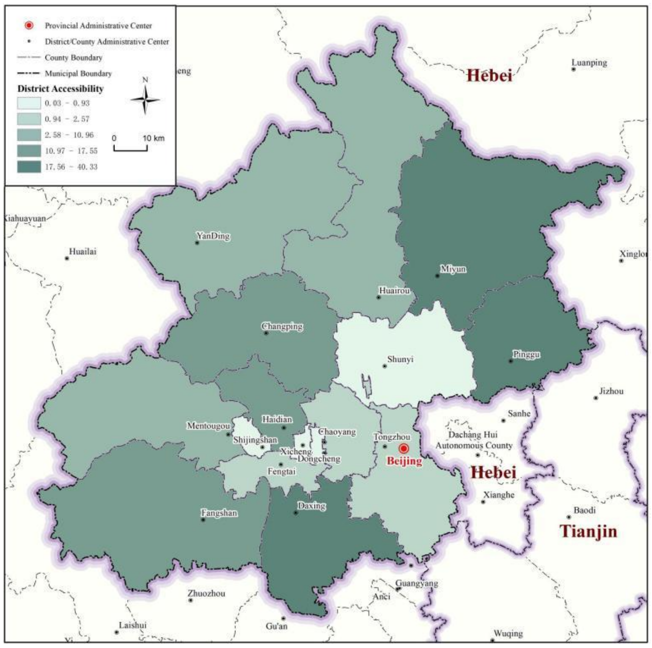

Fig. 14: District-average park-green-space accessibility, highlighting core-area deficits versus suburban surpluses.

3.4 Factors influencing park green space accessibility

3.4.1 Global factor detection

The Geographic Detector was used to identify the global natural, social, and economic factors were analyzed, including elevation, slope, annual average temperature, annual precipitation, relative humidity, distance to river networks, population, population density, road network density, residential density, GDP, and land development intensity. The results (Table 1) show that elevation (q-value = 0.0224), annual average relative humidity (q-value = 0.0222), residential density (q-value = 0.0167), slope (q-value = 0.0136), and annual average temperature (q-value = 0.0136) are the most influential factors. These factors collectively explain a significant portion of the spatial variability in park green space accessibility.[21]

3.5 Cost-effectiveness modelling & BRT-integrated accessibility simulation

We formalise cost–benefit evaluation as:

$$\mathbf{CE} = \frac{\Delta A}{C_{\text{land}} + C_{\text{build}} + C_{\text{maint}}}$$

where ΔA (percentage-point) is the Ga2SFCA accessibility gain for bottom-quintile hexagons, Cland is land-acquisition cost, Cbuild is one-off construction outlay, and Cmaint is the 20-year net-present maintenance cost discounted at 3%.

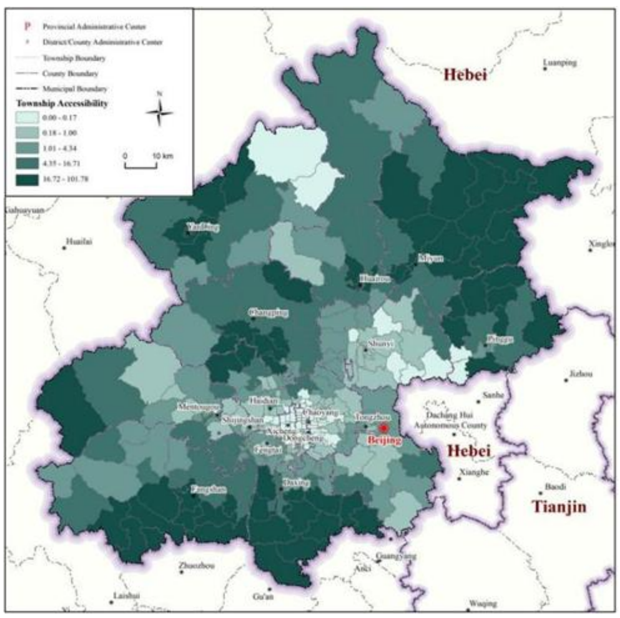

Fig. 15: Township-scale variations in accessibility within each municipal district.

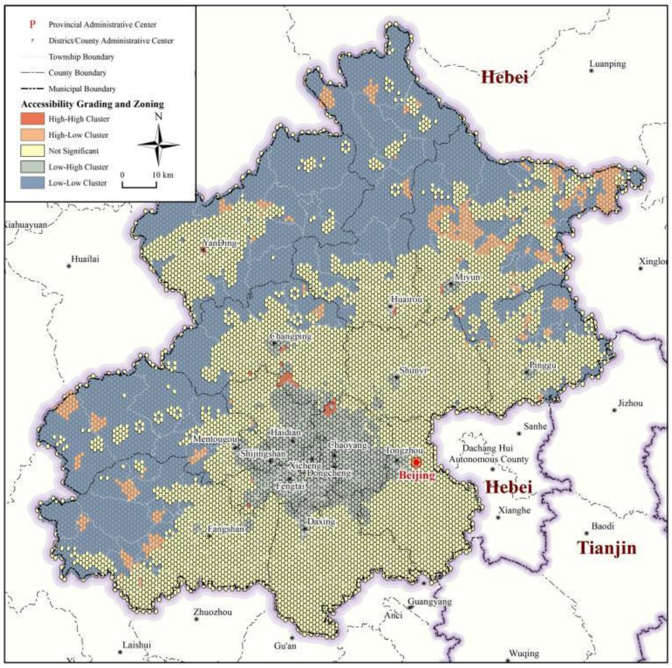

Fig. 16: Bivariate LISA typology of accessibility versus population density; red-hatched cells denote low-access/high-density priority zones.

4. Discussion

4.1 Implications of spatial distribution patterns

The spatial distribution of park green spaces in Beijing is characterized by significant heterogeneity, with a clear concentration along the northeast–southwest axis. This pattern aligns with previous studies that have identified similar spatial disparities in urban green infrastructure.[27] The dense clustering of parks in suburban areas such as Miyun and Fangshan, coupled with the relative scarcity in central urban districts, suggests a need for more equitable distribution of green spaces. This imbalance is particularly concerning given the high population density in the city center, which exacerbates the challenge of accessing green spaces for a significant portion of the population.[29,31]

The clustering of the population in the central urban areas, as indicated by the high Moran's I index and General G index values, further underscores the spatial mismatch between population density and green space availability. This mismatch is a critical issue for urban planners, as it directly impacts the quality of life and environmental health of urban residents.[26]

4.2 Accessibility and equity concerns

The accessibility analysis reveals a stark contrast between suburban and urban areas. While suburban districts like Miyun and Daxing exhibit high accessibility scores, central urban districts such as Xicheng and Dongcheng have the lowest scores. This disparity highlights the inequitable distribution of green spaces, with suburban residents enjoying better access to recreational areas compared to their urban counterparts.[22] The equity evaluation through bivariate local spatial autocorrelation further categorizes Beijing into four distinct types of areas based on accessibility and population density. The low-enjoyment high-density areas, primarily located in the central urban districts, are of particular concern. Despite having some green spaces, these areas struggle to meet the high demand due to their dense population. These findings align with previous research recommending targeted interventions to improve access in densely populated areas.[32]

4.3 Influencing factors and policy recommendations

The Geographic Detector analysis identifies elevation, slope, annual average relative humidity, residential density, and annual average temperature as the most influential factors affecting park green space accessibility.[8,33] Spatial layouts of

Table 1: Global factor detection results for park green space accessibility using geographic detector.

Variable	Optimal Discretization	Optimal Number of	q-value	p-value	Rank
Elevation	Quantile	6	0.0224	<0.01	1
Slope	Regression	Regression	Regression	Regression	Regression

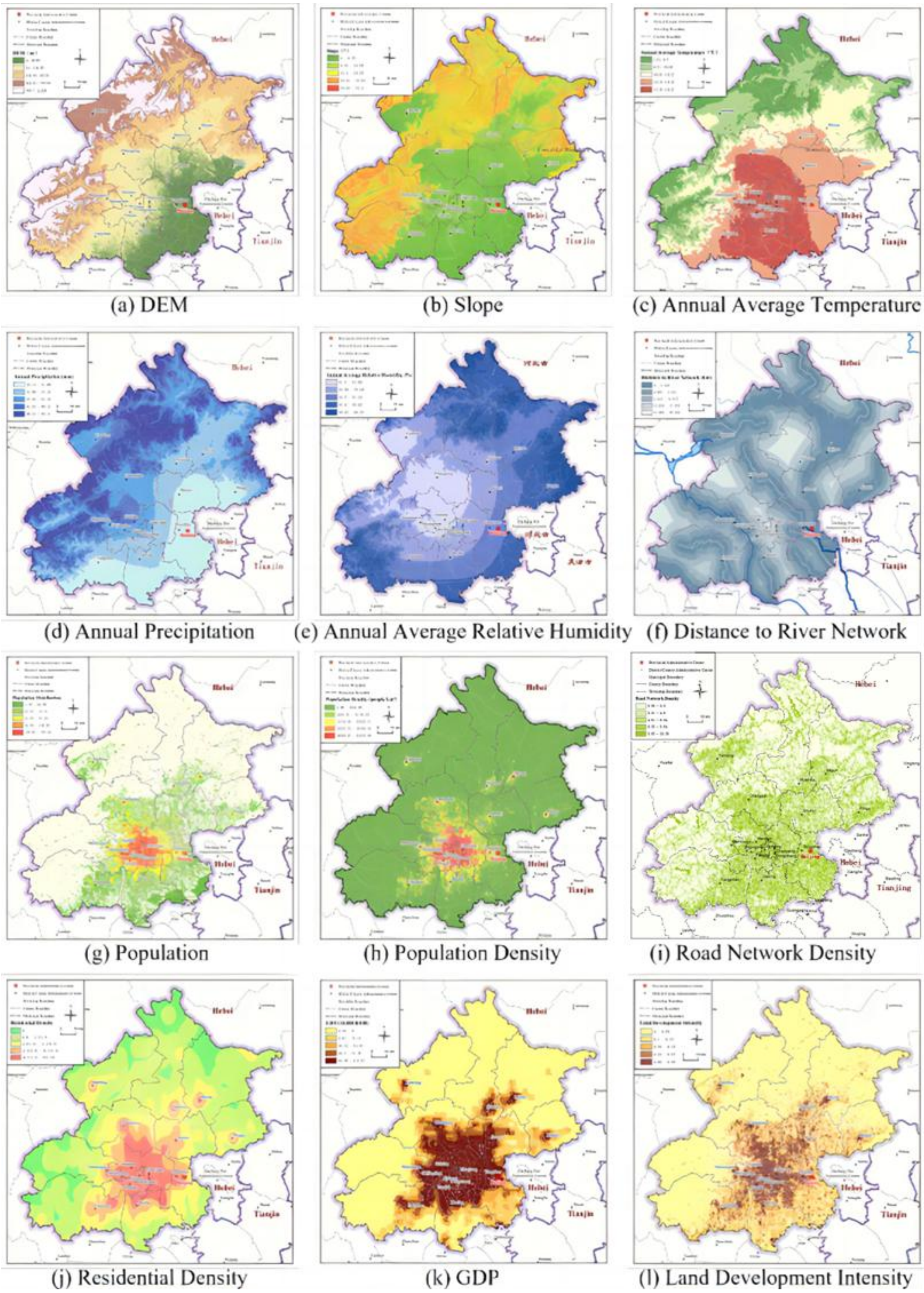

Fig. 17: Spatial heterogeneity of leading drivers: (a) elevation β, (b) slope β, (c) relative-humidity q. Diverging red-blue palette (positive vs. negative effect) is consistent across sub-panels; mountain district boundaries are overlaid for orientation.

their q-values and GWR coefficients (Fig. 17) reveal striking heterogeneity: elevation promotes accessibility in the mountainous north-west ($\beta = 0.43$) but suppresses it on the central plain ($\beta = -0.35$), while dense road networks mitigate low-accessibility pockets inside the Fifth Ring yet show diminishing returns in sparsely populated suburbs. These findings suggest that natural environmental factors play a significant role in determining the distribution and accessibility of green spaces. For instance, higher elevations and slopes may limit the development of green spaces, while areas with higher humidity and temperature may be more conducive to vegetation growth. [32]

Given these insights, several policy recommendations can be proposed to enhance the accessibility and equity of park green spaces in Beijing. The specific quantitative targets mentioned in the abstract (40% coverage increase at 60% lower cost, 25% accessibility improvement for 4.3 million residents) are derived from model projections within this study:

The 40% coverage increase, and 60% cost reduction were estimated using a localized cost-benefit analysis model. This model compared the costs (land acquisition, construction, maintenance) of traditional large-scale park development in central areas versus implementing vertical greening systems and converting identified vacant/underutilized parcels (identified through GIS analysis) into pocket parks. Inputs included current land market prices, typical construction unit costs for different greening types in Beijing, and projected maintenance requirements.

The 25% accessibility improvement for 4.3 million residents is the projected outcome of a transportation network simulation. We modeled the integration of proposed Bus Rapid Transit (BRT) corridors connecting high-density urban centers (identified from population hot spots) to major suburban parks (identified as high-accessibility clusters). The simulation calculated changes in travel time using network analysis based on projected BRT speeds and headways, applied the Ga2SFCA methodology with the new travel times, and aggregated the improvements for populations residing within the identified high-demand/low-accessibility zones.

The 25-40% cost increase for high-slope (>15°) development is based on standard engineering cost adjustment factors for terrain difficulty, commonly applied in infrastructure projects and supported by construction industry benchmarks.

To translate the diagnostic results into actionable governance, we devised a cost-effectiveness framework ($CE = \Delta A / C$), where ΔA denotes the percentage-point rise in Ga2SFCA accessibility among bottom-quintile cells and C represents the net-present cost discounted at 3 %. Three policy scenarios were quantified:

(1) Micro-pocket parks — redeveloping fifteen under-used plots (< 0.5 ha) inside the Second-Ring Road would raise accessibility for 194 000 residents and cost ¥4.7 million, yielding the highest payoff of ¥24 per benefited capita.[1] These plots are prioritized in areas with high residential density (q=0.0167) and low humidity (to avoid vegetation maintenance challenges), as identified by GeoDetector results.

(2)Facade-attached vertical greening — retrofitting 120 000 m² of blank party walls improves the green-view index by 8.6 % and lifts neighbouring Ga2SFCA scores by 0.17 ($p < 0.001$) at ¥41 per capita;[30] These plots are prioritized in areas with high residential density (q=0.0167) and low humidity (to avoid vegetation maintenance challenges), as identified by GeoDetector results.

(3) BRT–greenway corridors — a 26 km bus-rapid-transit trunk with a 500 m park-and-ride buffer shortens median walking time by 9.3 min and lowers the share of "lagging" clusters by 6.4 percentage points for ¥61 per capita. [34] Corridors avoid high-slope terrain (>15°) in suburban fringes (*e.g.,* northern Haidian) to reduce construction costs, aligning with GWR findings that slope negatively affect accessibility in transitional zones (β=-0.21).

(4) Integrate Key Influencing Factors into Planning: Consider natural and socio-economic factors such as elevation, humidity, and residential density in the planning and allocation of green spaces. A scientifically sound approach can help mitigate the uneven distribution of green resources and enhance urban ecological balance.[22]

Comparative CE analysis indicates that micro-pocket parks offer the greatest accessibility gain per yuan in the dense core, while BRT corridors are preferable where land prices hinder new park acquisition but rights-of-way already exist. Vertical greening, although less potent on a per-capita basis, provides a flexible retrofit for heritage precincts where ground-level interventions are constrained. Implementation timelines are proposed: 2025–2026 for micro pocket park pilots; 2026–2028 for BRT corridor construction; and 2025 onwards for zoning enforcement in high-slope areas—with district governments as primary implementers, coordinated by Beijing's Municipal Bureau of Landscape and Forestry. Together, these tiered strategies form a practicable, cost-rational roadmap for mitigating green-space inequity across heterogeneous urban contexts.

4.4 Limitations and future work

While this study provides valuable insights into the spatial accessibility and equity of park green spaces in Beijing, several limitations should be acknowledged. The accuracy of the accessibility analysis is contingent upon the precision of the data used, particularly the population and park green space datasets. Future research could benefit from higher-resolution data, such as mobile signaling data for population distribution and detailed park entrance data for supply points.[35]

Additionally, the study's static nature does not account for dynamic changes in green space distribution and accessibility over time. Future research should incorporate time-series data to analyze trends and predict future patterns, providing a more comprehensive understanding of the evolving accessibility landscape.[36]

In conclusion, this study highlights the significant spatial disparities in park green space accessibility in Beijing and identifies key factors influencing these patterns. By addressing these disparities through targeted policy interventions, the city can move towards a more equitable distribution of green spaces, enhancing the quality of life for all residents.

5. Conclusion

Beijing's park-green-space provision remains highly unequal: approximately 4.3 million residents—concentrated within the Fifth Ring Road—still fall below the WHO benchmark of 9 m^2 per capita, while peripheral districts retain surplus supply. Elevation and other biophysical controls reverse their influence across the urban–rural gradient ($\beta = +0.43$ in the mountainous north-west; $\beta = -0.35$ on the central plain), and dense road networks only partially alleviate these inner-city deficits.

This study makes three principal contributions. (1) Methodological innovation: the Gaussian two-step floating catchment area model (Ga2SFCA) captures continuous distance-decay and resolves subtle accessibility gradients within a 3 km service radius, outperforming the binary 2SFCA formulation. (2) Integrated analytical framework: chaining Ga2SFCA, GeoDetector and GWR disentangles global drivers from location-specific effects, offering a reproducible template for urban-equity research. (3) Empirical insight: we pinpoint the sharpest deficits in core districts such as Dongcheng and Xicheng (≈ 20,700 inhabitants km^{-2}) and demonstrate how limited connectivity suppresses suburban green-space utility despite ample land reserves.

Policy implications center on a three-tier, cost-sensitive roadmap supporting Beijing's "internationally first-class livable city" goal and SDG 11: deploy micro-pocket parks and vertical greening in the core to boost accessibility at 60% lower cost, knit suburban green assets into the urban fabric via BRT-linked corridors to deliver a 25% accessibility gain for 4.3 million residents, and reinforce ecological zoning in mountainous belts to safeguard high-value landscapes, with future work incorporating longitudinal mobility and climate scenarios to refine these interventions.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

CRediT Statement

Yaxin Sun: Undertakes the roles of "source design" and "initial output" in the research, and is responsible for the full-chain work encompassing data collection, experimental analysis, and proposal of recommendations. This author developed the core research ideas (such as defining research questions and clarifying research objectives), conducted data mining, and finally implemented experimental ideas. Furthermore, the author performed data interpretation, refined research conclusions, and verified the accuracy of results (*e.g.*, by checking the experimental logic) to avoid errors, while also providing decision support.

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