

Generalizing predictive LiDAR models of forest inventory attributes using an area-based approach

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LiDAR measurements

Lidar is an active RS technology

- Emission / reception of a laser beam
- Information from top of canopy to the ground
- 3D structure measurements are expected to overcome some limitations of optical and radar data



[Durrieu et al., submitted]

- A diversity of application domains
 - Forest inventories
 - Topography (DEM)
 - Bathymetry / Hydrology
 - Archaeology...

Principle of Lidar measurement An echo is backscattered toward the sensor every time the laser beam is partially or totally intercepted by an obstacle



LiDAR, an interesting tool for forestry

- Useful to map some structural and biophysical forest parameters
- Used as an operational tool for NFI in some countries
- Most studies have focused upon simple stand structures [Lim et al, 2003]
- Considerable variability in the accuracy of stand attribute predictions [Zolkos et al, 2013]





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Two main approaches

- Tree-based
- Area-based





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1/ Area-based approaches

2/ Study sites

3/ Model development & Results

4/ Influence of sampling parameters

5/ Conclusions



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Stand-level inventory



ALS Point Cloud

1





J











Has proven its usefulness for forest inventory and mapping [Næsset, 2002]

- Numerous metrics are derived from point height distributions at the plot-level
- Metrics that provide the greatest explanation are then selected
- Only a few metrics remaining in the final model



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Four major drawbacks

- Metrics generated from LiDAR data are known to be strongly inter-correlated [Chen, 2013]
- Metric selection and development of robust models are complicated by too many candidate metrics [Khan et al. 2007]
- One model per study site
- Insufficient result accuracy in complex stands



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Hypothesis : the use of few metrics designed to describe main forest structural properties can help overcome the current limitations of area based approaches



Objectives

Development of model with high generalization potential

- Same metrics and model shape
- Prediction of diverse stand attributes
 - Wood volume, stem volume, biomass, and basal area
- Across diverse forest area types

Assessment of model robustness

- Analysis of the influence of key sampling design parameters on result accuracy
 - Lidar and field measurements
- Prioritize the influence of field parameters on AGB predictions



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Study sites

Landes

- 60 km² area
- Flat topography
- Composed of coniferous stands
- Mono-specific stands of maritime pine in even-aged plantations







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Bure (OPE)

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- Multi-layered stands
- 2 acquisitions: leaf-on / leaf-off





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8 pulses / m²

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- Multi-layered stands
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20,5 and 18 pulses / m²

Vosges

- 1200 km² area
- Hilly topography
- Composed of coniferous, deciduous, and mixed stands
- Heterogeneous and uneven-aged stands







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Model development

Four complementary LiDAR metrics

- Mean stand height Mean of first return heights
- Height heterogeneity
 Variance of first return heights
- Horizontal canopy distribution
 Ratio between the number of 1st returns below 2 m and the total number of 1st returns
- Leaf area density profile

Ratio between the standard deviation and the mean of LAD

Heterogeneity of the canopy surface

Vertical heterogeneity





$$\hat{y} = \beta_0 \mu_{CH}^{\beta_1} \sigma_{CH}^{2\beta_2} P_f^{\beta_3} C v_{LAD}^{\beta_4}$$

Results



Model accuracy for several forest parameters & 3 study sites

	Coniferous site (39 field plots)		Decio	duous site	Mountainous site (92 field plots)			
			Leaf-off					Leaf-on
	R²	RSD (%)	R²	RSD (%)	R²	RSD (%)	R²	RSD (%)
Wood volume	0.98	12.42	0.87	17.37	0.86	19.36	0.82	21.86
Stem volume	0.95	14.58	0.88	16.90	0.89	17.08	0.81	24.19
AGB	0.94	12.86	0.86	18.09	0.85	19.43	0.77	22.26
ВА	0.84	14.96	0.81	19.61	0.78	20.67	0.59	23.74



Results

Bure

RSD = 19 %

Conifer vs deciduous stands



Various stand types





400

300

200

Model parameters:

400

0

1000

10

 $\beta_0 = -1$

 $\beta_1 = 2.24$ $\beta_2 = 0.16$

 $\beta_3 = 0.12$ $\beta_4 = 0.41$



Results vs accuracy requirements

AGB should be predicted within 20 % of field estimates [Hall et al., 2011] And volume predicted with a RDS < 10%

- Accuracy was significantly improved in complex stands when shifting from a single model to three stand specific models → stratification issues
- Developed models provided AGB predictions with a RSD ranging from 12.9 % to 21.2 %, depending upon the forest type
- Volumes with a RSD ranging from 12.4% to 19.7 %
- Less good results for « Les Vosges »

Point density? Stand complexity? Topography? Field measurements?

Are these prediction accuracies impacted by Lidar and field data characteristics?



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Influence of sampling parameters

Studied parameters

- Lidar data acquisition *Lidar pulse density*
- Field data acquisition
 - Number of field plot Allometric equation Plot location accuracy Plot radius H and DBH accuracy



Influence of sampling parameters

A

1 km

Studied parameters

- Lidar data acquisition Lidar pulse density
 - Field data acquisition Number of field plot Allometric equation Plot location accuracy Plot radius H and DBH accuracy

Study sites

• Landes :

Accurate geolocation of field data All the trees measured

• BV du Tagon

60 km² area Close to the Landes site Maritime pines 100 field plots (INRA)





Analysis of the influence of each parameter individually on result accuracy for AGB prediction model

Global sensitive analysis for field plot parameters (except the number of plot)

- Sobol's method based on Monte-Carlo analysis [Sobol', 1974]
- Enables to deal with spatially distributed data [Saint Geours et al, 2011]
- Analysis of interactions between parameters



pulse/m²	R²	RMSE (Mg/ha)	Bias (Mg/ha)
0.5	0.86	19.77	-5.75
1	0.87	19.53	-6.20
2	0.87	19.37	-6.09
4	0.87	19.15	-5.87

Prediction accuracy relatively unaffected by pulse density

Slightly less good than for the "Landes" site with 8 pts/m² (R^2 = 0,94)







Allometric equations for AGB of maritime pines

Référence	Variable	N trees	Domain of validity
Shaiek et al. 2011	DBH et H	178	5 < DBH < 48 cm
Cacot, 2007	DBH	NA	Age de récolte
Fraysse and Cotten, 2008	DBH	14	29 < DBH < 52 cm
Baldini et al. 1989	DBH	8	1.5 < DBH < 16 cm



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Reference	R²	<i>RMSE</i> (Mg/ha)	<i>Bias</i> (Mg/ha)
Shaiek et al. 2011	0.93	10.73	-1.56
Cacot, 2007	0.79	18.98	-3.75
Fraysse and Cotten, 2008	0.91	11.89	-3.22
Baldini et al. 1989	0.59	14.01	-4.16



Accuracy of plot geolocation

- GPS unit was placed away from dense cover
- Total station was used to measure the exact distance to each plot centre (<10 cm)





Parameters		Part of variance explained				
		1st order	Total			
Allometric eq.	4 equations	0.26	0.52			
GPS accuracy	σ = 5 m	0.08	0.33			
Radius	15 m or 11.28 m	0.23	0.20			
DBH	$\sigma = 3 \text{ cm}$	0.18	0.19			
н	σ = 3 m	-0.01	0.02			

High impact of allometric equation, geolocation accuracy of field plots and plot radius

To be continued...



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An approach breaking with conventional models using many statistical ALS metrics

- A single model shape using only four ALS metrics to predict stand attributes
- Metrics based on height features, gaps and LAI profiles grasp forest structural properties
- Models avoid data over-fitting and are adaptable to a wide range of environments

Need for more « mechanistic » models based on knowledge of both dendrometry and processes



Sensitivity analysis can provide some technical guidelines for forest managers

- Pulse density doesn't affect prediction accuracy (0.5 to 4 pulses/m2)
- Number of field plot must be higher than 40 for cal/val
- Allometric equation is the first source of error
- Lidar/field coresgistration accuracy: major source of error impacting indirectly prediction accuracy

To what extend can these first results be generalized?

- Homogeneous stands
- Threshold values?

Recommendations for FORESEE 2: a study site with different stand types, several lidar surveys, specific design for field measurements







UCFF

ANDRA





Results

		Coniferous stands (33 field plots)		Mixed stands (23 field plots)			Deciduous stands (36 field plots)			
		R²	RSD (%)	MPE (%)	R²	RSD (%)	MPE (%)	R²	RSD (%)	MPE (%)
General model	Wood volume	0.82	19.94	3.68	0.83	16.31	-5.83	0.63	28.23	-22.86
	Stem volume	0.82	20.60	8.79	0.85	16.50	-7.04	0.65	31.41	-34.38
	AGB	0.83	21.78	-13.17	0.74	18.61	-7.41	0.71	23.17	-3.71
	BA	0.60	20.91	2.99	0.52	20.54	-8.45	0.29	27.75	-16.77
Separate models	Wood volume	0.85	17.97	-4.31	0.85	15.64	-3.64	0.82	19.47	-5.68
	Stem volume	0.87	18.01	-4.07	0.87	15.94	-3.90	0.85	19.66	-5.85
	AGB	0.87	16.50	-4.08	0.80	16.21	-3.41	0.80	21.23	-6.19
	BA	0.67	18.91	-4.77	0.60	18.89	-4.42	0.51	22.75	-5.75



Allometric equations





Lidar a promising technology

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