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Improvements in airborne laser scanning based forest structural type assessment

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Abstract

Accurate forest structural types (FSTs) assessment helps to provide valuable support tools to distinguish different structures in forest stands and formulate effective management decisions. We used data from -Boreal, Mediterranean and Atlantic- biogeographical regions and developed reliable methodologies for the FSTs assessment. First, we used the Gini coefficient (GC) of tree size inequality and evaluated the effects of plot size, stand density and point density of the airborne laser scanning (ALS) on the ALS-assisted GC estimations in Boreal conditions. Second, we used four structural variables -quadratic mean diameter (QMD), GC, basal area larger than mean (BALM) and stand density (N)- from the three biogeographical regions and developed region-independent methods for the FSTs assessment. Lastly, we detected FSTs directly from ALS data, predicted the aboveground biomass (AGB) at each FST, and compared it with the AGB prediction without pre-stratification. Results showed that (a) plot size had a greater effect on the ALS-assisted GC estimation as compared to the stand and point density and 250-450 m² plot size is the optimal plot size for reliable ALS-assisted GC estimation. (b) GC and $BALM$ were the most important descriptors for the FSTs assessment and single storey, multi-storey and reversed-J types of forest structures can be separated by lower, medium and high values of GC and $BALM$, respectively, while QMD and N were relevant to separate young/mature and sparse/dense subtypes.(c) We observed marginal improvements in the AGB predictions from the direct ALS-based FSTs but identified critical differences in the selection of ALS metrics by the prediction models such as higher percentiles are more relevant in the open canopies while cover metrics and average percentiles are important in the closed canopies. These results are thus very useful in improving our understanding on the causality behind the choice of ALS predictors in structurally complex forests.

Scope

Forest structural assessment is important because it affects the growth and mortality of seedlings and saplings, wildlife habitat, plant habitats, biodiversity, long-term biomass predictions and carbon storage.
ALS-derived metrics describe the key characteristics of a forest and are valuable for the prediction and monitoring of various attributes, such as height, spatial patterns of the trees and structural complexity of the forests

Objectives

1. To study plot size, stand density and ALS point density effects on the relationship between GC of tree size inequality and ALS metrics.
2. To develop region-independent methodologies for FST assessment by using four forest attributes –GC, $BALM$, QMD and N– obtained from Boreal, Mediterranean and Atlantic biogeographical regions.
3. To detect various FST directly from ALS data, develop AGB prediction model for each FST and compare that model with a general AGB prediction model that contains the full dataset without prior stratification.

Methods

For objective 1, two criteria were defined to achieve the optimal plot size and sample size,
1st, stabilisation of the GC values at a given simulated circular plot size (s) or sample size (n), and
2nd, maximisation of the absolute correlation $|r|$ between the GC values and ALS metrics. For point density effect, we reduced the point density and performed a correlation between GC values and the same ALS metrics.

For Objective 2, four forest attributes –GC, BALM, QMD and N– were calculated from the three biogeographical regions –Boreal, Mediterranean and Atlantic–, hierarchal clustering analysis (HCA) and CART analysis (classification and regression tree) were used to separate different FSTs and lastly, k-nearest neighbour (kNN) was used to predict those FSTs from ALS.

For Objective 3, different FSTs were directly separated from ALS data using L-coefficient of variation (L_{cv}) and L-s kewness (L_{skew}). aboveground biomass (kg) was calculated using species-specific biomass equations. The AGB predicted for the whole data without stratification was compared with the prediction in each FST.

Results

Study 1 Results

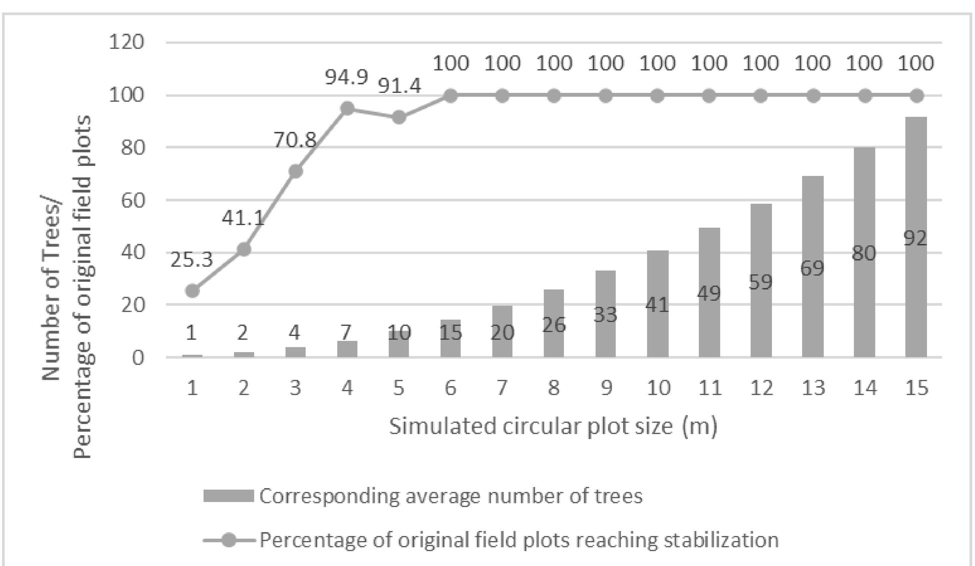


Figure 1.1 Average number of trees in each simulated circular plot and the proportion of original field plots that fell within the $\overline{GC}_{diff} < 0.05$ limit and reached stabilisation (first criterion) (Adnan et al. 2017, 2020).

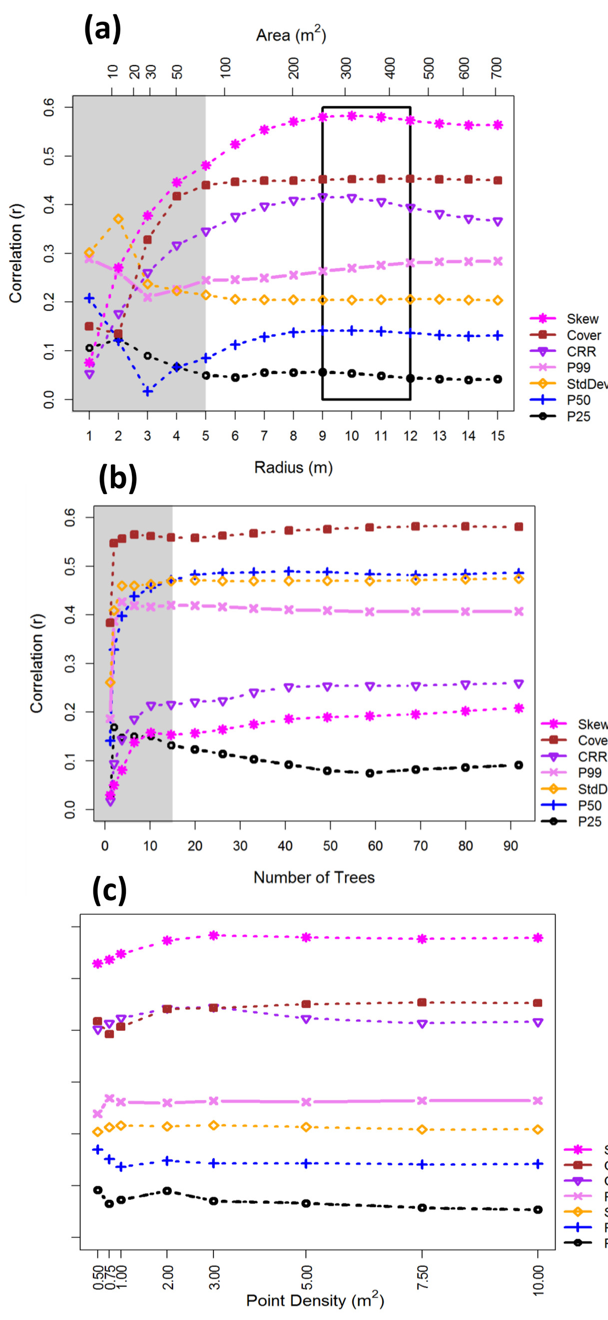
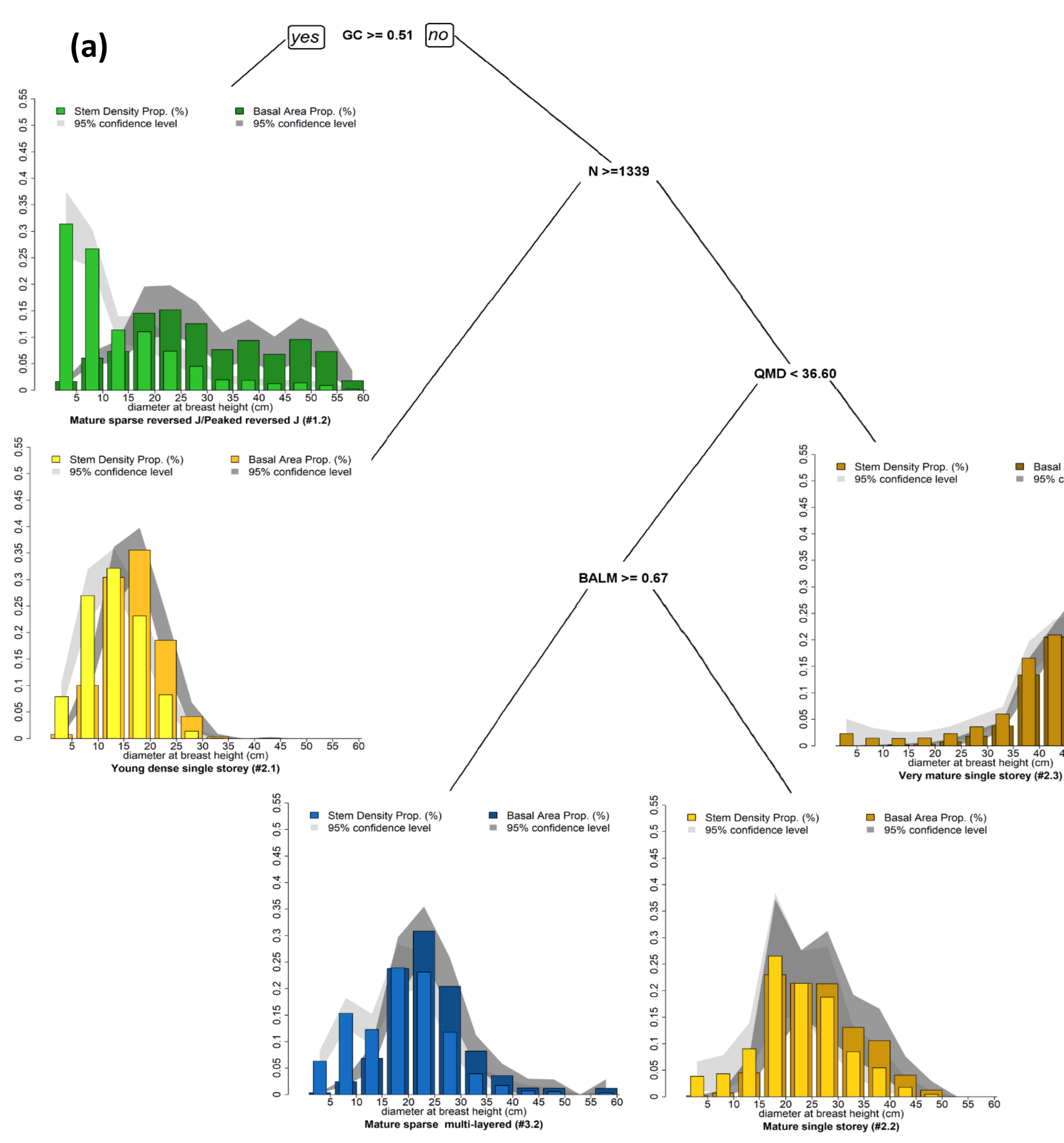


Figure 1.2. Absolute correlation of the field GC with ALS metrics for increasing (a) simulated circular plots and (b) number of trees (second criterion) while the (c) shows the effect of ALS point density. (Adnan et al. 2017)

Skew: Skewness of ALS returns
StdDev: Standard Deviation
Cover: Percentage of all returns above 0.1 m
CRR: Canopy relief ratio
P25,P50,P99: 25th, 50th and 99th percentiles of ALS returns

Study 2 Results



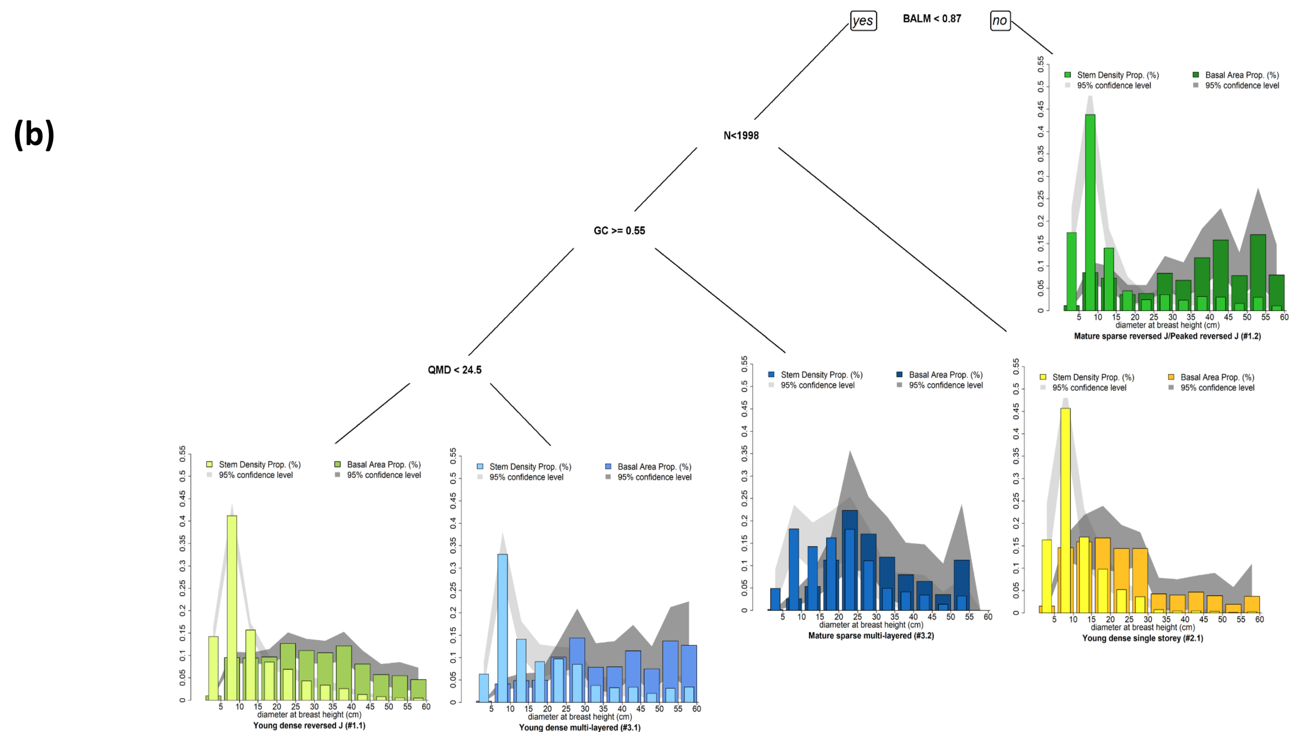


Figure 2.1. Classification tree from (a) coniferous forest and (b) deciduous forest as a result classification and regression tree (CART) analysis. QMD: quadratic mean diameter (cm); GC: Gini coefficient; $BALM$: basal areal larger than mean; and N: stand density (stems.ha^{-1}) (Adnan et al. 2019).

Table 2.1. Contingency matrix showing the observed and predicted forest structural types (FST) in (a) coniferous, and (b) deciduous forests using the nearest neighbour imputation method.

(a)

Predicted	Observed #1.2	#2.1	#2.2	#2.3	#3.2	User's Accuracy
#1.2	26	7	0	0	1	0.76
#2.1	4	11	0	0	1	0.69
#2.2	0	0	3	0	3	0.50
#2.3	4	0	0	19	0	0.83
#3.2	0	4	8	0	25	0.68
Producer's Accuracy	0.76	0.50	0.27	1.00	0.83	

(b)

Predicted	Observed #1.1	#1.2	#2.1	#3.1	#3.2	User's Accuracy
#1.1	40	0	2	1	0	0.93
#1.2	0	41	0	2	2	0.91
#2.1	0	0	5	1	0	0.83
#3.1	1	1	0	10	2	0.71
#3.2	0	1	0	2	5	0.62
Producer's Accuracy	0.98	0.95	0.71	0.62	0.56	

#1.1: young, dense reversed J; #1.2: mature, sparse reversed J; #2.1: young, dense single storey; #2.2: mature, single storey; #2.3: very mature, single storey; #3.1: young, dense multi-layered; #3.2: mature, sparse multi-layered.

Study 3 Results

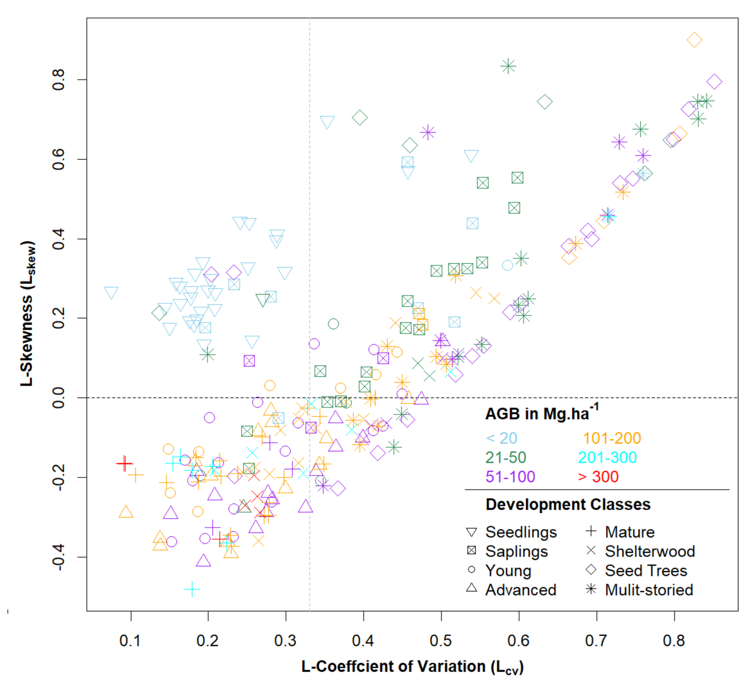


Figure 3.1. Separation of the development classes that represent various FSTs in a boreal forest by the boundary lines $L_{cv} = 0.33$ and $L_{skew} = 0$. (Adnan, 2020)

Table 3.1. Accuracy assessment of the observed and predicted aboveground biomass of the general model

	Whole Data	GC_H (L_{cv}) Even (<0.33)	Uneven (>0.33)	L_{skew} Closed (<0)	Open (>0)
Sample size	244	120	124	119	125
MD	-3.55	-2.09	-4.97	-4.56	-4.31
MD (%)	-3.95	-2.33	-5.54	-5.08	-4.81
RMSD	37.4	37.1	37.6	37.6	37.3
RMSD (%)	41.7	41.4	41.9	41.9	41.6
SSR	1.03	1.02	1.04	1.04	0.98

Table 3.2. Accuracy assessment of the observed and predicted aboveground biomass of each FST specific model.

a) Even versus uneven-sized structure

	Whole Data	GC_H (L_{cv}) Even (<0.33)	Uneven (>0.33)
Sample size	244	120	124
MD	-2.52	-2.30	-2.72
MD (%)	-2.81	-2.57	-3.03
RMSD	34.9	34.6	35.3
RMSD (%)	38.9	38.6	39.4
SSR	0.97	0.96	0.99

b) Closed versus open forest canopy

	Whole Data	L_{skew} Closed (<0)	Open (>0)
Sample size	244	119	125
MD	-2.37	-2.22	-2.52
MD (%)	-2.64	-2.48	-2.81
RMSD	33.2	33.5	32.9
RMSD (%)	37.0	37.4	36.7
SSR	0.98	0.98	0.98

$GC_H(L_{cv})$: Gini coefficient/L-coefficient of variation of LiDAR heights; L_{skew}: L-skewness of LiDAR heights; MD: mean difference; RMSD: relative mean square difference; SSR: sum of square ratio.

Conclusion

1. In boreal conditions, a minimum 6 m radius plot size (113 m²) and 15 trees are needed to achieve a stable GC estimation while 9 to 12 m radius (250–450 m² area) is the optimal plot size for a reliable ALS-assisted GC estimation. Any point density above 3-point m^{-2} is suitable for FST assessment.
2. Study 2 presents a simple two-tier approach for FST assessment. In the upper tier, GC and $BALM$ which identified reversed J-type, single storey and multi-layered FST are useful, while in the lower tier, QMD and N separated the young and mature, and sparse and dense FST, respectively. These FST can also be reliably predicted from the ALS data.
3. A threshold value of L_{cv} =0.33 should be used to represent maximum entropy, rather than the 0.50 value used in previous literature. The aboveground biomass predictions in the FST specific models were minor as compared to the general model but the ALS metrics selected in each model were critical.

References

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Study 3: Adnan, S., Maltamo, M., Mehtätalo, L., Ammaturo, N.L., Packalen, P., Valbuena, R., 2021. Determining maximum entropy in 3D remote sensing height distributions and using it to improve aboveground biomass modelling via stratification. Remote Sensing of Environment, 260 (2021):112464.

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