Sensors and Materials, Vol. 38, No. 3 (2026) 1241–1258
MYU Tokyo

S & M 4374

Evaluation of Public Transport Accessibility from a Supply–Demand Matching Perspective: Evidence from Zhuhai's Central District

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(Received October 2, 2025; accepted January 26, 2026)

Keywords: public transport, accessibility, mobile phone signaling data, travel demand, PTAL, equity, Zhuhai

Public transport accessibility is central to evaluating the performance, equity, and efficiency of urban transit systems. However, mainstream assessments remain supply-centric and largely static, overlooking how service provision aligns with spatiotemporally varying travel demand. We propose a multiscale evaluation framework that integrates supply–demand synergy and apply it to Zhuhai's central district (China). Using mobile phone signaling records from April 2023 and public transport data collected in June 2023, we examine spatial heterogeneity and the spatial matching between accessibility and travel demand at both citywide and local scales. Methods include the Gini coefficient, bivariate spatial autocorrelation, and a coupling-coordination model. Results show that (1) at the citywide scale, high-accessibility areas account for 34.1% of the land but cover 69.1% of travelers. Gini and Moran's I indicates relatively equitable provision and significant spatial clustering between accessibility and trip volume. (2) At the local scale, a prominent "low accessibility–high demand" mismatch emerges, indicating weak supply–demand coordination in parts of the study area. (3) Policy suggestions are proposed to recalibrate stop locations, headways, and route supply to improve matching. The framework advances a more comprehensive understanding of the interplay between accessibility and demand, and offers decision support for optimizing urban transport planning.

1. Introduction

China's rapid urbanization has intensified congestion pressures. As the backbone of urban mobility, public transport has strategic value for optimizing modal structures, enhancing service efficiency, promoting spatial equity, and supporting low-carbon transitions.(1,2) Accessibility—which reflects the efficiency of transport–space interactions—has evolved from simple isochrone coverage to a multidimensional construct encompassing spatial reach, time-cost thresholds, and service balance.(3) Studying public transport accessibility not only illuminates

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https://doi.org/10.18494/SAM5960

ISSN 0914-4935 © MYU K.K.
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the current performance of transit systems but also provides information for rational network planning and the spatial allocation of public services.[4]

Research on public transport accessibility has progressed from static, single-dimension measures to dynamic, multidimensional frameworks. Early work typically relied on geometric distance metrics—such as Euclidean and Manhattan distances—and buffer analyses, employing static indicators including stop coverage, line coverage, nonlinearity indices, and redundancy indices to characterize accessibility. These approaches are well suited to macrolevel applications, such as the conventional transit planning and system-wide appraisal of urban public transport systems.[5] With advances in geographic information technologies, scholars began modeling accessibility on real transport networks, establishing topological relationships among roads and transit routes to simulate spatiotemporal access on actual networks.[6] As the field deepened, time-windowed approaches, most notably opportunity accumulation[7] and isochrone analysis,[8] were introduced to evaluate access to opportunities under explicit spatiotemporal constraints.

Powered by big data, the integration of multisource heterogeneous datasets has become central to contemporary transport research. The Public Transport Accessibility Level (PTAL) framework proposed by Transport for London[8] synthesizes walking networks, bus service frequencies, and stop locations, and is now widely used for the preparation, evaluation, and monitoring of urban spatial and transport plans. As transport systems have matured, the research focus has shifted from isolated transit-network analysis to the complete trip chains in multimodal contexts; accordingly, scholars have developed multimodal spatiotemporal accessibility models that quantify complementarities among modes via dynamically allocated weights.[9] Beyond traditional network data, studies now leverage high-resolution and real-time sources, e.g., smart-card records, GPS traces,[7] population distribution provided by Internet map platforms,[10] real-time traffic conditions, and path-planning outputs.[11] There is also the use of microphones, cellular networks, and accelerometers, a simple combination of sensors, instead of GPS and specialized equipment, to accurately perform bus tracking and traffic speed estimation.[12] With GPS and weather detector data, real-time prediction models have been used to improve the reliability of aggregated bus schedules for public transportation systems.[13] Spatiotemporal path planning based on open map Application Programming Interfaces (APIs) enables the seamless integration of pedestrian connectivity with public transport networks, mitigating the linear bias inherent in Euclidean distances through gridded spatial probing and multidirectional path analysis.[14]

Consequently, accessibility research has moved beyond the sole emphasis on transport efficiency toward broader evaluations of equity and inclusiveness, and from static facility layouts to dynamic usage processes. Using dynamic, real-time monitoring, researchers have built spatiotemporal evolution models; for example, in Hefei, a time-series model based on floating-vehicle data was used to identify accessibility shifts during AM/PM peaks,[15] enabling the temporal assessment of network service effectiveness.[16,17] Moreover, scholars incorporate employment distribution,[18,19] mobility constraints of vulnerable groups[1,20] and other contextual factors, while developing scenario-specific frameworks for special populations,[21] thereby unpacking the complex manifestations of fairness in public transport. In some megacities, despite higher stop coverage among low-income groups, fare sensitivity and insufficient access to employment centers produce a paradox of "high supply–low utility".[22] By systematically integrating key parameters, such as the quantitative travel-cost index,[23] job–housing matching, and passenger perception weights,[24] recent analyses of the coupling mechanisms linking accessibility with socio-economic structures have revealed multidimensional synergies between the public transport system and the urban spatial form.

Most existing studies remain confined to the topology-based analyses of transport networks from a unidimensional, supply-side perspective, lacking an explicit supply–demand coupling mechanism in their theoretical frameworks. This limitation was mainly due to the lack of data that can accurately reflect the dynamic travel behavior of the population in the past, as well as the limited computational level of computers, which made it difficult to capture the characteristics of spatial and temporal changes in the travel demand of the population. This static, supply-centric accessibility paradigm fails to account for the spatial heterogeneity and temporal dynamics of residents' travel patterns, leading to systematic divergences between indicator systems and realized demand.[25] In recent years, the effectiveness of public transport services in many Chinese cities has declined, and operators have faced persistent deficits, revealing that simply expanding supply inputs can, paradoxically, exacerbate spatial supply–demand mismatches.[26] Accordingly, adopting a supply–demand matching perspective that jointly considers residents' travel demand and the configuration of the bus network offers greater practical relevance for accessibility assessment and planning.[27]

Amid the rapid rollout of new information infrastructure, the exponential growth of spatiotemporal big data is reshaping research paradigms on urban travel behaviors. Among these sources, anonymized mobile-phone signaling data—by virtue of its broad coverage and high temporal frequency—has become a core resource for revealing residents' spatiotemporal movement patterns. Empirical studies show that such data can reconstruct complete trip-chain trajectories and provide dynamic decision support for transport planning,[28] including inferring commuting patterns,[29,30] identifying jobs–housing relationships,[29,31] and predicting travel demand.[32]

In this study, we propose a supply–demand coupling-oriented framework for public transport accessibility. We integrate PTAL-based supply metrics with mobile-phone-signaling-derived demand and deploy a multiscale toolkit, Gini, bivariate Moran's I (with permutation inference), and a coupling-coordination model to diagnose equity, spatial association, and local mismatches. Empirically, using Zhuhai's central district, we quantify citywide equity and reveal intraday/holiday coordination gaps. The framework is replicable and extensible, offering actionable guidance for route design, headway management, and bus stop siting in demand-responsive planning.

2. Materials and Methods

2.1 Methodological framework

Aiming at the core contradiction of the mismatch between the supply and demand of public transportation, we develop a supply–demand matching framework grounded in spatial equity and supported by multisource data. Supply is quantified via London's PTAL, overall equity is assessed using the Gini coefficient and bivariate Moran's I, and local suitability is examined through a coupling–coordination model. The study results systematically reveal the spatial differences in the matching of the supply and demand of public transport services, and provide the methodological support for the precise optimization of public transport resource allocation. Figure 1 outlines the workflow.

2.1.1 Multidimensional transit accessibility

Our work is based on the methodological framework of PTAL,[8,33] which quantitatively characterizes the level of public transport service provision in each spatial unit of the central city. The advantages of this method are that it is oriented to the actual use experience of residents, integrates the service range and departure frequency of bus stops, circumvents the limitations of a single distance or speed indicator, has calculation logic that is simple and reproducible, and has been verified to be effective in the assessment of public transportation in London, Shanghai, Hangzhou, and other cities.[33] The specific calculation process is as follows: first, the stations that can serve the analysis unit are delineated on the basis of the walking time (WT) from the analysis unit to a public transportation service point. For each line, the scheduled waiting time (SWT) is calculated taking into account the departure frequency, the reliability

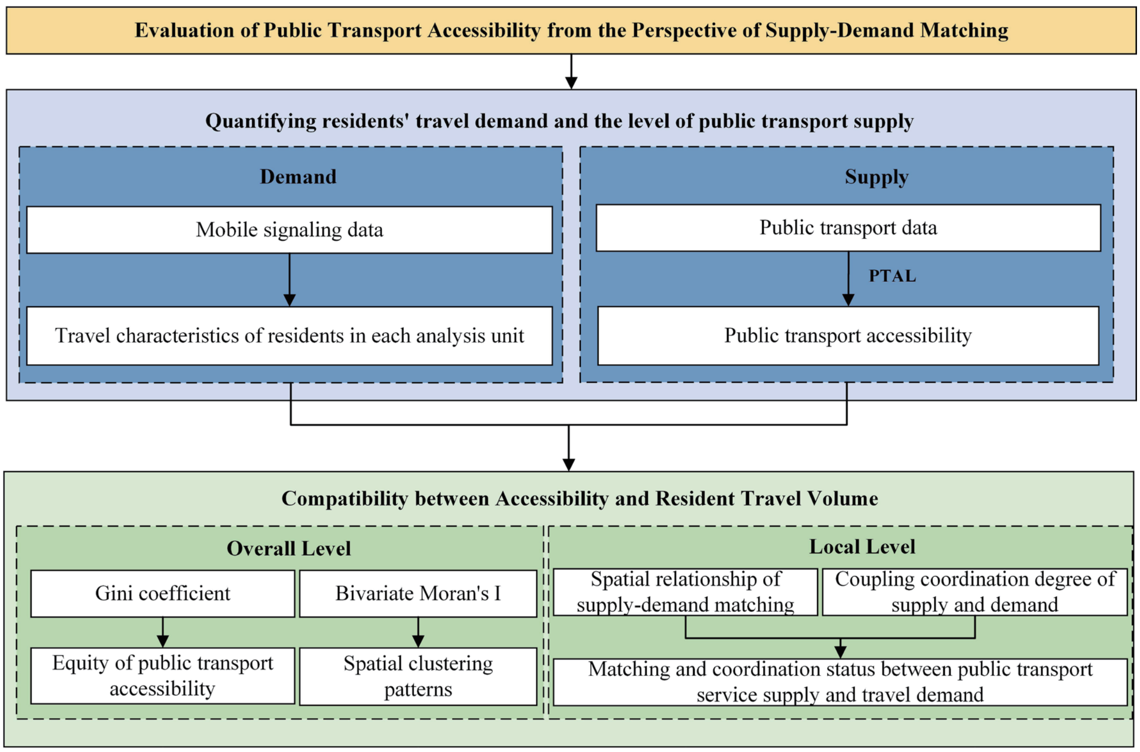


Fig. 1. (Color online) Technical roadmap for research on accessibility and travel volume from supply and demand perspective.

correction factor is superimposed, and the total WT is superimposed on the average waiting time (AWT) to calculate the total access time (TAT). Then, TAT is converted to the equivalent doorstep frequency (EDF). Finally, weights are assigned in accordance with the equivalent service frequency of the line and summed to obtain the access index (AI). The calculation flow is shown in Fig. 2.

The correspondence between the AI and the accessibility level is shown in Table 1.[8] On the basis of the level of accessibility, we further construct a multiscale evaluation system and carry out accessibility analysis from the perspectives of overall regional equity and local spatial suitability.

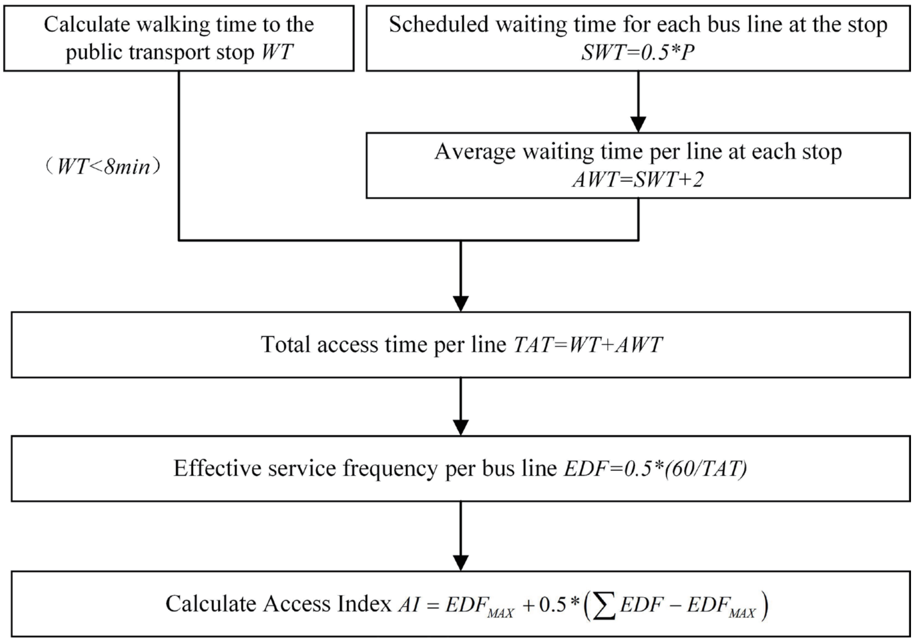


Fig. 2. Accessibility calculation flowchart.

Table 1
Correspondence between AI and accessibility level.

Access index	Accessibility level
0	low
≤2.5	low
>2.5–5	low
>5–10	medium
>10–15	medium
>15–20	medium
>20–25	medium
>25–40	high
>40	high

2.1.2 Equity at the overall scale

2.1.2.1 Gini coefficient

The Gini coefficient is an indicator of the fairness of income distribution within a country or region. The social equity connotations of public resource allocation and income distribution are similar, so the Gini coefficient and the Lorenz curve are also used to carry out public transportation accessibility equity research,[34,35] focusing on the spatial resource allocation perspective, to explore the degree of spatial matching between the supply of public transportation services and the demand of residents' trips in a specific region. The Gini coefficient is calculated on the basis of the geometric definition of the Lorenz curve. In this study, the accessibility values of each grid in the study area are arranged in ascending order to construct the Lorenz curve of public transportation service supply. The horizontal axis represents the cumulative value of the population travel demand in each grid as a percentage of the total, and the vertical axis represents the cumulative value of the public transportation service supply as a percentage of the total. The calculation formula is

$$G = \frac{S_A}{S_A + S_B} = \frac{2\sum_{i=1}^{n} i \cdot Y_i}{n\sum_{i=1}^{n} Y_i} - \frac{n+1}{n}. \quad (1)$$

In the formula, S_A is the area sandwiched between the fair line and the Lorenz curve, S_B is the area bounded by the Lorenz curve, the x-axis, and $x = 1$, n is the number of units of analysis. Y_i is the AI of the ith unit of analysis, where the units are arranged in ascending order of AI ($Y_1 \leq Y_2 \leq ... \leq Y_n$). Thus, intuitively, the smaller the arc of the Lorenz curve, the closer it is to the fairness line, which means that the fairness of the distribution is better. Conversely, the larger the arc, the worse the fairness of the allocation (Fig. 3).

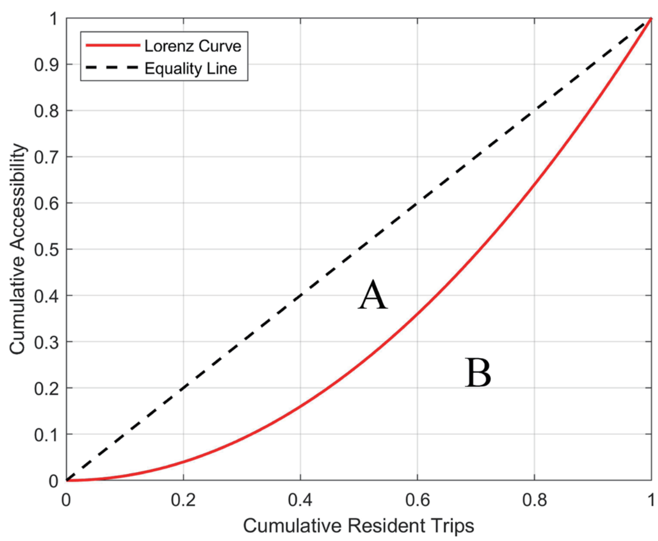


Fig. 3. (Color online) Schematic diagram of Lorenz curve.

2.1.2.2 Moran's I

Because the Gini coefficient and Lorenz curve are aspatial measures that do not incorporate geographic location, we use bivariate Moran's I to quantify the spatial association between accessibility (supply) and trip volume (demand). Moran's I measures spatial autocorrelation by jointly considering the spatial arrangement of observations and their attribute values.(36) Its bivariate extension indicates whether high (or low) values of one variable tend to occur near high (or low) values of another variable, thereby capturing cross-variable spatial dependence.(37) Positive values indicate co-clustering (high–high, low–low), whereas negative values indicate spatial dissimilarity (high–low).

$$I = \frac{n}{W} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(x_i - \bar{x} \right) \left(y_i - \bar{y} \right)}{\sqrt{\sum_{i=1}^{n} \left(x_i - \bar{x} \right)^2 \sum_{j=1}^{n} \left(y_i - \bar{y} \right)^2}} \tag{2}$$

In Eq. (2), x and y are the values of two different variables at location i; $\bar{x}$ and $\bar{y}$ are the mean values of the variables x and y, respectively. w_{ij} denotes the weight between the i position and the j position, constructed by Queen's Neighborhood Rule; W is the sum of weight matrices; and n is the total number of analysis units. I is the bivariate Moran's I, and it is generally considered that the closer $|I|$ is to 1, the stronger the correlation: $I > 1$ positive correlation and $I < 1$ negative correlation. On the basis of the Gini coefficient calculation, the spatial weight matrix is introduced to measure the characteristics of regional resource allocation differences in the overall dimension, which further reveals the clustering pattern of public transportation service supply and travel demand among spatial units. The combination of the two realizes the multidimensional analysis of "overall difference measurement–local spatial correlation".

2.1.3 Local supply–demand fitness and coupling coordination

2.1.3.1 Local matching typology

The evaluation method of accessibility spatial matching on the local scale mainly evaluates a positive hexagonal analysis unit with a side length of 100 m, and evaluates the matching results on the local scale in accordance with the level of accessibility and the level of resident travel volume, and matches the results of each unit. First, the data of residential trips on weekdays, public holidays, and weekends calculated from cell phone signaling data were classified into three categories using the quantile grading method with 25 and 75% as grading points. The categories correspond to the three levels of "low, medium, and high", respectively. The "High–Medium–Low" level of transit accessibility of each analysis unit was matched with the "High–Medium–Low" level of residential trips, and a total of nine matching results were obtained. We conclude that the supply and demand of the analyzed units with the results of "High–High", "Medium–Medium", and "Low–Low" are well adapted; "High–Medium", "Medium–High", "Medium–Low", and "Low–Medium" are well adapted. The supply–demand fit is poor for the

"High–Low" and "Low–High" units of analysis. In this study, we focused on the "high travel-low accessibility" and "high accessibility–low travel" units of analysis, which have a poor supply–demand fit.

2.1.3.2 Coupling coordination

The degree of coordination of supply and demand coupling is an important indicator for measuring the interaction and synergistic development level between supply and demand subsystems in the system, the concept of which originated from the theory of "coupling" in physics, and has been expanded and applied to economics, geography, management, and other fields. By quantitatively analyzing the dynamic relationship between supply and demand, the model reveals the synergistic mechanism between the two in resource allocation, efficiency optimization, and sustainable development. The calculation method uses the following equations:

$$C = \sqrt{\frac{U_1 U_2}{\left(\frac{U_1 + U_2}{2}\right)^2}}, \tag{3}$$

$$T = aU_1 + bU_2, \tag{4}$$

$$D = \sqrt{CT}. \tag{5}$$

Here, C is the coupling degree, and U_1 and U_2 are the normalized supply and demand of public transport services, respectively. T is the overall coordination index, and a and b are the weights of supply and demand, where $a = b = 0.5$. D is the calculated coupling coordination degree. $0 \leq D < 0.2$ is severe dissonance, $0.2 \leq D < 0.4$ is moderate dissonance, $0.4 \leq D < 0.6$ is basic coordination, $0.6 \leq D < 0.8$ is moderate coordination, and $0.8 \leq D \leq 1$ is high coordination.

2.2 Study area

Zhuhai City is a rapidly developing second-tier city in China. Its transportation system is confronted with typical challenges in resource allocation and equity. Moreover, the terrain in the study area is complex, with interlaced plains and hills. The study area covers nine subdistricts/towns in Zhuhai's central district (Fig. 4). The terrain consists of plains interspersed with low hills—Fenghuang Hill in the north, Banzhang Hill in the central area, and Jiangjun Hill in the south—while densely populated plains host the main urban fabric. This enables us to analyze the differences in public transportation accessibility in different geographical environments and the relationship between it and the matching of residents' demands. It is highly representative and has good data availability.

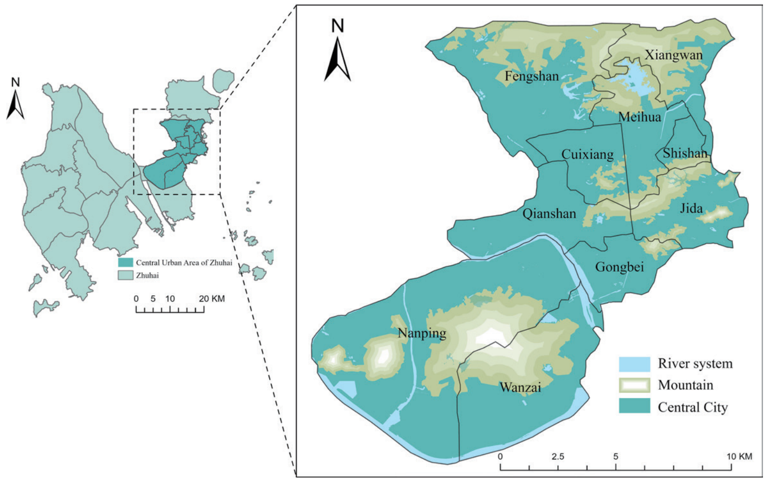


Fig. 4. (Color online) Overview of 10 subdistricts and towns in Zhuhai's central district.

2.3 Datasets

2.3.1 Public transport data

We assembled stop locations, headways, and pedestrian path distances (June 2023). Route and stop names were extracted from the ‘8684 Bus’ website and then geocoded via Amap’s POI API. Headways were compiled from operator timetables and cross-checked with weekday expected departures from the vehicle-arrival platform. Walking distances from each grid centroid to the nearest stop were obtained through Amap’s walking path planning API (key, origin, destination). Structured attributes are summarized in Table 2. Since bus stops, routes, and departure times usually remain stable over a period of time, they are considered to be representative of public transportation over time.

2.3.2 Mobile phone signaling data

Anonymized signaling records for April 1–30, 2023 were used to infer travel demand. The data contains two Chinese public holidays totaling 3 days, 20 weekdays, and 7 weekend days (Saturdays and Sundays), with a data volume close to 10 million. Following the common practice that public transport primarily serves trips with distances ≥1 km,[38] we filter observations by displacement >1 km and reproject to WGS-84, restricted to within the study area. Records are aggregated to 100 m hexagonal grids based on serving base-station coordinates, producing weekday, weekend, and holiday trip volumes per grid (Table 3).

Table 2
Public transport data attributes.

ID	Station ID	line	Longitude	Latitude	Headway (min)
0	BV10251018	502	502	502	502
1	BV11015319	502	502	502	502
2	BV11351997	26	26	26	26
3	BV10250577	26	26	26	26
4	BV11109102	303	303	303	303
5	BV11257446	303	303	303	303
……					

Table 3
Volume of residential trips in Zhuhai city center.

GID (Grid ID)	PF_GZ (trip generation volume on weekdays)	PF_ZM (trip generation volume on weekends)	PF_JJ (trip generation volume on holidays)
EW-96	38	43	46
EO-208	378	282	208
FB-156	159	172	221
DY-112	14	17	20
……			

3. Results

3.1 Spatial distribution of accessibility

Zhuhai currently operates bus services but no urban rail service; thus, PTAL reflects bus-only accessibility. With 100 m hexagonal grids, PTAL results (Fig. 5) show generally good accessibility with clear inter-subdistrict variation (Table 4). In Shishan and Gongbei, >60% of their areas have high accessibility, whereas Nanping, Fengshan, and Wanzai have <20%, partly owing to higher shares of hilly terrain (≈30–36% vs ≈9–22% in Shishan/Gongbei).

3.2 Overall scale equity and spatial association

At the citywide scale of Zhuhai's central district and its subdistricts, we evaluated distributional equity in public transport services using the Gini coefficient and assessed spatial clustering between accessibility and resident trips with bivariate Moran's I (Table 5). The Gini coefficient is a standard equity metric: values < 0.20 typically indicate highly even provision, whereas values > 0.40 reflect pronounced inequality. Our calculations (Table 5) show that, overall, public transport accessibility is generally equitable across the study area.

Lorenz curves for selected subdistricts (Fig. 6) further illustrate these patterns. Wanzai Subdistrict exhibits a relatively flat lower segment and a steep upper tail: the bottom 30% of travelers receive near-zero shares of accessibility, whereas the top 10% have nearly 20%. Xiangwan Subdistrict shows a similar but less extreme profile, implying better overall equity than Wanzai. In line with these curves, all subdistricts except Wanzai have Gini values below 0.40, indicating a broadly reasonable distribution of accessibility, albeit with discernible inter-subdistrict disparities.

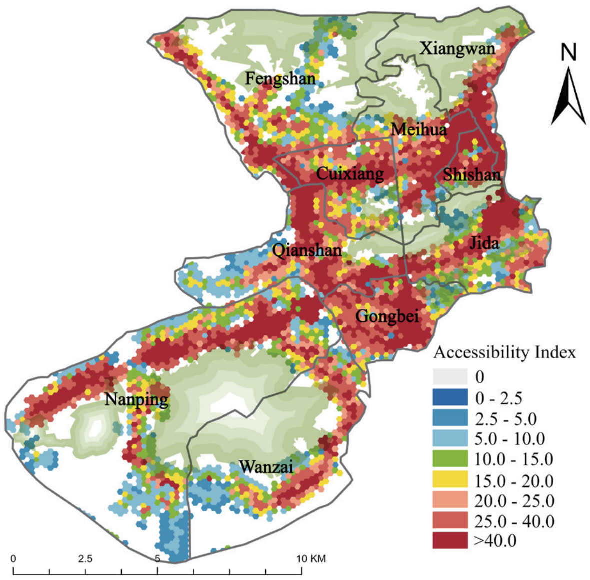


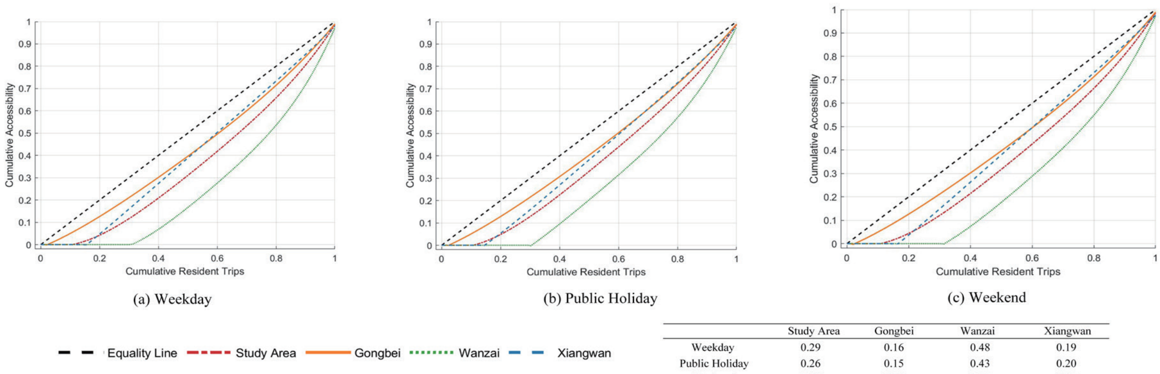
Fig. 5. (Color online) Results of PTAL-based public transport accessibility.

Table 4
Percentage of accessibility ratings by street and town.

	Cuixiang	Fengshan	Gongbei	Jida	Meihua
Low	15.67%	59.57%	7.67%	22.62%	44.47%
Medium	36.99%	25.56%	28.22%	41.23%	19.76%
High	47.34%	14.87%	64.11%	36.15%	35.76%
	Nanping	Qianshan	Shishan	Wanzai	Xiangwan
Low	55.71%	26.54%	14.55%	64.54%	65.05%
Medium	24.43%	33.64%	17.27%	21.51%	9.67%
High	19.86%	39.81%	68.18%	13.95%	25.27%

Table 5
Gini coefficient and Moran's I for central city streets and towns.

Street/town	Weekday		Public holiday		Weekend	
	Gini coefficient	Moran's I	Gini coefficient	Moran's I	Gini coefficient	Moran's I
Cuixiang	0.30	0.48	0.29	0.50	0.31	0.47
Fengshan	0.33	0.66	0.32	0.64	0.32	0.66
Gongbei	0.16	0.54	0.15	0.55	0.16	0.55
Jida	0.28	0.47	0.27	0.53	0.29	0.47
Meihua	0.27	0.72	0.26	0.72	0.26	0.72
Nanping	0.35	0.61	0.33	0.56	0.34	0.59
Qianshan	0.32	0.65	0.29	0.63	0.31	0.65
Shishan	0.27	0.57	0.27	0.58	0.26	0.59
Wanzai	0.48	0.54	0.43	0.55	0.46	0.54
Xiangwan	0.19	0.74	0.20	0.77	0.20	0.74
Study Area	0.29	0.63	0.26	0.63	0.28	0.63



	Study Area	Gongbei	Wanzai	Xiangwan
Weekday	0.29	0.16	0.48	0.19
Public Holiday	0.26	0.15	0.43	0.20
Weekend	0.28	0.16	0.46	0.20

Fig. 6. (Color online) Results of Lorenz curve analysis.

Temporally, Gini values vary little across weekdays, weekends, and holidays; nonetheless, holidays tend to be slightly more equitable, whereas weekdays are less so. Because equity differs both across space and within the same locations over time, efforts to improve public transport accessibility should explicitly consider temporal equity alongside spatial targeting.

The bivariate Moran's I quantifies the spatial covariation between accessibility and resident trip volumes at the subdistrict (street/town) level. Across all time segments, values are positive (Table 5), indicating that higher accessibility tends to coincide with higher trip volume. Meihua and Xiangwan exhibit relatively strong associations.

Considering Gini coefficients alongside Moran's I provides complementary insights. Gongbei and Xiangwan both have Gini ≤ 0.20, reflecting high equity; in purely distributional terms, Gongbei is marginally more equitable than Xiangwan. Their mean bivariate Moran's I values are 0.750 (Gongbei) and 0.547 (Xiangwan), implying a stronger spatial alignment between accessibility and trips in Gongbei than in Xiangwan. Together, these metrics suggest that while both subdistricts are equitable, Gongbei achieves better spatial matching between supply and demand.

3.3 Local-scale matching and coupling coordination

Figure 7 summarizes the travel characteristics of residents in Zhuhai's central city. As a result of a hexagonal-grid analysis, a nine-category supply–demand matching typology is shown in Fig. 8. We emphasize units where public transport accessibility and observed trips are misaligned; in the figure, darker tones denote the two mismatch types: high trip volume–low accessibility and high accessibility–low trip volume.

Temporally, results are broadly consistent across weekdays, weekends, and public holidays. Using weekdays as an example, well-matched units account for 56.82% of the study area, whereas mismatched units account for 1.62%. Among mismatches, low accessibility–high trip volume dominates (98.98%), whereas high accessibility–low trip volume is relatively rare (1.02%). Spatially, the prevalent low-accessibility–high-trip-volume pattern is concentrated along the western fringe of Qianshan Subdistrict and the eastern side of Wanzai Subdistrict. In

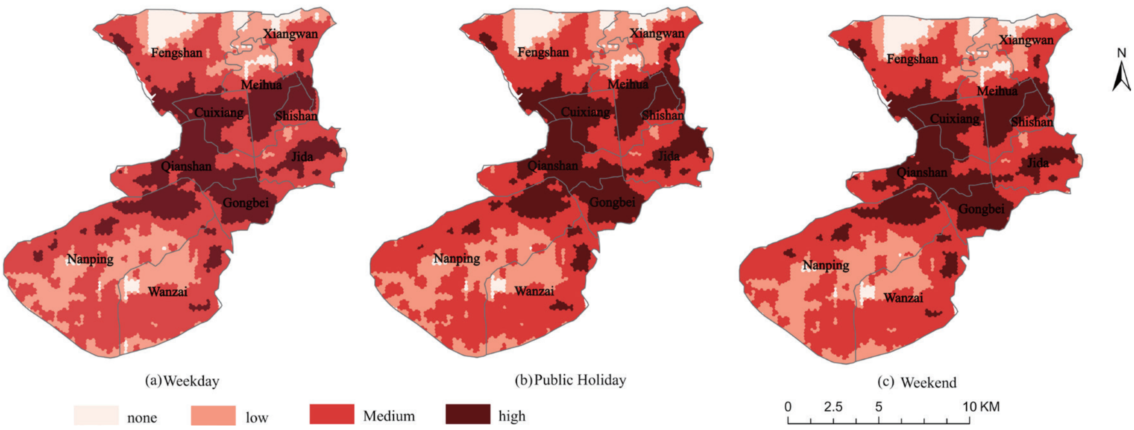
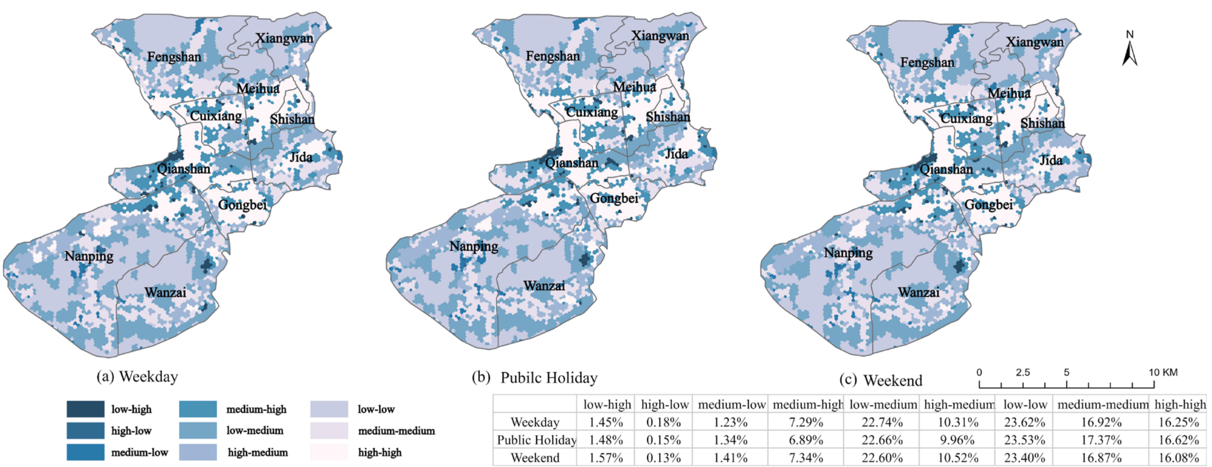


Fig. 7. (Color online) Residents traveling in Zhuhai Central Region.



	low-high	high-low	medium-low	medium-high	low-medium	high-medium	low-low	medium-medium	high-high
Weekday	1.45%	0.18%	1.23%	7.29%	22.74%	10.31%	23.62%	16.92%	16.25%
Public Holiday	1.48%	0.15%	1.34%	6.89%	22.66%	9.96%	23.53%	17.37%	16.62%
Weekend	1.57%	0.13%	1.41%	7.34%	22.60%	10.52%	23.40%	16.87%	16.08%

Fig. 8. (Color online) Public transport accessibility and travel volume classification.

contrast, high-accessibility–low-trip-volume pockets occur sporadically in Nanping Town without clear clustering.

Policy implications are twofold. For "high-demand–low-supply" areas, stop siting optimization, increased service frequency (shorter headways), and selective route extensions should be prioritized. For low-trip-volume–high-accessibility areas, consider stop consolidation, timetable rationalization, or in coordination with land-use planning, encouraging complementary trip-generating uses nearby (e.g., education, healthcare, and residential) where appropriate. To address intraday variability at the same locations, adopt time-of-day operating strategies such as weekday peak commuter boosts and holiday tourist services to better align short-term supply with observed demand.

Figure 9 reveals pronounced spatiotemporal heterogeneity in the degree of coupling coordination between public transport supply and demand across the study area. Overall, most parts of Zhuhai's central city do not attain an ideal coordination state: there are no highly

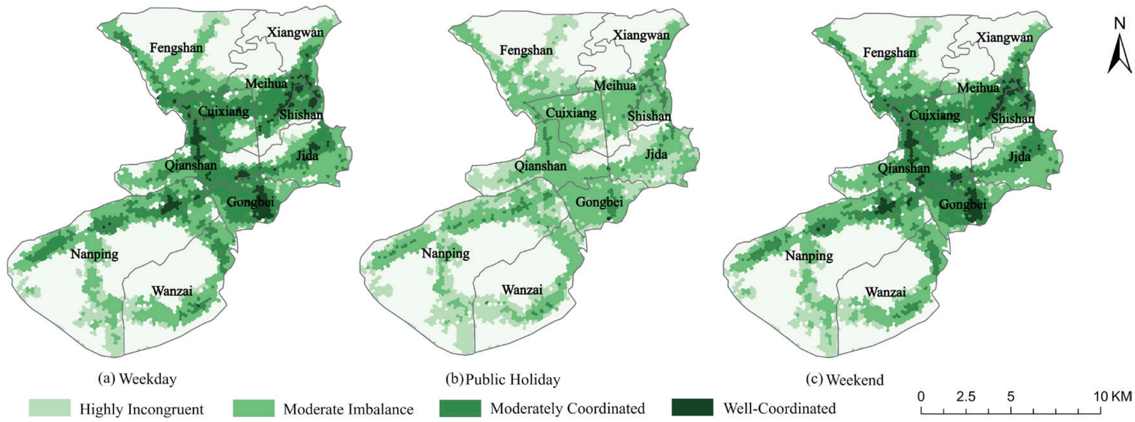


Fig. 9. (Color online) Spatial distribution of public transport supply–demand balance.

Table 6
Volume-weighted coupling coordination share statistics for trips.

	Highly incongruent	Moderate imbalance	Moderately coordinated	Well-coordinated	Highly coordinated
Weekday	0.12	0.27	0.49	0.12	0
Public Holiday	0.28	0.65	0.07	0	0
Weekend	0.12	0.28	0.48	0.12	0

coordinated zones, few areas exhibiting moderate or basic coordination, and several pockets of severe disharmony. Temporally, coordination is stronger on weekdays and weekends but deteriorates on holidays.

Areas with poor coupling coordination between public transport supply and demand are concentrated primarily in hilly terrain. Many of these hillsides are not directly served by buses, yet they attract residents for recreation and leisure, generating episodic flows that translate into severe disharmony in the coordination metric. We computed trip-weighted statistics at the grid level and excluded grids with ≤1 trip; the resulting summaries (Table 6) indicate that over half of the central-city area achieves at least basic coordination on weekdays and weekends, whereas holiday coordination is weaker overall, with most areas exhibiting moderate disharmony.

4. Conclusions

Public transport accessibility is a core indicator of the performance and development of urban transit systems. While numerous strategies exist to improve accessibility, indiscriminate enhancement across all areas risks inefficient allocation of scarce service resources. To prioritize interventions, in this study, we first used anonymized mobile-phone signaling data to characterize travel in Zhuhai's central urban area and then evaluated public transport accessibility at both the citywide and local scales. The following are the main findings:

(1) On the overall scale, public transport accessibility is moderate. Specifically, 34.1% of the area attains a PTAL of ≥6, whereas 44.16% exhibits low accessibility. Although high-accessibility

zones cover a smaller land share, they accommodate 69.08% of travelers, whereas low-accessibility zones host only 0.58%. Overall, the supply–demand alignment is therefore relatively favorable.

(2) At the local scale, the predominant mismatch type is high trip volume–low accessibility. These areas merit targeted upgrades, such as extending route coverage and increasing service frequencies, and vehicle allocations can be further optimized by adding trips or switching to high-capacity buses during high trip volumes, to better align with resident travel needs. Conversely, low-trip-volume–high-accessibility pockets indicate potential resource inefficiency; options such as skipping stops, timetable consolidation, or stop layout optimization can raise line efficiency, and switching to small-capacity buses can also reduce workforce configurations and costs, thereby cutting down on waste.

(3) Regionally, the coupling coordination degree of supply and demand is largely characterized by basic coordination and moderate imbalance, with severe imbalance in specific locations. Severe cases are closely associated with Zhuhai's mountainous terrain, whereas densely populated residential areas (with high demand) tend to show acceptable coordination. Service adjustments should therefore be area-specific, calibrated to local matching conditions to improve coupling coordination. For regions with poor supply–demand coupling, efforts can be made to collect residents' travel plan points, improve transportation supporting measures, launch customized mountain buses, and select small-capacity buses to adapt to the mountainous environment.

We integrated the PTAL framework with anonymized mobile-phone signaling data to develop a two-dimensional supply-demand evaluation. On the supply side, bus route topology, scheduled departure frequencies, and walking-path APIs were fused to quantify grid-level accessibility with precision. On the demand side, signaling records were used to infer travelers' spatiotemporal demand. We further linked the Gini coefficient, bivariate Moran's I, and a coupling-coordination model into a citywide-to-local, multiscale analysis chain, addressing the limitations of supply-only, static assessments. Applied to Zhuhai's central district, the framework revealed the supply characteristics of bus accessibility and yielded a replicable, extensible toolkit that provides information for transit network optimization and spatial planning under China's new urbanization agenda.

The present analysis distinguishes weekdays, weekends, and holidays. In future work, the high spatiotemporal resolution of signaling data can be exploited to examine peak and off-peak dynamics (e.g., AM and PM peaks on weekdays) and to benchmark period-specific patterns against overall baselines, thereby capturing short-term supply–demand fluctuations more precisely. While large signaling samples mitigate sampling error and reveal macro–level regularities, inferred trip volumes may overstate realized bus demand because micro–behavioral attributes (e.g., habitual choices and mode preferences) are not explicitly modeled. In subsequent research, signaling data can be combined with structured questionnaires, semistructured interviews, and field observations to elucidate actual bus usage and latent intentions. In addition, the current research framework can be expanded by combining data from public transportation IC cards, GPS, and various environmental sensor devices for an in-depth analysis of the relationship between public transportation accessibility and residents' emergent demand under different weather conditions and seasons. Such evidence would support more targeted adjustments to operating zones, departure windows, and headways, improving the dynamic matching between service provision and traveler demand.

Acknowledgments

This work was supported by the 2023 Annual Ministerial–Provincial Cooperation Pilot Projects of the Ministry of Natural Resources (2023ZRBSHZ075), 2025 Tianjin Municipal Bureau of Planning and Natural Resources Task-Oriented Open Competition Program (2025GHZYJB005), and Tianjin Normal University Undergraduate Innovation Program (202510065241).

References

1 G. Currie: Social Research in Transport (SORT) Clearinghouse **1895** (2004) 137. https://doi.org/10.3141/1895-18
2 A. Zhang, C. Xia, J. Chu, J. Lin, W. Li, and J. Wu: Sustainable Cities Soc. **46** (2019) 101396. https://doi.org/https://doi.org/10.1016/j.scs.2018.12.024
3 Y.-H. Cheng and S.-Y. Chen: Transp. Res. Part A Policy Pract. **77** (2015) 386. https://doi.org/https://doi.org/10.1016/j.tra.2015.05.003
4 D. Banister: Transp. Policy **15** (2008) 73. https://doi.org/https://doi.org/10.1016/j.tranpol.2007.10.005
5 Y. Ying and Z. Jizhou: J. Transp. Sci. Eng. **36** (2020) 94. https://doi.org/10.16544/j.cnki.cn43-1494/u.2020.03.015
6 T. Yigitcanlar, N. Sipe, R. Evans, and M. Pitot: Australian Planner **44** (2007) 30. https://doi.org/10.1080/07293682.2007.9982586
7 Y. Zuo, Z. Liu, and X. Fu: Geo-spatial Inf. Sci. **23** (2020) 248. https://doi.org/10.1080/10095020.2020.1783189
8 Transport for London, Assessing Transport Connectivity in London: https://www.tfl.gov.uk/cdn/static/cms/documents/connectivity-assessment-guide.pdf (accessed December 2025).
9 Measuring Spatiotemporal Accessibility for Pediatric Clinical Services with Multimodal Transport Modes: An Exploratory Analysis in Nanjing, China: https://assets-eu.researchsquare.com/files/rs-34168/v1_covered.pdf?c=1631836096 (accessed December 2025).
10 W. Jie, W. Qingguo, and G. Fucheng: Logistics Sci-Tech **45** (2022) 16. https://doi.org/10.13714/j.cnki.1002-3100.2022.11.003
11 N. Qiang, T. Mengshuai, L. Xiaoqian, and Yangxiu: Chin. Geogr. Sci. **44** (2024) 2134. https://doi.org/10.13249/j.cnki.sgs.20230754
12 Z. Liu, S. Jiang, P. Zhou, and M. Li: IEEE Trans. Intell. Transp. Syst. **18** (2017) 2851. https://doi.org/10.1109/TITS.2017.2650215
13 N. Rashvand, S. S. Hosseini, M. Azarbayjani, and H. Tabkhi: IoT **5** (2024) 650. https://doi.org/10.3390/iot5040029
14 J. Haitao, F. Jin, H. Qing, Z. He, and Y. Xue: Open Transp. J. **13** (2019) 93. https://doi.org/10.2174/1874447801913010093
15 C. Wang, S.-J. Zhao, Z.-Q. Ren, and Q. Long: ISPRS Int. J. Geo-Inf. **12** (2023) 285. https://doi.org/10.3390/ijgi12070285
16 H. Yao, X. Liuyuan, L. Dingli, T. Jiafu, and L. Weijun: J. Safety Environ. **24** (2024) 3573. https://doi.org/10.13637/j.issn.1009-6094.2024.0010
17 Y. Chen, L. Cuilin, Y. Mingfei, and R. Bowen: Tourism Res. **16** (2024) 74. https://doi.org/10.3969/j.issn.1674-5811.2024.04.006
18 S. Farber and L. Fu: Comput. Environ. Urban Syst. **62** (2017) 30. https://doi.org/https://doi.org/10.1016/j.compenvurbsys.2016.10.005
19 A. Golub and K. Martens: J. Transp. Geogr. **41** (2014) 10. https://doi.org/https://doi.org/10.1016/j.jtrangeo.2014.07.014
20 J. R. Mayaud, M. Tran, R. H. M. Pereira, and R. Nuttall: Comput. Environ. Urban Syst. **73** (2019) 1. https://doi.org/https://doi.org/10.1016/j.compenvurbsys.2018.07.005

21 W. Wei, Z. Hang, L. Limei, D. Meihua, and H. Yong: Geogr. Geo-Inf. Sci. **37** (2021) 64. https://doi.org/10.3969/j.issn.1672-0504.2021.06.010
22 D. Liu and M.-P. Kwan: Travel Behav. Soc. **19** (2020) 184. https://doi.org/https://doi.org/10.1016/j.tbs.2020.01.005
23 X. Qi, C. Yue, H. Jinru, G. Shunxing, and Z. Zhijian: J. Transp. Syst. Eng. Inf. Technol. **22** (2022) 37. https://doi.org/10.16097/j.cnki.1009-6744.2022.02.004
24 N. Chaloux, G. Boisjoly, E. Grisé, A. El-Geneidy, and D. Levinson: Transp. Res. Part F Psychol. Behav. **62** (2019) 833. https://doi.org/https://doi.org/10.1016/j.trf.2019.03.008
25 D. Hongxing, H. Yi, and H. Wei: J. Chongqing Univ. Technol. (Nat. Sci.) **36** (2022) 196. https://doi.org/10.3969/j.issn.1674-8425(z).2022.04.024
26 W. Dengzhong, M. Dongfang, F. Bo, W. Rujie, and Y. Chao: J. Chongqing Jiaotong Univ. (Nat. Sci.) **43** (2024) 59. https://doi.org/10.3969/j.issn.1674-0696.2024.01.09
27 Z. Pengjun, L. Wenzhou, Y. Ling, W. Hao, Z. Dongyi, Z. Haoran, and L. Ling: J. Hum. Settlements West China **39** (2024) 155. https://doi.org/10.13791/j.cnki.hsfwest.20240322
28 L. Sihan, L. Shijia, Z. Zhujun, and N. Xinyi: J. Hum. Settlements West China **36** (2021) 113. https://doi.org/10.13791/j.cnki.hsfwest.20210515
29 L. Jiexuan, B. Mengyuan, and G. Zhihui: J. Geo-inf. Sci. **26** (2024) 2419. https://doi.org/10.12082/dqxxkx.2024.240280
30 Z. Jialin and W. De: Hum. Geogr. **38** (2023) 81. https://doi.org/10.13959/j.issn.1003-2398.2023.04.010
31 W. Gao, M. Cui, E. Pan, and B. P. Y. Loo: J. Transp. Geogr. **121** (2024) 104003. https://doi.org/https://doi.org/10.1016/j.jtrangeo.2024.104003
32 Y. Tong, L. Xiaohang, M. Bin, S. Changsheng, and W. Huoqi: Geogr. Res. **43** (2024) 2425. https://doi.org/10.13249/j.cnki.sgs.20230754
33 Z. Tianran and Z. Chunjie: Urban Transp. China **17** (2019) 70. https://doi.org/10.13813/j.cn11-5141/u.2019.0111
34 A. Delbosc and G. Currie: J. Transp. Geogr. **19** (2011) 1252. https://doi.org/10.1016/j.jtrangeo.2011.02.008
35 B. Wang, C. Liu, and H. Zhang: J. Transp. Geogr. **98** (2022) 103275. https://doi.org/10.1016/j.jtrangeo.2021.103275
36 C. Yanguang: Geogr. Res. **28** (2009) 1449. https://doi.org/10.11821/yj2009060002
37 L. Bowen, H. Zhengdong, K. Xi, and Y. Xi: Prog. Geogr. **40** (2021) 958. https://doi.org/10.18306/dlkxjz.2021.06.006
38 Z. Yajuan, Z. Zhiyuan, W. Sheng, F. Zhixiang, and C. Zuoqi: J. Geo-Inf. Sci. **22** (2020) 1282. https://doi.org/10.12082/dqxxkx.2020.190623

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