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Modeling Mediterranean forest structure using airborne laser scanning data

Francesca Bottalico[a], Gherardo Chirici[a], Raffaello Giannini[a], Salvatore Mele[b], Matteo Mura[a], Michele Puxeddu[b], Ronald E. McRoberts[c], Ruben Valbuena[d,e], Davide Travaglini[a,*]

[a] Dipartimento di Gestione dei Sistemi Agrari Alimentari e Forestali, Università degli Studi di Firenze, via San Bonaventura 13, 50145 Florence, Italy
[b] Ente Foreste della Sardegna, Viale Luigi Merello 86, 09123 Cagliari, Italy
[c] Northern Research Station, U.S. Forest Service, Saint Paul, MN 55108, USA
[d] University of Eastern Finland, School of Forest Sciences, Yliopistokatu 7, FI-80100 Joensuu, Finland
[e] European Forest Institute HQ, Yliopistokatu 6, FI-80100 Joensuu, Finland

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ABSTRACT

The conservation of biological diversity is recognized as a fundamental component of sustainable development, and forests contribute greatly to its preservation. Structural complexity increases the potential biological diversity of a forest by creating multiple niches that can host a wide variety of species. To facilitate greater understanding of the contributions of forest structure to forest biological diversity, we modeled relationships between 14 forest structure variables and airborne laser scanning (ALS) data for two Italian study areas representing two common Mediterranean forests, conifer plantations and coppice oaks subjected to irregular intervals of unplanned and non-standard silvicultural interventions. The objectives were twofold: (i) to compare model prediction accuracies when using two types of ALS metrics, echo-based metrics and canopy height model (CHM)-based metrics, and (ii) to construct inferences in the form of confidence intervals for large area structural complexity parameters.

Our results showed that the effects of the two study areas on accuracies were greater than the effects of the two types of ALS metrics. In particular, accuracies were less for the more complex study area in terms of species composition and forest structure. However, accuracies achieved using the echo-based metrics were only slightly greater than when using the CHM-based metrics, thus demonstrating that both options yield reliable and comparable results. Accuracies were greatest for dominant height (Hd) ($R^2 = 0.91$; RMSE% = 8.2%) and mean height weighted by basal area ($R^2 = 0.83$; RMSE% = 10.5%) when using the echo-based metrics, 99th percentile of the echo height distribution and interquantile distance. For the forested area, the generalized regression (GREG) estimate of mean Hd was similar to the simple random sampling (SRS) estimate, 15.5 m for GREG and 16.2 m SRS. Further, the GREG estimator with standard error of 0.10 m was considerable more precise than the SRS estimator with standard error of 0.69 m.

1. Introduction

Biological diversity is currently recognized as one of the pillars of sustainable development (UNCBD, 1992), and forests, which cover almost one-third of the globe, contribute greatly to preserving this biological richness (FAO, 2015). In this context, techniques and tools for assessing and monitoring the status of biodiversity at the global scale, or even for relatively large areas, are of undoubted value. Remotely sensed data assist in this effort by offering the possibility of synoptic views across large areas (Nagendra, 2001; Turner et al., 2003; Nagendra et al., 2013). Although biodiversity is frequently expressed in terms of species diversity, structural complexity is one of the most straightforward indicators of potential biodiversity and habitat suitability for woodlands (Winter et al., 2008; Chirici et al., 2011, 2012). Structurally diverse forest stands with vertical canopy layering and a variety of tree diameters provide a greater mix of potential habitats for birds, mammals, insects and microorganisms and, therefore, contribute more to preserving biodiversity (McElhinny et al., 2005). In addition, the importance of structure

* Corresponding author.
E-mail addresses: matteo.mura@unifi.it (M. Mura), davide.travaglini@unifi.it (D. Travaglini).

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in contributing to the preservation of forest biological diversity is recognized at international levels (MCPFE, 2011) and has been demonstrated in multiple studies (Lähde et al., 1999; Puumalainen et al., 2003; Kuuluvainen, 2009).

Multiple variables can be used to quantify forest structure. Common forest inventory variables such as tree diameters and tree heights are often used (Franklin et al., 1981; Acker et al., 1998; Zenner, 2000; Lexerød and Eid, 2006) as is growing stock volume (Kuuluvainen et al., 1998; Uotila et al., 2002) which is often used to define old-growth (Wirth et al., 2009) and high nature value forests (European Environmental Agency, 2012). In addition, a variety of structural complexity indices have been tested and reported in the literature for assessing habitat functions (Neumann and Starlinger, 2001) and for forest management planning (Pommerening, 2002). The most commonly used structural complexity indices are based on tree diameters, heights, or both (Staudhammer and LeMay, 2001; Müller and Vierling, 2014) with indices based on diameter of particular relevance for forest management purposes (Lexerød and Eid, 2006; Valbuena et al., 2013).

Latifi (2011) exploited the potential of remotely sensed data as a source of auxiliary information for predicting forest structure, finding that airborne laser scanning (ALS) data outperform other sources of remotely sensed data. ALS data have been used successfully to predict and analyze forest structure (Evans et al., 2009; Lefsky et al., 2002; Lim et al., 2003; Zimble et al., 2003; Wulder et al., 2008; Valbuena et al., 2014; Mura et al., 2015, 2016). Further, ALS data have been used effectively for habitat modelling (Simonson et al., 2014; Vihervaara et al., 2015) for taxa such as terrestrial birds (Graf et al., 2009), beetles (Müller and Brandl, 2009), spiders (Vierling et al., 2011), and mammals such as bats (Jung et al., 2012), deer (Ewald et al., 2014) and squirrels (Nelson et al., 2005). However, few studies (Mura et al., 2015; Valbuena, 2015) have focused specifically on predicting Mediterranean diameter- and height-based forest structure variables using ALS data, or have assessed the implications for biodiversity.

Information extracted from ALS pulse return heights is commonly formulated into metrics that serve to describe and quantify the distributions of those heights. Two main classes of metrics are extracted from ALS data for use as covariates with predictive models: (i) echo-based metrics, and (ii) canopy height model (CHM)-based metrics (Popescu and Hauglin, 2014). Echo-based metrics are statistics extracted directly from the ALS point cloud and require access to the raw ALS data, usually in native ".LAS" format (ASPRS, 2013). However, ALS data acquired for other purposes are often not available for forestry applications with the result that calculation of echo-based metrics from the raw data necessary is not possible (Montaghi et al., 2013). Instead, interpolations of the raw ALS echo heights are often available in the form of two gridded raster layers: ground heights for all pixels characterized as a digital elevation model (DEM) and absolute heights for all pixels characterized as a digital surface model (DSM). A CHM is constructed by calculating pixel-by-pixel differences between the DSM and the DEM (Kraus and Pfeifer, 1998) and represents the top canopy height for each pixel. A CHM is the main layer used for forestry applications when raw ALS data are not available.

The objectives of the study were twofold: (i) to compare model prediction accuracies when using two types of ALS metrics, echo-based metrics and CHM-based metrics, and (ii) to construct inferences in the form of confidence intervals for large area structural complexity parameters. The novelty of the study includes assessment of forest structure in Mediterranean forests in the form of multi-species and multi-layered structures resulting from irregular intervals of unplanned and non-standard silvicultural interventions. Although ALS data have been used to predict forest structure in Mediterranean forests (e.g., Morsdorf et al., 2010; Bottalico et al., 2014), the reported studies were conducted in forests managed using standard silvilcultural approaches but not in forests whose complexity results from irregular and non-standard management. A map and an inference for a selected index are provided as a practical example of how the findings of the study can be applied.

2. Material and methods

2.1. Study areas

The study was carried out in two Italian study areas, one in Tuscany and one in Sardinia (Fig. 1). The Tuscany study area extends for more than 700 ha of which 540 ha (77%) is forest. The dominant species are conifers (*Cupressus sempervirens* L., *Pinus nigra* Arn.) that originated from reforestation projects carried out between 1909 and 1985 (Gatteschi and Meli, 1994), and oaks (*Quercus cerris* L., *Quercus ilex* L., *Quercus pubescens* L.). Agricultural land uses, especially olive groves, prevail in non-forest areas.

The Sardinia study area extends for more than 17,000 ha of which 6140 ha (36%) is forest. Forests in the study area are dominated by oaks (*Quercus ilex* L.) and conifer plantations (*Cedrus atlantica* Man., *Cupressuss* sp., *Pinus canariensis* Smith, *Pinus halepensis* Mill., *Pinus nigra* Arn., *Pinus pinaster* Aiton, *Pinus pinea* L., *Pinus radiata* Don.). Reforestation projects started in 1923, but the ages of most of the conifer plantations are less than 50 years. Pastures, shrublands and abandoned lands prevail in the non-forest areas.

In both study areas, no scheduled management activities have been carried out for decades, except for recent moderate thinning from below to prevent wildfires in the coniferous forests and irregular "coppice-like" cuts for firewood in the oak forests. Especially in Sardinia, such limited management combined with the effects of wildfires and uncontrolled grazing produces multi-species and multi-layered, irregular structures with shrub understories typical of the Mediterranean maquis and overstories of conifers and oaks that tend to merge and produce continuous closed canopies.

2.2. Field data

Local forest inventories were carried out using tessellation stratified sampling schemes (Barabesi and Franceschi, 2011) based on a 0.4×0.4 km grid in Tuscany and a 2.0×1.0 km grid in Sardinia (Fig. 1). Although the sampling intensities for the two study areas differ, the relative ratios of grid spacing to total forest area are approximately equal. For each study area, a sampling point was randomly located in forest in each grid unit, producing 41 points in Tuscany and 85 points in Sardinia (Fig. 1). A 13-m radius circular plot was established with centre at each sampling point, and plot coordinates were recorded using a GNSS receiver Trimble Juno 3 B Handheld with 2–5 m positional accuracy. Diameters at breast height (DBH, 1.30 m) were measured for all living trees with DBH $\geq$ 2.5 cm. In Tuscany, total tree height (H) was measured with a Vertex III device for all trees, but in Sardinia, total tree height was measured only for a sub-sample of trees. For the remaining non-sampled trees in Sardinia, H was predicted using allometric models with DBH as the independent variable. Field work was carried out in 2012–2013 in Sardinia and in 2013–2014 in Tuscany.

2.3. ALS data

In Tuscany, an ALS survey was carried out in winter 2008 with an ALS ALTM (Airborne Laser Terrain Mapper) Gemini sensor that operated at a flight height of 3000 m a.s.l. The sensor recorded two echoes per pulse with an average density of approximately 0.7 points/m^2. In Sardinia, the ALS dataset was acquired in summer

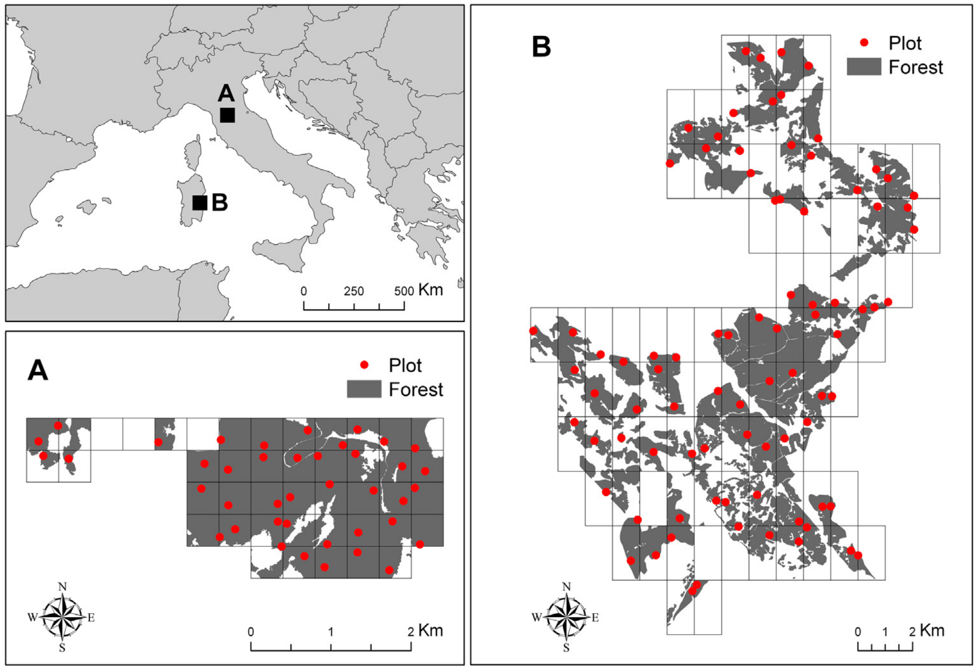

Fig. 1. Tuscany (A) and Sardinia (B) study areas.

2009 with a Riegl LMS-Q560 sensor from a flight height of 800 m a.s.l. with a density of approximately 5 points/m^2.

For both study areas, standard pre-processing routines were used to remove noise in the ALS data in the forms of isolated and air points due to sensor errors or backscatter by flying objects (Terrasolid, 2005). The adaptive triangulated irregular network model algorithm reported by Axelsson (2000) was used to classify all ALS echoes as either ground or non-ground. Heights above ground for non-ground echoes were calculated and used to construct a CHM with a spatial resolution of 1 m. For each plot, 42 echo-based and seven CHM-based metrics were calculated based on reports in the literature (Næsset, 2002; Nord-Larsen and Schumacher, 2012; Mura et al., 2015; McGaughey, 2015) (Table 1).

2.4. Forest structure variables

The selected forest structure variables included common forest inventory variables used for management purposes and structural complexity indices. The choice of variables was based on multiple factors: (i) they have been commonly used for forestry studies (Uuttera et al., 2000; Neumann and Starlinger, 2001; Sullivan et al., 2001; McElhinny et al., 2005; Lexerød and Eid, 2006; McRoberts et al., 2008; Motz et al., 2010; Valbuena, 2015), (ii) they are good drivers as biodiversity indicators (European Environmental Agency, 2012; MCPFE, 2011; Puumalainen et al., 2003; Chirici et al., 2011), and (iii) they can be applied at national levels because they are easily estimated from common national forest inventory (NFI) data, a considerable advantage for large area biodiversity assessment and monitoring (Winter et al., 2008, 2012; Chirici et al., 2012).

In total, 14 forest structure variables consisting of 10 forest inventory variables and four structural complexity indices were selected and calculated for each plot using the data gathered during the field surveys (Table 2). The 10 forest inventory variables were: number of stems (Nstems), basal area (BA), growing stock volume (V), stem biomass including small branches with diameter <5 cm (BS) or stem biomass including large branches with diameter ≥5 cm (BL), arithmetic mean diameter (Dm), quadratic mean diameter (Dg) defined as the DBH of the tree with average basal area, mean tree height (Hg) defined as H for the tree with average basal area, dominant height (Hd) defined as mean H for the 100 trees per hectare with the largest DBHs, arithmetic mean height (Hm) (Pretzsch, 2009; Tomppo et al., 2010). Growing stock volume and biomass were predicted using the allometric models developed for Italian tree species by Tabacchi et al. (2011) with DBH and H as predictor variables.

The four structural complexity indices were selected on the basis of key references (McElhinny et al., 2005; McRoberts et al., 2008; Cantarello and Newton, 2008; Mura et al., 2015; Valbuena 2015) and the activities of Working Group 3 of COST Action E43 "Contributions of field data acquired in NFI for forest biodiversity assessments" (Chirici et al., 2011; Cienciala and Korhonen, 2011): standard deviation of DBH (SDD), coefficient of variation of diameter (CVD), standard deviation of H (SDH), coefficient of variation of H (CVH). Variation in tree size is an important attribute of forest structural complexity because stands with varieties of tree diameters and heights are likely to include a variety of tree ages and species thereby provide more diverse micro-habitats (Zenner, 2000; Michel and Winter, 2009; Vuidot et al., 2011; Nascimbene et al., 2013; Giorgio et al., 2015). Variability in tree size can be expressed by the standard deviation of DBH or H, a straightforward indicator that is as valid as more complex attributes and indices as a descriptor of stand structural complexity (Neumann and Starlinger, 2001). However, because the standard deviation reflects dispersion in the tree size distribution in absolute terms, the coefficient of variation (Franklin et al., 1981) is among the preferred measures when comparing different stands (e.g., old-growth vs managed stand). Summary statistics for the forest structure variables are reported in Table 3.

2.5. Regression models

Multiple linear regression models were used to estimate relationships between the forest structure variables and both the echo-based and CHM-based metrics. Linear regression models were selected because of their simplicity and efficiency and reports that these models reliably characterize the relationship between

Table 1
ALS metrics.

Approach	ALS-metric	Descriptive feature
Echo-based	pTNR	Total number of returns
	pMIN	Minimum
	pMAX	Maximum
	pMEAN	Mean
	pSD	Standard deviation
	pVAR	Variance
	pCV	Coefficient of variation
	pIQ	Interquantile distance
	pSK	Skewness
	pKU	Kurtosis
	pAAD	Average absolute deviation
	pMMED	Median of absolute deviation from the overall median
	pMMODE	Median of absolute deviation from the overall mode
	pL1	L-moment 1
	pL2	L-moment 2
	pL3	L-moment 3
	pL4	L-moment 4
	pLCV	L-moment CV
	pLSK	L-moment skewness
	pLKU	L-moment kurtosis
	pP01	Percentile 1 of heights distribution
	pP05	Percentile 5 of heights distribution
	pP10	Percentile 10 of heights distribution
	pP20	Percentile 20 of heights distribution
	pP25	Percentile 25 of heights distribution
	pP30	Percentile 30 of heights distribution
	pP40	Percentile 40 of heights distribution
	pP50	Percentile 50 of heights distribution
	pP60	Percentile 60 of heights distribution
	pP70	Percentile 70 of heights distribution
	pP75	Percentile 75 of heights distribution
	pP80	Percentile 80 of heights distribution
	pP90	Percentile 90 of heights distribution
	pP95	Percentile 95 of heights distribution
	pP99	Percentile 99 of heights distribution
	pP99/pP25	Ratio of percentiles
	pP99/pP50	Ratio of percentiles
	pP99/pP75	Ratio of percentiles
	pP99/pP90	Ratio of percentiles
	pCRR	Canopy relief ratio
	pSQMEAN	Generalized means for the 2nd power
	pCUMEAN	Generalized means for the 3rd power
CHM-based	gMIN	Minimum
	gMAX	Maximum
	gSUM	Sum
	gMEAN	Mean
	gRANGE	Range
	gSD	Standard deviation
	gCV	Coefficient of variation

Table 2
Forest variable descriptions.

Forest structure variable	Description
Forest inventory variable	
Nstems	Number of stems (n/ha)
BA	Basal area (m^2/ha)
V	Growing stock volume (m^3/ha)
BL	Biomass of stem and large branches (diameter ≥ 5 cm) (Mg/ha)
BS	Biomass of stem and small branches (diameter < 5 cm) (Mg/ha)
Dg	Quadratic mean diameter (cm)
Dm	Arithmetic mean of the diameters (cm)
Hg	Mean height (m)
Hd	Dominant height (m)
Hm	Arithmetic mean of the heights (m)
Structural complexity index	
SDD	Standard deviation of diameters (cm)
CVD	Coefficient of variation of diameters (%)
SDH	Standard deviation of heights (m)
CVH	Coefficient of variation of heights (%)

forest structure and ALS metrics (Mura et al., 2015). A stepwise algorithm was used to select optimal subsets of echo-based and CHM-based metrics for each response variable. However, because stepwise techniques often perform poorly when the predictor variables are highly correlated (Harrell, 2001; p. 64–65), only ALS metrics that were not highly mutually correlated were permitted to enter into the models. To this end, correlation analyses were carried out using Pearson's product moment correlation (r) matrix. In the case of two ALS-metrics with $r > 0.85$, only the ALS metric with the least correlation with other metrics was considered.

Using these criteria, the simplest models in terms of smallest numbers of predictor variables were chosen because such models are easier to understand and evaluate in replicated and cross-validation studies. The selected models were also evaluated with respect to relative root mean square error (RMSE%) and residual standard error (RSE). RMSE% was calculated as

$$RMSE\% = \frac{RMSE}{\bar{\hat{y}}} \cdot 100$$

where

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} \left(\hat{y}_i - y_i\right)^2}{n}}$$

and $\bar{\hat{y}}$ is the mean predicted value of the variable in the sample. RSE was calculated as

$$RSE = \sqrt{\frac{\sum_{i=1}^{n} \left(\hat{y}_i - y_i\right)^2}{n-p}}$$

where $\hat{y}_i$ is the predicted value for the i-th sample unit, y_i is the observed value for the i-th sample unit, n is the number of observations, and p is the number of coefficients estimated (number of predictors + 1, i.e., the constant, the intercept in linear modelling).

2.6. Mapping and area-wide estimation

Our findings can be used for both mapping and large area estimation for a selected index. Once the most statistically significant model with the fewest predictor variables was selected, it was applied to gridded ALS metrics to predict the index of choice for all pixels in the study area. In particular, the gridded ALS metrics and the structural index were calculated for the 23-m × 23-m pixels that served as population units and whose resolution matched the area of the 13-m radius plots.

To construct an inference for the mean value of the index for the entire study area, the model-assisted, generalized regression (GREG) estimators of means and variances were used (Särndal et al., 1992). The GREG estimator of the mean was calculated as

$$\hat{\mu}_{GREG} = \frac{1}{N}\sum_{j=1}^{N}\hat{y}_j - \frac{1}{n}\left[\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)\right]$$

where N is the number of 23-m × 23-m forested population units in the study area, $\hat{y}_j$ is the model prediction for the j-th population unit, n is the sample size, $\hat{y}_i$ is the model prediction for the i-th sample plot and y_i is the observed value for the i-th plot. The second term adjusts the estimate for systematic model prediction errors and can be considered as a bias estimator,

$$\hat{Bias}\left(\hat{\mu}_{initial}\right) = \frac{1}{n}\left[\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)\right],$$

where $\hat{\mu}_{initial}$ is the unadjusted estimated population mean. The corresponding variance estimator is,

$$V\hat{a}r\left(\hat{\mu}_{GREG}\right) = \frac{1}{n(n-1)}\sum_{i=1}^{n}(\varepsilon_i - \bar{\varepsilon})^2$$

where

$$\varepsilon_i = \left(\hat{y}_i - y_i\right)$$

and

$$\bar{\varepsilon} = \frac{1}{n}\sum_{i=1}^{n}\varepsilon_i$$

A confidence interval for the population mean is then estimated as,

$$\hat{\mu}_{GREG} \pm t \cdot \sqrt{V\hat{a}r\left(\hat{\mu}_{GREG}\right)},$$

where t is related to the confidence level. The design-based simple random sampling (SRS) estimator for the population mean ($\hat{\mu}$) obtained from the field plot information only was used as basis for comparison with the GREG estimator.

3. Results

3.1. Regression models

We chose models with minimal numbers of predictors subject to our evaluation criteria. The stepwise algorithm accomplished this task, and selected models with numbers of predictors ranging between 1 and 4, but mostly models with only a single predictor variable were selected. For the sake of simplicity and clarity in reporting results, and unless specifically noted otherwise, hereafter we do not distinguish between echo-based or CHM-based model predictors when reporting the model performances because, even if the echo-based metrics produced slightly greater accuracies, practically there are no meaningful differences with respect to accuracy between them.

The results of the modelling process are summarized in Table 4 for Tuscany and in Table 5 for Sardinia.

For the forest inventory variables, R^2 ranged between 0.11 and 0.91, with RMSE% between 8.2% and 89.6%. The greatest accuracies were achieved for Hd ($R^2 = 0.91$; RMSE% = 8.2%), Hg ($R^2 = 0.83$; RMSE% = 10.5%) and V ($R^2 = 0.83$; RMSE% = 21.7%). The least accuracy was found for Nstems ($0.11 \leq R^2 \leq 0.31$; 47.8% ≤ RMSE% ≤ 89.6%). For the four structural complexity indices, $0.05 \leq R^2 \leq 0.86$ and 12.4% ≤ RMSE% ≤ 94%, where SDH had the greatest accuracy ($R^2 = 0.86$; RMSE% = 13.7%), followed by CVH ($R^2 = 0.72$; RMSE% = 12.4%), SDD ($R^2 = 0.68$; RMSE% = 17.5 %), and CVD ($R^2 = 0.33$; RMSE% = 18.7%).

In Tuscany, the most frequently selected echo-based predictors were percentiles corresponding to high pulse returns (pP95) and measures describing the plot echo distribution (pIQ). In Sardinia, pMEAN and pSD were the most influential echo-based predictors. For the CHM-based predictors, similar results were found with gMEAN, gSD and gCV as the most preferable in Tuscany. Conversely, in Sardinia only three CHM-based predictors were selected overall, with gMAX being the most frequently selected, followed by gCV and gMEAN.

3.2. Mapping and area-wide estimation

For illustrative purposes, we map and estimate Hd for the Tuscany study area using the echo-based metrics. Dominant height is widely used in forestry for both management and ecological purposes because it acts as a main indicator of site productivity (Skovsgaard and Vanclay, 2008). Because the height growth of dominant trees is less responsive to forest management, Hd better reflects site growing conditions (Pretzsch, 2009).

We mapped Hd for the Tuscany area by applying the selected model developed with the echo-based metrics (Fig. 2). This model used pP99 metric as the single predictor and took the form,

$$\hat{H}_d = 2.048 + 0.978 \cdot pP99,$$

and yielded $R^2 = 0.91$, RMSE% = 8.2% and RSE = 1.4 ($p = 0.000$). For the entire study area, the SRS estimate of mean Hd was 16.2 m with standard error of 0.69 m, whereas the GREG estimate ($\hat{\mu}_{GREG}$) was 15.5 with standard error of 0.10 m with 13.46 m and 16.73 m as lower and upper confidence limits at $\alpha = 0.05$.

4. Discussion

The present study focused on two objectives: (i) to compare model prediction accuracies when using two types of ALS metrics, echo-based metrics and canopy height model (CHM)-based metrics, and (ii) to construct inferences in the form of confidence intervals for large area structural complexity parameters.

In Tuscany, we found strong relationships ($R^2 > 0.70$; $p < 0.001$; 8.2% ≤ RMSE% ≤ 21.7%) in the models for four forest variables (V, BL, Hg and Hd) and the structural complexity indices SDH and CVH. Accurate prediction for the Sardinia study area was more difficult with only the models of V and Hd having $R^2 > 0.70$. These results are in line with Heurich and Thoma (2008) who found, as in our study, greater model prediction accuracies for biomass/volume and H-related variables, namely V, Hg and Hd. In similar Mediterranean forest types, Morsdorf et al. (2010) also found that H-related variables (H mean and H max) were well-estimated by ALS data in Mediterranean conifers and evergreen oak forests. These findings have also been confirmed in other studies such as González-Ferreiro et al. (2012) who reported that height, woody biomass/volume and crown biomass were the variables most accurately predicted using ALS metrics and Ozdemir and Donoghue (2013) who reported the best fitting models were for describing tree height heterogeneity.

For the structural complexity indicators SDD and SDH, our results are in line with those reported by Mura et al. (2015) for central Italy. The difference in model performances between our two areas is likely attributable to the more heterogeneous geomorphological and vegetative structural characteristics of the Sardinia area as can be deduced from Table 3. These findings are in line with Montealegre et al. (2015) who reported that greater topographical slope adversely affected preliminary ALS data processing and filtering.

The greater heterogeneity in terms of species composition and forest structure for the Sardinia study area is reflected in the less accurate predictions for all variables/indicators relative to results for the Tuscany study area. This greater heterogeneity is also reflected in the predictors selected for the same response variables.

Although Heurich and Thoma (2008) indicate that stratification (e.g., conifers and broadleaves) can improve the accuracy of estimates, we did not use this approach because of the limited number of plots available in our study areas.

Although we adopted a simple and conservative modelling approach using multiple linear regression with as few predictors as possible, our results are comparable to results reported in the literature where more complex exponential and power models were used (González-Ferreiro et al., 2012). This finding is not surprising because, as has been widely demonstrated, ALS metrics are such good predictors of forest structure that complex models are often not necessary (Mura et al., 2015; Chirici et al., 2016).

Table 3
Forest variable statistical summaries.

Forest structure variable[a]	Tuscany (n = 41 plots)				Sardinia (n = 85 plots)			
	Mean	Max	Min	St.dev.	Mean	Max	Min	St.dev.
Forestry inventory variable								
Nstems	2199	5763	735	1138	1818	9920	151	1824
BA	32.5	64.7	17.1	10.0	36.8	66.9	5.0	15.0
V	225.7	674.7	89.4	120.0	240.3	584.3	9.9	132.4
BL	117.7	312.1	46.7	53.1	152.7	341.2	11.5	80.3
BS	48.4	90.1	19.3	17.0	49.4	112.0	3.3	27.0
Dg	14.7	24.5	7.9	4.1	20.2	61.6	6.1	10.1
Dm	12.3	23.3	6.4	4.0	17.9	58.7	4.8	9.9
Hg	11.5	19.7	6.9	2.9	11.5	25.9	4.7	3.8
Hd	16.2	33.3	9.3	4.4	14.6	30.0	8.0	4.3
Hm	9.3	16.1	6.0	2.3	10.0	25.4	4.4	3.9
Structural complexity index								
SDD	7.8	14.9	3.8	2.4	9.0	22.0	2.7	4.3
CVD	0.7	1.0	0.2	0.1	0.6	1.5	0.1	0.3
SDH	3.8	8.8	1.7	1.4	3.0	8.3	0.8	1.2
CVH	0.4	0.7	0.2	0.1	0.3	0.7	0.1	0.1

[a] Variables described in Table 2.

Table 4
Selected predictor variables and model accuracies for Tuscany study area.

Forest structure variable[a]	Echo-based				CHM-based			
	ALS-metric[b]	R^2	RMSE%	RSE	ALS-metric[b]	R^2	RMSE%	RSE
Forest inventory variable								
Nstems	pP95	0.12	47.8	1051.5	gSD	0.11	48.2	1087.7
BA	pP60	0.53	20.8	6.6	gSUM	0.50	21.7	7.2
V	pMEAN	0.83	21.7	48.9	gMEAN; gCV	0.83	21.8	50.4
BL	pP60	0.77	21.3	25.0	gMEAN	0.74	22.5	27.1
BS	pLCV	0.49	24.7	11.9	gMEAN	0.34	28.3	14.0
Dg	pIQ	0.53	19.1	2.9	gSD	0.47	20.1	3.0
Dm	pCRR	0.40	24.8	3.1	gSUM	0.34	26.1	3.3
Hg	pIQ	0.83	10.5	1.2	gSD	0.80	11.3	1.3
Hd	pP99	0.91	8.2	1.4	gRANGE	0.88	9.5	1.6
Hm	PIQ	0.66	14.6	1.4	gSD	0.52	17.3	1.6
Structural complexity index								
SDD	pP95; pLSK	0.68	17.5	1.4	gSD; gCV	0.63	18.7	1.5
CVD	pLKU; pP25	0.33	18.7	0.1	gRANGE; gCV	0.31	18.8	0.1
SDH	pP95; pLSK	0.86	13.7	0.5	gSD; gCV	0.81	15.6	0.6
CVH	pP25; pL3; pP95	0.72	12.4	0.1	gRANGE; gCV	0.45	17.2	0.1

[a] Variables described in Table 2.
[b] Metrics described in Table 1.

Table 5
Selected predictor variables and model accuracies for Sardinia study area.

Forest structure variable[a]	Echo-based				CHM-based			
	ALS-metric[b]	R^2	RMSE%	RSE	ALS-metric[b]	R^2	RMSE%	RSE
Forest inventory variable								
Nstems	pSD; pCV; pP40; pLCV	0.31	82.9	1508.1	gMAX; gCV	0.19	89.6	1628.9
BA	pP60	0.54	27.6	10.0	gSUM	0.58	26.5	9.7
V	pCUMEAN	0.69	30.3	72.8	gSUM	0.70	29.8	71.6
BL	pMEAN	0.66	30.5	46524.6	gMEAN	0.62	32.4	49450.4
BS	pMEAN	0.61	33.9	16751.7	gMEAN	0.58	35.0	17311.7
Dg	pSD	0.40	38.5	7.7	gMAX	0.34	40.5	8.1
Dm	pSD; pL2	0.41	42.2	7.4	gMAX	0.29	46.1	8.2
Hg	pSD	0.64	19.8	1.8	gMAX	0.61	20.6	1.9
Hd	pMAX	0.76	14.3	1.5	gMAX	0.76	14.4	1.6
Hm	pVAR; pMMED; pIQ	0.50	27.4	2.4	gMAX	0.37	30.9	2.8
Structural complexity index								
SDD	pP99	0.25	41.2	3.4	gMAX	0.23	41.9	3.5
CVD	pL3; pMMED; pIQ	0.22	94.0	0.6	–	–	–	–
SDH	pMMED; pP99/pP50	0.25	35.7	1.1	gMAX; gCV	0.17	37.5	1.1
CVH	pSK	0.10	44.4	0.2	gCV	0.05	45.2	0.2

[a] Variables described in Table 2.
[b] Metrics described in Table 1.

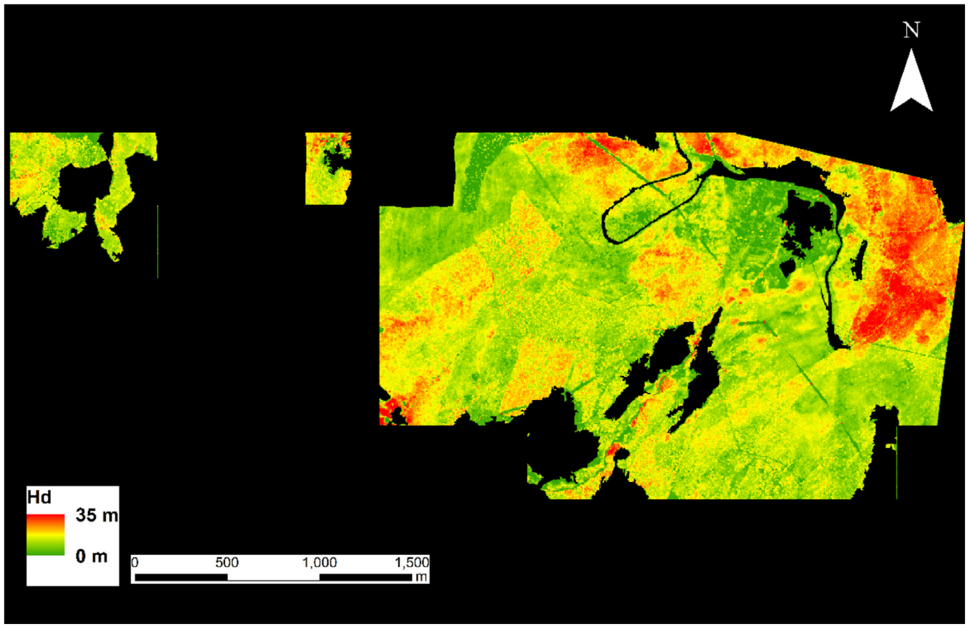

Fig. 2. Map of dominant height (Hd) in the forest portion of the Tuscany area.

Although model prediction accuracies were slightly greater when using echo-based metrics than when using CHM-based metrics, from a practical perspective the differences relative to accuracy were marginal. Thus, our study, along with Ozdemir and Donoghue (2013) and Chirici et al. (2016), clearly demonstrate that for practical applications aimed at modelling forest structure, either echo-based or CHM-based metrics can be used.

To estimate large area population means, we used the model-assisted GREG estimator which is widely used in combination with mapped predictions (Baffetta et al., 2009; McRoberts et al., 2013; Mura et al., 2015). This estimator functions independently of the prediction method by adjusting for estimated bias resulting from systematic deviations between observations and predictions. One practical advantage of the GREG estimator is that it compensates for effects such as small time lags between the field inventories and the ALS surveys. Although this lag may cause a slight increase in the uncertainty of the estimate $\hat{\mu}_{GREG}$, the estimator of the population mean is still unbiased.

The different point densities in the two study areas did not substantially affect model performance because, as has been reported by other studies (Treitz et al., 2012; Ruiz et al., 2014), plot size affects forest structure attributes estimates more than point densities. In addition, as noted by Vauhkonen et al. (2014), number of pulses per plot is more important than either pulse density or plot size alone. In particular, numbers of pulses per plot for this study were greater than 350 for the Tuscany study area and greater than 2500 for the Sardina study area, both of which exceed the 100–225 pulses per plot reported as sufficient by Vauhkonen et al. (2014). The fact that we obtained similar results from both surveys is an indication that our conclusions are not affected by varying survey specifications. Also, our results suggest that most low-density datasets typically found in national ALS programs can be useful for decreasing the uncertainty of population estimates of structural attributes in complex Mediterranean forest ecosystems. Since many of these national ALS datasets are publicly available free of cost, their use for decreasing the uncertainty of population estimates using the GREG estimator is clearly a cost-efficient approach.

The GREG estimate of mean Hd in the forested area was similar to the SRS estimate that used only the field plot data. However, the GREG estimator had considerably greater precision. These results are likely because of the good fit of the predictive model to the data and because the model-assisted estimators capitalize on the relationship between the observations and the auxiliary information to reduce the variance of the population parameter estimator (McRoberts et al., 2013).

The map of Hd (Fig. 2) for the Tuscany area clearly reflects the structural diversity of the forest which is related to the tree species distribution. Indeed, large predictions for Hd were obtained for the northeastern portion of the area which is dominated by conifers, whereas small predictions were obtained for the rest of the study area which is dominated by coppice oaks.

Models of relationships between forest structure variables and remotely sensed data facilitate forest structure mapping which, in turn, enhances assessment of the potential for greater overall biodiversity (Mura et al., 2015) and supports planning for large area monitoring and management interventions that would not be feasible using only ground data. Such maps assist in locating spots with potential high diversity value that need to be prioritized when developing conservation strategies (Myers et al., 2000), and also contribute to consideration of landscape ecology for biodiversity purposes (Ro and Hong, 2007).

5. Conclusions

Four conclusions can be drawn from the study. Firstly, ALS data are confirmed as a reliable and efficient source of information for characterizing forest structure, even in large and complex areas for H- and biomass- related response variables. Secondly, the capability of ALS data to predict forest structure accurately allows use of even simple linear models to characterize the relationship between the forest parameters representing forest structural diversity and the ALS metrics. This finding simplifies planning and monitoring for forest practitioners who are often not expert modelers but yet need to estimate forest structural diversity for management and planning purposes. Thirdly, the GREG estimator yielded an estimate in line with the SRS estimate, albeit with greater precision, and is confirmed as a valid tool for map-based area inference. Lastly, there is no practical difference with respect to accuracy when using echo-based metrics rather than CHM-based metrics. In addition, CHM-based metrics can be used in a GIS system which is a more common environment for most technicians and forest operators. Thus, the greater storage, skill, and computationally intensive requirements associated with point cloud analyses can be circumvented.

In the general framework of the study, future research should focus on integrating the methods and approaches described in this study with information on tree species composition and ecosystem functionality for purposes of better understanding of animal habitat assessment and modelling.

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