



The effects of host age and spatial location on bacterial community composition in the English Oak tree (*Quercus robur*)

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1 **The effects of host age and spatial location on bacterial community**
2 **composition in the English Oak tree (*Quercus robur*)**

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31 **Summary**

32 Drivers of bacterial community assemblages associated with plants are
33 diverse and include biotic factors, such as competitors and host traits, and
34 abiotic factors, including environmental conditions and dispersal mechanisms.
35 We examine the roles of spatial distribution and host size, as an
36 approximation for age, in shaping the microbiome associated with *Quercus*
37 *robur* woody tissue using culture-independent 16S rRNA gene amplicon
38 sequencing. In addition to providing a baseline survey of the *Q. robur*
39 microbiome, we screened for the pathogen of acute oak decline. Our results
40 suggest that age is a predictor of bacterial community composition,
41 demonstrating a surprising negative correlation between tree age and alpha
42 diversity. We find no signature of dispersal limitation within the Wytham
43 Woods plot sampled. Together, these results provide evidence for niche-
44 based hypotheses of community assembly and the importance of tree age in
45 bacterial community structure, as well as highlighting that caution must be
46 applied when diagnosing dysbiosis in a long-lived plant host.

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56 Introduction

57 Many lines of evidence suggest that microbes are crucial for plant health and
58 function (Kim *et al.*, 2011; Berendsen *et al.*, 2012), and yet we have a
59 relatively poor understanding of which mechanisms shape the plant-
60 associated microbial community or how this might in-turn influence host traits.
61 Furthermore, although plant microbiome research has primarily focused on
62 the below ground portion of the plant (the rhizosphere), knowledge of the
63 phylloplane (the microbial composition of leaves) is increasing (Lindow and
64 Brandl, 2003; Vorholt, 2012), demonstrating an equally important role in
65 shaping plant phenotype. Still less is known regarding the microbial
66 composition of other organs, with distinct communities reported across tissues
67 within the host, often playing a more important role than biogeography
68 (Ottesen *et al.*, 2013; Leff *et al.*, 2014; Coleman-Derr *et al.*, 2016). For tree
69 species in particular, the dermosphere (bark associated microbial community,
70 (Lambais *et al.*, 2014) may be particularly important given that bacterial
71 pathogens often invade the host through wounds in the bark (Tattar, 2012;
72 Misas-Villamil *et al.*, 2013). This variation among tissues mirrors what is
73 observed in other long-lived hosts, including humans, where data is most
74 abundant; distinct bacterial communities have been isolated from different
75 skin sites (Grice *et al.*, 2009) and these differences appear stable over time
76 (Costello *et al.*, 2009). Such variation is also likely to exist across individual
77 plant microbiomes given that they can be heritable (Peiffer *et al.*, 2013),
78 shaped by host genetics (Bodenhausen *et al.*, 2014; Beckers *et al.*, 2016),
79 and play functional roles that include sensitizing the plant immune system
80 (Pieterse *et al.*, 2014).

81

82 The root-associated microbiomes of healthy *Arabidopsis* plants are arguably
83 the best understood plant microbiome (Lundberg *et al.*, 2012) with the
84 mechanisms behind host regulation recently coming to light (Lebeis *et al.*,
85 2015). However, many more non-model plant species have had their
86 microbiomes characterized. For example, a number of studies have explored
87 the nature of tree microbiomes, providing baseline taxonomic surveys and
88 assessing the drivers of community composition, typically contrasting host
89 traits with climatic or geographic variables. Many of these studies find a strong
90 effect of host phylogeny on the bacterial community, with a greater effect of
91 tree species than geographic distance, even across continents (Redford *et al.*,
92 2010; Lambais *et al.*, 2014). Similarly, in a tropical environment in Malaysia,
93 Kim *et al.* (Kim *et al.*, 2012) found a strong signal of host phylogeny on
94 bacterial community composition. Functional host traits such as growth rate
95 and leaf mass have also been demonstrated as key drivers of composition,
96 alongside phylogeny (Kembel *et al.*, 2014). In contrast, Finkel *et al.* (Finkel *et*
97 *al.*, 2012) found trees of the same species in a different desert locations host
98 distinct microbial communities. Given these conflicting results across the
99 scales examined, it is unclear whether phylloplane microbiomes are subject to
100 niche-based or neutral models of community assembly.

101

102 Specifically, the roles of dispersal and immigration, in combination with
103 ecological selection and drift (Vellend, 2010), have been the focus of a
104 number of theoretical models of community assembly, many of which are
105 applicable to microbes (Sloan *et al.*, 2006; Nemergut *et al.*, 2013). The niche

106 assembly model states that the dispersal of bacteria is unhindered by physical
107 constraints, and all organisms can be found anywhere but it is the
108 environment which selects for their persistence (de Wit and Bouvier, 2006).
109 Conversely, the dispersal assembly hypothesis states that the biodiversity we
110 observe can largely be explained by stochastic local extinctions and dispersal-
111 limitation, typified by the idea of island biogeography (Hubbell, 2001; Volkov
112 *et al.*, 2003). Whilst this is essentially the “niche vs. neutral” debate, Fierer
113 (Fierer, 2008) provides the nuances of the microbial context including the
114 much higher species richness and evenness, and the rapidity of species
115 turnover typical of most bacterial communities.

116

117 The English oak tree, *Quercus robur*, study system provides an opportunity to
118 test these competing hypotheses. If microbial community assembly is purely a
119 dispersal-driven process, we would predict a positive relationship between
120 tree age and diversity, as older organisms will have experienced more
121 colonization events. Such a positive relationship has been demonstrated for
122 trees and their plant epiphytes and lichens (Flores-Palacios and Garcia-
123 Franco, 2006; Johansson *et al.*, 2007), but has not been shown before in tree-
124 associated bacterial communities. Alternatively, if the process is strictly niche-
125 driven, older trees could represent an alternative environment to smaller
126 trees, favoring proliferation of particular species but not necessarily harboring
127 a greater diversity.

128

129 As well as dispersal, host traits are likely to govern the microbes present.

130 Among the host factors known to influence microbial diversity, host age is

131 often a key predictor. Data from humans suggests diversity consistently
132 increases with age from birth across populations (Yatsunenکو *et al.*, 2012). In
133 insects, honey bee queens undergo massive compositional shifts in their
134 microbiome as they age (Tarpy *et al.*, 2015) and in a wild bird, *Rissa*
135 *tridactyla*, chicks harbor a greater diversity of bacteria than adults (van
136 Dongen *et al.*, 2013). In plants, bacterial diversity can be highest on younger
137 leaves in lettuces (Dees *et al.*, 2015), however the evidence is mixed as tree-
138 associated bacterial communities can be strongly influenced by season
139 (Peñuelas *et al.*, 2012).

140

141 In this study we describe and explore the bacterial composition of *Q. robur* tree
142 cores in a well-studied UK forest, Wytham Woods, in order to answer three
143 key questions: firstly, what are the typical bacterial taxa associated with this
144 Woodland site; secondly, does geographic distance affect dispersal, such that
145 there is a spatial pattern of community composition and distance between
146 trees; and thirdly, is *Q. robur* host age or location important in structuring
147 bacterial communities. To answer these questions, we first describe the tree-
148 associated microbiota using amplicon sequencing of the 16S rDNA gene of 64
149 trees. Using a long-term woodland census we then assess correlations
150 between alpha and beta diversity and factors such as age and spatial
151 location. Additionally, we use these data to compare the predicted metabolic
152 functionality and screen our dataset for the pathogenic clade *Brenneria*, the
153 causative agent of acute oak decline, from which the UK *Q. robur* population
154 is currently experiencing an epidemic (Denman *et al.*, 2012). This survey
155 presents a unique opportunity to assess the practicality of high throughput

156 sequencing in environmental monitoring. Given the critical importance of
157 detecting and preventing the emergence of tree diseases before large-scale
158 spread, a better understanding of tree microbiomes offers additional value in
159 surveillance.

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161

162 **Experimental Procedures**

163 *Study System*

164 Wytham Woods is one of the most intensively studied tree populations in
165 Europe and undergoes extensive surveys every 2 years. As such, it provides
166 a practical system for correlating a vast number of ecological variables and
167 demographic traits and has been the source of numerous important papers
168 (Hunter *et al.*, 1997; Morecroft *et al.*, 2003; Butt *et al.*, 2009). The UK *Q. robur*
169 population is suffering a number of infectious diseases, collectively known as
170 oak decline. This comprises chronic oak decline, sudden oak decline and
171 acute oak decline (AOD) (Denman and Webber, 2009). Symptoms, such as
172 stem bleeding, are strikingly similar, which makes misdiagnosis with
173 Phytophthora or bupestrid beetles possible. A number of bacterial species
174 from the *Brenneria* genus have been isolated from *Q. robur* trees suffering
175 from AOD and it is likely that this species is the causal agent (Denman *et al.*,
176 2012). The disease has not yet been reported in Wytham Woods (Kirby *et al.*,
177 2014) so the absence of *Brenneria* species on healthy trees would buttress
178 the existing evidence that *Brenneria* is the primary pathogen.

179

180 *Site sampling*

181 We sampled 64 *Q. robur* trees in a single hectare, collecting 192 samples in
182 over 3 days in September, 2013. Tree diameter at breast height (DBH) was
183 recorded as a proxy for tree age. This method is endorsed by the UK forestry
184 commission as a non-destructive mode of estimating tree age (Commission,
185 1998). Whilst comparisons among trees at different sites due to crowding may
186 be inaccurate, comparisons of the same species at the same site provides
187 reliable estimates of tree age. Further, using trees from our dataset that had
188 known planting dates, we observe a linear relationship between diameter and
189 age, reinforcing the view that DBH is a good proxy for age (SI, Figure 1).

190

191 Core tissue samples were obtained using the Trephor tool (Rossi *et al.*, 2006),
192 allowing for three small (approximately 3 cm) microcore samples to be taken
193 at breast height at three separate sites (North, Southwest, and Southeast).
194 The tool was sterilized and wiped thoroughly using 70% ethanol in between
195 each sample extraction. Samples were flash frozen in the field for
196 transportation back to the laboratory. Upon return to the laboratory, samples
197 were homogenized using a Fast-Prep 24 instrument (MP Biomedicals) for five
198 minutes with the addition of two 0.5cm steel beads. Total DNA was then
199 extracted from the resulting homogenate using a Qiagen DNeasy Plant Mini
200 Kit, following the protocol provided. For amplification of the V4 region of the
201 16S rDNA gene, the universal primer set GTGCCAGCMGCCGCGGTAA (5' --
202 - 3') and GGACTACHVGGGTWTCTAAT (5' --- 3') was used.

203

204 *Brenneria amplification*

205 To demonstrate that the primers used in our study could amplify *Brenneria*
206 *goodwinii* we cultured strain 931-23 (provided by R. Jackson, University of
207 Reading) and chose a random subset of 5 of the primers used to amplify the
208 V4 region to test for amplification in these positive controls.

209

210 *Bioinformatic analysis*

211 Illumina MiSeq 250bp paired-end reads were demultiplexed and de-barcoded
212 at the sequencing centre (Source Biosciences, Oxford). Sequences have
213 been deposited in the NCBI short-read archive (accession PRJNA 298668).
214 Quality filtering of reads was conducted using the Qiime (1.9.0) pipeline
215 (Caporaso *et al.*, 2010). Reads were joined and filtered with the default
216 settings (Bokulich *et al.*, 2013). Briefly, a maximum of 3 consecutive low
217 quality base calls was allowed before truncating the read, phred-score
218 threshold was set at 30 (which provides a 99.9% accuracy of base call), 75%
219 of the read was required to consist of high-quality, consecutive base call and
220 all reads with N character base calls were dropped. Open reference OTU
221 picking was conducted using the Uclust algorithm and the Silva 111 16S
222 rDNA database at the 97% identity level (Pruesse *et al.*, 2007; Edgar, 2010).
223 Chimera removal was performed with Chimera Slayer (Haas *et al.*, 2011);
224 OTUs present at abundances less than 0.005% of the dataset were removed
225 as were OTUs observed in only a single instance, as both are known to inflate
226 diversity estimates (Bokulich *et al.*, 2013). Mitochondrial and chloroplast
227 sequences were also removed. This left a remaining dataset with a total of
228 1013881 sequences spread across 115 samples, containing a median count
229 of 1830 sequences per sample (mean 8816, length: 251.8 bp). Using the

230 same trimmed sequence files, closed-reference OTU picking was performed
231 against the GreenGenes (1.5) (DeSantis *et al.*, 2006) database (as required
232 by Picrust) using the uclust algorithm implemented in Qiime (1.9). Functional
233 predictions of observed taxa was made using the Picrust program (Langille *et*
234 *al.*, 2013) using the Kegg orthology database (Kanehisa *et al.*, 2014).

235

236

237 **Statistical analysis**

238 Rarefaction was performed for diversity analyses to a depth of 500 sequences
239 per sample. Whilst this is relatively low for microbiome studies, we aimed to
240 maintain high levels of biological replication at the cost of sampling depth
241 within individual samples. Pseudo R^2 values were calculated using the
242 residual and null deviance from model outputs as described in Faraway
243 (2006). UniFrac scores were generated in Qiime and statistical analyses were
244 performed in R (R Core Team, 2015) using the packages 'vegan' (Oksanen *et*
245 *al.*, 2016) and 'cluster' (Maechler *et al.*, 2015).

246

247 **Results**

248

249 *Baseline survey of the Quercus robur microbiome*

250 The most abundant bacterial class observed within our samples was the
251 alphaproteobacteria, with a mean relative abundance of 26% (+/- 12 S.D.),
252 followed by the thermoleophilia with 22% (+/- 15 S.D.), and the
253 betaproteobacteria, contributing a mean of 13% (+/- 15 S.D.). Overall,
254 acidobacteria, actinobacteria and proteobacteria were the three most
255 abundant phyla, making up over 80% of OTUs (Figure 1).

256

257 *Age related decline in microbial diversity*

258 We identified a weak negative correlation between tree size and species
259 richness (using observed OTUs) when controlling for uneven sampling of
260 individual trees (GLM, $F_{1,87}=4.13$, $p=0.0453$, pseudo $R^2=0.048$) (Figure 2.).
261 Observed OTU count was used as the measure of species richness, however
262 the result was non-significant when Faith's phylogenetic distance or Chao 1
263 estimator (Chao *et al.*, 2004) was used ($p=0.12$ and 0.16 respectively). There
264 was no effect of sample orientation (cardinal direction), and this factor was
265 therefore excluded from the model during stepwise model simplification.
266 Interestingly, these correlations strengthened when sample size was
267 increased to 110 samples by using a lower rarefaction depth (100 sequences,
268 data not shown). A similar result was mirrored by beta-diversity, where tree
269 size was a significant predictor of microbial community composition using both
270 abundance weighted UniFrac scores (PERMANOVA, $F_{1,87}=4.63$, $p=0.0036$,
271 $R^2=0.052$, permutations=9999) and unweighted UniFrac scores
272 (PERMANOVA, $F_{1,87}=2.93$, $p=0.027$, $R^2=0.033$, permutations=9999) when
273 tree ID was controlled for.

274

275 *Taxa correlations*

276 To investigate changes in composition further we performed Spearman rank
277 correlations against tree size for each OTU in the dataset, and found no
278 significant associations following correction for multiple testing. To further
279 assess whether there were higher taxonomic level associations between
280 specific bacterial clades and tree size we selected the three most abundant

281 phyla. Collectively, the Proteobacteria, Actinobacteria and Acidobacteria
282 made up over 80% of our sequences. We found a significant decrease in the
283 relative abundance of Proteobacteria with tree size (Kendall's rank correlation,
284 $\tau=-0.22$, $z=-3.39$, $p=0.0007$), a significant increase in the relative abundance
285 of Actinobacteria ($\tau=0.19$, $z=3.04$, $p=0.0023$) and a non-significant decrease
286 in Acidobacteria ($\tau=-0.14$, $z=-2.13$, $p=0.033$) following Bonferroni correction
287 (Figure 3).

288

289 *Functional predictions*

290 In order to predict how the function of communities associated with our *Q.*
291 *robur* trees changed as they aged we created a predicted metagenome using
292 the Picrust program (Langille *et al.*, 2013). However, we found no correlation
293 between any of the predicted individual genes or functional pathways
294 associated with our observed microbiome and tree size, perhaps indicating
295 high functional redundancy of the more diverse microbiota of smaller trees.

296

297 *Assessing spatial patterns*

298 Finally, to look for patterns of biogeography, or dispersal limitation, we
299 performed Mantel correlations between a spatial matrix from the Euclidean
300 distances between trees and the UniFrac scores that measure bacterial
301 community composition. A correlation would be indicative that the spatial
302 distribution of trees does indeed affect the bacterial composition of the
303 community. There was no effect of abundance for either weighted (Mantel $r =$
304 0.0009 , $p=0.47$, permutations=9999) or unweighted UniFrac scores ($r=0.002$,
305 $p=0.46$, permutations=9999), suggesting an absence of dispersal limitation.

306

307 *Brenneria*

308 Reassuringly, we found no sequences identified as *Brenneria* in our dataset
309 (prior to rarefaction), despite confirming that all our tested primers could
310 successfully amplify this species following culture *in vitro*.

311

312 **Discussion**

313 Our study of the bacterial microbiomes of 64 English oak trees (*Quercus*
314 *robur*) in a single woodland provides a number of insights into the drivers of
315 bacterial community structure and dispersal. Firstly, our census of the
316 microbiome of *Q. robur* tissue is consistent with a previous report that found
317 the same 3 most dominant phyla in the roots of oak trees: Actinobacter,
318 Proteobacteria and Acidobacter (Uroz *et al.*, 2010). The high abundance of
319 Acidobacter is also consistent with other culture-independent studies of the
320 phyllospheric microbiota from tropical trees (Kim *et al.*, 2012).

321

322 By comparing tree size with species richness, we found no sign of an increase
323 in bacterial diversity as trees age. This is of particular interest as it suggests
324 factors other than dispersal affect microbiome structure, as would be
325 expected by an increase in microbial diversity with growth as a result of
326 species accumulation. When observed OTUs was used as the measure of
327 alpha diversity we found a weak but significant decline in species richness
328 with tree age. Furthermore, negative correlations between tree age and
329 species richness were significant when the sample size was increased by
330 reducing rarefaction depth (and therefore excluding fewer samples). Detecting
331 subtle changes in species diversity require maximal statistical power, and

332 there is clearly a trade-off between sampling depth and statistical power.
333 Exploring this trade-off in regard to microbial community sampling clearly
334 warrants further study as alternative approaches have yet to be widely
335 adopted (McMurdie and Holmes, 2014). Moreover, quantifying the shape of
336 the age-diversity relationship through the tree lifetime requires longitudinal
337 studies to build on cross-sectional studies like the data presented here. One
338 suggestion for observed age-related differences is variation in the chemical
339 and physiological state of the host tissue (van Dongen *et al.*, 2013) and this
340 could be the case between younger and older *Q.robur* tree tissues.

341

342

343 A flat or negative correlation between tree age and bacterial alpha diversity
344 contrasts the positive association found between epiphytic plants and lichens
345 and tree host age (Flores-Palacios and Garcia-Franco, 2006; Johansson *et*
346 *al.*, 2007) perhaps suggesting that bacteria are less dispersal-limited than
347 other tree-associated organisms. To explore these ideas further, and based
348 on the conflicting niche assembly and dispersal assembly hypotheses
349 (Hubbell, 2001; de Wit and Bouvier, 2006), we predicted that if microbiome
350 structure is purely a function of dispersal, such that communities are
351 assembled by stochastic dispersal events and local extinctions, we would find
352 a correlation between spatial distance among trees and community
353 dissimilarity scores (beta diversity). Conversely, if microbes have unlimited
354 dispersal within the forest, as is often assumed, one would expect no
355 correlation with beta diversity. Our results suggest that latter models are most
356 informative, whereby we find no signature of dispersal limitation (i.e. the

357 community composition of our samples are not influenced by the proximity of
358 others). There is the potential for microbes to disperse at global scales (Morris
359 *et al.*, 2008), however evidence for true cosmopolitan distribution has been
360 mixed to date (Caporaso *et al.*, 2012; Finkel *et al.*, 2012; Sul *et al.*, 2013) and,
361 as demonstrated by Bell (Bell, 2010) also in Wytham Woods, microbial
362 dispersal limitation may be more important over short time scales.

363

364

365 We also found an increase in the relative abundance of Actinobacter and a
366 decrease in Proteobacter and Acidobacter (although the latter was only
367 nearing significance) with tree size. Mechanistically, it is hard to ascribe
368 functions to whole phyla as they encompass a range of morphologies,
369 metabolic diversity and pathogenicity (Dworkin *et al.*, 2006). The Acidobacter
370 are, however, reported to be slow growing with low metabolic rates (Ward *et*
371 *al.*, 2009), sometimes referred to as k-selection strategists due to their higher
372 abundances in soils with lower resource availability (Fierer *et al.*, 2008).

373 Carbon mineralization rate can also be a good predictor of Acidobacter soil
374 abundance, but how well these finding translates to an alternative niche, such
375 as tree cores, remains unknown (Fierer *et al.*, 2008). If this were the case in
376 our system we would expect Acidobacter and Proteobacteria to be inversely
377 correlated; but we find the opposite. Maignien *et al.* (Maignien *et al.*, 2014)
378 have also suggested that phyllosphere communities are first colonized by r-
379 strategists (such as Acinetobacter and Pseudomonas). Moreover, when
380 multiple OTUs of the same species are present in the source community, for
381 example rainfall, only one becomes established in the phyllosphere

382 community, indicative of niche competition (Maignien *et al.*, 2014). Given that
383 the Acidobacter are consistently isolated at high relative abundances from soil
384 it seems likely that the soil is the major contributing source for the interior
385 microbiota of oak trees. Acidobacter have also been detected at high relative
386 abundances in the trunk of *Gingko bilbao* trees but not in the leaves of the
387 same trees, again suggesting soil derived rather than phyllospheric dispersal
388 (Leff *et al.*, 2014). Whether this is through transport of microbes through the
389 phloem or a function of early, seedling colonization remains undetermined.
390 Interestingly, and as a word of caution, we identified the presence of *Ralstonia*
391 in our negative sequencing controls, which has been identified by Salter *et al.*
392 (Salter *et al.*, 2014) as a common kit contaminant. However this group also
393 includes many plant pathogens and wouldn't be unexpected in our
394 environmental samples, highlighting the difficulty in identifying contaminant
395 sequences from environmental samples and the need for negative controls.
396
397 Whilst we have described a shift in bacterial community structure with age,
398 the correlations between specific taxa and age are only present at the phylum
399 level and not at the OTU level. The variability in genomic content, even
400 among closely related bacteria (Perna *et al.*, 2001; Guidot *et al.*, 2007), is
401 often used to justify a lack of ecological or metabolic similarity among hosts.
402 However there is evidence for functional convergence at higher taxonomic
403 ranks (Philippot *et al.*, 2010), including trophic and biogeographic differences
404 (Fierer *et al.*, 2008; Philippot *et al.*, 2009). One mechanism for our observation
405 of size-based differences could be that the age of a plant is the most
406 important factor in determining its induced defenses (Quintero and Bowers,

407 2011). Indeed, the complex interactions between host immune systems and
408 commensal bacteria are coming to light in different systems (Brestoff and
409 Artis, 2013; Franzenburg *et al.*, 2013). For example, the presence of
410 commensal microbes is non-random in a tropical tree host and has been
411 demonstrated to prevent pathogen success, particularly in fungal endophytes
412 (Arnold *et al.*, 2003).

413

414 Despite being present at low numbers, many species could collectively play a
415 role in microbial community function. To explore this idea further we used
416 metagenomic predictions based on our 16S sequences to assess functional
417 diversity. Given that we found a significant shift in the microbial composition
418 (at the Phylum level) with tree age, we expected to find a similar effect of
419 functional traits. We found no such trend, as no individual genes or functional
420 pathways were over or under represented in older tree samples. This lack of
421 functional correlation, despite a taxonomic correlation implies a level of
422 redundancy in gene pathways among bacterial phyla, or lack of sensitivity in
423 the methods used to predict a metagenome. If the latter is true, and the
424 limitation is the quality of annotation in metagenomic databases then
425 ultimately, more metagenomic sequencing may not yield more insight into
426 community function.

427

428 A focus on *Q. robur* allows us to answer some important applied questions: A
429 reassuring outcome of this analysis was that we failed to identify a single
430 sequence from *Brenneria* species. The UK oak population is undergoing an
431 epidemic of acute oak decline (AOD) and the *Brenneria* clade of bacteria have

432 been isolated from oaks experiencing the disease (Denman *et al.*, 2012).
433 Koch's postulates have also been reported in the Spanish oak (*Quercus ilex*)
434 (Poza-Carrión *et al.*, 2008). However acute oak decline was not found to be
435 present in Wytham in 2014 (Kirby *et al.*, 2014) and our data supports that
436 conclusion. This further strengthens the inference that *Brenneria* is a
437 causative agent of the disease, as suggested by Denman *et al.* (Denman *et*
438 *al.*, 2012). Our census provides a baseline of healthy microbial flora in UK *Q.*
439 *robur* and comparison with trees in diseased states is a crucial area for further
440 study. Additionally, the observed differences in microbiome among differently
441 aged trees provides a caution for defining tree microbiome health. The healthy
442 microbiome of a young tree may well appear similar as that of a dysbiotic
443 microbiome of an old tree. As such, when using microbiome studies in the
444 context of plant health, fair comparisons among plant demographics must be
445 made in order to make useful diagnoses.

446

447

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457

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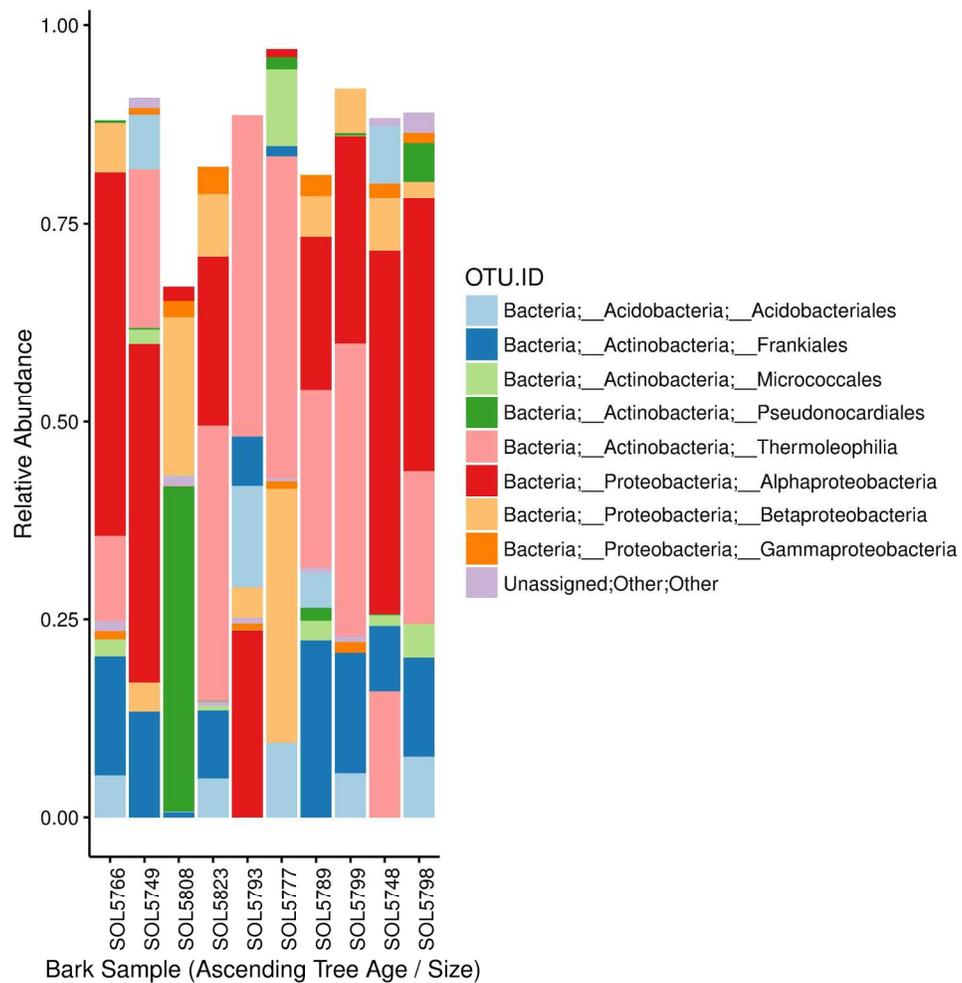
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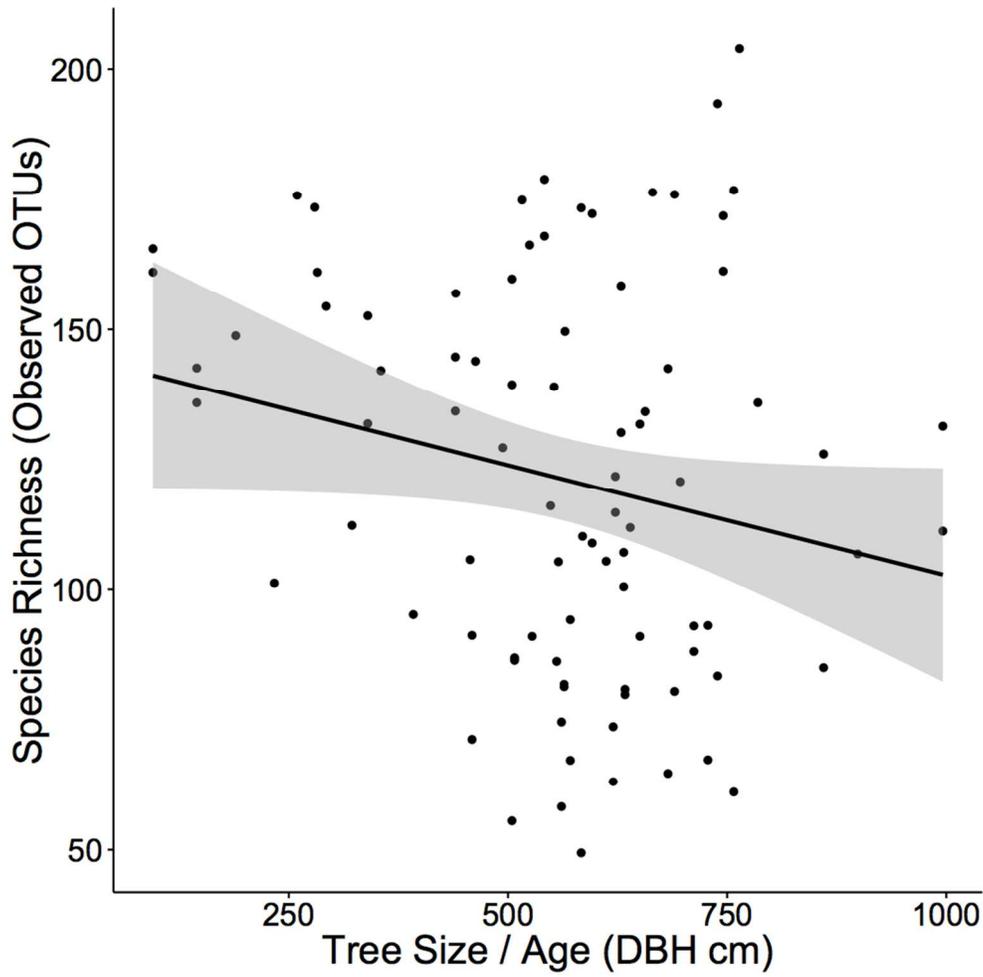
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Randomly selected barplots showing the 9 most common bacterial taxa ordered by ascending tree age (from left to right). Alpha diversity decreases in older trees and there is much variation in beta-diversity. Only those taxa with a mean relative abundance greater than 2.5% across the entire dataset were retained for the figure for clarity.

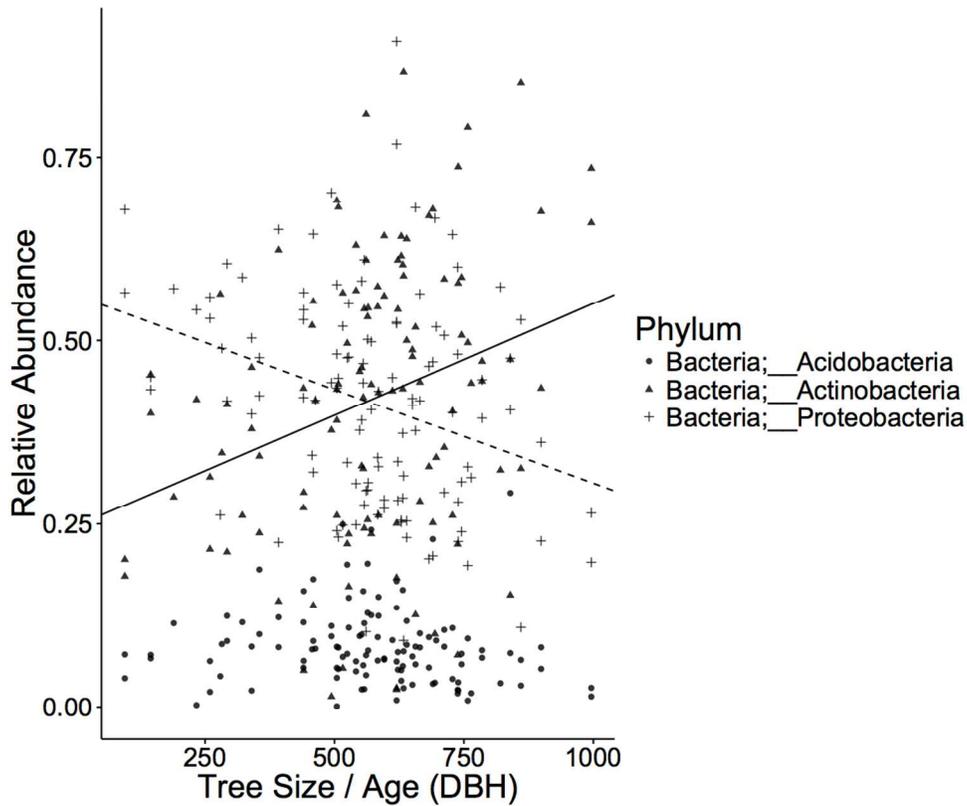
177x177mm (300 x 300 DPI)





Age based decline in species richness based on species richness, as measured by observed OTUs, following rarefaction to a depth of 500 sequences per sample. GLM, $F_{1,87}=4.13$, $p=0.0453$. Intercept = 142, slope = -0.045.
180x177mm (150 x 150 DPI)

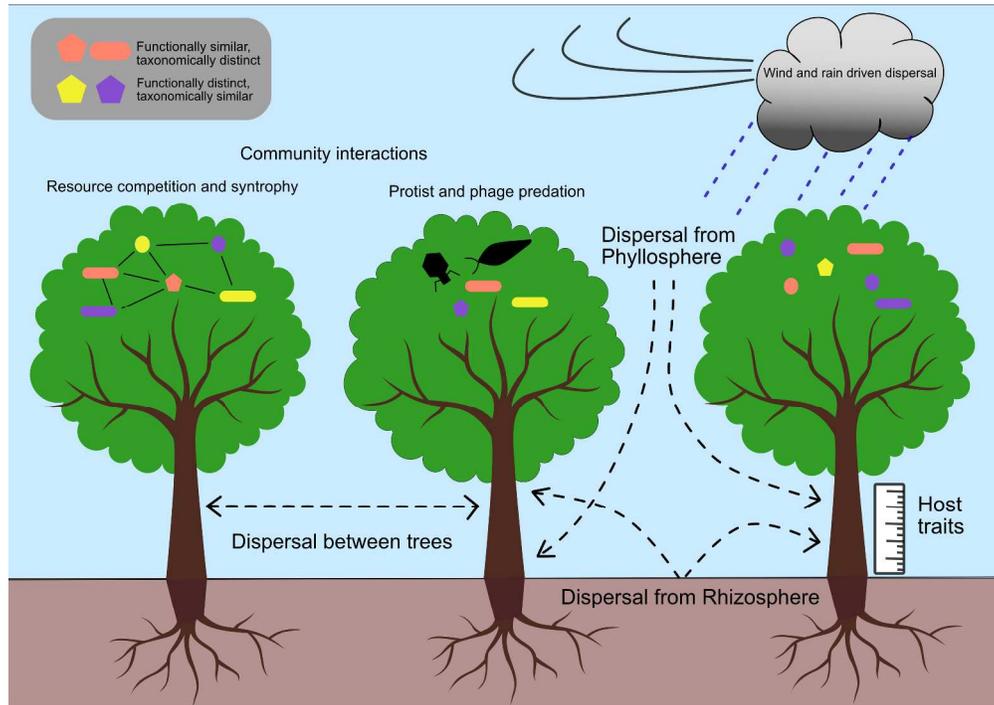




Taxa-specific correlations with Oak Tree age. The relative abundance of Actinobacteria increases with tree age (triangles, solid line, intercept = 0.25, slope = 0.00030) (Kendall's rank correlation, $\tau=0.19$, $z=3.04$, $p=0.0023$), whilst the relative abundance of Proteobacteria declines (crosses, dashed line, intercept = 0.56, slope = -0.00026) ($\tau=-0.22$, $z=-3.39$, $p=0.0007$). The relative abundance of Acidobacteria also declines however this is non-significant after Bonferroni correction ($\tau=-0.14$, $z=-2.13$, $p=0.033$).

217x177mm (150 x 150 DPI)

Only



Conceptual diagram of potential drivers of bacterial community composition in our Oak tree system. Communities may be seeded from wind and rain driven dispersal, or colonize the plant directly from the soil during growth. Following initial colonization, the microbes must survive, and potentially thrive, in the observed niche. The niche is likely to be dictated by, among others, competition for host resources, predation and environmental conditions.