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The impacts of the built environment on bicycle-metro transfer trips: A new method to delineate metro catchment area based on people's actual cycling space

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ABSTRACT

Bicycle-metro integration is an efficient method of solving the "last mile" issue around metro stations. Built environment is believed to have a significant effect on cycling behavior. However, transfer cycling around metro stations, as a specific type of cycling behavior, has often been overlooked in transport research. In addition, static contextual units such as circular or street-network buffers are typically used to delineate metro catchment areas of transfer cycling trips. These methods are inaccurate to represent the actual geographic contexts of cycling trips, according to the uncertain geographic context problem (UGCoP). Thus, in this study, bicycle-metro catchment areas are delineated based on aggregating the end points of over three million transfer cycling trips. The impact of the built environment on transfer cycling behavior is also explored.

First, we find that the aggregate-points buffer outperforms traditional static buffers in predicting transfer cycling trips. Second, we also identify a high level of spatial heterogeneity in catchment area and transfer cycling density between urban and suburban areas. Third, residential and working population density, bus stop density, and metro stations accessibility have a significant effect on bicycle-metro transfer cycling.

1. Introduction

The metro has become essential in the daily lives of city dwellers, as it offers a high-capacity, reliable, safe, and efficient mode of transport (Sun and Zacharias, 2017). The first or last mile issue, involving short connecting trips to metro stations from other destinations or vice versa, is gaining more attention, and several researchers have proposed the concept of bicycle-metro integration, in which metro passengers are encouraged to use bicycles as a transfer mode to and from stations (W. Li et al., 2021; Pengjun Zhao and Li, 2017). This is regarded as the second most common feeder mode after walking. A well-integrated bicycle-metro system can encourage both cycling and metro usage (Mohanty et al., 2017; Pengjun Zhao and Li, 2017). Many governments have also advocated the strategy of bicycle-metro integration to promote active transport (R. Wang and Liu, 2013; Wu et al., 2019).

Many studies have demonstrated that the built environment plays an important role in different types of cycling behavior, such as recreational and commuter cycling (Foster et al., 2011; Fraser and Lock, 2010; Mateo-Babiano et al., 2016; Pengjun Zhao, 2013). However, the effects of the built environment may vary with the type of cycling behavior (Sener et al., 2009). For example, commuter cyclists are typically concerned about destination accessibility and the availability of bicycle infrastructure, while recreational cyclists prefer routes with pleasant views or moderate to steep hills (C. F. Chen and Chen, 2013; Heesch et al., 2015). Cycling to and from metro stations as a transfer trip is, however, distinct in many aspects such as the specific motivation for cycling, the time, and the cycling locations (mainly around metro stations). Hence, the first research question is, are the elements of the built

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environment that affect bicycle-metro transfer trips the same as those affecting recreational or commuter trips? It requires further investigation.

Besides, the bias of the uncertain geographic context problem (UGCoP) can also affect this line of research, as the extent to which area-based attributes affect individual behavior can depend on how the contextual units are delineated (X. Chen and Kwan, 2015; James et al., 2014; Kwan, 2012). The metro catchment area is often used as the contextual unit when exploring the impact of built environment attributes on cycling behavior, and these areas have been defined as the geographical areas that most metro users will come from (D. Lin et al., 2019). In previous studies, metro catchment area is usually delineated as a fix area centered around a metro station, e.g., 800 m, 1500 m, or 2400 m circular buffers (X. Chen and Kwan, 2015; Hochmair, 2014; Jäppinen et al., 2013; Pengjun Zhao, 2013). However, using fixed contextual units is not appropriate because the actual cycling space around each specific metro station may differ. Although the UGCoP has been recognized as a major source of bias in cycling-metro integration studies (Kwan, 2012), addressing this issue remains difficult because of the lack of detailed information about the precise spatial context of metro transfer cycling behavior. Hence, the second research question is whether it is possible to find a proper way to accurately delineate the actual cycling space boundary of transfer cycling, thus can accurately explore the influencing factors of bicycle-metro transfer cycling.

Dockless shared bike programs equipped with global position system (GPS) devices have recently been implemented in many cities, and provide an extensive and precise data source for examining transfer cycling behavior around metro stations (Wu et al., 2019; Xin et al., 2018). Dockless shared bikes are more flexible and convenient to use than those with docks, as they are not constrained by the distribution of fixed docking stations (X. Li et al., 2018; Shen et al., 2018). The dockless shared-bike data can reveal the cycling behavior of users along with geographic details. Such detailed data can provide researchers with opportunities to delineate precise bicycle-metro catchment areas and address the UGCoP issue.

To address these research gaps and questions, we explored the impact of the built environment on bicycle-metro transfer trips based on the "true causally relevant" geographic context, using cycling data from a large dockless shared bike program (Diez Roux and Mair, 2010). First, the bicycle-metro catchment area of each metro station is delineated using a novel method based on actual cycling end locations. Second, to compare the new method and the traditional ones using fixed catchment areas, circular and street-network based catchment areas are also generated for each station. Third, three regression models using different catchment areas were used to explore the relationship between built environment factors around metro and bicycle-metro transfer cycling, and to compared the performance of the new method with the traditional methods. Forth, the characteristics of the dynamic method and the specific relationships between the built environment and transfer cycling are also discussed.

The remainder of this paper is organized as follows. Section 2 reviews the literature about the impact of built environment on different cycling behaviors and the delineating method of catchment areas. Sections 3 introduces the cycling data, methodology of generating the bicycle-metro catchment areas, and statistical models. Section 4 reports the features of bicycle-metro catchment areas and the result of models. In the last section, we discuss the research findings and implications, also summarize the limitations.

2. Literature review

2.1. Cycling behavior and the built environment

Many researchers have found a strong association between cycling behavior and built environment characteristics (e.g., urban density, destination accessibility, or bicycle lanes and trails) (Cervero et al., 2009; El-Assi et al., 2015; Faghih-Imani et al., 2014; Yanyong Guo et al., 2017; Mateo-Babiano et al., 2016; Mertens et al., 2017; Zhang et al., 2017). However, the built environment factors examined in these studies vary, probably because they focus on different types of cycling behavior or have different urban or social contexts.

Depending on the cycling purpose, cycling behavior can be divided into transportation, commuting, and recreational cycling (See Table 1) (Yang et al., 2019). Transportation cycling refers to travel to destinations by bicycles. Previous studies found that cycling routes and access to non-residential destinations were associated with transportation cycling behavior (Fraser and Lock, 2010; Heinen et al., 2010). Commuting cycling involves trips from home to work or study locations, and is a specific type of transportation cycling. Associations have consistently been found between commuting cycling and land use mix, street connectivity, green space and cycling facilities (Cervero et al., 2009; Yang et al., 2019). Recreational cycling involves trips for leisure purposes, and no clear associations with environmental factors have been identified (Heinen et al., 2010).

As a specific type of transport cycling, transfer cycling to or from metro stations has been recognized as an effective way of promoting cycling and solving the "last mile" issue around metro stations (Wu et al., 2019). However, few studies have explored how the built environment around metro stations can affect transfer cycling behavior. Pengjun Zhao and Li (2017) analyzed survey data and found that land use mix and parks around metro stations were associated with greater rates of transfer cycling. W. Li et al. (2021) explored the relationship between bicycle-metro transfer distance and built environment using the dockless bike-sharing data. Evidence has shown that population density, bus stop density around metro stations were correlated with the transfer distance. Similarly, Yuanyuan Guo and He (2020) investigated the impact of built environment on bicycle-metro integration trips and found that residential areas, industrial areas, parks, bus stops and bike lanes were positively related to the transfer cycling.

2.2. Methods to delineate catchment areas

Bicycle-metro catchment areas refer to the service coverage of metro stations for transfer cycling trips (W. Li et al., 2021). Existing studies related to bicycle-metro catchment areas have mainly focused on private or docked shared bicycles (Cheng and Lin, 2018; Ma et al., 2018). For example, Cheng and Lin (2018) explored the expansion effect of metro service coverage around metro stations using docked shared bicycles data. They found that shorter distances between bicycles and metro stations and adequate parking facilities positively associated with this expansion. However, dockless bicycle-metro catchment areas have only been directly explored in one study, which reported that bicycle catchment areas increased in size from the city center to suburban areas, and factors such as excellent metro services, frequent morning trips and longer distance to city center and terminal stations were positively associated with catchment areas (D. Lin et al., 2019).

The most common method of delineating the bicycle-metro

Table 1
Four main types of cycling behavior.

Cycling behavior	Definition	Representative related built environment factors
Transportation cycling	Travel to destinations by bicycles	Cycling routes, access to non-residential destinations
Commuting cycling	Travel from home to work or study locations, a specific type of transportation cycling	Land use mix, street connectivity, green space and cycling facilities
Recreational cycling	Cycling for leisure purposes	No clear associations with environmental factors have been identified
Transfer cycling	Cycling to or from metro stations, a specific type of transportation cycling	Population density, bus stop density, parks, residential and industrial areas,

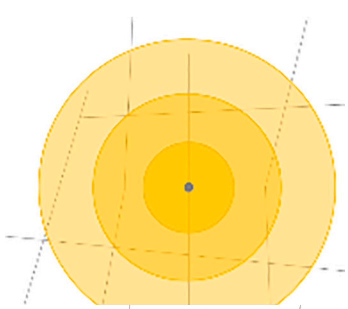
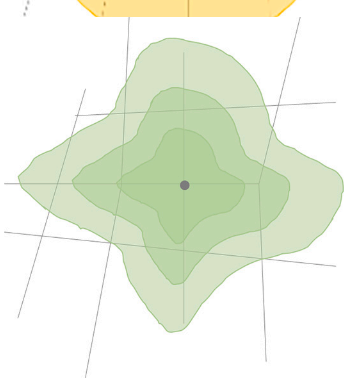
catchment areas (See Table 2) is the static buffer with an estimated fixed radius (e.g., circular buffer or street-network buffer with a 800 m, 1500 m radius), as it is straightforward to implement (Gutierrez and Garcia-palomares, 2008; Riggs and Chamberlain, 2018). Access distance (or acceptable distance) is usually used as a distance radius to generate such circular or street-network buffers (W. Li et al., 2021). The 85th percentiles value of the cumulative distribution of transfer cycling distance are commonly used to represent the distance of most cycling trips and thus to generate buffers, which means that 85% of cycling trips or more are covered by the catchment area (Yuanyuan Guo and He, 2020; W. Li et al., 2021; Zuo et al., 2018).

2.3. Research gaps

Thus, there are two major research gaps. First, little is known about how built environments around metro stations influence bicycle-metro transfer trips. Second, the metro catchment areas for such trips are typically estimated by static buffering with a fixed radius, thus potentially producing a mismatch between the unidirectional buffer and the actual cycling space. In addition, data sourced from surveys or from docked shared bikes may not accurately reflect cycling behavior.

In this study, we address these gaps with a new method that depicts the catchment area using actual cycling data from a dockless bike-share system.

Table 2
Common method of delineating the bicycle-metro catchment areas.

Common catchment area	Diagram	Common radius
Circular buffer		400 m, 500 m, 800 m, 1000 m, 1500 m
street-network buffer		400 m, 500 m, 800 m, 1000 m, 1500 m

3. Data and methods

3.1. Study area and data

Shenzhen is a megacity located in South of China with a population of over 10 million. To reduce private automobile usage in Shenzhen, metro system has been intensively developed in the past decade. Eight metro lines with 167 metro stations has been construed and were in service by 2017. All of these metro stations were included in this study.

The original cycling data in this study consisted of approximately 20 million trips for 14 days from December 1 to 14, 2017 in Shenzhen, which was obtained from a large commercial bike-share company. The data contained the latitude, longitude and the time stamps of each trip's origins and destinations.

Our aim is to explore the bicycle-metro transfer behavior around metro stations, so we choose all transfer cycling trips from or to metro stations in following three steps. First, cycling trips that lacked necessary trip information or rode at abnormal duration or speed were excluded from the original data. Through statistical analysis of the cycling data, we found the 85th quantile value of cycling speed and time is 3 m/s and 30 min respectively. Hence, we consider 1–30 min to be a normal cycling time (Wu et al., 2019). Trips that exceeded or were less than this time period were excluded from the original data. Cycling trips with a speed faster than 3 m/s were excluded. Second, bicycle-metro transfer trips were selected using a defined standard. Trips that started or ended within 100 m of metro station entrances were defined as transfer trips. Third, the trips selected using the above steps were all assigned to the nearest metro station in ArcGIS (ver. 10.4, CA, USA). The number of transfer trips of each metro station was then counted.

3.2. Generating bicycle-metro catchment areas (basic space unit) based on users' cycling space

The literature review presented in section 2.2 indicates that the common delineating methods for catchment areas are buffer-based, including circular and street-network buffers. To better understand the characteristics of the bicycle-metro catchment areas delineated by these methods, we chose Zhuguang metro station in Shenzhen as an example. The 85th percentile value of transfer cycling distance of this station was 1479 m, and thus 85% of cycling trips were shorter than 1479 m. The bicycle-metro catchment areas delineated by the circular buffer and the street-network buffer are presented in Fig. 1 (a and b, respectively).

The buffers generated by these two methods cannot accurately represent the spatial boundaries of the bicycle-metro transfer trips. A mismatch was found between the buffers and the end points of the transfer trips in stations. Specifically, Tanglang Hill was delineated into the catchment area even though no transfer trips occurred.

To overcome the limitations of these traditional methods, a new method of generating bicycle-metro catchment areas based on the actual cycling space was proposed, by aggregating all end points of transfer trips, as shown in Fig. 1 (c). This consisted of three steps.

In our study, each metro station has a unique value of the 85th percentile of transfer cycling distance, which was first calculated. Second, the cycling trips with a distance less than the 85th percentile distance of each station were selected. All of the end points of the selected trips could then be mapped in ArcGIS. Third, all end points of each station were aggregated in ArcGIS using Aggregate Points in the toolbox, which can create polygon features around clusters of proximate point features. The aggregation distance for all metro stations was 600 m, which is equivalent to a ten-minute walking distance. More specifically, if there are no other points within 600 m of a point, this point will not be aggregated into the buffer.

Since the Aggregate Points can only create one buffer for one station at a time, the model builder was used to generate buffers quickly for all metro stations. The new method can delineate the actual cycling space more accurately than the traditional methods, because the concave and

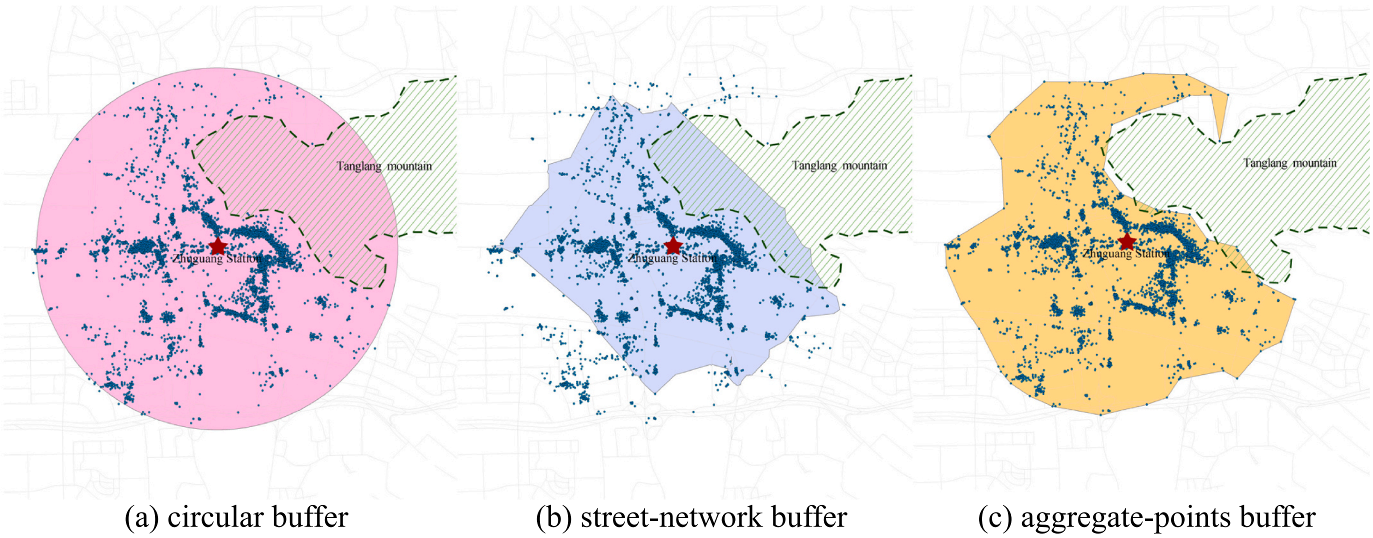


Fig. 1. Three methods of generating bicycle-metro catchment areas. The end points of all cycling trips of less than 1479 m were plotted to compare the fit of different catchment areas with the actual cycling space.

convex parts of the generated polygon can better fit the cluster of points than a circle or street-network-based polygon. The bicycle-metro catchment areas in Shenzhen generated by the new method are shown in Fig. 2.

We also generated the traditional circular buffer (Appendix A) and street-network buffer (Appendix B) for every metro station as a comparison. The radius of circular and street-network buffer in each station is the unique 85th percentile transfer cycling distance of each station.

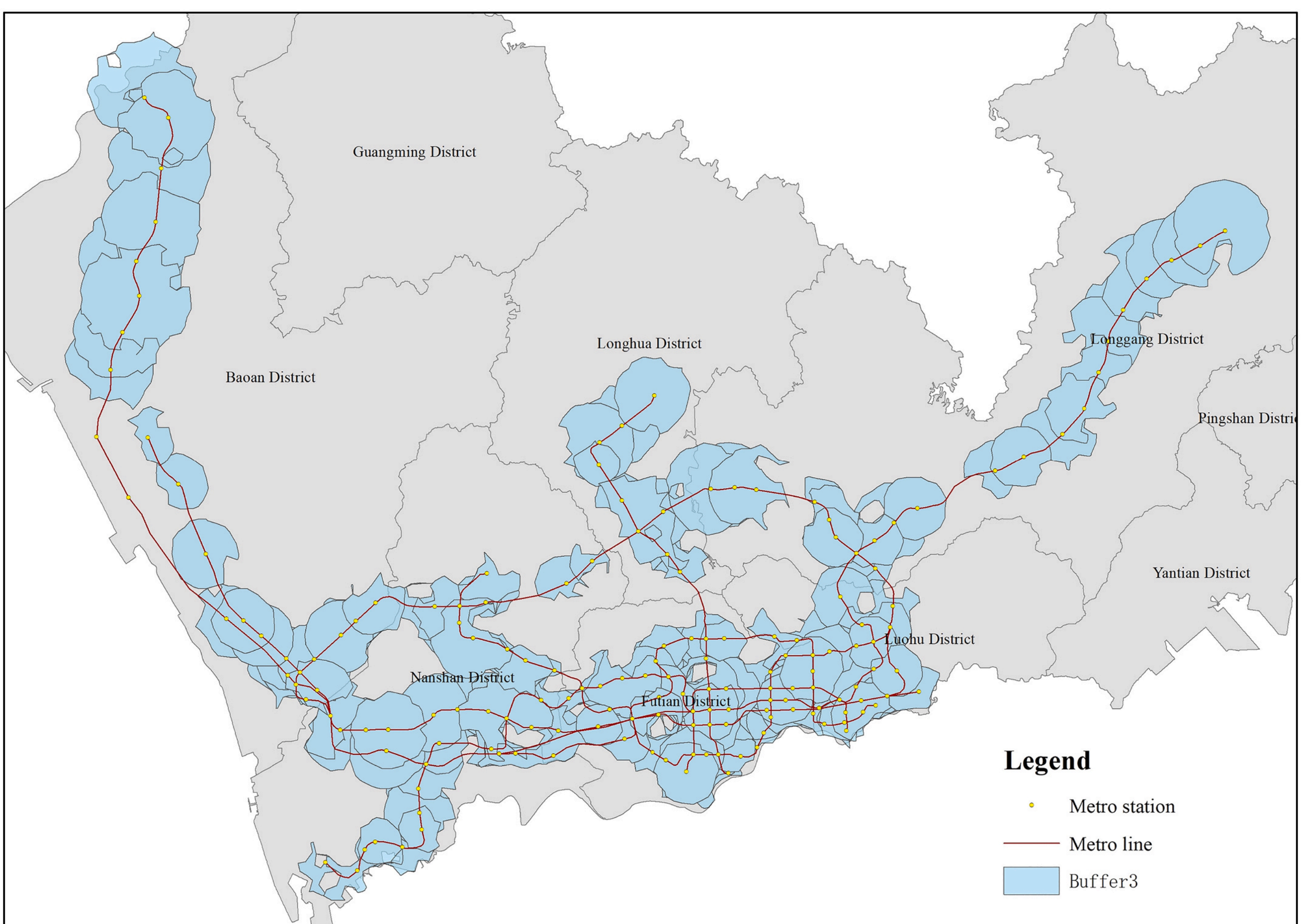


Fig. 2. The bicycle-metro catchment areas generated by aggregating the end points in Shenzhen.

We used the Service Area tool in Network Analyst module in ArcGIS 10.4 to create the street-network buffer based on the street network.

3.3. Dependent variable

The dependent variable is the density of bicycle-metro transfer trips for each metro station, i.e., the number of bicycle-metro transfer trips per unit area in the corresponding catchment areas. We chose the density of trips rather than number of trips because the catchment area size varies by metro station.

3.4. Independent variables

Population density, destination accessibility, cycling facilities, aesthetics, and the attributes of metro stations were included as independent variables, as these have been suggested to also affect cycling behavior (El-Assi et al., 2015; Faghih-Imani and Eluru, 2016; Hochmair, 2014; J. J. Lin et al., 2018; Zhang et al., 2017).

Density has been widely proved that can significantly affect cycling behavior (W. Li et al., 2021; Zuo et al., 2018). Places with high population density tends to have more cycling trips. The bicycle-metro transfer cycling mainly serves as addressing the last mile issue for people who live or work around metro stations. In this study, both the residential population density and working population density were accessed from the government department (SZDMB, 2021).

Destination accessibility is generally considered to be important determinant of transit use, and may have a positive effect on transfer cycling trips (Handy, 2005; Wu et al., 2019). Three types of destination around metro stations were considered: commercial (e.g., shopping malls, large supermarkets), park, and education (e.g., middle and high schools, colleges, universities) points of interest (POIs). The closest-facility tool in ArcGIS was used to calculate the shortest street-network distance between each of destinations and a metro station. The average distance between each of three types of destinations and metro stations were used to represent destination accessibility.

Public transportation facility, such as bus stops around metro stations, may affect the transfer cycling (Yuanyuan Guo and He, 2020). Metro-bus integration is a common long-distance transfer travel mode. Bus stops around metro are likely to be potential transfer cycling destinations for metro-bus integration. We choose the density of bus stops to represent the public transportation facility around metro.

Cycling facilities, including slope and road density, are factors associated with cycling behaviors. It has been proved that people prefer to ride in areas with high road density and flat terrain (Pengjun Zhao, 2013). Besides, the aesthetics of a trip environment, and particularly greenness, can also encourage cycling (Lu, 2019). This can be measured by the normalized difference vegetation index (NDVI) extracted from the 10-m resolution satellite imagery.

The metro station's accessibility may also affect passenger volume and thus transfer cycling trips (X. Wang et al., 2015). In this study, the average travel time from one station to all the other stations was considered as the accessibility of this metro station. It was calculated by the sum network distance of one metro station to the other divided by the average metro speed (80 km/h).

A variance inflation factor (VIF) value of 4 or above generally indicates possible collinearity, and a value of above 10 indicates serious collinearity (Mohammad et al., 1999). In this study, all independent variables in Table 3 were checked to ensure there was no multicollinearity between these factors (VIF $<$ 4) (El-Assi et al., 2015).

A linear regression model (Model 3 in Fig. 3) was built to predict the density of bicycle-metro transfer trips in the aggregate-points catchment area. As a comparison, we built two additional models with a circular buffer catchment area and a street-network buffer catchment area (Models 1 and 2 in Fig. 3). In these three models, each independent variable and dependent variable was calculated with the corresponding buffer of the model. The R-square, beta, and SE were reported for both these models (Table 2).

Table 3
The definitions and units of the dependent and independent variables.

Variables	Indicators	Definition	Unit
Dependent variable			
Transfer cycling behavior	Density of bicycle-metro transfer trips	The number of bicycle-metro transfer trips divided by the bicycle-metro catchment area	Trips/ m^2
Independent variables			
Density	Resident population density Working population density	The number of resident/ working population divided by the bicycle-metro catchment area	People/ m^2
Destination accessibility	Commercial accessibility Park accurately Education accessibility	The average road network distance between metro station and each type of POI in bicycle-metro catchment area	m
Public transportation facility	Bus stop density	The number of bus stops divided by the bicycle-metro catchment area	Number/ m^2
Cycling infrastructure	Road density	The length of road divided by the bicycle-metro catchment area	m/ m^2
	Terrain slope	Average slope	Degree
Aesthetics	Greenness	Average NDVI	–
Attribute of metro stations	Metro station accessibility	The average time from one station to all other stations	Minute

4. Results

4.1. Characteristics of bicycle-metro catchment areas and the density of transfer cycling

All bicycle-metro catchment areas were delineated by the Aggregate Points toolbox in ArcGIS. Each catchment area and the cycling density of each metro station are shown in Figs. 4 and 5. The characteristics of these catchment areas were identified as follows.

First, the bicycle-metro catchment areas of metro stations in suburban locations were generally larger than those of stations in the urban center. For example, on metro line 3, most stations in Longhua district such as Shuanglong and Nanlian had larger catchment areas than those in Luohu district. Because the density of metro stations in the central area is higher than in suburban area, people only need to ride a shorter distance from/ to a station, thus the bicycle-metro catchment areas in urban center is smaller than in suburban locations. However, the densities of the transfer cycling trips in the suburban areas were generally lower than those of metro stations in the urban center. Third, the stations farther away from other surrounding stations, such as Gaoxinyuan and Nanshan, had relatively large catchment areas.

We compared the distribution characteristics of the bicycle-metro catchment areas with the densities of the bicycle-metro transfer trips and found that they were oppositely distributed in the urban center and the suburban areas. Those living in suburban areas, where the density of metro stations was low, had further to travel to reach the metro stations. Hence, the bicycle-metro transfer distances and catchment areas of these stations were relatively longer and larger than those in the urban center. Conversely, metro stations in the urban center had greater passenger volumes than those in suburban areas. More transfer cycling trips may therefore be generated around stations in the urban center.

4.2. Regression results

The regression results of the three models are given in Table 4. Model 3 with the aggregate-points buffer had a stronger association with the

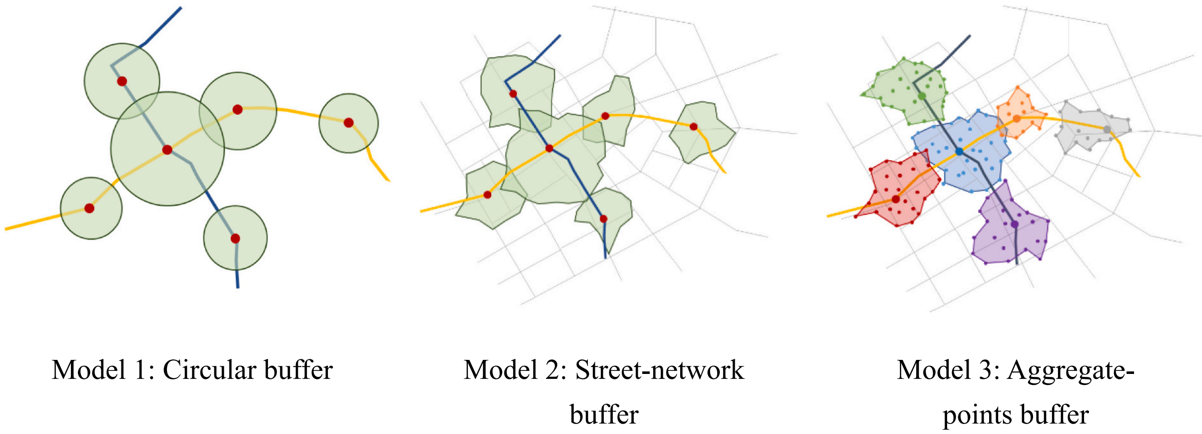


Fig. 3. Diagram of the three catchment areas used in models 1–3, respectively.

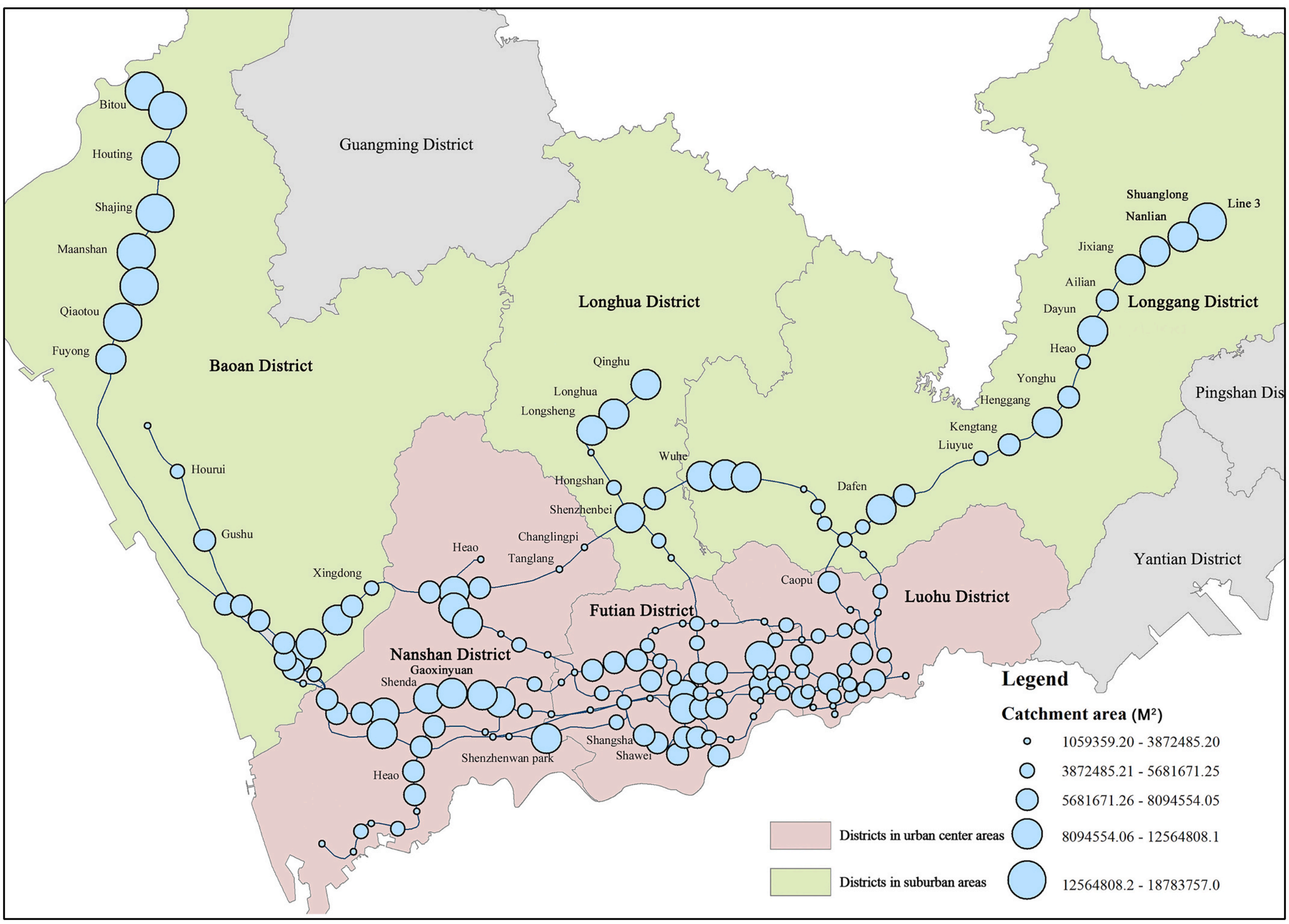


Fig. 4. The bicycle-metro catchment areas of all metro stations in Shenzhen. Note: the shapes of these catchment areas are not circular. The circles only indicate the size of these catchment areas.

density of transfer cycling trips ($R^2 = 0.813$) than model 1 ($R^2 = 0.793$) and model 2 ($R^2 = 0.402$). Working population density was significant in the three models and positively associated with the density of transfer cycling trips. Resident population density and commercial accessibility was significant in model 2 and 3, where resident population density was positively correlated with transfer cycling, while commercial accessibility was the opposite. Bus stop density and metro station accessibility were significant in models 1 and 3. Road density was only significant in model 2. In summary, both the R^2 value and the number of significant variables in model 3 outperformed model 1 and 2. It proved that, compared with the traditional buffers, the newly proposed aggregate-points buffer had a better performance in modelling the transfer cycling.

In addition, we found that circular buffers outperformed street-network buffers in predicting transfer cycling trips. However, other studies have reported that street-network buffers outperformed circular buffers (Z. Wang et al., 2016). Inaccurate street data may lead to this

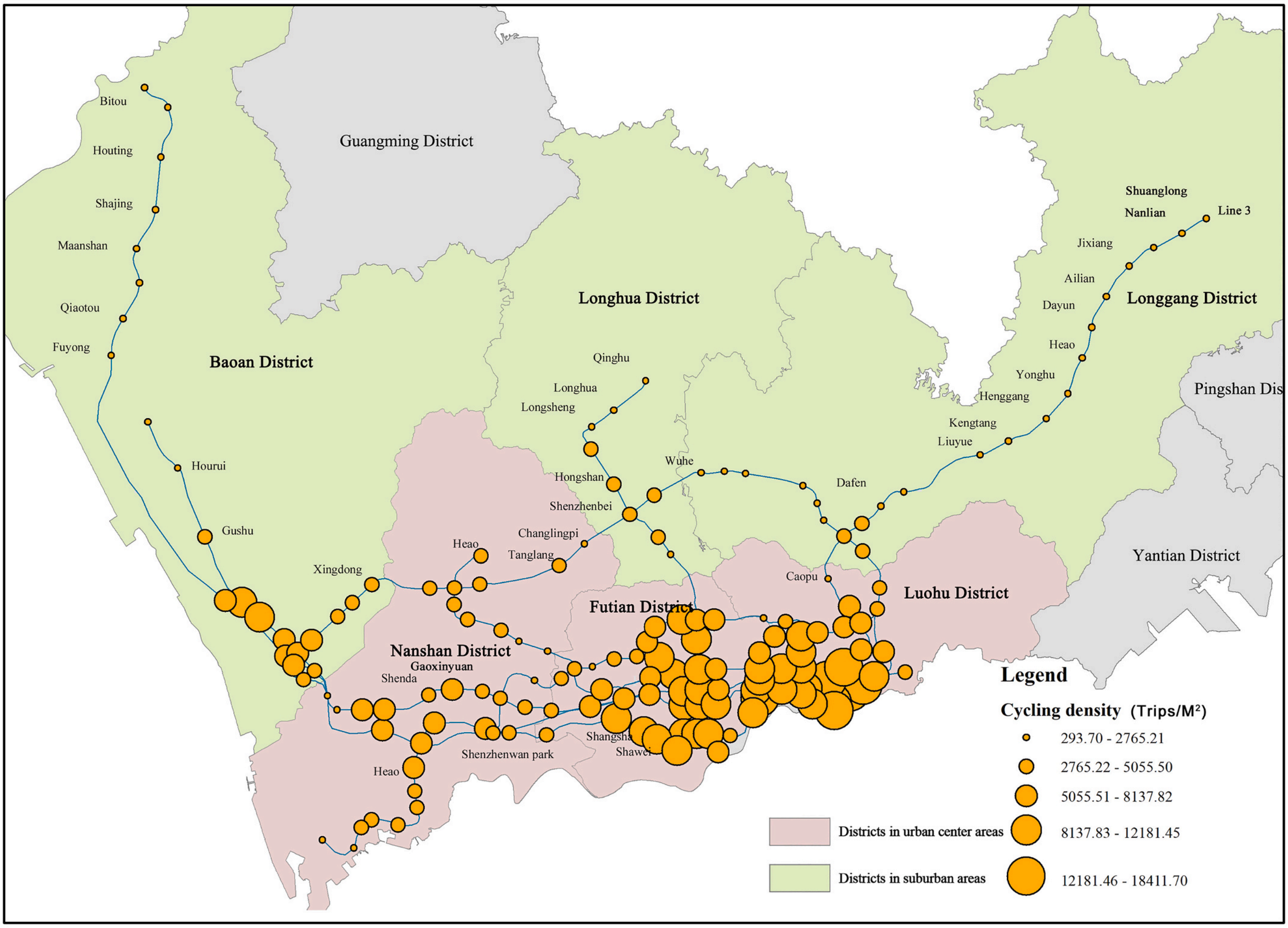


Fig. 5. Density of transfer trips of all metro stations in Shenzhen.

Table 4
Regression results of predicting the density of bicycle-metro transfer trips.

Independent variables	Indicator	Model 1 (circular)			Model 2 (street-network)			Model 3 (aggregate-points)		
		Beta	S.E	Sig	B	S.E	Sig	B	S.E	Sig
Density	Resident population density	0.037	0.031	0.232	0.063	0.037	0.089*	. 070	0.034	0.038*
	Working population density	6.453	1.145	0.000***	2.724	1.018	0.008**	0.131	0.018	0.000***
Destination accessibility	Commercial accessibility	−0.037	0.614	0.952	−1.424	0.680	0.038*	−1.259	0.456	0.007**
	Park accessibility	0.059	0.399	0.882	0.386	0.403	0.339	−0.100	0.269	0.710
	Education accessibility	1.100	0.580	0.060	0.089	0.488	0.856	−0.087	0.374	0.816
Public transportation facility	Bus stop density	45.250	7.146	0.000***	7.960	6.279	0.207	21.966	7.005	0.002**
Cycling infrastructure	Road density	22,529.245	38,596.598	0.560	96,200.716	46,217.638	0.039*	42,384.243	45,840.518	0.357
	Slope	67.398	97.412	0.490	131.147	140.421	0.352	−60.409	139.088	0.665
Aesthetics	Greenness	−7020.372	5648.418	0.216	4814.035	5086.582	0.345	−2123.356	7508.294	0.778
Metro station attributes	Metro station accessibility	−83.477	16.875	0.000***	−6.652	25.470	0.794	−50.424	22.735	0.028*
Model fit information	Adjusted R^2	0.793***			0.402***			0.813***		

*$p < 0.1$; **$p < 0.01$; ***$p < 0.001$.

disagreement. We obtained street data from Open Street Map, and some sidewalks or cycling trails were missing, which are generally where people cycle. Thus, a biased estimation of street-network buffers may lead to inconsistent findings.

5. Discussion

Bicycle-metro integration is an efficient method of promoting both cycling and transit ridership and has been advocated in many countries. The built environment is believed to have a significant effect on cycling behavior. However, transfer cycling behavior has often been overlooked in the research. In addition, in most built environment cycling studies the cycling space is defined as a fixed buffer (either circular or street-network), thus omitting the variations in cycling space across metro stations. In this study, we delineated the bicycle-metro catchment area by aggregating the trip end points of transfer cycling trips. We found that metro stations in suburban locations had larger bicycle-metro catchment areas but lower cycling density than those in the urban center. The new aggregate-points buffer outperformed the circular and street-network buffers in predicting the transfer trips. We can identify five main findings from our study.

First, the aggregate-points buffer provides a new method that partly overcomes the UGCoP issue. Most built environment cycling studies have used circular/network buffers or administrative units, which are static and convenient to calculate (Pengxiang Zhao et al., 2018). However, fixed areas may not appropriately represent the actual areas that contextually influence behavior, as they may over- or under-estimate the actual service areas of different metro stations. Identifying and delineating geographic units that capture people's actual activity space is a major research challenge, as represented by the UGCoP (X. Chen and Kwan, 2015). By applying the big data of travel cycling, the geographic locations of individual cycling trips (e.g., start and end points) can be recorded. This enables actual cycling spaces to be delineated more accurately and be more consistent with the actual situation. Over three million transfer cycling trips were used in this study to delineate bicycle-metro catchment areas. The aggregate-points buffer outperformed the traditional circular and street-network buffers in predicting transfer cycling behavior.

Second, high levels of heterogeneity were found between the urban center and suburban areas in terms of the catchment areas and cycling densities of metro stations. The average catchment area in the urban center (including Luohu, Futian, and Nanshan) was 5.26 km^2, and smaller than the 8.15 km^2 in suburban areas. This finding is consistent with those in studies that focus on transfer walking behavior around metro stations (El-Geneidy et al., 2014; Z. Wang et al., 2016). In urban center, the dense metro stations not only gather more travel demands, but also provide more choices of metro stations for travelers. The dense distribution of metro stations has led to more but shorter "last mile" trips. On the contrary, due to the relatively low density of metro stations in suburban areas, transfer trips are fewer but longer.

Third, resident population density and working population density were found to have a significant positive effect on bicycle-metro transfer cycling trips. In particular, the working population density has a remarkably stable performance across different models. This suggests that bicycle-metro transfer cycling mainly occurs among the working population and may have become an essential part of commuting trips. Similarly, the resident population around metro stations were also an important group of transfer cycling. This is also consistent with previous findings that the population and the number of jobs were positively affect the popularity of cycling (Fishman et al., 2014; Tran et al., 2015; Pengjun Zhao and Li, 2017). The above two points also indirectly proved that transfer cycling played a crucial role in solving the "last mile" issue.

Forth, unexpectedly, commercial accessibility was negatively associated with transfer cycling, that is the longer distance from commercial facilities to metro station, the lower dense of transfer cycling. This may be related to the development and construction of Transit-Oriented Development (TOD) planning in Shenzhen (Shao et al., 2020). Specifically, the mode of TOD encourages a mix of commercial, residential and transportation facilities (Cervero, 2004). As a result, most of the large shopping malls in Shenzhen are often directly connected to or close to metro stations entrances, which only needs a few minutes' walk to reach from metro stations. Furthermore, some small-scale commercial facilities along the streets are also included in the commercial POI data. Although these commercial facilities are farther away from metro stations than those large shopping malls, they may not attract many people by cycling.

Fifth, both bus stop density and metro accessibility positively affect the transfer cycling around metro stations. Bus–metro integration affects the attractiveness of a metro system (Z. Wang et al., 2018). Transfer cycling can effectively solve the interchange need between bus stops and metro stations. As the number of bus stops around metro increases, the demand for bus–metro interchange may rise, leading to more transfer cycling trips between bus stops and metro stations. This also shows that sharing bike system plays a positive role in the bus–metro integration. As for the metro station' accessibility, measured by average travel time in the metro network, it represented the degree to which a station is accessible by other metro stations in the entire metro system (L. Li et al., 2017). Metro stations with higher accessibility may have higher passenger volumes, and hence generate more transfer cycling trips. However, metro passenger volume data were unavailable for this study. Further studies should explore the effect of metro passenger volume on transfer cycling trips.

6. Conclusion

In this study, we innovatively proposed a method of delineating bicycle-metro catchment area based on the actual cycling data, thus partly addressing the UGCoP. As shown by the regression models, our newly proposed aggregate-point buffer outperformed static buffers (e.g., circular and street-network buffers) in predicting the density of bicycle-metro transfer cycling trips. Besides, we also explored the impact of the built environment on bicycle-metro transfer cycling by examining over three million transfer cycling trips with geocoded trip origin and destination information, which address many limitations of traditional methods of data collection (e.g., surveys or travel diaries). We found a notable spatial heterogeneity between the urban center and suburban areas in terms of the catchment areas of metro stations and transfer cycling density. Stations in the urban center have smaller catchment areas but higher cycling densities than those in suburban areas. Resident population density, working population density, bus stop density, and metro accessibility all positively affected the density of bicycle-metro transfer cycling trips. Besides, this study also provides direction and insight for further environmental behavior research, by precisely defining spatial contexts of human behaviors and exploring the potential influencing built environment factors.

There are four limitations to be acknowledged, some representing opportunities for further research. First, the original dockless shared bike data may lead to bias, as bike-share services are not used by everyone. No cycling trajectory information or personal factors of cyclists such as their age, gender, or income were included, due to privacy concerns. Thus, we could not directly delineate the catchment area based on all cycling trajectories and control the influence of individual factors on transfer cycling behavior. Second, the availability of sharing bicycles around metro stations may also affect transfer cycling. Demands for bikes may increase rapidly at peak hours, which may lead to insufficient bikes and thus affect the transfer trips. Third, as the road network was incomplete, with missing bike lanes and sidewalks, the street-network buffer may have been inaccurate, which may have affected the comparison of our regression results. Future studies can include more comprehensive and accurate data to address these limitations. Forth, many aspects in aesthetic dimension (e.g., cleanness and quietness of streets, the presence of historical buildings) and other important factors (e.g., traffic safety, lighting conditions, and shading) were not included in our model due to the lack of data. In the future, more indicators can be added to explore the relationship between built environment characteristics and transfer cycling trips.

Appendix A

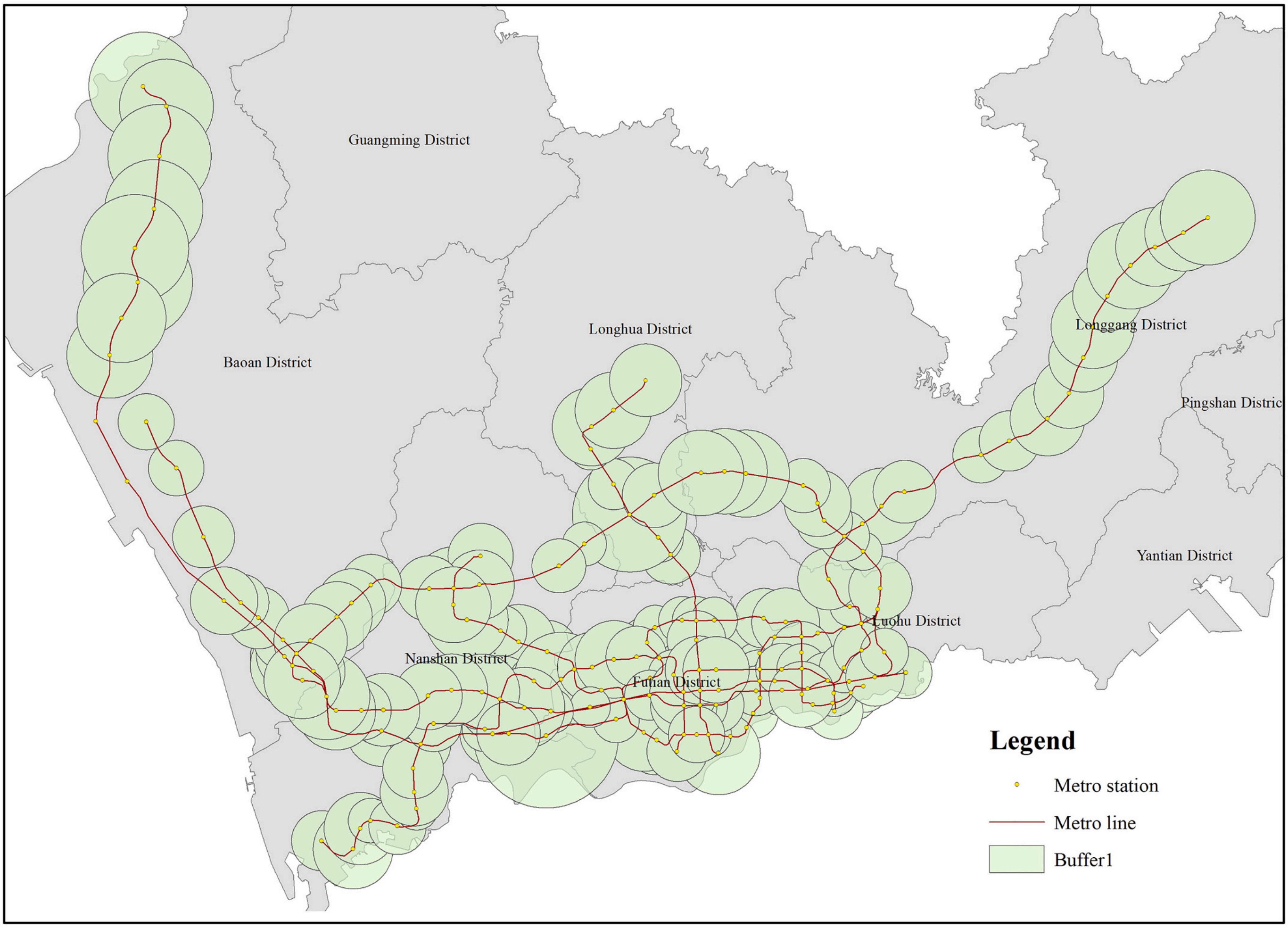


Fig. A1. Circular buffer.

Appendix B

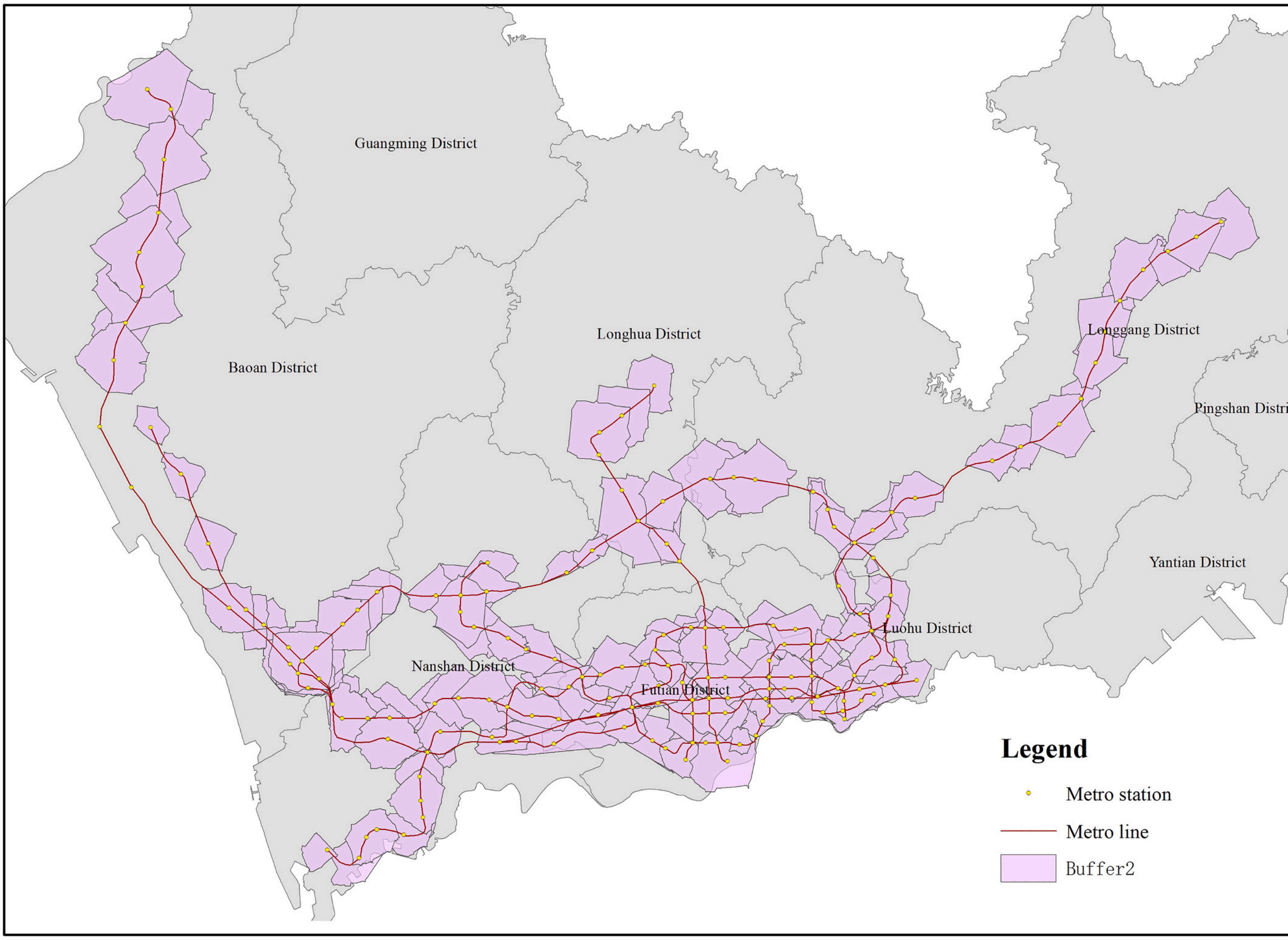


Fig. A2. Street-network buffer.

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