Landscape and Urban Planning xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Landscape and Urban Planning

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

Research Paper

Measuring daily accessed street greenery: A human-scale approach for informing better urban planning practices

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ARTICLE INFO

Keywords:
Visible greenery
Google Street View
Space syntax
Human-scale
Accessible greenery
Machine learning

ABSTRACT

The public benefits of visible street greenery have been well recognised in a growing literature. Nevertheless, this issue was rare to be included into urban greenery and planning practices. As a response to this situation, we proposed an actionable approach for quantifying the daily exposure of urban residents to eye-level street greenery by integrating high resolution measurements on both greenery and accessibility. Google Street View (GSV) images in Singapore were collected and extracted through machine learning algorithms to achieve an accurate measurement on visible greenery. Street networks collected from Open Street Map (OSM) were analysed through spatial design network analysis (sDNA) to quantify the accessibility value of each street. The integration of street greenery and accessibility helps to measure greenery from a human-centred perspective, and it provides a decision-support tool for urban planners to highlight areas with prioritisation for planning interventions. Moreover, the performance between GSV-based street greenery and the urban green cover mapped by remote sensing was compared to justify the contribution of this new measurement. It suggested there was a mismatch between these two measurements, i.e., existing top-down viewpoint through satellites might not be equivalent to the benefits enjoyed by city residents. In short, this analytical approach contributes to a growing trend in integrating large, freely-available datasets with machine learning to inform planners, and it makes a step forward for urban planning practices through focusing on the human-scale measurement of accessed street greenery.

1. Introduction

Urban greenery, including roadside trees, shrubs, and associated vegetation, has long been recognised for its importance in improving environmental, recreational, and aesthetic conditions within urban areas (Jim & Shan, 2013; Krellenberg, Welz, & Reyes-Päcke, 2014). Interest in urban sustainability and quality-of-life has led to increasing demand for human-scale urban greenery in recent decades (Chiesura, 2004; Lu, 2018; Lu, Sarkar, & Xiao, 2018). Herein, the "human-scale" means a fine scale characterised by human body and its surroundings, i.e., a scale can be directly visible, touchable, and appreciable in a person's daily lives (Long & Ye, 2016). There is existed research evidence for the importance of visible street greenery in improving the quality of people's experiences in urban areas, and accessed street greenery contributes to the liveliness and walkability (Wolf, 2005). Similarly, street greenery helps to increase people's aesthetic appreciation of urban places (Camacho-Cervantes, Schondube, Castillo, & MacGregor-Fors, 2014) and encourages people to spend more time outdoors, which in turn can decrease personal stress levels (Arbogast, Kane, Kirwan, & Hertel, 2009; Li & Sullivan, 2016). A set of studies have claimed the importance of utilising the aesthetic and environmental benefits by incorporating vegetation within streetscape equitably around cities, in areas that are accessed by the population (Barau, 2015; Lee & Kim, 2016).

Nevertheless, the accessibility and visibility of street greenery are not often considered in urban planning practices even after the importance of human-scale street greenery has been recognised. One of the main reasons is the measurement of street greenery taken at eye-level is always time-consuming and hard to achieve. In turn, efficiency and easy to use are always key concerns for urban planning

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https://doi.org/10.1016/j.landurbplan.2018.08.028
Received 22 July 2017; Received in revised form 8 August 2018; Accepted 12 August 2018

professionals. Therefore, current spatial indices of urban greenery are typically quantified using remote sensing techniques as urban green cover, which is regarded as the dominant criterion in urban greenery planning (Chen & Wang, 2013; Nowak & Greenfield, 2012). Several studies comparing between urban green cover and green view collected from GSV have been done at a neighbourhood scale (Li et al., 2015; Yang, Zhao, Mcbride, & Gong, 2009). It shows that there is a significantly positive correlation between the two measurements within appropriate distance, but the correlation coefficients decrease sharply with increase of the buffer distances. Therefore, an overhead view of urban vegetation might not necessarily correspond to the visual experience that urban residents would have at ground level, although remote sensing enables large areas to be mapped relatively quickly.

There are two key questions should be addressed for assisting urban planners to achieve higher benefits of urban greenery from a human-oriented perspective: 1) how to quantitatively measure daily accessed and visible street greenery? 2) how to compare the performance of this eye-level metric with widely used urban green cover? Addressing these two questions requires to explore an efficient approach for measuring both visibility and accessibility of street greenery inside large urban areas, which were hard to achieve. Nevertheless, emerging analytical techniques, e.g., machine learning algorithms and space syntax tools, and new urban data, e.g., large amount of geo-referenced data provided by street view images and open street map, bring new research potentials. To achieve a combined analysis of accessibility and visibility of street greenery at human-scale, this paper: 1) quantifies street greenery using images from Google Street View across the case study city of Singapore; 2) assesses the mismatch between visible street greenery derived from Google Street View and street accessibility measured by space syntax as a decision-support analysis to highlight areas where planning authorities should consider to increase street greenery; and 3) compares street greenery measurements containing both visible street greenery at eye-level and accessed greenery with the urban green cover derived from satellite imagery.

2. Literature review

2.1. Measuring visible street greenery: traditional and innovative approaches

There are four main approaches have been developed in quantitatively measuring of visible street greenery (Table 1). Previous studies focusing on this field usually uses self-collected data. A pioneering study uses a grid pattern of 588 squares to measure the percentage of visible greenery at eye-level, by counting the number of squares which have a proportion of green area more than fifty percent (Nordh, Hartig, Hagerhall, & Fry, 2009). Better precision has been attained through image manipulation software to calculate the percentage of green pixels in photographs (Jiang, Chang, & Sullivan, 2014; Jiang et al., 2017; Yang et al., 2009). Such methods of quantifying street vegetation can inform the design of small urban areas, but the manual analysis of colour photographs is time-consuming to collect large numbers of photographs in the field and process them, thus limiting the application over large-scales to inform urban greenery planning in real practices. There are also other quantitative methods beside on-site photography to assess visual street greenery, e.g., applying airborne Lidar data to measure tree sizes and shapes (Chen, Xu, & Gao, 2015). But it is still expensive to use and time-costing to cover large areas if human-centred viewpoint and high spatial resolution are required.

Recently, the availability of large datasets of panoramic images taken at street level, such as Google Street View (GSV), has opened new opportunities to analyse built environment qualities, e.g., auditing the spatial quality of neighbourhood environment (Rundle, Bader, Richards, Neckerman, & Teitler, 2011), mapping perceived street safety (Naik, Philipoom, Raskar, & Hidalgo, 2014), and measuring walkability (Yin & Wang, 2016). Following this trend, the using of GSV images has been extended to the measure of street greenery. Li et al. (2015) proposes an unsupervised classification approach based on colour bands to assess street greenery using GSV images. This approach has then been used in studying social impacts of visible street greenery (Li, Zhang, & Li, 2015), mapping the openness of street canyons (Li, Ratti, & Seiferling, 2017), and quantifying street tree related ecosystem service (Richards & Edwards, 2017).

Meanwhile, the raising of machine learning algorithms has brought computer vision tools in smartly extracting visible street greenery, which performs well in identifying greenery from complex urban environment. For instance, SegNet, a deep convolutional network for achieving an objective and accurate pixel-width image segmentation, could help to handle the tricky problem that how to accurately extract greenery from the GSV images (Badrinarayanan, Kendall, & Cipolla, 2015). This kind of new image segmentation could smartly identify street greenery from building materials with green colour and dark shadow, which were hard to be done in previous studies applying GSV images. A few studies have recently tested the possibility of measuring street greenery with the help of machine learning algorithms at neighbourhood and national scales (Long & Liu, 2017; Seiferling, Naik, Ratti, & Proulx, 2017).

2.2. Accessed street greenery: space syntax

The likelihood that people will access and interact with urban greenery should be considered as a key issue of sustainable urban planning, especially in topics such as environmental justice and health (La Rosa, 2014). At present, the geographical accessibility, e.g., shortest distance or travel time, of green spaces such as parks and woodlands has been well studied through the application of GIS (Comber, Brunsdon, & Green, 2008; Randall, Churchill, & Baetz, 2003). However, less research has focused on the accessibility of roadside vegetation, which is a highly visible form of urban vegetation that many residents may go through and experience daily (Tan, Wang, & Sia, 2013).

Space syntax, a quantitative analysis of how a street interrelates spatially with the rest of the street network, can be used to estimate accessibility and predict movement flows within a given street network configuration (Hillier, 1996; Hillier, Penn, Banister, & Xu, 1998). With the help of computer software, such as Depthmap developed by University College London or sDNA developed by Cardiff University, it is possible to quantify the high or low potential of go-through movement in a street network. Different analytical radii in pedestrian and commute behaviours help reveal the degree of accessibility at different scales, which will be discussed in the following section.

In short, a new research potential is emerging in the context of new data and new techniques for in-depth measuring of daily accessed, visible street greenery. Although some studies have applied machine learning algorithms to measure visible street greenery, a human-

Table 1
Representative studies measuring street greenery with different approaches.

Self-collected data		Street view images	
on-site photography	Nordh et al. (2009), Yang et al. (2009), Jiang et al. (2014), Jiang et al. (2017)	*unsupervised classification using colour bands*	Li et al. (2015), Li et al. (2015), Li et al. (2017), Richards and Edwards (2017)
Lidar sensors	Chen, Xu, and Gao (2015)	*machine-learning algorithms*	Seiferling et al. (2017), Long and Liu (2017)

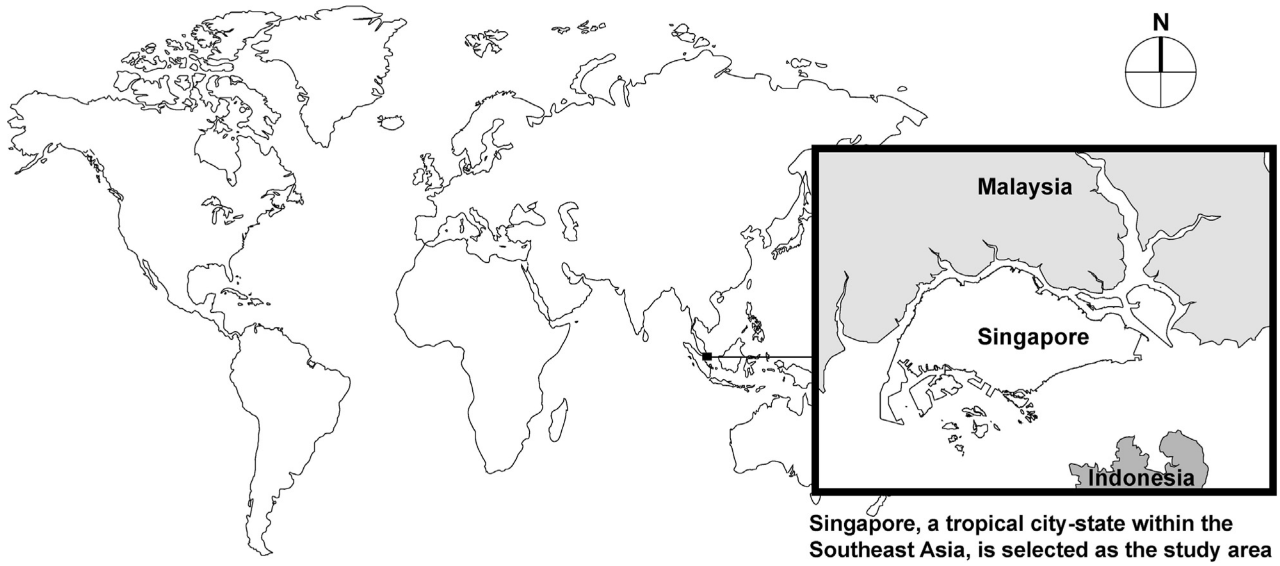


Fig. 1. Study area: Singapore.

centred combination of accessibility in daily lives and visible street greenery is still unobserved. Meanwhile, the co-presenting of city-scale analyses over hundred square kilometres and high spatial resolution at human-scale is also rare. Appropriate settings in the collection process of GSV images and the classification of high or low values of greenery at eye-level deserve further explorations as well. It is also interesting to compare this newly-proposed green view index integrating eye-level visibility and daily accessibility with satellite-based green cover that is used as the dominant index in urban planning practices. Researches in this direction may assist practitioners to accept and apply this new technique in practices.

3. Method

3.1. Study area

Our analysis was conducted in Singapore, a tropical city-state within the Southeast Asia (Fig. 1). Considerable urban greening efforts have been ongoing in this country for more than half a century (Lee & Chua, 1992), owing to a concerted effort by the country's government and public agencies. Despite the high-rise and high-density urban development in this compact city, the importance of greenery to urban planning in this city is exemplified by an extensive network of tree-lined roads and park connectors, as well as parks and nature reserves.

3.2. Research framework

This study contains four main phases. First, GSV images and detailed street networks of Singapore were collected through the Google API and Open Street Map (OSM), respectively. Subsequent image processing was performed via Python. This phase focused on collecting large amount of street view images covering city-wide region but also obtaining high spatial resolution. Second, the greenery extraction was then processed through SegNet to achieve an objective and accurate pixel-width image segmentation and classification. Support vector machine (SVM), a supervised learning model with associated learning algorithm, was then used to accurately classify high or low values of street greenery according to the measured green view index. Applying SVM in small-size labelled sample could answer the question that to which extent the greenery would be high enough or obviously too low, and then to be applied in the classification of a large amount of data to achieve high validation. Third, street accessibility, in terms of daily commuting distance and daily pedestrian distance, were quantified using space syntax analyses. In this study, "daily" referred to activities that happened frequently in an urban resident's routine, e.g., travelling to work or school. Occasional activities were therefore not considered herein. After that, the integration of visibility and accessibility of street greenery enabled efficient quantification of "daily accessed greenery" at the city-scale, as well as subsequent identification of high and low priority streets for potential greening efforts. This newly-generated human-scale measurement was then compared against a remotely sensed quantification of green cover from top-down viewpoint (Fig. 2).

3.3. GSV data collection

To achieve a comprehensive representation of greenery across the Singapore streetscape, a GSV panoramic street image was analysed every 50 m. A total of 182,792 sample sites were generated along the OSM street network in the whole Singapore. Fig. 3 shows the sampling points across the Singapore street network. A randomly-selected area was magnified to visualise sampling points.

GSV images were requested in a HTTP URL form using the GSV Image API (Google, 2014). By defining the URL parameters sent through a standard HTTP request using the GSV Image API, users can obtain a static GSV image from any direction and angle of view, for any point where GSV is available. Existed GSV-related studies are usually using true directions, i.e., the heading angles toward direction of the north geographical pole, in the collecting process because it is a constant direction reference in Google API. However, most of street layouts obtain certain angles with true north. A simplified setting of heading angles as 0° (true north), 90° (true west), 180° (true south), etc., would work for achieving a panoramic measuring of surrounded greenery. Nevertheless, it might exist certain difference with local resident's behaviours and the way they experience the environment. According to the priming theory in environmental psychology (Bargh, Chen, & Burrows, 1996), local residents' behaviour can be regarded as a stereotyping that does not change too much in daily lives. Tourists may look up and down when walking in an inexperienced environment, but the local residents' view generally follow the street layout and would not look up into the sky frequently. Thus, a Python script was developed to read the coordinates of each collecting point and analyse the typological feature of surrounding street networks to calculate heading view angles for each collecting point. The main aim is to make sure the front and rear views could be always parallel to the street segment where the collecting point located on, and the left-hand and right-hand views could be always vertical to the street segment (Fig. 4).

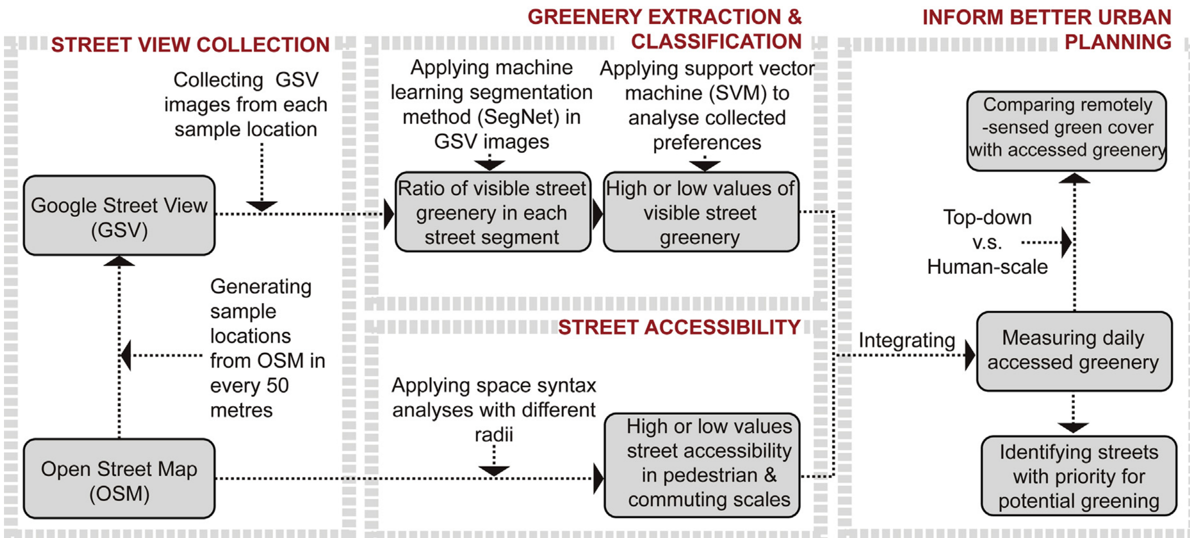


Fig. 2. Research flow.

As shown in the bottom of Fig. 4, four GSV images with the size of 480*360 pixels are enough to achieve a panoramic view for surrounding environment. Moreover, a zero-degree vertical view angle were downloaded to compute the visually-available greenery to pedestrians following previous, human-scale studies (Li et al., 2015; Yang et al., 2009). This kind of heading and vertical view angles helped to measure street greenery in the way people experienced it.

3.4. Machine-learning based extraction and classification of green view index

A semantic pixel-width image segmentation method based on convolutional network, SegNet, was applied in this study. SegNet is a fully trainable approach for joint feature learning and image mapping to its pixel-wise semantic labels (Kendall, Badrinarayanan, & Cipolla, 2015), which turns out to be one of the first deep learning algorithms works well in identifying spatial feature using low-resolution images. We inputted all the GSV images collected into the SegNet and interpreted them into coloured categories via SegNet decoder. As the Fig. 5 shows, all the vegetation inside the images, including both trees and grass, can be clearly extracted, even these street greenery is co-present with complex scenarios, e.g., the presence of shadows, green fences, textured walls. The validation of greenery extraction was conducted using 57 randomly selected GSV images. The reference data was manually collected using Photoshop. The Pearson correlation between Photoshop-derived green ratios and those obtained through our study was 0.899, indicating an acceptable accuracy.

The green view index of each image was measured based on the proportion result calculated by SegNet. The result of each sample site was calculated following Li et al. (2015)'s approach by combining the results of pictures taken at different directions. Specifically, it was subsequently calculated using the follow equation:

$$\text{Green view index} = \sum_{i=1}^{4} Pixel_{g\_i} / \sum_{i=1}^{4} Pxiel_{t\_i}$$

where $Pixel_{g\text{-}i}$ $Pixel_{g\text{-}i}$is the number of green pixels in the picture taken in the ith point (numbers 1, 2, 3, and 4 correspond to the directions of front, rear, left-hand and right-hand, respectively), and $Pixel_{t\text{-}i}Pixel_{t\text{-}i}$ is the total number of pixels in the picture taken in the tth point.

The evaluation and classification of green view index were achieved through collecting experts' judgements (Fig. 6). First, 500 sample images were selected considering the representativeness in geometric distributions and image features. A Java script was developed to collect participants' judgements on which kinds of greenery can be identified as high, medium and low. In other words, to which extent this street view was greenery enough or not yet. Ten participants had living experiences in Singapore and obtaining expertise in urban planning, urban design and landscape architecture were involved. Due to different personal perceptions, their subjective judgements would be complex and hard to simply classify. For instance, some images labelled as high by part of participants were labelled as medium by others simultaneously. Therefore, we used the SVM, a supervised learning model, to train an objective classification model worked well in participants' judgements on representative samples. After that, we applied it into the whole Singapore. Specifically, we randomly split the sample dataset into 75% for training and 25% for testing. One-versus-rest approach of SVM was firstly applied in training data to achieve an accurate classification model identifying the high, medium and low values for GSV images, and then its validation would be verified in the testing data. This training process would be kept for many rounds until 99% accuracy was achieved in the testing dataset. Considering the sample size would be much smaller than the whole dataset, radial basis function (RBF) kernel was used to train the sample set for achieving higher accuracy in following classifications. Due to the lack of standard references, the validation of this classification method was achieved through expert scoring. Two experts with urban planning background were invited to assess 100 randomly selected images classified by SVM. The Cohen's kappa coefficients between experts' categorical judgements and SVM's automatic classification show significant, highly positive results. The kappa (k) values are 0.910 and 0.925 respectively, indicating an acceptable accuracy.

3.5. Measuring street accessibility and integrating it with visible street greenery

The measuring of street accessibility was performed using space syntax. Space syntax focuses on the open space system to pursue the spatial representation of connectivity and how this spatial feature affects behaviours. A series of distance metrics in terms of metric distance (measuring paths with the shortest length), topological distance (measuring paths with the fewest turns), and geometric distance (measuring paths with the least angular change) have been developed to represent accessibility (Hillier & Iida, 2005). A set of quantitative comparisons show that geometric analytics with a metric radius works best to capture the spatial layout design and the distance in relation to the movement levels. The measurement of *choice* (so-called betweenness in spatial network analyses), which represents the number of least-angle-

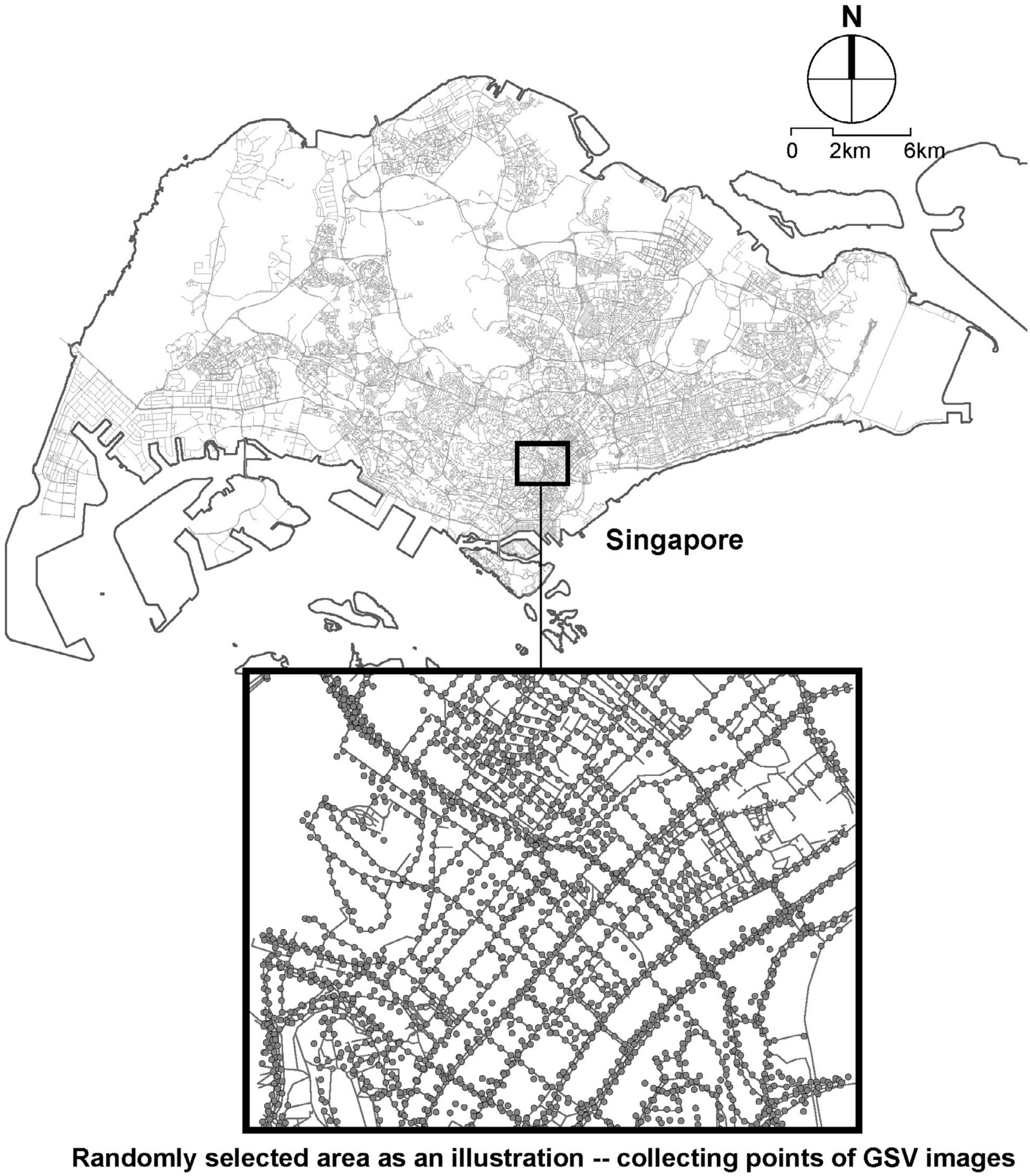


Fig. 3. Sampling points across the Singapore street network.

change paths between all of the other links that pass-through a given segment, was used herein. It reflects the "through-movement" potentials, i.e., the potential of each segment element to be selected by pedestrians or drivers as the path. Thus, it can be used to predict the most easily accessed streets of the site (Al_Sayed, Turner, Hillier, Iida, & Penn, 2014).

The choice (betweenness) is defined by Hillier and Iida (2005, p. 558):

$$C_b(P_i) = \sum_{j=1}^{n} \sum_{k=1}^{n} g_{ik}(p_i)/g_{jk}(j < k)$$

where $g_{jk}(p_i)$ = the number of geodesics between node p_j and p_k which contain node p_i, and g_{jk} = the number of all geodesics between p_j and p_k.

More specifically, we use the spatial design network analysis (sDNA) tool to operationalize the *choice* measurement (*betweenness* in sDNA's term) in space syntax. The sDNA is the first space syntax tool obtaining an industry standard and can use central road lines to run analyses (Chiaradia, Cooper, & Webster, 2013). Two radii of accessibility were used in two analytical scales. The radius refers to the metric distance from each segment along all of the available streets and roads from that segment up to the radius distance (Al_Sayed et al., 2014). Following this definition, a small radius, e.g. 500 m (5 min walking), would only calculate angular turns of all segments within 500 m from the current segment, any segments beyond that radius would not be calculated. This means that the system would only identify the local relationships

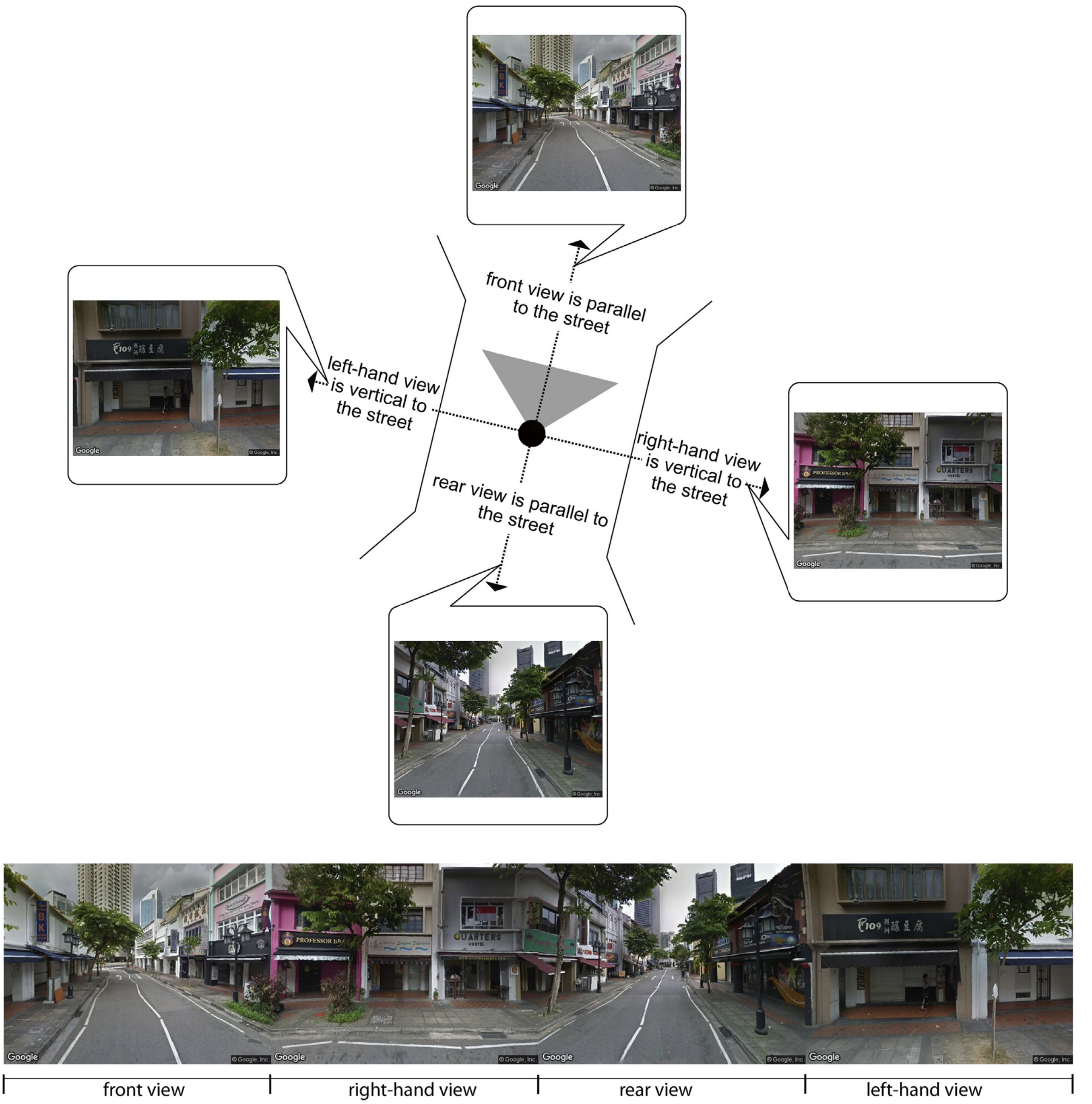


Fig. 4. GSV images captured in four directions at a sample site.

between street segments, i.e., highly connected interior streets. In turn, a large radius would consider a broader area and highlight main arteries that are highly accessible for commuting.

Specifically, there was one for commuters travelling for long distances, and one for pedestrians walking in short distances in this study. According to the Singapore Land Transport Authority (LTA, 2014), the average daily commuting distance in Singapore is 9.7 km. A large-scale survey conducted on walkability in Singapore showed that pedestrians on average were willing to walk no more than 300 m (Erath, van Eggermond, Ordonez, & Axhausen, 2016). Thus, 9.7 km and 300 m were selected as the two distance radii represented accessibility at both a large (commuting) and small (pedestrian walkability) scales, respectively.

The overlay analysis, in which the low value of visible street greenery was cross referenced with the high value of streets accessibility, was made to highlight priority areas for future greening. It helped provide efficient guidance for planning practices.

3.6. Comparing remotely-sensed green cover with street green view indices based on GSV

The street green view indices containing both visible street greenery at eye-level and daily accessed greenery within Singapore's planning regions were compared against a green cover measurement derived from satellite imagery. Most of planning areas (46 in total) containing urban functions were compared. Planning areas belonging to offshore islands were excluded to avoid bias. The green cover measured by remote sensing Normalized Difference Vegetation Index (NDVI) from top-down viewpoint and street green view indices measured from human-scale viewpoint were firstly compared using a Pearson's r correlation test. The NDVI data of Singapore was collected from LANDSAT 8 with 30-metre resolution.

Fig. 5. Greenery extraction examples through SegNet.

After that, the performance of two greenery measurements from top-down and human-scale viewpoints was then compared. Besides the visible street greenery, two types of daily accessed greenery were proposed through integrating visible greenery from GSV data and street accessibility – pedestrian accessed greenery (well), commuting accessed greenery (well). Specifically, these two measurements represented percentages of street segments that could co-present the high value of visible greenery and accessibility among all street segments.

4. Results

4.1. Street greenery analysis based on GSV images

Fig. 7 shows the visible street greenery of each GSV point, as well as an overlaying analysis that integrated the green view index of the sampling points across each street. The green view index on each street segment was calculated based on the mean value of all the GSV images geographically proximate to this street (Fig. 7b). The geographical proximity herein was set at 5 m.

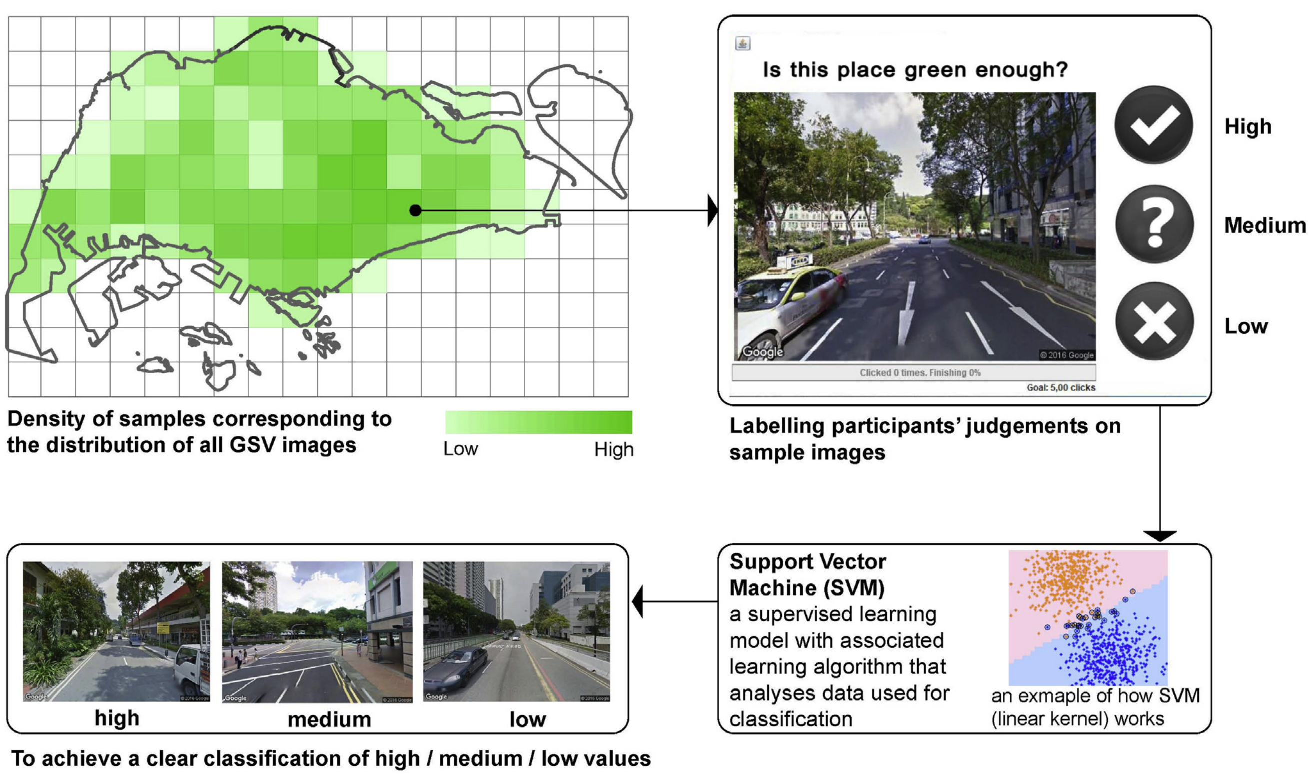


Fig. 6. The approach for classifying high or low values of green view index. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

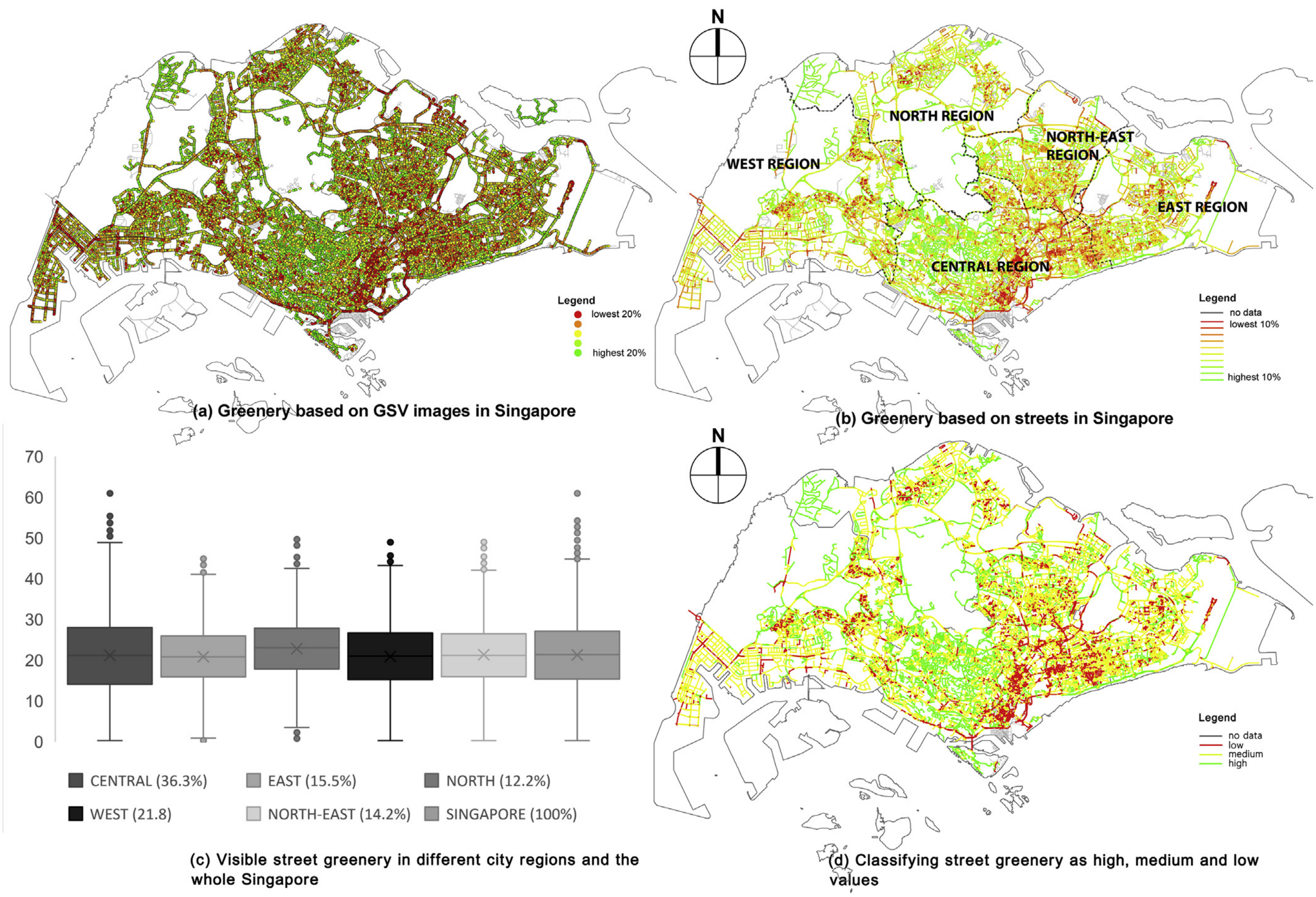


Fig. 7. The analysis of street greenery in Singapore. (a) Green view index of each GSV point; (b) Street greenery based on an overlaying analysis integrating the green view index of collecting points on each street; (c) Visible street greenery in different city regions and the whole Singapore; (d) Classifying street greenery as high, medium and low values. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

As shown in the following boxplots (Fig. 7c), the average street greenery is 21.0%, with a maximum value of 60.7% island wide. The median value of visible street greenery among different regions are relatively similar, arranging between 20.6% and 21.0%. The Central as the most well development region obtains the longest street length (36.3% of total street length), as well as widest distribution from the lowest (0.0%) to highest (60.7%) levels of visible greenery. The North region has the shortest street length (12.2% of total street length), as well as the highest median level of visible greenery. Street greenery values are classified as high, medium and low values through the SVM-based classification (Fig. 7d).

4.2. Street accessibility analysis based on space syntax

Fig. 8 shows the street accessibility across the city of Singapore, based on two distance radii that represented daily commuting and pedestrian activity. Detailed explanations of street accessibility were given in the method Section 3.5. As the Fig. 8a shows, important highways and main streets are identified as having high accessibility (shown in red) for daily commuting, while streets with low accessibility are shown as blue. Street accessibility for pedestrians, in terms of walkability, is generally low in Singapore. Only downtown areas within the Central region, and certain areas within the East region obtain good pedestrian accessibility (Fig. 8b).

4.3. Combined analyses between visible street greenery and street accessibility

We identified priority streets for urban greening by overlaying the accessibility and greenery issues. Specifically, these easily accessed streets with low greenery had a priority to be further improved as they were frequently used by people but lacked street greenery. In turn, the streets obtained both high accessibility and visible greenery would be frequently used by people and enjoy greening space. Therefore, the priority should be given to streets with relatively high accessibility values but low street greenery. Following this understanding, Fig. 9 identifies the streets with priority to be further developed, which are marked from red to green.

To aggregate the values from pedestrian accessibility, commuting accessibility, and street greenery into one framework, the three measurements were assigned into three values: high, medium and low. The accessibility values were divided according to the nature break method in GIS. A series of empirical studies on space syntax and urban form show that this classification works well in measuring accessibility-based characters, e.g. urban vitality and functional mixture (Ye & van Nes, 2014; Ye, Yeh, Zhuang, van Nes, & Liu, 2017; Ye, Li, & Liu, 2018). The greenery values were divided according to previous SVM classification. The priority streets can be separated into the following four groups, ranking from very high priority to low priority. The first group (H/H/L) obtained the highest accessibility but low greenery and thus should be given priority in urban greenery planning and interventions. In turn, the last group (M/M/L) are relatively less accessed and thus obtain

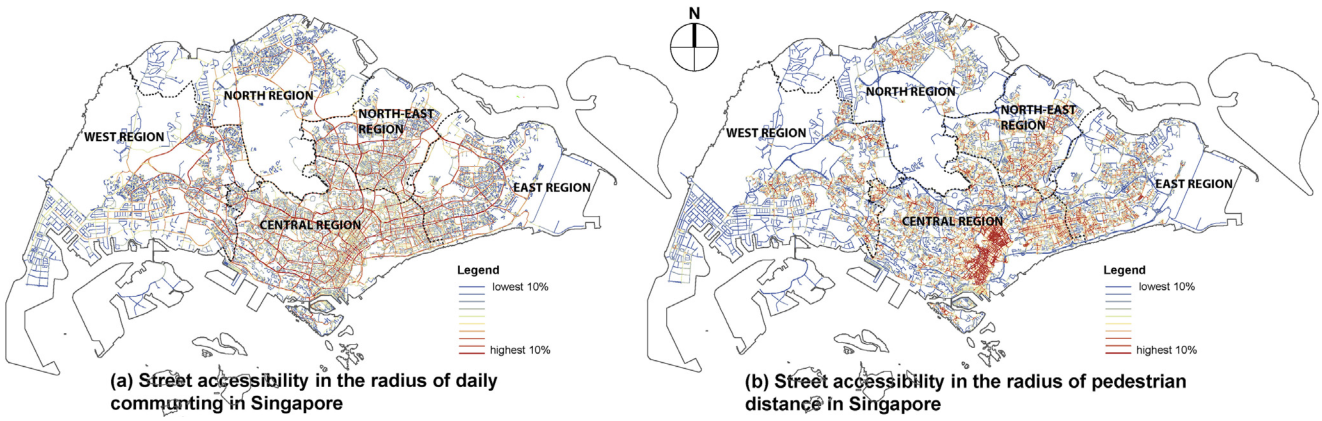


Fig. 8. Singapore street accessibility at both the daily commuting and pedestrian scales.

lower priority. The second group (H/M/L) obtained higher priority than the third group (M/H/L) because pedestrian accessibility usually plays a more important role in place-making and quality of life according to previous space syntax studies (van Nes, 2002; Ye & van Nes, 2013).

4.4. Comparison of street green view indices derived from GSV and remotely-sensed green cover

The first comparison is made between street-level visible greenery and remotely-sensed urban green cover at different buffer distances (Table 2). The visible street greenery has a significantly positive correlation with urban green cover in the buffered zones. Nevertheless, the correlation coefficient (Pearson's r) gradually decrease with the increase of the buffer distances, from 0.573 (20 m buffer distance) to 0.423 (100 m buffer distance). This gradually decreasing trend inspired us to analyse the relationship of two measurements in representative planning areas.

Second, a correlation analysis between urban green cover and street green view indices derived from GSV was made inside 46 representative planning areas in Singapore (Table 3). There was a positive, significant correlation between NDVI and visible street greenery (Pearson's $r = 0.606$, $n = 46$). The significant correlations match with Li et al. (2015)'s pioneering study comparing GSV-based greenery with green cover. Nevertheless, the green cover measured by remote sensing was not significantly correlated with well accessed pedestrian (Pearson's $r = -0.227$, $p = 0.129$) and well accessed commuting greenery (Pearson's $r = 0.174$, $p = 0.248$). This result illustrated certain mismatch between satellite's top-down viewpoint and human-scale viewpoint. Therefore, a further analysis was made to compare these two different greenery measurements.

Satellite-based green cover and accessed street greenery at human-scale was compared at the scale of Singapore's planning areas. The high or low values of green cover was decided by the vegetation ratio measured through NDVI. The values at human-scale was an equally combination of two ratios, i.e., well accessed street greenery in pedestrian and commuting scales. These ratios were normalized by scaling between 0 and 1 through min-max normalization strategy to assist the comparison between these two measurements. As the comparison shows in Fig. 10, there are similarity and also differences between these two measurements. Some historical planning areas close to city centre, e.g., Geylang, Kallang, and Downtown Core, show similar low values in both top-down and human-scale viewpoints (Type A) due to the lack of green cover and street greenery. Some other planning areas, e.g., Mandai, Western and Central Water Catchment, located at the edge of the town show high values from top-down viewpoint (Type B) due to the large forests. It is also interesting to find that a series of planning areas, e.g., Clementi, Queenstown, and Jurong East, show better performance from human-scale viewpoint (Type C). Developed under Singapore's garden city vision, many neighbourhoods inside these planning areas were well developed with the consideration of street greenery. But the vegetation cover among these areas is not too high due to limited space.

5. Discussion and conclusion

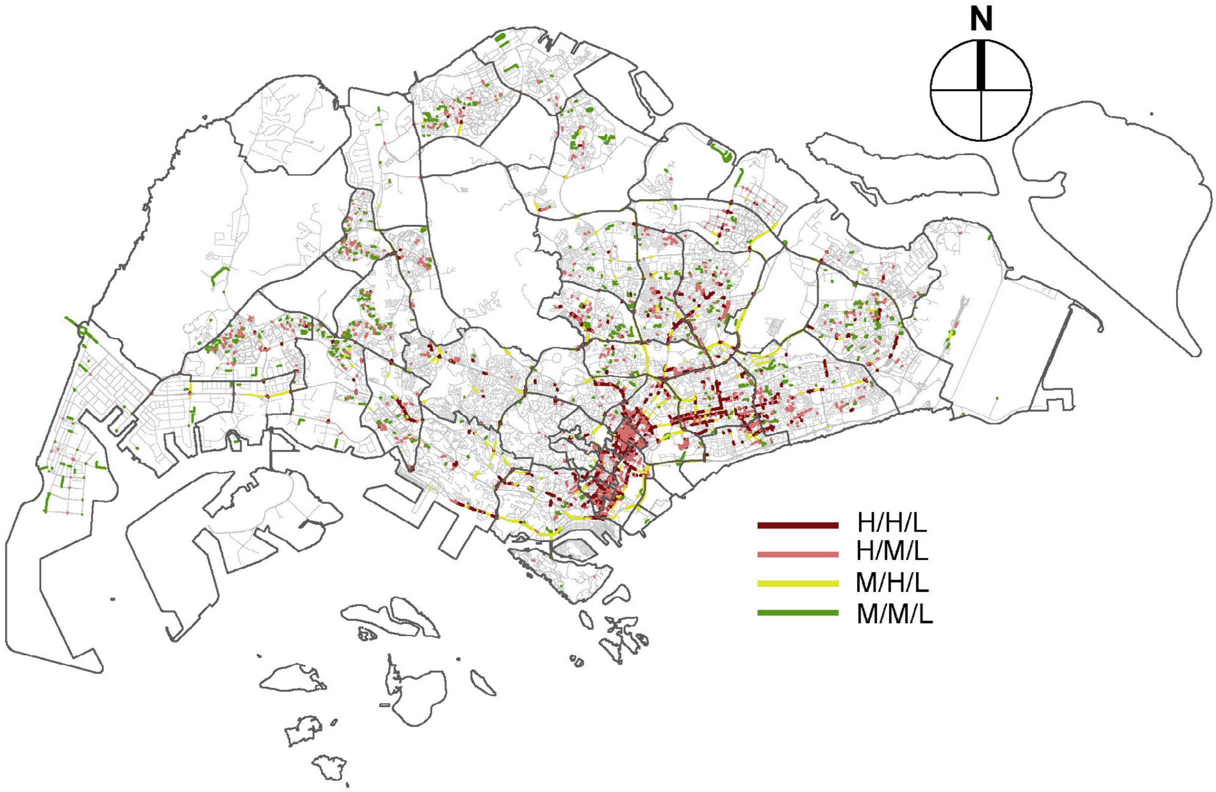
5.1. Measuring daily accessed street greenery as an exploration of human-scale planning practices

Differ with recent studies focusing on eye-level street greenery (Li et al., 2015; Long & Liu, 2017; Seiferling et al., 2017), overlaying street accessibility against their greenery values could improve the accuracy of estimating the actual benefits enjoyed by city residents and identify high priority streets for urban greening interventions. The combination provided a quantitative approach to highlight possible areas of focus for urban greening by revealing disparities between street greenery and accessibility, and inform planners make better-informed decisions. In particular, high demand for space in the downtown areas along the southern coast of Singapore resulted in high-rise, high-density conditions that limited the space available for tree-planting. This was reflected in the large aggregation of streets with high pedestrian accessibility but low visible greenery. In view of this, other forms of urban greening, such as the incorporation of vertical greenery into building facades, could be considered, especially within these space-limited environments (Wong et al., 2010). It could also serve to provide an important supplementary index of street greenery from a human perspective by providing quantifiable visible greenery requirements in city zoning and urban design guidelines.

In short, a main contribution of this study is that it prioritises an actionable approach of measuring visible street greenery relevant to human behaviours and experience. It is a quick and straightforward approach to quantifying the greenery that city residents enjoy. Human-scale quality has been a key concern in planning-related theories and researches over decades, but it was hard to be applied in practices due to the lack of time- and cost-effective measuring approach. Inspired by recent studies applied GSV data, we take a step further to seek for objective assessments of human-scale greenery in planning practices.

5.2. The mismatch between daily accessed street greenery and urban green cover

The correlation analysis (Table 3) between visible, accessed street greenery and remotely-sensed green cover suggests that existing top-down viewpoint in urban planning might not be equivalent to the benefits enjoyed by city residents from a human-scale viewpoint. The relatively weak correlation coefficients suggest that urban greening efforts in many countries, e.g., Singapore, might not be prioritised



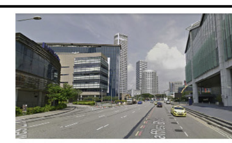
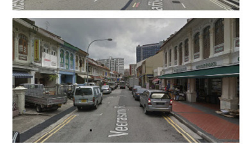
PRIORITY FOR PLANNING INTERVENTIONS	THE DIVISION OF VALUES OF PEDESTRIAN ACCESSIBILITY, COMMUTING ACCESSIBILITY & STREET GREENERY	EXAMPLES
1) Very High Priority	H/H/L (high pedestrian accessibility, high commuting accessibility, low street greenery)	
2) High Priority	H/M/L (high pedestrian accessibility, medium commuting accessibility, low street greenery)	
3) Medium Priority	M/H/L (medium pedestrian accessibility, high commuting accessibility, low street greenery)	
4) Low Priority	M/M/L (medium pedestrian accessibility, medium commuting accessibility, low street greenery)	

Fig. 9. Identifying priority streets for urban greening efforts.

Table 2
Pearson's correlation coefficients (r) between visible street greenery and urban green cover with different buffer distances.

		green cover with 20 m buffer distance	green cover with 40 m buffer distance	green cover with 60 m buffer distance	green cover with 80 m buffer distance	green cover with 100 m buffer distance
Visible street greenery on each street segment	Pearson Correlation	0.573**	0.526**	0.484**	0.451**	0.423**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000
	N	27,782	27,782	27,782	27,782	27,782

** Correlation is significant at the 0.01 level.

Table 3
Pearson's correlation coefficients (r) between street green view indices and urban green cover in different planning areas of Singapore.

		Visible street greenery: mean value of each street in planning areas	Percentage of pedestrian accessed greenery (well)	Percentage of commuting accessed greenery (well)
Green cover	Pearson Correlation	0.606**	−0.227	0.174
	Sig. (2-tailed)	0.000	0.129	0.248
	N	46	46	46

** Correlation is significant at the 0.01 level.

based on levels of human accessibility. In other words, urban green cover might not be able to reflect an accurate daily exposure of greenery of people. This result matches with a previous study at the community-scale (Jiang et al., 2017).

Nevertheless, we do not suggest that the urban green cover generated from remotely-sensed techniques should be abandoned. These two measurements could complement rather than substitute each other. The further comparison (Fig. 10) based on planning regions of Singapore shows two interesting issues. On one hand, high value of urban green cover of an area cannot ensure the co-present of high daily accessed greenery. The building of large green park and urban forests would easily achieve high performance of urban greenery planning's key indicator – high urban green cover, although it might not help too much in achieving efficient increase in daily accessed street greenery (See Type B). On the other, well-developed neighbourhoods with high values in daily accessed street greenery might not performance well in urban greenery planning's key indicator (See Type C).

This empirical observation can be regarded as another contribution of this study, which provides a viewpoint to review current urban greenery planning that mainly replies on the measurement of urban green cover but underrating the concern of to what extent the greenery is accessed at human-scale. Therefore, it might be necessary to add the human-centred measurement of eye-level street greenery as another key indicator to assist a comprehensive consideration of urban greenery in planning practices. The improved assessment using this new methodology would allow urban planners and designers to allocate resources more efficiently for improving city residents' exposure to visible greenery. Nevertheless, it is important to claim that some factors affecting street greening, e.g., traffic safety, availability of lands, and socioeconomic concerns, are not included into current analysis. Related planning practices should be made with a comprehensive consideration combining human-centred measurement of street greenery with other factors in built environment.

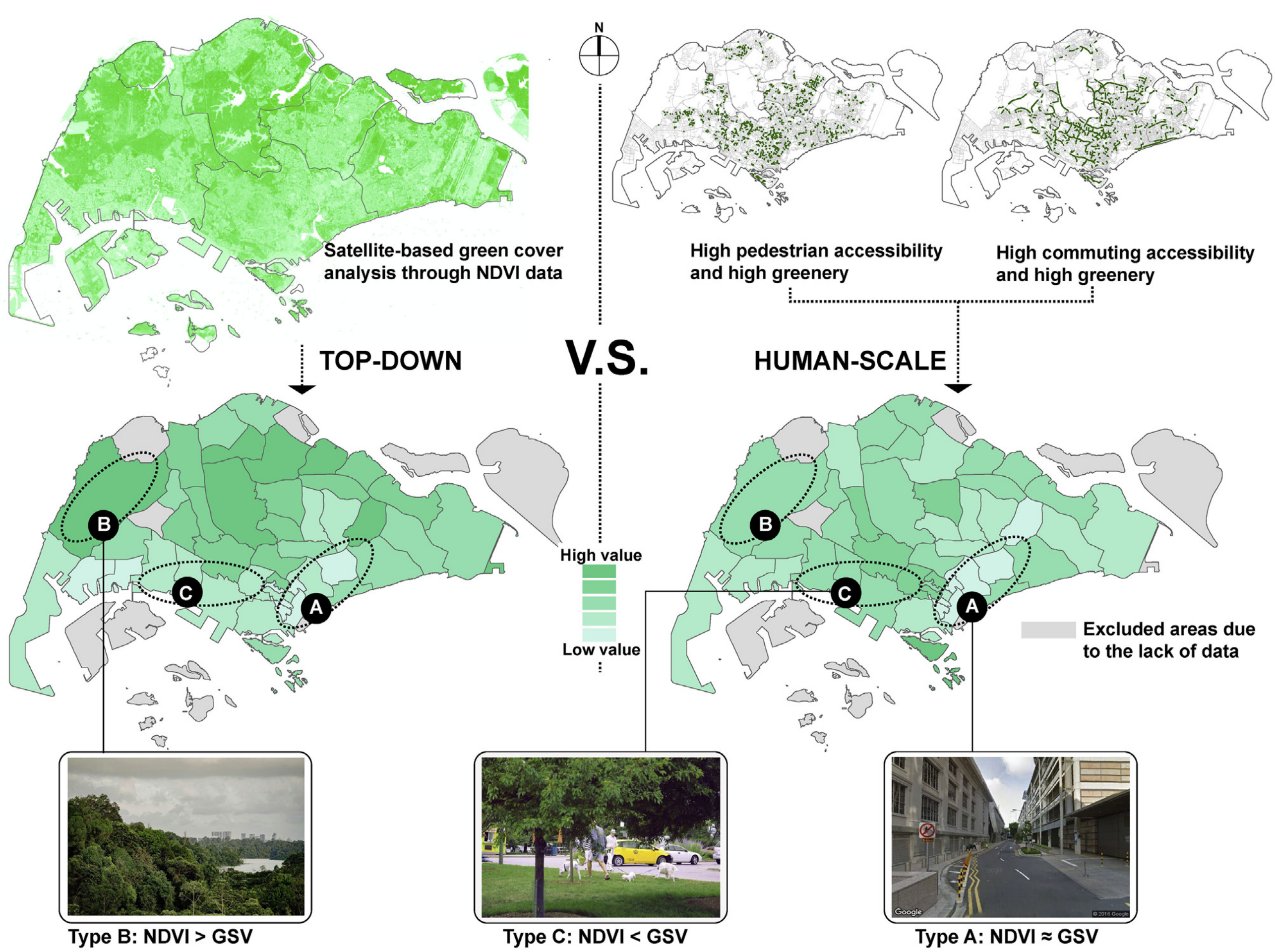


Fig. 10. Comparing two greenery measurements: top-down and human-scale viewpoints.

5.3. The co-present of human-scale measurement and city-wide analysis

Another contribution of this study is it achieves the co-present of human-scale measurement with high spatial-resolution and city-wide analysis, which is different with existed studies either focusing on high spatial-resolution visible greenery (Li et al., 2015) or large-scale green view index comparison among many cities (Long & Liu, 2017). Large-scale analyses in city-wide were hard to take into the account of human-scale data. In turn, analyses focusing on human-scale data were mainly operated at small-scale, e.g., block or neighbourhood scales, with the concern of time-costing. Now this shortcoming could be overcome with the combined application of emerging data and techniques. The practitioners of urban planning and design might not be troubled by either using human-scale, high spatial-resolution data to predict large-scale situations or replying on city-wide data missing human-oriented concerns. The initial exploration in this study indicates that a big but clear picture could be presented with the transition into a new science of cities integrating scientific thinking, computer techniques with human-oriented concerns (Batty, 2012; Townsend, 2015). More detailed explorations into the potential of new data and its implementation into planning and design practices can pave the way towards becoming “common practice” in human-centred design.

6. Future applicability and limitations

This human-scale approach integrating GSV data and machine learning techniques would help to highlight areas where planning authorities may consider increase street greenery. Local planning authorities could then review these suggestions with many other considerations together, e.g., availability of lands, traffic flow density, transportation regulations, and socio-economic concerns, to choose suitable places for design interventions to increase greenery. For instance, many cities require no planting at certain distance to intersections to avoid blocking drivers' and pedestrian's' views and traffic signage for safety reason. These factors mentioned above are not addressed by current analytical approach we developed. Street sections marked with high priority in this analysis are still preliminary results, which requires further analyses adding the concerns of Singapore city code and other extra factors. At present, we propose this approach as part of a decision-support analysis, providing suggestions, rather than a decision-making indicator for identifying the best places to plant vegetation automatically. Endeavours should be made in future works to further develop this analysis towards a decision-making platform in urban greenery planning.

Besides improvements in that direction, future research could consider extending the scope of analysis by collecting historical imagery from GSV, which would also allow planners to monitor changes in accessed street greenery across time. Quantified values of accessed street greenery could also be considered in investigating the effects of urban greenery on the health and well-being of city residents. A set of public goods, like relaxation, mental well-being, thus have the potential to be further analysed and better provided. Previous studies have examined the relationships between an unbalanced allocation of urban greenery with the risk of health challenges (Jiang, Chang, & Sullivan, 2014; Kuo & Sullivan, 2001), and the high spatial resolution of results provided by this technique may bring new insights to such analyses.

Despite these new research potentials, there are several limitations to the methodology described in our paper. Firstly, weather seasonality and plant leaf attrition would affect the level of visible greenery quantified at various locations. Plants in tropical cities such as Singapore generally maintain their green cover throughout the year, but such a limitation would be addressed when applying this new analytical approach to cities under different climatic conditions. Although the GSV API would not provide time stamps by specifying location parameter, it is possible to collect this information through Google Maps JavaScript API according to Li, Zhang, Li and Kuzovkina (2016)’s exploration. Further endeavours would be made in this direction to select GSV images in the same season for valid analyses. Secondly, the species of roadside trees, e.g., the height of the lowest branches, density of foliage, might affect the relationship between the new green view index measured at human-scale with results of satellite-based green cover. We are going to apply this analytical approach in many other cities located at different climate zones, e.g., London and Shanghai, to test the potential effects of tree species composition in our following studies. In addition, classifications of high, medium and low values of street accessibility in this study was set according to previous empirical observations. Standard references for the SVM and sDNA analyses are lacking. There is still some distance away from a highly rigorous method producing results that can be validated scientifically, which should be handled in future studies. Moreover, the horizontal view angle applied in this study might not be able to completely include tall canopy trees that can only be fully watched from a far distance. Thus, the current view angle might undercount potential benefits of tall canopy trees in eye-level greenery. Pursuing a convincing angle able to achieve the best representation of people’s perception of street greenery should be considered as a future research direction by applying environmental psychology studies.

Acknowledgement

We want to thank the editor and three anonymous referees for their valuable comments and guidance. We are also grateful for the financial support from National Natural Science Foundation of China (51708410, 51838002), Science and Technology Plans of Ministry of Housing and Urban-Rural Development of the People’s Republic of China, and Opening Projects of Beijing Advanced Innovation Center for Future Urban Design, Beijing University of Civil Engineering and Architecture (UDC2017010412), Shanghai Pujiang Program (17PJC107). Thanks the help from Zhaoxi Zhang in data preparation.

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