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# Comparison of managed and unmanaged forest stands in France based on diameter diversity and spatial forest structure indices

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## Master Thesis

Presented by

Alexandra GILLESPIE

In order to obtain the diploma of  
MSc Sustainable Tropical Forestry

Subject :

**Comparison of managed and unmanaged forest stands in  
France based on diameter diversity and spatial forest  
structure indices**

Defended publically on the 19<sup>th</sup> of December 2014

at AgroParisTech,  
Montpellier Center

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# FOREWORD

The six-month internship took place within the *Institut de recherche en sciences et technologies pour l'environnement et l'agriculture* (Irstea), a French research body with more than 30 years' experience in studying major issues including: a responsible agriculture, the sustainable land management of territories, water management and associated risks, droughts, floods, the study of complex ecosystems and of biodiversity and its relationship with human activity. The multi-disciplinary research conducted supports public policies and works in partnership with regional authorities and socio-economic entities (Irstea, 2014).

The project I worked for during my six-month internship is a research project called "Construction and potential indicator value of multi-scale forest structure indices (CONSPIIRE)". It aims at increasing the knowledge on the link between forest structure and biodiversity and improving the indicator value of forest structure indices. Funded by Irstea, the project started in late 2013 for a duration of two years and is a collaboration between researchers in the Nogent-sur Vernisson, Grenoble and Aix-en-Provence Irstea centers.

## ABSTRACT

Nineteen forest structure indices were compiled and compared to test how they differ in their characterization of managed and unmanaged stands in French forests. Thirteen distance-independent diameter diversity forest structure indices and six distance-dependent indices were used to characterize and compare 257 managed and unmanaged stands in 20 lowland and mountain sites part of a national stand network in France. Most spatially-implicit diameter diversity indices characterized unmanaged lowland forest stands as more complex to a certain degree with significantly superior basal areas, variability, diversity, dominance and inequality than their managed counterparts. Management differences were not as evident in the case of mountain forest sites due to their uneven-aged long rotation cycles. Distance-dependent indices were unable to provide clear results as to the spatial pattern of stands, due to the small fixed area plot size. Additional neighbor measurements as part of the larger angle-count method could help characterize the stands spatially. Indices with the best discriminant ability and reliability that can be used to monitor the forest structure of these stands and the shift from forest management to natural forest development include the basal area, the coefficient of variation of the diameter, the Shannon index, and the Gini coefficient.

## RESUME

Dix-neuf indices de structure forestière furent compilés et comparés pour déterminer en quoi ils diffèrent dans leur description de placettes exploitées et non-exploitées françaises. Treize indices de diamètre et six indices spatiaux quantifièrent la structure de 257 placettes forestières exploitées et non-exploitées réparties sur 20 massifs de plaines et de montagnes dans un réseau national de placettes en France. La majorité des indices de diamètre caractérisèrent les zones non-exploitées en plaine avec des surfaces terrières plus élevées, et des diamètres plus variables, diverses, dominants, et inégaux, que les forêts exploitées. En montagne, les écarts étaient moins significatifs à cause de la structure équiennne et des rotations à long terme des placettes exploitées. Pour la structure spatiale des placettes, les résultats obtenus ne furent pas concluants car la dimension des placettes à rayon fixe était trop petite. La mesure d'arbres voisins supplémentaires dans la mesure d'arbres à angle fixe aiderait à caractériser les placettes spatialement. Les indices les mieux capables de discerner entre placettes exploitées et non-exploitées peuvent cerner leur structure forestière et leur passage d'une forêt exploitée à une forêt naturelle – ceux-ci sont : la surface terrière, le coefficient de variation du diamètre, l'indice de Shannon et l'indice de Gini.

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# 1. INTRODUCTION

The importance of forest ecosystems and their management have risen to the public attention in the past few decades since the establishment of the Convention on Biological Diversity (CBD) in 1992. While tropical forests are experiencing high rates of deforestation, the area of temperate forests has broadly stabilized, with a slight increase in Europe (CBD, 2014a, CBD, 2014b, United Nations Environment Programme et al., 2009).

In mainland France, forests cover about 30% of the territory with 17.6 million hectares, out of which one quarter are public and the rest are private (Ministère de l'écologie, 2015). France has put the accent on biodiversity and its preservation with its adherence to the CBD, its own national policies towards protecting the environment under its National Strategy for Biodiversity adopted in 2004 and the adoption of the Grenelle Environment framework of 2007, which includes forest logging and biodiversity (Gosselin & Laroussinie, 2004). The French state monitors whether it has met its biodiversity and forestry targets mainly via the National Observatory of Biodiversity (ONB) indicators, which focus on dead wood and forest surfaces with multi-stories (ONB, 2011). At a European level, six criteria are used for sustainable forest management, including the promotion of forests' biological diversity, health and vitality and productive functions (Forest Europe, 2014).

French forest management along with forest and biodiversity levels has also been monitored via the comparison of the structure of managed (i.e. exploited) and unmanaged (i.e. forest reserves) stands (Paillet et al., 2010). Natural dynamics, lacking in anthropogenic pressures, tend to result in more complex forest structures (Hett & Loucks, 1976, Paillet et al., 2010), whereas management decisions can lead to structures that are more uniform (Lähde et al., 1999). Forest structure can thus be a proxy to biodiversity since a positive correlation has been found between structural variables and richness (Tews et al., 2004).

Forest structure is an important element of biodiversity, and more precisely forest stand biodiversity (LeMay & Staudhammer, 2005, MacArthur & MacArthur, 1961). Stands with a variation of tree sizes tend to have higher biodiversity and structural diversity, which is why tree size is one of the most significant indicators of forest diversity (Buongiorno et al., 1994, MacArthur & MacArthur, 1961).

Since forest stands tend to have multiple dimensions, it is sometimes challenging to describe forest structure adequately. McElhinny (2002) defined forest structure as a polysemic term divided into three different attribute groupings: structure, function and composition, whereby structure means the spatial arrangement between components of an ecosystem, function stands for ecological processes and composition refers to the variety and identity of elements (McElhinny, 2002). Stand structure includes vertical structure (e.g. understory trees, number of tree layers), defined as the differentiation of layers between ground and the canopy (Bourgeron, 1983, Maltamo et al., 2005, Zimble et al., 2003), and horizontal structures (e.g. spatial pattern of trees, gaps), referring to the diameter size distribution of either individual or trees species within one community (Davis & Johnson, 1987, Maltamo et al., 2005, Zimble et al., 2003).

According to Pretzsch (2009), the most important aspects of stand structure are the horizontal distribution configuration of trees, density of the stand, the differentiation of sizes, and species intermingling since they affect habitats, growth processes, and the stability of the ecosystems. Since the most common elements of stand structure measured in France include (but is not limited to) live tree diameter and geographical position (Bruciamacchie et al., 2007, Tomppo et al., 2010), this study focuses on these elements of horizontal structure and defines stand structure as the distribution of live tree sizes within a forest stand (Newton, 2007).

Indices are often used for describing changes in the structure of a forest stand or for stand comparison since they compress multiple dimensions concisely into a single number (Magurran, 2004, McElhinny et al., 2005). Measurements of a few structural attributes such as live-tree sizes

or horizontal variation in canopy density can help estimate other structural conditions and the ecological state of a forest (Spies, 1998). Structural complexity can be a surrogate for the potential of forest stands for biodiversity, and as such differentiating stands with different structural states can be useful as metrics and indices but also provide clues as to the driving structure of ecological processes (Peck et al., 2013). Structural complexity can be defined as the spatial horizontal and vertical arrangement of plant dimensions (Zenner, 2000).

The majority of comparative studies in the past have focused on classical old growth forest structure measures such as basal area, large trees and dead wood for the characterization of unmanaged old growth stands and their comparison to managed stands (Christensen & Emborg, 1996, McElhinny, 2002, Nilsson & Baranowski, 1997, Pernot et al., 2013). In terms of other measures or indices that can be used, there is no single forest structure index preferred over the others, so selecting an appropriate index for the comparison of stands can be difficult (McElhinny et al., 2005). Authors differ in their preference of stand elements (e.g. diameter, height, tree spacing) or structural attributes<sup>1</sup>, construction of the index as well as the use of spatial patterns (LeMay & Staudhammer, 2005, McElhinny, 2002).

Authors that have applied structural indices to forest stands have made a distinction between plantations, even-aged, managed stands and uneven-aged, semi-natural and natural (or primary) forests stands (Commarmot et al., 2005, Ex & Smith, 2013, Lexerød & Eid, 2006, Marinšek & Dlaci, 2011, Mason et al., 2007, Sterba, 2008, Sterba & Zingg, 2006, Szmyt, 2012, Uuttera et al., 2000, Vencurik et al., 2012). One case-study by Bilek et al. (2011) in Central Bohemia compared spatially-implicit (i.e. distance-independent) and spatially-explicit (i.e. distance-dependent) indices in managed and unmanaged stands over time. Nevertheless, a large scale comparative investigation of forest structural complexities through a broad national stand network has not been attempted to date (to this author's knowledge) and can help represent the structural variability of French temperate forests between managed and unmanaged stands (Clark, 2007, Wagner et al., 2010).

The six-month internship that led to the writing of this master thesis took place within the *Institut de recherche en sciences et technologies pour l'environnement et l'agriculture* (Irstea). The Irstea project that funded the internship is called the "Construction and indicator value of multi-scale forest structural indices" (CONSPIIRE) project and aims at finding a relevant indicator value of forest structure indices and its link to biodiversity (Irstea, 2015). The research will feed into the ongoing efforts to improve the Indicators of Sustainable French Forests Management and the European reporting on the state of forests coordinated by Forest Europe (see Annex 1 for more details on the CONSPIIRE project).

The internship focused purely on horizontal and spatial forest structure indices, because, as was argued above, they can be a reliable proxy to biodiversity and management differences. The internship represents a first step towards increasing the knowledge on forest structure indices already in use in the literature and their usefulness in comparing management structures. The first internship objective was to conduct a literature review of forest structure indices and the subsequent selection of appropriate indices for a comparison of managed and unmanaged stands. The selected indices were narrowed down based on the literature review on diameter diversity and spatial forest structure indices at the stand level as well as data availability so that the second aim of the study can be completed.

Once indices have been selected, the second objectives of the study is to calculate the selected indices in order to compare managed and unmanaged stands using pre-existing data. The data for the calculation of the indices stems from data compiled in a French national forest stand network, which included the measurements of live tree diameter and location and further narrowed down the choice of indices. Once calculated, the thesis will investigate which indices can best indicate which diameter diversity and spatial forest structure indices can detect a management difference.

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<sup>1</sup> Stand attributes describe the identity and variety of stand elements, their spatial arrangement or the types and rates of ecological processes; common stand attributes are tree diameter at breast height (DBH), standard deviation of DBH, diameter distribution, and basal area (McElhinny et al, 2005).

The study will examine whether managed and unmanaged forest stands differ in a French plot network according to diameter diversity and spatial forest structure indices. The null hypothesis is that there is no significant difference in the forest structure indices selected between managed and unmanaged zones.

The problem statement of the thesis is therefore: how do the forest structure indices selected differ between managed and unmanaged stands? The aim of the thesis is to look at the difference in diameter sizes and spatial patterns characteristics in managed stands where human interventions have influenced forest stands and how these stands differ from unmanaged adjacent plots (for a minimum of 20 years and an average of 50 years) in similar stand conditions<sup>2</sup>. With the majority of forest structures exploited in Europe at a time or another, forest structures between managed and unmanaged stands would be expected to show a variation ranging from old growth characteristics to forest plantations although unmanaged stands would be expected to have more old growth characteristics (Wolf, 2005). Managed plots can be used as a benchmark or a control since they are the starting point for restored unmanaged plots and how these are progressing to a more natural state (Sterba, 2008).

This study will take place in the Forest Management, Naturality and Biodiversity (GNB, <http://gnb.irstea.fr>) stand network in France comprising of a total of 20 forests and 257 stands inventoried. Nineteen indices were calculated for the stands in order to gauge which indices can detect a difference in management. In the first part of the study, materials and methods are described which includes the study site description, and details on data collection and data analysis. A short review of index literature and a list of the indices selected for the analysis and details on their calculation is included in this first part. In the second part of the study, the results of the indices are revealed. The last part includes a discussion on the characteristics of managed and unmanaged stands, on the management differences between lowland and mountain stands, and on which indices were able to detect a management difference and can be relevant for future studies. The relevance of the spatial indices and the sampling method used for the study are also discussed.

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<sup>2</sup> For a study on how discontinuing logging activity affects forest structure in French forest reserves, please refer to Pernot et al, 2014.

## 2. MATERIAL AND METHODS

### 2.1. Description of the study sites

The study uses data gathered as part of the *Gestion forestière, Naturalité et Biodiversité* (GNB, <http://gnb.irstea.fr>) forest stand network illustrated in Figure 1. The GNB project began in 2008 in partnership with the National Forest Service (ONF) and the Natural Reserves of France (NR) and aims at evaluating the impact of forest exploitation on biodiversity (Irstea, 2015, Pernot et al., 2013). The network comprises of a total of 20 beech-dominated forest sites, representing around 40% of the total woodland in mainland France (IGN, 2014), including managed and unmanaged areas in controlled site conditions.

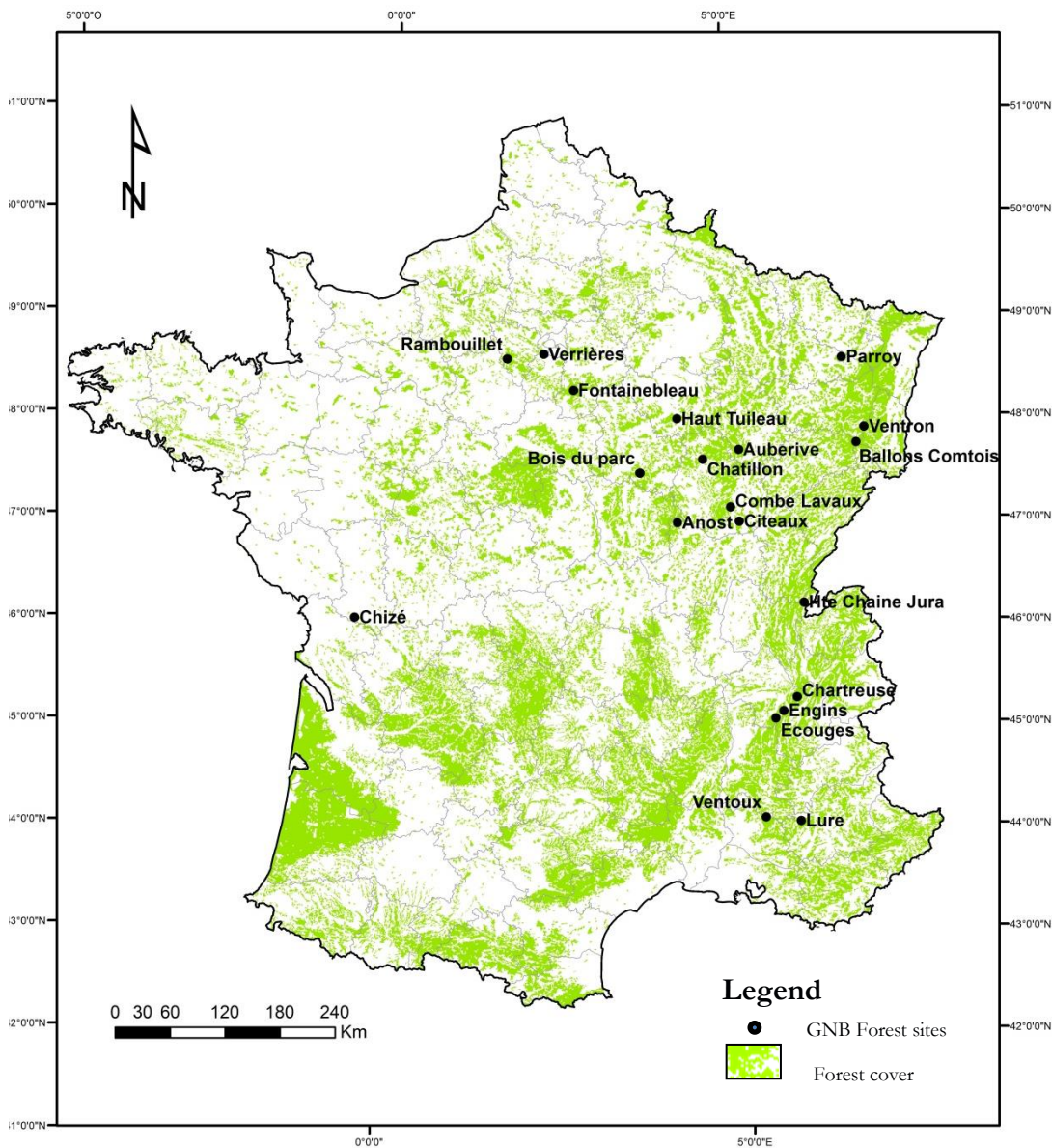


Figure 1: Existing GNB forest stand network in metropolitan France as of mid-2014 (Modified from GNB, 2014)

The GNB forest sites were selected according to the following criteria<sup>3</sup>:

- Existence of a strict reserve at least 20 years old;
- Forests were also chosen based on their predominant tree species - beech (*Fagus sylvatica* L.) and oak (*Quercus robur* L.) were favored for lowland/plain sites (elevation  $\leq$  800 meters (m)) and fir (*Abies alba* Mill.) and spruce (*Picea abies* Karst.) were favored in mountain sites (elevation  $>$  800m).

Table 1: GNB forest sites as of mid-2014

Forest sites	MAN stands	UNM stands	Average altitude	Class of altitude *	Management type	Surface (ha)	UNM surface (ha)
Anost (ANO)	4	4	686	LOW	Even-aged	1,030	68
Auberive (AUB)	12	12	455	LOW	Uneven-aged	5,580	232
Bois du Parc (BDP)	5	5	183	LOW	Even-aged	1,600	45
Chatillon-sur-Seine (CHS)	4	4	354	LOW	Even-aged & uneven-aged	8,900	76
Chizé (CHZ)	12	12	80	LOW	Even-aged	4,820	2,579
Cîteaux (CIT)	6	6	232	LOW	Even-aged	3,561	47
Combe-Lavaux (CL)	4	4	428	LOW	Even-aged	4,056	300
Fontainebleau (FTB)	13	16	132	LOW	Even-aged	17,072	444
Haut Tuileau (HT)	7	7	164	LOW	Even-aged	2,567	127
Parroy (PAR)	4	4	272	LOW	Even-aged	2,790	161
Rambouillet (RMB)	8	8	168	LOW	Even-aged	14,090	115
Verrières (VER)	4	4	173	LOW	Even-aged	576	42
Ballons-Comtois (BC)	8	8	1,013	MON	Uneven-aged	2,259	274
Chartreuse (CHA)	5	5	1,278	MON	Uneven-aged	NA	50
Ecouges (ECO)	5	5	NA	MON	Uneven-aged	NA	248
Engins (ENG)	5	5	1,581	MON	Uneven-aged	1,016	190
Haute Chaîne du Jura (HCJ)	8	8	816	MON	Uneven-aged	7,989	2,130
Lure (LR)	4	4	1,463	MON	Uneven-aged	3,981	553
Ventoux (VTX)	5	5	1,343	MON	Uneven-aged	3,474	907
Ventron (VEN)	4	4	933	MON	Uneven-aged	1,648	397
Total	127	130				39,282	8,985

\* LOW stands for lowland sites and MON for mountain sites; MAN stands for managed stands and UNM for unmanaged stands; NA= Not available.

In order to avoid a possible bias because of site factors (such as biogeographic regions, altitude, slope and soil acidity) between unmanaged and managed stands, the locations of the stands were picked at random with a site-specific constraint to make sure each managed stand had an unmanaged stand equivalent. Managed plots were selected in a radius of 5 kilometers from the forest reserve boundary and included only native tree species. The 257 sites cover a broad array of

<sup>3</sup> Details on the GNB forest site criteria and how they were determined are available on the GNB website ([gnb.irstea.fr](http://gnb.irstea.fr)) but are not discussed further in this thesis since they do not fall within the purview of this study.

stand structural stages ranging from regeneration to old growth stands. Due to field constraints, the final sample of 257 stands is not entirely balanced and comprises of more lowland sites than mountain sites. Most of the uneven-aged forests were located in the mountains whereas the even-aged high forests were located in lowland sites as shown by Table 1. As of mid-2014, the project had inventoried a total of 257 individual stands in 20 forests in lowland/plain and mountain sites (see Figure 1), which are divided into lowland and mountain categories in Table 1.

## 2.2. Data collection

GNB data were recorded for the 257 stands from 2008 to mid-2014 by Irstea, ONF and NR staff members as well as Irstea interns. The year period for the inventories vary (details of when inventories took place are available in Annex 2).

The GNB protocol followed the national forest evaluation protocol (Bruciamacchie et al., 2007, Paillet et al., In prep) and included diameter measurements and species documenting of live trees, dead and regenerating trees as well as biodiversity data on seven taxa (vascular flora, bryophytes, mushrooms, beetles, birds, bats and deer) (GNB, 2014).

Relevant measures to the study include diameter at breast height (1.3 m above the ground, dbh) at two different angles and tree locations using a combination of fixed-angle and fixed-area tree-sampling methods (see Figure 2 for an illustration of the two methods). Within a fixed area with a radius of 10 m (314 m<sup>2</sup>), the dbh of living trees was measured for trees ranging from 7.5 to 20 cm in the plains (7.5 to 30cm in mountain stands). A fixed-angle method was used to inventory living trees over 20 cm in dbh (30 cm in mountains) where trees within a fixed relascope angle of 2% (3% in mountains) were measured at a maximum distance of 40 m. The Global Positioning System (GPS) coordinates of each stand center were recorded, as well as the azimuth and distance of each live tree from the center of the stand. The protocol varied in mountains due to rougher conditions. Annex 2 contains summary statistics for each of the 257 stands, including mean dbh, the number of trees at 40 m, 20 m and 10 m as well as the XY GPS coordinates of each stand.

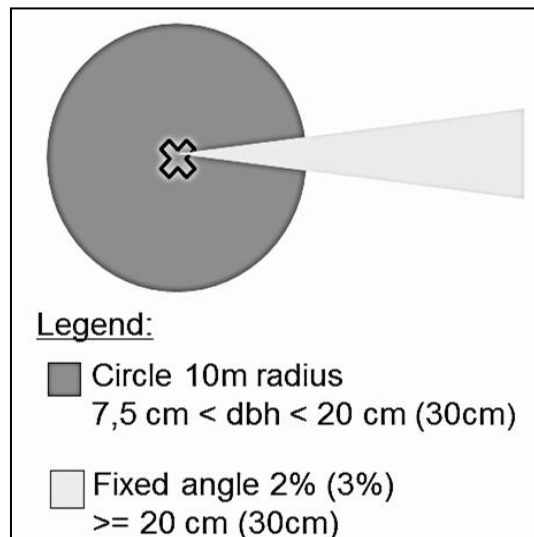


Figure 2: Illustration of the two sampling methods used by GNB

During the internship, a second complementary protocol to the GNB protocol was developed and carried out, available in French in Annex 3. The two-month fieldwork consisted of measuring the height of the five trees with the largest diameters in the 257 stands, the canopy cover of each stand, and the cover of vertical strata of each stand. While the data extracted from the internship fieldwork was not used in the purview of this study, it will be used for future CONSPIIRE work.

## 2.3. Description of the indices

During the internship, a literature review of forest structure indices has been carried out and 19 forest structure indices were selected at the stand level for the comparison of managed and unmanaged stands. The literature protocol in Annex 4, based on Pullin and Stewart (2006) guidelines for systematic literature reviews, was used to conduct the literature review.

Since there are a myriad of indices in the literature used for analyzing forest stands, reviews can be particularly useful for grouping and selecting indices. Reviews on forest structure indices at the stand level include works from Staudhammer (1999), McElhinny (2002), Pommerening (2002), and LeMay and Staudhammer (2005). These and other authors have grouped indices in various

ways. LeMay and Staudhammer (2005) have the following groupings: indices based on tree attributes, indices based on spatial heterogeneity, and a combination of the two. Pommerening (2002 & 2006) classed them in terms of their diversity of tree dimensions; tree species diversity; and tree positions diversity (or spatial distribution), and then further divided them into distance-dependent and distance-independent measures. Valbuena et al. (2012) identified four types of distance-independent indices that describe the diversity of tree size classes: adapted species biodiversity indices, adapted species equitability indices, indices based on dispersion estimates of tree size and methods based on descriptors of a histogram's shape. On the other hand, distance-dependent indices can be divided as tree-level nearest neighbor or competition indices; stand level aggregation or neighborhood indices (Aguirre et al., 2003, Gadow & Hui, 2002, Hui et al., 1998); and second order characteristics (Neumann & Starlinger, 2001, Ni et al., 2014, Pommerening, 2006, Sterba & Zingg, 2006, Szmyt, 2014). Some authors have also developed multi-attribute (or complex) indices and synthetic (or composite) indices which incorporate more than one index (Becagli et al., 2009, Jaehne & Dohrenbusch, 1997, LeMay & Staudhammer, 2006, Pastorella & Paletto, 2013, Staudhammer & LeMay, 2001). Figure 2 provides an overview of the different groups of forest structure indices found within the literature (with the exclusion of the species diversity indices as it is outside the scope of this study).

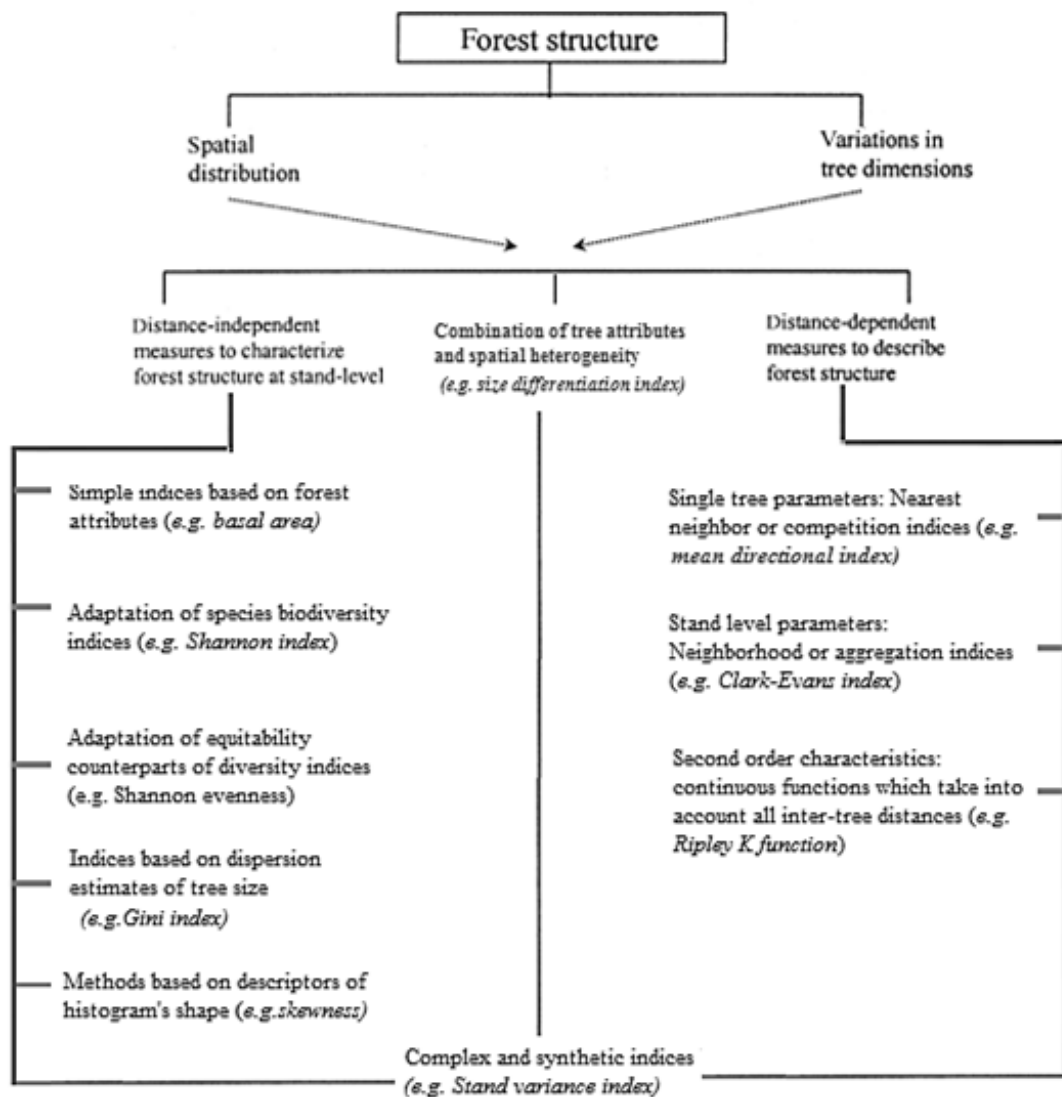


Figure 3: Overview of the groups of indices by which forest structure is assessed (modified from Pommerening, 2002)



The 19 indices selected for the study were based on the following criteria:

- Appropriateness, mention and use in literature – at least two journal articles on forest structure need to have mentioned the indices;
- Use of diameter, diameter classes and/or location (since this is the data available for the study);
- Resulting in a single index value;
- Ease of calculation as well as access and availability of R scripts and R packages for their calculation;
- At least one index (and a maximum of three indices) per the categories illustrated in Figure 2 was selected – apart from complex and synthetic indices, which lay outside the bounds of this study.

Table 2 gives an overview of the indices used in this study based on the criteria above. The indices have been divided into distance-independent and distance-dependent categories and are described below.

Table 2: Description of indices selected and related R software resources

Index	Formula	Where	Range	R package / script
Standard deviation	$s = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (x_i - \bar{x})^2}$ (1)	$\bar{x}$ = sample mean $x_i$ =ith observation in sample N=sample size		stats (R Core Team, 2014)
Coefficient of variation	$cv(\%) = \left(\frac{s}{\bar{x}}\right) * 100$ (2)	s=standard deviation x=sample population		stats (R Core Team, 2014)
Basal area	$g = \frac{\pi d^2}{4}$ (3)	d = tree dbh		stats (R Core Team, 2014)
Stand density index	$SDI = N * (QMD / 25.4)^{1.605}$ (4)	QMD= Quadratic mean diameter i= ranges from 1 to N N = number of trees per hectare		stats (R Core Team, 2014)
Shannon index	$H' = - \sum_{j=1}^s p_j \ln p_j$ (5)	$p_i$ = proportion of individuals in the ith diameter class, S= number of size classes	[0; 2.39*] * $H'_{max} = \ln(S)$	BiodiversityR (Kindt, 2005)
Simpson index	$D_s = \frac{1}{\sum_{i=1}^s (p_i)^2}$ (6)	$p_i$ = relative frequency of number of stems at each size class	[0; 11*] * $D_{max} = S$	BiodiversityR (Kindt, 2005)
Berger-Parker index	$D_{BP} = 1 / \max(p_i)$ (7)	p= relative frequency of number of stems at each size class	[0; 1]	BiodiversityR (Kindt, 2005)
Shannon Evenness	$E = H' / H'_{max} = H' / \ln S$ (8)	$H'$ =Shannon index $H'_{max}$ = Max Shannon S= number of size classes	[0; 1]	BiodiversityR (Kindt, 2005)
Simpson Evenness	$E_s = 1 \left( 1 + \left( \frac{Var(pi)}{D_s^2} \right) \right)$ (9)	$D_s$ = Simpson index $Var(p_i)$ =variance of abundance $p_i$	[0; 1]	BiodiversityR (Kindt, 2005)

Index	Formula	Where	Range	R package / script
Gini index	$G = \frac{\sum_1^n (2i - n - 1) di}{\sum di(n - 1)} \quad (10)$	d = dbh in diameter size class i = rank of a tree in ascending order n = total number of trees	[0;1] = 0 – equality = 1 – inequality	reldist (Handcock, 2014)
Skewness	$g_1 = \frac{n \sum (X_i - \bar{X})^3 / ((n - 1)(n - 2))}{s^3} \quad (11)$	n = number of sample trees/ plot x <sub>i</sub> = individual tree dbh, $\bar{x}$ = mean tree dbh s = standard deviation of tree dbh	< 0 - negatively skewed = 0 - symmetric > 0 - positively skewed	moments (Komsta, 2012)
Lorimer index	$I = \frac{M - X_L}{X_{0.95} - X_L} \quad (12)$	M = the mode, X <sub>L</sub> = the lower threshold dbh X <sub>0.95</sub> = the 95th percentile of the diameter distribution	< 0.5 - negatively skewed = 0.5 - symmetric > 0.5 - positively skewed	stats (R Core Team, 2014)
Kurtosis	$g_2 = \frac{\sum (X_i - \bar{X})^4 n(n + 1)(n - 1) - 3 \left[ \sum (X_i - \bar{X})^2 \right]^2}{(n - 2)(n - 3) s^4} \quad (13)$	n = number of sample trees/ plot x <sub>i</sub> = individual tree dbh, $\bar{x}$ = mean tree dbh s = standard deviation of tree dbh	> 3 – leptokurtic = 3 – mesokurtic < 3 – platykurtic	moments (Komsta, 2012)
Mean directional index	$R_i = \sqrt{1 + \sum_{j=4}^n \cos(a_{ij}) + \sum_{j=4}^n \sin(a_{ij})} \quad (14)$	a <sub>ij</sub> = angle between i and j points	= 0 – square lattice arrangement > 0 – clustered arrangement	Diversity indices script (Pommerening, 2012)
Clark Evans index	$R = \frac{\bar{r}_{observed}}{E(r)} \quad (15)$	$\bar{r}_{observed}$ = observed mean distances between trees E(r) = mean nearest neighbor distance in stand with completely random tree locations of intensity N/A, whereby: $E(r) = 1 / 2 \left( \sqrt{N / A} \right) \quad (16)$ A = area of forest stand (m <sup>2</sup> ) N = number of trees	[0;2.1491] > 1 - regular pattern = 1 - a random pattern < 1 - a clustered pattern	spatstat (Baddeley, 2005)

Index	Formula	Where	Range	R package / script
Hopkins-Skellam index	$A = \frac{\sum_{i=1}^N \omega'_i}{\sum_{i=1}^N \omega'_i + \sum_{i=1}^N \omega_i} \quad (17)$	$\omega'_i$ = quadratic distance from sample point to nearest tree $\omega_i$ = quadratic distance from tree to nearest neighboring tree	$> 1$ - aggregated population $= 1$ - randomly distributed population $< 1$ - regular population	spatstat (Baddeley, 2005)
Ripley L function	$\hat{L}(d) = \sqrt{\frac{\hat{K}(d)}{\pi}} - d \quad (18)$	$K(d) = \frac{1}{\sum_{0 < \ x_i - x_j\  \leq d} \lambda^2 s(\ x_i - x_j\ )} \quad (19)$ $s(r) = \frac{ab - r(2a + 2b - r)}{\pi} \quad (20)$ <p>stand <math>\lambda</math> = density  <math>r</math> = distance  <math>\ x_i - x_j\ </math> = distance between tree <math>i</math> and <math>j</math>  <math>s(r)</math> = edge effect correction where <math>a, b</math> are dimensions of the rectangular plot</p>	$[0;1]$ $= 0$ - random population $> 0$ - clustering $< 0$ - regularity	splanx (Rowlingson, 2014)
Dbh Differentiation	$T_{ij} = 1 - \frac{\min(DBH_i, DBH_j)}{\max(DBH_i, DBH_j)} \quad (21)$	DBH = breast height diameter	$[0;1]$ $= 0$ - No differentiation $= 1$ - very strong differentiation	Diversity indices script (Pommerening, 2012)
Dbh dominance	$U_i = \frac{1}{n} \sum_{j=4}^n u_j \quad (22)$	$n$ = number of neighbor trees $j$ = DBH of neighbor trees $n$ $u_j = 1$ , if $DBH_j \geq DBH_i$ ; otherwise 0	$[0;1]$ $= 0$ - No dominance $= 1$ - very strong dominance	Diversity indices script (Pommerening, 2012)



### 2.3.1. Distance-independent indices

The distance independent indices are the following:

#### 2.3.1.1 *Simple indices*

The standard deviation (Husch et al., 2003) of tree dbh measures the variability in tree dimension, thus is a straightforward attribute to calculate. It has been compared in its usefulness to describe stand structure to more complex attributes and indices (Neumann & Starlinger, 2001).

The coefficient of variation of tree dbh measures size inequality (Hutchings, 1997) – it is the percentage of the arithmetic mean of the standard deviation and is used to compare population samples in relative variability.

Basal area is a useful measure of stand density and competition since it incorporates the number of trees and diameters in a stand. It is calculated by summing the section at 1.30m of each individual tree (Husch et al., 2003).

The stand density index (Reineke, 1933) describes stand density by calculating the quadratic mean diameter and number of stems per unit area. It uses an index tree diameter of 25cm in Europe (10 inches in the U.S.) and a constant  $b$  of -1.605, which Reineke (1933) found was consistent with several species and age and site quality independent (Pretzsch & Biber, 2005).

#### 2.3.1.2 *Adapted species biodiversity indices*

A straightforward way to describe forest complexity would be to just determine the number of size classes in a stand (richness) (Valbuena et al., 2012). The following six indices are based on size classes.

Adapted from the Shannon diversity index for species (Shannon & Weaver, 1949), the Shannon index for diameter classes describes the class richness and relative abundance of every class as well as its rarity by measuring the uncertainty of a tree belonging to a class as a weighted average (Buongiorno et al., 1994, LeMay & Staudhammer, 2005, Pommerening, 2002, Staudhammer, 1999, Valbuena et al., 2012). In this case, the Shannon index has a minimum of zero when all trees are in the same diameter class and a maximum of the logarithm of the total number of classes when trees are evenly distributed in all diameter classes (Lexerød & Eid, 2006).

The Simpson concentration index (Simpson, 1949) for diameter classes is an index of dominance (weighted to the most abundant class) and expresses the chance that any two random trees belong to the same size class (Lexerød & Eid, 2006, Valbuena et al., 2012). A reciprocal form of the index was used in this study ( $1/\text{index value}$ ), also known as the inverse Simpson index of diversity, so that the index values increase with any diversity increase (Lexerød & Eid, 2006). The Simpson index ranges from a minimum of zero to a maximum equaling the total number of diameter classes. It accounts for dominance in a similar way to Shannon (the more dominant a class, the higher its Simpson index).

Described as one of the “most satisfactory indices of diversity available” (Magurran, 2004), the Berger-Parker index (Berger & Parker, 1970) is another dominance measure independent of the number of classes of diameter. It is the reciprocal of probability of the most dominant diameter class, therefore ignoring the frequency of the rarer size classes (Lexerød & Eid, 2006, Valbuena et al., 2012). The reciprocal value of the Berger-Parker index ranges from 0 to 1 and increases with more evenness and lower dominance.

#### 2.3.1.3 *Adapted equitability biodiversity indices*

The Shannon or Pielou index (Pielou, 1969) is a measure of evenness between size classes as it is the ratio of absolute diversity to the maximum diversity of classes possible (Lexerød & Eid, 2006, Staudhammer, 1999).

The Simpson evenness (Magurran, 2004, Pielou, 1969) measures the relative abundance of the size classes in a stand – and therefore normalizes the figures with respect to the maximum value possible (Valbuena et al., 2012).

Both Shannon evenness and Simpson evenness indices range from 0 (distribution between size classes not even) to 1 (distribution between size classes completely even) and measure the abundance of the different dbh classes within a forest stand.

#### 2.3.1.4 *Dispersion indices*

The Gini index (Gini, 1921) measures size inequality and quantifies the deviation from perfect equality by calculating the area under the Lorenz curve derived by plotting the cumulative size classes of trees per hectare against the proportions of the number of stems per hectare (Bilek et al., 2011, McCarthy & Weetman, 2007). It has been described as an indicator that performs better than other forest structure indices at gauging the heterogeneity of tree sizes (Lexerød & Eid, 2006, Valbuena et al., 2012). The Gini coefficient has a value close to 0 for a homogeneous forest stand and closer to 1 for a heterogeneous forest stand.

#### 2.3.1.5 *Descriptors of histogram's shape*

Skewness or asymmetry of the diameter distribution is an important diversity measure and is described as the departure from symmetry, with the assumption of normal distribution (Hui & Pommerening, 2014, McCarthy & Weetman, 2007, Siipilehto, 2011, Sterba & Zingg, 2006).

Lorimer's index of symmetry (Lorimer & Krug, 1983) can distinguish between descending monotonic, skewed and symmetric unimodal tree diameters (McCarthy & Weetman, 2007).

The skewness and Lorimer index are both related to the shape of the histogram and its symmetry, whereby a symmetric distribution would have a skewness of 0 and a lorimer index of 0.5. A positively skewed distribution would have a positive skewness ( $>0$ ) and a lorimer index above 0 and under 0.5 while a negative skewed distribution would have a negative skewness value ( $<0$ ) and a lorimer index above 0.5 and under 1. The main difference between the two is that Lorimer takes into account the difference between median and mode while for skewness the distribution is symmetrical around the mean and median.

Kurtosis is an indicator of the diameter distribution as well that describes the shape (or peakedness) of a distribution that is assumed to be normal; it tends to be more influenced by a few extreme differences from the mean than a lot of small differences (McCarthy & Weetman, 2007, Siipilehto, 2011). The kurtosis distribution analysis distinguishes between the normal distribution or mesokurtic ( $=3$ ), platykurtic ( $<3$ ) and leptokurtic ( $>3$ ) distribution. A higher kurtosis means there is more variability due to a few extreme differences from the mean.

### 2.3.2. Distance-dependent indices

Spatially explicit indices indicate whether a spatial point process has complete spatial randomness (CSR), i.e. if it follows a non-heterogeneous Poisson process, regularity or clustering in a stand (Diggle, 1983). The distance-dependent indices are the following:

#### 2.3.2.1 *Nearest neighbor indices*

An angle-based index, the mean directional index (Corral-Rivas, 2006) is a nearest neighbor tree parameter index representing the spatial arrangement of trees. It aims to characterize a reference tree by the different directions under which the  $n$  nearest neighbors can be seen (Corral-Rivas, 2006, Motz et al., 2010). It is easy to calculate and interpret as it does not require tree to tree distances and is a good estimation of non-randomness: if it has a value of 0, it means the spatial arrangement is in a square lattice and increasing values indicate more clustered patterns (Corral-Rivas et al., 2010, Motz et al., 2010, Szmyt, 2014).

#### 2.3.2.2 *Neighborhood indices*

The aggregation, clumping or Clark-Evans index (Clark & Evans, 1965) represents the variability of tree locations in a forest stand. It is based on the distance of a tree to its nearest neighbor and describes the degree of departure from CSR in a spatial point process (Sterba & Zingg, 2006).

The Hopkins-Skellam aggregation index (Hopkins & Skellam, 1954) can be used in combination with the Clark-Evans index in order to evaluate the spatial pattern of stands. It is the sum of the squared distances from point to plant divided by the sum of the squared distances from tree to tree (Bilek et al., 2011).

Clark-Evans aggregation index (CE) and Hopkins-Skellam aggregation index (HS) are both distance methods used to evaluate the pattern of tree locations based on an assumption of a randomly distributed population. If a population is random, both indices equal 1 ( $=1$ ). For an aggregated distribution of trees, CE would be inferior to 1 ( $CE < 1$ ) and HS superior to 1 ( $HS > 1$ ), while a regular distribution CE would be greater than 1 ( $CE > 1$ ) and HS would be below 1 ( $HS < 1$ ).

### 2.3.2.3 *Second order characteristics*

The K function (Ripley, 1976, Ripley, 1977) tends to be a good indicator for spatial forest structures as it provides an idea of how many trees are within a certain distance from the average tree (its formula is available in Table 2) (Besag, 1977, Diggle, 1983, Mason et al., 2007). It tests the departures of tree distances from CSR and considers the distances between all trees in a population (Mason et al., 2007, Szmyt, 2014). Its output is normally a graph where Ripley's K is graphed against an increasing radius (LeMay & Staudhammer, 2005). In this case, due to practical limitations, Ripley's K has been determined as a single index value at a distance of 5 m and 10 m. In order to make the results easy to interpret, Besag's L transformation (Besag, 1977) has been used, which linearizes and standardizes the variance of Ripley's K function, where  $L=0$  if there is CSR (Mason et al., 2007, Montes et al., 2008, Szmyt, 2014).

### 2.3.3. Combination indices

The size differentiation index and dominance index are single tree parameter indices used to calculate the neighbors around one single tree (i.e. the reference tree). The dbh differentiation index describes the variability of dbh in neighboring trees in a stand (Füldner, 1995, Motz et al., 2010, Sterba & Zingg, 2006). The larger the differences between the dbh of the reference tree and its  $n$  nearest neighbors, the larger the index value which ranges from 0 to 1 (Füldner, 1995, Motz et al., 2010, Pommerening, 2002).

The dominance index (or size/dbh dominance index) (Hui et al., 1998) measures the diversity of tree dimensions based on dbh, and gives the proportion of the  $n$  nearest neighbor trees smaller than the reference tree (Motz et al., 2010). Similar to the dbh differentiation index, the larger the dominance of a reference tree to its neighbors, the larger the index value ranging from 0 to 1 (Motz et al., 2010).

## 2.4. Calculation of the indices

The R v.3.1.1 software (R Core Team, 2014) was used to calculate all the selected indices – the R packages or scripts used for each index are detailed in Table 2. One R script called “Diversity indices script” is available online at <http://www.crancod.org/wiki/images/8/84/TreeDiversityIndices.R> for the calculation of the diameter differentiation index, the diameter dominance index and the mean directional index (Pommerening, 2012) – its modified version is available in Annex 5. The rest of the 16 indices were calculated in R by the thesis author and are available in Annex 6.

### 2.4.1. Distance-independent indices

Spatially inexplicit indices of structural diversity were calculated based on a stand radius of 40 meters, where both angle count and fixed radius plot sampling were used (see Section 2.2). Basal area and dbh related diversity indices (i.e. Shannon and Simpson indices) can be estimated by both sampling methods with at least the same accuracy according to Motz et al. (2010).



Mean dbh in cm was calculated by taking the average of the two dbh measurements collected – when only one measurement was available, that same measurement was used. For some indices (Berger Parker, Shannon evenness, Simpson evenness, Gini index), the particular R function (see table 2 for more details on the functions used) required that stands with no trees (representing three regeneration stands in the data) be removed, while the Lorimer index function required that stands with no trees and only one tree (a total of two stands in the data) be removed for the function to work.

The adapted species indices, adapted equitability indices and dispersion index are based on size classes and therefore required that the stems be divided into different classes. Eleven classes were created and each tree was classified in 10 centimeter (cm) diameter classes ranging from under 10 cm (<10) to over 100 cm (>100) in tree dbh.

#### 2.4.2. Distance-dependent indices and combination indices

Since most spatially explicit indices are more accurately estimated by using fixed angle stands instead of angle count sampling (Motz et al., 2010, Zenner, 2014), spatial indices have been calculated using a 10 m radius from the center of the plots (includes all the trees above 7.5 cm). Indices were also calculated at 20 m and 40 m (includes trees identified by angle count) for comparison purposes, however unless a significant result was identified, only the 10 m results will be used for accuracy purposes. Since spatial indices require that at least two trees be present in a stand, stands with less than two trees were removed from the data, leaving a total of 244 stands for the calculation of the mean directional index, the Clark Evans index, the size differentiation and the size dominance index. The Hopkins Skellam index and the L function index required a minimum of one tree per stand and therefore included a total of 249 stands at 10 meters.

Bearing (azimuth) coordinates for each live tree from the center of the plot was converted to xy coordinates in order to be able to calculate the spatially-implicit indices. Each azimuth in grades was converted to an arithmetic angle by converting the grades to degrees (degrees=grades\*360/400). The distance and bearing was then translated into a Cartesian coordinate:

x coordinate = distance \* cos(bearing degree)

y coordinate = distance \* sin (bearing degree)

Each coordinate was then included in a plot with maximum and minimum coordinates for x and y from the plot center. In order to correct for the edge effect, calculations of the Clark-Evans index and the Hopkins-Skellam index took place within a finite study area with a radius of 10 m, 20 m or 40 m – points outside this boundary were not included in any calculations. The L function also took place within a finite window area and was calculated for five default distances from 0 to 10 meters – the L function single index value for 5 m and 10 m was then selected for each modality.

The mean directional index, size differentiation and size dominance indices are tree-parameter indices, nevertheless their arithmetic mean can be calculated to describe the structure of a stand (Motz et al., 2010, Pommerening, 2006). These three indices were calculated for the four nearest neighbors (n=4). Since the number of trees for each stand at a 10 meter radius is under 100, no edge correction was used since in order to avoid large bias values as explained in Pommerening and Stoyan (2006). Nonetheless, no edge correction results were compared with the nearest neighbor edge-correction concept (NN1) results (which eliminates trees not within the plot), which is proposed by Pommerening and Stoyan (2006) particularly for angle-dependent indices. The differences detected between the two sets of results were minimal for the mean directional index, size differentiation index and size dominance index, therefore no edge correction results are used here.

## 2.5. Data analysis

The analysis is based on a bivariate interaction linear mixed model used to test the effect of management, with the incorporation of nested random effects (Bolker et al., 2009). The interaction term informs the reader whether there are any differences between managed and unmanaged stands. The response variable for each model is each of the 19 indices calculated. The explanatory variable used for the analysis was the management type, i.e. whether a forest stand was managed (Man) or unmanaged (Unm). A covariate was also added to take into account the altitude factor by differentiating mountain (Mon) and lowland (Low) sites. This gave rise to four modalities: Man Low; Unm Low; Man Mon; Unm Mon.

Taking care of numerous random effects that are hierarchically structured is also particularly important in the data because the probability that two stands from the same forest site share the same characteristics is higher than if the two stands came from two different forest sites (Bolker et al., 2009). In order to account for this source of spatial correlation, a random “site” effect was included in the model.

An interaction bivariate model was selected instead of a multivariate model to analyze the data because including the forest sites as an additional variable would have mainly shown a difference between forest sites (per discussion and previous modeling trials on the same data; (Paillet, 2014) as related from the master thesis supervisor). Moreover, the analysis only looked for a clear two-way relationship between indices and management (and potentially altitude) as a first stage of the analysis (Zuur, 2010). Future analysis could include models with multiple explanatory variables to see whether they provide a good fit as well as further examination of outliers, which was not performed in this case.

Analyses in the R v.3.1.1 software (R Core Team, 2014) used the linear mixed-effects model (lme) function of the linear and nonlinear mixed effects models (nlme) package, which fits and compares Gaussian linear mixed-effects models (Pinheiro, 2014), in order to model the response of the indices to management type and elevation class.

The R script and coding of the model and the analyses of the indices is available in Annex 7. Analyses results consisted of a coefficient for each modality, which were then compared to each other to reject the null hypothesis that managed lowland indices equal unmanaged Lowland indices (Low=Unm Low) and that managed mountain indices equal unmanaged mountain indices (Man Mon=Unm Mon). To detect differences between the four modalities, a Tukey multiple comparison test was performed with the general linear hypotheses glht function of the simultaneous inference in general parametric models multcomp package (Hothorn et al., 2008). The letter summary of similarities and differences multcompleters function of the visualizations of paired comparisons multcompView package (Graves, 2012) permitted to assign a letter to each modality to flag whether there was a significance difference between modalities.

According to Pinheiro and Bates (2013), the linear mixed-effects model in matrix notation is as follows:

$$\mathbf{Y}_i = \mathbf{X}_i \boldsymbol{\beta} + \mathbf{Z}_i \mathbf{b}_i + \boldsymbol{\varepsilon}_i \quad (23)$$

fixed    random    error

Where

$\mathbf{X}_i \boldsymbol{\beta}$  is the fixed effects term,

$\mathbf{Z}_i \mathbf{b}_i$  is the random effects term, and

$\boldsymbol{\varepsilon}_i$  is the residual variation unaccounted for by the rest of the model.

Specifically,

$$\mathbf{Y}_i = \begin{pmatrix} \mathbf{y}_{i1} \\ \mathbf{y}_{i2} \\ \vdots \\ \mathbf{y}_{in_i} \end{pmatrix} \quad (24)$$

$\mathbf{Y}_i$  is the vector of responses in group  $i$ , while  $n_i$  is how many observations are in group  $i$ ,

$$\mathbf{X}_i = \begin{pmatrix} \mathbf{1} & \mathbf{x}_{i11} & \mathbf{x}_{i12} & \cdots & \mathbf{x}_{i1p} \\ \mathbf{1} & \mathbf{x}_{i21} & \mathbf{x}_{i22} & \cdots & \mathbf{x}_{i2p} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathbf{1} & \mathbf{x}_{in_i,2} & \mathbf{x}_{in_i,2} & \cdots & \mathbf{x}_{in_i,p} \end{pmatrix} \quad (25)$$

$\mathbf{X}_i$  is the matrix of the  $p$  predictor variables for every single observation in  $i$  with a corresponding  $p$ -length fixed effects regression coefficient vector  $\beta$ ,

$$\mathbf{b}_i = \begin{pmatrix} \mathbf{b}_{i0} \\ \mathbf{b}_{i1} \\ \vdots \\ \mathbf{b}_{im} \end{pmatrix} \quad (26)$$

$\mathbf{b}_i$  is the  $m$  length vector of random effects,

$$\mathbf{Z}_i = \begin{pmatrix} \mathbf{1} & \mathbf{z}_{i11} & \mathbf{z}_{i12} & \cdots & \mathbf{z}_{i1m} \\ \mathbf{1} & \mathbf{x}_{i21} & \mathbf{z}_{i22} & \cdots & \mathbf{z}_{i2m} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \mathbf{1} & \mathbf{z}_{in_i,2} & \mathbf{z}_{in_i,2} & \cdots & \mathbf{z}_{in_i,m} \end{pmatrix} \quad (27)$$

$\mathbf{Z}_i$  is the random effects design matrix for group  $i$  and

$$\boldsymbol{\varepsilon}_i = \begin{pmatrix} \boldsymbol{\varepsilon}_{i1} \\ \boldsymbol{\varepsilon}_{i2} \\ \vdots \\ \boldsymbol{\varepsilon}_{in_i} \end{pmatrix} \quad (28)$$

$\boldsymbol{\varepsilon}_i$  is the vector of errors (StackExchange, 2015).

The assumptions for the linear mixed-effects model are as follows:

- The random-effect vector,  $b$ , and the error vector,  $\varepsilon$ , are independent from each other and have as prior distributions:

$$\mathbf{b} \sim \mathbf{N}(0, \sigma^2 \mathbf{D}(\theta)) \quad (29)$$

$$\boldsymbol{\varepsilon} \sim \mathbf{N}(0, \sigma^2 \mathbf{I}) \quad (30)$$

where  $D$  is a positive semi-definite and symmetric matrix, parametrized by a variance component vector  $\theta$ ,  $I$  is an  $n$ -by- $n$  identity matrix, and  $\sigma^2$  is the error variance (MathWorks, 2015).

In clustered-data situations though as is the case with the GNB data, it is more convenient to organize the model as a series of  $M$  clusters and to use the following similar model:

$$\mathbf{Y}_j = \mathbf{X}_j \boldsymbol{\beta} + \mathbf{Z}_j \mathbf{b}_j + \boldsymbol{\varepsilon}_j \quad (31)$$

(Laird & Ware, 1982)

Where

$\mathbf{X}_j\boldsymbol{\beta}$  is the fixed effects term represented by four clusters borne out of the interaction of the parameters “Management” and “Altitude” (Management \*Altitude) (i.e. Managed Lowlands, Unmanaged Lowlands, Managed Mountains, Unmanaged Mountains),

$\mathbf{Z}_j\mathbf{b}_j$  is the random effects term represented by the 257 forest sites,

$\boldsymbol{\varepsilon}_j$  is the residual variation unaccounted for by the rest of the model,

$j=1,\dots,M$ , with cluster  $j$  including  $n_j$  observations. The response  $Y_j$  includes the rows of  $Y$  corresponding to the  $j$ th cluster, with  $X_j$  and  $\boldsymbol{\varepsilon}_j$  defined in the same way. The random effects  $\mathbf{b}_j$  are  $M$  realizations of a  $q \times 1$  vector normally distributed (with mean 0) and a variance matrix  $\Sigma q \times q$ , while the matrix  $\mathbf{Z}_j$  is the  $n_j \times q$  design matrix for the  $j$ th cluster random effects (Laird & Ware, 1982):

$$\mathbf{Z} = \begin{pmatrix} \mathbf{Z}_1 & 0 & \dots & 0 \\ 0 & \mathbf{Z}_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \mathbf{Z}_M \end{pmatrix} \quad (32)$$

A second simplified analysis test was performed in addition to the Tukey multiple comparison test: an analysis of variance (Anova) with the Anova function of the stats package (R Core Team, 2014). This was meant to test any significant difference between the modality means for management only, not taking into account altitude. The model for this simplified test is:

$$\mathbf{Y}_k = \mathbf{X}_k\boldsymbol{\beta} + \mathbf{Z}_k\mathbf{b}_k + \boldsymbol{\varepsilon}_k \quad (33)$$

Where

$\mathbf{X}_k\boldsymbol{\beta}$  is the fixed effects term represented by the parameter of “Management”,

$\mathbf{Z}_k\mathbf{b}_k$  is the random effects term represented by the 257 forest sites, and

$\boldsymbol{\varepsilon}_k$  is the residual variation unaccounted for by the rest of the model.

Residuals, homoscedasticity and outliers were also reviewed as part of the analyses; however those will not be taken into account at this first stage of analysis. The output of the Tukey multiple comparison tests and the Anova tests for management is available in Annex 8. Statistical significance for all tests was assessed by using the critical probability value (p-value) threshold  $*p(H_0) < 0.05$ .

A pairwise correlation analysis was applied to the indices at 10m, 20m and 40m by using the corr.test function of the psych package (Revelle, 2014), which provides the correlation ( $R^2$ ) between all the indices (available in Annex 9).

### 3. RESULTS

The estimators of the four modalities for the 19 indices are shown in Table 4 and are also illustrated as graphs in Annex 10. The values represented in Table 4 are the mean coefficients for each index and the four modalities (Man Low; Unm Low; Man Mon; Unm Mon) at a distance of 40 meters (m), 20 m or 10 m.

The margin of error of the sample means is represented with the notation " $\pm$ " to indicate the radius (i.e. half the width) of the 95% confidence interval for each mean represented. The margin error was calculated as follows:

Margin of error = Standard error \* t distribution critical value

A critical value of 2 (t=2) at a confidence level of 95% was used to calculate the margin of error since the degrees of freedom for each modality were as follows:

Table 3: T distribution critical value

Modality	Degrees of freedom	value
Managed *Lowland	85	1.99
Unmanaged *Lowland	82	1.99
Managed*Mountain	43	2.02
Unmanaged*Mountain	43	2.02

The results of the Tukey multi-comparison test among the set of modalities are also shown in Table 4 illustrated by a letter display ranging from the letter "a" to the letter "d". Modalities with means that do not differ significantly at the  $p(H_0) < 0.05$  threshold are connected by the same common letter (e.g. "a" is displayed for each modality or "ab" is displayed for a modality not significantly different from a modality with the group label "a" or "b"), while modalities that are significantly different have different letters (e.g. "a", "b", "c", "d"). The different letters only show a significant difference between one or more of the four modalities but the order of the letters is not increasing or descending in terms of the magnitude of the significant difference. This letter display follows the letter-based representation system developed by Piepho (2004) and applied with the multcomletters and multcompView functions in the R software (Graves, 2012) (see Section 2.5 for more details).

Table 5 illustrates the results of the Anova test meant to test significant differences between the modality means for management only (managed stands vs. unmanaged stands), not taking into account the lowland/mountain altitude dichotomy. The Anova p-values represent the p-values resulting from the Anova test for management, the significance codes are:  $***p(H_0) < 0.001$ ,  $**p(H_0) < 0.01$ ,  $*p(H_0) < 0.05$ ,  $\blacksquare p(H_0) < 0.1$ .

Table 4: Means of indices, margins of error and significant differences<sup>4</sup> by modality\*

	Index	m	Man Low	Unm Low	Man Mon	Unm Mon
Distance-Independent Indices	Sd	40	<b>14.3 ±2.72 a</b>	<b>17.8 ±2.74 b</b>	17.7 ±3.44 ab	19.5 ±3.44 ab
	Cv (%)	40	<b>46.5 ±5.48 a</b>	<b>53.8 ±5.52 b</b>	53.9 ±7.14 ab	56.7 ±7.14 ab
	Ba (m <sup>2</sup> ha <sup>-1</sup> )	40	<b>20.5 ±2.72 a</b>	<b>24 ±2.72 b</b>	<b>29.4 ±3.44 b</b>	<b>34.1 ±3.44 c</b>
	Sdi	40	<b>412 ±50.1 a</b>	<b>480 ±50.2 b</b>	<b>553 ±63.6 b</b>	<b>637 ±63.6 c</b>
	Shannon	40	<b>1.43 ±0.12 a</b>	<b>1.57 ±0.12 b</b>	1.57 ±0.16 ab	1.67 ±0.16 ab
	Simpson	40	<b>3.97 ±0.48 a</b>	<b>4.47 ±0.48 b</b>	4.36 ±0.61 ab	4.69 ±0.60 ab
	BP	40	0.40 ±0.04 a	0.37 ±0.04 a	0.35 ±0.05 a	0.33 ±0.05 a
	Shannon E	40	0.83 ±0.03 a	0.84 ±0.03 a	0.88 ±0.04 a	0.88 ±0.04 a
	Simpson E	40	0.69 ±0.03 a	0.67 ±0.03 a	0.71 ±0.04 a	0.69 ±0.04 a
	Gini	40	0.25 ±0.03 a <sup>■</sup>	0.28 ±0.03 a <sup>■</sup>	0.28 ±0.03 a	0.30 ±0.03 a
	Skewness	40	0.39 ±0.22 a	0.53 ±0.22 a	0.31 ±0.28 a	0.52 ±0.28 a
	Lorimer	40	0.50 ±0.29 a <sup>■</sup>	0.30 ±0.29 a <sup>■</sup>	0.72 ±0.37 a	0.41 ±0.37 a
	Kurtosis	40	2.97 ±0.44 a	2.95 ±0.44 a	2.71 ±0.60 a	2.90 ±0.60 a
Distance-Dependent Indices	Mdi1 <sup>4,5</sup>	10	2.97 ±0.07 a	2.89 ±0.08 a	2.99 ±0.11 a	2.94 ±0.11 a
	Mdi2 <sup>4,5</sup>	20	<b>3.06 ±0.07 a</b>	<b>2.97 ±0.07 b</b>	2.94 ±0.12 ab	2.93 ±0.12 ab
	CE <sup>5</sup>	10	0.19 ±0.01 a	0.18 ±0.01 a	0.19 ±0.02 a	0.19 ±0.02 a
	HS1	10	1.64 ±1.10 a	1.75 ±1.04 a	1.52 ±1.78 a	0.95 ±1.78 a
	HS2	40	0.42 ±0.17 a	0.34 ±0.17 a	0.85 ±0.22 b <sup>■</sup>	0.53 ±0.22 ab <sup>■</sup>
	L - 5 m	10	0.16 ±0.29 a	0.27 ±0.34 a	0.14 ±0.48 a	0.33 ±0.48 a
	L - 10 m	10	0.47 ±0.22 a	0.58 ±0.27 a	0.79 ±0.37 a	0.50 ±0.37 a
Combi nation Indices	DDiff <sup>4,6</sup>	10	0.44 ±0.02 a	0.45 ±0.02 a	0.45 ±0.03 a	0.44 ±0.03 a
	DDom <sup>4,5</sup>	10	0.36 ±0.07 a	0.35 ±0.05 a	0.48 ±0.12 a	0.44 ±0.12 a

\*The indices are: distance-independent indices (standard deviation (Sd), coefficient of variation (Cv), basal area (Ba), stand density index (SDI), Shannon, Simpson, Berger-Parker (BP), Shannon Evenness (Shannon E), Simpson Evenness (Simpson E), Gini, Skewness, Lorimer, Kurtosis), distance-dependent indices (mean directional index (Mdi), Clark Evans index (CE), Hopkins-Skellam index (HS), L function (L)), combination indices (diameter differentiation index (DDiff), diameter dominance index (DDom)).

<sup>4</sup> Significant differences are indicated in bold for \*p(H0)<0.05 and followed by symbol “■” for p(H0)<0.1. The letters represent any significant difference between one modality and the other modalities. Modalities sharing a letter in the group label are not significantly different.

<sup>5</sup> Only plots with at least two trees were included for the calculation of the indices.

<sup>6</sup> Indices calculated with no edge correction.

Table 5: Anova test results for significant differences<sup>7</sup> between managed and unmanaged stands\*

	<i>Index</i>	<i>m</i>	<i>p(H0)</i>
Distance-Independent Indices	Sd	40	<b>0.00001</b>
	Cv (%)	40	<b>0.0134</b>
	Ba (m <sup>2</sup> ha <sup>-1</sup> )	40	<b>&lt;.0001</b>
	Sdi	40	<b>&lt;.0001</b>
	Shannon	40	<b>0.0054</b>
	Simpson	40	<b>0.0047</b>
	BP	40	0.1485
	Shannon E	40	0.6975
	Simpson E	40	0.2894
	Gini	40	<b>0.0103</b>
	Skewness	40	0.0764 <sup>■</sup>
	Lorimer	40	<b>0.0151</b>
	Kurtosis	40	0.8309
Distance-Dependent Indices	Mdi1 <sup>4 5</sup>	10	<b>0.0389</b>
	Mdi2 <sup>4 5</sup>	20	<b>0.0347</b>
	CE <sup>8</sup>	10	0.3971
	HS1	10	0.7673
	HS2	40	<b>0.0364</b>
	L - 5 m	10	0.3187
	L - 10 m	10	0.8064
Combination Indices	DDiff <sup>4 9</sup>	10	0.7973
	DDom <sup>4 5</sup>	10	0.3233

\*The following indices were calculated: distance-independent indices (standard deviation (Sd), coefficient of variation (Cv), basal area (Ba), stand density index (SDI), Shannon index, Simpson index, Berger-Parker index (BP), Shannon Evenness index (Shannon E), Simpson Evenness index (Simpson E), Gini index, Skewness, Lorimer, Kurtosis), distance-dependent indices (mean directional index (Mdi), Clark Evans index (CE), Hopkins-Skellam index (HS), L function (L)), combination indices (diameter differentiation index (DDiff), diameter dominance index (DDom)).

<sup>7</sup> Significant differences indicated in bold for \*p(H0)<0.05 and followed by symbol “■” for p(H0)<0.1.

<sup>8</sup> Only plots with at least two trees were included for the calculation of the indices.

<sup>9</sup> Indices calculated with no edge correction.

### 3.1.1. Distance-independent indices

#### 3.1.1.1 *Basic indices*

The standard deviation (Sd), coefficient of variation (Cv), basal area (Ba) and stand density index (SDI) show that unmanaged lowland sites have a higher dbh variability, basal area and density than managed lowland sites. Similarly, unmanaged mountain sites have a higher basal area and density than managed mountain sites. The coefficient of variation shows similar results to the standard deviation but with a better interval of confidence. In general, mountain sites seem to have more and larger stems and more variability in their diameters than their lowland counterparts. To note, the unmanaged lowland and managed mountain sites have almost the same standard deviation and coefficient of variation.

The Tukey multi-comparisons reveals a significant difference between managed and unmanaged lowland sites for the standard deviation and coefficient of variation (\*\*p(H0)=0.013 and \*p(H0)=0.0473 respectively). The Anova test for management also shows a highly significant difference for the standard deviation (\*\*p(H0)=0.00002) and a small significant difference for the coefficient of variation (\*p(H0)=0.0134). The basal area and stand density index show highly significant response in the Tukey test to managed/unmanaged lowlands (\*\*p(H0)=0.004967 for Ba; \*\*p(h0)=0.00732 for SDI) as well as for managed/unmanaged mountain sites (\*\*p(H0)=0.007613 for Ba; \*p(H0)=0.02142 for SDI). The Anova tests reveal a highly significant p-value for both indices (\*\*p(H0)=<.0001).

#### 3.1.1.2 *Adapted diversity indices*

The Shannon and Simpson indices rank as follows for each modality: managed lowlands have lower dbh class diversity than unmanaged lowlands, which have lower dbh class diversity than managed mountains, which have lower dbh class diversity than unmanaged mountains. Similarly, the Berger Parker (BP) index shows less dominance in managed lowlands than unmanaged lowlands and less dominance in managed mountains than unmanaged mountains. Shannon and BP suggest that the size class diversity is quite high no matter the modality and that the probability of concentration or dominance is low since their values are above 1.4 for Shannon (maximum is 2.39) and under 0.5 for the BP index (maximum is 1). This is less the case for the Simpson index, which has slightly less class diversity with its values being above 3.9 (maximum is 11), Managed sites are observed as less diverse than unmanaged sites, nevertheless unmanaged lowland sites and managed mountain sites share the same coefficients for Shannon, and similar coefficients for Simpson.

The Tukey multi-comparison is consistent with this result for managed and unmanaged lowland stands with a small significant difference for the Shannon and Simpson indices (\*p(H0)=0.0441 and \*p(H0)=0.0397 respectively). The Anova test for management shows a similar small significant difference for Shannon and Simpson (\*\*p(H0)=0.0366 and \*p(H0)=0.047 respectively). Neither test reveals any significant differences for the BP index.

#### 3.1.1.3 *Adapted evenness indices*

While both the Shannon Evenness (Shannon E) and Simpson Evenness (Simpson E) indices measure evenness, their coefficients for the four modalities are not the same and they show slightly different results. Shannon E shows a slightly higher evenness for managed lowlands than unmanaged lowlands while Simpson E shows the opposite. Shannon E. shows the same coefficient for managed and unmanaged mountains while Simpson E. shows that managed mountains have a slightly higher unevenness than unmanaged mountains. Shannon E. shows a much more even distribution among size classes (above 0.8 and close to 1 when all diameter classes are equally abundant) than the Simpson index (hovering around 0.7). Neither do the Tukey comparisons nor the Anova test show any significant differences between the four modalities or management modalities.



#### 3.1.1.4 *Dispersion index*

The Gini coefficient indicates that the managed lowland sites are more homogeneous than the unmanaged lowland sites. Overall, all modalities hover around 0.3 which is closer to dbh class equality (which is zero). This is also the case for the managed mountains and the unmanaged mountains. The Tukey multiple comparisons show a marginally significant difference between managed lowland and unmanaged lowland sites at the 0.1 threshold level ( $p(H_0)=0.054$ ), which is therefore not observed in table 4. The Anova test for management for the Gini index shows a small significant difference for management ( $*p(H_0)=0.010$ ).

#### 3.1.1.5 *Descriptor of histogram shape*

The skewness index indicates that all scenarios are positively skewed (since they are above zero) with more small trees than big trees and that managed lowland/mountain stands are less skewed than unmanaged lowland/mountain sites.

Meanwhile the Lorimer index indicates that managed lowlands have a normal symmetric unimodal form (close to 0.5) while unmanaged lowlands have a positively skewed shape (over 0.5). The Lorimer index also shows that unmanaged mountains also have a slightly positively skewed form while managed mountains have a negatively skewed index of symmetry (under 0.5), which means that those sites have more big trees than small trees, which contradicts the findings of the skewness index (more small trees than big trees).

The confidence range for the Lorimer index of symmetry ranges from 67% for managed mountain stands to 100% for the unmanaged lowland stands – the same is the case for the skewness index confidence interval, which ranges from 59% for unmanaged lowland stands to 95% for managed mountain stands.

The kurtosis results do not show major differences between the modalities. All modalities are slightly platykurtic (close to 3) with unmanaged lowlands having a slightly lower kurtosis than unmanaged lowlands, while the opposite is true for mountain sites – the kurtosis is slightly higher for unmanaged mountains. This means that all coefficients are a little more spread out around the mean and that the probability for extreme values is slightly less than for a normal distribution (lower broad peak and shorter, thinner tails).

In terms of significance differences between the modalities, the Lorimer index shows a marginal significant difference between managed and unmanaged lowlands at the 0.1 threshold ( $p(H_0)=0.069$ ) in the Tukey multi-comparison test. The Anova test for management shows a small significant difference for the Lorimer index and a marginal significant difference for the skewness index ( $*p(H_0)=0.015$  and  $p(H_0)=0.7640$  respectively). There were no significant differences for the kurtosis index.

### 3.1.2. Distance-dependent indices

#### 3.1.2.1 *Nearest Neighbor index*

The mean directional index (Mdi) at 10m shows that all scenarios are significantly clustered with the managed lowland/mountains being slightly more clustered. These results reject the assumption of regularity for managed sites. There is no significant difference between the managed and unmanaged modalities at 10m. Nevertheless, there is a significant difference at 20m according to the Anova test for management ( $*p(H_0)=0.039$ ). At 20m, the ranking of modalities is the same but the clustering increases for the managed lowlands and slightly for the unmanaged lowlands while it decreases slightly for the mountain stands.

#### 3.1.2.2 *Neighborhood indices*

The four modalities have almost the same coefficient for the Clark Evans (CE) index, which indicates that all stands are aggregated ( $<1$ ). The Hopkins Skellam index (HS) also indicates high aggregation levels. The lowlands in general are more aggregated with unmanaged lowlands being slightly more aggregated than the managed lowlands. Unmanaged mountain stands have a near

random distribution (close to 1) and are less aggregated than managed mountain stands. The 95% confidence range for HS is high and ranges from 75% to 130% while CE ranges from 8% to 16%.

CE and HS do not show any significant effect at 10 meters. At 40 meters, the Tukey multi-comparison test for HS indicates that managed mountains and unmanaged mountains are marginally significantly different ( $p(H_0)=0.067$ ) while the HS Anova test for management shows a small significant difference ( $*p(H_0)=0.036$ ). However, the coefficients for lowland stands at 40m differ from the 10m coefficients showing a regular spatial distribution for managed and unmanaged lowland stands. At 40m, managed mountain stands show a spatial distribution close to random and unmanaged stands show a more regular distribution. The confidence range also lowers for HS at 40 meters and ranges from 41% to 67%.

3.1.2.3 *Second-order characteristics index*

Ripley’s L function (L) was calculated at 5m and 10m. At 5m, all modalities are slightly clustered, while at 10m, the values increase indicating a more clustered pattern. Managed lowlands and mountain stands are quite close to CSR at 5m while unmanaged lowland and mountain stands are more clustered. Managed lowland sites are less clustered than their unmanaged counterparts at 10m, but this is not the case for managed and unmanaged mountain stands. The confidence range is quite high (from 111% to 154% at 5m and hovering around 60% at 10m) and there are no significant differences for either distance.

3.1.3. Combination indices

The dbh differentiation (DDiff) at 10 m does not indicate any striking differences between any of the four modalities – they all range between 0.44 and 0.45, which indicates an obvious dbh differentiation (above 0.4). Managed lowlands have a slightly lower differentiation than unmanaged lowlands and the opposite is true for mountain stands. Almost the same is the case for the dbh dominance (DDom) index which shows only a minimal difference between managed and unmanaged lowlands. Managed mountains have minimal dbh dominance over unmanaged mountains. All the coefficient means fall around the 0.25 – 0.5 threshold, meaning that some neighbors tend to be smaller than the reference tree. No significance difference was detected for either index.

Table 6 sums up the instances where managed stands were found to be significantly different from unmanaged stands as observed by applying the Tukey multi-comparison test and Anova test for management or just the Anova test.

Table 6: Indices that rejected null hypothesis that managed and unmanaged stands are equal with and without altitude variable (at  $*p(H_0)p<0.05$  level unless otherwise noted)

<b>Hypothesis (H0) tested and rejected</b>				
Tests	Man Low = Unm Low Only	Man Mon = Unm Mon Only	Man Low = Unm Low & Man Mon = Unm Mon	Managed stands = Unmanaged stands
Tukey	✓ Sd		✓ Ba	
Multi-comp	✓ Cv		✓ SDI	
&	✓ Shannon			
	✓ Simpson			
	✓ Mdi2 (20m)			
Anova	<u>At <math>p(H_0)&lt;0.1</math> level:</u>			
	✓ Gini			
	✓ Lorimer			
	✓ HSI2 (40m)			
Anova only				✓ Mdi (10m) <u>At <math>p(H_0)&lt;0.1</math> level:</u> ✓ Skewness

#### 3.1.4. Correlations between indices

Among the indices that successfully distinguish between managed and unmanaged stands, a few are correlated at 40 meters. The standard deviation and coefficient of variation are highly correlated ( $R^2=0.75$ ), as is the case for basal area and stand density index ( $R^2=0.93$ ). The Shannon and Simpson indices ( $R^2=0.74$ ) are positively correlated, while the Berger Parker index is negatively correlated to both Shannon and Simpson indices ( $R^2=-0.89$  and  $-0.95$  respectively). The Lorimer index is correlated to the coefficient of variation ( $R^2=0.62$ ). The correlation value tends to decrease when the plot size also decreases. All correlation results can be found in Annex 9.

## 4. DISCUSSION

### 4.1. Characteristics of managed and unmanaged stands according to the distance-independent indices

Since most forests in Europe have been managed at some point, designated nature reserves less than a century old will not have old-growth characteristics such as dead wood, large trees, reverse-J shaped dbh distribution and high degree of heterogeneity (Foster et al., 1996, Wolf, 2005). Instead, recently restored reserves would have structural attributes that range from managed forests and old growth forests (Foster et al., 1996). Nevertheless, even-aged managed forests can be more easily characterized by having a majority of trees around the same dbh with a symmetrical diameter distribution in a regular spatial pattern in the case of even-aged plots (Bilek et al., 2011). Old-growth stands on the other hand are expected to have an even diameter distribution with low densities of stems across all diameter classes and a Poisson spatial distribution (LeMay & Staudhammer, 2005). Distance-independent indices are somewhat consistent with the literature for managed even-aged stands. The distance independent indices for managed stands indicate that they are less variable, diverse and concentrated than for unmanaged stands in terms of tree numbers and sizes according to the coefficient of variation, standard deviation, Shannon, Simpson and Berger Parker indices. The managed sites have a lower basal area and therefore a lower stand density index than unmanaged sites. They are also more equal in terms of tree sizes according to the Gini index. The degree of evenness in lowland and mountain stands is unclear as Shannon and Simpson evenness indices showed contradictory results with no significant differences perceived. These results reflect the Pernot et al. (2013) study in the same GNB sites that states that there is a higher number of larger trees in the natural reserves that have reached a more mature stage (therefore a more complex forest structure) than in managed forests (Gilg, 2004, Gosselin & Laroussinie, 2004, Pernot et al., 2013).

Apart from the basic indices category, the differences detected between the managed and unmanaged coefficients in the other categories were either small ( $*p(H_0) < 0.05$  in the case of Shannon and Simpson) or marginal ( $*p(H_0) < 0.1$ ) for the Gini index in the Tukey multi-comparison tests. This is probably because there is still some homogeneity (rather than heterogeneity) in the stands, including the unmanaged stands. This parallels the study by Pernot et al. (2013) that pointed out that French forest reserves are still at a young stage in the sylvogenetic cycle compared to other European natural forests which have a higher number of very big living trees. This transition can be better monitored by using forest structure indices instead of the classical measures of forest structure (large trees, deadwood), since they can provide a better representation of forest complexity as well as a better proxy for biodiversity (Peck et al., 2013, Tews et al., 2004).

### 4.2. Differences between lowland and mountain sites

Forest management practices, including various silvicultural and thinning practices, can result in managed stands being as structurally heterogeneous as natural stands in the case of uneven-aged stands (Newton, 2008). This partly explains why indices were more successful in detecting management differences in lowland sites than mountain sites. First, lowland stands are mostly even-aged (refer to Table 1 for more details) while all mountain stands were uneven-aged with long rotations (up to 16 years in some cases), which nears the age of some reserves (minimum of 20 years). Similarities in terms of forest species, tree age or vertical structure are therefore to be expected between managed and unmanaged mountain sites, and explains why unmanaged lowland sites had similar means as managed mountains (in the case of standard deviation, coefficient of variation, Shannon index, Simpson index, Berger Parker index and Gini index) (Bergès, 2004, Pernot et al., 2013). Second, harvesting is more difficult in mountain stands and therefore less intensive than in the lowland stands, which translates into more forest cover (and therefore a different structure) since the harvests in mountain stands are less frequent. Hence, uneven-aged management coupled with altitude restrictions made mountain stands more difficult to compare

in terms of management (Pernot et al., 2013). In general, the Anova test for management, by not taking altitude into account, finds a higher degree of significant differences between managed and unmanaged sites than the Tukey multi-comparison test (as seen in Table 6 and Annex 8). For instance, the Anova test for management reveals a significant difference at the  $**p(H_0) < 0.01$  level for Simpson and Shannon (only small at the  $*p(H_0) < 0.05$  level with the Tukey test), and at the  $*p(H_0) < 0.05$  level for the Gini index (only marginal at the  $p(H_0) < 0.1$  level with the Tukey test).

The Anova test might be better at detecting a difference in management by not taking the altitude into account (for instance, it finds a significant difference at the  $p(H_0) < 0.1$  level for the skewness index, which was not perceived in the Tukey test) but then the observed differences might be due to underlying elevation patterns (but this is beyond the scope of the study). Another explanation for the lack of significant differences found in the mountain sites (beyond the uneven-aged versus even-aged explanation) can also be the unbalanced sampling of the data (mentioned in Section 2.1), which tended to skew heavily towards even-aged lowland sites and could affect the analysis negatively (Zuur, 2010). In future analysis, it would be useful to probe further into these issues.

### 4.3. Indices that rejected the null hypothesis

Each stand development stage is characterized by its own distinctive structure as presented in forest stand dynamics theory (Kohm & Franklin, 1996, Oliver & Larson, 1996). Attempting to summarize different stands within a single value can be tricky, especially while also trying to include different types of management and different altitude levels. Being able to distinguish between stands with different structural conditions is what useful indices are able to do as they can also provide clues to the ecological processes driving structure such as competition or gap dynamics (Peck et al., 2013, Wolf, 2005).

Overall, the following spatially-implicit indices: the standard deviation, coefficient of variation, basal area, stand density index, Shannon index, Simpson index and the Gini coefficient rejected the null hypothesis with varying degrees of success (see Tables 5 and 6 for a list of indices that rejected the null hypothesis). Discriminant ability, low sample errors and correlation values are important selection criteria for the indices to determine which indices fared best for the study – this parallels the selection criteria in Lexerød and Eid (2006).

The standard deviation of dbh was one of the indices able to distinguish between managed and unmanaged lowland plots, partly because the range of diameters in unmanaged forests is wider, and more marked in lowland stands. The standard deviation has been found to be a useful measure of forest diversity and has been correlated with other spatial structural complexity indices including the structural complexity index (Neumann & Starlinger, 2001, Spies, 1998, Zenner, 2000). Generally, the coefficient of variation is preferred over the standard deviation since it can easily be compared between stands, is highly correlated to the standard deviation and has a lower variation, even though its degree of statistical difference between the modalities was lower than for the standard deviation (Hui & Pommerening, 2014, Hutchings, 1997, Porkess, 2004, Sterba & Zingg, 2006).

Both Shannon and Simpson detected a management difference with the Tukey and Anova test for management. However, Shannon had a lower variation than the Simpson index. Since both indices are correlated, there is no need to evaluate them both. Shannon is commonly used in studies for relative frequencies of stems among diameter classes, especially since it is a good proxy for height diversity of foliage (Buongiorno et al., 1994, Gove & Ducey, 2014, Valbuena et al., 2012). However, the partitioning into subjective size classes (which in this case was divided into 11 classes of 10cm each) means a loss of information especially since they are sensitive to sample size and plot dimensions (Barbeito et al., 2009, Lexerød & Eid, 2006)

The Gini coefficient rejected the null hypothesis with the Tukey test at the  $p(H_0) < 0.1$  level and with the Anova test at the  $*p(H_0) < 0.5$  level. It has a similar purpose than the Shannon evenness and Simpson evenness indices (with its concept of equality), out of which neither rejected the null hypothesis. The Gini index can thus prove useful to compare tree size diversity in stands and assess changes over time since it is easy to interpret and is able to discriminate between different

types of diameter distributions (such as uniform, reverse J-shape) and has a low sensitivity to sample size since it is independent of density (Lexerød & Eid, 2006). One of its disadvantages, however, is that it does not account for random distribution (Sterba, 2008).

The dbh distribution shape according to the skewness and Lorimer index show that both the unmanaged lowland and mountain stands have more small trees than big trees, are left-skewed and therefore closer to a reverse J curve distribution, which is as would be expected. Lorimer shows a statistical difference for management at the  $p(H_0) < 0.1$  level with the Tukey test and  $*p(H_0) < 0.05$  level with the Anova test for management, while the skewness index shows a statistical difference at the  $p(H_0) < 0.1$  level with the Anova test. The Lorimer and skewness results though do not match for the managed lowland and mountain stands and are imprecise with significantly high margins of error due to extreme and skewed values in the variation of diameter distribution, which includes a broad array of stand structural stages ranging from regeneration to old growth stands. While these results are inaccurate with marginal significant differences, skewness has been found to be useful to help monitor the shift from even-aged management to individual tree selection system (Sterba, 2008).

In terms of the distance-dependent indices, the results are also inconclusive. The mean directional index, Clark-Evans index, Hopkins Skellam index, and Ripley L function show conflicting results and have rather high confidence intervals (apart from the Clark Evans index). It is therefore unclear which index to use to characterize the spatial pattern of stands, even though the mean directional index and Hopkins-Skellam detect a management difference. Moreover, because these two indices are based on small-scale data, they only provide information on variability within a small fixed radius and therefore their risk of misinterpretation can be quite high (Corral-Rivas et al., 2010).

Overall, only two indices were able to distinguish between managed and unmanaged sites both in the lowlands and mountain sites - the basal area and stand density index, which were highly correlated and had similar variations (close to 10%). The stand density index tends to be used mainly for even-aged same species stands analysis and has been criticized as being biased towards small trees in uneven-aged stands, which would be an issue with the current forest stands (Woodall et al., 2003). On the other hand, basal area has often been used as a forest structure measure and can successfully discriminate between different types of forests (such as primary, secondary, successional stages) (McElhinny et al., 2005). Even though basal area and stand density index are common descriptors of forest stands, they fail to take into account differences in the size of individual stems (Newton, 2008). They should therefore be coupled with other indices such as the coefficient of variation, the Shannon index and the Gini index, which characterize different aspects of the dbh diversity of forest stands and the overall forest structure stands (Sterba, 2008, Valbuena et al., 2012). Even though the current forest stand inventory has used a mixture of sampling methods, these findings match the study by Sterba (2008) which concluded that the Shannon index, coefficient of variation, and Gini coefficient can be used in angle count sampling data to detect management transitions between even-aged systems and spontaneous forest development.

#### 4.4. Spatial indices, Plot size and Angle count sampling method

The conflicting and unclear results of the spatially explicit indices can be explained partly by the size of the stand, which at 10 meters cannot provide a proper snapshot of average distance and spatial distribution within a plot with an average of 17 trees per plot. Moreover, in the present analyses, rather small stems above 7.5 cm were counted as part of the data instead of only focusing on trees with slightly larger diameters. The mean directional index and Hopkins-Skellam index might have been better at picking up management differences in larger plots (at 20m and 40m respectively) because of the plot sizes and number of trees increased but also because a number of larger trees were selected (and were therefore not 'true' neighbors) with the angle count at 20 m and smaller trees were not taken into account in the 10m – 20 m/40m ranges (please refer to figure 2 for an illustration of the two sampling methods used for the data).

Due to the ambiguity of the results of the distance-dependent indices, it would be difficult to use them unless the radius could be increased to include at least 100 stems and cover at least 1.5% of total stem number, although Kint et al. (2004) states that at least 20% of the total stem number is necessary for a meaningful analysis (Merganič & Sterba, 2006, Pommerening & Stoyan, 2006). Angle-count can be successfully used as a sampling method for spatial analysis, however it requires a large area and additional measurements (Sterba, 2008). For instance, Sterba (2008) used an angle count sampling method for his comparison of managed and unmanaged stands and measured one neighbor tree (whether it was within the angle count or not) for each tree that was within the angle count. Pommerening and Stoyan (2006) on the other hand advise on the use of plus-sampling in the case of a small-sized circular plot whereby neighbors immediately outside the plot should be included in the survey. If plus-sampling or neighbor trees within an angle count were added to the inventory, the total number of neighbors might have to be adjusted as a result. For instance, Sterba (2008) only used one neighbor, instead of four (as used in the current analysis) but this would mean the use of new indices as some indices require at least three neighbors for their calculation (Pommerening & Stoyan, 2006). These additional measurements would be costly but would provide additional spatial information about the forest stands and their spatial patterns.

## 5. CONCLUSION

Spatially-implicit indices characterized unmanaged lowland stands as more complex with a significantly superior basal area and more variable and diverse tree sizes than managed lowland stands as revealed by the standard deviation, coefficient of variation, Shannon index and Simpson index. However, this was not as evident in the case of mountain stands due to the uneven-aged and long rotation cycles practiced at that altitude. Anova tests not taking into account altitude effects were more likely to distinguish a difference in management at a higher degree of significance than the Tukey multiple comparison test. Overall, tests need to be refined in order to provide summary data which makes sense. For instance, more clusters of stands could be created based on their harvesting details (i.e. type, intensity, rotation cycles) and their history. More tests should be run based on the type of management in each forest site and to determine whether the age of the forest reserves and their prior use has played an important part in their current structure.

Indices with the best discriminant ability and lower standard errors can be used in the future to monitor the forest structure of the GNB stands and as a proxy to biodiversity as they can differentiate the shift from forest management to natural forest development – these include the basal area, the coefficient of variation, the Shannon index, and the Gini coefficient. Forest managers and researchers can calculate these indices in order to gain a richer perspective on the status of their forests since dbh is a common measure in inventories. The GNB stands are due to be re-measured in ten years' time and these indices could provide an insight on how forest stands, particularly natural forests are progressing. Moreover, this research can be taken into account to help the overall reporting on the state of forests in Europe as well as to help improve the Indicators of Sustainable French Forests Management.

Distance-independent indices were unable to provide clear results as to the spatial pattern of stands, due to the small fixed area plot sizes used for the analysis. Additional measures of neighbors of angle-count trees or plus sampling could help further characterize the stands spatially in the future, however that could prove costly and time-consuming. Nevertheless, the results could potentially be insightful when used in a number of composite indices that include spatial distances and describe the forest stand from a structural and functional point of view such as the complex stand index S (Pastorella & Paletto, 2013) or the structural complexity index (Zenner, 2014).

The data from the second complementary protocol to the GNB protocol, which includes a vertical component of forest structure (height, canopy cover and vertical strata), will be used as part of CONSPIIRE to calculate more indices such as simple indices (standard deviation, coefficient of variation), adapted biodiversity indices (Shannon and Simpson) and the dispersion estimate index (Gini). It can also be used to calculate vertical indices such as the vertical evenness index (Neumann & Starlinger, 2001) This will provide yet another layer of description for the GNB forest stands. Previous Irstea work on biodiversity taxa (such as identification of tree species) can also be combined with the diameter classes indices, for instance, to calculate a composite index such as the stand diversity index (Bacaro et al., 2013), which incorporates diameter classes and tree species. Or a complex index such as the stand variance index (Staudhammer, 1999, Staudhammer & LeMay, 2001), which comprises of tree dbh, tree height and tree species, can be computed to provide further information on biodiversity within managed and unmanaged stands in the GNB network. The vertical component of forest stands can also provide more information on the level of light within stands, particularly the canopy cover and the vertical strata data. This can provide a useful link to the level of disturbance within a forest and subsequently provide yet another link to the state of biodiversity within the forest stands, according to the intermediate disturbance hypothesis (Connell, 1978).



## 6. REFERENCES

- Aguirre O., Hui G., Von Gadow K. & Jiménez J., 2003. An analysis of spatial forest structure using neighbourhood-based variables. *Forest Ecology and Management*, 183(1-3): 137-145.
- Bacaro G., Ricotta C., Marignani M., Torri D. & Chiarucci A., 2013. Using Shannon's recursivity to summarize forest structural diversity. *Forests Trees and Livelihoods*.
- Balandier P., Pauwels D., Landré F. & Jouvie R., 2002. La lumière : outils sylvicole pour favoriser la diversité végétale ou la gestion cynégétique des peuplements de mélèze (*Larix* sp.). *Forêt Wallonne*, 61(Novembre-Décembre 2002): 9-13.
- Balandier P., Sonohat G., Sinoquet H., Varlet-Grancher C. & Dumas Y., 2006. Characterisation, prediction and relationships between different wavebands of solar radiation transmitted in the understorey of even-aged oak (*Quercus petraea*, *Q. robur*) stands. *Trees - Structure and Function*, 20(3): 363-370.
- Barbeito I., Cañellas I. & Montes F., 2009. Evaluating the behaviour of vertical structure indices in Scots pine forests. *Annals of Forest Science*, 66(7): 710p1-710p10.
- Barbier S., Chevalier R., Loussot P., Berges L. & Gosselin F., 2009. Improving biodiversity indicators of sustainable forest management: Tree genus abundance rather than tree genus richness and dominance for understory vegetation in French lowland oak hornbeam forests. *Forest Ecology and Management*, 258: S176-S186.
- Berger W. H. & Parker F. L., 1970. Diversity of planktonic Foraminifera in deep sea sediments. *Science*, 168: 1345-1347.
- Bergès L., 2004. Rôle des coupes, de la stratification verticale et du mode de traitement sur la biodiversité. In: G. M. and O. Laroussine (Eds.), *Gestion forestière et Biodiversité: connaître pour préserver - synthèse bibliographique*. GIP Ecofor, Paris, pp. 149-215.
- Besag J. E., 1977. Comments on Ripley's paper. *Journal of the Royal Statistical Society*, 39(2): 193-195.
- Bilek L., Remes J. & Zahradnik D., 2011. Managed vs. unmanaged. structure of beech forest stands (*Fagus sylvatica* L.) after 50 years of development, Central Bohemia. *Gestión versus no gestión. estructura de bosque de hayas (Fagus sylvatica L.) al cabo de 50 años de crecimiento, Bohemia central*, 20(1): 122-138.
- Bourgeron P. S., 1983. Spatial aspects of vegetation structure. In: F. B. Golley (Ed.) *Ecosystems of the world 14A – Tropical rain forest ecosystems, structure and function*. Elsevier, Amsterdam, pp. 29-47.
- Bruciamacchie M., Gilg O. & Despert Y., 2007. Un nouveau protocole pour le suivi des forêts dans les espaces naturels protégés. *Espaces Naturels*, 18: 20-21.
- Buongiorno J., Dahir S., Lu H. C. & Lin C. R., 1994. Tree size diversity and economic returns in uneven-aged forest stands. *Forest Science*(40): 20.
- Burrascano S., Rosati L. & Blasi C., 2009. Plant species diversity in Mediterranean old-growth forests: A case study from central Italy. *Plant Biosystems*, 143(1): 190-200.
- Burrascano S., Sabatini F. M. & Blasi C., 2011. Testing indicators of sustainable forest management on understorey composition and diversity in southern Italy through variation partitioning. *Plant Ecology*, 212(5): 829-841.

- CBD, 2014a. *About Forest Biodiversity* [en ligne]. Disponible sur Internet, <<https://www.cbd.int/forest/about.shtml>>, [consulté le 10/31/2014].
- CBD, 2014b. *Convention Text* [en ligne]. Disponible sur Internet, <<https://www.cbd.int/convention/text/>>, [consulté le 10/31/2014].
- Christensen M. & Emborg J., 1996. Biodiversity in natural versus managed forest in Denmark. *Ecological Bulletin*, 53: 77-94.
- Clark D. A., 2007. Detecting tropical forests' responses to global climatic and atmospheric change: Current challenges and a way forward. . *Biotropica*, 39: 4-19.
- Clark P. J. & Evans F., 1965. Distance to nearest neighbour as a measure of spatial relationships in populations. . *Ecology*, 35: 445-453.
- Commarmot B., Bachofen H., Bundziak Y., Bürgi A., Ramp B., Shparyk Y., Sukhariuk D., Viter R. & Zingg A., 2005. Structures of virgin and managed beech forests in Uholka (Ukraine) and Sihlwald (Switzerland): A comparative study. *Forest Snow and Landscape Research*, 79(1-2): 45-56.
- Connell J. H., 1978. Diversity in tropical rain forests and coral reefs: high diversity of trees and corals is maintained only in a non-equilibrium state. *Science*, 199: 1302-1310.
- Corral-Rivas J. J., 2006. *Models of tree growth and spatial structure for multi-species, uneven-aged forests in Durango (Mexico)*, University of Göttingen, Germany.
- Corral-Rivas J. J., Wehenkel C., Castellanos-Bocaz H. A., Vargas-Larreta B. & Diéguez-Aranda U., 2010. A permutation test of spatial randomness: Application to nearest neighbour indices in forest stands. *Journal of Forest Research*, 15(4): 218-225.
- Davis L. S. & Johnson K. N., 1987. *Forest Management*. third ed. McGraw-Hill, New York.
- Diggle P. J., 1983. *Statistical analysis of spatial point patterns*. Academic, London.
- Ex S. A. & Smith F. W., 2013. Stand density index estimates leaf area index in uneven-aged ponderosa pine stands. *Western Journal of Applied Forestry*, 28(1): 9-12.
- Forest Europe, 2014. *SFM Criteria & Indicators* [en ligne]. Disponible sur Internet, <[http://www.foresteurope.org/sfm\\_criteria/criteria](http://www.foresteurope.org/sfm_criteria/criteria)>, [consulté le 12/10/2014].
- Foster D. R., Orwig D. A. & McLachlan J. S., 1996. Ecological and conservation insights from reconstructive studies of temperate old-growth forests. *Trends in Ecology & Evolution*, 11(10): 419-424.
- Füldner K., 1995. *Strukturbeschreibung von Buchen-Edellaubholz-Mischwäldern [Describing forest structures in mixed beech-ash-maple-sycamore stands]*. PhD Dissertation, Göttingen University, Göttingen.
- Gadow K. V. & Hui G., 2002. Characterising forest spatial structure and diversity. In: L. Bjoerk (Ed.) *Proceedings of the IUFRO International workshop 'Sustainable forestry in temperate regions'*. Lund, Sweden, pp. 20-30.
- Gini C., 1921. Measurement of inequality on income. *Economic Journal*, 31: 22-43.
- Gosselin M. & Laroussinie O., 2004. *Biodiversité et gestion forestière. Connaître pour préserver*. Cemagref éditions, Paris, 308 p.

- Gosselin M. & Paillet Y., 2010. *Mieux intégrer la biodiversité dans la gestion forestière*. Quae eds, Versailles.
- Gove J. H. & Ducey M. J., 2014. Optimal uneven-aged stocking guides: An application to spruce-fir stands in New England. *Forestry*, 87(1): 61-70.
- Graves S., Piepho, H-P., Selzer, L., Dorai-Raj, S., 2012. *multcompView: Visualizations of Paired Comparisons*, R package version 0.1-5. [en ligne]. Disponible sur Internet, <<http://CRAN.R-project.org/package=multcompView>>, [consulté le 13/10/2014].
- Hett J. M. & Loucks O. L., 1976. Age structure models of Balsam Fir and Eastern Hemlock. *Journal of Ecology*, 64: 1029-1044.
- Hopkins B. & Skellam J. G., 1954. A new method for determining the type of distribution of plant individuals. *Annals of botany*, 18: 213-227.
- Hothorn T., Bretz F. & Westfall P., 2008. Simultaneous Inference in General Parametric Models. *Biometrical Journal*, 50(3): 346-363.
- Hui G. & Pommerening A., 2014. Analysing tree species and size diversity patterns in multi-species uneven-aged forests of Northern China. *Forest Ecology and Management*, 316(0): 125-138.
- Hui G. Y., Albert M. & Gadow K. V., 1998. The measure of neighbourhood dimensions as a parameter to reproduce stand structures. *Das Umgebungsmaß als Parameter zur Nachbildung von Bestandesstrukturen*, 117(5): 258-266.
- Husch B., Beers T. W. & Kershaw Jr J. A., 2003. *Forest Mensuration*. Fourth ed. John Wiley & Sons, Hoboken, New Jersey.
- Hutchings M. J., 1997. The structure of plant populations. *Plant Ecology*: 325-58.
- IGN, 2014. *Inventaire Forestier* [en ligne]. Disponible sur Internet, <<http://inventaire-forestier.ign.fr>>, [consulté le 12/10/2014].
- Irstea, 2014. *Irstea* [en ligne]. Disponible sur Internet, <<http://www.irstea.fr>>, [consulté le 10/31/2014].
- Irstea, 2015. *Gestion forestière, Naturalité et Biodiversité* [en ligne]. Disponible sur Internet, <<http://gnb.irstea.fr/>>, [consulté le 02/04/2015].
- Jaehne S. & Dohrenbusch A., 1997. A method to evaluate forest stand diversity. *Ein Verfahren zur Beurteilung der Bestandesdiversität*, 116(6): 333-345.
- Kint V., Robert D. W. & Noël L., 2004. Evaluation of sampling methods for the estimation of structural indices in forest stands. *Ecological Modelling*, 180(4): 461-476.
- Kohm A. K. & Franklin J. F., 1996. *Creating a Forestry for the 21st Century – The Science of Ecosystem Management*. Island Press, Washington, DC, 1-30 p.
- Lähde E., Laiho O., Norokorpi Y. & Saksala T., 1999. Stand structure as the basis of diversity index. *Forest Ecology and Management*, 115(2-3): 213-220.
- Laird N. M. & Ware J. H., 1982. Random-effects models for longitudinal data. *Biometrics*, 38: 963-974.

- LeMay V. & Staudhammer C., 2005. Indices of Stand Structural Diversity: Mixing Discrete, Continuous, and Spatial Variables. *In, IUFRO Sustainable Forestry in Theory and Practice: Recent Advances in Inventory & Monitoring, Statistics, Information & Knowledge Management, and Policy Science Conference*, Edinburgh, Scotland, April 5 to 8, 2005. p. 4.
- LeMay V. & Staudhammer C., 2006. Indices of stand structural diversity: Adding spatial diversity to a stand structural index. *USDA Forest Service - General Technical Report PNW(688)*.
- Lexerød N. L. & Eid T., 2006. An evaluation of different diameter diversity indices based on criteria related to forest management planning. *Forest Ecology and Management*, 222(1-3): 17-28.
- Lorimer C. G. & Krug A. G., 1983. Diameter distributions in even-aged stands of shade-tolerant and midtolerant tree species. *American Midland Naturalist Journal*, 109: 331-345.
- MacArthur R. H. & MacArthur J. W., 1961. On Bird Species Diversity. *Ecology*, 42(3): 594-598.
- Magurran A. E., 2004. An index of diversity. *In: Measuring Biological Diversity*. Blackwell Science Ltd ed. Croom Helm, London, pp. 100-130.
- Maltamo M., Packalén P., Yu X., Eerikäinen K., Hyyppä J. & Pitkänen J., 2005. Identifying and quantifying structural characteristics of heterogeneous boreal forests using laser scanner data. *Forest Ecology and Management*, 216: 41-50.
- Marinšek A. & Dlačič J., 2011. A comparison of structural characteristics and ecological factors between forest reserves and managed silver fir - Norway spruce forests in Slovenia. *Ekologija Bratislava*, 30(1): 51-66.
- Mason W. L., Connolly T., Pommerening A. & Edwards C., 2007. Spatial structure of semi-natural and plantation stands of Scots pine (*Pinus sylvestris* L.) in northern Scotland. *Forestry*, 80(5): 567-586.
- MathWorks, 2015. *Linear Mixed-Effects Models - MATLAB & Simulink - MathWorks United Kingdom* [en ligne]. Disponible sur Internet, <<http://uk.mathworks.com/help/stats/linear-mixed-effects-models.html>>, [consulté le 2/4/2015].
- McCarthy J. W. & Weetman G., 2007. Stand structure and development of an insect-mediated boreal forest landscape. *Forest Ecology and Management*, 241(1-3): 101-114.
- McElhinny C., 2002. *Forest and woodland structure as an index of biodiversity: a review*, Australian National University, Acton, 84 p.
- McElhinny C., Gibbons P., Brack C. & Bauhus J., 2005. Forest and woodland stand structural complexity: Its definition and measurement. *Forest Ecology and Management*, 218(1-3): 1-24.
- Merganič J. & Sterba H., 2006. Characterisation of diameter distribution using the Weibull function: Method of moments. *European Journal of Forest Research*, 125(4): 427-439.
- Ministère de l'écologie, du développement durable et de l'énergie., 2015. *Infographie : la forêt française en chiffres* [en ligne]. Disponible sur Internet, <<http://www.developpement-durable.gouv.fr/Infographie-la-foret-francaise-en.html>>, [consulté le 03/04/2015].
- Montes F., Barbeito I., Rubio A. & Cañellas I., 2008. Evaluating height structure in Scots pine forests using marked point processes. *Canadian Journal of Forest Research*, 38(7): 1924-1934.
- Motz K., Sterba H. & Pommerening A., 2010. Sampling measures of tree diversity. *Forest Ecology and Management*, 260(11): 1985-1996.

- Neumann M. & Starlinger F., 2001. The significance of different indices for stand structure and diversity in forests. *Forest Ecology and Management*, 145(1-2): 91-106.
- Newton A. C., 2007. *Forest ecology and conservation, a handbook of techniques*. Oxford University Press, Oxford.
- Newton P. F., 2008. Complex stand structures and associated dynamics: measurement indices and modelling approaches. *Forestry*, 81(5): 573-574.
- Ni R., Baiketuerhan Y., Zhang C., Zhao X. & Gadow K. v., 2014. Analysing structural diversity in two temperate forests in northeastern China. *Forest Ecology and Management*, 316(0): 139-147.
- Nilsson S. G. & Baranowski R., 1997. Habitat predictability and the occurrence of wood beetles in old-growth beech forests. *Ecography*, 20: 491-498.
- Oliver D. C. & Larson C. L., 1996. *Forest Stand Dynamics*. John Wiley & Sons, Oxford.
- ONB, 2011. [mis à jour: 2011]. *Évolution en métropole des volumes de bois particulièrement favorable à la biodiversité liée aux stades vieillissants des arbres | Indicateurs ONB* [en ligne]. Disponible sur Internet, <<http://indicateurs-biodiversite.naturefrance.fr/indicateurs/evolution-en-metropole-des-volumes-de-bois-particulierement-favorables-a-la-biodiversite>>, [consulté le 10/10/2014].
- Paillet Y., Berges L., Hjalten J., Odor P., Avon C., Bernhardt-Roemermann M., Bijlsma R.-J., De Bruyn L., Fuhr M., Grandin U., Kanka R., Lundin L., Luque S., Magura T., Matesanz S., Meszaros I., Teresa Sebastia M., Schmidt W., Standovar T., Tothmeresz B., Uotila A., Valladares F., Vellak K. & Virtanen R., 2010. Biodiversity Differences between Managed and Unmanaged Forests: Meta-Analysis of Species Richness in Europe. *Conservation Biology*, 24(1): 101-112.
- Paillet Y., Pernot C., Boulanger V., Debaive N., Fuhr M., Gilg O. & Gosselin F., In prep. Quantifying the recovery of old-growth forest attributes in forest reserves: lessons from management abandonment.
- Pastorella F. & Paletto A., 2013. Stand structure indices as tools to support forest management: An application in Trentino forests (Italy). *Journal of Forest Science*, 59(4): 159-168.
- Peck J. E., Zenner E. K., Brang P. & Zingg A., 2013. Tree size distribution and abundance explain structural complexity differentially within stands of even-aged and uneven-aged structure types. *European Journal of Forest Research*: 1-12.
- Pernot C., Paillet Y., Boulanger V., Debaive N., Fuhr M., Gilg O. & Gosselin F., 2013. Impact de l'arrêt d'exploitation forestière sur la structure dendrométrique des hêtraies mélangées en France. *Revue Forestière Française*, 65(5): 17.
- Pielou E. C., 1969. *An Introduction to Mathematical Ecology*. Wiley, New York, NY.
- Piepho H.-P., 2004. An Algorithm for a Letter-Based Representation of All-Pairwise Comparisons. *Journal of Computational and Graphical Statistics*, 13(2): 10.
- Pinheiro J. C. & Bates D. M., 2013. *Mixed-Effects Models in S and S-PLUS* Springer, 528 p.
- Pinheiro J. C., Bates, D.M., DebRoy, S., Sarkar, D., and R Core Team, 2014. *nlme: Linear and Nonlinear Mixed Effects Models*. [en ligne]. Disponible sur Internet, <<http://CRAN.R-project.org/package=nlme>>, [consulté le 06/10/2014].

- Pommerening A., 2002. Approaches to quantifying forest structures. *Forestry*, 75(3): 305-324.
- Pommerening A. & Stoyan D., 2006. Edge-correction needs in estimating indices of spatial forest structure. *Canadian Journal of Forest Research*, 36(7): 1723-1739.
- Pommerening A., 2006. Evaluating structural indices by reversing forest structural analysis. *Forest Ecology and Management*, 224(3): 266-277.
- Pommerening A., 2012. [mis à jour: 19/09/2012]. *Estimating spatially explicit tree diversity indices* [en ligne]. Disponible sur Internet, <<http://www.crancod.org/wiki/images/8/84/TreeDiversityIndices.R>>, [consulté le ...].
- Porkess R., 2004. *Collins Dictionary Statistics*. Second ed. Collins Dictionary Series. Harper Collins, 336 p.
- Pretzsch H. & Biber P., 2005. A re-evaluation of Reineke's rule and stand density index. *Forest science*, 51(4): 304-320.
- Pretzsch H., 2009. *Forest dynamics, growth and yield: From measurement to model*. Springer Verlag, Berlin.
- Pullin A. S. & Stewart G. B., 2006. Guidelines for Systematic Review in Conservation and Environmental Management. *Conservation Biology*, 20: 1647-1656.
- R Core Team, 2014. *R: A language and environment for statistical computing*. [en ligne]. Vienna, Austria, R Foundation for Statistical Computing. Disponible sur Internet, <<http://www.R-project.org>>, [consulté le 02/10/2014].
- Reineke L. H., 1933. Perfecting a stand-density index for even-aged forests. *Journal of Agricultural Research*, 46: 574-592.
- Revelle W., 2014. *psych: Procedures for Psychological, Psychometric, and Personality Research* [en ligne]. Evanston, Illinois, Northwestern University. Disponible sur Internet, <<http://CRAN.R-project.org/package=psych>>, [consulté le 08/10/2014].
- Ripley B. D., 1976. The Second-Order Analysis of Stationary Point Processes. *Journal of Applied Probability*, 13: 255-266.
- Ripley B. D., 1977. Modelling spatial patterns. *Journal of the Royal Statistical Society*, 39(2): 172-212.
- Shannon C. E. & Weaver W., 1949. *The mathematical theory of communication*. University of Illinois Press, Urbana, IL, 117 p.
- Siipilehto J., 2011. Local prediction of stand structure using linear prediction theory in Scots pine-dominated stands in Finland. *Silva Fennica*, 45(4): 669-692.
- Simpson E. H., 1949. The Measurement of diversity. *Nature*, 163(688).
- Sonohat G., Balandier P. & Ruchaud F., 2004. Predicting solar radiation transmittance in the understory of even-aged coniferous stands in temperate forests. *Annals of Forest Science*, 61(7): 629-641.
- Spies T. A., 1998. Forest structure: A key to the ecosystem. *Northwest Science*, 72(SPEC. ISS. 2): 34-39.
- StackExchange, 2015. *Understanding the linear mixed effects model equation and fitting a random effects model with weights in R* [en ligne]. @StackStats. Disponible sur Internet,

<<http://stats.stackexchange.com/questions/30970/understanding-the-linear-mixed-effects-model-equation-and-fitting-a-random-effec>>, [consulté le 02/04/2015].

- Staudhammer C., 1999. *Quantifying forest stand diversity using stand structure*. Master of Science - MSc in Forestry, University of British Columbia.
- Staudhammer C. L. & LeMay V. M., 2001. Introduction and evaluation of possible indices of stand structural diversity. *Canadian Journal of Forest Research*, 31(7): 1105-1115.
- Sterba H. & Zingg A., 2006. Distance dependent and distance independent description of stand structure. *Abstandsabhängige und abstandsunabhängige bestandesstrukturbeschreibung*, 177(8-9): 169-176.
- Sterba H., 2008. Diversity indices based on angle count sampling and their interrelationships when used in forest inventories. *Forestry*, 81(5): 587-597.
- Szmyt J., 2012. Spatial structure of managed beech-dominated forest: Applicability of nearest neighbors indices. *Dendrobiology*, 68: 69-76.
- Szmyt J., 2014. *Spatial statistics in ecological analysis: from indices to functions*. Vol. 48.
- Tews J., Brose U., Grimm V., Tielbörger K., Wichmann M. C., Schwager M. & Jeltsch F., 2004. Animal species diversity driven by habitat heterogeneity/diversity: the importance of keystone structures. *Journal of Biogeography*, 31(1): 79-92.
- Toïgo M., Paillet Y., Noblecourt T., Soldati F., Gosselin F. & Dauffy-Richard E., 2013. Does forest management abandonment matter more than habitat characteristics for ground beetles? *Biological Conservation*, 157: 215-224.
- Tomppo E., Gschwantner T. & Lawrence M., 2010. *National Forest Inventories: pathways for common reporting*. Lavoisier, Paris, France, 672 p.
- United Nations Environment Programme, Food, Agriculture Organization & Forests U. N. F. o., 2009. *Vital Forest Graphics*. UNEP/GRID-Arendal, Nairobi.
- Utterer J., Tokola T. & Maltamo M., 2000. Differences in the structure of primary and managed forests in East Kalimantan, Indonesia. *Forest Ecology and Management*, 129(1-3): 63-74.
- Valbuena R., Packalén P., Martín-Fernández S. & Maltamo M., 2012. Diversity and equitability ordering profiles applied to study forest structure. *Forest Ecology and Management*, 276: 185-195.
- Vencurik J., Kucbel S. & Jaloviar P., 2012. Types of forest stand structures and analysis of natural regeneration in mixed forest of national nature reserve Mláčik (Central Slovakia). *Typizácia porastových štruktúr a analýza stavu prirodzenej obnovy zmiešaného lesa v národnej prírodnej rezervácii Mláčik*, 2012(2): 93-100.
- Wagner F., Rutishauser E., Blanc L. & Hérault B., 2010. Effects of plot size and census interval on descriptors of forest structure and dynamics. *Biotropica*, 42(6): 664-671.
- Wolf A., 2005. Fifty year record of change in tree spatial patterns within a mixed deciduous forest. *Forest Ecology and Management*, 215(1-3): 212-223.
- Woodall C. W., Fiedler C. E. & Milner K. S., 2003. Stand density index in uneven-aged ponderosa pine stands. *Canadian Journal of Forest Research*, 33(1): 96-100.

- Zenner E. K., 2000. Do residual trees increase structural complexity in pacific northwest coniferous forests? *Ecological Applications*, 10(3): 800-810.
- Zenner E. K., 2014. Personal email to author on 14/09/2014.
- Zimble D. A., Evans D. L., Carlson G. C., Parker R. C., Grado S. C. & Gerard P. D., 2003. Characterizing vertical forest structure using small-footprint airborne LIDAR. *Remote Sensing of Environment*, 87: 171-182.
- Zuur A. F., Ieno, E.N., Elphick, C.S., 2010. A protocol for data exploration to avoid common statistical problems. *Methods in Ecology and Evolution*, 1: 3-14.



## 7. LIST OF ACCRONYMS

Anova	Analysis of Variance
Ba	Basal area
BP	Berger-Parker
CBD	Convention of Biological Diversity
CE	Clark Evans index
Cm	Centimeter
CONSPIIRE	Construction and indicator value of multi-scale forest structural indices
CSR	Complete Spatial Randomness
Cv	Coefficient of Variation
Dbh	Diameter at breast height
Ddiff	Diameter Differentiation
Ddom	Diameter Dominance
Glht	General linear hypotheses
Ha	Hectare
HS	Hopkins Skellam index
Irstea	<i>Institut de recherche en sciences et technologies pour l'environnement et l'agriculture</i>
IGN	<i>Institut National de l'Information Géographique et Forestière</i>
K	K function
L	L function
Lme	Linear mixed model
Low	Lowland
M	Meter
Man	Managed
Mdi	Mean directional index
Mon	Mountain
Multcomp	Multiple comparison
NN1	Nearest neighbor edge-correction concept
ONB	National Observatory of Biodiversity
ONF	<i>Office National des Forêts</i>
RN	<i>Réserves Naturelles</i>
Sd	Standard deviation
SDI	Stand density index
Shannon E	Shannon Evenness
Simpson E	Simpson Evenness
Unm	Unmanaged

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# 10. ANNEXES

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## Annex 1 - Description of CONSPIRE project

Titre du projet : CONSTRUCTION et Potentiel Indicateur des Indices de structure forestière à plusieurs échelles

Acronyme : CONSPIRE

Composition de l'équipe projet (mettre le porteur en 1<sup>er</sup> ligne)

Nom du Contact	Organisme	UR (préciser centre de recherche pour MINES et TR pour Irstea)	Autres scientifiques de l'UR
Yoan Paillet	Irstea	EFNO (SEDYVIN)	Philippe Balandier
			Frédéric Gosselin
			Jean-Pierre Hamard
			Emmanuelle Dauffy-Richard
Marc Fuhr	Irstea	EMGR (SEDYVIN)	Thomas Cordonnier
Bernard Prévosto	Irstea	EMAX (SEDYVIN)	

Résumé : 20 lignes maxi

L'influence de la structure forestière, i.e. la distribution des dimensions verticales et horizontales des arbres ou des unités de gestion, sur la biodiversité a souvent été étudiée et parfois quantifiée pour certaines composantes comme le bois mort, les microhabitats ou la surface terrière. Cependant, peu d'études ont cherché à comparer la pertinence d'indices dendrométriques de structure forestière (distribution en classes diamètre, recouvrement des strates...) comme proxy de biodiversité taxonomique, et à comprendre les mécanismes associés. Par exemple, la surface terrière est parfois citée comme indicateur de biodiversité floristique ou carabique, mais les mécanismes sous-jacents, notamment le lien à la lumière, ont plus été discutés que quantifiés. La structure forestière peut s'appréhender au moins à deux échelles distinctes : celle locale de la placette (« stand level ») où la structure est le plus souvent déterminée par le recouvrement des différentes strates arborées et/ou la distribution en classes de diamètre, et l'échelle plus globale du massif forestier (« forest level ») où la structure est appréhendée par les variations de classes d'âge (ou de hauteur) des différentes unités de gestion composant le massif. Du point de vue de la biodiversité, ces différentes structures n'agissent probablement pas sur les mêmes descripteurs (alpha- vs. gamma-diversité). Ce projet propose la mise en place d'un groupe de réflexion autour d'indices dendrométriques permettant de décrire la structure forestière et une comparaison de leur pertinence à décrire la biodiversité de plusieurs taxons. Certains mécanismes notamment la lumière et l'encombrement vertical pourront être analysés.

Adéquation par rapport à l'appel à projet :

Le présent projet émerge à deux axes thématiques de l'AO-INDECO :

Axe 2.1 Processus de construction d'un indicateur environnemental

Amélioration méthodologique au travers de la synthèse et la comparaison d'indices de structure forestière ;

Développement et évaluation de la pertinence de nouveaux indicateurs indirects de biodiversité.

### Axe 2.3 : Granularité / Echelles / Dimension spatio-temporelle

Nouvelles méthodes et outils intégrant l'information à différentes granularités (échelles placette et massif) et lien avec alpha et gamma diversités.

Originalité, innovation :

Au sens large, le terme « structure forestière » désigne la distribution des dimensions verticales et horizontales des arbres ou des unités de gestion. Si les relations entre structure forestière et lumière sont relativement bien connues et modélisées, au moins en peuplements réguliers (Balandier et al., 2006, Sonohat et al., 2004), il n'en va pas de même pour le lien avec la biodiversité (voir cependant Balandier et al., 2002). Cette mise en relation est sans doute difficile pour deux raisons. D'une part, il existe une confusion persistante entre mode de traitement et structure effective du peuplement (ex. typiquement taillis sous futaie en conversion), d'autre part parce que la réponse de la biodiversité peut varier en fonction des groupes taxonomiques considérés, mais également des guildes composant ces groupes. A titre d'exemple, si la surface terrière apparaît comme un élément structurant la biodiversité des coléoptères carabiques en forêt (Toïgo et al., 2013), les mécanismes sous-jacents sont le plus souvent discutés, mais rarement analysés (ouverture du peuplement, lumière, présence de sous-étage, gros arbres). Ainsi, un même niveau de surface terrière peut caractériser des peuplements à la structure dendrométrique (verticale et horizontale) très différente et ne prend en général en compte que des arbres précomptables (i.e. d'un diamètre supérieur à 7.5cm à hauteur de poitrine), sans tenir compte du sous-étage.

Le présent projet propose de s'inspirer des travaux sur le lien entre structure et lumière pour comparer différents indices descripteurs de structures sur différents taxons modèles pour lesquels nous disposons de données précédemment acquises: flore vasculaire, oiseaux, chiroptères, coléoptères carabiques, cervidés. Nous ciblons une caractérisation de la structure forestière à deux échelles, définies comme suit :

À l'échelle de la placette élémentaire : si des indices simples comme la surface terrière ou le nombre de tiges sont couramment utilisés pour décrire la biodiversité car accessibles aux gestionnaires, d'autres indices – plus complexes mais peut être plus pertinents – apparaissent rarement dans la littérature :

Diversité et distribution des diamètres des arbres ou de la surface terrière : nombre de classes, indice de Shannon (e.g. Burrascano et al., 2009, Burrascano et al., 2011 pour un exemple sur la flore vasculaire), distribution (skewness, kurtosis), agencement spatial des arbres...

Couvert total : évalué par observation ou par des méthodes plus standardisées (densiomètre sphérique, photos hémisphériques) ;

Stratification verticale et couvert par strate, incluant les arbres non précomptables (sous-étage, diamètre < 7.5cm).

À l'échelle du paysage : les préconisations de gestion en faveur de la biodiversité recommandent de diversifier les structures, en faisant un lien avec le type de structure dominante au niveau régional (Gosselin & Paillet, 2010). Or une traduction de ces recommandations en termes d'indice de structure à l'échelle d'un massif n'est ni évidente, ni triviale. En effet, de nombreux indices descripteurs d'une diversité à large échelle (bêta ou gamma) à partir de relevés à l'échelle locale (alpha, type placette élémentaire IGN) peuvent être envisagés : variations de stratification verticale inter-placettes ou inter-parcelles, nombre de structures représentées à surface donnée, indice de Shannon appliqué aux structures verticales ou aux grands types structuraux (futaie régulière, taillis-sous-futaie)... A ce stade de la réflexion, aucun ne semble prendre en compte une structure moyenne à échelle régionale.

Nous proposons par conséquent à la fois un développement méthodologique au travers d'une analyse bibliographique, et le test comparatif de la pertinence de ces différents indices comme descripteurs de biodiversité.

Retombées socioéconomiques :

L'Observatoire National de la Biodiversité (ONB) a été mis en place en 2010 pour répondre aux engagements de la Stratégie Nationale de la Biodiversité et du Grenelle de l'Environnement. Il dispose à ce jour de 27 indicateurs dans le jeu « de synthèse » et 26 dans le jeu « nature » (<http://indicateurs-biodiversite.naturefrance.fr/indicateurs/tous>), dont 2 sont forestiers et incluent la structure forestière d'une manière peu satisfaisante. En effet, l'indicateur « Diversité structurelle des forêts métropolitaines : Proportion des surfaces forestières métropolitaines comportant plusieurs strates arborées superposées » ne prend pas en compte le contexte régional dans sa définition et assume un effet global positif sur la biodiversité en général, alors que différents groupes écologiques sont sans doute impactés de manière variable (ex. spécialistes forestières vs. espèces de milieux ouverts). Dans ce cadre, le présent projet viendrait nourrir la démarche ONB par une réflexion sur la manière de prendre en compte la structure forestière en tant qu'indicateur de biodiversité. Plus largement, ce travail viendra alimenter les travaux d'intercession pour l'amélioration des Indicateurs de Gestion Durable des Forêts Françaises et le rapportage européen sur l'état des forêts coordonné par Forest Europe. Il pourra par ailleurs servir de modèle à une réflexion plus globale sur l'ensemble des indicateurs du Critère 4 « biodiversité » du processus européen.

Démarche envisagée : quels moyens, quelle méthode, plan de travail, répartition des tâches et complémentarité entre les partenaires

Le projet s'articule en 3 tâches réparties sur 2 années : il s'agit avant tout d'une synthèse autour des indices de structure forestière basée sur la bibliographie, notamment celle traitant du lien entre structure et lumière (Tâche 1).

Sur la base des plans expérimentaux et d'échantillonnages issus de différents projets en cours ou passés, nous compléterons les mesures environnementales (estimation du couvert, hauteurs dominantes) déjà réalisées (Tâche 2). La validation des indices identifiés utilisera des données de biodiversité issues de ces projets, avec au moins 5 taxons cible : flore vasculaire, coléoptères carabiques, oiseaux, chiroptères et cervidés (Tâche 3).

Une réunion de lancement du projet fin 2013 à Nogent permettra de constituer le groupe de travail et de poser clairement les bases de la réflexion méthodologique, d'évaluer le potentiel des différents sites d'études gérés par les 3 équipes impliquées, ainsi que les données disponibles et leur utilisation. Cette réunion sera également l'occasion d'associer les membres du projet BioLid (UMR TETIS, Montpellier, EFNO) pour évaluer les possibilités de collaboration autour des deux projets.

### **Définition des contours du projet et analyse bibliographique sur le lien entre indicateur de structure forestière biodiversité**

L'un des premiers objectifs du groupe de travail sera de préciser la définition de structure forestière afin de clairement délimiter les contours du projet. Ce travail sera l'objet principal de la réunion de lancement du projet en Année 1.

En s'inspirant des travaux effectués sur la lumière et de la bibliographie existante reliant structure forestière et biodiversité, nous établirons une liste de descripteurs potentiels de structure verticale et horizontale à l'échelle de la placette forestière (e.g. distribution en classes de diamètre ou de surface terrière, présence d'éléments structurants du couvert, e.g. gros arbres), et à plus large échelle, sur l'agencement spatial des unités de régénération.

Ce travail de synthèse sera réalisé lors de la première partie d'un stage de M2 courant 2014 à Nogent-sur-Vernisson (co-encadrement P. Balandier, Y. Paillet). Il bénéficiera des réflexions issues de la première réunion de travail.

### **Prise de données nécessaires au calcul des indices de structure identifiés sur un réseau de placettes existantes**

Ce travail s'appuiera largement sur plusieurs réseaux issus d'autres projets des équipes impliquées, notamment le projet « Gestion forestière, Naturalité et Biodiversité » (<https://gnb.irstea.fr>) sur lequel des mesures de couvert forestier et de hauteurs seront effectuées. Ce projet, initié en 2008 en partenariat avec l'Office National des Forêts et les Réserves Naturelles de France, a pour but de comparer la biodiversité de 7 groupes taxonomiques (flore vasculaire, bryophytes, champignons, chiroptères, oiseaux, coléoptères saproxyliques et carabiques) entre forêts exploitées et non exploitées en France.

Fin 2012, le plan d'échantillonnage comptait 213 placettes individuelles situées en plaine et en montagne, sur lesquelles des données pour les 7 groupes étudiés sont disponibles, ainsi que des relevés d'abrutissement par les cervidés, et un descriptif fin des quantités de bois vivants, morts et de la régénération. Grâce aux données acquises et aux compléments réalisés dans le cadre de ce projet, nous pourrions tester la faisabilité et la pertinence des indices retenus lors de la Tache 1. Le travail de terrain sur ce projet constituera la deuxième moitié du stage de M2 en 2014 (mesures de couvert et photos hémisphériques – cette seconde mesure sera conditionnée par la possibilité de financer un appareil photo dédié). Il implique une visite de l'ensemble des sites d'études et sera réalisé en collaboration entre les équipes de Nogent, de Grenoble et d'Aix.

Il pourra également impliquer des données issues d'autres projets :

FORGECO (ANR 2010-2014) : sur les massifs du Vercors et d'Orléans, le projet dispose d'un plan d'échantillonnage stratifié sur l'ancienneté des forêts sur lequel ont été relevés les coléoptères carabiques et la flore vasculaire ;

les données dendrométriques et naturalistes de la thèse "Réponse de la biodiversité à l'ancienneté des forêts vs. vieillissement des peuplements" (Irstea Grenoble). Ce travail qui démarrera fin 2013, s'appuie lui aussi sur une sélection de groupes taxonomiques échantillonnés selon un plan croisant ancienneté du couvert et vieillissement des peuplements dans plusieurs massifs alpins (phase de terrain prévue en année 1) ;

le réseau de placettes dans les peuplements de Pin d'Alep mis en place par EMAX.

### **Analyses comparatives de l'influence des différents indices de structure sur la biodiversité de plusieurs taxons et rédaction d'articles scientifiques.**

Les premières analyses liant indices de structure et biodiversité commenceront en deuxième année du projet, notamment sur les données GNB disponibles pour les groupes cibles : flore vasculaire, carabiques, oiseaux, chauve-souris, cervidés. Ces analyses concerneront aussi bien la richesse totale que celle par groupe écologiques, voir par traits communs à plusieurs taxons (e.g. toutes les espèces forestières).

Etant donné le manque de données de biodiversité représentatives à l'échelle du massif, nous pourrions tester une approche par modélisation dans le cadre du projet ISCAR (Indicateurs de Structure de Composition et Analyse de scenaRio, projet DEB 2012-2014). Ce projet associe approche de terrain sur l'aspect biodiversité (flore vasculaire, rapaces, bryophytes) et une approche par modélisation de la croissance des peuplements. Ce couplage pourra être utilisé pour réfléchir à l'élargissement d'échelle de prise en compte de la structure forestière. Suivant l'avancée respective des deux projets, un travail mixte avec le volet flore vasculaire du projet ISCAR pourra être effectué sur les indicateurs de structure horizontale et verticale (Année 2).

Perspectives au-delà du projet d'amorçage : montage projet ANR, ...

Les résultats obtenus au cours du présent projet viendront appuyer une réflexion plus générale sur une meilleure prise en compte de la structure forestière comme indicateur indirect de biodiversité. Des projets de plus grande envergure peuvent être envisagés, notamment autour des systèmes de suivi de la biodiversité en place (programme STOC) ou en construction (ONB), dans lesquels les membres de l'UR EFNO sont impliqués. Une traduction des résultats obtenus pour les indicateurs de gestion durable des forêts françaises au travers de l'exploitation des données de l'IGN pourrait être envisagée au niveau français (appel d'offre BGF, GIP-Ecofor), ou plus



largement au niveau européen, en impliquant des partenaires ayant les mêmes problématiques. Par exemple, les travaux récents sur le lien entre diversité du couvert forestier et flore vasculaire ont montré la nécessité de prendre en compte la nature des essences en présence dans les analyses (Barbier et al., 2009). Il serait par conséquent intéressant d'évaluer la part relative des effets liés aux essences forestières et à la structure forestière sur des jeux de données partagés au niveau européen (projet type COST).

Production scientifique prévue (titre des publications potentielles, journal potentiel, date, approximative de la soumission) :

Au moins un article sur un des taxons cible, voire multitaxon :

How to take into account vertical and horizontal forest structure in biodiversity assessment? A multitaxonomic test. Cible : *Biological Conservation / Ecological Indicators / Forest Ecology and Management*, soumission fin 2015 si multitaxon, sans doute avant si monotaxon.

Un article de vulgarisation sur les indices de structure calculables à partir des relevés dendrométriques et leur lien à la biodiversité (issu notamment des résultats du stage en année 1) :

Hétérogénéité structurale des peuplements forestiers : synthèse des indices disponibles et lien avec la biodiversité. Cible : *Revue Forestière Française*, soumission fin 2015.

Bibliographie :

Balandier, P., D. Pauwels, F. Landré & R. Jouvie 2002. La lumière : outils sylvicole pour favoriser la diversité végétale ou la gestion cynégétique des peuplements de mélèze (*Larix* sp.). Forêt Wallonne 61 (Novembre-Décembre 2002): 9-13.

Balandier, P., G. Sonohat, H. Sinoquet, C. Varlet-Grancher & Y. Dumas 2006. Characterisation, prediction and relationships between different wavebands of solar radiation transmitted in the understorey of even-aged oak (*Quercus petraea*, *Q. robur*) stands. *Trees - Structure and Function* 20 (3): 363-370.

Barbier, S., R. Chevalier, P. Loussot, L. Berges & F. Gosselin 2009. Improving biodiversity indicators of sustainable forest management: Tree genus abundance rather than tree genus richness and dominance for understorey vegetation in French lowland oak hornbeam forests. *Forest Ecology and Management* 258: S176-S186.

Burrascano, S., L. Rosati & C. Blasi 2009. Plant species diversity in Mediterranean old-growth forests: A case study from central Italy. *Plant Biosystems* 143 (1): 190-200.

Burrascano, S., F. M. Sabatini & C. Blasi 2011. Testing indicators of sustainable forest management on understorey composition and diversity in southern Italy through variation partitioning. *Plant Ecology* 212 (5): 829-841.

Gosselin, M. & Y. Paillet. 2010. Mieux intégrer la biodiversité dans la gestion forestière. Quae eds, Versailles.

Sonohat, G., P. Balandier & F. Ruchaud 2004. Predicting solar radiation transmittance in the understorey of even-aged coniferous stands in temperate forests. *Annals of Forest Science* 61 (7): 629-641.

Toïgo, M., Y. Paillet, T. Noblecourt, F. Soldati, F. Gosselin & E. Dauffy-Richard 2013. Does forest management abandonment matter more than habitat characteristics for ground beetles? *Biological Conservation* 157: 215-224.

## Annex 2 - Summary data per forest stand



Sites arranged in alphabetical order. For explanation of the forest site codes, please refer to Table 1, Section 2.2.

Key: LOW = Lowland; MON = Mountain; MAN=Managed; UNM=Unmanaged; Sd=Standard deviation; Ba=Baal area

Site code	Name of stand	Inventory date	X coordinate	Y coordinate	MAN/ UNM	LOW/ MON	dbh (cm)					Ba (m <sup>2</sup> ha)	Density/ ha				
							Mean	Mode	Min	Max	Sd		40m	20m	10m		
1	ANO	ANO-2316	NA	730807	2235026	MAN	LOW	33	22	16	48	9	19.5	286	22	21	5
2	ANO	ANO-2456	NA	731009	2235328	MAN	LOW	37	21	16	54	8	20.6	231	21	19	9
3	ANO	ANO-2590	NA	730608	2235628	MAN	LOW	43	25	13	66	12	20.9	174	25	18	3
4	ANO	ANO-2731	NA	730907	2235928	MAN	LOW	38	24	16	64	12	20.0	203	24	20	6
5	ANO	ANO-RBI-106	NA	730354	2235828	UNM	LOW	48	36	19	80	15	35.8	285	36	28	9
6	ANO	ANO-RBI-111	NA	730671	2236138	UNM	LOW	33	31	16	56	10	29.6	427	31	31	12
7	ANO	ANO-RBI-127	NA	730612	2236205	UNM	LOW	37	32	11	57	10	31.3	349	32	28	10
8	ANO	ANO-RBI-155	NA	730355	2236207	UNM	LOW	34	38	13	60	11	35.1	519	38	38	20
9	AUB	1551	4/22/2008	804463	2314166	MAN	LOW	35	18	24	46	6	16.0	191	18	17	6
10	AUB	1584	4/22/2008	808612	2314177	MAN	LOW	35	28	8	61	15	22.9	397	28	24	11
11	AUB	4099	4/24/2008	803979	2311419	MAN	LOW	31	26	8	75	20	19.8	472	26	23	16
12	AUB	4551	4/24/2008	802492	2310921	MAN	LOW	34	22	8	53	10	20.1	281	22	21	8
13	AUB	5486	4/24/2008	803367	2309897	MAN	LOW	35	20	9	72	21	15.7	323	20	17	11
14	AUB	7504	4/24/2008	809095	2307811	MAN	LOW	21	26	9	63	14	13.6	617	26	25	20
15	AUB	8873	4/22/2008	806237	2306302	MAN	LOW	29	29	8	65	17	19.7	514	29	25	15
16	AUB	9770	4/10/2009	802369	2305293	MAN	LOW	31	24	8	73	22	15.8	417	24	21	13
17	AUB	13394	4/24/2008	805861	2301428	MAN	LOW	18	42	8	42	12	18.8	1013	42	42	33
18	AUB	CHALM22	4/25/2008	806642	2305272	UNM	LOW	33	30	8	93	26	39.1	725	30	29	23
19	AUB	CHALM6	4/25/2008	807030	2305605	UNM	LOW	50	18	12	92	27	31.2	290	18	17	10
20	AUB	POISIGFRA75	4/10/2009	800508	2305703	MAN	LOW	23	22	8	43	12	16.0	522	22	22	16
21	AUB	RONC116	4/21/2008	804938	2309044	UNM	LOW	34	16	8	53	14	12.9	224	16	15	8

Site code	Name of stand	Inventory date	X coordinate	Y coordinate	MAN/ UNM	LOW/ MON	dbh (cm)					Ba (m <sup>2</sup> ha)	Density/ ha				
							Mean	Mode	Min	Max	Sd		40m	20m	10m		
22	AUB	RONC120	4/21/2008	804310	2308968	UNM	LOW	33	20	8	61	19	14.5	327	20	17	12
23	AUB	RONC13	4/23/2008	804891	2310179	UNM	LOW	26	12	9	39	10	10.2	239	12	12	8
24	AUB	RONC135	4/21/2008	804411	2308720	UNM	LOW	22	50	8	62	15	28.3	1110	50	47	35
25	AUB	RONC27	4/23/2008	805131	2310039	UNM	LOW	23	41	8	54	17	22.6	959	41	35	30
26	AUB	RONC36	4/23/2008	804616	2309940	UNM	LOW	29	25	7	61	18	16.3	424	25	22	16
27	AUB	RONC51	4/23/2008	804867	2309805	UNM	LOW	26	37	8	66	19	20.9	758	37	35	25
28	AUB	RONC53	4/23/2008	805117	2309787	UNM	LOW	46	21	30	60	8	21.0	138	21	14	5
29	AUB	RONC6	4/24/2008	805024	2310292	UNM	LOW	0	NA	NA	NA	0	0.0	0	0	0	0
30	AUB	RONC93	4/21/2008	804458	2309333	UNM	LOW	36	22	10	64	15	19.9	280	22	21	9
31	AUB	VIVSIGFRA147	4/22/2008	804982	2307203	MAN	LOW	33	21	8	66	19	14.4	300	21	17	9
32	AUB	VIVSIGFRA59	4/22/2008	802722	2308891	MAN	LOW	31	27	8	74	20	21.3	506	27	26	18
33	BC	BC1	5/11/2010	932650	2322838	MAN	MON	45	15	16	59	12	25.0	213	15	14	6
34	BC	BC1973	10/28/2009	935652	2322822	MAN	MON	34	16	8	67	22	21.4	315	16	16	9
35	BC	BC377	5/11/2010	932197	2316210	MAN	MON	55	11	33	67	11	22.5	121	11	11	6
36	BC	BC382	5/11/2010	932249	2316413	MAN	MON	47	8	36	62	9	18.0	111	8	8	4
37	BC	BS3504	10/28/2009	932214	2320713	UNM	MON	30	21	8	68	21	21.0	413	21	20	13
38	BC	CA24	10/27/2009	933800	2323000	UNM	MON	40	17	8	72	23	26.8	242	17	17	8
39	BC	CB23	10/27/2009	934000	2323200	UNM	MON	49	19	8	87	19	37.5	225	19	17	8
40	BC	CC23	10/27/2009	934200	2323200	UNM	MON	34	28	9	99	22	40.4	570	28	28	18
41	BC	CE26	10/27/2009	934600	2322600	UNM	MON	25	40	8	67	20	36.3	1012	40	40	30
42	BC	CH22	5/10/2010	935200	2323400	UNM	MON	62	8	23	101	30	14.1	98	8	4	2
43	BC	CO2801	10/30/2009	936449	2322155	UNM	MON	54	25	15	88	19	49.8	293	25	23	11
44	BC	CP2901	10/26/2009	936703	2322001	UNM	MON	28	38	8	79	17	50.6	988	38	37	30

Site code	Name of stand	Inventory date	X coordinate	Y coordinate	MAN/ UNM	LOW/ MON	dbh (cm)					Ba (m <sup>2</sup> ha)	Density/ ha				
							Mean	Mode	Min	Max	Sd		40m	20m	10m		
45	BC	D23	10/29/2009	934043	2319844	MAN	MON	38	25	8	76	24	36.0	490	25	24	14
46	BC	D37	10/29/2009	934612	2320380	MAN	MON	49	21	16	88	20	37.5	270	21	19	9
47	BC	S23	10/28/2009	932806	2323757	MAN	MON	32	27	8	82	24	30.0	602	27	23	20
48	BC	S41	10/30/2009	933387	2322786	MAN	MON	39	26	10	62	14	45.8	467	26	26	12
49	BDP	BDP-105	3/9/2011	703379	2286112	MAN	LOW	16	56	8	39	9	26.9	1531	56	56	48
50	BDP	BDP-139	3/9/2011	703363	2286314	MAN	LOW	18	53	8	43	12	26.6	1343	53	53	41
51	BDP	BDP-297	3/9/2011	704037	2287120	MAN	LOW	31	17	8	66	19	12.8	269	17	17	10
52	BDP	BDP-463	3/9/2011	696058	2290907	MAN	LOW	15	41	8	39	10	17.4	1130	41	41	36
53	BDP	BDP-470	3/9/2011	695947	2290997	MAN	LOW	15	23	8	29	8	11.2	653	23	23	22
54	BDP	BDP-RN12	3/8/2011	698746	2288130	UNM	LOW	25	20	12	36	7	18.4	434	20	20	19
55	BDP	BDP-RN15	3/8/2011	698662	2288043	UNM	LOW	12	69	8	26	4	27.0	2166	69	69	68
56	BDP	BDP-RN22	3/8/2011	698649	2287841	UNM	LOW	14	59	8	27	5	27.7	1828	59	59	59
57	BDP	BDP-RN29	3/8/2011	698947	2287759	UNM	LOW	13	55	8	26	4	25.1	1732	55	55	54
58	BDP	BDP-RN32	3/8/2011	698945	2287640	UNM	LOW	12	63	8	29	4	25.3	1972	63	63	63
59	CHA	CHA-G-1	NA	868240	2039356	MAN	MON	31	15	8	65	21	19.4	337	15	15	10
60	CHA	CHA-G-2	NA	868195	2039239	MAN	MON	33	20	8	69	22	26.5	435	20	19	16
61	CHA	CHA-G-3	NA	868298	2039218	MAN	MON	46	19	8	103	27	32.8	326	19	18	8
62	CHA	CHA-G-4	NA	868041	203915	MAN	MON	46	13	9	69	20	21.9	192	13	12	9
63	CHA	CHA-G-5	NA	868282	2039340	MAN	MON	52	16	9	76	20	31.5	217	16	16	6
64	CHA	CHA-RI-1	NA	868484	2043419	UNM	MON	46	28	8	111	33	42.6	488	28	24	13
65	CHA	CHA-RI-2	NA	868546	2043452	UNM	MON	32	35	8	99	26	38.9	829	35	32	28
66	CHA	CHA-RI-3	NA	868579	2043413	UNM	MON	30	25	8	78	24	29.8	626	25	25	18
67	CHA	CHA-RI-4	NA	868598	2043513	UNM	MON	22	35	8	52	14	21.8	816	35	34	29

Site code	Name of stand	Inventory date	X coordinate	Y coordinate	MAN/ UNM	LOW/ MON	dbh (cm)					Ba (m <sup>2</sup> ha)	Density/ ha				
							Mean	Mode	Min	Max	Sd		40m	20m	10m		
68	CHA	CHA-RI-5	NA	868435	2043425	UNM	MON	19	33	8	60	13	18.1	855	33	32	28
69	CHS	CHS-11564	NA	777991	2314872	MAN	LOW	18	27	8	50	12	14.4	729	27	27	25
70	CHS	CHS-11603	NA	781889	2314861	MAN	LOW	35	18	13	70	15	17.0	277	18	18	9
71	CHS	CHS-5478	NA	781391	2310862	MAN	LOW	29	19	8	61	16	15.3	356	19	19	14
72	CHS	CHS-9267	NA	777787	2313357	MAN	LOW	19	25	8	41	9	17.0	685	25	25	23
73	CHS	CHS-RBI-18	NA	781222	2313363	UNM	LOW	35	20	9	66	19	14.5	295	20	20	11
74	CHS	CHS-RBI-22	NA	781760	2313372	UNM	LOW	22	31	8	57	13	19.7	679	31	29	23
75	CHS	CHS-RBI-26	NA	781489	2313457	UNM	LOW	35	21	8	58	18	16.0	255	21	19	8
76	CHS	CHS-RBI-59	NA	782034	2313892	UNM	LOW	30	26	10	64	15	21.1	458	26	24	14
77	CHZ	CHZ-137	4/28/2010	386300	2132901	MAN	LOW	8	9	8	9	0	1.5	286	9	9	9
78	CHZ	CHZ-169	4/28/2010	387098	2131705	MAN	LOW	22	53	8	61	16	31.4	1354	53	51	43
79	CHZ	CHZ-181	4/28/2010	387092	2132907	MAN	LOW	23	22	8	60	19	12.2	517	22	20	17
80	CHZ	CHZ-185	4/29/2010	387507	2131708	MAN	LOW	19	61	8	99	17	28.8	1624	61	55	53
81	CHZ	CHZ-193	4/28/2010	387506	2132910	MAN	LOW	21	31	8	50	12	20.3	769	31	31	23
82	CHZ	CHZ-329	4/28/2010	389508	2134096	MAN	LOW	23	16	8	40	10	12.6	358	16	16	11
83	CHZ	CHZ-349	4/29/2010	389914	2131697	MAN	LOW	18	29	8	34	7	19.4	809	29	29	22
84	CHZ	CHZ-353	4/29/2010	389910	2132128	MAN	LOW	21	27	12	34	6	22.0	675	27	27	20
85	CHZ	CHZ-393	4/29/2010	390293	2131714	MAN	LOW	15	29	8	27	5	15.6	890	29	29	26
86	CHZ	CHZ-417	4/29/2010	390697	2130908	MAN	LOW	21	27	9	38	8	19.0	647	27	27	20
87	CHZ	CHZ-421	4/29/2010	390675	2131302	MAN	LOW	16	34	8	41	8	18.6	961	34	34	33
88	CHZ	CHZ-453	4/28/2010	391092	2130911	MAN	LOW	16	33	8	31	8	18.8	906	33	33	30
89	CHZ	CHZ-RBI-103	2/23/2011	386379	2127928	UNM	LOW	22	12	8	44	12	8.2	280	12	12	9
90	CHZ	CHZ-RBI-105	2/23/2011	387168	2127895	UNM	LOW	18	25	8	38	9	15.8	679	25	25	25

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91	CHZ	CHZ-RBI-114	2/24/2011	385561	2127560	UNM	LOW	13	46	7	21	4	19.9	1461	46	46	46
92	CHZ	CHZ-RBI-149	2/23/2011	385488	2125953	UNM	LOW	12	53	7	21	4	20.8	1681	53	53	52
93	CHZ	CHZ-RBI-31	2/22/2011	390036	2129807	UNM	LOW	18	49	7	55	14	22.7	1300	49	48	42
94	CHZ	CHZ-RBI-43	2/22/2011	389622	2129414	UNM	LOW	17	27	7	53	15	11.3	693	27	26	20
95	CHZ	CHZ-RBI-44	2/22/2011	390024	2129405	UNM	LOW	31	23	10	55	15	19.4	405	23	22	13
96	CHZ	CHZ-RBI-68	2/23/2011	385994	2128741	UNM	LOW	20	18	8	47	12	11.3	472	18	18	16
97	CHZ	CHZ-RBI-71	2/22/2011	387188	2128696	UNM	LOW	13	64	7	47	8	24.7	1890	64	64	59
98	CHZ	CHZ-RBI-80	2/23/2011	383580	2128421	UNM	LOW	18	52	7	72	16	24.6	1439	52	49	47
99	CHZ	CHZ-RBI-94	2/22/2011	389174	2128235	UNM	LOW	15	34	7	79	17	10.8	982	34	34	31
100	CHZ	CHZ-RBI-98	2/23/2011	384366	2127993	UNM	LOW	18	30	7	44	11	16.4	804	30	30	25
101	CIT	CIT-1315	4/22/2010	804612	2237946	MAN	LOW	37	26	9	62	16	23.2	361	26	22	11
102	CIT	CIT-1514	4/22/2010	804539	2238314	MAN	LOW	31	36	10	52	16	27.0	612	36	33	19
103	CIT	CIT-2060	4/22/2010	808802	2237542	MAN	LOW	56	25	9	94	23	21.1	180	25	15	5
104	CIT	CIT-2165	4/22/2010	809598	2237600	MAN	LOW	32	46	8	97	27	28.2	925	46	37	29
105	CIT	CIT-463	4/22/2010	806935	2233844	MAN	LOW	30	38	8	96	24	28.0	781	38	33	24
106	CIT	CIT-855	4/22/2010	804132	2237202	MAN	LOW	42	35	9	85	22	28.8	477	35	23	16
107	CIT	CIT-RI-08	4/21/2010	805873	2234194	UNM	LOW	66	48	8	104	26	46.7	319	48	22	11
108	CIT	CIT-RI-11	4/21/2010	805967	2234310	UNM	LOW	65	35	9	125	26	36.1	228	35	14	7
109	CIT	CIT-RI-15	4/23/2010	806074	2234300	UNM	LOW	64	40	8	150	30	42.5	255	40	21	8
110	CIT	CIT-RI-21	4/21/2010	806973	2234053	UNM	LOW	56	27	13	113	28	29.5	239	27	15	5
111	CIT	CIT-RI-23	4/21/2010	807123	2233975	UNM	LOW	44	37	8	100	25	34.4	458	37	30	16
112	CIT	CIT-RI-25	4/21/2010	806944	2234214	UNM	LOW	59	24	12	126	31	27.2	189	24	16	7
113	CL	RNCL-1023	4/20/2010	797247	2248956	MAN	LOW	44	24	10	73	22	20.8	272	24	18	9
114	CL	RNCL-2065	4/20/2010	796757	2254797	MAN	LOW	32	35	8	72	21	26.9	650	35	31	20



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115	CL	RNCL-2521	4/20/2010	797950	2256820	MAN	LOW	24	31	8	62	12	22.4	644	31	29	20
116	CL	RNCL-563	4/20/2010	796338	2247449	MAN	LOW	14	41	8	38	10	15.9	1109	41	41	35
117	CL	RNCL-RI-15	4/20/2010	796980	2249927	UNM	LOW	49	16	25	90	20	16.3	132	16	13	6
118	CL	RNCL-RI-21	4/20/2010	797869	2250210	UNM	LOW	26	24	8	53	10	17.6	422	24	24	14
119	CL	RNCL-RI-30	4/19/2010	795995	2251208	UNM	LOW	15	47	8	40	8	20.0	1293	47	45	40
120	CL	RNCL-RI-33	4/19/2010	796268	2251018	UNM	LOW	24	25	9	38	8	19.4	518	25	25	16
121	ECO	VER-G-1	NA	849855	2025759	MAN	MON	24	24	8	66	19	24.3	610	24	23	20
122	ECO	VER-G-2	NA	849705	2025609	MAN	MON	40	28	9	88	29	37.5	524	28	26	19
123	ECO	VER-G-3	NA	849555	2025459	MAN	MON	38	29	7	76	21	49.4	611	29	29	20
124	ECO	VER-G-4	NA	849405	2025609	MAN	MON	40	22	8	65	17	42.9	442	22	22	15
125	ECO	VER-G-5	NA	849405	2025459	MAN	MON	33	31	8	84	25	39.4	675	31	30	21
126	ECO	VER-RI-1	NA	848955	2023809	UNM	MON	52	21	24	118	21	46.0	293	21	19	9
127	ECO	VER-RI-2	NA	849105	2023809	UNM	MON	40	29	7	80	26	45.1	555	29	27	16
128	ECO	VER-RI-3	NA	849105	2023959	UNM	MON	51	23	10	87	28	37.4	347	23	18	9
129	ECO	VER-RI-4	NA	849105	2023659	UNM	MON	64	21	9	114	24	41.5	195	21	16	5
130	ECO	VER-RI-5	NA	849255	2023509	UNM	MON	33	30	7	97	22	34.4	598	30	30	19
131	ENG	ENG-13	10/7/2010	855620	2030209	MAN	MON	49	15	16	65	11	29.9	176	15	14	5
132	ENG	ENG-17	10/7/2010	855700	2029546	MAN	MON	33	20	14	58	13	34.7	451	20	20	15
133	ENG	ENG-20	10/7/2010	855690	2028098	MAN	MON	40	16	8	68	16	32.0	309	16	16	11
134	ENG	ENG-21	10/7/2010	855635	2027850	MAN	MON	47	13	11	85	21	26.1	213	13	13	8
135	ENG	ENG-33	10/7/2010	855244	2025068	MAN	MON	48	15	34	69	10	31.5	194	15	14	6
136	ENG	ENGRBI-254	10/6/2010	856742	2029140	UNM	MON	29	36	11	65	15	49.6	886	36	36	26
137	ENG	ENGRBI-282	10/6/2010	855802	2029500	UNM	MON	49	20	21	130	24	40.6	295	20	19	8

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							Mean	Mode	Min	Max	Sd		40m	20m	10m		
138	ENG	ENGRBI-294	10/6/2010	855875	2030869	UNM	MON	30	22	9	62	17	32.3	529	22	22	17
139	ENG	ENGRBI-360	10/6/2010	855966	2030084	UNM	MON	39	13	16	63	13	26.7	277	13	13	8
140	ENG	ENGRBI-361	10/6/2010	856527	2029059	UNM	MON	49	18	18	90	14	32.3	199	18	17	6
141	FBL	CB14	3/23/2009	622084	2379144	UNM	LOW	28	32	8	80	24	20.9	774	32	27	24
142	FBL	CB33	3/23/2009	621941	2379311	UNM	LOW	40	13	15	56	13	12.2	148	13	13	7
143	FBL	CB39	3/23/2009	622582	2379354	UNM	LOW	36	22	8	100	32	15.4	409	22	17	12
144	FBL	CB51	3/23/2009	622285	2379465	UNM	LOW	50	23	8	102	23	21.8	200	23	19	8
145	FBL	FBL1063	4/16/2009	620491	2374474	MAN	LOW	39	15	9	63	17	12.9	174	15	12	8
146	FBL	FBL107	4/16/2009	624154	2383857	MAN	LOW	0	NA	NA	NA	0	0.0	0	0	0	0
147	FBL	FBL1099	4/16/2009	621742	2374052	MAN	LOW	40	30	8	78	23	23.5	443	30	20	14
148	FBL	FBL117	3/27/2009	623682	2383754	MAN	LOW	35	17	24	50	8	15.0	168	17	17	8
149	FBL	FBL13	4/16/2009	622956	2384658	MAN	LOW	63	1	63	63	0	1.0	3	1	0	0
150	FBL	FBL133	3/27/2009	624563	2383658	MAN	LOW	50	26	11	77	17	22.6	205	26	14	6
151	FBL	FBL166	3/27/2009	624429	2383365	MAN	LOW	45	21	8	72	17	18.5	185	21	17	9
152	FBL	FBL273	3/27/2009	624466	2381772	MAN	LOW	36	19	12	70	16	17.8	258	19	17	9
153	FBL	FBL333	3/26/2009	620316	2381145	MAN	LOW	38	34	9	80	17	28.0	404	34	28	11
154	FBL	FBL374	3/26/2009	621769	2380894	MAN	LOW	45	30	8	80	24	23.2	349	30	23	10
155	FBL	FBL413	3/26/2009	621697	2380797	MAN	LOW	31	21	9	46	11	16.8	306	21	17	9
156	FBL	FBL420	4/16/2009	623266	2380748	MAN	LOW	101	1	101	101	0	1.6	2	1	0	0
157	FBL	FBL589	3/26/2009	624645	2379468	MAN	LOW	32	28	8	65	17	19.9	446	28	25	14
158	FBL	FBL604	3/26/2009	625158	2379261	MAN	LOW	38	25	8	91	22	18.9	390	25	18	13
159	FBL	FBL860	3/27/2009	623554	2376459	MAN	LOW	28	30	8	54	15	20.4	541	30	28	17
160	FBL	FBL889	4/16/2009	620836	2375848	MAN	LOW	25	35	9	62	13	24.9	728	35	34	24

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							Mean	Mode	Min	Max	Sd		40m	20m	10m		
161	FBL	GFT124	3/24/2009	624634	2380703	UNM	LOW	49	26	9	111	25	22.7	227	26	15	5
162	FBL	GFT13	3/24/2009	625958	2379815	UNM	LOW	43	30	9	92	28	24.7	476	30	19	15
163	FBL	GFT21	3/24/2009	625694	2379961	UNM	LOW	60	25	8	121	30	24.7	196	25	13	6
164	FBL	GFT59	3/24/2009	625076	2380310	UNM	LOW	47	23	8	112	24	19.9	235	23	15	10
165	FBL	GFT67	3/25/2009	625866	2380328	UNM	LOW	63	23	15	158	41	29.0	197	23	13	5
166	FBL	GFT78	4/16/2009	625469	2380409	UNM	LOW	14	19	8	40	7	8.2	581	19	19	18
167	FBL	GFT94	3/25/2009	625475	2380510	UNM	LOW	23	23	8	54	17	13.5	534	23	21	17
168	FBL	TL43	3/25/2009	623949	2380486	UNM	LOW	40	25	7	91	32	17.5	389	25	18	11
169	FBL	TL45	3/25/2009	623768	2380492	UNM	LOW	40	34	9	112	28	30.1	512	34	25	14
170	HCJ	HCJ-RI-03	6/27/2012	883033	2155063	UNM	MON	42	27	11	103	27	39.9	498	27	23	14
171	HCJ	HCJ-RI-04	6/25/2012	883508	2155067	UNM	MON	47	24	10	85	23	43.9	407	24	22	11
172	HCJ	HCJ-RI-08	6/25/2012	883971	2155530	UNM	MON	33	16	8	78	26	19.4	362	16	16	14
173	HCJ	HCJ-RI-106	6/28/2012	884276	2158324	UNM	MON	38	22	8	75	24	33.2	436	22	22	14
174	HCJ	HCJ-RI-115	6/26/2012	888000	2158939	UNM	MON	29	25	8	73	18	33.6	638	25	25	19
175	HCJ	HCJ-RI-134	6/26/2012	889859	2160854	UNM	MON	13	40	8	26	5	19.6	1273	40	40	40
176	HCJ	HCJ-RI-40	6/28/2012	879036	2146552	UNM	MON	23	23	8	57	13	25.9	650	23	23	20
177	HCJ	HCJ-RI-80	6/29/2012	873746	2132893	UNM	MON	33	16	9	76	16	27.9	373	16	16	15
178	HCJ	HCJ-RN-108	6/28/2012	886130	2158317	MAN	MON	53	20	14	94	23	41.1	282	20	16	10
179	HCJ	HCJ-RN-120	6/26/2012	888616	2159560	MAN	MON	34	15	12	54	13	23.4	301	15	15	8
180	HCJ	HCJ-RN-127	6/26/2012	889251	2160141	MAN	MON	21	25	8	52	12	25.2	735	25	25	23
181	HCJ	HCJ-RN-160	6/27/2012	884460	2155990	MAN	MON	36	18	8	77	24	27.3	399	18	18	14
182	HCJ	HCJ-RN-161	6/27/2012	883501	2156473	MAN	MON	38	28	9	116	38	30.0	631	28	26	19
183	HCJ	HCJ-RN-211	6/29/2012	873718	2133816	MAN	MON	24	18	9	61	14	22.4	497	18	18	17

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							Mean	Mode	Min	Max	Sd		40m	20m	10m		
184	HCJ	HCJ-RN-41	6/28/2012	879321	2146540	MAN	MON	14	48	8	36	6	26.4	1518	48	48	48
185	HCJ	HCJ-RN-94	6/27/2012	884877	2155841	MAN	MON	20	19	12	37	7	19.0	582	19	19	17
186	HT	HT-149	3/22/2011	738228	2344798	MAN	LOW	58	24	14	108	18	23.3	130	24	12	6
187	HT	HT-2160	3/23/2011	736801	2349950	MAN	LOW	27	34	8	55	13	25.0	649	34	32	20
188	HT	HT-2186	3/23/2011	736400	2349975	MAN	LOW	52	33	10	84	24	29.8	317	33	18	9
189	HT	HT-2271	3/23/2011	739017	2350201	MAN	LOW	36	33	9	62	15	28.9	472	33	25	15
190	HT	HT-486	3/23/2011	733635	2346113	MAN	LOW	37	22	8	76	24	15.9	353	22	20	9
191	HT	HT-909	3/22/2011	737924	2347020	MAN	LOW	30	26	12	81	20	21.7	557	26	24	18
192	HT	HT-921	3/22/2011	739126	2347017	MAN	LOW	29	43	8	79	23	25.9	888	43	35	27
193	HT	HT-RBI-C0417	3/21/2011	737882	2345594	UNM	LOW	34	50	8	103	29	33.9	1004	50	40	34
194	HT	HT-RBI-C0511	3/21/2011	737533	2345938	UNM	LOW	26	48	8	85	21	30.0	1066	48	43	35
195	HT	HT-RBI-C0613	3/21/2011	737723	2345969	UNM	LOW	27	37	9	64	20	22.9	785	37	31	28
196	HT	HT-RBI-C0912	3/22/2011	737819	2346258	UNM	LOW	23	58	8	84	20	33.6	1481	58	51	47
197	HT	HT-RBI-C1010	3/22/2011	737760	2346414	UNM	LOW	26	49	8	88	21	31.0	1108	49	40	35
198	HT	HT-RBI-C1310	3/21/2011	737942	2346635	UNM	LOW	32	38	8	66	20	28.1	689	38	31	18
199	HT	HT-RBI-C1314	3/21/2011	738183	2346477	UNM	LOW	44	23	10	71	17	21.9	231	23	17	7
200	LURE	LURE-01	8/16/2011	880272	1908134	MAN	MON	25	20	8	44	11	29.5	578	20	20	18
201	LURE	LURE-02	8/16/2011	880930	1908026	MAN	MON	24	31	8	54	13	38.9	879	31	31	28
202	LURE	LURE-03	8/17/2011	879016	1908614	MAN	MON	20	22	8	58	15	21.2	624	22	22	20
203	LURE	LURE-04	8/18/2011	878056	1909100	MAN	MON	23	28	8	57	14	31.0	787	28	28	26
204	LURE	LURE-RBI01	8/17/2011	870518	1909792	UNM	MON	16	56	8	39	9	41.5	1739	56	56	56
205	LURE	LURE-RBI106	8/18/2011	877798	1908917	UNM	MON	22	30	8	68	13	35.3	880	30	29	26
206	LURE	LURE-RBI17	8/16/2011	880738	1907941	UNM	MON	26	23	8	49	15	30.5	588	23	23	19

Site code	Name of stand	Inventory date	X coordinate	Y coordinate	MAN/ UNM	LOW/ MON	dbh (cm)					Ba (m <sup>2</sup> ha)	Density/ ha				
							Mean	Mode	Min	Max	Sd		40m	20m	10m		
207	LURE	LURE-RBI174	8/17/2011	871386	1909451	UNM	MON	30	41	8	81	22	49.9	985	41	41	28
208	PAR	PAR-3412	NA	915214	2412622	MAN	LOW	0	NA	NA	NA	0	0.0	0	0	0	0
209	PAR	PAR-4932	NA	914214	2413622	MAN	LOW	29	57	13	70	10	29.9	505	57	57	14
210	PAR	PAR-6316	NA	914914	2414522	MAN	LOW	36	26	8	80	20	21.9	407	26	20	15
211	PAR	PAR-8324	NA	916814	2415822	MAN	LOW	28	46	8	77	19	26.9	889	46	42	27
212	PAR	PAR-RBI-12	NA	918378	2412872	UNM	LOW	33	42	10	63	14	28.6	452	42	37	16
213	PAR	PAR-RBI-301	NA	917938	2412437	UNM	LOW	32	39	8	91	22	26.5	649	39	33	20
214	PAR	PAR-RBI-303	NA	918285	2412437	UNM	LOW	28	60	8	67	14	31.2	776	60	57	28
215	PAR	PAR-RBI-9	NA	917841	2412873	UNM	LOW	35	47	8	73	19	30.8	552	47	39	20
216	RMB	RBX-59	2/28/2012	557329	2407274	UNM	LOW	43	37	8	85	25	28.6	512	37	27	17
217	RMB	RBX-76	2/27/2012	558134	2407289	UNM	LOW	40	20	8	84	20	17.9	259	20	17	8
218	RMB	RBX-89	2/27/2012	558241	2407439	UNM	LOW	42	20	14	75	19	18.5	234	20	16	6
219	RMB	RMB-1733	2/29/2012	560273	2411332	MAN	LOW	46	23	16	68	14	22.6	197	23	18	4
220	RMB	RMB-3513	2/29/2012	555497	2416982	MAN	LOW	72	17	11	110	21	18.4	73	17	8	2
221	RMB	RMB-3543	2/29/2012	559450	2417011	MAN	LOW	26	26	8	44	11	20.0	471	26	25	14
222	RMB	RMB-579	2/29/2012	558376	2406992	MAN	LOW	59	22	41	76	10	22.0	90	22	10	4
223	RMB	RMB-806	3/5/2012	558875	2407575	MAN	LOW	52	14	10	88	21	12.8	117	14	10	3
224	RMB	RMB-923	2/28/2012	559052	2408112	MAN	LOW	59	18	16	85	17	17.8	100	18	9	5
225	RMB	RMB-941	2/28/2012	554050	2408210	MAN	LOW	29	16	10	60	15	13.5	302	16	15	11
226	RMB	RMB-967	3/5/2012	559280	2408055	MAN	LOW	74	4	64	85	9	4.1	10	4	1	1
227	RMB	RMB-RBI-18	2/28/2012	556845	2406908	UNM	LOW	31	36	8	73	19	28.9	713	36	32	24
228	RMB	RMB-RBI-191	2/28/2012	553149	2416110	UNM	LOW	51	11	13	76	19	10.4	87	11	8	5
229	RMB	RMB-RBI-261	2/27/2012	552344	2416512	UNM	LOW	59	26	13	81	14	23.4	116	26	12	3

Site code	Name of stand	Inventory date	X coordinate	Y coordinate	MAN/ UNM	LOW/ MON	dbh (cm)					Ba (m <sup>2</sup> ha)	Density/ ha				
							Mean	Mode	Min	Max	Sd		40m	20m	10m		
230	RMB	RMB-RBI-266	2/27/2012	552176	2416588	UNM	LOW	39	24	13	76	21	20.7	306	24	19	10
231	RMB	RMB-RBI-274	2/27/2012	551950	2416808	UNM	LOW	30	43	8	85	21	33.6	903	43	39	29
232	VEN	RBI-22	4/30/2008	943125	2336437	UNM	MON	53	14	8	84	23	25.1	189	14	12	5
233	VEN	RBI-28	4/29/2008	942521	2337234	UNM	MON	36	30	8	118	37	26.1	648	30	26	20
234	VEN	RBI-30	4/29/2008	942521	2337434	UNM	MON	51	19	33	75	11	38.3	228	19	18	6
235	VEN	RBI-35	4/28/2008	944145	2340418	UNM	MON	48	22	10	70	18	43.9	298	22	22	12
236	VEN	Ven2	4/28/2008	944306	2340441	MAN	MON	18	28	8	67	16	14.6	742	28	27	22
237	VEN	Ven3	4/29/2008	942906	2337441	MAN	MON	48	13	8	69	19	22.6	181	13	12	7
238	VEN	Ven4	4/29/2008	942706	2337241	MAN	MON	27	27	8	100	26	26.4	685	27	26	21
239	VEN	Ven5	4/30/2008	943114	2336626	MAN	MON	41	14	8	80	28	21.7	290	14	14	9
240	VER	VER-416	3/2/2012	593706	2417173	MAN	LOW	17	33	8	71	10	21.2	1002	33	33	32
241	VER	VER-540	3/2/2012	592905	2417569	MAN	LOW	53	23	8	94	28	19.9	235	23	15	8
242	VER	VER-678	3/2/2012	593503	2417976	MAN	LOW	20	31	10	33	6	24.6	855	31	31	27
243	VER	VER-704	3/2/2012	592806	2418070	MAN	LOW	45	29	8	90	29	22.4	418	29	22	13
244	VER	VER-RBI-05	3/1/2012	593663	2417434	UNM	LOW	40	30	8	94	28	22.8	470	30	24	13
245	VER	VER-RBI-19	3/1/2012	593761	2417586	UNM	LOW	37	36	10	86	26	27.4	612	36	30	19
246	VER	VER-RBI-24	3/1/2012	593898	2417539	UNM	LOW	43	30	8	101	28	22.0	392	30	26	13
247	VER	VER-RBI-32	3/1/2012	594095	2417590	UNM	LOW	51	22	8	82	25	19.8	234	22	16	7
248	VTX	VTX-8201	4/11/2011	832410	1912968	MAN	MON	27	43	8	52	12	35.2	808	43	43	25
249	VTX	VTX-8203	4/11/2011	832615	1912995	MAN	MON	18	39	8	51	13	18.5	983	39	39	33
250	VTX	VTX-8601	4/11/2011	832805	1913179	MAN	MON	20	50	8	42	9	35.2	1259	50	50	42
251	VTX	VTX-8804	4/11/2011	833327	1913285	MAN	MON	20	45	8	46	9	33.0	1164	45	45	40
252	VTX	VTX-9999	4/11/2011	834002	1913877	MAN	MON	38	32	8	127	28	28.9	558	32	30	18

Site code	Name of stand	Inventory date	X coordinate	Y coordinate	MAN/ UNM	LOW/ MON	dbh (cm)					Ba (m <sup>2</sup> ha)	Density/ ha				
							Mean	Mode	Min	Max	Sd		40m	20m	10m		
253	VTX	VTX-RBI-15	6/15/2011	835275	1914375	UNM	MON	26	44	8	73	19	27.3	956	44	40	32
254	VTX	VTX-RBI-168	4/13/2011	837550	1912100	UNM	MON	31	28	8	60	16	24.2	507	28	27	18
255	VTX	VTX-RBI-185	4/12/2011	838076	1911924	UNM	MON	24	24	9	40	11	18.2	532	24	24	19
256	VTX	VTX-RBI-39	4/12/2011	835800	1913500	UNM	MON	25	68	8	80	15	47.7	1470	68	65	46
257	VTX	VTX-RBI-76	4/13/2011	836496	1912961	UNM	MON	35	33	8	75	16	28.7	484	33	32	20

### Annex 3 - GNB Secondary protocol

#### **PROTOCOLE - Saisie de données complémentaires sur dispositif GNB**

##### **OBJECTIF :**

L'objectif de cet exercice est de repasser par les placettes du projet Gestion Forestière, Nature et Biodiversité (GNB) avec la fiche de relevés ci-jointe pour des mesures complémentaires de couverture de canopée et d hauteurs de bois vivants pour aider aux objectifs du projet CONSPIIRE qui vise à caractériser la structure forestière en tant qu'indicateur proxy pour la biodiversité. Dans un inventaire précédent, le projet GNB a repéré les tiges à mesurer en utilisant un angle mort et a ensuite localisé chaque tige de chaque placette, mesuré le diamètre à hauteur de la poitrine à deux angles différents et a relevé l'espèce de chaque arbre.

##### **CHEMINEMENT :**

Des points GPS ont été calés pour le centre de chaque placette. Nous utiliserons les points GPS pour retrouver le centre de la placette ainsi que les arbres les plus près de la placette marqués avec de la peinture et la tige en fer avec l'aide d'un détecteur de métaux si nécessaire. Une borne métallique sera ensuite placée dans le sol au centre de la placette à l'aide d'un marteau. Si le centre n'est pas retrouvé, il faut se recalculer par rapport aux arbres marqués et à l'azimut et distances des arbres de l'inventaire précédent. Si cela n'est pas possible, il faudra mettre la borne au point GPS.

##### **MESURE DES HAUTEURS**

Nous commencerons par retrouver les cinq arbres avec les plus gros diamètres à un maximum de 40 m de distance du centre de la placette en utilisant l'azimut des arbres à l'aide d'une boussole et si nécessaire la location des arbres morts pour mieux se situer sur la placette. Dans le cas d'une placette avec des arbres feuillus et résineux, selon le nombre de gros arbres inventoriés pour chaque type d'arbre, des arbres supplémentaires (pas plus de trois) avec un diamètre de plus de 30 cm peuvent aussi être mesurés pour avoir une bonne idée de la hauteur pour résineux et feuillus. Si des arbres ont été coupés ou sont morts lors du prélèvement, l'arbre plus gros suivant sera mesuré. La hauteur des arbres sera ensuite mesurée en utilisant un hypsomètre Vertex. La procédure est :

- Mettre le transpondeur du Vertex sur l'arbre à mesurer à 1m30 d hauteur
- S'éloigner de l'arbre à une distance plus ou moins équivalente de la hauteur de l'arbre.
- Il faut pouvoir voir aussi bien le transpondeur que le sommet de l'arbre.
- Viser le transpondeur avec le Vertex jusqu'à ce qu'il émette un son.
- Viser le sommet de l'arbre. Le sommet est visé à plusieurs points de la canopée de l'arbre et une moyenne établie à partir de ces points.

*Note* : Il faudra recalibrer le Vertex au moins une fois par semaine pour s'assurer de la précision de ses mesures. Pour bien s'étalonner entre opérateurs, il faudrait comparer les mesures des hauteurs d'arbres au moins une fois par semaine.

##### **COUVERTURE DE CANOPEE**

Pour mesurer la couverture de canopée, on place d'abord une tige en plastique aux 4 directions cardinales à 10 m du centre de la placette à l'aide d'une boussole. Ensuite, on utilise un densiomètre sphérique convexe au centre de la placette et on réalise quatre mesures dans les directions cardinales (Nord, Est, Sud, Ouest) à 10 mètre du centre de la placette. La procédure est :

- Se placer à côté de la tige en plastique tournant le dos au centre de la placette ;
- Le densiomètre doit être à plat à 50 cm du visage de l'opérateur ;
- Tenir l'instrument le plus horizontal possible ;
- La grille est composée de 24 carrés, dans chacun d'eux, l'opérateur doit imaginer 4 points placés à la manière d'un dé ;
- L'opérateur compte le nombre de points imaginaires qui n'interceptent pas la canopée ;



- Si il y a un gros tronc dans la grille, il faut essayer de se déplacer un peu en tournant sur soi ou en se déplaçant de quelques centimètres (mais moins d'un mètre) ;
- On peut utiliser un monopode pour soutenir le densiomètre pour le rendre plus stable.

La moyenne de ces quatre mesures fournit une estimation de l'ouverture du couvert en un point donné. La somme du nombre de points imaginaires doit être multipliée par 1.04 pour obtenir un pourcentage. Pour réduire la variabilité inter-opérateur, on commence par comparer les mesures pour avoir un bon étalonnage.

### PHOTOS

Une photo grande angle au centre de la placette ainsi que quatre photos grand angle dans les quatre directions cardinales à 10 m du centre de la placette doivent être prises pour fournir une vision générale de la végétation et garder une trace du relevé.

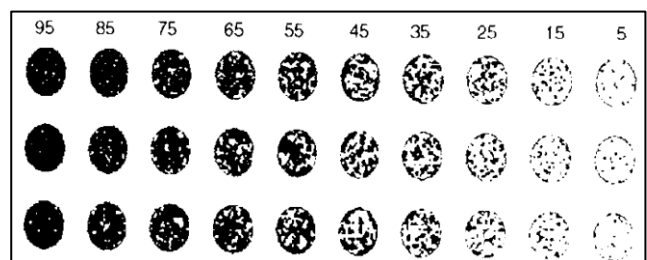
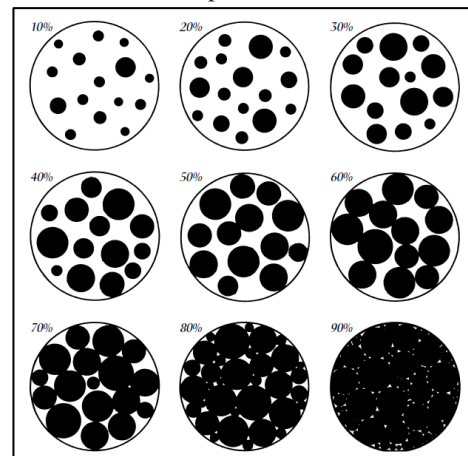
### COUVERT DE STRATES

La hauteur moyenne de la strate dominante (excluant arbres émergents ou codominants) est calculée en utilisant la moyenne des cinq (ou six) plus gros arbres mesurés sur la placette. La hauteur dominante est ensuite divisée par 4 et chaque quart correspond donc à une strate. L'abaque suivant peut être utilisé pour calculer les strates.

Tableau 1 -Abaque pour le calcul des strates :

Strate 1	Strate 2	Strate 3	Strate 4
40	30	20	10
39	29,25	19,5	9,75
38	28,5	19	9,5
37	27,75	18,5	9,25
36	27	18	9
35	26,25	17,5	8,75
34	25,5	17	8,5
33	24,75	16,5	8,25
32	24	16	8
31	23,25	15,5	7,75
30	22,5	15	7,5
29	21,75	14,5	7,25
28	21	14	7
27	20,25	13,5	6,75
26	19,5	13	6,5
25	18,75	12,5	6,25
24	18	12	6
23	17,25	11,5	5,75
22	16,5	11	5,5
21	15,75	10,5	5,25
20	15	10	5
19	14,25	9,5	4,75
18	13,5	9	4,5

Figures 1 et 2 - Références pour estimation du couvert



Le couvert en 1/10 de recouvrement absolu du sol sera estimé pour les arbres (seulement) qui composent les strates 1, 2, 3 et 4 en s'aidant si nécessaire du Vertex à partir du centre de la placette mais pas plus loin que 20m du centre de la placette.

- On détermine ensuite si chacune de ces strates est :
  - o Prépondérante : couvert supérieur ou égal à 5/10
  - o Moyenne : couvert égal à 3/10 ou 4/10
  - o Majoritaire : strate moyenne associée à 2 strates déficitaires
  - o Déficitaire : couvert inférieur ou égal à 2/10

Dans le cas où la placette n'a pas d'arbres adultes mais juste de la régénération, il faudra estimer une hauteur potentielle dominante et estimer les strates par rapport à cette hauteur

potentielle. Les figures de référence ci-dessus peuvent aider dans l'estimation du couvert et pour être sûr que les opérateurs sont bien calés vis-à-vis leur estimation du couvert.

### **LISTE DU MATERIEL**

- 1 Vertex, 1 transpondeur et un monopode pour tenir le transpondeur au milieu de la placette
- Bornes pour le milieu de la placette (1 borne/placette)
- 2 boussoles pour la détermination de l'azimut
- 1 décamètre (30 m) pour la mesure des distances
- 2 densiomètres sphériques convexes
- 1 ruban de mesure de diamètre
- Les fiches de relevé d'inventaire
- 2 planches dures de support en guise de sous-main, 2 crayons plus du papier
- 1 GPS
- 4 tiges en pour les 4 directions cardinales autour de la placette
- Cartes topographiques / Carte des placettes
- 1 monopode
- Appareil photo pour photos grand angle et trépied

**GNB - FEUILLE DE SAISIE TERRAIN – Saisie de donnée complémentaire**

Massif		Date		Placette	
Heure début		Heure fin		Opérateur	

**I. HAUTEUR DES BOIS VIVANTS : Mesure des 5 plus gros arbres de diamètre.**

Essence	Azimut	Distance	Diamètre 1 (cm)	Hauteur Totale (m)
<b>Moyenne</b>				

**II. CLASSIFICATION D'HAUTEUR : Moyenne de la hauteur dominante divisée par 4 (cf. étape I) et estimation du couvert pour chaque strate en 1/10 de recouvrement de strate.**

Strates	Classe de hauteur	Couvert
Strate 1		/10
Strate 2		/10
Strate 3		/10
Strate 4		/10

Strate 1	Strate 2	Strate 3	Strate 4
40	30	20	10
39	29,25	19,5	9,75
38	28,5	19	9,5
37	27,75	18,5	9,25
36	27	18	9
35	26,25	17,5	8,75
34	25,5	17	8,5
33	24,75	16,5	8,25
32	24	16	8
31	23,25	15,5	7,75
30	22,5	15	7,5
29	21,75	14,5	7,25
28	21	14	7
27	20,25	13,5	6,75
26	19,5	13	6,5
25	18,75	12,5	6,25
24	18	12	6
23	17,25	11,5	5,75
22	16,5	11	5,5
21	15,75	10,5	5,25
20	15	10	5
19	14,25	9,5	4,75
18	13,5	9	4,5

**III. OUVERTURE DE CANOPÉE : Mesure avec densiomètre sphérique aux 4 points cardinaux (100 grades) à 10 m du centre de la placette.**

Points cardinaux	Ouverture
Nord	
Est	
Sud	
Ouest	

**IV. PHOTOS : Photo du centre de la placette et aux 4 points cardinaux à 10 m du centre de la placette.**

*Abaque pour calcul de strates*

Numéros de photos: Centre \_\_\_\_\_ N \_\_\_\_\_ E \_\_\_\_\_  
S \_\_\_\_\_ O \_\_\_\_\_

Autres observations :

## **Annex 4 - Systematic Review Protocol**

### **1. Objective of the review**

#### **1.1 Primary question**

What indices currently exist in the literature to describe forest structure at the forest stand level?

#### **Definitions:**

Forest structure is a polysemic term, which can be divided into three different attribute groupings: structure, function and composition, whereby structure means the spatial arrangement between components of an ecosystem, function stands for ecological processes and composition refers to the variety and identity of elements (McElhinny, 2002). The CONSPIIRE team defined forest structure as the distribution of vertical and horizontal structure of trees during a meeting in January 2014.

Stand structure means the species composition, spatial distribution of trees and other underground and size (Bourgeron, 1983).

Vertical structure is defined as the different layers between the ground and the canopy, thus the number of tree layers and understory vegetation (Maltamo et al., 2005).

Horizontal structure includes the diameter size distribution of either individual or trees species (i.e. abundance) within one community, thus the spatial pattern of trees, gaps and species richness (Maltamo et al., 2005).

Stand structural complexity: a measure of the number of different attributes present and the relative abundance of each of these attributes. It therefore involves the interaction of a number of different variables so that quantitative comparisons between stands can require complex multivariate analysis (McElhinny, 2002)..

OR “the variability of the three-dimensional spatial arrangement of trees and other structural elements within a forest” (Ishii et al., 2004)

Stand level: area of forest or woodland with a relatively uniform structure which can be managed as a single unit (McElhinny, 2002).

Structural indices: → quantify spatial stand structure. Structural indices have been developed which describe, as mean values or distributions, certain horizontal aspects of forest stand structure (McElhinny, 2002). Since the 1970s, statisticians have been developing functions which not only express forest stand structures as mean values or as an empirical distribution, but are also able to describe spatial structure on a continuous basis (McElhinny, 2002).

## **2. Methods**

### **2.1 Search strategy**

The search aims to capture a representative sample of literature published in peer-reviewed journals as well as other relevant literature. The following literature databases will be searched:

- Web of Science
- Scopus

In addition, the following internet search engines will be used in order to maximize coverage:

[www.google.com](http://www.google.com)

[www.scholar.google.com](http://www.scholar.google.com)

Bibliographies of articles included in the review and previously published reviews will be checked for references. Internship supervisors will be contacted to provide further recommendations. The protocol will be updated if any additional source of information outside those listed is used.

Variations in spelling of each term will be checked. All returned hits from academic databases will be checked for relevance. When searching the internet, only the first fifty hits will be checked.

## **2.2 Study inclusion criteria**

The criteria listed below will be used to assess the title, keywords, and the abstract for relevance. If there is uncertainty whether an article should be included or not based on the title, keywords, and the abstract, the article will be read in full to determine suitability.

Relevant studies must discuss the following elements:

- Name of index
- Relevance to forest structure
- Forest attributes used
- Measuring/assessing method

### **2.2.1 Primary study question: What indices currently exist in the literature to describe forest structure at the forest stand level?**

- **Geographical location:** Study area can be in temperate, boreal or tropical forests – they can be plantations, even-aged or uneven-aged, heterogeneous/ homogeneous/ mixed/ composite forests.
- **Relevant subject(s):** Forest structure and indices
- **Types of comparator:** Although single index papers will be looked at, it will be useful if studies can compare one or more forest structure indices. Depending on the number of single methodology papers, it will be determined whether it is feasible to include them in the final review.
- **Types of study:** Any primary study that attempts to assess an index against clear criteria or that compares indices will be included.
- **Between-reviewer bias:** No between-reviewer bias will be applied due to lack of time and personnel.
- **Heterogeneity:** No sources of heterogeneity will be applied due to lack of time and personnel.

### **SEARCH TERMS:**

#### **FOREST STRUCTURE:**

Forest structure / Stand structure

Forest canopy/ forest area/ canopy layer / canopy cover / crown closure /

Structural attribute

Distribution of Vertical structure of trees alternative search terms: Tree/forest layers/ Multi-story/upper story/upper storey/ overstorey / under storey/ understory/ Stand stratification / multi scale

Horizontal structure alternative search terms: Spatial pattern of trees /gap dynamics

Spatial heterogeneity/Spatial arrangement / Spatial distribution

Managed/unmanaged forest stands

**INDICES SYNONYMS:**

Index/indices/indexes

Correlation function / equations

Measures / measurement

Indicators

Simple / composite / complex

Proxy / surrogate

Estimator

Method

Variable

Descriptor

Attribute / Element

Quantification of stand structure

**Indices:**

Stand level Attributes: foliage / tree diameter / tree height / tree spacing

Basal area

Density of stems

Diameter class distribution

Shannon-Weiner index

Distribution (skewness/kurtosis)

Spatial distribution

Total cover / Canopy cover / Strata cover

Vertical stratification

Cover by stratum

## Annex 5 - R script: Calculation of diameter differentiation, dominance and mean directional index

R script modified from Pommerening (2012)

```
library(spatstat)
library(Rcpp)

# Estimating spatially explicit tree diversity indices, Ap - 01.06.2010. Last updated on 19.09.2012.
# Functions
translateX <- function(xmax, x1, y1, x2, y2) {
  dx <- x2 - x1
  dy <- y2 - y1
  r <- dx^2 + dy^2
  xx2 <- x2
  if(dx > xmax * 0.5) {
    w <- (dx - xmax)^2
    if(w + dy^2 < r)
      xx2 = x2 - xmax
  }
  if(dx < -xmax * 0.5) {
    w <- (dx + xmax)^2
    if(w + dy^2 < r)
      xx2 = x2 + xmax
  }
  return(xx2)
}

translateY <- function(ymax, x1, y1, x2, y2) {
  dx <- x2 - x1
  dy <- y2 - y1
  r <- dx^2 + dy^2
  yy2 <- y2
  if(dy > ymax * 0.5) {
    w <- (dy - ymax)^2
    if(w + dx^2 < r)
      yy2 = y2 - ymax
  }
  if(dy < -ymax * 0.5) {
    w <- (dy + ymax)^2
    if(w + dx^2 < r)
      yy2 = y2 + ymax
  }
  return(yy2)
}

getEuclideanDistance <- function(edgeCorrection, xmax, ymax, x1, y1, x2, y2) {
  xx2 <- x2
  yy2 <- y2
  if(edgeCorrection == 1) {
    xx2 <- translateX(xmax, x1, y1, x2, y2)
    yy2 <- translateY(ymax, x1, y1, x2, y2)
  }
  dx <- abs(xx2 - x1)
```

```

dy <- abs(yy2 - y1)
dz <- dx^2 + dy^2
return(dz^0.5)
}

neighbourEdgeOk <- function(xmax, ymax, x, y, distance) {
  distxy.edge <- distanceEdge(xmax, ymax, x, y)
  if(distxy.edge > distance)
    ateb = 1
  else
    ateb = 0
  return(ateb)
}

distanceEdge <- function(xmax, ymax, x, y) {
  distxy.edge1 <- min(xmax - x, ymax - y)
  distxy.edge2 <- min(x - 0, y - 0)
  distxy.edge <- min(distxy.edge1, distxy.edge2)
  return(distxy.edge)
}

calcRepFactor <- function(edgeCorrection, bufferWidth, xmax, ymax, x, y, distance) {
  ci <- 0
  RF <- 1
  if (edgeCorrection == 3) {
    distxy.edge <- distanceEdge(xmax, ymax, x, y)
    if (distxy.edge <= bufferWidth)
      RF = 0
  }
  if (edgeCorrection > 3) {
    if(edgeCorrection == 4)
      ci <- distance
    plot.area.ha <- ((xmax - 2 * ci) * (ymax - 2 * ci)) / 10000
    RF <- neighbourEdgeOk(xmax, ymax, x, y, distance) * 1 / plot.area.ha
  }
  return(RF)
}

calcRepFactors <- function(data, edgeCorrection, bufferWidth, xmax, ymax, mi) {
  for (i in 1 : length(data$Number)) {
    if(mi > 1)
      data$rf4[i] <- calcRepFactor(edgeCorrection, bufferWidth, xmax, ymax, data$x[i], data$y[i],
data$distance[i, mi])
    else
      data$rf1[i] <- calcRepFactor(edgeCorrection, bufferWidth, xmax, ymax, data$x[i], data$y[i],
data$distance[i, mi])
  }
  return(data)
}

getNearestNeighbour <- function(edgeCorrection, xmax, ymax, x, y, data, threshold) {
  distance <- 0
  minValue <- 1E+60
  neighbour <- 0
  for (i in 1 : length(data$dbh)) {
    distance <- getEuclideanDistance(edgeCorrection, xmax, ymax, x, y, data$x[i], data$y[i])

```



```
if(distance > threshold) {  
  if(distance < minValue) {  
    minValue <- distance  
    neighbour <- data$Number[i]  
  }  
}  
}  
return(neighbour)  
}
```

```
getNearestNeighbourDistance <- function(edgeCorrection, xmax, ymax, x, y, number, data) {  
  distance = 0  
  for (i in 1 : length(data$dbh)) {  
    if(data$Number[i] == number)  
      distance = getEuclideanDistance(edgeCorrection, xmax, ymax, x, y, data$x[i], data$y[i])  
  }  
  return(distance)  
}
```

```
calcNearestNeighbours <- function(edgeCorrection, xmax, ymax, data, mi) {  
  data$neighbour <- matrix(0, nrow=length(data$dbh), ncol=mi)  
  data$distance <- matrix(0, nrow=length(data$dbh), ncol=mi)  
  for (j in 1 : mi) {  
    for (i in 1 : length(data$dbh)) {  
      if(j == 1)  
        to <- 0  
      else  
        to <- data$distance[i, j-1]  
      data$neighbour[i, j] <- getNearestNeighbour(edgeCorrection, xmax, ymax, data$x[i], data$y[i],  
data, to)  
      data$distance[i, j] <- getNearestNeighbourDistance(edgeCorrection, xmax, ymax, data$x[i],  
data$y[i], data$neighbour[i, j], data)  
    }  
  }  
  return(data)  
}
```

```
getSpecies <- function(number, data) {  
  species <- 0  
  for (i in 1 : length(data$Species)) {  
    if(data$Number[i] == number)  
      species <- data$Species[i]  
  }  
  return(species)  
}
```

```
getDBH <- function(number, data) {  
  dbh <- 0  
  for (i in 1 : length(data$dbh)) {  
    if(data$Number[i] == number)  
      dbh <- data$dbh[i]  
  }  
  return(dbh)  
}
```

```
getX <- function(number, data) {
```

```
xx <- 0
for (i in 1 : length(data$x)) {
  if(data$Number[i] == number)
    xx <- data$x[i]
}
return(xx)
}

getY <- function(number, data) {
  yy <- 0
  for (i in 1 : length(data$y)) {
    if(data$Number[i] == number)
      yy <- data$y[i]
  }
  return(yy)
}

calcMingling <- function(data, mi) {
  for (i in 1 : length(data$Species)) {
    sum <- 0
    for (j in 1 : mi) {
      if(data$Species[i] != getSpecies(data$neighbour[i, j], data))
        sum <- sum + 1
    }
    data$mingling[i] <- sum / mi
  }
  return(data)
}

calcDominance <- function(data, mi) {
  for (i in 1 : length(data$dbh)) {
    sum <- 0
    for (j in 1 : mi) {
      if(data$dbh[i] > getDBH(data$neighbour[i, j], data))
        sum <- sum + 1
    }
    data$dom[i] <- sum / mi
  }
  return(data)
}

multiplySumAndAverage <- function(variable, factor) {
  sum1 <- sum(variable * factor)
  sum2 <- sum(factor)
  return(sum1/sum2)
}

calcMeanMingling <- function(mingling, rf) {
  return(multiplySumAndAverage(mingling, rf))
}

calcMinglingDistribution <- function(data, mi) {
  mingDistr <- matrix(0, nrow = mi + 1, ncol = 1)
  for (i in 1 : (mi + 1))
    mingDistr[i] <- sum(data$rf4[data$mingling == c((i-1)/mi)])
  sum1 <- sum(mingDistr)
}
```

```
return(mingDistr/sum1)
}

calcDominanceDistribution <- function(data, mi) {
  domDistr <- matrix(0, nrow = mi + 1, ncol = 1)
  for (i in 1 : (mi + 1))
    domDistr[i] <- sum(data$rf4[data$dom == c((i-1)/mi)])
  sum1 <- sum(domDistr)
  return(domDistr/sum1)
}

calcMDIDistribution <- function(data, mi) {
  mdiDistr <- matrix(0, nrow = mi + 1, ncol = 1)
  for (i in 1 : (mi + 1))
    mdiDistr[i] <- sum(data$rf4[round(data$mdi) == i - 1])
  sum1 <- sum(mdiDistr)
  return(mdiDistr/sum1)
}

tdToClass4 <- function(td) {
  td <- td + 1e-08
  xclass <- 5
  if((td >= 0) & (td < 0.3))
    xclass <- 1
  if((td >= 0.3) & (td < 0.5))
    xclass <- 2
  if((td >= 0.5) & (td < 0.7))
    xclass <- 3
  if(td >= 0.7)
    xclass <- 4
  return(xclass)
}

calcDifferentiationDistribution <- function(data, mi) {
  diffDistr <- matrix(0, nrow = mi, ncol = 1)
  for (i in 1 : length(data$td1))
    diffDistr[tdToClass4(data$td1[i])] <- diffDistr[tdToClass4(data$td1[i])] + data$rf1[i]
  sum1 <- sum(data$rf1)
  return(diffDistr/sum1)
}

v1ToClass <- function(v1) {
  v1 <- v1 + 1e-08
  return(ceiling(v1/0.5))
}

calcVariogramDistribution <- function(data, v1max) {
  v1Distr <- matrix(0, nrow = v1max, ncol = 1)
  for (i in 1 : length(data$varInd))
    v1Distr[v1ToClass(data$varInd[i])] <- v1Distr[v1ToClass(data$varInd[i])] + data$rf1[i]
  sum1 <- sum(data$rf1)
  return(v1Distr/sum1)
}

calcD1Distribution <- function(data, d1max) {
```

```

d1Distr <- matrix(0, nrow = d1max, ncol = 1)
for (i in 1 : length(data$distance[,1]))
  d1Distr[v1ToClass(data$distance[i,1])] <- d1Distr[v1ToClass(data$distance[i,1])] + data$rf1[i]
sum1 <- sum(data$rf1)
return(d1Distr/sum1)
}

getMinglingLegend <- function(mi) {
  legend <- matrix(0, nrow= mi + 1, ncol=1)
  for (i in 1 : (mi + 1))
    legend[i] <- (i-1)/mi
  return(legend)
}

calcExpectedMinglingAllSpecies <- function(species) {
  ta <- table(species)
  s <- length(ta)
  ka <- length(species)
  swm <- 0
  for (i in 1 : s)
    swm <- swm + ta[[i]] * (ka - ta[[i]]) / (ka * (ka - 1))
  return(swm)
}

calcExpectedMinglingOneSpecies <- function(species.vector, species) {
  ka <- length(species.vector)
  swm <- (ka - length(species.vector[species.vector == species])) / (ka - 1)
  return(swm)
}

xdiff <- function(d1, d2) {
  stopifnot(all(d1 > 0))
  stopifnot(all(d2 > 0))
  d <- d1 / d2
  if(d > 1)
    d <- 1 / d
  return(d)
}

getDBH <- function(number, data) {
  dbh <- 0
  for (i in 1 : length(data$dbh)) {
    if(data$Number[i] == number)
      dbh <- data$dbh[i]
  }
  return(dbh)
}

calcDiff1 <- function(data) {
  for (i in 1 : length(data$Number)) {
    data$td1[i] <- 1 - xdiff(data$dbh[i], getDBH(data$neighbour[i, 1], data))
  }
  return(data)
}

```

```
calcVarIndex <- function(data, var) {
  for (i in 1 : length(data$Number)) {
    data$varInd[i] <- 0.5 * (data$dbh[i] - getDBH(data$neighbour[i, 1], data))^2
    data$varInd[i] <- data$varInd[i] / var
  }
  return(data)
}
```

```
calcMeanTD1 <- function(td1, rf) {
  return(multiplySumAndAverage(td1, rf))
}
```

```
calcMDI <- function(data, mi, edge, xmax, ymax) {
  for (i in 1 : length(data$dbh)) {
    ex <- 0
    ey <- 0
    for (j in 1 : mi) {
      xx2 <- getX(data$neighbour[i, j], data)
      yy2 <- getY(data$neighbour[i, j], data)
      if(edge == 1) {
        xx2 <- translateX(xmax, data$x[i], data$y[i], xx2, yy2)
        yy2 <- translateY(ymax, data$x[i], data$y[i], xx2, yy2)
      }
      exx <- data$x[i] - xx2
      eyy <- data$y[i] - yy2
      dist <- data$distance[i, j]
      ex <- ex + exx / dist
      ey <- ey + eyy / dist
    }
    data$mdi[i] <- (ex ^ 2 + ey ^ 2) ^ 0.5
  }
  return(data)
}
```

### # Implementation

```
mi <- 4 # "=n, which is number of nearest neighbours included in the determination of the
index". n is set to 4 neighbors - according to Pommerening (2006).
edgeCorrection <- 0 # No edge correction taken into effect because plot is too small according to
Pommerening (2006).
```

### # Load data

```
library(gdata)
crancod.data.all <-
read.xls("//Datafile/biodiversite/projets/GNB/Données/Dendroeco/Data_GNB_dendroeco_
2008-2014.xls", sheet=2, skip=0, as.is=F, header=T, perl="C:\\Perl64\\bin\\perl.exe")
```

### # Subset Bois Vivant

```
crancod.data <- subset(crancod.data.all, type.objet=="BV")
crancod.data$type.objet <- factor(crancod.data$type.objet)
crancod.data <- crancod.data[,c("Alti", "Massif", "Management", "numpla.GNB",
"Essence", "azimzut", "distance", "diam1", "diam2", "diam.med")]
```

### # Mean DBH

```
crancod.data$dbh <- ifelse(is.na(crancod.data$diam2) == T, (crancod.data$diam1),
((crancod.data$diam1 + crancod.data$diam2) / 2))
```

```
crancod.data$Species<-crancod.data$Essence
```

**#Creation of number of trees in a sequence and number of plots**

```
crancod.data$Number <- ave(crancod.data$dbh, crancod.data$numpla.GNB, FUN = seq_along)
crancod.data$Plot<-crancod.data$numpla.GNB
levels(crancod.data$Plot)<-c(seq(1:nlevels(crancod.data$Plot)))
```

**#Remove columns with NAs**

```
crancod.data$Essence<-NULL
crancod.data$diam.med <- NULL
crancod.data$longueur<-NULL
crancod.data$G.BV<-NULL
crancod.data$N.BV<-NULL
crancod.data$diam2<-NULL
crancod.data$diam1<-NULL
##To return stands with more than 1 tree for d1>0
keep.crancod.data <- levels(crancod.data$Plot)[table(crancod.data$Plot) > 2]
crancod.data <- crancod.data[crancod.data$Plot %in% keep.crancod.data, ]
#To limit stands to 10 meter distance for spatial reasons!
row.names(crancod.data) <- NULL
crancod.data<- subset(crancod.data, distance <=10)
```

**#Convert distance and bearing (azimuth) to XY coordinates**

```
#1. Convert azimuth to arithmetic angle
crancod.data$azimut<-as.double(as.character(crancod.data$azimut))
crancod.data$bearing.deg<-(crancod.data$azimut*360)/400
crancod.data$bearing.rad<-crancod.data$bearing.deg*pi/180
```

**#2. Translate distance, and bearing into Cartesian coordinates**

```
#crancod.data$e<- runif(4565,0.0001,0.000001)
#crancod.data$e<-NULL
crancod.data$x<-crancod.data$distance*cos(crancod.data$bearing.deg)
crancod.data$y<-crancod.data$distance*sin(crancod.data$bearing.deg)
```

**#Reorder columns**

```
crancod.data1<-crancod.data[,c(10,9,8,13,14,7,1:6,11,12)]
crancod.data<-crancod.data1
```

**# Transform coordinates if necessary**

```
(minx <- min(crancod.data$x))
(miny <- min(crancod.data$y))
(subx <- trunc(minx))
(suby <- trunc(miny))
```

```
crancod.data$x <- crancod.data$x - subx
crancod.data$y <- crancod.data$y - suby
xmax <- max(crancod.data$x)
ymax <- max(crancod.data$y)
range(crancod.data$x)
range(crancod.data$y)
```

**# Nearest neighbours and representation factors - all trees**

```
crancod.data <- calcNearestNeighbours(edgeCorrection, xmax, ymax, crancod.data, mi)
crancod.data <- calcRepFactors(crancod.data, edgeCorrection, bufferWidth, xmax, ymax, mi)
crancod.data <- calcRepFactors(crancod.data, edgeCorrection, bufferWidth, xmax, ymax, 1)
```

### # Mingling - all trees

```
crancod.data <- calcMingling(crancod.data, mi)
(mm <- sum(crancod.data$mingling * crancod.data$rf4) / sum(crancod.data$rf4))
(em <- calcExpectedMinglingAllSpecies(crancod.data$Species))
(m.s <- 1 - mm / em)
mh <- calcMinglingDistribution(crancod.data, mi)
```

### # Diameter differentiation - all trees

```
crancod.data <- calcDiff1(crancod.data)
(td1 <- sum(crancod.data$td1 * crancod.data$rf1) / sum(crancod.data$rf1))
(td1Distr <- calcDifferentiationDistribution(crancod.data, 4))
```

### # Diameter dominance - all trees (Aguirre et al., 2003)

```
crancod.data <- calcDominance(crancod.data, mi)
(md <- sum(crancod.data$dom * crancod.data$rf4) / sum(crancod.data$rf4))
domDistr <- calcDominanceDistribution(crancod.data, mi)
```

### # Mean directional index

```
crancod.data <- calcMDI(crancod.data, mi, edgeCorrection, xmax, ymax)
(mdi <- sum(crancod.data$mdi * crancod.data$rf4) / sum(crancod.data$rf4))
(mdiDistr <- calcMDIDistribution(crancod.data, mi))
```

### #Per plot - arithmetic mean of Diameter differentiation, diameter dominance and mean directional index

```
diam.diff<-tapply(crancod.data$td1,crancod.data$numpla.GNB,mean,na.rm=T)
numpla.GNB<-rownames(diam.diff)
crancod.plot<-as.data.frame(cbind(numpla.GNB,diam.diff))
crancod.plot$distance.dist<-tapply(crancod.data$d1,crancod.data$numpla.GNB,mean,na.rm=T)
crancod.plot$Clark.Evans<-
tapply(crancod.data$d1Poisson,crancod.data$numpla.GNB,mean,na.rm=T)
crancod.plot$Variogram<-
tapply(crancod.data$VarInd,crancod.data$numpla.GNB,mean,na.rm=T)
crancod.plot$diam.dom<-tapply(crancod.data$dom,crancod.data$numpla.GNB,mean,na.rm=T)
crancod.plot$mean.direct.index<-
tapply(crancod.data$mdi,crancod.data$numpla.GNB,mean,na.rm=T)
crancod.plot$rf1<-tapply(crancod.data$rf1,crancod.data$numpla.GNB,mean,na.rm=T)
```

### #Save tables

```
write.table(crancod.data, "P:/R/data_10m_No
edge_crancod_Sept9.csv",sep=";",row.names=F,col.names=T)
write.table(crancod.plot,
"P:/R/Crancod_per_plot_10m_No_edge_Sept9.csv",sep=";",row.names=F,col.names=T)
```

## Annex 6 - R script: Calculation of 16 other indices

```

#Read excel sheet
library(gdata)
data.tree<-
read.xls("//Datafile/biodiversite/projets/GNB/Données/Dendroeco/Data_GNB_dendroeco_
2008-2014.xls",sheet=2,skip=0,as.is=F,header=T,perl="C:\\perl\\bin\\perl.exe")

metadata.dendro<-read.xls("//Datafile/biodiversite/projets/Indeco-
CONSPIIRE/Stage_A_Gillespie/Data_GNB_Metadate_AGillespie_6aout14.xls",sheet=1,skip=
0,as.is=F,header=T,perl="C:\\perl\\bin\\perl.exe")

row.names(metadata.dendro)<-metadata.dendro$numpla.GNB

data.dendro<-
metadata.dendro[,c("numpla.GNB","X_L2E","Y_L2E","Code.massif","Management","Alti","aci
dite","S1","S2","S3","S4","Ouvert.N","Ouvert.E","Ouvert.S","Ouvert.W")]
head(data.dendro)

#Subset "Bois Vivant"
data.living<-subset(data.tree,type.objet=="BV")
data.living$type.objet <- factor(data.living$type.objet)
data.living <-data.living[,c("Alti","Massif","Management","numpla.GNB",
"type.objet","Essence","azimut","distance","diam1","diam2","diam.med","longueur","G.BV",
"N.BV")]

#To limit stands to 40 meter distance
row.names(data.living) <- NULL
data.living<- subset(data.living, distance <=40)

#To calculate mean DBH
data.living$mean.DBH<-ifelse(is.na(data.living$diam2) == T,(data.living$diam1),
((data.living$diam1+data.living$diam2)/2))

#Omitting NAs in data.living$mean.DBH
cc=is.na(data.living$mean.DBH)
m=which(cc==c("TRUE"))
data.living=data.living[-m,]

%%%%%%%%%%%%%%INDICES CALCULATIONS %%%%%%%%%%%%%%%
#^^^^^^^^^^^^^^^^^^^^NON-SPATIAL INDICES^^^^^^^^^^^^^^^^^^^^

#Table data.plot that will house all the indices
data.plot<-data.dendro

#No of trees per plot - Limit to 40meters radius
data.living$No.of.trees.40m<-ifelse(data.living$distance<=40,1, 0)
data.plot$No.of.trees.40m<-tapply(data.living$No.of.trees.40m, data.living$numpla.GNB,
sum,na.rm=T)
data.plot[,"No.of.trees.40m"][is.na(data.plot[,"No.of.trees.40m"])] <- 0
data.plot$No.of.trees.40m<-as.double(as.character(data.plot$No.of.trees.40m))

#No of trees per plot - Limit to 20meters radius
data.living$No.of.trees.20m<-ifelse(data.living$distance<=20,1, 0)
data.plot$No.of.trees.20m<-tapply(data.living$No.of.trees.20m, data.living$numpla.GNB,
sum,na.rm=T)
data.plot[,"No.of.trees.20m"][is.na(data.plot[,"No.of.trees.20m"])] <- 0
data.plot$No.of.trees.20m<-as.double(as.character(data.plot$No.of.trees.20m))

```



### #No of trees per plot - Limit to 10meters radius

```
data.living$No.of.trees.10m<-ifelse(data.living$distance<=10,1, 0)
data.plot$No.of.trees.10m<-tapply(data.living$No.of.trees.10m, data.living$numpla.GNB,
sum,na.rm=T)
data.plot[,"No.of.trees.10m"][is.na(data.plot[,"No.of.trees.10m"])] <- 0
data.plot$No.of.trees.10m<-as.double(as.character(data.plot$No.of.trees.10m))
```

### #Number of stems

```
data.plot$stems<-tapply(data.living$type.objet,data.living$numpla.GNB,length)
data.plot$stems<-as.double(as.numeric(data.plot$stems))
data.plot[,"stems"][is.na(data.plot[,"stems"])] <- 0
```

### #Mean DBH & sd for each plot

```
data.plot$plot.mean.DBH<-tapply(data.living$mean.DBH,
data.living$numpla.GNB,mean,na.rm=T)
data.plot$plot.mean.DBH<-as.double(as.character(data.plot$plot.mean.DBH))
data.plot[,"plot.mean.DBH"][is.na(data.plot[,"plot.mean.DBH"])] <- 0
```

### #STANDARD DEVIATION (sd)

```
sd.DBH<-tapply(data.living$mean.DBH,data.living$numpla.GNB,sd,na.rm=T)
data.plot$sd.DBH<-as.double(as.character(sd.DBH))
data.plot[,"sd.DBH"][is.na(data.plot[,"sd.DBH"])] <- 0
```

### #COEFFICIENT OF VARIATION (cv)

```
data.plot$cv.DBH<-((data.plot$sd.DBH/data.plot$plot.mean.DBH)*100)
data.plot[,"cv.DBH"][is.na(data.plot[,"cv.DBH"])] <- 0
```

### #SKEWNESS - characterizes whether the distribution is symmetric (skewness=0)

```
library(moments)
skewness.DBH<-tapply(data.living$mean.DBH, data.living$numpla.GNB, skewness,na.rm=T)
data.plot$skewness.DBH<-as.double(as.character(data.plot$skewness.DBH))
#dotchart(data.plot$skewness.DBH | numpla.GNB, data = data.plot, main="Skewness of stand
diameter distribution") ### Want skewness for each plot but it's not working...
```

### #KURTOSIS - characterizes peakedness, where the normal distribution has a value of 3 and smaller values correspond to thinner tails (less peakedness)

```
kurtosis.DBH<-tapply(data.living$mean.DBH, data.living$numpla.GNB, kurtosis,na.rm=T)
data.plot$kurtosis.DBH<-as.double(as.character(kurtosis.DBH))
#dotchart(data.plot$kurtosis.DBH | numpla.GNB, data = data.plot, main="Kurtosis of stand
diameter distribution")
```

### #BASAL AREA

```
data.plot$Basal.area<-tapply(data.living$G.BV,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$Basal.area<-as.double(as.numeric(data.plot$Basal.area))
```

### #DENSITY: Live trees per hectare: N.BV.ha

```
data.plot$N.BV.ha<-tapply(data.living$N.BV,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$N.BV.ha<-as.double(as.character(data.plot$N.BV.ha))
```

### #STAND DENSITY INDEX (SDI) - using index diameter of 25.4cm and b constant for - 1.605

```
###Calculate Quadratic Mean Diameter first ---> QDM
data.plot$QDM<-sqrt((data.plot$Basal.area/data.plot$N.BV.ha)/0.00007854)
data.plot$QDM<-as.double(as.character(data.plot$QDM))
```

```
data.plot$SDI<-(data.plot$N.BV.ha*((data.plot$QDM/25.4)^1.605))
data.plot$SDI<-as.double(as.character(data.plot$SDI))
```

### #SHANNON INDEX

```
library(BiodiversityR)
```

```
#####Splitting the DBH data into 10 columns in data.living
data.living$DBH.0.9 <- ifelse(data.living$mean.DBH<10.0, 1, 0)
data.living$DBH.10.19 <- ifelse(data.living$mean.DBH>=10.0 &data.living$mean.DBH <20, 1,
0)
data.living$DBH.20.29 <- ifelse(data.living$mean.DBH>=20.0 &data.living$mean.DBH <30, 1,
0)
data.living$DBH.30.39 <- ifelse(data.living$mean.DBH>=30.0 &data.living$mean.DBH <40, 1,
0)
data.living$DBH.40.49 <- ifelse(data.living$mean.DBH>=40.0 &data.living$mean.DBH <50, 1,
0)
data.living$DBH.50.59 <- ifelse(data.living$mean.DBH>=50.0 &data.living$mean.DBH <60, 1,
0)
data.living$DBH.60.69 <- ifelse(data.living$mean.DBH>=60.0 &data.living$mean.DBH <70, 1,
0)
data.living$DBH.70.79 <- ifelse(data.living$mean.DBH>=70.0 &data.living$mean.DBH <80, 1,
0)
data.living$DBH.80.89 <- ifelse(data.living$mean.DBH>=80.0 &data.living$mean.DBH <90, 1,
0)
data.living$DBH.90.99 <- ifelse(data.living$mean.DBH>=90.0 &data.living$mean.DBH <100, 1,
0)
data.living$DBH.100.and.up <- ifelse(data.living$mean.DBH>=100, 1, 0)
```

```
#####Including them in data.plot
data.plot$DBH.0.9<-tapply(data.living$DBH.0.9,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$DBH.10.19<-
tapply(data.living$DBH.10.19,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$DBH.20.29<-
tapply(data.living$DBH.20.29,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$DBH.30.39<-
tapply(data.living$DBH.30.39,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$DBH.40.49<-
tapply(data.living$DBH.40.49,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$DBH.50.59<-
tapply(data.living$DBH.50.59,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$DBH.60.69<-
tapply(data.living$DBH.60.69,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$DBH.70.79<-
tapply(data.living$DBH.70.79,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$DBH.80.89<-
tapply(data.living$DBH.80.89,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$DBH.90.99<-
tapply(data.living$DBH.90.99,data.living$numpla.GNB,FUN=sum,na.rm=T)
data.plot$DBH.100.and.up<-
tapply(data.living$DBH.100.and.up,data.living$numpla.GNB,FUN=sum,na.rm=T)
```

```
data.plot$DBH.0.9<-as.double(as.character(data.plot$DBH.0.9))
data.plot$DBH.10.19<-as.double(as.character(data.plot$DBH.10.19))
data.plot$DBH.20.29<-as.double(as.character(data.plot$DBH.20.29))
data.plot$DBH.30.39<-as.double(as.character(data.plot$DBH.30.39))
data.plot$DBH.40.49<-as.double(as.character(data.plot$DBH.40.49))
```

```
data.plot$DBH.50.59<-as.double(as.character(data.plot$DBH.50.59))
data.plot$DBH.60.69<-as.double(as.character(data.plot$DBH.60.69))
data.plot$DBH.70.79<-as.double(as.character(data.plot$DBH.70.79))
data.plot$DBH.80.89<-as.double(as.character(data.plot$DBH.80.89))
data.plot$DBH.90.99<-as.double(as.character(data.plot$DBH.90.99))
data.plot$DBH.100.and.up<-as.double(as.character(data.plot$DBH.100.and.up))

data.plot$DBH.0.9<-as.double(as.numeric(data.plot$DBH.0.9))
data.plot$DBH.10.19<-as.double(as.numeric(data.plot$DBH.10.19))
data.plot$DBH.20.29<-as.double(as.numeric(data.plot$DBH.20.29))
data.plot$DBH.30.39<-as.double(as.numeric(data.plot$DBH.30.39))
data.plot$DBH.40.49<-as.double(as.numeric(data.plot$DBH.40.49))
data.plot$DBH.50.59<-as.double(as.numeric(data.plot$DBH.50.59))
data.plot$DBH.60.69<-as.double(as.numeric(data.plot$DBH.60.69))
data.plot$DBH.70.79<-as.double(as.numeric(data.plot$DBH.70.79))
data.plot$DBH.80.89<-as.double(as.numeric(data.plot$DBH.80.89))
data.plot$DBH.90.99<-as.double(as.numeric(data.plot$DBH.90.99))
data.plot$DBH.100.and.up<-as.double(as.numeric(data.plot$DBH.100.and.up))

#Exclude NAs
data.plot[,29:39][is.na(data.plot[,29:39])] <- 0

####Creating a table with all SIZE CLASSES for Shannon/Simpson indices
DBH.classes<-rbind(data.plot$DBH.0.9,data.plot$DBH.10.19,data.plot$DBH.20.29,
data.plot$DBH.30.39,data.plot$DBH.40.49, data.plot$DBH.50.59, data.plot$DBH.60.69,
data.plot$DBH.70.79, data.plot$DBH.80.89, data.plot$DBH.90.99,data.plot$DBH.100.and.up)
DBH.classes<-t(DBH.classes)
colnames(DBH.classes)<-c("DBH.0.9","DBH.10.19","DBH.20.29", "DBH.30.39", "DBH.40.49",
"DBH.50.59","DBH.60.69","DBH.70.79","DBH.80.89","DBH.90.99","DBH.100.and.up")
rownames(DBH.classes)<-data.plot$numpla.GNB
head(DBH.classes)

#Calculating SHANNON index H
## defined as  $H = -\sum p_i \log(b) p_i$ , where  $p_i$  is the proportional abundance of species  $i$  and
 $b$  is the base of the logarithm
data.plot$Size.Classes<-specnumber(DBH.classes)
data.plot$Size.Classes<-as.double(as.numeric(data.plot$Size.Classes))
data.plot$Classes.Shannon<-diversity(DBH.classes)
#plot(Classes.Shannon)

#SIMPSON's diversity index (rarefaction)
##Both variants of Simpson's index are based on  $D = \sum p_i^2$ .
data.plot$Classes.Simpson<-diversity(DBH.classes,"simpson") #Choice simpson returns 1-D
data.plot$Classes.Simpson.inv<-diversity(DBH.classes,"invsimpson") #invsimpson returns 1/D

#BERGER-PARKER - index of dominance
data.plot$Classes.Berger<-diversityresult(DBH.classes, index="Berger",method="s")
data.plot$Classes.Berger<-transform(data.plot$Classes.Berger, char = as.numeric(char))
data.plot$Classes.Berger<-sapply(data.plot$Classes.Berger, as.numeric)
data.plot$Classes.Berger<-as.double(as.numeric(data.plot$Classes.Berger))

#SHANNON OR PIELOU - EVENNESS INDEX:
#Formula is:  $J = \text{Shannon } H / \log(S)$ 
data.plot$Classes.Shannon.Evenness<-data.plot$Classes.Shannon / log(data.plot$Size.Classes)
```

**#SIMPSON INDEX OF EVENNESS**

##Formula is: ESimpson =  $I_{InvSimp} / S$   
data.plot\$Classes.Simpson.Evenness<-data.plot\$Classes.Simpson.inv/data.plot\$Size.Classes  
data.plot\$Classes.Simpson.Evenness[data.plot\$Classes.Simpson.Evenness==Inf] <- NA

**#GINI COEFFICIENT**

library(reldist)  
## Gini coefficient of tree diameters (DBH diversity)  
data.plot\$gini.DBH<-tapply(data.living\$mean.DBH, data.living\$numpla.GNB, FUN="gini")  
data.plot\$gini.DBH<-as.double(as.character(data.plot\$gini.DBH))  
  
##Gini coefficient of basal areas (basal area diversity)  
data.plot\$gini.ba<-tapply(data.living\$G.BV, data.living\$numpla.GNB, FUN="gini")  
data.plot\$gini.ba<-as.double(as.character(data.plot\$gini.ba))

**#LORIMER INDEX OF SYMMETRY**

##Formula:  $I = (M - X_L) / (X_{0.95} - X_L)$   
  
##Calculating the mode and 95th percentale of diameter distribution (X0.95), lower threshold diameter (minimum)  
library(modeest)  
library(plyr)  
  
data.plot\$mode.DBH<- tapply(data.living\$mean.DBH, data.living\$numpla.GNB,length)#Mode  
data.plot\$DBH.095<-tapply(data.living\$mean.DBH, data.living\$numpla.GNB, quantile,  
probs=0.95, na.rm=TRUE) #95th percentile of diameter distribution  
data.plot\$min.DBH<-tapply(data.living\$mean.DBH, data.living\$numpla.GNB, min,  
na.rm=TRUE) #lower threshold diameter, i.e. minimum diameter  
  
##Converting to numbers  
data.plot\$mode.DBH<-as.double(as.character(data.plot\$mode.DBH))  
data.plot\$DBH.095<-as.double(as.character(data.plot\$DBH.095))  
data.plot\$min.DBH<-as.double(as.character(data.plot\$min.DBH))  
  
##Calculation of Lorimer index of symmetry  
data.plot\$Lorimer<-(data.plot\$mode.DBH-data.plot\$min.DBH)/(data.plot\$DBH.095-  
data.plot\$min.DBH)  
##Problem on inf for plots with only one tree -->converted into NAS:  
data.plot\$Lorimer[data.plot\$Lorimer==Inf] <- NA

#^^^^^^^^^^^^^DISTANCE - DEPENDENT INDICES^^  
^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^ONLY AT 10 Meters^^  
#Convert distance and bearing (azimuth) to XY coordinates  
#1. Convert azimuth to arithmetic angle  
data.living\$azimut<-as.double(as.character(data.living\$azimut))  
data.living\$bearing.deg<-(data.living\$azimut\*360)/400  
data.living\$bearing.rad<-data.living\$bearing.deg\*pi/180  
  
#2. Translate distance, and bearing into Cartesian coordinates  
data.living\$e<- runif(7248,0.00001,0.0001) #Adding small random numbers to x,y coordinates to  
make sure that x,y coordinates are not the same  
data.living\$x<-data.living\$distance\*cos(data.living\$bearing.deg) +data.living\$e  
data.living\$y<-data.living\$distance\*sin(data.living\$bearing.deg) +data.living\$e  
  
#plot(data.living\$x ,data.living\$y,xlim=c(-10,10),ylim=c(-10,10))  
#points(data.living\$x,data.living\$y,col="red")

### **##DISTANCE DEPENDENT PACKAGES**

```
library(spatstat)
library(sp)
library(maptools)
library(spatial)
library(splancs)
require(stats)

#Main Information for use of splancs/spatstat functions
poly <- cbind(c(-40,40,40,-40), c(-40,-40,40,40)) #plot with maximum and minimum coordinates
for x and y between [-20 20] which indicates location from plot centre
w <- owin(c(-40,40),c(-40,40),unitname=c("metres","metres")) # Defines the point process
window area
s <- seq(0,40,length=5)

data.living.na<-subset(data.living, distance <=40,na.rm=T) #Excludes trees with NAs from
subset in order to calculate khat for plots that have at least a tree
data.living.na$diam2<-NULL #

#Keep only stands with more than 2 trees
keep.data.living.na <- levels(data.living.na$numpla.GNB)[table(data.living.na$numpla.GNB) > 2]
##To return stands with more than 1 tree
data.living.na <- data.living.na[data.living.na$numpla.GNB %in% keep.data.living.na, ] ##To
return stands with more than 1 tree

data.living.na$numpla.GNB <- as.factor(as.character(data.living.na$numpla.GNB))
levels(data.living.na$numpla.GNB)

data.living.na <- data.living.na[,c("numpla.GNB", "x", "y","mean.DBH","distance")]

#To remove NAs from dbh
row.has.na <- apply(data.living.na, 1, function(x){any(is.na(x))})
sum(row.has.na)
data.living.na <- data.living.na[!row.has.na,]
#!colSums(is.na(data.living.na))

#####SPATIAL FUNCTIONS #####
#RIPLEY L using khat {splancs}
numpla.GNB.levels<-levels(data.living.na$numpla.GNB) #Defines levels by stand number
n<-list() #Creates a list in which to place all the k rows

#in order to calculate L function per plot
for(i in 1:nlevels(data.living.na$numpla.GNB)){
  sub<-subset(data.living.na, data.living.na$numpla.GNB==numpla.GNB.levels[i])
  plot1<-as.data.frame(cbind(sub$x, sub$y))
  plot1$x<-as.double(as.character(plot1$V1))
  plot1$y<-as.double(as.character(plot1$V2))
  plot1.pts <- spoints(rbind(plot1$x,plot1$y),length(plot1$x))
  plot1.s.points<-as.points(plot1.pts)

  k1<-khat(plot1.s.points,poly=poly,s)
  l1<-sqrt(k1/pi)-s
  l1<- as.data.frame(l1)
  l1$numpla<- as.character(numpla.GNB.levels[i])
  n[[i]]=l1
}
```

```
}
Ripleykhat.Lresults<-do.call(rbind,(n))
Ripleykhat.Lresults$seq<-s
Ripleykhat.Lresults$k1<-k1

#####SINGLE VALUE SPATIAL INDICES#####
#CLARK-EVANS AGGREGATION INDEX R
numpla.GNB.levels<-levels(data.living.na$numpla.GNB)
CE<-list()
for(i in 1:nlevels(data.living.na$numpla.GNB)){
  sub<-subset(data.living.na, data.living.na$numpla.GNB==numpla.GNB.levels[i])
  plot1<-as.data.frame(cbind(sub$x, sub$y))
  plot1$x<-as.double(as.character(plot1$V1))
  plot1$y<-as.double(as.character(plot1$V2))
  plot1.pts <- spoints(rbind(plot1$x,plot1$y),length(plot1$x))
  plot1.s.points<-as.points(plot1.pts)
  ppts2<-ppp(sub$x, sub$y, window=w)

  Clark.Evans1<-clarkevans(ppts2,correction="cdf")
  Clark.Evans1<- as.data.frame(Clark.Evans1)
  Clark.Evans1$numpla<- as.character(numpla.GNB.levels[i])
  CE[[i]]=Clark.Evans1
}
ClarkEvans.results<-do.call(rbind,(CE))
data.plot<-merge(data.plot, ClarkEvans.results, by.x="numpla.GNB", by.y="numpla",
all.x=TRUE)

#HOPKINS-SKELLAM INDEX
#Hopkins-Skellam aggregation index -The index is defined as the ratio of the sum of the squared
distances from point-to-plant to the sum of the squared distances from plant-to-plant
numpla.GNB.levels<-levels(data.living.na$numpla.GNB)
HSI.list<-list()
for(i in 1:nlevels(data.living.na$numpla.GNB)){
  sub<-subset(data.living.na, data.living.na$numpla.GNB==numpla.GNB.levels[i])
  plot1<-as.data.frame(cbind(sub$x, sub$y))
  plot1$x<-as.double(as.character(plot1$V1))
  plot1$y<-as.double(as.character(plot1$V2))
  plot1.pts <- spoints(rbind(plot1$x,plot1$y),length(plot1$x))
  plot1.s.points<-as.points(plot1.pts)
  ppts2<-ppp(sub$x, sub$y, window=w)
  ppts2 <- rescale(ppts2,1/9) #To rescale to meters
  dist.xy<-pairedist(ppts2) #returns matrix of pairwise distances
  HSI1<-sum(data.living.na$distance^2)/sum((dist.xy/2)^2) #dist.xy divided by 2 because vector
repeats itself
  HSI1<- as.data.frame(HSI1)
  HSI1$numpla<- as.character(numpla.GNB.levels[i])
  HSI.list[[i]]=HSI1
}
HSI.results<-do.call(rbind,(HSI.list))
data.plot<-merge(data.plot, HSI.results, by.x="numpla.GNB", by.y="numpla", all.x=TRUE)

#####FINALIZING DATA.PLOT#####
data.plot$Alti<-data.plot2$Alti
data.plot$Management<-data.plot2$Management
data.plot$acidite<-data.plot2$acidite
data.plot$Code.massif<-data.plot2$Code.massif
```

```
head(data.plot)
```

### **#Write tables**

```
#write.table(data.living,  
"P:/R/40m/data_living_40m_Sept23.csv",sep=";",row.names=F,col.names=T)  
write.table(data.plot,"//datafile/Biodiversite/projets/Indeco-  
CONSPIIRE/Stage_A_Gillespie/Resultats_R  
scripts/40m/Tables/Data_plot_40m_Oct21.csv",sep=";",row.names=F,col.names=T)  
write.table(Ripleykhat.Lresults,"P:/R/40m/Ripley_khat40m_Sept22.csv",sep=";",row.names=F,c  
ol.names=T)
```

## Annex 7 - R script: Linear mixed model analysis of indices

```

library(nlme)
library(multcomp)
library(multcompView)

plot.indices40m<-read.csv("//datafile/Biodiversite/projets/Indeco-
CONSPIIRE/Stage_A_Gillespie/Resultats_R scripts/40m/Tables/Data_plot_40m_Oct21.csv",
header=T,sep=";",dec=".")
head(plot.indices40m)

plot.indices40m$ManAlti <- interaction(plot.indices40m$Management, plot.indices40m$Alti)

#####STANDARD DEVIATION#####
#LME model for Management and Altitude
lme.alti.sd<-lme(sd.DBH~ManAlti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
summary(lme.alti.sd)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.sd <- summary(glht(lme.alti.sd, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.sd<-mcomp.sd$test$pvalues
names(pvalues.mcomp.sd)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
multcompLetters(pvalues.mcomp.sd)$Letters
multcompLetters(pvalues.mcomp.sd)$LetterMatrix
summary(mcomp.sd) #Gives Pvalue and standard error for each scenario
mcomp.sd

#LME model for Management only
lme.sd<-lme(sd.DBH~Management, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
anova(lme.sd)

#Graphically#
dotchart(plot.indices40m$sd.DBH,xlab="Standard deviation") #Literally gives a dot chart
plot(plot.indices40m$sd.DBH~plot.indices40m$Basal.area)
identify(plot.indices40m$sd.DBH) #identifies points in a dot chart

sd.boxplot<-boxplot(plot.indices40m$sd.DBH~plot.indices40m$Management,xlab="Standard
deviation by Management")
sd.boxplot.Alti<-boxplot(plot.indices40m$sd.DBH~plot.indices40m$Alti)
sd.boxplot.Alti<-boxplot(plot.indices40m$sd.DBH~plot.indices40m$ManAlti,xlab="Standard
deviation - Mangement & Altitude")

#Residuals#
plot(lme.alti.sd, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.alti.sd, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.sd<-residuals(lme.sd)
hist(res.lme.sd)
par(pty="s")
qqnorm(res.lme.sd)
qqline(res.lme.sd)
fit.lme.sd<-fitted(lme.sd)
plot(fit.lme.sd, res.lme.sd)

```



```
#####COEFFICIENT OF VARIATION#####  
#LME model for Management and Altitude  
lme.cv<-lme(cv.DBH~ManAlti, random=~1 | Code.massif,data=plot.indices40m,  
na.action=na.omit)  
summary(lme.cv)  
  
#General Linear Hypotheses/Multiple comparisons of Means of each Scenario  
mcomp.cv <- summary(glht(lme.cv, linfct=mcp(ManAlti="Tukey")))  
pvalues.mcomp.cv<-mcomp.cv$test$pvalues  
names(pvalues.mcomp.cv)<-c("UNM.LWL-MAN.LWL","MAN.MON-  
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-  
UNM.LWL","UNM.MON-MAN.MON")  
multcompLetters(pvalues.mcomp.cv)$Letters  
multcompLetters(pvalues.mcomp.cv)$LetterMatrix  
summary(mcomp.cv) #Gives Pvalue and standard error for each scenario  
  
#ANOVA#####  
#Linear mixed-effects model with random effect#  
lme.cv2<-lme(cv.DBH~Management*Alti, random=~1 | Code.massif,data=plot.indices40m,  
na.action=na.omit)  
anova(lme.cv2) #gives the F and P value for Management/Altitude and Interaction  
Management:Altitude  
  
#LME model for Management only  
lme.sd<-lme(sd.DBH~Management, random=~1 | Code.massif,data=plot.indices40m,  
na.action=na.omit)  
#General Linear Hypotheses/Multiple comparisons of Means of each Scenario  
mcomp.sd <- summary(glht(lme.alti.sd, linfct=mcp(ManAlti="Tukey")))  
  
#GRAPHICALLY#####  
dotchart(plot.indices40m$cv.DBH,xlab="Coefficient of variation") #Literally gives a dot chart  
plot(plot.indices40m$cv.DBH~plot.indices40m$Basal.area)  
#identify(plot.indices40m$cv.DBH) #identifies points in a dot chart  
  
boxplot(plot.indices40m$sd.DBH~plot.indices40m$Management,xlab="Coefficient of Variation  
by Management")  
boxplot(plot.indices40m$sd.DBH~plot.indices40m$Alti)  
boxplot(plot.indices40m$sd.DBH~plot.indices40m$ManAlti,xlab="Coefficient of Variation -  
Management & Altitude")  
  
#RESIDUALS#####  
####  
plot(lme.cv, resid(., type = "p") ~ fitted(.) , abline = 0)  
plot(lme.cv, resid(., type = "p") ~ fitted(.) | Management, abline = 0)  
plot(lme.cv, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)  
  
res.lme.cv<-residuals(lme.cv)  
hist(res.lme.cv)  
par(pty="s")  
qqnorm(res.lme.cv)  
qqline(res.lme.cv)  
fit.lme.sd<-fitted(lme.cv)  
plot(fit.lme.sd, res.lme.cv)  
  
#####BASAL AREA#####
```

```
#LME model for Management and Altitude
lme.ba<-lme(Basal.area~ManAlti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
summary(lme.ba)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.ba <- summary(glht(lme.ba, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.ba<-mcomp.ba$test$pvalues
names(pvalues.mcomp.ba)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
multcompLetters(pvalues.mcomp.ba)$Letters
multcompLetters(pvalues.mcomp.ba)$LetterMatrix

summary(mcomp.ba) #Gives Pvalue and standard error for each scenario

#ANOVA#####
#Linear mixed-effects model with random effect#
lme.ba2<-lme(Basal.area~Management, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
anova(lme.ba2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
dotchart(plot.indices40m$Basal.area,xlab="Basal area") #Literally gives a dot chart

boxplot(plot.indices40m$Basal.area~plot.indices40m$Management,xlab="Basal area by
Management")
boxplot(plot.indices40m$Basal.area~plot.indices40m$Alti)
boxplot(plot.indices40m$Basal.area~plot.indices40m$ManAlti,xlab="Basal area - Management &
Altitude")

#RESIDUALS#####
plot(lme.ba, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.ba, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.ba<-residuals(lme.ba)
hist(res.lme.ba)
par(pty="s")
qqnorm(res.lme.ba)
qqline(res.lme.ba)
fit.lme.sd<-fitted(lme.ba)
plot(fit.lme.sd, res.lme.ba)

#####SKEWNESS#####
#LME model for Management and Altitude
lme.sk<-lme(skewness.DBH~ManAlti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
summary(lme.sk)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.sk <- summary(glht(lme.sk, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.sk<-mcomp.sk$test$pvalues
names(pvalues.mcomp.sk)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
```

```
summary(mcomp.sk) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.sk)$Letters
multcompLetters(pvalues.mcomp.sk)$LetterMatrix

#ANOVA#####Linear mixed-effects model with random effect#
lme.sk2<-lme(skewness.DBH~Management, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
anova(lme.sk2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude
summary(anova(lme.sk))
#GRAPHICALLY#####
#####
dotchart(plot.indices40m$skewness.DBH,xlab="Skewness") #Literally gives a dot chart

par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(plot.indices40m$skewness.DBH~plot.indices40m$Management,xlab="Skewness")
boxplot(plot.indices40m$skewness.DBH~plot.indices40m$Alti, xlab="Skewness")
boxplot(plot.indices40m$skewness.DBH~plot.indices40m$ManAlti,xlab="Skewness")

#RESIDUALS#####
####
plot(lme.sk, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.sk, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.sk<-residuals(lme.sk)
hist(res.lme.sk)
par(pty="s")
qqnorm(res.lme.sk)
qqline(res.lme.sk)
fit.lme.sd<-fitted(lme.sk)
plot(fit.lme.sd, res.lme.sk)

#####KURTOSIS#####
#LME model for Management and Altitude
lme.ku<-lme(kurtosis.DBH~ManAlti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
summary(lme.ku)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.ku <- summary(glht(lme.ku, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.ku<-mcomp.ku$test$pvalues
names(pvalues.mcomp.ku)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
summary(mcomp.ku) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.ku)$Letters
multcompLetters(pvalues.mcomp.ku)$LetterMatrix
#ANOVA#####Linear mixed-effects model with random
effect#
lme.ku2<-lme(kurtosis.DBH~Management*Alti,
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
anova(lme.ku2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
#####
```

```

dotchart(plot.indices40m$kurtosis.DBH,xlab="kurtosis") #Literally gives a dot chart

par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(plot.indices40m$kurtosis.DBH~plot.indices40m$Management,xlab="kurtosis")
boxplot(plot.indices40m$kurtosis.DBH~plot.indices40m$Alti, xlab="kurtosis")
boxplot(plot.indices40m$kurtosis.DBH~plot.indices40m$ManAlti,xlab="kurtosis")

#####
####
plot(lme.ku, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.ku, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.ku<-residuals(lme.ku)
hist(res.lme.ku)
par(pty="s")
qqnorm(res.lme.ku)
qqline(res.lme.ku)
fit.lme.sd<-fitted(lme.ku)
plot(fit.lme.sd, res.lme.ku)

#####STAND DENSITY INDEX #####
#LME model for Management and Altitude
lme.sdi<-lme(SDI~ManAlti, random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
summary(lme.sdi)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.sdi <- summary(glht(lme.sdi, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.sdi<-mcomp.sdi$test$pvalues
names(pvalues.mcomp.sdi)<-c("UNML.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
summary(mcomp.sdi) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.sdi)$Letters
multcompLetters(pvalues.mcomp.sdi)$LetterMatrix
#ANOVA#####Linear mixed-effects model with random
effect#
lme.sdi2<-lme(SDI~Management*Alti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
anova(lme.sdi2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
dotchart(plot.indices40m$SDI,xlab="Stand density index") #Literally gives a dot chart

par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(plot.indices40m$SDI~plot.indices40m$Management,xlab="Stand density index")
boxplot(plot.indices40m$SDI~plot.indices40m$Alti, xlab="Stand density index")
boxplot(plot.indices40m$SDI~plot.indices40m$ManAlti,xlab="Stand density index")

#####
plot(lme.sdi, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.sdi, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.sdi<-residuals(lme.sdi)
hist(res.lme.sdi)
par(pty="s")

```

```
qqnorm(res.lme.sdi)
qqline(res.lme.sdi)
fit.lme.sd<-fitted(lme.sdi)
plot(fit.lme.sd, res.lme.sdi)
```

### #####SHANNON INDEX OF DIVERSITY#####

```
#LME model for Management and Altitude
lme.shannon<-lme(Classes.Shannon~ManAlti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
summary(lme.shannon)
```

```
#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.shannon <- summary(glht(lme.shannon, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.shannon<-mcomp.shannon$test$pvalues
names(pvalues.mcomp.shannon)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
summary(mcomp.shannon) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.shannon)$Letters
multcompLetters(pvalues.mcomp.shannon)$LetterMatrix
#ANOVA#####Linear mixed-effects model with random
effect#
lme.shannon2<-lme(Classes.Shannon~Management*Alti,
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
anova(lme.shannon2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude
```

```
#GRAPHICALLY#####
dotchart(plot.indices40m$Classes.Shannon,xlab="Shannon index") #Literally gives a dot chart
```

```
par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(plot.indices40m$Classes.Shannon~plot.indices40m$Management,xlab="Stand density
index")
boxplot(plot.indices40m$Classes.Shannon~plot.indices40m$Alti, xlab="Stand density index")
boxplot(plot.indices40m$Classes.Shannon~plot.indices40m$ManAlti,xlab="Stand density index")
```

### #RESIDUALS#####

```
plot(lme.shannon, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.shannon, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)
```

```
res.lme.shannon<-residuals(lme.shannon)
hist(res.lme.shannon)
par(pty="s")
qqnorm(res.lme.shannon)
qqline(res.lme.shannon)
fit.lme.sd<-fitted(lme.shannon)
plot(fit.lme.sd, res.lme.shannon)
```

### #####\$SIMPSON INDEX #####

```
#LME model for Management and Altitude
lme.simpson<-lme(Classes.Simpson~ManAlti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
summary(lme.simpson)
```

```
#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.simpson <- summary(glht(lme.simpson, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.simpson<-mcomp.simpson$test$pvalues
```

```
names(pvalues.mcomp.simpson)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
summary(mcomp.simpson) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.simpson)$Letters
multcompLetters(pvalues.mcomp.simpson)$LetterMatrix
#ANOVA#####Linear mixed-effects model with random effect#
lme.simpson2<-lme(Classes.Simpson~Management*Alti,
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
anova(lme.simpson2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
dotchart(plot.indices40m$Classes.Simpson,xlab="Simpson index") #Literally gives a dot chart

par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(plot.indices40m$Classes.Simpson~plot.indices40m$Management,xlab="Simpson index")
boxplot(plot.indices40m$Classes.Simpson~plot.indices40m$Alti, xlab="Simpson index")
boxplot(plot.indices40m$Classes.Simpson~plot.indices40m$ManAlti,xlab="Simpson index")

#RESIDUALS#####
plot(lme.simpson, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.simpson, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.simpson<-residuals(lme.simpson)
hist(res.lme.simpson)
par(pty="s")
qqnorm(res.lme.simpson)
qqline(res.lme.simpson)
fit.lme.sd<-fitted(lme.simpson)
plot(fit.lme.sd, res.lme.simpson)

#####SIMPSON INDEX INVERTED#####
#LME model for Management and Altitude
lme.simpson.inv<-lme(Classes.Simpson.inv~ManAlti,
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
summary(lme.simpson.inv)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.simpson.inv <- summary(glht(lme.simpson.inv, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.simpson.inv<-mcomp.simpson.inv$test$pvalues
names(pvalues.mcomp.simpson.inv)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
summary(mcomp.simpson.inv) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.simpson.inv)$Letters
multcompLetters(pvalues.mcomp.simpson.inv)$LetterMatrix
#ANOVA#####Linear mixed-effects model with random
effect#
lme.simpson.inv2<-lme(Classes.Simpson.inv~Management*Alti,
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
anova(lme.simpson.inv2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
```

```
dotchart(plot.indices40m$Classes.Simpson.inv,xlab="Stand density index") #Literally gives a dot chart
```

```
par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))  
boxplot(plot.indices40m$Classes.Simpson.inv~plot.indices40m$Management,xlab="Stand density index")  
boxplot(plot.indices40m$Classes.Simpson.inv~plot.indices40m$Alti, xlab="Stand density index")  
boxplot(plot.indices40m$Classes.Simpson.inv~plot.indices40m$ManAlti,xlab="Stand density index")
```

```
#####  
plot(lme.simpson.inv, resid(., type = "p") ~ fitted(.) | Management, abline = 0)  
plot(lme.simpson.inv, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)
```

```
res.lme.simpson.inv<-residuals(lme.simpson.inv)  
hist(res.lme.simpson.inv)  
par(pty="s")  
qqnorm(res.lme.simpson.inv)  
qqline(res.lme.simpson.inv)  
fit.lme.sd<-fitted(lme.simpson.inv)  
plot(fit.lme.sd, res.lme.simpson.inv)
```

**#####BERGER-PARKER INDEX #####**

```
#LME model for Management and Altitude  
lme.berger<-lme(Classes.Berger~ManAlti, random=~1 | Code.massif,data=plot.indices40m,  
na.action=na.omit)  
summary(lme.berger)
```

```
#General Linear Hypotheses/Multiple comparisons of Means of each Scenario  
mcomp.berger <- summary(glht(lme.berger, linfct=mcp(ManAlti="Tukey")))  
pvalues.mcomp.berger<-mcomp.berger$stest$pvalues  
names(pvalues.mcomp.berger)<-c("UNM.LWL-MAN.LWL","MAN.MON-MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-UNM.LWL","UNM.MON-MAN.MON")  
summary(mcomp.berger) #Gives Pvalue and standard error for each scenario  
multcompLetters(pvalues.mcomp.berger)$Letters  
multcompLetters(pvalues.mcomp.berger)$LetterMatrix  
#ANOVA#####Linear mixed-effects model with random effect#  
lme.berger2<-lme(Classes.Berger~Management*Alti,  
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)  
anova(lme.berger2) #gives the F and P value for Management/Altitude and Interaction  
Management:Altitude
```

```
#####  
dotchart(plot.indices40m$Classes.Berger,xlab="Berger index") #Literally gives a dot chart
```

```
par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))  
boxplot(plot.indices40m$Classes.Berger~plot.indices40m$Management,xlab="Bergerindex")  
boxplot(plot.indices40m$Classes.Berger~plot.indices40m$Alti, xlab="Berger index")  
boxplot(plot.indices40m$Classes.Berger~plot.indices40m$ManAlti,xlab="Berger index")
```

```
#####  
#####  
plot(lme.berger, resid(., type = "p") ~ fitted(.) | Management, abline = 0)  
plot(lme.berger, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)
```

```
res.lme.berger<-residuals(lme.berger)
hist(res.lme.berger)
par(pty="s")
qqnorm(res.lme.berger)
qqline(res.lme.berger)
fit.lme.sd<-fitted(lme.berger)
plot(fit.lme.sd, res.lme.berger)

#####SHANNON INDEX – EVENNESS#####
#LME model for Management and Altitude
lme.shannon.e<-lme(Classes.Shannon.Evenness~ManAlti,
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
summary(lme.shannon.e)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.shannon.e <- summary(glht(lme.shannon.e, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.shannon.e<-mcomp.shannon.e$test$pvalues
names(pvalues.mcomp.shannon.e)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
summary(mcomp.shannon.e) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.shannon.e)$Letters
multcompLetters(pvalues.mcomp.shannon.e)$LetterMatrix
#ANOVA#####Linear mixed-effects model with random
effect#
lme.shannon.e2<-lme(Classes.Shannon.Evenness~Management*Alti,
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
anova(lme.shannon.e2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
dotchart(plot.indices40m$Classes.Shannon.Evenness,xlab="Shannon evenness") #Literally gives
a dot chart

#par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(plot.indices40m$Classes.Shannon.Evenness~plot.indices40m$Management,xlab="Shann
on evenness")
boxplot(plot.indices40m$Classes.Shannon.Evenness~plot.indices40m$Alti, xlab="Shannon
evenness")
boxplot(plot.indices40m$Classes.Shannon.Evenness~plot.indices40m$ManAlti,xlab="Shannon
evenness")

#RESIDUALS#####
plot(lme.shannon.e, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.shannon.e, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.shannon.e<-residuals(lme.shannon.e)
hist(res.lme.shannon.e)
par(pty="s")
qqnorm(res.lme.shannon.e)
qqline(res.lme.shannon.e)
fit.lme.sd<-fitted(lme.shannon.e)
plot(fit.lme.sd, res.lme.shannon.e)

##### SIMPSON INDEX - EVENNESS #####
#LME model for Management and Altitude
```



```
lme.simpson.e<-lme(Classes.Simpson.Evenness~ManAlti,
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
summary(lme.simpson.e)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.simpson.e <- summary(glht(lme.simpson.e, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.simpson.e<-mcomp.simpson.e$test$pvalues
names(pvalues.mcomp.simpson.e)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
summary(mcomp.simpson.e) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.simpson.e)$Letters
multcompLetters(pvalues.mcomp.simpson.e)$LetterMatrix
#ANOVA#####Linear mixed-effects model with random
effect#
lme.simpson.e2<-lme(Classes.Simpson.Evenness~Management*Alti,
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
anova(lme.simpson.e2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
#####
dotchart(plot.indices40m$Classes.Simpson.Evenness,xlab="Simpson evenness index") #Literally
gives a dot chart

par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(plot.indices40m$Classes.Simpson.Evenness~plot.indices40m$Management,xlab="Simpson
evenness index")
boxplot(plot.indices40m$Classes.Simpson.Evenness~plot.indices40m$Alti, xlab="Simpson
evenness index")
boxplot(plot.indices40m$Classes.Simpson.Evenness~plot.indices40m$ManAlti,xlab="Simpson
evenness index")

#RESIDUALS#####
####
plot(lme.simpson.e, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.simpson.e, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.simpson.e<-residuals(lme.simpson.e)
hist(res.lme.simpson.e)
par(pty="s")
qqnorm(res.lme.simpson.e)
qqline(res.lme.simpson.e)
fit.lme.sd<-fitted(lme.simpson.e)
plot(fit.lme.sd, res.lme.simpson.e)

#####Gini index #####
#LME model for Management and Altitude
lme.gini<-lme(gini.DBH~ManAlti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
summary(lme.gini)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.gini <- summary(glht(lme.gini, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.gini<-mcomp.gini$test$pvalues
```

```
names(pvalues.mcomp.gini)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
summary(mcomp.gini) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.gini)$Letters
multcompLetters(pvalues.mcomp.gini)$LetterMatrix
#ANOVA#####Linear mixed-effects model with random
effect#
lme.gini2<-lme(gini.DBH~Management*Alti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
anova(lme.gini2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
#####
dotchart(plot.indices40m$gini.DBH,xlab="Vertical evenness index") #Literally gives a dot chart

par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(plot.indices40m$gini.DBH~plot.indices40m$Management,xlab="Vertical evenness
index")
boxplot(plot.indices40m$gini.DBH~plot.indices40m$Alti, xlab="Vertical evenness index")
boxplot(plot.indices40m$gini.DBH~plot.indices40m$ManAlti,xlab="Vertical evenness index")

#RESIDUALS#####
####
plot(lme.gini, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.gini, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.gini<-residuals(lme.gini)
hist(res.lme.gini)
par(pty="s")
qqnorm(res.lme.gini)
qqline(res.lme.gini)
fit.lme.sd<-fitted(lme.gini)
plot(fit.lme.sd, res.lme.gini)

#####LORIMER index#####
#LME model for Management and Altitude
lme.Lorimer<-lme(Lorimer~ManAlti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
summary(lme.Lorimer)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.Lorimer <- summary(glht(lme.Lorimer, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.Lorimer<-mcomp.Lorimer$test$pvalues
names(pvalues.mcomp.Lorimer)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
summary(mcomp.Lorimer) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.Lorimer)$Letters
multcompLetters(pvalues.mcomp.Lorimer)$LetterMatrix
#ANOVA#####Linear mixed-effects model with random
effect#
lme.Clark.Evans2<-lme(Lorimer~Management*Alti,
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
```

```
anova(lme.Clark.Evans2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
dotchart(plot.indices40m$Lorimer,xlab="Lorimer index") #Literally gives a dot chart

par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(plot.indices40m$Lorimer~plot.indices40m$Management,xlab="Lorimer index")
boxplot(plot.indices40m$Lorimer~plot.indices40m$Alti, xlab="Lorimer index")
boxplot(plot.indices40m$Lorimer~plot.indices40m$ManAlti,xlab="Lorimer index")

#RESIDUALS#####
plot(lme.Lorimer, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.Lorimer, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.Lorimer<-residuals(lme.Lorimer)
hist(res.lme.Lorimer)
par(pty="s")
qqnorm(res.lme.Lorimer)
qqline(res.lme.Lorimer)
fit.lme.sd<-fitted(lme.Lorimer)
plot(fit.lme.sd, res.lme.Lorimer)

#####Clark Evans index#####
LME model for Management and Altitude
lme.Clark.Evans1<-lme(Clark.Evans1~ManAlti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
summary(lme.Clark.Evans1)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.Clark.Evans1 <- summary(glht(lme.Clark.Evans1, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.Clark.Evans1<-mcomp.Clark.Evans1$test$pvalues
names(pvalues.mcomp.Clark.Evans1)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
summary(mcomp.Clark.Evans1) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.Clark.Evans1)$Letters
multcompLetters(pvalues.mcomp.Clark.Evans1)$LetterMatrix
#ANOVA#####Linear mixed-effects model with random
effect#
lme.Clark.Evans2<-lme(Clark.Evans1~Management*Alti,
random=~1 | Code.massif,data=plot.indices40m, na.action=na.omit)
anova(lme.Clark.Evans2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
dotchart(plot.indices40m$Clark.Evans1,xlab="Clark.Evans1 index") #Literally gives a dot chart

par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(plot.indices40m$Clark.Evans1~plot.indices40m$Management,xlab="Clark.Evans1
index")
boxplot(plot.indices40m$Clark.Evans1~plot.indices40m$Alti, xlab="Clark.Evans1 index")
boxplot(plot.indices40m$Clark.Evans1~plot.indices40m$ManAlti,xlab="Clark.Evans1 index")

#RESIDUALS#####
plot(lme.Clark.Evans1, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
```

```
plot(lme.Clark.Evans1, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.Clark.Evans1<-residuals(lme.Clark.Evans1)
hist(res.lme.Clark.Evans1)
par(pty="s")
qqnorm(res.lme.Clark.Evans1)
qqline(res.lme.Clark.Evans1)
fit.lme.sd<-fitted(lme.Clark.Evans1)
plot(fit.lme.sd, res.lme.Clark.Evans1)

#####HOPKINS SKELLAM INDEX#####
#LME model for Management and Altitude
lme.HSI1<-lme(HSI1~ManAlti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
summary(lme.HSI1)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.HSI1 <- summary(glht(lme.HSI1, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.HSI1<-mcomp.HSI1$test$pvalues
names(pvalues.mcomp.HSI1)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
summary(mcomp.HSI1) #Gives Pvalue and standard error for each scenario
multcompLetters(pvalues.mcomp.HSI1)$Letters
multcompLetters(pvalues.mcomp.HSI1)$LetterMatrix

#ANOVA#####Linear mixed-effects model with random effect#
lme.HSI2<-lme(HSI1~Management*Alti, random=~1 | Code.massif,data=plot.indices40m,
na.action=na.omit)
anova(lme.HSI2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
dotchart(plot.indices40m$HSI1,xlab="HSI1 index") #Literally gives a dot chart

par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(plot.indices40m$HSI1~plot.indices40m$Management,xlab="HSI1 index")
boxplot(plot.indices40m$HSI1~plot.indices40m$Alti, xlab="HSI1 index")
boxplot(plot.indices40m$HSI1~plot.indices40m$ManAlti,xlab="HSI1 index")

#RESIDUALS#####
plot(lme.HSI1, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.HSI1, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.HSI1<-residuals(lme.HSI1)
hist(res.lme.HSI1)
par(pty="s")
qqnorm(res.lme.HSI1)
qqline(res.lme.HSI1)
fit.lme.sd<-fitted(lme.HSI1)
plot(fit.lme.sd, res.lme.HSI1)

###ADD R SCRIPT FOR DIAMETER DIFFERENTIATION, DOMINANCE AND
MEAN DIRECTIONAL INDEX AT 10 meters#####
crancod.indices.40m<-read.csv("//datafile/Biodiversite/projets/Indeco-
CONSPIIRE/Stage_A_Gillespie/Resultats_R
```

```
scripts/40m/Tables/Crancod_per_plot_40m_4n_No  
correction_Sept24.csv",header=T,sep=";",dec=".")  
summary(crancod.indices)  
head(crancod.indices)  
crancod.indices$rf1<-NULL
```

### **#MERGE ALL INDICES INTO ONE TABLE**

```
all.plot.indices.40m<-merge(plot.indices.40m, crancod.indices.40m, by.x="numpla.GNB",  
by.y="numpla.GNB", all.x=TRUE)  
write.table(all.plot.indices.40m,"//datafile/Biodiversite/projets/Indeco-  
CONSPIIRE/Stage_A_Gillespie/Resultats_R  
scripts/40m/Tables/ALL_plot_indices.csv",header=T,sep=";",dec=".")
```

### **#SUBSET DISTANCE LESS THAN 10m and PLOTS WITH MORE THAN 2 TREES**

```
plot.indices.10m<-subset(all.plot.indices, na.rm=T) #Excludes plots with NAs from subset  
#Keep only stands with more than 2 trees  
keep.data <- (plot.indices.10m$No.of.trees.10m)[table(plot.indices.10m$No.of.trees.10m) > 2]  
##To return stands with more than 1 tree  
plot.indices.10m <- plot.indices.10m[plot.indices.10m$No.of.trees.10m %in% keep.data, ]
```

```
write.table(plot.indices.10m, "//datafile/Biodiversite/projets/Indeco-  
CONSPIIRE/Stage_A_Gillespie/Resultats_R  
scripts/10m/Tables/All_indices10m_Oct6.csv",sep=";",row.names=F,col.names=T)
```

### **#####DIAMETER DIFFERENTIATION#####**

```
#LME model  
lme.dd<-lme(diam.diff~ManAlti, random=~1 | Code.massif,data=plot.indices.10m,  
na.action=na.omit)  
summary(lme.dd)
```

```
#General Linear Hypotheses/Multiple comparisons of Means of each Scenario  
mcomp.dd <- summary(glht(lme.dd, linfct=mcp(ManAlti="Tukey")))  
pvalues.mcomp.dd<-mcomp.dd$test$pvalues  
names(pvalues.mcomp.dd)<-c("UNM.LWL-MAN.LWL","MAN.MON-  
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-  
UNM.LWL","UNM.MON-MAN.MON")  
multcompLetters(pvalues.mcomp.dd)$Letters  
multcompLetters(pvalues.mcomp.dd)$LetterMatrix
```

```
summary(mcomp.dd) #Gives Pvalue and standard error for each scenario
```

```
#For Anova -Linear mixed-effects model with random effect  
lme.dd2<-lme(diam.diff~Management*Alti, random=~1 | Code.massif,data=plot.indices.10m,  
na.action=na.omit)  
anova(lme.dd2) #gives the F and P value for Management/Altitude and Interaction
```

```
#Graphically#  
dotchart(plot.indices.10m$diam.diff,xlab="Diameter Differentiation") #Literally gives a dot chart
```

```
boxplot(plot.indices.10m$diam.diff~plot.indices.10m$Management,xlab="Diameter  
Differentiation by Management")  
boxplot(plot.indices.10m$diam.diff~plot.indices.10m$Alti)  
boxplot(plot.indices.10m$diam.diff~plot.indices.10m$ManAlti,xlab="Diameter Differentiation -  
Mangement & Altitude")
```

```
#Residuals#
```

```
plot(lme.dd, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.dd, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.dd<-residuals(lme.dd)
hist(res.lme.dd)
par(pty="s")
qqnorm(res.lme.dd)
qqline(res.lme.dd)
fit.lme.sd<-fitted(lme.dd)
plot(fit.lme.sd, res.lme.dd)

#####DIAMETER DOMINANCE#####
#LME model
lme.ddom<-lme(diam.dom~ManAlti, random=~1 | Code.massif,data=plot.indices.10m,
na.action=na.omit)
summary(lme.ddom)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.ddom <- summary(glht(lme.ddom, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.ddom<-mcomp.ddom$test$pvalues
names(pvalues.mcomp.ddom)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
multcompLetters(pvalues.mcomp.ddom)$Letters
multcompLetters(pvalues.mcomp.ddom)$LetterMatrix

summary(mcomp.ddom) #Gives Pvalue and standard error for each scenario

#For Anova -Linear mixed-effects model with random effect
lme.ddom2<-lme(diam.dom~Management*Alti,
random=~1 | Code.massif,data=plot.indices.10m, na.action=na.omit)
anova(lme.ddom2) #gives the F and P value for Management/Altitude and Interaction

#Graphically#
dotchart(plot.indices.10m$diam.dom,xlab="Diameter Dominance") #Literally gives a dot chart
plot(plot.indices.10m$diam.dom~plot.indices.10m$Basal.area)
boxplot(plot.indices.10m$diam.dom~plot.indices.10m$Management,xlab="Diameter Dominance
by Management")
boxplot(plot.indices.10m$diam.dom~plot.indices.10m$Alti)
boxplot(plot.indices.10m$diam.dom~plot.indices.10m$ManAlti,xlab="Diameter Dominance-
Mangement & Altitude")

#Residuals#
plot(lme.ddom, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.ddom, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.ddom<-residuals(lme.ddom)
hist(res.lme.ddom)
par(pty="s")
qqnorm(res.lme.ddom)
qqline(res.lme.ddom)
fit.lme.sd<-fitted(lme.ddom)
plot(fit.lme.sd, res.lme.ddom)

#####MEAN DIRECTIONAL INDEX#####
#need to remove Inf first:
```

```
plot.indices.10m$mean.direct.index[plot.indices.10m$mean.direct.index==Inf] <- NA
plot.indices.10m$mean.direct.index[plot.indices.10m$mean.direct.index==Inf] <- NA
#LME model
lme.mdi<-lme(mean.direct.index~ManAlti, random=~1 | Code.massif,data=plot.indices.10m,
na.action=na.omit)
summary(lme.mdi)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.mdi <- summary(glht(lme.mdi, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.mdi<-mcomp.mdi$test$pvalues
names(pvalues.mcomp.mdi)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
multcompLetters(pvalues.mcomp.mdi)$Letters
multcompLetters(pvalues.mcomp.mdi)$LetterMatrix
summary(mcomp.mdi) #Gives Pvalue and standard error for each scenario

#For Anova -Linear mixed-effects model with random effect
lme.mdi2<-lme(mean.direct.index~Management*Alti,
random=~1 | Code.massif,data=plot.indices.10m, na.action=na.omit)
anova(lme.mdi2) #gives the F and P value for Management/Altitude and Interaction

#Graphically#
dotchart(plot.indices.10m$mean.direct.index,xlab="Mean Directional index") #Literally gives a
dot chart
plot(plot.indices.10m$mean.direct.index~plot.indices.10m$Basal.area)
boxplot(plot.indices.10m$mean.direct.index~plot.indices.10m$Management,xlab="Mean
Directional index by Management")
boxplot(plot.indices.10m$mean.direct.index~plot.indices.10m$Alti)
boxplot(plot.indices.10m$mean.direct.index~plot.indices.10m$ManAlti,xlab="Mean Directional
index- Mangement & Altitude")

#Residuals#
plot(lme.mdi, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.mdi, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.mdi<-residuals(lme.mdi)
hist(res.lme.mdi)
par(pty="s")
qqnorm(res.lme.mdi)
qqline(res.lme.mdi)
fit.lme.sd<-fitted(lme.mdi)
plot(fit.lme.sd, res.lme.mdi)

##### ADD RIPLEY L FUNCTION#####
Ripley10m<-read.csv("//datafile/Biodiversite/projets/Indeco-
CONSPIIRE/Stage_A_Gillespie/Resultats_R scripts/20m/Tables/Ripley_khat10m_Sept22.csv",
header=T,sep=";",dec=".")
head(Ripley10m)

#Table for 5 meters L test #
Ripley5m<-subset(Ripley10m, seq==5)
Ripley5m$seq<-NULL
Ripley5m$k1<-NULL
Ripley5m$L.fn.5m<-Ripley5m$L1
Ripley5m$L1<-NULL
```

```
head(Ripley5m)

#Table for 10 meters L test #
Ripley10m2<-subset(Ripley10m, seq==10)
Ripley10m2$seq<-NULL
Ripley10m2$k1<-NULL
Ripley10m2$L.fn.10m<-Ripley10m2$L1
Ripley10m2$L1<-NULL
head(Ripley10m2)
Ripley5m_10m<-merge(Ripley10m2,Ripley5m, by.x="numpla", by.y="numpla", all.x=TRUE)

#Merge the two columns back into "all.plot.indices"
all.plot.indices10m<-merge(all.plot.indices10m,Ripley5m_10m, by.x="numpla.GNB",
by.y="numpla", all.x=TRUE)

#####TESTS - RIPLEY L FUNCTION #####
#####FOR 5 METERS #####
#LME model for Management and Altitude
lme.L.fn.5m<-lme(L.fn.5m~ManAlti, random=~1 | Code.massif,data=all.plot.indices,
na.action=na.omit)
summary(lme.L.fn.5m)

#General Linear Hypotheses/Multiple comparisons of Means of each Scenario
mcomp.L.fn.5m <- summary(glht(lme.L.fn.5m, linfct=mcp(ManAlti="Tukey")))
pvalues.mcomp.L.fn.5m<-mcomp.L.fn.5m$test$pvalues
names(pvalues.mcomp.L.fn.5m)<-c("UNM.LWL-MAN.LWL","MAN.MON-
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-
UNM.LWL","UNM.MON-MAN.MON")
multcompLetters(pvalues.mcomp.L.fn.5m)$Letters
multcompLetters(pvalues.mcomp.L.fn.5m)$LetterMatrix
summary(mcomp.L.fn.5m) #Gives Pvalue and standard error for each scenario

#ANOVA#####Linear mixed-effects model with random effect#
lme.L.fn.5m2<-lme(L.fn.5m~Management*Alti, random=~1 | Code.massif,data=all.plot.indices,
na.action=na.omit)
anova(lme.L.fn.5m2) #gives the F and P value for Management/Altitude and Interaction
Management:Altitude

#GRAPHICALLY#####
dotchart(all.plot.indices$L.fn.5m,xlab="L.fn.5m index") #Literally gives a dot chart

par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))
boxplot(all.plot.indices$L.fn.5m~all.plot.indices$Management,xlab="L.fn.5m index")
boxplot(all.plot.indices$L.fn.5m~all.plot.indices$Alti, xlab="L.fn.5m index")
boxplot(all.plot.indices$L.fn.5m~all.plot.indices$ManAlti,xlab="L.fn.5m index")

#RESIDUALS#####
plot(lme.L.fn.5m, resid(., type = "p") ~ fitted(.) | Management, abline = 0)
plot(lme.L.fn.5m, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)

res.lme.L.fn.5m<-residuals(lme.L.fn.5m)
hist(res.lme.L.fn.5m)
par(pty="s")
qqnorm(res.lme.L.fn.5m)
qqline(res.lme.L.fn.5m)
fit.lme.sd<-fitted(lme.L.fn.5m)
```



```
plot(fit.lme.sd, res.lme.L.fn.5m)
```

```
#####FOR 10 METERS #####
```

```
#LME model for Management and Altitude  
lme.L.fn.10m<-lme(L.fn.10m~ManAlti, random=~1 | Code.massif,data=all.plot.indices,  
na.action=na.omit)  
summary(lme.L.fn.10m)
```

```
#General Linear Hypotheses/Multiple comparisons of Means of each Scenario  
mcomp.L.fn.10m <- summary(glht(lme.L.fn.10m, linfct=mcp(ManAlti="Tukey")))  
pvalues.mcomp.L.fn.10m<-mcomp.L.fn.10m$test$pvalues  
names(pvalues.mcomp.L.fn.10m)<-c("UNM.LWL-MAN.LWL","MAN.MON-  
MAN.LWL","UNM.MON-MAN.LWL","MAN.MON-UNM.LWL","UNM.MON-  
UNMLWL","UNM.MON-MAN.MON")  
summary(mcomp.L.fn.10m) #Gives Pvalue and standard error for each scenario
```

```
#ANOVA#####Linear mixed-effects model with random  
effect#  
lme.L.fn.10m2<-lme(L.fn.10m~Management, random=~1 | Code.massif,data=all.plot.indices,  
na.action=na.omit)  
anova(lme.L.fn.10m2) #gives the F and P value for Management/Altitude and Interaction  
Management:Altitude
```

```
#GRAPHICALLY#####  
dotchart(all.plot.indices$L.fn.10m,xlab="L.fn.10m index") #Literally gives a dot chart
```

```
par(mfrow = c(1, 1)) #if want two plots into one window par(mfrow=c(1,1))  
boxplot(all.plot.indices$L.fn.10m~all.plot.indices$Management,xlab="L.fn.10m index")  
boxplot(all.plot.indices$L.fn.10m~all.plot.indices$Alti, xlab="L.fn.10m index")  
boxplot(all.plot.indices$L.fn.10m~all.plot.indices$ManAlti,xlab="L.fn.10m index")
```

```
#RESIDUALS#####  
plot(lme.L.fn.10m, resid(., type = "p") ~ fitted(.) | Management, abline = 0)  
plot(lme.L.fn.10m, resid(., type = "p") ~ fitted(.) | ManAlti, abline = 0)
```

```
res.lme.L.fn.10m<-residuals(lme.L.fn.10m)  
hist(res.lme.L.fn.10m)  
par(pty="s")  
qqnorm(res.lme.L.fn.10m)  
qqline(res.lme.L.fn.10m)  
fit.lme.sd<-fitted(lme.L.fn.10m)  
plot(fit.lme.sd, res.lme.L.fn.10m)
```

```
#####CORRELATION table#####  
#####ALL INDICES #####  
#Test hypothesis of coefficient of correlation r being 0 --> Pearson  
cor.indices40m<-all.plot.indices.40m
```

```
#Remove unwanted columns  
cor.indices40m$ManAlti<-NULL  
cor.indices40m$Alti<-NULL  
cor.indices40m$Management<-NULL  
cor.indices40m$Classes.Simpson.inv<-NULL  
cor.indices40m$N.BV.ha<-NULL  
cor.indices40m$QDM<-NULL  
cor.indices40m$DBH.095<-NULL
```

```
cor.indices40m$min.DBH<-NULL
cor.indices40m$plot.mean.DBH<-NULL
cor.indices40m$ManAlti<-NULL
cor.indices40m$Alti<-NULL
cor.indices40m$Management<-NULL
cor.indices40m$Code.massif<-NULL
cor.indices40m$acidite<-NULL
cor.indices40m$mode.DBH<-NULL
cor.indices40m$stems<-NULL
cor.indices40m$numpla.GNB<-NULL
cor.indices40m$No.of.trees.40m<-NULL
cor.indices40m$No.of.trees.20m<-NULL
cor.indices40m$No.of.trees.10m<-NULL
cor.indices40m$DBH.0.9<-NULL
cor.indices40m$DBH.10.19<-NULL
cor.indices40m$DBH.20.29<-NULL
cor.indices40m$DBH.30.39<-NULL
cor.indices40m$DBH.40.49<-NULL
cor.indices40m$DBH.50.59<-NULL
cor.indices40m$DBH.60.69<-NULL
cor.indices40m$DBH.70.79<-NULL
cor.indices40m$DBH.80.89<-NULL
cor.indices40m$DBH.90.99<-NULL
cor.indices40m$DBH.100.and.up<-NULL
cor.indices40m$Size.Classes<-NULL

correlation.matrix40m<-as.data.frame(cor(cor.indices40m,use="pairwise.complete.obs"))
head(correlation.matrix40m)
write.table(correlation.matrix40m, "//datafile/Biodiversite/projets/Indeco-
CONSPIIRE/Stage_A_Gillespie/Resultats_R
scripts/40m/Tables/Correlation_matrix_40m_Oct6.csv",sep=";",row.names=F,col.names=T)

library("psych")
corr.test40m<-corr.test(cor.indices40m, adjust="none") #In order to calculate probabilities of
pairwise observations (null hypothesis whether the two indices are significantly different)
corr.testp40m<-as.data.frame(corr.test40m$p) #Saves ONLY p-test in a data.frame
head(corr.testp40m)
write.table(corr.testp40m, "//datafile/Biodiversite/projets/Indeco-
CONSPIIRE/Stage_A_Gillespie/Resultats_R
scripts/40m/Tables/Correlation_matrix_40m_Oct6.csv",sep=";",row.names=F,col.names=T)
```



## Annex 8 - Results of Tests in R: Tukey multiple comparison of means and Analysis of variance

This annex contains the results of the Tukey multiple comparisons of means of each modality and the results of the analysis of variance for management for the 19 indices.

### Note:

UNM stands for unmanaged sites; MAN stands for managed sites; LWL stands for lowland sites; MON stands for mountain sites

For more information on the scripts used for each analysis, please refer to Annex 7.

### STANDARD DEVIATION

#### *Multiple Comparisons of Means: Tukey Contrasts*

Linear Hypotheses:

	Estimate	Std. Error	z value	P(> z )
UNM.LWL - MAN.LWL == 0	3.47776	0.95429	3.644	0.00129 **
MAN.MON - MAN.LWL == 0	3.38627	2.20030	1.539	0.38424
UNM.MON - MAN.LWL == 0	5.25125	2.20030	2.387	0.06904 .
MAN.MON - UNM.LWL == 0 -	0.09149	2.20228	-0.042	0.99997
UNM.MON - UNM.LWL == 0	1.77349	2.20228	0.805	0.83702
UNM.MON - MAN.MON == 0	1.86499	1.32133	1.411	0.46190

#### *Anova test for management*

	numDF	denDF	F-value	p-value
(Intercept)	1	236	281.89183	<.0001
Management	1	236	14.31155	2e-04

### COEFFICIENT OF VARIATION

#### *Multiple Comparisons of Means: Tukey Contrasts*

Linear Hypotheses

	Estimate	Std. Error	z value	P(> z )
NM.LWL - MAN.LWL == 0	7.2690	2.8274	2.571	0.0471 *
MAN.MON - MAN.LWL == 0	7.4761	4.5053	1.659	0.3347
UNM.MON - MAN.LWL == 0	10.1766	4.5053	2.259	0.1028
MAN.MON - UNM.LWL == 0	0.2071	4.5154	0.046	1.0000
UNM.MON - UNM.LWL == 0	2.9076	4.5154	0.644	0.9143
UNM.MON - MAN.MON == 0	2.7006	3.9153	0.690	0.8970

#### *Anova test for management*

	numDF	denDF	F-value	p-value
(Intercept)	1	235	791.4056	<.0001
Management	1	235	6.2123	0.0134

### BASAL AREA

#### *Multiple Comparisons of Means: Tukey Contrasts*

Linear Hypotheses

	Estimate	Std. Error	z value	P(> z )
UNM.LWL - MAN.LWL == 0	3.553	1.082	3.283	0.00496 **
MAN.MON - MAN.LWL == 0	8.904	2.199	4.050	0.00027 ***
UNM.MON - MAN.LWL == 0	13.593	2.199	6.182	< 1e-04 ***
MAN.MON - UNM.LWL == 0	5.351	2.199	2.433	0.06331 .
UNM.MON - UNM.LWL == 0	10.039	2.199	4.566	< 1e-04 ***
UNM.MON - MAN.MON == 0	4.689	1.485	3.157	0.00761 **

#### *Anova test for management*

	numDF	denDF	F-value	p-value
(Intercept)	1	235	721.0174	<.0001
Management	1	235	21.4198	<.0001

### STAND DENSITY INDEX

#### *Multiple Comparisons of Means: Tukey Contrasts*

Linear Hypotheses

	Estimate	Std. Error	z value	Pr(> z )
NM.LWL - MAN.LWL == 0	68.55	21.58	3.177	0.007279 **
MAN.MON - MAN.LWL == 0	140.98	40.50	3.481	0.002538 **
UNM.MON - MAN.LWL == 0	224.94	40.50	5.554	< 1e-04 ***
MAN.MON - UNM.LWL == 0	72.43	40.51	1.788	0.262009
UNM.MON - UNM.LWL == 0	156.39	40.51	3.861	0.000602 ***
UNM.MON - MAN.MON == 0	83.96	29.61	2.835	0.021411 *

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	235	826.5139	<.0001
Management	1	235	18.3517	<.0001

**SKEWNESS**

**Multiple Comparisons of Means: Tukey Contrasts**

**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	0.13634	0.11359	1.200	0.615
MAN.MON - MAN.LWL == 0	-0.08087	0.18450	-0.438	0.970
UNM.MON - MAN.LWL == 0	0.13079	0.18450	0.709	0.889
MAN.MON - UNM.LWL == 0	-0.21721	0.18433	-1.178	0.629
UNM.MON - UNM.LWL == 0	-0.00555	0.18433	-0.030	1.000
UNM.MON - MAN.MON == 0	0.21166	0.15501	1.365	0.509

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	235	33.22571	<.0001
Management	1	235	3.62962	0.0764

**LORIMER INDEX**

**Multiple Comparisons of Means: Tukey Contrasts**

**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	0.22133	0.09315	2.376	0.0691 .
MAN.MON - MAN.LWL == 0	-0.19995	0.23601	-0.847	0.8126
UNM.MON - MAN.LWL == 0	-0.08646	0.23601	-0.366	0.9808
MAN.MON - UNM.LWL == 0	-0.42129	0.23588	-1.786	0.2500
UNM.MON - UNM.LWL == 0	-0.30779	0.23588	-1.305	0.5256
UNM.MON - MAN.MON == 0	0.11349	0.12711	0.893	0.7873

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	230	21.530505	<.0001
Management	1	230	6.035772	0.0148

**KURTOSIS**

**Multiple Comparisons of Means: Tukey Contrasts**

**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	-0.02129	0.30544	-0.070	1.000
MAN.MON - MAN.LWL == 0	-0.25922	0.37334	-0.694	0.898
UNM.MON - MAN.LWL == 0	-0.07012	0.37334	-0.188	0.998
MAN.MON - UNM.LWL == 0	-0.23794	0.37326	-0.637	0.919
UNM.MON - UNM.LWL == 0	-0.04883	0.37326	-0.131	0.999
UNM.MON - MAN.MON == 0	0.18910	0.41695	0.454	0.969

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	235	457.0961	<.0001
Management	1	235	0.2251	0.8309

**SHANNON INDEX**

**Multiple Comparisons of Means: Tukey Contrasts**

**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	0.143658	0.055581	2.585	0.0441 *
MAN.MON - MAN.LWL == 0	0.141409	0.099964	1.415	0.4727
UNM.MON - MAN.LWL == 0	0.234101	0.099964	2.342	0.0820 .
MAN.MON - UNM.LWL == 0	-0.002249	0.100126	-0.022	1.0000
UNM.MON - UNM.LWL == 0	0.090442	0.100126	0.903	0.7923
UNM.MON - MAN.MON == 0	0.092691	0.076964	1.204	0.6080

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	235	1282.0271	<.0001
Management	1	235	7.9279	0.0054

**SIMPSON INDEX**

*Multiple Comparisons of Means: Tukey Contrasts*

*Linear Hypotheses*

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	0.4949	0.1896	2.610	0.0397
MAN.MON - MAN.LWL == 0	0.3882	0.3885	0.999	0.7319
UNM.MON - MAN.LWL == 0	0.7159	0.3885	1.843	0.2334
MAN.MON - UNM.LWL == 0	-0.1066	0.3885	-0.274	0.9920
UNM.MON - UNM.LWL == 0	0.2210	0.3885	0.569	0.9359
UNM.MON - MAN.MON == 0	0.3276	0.2602	1.259	0.5658

*Anova test for management*

	numDF	denDF	F-value	p-value
(Intercept)	1	235	3459.165	<.0001
Management	1	235	4.410	0.0047

**BERGER-PARKER INDEX**

*Multiple Comparisons of Means: Tukey Contrasts*

*Linear Hypotheses*

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	-0.025146	0.020310	-1.238	0.590
MAN.MON - MAN.LWL == 0	-0.034248	0.033920	-1.010	0.734
UNM.MON - MAN.LWL == 0	-0.055368	0.033920	-1.632	0.347
MAN.MON - UNM.LWL == 0	-0.009102	0.033987	-0.268	0.993
UNM.MON - UNM.LWL == 0	-0.030222	0.033987	-0.889	0.802

*Anova test for management*

	numDF	denDF	F-value	p-value
(Intercept)	1	232	731.1848	<.0001
Management	1	232	2.8606	0.1485

**SHANNON EVENNESS INDEX**

*Multiple Comparisons of Means: Tukey Contrasts*

*Linear Hypotheses*

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	0.009543	0.018724	0.510	0.956
MAN.MON - MAN.LWL == 0	0.040893	0.022494	1.818	0.262
UNM.MON - MAN.LWL == 0	0.039766	0.022494	1.768	0.286
MAN.MON - UNM.LWL == 0	0.031350	0.022494	1.394	0.500
UNM.MON - UNM.LWL == 0	0.030222	0.022494	1.344	0.532
UNM.MON - MAN.MON == 0	-0.001127	0.025717	-0.044	1.000

*Anova test for management*

	numDF	denDF	F-value	p-value
(Intercept)	1	232	12749.379	<.0001
Management	1	232	0.149	0.6995

**SIMPSON EVENNESS INDEX**

*Multiple Comparisons of Means: Tukey Contrasts*

*Linear Hypotheses*

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	-0.017454	0.019474	-0.896	0.804
MAN.MON - MAN.LWL == 0	0.018270	0.026074	0.701	0.895
UNM.MON - MAN.LWL == 0	0.002936	0.026074	0.113	0.999
MAN.MON - UNM.LWL == 0	0.035724	0.026125	1.367	0.515
UNM.MON - UNM.LWL == 0	0.020390	0.026125	0.780	0.861
UNM.MON - MAN.MON == 0	-0.015334	0.026736	-0.574	0.939

*Anova test for management*

	numDF	denDF	F-value	p-value
(Intercept)	1	232	5014.929	<.0001
Management	1	232	1.124	0.2894

**GINI INDEX**

*Multiple Comparisons of Means: Tukey Contrasts*

**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	0.033690	0.013413	2.512	0.0542
MAN.MON - MAN.LWL == 0	0.031927	0.022785	1.401	0.4838
UNM.MON - MAN.LWL == 0	0.049211	0.022785	2.160	0.1269
MAN.MON - UNM.LWL == 0	-0.001763	0.022794	-0.077	0.9998
UNM.MON - UNM.LWL == 0	0.015521	0.022794	0.681	0.8993
UNM.MON - MAN.MON == 0	0.017284	0.018410	0.939	0.7742

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	232	829.0255	<.0001
Management	1	232	6.6763	0.0103

**MEAN DIRECTIONAL INDEX (10m)**

**Multiple Comparisons of Means: Tukey Contrasts**

**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	-0.078550	0.041704	-1.8835	0.2322
MAN.MON - MAN.LWL == 0	0.023311	0.054651	0.4265	0.9736
UNM.MON - MAN.LWL == 0	-0.030781	0.053881	-0.5713	0.9398
MAN.MON - UNM.LWL == 0	0.101861	0.054267	1.8770	0.2350
UNM.MON - UNM.LWL == 0	0.047769	0.053492	0.8930	0.8063
UNM.MON - MAN.MON == 0	-0.054093	0.057375	-0.9428	0.7793

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	221	22374.5978	<.0001
Management	1	221	4.3156	0.0389

**MEAN DIRECTIONAL INDEX (40m)**

**Multiple Comparisons of Means: Tukey Contrasts**

**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	-0.0872957	0.0342383	-2.5496	0.04923 *
MAN.MON - MAN.LWL == 0	-0.1183913	0.0580186	-2.0406	0.16381
UNM.MON - MAN.LWL == 0	-0.1239679	0.0580186	-2.1367	0.13349
MAN.MON - UNM.LWL == 0	-0.0310956	0.0579653	-0.5365	0.94735
UNM.MON - UNM.LWL == 0	-0.0366722	0.0579653	-0.6327	0.91730
UNM.MON - MAN.MON == 0	-0.0055766	0.0467246	-0.1194	0.99935

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	230	19.4129	<.0001
Management	1	230	4.5153	0.0347

**CLARK-EVANS INDEX**

**Multiple Comparisons of Means: Tukey Contrasts**

**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	-0.00599969	0.00680659	-0.8815	0.8127
MAN.MON - MAN.LWL == 0	0.00325589	0.00828535	0.3930	0.9792
UNM.MON - MAN.LWL == 0	0.00086871	0.00815752	0.1065	0.9996
MAN.MON - UNM.LWL == 0	0.00925558	0.00825033	1.1218	0.6734
UNM.MON - UNM.LWL == 0	0.00686840	0.00812194	0.8457	0.8309
UNM.MON - MAN.MON == 0	-0.00238717	0.00939592	-0.2541	0.9942

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	222	4511.9303	<.0001
Management	1	222	0.7365	0.3917

**HOPKINS-SKELLAM INDEX (10m)**

**Multiple Comparisons of Means: Tukey Contrasts**  
**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	0.10953	0.52078	0.2103	0.9965
MAN.MON - MAN.LWL == 0	-0.12164	0.88804	-0.1370	0.9990
UNM.MON - MAN.LWL == 0	-0.68635	0.89070	-0.7706	0.8610
MAN.MON - UNM.LWL == 0	-0.23117	0.88529	-0.2611	0.9934
UNM.MON - UNM.LWL == 0	-0.79589	0.88795	-0.8963	0.7976
UNM.MON - MAN.MON == 0	-0.56472	0.71014	-0.7952	0.8494

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	227	16.2781175	0.0001
Management	1	227	0.0877643	0.7673

**HOPKINS-SKELLAM INDEX (40m)**

**Multiple Comparisons of Means: Tukey Contrasts**  
**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	-0.07939	0.09551	-0.831	0.83557
MAN.MON - MAN.LWL == 0	0.43599	0.14008	3.112	0.00968 **
UNM.MON - MAN.LWL == 0	0.11751	0.14008	0.839	0.83175
MAN.MON - UNM.LWL == 0	0.51538	0.13996	3.682	0.00128 **
UNM.MON - UNM.LWL == 0	0.19689	0.13996	1.407	0.48721
UNM.MON - MAN.MON == 0	-0.31849	0.13036	-2.443	0.06684 .

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	230	80.082639	<.0001
Management	1	230	4.486063	0.0364

**DIAMETER DIFFERENTIATION INDEX**

**Multiple Comparisons of Means: Tukey Contrasts**  
**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	0.01197501	0.01116593	1.0725	0.7024
MAN.MON - MAN.LWL == 0	0.01210887	0.01530811	0.7910	0.8563
UNM.MON - MAN.LWL == 0	-0.00393720	0.01510395	-0.2607	0.9937
MAN.MON - UNM.LWL == 0	0.00013386	0.01523464	0.0088	1.0000
UNM.MON - UNM.LWL == 0	-0.01591221	0.01502949	-1.0587	0.7108
UNM.MON - MAN.MON == 0	-0.01604607	0.01541286	-1.0411	0.7215

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	222	6111.5753	<.0001
Management	1	222	0.0661	0.7973

**DIAMETER DOMINANCE INDEX**

**Multiple Comparisons of Means: Tukey Contrasts**  
**Linear Hypotheses**

	Estimate	Std. Error	z value	Pr(> z )
UNM.LWL - MAN.LWL == 0	-0.0094186	0.0257417	-0.3659	0.9813
MAN.MON - MAN.LWL == 0	0.1147003	0.0583626	1.9653	0.1805
UNM.MON - MAN.LWL == 0	0.0725615	0.0580355	1.2503	0.5670
MAN.MON - UNM.LWL == 0	0.1241189	0.0582258	2.1317	0.1267
UNM.MON - UNM.LWL == 0	0.0819801	0.0578979	1.4159	0.4600
UNM.MON - MAN.MON == 0	-0.0421388	0.0355365	-1.1858	0.6093

**Anova test for management**

	numDF	denDF	F-value	p-value
(Intercept)	1	222	227.767523	<.0001
Management	1	222	0.979712	0.3233



## **Annex 9 - Correlation Tables**

Correlation tables appear as follows:

Table 1: Correlation test at 10 meters

Table 2: Correlation test at 20 meters

Table 3: Correlation test at 40 meters

For more information on the scripts used, please refer to Annex 7.

**Table 1: Correlation test at 10 meters**

Index	Sd	CV	Skewness	Kurtosis	Ba	SDI	Shannon	Simpson	BP	Shann E	Simp E	Gini	Lorimer	CE	HS	Dbh Diff	Dbh dom	Mdi	L - 10m
<b>CV</b>	0.86																		
<b>Skewness</b>	0.08	0.35																	
<b>Kurtosis</b>	0.08	0.31	0.89																
<b>Ba</b>	0.15	0.22	0.13	0.11															
<b>SDI</b>	0.21	0.35	0.26	0.21	0.97														
<b>Shannon</b>	-0.03	-0.22	-0.06	-0.12	0.23	0.13													
<b>Simpson</b>	-0.18	-0.34	-0.23	-0.29	0.00	-0.10	0.61												
<b>BP</b>	0.11	0.31	0.25	0.26	-0.02	0.09	-0.86	-0.94											
<b>Shann E</b>	-0.15	-0.43	-0.59	-0.56	-0.25	-0.38	0.55	0.72	-0.79										
<b>Simps E</b>	-0.07	-0.28	-0.59	-0.49	-0.33	-0.43	0.11	0.25	-0.48	0.90									
<b>Gini</b>	-0.10	-0.18	0.28	0.06	-0.11	-0.10	0.60	0.54	-0.42	0.11	-0.20								
<b>Lorimer</b>	0.28	0.52	0.36	0.36	0.41	0.54	-0.11	-0.09	0.15	-0.56	-0.39	0.00							
<b>CE</b>	0.08	-0.01	-0.01	0.02	0.05	0.03	0.11	0.11	-0.10	0.04	0.02	0.04	0.00						
<b>HS</b>	0.00	-0.18	-0.31	-0.23	-0.35	-0.39	-0.03	0.06	-0.17	0.35	0.41	-0.08	-0.32	-0.13					
<b>Dbh diff</b>	0.16	0.21	0.17	0.16	-0.16	-0.09	-0.08	-0.09	0.07	-0.10	-0.07	0.28	0.17	-0.03	0.13				
<b>Dbh dom</b>	-0.19	-0.56	-0.67	-0.49	-0.14	-0.33	0.39	0.45	-0.47	0.62	0.52	-0.16	-0.67	0.06	0.44	-0.19			
<b>Mdi</b>	0.05	-0.01	-0.10	-0.08	-0.02	-0.03	-0.04	-0.03	0.01	0.06	0.09	-0.04	-0.05	0.14	0.10	0.14	0.07		
<b>L -10m</b>	0.04	-0.01	-0.01	0.04	-0.02	-0.05	0.01	0.02	-0.02	0.00	0.01	-0.01	0.03	-0.11	-0.10	0.15	0.02	0.07	
<b>L - 5m</b>	0.00	0.04	0.18	0.04	-0.01	0.04	-0.06	-0.07	0.06	-0.06	-0.05	-0.10	0.14		-0.28	-0.05	0.05	-0.18	0.23

**Table 2: Correlation test at 20 meters**

<b>Index</b>	<b>Sd</b>	<b>CV</b>	<b>Skewness</b>	<b>Kurtosis</b>	<b>Ba</b>	<b>SDI</b>	<b>Shannon</b>	<b>Simpson</b>	<b>BP</b>	<b>Shann E</b>	<b>Simp E</b>	<b>Gini</b>	<b>Lorimer</b>	<b>CE</b>	<b>HS</b>	<b>DDiff</b>	<b>DDom</b>
<b>CV</b>	0.78																
<b>Skewness</b>	0.04	0.32															
<b>Kurtosis</b>	-0.05	0.13	0.65														
<b>Ba</b>	0.13	0.06	0.01	0.05													
<b>SDI</b>	0.15	0.23	0.23	0.14	0.95												
<b>Shannon</b>	0.13	-0.23	-0.12	-0.16	0.37	0.27											
<b>Simpson</b>	-0.08	-0.38	-0.29	-0.40	0.10	-0.02	0.58										
<b>BP</b>	0.00	0.35	0.36	0.40	-0.18	-0.03	-0.87	-0.94									
<b>Shann E</b>	0.02	-0.32	-0.60	-0.62	-0.04	-0.22	0.59	0.76	-0.81								
<b>Simps E</b>	0.07	-0.12	-0.58	-0.49	-0.15	-0.30	0.14	0.25	-0.46	0.89							
<b>Gini</b>	0.08	0.01	0.43	-0.04	0.03	0.15	0.53	0.45	-0.33	-0.02	-0.31						
<b>Lorimer</b>	0.15	0.61	0.42	0.29	0.14	0.40	-0.47	-0.51	0.49	-0.53	-0.31	-0.04					
<b>CE</b>	-0.04	-0.40	-0.51	-0.26	-0.08	-0.28	0.36	0.41	-0.42	0.44	0.33	-0.20	-0.50				
<b>HS</b>	-0.03	-0.15	-0.19	-0.09	-0.34	-0.43	-0.18	-0.15	0.10	0.24	0.32	-0.22	-0.32	0.21			
<b>DDiff</b>	0.24	0.50	0.53	0.18	-0.14	0.07	-0.28	-0.34	0.34	-0.35	-0.22	0.40	0.51	-0.50	-0.09		
<b>DDom</b>	0.00	-0.46	-0.68	-0.29	0.09	-0.20	0.38	0.36	-0.41	0.54	0.42	-0.28	-0.64	0.61	0.20	-0.51	
<b>Mdi</b>	-0.08	-0.32	-0.37	-0.15	-0.10	-0.26	0.16	0.14	-0.21	0.32	0.30	-0.25	-0.35	0.45	-0.08	-0.34	0.46

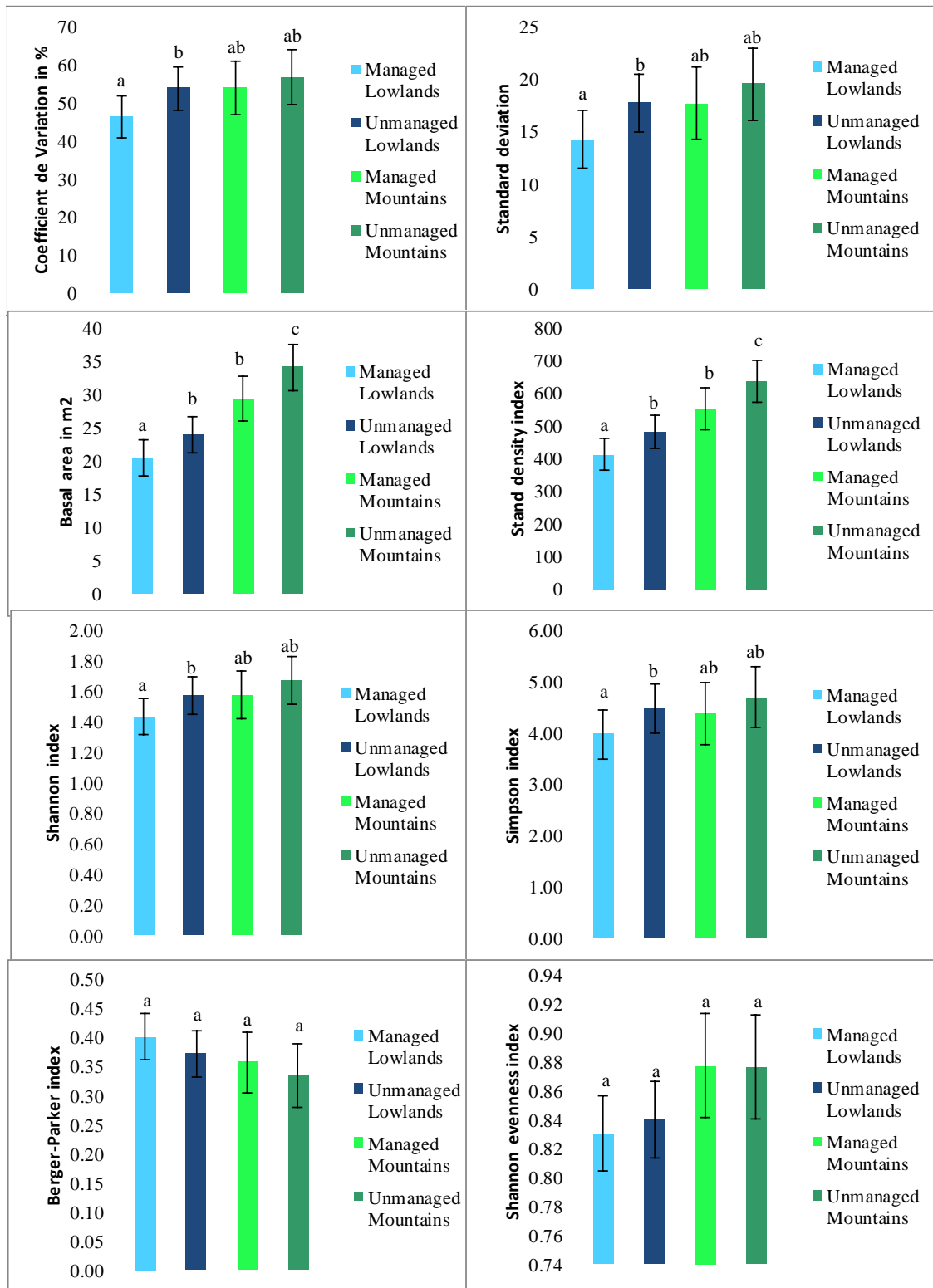
Table 3: Correlation test at 40 meters

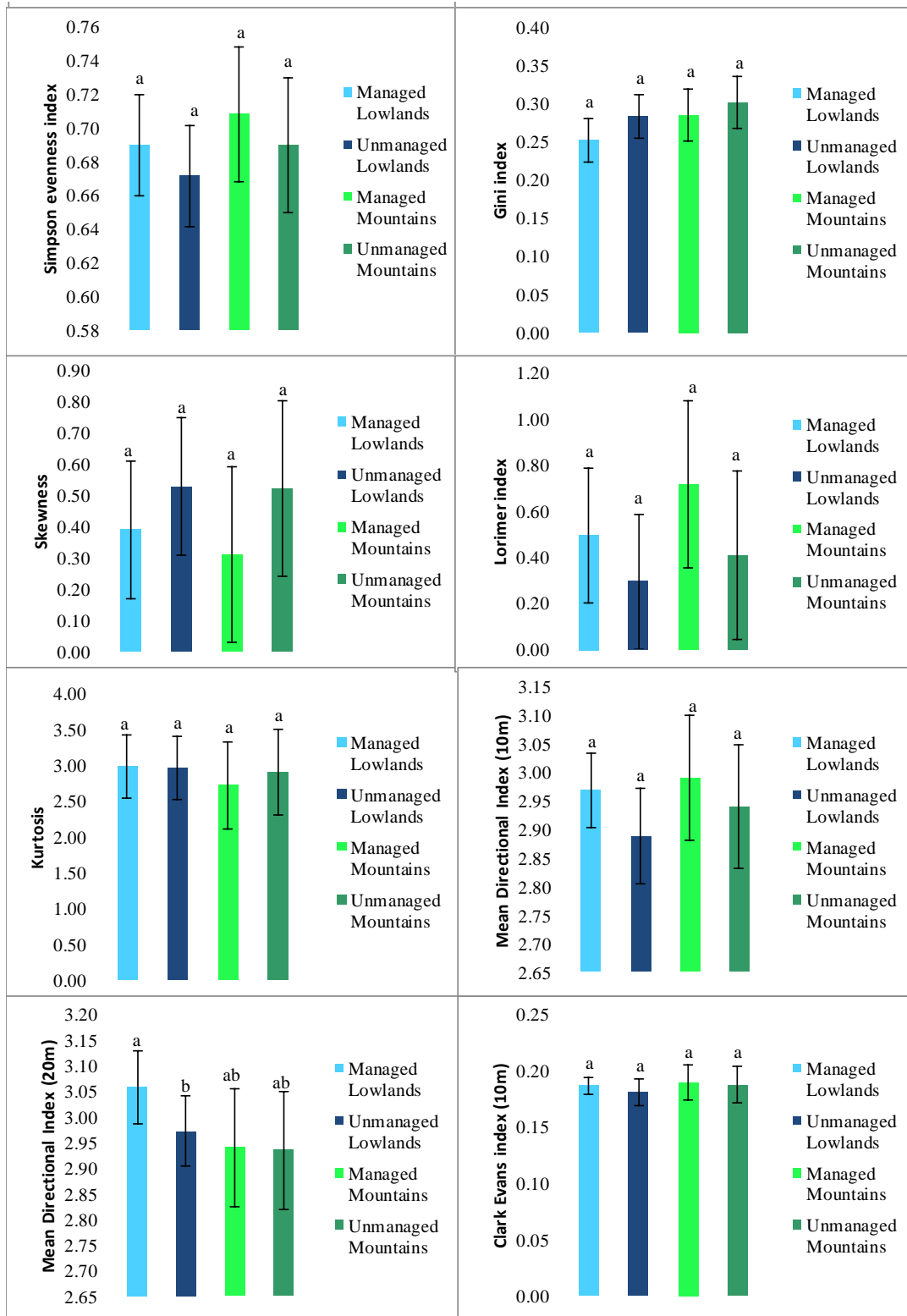
Index	Sd	CV	Skewness	Kurtosis	Ba	SDI	Shannon	Simpson	BP	Shan E	Simp E	Gini	Lorimer	CE	HS	DDiff	DDom
<b>CV</b>	0.75																
<b>Skewness</b>	0.09	0.36															
<b>Kurtosis</b>	-0.05	0.13	0.59														
<b>Ba</b>	0.15	-0.03	0.02	0.08													
<b>SDI</b>	0.19	0.18	0.26	0.14	0.93												
<b>Shannon</b>	0.16	-0.29	-0.17	-0.18	0.48	0.35											
<b>Simpson</b>	0.01	-0.35	-0.27	-0.31	0.29	0.16	0.74										
<b>BP</b>	-0.03	0.36	0.34	0.33	-0.33	-0.17	-0.89	-0.95									
<b>Shann E</b>	-0.04	-0.36	-0.53	-0.59	0.03	-0.18	0.59	0.75	-0.79								
<b>Simps E</b>	-0.05	-0.14	-0.46	-0.43	-0.20	-0.35	0.03	0.10	-0.31	0.85							
<b>Gini</b>	0.14	0.03	0.40	-0.11	0.17	0.32	0.53	0.47	-0.36	0.00	0.24						
<b>Lorimer</b>	0.16	0.63	0.41	0.27	0.06	0.34	-0.45	-0.50	0.49	-0.53	-0.06	0.38					
<b>CE</b>	0.11	-0.37	-0.48	-0.21	0.04	-0.18	0.56	0.52	-0.49	0.36	0.01	-0.42	-0.50				
<b>HS</b>	-0.14	-0.11	-0.08	-0.02	-0.35	-0.41	-0.36	-0.34	0.25	0.19	-0.10	-0.17	-0.27	-0.26			
<b>DDiff</b>	0.27	0.55	0.56	0.16	-0.14	0.12	-0.32	-0.36	0.37	-0.35	0.12	0.67	0.50	-0.49	0.08		
<b>DDdom</b>	0.03	-0.48	-0.64	-0.18	0.25	-0.10	0.54	0.54	-0.54	0.50	0.04	-0.58	-0.63	0.74	-0.02	-0.61	
<b>Mdi</b>	0.03	-0.34	-0.41	-0.12	0.01	-0.21	0.39	0.36	-0.38	0.33	-0.01	-0.41	-0.41	0.72	-0.19	-0.48	0.60

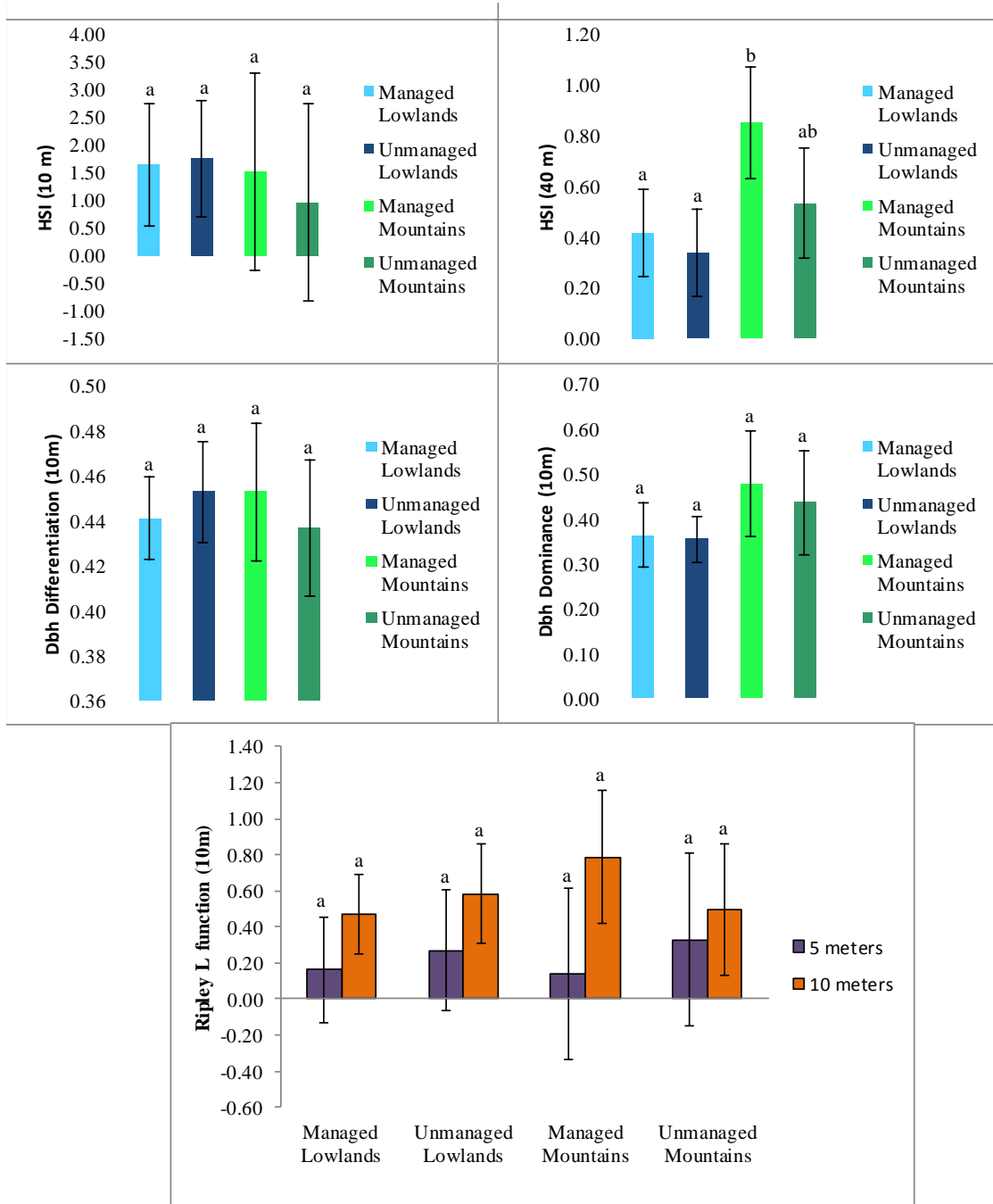


### Annex 10 - Graphs of selected indices

Graphs of selected structural indices with confidence interval and letter-based representation of significant differences characterizing the managed and unmanaged lowland and mountain sites\*







\*The four modalities (Managed Lowlands, Unmanaged Lowlands, Managed Mountains, Unmanaged Mountains) are represented by a bar each for each index graph along with their confidence interval. The letters represent any significant difference between one modality and the other modalities. Modalities sharing a letter in the group label are not significantly different at the  $p(H_0) < 0.05$  level (see Section 2.5 and Section 3 for more details on this type of letter-based representation).