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COMBINING AIRBORNE LASER SCANNING AND LOCAL MAXIMA ALGORITHM FOR INDIVIDUAL TREE DETECTION IN COCONUT (*Cocos Nucifera* L.) FOREST PLANTATIONS

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ABSTRACT

Forest Inventory and monitoring is important for coconut plantation owners as it helps them in tracking forest growth, fruit production rates and plantation vitality. From this aspect, automated Individual Tree Detection (ITD) is very helpful as it makes the aforementioned processes less time-consuming, affordable, and efficient; however, applications of ITD is still at a latent stage in several emerging economies such as Brazil. Herein, we combined Light Detection and Ranging (lidar) and local maxima algorithm to automatically detect coconut tree tops from a plantation having plots of varying canopy cover densities. Our accuracy assessment results (average tree detection accuracy = 79.77%) shows that application of local maxima algorithm on lidar-derived canopy height models (CHM) - along with suitable filter window sizes and fixed window sizes, according to plantation density and within-plot tree distribution - can predict coconut trees with satisfiable accuracy (F-score > 0.85) and thereby assist the plantation sector's monitoring practices.

Key words — lidar 3D point clouds, canopy cover density, smoothing window sizes, plantation forestry, irregular tree crown

1. INTRODUCTION

Forest Inventory and monitoring is important for forest and plantation managers as it helps in tracking forest growth, fruit production rates and plantation vitality as well as assist in addressing global climatic change issues through quantification and tracking of carbon storage and sequestration regimes [1-3]. From this point of view,

automation of Individual Tree Detection (ITD) processes, through conglomeration of remote sensing techniques and statistical methods, can be perceived as an imperative strategy for making the aforementioned tasks less time-consuming, affordable, more frequent, and efficient.

Nonetheless, application of remote sensing techniques for the optimization and management of coconut plantation in Brazil is still being quiescent due to the lack of available high quality spatial data. Studies along this direction has the potential to enhance ongoing coconut plantation practices and to possibly assist the coconut plantation sector in navigating various globally prevailing issues – such as competition from oil palm plantations, improper farming practices, lack of environmental awareness and site-specific challenges [4].

The core objective of this study is to demonstrate the applicability of lidar and local maxima algorithm, along with different combinations of fixed tree window sizes (TWS) and smoothing window sizes (SWS), for detecting individual coconut trees at multiple plots of varying canopy cover densities.

2. MATERIAL AND METHODS

2.1. Study Area and Data Collection

The study area (figure 1) encompasses 11 ha of a coconut plantation in a rural settlement located northeast of Japeri municipality, in the state of Rio de Janeiro, Brazil. A total of 7 sites – comprising of 19 plots (20m x 20m) with varying levels of canopy cover density, were considered. The sites were further classified into three categories: Type A Stands - plantations with high canopy cover densities (sites 1, 2 and 3), Type B Stands – plantations with medium canopy cover

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densities (sites 4 and 5) and, Type C Stands – plantations with low canopy cover densities (sites 6 and 7).

The lidar data were acquired through a private company named Topocart and they employed a Leica Geosystems ALS60 sensor scanning with a camera RCD for data acquisition purpose. Using functionalities available in US Forest Service FUSION/LDV3.42 software [5] and LASTools [6] - GridSurfaceCreate function, CanopyModel tool and ClipData tool - Digital Terrain Models (DTMs) with a spatial resolution of 1.0 m and Digital Surface Models (DSMs) with a spatial resolution of 0.5 m were generated and heights were normalized. Afterwards, a Canopy Height Model (CHM), with a spatial resolution of 0.5 m, was built using the pit-free algorithm developed by Khosravipour et al. (2014) [7].

2.2. Individual Tree Detection and Accuracy Assessment

After generating the CHM, FindTreeCHM function available in rLiDAR package [8,9] was employed for ITD; here, the function makes use of a moving window with a fixed treetop window size for detecting tree tops and the underlying methodology incorporated is the local maximum algorithm. Combination of various TWS (3×3 , 5×5 , and 7×7 pixels) with an unsmoothed CHM as well as with multiple fixed smoothing window sizes (SWS; 3×3 and 5×5 pixels) were tested and parameters were chosen accordingly, for attaining an optimal tree detection result with the spatial filter employed being the mean filter.

For evaluation purposes, initially, the number of trees detected (NTD) per plot using lidar were manually compared with reference data gathered through visual assessment of high resolution imagery of the study sites. Later on, accuracy

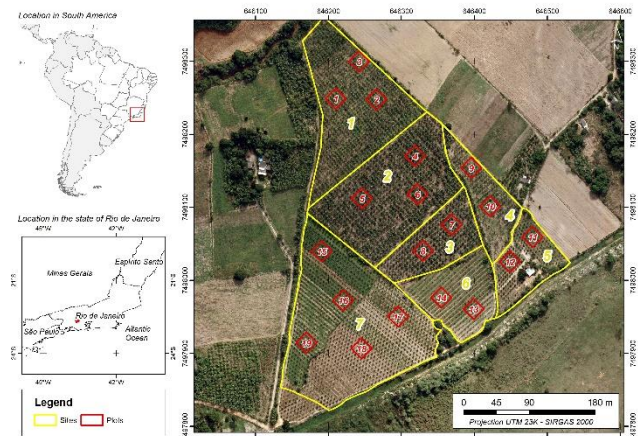


Figure 1. Location of the study area, plots, and sites 134 of the coconut plantation at northeast of Japeri municipality, in state of Rio de Janeiro (Brazil).

assessment was performed on the best combination, which involved evaluation of the accuracy in terms of true positive (TP, correct detection), false negative (FN, omission error) and false positive (FP, commission error), as well as with respect to recall (r), precision (p) and F-score (F) as per the equations listed in [10-12]. See figure 2 for overall workflow.

3. RESULTS

On the whole, we observed the increase in canopy cover density having a detrimental effect towards the tree detection ability of the algorithm. The best combinations for ITD was found to be 5×5 TWS and 3×3 SWS, and 7×7 TWS and 5×5

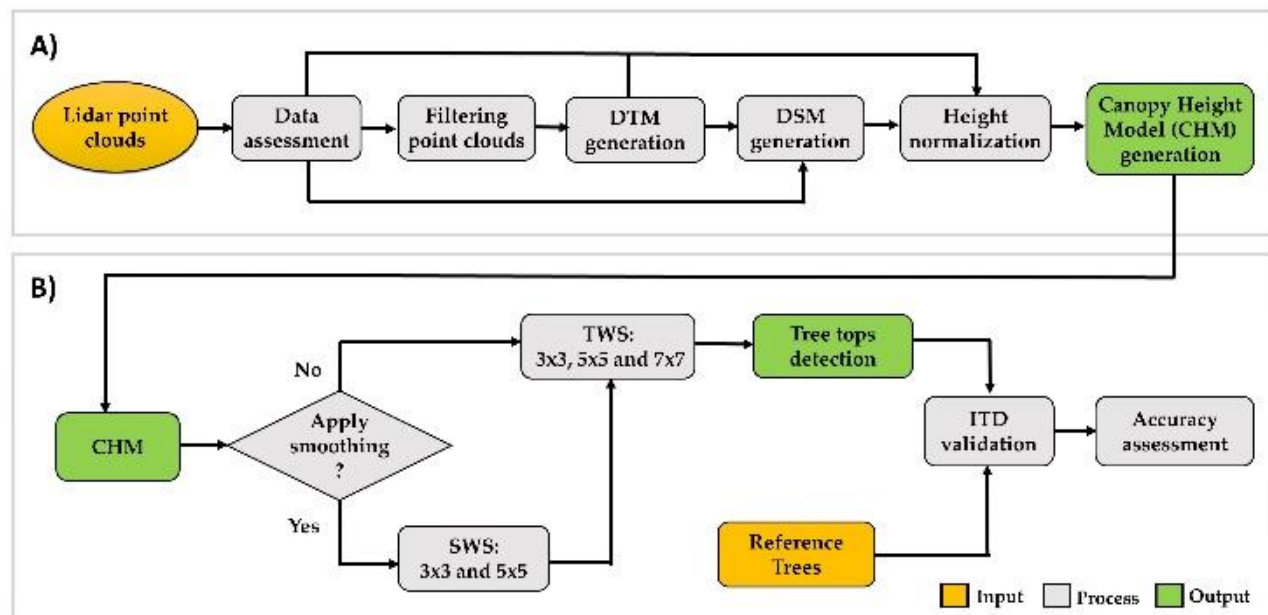


Figure 2. Workflow of A) lidar data pre-processing and B) local-maxima based Individual Tree Detection methodology.

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SWS (table 1). In both the cases, 6 out of 19 instances gave optimal tree detection results. However, we performed accuracy assessment only for the latter combination, as its performance was proven superior when relative error % for each observation was calculated and compared. On performing accuracy assessment (table 2) for the best found combination (7x7 TWS and 5x5 SWS), we obtained recall (r), precision (p) and F-Score values of 0.82 (range: 0.54 to 1.00), 0.97 (range: 0.88 to 1.00) and 0.88 (range: 0.67 to 1.00) respectively. A count of 272 (79.77%) successful tree tops was reported from the ITD process. From a total of 341 trees, the algorithm missed 69 trees and falsely detected 8 trees, giving an estimate of 280 trees.

Table 1: ITD results; the values in bold represents the best results, 226 which were determined by comparing the number of trees detected (NTD) to the observed tree inventory (N).

Sites	Plot (ID)	Ref. (N)	TWS								
			3x3			5x5			7x7		
			SWS			SWS			SWS		
			NF	3x3	5x5	NF	3x3	5x5	NF	3x3	5x5
1	1	24	358	40	29	158	25	20	96	19	16
	2	26	365	32	23	157	19	19	108	14	12
	3	21	311	27	21	133	20	16	85	14	16
2	4	19	368	39	21	159	25	15	96	17	12
	5	14	408	32	25	159	21	17	99	19	11
	6	16	379	40	26	182	20	13	114	18	13
3	7	14	393	42	22	160	21	16	100	17	15
	8	16	383	40	21	194	24	13	117	18	13
	9	20	345	31	21	159	20	17	111	18	16
4	10	16	397	30	23	166	19	17	106	13	15
	11	24	314	24	20	160	21	19	145	20	19
	12	19	275	22	20	137	19	19	109	19	18
5	13	15	356	27	18	137	15	14	99	14	14
	14	12	397	37	29	201	29	17	134	17	13
	15	18	342	32	15	148	15	15	95	14	13
7	16	17	315	28	16	133	18	16	100	17	16
	17	16	334	26	18	147	19	17	100	17	16
	18	18	294	18	16	110	16	16	97	16	16
	19	16	339	22	16	135	16	16	108	16	16
	Total	341	6673	589	399	2935	383	312	2019	317	280

4. DISCUSSION

In our study, we evaluated the applicability of a local-maxima based algorithm in detecting and delineating individual coconut trees within a coconut plantation comprising of sites with uneven canopy cover densities. In alignment with the basic assumptions of the local-maxima algorithm – that is, each imaged tree crown has a single ‘brightest spot’ with darker areas between tree crowns [13] - we observed the tree tops being represented as ‘brightest spots’ within the CHM. Depending on the varying levels of canopy cover densities – from high to low – there occurred glaring increase in darker areas between the ‘brightest spots’. Even though, coconut tree crowns, with its irregular canopy cover and often slanted stems, were expected to be comparatively harder for ITD, with careful selection of local maxima approach and varying combinations of SWS and TWS we were able to achieve

optimal accuracy with the tree top detections, similar to previous studies done in pine plantations [2].

The accuracy rates for ITD - which were verified in terms of precision, recall and F-score - shows that with the increase in canopy cover density, accurate ITD becomes more challenging in case of coconut plantations. This can be attributed to issues associated with occlusion, shadows,

Table 2: Accuracy assessment results for 7x7 TWS and 5x5 SWS combination

Sites	Plot (ID)	Number of Trees detected					r	p	F
		Ref. (N)	Lidar	FP	FN	TP			
1	1	24	16	1	9	15	0.63	0.94	0.75
	2	21	12	0	9	12	0.57	1.00	0.73
	3	26	16	2	12	14	0.54	0.88	0.67
2	4	19	12	1	8	11	0.58	0.92	0.71
	5	14	11	0	3	11	0.79	1.00	0.88
	6	16	13	1	4	12	0.75	0.92	0.83
3	7	14	15	1	0	14	1.00	0.93	0.97
	8	16	13	0	3	13	0.81	1.00	0.90
4	9	20	16	0	4	16	0.80	1.00	0.89
	10	16	15	1	2	14	0.88	0.93	0.90
5	11	24	19	0	5	19	0.79	1.00	0.88
	12	19	18	0	1	18	0.95	1.00	0.97
6	13	15	14	0	1	14	0.93	1.00	0.97
	14	12	13	1	0	12	1.00	0.92	0.96
	15	18	13	0	5	13	0.72	1.00	0.84
	16	17	16	0	1	16	0.94	1.00	0.97
	17	16	16	0	0	16	1.00	1.00	1.00
	18	18	16	0	2	16	0.89	1.00	0.94
	19	16	16	0	0	16	1.00	1.00	1.00
Total		341	280	8	69	272	0.82	0.97	0.88

variation in light reflectance, canopy overlap and closure, size, and tree spacing as listed in similar studies [2,14]. In case of plots in Type A (high canopy cover density) Stands, inaccurate estimation of results happened in most of the TWS-SWS combinations; this can be related with the irregular canopy of the coconut trees, which has many leaves identified with the local maximum; this can be a serious hurdle in plots having high canopy cover densities, especially when most of trees are old aged tall trees. On the other hand, in case of Type C (low canopy cover density) Stands, 5 in 7 plots (19 out of 63 TWS-SWS combination cases) gave satisfactory results with multiple combinations of TWS and SWS. Among Type B (medium canopy cover density) Stands, TWS-SWS combinations performed moderately well. Only the trees in plot 10 were not able to be detected with 100% accuracy by any TWS-SWS combination. We expect this oddity to arise from the differences in within-plot tree distribution and canopy gap patterns and look forward to exploring more in this direction in our subsequent study.

Based on our findings, using a TWS of 5x5 or 7x7 can be viewed as reliable strategy for estimating ITD in coconut plantations. The omission error was found to be 20.2 % and the commission error 2.8 % in this case; omission errors due to underestimation of trees happened majorly in plantations with high canopy cover density - out of the 63 missed trees,

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47 trees were missed while performing ITD in Type A Stands. Whereas, plots in Type C (low canopy cover density) Stands gave the best results; an average precision value of 0.99 and an average F-score of 0.95 was attained in this case. On that account, it can be inferred that when the trees are widely spaced - as in study plot 19 - the algorithm's efficiency in detecting trees correctly is very high and the combinations of TWS and SWS have comparatively minor influence on ITD performance here.

The takeaways from our study underscore that successful selection of TWS and SWS depending on tree crown structure, within-plot tree distribution patterns and canopy cover density can optimize the accuracy of adaptive ITD models. Considering the proliferation of tree detection algorithm, software technology and remote sensing platforms, applications of ITD are expected to get ten-fold in the coming decades. This will empower the plantation sector with efficient forest management and modeling paradigms. In essence, through our research we stretched the horizons of ITD to trees with irregular and attenuated canopy covers such as coconut trees and provided recommendations for heralding advanced and automated plantation monitoring and inventory practices.

5. CONCLUSIONS

To reiterate, our study reveals the potential of lidar data along with suitable tree detection algorithm and window sizes in delineating individual trees and thereby pave a way for estimating a wide range of tree and canopy characteristics. Our findings further emphasize the importance of TWS and SWS parameter selection, depending on species types, forest structure and management objectives, and bespeaks the potential of ITD algorithm in attaining satisfactory results in cases of trees with irregular and attenuated canopy structures such as coconut trees.

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