Using Precision Forestry Technologies to Assess Structure and Diversity in Mixed Broadleaf Forest

by

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A thesis submitted in conformity with the requirements
for the degree of Ph.D. in Science, Technology, and Biotechnology for Sustainability under curriculum Forest Ecology and Environmental Technologies- Cycle XXXI

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DIPARTIMENTO PER L'INNOVAZIONE NEI SISTEMI BIOLOGICI, AGROALIMENTARI E FORESTALI (DIBAF)

CORSO DI DOTTORATO DI RICERCA

IN SCIENZE, TECNOLOGIE E BIOTECNOLOGIE PER LA SOSTENIBILITA' ILCURRICULUM ECOLOGIA FORESTALE E TECNOLOGIE AMBIENTALI- CICLO XXXI

USING PRECISION FORESTRY TECHNOLOGIES TO ASSESS STRUCTURE AND DIVERSITY IN MIXED BROADLEAF FORESTS

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Acknowledgments

I wish to express my heartfelt gratitude and profound appreciation to the following who in various ways have contributed directly or indirectly to completion of the research work.

I would like to thank my tutor Dr. Andrea Cutini for his guidance and meaningful suggestion. Also, I would like to express my special thanks to my co-tutor Prof. Piermaria Corona for his sustain guidance, constructive criticism, suggestion, encouragement, and inspiration throughout the conduct of this study.

I would like to thank Dr. Francesco Chianucci and Dr. Nicola Puletti for their contribution and valuable assistance to do the measurement, field campaigns and analysis the data. Also, they always encourages me to overcome the problems and provide help in a friendly manner. I would like also to thank Dr. Cristiano Castaldi for his assistance during field measurement. I would like to thanks Emma Minari and Franco Mason for their contribution during field measurement campaign in Bosco Fontana. Also, I would like to acknowledge Dr. Dominik Seidel for his support and help to do an analysis of terrestrial laser scanning data during my abroad period.

The financial support of the Ph.D. program in Forest Ecology and Environmental Technologies (XXXI Cycle) at University of Tuscia, Viterbo and Research Center for Forestry and Wood, Arezzo, Italy for this research are acknowledged.

Finally, I would like to thank all of my teachers, PhD fellows, all SiSFOR lab members, my parents, my husband, my sisters, my brothers, my parent-in-law and friends because all of my achievements are the outcome of their sacrifice.

Dedication

To my parents

To my beloved husband

To all my family members and friends

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Abstract

Mixed forests are particularly interesting for forest structure and diversity analyses, as higher complexity and diversity can be expected in these forests. However, most previous studies on spatial structure and diversity in mixed forests have analyzed tropical and sub-tropical forests, while similar studies on temperate mixed forests are scarce. The repeated spatio-temporal analysis in these forests may provide insight on stand dynamics over time, allowing the subsequent evaluation of its influence on stand and tree diversity and growth. However, because of cost and time constraints, very few studies have performed spatial-temporal analysis of forest stands dynamics. In addition, most studies employed chronosequences rather than true time series (repeated measures on permanent plots), which may introduce some uncertainties in interpreting trends over time.

The recent advances of information and communication technologies (ICT) have provided various instruments, software, and tools to characterize the forest structure and diversity with unprecedented spatial and temporal resolution. Among these technologies, terrestrial laser scanning is a particularly interesting due to its ability to characterizing the 3D structure and spatial distribution of vegetation with the highest detail. However, there are still challenging to integrate tools and techniques, access data from open source, evaluate the cost-effectiveness of the technologies and their accuracy into a precision forestry framework.

The objectives of the thesis are three-fold. First, a review of existing precision forestry technologies is provided, with a particular focus on the existing applications, instruments, software and tools available to assess forest structure and diversity. In a second step, a field campaign was conducted to test the application of precision forestry technologies in real mixed forest structure and diversity analyses. Traditional field inventory and other analytical tools (digital hemispherical photography, terrestrial laser scanning) were employed in three 1 ha mixed hornbeam-oak floodplain forest stands (Core Areas – CA) left to develop naturally. The data have been integrated with historical records available in these stands to compile a spatio-temporal dataset of forest mensuration. In the third step, the study used the dataset compiled to perform an integrated approach to evaluate stand structure, diversity and dynamics of mixed floodplain forests.

Results indicate that trees of all core areas are randomly distributed and clumped as a result of the high number of small trees since 1995. Species abundance varies according to different species composition and soil water availability. The dominant and common species hornbeam and pedunculate oak are decreasing in all core areas over time, as a result of the reduction of regeneration of those species. The understory of CA1 (xeric site) and CA2 (mesic site) were dominated by butcher's broom (53%) while CA3 (moist site) occur by 29%. There was a negative relationship between species richness of overstory and understory layers. The drought tolerance species and total basal area are gradually increasing in CA1 (xeric site) over time due to the increase number of small diameter trees *Corylus avellana* (dbh<10 cm). Functional dispersion of drought tolerance trait found a positive relationship between overstory and understory layers. Non-spatial and functional richness analysis showed that CA3 has high structural diversity and more disperse of species in trait space over time. Moreover, the analysis of diversity indicates that spatial diversity indices did not show strong differences between CAs. On the contrary, functional diversity showed the largest differentiation between CAs. Moreover, the study revealed that stand structural complexity measured using terrestrial laser scanning varied according to the different water availability and tree size differentiation. Finally, it can be concluded that the integration of different approaches is meaningful to gain a deeper understanding of forest structure and diversity.

Keywords: Mixed forest, non-spatial diversity, spatial diversity, functional diversity, stand structural complexity index

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Chapter 1

1 Introduction

1.1 Background

Forest structure is the spatial arrangement of the various components of a forest ecosystem and it is determined by attributes like tree species composition, tree age, size distribution, canopy layering, horizontal and vertical tree distribution pattern (Husch *et al.*, 2003; del Río *et al.*, 2016). Forest structure is a key element in understanding the functionality and resilience of forest ecosystems (Seidl *et al.*, 2014) and a basic element of species diversity (Staudhammer and LeMay, 2001). Forest structural parameters at the macro, meso, and micro-scale are both reliable indicators of ecological diversity, ecosystem resilience and management outcome (Haber, 1982). Mixed forests are particularly interesting for forest structure and diversity analyses, as higher complexity and diversity can be expected in these forests (Pretzsch *et al.*, 2010; 2013). However, most previous studies on spatial structure and diversity in mixed forests have analyzed tropical and sub-tropical forests (Wright, 2002; Wiegand *et al.*, 2007), while similar studies on temperate forests are scarce (e.g. Hui and Pommerening, 2014). The repeated spatio-temporal analysis in these forests may provide insight on stand dynamics over time, allowing the subsequent evaluation of its influence on stand and tree diversity and growth (Pretzsch, 2009). However, because of cost and time constraints, very few studies have performed spatial-temporal analysis of forest stands dynamics (e.g. LeMay *et al.*, 2009). In addition, most studies employed chronosequences rather than true time series (repeated measures on permanent plots), which may introduce some uncertainties in interpreting trends over time.

Analyses of forest structure and diversity have traditionally employed non-spatial measures, due to the simplicity of such an approach (e.g. Neumann and Starlinger, 2001). However, the spatial structure provides a more detailed description of a forest and largely determines the properties of the system as a whole, including total biomass production, biodiversity, habitat functions, and the quality of ecosystem services (Gadow *et al.*, 2012). Many indices and attributes were used to quantify the spatial structure of the forest and detailed review on it describe by Pommerening (2002) and McElhinny *et al.* (2005). In addition, the recent advancement of information and communication technologies (ICT) has provided various precision technologies, software, and tools that measure, record, analysis and actuates multi-source data at high spatial and temporal resolution to enable measuring forest structure and diversity. For this reason, over the last few decades, a large number of studies have been performed to quantify forest structure and related forest functions such as biomass from airborne laser scanning-ALS and terrestrial laser scanning-TLS (Greaves *et al.*, 2015; Nie *et al.*, 2017), stem volume from TLS (Kelbe *et al.*, 2013), canopy height from unmanned aerial vehicles-UAV (Zarco-Tejada *et al.*, 2014). At another level, functional diversity approach allows integrating ecosystem processes and diversity analyses (Mason *et al.*, 2005; Ville´ger *et al.*, 2008; Laliberté and Legendre, 2010). Recently, the functional diversity approach has been included in forestry studies (e.g. Hui and Pommerening, 2014; Chianucci *et al.*, 2016a).

However, these non-spatial, spatial, and functional measures are important, but they don't demonstrate completely the overall forest complexity due to the three-dimensional arrangement of the tree component. Pretzsch (2009) highlighted that the three-dimensional structures of a forest stand are its most important characteristic, none of the previous research explicitly considered the actual spatial arrangement of vegetation objects in a forest. This was due to a lack of methods to describe the overall forest structure (e.g. Seidel *et al.*, 2011). The vertical structure can be characterized by tree size diversity (e.g. Lexerod and Eid, 2006) or through indices determining vertical layering, such as foliage height diversity (MacArthur and MacArthur, 1961, Seidel *et al.*, 2016) or the effective number of layers, (Ehbrecht *et al.*, 2016). The vertical and horizontal pattern may be estimated from indices that are based on single tree measures, such as the structural complexity index (SCI; Zenner and Hibbs, 2000) or the enhanced structural complexity index (ESCI, Beckschäfer *et al.*, 2013).

Other attributes related to canopy structure such as leaf area index (LAI) and canopy openness can be used as a proxy of vertical structure to demonstrate the complexity of forest canopies. LAI varies with species, their composition, stand developmental stage, site conditions, climate or biogeography, seasonality and management practices (Jonckheere *et al.*, 2004; Ellis and Hatton, 2008; Angelini *et al.*, 2015); and may also be affected by drought and other disturbances especially in temperate deciduous forest (Toda *et al.*, 2018).

Since stand structural complexity emerges from variation in tree size, spatial arrangement (both horizontally and vertically), and the structure of the individual trees forming the forest (McElhinny *et al.*, 2005) it seems impossible to address it based on selected measures taken at individual tree attributes, such as diameter or height.

To overcome this simplification, the recently developed stand structural complexity index (SSCI) addresses the structural complexity of a forest in a holistic way based on detailed three-dimensional data on the spatial arrangement of vegetation elements derived from terrestrial laser scanning- TLS (Ehbrecht *et al.*, 2017) under precision forestry framework.

1.2 Problem definition

The structure of forests is the main component of a several developmental processes of the forest. Different attributes can be used to assess forest structure. Monitoring of forest structure and its spatial and temporal changes is one of the prerequisites for biodiversity conservation in forest management. From a cost-benefit and time efficiency perspective, National forest inventory is a major component of sustainable forest management. National forest inventory collected different stand structural attributes which would be a viable option to derive the indicators of biodiversity from existing dataset (Chirici *et al.*, 2012). It also can be used to assess changes of forest structure at temporal and spatial scale for conservation and sustainability at local, national and global level (Kuuluvainen *et al.*, 1996; Gao *et al.*, 2014). In plot level, long-term data set allow insight to get a comprehensive understanding of ecological process and dynamics (Luo *et al.*, 2011). Several studies have used permanent monitoring plot from a single site to provide detailed understanding of forest dynamics over time in response to a given management (O'Hara *et al.*, 2007; Saunders and Wagner, 2008), but collection of these long-term dataset at broad spatial scales are rare that restrict understanding of the natural changes of compositional and structural of forest (Pontius *et al.*, 2016; del Río *et al.*, 2016). Moreover, many studies focused on mixed stand structure and dynamics at large spatial scale and the data use from various research institutions or sources (e.g. Pretzsch *et al.,* 2010; 2013; 2015).

Tree species of mixed forest have a different architectural model of the canopy (Hallé *et al.*, 1978) and canopy structure are crucial indicators of stand dynamic which lead interest to study canopy properties for monitor forest structure. Leaf area index-LAI is a useful variable to quantify forest canopy structure and it has been used as an estimator for various ecological processes for management of forest (Arias *et al.*, 2007; Sprintsin *et al.*, 2011; Richardson *et al.*, 2011; Liu *et al.*, 2015). Several researchers and forest managers have been demonstrating that digital hemispherical photography is one of a most promising tool for estimating LAI (Gonsamo and Pellikka, 2009; Leblanc and Fournier, 2014; Chianucci *et al.*, 2016a). Moreover, Canopy openness has an effect on tree growth (Nakamura *et al.*, 2005). Hemispherical photography is also a good source of gap fraction data which help to calculate canopy openness (Frazer *et al.*, 1997).

However, forest structure is generally simplified by metrics such as leaf area index (LAI), canopy cover, vegetation height (Wilson, 2011) or canopy openness, which hide much of the three-dimensional complexity of vegetation structure which is important characteristics of forest stand (Pretzsch, 2009). Terrestrial laser scanning (TLS) provides data in form of dense, detailed three-dimensional point clouds. Using it to assess the three-dimensional distribution of vegetation holds potential for providing a deeper understanding of forest structures and related forest functions (Li *et al.*, 2014; Kelbe, 2015). For TLS- based forest inventories, two types of data acquisition approaches (single-scan vs. multi-scan) have been reported (Habib *et al.*, 2010; Liang *et al.*, 2016). The single-scan approach has the simplest data acquisition setting and the fastest speed between two approaches (Seidel *et al.*, 2016; Liu *et al.*, 2017). Despite some limitation of single-scan, many studies have focused on the development of methods to derive information on foliage height diversity (Seidel *et al.*, 2016), vertical profile of plant (Calders *et al.*, 2014), wood volume (Astrup *et al.*, 2014), basal area (Seidel and Ammer, 2014) and stem mapping (Liang *et al.*, 2012). But still, studies are needed to estimate additional tree attributes which enlarge the range of single-scan applications and define the future use of TLS. All these factors call for an improved understanding of structure and diversity in mixed forest stands.

1.3 Research objectives

The aim of this research is three phases. Firstly, reviewed the existing precision forestry technologies to indicate what are the most important instruments, software, and tools for forest structure and diversity analysis. In second phase, a field campaign was conducted to test the different traditional and ICT approaches to produce a dataset for forest structure diversity analyses in a real mixed forest. For the purpose, traditional field inventory and other analytical tools (digital hemispherical photography, terrestrial laser scanning) were employed in three 1 ha permanent plots (Core Areas – CAs) at mixed hornbeam-oak floodplain forest which was left to develop naturally. All standing trees were mapped from historical inventory data (1995, 2005) and newly collected inventory data (2016). Also, the new inventoried data have been integrated with historical records available in these plots to provide a spatio-temporal dataset of forest mensuration. In the third phase, perform studies using the dataset produced to evaluate stand structure, diversity and dynamics in mixed floodplain forests have been done.

The specific objectives of the research were:

- To perform a literature review to identify the geospatial-information tools for forest structure and diversity analysis under precision forestry framework.

- To produce an open-access dataset for analysis of forest structure and diversity in a semi-natural mixed floodplain forest from three (1995, 2005, 2016) spatially-explicit tree inventories data.

- To create spatial distribution maps of standing tree species in three core area (CA1, CA2, CA3) at Bosco Fontana from available inventories data.

- To investigate the spatio-temporal changes in structure and diversity at Bosco Fontana over time by calculating stand structural parameters and diversity including non-spatial, spatial and functional diversity attributes of three stands since 1995.

- To integrate multiscale analysis (field inventory data, digital hemispherical photography and terrestrial laser scanning) to address the drivers of stand structural complexity in Bosco Fontana.

Chapter 2

2 Literature review on precision forestry technologies and application

2.1 Concept of precision forestry

The concept of precision has emerged in farming since the 1990s. Precision forestry has rapidly gained ground in various application like forest inventory, management, engineering, and operations community applications (IUFRO, 2015), especially in Europe and North America. In spite of its wider potential domain of application, it is remarkable that the term "precision forestry" has received less consideration than the more comprehensive precision agriculture terminology (Corona *et al.*, 2017). The precision forestry discipline exploits information technology and analytical tools to support economic, environmental and sustainable decisions (Gallo and Mazzetto, 2013; Gallo *et al.*, 2013). The use of such technology enables highly repeatable measurements, actions, and processes to manage and forest stands (Dyck, 2003). Moreover, the demand for high-quality geospatial information about forests supporting technologies to converge with the field of applications to provide the measurements, storage, analysis, and decision-making needs of the forest sector.

Notwithstanding cultural and technological advances, there are currently some difficulties in introducing precision technologies in forestry. In relatively few cases forestry applications have driven research efforts related to precision technologies (Schmoldt and Thomson, 2003). More often, once precision technologies have been developed and made available, they often find ready application to the research of environmental and ecological systems. However, many Precision Forestry applications are still at an initial stage of implementation. At another level, the push in technology use in the forestry sector often contrasts with its slow adoption from the end-users community, which is often poorly informed about how technology potential can improve and optimize their work.

2.2 Definition of precision forestry

As outlined in the 'First international conference on Precision Forestry' in Seattle, USA (Sarre, 2014), there are several definitions of Precision Forestry for instance: "*Precision Forestry uses high technology sensing and analytical tools to support site-specific, economic, environmental, and sustainable decision-making for the forestry sector supporting the forestry value chain from bare land to the customer buying a sheet of paper or board*" (IUFRO, 2014; IUFRO, 2015). Taylor *et al.* (2002) proposed to define Precision Forestry as "*planning and conducting site-specific forest management activities and operations to improve wood product quality and utilization, reduce waste, and increase profits, and maintain the quality of the environment"*.

However, the term precision should be understood as a new priority focus of land cultivation, including forestry, where the central concern is to deal with the environment, its variability and heterogeneity (Auernhammer, 2001). In this view, Precision Forestry can be regarded as an "*environment friendly system solution that optimizes product quality and quantity while minimizing cost, human impact and intervention, and the variation caused by unpredictable nature"* (Joint Research Centre of the European Commission, 2014).

2.3 Precision forestry applications

Measurements of forest variables are taken at spatial scales from millimeters range (e.g. nitrogen fixation in the soil) to the kilometer range (e.g. stand volume) up to global scale. In this section, the study focuses the analysis on geospatial-information tools and techniques for forest data collection under precision forestry framework, which can be subdivided into three activity fields:

i) Remote sensing technologies
ii) Field survey technologies
iii) Decision Support Systems

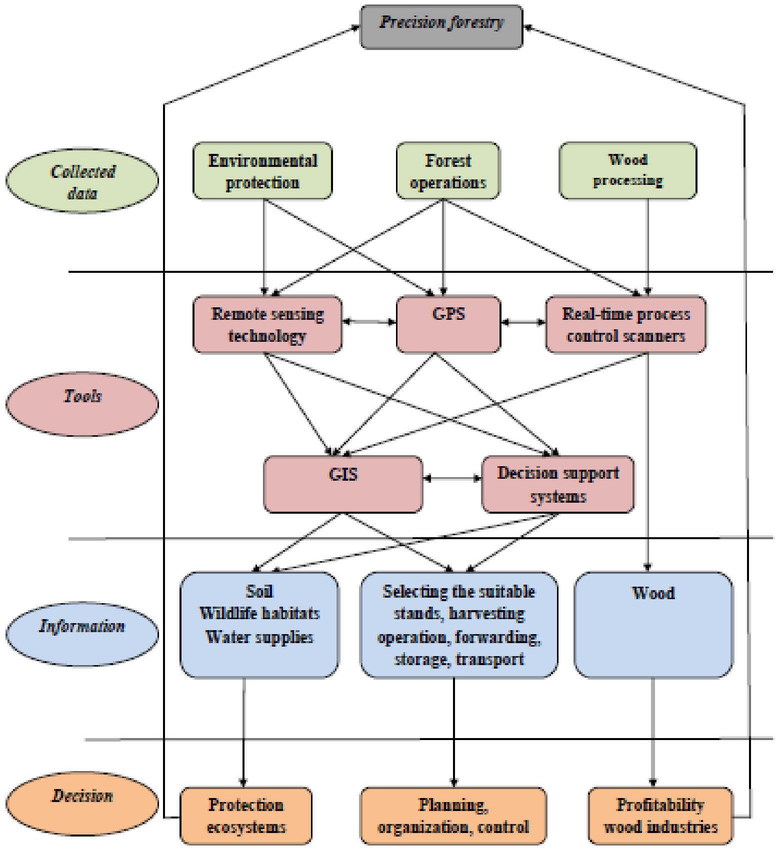


Figure 1- Diagram of precision forestry (modified from Kovácsová, 2016).

2.3.1 Remote sensing technologies

Airborne and satellite data provides a unique way for mapping forest attributes on wide areas, from regional to global scale. For this reason, remote sensing products have long been widely used for many forestry application including forest inventory (Corona *et al.*, 2012), biodiversity assessment and monitoring, global change (Trumbore *et al.*, 2015), as well as to support decision-making sustainable forest management (Franklin, 2001). Traditionally used remotely sensed products include satellite and/or air-borne passive (multispectral, hyperspectral) and active (radio detection and ranging- RADAR, light detection and ranging- LIDAR) sensors. More recent advancements are bringing unmanned aerial vehicles (UAV) as a promising platform for the high-resolution application (Tang and Shao, 2015).

The literature trends showed a constant increase of remote sensing application in forestry over the last few decades. Such a trend is mainly supported by the increased availability of airborne hyperspectral and particularly for the forestry sector LIDAR data. Both data sources have been frequently applied in forest inventory and forest tree species classification (for a review, see Fassnacht *et al.*, 2016). The significant progress that has been achieved in remote sensing of forests in recent years is related to the seven linked drivers: i) technological sophistication in sensor design and deployment; ii) growth in data processing techniques and user-driven tools for image analysis; iii) increasing computational capabilities; iv) development of open source code; v) remote sensing imager archives opened free of charge on-line; vi) increased understanding of how and why remotely sensed information are important in forestry for information synthesis (Wulder and Franklin, 2012) and vii) continuing advance of IMU sensors, particularly low-cost MEMS solutions, which are becoming the primary georeferencing components. In addition, new platforms such as unmanned aerial vehicles are opening an unprecedented opportunity for scale-appropriate measurements of ecological phenomena (Anderson and Gaston, 2013), with large potential in precision forestry applications (Tang and Shao, 2015).

In the next section, the study focuses mainly on the most consolidated and promising technologies in precision forestry, related to multispectral/hyperspectral satellite sensors, airborne laser scanning, synthetic aperture RADAR, and unmanned aerial vehicles (UAV).

2.3.1.1 Multispectral and Hyperspectral satellite sensors

Spaceborne sensors have been around for more than 40 years. On the basis of the number of bands and their spectral resolution satellite optical sensors can be divided into multispectral and hyperspectral (also called imaging spectroscopy) systems. Both multispectral and hyperspectral sensors have been widely used in forestry application including forest inventory (Corona *et al.*, 2012; Babcock *et al.*, 2016; Ferreira *et al.*, 2016) and tree species classification (Ke *et al.*, 2010; Dalponte *et al.*, 2012; Fassnacht *et al.*, 2016). The advantage of hyperspectral sensors is the use of narrow-band vegetation indices from it allows a variety of ecophysiological processes (e.g. photosynthesis, light use efficiency, chlorophyll content) to be monitored (Marshall *et al.*, 2016; Zarco-Tejada *et al.*, 2016) than is possible with multispectral sensors. The recent launch of Sentinel-2 (not a hyperspectral sensor) mission from the European Science Agency is specifically designed for vegetation sensing, due to a combination of fine-tuned spectral capabilities (e.g., three narrow-bands in red edge wavelength), high spatial resolution (10 m), wide swath and quick turnaround (up to 5 days).

2.3.1.2 Airborne Laser Scanning

Airborne Laser Scanning (ALS) are commonly used as light detection and ranging (LIDAR) has significant advantages over optical passive remote sensing because it is capable of collecting highly detailed 3D data quickly from a large area with varying conditions at repeated time intervals. Recent advancements in this technology in forestry is allows very dense point clouds to be generated at decreasing costs, becoming operational in many regional and national forest inventories (Næsset, 2007; Wulder *et al.*, 2012). Currently, ALS represents one of the most promising and effective technology for a wide range of forestry applications, above ground biomass estimation (Laurin *et al.*, 2016; Nie *et al.*, 2017), bole biomass (Figueiredo *et al.*, 2016), stemming from inventorying (Corona *et al.*, 2012), automatic forest area delineation (Alivernini *et al.*, 2016), to supply chain network (Heinimann and Breschan, 2012). However, the standardization of the point cloud processing, the comparability between different products generated by different resolution ALS data, and the influence of LIDAR accuracy's on topography, land cover categories, canopy density, represent still critical issues to operational use of ALS data (Scrinzi and Clementel, 2014).

2.3.1.3 Synthetic Aperture RADAR

Synthetic Aperture RADAR (SAR) is an active remote sensing technology which demonstrated relationships with biomass, and the all-weather data collection capacity (Tsui *et al.*, 2013). According to Wulder *et al.* (2012), it provides complimentary sets of information for estimating forest biomass. Interferometric SAR is height sensitive, and multiple baseline DEM generation has the potential to resolve phase ambiguities in an area with high vegetation and to solve the problems from foreshortening and layover. In addition, SAR tomography has the potential to resolve image distortion due to layover and foreshortening (Krieger *et al.*, 2010). Spaceborne radar systems have seen major advancement recently and provided progressively informative data worldwide. In general, the application of RADAR technology has been less frequent in forestry than LIDAR and optical remote sensing. However, the recent Sentinel-1 radar system can represent a potential mission to support improvements in the remote sensing of vegetation via SAR sensors.

2.3.1.4 Unmanned aerial vehicles (UAV)

Unmanned aerial vehicles (also referred to drones) systems have emerged over the past few years as remote sensing platforms. The benefits of UAV include low material and operational costs, flexible control of spatial and temporal resolution, high-intensity data collection, and the absence of risk to crews. The current forestry applications of drone remote sensing are still at an experimental stage, but they are expected to expand very rapidly (Tang and Shao, 2015). Recent forest application tested drone remote sensing to measure forest canopy height (Lisein *et al.*, 2013; Tulldahl and Larsson, 2014; Wallace *et al.*, 2014; Zarco-Tejada *et al.*, 2014), mapping canopy gap (Getzin *et al.*, 2012), canopy cover (Chianucci *et al.*, 2016b), forest growing stock volume (Giannetti *et al.*, 2018a), to detect fallen trees (Inoue *et al.*, 2014) or pest infestation (Lehmann *et al.*, 2015) and tracking forest wildfires (Hinkley and Zajkowski, 2011). The sensors currently used on remote sensing UAV are predominantly optical cameras, as they are widely available in lightweight and inexpensive versions. Currently, the main challenge in UAV technology is related to the development of sensor technologies, particularly regarding the radiometric and geometric resolution of payload cameras.

2.3.2 Field survey technologies

Field survey technologies can support forest management and planning by reducing the time and cost of ground sampling. Among the available techniques, the most promising and effective are related to terrestrial laser scanning and Field Map, which are described in detail in the following sections. Other instruments are also briefly considered.

2.3.2.1 Terrestrial laser scanning system (TLS)

TLS has been demonstrated to be a promising mobile-system tool for plot-level advanced field inventories (Liang *et al.*, 2011; Seidel *et al.*, 2011). The main advantages of using TLS to support forest planning and management lie in its capability to document the forest details automatically and at very fine (millimeter) spatial scales. In the last few years, TLS has been widely used in different forestry applications, such as tree mapping (Pueschel *et al.*, 2013; Giannetti *et al.*, 2018b), callipering (Srinivasan *et al.*, 2015), tree height estimation (Olofsson *et al.*, 2014; Srinivasan *et al.*, 2015; Giannetti *et al.*, 2018b) and forest biomass calculation (Yao *et al.*, 2011; Seidel *et al.*, 2012; Srinivasan *et al.*, 2014; Greaves *et al.*, 2015), estimation of canopy structural parameters (Huang and Pretzsch, 2010; Béland *et al.*, 2011; Van der Zande *et al.*, 2011; Moorthy *et al.*, 2011; Seidel *et al.*, 2012; Zhao *et al.*, 2012; Zheng *et al.*, 2013; Bayer *et al.*, 2013; Hopkinson *et al.*, 2013; van Leeuwen *et al.*, 2013; Cifuentes *et al.*, 2014; Giannetti *et al.*, 2018b). Notwithstanding these improvements, the current main limitation of TLS is the cost of the instrument and the complexity of data processing which requires well-trained operators. In addition, TLS data accuracy is still heavily dependent on operator, resolution scan and instrument accuracy, all factors that affect the replicability of TLS products depending on the acquisition setup (point cloud density, scan-time, the field of view), stand structure (canopy cover, tree density, phenological period). Another major problem when using TLS in the forest environment is occlusions caused by lower branches, surrounding trees, and understory. This phenomenon leads to lower point density and, therefore, to poor descriptions in the upper part of crowns and partially or totally hidden trees (Van Der Zande *et al.*, 2006).

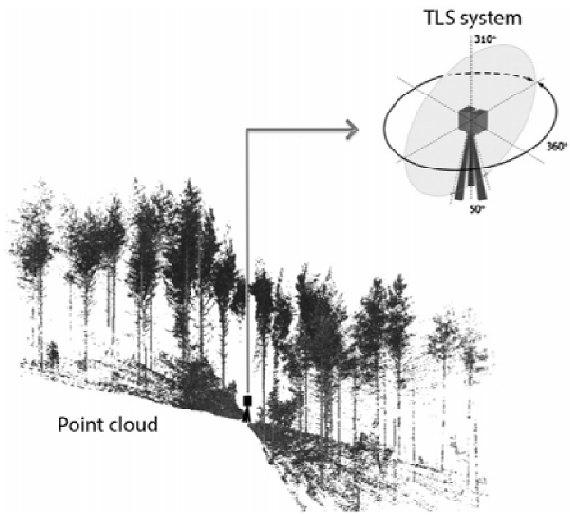


Figure 2- The scanning mechanism of the TLS scanner and point cloud data (Source: Liang *et al.*, 2016)

2.3.2.2 Global Navigation Satellite System (GNSS)

Historically, except for space platforms, such as the International Space Station, GPS is the core component of any georeferencing system, providing highly accurate absolute positioning in open areas worldwide (Toth and Jóźków, 2016). The GPS/GIS on the GNSS is effective in data collection for predicting important attributes of forest plots including mean tree height, mean diameter at breast height, basal area, stem volume and tree biomass (Liu *et al.*, 2016) and detailed object location in thematic mapping which increase the accuracy and availability of GNSS technology in forest. The application of GNSS on harvesting operations has already permitted to evaluate the efficiency of the forest operations (Gallo *et al.*, 2013). But the signal shading from the foliage is one of the main problems of GNSS.

2.3.2.3 FieldMap

Field map is a very useful tool for forest inventorying, which computes field data collected during fieldworks (Figure 3). FieldMap is used for forest mapping and field measurements (tree height, crown projection, and profile, stem profile, estimation of timber volume), assessment of biomass and growth (Kovácsová and Antalová, 2010). The disadvantage of the tool is that it is quite expensive and time-consuming, which may limit its application in practical forest inventory.

Figure 3- FieldMap data collector (Source: http://www.fieldmap.cz/)

2.3.2.4 Other field instruments

Other commonly employed advanced field instruments in forestry include SilvaScan, and ultrasound decays detectors (UDD), which are used to carry out *in situ* wood quality measurements like density, stiffness (modulus of elasticity), microfibril angle, dimensional stability, and so on (Figure 4). These wood quality measurements can be incorporated into operational inventories to allow the improved characterization of the resources that will allow for raw material be allocated to the most appropriate manufacturing plant (Ritland *et al.*, 2011)

(Figure 5). With continuous advancements and refinements, this technology could assist in managing wood quality, assessing forest value, and improving the timber quality of future plantations (Wang, 2012). Another ground instrument employed in precision forestry includes Ground Penetrating Radar (GPR), which can be used for estimating soil moisture, root architecture, and wood properties (Ferrara *et al.*, 2013).

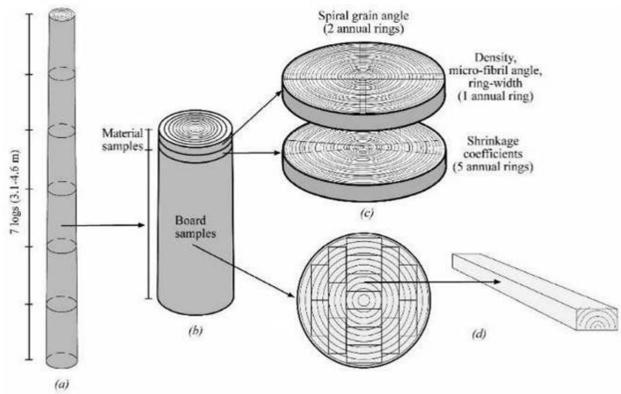


Figure 4- Wood density and microfibril angle measure from wood disc by SilvaScan (Source: Ormarsson and Cown, 2005)

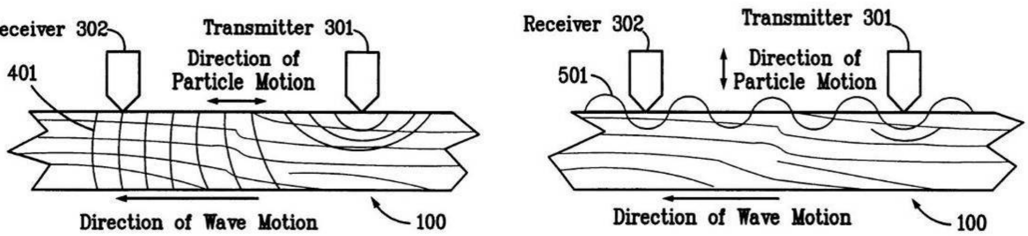


Figure 5- Schematic diagram of the ultrasonic propagation time tests on the thick wood (Source: https://www.google.si/patents/US6276209).

2.3.3 Decision Support System

Decision Support Systems refer to an approach that integrates decision maker's own insights with computer's information processing capabilities for improving the quality of decision making. Decision support systems for forest management (FMDSS) have been developed world-wide to account for a broad range of forest ecosystems, management goals, and organizational frameworks. The decision support role of a geographic information system is particularly notable. Geographic information systems (GIS) assist in the evaluation of a greater number of alternatives. Examples include the INVEST model for assessing ecosystem services (Tallis *et al.*, 2013), which has been developed in North America and it has been also adopted in Europe (e.g. Bottalico *et al.*, 2016). Other application includes planning of forest road (Karlsson *et al.*, 2007), transportation planning (Forsberg *et al.*, 2013), selecting timber harvesting system (Kühmaier and Stampfer, 2010) participatory planning (Pastorella *et al.*, 2016) and harvesting plan (Scrinzi and Clementel, 2014). The main current challenge is that there is an increasing number of DSS, which significantly vary in scope and underlined approaches, and which not often allow determining what DSS is more suited to the applied forest reality.

2.4 General challenges and recommendations

Introducing precision tools and technologies into forest management and planning is still challenging. General needs and issues are outlined here below:

2.4.1 Tools integration

Remote sensing, computing science, and information technologies are greatly affected by universal development trends (Toth and Jóźków, 2016), which are mainly driven by the fast pace of technological advances in material sciences, optical physics, nanotechnologies, and so on. Consequently, algorithmic research and software are generally lagging behind the potential offered by emerging hardware. Hence, there is an increasing need for integrating the existing tools, techniques, and sensors in a way that allow the coupling of all the different information available in a multi-scale and multi-source system.

2.4.2 Open access data

Appropriate access to data and software has both technical and intellectual components. The real question is more about to accessing the sensory data, which directly connects to communication and the general IT infrastructure. In 2012, about 2.5 quintillions bytes of data were acquired worldwide per day (IBM, 2012). Exploiting the potential of crowd sensing data leads to new methods, including Data Analytics and Big Data (Najafabadi *et al.*, 2015). Accessibility is also challenging if results are presented inappropriately. For example, data may be aggregated at a fixed scale that may have limited value for many users. In other cases, language and concepts beyond the end user's understanding or vernacular might render a decision support system useless for a large audience segment. The continuous, transparent, and "user-friendly" information access makes interoperability a required attribute of databases, systems, and vocabularies. Because end-users of data are not necessarily local or regional and because large-scale forest assessments are becoming more important, standards and protocols for forest data are looming on the horizon.

2.4.3 Cost-effectiveness

Despite the potential, Precision Forestry tools have only just begun to be used in forestry communities (especially in the research environment) and are still not considered as standard tools. The main reason lies in the cost of instruments and peripherals (reference targets, software suites, graphic workstations). However, the price of devices has decreased by half during few last years. This trend should continue for some time. When prices become acceptable for foresters, Precision Forestry instruments should become essential tools to provide extensive information about forests with a smaller investment in time and labor than current operations.

Chapter 3

3 Materials and Methods

3.1 Study area

The study was conducted in the National Natural Reserve of “Bosco della Fontana”, which is a semi-natural mixed floodplain forest belonging to the Sub-Atlantic and medio-European oak or oak-hornbeam forests of the *Carpinion betuli* (code 9160, Habitats Directive – 1992/43/CEE), European Forest Type 5.1 (pedunculate oak–hornbeam forests; Barbati *et al.*, 2014) and located in Northern Italy (Marmirolo, province of Mantua, Region Lombardy, Figure 6). The Reserve is one of the best-preserved (233ha) floodplain broadleaf forest in Italy (Tini *et al.*, 2017), with a continuous cover of woodland since at least 1600 A.D. (Mason *et al.*, 2002). The central point of the forest area used for our study was located at 45°12′ N, 10°44′ E on flat terrain. The climate of the site can be described as continental with cold winters and hot summers (Longo, 2006). The mean annual air temperature and mean annual rainfall are 13.2° C and 658 mm, respectively. There is a dry period in July when the precipitation minimum corresponds with the maximum in air temperature (Mason, 2004; Travaglini *et al.*, 2007; Capano and Pignatelli, 2007). Around 85% of the reserve is covered by semi-natural broadleaf forests (Tini *et al.*, 2017). Silvicultural practices were officially ceased in 1994 (Mason, 2004). This forest has a heterogeneous structure due to the absence of human impact for a quarter of a century. The forest is characterized by dense growing pattern, great tree species diversity, coexistence of multiple tree species from the same family (i.e *Quercus cerris* and *Quercus robur, or Fraxinus ornus* and *Fraxinus angustifolia*), and no systematic pattern in the spatial distribution of tree individuals of the different species (Dalponte *et al.*, 2009).

Figure 6- Study area -Natural Reserve of Bosco Fontana in Italy (Source: Castaldi *et al.,* 2017)

Since 2007, the State Reserve was part of the Italian Long-Term Ecological Research Network (LTER-Italy). Six permanent plots have been established in previous studies. The sampling protocol was based on the SILVI-STAR nested protocol by Koop (1989) as illustrated in Figure 7. All the Reserve forest area was divided into forest type areas (FTA), each containing a stand with homogeneous structure and composition. In particular, three core areas (CA) each 70x140 m (~1 ha) in size were established to monitor vegetation structure and dynamics in these forests since 90s. Within each CA, a 100x10 m woody transect area (WTA) was established for analysis of shrub, short vegetation. Finally, an Herbaceous transect area (HTA) was established at the centre of the WTA and consists of 50 2x2 m plots where understory survey was conducted (considering plants below 0.4 m as understory vegetation). Mason (2004) categorized these three core areas (CA1, CA2, CA3) and additional three WTA (WTA4, WTA5, WTA6) based on soil moisture measurement, which represents homogeneous forest type areas: CA- xeric, mesic, and moist, WTA- xeric, mesic and mesic regime variants of the *Carpinion betuli*, respectively. Periodic inventories were conducted in the CAs, with the last field inventory performed in 2016.

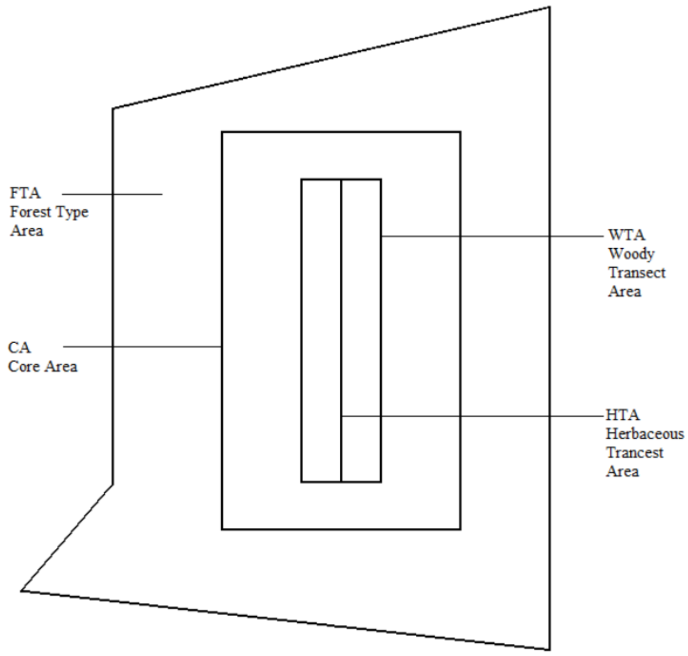


Figure 7- Layout of the sampling plot

3.2 Stand Composition

The dominating tree species were *Carpinus betulus, Quercus robur and Q. cerris* with a minor presence of *Prunus avium, Acer campestre, Ulmus minor* in the xeric and mesic area. *Q. robur* and *Q. cerris* prevailed in the overstory with an average height of 30 m. Tree species composition was shown to be different in the moist site were *Fraxinus angustifolia* and *Alnus glutinosa* were the prevalent species (Mason, 2004; Travaglini *et al.*, 2007; Gerosa *et al.*, 2017).

In all three areas, *Corylus avellana, Cornus mas, Sambuscus nigra, Sorbus torminalis* and *Crataegus monogyna*, *Malus sylvestris* were part of the dominant tree layer, with a dense layer of shrub-*Ruscus aculeatus*. Alien species were also present such as *Robinia pseudoacacia* and *Platanus hispanica* (Dalponte *et al.*, 2007; Gerosa *et al.*, 2017). There is a exception in WTA5, where the species (e.g. *Quercus robur* Linneo) was established after Second World War, which is currently eliminated and preserve of dead woods in all its form (Cavalli and Mason; 2003, Zapponi *et al.*, 2014; Campaanaro, 2014).

Chapter 4

4 Spatio-temporal dataset of forest mensuration for the analysis of tree structure and diversity

4.1 Methods

Each CA was divided into 10x10 m sub-plots (Figure 8), in which all standing trees (individuals with a stem diameter at 1.30 m ≥ 5 cm classified as overstory) were labelled, their species identified, and their position mapped using a total station (an electronic distance measurement instrument for coordinate calculation), and georeferenced in a relative X, Y coordinate system (Figure 8). For each standing tree, the following parameters were recorded: species, diameter at breast height (1.30 m), total height and vitality (alive tree/dead tree). Standing tree measurements were carried out in three inventories made in winter 1995, 2005 and 2016 and included in the dataset. A total of 20 different standing tree species were identified in these three CAs and total of 5015 trees had included in the dataset.

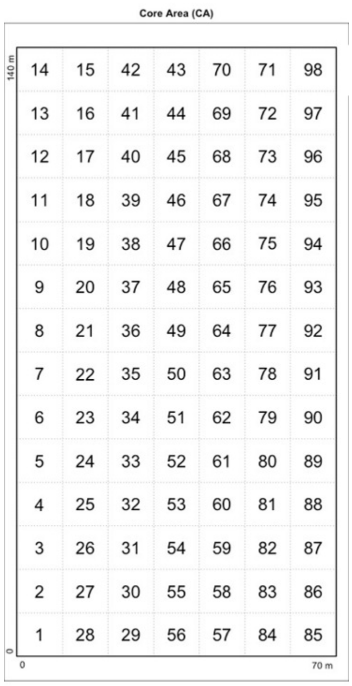


Figure 8- Characteristics of the surveyed permanent plots (Core Areas - CAs). The number indicates the 10x10 sub-plots squares. (Labelled as “Square_no” field in the dataset).

4.2 Results

4.2.1 Open access dataset and metadata description

The dataset (“dataset_Bosco_Fontana.csv”) is available using the following reference and doi: Fardusi MJ, Castaldi C, Chianucci F, Corona P, Minari E, Mason F, Puletti N (2017), A spatio-temporal dataset of forest mensuration for the analysis of tree species structure and diversity in semi-natural mixed floodplain forests, V2, Mendeley data [dataset] http://dx.doi.org/10.17632/n8827ssnv7.2 under the Creative Commons Attribution-Non Commercial 4.0 License. Table 1 lists the variables contained in the dataset. For each variable, a data dictionary in text format is also provided as supplementary material, which comprises a complete list of the tables in the dataset, the data format and the description of each variable.

Metadata to the whole dataset (“metadata.xlsx”) are given to the following link: [http://dx.doi.org/10.17632/n8827ssnv7.2]. The metadata includes several tables, including (1) a documentation on data provision and discovery; (2) information on the origin and context of the dataset; (3) a technical documentation of the meaning of all variable names; (4) the key code tables for the list variables (see Table 1).

Table 1: Variables reported in the dataset.

Variable Name	Variable Definition	Units	Data Type	Range	List variable
CA	Core Area Number		Text	1 – 3	Yes
Square_no	Number of 10x10 sub-plot square		Integer number	1 – 98	
Treeid	Reference tree identification number		Integer number	1 – 929	
Inv_year	Inventory Year		Integer number	1 – 3	Yes
Id_old	Tree identification number used during field measurements (may include letters in case of stools)		Text		
VIT	Vitality condition of tree		Integer number	1 – 2	Yes
SP	Species abbreviation code		Text		Yes
BX	x-coordinates of tree	m	Float number	0 – 70	
BY	y-coordinates of tree	m	Float number	0 – 140	
TH	Tree height	m	Float number	1.3 – 36.9	
DBH	Tree diameter measured at 1.3 m (breast height)	cm	Float number	5.0 – 96.5	

4.2.2 Data Validation

Data cleansing have been performed to check for data quality. Data inconsistency that may have been originating by errors in user entry (e.g. typographical errors), data type storage, and field measurements have been checked by two independent expert users. Example of analysis of data quality included data type constraints (e.g., values in a field must meet the desired data type), range constraints (minimum and maximum values allowed for numerical variables), numeric constraints (e.g., the diameter must not decrease through time), unique constraints (e.g. the same trees must have the same species code in the different inventories).

4.3 Discussion

4.3.1 Potentiality of dataset

The spatio-temporal resolution of data allows a various set of forest-related indices, useful to describe ecological dynamics (Neumann and Starlinger, 2001). In addition, sampling design allows integration of this dataset with other ones available from previous studies (e.g. Aguirre *et al.*, 2003; Hui and Pommerening, 2014; LeMay *et al.*, 2009), useful for comparative, large-scale studies.

The data allowed a traditional set of forest parameters to be extracted like stand variables (stocking rate, basal area, species composition, dominant height, mean diameter). Volumes could be easily calculated with 'ForIT' package of R (Puletti *et al.*, 2017), which implements all volume equations used for the last Italian National Forest Inventory.
A wide range of diversity measures can be computed from the dataset, including traditional, non-spatial measures (species richness, Shannon Index, Simpson Index) and spatial-measures; the latter includes single tree neighboring indices, distance-dependent stand indices and continuous functions (for details, see Pommerening, 2002). The dataset format (comma separated value file, easily convertible in a text file format) allows calculation of such indices from the CRANCOD program developed by Arne Pommerening

(http://www.pommerening.org/wiki/index.php?title=CRANCOD_A_Program_for_the_Analysis_and_Reconstruction_of_Spatial_Forest_Structure) or using a statistical program such as R enviroment, using for example the 'spatstat' package (Baddeley *et al.*, 2015).

Data on species composition can also be used as community-weighted-means information to compute functional diversity indices. The dataset format allows computation of functional diversity indices using the ‘FD’ package of R (Laliberté and Legendre, 2010) integrating species abundances with functional traits available from literature or using the ‘TR8’ package of R (Bocci 2015). An example of such approach is described in Chianucci *et al.*, (2016a).

4.4 Conclusion

The strength of the dataset is that it allows performing an integrated set of tree structure and diversity analyses at both spatial and temporal scales. To date, no comparable spatio-temporal measurements were provided for mixed broadleaved forests. This information may strength the knowledge of structure, diversity and species interactions naturally occurring in mixed broadleaved forests. Moreover, the study predicts that periodically replicate tree inventory measurements will make at 10-years interval. So, next research can include new measurements once they will be made available in future field campaigns.

Chapter 5

5 Investigation of spatio-temporal pattern in a mixed forest

5.1 Methods

The produced dataset as shown in Chapter 4 have been used to get a suite of stand overstory structure and diversity attributes. The understory survey was only conducted during periods of peak vegetation cover (July-August) in both surveys (1995 and 2005) at six plots whereas this survey has not been performed in 2016. Each vascular plant was identified at the species level and its cover-abundance estimated using the Braun-Blanquet scale, which was converted to percentage cover values.

5.1.1 Tree distribution maps

Since 1995, all standing tree stems were mapped for each core area based on the X and Y coordinates of each standing tree located in the core area and its corresponding diameter. The maps were produced using the spatstat library (Baddeley and Turner, 2005) in R. Each map was saved as tiff-file with a fixed 679 by 346 pixels and resolution with the white background color.

5.1.2 Analytical approach

5.1.2.1 Stand structure characterization

The following overstory structural variables in core areas, including tree species abundance, tree density per plot (N, number of standing stems per hectare), basal area (BA, basal area of the standing trees per hectare), mean DBH (d), mean height (H) and percentage of small trees (dbh< 10 cm) were determined on the inventories data to assess the change of stand structure and composition with time. D and BA were calculated by tree numbers and diameter at breast height (DBH) in the core areas.

5.1.2.2 Diversity of overstory and understory

The fundamental thought of a diversity index is to get a mathematical measure of variability that can be used to analyze different stands of forest. Diversity index is the value of an attributes for diversity itself. Stand diversity depends on the species richness and evenness. Species richness is determined of the total number of species in the stand. Evenness indicates how evenly the individuals in the stand are distributed over the different species. Many indices have been proposed to measure diversity. In ecology, stand diversity often reflects non-spatial (structural), spatial and functional diversity of stands.

5.1.2.2.1 Non-spatial diversity attributes

For the quantification of non-spatial diversity attributes, the Shannon (*H'*; Shannon and Weaver, 1949; Eq. (1)), Simpson (*D*; Simpson, 1949; Eq. (2)) and Pielou's evenness (*J*, Pielou, 1977; Eq. (3)) indices with basal area abundance rather than individual abundance are most meaningful diversity indices in ecological literature and they were used to measure overstory and understory (H'_U) structural diversity within the plot. The *H'* index value is 0 if only one species is present in the sample. The *D* index values can range between 0- no diversity and 1-infinite diversity. The *J* index value is composed between 0 and 1.

$$H' = -\sum_{i=1}^{n_s} p_i ln\,(p_i) \tag{1}$$

$$D = 1 - \sum_{i=1}^{n_s} p_i^2 \tag{2}$$

$$J = \frac{H'}{\ln\,(n_s)} \tag{3}$$

Where, p_i is the proportion of species *i* by basal area and n_s is the number of species.

Another non-spatial diversity attribute used this study is skewness index which is also important for size diversity (Sterba and Zingg, 2006). The index value are sk < 0 (left-skewed means there is more tall trees and rare small trees in size distribution), sk= 0 (symmetric pattern) and sk> 0 (right-skewed means there is many small trees and a low number of tall trees in size distribution). Skewness of the diameter distribution can be computed by the Bortz (1993) formula:

$$sk = \frac{\sum_{i=1}^{n}(dbh_i - \overline{dbh})}{(n-1) \cdot sd_{dbh}^3} \tag{4}$$

Where, n is the number of individual trees, dbh_i is the stem diameter of *i*th species and $\overline{dbh}$ is the arithmetic mean *dbh*.

Moreover, species richness (*SR*) were measures at both overstory and understory level.

5.1.2.2.2 Spatial diversity attributes

5.1.2.2.2.1 *Mingling index*

Mingling index describes the degree of mixing of tree species in a stand (Von Gadow, 1998). This index has a range from 0 to 1; values close to 0 indicate a low mixture of species, while high values indicate high species diversity. The mingling (M_i) can be calculated as

$$M_i = \frac{1}{n}\sum_{j=1}^{n} \quad v_{ij} \tag{5}$$

Where n= total number of neighbor trees from an i^{th} reference tree. In a constellation involving four neighbours M_i can assume five possible values (0, 0.25, 0.5, 0.75, 1.0); *n*= 4 was considered effective for developing forest structure decisions (Hui *et al*., 2011). The mean mingling was calculated by summing all the M_i values and dividing by the number of stand trees. The species mingling index has been widely used as the nearest neighbor statistic to describe the spatial structure of a forest (Ni *et al*., 2014) and to assess admixture degree in mixed forests (Alberti *et al*., 2014).

5.1.2.2.2.2 *Diameter differentiation index*

Diameter differentiation (T_{ij}) describes the diameter differentiation in neighboring trees. The formula to calculate T_{ij} is (Pommerening, 2002):

$$T_{ij} = 1 - \sum_{i=1}^{n} \frac{\min(DBHi, DBHj)}{\max(DBHi, DBHj)} \quad (6)$$

Where DBH*i*= diameter of the i^{th} reference tree; *DBHj*= diameter of the j^{th} nearest neighbor of the reference tree. The mean diameter differentiation was calculated by summing all the T_{ij} values and dividing by the number of stand trees. This index has a range from 0 (no differentiation) to 1 (highest differentiation).

5.1.2.2.2.3 *Clark and Evan index*

Clark and Evan's index describe the aggregation/clustering in forest stand by a single value. The index showed that $0 \leq R \leq 2.1491$. When $R > 1$ (regular pattern), $R = 1$(random pattern) and $R < 1$ (clustering pattern). The Clark and Evans (1954) aggregation index (*R*) is defined as:

$$R = \frac{\bar{r}_{observed}}{E(r)} \quad where \quad E(r) = \frac{1}{2.\sqrt{\frac{N}{A}}} \quad (7)$$

Where, $\bar{r}_{observed}$ = the observed mean nearest neighbour distance in a stand, $E(r)$= the expected distance for a Poisson forest stand of intensity $\lambda = N/A$ with A= area of the forest stand and *N*= number of trees.

5.1.2.2.3 Functional diversity attributes

The literature has been suggested that functional diversity attributes can improve forecast on the interaction between ecosystem functioning and diversity than taxonomic diversity (Hooper *et al.*, 2005; Mokany *et al.*, 2008; Gagic *et al.*, 2015; Lozanovska *et al.*, 2018); and the use of functional trait and estimation of it to measure the diversity of species functions or niches which link species to ecosystem functioning and it's dynamics (Díaz *et al.*, 2001). This study was used multiple-traits approaches to calculate functional diversity indices (functional richness, divergence, dispersion and community-weighted mean of trait). The traits chosen retained an explicit management implication and were sourced by Niinemets and Villadares (2006) and Chianucci *et al.*, (2016a): i) shade tolerance; ii) drought tolerance; iii) waterlogging tolerance.

5.1.2.2.3.1 *Functional richness (FRic) index*

This index is characterizing the amount of niche space filled by species in the community (Mason *et al.*, 2005). It is based on the complementarity of multiple trait levels non-weighted by abundance (Lozanovska *et al.*, 2018). It measures the species dispersion in trait space. It was computed by calculating the convex hull volume (Cornwell *et al.,* 2006; Layman et al., 2007), where the convex hull volume is the minimum convex hull which includes all species of interest. This study considers that the value of the convex hull volume filled by the community as a multidimensional measure of the functional richness. High FRic indicates that many traits are present within a community (Ville´ger *et al.*, 2008; Laliberté and Legendre, 2010).

5.1.2.2.3.2 *Functional divergence (FDiv) index*

The functional divergence represents how abundance is distributed within the volume of functional trait space occupied by species in multiple traits. It is based on the complementarity of multiple trait levels weighted by abundance (Lozanovska *et al.*, 2018). This index measures the volume of functional trait space occupied and the evenness of abundance distribution with that volume. It was calculated by the formula of Ville´ger *et al.*, (2008):

$$FDiv = \frac{\sum_{i=1}^{s} W_i(dG_i - dG) + dG}{\sum_{i=1}^{s} W_i|dG_i - dG| + dG} \tag{8}$$

Where, dG_i is the functional distance from species i to the gravity center of species that from the vertices of the convex hull, dG is the mean distance of the S species to the center of gravity, and W_i is the relative abundance of species i. *FDiv* is low when abundant species have trait values that are close to the centre of functional trait space, but high when abundant species have extreme trait values (Villéger *et al.*, 2008). This can be seen as a measure of the niche differentiation within a community, such that if *FDiv* is high, then there are high levels of niche differentiation (Prescott *et al.*, 2016).

5.1.2.2.3.3 *Functional dispersion (FDis) index*

Functional dispersion measures the weighted mean distance of individual species to their weighted centroid, where weights are their relative abundances. It is not affected by richness. It has ranged from 0 to 1. It's calculated at both overstory and understory level by the proposed formula of Laliberté and Legendre (2010).

First, the mean distance of each species to the centroid c_i of the x_j species-by-trait matrix is calculated (Eq. 9):

$$c_i = \frac{\sum a_j x_{ij}}{a_j} \quad (9)$$

Where, a_j is the abundance of the species *j* and x_{ij} is the attribute of the species *j* for the trait *i*. The index *FD* is then computed as the weighted mean distance *z* to the weighted centroid (Eq. 10):

$$FDis = \frac{\sum a_j z_j}{a_j} \quad (10)$$

Where, a_i is the abundance of the species *j* and z_j is the Euclidean distance of the species *j* to the centroid of the species-by trait matrix.

Drought tolerance was the functional traits considered in both the overstory functional dispersion (FD_O) and understory functional dispersion (FD_U) analysis in two inventories (1995, 2005). Species' values for the traits were obtained from Niinemets and Valladares (2006). For the overstory layer, species basal area was used a surrogate of abundance in the computation of overstory functional dispersion (FD_O). And the species' cover was used as a surrogate of species abundance to compute understory functional dispersion (FD_U).

5.1.2.2.3.4 Community- weighted mean (*CWM*)

The community-weighted mean trait measures the variation such as plot level and trait values weighted by species abundance. The CWM trait values for each trait (shade tolerance, drought tolerance and waterlogging tolerance) were calculated by the following formula of Lavorel *et al.*, (2008):

$$CWM = \sum_{i=1}^{n} p_i \; x \; trait_i \tag{11}$$

Where n is the species richness, p_i is the relative contribution of species and $trait_i$ is the trait value of species i.

5.1.2.2.4 Statistical analysis

To evaluate the change in the overstory structure among sites, the study compared the composition and the structure of the stands from 1995 to 2016. All non-spatial diversity attributes were estimated by using EXCEL 2007. Spatial diversity analysis was completed by CONCORD program developed by Arne Pommerening. All functional diversity indices were calculated using the FD package (Lalibertè and Legendre, 2010) in R. This study also tested the correlation between overstory and understory attributes and between the different diversity indices using Pearson's coefficients of correlation in R (R Development Core Team, 2017).

5.2 Results

5.2.1 Tree distribution maps

Distribution maps of the standing tree species across three core areas were plotted (Figure 9) since 1995. Three dominant tree species were presented in color and others in white. These maps clearly show that tree distributions are not uniform across the area which suggested that most of the tree species appeared to be randomly dispersed from 1995 to 2016. Closer inspection in Figure 9 indicating: the map of trees in CA1 showed smaller trees appears more than other core areas particularly in 2005. There were no obvious changes in CA2 and all the trees species appeared to be randomly distributed and had fewer smaller trees in three inventories. A very similar trend was visible in CA3. The shift towards larger trees was visible in both CA2 and CA3 over time. Moreover, this study also suggests from visual inspection of the map that the trees with large diameter were always aggregated with other species.

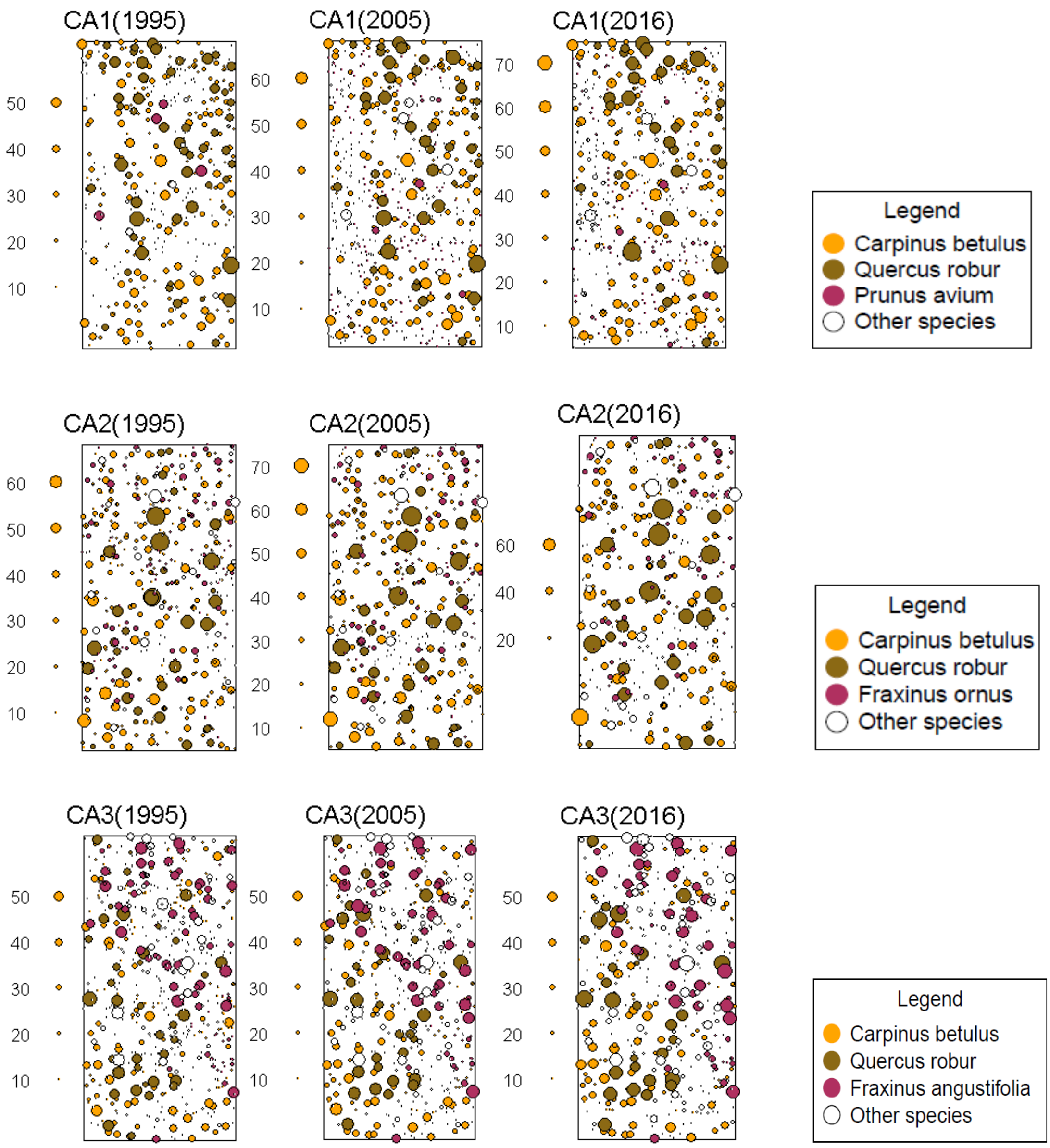


Figure 9- Spatial distribution pattern of three inventoried standing trees in core area CA1 (top), CA2 (middle) and CA3 (bottom) at Bosco Fontana. Circle representing tree location and the size of the circle are scaled by tree diameters.

5.2.2 Stand structure characterization

The study quantified stand structural variables at each core area for 20 years (1995 to 2016) period. The studied forest was a mixed oak-hornbeam forest with other associated tree species. The abundance of standing trees was quite irregular among core areas. The histogram (Figure 10) shows six tree species abundance in core areas at three inventories (1995, 2005 and 2016). Species composition was similar in CA1 and CA2. The abundance indicated that hornbeam (*Carpinus betulus*), pedunculate oak (*Quercus robur*) and european hazel (*Corylus avellana*) are most common and important species out of the six tree species and *C. betulus* have the highest number of species in all core areas. The results finding showed that number of tree species of *C. betulus* and *Q. robur* were decreasing with increasing of time for overstory layers in three core areas although *Q. robur* is numerically irrelevant if compared to the *C. betulus*, but it can influence the total basal area, while *C. avellana* increases through time but noticely in CA1 (see Figure 10). Moreover, tree species number of *Fraxinus ornus* in CA2, *Fraxinus angustifolia* and *Alnus glutinosa* in CA3 were also decreasing over time.

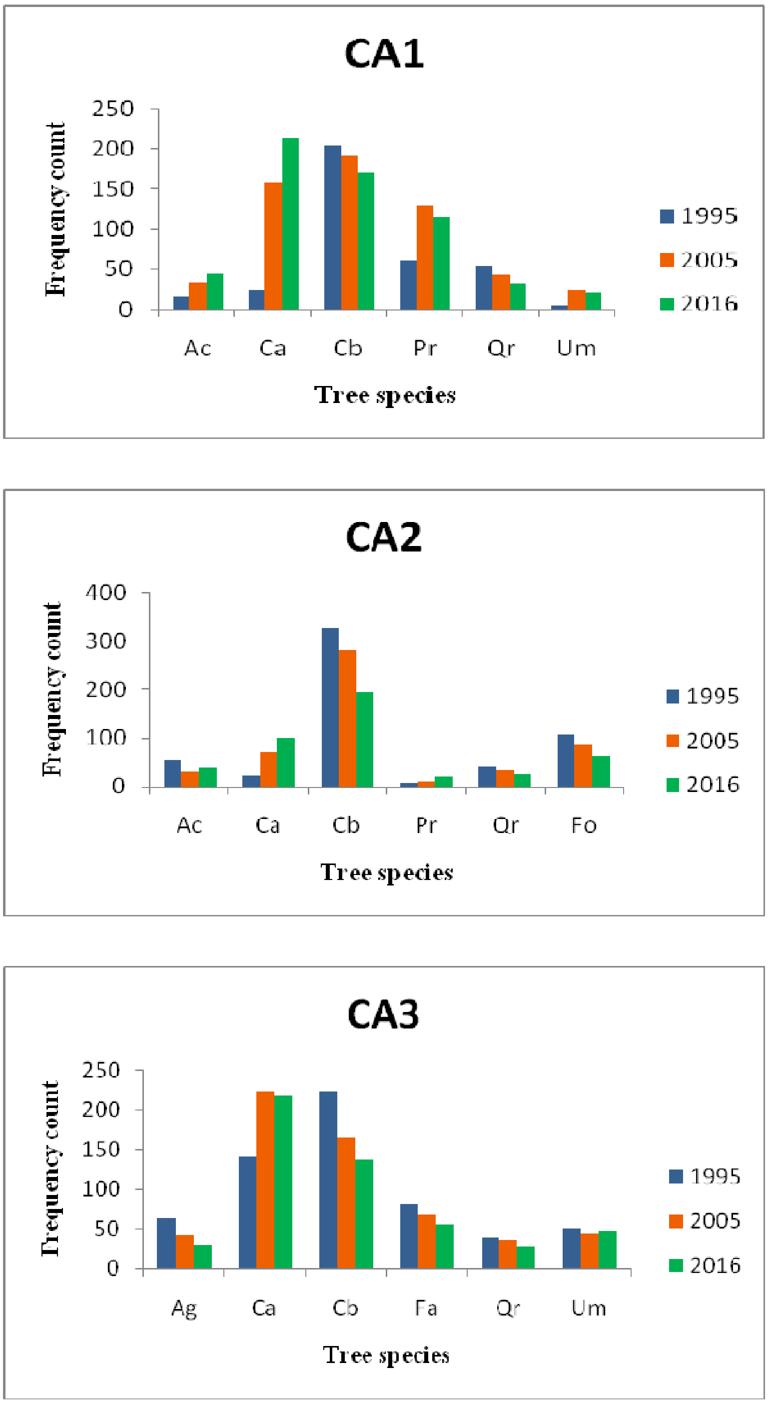


Figure 10- Tree species (Ac- *Acer campestre*, Ag- *Alnus glutinosa* Ca- *Corylus avellana*, Cb- *Carpinus betulus*, Fa- *Fraxinus angustifolia*, Fo- *Fraxinus ornus*, Pr- *Prunus avium*, Qr- *Quercus robur,* Um- *Ulmus minor*) abundance in core areas (CAs) at Bosco Fontana.

Considering overall scenarios in mixed forest other stand structural variables were recorded in Table 2. The total number of tree species recorded from 1995 to 2016 and the tree density in both CA2 (mesic site) and CA3 (moist site) were reduced only 20% observed through increasing time, while CA1 (xeric site) showed different pattern over time due to the high percentage of small trees (dbh< 10cm) in that area (see Table 2). On the contrary, stand basal area were increased by 20% of the values in CA1 since 1995 because the total basal area of this stand is determined by half of the new small tree population, whereas the CA2 and CA3 released various pattern in the total basal area of the stand at the different time of inventories. However, when this study consider tree diameter and height, the finding showed that more than half of the tree species diameter and average height of trees were increasing by 17% in CA3 with time due to the highest level of soil water availability, while this contribution varied among inventories in CA1 and CA2 due to the limited soil water availability.

Table 2: Tree density (Density), total basal area (BA), mean diameter, mean height and percentage of small trees (Small trees %) per ha in the study area over time.

Core area	**Year**	**Density (N/plot)**	**BA (m^2/plot)**	**Mean diameter (cm)**	**Mean height (m)**	**Small trees % (dbh<10 cm)**
CA1	1995	367	19.97	26	15.1	34
	2005	586	23.9	23	14.5	51
	2016	533	23.97	24	15.1	44
CA2	1995	507	23.99	25	17.2	20
	2005	415	25.83	28	18.7	23
	2016	401	22.86	27	17.1	35
CA3	1995	612	24.93	23	13.9	43
	2005	541	29.07	26	16.0	36
	2016	487	28.51	27	16.3	38

5.2.3 Stand diversity

This study was calculated non-spatial, spatial and functional diversity attributes of mapped standing trees for each core area from three inventories (1995, 2005 and 2016) to illustrate the stand diversity. The following Figure 12 is a graphical presentation of all indices values. In non-spatial diversity, as indexed by Shannon index (*H′*), Simpson (*D*) and Pielou's evenness (*J*) were highly variable across area and it ranged between 1.02 to 1.72, 0.63 to 0.79 and 0.38 to 0.71, respectively which suggested that the species richness and evenness are high in all core areas. For all the non-spatial diversity indices, CA3 has always the highest representation in the index values since 1995 indicate that the stand in moist site showed the highest diversity in a structure in the period 1995 to 2016. Moreover, the skewness indices were always right-skewed means there are many small diameter trees and a low number of large diameter trees in all stands at three inventories year. However, the statistical comparison of non-spatial diversity indices across core areas indicates that the structural diversity patterns were not significant between core areas except the skewness index which really shows a significant pattern between core areas. In addition, understory species richness was slightly negatively correlated with overstory species richness (r = -0.57, n = 12, p = 0.055; Figure 11).

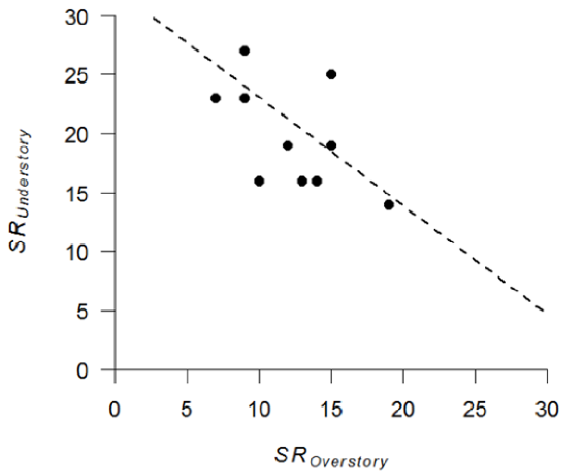


Figure 11- Relationship between species richness of overstory and understory layers from two inventories-1995, 2005 (n=12).

The values of the spatial diversity attribute, as indexed by mingling, diameter differentiation and clark and evans. There were not so much variability trends in average mingling degree for all stand over time (Figure 12), but always showed a medium-high degree of mingling in all core area and its ranged between 0.5 to 0.7 which suggested that all stands occur in constellation with three to four neighbours that belong to a different species. A very similar pattern was visible for the diameter differentiation index measure value of the three core areas (Figure 12) and it is clearly visible that the index value comprises between 0.39 and 0.50 which indicate diameter differing mediumly from their nearest neighbours in all three stands over time. Additional, Clark and Evan index calculation value calculation was always more than 1 in all core areas at each inventory which indicates that all stands have more clustering pattern since 1995. Despite having these patterns, statistical analysis of spatial diversity indices did not show strong differences between core areas.

The measurement of functional diversity attributes in core areas is indexed by functional richness- FRic, functional divergence- FDiv and functional dispersion-FDis from 1995 to 2016. The analysis results recorded that FRic value ranged from 4.53 to 5.60 in CA1, from 4.26 to 5.23 in CA2 and from 8.09 to 10.86 in CA3 (Figure 12). This FRic value was increasing in CA1 and on the other hand, this value is decreasing in CA3 over time, while CA2 showed a different pattern in different inventory times. But CA3 showed always higher FRic value which indicates that CA3 has more dispersion of species in trait space. The value of FDiv was obtained from 0.70 to 0.92 in core areas during the period 1995-2016 (Figure 12). Functional divergence was decreasing in CA2 whereas CA1 and CA3 shows almost unchanged pattern with time. Using FDis for measurement of functional diversity was presented that functional dispersion is decreasing in all stands over time and the index value composed from 0.74 to 1.36. Further statistical analysis exhibited that functional diversity indices show the largest differentiation between core areas. There were also obtained a strong negative correlation ($r < -0.80$) between functional diversity and another diversity index (see Appendix S8).

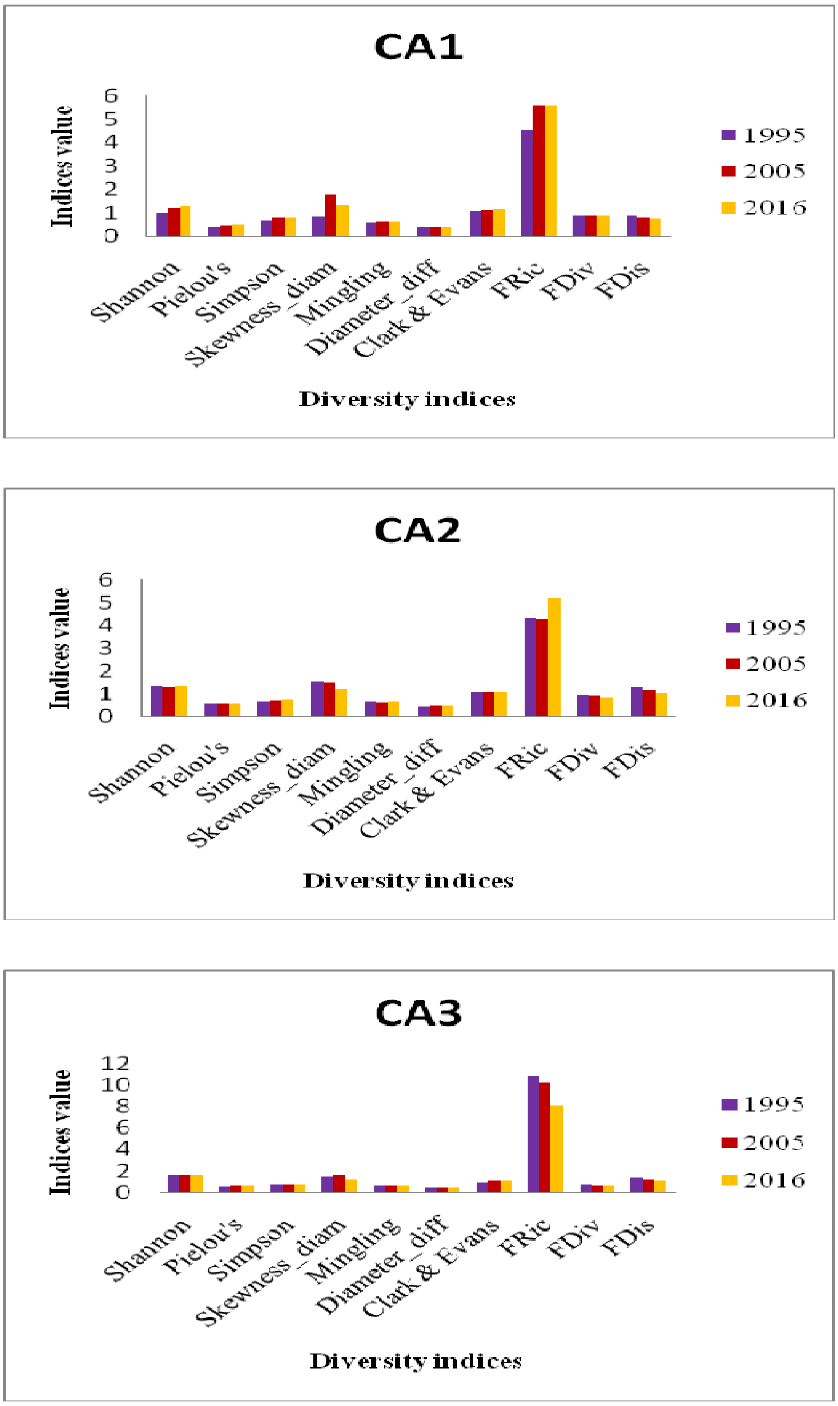


Figure 12- Non-spatial diversity indices (Shannon, Pielou's, Simpson, Skewness_diam-Skewness of Diameter Distribution), Spatial diversity indices (Mingling-Species mingling, Diameter_diff- Diameter Differentiation, Clark & Evans) Functional diveristy indices (FRic-Functional richness, FDiv-Functional divergence, FDis-Functioanl dispersion) measured from three inventories (1995, 2005, 2016) of standing trees in core areas (CAs) at Bosco Fontana.

Moreover, overstory functional dispersion (FD_O) in drought tolerance trait ranged from 0.16 to 1.12 (average ± standard deviation: 0.44 ± 0.30) in two inventories (1995, 2005). Understory functional dispersion (FD_U) in drought tolerance trait was ranged from 0.12 to 1.14 (0.53 ± 0.19) between two inventories years (1995, 2005). Analysis of overstory and understory relationship revealed a significant positive correlation in drought tolerance trait between the two layers (r = 0.82, n = 12, p = 0.01; Figure 13).

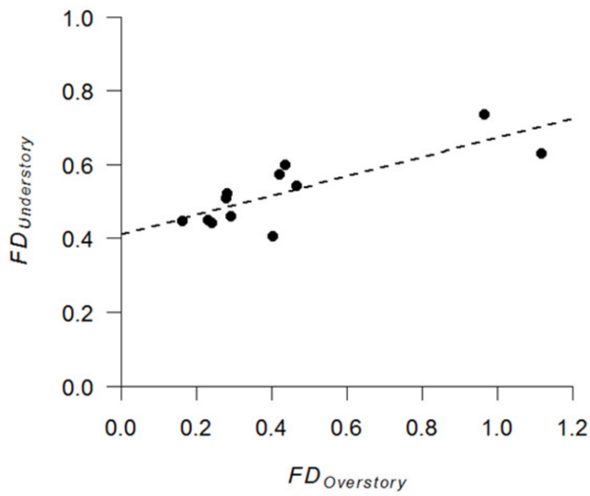
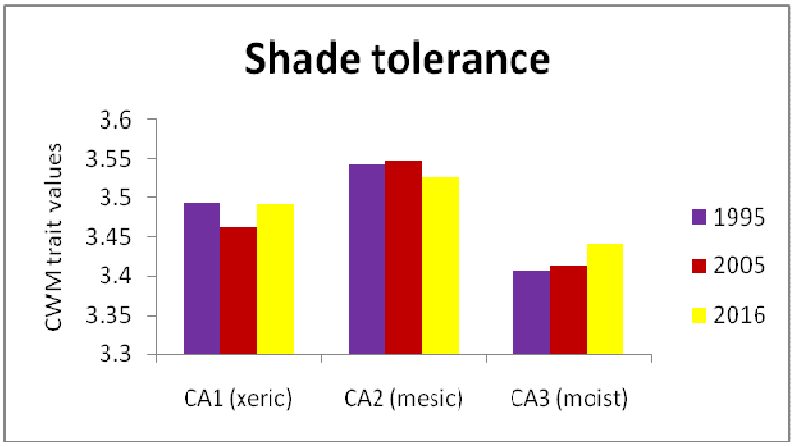
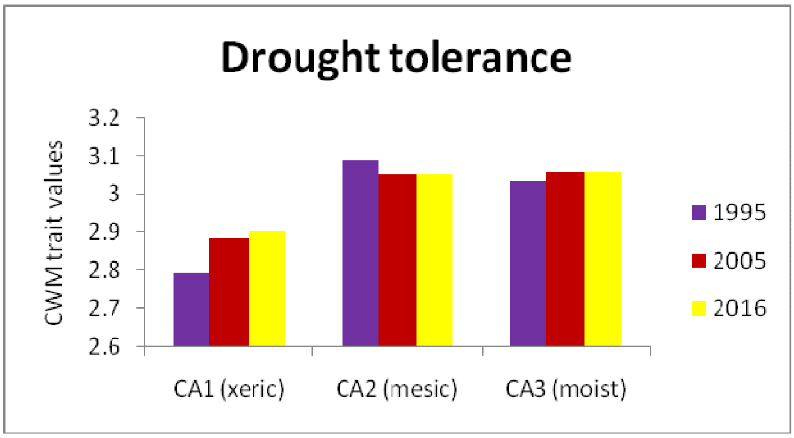


Figure 13- Relationship between functional dispersion of drought tolerance (FD) in overstory and understory layers (n=12) in two inventories (1995, 2005) at Bosco Fontana.

Another functional diversity attribute community-weighted mean (CWM) trait values were also measured in core areas at three inventories (1995, 2005 and 2016). The CWM value in shade tolerance, drought tolerance, and waterlogging tolerance traits ranged from 3.40 to 3.54, from 2.79 to 3.08 and 1.61 to 2.01, respectively (Figure 14). This index analysis found that functional diversity of shade tolerance species in moist site and drought tolerance species in the xeric site were increasing with time in the studied area. On the contrary, functional diversity of drought tolerance species in mesic site and waterlogging tolerance species in the moist site were slightly decreasing over time even having moderate and highest level of soil water availability. Despite having these trends in the functional diversity indices, a strong positive correlation (r > 0.80) was found between non-spatial diversity indices and waterlogging tolerance (see Appendix S8).





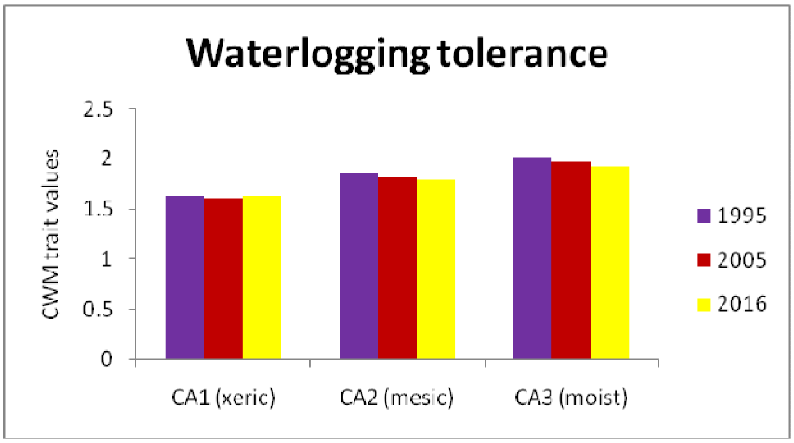


Figure 14- Functional diversity of shade tolerance (top left), drought tolerance (top right) and waterlogging tolerance (bottom) species in core areas (CAs) at three inventories (1995, 2005, 2016).

5.3 Discussion

Monitoring of long-term forest plots plays the main role in sustainable forest management and National Forest Inventory programs are usually designed to produce long-term data on monitoring plot (Kangas and Maltamo, 2006; MacDicken 2015). Long-term monitoring plots can provide unique information about long-term changes on stand level (Nagel *et al.*, 2012). Recently, Coll *et al.* (2018) proposed from scientific literature that there is a critical lack of long-term monitoring plot in mixed forest and research needs on it to improving our understanding of how to manage mixed forest in different forest types over time; and also lack of integrated assessment of mixed species composition, structure and diversity for understanding of the biodiversity-ecosystem function relationship at all relevant spatial and temporal scales. This study aimed at reducing this knowledge gap by integrating assessment of data from long-term monitoring plots of mixed forest with respect to mapping standing tree stems, stand structure characterization and stand diversity since 1995.

Using all standing trees, this study result found spatial distribution patterns of trees are random and clumped within and between maps as a consequence of high number of small trees and low number of large trees in size at all core areas over the 1995-2016 periods which also confirmed by the calculation of skewness and clark and evan indices. These results were consistent with the hypothesis proposed for this study as mixed species arranged normally in a random fashion where species diversity is high (Pommerening, 2002; Illian *et al.*, 2008) and non-spatial diversity measure also provide evidence that all core areas have high species diversity. Another spatio-temporal analysis indicated that spatial patterns are remaining clumped in multi-storied and multi-aged stands over time (LeMay *et al.*, 2009). Normally these kind of clumped spatial distribution patterns over time are extremely common among tropical tree species (Condit *et al.*, 2000; Bunyavejchewin *et al.,* 2003; Lan *et al.*, 2009), uneven-aged mixed coniferous stands (Peterson and Squiers, 1995; Hanewinkel, 2004). Moreover, the maps presented in this study was the extension of the previous study in which there focused on only two inventories (1995, 2005) year of the studied mixed forest (Travaglini *et al.*, 2007).

This study work demonstrates that an integrated approach is useful for preserving the mixed forest in natural ecosystems by characterizing forest structure, diversity and dynamic pattern in three mixed forest stands from 1995 to 2016. This integrated analysis used indices of non-spatial,

spatial by first-order characteristics and functional diversity by multiple-traits variants along with dendrometric parameters in three mixed forest stands. While, Hui and Pommerening (2014) used the integrated analysis of non-spatial, spatial by second-order characteristics and functional diversity by single-trait variant to understand the structure and diversity in semi-natural mixed forest, but they have not been used long-term recordable data to get deeper inside on dynamic pattern of the forest.

The study results clearly indicated that these natural mixed broadleaf forest stands and their species compositions are very similar to the broadleaf stand in northern Turkey, central Europe and Caucasus (Adel *et al.*, 2014; Bayranvand *et al.*, 2017). The analysis showed the different pattern in species abundance due to the different species composition and soil water availability that suggested the study (Chianucci *et al.*, 2016a). Another study also indicated that mixed forest stand varies due to the site conditions (Toïgo *et al.*, 2015) and different tree species composition (Parrotta, 1999). In all core areas, the most dominant and common tree species hornbeam and pedunculate oak are decreasing over time which can be happened by reducing regeneration of pedunculate oak (Mason, 2004; Travaglini *et al.*, 2007) and hornbeam. The functional dispersion was also followed the decreasing trend with times in all core areas because the functional dispersion index uses species abundance and size as an abundance of weighted size values (Lavorel *et al.*, 2008; Laliberté and Legendre, 2010; Hui and Pommerening, 2014). Moreover, the significant and positive correlation observed in the functional dispersion of drought tolerance between understory and overstory layers suggest a mutual influence on the structure and dynamics of the two layers in temperate broadleaf forests. The understory of mesic and xeric plots analyzed in this study was dominated by Butcher's broom (*Ruscus aculeatus*, average cover 53%). In the moist plot, Butcher's broom showed a lower occurrence (29%) in the understory. The large dominance of *Ruscus aculeatus*, combined with its high tolerance, may further displace other species in the understory by strong competition, thus limiting their presence in the successional stage (Campetella *et al.*, 2004). In resource-limited stands, a strong interplay between the overstory and understory layers may facilitate nutrient pool (Swanson *et al.*, 2010) and provide a greater resilience to environmental stresses (Ares *et al.*, 2010).

Measures for characterizing tree density, basal area, tree diameter, tree height, and functional diversity can reveal differences between core areas whereas non-spatial and spatial diversity was not able to differentiate between core areas over time. Tree density resulted in 20% reduction in moist site, even has been increased 17% of tree diameter and height with time due to existence of some very large trees which also reflecting by the non-spatial and functional richness indices because these diversity indices showed that moist site has always high structural diversity pattern and more disperse of species in trait space than other two areas; also functional diversity of shade tolerance species were increasing but waterlogging tolerance species are decreasing in moist site over time. Whereas tree density varied in the xeric site through time, but the total basal area is increases almost 20% due to the high percentage of new small trees (dbh< 10 cm) at last two inventories than other two areas which also causing the increment of functional diversity of drought tolerance species over time.

5.4 Conclusion

The inventoried data of studied area constituted a sound foundation for analysis mixed forest dynamic pattern over time. This study emphasizes the contribution of long-term monitoring plot for indicating changes in structure and diversity in mixed forest. The mapping of studied plot across all core areas and assessing spatio-temporal dynamic patterns suggested that the management activities will be required based on site condition of mixed forest in different forest types to maintain the sustainability of ecosystem. There has been steady progression of all core area tree distribution towards more clumped due to high number of small trees over time. Species abundance varies with species composition and site conditions. Species richness analysis found a negative relationship between overstory and understory layers. The study results have shown that xeric site became enriched by drought tolerance species and total basal area are increasing in space and time as result of high number of new small trees (dbh< 10 cm). Moist site found more dispersion of species in trait space than other areas by the functional richness analysis. Also the analysis of drought tolerance trait of functional dispersion revealed a positive relationship between overstory and understory layers. Finally, the study suggests that measures of stand structural parameters and different diversity indices may be easily integrated into management outcomes evaluated in spatio-temporal dynamic pattern of mixed floodplain forest.

Chapter 6

6 Estimation of stand structural complexity and their drivers in a mixed forest

6.1 Materials and methods

6.1.1 Sampling pattern, scan data collection and post-processing

For this study purpose, the terrestrial laser scan data collected from scanning campaigns during the summer in 2016 in leaf-on conditions (e.g. Figure 16). Ten single-scans were performed along a grid with sampling points spaced 30 m (Figure 15). The scan was acquired using a Faro Focus 3D x 130 (FARO Technologies Inc., Florida, USA) terrestrial laser scanner. Scans were carried out under a clear sky and windless day conditions. The laser scanner height was 1.3 m. The scanner was set to scan a field of view with 360 horizontal (0°-360° azimuth range) and 300° vertical (0°- 300° zenith range) direction. The maximum distance of the scanner was 130 m. All the point cloud imported to FARO Scene (Vers. 5, Faro Technologies Inc., Lake Mary, FL, USA) for delete all erroneous point by using a standard filter of software (see Faro, 2004). Then each point cloud was exported as ASCII files. A single-scan in CA3 was lost due to instrument malfunction.

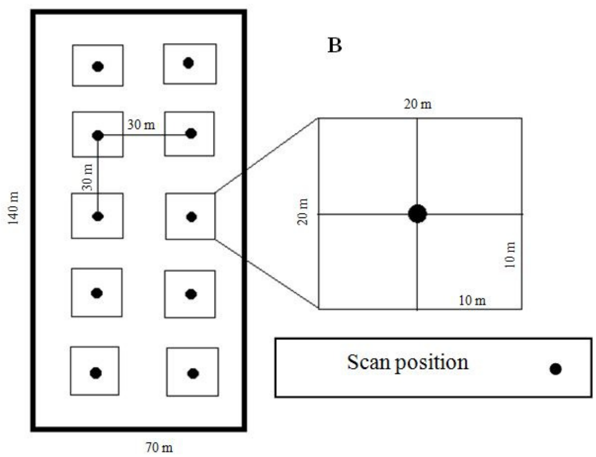


Figure 15- Layout of sampling design for single-scan, cover photography and field data (B) in core areas at Bosco Fontana.

Figure 16- TLS point cloud of core area (e.g CA3) at Bosco Fontana in summer 2016.

6.1.2 Stand structural complexity index (SSCI)

The research used the stand structural complexity index (SSCI) as introduced by Ehbrecht *et al.*, (2017) to quantify the complexity of biomass distribution in three-dimensional space. The index is based on point clouds obtained from single terrestrial laser scans. From each point cloud, 1280 cross-sectional polygons are derived by using Mathematica software (Wolfram Research, Champaign, USA) from which the fractal dimension is computed as a measure of shape complexity (see Ehbrecht *et al.*, 2017 for a detailed description). As the fractal dimension itself is scale-independent, the effective number of layers (ENL, see Ehbrecht *et al.*, 2016) is used to scale the obtained fractal dimension values to take stand size into account. Here, increasing stand height and a more even filling along the z-axis by foliage and woody components results in higher index values. Details on the index creation can be found in Ehbrecht *et al.* (2017).

6.1.3 Digital hemispherical photography

Full-frame hemispherical images were acquired in the same grid used for TLS scans (see 6.1.1; Figure 17) using a Nikon D90 Digital Single-Lens Reflex (DSLR) camera equipped with an AF Fisheye Nikon 10.5 mm 1:2.8 G lens. Images were acquired in diffuse sky conditions as maximum resolution (4288 x 2848 pixels) JPEGs with the camera set in Aperture-priority mode and the exposure set to underexpose images by 1 stop in comparison with the metered exposure. Following the protocol by Chianucci and Cutini (2013), images were gamma corrected to a gamma of 1.0 and then processed in Winscanopy 2012 (Regent Instruments, Ste-Foy, Quebec, Canada). The images were sharpened (medium) and then divided into seven zenith angle rings covering a FOV of 0°-70° and eight azimuth segments. Leaf area index, non-corrected for clumping, was obtained by averaging the generalized LAI-2000 and the Ellipsoidal LAI, from unmodified gap fraction data (linear method); leaf area index, corrected for clumping, was also obtained from logarithm-averaged gap fraction data from the two methods above (log method). Canopy openness was calculated from gap fraction data. LAI and canopy openness were used as a conventional measure of stand structure.

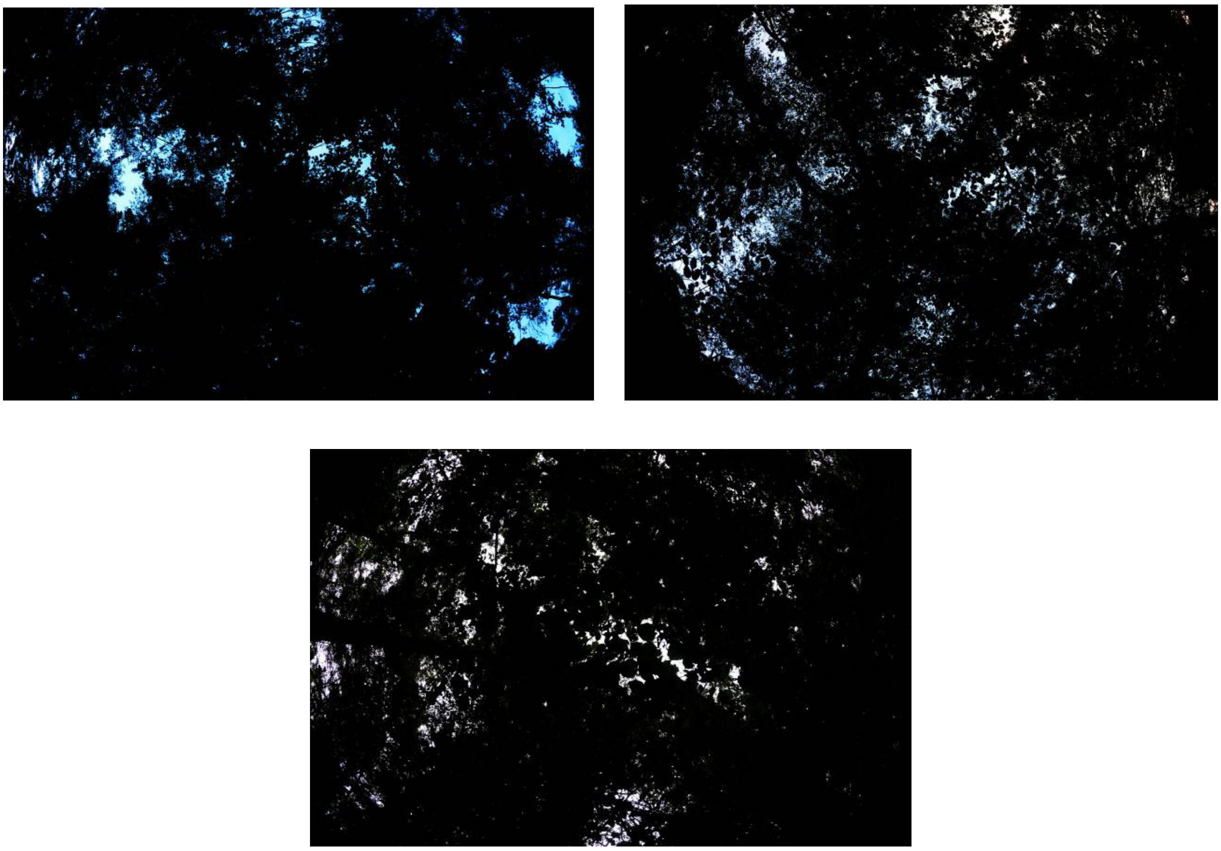


Figure 17- Hemispherical photo of each area (CA1-top left, CA2-top right, CA3-bottom) at Bosco Fontana in summer 2016.

6.1.4 Inventory data

Forest inventory data collected in 2016 was used to evaluate their relationship with measures derived from the terrestrial laser scanning and stand structural attributes that delineate stand structural complexity. In each core area, species, height, diameter at breast height (DBH) of all standing tree stems ≥ 5cm were measured within 20 x 20 m plot at each scanning position (Figure 15B). The method of tree species identity and position were described in Fardusi *et al.,* (2018). The conventional stand structural attributes: i) species-specific basal area ii) coefficient of variation of height and iii) tree species diversity were calculated based on this data. The latter was calculated Shannon (*H')* and Simpson (*D*) indices based on basal area to estimate tree species diversity (Shannon and Weaver, 1949; Simpson, 1949; see calculation detailed at 5.1.2.2.1 in chapter 5 above).

6.1.5 Statistical analysis

Linear regressions models were used to study the relationship between SSCI and site conditions, and stand structural attributes. Analysis of variance (ANOVA) and Tukey post hoc tests was conducted to determine whether the mean variables vary among the studied core areas. Multiple linear regression models were used to investigate the relationship between SSCI, site condition, and stand structural attributes. In terms to find only significant main effects, this study analyzed pairwise interaction effects of selected variables on SSCI. Thus, this study included main effects with other conventional measure of stand structure in the multiple linear regression model and having highest coefficient of determination (R^2) and lowest akaike information criterion- AIC (Burnham and Anderson, 2002). The statistical analyses were made using R, version 3.3.3 (R Development Core Team, 2017).

6.2 Results

6.2.1 Stand structural complexity vs. water availability

The stand structural complexity varied across the core areas. The stand structural complexity index-SSCI values ranged between 2.5 and 6.7 (Figure 18, see details Appendix S9). The highest average SSCI value was found in the core areas located in mesic site (CA2) and moist site (CA3), while it was significantly lower in the xeric site (CA1). The mean values obtained in CA2 in CA2 and CA3 were not significantly different each other.

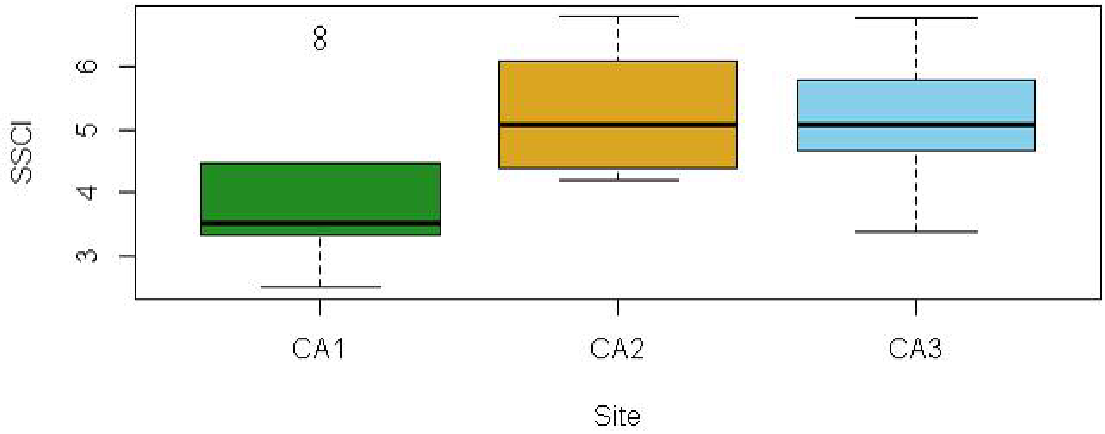


Figure 18- Box-and-Whisker plots of stand structural complexity index (SSCI) for the three study sites with increasing water-availability from CA1 to CA3.

6.2.2 Effect of species diversity on stand structural complexity

No relationship was found between species richness (*H* and *D*) and the stand structural complexity, whereas the highest index value was found in CA3. In all core areas, analysis of tree species identity did not found significant relationship between SSCI and basal area contribution of any tree species, but *C. Betulus* alone was significantly and negatively, but weakly related to SSCI (r^2= 0.10), which suggest that *C. betulus* (species with a complex structure) has an negative effect on stand structural complexity in core areas (Figure 19).

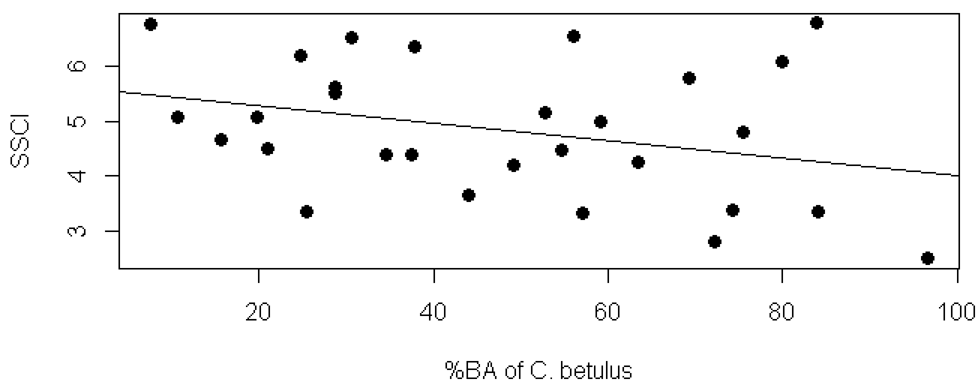


Figure 19- Scatterplot of SSCI over the basal area percentage of *C. betulus*.

6.2.3 Relationship between conventional measures of forest structure and stand structural complexity

The linear regression analysis indicates that the coefficient of variation of height (tree size variation) had significant (positive) effect on SSCI (r^2= 0.19, p< 0.05, Figure 20).

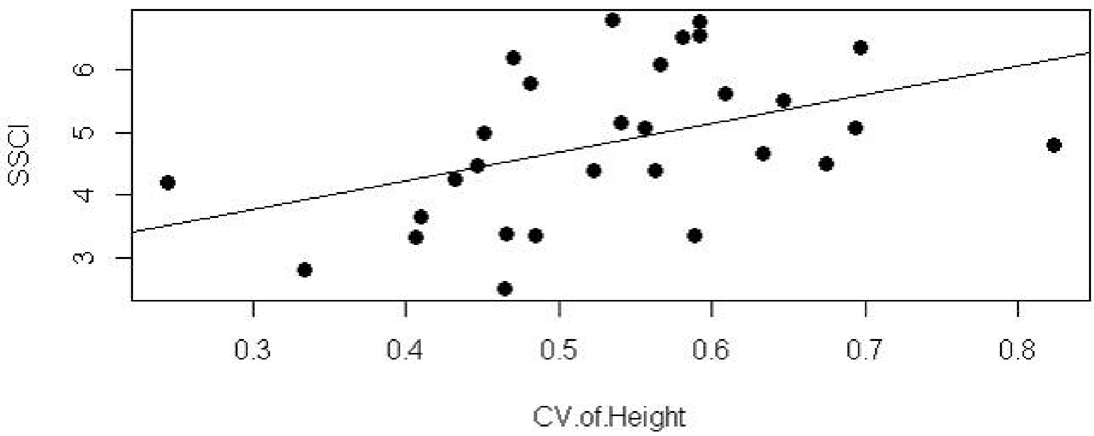


Figure 20- Scatterplot of SSCI over the coefficient of tree height (CV.of.height).

Mean LAI (± SE) were 4.1 ± 0.1, 3.9 ± 0.1 and 4.8 ± 0.1 in the xeric, mesic and moist sites, respectively. Mean canopy openness (± SE) were 5.46 ± 1, 6.4 ± 1.2 and 3.3 ± 0.4. Neither LAI nor opens had no significant effect on SSCI at all sites (Figure 21 and 22).

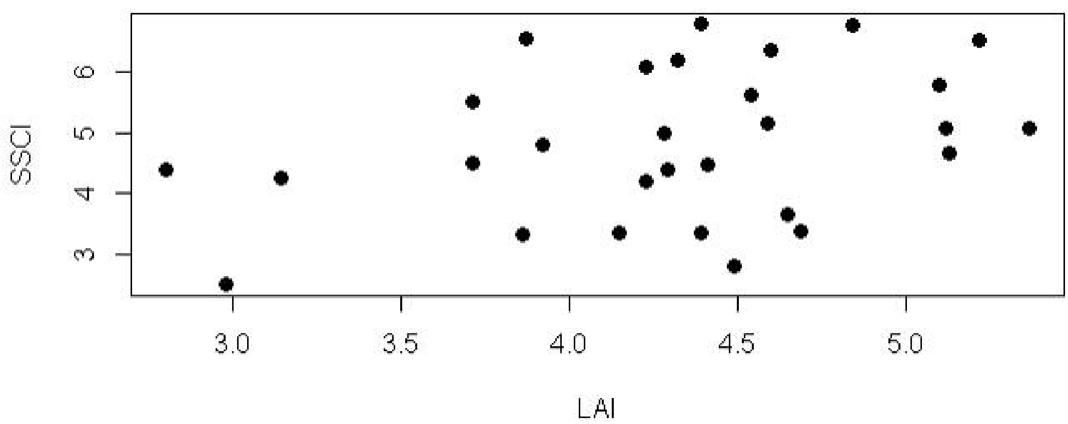


Figure 21- Scatterplot of SSCI over the LAI.

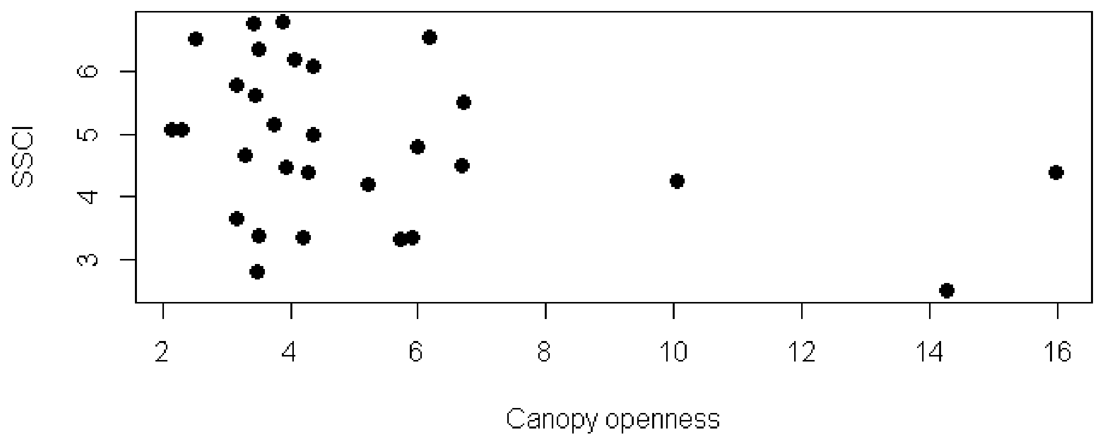


Figure 22- Scatterplot of SSCI over the canopy openness.

Finally, this study found that the combination of site conditions (xeric, mesic, moist), tree height variation (CV_of_height) and leaf area index (LAI) in the multiple linear model explained the stand structural complexity best (highest R^2 value 0.45 ($p < 0.01$) and lowest AIC value, Table 3-model 3).

Table 3: Model comparison to test the relationship between conventional stand structural measures and SSCI.

Model	**Rcode**	**df**	**R^2**	**AIC**	**p-value**
1	lm(SSCI~ Site condition+ CV of height)	25	0.33	91.09	0.0146
2	lm(SSCI~ Site condition+ CV of height+ Canopy openness)	24	0.45	87.58	0.0046
3	lm(SSCI~ Site condition+ CV of height+ LAI)	24	0.45	87.44	0.0044

6.3 Discussion

Our results indicate that stand structural complexity was only constrained by the reduce water availability under dry conditions. In the mesic site, the water availability seemed high enough to allow the vegetation to grow to full structural complexity, as achieved in the moist area (SSCI mesic = SSCI moist). This indicates that water availability is only a limited indicator for stand structural complexity in the investigated stand. Pretzsch *et al.* (2016) also found that mixed stand structural heterogeneity/complexity is increasing from dry to moist sites than monoculture. By contrast, Chianucci *et al.* (2016a) observed that site condition (soil condition and water availability) are the main drivers of overstory and understory dynamics, and site condition must be a priori considered in forest management decision.

Species diversity did not explain SSCI at studied sites, which is in contrast to earlier studies (Ehbrecht *et al.*, 2018). The results also confirmed from the calculation of species diversity (Shannon, Simpson, Pielou's) on the studied core areas from 1995 to 2016 which found that all the core areas have high species diversity since 1995 (Fardusi *et al.*, 2018).

The study results on the relationship between the variability in tree height and SSCI confirm the findings from Ehbrecht *et al.*, (2017), who reported a significant positive relationship between SSCI and tree size differentiation. Since tree size differentiations are essential to understanding the complex forest structure and diversity in the multi-species uneven-aged forest (Hui and Pommerening, 2014).

The absence of a relationship between LAI and SSCI is not surprising. LAI is not a spatially explicit measure as it does not account the vertical distribution of leave layers in the stand but only the number of layers, or, more precisely, their total area above a given unit of ground surface, usually a single square meter. Hence, LAI does not differ with varying vertical structures but only with the amount of leaves area. The laser-based and spatially explicit measure SSCI, in contrast, is sensitive to small changes in the distribution of biomass. Hence, the two measures are not related.

Similar to LAI, canopy openness is not related with SSCI in the studied sites and these can be happened due to small canopy gap which created by small-scale disturbance event (e.g. mortality of individual trees). This result supports the finding of Ehbrecht *et al.,* (2017) who found a negative relationship between larger canopy gap and SSCI.

Furthermore, this study also showed that the LAI might affect stand structural complexity along with other main drivers. Since LAI is the main descriptor of vegetation structure, function and condition (GCOS, 2011; Woodgate *et al.*, 2015) it should be considered when investigating the stand structural complexity of mixed forest.

6.4 Conclusion

This study found that stand structural complexity mainly varies due to the variation of the different level of water availability and tree size differentiation in the various forest types of mixed forest. Although the study also indicates that the stand structural complexity is not increasing with species diversity in the studied forest. Moreover, the findings suggested that LAI alone may not be enough to describe stand structural complexity but combined with tree size variation and soil water availability would help to better understand the stand structural complexity in the mixed forest.

Chapter 7

7 Conclusions and Future perspectives

7.1 Conclusive considerations and further research perspectives

Main three research problems were addressed in this thesis. First, a review was performed to discuss the most recent advances in precision forestry technologies and application with specific reference to geospatial-information tools, software, and instrument for forest structure and diversity analysis. Second, this study was conducted a field campaign to test the application of precision forestry technologies. Traditional field inventory and other ICT (terrestrial laser scanning and digital hemispherical photography) approaches were employed in three core areas (CAs) of mixed hornbeam-oak floodplain forest and collected data integrate with historical data to produce a spatio-temporal dataset of forest mensuration. Third, perform long-term and integrate analysis using this produced dataset. The main conclusions and future perspectives emerging from the research are given below.

Precision Forestry could generate future forestry operations at a macro and micro level in a more economically and ecologically sustainable way. Modern Information and Communication Technologies can contribute to higher precision in forest structure and diversity analysis. The evaluation of precision technologies holds great potential to develop automated monitoring and thus reduce labor requirements. Modern technologies such as terrestrial laser scanning- TLS may contribute for higher precision in forest structure and diversity analysis. Adopting precision forestry technologies would allow repeatable, reproducible, more precise and spatially-explicit information on forestry processes, which is a preliminary step towards standardization and efficiency of forest procedures. It can be applied to increase the efficiency and information basis of existing national forest inventories. However, there are still challenging to integrate tools and techniques, access data from the open source, evaluate the cost-effectiveness of the technologies and their accuracy into a precision forestry framework.

The produced open access dataset is provided a comparable spatio-temporal measurement of three stands in mixed floodplain forest and to best of our knowledge no previous study is produced this kind of dataset which allow researchers to perform an integrated analysis of mixed forest structure and diversity from 1995 to 2016 and compare with another forest in large-scale study.

The integrated analysis of non-spatial, spatial and functional diversity indices and dendrometric parameters provided good information on spatio-temporal changes in structure and dynamic of mixed floodplain forest to understand these forest structure-ecosystem function and services to enable for a sustainable forest management. Overall results of the analysis suggested that the site condition must be given special consideration in mixed forest stand management. The spatial tree distribution revealed that all the core areas are not uniformly distributed and clustered due to a high number of small trees over time. The species abundance varied due to different species composition and soil water availability. In all core areas, hornbeam and pedunculate oak (dominant and common species in all core area) are decreasing over time as consequences of regeneration reduction of these two species. The understory analysis revealed that CA1 and CA2 were dominated by butcher's broom (53%). The negative relationship found between overstory and understory species richness. Total basal area and drought tolerance species are gradually increasing due to the high percentage of small trees in CA1 (xeric site) over time. CA3 showed the higher structural diversity and more dispersion of species in trait space than other areas over time. Analysis of overstory and understory revealed a significant positive correlation in drought tolerance between the two layers. Spatial diversity indices were not able to reveal any significant differences between core areas. On the other hand, functional diversity indices found significant differences between core areas. There was a strong negative relationship between functional diversity and other diversity indices (non-spatial, spatial). However, this integrated analysis is helpful with regards to quantifying structure, diversity and dynamic patterns of mixed forest in space and time from long-term, repeated inventories data on permanent plots. Moreover, the use of spatially-explicit and functional diversity indices may provide more through information on diversity pattern than traditional structural diversity indices.

The multiscale analysis, to our knowledge, is the first to combine the power of field inventory data with Terrestrial laser scanning-TLS and digital hemispherical photography that allow studying stand structural complexity of mixed forest in different types of forest and addressing their drivers. The result indicated that stand structural complexity is increasing with water availability due to better growing conditions. Tree size differentiation has an effect on stand structural complexity. On the contrary, species diversity showed opposite behavior that it has no effect on stand structural complexity in studied sites. The conventional canopy attributes LAI and openness has no individual effect on stand structural complexity. But LAI combined with other main drivers showed a strong effect on stand structural complexity. However, TLS can provide higher precision three-dimensional data related to spatial arrangement (both horizontal and vertical) of vegetation elements. These three-dimensional data allow integrating analysis with other instruments and tools to estimate forest structure, which is not possible with any other instrument or approach. For instance, spatially-explicit indices like mark differentiation can consider diameter (horizontal distribution) or height (vertical distribution) but in a separated way.

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Appendices

Appendix S1: List of core area number "CA" (Core Area) in Bosco Fontana, Italy.

Code	Description
CA1	Core Area 1
CA2	Core Area 2
CA3	Core Area 3

Appendix S2: List of inventory year in Bosco Fontana, Italy.

Code	Description	Note
1995	Inventory year	First inventory
2005	Inventory year	Second inventory
2016	Inventory year	Third inventory

Appendix S3: List of species in Bosco Fontana, Italy.

Code	Species_abbr.	Genus and Species	Species Authority	Full name of Species Author	English common name	Italian common name
1	Ac	*Acer campestre*	L.	Carolus Linnaeus	Field maple	Acero campestre
2	Ag	*Alnus glutinosa*	(L.) Gaertn.	(Carolus Linnaeus), Joseph Gaertner	Common European alder	Ontano nero
3	Ca	*Corylus avellana*	L.	Carolus Linnaeus	Hazel	Nocciolo
4	Cb	*Carpinus betulus*	L.	Carolus Linnaeus	Common European hornbeam	Carpino bianco
5	Cm	*Cornus mas*	L.	Carolus Linnaeus	Cornelian cherry	Corniolo
6	Co	*Crataegus monogyna*	Jacq.	Nikolaus Joseph Freiherr von Jacquin	Common hawthorn	Biancospino comune
7	Cs	*Cornus sanguinea*	L.	Carolus Linnaeus	Common dogwood	Sanguinella
8	Fa	Fraxinus angustifolia	Vahl.	Martin Vahl	Narrow-leaved ash	Frassino oxifillo
9	Fo	*Fraxinus ornus*	L.	Carolus Linnaeus	Manna ash	Orniello
10	Ms	*Malus sylvestris*	(L.) Mill.	(Carolus Linnaeus), Philip Miller	Crab apple	Melo selvatico
11	Pr	*Prunus avium*	L.	Carolus Linnaeus	Sweet cherry	Ciliegio
12	Pt	Platanus hispanica	Mill. ex Münchh.	Philip Miller ex Otto von Münchhausen	London plane	Platano ibrido
13	Qc	*Quercus cerris*	L.	Carolus Linnaeus	Turkey oak	Cerro
14	Qr	*Quercus robur*	L.	Carolus Linnaeus	English oak	Farnia
15	Rp	*Robinia pseudoacacia*	L.	Carolus Linnaeus	Black locust	Robinia
16	Sd	*Sorbus domestica*	L.	Carolus Linnaeus	Service tree	Sorbo domestico
17	Sn	*Sambucus nigra*	L.	Carolus Linnaeus	Common elder	Sambucocomune
18	St	*Sorbus torminalis*	(L.) Crantz	(Carolus Linnaeus), Heinrich Johann Nepomuk von Crantz	Wild service tree	Ciavardello
19	Tb	*Taxus baccata*	L.	Carolus Linnaeus	English yew	Tasso
20	Um	*Ulmus minor*	Mill.	Philip Miller	Field elm	Olmo campestre

Appendix S4: Non-spatial diversity indices values.

Core area	Year	Shannon	Pielou's	Simpson	Skewness_diam
CA1	1995	1.025	0.388	0.678	0.855
	2005	1.209	0.458	0.786	1.785
	2016	1.292	0.489	0.775	1.322
CA2	1995	1.315	0.548	0.632	1.511
	2005	1.271	0.552	0.676	1.452
	2016	1.335	0.537	0.744	1.175
CA3	1995	1.696	0.612	0.791	1.51
	2005	1.688	0.679	0.774	1.654
	2016	1.723	0.718	0.756	1.23

Appendix S5: Spatial diversity indices values.

Core area	Year	Mingling	Diameter_diff	Clark & Evans
CA1	1995	0.574	0.419	1.055
	2005	0.616	0.394	1.093
	2016	0.619	0.411	1.129
CA2	1995	0.623	0.419	1.04
	2005	0.596	0.446	1.061
	2016	0.66	0.478	1.067
CA3	1995	0.705	0.477	0.978
	2005	0.696	0.471	1.045
	2016	0.687	0.503	1.11

Appendix S6: Functional diversity indices values.

Core area	**Year**	**Fric-Functional richness**	**Fdiv-Functional divergence**	**Fdis-Functional dispersion**
CA1	1995	4.531	0.902	0.903
	2005	5.609	0.884	0.801
	2016	5.609	0.877	0.74
CA2	1995	4.311	0.923	1.277
	2005	4.264	0.891	1.137
	2016	5.235	0.772	1.008
CA3	1995	10.868	0.788	1.36
	2005	10.241	0.709	1.203
	2016	8.093	0.727	1.073

Appendix S7: Community-weighted mean trait values.

Core area	**Year**	**Shade.tolerance**	**Drought.tolerance**	**Waterlogging.tolerance**
CA1 (xeric)	1995	3.494	2.794	1.626
	2005	3.464	2.884	1.611
	2016	3.492	2.905	1.636
CA2 (mesic)	1995	3.543	3.089	1.849
	2005	3.548	3.054	1.816
	2016	3.527	3.051	1.792
CA3 (moist)	1995	3.406	3.036	2.017
	2005	3.414	3.06	1.974
	2016	3.441	3.058	1.928

Appendix S8: Pearson's coefficient of correlation values between different diversity indices.

Diversity indices	Shannon	Pielou's	Simpson	Skewness_diam	Mingling	Diameter_diff	ClarkEvans	FRic	FDiv	FDis	Shade.tolerance	Drought.tolerance	Waterlogging.tolerance
Shannon	1	0.94	0.51	-0.05	0.95	0.79	-0.26	0.88	-0.84	0.6	-0.7	0.67	0.88
Pielou	0.94	1	0.29	0.02	0.84	0.82	-0.14	0.7	-0.8	0.61	-0.49	0.8	0.88
Simpson	0.51	0.29	1	-0.13	0.6	0.26	0.13	0.68	-0.6	-0.22	-0.76	-0.09	0.13
Skewness_diam	-0.05	0.02	-0.13	1	0.02	-0.18	0.1	-0.33	0.24	0.08	0.5	0.48	-0.01
Mingling	0.95	0.84	0.6	0.02	1	0.78	-0.32	0.88	-0.88	0.55	-0.71	0.62	0.83
Diameter_diff	0.79	0.82	0.26	-0.18	0.78	1	-0.24	0.61	-0.86	0.55	-0.4	0.65	0.81
ClarkEvans	-0.26	-0.14	0.13	0.1	-0.32	-0.24	1	-0.42	0.09	-0.8	0.24	-0.31	-0.58
FRic	0.88	0.7	0.68	-0.33	0.88	0.61	-0.42	1	-0.78	0.49	-0.92	0.33	0.74
FDiv	-0.84	-0.8	-0.6	0.24	-0.88	-0.86	0.09	-0.78	1	-0.32	0.67	-0.47	-0.68
FDis	0.6	0.61	-0.22	0.08	0.55	0.55	-0.8	0.49	-0.32	1	-0.19	0.76	0.89
Shade.tolerance	-0.7	-0.49	-0.76	0.5	-0.71	-0.4	0.24	-0.92	0.67	-0.19	1	0.02	-0.46
Drought.tolerance	0.67	0.8	-0.09	0.48	0.62	0.65	-0.31	0.33	-0.47	0.76	0.02	1	0.82
Waterlogging.tolerance	0.88	0.88	0.13	-0.01	0.83	0.81	-0.58	0.74	-0.68	0.89	-0.46	0.82	1

Appendix S9: Calculated value from terrestrial laser scanning data (stand structural complexity-SSCI), from field inventory data (CV of height, Shannon, Simpson, basal area percentage- %BA), from hemispherical image (Canopy openness, leaf area index-LAI).

Site	SSCI	Sampling_point	Site Condition	CV of Height	Shannon	Simpson	%BA of Cb	Openness	LAI
CA1	2.51	31	Xeric	0.46	0.24	0.06	96.67	14.26	2.98
CA1	3.37	35	Xeric	0.48	1.92	0.65	25.46	5.91	4.15
CA1	3.32	37	Xeric	0.41	1.90	0.63	57.10	5.72	3.86
CA1	2.82	40	Xeric	0.33	1.02	0.42	72.21	3.48	4.49
CA1	3.65	43	Xeric	0.41	1.15	0.52	43.98	3.15	4.65
CA1	4.39	76	Xeric	0.56	1.31	0.52	34.63	4.29	4.29
CA1	6.36	79	Xeric	0.70	1.27	0.53	37.88	3.5	4.6
CA1	6.53	82	Xeric	0.59	1.35	0.57	56.01	6.17	3.87
CA1	4.46	85	Xeric	0.45	1.78	0.63	54.72	3.92	4.41
CA1	3.35	88	Xeric	0.59	0.84	0.28	83.98	4.2	4.39
CA2	6.06	43	Mesic	0.57	0.98	0.34	79.86	4.36	4.23
CA2	4.20	76	Mesic	0.24	1.04	0.51	49.20	5.21	4.23
CA2	4.81	79	Mesic	0.82	0.99	0.38	75.39	5.98	3.92
CA2	6.77	82	Mesic	0.54	0.74	0.28	83.85	3.88	4.39
CA2	5.15	85	Mesic	0.54	1.59	0.62	52.75	3.74	4.59
CA2	6.19	88	Mesic	0.47	0.94	0.40	24.75	4.07	4.32
CA2	5.49	31	Mesic	0.65	1.78	0.69	28.77	6.72	3.71
CA2	4.38	34	Mesic	0.52	2.00	0.72	37.58	15.99	2.8
CA2	4.26	37	Mesic	0.43	1.11	0.48	63.38	10.04	3.14
CA2	4.99	40	Mesic	0.45	1.20	0.51	59.20	4.36	4.28
CA3	4.67	40	Moist	0.63	2.15	0.73	15.74	3.28	5.13
CA3	5.62	37	Moist	0.61	1.17	0.48	28.72	3.44	4.54
CA3	6.52	34	Moist	0.58	1.75	0.67	30.71	2.52	5.22
CA3	3.38	31	Moist	0.47	0.84	0.38	74.29	3.51	4.69
CA3	5.78	88	Moist	0.48	1.35	0.48	69.23	3.15	5.1
CA3	5.07	85	Moist	0.56	2.52	0.81	19.75	2.14	5.37
CA3	6.75	79	Moist	0.59	1.57	0.53	7.61	3.41	4.84
CA3	4.50	76	Moist	0.67	1.38	0.52	21.03	6.67	3.71
CA3	5.08	43	Moist	0.69	1.61	0.62	10.68	2.29	5.12

Appendix S10: Calculation of effective number of layers for stand structural complexity index.

In chapter 6, an algorithm was compiled in Mathematica software (Wolfram Research, Champaign, USA) to calculate a list of variables for construct stand structural complexity index-SSCI of each independent single scan in each core area.

The fractal dimension index (FRAC) of each of the 1280 polygon was determined based on the formula provided by McGarigal and Marks (1994) and index value ranges from 1-2 when calculated with rectangle:

$$FRAC = \frac{2 * \ln(0.25 * P)}{\ln(A)} \tag{12}$$

Where, *ln* is the natural logarithm to the base *e*, *P* is the perimeter and *A* the area of the polygon. Then *MeanFrac* was derived from the 1280 FRAC values per scan.

Vertical stand structure was calculated by effective number of layers (ENL) and ENL computed using vertical layers of 1 m thickness and number of voxel (20 cm side length) inside each layer. ENL estimated by the following formula:

$$ENL = \frac{1}{\sum_{i=1}^{N_{top}} P_i^2} \tag{13}$$

Here, *pi* is the proportion of filled voxels in the i^{th} vertical layer to the sum of filled voxel in the entire volume analyzed. *Ntop* refers to the top stand height, and *ln* is the natural logarithm.

Then the natural logarithm of ENL was used to calculate SSCI value to compare among core areas.

$$SSCI = MeanFrac^{\ln(ENL)} \tag{14}$$