# Species diversity and stand structure as drivers of canopy complexity in southern African woodlands

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1 Abstract

Atmospheric CO<sub>2</sub> enrichment and human-induced climate change are expected to drive woody encroachment and an increase in tree cover across African savannas, with consequences for ecosystem function, particularly related to carbon dynamics. The patch dynamics of savanna-woodland mosaics are complex however, as woody growth is mediated by seasonal fire that is itself driven by woody canopy structure. It is unclear how variation in existing tree species composition and stand structure in this ecosystem affects canopy structure, and how this might determine vegetation dynamics. Here, I conducted the first study of canopy structure using terrestrial LiDAR in southern African savannas, at sites in Angola and Tanzania, to explore relationships between tree species diversity, species composition, stand structure, and canopy structure. I found that WHAT

# 1 Introduction

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Atmospheric CO<sub>2</sub> enrichment, coupled with climate change and changing disturbance regimes, 13 is expected to drive woody encroachment, i.e. proliferation of trees in previously non-wooded 14 areas, and woody thickening, i.e. increased growth of trees in currently wooded areas, across the 15 savanna biome over the coming century (Criado et al., 2020; Stevens et al., 2016; Mitchard & 16 Flintrop, 2013). As atmospheric CO<sub>2</sub> concentrations increase, C<sub>3</sub> trees are expected to gain a 17 competitive edge over C<sub>4</sub> grasses due to differences in photosynthetic pathway (Buitenwerf et al., 2012), with cascading effects on canopy cover, grass growth, and therefore disturbance regime 19 (Bond & Midgley, 2012). If realised, woody encroachment and thickening will have significant 20 effects on the global carbon cycle, as more CO<sub>2</sub> is stored as woody biomass, as well as myriad 21 other effects on ecosystem structure (Donohue et al., 2013). Indeed, tropical savannas have 22 been identified as the fastest increasing component of the terrestrial carbon sink (Sitch et al., 23 2015). Previous studies however, have reported wide variation in rates of woody encroachment 24 and thickening (Mitchard & Flintrop, 2013), particularly in disturbance-prone savannas such as 25 miombo woodlands in southern Africa (Lewis et al., 2009), and it is unclear how the fertilisation 26 effect of atmospheric CO<sub>2</sub> enrichment will interact ecosystem properties to alter vegetation 27 (Körner, 2017; Reich et al., 2014). 28 Savanna vegetation is defined by the coexistence of trees and grasses (Scholes & Archer, 1997). 29 In the tropical mesic savannas of southern Africa, disturbance by fire and herbivory are the main 30 limitations on tree cover, preventing the competitive exclusion of shade-sensitive C<sub>4</sub> grasses 31 where climatic conditions would otherwise allow for closed canopy forest (Sankaran et al., 2005). C<sub>4</sub> grasses also provide the main fuel source for seasonal fires in these savannas (Frost, 1996), 33 producing a positive feedback where an increase in tree cover reduces grass fuel load, reducing 34 fire frequency and intensity, increasing tree cover, and so on (Staver & Koerner, 2015). As such, 35 even small perturbations in tree cover can lead to large changes in vegetation structure if critical 36 thresholds of tree cover are crossed (Hirota et al., 2011). Previous research has sought to identify 37 environmental factors which affect tree cover and its responses to atmospheric CO<sub>2</sub> enrichment, but few have considered the functional role of the existing tree community and its effect on ecosystem processes.

Canopy structure describes the spatial distribution and density of tree canopy foliage (Lowman & 41 Rinker, 2004). Canopy structural complexity, i.e. the spatial heterogeneity of foliage distribution 42 within the canopy, has been linked to increased net ecosystem productivity (Hardiman et al., 2011; 43 Chen et al., 2012; Law et al., 2001; Baldocchi & Wilson, 2001; Morin, 2015), increased resilience 44 of productivity (Pretzsch, 2014), reduced understorey light penetration (Scheuermann et al., 45 2018; Fotis et al., 2018), and greater moderation of understorey micro-climate (Wright et al., 2017). Furthermore, in temperate and boreal forests, functional differences among coexisting 47 tree species in their vertical and horizontal canopy occupation provide a link between species 48 diversity, canopy structural complexity and canopy density, with canopy structure constituting 49 a mechanism for observed positive biodiversity-ecosystem function effects in wooded ecosystems 50 (Pretzsch, 2014; Barry et al., 2019). In tropical savannas, tree species diversity might therefore 51 influence ecosystem-level woody thickening in response to elevated atmospheric CO<sub>2</sub>, where 52 diverse tree communities are less limited by competition due to niche separation, and can more 53 effectively increase foliage density and reduce understorey light penetration, excluding grass and 54 thus reducing disturbance. 55

As well as the species diversity of trees, the spatial distribution and relative size of trees, i.e. 56 stand structure, is also expected to affect canopy structural complexity (Stark et al., 2015). 57 Heterogeneity in tree size, whether a result of species diversity, disturbance history or some 58 other factor, is expected to increase canopy complexity and canopy density as individuals of 59 different sizes occupy different parts of the vertical canopy space (Panzou et al., 2020), and 60 may differ in light requirements (Charles-Dominique et al., 2018). Additionally, clustering of individuals in space is expected to increase canopy structural heterogeneity across the wider 62 savanna landscape, but ultimately decrease total foliage density due to an increase in competitive 63 interactions (Dohn et al., 2017). Clustering may occur as a result of disturbance history, or 64 as a result of strong facilitation effects among individuals in stressful environments (Ratcliffe 65 et al., 2017). More diverse communities may allow more dense clustering, as differences in canopy occupancy among species can reduce competition, meaning that diversity may reduce 67 the negative effect of disturbance on tree cover (). 68

Functional differences among floristic types of savanna may also drive variation in canopy structure, irrespective of species diversity. Some savanna trees form denser canopies than others, 70 as a result of variation in leaf size and branch architecture. Previous studies have compared 71 the branch architecture of ex-Acacia (e.g. Senegalia and Vachellia spp.) and miombo (e.g. 72 Julberardia, Brachustegia, and Isoberlinia) archetypal tree species. While ex-Acacia species 73 tend to inhabit drier, heavily grazed areas, miombo species tend to inhabit dystrophic wetter 74 areas structured heavily by fire (Ribeiro et al., 2020). These studies have shown that ex-Acacia 75 species develop sparser canopies, cagey branch architecture, and wider spreading crowns, while 76 miombo species develop thicker, taller canopies, and can grow to large trees (Mugasha et al., 77 2013; Archibald & Bond, 2003; Privette et al., 2004). Under identical stem densities, miombo 78 woodland species may therefore exclude grass more effectively than ex-Acacia species given these 79 differences in growth form. 80

Canopy structure is multi-dimensional and has previously been explained using a plethora 81 of simple metrics that originated in forest and community ecology (Kershaw et al., 2017). 82 Assessments of canopy structure have most often modelled tree canopies as a series of ellipses 83 (2D), ellipsoids or cones (3D) based on field measurements with measuring tapes (Jucker et al., 2015), or used surrogate proxies for 3D canopy structure due to its inherent complexity (Seidel 85 et al., 2011). Measurements of this kind are time consuming and yet remain an over-simplification 86 of canopy structure. Alternatively, canopy cover is often measured using indirect optical methods 87 which partition sky from canopy material, i.e. with hemispherical photography or the commonly 88 used LAI-2000, providing a 2D representation of the canopy but lacking information on vertical canopy structure (Jonckheere et al., 2004). In recent years, particularly in temperate and boreal

forests, LiDAR (Light Detection And Ranging) has emerged as a suitable technology for rapidly and precisely assessing canopy structure in 3D, conserving information on 3D structure of the 92 calibre that is required to understand it's complexities (Muir et al., 2018; Calders et al., 2020). 93 In tropical savannas, very few studies have used terrestrial LiDAR for vegetation analyses, 94 and in southern Africa all existing studies have been located at the Skukuza Flux Tower in 95 Kruger National Park, South Africa (Muumbe et al., 2021). Pioneering work describing the ecology of southern African savannas placed large emphasis on canopy structural diversity as a 97 mediator of ecosystem function (Solbrig et al., 1996), but much of that understanding of savanna 98 vegetation structure was derived from traditional mensuration methods. Using terrestrial LiDAR 99 to measure canopy structure in southern African savannas therefore offers a unique chance 100 to validate accepted theory and describe differences in ecosystem structure among savanna 101 vegetation types in finer detail than previously possible. 102

In this study I applied terrestrial LiDAR techniques to woodland-savanna mosaics at two sites 103 in southern Africa, with the aim of increasing our understanding of how various metrics of tree 104 canopy structural complexity relate to tree neighbourhood diversity and stand structure. I aim 105 to develop our understanding of how biotic ecosystem properties in savannas might mediate 106 responses to atmospheric CO<sub>2</sub> enrichment and climate change. I hypothesise that neighbourhoods 107 with greater tree diversity and greater structural diversity allow greater canopy complexity 108 and foliage density. Thus, more diverse savannas might more effectively increase growth under 109 elevated atmospheric CO<sub>2</sub> and are more likely to experience woody thickening through their 110 greater occupation of environmental niche space. I also consider the functional differences among 111 tree communities and how they affect canopy closure and the ability to exclude grasses. 112

# 113 2 Materials and methods

# 114 2.1 Study sites

Field measurements were conducted at two sites, the first in Bicuar National Park, southwest 115 Angola (S15.1°, E14.8°), and the second in and around Mtarure Forest Reserve, southeast 116 Tanzania (S9.0°, E39.0°) (Figure 1). At each site, 1 ha (100x100 m) plots were located in areas of 117 savanna-woodland vegetation, across a gradient of stem density and a range of savanna floristic 118 archetypes. In Angola, 15 plots were sampled, while in Tanzania, seven were sampled following 119 the curtailment of fieldwork due to COVID-19 travel restrictions. Fieldwork was conducted 120 between February and April at both sites, during the peak growth period of each site in order to 121 capture the maximum foliage volume in the canopy. 122

#### 2.2 Field measurements

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Within each 1 ha plot I identified each woody stem >5 cm stem diameter to species, measured 124 stem diameter (Diameter at Breast Height - 1.3 m) and recorded stem location within the plot 125 using tape measures. Each 1 ha plot was further subdivided into nine 10 m diameter circular 126 subplots arranged in a regular grid, with a 15 m buffer from the plot edge and 35 m between 127 subplots. For each subplot, the distance and direction from the subplot centre of each stem 128 >5 cm diameter with canopy material inside the subplot was recorded. Within each subplot, 129 a variable number of scans were recorded using a Leica HDS6100 phase-shift Terrestrial Laser 130 Scanner (TLS). The number and position of scans within a subplot was determined by the 131 arrangement of canopy material in the subplot, to minimise shadows within the canopy of the subplot, and to maximise canopy penetration. The number of scans per subplot ranged between 133 one and five across both sites. Extended field methods and data analysis methods are described 134 in Chapter 6.

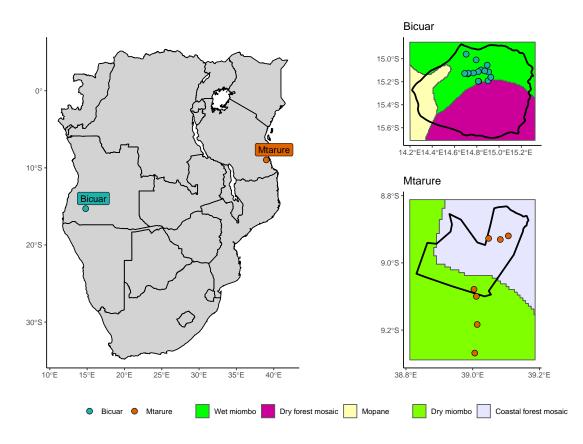


Figure 1: Location of study sites within southern Africa (left), and of 1 ha plots within each site (right). The black outlines in each site map denote the boundaries of protected areas which encompass the majority of study sites, Bicuar National Park in Angola (top), and Mtarure Forest Reserve in Tanzania (bottom). The background of each site map is a re-classified version of White's vegetation map (White, 1983). Note that all maps are on different scales.

# 136 2.3 Data analysis

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#### 2.3.1 TLS processing

Point clouds from scans in each subplot were registered and unified using Leica Cyclone (version 138 9.1), using five reflective cross targets visible to all scans. Point clouds were voxelised to 139 cubic voxels of different sizes depending on the application of the data. Subplot height profile 140 estimation and gap fraction was conducted using 5 cm<sup>3</sup> voxels, while whole plot canopy rugosity was estimated using 50 cm<sup>3</sup> voxels. Voxels were classified as 'filled' if they intersected one or 142 more points. Variation in voxel size reflects the spatial scale of each analysis, and is bounded 143 by the beam divergence of the scanner over longer distances (Cifuentes et al., 2014). Choosing 144 voxels that are too small can result in pock-marked representations of surfaces that are especially 145 problematic when calculating larger scale canopy structure metrics such as canopy top roughness, 146 while voxels that are too large can result in an over-estimation of plant volume when estimating 147 canopy foliage density at the subplot scale (Seidel et al., 2012; Cifuentes et al., 2014). The noise 148 reduction algorithm from Rusu et al. (2008) was used to discard points based on mean nearest 149 neighbour distances, with a mean number of neighbours of eight, and a standard deviation 150 threshold of 1.96. This effectively removed 'ghost points' produced by partial beam interceptions 151 and also removed many erroneous returns caused by airborne dust particles, which was common 152 at these study sites. Raw points clouds for each subplot had a mean of ~2.9e+08 points, ~4.5e+07 153 points after voxelisation to 5 cm<sup>3</sup>, and ~2.1e+07 points after noise reduction. Ground points 154 were classified using the Progressive Morphological Filter (PMF) from Zhang et al. (2003). Point 155 cloud height was reclassified height based on this revised ground layer by measuring the vertical 156 distance between the nearest ground point and each point. 157

Ray-tracing was used to estimate canopy closure in each subplot, i.e. the proportion of the sky hemisphere occluded by plant material at the subplot centre from multiple TLS scans. Hemispherical images were created using the POV-Ray ray-tracing software (Persistence of Vision Pty. Ltd., 2004). Filled voxels were represented as matt black cubes filling the voxel volume, with a white sky box and no light source. A 'camera' with a 180° fisheye lens was placed at the subplot centre within POV-Ray, at a height of 1.8 m pointing directly upwards. The images produced by POV-Ray were analysed using Hemiphot (ter Steege, 2018) to estimate canopy closure. Canopy closure estimates from the TLS were validated with hemispherical photographs taken at the same location and processed using the same method in Hemiphot, and compared using Pearson's correlation (r(195) = 0.89, p < 0.001). The Effective Number of Layers (ENL) measures subplot vertical canopy complexity and was calculated as the Shannon entropy of foliage density among 50 cm height bins within each subplot. The uniformity of foliage distribution was calculated by fitting a linear model to the cumulative foliage density profile, then extracting the squared residual deviations of the foliage density profile from this model. Total foliage density was calculated as the area under the curve of the foliage height profile.

Plot level canopy surface models were extracted using the 99th percentile of canopy height in 10 cm<sup>2</sup> columns, followed by pit-filling according to Khosravipour et al. (2014) at 50 cm<sup>2</sup> resolution. Whole plot canopy complexity was measured by two metrics. Canopy top roughness was measured as the standard deviation of canopy height across the plot. Canopy rugosity was measured according to Hardiman et al. (2011), as the standard deviation of vertical and horizontal foliage density within 0.5 m<sup>3</sup> cubic bins. Additionally, plot level canopy closure was calculated as the mean of canopy closure values from each subplot.

#### 181 2.3.2 Stand structure

For each subplot, an adapted version of the Iterative Hegyi index was used to estimate crowding, as an alternative to stem density which does not adequately capture crowding at small spatial scales when only a small number of trees are included in the sample (Hegyi, 1974). The coefficient of variation of stem diameter was calculated as a measure of the heterogeneity of tree size in the neighbourhood.

At the plot level, the regularity of species spatial distribution was estimated using the spatial mingling index (von Gadow & Hui, 2002), which scores each tree based on whether it shares species identity with its nearest neighbours. The spatial clustering of trees was also estimated using the winkelmass (von Gadow & Hui, 2002), which scores each tree based on the angles between nearest neighbours. Finally, plot level tree density was calculated to estimate crowding at the plot scale. See Chapter 6 for more information on the behaviour of the spatial mingling index and winkelmass.

#### 194 2.3.3 Statistical analysis

Non-metric Multi-dimensional Scaling (NMDS) was used to describe variation in species composition among plots, using genus-level basal area weighted abundance in each plot. Stems that could not be identified to genus were excluded from this analysis, which accounted for 0.2% of the total basal area recorded. Four distinct vegetation types were identified, two from each site (Table 1).

Linear mixed effects models tested the effects of tree species diversity and stand structural 200 diversity on subplot canopy complexity metrics. Mixed models used a nested random intercept 201 structure to account for the sampling design of subplots within plots and plots within vegetation 202 types. Separate models were fitted for each canopy complexity metric, resulting in four models 203 at the subplot level. Effect sizes among fixed effects in maximal models were compared for 204 each canopy complexity metric, using the 95% confidence interval of the effect size to ascertain 205 whether a fixed effect was significant by whether the confidence interval overlapped zero (). AIC 206 values and Akaike weights of models with different combinations of fixed effects were compared 207 to determine which combination of diversity and structural metrics best explained variation in 208 each canopy complexity metric. 209

Path analysis was used to test whether tree species diversity may influence canopy complexity indirectly through its effect on stand structure, using the piecewiseSEM R package (Lefcheck, 2016). The path analysis investigated the direct effect of plot species richness on mean plot canopy closure, as well as the indirect effect of richness on canopy closure via the coefficient of variation of basal area, with random intercept terms for each vegetation type. The ex-Acacia vegetation type was represented by only two plots and could not be included in this model due to lack of replication.

Statistical analysis of the determinants of plot level canopy complexity metrics were conducted using linear models. Again, these models excluded the ex-Acacia vegetation type due to lack of replication. As with the subplot linear mixed models, predictor variable effect sizes were used to assess predictor variable significance, and comparison of candidate models using AIC, Akaike weights, and model R

textsuperscript2 values was used to determine which combination of predictors best explained each canopy complexity metric.

Table 1: Description of the vegetation type clusters, identified using the Ward algorithm based on basal area weighted genus abundance. AGB = Above-Ground woody Biomass. Species richness, stem density and AGB are reported as the median among plots, with the interquartile range in parentheses.

Site	Cluster	N sites	Richness	Stem density (stems ha <sup>-1</sup> )	AGB (t ha <sup>-1</sup> )
Bicuar	1	12	17(2)	642(194)	41( 8.4)
Mtarure	2	5	23(4)	411(137)	72(11.9)
Bicuar	3	3	6(1)	196(55)	77(7.3)
Mtarure	4	2	12(2)	288(73)	9(0.2)

Table 2: Floristic description of the vegetation type clusters. Dominant species are the most abundant individuals across all plots per cluster. Indicator species are derived from Dufrêne-Legendre indicator species analysis with the three highest indicator values.

Cluster	Dominant species	Indicator species	Indicator value
1	Julbernardia paniculata	Strychnos spinosa	0.83
1	Burkea africana	Combretum collinum	0.74
1	Combretum collinum	Julbernardia paniculata	0.70
2	Diplorhynchus condylocarpon	Pteleopsis myrtifolia	1.00
2	Pseudolachnostylis maprouneifolia	Diplorhynchus condylocarpon	0.89
2	Gymnosporia senegalensis	Pseudolachnostylis maprouneifolia	0.81
3	Baikiaea plurijuga	Baikiaea plurijuga	0.94
3	Baphia massaiensis	Baphia massaiensis	0.83
3	Philenoptera nelsii	Philenoptera nelsii	0.45
4	Combretum apiculatum	Vachellia nilotica	0.99
4	Burkea africana	Combretum apiculatum	0.70
4	Bauhinia petersiana	Senegalia polyacantha	0.62

# 224 3 Results

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# 3.1 Description of vegetation types

Indicator species analysis shows that the four identified vegetation types constitute common 226 southern African savanna floristic archetypes (Table 2). Cluster 1, found in Bicuar National 227 Park contains typical miombo species from the Detarioideae subfamily, such as Julbernardia 228 paniculata. This vegetation type is the most common in our study, with 12 plots. Cluster 1 has 229 the highest stem density, but lower AGB than Clusters 2 or 3, which contain larger individuals 230 with disproportionately higher biomass. Cluster 2, found in Mtarure, is dominated by Pteleopsis 231 myrtifolia, a common miombo species from the Combretaceae family. Indeed, Cluster 2 also 232 contained other common miombo species shared with plots in Cluster 1, such as Julbernardia 233 globiflora and Pseudolachnostylis maprouneifolia, but these clusters remain distinct due to genera 234 endemic to different parts of the miombo ecoregion. Cluster 3 represents Baikiaea woodland, 235 found on Kalahari sands in southern Angola. It is species poor and dominated by Baikiaea 236 plurijuqa which forms large spreading canopy trees with high AGB. Other shrubby species that 237 coppice readily in response to disturbance by fire such as Baphia massaiensis are also common. Cluster 4, found in Mtarure is a type of ex-Acacia woodland, dominated by Vachellia and 239 Senegalia spp. This vegetation type was not well represented in our study, with only two plots, 240 precluding its use in some multi-level statistical analyses due to lack of replication. Cluster 4 241 had far lower AGB than the other clusters (Table 1). 242

Differences in canopy structure among the four vegetation types are evident through observation of canopy surface models for typical plots within each vegetation type (Figure 4). Cluster 1 shows many overlapping crowns forming a nearly contiguous canopy surface. Though most trees in Cluster 1 have smaller crowns than those in Cluster 2, which also forms a nearly contiguous canopy. The largest trees in Cluster 2 grow taller and have a wider spreading canopy than those in other vegetation types. Cluster 3 shows two distinct size classes of tree, the large *Baikiaea plurijuga* forming clear isolated canopies, and much smaller scattered shrubby individuals in the understorey. Cluster 4 shows many small shrubby individuals with irregular canopy shapes, but a greater total crown area coverage than Cluster 3.

#### 3.2 Bivariate relationships

Bivariate plots show that subplot species diversity, measured by species richness of the tree 253 neighbourhood around each 10 m diameter subplot, appears to have weak positive effects 254 on subplot canopy layer diversity ( $\beta=1\pm0.22$ , F(2,184)=24, p<0.001, R<sup>2</sup>=0.1), canopy closure 255  $(\beta=0.05\pm0.013, F(2,185)=17, p<0.001, R^2=0.08)$  and foliage density  $(\beta=3055\pm669, F(2,184)=21.001)$ 256 p<0.001, R<sup>2</sup>=0.1) (Figure 3). The Hegyi crowding index had strong positive effects on all canopy 257 complexity metrics, as expected. The effect of Hegyi crowding on subplot canopy complexity 258 metrics was similar across all vegetation types. Structural diversity, measured as the coefficient of variation of subplot basal area had significant very weak positive effects on total 260 canopy foliage ( $\beta$ =80±23, F(2,167)=12, p<0.001, R<sup>2</sup>=0.07), but negligible effects on layer di-261 versity ( $\beta = 0.03 \pm 0.0076$ , F(2.167)=18, p<0.001, R<sup>2</sup>=0.1), and canopy closure ( $\beta = 0.001 \pm 0.00044$ , 262 F(2,168)=6.5, p<0.05,  $R^2=0.04$ ). 263

At the plot level, effects of species diversity and stand structure on canopy structure were similarly weak (Figure 3). Spatial clustering of stems, measured by winkelmass, on canopy cover, was clearly negative ( $\beta$ =-4±1.6, F(2,20)=6, p<0.05, R<sup>2</sup>=0.2). Additionally, there was a non-significant negative effect of coefficient of variation of basal area on whole canopy rugosity ( $\beta$ =-1±0.53, F(2,16)=3.7, p=0.07, R<sup>2</sup>=0.2). Species richness appeared to have strong positive relationships with canopy closure and canopy height, though this was driven mainly by one

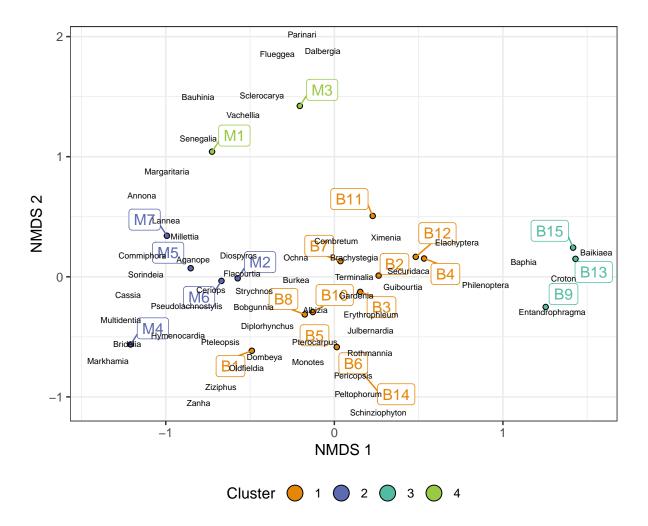


Figure 2: The first two axes of a Non-metric Multi-Dimensional Scaling (NMDS) analysis of tree genus diversity in each plot. Genus scores are labelled as black text, while plot scores are labelled as coloured points. Plots can be split into four principal floristically defined vegetation types: 1) B1-B8, B10-B12, B14, dominated by core miombo species such as *Julbernardia* spp., *Brachystegia* spp.; 2) M2, M5, M6, and M7, also dominated by core miombo genera with some genera not found in Angola to such a great extent such as *Commiphora* and *Sorindeia*; 3) B9, B13 and B15, dominated by *Baikiaea plurijuga*; and 4) M1, M3, and M4, dominated by *Senegalia* spp. and *Vachellia* spp..

particularly speciose plot in Cluster 2, with over 40 species. Cluster 4 represented an outlier in
 plot level bivariate relationships, with very low canopy closure, and low canopy height, as well
 as low species richness and low variation in stem size.

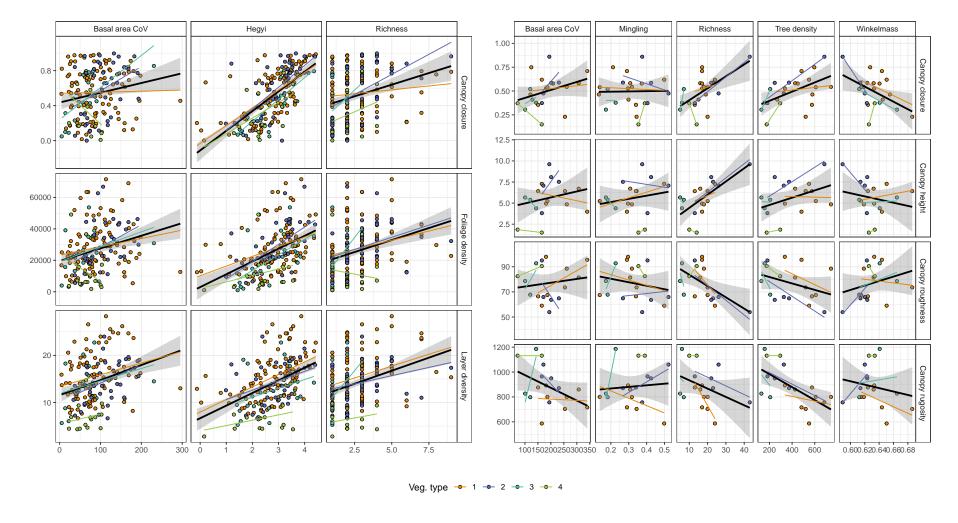


Figure 3: Bivariate relationships between diversity/stand structure metrics (x axis) and canopy structure metrics (y axis), at both the subplot level (left) and the plot level (right). Points and linear model lines of best fit are coloured by vegetation type. Black lines of best fit are linear models including all plots, with a 95% confidence interval. See Table 5 for a comparison of linear model fits by vegetation type.

Table 3: Explanatory variables included in the best model for each canopy structure variable.  $\Delta AIC$  shows the difference in model AIC value compared to a null model which included only the hegyi crowding index and the random effects of vegetation type and plot.  $R^2_c$  is the  $R^2$  of the best model, while  $R^2_m$  is the  $R^2$  of the model fixed effects only.

Response	Hegyi	Richness	CoV basal area	$\Delta { m AIC}$	$R^2_c$	$R^2_{m}$
Layer diversity	$\checkmark$		$\checkmark$	37.4	0.50	0.17
Foliage density	$\checkmark$		$\checkmark$	77.7	0.28	0.19
Foliage uniformity	$\checkmark$			54.4	0.08	0.04
Canopy closure	$\checkmark$			104.0	0.63	0.49

# 3.3 Subplot mixed models

Linear mixed effects models showed that species richness of the subplot neighbourhood had negligible effects on canopy structure (Figure 5). As seen in Figure 3, the Hegyi crowding index had strong positive effects on all measured canopy complexity metrics. Heterogeneity of stem basal area had a significant positive effect on layer diversity, but there was wide variation in vegetation type marginal effects for Clusters 3 and 4, due to low levels of replication. Cluster 3 had a significant positive effect of species richness on foliage distribution uniformity, while none of the other vegetation clusters did.

Model selection showed that none of the best models for subplot canopy complexity metrics included species richness (Table 3). Basal area coefficient of variation was included in the best models for layer diversity and foliage density, with the fixed effects for these models explaining 17% and 19% of the variation in these metrics, respectively. The random effects of vegetation type and plot identity described most of the variation in layer diversity and total canopy foliage density. Uniformity of foliage distribution was poorly described by all candidate models, with the best model only describing 8% of the variation in this metric. All models were better than random effects only models according to AIC values.

#### 289 3.4 Whole-plot linear models

While species diversity had varying effects on different plot level canopy structural metrics, the confidence intervals on these effect sizes were wide (Figure 6). Species richness had a significant positive effect on canopy height, a non-significant positive effect on canopy closure, but a negative effect on canopy surface roughness. Plot tree density had negligible effects on canopy complexity, in contrast to the effect of Hegyi crowding on subplot canopy complexity. Structural diversity, measured by the coefficient of variation of basal area had a positive effect on canopy roughness. Spatially explicit measures of structural and species diversity, measured by winkelmass and spatial mingling index respectively, had negligible effects on all canopy complexity metrics. One exception was the effect of winkelmass, i.e. the spatial clustering of stems, on canopy cover, which was negative.

Despite the weak fixed effect sizes of species richness at the plot level, model selection showed that canopy height, canopy roughness, and canopy closure were better explained by models which included species richness (Table 4). Though the model for canopy roughness was only marginally better than a null model, and had a non-significant p-value. Canopy rugosity was poorly predicted by all candidate models.

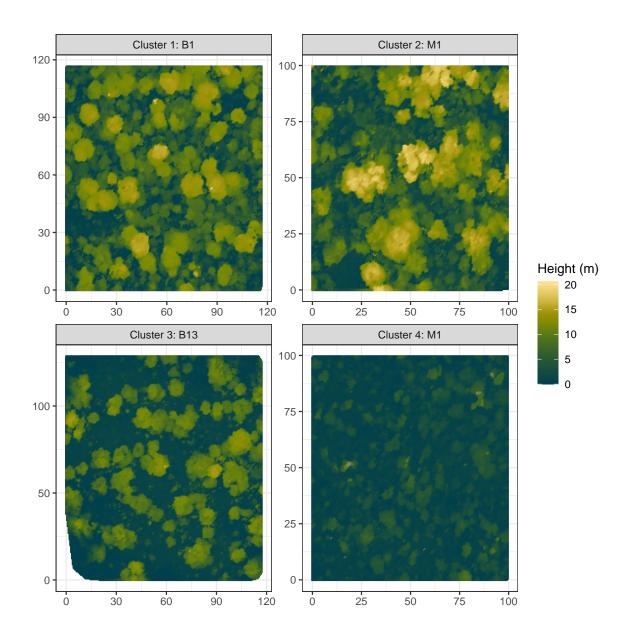


Figure 4: Representative canopy surface models for each vegetation type identified in the Non-metric Multi-dimensional Scaling (NMDS) analysis. Plot titles show the plot name and the vegetation type.

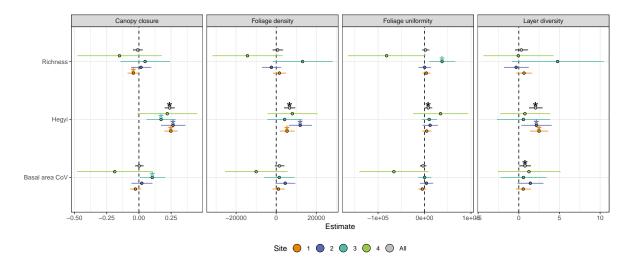


Figure 5: Standardized fixed effect slopes for each model of a canopy structure metric. Slope estimates are  $\pm 1$  standard error. Slope estimates where the interval (standard error) does not overlap zero are considered to be significant effects. Points are coloured according to site.

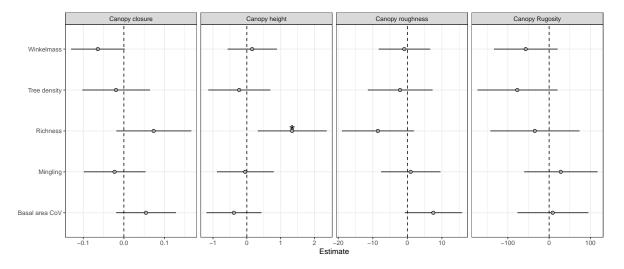


Figure 6: Standardized fixed effect slopes for whole-plot canopy rugosity. Slope estimates are  $\pm 1$  standard error. Slope estimates where the interval (standard error) does not overlap zero are considered to be significant effects.

Table 4: Explanatory variables included in the best linear model for each plot-level canopy complexity metric.  $\Delta$ AIC shows the difference in model AIC value compared to a null model.

Response	Rich.	Tree dens.	CoV BA	Μ	W	$\Delta { m AIC}$	$\mathbb{R}^2$	Prob.
Canopy closure	$\checkmark$				$\checkmark$	8.7	0.69	< 0.05
Canopy height	$\checkmark$					5.9	0.63	0.05
Canopy roughness	$\checkmark$		$\checkmark$			1.7	0.52	0.14
Canopy Rugosity		$\checkmark$				0.6	0.48	0.19

# 3.5 Comparing subplot and plot measures of canopy structure

Plot and subplot canopy structure metrics were highly correlated in many cases, with similar relationships among vegetation types (Figure 6). Most subplot and plot level canopy metrics covaried in a predictable manner. For example, as canopy height increases, so does canopy cover. Plot canopy height especially, tended to be strongly positively correlated with subplot canopy complexity metrics. Additionally, as canopy rugosity increased, many subplot canopy complexity and density metrics decreased. Subplot metrics varied greatly within plots, producing large uncertainty in plot level estimates of these metrics.

# 313 4 Discussion

This study investigated relationships between tree species diversity, stand structure, and several metrics of tree canopy complexity in southern African savannas. While species diversity appeared to generally have weak positive effects on canopy complexity at both the subplot and plot scales, variability in canopy structure among plots due to other factors made it difficult to conclusively infer a species diversity effect. The strongest determinant of canopy complexity was stem crowding, as measured by the Hegyi crowding index (subplot) and stem density (plot). Effects of vegetation type on canopy structure were strong, suggesting that species identity more than diversity per se may be a stronger predictor of canopy structure.

The positive relationships between species richness and subplot canopy complexity metrics observed in the subplot bivariate models were not seen in the linear mixed effects models. This is likely because the observed species richness effect was itself driven by stand structure. The Hegyi crowding index increases with stem density, i.e. decreased distance of individuals from the subplot centre. Species richness also increases with stem density, as a greater number of individuals is more likely to hold more species simply through sampling effects. Jucker et al. (2015) however, did find that increased species diversity led to greater canopy packing in European forests, with trees in mixed forests having generally larger crowns. Our result that species diversity did not have consistent effects on canopy complexity may be specific to the vegetation type studied here. Southern African open woodlands are much more heavily affected by disturbance from fire and herbivory than temperate forests, meaning the effects of inter-specific competition are weakened as a driver of stand and canopy structure ().

Canopy structure at the plot level was less well predicted by stand structure and species diversity than subplot level canopy structure. Results at the plot level suggest that woodland vegetation type and basal area has the greatest effect on canopy complexity. The two thorny savanna plots in Mtarure produced strong positive effects of basal area and diameter variation on canopy closure, canopy height, and canopy roughness, but when these plots are removed the remaining points do not produce strong relationships.

40 Disturbance

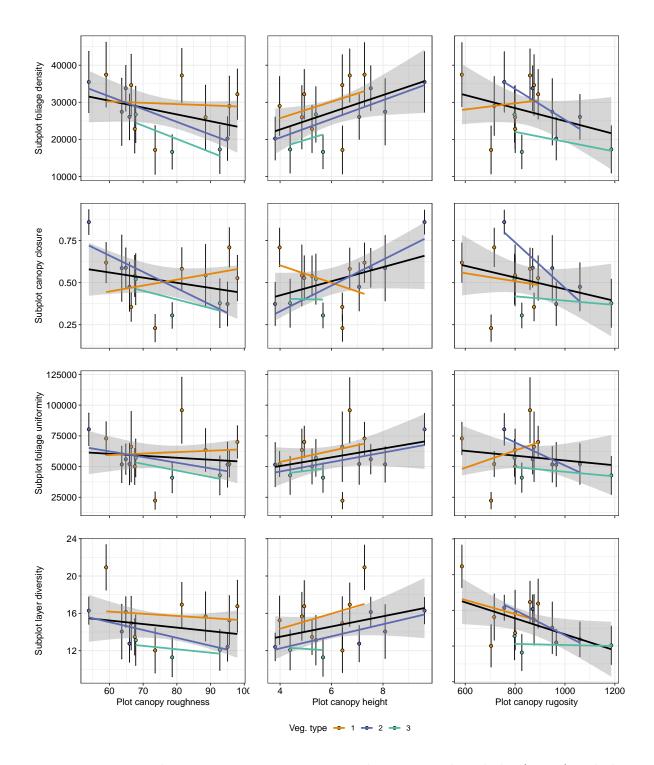


Figure 7: Bivariate plots comparing canopy structural metrics at the subplot (y axis) and plot level (x axis). Each point represents the mean values of a single plot. Points and linear model fits are coloured according to vegetation type. The black linear model combines all vegetation types. Error bars on points are the standard deviation of mean subplot metrics across the plot.

- Facilitation might be more important in these woodlands than in temperate woodlands. Large 341
- canopy trees may cause micro-climate amelioration for understorey saplings, protecting them 342
- from drying conditions caused by the sun and wind. Facilitation has been under-played in BEFR 343
- research (Wright et al., 2021). 344
- Scheuermann 2018 Canopy rugosity didn't vary regardless of the LAI and species diversity it 345
- just increased linearly throughout succession, for the first 100 years before becoming stable. 346
- A more heterogeneous vegetation arrangement allows for deeper light vegetation into the canopy
- and when paired with a higher LAI lead to greater light interception by the subcanopy, and 348
- thus the canopy as a whole. 349
- NPP may increase with increased canopy heterogeneity, because subcanopy plants are normally 350
- light limited and sensitive to small increases in available light such as those provided by deeper 351
- light penetration in a heterogenous canopy. 352
- Fotis2017 Hardiman et al. 2011, 2013a, found that increased rugosity in the canopy increased 353
- NPP in temperature forests. Fahey et al. 2015 in an old-growth forest. 354
- Canopy structure can affect canopy-level photosynthesis (Kira et al. 1969, Chen et al. 2012),
- light-use efficiency (Walcroft et al. 2005, Duursma and Makela 2007) and NEE (Baldochii and 356
- Wilson 2001, Law et al. 2001) through its influence on both total light interception and its 357
- variability within the canopy. 358
- While other studies have found links between light environment and canopy structure, in our 359
- sites maybe the canopy is too sparse for this to be an issue. 360
- Shirima2015 \* In Miombo woodlands, AGB higher under denser vegetation canopies \* Maybe
- the canopy provides amelioration of harsher environmental conditions in this system 362

#### 5 Conclusion 363

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Table 5: Summary statistics of bivariate linear models comparing canopy complexity metrics with diversity and stand structural metrics. Slope refers to the slope of the predictor term in the model,  $\pm$  1 standard error.  $R^2$  refers to the whole model. T is the t-value of the slope of the predictor term in the model, Asterisks indicate the p-value of these terms (\*\*\*<0.001, \*\*<0.01, \*<0.05).

Response	Predictor	Cluster	Slope	F	$\mathbb{R}^2$	T
Foliage density	Basal area CoV	1	53.2	$\pm 28.73.4(2,97)$	0.03	1.85-
Foliage density	Basal area CoV	2	143.4	$\pm 49.18.5(2,38)$	0.18	2.92**
Foliage density	Basal area CoV	3	94.7	$\pm 63.5$ <b>2</b> .2(2,14)	0.14	1.49-
Foliage density	Basal area CoV	4	-173.1	$\pm 143.485(2,12)$	0.11	-1.21-
Foliage density	Basal area CoV	All	80.4	$\pm 221$ <b>2</b> 65 $(2,167)$	0.07	3.53***
Foliage density	Hegyi	1	6170.5	±1516%.5%2,102)	0.13	3.93***
Foliage density	Hegyi	2	11,022.0	$\pm 2343200(2,40)$	0.36	4.69***
Foliage density	Hegyi	3	9972.6	$\pm 2370799(2,23)$	0.43	4.21***
Foliage density	Hegyi	4	4116.2	$\pm 4028188(2,13)$	0.07	1.02-
Foliage density	Hegyi	All	8163.7	$\pm 11506.76(2,184)$	0.22	7.12***
Foliage density	Richness	1	2337.8	±876746(2,102)	0.07	2.67**
Foliage density	Richness	2	3090.2	$\pm 1262610(2,40)$	0.13	2.45*
Foliage density	Richness	3	12,337.1	$\pm 3601127(2,23)$	0.34	3.43**
Foliage density	Richness	4	-1799.1	±39200428(2,13)	0.02	-0.46-
Foliage density	Richness	All	3054.8	$\pm 662018(2,184)$	0.10	4.57***
Canopy closure	Basal area CoV	1	0.0	$\pm 0.000.1(2,97)$	0.00	0.24-
Canopy closure	Basal area CoV	2	0.0	$\pm 0.007.3(2,39)$	0.16	2.70*
Canopy closure	Basal area CoV	3	0.0	$\pm 0.0$ <b>0</b> $4.3(2,14)$	0.50	3.78**
Canopy closure	Basal area CoV	4	-0.0	$\pm 0.002.3(2,12)$	0.16	-1.53-
Canopy closure	Basal area CoV	All	0.0	$\pm 0.0$ <b>6</b> .5(2,168)	0.04	2.55*
Canopy closure	Hegyi	1	0.2	±0. <b>72</b> .2(2,102)	0.41	8.44***
Canopy closure	Hegyi	2	0.2	$\pm 0.038.8(2,41)$	0.41	5.37***
Canopy closure	Hegyi	3	0.2	$\pm 0.032.4(2,23)$	0.69	7.24***
Canopy closure	Hegyi	4	0.2	$\pm 0.076.4(2,13)$	0.33	2.52*
Canopy closure	Hegyi	All	0.2	$\pm 0148.0(2,185)$	0.44	12.16***
Canopy closure	Richness	1	0.0	$\pm 0.0$ <b>2</b> .1(2,102)	0.01	1.06-
Canopy closure	Richness	2	0.1	$\pm 0.024.7(2,41)$	0.26	3.83***
Canopy closure	Richness	3	0.2	$\pm 0.083.9(2,23)$	0.14	1.97-
Canopy closure	Richness	4	0.1	$\pm 0.080.9(2,13)$	0.06	0.95-
Canopy closure	Richness	All	0.1	$\pm 0.06.9(2,185)$	0.08	4.11***
Layer diversity	Basal area CoV	1	0.0	$\pm 0.017.1(2,97)$	0.07	2.66**
Layer diversity	Basal area CoV	2	0.0	$\pm 0.018.0(2,38)$	0.17	2.83**
Layer diversity	Basal area CoV	3	0.0	$\pm 0.021.3(2,14)$	0.09	1.15-
Layer diversity	Basal area CoV	4	0.0	$\pm 0.030.5(2,12)$	0.04	0.67-
Layer diversity	Basal area CoV	All	0.0	$\pm 0.07.6(2,167)$	0.10	4.20***
Layer diversity	Hegyi	1	2.7	±0. <b>29</b> .1(2,102)	0.22	5.39***
Layer diversity	Hegyi	2	2.0	$\pm 0.757.1(2,40)$	0.15	2.66*
Layer diversity	Hegyi	3	1.9	$\pm 1.003.6(2,23)$	0.13	1.89-
Layer diversity	Hegyi	4	1.1	$\pm 0.851.8(2,13)$	0.12	1.33-
Layer diversity	Hegyi	All	2.7	$\pm 0.36.8(2,184)$	0.20	6.84***
Layer diversity	Richness	1	1.0	$\pm 0.28.5(2,102)$	0.11	3.54***

Layer diversity	Richness	2	0.7	$\pm 0.363.8(2,40)$	0.09	1.94-
Layer diversity	Richness	3	3.8	$\pm 1.288.8(2,23)$	0.28	2.97**
Layer diversity	Richness	4	0.6	$\pm 0.840.5(2,13)$	0.03	0.68-
Layer diversity	Richness	All	1.1	$\pm 0.22.3(2,184)$	0.12	4.93***
Canopy roughness	Basal area CoV	1	0.1	$\pm 0.07 \ 2.9(2,6)$	0.33	1.72-
Canopy roughness	Basal area CoV	2	-0.3	$\pm 0.29 \ 1.2(2,3)$	0.29	-1.10-
Canopy roughness	Basal area CoV	3	0.4	$\pm 0.47 \ 0.6(2,1)$	0.36	0.74-
Canopy roughness	Basal area CoV	4	0.1	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy roughness	Basal area CoV	All	0.0	$\pm 0.050.4(2,16)$	0.02	0.60-
Canopy roughness	Mingling	1	-42.4	$\pm 57.260.5(2,6)$	0.08	-0.74-
Canopy roughness	Mingling	2	16.0	$\pm 97.050.0(2,3)$	0.01	0.17-
Canopy roughness	Mingling	3	352.2	$\pm 248.1 \ 2.0(2,1)$	0.67	1.42-
Canopy roughness	Mingling	4	-225.9	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy roughness	Mingling	All	-28.0	$\pm 32.5 \center{0.7}(2,16)$	0.04	-0.86-
Canopy roughness	Richness	1	-1.8	$\pm 1.65 \ 1.1(2,6)$	0.16	-1.06-
Canopy roughness	Richness	$\frac{1}{2}$	-1.2	$\pm 0.46 \ 6.5(2,3)$	0.68	-2.55-
Canopy roughness	Richness	3	-5.4	$\pm 0.40^{\circ} 0.3(2,3)$ $\pm 11.280.2(2,1)$	0.19	-0.48-
Canopy roughness	Richness	$\frac{3}{4}$	2.0	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy roughness	Richness	All	-0.9	$\pm 0.327.8(2,16)$	0.33	-2.79*
Canopy roughness	Tree density	1	-0.0	$\pm 0.04 \ 0.9(2,6)$	0.13	-0.96-
Canopy roughness	Tree density	2	-0.1	$\pm 0.03 \ 3.6(2,3)$	0.54	-1.89-
Canopy roughness	Tree density	3	-0.2	$\pm 0.26 \ 0.5(2,1)$	0.31	-0.68-
Canopy roughness	Tree density	4	-0.1	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy roughness	Tree density	All	-0.0	$\pm 0.022.3(2,16)$	0.12	-1.51-
Canopy roughness	Winkelmass	1	-72.9	$\pm 255.7$ <b>0</b> .1(2,6)	0.01	-0.29-
Canopy roughness	Winkelmass	2	655.1	$\pm 496.49.7(2,3)$	0.37	1.32-
Canopy roughness	Winkelmass	3	227.5	$\pm 418.96.3(2,1)$	0.23	0.54 -
Canopy roughness	Winkelmass	4	-981.1	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy roughness	Winkelmass	All	177.4	$\pm 155.723(2,16)$	0.08	1.14-
Canopy height	Basal area CoV	1	-0.0	$\pm 0.01 \ 1.1(2,6)$	0.16	-1.07-
Canopy height	Basal area CoV	$\frac{1}{2}$	-0.0 0.0	$\pm 0.01  1.1(2,0)$ $\pm 0.04  1.2(2,3)$	0.10 $0.28$	1.08-
Canopy height	Basal area CoV	$\frac{2}{3}$	-0.0	$\pm 0.04  1.2(2,3)$ $\pm 0.0112.3(2,1)$	0.28 $0.92$	-3.51-
Canopy height	Basal area CoV	3 4	$-0.0 \\ -0.0$	$\pm 0.0112.3(2,1)$ $\pm NaNaN(2,0)$		-3.51- NA
10 0				( / /	1.00	
Canopy height	Basal area CoV	All	0.0	$\pm 0.010.9(2,16)$	0.06	0.97-
Canopy height	Mingling	1	6.8	$\pm 3.82 \ \ 3.2(2,6)$	0.34	1.78-
Canopy height	Mingling	2	-3.3	$\pm 13.280.1(2,3)$	0.02	-0.25-
Canopy height	Mingling	3	-23.1	$\pm 0.9$ <b>6</b> 19.2(2,1)	1.00	-24.88*
Canopy height	Mingling	4	9.8	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy height	Mingling	All	3.8	$\pm 4.830.6(2,16)$	0.04	0.79 -
Canopy height	Richness	1	0.1	$\pm 0.14 \ 0.4(2,6)$	0.07	0.67-
Canopy height	Richness	$\frac{1}{2}$	0.2	$\pm 0.06 \ 8.6(2,3)$	0.74	2.94-
Canopy height	Richness	3	-0.1	$\pm 0.66 \ 0.0(2,1)$	0.04	-0.21-
Canopy height	Richness	4	-0.1	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy height	Richness	All	0.2	$\pm 0.043.2(2,16)$	0.45	3.63**
Canopy height	Tree density	1	-0.0	$\pm 0.00 \ 0.0(2,6)$	0.00	-0.09-
Canopy height		• )	$\alpha \alpha$	エロ ロロ オフバソソ	0.61	9.16
	Tree density	2	0.0	$\pm 0.00 \ 4.7(2,3)$	0.61	2.16-
Canopy height Canopy height	Tree density Tree density Tree density	$\frac{2}{3}$	-0.0 $0.0$	$\pm 0.00^{\circ} 4.7(2,3)$ $\pm 0.02^{\circ} 0.0(2,1)$ $\pm \text{NaNNaN}(2,0)$	0.00 1.00	-0.06- NA

Canopy height	Tree density	All	0.0	$\pm 0.003.1(2,16)$	0.16	1.76-
Canopy height	Winkelmass	1	16.3	$\pm 19.190.7(2,6)$	0.11	0.85-
Canopy height	Winkelmass	2	-100.4	$\pm 63.422.5(2,3)$	0.46	-1.58-
Canopy height	Winkelmass	3	4.0	$\pm 25.310.0(2,1)$	0.02	0.16-
Canopy height	Winkelmass	4	42.7	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy height	Winkelmass	All	-18.8	$\pm 23.48.6(2,16)$	0.04	-0.80-
Canopy closure	Basal area CoV	1	0.0	$\pm 0.000.3(2,10)$	0.02	0.50-
Canopy closure	Basal area CoV	2	0.0	$\pm 0.00 \ 0.8(2,3)$	0.21	0.88-
Canopy closure	Basal area CoV	3	0.0	$\pm 0.00 \ 0.1(2,1)$	0.09	0.31-
Canopy closure	Basal area CoV	4	-0.0	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy closure	Basal area CoV	All	0.0	$\pm 0.002.4(2,20)$	0.11	1.56-
Canopy closure	Mingling	1	-0.1	$\pm 0.460.0(2,10)$	0.00	-0.20-
Canopy closure	Mingling	2	-0.6	$\pm 1.08 \ 0.4(2,3)$	0.11	-0.60-
Canopy closure	Mingling	3	-0.1	$\pm 3.78 \ 0.0(2,1)$	0.00	-0.02-
Canopy closure	Mingling	4	6.2	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy closure	Mingling	All	0.0	$\pm 0.350.0(2,20)$	0.00	0.08-
Canopy closure	Richness	1	0.0	$\pm 0.020.2(2,10)$	0.02	0.40-
Canopy closure	Richness	2	0.0	$\pm 0.0018.1(2,3)$	0.86	4.25*
Canopy closure	Richness	3	0.1	$\pm 0.0228.0(2,1)$	0.97	5.29 -
Canopy closure	Richness	4	-0.1	$\pm NaNaN(2,0)$	1.00	NA
Canopy closure	Richness	All	0.0	$\pm 0.0$ <b>0</b> $1.0(2,20)$	0.35	3.32**
Canopy closure	Tree density	1	0.0	$\pm 0.000.1(2,10)$	0.01	0.39-
Canopy closure	Tree density	2	0.0	$\pm 0.0017.6(2,3)$	0.85	4.20*
Canopy closure	Tree density	3	0.0	$\pm 0.0634.0(2,1)$	1.00	25.18*
Canopy closure	Tree density	4	0.0	$\pm NaNaN(2,0)$	1.00	NA
Canopy closure	Tree density	All	0.0	$\pm 0.007.8(2,20)$	0.28	2.80*
Canopy closure	Winkelmass	1	-3.6	$\pm 2.103.0(2,10)$	0.23	-1.72-
Canopy closure	Winkelmass	2	-11.4	$\pm 3.2012.7(2,3)$	0.81	-3.56*
Canopy closure	Winkelmass	3	-4.1	$\pm 0.5753.4(2,1)$	0.98	-7.30-
Canopy closure	Winkelmass	4	27.0	$\pm NaMaN(2,0)$	1.00	NA
Canopy closure	Winkelmass	All	-4.0	$\pm 1.626.0(2,20)$	0.23	-2.45*
Canopy rugosity	Basal area CoV	1	-0.1	$\pm 0.61 \ 0.0(2,6)$	0.00	-0.17-
Canopy rugosity	Basal area CoV	2	-2.2	$\pm 2.15 \ 1.1(2,3)$	0.26	-1.03-
Canopy rugosity	Basal area CoV	3	8.7	$\pm 5.35 \ 2.6(2,1)$	0.73	1.62-
Canopy rugosity	Basal area CoV	4	0.0	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy rugosity	Basal area CoV	All	-1.0	$\pm 0.533.7(2,16)$	0.19	-1.92-
Canopy rugosity	Mingling	1	-590.6	$\pm 361.2$ <b>7</b> .7(2,6)	0.31	-1.63-
Canopy rugosity	Mingling	2	849.7	$\pm 520.23.7(2,3)$	0.47	1.63-
Canopy rugosity	Mingling	3	7239.0	$\pm 17271676(2,1)$	0.95	4.19-
Canopy rugosity	Mingling	4	-6.8	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy rugosity	Mingling	All	127.8	$\pm 384.691(2,16)$	0.01	0.33-
Canopy rugosity	Richness	1	-26.2	$\pm 7.4612.3(2,6)$	0.67	-3.51*
Canopy rugosity	Richness	2	-6.9	$\pm 4.45 \ \ 2.4(2,3)$	0.45	-1.56-
Canopy rugosity	Richness	3	-14.6	$\pm 215.6$ 0.0(2,1)	0.00	-0.07-
Canopy rugosity	Richness	4	0.1	$\pm \text{NaNaN}(2,0)$	1.00	NA
Canopy rugosity	Richness	All	-6.7	$\pm 4.252.5(2,16)$	0.13	-1.58-
Canopy rugosity	Tree density	1	-0.2	$\pm 0.34 \ 0.3(2,6)$	0.05	-0.56-

Canopy rugosity Canopy rugosity Canopy rugosity Canopy rugosity	Tree density Tree density Tree density Tree density	2 3 4 All	-0.5 $-1.2$ $-0.0$ $-0.5$	$\begin{array}{l} \pm 0.21 \ 4.9(2,3) \\ \pm 5.36 \ 0.0(2,1) \\ \pm \mathrm{NaNaN}(2,0) \\ \pm 0.170.0(2,16) \end{array}$	0.62 0.05 1.00 0.38	-2.22- -0.22- NA -3.16**
Canopy rugosity	Winkelmass	1	-2639.6	$\pm 1527.380(2,6)$	0.33	-1.73-
Canopy rugosity	Winkelmass	2	6793.4	$\pm 2360.6\mathfrak{B}(2,3)$	0.73	2.88-
Canopy rugosity	Winkelmass	3	969.9	$\pm 8178.980(2,1)$	0.01	0.12 -
Canopy rugosity	Winkelmass	4	-29.4	$\pm \text{NaN}(2,0)$	1.00	NA
Canopy rugosity	Winkelmass	All	-1377.6	$\pm 1844006(2,16)$	0.03	-0.75-