

## Identification and characterization of gaps and roads in the Amazon rainforest with LiDAR data

José Augusto Spiazzi Favarin <sup>(1)</sup>,  
Mateus Sabadi Schuh <sup>(2)</sup>,  
Juliana Marchesan <sup>(2)</sup>,  
Elisiane Alba <sup>(3)</sup>,  
Rudiney Soares Pereira <sup>(4)</sup>

Gap formations in the forest canopy have natural causes, such as bad weather, and anthropic ones, such as sustainable selective extraction of trees and illegal logging, which can already be detected through orbital remote sensing. However, the Amazon region is under frequent cloud cover, which makes it challenging to detect gaps using passive sensors. This study aimed to identify and delimit gaps in the Amazon forest canopy through airborne LiDAR (Light Detection and Ranging) sensor application while testing six different return densities. LiDAR and forest inventory data were obtained over an Amazon rainforest region, defining the minimum area as a forest canopy gap. The point cloud was processed to obtain six return densities with the generation of their respective CHM (Canopy Height Model), which were applied for segmentation and subsequent identification of gap areas and roads. The minimum gap area found was 34 m<sup>2</sup>, and the Kruskal Wallis test showed no significant difference among the six densities in gap detection; however, road identification decreased as the return density decreased. We concluded that LiDAR data proved promising as point clouds with low return density can be used without impairing gap identification. However, reducing the return density for road identification is not recommended.

**Keywords:** Forest Canopy Gaps, Aerial Laser Scanning, Point Density, Remote Sensing

### Introduction

Rainforests are subject to natural disturbances of varying intensity, duration, and frequency, making these ecosystems in a continuous and dynamic change (Chazdon 2016). Forests undergo periodic disturbances (such as fires, strong winds, intense storms, or simply senescence and falls of large trees) that open different-sized gaps in the canopy, restarting a new process of secondary forest succession in these specific sections (Gandolfi 2007). Additional disturbances may occur due to anthropic causes, such as global warming, forest fires, and deforestation (Nobre et al. 2007). The latter is widely used to convert land for

the production of food crops or pastures, and represents the most significant destructive factor in tropical forests (Asner et al. 2005). These actions leave behind large areas without forest cover and openings within the forests. Gaps can also be opened by damage caused by insects and diseases (Araki & Awaya 2021) and logging activities (Carvalho et al. 2017).

Another significant anthropic disturbance is represented by the opening of roads in the forest, which results in vegetation suppression. According to Grigolato et al. (2013), forest road networks connect forested areas to the primary road network and play an essential role in fire-fighting

support and logging activities. To build/open a main forest road, it is necessary to deforest an approximately 20-meter-wide forest section, considering the axis of the road to build (Costa Filho & Da Costa 1980). Mapping roads under the dense canopy of the tropical forest is still challenging (Santos et al. 2018). According to Aricak (2015), millions of dollars are spent annually to build and access roads for forestry activities.

Gaps play an essential role in forest regeneration since gap formation favors the growth of seedlings on the forest floor (Araki & Awaya 2021), and therefore affecting the understory species diversity (Mao et al. 2020). Knowing the gaps' physical, floristic, and structural characteristics is essential in studying gap dynamics, considering their interrelationship with the natural regeneration process in the disturbances (Martins & Rodrigues 2002). Indeed, these openings constitute ecologically important patches of pronounced tree recruitment and plant growth (Dietmaier et al. 2019). To perform fine-scale gap monitoring, including small gaps caused by the fall or damage of single trees, it is necessary to obtain detailed data on the structure of the forest canopy (Araki & Awaya 2021).

Orbital remote sensing techniques are already used in forest monitoring. Passive optical remote sensing has been utilized to classify and quantify local changes in forest structures, e.g., selective logging (Pinage et al. 2019). However, according to Hunter

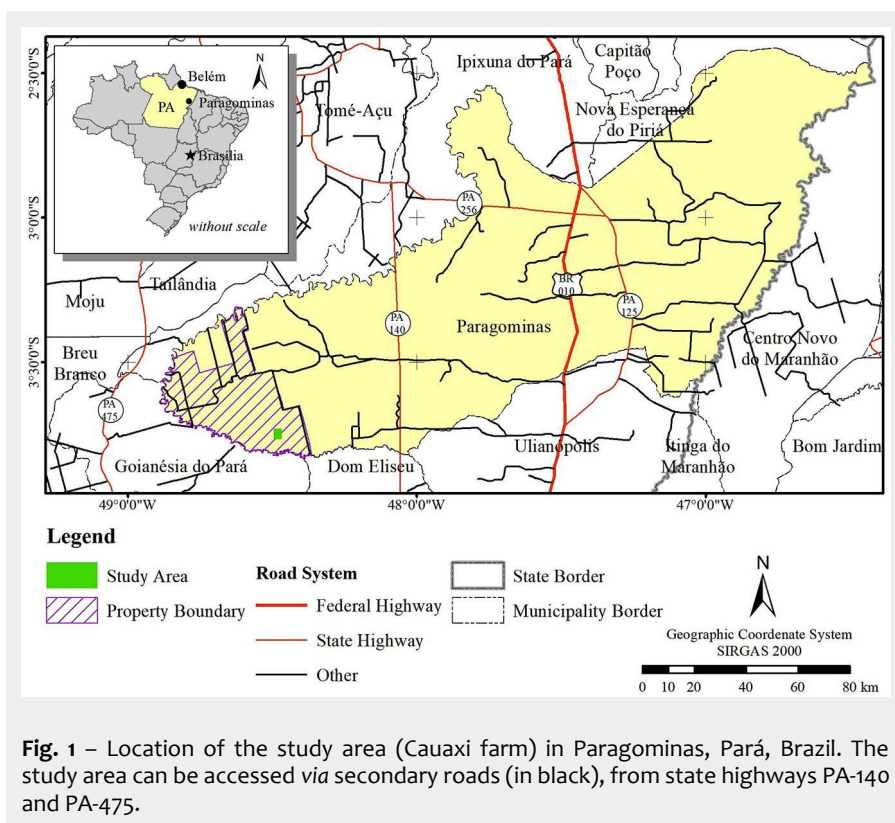
□ (1) Postgraduate Program in Forest Sciences, Federal University of Paraná /UFPR, Lothário Meissner Avenue, 632, Jardim Botânico, 80210-170, Curitiba, PR (Brazil); (2) Postgraduate Program in Forest Engineering, Federal University of Santa Maria/UFSM, Roraima Avenue, 1000, Camobi, 97105-900, Santa Maria, RS (Brazil); (3) Academic Unity of Serra Talhada, Federal Rural University of Pernambuco/UFPE, Gregório Ferraz Nogueira Av., 56909-535, Serra Talhada, PE (Brazil); (4) Rural Engineering Department, Federal University of Santa Maria/UFSM, Roraima Avenue, 1000, Camobi, 97105-900, Santa Maria, RS (Brazil)

@ José Augusto Spiazzi Favarin ([jaspiazzi@gmail.com](mailto:jaspiazzi@gmail.com))

Received: Dec 27, 2022 - Accepted: Jun 11, 2024

**Citation:** Spiazzi Favarin JA, Sabadi Schuh M, Marchesan J, Alba E, Soares Pereira R (2024). Identification and characterization of gaps and roads in the Amazon rainforest with LiDAR data. *iForest* 17: 229-235. - doi: [10.3832/ifor4295-017](https://doi.org/10.3832/ifor4295-017) [online 2024-08-03]

Communicated by: Matteo Garbarino



this reason, according to Yoga et al. (2017), it is necessary to investigate whether factors such as the spatial distribution of returns may influence the prediction or uncertainty of forest attribute models.

This study did not aim to evaluate the accuracy of gap detection using LiDAR data but rather the possibility of their detection using a low density of points, starting from the initial density of the point cloud. Our main goal was to identify and delimit gaps and roads in tropical forests using processing techniques applied to active remote sensing data obtained by LiDAR sensor, with six distinct point densities, under the hypothesis that differences might exist in gap detection using different point density data. Additionally, we aimed to assess the carbon dioxide emissions from the detected gaps.

## Methodology and data

### Study area

The study area is located at 03° 44' 59" South latitude and 48° 28' 51" West longitude, in Cauaxi Farm, comprising an area of 1216 ha. The farm belongs to the Rio Capim farm complex, located in the municipality of Paragominas, state of Pará, Brazil, which is part of the Cikel Group domain area (Fig. 1).

The Köppen climate classification for the region is "Aw" type, which is tropical rainy with a well-defined dry season. Annual precipitation is around 1800 mm, the average yearly temperature is 26.3 °C, and relative air humidity is 81% (Alvares et al. 2013).

The topography of the studied area ranges from flat to gently undulating, and belongs to the Pará-Maranhão Northern Plateau Geomorphological Region (DNPM 1973). According to Radambrasil (1983), the soils are classified as Dystrophic Yellow Latosol.

The dense forest of the high plateau sub-region of Pará-Maranhão, the dense floodplain forest, and the terraces characterize the original landscape of the area. Today, it consists of extensive secondary forests characterized by capoeira in various stages of development (Cardona 2012).

### Ground and LiDAR data acquisition

LiDAR data were obtained from the "Sustainable Landscapes" project of the Brazilian Agricultural Research Corporation (EMBRAPA), which is a technical cooperation project funded by the US Agency for International Development and the US Department of State, and involves the USDA Forest Service and EMBRAPA (2014) with the aim to generate detailed information on the land surface and vegetation, thus contributing to the measurement of carbon dioxide and other greenhouse gases as well as to the development of mitigation techniques. The project has implemented a WebGIS (<https://www.paisagenslidar.cnptia.embrapa.br/webgis/>) that makes available the LiDAR data and the forest inven-

et al. (2015), passive optical images must deal with the problems related to cloud formations, which are predominant in the humid tropics. The limited spatial resolution provided by some sensors, like Landsat satellites, makes it difficult to detect all the small-scale disturbances associated with logging, particularly those of low impact (Dalagnol et al. 2019).

LiDAR (Light Detection and Ranging) technique use active sensors based on electromagnetic signals which can be mounted on an aircraft, thus collecting forest data below the cloud cover and overcoming the limitations inherent to forest inventory. LiDAR has the potential to obtain direct three-dimensional forest canopy measurements which are used to estimate forest inventory parameters such as tree height, stem volume, and biomass (Popeacu et al. 2011, Marchesan et al. 2020, Neto et al. 2021, Dalla Corte et al. 2022). For example, Melendy et al. (2018) recommend using LiDAR to monitor and measure the impact caused by selective logging (opening of gaps, roads, and draglines), whether performed legally or illegally. LiDAR has been largely applied in forest canopy gap classification as accurate topographic data can be obtained and used in the construc-

tion of a canopy height model representing trees or vegetation height (Mao & Hou 2019). According to Joyce et al. (2019), even individual pieces of coarse woody debris on the forest ground can be detected regardless of canopy density, shrub density, or forest type.

The accuracy in the reconstruction of the forest structure from LiDAR-acquired point clouds largely depends on the point density (Vepakomma et al. 2008, Jakubowski et al. 2013). The point density is directly affected by the flight height, which influences the area covered by the sensor. If the reduction in point density does not result in a loss of accuracy of the derived metrics, it will be possible to cover a larger forest area. This will enable the study of the dynamics and regeneration of gaps, including detecting gaps created by illegal deforestation.

Due to the ecological importance of gaps, it is necessary to quantify these disturbances. In gaps, ecological succession begins with increased solar radiation in the forest, causing seed germination in the soil (Gomes et al. 2010). Therefore, gaps play an essential role in forest regeneration, species turnover, and the dynamics of forest ecosystems (St-Onge et al. 2014). For

**Tab. 1** - Classes of gap areas used in this study. (a.min): minimum gap area found.

Area (m <sup>2</sup> )	Class	Class Code	Reference
a.min - 149	Small Gaps	Class 1	Tabarelli & Mantovani (2000)
150 - 399	Medium Gaps	Class 2	Brokaw (1985), Tabarelli & Mantovani (2000)
≥ 400	Large and Rare Gaps	Class 3	Brokaw (1985), Lima (2005)

tory database in areas of the Amazon, Cerrado, and Atlantic Forest biomes (EMBRA-PA 2016).

The forest inventory was conducted in 2014 by establishing 22 plots of 20 × 500 m, comprising an area of 10,000 m<sup>2</sup> each and totaling 22 ha. Trees with a diameter at breast height (DBH) ≥ 35 cm were measured for the DBH and crown radius.

LiDAR data were acquired using an aerial platform at an average flight altitude of 850 m. The covered area was 1216 ha, recorded in 20 scenes composed of a point cloud with X, Y, and Z coordinates. The LiDAR data was already georeferenced, and the datum used was SIRGAS 2000 with the Universal Transverse Mercator Projection System (UTM), spindle 22 South.

#### Definition of minimum gap area

The minimum area of a canopy gap was defined by adapting the method of Hunter et al. (2015), as the area occupied by a tree crown after its falling/removal. The mean crown radius of each tree was calculated by averaging the four measures (North, South, East, and West) taken in the forest inventory, and its crown area was derived from the average radius. Areas smaller than one m<sup>2</sup> were excluded because they are smaller than the 1 m spatial resolution of the generated raster files.

#### LiDAR point cloud processing

The point clouds generated by the LiDAR sensor were processed using the FUSION/LDV software (McGaughey 2016). The lowest point density among the 20 different scenes was taken as the minimum point density. This value was used as a reference to standardize the returned point density across the study area. The subsequent analyses were carried out using the calculated minimum density as the reference value (100%) and by resampling fractions of this point density, namely, 75%, 50%, 25%, 10%, and 2% of the reference value. Each of the above six point cloud densities represents a “trial”, which was labeled with the relative number of return points per square meter (ppm<sup>2</sup> - see Results).

The “TreeSeg” tool, which performs canopy segmentation, was applied to carry out the gap segmentation. The height threshold was adjusted to 2 m, as reported by Brokaw (1982). The cells of the canopy height model (CHM) showing values above this threshold were segmented into a single class, while values lower than the threshold were discarded. Also, the maximum height was set at 2 m, therefore only points below this threshold were segmented. The final product was a raster segmented into canopy and gap areas, which was exported (.asc file) for later analyses.

#### Identification of gap areas and roads

The raster files resulting from the TreeSeg tool were imported in the software QGIS (<https://www.qgis.org/>) to transform the data in TIFF files and enable the geo-

spatial analysis of the rasters. A surrounding rectangle was used to crop the raster files and eliminate spurious cells from the edges.

A similar identifier was assigned to the raster cells belonging to the same gap area identified, thus allowing each clearing to be analyzed separately. The area of each gap was calculated (in m<sup>2</sup>) and the “area\_m2” value was added to the attribute table. Gaps were then classified in three groups based on their extension, following criteria adapted from the literature (Tab. 1): (i) Class 1, small gaps from minimum gap area found (a.min) to 149 m<sup>2</sup>; (ii) Class 2, medium gaps from 150 to 399 m<sup>2</sup>; (iii) Class 3, large and rare gaps ≥ 400 m<sup>2</sup>.

The roads were identified using the segmented raster analysis, with no area classification. The different return point densities used to identify the gaps were analyzed to determine the road layout below the canopy. The visual analysis of the segmented areas allowed to manually design the road paths on the raster, which were then transformed to vectors. Different shapefiles were created for each point den-

**Tab. 2** - Descriptive statistics of the tree crown areas based on the average crown radius.

Statistics	Area (m <sup>2</sup> )
Mean	55.404
Median	34.732
Mode	28.274
Standard deviation	64.878
Minimum	1.039
Maximum	1,069.406
Counts	2,215 (trees)

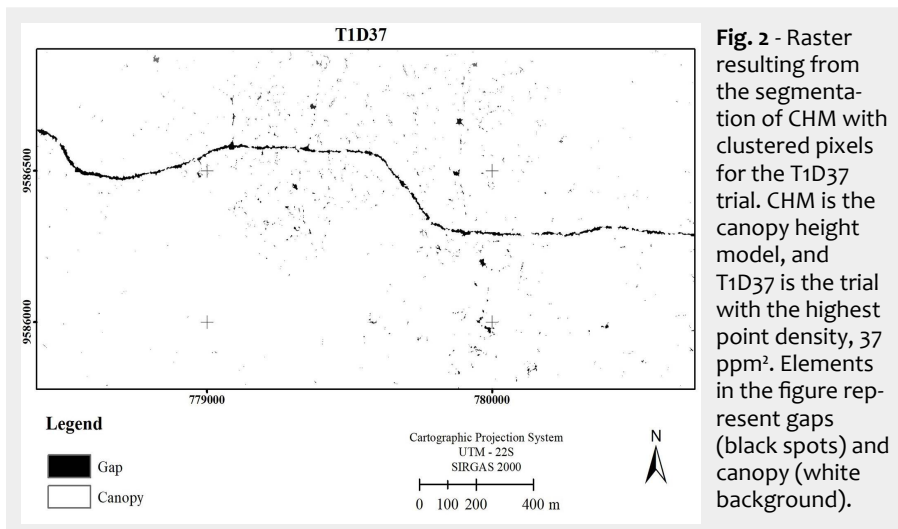
sity data (= trial) to assess the segments' length. In addition, the DTM generated from LiDAR data was used to identify the position and the possible layout of water-courses.

#### Statistical analysis

As the low density of return points from LiDAR can impair the detection of gaps, we verified possible differences in the detec-

**Tab. 3** - Descriptive statistics of the gap area detected by different return point density (trials, in columns) by class of gap size (in rows, see also Tab. 1). The last number in the trial label correspond to the point density in ppm<sup>2</sup>. (A.tot): total area (m<sup>2</sup>); (A.min): minimum area (m<sup>2</sup>); (A.max): maximum area (m<sup>2</sup>); (A.avg): average area (m<sup>2</sup>); (var): variance; (sd): standard deviation; (N): number of gaps.

Gap Class	Parameter	Trial (% of the reference point cloud density)					
		T1D37 (100%)	T2D28 (75%)	T3D18 (50%)	T4D09 (25%)	T5D04 (10%)	T6D01 (2%)
Class 1 (34-149 m <sup>2</sup> )	A.tot	9,742.00	10,267.00	11,738.00	10,167.00	19,130.00	17,379.00
	A.min	34.00	34.00	34.00	34.00	34.00	34.00
	A.max	147.00	147.00	147.00	147.00	146.00	149.00
	A.avg	62.85	63.38	62.44	63.54	61.51	63.66
	var	810.92	876.91	888.96	881.36	791.55	775.43
	sd	28.48	29.61	29.82	29.69	28.13	27.85
Class 2 (150-399 m <sup>2</sup> )	A.tot	9,084.00	8,800.00	9,063.00	8,797.00	12,220.00	12,046.00
	A.min	151.00	153.00	151.00	153.00	151.00	150.00
	A.max	397.00	386.00	396.00	386.00	392.00	382.00
	A.avg	232.92	231.58	232.38	231.50	244.40	231.65
	var	5,492.44	5,013.44	4,755.45	4,997.28	5,477.59	3,852.94
	sd	74.11	70.81	68.96	70.69	74.01	52.07
Class 3 (≥ 400 m <sup>2</sup> )	A.tot	17,665.00	18,213.00	18,979.00	18,221.00	20,939.00	12,911.00
	A.min	419.00	403.00	414.00	403.00	405.00	401.00
	A.max	3,391.00	3,398.00	3,802.00	3,399.00	3,708.00	3,297.00
	A.avg	929.74	910.65	948.95	910.55	1,046.95	860.73
	var	496,073.90	485,124.70	598,175.70	485,133.10	587,919.00	542,360.10
	sd	704.33	696.51	773.42	696.52	766.76	736.45
Gaps (ha)	-	3.65	3.73	3.98	3.72	5.23	4.23
	-	1,170.35	1,170.27	1,170.02	1,170.28	1,168.77	1,169.77
Total area (ha)	-	1,174.00	1,174.00	1,174.00	1,174.00	1,174.00	1,174.00
	-	1,174.00	1,174.00	1,174.00	1,174.00	1,174.00	1,174.00



**Fig. 2** - Raster resulting from the segmentation of CHM with clustered pixels for the T1D37 trial. CHM is the canopy height model, and T1D37 is the trial with the highest point density, 37 ppm<sup>2</sup>. Elements in the figure represent gaps (black spots) and canopy (white background).

**Tab. 4** - Results of the normality and homoscedasticity tests. (D): Kolmogorov-Smirnov statistics; ( $\chi^2$ ): Chi-square test.

Class	Kolmogorov-Smirnov		Bartlett	
	D	p-value	$\chi^2$	p-value
Class 1	0.1581	2.2e-16	1.9812	0.8517
Class 2	0.13271	0.0002427	1.9507	0.8559
Class 3	0.26658	1.837e-7	0.42698	0.9946

**Tab. 5** - Kruskal-Wallis test result. ( $\chi^2$ ): Chi-square test.

Class	$\chi^2$	p-value
Class 1	2.1751	0.8244
Class 2	1.4967	0.9135
Class 3	3.2096	0.6677

tion of gaps using different point densities. The Kolmogorov-Smirnov test was applied to test for departure from normal distribution of the area in the three gap classes described above, while the Bartlett’s test was applied to test for equality of variances across the classes. Finally, the non-parametric Kruskal-Wallis test ( $\alpha = 0.05$ ) was used to test for differences in the estimates of gap area between the different trials (point cloud densities) analyzed.

All the statistical procedures were performed by developing suitable scripts in R v. 3.5.1 and using the RStudio v. 1.1.453 integrated development environment (RStudio Team 2020).

**Results**

*Definition of the minimum gap area*

The mean tree crown area for the study area was  $55.40 \pm 64.88$  m<sup>2</sup>, indicating considerable variability in the data set (Tab. 2). As extreme values may compromise the comparison of data based on the mean (Mello & Peternelli 2013), the median value of tree crown area distribution (34 m<sup>2</sup>) was chosen as the minimum gap area (a.min) in further analyses.

*LiDAR point cloud processing*

The initial processing of the point clouds

in FUSION/LDV using the “Catalog” tool revealed an average return density of 61.38 ppm<sup>2</sup> (points per squared meters), while the scene with the lowest average density had 37.55 ppm<sup>2</sup>. Therefore, the latter value was taken as the reference point density to standardize the return density values throughout the study area. The applied return densities were 37, 28, 18, 9, 4, and 1 ppm<sup>2</sup> (100%, 75%, 50%, 25%, 10%, and 2% of the reference density, respectively). Consequently, the trials were labelled as T1D37, T2D28, T3D18, T4D09, T5D04, and T6D01, corresponding to the point densities of 37, 28, 18, 9, 4, and 1 ppm<sup>2</sup>, respectively (Tab. 3).

*Gap area identification*

The canopy gaps with area  $\geq$  to 34 m<sup>2</sup> (the median value of tree crown areas calculated from the forest inventory) were classified according to the three classes listed in Tab. 1, while smaller areas were not considered as gaps and therefore incorporated into the “Canopy” class (Tab. 3). The pixels of the CHM were grouped according to the height threshold of 2 m; the resulting raster had only two classes (gaps and canopy) and each of the segmented polygons (the canopy gaps) was tagged with its own identifier (Fig. 2).

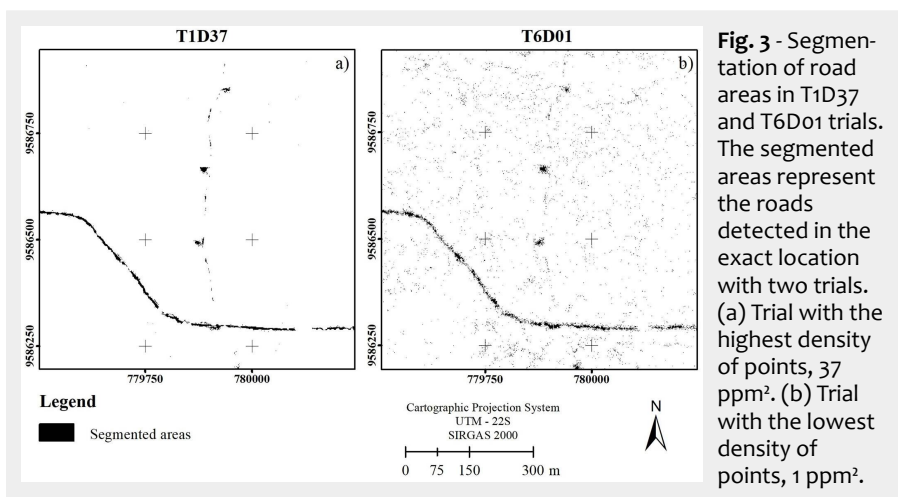
The result of the Kolmogorov-Smirnov test revealed significant departures ( $p < 0.05$ ) from the normality in the gap area in all classes, meaning that the residues of the three classes did not follow a normal distribution. The homoscedasticity of the data was verified through the Bartlett’s test, which revealed that the variances are homogeneous across the three classes of gap size ( $p > 0.05$ ). The results for both tests are reported in Tab. 4.

A non-parametric test was adopted to evaluate if there was a significant difference between the trials used; thus, the Kruskal-Wallis test was applied. The test results are in Tab. 5.

The results of the non-parametric Kruskal-Wallis test (Tab. 5) indicate that there were no significant difference in the between trials ( $p > 0.05$ ) in any of the three gap area classes. This indicate that any of the six trials (point cloud densities) could be used to identify gaps in the rainforest canopy based on LiDAR sensor data without impairing the gap area estimation.

*Road identification*

The roads were analyzed qualitatively as they could be identified on the raster resulting from the segmentation. As the return point densities decreased, so did the ability to identify segments that suggested a road layout. Only the main roads could be determined at the lowest point cloud densities, making difficult to detect their presence below the forest canopy. From T3D18 (18 ppm<sup>2</sup>, i.e., 50% of the reference point density) to the lower-density trials, defining an apparent road layout became more and more challenging, as many segments



**Fig. 3** - Segmentation of road areas in T1D37 and T6D01 trials. The segmented areas represent the roads detected in the exact location with two trials. (a) Trial with the highest density of points, 37 ppm<sup>2</sup>. (b) Trial with the lowest density of points, 1 ppm<sup>2</sup>.

became discontinuous and because many segments with small areas were generated at lower return densities. Fig. 3 shows the segmentation difference in the T1D37 trial with the highest point cloud density and the T6D01 trial with the lowest point cloud density.

## Discussion

To our best knowledge, this is the first study to test the influence of LiDAR return point density on identifying gaps in the Amazon forest. The results evidenced the identification viability by adopting a pre-defined minimum gap area, where the smallest class of gap area had the highest frequency. Based on the results of this study, we reject the hypothesis that there would be a significant difference in identifying forest gaps using different return point densities from LiDAR data in the study area.

The minimum gap area found was similar to that defined by Blackburn et al. (2014) of 30 m<sup>2</sup> in Southern England in a deciduous broadleaved temperate forest. Similar values (35 m<sup>2</sup>) are reported by Martins et al. (2004) in the mesophytic semi-deciduous forest in Southeastern Brazil, and by Tabarelli & Mantovani (2000) in the Atlantic Forest in Serra do Mar, Brazil (30.3 m<sup>2</sup>). Therefore, both these studies corroborate the minimum gap area found in our study.

Using all trials, the highest number of gaps was found in Class 1 (smaller gaps, 34 to 149 m<sup>2</sup>). Similar findings were also found by Martins & Rodrigues (2002) and Martins et al. (2004) in a mesophytic semi-deciduous forest in Southeastern Brazil, where most of the gaps had area less than 100 m<sup>2</sup>. Dalagnol et al. (2019) also found predominantly small gaps (5 to 25 m<sup>2</sup>), namely 55.3% of 724 gaps. It is worth noting that the different trials (i.e., different point cloud densities) allowed the detection of different gap numbers and areas within the same class, and these differences decreased as the gap area increased (Tab. 3), especially in the number of gaps identified.

In Class 2 (medium gap size), trials T1D37 (100% of the reference point cloud) and T3D18 (50%) allowed the detection of 39 gaps in the forest canopy of the study area, whereas trials T2D28 (75%) and T4D09 (25%) allowed identifying 38 gaps, a difference of only one gap; meanwhile, trials T5D04 (10% of the reference point cloud) and T6D01 (2%) allowed the detection of a larger number of gaps, 50 and 52, respectively. In Class 3 (larger or rare gaps), there was a substantial similarity between trials regarding gap counting, as 20 gaps were identified using trials T2D28, T3D18, T4D09, and T5D04. In the same class, one less gap was identified using the T1D37 trial, while the T6D01 trial allowed to detect 15 gaps.

Regarding the gap area estimates, our results suggest that smaller gaps have more influence on the total gap area at the study site. Indeed, considering Class 2 and Class 3 only, the total gap area was estimated in 2.67 ha using trial T1D37 and 2.70 ha using

T2D28 and T4D09. In comparison, T3D18 and T5D04 allowed to estimate larger areas (2.80 ha and 3.32 ha, respectively), while using T6D01 a smaller total area of 2.50 ha was obtained. In a study by Brokaw (1985) using field measurement methods in the tropical forest in Panama, gaps with areas between 20 and 705 m<sup>2</sup> were found. In Martins & Rodrigues (2002), forest canopy gaps measured with hemispheric photographs (fish-eye lens) in the mesophytic semi-deciduous forest in Southeast Brazil, varied between 20 and 468 m<sup>2</sup>. The above findings suggest that estimating gap areas from LiDAR data could lead to results consistent with those obtained using traditional methods.

It is important to highlight that the analysis of gap areas carried out in this study evaluated whether there is a significant difference in the size of gaps detected and by size class, not in the total area detected. Indeed, the number of forest canopy gaps detected varied, which could change the total area, but the size of the gaps did not vary.

Using LiDAR detection in a mixed boreal forest in Quebec, Canada, St-Onge & Vepakomma (2012) found an average gap area of 79.4 m<sup>2</sup>, and the largest detected areas reached 1743, 1721, and 798 m<sup>2</sup>. Their findings suggest LiDAR technology as an excellent tool for mapping gaps using a return density of 3 ppm<sup>2</sup>, which is similar to the point density of the T5D04 trial (4 ppm<sup>2</sup>) in this study. Treitz et al. (2012) carried out a plot-level study with different pulse densities, finding that the reduction in density did not reduce the precision of the prediction of forest inventory variables. Similarly, a survey by Jakubowski et al. (2013) indicated that a high pulse density is not necessary to predict metrics of forest structures at plot level (pixel of approximately 24 m). However, high density is required at the level of individual trees, including the accuracy of tree species identification (Kartinen et al. 2012) since, according to the authors, the accuracy of metrics decreased as point density decreased.

Using T1D37 trial, a more restricted segmentation in the study area was observed, allowing the detection of a trace following a same direction below the forest canopy (Fig. 3). Using the T6D01 trial, the segmented areas became more diffuse, hampering the identification of the road layout in the raster. Similarly, other free spaces between the tree crowns could lead to the misidentification of forest roads running beneath the canopy, especially using the lower point densities.

Research addressing the detection of forest roads under forest canopy has already been carried out. For example, Azizi et al. (2014) conducted a study to determine the suitability of LiDAR for forest road detection and extraction, showing that the characteristics of roads obtained using LiDAR data were highly accurate. Similarly, Matinnia et al. (2018) extracted accurate road

longitudinal sections through DTM generated from LiDAR data. The low-density LiDAR data is suitable for detecting and digitizing forest roads over large areas, especially those where forest roads are wide (> 4 m) and are not surrounded by broad-leaved stands (Prendes et al. 2019).

Regarding point density, Kiss et al. (2016) evaluated the conditions of forest roads in terms of structural and surface conditions using high point cloud density. The results of a survey conducted by Matinnia et al. (2017) indicated that the geometric properties of existing forest roads could be monitored under dense forest canopy using LiDAR data.

Airborne LiDAR is widely applied to forests, but its use in the detection of roads and unpaved forest roads is relatively new (Kiss et al. 2016). To this end, this study could represent the starting point for more complex methods of road detection, such as developing algorithms for their automatic identification.

The main limitation of this study is the lack of validation of the results based on field data. This is due to the fact that data were not obtained by the authors but from a research project (EMBRAPA 2014). Moreover, the issue of the minimum gap area was overcome by adapting a method available in the literature, based on the crown radii measured in the forest inventory. Nonetheless, the main goal of this study was to test whether the reduction in point density of LiDAR data would compromise the detection of gaps, using as a reference the density of the point cloud obtained without degradation of point density.

## Conclusions

The reduction in the LiDAR return point density did not affect the detection of gap areas in a tropical forest canopy, rejecting the starting hypothesis of this study. LiDAR data acquisition with a low pulse density, which affect the return point density, seems a feasible option that reduce acquisition costs and improve processing performance. However, the reduction in return densities hampers the detection of roads running underneath the forest canopy. Therefore, the return density reduction for road layout assessment is not recommended in the study area.

LiDAR technology has proven to be an efficient tool for identifying gaps in the forest canopy. It has huge potential for monitoring and planning sustainable forest exploitation. Similarly, it can be applied to monitoring deforestation and illegal logging in tropical forests.

## Acknowledgments

The authors thank the Brazilian Agricultural Research Company (EMBRAPA) for providing the data of this study and the Coordination for the Improvement of Higher Level Personnel (CAPES) for financial support (grant no. 1703355).

## Conflict of interest

The authors declare no conflict of interest.

## Authors contribution

JASF: conceptualization, methodology, investigation, formal analysis, writing - original draft; MSS: methodology, data curation, validation; JM: data curation, writing - review and editing; EA: writing - review & editing; RSP: supervision, validation.

## References

- Alvares CA, Stape JL, Sentelhas PC, Gonçalves JLM, Sparovek G (2013). Köppen's climate classification map for Brazil. *Meteorologische Zeitschrift* 22: 711-728. - doi: [10.1127/0941-2948/2013/0507](https://doi.org/10.1127/0941-2948/2013/0507)
- Araki K, Awaya Y (2021). Analysis and prediction of gap dynamics in a secondary deciduous broadleaf forest of Central Japan using airborne multi-LiDAR observations. *Remote Sensing* 13: 100.
- Arıcak B (2015). Using remote sensing data to predict road fill areas and areas affected by fill erosion with planned forest road construction: a case study in Kastamonu Regional Forest Directorate (Turkey). *Environment Monitoring Assessment* 187 (417): 1-10. - doi: [10.1007/s10661-015-4663-7](https://doi.org/10.1007/s10661-015-4663-7)
- Asner GP, Knapp DE, Broadbent EN, Oliveira PJC, Keller M, Silva JN (2005). Selective logging in the Brazilian Amazon. *Science* 310 (5747): 480-482. - doi: [10.1126/science.1118051](https://doi.org/10.1126/science.1118051)
- Azizi Z, Najafi A, Sadeghian S (2014). Forest road detection using LiDAR data. *Journal of Forestry Research* 25 (4): 975-980. - doi: [10.1007/s11676-014-0544-0](https://doi.org/10.1007/s11676-014-0544-0)
- Blackburn GA, Abd Latif Z, Boyd DS (2014). Forest disturbance and regeneration: a mosaic of discrete gap dynamics and open matrix regimes? *Journal of Vegetation Science* 25: 1341-1354. - doi: [10.1111/jvs.12201](https://doi.org/10.1111/jvs.12201)
- Brokaw NVL (1982). Treefalls: frequency, time, and consequences. In: "The Ecology of a Tropical Forest: Seasonal Rhythms and Long-Term Changes" (Leight EG, JR, Rand AS, Windsor DM eds). Smithsonian Institution Press, Washington, DC, USA, pp. 101-108.
- Brokaw NVL (1985). Gap-phase regeneration in a tropical forest. *Ecology* 66 (3): 682-687. - doi: [10.2307/1940529](https://doi.org/10.2307/1940529)
- Cardona MAQ (2012). Efeitos do manejo florestal na estrutura da avifauna na floresta Amazônica de Paragominas (Pará) [Effects of forest management on the structure of the avifauna in the Amazon forest of Paragominas (Pará)]. PhD thesis, Escola Superior de Agricultura Luiz de Queiroz, Universidade de São Paulo, Piracicaba, SP, Brazil, pp. 108. [in Portuguese]
- Carvalho AL, De Oliveira MVN, Putz FE, Oliveira LC (2017). Natural regeneration of trees in selectively logged forest in western Amazonia. *Forest Ecology and Management* 392: 36-44. - doi: [10.1016/j.foreco.2017.02.049](https://doi.org/10.1016/j.foreco.2017.02.049)
- Chazdon RL (2016). Renascimento de florestas: regeneração da era do desmatamento [Rebirth of forests: regeneration from the era of deforestation]. Oficina de Textos, São Paulo, Brazil, pp. 430. [in Portuguese]
- Costa Filho PP, Da Costa HB (1980). Construção de estradas florestais e transporte florestal rodoviário na região amazônica. Circular Técnica 6 [Construction of forest roads and road forest transport in the Amazon region. Technical Circular 6]. EMBRAPA/CPATU, Belém, PA, Brazil, pp. 30. [in Portuguese]
- Dalagnol R, Philips O, Gloor E, Galvão L, Wagner FH, Locks CJ, Aragão LEOC (2019). Quantifying canopy tree loss and gap recovery in tropical forests under low-intensity logging using VHR satellite imagery and airborne LiDAR. *Remote Sensing* 11 (7): 817. - doi: [10.3390/rs11070817](https://doi.org/10.3390/rs11070817)
- Dalla Corte AP, De Vasconcellos BN, Rex FE, Sanquetta CR, Mohan M, Silva CA, Klauberg C, De Almeida DRA, Zambrano AMA, Trautenmüller JW, Leite RV, Amaral CH, Veras HFP, Rocha KS, Moraes A, Karasinski MA, Sanquetta MNI, Broadbent EN (2022). Applying high-resolution UAV-LiDAR and quantitative structure modeling for estimating tree attributes in a crop-live-stock-forest system. *Land* 11 (4): 507. - doi: [10.3390/land11040507](https://doi.org/10.3390/land11040507)
- Dietmaier A, Mcdermid GJ, Rahman MM, Linke J, Ludwig R (2019). Comparison of LiDAR and digital aerial photogrammetry for characterizing canopy openings in the boreal forest of Northern Alberta. *Remote Sensing* 11 (16): 1919. - doi: [10.3390/rs11161919](https://doi.org/10.3390/rs11161919)
- DNPM (1973). Levantamento de recursos minerais. Folha SA. 23 - São Luís e parte da folha SA. 24 - Fortaleza. Geologia, geomorfologia, solos, vegetação e uso potencial da terra - vol. 3 [Survey of mineral resources. Sheet SA. 23 - São Luís and part of sheet SA. 24 - Fortaleza. Geology, geomorphology, soils, vegetation, and potential land use - vol. 3]. Departamento Nacional de Produção Mineral - DNPM, Ministério de Minas e Energia, Rio de Janeiro, Brazil. [in Portuguese]
- EMBRAPA (2014). Programa internacional reúne cientistas em evento sobre uso de dados LiDAR e inventários florestais [International program brings together scientists at an event on the use of LiDAR data and forest inventories]. Empresa Brasileira de Pesquisa Agropecuária - EMBRAPA, Brasília, Brazil, web site. - [in Portuguese] [online] URL: <http://www.embrapa.br/busca-de-noticias/-/noticia/1671905/programa-internacional-reune-cientistas-em-evento-sobre-uso-de-dados-lidar-e-inventarios-florestais>
- EMBRAPA (2016). Paisagens sustentáveis [Sustainable landscapes]. Empresa Brasileira de Pesquisa Agropecuária - EMBRAPA, Brasília, Brazil, web site. [in Portuguese] [online] URL: <http://www.embrapa.br/busca-de-solucoes-tecnologicas/-/produto-servico/3862/paisagens-sustentaveis>
- Gandolfi S (2007). Sucessão florestal e as florestas brasileiras: Conceitos e problemas [Forest succession and Brazilian forests: Concepts and problems]. In: Proceedings of the "VIII Congresso de Ecologia do Brasil". Caxambu (MG, Brazil) 23-28 Sept 2007. Sociedade de Ecologia do Brasil, Caxambu, MG, Brazil, pp. 2. [in Portuguese] [online] URL: <https://www.sebecologia.org.br/revistas/indexar/anais/viiiceb/palestrantes/Sergius.pdf>
- Gomes JM, Carvalho JOP, Silva MG, Nobre DNV, Taffarel M, Ferreira JER, Santos RNJ (2010). Sobrevivência de espécies arbóreas plantadas em clareiras causadas pela colheita de madeira em uma floresta de terra firme no município de Paragominas na Amazônia brasileira [Survival of seedlings planted in gaps after harvesting in a terra firme rain forest in Paragominas region in the Brazilian Amazon]. *Acta Amazonica* 40 (1): 171-178. - doi: [10.1590/S0044-59672010000100022](https://doi.org/10.1590/S0044-59672010000100022)
- Grigolato S, Pellegrini M, Cavalli R (2013). Temporal analysis of the traffic loads on forest road networks. *iForest - Biogeosciences and Forestry* 6 (4): 255-261. - doi: [10.3832/iforo773-006](https://doi.org/10.3832/iforo773-006)
- Hunter MO, Keller M, Morton D, Cook B, Lefsky M, Ducey M, Saleska S, Oliveira Jr RC, Schiatti J (2015). Structural dynamics of tropical moist forest gaps. *PLoS One* 10 (7): e0132144. - doi: [10.1371/journal.pone.0132144](https://doi.org/10.1371/journal.pone.0132144)
- Jakubowski MK, Guo Q, Kelly M (2013). Tradeoffs between LiDAR pulse density and forest measurement accuracy. *Remote Sensing of Environment* 130: 245-253. - doi: [10.1016/j.rse.2012.11.024](https://doi.org/10.1016/j.rse.2012.11.024)
- Joyce MJ, Erb JD, Sampson BA, Moen RA (2019). Detection of coarse woody debris using airborne light detection and ranging (LiDAR). *Forest Ecology and Management* 433: 678-689. - doi: [10.1016/j.foreco.2018.11.049](https://doi.org/10.1016/j.foreco.2018.11.049)
- Kaartinen H, Hyyppä J, Yu X, Vastaranta M, Hyyppä H, Kukko A, Holopainen M, Heipke C, Hirschmugl M, Morsdorf F, Pitkänen J, Popescu S, Solberg S, Wolf BM, Wu J-C (2012). An international comparison of individual tree detection and extraction using airborne laser scanning. *Remote Sensing* 4 (4): 950-974. - doi: [10.3390/rs4040950](https://doi.org/10.3390/rs4040950)
- Kiss K, Malinen J, Tokola T (2016). Comparison of high and low density airborne LiDAR data for forest road quality assessment. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. III-8, Prague, Czech Republic, pp. 167-172. - doi: [10.5194/isprs-annals-III-8-167-2016](https://doi.org/10.5194/isprs-annals-III-8-167-2016)
- Lima RAF (2005). Gap size measurement: the proposal of a new field method. *Forest Ecology and Management* 214: 413-419. - doi: [10.1016/j.foreco.2005.04.011](https://doi.org/10.1016/j.foreco.2005.04.011)
- Mao X, Hou J (2019). Object-based forest gaps classification using airborne LiDAR data. *Journal of Forest Research* 30: 617-627. - doi: [10.1007/s11676-018-0652-3](https://doi.org/10.1007/s11676-018-0652-3)
- Mao X, Zhu L, Wenyi F (2020). Object-oriented automatic identification of forest gaps using digital orthophoto maps and LiDAR data. *Canadian Journal of Remote Sensing* 46 (2): 177-192. - doi: [10.1080/07038992.2020.1768515](https://doi.org/10.1080/07038992.2020.1768515)
- Marchesan J, Alba E, Schuh MS, Favarin JAS, Pereira RS (2020). Aboveground biomass estimation in a tropical forest with selective logging using random forest and LiDAR data. *Floresta* 50 (4): 1873-1882. - doi: [10.5380/rf.v50](https://doi.org/10.5380/rf.v50)
- Martins SV, Rodrigues RR (2002). Gap-phase regeneration in a semideciduous mesophytic forest, South-eastern Brazil. *Plant Ecology* 163 (1): 51-62. - doi: [10.1023/A:1020395519430](https://doi.org/10.1023/A:1020395519430)
- Martins SV, Júnior RC, Rodrigues RR, Gandolfi S (2004). Colonization of gaps produced by death of bamboo clumps in a semideciduous mesophytic forest in south-eastern Brazil. *Plant Ecology* 172: 121-131. - doi: [10.1023/B:VEGE.0000026030.93687.c4](https://doi.org/10.1023/B:VEGE.0000026030.93687.c4)
- Matinnia B, Parsakhoo A, Mohamadi J, Shataee

- Jouibary S (2017). Monitoring geometric properties of an existing forest road using airborne LiDAR data. *Journal of Forest Science* 63 (11): 490-495. - doi: [10.17221/95/2017-JFS](https://doi.org/10.17221/95/2017-JFS)
- Matinnia B, Parsakhoo A, Mohamadi J, Shataee Jouibary S (2018). Study of the LiDAR accuracy in mapping forest road alignments and estimating the earthwork volume. *Journal of Forest Science* 64 (11): 469-477. - doi: [10.17221/87/2018-JFS](https://doi.org/10.17221/87/2018-JFS)
- McGaughey RJ (2016). FUSION/LDV: software for LIDAR data analysis and visualization. USDA Forest Service, Washington, DC, USA.
- Melendy L, Hagen SC, Sullivan FB, Pearson TRH, Walker SM, Ellis P, Kusiyo Sambodo AK, Roswintarti O, Hanson MA, Klassen AW, Palace MW, Braswell BH, Delgado GM (2018). Automated method for measuring the extent of selective logging damage with airborne LiDAR data. *ISPRS Journal of Photogrammetry and Remote Sensing* 139: 228-240. - doi: [10.1016/j.isprsjprs.2018.02.022](https://doi.org/10.1016/j.isprsjprs.2018.02.022)
- Mello MP, Peternelli LA (2013). Conhecendo o R - Uma visão mais que Estatística [Knowing R - A vision more than Statistics]. UFV, Viçosa, MG, Brazil, pp. 222. [in Portuguese]
- Neto EMC, Rex FE, Veras HFP, Moura MM, Sanquetta CR, Käfer PS, Sanquetta MNI, Zambrano AMA, Broadbent EM, Dalla Corte AP (2021). Using high-density UAV-LiDAR for deriving tree height of *Araucaria angustifolia* in an urban Atlantic rain forest. *Urban Forestry and Urban Greening* 63: 127197. - doi: [10.1016/j.ufug.2021.127197](https://doi.org/10.1016/j.ufug.2021.127197)
- Nobre CA, Sampaio G, Salazar L (2007). Mudanças climáticas e Amazônia [Climate change and the Amazon]. *Ciência e Cultura* 59: 22-27. [in Portuguese]
- Pinage ER, Keller M, Duffy P, Longo M, Dos-Santos MN, Morton DC (2019). Long-term impacts of selective logging on Amazon forest dynamics from multi-temporal airborne LiDAR. *Remote Sensing* 11 (6): 709. - doi: [10.3390/rs11060709](https://doi.org/10.3390/rs11060709)
- Popescu SC, Zhao K, Neuenschwander A, Lin C (2011). Satellite LiDAR vs. small footprint airborne LiDAR: comparing the accuracy of aboveground biomass estimates and forest structure metrics at footprint level. *Remote Sensing of Environment* 115 (11): 2786-2797. - doi: [10.1016/j.rse.2011.01.026](https://doi.org/10.1016/j.rse.2011.01.026)
- Prendes C, Buján S, Ordoñez C, Canga E (2019). Large scale semi-automatic detection of forest roads from low density LiDAR data on steep terrain in Northern Spain. *iForest - Biogeosciences and Forestry* 12: 366-374. - doi: [10.3832/ifor2989-012](https://doi.org/10.3832/ifor2989-012)
- Radambrasil (1983). Levantamento de Recursos Naturais - Folhas SF. 23/24 Rio de Janeiro/Vitória: geologia, geomorfologia, pedologia, vegetação e uso potencial da terra [Survey of Natural Resources - Sheets SF. 23/24 Rio de Janeiro/Vitória: geology, geomorphology, pedology, vegetation, and potential land use]. Ministério de Minas e Energia, Rio de Janeiro, Brazil, pp. 775. [in Portuguese]
- RStudio Team (2020). RStudio: integrated development for R. RStudio, PBC, Boston, MA, USA. [online] URL: <http://www.rstudio.com/>
- Santos MJ, Disney M, Chave J (2018). Detecting human presence and influence on Neotropical forests with remote sensing. *Remote Sensing* 10 (10): 1593. - doi: [10.3390/rs10101593](https://doi.org/10.3390/rs10101593)
- St-Onge B, Vepakomma U (2012). Assessing forest gap dynamics and growth using multi-temporal laser-scanner data. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences* 34 (8-W2): 173-178.
- St-Onge B, Vepakoma U, Senacal JF, Kneeshaw D, Doyon F (2014). Canopy gap detection and analysis with airborne laser scanning. In: "Forestry Applications of Airborne Laser Scanning", vol. 27 (Maltamo M, Næsset E, Vauhkonen J eds). Springer, Dordrecht, Netherlands, pp. 419-437.
- Tabarelli M, Mantovani W (2000). Gap-phase regeneration in a tropical montane forest: the effects of gap structure and bamboo species. *Plant Ecology* 148: 149-155. - doi: [10.1023/A:1009823510688](https://doi.org/10.1023/A:1009823510688)
- Treitz P, Lim K, Woods M, Pitt D, Nesbitt D, Etheridge D (2012). LiDAR sampling density for forest resource inventories in Ontario, Canada. *Remote Sensing* 4 (4): 830-848. - doi: [10.3390/rs4040830](https://doi.org/10.3390/rs4040830)
- Vepakomma U, St-Onge B, Kneeshaw D (2008). Spatially explicit characterization of boreal forest gap dynamics using multi-temporal LiDAR data. *Remote Sensing of Environment* 112: 2326-2340. - doi: [10.1016/j.rse.2007.10.001](https://doi.org/10.1016/j.rse.2007.10.001)
- Yoga S, Bégin J, St-Onge B, Riopel M (2017). Modeling the effect of the spatial pattern of airborne LiDAR returns on the prediction and the uncertainty of timber merchantable volume. *Remote Sensing* 9 (8): 808. - doi: [10.3390/rs9080808](https://doi.org/10.3390/rs9080808)