Evaluation of Electric Vehicle Charging Station Accessibility Based on an Improved Gravity Model

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Abstract: The accessibility of charging infrastructure is a core factor influencing the development of electric vehicles. Evaluations based on traditional gravity models often exhibit limitations: first, the quantitative indicators for supply point service capacity are overly simplistic, failing to reflect variations among different charging stations; second, they neglect spatial competition effects between demand points and users' utility-maximizing choice behaviors, leading to discrepancies between evaluation results and actual conditions.To address these shortcomings, this study proposes a multidimensional evaluation system for charging station service capacity. Key indicators such as the number of charging piles and charging power are selected, with weights determined using the entropy weight method to accurately quantify the comprehensive service capacity of each charging station.Second, a maximum utility function is introduced to define the competitive service range of charging stations by calculating user choice probabilities under varying travel costs. This improves the traditional gravity model's method for delineating supply point service areas and is applied to assess the accessibility of electric vehicle charging stations in Guangzhou's central urban districts.The evaluation results indicate: (1) The spatial pattern of electric vehicle accessibility in Guangzhou's central urban area is imbalanced, exhibiting strong spatial polarization. Over 59.1% of streets have charging station accessibility below the citywide average,while only a few streets exhibit high accessibility. (2) A clear positive spatial correlation exists among charging facility accessibility levels in central Guangzhou. Influenced by regional functions and population distribution, distinct "high-high" (H-H) and "low-low" (L-L) agglomeration zones are evident, with a notable absence of "low-high" (L-H) and "high-low" (H-L) agglomeration zones.

Keywords: Electric Vehicle Charging Stations; Accessibility; Gravity Model; Guangzhou

1. Introduction

Amidst the dual challenges of global energy crises and environmental pollution, electric vehicles emerge as green, sustainable new energy transportation solutions. They offer significant advantages in combating air pollution, reducing petroleum dependency, and optimizing energy structures, thereby establishing themselves as the strategic cornerstone for the international motor sector's transition toward sustainable modernization and industrial advancement. As the scale of new energy vehicles continues to expand, their supporting infrastructure-charging stations-has gradually become one of the key emerging industries receiving national support in recent years, driven by robust market demand.

The adequacy of charging infrastructure, particularly its spatial accessibility (reachability), is a core factor influencing consumer purchasing intent, alleviating range anxiety, and ultimately shaping the development of electric vehicles. Consequently, scholars worldwide have extensively studied the spatial layout of charging stations.Regarding site selection planning, Wang et al. proposed a multi-objective planning model that comprehensively considers EV development trends, charging station service capacity, and municipal planning factors, designing a demand-priority-based charging station layout strategy[1]. Huang et al. proposed a geometric segmentation method for fast and slow charging stations, effectively addressing the partial coverage problem in traditional point demand models to more accurately optimize charging network coverage[2]. Liu Zhipeng et al. proposed a two-step screening method considering environmental factors and charging station service radii. Utilizing Voronoi diagrams to partition service areas, they established a mathematical model aiming to minimize total costs and network loss expenses during the planning period[3].Regarding charging convenience optimization, Davidov introduced the concept of "Time of Convenience" buffers. By setting user-defined waiting time limits, this approach optimizes hybrid configurations of charging technologies to balance charging reliability and user convenience[4]·Çelik et al. combined genetic algorithms for solving the P-median problem with Arena simulation modeling. By simulating traffic flow and queueing times, they determined optimal charging station locations and capacities to minimize user wait times [5]. Ren et al. applied dynamic traffic network concepts to establish a charging station layout model constrained by hard time windows, aiming to minimize charging costs for users[6].In charging station accessibility research, Kłos and Sierpiński proposed a GIS-based " " site selection method, specifically focusing on pedestrian accessibility after drivers park. They optimized site distribution within urban areas by analyzing walking isochrones [7].Falchetta and Noussan analyzed accessibility of European EV charging networks using crowdsourced databases, revealing significant variations across countries and urban/rural areas by calculating travel times to nearest stations[8].

Although existing research has examined electric vehicle charging station development, most studies rely on models and algorithms to address optimization issues in station siting, lacking evaluations of accessibility and spatial distribution for existing infrastructure.This study integrates Guangzhou's charging station attribute and spatial distribution data. Based on an improved gravity model, it calculates the accessibility of charging stations within the region and analyzes the spatial distribution characteristics of the existing charging station layout. This provides research insights for the field of charging facility site selection, ultimately promoting the efficient layout of charging networks and the sustainable development of the new energy vehicle industry.

2. Study Area and Data Sources

2.1 Study Area

The study area for charging facility accessibility is the central urban districts of Guangzhou. Located in Guangdong Province, Guangzhou ranks among China's most economically dynamic, open, and innovative regions, with its electric vehicle ownership and charging station numbers consistently leading the nation. The Guangzhou Territorial Spatial Master Plan (2021–2035) stipulates that the planned scope of Guangzhou’s central urban area encompasses the entire territories of the Yuexiu, Haizhu, Liwan, and Tianhe districts; the area of Baiyun District situated south of the Northern Second Ring Expressway; and the areas of Huangpu District excluding Jiufu Subdistrict, Longhu Subdistrict, and Xinlong Town-covering a total area of approximately 933 square kilometers (Figure 1).

2.2 Data Sources and Preprocessing

Charging infrastructure encompasses charging equipment, power supply and distribution equipment, monitoring devices, firefighting facilities, and other related installations.[9] The term “charging infrastructure” as used herein specifically refers to electric vehicle charging stations. Data on Guangzhou's charging infrastructure originates from the Guangdong Provincial Government's Open Guangdong data platform (gddata.gd.gov.cn), while spatial data is sourced from the AutoNavi Open Platform (lbs.amap.com), as illustrated in Figure 1.Residential settlement data was obtained through Anjuke, from which household counts and vehicle ownership figures were extracted for analysis.

Table 1. Statistics on Residential Areas and Charging Stations in the Central Urban Area of Guangzhou

Administrative District	**Number of Residential Points**	**Total Number of Households**	**Number of Charging Stations**	**Number of DC Piles**	**Number of AC Piles**	**Average Rated Power (kW)**
Baiyun	789	517,484	559	5,888	2,691	1,275.73
Tianhe	1,087	605,774	462	4,403	2,144	1,108.49
Liwan	610	469,713	155	1,645	627	1,205.94
Haizhu	918	646,499	244	2,665	1,274	1,176.42
Huangpu	316	303,987	319	2,900	1,639	945.44
Yuexiu	925	561,836	143	667	1,016	618.60

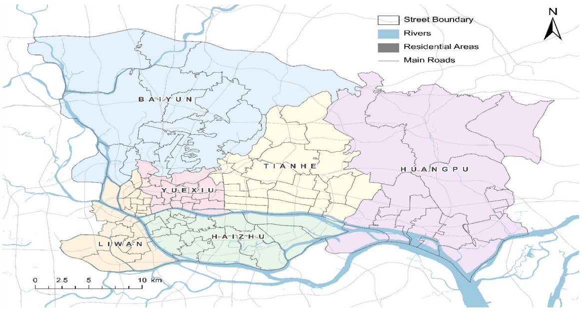

Figure 1. Street Divisions in the Central Urban Area of Guangzhou

3. Research Methods and Models

3.1 Gravity Model

3.1.1 Traditional gravity models

Research methods for accessibility primarily include buffer analysis, network analysis, minimum proximity distance analysis, cost-weighted distance analysis, and gravity models. Through continuous refinement, these methods aim to achieve more precise calculations of accessibility. Buffer analysis and network analysis examine accessibility primarily from the perspective of supply, whereas minimum proximity distance analysis and cost-weighted distance analysis explore accessibility primarily from the perspective of demand. Built upon an analysis of supply-and-demand relationships, the gravity model comprehensively integrates both supply and demand factors, thereby enabling a relatively comprehensive analysis of accessibility.

First proposed by Hansen, the gravity model calculates the strength of interactions between residents and all healthcare facilities within a study area.[10] The model expression is:

$$A_i^H=\sum\nolimits_{j=1}^{n} S_j d_{ij}^{-\beta} \qquad (1)$$

where A_i^H represents the accessibility index; S_j denotes the service capacity of supply points; n indicates the number of supply points; d_{ij} measures the distance between supply and demand points; and β is the impedance coefficient, typically ranging between 1 and 2.

Early gravity models only considered the supply-side service capacity and distance decay effect, neglecting the competition on the demand side . Luo et al. improved the model by introducing the supply-demand ratio to evaluate the impact of internal competition on the demand side on accessibility[11]. The improved expression is:

$$A_i^G=\sum\nolimits_{j=1}^{n} \frac{S_j d_{ij}^{-\beta}}{V_j}, V_j=\sum\nolimits_{k=1}^{m} D_k d_{kj}^{-\beta} \qquad (2)$$

where A_i^G represents the modified accessibility index; V_j denotes the competitive intensity; S_j signifies the service capacity of supply point; D_k indicates the magnitude of demand point; n is the number of supply points; m is the number of demand points; d_{kj} is the distance between demand point and supply point; and β is the impedance coefficient, typically taking a value between 1 and 2.

3.1.2 Improved gravitational model

Traditional gravity models define competitive intensity as the cumulative effect of all demand points within a study area competing for a single supply point. This approach overlooks distance decay patterns. Every supply point has an effective service range, and only demand points within this range exhibit competitive effects; those beyond it do not participate in competition.[12] Therefore, to more accurately measure competitive intensity, the effective competitive range of each supply point must first be defined.Existing studies often employ the Voronoi polygon method, which divides the space into Voronoi polygon regions based on supply point distribution, allowing demand points within the same region to compete. However, this method assumes consumers always prefer the spatially nearest supply point, ignoring variations in the supply points' service capacities. Therefore, this paper introduces a utility function to refine the method for delineating competitive ranges. The utility function is calculated as follows:

$$U_{kj}=\frac{S_j}{d_{kj}^{\beta}} \qquad (3)$$

where U_{kj} represents the utility of a supply point;S_j denotes the service capacity of a supply point; $d_{kj}$is the distance between the supply side and the demand side.; and β is the impedance coefficient.

The improved competitive range is defined as:

$$G_j=\{k \mid U_{kj}\geq U_{kz}, \forall z\neq j\} \qquad (4)$$

Where G_j represents the service area of supply point$j$;U_{kj} andU_{kz} denote the utility values of supply points$j$ and$z$, respectively, for the same demand point$k$.

The improved gravity model is:

$$A_i^G=\sum\nolimits_{j=1}^{n} \frac{S_j d_{ij}^{-\beta}}{V_j}, V_j=\sum\nolimits_{k\in G_j} D_k d_{kj}^{-\beta} \qquad (5)$$

Where A_i^G represents the improved accessibility; G_j denotes the service coverage of supply point j; V_j represents the intensity of competition; S_j denotes the service capacity of supply point j; D_k represents the scale of demand point k; n is the number of supply points; d_{kj} is the distance between demand point k and supply point j; and β is the impedance coefficient, typically taking a value between 1 and 2.

3.2 Kriging Spatial Interpolation

The accessibility results calculated using the gravity model are assigned to each settlement. To obtain accessibility estimates for any location within the entire study area, spatial interpolation of the discrete settlement accessibility values is required.[13]

Inferring values at unknown points from known sample points is typically addressed using local spatial interpolation methods. Common local interpolation methods include nearest-neighbor interpolation, inverse distance weighting, spline interpolation, and Kriging spatial interpolation. This study employs Kriging spatial interpolation, also known as optimal spatial autocorrelation interpolation. Compared to other deterministic interpolation methods, Kriging incorporates spatial relationships between neighboring settlements through the use of a semivariogram, enabling more accurate simulation of the continuous distribution of accessibility[14]. Its calculation method is:

$$\hat{Z}(s_0)=\sum_{i=1}^{n} \lambda_i Z(s_i) \qquad (6)$$

where $\hat{Z}(s_0)$ is the Kriging estimate at the prediction point s_0; $Z(s_i)$ is the observed value at the sampling point s_i ; n is the number of sampling points; and λ_i is the weight assigned to the sampling point s_i . The formula for calculating λ_i is:

$$\sum_{i=1}^{n} \lambda_i \gamma(s_i,s_j)+\mu=\gamma(s_i,s_0), \sum_{i=1}^{n} \lambda_i=1 \qquad (7)$$

where $\gamma(s_i,s_j)$ is the semivariogram value between observation point s_i and s_j ; $\gamma(s_i,s_0)$ is the semivariogram value between sampling point s_i and prediction point s_0 ; μ is the Lagrange multiplier introduced to minimize the estimation variance.

3.3 Spatial Autocorrelation Analysis

3.3.1 Global spatial autocorrelation

To comprehensively analyze the spatial clustering characteristics of charging station accessibility across the various sub-districts within Guangzhou's central urban area-and to determine whether this accessibility exhibits a clustered, dispersed, or random spatial distribution pattern-this study employs the sub-district as the unit of analysis and utilizes the Global Moran's I statistic. The Global Moran's I is one of the most widely used indicators for measuring spatial autocorrelation; it reflects the degree of spatial dependence among attribute values across the entire study area[15]. Its calculation formula is as follows:

$$I=\frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S_0\sum_{i=1}^{n}(x_i-\bar{x})^2}, S_0=\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij} \qquad (8)$$

Among these, I represents the global Moran index; n denotes the number of streets in Guangzhou's central urban area; x_i and x_j respectively indicate the charging station accessibility for streets i and j ; $\bar{x}$ is the average charging station accessibility across all streets; S_0 is the sum of all spatial weights; w_{ij} satisfies the following requirements:

$$w_{ij}=\begin{cases} 1, i \text{ is adjacent to } j \\ 0, i \text{ and } j \text{ are not adjacent, or } i=j \end{cases} \qquad (9)$$

The global Moran's I index ranges from [-1,1]. When $I>0$, it indicates spatial positive correlation in accessibility, meaning high-accessibility areas are adjacent to other high-accessibility areas or low-accessibility areas are adjacent to other low-accessibility areas, resulting in clustered spatial distribution; When $I<0$, it indicates spatial negative correlation, meaning high-accessibility areas are interleaved with low-accessibility areas, exhibiting a dispersed spatial distribution; When I approaches 0, it indicates that accessibility is randomly distributed in space. Additionally, the statistical significance of the index must be tested using Z-scores and P-values.

3.3.2 Local Spatial Autocorrelation

While the Global Moran's I can reveal the degree of spatial clustering of accessibility across the entire municipality of Guangzhou, it overlooks local spatial instability and struggles to detect the specific spatial clustering patterns of individual regions. This study therefore introduces the Local Moran's I to investigate the local spatial association patterns of charging station accessibility among various sub-districts[16]. The formula for calculating the local spatial association indicator is as follows:

$$LISA_i=\frac{(x_i-\bar{x})\sum_{j=1}^{n} w_{ij}(x_j-\bar{x})}{S^2},S^2=\frac{1}{n}\sum_{i=1}^{n}(x_i-\bar{x})^2 \quad (10)$$

where $LISA_i$ denotes the local Moran's I for subdistrict i ; n represents the total number of subdistricts in Guangzhou; x_i and x_j denote the accessibility scores for charging stations in subdistrict i and subdistrict j , respectively; S^2 is the variance of the observed values; and w_{ij} is the spatial weight, defined identically to the global Moran's I.

Through local spatial autocorrelation analysis, Moran's scatter plots can be generated to classify the spatial association patterns of study units into four types[17]:

High-High Aggregation (H-H): Indicates that the street has high accessibility, and the surrounding streets also have high accessibility, collectively forming a high-accessibility cluster with the surrounding area.

Low-Low Aggregation (L-L): Indicates that the street has low accessibility, and the surrounding streets also have low accessibility, collectively forming a low-accessibility cluster with the surrounding area.

High-Low Aggregation (H-L): Indicates that the street has high accessibility, but surrounding streets have low accessibility, revealing the area as a high-value anomaly.

Low-High Agglomeration (L-H): Indicates that the street has low accessibility, while surrounding streets have high accessibility, revealing the area as a low-value anomaly.

Although the local Moran's I is capable of measuring regional spatial dependency, its robustness is often susceptible to inherent spatial stochasticity. The magnitude of the index alone cannot determine whether the clustering characteristics are significant. Therefore, a conditional permutation test based on Monte Carlo simulation is employed for significance testing.

The verification process involves proposing the null hypothesis: The accessibility attribute values of the target streets exhibit a spatially random distribution with no significant spatial dependency.Under the condition that the attribute value x_i of the target study unit i remains unchanged, the attribute values of the remaining n-1 study units are spatially rearranged randomly, and the local Moran's I is recalculated. Through M random permutations, the empirical distribution of the local Moran's I under the assumption of random distribution is constructed, and the pseudo p-value is calculated accordingly.[18] The calculation formula is as follows:

$$P=\frac{R+1}{M+1} \quad (11)$$

Where P represents the pseudo p-value; M denotes the total number of simulations; and R represents the frequency with which the simulated statistics deviate from or reach the observed threshold during stochastic permutations.

The significance level α is taken as the threshold. A calculated P-value of less than 0.05 warrants the dismissal of the null hypothesis, signifying that street accessibility demonstrates pronounced spatial agglomeration. If the P-value exceeds 0.05, we fail to reject the null hypothesis, suggesting that the spatial clustering of the study area lacks statistical significance, which points to a stochastic distribution of accessibility.

4. Results and Analysis

4.1 Charging Station Service Capacity Assessment

The service capacity of an electric vehicle charging station is influenced by a variety of factors; among these, the number of charging piles, the number of charging guns, the station's rated power, the number and power output of DC piles, and the number and power output of AC piles are the key determinants of its service capacity.[19] Establishing a scientifically sound weighting system is crucial to ensuring that evaluation results accurately reflect the service level of electric vehicle charging stations.Currently, academia commonly employs the weighted average of multiple indicators to evaluate charging station service capacity. Traditional weight determination methods often rely on expert experience, making them susceptible to subjective factors and leading to inconsistent evaluation outcomes.[20] Therefore, this paper adopts the generalized entropy weight method, which directly extracts information from interval data to derive weights. The calculation method is as follows:

First, normalize all indicators to eliminate the impact of different units:[21]

$$x_{ij}^{'}=\frac{X_{ij}-\min(X_j)}{\max(X_j)-\min(X_j)} \quad (12)$$

Where: $x_{ij}^{'}$ represents the normalized indicator value; X_{ij} denotes the raw value of the j th indicator for the i th charging station; $\max\left(X_j\right)$ and $\min(X_j)$ represent the maximum and minimum values of this indicator across all samples.

Subsequently, the characteristic weight of the charging station for the evaluation indicator is calculated using the formula:

$$p_{ij}=\frac{x'_{ij}}{\sum_{i=1}^{m} x'_{ij}} \tag{13}$$

Where: p_{ij} represents the characteristic weight of the i -th charging station under the j -th indicator; x'_{ij} denotes the standardized indicator value; and m is the total number of charging stations.

Finally, the information entropy and indicator weights for each metric are calculated using the following formula[22]:

$$K_j=-k\sum_{i=1}^{m} p_{ij}\ln p_{ij}\,,\quad k=\frac{1}{\ln m} \tag{14}$$

Where: K_j is the information entropy of the jth indicator; k is the adjustment coefficient; m is the total number of charging stations; p_{ij} is the feature weight of the i th charging station under the j th indicator.

Where, K_j represents the information entropy of the j-th indicator; k is the adjustment coefficient; m is the total number of charging stations; and p_{ij} is the characteristic weight of the i -th charging station under the j-th indicator.

Information entropy can represent the importance of an indicator within an evaluation; specifically, the lower the information entropy of a given indicator, the greater the amount of information it conveys, and consequently, the larger its corresponding weight.It can filter redundant information from raw data and calculate indicator weights. The formula is:

$$w_j=\frac{1-K_j}{\sum_{j=1}^{n}(1-K_j)} \tag{15}$$

Where: w_j represents the weight of the jth indicator; K_j denotes the information entropy of the jth indicator; n indicates the total number of evaluation indicators.

The weight vector $w=[w_1,w_2,\ldots\ldots,w_n]$ calculated through the above steps will be used in subsequent calculations.[23] By combining the numerical values of each charging station indicator and performing a weighted sum, the final service capability score is derived.

4.2 Overall Characteristics of Charging Station Accessibility

Using the natural breakpoint classification method, the accessibility of electric vehicle charging facilities along streets in Guangzhou's central urban area-calculated based on an improved gravity model-was categorized into five tiers: "high," "relatively high," "average," "relatively low," and "low." Creating a thematic map based on classification levels (Figure 2).

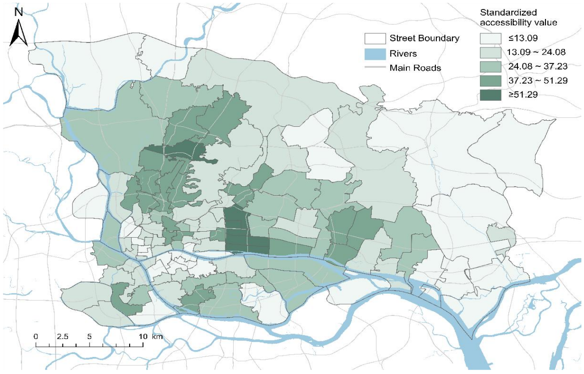

Figure 2. Accessibility Classification of Charging Stations in the Central Urban Area of Guangzhou.

Statistical data indicates an average accessibility score of 25.70, with a standard deviation of 15.86 and a skewness coefficient of 1.06, exhibiting a pronounced right-skewed distribution. Streets classified as "low" and "relatively low" accounted for a combined 59.1% of the total, representing the dominant category. In contrast, high-quality streets rated 'high' and "relatively high" constituted only 25.4%. This indicates that effective per capita charging resource accessibility remains low for most streets in Guangzhou's central urban area, exhibiting certain spatial polarization characteristics.

4.3 Spatial Distribution Characteristics of Charging Station Accessibility

In terms of spatial distribution, charging station accessibility exhibits distinct characteristics of spatial differentiation. Figure 3 indicates that areas with high accessibility are primarily concentrated in Tianhe and Baiyun Districts.This is because these districts belong to the city's core functional zones, where charging station construction began early and density is high. Accessibility in Baiyun and Haizhu Districts is relatively average. Although charging stations are densely distributed in these areas, their extremely high population density and limited land resources create intense demand-side competition, reducing the likelihood of individual residential areas accessing services.

Huangpu District and Liwan District exhibit low electric vehicle accessibility. These areas are distant from the city center, featuring predominantly scattered small-scale charging stations with sparse distribution. The significant distance between residential areas and the nearest stations creates high access barriers, resulting in low charging station accessibility.

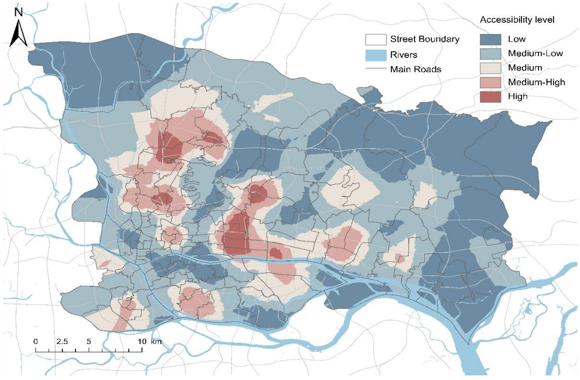

Figure 3. Accessibility of Charging Stations in Guangzhou's Central Urban Area

4.4 Spatial Aggregation Characteristics of Charging Station Accessibility

Based on the results of global and local spatial autocorrelation analyses presented in Table 2, the Global Moran's I index stands at 0.4059, indicating that the accessibility of charging facilities in Guangzhou's central urban area exhibits significant positive spatial autocorrelation. Specifically, streets with high accessibility tend to be adjacent to other streets with similarly high accessibility, while streets with low accessibility tend to be adjacent to other streets with similarly low accessibility. Statistics indicate that the accessibility values for the vast majority of streets fall within two standard deviations of the mean, suggesting a relatively stable overall spatial structure.

Further analysis of electric vehicle accessibility in Guangzhou's central urban area was conducted using the LISA index. With 999 random replacements set for the Monte Carlo simulation and a significance filter < 0.05, a Moran's dot plot for charging facility accessibility in the central urban area was generated.

The Moran scatter plot (Figure 4) reveals that, within the central urban area of Guangzhou, electric vehicle accessibility exhibits significant "High-High" (H-H) and "Low-Low" (L-L) clustering characteristics, while "Low-High" (L-H) clusters are notably absent. Specifically, "High-High" clusters are predominantly distributed within the established zones of the urban core-areas that integrate commercial, residential, and office functions, and are characterized by dense road networks and exceptionally high accessibility to charging service resources. In contrast, low-low clusters are concentrated in peripheral industrial belts where public charging infrastructure is scarce. These areas exhibit low accessibility clusters due to distance impedance caused by larger street areas.

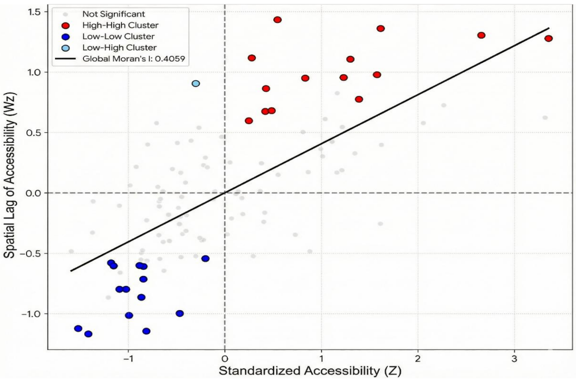

Figure 4. Moran Scatterplot of Street Accessibility in Guangzhou

Table 2. Statistics of Local Moran's I Cluster Types of Streets in Guangzhou

Cluster Type	Quantity	Street Name
High-High Cluster	14	Pazhou, Shipai, Chebei, Wushan, Xiancun, Yuancun, Tianhenan, Meihuacun, Tianyuan, Jiahe, Tangjing, Xinshi, Shijing, Sanyuanli
Low-Low Cluster	14	Nangang, Dongqu, Xiagang, Suidong, Lilian, Fengyuan, Haizhuang, Binjiang, Jiangnanzhong, Caihong, Xingang, Longfeng, Sushe, Taihe
Low-High Cluster	1	Dongshan
Not Significant	81	Huangpu, Hongshan, Dasha, Wenchong, Yonghe, Lianhe, Yuzhu, Luogang, Changzhou, Duobao, Qianjin, Linhe, Shahe, Hailong, Datang, Huangcun, Changgang, Nanhuaxi, Liede, Renmin, Changhua, Qiaozhong, Lingnan, Xicun, Fengyang, Huazhou, Nanzhou, Guanzhou, Shayuan, Jianghai, Ruibao, Chigang, Nanshitou, Changxing, Yuangang, Fenghuang, Xinghua, Zhuji, Xintang, Tangxia, Shadong, Longdong, Jinhua, Longjin, Dongsha, Hualin, Dongjiao, Zhongnan, Nanyuan, Huadi, Chongkou, Nonglin, Zhanqian, Chajiao, Baihedong, Shiweitang, Guangta, Liurong, Beijing, Huale, Dadong, Hongqiao, Huanghuagang, Liuhua, Dengfeng, Baiyun, Kuangquan, Jianshe, Shamian, Zhuguang, Tongde, Jingxi, Junhe, Jingtai, Songzhou, Yongping, Jinsha, Huangshi, Tonghe, Renhe, Jianggao

5. Conclusions and Outlook

This paper proposes an improved gravity model that accounts for electric vehicle ownership and service competition effects. It overcomes the shortcomings of traditional models that neglect service capacity differences when delineating service areas. First, it quantifies charging station service capacity using the entropy weight method. Second, it constructs competitive service areas for charging stations based on the principle of maximum utility, making accessibility evaluation results more aligned with actual supply and demand conditions.

Although this study achieves progress in model refinement and empirical analysis, limitations in data acquisition persist, necessitating further exploration in future research. The model assumes residents always choose the most efficient station, yet real-world charging behavior is influenced by random factors like parking fees, commercial district preferences, and charging stastions failure rates. Future work could integrate actual charging order data for more precise analysis of user station selection.The road network distance used in this study is primarily calculated based on latitude and longitude, without fully accounting for Guangzhou's road network structure, traffic congestion, and traffic light waiting times. Integrating API data to obtain real-time driving navigation distances or time costs could enhance the accuracy of accessibility calculations.

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