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Research article

"Green transit-oriented development": Exploring the association between TOD and visible green space provision using street view data

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ABSTRACT

Environmental inequalities generated by transit—oriented development (TOD) are of planning and policy relevance in developing countries. Existing literature has pointed out that TOD has the effect of 'place making', which means the newly developed transit systems may be able to change the environment and amenities of a certain area. While previous studies have largely focused on environment hazards such as noise and pollution induced by transit systems, scant attention has been paid to visible green space provision at station areas. This study develops a new and systematic framework to assess potential disparities in quality and quantity aspects of visible green space provision around subway stations. We explore the effects of TOD on visible green space provision around subway stations using spatial regression models. The results show that there are disparities in visible green space provision around subway stations, but such disparities tend to fade with distance away from stations. We also find that population density, land use mix, intersection density and bus stop density are significantly associated with quantity and quality aspects of visible green space provision around subway stations.

1. Introduction

Transit Oriented Development (TOD) is a planning strategy aiming to improve public transit systems (Schlossberg and Brown, 2004; Wang et al., 2022). The benefits of the TOD not only include encouraging the use of public transportation and reducing car dependency, but also include facilitating regional economic, environmental and amenities development (Gu et al., 2019; Knowles et al., 2020; W. Wu et al., 2022; Y. Wu et al., 2022; Xiao et al., 2021). The concept of 'Green TOD' indicates that the TOD may reduce energy consumption, carbon dioxide emissions, acid rain pollution and waste (Cervero and Sullivan, 2011). Also, such concept highlights that since the improvement of public transit systems may reduce car usages and the demand for parking lots, it is likely that surface parking lots will be replaced by other amenities such as parks or greenways (Cervero and Sullivan, 2011). While a number of studies have focused on the effect of TOD on environment hazards such as emissions (Ashik et al., 2022; Trepci et al., 2020), noise (Yildirim and Arefi, 2021), and air quality (Gu et al., 2019), scant attention has been paid to the influence from TOD on green space provision around transit stations (Niu et al., 2021). Understanding whether TOD promotes visible green space provision for urban residents is important for planning the healthy city movements.

Green justice indicates that socio-economic disadvantaged areas tend to have less green space provision, since residents may not be able to afford the maintenance and provision of green space (Boone et al., 2009; Dai, 2011; Hughey et al., 2016; Rigolon, 2016; Yasumoto et al., 2014). The land use configuration of TOD across different transit stations varies differently. This type of spatial variation can lead to uneven development around the transit stations (Padeiro, Louro, & da Costa, 2019). It is likely that TOD may generate disparities in amenities provision such as green space around the stations. However, studies regarding the association between disparities in green space provision and exposure mainly focused on residential areas (Boone et al., 2009; Dai, 2011; Hughey et al., 2016; Rigolon, 2016; Yasumoto et al., 2014), while other activity places such as public transit stations have received much less attention. Existing studies have documented the various

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benefits of green space including reducing health (e.g., cardiovascular disease and depression) (Markevych et al., 2017; Liu et al., 2022) and environment burdens (e.g., air pollution and climate changes) (Kabisch et al., 2016). Therefore, it is important to examine the association between TOD and disparities in green space provision around the transit stations, since such disparities may further lead to unexpected public health and environmental issues.

While an increasing amount of scholarly attention has been paid specifically to the general green space such as urban parks, there has been surprisingly little empirical research on the provision of visible green space (Wang et al., 2021a–c; Yang et al., 2016). Previous studies suggested that visible green space may have more influence on public health, since it can be directly perceived residents (Wang et al., 2021a–c; Yang et al., 2016). In recent years, with the development of computer vision and online mapping services, visible green space provision has begun to attract more attention (Wang et al., 2021a–c; Yang et al., 2016). However, although scholars have realized the importance of visible green space, there is currently no systematic framework for assessing it.

This paper examines the spatial inequalities of visual green space provision around subways stations in Beijing, China. It also investigates whether and to what extent TOD of subways stations have effect on its surrounding visual green space provision. The definition of TOD in this study mainly refers to the development of subways, and we mainly focused on subway stations since the rails are underground. As shown in Fig. 1, we contribute to the existing literature in two aspects.

First, we are among the first to propose a 4 'A' (availability, accessibility, attractiveness, and aesthetics) framework to assess visible green space provision around subway station using street view images and machine learning approach. Also, we quantify the effects of TOD by classifying it into 8 dimensions (density, land use diversity, walkability, economic development, capacity utilization of transit, user-friendliness of transit system, access to and from the station, parking supply at the station) following Singh et al. (2017). Second, we further focus on disparities in 4 'A' visible green space provision around subway stations and examine the effect of TOD (8 dimensions) on visible green space provision around subway stations using spatial regression models. This enhances the current conceptual framework of 'Green TOD'.

2. Literature review

'Green TOD' is a combination of TOD and green urbanism (Cervero and Sullivan, 2011). TOD highlights the importance of urban planning for encouraging public transport use (Gu et al., 2019; Knowles et al., 2020; Wu and Hong, 2017; Wu et al., 2022; Yildirim and Arefi, 2020), while green urbanism has been defined as a goal of achieving sustainable cities and society under the raid development of urbanization (Beatley, 2012). Therefore, 'Green TOD' has been considered as a 'kill two birds with one stone' strategy, which aims to achieve green urbanism through urban planning policy. Greening cities, namely building up new green spaces in cities, undoubtedly contributes greatly to green urbanism (Esmail et al., 2022). However, there is few evidence regarding whether and how TOD is related to greening cities (the provision of green spaces) under the concept of 'Green TOD'.

One of the multiple co-benefits of TOD is 'place marking', which means TOD can reshape the local environment (Appleyard et al., 2019; Dorsey and Mulder, 2013). Although there is no direct evidence regarding the association between TOD and green space provision, previous studies have identified several mechanisms through which TOD may have influence on environment promotion: replacement of car-related facilities (Cervero and Sullivan, 2011; Liang et al., 2020; Niu et al., 2021), increase of land value (Kay et al., 2014; Knowles, 2012; Padeiro et al., 2019), and fulfilling passengers travel satisfaction (Gu et al., 2019; Wey et al., 2016; Yildirim and Arefi, 2021), which all may further lead to increase of green space provision. The first set of mechanisms is the replacement of car-related facilities, which indicates that TOD may reduce car dependency (Ibraeva et al., 2021). Hence, the decrease of demands for cars may finally lead to the replacement of parking lots with other amenities such as parks or greenways (Cervero and Sullivan, 2011; Liang et al., 2020; Niu et al., 2021). For example, Niu et al. (2021) found that TOD results in less car-related facilities and more open spaces for other amenities such as parks around rail station areas in Singapore. As for the second mechanism, existing literature indicated that TOD would increase the land and property values around the transit stations, which attracts more socioeconomically advantaged groups (Padeiro et al., 2019). Hence, they are more willing to pay more for green space services than socioeconomically disadvantaged groups

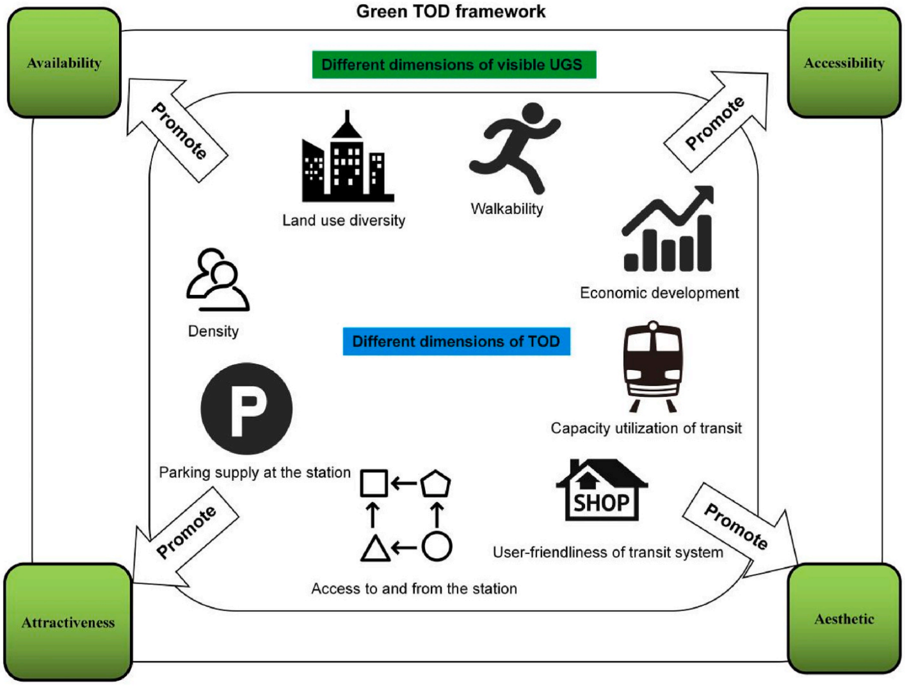


Fig. 1. The conceptual framework in this study.

(Xiao et al., 2017), so the provision of green space tend to grow after the implement of TOD project. For instance, Kay et al. (2014) pointed out that areas with transit-oriented development are more valued than other areas, which attracts more socioeconomically advantaged groups to reside. Last, since TOD aims to encourage people to use public transit system, the passenger volumes may significantly increase around the transit stations (Liang et al., 2020). With the growth of passengers, their voice for improving travel satisfaction will get more and more important, which may finally have influence on policy regarding the environment promotion around transit stations (Wey et al., 2016).

Findings regarding disparities in green space provision are mainly from developed countries, and most of them only focused on residential areas (Boone et al., 2009; Dai, 2011; Hughey et al., 2016; Rigolon, 2016; Yasumoto et al., 2014). For example, Hughey et al. (2016) found that socioeconomically disadvantaged groups have poorer access to urban parks than the socioeconomically advantaged groups in US counties. Dai (2011) also suggested there are that socioeconomically disadvantaged groups, such as Asian and African Americans, and people living in socioeconomically disadvantaged areas have more limited access to green spaces in US cities. Empirical evidence regarding green justice in the Chinese context is still relatively scant. Most existing studies in the Chinese context have confirmed that socioeconomically advantaged groups tend to have better access to urban green space (Guo et al., 2019; H. Li and Liu, 2016; Sörensen et al., 2021; Shen et al., 2017; Xu et al., 2017a; Teixeira et al., 2022; Zhang et al., 2020a,b; Zhang et al., 2021). For instance, Xu et al., 2017a suggested there are significant social inequalities in park accessibility in Shenzhen, China. In recent years, the disparities in visible green space provision have begun to attract more and more attention, since existing studies suggested that visible green space more be more important for people's wellbeing than the general green space (W. Liu et al., 2020; L. Wang et al., 2021; R. Wang et al., 2021a–c; Zhu et al., 2021). However, only two studies carried in China have paid attention to disparities in the provision of visible green space (Chen et al., 2020; Wang et al., 2021a–c Yang et al., 2016), but they are still based on residential areas.

As for the assessment of visible green space, the traditional method is based on field audit, which means human raters must walk across the targeted areas and manually audit the visible vegetation (De Vries, Van Dillen, Groenewegen and Spreeuwenberg, 2013). However, such a method is too labor-intensive and time-consuming to be applied for a large research area (R. Wang, Z. Feng, J. Pearce, Y. Yang et al., 2016). In recent years, with the development of computer vision technique and online mapping services, a method combing machine learning and street view data has been proposed to measure visible green space (R. Wang, Z. Feng, J. Pearce, Y. Liu et al., 2020; R. Wang, Z. Feng, J. Pearce, S. Zhu et al., 2021; R. Wang et al., 2020). Although this method is much more efficient than the traditional method, most of the previous studies only measure visible green space from a simple quantitative perspective (R. Wang, Z. Feng, J. Pearce, Y. Yang et al., 2016). Existing studies have suggested that qualitative perspective of green space also matters (Liu et al., 2020; Wang et al., 2021a–c Zhu et al., 2021), so some scholars have begun to explore the feasibility of further using street view data to measure it (Wang et al., 2021a–c; Yang et al., 2016). For example, R. Wang et al. (2021) proposed a method for assessing visible green space provision using street view data and random forest approach. However, these is still no systematic framework for assessing visible green space, which may result in a lack of reliability for visible green space evaluation.

3. Methodology

3.1. Study area

Beijing was selected as the research area for our study. We selected the inner-city area (the area within the Fifth Ring Road) of Beijing city as the main research area. In total, 13 subway lines (line 1, 2, 4, 5, 6, 8, 9, 10, 13, 14, 15, airport, and Changping) and 236 stations were included in the study. These subway lines were all opened before 2013, so most of data were also collected for 2013. After 2013, the new setup subway line was mainly out of the Fifth Ring Road. The population density in our research area was 5999 persons/km^2. We created four different size of buffers (400-m, 600-m, 800-m and 1000-m) around each of the subway station to measure green space and the effect of TOD factors. Fig. 2 shows the distribution of subway systems (including subway lines, road networks and bus stations) in 2013 Beijing.

3.2. Data and variables

3.2.1. Dependent variables

The visible green space assessed in this study mainly refers to street-level vegetation, which can be viewed by pedestrians around the subway stations. We used street view images from Tencent Map (https://map.qq.com/) to estimate visible green space provision. Tencent Map is the most comprehensive online map in China, which has been used in previous studies (Liu et al., 2020; Wang et al., 2021a–c; Wu et al., 2022; Zhu et al., 2021). We constructed sampling points around the subway stations along the road network which was provided by OpenStreetMap (Bennett, 2010). Following previous studies (Liu et al., 2020; Wang et al., 2021a–c; Zhu et al., 2021), street view images were collected from four cardinal directions (0, 90, 180, and 270°). In total, 148,388 images were obtained for all subway stations.

As for the image segmentation process, we followed previous studies and used a machine learning approach to extract objects from street view images (Liu et al., 2020; Wang et al., 2021a–cZhu et al., 2021; Wu et al., 2021a,b; Yang et al., 2016;). We applied a fully convolutional neural network for image segmentation (FCN-8s) (J. Long et al., 2015), which segments the images into different objects, and this can be further used to identify street-level visible objects. We trained the FCN-8s model using ADE20K scene parsing and segmentation databases (Zhou et al., 2019). The FCN-8s consists of multiple processing layers linking the input layer (street view images) and the output layer (pixel-based ground objects). Given an image, FCN-8s was trained to identify object through the forward/inference and backward/learning process (Krizhevsky et al., 2017). Then, it uses cross entropy to adjust the parameters of each layer and obtains a high-accuracy semantic segmentation network through multiple rounds of training (Krizhevsky et al., 2017). Since the images of ADE20K database were labeled, the image segmentation results from FCN-8s model can be directly compared to the labeled (actual) results. The accuracy of our model can be calculated by the number of correct pixels to the total number of pixels. The accuracy of our model was 86.57% for both the testing and trained data. After the image segmentation process, the proportion of different objects was calculated for each image at each sampling point. Street-level visible green space (SVG) per sampling point was calculated by the proportion of the vegetation pixels per image. Based on existing literature (Kronenberg et al., 2020; Stoltz and Grahn, 2021; Yang et al., 2016), we developed a 4 'A' framework (Fig. 1) to systematically evaluate visible green space provision around subway stations including availability, accessibility, attractiveness, and aesthetics.

3.2.2. Availability

Following previous studies (Liu et al., 2020), we used Tencent mobile phone data from the Tencent Big Data Centre (http://data.qq.com/). Tencent mobile phone big data records the location of WeChat users, which is representative for smart phone users in China (W. Y. Liu et al., 2020). The data consisted of the location information for each smart phone user in Beijing with the spatial resolution of 100-m in grids.

We assessed availability-based SVG provision using street view images and Tencent mobile phone data. It measures whether people have access to green space (Kronenberg et al., 2020), so we

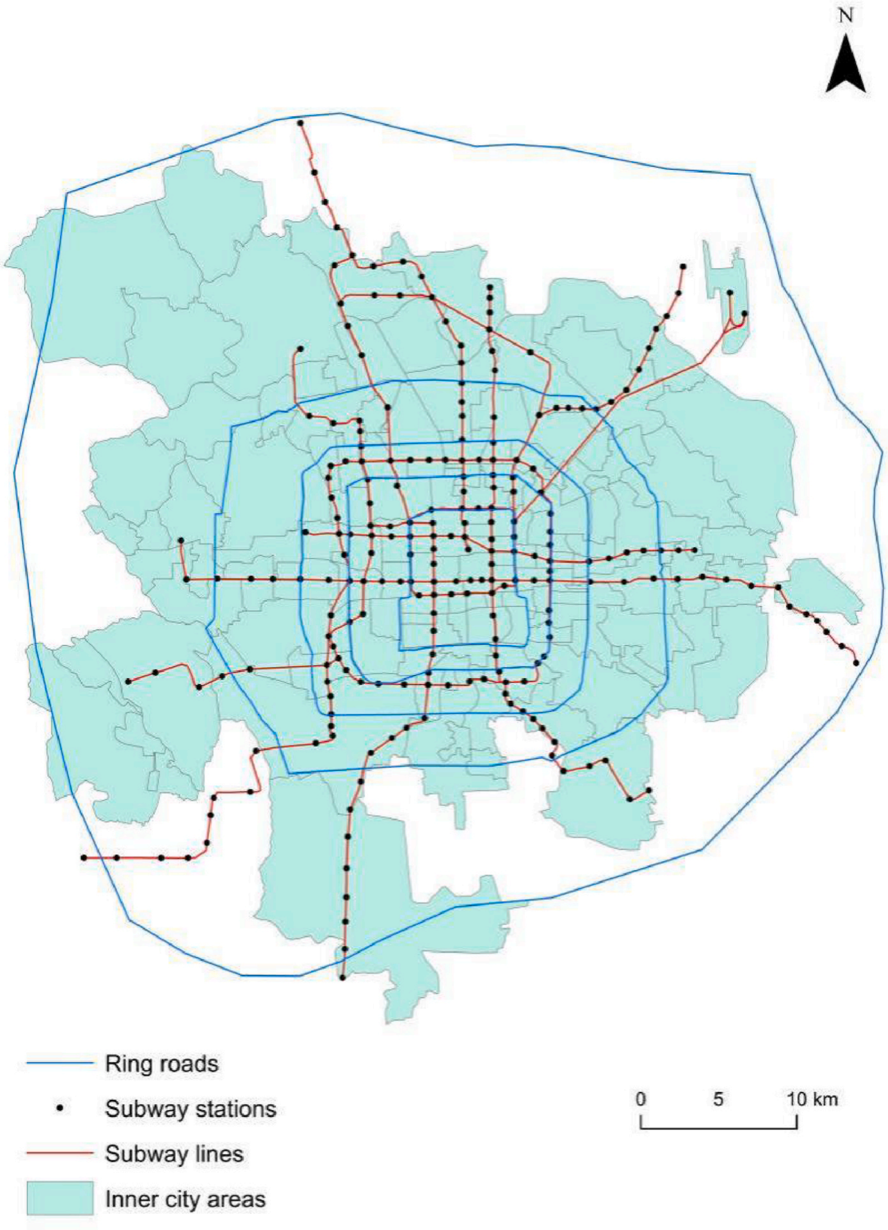


Fig. 2. The research area in Beijing inner city, China.

calculated it by weighting SVG based on real-time population data. The detailed formula can be found in supplement file.

3.2.3. *Accessibility*

Accessibility reflects how easily people can get access to SVG (Kronenberg et al., 2020), so we calculated the accessibility-based SVG by weighting it based on its proximity to subway stations. The detailed formula can be found in supplement file.

3.2.4. *Attractiveness*

Attractiveness reflects the general quality of SVG (Kronenberg et al., 2020), so we calculated the attractiveness-based SVG using the method proposed by R. Wang et al. (2021). The details of the calculation process can be found in supplement file.

Aesthetics.

Aesthetics measures how people perceive the beauty and tastefulness of SVG and it has multiple dimensions (Stoltz and Grahn, 2021). We used the diversity dimension proposed by Stoltz and Grahn (2021) to measure the aesthetics-based SVG. Since the more diverse the natural elements are, the more aesthetics people can perceive from SVG (Stoltz and Grahn, 2021), we calculated the aesthetics-based SVG using the entropy of natural elements (e.g., water bodies, vegetation and living creatures). The detailed formula can be found in supplement file.

3.2.5. *Independent variables*

Following Singh et al. (2017), we evaluated the TOD factors around subway stations from 8 dimensions including density, land use diversity, walkability, economic development, capacity utilization of transit, user-friendliness of transit system, access to and from the station, and parking supply at the station. (1) Density: The density was measured by population density (persons/km^2) and commercial density (number of commercial enterprises/km^2). The population data was from WorldPop in 2013 (https://www.worldpop.org/). The commercial enterprises data was based on the POI (points of interest data); (2) Land use diversity: Land use diversity was measured by the entropy of POI data (land use mix scores), and the detailed formula can be found in supplement file;

(3) Walkability: Walkability was measured by both amenity-based walking scores (Gilderbloom et al., 2015) and intersection density (number of intersections/km^2). The road network was from OpenStreetMap. Also, the amenity-based walking scores was calculated using both POI data and road networks data, and the detailed formula can be found in supplement file; (4) Economic development: Economic development level was calculated based on VIIRS night-time light data (night light value) from the WorldPop data. Previous studies have shown that the brightness of night-time light data can reflect the economic level of a specific area (Wu et al., 2018). Therefore, we calculated the average pixel values of night-time light data for each subway station; (5) Capacity utilization of transit: Capacity utilization of transit was measured by the daily passenger flow volumes (persons/day). Tencent mobile phone big data has the real-time information, so we used it to measure the daily passenger load volumes from 5am to 11pm for each subway station; (6) User-friendliness of transit system: We assessed user-friendliness of transit system from a amenity-supply perspective. We created a binary variable to measure whether a subway station is user-friendly or not (1 = with shops inside the station, 0 = without any shop inside the station); (7) Access to and from the station: We measured access to and from the station using interchange to different routes of same transit (number of routes) length of the subways (km), and interchange to other transit modes. Bus stop density (numbers/km^2) was used as the proxy for interchange to other transit modes; (8) Parking supply at the station: We also estimated the parking lot density (numbers/km^2) around each subway station. Descriptive statistics of all variables was shown in Table 1.

3.3. Statistical methods

In order to understand the contribution of TOD to SVG around the subway stations, we proceeded the analysis in two-steps. At the first step, we mainly aimed to assess the inequalities of different dimensions of SVG, we used spatial analysis and inequality indices. First, to identify general inequalities in SVG, we calculated the Gini index (Gini, 1921) for different SVG indicators using different buffers. Also, we used the Global Moran's I (Moran, 1950) to examine the spatial inequality of SVG using different buffers for subway stations with inverse distance weighted spatial matrix. Previous studies pointed out that to understand the built environments around transits, it is recommended to use 5-min to 10-min walking distance buffers (Wey et al., 2016). Therefore, the above analysis was performed with four different size of buffers (400-m, 600-m, 800-m and 1000-m) around each of the subway station. At the second step, we aimed to link TOD factors to different SVG indicators using spatial regression models, which includes both spatial lag model (SLM) and spatial error model (SEM) (Anselin, 2009). If there is spatial dependence for green space, OLS (ordinary least squares) models may lead to bias of estimation. SLM has a spatial lag term to control for the spatial dependence among dependent variables while SEM has a spatial lag term to control for the spatial dependence among error terms. Based on the robust LM tests, robust LM lags are significant and larger than robust LM errors, so we finally selected SLM as our regression model. The analyses were carried out with ArcGIS 10.8.1 (Esri Inc., College Station, Aylesbury, UK) and Stata 15.1 (StataCorp., College Station, TX, USA). The formulas on calculating Gini index and Global Moran's I and SLM can be found in supplement file.

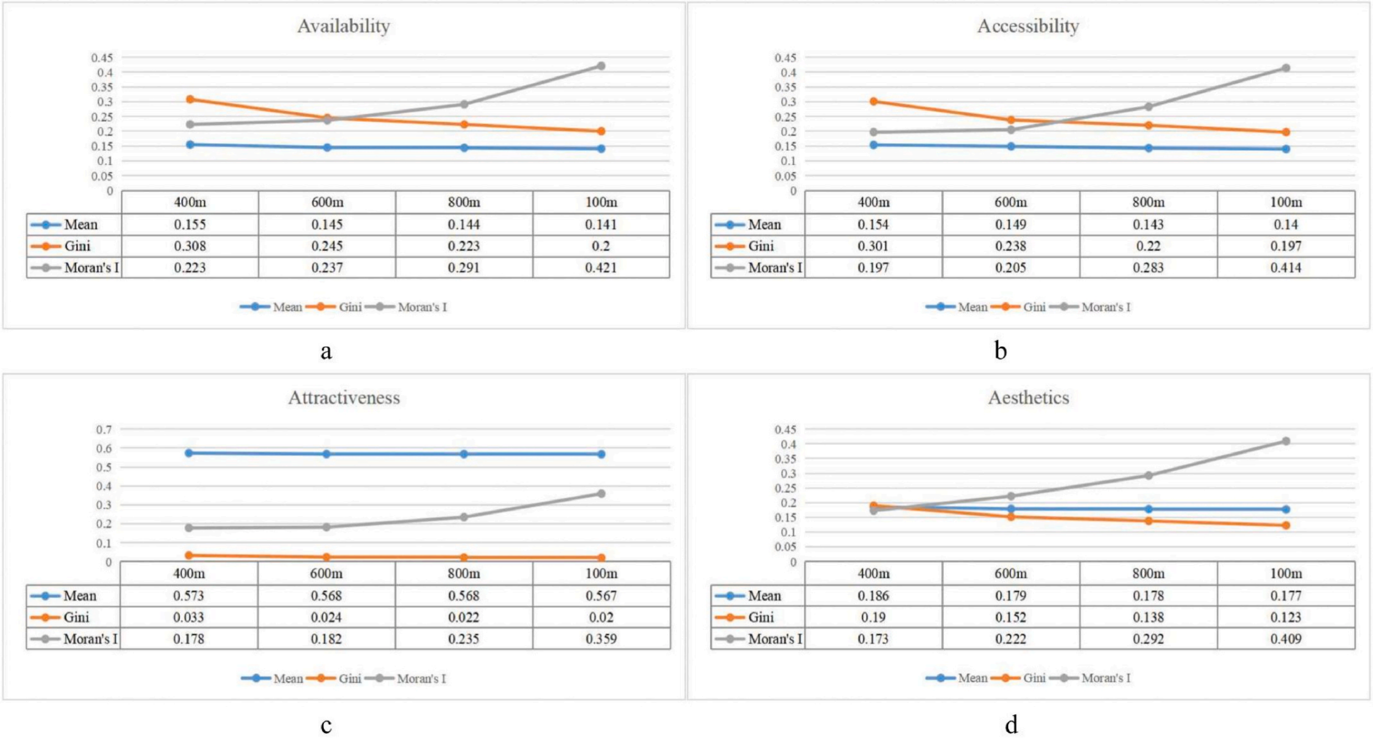
4. Results

Before turning to the regression results, we first present the graphical evidence to explore the general and spatial inequalities of SVG around subway stations. Fig. 3 shows the mean value, Gini index and Moran's I of SVG around subway stations in Beijing inner city, China. Overall, the mean value and Gini index of SVG decrease as the increase of the buffer size, while Moran's I (with p-values all less than 0.05) of SVG increases as the increase of the buffer size. As shown in Fig. 3 and Table S2, the mean values of quantitative perspective of SVG (availability and accessibility) were lower than that of qualitative perspective of SVG (aesthetics and attractiveness), which indicates that the development of quantitative perspective of SVG (availability and accessibility) were lower than that of qualitative perspective of SVG (aesthetics and attractiveness). However, the Gini index and Moran's I of quantitative perspective of SVG (availability and accessibility) were higher than that of qualitative perspective of SVG (aesthetics and attractiveness), which suggests that there are more obvious general and spatial inequalities for quantitative perspective of SVG (availability and accessibility) around

Table 1
Descriptive statistics.

Variables		Proportion/mean (SD)			
		400 m	600 m	800 m	1000 m
Dependent variables					
Quantity perspective	Availability	0.155(0.087)	0.145(0.063)	0.144(0.058)	0.141(0.050)
	Accessibility	0.154(0.085)	0.149(0.060)	0.143(0.056)	0.140(0.049)
Quality perspective	Attractiveness	0.573(0.033)	0.568(0.024)	0.568(0.023)	0.567(0.020)
	Aesthetics	0.186(0.062)	0.179(0.048)	0.178(0.044)	0.177(0.038)
Independent variables					
Density	Population density (persons/km2)	18,268.188 (9533.489)	17,904.968 (9104.447)	17,849.214 (8816.680)	17,619.201 (8636.041)
	Commercial density (number of commercial enterprises/km2)	46.459(34.596)	44.579(30.745)	43.012(27.893)	42.291(26.687)
Land use diversity	Land use mix	0.457(0.336)	0.272(0.242)	0.173(0.157)	0.122(0.110)
Walkability	Walking score	78.676(15.122)	78.532(14.452)	78.702(13.667)	78.337(13.413)
	Intersection density (number of intersections/ km2)	23.881(13.052)	23.360(11.140)	22.903(10.317)	22.697(9.434)
Economic development	Night light value	38.168(16.079)	37.158(15.148)	36.454(14.323)	35.747(13.408)
Capacity utilization of transit	Passenger flow volume (persons/day)	47,859.68 (31,222.023)	46,736.100 (31,273.757)	46,499.339 (31,194.862)	45,682.534 (31,263.409)
User-friendliness of transit system	With shops inside the station (%)	55.307	53.763	53.191	51.813
	without shops inside the station (%)	44.693	46.237	46.809	48.187
Access to and from the station	Interchange to different routes of same transit (number of routes)	7.318(1.828)	7.284(1.813)	7.234(1.870)	7.191(1.876)
	Length of the subway (km)	40.856(12.183)	40.687(12.093)	40.404(12.336)	40.257(12.384)
	Bus stop density (numbers/km2)	30.680(34.289)	21.003(20.651)	18.028(16.341)	17.778(14.536)
Parking supply at the station	Parking lots density (numbers/km2)	8.929(14.923)	10.701(25.694)	9.600(15.843)	10.049(15.168)

Note: SD = standard deviation.



a b

c d

Fig. 3. The mean value, Gini index and Moran's of SVG around subway stations in Beijing inner city, China for: (a) Availability; (b) Accessibility; (c) Attractiveness; (d) Aesthetics.

the subway stations in Beijing. The graphical analysis confirmed the existence of both general and spatial inequalities (p values for all Moran's I < 0.05) of SVG around subway stations in Beijing, on which we can perform the regression-based assessment (SLM) to further understand contribution of different dimensions of TOD to such inequalities of SVG. We further performed T-test for all SVG metrics among different buffers (Table S1), and the results indicated that SVG metrics were significantly different across different buffers.

Table 2, 3, 4 and 5 show the relationship between TOD factors and SVG metrics around subway stations using SLM. Following Anselin (2009), as robust LM tests indicates SLM performs better than SEM, and the TOD - SVG associations remained similar across all SEM models (compared to SLM models) despite some differences in magnitude, we only displayed the results of SLM. The significance of Lag Coef indicats that the SVG among different subway stations had positive spatial dependence. SLM in Table 2 shows that population density, land use mix, intersection density, bus stop density and user-friendliness of transit system were all positively associated with availability-based SVG, while night light value was negatively associated with availability-based SVG within the 400 m buffer. Also, population density, land use mix and bus stop density were positively associated with availability-based SVG, while night light value was negatively associated with availability-based SVG within the 600 m buffer. As for the 800 m and 1000 m buffer, only night light value was negatively associated with availability-based SVG. This indicates that the effect of TOD on availability-based SVG around subway stations may decrease with the increase of buffer size.

SLM in Table 3 shows that population density, land use mix, intersection density, bus stop density and user-friendliness of transit system were all positively associated with accessibility-based SVG, while night light value was negatively associated with accessibility-based SVG within the 400 m buffer. Also, population density, land use mix, interchange to different routes of same transit and bus stop density were positively associated with accessibility-based SVG, while night light value was negatively associated with accessibility-based SVG within the 600 m buffer. As for the 800 m and 1000 m buffer, only night light value was negatively associated with accessibility-based SVG. This indicates that the effect of TOD on accessibility-based SVG around subway stations may decrease with the increase of buffer size.

SLM in Table 4 shows that population density, land use mix, intersection density and bus stop density were all positively associated with attractiveness-based SVG within the 400 m buffer. As for the 600 m, 800 m and 1000 m buffer, only land use mix was positively associated with attractiveness-based SVG. This indicates that the effect of TOD on attractiveness-based SVG around subway stations may decrease with the increase of buffer size.

SLM in Table 5 shows that population density, land use mix and bus stop density were all positively associated with aesthetics-based SVG within the 400 m and 600 m buffers. As for the 800 m and 1000 m buffer, there was no evidence TOD factors were associated with aesthetics-based SVG. This indicates that the effect of TOD on aesthetics-based SVG around subway stations may decrease with the increase of buffer size. Sensitivity analysis was ran by using another 1200-m buffer (Table S3) to test the effect of TOD under the background of 15-min Community-life Circle scheme (Cai and Gao, 2022; Zhang et al., 2020a,b). Despite some differences in magnitude, the results remained the same as the results for 1000-m buffer.

5. Discussion

This study extends previous research on the effect of TOD on local environment promotion in several respects. First, it proposed a systematic framework to assess both the quantity and quality perspective of visible green space provision around subway stations in the Chinese context. Second, it systematically explores the general and spatial inequalities in visible green space provision around the subway stations. Third, it further investigates the extent to which TOD is statistically associated with visible green space provision around subway stations from a spatial perspective.

Table 2
Spatial regression models of availability-based SVG for subway stations in inner-city area, Beijing, China.

	400 m	600 m	800 m	1000 m
	Coef.(SE)	Coef.(SE)	Coef.(SE)	Coef.(SE)
Population density	0.030**	0.023**	−0.002	−0.003
	(0.013)	(0.010)	(0.009)	(0.008)
Commercial density	0.004	0.003	0.008	0.004
	(0.006)	(0.006)	(0.006)	(0.005)
Land use mix	0.125***	0.068**	0.059	0.035
	(0.047)	(0.030)	(0.042)	(0.028)
Walking score	0.031	0.024	0.010	0.029
	(0.031)	(0.027)	(0.029)	(0.024)
Intersection density	0.022**	0.013	0.020*	−0.004
	(0.010)	(0.010)	(0.011)	(0.011)
Night light value	−0.053***	−0.039***	−0.052***	−0.044***
	(0.019)	(0.015)	(0.014)	(0.013)
Passenger flow volume	−0.006	−0.005	0.001	0.002
	(0.007)	(0.005)	(0.005)	(0.004)
With shops inside the station (ref: without shops inside the station)	0.026**	0.005	0.004	0.001
	(0.013)	(0.010)	(0.009)	(0.007)
Interchange to different routes of same transit	0.002	0.005*	0.003	0.003
	(0.004)	(0.003)	(0.003)	(0.002)
Length of the subway	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Bus stop density	0.011**	0.010**	0.002	0.006
	(0.004)	(0.004)	(0.004)	(0.004)
Parking lots density	−0.010	−0.004	0.004	0.005
	(0.008)	(0.006)	(0.006)	(0.005)
Constant	−0.137	−0.152	0.083	−0.031
	(0.163)	(0.143)	(0.144)	(0.118)
Lag Coef	0.477***	0.361***	0.608***	0.543***
	(0.136)	(0.147)	(0.111)	(0.081)
R2	0.237	0.235	0.273	0.372
AIC	−386.431	−521.849	−565.362	−658.874

Note: Coef = coefficient; SE = standard error; AIC = Akaike information criterion. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3
Spatial regression models of accessibility-based SVG for subway stations in inner-city area, Beijing, China.

	400 m	600 m	800 m	1000 m
	Coef.(SE)	Coef.(SE)	Coef.(SE)	Coef.(SE)
Population density	0.031**	0.022**	−0.005	−0.003
	(0.013)	(0.009)	(0.009)	(0.008)
Commercial density	0.003	0.003	0.009	0.004
	(0.006)	(0.005)	(0.005)	(0.005)
Land use mix	0.130***	0.068**	0.066	0.034
	(0.046)	(0.029)	(0.041)	(0.028)
Walking score	0.034	0.024	0.008	0.032
	(0.03)	(0.026)	(0.028)	(0.023)
Intersection density	0.023**	0.010	0.020*	−0.005
	(0.010)	(0.010)	(0.011)	(0.011)
Night light value	−0.047**	−0.032**	−0.049***	−0.043***
	(0.019)	(0.015)	(0.014)	(0.012)
Passenger flow volume	−0.007	−0.005	0.000	0.002
	(0.007)	(0.005)	(0.005)	(0.004)
With shops inside the station (ref: without shops inside the station)	0.026**	−0.001	−0.002	−0.003
	(0.013)	(0.010)	(0.009)	(0.007)
Interchange to different routes of same transit	0.002	0.006**	0.002	0.002
	(0.004)	(0.003)	(0.002)	(0.002)
Length of the subway	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
Bus stop density	0.010**	0.009**	0.002	0.006
	(0.004)	(0.004)	(0.004)	(0.004)
Parking lots density	−0.010	−0.003	0.007	0.005
	(0.008)	(0.006)	(0.006)	(0.005)
Constant	−0.161	−0.158	0.108	−0.060
	(0.162)	(0.139)	(0.139)	(0.116)
Lag Coef	0.453***	0.324**	0.633***	0.539***
	(0.140)	(0.153)	(0.106)	(0.081)
R2	0.213	0.205	0.276	0.368
AIC	−389.544	−532.828	−575.785	−668.216

Note: Coef = coefficient; SE = standard error; AIC = Akaike information criterion. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5.1. Main findings

The results suggest that the Gini index of SVG factors decreases with the increase of buffer size. This indicates that the disparities in visible green space provision around subway stations was more significant within inner layers centered on the subway station than the outer layers. Existing literature showed that the difference and changes in land use patterns are significantly greater around subway transits than away from subway transits since areas closer to transit stations may be more influence by the accessibility changes due to the TOD strategy (Bhattacharjee and Goetz, 2016; Higgins et al., 2014; Lee and Sener, 2017; Wenner and Thierstein, 2022). After the improvement of accessibility, more resources such as funding may get into the nearby areas thorough the transit system and have influence on local environment (Miller, 2004). According to the first law of geography, the areas closer to transit stations are more likely to be influenced by the newly coming resources, so the variations in their local environment are more significant than the outer areas (Tong et al., 2018). Also, urban planning policy play an important role in local environment development especially in the Chinese context (H. Long et al., 2014). However, the areas closer to the stations are more likely to be influenced by the market-oriented economy factors, while the outer areas are more influenced by government's planning policy (X. Li et al., 2022; Su et al., 2021; Xu et al., 2017b). Therefore, the visible green space provision away from the stations are more likely to be planned and have more equal distribution.

We found that the Moran's I of SVG factors increase with the increase of buffer size, which indicates that the closer the stations were, the greater spatial inequalities in visible green space provision around stations were found. One possible explanation for our finding is that when stations get closer, their nearby areas may not be only influenced by themselves, but also influenced by other stations (Bardaka et al., 2018; L. L. Wang et al., 2021; Zheng et al., 2019). Therefore, the effect of TOD may be mutually strengthened among stations and lead to spatial inequalities. Also, the significance of the Moran's I of SVG factors confirmed the existence of spatial inequalities in visible green space provision around subway stations in Beijing, China. Although such a finding has not been reported by previous studies, they found the spatial autocorrelation effects of TOD on property values, populations, and other factors (Bardaka et al., 2018; L. Wang et al., 2021; Zheng et al., 2019).

The spatial regression models show that population density, land use mix, intersection density, bus stop density was positively associated with all SVG factors. First, population density reflects intensity of human activities of the local areas around the subway station, so when population density grows, local government may have more fiscal revenue to pay for the environment proportion projects (e.g., green space) around subway stations (Boarnet et al., 2020; Fei et al., 2016). Second, land use mix factor is associated with property values, since it reflects how easily residents can get access to different kinds of services (Ihlanfeldt, 2007; Matthews and Turnbull, 2007; Song and Knaap, 2004). After the growth of property values, more socioeconomically advantaged groups will move in and are more willing to pay for better amenities such as improving green space provision (Xiao et al., 2017). Third, intersection density reflects the connectivity of the surrounding areas, so it can be considered as an important proxy for measuring walkability (Schlossberg and Brown, 2004). With the increase of walkability, people's dependence on car decreases, which may result in less parking lots and more green space (Cervero and Sullivan, 2011; Liang et al., 2020; Niu

Table 4
Spatial regression models of attractiveness-based SVG for subway stations in inner-city area, Beijing, China.

	400 m	600 m	800 m	1000 m
	Coef.(SE)	Coef.(SE)	Coef.(SE)	Coef.(SE)
Population density	0.010**	0.005	0.001	0.000
	(0.005)	(0.004)	(0.004)	(0.003)
Commercial density	−0.002	−0.002	0.000	−0.001
	(0.003)	(0.002)	(0.002)	(0.002)
Land use mix	0.027**	0.036***	0.035**	0.057***
	(0.011)	(0.012)	(0.018)	(0.020)
Walking score	0.001	0.007	0.002	0.010
	(0.012)	(0.011)	(0.012)	(0.010)
Intersection density	0.009**	0.001	0.007	0.007
	(0.004)	(0.005)	(0.005)	(0.005)
Night light value	−0.008	−0.004	−0.009	−0.009
	(0.008)	(0.006)	(0.006)	(0.005)
Passenger flow volume	0.000	0.000	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.002)
With shops inside the station (ref: without shops inside the station)	0.008 (0.005)	0.002 (0.004)	0.000 (0.004)	0.000 (0.003)
Interchange to different routes of same transit	0.000 (0.002)	0.002 (0.001)	0.001 (0.001)	0.001 (0.001)
Length of the subway	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Bus stop density	0.005**	0.003	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Parking lots density	−0.003	−0.003	0.000	0.000
	(0.003)	(0.002)	(0.003)	(0.002)
Constant	0.197*	0.252**	0.235**	0.229***
	(0.103)	(0.104)	(0.095)	(0.070)
Lag Coef	0.047***	0.035**	0.050***	0.047***
	(0.014)	(0.016)	(0.013)	(0.009)
R2	0.164	0.146	0.163	0.243
AIC	113.619	4.802	−30.278	−91.822

Note: Coef = coefficient; SE = standard error; AIC = Akaike information criterion. *p < 0.10, **p < 0.05, ***p < 0.01.

Table 5
Spatial regression models of aesthetics-based SVG for subway stations in inner-city area, Beijing, China.

	400 m	600 m	800 m	1000 m
	Coef.(SE)	Coef.(SE)	Coef.(SE)	Coef.(SE)
Population density	0.021**	0.017**	0.002	0.003
	(0.009)	(0.007)	(0.007)	(0.006)
Commercial density	−0.003	−0.004	0.000	−0.002
	(0.005)	(0.004)	(0.004)	(0.004)
Land use mix	0.100***	0.057**	0.039*	0.049
	(0.037)	(0.023)	(0.021)	(0.032)
Walking score	−0.005	−0.007	−0.027	0.000
	(0.023)	(0.021)	(0.022)	(0.019)
Intersection density	−0.005	0.011	0.012	0.014*
	(0.008)	(0.008)	(0.009)	(0.008)
Night light value	−0.021	−0.012	−0.019*	−0.016
	(0.014)	(0.012)	(0.011)	(0.010)
Passenger flow volume	−0.004	−0.002	0.002	0.002
	(0.005)	(0.004)	(0.004)	(0.003)
With shops inside the station (ref: without shops inside the station)	0.016 (0.010)	0.004 (0.008)	0.001 (0.007)	0.000 (0.006)
Interchange to different routes of same transit	0.002 (0.003)	0.004* (0.002)	0.002 (0.002)	0.002 (0.002)
Length of the subway	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Bus stop density	0.010***	0.007**	0.003	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Parking lots density	−0.004	−0.003	0.003	0.002
	(0.006)	(0.005)	(0.005)	(0.004)
Constant	0.004	−0.037	0.136	0.007
	(0.124)	(0.113)	(0.113)	(0.094)
Lag Coef	0.448***	0.403***	0.634***	0.527***
	(0.144)	(0.145)	(0.107)	(0.085)
R2	0.18	0.201	0.249	0.312
AIC	−491.536	−614.563	−663.762	−747.647

Note: Coef = coefficient; SE = standard error; AIC = Akaike information criterion. *p < 0.10, **p < 0.05, ***p < 0.01.

et al., 2021). Fourth, bus stop density reflects how easily passengers can interchange from subway stations to other transit modes, which is an important factor influencing people's motivation to use subway systems (Singh et al., 2017). Also, with more bus stations, people tend to depend less on cars, which may lead to more space for other amenities such as green space (Cervero and Sullivan, 2011; Liang et al., 2020; Niu et al., 2021). Last, user-friendliness of transit system is also an important factor, since people are more likely to choose public transits with better services, which may decrease people's dependence on car usage (Buehler et al., 2017). However, we found night light value was negatively associated with only quantitative perspective of visible green space provision (availability and accessibility). Night light value is a proxy for economic development, which is related to land value (C. Li et al., 2020). When the land value goes too high around transits, it is likely that there will be no affordable space for a large amount of visible green space (Wolch et al., 2014). Another finding from this study is that as the increase of buffer size the effect of TOD factors become insignificant, which indicates that the effect of TOD on visible green space provision around subway stations may decrease with the increase of buffer size. A possible explanation is that the effect of TOD will first exert an influence around the transits, but the resource related to TOD (e.g., population and funding) may be able to reach areas away from transits (Bardaka et al., 2018; L. R. Wang et al., 2021; Zheng et al., 2019).

5.2. *Policy implications*

Assessing the effect of TOD on visible green space provision has implications for urban planning and policy in Beijing. First, this study confirmed that the promotion of visible green space provision is one of the co-benefits of TOD strategy, so policy makers can also consider it as a strategy to facilitate greening city for future policy intervention for central area in Beijing. Second, since the effect of TOD on visible green space provision decreased with the increase of buffer size, it is important for the policy makers to shed light on the potential disparities in visible green space provision between inner and outer layers centered on the subway station in Beijing. Third, there were disparities in visible green space provision among different surrounding areas of subway stations, so policy makers should pay attention to the unequal level of TOD among different transit stations. As the development of subways in Beijing is not spatially equality (Yang et al., 2016), policy makers should prevent such disparities further lead to issue of green injustice in Beijing. Last, the spatial inequalities of visible green space provision increased with the buffer size, this indicates the overcrowd of transit stations may further lead to unequal visible green space provision. Therefore, the distance among different transit stations should not be planned too close in Beijing.

5.3. *Limitations*

It should be noted that this study has the following limitations. First, our proposed 4 "A framework may not be systematic enough to cover all dimensions of visible green space. For instance, tridimensional characters of green space can only be assessed through 3D model (S. Zhu et al., 2021). Some data such as LiDAR can reflect 3D characters of green view (Münzinger et al., 2022), but our street view data is still a 2D model, which is not able to assess 3D characters of visible green space. Second, street view data were collected for a static period, so they are not able to reflect the dynamic changes of variations in visible green space provision. The vegetation is greener in spring and summer than in autumn and winter, this means that using a single image to represent the average green view exposure for the whole year may cause bias. Third, our research is based on a cross-sectional study design which may prevent us from getting casual inference regarding the effect of TOD on visible green space provision. Fourth, although we used different buffer sizes for the analysis, there are still chances that the modifiable areal unit problem (MAUP) (Fotheringham and Wong, 1991) may exist, since the interaction between TOD and visible green space provision may occur within a larger buffer or even through different scales. Fifth, the effect of TOD may not be accurately captured since the assessment framework proposed by Singh et al. (2017) may not include all TOD-related factors. Lastly, it is also worth noting that areas around subways may not equal to TOD areas. In Beijing, many urban areas may be well-developed before the opening of subway stations in those areas, rather than the other way around. For example, the city centre was planned and developed around subway stations.

6. Conclusion

Based on street view data in Beijing, it explored inequalities in four different dimensions of visible green space provision around subway stations. More importantly, this study constitutes the first attempt to evaluate the effects of TOD on visible green space around subway stations in the Chinese context. The results of the statistical analysis suggested that there were disparities in visible green space provision around subway stations, but they got weaker as the increase of buffer size around stations. Also, TOD factors including population density, land use mix, intersection density and bus stop density were the main determinants for visible green space provision around subway stations. Such effect also got weaker as the increase of buffer size around stations. To help achieve the goal of green TOD through urban planning and design, policymakers and urban planners should pay more attention to TOD strategies, since it contributes to both absolute provision and inequalities in visible green space provision.

Author statement

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2023.118093.

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