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Monitoring the structure of forest restoration plantations with a drone-lidar system

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ABSTRACT

We are in an unprecedented moment for promoting forest restoration globally, with international and regional pledges to restore at least 350 million hectares by 2030. To achieve these ambitious goals, it is necessary to go beyond traditional plot-scale assessments and develop cost-effective technologies that can monitor the structure and function of restored forests at much broader scales. Lidar remote sensing in unmanned aerial vehicle (UAV) platforms can be an agile and autonomous method for monitoring forest restoration projects, especially under conditions when information updates are frequently needed in relatively small areas or, when using an airplane-borne lidar system may be not financially viable. Here, we explored the potential of an UAV-borne lidar system to assess the outcomes of a mixed-species restoration plantation experiment, designed to maximize aboveground biomass (AGB) accumulation. The experiment was established in Brazil's Atlantic Forest, with 20 native tree species, by combining two levels of planting density and two management levels, totaling four treatment combinations and one control (plots left over for natural regeneration). We analyzed three structural variables from lidar data (canopy height, gap fraction and leaf area index) and one from field inventory data (AGB). Structural differences between the treatments and the control plots were reliably distinguished by the UAV-borne lidar system. AGB was strongly correlated with canopy height, allowing us to elaborate a predictive equation to use the UAV-borne lidar system for monitoring structural features in other restoration plantations in the region. UAV-borne lidar systems showed enormous potential for monitoring relatively broad-scale (thousands of hectares) forest restoration projects, providing an important tool to aid decision making and accountability in forest landscape restoration.

1. Introduction

We are in an unprecedented moment for promoting forest landscape restoration (FLR) globally, with international (see Bonn Challenge, 2018) and regional (see World Resources Institute, 2018) restoration pledges to restore at least 350 million hectares of degraded and deforested lands by 2030 (Suding et al., 2015). Achieving these pledges can bring diverse benefits to society, such as biodiversity conservation, climate change mitigation and adaptation, watershed protection, soil recovery, and recreation (Chazdon et al., 2017). Although FLR has been promoted as a multipurpose activity, its accountability is still limited to the simplistic quantification of how much land has been restored or how many trees have been planted. It is timely and important to develop cost-effective innovations to monitor restoration outcomes at large spatial scales, going beyond simple quantification of forest areas, and providing more detailed information about of forest structural

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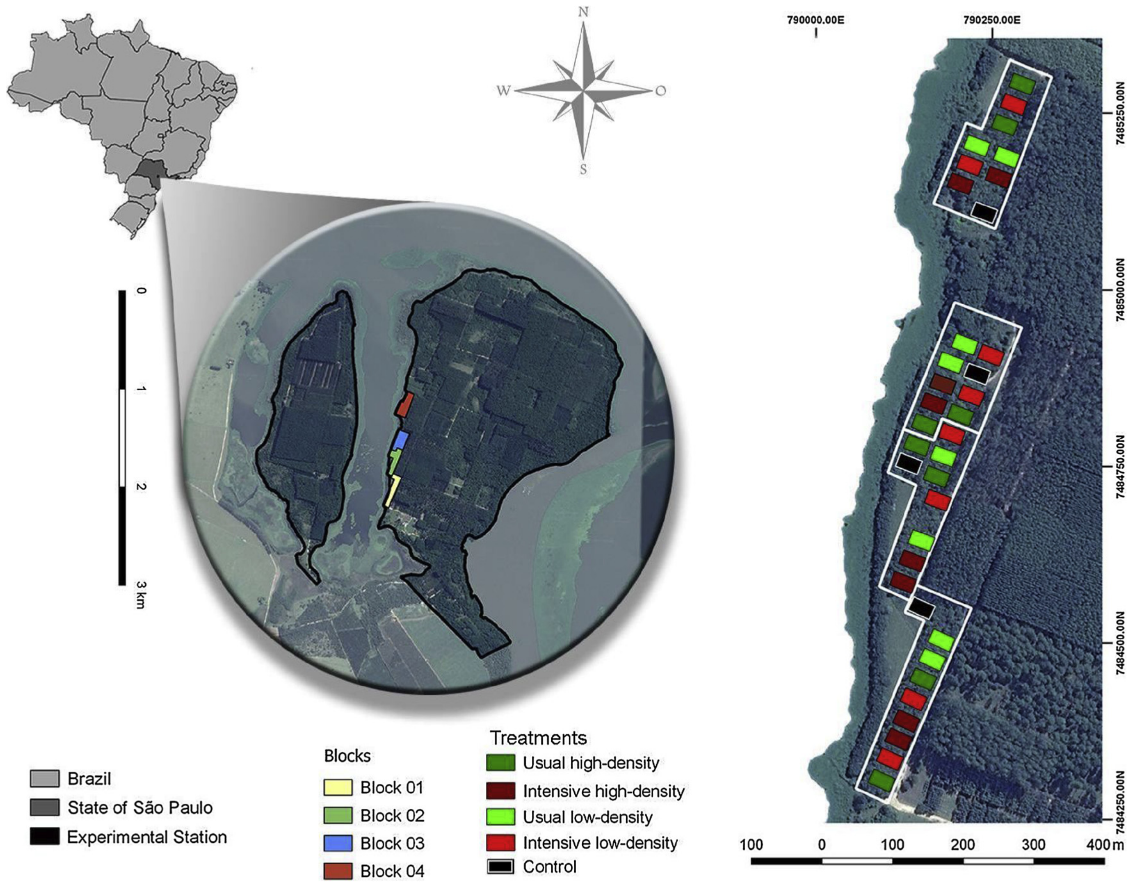

Fig. 1. The blocks and plots where the restoration experiments were established. Different silvicultural management intensities were carried out, aiming a maximizing aboveground biomass accumulation.

attributes (Brancalion and Chazdon, 2017). Moreover, it is critical to assess the outcomes of different restoration approaches in order to disseminate best-practices and promote cost-efficient silvicultural solutions to overcome the ecological barriers for forest development in degraded sites (Holl, 2017; Brancalion and van Melis, 2017).

The restoration strategy used to restore a degraded site depends on its past land-use history and levels of degradation and resilience (Holl and Aide, 2011). In sites with lower degradation levels and, therefore, higher resilience, the most cost-effective restoration strategy is usually to promote natural regeneration by isolating the site from disturbances (Chazdon and Guariguata, 2016). In sites with intermediate degradation level, natural regeneration may have to be assisted, for instance through the control of lianas and ruderal plants, and enrichment planting (Brancalion et al., 2016). Finally, more degraded and less resilient sites may require more intensive interventions (i.e., active restoration), usually a combination of soil preparation and fertilization, weed control, and tree seedling plantation or direct seeding to reforest the entire area with desired tree species (Molin et al., 2018). In active restoration, planting density, soil fertilization and weed control intensity may play a key role in the success and viability of forest restoration strategies (Campoe et al., 2010; Brancalion et al., 2019). These decisions are critically important given the limited resources available for restoration and the challenge of reestablishing tropical forests in highly degraded sites (Rodrigues et al., 2011; Shoo et al., 2016).

In this context, frequent monitoring of restoration outcomes and processes is crucial to support the development of novel and more effective restoration strategies and for adaptive management. Usually, forest restoration outcomes are monitored through field inventories evaluating forest structure parameters, such as canopy openness, tree diameter and height (which also allow biomass and carbon stock estimates), and diversity parameters (Ruiz-Jaen and Aide, 2005; Wortley et al., 2013; Viani et al., 2017). Aboveground biomass (AGB), in particular, is a critical variable measured in restoration projects as it represents one of the most important restoration outcomes targeted in tropical forest regions (i.e., climate change mitigation potential) (Locatelli et al., 2015; Griscom et al., 2017), and is an excellent proxy for many other indicators associated with tropical forest successional development (Chazdon, 2014; Lennox et al., 2018). In restoration plantations, canopy openness is another key ecological indicator, which is associated with the suppression of ruderal grasses and understory recolonization by shade-tolerant and late-successional species, essential for tropical forest development (Viani et al., 2017).

Monitoring forest structure through field inventories at large spatial scales is, however, economically and operationally limited. Current active remote sensing technologies such as lidar (Light Detection and Ranging) have the potential to describe the three-dimensional forest structure, allowing the estimation of AGB and canopy openness for large areas (Longo et al., 2016; Leitold et al., 2018). Airplane-borne lidar systems have been increasingly used in forested areas (van Leeuwen and Nieuwenhuis, 2010), ensuring the coverage of a large area in a single flight (e.g. over 1,000 ha). However, their costs are high, as surveying depends on companies that own airplanes to carry out data collection. Thus, Unmanned Aerial Vehicles (UAV, a.k.a. drones) platforms represent a low-cost, agile, and autonomous opportunity for collection of spatially-continuous data in areas not so large as to financially justify data acquisition with airplane-borne systems. At present, the use of UAVs for natural resource management is increasing (Shahbazi et al., 2014). UAVs have become capable of carrying light lidar systems in autonomous flight only since recently (Sankey et al., 2017; GatorEye, 2018). For this reason, little is known about the potential use of these new systems in the context of forest restoration projects and their efficiency in monitoring forest structure parameters in mixed-species plantations.

Here, we explored the potential of an UAV-borne lidar system to assess the outcomes of a mixed-species restoration plantation experiment, designed to maximize AGB accumulation. We used the UAV-borne lidar system to quantify forest structure variables that are difficult to measure in traditional forest inventories (e.g., gap fraction, mean canopy height, leaf area index and leaf area density), and associated these variables with AGB stocks measured in the field, to assess the reliability of using lidar to monitor forest AGB in restoration plantations. In addition to comparing the development of forest structure in different silvicultural treatments, we aimed to test the usefulness of an UAV-borne lidar system for spatially-continuous monitoring forest landscape restoration, beyond traditional sampling plot-based measurements, while avoiding expensive airborne systems.

2. Material and methods

2.1. Study area and experimental design

The study was conducted at the Anhembi Experimental Station of Forest Sciences of the Luiz de Queiroz College of Agriculture, University of São Paulo (ESALQ/USP), located in southeastern Brazil (22° 43′S, 48° 11′W, 455 m above sea level and slope < 5%) (Fig. 1). The climate is dry in the winter and humid in the summer, with average annual precipitation of 1300 mm (average of 48 mm per month in the dry period, between April and September). The average annual temperature is 20.6 °C, with averages of 16.8 °C in July and 23.5 °C in February.

In March 2004, a 2^3 factorial design experiment was established based on the following treatments and levels: (i) pioneer/non-pioneer species proportion (50:50 and 67:33), (ii) planting density (low: 1,667; high: 3,333 trees ha^{-1}), and (iii) silvicultural management intensity (usual: mechanical mowing and moderate levels of fertilization; intensive: herbicide spraying and high levels of fertilization); see Campoe et al. (2010) and Brancalion et al. (2019) for more details. We also included four control plots, fenced for livestock exclusion and without any tree planting or management activity. Since previous studies have not found a significant effect of the proportion of pioneers on AGB accumulation (Brancalion et al., 2019), we did not consider this factor. By doing so, the experiment was assessed based on two factors (*i.e.*, planting density and management intensity) (Fig. 2) with eight replicates each, and four replicates for control plots. The experiment was established with 20 native tree species in 42 × 30 m (1,260 m^2) plots (Fig. 1), in an area previously occupied by a pasture of the African fodder grass *Urochloa decumbens* (Stapf) R.D. Webster, the most important weed species in the region (Brancalion et al., 2016).

2.2. Data collection

In 2016, twelve years after planting, we measured tree height and diameter (0.3 m aboveground) for all trees within the effective area of each plot (36 × 22 m, 792 m^2), excluding border lines to avoid edge effects. The AGB was estimated based on an allometric equation developed in the same study area (Ferez et al., 2015). The AGB equation considered as predictor the diameter (0.3 m above the ground), tree height and wood density (obtained at the time of tree harvesting for the development of the equation). In 2018, we collected lidar data using an UAV platform (GatorEye Unmanned Flying Laboratory; Fig. 3) with a flying height of 60 m above the ground at a speed of 10 m s^{-1}, and an approximate horizontal distance between adjacent flight lines of 50 m, producing a lidar point cloud density of 190 returns m^{-2}.

The GatorEye system (www.gatoreye.org) includes a vertical takeoff and landing DJI Matrice 600 Pro hexacopter, with 16–22 minutes flight autonomy for smaller areas with five sets of batteries for multiple flights per day, and a 5 km telemetry/control range. The Phoenix LiDAR system sensor suite consists of a Velodyne VLP-16 dual-return laser scanner head, capable of 600,000 returns per second, with live and post-processing software. The GNSS work with ± 2.5 cm precision using a L1/L2 dual-frequency receiver and a tactical grade STIM 300 inertial measurement unit. The georeferenced data was post-processed relative to a local base station (X900S-OPUS), using Novatel Inertial Explorer software. The location of the base station itself was determined using the online Trimble CenterPoint RTX post-processing platform for more than 8 h of combined location data collected over 2 days.

2.3. Data processing and analysis

Lidar data processing and analysis were performed in the R environment (R Core Team, 2017), using the software LAStools (Isenburg, 2018). From the raw 3D lidar point cloud, we classify the ground returns and generate the digital terrain model (DTM) with 0.5 m

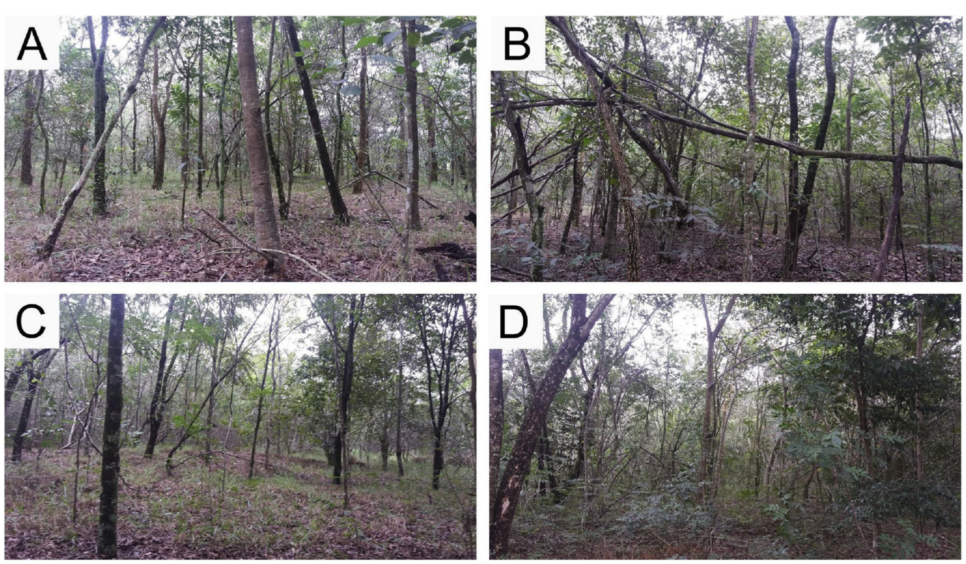

Fig. 2. Restoration plantation treatment combinations: A) Usual and high-density; B) Intensive and high-density; C) Usual and low-density; and D) Intensive and low-density.

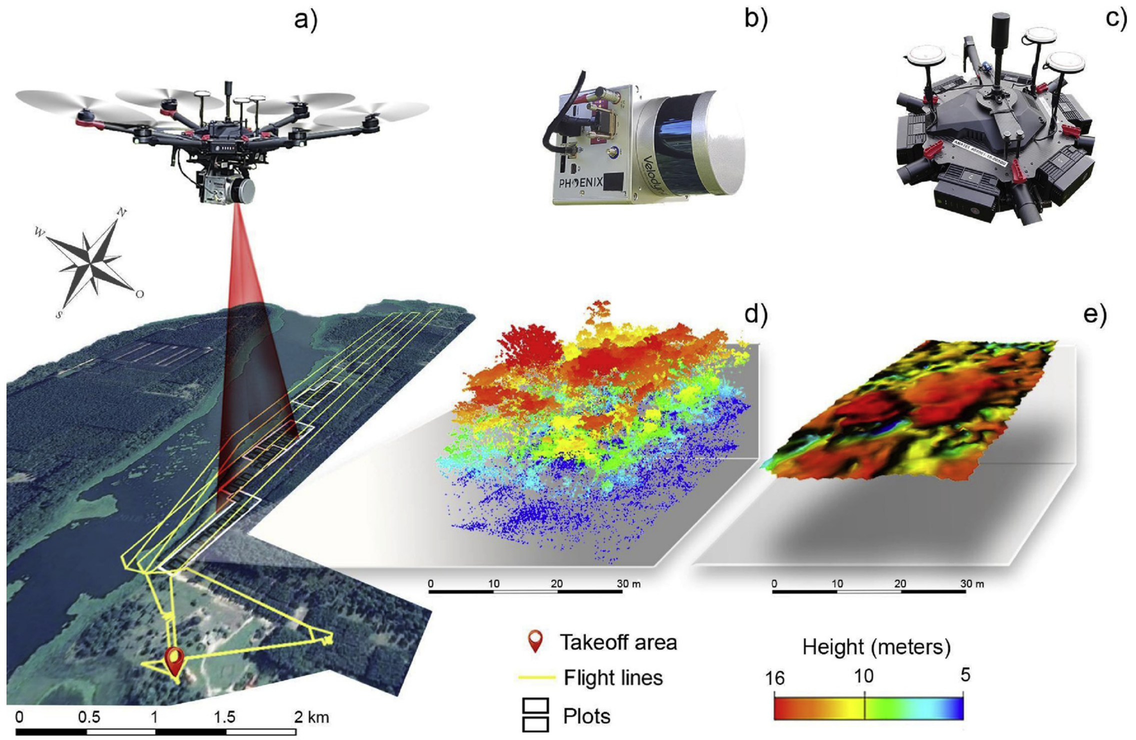

Fig. 3. GatorEye system and data: (a) illustration of the unmanned aerial vehicle flying over the experimental sites; (b) lidar-hardware system; (c) GNSS system; (d) cloud lidar data of one plot (treatment low-density intensive); (e) canopy height model of the plot.

resolution. Then, also from the raw lidar cloud, we applied a spurious-return filter and generated the raster digital surface model (DSM) with 0.5 m resolution. Finally, based on DTM, we generated the normalized lidar point cloud and the canopy height model (CHM) with a 0.5 m resolution.

The CHM and the normalized point cloud were clipped based on the polygons of the georeferenced field plots. The four corners of each rectangular plot were georeferenced with a high-precision RTK GNSS system. Three structural variables were estimated (two derived from the CHM and one from the normalized cloud) for each plot: (*i*) canopy height (mean of the CHM), (*ii*) gap fraction (CHM fraction below 5 m, and area greater or equal to 10 m^2), (*iii*) leaf area index (LAI) and (*iv*) $LAI_{understory}$ (sum of the LAD where canopy height 1–4 m). LAI was calculated as the sum of leaf area density (LAD) profile (Almeida et al., 2019).

The LAD profile was estimated by the MacArthur-Horn equation (MacArthur and Horn, 1969), using a method based on the rates at which ranging pulses pass through (vs. are reflected) units of canopy volume called voxels (Almeida et al., 2019). This method provides a basis to estimate volumetric variation in vegetation density from optical transmission rates (MacArthur and Horn, 1969; Parker et al., 2004; Stark et al., 2012). LAD profiles were calculated from 1 m above the ground (to avoid possible ground returns), using 1 m^3-voxels. Only first returns within 10° of scan nadir view angle were considered in the computation. We fixed $K = 1$ (from MacArthur-Horn equation), so we calculated an “effective LAD” and “effective LAI”. For convenience, these are hereafter referred to as simply LAD and LAI.

The canopy variables (canopy height, gap fraction and LAI) and AGB were tested by analysis of variance (ANOVA) and *post hoc* Tukey-HSD (honest significant differences). Furthermore, we developed an equation for AGB estimation from the lidar-derived structural variables (*i-iii* described above) using linear regression and least-squares method. To identify and eliminate outliers we used *outlierTest* function from “car” R package (Fox and Weisberg, 2011). For model accuracy assessment, we computed a leave-one-out cross-validation (LOOCV). The quality of the 1:1 correspondence between the observed values (obs_i) and those predicted by LOOCV ($pred_i$) was assured by not rejecting the null hypotheses that H0: $\alpha = 0$ and H0: $\beta = 1$, α and β being the coefficients of their regression ($obs_i = \alpha + \beta \cdot pred_i$) (Valbuena et al., 2017). Absolute and relative bias from the model was assessed by residuals distribution (Fig. S1, Supplementary material).

3. Results

The best predictive model (highest r2) for AGB produced with lidar-derived canopy variables was a simple linear regression using canopy height ($r2 = 0.84$, $p < 0.001$, RMSE = 8.7, relative RMSE = 15.5%) (Fig. 4A). Observed and leave-one-out predicted values follow the 1:1 correspondence (Fig. 4B). The model presented a normal distribution of residuals (Shapiro test $p = 0.069$, after outlier removal), non-tendentious and with the presence of one single outlier (Fig. S1, Supplementary material). With the outlier removal, the coefficient of determination (r2) increased from 0.75 to 0.84. LAI also showed a significant correlation with AGB (Fig. S2, Supplementary material), but because of its high correlation with canopy height, it was not significant in the multiple linear regression.

Both intensive weed management/fertilization and high seedling density planting maximized AGB accumulation (field-observed), but the combination of these two silvicultural approaches did not result in higher AGB than that promoted by these approaches separately lots planted at lower seedling density and submitted to low intensity management accumulated significantly lower ABG (Fig. 5A).

Canopy height showed similar results, being lower in the usual low-density treatment, but not significantly different in intensive low-density (Fig. 5B). Natural regeneration (control) plots showed significantly lower canopy height and gap fraction values than planting treatments, which did not differ the silvicultural treatments (Fig. 5B, C).

Leaf area index was lowest under natural regeneration and showed an increasing trend with respect to the management type (from traditional to intensive) than to planting density (from high to low), as

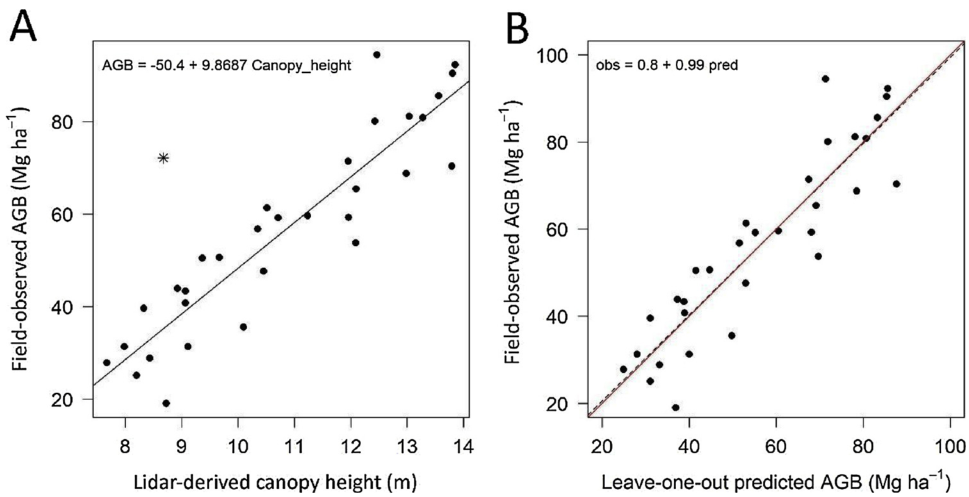

Fig. 4. Best prediction model of AGB (field-observed) in relation to canopy variables height (lidar-derived), resulted from different silvicultural intensity treatments applied to experimental tree plantations established in the Atlantic Forest of Brazil. On the left is scatterplot of AGB as function of canopy height ($r2 = 0.84$, $p < 0.001$, RMSE = 8.7, relative RMSE = 15.5%). The "*" point is an outlier not considered in the equation. On the right is the leave-one-out validation: the solid line represents the 1:1 correspondence. The dashed line is the linear regression fit between observed and leave-one-out predicted ($obs_i = \alpha + \beta \cdot pred_i$). The values of α and β showed no significant difference of 0 and 1 respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

follows: natural regeneration < traditional-high < intensive -high < traditional-low < intensive-low (Fig. 5D). The LAD profile also differed among silvicultural treatments (Fig. 6). The usual low-density treatment had lower $LAI_{above7m}$ (sum of the LAD where canopy height ≥ 7 m) than the high-density treatments (p-value < 0.001; Fig. S2). All treatments showed similar $LAI_{understory}$ ($p = 0.09$; Fig. S3). Natural regeneration showed an evident difference in the LAD profile (Fig. 6).

4. Discussion and conclusions

We demonstrated that an UAV-borne lidar system can effectively assess the structure of forest restoration plantations and distinguish outcomes of different silviculture strategies. A previous study used an UAV and photogrammetric techniques from RGB images to monitor the differential outcomes of tree plantations, nucleation, and natural regeneration in the restoration of tropical forests in Costa Rica (Zahawi et al., 2015). However, this is the first study using an UAV-borne lidar system to monitor tropical forest restoration.

Photogrammetry techniques allow the production of three-dimensional clouds from photographs (RGB images), allowing the estimation of vegetation height from DSM and DTM, or the automatic counting of tree seedlings (first stage of the restoration), with the support of vegetation indexes (Mohan et al., 2017; Albuquerque et al., 2017). The main advantage of RGB-photogrammetry compared to lidar is the cost of the equipment. However, in closed canopy forests, this technique has limitations for estimating the DTM (Zahawi et al., 2015). The main advantage of lidar is the potential to pass through the forest canopy, reaching the ground (Sankey et al., 2017).

In our research, we are comparing field and lidar-derived forest structure variables. Although presenting a high r^2 (0.84), the AGB equation can be certainly be improved if developed with field inventory data collected close to the time of lidar data collection (in this work, forest inventories were performed two years before UAV flights) and if an updated AGB equation is used (we quantified AGB for the 10-year-old plantation with an equation developed for the 5-year-old plantation and used wood density data collected in the 5-year-old plantation too).

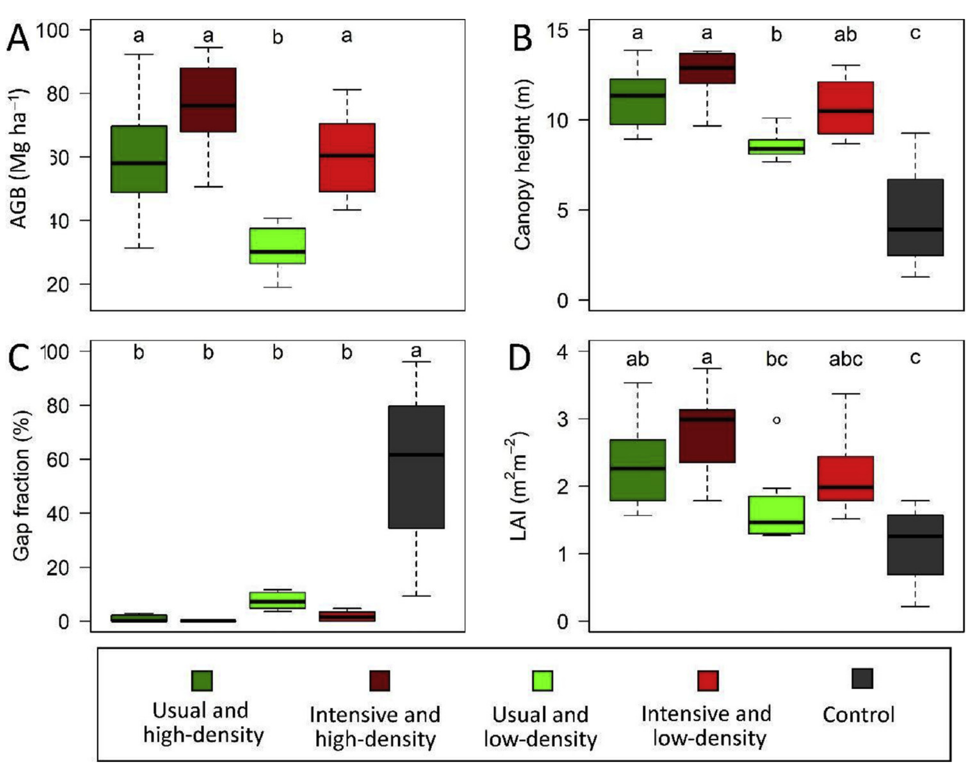

Fig. 5. Boxplot of the structural variables in function of different silvicultural intensity treatments applied to experimental tree plantations established in the Atlantic Forest of Brazil. Variables: AGB (aboveground dry wood biomass; A), canopy height (B), gap fraction (C), and LAI (leaf area index; D). AGB was observed from the field inventory and canopy variables were derived from UAV-lidar. The silviculture treatments were established based on a combination between usual and intensive management with high (3,333 plants ha-1) and low (1,667 plants ha^{-1}) planting density; control plots were left over for natural regeneration, without tree planting or any type of silvicultural intervention. All variables had a significant ANOVA test with $p < 0.001$. *Posthoc* Tukey-HSD (α = 0.05) results are the letters "abc" in the graphs.

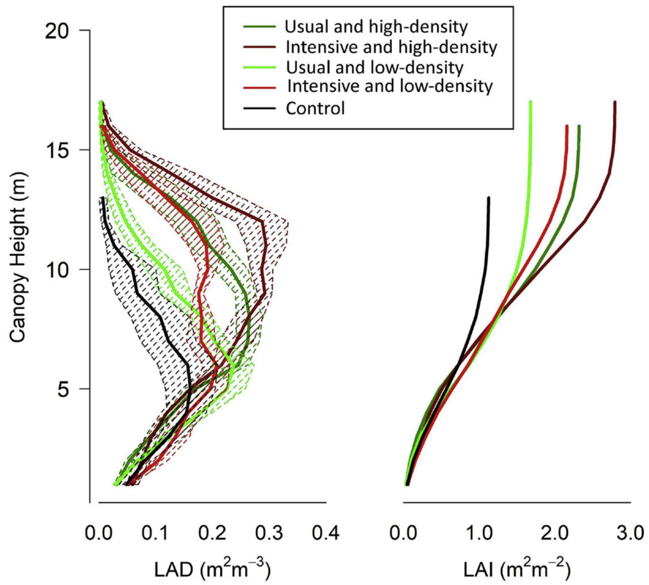

Fig. 6. Vertical profiles of Leaf Area Density (LAD) and accumulated Leaf Area Index (LAI) obtained with a UAV-borne lidar for experimental tree plantations managed under different silvicultural intensity treatments in the Atlantic Forest of Brazil.

The use of an UAV-lidar system allowed the evaluation of forest structure metrics that were not previously assessed in this experiment (Campoe et al., 2010; Ferez et al., 2015; Brancalion et al., 2019). Gap fraction and leaf area index are important variables that can represent the effectiveness of restoration interventions forreestablishing forest structure and creating a favorable habitat for native biota and shading out invasive grasses (Viani et al., 2017). In this work, all silvicultural treatments resulted in plantations with a gap fraction below 15%, whereas natural regeneration resulted in much higher values.

As a recognition of the importance of these variables for assessing restoration success, the Environmental Secretary of São Paulo State in southeastern Brazil (where the project was established) included canopy cover as one of the three ecological indicators that have to be monitored to assess the quality of restoration projects established with public funds or as means of legal compliance (Chaves et al., 2015). According to this legal instrument, forest restoration projects must achieve a canopy cover of at least 80%. The field method usually used for monitoring restoration has high costs and is difficult to apply to very large areas. Another important limitation is that the average canopy cover is calculated based on samples, so its accuracy is highly dependent on the use of an appropriate number and allocation of samples, which has proven to be challenging (Viani et al., 2018). The UAV-lidar system makes it possible to obtain a census of multiple restoration sites, which allows for more robust and reliable assessments of restoration quality and compliance with legal instruments.

Obtaining detailed LAI and LAD profiles is another advantage of the UAV-lidar system. Although planting treatments showed different LAD profile distribution, they generally have a monomodal LAD distribution (similar to a normal distribution) with a greater accumulation of vegetation at certain canopy height stratum. This LAD distribution occurs because in a relatively young forest plantation (14 years) most of the individuals are of the same age and height, resulting in greater accumulation of vegetation within a single vertical stratum.

LAD profiles in primary forests normally show a homogenous distribution of vegetation along the LAD profile (Stark et al., 2012; Almeida et al., 2016, 2019b). We expect that the LAD profile of these restoration plantations will change as forest succession proceeds, with the senescence of pioneer trees, regeneration of colonizing species in the understory, and a more pronounced growth differentiation among the non-pioneer tree species of the forest. Consequently, the use of LAD profiles can be very useful for monitoring older restoration sites.

In this work, the young structure of the forest plantation and the similar diversity among the treatments made it impossible to infer about tree species diversity. Some studies have used lidar to estimate tree diversity in temperate forests (Bergen et al., 2009). However, for species-rich tropical forests estimating diversity from vegetation structure is still a major challenge. Fusion of lidar and hyperspectral data offers great promise in this direction (Asner et al., 2015). For example, Sankey et al. (2017) used a UAV-borne lidar system to characterize forest plots in Arizona (southwestern United States), and also a hyperspectral sensor (272 spectral bands ranging 400–1000 nm) to allow the distinction and classification of plant species.

The UAV system used in this work can also be also equipped with a hyperspectral sensor (Headwall Photonics Nano-Hyperspec sensor, with 270 spectral bands in the VISNIR region, 400 − 100 nm), whose data can be combined with lidar data to assess tree diversity patterns in the forest. In the future, we hope to combine lidar and hyperspectral data to monitor restoration.

The use of UAV-borne remote sensors in applied to forestry and ecological studies is increasing (Anderson and Gaston, 2013; Goodbody et al., 2017), as it enables the collection of data in suitable climatic situations, and in greater frequencies and details when compared to airplanes or satellites platforms (Anderson and Gaston, 2013). The UAV-borne sensors present enormous potential for use in rural properties and can be a crucial tool to aid decision making and accountability in forest landscape restoration.

Up-scaling tropical forest restoration relies on the development of disruptive innovations to increase efficiency and reduce costs of planning, implementation, and monitoring forest restoration interventions. These innovations would certainly not happen through the massive replication of plot-scale, traditional restoration approaches (Holl, 2017; Brancalion and van Melis, 2017). The UAV-lidar system is one of these potentially disruptive technologies able to revolutionize forest landscape restoration and will certainly be a protagonist in future research and development projects in this field.

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