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Who lives in greener neighborhoods? The distribution of street greenery and its association with residents' socioeconomic conditions in Hartford, Connecticut, USA

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ABSTRACT

Street greenery plays an important role in enhancing the environmental quality of a city. Current urban environmental studies mainly focus on the distribution of desirable land uses (e.g., open spaces and parks). Few studies have been conducted on street greenery in residential areas, although it may provide a series of benefits to urban residents, such as energy saving, provision of shade, and aesthetic values. Google Street View (GSV) provides profile views of urban landscapes, and thus may be used for residential street greenery assessment. In this project, GSV was used in a case study to examine the relationships between the spatial distributions of residential street greenery and some socioeconomic variables in different block groups of Hartford, Connecticut, USA. The green view index was calculated based on the GSV images captured at different horizontal and vertical view angles to quantitatively represent how much greenery a pedestrian can see from ground level. Results showed that people with various social conditions have different amounts of street greenery in their living environments in Hartford. People with higher incomes tend to live in places with more street greenery. In summary, this study makes contribution to literature by providing insights into the living environments of urban residents in terms of street greenery, and it also generates valuable reference data for future urban greening programs.

1. Introduction

Urban green spaces, including urban forests, shrubs, lawns, and other kinds of green areas, are important elements of cityscapes, which have long been recognized for their importance in urban environments. Urban green spaces bring huge benefits to cities, meeting diverse and overlapping goals (Bain et al., 2012). The benefits include carbon sequestration (Nowak and Crane, 2002), purification of airborne pollutants (Lawrence, 1995; Jim and Chen, 2008), mitigation of urban heat islands (Chen et al., 2006; Onishi et al., 2010), and filtration and attenuation of storm-water runoff (Zhang et al., 2012; Liu et al., 2014). For urban residents, urban green spaces also offer opportunities for social integration and physical exercises (e.g., walking and bicycling), which further benefit human mental health (Leslie et al., 2010; Lee and Maheswaran, 2011; Bain et al., 2012; Coutts, 2008) and reduce aggression and crimes (Kuo and Sullivan, 2001; Troy et al., 2012; Wolfe and Mennis, 2012). Therefore, spatial access of urban green spaces is important for urban residents (Landry and Chakraborty, 2009).

Recently, urban environmental injustice has received considerable attention in urban studies. Unequal access to green spaces represents environmental disparities when some urban residents are deprived of the benefits that green spaces provide. There are considerable studies on environmental inequity, mainly focusing on the uneven distribution of vegetation coverage or vegetation indices (Pham et al., 2011, 2012, 2013; Jennings et al., 2012; Zhou and Kim, 2013; Jesdale et al., 2013; Leslie et al., 2010; Landry and Chakraborty, 2009; Jensen et al., 2004), and visiting distances to green spaces (Zhou and Kim, 2013; Boone et al., 2009; Leslie et al., 2010; Lotfi and Koohsari, 2011). Growing evidence shows that racial and/or visible ethnic minorities, low-income people, and underprivileged populations have disproportionally less access to vegetation than affluent groups across North American cities (Pham et al., 2012; Jesdale et al., 2013; Zhou and Kim, 2013). In terms of the distribution of vegetation coverage or vegetation indices, vegetation is often unevenly distributed within cities. Heynen et al. (2006) found a negative relationship between canopy cover and

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proportion of Hispanics in Milwaukee, Wisconsin, USA, a predominantly White city, but a positive relationship between canopy cover and proportion of non-Hispanic Whites. Jensen et al. (2004) used LAI (leaf area index) to indicate the spatial distribution of urban green spaces, and found a positive relationship between urban LAI and median household income. Based on the National Land Cover Dataset, Jesdale et al. (2013) examined the distribution of heat risk–related land cover across racial/ethnic groups at the national scale, and found environmental disparities in terms of vegetation coverage among different racial/ethnic groups in the United States. However, the findings on disparities of accessibility to green spaces are not consistent. Boone et al. (2009) examined the distribution of parks in Baltimore, Maryland, USA, and found that a higher proportion of African American residents have access to parks within walking distances than do other groups, while Whites have access to a larger acreage of parks. Zhou and Kim (2013) developed an accessibility index based on the Google Map application programming interface to evaluate the accessibility of different racial/ethnic groups to parks in six Illinois cities, USA, and their results showed that there is no significant difference among different racial/ethnic groups.

Few studies have examined the distribution of street greenery (Landry and Chakraborty, 2009; Pham et al., 2013), which includes street trees, lawns, and other kinds of green spaces along streets. As one component of urban green spaces, residential street greenery makes an important contribution to the attractiveness and walkability of streets (Schroeder and Cannon, 1983; Wolf, 2005; Bain et al., 2012). The aesthetic attractiveness of a neighborhood is greatly influenced by the amount of greenery that can be visually and aesthetically enjoyed. Street trees growing on rights-of-way provide a range of health benefits by promoting outdoor exercises (Wolch et al., 2005; Takano et al., 2002). Street greenery also provides sensory functions addressing the visual effects of greenery. It can mitigate visual intrusions of vehicular traffic, and contribute to the beauty of green cityscapes. Studies have shown that urban greenery with more visible vegetation can obtain stronger public support than that with less visible vegetation, even though they may have the same coverage (Yang et al., 2009). The visibility of greenery helps to increase satisfaction of citizens to their residential environments and plays an important role in comforting citizens. However, the evaluation (or assessment) of green spaces like street greenery can only be derived using in situ inventories or high-resolution remotely sensed images. With the availability of high-resolution remotely sensed images, studies focusing on green spaces at building block level have increased (Li et al., 2014; Pham et al., 2012, 2013; Landry and Chakraborty, 2009; Zhou and Troy, 2008). While high-resolution images provide a good tool for delineating green spaces at fine level, they are not always available and are also expensive to collect. In addition, there is little agreement between objectively derived greenness from remotely sensed images and human perceived greenness (Leslie et al., 2010), while perceived greenness has a direct connection with the benefits provided by street greenery. While many studies, as aforementioned, have been conducted to explore the association between the spatial distribution of vegetation coverage and socioeconomic conditions, they mainly focuses on green coverage derived from satellite images or aerial photographs. The overhead view of green cover from satellite images or aerial photographs is useful. Nevertheless, they do not take into account the profile view of green cover, which represents what people really see from the ground. For example, people see trees as 3-dimensional objects on the ground, rather than as the green cover shown in satellite images. Leslie et al. (2010) argued that the mixed findings on the association between neighborhood greenness and physical activities might be because different measures of neighborhood greenness capture different aspects of neighborhood greenness, especially perceived greenness and objectively measured greenness. The objectively measured greenness involves quantity of green elements, but the perceived greenness is concerned with the quality of greenness (Leslie et al., 2010). The greenness indicators based on remotely sensed images or aerial photographs may not fully represent neighborhood greenness, especially the greenness perceived by residents.

Different from previous studies using the canopy cover or vegetation indices (Grove et al., 2006; Mennis, 2006; Landry and Chakraborty, 2009; Leslie et al., 2010; Jesdale et al., 2013), in this study we used the modified green view index to represent the distribution of street greenery in residential areas and to check if the minorities and economically disadvantaged groups live in places with less street greenery. The green view index was initially proposed by Yang et al. (2009) as the averaged value of the area proportions of green vegetation in street level images captured at different directions. It quantitatively represents how much greenery a pedestrian can see from ground level (Yang et al., 2009).

In this study, the green view index was, for the first time, used to explore the association between urban street greenery in residential areas and different socioeconomic or racial/ethnic groups. Our objective is to test the hypothesis that environmental disparities in terms of urban street greenery are linked to the racial/ethnic makeup or socioeconomic status of residents.

2. Study area

Hartford is the capital city and fourth-largest city in Connecticut, USA (Fig. 1), with population of approximately 125,000. Based on the 5-year aggregated census data from American Community Survey (US Census Bureau, 2012), African Americans and Hispanics are the two largest racial/ethnic groups in Hartford, which account for 37.65% and 43.05% of the total population, respectively. Block groups are the finest-level area units for most social variables used in Hartford, therefore, they were used to provide the common boundaries for all geospatial operations in this study. There are 96 block groups in Hartford. Because the focus of this study is limited to residential housing units, nine block groups, which are largely located in downtown, commercial, or industrial areas with almost no residential neighborhoods, were not considered.

3. Methodology

3.1. Collection of Google Street View (GSV) images

Two steps for collecting GSV images were implemented. The first step was to generate the sample sites along streets. We initially downloaded a road map of Hartford, which includes interstate highways, state highways, and streets, from the TIGER datasets. Although GSV images were used to quantify urban green spaces, not all GSV images captured along different types of roads represent the street greenery in residential areas. Because this study focused on studying the street greenery in residential areas, only those streets in front of housing blocks were chosen. Other roads, such as state highways and interstate highways, were removed manually from the original road map by checking the Google Street View and the Google Map. In order to represent the street greenery of the study area, three thousand sample sites were generated randomly along the chosen streets in the road map using ArcGIS 10.2, and the shortest distance allowed between any two randomly placed points was set to 100 m arbitrarily. Fig. 1a shows the final chosen streets and GSV sample sites in different block groups of Hartford. The

Fig. 1. Study area: (a) street map and chosen GSV sample sites in Hartford, (b) location of Hartford, Connecticut, USA.

sample sites located on the border between two adjacent block groups were excluded to reduce the influence of neighboring block groups. Because the GSV images we obtained have no capture-time information and some images were captured during non-green seasons, we manually deleted those sites with images captured during non-green seasons, by visually checking the vegetation conditions in images.

The second step was collecting GSV images for each chosen sample site. GSV images taken by cars were processed to provide panoramic, street-level views of city streets (Fig. 2). All GSV images were requested using a HTTP URL form through the Google Street View Image API (Google, 2014). By specifying coordinates, directions, and pitch angles in a HTTP URL requested form, users can get the corresponding GSV images in any direction with any angle for any available site (Li et al., 2015).

A Python script was developed to read the longitude and latitude of each selected sample site and download the Google Street View Images. For each sample site, 18 GSV images were downloaded at six horizontal directions (0°, 60°, 120°, 180°, 240°, and 300°) and three vertical directions (−45°, 0°, and 45°), using the Google Street View image API (Google, 2014).

3.2. Green view index calculation and mapping

In this study, object-based image analysis was used to classify green vegetation from GSV images. The object-based method initially segmented an image into homogeneous polygons that are physically meaningful, and then assigned the polygons to different classes based on the spectral and geometrical properties of each polygon (Li et al., 2013). Thus, the object-based classification method helps to eliminate spectral variability of the original GSV images and keep the integrity of different urban features as objects. Therefore, the object-based classification method is more suitable for green vegetation extraction from GSV images compared with pixel-based methods.

The spectral R, G and B components in the original 8-bit color RGB GSV images were normalized to the range of [0, 1] for segmentation using the mean-shift algorithm (Comaniciu and Meer, 2002). We used a Python module *pymeanshift* to conduct the image segmentation in this study. After segmentation, new thematic images were generated by setting the attribute of each object to the average value of pixels within that object in each of the three RGB bands. The thematic images were used to extract green vegetation in the next step. Spectral analysis showed that the green vegetation has high reflectance in the green band and relatively low reflectance in both the red and blue bands. Therefore, we used the following rules to differentiate green vegetation features from non-vegetation features:

Spectral rules for vegetation classification based on the segmented GSV images
Comment: *green*, *red*, and *blue* are three bands in segmented images
Comment: *vegetation* is the vegetation extraction results
diff1 = green − red
diff2 = green − blue
diff_Image = diff1 × diff2
for each pixel [i, j] in diff_Image:
    if diff_Image [i,j] > 0 AND diff1 [i,j] > 0:
        Classify vegetation [i,j] as green vegetation
Mask out pixels with values in green, red, and blue bands higher than 0.7 in the vegetation image

Those pixels that have higher values in the green band than in the other two bands were classified as green vegetation. The vegetation classification algorithm was tested on 100 randomly chosen GSV images. Adobe Photoshop 7.01 software package was used to extract the green vegetation manually from those 100 GSV images as the reference data to validate the classification results. The discrepancy in green vegetation percentages between the classified results and the reference maps was used to evaluate the extraction results. Fig. 3 shows the scatter plot of green vegetation percentages between classification results and corresponding reference data. It is evident that these scattered points are distributed near the 45° line and the correlation coefficient is 0.94. These indicate that the classification results are qualified for further analysis.

The modified green view index is the average percentage of green vegetation in GSV images for six horizontal directions and

Fig. 2. Some scenes of different neighborhoods in Hartford, (a) more affluent, with much more street greenery, (b) less affluent, with little street greenery.

three vertical directions at each sample site (Li et al., 2015). It was calculated using formula (1),

$$\text{Green View} = \frac{\sum_{i=1}^{6}\sum_{j=1}^{3}\text{Area}_{g\_ij}}{\sum_{i=1}^{6}\sum_{j=1}^{3}\text{Area}_{t\_ij}} \times 100\% \tag{1}$$

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.

The median value of the green view index values in each block group was chosen to represent the green view index of the block group.

3.3. Extraction of social variables from census data

Based on previous environmental equity studies (Landry and Chakraborty, 2009; Huang et al., 2011; Pham et al., 2012), seven social variables at the block group level were chosen to represent the racial/ethnic and socio-economic status used in this study. The seven selected social variables include per capita income, proportion of African Americans, proportion of non-Hispanic Whites, proportion of Hispanics, proportion of owner-occupied units, proportion of people with a bachelor or higher degree, and proportion of people without a high school degree.

Economic status is an indicator of people's interaction with their physical environments, because it affects their capability to improve their physical environments. Many variables have been used to indicate the economic status of a resident in previous studies, such as household income (Landry and Chakraborty, 2009; Heynen, 2006) and proportion of households with income below the poverty line (Huang et al., 2011). Considering the fact that household income does not consider the household size, in this study the per capita income was chosen instead of household income as the indicator of a resident's economic status. The proportions of African Americans and Hispanics were chosen as the race/ethnicity variables, because

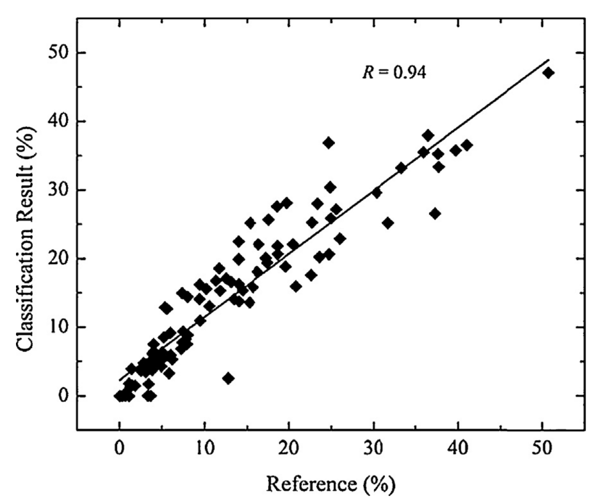

Fig. 3. The scatter plot of green vegetation percentages between classification results and reference data.

African Americans and Hispanics comprise the two largest racial/ethnic groups in Hartford. For comparison, the proportion of non-Hispanic White residents was also included in this study. Considering that previous studies have shown the association between green cover and people's levels of education, two educational variables (the proportion of people with a bachelor or higher degree and the proportion of people without a high school degree) were included in this study. In order to control the impact of building environment on street greenery, median building age was also considered (Grove et al., 2006; Pham et al., 2012; Landry and Chakraborty, 2009).

Due to the fact that most GSV images in Hartford were taken during 2007–2012, all of the aforementioned social variables were derived based upon the 2008–2012 American Community Survey (ACS) at the block group level.

3.4. Statistical analyses

To determine whether the green view index has an unequal distribution across different racial/ethnic and socio-economic groups in Hartford, we performed statistical analyses of the green view index versus the selected social variables. Statistical analyses were conducted in three stages. First, bivariate correlation was used to explore the associations between the green view index and each of the social variables at the block group level. Table 1 provides a description of the green view index and the chosen social variables at the block group level in the study area. Second, an ordinary least square (OLS) multivariate regression was conducted to model the relationships between dependent (the green view index) and independent variables (social variables). Only those independent variables indicating statistically significant ($p < 0.05$) correlations with the green view index were selected for regression analysis. Educational attainment variables (proportion of people without high school degree and proportion of people with bachelor or higher degrees), were identified as confounded variables of per capita income, and were excluded from the study. The final list of the independent variables in the regression model includes per capita income, proportion of owner-occupied units, and proportion of Hispanics.

Finally, the spatial autocorrelation of regression residuals was analyzed using the global Moran's I-statistics to determine whether the regression results were spatially biased (Landry and Chakraborty, 2009). In Moran's I analysis, the spatial weight matrix was calculated based on the Euclidean distances between centroids of block groups. Spatial regression was conducted when the Moran's I indicated significant spatial autocorrelation in the study area.

4. Results

Among all chosen sample sites in Hartford, the green view index values varied from 2.6 to 61.8, with a mean value of 24.4 and a standard deviation of 9.1 (Fig. 4). The green view index is affected by the layout of buildings and vegetation, the size of urban trees, the vertical structure of trees, and the distance between trees and viewers (Yang et al., 2009). Fig. 5 presents several GSV sites in Hartford with different green view index values. In general, those sites with high street greenery cover tend to have higher green view values, and those sites with large-size street trees, multi-layer vegetation, and lawns along streets usually have higher green view index values. This is not difficult to understand because the modified green view index was calculated by 18 GSV images captured in six horizontal and three vertical angles and the lawns and large street trees were counted into the green view index.

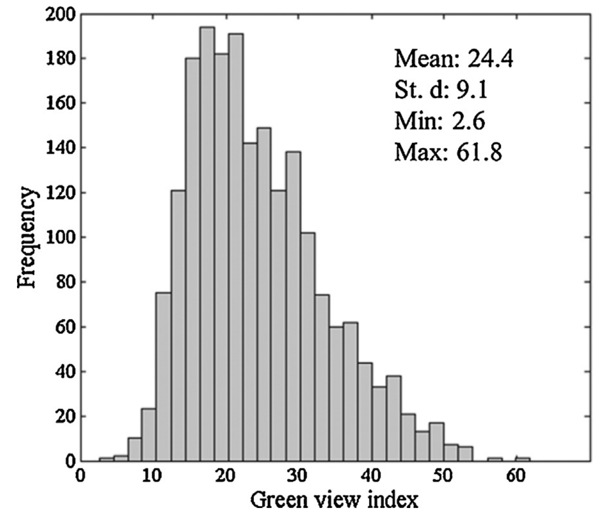

Fig. 4. Histogram of the green view index in the study area.

The spatial distribution of the green view index within the entire study area is illustrated in Fig. 6a. Locations with high green view index values are mostly distributed in the west, north, and southwest subareas. Fig. 6b presents the aggregated green view index values at block group level. The value for each block group was the median of the green view index values at all sites within the block group.

A descriptive analysis of the data at the block group level is provided in Table 1. Among those chosen 87 block groups in Hartford, the green view index values vary from 14.17 to 38.57, with a mean value of 22.82, and a standard deviation of 5.40. The high values have a similar distribution trend to that of the high values in the site map (Fig. 6a), and are mainly distributed in the west, north and southwest subareas.

Table 2 shows the correlation analysis results between the green view index and the selected social variables. The green view index was significantly positively associated with the per capita income, the proportion of people with bachelor or higher degrees, the proportion of owner-occupied units, and the proportion of non-Hispanic Whites, respectively. There was a significant negative correlation between the green view index and the proportion of Hispanics at 99% confidence level; however, no significant correlation was detected between the green view index and the proportion of African Americans. The green view index was also negatively correlated with the proportion of people without a high school degree, and the proportion of people under 18 years of age at 99% confidence level. There exists no significant association between the median building age and the green view index.

Results of regression models, such as coefficients, z-values and significance levels, are presented in Table 3. The adjusted R^2 indicates that the OLS regression explains about 27% of the variation in the green view index change in the 87 block groups. Diagnostics for spatial dependence of the residual showed that the Moran's I value was significant (Moran's $I = 0.15$, z score = 2.80). This means that the OLS regression did suffer from spatial autocorrelation in terms of the residuals. Therefore, a spatial regression was deployed to conduct a further analysis of the relationship between the green view index and the chosen independent variables. Spatial lag regression (SAR_{lag}) was chosen since Lagrange multiplier test shows that SAR_{lag} was more appropriate than the spatial error regression model in this study. The higher R^2 for SAR_{lag} than that for OLS model suggests the improved goodness of fit for SAR_{lag}. The significant value for the spatial lag coefficient, rho, for SAR_{lag} indicates there is strong spatial dependence in the green view index map. For both OLS and SAR_{lag} models, the green view index increases

Table 1
Description of related variables.

Variables	Min	Max	Mean (Std. Dev.)
Green view index (%)	14.17	38.57	22.82 (5.40)
Per capita income (thousand USD)	6.61	48.78	17.09 (7.84)
Proportion of people without high school degree	0.03	0.59	0.31 (0.13)
Proportion of people with bachelor or higher degrees	0.00	0.75	0.14 (0.14)
Proportion of owner-occupied units	0.00	0.86	0.28 (0.24)
Median building age (years)	44	76	67 (9.52)
Proportion of non-Hispanic Whites	0.00	0.77	0.16 (0.18)
Proportion of Hispanics	0.00	0.90	0.41 (0.25)
Proportion of African Americans	0.03	0.97	0.41 (0.28)
Proportion of people under 18 years of age	0.00	0.51	0.26 (0.10)
Proportion of people older than 65 years of age	0.00	0.40	0.10 (0.08)

Table 2
Pearson's correlation coefficients (r) between the green view index and the selected social variables.

Category	Variables	Pearson's correlation	Sig (2-tailed)	N
Economic status	Per capita income	0.513**	0.000	87
Education	Proportion of people without high school degree	−0.48**	0.000	
	Proportion of people with bachelor or higher degrees	0.38**	0.000	
Lifestyle	Proportion of owner-occupied units	0.33**	0.002	
Built environment	Median building age	0.09	0.385	
Race and ethnicity	Proportion of non-Hispanic Whites	0.29**	0.006	
	Proportion of Hispanics	−0.32**	0.002	
	Proportion of African Americans	0.09	0.385	
Age	Proportion of people under 18 years of age	−0.29**	0.006	
	Proportion of people older than 65 years of age	0.20	0.067	

** Correlation is significant at the 0.01 level (2-tailed).

Table 3
Ordinary least squares (OLS) regression model and spatial lag model (SAR_{lag}) of green view index for residential areas in Hartford, Connecticut, USA.

	OLS		SAR_{lag}	
	Coefficient	z-values	Coefficient	z-values
Constant	18.75	10.83**	9.83	3.20**
Per capita income	0.28	3.75**	0.23	3.33**
Proportion of Hispanics	−3.40	−1.62	−1.44	−0.74
Proportion of owner-occupied units	2.15	0.90	2.13	0.96
Rho			0.39	3.23**
R^2	0.29		0.38	
Adjusted R^2	0.27			
F-statistic	11.53**			
Akaike info criterion			510.34	
Moran's I of residuals	0.15 (2.80**)			
Jarque-Bera test	1.83 (0.40)			

** Significant at the 0.01 level (2-tailed).

significantly with per capita income ($p < 0.01$). The significantly positive coefficients of per capita income indicate that people with higher incomes tend to live in neighborhoods with more street greenery. In terms of the race/ethnicity variables, there is no significant association between proportion of Hispanics and green view index in both OLS and SAR_{lag} models. Regression results show that the association between green view index and proportion of Hispanics may be spurious, and the apparent negative relationship disappears when per capita income and spatial dependence are taken into account. This means that green view index may have less to do with the issue of race/ethnicity than it does with the issue of per capita income.

5. Discussion

The aim of this study was to map the spatial distribution of street greenery in residential areas and to assess its association with the social and economic status of residents in Hartford. Different from previous studies, which used canopy cover or vegetation indices as proxy for mapping the distribution of urban green spaces, in this study the green view index (Yang et al., 2009) was modified and utilized to represent street greenery in residential areas of Hartford. The modified green view index was calculated based on street level images captured at different horizontal and vertical view angles, thus representing the amount of street greenery people can see from the ground. Compared with canopy cover and vegetation indices, the green view index may be more suitable for quantifying the amount of street greenery in residential areas (Yang et al., 2009; Leslie et al., 2010).

Our results showed that per capita income is the major contributor of green view index. Residents with higher per capita incomes tend to live in areas with more street greenery compared with those with lower per capita incomes. These findings are similar to previous studies that lower income people tend to live in areas with less access to green spaces and less vegetation cover (Jesdale et al., 2013; Jensen et al., 2004; Pedlowski et al., 2002; Landry and Chakraborty, 2009). This trend could be explained by the fact that people with higher incomes tend to spend more money to choose or improve their living environments with more greenery for a series of benefits. Those areas with less street greenery may be

(a) Green view index values of four chosen representative GSV sites

(b) GSV images at six different heading angles (vertical angle = 0) for four chosen representative sites

Fig. 5. GSV sites in Hartford with different green view index values.

more affordable for low-income people (Pham et al., 2012), and low-income people have fewer budgets to maintain or increase the green space around their properties. The green view index has a negative correlation with the proportion of people under 18 years of age. This means that those families with young children in Hartford tend to live in neighborhoods with less street greenery. It is likely that people with higher educational levels have living environments with more street greenery compared with those with lower educational attainment levels. The green view index has a significant negative correlation with the proportion of Hispanics, but the regression results show that the association is not statistically significant after controlling the per capita income and spatial dependence in spatial regression model. The negative correlation between proportion of Hispanics and green view index could be

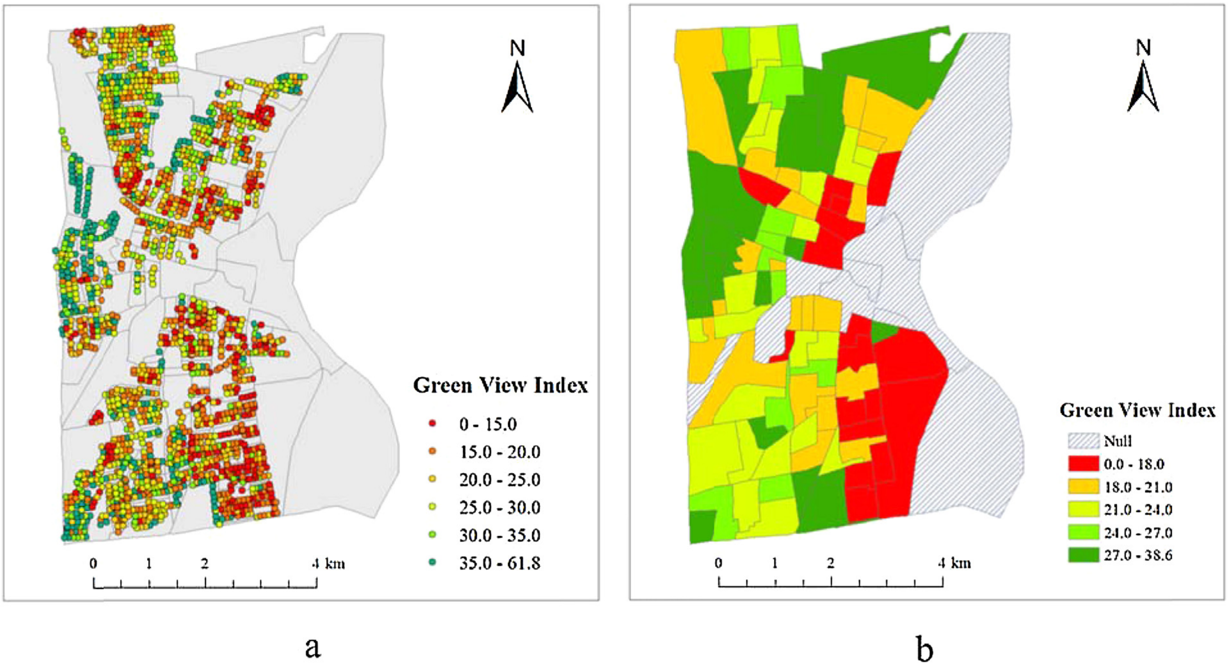

Fig. 6. Spatial distribution of the green view index in Hartford, Connecticut: (a) the distribution of the green view index values for the chosen sample sites; (b) the distribution of the aggregated green view index values at the block group level.

explained by the significantly negative correlation between proportion of Hispanics and per capita income in Hartford ($r = -0.34$, $p = 0.001$). Different from the significantly negative correlation with proportion of Hispanics, per capita income has significantly positive and non-significant correlations with proportion of non-Hispanic Whites ($r = 0.44$, $p = 0.000$) and proportion of African Americans ($r = -0.09$, $p = 0.436$), respectively.

The modified green view index derived from GSV images can provide additional information for measures of street greenery, which is different with vegetation indicators derived from a land cover map or remotely sensed imagery. GSV images may be seen as additional information/data to help urban planners and others to more accurately evaluate or quantify street greenery in residential areas.

A map of the modified green view index can effectively provide urban planners with detailed spatial information on the quantity of street greenery at the site level, which is usually unavailable through other methods. Although canopy coverage may be used to map the overall level of greenness in a specific area, it is difficult to quantify the amount of street greenery. The existence of street greenery helps to increase the satisfaction of citizens with their residential environments. Planting trees or gardening along streets and boulevards would improve the aesthetics of a city, and may provide relief from climatic extremes and urban heat island effects. These benefits are more important for those relatively vulnerable age groups (people under 18 and people older than 65) (Huang et al., 2011). In the future, more attention needs to be paid on increasing the street greenery in residential areas, especially in those critical areas where lower income people live. This could help to balance the living greenness among different socioeconomic groups in Hartford. Aoki (1991) suggested that most people would have a favorable impression of a street landscape if more than 30% of the view includes greenery. Based on Aoki's criterion, many streets in the residential areas in Hartford, especially in those streets in east and southeast of Hartford (Fig. 6a) should be given higher priority in future urban greening projects.

This study also shows that the GSV is a suitable and free tool for urban street greenery studies. GSV images can be downloaded and processed automatically to extract the greenery and calculate the green view index. The method is fast and can be used for green space assessment for any place where GSV is available. In some areas, where high-resolution images are not available, the GSV would provide a free data source for mapping the spatial distribution of street greenery.

While this study demonstrates that GSV is feasible for assessing street greenery and may deliver useful urban greenery information that was unavailable previously, there are still some issues that need to be resolved in future studies. The first issue concerns the time consistency of GSV images. Google includes the acquisition date of street view images, which provides the information for researchers and practitioners to better match environmental conditions with their data analysis and study outcome. Because we analyzed the street greenery over a period of 5 years, the neglect of accurate image dates may not have much effect on the analysis in this study. However, for some studies focusing on a specific time point, the time consistency could matter. Therefore, how to keep the time consistency is an important issue for future GSV applications in assessing urban green spaces. Second, the statistical analysis is at the block group level, and the green view index for each block group was set to the median of all green view index values in the block group. The variation of the green view index within each block group was ignored in this study.

6. Conclusions

The study developed a modified green view index as an indicator of street greenery to explore the relationships between urban street greenery and the status (economic and racial/ethnic) of residents at the block group level in Hartford, Connecticut, USA. Results show that in Hartford, people with lower income levels tend to live in areas with less street greenery while those with higher incomes tend to live in areas with more street greenery.

The green view index method used in this study provides a new tool for measuring the amount of street greenery at site level. Based on the site level green view index map, the potential street greening sites can be easily delineated, which seems difficult using the canopy coverage indicators for this purpose. The green view index is affected by the layout of buildings and vegetation, the size and vertical structure of street trees, and the distance between trees and viewers. In urban greening projects, planting trees close to pedestrians, choosing tree species with large canopies, using large-size trees, or increasing the presence of lawns along streets all help to augment the green view index.

Google Street View provides a free data source for street greenery studies. This is especially meaningful for some areas, where high-resolution images are not available or too expensive to collect.

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