Three attempts to detect changes in tropical forests using repeat LiDAR scans

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1. Introduction

Networks of permanent field plots have detected an increase in the carbon stored in tropical forests over recent decades[1]. This increase is thought to be driven in part by CO_2 fertilization. However, uncertainty remains about the scale and frequency of disturbance events, and whether they too are increasing with climate change. Recent work has shown that small-scale disturbance events (<0.1 ha) account for the majority of biomass turnover in tropical forests[2]. Airborne Laser Scanning (ALS) provides data at the appropriate scale and spatial resolution to study these processes. We use repeat ALS data to measure these changes in three ways:

1. By tracking large trees over time to determine whether their mortality rate is it balanced by recruitment.
2. Studying changes in the number and size distribution of canopy gaps, which are markers of disturbance.
3. By measuring the overall change in canopy height and comparing this with repeat field inventory data.

2. Data and Methods

2.1 Airborne Laser Scanning data and processing

ALS data was collected for two sites in Malaysia (Sepilok and Danum) and two sites in French Guiana (Paracou and Nouragues), covering a total area of 84 km^2 (or 8400 ha). ALS data was processed with LASTools[3] to create a Digital Surface Model (DSM), Digital Terrain Model (DTM) and Canopy Height Model (CHM) at 1 m spatial resolution. We cropped the short Kerangas forest in Sepilok out of these analyses since it has a distinct forest structure and may bias comparisons between sites.

Table 1. Overview of study sites, ALS data and canopy gap dynamics.

Site	Country	Years scanned	Area (km^2)	Canopy gaps (# km^{-2})		
				Initial	Recovered (yr^{-1})	New (yr^{-1})
Danum	Malaysia	2014 2020	23	966	80	47
Sepilok			25	710	44	48
Paracou	French Guiana	2016 2019	10	280	65	53
Nouragues			26	565	96	62

2.2 Individual tree growth and mortality rates

We manually delineated tree crowns using the CHM and RGB images, which were captured alongside the ALS data. This manual data set prioritizes large trees (those easily visible from above) which account

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for the majority of aboveground biomass[4]. Using this data set we then optimized a watershed-type segmentation algorithm (https://github.com/swinersha/UAVforestR) using Bayesian optimisation to segment large trees from the CHM. Independently, we trained a convolutional neural network, based on a Mask RCNN architecture, to segment trees in the RGB images. We then combined results from these two independent segmentation methods to give a dataset of accurately delineated large trees across Sepilok Reserve. Finally, we extracted the canopy height for each tree in both years from the ALS data. This allowed us to count how many large trees had died between scans and estimate their mortality rate.

2.4 Canopy gap dynamics

We defined canopy gaps as contiguous areas in the CHM < 10 m above ground level between 10 m^2 and 10,000 m^2 using ForestGapR[5]. For each site, we matched gaps which overlap in both years to determine how many new gaps occurred during the interval between scans, and how many gaps recovered.

2.3 Canopy height change

We calculated the change in canopy height (ΔH) in two ways: (a) as the difference between the first and second CHM and (b) the difference between DSMs. (a) is robust to any vertical misalignment between the scans while (b) is robust to any bias in ground detection. We found that low pulse densities caused underestimation of canopy height and so confined our analysis to areas with pulse densities greater than 10 pulses per square metre. In order to reduce noise (from geolocation errors, wind etc) we aggregated the ΔH rasters to 20 m spatial resolution. We calculated slope, aspect and topographic position index (TPI) for each site and tested whether spatial patterns in ΔH were related to topography using multiple linear regression.

3. Results and discussion

3.1 Individual tree analysis

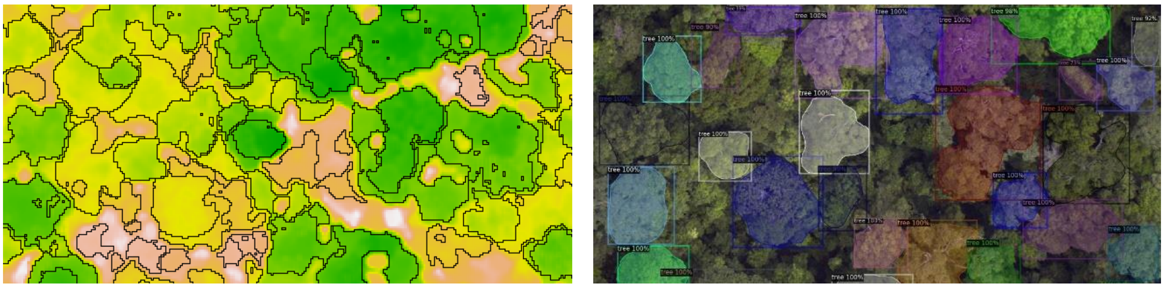

Figure 1: Watershed tree crown delineation from the canopy height model using UAVforestR (left), and instance segmentation of tree crowns from RGB imagery using Mask RCNN (right).

Large trees were often found growing close together with interlocking crowns. ALS segmentation methods rely on structural assumptions (such as crown radius allometry) to segment these difficult cases, but allometry data is severely limited for these large trees. We found that differences in colour helped distinguish trees, but the exact boundary of the crown was difficult to accurately delineate either manually or automatically. Therefore, we have a high level of confidence that each polygon represents a single tree, but uncertainty over the exact boundary. This limits our ability to detect lateral growth of the tree crowns, which is an important component of tree growth, particularly for large trees.

From the 861 manually segmented trees in Danum and Sepilok we found that just under 10% (76 trees) had died (reduction in height by >5 m) between 2014 and 2020. We found no trend with tree height. Ongoing work will dramatically increase this sample size using automatically segmented trees crown.

3.2 Decrease in the number and size of canopy gaps

The number of canopy gaps decreased in three out of the four sites (Table 1). In Sepilok there was a slight increase in the number of canopy gaps, but a decrease in the total area of gaps. This suggests that, over the interval between scans, recovery outpaced new disturbances in these forests. Further analysis will determine whether new gaps were spatially clustered, e.g. near existing gaps or on hilltops.

3.3 Increase in canopy height

All sites showed a net increase in canopy height over time. This suggests an increase in carbon storage, although field data are needed to confirm this (analysis ongoing). This increase in canopy height was robust to variations in pulse density and ground detection accuracy, since a similar increase was observed in both the CHMs and DSMs at high pulse densities. Further work is needed to test whether this increase is sensitive to other differences in ALS scanning parameters between years. Also, we found that these height changes were sensitive to the scale of spatial aggregation, with much lower growth rates at 1 m resolution. After accounting for initial canopy height, topographic metrics explained less than 10% of the variation in ΔH.

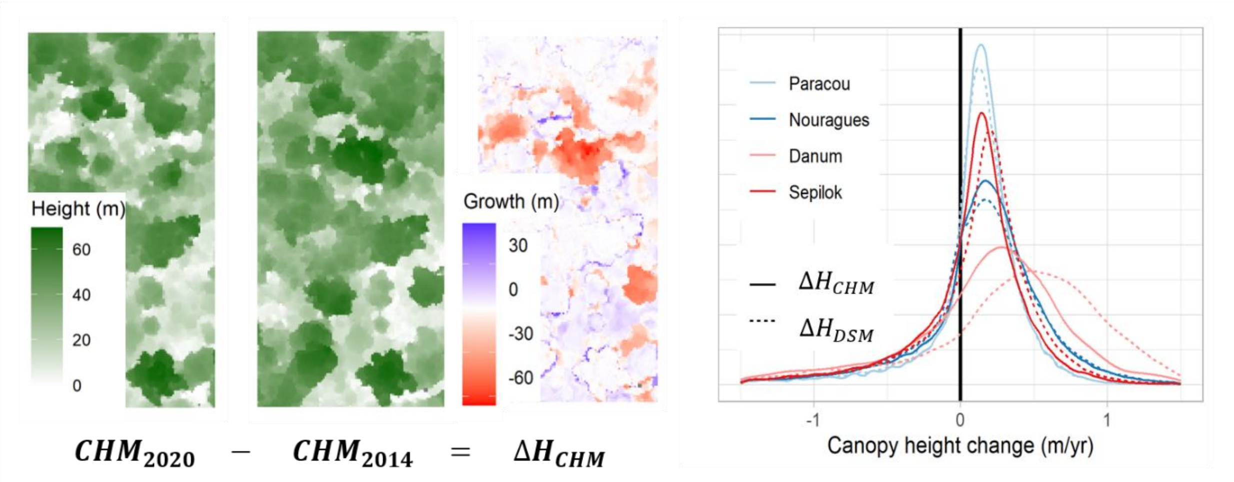

Figure 2: Left – example canopy height models and height change raster for Sepilok. Right - change in canopy height across four tropical forest sites (20 m resolution, > 10 pulses m^{-2})

4. Conclusions

Repeat airborne laser scanning data were used to study changes in tropical forests canopy structure over time. We found an overall increase in canopy height (although further analysis is needed to confirm this) and a decrease in the number of canopy gaps. Ongoing work will determine whether these findings align with field data, and whether large trees are growing or dying.

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