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ASSOCIATIONS BETWEEN LAND-USE MIX AND THE DIVERSITY OF URBAN PARK ACTIVITIES: EVIDENCE FROM SIX DISTRICTS OF GUANGZHOU, CHINA

Xuan Qiu[1], Mengxiao Jin[2] and Quanyi Zheng[3,*]

[1]College of Intelligent Building Engineering
Guangxi City Vocational University
No. 655, Tongzheng Road, Konggangjingji District, Nanning 532100, P. R. China
xuanqiu_harbin@163.com

[2]School of Innovation and Creative Design
Shenzhen Polytechnic University
No. 3, Vocational Education Street, Futian District, Shenzhen 518052, P. R. China
jinmengxiao@szpu.edu.cn

[3]Department of Tourism Management
Shenzhen Tourism College of Jinan University
No. 6, Qiaocheng East Street, Nanshan District, Shenzhen 518053, P. R. China
*Corresponding author: zhengquanyi@jnu.edu.cn

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Abstract. *Given the critical role of the Diversity of Leisure Activity Types (DLAT) as an indicator of park vitality and equitable green space access, it has become a strategic priority in urban planning. However, most existing studies have focused on internal park characteristics, while the impacts of the surrounding land-use composition (Degree of Land-Use Mix, DLUM) remain underexplored. To address this gap, this study investigates the relationship between DLUM and DLAT for urban parks and open squares across six central districts of Guangzhou, China. Based on multi-source POI and activity data, we quantify DLAT and POI-based DLUM using Hill numbers, link activity records to park areas of interest, measure POI mixing on a 1000 × 1000 m grid and aggregate to individual parks, and examine relationships using correlation analysis, quadratic regression, and factor analysis with spatial robustness checks. Results demonstrate a significant association between DLUM and park DLAT and reveal that parks and open squares differ in sensitivity to POI combinations: parks respond most strongly to combinations of shopping, leisure/entertainment and transportation POIs, whereas open squares are most sensitive to leisure, residential and shopping POIs. These findings provide empirical guidance for optimizing surrounding land-use mix to improve park activity diversity and support urban green-space planning and management.*
Keywords: Diversity of Leisure Activity Types (DLAT), Degree of Land Use Mix (DLUM), Urban park, POI type, Leisure activities

1. Introduction.

1.1. Background.
As a core indicator of park vitality, attractiveness, and the level of spatial service provision, the Diversity of Leisure Activity Types (DLAT) acts as a crucial measure for assessing the effectiveness of urban park planning [1]. Urban parks function as central hubs for recreation, physical activity, and social interaction, and the enhancement of their DLAT is directly linked to the promotion of public health [2,3]. In contrast to the depth of research on internal park features, the impact of the surrounding urban fabric,

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particularly the mix of land uses, is less understood, even though land-use mixing is known to increase active leisure [4]. Challenges in park planning often stem from insufficient consideration of this contextual factor [5]. Reasonable allocation of land functions around urban parks can enhance their vitality and attract more users, thus becoming a key concern for urban planners and managers aiming to improve park service effectiveness.

1.2. **Literature review.**

1) Land-use mix and its measurement. Land-use mix denotes the coexistence of multiple functions within a spatial unit, achieved through planning and regulation [6]. The Degree of Land-Use Mix (DLUM) quantifies the functional heterogeneity and spatial aggregation in a given area. Conventional land-use inventories are often too coarse to capture fine-grained, on-the-ground functional patterns. In contrast, Point-of-Interest (POI) data, which reflect activity-supporting urban functions at a near-building scale, enable more precise measurement [7-10]. To quantify such functional diversity, Hill numbers – a family of diversity indices – are widely adopted as they integrate richness, evenness, and aggregation of categories into a comprehensive metric [11,12]. Their application to POI data has been validated as an effective approach for assessing mixed urban functions [9].

2) Leisure activities. Leisure, as formally defined by the 1970 *Leisure Charter*, refers to the discretionary time when individuals are free to pursue activities that realize personal and social values [13]. Urban parks are outdoor public green spaces that serve core functions of recreation, fitness and viewing, and they also provide important venues for social interaction and various leisure pursuits [8,14,15]. Empirical studies of park utilization have traditionally relied on single-source data such as GPS tracking, travel surveys or social media check-in records to measure activity intensity and patterns [16,17]. While these approaches have yielded important insights, single-source datasets can be biased in terms of user demographics or temporal coverage.

3) Diversity of Leisure Activity Types (DLAT) and its determinants. DLAT captures the range of activity types a park supports and is used as a proxy for park vitality and service provision. Existing measurement methods (e.g., GPS traces, and check-in data) primarily emphasize activity intensity or frequency but often lack comprehensive diversity-oriented metrics. Several studies have linked built-environment features to leisure and physical activities – showing, for example, that higher land-use mixing is associated with greater participation or longer durations of active leisure [4]. However, most of this work has focused on either intra-park attributes or single data sources, leaving open the question of how surrounding land-use mix (as a multi-dimensional measure) relates to DLAT at the city scale.

Building on the preceding discussion, the existing literature exhibits the following significant gaps. First, there is a lack of data integration. Most studies rely on single data sources (e.g., GPS or social media) to analyze park activities, with limited use of multi-source behavioral data to comprehensively capture diverse user groups and activity types. Second, methodological integration remains insufficient. Although various methods are available for measuring the Degree of Land-Use Mix (DLUM), few studies combine POI-based Hill-number diversity metrics with multi-source activity data to explore the Diversity of Leisure Activity Types (DLAT) in parks. Third, there is inadequate comparative and nonlinear analysis. Empirical evidence is lacking on whether different park types exhibit distinct responses to specific POI combinations or if the relationship between DLUM and DLAT is nonlinear.

1.3. **Objectives and research questions.** This study addresses these gaps by examining the relationship between the surrounding land-use mix – measured as POI-based DLUM using Hill numbers – and the Diversity of Activity Types (DLAT) in urban parks and open squares across six central districts of Guangzhou, China. Expanding upon previous district-scale research [15], it broadens both spatial coverage and data diversity. The specific objectives are to 1) quantify DLAT for a large sample of parks and squares using multi-source behavioral data; 2) measure surrounding POI mixing (DLUM) with Hill-number indices derived from fine-scale POI data; and 3) analyze the associations between DLUM and DLAT, assessing nonlinear patterns and differential sensitivities by park type and POI combinations. Correspondingly, the study seeks to answer 1) whether a significant association exists between park DLAT and surrounding POI mixing; 2) if parks and squares show different sensitivities to POI types and mixtures; and 3) which POI types or combinations are most strongly linked to higher DLAT.

1.4. **Contributions of the study.** The contributions of this study are fourfold. First, it extends the spatial scope from a single district to six central districts of Guangzhou (encompassing 349 parks and squares), enhancing representativeness and statistical robustness. Second, it integrates multi-source data (e.g., Tencent Pintu VGI and social media check-ins) to improve population coverage and reduce age-related biases. Third, it methodologically integrates multi-source behavioral data with POI-based Hill-number measures to quantify DLAT and DLUM at a fine spatial scale. Fourth, moving beyond aggregate associations, it reveals typological differences in sensitivity to POI mixes and identifies a nonlinear (concave) relationship – suggesting an optimal range of POI mixing for maximizing park vitality.

The rest of this paper is structured as follows. Section 2 describes the data and methods; Section 3 reports empirical results; Section 4 discusses implications for urban planning and park management; and Section 5 presents the conclusions.

2. Data and Methods.

2.1. Study data.

2.1.1. *Study scope.* Located in the southern part of Guangdong Province, China, Guangzhou City is one of the important cities in the Guangdong-Hong Kong-Macao Greater Bay Area. In 2024, Guangzhou has 11 districts under its jurisdiction, covering a total area of 7434.40 km^2 with a population of 18.98 million. This study investigated the main urban area of Guangzhou, including the six administrative districts of Yuexiu, Liwan, Haizhu, Tianhe, Baiyun and Huangpu, with a total area of 1559.59 km^2, which is the center of Guangzhou's administration, culture, finance and information (Figure 1).

2.1.2. *Data sources.*

1) POI data. Based on the API port of Baidu Map Open Platform, a total of 482,680 POI data was collected and then visualized through ArcGIS platform (Figure 2). Since the amount of data is large and complicated, and the coordinate system is the Mars coordinate system, the data cannot be calculated directly. Therefore, the data needs to be preprocessed, the data irrelevant to the study needs to be deleted, and the coordinate system needs to be converted to the WGS-84 coordinate system. According to China's "Urban Land Classification and Planning and Construction Land Standard (GB 50137-2011)", POI data is divided into residential, management services and public facilities, medical and scientific and educational services, leisure and entertainment, public service facilities, industrial land, transportation facilities, shopping, catering services, hostel land, etc. (Figure 3).

In addition, POI data for 349 urban parks, each covering an area of at least 2 hm^2, was obtatined from the six districts within the study area. According to Guangzhou's "Urban Park Classification", urban parks are divided into open squares (squares, linear green

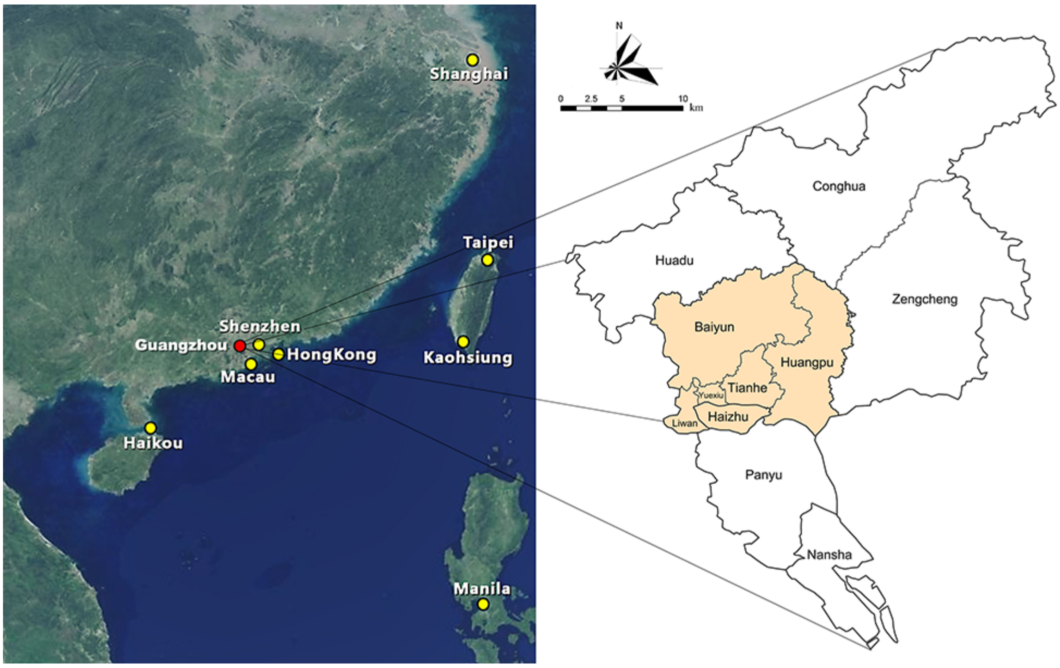


FIGURE 1. Location of study area: 6 districts of Guangzhou

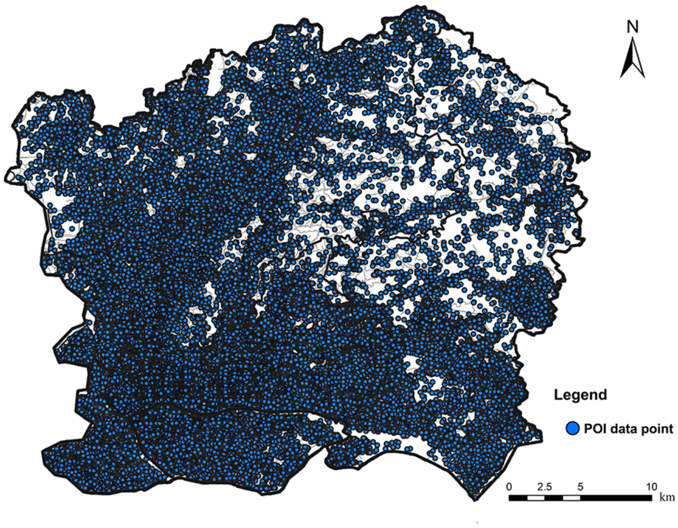


FIGURE 2. Distribution map of POIs in the study area

spaces, and street-side green spaces) and parks (comprehensive parks and community parks). All these places are free to enter.

2) Weibo check-in data. A total of 34,332 Weibo check-ins (collected from 2025-07-08 to 2025-10-08) were obtained via the Weibo API. Raw Weibo data were preprocessed as follows. First, we conducted semantic filtering to remove non-leisure posts: an initial keyword-based filter (e.g., "walk", "jog", "exercise", "dance", "park", "square", "outing", and "playing") was applied, followed by manual inspection of a random sample to refine the keyword list and remove systematic false positives. Second, records lacking geolocation (longitude/latitude) or with invalid coordinates were excluded. Third, duplicate check-ins (same user ID at identical coordinates and timestamp, or within a 5-minute window at the same location) were deduplicated. Fourth, text content and timestamps were parsed

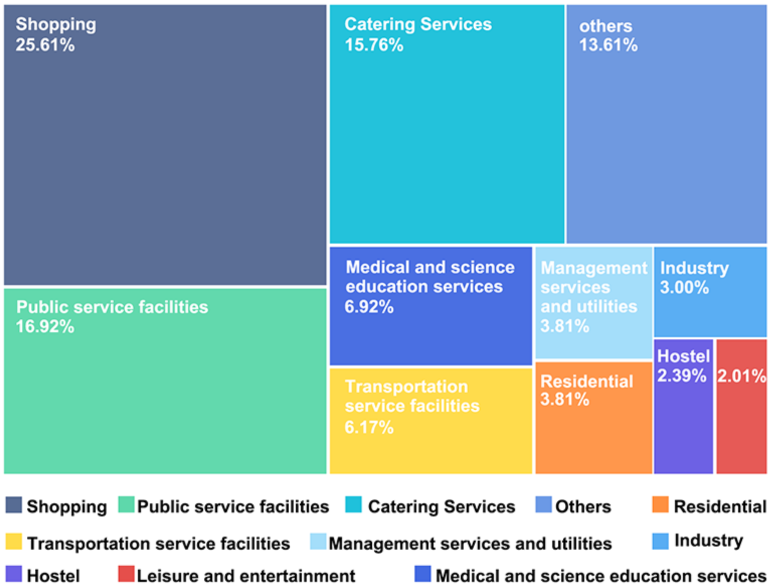


FIGURE 3. Classification map of POIs

to extract activity type and time-of-day labels. After these steps, the number of retained Weibo records used for DLAT calculation was 33,291.

3) VGI data of Tencent Pintu. Pintu is a cross-platform geographic information data collection platform developed by Tencent. It can collect geographic information on research objects on PC and mobile phones. The researchers collected data on adolescents under the age of 18 and older adults over the age of 60. VGI (Volunteered Geographic Information) data obtained from Tencent Pintu, a WeChat-based participatory mapping platform, includes the user's personal attributes (such as gender, age, and occupation), location information, and leisure activity data (activity type, activity intensity, frequency, and duration). The researchers used Pintu to obtain 2,422 VGI data points within three months (2024.10.6-2025.1.9), including 1,183 records on the elderly. This dataset compensated for the inadequate coverage of certain demographic groups inherent in Weibo check-in data. The remaining 1,239 records are for teenagers under the age of 18. Finally, Weibo check-in data and VGI data were merged and visualized by ArcGIS. A total of 35,713 data points of location data were acquired.

4) Other data. The electronic map data were obtained from the Open Street Map (OSM) website in 2025. OSM is a global open source city map data, and the map data of cities around the world can be downloaded for free. The administrative boundary data comes from the data of Guangzhou urban planning land use vector map in 2025.

2.1.3. *Data preprocessing and merging.* The VGI (Tencent Pintu) dataset comprises 2,422 records collected from 2024-10-06 to 2025-01-09, including 1,183 records identified as elderly respondents (age ≥ 60). After the separate preprocessing of each source (semantic filtering, coordinate validation and deduplication as described above), Weibo and VGI datasets were merged using a spatial and attribute-based procedure to link activity records to park AOIs (200-m walking buffer). The merging steps were

1) Coordinate system harmonization: All geographic coordinates were converted to WGS-84.

2) Spatial linkage: Each check-in/VGI point was spatially joined to park AOIs (200-m buffers) to assign park IDs. Records outside any park AOI were excluded from park-level DLAT analysis.

3) Temporal and duplicate handling: Where records from both sources referred to the same user/time/location (same user ID or identical coordinates within a 30-second window), duplicates were consolidated and a single record retained. Where user identifiers differed but spatio-temporal proximity indicated potential duplication (i.e., identical coordinates within 5 minutes), records were considered distinct unless metadata suggested otherwise.

4) Attribute priority rules: For demographic attributes (age, gender), values from VGI were prioritized because VGI includes explicit user attributes. In case where VGI were missing, available Weibo metadata were utilized; otherwise, age/gender were labeled as missing.

5) Final merged dataset: After merging, the combined dataset comprised 35,713 location/activity records (33,291 Weibo + 2,422 VGI). Of the 2,422 VGI records, 1,183 (48.84%) were elderly (age $\geq$ 60), accounting for 1,183/35,713 $\approx$ 3.31% of the merged dataset. It is important to note that Weibo profiles generally lack reliable age labels, consequently the proportion of elderly in the Weibo-only subset could not be directly computed; therefore, the VGI data were used to supplement under-represented age groups (adolescents and elderly) and to improve age coverage in the merged dataset. Where possible, missing ages in Weibo were estimated via user profile and textual cues and flagged as estimated.

All personal identifiers were removed prior to analysis to protect privacy. Spatial aggregation was performed at the park AOI level (using a 200-m buffer) so that no individual trajectories were reported. Finally, coordinate validation and conversions were conducted in ArcGIS to guarantee spatial accuracy.

2.2. **Method.**

2.2.1. *Calculation of DLUM.* Kudas et al. utilized Hill Numbers to calculate DLUM from multiple dimensions, and demonstrated that the POI mixture degree can characterize land use at a finer scale [12]. The formula is expressed as follows:

$$D = \left(\sum_{i=1}^{n} p_i^q \right)^{1/(1-q)} \tag{1}$$

In the formula, D is the diversity; n is the number of POI species; p_i is the relative diversity of the i-th POIs, which can be the area ratio or the number ratio; The parameter q is the order, which reflects the sensitivity of the diversity index to species, and the value of q is 0-2. The Gini-Simpson concentration index ($q = 2$) in the Hill Numbers diversity index was selected to measure the POI mixture in the six districts of Guangzhou [18]. The formula is as follows:

$$D = 1 \bigg/ \left(\sum_{i=1}^{n} p_i^2 \right) \tag{2}$$

We selected urban parks and open squares with an area $\geq$ 2 ha to ensure sufficient activity space and reliable behavioral records for DLAT estimation (this threshold aligns with common park-classification criteria). For measuring POI mixing, we compared three grid resolutions (500 $\times$ 500 m, 1000 $\times$ 1000 m and 2000 $\times$ 2000 m). A finer grid (500 m) tends to split individual parks across multiple cells, requiring aggregation of cell-level POI measures for a single park; a coarser grid (2000 m) often contains multiple parks within one cell, reducing sensitivity to local land-use differences. The 1000 $\times$ 1000 m grid was chosen as the primary resolution because it offers a practical balance between minimizing excessive park fragmentation and preserving variability in surrounding land-use. When a park's 200 m AOI overlapped several grid cells, we aggregated POI mixing by averaging the DLUM values of the overlapping cells to obtain the park-level DLUM. Where a grid cell contained multiple parks, the same cell-level DLUM value was assigned to each overlapping park.

2.2.2. *Calculation of DLAT for urban parks.* The calculation of DLAT for urban parks is based on Weibo check-in data and VGI data. Since different leisure activity types and land function types are essentially characterized by their type diversity, the calculation principle of DLAT is consistent with that for POI mixing. Therefore, the DLAT of urban parks is calculated using Formula (2). The land function around the urban park has an impact on the DLAT of urban parks within a certain range. Studies have shown that the 200 m threshold is the maximum acceptable walking distance for park visitors [8]. Consequently, the 200 m buffer zone derived form the urban park vector AOI was defined as the study area. If the AOI of the city park has overlapping parts, take the average value. The merged data (VGI data and Weibo check-in data) will be linked with the AOI vector data in the 200 m buffer of urban parks. Finally, DLAT of urban parks is calculated according to the formula, and the calculated results are correlated with the original vector data of city parks (Figure 4).

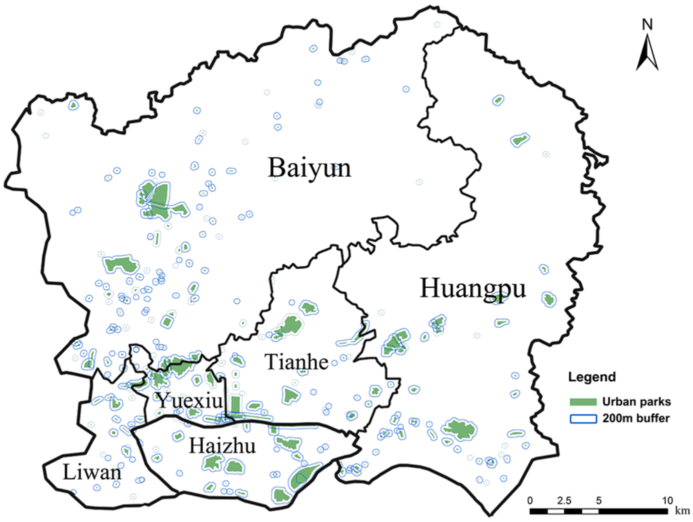


FIGURE 4. AOI distribution of urban parks and their 200 m buffer zone

2.2.3. *Influence mechanism of POI mixture degree on DLAT in urban parks.* From the Tencent Pintu VGI dataset described in Section 2.1.2, 1,183 (1,183/2,422 = 48.84% of VGI; 1,183/35,713 ≈ 3.31% of merged dataset) records were from respondents aged ≥ 60 (hereafter "elderly VGI respondents"). Among those 1,183 elderly respondents, 812 indicated that they were willing/able to walk up to 1 km to reach an urban park. We therefore use a 1-km service radius as a conservative upper bound for examining the broader influence of surrounding land functions on park DLAT in the influence-mechanism analysis. Note that DLAT calculations themselves use the 200-m AOI described in Section 2.2.2 (to capture immediate park catchment), and we explicitly distinguish these two spatial choices in the manuscript. The 1 km distance threshold is mainly inferred from VGI data collected from elderly respondents and may therefore not be directly generalizable to other age groups. To mitigate this limitation, we tested multiple spatial thresholds, including the 200-m AOI used in the DLAT calculation and alternative buffer distances. While the magnitude of the estimated coefficients shows some sensitivity to spatial scale, the overall patterns and statistical significance of the key variables remain largely unchanged. These results indicate that the core conclusions of this study are robust to reasonable variations in the assumed walking distance. First, the POI mixture calculated above will be linked with the AOI surface of the urban park DLAT. If the AOI area of an urban park covers multiple square grids, the covered square grids need to be averaged. Second, the linked data were mapped and visualized using ArcGIS. Finally, the calculation results of the two are correlated by SPSS software, and then the influence mechanism of POI mixture degree around urban parks on DLAT of urban parks is examined. In addition, the method for the impact mechanism of POI mixture around urban parks on different types of parks is the same as above.

2.2.4. *Influence of POI types on DLAT in various urban parks.* Different POI types have different effects on different types of urban parks, and there are many variables and complex interactions. Therefore, factor analysis was chosen to analyze this issue, and the effects of different combinations of POI types on different types of urban parks were explored. Factor analysis is a multivariate statistical analysis method to study the internal dependence of indicators. It aims to find a few dominant factors in many related factors through dimensionality reduction technology, to comprehensively reflect most of the information of all variables, and remaining mutually independent. Then, the influence of each factor, that is, the degree of importance, is determined according to the variance contribution rate of the factor [19]. The types and sizes of POIs vary greatly. Some POI types are smaller in size and related POI types are merged. In order to facilitate the calculation and analysis in the following text, the 11 types of POI in the previous article are reduced to 8 types: catering services, leisure and entertainment, residential, industrial, shopping, transportation facilities, hotel, and comprehensive public facilities.

To examine associations between park DLAT and surrounding POI mixing (DLUM) and to identify potential non-linear patterns, correlation and curve estimation analyses were conducted. Variable distributions were first assessed using the Shapiro-Wilk test; Pearson correlation coefficients were reported for normal distributed variables, with Spearman rank correlations used as robustness checks when normality was violated or outliers were present. Correlation analyses were performed for the full sample and separately by park type (parks vs. open squares).

To examine potential non-linear relationships between surrounding land-use mix and park activity diversity, we performed a quadratic curve estimation using the following model:

$$\mathrm{DLAT}_i = \beta_0 + \beta_1 \mathrm{DLUM}_i + \beta_2 \mathrm{DLUM}_i^2 + \varepsilon_i \tag{3}$$

where DLAT_i denotes the diversity of leisure activity types of park i, DLUM_i is the level of surrounding land-use mix, β_0-β_2 are estimated coefficients, and ε_i represents the random error term capturing unobserved influences on DLAT.

All correlation and quadratic models were estimated for the full sample and for samples stratified by park type (parks vs. open squares) to identify differential sensitivities. Additional robustness checks were conducted using alternative grid and buffer sizes. Spatial autocorrelation in both DLAT and model residuals was assessed using Moran's I; when significant, spatial regression models (spatial lag or spatial error) were applied as robustness checks. For each analysis, we report correlation coefficients, sample size, p-values, quadratic regression parameters and goodness-of-fit statistics, and present results using scatterplots with LOESS smoothers and fitted curves.

3. Results and Analysis.

3.1. **Measurement of POI mixing degree.** POI density is the basis for POI mixing degree calculation. The obtained POI data were analyzed by ArcGIS for visualization of POI density (Figure 5). The POI density gradually increased from northeast to southwest. The northeastern part of Baiyun District and the northern part of Huangpu District are mostly parks, mountains and other natural environments, and the POI density in these areas is very low. Yuexiu District, the western part of Tianhe District, the northern part of Haizhu District and the northeastern part of Liwan District are the centers of office, transportation, commerce and residential, and the POI density in this area is very high. The basis of POI mixing is POI density. The high density of POI indicates that the land has multiple functions. The combination of various types of land functions is conducive to enhancing the vitality of the city, and will also enhance the mixed use of land functions [20]. Therefore, the greater the density of POIs, the higher the urban vitality of the area. Urban vitality is positively correlated with the degree of land-use mix [18].

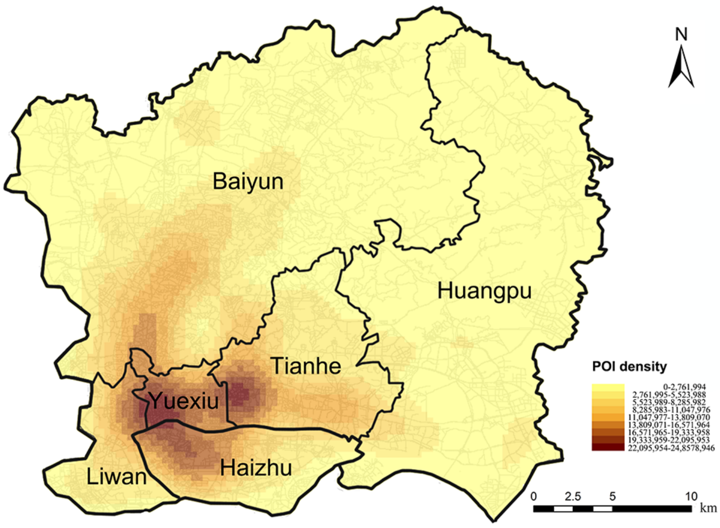


FIGURE 5. (color online) Spatial distribution of POI density in the study area

The POI mixture degree values of the six districts in Guangzhou were calculated by Formula (2), and the calculation results were visualized in ArcGIS. A higher value indicates a high degree of mixed land use, whereas the opposite indicates that the area is a single function or empty land. The POI mixing degree varies greatly among administrative regions (Figure 6). The low value area (0.000-1.213) is mainly concentrated in the north and east of Baiyun District and most of the Huangpu District. Since the area is mostly production land, country parks and natural environment, the population density and POI density are low. The high-value areas (5.633-7.742) are in the southern part of Baiyun District, Yuexiu District, eastern Liwan District, northern Haizhu District and Tianhe District. This is the area where multiple types POIs are concentrated. Compared with Figure 5, the regions with high POIs density have higher mixing degree. Conversely, the degree of mixing is lower. Low-value areas are mostly natural environment, green space, production land, wasteland or land with single function. However, there are also special areas, such as Yuexiu District, where the POI density value is very high, but the degree of mixing is not high. This is because the single land function in this area is strong, so that other land functions are homogenized, forming a single function center for office and business. POIs mixed degree value can describe the degree of diversity of land-use mix, and

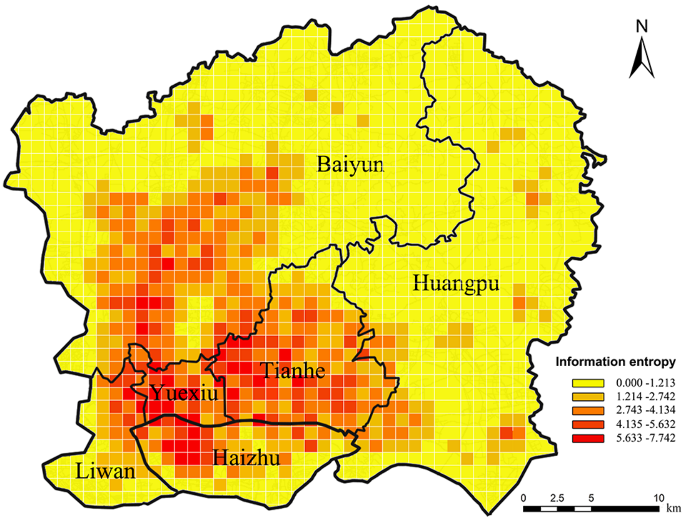


FIGURE 6. (color online) Spatial pattern of POI mixing degree in the study area

the data is visually analyzed by ArcGIS, which can describe the structural characteristics of urban space.

3.2. **Measure of DLAT in urban parks.** The calculated DLAT values in the study area were visually analyzed by ArcGIS (Figure 7). The overall vitality of urban parks in the study area is poor. If the value is high, the vitality of urban park is good; otherwise, the vitality of urban park is poor. The urban parks with high DLAT (≥ 5.213554) are mainly concentrated in Yuexiu District, west of Tianhe District, north of Liwan District and northwest of Haizhu District. These places are the concentrated areas of high-quality parks in Guangzhou, and they are representatives of urban parks with high vitality. The urban parks with low urban vitality (≤ 2.021002) are mainly concentrated in the central parts of Baiyun and Huangpu District, as well as the central and southern part of Haizhu District. The urban parks in the central Huangpu District of Baiyun District have the lowest DLAT values. Overall, urban parks with a DLAT value higher than 4.142081 are urban parks with high urban vitality, accounting for 31.34%. The DLAT value of

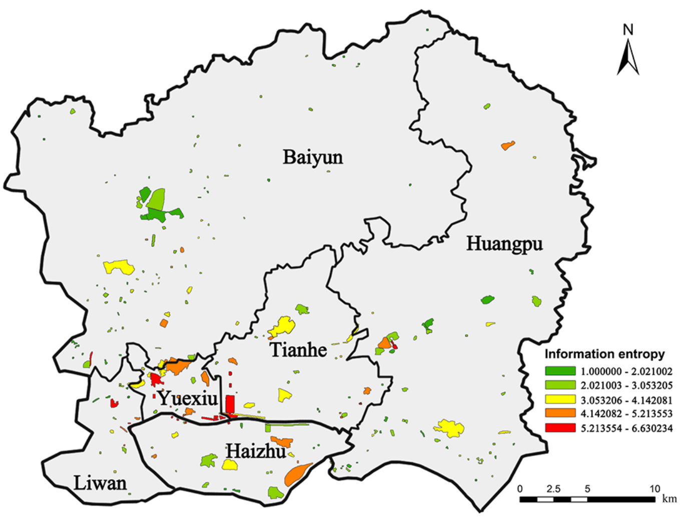
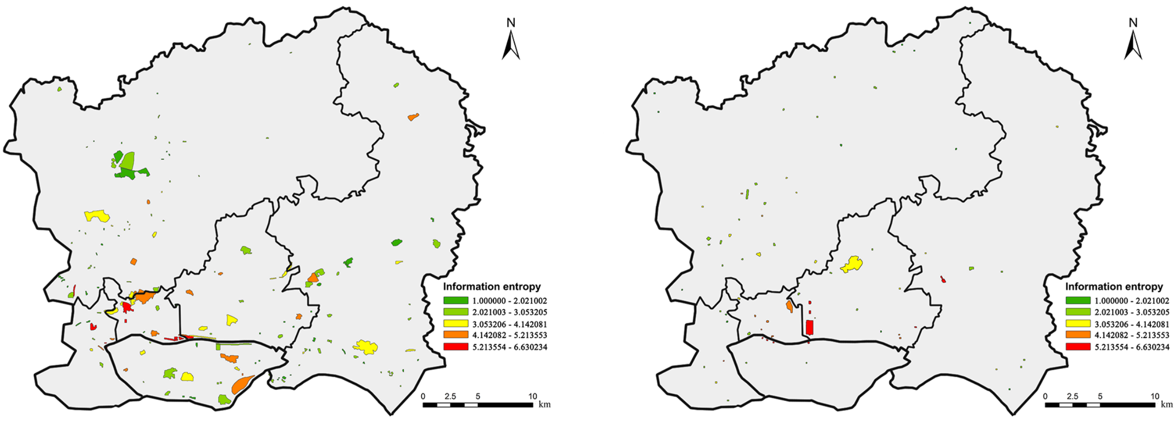


FIGURE 7. (color online) Total DLAT of urban parks in the study area

3.053206-4.142081 belongs to urban parks with moderate urban vitality, accounting for 19.56%. Urban parks with a DLAT value lower than 3.053206 belong to urban parks with poor urban vitality, accounting for 49.1%.

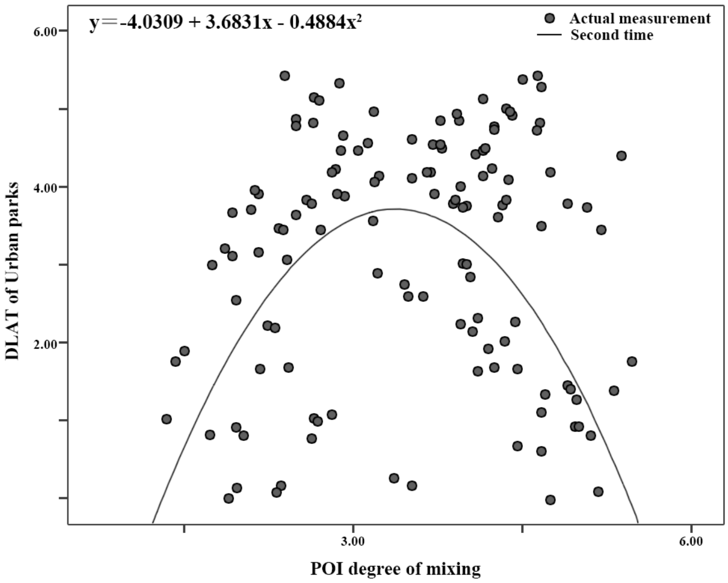
The DLAT of different types of urban parks varies greatly. Comparing parks and open squares, the overall DLAT value of parks is higher than that of open squares (Figure 8(a)). The high-vitality parks with a DLAT value higher than 4.142081 accounted for 43.58%, while the proportion of open squares was only 23.13% (Figure 8(b)). On the one hand, the function of the open square is single. Although the activity area is large, there are few types of space inside. As a result, the types of leisure activities are limited, open squares are underutilized, and residents are unable to visit. On the other hand, the poor environmental quality of open squares and the aging and insufficient supporting service facilities are the reasons for their low DLAT values. Compared with the open square, parks' geographical location, natural environment, internal space, supporting facilities and service management level are very high, which is the main reason why they attract residents to visit.



(a) (b)

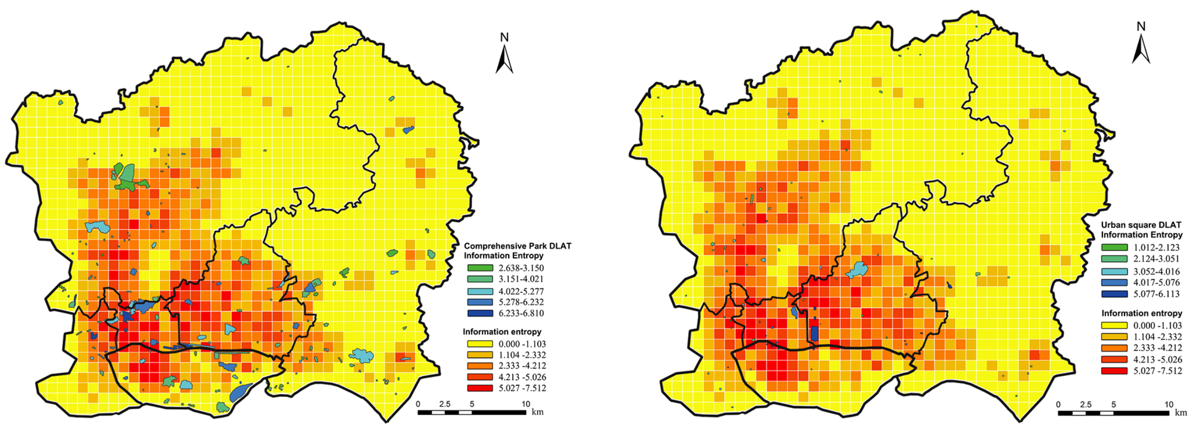
FIGURE 8. (color online) DLAT of urban parks: (a) Park DLAT in the study area; (b) open square DLAT in the study area

3.3. **Influence mechanism of POI mixing degree on DLAT.** The data of POI mixing degree and urban park DLAT were correlated in SPSS. It was found that there was a significant correlation between the two (Figure 9). The relationship follows an inverted U-shaped trajectory: initially rising and subsequently declining. In the ascending phase, land-use mix and DLAT are positively correlated. Theoretically, land surrounding urban parks that is single-function or vacant fails to attract visitors. People are the source of vitality of urban space. The greater the flow of people per unit area, the greater the probability of residents going to urban parks for leisure activities, and the higher the DLAT of urban parks [2]. The higher land-use mix around urban park, the more residents will be attracted, which will greatly increase the probability of residents' leisure activities, and the DLAT value will be higher. The model was estimated using Ordinary Least Squares (OLS). When heteroskedasticity was detected, robust standard errors were applied. As shown in Figure 9, DLAT exhibits a significant concave relationship with surrounding DLUM. Based on the estimated coefficients, the maximum of the fitted curve occurs at DLUM ≈ 3.77, with a corresponding predicted DLAT ≈ 2.91. Although the present analysis is correlational, this pattern may reflect a potential competitive relationship



Note: The curve represents the fitted quadratic regression between the degree of land-use mix (DLUM), measured by the POI degree of mixing, and the diversity of leisure activity types (DLAT). The equation $y = -4.0309 + 3.6831x - 0.4884x^2$ was obtained by estimating a second-order polynomial regression model using ordinary least squares (OLS), where DLAT is the dependent variable (y) and DLUM is the independent variable (x).

Figure 9. Correlation between POI mixture and DLAT in urban parks



(a) (b)

Figure 10. (color online) Coupling of urban parks DLAT and POI mixing degree: (a) Coupling of park DLAT and POI mixing degree; (b) coupling of open square DLAT and POI mixing degree

between urban parks and surrounding land uses at high levels of land-use mix. Highly mixed surrounding environments may offer alternative leisure opportunities, which could reduce the relative concentration and diversity of leisure activities occurring within urban parks. Further studies using causal or behavioral data are needed to test this mechanism.

To understand the impact of POI mixture on different types of urban parks, the DLAT of POIs for parks and open squares was calculated separately by type, and they were coupled with their surrounding POI mixtures, and their correlations were calculated (Figures 10(a) and 10(b)).

From the results of the correlation analysis, it can be seen that the fitting curves of parks and open squares are consistent with the overall curves, and they are both inverted U-shaped distributions that initially rise and then fall (Figures 11(a) and 11(b)). Most of the parks are concentrated in the ascending interval, and the mixture of parks and POI is positively correlated (Figure 11(a)). Most of the open squares are concentrated in the descending interval, and open squares and POI mixing are negatively correlated (Figure 11(b)). Compared with the park, the curve for open squares is narrower, and the downward trend is more obvious. It shows that open squares are more sensitive to the POI mixing degree.

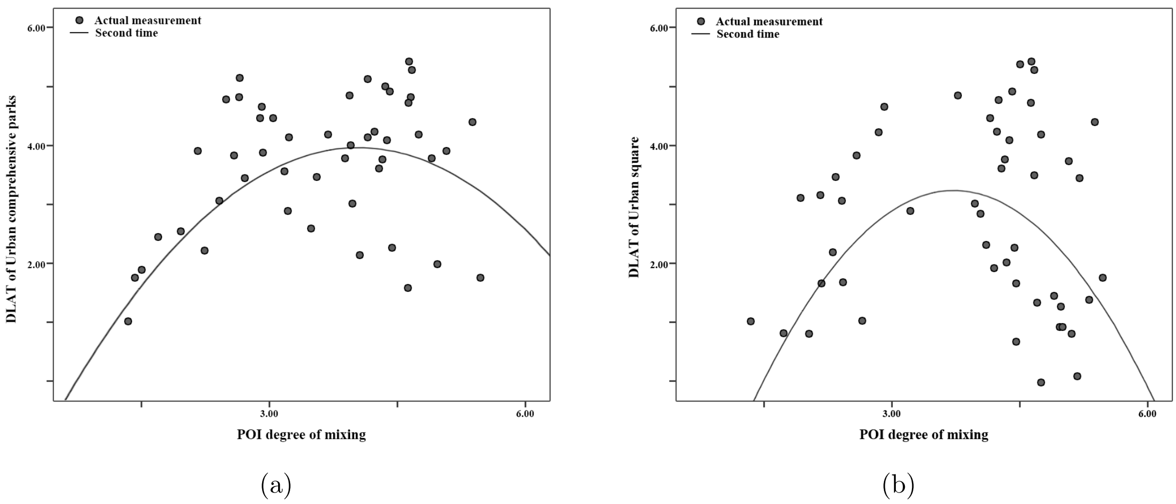


Figure 11. Correlation between POI mixture degree and DLAT of urban parks: (a) Correlation between POI mixture degree and DLAT of parks; (b) correlation between POI mixture degree and DLAT of open squares

3.4. **Influence of POI types on DPAT of various urban parks.** As shown in the results above, the DLAT of parks and open squares has different sensitivity to POI mixing, which is caused by different POI types affecting the DLAT of different types of urban parks. After calculation, the sensitivity of parks to POI types (Table 1 and Table 2): shopping > leisure and entertainment > transportation facilities > catering services > industrial land > residential > comprehensive public facilities > hotel land. The sensitivity of open square DLAT to POI types (Table 3 and Table 4): leisure and entertainment > residential > shopping > catering service > industrial land > hotel land > transportation facilities > complex public facilities. After comparison, it is found that the POIs of shopping, leisure and entertainment and catering services have a great influence on the DLAT of parks and open squares. These three types of functions account for as high as 43.38% of POI, and the combination of the three types of land functions can attract a lot of passenger flow. There is an interactive and complementary relationship between business activities and leisure activities [12]. Residents who complete commercial activities are more likely to go to nearby parks for leisure activities. In addition, the POI of transportation facilities has a greater impact on the DLAT of parks; the POI of the residential areas has a greater impact on the DLAT of open squares. Notably, urban parks are sensitive to POI of industrial land. In Guangzhou, industrial zones often includes high-tech industrial parks rather than traditional manufacturing sites. They are high-tech industrial parks with complex functions, which are equipped with a large number of shopping, entertainment, catering and other functions. Therefore, it will attract a large number of residents. To sum up, the POI combination of shopping, leisure and entertainment and transportation facilities has the greatest impact on the DLAT of parks; the POI combination of leisure and entertainment, residential and shopping has the greatest impact on the DLAT of open squares.

TABLE 1. Sensitivity quantification of park DLAT to different POI types (1)

Type	Common factor variance Initial	Common factor variance Extract	Type	Component matrix α Component 1	Component matrix α Component 2	Type	Factor analysis results	Contribution
Catering Services	1.000	0.814	Catering Services	0.887	−0.038	Shopping	0.867	0.140184
Shopping	1.000	0.872	Shopping	0.141	0.916	Leisure and entertainment	0.842	0.138518
Public facilities	1.000	0.677	Public facilities	0.813	0.061	Transportation facilities	0.831	0.133891
Transportation facilities	1.000	0.835	Transportation facilities	0.914	0.081	Catering Services	0.803	0.130125
Residential	1.000	0.721	Residential	0.843	−0.142	Industry	0.786	0.129932
Industry	1.000	0.786	Industry	0.867	−0.159	Residential	0.721	0.121561
Hostel	1.000	0.584	Hostel	0.686	0.337	Public facilities	0.682	0.109514
Leisure and entertainment	1.000	0.843	Leisure and entertainment	0.908	−0.198	Hostel	0.585	0.096275

TABLE 2. Sensitivity quantification of park DLAT to different POI types (2)

Composition	Total variance explained					
	Initial eigenvalues			Extract the load sum of squares		
	Total	Percent variance	Cumulative percentage	Total	Percent variance	Cumulative percentage
1	4.936	62.114	62.114	4.936	62.114	62.114
2	1.138	12.912	75.026	1.138	12.912	75.026
3	0.673	9.178	84.204			
4	0.532	6.972	91.176			
5	0.312	4.810	95.986			
6	0.286	2.512	98.498			
7	0.085	1.021	99.519			
8	0.038	0.481	100			

TABLE 3. Sensitivity quantification of open square DLAT to different POI types (1)

Type	Common factor variance Initial	Common factor variance Extract	Type	Component matrix α Component 1	Component matrix α Component 2	Type	Factor analysis results	Contribution
Catering Services	1.000	0.763	Catering Services	0.863	−0.147	Leisure and entertainment	0.921	0.146283
Industry	1.000	0.781	Industry	−0.032	0.878	Residential	0.802	0.134595
Public facilities	1.000	0.703	Public facilities	0.788	0.268	Shopping	0.781	0.126286
Transportation facilities	1.000	0.731	Transportation facilities	0.851	0.059	Catering Services	0.765	0.124371
Residential	1.000	0.825	Residential	0.883	−0.221	Industry	0.749	0.122534
Shopping	1.000	0.768	Shopping	0.867	−0.063	Hostel	0.731	0.117881
Hostel	1.000	0.731	Hostel	0.371	0.779	Transportation facilities	0.727	0.114129
Leisure and entertainment	1.000	0.898	Leisure and entertainment	0.928	−0.168	Public facilities	0.711	0.113921

Table 4. Sensitivity quantification of open square DLAT to different POI types (2)

Total variance explained						
	Initial eigenvalues			Extract the load sum of squares		
Composition	**Total**	**Percent variance**	**Cumulative percentage**	**Total**	**Percent variance**	**Cumulative percentage**
1	4.512	56.825	56.825	4.512	56.825	56.825
2	1.446	19.251	76.076	1.446	19.251	76.076
3	0.787	9.022	85.098			
4	0.541	5.692	90.79			
5	0.336	4.081	94.871			
6	0.181	2.726	97.597			
7	0.134	1.821	99.418			
8	0.053	0.582	100			

4. **Discussion.** The results of the study show that different types of urban parks have obvious differences in adapting to the surrounding support environment. In China, traditional urban planning usually adops the planning area as the unit, the "per capita" as the indicator, and the balance of land use as the goal when configuring the supporting environment around urban parks. Norminally, this achieves per capita targets, but in pratice, the outcomes are often suboptimal. Overall, the DLAT of urban parks and the POI mixture around urban parks show a normal distribution curve that first increases and then decreases. When their fitting function reaches the peak, it begins to show a negative correlation, and open squares are more affected by POI mixing than parks. The reason is that the location of parks and open squares is different in the city. Parks usually occupy better locations in the city, while open squares take less attractive fields. The impact of location on land functions will form various combinations with social development and time changes, and of course, will also affect residents' access. In China, traditional urban planning emphasizes meeting the needs of residents when adapting to the environment, but often overlooks the implememtation mechanisms and functional efficiency of land functions; The "compatibility" of land functions is emphasized, while the impact of land functions on the surrounding environment is less considered.

In summary, the DLAT of parks is most sensitive to the combination of land function types of shopping, recreation and transport; the DLAT of open plazas is most sensitive to the combination of land function types of leisure and entertainment, residential and shopping. Therefore, the DLAT of urban parks can be improved to attract residents to visit urban parks by adjusting the mix of land functions around urban parks. The process is as follows. On the one hand, it is necessary to determine the stage of the relationship curve between the DLAT of urban parks and the surrounding land functions. If they are in the rising stage, the DLAT of the park can be improved by increasing the land function of shopping, recreation and transportation facilities around the park; The DLAT of the open plaza can be enhanced by adding land functions for recreation, living and shopping. On the other hand, if they are in the declining stage, the disordered land use can be simplified or the existing part of the land functions can be replaced with land functions sensitive to the DLAT of urban parks.

Residents' leisure activities in urban parks will also be affected by other factors, such as socioeconomic status and transportation accessibility. However, the scale of this study is small, and the social and economic factors in the study area are similar, and the error is within an acceptable range. From the previous survey, it can be known that 1 km represents the maximum acceptable walking distance for park visits, a threshold that encompasses the majority of travel modes. The distance has little effect on the calculation result.

The use of big data research methods transforms urban space research mode from the traditional “space and place” to “people-activity-space and their relationship”. At present, the mismatch between the growing demand for leisure activities of residents and the lack of supportive environment needs to be solved urgently. This study further explored how to guide residents to facilitate leisure activities by planning methods. Specifically, it does so by examining the DLAT of urban parks and the degree of POI mixing around urban parks.

This study also has some limitations, for example, the study did not include factors such as time dimension, population density and traffic network. Although our analytical framework (POI + Weibo + VGI, Hill numbers, correlation and quadratic modeling) is directly transferable to other cities, the empirical findings reported here may depend on local context – urban form, land-use mix, cultural norms, travel behavior, and the availability/representativeness of social-media and VGI data. Therefore, caution is warranted when extrapolating results beyond Guangzhou. We recommend that practitioners and researchers replicate the analysis in other urban contexts, control for socioeconomic and accessibility covariates, perform multi-scale robustness checks, and, where possible, assemble multi-city or longitudinal datasets to assess the boundary conditions of the observed relationships. Such follow-up work would clarify where and when the identified POI – DLAT patterns hold and increase policy relevance across diverse settings.

5. **Conclusions.** Based on multi-source data such as POI data, Weibo check-in data, and Tencent Pintu’s VGI data, the Hill numbers index was used to calculate the DLAT of urban parks and the degree of POI mixing around them. Then, their correlation analysis was carried out, and the six districts of Guangzhou were used as an example. The results show that there is a significant correlation between the DLAT of urban parks and their surrounding the degree of POI mixing, and the relationship between the two shows a normal distribution. Most of the DLAT of parks and the degree of POI mixing around them showed an upward trend. The land function surrounding the park facilitates residents’ access to the park; Most of the DLAT of open squares and the degree of POI mixing around them trended down. The land function around the open square inhibits resident access. The park is sensitive to the combination of POI types such as shopping, leisure and entertainment, and transportation facilities, and the open square is sensitive to the combination of POI types such as leisure and entertainment, residential, and shopping. The findings can help planners manage urban parks and improve the health of the entire population, by adjusting land functions to promote residents’ leisure activities in urban parks. This approach is complementary to the traditional greenfield system planning approach. The methodology is transferable to other cities, but empirical application should be validated locally – taking account of urban form, socioeconomic context and data availability – via cross-city replication studies.

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Author Biography

Xuan Qiu received her Bachelor's degree in Engineering from Hainan University, China, in 2017; the Master's degree in Engineering from Harbin Institute of Technology, China, in 2020. She is now a lecturer at Guangxi City Vocational University, China. Her main research interests include planning and design of health landscape and its theory, ecological oriented urban design.

Mengxiao Jin obtained a Bachelor's degree in Architecture from Harbin University of Science and Technology, China, in 2010; obtained a Master's degree in Architectural Design and Theory from Harbin Institute of Technology, China, in 2013; obtained a Ph.D. degree in Environmental Science and Engineering from Harbin Institute of Technology, China, in 2023. Dr. Jin is currently a full-time lecturer at the School of Innovation and Creative Design, Shenzhen Polytechnic University, China. The main research directions are resilient urban management and urban sustainable development. She has published over 20 academic papers.

Quanyi Zheng obtained a Bachelor's degree in Architecture from Jilin Jianzhu University, China, in 2008; obtained a Master's degree in Architectural Design and Theory from Harbin Institute of Technology, China, in 2013; obtained a Ph.D. degree in Landscape Architecture from Harbin Institute of Technology, China, in 2021. Dr. Zheng is currently a full-time lecturer at the Shenzhen Tourism College of Jinan University, China. The main research directions are urban big data, disaster recovery conversion of green space systems, and urban disaster prevention. He has published over 20 articles in journals and conferences.