Evaluating multiple greenness measures in Tokyo

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Abstract: Urban greenness is thought to be critical factor of people's health behaviors and its outcome. The degree of area-level greenness is generally measured by greenspace ratio based on land use database, vegetation indices based on satellite imageries and street-level greenness measures. In this study, we examined the agreement between them to discuss the potential of integrating them. To test this, we measured the greenness in three ways in Setagaya ward, Tokyo.

Keywords: street-level greenness, green space ratio, vegetation index, Google Street View (GSV), Pyramid Scene Parsing Network (PSPNet)

1. Introduction

Exposure to natural environment or greenness has been found to be associated with various health outcomes, such as promoting physical activity and social contact; decreasing stress; and mitigating air pollution, noise, and heat exposure (Hartig et al., 2003; Almanza et al., 2012; James et al., 2015) People living greener environment also reported better health status than those living in less green areas (Mitchell et al., 2008).

The way to quantify greenness can often be divided into subjective and objective measures. Subjective measures of greenness (e.g. questionnaires, interviews) are able to evaluate greenness based on human perception but are prone to recall bias or social desirability bias (Sallis et al., 2009). Objective measures predominantly assess quantity of greenness based on land use datasets or satellite imagery.

Assessments based on land use datasets are predominantly calculating the percentage of a spatial area covered by green space, typically including parks and other open spaces, sometimes including agricultural land and other vegetated area (Mitchell et al., 2008; Astell-burt et al., 2013). This type of measure is believed to be able to distinguish the types of green space, thus potentially giving an indication of their quality or usability (James et al., 2015). Emerging method to evaluate greenness using satellite imagery techniques provides the opportunity to evaluate the gross greenness within area. It assesses quantity of vegetation based on the photometric characteristics of plants which can be detected from satellite imagery.

In addition to the above two measurements, street-level greenness is traditionally measured by analyzing photos taken manually in the field (Suginami city, 2018; Shinjuku city, 2017). Recently, a novel method combined online streetscape image service (typically from Google Street View (GSV)) with deep learning method provides an opportunity for obtain the area-value by realizing rapid acquisition and analyzation of street views (Li et al., 2015; Lu, 2018). Street-level greenness has been reported more related with mental and physical health since it might be more likely to reflect the greenness perceived by human (Lu et al., 2019; Villeneuve et al., 2018).

Green space ratio and over-view greenness is widely used to evaluate area-level greenness due to the

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convenience of data acquisition in a wide area. Nevertheless, as street-level greenness value is the result obtained by the evaluation of the streetscape images at one point, in practical applications, how to determine the selection of points in area and the way of integration values of these points make it relatively difficult to get an area value. However, based on previous research, we assume that combining these different types of assessments might be able to better reflect urban greenness characteristics related to health. As the preliminary examination for this assumption, we explored relationship between these assessments in this study. We believe that a sufficiently large difference can provide the basis for the integration. To date, some studies have reported the inconsistence between different types of greenness assessments. For example, Li et al. (2016) compared different types of urban greenery including street greenery, proximity to urban parks and residential yard greenery in USA; Lu et al. (2019) explored the relationship between spatial distribution of over-view greenness and street-level greenness. Whereas, little research has been done in Japan. In Japan, the street-level greenness is more likely affected by other facilities along streets rather green spaces due to the high-density urban development with less green space along streets. Moreover, some types of urban greenery in Japan like agricultural land are rarely seen in other countries.

In this study, we first developed a method to assess area street-level greenness according to the urban characteristics of Japan. And then the agreement between the three main assessments were examined to discuss the potential of integrating them. In order to do that, we compared the greenness results in Setagaya ward, across the three different measures of green space ratio based on land use database, over-view greenness based on satellite imagery, and street-level greenness by GSV and deep learning method.

2. Procedures and measures

2.1. Study area

Our research was conducted in Setagaya ward (population 903,346), which is one of Tokyo's 23 wards, with an area of 58.05 square kilometers (66.9% residential land use) (Setagaya city, 2015). The greenness values by different greenness measurements were collected and calculated on Cho-Cho-Moku level (hereinafter called zone). Cho-Cho-Moku is the sub-municipality-district used in Japan for statistical purposes (277 towns in Setagaya ward).

According to Setagaya city government (Setagaya city, 2018), Setagaya ward can be divided in to 5 districts (Fig. 1) namely Karasuyama area, Kinuta area, Tamagawa area, Kitazawa area and Setagaya area. Kitazawa area and Setagaya area are dominated by highly developed urban land with less greenery. Karasuyama area is dominated by residential area with lots of Shajirin (temple forest) in the north. Tama river and Kokubunji Cliff located in the southwest of Kinuta area and Tamagawa area provide many greenness. Unlike Kitazawa and Setagaya area, small-scale agricultural lands scatter in the residential land within the west parts of Setagaya ward.

Figure 1. Five districts in Setagaya ward

2.2. Measures and instruments

The study measured urban greenness in three different ways: green space ratio based on land use data, over-view greenness based on satellite imagery and street-level greenness by GSV.

1) Green space ratio based on land use database

The assessment of greenness based on land use database is calculated by the ratio of green space land use to the whole zone area. The land use database is extracted from the basic survey of city planning in 2016 by Tokyo Metropolitan Government. We included land use categories of parks, sport field, agricultural land and other natural environment like woodland, wildland as green space.

2) Over-view greenness based on satellite imagery

We extracted the over-view greenness data from the high-resolution land cover classification maps created by Japan Aerospace Exploration Agency (JAXA) Earth Observation Research Center (EORC). Data with a resolution of 10m × 10m cell size of a latest version was used to calculate over-view greenness. The new version of the map data reflects the latest situation over the entire Japan during the period from 2018 to 2020. It classified land into 12 categories using various indices including Normalized Difference Vegetation Index (NDVI), Green and Red Ratio Vegetation Index (GRVI), Normalized Difference Water Index (NDWI) and Grain Size Index (GSI) (JAXA EORC, 2021). The total percentage of land covered by rice paddy, crops, grassland, deciduous broad-leaved forest (DBF), deciduous needle-leaved forest (DNF), evergreen broad-leaved forest (EBF), evergreen needle-leaved forest (ENF) and Bamboo in each zone was calculated as over-view greenness.

3) Street-level greenness by GSV

The present study used GSV technique to assess street-level greenness. The GSV panoramic images have 360° horizontal and 180° vertical coverage (Tsai and Chang, 2013) and the static images in specified location, size, direction and angle can be requested using Street View Static API by defining URL parameters. To cover the 360° horizontal surroundings by statics images, in this study, we extracted four 90°-view outdoor images from one point based on the methodology previously described (Lu et al., 2019). In order to do that, the URL parameters were defined as is shown below (Table 1). Fig. 2 shows an example of requesting four GSV static images from one location.

To represent street-level greenery, we created GSV-generating points based on the midpoints of each street segment. The street map of the study area was processed and generated based on digital map by Geospatial Information Authority of Japan. In order to represent urban greenness along streets where people take daily activities, we selected the main roadways excluding highways and pedestrian pathways in parks and other open spaces. We obtained GSV images at the midpoints of road reflect the value of specific road. Street segments were extracted within each two intersections unless the segments length is less than 10 meters. Since the average length of street segments is 50.60m, selections of midpoints in these segments can also help to guarantee that on average about every 50m on street there is at least on GSV.

Totally 33,178 GSV-generating points were created in Setagaya ward with an average of about 120 points in each zone. To represent the street greenery on large number of zones in an efficient way, 10% sample points were extracted randomly from the total GSV-generating points. Table 2 shows the rules to determine the number sample points and fig.3 shows the example of sample points selection in *2-Chome Chitosedai*. Finally, 3,567 sample points were created in study area and 14,144 available images were collected from 3,536 points.

Table 1. The value of parameter in URL

Parameter	**Value**
location	{latitude, longitude}
heading	0°, 90°, 180° and 270°
Size	400 × 400
fov	90
source	outdoor

GSV URL for location: https://maps.googleapis.com/maps/api/streetview?size=400x400&location=35.64899445,139.614547&fov=90&heading=0&key={API_KEY}

Figure 2. Example of requesting GSV images from one point

Table 2. The rules to select sample points

Number of points n	n < 10	10 ≤ n < 100	n ≥ 100
Result	n	10	n × 10%

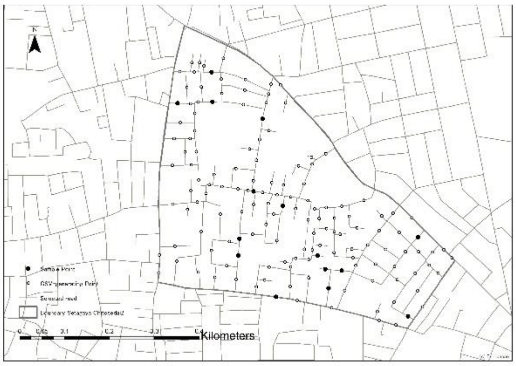

Figure 3. GSV-generating points in *2-Chome Chitosedai*

We detected the level of greenness using a deep learning model of Pyramid Scene Parsing Network (PSPNet) which is developed for scene parsing based on semantic image segmentation (Zhao et al., 2017). Semantic image segmentation is the process of classifying each pixel belonging to a particular label. This process can help to extract the pixels in a streetscape image assigned to the category labels related to vegetation. PSPNet architecture improves the reliability by taking into account the global context information by different-region based context aggregation.

In this study, we used PSPNet trained by Cityscapes Dataset. The model is published at GluonCV (https://cv.gluon.ai/). The Cityscapes Dataset is comprised of a large, diverse set of stereo video sequences recorded in streets from 50 different cities in Germany and 5,000 of these images are with fine annotations. These annotations are defined as 30 classes and 19 of them (Table 3), which is commonly seen on streets, are defined in images (Cordts et al., 2016). In this study, percentages of two segments of *Vegetation* and *Terrain* in each GSV image were calculated to determine the street-level greenery. Cityscapes Dataset defined the class of *Vegetation* as "tree hedge, all kinds of vertical vegetation". The class of *Terrain* is defined as "grass, all kinds of horizontal vegetation, soil, or sand". Note that the visible parts of mountains in images is treated as *void* according to the segment definition.

Table 3. The segment classes in Cityscapes Dataset

Group	**Classes**
Flat	*Road, Sidewalk*
Human	*Person, Rider*
Vehicle	*Car, Truck, Bus, On rails, Motorcycle, Bicycle*
Construction	*Building, Wall, Fence*
Object	*Pole, Traffic sign, Traffic Light*
Nature	*Vegetation, Terrain*
Sky	*Sky*

Note: this table is retrieved from the website of Cityscapes Dataset. More detailed information is available at the website (https://www.cityscapes-dataset.com/)

The average value of greenness ratio from four GSV images from a sample point was used to define the street-level greenness for that sample point. And then the average value for all sample points within a zone area was used to assess the street-level greenness of that zone.

3. Result

2.2. Greenness measurements

1) Green space ratio and over-view greenness

The mean green space ratio in 277 zones was 7.32% (SD = 11.23%), ranges from 0.00% to 79.80%. the mean over-view greenness is 8.36% (SD = 11.43%), ranges from 0.00% to 83.12%. The geographic distribution of green space is similar to the one of over-view greenness and is generally high in the west and low in the east (Fig.4; Fig.5). In addition, most of zones have a low green space ratio and over-view greenness level (Fig. 6).

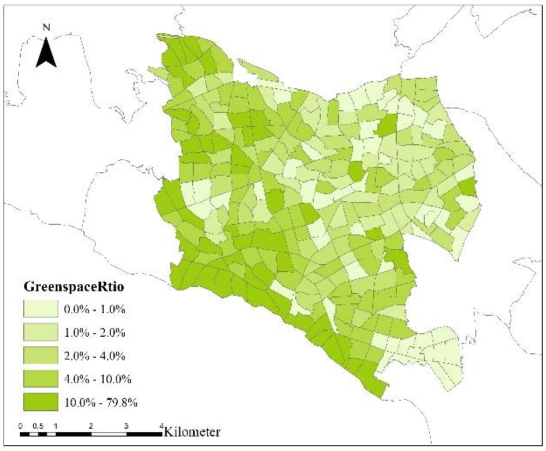

Figure 4. Green space ratio in Setagaya ward

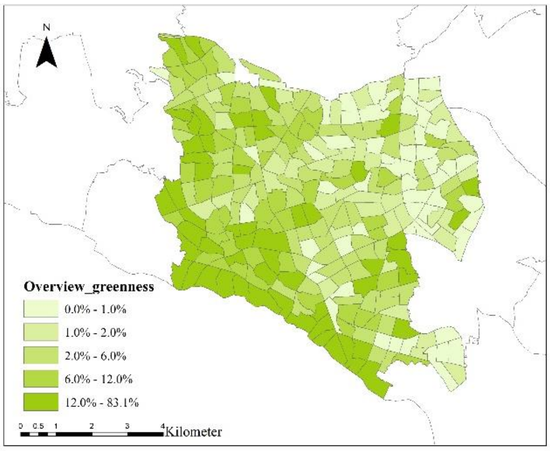

Figure 5. Over-view greenness in Setagaya ward

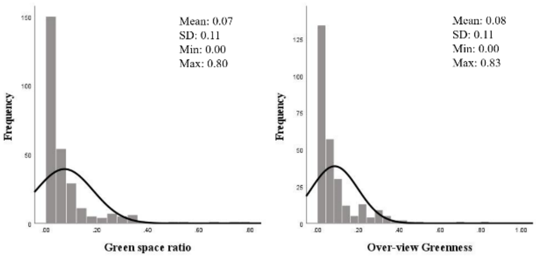

Figure 6. Histogram of green space ratio (left) and over-view greenness (right) in Setagaya ward

2) Street-level greenness based on GSV

14144 available streetscape images from 3,536 sample points were collected by Street View Static API within 277 zones. According to the privacy policy, Google Street View blurs some parts of images to protect privacy and anonymity. The blurred parts ranges from human faces, car number plates to the whole buildings or parts of streetscape depending on situations. Detecting greenery based on images have large parts blurred might fail to reflect the real level of greenery and receive a lower result. The points contained at least one image that having a large part of possible vegetation area blurred were excluded. In this study, we excluded these points manually by looking at these images data directly. As a result, 284 images from 71 points were excluded and we used 13,860 images from 3,465 points to calculate the level of greenery. Fig.7 shows the example of segmentation at one sample point and the process of calculating the ratio of pixel assigned as greenness based on these four images.

The mean street-level greenness was 13.43% (SD = 5.14%), ranges from 4.37% to 34.75%. We defined the high value of street-level greenness as 25% since it is reported to be perceived as “a lot of greenness” by human (MLIT, 2005). Fig. 8 shows the representative GSV images with different values. Generally, street-level greenness is also generally higher in west area and lower in east (Fig. 9).

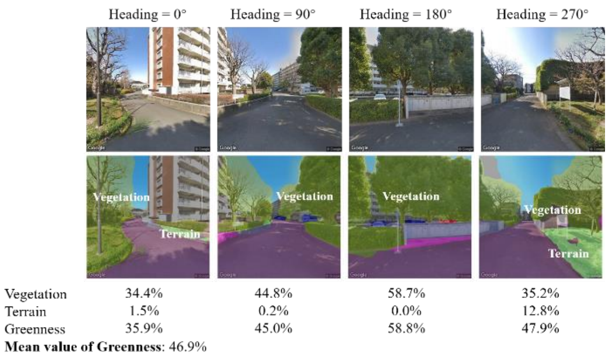

Figure 7. Examples of semantic segmentation results

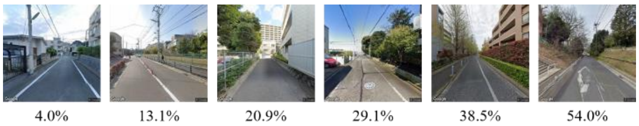

Figure 8. Representative GSV images with different values

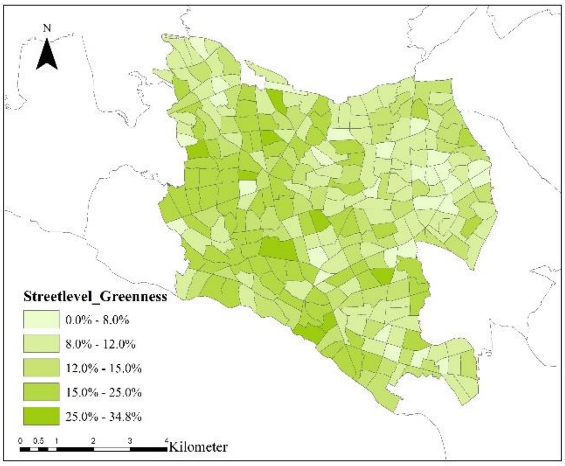

Figure 9. Street-level greenness in Setagaya ward

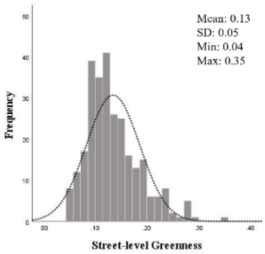

Figure 10. Histogram of street-level greenness in Setagaya ward

2.3. Correlation

The over-view greenness and green space ratio were strongly correlated (Pearson correlation r = 0.864, p < 0.01), while street-level greenness only exhibits low correlations with them (Pearson correlation r = 0.479, 0.336, p < 0.01 with over-view greenness and green space ratio respectively).

2.4 Case study

1) Scatter Plot

The scatter plot of the log street-level greenness value and the log green space ratio (Fig. 11) indicates that many of these scattered points are distributed far away from 45° line. The scatter plot indicates the inconsistence between these two measures. And then, some areas were selected as case study for distinct reasons causing the substantial differences.

Table 4. Pearson's correlation coefficient (r) between three greenness indices

Greenness index	1	2	3
1. Green space ratio	-		
2. Over-view greenness	.864**	-	
3. Street-level greenness	.336**	.479**	-

** $p < 0.01$

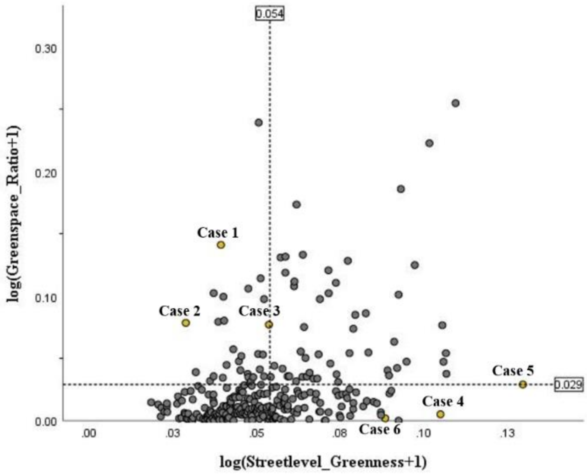

Figure 11. The scatter plot of the log street-level greenness values and the log green space ratio

2) Case study

The greenness values of six zones we selected for case study are displayed in Table 5. The locations of the case study zones were reported in Fig.12.

Three zones were listed with high greenspace ratio but relatively low street-level greenness values for different reasons (Fig. 13). *1-Chome Kyuden* (case1) located in Karasuyama area. Based on the land use data, we found that the high value of green space ratio (38.38%) in this area is due to the large area of park land (*the Dai-*

Table 5. Greenness values of six zones for case study

	Zone name	GSR	OVG	SLG
1	1-Chome Kyuden	38.38%	39.65%	9.50%
2	4-Chome Kitakarasuyama	19.80%	12.66%	6.88%
3	3-Chome Unane	19.40%	9.34%	13.17%
4	2-Chome Kamikitazawa	1.18%	45.21%	27.33%
5	3-Chome Kaminoge	6.91%	21.20%	34.75%
6	7-Chome Fukasawa	0.43%	4.10%	22.59%

GSR: Green space ratio; OVG: Over-view greenness; SLG: Street-level greenness

Figure 12. Locations of case study zones

Ichi Seimei Ground) in the east. By overlaying the land use map with the street-level greenness point data, we identified that these points were located in residential area with less greenness thus received relatively low street-level greenness (9.50%). *4-Chome Kitakarasuyama* (case2) is located in the northern part of Karasuyama area, characterized by lots of temples. Although the large number of cemeteries increased the ratio of green space (19.80%) in this area, they failed to achieve a high street-level greenness (6.88%) like other green space. *3-Chome Unane* (case 3) is located in the farmland preservation area of the Kinuta area. Agricultural land scattered in the residential area increased the overall green space ratio (19.40%). However, low vegetation in these agricultural lands fail to provide high street-level greenness (13.17%) even though these sample points were located near these natural lands.

We also listed three areas with low greenspace ratio but high street-level greenness caused by different reasons (Fig. 13). *2-Chome Kamikitazawa* (case 4) is also located in the Karasuyama area and is dominated by public facilities. We observed that the low green space ratio (1.18%) but relatively high over-view greenness (45.21%) and street-level greenness (27.33%) in this area. This is due to the large quantity of green space in the medical land (*Tokyo Metropolitan Matsuzawa Hospital*). *3-Chome Kaminoge* (case 5) is located in Tamagawa area. The high street-level greenness (34.75%) is mostly provided by the detached house with large private garden rather than the forest (*Inari Maru Ancient Tomb*). *7-Chome Fukasawa* (case 6) is located in Tamagawa area. As one of the oldest residential development areas, there are little green space (Green space ratio: 0.43%) but large number of trees and visible private garden along the streets (Street-level greenness: 22.59%) in this area.

4. Conclusion

The results of this study indicate that there is a low agreement between street-level greenness and other two measurements. Notably, these correlations are relatively weak compared with the results from previous research (from 0.62 to 0.77) in HongKong (Lu et al., 2019). It is probably due to the urban characteristics of Japan, such as large proportion of detached house with private garden, and agricultural land scattered within residential area.

In line with the previous research (Leslie et al., 2010), we found that these three measures assess different aspects of greenness characteristics thus causing the inconsistence. The inconsistence between green space ratio and street-level greenness mainly caused by the mischaracterizing the greenness by land use dataset. Some categories of land use tend to be full of greenness

Figure 13. The land use map and representative streetscape images of case study area

(like medical facilities and residential land) are not included in green space, while some types of green space are prone to offer lower greenness (like ceremonies, agricultural land) than expected. Even though the over-view greenness based on satellite imageries can reflect the real vegetation situation and receive a higher correlation with street-level greenness, the still weak correlation (0.479) might due to the coarse data source, which is 10m × 10m in this study. Greenness elements like small-scale private garden and street trees might fail to be detected in the data with a resolution of 10m × 10m.

The way we calculated street-level greenness based on GSV and deep learning provides the opportunity to obtain an area value efficiently. The inconsistence with other two measurements indicates that this novel measurement might be able to measure a new aspect of greenness characteristics, which is potentially closer to what people perceived. However, only applying one type of this measurement also tend to overlook some important aspects, such as the amount of green space which is available for physical activity or the quantity of gross vegetation within area.

Based on these results, we suggest that combing the traditional measures with street-level greenness might be able to measure urban green characteristics more comprehensively.

5. Future work

Future work will be processed to develop new assessment combining these single indices in some way (such as setting the weights of index based on land characteristics). The focus of our future work will be on the impact of the new assessment on various health outcomes like promoting physical activity, increasing social interactions and improving mental health.

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