Assessing inequality in urban blue-green space exposure through a preference-driven and network-based approach

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Abstract: Urban blue-green spaces (UBGS) are vital for human health and sustainable urban transitions, yet existing assessments of UBGS exposure largely rely on assumptions of homogeneous demand and Euclidean distance. Consequently, how actual road network constraints and heterogeneous group preferences drive exposure disparities remain poorly understood. Here, we developed a novel preference-driven and network-based two-step floating catchment area (PN-2SFCA) model to evaluate UBGS exposure inequality. By integrating Weibo check-in data and actual walking paths, our approach comprehensively captures group-specific visitation preferences and realistic travel constraints across multiple walking time thresholds. Our findings reveal pronounced spatial disparities in UBGS accessibility, demonstrating that exposure inequality primarily originates within, rather than between, social groups (intra-group inequality). While certain demographic segments achieve broad access, the elderly and males experience structurally limited service coverage. Notably, the 10-minute walking threshold emerges as the critical scale at which these inequalities are most pronounced. These hidden disparities underscore the limitations of conventional, quantity-oriented assessments. By uncovering inequality patterns easily neglected by traditional methods, these insights provide a robust foundation for targeted, preference-oriented UBGS planning, ensuring equitable resource allocation and fostering inclusive urban development under limited-resource conditions.

Cities serve as critical settings for achieving China's 2035 low-carbon development goals and the United Nations' 11th Sustainable Development Goal (SDG)[1]. As one of the most representative forms of natural infrastructure within urban ecosystems, urban blue-green space (UBGS), defined as urban green spaces, water bodies, and their integrated spaces that provide ecological services, recreational opportunities, and environmental regulation functions, plays a vital role in enhancing urban carbon sequestration capacity, alleviating environmental pressure, and supporting the low-carbon transition[2-5]. Against the dual pressures of emission reduction and sustainable development faced by cities worldwide, the continuous expansion and optimization of UBGS has become an imperative planning action. However, many previous studies have shown that simply increasing the total amount of UBGS without considering whether its spatial distribution can be transformed into ecological resources that residents can actually access and use may lead to, or even exacerbate, inequality in UBGS exposure[6-8]. This indicates that UBGS planning should not only focus on the total amount of supply, but should also pay greater attention to differences in the needs of different social groups. Therefore, understanding the heterogeneity of group needs, the spatial patterns of UBGS accessibility, and their associated inequality characteristics, and, on this basis, promoting preference-oriented spatial allocation of UBGS is essential for improving the practical effectiveness of UBGS planning.

Previous studies on inequality in UBGS exposure have primarily focused on statistical indicators, such as total area and per capita green space[9,10]. Some studies have applied spatial analysis methods to assess UBGS exposure, including geographic distance measures[11], population-weighted exposure models[12], geographic field effect methods[13], and the Huff model[14]. They have also employed the two-step floating catchment area (2SFCA) method, the three-step floating catchment area (3SFCA) method, and their further developed models to estimate supply-demand interactions[15-17], such as AG2SFCA[18], FSD-2SFCA[19], and Improved 3SFCA[20,21]. These methods have been widely used to quantify UBGS exposure and have been shown to capture real-world complexity better. Meanwhile, inequality metrics such as the Theil index[22], the Gini coefficient[23,24], and the Palma ratio[25] have been proposed to quantify inequality. However, previous studies have not sufficiently accounted for several critical factors that can substantially influence results, including actual travel behavior under real road network path constraints and differences in preferences for UBGS types across social groups.

Previous studies that used 2SFCA and its further developed models have typically relied on simplified spatial distance assumptions to represent accessibility[18,19]. However, the use of Euclidean distance alone may struggle to fully and accurately capture actual travel behavior under real-world road network path constraints. In addition, demand estimates were often derived from homogeneous residential population data, emphasizing aggregate benefits[26]. Such data may struggle to reflect actual population demand preferences, as substantial differences in landscape characteristics, ecological functions, and facility configurations across UBGS types can influence usage patterns[27,28]. Consequently, the UBGS exposure inequality inferred from these assessments does not necessarily translate into equitable access for different social groups in reality, potentially leading to misinterpretation of exposure inequality. A more comprehensive evaluation requires composite indicators that incorporate both the actual preference structures of different social groups and the varying attractiveness of different UBGS types, thereby capturing heterogeneous demand more accurately. Some studies on variations in park visitation behavior have attempted to account for and refine urban residents' travel willingness to access UBGS[29]. However, few have systematically integrated the actual preferences of different social groups into accessibility assessment frameworks, let alone examined the mismatch between demand and supply in UBGS exposure. Without adequately capturing group-specific visitation preferences, it is difficult to fully understand inequality patterns in UBGS exposure or to design effective and targeted interventions, particularly under conditions of limited resources. Therefore, to better understand inequality in UBGS exposure based on actual residents' needs and visitation behaviors, it is important to account for the diverse preferences of different social groups across multiple UBGS types.

To validate the applicability of this framework in real-world urban scenarios, this study focused on Harbin, China, a typical old industrial city facing both substantial carbon reduction pressure and an urgent need for optimized UBGS planning. Specifically, from the perspective of neighborhood-scale walking accessibility under the 15min living circle concept, this study evaluated the accessibility of preferred UBGS for different social groups in Harbin based on three walking time thresholds, and quantified the inequality of UBGS exposure using an inequality assessment framework comprising the Theil index and Coverage ratio. The specific objectives of this study are to: (1) identify the actual visitation preferences of different social groups toward UBGS based on Weibo check-in data, and construct a set of UBGS types preferred by each group; (2) construct a (Preference-driven and Network-based 2SFCA) PN-2SFCA model that integrates social group preferences, shortest-path distance, and Gaussian distance decay, based on mobile signaling data, UBGS spatial distribution data, and road network data, to measure the accessibility of preferred UBGS for different social groups at various walking time thresholds; (3) reveal inequality of UBGS exposure among different social groups using two dimensions: Theil index decomposition and Coverage ratio.

Results

Behavioral patterns of UBGS visitation across social groups

Based on Weibo check-in data from 2024, this study quantified the actual visitation behavior of different social groups across 5 UBGS types (Urban Forest, Vegetated Open Space, Pocket Park, Wetland, and Aquatic Ecosystem) to characterize differences in their type preferences (Table 3).

Table 3. Visitation preferences of different social groups for various UBGS types based on check-in data.

UBGS Type	Variable	Category	Sample size (n)	Percentage (%)
Urban Forest	Gender	Male	571	**41.0**
		Female	822	59.0
		Unknown	0	0.0
	Age (years)	18–22	38	2.7
		23–30	128	9.2
		31–40	150	10.8
		41–50	47	3.4
		51–60	41	2.9
		60+	18	1.3
		Unknown	971	68.1
Vegetated Open Space	Gender	Male	3,949	31.5
		Female	8,587	68.5
		Unknown	0	0.0
	Age (years)	18–22	949	7.6
		23–30	2,804	22.4
		31–40	1,210	9.7
		41–50	420	3.4
		51–60	542	**4.3**
		60+	267	2.1
		Unknown	6,344	50.6
Pocket Park	Gender	Male	22	36.1
		Female	39	63.9
		Unknown	0	0.0
	Age (years)	18–22	3	4.9
		23–30	9	14.8
		31–40	7	**11.5**
		41–50	3	**4.9**
		51–60	0	0.0
		60+	1	1.6
		Unknown	38	62.3
Wetland	Gender	Male	1,016	31.4
		Female	2,220	68.6
		Unknown	0	0.0
	Age (years)	18–22	196	6.1
		23–30	656	20.3

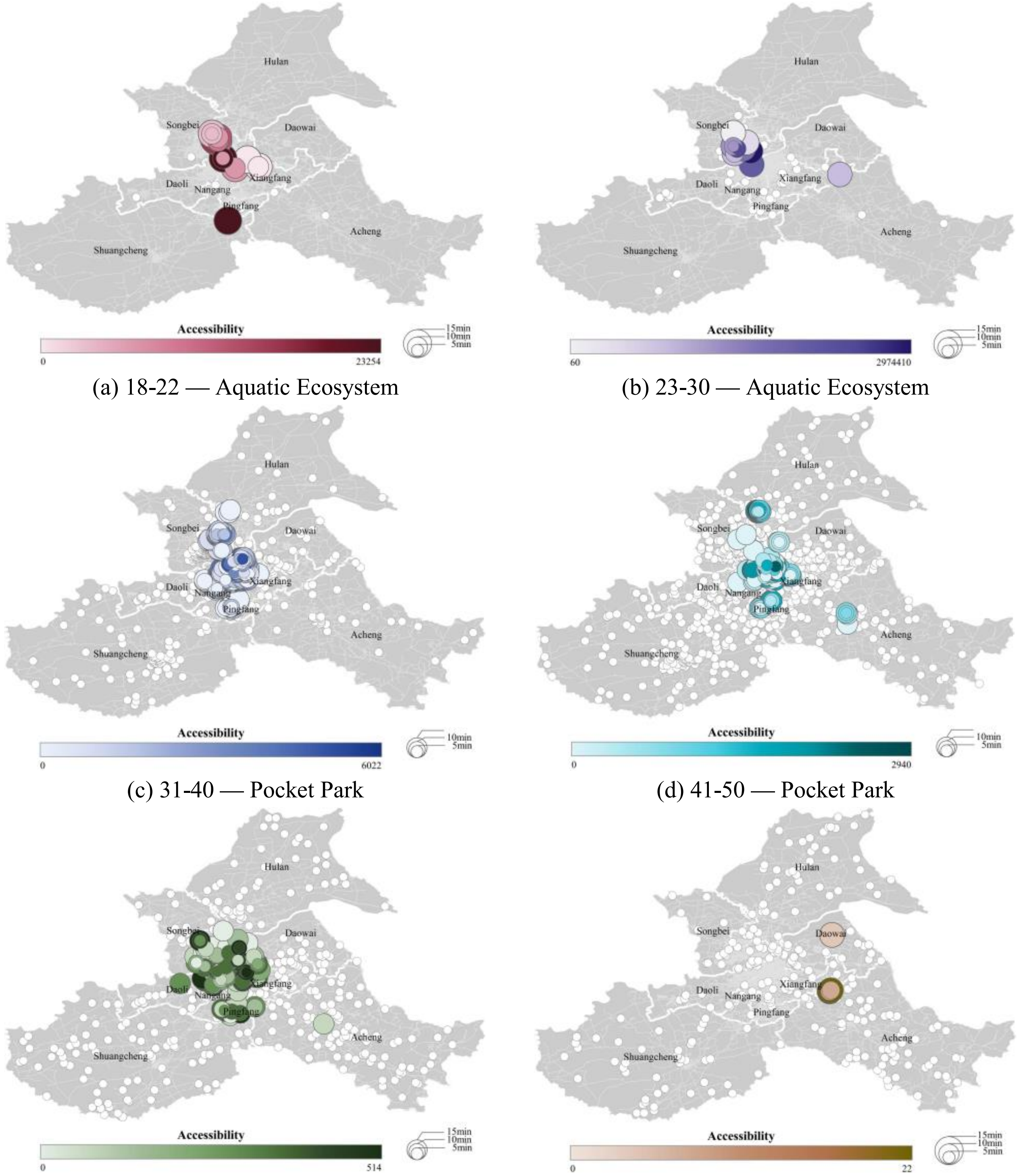
		31–40	363	11.2
		41–50	90	2.8
		51–60	93	2.9
		60+	90	**2.8**
		Unknown	1,748	54.0
Aquatic Ecosystem	Gender	Male	1,775	29.2
		Female	4,304	**70.8**
		Unknown	0	0.0
	Age (years)	18–22	472	**7.8**
		23–30	1,376	**22.6**
		31–40	649	10.7
		41–50	127	2.1
		51–60	187	3.1
		60+	108	1.8
		Unknown	3,160	52.0

Overall, different social groups exhibited pronounced structural differences in their selection of UBGS types. Visitation behavior did not follow a homogeneous distribution; instead, a clear pattern of group differentiation emerged at the level of UBGS types (Fig. 1). In terms of gender, Urban Forests accounted for the largest share of male users' check-in records (41.0%), while female users' visitation behavior was more concentrated in Aquatic Ecosystems (70.8%), a proportion substantially higher than that observed for other UBGS types. As for age, younger groups (18–22 and 23–30) showed a strong concentration of visits to Aquatic Ecosystems, with the 23–30 age group reaching 22.6% of visits to this type, significantly higher than their visitation levels to other UBGS types. As age increased, the visitation focus of the 31–40 and 41–50 groups shifted markedly toward Pocket Parks. Furthermore, the 51–60 group exhibited the highest visitation share in Vegetated Open Spaces, while the 60+ group most frequently visited Wetlands. These differences indicate that, in practice, different social groups did not rely on the same UBGS types for everyday ecological and recreational use, but on different types of UBGS to obtain their preferred services.

Fig. 1. Radar chart of visitation preferences of different social groups for various UBGS types based on check-in data.

Spatial characteristics of UBGS accessibility across social groups

Based on the PN-2SFCA model, the accessibility indices of different social groups to their preferred UBGS types were calculated at three walking time thresholds (5min, 10min, and 15min), and the corresponding spatial distribution maps were generated (Figs. 2 and 3).



(a) 18-22 — Aquatic Ecosystem (b) 23-30 — Aquatic Ecosystem

(c) 31-40 — Pocket Park (d) 41-50 — Pocket Park

(e) 51-60 — Vegetated Open Space (f) 60+ — Wetland

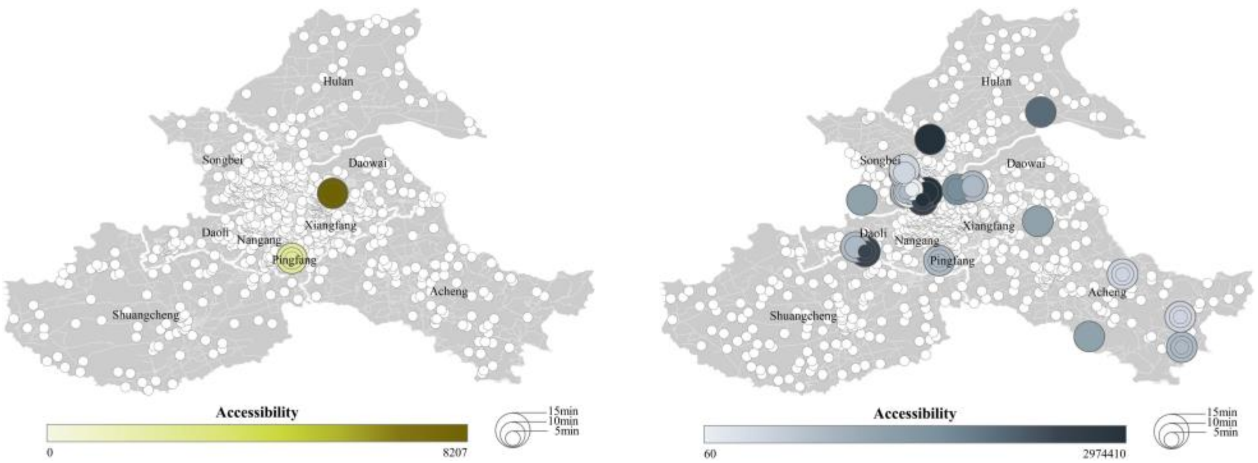
Fig. 2. Spatial distribution of accessibility to preferred UBGS across age groups.

Overall, accessibility exhibited pronounced spatial disparities across age groups and increased markedly with the expansion of walking time thresholds. At the 5min threshold, the number of accessible residential clusters was limited and primarily confined to a small number of locations near major resource areas, indicating that strict time and network path constraints substantially restricted the effective service coverage of UBGS. As the walking time threshold expanded to 10min and 15min, the proportion of accessible residential clusters increased significantly; however, the magnitude of growth varied considerably across age groups. For example, the proportion for the 18–22 group increased from 10.00% to 50.00%, for the 41–50 group from 2.90% to 20.20%, and for the 51–60 group from 2.70% to 14.10%. These patterns suggest that, although expanding the walking time threshold increased potential service coverage, the gains were distributed unevenly across groups, meaning that residents did not benefit equally from the same expansion of neighborhood walking range.

From a spatial perspective, at shorter walking time thresholds, accessible residential clusters were mainly concentrated in the central urban area and along the Songhua River, while coverage in peripheral areas remained limited. At the 15min threshold, accessible residential clusters expanded toward peripheral districts such as Pingfang District and Acheng District, forming new medium- to high-value regions. This pattern was particularly evident for the 18–30 age group, which prefers Aquatic Ecosystems. In these groups, high-value regions appeared not only along the river corridor but also in some peripheral areas, indicating that large-scale and continuously distributed water resources could maintain relatively strong service capacity over longer network distances. Similarly, for the 51–60 age group, which prefers Vegetated Open Spaces, the number of accessible residential clusters increased markedly at the 15min threshold, with some peripheral areas entering the effective service range. This suggests that residents living near the river corridor and central resource areas gained access to preferred UBGS earlier, while many peripheral neighborhoods only entered the effective service range at the widest walking time threshold. From a structural perspective, this spatial disparity was fundamentally linked to the mismatch between the allocation of UBGS resources, functional zoning, and urban development structure. In Harbin, as in most cities, UBGS resources and denser road networks tended to be preferentially located in central areas with higher development intensity and along key ecological corridors like the Songhua River. In contrast, peripheral areas were often dominated by residential expansion or industrial land use, resulting in a relative shortage of UBGS supply and leaving them relatively underserved.

In contrast, UBGS types with limited spatial distribution imposed substantial constraints on accessibility. For example, among the 60+ age group, only 3 out of 260 residential clusters (1.20%) were able to access Wetland resources at the 15min threshold, while none were accessible at the 5min threshold. This finding indicates that the spatial scarcity of Wetland resources severely restricted their service coverage and left most older residents without access to their preferred UBGS within ordinary walking ranges.

Differences in accessibility across age groups further reflected the role of residential location. For example, although the 31–40 age group had the largest number of residential clusters (1,047), its proportion of accessible residential clusters at the 15min threshold was only 8.40%, significantly lower than that of the 41–50 age group (20.20%). This indicates that actual accessibility depended more on the spatial proximity between residential areas and preferred UBGS than on group size alone. Against this context of structural and functional mismatch, differences in residential location were profoundly reflected in intra-group disparities in service provision. In other words, accessibility varied significantly even among residents within the same age or gender group depending on their specific locational conditions. Similar conclusions have been reported in other contexts; for example, studies in Australia have shown that locational conditions, rather than group identity, are the primary determinants of green space accessibility[30].



(a) Male — Urban Forest (b) Female — Aquatic Ecosystem

Fig. 3. Spatial distribution of accessibility to preferred UBGS across gender groups.

Accessibility differences between gender groups were also pronounced. Overall, the expansion of walking time thresholds increased the range of accessibility for both groups; however, differences in the spatial patterns of preferred UBGS types led to markedly different accessibility levels. Specifically, Urban Forest resources preferred by the male group were mainly distributed in peripheral areas. Among 696 residential clusters, only 0.30% were accessible at the 15min threshold, and they were nearly inaccessible at shorter walking time thresholds. In contrast, Aquatic Ecosystem resources preferred by the female group, due to their continuous distribution along the river, achieved an accessibility proportion of 2.50% among 797 residential clusters and maintained a certain level of coverage even at shorter walking time thresholds such as 5min. These results indicate that the spatial scale and continuity of UBGS strongly influenced accessibility: large-scale and continuously distributed resources were more likely to form stable service areas, while fragmented resources struggled to achieve widespread coverage. In practical terms, females were more likely to encounter their preferred UBGS within ordinary walking ranges, while males faced highly limited opportunities to access preferred Urban Forest resources even under the widest threshold considered.

Inequality analysis

Inequality analysis based on the Theil index

To examine inequality, this study employed a Theil index decomposition approach, decomposing accessibility inequality into two components: intra- and inter-group inequality. Compared with a single indicator that only reflects overall disparities, this approach further revealed whether inequality primarily arose from spatial variations within groups or from structural differences between social groups. To evaluate the effectiveness of the PN-2SFCA model in identifying accessibility inequality, it was compared with three baseline scenarios (Fig. 4): (a) Baseline 1, which incorporated group preferences but used Euclidean distance; (b) Baseline 2, which treated UBGS as homogeneous and used shortest-path distance; and (c) Baseline 3, which treated UBGS as homogeneous and used Euclidean distance.

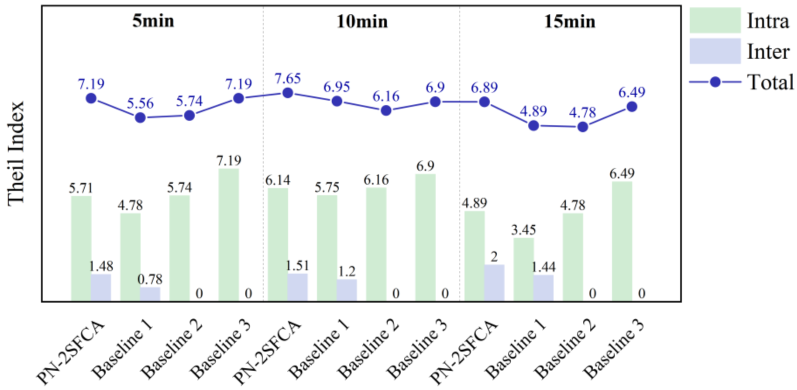


Fig. 4. Decomposition of the Theil index into within-group and between-group components across different walking time thresholds.

At the micro-scale, Fig. 5 illustrates a typical residential cluster to demonstrate that PN-2SFCA provided a more realistic measure of accessibility. The results show that, under the PN-2SFCA model, the accessibility of this residential cluster at the 10min threshold was 0, while all three baseline methods identified varying numbers of accessible UBGS resources, with the number increasing as model assumptions became more simplified. This indicates that PN-2SFCA was better able to capture actual accessibility levels under real-world travel constraints and to avoid overstating service opportunities that residents could not realistically obtain.

Fig. 5. Comparison of UBGS exposure across PN-2SFCA and baseline methods at the 10min threshold (780m) for a representative residential cluster (aged 51–60). **Note**: Under the PN-2SFCA model, accessibility of the selected residential cluster is **0** at the 10min threshold. (a) **Baseline 1** (type-specific + Euclidean distance): **one** accessible preferred **Vegetated Open Spaces** at 188m. (b) **Baseline 2** (non-type-specific + shortest-path distance): one accessible **UBGS** at 143m. (c) **Baseline 3** (non-type-specific + Euclidean distance): **two** accessible **UBGS** at 104m and 188m. (Baseline 1 distinguishes group preferences, while Baselines 2 – 3 treat UBGS as homogeneous.)

From the perspective of whether road network path constraints were considered, the differences between PN-2SFCA and Baseline 1 reflect the impact of distance measurement on inequality identification. At thresholds of 5min, 10min, and 15min, the total Theil indices for PN-2SFCA were 7.19, 7.65, and 6.89, respectively, all higher than those of Baseline 1 (5.56, 6.95, and 4.89). Meanwhile, the inter-group inequalites identified by PN-2SFCA were 1.48, 1.51, and 2.00, respectively, also significantly higher than the corresponding values of Baseline 1 (0.78, 1.20, and 1.44). These results indicate that Euclidean distance–based measures underestimate the degree of inequality under actual spatial constraints. This pattern was further confirmed by the comparison between Baseline 2 and Baseline 3, both of which did not distinguish between social groups. The total Theil indices for Baseline 2 were 5.74, 6.16, and 4.78, while those for Baseline 3 were 7.19, 6.90, and 6.49. Together, these results suggest that ignoring the road network structure weakened the ability to capture accessibility disparities and masked part of the inequality that residents actually faced in urban space.

From the perspective of whether social groups were differentiated, the comparisons between PN-2SFCA and Baseline 2, as well as between Baseline 1 and Baseline 2, highlight the critical role of group heterogeneity in inequality identification. Because Baseline 2 did not distinguish between social groups, its total Theil indices (5.74, 6.16, and 4.78) only reflected overall spatial disparities. In contrast, after incorporating group preferences, PN-2SFCA produced significantly higher total Theil indices (7.19, 7.65, and 6.89) and further identified inter-group inequality contributions of 1.48, 1.51, and 2.00. These findings suggest that, without group preferences, part of the inequality associated with differences in preferred UBGS was absorbed by averages and could not be directly identified.

A further comparison across different walking time thresholds revealed that the total Theil indices of PN-2SFCA, Baseline 1, and Baseline 2 all peaked at the 10min threshold. Specifically, the Theil index of PN-2SFCA was 7.19 at 5min, 7.65 at 10min, and 6.89 at 15min. Similarly, the corresponding values for Baseline 1 were 5.56, 6.95, and 4.89, while those for Baseline 2 were 5.74, 6.16, and 4.78. These patterns indicate that, as the walking time threshold expanded from 5min to 10min, locations and groups with more favorable locational conditions were able to access additional UBGS resources more rapidly, while improvements in less advantaged locations remained limited. The accessibility gap, therefore, widened most strongly at the 10min threshold, suggesting that this neighborhood-scale walking time threshold was the stage at which locational advantages and disadvantages were translated most clearly into unequal access. When the walking time threshold was further expanded to 15min, more peripheral areas gradually entered the service range, partially alleviating existing disparities and leading to a reduction in overall inequality. In contrast, the total Theil index of Baseline 3 declined from 7.19 at 5min to 6.90 at 10min and 6.49 at 15min, indicating that models ignoring group preferences, road network structure, and spatial barriers tended to overestimate the equalizing effect of increasing travel distance.

Based on the inequality decomposition using PN-2SFCA, the total Theil indices at the 5min, 10min, and 15min thresholds were 7.19, 7.65, and 6.89, respectively, with intra-group inequality accounting for 79.4%, 80.3%, and 71.0% of the total. Overall, regardless of the walking time threshold, intra-group disparities consistently dominated, contributing approximately 70%–80% of overall inequality. This indicates that inequality in UBGS exposure primarily arose from spatial differences among residential locations within the same social group, rather than between groups. In practical terms, even residents belonging to the same age or gender group could face markedly different opportunities to access preferred UBGS services, depending on where they lived.

Inequality analysis based on the Coverage ratio

Based on the Theil index, which revealed that inequality primarily arose from spatial disparities in residential locations within the same social group, the Coverage ratio further validated the disparity in the opportunities of different groups to access their preferred UBGS services from the perspective of accessibility proportions (Fig. 6).

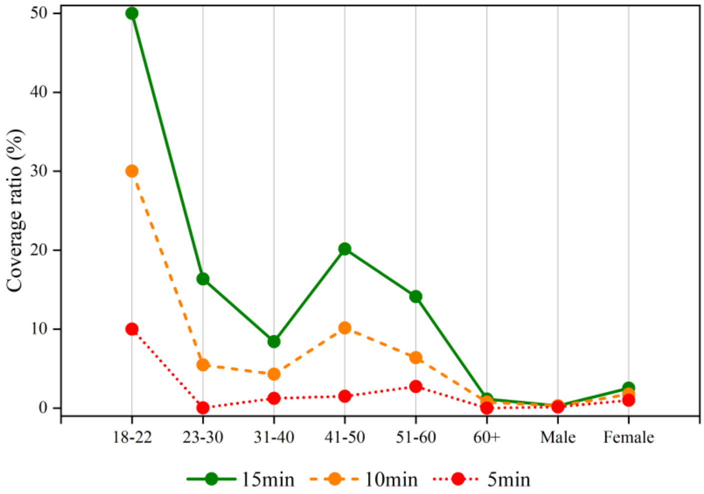


Fig. 6. Coverage ratio of preferred UBGS accessibility across social groups and walking time thresholds.

Overall, younger groups exhibited higher levels of service coverage. For the 18–22 age group, the Coverage ratio reached 50.00% at the 15min threshold, which was 1.67 times and 5 times higher than those at the 10min (30.00%) and 5min (10.00%) thresholds, respectively, indicating that half of their residential clusters were able to access preferred UBGS services within a reasonable walking distance. In contrast, the Coverage ratios for the 23–30 and 31–40 age groups were 16.36% and 8.40%, respectively, showing a declining trend. This suggests that, as the spatial distribution of residences expands, the degree of spatial matching between these groups and their preferred UBGS gradually decreases. The Coverage ratios for the 41–50 and 51–60 age groups increased again to 20.15% and 14.12%, respectively, indicating that the Vegetated Open Space types preferred by these groups had a broader spatial distribution and could therefore provide service opportunities to a larger share of residential space.

The elderly exhibited the most pronounced service deficiency. For the 60+ age group, the Coverage ratio was only 1.15% at the 15min threshold and declined to 0.77% and 0.00% at the 10min and 5min thresholds, respectively. This indicates that the vast majority of the elderly were unable to access their preferred Wetland resources within an acceptable walking distance. This finding is consistent with the high level of inequality reflected by the Theil index, suggesting that this group not only experienced uneven accessibility within the group but also suffered from an extremely low overall level of service coverage, representing a typical case of structural service deprivation in everyday residential space.

Gender differences were equally pronounced. The Coverage ratio for the male group was only 0.29% at the 15min threshold and showed no significant improvement at the 10min threshold, indicating that the limited supply of Urban Forest resources severely constrained service coverage. In contrast, the Coverage ratio for the female group reached 2.51% at the 15min threshold—approximately 8.7 times that of males—and remained relatively stable at the 10min and 5min thresholds (1.76% and 1.00%, respectively). This disparity reflects the fact that Aquatic Ecosystem resources preferred by females were widely distributed along the Songhua River and its tributaries, providing accessible opportunities for a larger number of residential clusters. By contrast, Urban Forests are sparsely distributed and predominantly located in peripheral areas, making it difficult for the male group to achieve effective coverage despite having a larger number of residential clusters.

Further analysis combining the Theil index with the Coverage ratio reveals that the 60+ age group and the male group constitute the most typical vulnerable groups. Their Coverage ratios at the 15min threshold were only 1.15% and 0.29%, respectively, far lower than those of other groups, indicating extremely limited overall access to UBGS services. At the same time, the total Theil index remained relatively high (6.89), with approximately 71.0% attributable to intra-group differences, suggesting that the limited service opportunities were concentrated in a small number of advantaged locations. In contrast, the 18–22 age group achieved a Coverage ratio of 50.00% at the 15min threshold, yet the overall level of inequality remained high, indicating that although service coverage was extensive, its spatial distribution was highly uneven. Spatially, this pattern—characterized by low Coverage ratios and high Theil index values—was primarily concentrated in peripheral areas distant from the Songhua River and the central urban area. Overall, the Theil index captured the intensity of spatial inequality, while the Coverage ratio further identified the disadvantaged groups and critical locations. Together, these results indicate that older adults and males experienced the greatest inequality in access to their preferred UBGS resources and had the most limited chances of actually encountering preferred UBGS services within everyday walking space.

Discussion

A new paradigm for assessing UBGS exposure

UBGS serve as a key medium for promoting public health and advancing low-carbon transitions, yet exposure has long been evaluated under a uniform demand assumption, namely, that different social groups share similar preferences for various UBGS types. Although intuitive, this approach neglects substantial differences in actual visitation behavior across populations and may therefore struggle to reflect real service conditions. The core innovation of this study lies in the development of an accessibility evaluation model that incorporates both group-specific visitation preferences and realistic road network path constraints, thereby establishing a behavior-based framework for assessing inequality in UBGS exposure. By integrating group-specific visitation tendencies and realistic travel conditions into the supply calculation process, the PN-2SFCA model shifts the assessment from nominal proximity to preferred UBGS accessibility under actual walking constraints.

The results showed consistent differences across gender and age groups in their selection of UBGS types and demonstrated that introducing road network path constraints and group preferences substantially changed the identified pattern of accessibility inequality[31,32]. These findings are consistent with previous studies showing that social groups differ in their use of green space and that network-based accessibility models better capture actual travel processes and spatial disparities[33-35].

Structural interpretation of UBGS exposure inequality

A key finding of this study is that inequality in UBGS exposure was primarily characterized by dominant intra-group disparities. Specifically, the Theil index decomposition showed that intra-group inequality consistently accounted for approximately 70%–80% of total inequality, while the Coverage ratio further revealed that older adults and males had the lowest levels of access to preferred UBGS services.

It should also be emphasized that this location-driven pattern of inequality varies markedly across different types of cities. In cities characterized by high-density development and compact spatial structures, such as Beijing and other northern Chinese cities, UBGS resources are often concentrated in limited center areas, while peripheral areas experience insufficient service coverage, making pronounced spatial disparities more likely to emerge. By contrast, in cities such as Guangzhou, where river networks are dense or green spaces are more evenly distributed, UBGS may form continuous patterns along waterways or ecological corridors, thereby partially mitigating the effects of locational differences. In such contexts, simply increasing the quantity of UBGS does not necessarily lead to a proportional improvement in accessibility for residents across different locations. Evidence from Taiwan[36] and the Tree City USA program[37] suggests that the uneven or uncoordinated distribution of newly added UBGS may exacerbate environmental inequality. In particular, when resources are already spatially concentrated or unevenly distributed, additional supply may further reinforce existing advantages in well-served areas. Under conditions of limited resources, optimizing the spatial allocation of UBGS in a targeted manner—by incorporating the preference characteristics of different social groups—becomes a critical pathway for reducing accessibility disparities, thereby underscoring the necessity of differentiated planning strategies.

This study further indicates that the degree of inequality varied significantly across different walking time thresholds. Specifically, the total Theil index calculated by the PN-2SFCA model peaked at the 10min range. This pattern suggests that, at moderate travel distances, the advantages of central areas were realized earlier, while improvements in peripheral areas lagged behind, thereby widening the overall disparity. This finding is consistent with previous studies indicating that the initial expansion of travel distance may exacerbate spatial inequality[38]. Recent studies on green space based on a 10min threshold have also highlighted the critical role of this scale in UGS planning[29,39]. This result provides empirical support for the 10min threshold as the most critical intervention scale within the 15min living circle framework for optimizing the spatial allocation of UBGS.

Practical implications of preference-oriented UBGS expansion

The findings indicate that simply increasing the total supply of UBGS is unlikely to achieve the intended planning goals if the added spaces do not correspond to the actual visitation preferences of different social groups. Under conventional quantity-oriented planning, UBGS may become physically accessible in spatial terms, yet still remain underused in practice when the provided types fail to match group-specific preferences. In such cases, the expansion of UBGS supply may improve nominal accessibility, but not necessarily translate into effective opportunities for use. This mismatch not only reduces the practical efficiency of newly added ecological resources but also makes it difficult for the benefits of UBGS provision to be more equitably realized across social groups.

By contrast, a supplementary estimation in this study shows that, under the same scale of UBGS supply increase, preference-oriented planning could raise the overall utilization rate by 9.36% compared with random matching. This suggests that when newly added UBGS are configured in a way that better responds to differentiated social demand, a larger share of residents can effectively benefit from the expanded supply. Therefore, the planning significance of UBGS expansion lies not only in increasing quantity but also in improving the extent to which additional supply can be converted into actual use. Under limited-resource conditions, incorporating group-specific preferences into UBGS planning provides a more effective pathway for enhancing utilization and promoting more substantive gains in equitable access.

Planning and governance strategies

Based on the above findings, this study proposes the following planning interventions.

The dominance of intra-group inequality indicates that disparities in UBGS accessibility primarily arise from spatial differences among residential locations within the same social group, rather than from overall differences between groups. Under such circumstances, planning strategies that rely solely on increasing the total area of UBGS may be insufficient to effectively address accessibility inequality. If newly added resources continue to concentrate in areas where UBGS are already densely distributed, the improvement in equity will be limited. Therefore, planning practice should place greater emphasis on the alignment between spatial location and service coverage.

The elderly and males represent the most urgent targets for intervention, as their Coverage ratios are extremely low, indicating typical structural service deprivation. For the elderly, it is recommended to prioritize the development of small-scale constructed Wetland parks near their residential clusters by leveraging existing water networks, thereby reducing the difficulty of large-scale site selection through an embedded layout approach. For Urban Forests preferred by males, it is recommended to enhance walkable accessibility by connecting existing peripheral forest resources to the central urban area through the development of ecological corridors.

Within the 15min living circle framework, the 10min threshold represents the critical scale at which inequality is most pronounced. Within this range, the spatial mismatch between supply and demand across different groups is greatest, making it the most effective window for planning interventions. Planners should systematically identify residential clusters where gaps in the provision of preferred resources are most concentrated within the 10min walking range for each group and develop targeted supply strategies accordingly. For example, for middle-aged groups (31–50), deficiencies in Pocket Park accessibility can be addressed by optimizing the layout of nearby green spaces; for younger groups, disparities in access to Aquatic Ecosystem spaces can be mitigated by enhancing the connectivity of waterfront pedestrian networks. This differentiated intervention approach, guided by group preferences and focused on locational supply gaps, can achieve greater improvements in equity under limited resource conditions than homogeneous strategies that increase the total area of UBGS.

Limitations and future research

This study proposed the PN-2SFCA model, and the results demonstrated its strong potential for assessing inequality in UBGS exposure by incorporating group preferences. Nevertheless, several limitations remain and may introduce uncertainty into the findings. First, although this study focused on Harbin, the proposed framework is generalizable to other industrial cities with comparable urban development and UBGS conditions. Future research will further classify industrial cities worldwide and use empirical data to compare the performance of the framework across different city types, thereby refining its application and supporting more targeted UBGS planning. Second, the centers of residential clusters and UBGS were used as the origins and destinations in the accessibility analysis. Given that the sizes and shapes of these vary across the study area, this approach is susceptible to the modifiable areal unit problem and may introduce bias compared with analyses based on actual travel points. Future research will attempt to use more precise UBGS entrance locations to improve the accuracy of accessibility estimation. Third, although Weibo check-in data provide a convenient and cost-effective means of estimating the distribution of group preferences, they have inherent coverage limitations. The data do not fully represent all residents, and certain population groups—particularly children, who have limited mobile phone usage—were not included in this analysis. As the availability of open data sources improves, future studies will be better positioned to capture patterns and relationships across a broader range of social groups.

Methods

The methodological flowchart of this study is shown in Fig. 7.

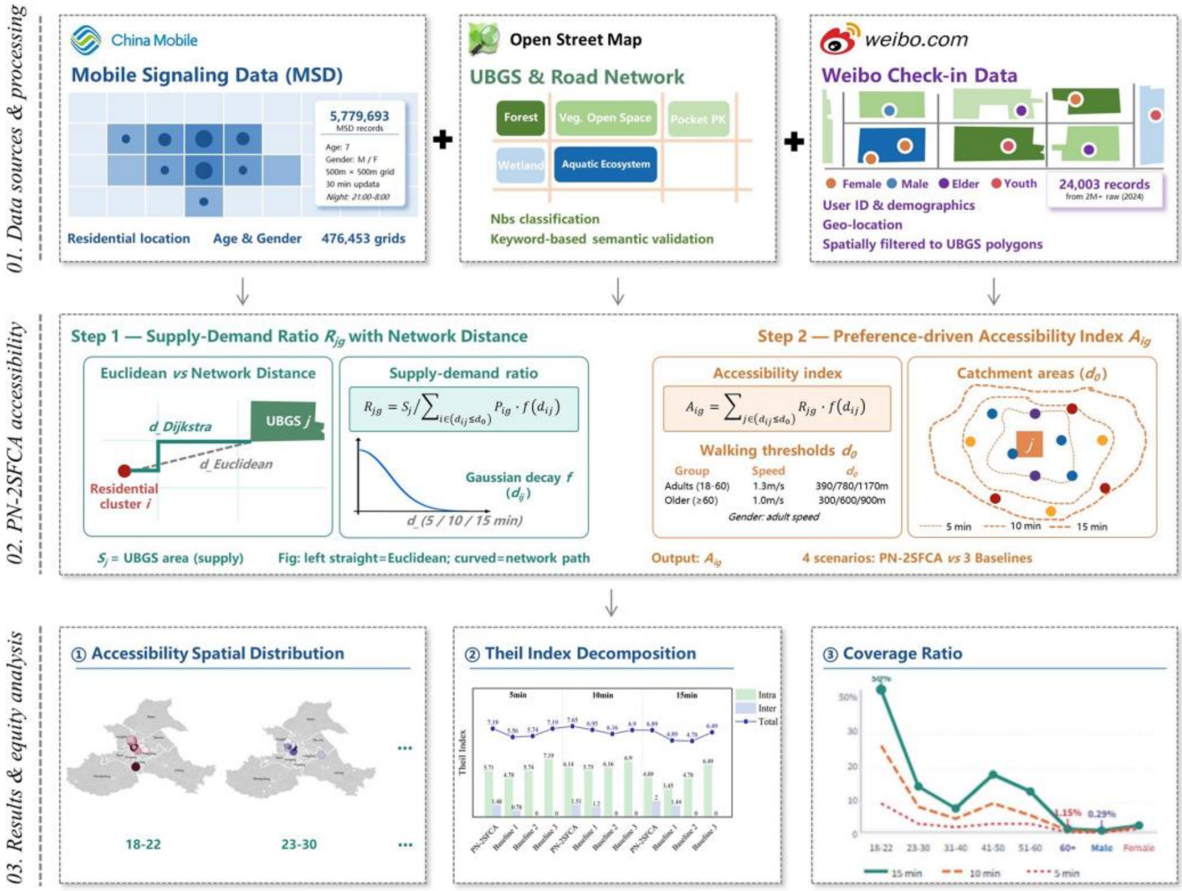


Fig. 7. The methodological flowchart.

Study area

Harbin (125° 42′–130° 10′ E longitude, 44° 04′–46° 40′ N latitude) is a typical old industrial city in Northeast China. Studies show that Harbin's per capita CO_2 emissions are approximately 0.0176 metric tons per day, far exceeding the level of service-based cities (0.11 metric tons of CO_2 per ¥1000 GDP), indicating greater pressure to reduce carbon emissions[40]. Meanwhile, as a core infrastructure for carbon control, Harbin's current UBGS Greening Coverage Rate stands at only 33.7%, which is lower than the 43% target set by the National Land Greening Plan Outline (2022–2030)[41]. Accordingly, to respond to the national carbon reduction agenda while ensuring that the diverse needs of social groups regarding UBGS are met, this study closely integrates the key provisions on urban renewal and ecological governance outlined in Harbin's "Territorial and Spatial Planning (2021–2035)". It conducts an in-depth analysis of the distribution characteristics of Harbin's UBGS.

Data acquisition and preprocessing

The data used in this study comprised mobile phone signaling data (MSD), spatial distribution data for UBGS and road networks, and Weibo check-in data.

(1) Mobile phone signaling data (MSD): the MSD used in this study was sourced from China Mobile in Harbin, which has over 900 million users, providing strong population representativeness. A total of 5,779,693 MSD records were collected from July 14 to 20, 2025, covering 476,453 grids. Each MSD record contains demographic attributes (age and gender), spatial coordinates, and temporal timestamps[42]. To ensure privacy protection, all personal information was anonymized through desensitization protocols. Given that minors may have limitations in independent mobility, social media usage, and the completeness of mobile signaling records, the demographic data were categorized into seven age groups (18–22, 23–30, 31–40, 41–

50, 51–60, 60+, and Unknown) and three gender groups (male, female, and Unknown). Within this dataset, the location with the longest nighttime stay (from 9:00 PM to 8:00 AM) within a month was identified as the individual's residence[43].

(2) Spatial distribution data for UBGS and road networks: The data were obtained from OpenStreetMap in August 2025 using OSMnx. The UBGS dataset included the spatial boundaries and attribute information of 896 urban green spaces (UGSs) and 745 urban blue spaces (UBSs). This study combined the Nature-based Solutions (NbS) classification framework with keywords (Table 1) extracted from comment texts in Weibo check-in data to perform semantic validation and typological integration of the UBGS. When a check-in record matched multiple UBGS categories, its type was determined using a spatial-priority and specificity-weighted semantic matching strategy, with broad shared keywords down-weighted and unresolved ambiguous records excluded from the preference calculation. UBGS were consistently categorized into five types: urban forests, open green spaces, pocket parks, wetlands, and aquatic ecosystems. Road network data were used to introduce actual road connectivity and network path constraints.

Table 1. Keyword-based semantic framework for typological integration of UBGS based on Weibo check-in data.

UBGS Type	Associated Keywords
Urban Forest	Urban woodland; urban forest; forest park; urban tree canopy; tree-lined streets; urban green corridor; urban ecological forest; urban vegetation; urban green belt; ecological corridor; vertical greening; three-dimensional greening; carbon sink forest; shelterbelt; ecological restoration park; near-natural woodland; biodiversity park; native tree forest; multi-layer vegetation; ecological buffer zone; forest carbon storage
Vegetated Open Space	Green space; open green space; lawn; grassland; landscaped plaza; recreational green plaza; rain garden; public garden; picnic green space; ecological plaza; sponge green space; multifunctional lawn; open space; park; linear park; sports lawn; botanical garden
Pocket Park	Pocket park; community park; small green space; mini park; micro green space; street-corner park; roadside green space; neighborhood park; pocket plaza; micro landscape; street garden; community green space; small neighborhood park; green space in old residential areas; vacant land redevelopment park; 5min walking park; doorstep park
Wetland	Urban wetland; wetland park; natural wetland; constructed wetland; restored wetland; riparian wetland; riverside wetland; lakeside wetland; inland wetland; marsh wetland; floodplain wetland; seasonal wetland; wetland buffer zone; wetland ecological corridor; wetland ecological restoration area; wetland conservation area; stormwater wetland; retention wetland; purification wetland; wastewater treatment wetland; biodiversity wetland; migratory bird habitat; fish spawning wetland
Aquatic Ecosystem	Urban water body; blue space; river; urban river channel; canal; riparian zone; river corridor; lake; urban lake; artificial lake; reservoir; pond; landscape water feature; waterfront space; waterfront green space; waterfront park; waterside recreational space; accessible waterfront; waterfront open space

(3) Weibo check-in data: a total of 24,003 valid UBGS check-in records in Harbin for 2024 were collected through the Weibo application programming interface (API). Weibo is one of the major social media platforms in China, with its monthly active users exceeding 600 million as of 2023. Weibo records users' voluntarily shared geospatial information, including geotagged tweets, photos, and check-in data, which has been increasingly used to investigate users' actual visitation behavior[44,45]. It should be noted that older adults are relatively less active on social media platforms. Nevertheless, existing studies have demonstrated that large-scale social media check-in data can still effectively capture the overall spatial

patterns of urban public space use[46,47].

Behavior-based identification of group-specific UBGS preferences

Based on the Weibo check-in data, this study further identified the visitation preferences of different social groups for various UBGS types. First, all valid check-in records were assigned to the corresponding social group g according to the publicly available age and gender attributes of check-in users. Meanwhile, each check-in record was spatially matched to its corresponding UBGS type t using the spatial boundary information of UBGS. Based on this, the visit volume $N_{g,t}$ for group g across various UBGS types was calculated, representing the total number of check-ins made by group g in UBGS of type t. To eliminate the influence of differences in the total number of check-ins across groups, the visit proportion $P_{g,t}$ to different UBGS types within the group was further calculated to describe the usage intensity of the group across various UBGS types. Finally, the UBGS type with the highest visit proportion was defined as the preferred UBGS type for that social group, and the set of preferred UBGS types for group g was constructed as T_g, where $T_g = \{k \mid P_{g,k} = max(P_{g,1}, P_{g,2}, ..., P_{g,K})\}$. The set T_g was used to describe the group's type selection preferences in actual spatial usage.

It should be noted that the preference identification in this study is based on the relative visitation proportions within groups of users with known attributes. Records with missing attributes (Unknown) were excluded from the preference calculations for each group. To further verify the robustness of the preference identification, a sensitivity analysis was conducted on the preference results of each group. The results indicate that, after excluding Unknown records, the relative ranking of visitation across UBGS types remained largely consistent, suggesting that the overall structure of the preference identification results is reasonably robust.

Identification of residential clustering patterns of social groups

This study identified residential clustering patterns of different social groups based on the demographic composition within grids. A consistent analytical approach was applied to both gender and age.

Gender-based residential clustering

Let M_i, F_i, and $U_i^{(g)}$ denote the numbers of male, female, and unknown-gender individuals, respectively, in grid i. The Gender Dominance Index (GDI) is defined as:

$$GDI_i=\frac{M_i-F_i}{M_i+F_i} \ , (M_i+F_i>0) \tag{1}$$

Individuals with unknown gender were excluded from the index calculation. To reduce the potential impact of a high proportion of unknown-gender individuals, a reliability measure of known gender information was further defined as:

$$R_i^{(g)}=\frac{M_i+F_i}{M_i+F_i+U_i^{(g)}} \tag{2}$$

When $R_i^{(g)}<0.70$, the grid was classified as a gender-insufficient cell and excluded from subsequent clustering analysis. For grids satisfying the reliability constraints, significant clustering was identified using a quantile-based approach based on the overall distribution of GDI values: grids with GDI values below the 25th quantile were identified as significant female residential clusters, those above the 75th quantile as significant male residential clusters, and the remaining grids as non-significant clusters.

Age-based residential clustering

For the age, the number of individuals in grid i was recorded for the following groups: 18–22, 23–30, 31–40, 41–50, 51–60, 60+, and unknown age. The total population with known age was first calculated as:

$$K_i=\sum_k P_i^k \tag{3}$$

A reliability measure of age information was then defined as:

$$R_i^{(a)} = \frac{K_i}{K_i + U_i^{(a)}} \tag{4}$$

When $R_i^{(a)} < 0.70$, the grid was excluded from age-based clustering identification. For the remaining grids, the relative proportion of each age group within the known-age population was calculated as:

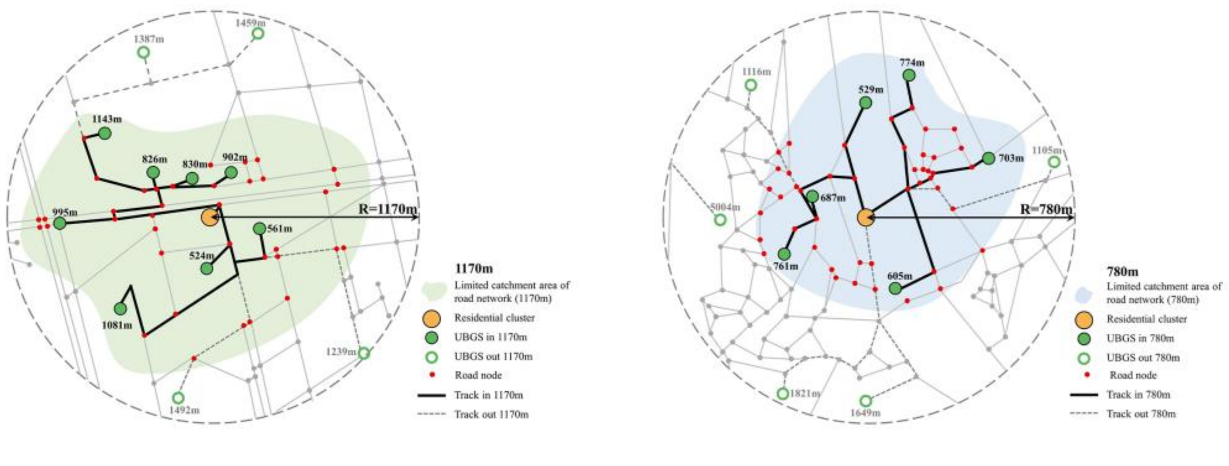
$$A_i^k = \frac{P_i^k}{K_i}, \ (K_i > 0) \tag{5}$$

The age group with the highest proportion was considered the dominant age group for that grid. Based on the distribution of these dominant proportions across all grids, a quantile-based approach was applied for significance identification: if the proportion of the dominant age group in a given grid exceeds the 75th quantile for that age group, the grid is identified as a significant residential cluster for that age group; otherwise, it is categorized as a non-significant cluster.

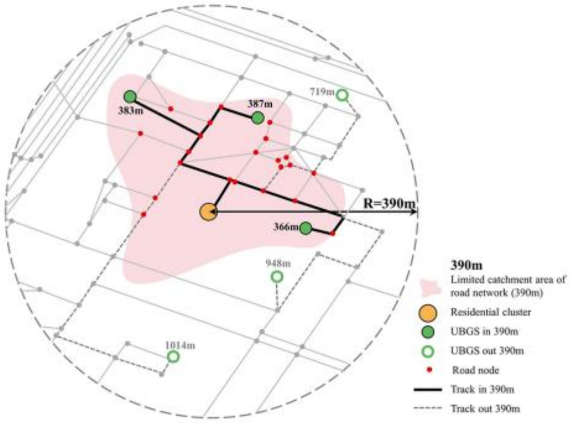
The PN-2SFCA method

The Gaussian 2SFCA is one of the most widely used methods in spatial accessibility assessment[48], particularly for examining how service supply matches population demand under catchment-area and distance-decay constraints. Its core procedure consists of two steps: first, calculating a supply–demand ratio for each service location within its catchment area; and second, aggregating the accessible supply–demand ratios for each population location to derive an accessibility index. This structure allows the model to jointly capture service capacity, demand competition, and spatial impedance, making it well-suited to UBGS accessibility assessment. Based on this framework, this study extended the conventional Gaussian 2SFCA by incorporating preference-driven mechanisms and road network path constraints to evaluate accessibility to preferred UBGS for different social groups under more realistic travel conditions.

The first step was to calculate the supply–demand ratio for each UBGS type relative to a specific social group. This study significantly advanced the conventional 2SFCA method through two key modifications: (1) group preferences were incorporated on the supply side, such that accessibility was calculated only for the set of UBGS types T_g preferred by each social group g; and (2) spatial impedance was modeled using the topology of the road network, where shortest-path distance replaced geometric Euclidean distance, as illustrated in Fig. 8. Specifically, the road network in the study area was modeled as a weighted graph $G=(V, E, w)$, where the node set V represents road intersections, the edge set E represents road segments, and the weight function w denotes walking distance. For each UBGS $j \in T_g$, its service catchment area is defined as S_j. Within a given service threshold d_0, all accessible residential clusters i belonging to social group g were identified based on the weighted road network, and the corresponding service population P_{ig} was calculated.



(a) 15min (b) 10min



(c) 5min

Fig. 8. Conceptual comparison of spatial impedance based on Euclidean distance and shortest-path distance.

Based on the road network topology, the shortest-path distance d_{ij} between residential cluster i and UBGS j was calculated in a Python environment using the Dijkstra algorithm[49]. This distance was defined as the minimum cumulative sum of edge weights along the road network, capturing urban road network path constraints such as network connectivity and path tortuosity, and thereby providing a more accurate representation of the actual walking cost for residents to access UBGS. A walking-based perspective was adopted in this study to align the accessibility assessment with the 15min living circle concept.

In the weighting process, a Gaussian distance decay function $f(d_{ij})$ was introduced to characterize the decline in the probability of accessing UBGS with increasing travel distance. By integrating the service population P_{ig} with the distance decay weight $f(d_{ij})$, the supply–demand ratio of UBGS j for social group g was calculated as:

$$R_{jg}=\frac{S_j}{\sum_{i\in\left(d_{ij}\leq d_0\right)} P_{ig}\cdot f\left(d_{ij}\right)}, j\in T_g \tag{6}$$

where S_j represents the supply scale of UBGS j (measured by area), and d_{ij} denotes the walking distance from residential cluster i to UBGS j, derived from the shortest-path based on the road network. The Gaussian distance decay function used in this study is defined as:

$$f\left(d_{ij}\right)=\begin{cases}\dfrac{e^{-\frac{1}{2}\left(\frac{d_{ij}}{d_0}\right)^2}-e^{-\frac{1}{2}}}{1-e^{-\frac{1}{2}}}, & d_{ij}<d_0\\ 0, & d_{ij}\geq d_0\end{cases} \tag{7}$$

For the setting of the service threshold d_0, this study did not adopt a single fixed distance; instead, three walking time thresholds (5min, 10min, and 15min) were introduced and converted into corresponding distance thresholds based on the average walking speeds of different age groups, as shown in Table 2. These thresholds were selected to reflect nested walking ranges within the 15min living circle, with 15min representing the overall planning scale and 5min and 10min capturing shorter-distance gradients of accessibility within it. This setting was motivated by the sensitivity of accessibility outcomes to walking time thresholds in accessibility analysis[23,50]. It should be noted that, in the accessibility comparisons related to gender-based clustering, d_0 was uniformly set to the average walking speed of the adult population. This treatment was intended to control for differences in mobility capacity, thereby isolating accessibility disparities under identical spatial supply conditions across gender groups, rather than reflecting physiological differences in travel ability.

Table 2. Walking distance thresholds by age group.

Age group	Walking time	Walking speed	Threshold distance (d_0)

Adults (18-60 years)	5min 10min 15min	1.3 m/s[51]	≈390m ≈780m ≈1170m
Older adults (60+ years)	5min 10min 15min	1.0 m/s[52]	≈300m ≈600m ≈900m

The second step was to evaluate the accessibility of preferred UBGS for each social group. Taking each residential cluster i as the center, all UBGS $j \in T_g$ accessible within the road network distance threshold d_0 were identified. The supply–demand ratios of these UBGSs were then aggregated using R_{ig}, weighted by the same Gaussian distance decay function, to obtain the accessibility level of preferred UBGS for group g at residential cluster i:

$$A_{ig}=\sum_{j \in (d_{ij} \leq d_0)} R_{jg} \cdot f(d_{ij}), j \in T_g \tag{8}$$

where A_{ig} represents the spatial accessibility index of UBGS obtained by group g at residential cluster i. A higher value of A_{ig} indicates a greater level of UBGS service available to that cluster.

Inequality evaluation of UBGS exposure

Two complementary inequality metrics were employed: the Theil index and the Coverage ratio. The Theil index, derived from information entropy theory[53], has the advantage of decomposing total inequality into intra-group and inter-group components, thereby identifying the structural sources of inequality. The Coverage ratio was used to measure the extent to which UBGS services actually cover the residential space of each group.

The total Theil index is defined as:

$$T=\frac{1}{n}\sum_{i=1}^{n}\frac{A_i}{\overline{A}}ln(\frac{A_i}{\overline{A}}) \tag{9}$$

where n denotes the total number of residential clusters, and $\overline{A}$ represents the overall average accessibility. By definition, $T \geq 0$; $T=0$ indicates perfect equality, and larger values indicate higher levels of inequality.

To further examine the sources of inequality, the total Theil index was decomposed into intra-group (T_{intra}) and inter-group (T_{inter}) components:

$$T=T_{intra}+T_{inter} \tag{10}$$

where:

$$T_{intra}=\sum_{g=1}^{G}\sum_{i=1}^{n_g}(\frac{1}{n}\frac{A_{ig}}{\overline{A}_g})ln(\frac{A_{ig}}{\overline{A}_g}) \tag{11}$$

$$T_{inter}=\sum_{g=1}^{G}(\frac{n_g}{n}\frac{\overline{A}_g}{\overline{A}})ln(\frac{\overline{A}_g}{\overline{A}}) \tag{12}$$

Here, G denotes the number of social groups, n_g is the number of residential clusters associated with group g, $\overline{A}_g$ represents the average accessibility of group g.

The Coverage ratio provides an additional perspective by focusing on whether UBGS services spatially cover group residential space. Unlike the decomposable Theil index, the Coverage ratio reflects the actual level of service coverage within the residential space of each group.

The Coverage ratio is defined as:

$$CR_g=\frac{n_g^{accessible}}{n_g} \tag{13}$$

where CR_g denotes the Coverage ratio of group g, $n_g^{accessible}$ is the number of residential clusters for group g with accessibility greater than 0. The value of CR_g ranges from 0 to 1; a higher value indicates that a larger proportion of the group's residential space has access to its preferred UBGS services, while a lower value suggests a greater share of underserved areas.

Ethics approval

This study did not involve human participants or animals, and therefore ethical approval was not required.

Consent to participate

Not applicable. This study did not involve human participants.

Data availability

Data is provided within the manuscript. UBGS and road networks data are obtained from the following websites: https://www.openstreetmap.org/. Administrative boundary data is obtained from the following websites: https://www.tianditu.gov.cn/. The mobile phone signaling data (MSD) and Weibo check-in data used in this study are not publicly available to protect the confidentiality of local residents. To prevent potential re-identification, access to anonymized versions of these datasets is available from the corresponding author upon reasonable request for research purposes.

Code availability

The underlying code for this study is not publicly available but may be made available to qualified researchers on reasonable request from the corresponding author.

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Author contributions

Y.J., X.J., and J.L. conceptualized the study. Y.J. developed the methodological framework, conducted the data collection, preprocessing, spatial accessibility modelling, inequality analysis, and visualization, and wrote the original manuscript. X.J. contributed to the study design, methodological refinement, interpretation of the results, and manuscript revision. M.S., H.X.H.B., M.P., E.W.-F., and N.S. contributed to the interpretation of the findings, discussion of urban sustainability and blue-green space planning implications, and critical revision of the manuscript. J.L. supervised the study, provided guidance on the research framework and manuscript structure, and contributed to the final revision. All authors read and approved the final manuscript.

Competing interests

The authors declare no financial or non-financial competing interests.

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