

1 **Tree size drives diversity and community structure of microbial communities on the bark of** 2 **beech (*Fagus sylvatica*)**

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14 **Keywords**

15 Algae, Bacteria, Community Ecology, Forest management, Fungi, Metabarcoding

16 **Abstract**

17 Tree bark constitutes ideal habitat for microbial communities, because it is a stable substrate, rich in
18 micro-niches. Bacteria, fungi, and terrestrial microalgae together form microbial communities,
19 which in turn support more bark-associated organisms, such as mosses, lichens, and invertebrates,
20 thus contributing to forest biodiversity. We have a limited understanding of the diversity and biotic
21 interactions of the bark-associated microbiome, as investigations have mainly focussed on
22 agriculturally relevant systems and on single taxonomic groups. Here we implemented a multi-
23 kingdom metabarcoding approach to analyse diversity and community structure of the green algal,
24 bacterial, and fungal components of the bark-associated microbial communities of beech, the most
25 common broadleaved tree of Central European forests. We identified the most abundant taxa, hub
26 taxa, and co-occurring taxa. We found that tree size (as a proxy for age) is an important driver of
27 community assembly, suggesting that environmental filtering leads to less diverse fungal and algal
28 communities over time. Conversely, forest management intensity had negligible effects on
29 microbial communities on bark. Our study suggests the presence of undescribed, yet ecologically
30 meaningful taxa, especially in the fungi, and highlights the importance of bark surfaces as a
31 reservoir of microbial diversity. Our results constitute a first, essential step towards an integrated
32 framework for understanding microbial community assembly processes on bark surfaces, an
33 understudied habitat and neglected component of terrestrial biodiversity. Finally, we propose a cost-

34 effective sampling strategy to study bark-associated microbial communities across large spatial or
35 environmental scales.

36 **Introduction**

37 The aboveground surfaces of plants are ideal substrates for microbial colonization. The bark surface
38 (or dermosphere; Lambais et al., (2014)), in particular, is one of such important aboveground
39 substrates in forests. The bark provides a range of microhabitats that promote colonization of
40 microbial communities with varied ecologies (Whitmore, 1963). On the one hand, microsites such
41 as holes, cracks, and lenticels retain humidity and nutrients, thus constituting stable microhabitats
42 suitable for slow-growing, stress-sensitive microbes. On the other hand, the exposed surfaces of the
43 bark may harbour more stress-resistant microbial communities that can cope with environmental
44 challenges (Vorholt, 2012; Aguirre-von-Wobeser et al., 2021), such as low nutrient availability,
45 increased exposure to light, fluctuating moisture conditions and desiccation (Lindow and Brandl,
46 2003; Vorholt, 2012; Leff et al., 2015), and presence of compounds that are resistant to microbial
47 degradation (e.g., suberin), or that directly inhibit microbial growth (Baldrian, 2017).

48 Compared to other aboveground components, such as leaves, branches or fruits, that undergo
49 seasonal and diurnal changes (Vitulo et al., 2019), bark represents a stable, long-lived substrate that
50 supports microbial colonization (Leff et al., 2015). Further, the bark surface is often screened from
51 excessive precipitation- and/or UV radiation by the tree canopy and changes slowly during
52 development over several years (Whitmore, 1963). A number of studies have investigated the bark-
53 associated microbial diversity, especially for fungi and bacteria, in various systems, e.g., grapevine
54 plants (Martins et al., 2013; Arrigoni et al., 2018), bark beetle-infested spruce (Strid et al., 2014),
55 *Ginkgo* (Leff et al., 2015) and avocado trees (Aguirre-von-Wobeser et al., 2021). These studies
56 report that the tree bark supports microbial communities that are often distinct from spatially-close
57 substrates like leaves and roots (Martins et al., 2013; Leff et al., 2015; Arrigoni et al., 2018),
58 indicating niche differentiation and a clearly structured habitat (Aguirre-von-Wobeser et al., 2021).
59 Furthermore, the dermosphere constitutes a reservoir for microbial diversity (Arrigoni et al., 2018;
60 Hagge et al., 2019; Kobayashi and Aoyagi, 2019), potentially harbouring undiscovered specialist
61 taxa (Aschenbrenner et al., 2017), and taxa that facilitate the colonization of other epiphytes,
62 including lichens (Aschenbrenner et al., 2017). The microbial communities on tree bark, and the
63 biofilm which they form, can indeed be considered the basis of a food web that supports
64 photosynthetic epiphytes (e.g., mosses and lichens), as well as a diverse microfauna (Andre, 1985).
65 With an estimated more than 3 trillion trees in the world (Crowther et al., 2015), bark communities
66 could thus be particularly important reservoirs of biological diversity. However, bark is a poorly

67 explored habitat with respect to microbial diversity and community structure, compared to other
68 substrates such as the phyllosphere and rhizosphere.

69 Biological and environmental factors driving diversity and community assembly in bark-
70 associated epiphytes have been linked to forestry management, e.g., management intensity (Boch et
71 al., 2021), forest homogeneity (Lamit et al., 2015), deadwood abundance (Boch et al., 2021), and
72 tree age. For the latter, higher epiphyte diversities have been linked to the availability of large, old-
73 growth trees (Aude and Poulsen, 2000; Nascimbene et al., 2013; Boch et al., 2021), probably
74 because of higher niche partitioning in older trees (Łubek et al., 2020). At smaller spatial scales,
75 abiotic drivers of bark-associated diversity and community structure include ultraviolet radiation,
76 water shortages and correlated desiccation, poor nutrient availability (Lindow and Brandl, 2003;
77 Vorholt, 2012; Leff et al., 2015), while biotic drivers include host traits, such as maturity of the
78 substrate and host genotype (Arrigoni et al., 2018, 2020). Community composition is therefore, to
79 some degree, host specific. A few studies showed that the trends observed for macroepiphytes (e.g.,
80 bryophytes, lichens) or components of the phyllosphere also appear in bark-associated microbes
81 (e.g., Vorholt, 2012; Arrigoni et al., 2020). However, our understanding of the factors shaping the
82 different components of the highly diverse bark-associated microbial communities is still limited.
83 Most of the studies focus on non-natural, commercially driven ecosystems like orchards or
84 vineyards (Martins et al., 2013; Arrigoni et al., 2018). Studies are often conducted over small spatial
85 scales with small sample sizes (e.g., Leff et al., 2015). Lastly, the focus often lies on only a single
86 group of microorganisms, with bacteria and fungi far outweighing terrestrial algae (Aschenbrenner
87 et al., 2017; Petrolli et al., 2021). Integrative sampling of major microbial contributors over regional
88 or potentially even global scales can help identifying not only the diversity of microorganisms but
89 also potential cooperative and competitive interactions among them. Revealing the diversity and
90 structure of these rather unique microbial communities is essential to predict their responses in a
91 changing environment. Furthermore, considering the importance of fungi, bacteria and algae to
92 ecosystem nutrient and energy budgets in terrestrial habitats, gaining information on the bark-
93 associated microbial communities and their dynamics is essential and directly relevant for
94 ecosystem service assessment.

95 In this study we present one of the first integrated investigations of the bark microbiome in
96 temperate forests. Here we use the term microbiome following the definition by Berg et al., (2020).
97 Specifically, we study the three main components of the bark microbiome, i.e. green algae, bacteria
98 and fungi. We sampled bark surfaces in forests under different management regimes, ranging from
99 highly-managed stands to relatively undisturbed sites in the core zone of a national park. We used
100 metabarcoding to analyse microbial diversity, community structure and species interactions from

101 the tree to the landscape level. Specifically, we asked the following questions: i) What is the
102 microbial diversity found on the bark of the most common broadleaved tree in central Europe
103 (*Fagus sylvatica*)?, ii) Which species co-occur and who are the main players in the identified
104 ecological modules?, iii) Which factors, i.e. management intensity and tree-size classes (as a proxy
105 for tree age), affect the bark-associated microbiome, both at tree and landscape level?

106 The comparison of diversities among trees of different size classes within a spatially-explicit
107 framework allowed us to test for the effects of sampling design on the estimation of microbial
108 diversity. This information is essential for further, larger scale sampling campaigns.

109

110 **Material & Methods**

111 *Study site and sampling*

112 Sampling sites are situated within the central European region of Hainich-Dün (Thuringia,
113 Germany), that is one of the three regions of the Biodiversity Exploratories project (Fischer et al.,
114 2010). The Hainich-Dün region is characterized by soils stemming from calcareous bedrock, an
115 annual rainfall between 500-800 mm, a mean temperature of 6.5-8 °C at an elevation of 285-550 m
116 above sea level (Fischer et al., 2010).

117 Sample collection took place in autumn between the 13th and 15th of October 2020. We chose
118 a subset of 16 out of the established 50 experimental plots (Fischer et al., 2010), sampling a subplot
119 of 20×20 m within the 100×100 m experimental plots. These plots were chosen to represent two
120 regimes of land-use intensity, namely a high and a low intensity forest management (eight plots
121 each), according to the Forest Management Index (ForMI, high > 1, low < 1). This is an index
122 combining measures of harvested stem volume, occurrence of non-natural species and deadwood
123 stemming from harvest (Kahl and Bauhus, 2014). Specifically, we defined three size classes: large
124 (i.e. >30 cm diameter at breast height (DBH)), medium (15 – 30cm DBH) and small (5 – 15cm
125 DBH). Two trees per size class were sampled. When one tree-size class was not available (three
126 plots), we sampled more trees of the other size classes depending on which was highly abundant in
127 the direct vicinity as judged in the field. Within each plot we recorded the spatial position of the
128 trees relative to each other by measuring distance (m) and azimuth (degrees) from the nearest
129 sampled tree.

130 We collected microbial bark surface communities using individually wrapped sterile nylon-
131 flocked medical swabs with a 30 mm breakpoint, typically used for medical specimen collection
132 (FLOQSwabs™, Copan, Brescia, Italy). The breakpoint mechanism minimises the possibility of
133 contamination when transferring the swab into the Eppendorf tube. Prior to collection the bark was
134 moisturised with deionized water to mobilize the surface biofilms. Then the tree was swabbed at

135 breast height in a 3 cm-wide band around the trunk, rolling the swab and moving it up and down
136 while applying gentle pressure. While swabbing, we took care to include smooth surfaces as well as
137 cracks and crevices in the bark, to ensure a good representation of micro-habitats. The swab head
138 was broken off into Eppendorf tubes pre-filled with 750 µl Nucleic Acid Preservation (NAP) buffer
139 (Camacho-Sanchez et al., 2013). Tubes were immediately placed in styrofoam boxes with ice and
140 the samples were subsequently stored at 4 °C until DNA extraction.

141

142 *DNA extraction*

143 Prior to DNA extraction we added 750 µl ice-cold phosphate-buffered saline (PBS) into the
144 Eppendorf tube and centrifuged the sample for 15 min at 6000×g as recommended by Menke et al.,
145 (2017). The supernatant was then discarded without disturbing the swab head or pellet. DNA was
146 extracted using the Quick-DNA Fecal/Soil Microbe Microprep kit (Zymo Research Europe GmbH,
147 Freiburg). Initial tissue lysis was achieved through mechanical disruption by bead beating, using the
148 beads included in the extraction kit. We modified the kit protocol by directly adding the beads and
149 bead-beating buffer into the tube containing the pellet and swab and shaking for a total of 6 min
150 (SpeedMill PLUS, Analytik Jena, Jena, Germany). In the later steps we followed the manufacturer's
151 protocol, using DNase-free water as elution buffer. We included six contamination controls, that
152 were sequenced as well. DNA extracts were frozen at -20 °C until PCR.

153

154 *PCR amplification and high-throughput sequencing*

155 Algal, bacterial and fungal fractions of the extracted microbial DNA were amplified, using primers
156 for the ITS2 region for fungi and algae, and the 16S hyper-variable region V3 – V4 for bacteria
157 (Table 1).

158 All samples were amplified in duplicate with forward and reverse primers individually
159 tagged with octamers allowing for a double index multiplexing approach. Every replicate contained
160 eight negative controls (i.e., master mix without sample), as well as 16 “Multiplex Controls” (i.e.,
161 empty wells) to allow detection of potential primer jump during sequencing (Schnell et al., 2015).
162 We set up 15 µl PCR reactions containing 5 ng of DNA, 7.5 µl of MyTaq™ HS Mix, 2x (Bioline
163 GmbH, Luckenwalde, Germany), 0.6 µl 10 µM of each primer, and 4.3 µl DNase free water.
164 Cycling conditions differed in cycle number and annealing temperature among organismal groups.
165 Conditions were as follows: an initial denaturation at 95 °C for one minute, followed by 30 (algae,
166 bacteria) or 35 (fungi) cycles of denaturation at 95 °C for 15 s, annealing at 54 °C (algae), 59 °C
167 (bacteria) or 56 °C (fungi) for 15 s and elongation at 72 °C for 10 s, with a final extension at 72 °C

168 for 1 min. Samples were randomly distributed over two 96-well plates, with both replicates
169 following the same placement scheme.

170 The amplicons were individually cleaned using magnetic beads (MagSI-NGS^{Prep} Plus,
171 magtivio B.V., Geelen, Netherlands) and DNA concentration was quantified with fluorescence
172 measurement using the Qubit dsDNA HS assay (Thermo Fisher Scientific, MA, USA) as specified
173 by the manufacturer. The replicates were equimolarly pooled within the respective organismal
174 groups, creating a total of three pools for sequencing. The pooled amplicons were sent for library
175 preparation and sequencing to Fasteris SA (Plan-les-Ouates, Switzerland). Libraries were prepared
176 for each pool according to the Fasteris MetaFast protocol (<https://www.fasteris.com/>), in order to
177 avoid PCR for library preparation and thus minimizing additional PCR bias and chimera creation.
178 The samples were sequenced on an Illumina MiSeq (Illumina Inc., San Diego, CA, USA) with
179 2×300 bp paired-end reads.

180

181 *Bioinformatics*

182 Adapter-trimmed reads trimmed with Trimmomatic (Bolger et al., 2014) were supplied by the
183 sequencing provider. We demultiplexed the reads using Cutadapt v3.3 (Martin, 2011) following the
184 demultiplexing combinatorial dual-indexes section of the manual. The error rate was set to 0.15,
185 allowing no insertions or deletions, and discarding reads shorter than 50 bp. Commands were run a
186 second time with the octamer tags in the reverse order to account for amplicons in mixed orientation
187 resulting from PCR-free library preparation. The resulting files were merged to obtain one R1 and
188 one R2 file per replicate. Reads were checked for remaining primer sequences, which were removed
189 using Cutadapt, if present.

190 The demultiplexed reads were further processed with the DADA2 pipeline (Callahan et al.,
191 2016). Filtering and trimming operations used DADA2 default parameters, except for setting a
192 truncation length ($\text{truncLen} = c(250,260)$) for bacteria, but not for algae and fungi since the length
193 of the ITS2 region can vary between taxa (Schoch et al., 2014). Furthermore, the maximum error
194 rates were relaxed to $\text{maxEE} = c(5,5)$ for bacteria and $\text{maxEE} = c(6,6)$ for algae and fungi. After de-
195 noising and sample inference, pairs were merged within each replicate, chimeras were removed and
196 one amplicon sequence variant (ASV) table was constructed per replicate. To account for the mixed
197 orientation of the libraries we checked the tables for reverse complement sequences, reversed them
198 and added their counts to the respective complement sequence using DADA2s *rc()* function.
199 Finally, the replicates were merged by summing up the read counts.

200 For taxonomic assignment the sequences were matched against publicly available databases,
201 namely UNITE general release 8.2 (Abarenkov et al., 2020) for fungal reads and SILVA 138.1 SSU

202 Ref NR 99 (Quast et al., 2012) for bacteria. Since no similar database is currently available for
203 green algae we used the program SEED2 v2.1.2 (Větrovský et al., 2018) to conduct a BLASTn
204 search against GenBank (Clark et al., 2016).

205 We then checked the reads for potential contamination with the *decontam* package (Davis et
206 al., 2018), using the combined prevalence and frequency approach. For all organismal groups
207 *decontam* only showed low numbers (algae = 0, bacteria = 8, fungi = 4) of potential contaminant
208 ASVs, which were discarded. The *decontam*-filtered ASV tables were curated using the LULU
209 algorithm (Frøslev et al., 2017) to merge highly similar ASVs and obtain more reliable diversity
210 metrics. Taxonomic information for all ASVs can be found in Supplementary Table 1.

211

212 *Diversity and community structure analyses*

213 All analyses were conducted in R (R Core Team, 2021, version 4.0.4) through RStudio (RStudio
214 Team, 2021). ASV tables, taxonomic information and accompanying metadata were combined
215 using the *phyloseq* R package (McMurdie and Holmes, 2013) to ease analyses. Figures were created
216 with *ggplot2* (Wickham, 2016) and *gridExtra* (Auguie, 2017). Samples were not rarefied as
217 recommended by McMurdie and Holmes (2014) and instead treated as compositional count data
218 (Gloor et al., 2017). Script of all analyses are available on GitHub at
219 https://github.com/LukDrey/beechn_micro_communities. [link active upon publication; the code is
220 made available to Reviewers as supplementary file].

221 *Intra-group diversities*

222 We calculated the Shannon Index (Shannon, 1948) as a measure of alpha diversity, using the
223 function *estimate_richness()* on the full untransformed ASV table as obtained from DADA2 and
224 LULU. Differences in Shannon diversity between tree sizes and management category were tested
225 with an Analysis of Variance (ANOVA) with the function *aov()* and verified via a Tukey Honest
226 Significant Differences test (Tukey HSD). Furthermore, we tested whether the Shannon diversity
227 for trees within a plot was spatially autocorrelated. For this purpose, we computed Moran's I
228 (method from Gittleman and Kot, 1990) as a measure of spatial autocorrelation with the function
229 *Moran.I* from the *ape* R package (Paradis and Schliep, 2019).

230 To create the community barplots we aggregated taxa at the order rank and subset the
231 datasets to the 25 relatively most abundant taxa with *get_top_taxa()* (Teunisse, 2017). The resulting
232 subsets were transformed to reflect their compositional nature by *transform()* and plotted using
233 *plot_composition()*, both from the *microbiome* R package (Lahti and Shetty, 2017).

234

235 *Inter-group differences*

236 Before comparing differences in community composition of differently sized trees and management
237 regimes, each full dataset was transformed based on centred log-ratios (CLR) with *transform()*.

238 After the transformation we conducted a principal component analysis (PCA) on the clr-
239 transformed datasets using the *phyloseq* function *ordinate()* (“RDA” method) which for clr-
240 transformed data is the same as PCA. In the ordination plots we show the first two Principal
241 Components (PC), with the axes scaled to the proportion of variance the PC explains, as
242 recommended by Nguyen and Holmes (2019).

243 To test if groups showed similar within-group variance, we used the *betadisper()* function
244 and verified the results with the accompanying permutation test *permutest()* from the *vegan* package
245 (Oksanen et al., 2020). To test for differences in community composition between tree sizes and
246 management intensity we performed Permutational Analysis of Variance (PERMANOVA) with a
247 distance matrix based on Aitchison’s distance (method = “euclidean” with the *phyloseq* function
248 *distance()* for clr-transformed data). The PERMANOVA was computed using the *vegan* function
249 *adonis2()* examining marginal effects of tree size and management intensity together.

250

251 *Species interactions*

252 The interaction networks were generated with the *SPIEC-EASI* method (Kurtz et al., 2015), a robust
253 method for the sparse and compositional nature of microbiome datasets implemented in the R
254 package *SpiecEasi*. Before network inference the ASV tables were subset to contain only ASVs
255 contributing at least one percent of the total reads to ease both visualization and computational load.
256 The main SPIEC-EASI algorithm was set to use the meinshausen-bühlmann’s neighborhood
257 selection (Meinshausen and Bühlmann, 2006) and Bounded StARS model selection (Müller et al.,
258 2016) on 50 subsamples (rep.num = 50), with lambda.min.ratio = 0.1, nlambda = 100, pulsar.select
259 = TRUE and seed = 10010. We calculated one network per organismal group, as well as one
260 containing all three groups together.

261 The obtained models were refit, turned into *igraph* (Csardi and Nepusz, 2006) objects and
262 loaded in *Gephi* v0.9.2 (Bastian et al., 2009) for visualisation. Modularity and betweenness
263 centrality (for visualisation purposes) were computed with *Gephi*’s internal algorithms (Brandes,
264 2001; Blondel et al., 2008). The graph layouts were constructed using the Fruchterman-Reingold
265 algorithm (Fruchterman and Reingold, 1991). For each network, hub taxa were calculated based on
266 vertex betweenness centrality using the *igraph* function *betweenness()* with default parameters,

267 except setting directed = FALSE. The top five hub taxa, based on vertex betweenness centrality,
268 were extracted.

269

270 *Differential abundance analysis*

271 Differential abundance analysis was conducted using *ALDEx2* (Fernandes et al., 2013, 2014; Gloor
272 et al., 2016). We compared abundances of two groups, i.e. high/low management intensity,
273 large/small, large/medium and medium/small trees, for each organismal group. *ALDEx2* generates
274 Monte Carlo samples (N = 128), drawn from the Dirichlet distribution for each individual sample,
275 and tests differences between specified groups through Wilcoxon rank-sum tests. *ALDEx2* is a
276 robust choice for compositional datasets because the data is clr-transformed internally. Taxa were
277 declared differentially abundant if they showed a Benjamini-Hochberg corrected p-value < 0.05.
278

279 **Results**

280 *Intra-group diversities*

281 In total we obtained on average 38,223 reads per sample for algae (min = 12,913, max = 87,526),
282 58,670 reads for bacteria (min = 223, max = 181,567) and 44,239 reads for fungi (min = 9,803, max
283 = 117,957), with minima of 93, 103 and 92 reads and maxima of 16,436, 19,798 and 76,422 reads
284 for the sequencing controls. From these reads, we retrieved 216 algal, 1,723 bacterial and 992
285 fungal ASVs. Overall algae and fungi displayed similar Shannon alpha diversity, while bacteria
286 showed a slightly higher diversity (Figure 1). Neither algae, fungi nor bacteria exhibited statistically
287 significant differences in alpha diversity when comparing low and high management intensity plots
288 (Figure 1 (A), (B) and (C)). Considering differences between tree sizes, smaller trees displayed
289 higher alpha diversity for algae and fungi (Figure 1 (D) and (F)). Overall, bacterial diversities were
290 more uniform, but displayed higher median Shannon diversity values for larger trees (Figure 1 (E)).
291 This trend was corroborated by the results of an ANOVA comparing the three tree-size classes. For
292 algae, we found a significant overall effect of tree size ($F = 4.163$, $p < 0.05$), that was driven by a
293 significant difference between large and small trees (post-hoc test p -value < 0.05). No significant
294 differences were found between large/medium and medium/small trees. Tree size had a significant
295 effect overall ($F = 16.499$, $p < 0.001$) in fungi, with significant differences between large and
296 medium ($p < 0.01$), as well as large and small trees ($p < 0.001$). For bacteria we found no significant
297 overall effect.

298 Spatial autocorrelation tests showed that only in four of 48 cases the null-hypothesis of no
299 spatial correlation could be rejected (Table 2). This indicates that the effect of spatial
300 autocorrelation within plots is negligible. Trees belonging to the same plot showed very similar
301 Shannon alpha diversity values. One exception is plot HEW8 where alpha diversity was
302 significantly spatially autocorrelated for both algae and bacteria.

303 Bark microbial communities were similar among trees, with only minor differences in rare
304 orders for all three organismal groups. For algae, the predominant orders were Trebouxiales and
305 Chlorellales, with Trebouxiales contributing more than 50% of the reads in many plots (Figure 2
306 (A)). Rare orders displayed a relatively high inter-plot variability, with Prasiolales being almost
307 absent for the plot HEW5. Compared to algae, Bacteria were more homogeneous, with the same
308 four orders - Rhizobiales, Sphingomonadales, Acetobacterales and Cytophagales - displaying
309 comparably high relative abundances in all plots (Figure 2 (B)). We found a higher rare-order
310 diversity in bacteria and fungi compared to algae. Capnoidiales were by far the most abundant
311 fungal order, and dominant in all plots (Figure 2 (C)). Compared to bacteria and algae, more fungal

312 reads could not be assigned at the order rank. These reads contributed more than 25% of the total
313 reads in some samples.

314 *Intra-group interactions*

315 We inferred ASV interaction networks for all three microbial groups (Figure 3). Each ASV entering
316 the networks was present in at least 1% of the samples resulting in 129 ASVs for the algae, 628 for
317 bacteria and 289 for fungi. The algal network (Figure 3 (A)) had a diameter of ten (i.e., the longest
318 shortest path between two nodes was through ten edges), an average path length of four and a
319 modularity score of 0.575. Modularity scores > 0.4 indicate strong modularity ((Newman, 2006).
320 The diameter for the fungal network (Figure 3 (C)) was 7, with an average path length of ~3.2 and a
321 modularity slightly lower than the algae at 0.434. The bacterial network (Figure 3 (B)) was denser
322 and more interconnected with a diameter of 5, an average path length of ~2.7 and a modularity of
323 0.335.

324 The algal network could be subdivided into 9 different modules, 5 of which consisting of
325 more than 10 ASVs (see table 3). There were also 8 ASVs that did not interact with any other taxon
326 in the network. The algal module with the highest number of nodes was module 2 (gold colour,
327 Figure 3 (A)) with the most abundant ASV belonging to the genus *Desmococcus* (relative
328 abundance = ~47% in the module, Table 3).

329 The bacterial network consisted of 7 modules, all of which with more than 10 ASVs and no
330 taxa that have no connections. In this case, module 6 (purple colour in Figure 3 (B)) was the module
331 with the highest count of taxa, with an ASV assigned to the genus *Abditibacterium* being the
332 predominant strain (12% of reads in the module, Table 3).

333 For fungi, the network clustered into 9 different modules, all containing more than ten ASVs
334 and no unconnected taxa. Also in this case, module two (purple colour, Figure 3 (C)) was the
335 module with the highest number of taxa for the fungal network, with an ASV belonging to the order
336 Capnodiales – not assignable to a higher taxonomic rank (Table 3) - with the highest relative
337 abundance in the module (14%).

338 Network structure was examined by identifying nodes with the highest number of shortest
339 path going through them (betweenness centrality), indicating taxa that are important for the
340 connectivity of the network. We defined so called hub taxa as the five taxa with the highest
341 betweenness centrality (Table 4). In the algal network these hub taxa belonged to two orders,
342 Chlorellales and Trebouxiales, and three different genera. Three ASVs were assigned to the genus
343 *Apatococcus*, and one to *Trebouxia* and *Symbiochloris*, respectively. Bacterial hub taxa showed a
344 higher diversity than the algae with hub taxa belonging to 5 different orders. The genera include

345 *Tundrisphaera*, *Hymenobacter*, *Actinomyces* and *Oligoflexus*. One of the ASVs was assigned
346 to the group 1174-901-12, a group of uncultured bacterial strains within the order Rhizobiales.
347 Many of the fungal hub taxa were not assigned at the genus rank, with the exception of two ASVs
348 belonging to the genera *Tremella* and *Aureobasidium*. Two more ASVs were assigned to the order
349 Capnodiales while one was only assigned at the phylum rank.

350 *Inter-group interactions*

351 The combined network of algae, bacteria and fungi (Figure 4) displayed a diameter of 4, an average
352 path length of ~2.6 and a modularity of 0.259, making this network more densely connected than
353 the bacterial network. Out of the eight modules, modules two (29%) and three (26%) accounted for
354 more than half of the total reads.

355 The top orders for algae, bacteria and fungi in the relatively most abundant module (module
356 2, pink colour in Figure 4 (B)) were Trebouxiales, Sphingomonadales and Capnodiales,
357 respectively. Algae and fungi accounted for up to 36 and 26% of the module reads, respectively,
358 while Sphingomonadales only contributed 5% of the reads. Trebouxiales contributed 87% of the
359 algal reads, Sphingomonadales 30% of bacterial reads, and Capnodiales 77% of the fungal reads. In
360 total, algae contributed 42%, bacteria 19%, and fungi 34% of the reads assigned to module 2.

361 In the second most abundant module (module 3, blue colour in Figure 4 (B)) Chlorellales
362 were the most important algal order, Rhizobiales the most important bacterial order, while the most
363 important fungal order was again Capnodiales. Chlorellales contributed 18%, Rhizobiales 16% and
364 Capnodiales only 5% of the module reads. Chlorellales accounted for 43% of the algal reads,
365 Rhizobiales 48% of the bacterial reads, and Capnodiales 34% of the fungal reads. Overall, module
366 three consisted of 42% algae, 34% bacteria and 10% fungi.

367 The hub taxa of the combined network (Table 4) contained members of all three microbial
368 groups, specifically one alga, two bacteria and two fungi. Four ASVs could be assigned down to
369 genus rank, while one fungal ASV – a hub taxon present also in the fungal network – could only be
370 assigned to order rank (Capnodiales). The other fungus belonged to the genus *Massarina*, while the
371 two bacteria ASVs belonged to the genus *Edaphobaculum* and the uncultured group LD29 within
372 the order Chthoniobacterales. The only algal taxon represented the common lichen-forming genus
373 *Trebouxia*.

374

375 *Drivers of changes in community composition*

376 To investigate differences in community composition we plotted the results of the PCA (Figure 5).
377 The differences between the high and low management intensity are not readily visible by looking

378 at the clusters of the two groups. Yet, there are significant differences between the groups as
379 revealed by the PERMANOVA results (algae: $p < 0.05$, bacteria: $p < 0.01$, fungi: $p < 0.001$). The
380 dispersion permutation test was significant (algae: $p < 0.05$, bacteria: $p < 0.05$, fungi: $p < 0.05$)
381 indicating a heterogeneous dispersion within groups. If on one hand this might suggest that the
382 results are not reliable, Anderson and Walsh (2013) showed that PERMANOVA is not sensitive
383 against heterogeneity, compared to other analyses. Management intensity explained only ~2% of the
384 variance in the dataset, suggesting a subtle yet significant effect.

385 The tree sizes clustered in a much clearer structure, with less overlap of the 95% confidence
386 interval ellipses. The PERMANOVA analysis confirmed this observation, with highly significant
387 results for all microbial groups ($p < 0.001$ for all), while the permutation test indicated homogenous
388 dispersion within the groups ($p > 0.05$).

389 Further examination of the community structure showed that the differences in community
390 composition were also visible through significantly differentially abundant taxa (Supplementary
391 Table 2). The difference between management intensities was little, with only four differentially
392 abundant ASVs. The tree-size classes, however, showed a different signal and confirmed the
393 stronger differences indicated by the PERMANOVA results. Between large and medium trees we
394 found nine algae, four bacteria and ten fungal taxa that showed significant abundance differences. A
395 larger difference in abundances could be seen between large and small trees, with 19 algae, 45
396 bacteria and 33 fungi that were differentially abundant. Almost no difference could be observed
397 between communities of medium and small trees with only two algal and one bacterial ASVs with
398 significant changes in abundance.

399 **Discussion**

400 In this study we used a multi-kingdom metabarcoding approach to investigate the microbiome
401 (algae, bacteria, fungi) on the bark of beech from sites with different forest management intensity in
402 the Hainich-Dün region, Thuringia, Germany. We provide a first characterization of aboveground
403 bark-associated microbial communities in beech forests, as well as an account of microbial inter-
404 kingdom interactions. Additionally, by testing how community diversity and structure of the
405 different organismal groups change in relation to land-use intensity and tree size, we identify
406 potential drivers of community assembly and provide sampling recommendations for studying the
407 bark microbiome at broader spatial scales.

408 *Diversity of the bark-associated beech microbiome*

409 Our results show that the bark of beech harbours highly diverse algal, bacterial and fungal
410 communities.

411 Algal diversity is mainly represented by species of the families Trebouxiophyceae and
412 Chlorophyceae, in particular by genera commonly found in subaerial environments and already
413 detected in forest settings (Štifterová and Neustupa (2015)). Algae of the genus *Apatococcus*, a
414 “flagship” taxon of above-ground ecosystems (Rindi 2007), are among the most abundant and
415 interconnected members of the algal microbiome. Another abundant alga is *Desmococcus* sp.,
416 which typically forms visible powdery, greenish layers on the bark of trees in association with
417 *Apatococcus* and other subaerial green algae (Rindi, 2007). Both are part of what is possibly the
418 most tolerant subaerial algal community, being able to thrive even in urban areas (Barkman, 1958).
419 Furthermore, our results confirm *Symbiochloris* as a common player in the dermo- and phyllosphere
420 (Škaloud et al., 2016; Zhu et al., 2018) as well as other Trebouxiales, an order consisting of free-
421 living as well as lichen-forming green algae (Sanders and Masumoto, 2021).

422 Compared to the algae and fungi, the bacterial community is far more diverse. Similar as in
423 Aschenbrenner et al., (2017), the bacterial community is dominated by the class
424 Alphaproteobacteria, in particular Rhizobiales and Acetobacteriales. Among the Rhizobiales we
425 detected *Methylocella* sp., a facultative methanotroph adapted to various nutrients (acetate,
426 pyruvate, succinate, malate, and ethanol) (Dedysh and Dunfield, 2011), and 1174-901-12,
427 previously described as an early colonizer of aerial environments (Romani et al., 2019) and a
428 known member of the phyllosphere (Ares et al., 2021). In the case of Acetobacteriales, *Acidiphilium*
429 is among the most abundant taxa. The genus consists of aerobic bacteria with photosynthetic
430 pigments, with a pH range that matches well to the pH of beech bark (~4.4 in Asplund et al., 2015)
431 and that do not overlap in metabolic demands with *Methylocella* (Hiraishi and Imhoff, 2015).
432 Another abundant class are the *Abditibacteria*, especially the genus *Abditibacterium* whose
433 representatives are well adapted to low-nutrient conditions and have already been reported on tree
434 bark (Tahon et al., 2018; Kobayashi and Aoyagi, 2019). Among the bacteria hub taxa we find
435 genera from classes already reported for tree-associated microbiomes, such as *Oligoflexus* in
436 bryophytes (Ma et al., 2017), *Actinomyces* and 1174-901-12 on tree bark and lichens
437 ((Yamamura et al., 2011), (Ares et al., 2021)), *Hymenobacter*, a desiccation- and radiation-tolerant
438 bacterium often found in soil (Buczolits and Busse, 2015), and *Tundrisphaera*, previously only
439 isolated from lichen-dominated tundra soils (Kulichevskaya et al., 2017). Contrarily to
440 Aschenbrenner et al., (2017), we did not find major contributions from the genera *Burkholderia* and
441 *Pseudomonas*, possibly indicating that these genera are specific to the sycamore maple (*Acer*
442 *pseudoplatanus*) bark.

443 The investigation of fungal diversity was somewhat hindered by low taxonomic resolution
444 with many ASVs that could not be assigned past phylum rank. This may result from a lack of

445 resolution in public fungal databases combined with the presence of several unknown taxa in our
446 dataset. Abundant members of the beech bark fungal community are the so-called black yeasts, e.g.,
447 *Capronia* and *Aureobasidium*, which are known to occur on tree bark and leaflets (Untereiner and
448 Malloch, 1999; Andrews et al., 2002), but also decaying wood (Cooke, 1959) and on other fungi or
449 lichens as secondary saprobionts (Untereiner and Malloch, 1999). Other common fungi belong to
450 the genus *Tremella*, known mycoparasites (Zugmaier et al., 1994). Among the lichen-forming fungi,
451 the most common fungus in our dataset belongs to the genus *Scoliciosporum*, a genus of crustose
452 lichens that was already reported on beech bark (e.g., Dymytrova, 2011). The biggest contributors at
453 the order rank are members of the Capnodiales (Dothideomycetes) and Helotiales (Leotiomycetes),
454 whose species have been shown to associate with the lichen microbiome (Suija et al., 2014; Smith
455 et al., 2020). Yet, more research into these orders is needed as they are taxonomically and
456 ecologically highly diverse and include a large diversity of life forms, from lichenized, to
457 mycoparasitic, epi-, ecto-, endophytic, as well as saprobiontic species (Tedersoo et al., 2009;
458 Abdollahzadeh et al., 2020). In conclusion, more research is needed in order to confirm the role of
459 the bark habitat as a reservoir of novel fungal diversity. This could possibly be done by combining
460 genetics with culture-based approaches.

461

462 *Biotic interactions and inter-kingdom synergies in the bark microbiome*

463 The higher modularity scores of the fungal and especially algal networks may indicate higher
464 specialization or niche differentiation in these groups (Augustyn et al., 2016). In contrast, bacteria
465 are less clearly divided into ecological modules, which potentially indicates closer interactions
466 between all taxa as there seems to be no split into specialized groups. Further analyses based on a
467 broader dataset are needed to exclude that the observed patterns are an artefact of the overall higher
468 diversity found in bacteria.

469 The results from the combined, inter-kingdom co-occurrence analysis indicate that algal and
470 fungal specialists might be connected through a common set of bacteria. It is tempting to speculate
471 that the interactions between Rhizobiales and Chlorellales (mostly represented by members of the
472 genus *Apatococcus*) observed in the main ecological cluster in our dataset are of symbiotic nature,
473 as Rhizobiales are well-known beneficial partners in plant-microbe interactions and common
474 associates of lichens (Erlacher et al., 2015; Grube et al., 2015). Positive interactions among
475 Sphingomonadales, Trebouxiales, and Capnodiales – all known occupants of bark substrates –
476 characterize the secondly most important cluster. The bacterial genus *Sphingomonas* is very
477 common in above-ground forest habitats (Vorholt, 2012), exhibiting facultative photosynthesis.

478 Finally, we identified the most highly connected taxa (hubs), i.e. taxa that are crucial for the
479 stability of the ecological network (Banerjee et al., 2018). For bacteria, the hub taxa belong to the
480 genera LD29 (Verrucomicrobiota) and *Edaphobaculum* (Bacteroidetes). Little is known about their
481 ecology, with LD29 particularly abundant in lichen thalli (Aschenbrenner et al., 2017), and
482 *Edaphobaculum* previously found in soils where it contributes to the creation of biofilms
483 (Keuschnig et al., 2021). As for the fungi, one of the hub taxa belongs to the genus *Massarina*
484 (Pleosporales, Dothideomycetes), a genus which is seemingly common on *Fagus sylvatica* (Zhang
485 et al., 2009). Interestingly, for the algae, the hub taxon is a member of the genus *Trebouxia*, the
486 most common lichen-forming alga.

487
488 *Bark microbiome responds to tree size, but not to intensity of forest management*

489 The intensity of the forest management regime has virtually no effect on microbial community
490 diversity and structure in our study area. This might be a result of a forest management plan that
491 avoids clear cuts and carefully selects trees to harvest, which leads to a uniform forest structure in
492 the study area (Schall et al., 2020). Based on a broader sampling including this and other two large
493 forest areas in Germany, Boch et al., (2021) showed that an increase in forest management intensity
494 is linked to reduced lichen species richness. A larger sampling effort covering a broader gradient of
495 land-use intensity is therefore required to test whether the bark-associated microbiome differs in
496 response compared to the macroepiphytes.

497 We found significant differences in diversity and composition of the bark microbiome
498 according to different tree-size classes. The lower microbial diversity found on larger (older) trees
499 for algae and fungi is probably the result of environmental filtering on highly heterogeneous pioneer
500 communities over time. This is particularly evident when comparing large and small trees, thus
501 suggesting slow succession of these microbiomes toward final community composition. Lastly,
502 results from the spatial autocorrelation analysis underpin random assembly of the microbial bark
503 community at the local (plot) level, with a high heterogeneity between trees.

504
505 *Conclusions and sampling recommendations*

506 In this pioneering study we provide novel insights into the diversity, spatial context, and biotic
507 interactions that characterize the beech bark microbiome in Central European forests. We showed
508 that there are predictable community shifts depending on tree age. These represent the first steps
509 towards proposing a framework of community assembly on forest tree bark, a ubiquitous,
510 ecologically relevant, yet overlooked component of terrestrial habitats.

511 Taken together, our results show that a single tree does not adequately characterize the bark-
512 associated microbial community at plot level. To capture most of the microbial diversity, we
513 recommend sampling using a spatially random approach with a balanced representation of the main
514 tree-size classes present in the plot. Samples taken from multiple trees can then be combined into a
515 composite sample. The use of composite samples ensures relatively low costs for obtaining
516 adequate sequencing depths while maximizing the spatial range of the study and the number of
517 plots, allowing for easy upscaling to large areas and/or environmental gradients.

518

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532

533 **Data availability statement**

534 All data necessary to replicate the analyses is publicly available in the repository of the Biodiversity
535 Exploratories BExIS (<https://www.bexis.uni-jena.de/>). Accession numbers: 31183, 31185, 31186
536 (taxonomy tables); 31160, 31161, 31162 (ASV tables); 31157, 31158, 31159 (DNA concentrations
537 for use with *decontam*), 31163, 31164, 31165, 31166 (modules obtained from *Gephi*) and 31167
538 (metadata table). Raw reads of the samples are available at Genbank: Accession number XXXX.
539 Sequences attributed to the ASVs are available at NCBI SRA under accession number XXXX. The
540 code for the processing of the raw reads, sample inference and all analyses is available from Github
541 at https://github.com/LukDrey/beechn_micro_communities.

542 [All this information will be made public after acceptance of the manuscript and is made available
543 to the reviewers as supplementary data.]

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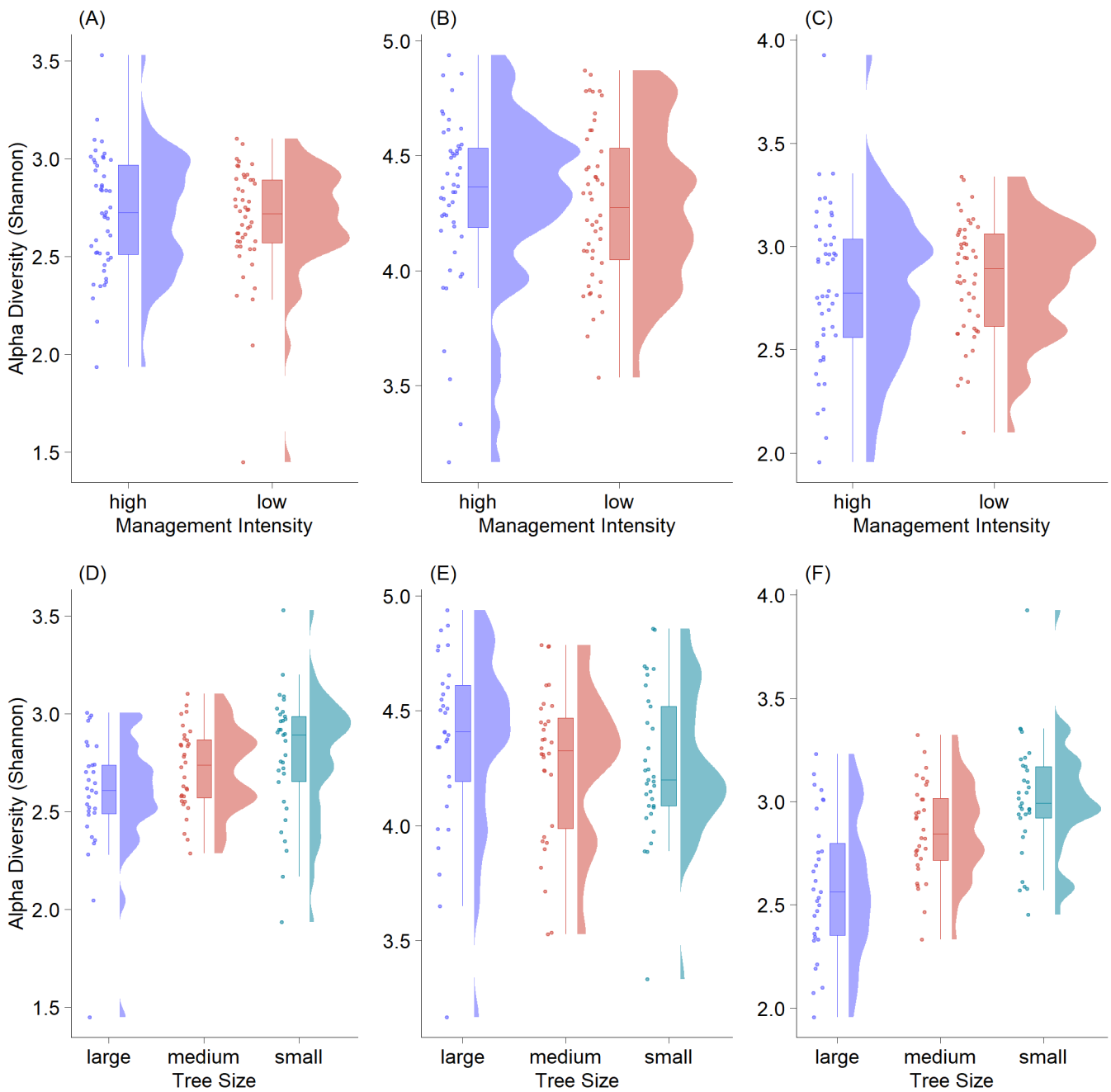
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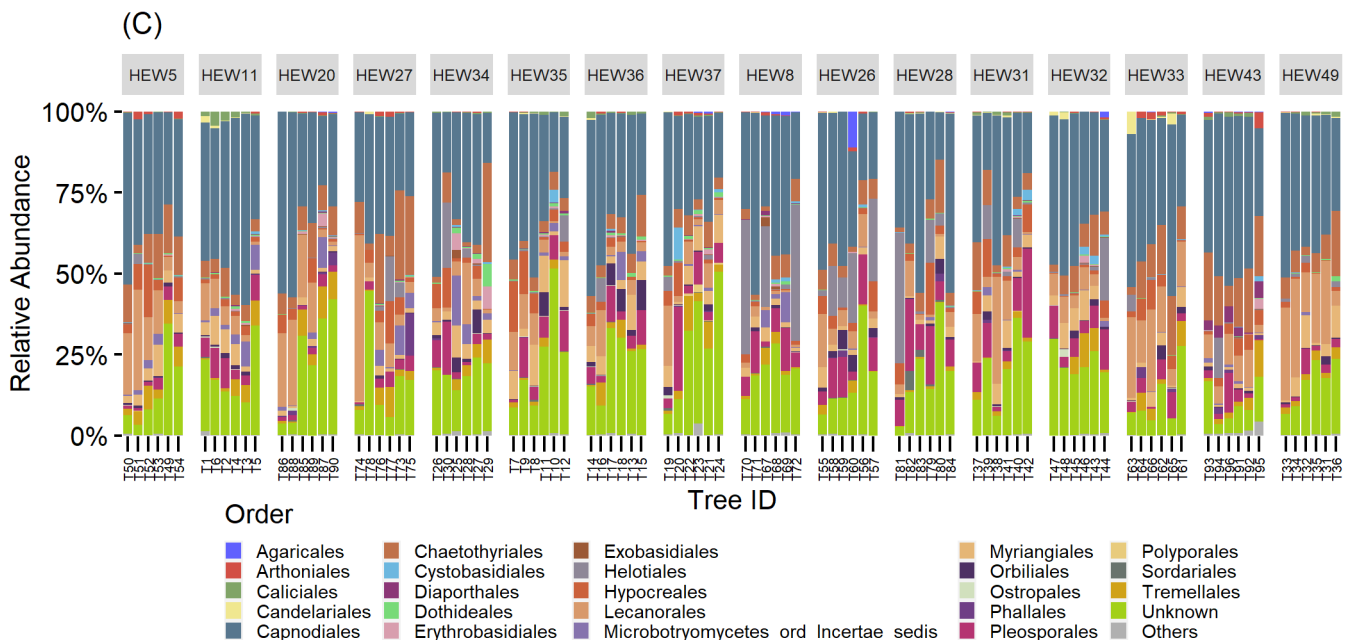
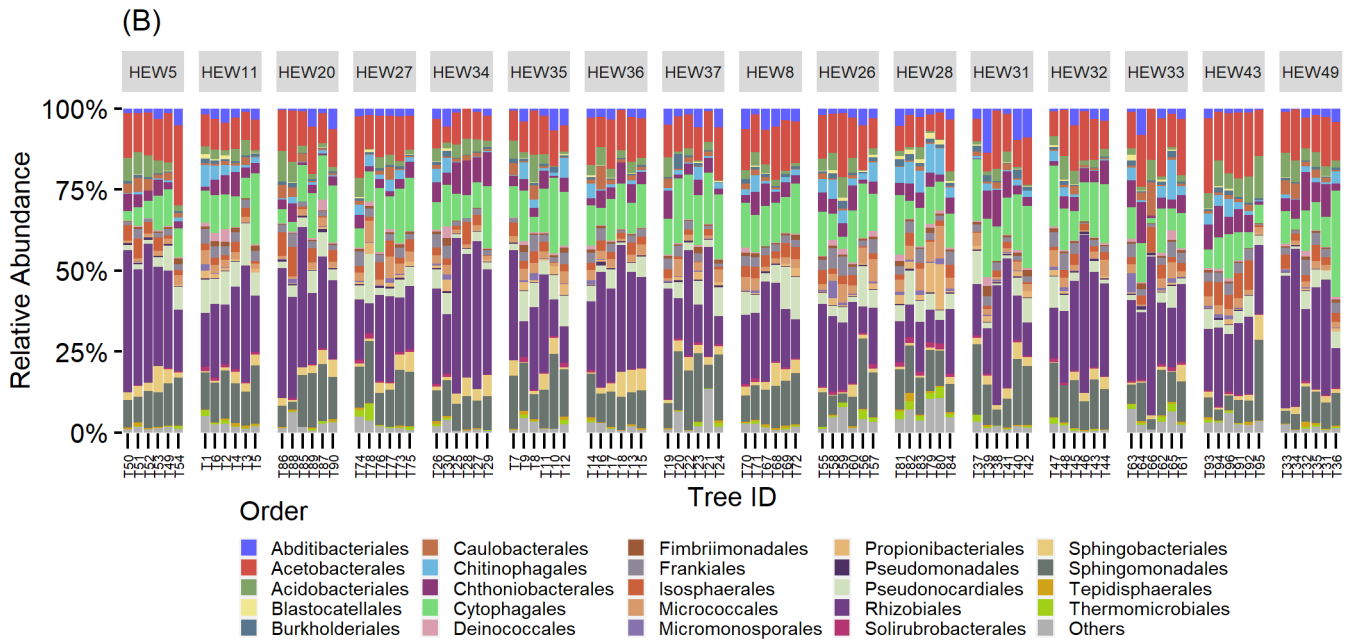
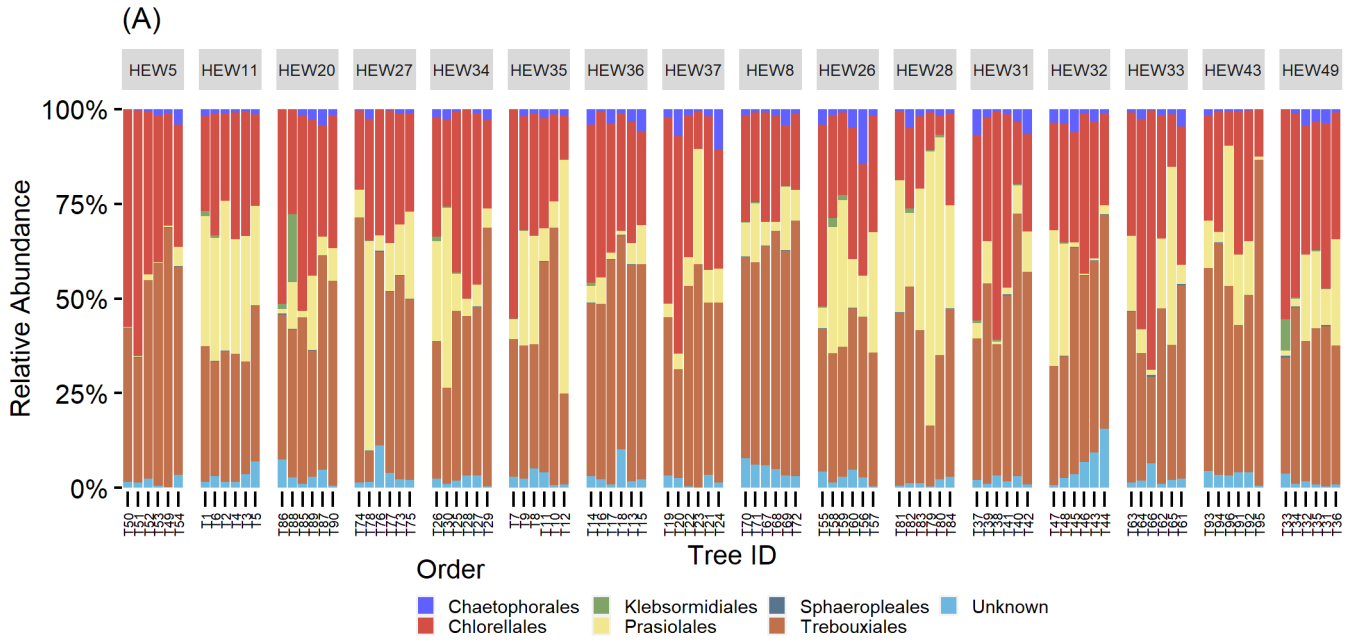
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820 **Figures**

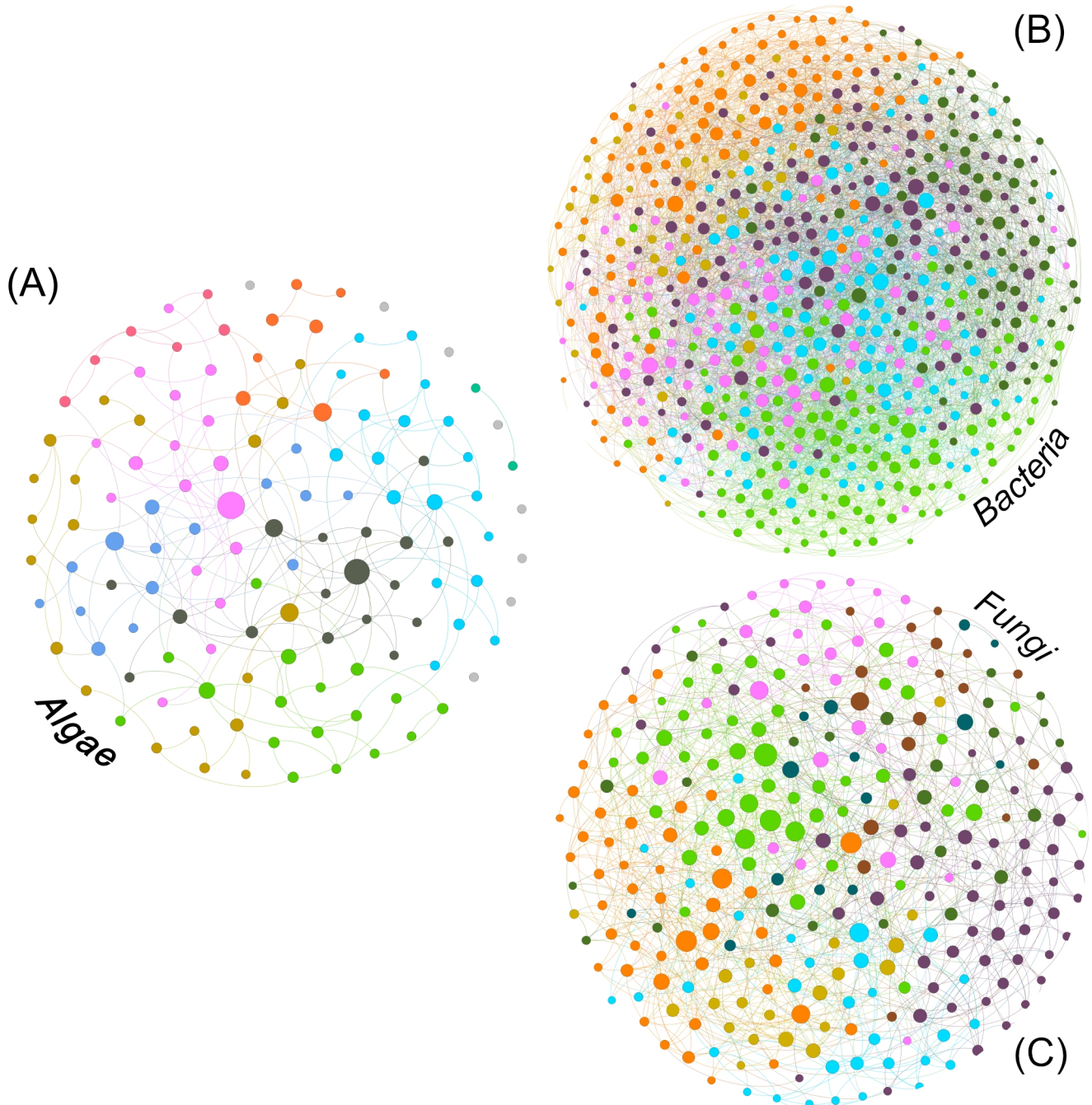


821 Figure 1 Rain-Cloud plots of alpha diversity (Shannon) against management regime and tree size
822 for algae (A and D), bacteria (B and E) and fungi (C and F). Differences are visible from the
823 boxplots, while the original data structure is visible from raw data scatters (randomly jittered) and
824 raw data distribution.

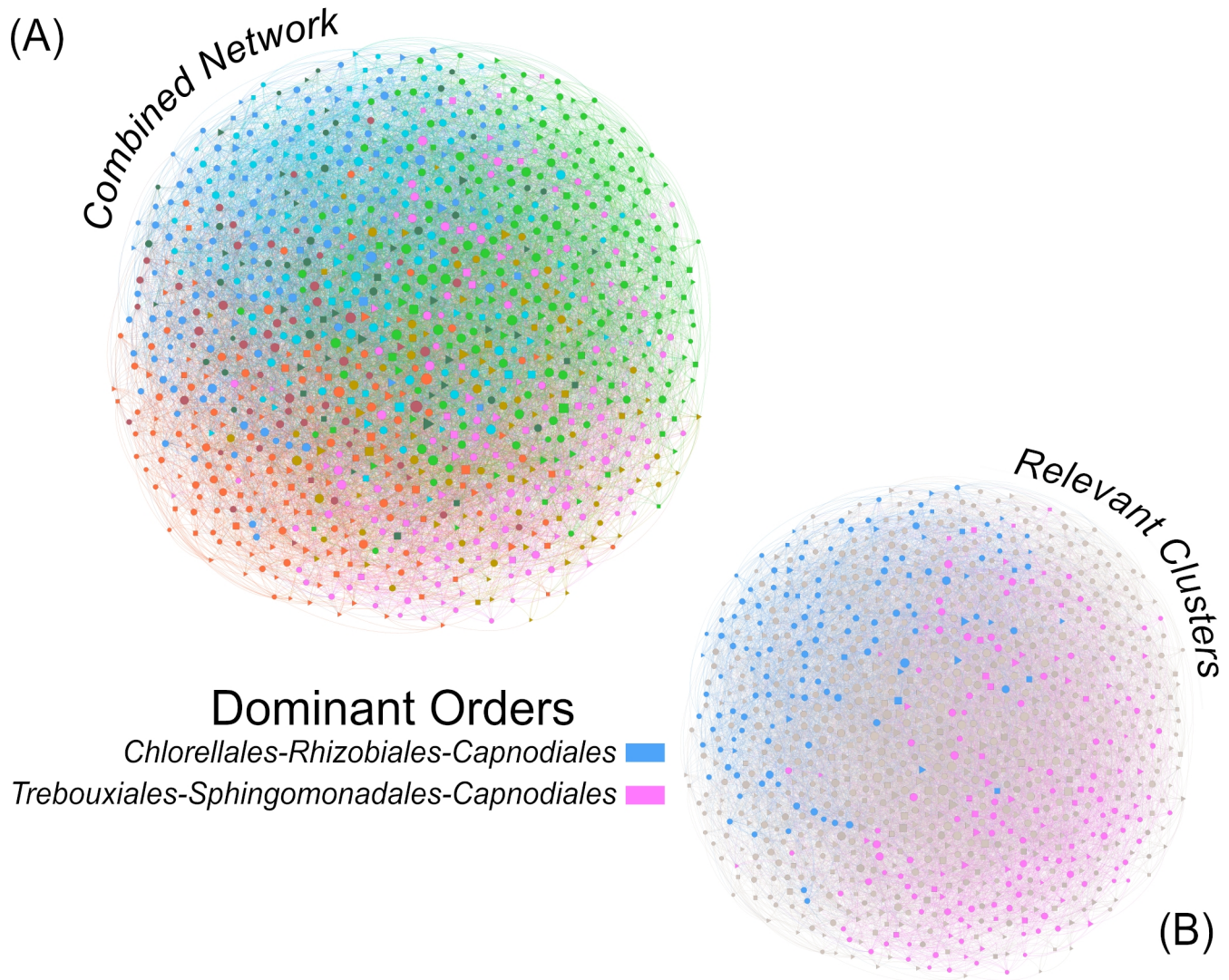


826 Figure 2 Community bar charts showing the relative abundance of the 25 most abundant orders split
827 by sampling plots. From left to right: the first eight plots are under a low-, and the next eight under
828 a high-management regime. Bars within plots represent individual trees, from large to small tree-
829 size class (2 trees each), from left to right.

830

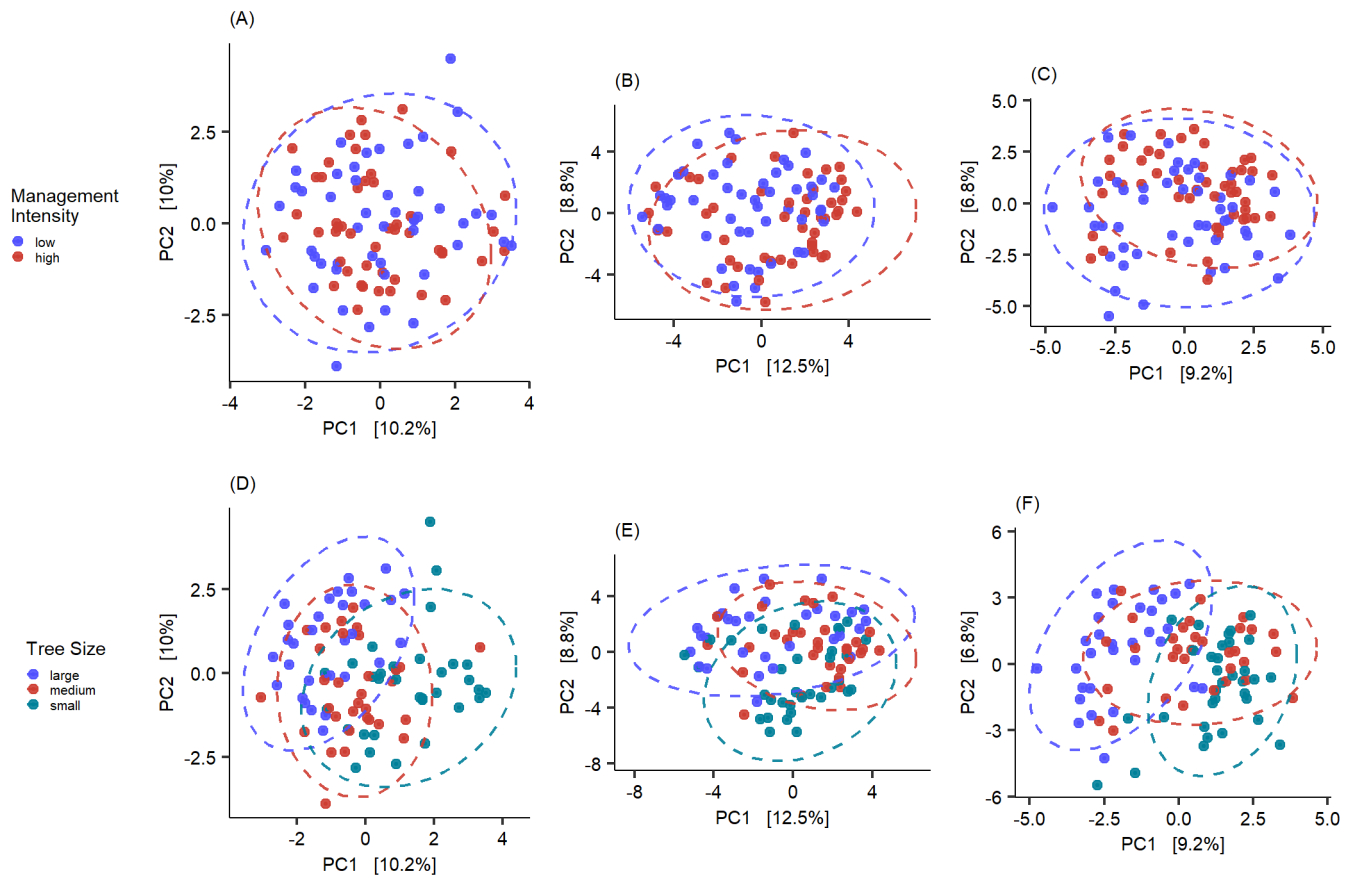


831 Figure 3 Intra-group ASV interaction network for algal (A), bacterial (B) and fungal (C) fractions of
832 the bark microbiome. The size of the nodes is proportional to the value of betweenness centrality
833 (based on Brandes, 2001) and colours correspond to modules (Blondel et al., 2008).



834 Figure 4: Inter-group ASV interaction network integrating algal, bacterial and fungal taxa for a
835 description of the interactions within the complete bark microbiome (A). The two coloured modules
836 (B) are the two most abundant modules of the whole dataset, accounting for 29% (pink) and 26%
837 (blue) of the total reads. The size of the nodes is proportional to the value of betweenness centrality
838 (based on Brandes, 2001) and colours correspond to modules (Blondel et al., 2008).

839



840 Figure 5 Overview of the Principle Component Analysis for algae (A and D), bacteria (B and E) and
841 fungi (C and F). Colours indicate the tested groups and axes are scaled to the proportion of variance
842 explained by the displayed Principal Component (Nguyen and Holmes, 2019).

843

844 **Tables**

Table 1: Primer names and sequences used in this study.

Direction	Name	Sequence	Source
Algae			
Forward	ITS-Cha3	CAACTCTCRRCAACGGATA	(Cheng et al., 2016)
Reverse	ITS u4	RGTTTCTTTTCCTCCGCTTA	(Cheng et al., 2016)
Bacteria			
Forward	341F (modified)	CCTACGGGWGGCWGCAG	(Vieira et al., 2020)
Reverse	785R	GACTACHVGGGTATCTAATCC	(Herlemann et al., 2011)
Fungi			
Forward	FITS7 (modified)	GTGARTCATCGAATCTTTG	(Leonhardt et al., 2019)
Reverse	ITS 4 (modified)	TCCTCCGCTTATTGATATGC	(Leonhardt et al., 2019)

845

846

Table 2 Overview of Moran's I (MI) values for all three organismal groups in the studied plots. An observed higher significant p-value (< 0.05) vs. expected indicates positive autocorrelation, whereas lower MI values indicate negative autocorrelation.

Plot ID	Algae			Bacteria				Fungi				
	MI (observed)	MI (expected)	sd	MI (observed)	MI (expected)	sd	P value	MI (observed)	MI (expected)	sd	P value	
HEW11	-0.19	-0.2	0.17	0.95 (n.s.)	-0.09	-0.2	0.12	0.32 (n.s.)	0	-0.2	0.24	0.41 (n.s.)
HEW20	-0.41	-0.2	0.16	0.17 (n.s.)	-0.15	-0.2	0.14	0.72 (n.s.)	-0.43	-0.2	0.16	0.13 (n.s.)
HEW26	-0.26	-0.2	0.24	0.8 (n.s.)	-0.55	-0.2	0.21	0.09 (n.s.)	-0.24	-0.2	0.23	0.86 (n.s.)
HEW27	-0.46	-0.2	0.2	0.19 (n.s.)	-0.09	-0.2	0.19	0.54 (n.s.)	-0.27	-0.2	0.24	0.77 (n.s.)
HEW28	0.32	-0.2	0.3	0.09 (n.s.)	-0.33	-0.2	0.22	0.55 (n.s.)	-0.39	-0.2	0.31	0.53 (n.s.)
HEW31	-0.09	-0.2	0.11	0.31 (n.s.)	-0.36	-0.2	0.16	0.31 (n.s.)	0.02	-0.2	0.14	0.12 (n.s.)
HEW32	0.04	-0.2	0.13	0.06 (n.s.)	-0.18	-0.2	0.09	0.84 (n.s.)	0.05	-0.2	0.15	0.09 (n.s.)
HEW33	-0.22	-0.2	0.25	0.93 (n.s.)	-0.21	-0.2	0.08	0.9 (n.s.)	0.04	-0.2	0.29	0.41 (n.s.)
HEW34	-0.3	-0.2	0.16	0.52 (n.s.)	-0.3	-0.2	0.19	0.62 (n.s.)	-0.35	-0.2	0.2	0.47 (n.s.)
HEW35	-0.35	-0.2	0.14	0.29 (n.s.)	-0.14	-0.2	0.15	0.71 (n.s.)	0.09	-0.2	0.13	0.03 (*)
HEW36	-0.31	-0.2	0.12	0.39 (n.s.)	-0.2	-0.2	0.11	0.99 (n.s.)	-0.12	-0.2	0.09	0.37 (n.s.)
HEW37	0.01	-0.2	0.11	0.07 (n.s.)	-0.2	-0.2	0.09	0.98 (n.s.)	-0.27	-0.2	0.11	0.53 (n.s.)
HEW43	-0.31	-0.2	0.15	0.48 (n.s.)	-0.34	-0.2	0.09	0.14 (n.s.)	-0.34	-0.2	0.08	0.08 (n.s.)
HEW49	-0.15	-0.2	0.1	0.58 (n.s.)	-0.38	-0.2	0.11	0.1 (n.s.)	-0.13	-0.2	0.08	0.44 (n.s.)
HEW5	-0.06	-0.2	0.09	0.09 (n.s.)	-0.29	-0.2	0.1	0.38 (n.s.)	-0.01	-0.2	0.09	0.04 (*)
HEW8	0.31	-0.2	0.22	0.02 (*)	0.38	-0.2	0.26	0.02 (*)	0.25	-0.2	0.28	0.11 (n.s.)

Table 3 Taxonomic description of the most abundant ASVs and their relative abundance for modules with more than 10 ASVs.

ASV ID	#	Kingdom	Phylum	Class	Order	Family	Genus	Rel. abund.
Algae								
ASV_4	2	Eukaryota	Chlorophyta	Trebouxiophyceae	Prasiolales	Prasiolaceae	Desmococcus	0.47
ASV_1	4	Eukaryota	Chlorophyta	Trebouxiophyceae	Trebouxiales	Trebouxiaceae	Symbiochloris	0.8
ASV_7	5	Eukaryota	Chlorophyta	Trebouxiophyceae	Trebouxiales	Trebouxiaceae	Trebouxia	0.4
ASV_2	7	Eukaryota	Chlorophyta	Trebouxiophyceae	Chlorellales	Chlorellaceae	Apatococcus	0.38
ASV_33	9	Eukaryota	Chlorophyta	Chlorophyceae	Chaetophorales	Chaetophoraceae	Diplosphaera	0.44
Bacteria								
ASV_2	0	Bacteria	Proteobacteria	Alphaproteobacteria	Acetobacterales	Acetobacteraceae	Acidiphilium	0.47
ASV_8	1	Bacteria	Proteobacteria	Alphaproteobacteria	Rhizobiales	Beijerinckiaceae	Methylocella	0.13
ASV_210	2	Bacteria	Abditibacteriota	Abditibacteria	Abditibacteriales	Abditibacteriaceae	Abditibacterium	0.08
ASV_54	3	Bacteria	Proteobacteria	Alphaproteobacteria	Acetobacterales	Acetobacteraceae	Acidiphilium	0.11
ASV_38	4	Bacteria	Proteobacteria	Alphaproteobacteria	Acetobacterales	Acetobacteraceae	Acidiphilium	0.11
ASV_6	5	Bacteria	Proteobacteria	Alphaproteobacteria	Rhizobiales	Beijerinckiaceae	1174-901-12	0.15
ASV_46	6	Bacteria	Abditibacteriota	Abditibacteria	Abditibacteriales	Abditibacteriaceae	Abditibacterium	0.13
Fungi								
ASV_11	0	Fungi	Ascomycota	Lecanoromycetes	Lecanorales	Lecanoraceae	Scoliciosporum	0.19
ASV_23	1	Fungi	Ascomycota	Eurotiomycetes	Chaetothyriales	Herpotrichiellaceae	Capronia	0.58
ASV_51	2	Fungi	Ascomycota	Dothideomycetes	Capnodiales			0.14
ASV_32	3	Fungi	Ascomycota	Dothideomycetes	Capnodiales	Mycosphaerellaceae		0.25
ASV_43	4	Fungi	Ascomycota	Dothideomycetes	Capnodiales			0.39
ASV_4	5	Fungi	Ascomycota					0.36
ASV_6	6	Fungi	Ascomycota	Leotiomycetes	Helotiales			0.3
ASV_1	7	Fungi	Ascomycota	Dothideomycetes	Capnodiales			0.88
ASV_61	8	Fungi	Ascomycota					0.18

Table 4 Taxonomic information for the hub taxa of the respective network, identified based on their betweenness centrality.

ASV ID	Kingdom	Phylum	Class	Order	Family	Genus
Algae						
ASV 10	Eukaryota	Chlorophyta	Trebouxiophyceae	Chlorellales	Chlorellaceae	Apatococcus
ASV 11	Eukaryota	Chlorophyta	Trebouxiophyceae	Chlorellales	Chlorellaceae	Apatococcus
ASV 13	Eukaryota	Chlorophyta	Trebouxiophyceae	Trebouxiales	Trebouxiaceae	Symbiochloris
ASV 22	Eukaryota	Chlorophyta	Trebouxiophyceae	Trebouxiales	Trebouxiaceae	Trebouxia
ASV 8	Eukaryota	Chlorophyta	Trebouxiophyceae	Chlorellales	Chlorellaceae	Apatococcus
Bacteria						
ASV 162	Bacteria	Planctomycetota	Planctomycetes	Isosphaerales	Isosphaeraceae	Tundrisphaera
ASV 19	Bacteria	Proteobacteria	Alphaproteobacteria	Rhizobiales	Beijerinckiaceae	1174-901-12
ASV 559	Bacteria	Bacteroidota	Bacteroidia	Cytophagales	Hymenobacteraceae	Hymenobacter
ASV 79	Bacteria	Actinobacteriota	Actinobacteria	Pseudonocardiales	Pseudonocardiaceae	Actinomycetospora
ASV 855	Bacteria	Bdellovibrionota	Oligoflexia	Oligoflexales	Oligoflexaceae	Oligoflexus
Fungi						
ASV 16	Fungi	Ascomycota	Dothideomycetes	Capnodiales		
ASV 18	Fungi	Basidiomycota	Tremellomycetes	Tremellales	Tremellaceae	Tremella
ASV 4	Fungi	Ascomycota				
ASV 56	Fungi	Ascomycota	Dothideomycetes	Dothideales	Aureobasidiaceae	Aureobasidium
ASV 65	Fungi	Ascomycota	Dothideomycetes	Capnodiales		
Combined						
ASV 116	Fungi	Ascomycota	Dothideomycetes	Pleosporales	Massarinaceae	Massarina
ASV 65	Fungi	Ascomycota	Dothideomycetes	Capnodiales		
ASV 116	Bacteria	Verrucomicrobiota	Verrucomicrobiae	Chthoniobacterales	Chthoniobacteraceae	LD29
ASV 713	Bacteria	Bacteroidota	Bacteroidia	Chitinophagales	Chitinophagaceae	Edaphobaculum
ASV 105	Eukaryota	Chlorophyta	Trebouxiophyceae	Trebouxiales	Trebouxiaceae	Trebouxia