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Classifying silvicultural systems (coppices vs. high forests) in Mediterranean oak forests by Airborne Laser Scanning data

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Abstract

Forest classification by silvicultural systems (coppices vs. high forests) is important for forest resource assessment as such systems relate to a wide variety of ecosystem services. In this paper the potential of Airborne Laser Scanning (ALS) data for Mediterranean oak forests classification of coppices with standards vs. high forests was investigated in three study areas in Italy. We addressed the following issues: can coppices and high forests be distinguished using a raster Canopy Height Model (CHM)? Which are the most efficient CHM-derived metrics? Does the scale of analysis influence the classification potential of CHM metrics? Our results show that CHM in grid format (1-m^2 pixel) provides support information to classify silvicultural systems.

Keywords: ALS; Canopy Height Model; image segmentation; classification.

Introduction

Forest management determines rotation length and the presence of different stages in forest succession. It implies important consequences in ecosystem functioning and services. Silvicultural systems are among the main drivers of differences in forest management and are mainly classified into high forest systems and coppice systems according to the method of tree regeneration. In high forest systems (conifer and broadleaved species) the stand is regenerated from seedlings, either natural or planted, or a combination of both, and rotation period is generally long. In coppice systems the regeneration of broadleaved species consists mainly of sprouts originating from cut stumps, and rotation is generally shorter. The conversion of a coppice to a high forest is the transition from a stand based on vegetative reproduction to a stand that regenerates by seed [Matthews, 1991]. In Europe coppice systems account for 16% of the area of forest available for wood supply, covering extensive areas in several countries, including France, Italy, Greece, Turkey, Spain and Bulgaria [UN/ECE-FAO, 2000].

In Italy forest and other wooded lands extend over 10.5 million hectares [INFC, 2005]; high forest systems represent 42% of total forest area, with a slight majority of even-aged stands; coppice systems represent the other 58% of total forest area. Most coppices are located along the lower slopes of the Alps and all along the Italian peninsula and the islands, from the coast to the upper mountain zone in the Apennines. The majority are coppices with standards, i.e. even-aged stands with 40-150 trees ha^{-1} of two to three times the rotation age which are released at coppicing [Ciancio and Nocentini, 2004; Ciancio et al., 2006]. Felling is carried out by clearcutting at the end of rotation (usually 15-35 years), on areas from a few square hundred meters up to 10-20 hectares, but clearcut size is most usually in the range of 1-5 hectares. Coppice with standards is the only silvicultural system for which clearcut is allowed in Italy [Chirici et al., 2011]. Only small areas are covered by selection coppices (uneven aged coppices) or compound coppices (a mixture of coppice and high forest). Oaks (*Quercus cerris* L., *Quercus pubescens* Willd, *Quercus ilex* L.), sweet chestnut (*Castanea sativa* Miller) and beech (*Fagus sylvatica* L.) are the most common species in coppices, and often form pure stands [Ciancio and Nocentini, 2004].

The main product from coppice systems is fuelwood and polewood, the latter from chestnut stands. In the last years increasing oil prices and growing interest towards energy from renewable sources have further increased fuelwood demand, for both domestic and industrial uses [Lasserre et al., 2010; Picchio et al., 2009] and coppicing has again become a profitable management option in many private forests. An example of the renewed interest towards coppices in Europe is COST Action FP 1301 [EuroCoppice, http://www.eurocoppice.uni-freiburg.de] started in 2013, which has the aim of bringing together European scientists, experts and young scholars to exchange knowledge on coppice forestry and to develop innovative management and harvesting concepts/techniques for modern multifunctional coppice management systems.

Classification of high forest vs. coppices is important for forest resource assessment as such different systems relate to a different variety of ecosystem processes and services, and it is necessary for sustainable forest management at the stand level, since they are characterized by different forest structures and require different felling patterns.

Under management framework, coppice and high forest classification is carried out at the forest compartment level and it is traditionally based on ground observation or is performed by manual delineation of aerial photographs with the support of local field knowledge and observation. Even if these methods provide accurate classification, they are costly and time consuming.

Recently, the key importance of silvicultural systems for sustainable forestry has been confirmed by the development of methods for mapping potential forest management, especially in relation to the difficulties of detecting such systems [Hengeveld et al., 2012]. Several studies have investigated the potential of multispectral sensor for forest structure variable estimation [e.g., Cohen and Spies, 1992; Hall et al., 2006; Lamonaca et al., 2008; Gebreslasie et al., 2010; Ozdemir and Karnieli, 2011]. However, as a general trend, passive optical sensors have limitations for characterizing vertical forest structure due do their relative insensitivity to canopy structure, especially when compared to Airborne Laser Scanning (ALS) [e.g., Lefsky et al., 2001; Hudak et al., 2002; Lu, 2006; Pflugmacher et al., 2012; Ozdemir and Donoghue, 2013].

ALS is an active remote sensing technology that can provide detailed information on forest canopy structure [Lefsky et al., 2002]. Several papers have documented the promising use of ALS data to predict relevant and basic forest structural attributes in boreal [e.g., Lim et al., 2003; Næsset, 2004; Hyyppä et al., 2008; van Leeuwen and Nieuwenhuis, 2010], Alpine [e.g., Hollaus et al., 2006; Clementel et al., 2012; Alberti et al., 2013], temperate and Mediterranean environments [Corona et al., 2012; Cartisano et al., 2013; Montaghi et al., 2013]. For instance, ALS data (alone or with spectral data) were used to estimate forest height [e.g., Magnussen and Boudewyn, 1998; Næsset and Økland, 2002], to predict biomass and volume of trees [e.g., Næsset, 1997; van Aardt et al., 2006; Corona and Fattorini, 2008] and shrubs [e.g., Estornell et al., 2012], to assess vertical stratification of forest vegetation [e.g., Zimble et al., 2003; Morsdorf et al., 2010; Ferraz et al., 2012], to map tree species composition [e.g., Ke et al., 2010; Cho et al., 2012], and to assess tree size and species diversity [e.g., Simons et al., 2012, 2013; Ozdemir and Donoghue, 2013].

Lefsky et al. [2005] found that mean height and height variability assessed by ALS data were useful to examine the relationships between comprehensive assemblages of forest canopy and stand structure indices. Pascual et al. [2008] found that median and standard deviation of height computed from ALS-derived digital Canopy Height Model (CHM) were slightly better than mean and standard deviation of height for distinguishing among forest structure types based on cluster analysis, especially in case of horizontally heterogeneous forests. Falkowski et al. [2009] used a variety of ALS metrics in conjunction with the Random Forests algorithm to classify forest successional stage across a structurally diverse mixed-species forest, and found that canopy cover and mean height were the most important ALS metrics for the classification.

Detecting silvicultural systems by ALS under temperate and Mediterranean conditions (i.e. the discrimination between high forest and coppice stands) has never been investigated (at least in our knowledge), even if this problem is still unresolved by conventional remote sensing approaches by optical imagery.

On the other hand, at least in Europe, it is quite frequent that ALS surveys are committed on large territories by governmental (national or local) administrations for purposes like topographical or hydrogeological investigations, and the ALS-derived CHM data are then released to the general public at low or no cost (the so called open data) [e.g., Corona et al., 2012; Montaghi et al., 2013].

Objectives

Taking into account the above considerations, in this study the potential of ALS-derived CHM data for Mediterranean oak forests classification into coppice stands and high forest

stands was investigated. We have addressed the following issues: 1) can coppices and high forests be distinguished using a raster CHM? 2) Which are the most efficient CHM metrics? 3) Does the scale of analysis influence the classification potential of CHM metrics to map coppices vs. high forests?
To our knowledge, this is the first attempt of using CHM metrics for coppice vs. high forest classification.

Material and methods

Study area

The work was carried out in three study areas in Italy, hereafter named A, B and C (Fig. 1). The study areas were selected on the basis of the availability of laser scanning data in forest regions with coppices and high forests.

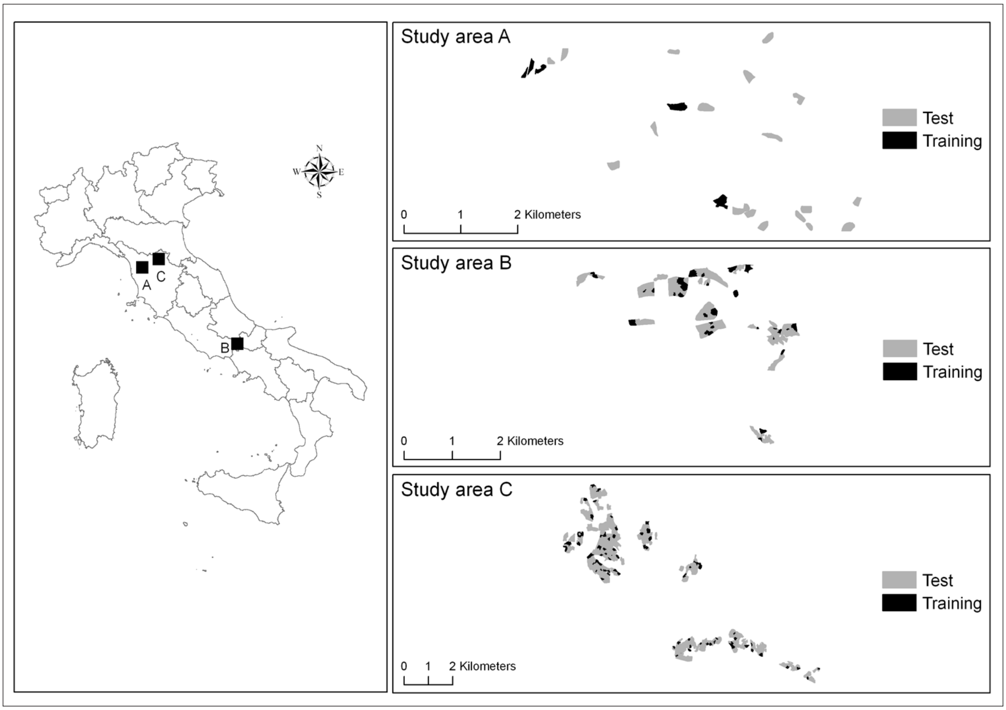

Figure 1 - Location of the study areas (on the left side) and distribution of forest stands according to their partitioning into training and test sites (on the right side).

Area A is located in the Tuscany Region, in the Province of Pisa (43° 43’ - 43° 45’ N, 10° 40’ - 10° 44’ E). It is a hilly area with gentle slopes and altitudes ranging between 0 and 100 m a.s.l. The average yearly temperature is 14 °C, and the average yearly precipitation is 910 mm. The forest landscape is characterized by maritime pine (*Pinus pinaster* Aiton) forests and mixed broadleaved forests dominated by turkey oak (*Quercus cerris* L.), the latter associated with other deciduous species, especially

manna ash (*Fraxinus ornus* L.), sessile oak (*Quercus petraea* Matt. Liebl.) and checker tree (*Sorbus torminalis* Crantz). The understory layer is composed by shrubs with density inversely related to tree cover [Travaglini et al., 2011].
Area B is located in the Molise Region, in the Province of Isernia (41° 33' - 41° 35' N, 14° 02' - 14° 05' E). The average yearly temperature is of 12 °C, and the average yearly precipitation is of 1180 mm. Altitude varies between 400 and 1000 m a.s.l. Turkey oak, downy oak (*Quercus pubescens* Willd.) and hop hornbeam (*Ostrya carpinifolia* Scop.) are the prevailing forest species [Garfì and Marchetti, 2011].
Area C is located in the Tuscany Region, in the Province of Florence (43° 55' - 44° 00' N, 11° 16' - 11° 24' E). It is a hilly area at the base of the Apennines mountain, with altitudes ranging between 150 and 550 m a.s.l. The average yearly temperature is 13 °C, and the average yearly precipitation is 1025 mm. Forests are dominated by oak stands (mainly turkey oak associated with manna ash, chestnut and hop hornbeam), chestnut stands, and European black pine stands (*Pinus nigra* Arn.), the latter originated from plantations.
In each study area the distribution of even-aged forest stands dominated by Turkey oak and downy oak were extracted from existing forest type maps (scale of 1:10,000) [Garfì and Marchetti, 2011; Nocentini et al., 2011]. A total forest surface of 45 ha, 107 ha, and 506 ha was considered for the study areas A, B and C, respectively. The silvicultural systems adopted in these forests are high forest and coppice with standards (herewith, coppice) under a regular felling regime, mainly addressed towards bioenergy assortments which have an increasing market value. Forest development stages varies from very young (i.e., stand after final cut) to adult (i.e., stand close to the rotation age) for coppices, while no young stands occur for high forests. This is a common situation for broadleaved forests in Italy (Table 1).

Table 1 - Forest height and canopy cover of coppices and high forests in the study areas.

Study area	Coppice		High forest	
	Forest height	Canopy cover	Forest height	Canopy cover
	m	%	m	%
A	4-16	30-80	15-25	>80
B	3-12	30-80	12-22	>90
C	3-15	30-80	12-25	>90

Airborne laser scanning data and pre-processing
In area A, ALS survey was performed in winter 2008; an ALS ALTM (Airborne Laser Terrain Mapper) Gemini sensor was used; the sensor recorded two echoes per pulse with an average laser point density of about 1.6 laser points per m^2. In area B, ALS dataset was acquired in June 2010 by Partenavia P68 I-GIFE aircraft carrying an Optech Pegasus sensor which recorded two echoes per pulse; the average laser point density was about 1.5 laser points per m^2. In area C, ALS survey was performed in winter 2007 by an ALS ALTM 3033 sensor which registered two echoes per pulse; the

average laser point density was about 1.0 laser points per m^2.
The ALS data were filtered and classified in order to separate points belonging to forest and natural vegetation cover from ground points. In order to do so, outlying pulses due to sensor errors were first identified and erased from the ALS dataset using TerraScan software [Terrasolid, 2005]. Subsequently, ground level echoes were separated from echoes of the outer forest canopy using the TerraScan software and the Axelsson [2000] algorithm. Both ground and canopy echoes, once separated, were spatially interpolated and resampled in a grid format with a geometric resolution of 1 m to produce, respectively, a Digital Terrain Model (DTM) and a Digital Surface Model (DSM).
A CHM was generated as result of the algebraic subtraction of DTM from DSM. Later, pixels with height < 2 m in the CHM were set to zero to avoid the influence of the shrub understory [Floris et al., 2010; Gonzáles-Ferreiro, 2012]. Power lines were also masked on the basis of a manual delineation of electric lines over the raster CHM. Finally, pixels outside the selected study areas were excluded.

Ground data
In each study area forest cover was classified into high forest stands (T1) and coppice stands on the basis of ground observations with the support of a GPS receiver Trimble Juno 3B Handheld with 2-5 m positional accuracy. Fieldwork was carried out in winter 2012 by visual interpretation of forest polygons generated on the basis of CHM (see Polygon delineation section). In case of coppice stands, two age classes were considered taking into account the time lag between ALS survey and ground observation: coppice with age > 10 years (called adult coppices, T2), and coppice with age < 10 years (called young coppices, T3). The surface covered by coppice stands and high forest stands in the three study areas is reported in Table 2.

Table 2 - Surface (in hectares) of high forest stands (T1), adult coppice stands (T2) and young coppice stands (T3) in the study areas.

Study area	T1	T2	T3	Total
	ha	ha	ha	ha
A	15.0	15.0	15.0	45.0
B	36.1	35.5	35.8	107.4
C	130.4	287.4	88.2	506.0

Mapping silvicultural systems
The mapping procedure involved five consecutive steps (Fig. 2): 1) polygon delineation from the CHM, 2) selection of training sites and test sites, 3) CHM-derived metrics extraction and analysis, 4) polygon classification, 5) accuracy assessment.

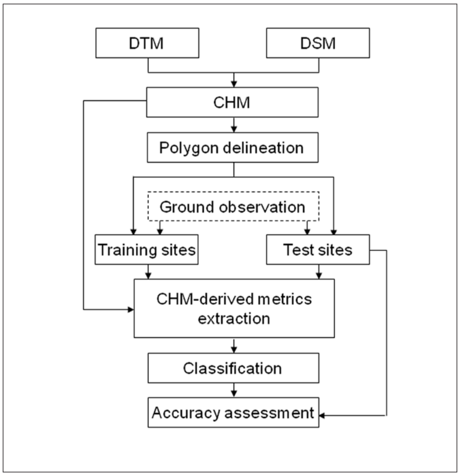

Figure 2 - Flow diagram of the proposed silvicultural systems classification procedure.

Polygon delineation

The aim of this step was to divide forest cover into forest regions with similar characteristics in terms of canopy structure. The object-oriented segmentation tool available in the Definiens (vers. 5) software was used to delineate polygons on the basis of CHM.

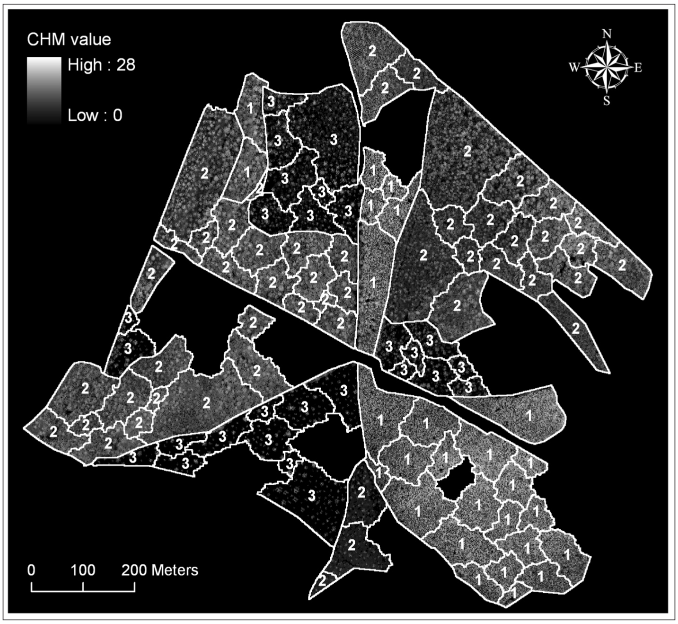

Figure 3 - Example of polygon delineation over the raster Canopy Height Model (CHM) generated by a scale parameter of 50. Numbers represent high forests (1), adult coppices (2) and young coppices (3).

Segmentation is the subdivision of an image into separated regions. Definiens uses a bottom-up approach to generate polygons based upon a multiresolution segmentation technique and criteria of homogeneity in term of colour, smoothness and compactness; the so-called scale parameter influences the average object size: a larger value leads to bigger objects and vice versa [Baatz and Shäpe, 2000]. In this study six consecutive segmentations were applied to the CHM. The CHM-based segmentation was expected to provide differentiation between forest stands with different height. After some preliminary tests which were carried out to assess the effect of different user-specified parameters through a trial-and-error approach, a first segmentation level with a scale parameter of 50 was derived, assigning a weight of 0.5 to colour, smoothness and compactness (Fig. 3). This setting was chosen empirically by visual inspection as it was judged able to delineate homogeneous forest regions representing coppices and high forest stands. These regions were later sub-segmented into five hierarchical levels with a scale parameter of 30, 20, 15, 10 and 5. Colour, smoothness and compactness were unchanged during the multiple level segmentation process. More details on LiDAR-based segmentation and related issues can be found in Ke et al. [2010].
At the first segmentation level a total of 30, 191, and 778 polygons were generated in the study areas A, B and C, respectively, with an average size of 1.19 ha, 0.56 ha and 0.65 ha, respectively. Total number and average size of polygons generated with the multiple level object-oriented segmentation are given in Table 3.

Table 3 - Total number and average size (in hectares), with standard deviation in brackets, of the polygons generated by the multiple level object-oriented segmentation.

Study area	Level 1 (scale parameter = 50)		Level 2 (scale parameter = 30)		Level 3 (scale parameter = 20)		Level 4 (scale parameter = 15)		Level 5 (scale parameter = 10)		Level 6 (scale parameter = 5)	
	Num.	Average size (ha)	Num.	Average size (ha)	Num.	Average size (ha)	Num.	Average size (ha)	Num.	Average size (ha)	Num	Average size (ha)
A	30	1.190 (0.821)	224	0.203 (0.176)	652	0.069 (0.066)	1311	0.034 (0.030)	3122	0.014 (0.011)	11346	0.004 (0.003)
B	191	0.560 (0.430)	564	0.190 (0.137)	1259	0.085 (0.061)	2345	0.046 (0.033)	5556	0.019 (0.015)	22341	0.005 (0.004)
C	778	0.650 (0.531)	2340	0.216 (0.179)	5799	0.087 (0.069)	11295	0.045 (0.034)	29144	0.017 (0.013)	132682	0.004 (0.003)

Training sites and test sites

In each study area training sites and test sites were selected from polygons delineated at the first segmentation level using a random selection method; 20% of the forest area was selected for training sites and the remaining 80% was used as test sites (Fig. 1). At the lower hierarchical levels training and test site distribution was the same as that adopted for the first segmentation level. Training and test site polygons were classified into silvicultural systems by observations in the field (see Ground data section).

Metrics extraction and analysis

For each polygon delineated by the multiple level object-oriented segmentation process, the following ALS metrics were computed on the basis of the CHM: minimum height, maximum height, mean height, range of the heights, standard deviation (SD) of the heights, and coefficient of variation (CV) of the heights. These metrics were selected as they are known to be related to forest stand structural characteristics [e.g., Zimble et al., 2003; Parker and Russ, 2004; Lefsky et al., 2005; Pascual et al., 2008; Barbati et al., 2009; Falkowski et al., 2009; Monnet et al., 2010; Corona et al., 2012]. Indeed, silvicultural systems are expected to be distinguished on the basis of forest height and height variations: the former should be lower in coppices which are, on average, younger than high forests, the latter should be higher in coppices due to the presence of standards which are taller than the shoots, even though these dissimilarities progressively decrease as coppice age increases.
To investigate the capability of each metric in distinguishing between high forest stands, adult coppice stands and young coppice stands, a statistical analysis was performed on CHM metrics computed on training sites using SPSS for Windows. To this end two non parametric tests (Kruskal-Wallis test and Median test) were used to check whether the selected metrics varied significantly among T1, T2 and T3. In case of statistically significant differences ($p < 0.001$) the Mann-Whitney U test (a Two-Independent-Samples Test) was used to determine the differences between groups.

Polygon classification and accuracy assessment

Polygon classification was performed using the Maximum Likelihood algorithm available in Idrisi Selva software, a well known classification method for remote sensing applications [Lillesand and Kiefer, 2000], with reference to the training sites described above (see Training sites and test sites section).
The thematic accuracy of the classification was estimated over the test sites by means of a comparison between the classification of remote sensing data and ground truth. The following indexes were computed: overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and kappa index of agreement (KIA) [Congalton, 1991].

Results

Results of the statistical analysis for study areas A, B and C are shown in Tables 4, 5 and 6. They indicate that the CHM metrics are able to discriminate between coppice and high forest stands.
Some metrics seem to be influenced by the scale of the analysis, as they produced different results in relation to the scale parameter adopted in the segmentation process. The ALS metrics that showed such behaviour were: minimum height (in all the areas), SD (in A and B), maximum height and range (in B and C). Minimum height was able to distinguish types T1, T2 and T3 when scale parameter was ≤ 15 in areas A and C, and ≤ 30 in area B; with a scale parameter of 20 the types T2 and T3 were not discriminated by minimum height in the study area A. These results can be explained by the fact that when larger polygons are delineated, gaps in the forest cover with CHM heights close to zero are not detected by the segmentation process, so that coppices and high forests cannot be discriminated. As shown by CHM height histograms computed on training sites (Figs. 4, 5 and 6), CHM heights equal to zero occur in every silvicultural system, even thought with a smaller proportion in high forest than in coppice stands. Maximum height distinguishes the target forest classes when

scale parameter is ≤ 15 in area B and ≤ 30 in area C, while it is not able to separate T2 from T3 when a greater scale parameter is used: when larger polygons are delineated, maximum height in young coppices corresponded to the height of the tallest standard, which is similar to the maximum height determined in adult coppices as shown by CHM height histograms (Figs. 5 and 6). The results provided by range are similar to those reported for maximum height: range worked well in area C when scale parameter was ≤ 30, while in area B it was able to discriminate the types T1, T2 and T3 only with a scale parameter of 5.

Table 4 - Study area A: results of the statistical analysis (Kruskal-Wallis test, Median test and Mann-Whitney test) carried out on CHM-derived metrics computed on training site polygons for high forest (T1), adult coppice (T2) and young coppice (T3) (SD = standard deviation, CV = coefficient of variation).

Level of segmentation (scale parameter)	Number of training site polygons			CHM-derived metric	Average value of the CHM-derived metric computed on training site polygons			Kruskal-Wallis test (p-level)	Median test (p-level)	Mann-Whitney test
	T1	T2	T3		T1	T2	T3			
L1 (50)	7	8	9	Min	0.0	0.0	0.0	-	-	-
				Max	26.5	20.5	13.0	0.000	0.001	T1≠T2; T2≠T3
				Mean	18.9	6.4	2.2	0.000	0.001	T1≠T2; T2≠T3
				Range	26.5	20.5	13.0	0.000	0.001	T1≠T2; T2≠T3
				SD	4.3	4.3	3.1	0.002	0.002	T1=T2; T2≠T3
				CV	0.2	0.7	1.4	0.000	0.000	T1≠T2; T2≠T3
L2 (30)	10	16	21	Min	0.4	0.0	0.0	0.157	0.151	T1=T2; T2=T3
				Max	26.8	20.1	12.9	0.000	0.000	T1≠T2; T2≠T3
				Mean	19.5	7.0	2.3	0.000	0.000	T1≠T2; T2≠T3
				Range	26.3	20.1	12.9	0.000	0.000	T1≠T2; T2≠T3
				SD	4.3	4.2	3.1	0.000	0.000	T1=T2; T2≠T3
				CV	0.2	0.7	1.5	0.000	0.000	T1≠T2; T2≠T3
L3 (20)	37	48	42	Min	1.7	0.5	0.0	0.000	0.000	T1≠T2; T2=T3
				Max	23.5	16.7	10.4	0.000	0.000	T1≠T2; T2≠T3
				Mean	17.5	7.1	2.0	0.000	0.000	T1≠T2; T2≠T3
				Range	21.9	16.3	10.4	0.000	0.000	T1≠T2; T2≠T3
				SD	3.6	3.5	2.6	0.000	0.001	T1=T2; T2≠T3
				CV	0.2	0.7	1.6	0.000	0.000	T1≠T2; T2≠T3
L4 (15)	73	102	80	Min	3.7	0.8	0.0	0.000	0.000	T1≠T2; T2≠T3
				Max	24.0	15.4	9.9	0.000	0.000	T1≠T2; T2≠T3
				Mean	18.4	7.2	2.2	0.000	0.000	T1≠T2; T2≠T3
				Range	20.2	14.5	9.9	0.000	0.000	T1≠T2; T2≠T3
				SD	3.4	3.3	2.5	0.000	0.000	T1=T2; T2≠T3
				CV	0.2	0.7	1.6	0.000	0.000	T1≠T2; T2≠T3
L5 (10)	169	235	212	Min	6.8	1.6	0.1	0.000	0.000	T1≠T2; T2≠T3
				Max	23.3	13.4	9.0	0.000	0.000	T1≠T2; T2≠T3
				Mean	18.3	7.3	2.6	0.000	0.000	T1≠T2; T2≠T3
				Range	16.5	11.8	8.9	0.000	0.000	T1≠T2; T2≠T3
				SD	3.2	2.8	2.4	0.000	0.029	T1≠T2; T2≠T3
				CV	0.2	0.6	1.6	0.000	0.000	T1≠T2; T2≠T3
L6 (5)	770	785	882	Min	12.1	2.9	0.6	0.000	0.000	T1≠T2; T2≠T3
				Max	21.9	10.7	6.2	0.000	0.000	T1≠T2; T2≠T3
				Mean	18.4	7.0	2.8	0.000	0.000	T1≠T2; T2≠T3
				Range	9.8	7.8	5.6	0.000	0.000	T1≠T2; T2≠T3
				SD	2.4	2.0	1.6	0.000	0.000	T1≠T2; T2≠T3
				CV	0.2	0.5	1.1	0.000	0.000	T1≠T2; T2≠T3

Table 5 - Study area B: results of the statistical analysis (Kruskal-Wallis test, Median test and Mann-Whitney test) carried out on CHM-derived metrics computed on training site polygons for high forest (T1), adult coppice (T2) and young coppice (T3) (SD = standard deviation, CV = coefficient of variation).

Level of segmentation (scale parameter)	Number of training site polygons			CHM-derived metric	Average value of the CHM-derived metric computed on training site polygons			Kruskal-Wallis test (p-level)	Median test (p-level)	Mann-Whitney test
	T1	T2	T3		T1	T2	T3			
L1 (50)	13	7	10	Min	2.4	0.4	0.0	0.132	0.143	T1=T2; T2=T3
				Max	25.0	17.9	16.5	0.000	0.000	T1≠T2; T2=T3
				Mean	17.8	9.3	4.4	0.000	0.000	T1≠T2; T2≠T3
				Range	22.6	17.4	16.5	0.018	0.023	T1=T2; T2=T3
				SD	2.5	3.2	3.5	0.053	0.296	T1=T2; T2=T3
				CV	0.1	0.3	0.8	0.000	0.000	T1≠T2; T2≠T3
L2 (30)	37	33	43	Min	4.5	1.1	0.0	0.000	0.000	T1≠T2; T2≠T3
				Max	23.5	15.6	14.8	0.000	0.000	T1≠T2; T2=T3
				Mean	17.2	8.7	4.4	0.000	0.000	T1≠T2; T2≠T3
				Range	19.0	14.6	14.8	0.000	0.003	T1≠T2; T2=T3
				SD	2.5	2.6	2.9	0.001	0.011	T1=T2; T2=T3
				CV	0.1	0.3	0.7	0.000	0.000	T1≠T2; T2≠T3
L3 (20)	79	77	87	Min	6.6	1.8	0.0	0.000	0.000	T1≠T2; T2≠T3
				Max	22.2	15.3	13.2	0.000	0.000	T1≠T2; T2=T3
				Mean	16.9	9.0	4.2	0.000	0.000	T1≠T2; T2≠T3
				Range	15.6	13.5	13.2	0.022	0.149	T1=T2; T2=T3
				SD	2.2	2.5	2.8	0.000	0.000	T1=T2; T2≠T3
				CV	0.1	0.3	0.9	0.000	0.000	T1≠T2; T2≠T3
L4 (15)	159	162	131	Min	8.4	2.5	0.1	0.000	0.000	T1≠T2; T2≠T3
				Max	21.0	14.8	12.5	0.000	0.000	T1≠T2; T2≠T3
				Mean	16.4	9.2	4.2	0.000	0.000	T1≠T2; T2≠T3
				Range	12.6	12.3	12.4	0.184	0.000	T1=T2; T2=T3
				SD	2.0	2.5	2.7	0.000	0.000	T1=T2; T2≠T3
				CV	0.1	0.3	0.9	0.000	0.000	T1≠T2; T2≠T3
L5 (10)	339	356	387	Min	10.5	3.7	0.6	0.000	0.000	T1≠T2; T2≠T3
				Max	20.3	13.5	11.2	0.000	0.000	T1≠T2; T2≠T3
				Mean	16.6	9.0	4.7	0.000	0.000	T1≠T2; T2≠T3
				Range	9.8	9.8	10.6	0.000	0.000	T1=T2; T2≠T3
				SD	1.7	2.1	2.4	0.000	0.000	T1≠T2; T2≠T3
				CV	0.1	0.3	0.8	0.000	0.000	T1≠T2; T2≠T3
L6 (5)	1231	1349	1742	Min	13.2	5.8	2.0	0.000	0.000	T1≠T2; T2≠T3
				Max	19.2	12.2	8.5	0.000	0.000	T1≠T2; T2≠T3
				Mean	16.7	9.2	5.0	0.000	0.000	T1≠T2; T2≠T3
				Range	6.0	6.3	6.5	0.000	0.000	T1≠T2; T2≠T3
				SD	1.3	1.5	1.7	0.000	0.000	T1≠T2; T2≠T3
				CV	0.1	0.2	0.6	0.000	0.000	T1≠T2; T2≠T3

Table 6 - Study area C: results of the statistical analysis (Kruskal-Wallis test, Median test and Mann-Whitney test) carried out on CHM-derived metrics computed on training site polygons for high forest (T1), adult coppice (T2) and young coppice (T3) (SD = standard deviation, CV = coefficient of variation).

Level of segmentation (scale parameter)	Number of training site polygons			CHM-derived metric	Average value of the CHM-derived metric computed on training site polygons			Kruskal-Wallis test (p-level)	Median test (p-level)	Mann-Whitney test
	T1	T2	T3		T1	T2	T3			
L1 (50)	20	45	13	Min	0.0	0.0	0.0	-	-	-
				Max	28.5	21.46	19.2	0.000	0.000	T1≠T2; T2=T3
				Mean	15.3	8.2	2.4	0.000	0.000	T1≠T2; T2≠T3
				Range	28.5	21.4	19.2	0.000	0.000	T1≠T2; T2=T3
				SD	6.5	4.4	3.7	0.000	0.000	T1≠T2; T2≠T3
				CV	0.4	0.6	1.8	0.000	0.000	T1≠T2; T2≠T3
L2 (30)	104	261	62	Min	0.0	0.0	0.0	-	-	-
				Max	26.5	18.8	16.9	0.000	0.000	T1≠T2; T2≠T3
				Mean	15.4	8.0	2.8	0.000	0.000	T1≠T2; T2≠T3
				Range	26.5	18.8	16.9	0.000	0.000	T1≠T2; T2≠T3
				SD	6.3	4.3	3.7	0.000	0.000	T1≠T2; T2≠T3
				CV	0.4	0.6	1.7	0.000	0.000	T1≠T2; T2≠T3
L3 (20)	294	639	233	Min	0.2	0.0	0.0	0.011	0.012	T1=T2; T2=T3
				Max	25.0	17.6	15.1	0.000	0.000	T1≠T2; T2≠T3
				Mean	15.0	8.1	3.0	0.000	0.000	T1≠T2; T2≠T3
				Range	24.8	17.5	15.1	0.000	0.000	T1≠T2; T2≠T3
				SD	5.9	4.1	3.4	0.000	0.000	T1≠T2; T2≠T3
				CV	0.4	0.6	2.1	0.000	0.000	T1≠T2; T2≠T3
L4 (15)	582	1202	491	Min	0.6	0.2	0.1	0.000	0.000	T1≠T2; T2=T3
				Max	24.1	16.7	13.3	0.000	0.000	T1≠T2; T2≠T3
				Mean	14.9	8.1	3.3	0.000	0.000	T1≠T2; T2≠T3
				Range	23.5	16.5	13.3	0.000	0.000	T1≠T2; T2≠T3
				SD	5.7	3.9	3.2	0.000	0.000	T1≠T2; T2≠T3
				CV	0.4	0.6	2.2	0.000	0.000	T1≠T2; T2≠T3
L5 (10)	1514	3129	1324	Min	1.9	0.7	0.3	0.000	0.000	T1≠T2; T2≠T3
				Max	22.9	15.3	10.5	0.000	0.000	T1≠T2; T2≠T3
				Mean	14.9	8.2	3.6	0.000	0.000	T1≠T2; T2≠T3
				Range	20.9	14.6	10.2	0.000	0.000	T1≠T2; T2≠T3
				SD	5.2	3.5	2.6	0.000	0.000	T1≠T2; T2≠T3
				CV	0.4	0.6	1.9	0.000	0.000	T1≠T2; T2≠T3
L6 (5)	8739	14118	4612	Min	6.6	2.6	0.8	0.000	0.000	T1≠T2; T2≠T3
				Max	20.9	13.1	7.4	0.000	0.000	T1≠T2; T2≠T3
				Mean	15.1	8.4	3.6	0.000	0.000	T1≠T2; T2≠T3
				Range	14.3	10.5	6.6	0.000	0.000	T1≠T2; T2≠T3
				SD	3.9	2.7	1.8	0.000	0.000	T1≠T2; T2≠T3
				CV	0.3	0.5	1.2	0.000	0.000	T1≠T2; T2≠T3

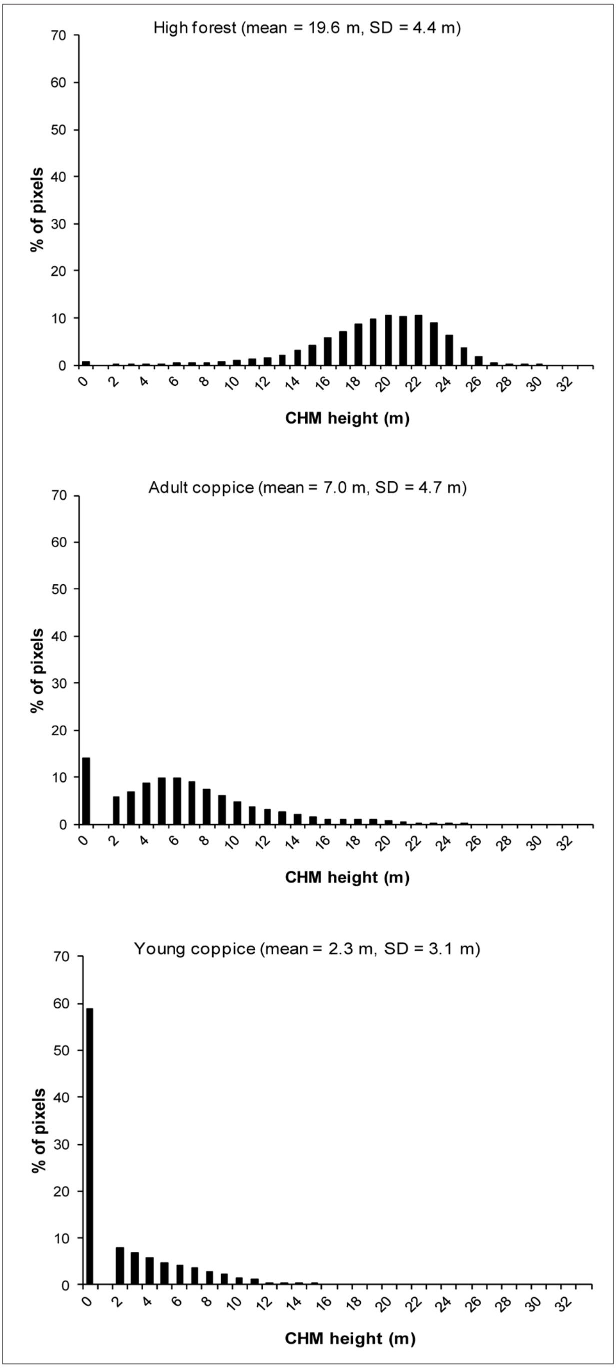

Figure 4 - Area A: CHM height histograms on training sites.

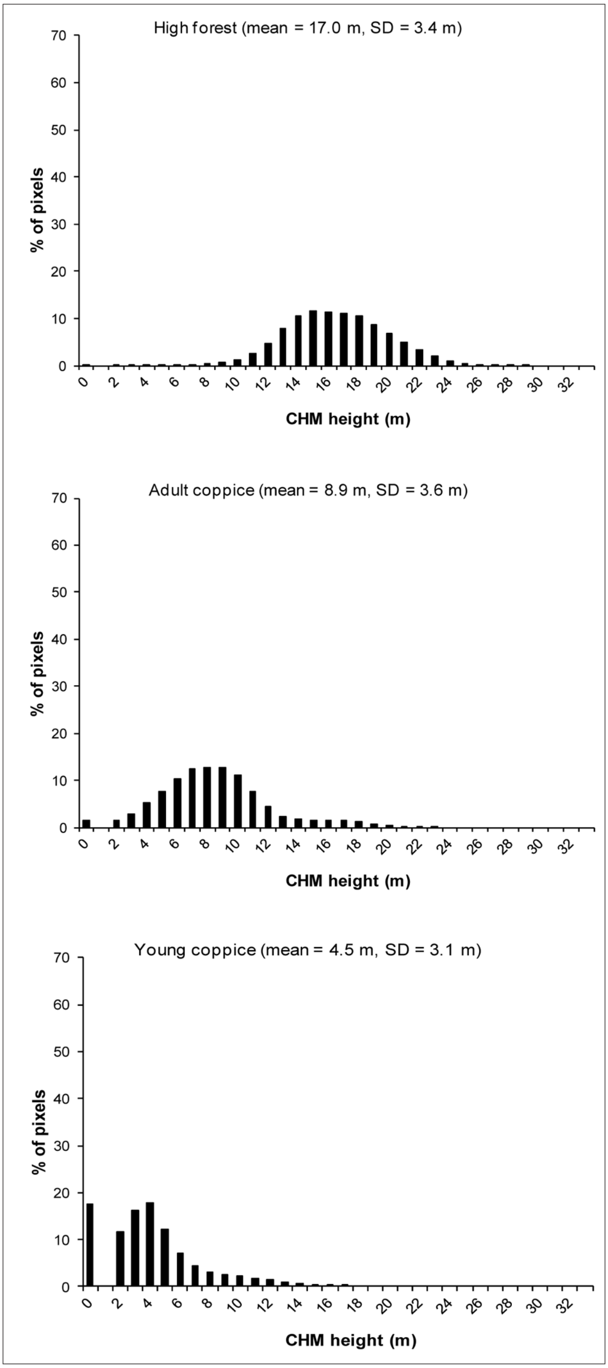

Figure 5 - Area B: CHM height histograms on training sites.

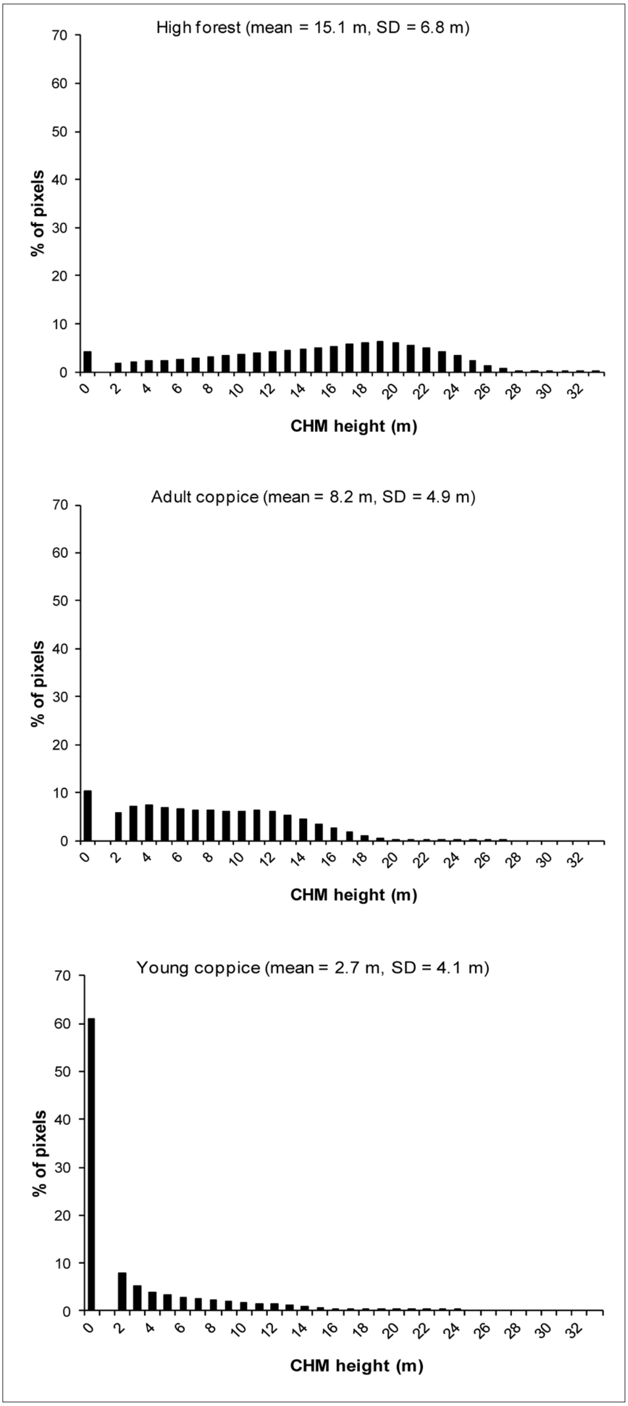

Figure 6 - Area C: CHM height histograms on training sites.

Conversely, the metrics which were not affected by the scale of the analyses were: mean height and CV (in all the areas), range and maximum height (in A), and SD (in C). Such results clearly indicated that mean height and CV are the only metrics capable of separating the target forest classes in all the investigated study areas independently from the scale of the analysis.
Mean height and CV were finally used to map high forests, adult coppices and young coppices. The classification was performed on polygons delineated at the first level of segmentation (scale parameter = 50). The final maps are shown in Figure 7. Thematic accuracy of the classification is shown in Tables 7, 8 and 9: overall accuracy was 85.9% in area C, 86.0% in area A and 92.7% in the area B. KIA was 0.75 in the area C, 0.79 in the area A and 0.89 in area B.
Classification errors between T1 and T2 and between T2 and T3 can be attributed to stand development (e.g., young high forests classified as mature coppices and mature coppices classified as high forests) and stand density (on one hand, a low tree density determines a reduction of the mean height computed by the raster CHM and, on the other hand, an increase of height variability). Other possible influencing factors are soil fertility, which influences stand height, or silvicultural practices such as leaving, at coppicing, a certain number of older standards, i.e. with ages > 2-3 times rotation period [Ciancio and Nocentini, 2004]. Since in the study areas soil conditions were quite uniform, this factor should have a limited influence on classification errors. Misclassification between T1 and T3 occurred only in area C, and on a very limited portion of the area characterized by large openings in the forest cover.
It is worth noting that thematic accuracy of the classification increases when no distinction is done between young (< 10 years) and adult (> 10 years) coppices: in this case the overall accuracy becomes greater than 91% in all the study areas (Tabs. 10, 11 and 12), and KIA is 0.76 in area C, 0.89 in area B, and 1 in area A.

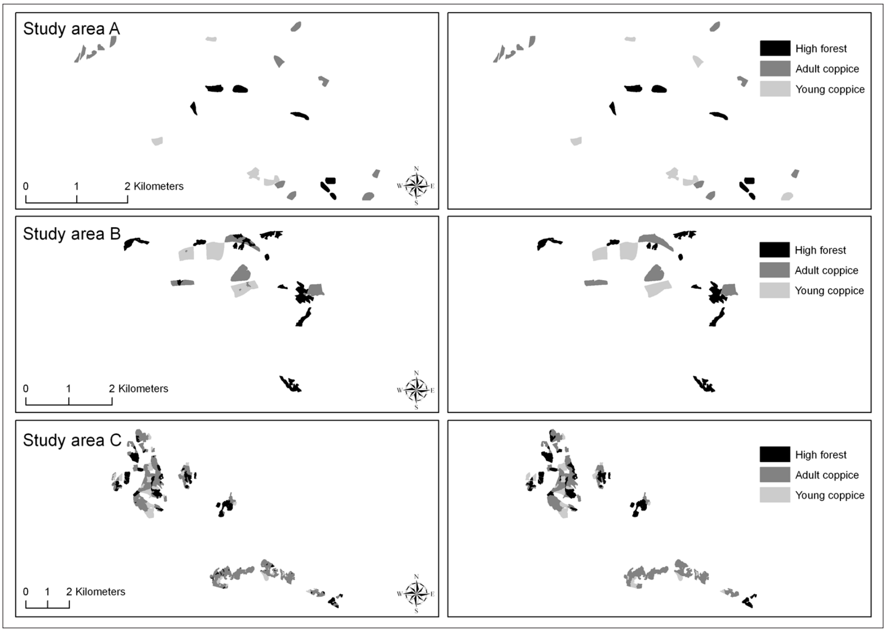

Figure 7 - Classification of silvicultural systems by ALS data (on the left side) and ground truth (on the right side).

Table 7 - Study area A: thematic accuracy (OA = overall accuracy, PA = producer's accuracy; UA = user's accuracy) of coppice (T2 = adult coppice, T3 = young coppice) and high forest (T1) classification computed on test sites.

		Ground truth			UA (%)
		T1 (ha)	T2 (ha)	T3 (ha)	
Classification	T1 (ha)	11.7	0.0	0.0	100.0
	T2 (ha)	0.0	11.9	4.9	70.6
	T3 (ha)	0.0	0.0	6.8	100.0
PA (%)		100.0	100.0	57.9	**OA (%) = 86.0**

Table 8 - Study area B: thematic accuracy (OA = overall accuracy, PA = producer's accuracy; UA = user's accuracy) of coppice (T2 = adult coppice, T3 = young coppice) and high forest (T1) classification computed on test sites.

		Ground truth			UA (%)
		T1 (ha)	T2 (ha)	T3 (ha)	
Classification	T1 (ha)	28.4	4.8	0.0	85.5
	T2 (ha)	0.3	23.5	1.1	94.3
	T3 (ha)	0.0	0.0	27.4	100.0
PA (%)		99.0	83.0	96.1	**OA (%) = 92.7**

Table 9 - Study area C: thematic accuracy (OA = overall accuracy, PA = producer's accuracy; UA = user's accuracy) of coppice (T2 = adult coppice, T3 = young coppice) and high forest (T1) classification computed on test sites.

		Ground truth			UA (%)
		T1 (ha)	T2 (ha)	T3 (ha)	
Classification	T1 (ha)	80.6	11.4	0.0	87.6
	T2 (ha)	23.6	209.7	13.4	85.0
	T3 (ha)	0.1	8.3	56.8	87.2
PA (%)		77.3	91.4	80.9	**OA (%) = 85.9**

Table 10 - Study area A: thematic accuracy (OA = overall accuracy, PA = producer's accuracy; UA = user's accuracy) of coppice (T2 = adult coppice, T3 = young coppice) and high forest (T1) classification computed on test sites.

		Ground truth		UA (%)
		T1 (ha)	T2+T3 (ha)	
Classification	T1 (ha)	11.7	0.0	100.0
	T2+T3 (ha)	0.0	23.6	100.0
PA (%)		100.0	100.0	**OA (%) = 100.0**

Table 11 - Study area B: thematic accuracy (OA = overall accuracy, PA = producer's accuracy; UA = user's accuracy) of coppice (T2 = adult coppice, T3 = young coppice) and high forest (T1) classification computed on test sites.

		Ground truth		UA (%)
		T1 (ha)	T2+T3 (ha)	
Classification	T1 (ha)	28.40	3.85	88.1
	T2+T3 (ha)	0.30	52.95	99.4
PA (%)		99.0	93.2	**OA (%) = 95.1**

Table 12 - Study area C: thematic accuracy (OA = overall accuracy, PA = producer's accuracy; UA = user's accuracy) of coppice (T2 = adult coppice, T3 = young coppice) and high forest (T1) classification computed on test sites.

		Ground truth		UA (%)
		T1 (ha)	T2+T3 (ha)	
Classification	T1 (ha)	80.6	11.4	87.6
	T2+T3 (ha)	23.7	288.1	92.4
PA (%)		77.3	96.2	**OA (%) = 91.3**

Discussion and conclusions

In this study we have assessed the performance of ALS-derived CHM metrics to classify silvicultural systems in Mediterranean deciduous oak forests. Such classification is traditionally carried out by means of ground observations. We believe our results show the potential of raster CHM (1-m^2 pixel) for classifying coppices vs. high forests.

We used a methodological approach similar to that by Pascual et al. [2008] in conifer stands. At least to our knowledge, this is the first time that ALS data is used for broadleaved forests classification by silvicultural systems.

The methodology is implicitly based on the assumption that even-aged coppices and high forests present different heights and height variations due to differences in age and structure determined by forest management in term of rotation length and felling patterns. Our work shows that mean and coefficient of variation of heights extracted from raster CHM derived from low point density ALS data (1-1.6 laser points per m^2) acquired in different season (winter and summer) provide effective support information to discriminate between high forest and coppice stands. The same two metrics have been proved relevant for forest structure classification by Falkowski et al. [2009], Lefsky et al. [2005] and Pascual et al. [2008]. The classification efficiency of other four CHM metrics have proven to be influenced by the scale of the analysis (minimum height, maximum height, range, and standard deviation). Conversely, mean and coefficient of variation of heights provide robust results for scale parameters up to 50, which is the maximum value considered in our work. It is worth noting that the scale parameter of 50, which in the examined study areas proved to successfully separate coppice polygons from high forest polygons, falls in the optimal scale range 20-150 suggested by Ke et al. [2010] for forest species classification.

In the examined study cases, classification errors have proven to be quite low: the overall accuracy of the semiautomatic classification produced by Maximum Likelihood algorithm is > 85% when three classes (high forest, adult coppice, young coppice) are considered, and it is > 91 % when only two classes are considered (high forest vs. coppice). However, it is worth noting that the high accuracy achieved in our study is influenced by the low number of considered classes. In addition, it is interesting to note that the overall accuracy in the study areas A and C was similar and lower than in the area B, probably because in A and C ALS data was acquired during leaf-off periods, and the derived CHM underestimated the canopy height more than in B where ALS was acquired during leaf-on conditions (Wasser et al., 2013).

The procedure presented in this paper can be used by forest managers for stand classification when drafting management plans, and also for stratified estimation of forest attributes to increase the precision of estimates under forest inventory applications [e.g., McRoberts et al., 2005; Corona and Marchetti, 2007; Corona et al., 2011], and even for generating auxiliary

information relevant for mapping fire risk [e.g., González-Olabarria et al., 2012].
It is important to stress the simplicity and feasibility of the proposed methodological approach, which exploits: (i) the raster ALS-derived CHM data, which are often available to the general public as open data, i.e. at no (or very low) cost (see Objectives section), (ii) conventional image segmentation techniques, and (iii) well known classification algorithm available in many commercial and open-source software.
On the other hand, further studies on this topic are needed to assess the efficiency of the proposed method for classifying silvicultural systems on large areas, in different forests types with different forest developmental stages; to test the eventual advantage of more complex classification algorithms; to investigate whether the original ALS point cloud might contain additional information to such an end [e.g., Jakubowski et al., 2013], and to assess the eventual added value provided by the integration of ALS data with remotely sensed multispectral information.

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