Assessing street-level urban greenery using Google Street View and a modified green view index

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ABSTRACT

We explored Google Street View (GSV) as a street-level, urban greenery assessment tool. Street-level greenery has long played a critical role in the visual quality of urban landscapes. This living landscape element can and should be assessed for the quality of visual impact with the GSV information, and the assessed street-level greenery information could be incorporated into urban landscape planning and management. Information on street-level views of urban greenery assessment, however, is rare or nonexistent. Planners and managers' ability to plan and manage urban landscapes effectively and efficiently is, therefore, limited. GSV is one tool that might provide street-level, profile views of urban landscape and greenery, yet no research on GSV for urban planning seems available in literature. We modified an existing Green View Index (GVI) formula and conducted a case study assessment of street greenery using GSV images in the area of East Village, Manhattan District, New York City. We found that GSV to be well suited for assessing street-level greenery. We suggest further that the modified GVI may be a relatively objective measurement of street-level greenery, and that GSV in combination with GVI may be well suited in guiding urban landscape planning and management.

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1. Introduction

Urban street greenery (i.e., street trees, shrubs, lawns, and other forms of vegetation) has long been recognized as critical landscape design elements in urban environments (e.g., Fernow, 1910; Schroeder and Cannon, 1983; Wolf, 2005). Street greenery provides multiple benefits to urban environments, meeting diverse and overlapping goals (Bain et al., 2012; Roy et al., 2012). Street greenery's instrumental functions (Appleyard, 1980) include carbon sequestration and oxygen production (Nowak et al., 2007), airborne pollutant absorption (Lawrence, 1995; Jim and Chen, 2008), urban heat island effect mitigation (Lafortezza et al., 2009), noise pollution abatement, and storm-water reduction (Chen et al., 2006; Miller, 1997; Onishi et al., 2010).

We know that people's viewing of street greenery is an important sensory function as well (Ulrich, 1984; Wolf, 2005). Urban street greenery makes an important contribution to the attractiveness and walkability of residential streets (Schroeder and Cannon,

1983; Wolf, 2005; Bain et al., 2012). The existence of vegetation usually increases people's esthetic rating of urban scenes (Camacho-Cervantes et al., 2014; Balram and Dragićević, 2005). People's accessibility to views of greenery seems to influence their recovery from surgery and increases restorative potential (Ulrich, 1984; Pazhouhanfar and Kamal, 2014). Street greenery also provides a welcoming environment for students and teachers, and encourages outside play (Arbogast et al., 2009). Understanding people's visualization of street greenery can help greening programs increase political support (Seymour et al., 2010; Wolch et al., 2014), which may dictate the success or failure of a greening program (Kuchelmeister and Braatz, 1993; McPherson et al., 1992).

Understanding (and explaining) the sensory functions of greenery better is constrained at least in part by the difficulty of *assessing* the visual quality of urban greenery on people. Methods for measuring people's opinions, attitudes, and perceptions of street-level profile views of urban greenery include survey, interview methods, and audits. The questionnaire survey method often evokes concerns over response bias (Downs and Stea, 1977). The audit method can be prohibitive in that requires highly skilled raters in applying specific criteria to assess or rate the visual esthetic quality (Ellaway et al., 2005; Hoenher et al., 2005; Meitner, 2004). One of

the most direct ways to conduct the subjective evaluation would be to transport raters to "real" locations and let them rate the environmental attributes (Meitner, 2004). However, the rating method to real locations is time consuming and expensive, and results are always subjective to different raters (Gupta et al., 2012). In addition, the rating method is also hard to carry out due to the difficulty in recruiting and transporting participants to real locations (Yao et al., 2012).

Objective assessment methods may be more efficient and accurate. However, there are only a few objective methods for measuring urban greenery. Remote sensing seems to be the most commonly used objective methods for measuring urban greenery (e.g., Gupta et al., 2012). This is probably due to a number of virtues (e.g., repeatability, synoptic view, and larger area coverage). From remotely sensed imagery, percentage green space, green space/built area ratio, green space density, and other measures, have been calculated for analyzing, assessing, and visualizing urban greenery (see, for example, Ruangrit and Sokhi, 2004; Faryadi and Taheri, 2009; Zhu et al., 2003).

However, the remote sensing method does have limitations. Remotely sensed data captured by sensors from above (aerial, space) do not capture the street-level, profile view of urban greenery. While green indexes derived from remotely sensed data may be good for quantifying urban greenery, they are poor at assessing profile views of urban greenery at street-level. The profile view of urban vegetation that people see on the ground—precisely the most common view people have of greenery—is different from the overhead view captured by most remote sensing methods.

This phenomenon can be illustrated. Yang et al. (2009), for example, using the Stand Visualization System developed by the USDA Forest Service, showed that two urban forests possessing the same canopy cover and leaf surface area look completely different from profile views. When viewing a green wall from above using remotely sensed data, the wall is missed. In a street-level, profile view of a green wall, however, it is acutely obvious and easily seen (see Fig. 1(a)). For another example, an overhead view from remotely sensed imagery may miss the shrubs and lawns under tree canopies in case of a multi-layer green space, as shown in Fig. 1(b). Therefore, while aerial/space remotely sensed imagery may provide useful information for measuring urban greenery, it usually fails to acquire what people actually and typically see (and respond to) at street-level on ground.

To date it has been difficult to efficiently and accurately represent and quantify of urban greenery at the street-level. Using color photographs or slides as surrogates for the natural environment has been chosen as a cost-effective method for evaluating urban greenery (Yao et al., 2012; Meitner, 2004). This method had been validated by various independent studies (Daniel and Boster, 1976; Shuttleworth, 1980; Stamps, 1990). Recently, Yang et al. (2009) used color pictures to evaluate the visibility of surrounding urban forests as representative of pedestrians' view of greenery through developing a Green View Index (GVI). These researchers used four pictures taken in four directions (north, south, east, and west) for each street intersection in their study area. These were processed to extract green areas, which were further used for computing their proposed GVI. They conducted field surveys in Berkeley, California, and combined these with photography interpretation. Results showed that their proposed GVI was effective and efficient in evaluating the visual effects of various planning and management practices on urban forests.

A drawback, however, was that the data collection and processing processes in their study were tedious and time consuming because the whole workflow (from collection of the pictures to extraction of the green areas) was conducted manually. This limited the application of the GVI proposed by them to only a very small area. In addition, people's perception to surrounding

environment is influenced by hemispherical scene (Asgarzadeh et al., 2012; Bishop, 1996). More importantly, the method proposed by Yang et al. (2009) has limitations in measuring the amount of visible greenery because only pictures in four directions were collected and used to calculate the GVI, which cannot cover the spherical view field of an observer.

To overcome these limitations, our research used Google Street View (GSV) images (which have view angles similar to those of pedestrians and open access) for assessing street-level, profile urban greenery. GSV, first introduced in 2007, is a library of video footage captured by cars driven down streets (Rundle et al., 2011). GSV creates what feels like a seamless (if pixelated) tour of city streets and it can give one the feeling of "being there." It is quite similar to what you or I see exploring a city by car, bike, or foot.

By stitching the pictures together, GSV images can create a continuous 360° image of a streetscape. In fact, the GSV image library has been proposed as an effective potential data source for urban studies (Rundle et al., 2011), such as identification of commercial entities (Zamir et al., 2011), 3D city modeling (Torii et al., 2009; Mičušík and Košecká, 2009), public open space audit (Edwards et al., 2013; Taylor et al., 2011), and neighborhood environmental audit (Charreire et al., 2014; Rundle et al., 2011; Odgers et al., 2012; Griew et al., 2013).

While we did not find any study in the literature using GSV images for urban planning or evaluation of street greenery, we decided to see whether or not the application of GSV images for assessing the human-viewed street greenery using a modified GVI would work based on the studies that suggested this might indeed be effective and efficient.

2. Study area and data

Our research was conducted in the East Village, a neighborhood in the borough of Manhattan, New York City (Fig. 2). The street map of the study area was processed and generated based on New York City Department of City Planning's LION file (MapPluto, 2009). Fig. 2 presents the road map of the study area.

3. Methodology

3.1. GSV images collection

Fig. 3 shows GSV of a site in Manhattan East Village, New York City. The street view is the same as a user sees a GSV panorama, which is presented interactively over the Web. GSV panorama is a 360° surrounding image generated from the eight original images captured by the eight horizontal cameras by stitching together in sequences (Tsai and Chang, 2013). The GSV panoramic images or panoramas have 360° horizontal coverage and 180° vertical coverage.

Each available GSV image can be requested in a HTTP URL form using the GSV Image API (Google, 2014) along with the position of the GSV car and its moving direction. By defining URL parameters sent through a standard HTTP request using the GSV Image API (Google, 2014), users can get a static GSV image in any direction and at any angle for any point where GSV is available. An example of requesting a GSV static image is shown below.

GSV URL example: http://maps.googleapis.com/maps/api/streetview?size=400x400&location=40.7225780677,%20-73.9871877804&fov=90&heading=270&pitch=10&sensor=false

Fig. 4 shows the above requested GSV static image. In this example, parameter *size* specifies the output size of the requested GSV image, *location* provides the geo-location of the GSV image (the GSV Image API will snap to the panorama photographed closest to this location), *heading* indicates the compass heading of the camera
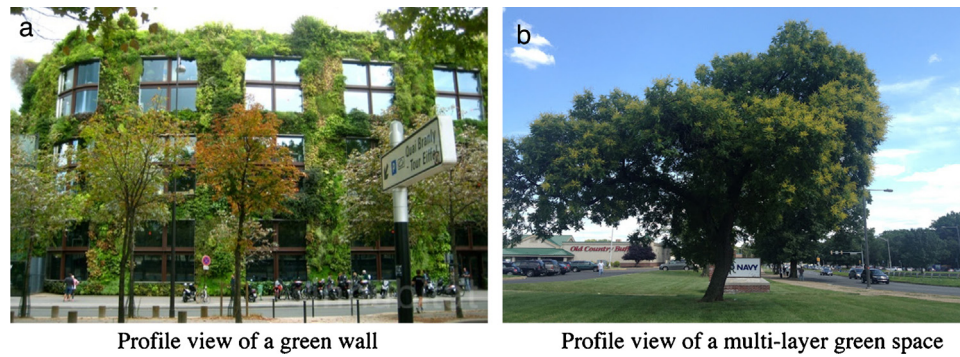
Profile view of a green wall   Profile view of a multi-layer green space

Fig. 1. Profile views of different types of green spaces: (a) profile view of a green wall and (b) profile view of a multi-layer green space.

(the heading values range from 0 to 360), *pitch* specifies the up or down angle of the camera relative to the street view vehicle, and *fov* determines the horizontal field view of the image. Previous visual assessment studies chose the horizontal field view setting between 50° and 60° (Yang et al., 2009; Walker et al., 1990). Considering the central field of vision for most people covers an angle of between 50° and 60° (Walker et al., 1990), for our research, we set the *fov* to 60°; thus, six images can cover the 360° horizontal surroundings.

To represent the urban greenery of the study area, 300 sample sites were generated randomly along the road map using ArcGIS 10.2, and the shortest distance allowed between any two randomly placed points was set to 30 m (Fig. 2). Since the total length of road is 28,448 m, so, 300 sample sites can help to guarantee that on average about every 100 m on street there is at least one GSV panorama. Therefore, the location parameters were set as a sequence of

coordinates of these 300 random points. In order to compute the green areas that a pedestrian can see, we captured the GSV images in six directions (Fig. 5(a)) and three vertical view angles (Fig. 5(b)) for each generated sample site. The heading parameters were set to 0, 60, 120, 180, 240, and 300, respectively and the pitch parameters were set to −45, 0, and 45. A Python script was developed to read the coordinates of each sample site and download the GSV images at that site by parsing GSV URL automatically.

The requested GSV images have no capture time information and with some images captured during winter. In the study area, there were 42 sites having GSV images captured during the winter. Compared with total number of chosen samples, the numbers of sites with GSV captured during winter were small. Therefore, we manually deleted those sites where images were captured during winter by visually checking the vegetation conditions in the images. Finally, 258 sample sites were used.
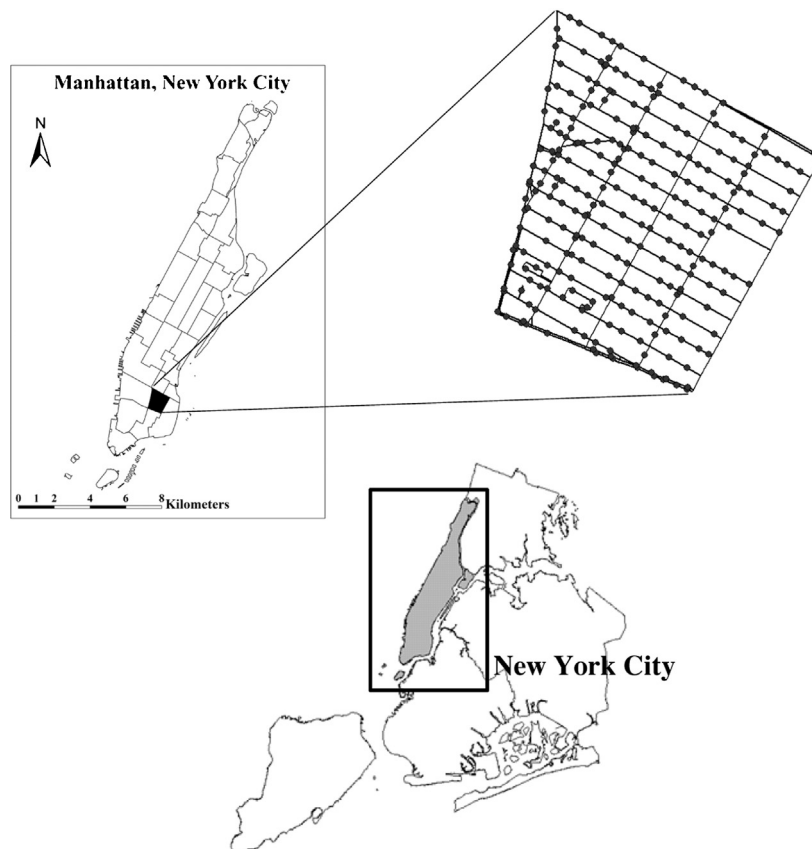

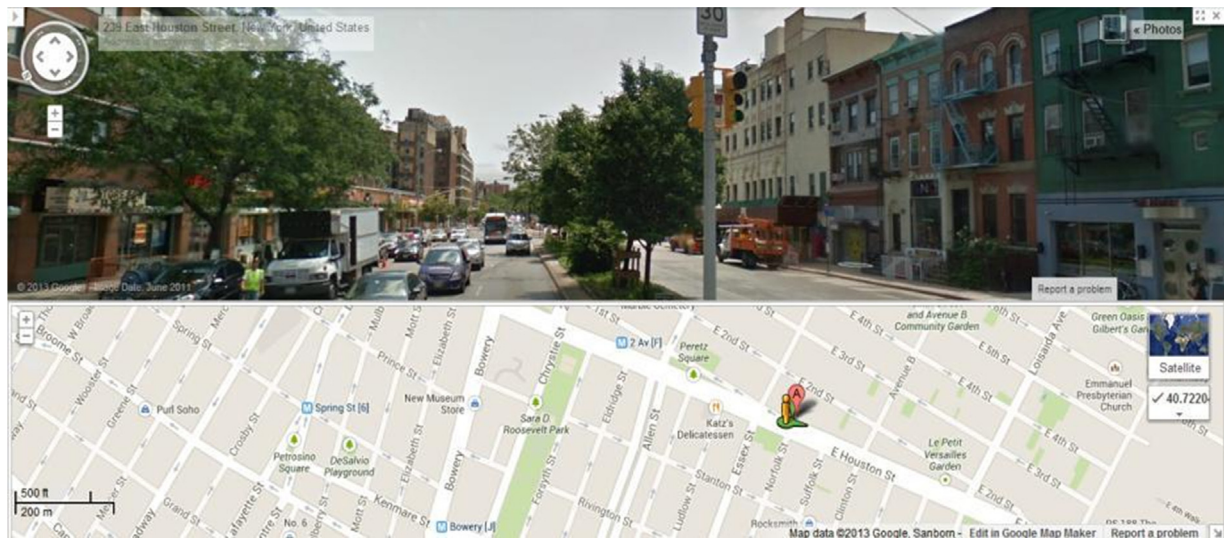**Fig. 2.** The location, road map, and randomly generated point features of the study area.

Fig. 3. GSV a site in Manhattan East Village, New York City.

3.2. Green area extraction from GSV images

Green vegetation extraction from multispectral remotely sensed imagery has been studied for three decades (Almeer, 2012). The near infrared band and red band are the most frequently used bands for detecting vegetation because vegetation shows high reflectance at near infrared band but shows high absorption at red band. However, GSV images only cover the red, green, blue bands, and the near infrared band is not available. Considering the unavailability of the near infrared band and the availability of a large number of GSV images, we developed and used a simple automatically unsupervised classification method to extract green vegetation from GSV images.

Based on the analysis of the spectral information of green vegetation on the selected GSV images, we found that the green vegetation has high reflectance at green band and relatively low reflectance at both red and blue bands. Considering this

Fig. 4. An example of the requested GSV static image.

phenomenon, therefore, a unique workflow (Fig. 6) was built for green vegetation extraction based on the natural colors of the GSV images. The workflow comprises several steps. First, two difference images *Diff 1* and *Diff 2* were generated by subtracting respectively red band and blue band from green band. Then the two difference images were multiplied to generate one *Diff* image. Considering green vegetation normally shows higher reflectance values in the green band than in the other two visible bands, the green vegetation pixels generally have positive values in the *Diff* image. Those pixels with smaller values in green band than in blue or red band show negative values in the *Diff* image. If pixel values in green band are smaller than those in both red and blue bands, the corresponding values in the *Diff* image are still positive. So an additional rule that pixel values in green band must be larger than those in red band was added. Fig. 6 shows the workflow for green vegetation extraction from the GSV images.

After the initial classification image was obtained using the above pixel-based classification method (Fig. 6), many spark points, which are called "salt and pepper" effects, usually existed in the result images (Blaschke et al., 2000). Because of the spectral variation of vegetation, single pixels were classified differently from their surrounding areas, which may further lead to spark points in the classified image. Therefore, the initially classified image was further refined to remove these spark points by using a filtering method (Jayaraman et al., 2009).

3.3. GVI calculation

Yang et al. (2009) proposed a "Green View" index to evaluate the visibility of urban forests. Their GVI was defined as the ratio of the total green area from four pictures taken at a street intersection to the total area of the four pictures, calculated using the following equation:

$$\text{Green View} = \frac{\sum_{i=1}^{4} Area_{g\_i}}{\sum_{i=1}^{4} Area_{t\_i}} \times 100\% \tag{1}$$

where $Area_{g\_i}$ is the number of green pixels in the picture taken in the ith direction among the four directions (north, east, south and west) for one intersection, and $Area_{t\_i}$ is the total pixel number of the picture taken in the ith direction.

Using the images captured in the four directions to calculate the GVI inevitably misses some surrounding vegetation, because only four pictures at the field of view of 55° cannot simulate the
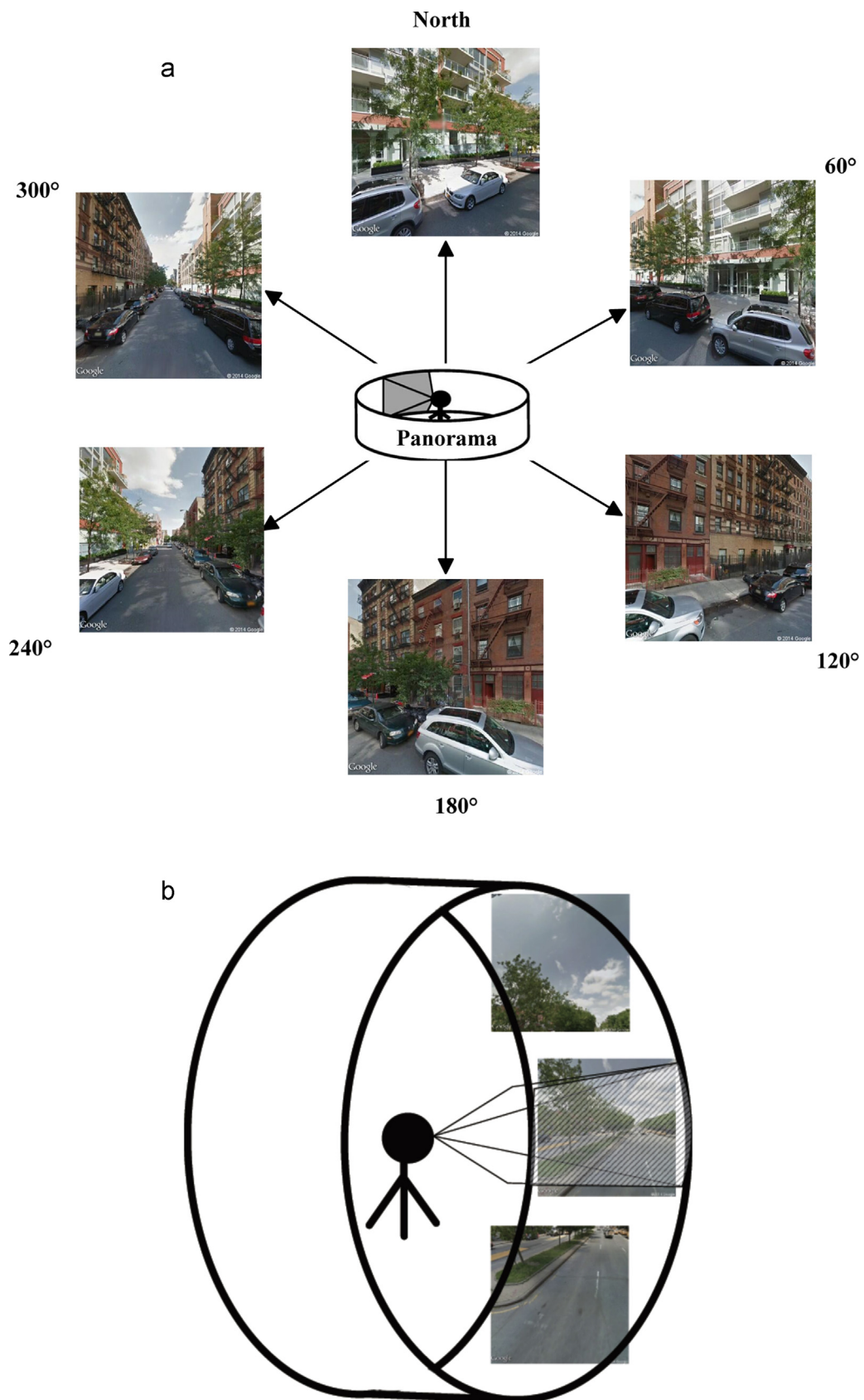
Fig. 5. GSV images captured in six directions at a sample site in the study area (a) and GSV images captured at three vertical view angles at a sample site (b).
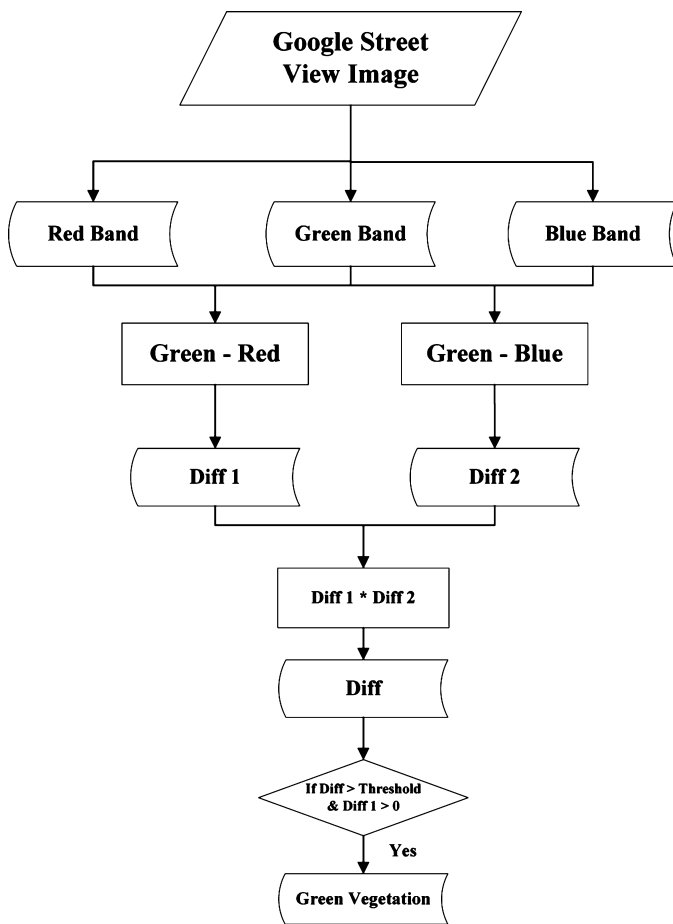
Fig. 6. The workflow for green vegetation extraction from GSV images.

whole scene pedestrians can see. We used six images covering the 360° horizontal surroundings to calculate the index for each sample site along streets. Furthermore, to effectively represent the surrounding greenness that pedestrians can see, one vertical view angle is apparently insufficient. Three different vertical view angles (Fig. 5(b)) were considered at each direction for calculating the GVI in this study. Consequently, the final modified GVI we used in this study was actually calculated using 18 GSV images for each site. The modified GVI calculation formula is written as

$$\text{Green View} = \frac{\sum_{i=1}^{6}\sum_{j=1}^{3} Area_{g\_ij}}{\sum_{i=1}^{6}\sum_{j=1}^{3} Area_{t\_ij}} \times 100\% \qquad (2)$$

where $Area_{g\_ij}$ is the number of green pixels in one of these images captured in six directions with three vertical view angles ($-45°$, $0°$, $45°$) for each sample site, and $Area_{t\_ij}$ is the total pixel number in one of the 18 GSV images.

4. Results

4.1. Green vegetation extraction results

Fig. 7 shows the green vegetation extraction results of three GSV images. Fig. 7(b) shows the initial vegetation classification results based on the workflow presented in Fig. 6. Compared with the original GSV images (Fig. 7(a)), most of the green vegetation pixels in the GSV image were correctly delineated in the pre-classified image. There, however, still exist some spark points in the pre-classified image. Those spark points are noises and should not be considered as green vegetation. Therefore, we filtered these out

using a filtering method with Fig. 7(c) shows the refined vegetation extraction results after filtering. In addition, Adobe Photoshop 7.01 software package was used to extract the green vegetation manually as references to validate the automatically unsupervised classification results. Fig. 7(d) shows the manually extracted green vegetation results. These results show that in general the algorithm can delineate the green vegetation although some artificial green features were classified as green vegetation. However, in real applications, considering the fact that artificial green features only possess a small portion of cityscapes, the misclassification results should have no much influence on the subsequent further analysis.

Accuracy assessment of the automatic classification results was conducted using 33 randomly selected GSV images. A scatter plot (Fig. 8) shows the relationship between the values of the modified GVI calculated using the proposed automatic classification method and the corresponding values calculated based on the reference data delineated manually using Photoshop. It is evident that the GVI values are distributed near the 45° line and the correlation coefficient is 0.96. These indicate that the GVI values calculated using the two different methods are quite similar. The (root mean square error) RMSE is 2.9, a small value, which means that the results calculated based on the proposed automatic classification method are of high quality.

4.2. GVI distribution

Fig. 9(a) shows the histogram distribution of the modified GVI calculated using Eq. (2) in the study area. Fig. 9(b) shows the highlighted sample sites with GVI values higher than 15. Most of the 258 sites have index values lower than 10 (Fig. 9(a)). In the chosen sample sites, only 21 sites have index values higher than 15 (Fig. 9(b)). Most of those sample sites with higher GVI values are located in the southwest and northeast of East Village. This means that the southwest and northeast of East Village may look "greener" than other places in the eyes of citizens, based on the chosen sample sites. Fig. 10 shows the sample sites in the land cover map of the study area, where solid dots represent sample sites and dot sizes denote the magnitudes of GVI values. Table 1 provides Pearson's correlation coefficients between GVI values and vegetation coverage at different buffer distances around the sample points. From Table 1 it can be seen that the GVI has a significantly positive correlation with the canopy coverage in the buffered zones. However, the correlation coefficients decrease sharply with increase of the buffer distances. Compared with the correlation between GVI and canopy coverage, the correlation between GVI and grass coverage is much weaker.

4.3. Comparison results of the modified and previous green view indices

The GVI values calculated using the previous formula (i.e., Eq. (1)) and the modified formula (i.e., Eq. (2)) are seemingly different (Fig. 11). At most locations, the values of the modified GVI are lower

Table 1
Pearson's correlation coefficients (r) between GVI and vegetation coverage variables.

Buffer distance	Pearson's correlation coefficients		N
	GVI and canopy coverage	GVI and grass coverage	
20 m	0.616[**]	0.065	258
40 m	0.449[**]	0.172[**]	
60 m	0.425[**]	0.283[**]	
80 m	0.386[**]	0.268[**]	
100 m	0.351[**]	0.216[**]	

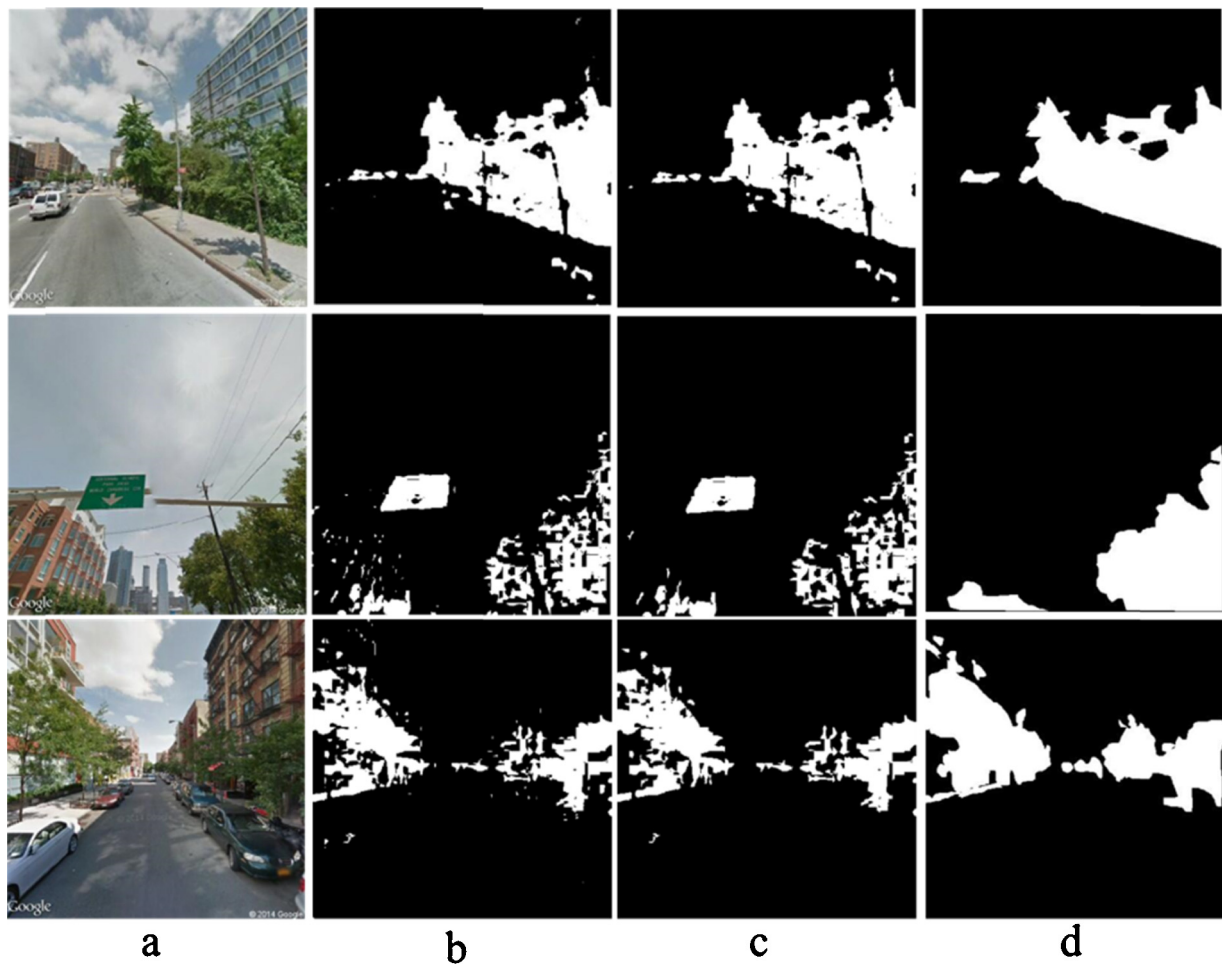[**] Correlation is significant at the 0.01 level (two-tailed).

Fig. 7. Green vegetation extraction results and references, (a) original GSV images, (b) initial classification results, (c) refined classification results, and (d) manually extracted green vegetation.
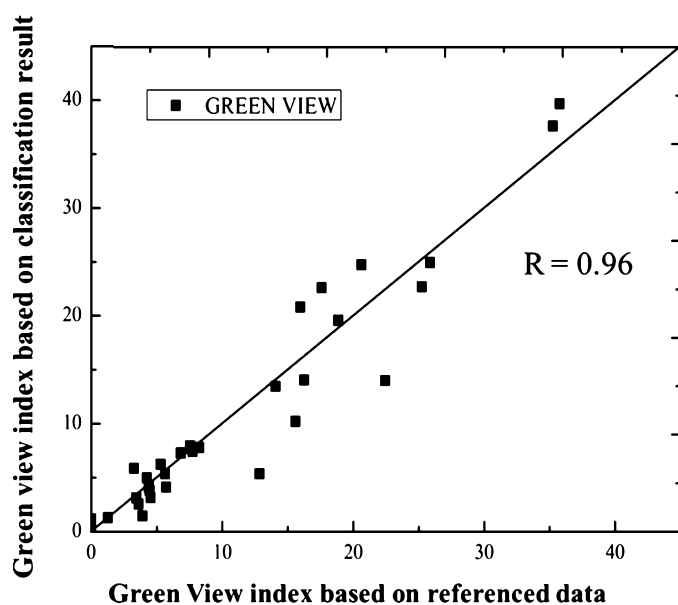

Fig. 8. A scatter plot of green view index values calculated using the suggested automatic classification method vs the reference data delineated manually using Photoshop.

than those of the previous GVI. Only at 58 sites of the total 258 sites does the modified GVI have higher values.

It is easy to understand the value differences between the previous GVI and the modified one. Except for the full coverage of 360° horizontal surroundings (i.e., the modified index considers six images in the horizontal view while the previous index considers only four), the major reason should be that the modified index takes those GSV images captured at different vertical view angles (45°, 0°, −45°) into consideration. Fig. 12 presents the GSV images at three different vertical view angles toward the north direction of one sample site, where the modified GVI value is much higher than the previous GVI. The areas of greenness in the GSV images at different vertical view angles are very different. Because the previous GVI calculated by Eq. (1) is based on images captured at the vertical angle of 0° (e.g., the middle picture in Fig. 12 in this case), the up-look and down-look views are ignored and consequently the results cannot represent the real amount of greenness in the viewing scope of a pedestrian on the ground, which includes the up-look, down-look and horizontal-look views (i.e., 45°, 0°, and −45° views). However, the modified GVI considers all of the three view images captured at different vertical view angles in each direction. In those cases that the up-look and down-look view images averagely contain more greenness than does the horizontal-look view image, the previous GVI tends to underestimate the real amount of greenness a pedestrian can perceive. However, when there are no tall trees ahead, the values of the previous GVI are relatively larger than those of the modified GVI, because the modified green view
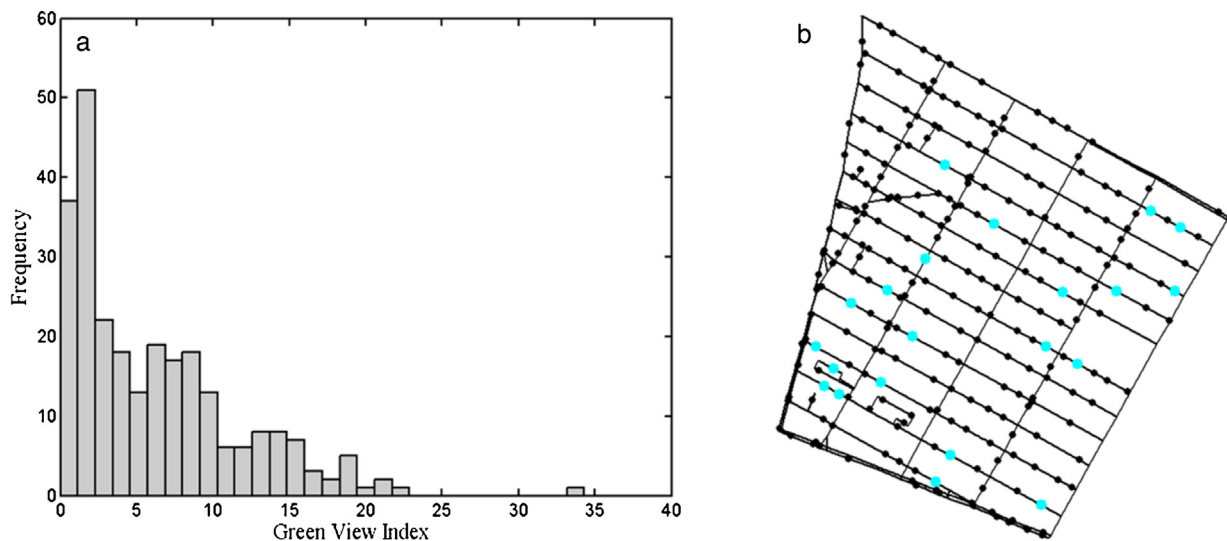
Fig. 9. Distributions of the calculated green view index: (a) Histogram of the calculated green view index values in the study area and (b) highlighted sample sites with the green view index values higher than 15.
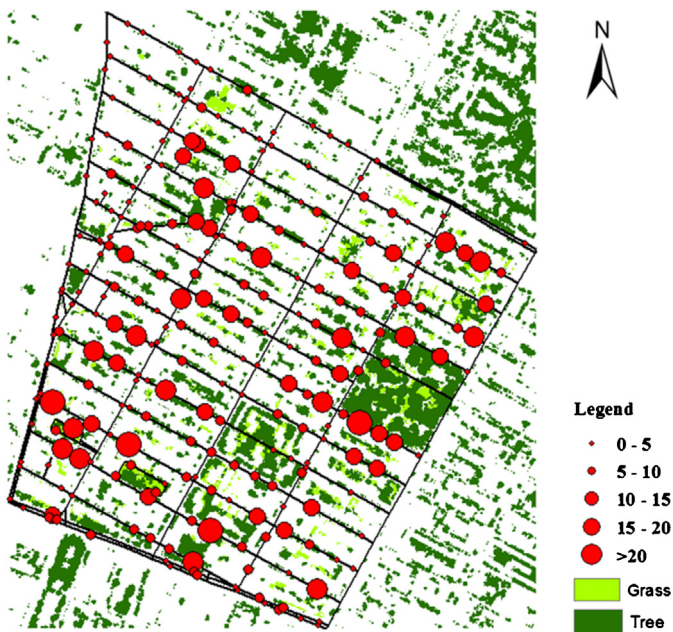

Fig. 10. GVI results calculated using the modified formula (i.e., Eq. (2)) at chosen sample sites in the study area, overlaid on the land cover map. The sizes of the solid dots represent the magnitudes of green view index values.

will cover a lot of sky and bare ground. In general, the modified GVI may describe more representatively the amount of greenness pedestrians can see with different view angles.

5. Discussion

In this study, we proposed to use GSV images to assess street greenery in an urban area. The GSV images, which were taken by Google on the ground and have view angles similar to those of pedestrians, were used for assessing abundance of street greenery. Since GSV images allow a horizontal and vertical representation, and cover the 360° horizontal surroundings and 180° vertical profile, we modified the GVI proposed by Yang et al. (2009) to make it more rational. The modified GVI should be more suitable for representing the greenery that a pedestrian can see on ground.

The spatial distribution of sample sites with higher GVI values does not match well with the spatial distribution of vegetation cover in the land cover map of the study area. This may be explained to some extent by the discrepancy between the profile view from the ground on a street (as indicated by the GVI) and the overhead view from the sky (as indicated by the land cover map). The profile view is affected by layout of buildings and vegetation, size of urban trees, vertical structure of trees, and distances between trees and viewers. However, the overhead views provided by remotely sensed imagery do not cover these factors. Correlation analysis shows that the GVI has a strong correlation with the canopy coverage close to sample sites, but the correlation is much weaker with canopy coverage beyond the buffer distance of 20 m. Some areas in the southwest of the study area have a low fraction of greenery in the land cover map, however, there do exist several sites with high green view represented by GVI. By checking the GSV images of these sites, we found that most of these sites located along alleys with big trees. In the overhead view, these trees along those alleys are not large patches of green covers, however, in the profile view, these sites look greener. On the contrary, some sites with a larger patch of greenery in the land cover map have GVI values lower than 10. The major reason should be related to the pedestrians' viewing scope on streets, which cannot cover the green spaces that are far from the streets or blocked by buildings. Therefore, a larger vegetation cover observed from the high space may not mean a higher GVI observed on a street. This indicates that it is not sufficient to measure urban greenery only based on greenery information in a vegetation cover map, which was usually derived from remotely sensed satellite imagery or air photos. The GVI may be used as additional information/data to help urban planners and others to more accurately evaluate or quantify urban greenery by considering the citizen visualized greenery at street-level.

Our GSV-based method is a feasible tool for assessing visible street greenery in cities. It is a flexible and efficient method, in which many processes can be done automatically. For example, instead of driving around to manually take pictures, this study automatically downloaded the GSV images in the study area by parsing the URL using GSV Image API. Then the downloaded GSV images were processed automatically to extract the greenery and calculate the GVI. The whole process is automatic without much human intervention. The method is fast and can be used for green space assessment for any place where GSV is available. Recently, Google announced that it had captured 20 petabytes of data for
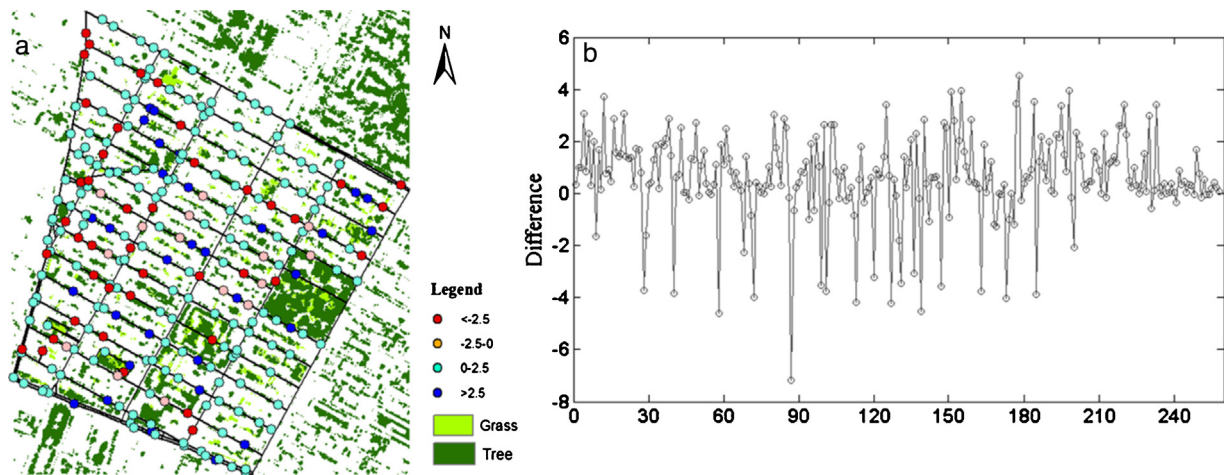
Fig. 11. Value differences between the previous green view index and the modified green view index values (value difference = the previous − the modified). (a) The spatial locations of positive and negative value differences. Red and yellow points denote negative values, and cyan and blue points denote positive values. (b) Exact value differences at different locations.

street view on June 6, 2012. The data comprise photos taken along 5 million miles of roads and cover 39 countries and about 3000 cities (Farber, 2012). It is expected that GSV images for more cities in more countries will be available in the near future.

The GVI based on GSV images can also be used in location-based services to calculate the amount of visible street greenery. It allows urban planners to identify areas within a city that can be considered greener than others. It may provide a monitoring tool for a differentiated analysis of gain or loss in urban street greenery. It may be used in the planning stage of an urban greening program to help urban planners select the locations, sizes, and types of greenery for maximum affect. It may also be used to check the visual impact of some urban forest management practices and document the visibility of urban greenery in cities. The proposed methodology for measuring GVI based on GSV images is easy to be understood and used by urban planners. Thus, it seems to be a promising tool for future urban planning and urban environmental management, rather than a simple gadget for users.

While we demonstrate here the feasibility of GSV for assessing urban green spaces and we show that GSV can deliver useful urban greenery information that was not previously understood, we believe there are several issues that need to be resolved. The first concern is the time consistency of GSV images. In our study area, not all GSV images were captured in same period, with some GSV images captured during winter, and others in summer. Google

is still continually updating the GSV imagery periodically, but users do not yet have access to the time information of GSV images through GSV Image API. In order to keep the time consistency, GSV images were checked manually in this study, and images taken in winter were excluded from further analysis. However, excluding GSV images captured in winter could bias the randomly chosen samples sites, which may have an influence on the GVI results. In addition, GSV imagery only provides a static environment of urban spaces, that is to say, the urban environment at the exact moment each photo was taken. Considering the facts that street greenery varies throughout the year and the urban environment is a dynamic surrounding, therefore, the calculated GVI values will potentially be dependent on the time of year GSV images were taken and be affected by changes in weather, or other things moving around such as cars and people. Recently Google added time stamp to the GSV, but time information is still not accessible using GSV image API. In the future, the time consistency problem could be solved once the time information of GSV images is accessible.

A second issue is that GSV imagery only covers a limited number of viewing points, which cannot capture the greenery from all places in a city. The greenery captured by GSV is limited to the greenery that can be seen from streets. This is because GSV images were gathered through custom-made cameras, which were usually mounted on top of cars.

Pitch=45, FOV = 60   Pitch=45, FOV = 60   Pitch=45, FOV = 60

Fig. 12. The GSV images of a site (Lat = 40.724937, Lon = −73.98939) with different vertical view angles (i.e., pitches): (a) pitch = 45, (b) pitch = 0 and (c) pitch = −45; fov = 60 for all the three images.

A third issue is the difficulty of accurately extracting green vegetation from GSV images. Accurately extracting green vegetation from street view images is a challenging issue due to many factors, such as existence of shadows and spectral confusion between vegetation and other manmade green features. Street view images are stored in three dimensions using RGB color space, and do not have near infrared bands, which are main indicators for vegetation. Limited spectral information makes extracting green vegetation from street view images more difficult. Although the proposed vegetation extraction method can compensate the unavailability of near infrared bands to some extent, it tends to misclassify the manmade green features (green brands, windows, shadows, etc.), which share similar spectral signatures with green vegetation in RGB bands. Future studies need to incorporate geometric information (i.e., manmade, non-vegetation features) into the vegetation classification algorithms, because these features are generally more regular and homogeneous than green vegetation.

Lastly, current GSV Image API has no capability of delivering multi-temporal GSV images for one location. GSV images cannot be used for cityscape changing detection until GSV Image API has the capability of requesting multi-temporal images. Recently, Google upgraded its GSV services so that users can travel back in time to see how specific locations have changed. This gives the light to future multi-temporal studies of cityscape. In addition, other issues that may affect the analysis, such as the arrangement of green and buildings, patterns of green distribution, topographic factors, and environmental psychological factors, are not addressed in the study.

6. Conclusions

We examined the use of GSV images for monitoring and measuring the amount of street greenery that people can see on the ground at different street sites in an urban area, with a modified GVI. We modified an existing GVI formula and conducted a case study to measure street-level views of urban greenery using GSV images for urban greenery visualization assessment in East Village, Manhattan District, New York City. Results show that GSV images are qualified for assessing street greenery and the modified GVI may be a more objective measurement of street-level greenery.

Taking advantage of the characteristics of GSV images, the modified GVI formula used 18 GSV images at different view angles and thus made the index more rational for assessing street greenery. The modified GVI formula is easier for ordinary people to understand because it measures the general visible urban greenery on the ground. Thus, the GVI may help urban planners and others to further understand the sensory functions of urban green spaces. GVI data can be regarded as additional information to reciprocally enrich the urban green information provided by remotely sensed imagery.

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