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1. Introduction

Thermal comfort plays an important role in determining the quality of life in cities. For example, there is ample evidence that the thermal comfort of urban pedestrians influences their choice and level of outdoor activities and the utilization of urban space (Huang, Lin, & Lien, 2015; Hwang, Lin, & Matzarakis, 2011). As such, study on how to increase thermal comfort levels in urban spaces, particularly under the contexts of global warming and rapid urbanization, has become a prominent topic in urban studies and of key interest to decision makers. The urban thermal environment is influenced by ground cover, including vegetation cover and impervious surfaces, as well as the geometry of street canyons (Johansson, 2006), the shade provision by trees and blocks (Hwang et al., 2011; Lin, Matzarakis, & Hwang, 2010). Vegetation cover absorbs, rather than reflects, solar radiation and, consequentially, evaporotranspiration moderates the microclimate (Chen, Zhao, Li, & Yin, 2006; Onishi, Cao, Ito, Shi, & Imura, 2010). The geometry of the street canyon (i.e., height to width ratio) influences the amount of solar radiation received on the ground (Algeciras, Consuegra, & Matzarakis, 2016). Finally, tree canopies provide shade by blocking direct solar radiation before it reaches the ground (Armson, Rahman, & Ennos, 2013). For example, Klemm, Heusinkveld, Lenzholzer, and van Hove (2015) found that, with every 10% of increased tree canopy coverage, the mean temperature within a street canyon is lowered by about 1 K.

Without modifying the existing built environment, urban greening projects are often considered a preferred method for adaption to the warming climate and urban heat island effects (Klemm et al., 2015). As such, quantitative information on the ecosystem services provided by street trees, particularly in terms of potential temperature reductions, would provide an important reference for urban greening projects in order to maximize those services. However, we still have little quantitative information about the extent and distribution of urban tree ecosystem services (Richards and Edwards, 2017).

Traditionally, a city’s “greenness” has been evaluated by measuring the extent of the tree canopy from satellite or aerial images. However, such 2-dimensional cover information cannot necessarily reflect how much solar radiation is blocked by street trees as it lacks the vertical dimension needed to estimate or model the path of light from the sun; and hence shading. Moreover, tree canopy cover estimates rarely, if

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ever, contain any information about the density of the foliage cover and assume a homogeneous cover. What’s more, the shading effect of street trees is influenced, not only by trees themselves, but also by the spatial configuration of the building blocks and orientation of the street canyons. Together, the canopy cover as measured from aerial or satellite imagery cannot fully capture the shading effectiveness of the street trees and any estimates derived from those methodologies are likely to have a large error.

As a dimensionless parameter of urban geometry, the sky view factor (SVF) indicates how much sky is obstructed by buildings and tree canopies (Chapman and Thornes, 2004; Oke, 1981). The SVF also represents the ratio between radiation received by a planar ground and that from the entire hemisphere’s input radiation (Watson and Johnson, 1987). When the sky is totally obstructed, the SVF is zero while the SVF is one when there is no obstruction. The SVF has been used as an indicator of the shading level, which is caused jointly by building blocks and street trees (Hwang et al., 2011; Lee, Holst, & Mayer, 2013; Lin, Tsai, Hwang, & Matzarakis, 2012). However, it remains difficult to measure the shading effect by street trees alone at a regional scale.

In this study, we propose to use Google Street View (GSV) panorama photographs together with a building height model to estimate the shading effectiveness of street trees. We first generated hemispherical (fish-eye) images from GSV panoramas by a geometrical transform and, subsequently, calculated the SVF from those images. To account for the shading effect only by buildings, we simulated the SVF based on a building height model of the study region. The building height-based simulation model tends to overestimate the SVF values since obstruction of street trees is not considered. To address this issue, we used the GSV-based photographic method to represent an accurate measure of the SVF, which includes all obstructions in the scene (buildings + trees). With this in mind, the difference between the two estimates of the SVF for a given scene is, therefore, representative of the shading effect of the street trees alone. We thus quantified the shade provision of street trees in the downtown of Boston using this technique.

2. Literature review

The sky view factor (SVF) has been widely applied in forestry, urban climate, air pollution, and urban heat island studies (Carrasco-Hernandez, Smedley, & Webb, 2015; Chen et al., 2012; Debbage, 2013; Eeftens et al., 2013; Grimmond, Potter, Zutter, & Souch, 2001; Hämmerle, Gál, Unger, & Matzarakis, 2011; Holmer, Postgärd, & Eriksson, 2001; Lin et al., 2012; Svensson, 2004; Unger, 2008). There are several developed methods for SVF calculation including the photographic method, GPS signal based method, and simulation method.

The photographic method calculates the SVF based on the projection of the hemispheric environment onto a circular plane (Chen et al., 2012). Traditionally, this projection is achieved mechanically by a fisheye camera lens (Anderson, 1964; Chen et al., 2012; Johnson and Watson, 1984; Steyn, 1980). With the resulting hemispherical photographs, sky areas are typically delineated manually from fisheye images and binary sky images are further divided into annuli (Steyn, 1980). The SVF is then calculated as the sum of all sky fractions in all annuli. However, the use of specialized lenses necessitates manual field data collection, which represents significant man-hours and resources.

The GPS-based method represents an indirect method to estimate the SVF using a regression model that estimates the SVF based on GPS signal information (Chapman, Thornes, & Bradley, 2002). This GPS information is acquired by GPS receivers and includes the number of visible satellites, the strength of satellite signals, and the dilution of precision. In urban environments, results based on this method have shown that the multiple-regression model explains up to 88% of the variation in SVF (Chapman et al., 2002). However, this method comes with significant caveats and sources of error being that it is an indirect, modeled estimate. For example, the regression model coefficients must be adjusted for different study areas and different land use types and considering the impact of different local vegetation.

To date, a significant limitation of both the photographic method and the GPS-based methods is that they require in situ measurements and several manual procedures. These limitations, which constitute high resource inputs, have limited their widespread use and the acquisition of broad-extent datasets on the SVF. In addition, and particular to urban environments, in situ measurements are usually collected on sidewalks. The optimal sampling area to compute the SVF in urban environments, however, should be at the centers of city roads in order to get a hemispherical image representation of the full street canyon.

With the availability of 3D city models or Digital Surface Models (DSMs), the SVF can also be estimated at large spatial scales using simulation methods. Simulation methods operate by simulating the incoming solar radiation and calculating the projection of building blocks on the ground (Gal, Lindberg, & Unger, 2009; Ratti and Richens, 2004). As such these methods are limited to areas for which 3D models or DSMs are available. Moreover, the accuracy of simulation methods are directly bound to the spatial resolution of data source; the higher the spatial resolution of the DSM, the more accurate the SVF estimation. However, 3D city models do not usually include any tree canopy information, which are of course a major feature of urban settings and contributor to the SVF. As such, SVF estimates based solely on a 3D city model simulation would overestimate the SVF since it ignores the solar radiation obstruction by trees.

In an extension of the photographic method, Carrasco-Hernandez et al. (2015) proposed to use an open source panorama-generating tool known as Hugin to create fisheye images based on static Google Street View (GSV) images instead of taking in situ fisheye images for calculating the SVF. Although fieldwork is not required, this method remains laborious and time-consuming due to the manual image stitching process. In addition, the image stitching on static GSV images is not typically reliable because the static images have been preprocessed to achieve a perspective projection of the scene and, thus, inherit large geometric distortions. In many cases it is difficult or even impossible to allocate suitable key points on the static GSV images to then generate fisheye images. Thus, despite exploiting an existing and expansive dataset of landscape imagery, the Carrasco-Hernandez et al.’s (2015) method does not solve the high labor and time constraints that prevent SVF computations accurately at large spatial scales.

3. Study area and data

The study area for this work is the downtown area of Boston, Massachusetts, USA (Fig. 1). We collected 319 GSV panoramas that were acquired during green, growing season months, along the streets in the study area. Among those 319 panoramas, 22 panoramas were taken in tunnels, thus 297 GSV panoramas remained after removing those taken in tunnels (Fig. 1(a)).

The datasets used in this study include a building footprint map, a street map of the city, a tree canopy cover map, and a normalized Digital Surface Model (nDSM). The building footprint map and street map were downloaded from MassGIS data (http://www.mass.gov). The nDSM was generated from LiDAR cloud point data with a spatial resolution of one meter (Fig. 1(b)). The LiDAR data of Boston, in the form of pre-processed x, y, z points cloud files, was obtained from NOAA Digital Coast (NOAA, 2015). The horizontal accuracy is 50 cm and vertical accuracy is reported as 15 cm. The LiDAR point cloud data includes two geospatial layers representing the first returns and the ground. The point cloud file was converted to a raster file using ArcGIS 10.2. The nDSM was then generated by subtracting the ground model from the first returns layer. We further overlaid the nDSM on the building footprint map to generate the building height model. The tree canopy cover data (Fig. 1(c)), which was derived from remotely sensed data with an overall accuracy of 95%, was collected from Raciti, X. Li et al. Landscape and Urban Planning 169 (2018) 81–91
This study proposed a GSV-based photographic method in combination with a building height model-based simulation method to calculate the “all-inclusive” sky view factor (SVF$_P$) and the “building-only” sky view factor (SVF$_S$), respectively. The difference between SVF$_P$ and SVF$_S$ was then calculated to quantify the shading effectiveness of the street trees in the study area. Fig. 2 shows the workflow of the methodology.

4.1. GSV panorama based SVF$_P$ estimation

The GSV-based photographic method for the SVF$_P$ estimation includes three primary steps (Fig. 2). The first step was to download GSV panoramas from Google’s database and transform the cylindrical GSV panoramas to azimuthal fisheye images. Object based image analysis was then applied on the generated fisheye images to classify sky areas. Finally, based on the classified sky images, SVF$_P$ was calculated.

4.1.1. Geometric transform of GSV panoramas

The seamless image tour of city streets that a user can navigate on Google Maps through a web browser is based on GSV panoramas. These GSV panoramas are readily available for download from Google’s server. Each GSV panorama has a unique ID, which can be requested through the Google Street View Image API (Google, 2016) using geographic coordinates as input. Once acquired, the panorama IDs can be used to download the tiles of a complete panorama from Google’s server. Fig. 3 shows one tile of a GSV panorama and its corresponding URL address together with the metadata of the panorama. In the URL, the panoid represents the unique panorama ID, while $x$ and $y$ represent the column and row number of the tile respectively. A complete GSV panorama includes 338 (26 × 13) tiles. We developed a Python script to generate a single image panorama by mosaicking the tiles for each site.

In order to collect a representative sample of GSV panoramas for the study area, we first created sample sites every 100 m along the street segments and downloaded the GSV metadata associated to each of those sampling points by their geographic coordinates. With the panorama ID metadata, we then downloaded all panoramas in the study area.

In the standard photographic method for SVF calculation, fisheye images are required and this has typically been achieved using specialized fisheye camera lenses at time of image acquisition. Here, we instead generated fisheye images by projecting GSV panoramas from

Fig. 1. The location and maps of study area, (a) the chosen GSV panorama sites along streets, (b) the nDSM derived from LiDAR, (c) canopy cover map in the study area, (d) the location of study area in Boston, Massachusetts, USA.
the cylindrical projection to azimuthal projection. Fig. 4 outlines the geometric model for the transformation of cylindrical projection to azimuthal projection.

The \( W_c \) and \( H_c \) are the width and height of the cylindrical panorama such that the radius of the fisheye image should be, \( r_0 = \frac{W_c}{2\pi} \), and the width and height of the fisheye image are \( W_f/\pi \). Therefore, the center pixel of the result fisheye image \((C_x, C_y)\) is,

\[
C_x = C_y = \frac{W_c}{2\pi}
\]

(1)

For any pixel \((x_f, y_f)\) on the resulting fisheye image, the corresponding pixel on the cylindrical panorama should be \((x_c, y_c)\),

\[
x_c = \frac{\theta}{\pi} W_c
\]

\[
y_c = \frac{y_f}{\pi} H_c
\]

(2)

where \( \theta \) and \( r \) are,

\[
\theta = \begin{cases} \frac{\pi}{2} + \arctan\left(\frac{y_f - C_y}{x_f - C_x}\right), & x_f < C_x \\ \frac{\pi}{2} + \arctan\left(\frac{y_f - C_y}{x_f - C_x}\right), & x_f > C_x \end{cases}
\]

(3)

\[
r = \sqrt{(y_f - C_y)^2 + (y_f - C_y)^2}
\]

(4)

In order to verify this geometric transformation model, we tested the model against images that were captured with a fisheye lens. That is we first took a fisheye image (Fig. 5(a)) captured using a fisheye lens and projected it to a cylindrical projection as Fig. 5(c). We then applied our cylindrical to fisheye transformation and compared this transformed image to the original fisheye-captured image. Indeed, compared with the original fisheye image, the simulated fisheye image (Fig. 5(b)) is almost identical to the original fisheye image. Thus using this

URL of a tile of a panorama:

http://cbh0.google.com/cbh?output=tile&panoid=0ihecq01fCjriGAdFgqB1faQ&ezoom=5&x=11&y=5

Fig. 2. Workflow chart of the methodology.

Fig. 3. A tile of one GSV panorama and its corresponding URL address together with the metadata of the GSV panorama.
methodology we transformed all GSV panoramas in the study area to generate corresponding azimuthal projection fisheye images.

4.1.2. Sky extraction

The automatic sky extraction is a requisite step for the automatic SVF calculation in the proposed GSV-based photographic method. In this study, we used object-based image analysis to extract sky areas from fisheye images. Compared with the pixel-based methods, the object-based methods initially segment an image into homogeneous polygons that are physically meaningful and then categorize those polygons semantically. Therefore, object-based classification methods help to keep the integrity of urban features as objects and, ultimately, achieve a better classification result (Li, Zhang, Li, Kuzovkina, & Weiner, 2015; Li, Zhang, & Li, 2015). The mean-shift image segmentation algorithm (Comaniciu and Meer, 2002) was used here to segment the fisheye images as it has been tested for automatic classification of GSV images in previous studies (Li, Zhang, Li, Kuzovkina et al., 2015; Li, Zhang, Li, 2015). In this study, we used the python module pymeanshift, which implements the mean-shift algorithm, to segment fisheye images.

Based on the segmentation results, we calculated an adjusted brightness to differentiate sky pixels from non-sky pixels. The adjusted brightness represents the overall brightness of pixels with more weight given to the blue band such that sky pixels are usually brighter than non-sky pixels. The adjusted brightness was calculated as stated in formula (5), in which the blue band gets more weight and the red band gets less weight.

$$\text{Brightness} = \frac{(0.5 \times \text{Red} + \text{Green} + 1.5 \times \text{Blue})}{3} \quad (5)$$

We then used Otsu’s method (Otsu, 1975) to find the optimum threshold to separate sky pixels from non-sky pixels based on the calculated Brightness images. The Otsu’s method chooses a global threshold automatically by minimizing the within-class variance and maximizing the between-class variance. All other pixels other than those
representing the sky were treated as non-sky pixels. The non-sky pixels were further classified as building pixels and tree canopy pixels. In this study, we used the ExG rule to differentiate buildings from the tree canopy.

\[ \text{ExG} = 2 \times \text{Green} - \text{Blue} - \text{Red} \] (6)

Performing the sky extraction process using solely the segmentation steps and spectral rules outlined above does not achieve a reliable sky extraction results in fisheye images because other urban features may have similar spectral signatures to sky pixels. Thus, the extraction results based only on spectral information may misclassify some urban features as sky area. To avoid such misclassifications, we developed geometrical rules to refine the sky extraction result. In street-level images and the GSV cylindrical panoramas (Fig. 3), the sky is always located above buildings in the image for each vertical series grid (Fig. 4(a)). With this in mind, in the azimuthal projection images (Fig. 4(c)), for all grids between two nearby radial lines, the inner grids should be higher than the outer grids. Based on this assumption, we applied a rule that for each vertical series grid in the fisheye image, if the inner grids are buildings, the outer grids cannot be labeled as the sky. While improving on the amount of pixels misclassified as sky, this geometrical rule does not necessarily correct all erroneously classified sky pixels by spectral rules; e.g., building pixels below vegetation can sometimes be erroneously classified as the sky.

Fig. 6(a) and (b) shows the original GSV panorama in the cylindrical projection and the generated azimuthal fisheye image projection of one site in the study area, respectively. Fig. 6(c) shows the image segmentation result of one simulated fisheye image using the mean-shift segmentation algorithm. Compared with the original fisheye image (Fig. 6(b)), the segmented image is smoother and the contrast between
sky pixels and non-sky pixels has been enhanced, making the segmented image more suitable for sky extraction. Fig. 6(d) is the preliminary classification result using the spectral rule alone. In this example, using only the spectral-based rules, many non-sky pixels are misclassified as sky pixels because of their similar spectral signatures with sky pixels. Fig. 6(e) is the refined sky extraction result based on geometrical rules. In the refined result, those sky pixels having building pixels above are removed.

4.1.3. SVF\(_p\) calculation

The original SVF is defined as (Steyn, 1980),

\[
SVF = \frac{1}{\pi r_0^2} \int_{\text{S}^0} dS^p 
\]

(7)

where \(r_0\) is the radius of the hemispheric radiating environment, \(S^0\) is the area of the circle sky area projected on the ground. The \(dS^p\) can be represented using polar coordinate as,

\[
dS^p = \frac{\pi r_0^2}{2} \sin(\frac{\pi}{2n_0}) \cos(\frac{\pi}{2n_0}) dr d\alpha 
\]

(8)

In this study, based on the previous steps of the image transformations on GSV panoramas and subsequent sky extraction, we proposed applying the standard photographic method to calculate the SVF to our transformed GSV images. The standard photographic method to calculate the SVF (Steyn, 1980) first divides the fisheye image into \(n\) concentric annular rings of equal width, and then sums up all annular sections representing the visible sky. The SVF\(_p\) is then calculated as,

\[
SVF_p = \frac{1}{2n} \sum_{i=1}^{n} \sin\left(\frac{\pi}{2n} (i - 1/2)\right) \cos\left(\frac{\pi}{2n} (i - 1/2)\right) \alpha_i 
\]

(9)

which can be further modified based on (Johnson and Watson, 1984) as,

\[
SVF_p = \frac{1}{2\pi} \sin\left(\frac{\pi}{2n} \sum_{i=1}^{n} \sin\left(\frac{\pi}{2n} (2i - 1)\right) \alpha_i \right) 
\]

(10)

where \(n\) is the total number of rings, \(i\) is the ring index, and \(\alpha_i\) is the angular width in \(i\)th ring. Previous studies usually set the value of \(n\) to be between 36 and 39 (Hämerle et al., 2011; Steyn, 1980; Chen et al., 2010). We found that there is no significant difference between the calculated SVF\(_p\) values with \(n\) ranging from 36 to 39. As such, we set \(n\) to 37 based on previous work (Chen et al., 2010).

4.2. The simulation-based SVF\(_s\) estimation

In the simulation method, SVF\(_s\) values were calculated by simulating the path of sunlight across the building height model. For each sampling site, which follows from above, we searched for all buildings in all 360° horizontal directions with a step of 1° (Fig. 7). The search radius was set as 500 m, assuming that buildings further than 500 m away do not act as obstructions. The obstruction angles of buildings in each horizontal direction were calculated with formula (11) considering that the GSV panoramas were captured at a height of 2.5 m (Fig. 7),

\[
\beta_{\alpha,i} = \arctan\left(\frac{H_{\alpha,i} - 2.5}{D_{\alpha,i}}\right) 
\]

(11)

Where \(\beta_{\alpha,i}\) is the obstruction angle of building \(i\) along the horizontal direction \(\alpha\), \(H_{\alpha,i}\) is the height of building \(i\), and \(D_{\alpha,i}\) is the distance between the building \(i\) and the site of the GSV panorama. For each horizontal direction, the obstruction angle \(\beta_{\alpha}\) should be the maximum of all building angles in that direction (Fig. 7(b)),

\[
\beta_{\alpha} = \max(\beta_{\alpha,i}) = \max(\arctan\left(\frac{H_{\alpha,i} - 2.5}{D_{\alpha,i}}\right)) 
\]

(12)

Previous studies have shown that raster-based methods to compute obstruction angles and shading are more time efficient than vector-based methods, while the differences between the two methods are negligible (Chen et al., 2012). Therefore, we converted the building footprint map and the nDSM of the study area into a raster building height model. The simulation method for calculating SVF\(_s\) is based on the classical formula (13) (Gal et al., 2009),

\[
SVF_s = 1 - \frac{1}{360} \sum_{\alpha=0}^{359} \sin^2 \beta_{\alpha} 
\]

(13)

where \(\beta_{\alpha}\) is the obstruction angle of the obstruction building at horizontal direction of \(\alpha\) (Fig. 7).

4.3. Shading effectiveness of street trees

The simulation method tends to overestimate the real SVF because the obstruction of street trees is not considered in the sunlight simulation of the building height model. On the other hand, the GSV-based photographic method can achieve a precise SVF estimation result with consideration of all obstructions, inclusive of both trees and building blocks. Fig. 8(c) shows the radar plots of the building obstruction angles generated based the simulation method at two sites in the study area. The visible sky areas have very similar patterns to the sky pixel classification results retrieved with the GSV-based photographic method. However, unlike the GSV-based photographic method (Fig. 8(b)), the simulation method misses the obstruction of tree canopies.

Therefore, we proposed estimating the shade provision of the street trees by calculating the difference between the photographic-based SVF (SVF\(_p\)) and the simulation method based SVF (SVF\(_s\)),

\[
SVF_{diff} = SVF_s - SVF_p 
\]

(14)

In order to investigate the relationship between the shade provision of street trees and nearby physical environment characteristics, we...
conducted a correlation analyses between the SVF decrease and the surrounding tree canopy cover and building height information. Three physical environment variables, percentage of canopy cover (PCC), averaged canopy height (ACH), and averaged building height (ABH), were calculated and used in the correlation analyses.

5. Results

Fig. 9(a) and (b) shows the spatial distributions of SVF_p and SVF_s estimated from the GSV-based photographic method and the simulation method, respectively. From these two maps, it can be seen that street canyon sites surrounded by high-rise buildings have low SVF values, while those with high SVF values are primarily located at the periphery of the study area. As expected, these results match well with the topography of their local cityscape since high-rise buildings would obstruct the sky and lead to low SVF values, while the periphery areas have lower building heights.

We used the simulation-based SVF_s results as reference to validate the SVF_p results as estimated by the GSV-based photographic method, seeing that the former method is a standard method and well-tested for SVF estimation. We split all chosen sites in the study area into two sets, with the first having sites that contain tree canopy cover within 30 m of the sampling point. The other set includes sites with no surrounding tree canopy cover within a distance of 30 m. Fig. 10(a) shows the scatter plot of the SVF values between these two data subsets, differentiating between sites with and without tree canopy cover around. The SVF_p values estimated from GSV-based photographic method were lower than the SVF_s values that were calculated by the simulation method and not very well correlated (r-square = 0.68). This is within our expectation, because the simulation method solely considers the obstruction of building blocks and the GSV-based photographic method considers the obstruction of both building blocks and street tree canopies. For those sites with no surrounding tree canopy, the SVF_p and SVF_s values are tightly correlated (r-square = 0.90, RMSE = 0.084; Fig. 10b).

The difference of the SVF_p and SVF_s (Fig. 9(c)) represents the contribution of the street trees to the obstruction of solar radiation and, as such, may be said to estimate the amount of shade provided by street trees. Overall, the street trees within the study area decrease the SVF by 18.52%. Generally, the western and northeastern parts of the study area have a larger SVF difference. When compared with the tree canopy map, a similar pattern between the SVF difference and the tree canopy cover is evident (Fig. 9(c)). Table 1 shows the correlation coefficients between the SVF differences and three different physical environment variables: percentage of canopy cover (PCC), average canopy height (ACH), and average building height (ABH) in buffer zones across varying buffer distances. The PCC and the ACH both have positive and significant correlations with the SVF value differences and the correlation coefficients decrease with increasing in buffer distance. This means that more canopy cover and larger canopy height tend to provide more shade in street canyons. The ABH has a significant and negative correlation with the SVF decrease. This is because the shade provided by buildings will cover the shade provided by the tree canopies. The overlap is more serious for high-rise buildings.

6. Discussions

This study investigated the shade provision of street trees in the downtown of Boston by proposing a novel method combining traditional simulation-based SVF estimate with that computed from street-level photographs. We used the GSV-based photographic method and the building height based simulation method to calculate the SVF_p and
SVF, respectively. The SVF<sub>P</sub> values that were calculated by the GSV-based photographic method should be interpreted as the true SVF as this method considers the obstructions of all features present in the street canyon scene (i.e., building blocks and tree canopies). On the other hand, the SVF<sub>S</sub> calculated by the traditional simulation methodology of using building height models tends to overestimate the true SVF values since tree canopies are not accounted for. Furthermore, the difference between the SVF<sub>S</sub> and SVF<sub>P</sub> values can be computed to...
represent the SVF contributed solely from the street trees and, thus, can be used to estimate the shade provision of street trees. Our application of this methodology illustrates that the street trees of our Boston-based study area decrease SVF values on average by 18.52%.

The shading effectiveness of street trees is affected by tree canopy and the height of building blocks along streets. In reference to the later, if buildings overshadow any trees present, then the shade provision of the trees is negated. Indeed, the building height has a significant and negative correlation with the shading effectiveness of street trees, indicating that high-rise buildings overshadow any trees growing below them. The surrounding tree canopy coverage and the canopy height, on the other hand, have significant and positive correlations with the shade provision by the street trees. Thus, the more expansive and, or, taller the tree canopy, the more shade provision provided. This is not surprising of course, but goes to validate the proposed new methodology while also offering a new tool to rapidly assess the SVF of street canyons and shade provision by street trees. As such, these methods can provide a meaningful reference for urban greening projects targeting urban heat island issues and improving the thermal comfort of cities.

What’s more, this methodology represents a rapid estimation of SVF that exploits publicly accessible, and geographically extensive, GSV panoramas and, as such, does not require any manual fieldwork or time-expensive manual processing. We developed a framework in which images are first transformed into fisheye projections, an object-based image classification method is applied to extract the sky area automatically and is then combined with spectral and geometrical rules to minimize misclassification of sky vs. non-sky pixels. Validation results show that the GSV-based SVF estimation methods achieve accurate SVF estimation results. Urban planners and designers should find the proposed method directly actionable and rate SVF estimation results. Urban planners and designers should consider studying the temporal changes of the SVF.

7. Conclusions

This study used the SVF decrease caused by street trees to quantify the shade provision of street trees in the downtown area of Boston. Results show that street trees act to decrease the SVF values by 18.52% in street canyons of the study area. Hence, street tree planting, and in particular large trees, are effective ways to increase the shade coverage in street canyons, particularly in areas where the building heights are moderate to low. For regions with many high-rise buildings, the shade provision of street trees is less effective.

In addition, the proposed GSV-based SVF estimation method offers an automatic method to compute the SVF and does so by utilizing publicly accessible, and geographically extensive, GSV data as input. Therefore, the proposed GSV-based SVF estimation method makes large-scale SVF estimation possible, a benefit to all studies working with SVF or attempting to estimate shade provision in cities.

References


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<tr>
<td></td>
<td>PCC</td>
<td>ACH</td>
</tr>
<tr>
<td>20 m</td>
<td>0.573**</td>
<td>0.514**</td>
</tr>
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<td>40 m</td>
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<td>100 m</td>
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<td>0.419**</td>
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** Correlation is significant at the 0.01 level (2-tailed).


