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How do computers see landscapes? comparisons of eye-level greenery assessments between computer and human perceptions

Pongsakorn Suppakittpaisarn [a,b,*], Yi Lu [c], Bin Jiang [d,e], Marcus Slavenas [f]

[a] Landscape Design and Environmental Management Studio, Department of Plant and Soil Sciences, Faculty of Agriculture, Chiang Mai University, Thailand
[b] Center of Excellence for Natural Disaster Management (CENDIM), Chiang Mai University, 239 Huay Kaew Road, Tumbol Suthep, Amphoe Mueang, Chiang Mai 50200, Thailand
[c] Department of Architecture and Civil Engineering, City University of Hong Kong, 83 Tat Chee Ave, Kowloon Tong 00000, Hong Kong,
[d] Urban Environments and Human Health Lab, HKUrbanlabs, Faculty of Architecture, The University of Hong Kong, SAR, China
[e] Division of Landscape Architecture, Department of Architecture, The University of Hong Kong, SAR, China
[f] National Center of Supercomputing Applications, University of Illinois at Urbana-Champaign, 1205 W Clark St, Urbana, IL 61801, United States

HIGHLIGHTS

- Assessments for eye-level vegetation density from computer visions and human perceptions were compared for accuracy.
- All three measurements agreed, but the selected color detection tool had higher agreements with human selection.
- Vegetation density predicted the odds of disagreements between the selected semantic segmentation tool and other tools.
- Landscape designers, planners, and researchers can use these tools to assess eye-level vegetation density of large number of photographs.

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ABSTRACT

Landscape architects and planners have been assessing eye-level vegetation to develop evidence-based designs, including the relationships between urban nature and human health. Measuring eye-level vegetation was often subjective and time-consuming in the past. Recent advances in computer vision have made it feasible to automatically measure eye-level greenery at a large scale. However, researchers still know little about the agreements of recent machine-based methods with human perception. The research gap may lead to inaccurate or even misleading findings that may prevent effective design and planning.

This study tested the agreements between eye-level greenery detected by two machine-based methods (Brown Dog Green Index Extractor (BDGI) and PSP-Net) and human perception (manual selection via Photoshop Histogram). These two machine-based tools were selected because of their distinctive mechanisms: color detection and semantic segmentation. Cronbach's alpha, correlation test, and Bland-Altman's Plots were used to test agreements. Then, logistic regressions were used to find relationships between shades and vegetation density and the disagreement odds. Both tools closely agreed with human assessment in predicting eye-level greenery, with BDGI slightly closer to human. Vegetation density, but not percentage of shade, predicted the higher disagreement odds between PSP-Net and others. This finding will help advancing computer-based assessment of urban nature and contribute to our knowledge in assessing and linking eye-level greenery with potential outcomes such as physical and mental health and other design assessments.

1. Introduction and literature review

Compiling evidence suggests that urban nature is a crucial infrastructure for cities (Austin, 2014). It provided multiple aspects of ecosystem services, including promoting human health and well-being (Coutts & Hahn, 2015; Jiang et al., 2015b; Sullivan et al., 2014;

* Corresponding author at: Landscape Design and Environmental Management Studio, Department of Plant and Soil Sciences, Faculty of Agriculture, Chiang Mai University, Thailand.

E-mail addresses: pongsakorn.sup@cmu.ac.th (P. Suppakittpaisarn), yilu24@cityu.edu.hk (Y. Lu), jiangbin@hku.hk (B. Jiang), slavenas@illinois.edu (M. Slavenas).

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Suppakittpaisarn et al., 2017; Tzoulas et al., 2007). However, in order to understand the relationships between the amount of nature and co-benefits towards human well-being, landscape researchers and practitioners need ways in which they can accurately assess the quantity of urban nature that humans experience in their everyday lives (Jiang et al., 2017; Kang et al., 2020).

Currently, researchers adopt three types of urban nature assessment: survey, top-down imagery, and eye-level imagery. More evidence suggests that eye-level imagery is the closest to human's experience (Jiang et al., 2017). However, a critical question remained unanswered clearly: How do researchers, planners, and designers accurately measure the level of greenness in urban settings?

In the past, the ways in which researchers assessed eye-level vegetation density were time-consuming. Recently, several computer vision tools have been introduced to measure the level of vegetation density in eye-level images with distinctive pathways (Padhy et al., 2015; Zhao et al., 2017), but they have never been compared to see the extent to which they agree with each other and with human-based perception. The measurement test is important because it allows the landscape designers, planners, and researchers to use these tools more confidently and make direct comparisons between the results. Understanding the relationships between the tools can help improve the computer-based assessment of urban nature. Furthermore, the deeper understanding of these tools might lead to a faster growing body of evidence towards the relationships regarding dose of nature and human health.

This study aims to find the extent of agreement between a measurement from each of the three current approaches in assessing vegetation density: human selection, color detection, and semantic segmentation.

1.1. Urban nature and human health

Urban natural elements have positive effects on human health and well-being (Coutts & Hahn, 2015). Evidence shows that being in contact with nature improves overall physical health (Astell-Burt & Feng, 2020; Becker et al., 2019; Hartig et al., 2014), reduces risks of mental morbidity (Cohen-Cline et al., 2015) and cardiovascular diseases (Mitchell & Popham, 2008) and promotes social engagements (Coley et al., 1997) and mental well-being (Ulrich, 1999).

This may be explained by several theories. Biophilia-Biophobia Hypothesis posits that humans still have deep physical and emotional bonds with the nature in which humans survive as a species (Kellert & Wilson, 1993). The hypothesis was later expanded upon by Stress Reduction Theory, or Psychoevolutionary Theory, which posits that humans evolve to perform well, physiologically and psychologically, in the environment in which they thrive: among trees and open spaces. In contrast, being removed from that environment for a long, consistent duration may cause physiological and emotional issues (Sullivan, 2005). Another theory involving human and nature is Attention Restoration Theory. The theory suggests that directed attention, a limited but crucial resource for everyday life, can restore more effectively while humans are interacting with nature (Kaplan, 1995).

These theories and large body of evidence all suggest that humans need regular and accessible contact with nature. Thus, even though people are living in the urban environment, designers and planners must make sure to include nature, especially trees and open spaces, in people's everyday lives to ensure and enhance their health and well-being.

1.2. Dose of urban nature and human well-being

One of the remaining questions regarding the relationships between urban nature and human health is dose. Landscape researchers are still finding and suggesting the relationships between different intensity, frequency, and duration levels of urban nature towards human health (Jiang, 2013; Sullivan et al., 2014).

Among those, the quantity of urban nature that humans can perceive can be directly influenced by landscape designers and planners. Urban spaces are highly in demand; thus, landscape designers and planners should find ways to balance urban nature with other infrastructure. This means that researchers, in support of planners and designers, must find ways to assess the quantity of urban nature to measure its relationship with human health and well-being.

There are three ways that researchers usually assess the quantity of urban nature, such as vegetation density, in a landscape: on-site survey, top-down imagery, and eye-level imagery. On-site survey had been used to assess landscape density for a long time. Mostly, the assessor estimated the quantity of landscape elements in the Likert scales of one to five. While this measurement addressed the human perception quite well, it may be subjective to the assessors' experiences and perspectives.

Another means of quantifying urban nature includes top-down imagery. It was one of the most widely used measurements in today's study about dose of nature and human health. Top-down vegetation density is calculated by percentage of vegetation shown in a space in proportion to the total area. It can be used to study sustainable urban development, quality of the forests, or human-nature relationships (Donovan et al., 2015; Gariepy et al., 2014; Kardan et al., 2015). However, the top-down vegetation density cannot accurately describe the greenness perceived by people from the eye level in daily life. Some parts of vegetation, while in proximity with people, may not be physically or visually accessible to those citizens depending on their locations, surroundings, and property types (Jiang et al., 2017).

Many researchers, then, argued that the more suitable way to measure quantity of urban nature is by combining the ways in which humans daily experience with urban nature with the percentage calculation often used for top-down vegetation density (Jiang et al., 2017; Lu, 2019). A study had shown that photograph assessment and on-site assessment of a place by humans provide similar results (Shuttleworth, 1980), and later study suggested that the vegetation density calculated from eye-level photographs is closer to what humans perceived (Jiang et al., 2017). The scene can be assessed from different angles to provide composite scores (Li et al., 2015). Furthermore, the emerging dataset of publicly available eye-level photographs, such as Google Street View, provides researchers to study these eye-level images in the spatial scale (Kang et al., 2020; Lu, 2019). Furthermore, studies conducted in the recent years have linked eye-level vegetation density to many positive human well-being (;Jiang et al., 2014a; Jiang et al., 2020; Li et al., 2018a). However, even though they are more similar to how people experience the landscape, the number of studies that use this assessment is far lower than satellite vegetation density (Suppakittpaisarn et al., 2017).

1.3. Eye-level landscape assessment: From human to computer-based tools

The quantification of landscape elements had been used as research tool for a long time. One of the earliest published examples include the study of Scenic Beauty Estimation Model (Daniel & Schroeder, 1979). Untrained panels of participants saw images of forests and estimate its openness, tree sizes, and groundcover density before correlating them with the perceived aesthetic of the forests measured by Scenic Beauty Estimation Method (Daniel & Boster, 1976). Later, the aesthetic assessments were tested between eye-level photographs and in-situ assessments via a *meta*-analysis study: They are found to be highly correlated (Shuttleworth, 1980).

The measurement of eye-level landscapes started having links with dose of nature and human well-being at the first decade of the 21st Century. From year 2000–2010, the field of landscape architecture was in the middle of transition from modernism into post-modernism design (Milburn et al., 2003). This shifting focus led research studies in the field towards well-being and sustainability. In 2001, a study in inner city housing used horticulture and landscape expert to rate the greenness of the housing grounds to assess levels of crime and aggression found (Kuo

& Sullivan, 2001). During these developments, Nordh et al. (2009) divided the landscape images into grids and assessed the contributions of those landscape elements with mental restoration.

In the same year, another technique in landscape assessment emerged. Photographs from street views were analyzed for vegetation density by calculating the percentages of vegetation pixels found in the images (Yang et al., 2009). In this paper, they briefly explained that the pixels were manually extracted using Photoshop Histogram tool, a hybrid between human judgement and machine calculation.

In the most recent decade (2011–2020), the ways of quantifying vegetation in the landscapes have been rapidly established, tested, and expanded. Street photography became a growing measurement of urban elements in design.

Among the most notable studies was a series of experiments establishing the dose of nature and human health and well-being. In 2014, a study used 50 panoramic videos comprising of varying level of vegetation density to understand the dose–response curve between vegetation density and stress recovery through cortisol level (Jiang et al., 2014a). The vegetation density levels from the videos were selected manually using Photoshop Histogram Tool. The distinctive quality of the study was that it presented the comprehensive steps in using manual selection of vegetation density by Photoshop Histogram Tool, making the tool more replicable and accessible to researchers. The subsequent studies were done with the same tool to find the dose-curve relationships between vegetation density and self-reported stress recovery and landscape preference Jiang et al., 2015a; Jiang et al., 2014a Suppakittpaisarn et al., 2020). In these studies, the researchers used the Quick Selection tool to manually pick the pixels that contained trees and shrubs. Then they used the Histogram Tool to determine the number of the pixels which were vegetation and calculate the percentage of vegetation from the picture. Their method is replicated again in their study comparing vegetation density between satellite imageries and eye-level images (Jiang et al., 2017). Another study has also used this method to determine dose–response curve between tree density, understory plant density, and bioretention planting density and preference (Suppakittpaisarn et al., 2019a). Photoshop Histogram was directly identified by subsequent studies as a tool for identifying vegetation density. For example, one study used it to relate street greenery and walking behavior (Zang et al., 2020), and another to identify sense of safety and privacy (Lis & Iwankowski, 2021).

While this hybrid assessment of vegetation density retained the benefits of human judgement and finer details of calculation, the process is highly time-consuming and may not be suitable with studies with larger dataset, which had grown larger due to the involvement of Google Street Views. Google Street Views became an important tools for this decade because they were readily available and effective representation of a place from eye-level perspectives (Kang et al., 2020). However, the dataset became too large to manually assess the eye-level greenery from these photographs. Thus, there were growing needs of computer aided assessment that could make the process more time efficient.

Concurrent with the development of the manual use of Photoshop Histogram Tool, computer vision and machine learning had developed rapidly in this decade. Two distinctive directions were used to detect vegetation in two-dimensional photographs: color detection and semantic segmentation.

Color detection has older roots from top-down imagery assessment. The machine can identify pixels with varying shades of greens from satellite photographs and calculate the percentage of the vegetation detected (Kadmon & Harari-Kremer, 1999). In this decade, the calculation and detection evolved to be more refined and can be used with different applications, including identifying greenery from eye-level photographs. This method had been tested with correlation to see its agreement with manual selection tool, using a script written by researchers (Li et al., 2015). It had also been used to link street level greenery with walking behavior and physical activities (Lu, 2019; Lu et al., 2018) and mental health (Kumakoshi et al., 2020). Another study used color-detection as a base to build a more complex visible vegetation index tool (Labib et al., 2021).

A notable color detection tool included Brown Dog Green Index Extractor (BDGI). BDGI Extractor is a part of Brown Dog a data transformation service platform. The extractor uses the CIELAB color space to separate the pixels into two categories: green and not green. Researchers set the three CIELAB color threshold components (lightness, green–red, blue-yellow) by iteratively varying the components and running the segmentation on a set of ten sample images, then visually inspecting the segmentation of the images for best fit to the images (Padhy et al., 2015). BDGI has been used in studies to identify vegetation density from street view images and eye-level photographs. The example of these studies included one that explored the fitting curves for the relationships between different types of vegetation and preference (Jiang et al., 2015a; Suppakittpaisarn et al., 2019a), a study relating geographical greenness with teenagers' experience with nature (Li et al., 2018a), and a relationship between the green density of a participant's route to work and their health outcomes (Jiang et al., 2020).

Meanwhile, as researchers have wider access to available big dataset of street photography, semantic segmentation technique has been developed to identify objects from photographs, including measuring eye-level density of vegetation (Yu & Wang, 2016). By deep learning, the algorithm assigns each pixel in an image a label, identifying the object it represents such as trees, terrain, or cars using the system called fully convolutional network (FCN) (Badrinarayanan et al., 2017). This technique had been tested for accuracy (Yu & Wang, 2016) and suggested for urban landscape studies (Li et al., 2018b). One of the advanced tools for this technique included PSP-Net. PSP-Net is a neural network architecture for pixel-wise semantic segmentation, which an advanced ability in considering the pixel's contexts through spatial pyramid pooling (Zhao et al., 2017). However, there is limited number of studies that mentioned PSP-Net as a tool to explore vegetation density and human well-being, but a few recently emerged. For example, a study used PSP-Net to identify green quantity in the relationship between green quantity and quality and number of park visitors (Yang et al., 2021).

1.4. Critical knowledge gap

For designers, planners, and researchers to establish the dose–response relationships between nature and human health and other studies regarding urban landscapes, clear ways to quantify urban nature as experienced by humans becomes important. While many tools are invented to assess the vegetation density of eye-level scenes, they have not been compared to see if they are consistent with each other. Without the test, the researchers might not be able to compare the data acquired from the older tools and the newer ones.

Furthermore, each tool might be beneficial in some area but not the other. For example, if there are many shaded areas that change the colors of the foliage so they are less green, would color detection method identify the vegetation density differently than manual detection and semantic segmentation? If the trees were denser, obstructing the shapes of the mass or if the lawn were too flat, would the semantic segmentation identify different vegetation density levels than the other two methods?

Thus, in this study, the researchers selected a measurement each from three different approaches in vegetation density assessment: manual selection by Photoshop Histogram Tool, color detection by BDGI, and semantic segmentation by PSP-Net. The researchers asked the following questions:

- To what extent do the vegetation density percentages measured by manual selection, BDGI, and PSP-Net agree with each other?
- To what extent do vegetation density and percentage of shades predict the odds of disagreement between measurements?

2. Methods

2.1. Eye-level imagery

In this study, the researchers used 201 photographs portraying different levels of urban nature from four different projects conducted across the Sustainable and Human Health Network (Jiang et al., 2014a; Jiang et al., 2015a; Jiang et al., 2014b; Jiang et al., 2015b; Suppakittpaisarn et al., 2019aJiang et al., 2014a; Jiang et al., 2015a; Jiang et al., 2014b; Suppakittpaisarn et al., 2019a). The photographs were taken from various stages of urban development across the United States, including city centers, urban parks, and suburban housing developments. The photographs were selected to represent different vegetation density across varying urban spaces. Most were taken in the Midwestern region. The region was selected due to two following reasons 1) the settlements were built on the flatter terrains, eliminating the possible effects of topography 2) the cities across the region contained several strategies towards GSI. The photographs were taken during summers of 2012–2015, between 10 am-3 pm to control for foliage color and lighting. The photographers aimed the camera straight forward at approximately 1.5 m above the ground. This height was chosen for the approximate eye-level based on the mean height of the US population in 1996 birth cohort, who would be an adult of 25-year-old at the time of the study (NCD Risk Factor Collaboration, 2016). Since the mean height is 1.65 m, the eye-level of the average population is 1.5 m accordingly. The subjects of the photographs included street trees, shrubs, grasses, and in some cases, bioretention planting. To control the variable and emphasize the landscape features, these photos contained minimal amount of people and unusual features such as sport cars, traffic cones, or unique architecture, and any stages of disrepair and construction were removed. These photographs were set at 300 dpi resolution before being measured for greenness. According to Qualtrics Sample Size Calculator, the sample size were sufficient for generalization at 90 % confidence level and 6 % margin of error.

2.2. Green indices

The researchers measured the green indices in three ways: manual selection via Photoshop Histogram, PSP-Net, and BDGI Extractor.

Manual selection via Photoshop Histogram: to obtain vegetation density values from the images, we trained the student members of Sustainability and Human Health Laboratory (US and Thailand) and Virtual Reality Laboratory of Urban Environments and Human Health (Hong Kong) to extract the vegetation density data (n = 5). These students were studying in landscape architecture and environmental psychology and were familiar with similar quantitative landscape studies. The researchers were preliminary tested to have good inter-rater reliability. The trained researchers used Quick Selection Tool to select the pixels within the images that represent any plants seen including trunks, stems, and non-green parts. The pixels selected were counted by Histogram Tool and calculate into percentage from total number of pixels in the images. The researchers coded this index as HTGI.

PSP-Net: to obtain vegetation density values from the images, researchers ran the images through the analytical code. The processed photographs were made into several layers of identified labels such as sky, vegetation, terrain, road, etc. For this study, the researchers combined the vegetation layer, which contained trees and shrubs, with the terrain layer, which contained grasses and groundcovers into one layer. The percentage of pixels that was the combination between these two layers were used for the comparisons with other vegetation density values. The researchers coded this index as PSPGI. The tool is accessible at the following link: https://github.com/hszhao/PSPNet.

BDGI Extractor: to obtain vegetation density values from the images, researchers uploaded the images into the cloud server of Brown Dog service. The computer will extract the metadata from the images, including the percentages of green pixels recorded as Brown Dog Green Index. The images generated from this process showed positive and negative spaces from green and non-green pixels. The researchers coded this index as BDGI. The tool is accessible at the following link: https://browndog.ncsa.illinois.edu/.

The extracted images were shown in Fig. 1.

2.3. Shades

The percentage of shades were analyzed by manually selected the shaded pixels with Quick Selection Tool and calculated with Photoshop Histogram Tool for further analysis.

2.4. Statistical analysis

To explore the agreements between the tools. The researchers calculated the Cronbach's alpha value of the three tools. Then, the researchers performed pair-wise comparisons through Cronbach's alpha, Pearson's correlation, and Bland-Altman's analysis. As Givarina (2015) suggested, while the correlation test or Bland-Altman's analysis alone might not make solid conclusions of the strength of agreements, the combination of more than one tools can demonstrate more reliable conclusions.

To test whether shadows and vegetation density may predict the chances of having disagreements between the tools, the researchers conducted binary logistic regressions between each pair of comparison, using the percentage of shade and vegetation density as the independent variables and the probability of the density values would disagree by Bland-Altman's analysis as the dependent variable.

3. Results

3.1. To what extent do the vegetation density percentages measured by manual selection via Photoshop Histogram, BDGI, and PSP-Net agree with each other?

To answer this question, the researchers ran three statistical tests: Cronbach's alpha calculations, correlation tests, and Bland-Altman analyses. If the measurements agreed, Cronbach's alpha should be above 0.8, correlation tests would provide $p < 0.05$ with r-value that is close to 1, and Bland-Altman's analysis should provide more than 95 % agreement.

All three measurements agreed with each other as tested by Cronbach's alpha ($\alpha = 0.97$). Pairwise, manual selection agreed with both BDGI ($\alpha = 0.98$) and PSP-Net ($\alpha = 0.94$), and BDGI and PSP-Net agreed with each other ($\alpha = 0.94$).

Pairwise correlations showed all pairs of measurements are significantly correlated with each other. In term of Bland-Altman's test, manual selection by Photoshop Histogram agreed with BDGI at more than 95 %, which was the same level of agreements with standard. The pairs between PSP-Net and other two measurements were still showing a high level at more than 90 %. The results for correlation test and Bland Altman's analyses are shown in Table 1.

With all the comparison methods combined, the researchers could conclude that all three measurements are highly in agreements. However, manual selection by Photoshop Histogram agreed more highly with BDGI, while PSP-Net showed a higher disagreement, if only slightly, from both other measurements. The disagreements between BDGI and PSP-Net, while still extremely low, were the highest among all comparisons.

3.2. To what extent do vegetation density and percentage of shades predict the odds of disagreement between measurements?

For this question, the researchers ran a binary logistic regression to explore the odds that the paired measurements of a photograph would disagree according to the Bland-Altman's analyses. Green Index

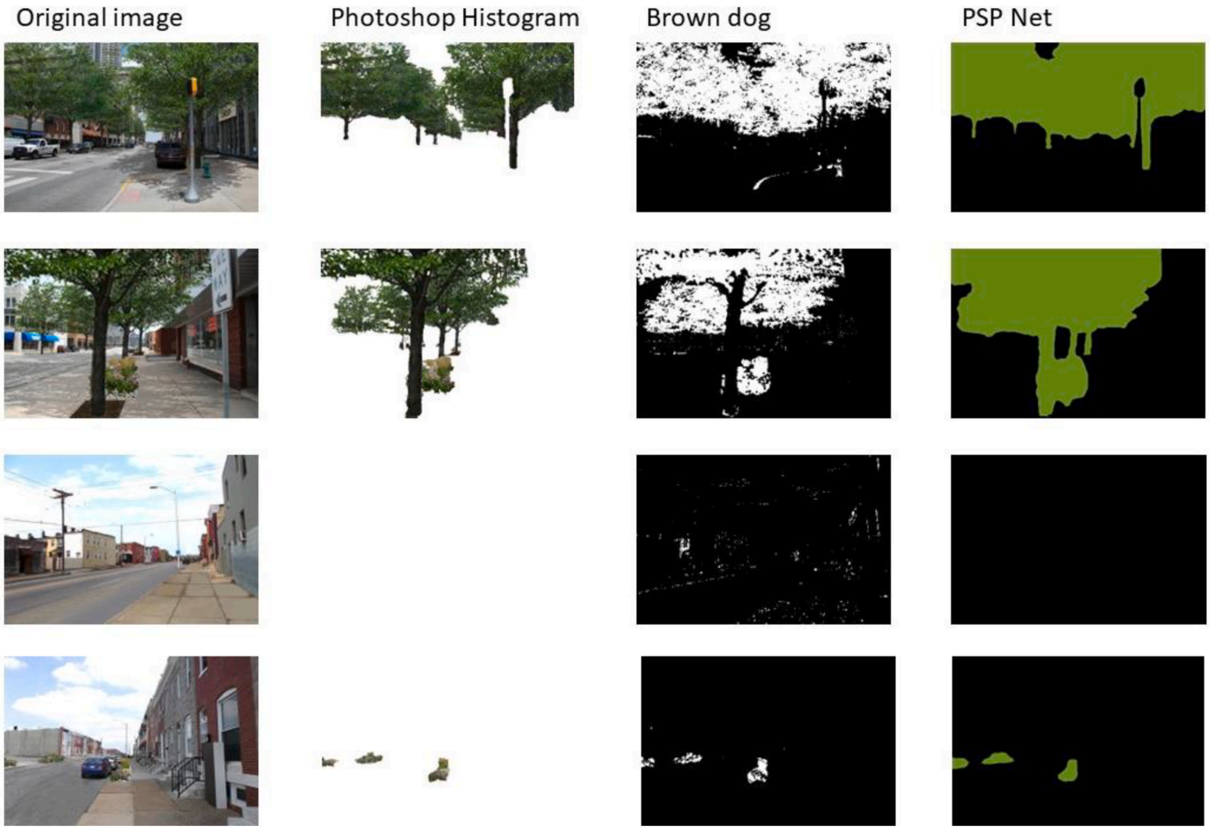

Fig. 1. The processed images from different extractors.

Table 1
Comparisons of the agreements between three pairs of tests.

Pair	Cronbach's Alpha	Correlation tests		Bland-Altman Plots		
		r (199)	Significance level	Mean differences	SD Differences	B-A Agreement
HTGI-BDGI	0.98	0.96	$p < 0.0001$	−6.2	6.5	**95.80 %**
PSPGI-HTGI	0.94	0.98	$p < 0.0001$	1.0	8.5	92.60 %
PSPGI-BDGI	0.94	0.98	$p < 0.0001$	−7.2	8.87	91.40 %

calculated by manual selection and percentage of shades were used as independent variables. The assumptions regarding logistic regression were tested and met.

For BDGI-HTGI relationships, a model logistic regression reported non-significant relationship Chi-square (2) = 0.48p = 0.79, The model explained 1 % of the variables (Nagelkerke R-square,) and is classified for 96.1 % of the case. Meaning that neither shadows nor vegetation density predicts the odds of errors between these measurements.

For PSPGI-HTGI relationships, a model logistic regression reported significant relationship Chi-square (2) = 11.15, $p < 0.05$, The model explained 14.7 % of the variables (Nagelkerke R-square,) and is classified for 94.1 % of the case. Percentage of shades was found not to be a significant predictor, but vegetation density was. According to the analysis, as the vegetation density increases for 1 %, the odds of the vegetation density in a photograph to disagree between these two measurements increases by 1.06.

For PSPGI-BDGI relationships, a model logistic regression reported significant relationship Chi-square (2) = 13.91, $p < 0.05$, The model

Table 2
The results of logistic regressions linking percentage of shades and vegetation density to the odds of disagreements between each pair of measurements.

		B	S.E.	Wald	df	Sig.	Odd Ratios	95 % C.I. for Odd Ratios	
								Lower	Upper
HTGI-BDGI	Vegetation density	0.01	0.02	0.44	1.00	0.51	1.01	0.98	1.05
	Shadows	0.00	0.02	0.04	1.00	0.85	1.00	0.96	1.03
	Constant	−3.63	0.79	21.23	1.00	0.00	0.03		
PSPGI-HTGI	Vegetation density	0.06	0.02	8.27	1.00	0.00	1.06	1.02	1.10
	Shadows	−0.01	0.01	0.64	1.00	0.42	0.99	0.96	1.02
	Constant	−5.17	1.02	25.46	1.00	0.00	0.01		
PSPGI-BDGI	Vegetation density	0.06	0.02	9.76	1.00	0.00	1.06	1.02	1.10
	Shadows	−0.01	0.01	0.61	1.00	0.44	0.99	0.96	1.02
	Constant	−5.39	1.05	26.36	1.00	0.00	0.00		

a. Variable(s) entered on step 1: Vegetation density, Shadows.

explained 17.4 % of the variables (Nagelkerke R-square,) and is classified for 93.7 % of the case. Percentage of shades was found not to be a significant predictor, but vegetation density was. According to the analysis, as the vegetation density increases for 1 %, the odds of the vegetation density in a photograph to disagree between these two measurements increases by 1.06. Table 2 shows the composite results of all three logistic regressions.

4. Discussion

4.1. Key findings

In this paper, researchers tested the agreements of three vegetation density measurements from three different human and computer-based approaches: manual selection by Photoshop Histogram, color detection by Brown Dog Green Index Extractor, and semantic segmentation by Pyramid Scene-Parsing Network. The researchers also tested the extent to which vegetation density and percentage of shade may influence the accuracy of the tools.

The findings suggested that all three were in good agreements, as suggested by Cronbach's alpha above 0.9 in all paired comparison and p-value under 0.001 from all the pairwise correlation tests. However, only the HTGI-BDGI pair passed Bland-Altman's Analysis at above 95 %. This means that among the three pair, Brown Dog Green Index Extractor provided slightly closer results with manual selection by Photoshop Histogram. Binary logistic regression suggested that the odds of the outlier increased as vegetation density increased. For every 1 % of vegetation density in a photograph, the odds for the disagreement between PSP-Net and other tools increased by 1.06. However, more factors may contribute to these disagreements.

With the results of this study and previous information about these three measurements, researchers can make better decisions for the tools most appropriate for their research. Table 3 made comparisons between three tools.

4.2. Contributions and implications

This study confirmed that these measurements are accurate and shed lights on further developments of vegetation assessment methods. The results reflected previous comparison between machine and human assessments (Li et al., 2015; Suppakittpaisarn, 2017). This study further confirmed that the vegetation density measured from all these three tools are comparable. However, higher margin of error may occur with PSPGI at higher vegetation density, although PSPGI might have potential above BDGI with seasonal foliage due to its assessment method that does not rely on color alone. Such discrepancies could point out the further development direction of eye-level vegetation assessment tools.

Landscape designers, planners, and policy makers can include these computer-based tools for assessing existing or future designs in terms of environmental performance, visual quality, and vegetation availability. Such effects may help us accumulate more evidence and lead to evidence-based design to improve human and ecological well-being. Furthermore, landscape researchers can use the results of the study to explore different research topics, e.g., the relationships between doses of urban nature towards human well-being, the changes in vegetation density and ecological well-being (Bergen et al., 2009; Sullivan et al., 2014). In addition, similar tools can be developed to explore the extent to which other landscape elements can provide human well-being in high-density environment that are difficult to grow plants.

Table 3
The comparisons of Histogram Tool, Brown Dog Green Index Extractor, and PSP-Net.

	Histogram tool	Browndog	PSP Net
Mechanisms	Human judgement and computer calculation	Color detection	Semantic segmentation
Cost	Depends on software	Free	Free for non-commercial use
Required skills	Graphic software	Website use	Basic coding
Agreement with human perception	n/a	Higher agreement	High, but not as high as Brown Dog
Limitations	Time-consuming	green under shadow or strong light non-green grass or vegetations	Lower level of agreements with higher vegetation density
Additional benefits	Fully flexible	Preference prediction (early stage); Can identify greenness of a route via map and GPS	Identify more than vegetation, such as cars, buildings, etc.

4.3. Limitations and opportunities for future studies

A few limitations must be addressed regarding this study. First, most testing images were taken during summer when plants have green leaves, thus might improve the accuracy of BDGI, a color-based detection method. Furthermore, most photographs were taken in the condition with bright sunlight and clear skies, which is most suitable for BDGI. In the future, researchers should also compare the performance of the same tools for images taken in other seasons or weather conditions.

Secondly, urban streetscapes are vibrant and dynamic, often filled with pedestrians and cars. Different streetscapes may also have unique architecture and street elements. In this study, we deliberately selected images containing the minimal number of human activities and distinctive features. Adding these elements into the images might affect the accuracy of these measurements and the physio-psychological impacts of the images. Future studies should compare the images with people and distinctive features to improve the research tools towards higher practicality.

Thirdly, the selected images came from a limited geographic area, mid-western United States. Such images are arguably representative to landscapes in a broad range of locations in the United States, but not those in other countries with distinct topography, culture, and street typology. While the computer vision and assessment of vegetation density is influenced by geographical locations, some environmental factors, such as plant species, shadows, and building density, may affect the results. Hence, future studies should be repeated in different street patterns from across different geographical and cultural locations to test out the generalizability of this study.

Fourthly, due to their landscape architectural background, the trained researchers may have different perception of vegetation density than laypeople (Suppakittpaisarn et al., 2019b). Future study may explore crowd-sourced options to assess vegetation density perceived by laypeople.

5. Conclusion

As the landscape researchers and practitioners seek ways to assess and analyze urban nature for evidence-based designs, they need new tools to assess different quantities of vegetation, including eye-level vegetation density. Several ways to assess vegetation density had been developed; however, their agreements may need to be assessed for future uses. This study compared three established tools to assess the eye-level vegetation density and found that while all three measurements agreed, higher vegetation density may influence a higher odd in disagreement for a semantic segmentation tool. This research helps confirm to landscape designers and planners that these tools are reliable, as tested with each other and suggest the improvement on these computer-based assessments. It also informs researchers about the tools they can use for landscape and human health research. Future studies should be conducted for agreements in different conditions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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