Landscape and Urban Planning 205 (2021) 103920

Contents lists available at ScienceDirect

Landscape and Urban Planning

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

Analyzing the effects of Green View Index of neighborhood streets on walking time using Google Street View and deep learning

Donghwan Ki, Sugie Lee*

Department of Urban Planning & Engineering, Hanyang University, Science & Technology Bld. 303-1, Hanyang University, 222 Wangsimni-ro Seongdong-gu, Seoul 04763, Republic of Korea

ARTICLE INFO

Keywords:
Walking time
Green View Index
Google Street View
Deep learning
Semantic segmentation

ABSTRACT

Previous research has reported that greenery is an important factor in walking activities, with greenery existing in various forms, including trees, gardens, green walls, and other examples. However, traditional methods of measuring urban greenery involve limitations in coverage of various forms of greenery and do not reflect the actual degree of exposure to pedestrians. Accordingly, this study examined the street Green View Index (GVI) and its associations with walking activities by different income groups using survey data on walking behaviors in 2350 residents in Seoul, Korea. This study utilized Google Street View (GSV) and deep learning to calculate the GVI by semantic segmentation, referring to greenness from the visual perspective of pedestrians. Correlation analyses between traditional greenery variables and GVI were conducted to examine differences, and multiple regression models were applied to identify the relationships between walking time and greenery variables. The results of this study show differences between conventional greenery variables and GVI in terms of specific greenery forms and perspectives. As hypothesized, GVI was more closely associated with walking time than the traditional greenery variables. Also, this study found that the low-income residents generally lived in low GVI neighborhood, but walking time is more sensitive to GVI. These results were because GVI represents the actual greenery exposure to pedestrians, and there was a difference between income groups in the degree of vehicle usage in daily life. The results of this study indicate that, when analyzing the relationship between urban greenness and walking behavior, it is necessary to examine the relationship from multiple angles and to investigate the importance of eye-level street greenery. Our findings provide useful insights for public policies to promote pedestrian walking environments.

1. Introduction

As interest in walking increases, significant studies have revealed an association between neighborhood environments and walking behavior. Among the features of environments, urban greenery is recognized as an important factor in physical activity and health (Bedimo-Rung et al., 2005; Gascon et al., 2016; Markevych et al., 2017; Thompson et al., 2012). Urban greenery exists in various forms, such as parks, trees, lawns and green walls (Konijnendijk et al., 2006), and urban greenery can be measured in diverse ways. However, most studies analyzing the impact of greenery on physical activity utilized variables from an overhead perspective, such as park areas and normalized difference vegetation index (NDVI) (Almanza et al., 2012; Chen et al., 2017; Cohen-Cline et al., 2015; Giles-corti & Donovan, 2002; Maas et al., 2008; Thompson et al., 2012).

These traditional methods of calculating greenery have some limitations. First, as mentioned above, urban greenery exists in various forms, but traditional variables do not include these various forms of urban greenery. Specifically, because of methods of data acquisition, most existing studies calculated urban greenery focusing only on parks. The method of focusing only on parks among various forms of greenery precludes street trees, green walls, lawns, and private greenery such as gardens and vegetation in apartment complexes. While the NDVI contains various forms of greenery rather than parks, the index does not include three-dimensional greenery forms such as green walls and vegetation under canopies of trees. The NDVI has a further limitation in that it includes considerable green areas such as a mountain, which are difficult to access in daily life (Ye et al., 2018), therefore it may not be associated with daily walking activities.

Second, these traditional greenery variables, such as park area and NDVI, calculated the amount of greenery from an overhead view and are thus two-dimensional indicators. Such measures may differ from the

* Corresponding author.
E-mail addresses: orient1477@naver.com (D. Ki), sugielee@hanyang.ac.kr (S. Lee).

https://doi.org/10.1016/j.landurbplan.2020.103920
Received 23 January 2020; Received in revised form 8 June 2020; Accepted 5 August 2020
Available online 07 October 2020
0169-2046/

amounts of greenery experienced by pedestrians (Li, Zhang, Li, Kuzovkina, & Weiner, 2015a; Lu, Sarkar, & Xiao, 2018; Wang et al., 2019; Ye et al., 2018). Accordingly, Cho et al. (2010) explained that existing variables for parks and green areas are supply-oriented and two-dimensional indicators, so are not reflective of actual greenery exposure. To overcome these limitations, the concept of the Green View Index (GVI) has emerged. The GVI indicates the degree to which a person standing in a certain position can view greenery or vegetation (Yang, Zhao, Mcbride, & Gong, 2009). Therefore, GVI reflects actual exposure of pedestrians to greenery (Cho et al., 2010).

Despite the importance of GVI, the calculation methods for GVI are limited to site surveys (Takano et al., 2002; Van Dillen et al., 2012). This conventional method is time-consuming and high cost, so cannot be applied to broad areas. As the availability of big data and machine learning increases, however, it seems that these limitations can be overcome. Recently, several studies have been conducted to extract the neighborhood environment from a pedestrian perspective using Google Street View (GSV) and computer vision, with some studies focusing on GVI among various neighborhood elements (Helbich et al., 2019; Li et al., 2015a; Lu, Yang, Sun, & Gou, 2019; Seiferling, Naik, Ratti, & Proulx, 2017). As representative early studies from the Treepedia project at MIT Senseable lab, Li et al. (2015a) analyzed the distribution of GVI in major cities around the world using GSV and computer vision. These studies noted that the GSV image is an efficient tool for calculating GVI and useful for objective street greenery measurements.

Accordingly, this research uses GSV and semantic segmentation (a deep learning technique) to calculate GVI. Subsequently, this study compares GVI to traditional variables examining the associations between walking time by purpose and greenery variables including park area, number of street trees, and GVI from various angles. We hypothesize that GVI is more closely related to walking time by purpose than traditional greenery variables.

2. Literature review

2.1. Neighborhood characteristics and physical activity

A significant number of studies has revealed the association between physical activity and neighborhood environment (Frank et al., 2005; Kaczynski, Koohsari, Stanis, Bergstrom, & Sugiyama, 2014; Li, Fisher, Brownson, & Bosworth, 2005; McCormack & Shiell, 2011; Saelens & Handy, 2008; Sung & Lee, 2015). These studies reported how individual and household characteristics, such as sex, age, job, income, and vehicle ownership, together with neighborhood features, such as density, traffic safety, transit, open space, intersection, and land use, impact physical activity. Specifically, high density, mixed land use, and well-connected street networks can create shorter distances from an origin to non-residential facilities, thereby encouraging walking activity (Saelens & Handy, 2008; Kaczynski et al., 2014).

Among existing research in walking, some studies subdivided walking activity as utilitarian and leisure purposes. In general, utilitarian walking includes walking to school, to stores, or to jobs and can be described as destination-oriented walking. In contrast, leisure walking includes strolling and walking for exercise (Mirzaei et al., 2018). Because of these differences, some studies emphasized that walking behaviors should be divided by purpose (Cho & Lee, 2016; Inoue et al., 2011; Mirzaei, Kheyroddin, Behzadfar, & Mignot, 2018; Owen, Humpel, Leslie, Bauman, & Sallis, 2004). These studies further mention that there are differences in neighborhood factors regarding promotion of walking activities. Moreover, the influences of these neighborhood factors can vary depending on individual characteristics, such as sex and age (Inoue et al., 2011; Li & Ghosh, 2018; Sander et al., 2017).

McCormack and Shiell (2011) systematically reviewed walking studies, pointing out that most were cross-sectional. Because of this, there are limitations in conclusions on cause and effect between neighborhood characteristics and walking behavior. Thus, several studies argued for the importance of self-selection in terms of walking will and residence selection (Handy et al., 2006; McCormack & Shiell, 2011). Specifically, McCormack and Shiell (2011) showed that the effects of neighborhood characteristics on walking were weakened when controlling for self-selection variables.

2.2. Green space and physical activity

Several studies focused on green space, concluding that green space is an important factor in physical activity (Almanza et al., 2012; James et al., 2015; Markevych et al., 2017; Mytton et al., 2012). The reason that green space has a positive impact on physical activity is because green space serves as an attractive and seemingly safe place for physical activity (Almanza et al., 2012; Mytton et al., 2012). Nevertheless, a few studies argued that the impact of green space on physical activity was limited and not significant (Hillsdon et al., 2006; Maas et al., 2008; Picavet et al., 2016).

One reason for inconsistent findings on the relationship between greenery and physical activity is different methods of defining or measuring greenery (Gascon et al., 2016; Klompmaker et al., 2018; Sugiyama et al., 2010). Gascon et al. (2016) analyzed the relationships between residents' health and several greenery variables calculated in land cover, land use, and NDVI. Despite being in the same neighborhood, the values of greenery variables were different by measurement method, and the relationships between health and greenery variables varied greatly according to the measuring method. Furthermore, due to the modifiable areal unit problem (MAUP), observed associations changed according to the buffer size.

Moreover, some research has argued that inconsistent findings are due both to methods of measuring greenery, and disparities by subgroup and physical activity type (Klompmaker et al., 2018; Picavet et al., 2016; Sander et al., 2017). For instance, the impact of greenery has been shown to vary by sex and age (Li & Ghosh, 2018; Sander et al., 2017). These findings indicate that research about greenery and physical activity should explore the relationship from various angles.

2.3. New method for measuring greenery

Due to the increased availability of big data, attempts to extract street landscapes at a pedestrian level have recently been launched (Rzotkiewicz et al., 2018). Google Street View (GSV) images are available for a considerable number of cities and have advantages of high accuracy and efficiency in terms of cost and acquisition time (Gong et al., 2018; Rzotkiewicz et al., 2018). Specifically, Gong et al. (2018) argued that GSV is accurate and efficient dataset by comparing three factors (e.g., a sky view factor, tree view factor, and building view factor) measured by GSV with field surveys.

Previous studies using GSV measure features of street landscapes, such as sky views (Gong et al., 2018; Li & Ratti, 2019), buildings (Gong et al., 2018), water (Helbich et al., 2019), and greenery (Li et al., 2015a; Lu et al., 2019; Seiferling et al., 2017; Wang et al., 2019; Ye et al., 2018; Yin & Wang, 2016). Overall, a significant number of studies focus on street greenery aspects regarding of GVI. Regarding the application of GSV for the street greenery, Berland & Lange (2017) mentioned the high efficiency and accuracy of the GSV method as a result of comparing the virtual survey through GSV with the street greenery by field survey. Additionally, Seiferling et al. (2017) noted that GVI extraction using GSV and machine learning is a unique indicator of the urban tree cover that can be recognized from a pedestrian perspective.

To extract these elements, studies used color band methods or the deep learning technique of semantic segmentation. Color band methods, however, extract elements based only on pixel color and therefore often falsely classify man-made or artificially colored green objects (Lu, 2018). In contrast, semantic segmentation can classify an image based both on color, and on distributions and component shapes. Therefore, semantic segmentation may overcome the limitations of color band methods.

Among previous studies, several have compared traditional greenery variables, such as NDVI, park area, and GVI (Helbich et al., 2019; Lu, 2018; Lu et al., 2019; Ye et al., 2018). Traditional variables of park area and NDVI can be distinguished from the GVI (Lu et al., 2018; Ye et al., 2018) in some cases. For instance, NDVI has been shown to be higher than GVI in certain city outskirts because of large green areas, such as mountains (Lu et al., 2019; Ye et al., 2018). The green space of mountains, however, cannot be considered greenery that is accessible on a daily basis, so traditional greenery variables can incorrectly measure the amount of green area that is close to daily life. In this way, as one example, traditional greenery variables do not reflect actual levels of exposure of residents to greenery (Ye et al., 2018). Hence, the relationship of greenery to physical activity and health has been shown to be more closely associated with GVI than with traditional greenery variables (Helbich et al., 2019; Lu et al., 2018, 2019; Villeneuve et al., 2018).

2.4. Research gap

Based on a literature review, limitations in previous research and distinctive of the current study are as follows. First, most walking studies that analyze the association between greenery and walking activity focused on parks and NDVI rather than on-street greenery. This approach cannot verify the impact of various greenery forms located along streets. In addition, traditional greenery variables are not able to reflect the degree of actual exposure of pedestrians to green space because they are measured from an overhead perspective. Given that walking activities take place mainly on streets (Saelens & Handy, 2008) and that traditional greenery measuring methods may overestimate green areas accessed daily (Ye et al., 2018), research needs to examine the impact of street greenery on walking behaviors. Accordingly, this study utilizes GSV and semantic segmentation as advanced methods for measuring street greenery to extract actual visual greenery indicators that is GVI. As mentioned, semantic segmentation can more accurately classify image components—including green components—than color band methods.

Second, the association between greenery and physical activity has been shown to vary by greenery measuring method, and by the domain of physical activity that is the purpose of walking. Also, there is a possibility that the impact of street greenery on walking activities may vary according to the characteristics of individuals and households. These mean that we should examine the association between greenery and walking activities from multiple angles to clarify this relationship. Specifically, this study subdivides walking time by the purpose of walking, and urban greenery is diversified into street greenery and parks. To address these issues, we conduct multiple regression analyses between walking time by purpose and greenery variables of park area, number of street trees, and GVI. Furthermore, to identify differences in the influence of GVI by income level, we add a term for income and GVI interaction in the statistics model.

Third, previous walking research mentioned that controlling for self-selection is needed to clarify the association between neighborhood environment and walking behavior. Therefore, our analysis controls for self-selection using two questions in survey data regarding the selection of walkable residential sites and the level of walking will.

3. Methodology

3.1. Research approach

The purpose of this study is to examine the relationship between built environment variables including urban greenery and pedestrian walking time by purpose. This study uses GSV and semantic segmentation to calculate GVI, which represents actual exposure of residents to greenery. This method can overcome the limitations of previous street greenery measuring methods based on the site surveys. Subsequently, this study compares GVI with traditional greenery variables in two ways.

First, this study compares traditional greenery measurement with GVI in terms of differences of specific greenery forms and perspectives. This study calculates greenery metrics of park area, number of street trees and GVI in neighborhoods of survey respondents, and conducts correlation analysis between these variables. This process reveals the gap between variables resulting from the inclusion of specific greenery forms. Also, this difference may also due to differences in perspectives that are overhead view and pedestrian level.

Next, this study conducts multiple regression analyses between greenery variables and walking time by purpose to examine which greenery variables are closely associated with walking behavior. We hypothesize that GVI has a strong association with walking time because the index represents actual greenery exposure and considerable walking behavior occurs on streets. However, we also expect that greenery variables have a differential impact on walking time by walking purpose. This is because walking activities by purpose tend to occur in different places—for example, utilitarian walking primarily occurs on streets, while leisure walking may be done at facilities such as parks.

As mentioned, the associations between walking behavior and neighborhood features should be analyzed from multiple angles. Utilitarian walking is that accompanying the activities of daily life, such as shopping and commuting, and is expected to be affected by the daily degree of vehicle usage. This suggests that higher-income groups are not as affected by GVI as lower-income groups because of higher vehicle usage. Therefore, this study subdivides both greenery variables, walking time, and income level to identify differences in sensitivity of walking time due to GVI.

Moreover, there are differences in greenery infrastructure by neighborhood (Jennings et al., 2012; Li, Zhang, Li, Kuzovkina, & Weiner, 2015b; Zhou et al., 2019). These differences are highly related to economic aspects such as income and unemployment rate (Li et al., 2015b; Zhou et al., 2019). As well-formed greenery infrastructure affects housing prices in Seoul (Kim & Kim, 2019), high-income groups generally may live in greener neighborhoods. Combining these two assumptions, we expect a mismatch between GVI and income group. Specifically, low-income groups may be highly affected by street greenery than high-income residents, however, they generally reside in low GVI neighborhood because of economic aspects. Accordingly, we calculate neighborhood GVI among survey respondents and compare it by income level.

3.2. Study area and walking data

To examine the relationship between GVI and walking time, this study focuses on Seoul, the capital city of South Korea. Seoul is one of the densest cities in the world, with a current size of 605 km^2 and a population of nearly 10 million people. Because of the high density, 41.6% of residents live in apartments (Ministry of Land, 2019). Green space, as shown in Fig. 1, comprises about 34.9% of the area, with about 67% of the total green space consisting of mountains (Song & Yoon, 2019). As mentioned, as mountains are not readily accessible during daily activity (Ye et al., 2018), use of traditional greenery variables such as park space or NDVI can overestimate the green space that residents utilize daily.

Walking behavior data were obtained from a survey developed for this research between September 5, 2016 and September 12, 2016. This survey was conducted in 2500 people aged 20 to 64 years who reported living in their current residences for more than two years. The data comprise respondent location, individual and household characteristics (e.g., sex, age, self-selection, household income, housing type, and

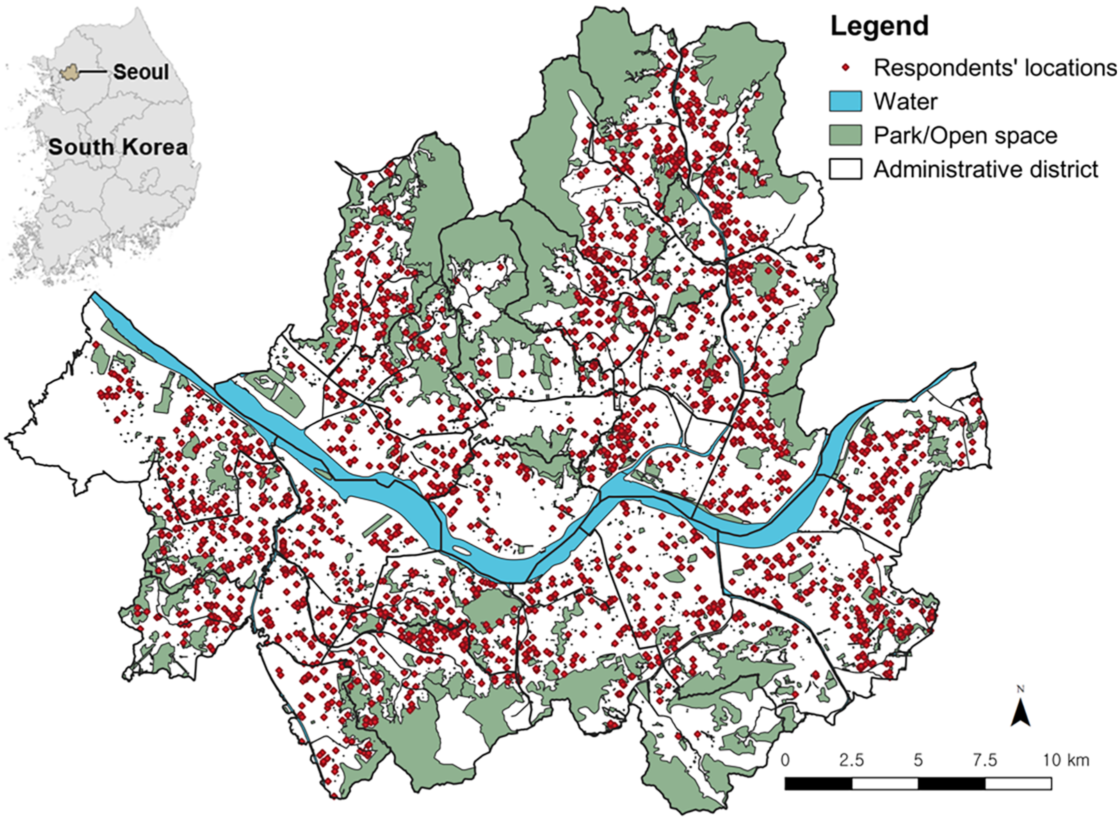

Fig. 1. Study area and locations of survey respondents.

other characteristics), and walking time by purpose (utilitarian and leisure).

Walking time by purpose was calculated by two questions: "How many days did you walk for leisure (or utilitarian) near your home during the last week?" and "How much time did you walk for leisure (or utilitarian) on average per day near your home during the last week?" By multiplying the values of these two questions, we calculated resopondents' walking time for one week. However, some respondents reported abnormal walking times. For instance, the maximum reported utilitarian walking time and leisure walking time were 1443 min (about 24 h) and 1215 min (about 20 h) per day, respectively. Therefore, we checked the distribution of walking time and excluded samples that reported walking more than three hours per day. In addition, one administrative district (Jongno-Gu) did not have street tree data, this study excluded samples residing in this district. Based on these criteria, the final sample of this study is 2,350.

Also, this survey contained items to measure self-selection in terms of 'willingness to walk regardless of neighborhood environment' and 'consideration of walking environment when choosing a residence.' The question to assess 'willingness to walk' was "do you tend to walk for (utilitarian / leisure purposes) near your home regardless of neighborhood environment?" The question to assess participant 'consideration of walking environment' was "how much do walking environments impact your selection of location for residence?" Scores for these self-selection questions were constructed on seven-point Likert scales.

3.3. Google street View images

We acquired Google Street View (GSV) images to calculate GVI, and these images provide cityscapes at the pedestrian level. We used GSV 360° panorama images, which differ from static images in that they contain entire cityscapes from a specific position (Fig. 2).

To obtain GSV panorama images, we established 50-m interval points along road networks and obtained images from these points. Previous studies that use GSV images established various interval criteria to calculate street greenery—for example, 20 m (Lu, 2018), 50 m (Lu et al., 2018, Lu et al., 2019; Ye et al., 2018), and 100 m (Helbich et al., 2019; Wang et al., 2019). Considering the time required to obtain GSV images and the efficacy of previous research with a 50-m interval criterion, we chose intervals of 50 m for our analysis.

However, image distortion occurs due to the characteristics of panorama images (Li et al., 2018; Tsai & Chang, 2013; Yin et al., 2015), which are not suitable for calculating GVI. Tsai & Chang (2013) mentioned that the distortion of panorama occurs severely at the top and bottom of the image, while the center of the image has a weak distortion. In this aspect, Yin & Wang (2016) cropped the center section of panorama images to measure visual enclosure for street walkability. Furthermore, the authors noted that this cropped section is less distorted and closer to the pedestrian's view. Therefore, this study used the same method as the study of Yin & Wang (2016), the part of the panorama image that corresponds to the pedestrian view and has a low degree of distortion was cropped and utilized (Fig. 2).

Because street greenery can differ by season, lack of consideration of the dates of images can result in over or underestimation of street greenery. The Google Street View metadata application programming interface (API) provides information on latitude, longitude, and dates of collected images. The result of metadata shows that most GSV images were taken in the spring and 2018 (Table 1). Therefore, considering the time of the walking survey and the number of images available, we used images collected in the spring between 2014 and 2018. We excluded images from roads that were inaccessible to pedestrians, such as highways. According to these criteria, we used 80,308 images, an average of 180 images per sample neighborhood.

3.4. Semantic segmentation

Semantic segmentation is an advanced method of classifying images into several components (e.g., buildings, sky, greenery, vehicles) by

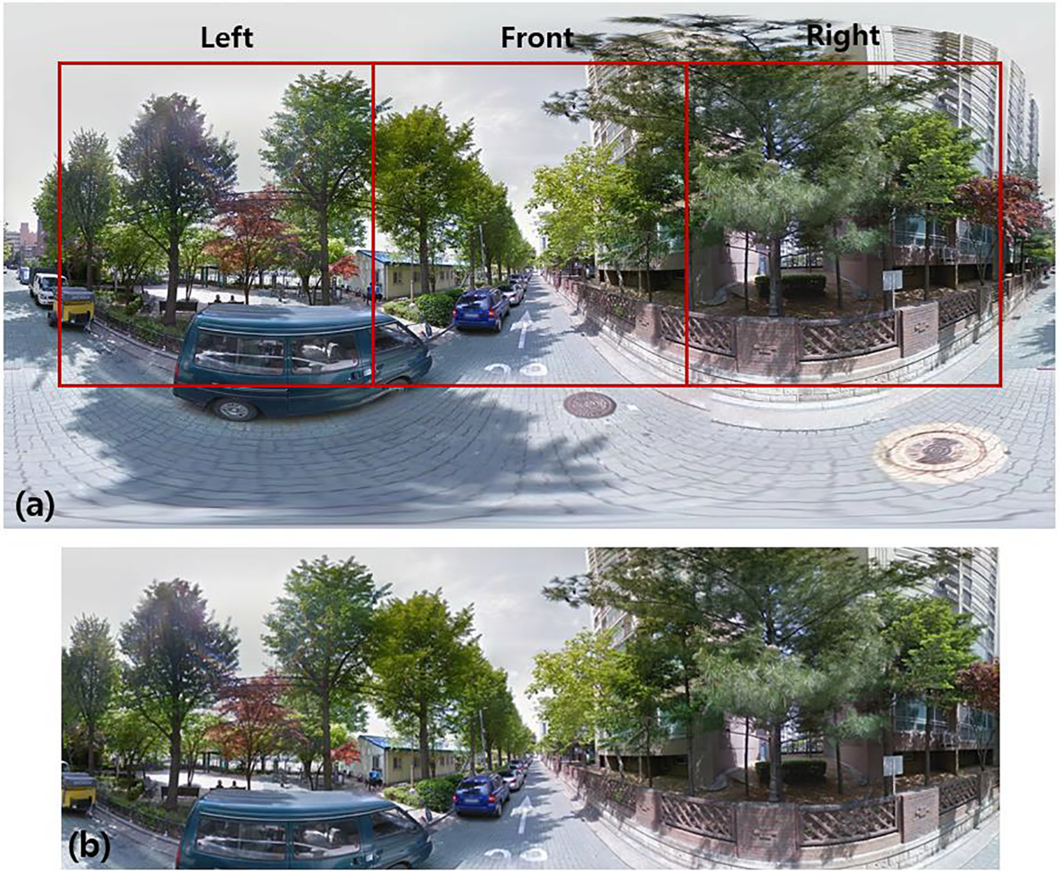

Fig. 2. Example of Google Street View image and image preprocessing (a) Original image (panorama), (b) Cropped image.

Table 1
Result of GSV metadata API.

Year	No. of images (%)	Seasons	No. of images (%)
2009	3849 (3.85)	Spring	**83,229 (83.35)**
2010	561(0.56)		
2011	9 (0.01)		
2012	2 (0.00)	Summer	2846 (2.85)
2013	4 (0.00)		
2014	2951 (2.96)		
2015	7672 (7.68)	Fall	9433 (9.45)
2016	16 (0.02)		
2017	80 (0.08)	Winter	4347 (4.35)
2018	**84,711 (84.83)**		
Total		**99,855 (100)**	

pixel. We used the deep neural network model fully convolutional network (FCN8s) (Long et al., 2015) that performed well for Pascal Visual Object Classes (Middel et al., 2019). This approach has been used in several previous studies of GSV and semantic segmentation (Helbich et al., 2019; Lu et al., 2019; Middel et al., 2019; Wang et al., 2019). For reference, among the various machine learning frameworks available, such as Caffe and Tensorflow, this study used Tensorflow to implement the FCN8s model.

In general, a deep learning model requires additional training to create a model suitable for its purpose. To train our model, we used the 'Cityscapes dataset' that contains cityscape images similar to those of GSV (Fig. 3). Even though there are several available datasets (e.g., PASCAL VOC, ADE20k) to train segmentation models, most of them do not contain the complexity of real-world landscapes (Cordts et al., 2016). The Cityscapes dataset has original and labeled images, so the model can be trained by comparing the two sets of images. This research used 22,973 images as a training set and 500 images as a validation set. For reference, the validation set is able to prevent overfitting and calculate model accuracy. Following training, the final model accuracy was 0.8456 for the validation set, and we segmented 80,308 GSV images using this model.

3.5. Green View index (GVI)

Examples of segmentation and GVI values are shown in Fig. 4. The original images (GSV) are shown at the top and segmented images are shown at the bottom. In the segmented images, street greenery is classified with the color green. The Green View Index (GVI) is the visibility of greenery from a specific position (Yang et al., 2009)and can be calculated as shown in the equation below (Li et al., 2015a). With the index ranging from 0 to 100, when a lot of greenery is visible from a specific position, the index value is high.

$$GVI = \frac{Number\ of\ Green\ pixels}{Number\ of\ Total\ pixels} * 100$$

3.6. Variables

Table 2 shows the variables used in multiple regression models. First, the dependent variable is walking time for one week, subdivided into utilitarian and leisure walking times. Independent variables comprise neighborhood characteristics as well as individual and household characteristics, because these variables have been reported to affect walking activities in previous studies.

Individual and household characteristics include sex, age, job, subjective health, self-selection, income, vehicle ownership, and other details reported by participants. Specifically, self-selection variables comprise a choice of residential location and walking will, which have

Fig. 3. Example of Cityscape dataset (left: original image, right: labeled image).

been reported to be important factors in distinct associations between walking activities and neighborhood environment.

Neighborhood environment variables of distance to transportation, land use mix, traffic safety, number of intersections, water area, park area, number of street trees, and GVI were measured within a buffer of 500 m. Although walkable distance varies by the purpose of walking (Gehl, 2010), 500 m is generally reported to be a walkable distance in existing walking studies (Almanza et al., 2012; Gehl, 2010; Sung et al., 2014; Wolch et al., 2011).

As the purpose of this study is to identify the relationships between various greenery variables and walking activities, the greenery variables of park area, number of street trees, and GVI were calculated. The GVI was calculated by averaging GVI values of GSV images acquired within a 500 m radius (Fig. 5). As mentioned, approximately 180 GSV images existed for each survey respondent, and these figures can be seen in sufficient numbers to represent the respondents' neighborhood GVI. Additionally, we added interaction terms between GVI and income groups in analysis models to examine the difference in sensitivity of walking time due to GVI.

Table 2
Descriptive analysis for variables.

Variables			Mean (std. dev.)/%
Dependent	Utilitarian walking time		231.68 (207.13)
	Leisure walking time		156.73 (184.86)
Individual and household characteristics	Sex (female)		60%
	Age	20–29 (ref.)	7.62%
		30–39	26.81%
		40–49	30.13%
		50–65	35.44%
	Job (yes)		70.81%
	Subjective health		4.45 (1.15)
	Walking will	Utilitarian	4.86 (1.13)
		Leisure	4.77 (1.19)
	Choice of residential location		5.09 (1.05)
	Household income		5.47 (1.72)
	Housing type (apartment)		63.06%
	Vehicle ownership (yes)		85.06%
Neighborhood characteristics	Distance to bus stop		123.60 (71.16)
	Distance to subway station		557.89 (387.52)
	Subjective land use mix		4.43 (1.42)
	Subjective traffic safety		4.20 (1.31)
	No. of intersections		200.7 (138.60)
	Water areas		14,841 (33,741)
	Park areas		71,115 (96,127)
	No. of street trees		505.60(299.32)
	GVI		10.80 (5.45)
	GVI × Income group	Low (ref.)	4.20 (6.12)
		High	6.60 (6.90)

4. Results and discussion

4.1. Correlation analysis

This research conducted correlation analyses between GVI and park area, number of street trees to verify differences. Considering the MAUP of greenery variables (Gascon et al., 2016), we calculated greenery matrices in four buffers (250, 500, 750, 1,000 m) and performed correlation analyses in these buffers.

Although there is a significant association between park area and GVI in each of the four buffers, the coefficients are small and decreased when buffer size increased (Table 3). In addition, there are several neighborhoods with a high GVI but few or no park areas (Fig. 6a). This is because of the difference between park area and GVI in terms of capturing specific greenery forms.

To identify this difference more concretely, we verified scatter plots classified according to survey respondents' housing types (Fig. 7a). Most of the neighborhoods that have a high GVI but small park area are apartment complexes. This is because, when using public greenery data, private greenery such as vegetation or gardens in an apartment complex is not captured. For example, the sample neighborhood represented by the blue circle in Fig. 7a has a small park (Fig. 7b), but it has a high GVI. As shown in the GSV image (Fig. 7c), there is a lot of vegetation in this apartment complex. Therefore, the use of previous methods has limitations in calculating pedestrians' actual exposure to greenery,

Fig. 4. GSV segmentation result of trained FCN8s GVI: 31.29 (a), 43.01 (b).

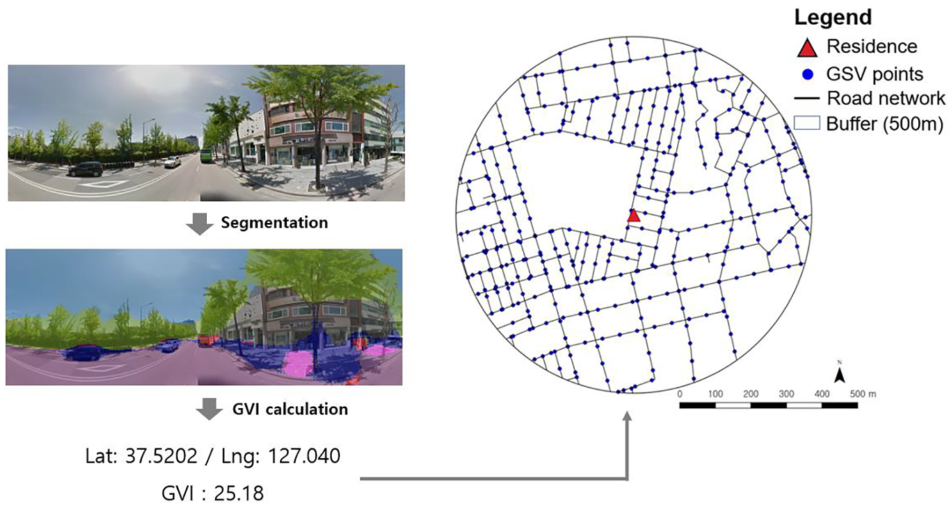

Fig. 5. Process of calculating neighborhood GVI.

Table 3
Correlation analyses between greenery variables.

Buffer size	Correlation coefficient between GVI and park area		Correlation coefficient between GVI and no. of street trees	
250 m	0.151	***	0.177	***
500 m	0.110	***	0.198	***
750 m	0.065	***	0.197	***
1,000 m	0.020	***	0.189	***

Note: * < 0.1; ** < 0.05; *** < 0.01.

especially for residents living in the apartments. Also as mentioned, approximately 40% of Seoul's residents live in apartments, so this underestimation can be problematic when calculating green areas in high-density cities such as Seoul.

Next, the results of correlation analysis between GVI and the number of street trees is shown in Fig. 6b. Conceptually, the street tree variable may have a close association with GVI, because street trees are located along streets, are visible to pedestrians, and GSV images accurately capture this form of street greenery. Even though coefficient values were 0.2, which is higher than the coefficients of park area (Table 3), several neighborhoods with no or few street trees were shown to have a high GVI. This is because GVI can contain both street trees, and green walls, gardens, and other forms of private vegetation. In addition, GVI can consider the vitality of observed vegetation, and there is a difference in perspective between GVI and existing greenery variables.

The results of correlation analyses showed a significant difference between GVI and traditional greenery variables. These results from the inclusion of specific greenery forms, and it also because of the difference in the perspectives. In terms of including specific forms of greenery, GVI captures private greenery such as vegetation in apartment complexes. This advantage better estimates actual greenery exposure relative to traditional greenery variables.

4.2. Mann-Whitney tests

To identify differences in GVI by neighborhood and income level, we used household size and income data in the survey. This study classifies the income classes of survey respondents into upper and lower classes based on median income by household size in 2016.

As shown in Fig. 8, there are differences in GVI by respondent neighborhoods, and this difference was associated with income classes (Table 4). The high-income group generally lived in greener neighborhoods than the low-income group. As mentioned, this is because greenery infrastructure has a positive association with housing prices in Seoul, so the high-income group generally populate residential spots that feature well-established greenery infrastructure.

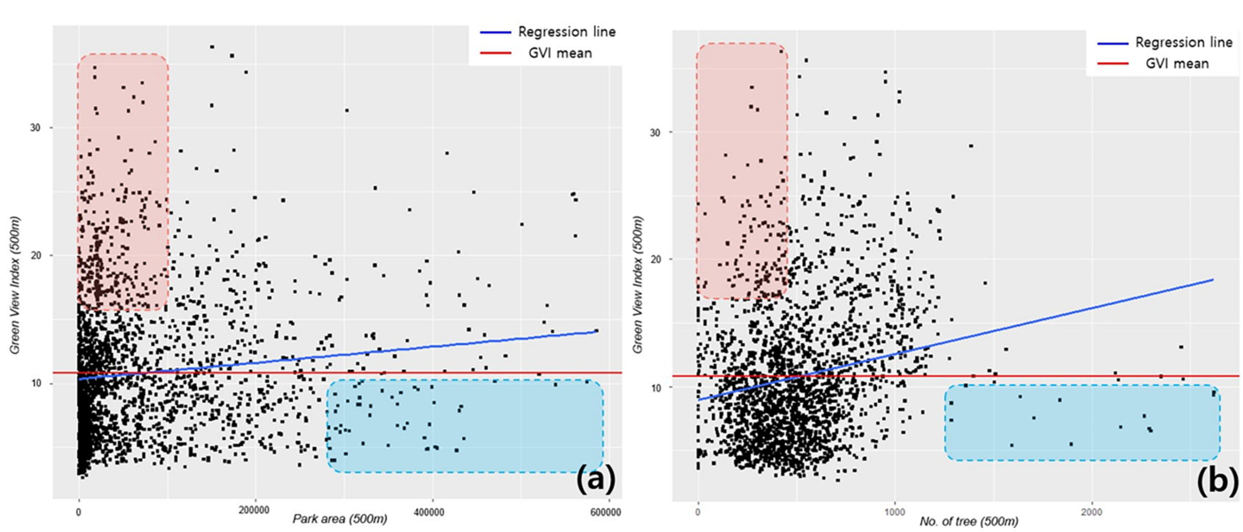

Fig. 6. Scatter plots between existing greenery calculation methods and GVI (buffer size: 500 m) (a): GVI—park areas, (b): GVI—no. of street trees.

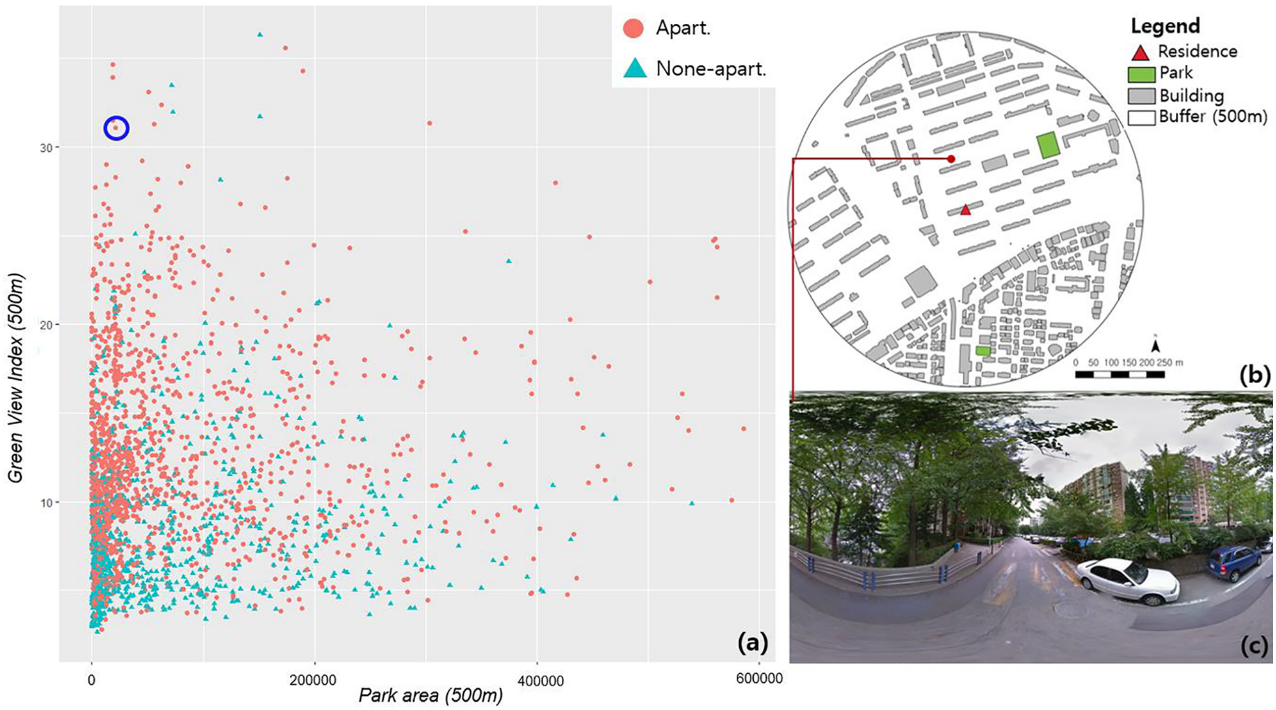

Fig. 7. Limitation of traditional green calculation methods.

To statistically verify these differences between income groups, we conducted Mann-Whitney tests. The advantage of the Mann-Whitney test is that it does not have to satisfy a normal distribution, which is the assumption of the *t*-test, as a technique for identifying statistical differences between groups (MacFarland & Yates, 2016). A p-value < 0.01 was considered statistically significant.

Table 4
GVI differences by income group.

Income class	Mean GVI			Mann-Whitney test
	Apartment	Non-apartment	Overall	
Low	11.71	8.08	10.25	***
High	12.97	8.36	11.18	

Note: * < 0.1; ** < 0.05; *** < 0.01.

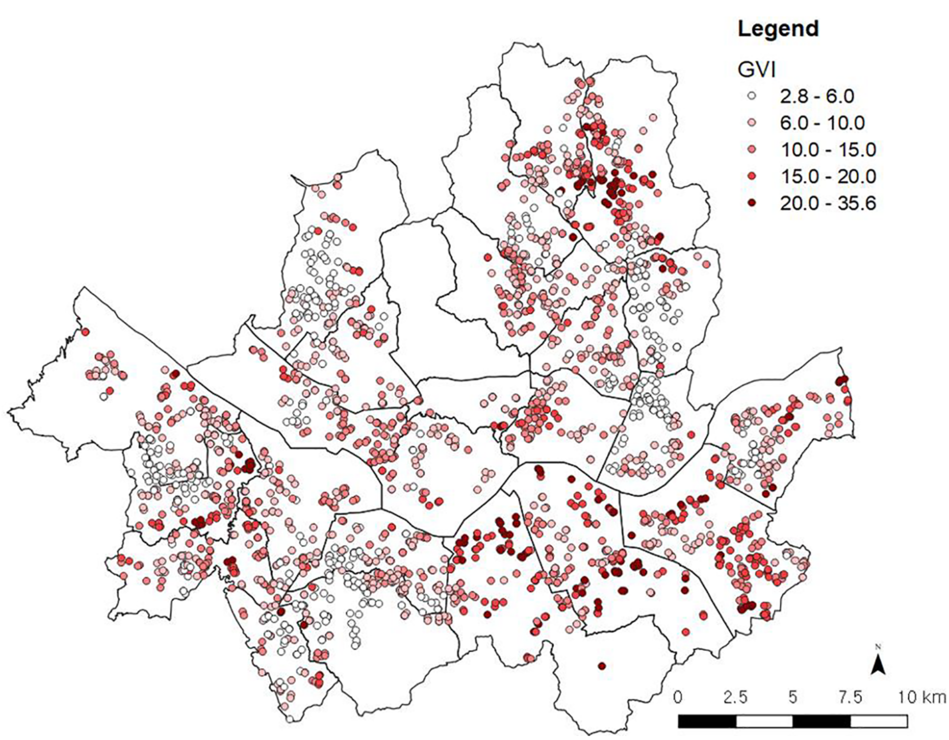

Fig. 8. GVI values of respondents' neighborhoods.

Table 5
Results of multiple regression analyses.

Variables			Model 1 Utilitarian Walking Time			Model 2 Leisure Walking Time		
			Coef.		t	Coef.		t
Individual & house-hold factors	Sex (ref.: male)	Female	28.110	**	2.56	−17.220	*	−1.89
	Age (ref.: 20–29 years)	30–39	–32.920	*	−1.65	−39.550	**	−2.40
		40–49	−40.480	**	−2.06	−31.630	*	−1.94
		50–64	−46.270	**	−2.38	7.652		0.48
	Job (ref.: no)	Yes	−11.540		−0.94	−18.930	*	−1.87
	Subjective health		5.882		1.31	7.940	**	2.13
	Walking will (utilitarian/leisure)		45.690	***	9.74	52.240	***	14.27
	Choice of residential location		3.276		0.66	9.267	**	2.26
	Household income		−1.170		−0.29	−4.194		−1.26
	Housing type (ref.: non-apartment)	Apartment	−16.510		−1.40	−6.742		−0.69
	Subjective land use mix		9.357	***	2.69	4.345		1.51
	Subjective traffic safety		4.253		1.10	14.640	***	4.59
	Vehicle ownership		−8.434		−0.59	6.504		0.55
Neigh-borhood factors	Distance to bus stop		−0.119	*	−1.77	−0.032		−0.57
	Distance to subway station		0.015		1.09	0.002		0.19
	No. of intersections		0.208	***	4.40	0.139	***	3.53
	Water areas		1.503e-04		1.02	5.992e-05		0.49
	Park area		4.684e-05		0.81	9.877e-05	**	2.07
	No. of street trees		−0.009		−0.50	0.002		0.10
	GVI		11.070	***	6.26	4.241	***	3.91
	GVI * Income group (ref.: low- income group)	High-income group	−2.779	**	−2.52	−0.062		−0.07
Constant			−159.400	***	−3.27	−261.400	***	−6.51
Obs.		2350						
R2 (Adj. R2)			0.151 (0.143)			0.192 (0.186)		

Note: * < 0.1; ** < 0.05; *** < 0.01.

4.3. Multiple regression models

The results of multiple regression models are shown in Table 5. The dependent variable of model 1 is utilitarian walking time, and that of model 2 is leisure walking time. For reference, the variance inflation factor (VIF) value for all variables was < 5, indicating no multi-collinearity issues in the models.

Analysis results for individual and household variables showed that sex, age, subjective health, and self-selection were significant factors for one or more of the models. Some of these variables have conflicting or different consequences for each dependent variable—for example, sex, subjective health, subjective traffic safety, and choice of residential location. These results may be caused by differences between walking purposes. Specifically, because utilitarian walking is more closely related to everyday life than leisure walking, utilitarian walking was carried out regardless of how respondents evaluated their own health. Particularly, both models showed that the self-selection variable of individual walking willingness was one of the most significant variables, indicating the impact of self-selection on walking activity.

Among the neighborhood factors, bus stops, land use mix, intersections, parks, and GVI had a significant association with walking time. Utilitarian walking includes walking that accompanies use of public transportation, so utilitarian walking was more common in residential areas that feature nearby bus stops. For this reason, leisure walking was not significant in proximity to bus stops. However, distance to the subway station was not statistically significant with respect to the utilitarian walking time. This finding is similar to that in the work of Sung and Lee (2015), which analyzed the impact of neighborhood environments including the distance to the subway station on walking activity in Seoul. As mentioned, an appropriate walking distance is 500 m (Almanza et al., 2012; Gehl, 2010; Sung et al., 2014; Wolch et al., 2011), but the average distance to subway stations in our sample was 558 m (Table 2). Hence, we assumed that the subway stations were located too far from samples' neighborhoods to inspire utilitarian walking activity.

Subjective land use mix was only associated with utilitarian walking time. Mixed land use means that distances from residential to non-residential facilities are close (Saelens & Handy, 2008). Thus, only utilitarian walking, which is destination-oriented walking, was shown to be related to the perceived land use mix. As objective built environmental variables, the number of intersections had a positive association with utilitarian and leisure walking. The presence of many intersections represents high connectivity, shorter distances to destinations, and more diverse walking paths. Therefore, a large number of intersections can promote walking activity both for a utilitarian purpose, and for leisure.

Among the greenery variables, the results demonstrated that a high GVI promotes both utilitarian and leisure walking time. In the utilitarian walking model, only GVI was significant among the greenery variables. Even though both number of street trees and GVI were measuring methods for amount of greenery located along streets, only GVI showed a significant association with utilitarian walking time. As previously assumed, this is because most utilitarian walking activities take place on streets, and GVI better represents the degree of pedestrian exposure to greenery than traditional greenery measuring methods.

In the leisure walking model, among the greenery variables, park area and GVI were found to be important factors for leisure walking time. The park area variable was found to have significant differences between the two models. This is because of the difference between walking purposes. As mentioned, utilitarian walking occurs on streets rather than in parks because it refers to walking during daily activities. Leisure walking, in contrast, takes place in facilities such as parks because it contains walking for exercise. Nevertheless, street greenery has the potential to promote leisure walking activities in two ways. First, leisure walking can take place on streets just like utilitarian walking. Second, considering that street greenery can increase the frequency of use of neighborhood facilities such as parks (Lee, 2011), residents living in neighborhoods with a high GVI are more likely to use neighborhood facilities, thereby facilitating leisure walking in parks.

The interaction term between GVI and income level had a negative association with the utilitarian walking model only. This result means that utilitarian walking time of low-income residents was more associated with GVI than high-income residents. In general, high-income people have higher vehicle usage in daily activities, such as commuting, and shopping, than low-income people, and this difference can impact the sensitivity of GVI. Leisure walking, however, is not related to the degree of vehicle usage in daily life because it is an intentional walking activity. Therefore, there seems to be no difference by GVI in leisure walking between income groups.

4.4. Discussion

This study reveals the association between walking activity and greenery from various angles utilizing GSV and semantic segmentation to calculate GVI. As hypothesized, this study finds that the association between greenery and walking time varies depending on methods of greenery measurements, the purpose of walking activities, and household income levels. This means that a fragmentary analysis of the relationships between greenery and walking activities may not accurately examine the influence of greenery on walking behaviors in pedestrians.

Our results demonstrate that the GVI, a new indicator of amount of greenery, is different from traditional greenery variables such as the number of street trees and park areas. Correlation analyses and scatter plots show that these differences result from the inclusion of specific greenery variables forms and perspectives. Especially, even though street trees were located along the street, those were found to be less related to GVI. This is because GVI can capture both street trees and other aspects of street greenery, such as private garden, lawn, green wall. Additionally, GVI can even consider the vitality of greenery, which can reflect the amount of three-dimensional greenery recognized by pedestrians. These advantages of GVI will be more effective in high-density cities with many mountains. Traditional methods of calculating greenery include a large amount of greenery, such as a mountain, that are not closely related to daily life (Ye et al., 2018), and do not include private greenery located in an apartment complex. Therefore, traditional green variables do not fully capture the impact of greenery on walking activities. Due to these advantages, GVI is more closely related to walking activities than other greenery variables (Lu et al., 2018, 2019; Villeneuve et al., 2018).

However, the impact of greenery variables varied by walking purpose. The GVI is more statistically associated with utilitarian walking time than with leisure walking, while parks only have a significant association with leisure walking time. This seems to be due to differences in location of walking activities (Saelens & Handy, 2008; Lu, 2018). Specifically, parks are chiefly places for leisure activities such as walking for exercise, while streets serve as places for leisure and utilitarian walking.

Among income groups, there were sensitivity differences due to GVI. This finding may be due to differences in the degree of daily vehicle usage between income groups. In general, however, for economic reasons, low-income people tend to live in areas with less greenery infrastructure (Li et al., 2015a; Zhou, He, Cai, Wang, & Su, 2019), and this condition is also demonstrated in this study. Considering these two findings, there is a mismatch between GVI and income groups. Specifically, even though low-income people are more likely to walk in the high-GVI neighborhoods, high cost of living prevents them from choosing residences in greener neighborhoods.

Besides, this study controls for self-selection dimensions of choice of residential location and walking will to elucidate the cause and effect relationship between neighborhood environment and walking time. Considering that this relationship may change after controlling for these aspects of self-selection (McCormack & Shiell, 2011), the relationship between street greenery and walking behavior can be more clearly identified.

The evidence from this study is expected to help the government's intervention policy to promote walking activities. First, urban planners need to consider GVI when supplying greenery to promote walking activities. Specifically, the results of this study show that street greenery rather than green area such as parks is more closely related to residents' walking time. Second, an appropriate target group needs to be considered when implementing the policy of green supply to promote residents' walking activities. Low-income households tend to live in neighborhoods with low GVI, but the utilitarian walking time of low-income group is more sensitive to GVI. Therefore, the greenery supply needs to be preferentially implemented around the residences of low-income group. Third, it is necessary to conduct a study on the inequity of street greenery, referring to the low GVI of low-income neighborhoods.

This study has a few limitations. First, GSV images were collected by vehicles, which may differ from the pedestrian perspective. This is an inherent limitation in that GSV images in a wide range of areas are collected from vehicles. Second, the model that we used has an accuracy of 0.8456, indicating the 15% possibility of false classification of observed greenery. Third, even though we used GSV images to control variations in street greenery by season, appearance of street greenery can change over time within the same season. Additionally, the appearance of street greenery is likely to change across four years, which is the time periods for images used in this study. Finally, this study may have missed some of the neighborhood environment variables that may affect walking activity.

5. Conclusion

Despite some limitations, this study contributes to an understanding of the relationships between urban greenery and walking activity in Seoul, Korea. In terms of methodology, GSV and semantic segmentation are effective and highly accurate methods to measure the actual exposure of pedestrians to urban greenery. With this advantage, GVI is expected to be able to properly access the impact of greenery on human behavior, such as walking. Besides, our findings are important for examining the complicated relationship between urban greenness and walking activity from various angles, especially regarding methods to measure greenery. Furthermore, this study shows that the relationship between GVI and walking time differs from different income groups. These findings indicate the importance of street greenery for walking activity and the need for established target groups to effectively promote walking times among urban residents.

CRediT authorship contribution statement

Donghwan Ki: Conceptualization, Methodology, Data curation, Writing - original draft, Writing - review & editing. **Sugie Lee:** Conceptualization, Writing - original draft, Writing - review & editing, Supervision.

Acknowledgement

This work was supported by the research fund of Hanyang University(HY-2020).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2020.103920.

References

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.
Bedimo-Rung, A. L., Mowen, A. J., & Cohen, D. A. (2005). The significance of parks to physical activity and public health: A conceptual model. *American Journal of Preventive Medicine, 28*(2), 159–168.
Berland, A., & Lange, D. A. (2017). Google Street View shows promise for virtual street tree surveys. *Urban Forestry & Urban Greening, 21*, 11–15.
Chen, P., Zhou, J., & Sun, F. (2017). Built environment determinants of bicycle volume: A longitudinal analysis. *Journal of Transport and Land Use, 10*(1), 655–674.
Cho, Y. H., Jo, H. K., & Han, B. H. (2010). Practice in application of the index of streetscape greenness on environmental impact assessment -Case Study of Street in

Seoul. *Journal of Environmental Impact Assessment, 19*(2), 205–213.
Cho, H. M., & Lee, S. G. (2016). Analysis of neighborhood environmental characteristics affecting walking activity time: Focused on the difference between subjectively measured and abjectively measured-neighborhood environment. *Journal of Korea Planners Association, 51*(4), 105–122.
Cohen-Cline, H., Turkheimer, E., & Duncan, G. E. (2015). Access to green space, physical activity and mental health: A twin study. *Journal of Epidemiology Community Health, 69*(6), 523–529.
Cordts, M., Omran, M., Ramos, S., Rehfeld, T., Enzweiler, M., Benenson, R., ... Schiele, B. (2016). The cityscapes dataset for semantic urban scene understanding. *In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 3213–3223). .
Frank, L. D., Schmid, T. L., Sallis, J. F., Chapman, J., & Saelens, B. E. (2005). Linking objectively measured physical activity with objectively measured urban form: Findings from SMARTRAQ. *American Journal of Preventive Medicine, 28*(2), 117–125.
Gascon, M., Cirach, M., Martínez, D., Dadvand, P., Valentín, A., Plasència, A., & Nieuwenhuijsen, M. J. (2016). Normalized difference vegetation index (NDVI) as a marker of surrounding greenness in epidemiological studies: The case of Barcelona city. *Urban Forestry & Urban Greening, 19*(1), 88–94.
Gehl, J., 2010. Cities for people. London: Island Press.
Giles-Corti, B., & Donovan, R. J. (2002). The relative influence of individual, social and physical environment determinants of physical activity. *Social Science & Medicine, 54*(12), 1793–1812.
Gong, F. Y., Zeng, Z. C., Zhang, F., Li, X., Ng, E., & Norford, L. K. (2018). Mapping sky, tree, and building view factors of street canyons in a high-density urban environment. *Building and Environment, 134*(15), 155–167.
Handy, S., Cao, X., & Mokhtarian, P. L. (2006). Self-selection in the relationship between the built environment and walking: Empirical evidence from Northern California. *Journal of the American Planning Association, 72*(1), 55–74.
Helbich, M., Yao, Y., Liu, Y., Zhang, J., Liu, P., & Wang, R. (2019). Using deep learning to examine street view green and blue spaces and their associations with geriatric depression in Beijing, China. *Environment International, 126*, 107–117.
Hillsdon, M., Panter, J., Foster, C., & Jones, A. (2006). The relationship between access and quality of urban green space with population physical activity. *Public Health, 120*(12), 1127–1132.
Inoue, S., Ohya, Y., Odagiri, Y., Takamiya, T., Kamada, M., Okada, S., ... Shimomitsu, T. (2011). Perceived neighborhood environment and walking for specific purposes among elderly Japanese. *Journal of Epidemiology, 21*, 1–10.
James, P., Banay, R. F., Hart, J. E., & Laden, F. (2015). A review of the health benefits of greenness. *Current Epidemiology Reports, 2*(2), 131–142.
Jennings, V., Johnson Gaither, C., & Gragg, R. S. (2012). Promoting environmental justice through urban green space access: A synopsis. *Environmental Justice, 5*(1), 1–7.
Kaczynski, A. T., Koohsari, M. J., Stanis, S. A. W., Bergstrom, R., & Sugiyama, T. (2014). Association of street connectivity and road traffic speed with park usage and park-based physical activity. *American Journal of Health Promotion, 28*(3), 197–203.
Kim, M. Y., & Kim, E. J. (2019). Effects of Neighborhood Environment on Multifamily Housing Price: Focused on Seoul Metropolitan City in Korea. *Journal of the Korean Urban Geographical Society, 22*(1), 163–175.
Klompmaker, J. O., Hoek, G., Bloemsma, L. D., Gehring, U., Strak, M., Wijga, A. H., Brink, C. V., Brunekreef, B., Lebret, E., & Janssen, N. A. (2018). Green space definition affects associations of green space with overweight and physical activity. *Environmental Research, 160*, 531–540.
Konijnendijk, C. C., Ricard, R. M., Kenney, A., & Randrup, T. B. (2006). Defining urban forestry–A comparative perspective of North America and Europe. *Urban Forestry & Urban Greening, 4*(3–4), 93–103.
Lee, H. S. (2011). Perception of proximity to and utilization of neighborhood services and facilities for senior citizens. *Journal of the Urban Design Institute of Korea, 12*(4), 63–74.
Li, F., Fisher, K. J., Brownson, R. C., & Bosworth, M. (2005). Multilevel modelling of built environment characteristics related to neighbourhood walking activity in older adults. *Journal of Epidemiology & Community Health, 59*(7), 558–564.
Li, X., & Ghosh, D. (2018). Associations between body mass index and urban "green" streetscape in Cleveland, Ohio, USA. *International Journal of Environmental Research and Public Health, 15*(10), 2186.
Li, X., & Ratti, C. (2019). Mapping the spatio-temporal distribution of solar radiation within street canyons of Boston using Google Street View panoramas and building height model. *Landscape and Urban Planning, 191*, Article 103387.
Li, X., Zhang, C., Li, W., Kuzovkina, Y. A., & Weiner, D. (2015a). Who lives in greener neighborhoods? The distribution of street greenery and its association with residents' socioeconomic conditions in Hartford, Connecticut, USA. *Urban Forestry & Urban Greening, 14*(4), 751–759.
Li, X., Zhang, C., Li, W., Ricard, R., Meng, Q., & Zhang, W. (2015b). Assessing street-level urban greenery using Google Street View and a modified green view index. *Urban Forestry & Urban Greening, 14*(3), 675–685.
Li, X., Ratti, C., & Seiferling, I. (2018). Quantifying the shade provision of street trees in urban landscape: A case study in Boston, USA, using Google Street View. *Landscape and Urban Planning, 169*, 81–91.
Long, J., Shelhamer, E., & Darrell, T. (2015). Fully convolutional networks for semantic segmentation. *In Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 3431–3440). .
Lu, Y. (2018). Using Google Street View to investigate the association between street greenery and physical activity. *Landscape and Urban Planning, 191*, 1–9.
Lu, Y., Sarkar, C., & Xiao, Y. (2018). The effect of street-level greenery on walking behavior: Evidence from Hong Kong. *Social Science & Medicine, 208*, 41–49.
Lu, Y., Yang, Y., Sun, G., & Gou, Z. (2019). Associations between overhead-view and eye-level urban greenness and cycling behaviors. *Cities, 88*, 10–18.
Maas, J., Verheij, R. A., Spreeuwenberg, P., & Groenewegen, P. P. (2008). Physical activity as a possible mechanism behind the relationship between green space and health: A multilevel analysis. *BMC Public Health, 8*(1), 1–13.
MacFarland, T. W., & Yates, J. M. (2016). Mann–whitney u test. *Introduction to nonparametric statistics for the biological sciences using R* (pp. 103–132). Cham: Springer.
Markevych, I., Schoierer, J., Hartig, T., Chudnovsky, A., Hystad, P., Dzhambov, A. M., ... Lupp, G. (2017). Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environmental Research, 158*, 301–317.
McCormack, G. R., & Shiell, A. (2011). In search of causality: A systematic review of the relationship between the built environment and physical activity among adults. *International Journal of Behavioral Nutrition and Physical Activity, 8*(1), 1–11.
Middel, A., Lukasczyk, J., Zakrzewski, S., Arnold, M., & Maciejewski, R. (2019). Urban form and composition of street canyons: A human-centric big data and deep learning approach. *Landscape and Urban Planning, 183*, 122–132.
Mirzaei, E., Kheyroddin, R., Behzadfar, M., & Mignot, D. (2018). Utilitarian and hedonic walking: Examining the impact of the built environment on walking behavior. *European Transport Research Review, 10*(2), 20.
Mytton, O. T., Townsend, N., Rutter, H., & Foster, C. (2012). Green space and physical activity: An observational study using health survey for England data. *Health & Place, 18*(5), 1034–1041.
Owen, N., Humpel, N., Leslie, E., Bauman, A., & Sallis, J. F. (2004). Understanding environmental influences on walking: Review and research agenda. *American Journal of Preventive Medicine, 27*(1), 67–76.
Picavet, H. S. J., Milder, I., Kruize, H., de Vries, S., Hermans, T., & Wendel-Vos, W. (2016). Greener living environment healthier people?: Exploring green space, physical activity and health in the Doetinchem cohort study. *Preventive Medicine, 89*, 7–14.
Rzotkiewicz, A., Pearson, A. L., Dougherty, B. V., Shortridge, A., & Wilson, N. (2018). Systematic review of the use of Google Street View in health research: Major themes, strengths, weaknesses and possibilities for future research. *Health & Place, 52*, 240–246.
Saelens, B. E., & Handy, S. L. (2008). Built environment correlates of walking: A review. *Medicine and Science in Sports and Exercise, 40*(7), S550–S556.
Sander, H. A., Ghosh, D., & Hodson, C. B. (2017). Varying age-gender associations between body mass index and urban greenspace. *Urban Forestry & Urban Greening, 26*, 1–10.
Seiferling, I., Naik, N., Ratti, C., & Proulx, R. (2017). Green streets− Quantifying and mapping urban trees with street-level imagery and computer vision. *Landscape and Urban Planning, 165*, 93–101.
Song, Y. J., & Yoon, C. R. (2019). *Development and application of biodiversity indicator in parks and green spaces in Seoul.* The Seoul Institute.
Sugiyama, T., Francis, J., Middleton, N. J., Owen, N., & Giles-Corti, B. (2010). Associations between recreational walking and attractiveness, size, and proximity of neighborhood open spaces. *American Journal of Public Health, 100*(9), 1752–1757.
Sung, H., & Lee, S. (2015). Residential built environment and walking activity: Empirical evidence of Jane Jacobs' urban vitality. *Transportation Research Part D: Transport and Environment, 41*, 318–329.
Sung, H., Lee, S., & Jung, S. (2014). Identifying the relationship between the objectively measured built environment and walking activity in the high-density and transit-oriented city, Seoul, Korea. *Environment and Planning B: Planning and Design, 41*(4), 637–660.
Takano, T., Nakamura, K., & Watanabe, M. (2002). Urban residential environments and senior citizens' longevity in megacity areas: The importance of walkable green spaces. *Journal of Epidemiology & Community Health, 56*(12), 913–918.
Thompson, C. W., 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. *Landscape and Urban Planning, 105*(3), 221–229.
Tsai, V. J., & Chang, C. T. (2013). Three-dimensional positioning from Google street view panoramas. *IET Image Processing, 7*(3), 229–239.
Van Dillen, S. M., de Vries, S., Groenewegen, P. P., & Spreeuwenberg, P. (2012). Greenspace in urban neighbourhoods and residents' health: Adding quality to quantity. *Journal of Epidemiology Community Health, 66*(6), 1–5.
Villeneuve, P., Ysseldyk, R., Root, A., Ambrose, S., DiMuzio, J., Kumar, N., Shehata, M., Xi, M., Seed, E., Li, X., Shooshtari, M., & Rainham, D. (2018). Comparing the normalized difference vegetation index with the Google Street View measure of vegetation to assess associations between greenness, walkability, recreational physical activity, and health in Ottawa, Canada. *International Journal of Environmental Research and Public Health, 15*(8), 1–10.
Wang, R., Lu, Y., Zhang, J., Liu, P., Yao, Y., & Liu, Y. (2019). The relationship between visual enclosure for neighbourhood street walkability and elders' mental health in China: Using street view images. *Journal of Transport & Health, 13*, 90–102.
Wolch, J., Jerrett, M., Reynolds, K., McConnell, R., Chang, R., Dahmann, N., ... Berhane, K. (2011). Childhood obesity and proximity to urban parks and recreational resources: A longitudinal cohort study. *Health & Place, 17*(1), 207–214.
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.
Ye, Y., Richards, D., Lu, Y., Song, X., Zhuang, Y., Zeng, W., & Zhong, T. (2018). Measuring daily accessed street greenery: A human-scale approach for informing better urban planning practices. *Landscape and Urban Planning, 191*, 1–13.
Yin, L., & Wang, Z. (2016). Measuring visual enclosure for street walkability: Using machine learning algorithms and Google Street View imagery. *Applied Geography, 76*, 147–153.
Yin, L., Cheng, Q., Wang, Z., & Shao, Z. (2015). 'Big data' for pedestrian volume: Exploring the use of Google Street View images for pedestrian counts. *Applied Geography, 63*, 337–345.
Zhou, H., He, S., Cai, Y., Wang, M., & Su, S. (2019). Social inequalities in neighborhood visual walkability: Using street view imagery and deep learning technologies to facilitate healthy city planning. *Sustainable Cities and Society, 50*, 1–15.
Ministry of Land, Infrastructure and Transport of South Korea, The current situation of housing in Seoul. Retrieved January 2, 2019 from https://data.seoul.go.kr/dataList/datasetView.do?infId=10762&srvType=S&serviceKind=2.