Examining Structural Complexity of Scots Pine Trees – A Comparison between Terrestrial Laser Scanning and Photogrammetric Point Clouds

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1. Introduction

Forest structural complexity is related to various ecological processes and ecosystem services (e.g. Pommerening 2002, Neill & Puettmann 2013, Hardiman et al. 2013). It can also improve the forests' ability to adapt to environmental changes. In order to implement the management for complexity and to estimate its functionality, the level of structural complexity must be defined.

Structural complexity can be described mathematically by fractal analysis (Mandelbrot 1977). Fractal dimension describes how complex a self-similar object is (Camarretta et al. 2020), and a box dimension is a method for estimating the fractal dimension of an object that is not exactly self-similar but fractal-like (Feldman 2012, Seidel 2018). In forestry applications, the box dimension has been used to measure the complexity of individual trees (e.g. Seidel et al. 2019a, b, Saarinen et al. 2021). The box dimension reflects simultaneously a number of different structural attributes (Seidel et al. 2019b) and has been associated, for example, with tree species, availability of light (Seidel 2018), type and strength of competition (Seidel 2018, Dorji et al. 2019), and tree growth (Seidel et al. 2019a, Saarinen et al. 2021).

This study compares the structural complexity of Scots pine (*Pinus sylvestris*, L.) trees measured by two remote sensing techniques, namely, terrestrial laser scanning (TLS) and aerial imagery acquired with unmanned aerial vehicle (UAV). The premise is that TLS provides the best available information on structural complexity as the point density in TLS point clouds is larger than in UAV, and as TLS is able to penetrate vegetation. Research question are: 1) do TLS and UAV measured structural complexity differ significantly from each other, 2) what explains the possible divergence between the structural complexity, and 3) does the forest structure affect the divergence between TLS and UAV measured structural complexity of individual Scots pine trees?

2. Data and Methods

The Scots pine tree dominated study area is located in southern Finland, site biome is southern boreal forest zone, and the fertility is mesic heath (Saarinen et al. 2021). During the 2000s, the study area was exposed to six different thinning treatments plus one control group with no treatment. Thinning treatments included two levels of thinning intensity (moderate, intensive) and three thinning types (from below, from above, systematic from above).

The study area was field measured during 2018–2019 (Saarinen et al. 2021). Both TLS and UAV measurements were implemented in the fall of 2018. TLS point clouds were acquired using Trimble TX5 3D phase-shift laser scanner, and UAV imagery was acquired using Gryphon Dynamics quadcopter equipped with two Sony A7R II digital cameras. TLS produced point clouds directly whereas aerial imagery was converted into point clouds with structure from motion (SfM) technology.

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Box dimension (D_b) values for each Scots pine tree (n=2065) were calculated from TLS and UAV measured 3D point clouds. D_b-values were calculated with the natural logarithms of boxes needed (N) and the edge length of each box divided by the initial box size (r). The slope of the trend line determined the D_b-value. Welch's t-test was used to compare the means of TLS and UAV measured D_b-values. The dispersions of D_b-values, tree heights and point clouds were examined with standard deviations, and the distribution of TLS and UAV measured points was examined by dividing trees longitudinally into two equal parts and calculating the proportion of points below and above. The differences between the ranges of TLS and UAV measured x-, y- and z-axes were examined by subtracting UAV ranges from TLS ranges. Simple linear regression was used to examine whether the number of TLS and UAV measured points explained the variation in D_b-values and whether the number of the smallest boxes explained the variation in D_b-values. Linear mixed-effect model was used to examine whether different thinning treatments affected TLS and UAV measured D_b-values. Tukey's honest significant test was used to scrutinise between which thinning treatments there was a statistically significant difference in D_b-values. The correlations between different variables were tested with Pearson correlation test.

3. Results

TLS and UAV measured D_b-values differed significantly from each other (p-value<0.001) and did not provide comparable information on the structural complexity of the individual Scots pine trees. On average, UAV measured D_b-values were 5% larger than TLS measured values. The divergence between the TLS and UAV measured D_b-values was explained by the differences in the number and distribution of the points in the point clouds and by the differences in the estimated tree heights and number of boxes in the box dimension method.

TLS measured 15 times more points than UAV. On average, 65% of TLS measured points were placed below and 35% above the midpoint of the tree height. With UAV, the percentages were 22% below and 78% above. The standard deviations of the points with respect to all axes were bigger in UAV measurements compared to TLS. High correlation occurred between TLS and UAV measured D_b-values (75%) and between the number of UAV measured points and D_b-values (71%). The enhancement in the amount of UAV measured points did not erase the divergence between TLS and UAV. Compared to field measurements, UAV underestimated the tree heights more than TLS, and the number of the smallest boxes was on average 64% bigger in UAV than in TLS. The number of the smallest boxes affected the variation in TLS and UAV measured D_b-values (R^2= 0.79, 0.68, respectively).

Forest structure significantly affected the variation of both TLS and UAV measured D_b-values (p-values <0.001), but the divergence between TLS and UAV measured Db-values remained in all the treatments. Plots with no treatment differed from all other thinning treatments except from the moderate systematic thinning. D_b-values were the largest with intensive thinning treatments and the smallest on plots with no treatment. The largest point densities were found on plots with intensive thinning from below and the lowest on control plots. In terms of the individual tree detection, the number of obtained points in the point cloud, and the distribution of these points, UAV measurements were better in sparse compared to dense forest structure.

4. Discussion

The standard deviations of the points were larger in UAV measurements compared to TLS since TLS measured points were more closely clustered near the stem, whereas with UAV, the outer edges of the crown affected more. With UAV, more points were obtained from the upper part of the tree but at the same time, the ground vegetation was not properly excluded, which increased the standard deviation of the points. The smaller ranges UAV measured points is explained by the fact that UAV method was not able to observe the extreme points as well as TLS and was averaging the treetops and sides. In general, the more the tree height is underestimated, the smaller the initial box size in D_b-calculations is, and the smaller the boxes, the more of them are needed to cover trees. Because a larger number of scattered boxes yields a higher D_b-value, the UAV measured D_b-values were higher than TLS measured.

The competitive pressure has been confirmed to reduce D_b-values (Juchheim et al. 2017, Dorji et al. 2019, Seidel et al. 2019a, Saarinen et al. 2021). In this study, the thinning intensity was observed to affect more than the thinning type. Largest D_b-values were reached on the plots with intensive thinnings (less competition and more space to grow). On the control plots, the D_b-values were smaller and also the standard deviations of the points were smaller. That is, the trees were structurally less complex and more similar to each other when compared to trees on the other plots.

5. Conclusions

Photogrammetric point clouds generated from UAV imagery did not result in comparable structural complexity information to TLS. UAV measurements were better in forests with intensive thinning indicating the method's better suitability in sparse forest conditions. Future research should study whether TLS and UAV can be used as complementary techniques to provide more accurate and holistic view of the structural complexity in the perspective of both tree- and stand-level. UAV-LiDAR data should be studied also as it may better characterize crown and stem.

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