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Assessing visual green effects of individual urban trees using airborne Lidar data

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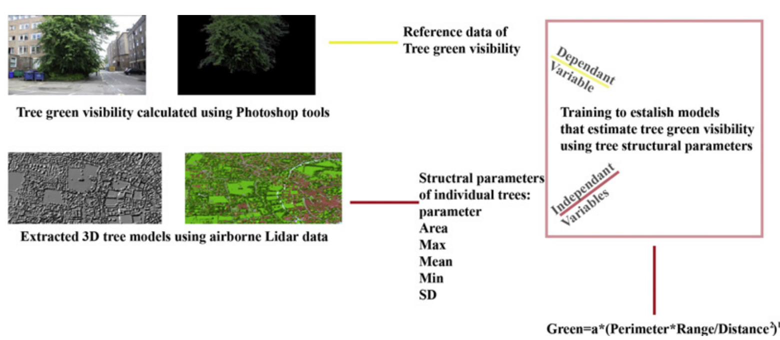
HIGHLIGHTS

- Field-collected photos are used to calculate visual green effects of individual trees.
- Airborne Lidar data is employed to extract key structural variables of sample trees.
- A model to estimate tree green visibility using structural variables is established.
- This approach is a practical tool for large-scale analysis of tree green presence.

GRAPHICAL ABSTRACT



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ABSTRACT

Urban trees benefit people's daily life in terms of air quality, local climate, recreation and aesthetics. Among these functions, a growing number of studies have been conducted to understand the relationship between residents' preference towards local environments and visual green effects of urban greenery. However, except for on-site photography, there are few quantitative methods to calculate green visibility, especially tree green visibility, from viewers' perspectives.

To fill this research gap, a case study was conducted in the city of Cambridge, which has a diversity of tree species, sizes and shapes. Firstly, a photograph-based survey was conducted to approximate the actual value of visual green effects of individual urban trees. In addition, small footprint airborne Lidar (Light detection and ranging) data was employed to measure the size and shape of individual trees. Next, correlations between visual tree green effects and tree structural parameters were examined. Through experiments and gradual refinement, a regression model with satisfactory R^2 and limited large errors is proposed. Considering the diversity of sample trees and the result of cross-validation, this model has the potential to be applied to other study sites. This research provides urban planners and decision makers with an innovative method to analyse and evaluate landscape patterns in terms of tree greenness.

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1. Introduction

Urban trees play an import role in residents' daily life in terms of air quality (Scott et al., 1998; Yang et al., 2005; Jim and Chen, 2009), local climates (Zhao et al., 2010) and recreation (Arnberger, 2006; Bernath and Roschewitz, 2008; Rosenberger et al. 2012). In addition, urban trees provide people with aesthetic benefits which are closely related to stress relief (Ulrich et al., 1991), mental and physical benefits (Ode and Fry, 2002; Bhatti and Church, 2003) and attraction to migrants (Waltert and Schlapfer, 2010). As a result, growing research emphasis is put on understanding the patterns and functions of urban trees.

Among various functions of urban trees, many studies (Thayer and Atwood, 1978; Buhyoff et al., 1984; Schroeder, 1988; Aoki, 1991; etc.) have been conducted to examine the role of visual effects of urban greenery plays in people's perception of local environments. These studies proved the positive correlation between people's preference towards local landscape design and the presence of greenery. However, most studies to calculate the visual effect of urban trees have been qualitative and subjective (Yang et al., 2009). The widely used research approach for greenery assessment involves the use of photographs and videos. Nevertheless, this type of on-site surveys requires substantial resources and time and is thus not suitable for large research sites. Remote sensing images can provide large-scale study with reliable data sources and some landscape metrics are commonly used for landscape pattern analysis. Nevertheless, Yang et al. (2009) pointed out that currently used metrics to quantify the structure of urban trees, such as canopy cover (Scott et al., 1998), leaf area index (Xiao et al., 2000), total leaf biomass (Nowak and Crane, 2002), leaf area density (Kenney, 2000), and green plot ratio (Ong, 2003), were not suitable for simulating visual effects of urban trees. Different tree species have a diversity of spatial structures. For some species, large crown area (2D structures) does not indicate a large height (3D structures). In addition, understory structures (e.g. the crown shape and tree leaf density), which have a significant influence on visual green effects of trees, can hardly be featured using 2D structure variables. Therefore, specific 3D metrics and alternative data sources are required for better analysing the visual green effects of individual urban trees.

Previous studies proved that people preferred more greenery in local environments (Aoki, 1991; Kuo et al., 1998; Jim and Chen, 2003) and Aoki (1991) proposed a quantitative finding that most people had a favourable impression of a street landscape if more than 30% of the view included greenery. Although some studies have been conducted, most of them remain qualitative and quantitative understanding of visual green effects is still challenging. Urban forests are very important sources that provide people with visual greenness in urban areas. In accordance with people's growing aesthetic needs of greenery and the lack of relevant research methodology, it is of both theoretical and practical significance to propose a more efficient approach for approximating the visual green effect of individual trees. Therefore, the main aim of this study is to establish a robust regression model to estimate the visual green effect of individual urban trees with specific variables derived using airborne Lidar data.

2. Material

2.1. Study site

Cambridge lies in East Anglia about 50 miles north-east of London, UK and has a typical urban landscape. There are many trees of different species, shapes and heights in the study site, making it possible to select a diversity of sample trees. Through experiments using sample trees with different sizes and understory structures, the acquired regression models can avoid the bias and limitation caused by unified sample units. In this case, the model from this study site is more likely to be transferred to other sites. Furthermore, the availability of qualified airborne Lidar data and the convenience to conduct fieldwork make this site an ideal choice for a case study.

2.2. Data preparation

2.2.1. Lidar data

The Lidar data used in this research was from an ALTM-3033 Lidar System carried on the Aircraft ULM_PA31. This survey was carried out in central Cambridge in June, 2009 and the average height of this flight was 800 m. The point cloud included about 10 million records (a comparatively small data set in Airborne Lidar terms) and the horizontal resolution of the point cloud is, on average, 2 points per m^2. The main task of data preparation was to filter some outliers that were caused by Lidar system error or such factors as clouds. The main approach for detecting and filtering the elevation and intensity outliers is the extended local minimum method (Chen et al., 2012).

2.2.2. Photographs of trees

The photographs of trees were taken across the study site at random using a Canon 50D camera with an EFS 18–135 mm lens (to avoid the effect of variation, which may cause error in calculating the value of tree green visibility, the length of focus was fixed as 18 mm in this survey). Since a SLR (Single Lens Reflex) camera uses the same lens for finding views and taking photographs, optical parallax effects are reduced effectively.

This on-site survey was conducted in July, 2012. Since the airborne Lidar data and the photo materials were not collected in the same year, the influence of three years' gap should be taken into account. Young trees grew and their shapes changed significantly in the three years whilst mature trees remained the same. As a result, some other data sources were also included for reference. Airborne Lidar data collected in June, 2002 and airborne photographs collected in June, 2012 (Fig. 1) were comprehensively considered for sample tree selection. For this research, only those trees that have been present since 2002 and have remained unchanged were regarded as valid sample units. In this case, the effect of tree growth was efficiently reduced. To make the results more reliable, photos of different tree genres, including beech, cedar, hazel, plane, lime, sorbus, horse chestnut and so forth, were taken for the following analysis.

As it was in summer, all trees provided the most visual greenness. Therefore, the factor of leaf-on and leaf-off situation was removed and the differences between evergreen types and deciduous types would not affect the final results. All these photos were taken under sunny weather condition to reduce bias from insufficient illumination in the following process of colour analysis. In addition, to reduce the influences from blocking effects by buildings, or the overlapping effects of neighbouring trees, photographs of isolated trees were taken from unblocked perspectives. For the convenience of measuring the distance between the photographer (observers) and trees, all these photographs were taken when the photographer stood on the edges of buildings or streets. Therefore, the distance, which is a useful variable in the following regression analysis, can be easily determined on the digital maps produced using airborne Lidar data. Whilst taking the photographs, the photographer also recorded the position of trees using RTK (Real-Time Kinematic) GPS tools. Therefore, the individual trees from the photographs can be geographically correlated with the tree objects extracted from the produced classification map using airborne Lidar data.

In accordance with the selection principle, 93 photographs of individual trees, whose view were not blocked or overlapped by neighbouring features, were selected for the analysis of tree greenery visibility.

Fig. 1. Landscape change from 2002 to 2012.

3. Methods

3.1. Classifying tree objects and analysing tree structures using airborne Lidar data

Airborne Lidar (Light detection and ranging) data is an advanced technology that provides researchers with positional data of high horizontal and vertical resolution. Raw Lidar point clouds include ground points and non-ground points. To accurately analyse the vertical pattern of landscape features, DTMs (Digital Terrain Models) needs to be extracted from the Lidar point clouds. Many studies have been conducted in this area and a diversity of filtering methods (Axelsson, 1999; Vosselman, 2000; Kraus and Pfeifer, 2001; Roggero, 2001; Lohmann, 2002; Bartels and Wei, 2010; Chen et al., 2012) have been designed for generating DTMs. Chen et al. (2012) proposed an upward-fusion DTM generation method specifically for deriving DTMs in urban areas. Thus this method was employed for this case study. Firstly, some preliminary DTMs of different resolution are extracted using the block-minimum method. Next, upward fusion is carried out between these DTMs. This process begins with the DTM of the largest grid size, which is treated as the trend surface. A finer DTM is compared with the large-scale DTM. By setting proper thresholds, a new DTM is acquired by updating qualified elevation values from the finer DTM and retaining the value of the trend surface when the elevation value from the finer DTM is beyond the threshold. This process continues until all preliminary DTMs have been included in the upward fusion processing and a final DTM of high resolution is achieved. When the DTM is generated from Lidar point clouds, vertical patterns of landscape features (or refer to nDSM) can be calculated by subtracting the DTM from the DSM (Digital Surface Model).

After ground points are filtered, researchers need to extract tree objects to acquire useful tree structure parameters. There have been two main approaches for extracting tree parameters: model-based tree extraction and area-based tree extraction. For years, many studies (Næsset, 1997; Persson et al., 2002; Brandtberg et al., 2003; Hyyppä et al., 2004; Peuhkurinen et al., 2007; Yu et al., 2011; Vastaranta et al., 2012; Kaartinen et al., 2012) have been conducted to extract and accurately analyse 3D tree structures. Although many algorithms for tree modelling proved to extract tree objects effectively, most methods have been designed for forest landscapes and have no pre-processing of separating trees and buildings, which is a necessary task in tree extraction in urban areas. Chen and Gao (2014a) proposed an object-based urban land cover classification method, which can efficiently separate tree and building objects in urban areas. Therefore this method is used for acquiring tree objects in this research. In accordance with this object-based approach, the raw point cloud needs to be interpolated to raster images and thus hierarchical image segmentation is conducted using these raster images. Based on image segmentation, unclassified objects can be classified into different categories using the feature of nDSM, intensity, elevation difference and intensity difference. Due to different landscape configurations, the types of land cover can differ across study sites. Nevertheless, this method can efficiently segment urban features and separate tree objects from buildings objects with high accuracy.

With extracted tree objects and the nDSM, a 3D structural model can be established for each tree objects. Based on this model, structural parameters of tree objects can be acquired for following analysis. Some candidate structural parameters are explained as follows:

Area: the crown area of the tree object.
Perimeter: the perimeter of the tree object.
Mean: the mean height value of all laser pulses within the tree object.
Max: the largest height value of all laser pulses within the tree object.
Min: the smallest height value of all laser pulses within the tree object.
Range: (Max–Min) / Max.
STD: The standard height deviation of all laser pulses within the tree object.

These candidate parameters can be regarded as independent variables in the following processing of designing regression models.

3.2. Photograph-based analysis of visual green effects

Yang et al. (2009) employed a photograph-based method for visual greenery analysis. Yang and other researchers took 2252 photographs at 563 selected intersections in Berkeley, U.S. By analysing the total number of pixels of green areas, including foliage of trees, shrubs, vines, and herbaceous plants, the Green View (GV) was calculated for each photograph by dividing the amount of total green pixels by the total amount of pixels within the photograph.

This research employs the photograph-based method to calculate visual green effects for reference data whilst the image analysis processing strategy employed in this research is slightly different from Yang's work. Visual greenness provided by 2D land cover types (e.g. a lawn) is purely decided by their size in the horizontal direction whilst visual green effects provided by trees can be greatly influenced by their vertical structures. As a result, instead of analysing all visual greenery in the neighbourhood, this research aims to specially analyse visual greenness provided by individual trees and quantifies visual green effects of urban trees using regression models. Therefore, this study does not include the analysis of 2D greenery and solely focus on visual greenness brought by individual trees (refer to "tree green visibility" in this paper).

This research attempts to establish a correlation between tree green visibility and their spatial structures using the software, Photoshop (Researchers may alternatively choose other image processing tools, such Erdas, Envi and so forth). Thus, green pixels from other greenery features are not included in the following analysis. To meet this requirement, a magic wand tool is employed to decide an area of interest (AOI), which fits the outline of the target tree. Next, some sample green pixels are selected from the target tree and the function "colour tolerance" is used to automatically extract other green pixels similar to sample green pixels. Since the shadow, light and other factors can influence the spectral characteristics of leaves in different photographs, the value of colour tolerance is adjusted respectively for each photograph to select the most green pixels from the target tree without bringing in pixels from other features. Finally, tree green visibility for each sample tree is calculated by dividing the amount of extracted green pixels of the target tree by the amount of total pixels within the photograph. The process of calculating tree green visibility for each sample tree is also explained in Fig. 2.

The calculated tree green visibility of each sample tree can be treated as the independent variable whilst the structure parameters of corresponding sample tree can be treated as independent variables for the training of regression models.

3.3. Establishing regression models of tree green visibility using Lidar-extracted indices

Yang et al. (2009) proved that specific structural and positional parameters, such as total number of viewable trees/shrubs (NTS) and average height of viewable trees/shrubs normalized by their distances to the photographer (AHT), strongly correlated with Green View. However, no quantitative model has been proposed to estimate tree green visibility using structural variables.

This research explores the correlation between tree green visibility and structural variables that can be directly acquired from airborne Lidar data and aims to establish a robust model to explain tree green visibility using these variables. Firstly, correlation analysis is conducted to find variables that are correlated with tree green visibility. Next, we attempt to establish a regression model to estimate tree green visibility using these relevant variables. Since there is no existing model to build on, we start to build a preliminary regression model with a basic form through experiments. To find a satisfactory preliminary model, both linear modelling and curve estimation are explored. Following this, additional elements can be added to the preliminary model and the regression model can be improved gradually. By comparing the efficiency of different regression models in terms of R^2 and the amount of large bias, the optimized regression model is obtained for estimating tree green visibility using structural variables.

In summary, the methodology of this case study is explained in brief as Fig. 3.

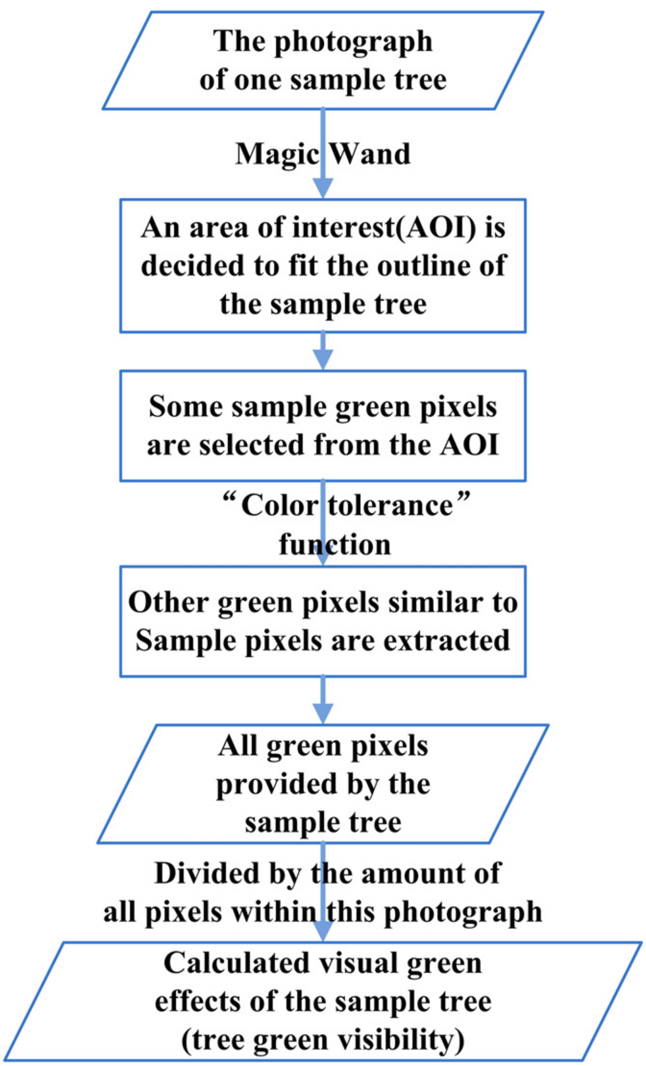

Fig. 2. The methodology of calculating tree green visibility.

4. Results

4.1. Tree structure parameters acquired using airborne Lidar data

By adopting the upward fusion method (Chen et al., 2012), an output DTM (Fig. 4b) of 2 m resolution was generated from the raw Lidar DSM (Fig. 4a). According to an accuracy assessment using 100 control points collected using Leica RTK GPS and manual filtering, the average vertical bias of the generated DTM was less than 12 cm (Chen et al., 2012), which met the requirements of following procedures.

We extracted tree objects from the Lidar DSM using an object-based land cover classification method (Chen and Gao, 2014). Different from specific studies of tree extracting method, this method aims to classify some main land cover types, including trees and buildings. This method suits this case study, as the existence of neighbouring buildings and trees causes common difficulties in applying specific methods for tree extraction, which are suitable in forest areas. By employing a set of features (e.g. nDSM, intensity, elevation difference, intensity difference, shape index and so forth), this method successfully classified a diversity of tree and building objects. To validate the performance of this classification, airborne photographs collected the same time as the Lidar data were employed and more than 500 reference points across the study site were randomly generated. The overall classification accuracy was 93.6% and the general classification of tree objects was more than 90%. Those misclassified tree objects mainly located in the clusters of trees and buildings. Specifically, this method successfully extracted all isolated tree objects, including the 93 tree sample trees. To further examine the extraction accuracy of the 93 tree samples, we compared the classified trees with manually generated reference objects. The results proved that the 93 sample trees were extracted with good accuracy. In terms of tree crown area and perimeter, the mean comparative difference between extracted trees and reference trees was 6.1% and 7.9%. Therefore, the accuracy of extracted sample trees was qualified for the following correlation analysis. In addition to trees and buildings, this method also classified such land cover types as bare ground, lawn, grass and crop, water and so forth. Since landscape compositions may differ significantly across different urban areas and these land cover types are not related to this case study, methodology of classifying other land cover types is not introduced here.

As the methodology of urban DTM generation and land cover classification were not the main focus of this research, parameter setting in details is not explained and only the outputs of DTM generation and tree extraction were listed as follows (Fig. 4b and c). Researchers can refer to the two references for more information of the methodology, results and accuracy assessment. By integrating classified tree objects with the nDSM (DSM–DTM) (Fig. 4d), structural parameters of trees were available for the correlation analysis.

4.2. Analysis of tree green visibility

According to the statistics of structural information of 93 sample trees based on the Lidar-generated tree objects, the range of tree heights was 1.8–23.9 m (STD: 5.62 m), the range of tree crown area was 7.4–586.6 m^2 (STD: 148.46 m), the range of shape index (Perimeter/2 $\sqrt{\pi * \text{Area}}$) was 1.02–1.20 (STD: 0.03) and the distance between trees

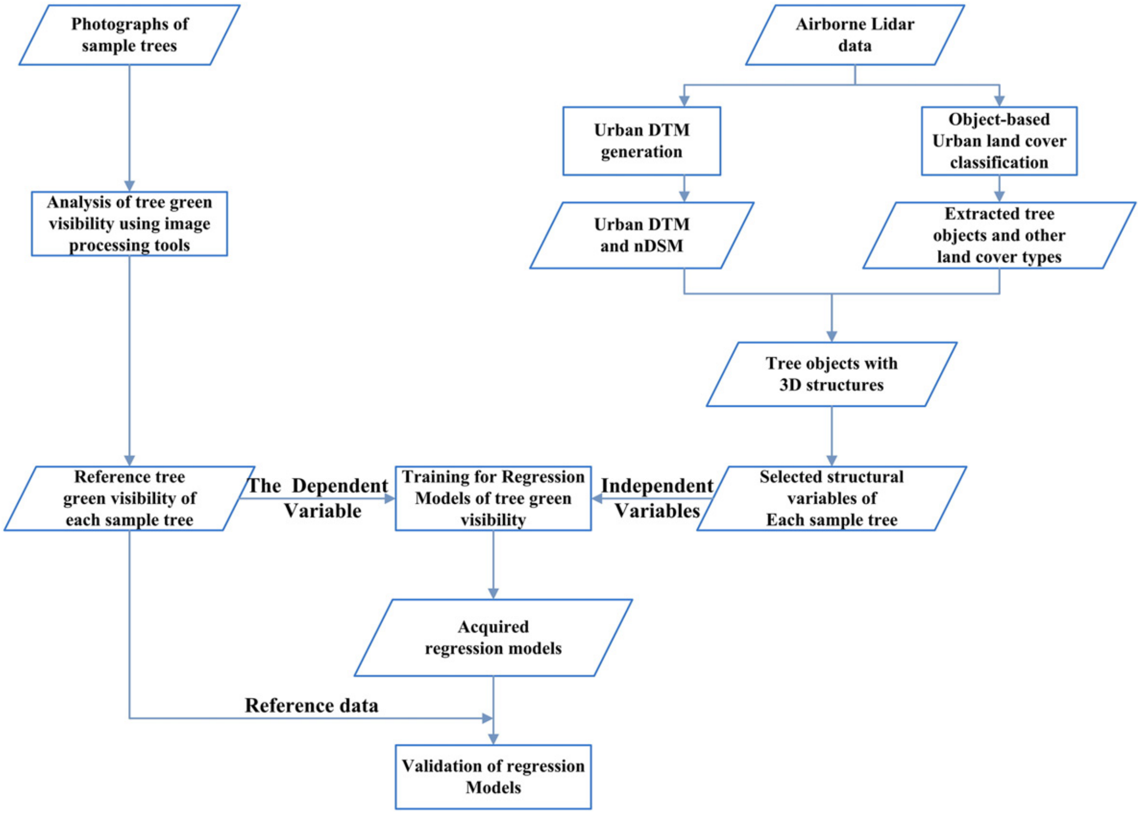

Fig. 3. The process of assessing tree green visibility using airborne Lidar data.

and the photographer ranged from 6 to 340 m (STD: 50.7 m), indicating a variety of sample units. (Fig. 5)

By processing photos of sample trees with the Photoshop tool, the analysis of tree green visibility was conducted and illustrated in Fig. 6 (When more than one trees appeared in the photograph, only the target tree would be included in the analysing area, outlined by the wand tool).

4.3. Regression analysis

Based on the classified sample trees, several preliminary variables can be calculated for each tree object using GIS tools. During the on-site survey, the position of the photographer (viewer) was recorded and then manually marked on the digital map. So the variable "**Distance**"

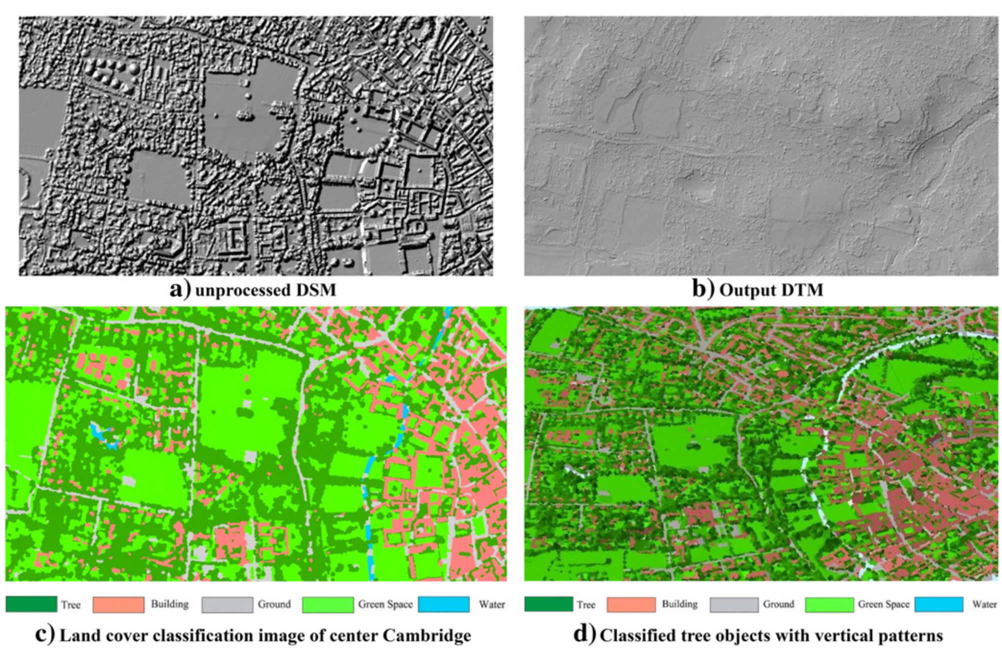

Fig. 4. Generated DTM and extracted tree objects using airborne Lidar data.

Fig. 5. Selected sample trees of different sizes and shapes.

(The distance between the photographer and the target sample tree), as well as structural parameters of sample trees, can be measured as a variable for further processing.

4.3.1. Correlation analysis

Correlation analysis was conducted to examine the connection between tree green visibility ("Green") calculated using field-collected photographs and structural parameters of trees obtained from airborne Lidar data. The result of correlation analysis is shown in Table 1.

In accordance with Table 1, "Distance" was the only variable that was strongly related to visual green effects whilst tree structural parameters (e.g. Max, Min, Perimeter, Area, Range) were closely related to each other.

4.3.2. Regression model

Since "Distance" was the only parameter that was strongly correlated with tree green visibility, we firstly explored the possibility of designing a regression model using this variable. By conducting a series of regression experiments using linear modelling or curve estimation, the optimum regression model was established as $\mathbf{Green} = \mathbf{2.417} * (\mathbf{Distance})^{-\mathbf{1.028}}$($R^2$: 0.735, F: 252.526, df1: 1, df2: 91, Sig: 0.000). The scatter plot and the trend line of this model are shown in Fig. 7.

Although an acceptable R^2 was achieved using "Distance" as the sole variable, problems existed in this regression model. According to the error statistics (Table 2), the mean error of this model was acceptable. However, there were a large proportion of tree objects with large absolute and relative error. The model estimated value of 20 trees differed significantly from the actual value of tree green visibility. As a result, this regression model requires further improvement.

This type of large bias mainly resulted from lacking variables which featured the tree size. As the 93 sample trees included in the present study were of different sizes and large trees can provide much more green visibility than small trees from the same distance away, this regression model was more likely to produce large bias when analysing large or small trees.

To enhance the reliability, more variables concerning the tree size need to be added to the regression model as well as "Distance". According to the result of correlation analysis, there were no other variables that were directly correlated with tree green visibility. Therefore, composite variables proposed using "Distance" and other variables were required for better regression models. Yang et al. (2009) indicated that such parameters as Average height of viewable trees/shrubs normalized by their distances to the photographer (AHT) were correlated with tree green visibility. Inspired by previous research, several composite variables were designed. Since "Area", "Perimeter", "Mean" and "Max" were direct indicators of the tree size and strongly correlated with each other, each composite variable was designed to include the "Distance" and one variable concerning tree size. The statistics and comparison of different regression models are shown in Fig. 8 and Table 3.

According to Table 3 and Fig. 8, all these composite variables strongly correlated with tree green visibility. The regression models established using these variables achieved satisfactory results in terms of R^2, mean error and so forth. Among the four composite variables, the regression model built using "Area/Distance^2" had the smallest R^2 and most large errors. The possible reason may be explained as follows. In the horizontal direction, tree green visibility is directly related to the crown diameter of the trees. On an orthophoto, the outline of ordinary trees is near-circular in shape. In this case, the map derived variable Perimeter $\approx \pi *$ Diameter and the variable Area $\approx \pi * (\text{Diameter}/2)^2$. Therefore, the variable "Perimeter" is linearly correlated with available tree size in the horizontal direction whilst the variable "Area" is not.

Although the R^2 and mean bias of regression models with composite variables were satisfactory, a large amount of sample trees with obvious bias (between the observed tree green visibility and model estimated tree green visibility) still existed. As a result, the factor of tree shapes, as well as tree sizes, should be added to these models. To further improve regression models, another variable, "Range" was included in composite variables. When the size of a tree object and the distance between the tree and the viewer are fixed, a larger Range value is more likely to produce larger green visibility. Therefore, several

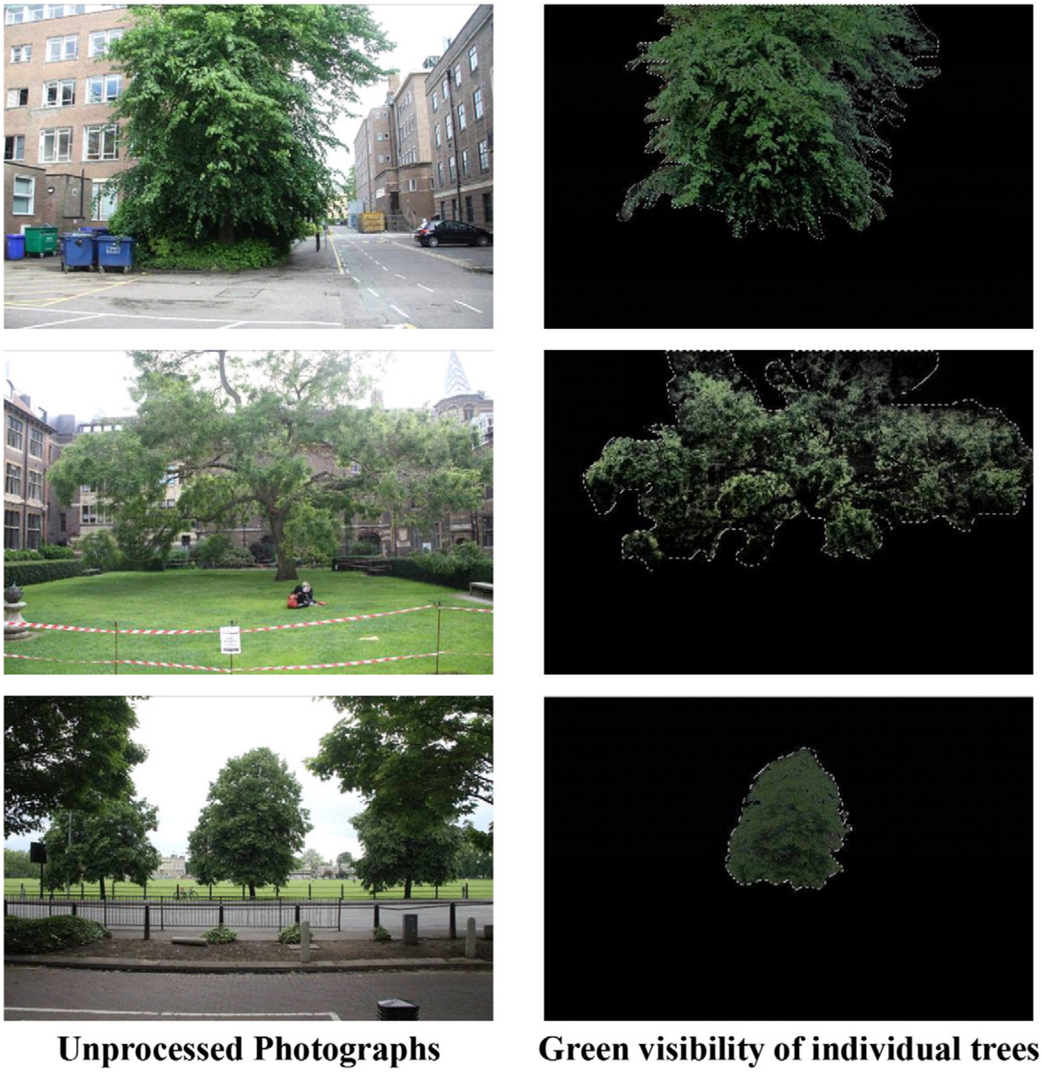

Fig. 6. Analysis of tree green visibility.

advanced composite variables were designed, such as Perimeter $*$ Range/Distance^2, Max $*$ Range/Distance^2, Mean $*$ Range/Distance^2 and Area $*$ Range/Distance^2. Based on these variables, regression models were established and compared (Table 4 and Fig. 9).

In accordance with Table 4 and Fig. 9, the accuracy of regression models using composite variables Perimeter $*$ (Range/Distance^2 and Max $*$ (Range/Distance^2 was notably improved from previous models in terms of the amount of sample units with large bias. Both models had small mean error and less than 10% sample trees had large relative error. The model **Green = 0.451** $*$ **(Perimeter** $*$ **Range/Distance^2)$^{0.559}$** achieved the best regression result. Through simulation, only 4 sample trees had large absolute bias and 1 tree had large comparative bias. In addition, the largest bias occurred in this model was the smallest amongst all regression models. The reason why the combination of

Table 1
Correlations between tree green visibility and shape parameters of tree objects.

Factors	Green	Area	Distance	Perimeter	Max	Mean	Min	STD	Range
Green		.188	−.461**	.197	.167	.140	−.128	.190	.257*
Area	.188		.257*	.979**	.820**	.690**	−.242*	.844**	.625**
Distance	−.461**	.257*		.260*	.299**	.285**	−.033	.148	.180
Perimeter	.197	.979**	.260*		.867**	.751**	−.225*	.874**	.703**
Max	.167	.820**	.299**	.867**		.946**	−.043	.904**	.728**
Mean	.140	.690**	.285**	.751**	.946**		.143	.789**	.624**
Min	−.128	−.242*	−.033	−.225*	−.043	.143		−.245*	−.428**
STD	.190	.844**	.148	.874**	.904**	.789**	−.245*		.700**
Range	.257*	.625**	.180	.703**	.728**	.624**	−.428**	.700**	

Correlation coefficient: Pearson; N = 93.
* Correlation is significant at the 0.05 level (2 tailed).
** Correlation is significant at the 0.01 level (2 tailed).

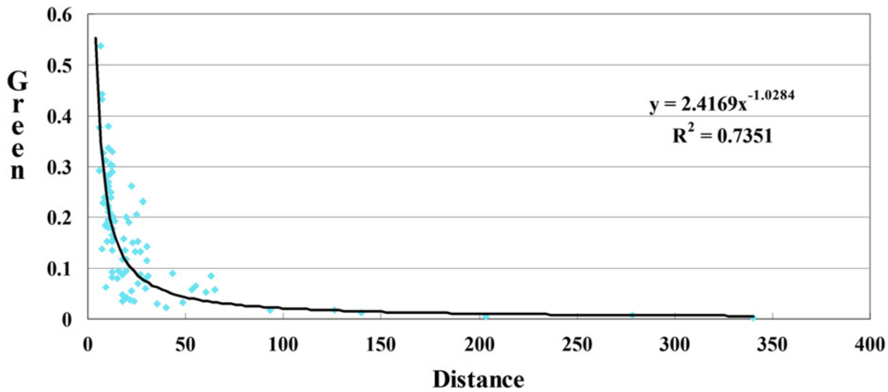

Fig. 7. Regression model of tree green visibility using variable "Distance".

"Perimeter" and "Range" had a better regression result may be that Perimeter and Range describe the characteristics of trees in different directions whilst both "Max" and "Range" describe the size and shape of trees in the vertical direction.

4.4. Cross-validation

To examine the validity of the optimum model $\mathbf{Green = a * (Perimeter * Range/Distance^2)^b}$, K-fold cross-validation was adopted for the accuracy assessment. According to the size of the sample, 93 sample units were randomly divided into 10 groups: 7 groups with 9 units and 3 groups with 10 units. Each time, 9 groups were used for training and 1 group was used for validation. Iteratively, every sample unit was used for accuracy assessment once. The result of cross-validation is shown in Table 5.

The result from Table 5 proved the validity of this regression model. Each test obtained similar regression parameters with satisfactory R^2 and small mean error and the amount of sample units with large error was controlled efficiently. Considering the diversity of sample trees, the general form of the regression model $\mathbf{Green = a * (Perimeter * Range/Distance^2)^b}$ has the potential to be transferred to other study sites. To decide the optimum setting of parameters for different study sites, researchers can choose some local sample trees (the more sample trees, the more reliable the regression model is) to conduct regression experiments following the same strategy employed in this research.

5. Discussion

5.1. The design and variations of the photography and modelling strategy

5.1.1. The setting of camera angle

The setting of SLR cameras and the design of photograph strategy was decided for the validity and practicality of the experiment. As introduced, the approach of taking tree photos was to approximate the viewing window to one eye of the photographer. The length of focus was minimized so that no additional zooming in effects was added to the viewer's scope. When taking photographs, the photographer was required to stand still and face the target tree directly with a vertical angle. Some sample trees did not show completely in corresponding photographs, especially those taken when the photographer was not far away from the target tree. The reason why the photographer did not adjust the angle of the camera accordingly to include the complete crown of all sample trees was explained as follows. If the photographer aimed to fully include the crown area of target trees, the angle of camera needed to be adjusted to different degrees. (Sometime, it was even impossible to include the entire crown of very big trees at a close distance). In this case, it would be very difficult, and sometimes impossible to normalize the value of tree green visibility in terms of camera angle. To make the calculated value of tree green visibility comparable between different photographs of sample trees, it was an efficient way to use a fixed angle. In addition, the vertical angle is more likely to simulate people's actual perception of local tree green presence. As a result, using a constant, vertical angle to take photographs of sample trees can efficiently reduce the uncertainty which may be caused by the changing angles and enhance the reliability of the regression model.

Another factor that may influence the calculation of tree green visibility is the height of viewers. The height of the photographer (camera) for this case study is 172 cm, which may be a bit shorter than the average. But the difference (usually several cm) causes very limited influence on the calculation of tree green visibility, considering the distance between the sample tree and the photographer (usually more than 10 m).

5.1.2. The size of photographs

In addition to the choice of focal length (in this research, it was fixed as 18 mm), another factor that could lead to uncertainties in the calculated value of tree green visibility was the size (more specifically, width–height ratio) of the photographs. In the photographs of sample trees, trees usually do not occupy the entire horizontal space. As the tree green visibility is calculated by dividing all pixels in the photographs with green pixels from the target tree, a larger value of width–height ratio can lead to a smaller value of tree green visibility. In this case study, the width–height ratio of all taken photographs was decided as a default setting: 3:2, which was similar to the default setting of most SLR cameras. Even if there were some differences in this parameter, it won't have much influence on the general form of the regression model. As long as the size (width–height ratio) of the photographs is fixed for a case study, it remains as a constant in calculating tree green visibility and establishing regression models. Therefore, the value of the photograph size only influences the value of the variable "a" in the regression model, $\mathbf{Green = a * (Perimeter * Range/Distance^2)^b}$ whilst the general form of the regression model remains the same.

Table 2
Error statistics of regression model established using variable "Distance".

	Mean error	Largest error	Error > 0.1
$\mathbf{Green = 2.4169 * (Distance)^{-1.0284}}$	0.054	0.192	15
	Mean relative error[1]	Largest relative error	Relative error > 50%
$\mathbf{Green = 2.4169 * (Distance)^{-1.0284}}$	45.37%	277.02%	20

[1] Relative error: Abs(estimated value − observed value) / observed value ∗ 100%.

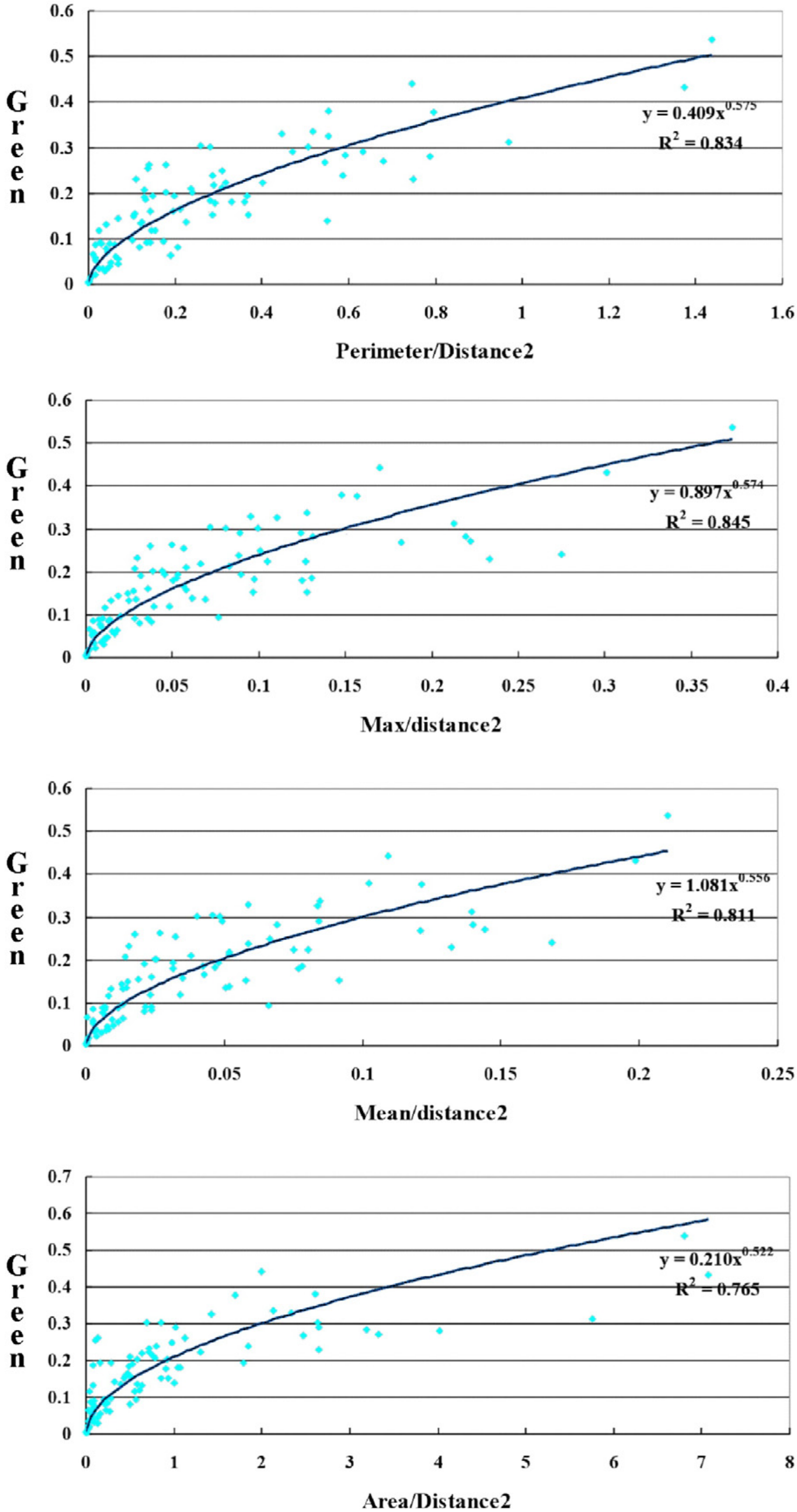

Fig. 8. Regression model of tree green visibility using composite variables.

5.1.3. The design of regression models

As discussed, the top structure of some sample trees did not show completely for such factors as the focal length, tree height, the distance between the viewer and the sample tree. A unified form of the regression model (without considering whether the complete tree crown can be seen or not) was proposed in this research to estimate tree

Table 3
Statistics of regression models established using different composite variables.

	R^2	F	Sig	Mean error	Largest error	Error > 0.1
Green = 0.409 * (Perimeter/Distance^2)$^{0.575}$	.834	457.0	.000	.0425	.153	7
Green = 0.897 * (Max/Distance^2)$^{0.574}$	.845	496.6	.000	.0464	.188	9
Green = 1.081 * (Mean/Distance^2)$^{0.556}$	.811	390.5	.000	.0478	.162	13
Green = 0.210 * (Area/Distance^2)$^{0.522}$	.765	296.3	.000	.0489	.211	13

	Mean relative error	Largest relative error	Relative error > 50%
Green = 0.409 * (Perimeter/Distance^2)$^{0.575}$	34.20%	136.07%	17
Green = 0.897 * (Max/Distance^2)$^{0.574}$	34.39%	132.66%	18
Green = 1.081 * (Mean/Distance^2)$^{0.556}$	36.69%	152.51%	21
Green = 0.210 * (Area/Distance^2)$^{0.522}$	38.77%	240.02%	25

green visibility and performed well in dealing with a variety of sample trees. In addition to a unified regression model, future researchers may also explore the possibility of employing piecewise functions to estimate tree green visibility according to the tree height and the distance between the viewer and the tree. By establishing the linear correlation using the focal length, the distance and the height of the tree, a distance threshold, where the complete tree crown can be observed, can be decided. Based on this threshold, researchers may establish different regression models of tree green visibility according to the distances between viewers and trees. Piecewise functions work efficiently to analyse tree green visibility in different situations, especially when only part of tree crowns appears in the viewers' scope. Due to detailed analysis of tree crown structures, one disadvantage of employing piecewise functions is that this type of regression model can be very complicated and requires much processing time when applies to large sites. On the other side, the unified regression model can be easily implemented for evaluating tree green visibility in large sites, which is discussed in the following part.

5.1.4. The shape and diversity of sample trees

On orthophotos, tree crowns are usually of a near-circle shape. However, generally, some trees have asymmetrical shapes from a horizontal perspective and viewers can observe different amount of tree greenness from different positions (with the same distance). To examine the influence of positions on observed tree green visibility, some experiments were conducted. The photographer took photographs for 10 randomly selected trees and compared tree green visibility from different positions. The results indicated that the mean comparative difference between calculated tree green visibility from different positions was only 5.6%. As a result, the fact of observation position would not influence the analysis of tree green visibility and the form of regression model significantly. In future study, however, tree green visibility from different frontal facets can be further examined based on individual tree models established using airborne Lidar data of very high resolution.

Although the methodology was only implemented in one study site, sample trees of different species, sizes and shapes were selected for establishing the regression model. As a result, the validity and generality of regression model would not be weakened significantly, which may be caused by the excessive use of single-species sample trees.

As most trees in the study site have a freely-growing shape, some trees included in the sample have irregular crown shapes (Fig. 10). According to error statistics, many large errors in the regression model were caused by these sample units. As a result, regression models proposed in this research may be more effective when applied to some sites with regular tree shapes.

5.2. Application of tree green visibility analysis

Yang et al. (2009) employed a photography-based approach to analyse the visual green effects of urban greenery. Although this study achieved high-quality results, the methodology required much time and human resources. On the other side, many studies have been conducted to accurately extract 3D tree structures. These studies mainly focused on analysing some key variables of trees and predicting the quantitative ecological and economic value of these trees, yet few studies attempted to link tree structures to visual greenness of individual trees, which is closely related to people's aesthetic and recreational perception (Arnberger, 2006; Bernath and Roschewitz, 2008). To fill this gap, this case study aims to link the two types of research by establishing correlations between visual green effects of individual urban trees and tree structural parameters extracted using airborne Lidar data. The proposed regression model provides researchers with a more efficient approach for analysing visual green effects of individual trees. In addition, as airborne Lidar detects trees from an overhead perspective whilst the photography method observes trees from the horizontal direction, this case study may also provide potential reference for research on integrating airborne Lidar data with other data sources from different perspectives (e.g. ground-based Lidar data).

The regression model of tree green visibility can be applied for such studies as landscape pattern evaluation. As introduced, the presence of

Table 4
Statistics of regression models established using advanced composite variables.

	R^2	F	Sig	Mean error	Largest error	Error > 0.1
Green = 0.451 * (Perimeter * Range/Distance^2)$^{0.559}$	.837	468.8	.000	.0413	.125	4
Green = 0.920 * (Max * Range/Distance^2)$^{0.545}$	.828	439.1	.000	.0490	.174	11
Green = 1.143 * (Mean * Range/Distance^2)$^{0.539}$	.811	389.9	.000	.0471	.175	13
Green = 0.223 * (Area * Range/Distance^2)$^{0.477}$	.721	235.0	.000	.0479	.182	12

	Mean relative error	Largest relative error	Relative error > 50%
Green = 0.451 * (Perimeter * Range/Distance^2)$^{0.559}$	16.73%	53.73%	1
Green = 0.920 * (Max * Range/Distance^2)$^{0.545}$	32.91%	121.36%	9
Green = 1.143 * (Mean * Range/Distance^2)$^{0.539}$	36.76%	173.30%	20
Green = 0.223 * (Area * Range/Distance^2)$^{0.477}$	42.78%	334.21%	23

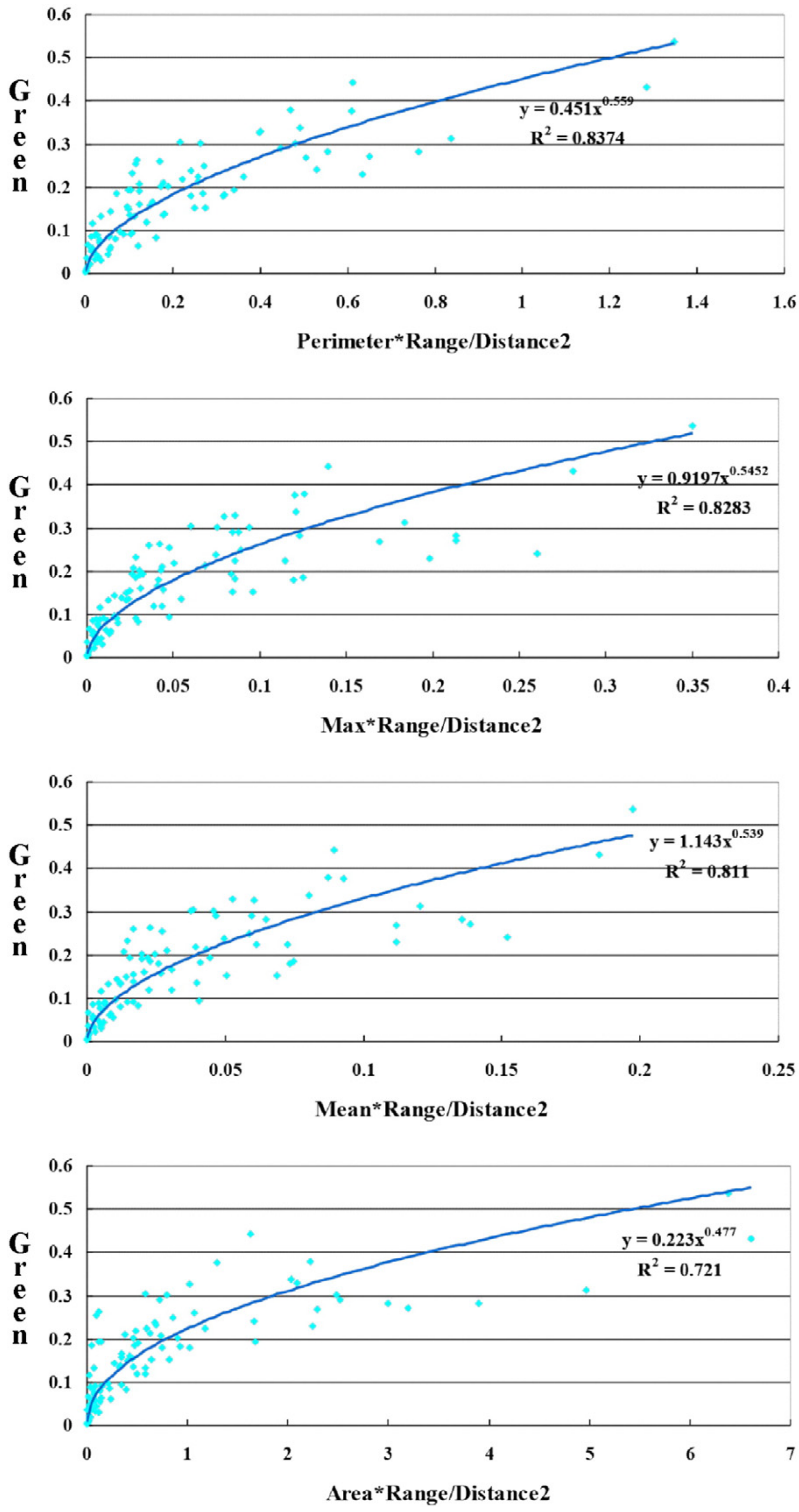

Fig. 9. Regression model of tree green visibility using advanced composite variables.

greenery is positively related to people's rating of local environment. This research proved that the size, height of trees were not the only factors that affected visual greenness, as the distribution and understory of trees also have some influences on tree green visibility. So a large value of total tree cover area and mean tree size does not necessarily indicate a satisfactory perception for local residents and the photograph-

Table 5
The result of cross-validation.

ID	Regression model	R^2	mean error	Largest error	Error > 0.1
1	$\mathbf{Green = 0.447 * (Perimeter * Range/Distance2)^{0.561}}$	0.840	0.064	0.117	1
2	$\mathbf{Green = 0.459 * (Perimeter * Range/Distance2)^{0.563}}$	0.843	0.063	0.102	1
3	$\mathbf{Green = 0.444 * (Perimeter * Range/Distance2)^{0.560}}$	0.844	0.035	0.064	0
4	$\mathbf{Green = 0.450 * (Perimeter * Range/Distance2)^{0.565}}$	0.865	0.063	0.127	2
5	$\mathbf{Green = 0.458 * (Perimeter * Range/Distance2)^{0.572}}$	0.854	0.035	0.074	0
6	$\mathbf{Green = 0.459 * (Perimeter * Range/Distance2)^{0.568}}$	0.841	0.016	0.032	0
7	$\mathbf{Green = 0.458 * (Perimeter * Range/Distance2)^{0.561}}$	0.839	0.030	0.060	0
8	$\mathbf{Green = 0.449 * (Perimeter * Range/Distance2)^{0.559}}$	0.825	0.034	0.094	0
9	$\mathbf{Green = 0.412^{*}(Perimeter * Range/Distance2)^{0.504}}$	0.768	0.040	0.078	0
10	$\mathbf{Green = 0.455 * (Perimeter * Range/Distance2)^{0.558}}$	0.840	0.033	0.066	0
Mean error and total large error		0.041		0.127	4

modelling method provides landscape planners a quantitative approach to analyse, evaluate and improve tree green visibility. Researchers may find the variable "Distance between the viewer and the target tree" difficult to apply with practical meaning. However, this variable may be transferred to "Distance between a building (street) and the target tree" when we aims to understand how much tree greenness can acquire from some given location. In this case, the implementation of this method can be of practical reference to urban planners. For instance, by calculating the distance between a building and its surrounding trees, as well as the structural characteristics of these trees, researchers can calculate total tree green visibility for each building in the study site. Based on the analysis of tree green visibility, urban planners may make some adjustments on local landscape patterns to enable people from most buildings to enjoy tree green presence. Chen et al. (2014) conducted a comparative study to compare 3D urban landscape patterns between Cambridge and residential area in Canvey, UK using Lidar-extracted 3D landscape models. This case study revealed the spatial structures of individual buildings and trees, as well as tree-building patterns, using a diversity of 3D landscape metrics. Based on high-resolution 3D urban landscape models, future researchers can analyse, compare and evaluate large-scale landscape configurations in terms of tree green visibility, which provides useful reference for enhancing urban landscapes to meet people's need for urban greenery.

The research of assessing tree green visibility can be further extended. Due to limited time and resources, all the photographs were taken from the side of streets or edge of buildings. In future studies, photographs can be taken from different floors of buildings (Fig. 11). In this case, by adding the vertical position of viewers to a regression model, people's perception of tree greenness from different floors may also be calculated.

The regression model proposed in this research is an idealized model, as the overlapping effects caused by neighbouring trees and view-blocking effects caused by neighbouring buildings have not been comprehensively considered. To improve the current model, more experiments including multiple trees and tree-building clusters should be carried out. By employing proper algorithms of geometric and spatial analysis, enhanced models of tree green visibility can provide more practical and reliable reference for urban planners.

To improve landscape configurations, quantitative analysis of tree green visibility can be integrated with peoples' aesthetic preferences towards the amount of tree green visibility, which may be acquired through normalized surveys across different study sites. In that case, landscape planners can have reliable and transferable criteria to quantify, compare and evaluate general tree greenness in different urban areas.

6. Conclusion

As proposed by previous studies, the average height of trees/crowns normalized by their distances to the photographer was correlated with visual greenery. This study proved that some composite variables, such as "Perimeter/Distance^2", "Perimeter $*$ Range/Distance^2", "Max/Distance^2", "Mean/Distance^2" and so forth were strongly correlated with the visual green effect of individual urban trees. In addition, some regression models were designed with variables derived from airborne Lidar data to quantitatively calculate tree green visibility which achieved satisfactory effects. Amongst these models, $\mathbf{Green = a * (Perimeter * Range/Distance^2)^b}$ proved to be the optimum model. This model had small mean error and the amount of sample units with large error was controlled efficiently. Considering the diversity of sample trees and the results of cross-validation, this model has the potential to be applied to other areas. Another model $\mathbf{Green = a * (Perimeter/Distance^2)^b}$, which includes no height variables and can be implemented using remote sensing images, may be employed alternatively by researchers who have no access to airborne Lidar data.

Fig. 10. Some sample trees with abnormal understory structures.

Fig. 11. Tree greenness observed from different heights.

Compared with on-site photographing, it is more feasible for researchers to conduct a large scale project assessing tree green visibility using airborne Lidar data. In line with the public's growing emphasis on local environment and natural perception, the visual green effect of urban trees is becoming an important factor which relates to people's aesthetic and recreational preferences. As a result, this research provides urban planners and policy makers with an approach to analyse, evaluate and enhance local landscape patterns to offer people more available tree greenery.

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