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# Applications of ALS (Airborne Laser Scanning) data to Forest Inventory. Experiences with pine stands from mountainous environments in Spain

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**Abstract.** The estimation of forest using Airborne Laser Scanning (ALS) data as auxiliary information has advanced substantially after more than three decades of studies. Numerous experiences have confirmed the potential of ALS data for the estimation of aggregated attributes such as volume, basal area or dominant height, and have developed methodologies to obtain predictions at a plot level.

This paper summarizes, interrelates and built new conclusions of different analyses on estimation of forest variables assisted with ALS data, in pine forests in the mountain systems of central Spain: *Pinus sylvestris* L., *Pinus nigra* Arn. and *Pinus pinaster* Ait. These studies also consider: 1) forest with different levels of heterogeneity, 2) different methodologies and protocols and 3) different spatial disaggregation units for forest inventory and management. All these factors make it difficult to directly compare certain results. However, the large amount of information provided by these studies allows having comparative examples, and providing references for future inventories. Other results regarding more methodological aspects, such as the sampling methods, plot sizes or ALS point densities can be extrapolated as procedures on a regional or local scale for the estimation of different stand features (species, basal area, dominant height, volume, etc.).

## 1. Introduction: application of ALS to forest inventory

Light Detection And Ranging (LIDAR) sensors have been used for a variety of applications. Airborne Laser Scanning (ALS) sensors (i.e. aerial LIDAR) were first used in forestry applications in the 1970s, but it was in the 1990s when a large number of tools and procedures were developed. The capacity of these sensors to obtain information about the three-dimensional structure of forest stands, and especially about their vertical structures, was demonstrated from the start [1, 2].

The high correlation shown by different LIDAR metrics with different stand variables makes them a primary source of auxiliary information for the estimation of forest variables. Estimates obtained for aggregated variables such as volume, basal area or dominant height, are better than those obtained from classic inventories based on random plots and basic stratification. The usefulness of LIDAR for the inventory and cartography transcends forest inventories and is useful for the survey of ecological and landscape aspects. LIDAR data has been incorporated into the set of tools required for Forest



Management Inventory in many countries [1]. Moreover, laser sensors can be installed on satellites and land-based platforms and then combined with ALS data. The applications to the inventory and cartography of natural resources have been more fruitful with ALS, because it provides detailed and accurate georeferenced data for large areas at a reasonable price. The use of ALS as an auxiliary variable also allows reducing the plot sizes in relation to classical inventories using visual assessment and photo-interpretation. LIDAR data can also be integrated with data from other type of sensors such as photogrammetric datasets or multi- or hyper-spectral imagery from airborne or satellite platforms that provide complementary information.

Two types of LIDAR sensors are currently used: 1) discrete pulse and 2) full wave form. Discrete pulse lasers have been used more frequently and full wave form sensors are still under research. For discrete LIDAR, pulse density is an important parameter because it relates to the capacity to identify volumes and shapes in the forest. Knowledge of the practical application of ALS data has improved and new contributions have been made continuously [1-4], but mainly focused on temperate/boreal forests.

Two approaches have been predominantly used to relate ALS auxiliary data and forest attributes: 1) the area-based method and 2) the individual tree method. Combinations of both approaches have been also used [1]. The area-based approach (ABA) [5] has been the most widely used, tested and systematized method, offering methodologies and tools to quantify and map forest variables of interest [6-8]. In the ABA method, the study area is covered by a mesh that contains auxiliary information for each pixel. The pixels have an area similar to that of the inventory plots and are considered as population units. For the field plots both LIDAR auxiliary variables and field measurements of the target variables are available. These LIDAR metrics act as independent variables in regression models that are fit and validated using the field plots. Then, those regression models can be applied to every pixel of the grid covering the entire study area because these cells have the necessary auxiliary information. In a final step pixel level predictions are aggregated at different levels (i.e. harvest units, stands ...) providing estimators for means or totals of the target variables at the considered level of spatial aggregation [5, 9, 10].

Even though some aspects of the ABA methodology have been thoroughly developed its operational application to forest inventories is still challenging. There are four fundamental aspects that must be addressed and solved before the use of ALS data and other remote sensors, is generalized to operational forest inventories. These issues are related to the level of disaggregation and accuracy that is required for the estimates.

- **Spatial disaggregation.** Estimation of inventory values at stand-level, or management units (MU), with the desired precision.
- **Disaggregation by sizes.** Estimation of diameter distribution.
- **Disaggregation by species.** Obtaining inventory variables by species.
- **Other factors to consider in practical applications.** Analysis of different factors that can degrade the precision or that should be considered for practical applications.

**Spatial disaggregation.** Both design based methods and model based methods have been applied under the ABA framework. Generalized regression estimators (GREG), are design-based techniques and have been successfully applied under an ABA framework to obtain estimates for averages or totals, in large areas for which large sample sizes are available. Forest managers typically need estimates for areas of interest (AOIs) such as stands, management units (MUs) or groups of MUs that are spatial sub-divisions of an entire forest or study area. Despite their flexibility, GREG estimators or similar direct estimators based on the sampling design present important disadvantages when estimates are needed for AOIs with a reduced sample size.

Small-area estimation (SAE), techniques can be applied under the ABA framework and allow obtaining unbiased estimates for AOIs that imply a high level of spatial disaggregation. SAE techniques also allow obtaining measures of the uncertainty for AOI specific estimates [7, 11].

The use of Empirical Best Linear Unbiased Predictor (EBLUP) based on mixed effect models appears in the literature as the most prevalent alternative to address the problem of estimating for

AOIs with small sample sizes [12]. Different authors [9, 13-17] have demonstrated the usefulness of EBLUPs in forest inventories assisted with remote sensing information. EBLUPs have been used to estimate stand averages or totals of [7]: top height (H, m), dominant height ( $H_o$ , m), mean height (Hm, m), Lorey's mean height (Hl, m), stem density (N, stems ha<sup>-1</sup>), quadratic mean diameter (Dg, cm), basal area (g, m<sup>2</sup> ha<sup>-1</sup>), total volume (V, m<sup>3</sup> ha<sup>-1</sup>), gross merchantable volume (Vc, m<sup>3</sup> ha<sup>-1</sup>) and total aboveground biomass (B, kg ha<sup>-1</sup>). It has been shown that the SAE + ABA methodology can be generalized to different temperate and boreal forests [e.g. 10].

Finally, SAE literature also provide EBLUP variants that can be applied outside of an ABA framework. These variants called area level EBLUPs. Comparisons of unit level EBLUPs and area level EBLUPs for N, V, g, Dg, Hm and Hl, showed that the root mean squared errors (RMSE) of unit level EBLUPs are lower than those obtained using area level EBLUPs, but area level EBLUPs are better for AOIs with small sample sizes (i.e. smaller than 25 plots per AOI) than estimates obtained using only using field data [16]. For the case studied in [16], for AOIs with more than 25 plots, area level EBLUPs provided less accurate estimates than estimates with field plots, for all variables, with the exception of Hl.

**Disaggregation by sizes and disaggregation by species.** Another crucial subject that is still under active research is the estimation of diameter distributions and the estimation of the forest variables by species; not only for decision-making about treatments and harvesting, but also for its relationship with the landscape and biodiversity.

Increasing the level of disaggregation (either by diameter or by species) results in poorer estimates [11]. Disaggregation by species typically imply making less categories than when considering diameter distribution classes. However, species composition correlates weakly with LIDAR. Different studies have shown that predictions of multiple attributes (disaggregated by species and/or diameters at breast height) can be improved with the integration of: data from multiple sensors [e.g. 18] or from local and regional inventories [11]. The installation of LIDAR sensors on unmanned aerial systems, also help to this end as it provides data at a finer spatial scales, which can be used for making operational decisions in a precise forest management [19].

**Other factors to consider in practical applications.** The cost-benefit ratio of incorporating ALS data to the inventory must always be studied and depends on the precision level that is required for the estimates. Costs of ALS data acquisition and required precision levels may represent limiting factors. The availability of open-access LIDAR data is aimed at reducing costs and facilitating the use LIDAR auxiliary information [11]. The validity of the data of a LIDAR flight (its shelf-life) can be long which reduces the cost of data acquisition [20]. Incorporating existing and newly-acquired datasets to improve the accuracy of estimates is another way to reduce costs [11, 21]. Integration of ALS data with other remote sensors for forest inventory also allows increasing the predictive performance of LIDAR therefore reducing the number of field plots that are required to meet certain precision specifications.

The use of LIDAR may not be as economically advantageous if the collection and processing of ALS and modelling times are included in the budget [e.g. 22]. Also, for very detailed (i.e. disaggregated) estimates, such as the diameter distribution, little gains in precision can be observed when comparing LIDAR estimates with field only methods. There are other scenarios where the use of LIDAR is a clear improvement. For example, inventories in remote areas, for which only aggregated variables are required and measurement of field plots involves a very high cost.

The precision of the estimates of forest attributes based on LIDAR predictors will depend on how correlated are the LIDAR auxiliary variables and the forest variables of interest. For variables closely related to tree heights (i.e. volume and or dominant height) accuracies should be expected to be high. For other variables related to N or Dg, both of which have weak correlations with the LIDAR variables, high estimation errors should be expected. Each particular application should consider beforehand that LIDAR data does not provide a universal solution for all the variables that are of interest for forest managers. Other factors affecting the precision of a LIDAR inventory derive from the number and distribution of plots sampled. There may be errors caused by poor plot georeferencing,

inadequate plot size, or insufficient density of ALS pulses. The error assessment of ALS-assisted inventories is a not solved problem, and such assessment is crucial for multi-purpose forest management [7, 10, 11].

## 2. Experiences with pine stands from mountainous environments in Spain

### 2.1. Objectives

The accuracy assessment of forest stand variables has been based on numerous empirical estimates, with varied conditions of sample design, intensity and plot size, density of LIDAR pulses, stand features, etc. Many accuracy assessments have been made with cross validation techniques, such as the leave-on-out method. The problem with the empirical estimates is that no extrapolation of accuracy values is valid from one area to another [11].

The objectives of this paper are to summarize, interrelate and built new conclusions carried out by the authors for the estimation of average stand variables assisted with ALS data, in pine forests from of central Spain mountain systems. The species studied are: *Pinus sylvestris* L., *Pinus nigra* Arn. and *Pinus pinaster* Ait.

The following sections present methodology, data analyses and synthesis of studies.

### 2.2. Material and methods (study area, inventory data and methods)

The study areas are shown in Figure 1. Table 1 shows the characteristics of the inventory and the ALS data used in each study area, for which results are presented and discussed in the following sections.



**Figure 1.** Location of Study Areas.

The study areas are located in natural pine dominated forests managed for both, production and conservation purposes. Pines occupy several million hectares in Spain, as is the case in other areas of the Mediterranean basin and the world. The treatments are shelterwood system for study areas 1 Cercedilla (Madrid), 2 Valsaín (Segovia) and 3 (Sierra de Cuenca), and clear cuts in small areas (less 10 ha) in location 4 Valle de las Caderechas (Burgos). Zones 1 and 3 are the most heterogeneous. The inventory plot design was systematic, except for zone 2, in which two sub-zones were considered:

zone 2.1, where simple random sampling was carried out, and zone 2.2, where 6 permanent plots were installed. For the calculation of variables, the ABA was used. Both the plot size and the LIDAR density were variable. Plot radius ranged between 10 and 25 m and LIDAR density from 2 to 11.6 pulses  $m^{-2}$ . The inventories were performed from 2006 to 2015.

**Table 1.** Characteristics of Study Areas.

Study Area		Elevation (MASL)	Spp. Dominant	Area	N° plots	Plot Radius, Size (m)	Year Inventory	Basal Area (m2)	Density Point Lidar (n°/ m <sup>2</sup> )	Year Lidar Data
1	1.1	1250-2050	<i>Pinus sylvestris</i>	147.5 ha.	60	18	2013-2014	32,66	11,6	2011
	1.2	Idem	<i>Pinus sylvestris</i>	147.5 ha.	80	15	2015	34,68	11,6	2011
2	2.1	1310-1450	<i>Pinus sylvestris</i>	300 ha.	37	20	2008	41,29	2	2006
	2.2	1350-1400	<i>Pinus sylvestris</i>	2,400 m2	6	60 x 40 m	2006	48.98	2	2006
3*		1100-1500	<i>Pinus nigra</i>	4,000	102	25	2008	11,41	11,4	2008
4		700-1170	<i>Pinus pinaster</i>	1,365.5	202	10	2009	21	2	2009
* In collaboration with Geo-Environmental Cartography and Remote Sensing Group, Department of Cartographic Engineering, Geodesy and Photogrammetry, Universitat Politècnica de València										

### 2.3. Results and discussion

**2.3.1. Positioning errors and plot size.** Global Navigation Satellite System (GNSS) positioning errors under forest cover have been studied. Precision improves by applying differential correction, decreasing the base-line between the receiver and the base station, combining Global Positioning System (GPS) and Global'naya Navigatsionnaya Sputnikovaya Sistema (GLONASS) constellations, increasing observation times and receiving bi-frequency [23]. However, the positioning error influences the estimation of forest variables. The plot size must be big enough to absorb positioning errors [24]. In zone 2.2, the variation of the estimation error with plot size was studied in 26 sampling points of a dense *Pinus sylvestris* stand, scanned at 2 pulses  $m^{-2}$ . Plots were georeferenced using a phase-differential GNSS receiver (Topcon HiperPro). Variables analyzed were: g, N, V, Hm and B. For 10 m radius plots, differences induced by the positioning error for Hm exceed 10% approximately in 5% of the occasions, while for the rest of the variables this frequency is approximately 20%. If the objective was to minimize the plot radius under the restriction that the differences in the stand variables exceed 10% at most 10% of the cases, for Hm we verified that the threshold plot radius was 8 m. This condition only was verified for all the stand variables at 15 m radius [24]. Plot size needed to estimate tree height distributions with 5 m intervals and using more than 25 trees per plot, was also analyzed. In this case, plots greater than 19 m were necessary [25].

**2.3.2. Relationship between plot size and LIDAR point density.** In zone 3 (Cuenca), a sparse *Pinus nigra* forest with an average basal area of 11.41  $m^2 ha^{-1}$ , the estimation precision was associated with plot size and with LIDAR density. Precision of the estimates was assessed with the coefficient of determination ( $R^2$ ) and the coefficient of variation (Cv) [26]. Optimal performances were obtained when combining the largest plot size (25 m radius) and highest LIDAR densities (6 pulses  $m^{-2}$ ). With 20 m-radius plots and scan densities of 5 pulses  $m^{-2}$  we obtained  $R^2 = 0.9$  for V, g and B. The rate of model improvement decreased from 12.5 to 13.5 m-radius plots (500-600  $m^2$ ). Smaller plots with higher scanning densities seem to be more practical as they don't imply a reduction in accuracy of the

models, but they clearly decreased the fieldwork cost. The accuracy of the canopy cover estimates had slight variations when the 300-400 m<sup>2</sup> were exceeded [26].

**2.3.3. Reducing the number of plots relative to traditional field inventory.** One of the main advantages of ALS-assisted inventories when compared to a traditional inventory is that they allow reducing the number of field plots for the same precision in aggregated variables. Tables 2 and 3 show the number of plots needed to obtain sampling errors of 5, 10 and 15%, with a traditional inventory and with ALS support, for different variables. In both cases, the ABA method and GREG estimators were used. Table 2 refers to study area 2.1 (Valsain), a 300 ha natural *Pinus sylvestris* forest with average g above 40 m<sup>2</sup> ha<sup>-1</sup>, treated by shelterwood system. Simple random sampling was performed in this area using 37 plots of 20 m radius. LIDAR density was 2 pulses m<sup>-2</sup> [27]. LIDAR auxiliary information allowed to reduce relative errors in the estimation of the average values of g, H, Ho, B and V for the entire forest. Relative errors lower than 10% were obtained when using at least 27 plots in the 300-ha area, with ALS support. Even using the maximum sampling intensity, errors were larger than 15% for N. Furthermore, for this variable, the inclusion of LIDAR auxiliary information did not reduce the uncertainty of the estimates.

**Table 2.** Number of plots needed to reach 5%, 10%, and 15% relative errors in study area 2.1, Valsain. Decrease in percentage of sampling intensity when including ALS data. Sampling intensity is calculated as the number of hectares corresponding to a plot, IScl: Sampling intensity for field only inventory. ISals: sampling intensity for ALS inventory.

relative Error %	Basal Area (g)					Dominant Heigh (Ho)				
	Classic Inventory	ABA	% decrease	IScl	ISals	Classic Inventory	ABA	% decrease	IScl	ISals
15	14	11	21.4	21	27	10	10	0	30	30
10	31	14	54.8	10	21	16	11	31.3	19	27
5	>>37	30	...	...	10	>37	20	...	...	15
relative Error %	Biomass (B)					Volume (V)				
	Classic Inventory	ABA	% decrease	IScl	ISals	Classic Inventory	ABA	% decrease	IScl	ISals
15	15	16	-7	20	19	29	10	66	10	30
10	34	27	20.60	9	11	>37	12	...	...	25
5	>>37	>37	...	...	...	>>37	26	...	...	12

**Table 3.** Number of plots needed to reach 5%, 10%, and 15% relative errors in study area 1, Ceredilla. Decrease in percentage of sampling intensity when including ALS data. Sampling intensity is calculated as the number of hectares corresponding to a plot, IScl: Sampling intensity for field only inventory. ISals: sampling intensity for ALS inventory.

	Basal Area (G)					Dominant Height (Ho)				
relative Error %	Classic Inventory	ABA	% decrease	IScl	ISals	Classic Inventory	ABA	% decrease	IScl	ISals
15	15.57	9.03	42.00	9.48	16.33	3<	...	...	...	...
10	32.02	16.66	47.97	4.61	8.85	6.13	4.74	22.68	24.06	31.12
5	106.92	46.67	56.35	1.38	3.16	35.87	14.67	59.09	4.11	10.05
	Biomass (B)					Volume (V)				
relative Error %	Classic Inventory	ABA	% decrease	IScl	ISals	Classic Inventory	ABA	% decrease	IScl	ISals
15	16.59	3<	...	8.89	...	17.60	12.39	29.58	8.38	11.90
10	34.14	7.00	79.50	4.32	53.90	36.42	17.60	51.69	4.05	8.38
5	114.81	53.06	53.79	1.29	36.46	>140	55.19	...	...	2.67
	Quadratic Mean Diameter (Dg)					Stem Density (N)				
relative Error %	Classic Inventory	ABA	% decrease	IScl	ISals	Classic Inventory	ABA	% decrease	IScl	ISals
15	11.53	15.21	-32.00	12.80	9.69	42.60	34.43	19.17	3.46	4.28
10	22.52	24.10	-7.04	6.55	6.12	90.41	71.28	21.16	1.63	2.07
5	78.54	72.84	7.25	1.88	2.03	>140	>140	...	...	...

Table 3 refers to zone 1(1.1 and 1.2), Ceredilla, a natural *Pinus sylvestris* forest with average  $g$  greater than  $30 \text{ m}^2 \text{ ha}^{-1}$ . The study area covered 147.5 ha, with 140 plots, the LIDAR density was  $11.6 \text{ pulses m}^{-2}$  [28]. As in the previous case the inventory with ALS allows to reduce number of plots for the same relative error for the variables  $g$ ,  $Ho$ ,  $B$ ,  $V$ , and  $N$ . For  $Dg$  there is no improvement with ALS except for 5% error. Several groups of variables with the same behavior can be distinguished. Tree height requires low sampling intensities with both classical and ALS sampling. Variables with significant improvements when including ALS data and with average or low sampling intensity requirements are  $g$ ,  $B$  and  $V$ . Variables without significant improvement with ALS are  $Dg$  and  $N$ .

**2.3.4. Estimation using SAE methods.** A comparison between two inventory systems: 1) a classical field, orthophoto and GIS-supported inventory, and 2) an ALS inventory using SAE techniques and EBLUPs was performed outside of the described study area [17]. Similar studies were conducted in Burgos (4) and Ceredilla (1). In Burgos, an inventory was carried out on 1,365.5 ha, which were subdivided into 54 stands. In Ceredilla, the sampling area can be considered a Management Unit, which was subdivided into 6 stands (Table 4). The main result of the study [17] is that the use of LIDAR data allows a significant reduction of estimation errors for areas of interest such as stands or groups of stands. The reduction of the uncertainty measured through the  $\text{difCv}\%$  parameter (which is defined as the normalized difference between coefficients of variation of the classic and the ALS-assisted inventories:  $(\text{Cvcl}-\text{CvALS}/\text{Cvcl}) \cdot 100$ ) reaches values close to 90% for some variables. The



mean values of this parameter in Burgos are 82.23% for V, 57.94% for N and 38.59% for g. For Cercedilla, these values were 29.43%, 10.53% and 57.53%. The lower reduction of uncertainty in this site is explained by the larger number of plots per unit area.

**Table 4.** Comparison of the errors for stand level estimates. Considered methods are a classic (field only) inventory and an inventory with ALS auxiliary information. Variables are volume (V), stand density (N) and basal area (g). Cvcl: is the coefficient of variation of the classic inventory. CvALS: is the average coefficient of variation of the ALS-assisted inventory. difCv%: normalized difference between coefficients of variation  $(Cvcl - CvALS / Cvcl)100$  of both methods. ErCl%: is the average stand relative error of the Classic Inventory (%). ErALS%: Average stand relative error of the ALS-assisted inventory (%).

Zone	Variable	(difCv% ) normalized difference between coefficients of variation $(Cvcl - CvALS / Cvcl) * 100$	(ErCl% ) Average stand relative error, Classic Inventory (%)	(ErALS% ) Average stand relative error, ALS data (%)
1. Cercedilla	V (m <sup>3</sup> /ha)	29,43	12,07	7,93
	N (trees/ha)	10,53	20,42	17,65
	g (m <sup>2</sup> /ha)	57,53	12,01	3,96
4. Burgos	V (m <sup>3</sup> /ha)	82,23	40,55	6,06
	N (trees/ha)	57,94	35,18	9,99
	g (m <sup>2</sup> /ha)	38,59	33,93	15,09

Considering only estimation errors obtained with each of the two techniques, the incorporation of LIDAR auxiliary information reduces the average relative errors for the AOIs from 40.55% to 6.06% for V, in the case of Burgos. In this site, for g, the relative errors of the traditional inventory are on average of 33.93 % while the incorporation of LIDAR auxiliary information reduces the error average relative to 15.09%. For N, estimates based on field data have an average relative error of 35.18% while using LIDAR data the average relative error is 9.99%. It is important to observe that in this case, with a sampling density of one plot every 6.75 ha, the incorporation of LIDAR auxiliary information improves accuracies, and relative errors descend below 15% in the subunits. The average area of these AOIs was 25.4 hectares and the average number of plots per AOI was 3.74 plots. In Cercedilla, when adding LIDAR auxiliary information, the average relative error for the areas of interest went from 12.07% to 7.93% for V, from 20.42% to 17.65% for N and for 12.01% to 3.96% for g. In this case, except for N, the high plot density used provided acceptable accuracies for practical applications even when using only field data. However, it is not common to have such a high plot density (23.3 plots per stand). These results are consistent with [16], in which estimates with only field data provided better estimates for subunits when the number of plots was greater than 25.

**2.3.5. Inventory costs with ALS compared to a traditional inventory.** In study area 2, a cost study was carried out comparing a traditional inventory and another with ALS auxiliary information. The costs included the installation of plots, the LIDAR flight and the processing costs [22]. Table 2 shows the number of plots required in the two types of inventory. For a 5% relative error the costs of a LIDAR inventory was lower than the cost of the traditional inventory for all forest variables, except for Ho. For a 10% sampling error, the opposite occurs. The traditional inventory costs are lower, except for V, for which the cost of a LIDAR inventory was lower. If the allowable sampling error was 15%, all forest variables could be obtained at a lower cost with a traditional inventory, except for N, which would have a similar cost. Therefore, only for inventories that require great precision, the costs are lower using LIDAR.

The cost comparison in case of freely accessible LIDAR data has also been done. The inventory costs with free access to LIDAR auxiliary variables for 15% sampling error are still higher than those of the traditional inventory for most variables except for N, and are equal for V. For 10% error, the cost difference between both types of inventories is reduced, the costs free LIDAR data are lower for V and similar for B and g. The costs is significantly lower for the inventory with free LIDAR data for all variables when the maximum allowable error is 5%. In addition, it must be borne in mind that diameter distribution can be estimated better with traditional inventory because it uses a greater number of plots.

The previous results show that many inventories carried out with ALS are economically inappropriate to estimates forest means and totals, since a simpler classic inventory would have sufficed in forest with good accessibility. In poorly communicated forests, the inventory with ALS data, can be profitable when only aggregated variables are needed. The application of the SAE method is also an advantage of ALS inventories. In section 2.5, for study area 4 (Burgos), the improvement in the estimation of stand-scale variables using ALS based methods with respect to traditional inventory methods, was assessed using the same number of plots [17] for both methods. Results showed that estimates for subpopulations using ALS are better than those obtained using only field plots. The improvement was errors 2 to 6 times smaller depending on the variable. In addition, in this case the estimation of diameter distributions using the same number plots as a classic inventory was also more advantageous with ALS data. This does not happen with lower density inventories that only consider the estimation error at the forest scale. A similar calculation can also be made for the case of zone 2.1, where the cost study also was carried out. Table 2 shows the reduction in the number of plots due to using an ALS inventory. If a 15% sampling error is set for the volume, 29 plots would be needed with a classic inventory and only 10 would be necessary with an ALS inventory, but if the number of plots is set 29 plots on the 300 ha area, an ALS inventory would provide more accurate information in the 7 AOIs of 42 ha, with an average 4 plots per AOI.

### 3. Conclusions

For decades, numerous forest inventories have been carried out with the support of ALS information in many countries, but with very heterogeneous ecological, stand, inventory and validation conditions. This heterogeneity means that it is not possible to directly transfer the precision of the estimates of a study area to another. However, the large amount of empirical information obtained from the numerous inventories with ALS support, carried out in many different countries provides comparative examples which may be used as references for future inventories. Some aspects of the inventory, can be systematized into procedures on a regional or local scale, and conclusions about the sampling methods, plot sizes or LIDAR pulse densities, for different characteristics of the forest stand (species, biomass, mean height, basal area, volume, etc.) can serve as guidelines. Results obtained in the estimation of stand variables in pine forests of the Spanish midland support this assertion and confirm the trends observed in other places. These results also give guidelines to future inventories in extensive pine forests of the Spanish mountains.

ALS technology has aroused great interest which has led to an inappropriate use of this technology in many cases where traditional inventory methods could have provided more accurate information at lower costs. Nevertheless, the small area estimation methods add advantages to the use of ALS data with respect to field only methods when subpopulations are considered. Cost -benefit studies should not only evaluate the decrease in the number of plots to obtain estimates at the forest level but also the sampling efforts required to estimate at a stand scale (or similar AOI). When this smaller units are considered ALS methods appear as more advantageous alternatives than those based on classical inventory. Therefore, it is necessary to increase the sampling intensity with ALS, in some cases reaching the intensity of a traditional inventory, but this also allows to improve the estimates of the diameter distribution in subpopulations (forest or management units) of the area where the sampling was designed. The estimation of the diameter distribution and disaggregation of stocks by species in mixed stands are still weak points in the use of ALS. The integration of ALS data with other sensors

and multitemporal information are currently areas under research. The utility and advantages of using both ALS and other technologies must be evaluated in each case.

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