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Increasing the use of expert opinion in forest characterisation approaches based on LiDAR data

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Abstract

• **Context** Forest structure characterisation approaches using LiDAR data and object-based image analysis remain scarce to forestry agencies as these automated procedures usually require the use of expensive software and highly skilled analysts. The integration of forest expert opinion into semi-automated approaches would simplify the access of forest managers to new technologies and would allow the incorporation of personal experience and the introduction of specific forest management criteria.

• **Aim** The aim of this study is to explore new alternatives to a previously published automated approach based on LiDAR data and object-based image analysis.

• **Methods** We compare four approaches, ranging from null to high incorporation of expert opinion and from fully automated to fully manual. These four approaches consist of three stages: (1) forest stand identification from LiDAR models, (2) forest stand classification into forest structure classes (manual and based on cluster analysis), and (3) validation.

• **Results** Quantitative attributes for validation (i.e. hypso-graphs and percentiles) provided slightly lower degree of separability for forest structure classes, in the mixed procedures with increasing incorporation of expert opinion than for the fully automated approach.

• **Conclusions** The new mixed approaches proposed are comparable to the automated procedures for the characterisation of forest structure in heterogeneous pine forest stands. They also offer additional advantages: (1) they make it possible to give a specific management focus and (2) they provide accessibility by the forest managers to the source of LiDAR information.

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1 Introduction

The traditional procedure for forest inventory can be synthesised into three main stages (Gillis and Leckie 1993; Wulder et al. 2008). First, forest stands representing homogeneous areas of specific forest attributes are delineated. These stands are then stratified by a specific combination of attributes and a sample is selected and assessed in the field. Finally, the field data collected are used (1) to generate new attributes that cannot be calculated based on photo-interpretation alone and (2) to adjust systematic errors in photo interpreter estimates. However, several studies reveal that these procedures are not exempt from error (i.e. miscalculation of long-term forest attribute predictions) (Thompson et al. 2007; Wulder et al. 2008).

In the last 15 years, alternative approaches for manual delineation and classification of forest stands—the two first stages of the forest inventory procedure—have been developed. Thus, newer approaches that use automatic segmentation algorithms and statistical modelling over high-spatial resolution remotely sensed data (i.e. IKONOS, Quickbird and digital aerial) (Kayitakire et al. 2002; Leckie et al. 2003; Fürst and Nepveu 2006; Wulder et al. 2008) and sometimes combined with LiDAR data (Mustonen et al. 2008; Koch et al. 2009; Haywood and Stone 2011) have been developed for forest inventory purposes.

There are two main types of approach for estimating forest attributes from LiDAR data (Hyypä et al. 2008): (1) methods based on statistical canopy height distribution (i.e. empirical regression methods) and (2) methods focusing on individual tree detection (i.e. physical methods). Naesset (2002, 2004) and Naesset et al. (2004) developed an operational forest inventory approach based on empirical regressions.

In a previous study an automatic approach for characterising forest structure in heterogeneous woods of *Pinus sylvestris* L. using LiDAR was proposed (Pascual et al. 2008). The approach consists of an object segmentation and a cluster analysis of the LiDAR-derived tree height distribution and validation of the classification obtained.

However, the actual application of these newer approaches using LiDAR data, high spatial resolution imagery and/or object-based image analysis remains scarce. Local governmental bodies, forestry agencies and private holders do not have the financial and technical capabilities required to implement these methodologies. This is due, among other reasons, to the inherent complexity of these automated procedures, which require the use of expensive software and highly skilled analysts (Pekkarinen and Holopainen 2006; Fernández-Rivas and Siabiato 2010).

The integration of forest expert opinion into semi-automated approaches would allow the delineation of homogeneous forest stands according to specific forest management criteria (wood production, species conservation or recreational use, to name some examples).

Finally, Mustonen et al. (2008) and Wulder et al. (2008) indicate that most automatic approaches for characterising forest structure only provide satisfactory results when applied to homogeneous woods. In addition, Haywood and Stone (2011) showed that classifications derived from manually delineated stands (from aerial photo-interpretation) provide better classification accuracy than those based on automated delineations since the interpreter can use additional features such as area, shape, context information, results of previous classifications and topographic information.

In this context, the objective of this study is to explore new alternatives to the automatic approach proposed by Pascual et al. (2008), which allow the consideration of forest expert opinion. We evaluated the potential of incorporating expert opinion

to (1) forest stand delimitation and (2) the cluster analysis from LiDAR data for characterising forest structure. By incorporating forest expert opinion, we aim (1) to enable greater significance to be given to the role of forest managers (2) to allow the consideration of specific criteria for the delineation of homogeneous forest stands and (3) to produce an operational tool for forest structure studies that can be implemented by end users at an affordable cost. The second objective is to compare the performance of the forest structure analyses developed. This work seeks to simplify the access of forest managers and end users to new technologies such as LiDAR data.

2 Materials and methods

2.1 Study area

An area of 127.10 ha (1,293 × 983 m) located on the western slopes of the Fuenfría Valley (40°45' N, 4°5' W) in central Spain was selected as the study area. The Fuenfría Valley is located in the northwest portion of the Madrid region (Fig. 1). The predominant forest is Scots pine (*P. sylvestris*, L.) with abundant shrubs of *Cytisus scoparius* (L.) Link., *Cytisus oromediterraneus* Rivas Mart. et al. and *Genista florida* (L.). There are also small pastures and an extensive rocky area in the north of the study site. Elevations range from 1,310 to 1,790 m above sea level, with slopes of between 20 and 45 %. The average aspect of the study site is east. The site has a mean annual temperature of 9.4 °C and a mean annual precipitation of 1,180 mm.

2.2 LiDAR data

A small-footprint first–last return LiDAR mission was flown by Toposys GmbH over the study area in August 2002 with the Toposys II LiDAR system, also known as FALCON II (<http://www.toposys.com>). The flying height was ~1,000 m and the scan angle was $\pm 7^\circ$, which renders a scan width of ~255 m (Riaño et al. 2007). The LiDAR system recorded first and last laser returns with a 0.5-m footprint diameter at a spatial density of 4.5 points m⁻², 2 m and 0.11 m in the across- and along-track directions, respectively. The raw data (*x*, *y* and *z* coordinates) were processed into two digital elevation models by TopoSys using a special local adaptive median filter developed by the data provider as the interpolation algorithm, as we did not have access to raw data. The digital surface model (DSM) was processed using the first pulse reflections, and the digital terrain model (DTM) was constructed using the last returns. Filtering algorithms were used to identify canopy and ground surface returns for an output pixel resolution of 1-m horizontal and 0.1-m vertical resolutions. To obtain a digital canopy height model (DCHM), the DTM

Fig. 1 Study site. Fuenfría Valley in the village of Cercedilla, northwest of Madrid (Spain)

was subtracted from the DSM. Both the DTM and DCHM were validated before use by land surveying and ground-based tree height measurements. The vertical accuracies (root mean square error (RMSEs)) obtained for the DTM in open areas and for the DCHM under forest canopy were 0.30 and 1.3 m, respectively. These accuracies were in agreement with previous studies. In tropical landscapes, Clark et al. (2004) reported RMSEs values ranging from 0.06 to 0.61 m for DTMs and from 0.23 to 2.41 m for DCHMs (Pascual et al. 2008).

2.3 Forest structure types

Based on field data measurements from ten plots, Pascual et al. (2008) described five forest structure types in the study area according to their forest attributes. These five forest types are summarised as follows:

- Type 1. Uneven-aged forest with very high crown cover/density. These forest stands are located in the southern part of the study area, representing 17 % of the forest cover. This forest type corresponds to a multi-layered, uneven-aged Scots pine formation with very high density (850 treeha^{-1}) and includes the tallest trees in the study area (Lorey's height of 17.8 m). The average diameter is 18.4 cm and basal area is $38.4 \text{ m}^2 \text{ ha}^{-1}$.
- Type 2. Multi-diameter forest with high crown cover. This pine formation occupies nearly 20 % of the forested areas of the study site and appears in the southern portion of the study area with some discontinuous stands in the north sector. This forest type can be described as having a multi-diameter distribution (which is closer in trend to an even-aged forest than forest type 1), two-story vertical distribution and high density (640 treeha^{-1}). Trees included in this forest type have a slightly lower height and diameter than those in the previous type (Lorey's height of 17.3 m; average diameter is 26.4 cm and basal area is $21.2 \text{ m}^2 \text{ ha}^{-1}$).
- Type 3. Multi-diameter forest with medium crown cover. This type occurs discontinuously across the study area and represents 25 % of the forested areas in the study site. This type of forest also has a multi-diameter distribution but is less dense (380 treeha^{-1}) than type 2 above, and trees are also smaller in height (Lorey's height of 15.4 m).
- Type 4. Even-aged forest (single story) with low crown cover (175 treeha^{-1}). These stands are distributed throughout the higher elevations of the study area (30 % of forested area). The distribution of diameter classes is close to an even-aged formation and single-story vertical height distribution. This forest type includes mature trees of greater diameter (41-cm geometric mean) but with a slightly lower

height (Lorey's height of 13.1 m) and larger crown diameters than other forest types.

- Type 5. Zones with scarce tree coverage (76 tree ha^{-1}). This forest type consists of dense shrub coverage (*Rosa* spp., *Adenocarpus hispanicus* (Lam.) DC., *Cytisus scoparius* (L.) Link, *Pteridium aquilinum* (L.) Kuhn and *G. florida* (L.) under isolated pine trees.

2.4 Mapping forest structure

We implemented and compared four approaches for forest structure characterisation, ranging from null to high incorporation of expert opinion and from fully automated to fully manual approaches, that we designated Aut-I, SAut-I, SAut-II and M-I. The fully automated approach, which does not include expert opinion (henceforth referred to as Aut-I), corresponds to the approach previously proposed by Pascual et al. (2008), and the other three, SAut-I, SAut-II and M-I, were specially developed for this study. The steps in each of these approaches are shown in Table 1 and described below:

2.4.1 Definition of height classes by forestry experts and statistical validation

We used expert knowledge from local forest managers to define height classes. Forest managers were asked to establish up to ten height classes that they considered useful for characterising structure variability in the study area. A maximum number of ten height classes were chosen as this represents the upper threshold for reliable human discrimination (van Gennip et al. 1997). The expert opinion height classes were validated using an analysis of variance

(ANOVA) test of the trees' diameters at breast height (DBH) with height class as a factor. The aim of this statistical validation was to verify whether the established height classes fulfil maximum internal homogeneity of diameter distributions within height classes and maximum heterogeneity among them. The ANOVA was carried out for 709 trees measured in 2003 from ten plots located throughout the study area. To reinforce this validation, an additional ANOVA test was applied to 892 trees measured in a previous forest inventory carried out for a broader area (Fuenfria Valley) in 1997. The expert opinion height classes were used for the SAut-I, SAut-II and M-I approaches.

2.4.2 Binning LiDAR-derived DCHM into expert opinion height classes

The DCHM cells were binned into one of the height classes defined by the forestry experts, thereby transforming the continuous DCHM into a categorical canopy height model. This process was carried out for the SAut-I, SAut-II and M-I approaches only.

2.4.3 Delineation of forest stands over binned LiDAR-derived DCHM

Manual delineation of forest stands For the SAut-I and M-I approaches, polygons corresponding to forest stands were manually digitised on-screen from the binned DCHM. These polygons were delineated using ArcGIS 9.3 software (Environmental Systems Research Institute, California 2004). The forest managers established the polygons' perimeter based on their experience, according to the spatial distribution pattern of the height classes (i.e. texture and colour of the binned

Table 1 Synopsis of the three forest structure characterisation approaches compared in this study and the previous proposed approach (Pascual et al. 2008). Increasing level of expert opinion

Object-based forest structure characterisation (Pascual et al. 2008) (Aut-I)	Automated segmentation of binned LiDAR-derived DCHM and statistical classification (SAut-II)	Manually delineated binned LiDAR-derived DCHM and statistical classification (SAut-I)	Manually delineated binned LiDAR-derived DCHM and manual classification (M-I)
	Definition of height classes by forestry experts and statistical validation	Definition of height classes by forestry experts and statistical validation	Definition of height classes by forestry experts and statistical validation
	Binning the LiDAR-derived DCHM into expert opinion height classes	Binning the LiDAR-derived DCHM into expert opinion height classes	Binning the LiDAR-derived DCHM into expert opinion height classes
Object segmentation of DCHM	Object segmentation of binned DCHM	Manual delineation of binned DCHM	Manual delineation of binned DCHM
Cluster of forest stands using LiDAR-derived metrics	Cluster of forest stands using LiDAR-derived metrics	Cluster of forest stands using LiDAR-derived metrics	Manual assignment of forest stands into forest classes
Validation (based on hypsographs and percentiles)	Validation (based on hypsographs and percentiles)	Validation (based on hypsographs and percentiles)	Validation (based on hypsographs and percentiles)

Table 2 Height classes used to bin the LiDAR-derived DCHM

Height classes	DCHM (m)
1	0–0.99
2	1–2.99
3	3–5.99
4	6–9.99
5	10–14.99
6	15–19.99
7	20–24.99
8	25–32

DCHM) and aided by a thorough knowledge of the area. This binned DCHM image provided information on forest canopy height, gaps and forest cover, which are commonly used parameters for manual polygon delineation in aerial photography (Franklin 2001). The delineation of polygons according to expert opinion was based on the management point of view and the criterion of preservation of the local environment.

Object segmentation of forest stands For the SAut-II approach, we developed a segmentation procedure that worked with the binned DCHM using eCognition 4.0 software (Definiens Imaging GmbH, Munich 2004), an object-based software which implements a segmentation algorithm developed by Haralick and Shapiro (1985). This algorithm identifies geographical features using the scale and homogeneity parameters, which were obtained in this study from the binned LiDAR DCHM. According to Suarez et al. (2005), scale relates to the minimum size required to identify a particular object, which depends on the resolution of the images. Homogeneity is

described by a mutually exclusive interaction between colour and shape. Colour refers to the spectral response of the objects (i.e. the binned LiDAR height classes in this study), whereas shape is divided into two equally exclusive properties: smoothness and compactness which respectively define the boundaries of the polygons (objects) and their transition to others. Three consecutive segmentation steps were applied to the binned DCHM. The first segmentation step was run for a scale parameter of 25, where 0.6 and 0.3 were the shape and smoothness parameters, respectively. The polygons obtained were later aggregated in higher levels, with scale parameters of 35 and 40, using weights of 0.3 and 0.2 for smoothness and shape, respectively. These segmentation settings produced polygons that correctly represent the forest stands, with a homogeneous structural typology.

Finally, for the Aut-I approach, the segmentation of forest stands was directly derived from the original DCHM (Pascual et al. 2008). These authors also performed three consecutive segmentations. A first segmentation with a scale parameter of 30 was derived, being 0.5 and 0.3 the shape and smoothness parameters, respectively. Later, the objects obtained were also aggregated into higher levels, with scale parameters of 50 and 70. The values for the smoothness and shape parameters were 0.3 and 0.4 for both the second and third segmentations, respectively (Pascual et al. 2008).

2.4.4 Classification of forest stands

This step was carried out using K-means cluster analyses for the automatic and semi-automatic approaches and by visual inspection and assignment of forest classes for the manual approach.

Fig. 2 LiDAR-derived DCHM binned into eight forest expert opinion height classes. Class 1, 0–0.99 m (areas with little to no vegetation); class 2, 1–2.99 m (areas with shrubs); class 3, 3–5.99 m; class 4, 6–9.99 m; class 5, 10–14.99 m; class 6, 15–19.99 m; class 7, 20–24.99 m; and class 8, 25–32 m

Fig. 3 Results for the three proposed forest structure characterisation approaches: **a** M-I approach (39 polygons); **b** SAut-I approach (39 polygons); and **c** SAut-II approach (88 polygons). The numbers inside the polygons indicate the forest structure type (1, 2, 3, 4 or 5) to which each polygon was assigned (forest structure type 1, uneven-aged forest with very high crown cover; forest structure type 2, multi-diameter forest with high crown cover; forest structure type 3, multi-diameter

forest with medium crown cover; forest structure type 4, even-aged forest (single-story) with low crown cover; and forest structure type 5, zones with scarce tree coverage (see Section 2.2 for descriptions). Polygons with no number indicate that they were non-forest stands and they were not included in forest structure classification. Dashed line indicates the manually delineated (a, b) or automated segmented polygons (c)

Cluster analyses (K-means) Following the approach described by Pascual et al. (2008), both manually delineated (approach SAut-I) and automatically segmented (approaches SAut-II and Aut-I) polygons were grouped into five structure types by K-means cluster analyses based on LiDAR-derived metrics. Two separate cluster analyses were performed, considering two different combinations of entry variables within each polygon: (1) mean and standard deviation (SD) of LiDAR-derived height (CombV1) and (2) median and SD of LiDAR-derived height (CombV2). In addition, an ANOVA test was done to assess the statistical significance of the forest structure types derived from the cluster analysis, and the Euclidean distances between the cluster's centroids were estimated in order to determine the proximity of the clusters.

Manual assignment For the manual approach, forestry experts visually inspected the manually delineated polygons

and assigned each one into a forest structure class. Their decision was based on a management point of view, considering the spatial distribution of texture patterns and colours of the binned DCHM (i.e. spatial distribution of heights and forest covers). Experts also incorporated their personal experience of forest management in this area. The assignment began with the forest structure types that were easier to distinguish (for example, mature forests and scarce tree cover). An ANOVA test was applied to assess the separability of the manually assigned forest structure types.

2.4.5 Validation based on percentiles and hypsographs

Hypsographs are the cumulative distribution of canopy heights as a function of proportional area within each polygon. These graphs are related to canopy height profiles, and are widely used both to analyse stand structure and to synthesise

Table 3 Mean and standard deviation (SD) of entry variables in both cluster combinations (CombV1 and CombV2) for M-I (manual delineation of binned LiDAR DCHM and visual assignment), SAut-I (manual delineation of binned LiDAR DCHM and statistical cluster) and SAut-II (object oriented segmentation of binned LiDAR DCHM and statistical cluster)

Cluster combinations	Variables	Forest type 1	Forest type 2	Forest type 3	Forest type 4	Forest type 5
M-I						
M-I	Mean height	13.9 (2.4)	12.8 (0.7)	10.4 (1.2)	8.7 (1.2)	5.3 (1.0)
	Median height	15.0 (2.7)	13.5 (0.7)	11.0 (1.2)	9.2 (1.5)	4.9 (1.4)
	SD height	5.8 (0.6)	4.4 (0.6)	4.1 (0.6)	5.3 (0.7)	4.1 (0.4)
	No. of members	5	6	10	12	5
SAut-I						
Comb V1_SAut-I	Mean height	13.7 (1.2)	10.8 (0.7)	9.8 (0.4)	7.9 (0.7)	4.5 (0.7)
	SD height	4.8 (1.0)	4.8 (1.0)	5.7 (0.4)	4.7 (0.7)	4.0 (0.3)
	No. of members	10	7	8	9	5
Comb V2_SAut-I	Median height	15.3 (1.2)	11.9 (1.0)	9.9 (0.5)	8.2 (0.9)	3.8 (1.2)
	SD height	5.2 (0.8)	4.2 (0.8)	5.7 (0.3)	4.7 (0.7)	4.0 (0.3)
	No. of members	7	12	7	8	5
SAut-II						
Comb V1_SAut-II	Mean height	14.1 (0.7)	12.6 (0.7)	10.9 (0.7)	9.1 (0.7)	7.0 (0.9)
	SD height	5.3 (0.9)	6.4 (0.5)	4.7 (0.5)	5.7 (0.7)	5.2 (0.6)
	No. of members	12	12	15	21	28
Comb V2_SAut-II	Median height	14.8 (0.9)	11.8 (0.8)	9.8 (0.6)	7.8 (0.7)	5.2 (1.0)
	SD height	5.9 (0.9)	5.0 (0.9)	5.6 (0.7)	5.2 (0.5)	5.2 (0.7)
	No. of members	21	18	17	22	10
Aut-I^a						
Comb V1_Aut-I	Mean height	14.3 (1.1)	11.4 (0.8)	9.1 (0.7)	6.7 (0.7)	3.8 (0.9)
	SD height	5.6 (0.9)	4.6 (0.9)	5.5 (0.7)	5.1 (0.7)	4.1 (0.7)
	No. of members	27	26	28	23	8
Comb V2_Aut-I	Median height	16.2 (0.8)	13.3 (0.9)	10.5 (0.7)	7.5 (1.0)	2.8 (1.3)
	SD height	5.6 (1.0)	5.1 (0.8)	4.8 (1.0)	5.2 (0.8)	4.7 (0.9)
	No. of members	17	27	27	28	13

Parentetical values are standard deviations of mean, median and SD of height for polygons in each forest type

^a Source: Pascual et al. (2008)

Table 4 Euclidean distance (in metres) among cluster (i.e. forest structure types) centres for CombV1 (mean and standard deviation (SD)) and CombV2 (median and SD) for SAut-I approach: manual delineation of polygons from a binned LiDAR DCHM and statistical cluster

	1*	2*	3*	4*
Comb V1 (mean and SD)_SAut-I				
2*	2.17	—	—	—
3*	2.85	1.37	—	—
4*	4.10	2.07	1.46	—
5*	6.5	4.38	3.86	2.43
Comb V2 (median and SD)_SAut-I				
2*	2.51	—	—	—
3*	3.82	1.77	—	—
4*	5.05	2.65	1.43	—
5*	8.17	5.72	4.49	3.13

1* forest type 1, 2* forest type 2, 3* forest type 3, 4* forest type 4, 5* forest type 5

Table 5 Euclidean distance (in metres) among cluster (i.e. forest structure types) centres for CombV1 (mean and standard deviation (SD)) and CombV2 (median and SD) for SAut-II approach: object oriented segmentation of polygons from a binned LiDAR DCHM and statistical cluster

	1*	2*	3*	4*
Comb V1 (mean and SD)_SAut-II				
2*	1.28	—	—	—
3*	2.23	1.73	—	—
4*	3.50	2.54	1.51	—
5*	4.95	4.05	2.80	1.51
Comb V2 (median and SD)_Aut-II				
2*	2.19	—	—	—
3*	3.52	1.47	—	—
4*	4.95	2.83	1.43	—
5*	6.84	4.72	3.31	1.89

1* forest type 1, 2* forest type 2, 3* forest type 3, 4* forest type 4, 5* forest type 5

Fig. 4 Hypsographs of the M-I approach for each forest structure type. *Numbers* are the identification code for each of the 39 manually delineated polygons

the three-dimensional distribution of forest canopies (Lefsky et al. 1999; Harding et al. 2001; Maltamo et al. 2005; Parker and Russ 2004). Hypsographs of each automatically segmented or manually delineated polygon were generated and used to estimate the statistical separability among cluster classes and also to validate and compare the four

classifications. Hypsographs were summarised as percentiles; i.e. heights at which 10, 25, 50, 75 and 90 % of the polygon surface area occurs within each polygon ($H_{10\%}$, $H_{25\%}$, $H_{50\%}$, $H_{75\%}$ and $H_{90\%}$, respectively). ANOVA tests with Tukey's honestly significant difference (HSD) method for post hoc analyses were used to assess whether indices describing

Fig. 5 Hypsographs of the SAut-I approach for each forest structure type. *Numbers* are the identification code for each of the 39 manually delineated polygons

Fig. 6 Hypsographs of the SAut-II approach for each forest structure type. Numbers are the identification code for each of the 88 segmented polygons

canopy height distributions (H_{10} %, H_{25} %, H_{50} %, H_{75} % and H_{90} %) varied significantly among forest structure types for both variable combinations (CombV1 or CombV2). These results were used to determine which variable combination provided the best separability of forest structure types and were therefore suitable as a tool for assessing the forest structure classifications obtained.

Forest structure types are considered to be an arbitrary process, and it is therefore impossible to compare the results against any one correct stand delineation (Koch et al. 2009; Wulder et al. 2008). According to Koch et al. (2009), Mustonen et al. (2008) and Falkowski et al. (2009), any reasonable stand classification should provide a separation of stands that differ from each other with respect to quantitative parameters. Following this same criterion, we validated and compared the performance of the approaches developed and tested in this study by assessing the statistical separability of quantitative parameters (i.e. hypsographs and percentiles) of the classifications obtained.

3 Results

Local forest managers defined eight height classes (Table 2) to aid manual forest stand delineation. Class 1 represents areas with little to no vegetation; class 2 represents areas with shrubs (<3 m height); and all remaining classes contain trees (at least 3 m in height). The expert opinion height classes were statistically validated using two ANOVA with post hoc Tukey's HSD tests. The first ANOVA used the DBHs of the trees measured from the ten plots located in the study area ($F=281.77$; $p<0.01$; $n=709$), and the second ANOVA used the DBHs collected for a previous forest inventory ($F=6456.32$; $p<0.01$; $n=892$). The post hoc Tukey's HSD tests were applied to compare the eight height classes in sets of two and indicated that the height classes were all statistically independent ($p<0.001$ in all cases). The LiDAR-derived DCHM was then binned into expert opinion height classes (Fig. 2).

Table 6 Tukey's HSD test

	Type 1	Type 2	Type 3	Type 4
Type 2	H_{10} %			
Type 3	H_{10} % H_{25} % H_{50} %	H_{10} % H_{25} % H_{50} %		
Type 4	H_{10} % H_{25} % H_{50} % H_{75} % H_{90} %	H_{10} % H_{25} % H_{50} % H_{75} % H_{90} %	H_{75} % H_{90} %	
Type 5	H_{10} % H_{25} % H_{50} % H_{75} % H_{90} %	H_{10} % H_{25} % H_{50} % H_{75} % H_{90} %	H_{10} % H_{25} % H_{50} % H_{75} % H_{90} %	H_{10} % H_{25} % H_{50} %

Significant differences between forest types ($p<0.05$): hypsograph indices for M-I approach (manual delineation and visual assignment of polygons)

Table 7 Tukey's HSD test

	Type 1	Type 2	Type 3	Type 4
Type 2	$H_{25} \% H_{50} \%$			
Type 3	–	$H_{10} \% H_{25} \% H_{50} \%$		
Type 4	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{10} \% H_{25} \% H_{50} \%$	$H_{10} \% H_{25} \% H_{50} \%$	
Type 5	$H_{10} \% H_{25} \% H_{50} \%$	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$

Significant differences between forest types ($p < 0.05$): hypsograph indices. CombV1_SAut-I (manual delineation and statistical cluster)

For the SAut-I and M-I approaches, 64 polygons were manually delineated from the binned DCHM (Fig. 3a, b). A total of 39 polygons contained Scots pine trees and 25 were non-forest, including components such as pasture, shrubs, rocks and bare soil. The 39 forest polygons varied in size from 0.48 to 10.56 ha and had an average area of 2.60 ha. For the SAut-II approach, the object segmentation of the binned DCHM produced 103 polygons (Fig. 3c). A total of 88 polygons corresponded to pine forest stands and 15 to non-forest stands (containing pasture, shrubs, rocks and bare soil). The average area of the segmented polygons was 1.27 ha, and the SD was 0.98 ha, with 0.20 and 5.48 as the minimum and maximum area, respectively.

For the SAut-I and SAut-II approaches, polygons were clustered into five forest structure types using K-means algorithm (Fig. 3b, c). Clustering of polygons was based on either mean and SD (CombV1) or median and SD (CombV2) of DCHM within the heights in each polygon. The ANOVA F ratios between cluster centres revealed that both CombV1 and CombV2 combinations were able to separate all five forest structure types in both semi-automatic approaches. The ANOVA results for the SAut-I approach were: (1) CombV1_SAut-I (mean $F = 106.5978$ ($p < 0.001$) and SD $F = 7.4179$ ($p < 0.001$)) and (2) CombV2_SAut-I (median $F = 110.0161$ ($p < 0.001$) and SD $F = 8.7116$ ($p < 0.001$)). Similarly, the ANOVA results for the SAut-II were: (1) CombV1_SAut-II (mean $F = 247.9159$ ($p < 0.001$) and SD $F = 14.7862$ ($p < 0.001$)) and (2) CombV2_SAut-II (median $F = 346.8224$ ($p < 0.001$) and SD $F = 3.7262$ ($p < 0.001$)).

For the M-I approach, manually delineated polygons were manually assigned to five forest structure types (Fig. 3a). We also applied an ANOVA test to check whether the manual groups achieved maximum variability among

groups, and minimum variability within a group, and also for the purpose of comparison. The ANOVA results for the M-I approach (mean $F = 36.474$ ($p < 0.001$), median $F = 36.120$ ($p < 0.001$) and SD $F = 9.537$ ($p < 0.001$)) indicated that forest experts were able to provide homogeneous forest structure groups.

Similar values for the LiDAR-derived summaries (i.e. mean, median and SD) were obtained for each forest structure type in the four approaches discussed, including the fully automated approach developed in our previous study (Table 3). This fact suggests that the new procedures (semi-automatic and fully manual) allow incorporation of expert opinion for forest structure characterisation. They achieved similar results to those obtained with the fully automated approach.

Euclidean distances between cluster centroids, used here as a statistical indicator of the proximity among clusters, provided better separabilities for the SAut-I approach than for the SAut-II in both variable combinations (CombV1 and CombV2) (Tables 4 and 5). Euclidean distances among clusters provided better separability for the fully automatic approach (Aut-I) than for both semi-automatic approaches (SAut-I and SAut-II) (see “Results” in Pascual et al. 2008). Additionally, both semi-automatic approaches provided better results (i.e. higher separability of forest structure types) for LiDAR median and SD combination (CombV2) than for mean and SD combination (CombV1) (Tables 4 and 5). This is consistent with the results for Aut-I approach (Pascual et al. 2008).

The validation analyses using hypsographs revealed marked differences among forest structure types for the three new approaches (M-I, SAut-I and SAut-II) (Figs. 4, 5 and 6). For the SAut-I approach, relatively homogeneous clusters were obtained, containing polygons with similar

Table 8 Tukey's HSD test

	Type 1	Type 2	Type 3	Type 4
Type 2	$H_{10} \% H_{25} \% H_{50} \% H_{75} \%$			
Type 3	$H_{10} \% H_{25} \% H_{50} \%$	$H_{50} \% H_{90} \%$		
Type 4	$H_{10} \% H_{25} \% H_{50} \% H_{75} \%$	$H_{10} \% H_{25} \% H_{50} \%$	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	
Type 5	$H_{10} \% H_{25} \% H_{50} \% H_{75} \%$	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{10} \% H_{25} \% H_{50} \%$	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$

Significant differences between forest types ($p < 0.05$): hypsograph indices. CombV2_SAut-I (manual delineation and statistical cluster)

Table 9 Tukey's HSD test

	Type 1	Type 2	Type 3	Type 4
Type 2	$H_{25} \% H_{50} \% H_{75} \% H_{90} \%$			
Type 3	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	—		
Type 4	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{50} \% H_{75} \% H_{90} \%$	
Type 5	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{10} \% H_{25} \%$

Significant differences between forest types ($p < 0.05$): hypsograph indices. CombV1_SA-ut-II (object-oriented segmentation and statistical cluster approach)

cumulative distribution of heights. In contrast, the hypsographs of approaches M-I and SAut-II showed higher dispersion within each forest structure type (less homogeneity).

A similar interpretation was achieved from the Tukey's HSD tests of hypsograph percentiles (Tables 6, 7, 8, 9 and 10). The M-I approach showed limited discrimination between forest structure types 1 and 2 ($p < 0.05$ for $H_{10} \%$ only). The SAut-II approach was unable to discriminate forest structure types 2 and 3, and forest structure types 4 and 5 ($p > 0.05$ in all hypsograph percentiles) and showed limited discrimination between forest structure types 3 and 4 and forest structure types ($p < 0.05$ for $H_{50} \%$ only) for the Comb_V2 variable combination (median and SD). Similar results were obtained for the Comb_V1 variable combination (mean and SD). The SAut-I provided better separability among forest structure types, with significant differences ($p < 0.05$) for at least two hypsograph percentiles for each pair of forest structure types for its best variable combination (Comb_V2). This approach produces slightly poorer results for the Comb_V1 variable combination. It was unable to separate forest structure types 1 from 3. The best separability among forest structure types was achieved for the Aut-I approach. Significant differences ($p < 0.05$) for at least four percentiles for each pair of forest structure types were obtained for Comb_V2 and at least three percentiles for Comb_V1 (see "Results" in Pascual et al. (2008)).

In summary, both the hypsographs and the Tukey's HSD tests for hypsograph percentiles highlighted the Aut-I and SAut-I approaches as being the best able to discriminate among forest structure types. Regarding variable combinations, Comb_V2 provided better separability of forest structure types.

4 Discussion

In this work, three methodologies were developed for forest structure characterisation which incorporate expert opinion in a progressive manner. These methods produced valid results which are comparable to the method described by Pascual et al (2008). Our results pointed out that the quantitative attributes for validation (i.e. hypsographs and percentiles) provided slightly lower degree of separability for the five forest structure classes in the mixed procedures with increasing incorporation of expert opinion than for the fully automated approach proposed in Pascual et al. (2008). However, the results (Table 3, hypsographs and percentiles) suggested that these new mixed approaches were comparable to the automated procedure for the forest structure characterisation of heterogeneous pine forest stands.

The fact that the methods M-I and SAut-I correctly discriminated forest structure types suggests that it may be advantageous to incorporate expert opinion and manual procedures in order to establish structure typologies which may be of use in forest management where specific software or trained users are not available. In fact, the quantitative attributes (Euclidean distance, percentiles and hypsographs) associated to the different forest structures (Tables 4, 5, 6, 7, 8, 9 and 10; Figs. 4, 5 and 6) showed a greater degree of statistical separation in the procedures with greater expert participation (M-I and SAut-I) than in the approach which included the segmentation with eCognition (SAut-II). These results are consistent with previous findings which considered that manual (based on expert opinion) and automated approaches should be mutually complementary, especially in heterogeneous forest areas (Wulder et al. 2008).

Table 10 Tukey's HSD test

	Type 1	Type 2	Type 3	Type 4
Type 2	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$			
Type 3	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	—		
Type 4	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{50} \%$	
Type 5	$H_{10} \% H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{25} \% H_{50} \% H_{75} \% H_{90} \%$	$H_{50} \% H_{75} \%$	—

Significant differences between forest types ($p < 0.05$): hypsograph indices. CombV2_SA-ut-II (object-oriented segmentation and statistical cluster approach)

The results obtained for approaches SAut-I, SAut-II and M-I showed that they were independent from the combination of variables chosen in the cluster step. That is to say, in all cases the greatest possible separation is obtained from the structure units with the combination CombV2 (median and SD) (Tables 4, 5, 6, 7, 8, 9 and 10), as proposed in Pascual et al. (2008).

The reclassification of the LiDAR-derived DCHM into expert opinion height classes is a suitable approach for the manual delineation of forest stands. Although binning the LiDAR-derived DCHM into height classes implies the simplification of the data and the loss of information, this prior step aided the manual delineation of forest stands. The reclassification of DCHM into height classes allowed the transformation of a grey-scale map of a continuous variable (i.e. LiDAR heights) into a map where the spatial pattern of colours and textures aided the identification of forest stands (Fig. 2). The colour distribution and texture of the binned LiDAR height categories accurately synthesised the spatial distribution of crown cover and gaps, attributes that describe forest structure (Maltamo et al. 2005; Poage and Tappeiner 2005). Falkowski et al. (2009) indicate that the LiDAR height and the degree of forest coverage are the LiDAR parameters that best discriminate the forest successional types in their study area. Thus, binning the LiDAR-derived DCHM allowed experts to distinguish and digitalise polygons in a similar way to in traditional methods (i.e. based on photo-interpretation) but more easily, as no stereoscopic restitution equipment was required. In addition, compared to the more individual work of the photo interpreter, this procedure facilitates team discussion among forest managers in order to delimit structure units according to the required management focus (productive, conservational etc.). Thus, our results indicate that the simplification of information implied by going from a continuous variable to a classified variable aids the interpretation of the forest structure and its classification by experts.

Our results (Tables 4, 5, 6, 7, 8, 9 and 10; Figs. 4, 5 and 6) demonstrate that the incorporation of expert opinion does not imply any improvement in precision as compared with the automated procedure proposed by Pascual et al. (2008) although nor does it represent a significant loss. The automated approach provides slightly better results. The quantitative parameters (i.e. hypsographs and HSD percentiles tests) which separate the forest structure types in the automated procedure (Pascual et al. 2008) indicate a greater separability between classes than in the mixed approaches with progressive incorporation of forest expert opinion. Our results (ANOVA test; Tables 3, 6, 7, 8, 9 and 10) indicate that the procedures with greater expert participation are valid and acceptable (M-I and SAut-I).

One of the main advantages of the approaches developed is that they allow the expert opinion of forest managers to be

included in the analysis, thus allowing the incorporation of external information sources such as personal experience, knowledge of ecological interactions and other ancillary data. For these reasons, Wulder et al. (2008) proposed applying a mixture of manual and automated approaches in lodgepole pine forests and other forests of spruce species in Canada. It should also be noted that the proposed approaches can easily be understood by a wide audience and do not require either the incorporation of image processing experts into forest management staff (public and private) or training current staff. Neither of these options is easy to implement for numerous forest services and companies.

5 Conclusions

This work proposes various procedures which incorporate expert opinion. These new approaches are comparable to the automated systems for the characterisation of forest structure in heterogeneous/irregular pine stands in our study area. Our results support the incorporation of experts in the classification of forest structures with the aim of optimising the forestry significance of the units established.

The procedures developed offer the following advantages: (1) they allow greater expert participation; (2) they make it possible to give a specific management focus in each case; and (3) they provide accessibility by the users (forest managers) to the source of LiDAR information.

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