Urban Forestry & Urban Greening 18 (2016) 163–172

Contents lists available at ScienceDirect

Urban Forestry & Urban Greening

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

Environmental inequities in terms of different types of urban greenery in Hartford, Connecticut

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ARTICLE INFO

Article history:
Received 9 December 2015
Received in revised form 26 April 2016
Accepted 8 June 2016
Available online 9 June 2016

Keywords:
Environmental inequity
Private yard vegetation
Street greenery
Urban parks

ABSTRACT

Urban greenery has long been recognized as an important component of urban ecosystem and provides many benefits to urban residents. However, different types of urban greenery provide different kinds of natural experiences to people. In this study, green metrics calculated based on multisource spatial datasets were used to quantify the spatial distribution of different types of urban greenery in Hartford, Connecticut. Geo-tagged Google Street View images, which capture the profile view of cityscape, were used to quantify street greenery by considering the time information. Land cover map and urban parks map were used to measure residential yard greenery and proximity to urban parks, respectively. We analyzed the associations of the calculated green metrics with socio-economic variables derived from census data. Statistical results show that: (1) people with higher income tend to live in neighborhoods with more street greenery; (2) census block groups with a higher proportion of owner-occupied units tend to have more yard vegetation and yard tree/shrub coverage; (3) Hispanics tend to live in block groups that have less yard vegetation but African Americans mostly live in block groups with more yard greenery; and (4) there are no significant environmental disparities among racial/ethnic groups in terms of proximity to urban parks. In general, this study provides an insight into the environments of urban residents in terms of urban greenery, and a valuable reference data for urban planning.

1. Introduction

Urban greenery, which includes urban parks, woodland, street and square trees, lawns and other kinds of vegetation (Konijnendijk et al., 2006), has long been recognized for its importance in the urban environment (Li et al., 2015a). Urban greenery provides many economic, environmental, social, and health benefits to residents (Chen et al., 2006; Jim and Chen, 2008; Onishi et al., 2010; Gidlow et al., 2012; van Dillen et al., 2012; Wendel et al., 2011). The spatial distribution of urban greenery is thus regarded as an important environmental amenity (Nichol and Wong, 2005; Dwivedi et al., 2009; Seymour et al., 2010).

Previous studies have reported environmental inequities in terms of urban greenery in North American cities (Heynen et al., 2006; Boone et al., 2009; Zhou and Kim, 2013; Dai, 2011; Pham et al., 2012; Landry and Chakraborty, 2009; Li et al., 2015b). Heynen et al. (2006) found that the degree of canopy coverage varies among the neighborhoods of different racial/ethnic groups in Milwaukee, Wisconsin. Compared with non-Hispanic Whites, Hispanics tend to live in places with less canopy coverage. Boone et al. (2009) investigated the residents' proximity to urban parks in Baltimore, Maryland, and found that Whites have access to a larger acreage of parks than other residents, but a higher proportion of African American residents have access to parks within walking distance. Zhou and Kim (2013) developed an accessibility index based on Google Maps application programming interface to evaluate the disparities in canopy cover and accessibility to parks in six cities in Illinois. Their results showed no significant disparities in terms of access to parks, but racial/ethnic minorities tend to have less tree canopy cover in their neighborhoods. Li et al. (2015b) developed a novel Google Street View–based method to study the distribution of street greenery in Hartford, Connecticut. Unlike green metrics derived from remotely sensed data, the Google Street View–based method quantifies how much street greenery people can see and feel on the ground. Their results showed that people with higher incomes tend to live in neighborhoods with more street greenery (Li et al., 2015b).

Different types of urban greenery play various roles in providing benefits to urban residents. Therefore, it may not be suitable to use the overall green vegetation cover numbers to represent the distribution of the environmental amenities. In addition, different types of greenery are maintained and managed in very different ways,

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http://dx.doi.org/10.1016/j.ufug.2016.06.002
1618-8667/

which may influence the spatial distribution of urban greenery. For example, street greenery and urban parks are publicly financed and managed. They provide benefits to the public. However, the vegetation in a private yard provides more benefits to the property owner than to others and it is maintained by the private property owner. Therefore, different types of urban greenery should be considered differently in studying the environmental inequities. However, a few studies have explored the uneven distribution of different types of urban greenery (Heynen et al., 2006; Pham et al., 2012; Shanahan et al., 2014). In this study, we categorized the greenery of Hartford, Connecticut, into four major types: street greenery, private yard total vegetation, private yard trees/shrubs, and urban parks. Four green metrics were calculated based on the Google Street View images, the land cover map, and the urban park map to indicate the spatial distribution of street greenery, yard total vegetation, yard trees/shrubs, and proximity to urban parks. Statistical analyses were then conducted to investigate the associations between those green metrics and urban residents' socio-economic status.

2. Literature review

2.1. Benefits of different types of urban greenery

Different types of urban greenery provide different kinds of natural experiences to human being (Shanahan et al., 2014). Private yard vegetation is usually managed by private owners and it is immediately accessible for private owners (Lachowycz and Jones, 2012; Li et al., 2014). The urban greenery in public parkland and Right-of-Way are maintained in very different ways compared with private backyard vegetation, and this may further influence people's nature experiences (Shanahan et al., 2014). View of greenery through windows is helpful in increasing restorative potentials and improving psychological wellbeing (Ulrich, 1984; Pazhouhanfar and Kamal, 2014; Kaplan, 2001). Residential tree canopy cover reduces cooling energy use in summer (Akbari et al., 2001). As a kind of public facilities, urban parks are also important for the quality of life in densely populated cities. Urban parks provide public places for recreations, physical exercises, interactions with nature, and social activities that can promote both personal health and social cohesion within communities (Zhou and Kim, 2013; Maas et al., 2006; Ellaway et al., 2005; Dai, 2011; Wolch et al., 2011). Street greenery on the public Right-of-Way makes an important contribution to the attractiveness and walkability of residential streets (Schroeder and Cannon, 1983; Wolf, 2005; Bain et al., 2012; Lachowycz and Jones, 2012). Street greenery also provides a range of health benefits by promoting outdoor exercises (Wolch et al., 2005; Takano et al., 2002) and beautifying neighborhoods while mitigating the visual intrusion of traffics (Li et al., 2015a). Planting street trees may provide more benefits to urban residents than planting trees in parks and private yards (Kardan et al., 2015).

2.2. Green metrics for urban greenery

There are many developed green metrics for different types of urban greenery in literature of environmental inequity studies. Vegetation/canopy coverage and the visiting distance to a green space are the two most widely used indices to quantify the spatial distribution of urban greenery.

Vegetation/canopy coverage, which literally represents the percentage of land covered by vegetation or canopy, has been widely used to study the yard vegetation (Pham et al., 2012; Shanahan et al., 2014; Troy et al., 2007; Grove et al., 2006). Remotely sensed data is the major data source for vegetation/canopy cover mapping. By overlapping vegetation/canopy cover maps with GIS boundary layers (parcels or blocks), the vegetation/canopy coverage can be then calculated and aggregated at different geographic units and compared with census data. There are a few studies about environmental inequities in terms of street greenery (Landry and Chakraborty, 2009; Li et al., 2015b). The spatial distribution of street greenery can be indicated by canopy cover. Landry and Chakraborty (2009) studied the street tree coverage on public Right-of-Ways based on a land cover map derived from high-resolution remotely sensed imagery. While high-resolution remotely sensed imagery provides a good data source for delineating green spaces at a fine level, it may not be very suitable for measuring the street greenery. The aesthetic benefits provided by street greenery can be greatly influenced by the amount of greenery that people can see or feel on the ground (Li et al., 2015a). In fact, there is little agreement between remote sensing based green metrics and human perceived greenness (Leslie et al., 2010). Recently, Li et al. (2015a) developed a novel Google Street View–based method to study the distribution of street greenery. Unlike green metrics derived from remotely sensed data, the Google Street View–based method quantifies how much street greenery people can see or feel on the ground, which could better represent the distribution of street greenery. However, the time information of the Google Street View images was not considered in their study.

Several methods have been developed for measuring people's proximity to urban parks (Dai, 2011; Zhou and Kim, 2013; Maroko et al., 2009; Boone et al., 2009; Wolch et al., 2005). The visiting distance method is one of the most widely used methods to measure human proximity to urban parks (Boone et al., 2009; Zhou and Kim, 2013). The visiting distance can be defined as walk distance (Zhou and Kim, 2013; Leslie et al., 2010; Wolch et al., 2005), travel distance by roads or other networks (Dai, 2011), or Euclidean distance (Kessel et al., 2009). In literature, the centroids of geographic units or randomly created points within those units were usually used to represent the points of origin (Kessel et al., 2009; Zhou and Kim, 2013). However, it is difficult to define the destination points, because parks often have multiple entry points or destinations (Boone et al., 2009). For a small park, it is reasonable to use the centroid of the park to indicate the destination point; however, for a large park, this designation will be less accurate, because any point along the boundary can serve as the destination (Boone et al., 2009). It seems using buffer analysis of the urban parks is a simple and efficient way to measure accessibility of parks at different geographic units (Boone et al., 2009; Wolch et al., 2005). By overlapping buffer zones of urban parks with census data, different metrics can be defined to indicate accessibility to urban parks (Wolch et al., 2005; Boone et al., 2009).

3. Study area and data sources

Hartford is the capital city of Connecticut, USA (Fig. 1), with a population of approximate 125,000. The Hispanics and African Americans are the two largest racial/ethnic groups in the city, which account for 43% and 38% of the total population, respectively. Recent satellite imagery–based analysis showed that more than 2870 acres of the city are covered by tree canopy, representing 26% of all lands in the city. A previous study reported the environmental inequity in terms of street greenery in Hartford, CT (Li et al., 2015b). Recently, Hartford began to implement the U.S. Environmental Protection Agency's (EPA) Greening America's Capitals program, which incorporates innovative green building and green infrastructure strategies to develop more environmental friendly neighborhoods.

Block group is the smallest area unit defined by the US Census Bureau in Hartford, therefore, block group was used as the geographic unit for measuring the spatial distribution of neighborhood greenery in this study. Among the 96 block groups in Hartford, nine

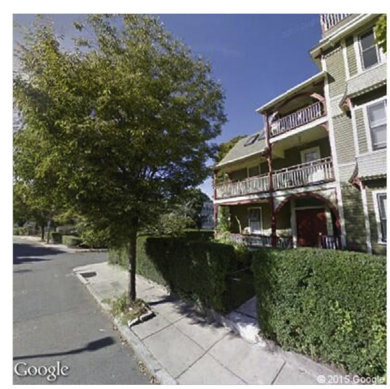
Fig. 1. The location of Hartford, Connecticut, USA.

were not included in this study because they are mainly located in the downtown industrial areas, the areas around the airport, and other primarily non-residential regions.

The data sources used for quantifying different types of urban greenery include Google Street View images, vegetation cover maps derived from satellite imagery, a residential parcel map, and an urban park map. Google Street View (GSV) images were used to quantify the street greenery, while the vegetation cover map, the residential parcel map, and the urban park map were used to measure the yard total vegetation coverage, the yard tree/shrub coverage, and the proximity to urban parks.

4. Methodology

This study relies on a two-step methodology. The first step was to calculate four green metrics to represent the distribution of street greenery, yard vegetation coverage, yard tree/shrub coverage, and proximity to urban parks. The second step was to perform statistical analyses for studying the associations between the calculated green metrics and the chosen social variables.



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Pano ID: https://maps.googleapis.com/maps/api/streetview?size=400x400&pano=Dk2NtD9gSqSQwfGlO-q7Ng&fov=90&heading=235&pitch=10

Fig. 2. A GSV static image and its corresponding Uniform Resource Locators.

4.1. Green metrics calculation

4.1.1. Street greenery

In this study, we used a Google Street View (GSV) based modified green view index to quantify the street greenery. This index measures how much street greenery people can see or feel on the ground; it is the average percentage of green vegetation of 18 GSV images captured at 18 different directions for a street location (Li et al., 2015a).

The GSV images were downloaded using the Google Street View static image API (Google, 2014). An example of a requested GSV static image and its corresponding Uniform Resource Locators (URLs) is shown in Fig. 2. By specifying different parameters in the Google Street View static image API, users can download GSV images of different *location*, *heading* angles, and *pitch* angles. Unfortunately, the Google Street View static image API is not able to obtain the time information of a GSV image by specifying the *location* parameter. However, Google has provided the time stamps for all GSV images, and the time information for the GSV images is accessible using the Google Maps JavaScript API (Google, 2015). Therefore, in this study we designed an indirect way to collect the GSV images and get their time information simultaneously. Firstly, the time information and GSV panorama IDs were accessed using the Google Maps JavaScript API by specifying the coordinate parameters (Google, 2015). The time information and GSV panorama IDs were then saved as a local text file (see the pseudo codes in Appendix A). Then, the GSV images were requested using the *pano* parameter instead of using the *location* parameter in the Google

Street View static image API based on the meta-data stored in the local text file. The *pano* parameter represents the unique panorama ID and it is usually more stable than the *location* parameter (Google, 2014). Fig. 2 shows the same requested static GSV image using both the *location* and *pano* parameters respectively.

Three thousand sample sites were generated along the residential streets using the *CreateRandomPoints* tool in ArcGIS 10.2. The minimum distance allowed between any two randomly placed points was set to 100 m to get evenly distributed sample sites. Based on the aforementioned method, we used the coordinates of those sample sites as input and saved the panorama IDs and time information of these panoramas into JavaScript arrays, which were further saved in a local text file. GSV images with time information were then collected for all sample sites based on the panorama IDs saved in the local text file.

The green vegetation classification was performed using an object-based image analysis method proposed by Li et al. (2015b). In order to eliminate the misclassification of green vegetation and other urban features, we combined the *Diff*-based rule (Li et al., 2015b) with the *ExG*-based rule (Li et al., 2015c) for the green vegetation classification. However, the proposed image classification method is not suitable for the GSV images captured in non-green seasons. In autumn and winter, some street trees appear as yellow or red or even leafless, and it is thus hard to classify the vegetation. Therefore, we deleted the sample sites having GSV images captured in non-green seasons based on the time information of those GSV images.

The modified green view index for each sample site was calculated using Formula (1) according to Li et al. (2015a):

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

where $Area_{g\_ij}$ is the number of vegetation pixels in one of the GSV images captured in six horizontal 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.

In order to represent the green view index at block group level, the median green view index values were summarized by block groups. Since the sample sites were created along streets, there were some sites located on the borders of some block groups. In order to eliminate the neighborhood effect, sites on the borders of block groups were not counted.

4.1.2. Private yard vegetation

The vegetation in private residential yards provides benefits directly to urban residents. In this study, we calculated the percentage of total vegetation coverage (*PerVeg*) and the percentage of tree/shrub coverage (*PerTree*) in residential property parcels for all chosen block groups to represent the distribution of private yard greenery. These two green metrics – *PerVeg* and *PerTree* were first calculated for each residential parcel by intersecting the residential parcel map and the land cover map using the following formulas,

$$PerVeg = \frac{Area_{veg}}{Area_{parcel}} \times 100\% \qquad (2)$$

$$PerTree = \frac{Area_{tree/shrub}}{Area_{parcel}} \times 100\% \qquad (3)$$

where $Area_{veg}$ is the area of total vegetation coverage in a residential parcel, $Area_{tree/shrub}$ is the area of tree/shrub coverage in a residential parcel, and $Area_{parcel}$ is the total area of the residential parcel. In order to make the yard vegetation maps comparable to census data, these parcel-level green metrics were then aggregated at block group level using their median values.

The land cover map of Hartford (http://gis.w3.uvm.edu/utc/) was derived from 1-m resolution remotely sensed data of 2008. The land cover classification was performed by Spatial Analysis Laboratory (SAL) at the University of Vermont, in consultation with the USDA Forest Service's Northern Research Station. The land cover map in Hartford includes seven land use types: tree canopy, grassland, barren land, water, building, road, and others (Fig. 3). In this study, the residential parcel map was delineated manually based on a parcel map and the land cover map by checking Google Map and Google Street View. Fig. 3 shows the satellite image, the land cover map, and the residential parcel map of a small portion of the study area.

4.1.3. Proximity to urban parks

Parks serve as fixed green hubs in cities (Zhou and Kim, 2013) and offer a range of social, environmental, and health benefits to urban residents. Based on previous studies, we used a buffer analysis method to measure park's accessibility in this study. We used a 400-m buffer zone around each park, a distance most people are willing to walk to an urban park (Boone et al., 2009; Lindsey et al., 2001; Wolch et al., 2005; Leslie et al., 2010). We calculated the proportion of residential parcels in the buffer zones for all block groups as the indicator of proximity to urban parks at the block group level. Since the boundaries of different block groups were not considered in calculating the buffer zones of urban parks, the results were not influenced by the boundary effect. If the centroid of a residential parcel is in the buffer zone of an urban park, then this parcel will be treated as in the service area of the park.

The urban park map in Hartford was obtained from the Hartford Open Data website (https://data.hartford.gov/). We deleted small cemeteries, monuments, and other small green spaces that should not be defined as parks by checking Google Map and Google Street View, since they are too small to offer significant benefits to residents.

4.2. Social variable selection

In order to investigate environmental inequities in terms of urban greenery, we compared the four green metrics with some social variables. Based on previous environmental inequity studies (Li et al., 2015b; Pham et al., 2012; Landry and Chakraborty, 2009; Huang et al., 2011), seven socio-economic variables at the block group level were selected to represent the socio-economic status of residents. These include an economic variable (per capita income); two education variables (proportion of people without high school degree and proportion of people with bachelor's or higher degrees); a lifestyle variable (proportion of owner-occupied units); and three race/ethnicity variables (proportion of non-Hispanic Whites, proportion of Hispanics, and proportion of African Americans). In addition, two age variables (proportion of people under 18 years of age and proportion of people older than 65 years of age) and a built environment variable (median building age) were also considered in this study. In order to keep time consistency with the previously calculated green metrics, all of the aforementioned variables were derived from the 2008–2012 American Community Survey (ACS) 5-year data at the block group level.

4.3. Statistical analyses

In order to determine whether there are environmental inequities in terms of urban greenery across different racial/ethnic and economic groups in Hartford, we first checked the correlations between the chosen social variables and the four green metrics.

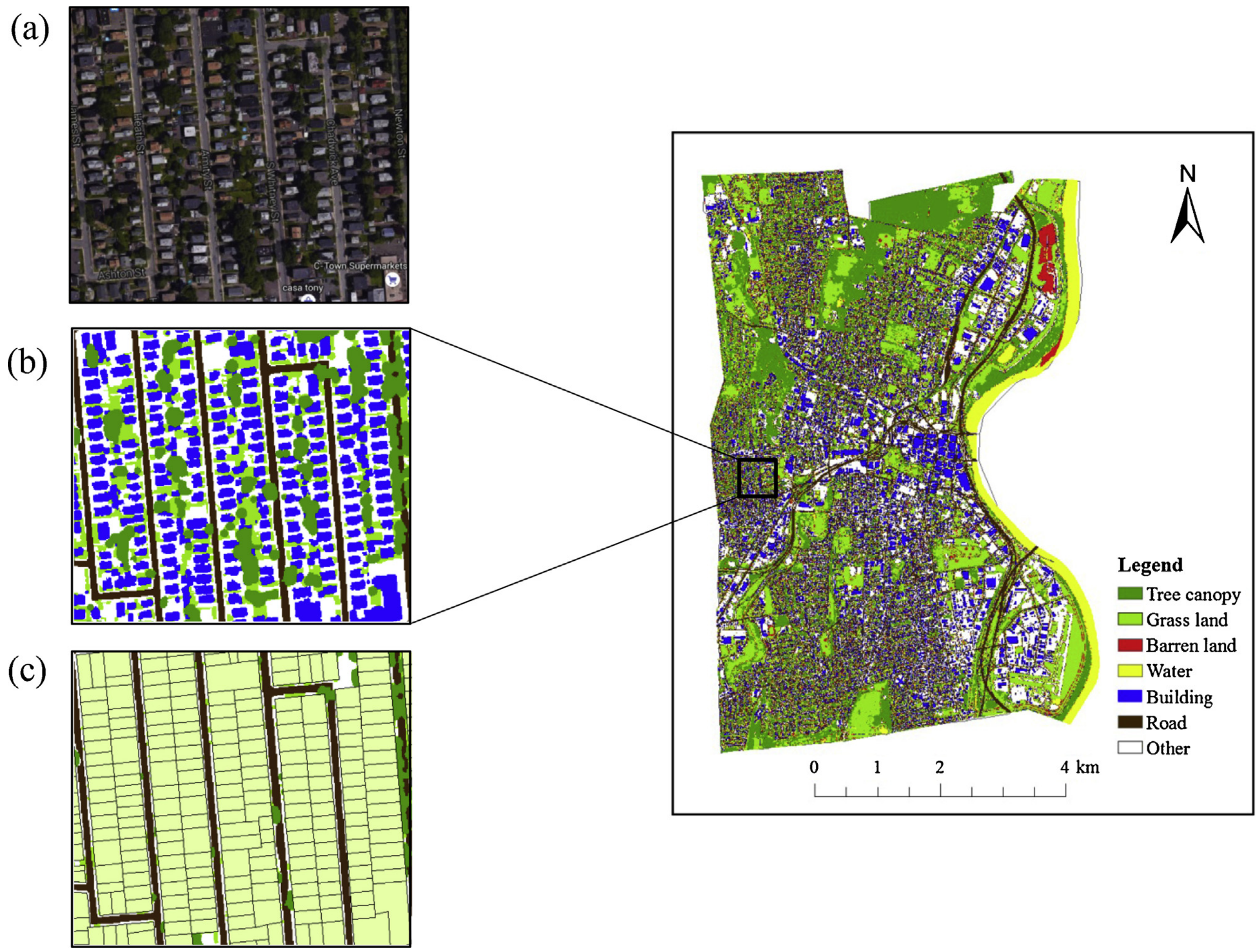

Fig. 3. The vegetation in private yards, shown by (a) a satellite image from Google Map, (b) a land cover map derived from the remotely sensed data, (c) a residential property parcel map.

Ordinary least square (OLS) multivariate regressions were then conducted to investigate the relationships between dependent variables (green metrics) and independent variables (chosen social variables). Only those independent variables that indicate significant ($p < 0.01$) correlations with dependent variables were selected for regression analysis. Education variables were identified as confounded variables of per capita income, and were not included in the regression analysis.

In order to investigate the spatial autocorrelation of OLS regression residuals, Moran's *I* statistics were calculated. The spatial weight matrix was calculated based on the Euclidean distances among centroids of block groups. GeoDa (Anselin, 2005) was further used to build spatial regression models between the dependent variables and independent variables in this study when OLS regression residuals had a significant spatial autocorrelation. There are two major spatial regression models, spatial lag regression model (SAR_{lag}) and spatial error regression model (SAR_{err}), which incorporate the spatial dependence into the dependent variable and error terms, respectively. In this study, for each type of urban greenery, the Lagrange Multiplier and Robust Lagrange Multiplier tests were conducted to judge whether to use a spatial lag regression model or a spatial error regression model.

5. Results

Of the 3000 sample sites in the study area, only 2838 sites have a GSV panorama coverage. Fig. 4a shows the spatial patterns of image date information for all 2838 GSV panorama sites. The GSV images for most of the sites (2042) were taken in June 2011 (Fig. 4b). Other time points include July 2015 (390 sites), August 2012 (216 sites), July 2011 (79 sites), and October 2011 (84 sites). A few of sites have GSV images captured in August 2007 (13 sites), August 2011 (10 sites), October 2012 (3 sites), and July 2008 (1 site). Those sites having GSV images taken in October were not considered in this study, because trees change colors in October and it is difficult to extract the vegetation from these GSV images. In addition, 14 sites captured in August 2007 and July 2008 were excluded from the analysis because of their bad image qualities. Fig. 4**c** shows the spatial distribution of the modified green view index values for the finally chosen sample sites. It can be seen clearly that most low green view index values are located in the east and south of the study area. Sites with high green view index values are mainly distributed in the western, southwestern, and northwestern areas.

Fig. 5 shows the spatial distribution of the aggregated green metrics at the block group level, which were used to indicate the street greenery (Fig. 5a), proximity to urban parks (Fig. 5b), percentage of yard total vegetation coverage (Fig. 5c), and percentage of yard tree/shrub coverage (Fig. 5d), respectively. In the aggregated green view index map (Fig. 5a), the modified green view index values have a spatial pattern similar to that in the site-level modified green view index map (Fig. 4c). Block groups in the west, northwest, and southwest of the study area have higher green view index values than block groups in the east. Yard vegetation and yard trees/shrubs (Figs. 5c and d) are more abundant in the north than in the south. The eastern and middle regions have closer proximity to urban parks than the other regions (Fig. 5b).

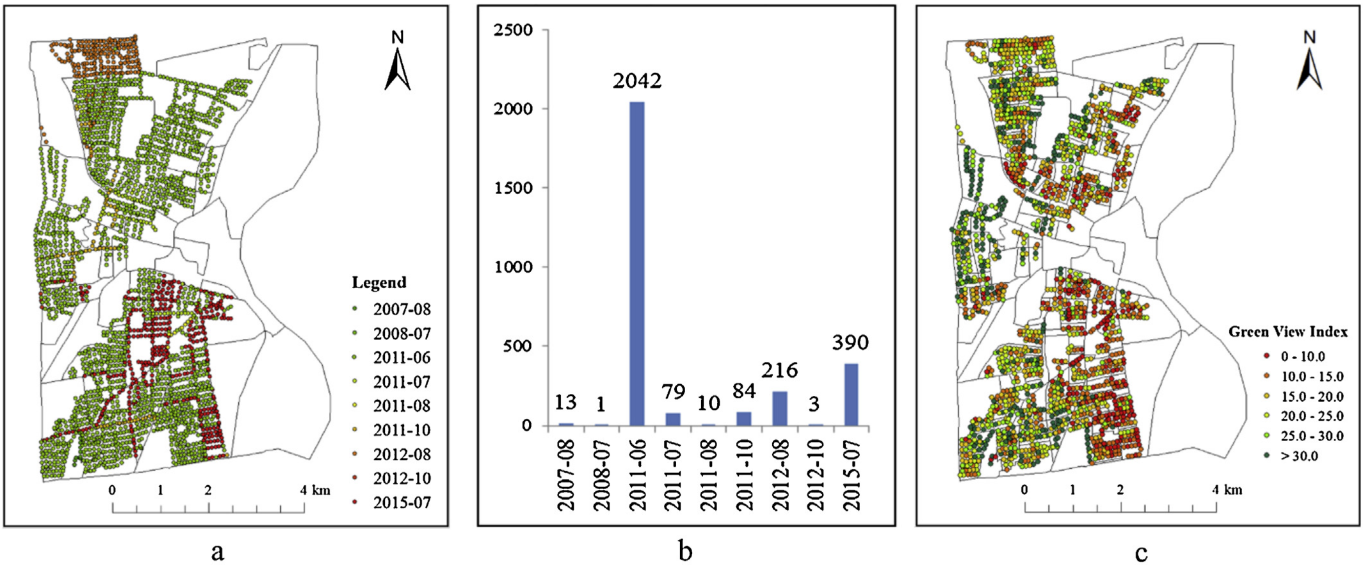

Fig. 4. Image date information of the chosen sample sites and the spatial distribution of the green view index values: (a) the spatial distribution of date information for all chosen GSV images, (b) the statistics of the date information for all chosen sample sites, (c) the spatial distribution of the green view index values for all chosen sample sites. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.).

Table 1
Pearson's correlation coefficients (r) between the green metrics and the chosen social variables at the block group level.

Correlation coefficients	Modified green view index	Percentage of yard vegetation	Percentage of yard trees/shrubs	Proximity to urban parks
Per capita income	0.438[a]	0.317[a]	0.350[a]	−0.147
Proportion of people without high school degree	−0.474[a]	−0.233	−0.287[a]	0.236
Proportion of people with bachelor's or higher degrees	0.282[a]	−0.002	0.087	−0.277[a]
Proportion of owner-occupied units	0.337[a]	0.572[a]	0.474[a]	−0.111
Median building age	0.019	−0.052	0.054	−0.050
Proportion of non-Hispanic Whites	0.240	0.132	0.170	−0.290[a]
Proportion of Hispanics	−0.321[a]	−0.472[a]	−0.509[a]	0.094
Proportion of African Americans	0.133	0.373[a]	0.370[a]	0.136
Proportion of people under 18 years of age	−0.244	−0.096	−0.142	0.378[a]
Proportion of people older than 65 years of age	0.261	0.355[a]	0.340[a]	−0.138

[a]Correlation is significant at the 0.01 level (2-tailed).

Table 1 presents the results of a bivariate correlation analysis between the four green metrics and the chosen social variables at the block group level. In terms of street greenery, there are significantly positive correlations between the modified green view index and per capita income, the proportion of people with bachelor's or higher degrees, and the proportion of owner-occupied units. The modified green view index is not significantly correlated with the proportion of non-Hispanic Whites and the proportion of African Americans; however, it is negatively correlated with both the proportion of Hispanics and the proportion of people without high school degree. The percentage of yard vegetation and the percentage of yard trees/shrubs have similar correlations with the chosen social variables. Both of these metrics have significantly positive correlations with per capita income, proportion of owner-occupied units, proportion of African Americans, and proportion of people older than 65 years of age, but have a significantly negative correlations with proportion of Hispanics. Unlike the other three green metrics, the proximity to urban parks has no significant correlations with per capita income and proportion of Hispanics. However, the proximity to urban parks is negatively correlated with proportion of non-Hispanic Whites and the proportion of people with bachelor's or higher degrees. None of the four green metrics has any significant correlation with the median building age.

Ordinary least square (OLS) multivariate regression models were developed between the four green metrics (dependent variables) and the social variables (independent variables) respectively. Tables 2–5 , show the coefficients, z-values, and significant levels of the OLS regression models. The significant Moran's I values indicate that the OLS residuals have a strong spatial dependence in all OLS regression models. This means that the OLS regression models are insufficient for modeling the relationships between the green metrics and related independent variables. Therefore, the spatial lag regression (SAR_{lag}) models were used to investigate the associations between each of the four green metrics and the chosen social variables. In the street greenery model (Table 2), the pseudo R^2 of 0.34 for the SAR_{lag} model indicates a relatively good model fit in the study area. Per capita income is significantly and positively associated with the amount of street greenery ($p < 0.05$). However, street greenery is not significantly associated with the proportion of Hispanics and the proportion of owner-occupied units. Yard vegetation coverage and the yard tree/shrub coverage have similar spatial patterns and similar associations with the independent variables (Tables 3 and 4). Since the proportion of Hispanics and the proportion of African American had a strong correlation ($r = -0.596$, $p < 0.01$), they were used separately in the regression models for investigating the associations of the yard green metrics with the related social variables (see OLS_H and SAR_{lag}_H with the proportion of Hispanics, and OLS_A and SAR_{lag}_A with the proportion of African Americans in Tables 3 and 4). Both the OLS and SAR_{lag} regression models show that the percentage of yard vegetation coverage and the percentage of yard tree/shrub coverage are significantly positively associated with the proportion of owner-occupied units. The

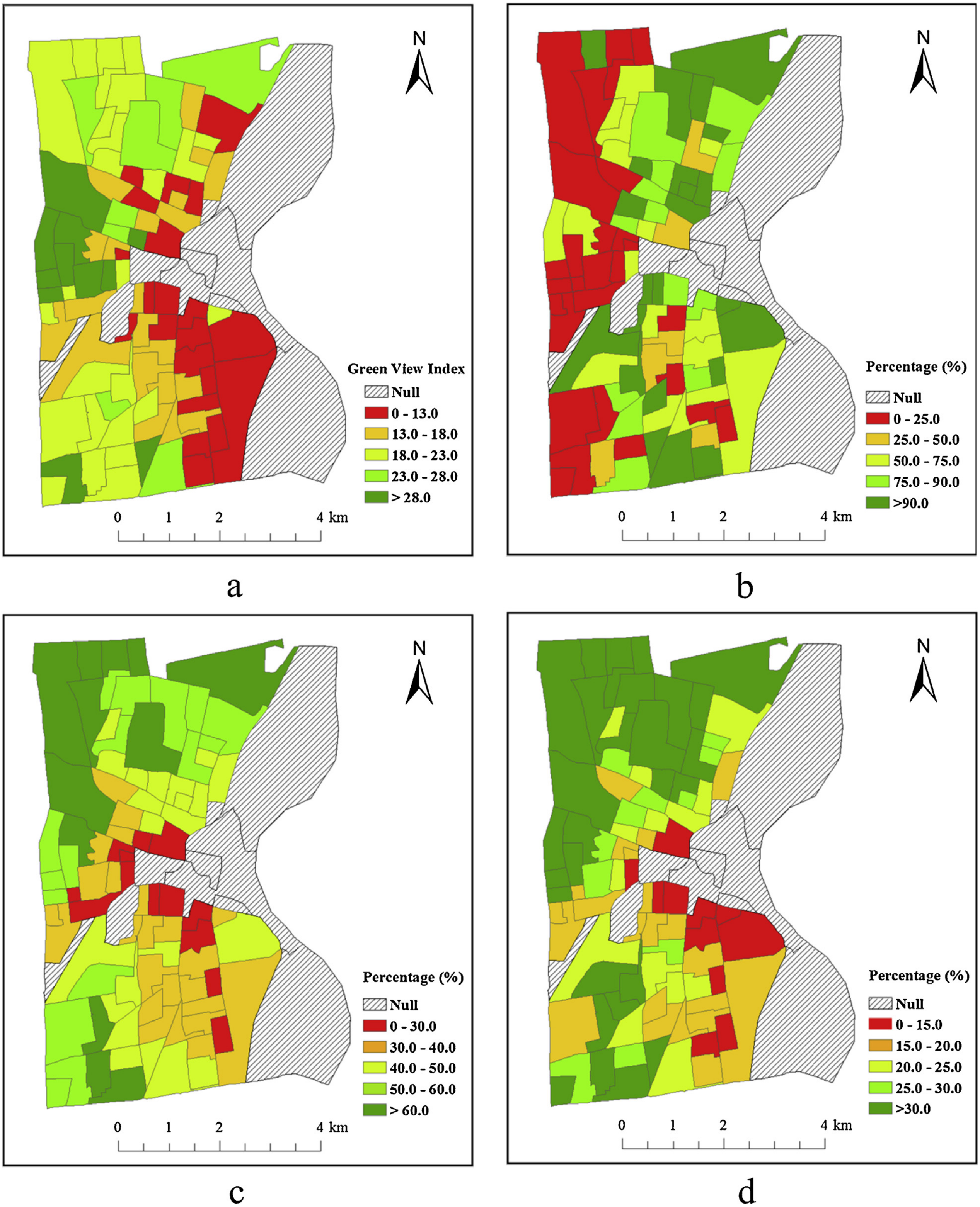

Fig. 5. Green metrics mapped at the block group level: (a) the modified green view index values, (b) proximity to urban parks (the proportion of residential parcels in 400 m buffer zones of urban parks), (c) percentage of yard vegetation coverage, and (d) percentage of yard tree/shrub coverage. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

coefficients of the spatial regression model with the proportion of Hispanics (SAR_{lag}_H) indicate that the proportion of Hispanics is negatively associated with the percentage of yard trees/shrubs, and per capita income has no significant association with either yard vegetation or yard trees/shrubs. In the spatial regression model with the proportion of African Americans (SAR_{lag}_A), the proportion of African Americans is positively associated with the percentages of yard vegetation and yard trees/shrubs, and the per capita income is also positively associated with the percentages of yard vegetation and yard trees/shrubs.

Table 2
The ordinary least squares (OLS) regression model and spatial lag model (SAR_{lag}) for the street greenery metric (i.e., the modified green view index) in Hartford, Connecticut. [b]Significant at the 0.01 level (2-tailed).

	OLS		SAR_{lag}	
	Coefficient	*z*-values	Coefficient	*z*-values
Constant	15.57	7.64[b]	9.03	2.89[b]
Per capita income (thousands of dollars)	0.24	2.68[b]	0.19	2.32[a]
Proportion of Hispanics	−4.45	−1.80	−3.06	−1.34
Proportion of owner-occupied units	3.69	1.30	2.78	1.06
Rho			0.38	3.12[b]
R^2 Adjusted R^2	0.24 0.21		0.34	
F-statistic Akaike info criterion	8.78[b]		537.87	
Moran's *I* of residuals	0.17	2.99[b]		

[a]Significant at the 0.05 level (2-tailed).
[b]Significant at the 0.01 level (2-tailed).

Table 3
The ordinary least squares (OLS) regression models and spatial lag models (SAR_{lag}) for yard vegetation coverage in Hartford, Connecticut. Note: *z*-values enclosed in brackets.

	OLS_H	OLS_A	SAR_{lag}_H	SAR_{lag}_A
	Coefficient	Coefficient	Coefficient	Coefficient
Constant	0.46[a] (12.07)	0.27[b] (8.38)	0.10[a] (2.40)	0.03 (1.03)
Per capita income (thousands of dollars)	-1.08×10^{-3} (−0.65)	1.69×10^{-3} (1.04)	1.47×10^{-3} (1.23)	2.43×10^{-3} [a] (2.13)
Proportion of Hispanics	−0.20[b] (−4.28)	–	−0.06 (−1.87)	–
Proportion of African Americans	–	0.17[b] (4.39)	–	0.07[b] (2.40)
Proportion of owner-occupied units	0.29[b] (5.50)	0.29[b] (5.44)	0.13[b] (3.14)	0.13[b] (3.16)
Rho			0.70[b] (10.24)	0.70[b] (10.29)
R^2 Adjusted R^2	0.45 0.43	0.46 0.44	0.71	0.72
F-statistic Akaike info criterion	22.68[b]	23.12	−186.75	−189.27
Moran's *I* of residuals	0.30[b] (4.85)	0.33[b] (5.26)		

[a] Significant at the 0.05 level (2-tailed).
[b] Significant at the 0.01 level (2-tailed).

Table 4
The ordinary least squares (OLS) regression models and spatial lag models (SAR_{lag}) for yard tree/shrub coverage in Hartford, Connecticut. Note: *z*-values enclosed in brackets.

	OLS_H Coefficient	OLS_A Coefficient	SAR_{lag}_H Coefficient	SAR_{lag}_A Coefficient
Constant	0.27[b] (9.15)	0.12[b] (4.59)	0.10[b] (2.81)	0.01 (0.51)
Per capita income (thousands of dollars)	0.40×10^{-3} (0.31)	2.64×10^{-3} [a] (2.06)	1.39×10^{-3} (1.28)	2.57×10^{-3} [a] (2.47)
Proportion of Hispanics	−0.16[b] (−4.54)	–	−0.08[b] (−2.63)	–
Proportion of African Americans	–	0.13[b] (4.26)	–	0.07[b] (2.71)
Proportion of owner-occupied units	0.15[b] (3.67)	0.15[b] (3.57)	0.09[a] (2.46)	0.09[a] (2.37)
Rho			0.56[b] (6.09)	0.57[b] (6.48)
R^2 Adjusted R^2	0.39 0.37	0.38 0.36	0.67	0.57
F-statistic Akaike info criterion	17.95[b]	16.85	−209.93	−210.98
Moran's *I* of residuals	0.39[b] (5.00)	0.31[b] (4.98)		

[a] Significant at the 0.05 level (2-tailed).
[b] Significant at the 0.01 level (2-tailed).

There is no significant difference across different racial/ethnic groups with regard to proximity to urban parks (Table 5). In the OLS model, the proportion of people under 18 is significantly and positively associated with proximity to urban parks ($p < 0.05$), but such a significant association does not exist in the SAR_{lag} model.

Table 5
The ordinary least squares (OLS) regression model and spatial lag model (SAR_{lag}) for proximity to urban parks in Hartford, Connecticut.

	OLS		SAR_{lag}	
	Coefficient	*z*-values	Coefficient	*z*-values
Constant	0.32	1.71	0.08	0.45
Proportion of non-Hispanic Whites	−0.19	−0.65	0.06	0.26
Proportion of people with bachelor's or higher degrees	−0.18	−0.50	−0.20	−0.63
Proportion of people under 18 years of age	1.09	2.07[a]	0.82	1.83
Rho			0.52	4.84[b]
R^2 Adjusted R^2	0.15		0.35	
	0.12			
F-statistic Akaike info criterion	4.96		58.64	
Moran's *I* of residuals	0.26	4.03[b]		

[a] Significant at the 0.05 level (2-tailed).
[b] Significant at the 0.01 level (2-tailed).

6. Discussion

This study investigated the spatial distributions of different types of urban greenery (street greenery, private yard greenery, and urban parks) and their associations with social variables. People with higher per capita incomes live in neighborhoods with more street greenery or higher modified green view index. This may be because street greenery makes neighborhoods more attractive, and people who can afford real estates in tree-lined neighborhoods tend to choose to live there. Bivariate correlation analyses results show that neither the proportion of African Americans nor the proportion of non-Hispanic Whites is significantly correlated with the modified green view index. Although the correlation analysis shows that the modified green view index is negatively correlated with the proportion of Hispanics, after controlling the effects of per capita income and proportion of owner-occupied units, the association between the modified green view index and the proportion of Hispanics is not significant. Therefore, the negative relationship between the modified green view index and the proportion of Hispanics could be because of relatively low incomes of Hispanics in the study area.

Private yard greenery, indicated by the percentage of yard vegetation and yard canopy coverage in this study, is relatively more abundant in the peripheral areas of Hartford. Regression coefficients (Tables 3 and 4) show that the proportion of owner-occupied units is significantly and positively associated with both percentage of yard vegetation coverage and percentage of yard tree/shrub coverage. This may be because owners tend to spend more money on environmental amenities than renters (Heynen et al., 2006; Perkins et al., 2004). Correlation analysis results show that the proportion of Hispanics is negatively correlated with both percentage of yard vegetation and percentage of yard tree/shrub coverage while the proportion of African Americans is positively correlated with both of them. The spatial regression models of SAR_{lag}_A and SAR_{lag}_H (Tables 3 and 4) further proved the environmental inequity in terms of yard greenery. Regression results show that the proportion of Hispanics is negatively associated with the percentage of yard tree/shrub coverage while the proportion of African Americans is positively associated with both the percentage of yard total vegetation and the percentage of yard trees/shrubs after controlling the effect of the proportion of owner-occupied units. This means that block groups with higher proportions of African Americans have higher yard total vegetation and yard tree/shrub coverage while block groups with higher proportions of Hispanics have lower yard tree/shrub coverage. The explorative correlation analysis shows that the people older than 65 tend to live in places with higher percentages of yard vegetation coverage ($r = 0.355$, $p < 0.01$) and yard tree/shrub coverage ($r = 0.340$, $p < 0.01$).

Urban parks in Hartford are distributed mainly in the eastern part of the city, which has the least street and yard greenery. The lack of a significant association (Table 5) between proximity to urban parks and the proportion of non-Hispanics Whites and the non-significant correlations (Table 1) between proximity to urban parks and other racial/ethnic variables show that there is no inequity in terms of proximity to urban parks in the study area. In addition, proximity to urban parks is not significantly associated with the proportion of people with bachelor's or higher degrees.

Our study results reveal some inequities in terms of different types of urban greenery in Hartford. The results of this study may provide a reference to urban planners as well as local residents for future urban greening practices. Different types of urban greenery show very different distributions across different neighborhoods and different socio-economic groups in the study area. Different types of urban greenery are managed and maintained in different ways, therefore, different measures should be taken to reduce the environmental inequities in terms of different types of urban greenery. In terms of street greenery, future urban greening projects may consider to plant more street trees in Hispanic neighborhoods in order to reduce environmental inequities. Municipal departments cannot influence the distribution of yard greenery directly, but measures could be taken to increase the yard greenery indirectly in neighborhoods with a higher proportion of Hispanics. This study also generates the spatial distribution of different types of urban greenery, and this could be helpful to locate the potential areas for future urban greening practices. In addition, this study demonstrates that GSV is a very suitable and cost-effective tool for study of street greenery, especially when care is taken to include the time information of the GSV images.

We used buffer analysis to calculate the proximity to urban parks, but park size and park quality are not considered. The proximity is not exactly equal to accessibility or people's willing to visit the parks because the buffer distance may not fully reflect the visiting distances. Future study should take park size, park quality, and different visiting distances into consideration to better quantify the potential benefits of urban parks. In addition, urban greenery is not always an environmental amenity. For example, it may increase the budget for cleaning the dead leaves and branches. The root of the street greenery could break the road conditions along the streets, especially the walkways. People from different cultural backgrounds may have very different opinions about the urban greenery. Future study should also investigate public opinions on different types of urban greenery.

7. Conclusion

Different types of urban greenery have different spatial distributions and different associations with the social status of residents in Hartford. Street greenery is associated with the per capita income of local residents and is mainly distributed in the western region of the study area. People with higher incomes tend to live in block groups with more street greenery. However, there exist no significant environmental disparities among different racial/ethnic groups in terms of street greenery. The yard greenery is positively associated with the proportion of owner-occupied units. Hispanics tend to live in neighborhoods with less yard greenery while African Americans tend to live in neighborhoods with more yard greenery. The urban parks have a very different distribution from those of the street greenery and the yard greenery, and they are mainly distributed in the eastern region of the study area. Statistical results proved that there exist no significant environmental disparities among different social classes in terms of the proximity to urban parks.

Appendix A.

Pseudo Codes for Meta-data collection of the GSV images.

Input: Coordinates of sample sites
Output: arrays of panorama IDs and time information of panoramas
Comment: *latlng* is the coordinates of a sample site
Comment: *panoIdArr* is the array to store the panorama ID of a sample site
Comment: *panoDateArr* is the array to store the time information of a sample site

```
var sv = new google.maps.StreetViewService();
// access to the GSV panorama, set radius parameter 5 meters
sv.getPanoramaByLocation(latlng, 5, storeGSV_Info);
function storeGSV_Info(data, status){
  if (status == google.maps.StreetViewStatus.OK) {
    panoIdArr.push(data.location.pano);
    panoDateArr.push(data.imageDate);
  } else {
    console.log('street view is not available in this point');
  }
 }
}
```

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