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ForestGapR: An R Package for Forest Gap Analysis from Canopy Height Models

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Summary

1. In forest ecosystems, many functional processes are governed by local canopy gap dynamics, caused by either natural or anthropogenic factors. Quantifying the size and spatial distribution of canopy gaps enables an improved understanding and predictive modeling of multiple environmental phenomena. For instance, knowledge of canopy gap dynamics can help us elucidate time-integrated effects of tree mortality, regrowth and succession rates, carbon flux patterns, species heterogeneity, and three-dimensional spacing within structurally complex forest ecosystems.
2. Airborne Laser Scanning (ALS) has emerged as a technology that is well-suited for mapping forest canopy gaps in a wide variety of forest ecosystems and across spatial scales. New technological and algorithmic advances, including ALS remote-sensing, coupled with optimized frameworks for data processing and detection of forest canopy gaps, are allowing an enhanced understanding of forest structure and functional processes.
3. This paper introduces *ForestGapR*, a cutting-edge open source R package for forest gap analysis from canopy height models derived from ALS and other remote sensing sources. The *ForestGapR* package offers tools to i) automate forest canopy gap detection, ii) compute a series of gap statistics, including gap-size frequency distributions and spatial distribution, iii) map gap dynamics (when multi-temporal ALS data are available), and iv) convert forest canopy gaps detected into raster or vector layers as per user requirements.
4. As case studies, we run *ForestGapR* on ALS data collected over four different tropical forest regions worldwide. We hope this new package will enable further research towards understanding the distribution, dynamics, and role of canopy gaps not only in tropical forests, but in other forest types elsewhere.

Key-words: ALS, R, Forest Canopy Gaps, Change Detection, Mapping

1. Introduction

Forests cover around 31 percent of global Earth's land area (Keenan et al, 2015). They have a critical role in the global carbon cycle and consist of the most important global repository of terrestrial biodiversity (Pan et al, 2011). In mature and old-growth forests, many forest functional processes are governed by local canopy gap dynamics (Vepakomma et al., 2008). Herein, by forest canopy gaps, we refer to the openings, at a certain height threshold, in forest canopies caused due to natural or anthropogenic disturbances. Furthermore, the concomitant patterns of plant regeneration following gaps are termed as gap dynamics (Asner et al., 2013). Hence, quantifying the size and spatial distribution of forest canopy gaps enables an improved understanding and predictive modeling capability of multiple environmental phenomena. For instance, knowledge of forest canopy gap dynamics can help us elucidate time-integrated effects of tree failure and mortality, regrowth and succession rates, carbon flux patterns, species heterogeneity, and three-dimensional spacing within structurally complex forest ecosystems (Chave 1999; Baker et al., 2005; Cuevas et al., 2003; Dietze et al., 2008; Dupuy, 2008; Asner et al., 2013; Farrior et al., 2016).

Remote sensing data can provide a means for accurate and spatially explicit mapping of canopy gaps and characterization of temporal forest canopy gap dynamics as well as the possibility to assess the effects of forest disturbances on mortality, wood volume, biomass, and carbon storage over time (Stark et al., 2012; Hopkinson et al., 2016; Valbuena et al., 2017). In the past years, remote sensing methods have been found to be highly efficient and useful for assessing forest structural properties at a variety of spatial scales. Among these, Airborne Laser Scanning (ALS), also known as airborne lidar (Light Detection and Ranging) has gained wide popularity due to its ability to extract vertical structural information of forest canopies with high accuracies (Heiskanen et al., 2015). This allows the detection and analysis of forest gap data along a vertical profile using ALS-derived

3D point clouds or canopy height models (CHM) (Figure 1) (Vepakomma et al., 2008; Kellner and Asner, 2009). In addition, multi-temporal ALS data offer unique opportunities to advance our knowledge on the transient nature of forest canopy gaps – through acquisition of detailed and spatially explicit dynamics of canopy gaps – as well, for both intact and disturbed forests (St-Onge and Vepakomma, 2004; Vepakomma et al., 2008).

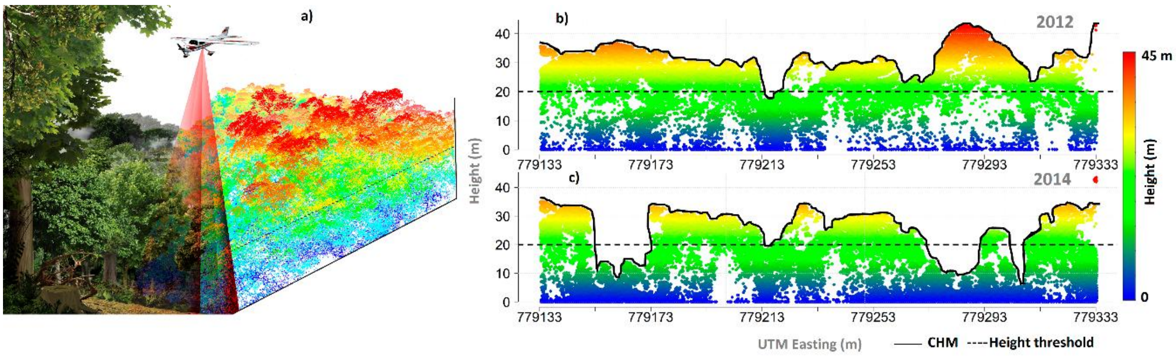

Figure 1. Schematic illustration of ALS data collection (a), profile of heights aboveground from ALS point clouds acquired in 2012 (b) and 2014 (c) at Fazenda Cauaxi, Paragominas Municipality, Pará State-Brazil. The black solid line illustrates an ALS-derived CHM and the black dashed line illustrates a height threshold for forest canopy gap detection.

Even though an in-depth understanding of forest structure is possible via ALS remote sensing, there is a lack of automated tools and standardized protocols, especially open source ones, that can be employed for performing canopy gap detection and associated analyses in a comprehensive manner. Also, the handling and basic processing of 3D point cloud data may be burdensome for scientists and other stakeholders specialized in tropical forest ecology and conservation, who are from outside the domains of programming and data science. For ALS data visualization and processing, some R packages have already been published, such as rLiDAR (Silva et al., 2015) and lidR (Roussel et al., 2019), but none of them have specific functionalities for forest canopy gap detection and their analysis. This limits research exploring the role and influence of forest gaps in large-scale disturbances caused by fire, storm, disease, and pests. Moreover, meaningful insights on the space-filling patterns of forests and climate change-related environmental shifts (such as changes in temperature, precipitation, water availability, carbon sink fluxes, etc.) can also be drawn by studying forest gap dynamics. Therefore, the availability of new open source automated tools for canopy gap detection and analysis is deemed necessary. This has the potential to further provide a quantitative basis to studies that have evidenced an increased tropical forest turnover over recent decades (Phillips et al., 2004). Herein, increased forest turnover implies a decrease in the meantime a stem, or a unit of basal area, or a unit of biomass, remains within a forest (Greenberg and Lewis, 2013).

The primary objective of this paper is to introduce *ForestGapR*, a cutting-edge open source R package for forest canopy gap analysis. *ForestGapR* provides the ecological community with a suite of tools for performing advanced spatial analysis operations. In particular, we offer capabilities to automate canopy gap detection, define gap size-frequency distributions (White et al., 2008; Farrior et al., 2016) and spatial patterns (Law et al., 2009), map gap dynamics (if multi-temporal lidar data is available) and to convert forest canopy gaps into raster or vector spatial formats. *ForestGapR* will consequently leverage the potential of CHM data to study forest structural and functional attributes and associated global phenomena.

2. Package Design and characteristics

ForestGapR package is developed with the aim of providing an open source and automated tool for forest canopy gap analysis in tropical forest. Herein, we chose R as the platform for the development (R Core Team, 2018), including a suite of selected tools integrated into a standard workflow for deriving ALS datasets into outputs meaningful to forest gap analysis. The version 0.0.2 of the *ForestGapR* package has been recently added to the CRAN (Silva et al., 2019) and it comprises six functions for forest canopy gap detection and analysis (Table 1). Fig. 2 shows the standard workflow to follow in order to yield the products and analyses included in the package. *ForestGapR* allows users to adjust the height threshold and the range of areas that would constitute a forest gap, which thus may be tailored to the relevant ecological questions addressed by each user. As of version 0.0.2 (Silva et al., 2019), the suite of functions yields three products and three types of analyses (Fig. 2). After the forest gaps are detected, they can be extracted as either a raster layer using *getForestGaps()*, or a vector layer of gap polygons using *GapSPDF()*. Additionally, *GapChangeDec()* yields a raster of differences between two datasets acquired at different times. The three analyses we deemed more useful for forest ecology are summary statistics of the gaps detected (*GapStats()*), second order statistics for analyzing their spatial pattern (*GapsSpatPattern()*), and the estimation of a power-law exponent from their size-frequency distributions (*GapSizeFDist()*), see Table 1 for more information. The reader may refer to details in the supplementary material included along with this article and the specifications and examples included in *ForestGapR* package help manual (Silva et al., 2019).

Table 1. List of functions included in *ForestGapR* package, and their characteristics

Function	Functionality	Input	Output	Examples	References
getForestGaps	Detects forest canopy gaps	ALS canopy height model (CHM) as a *RasterLayer* object (CHM-derived from other remote sensing sources can also be used)	Binary *RasterLayer* object of forest canopy gaps	Figs. 3 and 6	Stark et al. (2012); Asner et al. (2013)
GapStats	Summary statistics of forest canopy gaps. E.g.: area of gap (m2), maximum canopy height (m), minimum canopy height (m), mean canopy height (m), standard deviation of canopy height (m), Gini coefficient of canopy height (%) and range of canopy height (m)	Binary *RasterLayer* object of forest canopy gaps	*Dataframe* of forest canopy gap statistics	Fig. 4a and Table 2	Heiskanen et al. (2015); Hunter et al. (2015)
GapSizeFDist	Frequency distribution analysis of forest canopy gaps	*Dataframe* of forest canopy gap statistics	Maximum likelihood fit to a Zeta distribution and compute λ. E.g.: $\lambda \leq 2$ indicate forest dominated	Figs. 4b-c	White et al. (2008); Asner et al. (2013); Farrior et al. (2016)

			by smaller gaps and intense disturbance events while $\lambda > 2$ indicates smaller gaps and less intense disturbance events		
GapChangeDec	Multitemporal comparisons of forest canopy gaps	Binary *RasterLayer* objects of forest canopy gaps	Binary *RasterLayer* object of multitemporal differences	Fig. 6	Asner et al. (2004); Silva et al. (2017)
GapSPDF	Creates spatial objects of the forest canopy gaps	Binary *RasterLayer* object of forest canopy gaps	*SpatialPolygon* objects of forest canopy gaps	Fig. 3	Pebesma (2018)
GapsSpatPattern	Spatial pattern analysis of forest canopy gaps	*SpatialPolygon* objects of detected forest canopy gaps	Ripley's K and L functions and Clark-Evans index	Fig. 4d	Law et al. (2009)

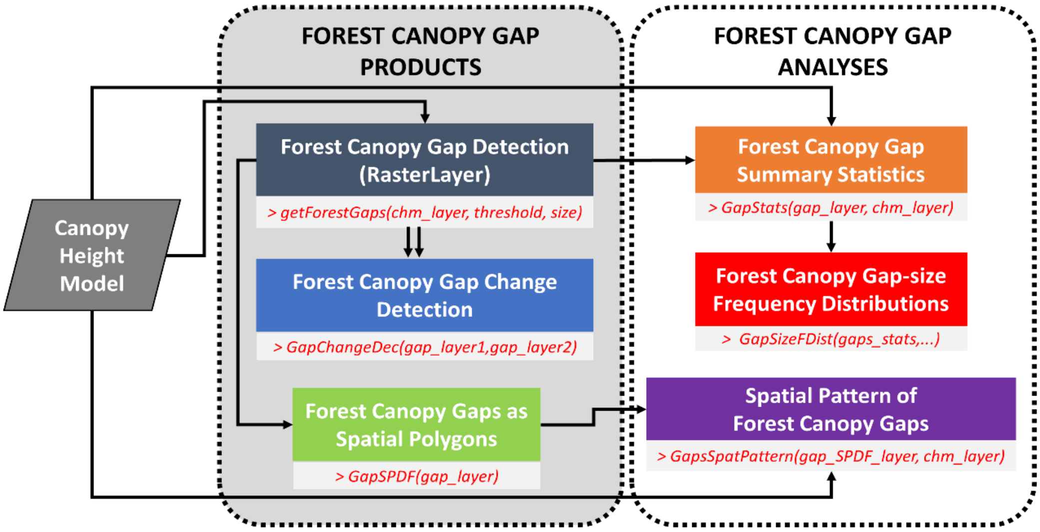

Figure 2. Flowchart of forest canopy gaps detection and subsequent analyses using *ForestGapR* package.

3. Example Applications

The main functionality of the package is to detect forest canopy gaps using CHMs derived from ALS or other remote sensing sources, and to generate gap statistics relevant to forest ecologists. The following two examples of applications illustrate the capabilities of the *ForestGapR* package for characterizing forest canopy gap structure in tropical forests across continents and their changes along timelines.

3.1 Characterization of Tropical Forest Canopy Gaps

The aim of this example is to show the capability of *ForestGapR* for detecting and analyzing forest canopy gaps across tropical forests located in different regions and continents. The ALS-data used in this example were collected at: i) Adolfo Ducke Forest Reserve (Sustainable Landscape Brazil, 2018) in the Brazilian Amazon forest; ii) La Selva Biological Station (TEAM Network, 2011) in the Costa Rican tropical forest; iii) Pasoh Forest Reserve in the Malaysian tropical forest (Wan-Mohd-Jaafar et al. 2017) and iv) Robson Creek Rainforest Supersite (TERN Auscover, 2012) in the Australian tropical forest. The canopy height distribution for each site is provided in Figure 3, and specifications of ALS data acquisition for each site are detailed in Table S1.

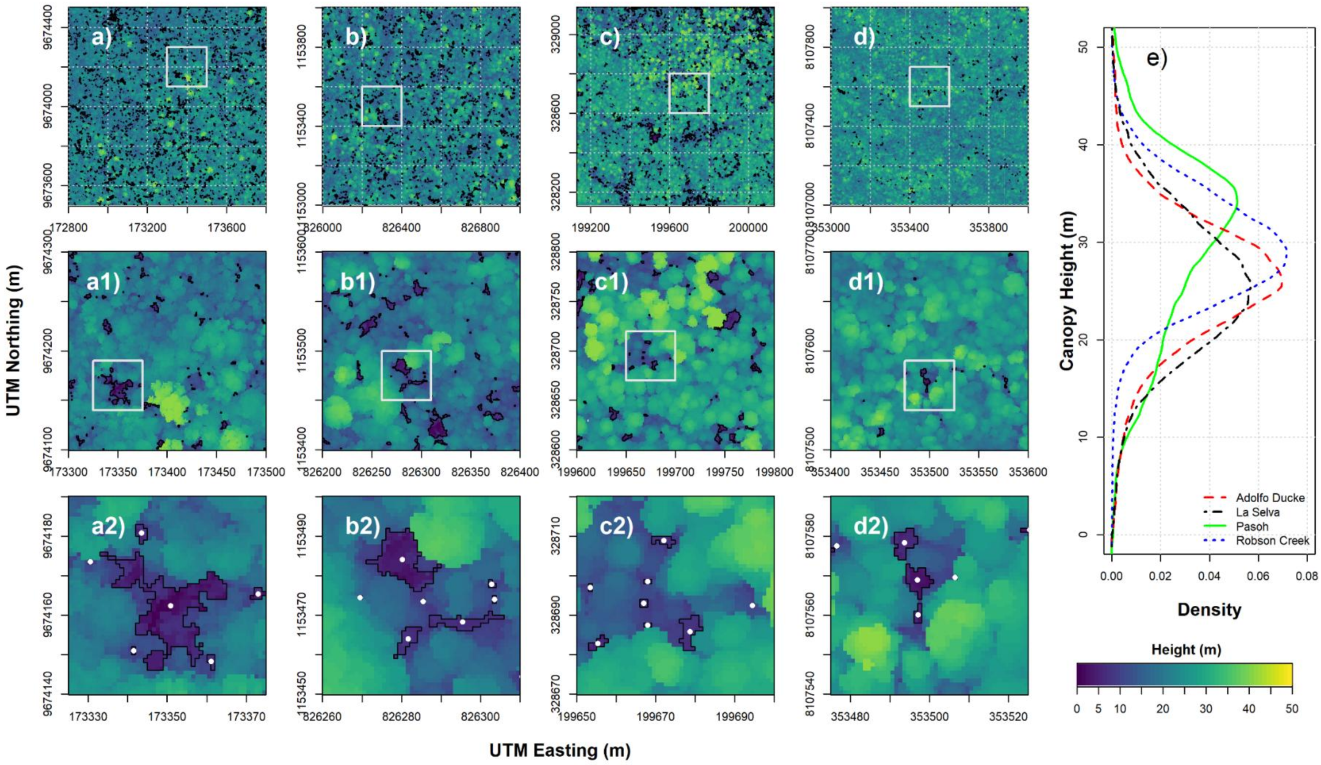

Figure 3. ALS-derived canopy height model (CHM; 1m grid cell) and canopy forest gaps (black polygons) detected at 10m for Adolfo Duke Forest Reserve (a); La Selva Biological Station (b); Pasoh Forest Reserve c) and Robson Creek Rainforest Supersite (d). Upper

plots represent an area of 100ha (a-d) while middle plots represent an area of 0.25ha inset (a1-d1), and lower plot enhance the 0.0625ha inset (a2-d2). Height distribution for all the example sites (a-d) (e). The white dots (a2-d2) represent the centroids of the forest canopy gaps detected.

Our goal is to highlight how *ForestGapR* can be employed to study differences and similarities in forest canopy gap distribution among these tropical forest ecosystems in various geographic locations. In this application we focus on the size-frequency and spatial pattern analyses available in *ForestGapR*. For the detection of canopy gaps, we used a height threshold of 10 m and minimum area of 1 m^2 (e.g. Hunter et al. 2015). The λ parameter from the zeta distribution of canopy gaps represents the magnitude of forest disturbance and canopy gaps sizes. For instance, large values of λ (≥2.0) would suggest a forest dominated by smaller gaps and with less intense disturbance events (White et al., 2008; Asner et al., 2013) while small λ -values (<2.0) would indicate the prevalence of larger canopy gaps associated with mortality of large canopy or emergent trees or alterations to whole stands (Asner et al., 2013). On the other hand, *ForestGapR* via *GapsSpatPattern()* function also shows the value of the Clark and Evans (1954) index *R*, which can be used to determine whether the spatial pattern of forest canopy gaps is clustered ($R < 1$), random ($R \cong 1$) or uniform ($R < 1$) (Law et al., 2009). Thus, differences and similarities in the power-law exponent λ and *R* index provide insights into how disturbance regimes may differ among our study locations. In particular, Asner et al. (2013) highlighted the similarity in their derived λ values across the Peruvian Amazon, which they interpreted as an indication of occurrences of similar disturbance mechanisms and dynamics across this region. Although topographic and edaphic differences do exist across our study areas, we were interested in testing *ForestGapR* at tropical forests located in geographically distinct regions.

Figure 3 illustrates some of the differences in both gap size and spatial distribution and clumpiness found across our sites. The λ value varied from a low of 1.515 for La Selva, to a high of 1.654 for Adolfo Duke (Figure 4b). Despite these differences in λ, the vertical distribution of λ-values in the forest canopies was similarly shaped across forest types (Figure 4b). This range is similar to those found by Asner et al. (2013) in the Peruvian Amazon, although slightly less than their mean calculated λ value of 1.83. The study of second order statistics of spatial patterns of the gaps detected may also shed some light on the causes for these differences. Second order properties of gap spatial patterns concern their interactions: does the presence of a forest gap attract or inhibit the formation of a new gap in the vicinity? Ripley's L function (Figure 4d) determined a clustered spatial pattern in canopy gaps shown for all these old-growth tropical forests (see white dots in Figure 3). However, the level of aggregation was different, with *R* indices ranging from 0.74 to 0.83. Further investigation is merited using this new toolset to compare tropical forest across bioclimatic and anthropogenic disturbance gradients, and for geographically distinct areas.

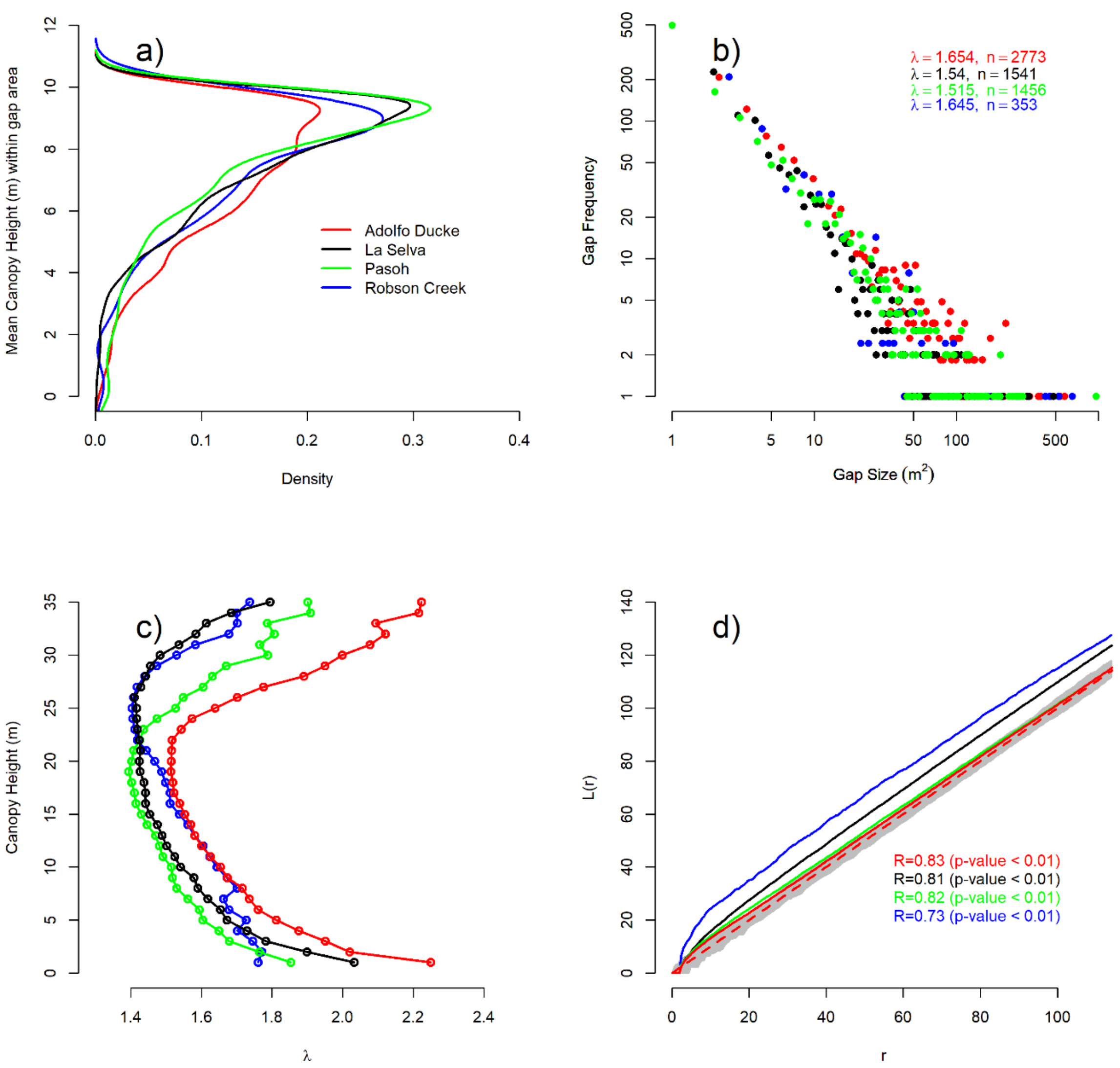

Figure 4. Distribution of mean canopy height within gaps (a); size frequency distribution of forest canopy gaps (b); vertical distribution of power-law exponents (λ) (c); and Ripley's L function and Clark-Evans index R (d) for Adolfo Duke Forest Reserve (red line), La Selva Biological Station (black line), Pasoh Forest Reserve (green line) and Robson Creek Forest (blue line) sites.

3.2 Dynamics of Forest Canopy Gaps in a Selectively Logged Tropical Forest

This case study was conducted at Fazenda Cauaxi, a private property in Paragominas Municipality, Pará State, in Eastern Amazon, Brazil. Demonstrations of RIL techniques have been conducted at this site since 1995, which led to an extensive set of studies including both field inventory and remote sensing approaches (Asner et al., 2004). These studies have highlighted the ecological and economical advantages of RIL compared to conventional logging. The chronosequence of Reduced Impact Logging (RIL) sites and time-series of ALS data at Fazenda Cauaxi make this site ideal for investigation of gap dynamics following selective logging.

Three ALS datasets were acquired at Fazenda Cauaxi (dos-Santos and Keller, 2016), covering approximately 1,200 ha of logged forests (from 2006 to 2013) and intact forests (specifications in Table S2). At this case study, we used a 100 ha subset of forests logged in 2012 and a 100 ha subset of intact forests. For the gaps and gap changes detection, we used a height threshold of 10 m and minimum gap area of 10 m^2, consistent with the dynamic gap definition for tropical forests from Hunter et al. (2015). By using ALS data and spatially explicit information about the logging history, we were able to compare gap dynamics of intact and selectively logged forests over five years (Figure 5).

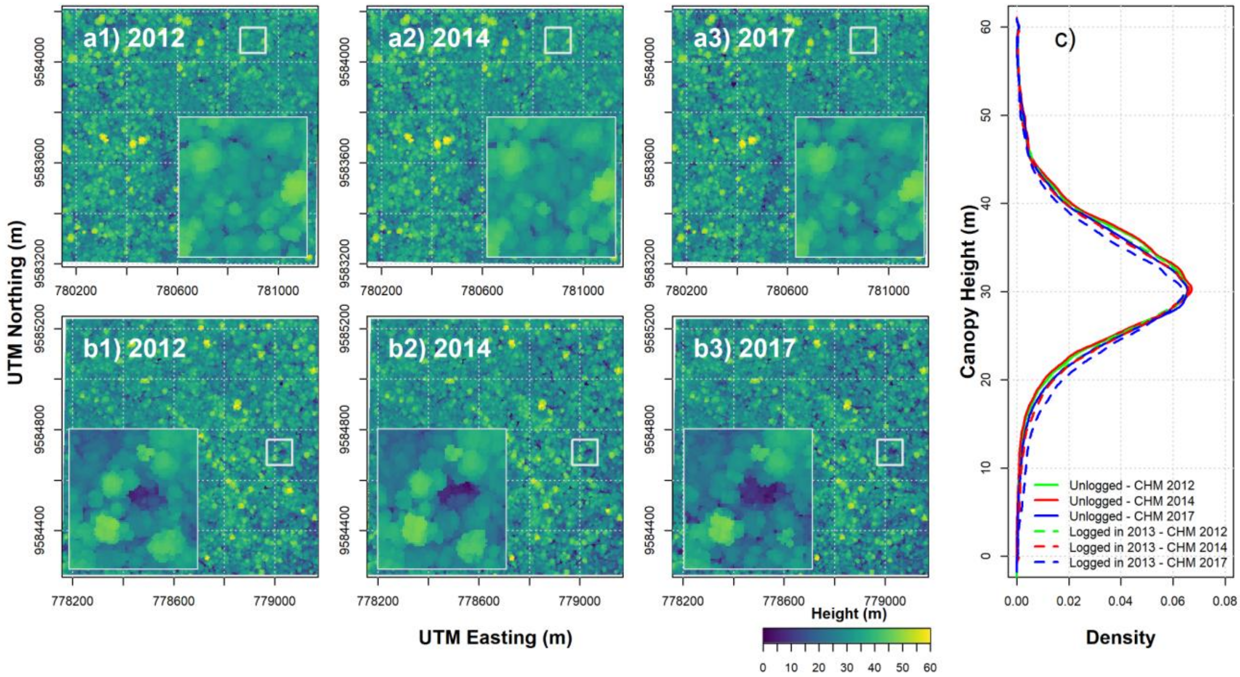

Figure 5. ALS-derived 2012, 2014 and 2017 CHMs (a1-a3;b1-b3) and canopy height distribution (c) across unlogged (a1-a3) and logged (b1-b3) areas. Subsets of the CHMs are enhanced from the insets outlined in gray.

When logging activities are conducted under RIL management practices they cause minor impacts in the forest canopy, because only a few canopy trees are removed at each harvesting cycle (Sist, 2000). In unlogged areas at Fazenda Cauaxi, only 0.34-0.6% of the total area had natural gaps, while in the logged area, the gap percentage changed from 0.56% before logging to 0.98% after logging. However, an important aspect emerged from the forest canopy gap detection: the significant gap frequency increase in both logging conditions in the 2017 ALS coverage (Table 2). Despite the different data acquisitions intervals (2.5 years between first and second, and 3 years between second and third), the amount of gaps more than doubled in 2017 acquisition at the unlogged forests, and had an increase of approximately 65% in the logged forests when the 2014 and 2017 gap detection are compared (Table 2, Fig. 6). It is important to mention that the increase in gap area percentage in 2014 compared to 2012 was due to logging activities, while no logging activities were conducted in the second acquisition interval. A plausible explanation for the observed results is the 2015/2016 El Niño event (Malhi et al., 2018). El Niño events cause extremely dry periods in Amazon region, which can lead to increased mortality rates, reported by Leitold et al. (2018).

The low values of Gini coefficient obtained (Gini coefficient ranges from 0 to 1; Table 2) is an additional indication that logging activities have not caused major disturbances in the light environment of the forest ecosystem (Valbuena et al., 2017). The canopy height distributions show median canopy heights at around 30 m (Figure 5), and similar height distribution patterns for logged and unlogged forests (Table 2). However, a slight shift in the entire distribution towards lower canopy heights is observed in logged stands (dashed lines in Fig. 5c).

Table 2. Forest canopy gap statistics at Fazenda Cauaxi across years 2012, 2014 and 2017 for an unlogged and a logged work units of 100ha each.

Year	**Unlogged**				**Logged in 2013**			
	number of gaps	**Gap area (mean ± sd)**	**% of total area with gaps**	**Gini Coefficient (mean ± sd)**	**number of gaps**	**Gap area (mean ± sd)**	**% of total area with gaps**	**Gini Coefficient (mean ± sd)**
2012	102	33.49 ± 29.50	0.34	0.11 ± 0.06	140	39.82 ± 42.84	0.55	0.15 ± 0.1
2014	81	33.38 ± 29.49	0.27	0.11 ± 0.06	217	45.26 ± 49.07	0.98	0.19 ± 0.17
2017	163	36.73 ± 42.99	0.60	0.17 ± 0.15	329	46.51 ± 53.76	1.53	0.14 ± 0.17

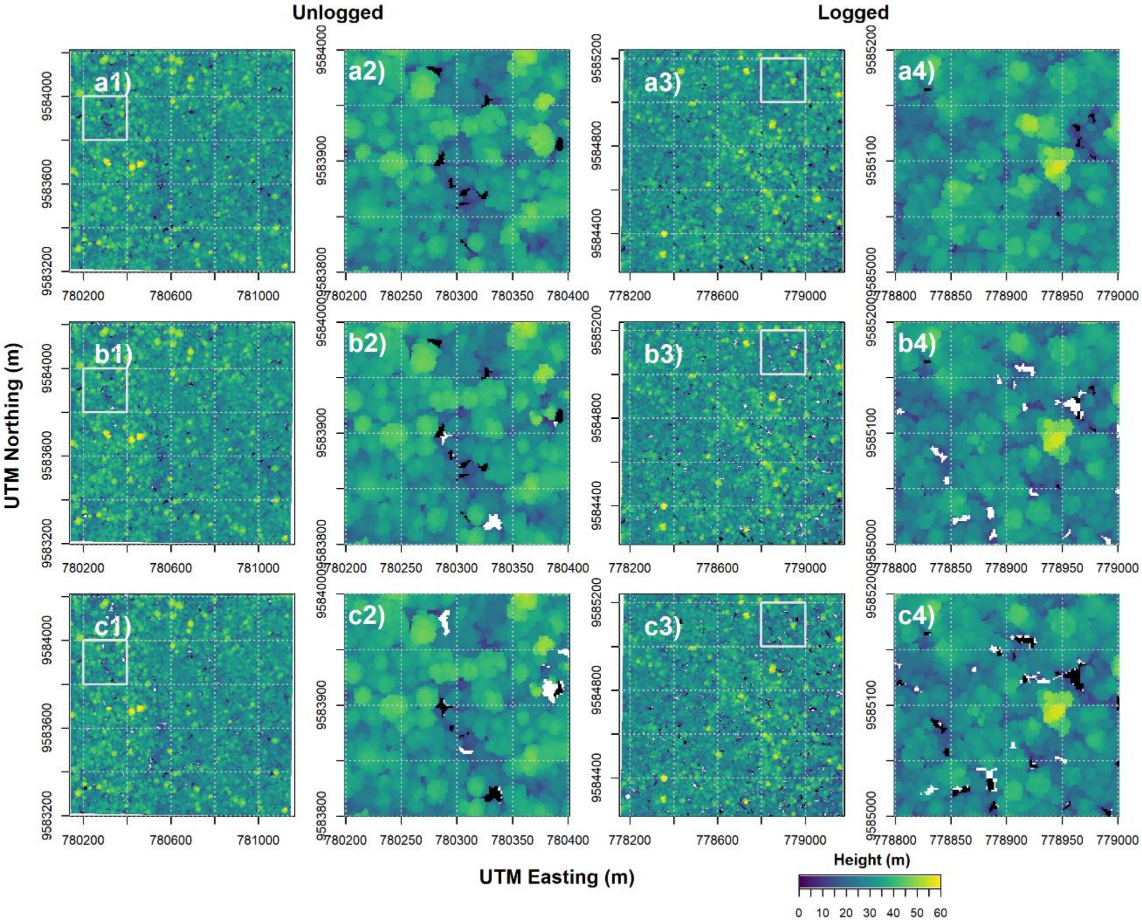

Figure 6. Forest canopy gaps and changes in 2012 (a1-4), 2014 (b1-4) and 2017 (c1-4). Canopy gaps for the corresponding year are shown in black, and the gap increment related to previous ALS coverage is shown in white. Second and fourth columns are enhanced from the insets outlined in gray in first and third columns.

4. **Final considerations**

This paper gives an overview of the design and usage of the *ForestGapR* package for tropical forest canopy gap detection and analyses in an automated and efficient manner in R. We developed *ForestGapR* package with the intention to simplify the processing of ALS datasets for tropical forest gaps analysis and make it more accessible to tropical ecologists. The package provides six functions which were described and exemplified by using ALS datasets collected at a variety of tropical forest regions. *ForestGapR* offers the possibility for the users to interactively define height and area thresholds for gap detection. This is a helpful feature because different height thresholds may apply to different ecological questions and structural characteristics of the forest environments under investigation. The applicability for change detection using multitemporal ALS datasets was also integrated into a simple workflow. Another functionality not available elsewhere is the possibility to convert the results into a *SpatialPolygonDataFrame* object, allowing the user to export the forest canopy gaps detected as spatial polygon objects (e.g. an ESRI shapefile). This capability provides enormous potential in deriving many other additional forest canopy gap statistics related to the shape of canopy gaps, e.g. for detecting roads and other features, which can become important for enhancing forest structure and function characterization. Continual improvements to the package (CRAN version 0.0.2) which incorporate new developments in spatial R packages will improve the limitation in converting forest canopy gap from *RasterLayer* objects to *SpatialPolygonDataFrame* objects when processing CHM at large spatial scales. In turn, we benefit from the open source nature of R packages and thus, we are open to further suggestions on enhanced capabilities that ecologists may find useful to add to next package versions. For this reason, we made *ForestGapR* v0.0.2 available under the GPL license and open to suggestions through the GitHub repository (https://github.com/carlos-alberto-silva/ForestGapR), which includes instructions on how to contribute, discuss any issues found in the package, suggest improvements, or report bugs. Although the focus of this manuscript has been in tropical forests, ForestGapR is designed to work in any type of forest, and we hope that the promising framework for forest canopy gap analysis in this study will stimulate further research and applications not just in tropical forest, but in other forest types elsewhere. The source code used in the case studies will be made available upon acceptance of the manuscript on GitHub repository (https://github.com/carlos-alberto-silva/ForestGapR_mee).

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Authors' contributions

All the authors have made a substantial contribution towards the successful completion of the package and manuscript. They all have been involved in designing the package, drafting the manuscript and engaging in critical discussion. C.A.S and R.V. coded the package. E.R.P., R.V., M.M, D.R.A.A, E.N.B., W.S.W.M.J., D.A.P., A.C and C.K. assisted with coding the functions and contributed to the interpretation, quality control and revisions of the package and manuscript.

Data Accessibility

The source code of the ForestGapR package is accessible via GitHub(https://github.com/carlos-alberto-silva/ForestGapR) and Zenodo (http://doi.org/10.5281/zenodo.2817952). Also, it can be downloaded from the Comprehensive R Archive Network at https://cran.r-project.org/web/packages/ForestGapR/index.html

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