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Research Paper

A dose–response curve describing the relationship between tree cover density and landscape preference

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HIGHLIGHTS

- The dose–response curve for the link between tree coverage and landscape preference.
- Measured tree cover density from ground and aerial photographs for each site.
- Found a power line model best describes the relationship.
- Found a threshold value of tree cover density to ensure a moderate preference.
- Planting trees in relatively treeless residential areas will offer greater impact.

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ABSTRACT

Does adding more and more trees to a residential street yield a reliable increase in preference? Or is there a point at which, in terms of preference, additional trees will have minimal effect, no effect, or even a negative effect? To address these questions, we selected 121 community streets in four Midwestern urban areas in the U.S. and produced a panoramic photograph of each site and then measured the density of tree cover visible at eye level (Panorama). We also collected Google Earth aerial photographs to measure the top-down tree cover density (Google) for the sites. Then, 320 individuals provided preference ratings for a randomized subset of the panoramic photographs (15 pictures per person). Through linear and curvilinear regression analysis, we found a power line model best describes the relationship between each measure of tree cover density and preference. The power lines have a similar shape: when sites are relatively barren, a slight increase in tree density yields a steep increase in preference. After tree cover density exceeded those values, however, higher tree densities yielded smaller, but still positive increases in preference. These findings suggest that to ensure a moderate level of preference, tree cover density should be not less than 41% as measured by panoramic photographs or 20% as measured by Google Earth aerial photographs. Planting trees in barren residential areas will result in considerably more impact than if the same trees were planted in already green areas. Still, the findings here demonstrate that, for preference, every tree matters.

1. Introduction

1.1. Background

In the last decade, bolstered by scientific theory and empirical evidence, cities all over the world have promoted urban forests as a way of improving environmental and economic conditions and keeping citizens healthy. Because establishing an urban forest is economically demanding, it can be helpful to find ways to allocate public resources that are fair and affordable (Zhu & Zhang, 2008). In many cities, urban forests compete with urban development

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for resources (Nowak & Greenfield, 2012). Thus, balancing land use and resources for urban development and urban forests is a significant challenge for planners and policy makers. In addition, although it is widely recognized that trees provide multiple benefits, trees are sometimes perceived by the public as a burden because of potential damages to property and infrastructure (Mullaney, Lucke, & Trueman, 2015). Under these circumstances, knowing citizens' preferences for street tree density could help city planners more efficiently allocate urban forest resources and develop more sustainable cities.

Why is public preference for street tree density important? There are four main reasons. First, landscape preference has been shown to be a reliable predictor of how well people will function in an environment (van den Berg, Koole, & van der Wulp, 2003). Second, understanding citizens' collective preference is crucial in a democratic society. Research on preference for trees can shape design guidelines in ways that reflect the will of the people (Sommer & Summit, 1995). Third, there are often differences in preferences between ordinary citizens and design professionals (Sommer, Guenther, Barker, & Swenson, 1993). Thus, understanding the public's preference is a necessary check on the unconscious preferences of designers (Daniel, 2001). And finally, given the increasing number of empirical studies that emphasize the physical and biological benefits of urban trees, it is important that we not lose sight of the esthetic values trees offer especially since the physical, biological, and esthetic values are interrelated (Schroeder, 2012).

Empirical studies have consistently shown that urban environments with greater tree cover are preferred over settings with less tree cover. Early research compared preference for five computer-generated tree icons with various levels of tree canopy size and reported a positive relationship between tree canopy size and preference (Sommer & Summit, 1995). Compared to settings with fewer trees, similar settings with more trees were associated with people's preference for agricultural buffers at the rural–urban fringe (Becker, Bonaiuto, Bilotta, & Bonnes, 2011), natural pastures (Ode, Fry, Tveit, Messager, & Miller, 2009), suburban communities (Sullivan, 1994), inner-city communities (Kuo, Bacaicoa, & Sullivan, 1998), small urban parks (Nordh, Hartig, Hagerhall, & Fry, 2009), urban streets (Todorova, Asakawa, & Aikoh, 2004), and riparian zones (Kenwick, Shammin, & Sullivan, 2009).

Although it is well established that people prefer environments with greater tree cover, it is not clear how much tree cover they prefer. This paper seeks to obtain a more complete profile of people's preference for street trees.

1.2. *Preference for environments with trees*

People make judgments about an environment quickly, with minimal cognitive or perceptual effort (Kaplan & Kaplan, 1989; Zajonc, 1980; Zajonc & Markus, 1982). These judgments, once made, are difficult to revoke. It may have been important for our ancestors to make quick judgments about an environment in order to survive in a dangerous and unpredictable world. Which settings did our ancestors prefer and why? What kinds of landscapes do modern humans prefer and why?

On the one hand, a handful of widely recognized theories suggest, for evolutionary or psychological reasons, humans prefer greener environments because they help them survive and thrive. These theories include Wilson's biophilia theory (1984), Appleton's prospect–refuge theory (2004), Orians' savannah theory (1986, 1993), Kaplan and Kaplan's landscape preference matrix theory (1989), and Ulrich's stress reduction theory (1991). A common underlying theme in these theories is that human perception of landscapes is "partially determined by genetic inheritance and that learning and culture are corresponding less important" (Nelson, Johnson, Strong, & Rudakewich, 2001, p. 316).

On the other hand, a large number of empirical studies report a significant association between greater tree coverage and healthier human functioning, which may explain higher preference of greener environments with greater tree density. Stress reduction, for instance, is an important benefit of a greener environment. A recent study found watching a 6-min 3-D video of residential streets with moderate eye-level tree cover density (29%) had a 3.1 times greater stress reduction effect assessed in psychological and hormonal measures than watching a similar video with a low tree cover density (2%) (Jiang, Chang, & Sullivan, 2014; Jiang, Li, Larsen, & Sullivan, 2014). Another related study reported a positive causal association between eye-level tree cover density and self-reported stress reduction (Jiang, Chang, et al., 2014; Jiang, Li, et al., 2014). Those two studies and several prior studies suggest that environments with higher tree cover density can produce greater stress reduction (Beil & Hanes, 2013; Roe et al., 2013; Tyrvainen et al., 2014; van den Berg, Hartig, & Staats, 2007; Ward Thompson et al., 2012). Moreover, a study found that tree density in a public neighborhood increased both residents' sense of safety and their preference (Kuo et al., 1998). Affective restoration – including improvement in mood – and capacity to focus one's attention are positively associated with measures of preference for natural environments (van den Berg et al., 2003). Another recent study found that natural scenes were rated as more restorative and more highly preferred than a mixture of natural and urban scenes (Korpela, 2013). In addition, exposure to green environments has been shown to improve mood (Chang & Chen, 2005), enhance one's ability to focus attention (Berman, Jonides, & Kaplan, 2008; Kuo & Taylor, 2004), increase the strength of neighborhood social ties (Holtan, Dieterlen, & Sullivan, 2014), and reduce the prevalence of respiratory diseases by removing fine particles (PM 2.5) in air (Nowak, Crane, & Stevens, 2006).

1.3. *A research gap*

Although a growing body of research shows that people prefer greener landscapes with higher levels of tree cover over less green settings, the shape of the dose–response curve describing the relationship between tree cover density and landscape preference is unclear. We do not know if a small increase in tree cover density results in a consistent increase in preference or if there is a tree cover density at beyond which there is no increase in preference. Alternatively, we do not know if, after some optimal tree cover density is reached, higher densities result in low preference. That is, we do not know if the relationship between tree cover density and preference is linear, S-shaped, an inverted U-shape or some other shape.

This study examines the dose–response curve for varying levels of tree cover density on people's landscape preference. The shape and key threshold values are identified. We use two methods for measuring tree density along community streets to mitigate methodological bias. The first method uses eye-level panoramic photographs (Panorama); the second method uses Google Earth aerial photographs (Google). A more precise understanding of people's preference for tree cover density will increase our understanding and support municipal decision-makers who have to allocate scarce resources.

1.4. *Empirical measures of tree cover density*

In urban forestry research and practice, there are two main types of empirical measures of tree cover density: aerial photography that provides a top-down measure and eye-level photography that provides a measure of density that is similar to what people typically experience. For environmental designers and urban forestry managers, aerial photography is the dominant tool. For example, i-Tree Canopy (2006), a widely used tool in the field of urban forestry, provides free online access to measure tree cover density from Google Earth aerial photography. Eye-level photography, which used to be the dominant tool, has lost favor. The shift toward Google Earth aerial photography as the dominant tool seems to have taken place because it is free, easy to use, and widely available. The majority of current planning regulations regarding urban forestry in the U.S. specify criteria based on aerial tree cover density. In addition, a handful of studies that examine the impact of tree cover density on human health use tree cover density (Donovan, Michael, Butry, Sullivan, & Chase, 2011; Holtan et al., 2014) or green cover density measurements (Maas et al., 2009; Mitchell & Popham, 2008) taken from aerial imagery or maps.

Compared to Google Earth aerial photography, eye-level photography is rarely adopted by urban forestry managers to evaluate tree cover density, largely because it is more expensive and less convenient than aerial photography. Yet, measuring eye-level tree cover density has a crucial advantage. Aerial tree cover density that is averaged over a large section of the landscape may not accurately capture a person's experience of walking around a place (Jiang, 2013). Normally, people perceive landscapes at eye-level as they walk or drive through a place, not from an aerial perspective (De Jong et al., 2011; Leslie, Sugiyama, Ierodiaconou, & Kremer, 2010). Therefore, measurements from eye-level tree cover density may more accurately reflect a person's actual perception of a particular landscape.

Because of the advantages and disadvantages of aerial and eye-level measures of tree cover density, we calculated tree cover density using both measures and then identified two dose–response curves for the relationship between tree cover density and landscape preference.

2. Methods

2.1. Site selection

We reviewed high-resolution Google Earth aerial images of 46 Census Block groups in four Midwestern urban areas in the U.S.: Champaign-Urbana, St. Louis, Indianapolis, and Springfield that have similar climate, topography, and biological conditions representative of typical residential street landscapes in the Midwestern U.S. Two investigators visited each neighborhood and took eye-level panoramic photographs of 255 community streets.

We employed several steps to limit potential confounding physical characteristics (other than tree cover density) among the sites. First, to limit the diversity in housing size and type, we used median annual income per household of $50,000–$75,000 at the block group level (data from Google Earth Pro) as a controlling factor. Second, we rejected streets without sidewalks or street curbs. Third, three experts in landscape architecture assessed the physical characteristics of 255 sites by viewing their panoramic photos. Experts chose sites with similar spatial attributes, including building density, building setback, flat terrain, and straight streets. In addition, sites with the following attributes were rejected: the presence of human beings or animals, moving cars, parked cars that blocked the view, and notable landscapes or objects (e.g., cars with striking colors or styles, landscapes with striking colors or shapes, poorly maintained infrastructure or landscapes, gloomy sky or clouds, unusual building or construction features). 121 street scenes were selected for data analysis.

2.2. Panoramic photographs of the sites

To create panoramic photographs of each street, we placed a tripod in the street beside the sidewalk and driveway entrance to a house, where casual conversation and physical activities might frequently occur. There were no large trees or other visual barriers within 10 m of the camera's view. A panoramic video for each street scene was taken on sunny days from 10 a.m. to 3:30 p.m., June–August 2011. An investigator shot the video by smoothly panning through approximately 150°, always in a clockwise motion. Then, we used video-editing software (Sony PMB) to extract three photographs from the left, middle, and right parts of the street scene from each video. Next, we combined the three photographs to create one panoramic photograph using the Photomerge command in Photoshop CS5. The panoramic photograph presents the whole viewshed of the street captured by the video camera and accurately depicts the onsite visual experience.

2.3. Measure from panoramic photographs

To quantify tree cover density from panoramic photographs, we used the Image Histogram function in Photoshop CS5 to measure the number of pixels in each image. A pixel is the smallest unit of a raster image that can be presented and controlled. A digital photo is a two-dimensional grid of pixels. We first selected areas of tree canopy and trunks in a panoramic photo and identified the number of pixels in those areas measured by Photoshop. Next, we identified the number of pixels contained in the entire photo. Panoramic tree cover density is the percentage of the pixels occupied by tree canopy and tree trunks in a panoramic photograph (Fig. 1, the top photograph).

2.4. Measure from Google Earth aerial photographs

To obtain our measure of tree cover density from aerial photography, we downloaded high-resolution aerial images from Google Earth Pro for all sites where we took panoramic photographs. We set the altitude at 600 m for all images so that each image had the same scale and the same resolution (4800 pixels). All satellite images were captured during early October 2011 to ensure that deciduous trees had fully developed canopies and were not yet defoliated.

To measure tree cover density from Google Earth aerial photographs, the first step was to identify the boundary of the viewshed. We define the viewshed as the street corridor shaped by ridgelines of houses. This procedure captured the majority of visible trees. To calculate percent tree cover, we divided the number of pixels occupied by tree canopy by the number of pixels occupied by the entire street corridor (Fig. 1, the bottom photograph).

2.5. Preference of street scenes

To assess preference for the street scenes, we created a photo-questionnaire and recruited adults to complete the questionnaire. Participants were recruited through flyers and posters at public places in the Champaign-Urbana area. We recruited young adults between 18 and 32 for this study because this research was part of a larger project that examined the impact of viewing green street scenes on stress recovery (Jiang, Chang, et al., 2014). For the stress recovery component, we needed to strictly control participants' age to mitigate biological differences associated with the age of participants. Because cultural factors have been shown to influence landscape preference (Bowler, Buyung-Ali, Knight, & Pullin, 2010; Kaplan & Herbert, 1987; Kenwick et al., 2009), we mitigated cultural differences by selecting participants who had lived in the U.S. for no less than 18 years (Yu, 1995). Each participant

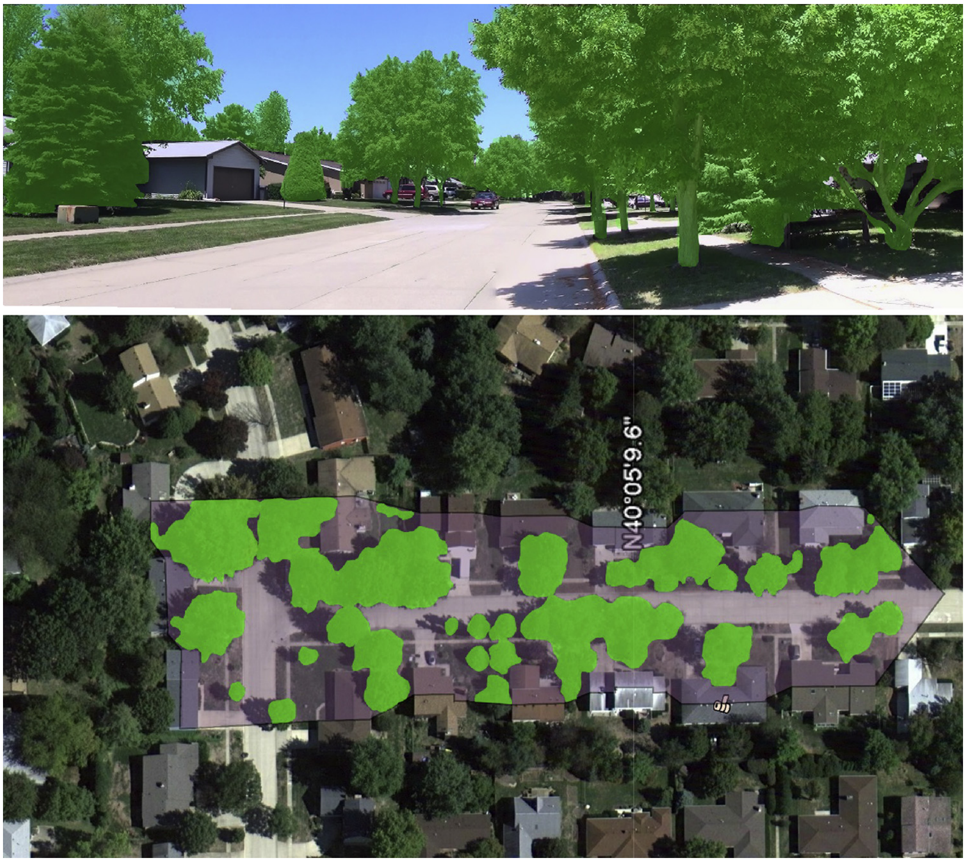

Fig. 1. Two measures of tree cover density for the same site: Panorama (top) and Google (bottom). For Panorama, tree cover density is the percentage of the pixels occupied by tree canopy and tree trunks (highlighted in the bright green color) divided by the total number of pixels in the photo. For Google, tree cover density is the percentage of pixels occupied by tree canopy (highlighted in the bright green color) divided by the total number of pixels in the street corridor (highlighted in the light purple color). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

was asked to complete a health history questionnaire after they signed a consent form. Those participants who had a history of diagnosed mental disorders were not allowed to participate in the study. In addition, we did not recruit individuals who received or were receiving education or professional training in Landscape Architecture, Architecture, or Urban Planning.

We administered the questionnaire via a computer to 320 adults, and got complete data from 314 individuals (167 women and 147 men, with a mean age of 21.4 years). Participants identified themselves as Caucasians (75 individuals), Asian Americans or Pacific Islanders (61), African Americans (8), Hispanics (7), Middle Eastern or Persians (4), and Native American or Alaska Natives (3).

Each participant was randomly assigned to rate 15 out of the 121 panoramic photographs. We used the eye-level photographs rather than Google Earth aerial images for two reasons: first, they contain rich, detailed visual information of the site; second, they provided participants a view that was close to what they might see on site. For each image, individuals were asked, "Imagining you are having a casual walk in this street, how much do you like this scene?" They were asked to quickly indicate their preference using a 5-point Likert scale that ranged from "not at all" (coded as 1), "a little" (2), "somewhat" (3), "quite a bit" (4), to "very much" (5). The preference value of each photograph is the mean of the participants' evaluation. Each photograph received an evaluation from a similar number of participants ($M = 32.51$, $SD = 5.69$). The questionnaire yielded analyzable data for 118 sites because 3 sites had incomplete data. The mean rating for all the sites was 2.78, $SD = 0.53$. The mean of standard deviation is 1.04 (0.73–1.44, $SD = 0.14$). Through conducting linear regression analysis, we found no significant association between mean value and standard deviation of preference values ($F = .02$, $p = .89$) and the regression standardized residuals are normally distributed, which suggest variation among preference values for the same site is acceptable.

2.6. *Identifying the best model*

In the results that follow, we generated both linear and curvilinear models that predict preference for varying densities of tree cover. To assess which of the various models had the best fit, we calculated Bayesian Information Criterion (BIC) for each model and compared the results. BIC is a widely used criterion employed to select among various models the one with the best fit (Razzaghi-asl & Zarei, 2014). The more parameters one adds to a regression model the more one risks over-fitting the model to the data. BIC addresses this problem by invoking a penalty for the number of parameters adopted by the model. For data with small or moderate sample sizes, BIC is superior to other popular model selection criteria (Beil & Hanes, 2013). The simplest model is favored when the difference between BICs is less than 2 (Beil & Hanes, 2013). The BIC value can be calculated as: $\mathrm{BIC} = n\ln(r) + (p+1)\ln(n) - n\ln(n)$. In the equation, r is the sum of squares of residuals, p is the number of the independent variable, and n is the sample size.

3. Results

Results are presented in five parts. First, to understand the relationship between preference and the two measures of tree cover density, we visually examine the data after fitting it with a scatter smoothing line. Second, to check whether the relationship between tree cover density and preference can be explained by a linear dose–response curve, we conducted a series of linear regression analyses. Then, to check whether the relationship can be better explained by a curvilinear dose–response curve, we conducted a series of curvilinear regression analyses. Fourth, we identified the most feasible model for predicting preference and the most accurate dose–response curve for that predictor. Finally, we examined whether there are gender differences in preference for tree cover density.

3.1. Using tree cover density as the indicator of greenness

It is possible that non-tree vegetation – such as turf, shrubs, and other herbaceous plants – were significantly different among the sampled panoramic photographs. If that was the case, this vegetation might impact people's preference and alter the relationship we seek to measure between tree cover density and preference. To examine this possibility, we followed the same procedure described above to measure the percent of each photo that included non-tree vegetation – herbaceous plants, shrubs, turf – and then created scatterplots showing the relationship between the non-tree vegetation and preference for both panoramic photographs and the Google Earth images (Fig. 2). Both scatterplots show an even distribution of points on the plots, which suggests there is no association between density of non-tree vegetation and preference for both kinds of photographs. To further examine this possibility, we ran linear regressions using non-tree vegetation as the independent variable and preference as the dependent variable for both Panoramic and Google photographs. Results confirm the insignificant association: for the Panoramic measure, adjusted $R^2 = -.01$, $F(1, 115) = 0.07$, $p = 0.80$; for the Google measure, adjusted $R^2 = .02$, $F(1, 115) = 0.71$, $p = 0.10$. These findings confirm that tree cover density is the only robust variable in the relationship between greenness and preference, which implies that it is reasonable to use tree cover density as the sole indicator of greenness in this study.

3.2. Scatterplots and smoothers

We used Locally Estimated Scatterplot Smoothing (LOESS) to examine the relationship between two measures of tree cover density (Panorama and Google) and landscape preference (Fig. 3). For each measure of tree density, it is possible that the dose–response relationship is linear because, as the scatter plots indicate, preference gradually increases as tree density increases. But it is also possible that curvilinear models might better explain these relationships, because the LOESS curves appear to be slightly curvilinear. To investigate these possibilities, we ran linear, and then curvilinear, regressions to identify the most feasible model to describe the dose–response curve.

3.3. A linear relationship?

A linear regression analysis suggests that a linear model can explain the relationship between the two measures of tree cover density and landscape preference. Results for the Panorama model are: adjusted $R^2 = .45$, $F(1, 115) = 96.34$, $p < .0001$, $Y = 1.561X + 2.326$. Results for the Google model are: adjusted $R^2 = .34$, $F(1, 115) = 59.542$, $p < .0001$, $Y = 1.779X + 2.505$.

The shape of LOESS curves, however, indicates the linear regressions may be misleading because of heteroscedasticity. To examine this possibility, we conducted White's test and found no significant heteroscedasticity effects in any of the linear regression models. For Panorama, $F(1, 115) = 2.64$ and $p = .11$; for Google, $F(1, 115) = 1.28$ and $p = .29$. Thus, the linear models described above provide a statistically significant linear relationship between landscape preference and both measures of tree cover density.

Table 1
Regression models that may describe the relationships between two measures of tree cover density (Panorama and Google) and landscape preference.

Models	Equations
Linear	$f(x) = a + b \times x$
Quadratic	$f(x) = a + b \times x + c \times x^2$
Cubic	$f(x) = a + b \times x + c \times x^2 + d \times x^3$
Logarithmic	$f(x) = a + b \times \log(x)$
Power	$f(x) = ax^b$
Exponential	$f(x) = a \times \exp^{(b \times x)}$

3.4. A curvilinear relationship?

Although a linear regression model can explain the relationship between tree cover density and preference, the LOESS curves suggest the possibility that curvilinear models may be more appropriate. Therefore, we examined five kinds of curvilinear models: quadratic, cubic, logarithmic, power, and exponential (Table 1). Then, for each model, we calculated Bayesian Information Criterion (BIC). Results show that the association between preference and each measure can be better described by curvilinear models than by linear models, as the curvilinear models have both higher R^2 and lower BIC values (Table 2). The power models have the lowest BIC values and are therefore the most feasible model for the two measures of tree cover density. Results show that Panorama is a significant predictor of landscape preference, adjusted $R^2 = .53$, $F(1, 115) = 130.76$, $p < .0001$. The power equation is $Y = 3.285X^{.101}$, where Y is preference and X is the Panorama measure. The Google measure is also a significant predictor of landscape preference: for Google, adjusted $R^2 = .53$, $F(1, 115) = 129.43$, $p < .0001$, equation: $Y = 3.386X^{.075}$, where Y is the Preference and X is the Google. The power lines are presented in Figs. 4 and 5. Tables 3 and 4 show the values of landscape preference for tree cover densities measured from Panorama or Google photography on the 5 percent scale. Notice that for both Panorama and Google, at low tree cover densities, a slight increase in density yields a considerable increase in preference, but that at higher tree cover densities, a slight increase in density yields only a small, but still positive, increase in preference.

3.5. Gender difference

Do these findings hold for both women and men? To check whether there are gender differences for preference, we ran paired *t*-test for preference values for each site rated by women and men. The results indicate there is no significant gender effect,

Table 2
Fitness of regression models that may describe the relationship between each of three measures of tree cover density and landscape preference (*F* values of all models are statistically significant at $p < .0001$. RSS: residual sum of squares).

	Models	Adjusted R^2	*F*	*SE*	*RSS*	*BIC*
Panorama ($n = 117$)	Linear	.45	96.34	.37	15.91	−223.92
	Logarithmic	.51	119.84	.35	14.32	−231.47
	Quadratic	.51	59.13	.36	14.36	−226.39
	Cubic	.55	47.58	.34	12.92	−248.27
	Power	.53	130.76	.13	1.97	−468.32
	Exponential	.46	97.76	.14	2.27	−451.74
Google ($n = 117$)	Linear	.34	59.54	.41	19.27	−201.50
	Logarithmic	.50	118.46	.35	14.41	−230.74
	Quadratic	.40	39.86	.39	17.21	−205.20
	Cubic	.44	31.03	.38	16.04	−222.96
	Power	.53	129.43	.13	1.98	−467.73
	Exponential	.33	58.25	.16	2.79	−427.60

Table 3
Preference values as Google tree cover density increases by 5%.

Google	0.001	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.4	0.45	0.5	0.55	0.60
Preference	2.02	2.70	2.85	2.94	3.00	3.05	3.09	3.13	3.16	3.19	3.21	3.24	3.26

Table 4
Preference values as Panorama tree cover density increases by 5%.

Panorama	0.001	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65
Preference	1.64	2.43	2.60	2.71	2.79	2.86	2.91	2.95	2.99	3.03	3.06	3.09	3.12	3.15

$t(116) = -.46$, $p = .64$. Therefore, it is not necessary to conduct separate analyses by gender.

4. Discussion

This study described the dose–response relationship between two measures of tree cover density and preference for residential street scenes. For each measure, the relationship was best described by a power model in which preference increases as tree density increases. The increase in preference ratings gradually attenuates as tree cover density increases. That is, for low tree cover streets, a slight increase in tree cover yielded a considerable increase in preference. But for streets with moderate or high tree cover, the same increase in tree cover added only a slight increase in landscape preference. We found no significant differences in preference responses between women and men.

4.1. Contributions and implications

Many previous studies have shown that landscape preference is positively related to the presence of trees or greater tree canopy size (Hernandez & Hidalgo, 2005; Kenwick et al., 2009; Kuo et al., 1998; Lohr & Pearson-Mims, 2006; Purcell & Lamb, 1998; Sommer & Summit, 1995; van den Berg et al., 2003). What we did not know, until this study, was the general shape of the dose–response curve for the impact of varying levels of street tree density on preference.

The results presented here suggest that to ensure a moderate preference value (preference ratings of at least 3), tree cover density should be not less than 41% for the eye-level measure (Panorama) and 20% for the top-down measure (Google). This new knowledge should be useful for design practitioners and urban forest managers. The findings provide professionals with evidence regarding the minimum tree cover density necessary to reach moderate levels of preference. Thus, decisions about how the minimum density of trees that should be planted can be based on scientific evidence in addition to intuitive experience.

These findings also indicate that planting trees in relatively treeless residential areas will offer greater impact for the investment than if the same trees were planted in already green areas. When public urban forest resources are limited, as they so often are, landscape architects and urban planners should give priority to planting in low tree cover neighborhoods over adding trees to neighborhoods that already have substantial tree cover. Planting trees in relatively low tree cover communities should be the top priority of urban forestry campaigns.

Still, the evidence presented here suggests that, for preference, every tree matters. A community may decide to plant well beyond the levels that will achieve moderate preference ratings for a host of reasons. Planting trees at densities of greater than 30% as measured from Google images may make sense in terms of reducing the urban heat island effect, increasing rain water filtration and water quality, increasing biodiversity and wildlife habitat, and because the addition of every tree has a slight, positive impact on people's preference.

4.2. Limitations and future research

Some limitations of this work raise questions for future research. First, this study used street scenes from middle-income, single-family communities in four major Midwestern cities in the U.S. that were selected because they fit a narrow pattern of physical conditions. Future research should duplicate this study in other urban environments in various regions that differ in their physical make up. This is important because we need to know more about the reaction people have to particular physical settings. It is also important because some settings are associated with specific populations of people who desperately need contact with nature. Thus, schools, low tree cover inner-city neighborhoods, senior centers,

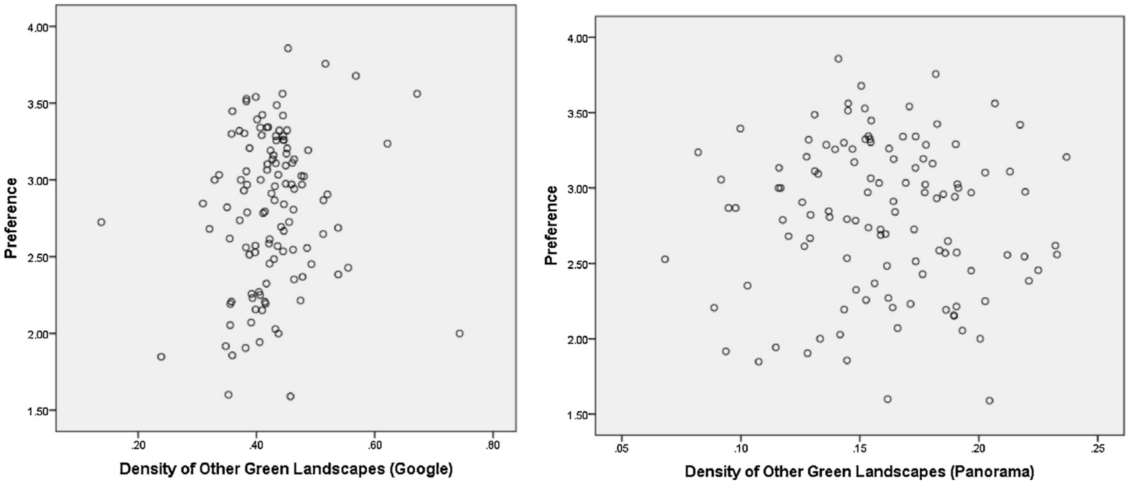

Fig. 2. The even distribution of spots on the plots suggests the density of other green landscapes measured in either Google or Panorama does not have a significant association with landscape preference.

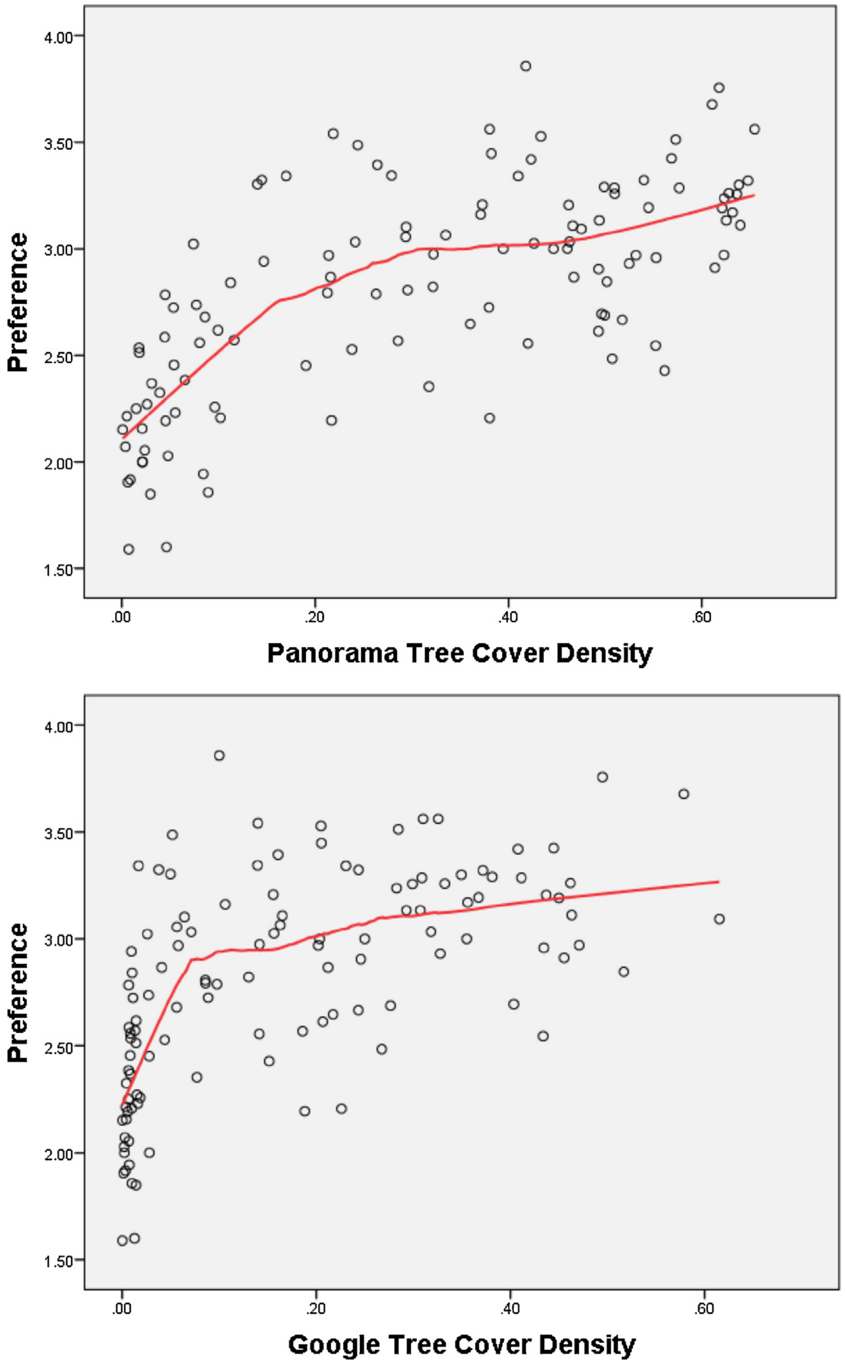

Fig. 3. Using scatterplots and LOESS curves (Kernel:Epanechnikov, $\alpha = .5$) to explore relationship between two measures of tree cover density and landscape preference.

office settings, and hospitals would be ideal environments to study next. By using the methods of this study, researchers may identify the dose–response curve for each specific type of urban environment and therefore encourage more effective design solutions or management regulations for urban forests.

Second, in this study, we investigated sites with similar spatial, cultural, and ecological attributes but varying levels of percent tree cover. Still, it is impossible to control all confounding factors perfectly. It is possible a slight difference of environmental attributes may have impacted preference. The only way to gain confidence despite this limitation is by accumulating knowledge across numerous studies. If the pattern of results found here turns out to be consistent despite the diversity in research participants and environmental conditions, our confidence in these findings will be considerably bolstered. Future research might measure the influence of a comprehensive list of tree features on preference (e.g., a high diversity of tree species, spatial configuration of trees, and various levels of street maintenance) (Schroeder & Orland, 1994; Sommer, Guenther, & Cecchettini, 1992; Yang, Li, Elder, & Wang, 2013).

Third, we recruited young adults who had lived in the U.S. for at least 18 years; therefore, the findings may not generalize to individuals from other cultures. Future research should examine how cultural differences influence the relationship between dose of tree cover and landscape preference. Also, future research should recruit people with a wider range of demographic characteristics, such as age, income, employment status, marriage status, experience with nature, and health status, to further enhance the generalizability

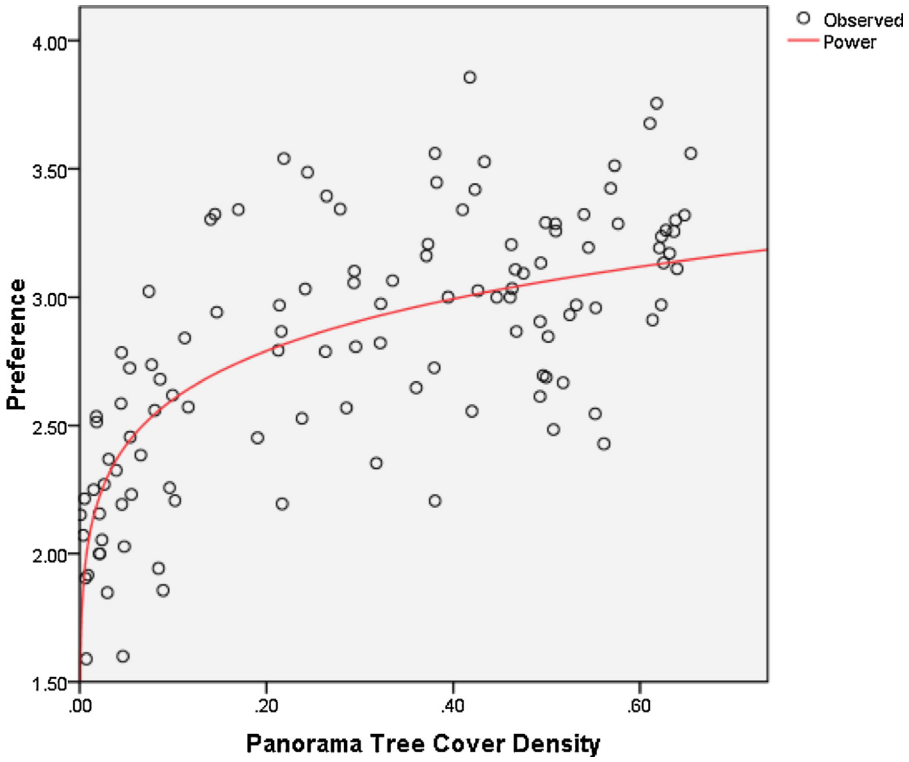

Fig. 4. The power trend curvilinear relationship between landscape preference and percent tree cover calculated from panoramic photograph (Panorama). $F(1115) = 130.76$, $\beta = .73$, adjusted $R^2 = .53$, $p < .0001$, BIC = −468.32. Equation: $y = 3.285x^{0.101}$, where is the preference and is the Panorama.

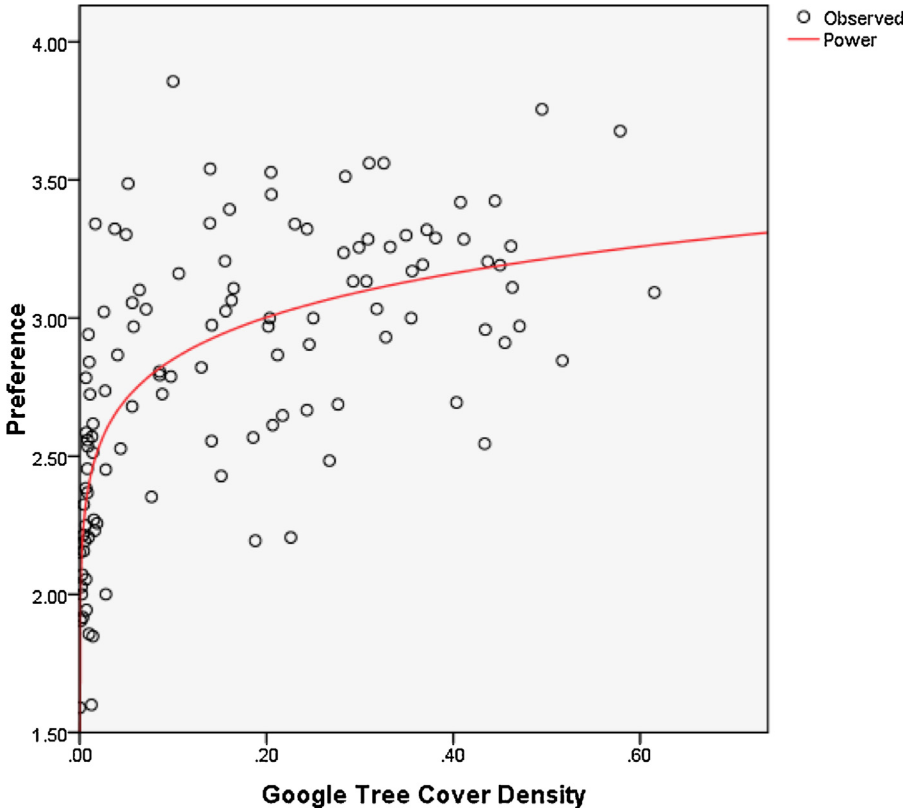

Fig. 5. The power trend curvilinear relationship between landscape preference and percent tree cover within street corridor calculated from Google Earth aerial photograph (Google). $F(1115) = 129.43$, $\beta = .73$, adjusted $R^2 = .50$, $p < .0001$, BIC = −467.73. Equation: $y = 3.386x^{.075}$, where y is the Preference and x is the Google.

of this study (Li et al., 2008). In addition, some may argue that we did not control for enough of the potential extraneous variables. The culture and socioeconomic status of participants may have influenced their preference, and future studies should more strictly control for confounding socioeconomic and cultural factors.

Fourth, people may argue that tree cover densities associated with a moderate preference score in this study are too low. One reason why these values may seem low is that we only examined community street corridors, in which the majority of ground area is occupied by paved surfaces, such as roads, driveways, and sidewalks. Compared to other urban environments, such as urban parks, campus lawns, or private gardens, neighborhood streets have less room for trees. Therefore, participants' preferred tree cover density might be lower in neighborhood streets than in other urban environments, especially recreational or restorative environments. Using the methods of this study, future research can examine people's preference for tree cover density in a variety of other urban settings.

Fifth, we did not examine sites with extremely dense tree cover (Panorama > 65% or Google > 62%) because such places were rare in the urban districts we visited and unlikely to exist in neighborhoods with a good deal of paved surfaces. It is possible that extremely dense tree cover is associated with low landscape preference. Extremely dense tree cover may block the sunlight, obstruct people's views, and make it difficult for people to plant gardens (Madge, 1997; Sreetheran & van den Bosch, 2014). Dense tree cover can also cause property or street infrastructure damage (Mullaney et al., 2015). Other studies, however, suggest trees would not block the view if the tree canopy is high enough; therefore, extremely dense tree cover may not negatively impact preference (Kuo & Sullivan, 2001). In short, preference of extremely dense tree cover in urban settings is still an open question, and more research needs to be done to resolve it.

Sixth, topography needs to be considered in future studies. The topography in the scenes we examined was typical of that of much of Midwest: most streets were on fairly flat land. In other regions of the world with a variety of landforms, the same eye-level tree cover density for different streets may be associated with different top-down tree cover densities, depending on the locations of trees. Therefore, the relationship between tree cover density measured by Google images and preference identified in this study may not be appropriate for other regions. In addition, season may influence landscape preference. The pictures in our study were taken in midsummer. Denser tree canopy might be more desirable in the summer because of trees' shading or cooling effects. Future studies should explore landscape preference in other seasons.

Finally, it is important to point out that empirical evidence supporting plausible connections between preference and human health and wellbeing is still surprisingly limited. Future studies should examine these possible connections. Possible indicators of human health and wellbeing include cognitive functioning, mental stress, moods, social capital, morbidity, and mortality.

5. Conclusion

This study, to our knowledge, is the first to identify a dose–response curve for two distinct measures of tree cover density and landscape preference. The findings demonstrate that panoramic photographs and Google Earth aerial photographs both reliably predict landscape preference. Furthermore, for both measures, a power trend line was the best description of the dose–response relationship, suggesting that preference increases sharply when trees are added to relatively treeless communities and then gradually attenuates, but still remains positive, as tree density becomes moderate or high. These findings provide clear evidence to support urban forest campaigns that seek to plant many trees. They also give clear direction to environmental designers and policymakers on how to allocate limited urban forest resources, address questions of equity in the distribution of urban trees, and to meet the preferences of the people they serve.

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