A comparison of spatialisation methods for the aggregation of LiDAR forest estimates at the compartment level

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Highlights: From the plot to compartment level, prediction error decreases from 15 to 6.4% for basal area, 26 to 7.7% for stem density and 6.5 to 3.4% for dominant diameter. The major criterion for spatialisation is to respect the calibration plot size, whereas for aggregation the issue of compartment borders depends on the forest parameter.

Key words: *forest inventory, airborne laser scanning, spatialisation, compartment.*

Introduction

Long term forest management planning is usually based on statistical inventories, which are not meant to provide information at the compartment level. The area-based approach is now a widely used method to derive continuous maps of forest parameters from airborne laser scanning (ALS) data and field calibration plots [1]. The accuracy of estimates is frequently based on cross-validation with plot-level data, whereas compartments are frequently the basic unit of forest management. The calibrated model first has to be used on a partition of the area of interest into a set of spatial entities for which the model is supposed to be valid. The most straightforward way is to apply a grid which pixel size is similar to plot size. Then to aggregate the pixel values into the forest compartments, the case of borders has to be handled carefully as border pixels may represent a significant proportion of the forest surface. The objective of this article is to compare different possibilities for the spatialisation step (spatial entity size, shape and spacing) and different border exclusion thresholds for the aggregation at the compartment level. The study is based on a dataset of 35 fully-callipered compartments (total 380 ha).

Material

The study area is located in the Jura mountains (France). The stands are uneven-aged, and dominated by silver fir (*Abies alba*), Norway spruce (*Picea abies*) and European beech (*Fagus sylvatica*). The ALS data were acquired with a LMS-Q560 full-waveform scanner. The final pulse density is 9.3 m^{-2}.

For the calibration of estimation models, 139 nested plots of 17 m radius are available in the 580 ha of public forests. 26 were excluded because harvesting occurred during the one year lapse between the ALS flight and field measures. Only trees with diameter at breast height (DBH) larger than 17.5 cm are considered. For each plot, three forest parameters are calculated: basal area, dominant diameter (diameter of the 8 largest trees) and stem density. For the validation, 35 compartments representing a total of 380 ha were fully-callipered. The three forest parameters are calculated for each compartment.

Methods

ALS models

ALS metrics are computed for each plot based on the normalised point cloud extracted over its spatial extent. Metrics include the usual height and density metrics, as well as tree metrics derived from a preliminary segmentation of the canopy height model.

A prediction models is calibrated for each forest parameter by fitting ordinary least squares regression with at most three ALS metrics as independent variables. Selection is based on the adjusted R^2. Models are automatically checked for linear model assumptions, and manually checked for dependencies to other forest parameters. Accuracy is evaluated by computing the root mean square error *rmse* in leave-one-out cross validation.

Spatialisation

Spatialisation scenarios are based on three parameters for the partition of the area of interest into a set of spatial entities, depending on the spacing, shape and size. The following scenarios are tested: disks of 17 m radius (surface and shape identical to calibration plots); squares of 20 m side (different surface and shape);

squares of 30 m side (different shape but similar surface). For square shapes, spacing is chosen equal to their side length. For disks, spacings of 10, 20, 30 and 40 meters are tested. Spacing modifies the amount of overlap between adjacent entities regarding the data used for metrics calculation.

Aggregation

Aggregation of ALS estimates in one compartment is done by computing the mean value of entities which centres lie inside the compartment, but at a minimum distance from the compartment border. Distance thresholds of 0, 10 and 20 m are tested. For validation the *Bias* and *RMSE* are computed by using the full-calliper data.

Results and discussion

Table 1 presents the accuracy of ALS estimates at the plot and compartment levels (spatialisation 17 m disk, 20 m spacing, aggregation with a 10 m threshold). In a study carried in Scandinavian forests [2], the standard deviation of plot-level error was 14.8 to 23.3% for basal area and 25.3 to 26.2% for stem density. At the compartment level, those values decreased to respectively 8.7 to 13.6% and 14.3 to 29.3%. The standard deviation of error was thus reduced by a factor of approximately 2. In our case it is also around 2 for basal area and dominant diameter, and 3 for stem density. The factor of surface increment between the plot and compartment levels is between 30 and 200, depending on compartment surface, compared to 16 in the Scandinavian study. This might explain why the compartment-level accuracy is better. Another explanation could be the uneven-aged structure, which should reduce the spatial correlation of errors. It is noteworthy that compartments with the largest errors are also those which differ most from the uneven-aged structure.

Table 1: Accuracy of ALS estimates at the plot and compartment levels.

Parameter	Plot level (n=113)			Compartment level (N=35)				
	R^2	*rmse*		R^2	*Bias*		*RMSE*	
Basal area ($m^2.ha^{-1}$)	0.76	4.5	15%	0.85	-0.4	-1.3%	1.9	6.4%
Stem density (ha^{-1})	0.57	72	26%	0.76	-7.4	-2.9%	20	7.7%
Dominant diameter (cm)	0.88	3.3	6.5%	0.91	-1.2	-2.5%	1.7	3.4%

Duplat and Perrotte [3] estimate that in the case of a full-calliper inventory 95% of the compartments have their basal area values within [-15%, 10%] of the true value. If those errors have a Gaussian distribution, then the distribution of differences between the full-calliper and ALS values is not significantly different from it. In this forest, the compartment-level accuracy of the ALS-based inventory is thus similar to a full-calliper inventory.

Regarding the spatialisation and aggregation parameters, it turns out that the compartment-level bias and error are higher in absolute value when the 20 m square entities are used, i.e. when the calibration plot size is not respected. Shape has only a limited effect as the 30 m square entities yield accuracies similar to disks of same surface and spacing for all forest parameters. The errors for disks with smaller or greater spacing are in general slightly higher. The distance thresholds for the aggregation step have different effects on bias and error, depending on the forest parameter. These differences may be due to the fact that the metrics selected in the models have different sensitivity regarding heterogeneous areas.

With compartments of a surface around a few hectares, the proportion of border entities is significant, especially when the perimeter to surface ratio is high. In the case of an uneven-aged forest, the entities located across two forested compartments should be less of a problem than for two adjacent, regular stands of different ages. However, the borders between forest and non-forest types should probably be tackled differently. One possibility could be to apply land-cover dependant strategies for the integration of border values. The other one would be to constrain the partition into the spatial entities with compartment borders, but the issue of respecting the surface criterion might turn out tricky.

Conclusion

The accuracy of ALS-based estimates for basal area, dominant diameter and stem density is more than twice better at the compartment level than at the plot level, and for basal area reaches a level similar to a full-calliper inventory. For the spatialisation step, it is crucial to respect the size of calibration plots, whereas for the aggregation the issue of compartment borders has to be tackled differently depending on the forest parameter.

References

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