COMPARISON OF METHODS FOR INDIVIDUAL TREE CROWN DELINEATION IN TROPICAL FORESTS USING VERY HIGH RESOLUTION SATELLITE MULTISPECTRAL AND AIRBORNE LASER SCANNING DATA

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ABSTRACT

Individual tree crown (ITC) delineation is the first step to study forest biodiversity and carbon using very high resolution remote sensing data. In order to study large areas, automatic methods for ITC delineation are necessary. In this paper, we compared three methods to delineate ITCs over the Jamari National Forest, a closed-canopy tropical forest in Amazonia, using very high resolution satellite multispectral (MS) and airborne laser scanning data (ALS). The best methods for ITC delineation over this tropical forest site were the voronoi-based method for ALS data and the marker-controlled watershed (MCWS) method for MS data. Window sizes of 3x3 (ALS) and 5x5 (MS) m provided the appropriate scale for extracting tree crowns over this forest. The performance of ITC delineation from ALS and MS datasets was similar. Results indicate that tree crown delineations can be retrieved from satellite MS data for forest monitoring.

Key words *— Forest monitoring, Amazon, Jamari National Forest, LiDAR, WorldView-2.*

1. INTRODUCTION

Forest studies using very high resolution (VHR) remote sensing data (pixel <= 1 meter) often require individual tree crown (ITC) delineation rather than pixel-by-pixel spectral response characterization. Hence, the ITC delineation is the first step of many studies addressing, for instance, tree species identification [1] and aboveground biomass (AGB) estimates [2]. In the last example, tree crown size/diameter and height have been used to estimate AGB for individual trees using allometric equations [2].

The manual delineation of ITCs is a time-consuming process and is not practical for operational applications over large forested areas, i.e. hundreds of hectares. Therefore, some automatic delineation methods have been proposed in the past decades. For tree detection, the traditional methods include local maxima, template matching, and multiscale analysis [3]. For tree crown delineation, the traditional methods include marker-controlled watershed (MCWS) [4], decision tree region growing [5] and voronoi tesselation [6]. However, even though different methods for ITC delineation exist, most of them have not been tested over different types of forests or canopy structures. In reality, most of the methods for ITC delineation have been designed for natural or planted open-canopy temperate forests with low species diversity [2]. Therefore, there is an urgent need to evaluate their performance over tropical forests that have, by contrast, high species diversity and closed- canopies.

In this paper, we compared three methods available in R language to delineate ITCs over a closed-canopy tropical forest in Amazonia using very high resolution multispectral (MS) and airborne laser scanning (ALS) data. Specifically, we aimed to: (i) determine the best method for tree crown delineation; (ii) compare results of delineation between satellite MS and ALS data; and (iii) identify the input data and parameters that best contribute for ITC delineation.

2. MATERIAL AND METHODS

2.1. Study area

The study area is the Jamari National Forest in the Rondônia state, Brazil (Figure 1). It is the first private natural forest concession in Brazilian Amazon. It comprises 220,000 ha of terra firme lowland dense ombrophylous forests [7], from which 96,000 ha have been allocated for selective logging since 2008. We focused the analyses on part of the forest management unit I, production unit 11, covering 140 ha.

2.2. Datasets

The ALS data was acquired on 9 October 2014 using a Trimble Harrier 68i sensor with 360 kHz scan frequency, onboard an Embraer SENECA II 810D airplane. The flight altitude was 500 m and the view angle was 15˚. The data consisted of a point cloud with a density of 51.8 points/m², providing the basis to obtain a Digital Terrain Model (DTM) and a Canopy Height Model (CHM). For this purpose, the point cloud was classified into ground or vegetation classes using the lasground, lasheight and lasclassify functions from LAStools 3.1.1 [8]. The ground points were used to create a DTM with 1 m spatial resolution, which was then used for normalization of the point cloud to height above ground. Finally, the CHM was extracted considering the highest height of vegetation in each cell. These previous steps were conducted using the TINSurfaceCreate, ClipData and CanopyModel functions from FUSION/LDV 3.6 [9].

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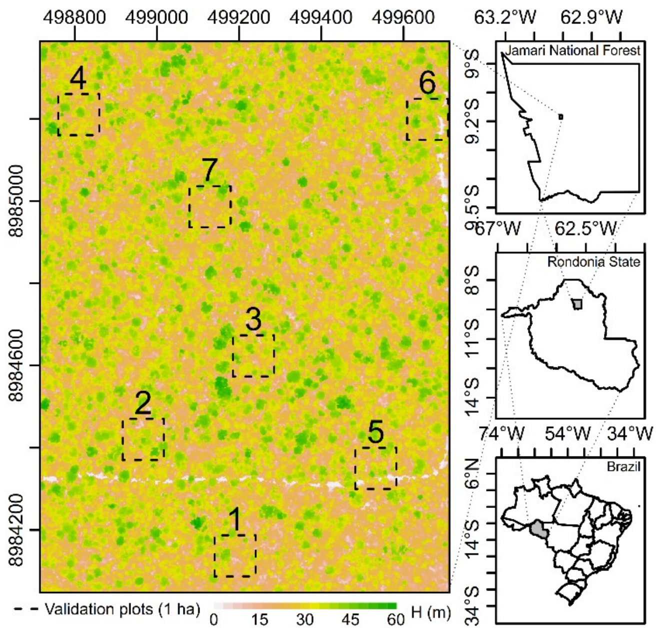

Figure 1 – Study area in the Jamari National Forest, Rondonia, Brazil. The seven plots (dashed lines, 100 x 100 m) were used for validation of the ITC delineation methods. The background image represents the ALS-CHM in meters. Coordinates at the left panel are UTM, zone 20, WGS84.

The satellite MS data was acquired on 10 October 2014 by the Worldview-2 satellite with the following geometry of data acquisition: solar elevation and azimuth angles of 69˚ and 85˚, respectively; viewing elevation and azimuth angles of 60˚ and 74˚, respectively; and sensor off-nadir pointing angle of 26.5˚. We used five available multispectral bands (2.4 m spatial resolution; blue, red, green, NIR-1, NIR-2) and one panchromatic band (0.5 m). In order to obtain surface reflectance data, we applied a top-of-atmosphere and atmospheric correction using the 6S radiative transfer model by the OpticalCalibration function from the Orfeo Toolbox 6.4 (OTB). To resample the pixel size of the MS data to 0.5 m, we applied the Bayes data fusion method implemented in OTB. This fusion method is a probabilistic framework that combines the higher spatial resolution from the panchromatic band with the resolution of the multispectral bands. The MS image was co-registered to the ALS-CHM to match the tree crowns. Only a translation of a few pixels was necessary to match the datasets.

2.3. Automatic ITC delineation

The ITCs were automatically delineated for MS and ALS data using three methods available in R v.3.4.3. All the methods were based on two steps: tree top detection and tree crown segmentation. The basic assumption for the tree top detection is that the tops have higher signal than the rest of the crown. Therefore, they reflect more electromagnetic energy and have high elevation. They can be detected over an image using a moving local maxima filter. The tree crown segmentation was performed differently between all methods. For all methods, in order to achieve optimal delineation, we tested different window size (*ws*) parameters: 3x3, 5x5, 7x7, 15x15 meters. For ALS, we used the CHM as input data, while for MS we tested the following bands: blue, red, green, NIR-1, NIR-2.

The first method used the *vwf* and *mcws* functions from ForestTools package [4]. It consists in a square local maxima filter to detect the tree tops, using the outputs as markers for the MCWS method. The MCWS considers the forest canopy as a topographic surface and segments the tree crowns by virtually flooding the surface with water from the tree tops to the crowns lowest values, which are usually shadows.

The second method was based on the *itcIMG* function from the itcSegment package [5]. It uses a circular local maxima filter to find the tree tops within the image, smoothed with a low-pass 3 x 3 mean filter. It then applies a decision tree method to grow individual crowns around the tree tops. This method has three parameters for the segmentation: seed and crown thresholds, and maximum tree diameter. In order to optimize the results, we iteratively tested the seed and crown parameters (*seedth* and *crownth*, alternating between 0.45 and 0.55), and maximum diameter (*md*, 15 and 30 m). To reduce noise in the delineation using ALS-CHM, a minimum tree height threshold was set to 8 meters.

The third method was based on the *FindTreesCHM* and *ForestCAS* functions from the rLiDAR package [6]. This method was only applied to ALS data because it requires elevation input data to properly work. First, it uses a square local maxima filter to find the tree tops over the CHM, smoothed with a low-pass 3x3 mean filter. Then, to delineate the tree crowns, it follows a series of steps: (1) defines an initial radius for each tree top based on a fixed *mc* parameter; (2) segments the data using the centroidal voronoi tessellation approach; (3) excludes cells with height below a percentage of the maximum height inside the tree crown, based on the *exclude* parameter. The *mc* (15 and 30 m) and *exclude* (0.3 and 0.7) parameters were iteratively tested. A minimum tree height threshold was also set to 8 meters as in method 2.

2.4. ITC validation

For validation of the automatic ITC delineation methods, we randomly selected seven plots of 100 x 100 m (1 ha), equivalent to 5% of the total area (140 ha). We then performed an independent visual assessment by manually delineating the tree crowns inside the plots based on a visual inspection of true-color composites from the MS data and of CHM from the ALS data. The manual delineation was performed separately for the MS and ALS datasets to ensure confidence on each ITC automatic delineation, because the tree crowns between ALS and MS do not always match.

We compared the manual and automatic ITC delineation using a set of statistical metrics. The tree detection was assessed considering the true positive (TP, correct detection), false positive (*FP*, commission error), false negative (*FN*, omission error), precision (*p*, eq.1), recall (r, eq.2) and F-score (*F*, eq.3) metrics, over-segmentation (*OS*) and relative tree density root mean square error (*RMSE*). OS was calculated as the ratio of over-segmented tree crowns to the total of delineated tree crowns. The tree density *RMSE* was calculated considering the number of reference trees and detected trees in each plot, and then converted to relative *RMSE* by dividing it by the average number of reference trees. The tree crown delineation, i.e. the area mapped by each tree crown, was assessed considering the intersection-over-union (*IoU*) metric. The *IoU* is calculated as the ratio between the intersection of areas and the union of areas of each ITC delineated between the manual and automatic methods.

$p = TP/(TP + F)$ (1)

$r = TP/(TP + FN)$ (2)

$F = (2 * p * r)/(p+r)$ (3)

2.5. Comparative Analysis

The ITC delineation methods were compared considering the average of statistical metrics from the seven plots. The best result, i.e. combination of parameters and input, for each method was identified based on the highest *F* and *IoU* and lowest tree density *RMSE* metrics. ITC map subsets for the best results were shown for qualitative assessment. We further analyzed the sensitivity of methods to variation of parameters and input data.

3. RESULTS AND DISCUSSION

When comparing the ITC detection results for each method (Table 1), the method 3 obtained the best results for ALS data (p = 0.88, r = 0.81), while the methods 1 (p = 0.79, r = 0.63) and 2 (p = 0.74, r = 0.68) obtained similar results for MS data. For the ALS, this means that 88% of the detected tree tops were located inside reference tree crowns, indicating a very low commission error (12%). In addition, 81% of the reference tree crowns were successfully mapped, indicating a low omission error (18%). Although the ITC detection over MS data obtained inferior results than ALS data, it still presented a good accuracy because 70% of the tree tops were located inside the reference tree crowns and over 60% of the trees were mapped.

The method 3 also presented the best tree crown delineation for ALS data (*IoU* = 0.39), while the methods 1 (*IoU* = 0.27) and 2 (*IoU* = 0.29) presented similar results for the MS data (Table 1). In this aspect, the difference in performance between datasets was more expressive, where 39% and 27-29% of the detected area presented intersection with the manual delineation when using ALS and MS data, respectively. This difference can also be observed in the ITC maps from plot six (Figure 2), where the area of each ITC delineated by the method 3 more precisely matched the manual delineation than the other methods over the datasets.

The number of detected trees (*Rdet* in Table 1) was overestimated by most methods when compared to the reference number of trees (*Rref* in Table 1), with relative RMSE, taking into account the seven plots, ranging from 20 to 38%. This is further explained by similar over-segmentation among the methods (*OS* from 26 to 36%). The number of detected trees is directly related to the window size, where the best *ws* for ITC detection in this site was 3x3 m for ALS data, and 5x5 m or 7x7 m for MS data using method 1 and 2, respectively. The reason why method 2 applied a larger *ws* than method 1, whilst still detecting a higher tree density, was probably associated with the type of window used for tree top detection. While method 1 uses a circular window, method 2 uses a square window.

Although the performance of methods 1 and 2 was comparable, method 1 should be superior and more useful for operational applications than method 2 because of three limitations in method 2. First, its ITC polygons do not comprise all the forest canopy area (i.e. gap in north-west of the Figure 2). Second, the circle-shaped polygons do not accurately represent the crown shapes in the image. Third, method 1 is at least 100-fold faster than method 2.

Regarding the sensitivity of the best methods to parameters variation, for method 3 and ALS data, while the *md* parameter did not have any effect on the results, there was an improvement in the delineation when increasing the *exclude* parameter from 0.3 (*IoU* = 0.34) to 0.7 (*IoU* = 0.39). In contrast, an *exclude* parameter of 0.3 is recommended for temperate forests [6]. We believe that this is probably because tree crown in those forests are predominantly cone or ellipsoid-shaped, and, thus, have a great height variation inside each tree crown. Hence, an increase in *exclude* parameter results in a better ITC delineation for tropical forests, where tree crowns are typically more tabular-shaped than temperate forests. For MS data, NIR-1 and NIR-2 bands showed equal accuracy (F = 0.7), and superior results than the rest of bands (F < 0.6). The NIR wavelength have been reported to produce the best ITC delineation in other studies because of its sensitivity to vegetation structure [3].

4. CONCLUSIONS

The performance of ITC delineations from ALS and MS datasets were similar, supporting that satellite multispectral data could be used for forest monitoring. Amongst the tested methods, the voronoi-based method for ALS data and MCWS method for MS data provided the best ITC delineation. Window sizes of 3x3 (ALS) and 5x5 (MS) m provided the appropriate scale for extracting tree crowns in this forest. The voronoid-based method was sensitive to the exclude parameter, from which higher values should provide better results for tropical forests. Meanwhile, the MCWS method obtained the best results when using NIR bands.

Table 1 – Best ITC delineation performance from each dataset and method.

Data-Method	Parameters	*Nref*	*Ndet*	*N RMSE %*	*p*	*r*	*F*	*OS*	*IoU*
ALS-M1	*ws* = 3	426	550	37.8	0.90	0.78	0.83	0.36	0.35
ALS-M2	*ws* = 3, *md* = 15, *seedth* = 0.55, *crownth* = 0.55	426	552	35.9	0.78	0.77	0.77	0.30	0.37
ALS-M3	*ws* = 3, *mc* = 15, *exclude* = 0.7	426	551	36.0	0.88	0.81	0.84	0.33	0.39
MS-M1	*ws* = 5, *band* = 7	598	591	20.0	0.79	0.63	0.70	0.26	0.27
MS-M2	*ws* = 7, *band* = 8, *md* =15, *seedth* = 0.45, *crownth* = 0.55	598	695	27.2	0.74	0.68	0.71	0.30	0.29

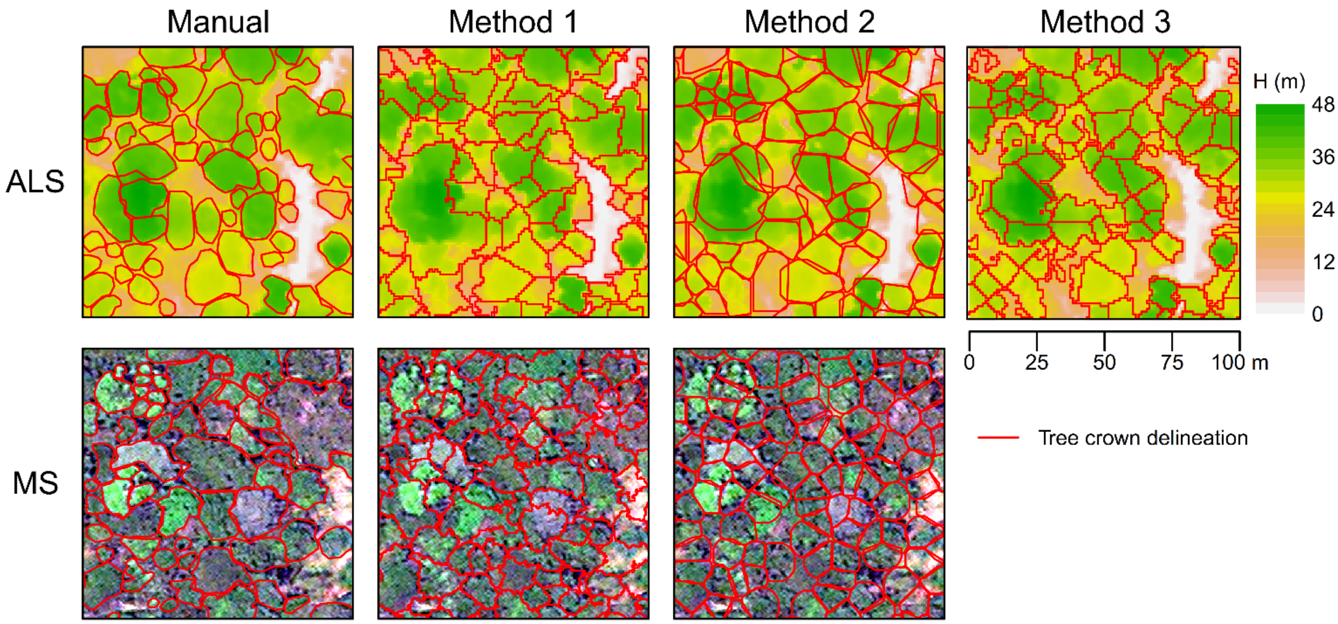

Figure 2 – ITC delineation maps from the manual delineation and three automatic methods (Table 1) using ALS (CHM at background) and MS data (RGB composite at background) over plot six. Satellite image(s) courtesy of DigitalGlobe Foundation.

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