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Remotely-sensed imagery vs. eye-level photography: Evaluating associations among measurements of tree cover density

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HIGHLIGHTS

- Association between aerial and eye-level tree cover density (TCD) is inconsistent.
- The significance of association diminishes as tree canopy coverage increases.
- Planners should not rely solely on aerial TCD to evaluate urban forestry resources.
- Eye-level TCD should be emphasized at strategic spots.
- Eye-level photographs and site visits are still indispensable tools for evaluating sites.

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ABSTRACT

The easy availability and widespread use of remotely-sensed imagery, especially Google Earth satellite imagery, makes it simple for urban forestry professionals to assess a site and measure tree cover density without visiting the site. Remotely-sensed tree cover density has become the dominant criterion for urban forestry regulations in many countries, but it is unclear how much such measures match the eye-level tree cover density that people experience; or the information gained through site visits, eye-level photography, or from consulting with citizens. To address this uncertainty, we assessed associations among two remotely-sensed and three eye-level tree cover density measures for 140 community street sites across the Midwestern United States with low, medium, or high tree cover coverage by using linear regression analysis. We found significant associations among the two remotely-sensed measures and the three eye-level measures across the three levels of tree cover. The associations between any pair of remotely-sensed and eye-level measures, however, diminish dramatically as canopy cover increased. At high levels of canopy cover, all associations between the remotely-sensed measures and the eye-level measures became statistically insignificant. These findings suggest that measures from remotely-sensed imagery fail to represent the amount of tree cover people perceive at eye-level when canopy cover is medium or high at the site scale. Therefore, the current urban forestry planning regulations, which rely heavily on remotely-sensed tree cover density measurements, need to be revised. We suggest strategic spots where eye-level measures of tree cover density should be emphasized.

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1. Introduction

A primary goal of urban forestry planning and management is reaching at least minimum levels of tree cover density (Nowak et al., 2010). Accurate measures of tree cover density are needed so planners know where to plant trees and how many trees to plant. Tree cover density is most often measured using remotely-sensed imagery (e.g., rectified satellite imagery). Google Earth produces high-quality remotely-sensed images of most places on earth that can be used to objectively calculate tree cover density at little or no cost to the user. This combination of no cost and easy access has made the use of remotely-sensed images for measuring tree cover density and for procuring information about a site ubiquitous in design and planning circles (Janssen & Rosu, 2012; Sheppard & Cizek, 2009).

Given the advantages provided by remotely-sensed images, it is likely that many designers and planners feel that they can assess a site and make rational decisions about it by relying on Google Earth imagery rather than on visiting a site and using other eye-level methods (Power, Neville, Devereux, Haynes, & Barnes, 2013). In recent years, tree cover density measurements derived from remotely-sensed images have been widely adopted to evaluate and compare tree cover density at the scale of states (Nowak & Greenfield, 2012a), cities (McPherson, Simpson, Xiao, & Wu, 2011; Nowak & Greenfield, 2012b), and communities (Kardan et al., 2015; Klemm, Heusinkveld, Lenzholzer, & van Hove, 2015). Eye-level tree cover density measurements are used much less often. Eye-level measures include calculating tree cover density from eye-level photography (Jiang, Chang, & Sullivan, 2014) and asking landscape experts or ordinary people to subjectively rate tree cover density from eye-level photographs of actual landscape scenes (Jiang, Larsen, Deal, & Sullivan, 2015; Nordh, Hartig, Hagerhall, & Fry, 2009). It is plausible, however, that eye-level photography, especially panoramic photography that has a similar visual scope to human vision, may better represent people's perceptions of landscapes than remotely-sensed imagery, and may be a better tool than remotely-sensed imagery in efforts to understand the impact of urban forestry on human health and well-being. Many studies have reported strong, positive associations between the density of vegetation in urban landscapes and the health and wellbeing of individuals (Li & Sullivan, 2016; Parsons, Tassinary, Ulrich, Hebl, & Grossman-Alexander, 1998; Ulrich, 1984; van den Berg, Koole, & van der Wulp, 2003). Previous studies suggest, moreover, that eye-level photographs are more accurate at measuring tree cover density and procuring information about a site than remotely sensed imagery (Kweon, Ellis, Lee, & Rogers, 2006; Leslie, Sugiyama, Ierodiaconou, & Kremer, 2010).

To our best knowledge, no empirical studies have examined the extent of agreement among remotely-sensed and eye-level methods of measuring tree cover density at the site scale. In addition, it is unclear whether remotely-sensed or eye-level methods would be better in certain circumstances (such as when tree cover density is low or high). To what extent can designers and planners eschew traditional forms of procuring information about a site (e.g., by measuring tree cover density from eye-level photographs or walking the site) and rely instead on information conveyed by remotely-sensed images? Should municipal officials establish standards of tree cover density in cities by relying on information conveyed solely by remotely-sensed images?

Lack of this knowledge may lead to bias or error when using remotely sensed imagery to manage urban forestry resources or when making landscape design decisions. Understanding the agreement or disagreement among these different measures of tree cover density will help landscape architects and planners use the best methods in their practice. Armed with the best methods, they can more accurately assess sites and more fairly allocate urban forest resources to meet tree cover density objectives.

1.1. Top-down tree cover density

Measuring tree cover density from remotely-sensed images has been the primary, if not the sole, method used in the U.S. for assessing urban forest density for decades. Clark, Matheny, Cross, & Wake (1997) regarded using city-wide GIS to measure tree canopy density as an optimal performance indicator of urban forest sustainability. In 2010, the USDA Forest Service published a general report on sustaining America's urban trees and forests using tree cover density derived from remotely-sensed imagery to quantify urban forest density from the county to national scales (Nowak et al., 2010).

The dominance of tree cover measurements derived from remotely-sensed imagery has been brought about in part by i-Tree, the most comprehensive urban forestry assessment tool in the U.S. i-Tree is a free, peer-reviewed software package released by the USDA Forest Service in 2006. One of the tools i-Tree offers, i-Tree Canopy, uses Google Earth imagery to assess tree cover density from the regional and community scale to the site scale but does not include measurement of eye-level tree canopy at the site scale ("i-Tree Canopy," n.d.). Another tool, i-Tree Streets, can be used by either professionals or non-professionals to assess tree cover density at the site or community scale, but it is not designed to quantify eye-level tree cover density at either scale ("i-Tree Streets," n.d.).

Another widely-used tool in the U.S., the Urban Forest Management Plan Toolkit, also emphasizes the importance of assessing tree cover density derived from remotely-sensed images for evaluating the status of the urban forest and establishing target density levels. The Toolkit, however, does not employ eye-level tree canopy density as an indicator of target tree cover density at different spatial scales or for different types of urban spaces ("Urban Forest Management Plan Toolkit," n.d.).

Even urban forestry professionals who do not use i-Tree or other toolkits can use free Google Earth software to procure information about a site and measure tree canopy cover. The easy availability and widespread use of Google Earth satellite imagery makes it easy for landscape architects to gain detailed knowledge of a site without getting their boots dirty. Compared to expensive and complicated GIS software and remote sensing imagery, Google Earth provides high-quality photos of most urban places on earth at no cost to the user (Storbeck & Clore, 2007). Using Google Earth photos, designers and researchers can easily and objectively calculate tree cover density. One such method, which we use in this study, uses graphic design software to divide the number of pixels in a satellite image associated with trees by the total number of pixels to calculate the amount of tree cover in a site.

Other advanced techniques and tools for urban forest assessment, such as Normalized Difference Vegetation Index (NDVI), Geographic Objective-Based Image Analysis (GEOBIA), and Light Detection and Ranging (LiDAR), further encourage professionals to rely on remotely-sensed imagery or maps to calculate top-down tree cover density and assess other site conditions (Nesbitt et al., 2015). Indeed, LiDAR has developed 3D measures of tree cover density, but its high cost prohibits many professionals from using the technology on a daily basis. Moreover, in developing countries, data availability restricts the application of these technologies. In addition, these measures are sometimes seen as too complicated to apply in design practice for many urban planners or landscape architects without in-depth training in advanced mapping techniques.

Remotely-sensed measures of tree cover density have several constraints. First, they often do not include scattered tree canopy in the analysis – that is, tree canopy not connected to large green patches but more spread out or isolated. Second, these methods often include nearby tree canopy within a specified buffer area – such as a 1000 m circular area or a census block – but it is unclear whether people have physical or visual access to those areas (Hu, Liebens, & Rao, 2008). Third, the accuracy of these methods for measuring trees with small canopies is questionable. Even the leading remotely-sensed mapping technology, LiDAR remote sensing, has a tendency to underestimate the density of trees with low height (lower than 20 m) (Richardson & Moskal, 2011). Fourth, people rarely experience landscapes from a remotely-sensed perspective, which may make measurements of tree cover density using Google Earth photographs less representative of the tree canopy cover people see on a site than measurements of tree cover from panoramic eye-level photographs (Beil & Hanes, 2013; Jiang et al., 2014).

1.2. Eye-level tree cover density

Until remotely-sensed imagery became ubiquitous, eye-level photography was widely used by designers, planners, and researchers to gain knowledge about the tree cover on a site and to examine people's responses to landscapes as a reliable surrogate of actual settings (De Kort, Meijnders, Sponselee, & Ijsselsteijn, 2006; Valtchanov, Barton, & Ellard, 2010).

Though it is more costly and time-consuming, eye-level photography can also be used to empirically measure visible tree cover. In a pioneering study, researchers used a grid pattern of 588 squares to measure the percentage of green landscape components from eye-level photographs by counting squares covered by more than 50% of a given landscape component (Nordh et al., 2009). A more precise way to make these measurements is to use Photoshop software to divide the number of pixels occupied by tree canopy by the number of pixels in the whole photograph (Jiang et al., 2014). This method should be a reliable representation of how much tree cover people perceive while standing on a site because the measure precisely calculates the visible tree cover presented in an eye-level photograph.

1.3. Human assessment of tree cover

In addition to calculating tree cover density using eye-level or remotely-sensed images, landscape architects and planners also subjectively assess tree cover from eye-level photographs or site visits. Less frequently, they involve the public in this site assessment. Public engagement can improve urban forest sustainability efforts (Clark et al., 1997). However, urban planners and landscape architects might be reluctant to engage the public when it is unclear how well they perform specific urban forest planning and management tasks (Sipilä & Tyrväinen, 2005). Previous studies suggest that the public can reliably complete many of these tasks, including collecting imagery data for urban forest inventory (Abd-Elrahman, Thornhill, Andreu, & Escobedo, 2010), reporting physical attributes and estimating the benefits of urban street trees (Sommer, Guenther, & Cecchettini, 1992), indicating landscape preference (Carvalho-Ribeiro & Lovett, 2011; Jiang, Larsen et al., 2015), designing and constructing public green spaces (Semenza, March, & Bontempo, 2007), conducting landscape surveys after a short training (Kuo & Sullivan, 2001a), and setting urban forestry goals (Sipilä & Tyrväinen, 2005). Other studies, however, found that ordinary people often do not have enough biodiversity-identification skills (Dallimer et al., 2012) and management understanding (Sipilä & Tyrväinen, 2005), and might have conflicts of interest depending on their occupational background (Sullivan, 1994).

1.4. Research objectives

Though there are a variety of ways to measure tree cover density, no previous studies have explored whether, and to what extent, remotely-sensed measures and eye-level measures agree at the site scale. Does the agreement change when tree cover density is low, medium, or high? We also do not know how empirically-calculated methods of measuring tree cover density compare to subjective assessments from experts and ordinary people. If all of these measures are strongly associated with each other, then practitioners can use any tree cover density measurement with confidence. However, if the different measures are not highly correlated, then it will be important to understand how they differ so that professionals can use the best methods in their practice.

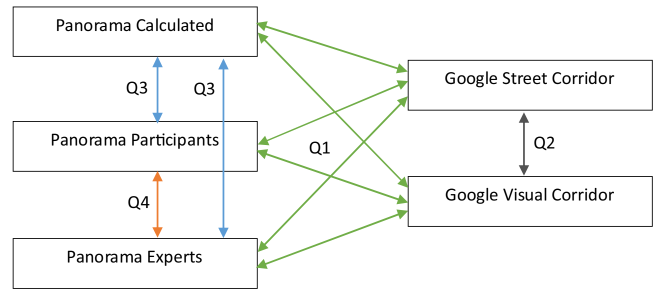

Fig. 1. Four research questions examining the relationships among five measures of tree cover density.

To identify the relationships among the different measures of tree cover density, we used two remotely-sensed methods and three eye-level methods to measure tree cover density at the community street scale and analyzed their associations.

For the remotely-sensed methods, we used Google Earth images to measure tree cover density. In the first method, we calculated percent tree cover of a street corridor from Google Earth remotely-sensed images (Google Street Corridor). In the second method, we calculated percent tree cover of a 100-m wide visual corridor from Google Earth remotely-sensed images (Google Visual Corridor).

For the three eye-level methods, we used panoramic photographs. In the first method, we objectively calculated percent tree cover from panoramic photographs (Panorama Calculated). For the second and third methods, we asked ordinary participants and landscape experts to rate the tree cover density they perceive in panoramic photographs (Panorama Participant and Panorama Expert).

We assume eye-level measures more accurately represent the tree canopy coverage perceived by people on site because panoramic photographs contain a similar viewshed as people experience on site. Based on this assumption, the association between eye-level and remotely-sensed imagery measures can reflect the reliability of remotely-sensed measures in describing the tree canopy cover perceived by people on site. We use multiple eye-level measures (three) to minimize the risk of bias for any single eye-level measure. The validity of each measure can be further demonstrated if all pairs of the three eye-level measures have correlations close to 1. We use two remotely-sensed imagery measures for similar reasons.

We asked four questions (Fig. 1). For each question, we also examined if the relationship changes when sites are grouped into low, medium, or high tree canopy cover. The first question below is the central question of this study. The three questions that follow seek to deepen our understanding of the central question.

1. To what extent are the two Google Earth measures associated with the three Panorama measures?
2. To what extent are the two Google Earth measures associated with each other?
3. To what extent is Panorama Calculated associated with Panorama Participant and Panorama Expert?

4. To what extent is Panorama Participant associated with Panorama Expert?

2. Method

To examine the agreement among the five measures of tree cover density, we used remotely-sensed images and panoramic eye-level photographs of neighborhood street sites and calculated tree cover density values using the 5 measures for each site. A Pearson Correlation analysis was conducted for all 140 samples. The sites were further divided into three groups with low, medium, and high tree canopy cover. Associations among the 5 measures were examined through linear regression analysis.

2.1. Selection of sites

To select sites for our study and limit the confounding physical characteristics that differed between sites, we employed the following steps: First, we identified 46 single-family home community block groups in four mid-western urban areas (Champaign-Urbana, St. Louis, Indianapolis, and Springfield) in the United States as candidate districts. We used median annual income between $50,000 and $75,000 per household at the block group level (data from Google Earth Pro) as a controlling socioeconomic factor (Jiang et al., 2014). We used this criterion as the first step to avoid community sites with poorly maintained or overly polished environmental characteristics. According to the USA census, the range of annual income adopted in this study represents income of the majority of middle class families in the mid-western region. Second, two investigators visited each block group and took eye-level panoramic photographs of 255 street sites with varying levels of tree cover. At this step, we rejected streets without sidewalks or curbs. Third, three experts in Landscape Architecture reviewed the panoramic photographs of the sites and removed sites from consideration that had unique environmental attributes other than tree cover density. We removed streets with unique physical characteristics (presence of humans, moving cars, parked cars that blocked the view, uncommon small or large buildings, etc.) to make sure all streets had similar spatial attributes but varying levels of tree cover density. This process left us with 140 sites that were used in the study.

2.2. Creating panoramic photographs

To photograph the initial 255 street scenes, we placed a tripod along the street curb near a driveway, where casual conversation and physical activities often occur. The investigator placed the camera on the tripod where the street scene could be captured, with no big trees or other visual barriers within 10 m of the camera. The camera lens was kept at a horizontal angle and placed approximately 165 cm from the ground, a height similar to human vision. All photographs were taken on sunny days from 10 a.m. to 3:30 p.m. from June to August 2011. The viewshed of the panoramic picture was approximately 150°. A panoramic photograph was created by combining photographs into a panoramic scene using the *Photomerge* command in Photoshop CS5.

2.3. Five measures of tree cover density

This study examines associations among five measures of tree cover density: two measures using Google Earth remotely-sensed imagery and three measures using eye-level panoramic photographs (Fig. 2).

2.3.1. Google Street Corridor and Google Visual Corridor

In order to calculate the density of tree cover from remotely-sensed imagery along each of the 140 streets, we downloaded high-resolution photographs from Google Earth Professional. We set the altitude at 600 m for all sites so that all photographs had the same scale and same resolution (4800 pixels). All remotely-sensed photographs were captured during the 2011 growing season to ensure that deciduous trees had fully developed canopies.

The next step was to identify the boundary of the viewshed. We defined the viewshed in two ways. The first way, which we call Google Street Corridor, included the street corridor outlined by ridges of houses on either side of the street. The second way, which we call Google Visual Corridor, included a 100-m-wide visual corridor that was measured from the center of the street (50 m on either side of the center line, Fig. 2, top-left). The Google Street Corridor viewshed contained the entire tree canopy within the street corridor, whereas the Google Visual Corridor contained other visible trees behind the houses up to 50 m away from the center line of the street (Fig. 2, top-right).

We used these two remotely-sensed measures because both methods are frequently used and can complement each other. The Google Street Corridor measures tree cover density strictly within the street corridor. In some cases, it might neglect tree canopy outside the street that can be seen from the street. The Google Visual Corridor solves that problem by including the nearby visible tree canopy. The Google Visual Corridor does not measure all tree canopy in the 100 m visual corridor because some trees are totally invisible from a site.

We used the Magnetic Laso Tool in Photoshop Software to select areas occupied by tree canopy shown in the remotely-sensed image. The area of overlapping tree canopy was only counted once. The features of the Laso tool were set as feather (0 px), anti-alias, width (1 px), contrast (10%), and Frequency (100). Then we used the histogram table to read the number of pixels in the selected areas and the total number of pixels of the entire photograph. Tree cover density is the percentile ratio between those two numbers.

2.3.2. Panorama calculated

To calculate the amount of tree cover density in the panoramic photographs, we used Photoshop again. We first selected areas of tree canopy and trunks in a panoramic photo and identified the number of pixels contained in those areas. As with the two Google measures, we identified the number of pixels contained in the entire photo and divided the number of pixels associated with trees by the total number of pixels (Fig. 2, bottom).

2.3.3. Panorama participant

Participants were drawn from a larger study that examined the impact of varying tree cover density on stress recovery and preference (Jiang et al., 2014; Jiang, Larsen et al., 2015; Jiang, Li, Larsen, & Sullivan, 2016). 314 adults participated in this study by completing a questionnaire in the lab (167 females and 147 males, *whose age ranged from* 18–32, *with mean* 21.4 years, and *standard deviation* of 2.6 years). Individuals who were receiving or had received professional training or education in Landscape Architecture, Architecture, or Urban Planning did not participate in this portion of the study.

Each participant was randomly assigned 15 out of 140 panoramic photographs and asked to rate the tree cover density using a Likert scale from 1 (no tree cover) to 10 (extremely dense tree cover). Each of the 140 sites was evaluated about 33 times by different participants. Complete data from five sites was missing so data from 135 sites were used for further analysis. We used the mean value of participants' ratings on each picture for the Panorama Participant measurement. The Cronbach's Alpha value for the Panorama Participant measure is 0.79, which suggests high inter-rater reliability. For convenience of analysis, the original rating scores were transformed to percentages.

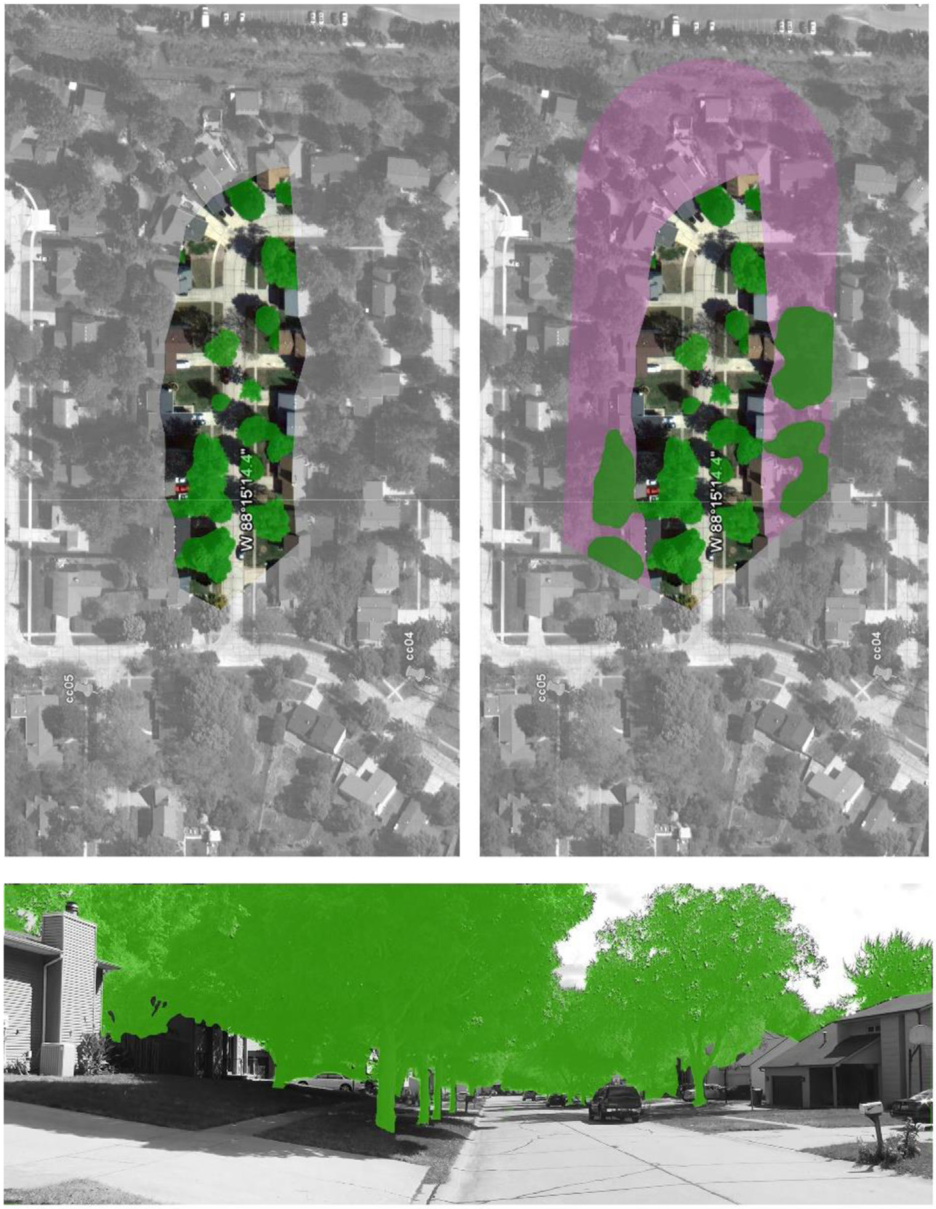

Fig. 2. Representation of three empirical methods of measuring tree cover density for a sample site: Panorama (top), Google Street Corridor (up-left, the colored map area is the street corridor) and Google visual corridor (up-right, the purple area is the 100m-wide visual corridor). The tree canopy in the equations is highlighted in the bright green color. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.3.4. Panorama expert

Fifty-eight graduate students in Landscape Architecture rated the tree cover density for the 140 panoramic photographs. Each photograph was displayed by a digital projector for 10 s and experts rated tree cover density using the same Likert scale the ordinary participants used. Complete data from one site was missing so data from 139 sites were used for further analysis. We used the mean value of experts' rating on each picture for the Panorama Expert measurement. The Cronbach's Alpha value for Panorama Expert is 0.83–a high level of inter-rater reliability. For convenience of analysis, the original rating scores were transformed to percentages.

2.4. Categorizing three levels of tree canopy cover

We conduct Pearson Correlation for all samples to investigate associations among 5 tree cover measures. We wondered, however, if the findings would be consistent for different tree cover densities. To examine this question, we categorized sites into low, medium, and high tree cover density, using density values from our Google Street Corridor measure. We chose Google Street Corridor to categorize sites because it is the method used by a majority of city managers, urban forestry planners, design professionals, and scholars to measure tree cover density. Using it to categorize levels of tree cover density enables us to connect our findings with current planning regulations, design solutions, and scientific evidence.

To determine the cutoff values for the three levels (low, medium, and high), we took several steps. First, we examined published surveys of percent tree cover in major North American cities to find possible ranges of tree cover density. In one study, among 68 cities, 15 had tree cover greater than 30%, 14 cities had tree cover between 16% and 30%, and 27 cities had tree cover equal to or less than 15% (Nowak et al., 1996). These findings suggest it is reasonable to regard a percentage around 15% as the cutoff between the low and medium tree cover groups and a percentage around 30% as the cut-

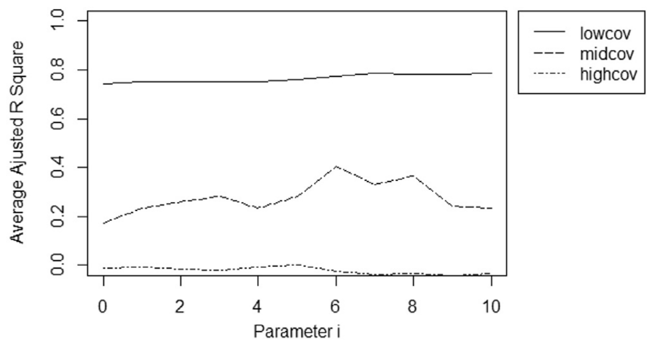

Fig. 3. Fluctuations of average "Adjusted R Square" for each group with given *i*. Lowcov, midcov, and highcov mean low, medium, and high tree canopy coverage.

off between the medium and high groups. Second, we examined the mean value of percent tree cover in urban areas for 12 states in the northern and central United States, with climate and demographic conditions similar to sites in our study – we found it to be 25.9% (ranging from 19% to 34.6%). Finally, we identified the mean values of perecent tree cover for the states represented in our study and found these values to be 26.4% for Illinois (SD = 2.4%), 22.3% for Missouri (SD = 3.0%), and 31.1% for Indiana (SD = 3.6%) (Nowak & Greenfield, 2012a, 2012b). These results suggest a cutoff value between 25% and 35% to separate the medium and high levels.

Even following the procedures described above, it is possible that any cutoff values we settled on would still be arbitrary. Thus we test a range of cutoff values including possible values suggested by the literature (around 15%, 25%, and 35%) to find the most robust cutoff points (Hansen & Sargent, 2001). We obtain regression model results for all combinations of cutoffs fluctuating around 15%, 25%, and 35% (which is represented by i below). Then we picked the cutoff values that were the most insensitive to small fluctuations in i – that is, when we added or decreased by 1% the selected cutoffs.

The cutoff values before the robustness test were: 10% + i between the low and moderate tree cover density group, and 25% + i between the medium and high tree cover density groups, where i is an integer parameter ranging from 0 to 10. This set of cutoff values ensures that there are enough samples in each group (at least 25) for different i values. Based on this robustness test result, we selected i = 5 for the cutoff value for the three densities of tree cover (Fig. 3).

We ran 16,500 regression models with the independent variable "Panorama Calculated" and the dependent variable "Google Street Corridor" for all possible values of *i* and for all 3 groups. To keep the number of samples consistent for all 3 groups, we used the statistical software R to script a code that allowed us to sample n data points from each group for each *i* value, where n is the smallest sample size of the 3 groups given a specific *i* value. The sampling was conducted 500 times for each group with a given *i* and the average Adjusted R^2 is reported for each group given each *i*. For the low tree cover group, the average Adjusted R^2 is generally stable for all *i* values. The medium and high groups begin to show more significant fluctuations for $i > 5$. For the medium group, which has the most significant fluctuations, $i = 5$ generally represents the average value of Adjusted R^2 for all i. Based on this robustness test result, we selected $i = 5$ for the cutoff value for the three densities of tree cover.

Table 1
Descriptive information of five measures of tree cover density.

Categories	Five measures	N	Min	Max	M	S.D.
Remotely-sensed	Google Street Corridor	140	0.1	61.5	17.3	17.0
	Google Visual Corridor	140	0.1	63.9	21.8	19.6
Eye-level	Panorama Calculated	140	0.0	65.5	31.0	21.7
	Panorama Participant	135	10.0	91.0	50.0	24.2
	Panorama Expert	139	10.0	83.0	44.1	22.3

Following these procedures, we came up with the following categories: low cover: Google Street Corridor tree cover that falls between 0 and 15.0%; 2) medium cover: Google Street Corridor tree cover that falls between 15.1% and 30.0%; 3) high cover: Google Street Corridor tree cover that falls between 30.1% and 62.0%. These categories are consistent with recently published work (Nowak & Greenfield, 2012a, 2012b).

In regression analysis examining the association among five measures for the three levels of tree cover density, we wanted to keep the number of samples run in each model consistent for all 3 groups. Thus we wrote a code using R script to sample n data points from each group, where n is the smallest sample size of the 3 groups (for $i = 5$, n is 29 from the medium cover group). The medium group is run with linear regression only once with all data from the group for the correlation between two selected measures, while 29 samples are randomly selected from each other group each time over 500 regressions applied to each group. The model results are used in the analyses that follow

3. Results

After reporting the Pearson correlations among the five measures for all sites, we examine the associations among the five different measures of tree cover density for three levels of density (low, medium, and high). We report descriptive statistics in Table 1.

3.1. Association among tree cover measures

The results of Pearson correlation among the five measures for all the sites show all measures were significantly, and highly, correlated with each other ($p < 0.001$, see Table 2). We notice, however, that there are 75 samples within the low tree canopy cover category, but only 29 samples within the medium cover category and 36 samples within the high cover category. It is likely that this uneven distribution of samples distorts the results of correlation analysis. Therefore, it is necessary to examine the association among the five measures when samples are evenly and randomly collected from the three different levels of tree cover density. We perform these analyses below.

Table 2
Two-tailed Pearson correlations among five measures of tree cover density for all sites.

	Tree cover density measures				
	Remotely-sensed		Eye-level		
	Google Street Corridor	Google Visual Corridor	Panorama Calculated	Panorama Participant	Panorama Expert
Google Street Corridor	1				
Google Visual Corridor	0.97^{***}	1			
Panorama Calculated	0.92^{***}	0.90^{***}	1		
Panorama Participant	0.96^{***}	0.94^{***}	0.95^{***}	1	
Panorama Expert	0.95^{***}	0.93^{***}	0.95^{***}	0.97^{***}	1

$^{***}p < 0.001$.

Table 3
Linear regression analysis of Google Street Corridor and three panorama measures of tree cover density across three groups.

		Panorama Calculated	Panorama Participant	Panorama Expert
Low	Adj. R^2	0.76***	0.82***	0.80***
	95% CI	0.68, 1.05	0.28, 0.40	0.33, 0.48
	Coef (SE)	0.86*** (0.09)	0.34*** (0.03)	0.40*** (0.04)
Medium	Adj. R^2	0.28**	0.14*	0.10
	95% CI	0.28, 1.10	0.03, 0.43	0.00, 0.33
	Coef (SE)	0.69** (0.20)	0.23* (0.10)	0.16 (0.08)
High	Adj. R^2	0.00	0.09	−0.02
	95% CI	− 0.16, 0.46	−0.01, 0.32	−0.13, 0.24
	Coef (SE)	0.15 (0.15)	0.16 (0.08)	0.05 (0.09)

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 4
Linear regression analysis of Google Visual Corridor and three panorama measures of tree cover density across three groups.

		Panorama Calculated	Panorama Participant	Panorama Expert
Low	Adj. R^2	0.65***	0.73***	0.68***
	95% CI	0.51, 0.90	0.22, 0.35	0.24, 0.41
	Coef (SE)	0.71*** (0.10)	0.28*** (0.03)	0.33*** (0.04)
Medium	Adj. R^2	0.12*	0.09	0.05
	95% CI	0.02, 0.60	−0.01, 0.25	−0.02, 0.19
	Coef (SE)	0.31* (0.14)	0.12 (0.06)	0.08 (0.05)
High	Adj. R^2	−0.02	0.06	−0.02
	95% CI	−0.20, 0.36	−0.03, 0.27	−0.12, 0.22
	Coef (SE)	0.08 (0.14)	0.12 (0.07)	0.05 (0.08)

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

3.2. Association among tree cover measures for three levels of tree cover density

First, we examined the central question: To what extent are the two Google Earth measures associated with the three panorama measures? Results in Table 3 show that Google Street Corridor is significantly, positively correlated with the three panorama measures when tree cover density is low ($p < 0.001$). As tree cover density increases to medium, the adjusted R^2 values decrease markedly, but two of the three associations remain statistically significant ($p < 0.01$ and $p < 0.05$). When tree cover density is high, the adjusted R^2 values reach low levels and none of the associations are significant.

Results in Table 4 show that Google Visual Corridor has a similar association with the three panorama measures as the Google Street Corridor. When tree cover denisty is low, all associations are significant and positive ($p < 0.001$). When tree cover density is medium, the adjusted R^2 values markedly decrease and only one association remains significant. When tree cover density is high, the adjusted R^2 values reach low levels and none of the associations are significant.

Second, we examined the extent to which measures within the remotely-sensed or eye-level categories are associated with each other. What is the association between Google Street Corridor and Google Visual Corridor? Both the R-squared and regression coefficient values show the two Google Earth measures are significantly associated with each other ($p < 0.001$) across the three levels of tree cover density (Table 5).

To what extent is Panorama Calculated associated with Panorama Participant and Panorama Expert? Results of the regression analysis in Table 6 show the associations between Panorama Calculated and the two subjective panorama measures are statistically significant across the three groups ($p < 0.01$ or $p < 0.001$). Together, these findings suggest that Panorama Calculated is a reliable objective measure to predict perceived tree cover density at the site scale. Note that Panorama Participant and Panorama Expert are both similarly associated with Panorama Calculated

Table 5
Linear regression analysis of Google Street Corridor and Google Visual Corridor measures of tree cover density across three groups.

	Google Visual Corridor	
Low	Adj. R^2	0.88***
	95% CI	0.92, 1.22
	Coef (SE)	1.07*** (0.07)
Medium	Adj. R^2	0.61***
	95% CI	0.86, 1.61
	Coef (SE)	1.23*** (0.18)
High	Adj. R^2	0.73***
	95% CI	0.74, 1.19
	Coef (SE)	0.97*** (0.11)

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 6
Linear regression analysis of Panorama Calculated and two subjective panorama measures of tree cover density across three groups.

		Panorama Participant	Panorama Expert
Low	Adj. R^2	0.84***	0.82***
	95% CI	0.29, 0.35	0.34, 0.49
	Coef (SE)	0.35*** (0.03)	0.41*** (0.04)
Medium	Adj. R^2	0.40***	0.26**
	95% C	0.15, 0.42	0.07, 0.31
	Coef (SE)	0.29*** (0.07)	0.19** (0.06)
High	Adj. R^2	0.34***	0.27**
	95% CI	0.16, 0.51	0.12, 0.51
	Coef (SE)	0.34** (0.09)	0.32** (0.10)

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

Table 7
Association between Panorama Participant and Panorama Expert across three groups.

		Panorama Expert
Low	Adj. R^2	0.89^{***}
	95% CI	0.99, 1.29
	Coef (SE)	1.14^{***} (0.07)
Medium	Adj. R^2	0.62^{***}
	95% CI	0.45, 0.84
	Coef (SE)	0.65^{***} (0.10)
High	Adj. R^2	0.31^{**}
	95% CI	0.26, 0.94
	Coef (SE)	0.60^{**} (0.17)

$^{*}p < 0.05$.
$^{**}p < 0.01$.

for the low tree density group (adj. $R^2 = 0.84$, $p < 0.001$ vs adj. $R^2 = 0.82$, $p < 0.001$). However, Panorama Participant has a significantly stronger association with Panorama Calculated than Panorama Expert for the medium group (adj. $R^2 = 0.40$, $p < 0.001$ vs adj. $R^2 = 0.26$, $p < 0.01$) and the high group (adj. $R^2 = 0.34$, $p < 0.001$ vs adj. $R^2 = 0.27$, $p < 0.01$).

To what extent is Panorama Participant associated with Panorama Expert? Both the R-squared and regression coefficient values shown in Table 7 show that Panorama Participant and Panorama Expert are significantly associated across the three levels of tree cover ($p < 0.01$ or $p < 0.001$), although the agreement for the medium and high groups is lower than the agreement for the low group.

4. Discussion

At first glance, we found all five measures of tree cover density have significant, positive associations. But after we sorted the street scenes into categories of low, medium, and high tree cover density, we found significant differences in the associations, and some associations were no longer significant. The association between the two Google Earth measures and the three panoramic measures diminished as tree cover density increased. When tree canopy cover was low, all associations were statistically significant, indicating good compatibility between remotely-sensed and eye-level measures. However, when tree canopy cover was at a medium level, associations became considerably weaker (three of six associations are statistically insignificant), and all associations became statistically insignificant when tree canopy cover was high. These findings suggest that Google Street Corridor and Google Visual Corridor do not reliably represent perceived or calculated eye-level tree cover density in community streets with high levels of tree cover. These findings are consistent with findings from a pioneering study (Leslie et al., 2010), but present a more complete picture of the associations for sites with different levels of tree cover density.

We found that associations between the two Google Earth measures (Google Street Corridor and Google Visual Corridor) were statistically significant across three levels of tree canopy cover and yield similar tree cover density measurements. The highly significant match between these two remotely-sensed measures implies they have similar capability in measuring tree canopy density at the site scale. Also, we found that associations between the two self-rated measures of panoramic tree cover density (Panorama Participant and Panorama Expert) were statistically significant across the three levels of tree canopy cover. We also found that associations between the tree densities calculated from panoramic photographs (Panorama Calculated) and perceived tree cover by ordinary participants (Panorama Participant) and experts (Panorama Expert) were positive and significant across the three density levels. This finding suggests that perceived eye-level tree

Fig. 4. As the tree canopy coverage increases from low (top) to medium (middle), and to high level (bottom), the diversity of tree species, canopy sizes, and distances between two adjacent trees increases.

cover measured from both ordinary people and experts yields similar results to empirically-measured eye-level tree cover density.

In the paragraphs that follow, we consider the mismatch between remotely-sensed and eye-level measures, discuss the contributions and implications of this work, and, before concluding, suggest ideas for future research.

4.1. Mismatch between remotely-sensed and eye-level measures

Our most important finding is that there is a mismatch between remotely-sensed and eye-level measures of tree cover density when tree cover is medium (15.1%–30.0%) or high (30.1%–62.0%). We explore five possible reasons for this mismatch.

First, people's perception of tree cover density along a street is likely to differ depending on where they stand, which direction they look, and where trees are located. Panoramic photographs can better capture these differences because they are taken at eye-level and represent a similar visual scope to what people experience. People rarely experience landscapes from a high altitude. Measures from Google Earth photographs can only describe the average remotely-sensed tree cover of a community street or a visual corridor.

Second, through further observation of the panoramic photographs and remotely-sensed images, we found most sites with low tree canopy cover in this study contain young, similarly-sized, small trees of limited species diversity, with uniform distance between trees (Fig. 4top). As tree canopy cover reaches a medium or high level, sites have a higher diversity of tree canopy size and distance between trees (Fig. 4middle and bottom), due to differences in planting regulations, tree species, tree age, maintenance, microclimate conditions, micro-soil and water conditions, or the death or removal of trees. People standing at different spots in these sites might perceive the tree cover differently because of this greater diversity. This observation reinforces the importance of site investigation because it is a challenge to fully understand the site and accurately record urban forest features when one relies solely on remotely-sensed photography.

Third, it is possible that the mismatch in associations may be influenced by the photographer's arbitrary choice of location and perspective. To minimize this bias, we established a clear set of controls for the location and height of camera, the height and angle of the eye-level photograph, and any visual disturbances. In this study, eye-level tree cover density was much more likely to be influenced by the distribution of tree canopy in the street corridor than by the photographer's arbitrary choice.

Another possible reason for the mismatch is that the effect of additional trees on our measure of eye-level density may diminish as tree density increases. That is, when tree canopy density is at a low level, additional trees are easily noticed and lead to significant and similar increases in both eye-level and remotely-sensed tree cover density measures. However, as tree canopy cover reaches a relatively high level, additional trees are more difficult to notice at eye-level. From an eye-level perspective, it may be hard to notice the additional trees, whereas an aerial perspective may be able to perceive these trees. Therefore, the regression association becomes weaker and weaker as tree canopy coverage increases from the low to high level.

Finally, it is important to note that tree canopy is not a solid object. Some trees have significantly more leaves or branches than others. The completeness of the tree canopy, or the density of leaves on branches, has been found to be significantly associated with human perception and preference (Nelson, Johnson, Strong, & Rudakewich, 2001). Google Earth measures cannot capture tree canopy completeness because multiple horizontal layers of leaves lead people to perceive a solid surface of tree canopy. It is much easier to identify leafless areas within a tree canopy in an eye-level photograph. We conclude that eye-level panoramic photographs more accurately depict the tree canopy density people perceive on site.

4.2. Contributions and implications

To our best knowledge, this study is the first to provide a strong rationale for questioning urban forest regulations in the U.S. and other countries that rely heavily on remotely-sensed measurements of tree cover to evaluate and allocate urban forest resources (Kweon et al., 2006; Leslie et al., 2010; Richardson & Moskal, 2011). The findings here identify a mismatch in the measurement of tree canopy density between remotely-sensed and eye-level measures. The finding also suggests that, at the site scale, remotely-sensed measurements are not always reliable, and eye-level measurements are likely more reliable measures of visible tree canopy. When tree canopy cover is at a medium or high level, remotely-sensed measures are not reliable to depict the amount of tree canopy people see on site. Nevertheless, it may be feasible to use any of those measures when the tree canopy cover on a site is low.

Because each panoramic photograph was shot on the street near a driveway and the edge of a front yard, our findings suggest, for sites with high tree cover, that calculated tree cover density from Google Earth remotely-sensed imagery might significantly misrepresent residents' perceived tree cover from their front yards. This disparity reinforces the importance of using panoramic photographs to assess visible tree canopy and to develop specific design solutions at the site scale. In addition, this disparity emphasizes the importance of visiting sites to gain a comprehensive impression of visible tree canopy at different locations and through different viewsheds.

We do not suggest that remotely-sensed measures be abandoned. Measuring eye-level tree cover density can be costly and time-consuming, and it is neither possible nor necessary to measure eye-level tree cover density at every spot where people can access nature. Indeed, at a regional or city scale, remotely-sensed measures of tree cover density may be a feasible choice because they can depict an average tree canopy cover for large urban areas. Instead, we recommend that designers and city planners combine methods of measuring tree cover: use remotely-sensed photographs, which are easy to use and free, to explore the general level of tree canopy cover for a larger area and then use panoramic photographs when tree canopy cover is medium or high at the site scale. This integration of remotely-sensed and eye-level measures of canopy density would require designers and urban forest professionals to do on-site investigations in addition to measuring canopy density from remotely-sensed images.

This study also provides evidence that measures of tree density calculated from panoramic photographs reliably represent ordinary participants' and experts', although their associations decrease when tree cover density increases. An unexpected finding is that ordinary participants' subjective measures of tree cover density more closely matched the objectively-calculated panoramic measure of tree cover density than the experts' subjective measures, though the difference was small. This finding suggests ordinary participants' collective evaluation of tree cover density can be trusted, providing new evidence to encourage public engagement.

4.3. Directions for future research

Access to moderate or high levels of tree canopy and other green landscapes has been shown to promote the health and well-being of individuals and communities. Unbalanced allocations of urban forest resources can create situations in which certain portions of a community are at higher risk for a range of health and wellbeing challenges compared to residents of the community who have greater access to medium and high levels of urban forests (Jiang et al., 2014; Kuo & Sullivan, 2001a, 2001b). A disparity in the density of urban forests within cities raises serious questions of social and environmental injustice (Gupta, Kumar, Pathan, & Sharma, 2012). To achieve equality in access to urban forests, we suggest that future research should work to develop an equality index for evaluation of eye-level tree cover density at strategic spots where visual contact to nature is most crucial for promoting residents' or visitors' health and well-being (See Table 8 for our initial list of potential categories and types of strategic spots). For example, the *Gini* Coefficient, which is co mmonly used to measure the inequality of income distribution (International Institute for Environment and Development, 2011) might be employed as a reference to measure inequalities in tree cover density.

Another promising avenue for future research would be to measure tree cover density not only from images from Google Earth but also from those from Google Street View. The wide-spread availability of Google Street View means that many public spaces can easily be assessed in this manner. Emerging machine learning technology already can accurately calculate the density of greenness from Google Street View (Suppakitpaisarn, Slavenas, Jiang, & Sullivan, 2016). We are optimistic it will soon be able to calculate eye-level tree canopy density or other specific green characteristics such as rain gardens and bioswales, in the near future. Still, Google Street View provides very little information about site conditions invisible from the street, and thus it has clear limitations. In addition, Google Street View may not equally represent urban places for social or ideological reasons, which would contribute to the stigmatization of deprived neighborhoods (Power et al., 2013). Nevertheless, these two resources, Google Earth and Google Street View, offer a rich set of possibilities for future research.

There is also a need to improve the methods of obtaining objective measurements of tree cover from eye-level photographs. Although Photoshop provides the Magnetic Lasso Tools (MLT) to assist researchers in selecting areas occupied by tree cover, the work is tedious because researchers must manually measure the

Table 8
Four categories of strategic spots where use of the eye-level tree cover density measure is important.

Categories	Examples
1. Spots with high visual or physical accessibility to individuals	Neighborhood street (Jiang et al., 2014; Sarkar et al., 2015); Todorova, Asakawa, & Aikoh, 2004), community courtyard (Sullivan, Kuo, & DePooter, 2004, community plaza (Semenza et al., 2007), small public park (Baur & Tynon, 2010; Nordh, Hartig, Hagerhall, & Fry, 2009), or vertical visual elements (main building façade, or hillside).
2. Spots where individuals spend most of their daily time living, working, learning, or recreating	Landscapes visible from windows of living room (Kaplan, 2001), office (Chang & Chen, 2005), dorm room (Tennessen & Cimprich, 1995), classroom (Li and Sullivan, 2016), school cafeteria (Matsuoka, 2010), factory plant and lunch area (Gilchrist, Brown, & Montarzino, 2015), private garden, or community garden.
3. Spots seen frequently by individuals who have physical, mental, or social-economic challenges but desperately need contact with nature	Nearby public or private spaces for individuals with disability, mothers with infants, low income individuals with limited transportation options (Kuo, 2013), pregnant woman (Donovan, Michael, Butry, Sullivan, & Chase, 2011), senior (Rappe, Kivela, & Rita, 2006), and child (Corraliza and Collado, 2011); recovery center or therapy garden for patients or victims (Detweiler and Warf, 2005), community playground (Fjortoft & Sageie, 2000), garden and yard for incarcerated people (Moore, 1981), hospital ward (Ulrich, 1984), hospital waiting area (Leather, Beale, Santos, Watts, & Lee, 2003; Ulrich, Simons, & Miles, 2003).
4. Public spaces where significant social interaction and communication occur	Landscapes surrounding city or neighborhood centers (Tyrvainen et al., 2014), coffee shop, church, farmer market (Center for Active Design, 2010), city plaza, student union, or community club (Xiao, Li, & Webster, 2016).

Note: Eye-level views of tree canopy at strategic spots should be emphasized if the space covers a long distance or a great area. Those spots may include entry and exit, gathering or resting locations, or entry or exit to main buildings.

percent tree cover for each site. An enterprising person or team might develop software that can automatically calculate percent tree cover.

Another technology that can measure tree cover density is Light Detection and Ranging (LiDAR). LiDAR can provide three-dimensional data on the attributes of tree canopy, including the shape and height of tree crown. Currently, obtaining LiDAR data is expensive and complicated even for experts. These challenges prevent LiDAR from becoming as user-friendly as Google Earth satellite imagery or eye-level photography (Nesbitt et al., 2015). Nevertheless, the 3D scanning qualities of LiDAR offer new possibilities for future research.

To enhance the validity of this study, we investigated community street sites that included only single-family housing in middle-class neighborhoods in Midwestern urban areas in the U.S. But by enhancing validity, we sacrificed the generalizability of our findings. To test the generalizable of our results, future researchers might replicate this research in other types of urban spaces, such as multi-family neighborhoods, high-rise inner-city apartments, urban parks, urban streets, schools, campuses, and hospital gardens. Researchers should pay attention to deprived communities whose residents are more vulnerable to the loss of nearby nature and whose health status is likely influenced by socio-economic inequality (Jiang, Zhang, & Sullivan, 2015; Mitchell & Popham, 2008; Roe et al., 2013; Ward Thompson et al., 2012; Ward Thompson, Roe, & Aspinall, 2013).

5. Conclusion

This study was an initial effort to understand the relationships among multiple measures of tree cover density. At the site scale, measures calculated using remotely-sensed images were not strongly associated with eye-level measures of tree cover density when tree canopy cover was medium (15.1%–30.0%) or high (30.1%–62.0%). The findings presented here challenge the widespread use of remotely-sensed tree cover density as the dominant tool for guiding the design and management of urban forests, at least at the site scale. One promising way to overcome the challenges identified here would be to integrate measures of tree density from remotely-sensed imagery and eye-level photography and develop a comprehensive index of greeness that can more sensitively depict the urban tree canopy that people experience on site. Our findings should caution designers, planners, and urban forest professionals that heavy reliance on digital aerial photographs and maps may lead to landscape assessments and decisions that do not represent individuals' experience of a site. Using eye-level photographs and visting a site in person are still indispensible tools when tree cover density is at medium or high levels.

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References

Abd-Elrahman, A. H., Thornhill, M. E., Andreu, M. G., & Escobedo, F. (2010). A community-based urban forest inventory using online mapping services and consumer-grade digital images. *International Journal of Applied Earth Observation and Geoinformation*, *12*(4), 249–260. http://dx.doi.org/10.1016/j.jag.2010.03.003

Baur, J. W. R., & Tynon, J. F. (2010). Small-Scale Urban Nature Parks: Why Should We Care? *Leisure Sciences*, *32*(2), 195–200. http://dx.doi.org/10.1080/01490400903547245

Beil, K., & Hanes, D. (2013). The influence of urban natural and built environments on physiological and psychological measures of stress—A pilot study. *International Journal of Environmental Research and Public Health*, *10*(4), 1250–1267. http://dx.doi.org/10.3390/ijerph10041250

Carvalho-Ribeiro, S. M., & Lovett, A. (2011). Is an attractive forest also considered well managed? Public preferences for forest cover and stand structure across a rural/urban gradient in northern Portugal. *Forest Policy and Economics*, *13*(1), 46–54. http://dx.doi.org/10.1016/j.forpol.2010.09.003

Center for Active Design. (2010). *Active densign guideline: Pronoting physical activity and health in design*. Retrieved from. http://centerforactivedesign.org/dl/guidelines.pdf

Chang, C. Y., & Chen, P. K. (2005). Human response to window views and indoor plants in the workplace. *Hortscience*, *40*(5), 1354–1359.

Clark, J. R., Matheny, N. P., Cross, G., & Wake, V. (1997). A model of urban forest sustainability. *Journal of Arboriculture*, *23*(1), 17–30.

Corraliza, J. A., & Collado, S. (2011). Nearby nature as a moderator of stress during childhood. *Psicothema*, *23*(2), 221–226.

Dallimer, M., Irvine, K. N., Skinner, A. M. J., Davies, Z. G., Rouquette, J. R., Maltby, L. L., . . . & Gaston, K. J. (2012). Biodiversity and the feel-good factor: Understanding associations between self-reported human well-being and species richness. *Bioscience*, *62*(1), 47–55.

De Kort, Y. A. W., Meijnders, A. L., Sponselee, A. A. G., & Ijsselsteijn, W. A. (2006). What's wrong with virtual trees? Restoring from stress in a mediated environment. (Author abstract). *Journal of Environmental Psychology*, *26*(4), 309(312).

Detweiler, M. B., & Warf, C. (2005). Dementia wander garden aids post cerebrovascular stroke restorative therapy: A case study. *Alternative Therapies in Health and Medicine*, *11*(4), 54–58.

Donovan, G. H., Michael, Y. L., Butry, D. T., Sullivan, A. D., & Chase, J. M. (2011). Urban trees and the risk of poor birth outcomes. *Health and Place*, *17*(1), 390–393.

Fjortoft, I., & Sageie, J. (2000). The natural environment as a playground for children—Landscape description and analyses of a natural playscape. *Landscape and Urban Planning*, *48*(1–2), 83–97. http://dx.doi.org/10.1016/s0169-2046(00)00045-1

Gilchrist, K., Brown, C., & Montarzino, A. (2015). Workplace settings and wellbeing: Greenspace use and views contribute to employee wellbeing at peri-urban business sites. *Landscape and Urban Planning*, *138*(0), 32–40. http://dx.doi.org/10.1016/j.landurbplan.2015.02.004

Gupta, K., Kumar, P., Pathan, S. K., & Sharma, K. P. (2012). Urban Neighborhood Green Index—A measure of green spaces in urban areas. *Landscape and Urban Planning*, *105*(3), 325–335. http://dx.doi.org/10.1016/j.landurbplan.2012.01.003

Hansen, L. P., & Sargent, T. J. (2001). Robust Control and Model Uncertainty. *American Economic Review*, *91*(2), 60–66.

Hu, Z. Y., Liebens, J., & Rao, K. R. (2008). Linking stroke mortality with air pollution, income, and greenness in northwest Florida: An ecological geographical study. *International Journal of Health Geographics*, *7* http://dx.doi.org/10.1186/1476-072x-7-20

International Institute for Environment and Development, UK. (2011). *The Informal Economy*.. Retrieved 03/25, 2016, from. http://pubs.iied.org/pdfs/15515IIED.pdf

i-Tree Canopy. (n.d.). Retrieved 7/29, 2015, from https://www.itreetools.org/canopy/index.php.

i-Tree Streets. (n.d.). Retrieved 7/29, 2015, from https://www.itreetools.org/streets/index.php.

Janssen, I., & Rosu, A. (2012). Measuring sidewalk distances using Google Earth. *BMC Medical Research Methodology*, *12*(1), 1–10. http://dx.doi.org/10.1186/1471-2288-12-39

Jiang, B., Chang, C.-Y., & Sullivan, W. C. (2014). A dose of nature: Tree cover, stress reduction, and gender differences. *Landscape and Urban Planning*, *132*(0), 26–36. http://dx.doi.org/10.1016/j.landurbplan.2014.08.005

Jiang, B., Li, D., Larsen, L., & Sullivan, W. C. (2016). A dose-response curve describing the relationship between urban tree cover density and self-reported stress recovery. *Environment and Behavior*, *48*(4), 607–629. http://dx.doi.org/10.1177/0013916514552321

Jiang, B., Larsen, L., Deal, B., & Sullivan, W. C. (2015). A dose-response curve describing the relationship between tree cover density and landscape preference. *Landscape and Urban Planning*, *139*(0), 16–25. http://dx.doi.org/10.1016/j.landurbplan.2015.02.018

Jiang, B., Zhang, T., & Sullivan, W. C. (2015). Healthy cities: Mechanisms and research questions regarding the impacts of urban green landscapes on public health and well-being. *Landscape Architecture Frontiers*, *3*(1), 24–35.

Kaplan, R. (2001). The nature of the view from home—Psychological benefits. *Environment and Behavior*, *33*(4), 507–542.

Kardan, O., Gozdyra, P., Misic, B., Moola, F., Palmer, L. J., Paus, T., & Berman, M. G. (2015). Neighborhood greenspace and health in a large urban center. *Scientific Reports*, *5* http://dx.doi.org/10.1038/srep11610

Klemm, W., Heusinkveld, B. G., Lenzholzer, S., & van Hove, B. (2015). Street greenery and its physical and psychological impact on thermal comfort. *Landscape and Urban Planning*, *138*, 87–98. http://dx.doi.org/10.1016/j.landurbplan.2015.02.009

Kuo, F. E., & Sullivan, W. C. (2001a). Aggression and violence in the inner city—Effects of environment via mental fatigue. *Environment and Behavior*, *33*(4), 543–571.

Kuo, F. E., & Sullivan, W. C. (2001b). Environment and crime in the inner city: Does vegetation reduce crime? *Environment & Behavior*, *33*(3), 343–367.

Kuo, F. E. M. (2013). Nature-deficit disorder: Evidence, dosage, and treatment. *Journal of Policy Research in Tourism, Leisure and Events*, *5*(2), 172–186. http://dx.doi.org/10.1080/19407963.2013.793520

Kweon, B.-S., Ellis, C. D., Lee, S.-W., & Rogers, G. O. (2006). Large-scale environmental knowledge: Investigating the relationship between self-reported and objectively measured physical environments. *Environment and Behavior*, *38*(1), 72–91. http://dx.doi.org/10.1177/0013916505280092

Leather, P., Beale, D., Santos, A., Watts, J., & Lee, L. (2003). Outcomes of environmental appraisal of different hospital waiting areas. *Environment and Behavior*, *35*(6), 842–869. http://dx.doi.org/10.1177/0013916503254777

Leslie, E., Sugiyama, T., Ierodiaconou, D., & Kremer, P. (2010). Perceived and objectively measured greenness of neighbourhoods: Are they measuring the same thing? *Landscape and Urban Planning*, *95*(1–2), 28–33. http://dx.doi.org/10.1016/j.landurbplan.2009.11.002

Li, D., & Sullivan, W. C. (2016). Impact of views to school landscapes on recovery from stress and mental fatigue. *Landscape and Urban Planning*, *148*, 149–158. http://dx.doi.org/10.1016/j.landurbplan.2015.12.015

Matsuoka, R. H. (2010). Student performance and high school landscapes: Examining the links. *Landscape and Urban Planning*, *97*(4), 273–282. http://dx.doi.org/10.1016/j.landurbplan.2010.06.011

McPherson, E. G., Simpson, J. R., Xiao, Q., & Wu, C. (2011). Million trees Los Angeles canopy cover and benefit assessment. *Landscape and Urban Planning*, *99*(1), 40–50.

Mitchell, R., & Popham, F. (2008). Effect of exposure to natural environment on health inequalities: An observational population study. *Lancet*, *372*(9650), 1655–1660.

Moore, E. O. (1981). Prison environment's effect on health care service demands. *Journal of Environmental Systems*, *11*(1), 17–34.

Nelson, T., Johnson, T., Strong, M., & Rudakewich, G. (2001). Perception of tree canopy. *Journal of Environmental Psychology*, *21*(3), 315–324. http://dx.doi.org/10.1006/jevp.2001.0223

Nesbitt, N. H. L., Cowan, S. B. J., Cheng, Z. C., PI, S. S., & Neuvonen, J. The social and economic values of Canada's urban forests: A national synthesis 2015.

Nordh, H., Hartig, T., Hagerhall, C. M., & Fry, G. (2009). Components of small urban parks that predict the possibility for restoration. *Urban Forestry & Urban Greening*, *8*(4), 225–235. http://dx.doi.org/10.1016/j.ufug.2009.06.003

Nowak, D. J., & Greenfield, E. J. (2012a). Tree and impervious cover in the United States. *Landscape and Urban Planning*, *107*(1), 21–30. http://dx.doi.org/10.1016/j.landurbplan.2012.04.005

Nowak, D. J., & Greenfield, E. J. (2012b). Tree and impervious cover change in U.S. cities. *Urban Forestry & Urban Greening*, *11*(1), 21–30. http://dx.doi.org/10.1016/j.ufug.2011.11.005

Nowak, D. J., Rowntree, R. A., McPherson, E. G., Sisinni, S. M., Kerkmann, E. R., & Stevens, J. C. (1996). Measuring and analyzing urban tree cover. *Landscape and Urban Planning*, *36*(1), 49–57.

Nowak, D. J., Stein, S. M., Randler, P. B., Greenfield, E. J., Comas, S. J., Carr, M. A., & Alig, R. J. (2010). *Sustaining America's urban trees and forests: A Forests on the Edge report*.

Parsons, R., Tassinary, L. G., Ulrich, R. S., Hebl, M. R., & Grossman-Alexander, M. (1998). The view from the road: Implications for stress recovery and immunization. *Journal of Environmental Psychology*, *18*(2), 113–140.

Power, M. J., Neville, P., Devereux, E., Haynes, A., & Barnes, C. (2013). 'Why bother seeing the world for real?': Google Street View and the representation of a stigmatised neighbourhood. *New Media & Society*, *15*(7), 1022–1040. http://dx.doi.org/10.1177/1461444812465138

Rappe, E., Kivela, S. L., & Rita, H. (2006). Visiting outdoor green environments positively impacts self-rated health among older people in long-term care. *Horttechnology*, *16*(1), 55–59.

Richardson, J. J., & Moskal, L. M. (2011). Strengths and limitations of assessing forest density and spatial configuration with aerial LiDAR. *Remote Sensing of Environment*, *115*(10), 2640–2651. http://dx.doi.org/10.1016/j.rse.2011.05.020

Roe, J. J., Ward Thompson, C., Aspinall, P. A., Brewer, M. J., Duff, E. I., Miller, D., . . . & Clow, A. (2013). Green space and stress: Evidence from cortisol measures in deprived urban communities. *International Journal of Environmental Research and Public Health*, *10*(9), 4086–4103.

Sarkar, C., Webster, C., Pryor, M., Tang, D., Melbourne, S., Chang, X., & Jianzheng, L. (2015). Exploring associations between urban green, street design and walking: Results from the Greater London boroughs. *Landscape and Urban Planning*, *143*, 112–125. http://dx.doi.org/10.1016/j.landurbplan.2015.06.013

Semenza, J. C., March, T. L., & Bontempo, B. D. (2007). Community-initiated urban development: An ecological intervention. *Journal of Urban Health-Bulletin of the New York Academy of Medicine*, *84*(1), 8–20. http://dx.doi.org/10.1007/s11524-006-9124-8

Sheppard, S. R. J., & Cizek, P. (2009). The ethics of Google Earth: Crossing thresholds from spatial data to landscape visualisation. *Journal of Environmental Management*, *90*(6), 2102–2117. http://dx.doi.org/10.1016/j.jenvman.2007.09.012

Sipilä, M., & Tyrväinen, L. (2005). Evaluation of collaborative urban forest planning in Helsinki, Finland. *Urban Forestry & Urban Greening*, *4*(1), 1–12. http://dx.doi.org/10.1016/j.ufug.2005.06.002

Sommer, R., Guenther, H., & Cecchettini, C. L. (1992). A user-based method for rating street trees. *Landscape Research*, *17*(3), 100–107. http://dx.doi.org/10.1080/01426399208706372

Storbeck, J., & Clore, G. L. (2007). On the interdependence of cognition and emotion. *Cognition & Emotion*, *21*(6), 1212–1237. http://dx.doi.org/10.1080/02699930701438020

Sullivan, W. C., Kuo, F. E., & DePooter, S. F. (2004). The fruit of urban nature—Vital neighborhood spaces. *Environment and Behavior*, *36*(5), 678–700. http://dx.doi.org/10.1177/0193841X04264945

Sullivan, W. C. (1994). Perceptions of the rural-urban fringe: Citizen preferences for natural and developed settings. *Landscape and Urban Planning*, *29*(2–3), 85–101.

Suppakitpaisarn, P., Slavenas, M., Jiang, B., & Sullivan, W. C. (2016). Scripting in Landscape Architecture: A vegetation density case study. In *Paper presented at the Council of Educators in Landscape Architecture conference*.

Tennessen, C. M., & Cimprich, B. (1995). Views to nature—effects on attention. *Journal of Environmental Psychology*, *15*(1), 77–85.

Todorova, A., Asakawa, S., & Aikoh, T. (2004). Preferences for and attitudes towards street flowers and trees in Sapporo, Japan. *Landscape and Urban Planning*, *69*(4), 403–416.

Tyrvainen, L., Ojala, A., Korpela, K., Lanki, T., Tsunetsugu, Y., & Kagawa, T. (2014). The influence of urban green environments on stress relief measures: A field experiment. *Journal of Environmental Psychology*, *38*, 1–9. http://dx.doi.org/10.1016/j.jenvp.2013.12.005

Ulrich, R. S., Simons, R. F., & Miles, M. A. (2003). Effects of environmental simulations and television on blood donor stress. *Journal of Architectural and Planning Research*, *20*(1), 38–47.

Ulrich, R. S. (1984). View through a window may influence recovery from surgery. *Science*, *224*(4647), 420–421.

Urban Forest Management Plan Toolkit. (n.d.). Retrieved 7/29, 2015, from http://ufmptoolkit.com/outline.htm.
Valtchanov, D., Barton, K. R., & Ellard, C. (2010). Restorative effects of virtual nature settings. *Cyberpsychology Behavior and Social Networking*, *13*(5), 503–512. http://dx.doi.org/10.1089/cyber.2009.0308
Ward Thompson, C., Roe, J., Aspinall, P., Mitchell, R., Clow, A., & Miller, D. (2012). More green space is linked to less stress in deprived communities: Evidence from salivary cortisol patterns. *Landscape and Urban Planning*, *105*(3), 221–229.
van den Berg, A. E., Koole, S. L., & van der Wulp, N. Y. (2003). Environmental preference and restoration: (How) are they related? *Journal of Environmental Psychology*, *23*(2), 135–146. http://dx.doi.org/10.1016/s0272-4944(02)00111-1
Ward Thompson, C., Roe, J., & Aspinall, P. (2013). Woodland improvements in deprived urban communities: What impact do they have on people's activities and quality of life? *Landscape and Urban Planning*, *118*, 79–89.
Xiao, Y., Li, Z., & Webster, C. (2016). Estimating the mediating effect of privately-supplied green space on the relationship between urban public green space and property value: Evidence from Shanghai, China. *Land Use Policy*, *54*, 439–447. http://dx.doi.org/10.1016/j.landusepol.2016.03.001

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