Distinguishing tropical forest typologies with UAV LiDAR

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1. Introduction

There is a gap in knowledge regarding the outcomes of different forest restoration strategies and the processes that occur within these new forests to effectively implement restoration strategies (Crouzeilles et al., 2016). To bridge this gap, it is important to identify the different forest typologies at a landscape scale, and subsequently to monitor restoration outcomes, such as forest composition, health, and functioning (Almeida et al., 2019a).

LiDAR is receiving much attention as an effective tool for forest monitoring due to its ability to capture forest structure efficiently (Almeida et al., 2019a). Due to recent technical advances, Unoccupied Aerial Vehicle (UAV)-LiDAR has become more available for forest monitoring. These systems are lightweight, field-portable, have a relatively low cost, can acquire data at fine spatial and temporal resolutions, and are more flexible in use than other LiDAR systems (Zahawi et al., 2015). In this way UAV-LiDAR could replace costly and time intensive field inventories (Almeida et al., 2019c). Nevertheless, little is known of the potential of UAV-LiDAR in a forest restoration context, or their ability to distinguish structural attributes in mixed-species plantations (Almeida et al., 2019b). The objective of this study was to explore the potential of UAV-LiDAR to distinguish tropical forest typologies at a plot level with classification, and to identify the most effective metrics for classification.

2. Data and Methods

The sample sites were 150 forest plots of 800-900 m^2 in the Atlantic Forest of Brazil of six forest typologies. The typologies were monoculture plantation (N = 56), abandoned monoculture (N = 25), and mixed plantation (N = 8) – which were simplified as 'plantation'; forest remnant (N = 7), natural regeneration (N = 24), and restoration plantation (N = 30) – simplified as 'natural'. LiDAR data was acquired with the GatorEye system in August 2019 with a Velodyne VLP-16 dual-return sensor (Almeida et al., 2019c). The pulse density was 216.14 ± 94.3 points m^{-2}.

Thirty-three metrics in total were extracted per forest plot point cloud. Mean CHM, CHM rugosity, and gap fraction were extracted from canopy height models (CHM). CHM contain the absolute vegetation height above ground. Twenty five metrics were extracted from the normalised point clouds: height percentile cloud metrics hp.nmean and hp.nSD, where n = [5,10,25,50,75,90]; cloud return density above quantile metrics dq.imean and dq.iSD, where i = [20,40,60,80]; minimum return height C_{min}mean and C_{min}SD; maximum return height C_{max}mean and C_{max}SD; and Gini coefficient (GC). The height percentile metrics represent the distribution of vegetation through the canopy, specifically at which height a proportion of vegetation is concentrated. Five metrics were extracted from three-dimensional voxel matrices: leaf area index (LAI) mean, LAI SD, LAI understory, Leaf Area Height Volume (LAHV), and Foliage Height Diversity (FHD). Voxel matrices, which represent square units of canopy volume, were computed per normalised height point cloud with the LeafR package (Almeida, 2019). Then Leaf Area Density (LAD) profiles were calculated, which are vertical distributions of the leaf area in voxels. LAI understory was computed as the sum of LAD at all heights below five metres

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(Almeida et al., 2019a). LAHV was calculated as the sum of vegetation volume over all heights, where z is the height in the canopy (z = 1, 2, 3, ...,max z) and LADz is the mean LAD at that height. FHD was calculated with Shannon's index applied to the plot mean LAD profile.

To distinguish the six non-simplified typologies, and the two simplified typologies, random forest was used to build supervised classification models. The models were tuned by iteratively removing the metric with the lowest importance until stabilisation of the accuracy was reached. The two random forest models were validated with Leave-one-out-cross-validation and their performance was assessed with confusion matrices. The importance of UAV-LiDAR metrics was assessed with their mean increase in MDA per standard deviation.

3.Results

3.1 Performance assessment of classification models

The six-typology classification model performed with a kappa statistic of 0.46 and overall accuracy (OA) of 58.7% (Table 1). Monoculture plantation and restoration plantation were most accurately classified, and mixed planation was never correctly classified (Table 1). Forest remnant, natural regeneration, and restoration plantation were most difficult to distinguish from each other. 48% of the abandoned monoculture plots were mis-classified as monoculture plantation. The simplified classification model performed better with a kappa statistic of 0.78 and OA of 90.0% (Table 2).

Table 1. Confusion matrix for classification of non-simplified typologies with User's Accuracy (UA), Producer's Accuracy (PA), and overall accuracy. The correctly classified plots are in bold.

		Predicted						
		Forest remnant	Natural re-generation	Restoration plantation	Mixed plantation	Abandoned mono-culture	Monoculture plantation	PA(%)
Reference	Forest remnant	**2**	2	2		1		28.6
	Natural regeneration	1	**13**	8		2		54.2
	Restoration plantation		7	**21**		1	1	70.0
	Mixed plantation	1		1		4	2	0
	Abandoned monoculture	1	2	1		**9**	12	36.0
	Monoculture plantation		1	2		10	**43**	76.8
	UA(%)	40.0	52.0	60.0	0	33.3	74.1	58.7

Table 2. Confusion matrix for classification of the simplified typologies.

		Predicted		
		Natural	Plantation	PA(%)
Reference	Natural	**56**	5	91.8
	Plantation	10	**79**	88.8
	UA(%)	84.8	94.0	90.0

3.2 Analysis of metric importance

The metrics included in the final non-simplified typologies model (in order of importance) were (LAI) understory, hp.50SD, dq.40SD, and CHM rugosity. LAI understory and hp.50SD were the two metrics used in the simplified classification model. LAI understory showed most variation between all typologies, and hp.50SD clearly distinguished the natural- from the plantation typologies.

4. Discussion

The successful classification of the simplified natural and plantation typologies is important, because in large scale restoration initiatives or forest assessments this distinction is often not made and forest cover is the primary indicator used (Chazdon et al, 2016). LAI understory and hp.50SD were able to capture the difference in active removal of undergrowth and regular planting structure of plantations from the natural typology growth forms. The overall lower accuracy in the non-simplified typology classification was due to low sample sizes, broad variation of growth forms within typologies, the difference in forest structure of early succession and later successional stages, and similarity of all typologies in an early successional stage. Nevertheless, the LAI understory metric showed potential for distinction of similar types. Furthermore, understory vegetation is used as an ecological indicator for forest health, biodiversity, and regeneration potential, but is laborious to measure in the field and inaccurate with low LiDAR point densities (Campbell et al., 2018). Therefore, UAV-LiDAR has potential for measuring understory vegetation as a useful restoration outcome indicator. For further distinction of similar typologies, and avoiding noise from different successional stages, future research should explore LiDAR fusion with optical sensors.

5. Conclusions

Plantation typologies were successfully discerned from natural typologies, but other non-structural features may be needed to separate similar typologies. The metric LAI understory showed the most potential as a unique feature to distinguish typologies, and it should be further explored. Overall, UAV-LiDAR can be used to identify structural differences in a broad range of forest restoration sites and can be of good use for existing and future forest restoration projects.

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