Within-Species Benefits of Back-projecting Airborne Laser Scanner and Multispectral Sensors in Monospecific Pinus sylvestris Forests

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Abstract
Back-projecting is an alternative to orthorectification for ALS-imagery fusion. It usually assists in improving forest estimations in mixed forests, by adding species information from optical sensors. In this study, we focused on the within-species advantages obtained. Results showed that estimating relative stem density improved significantly (from $R^2=0.76$ to $R^2=0.81$), as the multispectral signal may incorporate canopy closure-related shadowing conditions at plot-level. As a result, volume prediction also improved (from $R^2=0.65$ to $R^2=0.69$), even though Lorey’s height and basal area did not. Hence, monospecific conifer forests assessment may also benefit from ALS-imagery fusion.

Keywords: Sensor data fusion, Lidar, stem density, Stand Density Index, Snag detection, Forest Health.

Introduction
A variety of remote sensing projects may involve procedures for fusing airborne laser scanners (ALS) and multispectral sensors, as their application benefits from each other’s advantages simultaneously. ALS prediction can be supported by a pre-stratification of the study area into species or forest types, based on optical imagery [Asner, 2009; Gautam et al., 2010]. For this reason, a common remote sensing-based forest inventory workflow performs ALS estimations within forest stand boundaries obtained from aerial pictures [Leppänen et al., 2008]. ALS sampling can be combined with optical sensors for large-scale forest assessment, extending forest estimates to their wider coverage [Mcinerney et al., 2010; Andersen et al., 2011], and also benefiting from their larger temporal recurrence for baseline trend determination [Cohen et al., 2010]. Moreover, tree height is best retrieved from ALS, whereas thematic classification and index calculation are best performed from optical imagery [St-Onge and Achaichia, 2001]. Leckie et al. [2003] used ALS to study height and crown shape of individual trees previously recognized from aerial images. Multispectral
and hyperspectral sensors can also be used to add tree forest health information, water and chlorophyll content, to ALS estimations on forest biomass [Solberg et al., 2004]. For this reason, numerous studies have shown that incorporating predictors derived from satellite multispectral [Popescu et al., 2004; Pascual et al., 2010; Hou et al., 2011], airborne infrared cameras [Koukoulas and Blackburn, 2005; Packalén and Maltamo, 2006; Riaño et al., 2007] or hyperspectral scanners [Clark et al., 2011; Swatantran et al., 2011] to the models, can improve the accuracy of forest estimations obtained from ALS metrics alone.

Optical sensors are characterized by a perspective acquisition of incoming radiance, whereas ALS obtains positions with polar geometry. Consequently, ALS return coordinates are highly accurate [Baltsavias, 1999], and the success of fusion methodologies depends mainly on the strategy followed to correct the perspective acquisition of optical sensors. The variety of procedures for determining the coordinates of radiance digital numbers (DN) contained in raw optical images can be grouped into three strategies: a) orthorectification; b) back-projecting; and c) image matching. In this order, they provide increasing accuracy in the final coordinates of DNs. Errors in the horizontal coordinates of orthophotos depend mainly on the quality of the digital elevation model (DEM) used [Valbuena et al., 2008], whereas in back-projected ALS they are mainly around the magnitude of optical imagery’s spatial resolution [Valbuena et al., 2011], and sub-pixel accuracy is provided by multi-view redundancy in image matching [Leberl et al., 2010].

a) Orthorectification of optical imagery is the most common approach followed in data fusion schemes, as it has traditionally been the only means of allowing the use of optical sensor information for mapping purposes. The outcome is an orthophoto in raster format, which essentially differs from the 3-dimensional (3D) vector format of ALS. As a consequence, predictors have to be computed separately and joined afterwards, at plot-level if methods follow an area-based approach (ABA) [e.g. Maltamo et al., 2006], or at crown-level if based on individual tree detection (ITD) [e.g. Koukoulas and Blackburn, 2005]. Alternatively, for truly joint processing, either of them ought to be converted into each other’s format. Most frequently, a canopy height model is derived from the ALS data, and it is processed along with imagery using procedures designed for raster formats [e.g. Suárez et al., 2005]. If operating from the raw ALS return cloud is preferred, each point can be coloured with the DN from an orthophoto situated at its normal. This alternative may be more suitable for satellite than airborne optical imagery [Hou et al., 2011], as they are less dependent on the quality of the DEM due to their narrower nadir angles. However, it should be noted that orthorectification-led mismatches in imagery from sensors onboard airplanes have been reported to significantly affect forest assessment [Bright et al., 2012].

b) Back-projecting ALS has been demonstrated as a data fusion method superior to any orthorectification alternative [Valbuena et al., 2011]. While orthorectification aims at obtaining ground positions for DNs, back-projecting consists on computing the position of individual ALS returns on the original unrectified optical images. The outcome is a single coloured ALS cloud in 3D vector format. Hence, error-prone mosaicking and resampling procedures are unnecessary, avoiding errors and artefacts and keeping the original DNs for radiometric signal processing. Back-projecting has been used for determining species mixture at plot-level in ABA [Packalén et al., 2009] or semi-ITD [Breidenbach et al., 2010]. It has also been successful in discriminating among species at individual tree-level [Persson et al., 2004; Ørka et al., 2012]. Back-projecting assists in correctly positioning tree tops, fixing
the tree leaning effect observed in orthoimages [see Valbuena et al., 2008]. It may however be noteworthy to mention the difference between tree leaning and bidirectional reflectance effects, which remain unsolved in back-projected ALS. Radiometric information is still affected by within-image sunlit-shadow variation and the mutual shading of neighbouring trees which, in addition, are observed sideways at areas of the image other than near-nadir [Korpela et al., 2011].

c) Image matching has most recently been proved as a reliable alternative for correctly positioning the DNs of aerial imagery, thanks to latest improvements in digital cameras, automated image matching algorithms, and processing hardware [Leberl et al., 2010]. The method consists in triangulating the same position from several original images [Dandois and Ellis, 2012], and therefore relies on tailoring flight planning to obtain highly overlapping imagery collection. The outcome is a photogrammetric point cloud (PPC) in 3D vector format, which can be used for instance in percentile-based estimations of canopy height [Korpela and Anttila, 2004]. As a consequence, the PPC can be incorporated in the traditional workflow of ALS. Bohlin et al. [2012] successfully implemented an ABA to obtain forest estimates using PPC in combination with an ALS-derived DEM, as PPCs lack of ground positions. Depending on the degree of overlap, triangulation generally leads to a higher uncertainty in the vertical coordinate of PPCs, but their horizontal positioning of DNs benefits from higher accuracies than any of the alternatives hereby considered. Most previous approaches have utilized the optical sensors as a means of determining species mixture, information which is more difficult to retrieve from ALS datasets. In this study, we implemented the back-projecting method in a monospecific forest. Our aim was to research on whether optical sensor-derived metrics can also add a significant portion of explained variance in ABA predictive models of forest estimates. We wanted to obtain more detail on the intra-species variability of these metrics at plot-level, which can be used to comprehend inter-species separability. Furthermore, we tested the benefits of back-projecting technique at tree-level as well. A red-edge enhanced (REE) visualization of the coloured point cloud was developed, in order to emphasize forest health features. In this article we show an example for its application on snag detection, and discuss the possibilities of the back-projecting method in future research on radiometric correction of optical sensor information.

Materials and Methods

Plot establishment and forest response variables

The study area was a monospecific Scots pine (Pinus sylvestris L.) forest in Valsaín (Spain; latitude: 40°53′ – 41°15′N; longitude: 3°59′ – 4°18′W; 1300 – 1500 m above sea level), situated in the Sierra de Guadarrama mountain range. Field survey consisted of 37 circular plots of 20 metre-radius sampled in a systematic fashion, where diameter at breast height (dbh, cm) and tree top height (h, m) was recorded for every tree within plot belonging to dbh-classes >10 cm. Heights were determined with a Vertex III Hypsometer (Haglof, Sweden), and diameters were measured with a calliper in two perpendicular directions which were later averaged. To reduce field acquisition effort, saplings with dbh <10 cm were measured only within 10 m from plot centre, and they were repeated fourfold after assuring within-plot homogeneity in the field. All standing dead trees were recorded during field mensuration as well, in order to test the reliance of the technique for snag detection.
Table 1 summarizes the forest response considered in this study, which was computed from this field data at plot-level: stem density \((N, \text{ stems·ha}^{-1})\), stand density index \((SDI)\), quadratic mean diameter \((D_g, \text{cm})\), basal area \((G, \text{m}^2\cdot\text{ha}^{-1})\), Lorey’s height \((H_L, \text{m})\), standing volume \((V, \text{m}^3\cdot\text{ha}^{-1})\), and Gini coefficient \((GC)\), as detailed below.

Table 1 - Summary of statistics of explanatory variables obtained at plot-level from field measurements.

| Explanatory Variables          | n  | Mean (SD)       | Range            |
|-------------------------------|----|-----------------|------------------|
| Stem density                  | 37 | 732.34 (559.19) | 167.11 – 1917.82 |
| Stand density index           | 37 | 840.12 (455.70) | 209.17 – 1441.94 |
| Quadratic Mean Diameter       | 37 | 33.14 (12.32)   | 14.51 – 48.30    |
| Basal area                    | 37 | 41.77 (11.24)   | 21.08 – 57.74    |
| Lorey’s Height                | 37 | 23.69 (5.10)    | 15.35 – 31.12    |
| Standing Volume               | 37 | 390.72 (258.64) | 22.95 – 823.84   |
| Gini Coefficient              | 37 | 0.43 (0.25)     | 0.15 – 0.87      |

One of the most common variables of wood stocking used in forest management is basal area \((G)\), the cross-sectional area at breast height occupied by trees. For this reason, the most adequate descriptors of average \(dbh\) and \(h\) at plot and stand-level are basal area-weighted [Curtis and Marshall, 2000]. We therefore computed \(D_g\) and \(H_L\), variables which have been successfully predicted from ALS remote sensing [Næsset, 2002]. Additionally, absolute tree density was evaluated as the number of stems per hectare \((N)\), while \(SDI\) was also applied as a measure of density relative to the size of the trees. Reineke [1933] developed \(SDI\) as a dimensionless indicator of the number of stems compared to the maximum stocking capacity naturally regulated by competition and self-thinning. \(SDI\) provides an idea on the number of trees per unit area that a stand has at a reference quadratic mean diameter, which is generally fixed at 25 cm:

\[
SDI = N \left[ \frac{D_g}{25} \right]^{\beta} \tag{1}
\]

The \(\beta\) parameter is the slope of the density-size \((N-D_g)\) relation in fully stocked stands, to be determined empirically in logarithmic scale. Its value was estimated as 1.605 by Reineke [1933], though we used the value of \(\beta = 1.750\) suggested by Del-Río et al. [2001] on the basis of calculations carried out at the same Sierra de Guadarrama area, and as a compromise solution among other authors’ values specifically adjusted for by \textit{Pinus sylvestris} L. such as 1.593 in Germany [Pretzsch and Biber, 2005], 1.836 in Spain [Rojo and Montero, 1996], or 1.811 in Finland [Hynynen, 1993]. Moreover, we also computed \(V\) in order to consider a forest response involving all the previous properties altogether: the size, height of trees and their density. The models locally adjusted by Rojo and Montero [1996] for \textit{Pinus sylvestris} L. were therefore applied for calculating plot-level standing volume. Furthermore, we also selected \(GC\) in order to account for the inequality of sizes among the trees, because it has been suggested as measure of \(dbh\) dispersion better than...
variance [Knox et al., 1989], or entropy-based diversity indices [Valbuena et al., 2012a]. GC was calculated as the relative dissimilarities among individual tree basal areas (g; m²), i.e. average of tree-by-tree differences for all $n$ trees within a sample plot:

$$GC = \frac{n}{(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} \frac{|g_i - g_j|}{2n^2g}$$ [2]

Global Navigation Satellite Systems (GNSS) static observations were recorded at each plot centre with a survey-grade Hiper-Pro receiver (Topcon, California) during the time spent for forest mensuration, which was at least 30 min. Consequently, GNSS acquisition time was not a limiting factor and GNSS accuracy was uninfluenced by the heterogeneity of structural types [Valbuena et al., 2012b]. We acquired dual static observations from both GPS and GLONASS constellations at 1 Hz logging rates. To diminish the multipath effect of forested environment, antenna heights raised 1-2 m and a cut-off angle of 15° was masked. Differential corrections were computed at post-processing stage with simultaneous observation from the independent base station SGVA (designated by Technological Agricultural Institute of Castilla y León Region network [ITACYL, 2006]; lat.: 40°57′N; lon.: 4°7′W; baseline length=15-19 km), which in every case succeeded in fixing the initial phase ambiguity. This surveying configuration was selected as previous research found it to be the most optimal cost-efficient alternative providing centimetre accuracy [Valbuena et al., 2010], and therefore GNSS positional errors were assured not to influence forest response computation [Mauro et al., 2011].

**Remote sensing surveying**

Remote sensing data was simultaneously acquired with a digital mapping camera DMC (Zeiss-Intergraph, Germany) system consisting of several charge-coupled device (CCD) frame array sensors, and a discrete-pulse multi-return airborne laser scanner ALS50-II (Leica Geosystems, Switzerland). In clear sky conditions, Stereocarto (Spain) mounted both sensors onboard a 404-Titan (Cessna, Kansas) with double photogrammetric window, and flew at about 1500 m above terrain level with a ground speed of 72 m·s⁻¹. On-flight GNSS and inertial navigation systems (INS) were used to obtain the position and attitude of each sensor. Final georeferencing was also assisted by GNSS surveying of seven ground control points. Differential corrections were computed applying a network of three independent base stations: SGVA [ITACYL, 2006], YEBE (designated by Spanish National Geographic Institute network [IGN, 2006]; lat.: 40°31′N; lon.: 3°5′W; baseline length=85-88 km), and MAD2 (designated by NASA worldwide network [IGS, 2006]; lat.: 40°26′N; lon.: 4°15′W; baseline length=44-48 km). Planimetric coordinates were represented in the European Terrestrial Reference System 1989, using the Universal Transverse Mercator projection, zone 30-north. Orthometric altitudes were obtained according to the Ibergeo95 geoid model [Sevilla, 1995], and the altimetric datum was the mean sea level in Alicante, Spain. Optical sensor acquisition consisted in individual scenes captured at 5 ms-time of exposure with a 60% forward overlap and 40% sidelap. For the purpose of this study, we used only the scenes obtained from the multispectral heads with selective sensitivity for red (Red) and near-infrared (NIR), whose original 12 bit radiometric resolution was linearly stretched
to increase their dynamic range to 16 bit (2 byte) digital numbers (DN) in TIFF format [version 6.0, Adobe Systems, 1992]. Their ground sample spatial resolution was 60 cm, as Red and NIR heads had a focal length of 30 mm and CCD capacitors sized 12 μm. Original distortion-free and principal point corrected [Dörstel et al., 2003] imagery was used without any orthorectification procedure. Direct GNSS/INS georeferencing and ground control point aerotriangulation were combined for obtaining the final external orientation parameters for each image.

Four ALS scan lines of 665 m swath width were obtained with a 40% side lap. ALS50-II recorded a value of intensity for each one of a maximum of four discrete returns per pulse. Pulse repetition rate was set to 55 kHz, and therefore footprint diameter was about 0.5 m at nadir and average pulse density was 1.15 pulses·m⁻². For the given surveying conditions, the precision of both plan and height coordinates for returns is 0.17 m [Baltsavias, 1999]. Elevation differences between overlapping strips were under sensor tolerance, so that the resulting returns in LAS format [version 1.3, ASPRS Standards Committee, 2010] were georeferenced without additional adjustments. Figure 1 details how the return cloud was processed, filtered and classified using Terrascan software (Terrasolid, Finland). Returns from the ground were filtered following Axelsson [2000], iteratively including into a Triangulated Irregular Network lowest elevation returns within 2 m below a threshold angle ranging 12-75°. Points included in the Triangulated Irregular Network were classified as ground, and the remaining as vegetation. Terrain was characterized by DEM of 1 m pixel size interpolated from ground points, whose quality control by ground surveying proved a precision of 0.15 m [Valbuena et al., 2008]. The heights above ground level of ALS returns were finally obtained by subtracting the DEM value at their horizontal coordinates.

**Figure 1 - Flowchart of methodology followed to obtain the final plot-level models and the red edge enhanced (REE) visualization. Rectangles represent datasets and their subsets. Processing steps are represented by rhombi. Dashed lines group these processes according to the software used for each of them.**
Back-projecting ALS
Remote sensing data was further processed as a combination of procedures carried out with our self-developed software FUSENSOR [Valbuena et al., 2012c; De-Blas et al., 2013] for back-projecting ALS, and the assistance of software FUSION [version 3.1, McGaughey, 2012] for predictor computation at plot-level (Fig. 1). With the intention of enhancing the radiometric properties related to forest health and photosynthetic productivity, we computed the red edge for each original image at pixel-level as [c.f. Gautam et al., 2010]:

\[
\text{REDGE} = \text{NIR} - \text{Red} \ [3]
\]

With the objective of using REDGE for predictor computation, the resulting raster file was included in the imagery where back-projecting was applied, and also for visualization purposes as a substitute of the red channel in the final product. The original four-band multispectral scenes were therefore converted into three-channel TIFF images of 16 bit depth-DNs [Adobe Systems, 1992] containing the radiometric intensity for: red edge, green and blue (REDGE.G.B).

The original ALS return cloud was clipped for circular plots of 20 m-radii, according to their ground GNSS-determined positions (Fig. 1). For each individual ALS plot, back-projecting [Valbuena et al., 2011] was applied onto one REDGE.G.B image only. The reason for this was that no visibility algorithm was previously applied, therefore involving a risk for some ALS returns not to belong to the same projective ray than the radiometry that was assigned by back-projecting [Packalén et al., 2009]. For the purpose of this study, we considered that the ABA metrics computed at plot-level from the optical DNs would not be significantly affected by this type of errors. The most nadiral image was selected, in order to diminish bidirectional reflectance effects and enhance between-plot differences on tree size and gap fraction from the variation in their sunlit-shadow conditions. Using the external orientation parameters and the field GNSS plot centres, we determined the most nadiral picture which corresponded to each plot, under the criterion of lowest Euclidean distance of their horizontal coordinates.

FUSENSOR was used for back-projecting the ALS returns, according to their original 3D coordinates and the external orientation parameters which applied for each corresponding image (Fig. 1). After the absolute height was used in the collinearity equations [Valbuena et al., 2011] it was no longer needed, and therefore they were substituted by heights above ground level (above DEM) which are sounder in terms of forestry applications. The outcome was a height-normalized and REDGE.G.B-coloured ALS cloud, compiling with the specifications of the LAS format [ASPRS Standards Committee, 2010].

Predictor computation and nested models
The command cloudmetrics of FUSION was used for predictor computation (Fig. 1). State-of-the-art ALS metrics were computed from plot-level height above ground distributions. In addition, optical sensor-derived metrics were also computed from the within-plot radiometric intensity distributions, as available from version 3.1 [McGaughey, 2012]. The optical metrics were therefore computed from DNs fetched from REDGE image, which were located at the red channel of the LAS format [ASPRS Standards Committee, 2010]. Statistical analyses and modelling were carried out in R 2.15 environment [R Development...
An exploratory multivariate analysis was carried out with the intention of researching on the relations between the resulting remote sensing predictors and the forest response variables considered: \( N, SDI, D_g, G, H_l, V \) and \( GC \). We aimed at selecting few predictors which could equally be used for all the models. This would allow direct comparison of the relative benefit which can be obtained for each type of forest variable when adding the optical information. We selected predictors describing separate causal relations with the forest response: one for return height average, another for their dispersion, one around the higher percentiles, another for canopy cover, and a last one involving the red edge intensity observed at the optical sensor (Tab. 2). Canopy cover was considered as the percentage of returns with elevation larger than a 1 m above ground threshold, which was set as a height break in cloudbreaks [McGaughey, 2012]. The median \( (P_{50}) \) and coefficient of variation \( (CV) \) were selected as descriptors of central tendency and mean-normalized dispersion for the ALS return heights. The third quartile \( (P_{75}) \) was chosen as a descriptor for the position of the dominant canopy. The median of red edge DNs \( (\text{Redge}.P_{50}) \) was the selected optical predictor, based on its better correlation than the other optical metrics computed with at least some of the forest variables in study.

### Table 2 - Description of remote sensing predictors used.

| Sensor       | Property          | Symbol | Description                                                                 |
|--------------|-------------------|--------|-----------------------------------------------------------------------------|
| ALS          | height above DEM  | \( CV \) | Coefficient of Variation (standard deviation-mean ratio) of return heights within plot > 1 m. |
| ALS          | height above DEM  | \( P_{50} \) | Median (second quartile) of return heights within plot > 1 m.              |
| ALS          | height above DEM  | \( P_{75} \) | 75th percentile (third quartile) of return heights within plot > 1 m.     |
| ALS          | height above DEM  | \( \text{Cover} \) | Proportion of total returns within plot with heights > 1 m, i.e. canopy cover [McGaughey, 2012]. |
| Optical      | radiometric intensity | \( \text{Redge}.P_{50} \) | Median of DNs within plot for REDGE (eq. [3]).                          |

Linear models were adjusted separately by ordinary least squares, and their significances were tested with a t-Student statistic. Two models were tested for each individual forest response: one predicting from ALS metrics only \( X_{\text{without}} = \{CV, P_{50}, P_{75}, \text{Cover}\} \), and another including the optical metric as well \( X_{\text{with}} = \{CV, P_{50}, P_{75}, \text{Cover}, \text{Redge}.P_{50}\} \). As the second model included an additive term, the amount of explained variance at each of them was evaluated by their number of predictors-adjusted coefficients of determination (adj \( R^2 \)). Model comparison was performed by means of ANOVA test for nested models, as the model including the optical sensor information was exactly the same one with an additional term \( \text{Redge}.P_{50} \) appended. The significance of the relative reduction on the residual sum of squares induced by the second model (with optical metric) was tested with a Fisher-F statistic.

**Results**

All the model estimates adjusted for each of the forest response variables considered are summarized in Table 3. Significant regression was observed for all the adjusted models, although some of the selected predictors failed the significance test. The models succeeded
in explaining significant portions of the variance in the response variables: 59% for \( N \), 76% for \( SDI \), 75% for \( D_g \), 66% for \( H_L \), 65% for \( V \) and 65% for \( GC \). When the optical metric was included, the subsequent increase in the explained variance reached: 65% for \( N \), 81% for \( SDI \), 81% for \( D_g \), 75% for \( G \), 68% for \( H_L \), 69% for \( V \) and 67% for \( GC \). The ANOVA test showed that this increase was not significant in the case of \( G \) and \( H_L \), and therefore the optical sensor is unlikely to provide any predictive potential in terms of the size and height of trees, as compared with the capabilities of ALS for describing these variables. The case was similar for \( GC \), as the optical metric seemed to hardly add explained variance for the inequality of tree sizes.

Table 3 - Model estimates including (with) and excluding (without) the red-edge predictor (\textit{Redge.P50}) for each forest response (a-g). ANOVA test for model comparison was used for evaluating the significance of including \textit{Redge.P50}.

| a) Stem Density (\( N \)) | Coefficient Estimates | ANOVA |
|--------------------------|-----------------------|-------|
| Models                   | Intercept  | \( CV \) | \( P50 \) | \( P75 \) | \( Cover \) | \( Redge.P50 \) | \( adj R^2 \) | \( p-value \) | \( F (df) \) | \( p-value \) |
| \( N \) (without)        | 1766.614    | ***     | -1123.055 | ***     | -7.955 | **     | 2.457 | NS     | -11.453 | ***     | 0.59    | <0.001*** |
| \( N \) (with)           | 1790.220    | ***     | -1139.530 | ***     | -8.992 | **     | 3.435 | NS     | -10.140 | ***     | 0.65    | <0.001*** |

| b) Stand Density Index (\( SDI \)) | Coefficient Estimates | ANOVA |
|-----------------------------------|-----------------------|-------|
| Models                            | Intercept  | \( CV \) | \( P50 \) | \( P75 \) | \( Cover \) | \( Redge.P50 \) | \( adj R^2 \) | \( p-value \) | \( F (df) \) | \( p-value \) |
| \( SDI \) (without)              | -1100.458   | ***     | 772.253  | ***     | 7.513  | ***     | -0.843 | NS     | 7.951   | ***     | 0.76    | <0.001*** |
| \( SDI \) (with)                 | -1115.839   | ***     | 782.987  | ***     | 8.189  | ***     | -1.480 | NS     | 7.096   | ***     | 0.81    | <0.001*** |

| c) Quadratic Mean Diameter (\( D_g \)) | Coefficient Estimates | ANOVA |
|----------------------------------------|-----------------------|-------|
| Models                                 | Intercept  | \( CV \) | \( P50 \) | \( P75 \) | \( Cover \) | \( Redge.P50 \) | \( adj R^2 \) | \( p-value \) | \( F (df) \) | \( p-value \) |
| \( D_g \) (without)                   | -235.821   | ***     | 169.684  | ***     | 1.488  | ***     | -0.139 | NS     | 1.848   | ***     | 0.76    | <0.001*** |
| \( D_g \) (with)                      | -239.211   | ***     | 172.050  | ***     | 1.636  | ***     | -0.279 | NS     | 1.660   | ***     | 0.81    | <0.001*** |

| d) Basal Area (\( G \))              | Coefficient Estimates | ANOVA |
|---------------------------------------|-----------------------|-------|
| Models                                | Intercept  | \( CV \) | \( P50 \) | \( P75 \) | \( Cover \) | \( Redge.P50 \) | \( adj R^2 \) | \( p-value \) | \( F (df) \) | \( p-value \) |
| \( G \) (without)                     | 48.694     | *       | -38.474  | **       | 0.020  | NS      | 0.311  | NS      | -0.025  | NS      | 0.75    | <0.001*** |
| \( G \) (with)                        | 48.122     | *       | -38.075  | **       | 0.046  | NS      | 0.288  | NS      | -0.056  | NS      | 0.75    | <0.001*** |
On the other hand, the ANOVA model comparison showed that a significant amount of variance was explained by the additive term in many other cases. Including the optical metric was especially useful for those response variables describing stem density, such as N, and even more clearly for SDI. As a significant amount of variance was also added for Dg, the optical sensor showed a capacity for illustrating the mentioned N/Dg relations further from the ability of the ALS sensor. Significant results were also found in terms of an overall V prediction, being this one the most directly applicable benefit in ABA of the back-projecting methodology for ALS-imagery fusion hereby explained.

**Discussion**

**Improvement obtained in stem density estimation**

Results obtained for models only involving ALS metrics were consistent with previous research, as usually less variance is explained for N than for response variables dependent on basal area or canopy height [Næsset, 2002]. The main conclusion of this study was that adding the optical metric mainly benefited the estimation of those variables related to stem density. The relation between the canopy closure and the red edge properties observed at optical sensors is already well known. It allows for instance to monitor forest disturbance [Cohen et al., 2010] and health [Solberg et al., 2004; Bright et al., 2012]. The significant ANOVA results obtained at Table
3a-b for $N$ and $SDI$ demonstrate that including optical sensor surveying in ALS remote sensing can be highly beneficial whenever involving information on canopy closure is to be applied on forest management and monitoring. These results are important for the state-of-the-art in ALS remote sensing which, although commonly successful in volume and biomass estimation [Packalén and Maltamo, 2006; Asner, 2009], often obtains more modest results for $N$ [Næsset, 2002; Magnussen et al., 2010]. The most significant improvement in the predictive potential of the additional term was found for $SDI$, a result which we found most intriguing. It must be born in mind that $SDI$ provides a measure on the number of trees per unit area that a stand has at the 25 cm-reference quadratic mean diameter [Reineke, 1933]. From equation [1], $SDI$ can be understood as a basal area-weighted measure of stem density [Valbuena et al., 2012b], i.e. the density at the dominant canopy. In relation with this is the success in also improving the estimation of $D_g$, which is a combined measure on both $dbh$ mean and variance [Curtis and Marshall, 2000]. The optical sensor is therefore providing with valuable guidance on the relative stocking and canopy closure conditions, independently from the basal area itself. Hence, the optical metric measured at plot-level is a good indicator on the sunlit-shadow variation motivated by changes in the horizontal structure of the forest. The optical metric is therefore giving an indication of the amount of radiation reflected from the ground, in relation with the size of the trees casting a shadow over it. From these results, we therefore interpret that the addition of optical sensor information can be most useful in analyzing the divergence from a fully stocked stand. This could have different applications depending on the context, as it can be used in monospecific conifer stands, to evaluate the need for thinning in managed forests, or for monitoring forest disturbance in unmanaged areas.

**Potential for other forest estimates**

The improvement obtained when fusing both sensors was rather modest for those forest estimates which are already well predicted in ALS remote sensing: i.e., those depending on basal area and tree height. Nonetheless, conclusions reached from the results of the present study on the predictive potential of optical sensors should only be considered in terms of its comparison against the ALS metrics. Hence, optical sensors do have some predictive assets for forest variables such as $G$ and $H_l$, as demonstrated by previous research [Mcinerney et al., 2010; Hou et al., 2011], and these results only corroborate their lower possibilities compared to the more costly ALS remote sensing. Nonetheless, Magnussen et al. [2010] found that the random variation of ALS metrics leads to more reliable estimations of $H_l$ and $G$, than $V$ and $N$. The amount of variance explained by the optical sensor therefore seems to be closely related to the unreliability of ALS estimation, though more research would be needed in search for clarifying this hypothesis.

In terms of the internal structure of the forests, which was studied by means of $GC$ as suggested by Knox et al. [1989] and Valbuena et al. [2012a], the optical metric accounted for no significant amount of explained variance. A high inequality on tree sizes is likely to motivate within-plot changes in sunlit-shadow conditions, compared to the more homogeneous radiometric conditions of even-sized areas. However, the high capability of ALS remote sensing to characterize the balance between over and under-story has probably overcome any possibility for explaining any variance from the optical sensor. It must however be further researched whether plot-level textural features [Maltamo et al., 2006; Hou et al., 2011] may add any extra information on the structural conditions of diverse
within the forest areas. The results obtained in terms of those variables describing forest density, $N$ and SDI, suggest that the optical sensor is more suitable for the description of forest horizontal structure: i.e., gap fraction, canopy closure, and perhaps spatial patterns. The ALS metrics will, on the other hand, always provide with more predictive potential for descriptors of forests’ vertical structure, as it is the case of GC [Valbuena et al., 2012a].

On the other hand, a slightly significant improvement was found by the ANOVA test on the nested models for $V$. This has important consequences on the actual application of back-projecting ALS, as forest variables describing the total bulk of wood volume [Packalén and Maltamo, 2006; Breidenbach et al., 2010], biomass [Gautam et al., 2010; Andersen et al., 2011; Clark et al., 2011], or carbon stock [Asner, 2009; Bright et al., 2012], are of important concern of remote sensing-based forest inventories. Some studies already found that significant explained variance was added by optical sensor information [Maltamo et al., 2006; Swatantran et al., 2011]. For instance, the improvement obtained in total volume estimation slightly exceeded that obtained by Hou et al. [2011], who used orthorectification for data fusion and entropy as textural optical metric, based on the increase observed in adjusted $R^2$. A combination of both approaches would be ideal in future research: using back-projected ALS and computing textural metrics at plot-level.

Generally speaking, discriminating diverse components on the forest response may assist in understanding the relation of remote sensing ABA predictors with different aspects of the forest, as for instance we may regard an optical metric as a descriptor of relative density, while ALS return dispersion may be for basal area, or a high percentile for tree height. These relations are nevertheless of less concern when pursuing accurate prediction of volume or biomass in the forest. However, this type of information may still be useful when the cross-relations among sensors are of interest for selecting the most suitable optical-derived predictor [Pascual et al., 2010], for instance in ALS sampling schemes [Mcinerney et al., 2010; Andersen et al., 2011].

**Inter-specific consequences of observed intra-specific variation**

The variability in optical sensor DNs, which has been found in this study to depend on $N$, may also have important consequences for inter-specific discrimination. An important practical application of our results is that the forest area may require to be stratified according to stem density, as a prior step to species identification at plot-level. The intra-specific variability observed in the optical metric, and its relation with determined forest response variables, may also assist in comprehending the possibilities and limitations of the optical sensor for inter-species characterization. The ample range of variation in sunlit-shadow properties, led by canopy closure conditions, is a burden for the statistical spectral separability between tree species [Koukoulas and Blackburn, 2005; Korpela et al., 2011]. This can typically be observed in scatterplots comparing the red edge DNs for different tree species, as shown in numerous studies [e.g. Persson et al., 2004]. Species misclassification may occur at plot-level if, for instance, the density conditions of a pine forest makes it seemly as shadowy as spruce forest. This confusion in inter-specific radiometric properties of forest canopies is leading to difficulties in obtaining added explained variance in studies involving several species [Clark et al., 2011]. Packalén et al. [2009] solved this contingency by considering degrees of target species mixture. The results observed in this study can serve as a basis for further optimizing the synergies between the two sensors. The study of
plot-level optical metrics seems to require some sort of forest density normalization, which may for example be obtained from ALS metrics such as Cover. Further research may also test possibilities for new metrics themselves computed from properties of both sensors, therefore truly obtaining synergic benefits from data fusion.

**Red edge enhanced (REE) visualization**

The substitution of red by REDGE in the red channel while maintaining the original DNs for green and blue, which we called REE visualization (Fig. 2), may allow for a direct assessment of forest health at tree-level. The additive colour REDGE.G.B composite highlighted dead trees in green colour, against the rest of surrounding green vegetation. REE may be applied for snag detection by visual identification, as the crowns of individual snags can be easily distinguished and identified.

![Figure 2 - Red edge enhanced (REE) visualization of back-projected ALS returns from one sample circular forest plot. A standing dead tree, situated in the front, appears highlighted in green colour. Additive colour 3D perspective visualization generated with FugroViewer (Fugro Geospatial Services, Netherlands).](image)
Although no actual tree-level results were pursued in the present study, the resulting coloured LAS file showed a clear potential for forest health description. Figure 2 shows one of the plots which contained a snag within, which REE showed in a contrasting green colour. The REE visualization was undoubtedly useful for manual identification of standing dead wood, at least as long as it reached the dominant canopy so that its reflected radiation was acquired by the optical sensor. It is worth to note those green points situated on the ground, for which the linked REDGE.G.B intensities were clearly mistaking. The methodology, as it has been carried out in this study (Fig. 1), would therefore be unsuited for automated tree-level analyses. Figure 2, however, illustrates on the huge potential of back-projecting ALS in terms of the accurate within-crown positioning of radiometric properties.

In the present article we just showed a demonstration on the potential of back-projecting ALS on snag detection. The elevated accuracy obtained in data fusion at tree crown-level implies a high feasibility for addressing snag detection with ITD methods applied on coloured LAS files. Crowns segmented from a canopy height model may be automatically classified as snags, based on their red edge properties, while the volume of dead wood can be better estimated from the ALS returns. These ITD methods however require higher pulse densities than those used in the present study. We therefore advise to apply this technique in an ancient woodland (old-growth) forest area, surveyed with high density ALS data and optical sensors.

Potential benefits of back-projecting ALS on future research

A number of benefits have already been observed in using the back-projecting method for ALS fusion with DNs from irradiance intensity sensed at an optical camera mounted on the same platform. Valbuena et al. [2011] described the advantages obtained in terms of positional accuracy of horizontal coordinates, which would solve the leaning and mismatching effects that are usually observed when using orthorectification [Asner et al., 2012; Bright et al., 2012]. Although not in vertical coordinates and tree height estimation [Korpela and Anttila, 2004; Bohlin et al., 2012], the accuracy of optical data’s horizontal coordinates may in theory be still improved in PPCs processed by image matching [Leberl et al., 2010], therefore inducing further improvements in projects involving sensor fusion. Ørka et al. [2012] pointed out the improved potential in species classification which is found in back-projected ALS return clouds. The present study summarized a number of advantages in which can be also found within single tree species, in terms of expanding model reliability for response variables dependent on the relative density of different areas of the forest, as well as its potential in studying forest health up to tree level.

In addition to all the advantages already observed in recent investigations, there are a number of more potential benefits which are still on the remote sensing research agenda: including radiometric correction, visibility analysis, or data mining. The positional accuracy reached by back-projecting ALS can take the radiometric normalization of optical information up to the tree scale. Observe in Figure 2 how, once one single tree is isolated, the within-crown sunlit-shadow variation is clearly related to the position of the sun as relative to the tree. Further research can therefore take advantage of the precise data fusion outcome, for instance using ITD and ALS on crown shape information to apply radiometric normalization for bidirectional reflectance effects [Korpela et al., 2011]. It is noteworthy to point out that back-projecting ALS can be carried out using remote sensing data which has been surveyed from different platform or at differing times [e.g. Packalén et al., 2009]. Simultaneous acquisition is therefore not compulsory, although it is likely to reduce data acquisition costs if back-projecting is well planned in advance [Ørka et al., 2012].
Future research in adapting the back-projecting technique to hyperspectral sensors will be of most interests. First of all, the information to be included has to be adapted to the fields and bit depth currently available in LAS format. This is also important in terms of discriminating the band ratios or linear combinations that actually concern in the data fusion scheme [Asner et al., 2012]. Otherwise, the theoretical adaptation is straightforward, as it just requires a revision of the collinearity equations to the pushbroom scanner architecture. More important is to adjust the external orientation at each row of the raw image, and research on whether GNSS alone or a combined aerotriangulation is to be used for that purpose. Also regarding the possibilities for aerotriangulation, future research may focus on combinations of back-projected ALS with PPCs obtained by image matching [Leberl et al., 2010]. Vertical coordinate errors introduced by the bidirectional reflectance effects and intra-image variability [Korpela and Anttila, 2004] must be addressed, specifically for forested environments, through improved image matching algorithms. The introduction of optical metrics is a straightforward improvement from the results reached by Bohlin et al. [2012] in PPC processing for forest assessment. We foresee that forest inventory studies using both ALS and PPC point cloud simultaneously will obtain successful results, as the positional accuracy possibilities of each sensor and their synergic benefits would be at its optimum in such scheme.

Conclusions
The median of red edge differences computed at plot-level was found to significantly explain an additional portion of variance in relative stem density, which was not predicted by the ALS metrics alone. The significance of including this additive term was highest for the stand density index, therefore indicating that the optical sensor provides an idea on the deviation of the forest area from the maximum density situation found at fully stocked stands. This makes sense as the irradiation output from the forest at plot-level is then mostly dependent on the amount of ground reflexion, relative to the size of the trees casting a shadow over it. These results also have important consequences in terms of using the optical sensor information to discriminate among species, as the variance within the range of optical DNs has been found to depend on forest density within single species. A combined ALS-derived forest density normalization of the optical radiometry at plot-level may therefore be advised in studies on species’ spectral signature discrimination. Other forest response variables may as well obtain more accurate ABA estimations from the inclusion of an optical-derived predictor, though our results suggest that the magnitude of additional explained variance will be correlated with the influence of stem density in the given forest response. This may be the case for forest volume or biomass, while basal area and tree height are seemly better predicted from ALS remote sensing. In relation to the study of forest structure, we concluded that the optical sensor may provide with an asset in terms of describing horizontal structure, i.e., canopy gap fraction and perhaps spatial patterns. However, ALS sensors are more suited for characterizing the vertical structure profile, and for this reason the optical metric added no significant explained variance for the Gini coefficient of tree size inequality.

The successful relations found between the forest response and the optical DNs were probably enhanced by their accurate georefering achieved by the back-projecting ALS method. The high accuracy of this technique allows to perform data fusion up to tree or crown level. In this article, we also presented a red edge enhanced (REE) visualization, which may have straightforward applications on for snag detection. Many other can be suggested for example regarding radiometric correction, especially in combination with ITD methods.
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