Landscape and Urban Planning 214 (2021) 104179

Contents lists available at ScienceDirect

Landscape and Urban Planning

journal homepage: www.elsevier.com/locate/landurbplan

Can daily mobility alleviate green inequality from living and working environments?

Binhui Wang[a], Tiantian Xu[a,b], Hei Gao[c], Na Ta[d,e,*], Yanwei Chai[f], Jiayu Wu[g,*]

[a] College of Agriculture and Biotechnology, Zhejiang University, Hangzhou 310058, Zhejiang Province, PR China
[b] Center for Balanced Architecture, Zhejiang University, Hangzhou 310058, Zhejiang Province, PR China
[c] The Architectural Design & Research Institute of Zhejiang University Co., Ltd., Zhejiang University, Hangzhou 310028, Zhejiang Province, PR China
[d] Key Laboratory of Geographic Information Science (Ministry of Education), East China Normal University, Shanghai 200241, PR China
[e] School of Geographic Sciences, East China Normal University, Shanghai 200241, PR China
[f] Department of Urban and Economic Geography, College of Urban and Environmental Sciences, Peking University, Beijing 100871, PR China
[g] College of Agriculture and Biotechnology, Zhejiang University, Hangzhou 310058, Zhejiang Province, PR China

HIGHLIGHTS

- The measurement framework of green exposure under static and dynamic geographic background was constructed.
- Daily mobility cannot alleviate the green inequality of living and working environment.
- A convergence of green exposure exists between living and travel environment.
- Working in a poor green environment may lead to compensatory green exposure.
- Green justice research should focus more on the workplace and travel environment.

ARTICLE INFO

Keywords:
Green justice
Dynamic green exposure
Static geographical background

ABSTRACT

Urban green spaces are beneficial to residents' physical and mental health, but their spatial distribution is unequal. Green justice studies typically use static administrative areas as contextual areas to evaluate green spaces, which can lead to biased estimations, as it ignores daily mobility. However, the phenomenon that actual perceived green exposure may be averaged by daily mobility has yet to be tested. Based on a survey of Beijing residents' working, living, and daily travel environments, this study measures respondents' static and dynamic green exposure and tests whether dynamic green exposure intensifies or alleviates green inequality from living and working environments. The following results are obtained. (1) From the perspective of weekly travel, individuals living or working in a satisfactory green space environment have high levels of dynamic green exposure. (2) The difference in the amount of greenness of communities will lead to the further polarization of dynamic green exposure for trips beyond 2000 m from home. (3) When working in an environment with poor green space and street greenery quality, trips beyond 2000 m from the workplace will have high-quality and efficient dynamic green exposure. This study tests and reports on the disparity in dynamic green exposure under different static geographical backgrounds, which complements theoretical research on green justice.

1. Introduction

Exposure to urban green spaces (UGSs) is proven to have a series of direct and indirect physical and mental health benefits. Direct benefits include emotion regulation and stress relief (Grahn and Stigsdotter, 2010; Bratman et al., 2015), improving air pollution and reducing cardiopulmonary mortality (Li et al., 2020), while indirect benefits include sports, social cohesion, and wellbeing promotion through the increase of sports and social activities in UGSs (Lee and Maheswaran, 2011; Sandifer et al., 2015; Douglas et al., 2017).

* Corresponding authors at: No. 500 Dongchuan Road, Minhang District, Shanghai 200241, PR China (N. Ta) and College of Agriculture and Biotechnology, Zhejiang University, Hangzhou, 310058, Zhejiang Province, PR China (J. Wu).
E-mail addresses: 22016265@zju.edu.cn (B. Wang), 3170100590@zju.edu.cn (T. Xu), 77207026@qq.com (H. Gao), nta@geo.ecnu.edu.cn (N. Ta), chyw@pku.edu.cn (Y. Chai), wujiayula@gmail.com (J. Wu).

https://doi.org/10.1016/j.landurbplan.2021.104179
Received 26 January 2021; Received in revised form 19 June 2021; Accepted 22 June 2021
Available online 30 June 2021
0169-2046/

However, environmental justice and green justice problems occur worldwide (Dooling, 2009; Checker, 2011; Pearsall, 2018). Social segregation exists in the use of UGSs, which is related to social and economic characteristics, such as race, income, and age (Wolch et al., 2005; Dahmann et al., 2010; Apparicio et al., 2012). Social isolation is manifested mainly in uneven access to UGSs (Wu et al., 2020), the housing displacement of vulnerable groups (Gould and Lewis, 2016), and differences in neighborhood UGS identity (Goossens et al., 2020).

Research on green justice is typically based on static green exposure measurement, which generally has three dimensions, namely, availability, visibility, and accessibility (Chen and Jim, 2010; Kronenberg et al., 2020). Availability refers to whether people have the ability to visit surrounding UGSs, which is typically measured by the amount of UGSs, including the greening rate, green coverage, NDVI, and so on (Kronenberg et al., 2020). Visibility refers specifically to the proportion of greenery in street landscapes (Aoki, 1987) and employs the green view index (GVI) as the main measurement index. In recent years, open-source street views (e.g., Google Street View, Tencent Street View, and Baidu Street View) became common data sources (Rundle et al., 2011; Li et al., 2015). Moreover, GVI measurement developed from manual Photoshop (Yang et al., 2009) and spectral analysis (Li et al., 2015) to supervised classification or semantic segmentation (Zhang and Dong, 2018; Yu et al., 2019; Chen et al., 2019; Wu et al., 2019). Accessibility measurement methods were developed over the years, including the container model, coverage model, gravity-based model, and floating catchment model (Wu et al., 2019). Based on the two-step floating catchment method, the CFCA model considers the effects of traffic restrictions as well as the attenuation of UGS attraction with distance and emphasizes the contribution of street greenery to UGS attraction and green injustice mitigation (Wu et al., 2019). However, neglecting daily mobility and assessing only static green exposure (Chaix et al., 2013) can create the uncertain geographic context problem in which actual perceived greenness is measured with deviation (Kwan, 2012; Perchoux et al., 2016).

A static geographical environment differs from a dynamic exposure environment in many fields (Burgoine and Monsivais, 2013; Kwan, 2018). Residents' actual exposure environments can be averaged by daily mobility (Park and Kwan, 2017; Shafran-Nathan et al., 2017; Yu et al., 2018, 2020), which is summarized as the neighborhood effect averaging problem (NEAP; Kwan, 2018). This phenomenon may be related to the compensatory use of green spaces. The compensation hypothesis states that a group lacking UGSs around its place of residence may actively come in contact with UGSs in non-neighborhood environments to compensate for the shortcoming (Hall and Page, 2014). Although the NEAP is based on the theory of residential context, the study shows that high-income, employed, young, and male participants are more likely to have the NEAP due to their high daily mobility (Kim and Kwan, 2021; Ma et al., 2020). This group also has many daily utility trips and activities in the workplace, indicating that the workplace environment may play a significant role in determining people's green exposure. A prior study found that travelers are willing to ride long distances to gain green surroundings on their route (Vedel et al., 2017). Therefore, in the present research, we believe that people may be affected by a static green environment (i.e., residence and workplace) and produce corresponding "compensatory" green exposure in the travel environment. The daily mobility will alleviate the green inequality caused by the static green space environment difference to some extent (Fig. 1).

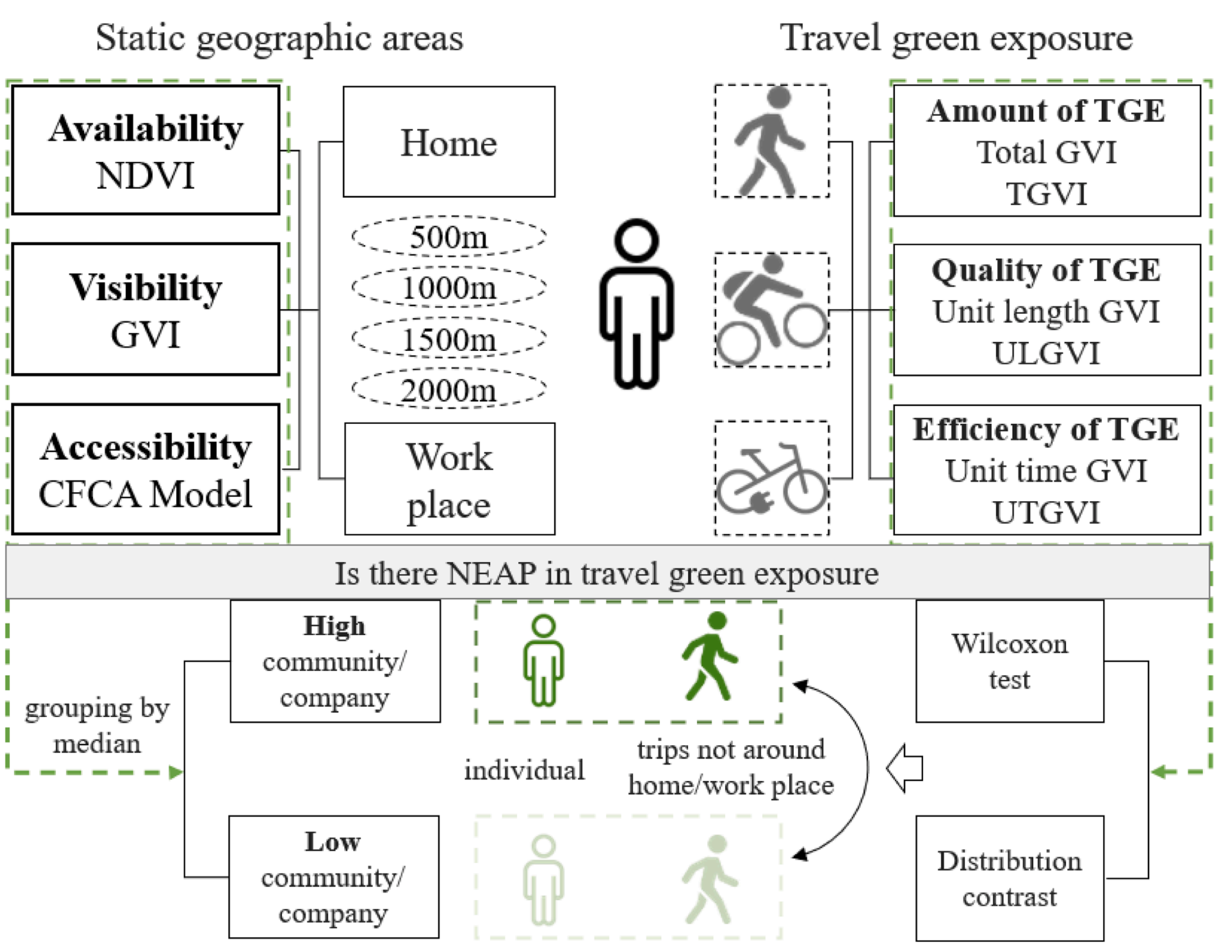

Fig. 1. Research framework design.

Under the background of green inequality and UGCoP, can daily mobility alleviate green inequality in living and working environment? We assume that people who lack green exposure will contact more greenness in their daily mobility out of compensation psychology to narrow the greenness gap between their static geographical environment (i.e., workplace and residence). On the basis of the above assumption, this study supplements the literature from the following aspects: (1) First, we develop a measurement framework to depict the static or dynamic green landscape perceived by individuals in their living, working, and travel environments accurately. (2) Second, we apply the proposed measurement framework, which adopts street-view big data and machine learning technology, to compare the dynamic green exposure of people living or working in different green environments. In this way, we can test whether compensation behavior exists and determine whether daily mobility alleviates the inequality among static green environments.

This study investigates the living and working green environments of 554 respondents and their dynamic green exposure during active travel (AT). According to the three dimensions of static green environmental indicators (i.e., availability, visibility, and accessibility) in four residence and workplace buffer zones (i.e., 500 m, 1000 m, 1500 m, and 2000 m), we divide the entire sample into 24 pairs in a high green index group and low green index group. By comparing whether significant differences in dynamic green exposure exist between the two groups, we test whether inequality in green exposure exists.

The rest of this paper is arranged as follows. Section 2 describes the study area and travel survey, and Sections 3 and 4 introduce the assessment methods for dynamic green exposure and static green exposure, respectively. Section 5 presents the data summary and test results, and Section 6 discusses the results and limitations of the study. Finally, Section 7 summarizes the main conclusions and contributions of the study.

2. Study area and travel survey

In this study, 554 residents of Shangdi-Qinghe Street in Haidian District, Beijing (Fig. 2), were selected as the sample. The urbanization process of China has created space for urban land development and economic activities (Li et al., 2017). The industry base of the study area changed from agriculture to information, which brought an influx of people, changes to the land use structure, and improvements in UGS quality. According to a government report, Beijing achieved an increase in per capita park green areas from 15 m^2 to 16 m^2 during the 12th Five Year Plan period (Beijing Gardening and Greening Bureau, 2016). However, with the increase of residents' income and improvement of the transportation system, the proportion of public transport travel increased steadily but the proportion of bicycle travel decreased gradually, from 62.7% in 1986 to 11.3% in 2014. Therefore, Beijing residents' green space exposure from AT (walking and cycling, including e-bike cycling) may not have increased with the improvement of green space quality.

With GPS positioning, a travel log, and a questionnaire, a week-long survey of Beijing residents' daily travels was conducted in eight waves in 2012. With the assistance of the neighborhood committee of each community and human resource department of a company, 0.5% to 1% of the residents were randomly selected from 46 communities or companies on Shangdi-Qinghe street. A total of 791 participants were recruited, and 709 respondents completed the survey, with a completion rate of 89.6%. As shown in the socioeconomic characteristics of the respondents in Table 1, the proportion of the women (54.51%) was slightly higher than that of the men (45.49%). Moreover, most of the participants were adults (18–64 years old) and employed. The proportion of the respondents with a bachelor's degree or higher was large (59.39%), but most (77.08%) had a monthly income below 6000 yuan. In the travel survey of the same year, Beijing had a per capita disposable income of approximately 3000 yuan per month. Low-income (the bottom 20%) and high-income households (the top 20%) reported a per capita disposable income of approximately 1365 and 5497 yuan per month, respectively. Therefore, we considered that the respondents with a monthly salary of less than 2000 yuan belong to low-income households in the region. By contrast, those with a monthly salary of more than 6000 yuan are among the high-income households. The proportion

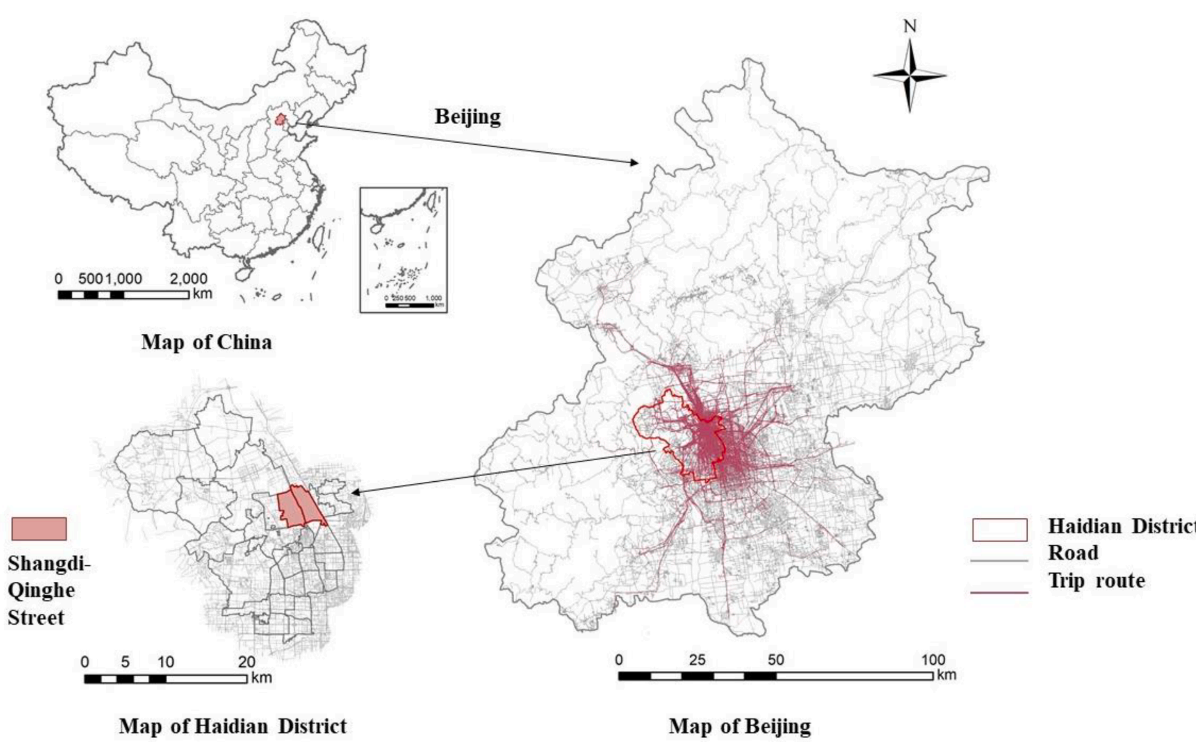

Fig. 2. Sample source location map.

Table 1
Summary of basic characteristics of respondents.

Characteristic	Category	%	Mean (std. dev.)
Gender	male	45.49	–
	female	54.51	
Age	–	–	33.76(8.45)
Education	high school and below	12.27	–
	junior college	28.34	
	bachelor degree	44.77	
	master degree and above	14.62	
Monthly income	2000yuan and below	11.55	–
	2000-4000yuan	41.88	
	4000-6000yuan	23.65	
	6000yuan and above	22.92	
Whether commute by AT	no	63.36	–
	yes	36.64	
Working-living distance (km)	–	–	7.36(6.65)
Average daily working hours	–	–	5.81(3.78)

of the respondents who commuted by AT was approximately one third of the entire sample. The workplace–residence distance of approximately 90% of the respondents was less than 16 km, with an average of 7.36 km. In addition, the participants' average working hours were 5.81 h, and approximately 90% of the respondents had working hours less than 9.61 h.

The coordinates of each respondent's residence and workplace were recorded. The respondents were required to carry a GPS tracking device for one week and record and upload their spatial and temporal co-ordinates every 30 s (Fig. 3). A travel log recorded details of each trip, such as vehicle type, duration, and origin and destination (home, workplace, or other). Excluding records with missing or invalid values, the valid sample consisted of 9802 trips, including 2156 ATs.

3. Dynamic green exposure

As walking and cycling provide the most direct contact with street greenery, green exposure is considered only from these two modes. First, the street view big data are sampled, and machine learning is used to calculate the GVI of each road. Then, the respondents' perception of green spaces is described using the total GVI (TGVI), unit length GVI (ULGVI), and unit time GVI (UTGVI) to represent the total amount, quality, and efficiency of dynamic green exposure.

3.1. Street view image acquisition and machine learning

The street view sampling process is as follows. First, based on the road network data obtained from Amap (https://www.amap.com/), approximately 100,000 sampling points are generated at an interval of 100 m. Images are collected at 60-degree intervals in the horizontal direction to cover a 360-degree street view, that is, six images at each sampling point. After sampling, 500,000 images are obtained after the manual cleaning of the captured images under the condition of defoliation or autumn color change. Deep-learning algorithms are used for the batch recognition of vegetation. A training set from Cityscape (https://www.cityscapes-dataset.com/) and an open-source urban streetscape image set with fine semantic annotations are provided, including 2975 images for training, 500 for verification, and 1525 for testing. TensorFlow and DeepLabv3 models are used in the training, and the parameters are set as follows: the batch size is 4, the initial learning rate is 0.001, the train crop size of the neural network is adjusted to the original size of the Cityscape images, and the other parameters are trained according to the default parameters of DeepLabv3. These hyperparameters play a vital role in the convergence rate and accuracy of deep learning and are limited by the performance of computers (Smith et al., 2017; Smith, 2018). The mIOU (an evaluation index of semantic segmentation accuracy) using 500 fine-annotation images from the Val folder of Cityscape is 75.79%. After the vegetation (including branches, leaves, and trunks) in each image is identified, the pixel proportion is calculated as the GVI value. The GVI value of each

Fig. 3. GPS points and travel trajectory (GPS points are above, travel trajectories are below).

road is the average value of the GVI of all the images sampled on the road. The specific process of acquisition, machine learning, and calculation is shown in Fig. 4.

3.2. Trip matching and dynamic green exposure calculation

After the road network with the GVI is obtained, the GVI of each trip is calculated. The matching mode of the travel path and road is not through the buffer but through the following procedure. First, for the two adjacent GPS points P_{ijk} and $P_{ij(k+1)}$ in the i-th trip of the j-th individual, their GVI value is recorded as GP_{ijk} and $GP_{ij(k+1)}$, which derive from the GVI value of the nearest road. Moreover, $Line_{ijk}$ is the segment between the two points, and its GVI value is:

$$GL_{ijk} = (GP_{ijk} + GP_{ij(k+1)})/2$$

The TGVI of $Line_{ijk}$ is calculated as:

$$TGL_{ijk} = GL_{ijk} \cdot L_{ijk}$$

where L_{ijk} is the length (m) of $Line_{ijk}$. Thus, the TGVI for a trip is:

$$TGVI_{ij} = \sum_k TGL_{ijk}$$

In addition, the TGVI of the weekly AT of the j-th individual is:

$$TGVI_j = \sum_i TGVI_{ij}$$

The perceived ULGVI of the j-th individual is:

$$ULGVI_j = TGVI_j / \sum_i \sum_k L_{ijk}$$

The perceived UTGVI of the j-th individual is:

$$UTGVI_j = TGVI_j / \sum_i \sum_k T_{ijk}$$

where T_{ijk} is the time of $Line_{ijk}$ went through, and $\sum_i \sum_k T_{ijk}$ is the total time (s) of the weekly AT of the j-th individual. The TGVI reflects the total amount of green landscape perceived by an individual in AT, and the difference in the TGVI may derive from the difference in the ULGVI or UTGVI.

4. Static green exposure

The static green exposure geographical areas are the four buffer zones (i.e., 500 m, 1000 m, 1500 m, and 2000 m) around the coordinates of each respondent's residence and workplace. According to the above content, static green exposure is described from three dimensions, namely, availability, visibility, and accessibility. The corresponding indices are the NDVI and average GVI of the roads within the buffer, and accessibility is based on the UGSs and surrounding street greenery.

4.1. Availability and visibility

The NDVI typically uses multiband remote sensing images as data materials to evaluate the greening level of a region by calculating the reflection value of near-infrared and red bands. In this study, Landsat 8 remote sensing images with a cloud cover of less than 0.1% under radiometric calibration and atmospheric correction before NDVI calculation (Fig. 5, left) are used. The NDVI equation is defined as follows:

$$NDVI = (NIR - Red)/(NIR + Red)$$

where NIR is the reflection value of the near-infrared band, and red is the reflection value of the red band. The NDVI is a dimensionless value with an interval between −1 and +1.

The GVI is the mean value of the GVI of all the roads within the buffer (Fig. 5, right). In Section 3.1, how to calculate the GVI of all the roads through street views and machine learning is described. Therefore, the average GVI of the roads in the buffer zone is the average GVI weighted by the road length. The 500-meter buffer GVI of the residence of the i-th individual is taken as an example, as follows:

$$H\_GVI\_500_i = \sum_j GVI_{ij} \cdot L_{ij} \Big/ \sum_j L_{ij}$$

where GVI_{ij} is the average GVI of the j-th road in the buffer, whose length (km) is L_{ij}.

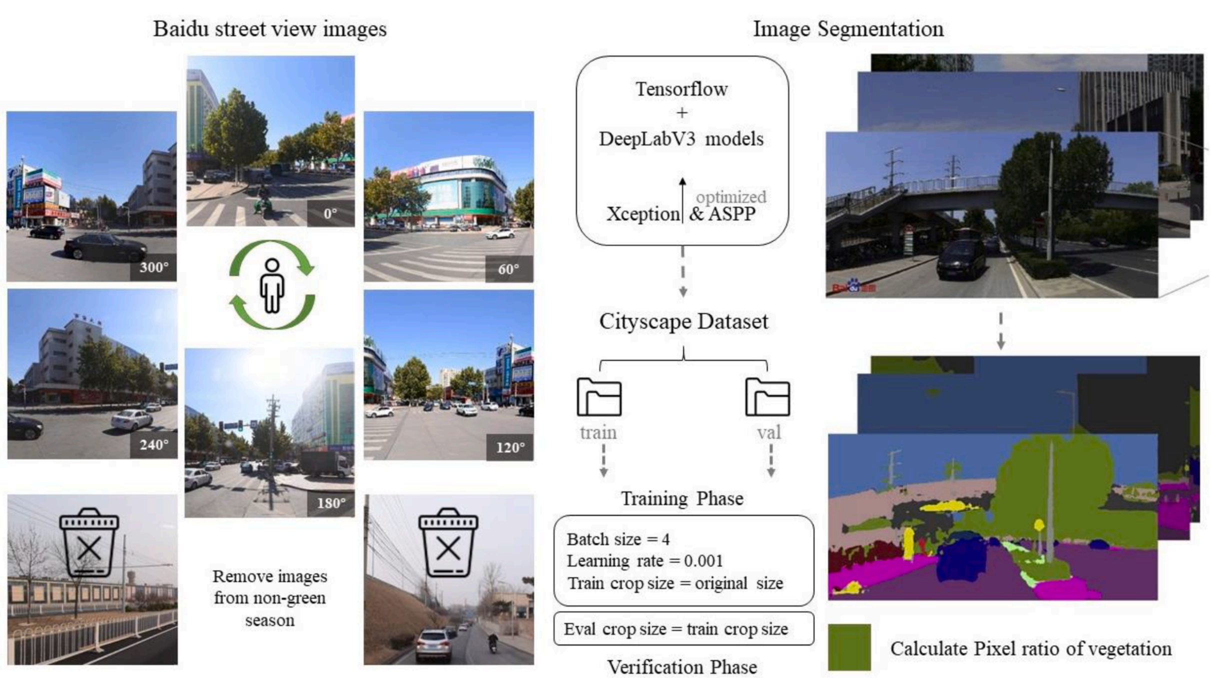

Fig. 4. Street view image acquisition, machine learning and GVI calculation process.

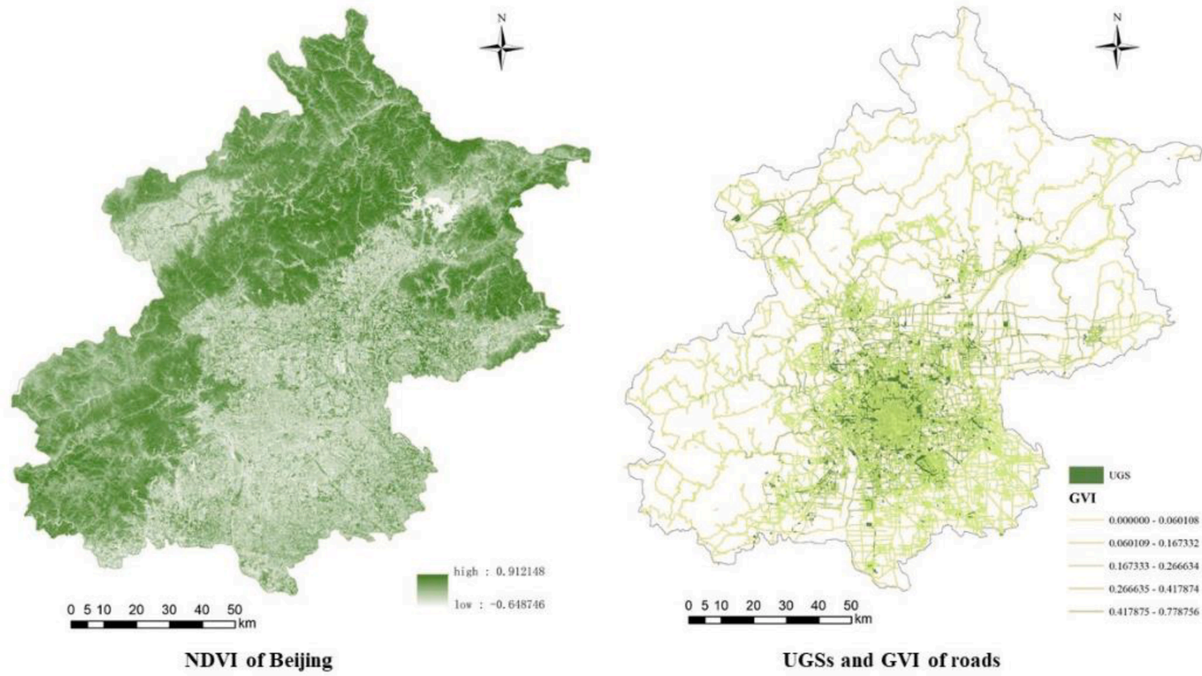

Fig. 5. Static green space index. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.2. Accessibility

The green accessibility calculation is adjusted according to the method of Wu et al. (2019), which considers the park scale and GVI of the surrounding streets as attractive UGS factors and different park sizes and travel modes. The specific process is described below.

First, based on the data of the second land survey in Beijing, 2042 UGSs labeled "parks and green spaces" and larger than 1 hm^2 are extracted (Fig. 5, right). Based on the code for the design of public parks (GB 51192-2016) in China, the UGSs are divided into five categories according to area size. The catchment size is estimated with the area and travel mode (Table 2). In this study, only walking and cycling are considered.

Second, UGS attraction is calculated. Each UGS has two attraction indicators, namely, area and the average GVI. The GVI attraction of walking and cycling should be calculated. The walking situation is taken as an example. First, the area of each UGS and average value of the surrounding GVI are calculated, and the specific calculation range is shown in Table 2. Through the use of min–max normalization to achieve nondimensionalization, the size and GVI of the UGSs are normalized to $Area_s$ and $GVI\_Walking_s$. The attraction of the i-th UGS in the walking mode is:

$$G\_Walking_i = \beta_1 Area_{si} + \beta_2 GVI\_Walking_{si}$$

where β_1 and β_2 represent the weights, and the total of β_1 and β_2 equals 1. The weight coefficient is calculated with the entropy weight method. For $Area_s$, the information entropy is:

Table 2
Catchment size corresponding to different area and travel mode.

Area (hm^2)	Number	%	Time (min)	d_0_*Biking*(km)	d_0_*Walking*(km)
≤2	1091	53.43	5	1.25	0.5
2–5	589	28.84	10	2.5	1
5–10	209	10.24	20	5	2
10–40	137	6.71	30	7.5	3
≥40	16	0.78	50	12.5	5

$$E_{area} = \begin{cases} -\ln(n)^{-1}\sum_{i=1}^{n} p_i ln(p_i), p_i \geq 0 \\ 0, p_i = 0 \end{cases}$$

where p_i is the proportion of the i-th UGS area in the total UGS area, as follows:

$$p_i = Area_{si} / \sum_{i=1} Area_{si}$$

The information entropy ($E_{GVI\_Walking}$) of $GVI\_Walking_s$ can be obtained in the same way, and β_1 and β_2 can be calculated as follows:

$$\beta_1 = \frac{1 - E_{area}}{2 - E_{area} - E_{GVI\_Walking}}$$

$$\beta_2 = 1 - \beta_1$$

Similarly, UGS attraction in the cycling mode (G_Biking_i) is calculated. Based on the principle that attraction decreases with distance, the accessibility of each residential or working point is calculated. The accessibility of the j-th individual's residence is taken as an example, as follows:

$$Access\_home_j = \sum_{i \in \{d_{ij} \leq d_0\}} G\_Walking_i D(d_{ij}, d_0) + \sum_{i \in \{d_{ij} \leq d_0\}} G\_Biking_i D(d_{ij}, d_0)$$

where

$$D(d_{ij}, d_0) = \begin{cases} \dfrac{e^{-\frac{1}{2} * \frac{d_{ij}}{d_0}} - e^{-\frac{1}{2}}}{1 - e^{-1/2}}, d_{ij} < d_0 \\ 0, d_{ij} \geq d_0 \end{cases}$$

where d_{ij} is the distance between the i-th UGS and j-th individual's residence, and d_0 refers to Table 2. The calculation in this step considers the walking and cycling scenarios. In the same way, the green accessibility of the workplace is calculated.

5. Analysis and results

5.1. Analysis method

To answer our research questions, we tested whether individuals generate compensatory green exposure in mobility to alleviate the greenness gap between their static environments (i.e., residence and workplace). On the basis of the above measurements of static and dynamic green exposure, we took the median of NDVI, GVI, and accessibility at each respondent's residence and workplace in four buffer zones as the standard line and divided the full sample into 24 pairs of high and low static green exposure (277 people in each group). After comparing the mean and difference of dynamic green exposure of each group pair, we analyzed the above problems using the individual and behavior basic analysis units.

Dynamic green exposure at the individual level integrated TGVI, ULGVI, and UTGVI in a week for each respondent to test whether people in a disadvantaged position of static green exposure would have higher dynamic green exposure, that is, whether daily mobility alleviated the inequality of static green exposure. Given the abnormality property of TGVI, ULGVI, and UTGVI, we used the Wilcoxon test to analyze the difference of dynamic green exposure between each pair of individual group pairs. However, 1750 trips (81.17%) were home-based, and the number of work-based trips was 1531 (71.01%) in our sample. The ATs were concentrated mainly around the respondents' residence and workplace. Thus, we could not judge whether compensation behavior occurred in a non-residential or non-workplace environment by conducting only the individual-level analysis.

Therefore, at the travel level, we separately extracted the travel in the background of a non-residential or non-workplace environment. We also tested whether the respondents with low static green exposure seek higher dynamic green exposure in the environment outside their residences or workplace to determine whether trips to a non-residential or non-workplace environment have any compensation behavior. We took home-based trips as an example and included non-home-based trips and home-based trips beyond 2000 m to non-neighborhood trips. The reasons for selecting 2000 m as the basis for long-distance travel were as follows: (1) The average distance of 2156 ATs is approximately 2000 m, and 2000 m also corresponds to the maximum buffer size of this study. (2) In addition to walking, the analysis includes bicycle travel. Prior studies typically used a 10-minute walking distance to distinguish between neighborhood and non-neighborhood environments, which is approximately 2000 m (in terms of 12 km/h for cycling). We applied the same definition to travel to non-workplace environments.

5.2. Dynamic green exposure test results at individual level

The mean value of the individual group pairs and test results of the groups are shown in Table 3. The table shows significant differences between the groups with median accessibility as the boundary value ($p > 0.001$) and that the employees from the companies with high accessibility and a 90% confidence probability have a high UTGVI. The TGVI, ULGVI, and UTGVI of the employees working in an environment with a high GVI within 500 m are also significantly high. Based on the significance results of the test, we show the difference in the frequency distribution of the group pairs according to accessibility and the GVI in the 500-meter buffer (static green exposure indicators are standardized) in Fig. 6 and 7.

Fig. 6 and Table 3 show that whether based on green accessibility or the GVI, living or working in an environment with high static green exposure will lead to high dynamic green exposure. Fig. 6 demonstrate two main aspects, that is, increased zero values in the dynamic green exposure of the residents or employees in low-accessibility communities or companies and the high frequency of the high dynamic green exposure of the residents or employees in high-accessibility communities or companies.

Table 3
average of weekly dynamical green exposure at individual level and the results of Wilcoxon test.[a]

Static green exposure b		Home			Workplace		
Buffer	group	TGVI	ULGVI	UTGVI	TGVI	ULGVI	UTGVI
Accessibility							
–	low	**1.013**	**0.112**	**0.117**	**1.396**	**0.114**	0.138
	high	**2.234**	**0.144**	**0.172**	**1.851**	**0.143**	0.151
NDVI							
500	low	1.902	0.136	0.156	1.32	0.123	0.125
	high	1.346	0.12	0.133	1.928	0.134	0.164
1000	low	1.936	0.13	0.138	1.474	0.122	0.125
	high	1.312	0.127	0.151	1.774	0.134	0.163
1500	low	1.865	0.127	0.139	1.684	0.128	0.14
	high	1.383	0.129	0.15	1.564	0.128	0.149
2000	low	1.931	0.129	0.152	1.663	0.127	0.138
	high	1.317	0.128	0.137	1.585	0.13	0.151
GVI							
500	low	1.54	**0.115**	0.127	**1.602**	**0.114**	**0.137**
	high	1.708	**0.141**	0.162	**1.646**	**0.142**	**0.152**
1000	low	1.873	0.131	0.145	1.774	0.133	0.146
	high	1.374	0.125	0.144	1.474	0.124	0.143
1500	low	1.795	0.129	0.142	1.503	0.129	0.142
	high	1.453	0.128	0.147	1.745	0.127	0.147
2000	low	1.779	0.131	0.144	1.421	0.124	0.129
	high	1.469	0.126	0.145	1.826	0.132	0.16

[a] The data in table is the mean value of dynamic green exposure of low green space index group or high green space index group, and the group with 95% significance in Wilcoxon test is bold. TGVI in the table has been divided by 1000.

5.3. Dynamic green exposure test results at travel level

To explore whether a significant difference exists in the trips beyond living and working environments, we conduct additional Wilcoxon tests. We take home-based trips as an example, and non-neighborhood trips include non-home-based trips and home-based trips beyond 2000 m. The reasons for selecting 2000 m as the basis for long-distance travel are as follows. (1) The average distance of 2156 ATs is approximately 2000 m; thus, 2000 m can be used as the reference value in this study to judge whether a trip is long distance. (2) Studies typically use a 10-minute walking distance to distinguish between neighborhood and non-neighborhood environments (Hurvitz and Moudon, 2012; Kang et al., 2017). In addition to walking, this study includes bicycle travel, and a 10-minute bicycle travel distance is approximately 2000 m (at a speed of 12 km/h). Furthermore, 2000 m corresponds to the maximum buffer size in this study. Travel to non-workplace environments is defined in the same way. Among the 2156 ATs, 1750 trips (81.17%) are home-based, and the number of work-based trips is 1531 (71.01%). The ATs are concentrated mainly around the respondents' residence and workplace.

The mean value of the travel group pairs and test results are shown in Table 4. The table provides the following information. (1) A significant difference in dynamic green exposure exists in non-neighborhood travel between high- and low-accessibility communities. The residents of high-accessibility communities have high average green exposure. (2) A relationship exists between a community with a high NDVI and high non-neighborhood dynamic green exposure quality. A low NDVI within a small range in the work environment will encourage workers to increase their dynamic green exposure beyond their work environment. (3) The higher the GVI within 500 m of a community, the easier for the respondents to increase the TGVI by choosing a high UTGVI in non-neighborhood travel. The GVI results in the working environment are similar to the NDVI results, but the difference is though the workers in the high GVI working environment have a low UTGVI and ULGVI, their TGVI remains high to a certain extent.

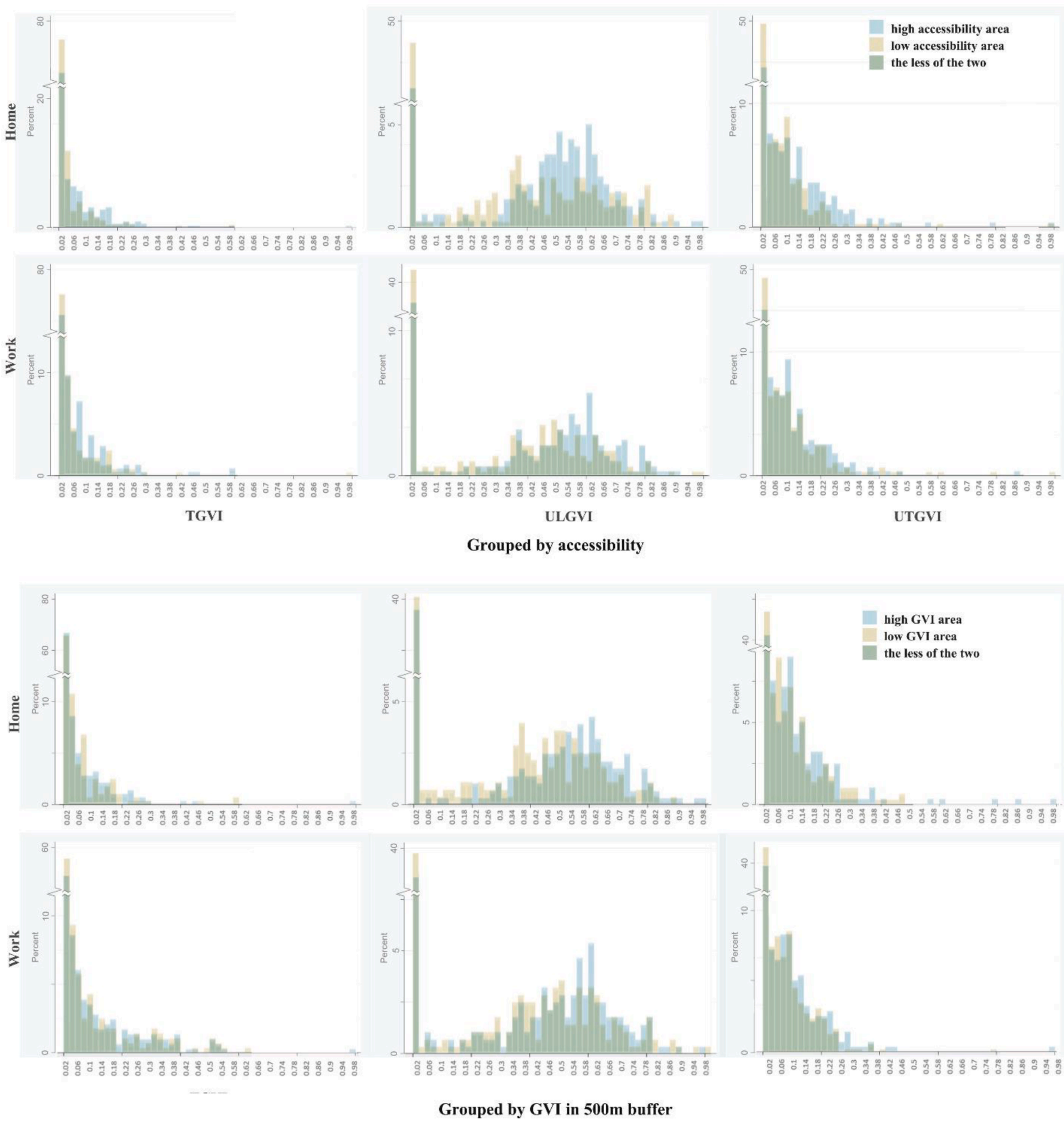

Fig. 6. Comparison of frequency distribution of individual travel green exposure in one week. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

6. Discussion

Through the Wilcoxon tests, this study explores the differences in the actual dynamic green exposure of groups exposed to different static green environments from the individual and travel levels.

6.1. Static green exposure versus dynamic green exposure

We assumed that people who lack green exposure in their living or working environment would actively seek more greenness when traveling. Yet, our results showed that at the individual level, people living in a highly green environment also maintain a higher dynamic green exposure. Therefore, the weekly dynamic green exposure of the individuals may be polarized given the green space environments of their residences or workplace, and daily mobility does not alleviate green inequality. When accessibility and number of green spaces are high, individuals will maintain high dynamic green exposure in their non-neighborhood trips. This result is consistent with that of Maat and de Vries (2006), which suggested that the more the green spaces around the residence, the more the households will use the green spaces.

The relationship between living and travel environments is considered, and the reason behind this result may derive from two factors. First, a satisfactory neighborhood green space environment may encourage residents to actively seek greenness in their travels. In a study in Beijing, respondents reported a habit of detouring through the park when shopping for food, and residents of traditional communities with

Table 4
Wilcoxon test results and the average of weekly dynamical green exposure of non-home/non-workplace neighborhood travel.[a]

Static green exposure [b]		Non-home neighborhood travel (n = 960)			Non-workplace neighborhood travel (n = 1129)		
buffer	group	TGVI	ULGVI	UTGVI	TGVI	ULGVI	UTGVI
Accessibility							
–	low	**0.564**	**0.204**	**0.337**	0.724	0.232	0.424
	high	**0.808**	**0.228**	**0.424**	0.567	0.195	0.306
NDVI							
500	low	0.727	**0.225**	**0.407**	**0.655**	**0.252**	**0.417**
	high	0.709	**0.211**	**0.373**	**0.622**	**0.174**	**0.305**
1000	low	0.720	**0.213**	0.385	**0.662**	0.252	**0.414**
	high	0.720	**0.229**	0.405	**0.613**	0.171	**0.303**
1500	low	0.723	**0.210**	0.394	0.689	0.251	0.416
	high	0.715	**0.233**	0.391	0.575	0.164	0.289
2000	low	0.744	**0.209**	**0.404**	0.674	0.242	**0.402**
	high	0.684	**0.234**	**0.377**	0.597	0.179	**0.312**
GVI							
500	low	**0.642**	0.216	**0.371**	**0.850**	0.257	**0.477**
	high	**0.802**	0.223	**0.416**	**0.458**	0.174	**0.260**
1000	low	0.762	0.216	0.392	0.712	**0.239**	0.413
	high	0.665	0.225	0.393	0.548	**0.180**	0.295
1500	low	0.727	**0.213**	0.386	**0.589**	0.237	**0.380**
	high	0.710	**0.228**	0.401	**0.691**	0.186	**0.338**
2000	low	0.747	0.216	0.377	**0.589**	**0.223**	**0.368**
	high	0.689	0.224	0.411	**0.687**	**0.202**	**0.352**

[a] The data in table is the mean value of dynamic green exposure of low green space index group or high green space index group, and the group with 95% significance in Wilcoxon test is bold. TGVI in the table has been divided by 1000.
[b] Static green exposure indicators correspond to travel, for example, non-neighborhood travel corresponds to living environment.

dense trees walk longer distances (Chen, 2019). Second, the choice of living and travel environments involves self-selection, which is affected by personal preferences (Ghekiere et al., 2015; van de Coevering et al., 2018; Nawrath et al., 2019). Residents who prefer AT tend to use considerable green spaces (Haybatollahi et al., 2015), thereby widening the gap between AT and green exposure. Third, the travel and living environments are inevitably restricted by socioeconomic factors and may present a similar social differentiation phenomenon. In our sample, the middle-income and education group (junior college and bachelor and 2000–6000 monthly salary) have different degrees of disadvantages in static and dynamic green exposures. The average value of green space accessibility and street greenery (GVI within 500 m) of the group with a monthly salary above 6000 is higher than that of the remaining groups. Its average value of dynamic green exposure is also significantly higher than that of the middle-income group. Given the special policies of talent introduction, household registration migration, and relocation compensation in Beijing, the process of green inequality caused by income, education, and other factors is extremely complex. The relationships among green space environment, income, and education are not simply linear. A part of migrant elite groups with higher education and income are likely to experience serious work, commuting burden, and work–housing imbalance and become "institutionalized disadvantaged groups" (Zhang et al., 2018). They may not even have as much access to green space as those who get huge demolition compensation but still suffer low wages and education.

However, the results at the travel level indicated that employees who are at a disadvantage in green would be exposed to higher-quality green spaces in non-workplace neighborhood travel. In the workplace context, the compensation behavior of green exposure is more likely to occur, although such compensation behavior may not change the current situation of their vulnerable green status. The contradiction between the individual and travel levels means that employees who are at a green disadvantage may be exposed to high-quality green spaces during their non-workplace neighborhood travels. Groups that experience considerable pressure tend to choose UGSs with natural elements (Grahn and Stigsdotter, 2010). Therefore, people's compensation behavior for green exposure in work-related travel may be related to the restorative effect of plant landscapes on work stress (Ulrich et al., 1991; Lee and Maheswaran, 2011).

6.2. Living environment versus working environment

In the results of travel level, green travel exposure in residential context is polarization, while that in work context is compensation. There may be two reasons for this difference. First, use of green space initiatives differ between the living environment and working environment. Neighborhood green spaces are important for residents for engaging in leisure and social activities (Zhang et al., 2013; Kang et al., 2017). However, those who work often "forget" or "have no time" to use green spaces owing to their busy schedules (Hitchings, 2010; Lottrup et al., 2012). In this study, the number of home-based leisure and entertainment AT is approximately 2.6 times that of work-based AT, which further shows that people's motivation to seek green spaces in their working environment is insufficient. Second, greenness may have different impact mechanisms on individuals' travel behavior in their residences, workplace, and actual travel space, resulting in different dynamic green exposures. Prior studies found that the attractiveness of workplace greenness to individuals' physical activity is not as good as that of their residences and determined a negative correlation between greenness and PA frequency around the workplace (Troped et al., 2010; Marquet et al., 2020). Marquet et al. (2020) pointed out that in addition to the lack of leisure opportunities in the workplace, the degree of urbanization, which has a negative correlation with greenness in their research, might be a more vital factor that affects individuals' behavior. Therefore, in the workplace context, the influence of urbanization density, traffic convenience, and land use mix on individuals' behavior is greater than that of greenness (Cervero, 2002; Maat and Timmermans, 2009; Kang et al., 2017; Marquet et al., 2020). The above studies also emphasized the links between living, working, and other environments and the possibility of compensatory behavior. A busy and high proportion of utilitarian behaviors lead to inefficient use of green space around the workplace. Consequently, people may tend to use green space of residence and travel space to compensate for the gap brought by working green space environment (Vedel et al., 2017).

In the study of green justice, the working environment should be considered complementary to the neighborhood environment. Considering only static geographical areas, especially residences, and ignoring workplace environments may lead to wrong judgment of green injustice. Individuals spend considerable amounts of time in non-neighborhood environments (Hurvitz and Moudon, 2012) but are affected by their workplace environment. The center of Beijing has numerous job opportunities and high housing prices and provides green space accessibility (Wu et al., 2019). The gap between income and housing prices led to the long-term employment–housing imbalance in Beijing. People can be exposed to relatively satisfactory green space environments in their working environment. Therefore, research on green justice should pay much attention to working and travel environments.

We collected the data supporting the above conclusions a few years before the emergence of public health emergencies. In the post-pandemic era, people may have different degrees of home isolation and travel restrictions on a global scale (Chinazzi et al., 2020), resulting in great changes in their office, commuting places, and behaviors. Most people have experienced three stages: (1) the range of activities caused by home isolation has decreased dramatically, and the green space under any geographical background is almost unusable (Gostin and Wiley, 2020). (2) The scope of activity restriction extended to urban areas, but home office and study continued. The daily travel still decreased significantly compared with that before the pandemic (Zhang et al., 2021). In this process, people's access to the surrounding environment of their residence is much greater than the working environment. (3) Except for some high-risk areas, most Chinese people have resumed normal commuting and office life. The nationwide vaccination and necessary protective measures in public places have made the post-pandemic situation in the country further enter a stable control stage. Given the economic effect brought by the pandemic outbreak, different forms are being adopted in all regions. For example, transportation discounts, preferential tickets, a flexible working system with a 4.5-day weekly work schedule but extended daily working hours (People's Government of Zhejiang Province., 2020) are implemented to encourage people to make more use of parks and carry out leisure and entertainment activities. Accordingly, the emergence of a short-term flexible work system may lead to fewer opportunities for leisure activities and access to green space in the workplace context. At the same time, people's initiative in using and the attraction of parks and green spaces will be improved as a whole. The possible result is that the living environment will be more crucial than the working environment. Thus, the green space compensation behavior under the background of working place is more serious.

6.3. Limitations

This research has several limitations. First, owing to the cross-sectional nature of the research data and lack of information on attitude toward the living environment, we could not judge whether preference for green spaces derives from the inherent (Haybatollahi et al., 2015; Ghekiere et al., 2015; Nawrath et al., 2019) or reverse impact of the living environment (Lin et al., 2017; van de Coevering et al., 2018; van Herick and Mokhtarian, 2020). Therefore, inferring causality in this study is difficult. Second, this study discusses only travel modes (i.e., walking and cycling) that provide direct exposure to greenness and does not consider "visual contact" modes, such as bus riding and driving. Third, this study fails to establish a relationship between socioeconomic attributes and static and dynamic green exposure. Finally, the range of our neighborhood environment samples and travel environment samples is not equal, which might have affected the reliability of nonparametric test results. Future research should continue to discuss the following issues by exploring the green exposure status of special groups (such as low-income, low education, and vulnerable groups) and the degree and mechanism of green inequality they experience. Follow-up studies should also determine the potential NEAP problems of green exposure and which groups of people it mainly affects.

7. Conclusions

Based on the data and technical basis of remote sensing images, street view images, machine learning, and a daily travel survey of 554 Beijing residents, we explore whether groups exposed to different static green environments experience inequality in dynamic green exposure owing to their daily mobility. We evaluate and distinguish between the static green exposure groups in terms of availability, visibility, and accessibility. By comparing differences in dynamic green exposure between high–low group pairs, we obtain the following results. First, at the individual level, differences in residence or workplace green accessibility and street greenery will lead to green inequality in dynamic green exposure. Second, non-neighborhood and non-workplace environment travels show opposite results. Specifically, residents of a community with considerable green spaces will be exposed to high-quality street greenery during trips. Moreover, when the level of greenness in the workplace and quality of street greenery are low, employees will be exposed to high-quality green spaces during trips. The contributions of this research to existing research methods and theories are described below.

In terms of method, we develop a measurement framework to evaluate dynamic and static green exposure. This measurement framework integrates existing static green exposure measurement dimensions and evaluates green spaces from three dimensions, namely, availability, visibility, and accessibility. Meanwhile, the street view big data method and machine learning are employed to measure dynamic green exposure, and street greenery during travel is described in terms of quantity, quality, and efficiency, which can accurately depict the green landscape perceived by residents in their daily travel.

At the theoretical level, our results provide evidence for dynamic green exposure in the study of green justice from two aspects. On the one hand, dynamic green exposure at the individual level is limited by static green environments. Compared with the NEAP in air pollution, people's use of green spaces is often an active process rather than a forced acceptance. Therefore, dynamic green exposure in static environments is likely limited by spatial constraints and individual preferences. On the other hand, the travel-level results indicate that the impact of the working environment on travel green exposure may differ from that of the living environment, and potential compensation may exist. This finding suggests that ignoring the working environment and its effect on dynamic green exposure may lead to a bias in the assessment of green injustice.

Funding

This work was supported by National Science Foundation of China (Nos. 51908488, 41971200), the Social Science Fund of Zhejiang Province (21NDJC034YB), the Fundamental Research Funds for the Central Universities, and Centre for Balance Architecture, Zhejiang University.

CRediT authorship contribution statement

Binhui Wang: Writing - original draft, Formal analysis. **Tiantian Xu:** Writing - review & editing. **Hei Gao:** Writing - review & editing. **Na Ta:** Writing - original draft, Writing - review & editing. **Yanwei Chai:** Investigation. **Jiayu Wu:** Conceptualization, Writing - original draft, Writing - review & editing.

References

Aoki, Y. (1987). Relationship between perceived greenery and width of visual fields. *Journal of the Japanese Institute of Landscape Architects, 51*(1), 1–10. https://doi.org/10.5632/jila1934.51.1.

Pham, T.-T.-H., Apparicio, P., Séguin, A.-M., Landry, S., & Gagnon, M. (2012). Spatial distribution of vegetation in Montreal: An uneven distribution or environmental inequity? *Landscape and urban planning, 107*(3), 214–224. https://doi.org/10.1016/j.landurbplan.2012.06.002.

Beijing Gardening and Greening Bureau. (2016). Summary of the 12th Five Year Plan Work of Beijing Municipal Bureau of landscape architecture and greening. URL: http://yllhj.beijing.gov.cn/zwgk/ghxx/jhzj/201606/t20160602_113743.shtml (Cited 18 November 2020) (in Chinese).

Bratman, G. N., Daily, G. C., Levy, B. J., & Gross, J. J. (2015). The benefits of nature experience: Improved affect and cognition. *Landscape and Urban Planning, 138*, 41–50. https://doi.org/10.1016/j.landurbplan.2015.02.005.

Burgoine, T., & Monsivais, P. (2013). Characterising food environment exposure at home, at work, and along commuting journeys using data on adults in the UK. *International Journal of Behavioral Nutrition and Physical Activity, 10*(1), 85. https://doi.org/10.1186/1479-5868-10-85.

Cervero, R. (2002). Built environments and mode choice: Toward a normative framework. *Transportation Research Part D: Transport and Environment, 7*(4), 265–284. https://doi.org/10.1016/S1361-9209(01)00024-4.

Chaix, B., Méline, J., Duncan, S., Merrien, C., Karusisi, N., Perchoux, C., … Kestens, Y. (2013). GPS tracking in neighborhood and health studies: A step forward for environmental exposure assessment, a step backward for causal inference? *Health & Place, 21*, 46–51. https://doi.org/10.1016/j.healthplace:2013.01.003.

Checker, M. (2011). Wiped out by the "greenwave": Environmental gentrification and the paradoxical politics of urban sustainability. *City & Society, 23*(2), 210–229. https://doi.org/10.1111/j.1548-744X.2011. 01063.x.

Chen, W. Y., & Jim, C. Y. (2010). Amenities and disamenities: A hedonic analysis of the heterogeneous urban landscape in Shenzhen (China). *Geographical Journal, 176*(3), 227–240. https://doi.org/10.1111/j.1475-4959.2010. 00358.x.

Chen, X., Meng, Q., Hu, D., Zhang, L., & Yang, J. (2019). Evaluating greenery around streets using Baidu panoramic street view images and the panoramic green view index. *Forests, 10*(12), 1109. https://doi.org/10.3390/f10121109.

Chen, Y. (2019). Neighborhood form and residents' walking and biking distance to food markets: Evidence from Beijing, China. *Transport Policy, 81*, 340–349. https://doi.org/10.1016/j.tranpol.2017.09.015.

Chinazzi, M., Davis, J. T., Ajelli, M., Gioannini, C., Litvinova, M., Merler, S., … Vespignani, A. (2020). The effect of travel restrictions on the spread of the 2019

novel coronavirus (COVID-19) outbreak. *Science, 368*(6489), 395–400. https://doi.org/10.1126/science:aba9757.
Dahmann, N., Wolch, J., Joassart-Marcelli, P., Reynolds, K., & Jerrett, M. (2010). The active city? Disparities in provision of urban public recreation resources. *Health & Place, 16*(3), 431–445. https://doi.org/10.1016/j.healthplace.2009.11.005.
Dooling, S. (2009). Ecological gentrification: A research agenda exploring justice in the city. *International Journal of Urban and Regional Research, 33*(3), 621–639. https://doi.org/10.1111/j.1468-2427.2009.00860.x.
Douglas, O., Lennon, M., & Scott, M. (2017). Green space benefits for health and well-being: A life-course approach for urban planning, design and management. *Cities, 66*, 53–62. https://doi.org/10.1016/j.cities.2017.03.011.
Ghekiere, A., Deforche, B., Mertens, L., De Bourdeaudhuij, I., Clarys, P., de Geus, B., … Olivier, J. (2015). Creating cycling-friendly environments for children: Which micro-scale factors are most important? An experimental study using manipulated photographs. *PloS one, 10*(12), e0143302. https://doi.org/10.1371/journal.pone.0143302.
Goossens, C., Oosterlynck, S., & Bradt, L. (2020). Livable streets? Green gentrification and the displacement of longtime residents in Ghent, Belgium. Urban Geography, 41 (4), 550-572. Doi: 10.1080/02723638.2019.1686307.
Gostin, L. O. & Wiley, L. F. (2020). Governmental public health powers during the COVID-19 pandemic: Stay-at-home orders, business closures, and travel restrictions. JAMA (21). doi:10.1001/JAMA.2020.5460. doi - 10.1001/jama.2020.5460.
Gould, K. A., & Lewis, T. L. (2016). *Green gentrification: Urban sustainability and the struggle for environmental justice*. Routledge.
Grahn, P., & Stigsdotter, U. K. (2010). The relation between perceived sensory dimensions of urban green space and stress restoration. *Landscape and urban planning, 94*(3–4), 264–275. https://doi.org/10.1016/j.landurbplan.2009.10.012.
Hall, C. M., & Page, S. J. (2014). *The geography of tourism and recreation: Environment, place and space*. Routledge.
Haybatollahi, M., Czepkiewicz, M., Laatikainen, T., & Kyttä, M. (2015). Neighbourhood preferences, AT behaviour, and built environment: An exploratory study. *Transportation Research Part F: Traffic Psychology and Behaviour, 29*, 57–69. https://doi.org/10.1016/j.trf.2015.01.001.
Hitchings, R. (2010). Urban greenspace from the inside out: An argument for the approach and a study with city workers. *Geoforum, 41*(6), 855–864. https://doi.org/10.1016/j.geoforum.2010.07.004.
Hurvitz, P. M., & Moudon, A. V. (2012). Home versus nonhome neighborhood: Quantifying differences in exposure to the built environment. *American Journal of Preventive Medicine, 42*(4), 411–417. https://doi.org/10.1016/j.amepre.2011.11.015.
Kang, B., Moudon, A. V., Hurvitz, P. M., & Saelens, B. E. (2017). Differences in behavior, time, location, and built environment between objectively measured utilitarian and recreational walking. *Transportation Research Part D: Transport and Environment, 57*, 185–194. https://doi.org/10.1016/j.trd.2017.09.026.
Kim, J., & Kwan, M. P. (2021). How neighborhood effect averaging might affect assessment of individual exposures to air pollution: A study of ozone exposures in Los Angeles. Annals of the American Association of Geographers, 111(1), 121-140. doi 10.1080/24694452.2020.1756208.
Kronenberg, J., Haase, A., Łaszkiewicz, E., Antal, A., Baravikova, A., Biernacka, M., … Onose, D. A. (2020). Environmental justice in the context of urban green space availability, accessibility, and attractiveness in postsocialist cities. *Cities, 106*, 102862. https://doi.org/10.1016/j.cities.2020.102862.
Kwan, M. P. (2018). The neighborhood effect averaging problem (NEAP): An elusive confounder of the neighborhood effect. *International Journal of Environmental Research and Public Health, 15*(9), 1841. https://doi.org/10.3390/ijerph15091841.
Kwan, M. P. (2012). The uncertain geographic context problem. Annals of the Association of American Geographers, 102(5), 958–968. Doi: 10.1080/00045608.2012.687349.
Lee, A. C., & Maheswaran, R. (2011). The health benefits of urban green spaces: A review of the evidence. *Journal of Public Health, 33*(2), 212–222. https://doi.org/10.1093/pubmed/fdq068.
Li, C., Song, Y., & Chen, Y. (2017). Infrastructure development and urbanization in China. In Z. Tang (Ed.), *China's Urbanization and Socioeconomic Impact* (pp. 91–107). Singapore: Springer Singapore.
Li, C., Song, Y., Tian, L., & Ouyang, W. (2020). Urban form, air quality, and cardiorespiratory mortality: A path analysis. *International Journal of Environmental Research and Public Health, 17*(4), 1202. https://doi.org/10.3390/ijerph17041202.
Li, X., Zhang, C., Li, W., Ricard, R., Meng, Q., & Zhang, W. (2015). Assessing street-level urban greenery using Google Street View and a modified green view index. *Urban Forestry & Urban Greening, 14*(3), 675–685. https://doi.org/10.1016/j.ufug.2015.06.006.
Lin, T., Wang, D., & Guan, X. (2017). The built environment, travel attitude, and travel behavior: Residential self-selection or residential determination? *Journal of Transport Geography, 65*, 111–122. https://doi.org/10.1016/j.jtrangeo.2017.10.004.
Lottrup, L., Stigsdotter, U. K., Meilby, H., & Corazon, S. S. (2012). Associations between use, activities and characteristics of the outdoor environment at workplaces. *Urban Forestry & Urban Greening, 11*(2), 159–168. https://doi.org/10.1016/j.ufug.2011.12.006.
Ma, X., Li, X., Kwan, M. P., & Chai, Y. (2020). Who could not avoid exposure to high levels of residence-based pollution by daily mobility? Evidence of air pollution exposure from the perspective of the neighborhood effect averaging problem (NEAP). *International Journal of Environmental Research and Public Health, 17*(4), 1223. https://doi.org/10.3390/ijerph17041223.
Maat, K., & De Vries, P. (2006). The influence of the residential environment on green-space travel: Testing the compensation hypothesis. *Environment and Planning A, 38* (11), 2111–2127. https://doi.org/10.1068/a37448.
Maat, K., & Timmermans, H. J. (2009). Influence of the residential and work environment on car use in dual-earner households. *Transportation Research Part A: Policy and Practice, 43*(7), 654–664. https://doi.org/10.1016/j.tra.2009.06.003.
Marquet, O., Floyd, M. F., James, P., Glanz, K., Jennings, V., Jankowska, M. M., … Hipp, J. A. (2020). Associations between workplace walkability, greenness, and physical activity around work. *Environment and Behavior, 52*(2), 139–163. https://doi.org/10.1177/0013916518797165.
Nawrath, M., Kowarik, I., & Fischer, L. K. (2019). The influence of green streets on cycling behavior in European cities. *Landscape and Urban Planning, 190*, 103598. https://doi.org/10.1016/j.landurbplan.2019.103598.
Park, Y. M., & Kwan, M. P. (2017). Individual exposure estimates may be erroneous when spatiotemporal variability of air pollution and human mobility are ignored. *Health & Place, 43*, 85–94. https://doi.org/10.1016/j.healthplace.2016.10.002.
Pearsall, H. (2018). New directions in urban environmental/green gentrification research. In L. Lees, & M. Phillips (Eds.), *Handbook of gentrification studies* (pp. 329–345). Edward Elgar Publishing. https://doi.org/10.4337/9781785361746.00031.
People's Government of Zhejiang Province. (2020). The Executive Opinions of the general office of Zhejiang Provincial People's Government on boosting consumption and promoting stable economic growth. URL: http://www.zj.gov.cn/art/2020/9/30/art_1229075588_58887160.html (Cited 27 April 2021) (in Chinese).
Perchoux, C., Chaix, B., Brondeel, R., & Kestens, Y. (2016). Residential buffer, perceived neighborhood, and individual activity space: New refinements in the definition of exposure areas–The RECORD Cohort Study. *Health & Place, 40*, 116–122. https://doi.org/10.1016/j.healthplace.2016.05.004.
Rundle, A. G., Bader, M. D., Richards, C. A., Neckerman, K. M., & Teitler, J. O. (2011). Using Google Street View to audit neighborhood environments. *American Journal of Preventive Medicine, 40*(1), 94–100. https://doi.org/10.1016/j.amepre.2010.09.034.
Sandifer, P. A., Sutton-Grier, A. E., & Ward, B. P. (2015). Exploring connections among nature, biodiversity, ecosystem services, and human health and well-being: Opportunities to enhance health and biodiversity conservation. *Ecosystem Services, 12*, 1–15. https://doi.org/10.1016/j.ecoser.2014.12.007.
Shafran-Nathan, R., Yuval, Levy, I., & Broday, D. M. (2017). Exposure estimation errors to nitrogen oxides on a population scale due to daytime activity away from home. *Science of the Total Environment, 580*, 1401–1409. https://doi.org/10.1016/j.scitotenv.2016.12.105.
Smith, L. N. (2018). A disciplined approach to neural network hyper-parameters: Part 1–learning rate, batch size, momentum, and weight decay. arXiv preprint arXiv:1803.09820.
Smith, S. L., Kindermans, P. J., Ying, C., & Le, Q. V. (2017). Don't decay the learning rate, increase the batch size. arXiv preprint arXiv:1711.00489.
Troped, P. J., Wilson, J. S., Matthews, C. E., Cromley, E. K., & Melly, S. J. (2010). The built environment and location-based physical activity. *American Journal of Preventive Medicine, 38*(4), 429–438. https://doi.org/10.1016/j.amepre.2009.12.032.
Ulrich, R. S., Simons, R. F., Losito, B. D., Fiorito, E., Miles, M. A., & Zelson, M. (1991). Stress recovery during exposure to natural and urban environments. *Journal of Environmental Psychology, 11*(3), 201–230. https://doi.org/10.1016/S0272-4944(05)80184-7.
van de Coevering, P., Maat, K., & van Wee, B. (2018). Residential self-selection, reverse causality and residential dissonance. A latent class transition model of interactions between the built environment, travel attitudes and travel behavior. *Transportation Research Part A: Policy and Practice, 118*, 466–479. https://doi.org/10.1016/j.tra.2018.08.035.
van Herick, D., & Mokhtarian, P. L. (2020). How much does the method matter? An empirical comparison of ways to quantify the influence of residential self-selection. *Travel Behaviour and Society, 18*, 68–82. https://doi.org/10.1016/j.tbs.2019.09.002.
Vedel, S. E., Jacobsen, J. B., & Skov-Petersen, H. (2017). Bicyclists' preferences for route characteristics and crowding in Copenhagen–A choice experiment study of commuters. *Transportation Research Part A: Policy and Practice, 100*, 53–64. https://doi.org/10.1016/j.tra.2017.04.006.
Wolch, J., Wilson, J. P., & Fehrenbach, J. (2005). Parks and park funding in Los Angeles: An equity-mapping analysis. *Urban Geography, 26*(1), 4–35. https://doi.org/10.2747/0272-3638.26.1.4.
Wu, J., Chen, H., Wang, H., He, Q., & Zhou, K. (2020). Will the opening community policy improve the equity of green accessibility and in what ways?—Response based on a 2-step floating catchment area method and genetic algorithm. *Journal of Cleaner Production*. https://doi.org/10.1016/j.jclepro.2020.121454, 121454.
Wu, J., Feng, Z., Peng, Y., Liu, Q., & He, Q. (2019). Neglected green street landscapes: A re-evaluation method of green justice. *Urban Forestry & Urban Greening, 41*, 344–353. https://doi.org/10.1016/j.ufug.2019.05.004.
Yang, J., Zhao, L., Mcbride, J., & Gong, P. (2009). Can you see green? Assessing the visibility of urban forests in cities. *Landscape and Urban Planning, 91*(2), 97–104. https://doi.org/10.1016/j.landurbplan.2008.12.004.
Yu, H., Russell, A., Mulholland, J., & Huang, Z. (2018). Using cell phone location to assess misclassification errors in air pollution exposure estimation. *Environmental Pollution, 233*, 261–266. https://doi.org/10.1016/j.envpol.2017.10.077.
Yu, X., Ivey, C., Huang, Z., Gurram, S., Sivaraman, V., Shen, H., … Zheng, J. (2020). Quantifying the impact of daily mobility on errors in air pollution exposure estimation using mobile phone location data. *Environment International, 141*, 105772. https://doi.org/10.1016/j.envint.2020.105772.
Yu, X., Zhao, G., Chang, C., Yuan, X., & Heng, F. (2019). Bgvi: A new index to estimate street-side greenery using baidu street view image. *Forests, 10*(1), 3. https://doi.org/10.3390/f10010003.

Zhang, H., Chen, B., Sun, Z., & Bao, Z. (2013). Landscape perception and recreation needs in urban green space in Fuyang, Hangzhou, China. *Urban Forestry & Urban Greening, 12*(1), 44–52. https://doi.org/10.1016/j.ufug.2012.11.001.
Zhang, M., He, S., & Zhao, P. (2018). Revisiting inequalities in the commuting burden: Institutional constraints and job-housing relationships in Beijing. *Journal of Transport Geography, 71*, 58–71. https://doi.org/10.1016/j.jtrangeo.2018.06.024.
Zhang, N., Jia, W., Wang, P., Dung, C.-H., Zhao, P., Leung, K., Su, B., Cheng, R., & Li, Y. (2021). Changes in local travel behaviour before and during the covid-19 pandemic in Hong Kong. *Cities, 112*, 103139. https://doi.org/10.1016/j.cities.2021.103139.
Zhang, Y., & Dong, R. (2018). Impacts of street-visible greenery on housing prices: Evidence from a hedonic price model and a massive street view image dataset in Beijing. *ISPRS International Journal of Geo-Information, 7*(3), 104. https://doi.org/10.3390/ijgi7030104.