Social Science & Medicine 208 (2018) 41–49

Contents lists available at ScienceDirect

Social Science & Medicine

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

# The effect of street-level greenery on walking behavior: Evidence from Hong Kong

Yi Lu[a,b,*], Chinmoy Sarkar[c], Yang Xiao[d]

[a] Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong SAR, China
[b] City University of Hong Kong Shenzhen Research Institute, Shenzhen, China
[c] Faculty of Architecture, University of Hong Kong, Hong Kong SAR, China
[d] Department of Urban Planning, Tongji University, Shanghai, China

ARTICLE INFO

*Keywords:*
Street greenery
Walking
Urban design
Physical activity
Walkability
Urban planning

ABSTRACT

Accumulating evidence shows that urban greenspaces have great health benefits, but establishing a causal relationship is difficult. It is often hypothesized that walking and physical activity are mediators in the relationship between urban greenspaces and health outcomes. Furthermore, most urban greenspace–physical activity studies have focused on parks rather than on landscaped streets, even though the latter are the most popular places for physical activity. The lack of research attention for landscaped streets is largely due to the fact that street greenery is difficult to measure, especially at eye level.

Using readily available Google Street View images, we developed methods and tools to assess the availability of eye-level street greenery. A two-layered study was developed that 1) examined the association between urban greenspaces and the odds of walking (versus not walking) for 90,445 participants in the Hong Kong Travel Characteristics Survey and 2) carried out sensitivity analysis of the association between urban greenspaces and total walking time for a subset of 6770 participants. Multilevel regression models were developed to reveal the associations between street greenery and walking behaviors while controlling for sociodemographic characteristics and other activity-influencing built environment factors, taking into account the inherent clustering within the data.

The results showed that both street greenery and the number of parks were associated with higher odds of walking; street greenery but not parks was associated with total walking time. Our results suggest that walking behavior is at least as strongly affected by eye-level street greenery as by parks. They also implicitly support the health benefits of urban greenspaces via walking and physical activity. With the large sample size, our findings pertain to the entire population of Hong Kong. Furthermore, the use of Google Street View is a sound and effective way to assess eye-level greenery, which may benefit further health studies.

## 1. Introduction

It is projected that nearly 70% of the global population will be living in urban areas by 2050. This rapid urbanization has made and will continue to make daily exposure to nature rarer. The lack of greenspaces in residential neighborhoods has been shown to have negative effects on residents' health and well-being (Gascon et al., 2015; Hartig et al., 2014; A. C. K. Lee and Maheswaran, 2011).

### 1.1. Effects of urban greenspaces on health

Many experimental studies have established that physical and visual exposure to greenspaces generate significant psychological and physiological benefits, such a reduction in long-term stress (Coon et al., 2011), increased recovery speed after surgery (Ulrich, 1984), healthier weight outcomes (Sarkar, 2017), lower risk of chronic diseases (Mitchell and Popham, 2008). Proximity to urban green spaces has been further linked to longevity and decreased mental stress (Takano et al., 2002; Ward Thompson et al., 2012).

### 1.2. Urban greenspaces and physical activity

In addition to its direct health benefits, exposure to greenspaces may indirectly promote health via three additional mediating pathways: 1) by providing settings that promote any form of physical activity; 2) by fostering social contact and a sense of community; and 3)

* Corresponding author. Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong.
*E-mail addresses:* yilu24@cityu.edu.hk (Y. Lu), csarkar@hku.hk (C. Sarkar), yxiao@tongji.edu.cn (Y. Xiao).

https://doi.org/10.1016/j.socscimed.2018.05.022
Received 11 December 2017; Received in revised form 14 February 2018; Accepted 8 May 2018
Available online 09 May 2018

by improving air quality (Hartig et al., 2014; Markevych et al., 2017). Many studies have focused on the *physical activity* pathway because physical activity in the presence of nature provides the synergistic beneficial effects of physical activity (Pretty et al., 2006; Pretty et al., 2005).

It is worth noting that most empirical greenspace–physical activity studies have focused on parks and open greenspaces. More precisely, however, urban greenspaces comprise landscaped streets, parks, open green fields, or any urban public areas with substantial green elements (Almanza et al., 2012). After reviewing 50 studies of parks, Kaczynski and Henderson (2007) reported that most studies revealed positive associations between the presence of parks in a neighborhood and physical activity. Some studies, however, have reported a counter-intuitive negative association (Duncan and Mummery, 2005) or no association (King et al., 2005) between greenspaces and physical activity. The ambiguity in the evidence may be explained by different definitions and the measurement accuracy of greenspace exposure (e.g., green streets are often excluded from empirical studies).

### *1.3. Street greenery and physical activity*

According to several national surveys, streets are the most popular setting for walking, cycling, and physical activity, followed by home and then parks (Bauman, 1997; Rosenberg et al., 2010). However, evidence on the relationship between street greenery and physical activity is scarce, although street greenery has shown demonstrated associations with various health outcomes. The density of street trees, for instance, has been linked to a decreased prevalence of obesity (Lovasi et al., 2013), and a decreased prevalence of asthma for children (Lovasi et al., 2008). The presence of walkable green streets is also related to longer life spans for older adults (Takano et al., 2002).

### *1.4. The gaps and our approach*

In a nutshell, urban greenspaces have been determined to provide significant health benefits to residents. Specific insights on how the design of greenspaces, including street-level greenery, may independently influence walking and physical activity patterns may help us gain deeper insight regarding which type of greenery has a health impact, what kinds of physical activity can be promoted, and what kinds of health benefits can be delivered (I. M. Lee et al., 2012; Sallis et al., 2012).

As shown in several reviews, street greenery has received less research attention than parks (Kaczynski and Henderson, 2007; Lachowycz and Jones, 2011). The omission is largely due to methodological limitations. Street greenery includes a variety of vegetation, such as street trees, shrubs, lawns, green walls, or front gardens next to streets. Nearly all current studies used one of three methods to assess street greenery in health studies: questionnaires (Takano et al., 2002), field audits (De Vries et al., 2013; van Dillen et al., 2012), and Geographic Information System (GIS) (Lovasi et al., 2008, 2011, 2013; Sarkar et al., 2015). All three methods have their strengths and inherent limits. Questionnaires may be subject to people's biases. Field audits are more objective, but they are time-consuming. GIS is objective and time-efficient; however, GIS data often do not include street vegetation, especially small one. Even when GIS data are available, such as street tree count or vegetation extraction from remote sensing imagery, the overhead-view street greenery assessed by GIS often differs from street greenery perceived by a person on the ground (Fig. 1). Thus, GIS assessment cannot accurately measure the level of street greenery perceived by a person on the street, especially in locations with high-density street greenery (Jiang et al., 2017; X. J. Li et al., 2015).

To address these inherent methodological limitations, we used Google Street View (GSV) images to assess the eye-level street imagery and associate it with residents' walking behaviors. GSV is a free image service that provides panoramic views from locations along streets in many worldwide cities. By retrieving GSV images with the GSV API, streetscape images of various locations can be obtained (Google Inc, 2016). Those panoramic images bear a close resemblance to what pedestrians see. It has already been demonstrated to be an effective and free data source for various built environment assessments, such as neighborhood environment audits (Rundle et al., 2011), urban open space evaluation (Edwards et al., 2013), and sky openness assessment (Liang et al., 2017). To our knowledge, it has not yet been used to study the association between greenspace and walking or physical activity.

In this study, we examined the associations of eye-level street greenery and the number of parks with walking behavior for a large population size in Hong Kong after adjusting for other activity-promoting built environments. Emerging from prior research evidence, we hypothesized positive effects of urban greenspaces upon individual walkability.

## 2. Methods

### *2.1. Participants and walking data*

Hong Kong is a highly dense global city on the southeast coast of China, with a population of 7.29 million and a gross population density of 6603 people per km$^2$ (Census & Statistics Department of Hong Kong, 2016).

The walking behavior data were obtained from Hong Kong Travel Characteristics Survey (HKTCS) of 2011, which was conducted by the Transport Department to study travel patterns among Hong Kong residents. The HKTCS of 2011 comprised one main survey and five linked supplemental surveys, one of which focused on walking behavior.

The main travel survey had a large sample size, comprising 101,385 residents of 35,401 households spatially distributed throughout the territory of Hong Kong. Interviews were conducted by trained interviewers to collect data about participants' demographic and household information, and travel behaviors. In the main travel survey, one question was asked about "Did you make any trips during the reference 24-h period? If so, have you used any mechanized mode of transport or a bicycle?" If a person responded "Yes, but I have not used any mechanized transport or a bicycle" (i.e., the participant only made walking trips) or "No, I did not make any trips," he or she was not required to report further detailed trip information. The participants who answered "Yes, and I have used mechanized transport or a bicycle" were required to report detailed information about any trips, including walking trips, made during the reference 24-h period. Hence, we identified participants who had done some walking versus those who had not done any walking using the main travel survey data. After excluding participants who made no trips, the study analytic sample comprised 90,445 participants. The total walking time could not be obtained because subjects who made only walking trips did not report trip information.

In addition to the main travel survey, a supplemental walking travel survey was carried out on a subset of 6770 participants who made at least one walking trip during the reference 24-h period to extract detailed information for all walking trips made during that period (including walk trip start time, ending time, and trip origin and destination). Hence, we further summed the total walking time (in minutes) for the subset of 6770 participants. The dwelling locations of all participants were geocoded to latitude and longitude coordinates and visualized on a map in ArcGIS 10.5 (Fig. 2).

Corresponding to the data structure of HKTCS, a two-layered analysis strategy was designed: 1) examination of the association between urban greenspaces and the odds of walking (versus not walking) for the 90,445 participants who responded to the main survey, 2) sensitivity analyses of the association of urban greenspace and total walking time for the subset of 6770 participants who responded to the supplemental walking travel survey.


**Fig. 1.** GIS-based greenery assessments, such as tree count or remote sensing imagery, may fail to represent what people perceive at the site. They often fail to include (a) lawns or shrubs under a tree canopy, (b) vegetation covered by a bridge, or (c) green walls. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

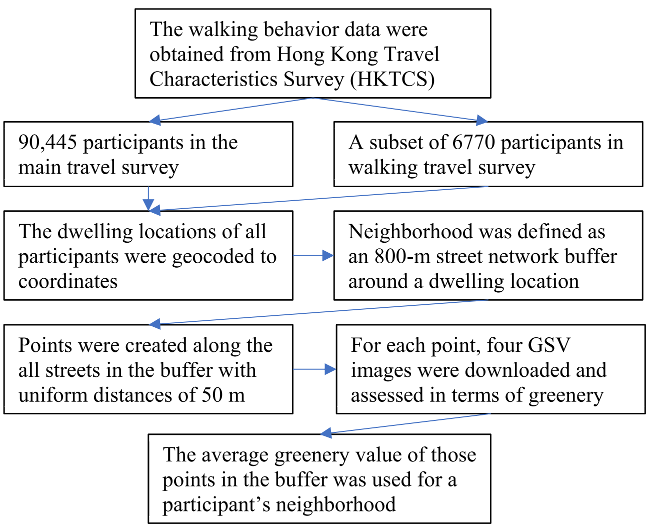


**Fig. 2.** The flow-chart of the procedure of street greenery assessment.

### 2.2. Urban greenspaces

The study measured two distinctive types of urban greenspaces in participants' neighborhoods: street greenery and parks.

A participant's neighborhood environment was defined as 800-m street network buffer around his or her dwelling location, which was created in ArcGIS 10.5 (Fig. 3a). "Street network buffer" refers to the entire catchment area that can be accessed by the street network from an origin location (dwelling), which is normally smaller and more accurate than a straight-line buffer for measuring accessibility. All street segments within the buffer was selected in ArcGIS (Fig. 3a). Then, GSV-generating points were created along the selected street segments at uniform distances of 50 m. The coordinates of those GSV-generating points were input into a Python script developed by the first author, and four GSV images were downloaded for each point, with a 90° field of view and headings of north, east, south, and west (Fig. 3b).

A separate script was developed to determine the level of greenery by identifying pixels representing greenery in an image based on color differences among green, red, and blue color bands (X. J. Li et al., 2015) (Fig. 3c). The ratio of greenery pixels to the total pixels from four images of a GSV-generating point was used to assess the level of street greenery for that point, which can be shown in the following equation:

$$Quantity\ of\ street\ greenery = \frac{\sum_{i=1}^{4} Greenery\ pixels_i}{\sum_{i=1}^{4} Total\ pixels_i}$$

The average value for all GSV-generating points within the 800-m street network buffer of a dwelling location was used to assess the level of street greenery of a participant's neighborhood.

One limitation of greenery extraction with GSV images is seasonal fluctuations in the level of street greenery. Currently, GSV images are taken and updated periodically; hence, it is possible to obtain images taken in different seasons. The street vegetation and the extracted level of street greenery may differ in winter compared with other seasons. The effect of seasonal variability in the street vegetation in Hong Kong was not considered to be significant because most of its vegetation comprises evergreens or semi-evergreens.

The automated greenery extraction was validated with manual extraction. In our pilot study, 30 GSV images were randomly selected. Their street greenery was manually extracted by a researcher using Adobe Photoshop. The values of the GSV greenery extraction were highly correlated with those from the manual extraction ($r[28] = 0.91$; $p < 0.01$). In accordance with previous validation studies (X. J. Li et al., 2015), our results demonstrate that GSV greenery extraction is a reliable method to assess the level of street greenery.

The second type of urban greenspace is parks, which can provide suitable environments for recreational physical activity. Studies often use parks as proxies for open greenspaces. The number of parks within the 800-m network buffer around a dwelling location was used to represent the quantity of open greenspaces in its neighborhood.

### 2.3. Covariates

Other activity-influencing built environment factors within the 800-m network buffer were also calculated in GIS and adjusted for in our models because of their evidenced links to walking behaviors. Those factors included urban density (F. Z. Li et al., 2005), street connectivity (Adkins et al., 2012; Chin et al., 2008; F. Z. Li et al., 2005), land-use mix, number of bus stops and retail stores, and distance to the closest Mass Transit Rail (MTR) station (Hajna et al., 2015; I. M. Lee et al., 2012). Urban density was assessed by population density, defined as the residential population per unit of land area in participants' neighborhoods. Street connectivity was assessed by street intersection density, defined as the number of intersections (three or more streets) per unit of land area. The land-use mix, or entropy score, was calculated by measuring the number of different land use types. Three land use types were considered: residential, retail, and office.

The participants' demographic (age, gender) and household (income and vehicle ownership) information were also included as potential confounding factors. The individual data were extracted from the main survey.

## 3. Data analysis

In the first layer of our analyses, walking was measured as a binary

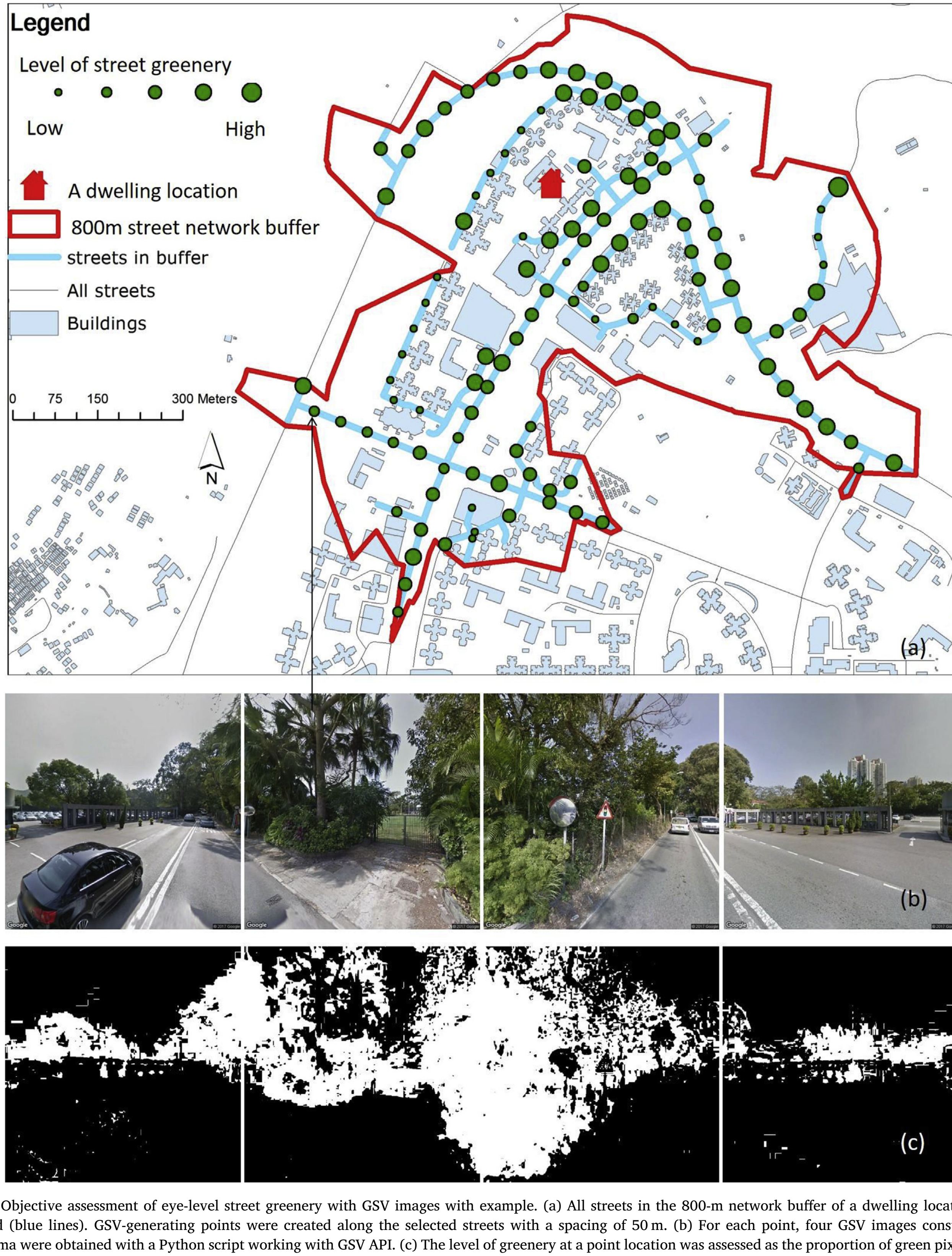


**Fig. 3.** Objective assessment of eye-level street greenery with GSV images with example. (a) All streets in the 800-m network buffer of a dwelling location were selected (blue lines). GSV-generating points were created along the selected streets with a spacing of 50 m. (b) For each point, four GSV images constituting a panorama were obtained with a Python script working with GSV API. (c) The level of greenery at a point location was assessed as the proportion of green pixels to the total pixels in the four GSV images. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

outcome (doing some walking versus not walking) for 90,445 participants. Multilevel logistic regression models were used to explore the independent associations of urban greenspaces with the odds of walking after controlling for other activity-influencing built environments and individual-level covariates. Multilevel modeling can account for the clustering in the walking behaviors of a neighborhood's participants. Individual participants (level 1) were clustered within street blocks (level 2), which are census-defined aggregates in Hong Kong delineated for town planning purposes.

For ease of interpretation of the odds ratios, the continuous predictor variables were transformed into quartiles, with the lowest quartile serving as the reference group. These variables included street greenery, the number of parks, population density, street intersection density, land-use mix, the number of bus stops and retail stores, and the distance to the MTR. The original 16-band household income was transformed into a categorical variable with four levels (< 15k, 15 to 25k, 25 to 50k, and > 50k HKD/month). The participants' ages were transformed into a categorical variable with four levels (2–17 years, 18–35 years, 35–65 years, and ≥65 years). Vehicle ownership was represented as a binary variable (no versus yes).

Model 1 included only the urban greenspace variables: street greenery and number of parks. Model 2 further included other built environment factors: population density, street intersection density, land-use mix, the number of bus stops and retail stores, and the distance to the MTR. Model 3 also controlled for individual covariates: gender, age, vehicle ownership, and household income.

In the second layer of our analyses, walking behavior was measured as a continuous outcome in terms of total walking time for a subset of 6770 participants for whom detailed data on walk trips were available. Multilevel linear regression models were used to explore the independent associations of urban greenspaces with the total walking time, after controlling for other built environments and individual-level covariates. As previously mentioned, Model 1 included only the urban greenspace variables. Model 2 also included other built environment factors, and Model 3 also included individual-level covariates.

All analyses were performed in statistical software R using the lme4 package for fitting and analyzing mixed-effects models. Point estimates (odds ratios and standardized β), their 95% confidence intervals or standardized errors, and *p* values were reported for all models.

## 4. Results

### 4.1. Analysis layer 1: is urban greenspace associated with the decision to walk (odds of walking)?

The descriptive statistics of individual variables for 90,445 participants within the street blocks in the first analyses of this study are presented in Table 1. Overall, 41.65% of people engaged in walking in the 24-h reference period. There were slightly more female participants than male (53.04% versus 46.96%), and women were more likely to walk than men (46.66% versus 35.99%). The age group of 35–64 years constituted 48.50% of the total population, whereas those 65 years of age and older comprised 67.73% of those who walked. Only 17.45% of people had access to private vehicles, which is significantly lower than in other developed countries. Proportionally, people with vehicles were less likely to walk than those without vehicles (33.76% versus 43.32%). The household income also affected the likelihood of walking. People with lower income were more likely to engage in walking than those with higher income; the proportion of people who engaged in walking was 52.99%, 41.22%, 36.41%, and 32.16% for low (< 15k), medium-low (15k to 25k), medium-high (25–50k), and high (> 50k) income groups, respectively.

**Table 1**
Individual covariates of 90,445 participants in level 1 of this study (Hong Kong SAR, China in 2011).

| Variable name | Number of participants | Percentage (%) | Do some walking (%) |
|---|---|---|---|
| Age (y) | | | |
| 2–17 | 13,868 | 15.33 | 48.63 |
| 18–34 | 22,071 | 24.4 | 32.18 |
| 35–64 | 43,863 | 48.5 | 37.87 |
| ≥65 | 10,643 | 11.77 | 67.73 |
| Gender | | | |
| Male | 42,473 | 46.96 | 35.99 |
| Female | 47,972 | 53.04 | 46.66 |
| Vehicle ownership | | | |
| No | 74,664 | 82.55 | 43.32 |
| Yes | 15,781 | 17.45 | 33.76 |
| Household income (HKD) | | | |
| Low(< 15k) | 24,327 | 26.9 | 52.99 |
| Medium-low (15–25k) | 25,736 | 28.45 | 41.22 |
| Medium-high (25–50k) | 27,747 | 30.68 | 36.41 |
| High (> 50k) | 12,635 | 13.97 | 32.16 |
| All participants | 90,445 | 100 | 41.65 |

In Table 2, the results of three logistic regression models in the first level of study show the odds ratio of engaging in walking versus not walking. Street-level greenery was beneficially associated with the odds of engaging in walking in Model 2 and Model 3. Participants exposed to the third and fourth quartiles of street-level greenery had significantly higher odds of walking (OR [95% CI]: $OR_{Q3}$ = 1.07 [1.01, 1.13] and $OR_{Q4}$ = 1.09 [1.02, 1.16], respectively) in our fully adjusted Model 3. The number of parks was positively associated with the probability of engaging in walking in Model 1 and Model 3. In reference to participants in the lowest quartiles of the number of parks within the 800-m neighborhood, those in the third and fourth quartiles reported significantly higher odds of walking ($OR_{Q3}$ = 1.07 [1.02, 1.13] and $OR_{Q4}$ = 1.07 [1.01, 1.14], respectively) in Model 3.

Among the activity-influencing built environment variables, the intersection density, the number of retail shops, and the distance to the MTR station were positively associated with the odds of walking. The number of bus stops was negatively associated with the odds of walking, and population density and land-use mix were not significantly associated. For individual variables, women had higher odds of walking than men (OR = 1.32, 1.28 to 1.36). Those who owned vehicles had lower odds of walking (OR = 0.90, 0.86 to 0.94) than those who did not. Age and household income were negatively associated with the odds of walking. The intra-class correlation coefficient (ICC) was 0.121, indicating that a 12.1% variation in walking propensity was attributed to the clustering structure of our participants.

### 4.2. Analysis layer 2 (sensitivity analysis): is urban greenspace associated with walking time?

The descriptive statistics of individual variables for 6770 participants spatially distributed within 1098 street blocks in our sensitivity analyses are presented in Table 3. Overall, for those who engaged in at least one walking trip, the mean walking time was 15.75 min (SD = 13.95) for the 24-h reference period. Women walked more than men (16.26 versus 15.08 min). Subjects 65 years of age and older walked more than those in the other age groups. People with cars walked less than those without cars (13.92 versus 16.10 min), and those in the lowest household income group (< 15k HKD) walked more than those in other income groups.

The results of the continuous regression models in the second level of the study are shown in Table 4. For urban greenspace variables, street greenery was positively associated with total walking time in all three models (β[SE] = 0.09[0.03] and $p < 0.001$ in Model 3). The number of parks, however, was not positively associated with walking time in any of the models (β[SE] = 0.01[0.03] and $p = 0.783$ in the fully adjusted Model 3).

For other built environment variables, land-use mix was barely associated with walking time (β[95% CI] = 0.05[0.01, 0.11]) in Model 3. The number of bus stops was also positively associated with walking time (β[CI] = 0.10[0.02, 0.17]) in Model 3. The number of retail shops and the distance to an MTR station were negatively associated with walking time. Population density and intersection density were not significantly associated with walking time. For individual variables, women walked significantly more than men (β[CI] = 0.07[0.03, 0.12]) in Model 3. Age was positively associated with walking time (β[CI] = 0.03[0.01, 0.05]) in Model 3. People with vehicles walked

**Table 2**
Logistic regression models for predicting the odds of walking vs. not walking in level 1 of this study (Hong Kong SAR, China in 2011, N = 90,445).

| Model predictors | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | OR (95% CI) | *p*-value | OR (95% CI) | *p*-value | OR (95% CI) | *p*-value |
| **Urban greenspace** | | | | | | |
| Street greenery | | | | | | |
| Q1(low)-Reference | | | | | | |
| Q2 | 1.09 (0.98, 1.21) | 0.149 | 1.02 (0.98, 1.07) | 0.346 | 1.00 (0.95, 1.05) | 0.998 |
| Q3 | 1.12 (0.98, 1.28) | 0.092 | 1.09 (1.03, 1.15) | 0.002 | 1.07 (1.01, 1.13) | 0.023 |
| Q4 (high) | 1.12 (0.97, 1.29) | 0.132 | 1.12 (1.06, 1.19) | < 0.001 | 1.09 (1.02, 1.16) | 0.009 |
| Number of parks | | | | | | |
| Q1(low)-Reference | | | | | | |
| Q2 | 1.07 (0.96, 1.20) | 0.233 | 0.96 (0.92, 1.00) | 0.050 | 1.00 (0.95, 1.05) | 0.944 |
| Q3 | 1.26 (1.13, 1.42) | < 0.001 | 1.00 (0.95, 1.05) | 0.998 | 1.07 (1.02, 1.13) | 0.008 |
| Q4 (high) | 1.35 (1.21, 1.51) | < 0.001 | 1.00 (0.95, 1.06) | 0.884 | 1.07 (1.01, 1.14) | 0.025 |
| **Built environment** | | | | | | |
| Population Density | | | | | | |
| Q1(low)-Reference | | | | | | |
| Q2 | | | 1.10 (1.05, 1.15) | < 0.001 | 1.11 (1.06, 1.16) | < 0.001 |
| Q3 | | | 1.05 (0.99, 1.10) | 0.092 | 1.00 (0.95, 1.06) | 0.878 |
| Q4 (high) | | | 1.04 (0.98, 1.10) | 0.192 | 0.99 (0.93, 1.05) | 0.643 |
| Land-use mix | | | | | | |
| Q1(low)-Reference | | | | | | |
| Q2 | | | 1.03 (0.99, 1.08) | 0.141 | 1.06 (1.01, 1.11) | 0.023 |
| Q3 | | | 1.04 (1.00, 1.09) | 0.063 | 1.06 (1.01, 1.11) | 0.018 |
| Q4 (high) | | | 1.00 (0.95, 1.06) | 0.954 | 1.03 (0.98, 1.09) | 0.269 |
| Intersection Density | | | | | | |
| Q1(low)-Reference | | | | | | |
| Q2 | | | 1.15 (1.10, 1.20) | < 0.001 | 1.14 (1.09, 1.20) | < 0.001 |
| Q3 | | | 1.34 (1.28, 1.41) | < 0.001 | 1.34 (1.27, 1.41) | < 0.001 |
| Q4 (high) | | | 1.26 (1.19, 1.33) | < 0.001 | 1.23 (1.16, 1.31) | < 0.001 |
| Number of retail shops | | | | | | |
| Q1(low)-Reference | | | | | | |
| Q2 | | | 1.00 (0.95, 1.04) | 0.907 | 1.00 (0.95, 1.05) | 0.976 |
| Q3 | | | 1.14 (1.08, 1.20) | < 0.001 | 1.12 (1.06, 1.19) | < 0.001 |
| Q4 (high) | | | 1.33 (1.24, 1.43) | < 0.001 | 1.37 (1.27, 1.49) | < 0.001 |
| Number of bus stops | | | | | | |
| Q1(low)-Reference | | | | | | |
| Q2 | | | 0.88 (0.84, 0.92) | < 0.001 | 0.83 (0.79, 0.88) | < 0.001 |
| Q3 | | | 0.91 (0.86, 0.96) | < 0.001 | 0.88 (0.83, 0.93) | < 0.001 |
| Q4 (high) | | | 0.84 (0.79, 0.90) | < 0.001 | 0.78 (0.72, 0.84) | < 0.001 |
| Distance to MTR station | | | | | | |
| Q1(low)-Reference | | | | | | |
| Q2 | | | 1.07 (1.03, 1.11) | < 0.001 | 1.07 (1.02, 1.11) | 0.003 |
| Q3 | | | 1.20 (1.15, 1.25) | < 0.001 | 1.20 (1.15, 1.26) | < 0.001 |
| Q4 (high) | | | 1.18 (1.13, 1.23) | < 0.001 | 1.18 (1.12, 1.24) | < 0.001 |
| **Individual factors** | | | | | | |
| Gender | | | | | | |
| Male-Reference | | | | | | |
| Female | | | | | 1.32 (1.28, 1.36) | < 0.001 |
| Age | | | | | | |
| 2–17-Reference | | | | | | |
| 18–34 | | | | | 0.47 (0.44, 0.51) | < 0.001 |
| 35–64 | | | | | 0.45 (0.42, 0.49) | < 0.001 |
| ≥65 | | | | | 0.57 (0.51, 0.62) | < 0.001 |
| Vehicle ownership | | | | | | |
| No-Reference | | | | | | |
| Yes | | | | | 0.90 (0.86, 0.94) | < 0.001 |
| Household income (HKD) | | | | | | |
| Low(< 15k)-Reference | | | | | | |
| Medium-low (15–25k) | | | | | 0.87 (0.84, 0.90) | < 0.001 |
| Medium-high (25–50k) | | | | | 0.79 (0.76, 0.82) | < 0.001 |
| high (> 50k) | | | | | 0.67 (0.64, 0.71) | < 0.001 |

significantly less than those without vehicles ($\beta[CI] = -0.11[-0.18, -0.04]$) in Model 3. The low-income group (< 15k) walked significantly more than the medium-low (15–25k) and medium-high (25–50k) income groups but not more than the high-income group (> 50k). The ICC was 0.209, indicating that 20.9% variation in walking time was attributed to clustering.

## 5. Discussion

Studies have shown in general that urban greenspaces have a beneficial effect upon residents' multiple health outcomes. It would therefore seem to make good sense to optimize the design of neighborhood greenspaces to promote active living and well-being. However, there is insufficient research to guide design or policy interventions, primarily because establishment of a causal relationship with respect to the environmental psychology of green-induced movement has thus far been difficult. Quantifying green-induced movement entails objective measurement of street-level greenery as perceived by pedestrians as they maneuver through the streets and their associations with walking and physical activity (I. M. Lee et al., 2012; Sallis et al., 2012).

**Table 3**
The individual covariates of 6770 participants in level 2 of this study (Hong Kong SAR, China in 2011).

| Variable name | Number of participants | Percentage (%) | Mean walking time in min (SD) |
|---|---|---|---|
| Age | | | |
| 2–17 | 1044 | 15.42 | 16.01 (12.03) |
| 18–34 | 1436 | 21.21 | 14.66 (12.29) |
| 35–64 | 3211 | 47.43 | 15.62 (13.98) |
| ≥65 | 1079 | 15.94 | 17.37 (17.14) |
| Gender | | | |
| Male | 2886 | 42.63 | 15.08 (13.11) |
| Female | 3884 | 57.37 | 16.26 (14.52) |
| Vehicle ownership | | | |
| No | 5686 | 83.99 | 16.10 (14.37) |
| Yes | 1084 | 16.01 | 13.92 (11.27) |
| Household income (HKD) | | | |
| Low(< 15k) | 1939 | 28.97 | 17.63 (15.84) |
| Medium-low (15–25k) | 1904 | 28.44 | 15.33 (13.53) |
| Medium-high (25–50k) | 2061 | 30.79 | 14.32 (11.81) |
| high (> 50k) | 790 | 11.8 | 15.26 (13.73) |
| All participants | 6770 | 100 | 15.75 (13.95) |

This study is one of the first to use GSV technology to assess street-level greenery and associate it with walking behavior for a large population sample after adjusting for activity-influencing built environments and other individual-level covariates. Both the street-level greenery measured by GSV technology and the number of parks were reported to be independently associated with higher odds of walking for 90,445 participants in Hong Kong. Sensitivity analyses indicated that only street greenery was associated with the total walking time for the subset of 6770 participants who walked at least once within the 24-h reference period. These are novel findings that are potentially generalizable to the entire population in Hong Kong given the large and diverse sample size.

Our results demonstrate that urban greenspaces in neighborhoods are positively related to walking behavior. In addition, walking behavior is as strongly affected by street-level greenery as by parks. Our findings supplement prior evidence that urban greenery can promote physical activity (Coombes et al., 2010; Floyd et al., 2008; Giles-Corti et al., 2005; Kaczynski et al., 2009; Koohsari et al., 2013). Our results indicate that street-level greenery is a potentially superior predictor of walkability than parks. The inherent superiority may originate from the following two reasons:

1) It is possible to differentiate two types of walking according to the walker's intention: transportation walking and recreational walking. People engage in transportation walking to reach a destination, such as walking to school or a workplace. People engage in recreational walking for pleasure, stress relief, exercise, and to improve health. Those two types of walking may occur in different settings and be affected by different attributes of the built environment (Saelens and Handy, 2008; Zimring et al., 2005). Parks may primarily serve as the setting for recreational walking, whereas streets may serve as the setting for both types of walking. Green streets may promote walking behaviors via two mechanisms: 1) by making walking routes aesthetically pleasant, thereby promoting transportation walking, and 2) by making the general neighborhood environment attractive, offering appropriate areas for recreational walking. The evidence suggests that the presence of street greenery indeed improves the perceived aesthetics and overall quality of a neighborhood's built environment, which have long been highlighted as key predictors of route choice and walkability (Saelens and Handy, 2008; Sallis et al., 2012); for example, residents are more likely to increase their preference for urban scenes with more trees (Agyemang et al., 2007; Buhyoff et al., 1984; Camacho-Cervantes et al., 2014; Thayer and Atwood, 1978). Furthermore, via the processes of evapotranspiration and providing shading, the urban greenery can significantly improve the outdoor thermal environment and air quality for pedestrians (Lin et al., 2017; Xue et al., 2017); the physiological effect of urban greenery may also promote walking behaviors. In a nutshell, green streets support both types of walking, whereas parks primarily support only recreational walking.

2) More specifically, in an urban environment, parks only constitute localized islands of green exposure, whereas street-level greenery constitutes line sources of green exposure and are much more pervasive. Urban residents undertake multiple trips daily, and visiting parks constitutes only one, if any, of these trips. It must be noted that residents are diurnally exposed to street-level greenery in the other trips they undertake, apart from spending time in urban parks. This has been

**Table 4**
Multilevel continuous regression models for predicting walking time in level 2 of this study (Hong Kong SAR, China in 2011, N = 6770).

| Model predictors | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| | β (95% CI) | p-value | β (95% CI) | p-value | β (95% CI) | p-value |
| **Urban greenspaces** | | | | | | |
| Street Green | 0.09 (0.04, 0.14) | < 0.001 | 0.10 (0.05, 0.15) | < 0.001 | 0.09 (0.04, 0.14) | < 0.001 |
| Number of parks | 0.03 (−0.01, 0.07) | 0.147 | 0.01 (−0.05, 0.06) | 0.776 | 0.01 (−0.05, 0.06) | 0.783 |
| **Built environment** | | | | | | |
| Population density | | | 0.04 (−0.01, 0.09) | 0.121 | 0.03 (−0.02, 0.08) | 0.260 |
| Land-use mix | | | 0.05 (0.00, 0.10) | 0.059 | 0.05 (0.00, 0.11) | 0.048 |
| Intersection density | | | −0.02 (−0.08, 0.05) | 0.647 | −0.01 (−0.08, 0.06) | 0.784 |
| Number of retail shops | | | −0.10 (−0.18, −0.03) | 0.004 | −0.11 (−0.18, −0.04) | 0.003 |
| Number of bus stops | | | 0.11 (0.03, 0.18) | 0.004 | 0.10 (0.02, 0.17) | 0.010 |
| Distance to MTR | | | −0.05 (−0.09, −0.01) | 0.025 | −0.05 (−0.09, 0.00) | 0.041 |
| **Individual factors** | | | | | | |
| Gender | | | | | | |
| Male-Reference | | | | | | |
| Female | | | | | 0.07 (0.03, 0.12) | < 0.001 |
| Age | | | | | 0.03 (0.01, 0.05) | 0.021 |
| Vehicle ownership | | | | | | |
| No-Reference | | | | | | |
| Yes | | | | | −0.11 (−0.18, −0.04) | 0.003 |
| Household income | | | | | | |
| Low(< 15k)-Reference | | | | | | |
| Medium-low (15–25k) | | | | | −0.08 (−0.15, −0.02) | 0.013 |
| Medium-high (25–50k) | | | | | −0.16 (−0.22, −0.09) | < 0.001 |
| high (> 50k) | | | | | −0.09 (−0.18, 0.01) | 0.088 |

corroborated by surveys, which have shown that streets surpass parks as the most popular places for walking and physical activity (Bauman, 1997; Rosenberg et al., 2010). Hence, street greenery may potentially have a greater effect on walking behaviors, as exemplified by our analyses. Further research of links between urban greenspaces and physical activity should consider the role of street-level greenery in an urban environment rather than the almost exclusive focus on parks.

Our results also concur with those of previous studies regarding the association between street greenery and health outcomes. The presence of green streets is strongly related to decreased odds of obesity and asthma in children (Lovasi et al., 2008, 2013), greater longevity for older adults (Takano et al., 2002), and self-reported physical and mental health (van Dillen et al., 2012; Xiao et al., 2017). Our analyses demonstrate a consistent significant association between street-level greenery and both the odds of walking and the total walking time. The evidence presented here will help with the development of more targeted interventions in the form of planning and designing green streets and pocket parks, as well as retrofitting the built environment to promote walking and the general health of residents over the long term. This is very relevant in a high-density vertical city such as Hong Kong, where optimizing space for allocation of green exposure within urban areas is a priority. Further longitudinal studies collected over multiple time points are needed to establish causality with confidence.

This study has several strengths and limitations. A large sample size ensured the reliability of the presented results and generalizability to the entire population of Hong Kong. On a methodological front, the study will contribute to the development of objective measures of green exposure for walkability studies. Most urban greenspace–physical activity studies have overlooked street-level greenery as perceived by pedestrians because street greenery data are often scarce and expensive to acquire in GIS. Even when GIS-based street greenery data are available, the GIS-street greenery assessment may markedly differ from what a pedestrian sees on the street because GIS data often miss smaller vegetation, such as shrubs and grass, and the data tends to overlook the three-dimensional morphology of trees or other plants (Fig. 1). This study has demonstrated that GSV can be exploited to objectively evaluate the availability of eye-level street greenery because the GSV method can accurately represent the general resident's *perception* of street greenery at the data sites. Furthermore, the GSV method is more time- and cost-effective than field audits, which involve the difficulty of transporting observers to sites. The objective assessment of street greenery also eliminates the response biases of the participants; hence, it may be more reliable and increase the research repeatability. Therefore, the method and tools developed in this study may benefit further studies of the associations between urban greenspaces and physical activity or health. Furthermore, the study adjusted for other activity-influencing built environment factors that were objectively assessed, thereby leading to greater robustness and reliability.

The study's limitations include its cross-sectional design, which limits causal inference. With respect to street-level green space assessment, the GSV service is currently unavailable for some cities or some locations of a city. It may thus not be applicable for certain study areas, although Google is actively expanding its global coverage (Google Inc, 2016). GSV images are taken and updated periodically; therefore, seasonal fluctuations exist, which affects the consistence of the extracted greenery values. The fluctuations raise no critical issues for the city of Hong Kong due to its subtopic climate and corresponding use of evergreen or semi-evergreen plants. For high-latitude cities, though, the GSV images should be filtered within a specific date range to ensure greater seasonal consistency. Another limitation is that self-reported walking behaviors are prone to recall bias. Further studies may objectively assess walking behaviors and physical activity with accelerometers and/or portable global position system (GPS) devices. Some additional built environment factors were reported to have impacts on walking behaviors, such as safety and crime rate (Cutts et al., 2009), sidewalk maintenance and condition (Frackelton et al., 2013). They were not included because those data were either unavailable or inaccessible for the researchers.

## 6. Conclusions

This study highlights the impact of eye-level street greenery on both the decision to walk and the total walking time for a large urban population of Hong Kong. From a methodological perspective, the use of Google Street View is an effective and reliable way to assess eye-level greenery, which can contribute to health studies. Finally, if the data points are accurate, we can tentatively draw some planning applications. Urban health planners and designers of healthy cities should redirect their attention from an exclusive focus on the planning parameters of urban greenspaces (e.g., location density and size) to one that also considers street-level greenness in terms of visibility of greenery from a pedestrian's perspective (e.g., eye-level street greenery). Our suggestion is, by redirecting proper attention toward the latter, we may not only create walkable streets and neighborhoods but also improve accessibility to existing parks, thereby promoting greater physical activity and related health benefits.

## Funding

This work was supported by the grants from the Research Grants Council of the Hong Kong Special Administrative Region, China [Project No. CityU11612615 & CityU11666716] and National Natural Science Foundation of China [Project No.51578474].

## References

Adkins, A., Dill, J., Luhr, G., Neal, M., 2012. Unpacking walkability: testing the influence of urban design features on perceptions of walking environment attractiveness. J. Urban Des. 17 (4), 499–510. http://dx.doi.org/10.1080/13574809.2012.706365.
Agyemang, C., van Hooijdonk, C., Wendel-Vos, W., Lindeman, E., Stronks, K., Droomers, M., 2007. The association of neighbourhood psychosocial stressors and self-rated health in Amsterdam, The Netherlands. J. Epidemiol. Community 61 (12), 1042–1049. http://dx.doi.org/10.1136/jech.2006.052548.
Almanza, E., Jerrett, M., Dunton, G., Seto, E., Pentz, M.A., 2012. A study of community design, greenness, and physical activity in children using satellite, GPS and accelerometer data. Health Place 18 (1), 46–54. http://dx.doi.org/10.1016/j.healthplace.2011.09.003.
Bauman, A., 1997. Physical Activity Levels of Australians: Results of the Active Australia Baseline Survey. November 1997: Unpublished report. .
Buhyoff, G.J., Gauthier, L.J., Wellman, J.D., 1984. Predicting scenic quality for urban forests using vegetation measurements. For. Sci. 30 (1), 71–82.
Camacho-Cervantes, M., Schondube, J.E., Castillo, A., MacGregor-Fors, I., 2014. How do people perceive urban trees? Assessing likes and dislikes in relation to the trees of a city. Urban Ecosyst. 17 (3), 761–773. http://dx.doi.org/10.1007/s11252-014-0343-6.
Census & Statistics Department of Hong Kong, 2016. Population estimates. Retrieved from. http://www.censtatd.gov.hk/hkstat/sub/so150.jsp.
Chin, G.K.W., Van Niel, K.P., Giles-Corti, B., Knuiman, M., 2008. Accessibility and connectivity in physical activity studies: the impact of missing pedestrian data. Prev. Med. 46 (1), 41–45. http://dx.doi.org/10.1016/j.ypmed.2007.08.004.
Coombes, E., Jones, A.P., Hillsdon, M., 2010. The relationship of physical activity and overweight to objectively measured green space accessibility and use. Soc. Sci. Med. 70 (6), 816–822. http://dx.doi.org/10.1016/j.socscimed.2009.11.020.
Coon, J.T., Boddy, K., Stein, K., Whear, R., Barton, J., Depledge, M.H., 2011. Does participating in physical activity in outdoor natural environments have a greater effect on physical and mental wellbeing than physical activity Indoors? A systematic review. ES T (Environ. Sci. Technol.) 45 (5), 1761–1772. http://dx.doi.org/10.1021/es102947t.
Cutts, B.B., Darby, K.J., Boone, C.G., Brewis, A., 2009. City structure, obesity, and environmental justice: an integrated analysis of physical and social barriers to walkable streets and park access. Soc. Sci. Med. 69 (9), 1314–1322. http://dx.doi.org/10.1016/j.socscimed.2009.08.020.
De Vries, S., van Dillen, S.M.E., Groenewegen, P.P., Spreeuwenberg, P., 2013. Streetscape greenery and health: stress, social cohesion and physical activity as mediators. Soc. Sci. Med. 94, 26–33. http://dx.doi.org/10.1016/j.socscimed.2013.06.030.
Duncan, M., Mummery, K., 2005. Psychosocial and environmental factors associated with physical activity among city dwellers in regional Queensland. Prev. Med. 40 (4), 363–372. http://dx.doi.org/10.1016/j.ypmed.2004.06.017.
Edwards, N., Hooper, P., Trapp, G.S.A., Bull, F., Boruff, B., Giles-Corti, B., 2013. Development of a public open space desktop auditing tool (POSDAT): a remote sensing approach. Appl. Geogr. 38, 22–30. http://dx.doi.org/10.1016/j.apgeog.2012.11.010.

Floyd, M.F., Spengler, J.O., Maddock, J.E., Gobster, P.H., Suau, L., 2008. Environmental and social correlates of physical activity in neighborhood parks: an observational study in Tampa and Chicago. Leisure Sci. 30 (4), 360–375. http://dx.doi.org/10.1080/01490400802165156.

Frackelton, A., Grossman, A., Palinginis, E., Castrillon, F., Elango, V., Guensler, R., 2013. Measuring walkability: development of an automated sidewalk quality assessment tool. Suburban Sustainability 1 (1), 4.

Gascon, M., Triguero-Mas, M., Martinez, D., Dadvand, P., Forns, J., Plasencia, A., Nieuwenhuijsen, M.J., 2015. Mental health benefits of long-term exposure to residential green and blue spaces: a systematic review. Int. J. Environ. Res. Publ. Health 12 (4), 4354–4379. http://dx.doi.org/10.3390/ijerph120404354.

Giles-Corti, B., Broomhall, M.H., Knuiman, M., Collins, C., Douglas, K., Ng, K., et al., 2005. Increasing walking - how important is distance to, attractiveness, and size of public open space? Am. J. Prev. Med. 28 (2), 169–176. http://dx.doi.org/10.1016/j.amepre.2004.10.018.

Google Inc, 2016. Understand Google street view. Retrieved from. https://www.google.com/streetview/understand/.

Hajna, S., Ross, N.A., Brazeau, A.-S., Bélisle, P., Joseph, L., Dasgupta, K., 2015. Associations between neighbourhood walkability and daily steps in adults: a systematic review and meta-analysis. BMC Publ. Health 15 (1), 1–8. http://dx.doi.org/10.1186/s12889-015-2082-x.

Hartig, T., Mitchell, R., de Vries, S., Frumkin, H., 2014. Nature and health. Annu. Rev. Publ. Health 35, 207–228. http://dx.doi.org/10.1146/annurev-publhealth-032013-182443.

Jiang, B., Deal, B., Pan, H.Z., Larsen, L., Hsieh, C.H., Chang, C.Y., Sullivan, W.C., 2017. Remotely-sensed imagery vs. eye-level photography: evaluating associations among measurements of tree cover density. Landsc. Urban Plann. 157, 270–281. http://dx.doi.org/10.1016/j.landurbplan.2016.07.010.

Kaczynski, A.T., Henderson, K.A., 2007. Environmental correlates of physical activity: a review of evidence about parks and recreation. Leisure Sci. 29 (4), 315–354. http://dx.doi.org/10.1080/01490400701394865.

Kaczynski, A.T., Potwarka, L.R., Smale, B.J.A., Havitz, M.E., 2009. Association of parkland proximity with neighborhood and park-based physical activity: variations by gender and age. Leisure Sci. 31 (2), 174–191. http://dx.doi.org/10.1080/01490400802686045.

King, W.C., Belle, S.H., Brach, J.S., Simkin-Silverman, L.R., Soska, T., Kriska, A.M., 2005. Objective measures of neighborhood environment and physical activity in older women. Am. J. Prev. Med. 28 (5), 461–469. http://dx.doi.org/10.1016/j.amepre.2005.02.001.

Koohsari, M.J., Karakiewicz, J.A., Kaczynski, A.T., 2013. Public open space and walking: the role of proximity, perceptual qualities of the surrounding built environment, and street configuration. Environ. Behav. 45 (6), 706–736. http://dx.doi.org/10.1177/0013916512440876.

Lachowycz, K., Jones, A.P., 2011. Greenspace and obesity: a systematic review of the evidence. Obes. Rev. 12 (501), e183–e189. http://dx.doi.org/10.1111/j.1467-789X.2010.00827.x.

Lee, A.C.K., Maheswaran, R., 2011. The health benefits of urban green spaces: a review of the evidence. J. Publ. Health 33 (2), 212–222. http://dx.doi.org/10.1093/pubmed/fdq068.

Lee, I.M., Shiroma, E.J., Lobelo, F., Puska, P., Blair, S.N., Katzmarzyk, P.T., 2012. Impact of physical inactivity on the World's major non-communicable diseases. Lancet 380 (9838), 219–229. http://dx.doi.org/10.1016/s0140-6736(12)61031-9.

Li, F.Z., Fisher, K.J., Brownson, R.C., Bosworth, M., 2005. Multilevel modelling of built environment characteristics related to neighbourhood walking activity in older adults. J. Epidemiol. Community 59 (7), 558–564. http://dx.doi.org/10.1136/jech.2004.028399.

Li, X.J., Zhang, C.R., Li, W.D., Ricard, R., Meng, Q.Y., Zhang, W.X., 2015. Assessing street-level urban greenery using Google Street View and a modified green view index. Urban For. Urban Green. 14 (3), 675–685. http://dx.doi.org/10.1016/j.ufug.2015.06.006.

Liang, J., Gong, J., Sun, J., Zhou, J., Li, W., Li, Y., et al., 2017. Automatic sky view factor estimation from street view photographs - a big data approach. Rem. Sens. 9 (5). http://dx.doi.org/10.3390/rs9050411.

Lin, P., Gou, Z., Lau, S., Qin, H., 2017. The impact of urban design descriptors on outdoor thermal environment: a literature review. Energies 10 (12), 2151.

Lovasi, G.S., Jacobson, J.S., Quinn, J.W., Neckerman, K.M., Ashby-Thompson, M.N., Rundle, A., 2011. Is the environment near home and school associated with physical activity and adiposity of urban preschool children? J. Urban Health 88 (6), 1143–1157. http://dx.doi.org/10.1007/s11524-011-9604-3.

Lovasi, G.S., Quinn, J.W., Neckerman, K.M., Perzanowski, M.S., Rundle, A., 2008. Children living in areas with more street trees have lower prevalence of asthma. J. Epidemiol. Community 62 (7), 647–649. http://dx.doi.org/10.1136/jech.2007.071894.

Lovasi, G.S., Schwartz-Soicher, O., Quinn, J.W., Berger, D.K., Neckerman, K.M., Jaslow, R., et al., 2013. Neighborhood safety and green space as predictors of obesity among preschool children from low-income families in New York City. Prev. Med. 57 (3), 189–193. http://dx.doi.org/10.1016/j.ypmed.2013.05.012.

Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A.M., et al., 2017. Exploring pathways linking greenspace to health: theoretical and methodological guidance. Environ. Res. 158, 301–317. http://dx.doi.org/10.1016/j.envres.2017.06.028.

Mitchell, R., Popham, F., 2008. Effect of exposure to natural environment on health inequalities: an observational population study. Lancet 372 (9650), 1655–1660. http://dx.doi.org/10.1016/S0140-6736(08)61689-X.

Pretty, J., Hine, R., Peacock, J., 2006. Green exercise: the benefits of activities in green places. Biologist 53 (3), 143–148.

Pretty, J., Peacock, J., Sellens, M., Griffin, M., 2005. The mental and physical health outcomes of green exercise. Int. J. Environ. Health Res. 15 (5), 319–337. http://dx.doi.org/10.1080/09603120500155963.

Rosenberg, M., Mills, C., McCormack, G., Martin, K., Grove, B., Pratt, S., Braham, R., 2010. Physical Activity Levels of Western Australian Adults 2009: Findings from the Physical Activity Taskforce Adult Physical Activity Survey. The University of Western Australia, Perth.

Rundle, A.G., Bader, M.D.M., Richards, C.A., Neckerman, K.M., Teitler, J.O., 2011. Using Google street view to audit neighborhood environments. Am. J. Prev. Med. 40 (1), 94–100. http://dx.doi.org/10.1016/j.amepre.2010.09.034.

Saelens, B.E., Handy, S.L., 2008. Built environment correlates of walking: a review. Med. Sci. Sports Exerc. 40 (7 Suppl. l.), S550–S566.

Sallis, J.F., Floyd, M.F., Rodríguez, D.A., Saelens, B.E., 2012. Role of built environments in physical activity, obesity, and cardiovascular disease. Circulation 125 (5), 729–737. http://dx.doi.org/10.1161/circulationaha.110.969022.

Sarkar, C., 2017. Residential greenness and adiposity: findings from the UK biobank. Environ. Int. 106, 1–10. http://dx.doi.org/10.1016/j.envint.2017.05.016.

Sarkar, C., Webster, C., Pryor, M., Tang, D., Melbourne, S., Zhang, X.H., Liu, J.Z., 2015. Exploring associations between urban green, street design and walking: results from the Greater London boroughs. Landsc. Urban Plann. 143, 112–125. http://dx.doi.org/10.1016/j.landurbplan.2015.06.013.

Takano, T., Nakamura, K., Watanabe, M., 2002. Urban residential environments and senior citizens' longevity in megacity areas: the importance of walkable green spaces. J. Epidemiol. Community 56 (12), 913–918. http://dx.doi.org/10.1136/jech.56.12.913.

Thayer, R.L., Atwood, B.G., 1978. Plants, complexity, and pleasure in urban and suburban environments. Environ. Psychol. Nonverbal Behav. 3 (2), 67–76. http://dx.doi.org/10.1007/Bf01135604.

Ulrich, R.S., 1984. View through a window may influence recovery from surgery. Science 224 (4647), 420.

van Dillen, S.M.E., de Vries, S., Groenewegen, P.P., Spreeuwenberg, P., 2012. Greenspace in urban neighbourhoods and residents' health: adding quality to quantity. J. Epidemiol. Community 66 (6). http://dx.doi.org/10.1136/jech.2009.104695.

Ward Thompson, C., Roe, J., Aspinall, P., Mitchell, R., Clow, A., Miller, D., 2012. More green space is linked to less stress in deprived communities: evidence from salivary cortisol patterns. Landsc. Urban Plann. 105 (3), 221–229. https://doi.org/10.1016/j.landurbplan.2011.12.015.

Xiao, Y., Lu, Y., Guo, Y., Yuan, Y., 2017. Estimating the willingness to pay for green space services in Shanghai: implications for social equity in urban China. Urban For. Urban Green. 26, 95–103. http://dx.doi.org/10.1016/j.ufug.2017.06.007.

Xue, F., Gou, Z., Lau, S.S.Y., 2017. Green open space in high-dense Asian cities: site configurations, microclimates and users' perceptions. Sustainable Cities and Society 34, 114–125. http://dx.doi.org/10.1016/j.scs.2017.06.014.

Zimring, C., Joseph, A., Nicoll, G.L., Tsepas, S., 2005. Influences of building design and site design on physical activity:: research and intervention opportunities. Am. J. Prev. Med. 28 (2), 186–193.