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Diagnosing Urban Service Inequality through Grid-Based Spatial Analysis of Multi-Source POI Data: Evidence from Changchun and Hohhot, China

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Abstract

Urban service inequality and intra-urban spatial heterogeneity have become major challenges for sustainable urban development. However, existing studies often rely on administrative-scale statistics or aggregated indicators, which fail to capture fine-scale spatial disparities in urban service distribution. To address this limitation, this study proposes a grid-based spatial diagnostic framework using multi-source Point of Interest (POI) data. A 1 km × 1 km grid system is employed to characterize the spatial distribution of six categories of urban services through service intensity and accessibility indicators, enabling fine-scale identification of spatial inequality patterns. The results reveal significant inter-city differences in urban service organization. Changchun exhibits a relatively balanced polycentric structure with more evenly distributed urban services, whereas Hohhot demonstrates a more centralized monocentric pattern characterized by pronounced deficiencies in accommodation and lifestyle-related services. Both cities exhibit persistent core-periphery disparities, with service accessibility declining significantly toward peripheral areas. The proposed framework provides a transferable and spatially explicit approach for diagnosing urban service inequality, offering methodological support for fine-scale urban planning, infrastructure optimization, and evidence-based governance.

Keywords

Urban Service Inequality, Spatial Heterogeneity, Grid-Based Analysis, Point of Interest (POI), Spatial Diagnostic Framework

1. Introduction

Rapid urbanization in China has been accompanied by growing spatial inequality in urban services, as well as profound demographic and socioeconomic transformations, including population aging and structural adjustment, which jointly pose challenges to sustainable urban governance [1] [2]. These processes are particularly evident in medium- and small-sized cities, where uneven resource allocation and differentiated development patterns have intensified core-periphery imbalance and urban spatial fragmentation.

Despite extensive research on urban development and sustainability, existing studies largely rely on administrative-level statistics or aggregated indicators, which fail to capture fine-scale spatial variations within cities. As a result, intra-urban heterogeneity and localized service deficits remain insufficiently identified. Moreover, most conventional urban evaluation approaches emphasize overall performance assessment rather than spatially explicit diagnosis, limiting their ability to reveal the underlying spatial structure of urban service inequality. Previous studies often adopt composite evaluation or MCDM-based methods, which, while useful for ranking or scoring urban systems, are limited in their capacity to represent spatially continuous patterns of urban inequality [3]. This indicates a critical gap between traditional urban evaluation frameworks and emerging needs for fine-scale spatial diagnostic approaches.

The emergence of multi-source geospatial big data provides new opportunities for addressing this limitation. In particular, Point of Interest (POI) data have been widely recognized as effective proxies for capturing human-scale urban activity and functional spatial organization [4] [5]. These data enable fine-grained representation of urban service distribution and have been increasingly applied in urban sustainability and vitality studies. However, despite these advances, few studies have systematically integrated POI data into a grid-based analytical framework to conduct spatial diagnosis of urban service inequality across multiple functional dimensions.

To address these limitations, this study develops a grid-based spatial diagnosis framework for urban service inequality. Using Changchun and Hohhot as comparative case cities, a 1 km × 1 km grid system is constructed to capture intra-urban spatial heterogeneity and identify service-deficient areas across multiple urban service categories. This framework shifts the analytical focus from aggregate urban evaluation to fine-scale spatial diagnosis, enabling a more precise understanding of intra-urban disparities.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on urban service inequality and spatial analysis. Section 3 introduces the data sources and preprocessing methods. Section 4 presents the grid-based spatial diagnosis framework. Section 5 reports and discusses the empirical results. Section 6 discusses the driving mechanisms of spatial differentiation and the theoretical implications of the proposed framework. Section 7 concludes the study and provides policy implications for urban planning and governance.

2. Related Work

2.1. Urban Service Inequality and Spatial Data Analysis

Urban service inequality has been widely recognized as a key dimension of urban spatial structure and socio-spatial equity. Early studies mainly relied on administrative statistics and aggregated socio-economic indicators, which provide macroscopic descriptions of urban development but fail to capture intra-urban spatial heterogeneity [6]. With the development of geospatial big data, research has increasingly shifted toward fine-scale spatial analysis of urban functions and human activity patterns.

In particular, Point of Interest (POI) data have been widely adopted to represent urban functional distribution and human-scale activity patterns, enabling more detailed identification of spatial variation in urban systems [5]. Recent studies have demonstrated that POI-based approaches can effectively capture spatial accessibility and inequality of public services, providing new insights into fine-scale urban structure analysis [7]. However, most existing studies remain descriptive in nature and are limited in their ability to systematically diagnose spatially continuous patterns of urban service inequality.

2.2. Limitations of Conventional Urban Evaluation Methods

Traditional urban evaluation frameworks are mainly based on multi-criteria decision-making (MCDM) methods, such as entropy weighting and the Analytic Hierarchy Process (AHP), which are widely used to construct composite indicators for urban sustainability and development assessment [8] [9]. These methods are effective in handling multi-dimensional indicators but primarily focus on attribute aggregation rather than spatial representation.

Although hybrid models combining entropy and AHP have been developed to improve evaluation robustness and reduce subjectivity, such as in sustainability assessment and infrastructure evaluation studies [10], they still operate within an evaluation-oriented paradigm. Similarly, TOPSIS- and entropy-based approaches have been widely applied in urban sustainability and resilience studies [11]-[15], yet they remain limited to ranking or scoring systems rather than spatially explicit diagnosis.

Moreover, urban resilience and sustainability research has increasingly adopted integrated frameworks to explore multidimensional urban performance, including ecological, economic, and social dimensions [11] [12]. However, these studies often treat resilience and sustainability as conceptual evaluation constructs rather than spatially explicit processes. Even when hybrid MCDM models are used in resilience assessment [13], they generally fail to capture intra-urban spatial heterogeneity and localized service deficits.

2.3. Research Gaps and Spatial Diagnosis Perspective

Despite substantial progress in urban big data analysis and evaluation methodologies, three key limitations remain. First, there is a persistent scale mismatch, as most studies rely on administrative units or aggregated indicators, which are insufficient for capturing fine-scale spatial heterogeneity. Second, existing frameworks are primarily evaluation-oriented, focusing on scoring or ranking urban systems rather than identifying spatial patterns of service deficiency. Third, there is a lack of spatial diagnostic frameworks capable of transforming multi-source geospatial data into fine-grained representations of urban inequality.

To address these limitations, this study adopts a spatial diagnosis perspective and develops a grid-based analytical framework for urban service inequality. Unlike conventional evaluation approaches, this framework emphasizes the identification of spatially continuous patterns of service deficiency at a fine scale, enabling a more precise understanding of intra-urban disparities and supporting spatially targeted urban governance strategies.

2.4. Contributions of the Proposed Framework

While previous POI-based studies have examined urban functional zones or service accessibility in isolation, the proposed grid-based diagnostic framework offers three distinctive advantages. First, it integrates both service intensity and spatial accessibility within a unified spatial unit, enabling simultaneous assessment of supply abundance and convenience. Second, by adopting a diagnostic rather than evaluative orientation, the framework prioritizes the identification of spatially contiguous service-deficient zones over composite rankings, directly informing targeted intervention strategies. Third, the grid-based design ensures cross-city comparability independent of administrative boundary configurations, a common confound in district-level analyses.

3. Data Sources and Preprocessing

3.1. Study Area

This study selects Changchun and Hohhot as representative case cities in Northeast and North China, respectively. Both cities are provincial capitals at different stages of urban development, providing a typical comparative setting for analyzing intra-urban disparities in urban service provision. The contrasting urban development patterns of the two cities provide a suitable context for examining spatial heterogeneity in service distribution under different socio-economic and planning regimes.

3.2. Data Sources

Multi-category POI data were collected from the Gaode Open Geographic Platform in October 2024. Raw records were processed by duplicate removal, GCJ-02 coordinate calibration, and filtering of invalid entries such as closed businesses and coordinate outliers. With reference to Gaode's industrial taxonomy, valid POIs were reclassified into six service categories: Accommodation-Lifestyle Services (ALS), Transport and Infrastructure Services (TIS), Finance and Commercial Services (FCS), Medical-Health Services (MHS), Education-Social-Organization Services (ESOS), and Geographic-Auxiliary Information Services (GAI). These valid POIs were further consolidated to meet the analytical demands of this study.

3.3. Spatial Data Processing and Grid Construction

For fine-grained spatial analysis, all POI data are projected under a unified coordinate system. The study area is partitioned into 1 km × 1 km grid cells as the fundamental unit to capture intra-urban spatial heterogeneity, converting discrete POI points into continuous patterns of urban-service distribution. Categorized POI quantities inside each grid are computed to reflect service intensity and diversity, yielding spatial indicators for the later diagnosis of public-service inequality.

The 1 km resolution is chosen for two reasons. It conforms to the standard grain of existing POI-related accessibility research [5] [7] for cross-study comparison. Pilot scale-sensitivity tests confirm 1 km as the optimal compromise: 2 km grids omit subtle spatial variations, while 500 m grids generate numerous zero-value cells caused by sparse facilities, especially in Hohhot's suburbs.

3.4. Data Standardization

Since multi-type service indicators vary in magnitude, min-max normalization is adopted to unify all metrics into a dimensionless 0 - 1 range for composite index calculation:

$$x_{i,\text{norm}} = \frac{x_{ij} - \min\left(x_j\right)}{\max\left(x_j\right) - \min\left(x_j\right)} \tag{1}$$

where x_{ij} stands for the raw value of indicator j in grid cell i. All indicators are positive-oriented, and the normalized results are comparable across grid units.

3.5. Output Dataset for Spatial Diagnosis

Following the above procedures, a spatially consistent and grid-based dataset is constructed for further analysis. The dataset includes: 1) grid-level POI distributions across six service categories, 2) spatial intensity indicators such as density and diversity measures, and 3) basic geographic grid attributes. This dataset provides the basis for subsequent spatial diagnosis of urban service inequality and supports the identification of fine-scale service-deficient areas.

The full preprocessing workflow is illustrated in **Figure 1**.

4. Methodology

4.1. Spatial Grid Partition and POI-Grid Matching

POI X/Y coordinates are adopted to plot facility distribution scatterplots. We first extract the study boundary from all POI coordinates $\left(x_{\max}, x_{\min}, y_{\max}, y_{\min}\right)$ and partition the whole area into uniform grids. The side length of each grid is calculated by Equation (2):

$$\begin{aligned} \text{grid\_size}_x &= \frac{x_{\max} - x_{\min}}{\text{num\_grids}} \\ \text{grid\_size}_y &= \frac{y_{\max} - y_{\min}}{\text{num\_grids}} \end{aligned} \tag{2}$$

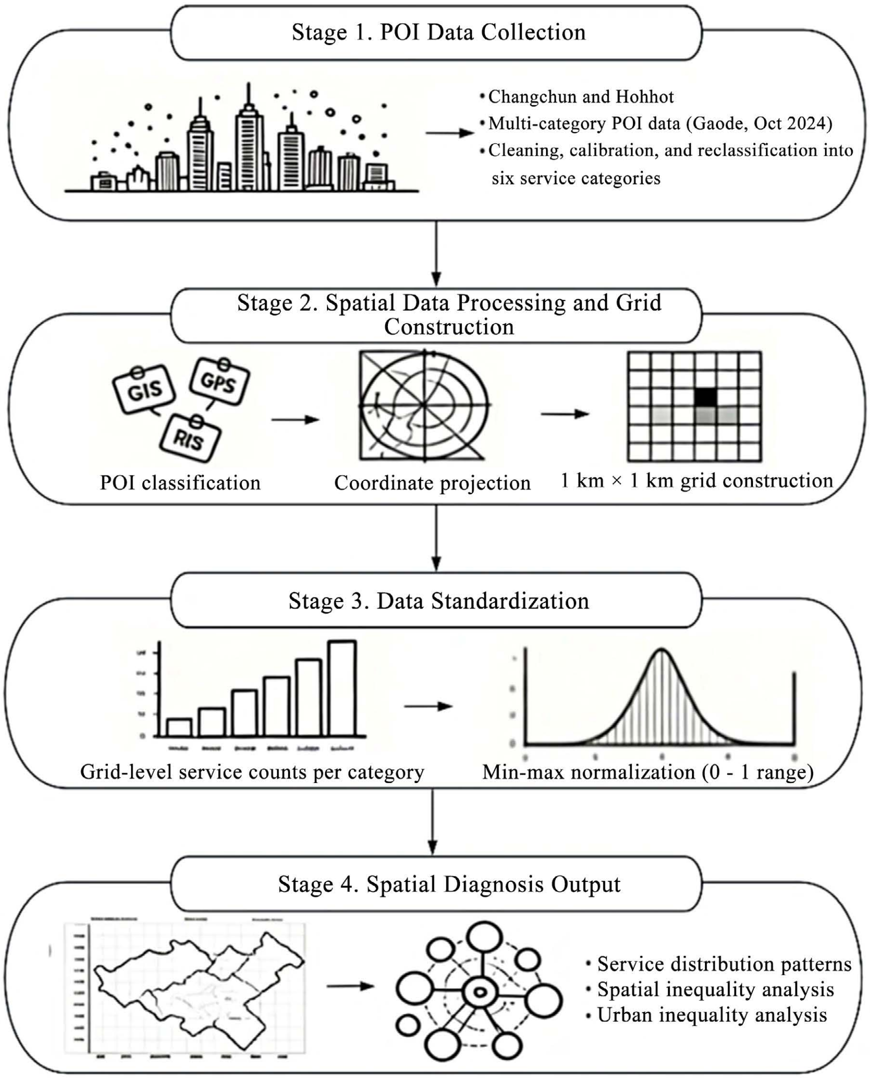

Figure 1. Workflow of multi-source data preprocessing.

Each POI is matched to its corresponding grid index via Equation (3):

$$x_{\text{grid}} = \frac{x_{\text{poi}} - x_{\min}}{\text{grid\_size}_x}$$
$$y_{\text{grid}} = \frac{y_{\text{poi}} - y_{\min}}{\text{grid\_size}_y} \tag{3}$$

where $x_{\text{poi}}, y_{\text{poi}}$ are the coordinate values of a single facility point.

4.2. Grid Centroid and Nearest-Neighbor Search

The centroid coordinate of grid $(x_{\text{grid}}, y_{\text{grid}})$ is calculated as Equation (4):

$$x_{\text{cen}} = x_{\min} + (x_{\text{grid}} + 0.5) * \text{grid\_size}_x$$
$$y_{\text{cen}} = y_{\min} + (y_{\text{grid}} + 0.5) * \text{grid\_size}_y \tag{4}$$

A KD-Tree spatial index is built from all POI coordinates to rapidly query the

Euclidean distance d_i between each grid centroid (x_{cen}, y_{cen}) and its closest facility.

4.3. Comprehensive Spatial Diagnosis Index

Let n_i represent the number of POIs inside grid i, n_{max} the maximum POI count across all grids; d_i the nearest facility distance of grid i, d_{max} the maximum nearest distance of all grids. Equal weights ($w_1 = w_2 = 0.5$) are assigned to density and accessibility dimensions. The integrated diagnosis index S_i for grid i is:

$$S_i = w_1 * \frac{n_i}{n_{max}} + w_2 * \left(1 - \frac{d_i}{d_{max}}\right) \tag{5}$$

The density term $\frac{n_i}{n_{max}}$ ranges from 0 to 1; the distance term uses reverse conversion to ensure larger S_i corresponds to better service supply.

4.4. Jenks Classification and Vulnerable Grid Judgement

All grid-level S_i values are divided into low, medium and high service tiers by the Jenks natural break method. Define N_{low} as the count of low-service grids, N_{med} as medium-service grids, N_{total} as the total number of grids. A grid region is judged as service-deficient vulnerable zone if:

$$\frac{N_{low} + N_{med}}{N_{total}} > 0.5 \tag{6}$$

High-value grid clusters denote central service agglomerations, while low-value grids stand for underserved peripheral areas. This classification is only used for spatial pattern visualization.

5. Results and Spatial Diagnosis

5.1. Analysis of Urban Comprehensive Service Capability

On the basis of six-way POI classification, the facility density (units/km^2) of each service category was calculated with the formula ($\rho = N/S$), where N denotes the POI quantity and S represents the urban land area (24,744 km^2 for Changchun and 17,200 km^2 for Hohhot). The statistical density results of public-service facilities for the two provincial capitals are listed in Table 1.

Table 1. Density of service types in two cities (units/km^2).

Service Category	Changchun density	Hohhot density
ALS	2.93	1.05
TIS	7.71	0.27
FCS	7.40	2.66
MHS	0.97	0.24
ESOS	1.68	0.46
GAI	3.33	0.24

Among all service categories, Transport & Infrastructure Services (TIS) and Finance & Commercial Services (FCS) exhibit the largest differences between the two cities. Changchun shows a dense and continuous distribution of transportation and commercial facilities, reflecting relatively developed infrastructure systems and stronger economic agglomeration capacity. In contrast, Hohhot presents comparatively sparse and fragmented service distributions, particularly in accommodation and lifestyle-related services.

5.2. Intra-Urban Spatial Heterogeneity

The spatial distribution of urban services exhibits pronounced intra-urban heterogeneity and significant differences in spatial organization between Changchun and Hohhot, reflecting distinct urban development patterns and functional structures.

5.2.1. Spatial Pattern in Changchun

Changchun exhibits a relatively balanced polycentric spatial structure, characterized by multiple high-value service clusters distributed across different urban districts, as shown in **Figure 2**.

These high-value clusters are not confined to a single core area but are dispersed across multiple urban sub-centers. Transportation, medical, and commercial services demonstrate strong spatial continuity within the urban core, reflecting well-developed infrastructure networks and functional integration across districts. In addition, transportation and commercial services tend to align along major urban corridors, while medical and social services exhibit a more multi-nodal distribution pattern. Overall, Changchun presents a relatively balanced spatial configuration with multiple functional centers.

5.2.2. Spatial Pattern in Hohhot

Hohhot exhibits a more concentrated monocentric spatial structure, characterized by a dominant high-value service core and weaker peripheral development, as shown in **Figure 3**.

High-value service clusters are primarily concentrated within central urban districts, while peripheral areas show significantly lower service intensity and accessibility. Service distribution reveals a clear core–periphery pattern, where accommodation, education, and social organization services are highly concentrated in the urban core, whereas peripheral districts remain relatively underserved. This spatial configuration reflects limited outward diffusion of urban functions and a strong dependence on the central urban area. Overall, Hohhot demonstrates a highly centralized spatial structure with pronounced spatial inequality.

5.3. Spatial Diagnosis of Service Strength and Deficiency

Spatial diagnostic results based on grid-level classification reveal significant differences in urban service performance between Changchun and Hohhot. Following the classification criteria defined in Section 4, service categories are identified

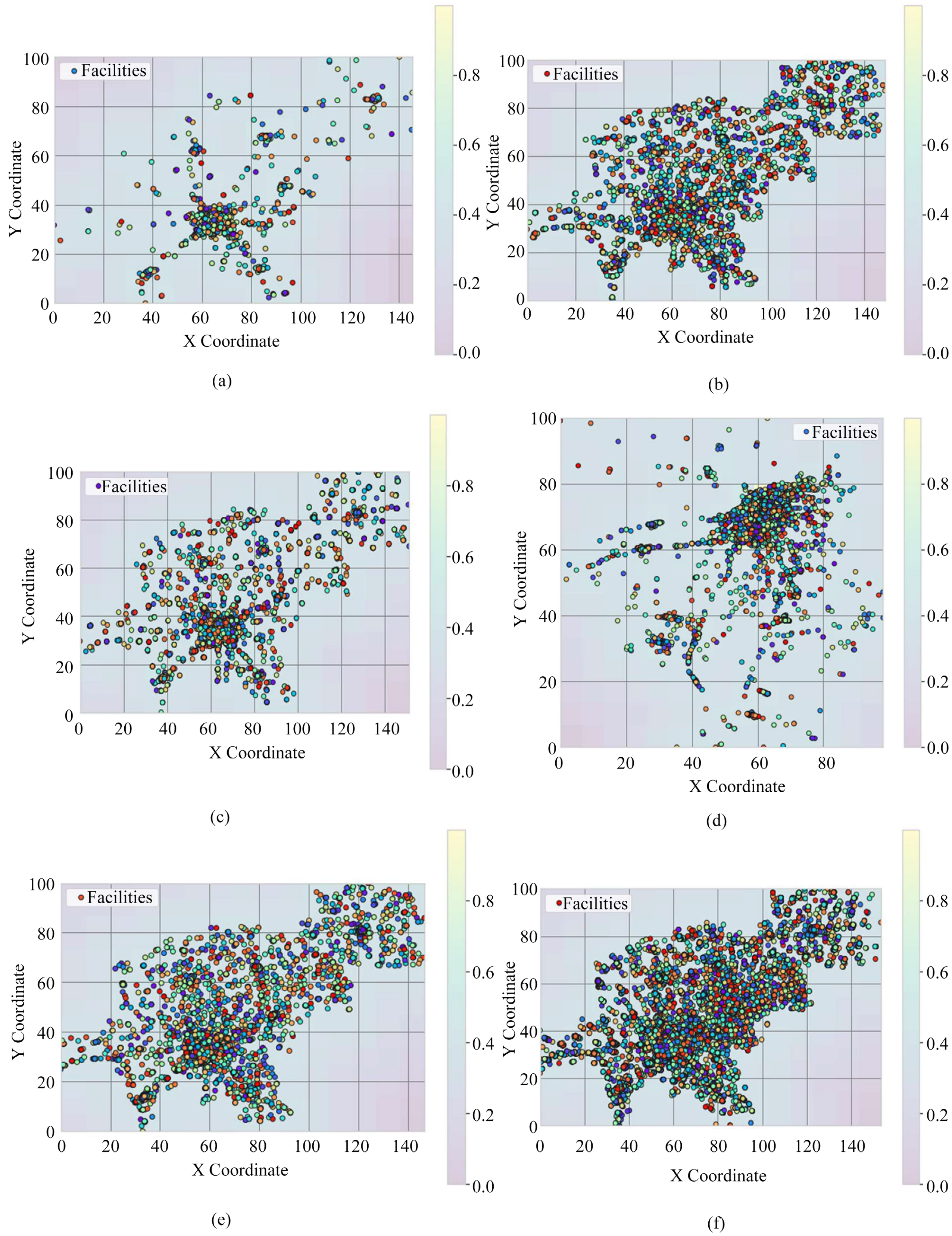

Figure 2. Spatial distribution patterns of urban service categories in Changchun; from top left to bottom right: (a) GAI, (b) ESOS, (c) MHS, (d) TIS, (e) ALS, and (f) FCS.

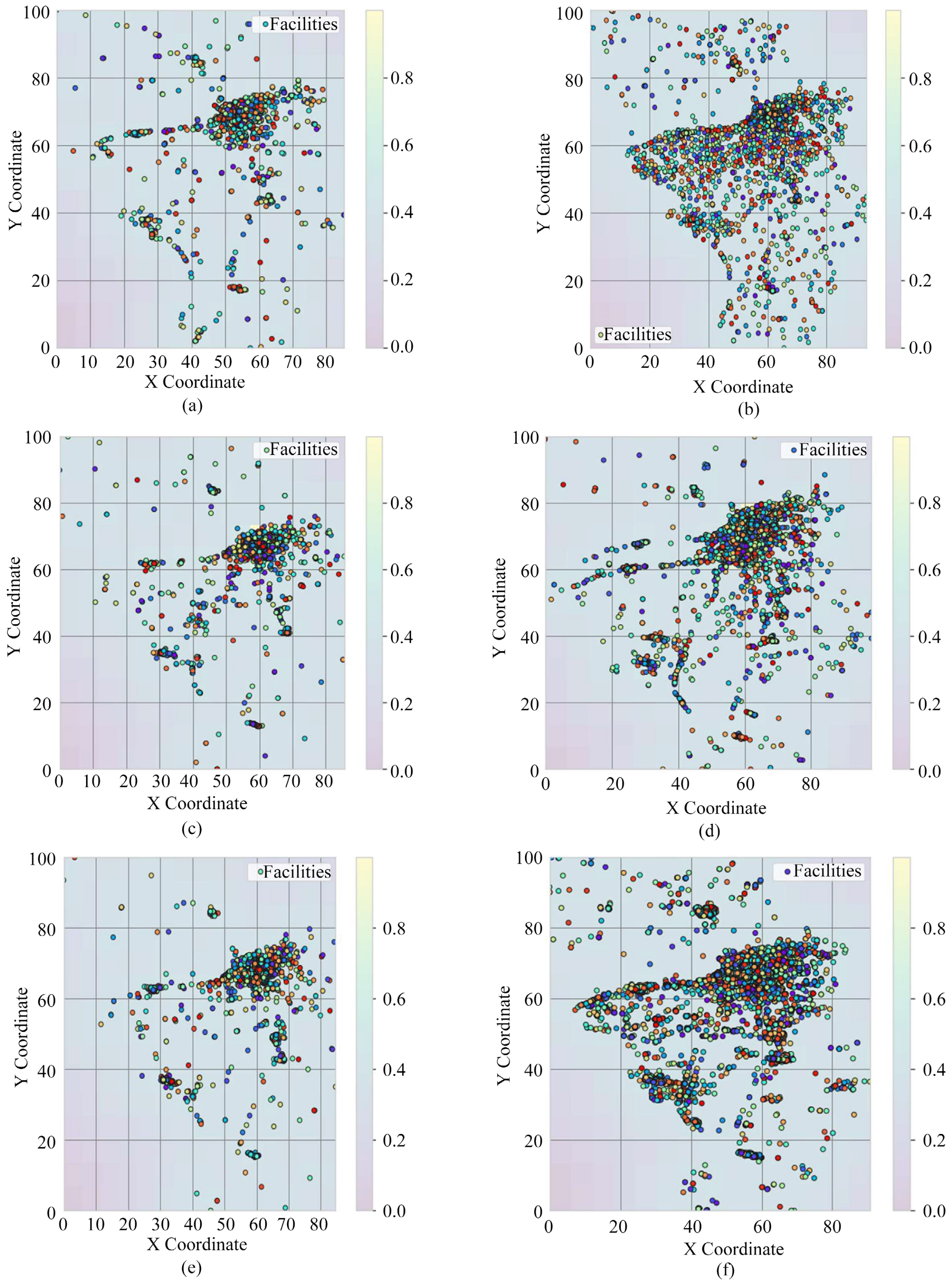

Figure 3. Spatial distribution patterns of urban service categories in Hohhot; from top left to bottom right: (a) GAI, (b) ESOS, (c) MHS, (d) TIS, (e) ALS, and (f) FCS.

as vulnerabilities when the combined proportion of low- and medium-value grids exceeds 50%, while those with high-value grids accounting for 50% or more are classified as spatial strengths (**Table 2**).

Table 2. Spatial diagnosis of urban service strengths and deficiencies.

City	Deficient Services	Strong Services
Changchun	GAI	ALS, TIS, FCS, ESOS
Hohhot	ALS, ESOS	FCS

In Changchun, transport, finance, accommodation, and education-related services demonstrate relatively strong spatial performance, indicating a comparatively balanced and diversified urban service structure. In contrast, geographic auxiliary services remain relatively weak, reflecting uneven distribution of supporting spatial information functions.

In Hohhot, financial and commercial services perform relatively well but are highly concentrated in the urban core. However, accommodation and education services show clear spatial deficiencies, with a large share of grids dominated by low and medium values, indicating limited functional diffusion toward peripheral areas.

Overall, the results reveal pronounced functional differentiation and persistent intra-urban inequality in both cities.

6. Discussion

6.1. Mechanisms of Spatial Differentiation

The observed spatial differences between Changchun and Hohhot are closely related to their divergent urban development trajectories and spatial planning patterns. Changchun, as a long-established industrial city, has experienced sustained infrastructure investment and more balanced urban expansion, contributing to a polycentric service structure.

In contrast, Hohhot exhibits a stronger monocentric pattern, which is associated with concentrated population distribution, uneven expansion of public facilities, and relatively weak service diffusion to peripheral areas. These differences jointly shape the observed patterns of urban service inequality.

6.2. Role of Transportation and Urban Structure

Transportation infrastructure plays a critical role in shaping urban service accessibility and spatial organization. Areas with dense transportation networks tend to attract higher concentrations of commercial and public services, while regions with weaker connectivity remain relatively underserved.

This suggests that transportation systems act as a key structural driver of urban service clustering and spatial inequality, reinforcing the core-periphery pattern observed in both cities.

6.3. Theoretical Implications

This study contributes to urban spatial analysis by providing a grid-based diagnostic perspective on service inequality. Unlike traditional administrative-scale evaluations, the proposed approach captures fine-scale spatial heterogeneity and functional differentiation of urban services.

The findings also support the understanding that urban service inequality is not only a matter of aggregate level differences, but also a spatially structured phenomenon shaped by infrastructure, accessibility, and urban form.

7. Conclusion

7.1. Key Findings

This study identifies significant spatial disparities in urban service distribution between Changchun and Hohhot. Changchun exhibits a relatively balanced polycentric structure, whereas Hohhot presents a more centralized and uneven spatial pattern. These differences are consistently observed across multiple service categories and spatial diagnostic results.

7.2. Policy Implications

The results highlight the importance of improving peripheral accessibility, particularly in monocentric cities. Strengthening transportation connectivity and promoting a more balanced distribution of public services are effective strategies for reducing urban service inequality.

Moreover, differentiated policy interventions should be applied across service categories rather than relying on uniform allocation strategies.

7.3. Methodological Contribution

This study demonstrates the effectiveness of a grid-based spatial diagnosis framework using multi-source POI data. The proposed approach provides a scalable and transferable tool for identifying urban service inequality at fine spatial scales.

7.4. Limitations and Future Work

This study is limited by the use of static POI data and a fixed grid resolution. Future research could integrate temporal dynamics, mobility flows, and multi-scale spatial analysis to improve the robustness and generalizability of urban service diagnosis.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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