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Statistical inference for forest structural diversity indices using airborne laser scanning data and the k-Nearest Neighbors technique

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ABSTRACT

Forest structural diversity plays a major role for forest management, conservation and restoration and is recognized as a fundamental aspect of forest biodiversity. The assessment, maintenance and restoration of a diversified forest structure have become major foci in the effort to preserve forest ecosystems from loss of biological diversity. However, the assessment of forest biodiversity is difficult because it involves multiple components and is characterized using multiple variables. The objective of the study was to develop a methodological approach for predicting, mapping, and constructing a statistical inference for a multiple-variable index of forest structural diversity. The method included three key components: (i) use of the k-Nearest Neighbors (k-NN) technique, field plot data, and airborne laser scanning metrics to predict multiple forest structural diversity variables simultaneously, (ii) incorporation of multiple diversity variable predictions into a single index, and (iii) construction of a statistically rigorous inference for the population mean of the index. Three structural diversity variables were selected to illustrate the method: growing stock volume and the standard deviations of tree diameter at breast-height and tree height. Optimization of the k-NN technique produced mean relative deviations less in absolute value than 0.04 for predictions for each of the three structural diversity variables, R^2 values between 0.50 and 0.66 which were in the range of values reported in the literature, and a confidence interval for the population mean of the index whose half-width was approximately 5% of the mean. Finally, the spatial pattern depicted in the resulting map of forest structural diversity for the study area contributed to validating the proposed method.

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1. Introduction

1.1. Forest structural diversity

Forest structural diversity has been recognized as a fundamental component of forest biodiversity assessment and monitoring (Chirici et al., 2011). Biodiversity, from both general ecological and applied forestry perspectives, is characterized by a larger number of plant and animal communities sharing a common multidimensional space of habitats and niches and making greater use of available resources (McElhinny et al., 2005). Loss of these habitats and niches triggers a loss of biodiversity (Heino et al., 2009; Michel and Winter, 2009). Forests and wooded lands are the richest ecosystems from biological and genetic perspectives (Holdridge, 1947, 1967; Dinerstein et al., 1995), with anthropogenic activities constituting the main causes of the loss of forest biodiversity worldwide (Foley et al., 2005). Thus, the assessment, maintenance and the restoration of forest structural diversity have become major foci in the effort to preserve forest ecosystems from loss of biological diversity.

Forests are complex and adaptive systems (Puettmann et al., 2009) and given the complexity of the biotic and abiotic interactions, compositional, structural, and functional attributes are all involved in the assessment of forest diversity. However, functional attributes describing cycles of mass and energy among the components can be only assumed and only rarely verified, while compositional aspects are rarely measured in the field; thus lack of data and failure to understand fully mechanisms underlying ecophysiological processes cause assessments to become approximate, possibly subjective, and applicable only for isolated cases (Chirici et al., 2011).

In addition, often the only data available to investigate forest diversity at large scales are from national forest inventories (NFI) (Chirici et al., 2011; Pommerening, 2002) for which the primary objective has traditionally been to quantify the amount and extent of forest woody resources while seeking a compromise between the precision of estimates and limited financial resources. This compromise leads to limiting acquisition of field data to information for trees that satisfy size thresholds in the form of minimum diameters at breast-height (DBH), to information for species that contribute most in terms of woody volume, but

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omission of important ecological information for herbs, shrubs, animals, habitat trees and smaller and younger trees that are important for the functional dynamics of an ecosystem.

However, the structural diversity attributes of the macro component of tree communities gathered by NFIs are objective, reliable, and easy to calculate and understand when compared to more complex indices relying on functional and compositional aspects which offer little useful information for non-expert policy-makers (Branquart and Latham, 2007). In their review which cites studies ranging geographically from boreal to tropical forests, McElhinny et al. (2005) assert that forest structure is more relevant than composition for biodiversity assessments; the rationale is that more diverse stand structures have more niches and, therefore, support more species which results in greater diversity and more efficient use of available resources.

Unmanaged forests tend to have greater structural heterogeneity than managed forests, can better resist the effects of influential internal and external adverse factors (Puettmann et al., 2009), and have greater resilience than managed forests. Moreover, measures of forest structural diversity are characterized by attributes that are judged indispensable for assessing forest diversity. They are reliable in producing objective, consistent and precise results (Uotila et al., 2002; Smith and Theberge, 1987; Liira et al., 2007); they are widely available and easy to calculate (Liira et al., 2007; Bartha et al., 2006); over time they respond to changes in forest dynamics (Angermeier and Karr, 1994); and they are appropriate for assessment at multiple scales (Bartha et al., 2006). Therefore, structural attributes may be reasonably assumed to constitute a reliable basis for objective assessments of forest diversity. Further, from a management perspective, maps of the spatially explicit patterns of structural diversity are of great use for locating hot spots where greater biodiversity is likely to occur, for assisting managers in planning adequate preservation strategies, and for assisting conservationists in prioritizing areas for biodiversity-oriented studies.

1.2. Forest structural diversity measures

Multiple measures of forest structural diversity have been proposed and evaluated. Lexerød and Eid (2006) evaluated eight diameter diversity measures for forest management purposes; Pommerening (2002) evaluated eight measures for habitat functions and forest management planning; Latifi (2011) considered multiple categories of measures that can be estimated using remotely sensed data; and Neumann and Starlinger (2001) evaluated 11 measures for assessing the effects of air pollution. Staudhammer and LeMay (2001) and Müller and Vierling (2014) both noted that of the many measures, the most commonly used include diameter, height (H), or both. With respect to particular measures, Staudhammer and LeMay (2001) reported that the Shannon index performed well for ranking spatial areas with respect to degree of diversity, but Lexerød and Eid (2006) reported that the Gini index was superior for boreal forest planning purposes. The relevant conclusions from the literature are that a multitude of measures of forest structural diversity are feasible, but that prospects for a globally superior measure are unlikely. Further, whereas the vast majority of proposed measures address only a single component of diversity such as height, diameter, or spatial location, diversity encompasses multiple components.

1.3. Objectives

The objective of the study was to develop a methodological approach for predicting, mapping, and constructing a statistical inference for a multiple-variable index of forest structural diversity. The proposed approach relies on prediction of forest structural diversity variables using airborne laser scanning (ALS) metrics (Lim et al., 2003; Zimble et al., 2003; Wulder et al., 2008; Mura et al., 2015) and features three innovative components: (i) use of the multivariate, non-parametric k-Nearest Neighbors technique (k-NN) to predict multiple forest structural diversity response variables simultaneously, (ii) development of a multiple-variable index that integrates any combination of particular single-variable forest structural diversity variables, and (iii) statistically rigorous inference for the population mean of the multiple-variable index. The k-NN technique is well-suited for this approach because it permits simultaneous prediction of multiple response variables, is not constrained by distributional assumptions, and is well-documented for use with forest inventory data (Tomppo et al., 2008). A bootstrap resampling technique was used to estimate the uncertainty of the estimated mean of the multiple-variable structural diversity index. Although the primary study objective was methodological, the approach is illustrated for a study area in Molise, Italy. Of importance, the selected forest structural diversity variables are intended to be illustrative only rather than definitive because relevant forest structural diversity variables vary for each application and study area. Nevertheless, the general approach consisting of the multivariate k-NN prediction technique, the multiple-variable index, and the inferential approach is applicable for any application and study area.

2. Materials and methods

2.1. Study area

The study area included 36,360 ha in the southwestern part of Molise Region in central Italy (Fig. 1). Approximately 56% of the area, corresponding to 20,518 ha, is covered by forests of which 60% is deciduous oaks (*Quercus cerris* L., *Quercus pubescens* Willd), 18% is hop hornbeam (*Ostrya carpinifolia* Scop.), 9% is beech (*Fagus sylvatica* L.), 7% is evergreen holm oak (*Quercus ilex* L.), 4% is hygrophilus forest, and the remainder is species of $<1\%$ each. The oak and hop hornbeam forests are mainly privately-owned and managed using a coppice with standards system characterized by rotation ages between 18 and 25 years, cuts of size 1–2 ha, and 100–200 residual standards/ha. Conversely, the beech forests are unmanaged and now have structures approaching natural, old-growth forest status.

2.2. Field data

The study area was tessellated into 437 hexagons, each with area of 1 km^2, and two-phase tessellation stratified sampling (TSS) was conducted (Chirici et al., 2015). In the first phase, a point was randomly selected in each hexagon and classified as “forest” or “non-forest” based on the Italian NFI definition of at least 10% tree cover, minimum area of 0.5 ha, and potential height of at least 5 m at maturity (Gasparini et al., 2013). The attribution of a point as “forest” or “non-forest” was based on interpretation of high-resolution aerial ortho-photography; of the 437 points, 197 were classified as “forest” (Fig. 1). In the second phase, a sampling rate of approximately 30% was applied to the 197 points classified as a “forest” to randomly select 62 points to be visited in the field during years 2009–2011 (Fig. 1). The plot configuration consisted of a circular plot of 13-m radius with measurement of all trees that satisfied the Italian NFI minimum DBH threshold of 9.5 cm (Gasparini et al., 2013). Height was measured for a sub-sample of approximately 10 trees per plot that included the three largest trees, the five trees nearest the plot center, and two trees selected from less frequently observed species and diameter classes. For the remaining trees, H was predicted using a model of the H-DBH relationship constructed using data for the measured trees.

2.3. Structural diversity index (SDI)

An index of forest structural diversity is formulated that incorporates multiple features suggested in the literature. First, the index incorporates multiple forest structural diversity variables as suggested by Neumann and Starlinger (2001), Loidi (1994, pp. 17–30), and Merganič et al. (2012). Second, the index includes variances of vertical and horizontal structure as suggested by Jaehne and Dohrenbusch (1997). Third, as suggested by Staudhammer and LeMay (2001), the

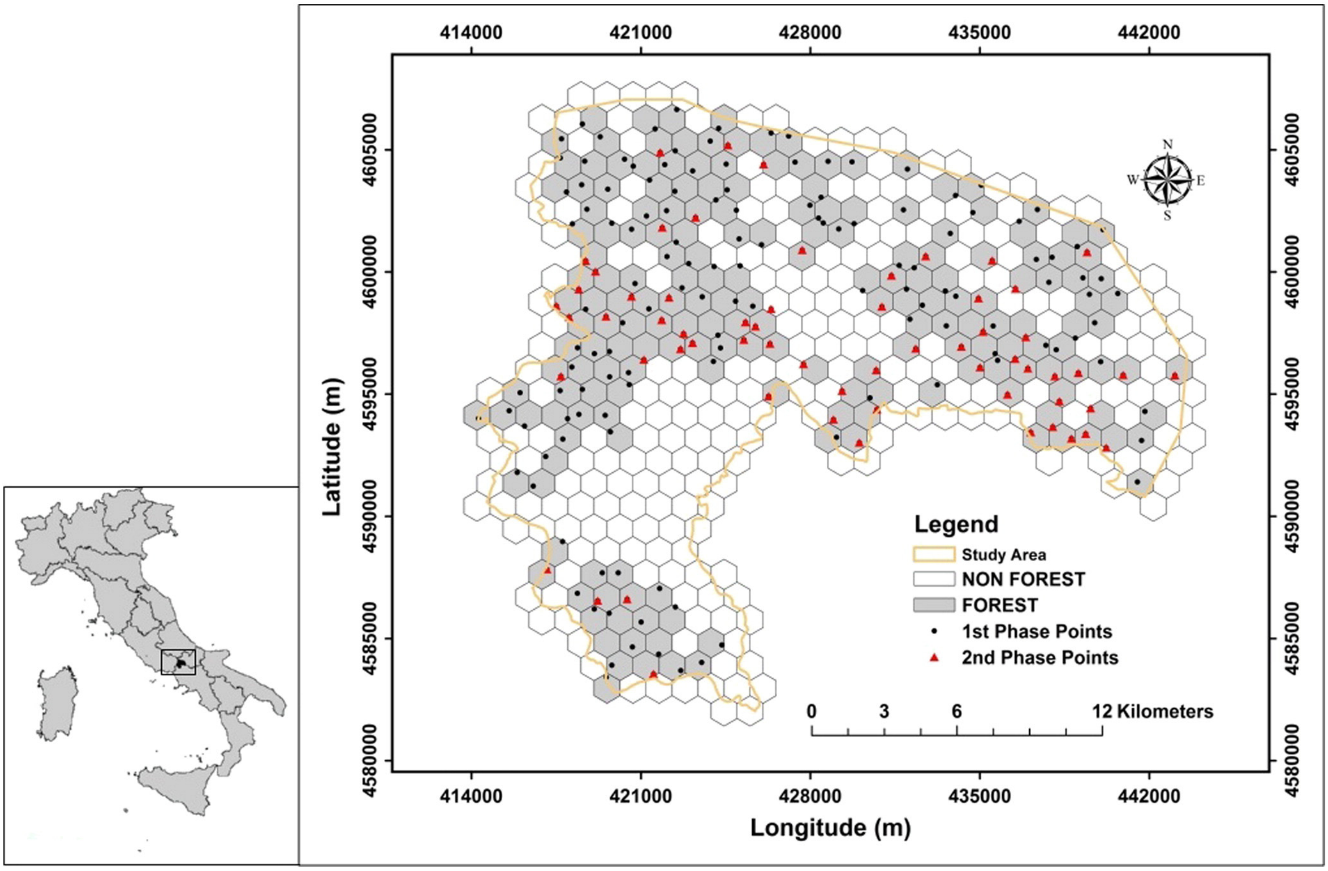

Fig. 1. Sampling design and plot locations in the study area (WGS84 UTM33 N coordinates).

index scales values of the diversity variables using reference values for those variables. The structural diversity index (SDI) formulated for this study combines multiple diversity measures and estimates forest structural diversity in terms of a conceptual distance to a set of reference values. Let $Y_1, Y_2, \ldots, Y_M$ denote the M diversity response variables with sample observations, and let $Y_1^{max}, Y_2^{max}, \ldots, Y_M^{max}$ denote the maximum observed values for these M variables which serve as the reference values. Further, let $\hat{y}_{i1}, \hat{y}_{i2}, \ldots, \hat{y}_{iM}$ be the k-NN predictions for these variables for the ith 23-m × 23-m population unit (Section 2.5). These predictions are standardized using the reference values as $\hat{z}_{i1} = \frac{\hat{y}_{i1}}{Y_1^{max}}, \ldots, \hat{z}_{im} = \frac{\hat{y}_{iM}}{Y_M^{max}}$ where $0 \le \hat{z}_{ij} \le 1$. The index, SDI, is then a distance metric calculated as,

$$\begin{aligned} SDI_i &= 1 - \sqrt{w_1 \cdot (\hat{z}_{i1} - 1)^2 + \cdots + w_M \cdot (\hat{z}_{iM} - 1)^2} \\ &= 1 - \sqrt{w_1 \cdot \left(\frac{\hat{y}_{il}}{Y_1^{Max}} - 1\right)^2 + \cdots + w_M \cdot \left(\frac{\hat{y}_{iM}}{Y_M^{max}} - 1\right)^2} \end{aligned} \tag{1}$$

where $\{w_1, w_2, \ldots, w_M\}$ are weights with $\sum_{m=1}^{M} w_m = 1$ that permit weighting of the individual diversity response variables. For this study, equal weighting was used because the particular variables were selected primarily for illustrative purposes. For the ith population unit, $0 \le SDI_i \le 1$ with values closer to 1 indicating greater structural diversity (Chirici et al., 2011; McRoberts et al., 2012).

2.4. Forest structural diversity variables

For purposes of illustrating the index, any combination of the very large number of forest structural diversity variables that have been described in various review and comparison articles could be selected (Pommerening, 2002; Lexerød and Eid, 2006; Latifi, 2011; Neumann and Starlinger, 2001). For this study, three commonly used structural diversity variables were selected. For each plot, growing stock volume (GS, m^3/ha), defined as the volume of the stem plus branches for trees with diameters of at least 5 cm, and the standard deviations of DBH (σ_{DBH}, cm) and H (σ_H, m) were calculated from the tree data collected in the field. Although the three structural diversity variables were selected primarily for illustrative purposes, they are justified by multiple factors: (i) they are commonly used in forestry research because of their relevance, reliability, and usefulness (Kuuluvainen et al., 1998; Uuttera et al., 2000; Sullivan et al., 2001; Neumann and Starlinger, 2001; Uotila et al., 2002; McElhinny et al., 2005; Motz et al., 2010; Latifi, 2011; Hyde et al., 2006; Ozdemir and Donoghue, 2013); (ii) they are recognized as biodiversity indicators in the framework of continental agreements (EEA, 2012; MCPFE, 2011; Puumalainen et al., 2003; Wirth et al., 2009) and international cooperative scientific research programs (Chirici et al., 2011); (iii) they can be easily estimated from common NFI data, a considerable advantage for large scale biodiversity assessing and monitoring (Winter et al., 2008, 2012; Chirici et al., 2012); and (iv) they can be used for temporal change detection (McRoberts et al., 2008).

For each plot, GS was estimated using the national models developed by Tabacchi et al. (2011) for the last Italian NFI (Gasparini et al., 2013). Both σ_{DBH} and σ_H were calculated as,

$$\sigma_Y = \sqrt{\frac{\sum_{s=1}^{S} (y_s - \bar{y})^2}{S - 1}} \tag{2}$$

where s indexes trees, S is the number of plot trees, y_s is either DBH or H, and $\bar{y}$ is the plot-level mean (Table 1).

Variogram analyses of the spatial relationships among plot-level observations of the selected forest structural diversity variables revealed that ranges of spatial correlation were comparable to or greater than the minimum distance between pairs of plots. Therefore no accommodation for spatial correlation among plot-level observations of the biodiversity variables was necessary in the analyses.

2.5. Airborne laser scanning (ALS) data

ALS data were acquired under leaf-on canopy conditions in June 2010 as part of the ITALID project "Use of LiDAR data to study Italian forests" (Scrinzi et al., 2013). The raw data were acquired using an Optech Gemini scanning instrument mounted on a fixed-wing Partenavia P68 aircraft with a maximum scan angle of 15° and a pulse repetition frequency of 70 kHz, resulting in an average density of 1.5 pulses/m^2. The original data were acquired for a different purpose and included four echoes per pulse, but only the first and last echoes were available for this study; in particular, first echoes included the only echo in the case of single echo returns, whereas last echoes were for multi-echo returns.

Processing of the raw point cloud included use of available software to identify and eliminate noise points and extremely high or low points outside the range of realistic elevations for the study area. Following these removals, the ground surface was modeled using an adaptive triangulated irregular network algorithm (Axelsson, 2000). Based on the estimated ground surface, relative height above ground for each echo was calculated and used to derive 21 height and canopy density metrics for each plot.

Metrics were constructed for pulse echoes with heights >1.3 m, the threshold below which the Italian NFI considers trees to be regeneration (Gasparini et al., 2013). Canopy cover (cov) was calculated as the proportion of all first echoes with heights >1.3 0 m. All other metrics were based on all echoes including two canopy density metrics: the proportion (d_{00}) of all echoes with heights in the lower canopy defined as between 1.3 m and 10 m, and the proportion (dns) of all echoes with heights >1.3 m. Canopy relief ratio, CRR, a plot-level quantitative measure of the relative shape of the canopy describing the proportion of all echoes above the mean value of all echoes heights, was calculated as,

$$CRR = \frac{H_{avg} - H_{min}}{H_{max} - H_{min}} \tag{3}$$

CRR ranges between 0 and 1 and reflects the degree to which outer canopy surfaces are in the upper or lower half of the echo height range (Parker and Russ, 2004). Canopy height metrics included percentiles ($p_{10}, p_{20}, \ldots, p_{90}, p_{99}$) of the distribution of all echo heights >1.3 m. Metrics based on summary statistics for the distribution of all echo heights included the minimum (H_{min}), maximum (H_{max}), average (H_{avg}), standard deviation (H_{std}), coefficient of variability (H_{cv}), skewness (H_{ske}) and kurtosis (H_{kur}). All metrics served as feature variables for k-NN predictions and were spatially gridded using 23-m × 23-m cells that mimicked as closely as possible the plot area of approximately 531 m^2 and that served as population units.

Table 1
Summary statistics for the response and feature variables.

Variable	Minimum	1st quartile	Median	Mean	3rd quartile	Maximum
Response variables						
GS (m^3/ha)	3.14	77.30	126.80	145.30	175.60	514.40
σ_{DBH} (cm)	1.50	3.84	5.20	5.56	7.25	25.21
σ_H (m)	1.31	2.12	2.58	2.90	3.22	8.18
Feature variables[a]						
H_{min}	1.37	1.37	1.38	1.48	1.43	2.72
H_{max}	4.39	9.23	13.06	13.33	16.03	24.98
H_{ske}	−1.55	−0.18	0.13	0.03	0.39	2.42
p_{60}	0.00	5.18	6.76	7.65	8.82	17.90
p_{70}	0.16	5.82	7.64	8.36	9.59	18.50

[a] Feature variables selected for the optimal k-NN configuration (Section 3.1).

2.6. k-Nearest Neighbors

The k-NN technique and its variations are intuitive, non-parametric approaches to either univariate or multivariate prediction based on the similarity in a covariate space between the population unit for which a prediction is desired and sample units for which observations are available (McRoberts, 2012). The reasons for selecting the k-NN technique for this study were threefold: (i) it is well-documented for use with forest inventory data (Tomppo et al., 2008; McRoberts, 2012; Chirici et al., 2016), (ii) it is non-parametric, thereby accommodating a variety of distributions for forest inventory variables, and (iii) it has the capability for multivariate prediction. Regarding the latter reason, use of multiple independent univariate approaches, one for each diversity response variable, would invariably lead to erroneous combinations of predictions for some plots such as very large DBH diversity together with very small H diversity. This error is mostly avoided when using simultaneous multivariate prediction.

For explanatory purposes, let **Y** denote a possibly multivariate vector of response variables with observations for a sample of size n from a finite population of size N, and let **X** denote a vector of auxiliary variables with observations for all population units. In the terminology of nearest neighbors techniques, the set of population units for which observations of both response and auxiliary variables are available is designated the *reference set*; the set of population units for which predictions of response variables are desired is designated the *target set*; the auxiliary variables, **X**, are designated *feature variables*; and the space defined by the auxiliary variables is designated the *feature space*. All units of both the reference and target sets are assumed to have a complete set of observations for all feature variables. For continuous response variables, the k-NN prediction, $\hat{y}_t$, for the tth target set unit is,

$$\hat{y}_t = \sum_{r=1}^{k} w_{tr} y_r^t \tag{4}$$

where $\{y_r^t, r = 1, 2, \ldots, k\}$ is the set of response variable observations for the k reference set units that are nearest to the tth target set unit in feature space with respect to a distance metric, d, and w_{tr} is the weight assigned to the rth nearest neighbor with $\sum_{r=1}^{k} w_{tr} = 1$. The most common approach to weighting neighbors is to use weights that are inversely proportional to a power, p, of the distance, d_{tr}, between the rth reference unit and the tth target unit,

$$w_{tr} \propto d_{tr}^{-p} \tag{5}$$

where p > 0. Commonly, albeit arbitrarily, selected values are often p = 0, p = 1, or p = 2, although there is no reason to restrict p to integer values.

Many distance measures can be expressed in matrix form as,

$$d_{tr} = \sqrt{(\mathbf{X}_t - \mathbf{X}_r)' \mathbf{M} (\mathbf{X}_t - \mathbf{X}_r)} \tag{6}$$

where t denotes a target set unit for which a prediction is sought, r denotes a reference set unit, $\mathbf{X}_t$ and $\mathbf{X}_r$ are the vectors of observations of feature space variables for the tth and rth units, respectively, and **M** is a square matrix. Popular choices for **M** include the identity matrix which results in Euclidean distance, and a non-identity diagonal matrix which results in weighted Euclidean distance. Mahalanobis distance results when **M** is the inverse of the covariance matrix of the feature space variables (Kendall and Buckland, 1982). Other choices for **M** are based on canonical correlation analyses (LeMay et al., 2008; Moeur and Stage, 1995) and canonical correspondence analyses (Ohmann and

Gregory, 2002). Chirici et al. (2008) evaluated additional distance metrics.

Given a reference and target set, the factors that affect k-NN predictions are the distance metric, the feature variables included in the distance metric, and the values of k and p. For the sake of simplicity in an otherwise complex estimation problem, the Euclidean distance metric was used. For variations of k-NN that permit $k > 1$, smaller values of k are generally preferred as a means of reducing complexity and computational intensity. However, caution must be exercised when selecting small values of k because such values could yield root mean square errors that are greater than the standard deviations of the response variable observations, meaning that the overall mean as a prediction for every target unit would better maximize accuracy than the k-NN predictions (McRoberts et al., 2012).

The most intuitive approach to selecting these values is to use an algorithm that optimizes a criterion in the reference set. A leave-one-out, cross-validation algorithm was used to select the combination of the minimum number and type of feature variables and k and p values that maximized the mean of the R^2 values for the three response variables. The optimal combination of feature variables and values of k and p were then used to predict the three response variables for each population unit (23-m × 23-m cell) in the study area, and the predictions were then combined to predict SDI.

2.7. Accuracy and uncertainty assessment

For this study, accuracy refers to the correspondence between the observations and k-NN predictions, whereas uncertainty refers to the variance of the large area estimators. For the entire study area, the population mean is estimated as the mean over all cell predictions,

$$\hat{\mu}_{Map} = \frac{1}{N}\sum_{i=1}^{N}\hat{y}_i \quad (7)$$

where i indexes cells serving as population units, N is the population size, and $\hat{y}_i$ is the prediction of SDI for the i^{th} cell. The overall, multivariate sum of squared errors, SSerr, is calculated as,

$$SSerr = \sum_{m=1}^{M}\sum_{r=1}^{n}(y_{mr}-\hat{y}_{mr})^2 \quad (8)$$

where m indexes response variables, M is the number of response variables, n is the reference set size, and y_{mr} and $\hat{y}_{mr}$ are the observed and predicted values of the m^{th} response variable for the r^{th} reference set unit.

However, this estimation procedure could be biased as the result of systematic deviations between k-NN predictions and observations. For the model-based approach to inference used for this study (McRoberts et al., 2007; McRoberts, 2012), the issue was assessed by calculating the mean and relative deviations and graphing the observations versus the predictions. Mean deviation, often characterized as estimated bias, is defined as the mean difference between the observed and predicted values,

$$\bar{e} = \frac{1}{n}\sum_{r=1}^{n}(\hat{y}_r - y_r) \quad (9)$$

where n is the reference set size, and y_r and $\hat{y}_r$ are the observation and prediction for the r^{th} reference unit, respectively. Mean deviation can also be reported in relative terms as the ratio,

$$\bar{e}_{rel} = \frac{\bar{e}}{\bar{y}} \quad (10)$$

where $\bar{y}$ is the reference set mean (McRoberts et al., 2011).

Resampling routines such as bootstrap resampling techniques are often used to assess uncertainty for non-parametric methods. The bootstrap technique was chosen for this study because it has been shown to be reliable and well-suited for k-NN uncertainty estimation for complex problems (McRoberts et al., 2011; McRoberts, 2012). Bootstrapping relies on the notion of a bootstrap sample, and the bootstrapping pairs approach was used to construct bootstrap samples for this study (Efron and Tibshirani, 1994). With this approach, each bootstrap sample consisted of a sample of n pairs (y_r, $\mathbf{X_r}$) drawn with replacement from the original reference set. As prescribed by Efron and Tibshirani (1994), each bootstrap sample is exactly the same size as the reference set and consists of plot-level observations of the response and feature variables, although observations for some plots are repeated and observations for some other plots are omitted. The bootstrap estimate of the population mean was calculated using Eq. (7), albeit with the bootstrap sample as the k-NN reference set rather than the original reference set. Although Efron and Tibshirani (1994) suggest at least $n_{boot} = 200$ bootstrap samples, McRoberts et al. (2011) found that much larger values were necessary to obtain stable results. Therefore, values as large as $n_{boot} = 500$ were considered. The estimate, $\hat{\mu}^b_{boot}$, is the estimate of the mean obtained from the b^{th} bootstrap sample, and the bootstrap estimate of the population mean is,

$$\hat{\mu}_{boot} = \frac{1}{n_{boot}}\sum_{b=1}^{n_{boot}}\hat{\mu}^b_{boot} \quad (11)$$

The bootstrap estimate of bias is calculated as,

$$\hat{Bias}_{boot}(\hat{\mu}) = \hat{\mu}_{boot} - \hat{\mu}_{Map} \quad (12)$$

where $\hat{\mu}_{Map}$ is the estimate obtained using Eq. (7) and the original reference set, and the bootstrap estimate of variance is calculated as,

$$\hat{Var}_{boot}(\hat{\mu}) = \frac{1}{n_{boot}-1}\sum_{b=1}^{n_{boot}}\left(\hat{\mu}^b_{boot} - \hat{\mu}_{boot}\right)^2 \quad (13)$$

with

$$SE_{boot}(\hat{\mu}) = \sqrt{\hat{Var}_{boot}(\hat{\mu})} \quad (14)$$

3. Results

3.1. k-Nearest Neighbors optimization and predictions

The optimal k-NN configuration was achieved using five feature variables, $k = 6$, and $p = 1.71$ (Table 2). This configuration included the five feature variables (H_{min}, H_{max}, H_{ske}, p_{60}, p_{70}) and yielded multivariate SSerr = 620.88 with corresponding mean $R^2 = 0.60$. For GS, $R^2 =$ 0.66 which was at the large end of the range of 0.41 to 0.71 reported

Table 2
Results of the k-NN optimization phase.

Number of feature variables	Mean R^2	k	p	SSerr	R^2_{GS}	$R_{\sigma_{DBH}}{}^2$	$R_{\sigma_H}{}^2$
1	0.545	10	0.94	694.10	0.608	0.444	0.583
2	0.573	10	2.00	674.69	0.660	0.460	0.600
3	0.588	6	1.94	627.06	0.659	0.498	0.608
4	0.593	6	1.71	629.90	0.667	0.496	0.617
5[a]	0.595	6	1.71	620.88	0.663	0.503	0.619
6	0.595	6	1.72	620.42	0.663	0.503	0.619
7	0.596	8	1.73	629.88	0.656	0.496	0.636
8	0.596	8	1.74	629.08	0.656	0.496	0.636
9	0.596	8	1.74	628.71	0.656	0.497	0.636
10	0.596	8	1.74	628.83	0.656	0.497	0.636

[a] Configuration yielding the greatest mean R^2 subject to the fewest feature variables.

in the literature for temperate, broadleaved forests (Chirici et al., 2015; Nord-Larsen and Cao, 2006; Skowronski et al., 2014). For σ_{DBH}, $R^2 = 0.50$ which was slightly less than the lower end of the range of 0.59 to 0.85 reported in the literature (Mura et al., 2015; Hyde et al., 2006; Monnet et al., 2010, pp. 586–594; Ozdemir and Donoghue, 2013). However, nearly all the literature references for σ_{DBH} were for coniferous rather than broadleaved forests for which ALS-assisted prediction is known to be more difficult. For σ_H, $R^2 = 0.62$ which was greater than the range of 0.50 to 0.59 reported in the literature. Finally, because the structural diversity response variables were predicted simultaneously, their accuracies should be expected to be less than if prediction had been optimized for each of the variables individually.

Graphs of the observations versus the predictions revealed no serious systematic lack of fit for any of GS, σ_{DBH}, or σ_H (Fig. 2). The accuracy of the k-NN predictions was confirmed by the mean ($\overline{e}$) and relative deviations ($\overline{e}_{rel}$): $\overline{e} = -5.33$ m^3/ha for GS, $\overline{e} = -0.07$ cm for σ_{DBH}, and $\overline{e} = -0.07$ m for σ_H, resulting in $\overline{e}_{rel}$ of -0.04, -0.01, and -0.02 respectively. The resulting map depicts the predictions of SDI for the entire study area, where greater values indicate greater structural diversity and vice versa (Fig. 3).

3.2. Bootstrap resampling

For both $\hat{\mu}_{boot}$ and $SE(\hat{\mu}_{boot})$, stabilization was achieved for $400 \leq n_{boot} \leq 500$ (Fig. 4). The population mean estimated from the map was $\hat{\mu}_{map} = 0.2626$ whereas the bootstrap estimate was $\hat{\mu}_{boot} = 0.2621$ with $SE_{boot}(\hat{\mu}_{boot}) = 0.0118$. An approximate 95%, confidence interval for the SDI population mean is $\hat{\mu}_{boot} \pm 2 \cdot SE_{boot}(\hat{\mu}_{boot}) = [0.24, 0.29]$ which is quite precise with a ratio of the half-width of the confidence interval to the estimate of the mean of only 0.05.

4. Discussion

The study objective was to develop a methodological approach aimed at predicting, mapping, and constructing a statistically rigorous inference in the form of a confidence interval for the population mean of a multiple-variable index of forest structural diversity. The method was illustrated using the k-NN technique and ALS metrics to predict three forest structural diversity variables whose observations were based on field plot data. For the study area in the Molise Region, Italy, mean deviations between observations and predictions for all three diversity variables were less in absolute value than 0.04 as proportions of the means, R^2 values were comparable to those reported in the literature for temperate broadleaved forests, graphs of observations versus predictions indicated no serious lack of fit, and the half-width of the confidence interval as a proportion of the estimate of the SDI population mean was approximately only 0.05. Based on these measures, the procedure achieved the objective for this particular study area.

The bootstrap resampling technique worked well and produced the desired outcome with only negligible deviation between the map-based and bootstrap means. Our finding that $n_{boot} > 400$ was required for bootstrap means and standard errors to stabilize confirms the previous finding reported by McRoberts et al. (2011) that $n_{boot} = 200$ as recommended by Efron and Tibshirani (1994) could be insufficient.

The index, SDI, as illustrated with the three selected diversity variables, is not necessarily comprehensive because it does not include compositional, functional, and other factors that may be relevant for this task. Although we assessed forest structural diversity relying only on the tree structural component of the ecosystem and not species composition, we note that forests in the study area are frequently monospecific or composed of no more than two or three closely related species, the exception being the hygrophilous forest where diversity resulting from more species was captured quite well using just the three structural variables. Thus, the management system is the main factor

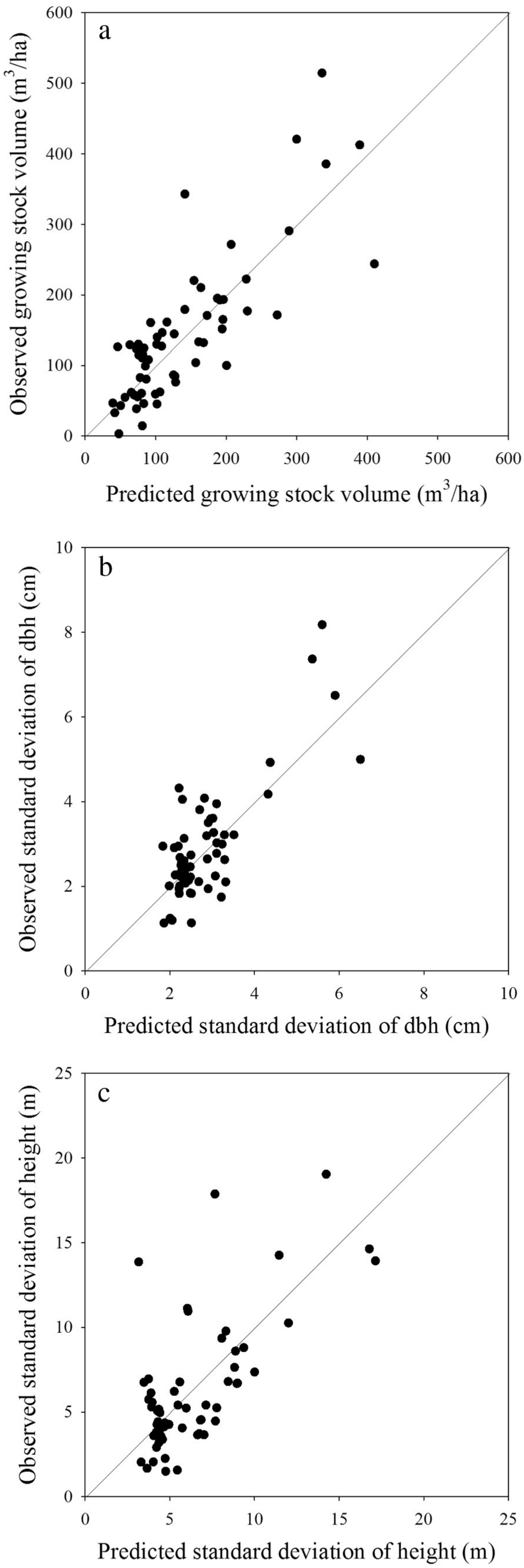

Fig. 2. Observations versus predictions: (a) growing stock volume (GS, m^3/ha), (b) standard deviation of diameter at breast-height (σ_{DBH}, cm), and (c) standard deviation of height (σ_{HT}, m).

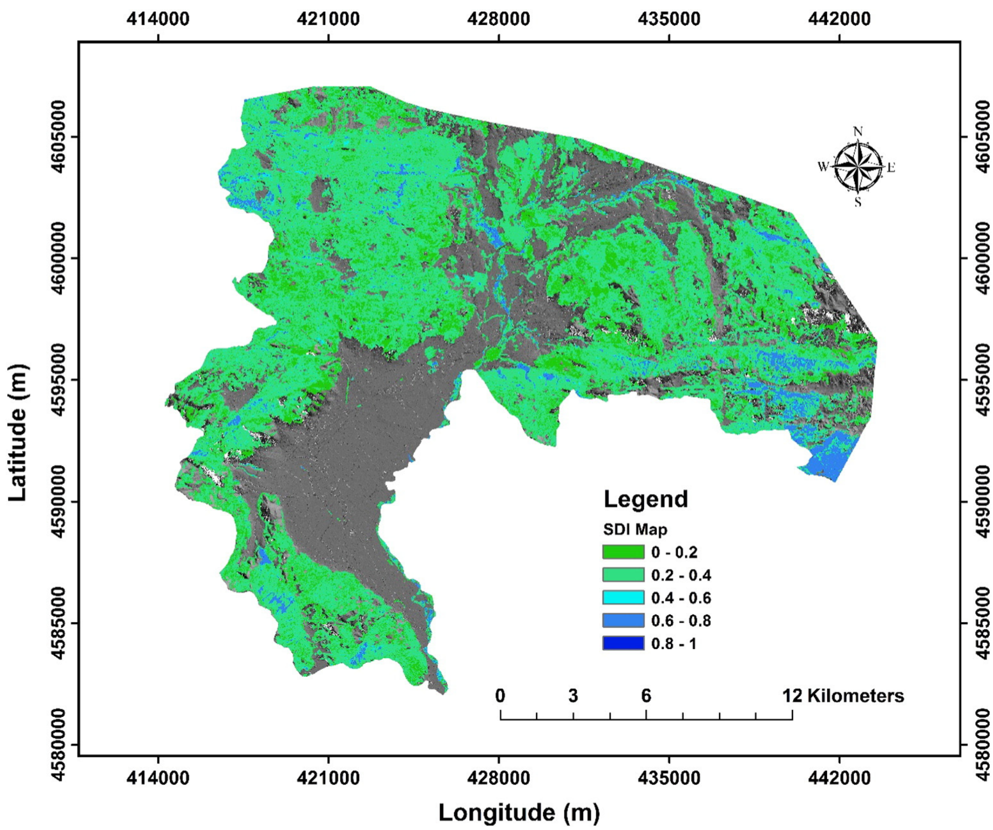

Fig. 3. Map of SDI where values closer to 1 indicate greater structural diversity (WGS84 UTM33 N coordinates).

influencing the degree of diversity in the study area which is affected more by structure than composition.

In situations where species composition does play a major role in determining diversity, the methodology and the index can be readily extended to include additional diversity variables that describe compositional, functional, and others aspects as a means of producing a more comprehensive index. The approach can be further improved if an area of undisturbed natural forest – ideally virgin forest – is available for which the full natural potential of the response variables can be determined and used as reference values. For this study, we used the maximum values of the response variables in the sample which resulted in a

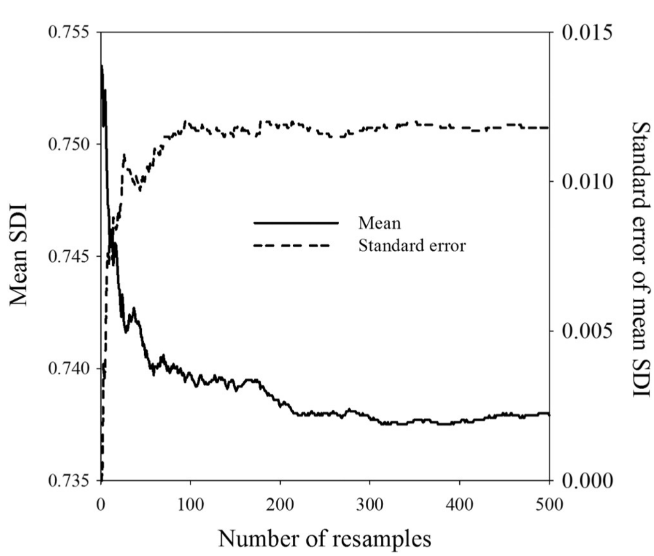

Fig. 4. Mean, $\hat{\mu}_{boot}$, and standard error of the mean, SE($\hat{\mu}_{boot}$), versus number of bootstrap samples.

measure of structural diversity relative to the range covered by the sample data. If the full natural potential of undisturbed forests is known, the associated values of the response variables should be used in Eq. (1) as the reference values expressing maximum diversity. However, obtaining such values is a difficult task because of the sparseness of areas with undisturbed forests which, in Europe excluding the Russian Federation, is only 4% of the total forest area (MCPFE, 2011 - Criterion 4.3 Naturalness).

Although our implementation of SDI did not include compositional and functional aspects of diversity, its relevance as a measure of forest structural diversity for the study area is confirmed by the spatial patterns of SDI depicted in the map. Greater values of SDI, which indicate greater structural diversity, occur in two regions: first, on the eastern side of the study area which is dominated by unmanaged beech forests, nowadays approaching old-growth forest status with uneven-aged structures and relatively large values of GS, and second, along the main rivers (linear patterns in the center of the map) which are dominated by hygrophilus forests which are typically unmanaged to enhance protection against the effects of flooding. Conversely, smaller values of SDI indicating less diversity are spread across the entire study area and represent the oak and hop hornbeam dominated forests that are managed using a coppice with standard system which leads to even-aged, simpler and mono-layered structures over time. The consistency between the mapped values of SDI and the actual status of the structural diversity of forests in the study area allows areas of greater structural diversity to be identified and accorded a more protection-oriented focus.

The utility of the approach for constructing indices of diversity is that it accommodates any number and any selection of forest structural variables. In addition, it provides a mechanism for constructing maps and a method for statistically rigorous uncertainty assessment. From a practical management perspective, spatially explicit patterns of structural diversity as depicted in the map (Fig. 3) can be used to locate and prioritize potential high diversity hotspots, to assist managers in planning management and conservation strategies, to assist conservationists in ranking areas for biodiversity studies, and to assist landscape ecologists in developing mitigation policies when habitats and populations are threatened by land use conversion, particularly urbanization (Ro and Hong, 2007).

Because our primary objective was development of a method for constructing an inference for a multiple-variable index of forest structural diversity index, not formulation of a globally definitive index, the particular diversity variables selected were intended to be only illustrative. Thus, investigations using a broader suite of diversity variables including herbs, shrubs, mosses, lichens and ecological variables related to compositional and functional aspects of forest diversity would be appropriate as would application in regions with greater species diversity.

5. Conclusions

Multiple conclusions were drawn from the study. Firstly, the utility of ALS data in combination with the k-NN technique for predicting and mapping forest attributes was confirmed once again. Although this finding has been reported previously, failure in this regard would have invalidated the entire study. Secondly, a k-NN optimization phase as used for this study is recommended to increase accuracy and reduce uncertainty. Thirdly, the bootstrap procedure worked well for estimating the mean and standard error of the mean for the entire population, although caution should be exercised when selecting the number of resamples, because different datasets require different numbers of resamples to achieve stabilization. Fourthly, although composition and functional aspects were not incorporated, the proposed index of forest structural diversity captured the main patterns of forest diversity in the study area and correctly identified local areas of greater structural diversity, thereby validating its reliability as technique for planning management and conservation strategies. Fifthly, the overall approach that incorporated k-NN for accurate multivariate predictions, a multiple-variable index of diversity, and bootstrap resampling for construction of an inference was reliable and efficient, produced the desired result, and can be applied generally, regardless of the study area and the particular diversity variables selected.

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