

Article

Resident Behavior-Driven Zonation and Optimization of Commercial Service Facilities at the Community Scale

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Highlights

What are the main findings?

- A behavior-informed analytical framework integrating 3D supply and multi-group demand reveals significant spatial mismatches at the community scale.
- Distinct mismatch patterns are identified across urban zones, including path dependency in central areas, fragmentation in growth poles, and persistent shortages in peripheral communities.

What are the implications of the main findings?

- Static, density-based planning approaches may misrepresent actual service accessibility in high-density megacities.
- The proposed framework supports data-driven, i-scale zoning and optimization toward more equitable and responsive urban service provision.

Abstract

Precise assessment of commercial service facilities (CSFs) is a vital pillar for megacity governance. However, existing evaluations rely on static population and 2D metrics, overlooking behavioral heterogeneity and 3D spatial supply at the micro scale. This study constructs a “3D Supply–Group Demand–Matching” framework at the community level. On the supply side, a Building Coupling Entropy (BCE) model integrates 3D volume and morphology to characterize service capacity. On the demand side, a dynamic behavioral model measures multi-group needs. Mismatch patterns are identified using the Entropy-modified Spatial Disparity Ratio (ESDR). Using Guangzhou as a case, the results reveal three paradigms: (1) Core districts exhibit rigid path dependency, where first-tier sub-districts rose from 48 to 51, and elderly service shortages in old areas plummeted by nearly 80% via micro-regeneration; (2) Growth poles show spatial fragmentation, with core labor demand spilling over but infrastructure lagging, creating a fast production–slow urbanism mismatch; (3) Far-suburban areas reduced extreme-shortage sub-districts from 38 to 34, identifying resource islands besieged by residential demand. Overall, the framework elucidates the shape–flow mismatch mechanism and provides a transferable basis for precision zonation governance, supporting a shift from static quantity-based allocation to dynamic quality-oriented provision in high-density megacities.



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1. Introduction

Commercial Service Facilities systems (CSFs)—characterized by diverse functional types and strong relevance to residents’ daily activities—constitute a vital component of the public service system [1]. The 14th Five-Year Plan for Public Services, jointly issued by the National Development and Reform Commission and other ministries, explicitly states that China’s public service system is transitioning from maximizing coverage to prioritizing quality and service excellence [2]. In this context, one of the key challenges facing megacities is how to achieve precise assessment and refined planning of public service resources under complex spatial structures and increasingly diverse population needs. However, existing urban planning and public service evaluation frameworks often overlook the rapid renewal and spatial flexibility of CSFs, making them insufficient for capturing demand differences arising from more complex commuting patterns and heterogeneous population profiles at fine spatial scales. As a result, a significant mismatch frequently emerges between residents’ perceived service accessibility and the actual supply capacity of CSFs [3,4]. Therefore, developing a refined evaluation system capable of integrating the three-dimensional spatial morphology of CSFs, accurately simulating residents’ dynamic behaviors, and effectively revealing multi-scale supply–demand coupling relationships has become an urgent need for promoting the high-quality development of urban public services. Meanwhile, under the guidance of national policies, accurately identifying residents’ diverse needs, optimizing spatial configurations, and achieving precise supply–demand matching have increasingly become key directions for enhancing urban governance capacity and service equity [5].

Facing this challenge, existing research has primarily focused on describing the status quo of supply and demand, as well as conducting large-scale matching analysis [6]. On the supply side, research primarily focuses on measuring commercial service elements and identifying spatial structures. Previous studies suggest that commercial activities exhibit significant hierarchy and agglomeration within urban space, progressively forming a multi-level, functionally complementary commercial service system, which is also widely observed in Western retail systems [7–9]. Building on this, research typically employs methods such as POI data and commercial center identification models to determine the hierarchical structure and spatial distribution of urban commercial centers, revealing the structural characteristics of municipal, district, and community-level commercial centers [10–12]. In recent years, the integration of multi-source data has further expanded research perspectives from traditional supply-side analysis toward consumer behavior analysis. Through questionnaires, heat maps, mobile signaling data, and other multi-source datasets, researchers have identified the functional positioning, vitality levels, and population characteristics of commercial areas [13–15]. These studies consistently find that CSFs display a clear polycentric spatial structure, while differences in center hierarchy lead to functional differentiation [16]. Regarding spatial scale, supply-side studies have predominantly focused on the entire city or central urban areas, emphasizing the hierarchical evolution and functional distribution of commercial systems [17,18].

On the demand side, studies mainly draw on demographic data, commuting flows, and behavioral proxy variables to reveal residents’ service needs and spatial preferences using dynamic datasets. Early research relied largely on static population data. In recent years, with advances in big data technologies, commuting OD data, traffic flow, passenger flow, and information flow have been widely used to depict functional linkages and activity

patterns within cities [19–21]. Among these, commute data has become a key data type for measuring the strength of urban functional connectivity and residents' service demand preferences, owing to its advantages in spatial coverage and behavioral directivity, which is consistent with recent international studies based on large-scale behavioral data [22]. Methodologically, scholars often employ tools such as centroid shift analysis, flow maps, and network-based indicators to characterize urban spatial structures and population mobility. These approaches help uncover the spatial differentiation of residents' needs and their relationships with urban functional zones.

To describe the state of supply–demand matching, scholars have developed a variety of quantitative evaluation models, while international studies have also emphasized the vulnerability and resilience of retail systems under shifting demand conditions [6]. Some studies reconstruct demand distribution using mobility data (e.g., signaling data, travel trajectories) or treat behavioral frequency as a weighting factor to more accurately estimate residents' demand responses to service facilities [23]. Common approaches include accessibility models, shortest-path matching, and supply–demand ratio analysis, which qualitatively assess inequalities in service resource allocation across different areas. Other studies apply machine learning and data-driven methods to conduct pattern recognition and demand prediction based on multi-source datasets, introducing development coefficient models, the CRITIC model, dimension-unified regression analysis, and hierarchical coefficient models [23–27]. Related research spans macro, meso, and micro scales. At the macro scale, studies emphasize the evolution of spatial structures in urban agglomerations and the mechanisms underlying polycentric development, highlighting regional network coordination and functional division of labor [28,29]. At the meso scale, research often focuses on the spatial distribution and optimization of service facilities within entire cities or core urban areas [30,31]. At the micro scale, studies concentrate on streets and various types of isochrone-based community life circles, examining the rationality of service resource allocation within residents' daily activity ranges and the behavioral mechanisms shaping their responses [32–34].

In summary, existing research in supply–demand coupling assessments faces several critical limitations. (1) On the supply side, most studies identify commercial centers using 2D spatial indicators, overlooking the 3D physical characteristics of buildings as service carriers. Consequently, the hierarchical structure of building volumes and their 3D service potential are insufficiently represented, making it difficult to capture the comprehensive supply capacity of CSFs. (2) On the demand side, analyses often rely on static demographic data or commuting distance parameters, neglecting behavioral heterogeneity across age groups and job-residence structures. Moreover, models of resident behavior rarely integrate actual road networks or dynamic traffic conditions, limiting their ability to reflect real accessibility and the nuanced route-choice mechanisms of diverse residents. Heavy reliance on traditional accessibility-based spatial methods further constrains the resolution of service attractiveness and behavioral decision modeling. Furthermore, many studies apply mathematical modeling approaches without fully considering their applicability to urban contexts or the potential for non-stationary processes. (3) Most analyses focus on large-scale regions or representative communities, making it difficult to capture dynamic interactions across scales and lacking multi-agent perspectives on matching patterns. Notably, service facility accessibility varies significantly at the community scale, and examining the supply–demand matching of commercial services from a micro-scale perspective has increasingly become essential for functional optimization [32]. This calls for the integration of more refined analytical scales and the development of a spatial–temporal process estimation scheme.

In response to the growing demand for precision urban governance, this study moves beyond the unilateral assessment of commercial quantity to propose a new “form–flow” integrated framework for evaluating supply–demand matching in megacities. The core of this framework lies in transitioning from static, linear estimations to a multi-dimensional process description of hierarchical capacity and dynamic performance network. In terms of the supply hierarchy, we redefine the measurement of CSFs from a planar density perspective to a 3D structural perspective. By introducing the Building Coupling Entropy (BCE) model—incorporating building footprint, height, and functional adjustment coefficients—we establish a capacity-potential logic. This allows for a more accurate representation of the physical supply capacity and its spatial complexity within high-density environments. In terms of the spatial interaction process, this study integrates a “flowing space” perspective to capture the dynamic temporal characteristics of resident demand. By incorporating actual road networks and multi-group commuting behaviors, we construct a performance relationship network. This approach enables the detection of spatiotemporal non-stationary phenomena—such as behavioral shifts following major social events—that are often obscured by global constants in traditional static models. Consequently, by analyzing 163 sub-districts in Guangzhou, this framework provides a research paradigm for the multi-scale evolution of urban services. It effectively bridges the gap between “fixed physical form” and “dynamic service demand,” offering a scientific foundation for identifying spatial mismatch targets and implementing elastic management strategies.

2. Data and Methods

2.1. Study Area and Data

As a national central city and a core node of the Guangdong–Hong Kong–Macao Greater Bay Area, Guangzhou is characterized by a highly concentrated population, intensive industrial clusters, and rapid spatial expansion (Figure 1) [35]. These features give rise to significant structural tensions and spatial heterogeneity in the matching between service facility supply and commuting-based demand. In the context of an evolving poly-centric urban structure and ongoing regional integration, Guangzhou exhibits complex building-scale characteristics, diverse daily activity patterns, and heterogeneous community needs—conditions well suited for constructing a multi-scale, multi-agent coupling analysis framework.

In alignment with the spatial framework defined in the Guangzhou Territorial Spatial Master Plan (2021–2035) and the functional roles of administrative divisions, this study covers all 11 administrative districts of Guangzhou, encompassing a total of 163 sub-districts and towns.

The Urban Core (T1) includes Liwan, Yuexiu, Haizhu, Baiyun, Tianhe, and Panyu districts, totaling 106 sub-districts. This zone comprises both highly mature, function-dense central blocks—such as Shipai in Tianhe and Beijing Road in Yuexiu—and secondary centers like Shiqiao in Panyu, which absorb population overflow from the core.

The Eastern Center (T2) covers Huangpu and Zengcheng districts, with 28 sub-districts. As the heart of the “Guangzhou Eastward Expansion” strategy, this area exhibits prominent industry–city integration, featuring high-tech clusters like Luogang in Huangpu and vital transit hubs and residential clusters like Xintang in Zengcheng.

Nansha New Area (T3) encompasses the entire Nansha District (9 sub-districts). Serving as a demonstration zone for comprehensive cooperation within the Guangdong–Hong Kong–Macao Greater Bay Area, its spatial development is characterized by distinct cluster-based expansion and policy-driven growth.

The Northern Growth Pole (T4) includes Huadu and Conghua districts, totaling 20 sub-districts. This region functions as an ecological barrier and a gateway hub, contain-

ing mature residential areas like Xinhua in Huadu and ecological functional towns like Liangkou in Conghua.

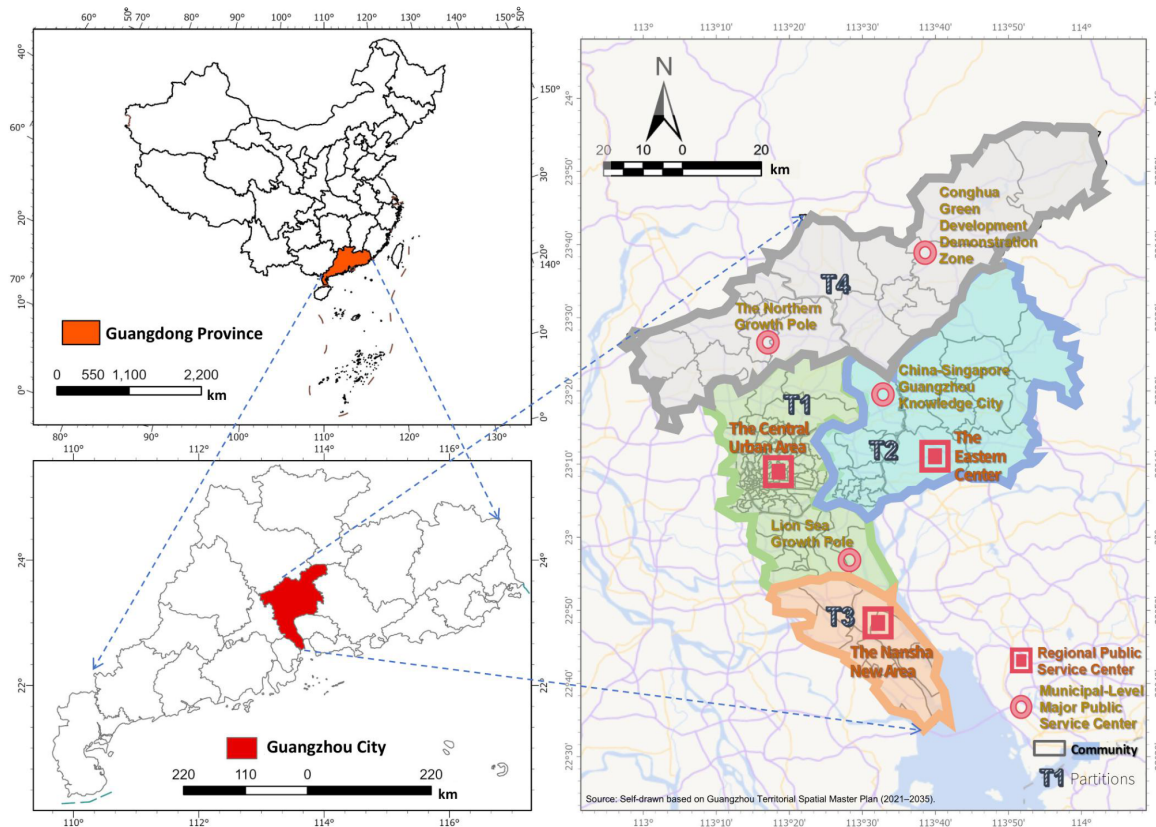


Figure 1. Study Area.

This study integrates multi-source data collected within the Guangzhou metropolitan area, specifically utilizing nine categories of Points of Interest (POIs) for CSFs scraped in 2019 and 2023, 3D building profile data (including building vector outlines and building height data), Origin–Destination (OD) commute data for specific working and non-working days, population diversity structure data, and urban road network data. These datasets were sourced from the Amap API (<https://lbs.amap.com/>), Baidu Maps (<https://map.baidu.com/>), official district-level Guangzhou Seventh National Population Census Bulletins, and the OpenStreetMap (OSM) website (<https://www.openstreetmap.org/>). The administrative division data was obtained from the National Geographic Information Center.

The selection of 2019 and 2023 as the study periods is strategically designed to capture the structural evolution of Guangzhou’s CSFs across the pre- and post-pandemic eras. The year 2019 serves as a stable baseline representing traditional urban service patterns before the global health crisis. Conversely, 2023 marks the first full year of comprehensive recovery and the establishment of a ‘New Normal’ in resident behavior, characterized by shifts in commuting frequency and a heightened reliance on localized community services. By comparing these two distinct temporal nodes, the model can effectively capture ‘spatiotemporal non-stationary phenomena’—behavioral shifts that are often obscured by short-term anomalies but reflect long-term structural resilience and path dependency in megacities. This longitudinal approach allows for a controlled observation of how the urban service system adapted to major social shocks while maintaining its functional core.

2.2. Research Design

This study establishes a refined analytical framework based on the Supply–Demand–Matching logic (Figure 2). On the supply side, by integrating 3D building data with

2D kernel density, a Building Coupling Entropy (BCE) model is constructed through the weighting of scale entropy and morphological entropy to characterize the spatial volume and morphological complexity of facilities. On the demand side, a community-scale spatial demand measurement model for commercial and service facilities system is developed by synthesizing behavioral variables, including travel networks, transportation accessibility, and frequency of visits. For the supply–demand matching phase, Entropy-modified Spatial Disparity Ratio (ESDR) model is employed to identify supply–demand deviations. Combined with the Gini coefficient, Standard Deviational Ellipse (SDE), and Local Indicators of Spatial Association (LISA), the logic of resource mismatch and its response mechanisms are revealed from the dual dimensions of spatial distribution patterns and social equity.

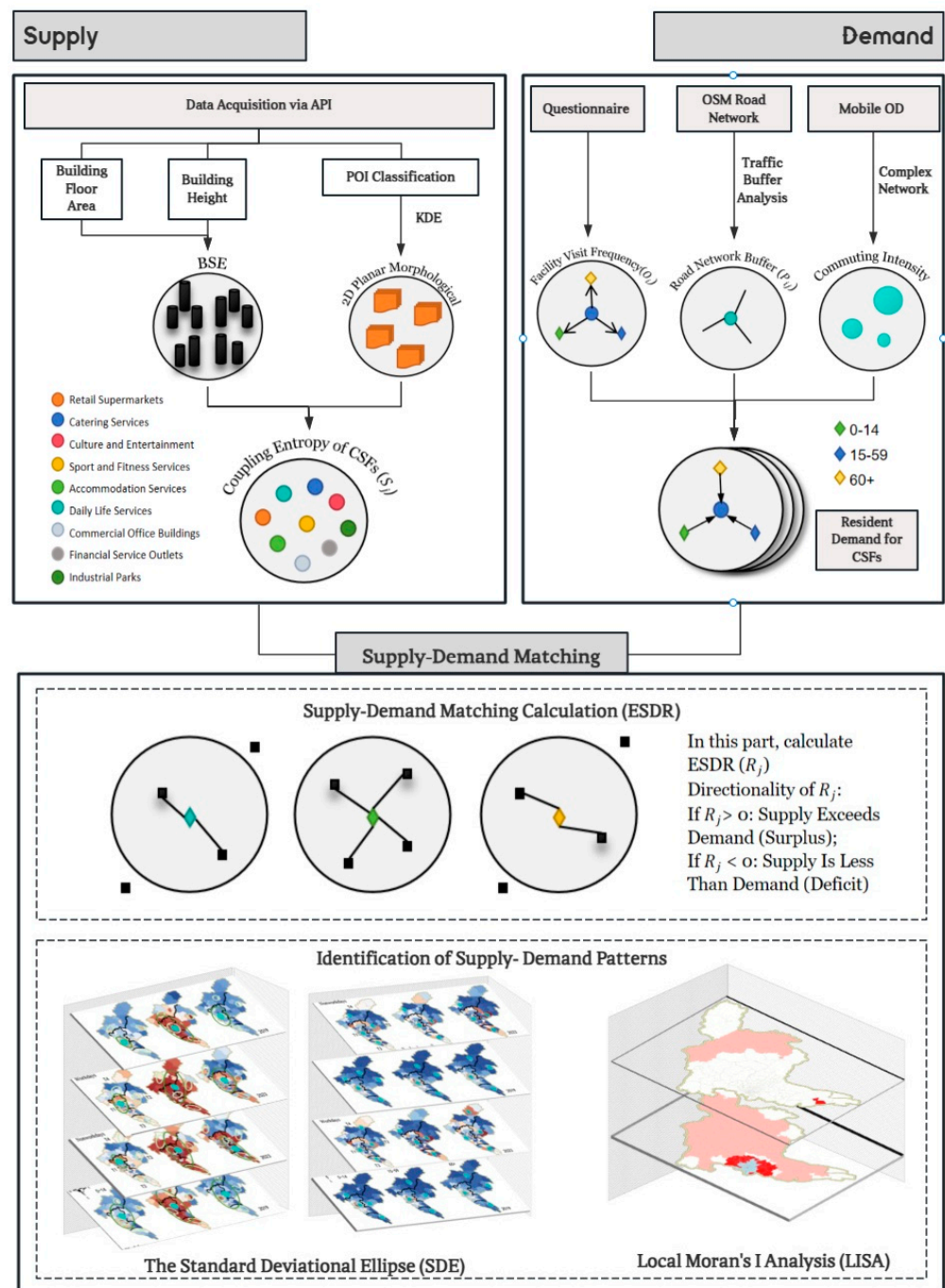


Figure 2. Research Flowchart.

2.3. Precise Measurement of CSFs Spatial Supply Capacity Based on 3D Entities

2.3.1. Data Selection and Cleaning

This study selects CSFs as the primary analysis objects. After classification and identification against the partitioned 3D building profile data, and subsequent invalid point removal, a total of 462,012 POI points were retained for 2019, and 648,895 POI points for 2023.

Subsequently, following the framework of the National Economic Industry Classification (GB/T 4754—2017) [36], and also based on the current planning standards, including the Planning Standards for Urban Public Service Facilities (GB50442) [37] and the Classification of Retail Formats (GB/T18106-2021) [38], nine core categories of CSFs were selected and reclassified: Catering Services, Retail Supermarkets, Industrial Parks, Commercial Office Buildings, Financial Service Outlets, Daily Life Services, Culture and Entertainment, Sports and Fitness Services, and Accommodation Services.

The selection of these nine categories aims to transcend the limitations of traditional public center studies, which often focus solely on residential supporting services. Instead, this research shifts its focus to the comprehensive supply of production and daily life service elements carried by CSFs, thereby providing a more holistic reflection of the complex functions and economic value of contemporary urban public centers.

Specifically, these categories not only represent the capacity of urban public centers to satisfy residents' demands for consumption, leisure, health, and daily support, forming the basis of CSFs' daily life service function, but also crucially introduce production supporting facilities that represent modern economic activities and are intensive in knowledge and technology elements, namely Industrial Parks, Commercial Office Buildings, and Financial Service Outlets. These facilities embody high-end CSFs, carrying the core functions of industrial agglomeration, high-end producer services, and capital allocation, respectively.

2.3.2. Calculation of 3D-BCE

Based on Guangzhou's 3D building data, this study extracts the core structural characteristics of various facilities at the building entity level, including building floor area and building height, to construct the scale dimension of service facilities. Concurrently, the KDE method is used to capture the degree of facility distribution and aggregation in planar space, extracting information for the morphological dimension. The building scale entropy (E_{capacity}) and building morphological entropy (E_{shape}) are calculated separately to characterize the spatial complexity of the facilities across dual dimensions: volume (scale) and form (morphology).

Subsequently, the Information Entropy theory is introduced to construct the BCE model. This model integrates and uses a weighted normalization function, reflecting the coupling coordination level of the supply system at the building entity layer.

The formula for E_{capacity} is as follows:

$$E_{\text{capacity}} = - \sum_{x=1}^n P_x \cdot \ln(P_x) \quad (1)$$

$$P_x = \frac{S_x}{\sum_{j=1}^n S_j} \quad (2)$$

$$S_x = A_x \cdot H_x \cdot \beta \quad (3)$$

where S_x represents the comprehensive service capacity value of the x -th building, calculated as $S_x = A_x \cdot H_x \cdot \beta$. In this formula, A_x denotes the building footprint area, H_x signifies the building height, and β is the functional adjustment coefficient of the building. To ensure the rigor of the supply capacity measurement, β is utilized as a calibration weight

based on the specific category of the POI and the primary land-use type. This coefficient addresses the vertical distribution heterogeneity of services within high-rise structures, ensuring that the volume S_x reflects the effective service potential contributed by the facility rather than a simple aggregation of raw physical volume.

The formula for E_{shape} is as follows:

$$E_{\text{shape}} = - \sum_{x=1}^n P_x \cdot \ln(P_x) \quad (4)$$

$$P_x = \frac{K_x}{\sum_{j=1}^n K_j} \quad (5)$$

where K_x is the KDE value of the POI at the x -th location; and n is the total number of partitioned regions in the study area.

The formula for BCE (S_j) is as follows:

$$S_j = \sqrt{\frac{E_{\text{shape}}^2}{E_{\text{capacity}}^2}} \times (1 - |E_{\text{shape}} - E_{\text{capacity}}|) \quad (6)$$

This formula not only comprehensively reflects the joint effect of the two indicators but also strengthens the sensitivity to their coordination level by introducing a difference constraint term. This ensures a high response of the model to the differentiation in building entity supply capacity. To ensure mathematical interpretability and facilitate cross-regional comparison, the calculated results are normalized using a Min-Max scaling method, constraining the BCE index within a closed interval of $[0, 1]$. A higher coupling entropy value indicates that the spatial volume and configuration of the building entities in that area are more matched and coordinated, implying a stronger public service potential.

2.4. Modeling the Spatial Demand of CSFs Based on Community Resident Behavior

2.4.1. Behavioral Model of Community Resident Visits

In the spatial context of megacities, which is dominated by residents' daily activities, the spatial demand of community residents for CSFs exhibits significant dynamism, structural complexity, and population heterogeneity.

To more accurately characterize the spatial demand features from the resident perspective, this study introduces community-scale complex commuting network modeling, traffic accessibility potential estimation, and an improved Huff model based on behavioral feedback. These elements are comprehensively integrated to construct the spatial demand measurement model for CSFs based on community residents. This approach systematically fuses the structural role of community nodes within the commuting network, actual traffic accessibility constraints, and resident behavioral preference feedback. Under the joint influence of multi-dimensional spatial and behavioral factors, it precisely characterizes residents' comprehensive demand intensity for CSFs at the micro scale.

(1) Measurement of Travel Intensity

The Origin–Destination (OD) data for this study were derived from cellular signaling data covering the entirety of Guangdong Province. To ensure a high-resolution comparative analysis, representative weekdays from the same periods in 2019 and 2023 were selected, as these dates represent the peak intervals of urban population mobility.

The raw dataset, reaching the Terabyte scale, was processed using Python 3.12 scripts to extract records exclusively within Guangzhou's administrative boundaries. Residents' locations were identified based on temporal stay thresholds: the "Home" location was defined as the administrative district with the longest cumulative stay between 23:00

and 07:00, while the “Work” location was identified between 09:00 and 18:00. This logic effectively isolates stable commuting flows from transient social activities.

Using ArcGIS, the WGS-84 coordinates were batch-processed through Spatial Join and Point in Polygon operations to map individual points to the vector boundaries of Guangzhou’s 163 sub-districts (streets/towns). The resulting trajectories were aggregated into a community-scale commuting flow matrix, comprising over 40,000 “street-pair” records for each year.

Complex networks possess distinct spatial topological characteristics, with small-world and scale-free networks being the most representative types [39]. The urban commuting system functions as a quintessential human–environment coupled complex network, whose structural features effectively reflect spatial phenomena such as job–housing separation, polycentric organization, and the aggregation of commuting flows.

The urban commuting system is treated as a quintessential human–environment coupled complex network, where community units serve as nodes and commuting flows constitute the edges. Within this network, network centrality measures—including degree centrality, closeness centrality, and betweenness centrality—are utilized to characterize the strength of inter-community linkages and their hierarchical status within the polycentric framework. Degree centrality reflects the local interaction capacity of a cluster; closeness centrality measures the ease of connection between a cluster and all others in the network; and betweenness centrality represents the cluster’s control over the overall flow across the entire network (Figure 3) [40].

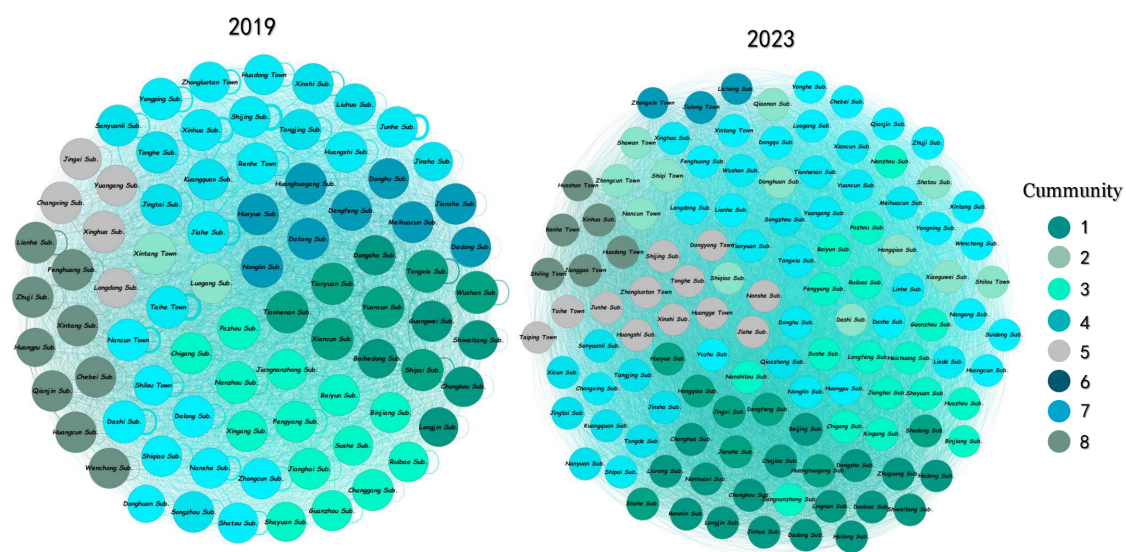


Figure 3. Network analysis of community-level commuting intensity and community classification over two years.

The formulas are as follows:

$$C_i = O_i + I_i; O_i = \sum_{j=1}^k g_{ij}; I_i = \sum_{j=1}^k g_{ji} \quad (7)$$

$$D_i = \sum_{j=1}^n d_{ij} (i \neq j) \quad (8)$$

$$M_i = \sum_j^n \sum_k^n \frac{g_{jk}^{(i)}}{g_{jk}} (j \neq i \neq k, j < k) \quad (9)$$

C_i represents the degree centrality of cluster i ; O_i and I_i represent the in-degree and out-degree, respectively; k denotes the number of nodes connected to cluster i ; g_{ij} and g_{ji} indicates the volume of inward and outward linkages between nodes i and j . d_{ij} is the shortest path distance between clusters i and j ; g_{jk} represents the total number of linkages between clusters j and k ; $g_{jk}(i)$ is the number of linkages between clusters j and k that pass through cluster i .

To further enhance measurement precision, this study introduces transportation accessibility as a constraint factor to calibrate the raw travel intensity extracted from the complex network. Traditional models often overlook the integrated impact of transportation network conditions, road service capacities, and population heterogeneity in megacities. Existing research indicates that consumers exhibit lower sensitivity toward long-distance travel [41]. Therefore, this study utilizes OSM road data and establishes a comprehensive index based on road hierarchy to represent differences in service capacity. Combined with road radiation density and average influence width, a linear buffer model tailored to different road grades is constructed.

By merging road buffers of various levels in ArcGIS Pro 3.0.2, the Transportation Accessibility Coverage (P_{ij}) index is derived. This index serves as a constraint coefficient to adjust commuting intensity: a coverage rate closer to 1 indicates a denser community transportation network, which more effectively supports and stimulates residents' travel responses to surrounding CSFs. Conversely, a lower rate exerts an inhibitory effect on potential travel intensity. Through this integration of structural features and spatial constraints, this study constructs a travel intensity measurement model that more accurately reflects real-world spatial interactions.

(2) Measurement of Visit Frequency

In this study, a behavior-oriented facility demand weight matrix is constructed based on resident visit frequencies and integrated into the supply–demand matching model. It should be noted that the visit frequency measured in this section is not strictly equivalent to the actual demand; rather, it serves as an observable variable of behavioral preferences, reflecting the relative response of different demographic groups to various facilities during commuting or daily travel.

The visit frequencies are derived from questionnaire data, which record the visitation patterns of residents across different facility categories—standardized for this study—during both workdays and non-workdays. The frequency is categorized into six levels and assigned numerical values to construct a behavioral response matrix. To eliminate the influence of sample size variations across different groups and to highlight the internal preference structure of each group, the matrix is normalized. After normalization, the sum of response weights for each population group across all facility categories equals 1. These normalized frequencies represent the relative visitation propensity of different groups toward specific CSFs.

2.4.2. Calculation of Demand Based on Visit Behavior and Accessibility Calibration

Integrating the elements described above, the improved Huff model constructed in this study no longer relies solely on distance or static population density. Instead, it estimates the weighted demand response intensity of community-scale residents for different service facilities, centered on a weighted selection response mechanism jointly driven by accessibility, population characteristics, and facility capacity. Specifically, the demand side incorporates three categories of population characteristics (as proxy variables for heterogeneity). On the supply side, the BCE (S_j) is utilized to measure the facility's scale, morphology, and functional density, thereby quantifying the service capacity. By integrating these elements, the improved model employs accessibility, population characteristics, and

facility capacity to collectively drive the resident selection probability, thus more genuinely characterizing the service demand response at the community scale.

The formula is as follows:

$$\text{Huff}_{ij,Mn} = \frac{S_j P_{ij}}{\sum_k S_k P_{ik}} \quad (10)$$

$$D_{i,Mn} = \text{Huff}_{ij,Mn} \times \beta_{i,Mn} \times P_{i,Mn} \times O_{i,Mn} \times Q_{i,Mn} \quad (11)$$

The traffic accessibility factor, denoted by P_{ij} , is calculated from the traffic buffer analysis, replacing the traditional distance decay function. The denominator of the core probability fraction, $\sum_k S_k P_{ik}$, represents the total attractiveness of all facilities to the residents at origin i . The core output, $\text{Huff}_{ij,Mn}$, measures the probability that the Mn -th population group at origin i selects facility j . To capture behavioral heterogeneity, the model introduces β_{Mn} , which denotes the population share of the Mn -th group; this study specifically divides the population into 0–14 years, 15–59 years, and 60+ years. $O_{i,Mn}$, collected via questionnaire survey, reflects the actual resident choice probability for various facilities. $Q_{i,Mn}$, derived from network analysis, quantifies the functional importance of the origin i in the urban commuting system, often used to refine the demand calculation.

2.5. Evaluation of Supply–Demand Matching and Pattern Recognition for Community-Scale CSFs

2.5.1. Precise Evaluation

To quantify the coordination relationship between CSFs supply capacity and resident demand in Guangzhou, and to identify various development patterns, this study employs the Entropy-modified Spatial Disparity Ratio (ESDR) model, which is an adaptation based on the local Gini coefficient. This model is utilized to isolate the surplus component from the raw supply–demand ratio, which is then used to mark the direction of spatial distribution imbalance. This process enables the identification of local spatial supply–demand coupling deviations. Furthermore, to evaluate the spatial equity of CSFs allocation, the Gini Coefficient is used to quantify the disparities in the actual service accessibility obtained by community residents.

The specific calculation methods are as follows:

$$\text{ESDR} = G_i \times \frac{S_c - D_{i,Mn}}{\max(S_c, D_{i,Mn})} \quad (12)$$

G_i represents the Local Gini Coefficient for the i -th unit. It is used to reflect the degree of imbalance in supply and demand levels among adjacent units. S_c and $D_{i,Mn}$ represent the supply and demand index for the i -th unit. The magnitude and sign of the ESDR value provide a direct measure of the supply–demand status: a value greater than zero signifies a condition where supply exceeds demand; a value equal to zero indicates perfect balance; and a scenario where demand exceeds supply.

2.5.2. Pattern Recognition

The final analysis step calculates the Comprehensive Accessibility Index ($A_{i,MN}$) for each age group, which represents their overall supply–demand matching level across all facility categories. This index serves as the output of the second layer of weighting. This yields the Comprehensive Accessibility Index for location i . The study further identifies the characteristics of the CSFs spatial supply–demand relationship based on community resident behavioral preferences. To provide supplementary interpretation and validation

of the model's output, two key dimensions are examined: spatial distribution pattern and spatial equity.

$$A_{i,MN} = \sum_{j=1}^J (ESDR_{MN,j} \times O_{i,Mn}) \quad (13)$$

$ESDR_{MN,j}$ quantifies the local supply–demand status (e.g., surplus or deficit) for a specific facility type, j . $O_{i,Mn}$ reflects the subjective importance of that facility type to the specific population group M_N based on their visit frequency.

Specifically, the Mean Center method identifies the average location of a set of geographical features, reflecting the central tendency of the ESDR spatial distribution. By calculating the Mean Center of both the overall ESDR values and specific supply/demand deficit clusters, the evolution of the central location of the coupling imbalance can be tracked over time.

The calculation formula for the Mean Center ($\bar{X}$, $\bar{Y}$) is:

$$\bar{X} = \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i} \quad (14)$$

$$\bar{Y} = \frac{\sum_{i=1}^n w_i y_i}{\sum_{i=1}^n w_i} \quad (15)$$

$\bar{X}$ and $\bar{Y}$ are the spatial coordinates of the i -th community unit (or feature). w_i is the weight associated with the i -th unit, typically represented by the ESDR value for that unit. n is the total number of community units.

Also, the Standard Deviation Ellipse (SDE) is a comprehensive method used to measure the central tendency, dispersion, and directional trend of the spatial distribution of a set of features. By fitting an ellipse to the ESDR values, the SDE can visually represent the main orientation and coverage area of the supply–demand imbalance patterns.

The SDE calculation involves three primary components: the center, the dispersion (long and short axes), and the orientation angle (θ).

$$\tan \theta = \frac{A + B}{C} \quad (16)$$

$$A = \sum_{i=1}^n w_i \tilde{x}_i^2 - \sum_{i=1}^n w_i \tilde{y}_i^2 \quad (17)$$

$$B = \sqrt{\left(\sum_{i=1}^n w_i \tilde{x}_i^2 - \sum_{i=1}^n w_i \tilde{y}_i^2 \right)^2 + 4 \left(\sum_{i=1}^n w_i \tilde{x}_i \tilde{y}_i \right)^2} \quad (18)$$

$$C = 2 \sum_{i=1}^n w_i \tilde{x}_i \tilde{y}_i \quad (19)$$

$\tilde{x}_i$ and $\tilde{y}_i$ are the deviations of the coordinates from the Mean Center. w_i is the weight. Standard Deviations along the Axes (σ_x and σ_y):

$$\sigma_x = \sqrt{\frac{\sum_{i=1}^n (w_i (\tilde{x}_i \cos \theta - \tilde{y}_i \sin \theta)^2)}{\sum_{i=1}^n w_i}} \quad (20)$$

$$\sigma_y = \sqrt{\frac{\sum_{i=1}^n (w_i (\tilde{x}_i \sin \theta + \tilde{y}_i \cos \theta)^2)}{\sum_{i=1}^n w_i}} \quad (21)$$

σ_x (Major Axis) measures the dispersion in the direction of maximum spread. σ_y (Minor Axis) measures the dispersion in the direction of minimum spread. The ratio of σ_x to σ_y indicates the directionality of the ESDR distribution.

3. Results

3.1. Analysis of Supply Characteristics of Community-Scale CSFs

3.1.1. Supply Intensity Analysis

The results of the physical BCE calculated at the community scale reveal distinct spatial gradient characteristics in facility carrying capacity across different regions (Figure 4). Data indicates that the mean coupling entropy for all types of facilities in T1 is generally higher than that of peripheral communities. This reflects that building spaces in the core area possess stronger spatial coupling intensity and synergistic potential for facility integration.

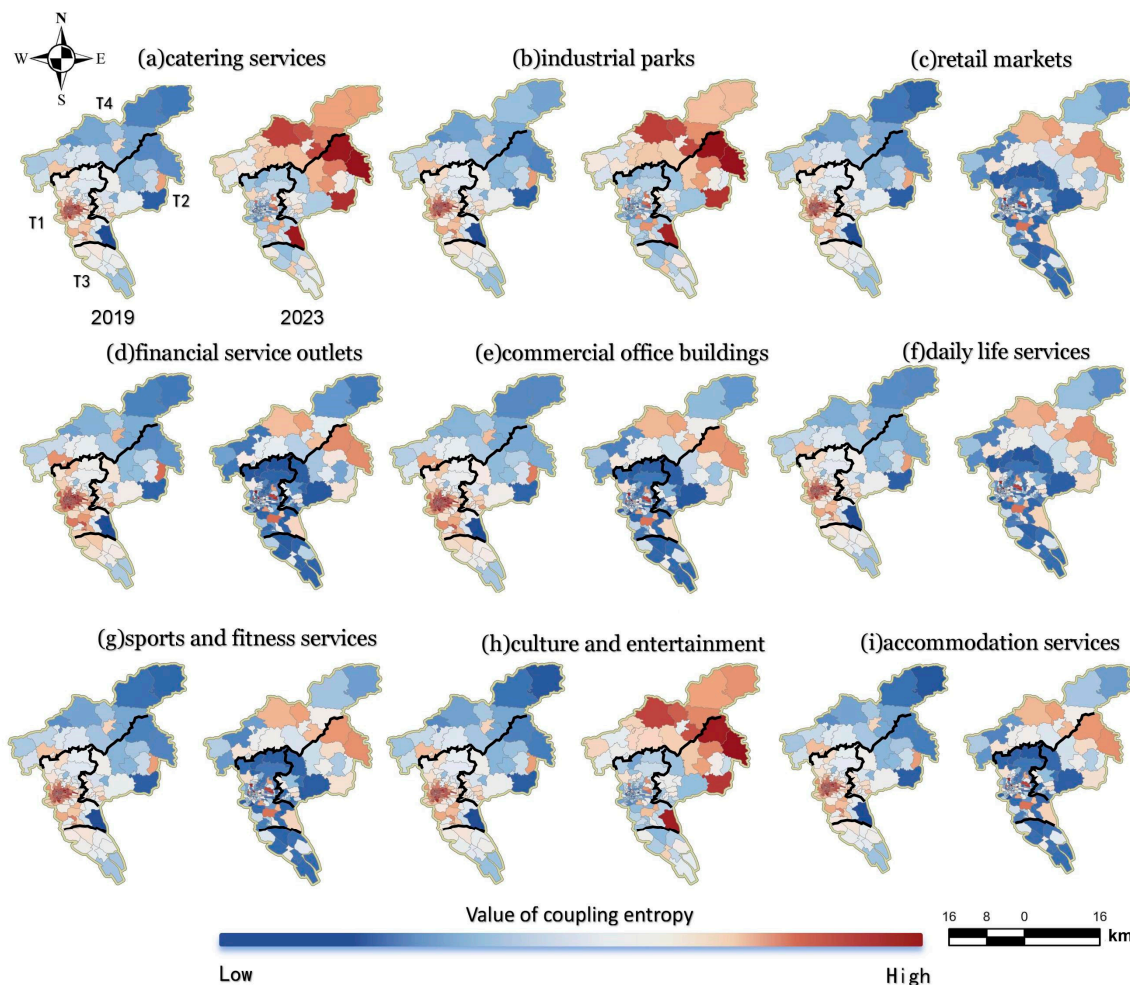


Figure 4. Coupling entropy of nine categories of commercial and service facility buildings at the community level (2019 & 2023).

From the perspective of internal equilibrium, the standard deviation of coupling entropy for various facilities in T1 is relatively small, indicating a more homogeneous distribution of supply intensity. In contrast, the standard deviations for peripheral communities (T2 and T3) are significantly larger, revealing a severe supply polarization within these areas: while the facility carrying capacity of certain emerging sub-districts approaches that of the center, a large number of fringe sub-districts remain in a state of development lag.

Regarding specific facility categories, spatial distributions exhibit certain variations. For instance, the gap in the mean value of industrial facilities between the core and periph-

ery is smaller than that of living services or sports and fitness venues. This suggests that certain areas in peripheral communities still host industrial parks or specialized industrial clusters, indicating that industrial zones in the periphery maintain a degree of carrying capacity and development potential.

Further observation of temporal evolution characteristics reveals significant intensity transitions in certain regions. For example, driven by the Nansha New Area planning, Wanqingsha Town in the T3 region showed a significant increase in the coupling entropy of living facilities. Conversely, some old community in the urban core (e.g., Sanyuanli) experienced a slight decrease in coupling entropy due to aging facilities or functional relocation. These disparities in intensity fluctuations reflect the dynamic replacement of urban resources in terms of spatial carrying capacity.

3.1.2. Spatiotemporal Differentiation Characteristics of Supply Structure

The evolution of the supply structure exhibits significant spatial and categorical heterogeneity (Figure 5). Within T1, the degree of coupling between various types of facilities is generally high, indicating superior performance in terms of architectural spatial carrying capacity, functional synergy, and service capability.

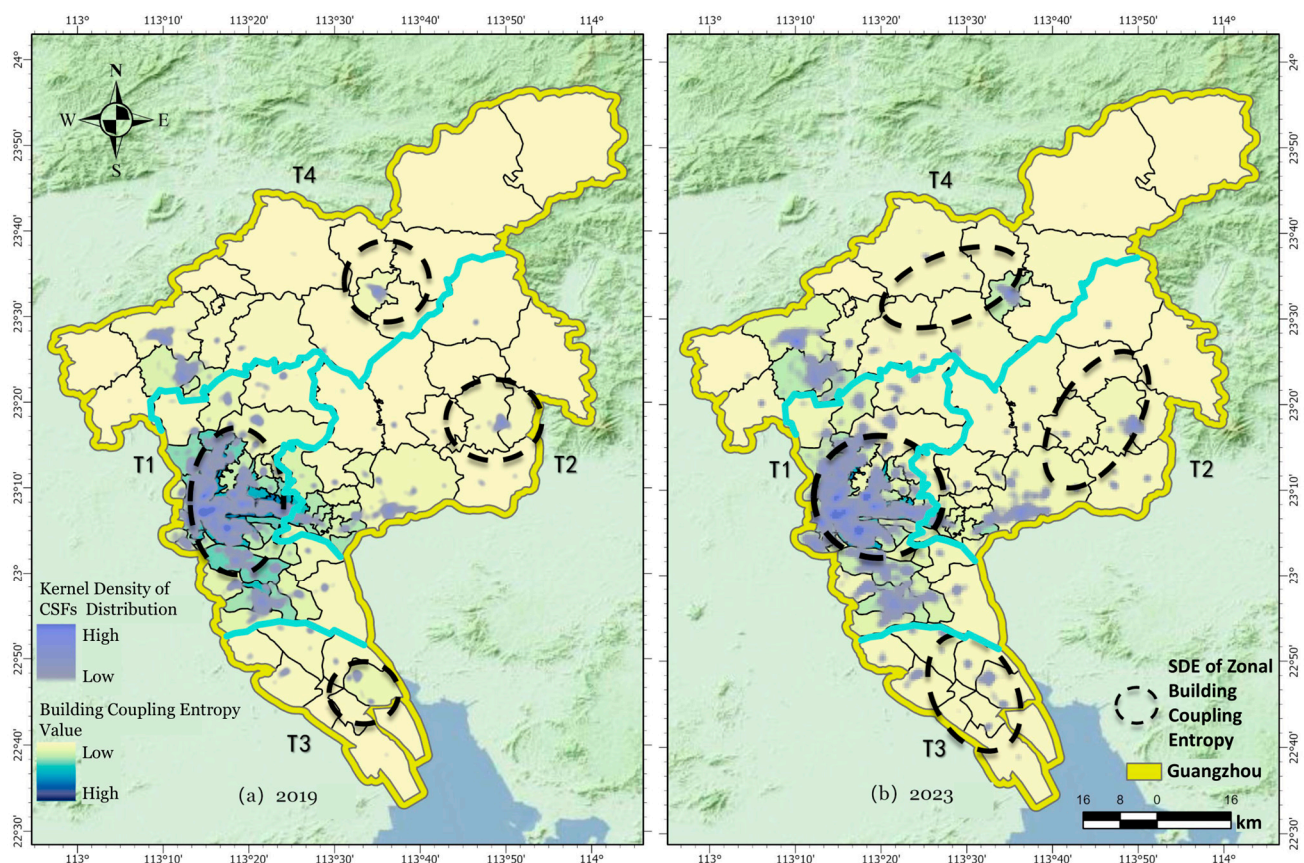


Figure 5. Comprehensive kernel density distribution and BCE of commercial and service facilities at the community level over two years.

In contrast, peripheral communities show an overall lower degree of coupling accompanied by marked internal disparities. This reflects an imbalanced state of facility development and spatial carrying capacity across different sub-districts: while some rapidly developing blocks achieve high levels of facility coupling, lagging areas remain at a low coupling level. These findings suggest that there is substantial room for improvement in spatial layout optimization and resource allocation within peripheral communities.

In T1, the supply structure exhibits steady growth, with the coupling levels of living services and sports and fitness venues increasing particularly rapidly. This demonstrates a proactive response of public service allocation to high-density demographic demands.

In contrast, the supply structures of peripheral clusters are heavily driven by industrial development. In key development areas of T3, such as Dongchong Town, the coupling degree of facilities related to industrial parks has risen significantly. However, this growth is spatially uneven, reflecting that the transformation of spatial structures by emerging industries is characterized by localized explosive expansion.

Simultaneously, the coupling entropy of business offices and financial and insurance facilities has shown marked improvements in specific sectors of Huangpu and Huadu districts. This indicates that urban commercial functions are extending beyond central boundaries toward peripheral strategic nodes.

The evolutionary trajectories at the district level further confirm the structural differentiation. Most facilities in Huadu and Huangpu Districts exhibit positive mean changes in coupling entropy, indicating a robust synergistic growth trend that even surpasses the more saturated central districts.

As shown in Figure 6, the mean change in coupling entropy for certain facility categories in Yuexiu District exhibits negative values. This reflects the dual challenges faced by old urban areas under the constraints of existing architectural space: the contraction of functional space and a decline in spatial synergy. Such divergent evolution profoundly reveals the functional fragmentation within the megacity regarding resource allocation, development potential, and upgrading strategies.

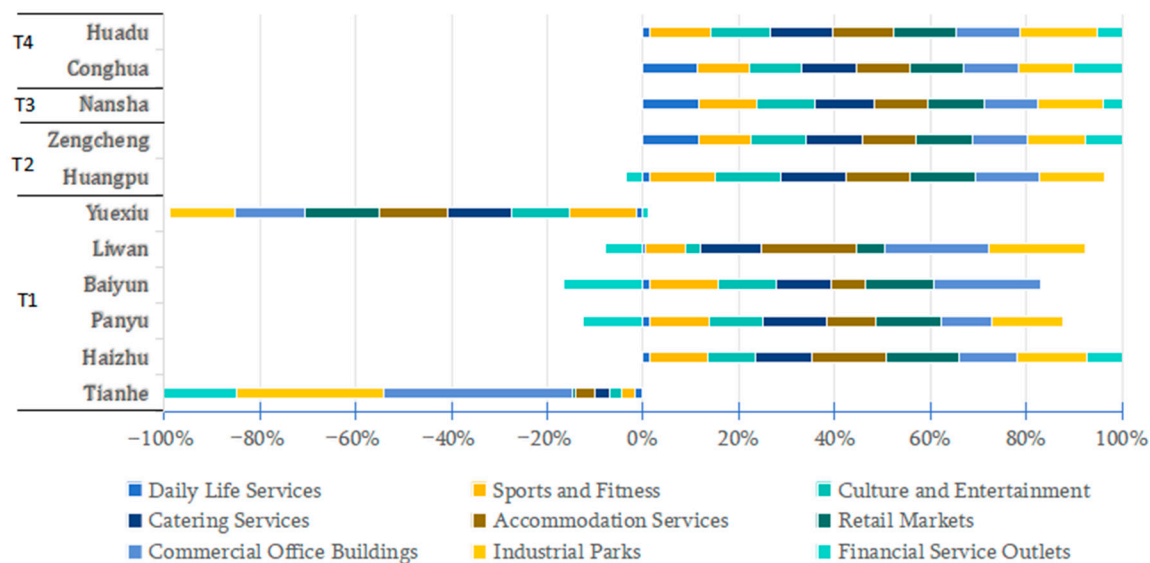


Figure 6. Changes in coupling entropy of various facilities at the district level.

3.2. Community-Level Demand Analysis of CSFs

3.2.1. Description of Resident Visitation Behavior

This section truly depicts the community-scale service demand by integrating the Commuting Intensity Index, the Age Structure Proportion, and the Resident Demand Perception alongside the resident choice probability ($P_{i,Mn}$). This study employs the Likert Scale to construct the resident demand perceived coefficient ($O_{i,Mn}$). This type of scale is known for its high reliability and broad applicability, capable of measuring multi-dimensional attitudes and complex concepts that are difficult to reflect using other scales. The total score obtained from the respondents reflects the intensity of their attitude and the state of variation on the scale [42].

For this investigation, valid questionnaires were collected across the city scale. The reliability and validity of the questionnaire were subsequently verified, and factor structure analysis was performed. To ensure sample representativeness and spatial coverage, this study employed a hybrid sampling strategy: Surveys were distributed via the online platform, with a 60 s minimum response-time filter to ensure data quality; face-to-face surveys were conducted in community elderly canteens and pocket parks, specifically addressing the “digital divide” to capture authentic behavior data from the 60+ age group.

A total of 364 valid responses were collected. Focused on typical communities in the T1 core and T3 strategic zones, this sample size provides a 95% confidence level with an approximate 5.6% margin of error. The demographics (covering age cohorts 0–14, 15–59, and 60+) demonstrate high congruence with the Seventh National Population Census of Guangzhou, ensuring robust group and spatial representativeness (Table 1).

Table 1. Socioeconomic Characteristics of Questionnaire Respondents.

Variable	Characteristic	Proportion (%)
Age	0–14	28
	15–59	45
	60+	27
Occupation	Student	31
	Education/Research Personnel	3.3
	Medical and Healthcare Worker	2.4
	Public Sector Employee	8.7
	Enterprise Employee	29.6
	Self-Employed	5.3
	Freelancer	7.2
	Retired Person	9.7
Household Income Level	Other	2.4
	¥2000 and below	3.3
	¥5000–9999	46.1
	¥10,000–19,999	32
	¥20,000–49,999	16
Highest Education Level	¥50,000 and above	2.4
	Primary School and below	0
	Junior High School	4.3
	Senior High School/Technical	18.4
	Secondary School	7.7
	Associate Degree/Junior College	0.9
	Bachelor’s Degree (Post-Associate)	39.3
	Bachelor’s Degree	28.1
	Master’s Degree	0.9
	Doctoral Degree and above	

The results are also highly satisfactory: The Cronbach’s Alpha coefficient was 0.934; The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.8044; Bartlett’s Test of Sphericity yielded a result of $p < 0.05$, confirming that the correlation matrix is significantly different from an identity matrix and is suitable for structural analysis.

These statistical results confirm the robustness and internal consistency of the questionnaire data, validating its use in constructing the demand model (Figure 7).

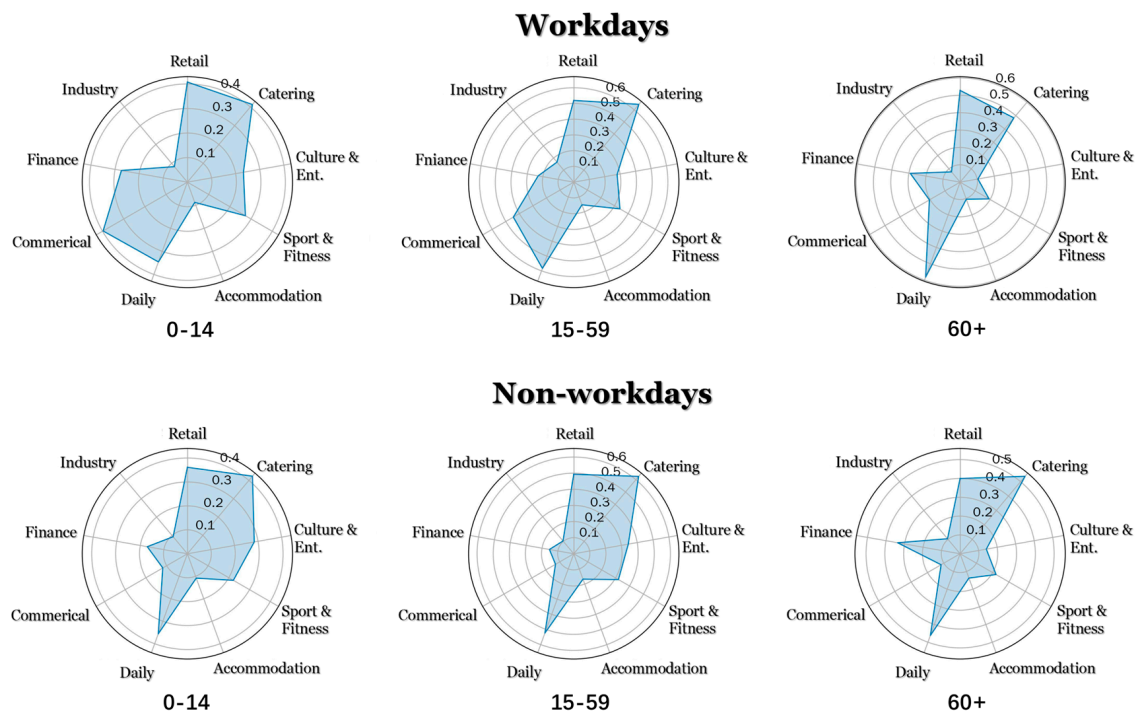


Figure 7. Comparison of demand intensity for nine facility categories among different age groups on workdays and non-workdays.

3.2.2. Spatio-Temporal Differentiation Characteristics of Community Resident Demand Behavior

Resident behavior patterns exhibit significant spatio-temporal differentiation between workdays and non-workdays, which deeply maps the evolution of life routines and consumption patterns among different age groups within the context of urban transformation (Table 2) [43].

During the workday period, the demand for urban CSFs is highly oriented toward business commuting. The 15–59 age group, the primary labor force, constitutes the absolute core of this demand. Their behavior keeps traditional Central Business District (CBD) communities, such as Linhe and Xiancun, consistently in the high-demand category, while also driving emerging areas on the periphery of the urban core—such as Nanshitou and Tongde in Haizhu District—to become new growth points in 2023. Comparative analysis of the two-year data reveals that demand distribution for this group is becoming more balanced at the district level, with narrowing gaps between core areas. This decentralized migration characteristic suggests that new employment and commuting centers are rapidly forming to cater to evolving urban demands.

Simultaneously, the elderly population over 60 exhibits significant off-peak behavior, with approximately 55% of their demand released during workdays. However, spatially, their demand is highly converged in old urban areas and traditional communities (e.g., Ruibao and Duobao), reflecting a strong spatial dependence on basic services surrounding their residences. Their behavioral patterns are highly coupled with social networks and established life inertia, forming a spatio-temporal mismatch with the commuting peaks of the younger and middle-aged populations. Meanwhile, the demand of the 0–14 age group remains in a relatively inhibited state due to academic constraints and has not yet formed significant spatial hotspots.

Table 2. Summary of the number and changes in sub-districts with specific facility demands across different population groups and time periods (2019 & 2023).

Facility Type(CSF)	Age Group	Workdays						Non-workdays					
		No. of High-Demand Streets (2019)	No. of High-Demand Streets (2023)	Comparison (2019/2023)	No. of Low-Demand Streets (2019)	No. of Low-Demand Streets (2023)	Comparison (2019/2023)	No. of High-Demand Streets (2019)	No. of High-Demand Streets (2023)	Comparison (2019/2023)	No. of Low-Demand Streets (2019)	No. of Low-Demand Streets (2023)	Comparison (2019/2023)
Catering Services	15–59	93	107	15%	23	15	−35%	100	112	12%	23	15	−35%
Industrial Parks		104	117	13%	22	14	−36%	92	106	15%	23	15	−35%
Retail Markets		90	100	11%	23	15	−35%	91	101	11%	21	15	−29%
Financial Service Outlets		96	86	−10%	25	18	−28%	90	79	−12%	26	18	−31%
Commercial Office Buildings		96	109	14%	20	14	−30%	94	107	14%	21	15	−29%
Daily Life Services		91	102	12%	23	15	−35%	92	102	11%	23	15	−35%
Sports and Fitness Services		95	110	16%	22	13	−41%	95	109	15%	22	13	−41%
Culture and Entertainment		98	114	16%	21	10	−52%	98	114	16%	21	10	−52%
Accommodation Services		94	107	14%	20	13	−35%	94	105	12%	22	14	−36%
Catering Services		27	12	−56%	58	62	7%	43	48	12%	43	45	5%
Industrial Parks	60+	0	0	0	68	80	18%	41	29	−29%	45	56	24%
Retail Markets		31	25	−19%	50	55	10%	32	19	−41%	54	58	7%
Financial Service Outlets		22	32	45%	57	61	7%	30	18	−40%	51	57	12%
Commercial Office Buildings		20	2	−90%	51	72	41%	30	19	−37%	52	57	10%
Daily Life Services		34	25	−26%	50	53	6%	27	13	−52%	49	52	6%
Sports and Fitness Services		19	7	−63%	61	65	7%	26	20	−23%	57	62	9%
Culture and Entertainment		6	0	−100%	66	76	15%	25	16	−36%	58	64	10%
Accommodation Services		23	15	−35%	56	62	11%	9	2	−78%	63	70	11%
Catering Services		1	0	−100%	45	48	7%	2	0	−100%	45	48	7%
Industrial Parks		0	0	0	51	58	14%	1	0	−100%	43	43	0%
Retail Markets	0–14	4	0	−100%	46	48	4%	4	0	−100%	46	48	4%
Financial Service Outlets		0	5	100%	43	46	7%	0	1	100%	46	52	13%
Commercial Office Buildings		27	3	−89%	36	40	11%	27	2	−93%	36	43	19%
Daily Life Services		1	0	−100%	50	52	4%	1	0	−100%	44	48	9%
Sports and Fitness Services		6	0	−100%	39	44	13%	5	0	−100%	43	45	5%
Culture and Entertainment		19	10	−47%	37	39	5%	17	7	−59%	37	39	5%
Accommodation Services		0	0	0	48	49	2%	2	0	−100%	45	48	7%

During non-workday periods, the dominant function of urban space shifts from business commuting to leisure and social interaction, with high-demand communities for commercial and service facilities exhibiting a trend of widespread diffusion toward mixed-use areas and community living circles.

The facility demand of the 0–14 age group is concentrated during this time, serving as the core driver of non-workday growth. Analysis from 2019 to 2023 reveals a significant migration of demand hotspots for this demographic, shifting from traditional commercial-led areas to residence-intensive communities such as Dadong and Qianjin. This profound return to the community living circle reflects both a transition in parenting models and an ongoing spatial imbalance in the provision of child-related services.

Correspondingly, the behavior patterns of the 15–59 age group on non-workdays are characterized by high-density, 24/7, and polycentricity. While traditional commercial districts like Shipai and Liuhua have seen a decline in leisure demand due to diversion by emerging commercial hubs and residential outward migration, several communities in T2 and T3 zones—where mixed commercial-residential functions have been strengthened—have emerged as new high-demand areas. This is driven by the lifestyle upgrades and

the increasing demand for supporting facilities for job–housing balance. In contrast, the demand distribution of the elderly population tends to be more balanced or even slightly contracted on non-workdays. The decrease in high-demand communities and the increase in low-demand areas confirm their preference for low-frequency, localized activities within their communities during holidays.

3.3. Spatiotemporal Differentiation of Supply–Demand Matching for CSFs

3.3.1. Structural Analysis of Supply–Demand Matching at the Community Scale

To measure the overall deviation of supply and demand for CSFs across the city, this study utilizes the absolute value of the ESDR to represent the intensity of imbalance, while employing SDE analysis to track spatial evolution from 2019 to 2023. The results indicate that the matching characteristics in Guangzhou exhibit not only significant spatial gradient disparities but also profound functional fragmentation driven by evolving behavioral patterns.

In terms of spatial gradients, the high-value matching areas in 2019 were heavily concentrated in traditional core districts like Yuexiu and Tianhe, creating a steep gradient radiating from a monocentric core. By 2023, however, balanced zones had expanded along rail transit axes toward peripheral sub-districts, causing the center-periphery gradient to level off into a polycentric collaborative spatial pattern.

Further observation of the centroid trajectories reveals that, the center of gravity for supply–demand imbalance across all age groups shifted eastward during the four-year period on workdays. This trajectory is highly synchronized with the broader trends of southern population migration and eastward industrial expansion in Guangzhou. In 2019, the imbalance center was primarily situated within the urban core, reflecting a sharp spatial antagonism between central surplus and peripheral scarcity. By 2023, the eastward shift indicates that as the population migrated to peripheral clusters, the time-lag effect of facility construction became more pronounced in emerging areas, causing the focus of contradiction to experience a geographical leap.

Simultaneously, the long axis of the 2023 SDE rotated northeast compared to 2019, suggesting that the distribution axis of imbalance shifted from a traditional North–South orientation to a cross-district horizontal axis. This implies that the conflict is no longer confined to core–periphery boundaries but has evolved into a territory-wide, multi-point dispersed pattern.

From the perspective of demographic differentiation, the ESDR values for the prime labor force remained generally low citywide in 2019, reflecting insufficient support for high-mobility populations at that time. By 2023, this value saw a structural rebound in industrial clusters such as Yuzhu and Yuangang, demonstrating a precise alignment of commercial amenities with commuting behavioral traits. For the elderly population, the matching characteristics in 2023 exhibited strong evolutionary traits; particularly in the old urban areas of the T1 zone, their ESDR values showed a dramatic leap. This signifies that facility provision has evolved from universal coverage toward a functional differentiation that prioritizes age-friendly and social-security-oriented services.

3.3.2. Analysis of Spatiotemporal Differentiation in Supply–Demand Matching

The comparative analysis between 2019 and 2023 reveals that the matching logic of CSFs in Guangzhou has shifted from the expansion of total scale to a deep structural spatial reorganization, characterized by differentiation across the three dimensions of region, period, and demographic group (Figure 8).

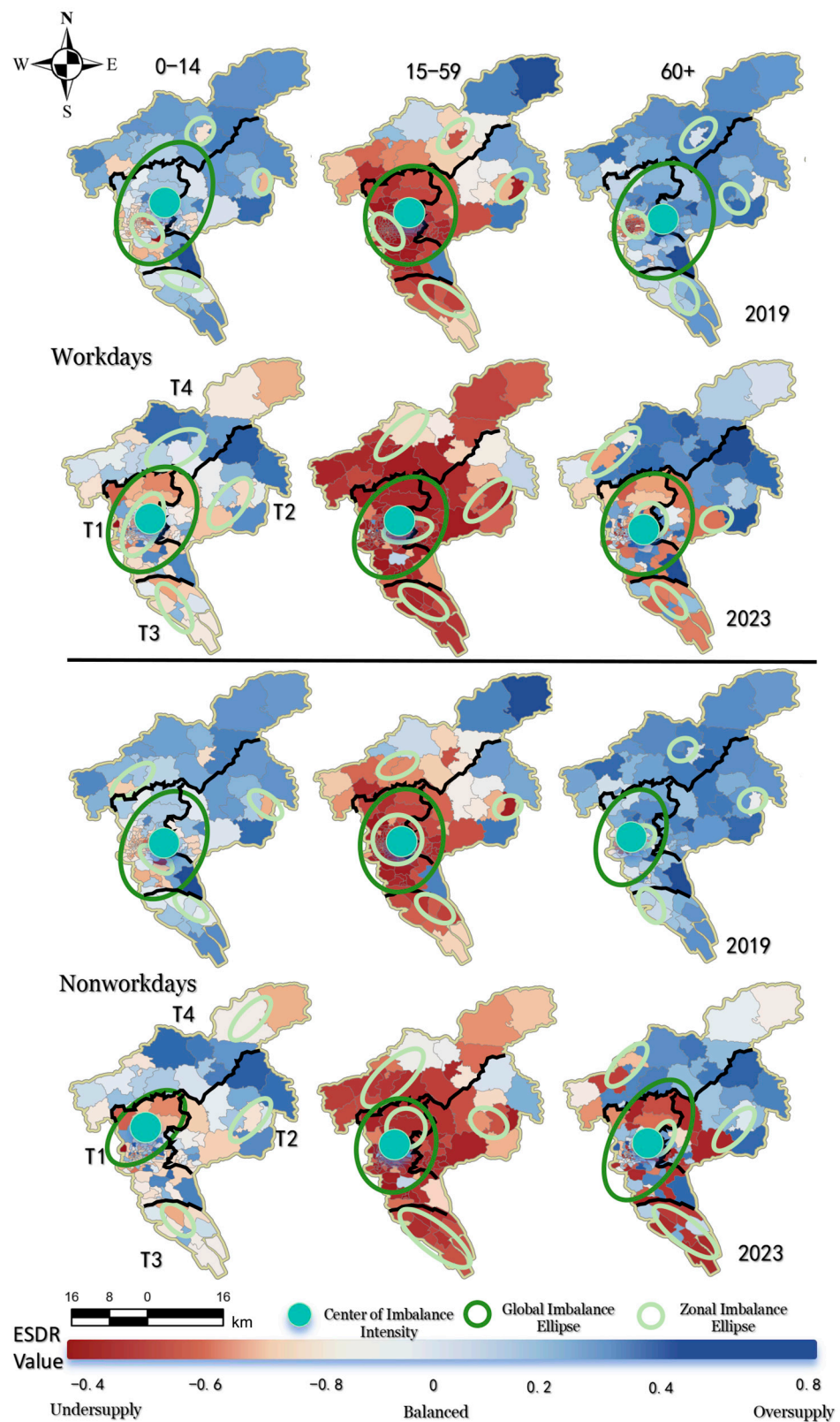


Figure 8. Imbalance intensity centers and global/zonal imbalance ellipse of ESDR values by age group and time period at the community level over two years.

At the scale of regional evolution, Guangzhou's supply–demand landscape exhibits gradient disparities described as central consolidation, northern-wing leapfrogging, and strategic zone imbalance. The T1 core layer shows stable resource concentration and

spatial consolidation; however, by 2023, the redundancy of service supply for the elderly exceeded 70%, revealing a deep entanglement between aging communities and legacy facilities in the urban core. This stands in sharp contrast to T4, which transitioned from overall backwardness in 2019 to precision-based replenishment by 2023. Notably, the matching degree for education and living services for the 0–14 age group in T4 rose to over 95%, reflecting the effectiveness of resource allocation tilting toward peripheral emerging communities. Meanwhile, T2 and T3—situated in the transition zone between the semi-core and inner suburbs—experienced the most volatile fluctuations in supply–demand patterns over the four-year period. In some localized areas, there were even signs of regression from equilibrium to shortage, highlighting a production–city contradiction where the influx of industrial population into strategic growth poles outpaces the development of supporting living facilities.

In terms of temporal differentiation, the analysis further reveals deep-seated functional imbalances in urban operations, particularly manifested in the constraints exerted by job–housing pressure on resource efficiency. On workdays, a significant structural mismatch is observed within the urban core: business hubs such as Tianhe and Yuexiu exhibit a high surplus in production-oriented amenities, while functional zones like Baiyun and Haizhu still face substantial deficits in cultural, entertainment, and business office facilities. This reflects the intense pressure of job–housing balance faced by the core labor force. On non-workdays, the young and middle-aged groups across the entire city generally present an illusion of supply surplus. This is not derived from absolute resource saturation, but rather reflects the group’s extremely high spatial mobility, which allows their activity range to transcend the constraints of the community scale.

From the perspective of deep demographic differentiation, the young and middle-aged group consistently represents the core crux of the supply–demand contradiction in Guangzhou, whereas the livelihood security for the elderly and children has been significantly strengthened. Over the four-year period, the shortage of living services for the elderly and children across the city has been substantially mitigated. For instance, there has been a significant reduction in communities lacking childcare facilities in the T4 region and elderly services in the T2 and T3 regions, signaling that livelihood functions are approaching maturation.

However, a functional imbalance persists between the demand for high-quality, diversified commercial formats by the young and middle-aged group and the actual supply. This is particularly evident in rapidly developing strategic growth areas, where traditional commercial formats have failed to keep pace with the emerging demands of this demographic. This spatiotemporal differentiation, rooted in behavioral heterogeneity, not only reveals the path dependency of Guangzhou’s commercial resource allocation but also underscores the necessity for future governance to implement differentiated precision strategies: focusing on efficiency enhancement in the urban core and quality upgrading in peripheral areas.

4. Discussion

4.1. Evolutionary Logic of Supply–Demand Zoning for CSFs

Based on the national territorial spatial planning framework, this study integrates the physical BCE and the supply–demand equilibrium index to reveal the differentiated logic underlying the evolution of facility distribution. These findings collectively constitute the spatial structural evolution of a megacity. By applying the Jenks Natural Breaks method to the ESDR values of 2019 and 2023, this study identifies four core mismatch patterns: High-level Surplus, Stock Equilibrium, Elastic Deficit, and Structural Vacuum. Observations at the community and district scales reveal that the evolution of Guangzhou’s CSFs involves

both intense micro-level shifts in individual units and the formation of significant macro-phenomena (Table 3).

The evolution of the T1 region is driven by the lock-in of core functions and the reallocation of stock space. The upward shift in “Hyper-Redundancy” sub-districts (from 48 to 51) confirms that urban renewal has reinforced the absolute dominance of high-value producer services. Conversely, a significant precise response is observed in traditional urban areas (Yuxiu and Liwan), where service shortages for the elderly plummeted by nearly 80%. This reflects that micro-regeneration policies have successfully secured the basic livelihood bottom line despite the constraints of existing architectural space.

Table 3. Community-District Level Distribution and Spatial–Temporal Dynamics of Commercial Facility Mismatch Patterns in Guangzhou.

Partition	Mismatch Pattern Level (Jenks)	No. of Streets in 2019 (Community Scale)	No. of Streets in 2023 (Community Scale)	Hierarchical Shift & Spatial Distribution Characteristics
T1: Urban Core	ESDR < −0.52 Level 1: Hyper-Redundancy	48	51	Lock-in Effect: Intensification of functional polarization; redundancy in the core further encroaches on living space.
	−0.52 < ESDR < 0 Level 2: Residual Equilibrium	12	9	Transition from equilibrium to redundancy.
T2/T3: Strategic New Zones	−0.52 < ESDR < 0 Level 2: Residual Equilibrium	25	18	Collapse of Equilibrium: Infrastructure fails to keep pace with rapid population growth.
	0.0 < ESDR < 0.42 Level 3: Elastic Deficit	11	19	Downward Slippage: Large-scale transition from equilibrium to deficit (e.g., Wanqingsha Town).
T4: Northern Growth Pole	0.0 < ESDR < 0.42 Level 3: Elastic Deficit	8	10	Deficit Expansion: Shift from localized shortage to broader spatial diffusion.
	ESDR > 0.42 Level 4: Structural Vacuum	38	34	Fragmentation & Dissipation: Despite policy interventions, ESDR remains high; clusters transition to scattered deficits.

Driven by a policy–industry–population–demand chain, the T2 and T3 regions exhibit a collective slide from “Stock Equilibrium” toward “Elastic Deficit”. This logic serves as quantitative evidence of Guangzhou’s transformation toward a polycentric networked model. A typical mismatch is seen in the Nansha Free Trade Zone, where the configuration speed of living services lags behind the massive influx of high-tech talent—a phenomenon of “fast production, slow urbanism”. Meanwhile, sub-centers like Zengcheng have rapidly satisfied basic needs through large-scale incremental allocation during early construction phases.

The T4 region’s logic is characterized by administrative intervention to forcefully remediate structural vacuums. Large-scale infrastructure investment in Conghua and Huadu has effectively reduced the number of “Structural Vacuum” sub-districts (from 38 to 34), particularly improving matching for the 0–14 and 60+ age groups. However, this “gap-filling” approach now faces a transition from quantitative growth to efficiency optimization, as uneven population density has led to localized low utilization of new facilities.

4.2. Mechanisms of Supply–Demand and Path Dependency in CSFs

Through multi-population and cross-period behavioral analysis from 2019 to 2023, this study finds that the evolution of Guangzhou's commercial system is not a simple linear growth (Figure 9). Instead, it is a complex process driven by urban development strategies, functional layouts, and residential habits. This mismatch manifests in distinct ways across different zones (Table 4):

- The Squeezing of Living Space by High-end Industries and Inertia

In the T1 urban core, the layout of commercial facilities demonstrates strong inertia. Data shows that the facility surplus for the working-age group rose from 95.8% to 97.4% over four years, with ESDR values locked at extreme levels.

Within the limited space of the core area, because high-end office and business development offer higher returns, spatial resources are occupied by functions like banking and corporate headquarters. This high functional concentration creates a “squeezing effect,” making it hard for low-profit but essential facilities (e.g., public gyms, convenience stores, social spaces) to survive near office buildings. This creates a paradox: while white-collar workers are in the most facility-dense areas, it remains difficult for them to find a place for exercise or daily shopping near work. This inconvenience caused by functional homogenization is the primary reason why the core area has low matching levels despite a high total volume of facilities.

- Mismatch between Physical Form and Activity Flow via Job–Housing Separation

As the frontier of urban expansion, the T2 and T3 strategic zones exhibit the most unstable matching patterns. The core contradiction here is the mismatch between completed infrastructure and actual movement patterns.

In their early stages, new zones often prioritize industrial capacity over urban living. While large industries are introduced quickly, surrounding dining, shopping, and entertainment facilities often lag behind. Data from 2023 shows that due to severe job–housing separation, the facility shortage on weekdays is 12.4% higher than on weekends.

As many young and middle-aged people move into these areas, the sparse commercial points are suddenly overwhelmed by massive daily needs. During the day, these areas are like islands of factories and offices, while at night or on weekends, the few existing malls become overloaded. This extreme temporal imbalance reflects the growing pains of transforming from an industrial park to a livable urban district.

- Social Equity Deficit in Resource Allocation

In the T4 northern peripheral areas, the mismatch manifests as a diffusion of shortages. Despite government efforts to fill gaps, the results are suboptimal.

Infrastructure expansion lags significantly behind the speed of population migration to the suburbs. Over four years, the shortage rate for medical and cultural facilities serving the elderly and children actually rose by about 10%.

Younger, highly mobile groups can solve their needs by traveling further, using cars or apps. This mobility masks the actual lack of resources within the community, making it seem like shortage hotspots have disappeared while average ESDR values remain high. The real victims are the elderly and children who rely heavily on local space; they have become the marginalized groups in the process of spatial expansion.

To further validate these mechanistic observations, Table 5 provides a detailed statistical comparison of supply–demand characteristics across the four years, while Table 6 presents the transition probability matrix of spatial hotspots. These quantitative datasets reflect the underlying stability in the spatial evolution of Guangzhou's CSFs.

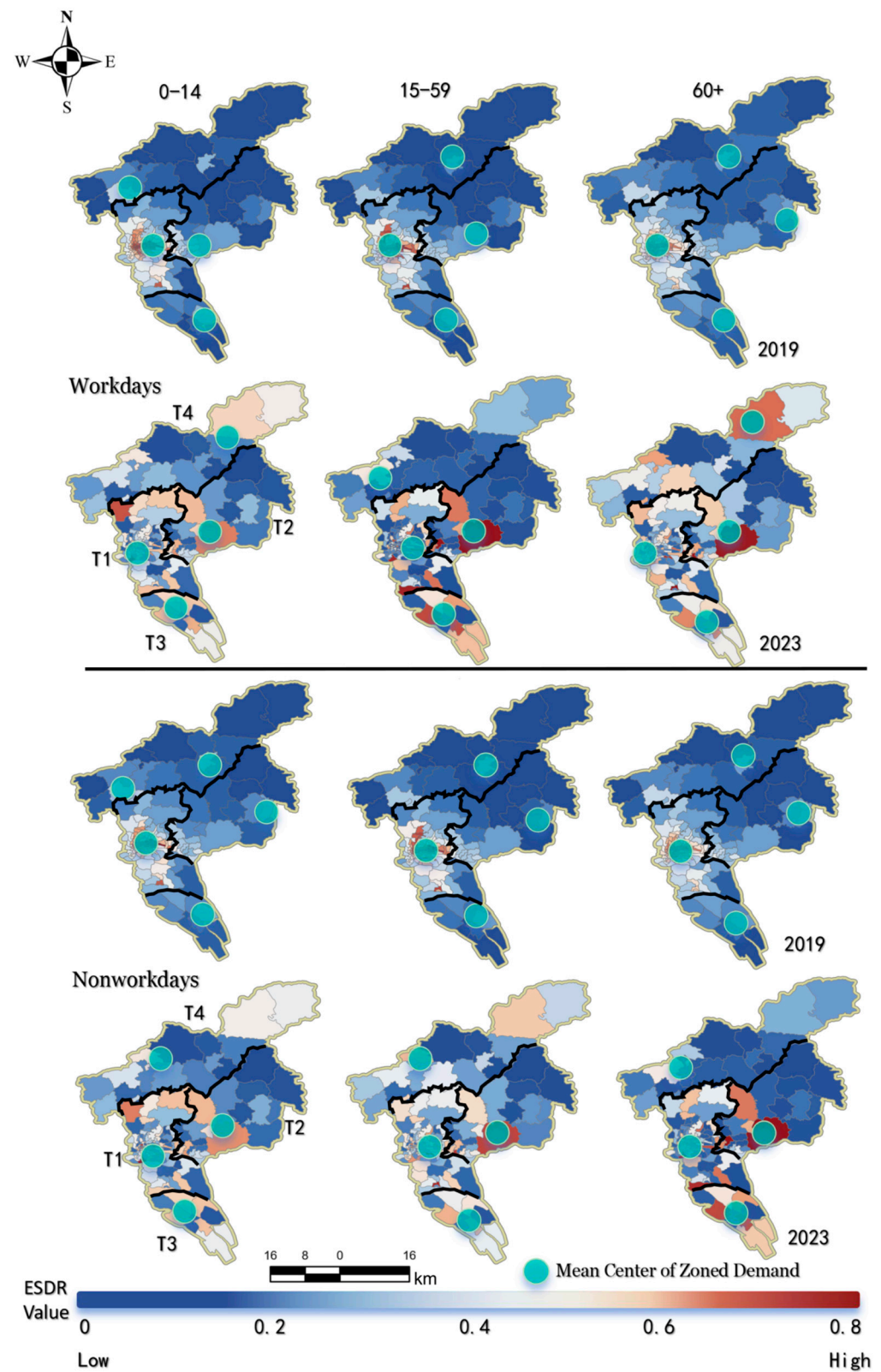


Figure 9. Mean centers of comprehensive demand zones by age group and time period at the community level over two years.

Table 4. Dominant Factors and Explanational Mechanisms of CSF Evolution across Guangzhou Partitions.

Partition	Dominant Factors	Data Manifestation	Phenomena and Causal Explanations
T1: Urban Core	Spatial Inertia and Industrial Prioritization	Weekday redundancy as high as 97.4%	Squeezing Effect: High-end business and headquarters monopoly over scarce spatial resources squeezes out daily life services, leading to a “paradox of plenty”.
T2/T3: Strategic New Zones	Job–Housing Separation and Construction Lag	Weekday shortage 12.4% higher than weekends	Island Effect: The “fast production, slow urbanism” pace results in severe daytime facility overload and extreme spatio-temporal imbalance.
T4: Northern Growth Pole	Infrastructure Lag and Equity Deficit	Shortage rate for elderly/child services rose by ~10%	Masking Effect: High mobility of younger groups hides the true resource scarcity within communities, causing spatial deprivation for the localized elderly and children.

Table 5. Comparison of Supply and Demand Characteristics of CSFs by Partition (2019 & 2023).

Year	Partition	Time	Age	Typical CSFs	Significant Shortage	Significant Surplus
2023	T1	Workdays	15–59	Financial/Commercial	0.00%	100.00%
			60+	Daily Service	5.30%	76.30%
		Nonworkdays	0–14	Sports/Culture	10.50%	31.60%
	T2	Workdays	15–59	Catering/Retail	17.40%	52.20%
		Nonworkdays	60+	Daily Service	8.70%	43.50%
	T3	Workdays	15–59	Industrial/Commercial	0.00%	78.60%
			0–14	Sports/Culture	21.40%	25.00%
	T4	Workdays	15–59	Daily Service	47.40%	26.30%
		Nonworkdays	60+	Sports/Culture	52.60%	15.80%
			0–14	Daily Service	42.10%	21.10%
2019	T1	Workdays	15–59	Financial/Commercial	0.00%	95.80%
			60+	Daily Service	10.50%	71.10%
		Nonworkdays	0–14	Sports/Culture	7.90%	34.20%
	T4	Workdays	15–59	Daily Service	44.80%	18.40%
			60+	Sports/Culture	47.40%	13.20%
		Nonworkdays	0–14	Sports/Culture	51.30%	10.50%
	T2/T3	Workdays	15–59	Industrial/Financial	4.30%	73.90%
			0–14	Daily Service	17.40%	30.40%
		Nonworkdays	60+	Catering/Retail	13.00%	47.80%

Table 6. Transition Probability Matrix of Spatial Hotspots for CSFs (2019–2023).

Scenario (Time & Age Group)	Overall Spatial Stability (%) (1)	HH → HH (Hotspot Stability) (%)	LL → LL (Coldspot Stability) (%)	NS → NS (Random Stability) (%)	Core Disinte- gration Flow: X → NS (%)	Critical Pattern Shift: LL → HL (%) (2)	Critical Pattern Formation: NS → HH (%) (3)
Non-workday 0–14	49.95	24	13.75	100	72.00	0	0
Non-workday 60+	39.97	20.41	35.71	94.74	77.55	38.57	5.26
Workday 0–14	40.35	19.23	7.59	100	76.92	0	0
Workday 60+	27.2	18.75	0	90	81.25	0	5
Workday 15–59	22.04	13.33	0	96.55	73.33	0	0

Notes: Overall Spatial Stability is the average retention rate across all diagonal elements, indicating the structural persistence of ESDR mismatch patterns. LL to HL (Coldspot Surrounded by Hotspots): A critical transfer indicating that a resource surplus area is now being surrounded by resource scarcity areas, suggesting accumulating spatial conflict. NS to HH: The percentage of streets where a previously Non-Significant/Random area evolves into a new High-High (resource scarcity) Hotspot.

4.3. Optimization Strategies for Supply–Demand Matching Patterns of CSFs

Based on the four pattern hierarchies identified through the Natural Breaks (Jenks) method, the optimization of Guangzhou’s CSFs should follow a multi-scale governance logic of community-level driving and district-level coordination. This hierarchical framework aims to resolve the structural contradictions of “flow space” by integrating regional strategic planning with precision micro-interventions.

At the macro-district level, governance must prioritize regional synergy to balance the strategic gravity center drift of commercial demand toward the east and south (Figure 10). In T2 and T3 strategic growth poles, such as Huangpu and Nansha, planning should transition from fragmented “point-by-point” gap-filling to “District-level Hub-driven Development.” By centrally constructing integrated cross-community shared service hubs at transit-oriented development (TOD) nodes, the city can leverage scale effects to support the rapidly growing workforce and bridge the resource islands created by rapid industrial expansion. In the T1 core area, district-level coordination should focus on the functional softening of inventory spaces. This involves the guided reduction in redundant productive functions and the strategic diversion of headquarters or financial services to peripheral nodes, thereby alleviating the high-intensity spatial pressure that currently squeezes essential living services.

At the micro-community scale, the focus shifts toward precision identification and age-appropriate urban acupuncture. For communities in T1 and high-density residential zones, governance should prioritize the awakening of underutilized assets, such as old factory ground floors or vacant retail shops, to safeguard the basic living standards of localized vulnerable groups. To resolve the masking effect where high commuter mobility obscures the deprivation of the elderly and children, specific interventions like embedding health micro-stations for the elderly (repurposed from redundant booths) and child-friendly reading spaces into the 15 min life circle are essential. Furthermore, addressing the tidal mismatches in T2 and T3 necessitates an elastic supply mechanism. By deploying mobile service modules (e.g., modular dining cars) and encouraging the time-shared use of commercial office buildings, allowing office plazas and cafeterias to serve residents during off-peak periods, so that planners can achieve a seamless coupling of productive and living spaces without increasing land consumption.

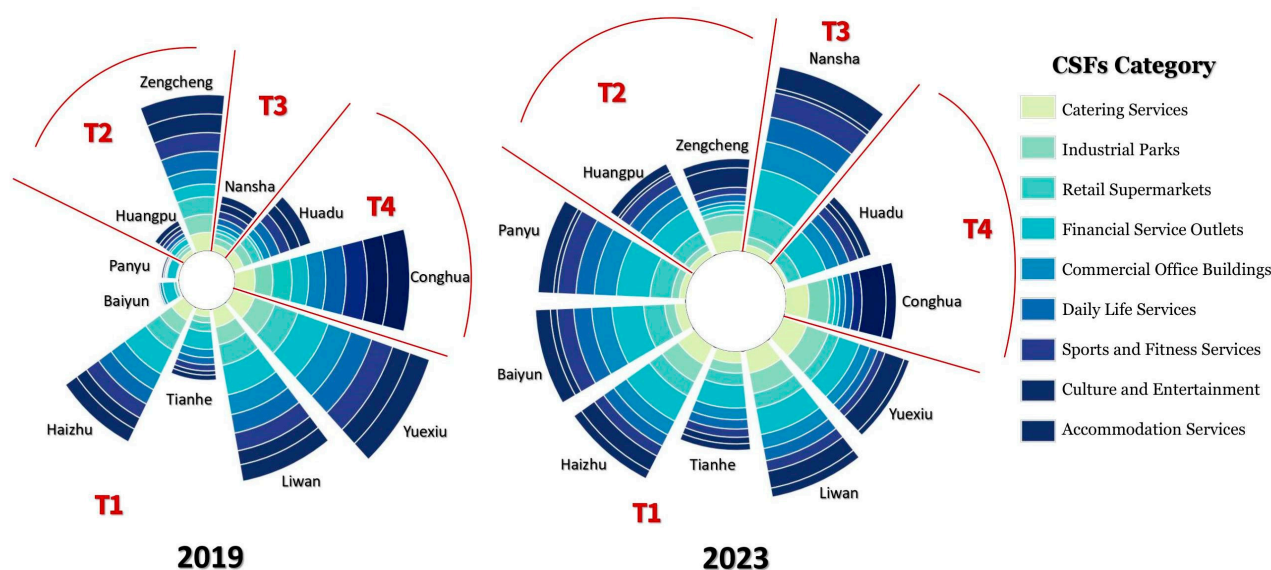


Figure 10. Difference maps of supply–demand optimization for nine categories of facilities at the district level over two years.

Finally, a scale-linking monitoring system should be established to ensure the long-term applicability of these strategies. By integrating dynamic ESDR indicators into the city's routine smart-governance platforms, Guangzhou can transition from static configuration to flow-responsive supply. This system would allow for real-time identification of structural vacuum zones and provide early-warning responses at the district level, ensuring that CSF provision remains resilient to the evolving mobility-driven demand of the workforce and the strong spatial dependence of the elderly and children.

5. Conclusions

5.1. Theoretical and Practical Contributions

This study advances the field of supply–demand matching for CSFs by transitioning from a static, binary framework to a structural dynamic evolution model. By attributing deep-seated imbalances to the structural mismatch between fixed facility forms and dynamic human flow demand, the research reveals how functional specialization, residential behavioral heterogeneity, and planning lags normalize these discrepancies in megacities.

Methodologically, the introduction of the BCE index provides a fine-grained tool to measure functional composition and quality, effectively replacing the limitations of single-quantity indicators. On the demand side, the Dynamic Demand Model integrates behavioral big data to overcome the biases of static census records, allowing the ESDR to capture multi-group and multi-temporal patterns.

Furthermore, by identifying the 15–59 core labor force as the focal point of supply–demand contradictions, the research clarifies the demand patterns and minimum matching degrees that urban planning must prioritize. These findings provide precise quantitative evidence for implementing elastic management and time-sharing strategies within polycentric urban networks, offering a valuable decision-support framework for megacities aiming to enhance governance elasticity and build people-centric service systems.

5.2. Research Limitations

Despite its innovations, this research faces constraints regarding data precision, parameter settings, and behavioral profiling. Minor discrepancies in statistical standards and update frequencies among multi-source data, such as POI, building vectors, and OD flows, may lead to spatial generalization errors at the micro-street scale. Furthermore, the BCE

model primarily utilizes physical attributes like area and height, potentially overlooking non-physical variables such as actual business turnover, rent levels, and operating hours that influence supply efficiency. The study has also yet to conduct deep-dive analyses into the behavioral fluctuations of specific vulnerable groups, such as persons with disabilities, during extreme weather or major holidays. Finally, because findings are rooted in Guangzhou's specific "Eastward Industry, Southward Population" structure, the ESDR thresholds may vary in cities with different topographical or morphological constraints.

5.3. Future Research Directions

To further refine megacity service systems, future research should explore the integration of higher-frequency data and advanced predictive tools. Integrating real-time anonymous signaling or social media check-in data could shift "flow space" analysis from the sub-district level down to the community micro-grid level, allowing for a more dynamic monitoring of urban system pressure.

Leveraging Digital Twin technology could further refine assessments by incorporating interior layouts and vertical business distribution into the coupling entropy model, moving beyond mere building envelopes. Additionally, developing machine learning-based predictive models to simulate behavioral responses under various urban renewal scenarios can provide intelligent decision support for community life circle optimizations.

Future studies should also transition toward longitudinal panel data and cross-city comparisons to verify the robustness of the BCE and ESDR framework across diverse urban morphologies.

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