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SPATIAL DISTRIBUTION CHARACTERISTICS AND DIFFERENCE ANALYSIS OF URBAN SERVICE FACILITIES IN NORTH CHINA

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Abstract: This study conducts a comparative analysis of urban service facilities in Changchun and Hohhot by constructing a service density index, applying the coefficient of variation method, and utilizing the Spatial Lag Model (SLM). Results indicate that Changchun achieves a higher overall service level (CV=347.64) compared to Hohhot (CV=307.55), with significant disparities across seven domains, most notably transportation infrastructure. SLM regression reveals that Changchun exhibits stronger spatial integration and spillover effects while Hohhot demonstrates localized competition and fragmented service allocation patterns. Partial differential decomposition further confirms these divergent spatial dependency structures. This research establishes a replicable quantitative framework for cross-city comparative analysis, offering valuable theoretical support and evidence-based insights for optimizing urban resource allocation, informing differentiated planning strategies, and enhancing urban resilience in northern China.
Keywords: Distribution characteristics; Service density index; Coefficient of variation method; Spatial lag model

1 INTRODUCTION

As global climate change intensifies and urbanization advances at an unprecedented pace, cities are not only facing challenges from extreme weather events and sudden disasters but also confronting the urgent need to optimize the supply and layout of service facilities to meet the growing demands of residents for a high-quality life. Urban service facilities, covering fields such as medical care, transportation, and public services, are the core carrier of urban functions and a key indicator reflecting the level of urban development and residents' well-being. The layout of urban service facilities directly affects the operational efficiency, social equity and sustainable development capacity of a city.

In the context of China's rapid urbanization and aging society, scholars have conducted extensive research on the spatial distribution and optimization of urban service facilities. Chu and Cao investigated the spatial distribution of community elderly care service stations in Beijing's central districts [1], revealing significant spatial imbalances in service provision. Wang et al. constructed a smart mobility monitoring platform for the elderly in Guangzhou [2], providing technological solutions for age-friendly urban services. Liu assessed public service facilities in Beilun urban area of Ningbo and proposed optimization strategies based on comprehensive evaluation indicators [3]. Zhang and Bi utilized POI data to analyze the spatial distribution characteristics of daily life service industries in Qiqihar's built-up area [4], demonstrating the effectiveness of big data in urban service research.

From the perspective of living circle planning, Xu et al. evaluated the coverage and suitability of public service facilities in Nanjing's main urban area based on the 15-minute living circle concept [5], offering valuable insights for equitable service allocation. In rural contexts, Ji et al. explored the allocation of public service facilities in townships with facility-based agriculture under the rural revitalization strategy [6], addressing the urban-rural service divide. Wang and Yao studied the spatial distribution and accessibility optimization of age-friendly sports and wellness spaces in Zhengzhou [7], highlighting the importance of adapting urban services to demographic shifts. Ye et al. examined the spatial correlation between traditional villages and urban-rural resources in Nanjing [8], revealing the complex interactions between heritage conservation and resource allocation. Zeng and Ye analyzed the spatial accessibility and supply-demand coupling of public elderly care facilities in Nanchang [9], emphasizing the need for demand-oriented facility planning. Zhang et al. investigated the coupling relationship between urban community livability and development intensity [10], providing a theoretical framework for integrated urban development.

Against this backdrop, there is a pressing need for a targeted, quantitative evaluation framework to compare the development status of urban service facilities across cities, identify commonalities, differences, and development gaps, and provide data support for optimizing service resource allocation. Changchun and Hohhot, as representative cities in northern China, have distinct urban functional orientations, economic structures, and demographic characteristics, which lead to differences in the supply and layout of service facilities. However, few studies have conducted a systematic comparative analysis of their service facility development based on objective quantitative methods. To fill this research gap, this study focuses on the development status of urban service facilities, taking Changchun and Hohhot as case studies. This paper starts with quantifiable indicators, including the types and quantities of service facilities and the coordinates of service points, to construct indicators for service facility coverage and service density. By refining and analyzing data from 14 shared service fields of the two cities, we establish a service density index to reflect the spatial distribution intensity of various service facilities.

2 DATA AND METHODOLOGY

2.1 Assumptions

Assuming that the standard service level of each service facility is comparable and the service level of each service point in the same category is comparable. Differences in service levels due to differences in the quality of service at each service point can be ignored in the calculation of service density. This assumption is justified by the fact that facilities within the same category typically adhere to unified national or regional construction standards and operational norms, thereby ensuring a fundamental consistency in their functional positioning and service scope. Furthermore, given that this study focuses on the macro-level spatial distribution patterns and resource allocation efficiency rather than specific micro-level quality assessments, such a simplification effectively reduces computational complexity while maintaining the validity of the comparative analysis between the two cities.

Assuming that the development of the city is continuous and reliable. Assuming that the government policies are relatively stable and do not lead to significant fluctuations in different service fields.

2.2 Data Specification

The data of this paper comes from Question D of the 2024 ShuWei Cup IMCM Competition, provided by the Inner Mongolia Innovation Education Society and the Inner Mongolia Basic Education Research Institute. The datasets used in this paper correspond to data from the Chinese cities of Changchun and Hohhot. Both cities possess data across 15 service fields, with 14 fields being identical. To objectively examine the commonalities and differences in service field density indexes between the two cities, this study conducted a comparative analysis by excluding data from city-specific service fields. Only the data from the shared 14 service fields were retained for research purposes.

2.3 Data Pre-Processing

Data cleaning is a crucial step in data pre-processing, with the primary purpose of correcting or removing errors and outliers in the data. For the data provided, the following cleaning and pre-processing operations are required:

Correcting column names: Check data, and use the pandas rename method to correct column names for existing column name problems. To facilitate subsequent analysis, unify the naming format.

Delete or fill missing values: Check for missing values in the data and decide whether to delete rows with missing values or fill in the missing values according to the specific situation.

Data Conversion: Data conversion refers to the process of transforming data from one format to another for subsequent analysis or processing. Ensure the correct data type is used, such as latitude and longitude should be floating-point types.

Data standardization: For example, if certain fields contain address information in different formats, they can be standardized into a uniform format.

2.4 Service Density Index

In order to further conduct a quantitative comparative analysis of the number and distribution of service points in different service fields of the two cities, this paper uses the service density index to reflect the distribution density of service facilities and products in this area. This is an important indicator for measuring the development level of the service industry in a region, mainly used to assess the development degree and agglomeration of the service industry in the region. It is generally expressed by the number of service industries per unit area of the region, and the calculation formula is:

$$p_{ij}=\frac{M_{ij}}{S} \tag{1}$$

among them, p represents the service density index and p_{ij} represents the service density index of the j-th type of city i. M_{ij} indicates the number of service points of the j-th type in city i. Among them, i=1,2; j=1,2,...,14. S represents the area of the region.

This paper considers using the shoelace formula to calculate the area of cities and regions. The shoelace formula is a classic algorithm used to calculate the area of simple polygons in the fields of plane geometry and spatial measurement. It has extensive and fundamental applications in surveying and mapping, GIS, computer graphics and other fields. Therefore, the calculation formula for the area S of the region is as follows:

For a simple polygon with vertex coordinates in order: $(x_1,y_1),(x_2,y_2),...,(x_n,y_n)$, where $(x_{n+1},y_{n+1})=(x_1,y_1)$, its area S is calculated by the formula:

$$S=\frac{1}{2}\left|\sum_{i=1}^{n}(x_i y_{i+1}-x_{i+1}y_i)\right| \tag{2}$$

among them, x and y are the projected coordinates of the service point on the plane; the absolute value symbol $|\cdot|$ eliminates the influence of the vertex arrangement direction on the sign of the computed area; the coefficient $\frac{1}{2}$ is the intrinsic scaling factor of the triangle area formula.

2.5 Coefficient of Variation (CV)

To quantitatively explore the commonality and individuality of two cities while reflecting indicator variability and avoiding subjective weighting biases, we adopt the coefficient of variation (CV) method - an objective weighting approach - to calculate system indicator variability using statistical techniques. Represented by the symbol CV, this metric compares variation across datasets with differing units or magnitudes as the ratio of standard deviation to mean. In statistics and data analysis, the coefficient of variation serves as a fundamental statistic for quantifying data dispersion relative to the mean. In mathematical formulas, the CV is usually expressed as:

$$CV=\frac{s}{\bar{x}}\times 100\% \tag{3}$$

among them, s is the standard deviation, $\bar{x}$ is the mean. $\bar{x}_j$ of the service density index were calculated for each service field of each city respectively:

$$\bar{x}_j=\frac{1}{n}\sum_{i=1}^{n} x_{ij} \tag{4}$$

S_j of the service density index were calculated for each service field of each city respectively:

$$S_j=\sqrt{\frac{\sum_{i=1}^{n}\left(x_{ij}-\bar{x}_j\right)^2}{n-1}} \tag{5}$$

among them, x_{ij} represents the index of service density in the j-th area of the i city, and n represents the number of cities (n=2). To make the CV comparable, normalize it. It is achieved by dividing the CV of each field by the sum of the CV of all fields. In this paper, the reciprocal of CV is adopted as the weight and assigned to the service density index of each city, thereby obtaining the comprehensive scores of the two cities and each field. The formula for calculating the weight is as follows:

$$w_j=\frac{1}{CV_j} \tag{6}$$

among them, w_j represents the weight of j domain, CV_j represents the CV of j domain, j=1,2,...,14. The comprehensive score of the city is calculated according to the weight and density index of each field. The comprehensive score of the city is calculated using the following formula:

$$CW_i=\sum_{j=1}^{N} w_j * p_{ij} \tag{7}$$

among them, p_{ij} represents the service density index of the j-th type of city i, i=1,2; j=1,2,...,14.

2.6 Spatial Lag Model (SLM)

The Spatial Lag Model (SLM) is the core model for dealing with spatial dependencies in spatial econometrics and is applicable to analyzing the mutual influence of variables in geospace. SLM can accurately capture the spatial spillover effects of service facility density between two cities and their internal regions, such as the radiation of service resources in the core urban area to the surrounding areas and the relationship of similar services between cities. The spatial lag model is formulated as:

$$Y=\rho W_y+X\beta+\varepsilon \tag{8}$$

among them, Y represents the explained variable, such as the service density index. The parameter ρ is the spatial lag coefficient that captures the strength of spatial dependence, with its value constrained to the interval [−1,1]. The matrix W defines the spatial weighting structure. The matrix X contains explanatory variables. The vector β comprises the regression coefficients, measuring the direct effects of these explanatory variables on the outcome. Finally, ε represents the random error term.

A positive ρ indicates positive spatial spillover - meaning higher service density in neighboring areas elevates the local level - while a negative ρ reflects a competitive or negative spillover effect. Constructing a spatial weight matrix is the prerequisite and foundation for conducting spatial econometric analysis. The spatial weight matrix (W) can reflect the different relationships exhibited by variables in different regions. It is based on the longitude and latitude of the center points of the observation units, calculate the Euclidean distance d_{ij} between each pair. The weights are defined as:

$$W_{ij}=\begin{cases}1/d_{ij}^2 & (i\neq j)\\ 0 & (i=j)\end{cases} \tag{9}$$

3 RESULTS

3.1 Proportion of the Service Sector

The effective allocation of urban service not only influences residents' quality of life and social equity but also plays a pivotal role in enhancing urban resilience, ensuring sustainable development, and fostering inclusive growth. To holistically depict the allocation of diverse service categories, such as retail, lifestyle amenities, healthcare, and public services across Changchun and Hohhot, this study conducts a comprehensive proportional analysis of 14 key service sectors. By systematically comparing their respective distributions, this paper aims to uncover structural disparities in service provision between the two cities, identify potential resource gaps or surpluses in specific sectors, and reveal underlying patterns in service accessibility.

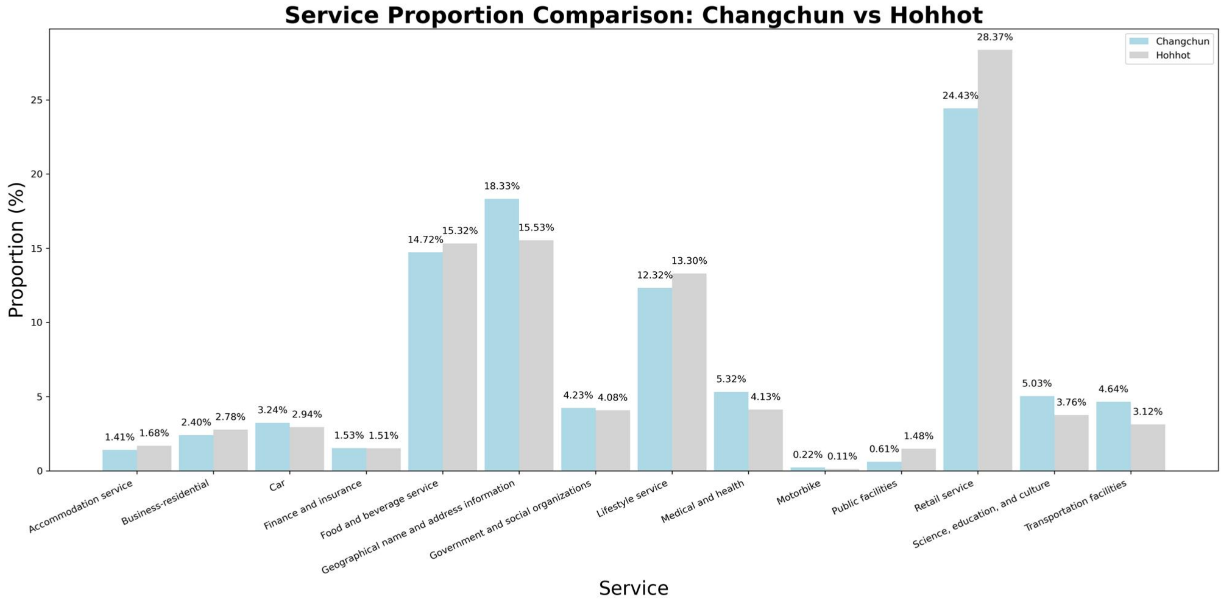


Figure 1 Proportion of Service Sectors in the Two Cities

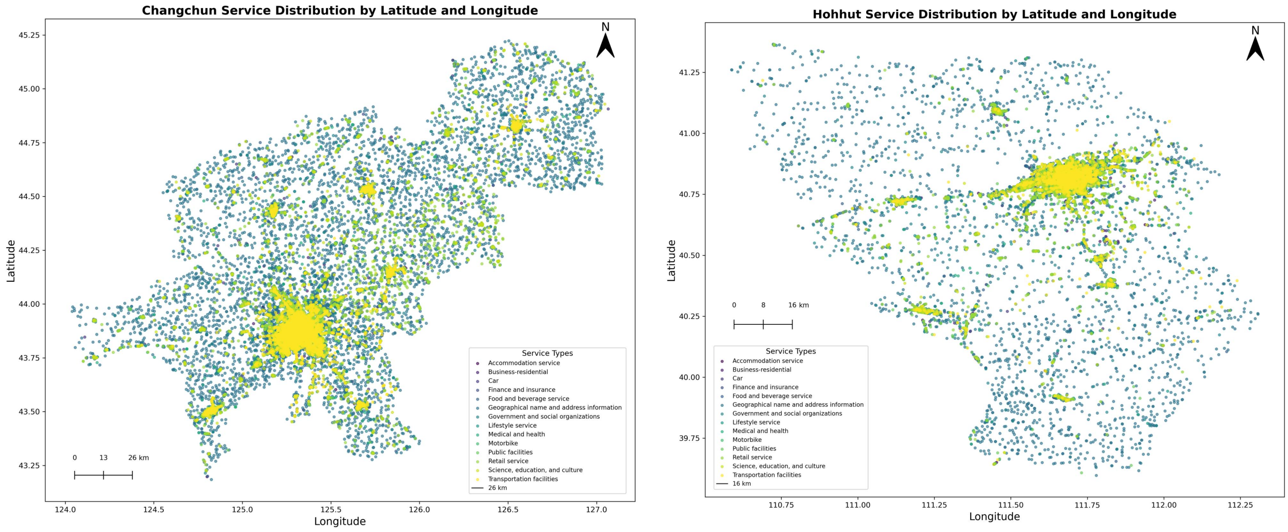
The Figure 1 evident that retail services account for the largest proportion in both cities, with Hohhot showing a higher percentage (28.37%) compared to Changchun (24.43%). However, when it comes to geographical name and address information services, Changchun has a higher proportion (18.33%) than Hohhot (15.53%), indicating that Changchun is more active in either the supply or demand side of this specific type of service. This analysis will provide valuable insights for urban planners and policymakers, aiding in the design of more equitable, efficient, and resilient service systems.

3.2 Service Type and Distribution

To ensure that the spatial layout of the 14 service departments is representative and efficiently visualized, a random sampling method is adopted. Due to the considerable differences in the number and types of service points among different categories, stratified sampling is used in this paper. Each service domain is regarded as an independent stratum, and sampling is performed separately within each category. This method retains the inherent structure of the data and ensures that even less frequent service types are fully captured in the example.

A sampling rate of r=0.3 is applied uniformly across all strata, balancing the need for computational efficiency with the requirement for spatial and statistical reliability. The sampled data are then used to generate geospatial scatter plots for both Changchun and Hohhot, with each service type visualized using a distinct color or marker. These plots not only illustrate the overall density and clustering tendencies of service points but also allow for a direct visual comparison between the two cities in terms of spatial coverage, centrality, and dispersion patterns within each sector.

The Figure 2 compares the distribution of service spaces between Changchun and Hohhot. It shows that Hohhot has a more compact density distribution, while the service points in Changchun are more scattered, with certain areas of concentration. The dense yellow area in Changchun indicates significant service agglomeration in the city's core. In Hohhot, service points are concentrated in the central yellow high-density area, while the distribution in the periphery is relatively sparse. This indicates that services in Hohhot are highly concentrated in the core area, demonstrating a stronger spatial concentration overall.



(a) Changchun's density (b) Hohhot's density

Figure 2 City Service Type Distribution by Latitude and Longitude

Note : The maps are drawn by the authors.

In order to further conduct a quantitative comparative analysis of the number and distribution of service points in different service fields of the two cities, this paper uses the service density index to reflect the distribution density of service facilities and products in this area. This is an important indicator for measuring the development level of the service industry in a region, mainly used to assess the development degree and agglomeration of the service industry in the region[11]. Therefore, based on the service density index constructed in the previous text, the values of 14 service areas in each of the two cities were calculated respectively.

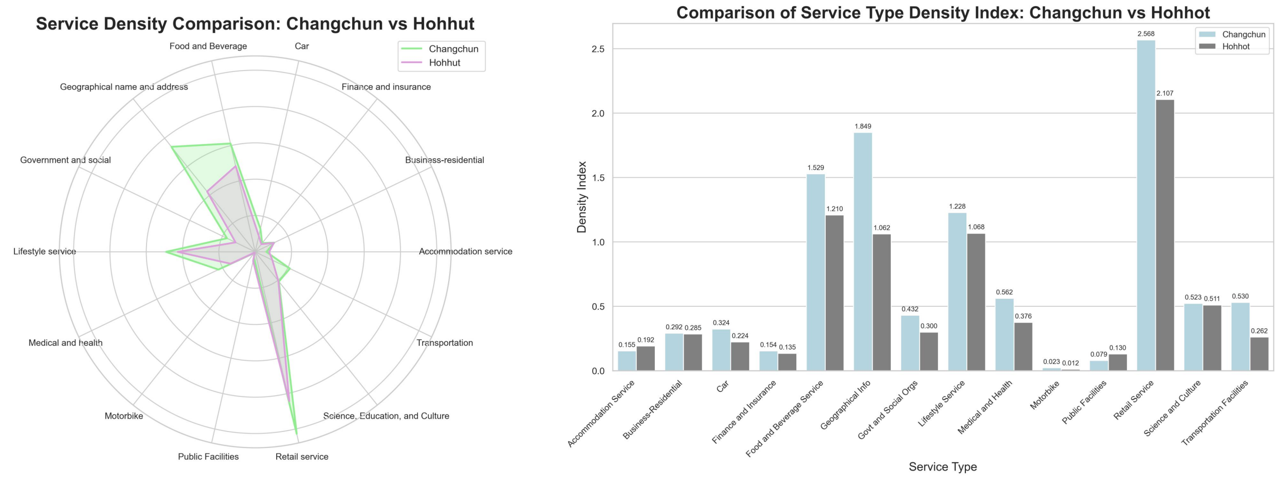
Table 1 Service Density Index and CV Score

Service Type	Density Index (units/km²)		Mean	S.t.	CV	Score	
	Changchun	Hohhot				Changchun	Hohhot
Accommodation service	0.52	0.64	0.58	0.09	0.15	3.36	4.18
Business-residential	0.97	0.95	0.96	0.02	0.02	59.14	57.78
Car	1.08	0.75	0.91	0.24	0.26	4.19	2.89
Finance and insurance	0.51	0.45	0.48	0.04	0.09	5.53	4.85
Food and beverage service	5.10	4.03	4.57	0.75	0.16	30.91	24.45
Geographical name and address information	6.16	3.54	4.85	1.86	0.38	16.13	9.26
Government and social organizations	1.44	1.00	1.22	0.31	0.25	5.66	3.93
Lifestyle service	4.09	3.56	3.83	0.38	0.10	41.40	35.98
Medical and health	1.87	1.25	1.56	0.44	0.28	6.67	4.46
Motorbike	0.08	0.04	0.06	0.02	0.42	0.18	0.10
Public facilities	0.26	0.43	0.35	0.12	0.34	0.77	1.27
Retail service	8.56	7.02	7.79	1.09	0.14	61.28	50.27
Science, education, and culture	1.74	1.70	1.72	0.03	0.02	108.74	106.30
Transportation facilities	1.77	0.87	1.32	0.63	0.48	3.69	1.83
Total	/	/	/	/	/	347.64	307.55

The Table 1 reveals distinct patterns of urban service distribution between the two cities. As a whole, there are differences in the service density index of the two cities in various service fields. The density index of some service areas in Changchun is high, while in Hohhot it is relatively low. The most pronounced differences appear in geographical name and address information and transportation facilities, where Changchun's density exceeds Hohhot's by 74% and 103% respectively. This indicates Changchun's stronger emphasis on spatial identification systems, commercial vitality, and transport infrastructure, likely linked to its larger urban scale and regional economic role.

This paper aims to visually and systematically analyze the differences in development between Changchun and Hohhot across various service fields. To achieve this, two visualization methods are employed: radar charts and bar charts. The radar chart utilizes a multi-dimensional, radiating graphic structure to comprehensively display the relative distribution and balance of density indices in different service fields for both cities. In contrast, the bar chart clearly highlights specific numerical differences in the density indexes under various service fields, presenting these differences in an easily understandable horizontal or vertical comparison format.

Based on Figures 3, we can know the relative strengths of the two cities in various service categories. The density indices of Accommodation, Business, Food, Public and Retail in Hohhot are higher than those in Changchun, indicating that Hohhot's service levels in these fields are relatively higher and its performance is more prosperous. Among them, the Public density index of Hohhot is much higher than that of Changchun, demonstrating the advantages of Hohhot in the construction of public facilities. The service density indices in the fields of Car, Finance, Government and Lifestyle service in the two cities are similar, indicating that the service development levels in these service aspects in the two cities are comparable. This indicates that the two cities have their own focuses in service provision, and at the same time provides valuable reference information for urban planning and policy-making.



(a) Service Density Comparison (b) Comparison of Service Type Density Index

Figure 3 Comparison of Service Density Indices in Different Fields

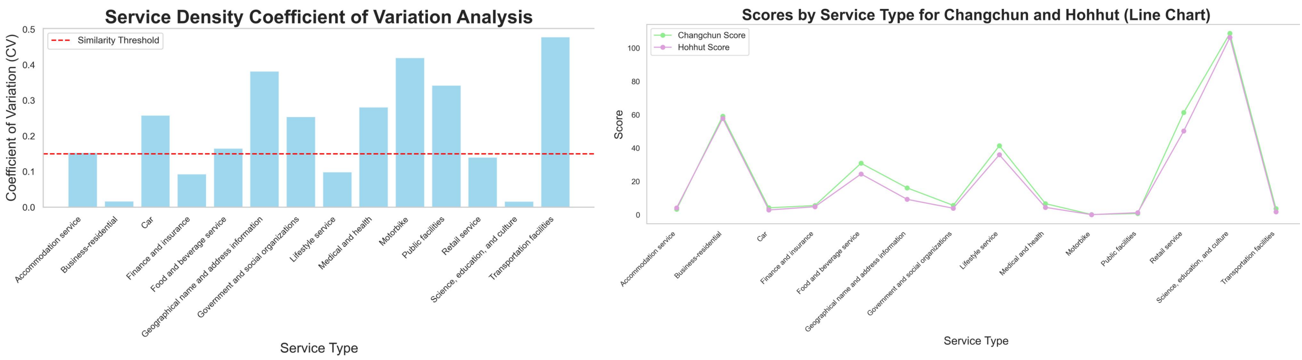
3.3 Urban Quantitative Score

To further examine the balance and disparities in service provision across regions, quantitatively identify commonalities and distinctions between the two cities, and mitigate potential biases arising from subjective weighting, this study employs the coefficient of variation (CV) method - an objective, statistically based weighting approach. In statistical analysis, the CV, defined as the ratio of the standard deviation to the mean, serves as a standardized measure of data dispersion. Using the service industry density index without sampling adjustments, this paper calculates key metrics including the mean density index, standard deviation, CV values, and corresponding city scores for both cities. The results are presented in Table 1.

As shown in the Table 1, the density indices across different service sectors exhibit significant variation, with CV values and composite scores indicating notable differences between the two cities. The overall composite score for Changchun is 347.64, compared to 307.55 for Hohhot, suggesting that Changchun demonstrates a higher level of service provision and development across the 14 service sectors examined.

The magnitude of the CV reflects the degree of data dispersion: a larger CV value indicates greater variability, whereas a smaller value suggests more consistency. This study adopts 0.15 as the empirical threshold for interpretation. Consequently, when comparing service sectors between the two cities, this value is used as the benchmark to assess whether variations are relatively low or high. The relationship between the calculated CV values and the threshold criterion is illustrated in the following figure.

As shown in Figure 4 above, the two cities exhibit commonalities across four service sectors: business-residential, finance and insurance, lifestyle services, and science, education, and culture. This indicates that their service levels or development stages in these areas are relatively comparable. In the three service sectors of accommodation services, food and beverage services, and retail service, the values barely close to the 0.15 threshold, indicating differences in service levels between the two cities in these areas. Notably, the CV values for car, geographic names and address information, government and social organizations, medical and health, motorcycles, public facilities, and transportation facilities all significantly exceed 0.15, indicating substantial differences between the two cities in these sectors. Further analysis of these seven areas is warranted to provide corresponding reference recommendations for the development of service levels in both cities.



(a) Bar Chart (b) Line Chart

Figure 4 Comparison of Service Density Coefficient of Variation and Scores in Different Fields

Table 2 Changchun's Regression Results of SLM

Variable	Coefficient	S.t.	z-value	P	95% CI Lower	95% CI Upper
Car	0.012	0.001	8.578	0.000	0.009	0.015
Geographic	0.012	0.001	15.929	0.000	0.011	0.013
Government	0.073	0.003	22.937	0.000	0.067	0.079
Medical	0.021	0.002	9.618	0.000	0.017	0.025
Motorcycles	0.353	0.023	15.082	0.000	0.307	0.399
Public facilities	0.001	0.011	0.066	0.947	-0.021	0.022
Transportation	-0.069	0.003	-24.303	0.000	-0.074	-0.063
Spatial Lag ρ	0.718	0.004	194.015	0.000	0.710	0.725

Analyze the specific scores of the two cities across seven service sectors exhibiting significant individual differences. In car services, geographical name and address information, government and social organizations, medical and health, and transportation facilities, Changchun outperforms Hohhot - evidenced by higher density indices and elevated scores. As shown in Figure 4b and Table 1 above, the most visibly, Changchun's peak score in transportation facilities contrasts sharply with Hohhot's near-zero performance. Among these, transportation facilities exhibit the largest gap (CV=0.48), marking it as the most differentiated domain. Conversely, public facilities favor Hohhot, with a higher density index (0.43 vs 0.26) and score (1.27 vs 0.77), reflecting its advantage in this area. For motorbike services, while both cities have low overall density, Changchun's index (0.08 vs 0.04) and the high CV indicate a notable relative gap.

Results of Spatial Lag Model

Based on the theoretical analysis, index measurement, variable selection and analysis in the previous text, the spatial spillover effect of service facilities in Changchun and Hohhot was analyzed by using the Spatial Lag Model (SLM), and the spatial Dubin model partial differential decomposition method was adopted to decompose the spatial spillover effect, further analyzing the spillover effect of different service fields on the urban spatial distribution. This paper uses 10,000 spatial units as the observation sample, covering three explanatory variables, and employs maximum likelihood (ML) estimation to conduct regression analysis on seven aspects with significant differences. The seven aspects demonstrating notable differences are: automobiles, place names and address information, government and social organizations, medical and healthcare services, motorcycles, public facilities, and transportation infrastructure.

The Table 2 presents the SLM regression results in Changchun. All variables except public facilities show statistically significant coefficients at conventional levels ($p<0.05$). The spatial lag coefficient ($\rho=0.718$) is highly significant ($z=194.015$, $p=0.000$), indicating strong positive spatial dependence and confirming substantial spillover effects from neighboring areas. Among specific service types, motorcycles exhibit the largest positive coefficient (0.353), suggesting that motorcycle-related services are particularly sensitive to spatial clustering. Government services (0.073), medical facilities (0.021), and carrelated services (0.012) also show significant positive associations. Notably, transportation facilities demonstrate a significant negative coefficient (-0.069), implying potential competitive or substitution effects in the spatial distribution of transportation infrastructure. Public facilities are statistically insignificant ($p=0.947$), indicating no systematic spatial relationship.

Table 3 Hohhot's Regression Results of SLM

Variable	Coefficient	S.t.	z-value	P	95% CI Lower	95% CI Upper
Car	0.042	0.003	13.338	0.000	0.036	0.048
Geographic	0.034	0.002	17.744	0.000	0.030	0.037
Government	0.113	0.005	20.967	0.000	0.103	0.124
Medical	-0.084	0.005	-18.004	0.000	-0.094	-0.075
Motorcycles	0.354	0.059	5.986	0.000	0.238	0.469
Public facilities	0.071	0.013	5.474	0.000	0.046	0.097
Transportation	-0.053	0.007	-7.506	0.000	-0.067	-0.039
Spatial Lag ρ	0.564	0.006	101.092	0.000	0.553	0.575

The Table 3 presents the SLM regression results in Hohhot. All variables, including the spatial lag term, show statistically significant coefficients ($p<0.05$). The spatial lag coefficient ($\rho=0.564$) is positive and highly significant ($z=101.092$, $p=0.000$), indicating moderate positive spatial dependence. Government services exhibit the largest positive coefficient (0.113), followed by motorcycles (0.354) and geographic information services (0.034), suggesting these facilities have strong positive associations with the outcome variable in Hohhot. Notably, medical facilities show a significant negative coefficient (-0.084), which may reflect different healthcare system structures or spatial competition patterns. Transportation facilities also display a negative coefficient (-0.053). Public facilities show a significant positive effect in Hohhot (0.071). The model reveals that while spatial autocorrelation exists in Hohhot's service distribution.

Table 4 Partial Differential Decomposition Results

Variable	Changchun	Hohhot

	Direct	Indirect	Total	Direct	Indirect	Total
Car	0.0122	0.0309	0.0430	0.0417	0.0539	0.0956
Geographic	0.0120	0.0305	0.0426	0.0337	0.0435	0.0772
Government	0.0730	0.1854	0.2584	0.1131	0.1462	0.2594
Medical	0.0208	0.0529	0.0737	-0.0843	-0.1090	-0.1933
Motorcycles	0.3529	0.8968	1.2497	0.3535	0.4570	0.8106
Public facilities	0.0007	0.0019	0.0026	0.0712	0.0920	0.1632
Transportation	-0.0685	-0.1742	-0.2427	-0.0529	-0.0684	-0.1213

From the overall estimation results above, it can be known that the different service fields of Changchun and Hohhot have spatial spillover effects on the urban spatial distribution. On this basis, the method of partial differential decomposition will be further adopted. The Table 4 presents the partial differential decomposition results for Changchun and Hohhot, distinguishing between direct effects and indirect effects. A clear contrast emerges between the two cities in both the magnitude and direction of effects. In Changchun, motorcycles exhibit the largest total effect (1.2497), driven primarily by strong indirect effects (0.8968), indicating significant spatial spillovers. Most strikingly, medical facilities in Hohhot show negative total effects (-0.1933), contrasting with positive effects in Changchun (0.0737). Public facilities show minimal impact in Changchun (0.0026) but moderate positive effects in Hohhot (0.1632). The decomposition reveals that spatial spillovers (indirect effects) generally constitute a larger proportion of total effects in Changchun across most variables, suggesting stronger spatial interdependence in its service network. These differential patterns reflect distinct urban structures, with Changchun exhibiting more spatially integrated service systems and Hohhot showing more localized or potentially competitive spatial dynamics.

4 DISCUSSION AND CONCLUSIONS

This paper aims to systematically evaluate the development status of urban service facilities, providing theoretical support and decision-making references for optimizing the layout of urban service resources, addressing development shortcomings, and ultimately advancing higher-quality urban sustainable development. The coefficient of variation method reveals that Changchun achieved a composite score of 347.64 points, while Hohhot scored 307.55 points. Both cities demonstrate strengths in their respective specialized fields, yet each also exhibits distinct weaknesses. For instance, Changchun dominates in infrastructure and administrative/life services, Hohhot holds an edge in public facilities, and transportation facilities and motorbike services stand out as the most diverged fields between the two cities. Whether in Changchun or Hohhot, cities should formulate scientifically sound development plans grounded in their actual circumstances, continuously enhancing service standards and development quality. Through enhanced exchange and cooperation, the two cities will achieve greater prosperity and development.

Based on the SLM regression and partial differential decomposition results, a clear divergence in spatial dependency structures emerges between Changchun and Hohhot. Changchun exhibits stronger overall spatial autocorrelation (ρ=0.718) and greater spillover effects across most service types, particularly in motorcycles and government services, where indirect effects dominate. In contrast, Hohhot shows moderate spatial dependence (ρ=0.564) and more variable directional effects with medical services displaying negative impacts and public facilities showing positive effects absent in Changchun. These patterns suggest that Changchun's service system is more spatially integrated and diffusion -oriented, whereas Hohhot's spatial dynamics reflect more localized competition and structurally distinct service allocations. The findings underscore that urban service networks are shaped by city-specific spatial logics, necessitating tailored planning strategies that account for differing magnitudes and mechanisms of spatial interaction.

This paper differs by conducting a direct inter-city comparative analysis rather than exploring regional coupling coordination, thus providing more targeted insights for bilateral development. This study's conclusion that public facilities are a strength of Hohhot aligns with the broader recognition of the importance of basic public services in urban development, while its detailed breakdown of 14 specific service domains fills the gap of macro-survey studies lacking in-depth inter-city sectoral comparisons. Furthermore, unlike existing literature that often focuses on single cities or large regional scales, this research's paired comparison of two representative cities enriches the empirical evidence for medium-sized urban resilience evaluation and offers a replicable framework for inter-city service level comparison using the CV method. A limitation worth noting is that this study primarily relies on service density indices, whereas future research could integrate more multi-dimensional indicators such as public satisfaction data or coupling coordination analysis to achieve a more comprehensive evaluation of urban sustainable development capacity.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

AUTHOR CONTRIBUTIONS

Gong Qin: Conceptualization, Methodology, Investigation, Formal analysis, Writing - Original Draft, Writing - Review & Editing. Yang Yanqiang: Conceptualization, Supervision, Writing - Review & Editing. Li Anna: Literature research, Format proofreading, Writing - Review & Editing.

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