remote sensing

Supplementary Materials: Quantifying Canopy Tree Loss and Gap Recovery in Tropical Forests Under Low-Intensity Logging Using VHR Satellite Imagery and Airborne LiDAR

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1. Individual Tree Crown (ITC) Delineation

Two methods were applied for ITC delineation in the study: the voronoi-based method for LiDAR data and the marker-controlled watershed segmentation (MCWS) for very high-resolution (VHR) satellite data. Both methods consisted of detecting the tree tops and then segmenting the tree crowns. The basic assumption for the tree top detection is that tree tops have a higher signal than the rest of the crown, i.e., they reflect more electromagnetic energy or have a higher elevation. Therefore, they can be detected over an image attribute using a moving local maxima filter given a window size. The tree crown segmentation was performed differently for the two methods, as described below.

The voronoi-based method for LiDAR data delineated the tree crowns following a series of steps: (1) defined an initial radius for each tree top based on a fixed maxcrown parameter; (2) segmented the data using the centroidal voronoi tessellation approach; and (3) excluded cells with a height below a percentage of the maximum height inside the tree crown, based on an exclusion percentage parameter. The parameters used for the ITC delineations were: 3x3 m window size, maxcrown of 15 m, exclusion of 0.7, and minimum height threshold of 8 m. The canopy height model (CHM) was used as the input.

The MCWS used with the VHR satellite data delineates the crowns using the watershed concept. 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 crown lowest values, which are usually shadows. The parameters used were: 5x5 m window size and the reflectance of the near infrared (NIR) band as the input.

For assessment of the automatic ITC delineation parameters, we compared them to a manual delineation by visual assessment. To do that, we randomly selected seven plots of 100 x 100 m (1 ha), equivalent to 5% of the total LiDAR data area, and performed an independent visual assessment where we manually delineated the tree crowns inside the plots based on the visual inspection of natural color composites (Red-Green-Blue) from the satellite data and the CHM from LiDAR data. Then, we calculated a set of statistical metrics: 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 tree crowns over-segmented to tree crowns delineated. 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 the RMSE by the average number of reference trees between the plots. 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.

$$p = TP/(TP + FP) \quad (1)$$

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

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

We found that the mean precision for determining the tree locations was high for both VHR satellite (p = 0.79) and LiDAR data (p = 0.88) (Table S1 and S2). However, the method using LiDAR data more precisely delineated the tree crowns in terms of area (IoU = 0.39) than the VHR satellite data (IoU = 0.27). Regarding the lower IoU of VHR satellite data, this means that the tree crowns automatically delineated using VHR data on average did not represent their true area; however, the ITCs should still show spectral similarity intra-objects, which is the main objective of this application. Overall, the automatic method using VHR satellite data showed a more similar density of trees (n = 591) to the reference (n = 598), than the automatic method with LiDAR data (n = 551) did with its reference (n = 426). This probably occurred because neighboring tree crowns, visually, are more easily distinguished by their color difference using VHR satellite data than by their elevation differences using airborne LiDAR data. However, we expect that the automatic method should be able to detect these subtle differences with LiDAR data. This is supported by the high precision, recall, and IoU with LiDAR data.

Table S1. ITC delineation assessment per plot for VHR satellite data.

Grid	Nref	Ndet	TP	FP	FN	p	r	F	OS	IoU
1	128	92	69	17	59	0.80	0.54	0.64	0.22	0.22
2	95	86	53	19	42	0.74	0.56	0.63	0.19	0.24
3	84	77	53	12	31	0.82	0.63	0.71	0.17	0.28
4	75	83	48	17	27	0.74	0.64	0.69	0.35	0.29
5	80	90	52	14	28	0.79	0.65	0.71	0.27	0.29
6	73	80	51	7	22	0.88	0.70	0.78	0.24	0.28
7	63	83	44	11	19	0.80	0.70	0.75	0.41	0.32
Total	598	591	370	97	228	0.79	0.62	0.69	0.26	0.27

Nref = Number of reference trees; Ndet = Number of detected trees; TP = true positive; FP = false positive; FN = false negative; p = precision; r = recall; F= F-Score; OS = over-segmentation; IoU = Intersection over Union

Table S2. ITC delineation assessment per plot for airborne LiDAR data.

Grid	Nref	Ndet	TP	FP	FN	p	r	F	OS	IoU
1	84	75	62	5	22	0.93	0.74	0.82	0.19	0.35
2	60	81	51	8	9	0.86	0.85	0.86	0.33	0.39
3	58	86	51	11	7	0.82	0.88	0.85	0.31	0.45
4	58	75	46	2	12	0.96	0.79	0.87	0.30	0.34
5	50	81	45	7	5	0.87	0.90	0.88	0.40	0.44
6	57	83	45	11	12	0.80	0.79	0.80	0.44	0.37
7	59	70	43	3	16	0.93	0.73	0.82	0.35	0.37
Total	426	551	343	47	83	0.88	0.80	0.84	0.33	0.39

Nref = Number of reference trees; Ndet = Number of detected trees; TP = true positive; FP = false positive; FN = false negative; p = precision; r = recall; F= F-Score; OS = over-segmentation; IoU = Intersection over Union