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Research Article

Individual Tree Location and Canopy Delineation Based on Quickbird Imagery

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Abstract: Remote sensing data with high spatial resolution can potentially be used to estimate the biomass of individual tree crowns. As a first step, the location of each tree must be identified; this step is particularly important in dense forests. Total station (Pentax R-400) and a handheld differential Global Positioning System (GPS) were used in tandem to determine accurate locations of single trees. The locations were then combined with high spatial resolution remote sensing data to extract additional forest vegetation information. Tree location data were interpreted visually and were also the inputs for a ray-based automated method of crown delineation. Compared to field-collected crown data, the mean accuracy of the visually interpreted data was 65% in plot B3 (RMSE = 0.60) and 79% in plot B15; plot B15 did not have a dense canopy and had a Smaller Error Statistic (RMSE = 0.32). The ray model was less accurate. Crown size estimated from both the visually interpreted data and the ray-based model was usually smaller than that estimated from field data. One conclusion of this study is that crowns with a narrower density distribution are correlated with a higher error rate. The crown delineation method proposed in this study was shown to be feasible.

Keywords: Canopy, GPS, individual tree, remote sensing, total station

INTRODUCTION

The present study was conducted in Jiufeng National Forest Park (39°54′N, 116°28′E), Haidian District, Beijing (Fig. 1). The park covers 811.173 hm^2 and is topographically varied, with a maximum elevation of 1153 m and a minimum elevation of 60 m. Naturally regenerated trees are rare in this forest. Most species, including *Pinus tabulaeformis* Carr, *Platycladus orientalis*, *Robinia pseudoacacia*, *Quercus variabilis* and *Quercus aliena*, were planted in the 1950s and 1960s. The study area has a sub-humid continental climate with cold dry winters and hot rainy summers. Upland forest stands are fragmented, sharing the area with patches of dense shrub. The lowland forests are more uniform and continuous. The relatively moderate slopes of the lowland forests were therefore selected as the site of the study plots.

Forests play an important role in maintaining ecosystem balance and supporting environmental, social and economic development. Forests not only provide renewable resources for human activities such as economic development and entertainment but also protect ecosystems by preserving biodiversity and preventing soil erosion and runoff. Forest managers need detailed inventory data to support decision making. Data collection needs include frequent estimation of average basal area, height, age and canopy density at the compartment level and the location, species and canopy size of individual trees (Ke and Quackenbush, 2011). It is theoretically feasible to estimate forest attributes from high resolution remote sensing data. High resolution panchromatic images can achieve sub-meter resolution and individual tree crowns are commonly more than 1 m and sometimes exceeding 8 m. Computer models are increasingly used to automate the process of extracting forest data from remotely sensed imagery (Leckie *et al*., 2003; Mallinis *et al*., 2008; Song *et al*., 2010; Wang *et al*., 2004). Visual interpretation and automated computer-based methods are two main approaches used to gather data on tree crowns. Computer-based methods of assessing forest characteristics are more efficient and have been the focus of remote sensing applications in forestry in recent years (Liu *et al*., 2010).

Forest inventory has traditionally involved periodic resurveys of trees in sample plots. Visual interpretation of aerial photographs became common during the 1960s, but labor and equipment costs were high for both the field and the office components. Currently, field survey techniques are resource and labor intensive. If we can extract characteristics such as crown diameter of the tree from remotely sensed images, we can then use these data to model attributes such as trunk diameter, height and biomass. These attributes are useful for forest resource inventory and growth assessments (Pouliot *et al*., 2002). Forestry analyses such as those needed for monitoring urban trees or for

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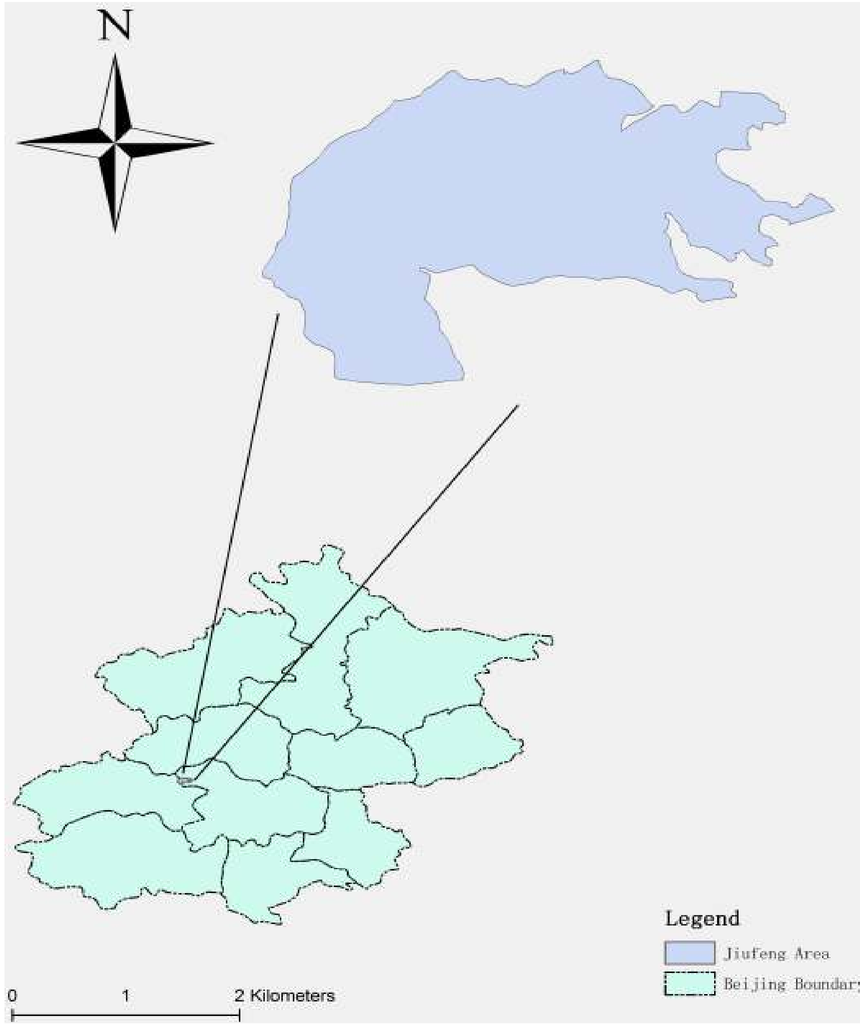

Fig. 1: Study area of Jiufeng National Forestry Park

timber harvest can benefit from identification of the spatial coordinates of single trees and forests. Spatial data can also be used for assessment of the single tree competition index, estimation of forest biomass (Santoso *et al*., 2011) and forest pest management (Zhang *et al*., 2011). High-resolution remote sensing is a promising method for reducing the uncertainty associated with estimates of carbon held in forest biomass. The uncertainty in canopy area estimates derived from high resolution images can be decreased by applying Monte Carlo methods to large samples. The use of Light Detection and Ranging (LIDAR) data to estimate parameters needed for biomass or carbon density calculations has become increasingly popular (Fransson *et al*., 2000). Tree heights can be accurately estimated from LIDAR data and biomass is highly correlated with tree height. Combined with field measurements and canopy information extracted from high resolution images, LIDAR data are therefore more effective than QuickBird data for estimating forest characteristics (Gonzalez *et al*., 2010; Holmgren and Persson, 2004). Additionally, crown detection algorithms based on high resolution remote sensing images underestimate the number of trees, whereas LIDAR has lower uncertainty and higher precision. The algorithm used to analyze high resolution remote sensing images can also be used to extract information about individual trees from LIDAR data (Chen *et al*., 2006). LIDAR data provide detailed information about forest vertical structure and canopy. We can therefore use LIDAR data to estimate tree height, trunk volume and stand biomass at the stand level (Gobakken and Naesset, 2005; Maltamo *et al*., 2006; Næsset, 2002) or crown diameter and tree height at the individual tree level (Brandtberg *et al*., 2003). Acquiring LIDAR data, however, is difficult and expensive. Therefore, tree crown data are still most commonly extracted from optical high resolution remote sensing images (Ke and Quackenbush, 2011).

The three main methods of using high resolution remote sensing imagery to delineate tree crowns are distinguished by the type of information derived from the image: tree location; tree location and crown dimensions; or full crown delineation (Gougeon and

Leckie, 2006). Crown detection is an important early step because it directly affects the accuracy of crown delineation. Identifying the position of individual trees in remotely sensed images typically involves an initial smoothing of the image followed by a local maximum detection method that identifies the canopy on the smoothed image (Dralle and Rudemo, 1996, 1997). The size of the detection filter convolution kernels should be appropriate for the tree size and image resolution. This technique produces good results in medium- to high-density coniferous stands; the point of the local maximum usually coincides with the tree top. Locally adaptive variations of the process that adjust the window size to fit the tree size have been developed and are being applied in other disciplines (Gougeon and Leckie, 1999; Wulder *et al*., 2000). This technique can be used to extract the number of tree trunks from the image, enabling the efficient estimation of stand density. The stand composition of the canopy can be determined by combining the above method with data obtained by applying traditional per-pixel classification methods to multispectral images (Leckie *et al*., 1992). The number of broad-leaved trees, however, cannot be precisely detected because there is more than one maximum brightness point. Detection of the local maximum and the edge of canopy is often used to determine crown position and crown dimensions such as diameter (Pouliot *et al*., 2002; Uuttera *et al*., 1998). The canopy edge detection method detects sudden changes, i.e., high gradients, in the transect running in each cardinal direction from the local maximum value. Canopy edge detection is typically more successful on the sunny side of the canopy because there are fewer shadows. The length of the transect represents the crown radius. Matching image features to two-dimensional projections of tree crown models is an more effective method to identify tree locations and crown dimensions (Larsen and Rudemo, 1998). The image must be analyzed multiple times and a sophisticated decision system also need to resolve conflicting evidence, once for each specific crown type and diameter and Currently, image segmentation is incorporated into tree crown delineation methods; this approach segments the crown to delineate the crown contours. An improved segmentation algorithm was used to extract crown information from abandoned farmland and achieved an overall accuracy of 84.67% by selecting features such as spectral signature, shape and texture (Wu and Peng, 2010). Most algorithms, however, can be applied only to specific stand types. Additional research needs to be conducted on stands with many overlapping crowns. An algorithm that analyzed canopy characteristics in panchromatic imagery has been used to extract forest parameters such as stand density, canopy coverage and tree height (Chopping, 2011). Valley-following algorithms and directional changes in image texture can also be used to derive individual tree parameters (Culvenor, 2003). Individual tree crowns can be identified with a fuzzy method that has been applied to two different high resolution remote sensing data sets (Ardila *et al*., 2012b). Changes in an urban forest were analyzed and an image analysis method based on geographic objects was used to locate and describe individual tree crowns; recognition accuracies reached 70 and 82%, respectively in two different places in Netherlands (Ardila *et al*., 2012a). A model of canopy structure and health has been developed from pixel decomposition and spatial analysis of QuickBird multispectral images (Levesque and King, 2003).

Accuracy assessments of methods for detecting individual tree crowns typically compare the results for visual extraction of individual trees to individual tree data from reference plots (Brandtberg and Walter, 1998; Gougeon, 1995). These methods have been tested in natural and planted forests (Wulder *et al*., 2000). The best correct recognition rate is 62%, with an 11% commission error. Validation of automated extraction methods aggregated at the stand level generally yields better error statistics than when data are evaluated at the individual tree level. When results are aggregated at the stand level, only the number of trees is required, not their exact location; the inability to identify incorrectly delineated trees prevents improvement of the algorithms. The precision of valley-following algorithms for detecting different age classes during forest regeneration can be evaluated by validation method aggregated at the stand level. The results showed that the average error ranged from 43 to 11% in jack pine stands of different ages (Gougeon and Leckie, 1998).

Many studies that identify individual tree locations apply local maximum extraction algorithms to remote sensing images to identify the center of each tree crown. In this study, however, a novel tree crown delineation method was developed by combining ground measurements and high resolution remotely sensed imagery with precise preprocessing. We identified the precise position of each tree with the Total Station (Pentax R-400 Made in Japan) and handheld Global Positioning System (GPS) and identified overlapping tree crowns using visual interpretation and a ray-based model. The accuracy of the two methods of identifying the tree crowns was assessed against the measured plot data. The points identified by the proposed method can be entered into a Geographic Information System (GIS) for further analysis.

METHODOLOGY

Acquisition of individual tree coordinates: The field work was carried out in August 2009. Two plots (20×20 m) were studied, B3 (*Platycladus orientalis*) and B15 (*Pinus tabulaeformis*, *Platycladus orientalis*). Both plots contain coniferous stands on minimal slope.

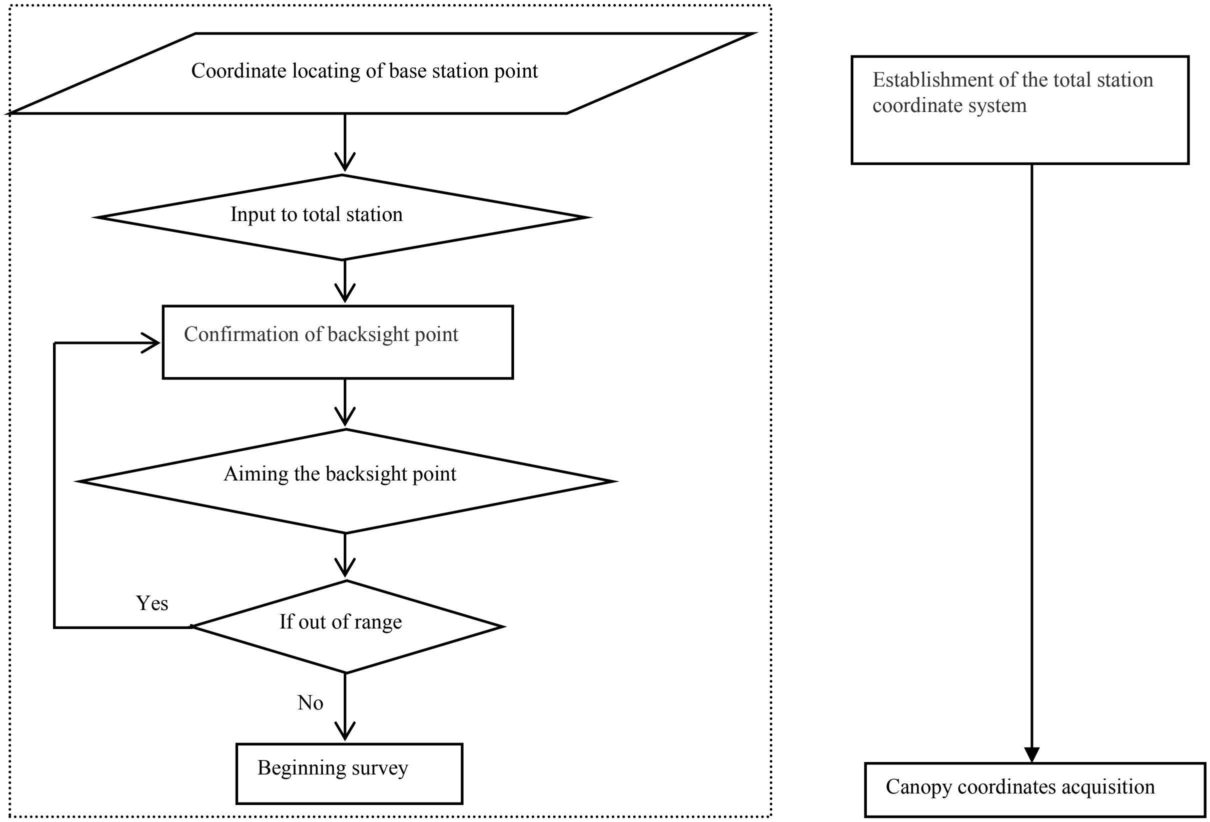

Fig. 2: Steps in determining the total station coordinates

The canopy density in B3, a half-mature forest with smaller crowns, reached 70%, with shrub coverage of 10% and grass coverage of 20%. The values are 40, 60 and 90%, respectively in B15, with larger crown areas in the overmature forest.

Many studies have addressed the problem of specifying the location of single trees. Feng *et al.* (2003) proposed measuring tree height with the total station. The same authors developed and patented mountain crown positioning technology (Feng *et al.* 2008). Precision forestry was furthered with the invention of advanced instruments such as the tree measuring gun (Xu *et al*., 2013) and smart station (Feng and Wang, 2012). Tree characteristics such as height, Diameter at Breast Height (DBH) and crown width can also be measured using the electronic total station (Feng and Yao, 2007; Yan *et al*., 2012). The total station can accurately determine the relative coordinates of objects and provide accurate relative positions of single stems. Problems occurred, however, when we tried to position the relative coordinates on a remote sensing image or to integrate them into a GIS environment. GPS, by contrast, can directly obtain an object's geodetic coordinates with high accuracy, generally below 2 m and down to 1-5 mm after processing (Yu *et al*., 2004), but the differential accuracy is usually low in forests because the trees block the signal. This study presents a single tree crown information acquisition scheme that uses both total station and GPS data.

Tree trunks were measured with a total station and designated as the center points of the tree crowns. A handheld differential GPS S740 (South Surveying and Mapping Instrument Corporation) was used to collect the reference points of the Total Station (Pentax R-400). The procedures were as follows:

- Base station coordinates were acquired at plot locations without tree cover to ensure precise GPS data.
- The back sight point was confirmed by taking a point at a distance D away from the base point to the south or north; with a compass, the value D can be chosen as 5 or 10 m. The coordinate of the back sight point can be inferred because the geodetic coordinates of the base station are known. When using the same abscissa as the base station, the ordinate value should be plus D if the back sight point is to the north of the base station and minus D if it is to the south of the base station.
- The back sight point was aimed.
- To address transfinite errors, we returned to step 2 if the error was greater than 0.01 m.
- We started measuring when the total station coordinate system was established. The establishment of the measurement system is diagrammed in Fig. 2.

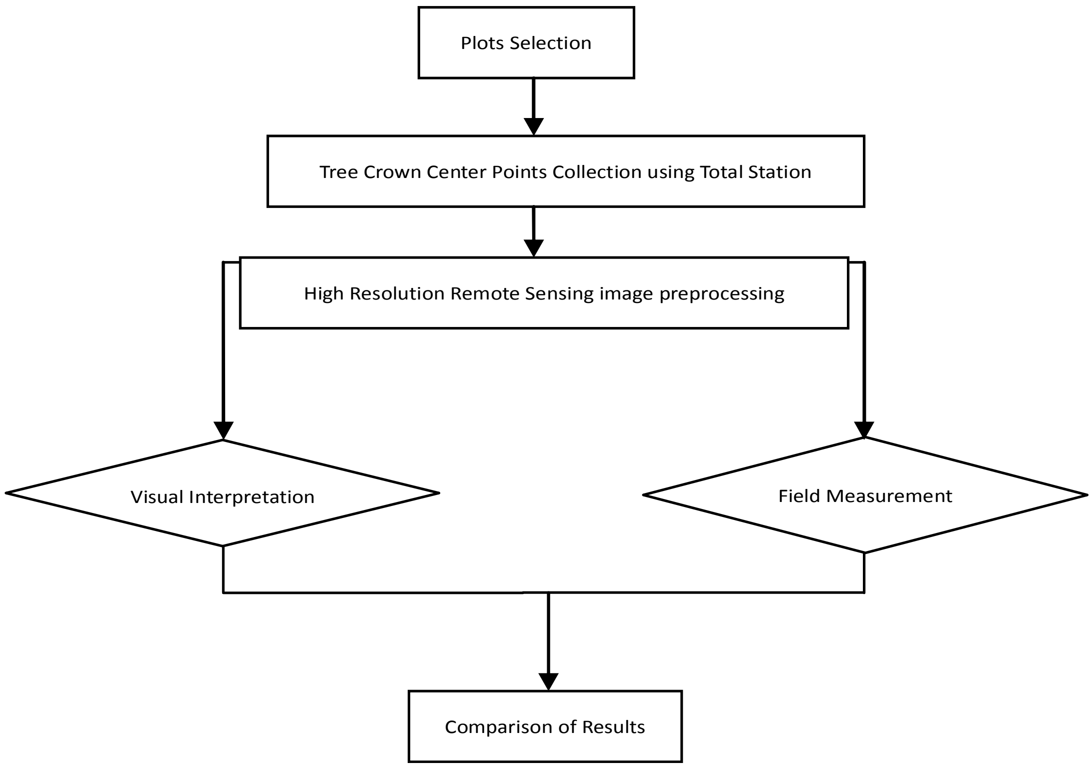

Fig. 3: Steps for extracting individual tree crowns visually and with field measurements

Remote sensing image preprocessing: We used 16-bit standard Level 2 (LV2A) QuickBird imagery with coarse geometric rectification. The imagery was acquired on 28 October 2008. The sun-elevation angle was 37.3° and the azimuth angle was 166.6°.

The QuickBird image has four multispectral bands with 2.4 m spatial resolution and one panchromatic band with 0.6 m spatial resolution. The wavelet merging technique is considered as one of the methods for preserving the multispectral features when improving spatial features (Li *et al*., 2002; Lu *et al*., 2008; Lu *et al*., 2010; Ulfarsson *et al*., 2003). Therefore, it was used to merge the QuickBird multispectral bands and panchromatic band into a new multispectral image with 0.6 m spatial resolution. The new fused multispectral images were used for visual interpretation of the tree crowns. Road intersections, houses and other obvious features in the 1:10000 topographic map were used as the control points. Geometric correction and orthorectification within an error of less than 5 pixels were performed by using a high accuracy Digital Elevation Model (DEM) extracted from the contour lines. We used a Transverse Mercator projection, Beijing 1954 ellipsoid, with a central longitude of 117° E and proportional factor of 1.

Canopy delineation based on the ray model: The size of a tree crown can be calculated from the tree's position. There are many methods for delineating tree crowns. We used a ray model combined with known individual tree locations. The first step of the ray model was to assign a specific number of rays of a given length to extend outward from the tree center point. The Digital Number (DN) of pixels in each ray was recorded and those values were fitted to a curve. The points at which the value of the second derivative of the curve approached zero were identified as the margin points of an individual tree (Pouliot *et al*., 2002). The ray model was implemented in the platform Visual Studio 2008 developed by Microsoft Corp (in Redmond, Washington, US) using the C#. NET language. The tree crown center points determined from field measurements were used for this semi-automatic delineation of individual trees.

Evaluation of individual tree location results: The results of the automatic and manual crown delineation methods can be compared with the ground measurements. The visual extraction and manual delineation of tree crowns was based on trunk locations (Fig. 3).

The feasibility of the method was validated using the following approach. After extracting the crown using the visual interpretation method and comparing the size of the manually drawn crown to ground-based crown measurements, we used the accuracy, E, to assess the difference between the two measurements. The Root Mean Square Error (RMSE) represents the overall deviation of the visual interpretation from the ground measurements. The accuracy, E, quantifies the

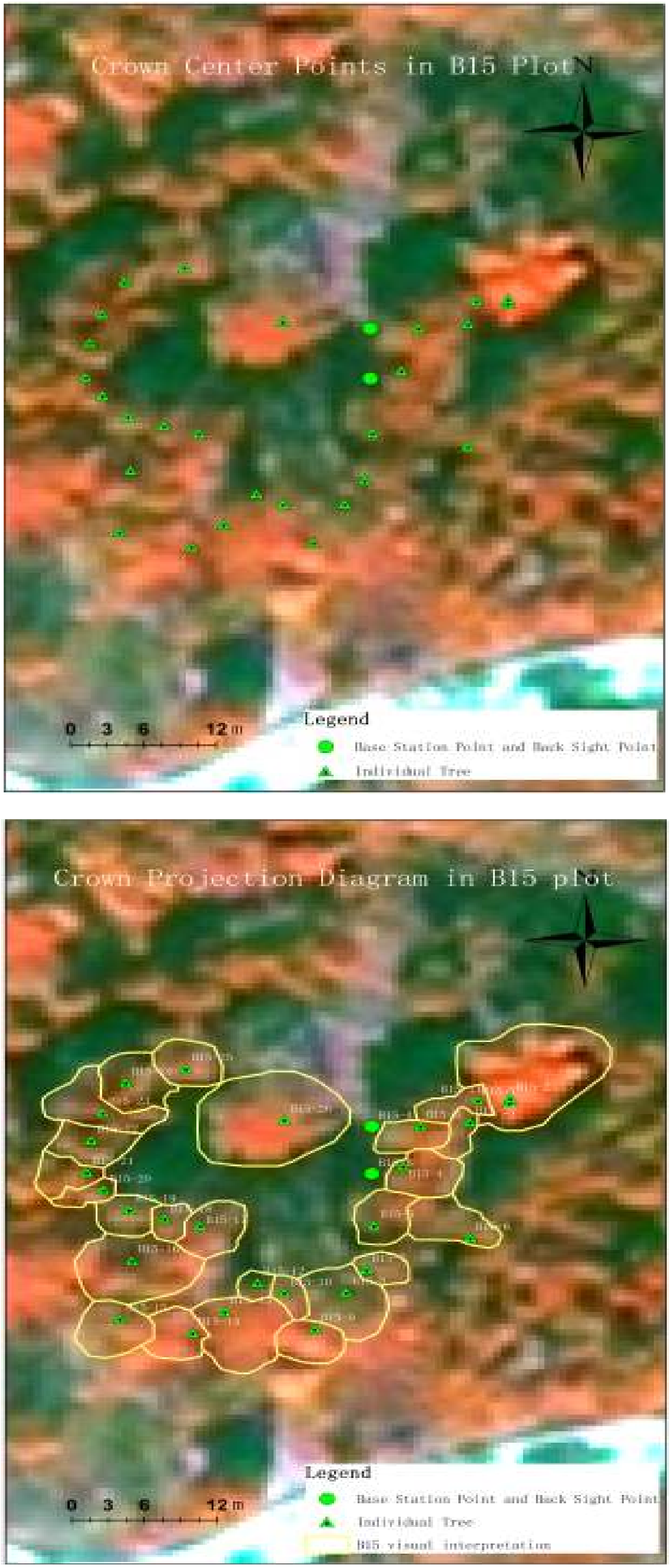

Fig. 4: Tree crown extraction using visual interpretation in plot B15

overall accuracy of crown extraction from the remote sensing image. The relative error is the difference between individual visual extraction and field measurement results. A positive relative error means the results of the visual interpretation are larger than those of the field measurements Eq. (3). The RMSE of the visually interpreted data was calculated as follows:

$$RMSE = \frac{\sqrt{\sum \frac{(A_i - B_i)^2}{n}}}{\overline{B}} \times 100\% \tag{1}$$

The formula for E is:

$$E = \overline{A} / \overline{B} \times 100\% \tag{2}$$

The formula for the relative error, V_i, is:

$$V_i = \frac{A_i - B_i}{B_i} \tag{3}$$

A_i is the crown area (m^2) derived from either visual interpretation or automated delineation using the ray model and B_i is the crown area (m^2) measured in the field. $\bar{A}$ and $\bar{B}$ are plot-level mean crown area from the visually interpreted or ray model data and from the field measurements, respectively. The data from the visual interpretation method were analyzed with GIS software; the field measurement results were calculated using the field-measured average crown diameter, assuming the canopy to be a circle (Fig. 4 and 5).

Table 1: Comparison of tree crown results from field measurement and visual interpretation

Number	Tree species	DBH/ (cm)	MVC/ (m)	TCA/ (m^2)	VTA/ (m^2)	RTA (m^2)
B15-1	*Styphnolobium japonicum*	68.0	11.55	104.72	98.63	50.37
B15-2	*Platycladus orientalis*	55.0	7.15	40.13	17.51	15.59
…	…	…	…	…	…	...
B15-24	*Platycladus orientalis*	40.2	6.35	31.65	29.58	27.82
B15-25	*Platycladus orientalis*	35.0	6.25	30.66	23.14	28.96
B15-26	*Pinus tabulaeformis* Carr	58.2	11.75	108.38	99.79	37.38
B15-27	*Platycladus orientalis*	18.8	4.70	17.34	10.71	20.95
B3-2	*Platycladus orientalis*	17.5	2.50	4.90	2.910	3.810
B3-3	*Platycladus orientalis*	16.3	4.65	16.97	9.610	10.84
…	...	…	…	…	…	…
B3-58	*Platycladus orientalis*	13.1	2.90	6.60	6.63	6.97
B3-59	*Platycladus orientalis*	10.6	3.00	7.07	5.90	6.32
B3-60	*Platycladus orientalis*	8.0	1.65	2.14	1.09	1.94
B3-63	*Platycladus orientalis*	4.2	3.30	8.55	8.54	7.52

DBH: Diameter at breast height; MVC: Mean value from east-west and north-south of one tree crown, (SN+WE) /2; TCA: Tree crown area from field measurement; VTA: Tree crown area from visual interpretation; RTA: Tree crown area from ray model

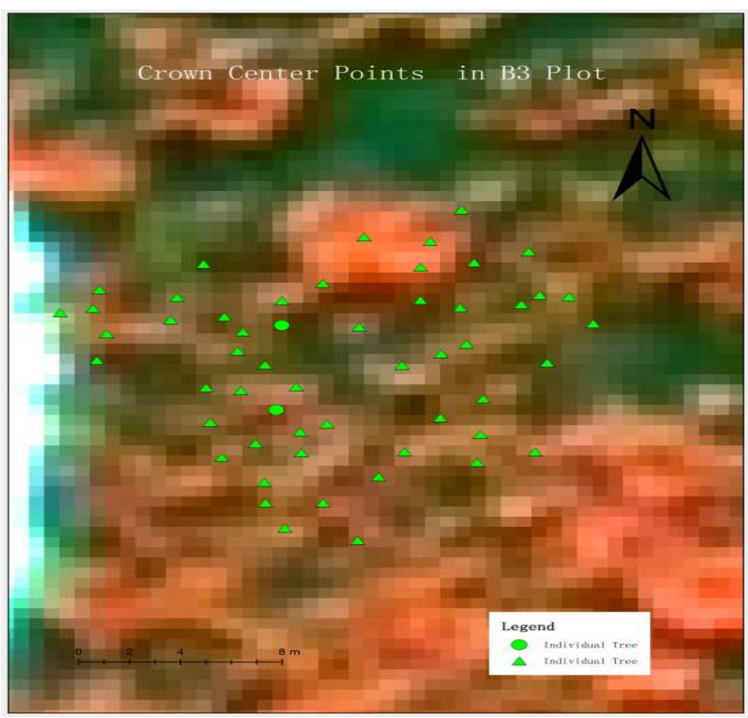

Fig. 5: Continue

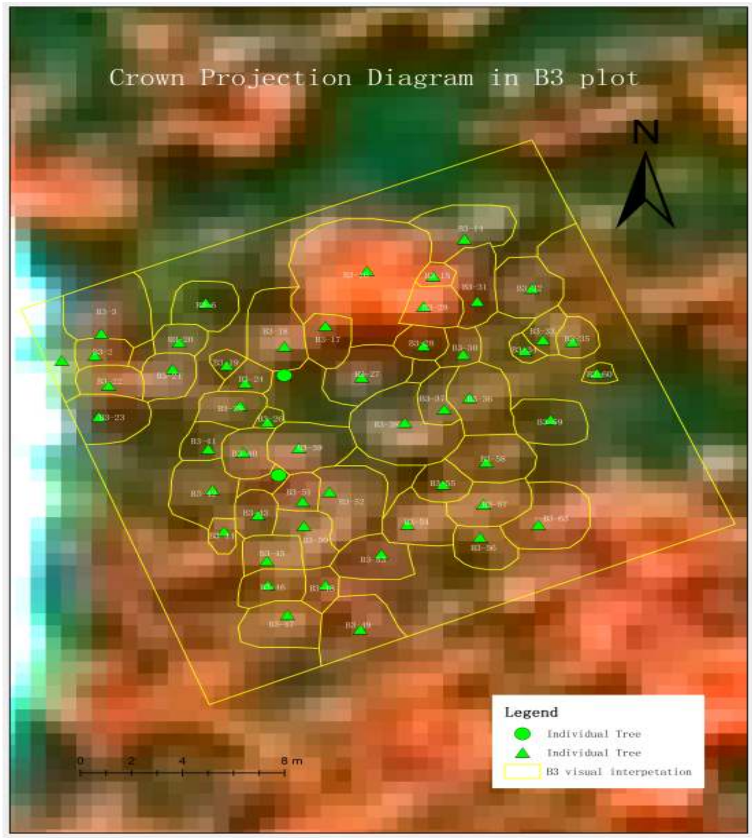

Fig. 5: Tree crown extraction using visual interpretation in plot B3

Table 2: Accuracy analysis of visual interpretation

Number	MAVI/ (m^2)	MAFM/ (m^2)	RMSE/ (%)	E/ (%)
B15	29.02	36.80	32	79.0
B3	5.22	8.00	60	65.3

MAVI: Mean area of visual interpretation; MAFM: Mean area of field measurement; MAAE: Maximum of absolute error; MIAE: Minimum of absolute error; RMSE: Root mean square error; E: Precision

Table 3: Accuracy analysis of automated delineation

Number	MARM/ (m^2)	MAFM/ (m^2)	RMSE/ (%)	E/ (%)
B15	23.020	36.80	60.7	62.6
B3	4.607	8.00	66.7	57.6

MARM: Mean area of ray model; MAFM: Mean area of field measurement; RMSE: Root mean square error; E: Precision

RESULTS AND DISCUSSION

Table 1 shows the crown areas derived from the visual extraction, automated delineation and field-based methods.

Mean tree crown parameters were calculated for each plot for each of the three crown measurement methods (Table 1). The accuracy of visually interpreted and automatically delineated tree crowns is shown in Table 2 and 3, respectively and the relative error percentage is shown in Fig. 6.

Figure 4 and 5 illustrate the visual extraction of tree crowns from trees with identified centers. Figure 7 shows the results of extracting the crown of tree 26, plot B15, with the ray model. Figure 8 shows the correlation analysis of visual interpretation and automated extraction with ground crown measurements.

Figure 6 shows the extraction accuracy for each individual tree, with the larger values on the histogram representing greater relative error. The accuracy of the visual interpretation of tree 26, plot B15, is relatively high (92.5%) because there are no overlapping tree crowns in the plot. Where crowns overlap, however, extraction accuracy varies greatly.

The average accuracy of visually extracted tree crowns is higher in plot B15 (79%) than in plot B3 (65.3%) and the RMSE in plot B15 (0.32) is smaller than that of plot B3 (0.60; Table 2). The methods of ray-based automated delineation and visual interpretation produce consistent results (Table 3). Whether using visual interpretation or ray-based methods, more accurate results are obtained when canopy density is lower, as in plot B15 and when individual tree crowns are larger, as is the case with

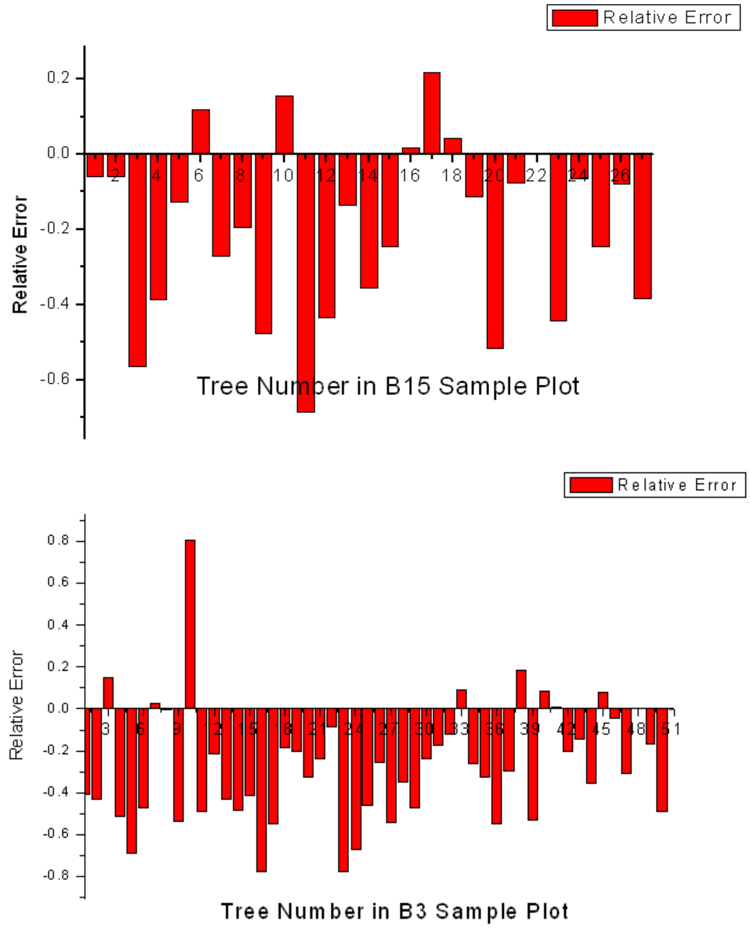

Fig. 6: Relative error in tree crown size in plots B15 and B3

Fig. 7: Extraction of the crown of tree 25, plot B15, using the ray method

plot B15 (36.8 m^2) compared to plot B3 (8.0 m^2). Crown extraction by visual interpretation is more accurate than by the ray method in both plots. The RMSE suggests that the results of visual interpretation are generally more reliable than those of the ray-based method. Whether visual interpretation or automatic delineation is used, the RMSE of crown area from plot B3 is larger than that from plot B15; this result suggests that crowns with a narrower density distribution are correlated with a higher error rate.

Figure 6 shows the degree to which crown size differs between the visually interpreted data and the ground survey. Trees 3, 4, 9, 11, 12, 20, 23 and 27, respectively in plot B15 have high relative errors; the error associated with Tree 11 is particularly high. This error occurred because crown overlap affected the accuracy of visual interpretation. More than 80% of the visually interpreted tree crown areas are smaller than the true value (Fig. 6), indicating that crown area is often underestimated when derived from visual interpretation of remote sensing images. The crown area of tree 26, plots B15, extracted by the ray-based model (37.38 m^2), is much smaller than the area determined by ground measurement (108.38 m^2). Using visual interpretation, however, the overall crown accuracy can reach 79% in the presence of overlapping crowns if precise locations have been determined.

Finally, Fig. 8 shows the linear fit of the ray-based method and the visual extraction method to ground measurements of individual tree crowns. The results show that regressing the visual interpretation data on the ground measurements can yield an R^2 of 0.8 or more in both plots. The fit of the ray-based method to the true values is relatively poor. The figure shows that the proposed crown extraction scheme in this study is feasible.

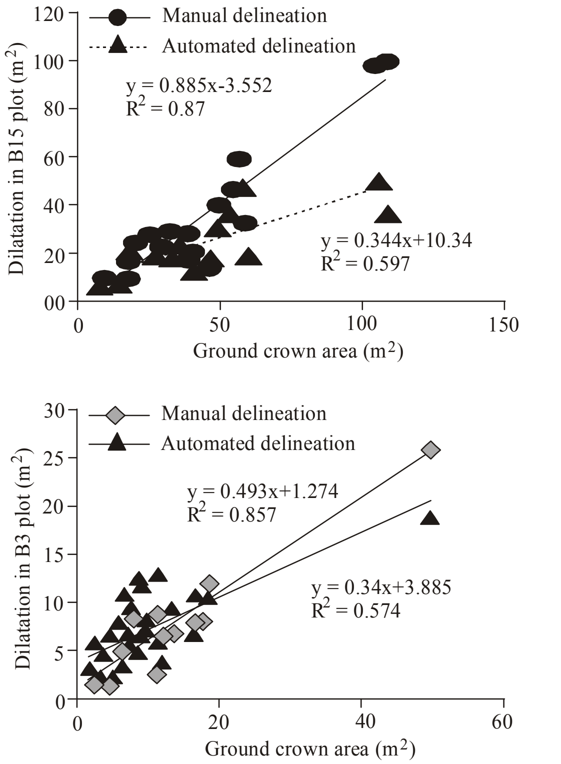

Fig. 8: The correlation analysis of tree crown extraction in plots B3 and B15

The crown area calculated from the ground survey is not a true value, however, because we used the average diameter in two directions (east-west and north-south) to calculate the area and assumed the crown to be a circle. Additional studies should focus on how to measure individual tree crowns; some researchers have already proposed direct canopy measurements using the Total Station. In addition, a 3D terrestrial laser scanner would be advantageous because the measurement point cloud data can be used to more accurately estimate crown attributes such as area and volume. These more accurate data would improve our ability to verify results. Accurate data acquisition is a topic for future research.

The accuracy of the tree locations measured in the field was relatively high (±1 m). In practice, however, most plots are in the forest interior where there are significant problems with blocked signals; this issue did not arise in plot B15, located on the forest edge. Although the relative position of the sample trees measured by Total Station is invariant, positioning precision can be very low because of the weak signal in forests. Therefore, assigning accurate locations to trees remains difficult when the canopy density is high or there are no obvious reference points in the surrounding area. Thus, the crown delineation method proposed in this study is not perfect and needs further improvement.

CONCLUSION

This study attempts to address the problem of accurately determining the spatial coordinates of single trees by using GPS in conjunction with Total Station. The conclusions are:

- The proposed method integrated field survey, remote sensing and GIS techniques and could be used to obtain accurate locations of single trees.
- Although the extraction methods performed poorly when tree crowns overlapped, the average accuracy of the visual interpretation method can be as high as 0.79 and the R^2 can exceed 0.85.
- The crown areas were usually underestimated and the extraction accuracy of the ray-based model was worse than that of visual interpretation.

Future research should focus on finding a better algorithm for this method. The method we proposed for determining accurate locations can be a springboard for studying issues such as the uncertainty in estimates of remotely sensed forest vegetation parameters, including leaf area index, biomass and 3D green biomass. The method is significant for both forestry research and forest management.

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