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► To cite this version:

Mathilde Jeanbille, Sana Romdhane, Marie-Christine Breuil, David Bru, Stefan Geisen, et al.. Size exclusion experiment in a grassland field unravels top-down control of the soil fauna on microbial community assembly. *Ecology Letters*, 2024, 27 (6), pp.e14442. 10.1111/ele.14442 . hal-04674236

HAL Id: hal-04674236

<https://hal.inrae.fr/hal-04674236v1>

Submitted on 21 Aug 2024

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1 **Size exclusion experiment in a grassland field unravels top-down control of the soil fauna on**
2 **microbial community assembly**

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15 **Authorship**

16 LP designed the study. DB, MJ, LP, SR, and AS were involved in the field work. MCB and MJ pro-
17 cessed the samples. DB and MJ carried out the molecular analysis. MJ, SR, AS and AM analysed the
18 data and performed the statistical analysis. MJ, SG, LP, SR, and AS discussed, interpreted and wrote
19 the manuscript. All authors reviewed the manuscript.

20

21 **Data availability statement**

22 Raw sequences were deposited at the NCBI database under the BioProjects PRJNA1024461,
23 PRJNA1024675 and PRJNA1024888 (<https://www.ncbi.nlm.nih.gov/bioproject/>). Source data and R
24 scripts are available at <https://doi.org/10.5281/zenodo.11072396>

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27

28 **Running title:** Microbial response to soil fauna exclusion

29

30 **Keywords:** interkingdom interactions, bacteria, fungi, protists, grassland soil, size-exclusion

31

32 **This article is submitted as a *Letter* and contains :**

33 - 149 words in abstract

34 - 4852 words in article

35 - 61 references

36 - 5 figures

37 **ABSTRACT**

38 Highly diverse and abundant organisms coexist in soils. However, the contribution of biotic
39 interactions between soil organisms to microbial community assembly remains to be explored. Here,
40 we assess the extent to which soil fauna can shape microbial community assembly using an exclusion
41 experiment in a grassland field to sort soil biota based on body size. After one year, the exclusion of
42 larger fauna favored phagotrophic protists, with increases up to 32% in their proportion compared to
43 the no-mesh treatment. In contrast, members of the bacterial community and to a lesser extent of the
44 fungal community were negatively impacted. Shifts in bacterial but not in fungal communities were
45 best explained by the response of the protistan community to exclusion. Our findings provide empirical
46 evidence of top-down control on the soil microbial communities and underline the importance of
47 integrating higher trophic levels for a better understanding of the soil microbiome assembly.

48 INTRODUCTION

49 Soil biota encompass highly diverse organisms representing more than half of Earth's
50 biodiversity (Anthony *et al.* 2023). Besides bacteria and fungi, which have traditionally been the most
51 studied groups of soil-dwelling microorganisms, soil also serves as unique habitat for a broad range of
52 protists, microfauna (e.g. nematodes, rotifers), mesofauna (eg. mites and collembolans) and
53 macrofauna (eg. earthworms and insect larvae) (Potapov *et al.* 2022). Not only body size but also
54 density of these organisms thriving in soil can span several orders of magnitude (Veresoglou *et al.*
55 2015, Coleman *et al.* 2024). A recent work showed that the community assembly of the smallest soil
56 organisms was influenced by dispersal-based stochastic processes compared to larger ones, which are
57 more structured by selection-based deterministic processes (Luan *et al.* 2020). It is recognized that
58 inter-kingdom biotic interactions are commonplace in soil, resulting in an extraordinarily complex soil
59 food web (Potapov *et al.* 2023; Scheu 2002). Understanding the importance of these interactions
60 between soil fauna, fungi and prokaryotes is crucial for linking soil biodiversity and terrestrial
61 ecosystem functioning (Bonkowski 2004; Crowther *et al.* 2015; Geisen *et al.* 2020). However, despite
62 the key role of the soil bacteria and fungi in biogeochemical cycling (Falkowski *et al.* 2008), we know
63 little about the contribution of biotic interactions between soil organisms to microbial community
64 assembly.

65 Soil bacteria and fungi can be preyed upon by many soil organisms including protists,
66 nematodes and collembolans (Potapov *et al.* 2022). For example, 75 % of the protistan soil community
67 includes bacterial predators (Oliverio *et al.* 2020) and more than 129 species of bacterivorous
68 nematodes have been identified (Martins *et al.* 2022). These microbial predators are themselves preyed
69 by larger soil animals such as mites and tardigrades (Potapov *et al.* 2022). The addition of microbial
70 predators in laboratory experiments revealed significant effects on fungal and bacterial communities

71 (Bell *et al.* 2010; Glücksman *et al.* 2010; Rosenberg *et al.* 2009), with preferential feeding on certain
72 microbial species (Amacker *et al.* 2022; Asiloglu *et al.* 2021; Shu *et al.* 2021). Indirect interactions
73 such as interference or exploitative competition are also numerous in terrestrial ecosystems (Neidig *et*
74 *al.* 2010), although their impact remains elusive. Previous reductionist studies manipulating prey or
75 predator communities have provided valuable insights into microbe-fauna interactions and feeding
76 preferences of individual species (Bell *et al.* 2010; Karakoç *et al.* 2020; Saleem *et al.* 2012), but they
77 often overlooked how these interactions are affected by larger organisms and by higher-order
78 interactions. In contrast, observational studies of natural environments using correlation-based
79 approaches for uncovering interactions between soil microbes are limited because correlations can
80 emerge as a result of both species interactions and of environmental filtering (Faust 2021). As such, the
81 relative importance of the different faunal groups in shaping the soil microbiome remains largely
82 unresolved.

83 Here, we seek to determine the extent to which micro-, meso- and macro- fauna mediate the
84 assembly of the soil microbiome. For this purpose, we used the large differences in body size between
85 organisms to fractionate the soil community (Bradford *et al.* 2002; Briones 2014) and conducted an *in*
86 *situ* exclusion experiment using microcosms with windows covered by various mesh sizes, for a
87 differential sorting of the soil organisms. These exclusion microcosms containing sterile soil were
88 buried in a grassland soil for up to 12 months and shifts in the soil biota were compared between size
89 exclusion treatments during soil recolonization. We hypothesized that differential exclusion of soil
90 fauna will lead to changes in community composition during soil recolonization therefore unraveling
91 the importance of top-down interactions for microbial community assembly. Differential abundance
92 analysis was used to identify the 18S rRNA and 16S rRNA OTUs exhibiting significant responses to
93 exclusion treatments. We also inferred networks using the exclusion treatments as covariate to

94 distinguish the associations between soil organisms that were specifically related to the exclusion
95 treatment from covariation patterns due to other mechanisms. Our results highlight the contribution of
96 the soil fauna in shaping microbial community assembly with cascading effects across the food web
97 and differential responses of protistan, bacterial and fungal communities, therefore further supporting
98 the importance of top-down controls on microbial communities.

99

100 **MATERIALS AND METHODS**

101 **Site description and design of the exclusion experiment**

102 The field experiment was set up in a permanent grassland at the INRAE center, located in Dijon,
103 France (47° 19' 01.7" N, 5° 04' 26.9" E). The soil properties were 33.8 % clay, 48.2 % silt, and 18 %
104 sand, pH 6.31, and C and N content 39.98 and 3.12 g.kg⁻¹ dry soil, respectively. To quantify the
105 importance of the micro- (< 100 µm), meso- (> 100 µm and < 2000 µm) and macro-fauna (>2000 µm)
106 for soil microbial community assembly, we used exclusion microcosms consisting in 70 x 33 mm PVC
107 pots with 6 windows (3 on the side, one on the bottom and one on the top, Fig. S1A), each covered and
108 sealed with nylon membranes having different mesh sizes (i.e. 31, 50, 100, 250, 500, 1000 µm;
109 Nitex®). The microcosms were filled with 4 mm sieved soil collected at the experimental field and
110 then γ-sterilized (min 60 kGy, at Conservatome, Dagneux, France). On September 1st 2020, the
111 exclusion microcosms were buried at a depth of c.a. 12 cm (Fig. S1B) following a complete
112 randomized block design. The soil was drilled with a saw hole, and the topsoil from the saw hole was
113 replaced over the microcosm after burial. Twelve exclusion cages per mesh size ($n=12$) were collected
114 after 3 months (08/12/20, T1), 9 months (06/11/2021, T2) and 12 months (09/23/21, T3) for a total of
115 216 microcosms (6 mesh sizes x 3 sampling times x 12 replicates). Six control microcosms ($n=6$) with

116 windows not covered with mesh were collected at T3 only. Soil cores collected randomly from each
117 block before microcosm burial (*i.e.* T0 original soil, 63 samples) were also used for subsequent
118 analyses. After sampling, water content in each microcosm was determined by drying the soil for 24h at
119 105°C (Fig. S1). Additionally, precipitation and temperature data were retrieved from the nearest
120 meteorological station (5.5 km away) (Fig. S1). Three microcosms from the 31 µm exclusion treatment
121 that had visible holes larger than 1 mm at the harvest time were excluded from the following analysis.

122

123 **DNA extraction and sequencing**

124 The soil from each microcosm was thoroughly homogenized before DNA extraction. DNA was
125 extracted from 285 samples (63 original soil samples and 222 microcosms) using the DNeasy
126 PowerSoil-htp 96 well DNA isolation kit (Qiagen, France) according to the manufacturer's instructions.
127 DNA concentration was estimated using Quant-IT™ dsDNA HS Assay kit (Invitrogen™, Carlsbad,
128 CA, USA). To generate amplicons for sequencing, a 2-step PCR approach was used according to ref.
129 (Berry *et al.* 2011). The V3-V4 hypervariable region of the 16S rRNA gene was amplified using the
130 341F (5'-CCTACGGGRSGCAGCAG-3') / 805R (5'-GACTACCAGGGTATCTAAT-3') primers. The
131 V4 hypervariable region of the 18S rRNA gene was amplified with the EK-565F (5'-
132 GCAGTTAAAAGCTCGTAGT-3') / 18S-EUK-1134-R–UnonMet (5'-
133 TTTAAGTTTCAGCCTTGCG-5') as well as with the M620F (5'-GCAGCCGCGGTAATTCC-3') /
134 M1041R (5'-RCGRTCCAAGAATTCACCTCT-3') primers, to study both metazoan and non-
135 metazoan eukaryotes (Bower *et al.* 2004; Capra *et al.* 2016). The amplicon size was checked with 2 %
136 agarose gel and the final PCR products were purified and their concentration normalized using the
137 SequalPrep Normalization plate kit (Invitrogen™, Carlsbad, CA, USA). Sequencing was performed on

138 MiSeq (Illumina, 2 x 250 bp and 2 x 300 pb for 16S and 18S rRNA amplicons respectively) using the
139 MiSeq reagent kit v2.

140

141 **Amplicon sequence analysis**

142 Demultiplexing and trimming of Illumina adaptors and barcodes was done with Illumina MiSeq
143 Reporter software (version 2.5.1.3). Sequence data from soil samples were analysed using an in-house
144 developed Python pipeline (available upon request). Briefly, 16S rRNA and 18S rRNA gene sequences
145 were assembled using PEAR (Zhang *et al.* 2014) with default settings. Further quality checks were
146 conducted using the QIIME pipeline (Caporaso *et al.* 2010) and short sequences were removed (< 400
147 bp for 16S rRNA gene and < 475 bp for 18S rRNA gene). Reference based and *de novo* chimera
148 detection, as well as OTUs clustering were performed using VSEARCH (Rognes *et al.* 2016) and the
149 adequate reference databases (SILVA 138 representative set of sequences (Quast *et al.* 2013) for 16S
150 rRNA gene and the PR2 sequence database version 4.11.1 for 18S rRNA gene (Guillou *et al.* 2013). For
151 18S rRNA data, the two datasets, fully overlapping in the V4 region, were merged before OTUs
152 clustering. The identity thresholds were set at 94 % for 16S based on replicate sequencing of a bacterial
153 mock community (Romdhane *et al.* 2022) and 97 % for 18S. Representative sequences for each OTU
154 were aligned using Infernal (Nawrocki & Eddy 2013) and phylogenetic trees were constructed using
155 FastTree (Price *et al.* 2010). Taxonomy was assigned using UCLUST (Edgar 2010) and the SILVA
156 database (138.1/2020) (Quast *et al.* 2013) for the 16S and 18S rRNA gene sequences, and the PR2
157 database (version 4.11.1) (Guillou *et al.* 2013) for the 18S rRNA sequences. 18S rRNA OTUs were
158 assigned to Fungi when congruent PR2 and SILVA taxonomic assignments were found. 18S rRNA gene
159 data was split into fungal, protistan and metazoan tables for further analysis. Trophic protist
160 assignments were based on reference tables from refs. (Dumack *et al.* 2020; Ramond *et al.* 2018).

161

162 **Statistical analysis**

163 All statistical analyses were conducted using R statistical software version 4.2.1 (R Core Team 2018).

164

165 *Alpha-diversity analyses*

166 Following rarefaction with subsample sizes of 10,696, 1817 and 1690 for bacteria, fungi and non-
167 fungal 18S rRNA OTUs respectively, observed richness was calculated using the vegan package
168 version 2.5-7 (Oksanen *et al.* 2013). Effects of sampling time and exclusion treatment were assessed
169 independently on alpha-diversity indices. Since normality and homoscedasticity of linear models
170 residuals was not achieved, non-parametric Kruskal-Wallis test followed by post-hoc Dunn's test were
171 performed using the package rstatix 0.7.0.

172

173 *Beta-diversity analyses*

174 Based on the whole datasets (singletons excluded), bayesian estimation of the sparse read counts using
175 the CoDaSeq package version 0.99.6 (Gloor & Reid 2016) was computed before a centered log-ratio
176 transformation with the zCompositions package version 1.3.4 (Palarea-Albaladejo & Martín-Fernández
177 2015), in order to account for compositionality of the data (Gloor *et al.* 2017). To assess the sources of
178 variation (i.e. sampling time and exclusion treatment) in the Euclidean matrices of the centered log-
179 ratio transformed bacterial, fungal, protistan and metazoan community data, we used principal
180 component analysis and one-way permutational multivariate analysis of variance (PerMANOVA
181 (McArdle & Anderson 2001)) with 10,000 permutations constrained by the block variable using the

182 'strata' option of the function `adonis` in the `vegan` package version 2.5-7 (Oksanen et al. 2013). For
183 each group, coordinates of control samples at T3 on the first and second axis of the principal
184 component analysis (PC1 and 2) were used to define the position of no-mesh control centroids (i.e., the
185 mean of the coordinates of control samples), and subsequently the distances of other sample positions
186 on PC1 and PC2 to these centroids. These distances to control centroids, referred as responses to
187 exclusion later on (accounting for the cumulated variance captured by the respective PCs), were then
188 used to perform stepwise multiple regressions, with the response to exclusion of each group as response
189 variable and other group responses as explanatory variables. Thus, these models aimed at inferring the
190 dependencies between the responses to exclusions of the bacterial, fungal, protistan and metazoan
191 communities. Best models were selected stepwisely using the Aikake Information Criterion (AIC) from
192 the `MASS` package version 7.3-58 (Venables & Ripley 2013), and model residuals checked for
193 normality and homoscedasticity.

194

195 *Assessment of community assembly processes*

196 The β -nearest taxon index (β NTI) was calculated according to Stegen et al. 2012, with 99 iterations and
197 weighted abundances using the `Picante` package version 1.8.2 (Kembel et al. 2010), in order to quantify
198 the turnover in phylogenetic composition. β NTI is the standard effect size between observed and null β -
199 mean nearest taxon distance (β MNTD). $|\beta$ NTI| > 2 shows a significant deviation from the null β MNTD
200 distribution, thus indicating a dominance of deterministic processes, while $|\beta$ NTI| < 2 indicates the
201 dominance of stochastic processes (Dini-Andreote et al. 2015). β NTI was quantified by pairwise
202 comparisons of communities from the same treatment at each sampling time. Because of skewed
203 distributions, Kruskal-Wallis tests followed by Dunn's test with Bonferroni corrections were used to
204 detect significant differences between times.

205

206 *Identification of differentially abundant OTUs in treatments*

207 Low-abundance OTUs were filtered out by keeping OTUs that (i) represented > 0.02 % of the
208 sequences across samples and (ii) were found in at least 60 % of one treatment replicates for each time
209 sampling time. This resulted in 416, 634 and 703 bacterial OTUs, 49, 66 and 72 fungal OTUs, 202,
210 215, and 215 protistan OTUs, and 2, 4, and 5 metazoan OTUs at T1, T2 and T3, respectively. We
211 referred to those OTUs with high abundances as “dominant” OTUs later on. To estimate differences in
212 relative abundances of the dominant OTUs between treatments, we used a generalized linear mixed
213 model (GLMM). Such model combines a generalized linear model, which allow to infer linear
214 regression from data that does not follow a Normal distribution as abundance data typically follow a
215 Poisson distribution, with a mixed model, containing both fixed (treatment effects) and random effects
216 (sampling effects). We considered that an OTU of abundance Y follows a Poisson law of parameter Λ
217 as $Y \sim P(\Lambda)$, in any replicates of any i treatment. Thus, we used the following model (Eq. 1):

218
$$\log(\Lambda_{ij}) = o_{ij} + \mu + \alpha_i + Z_{ij}, Z_{ij}_{1 \leq j \leq 12} \text{ iid } \sim N(0, \sigma^2) (1)$$

219 where o is the offset for each sample calculated as the log of the sample read sum, α is the effect of the
220 exclusion treatment coded as a factor, and Z is the random sampling effect modeling the data
221 overdispersion. $i = \{1, \dots, 6\}$ represents the exclusion treatments for each microbial group (bacteria,
222 fungi or fauna), and $j = \{1, \dots, 12\}$ represents the replicates. The analysis was performed using the
223 glmer function of the lme4 package version 1.1-27 (Bates *et al.* 2014). Subsequently, we performed
224 multiple pairwise comparisons with the emmeans function of the emmeans package version 1.6.1
225 (Lenth 2018) for each OTU i) between all exclusion treatments and 1000 μm mesh size treatment for
226 T1, T2, T3 and ii) between all exclusion treatments and no-mesh control for T3. The p-values were then

227 adjusted using the false discovery rate (FDR) method (Benjamini & Hochberg 1995). Log₂-fold
228 changes were calculated as the ratios of the mean relative abundance in treatment to the mean relative
229 abundance in control on a log₂ scale. Only OTUs with FDR adjusted p-values below or equal to 0.05
230 and log₂-fold change > 0.5 were considered as significantly affected by exclusion.

231

232 *Inference of co-occurrence networks*

233 Networks were constructed based on the dominant OTU count data (low-abundance OTUs filtered out)
234 using samples from T3 including no-mesh control cages ($n=78$). Networks were inferred using a sparse
235 multivariate Poisson log-normal (PLN) model with a latent Gaussian layer and an observed Poisson
236 layer using the PLNmodels package version 1.0.1 (Chiquet *et al.* 2019). A specific normalization
237 corresponding to the log-transformed number of reads in each sample was added as an offset in order to
238 take into account the heterogeneity of sequencing depth within and between groups. For each sample
239 set, we used one model without (null model, m0) and one model with the exclusion treatment (full
240 model, m1) as a covariate to identify nodes and links specific to the mesh treatment. In any case,
241 abiotic filtering was intrinsically limited by our approach since exclusion microcosms were filled with
242 sterile soil, which was previously sieved and homogenized, before burying the microcosms in a 36 m²
243 plot. All models included a block covariate to remove nodes and links related to the block effect. For
244 each model, the best network was selected using a Stability Approach to Regularization Selection
245 (StARS) (Liu *et al.* 2010), which performs a random subsampling of the input data to select a network
246 with a very high stability of the selected edges (stability criteria set to 0.99). The network m0 – m1 was
247 computed by subtracting edges of the m1 to edges of the m0 model.

248

249 **RESULTS**

250 **Colonization dynamics of the exclusion microcosms.** The colonization dynamic of the exclusion
251 microcosms was assessed by DNA metabarcoding targeting the bacterial, fungal, protistan and
252 metazoan communities at 3 months (T1), 9 months (T2) and 12 months (T3) (Fig. S2). We found
253 differential colonization dynamics between organisms, with the sampling time significantly affecting
254 the diversity and structure of the bacterial, fungal, protistan and metazoan communities (Figs S3 and
255 S4). Three months after burying the soil microcosms, the richness of all studied soil communities was
256 significantly lower than at T0, with a reduction ranging from 34% to 58 % (Fig. S3). After 9 and 12
257 months (T2 and T3, respectively), we observed that the richness increased compared to T1 but only the
258 diversity of the bacterial community reached the diversity observed in the natural soil at T0 (Fig. S3,
259 Dunn's test $p < 0.001$). Similarly, the bacterial, fungal, protistan and metazoan community
260 compositions also differed significantly across sampling time (Fig. S4), with a higher variance in
261 community structure explained by the sampling time for bacteria (29 %, $p < 0.001$) followed by fungi
262 (22 %, $p < 0.001$), protists (18 %, $p < 0.001$), and metazoa (14 %, $p < 0.001$). The higher differences
263 between T1 and T3 (16 % for bacteria, 11 % for fungi, 6 % for protists, and 7 % for metazoans
264 PerMANOVA $p < 0.001$) than between T1 and T2 (10 % for bacteria, 6 % for fungi, 5 % for protists,
265 and 6 % for metazoans, PerMANOVA $p < 0.001$), suggest that the colonization process slowdown with
266 time. We also calculated the β NNTI to evaluate the relative influences of distinct community assembly
267 processes during soil colonization (Fig S3). The same patterns of β NNTI were observed for most
268 communities, with the largest changes occurring at T1, and β NNTI values at T3 that were either closer to
269 or not different from those at T0. Notably, a greater influence of stochasticity was observed for the
270 bacteria at T1 during the initial phase of soil colonization while bacterial community assembly was
271 dominated by deterministic processes at T0.

272

273 **Shifts in community diversity and composition in response to exclusion**

274 After 12 months, we observed significant effects of the exclusion treatments on diversity but to
275 different extent depending on the organism group. The diversity of the bacterial community was
276 weakly impacted by exclusion in 31 μm exclusion treatment only compared to the no-mesh control
277 (Fig. 1A, Dunn's test, $p < 0.001$). Larger differences in protistan diversity were also observed between
278 the exclusion treatments and the no-mesh control with a decrease of up to 26 % in species richness,
279 respectively (Fig. 1A, Dunn's test, $p < 0.001$). A stronger response to exclusion was observed when
280 the mesh size was lower than 1000 μm and 100 μm for the fungal and metazoan community,
281 respectively (Fig. 1A, Dunn's test, $p < 0.001$). Exclusion also impacted the composition of the soil
282 communities with significant effects at all sampling dates (Fig. S5). At T3 including the no-mesh
283 control, 17 %, 14 %, 15 % and 12 % of variation in the bacterial, fungal, protistan and metazoan
284 communities, respectively, were related to the mesh size (Fig 1B, PerMANOVA, $p < 0.001$). However,
285 significant differences were mostly observed in the microcosms covered with a mesh size of 500 μm or
286 larger (Table S1). We also calculated the distances between the exclusion treatments and the no-mesh
287 control based on ordinations of centered log-ratio transformed community data (Fig 1B). By doing so,
288 we measured the responses to exclusion, captured as a portion of the amount of variance explained by
289 the ordinations, and then inferred the relationships between the responses to exclusion of the bacterial,
290 fungal, protistan and metazoan communities using stepwise multiple regressions. Our data revealed that
291 the response of the metazoan community significantly explained 58 % of the variance of that of the
292 protistan community to exclusion (Fig 1C, $p < 0.05$). The bacterial response also had a significant but
293 weaker importance for the protistan response with only 18 % of the variance explained. In return, 47 %
294 and 28 % of variation in the bacterial response were explained by the protistan and fungal responses,
295 respectively. Reciprocally, the fungal response to exclusion was explained by the bacterial response

296 only (Fig 1C). The explained variance in the metazoan response to the exclusion was the lowest and
297 driven by the protistan response (28 %).

298

299 **Identification of the exclusion-impacted OTUs**

300 To further identify OTUs that were affected by the mesh size, we used a generalized linear mixed
301 model accounting for the inherent compositional nature of the data to estimate significant differences in
302 the relative abundances of dominant OTUs between treatments for each sampling time. In accordance
303 with the observed shifts in community composition with time, the number of dominant OTUs
304 exhibiting significant changes in relative abundance was higher at T2 and T3 than at T1 (Figs. S6 to S8,
305 Table S2, *fdr*-adjusted $p < 0.05$). Regardless of the sampling time, the response to exclusion treatments
306 was asymmetrical with bacterial and fungal OTUs exhibiting a negative rather than a positive response,
307 whereas the opposite was observed for the protistan OTUs (Fig 2A, Fig. S6). Thus, using the no-mesh
308 control as reference at T3, we found that OTUs with significantly decreasing relative abundances
309 across treatments represented 63 % and 71 % of the affected bacterial and fungal OTUs respectively,
310 while 78 % of the affected protistan OTUs showed an increase in relative abundance in the exclusion
311 treatments (Table S2; *fdr*-adjusted $p < 0.05$). Overall, 46, 35 and 25 % of the dominant bacterial, fungal
312 and protistan OTUs were significantly affected by the exclusion treatments compared to the no-mesh
313 control at T3. Phagotrophic protists belonging to Cercozoa, Ciliophora and Stramenopiles lineages
314 represented 89 % of the protistan OTUs positively impacted by exclusion treatments (Fig. 3).
315 Conversely, more than half of the negatively impacted fungal OTUs belonged to the Ascomycota (Fig.
316 3). Alphaproteobacteria and Gammaproteobacteria represented 49 % of bacterial OTUs with positive
317 response to exclusion treatment, while 68 % of those with a negative response belonged to
318 Actinobacteria, Verrucomicrobia, Acidobacteria and Bacteroidetes (Fig. 4). Whatever the community,
319 the magnitude of changes in relative abundances (*i.e.* absolute log₂-fold changes) and the percentage of

320 impacted OTUs were the smallest in the 1000 μm exclusion treatment (Figs. 2 to 4, Dunn's test, $p <$
321 0.001). At the most 5 metazoan OTUs were affected by size exclusion at T3 including no-mesh controls
322 (Table S2).

323

324 **Exclusion-specific co-occurrence networks**

325 In order to evaluate how the exclusion treatments affected bacterial, fungal, protistan and metazoan co-
326 occurrences, we inferred inter-kingdom networks without covariate (m0) and with the exclusion
327 treatment as a qualitative covariate (m1). We then identified the nodes and edges that were statistically
328 related to the exclusion treatments exclusively (*i.e.* differentially identified between m0 and m1
329 models). After 12 months, we found that the most abundant interkingdom edges were between bacteria
330 and protists (327) or between fungi and bacteria (266) (Fig. 5). Interestingly, negative edges connecting
331 cercozoans to Bacteroidetes represented 65 % of the negative edges between bacteria and protists and
332 90 % of the negative edges between cercozoans and bacteria (Fig. 5B and C). Edges between fungi and
333 protists represented only 5.4 % of the total network edges while edges involving metazoans represented
334 less than 1 % of the network (Fig. 5A).

335

336 **DISCUSSION**

337 To assess the importance of the soil fauna in microbial community assembly, we buried sterile
338 soil microcosms covered with mesh sizes ranging between 31 and 1000 μm to prevent colonization by
339 soil organisms according to their body size. One year after microcosm burial in a grassland field, we
340 observed a decrease in faunal diversity along with shifts in faunal community composition in the
341 exclusion treatments compared to the no-mesh control. However, in contrast to our initial expectations

342 based on the large variations in body size among the studied organisms, weak to no differences were
343 found between microcosms with mesh size ranging from 31 to than 500 μm . This could be due to an
344 underestimation of the effect of the exclusion treatments on the soil fauna, given the lower probability
345 of retrieving organisms with low abundance in soil, such as members of the mesofauna and macrofauna
346 (Capra *et al.* 2016). In addition, the exclusion of larger organisms may also have limited the dispersal
347 capacities of other members of the soil communities. Thus, phoresy, which is a dispersal strategy in
348 which an organism attaches to an animal for transportation, is common in mites (Seeman & Walter
349 2023). Similarly, phoresy on mites or isopods has been shown to represent mechanisms of dispersal for
350 nematodes and protists (Bharti *et al.* 2020; Eng *et al.* 2005). Nevertheless, multiple regression analysis
351 showed that 58 % of the variation in the response of the protistan community to exclusion at T3 was
352 explained by that of metazoa. In return, the magnitude of the response of the protists was the main
353 driver influencing that of the bacterial community, which suggests cascading effects of the soil fauna
354 on microbial community assembly. However, note that the percentage of variance captured by the PCA
355 was at the most 19.4%. By using a generalized linear mixed model for differential abundance analysis,
356 we identified among the dominant taxa those responding significantly to the exclusion treatments. The
357 affected protistan OTUs exhibited an increase rather than a decrease in relative abundance in the
358 exclusion treatments. The most common soil protists have an average body size between 8 and 21 μm
359 (Luan *et al.* 2020) and, accordingly protists positively affected by exclusion were gradually more
360 numerous with decreasing mesh size until 31 μm . These affected protistan OTUs mostly belonged to
361 the phagotrophic protists, resulting in an increase of the general proportion of phagotrophic protists of
362 up to 32% compared to the no-mesh control. This suggests a competitive advantage of phagotrophic
363 protists, either directly or indirectly, when larger fauna was increasingly excluded. Thus, protists are
364 preyed upon by larger organisms like Oribatids or Collembola in grassland soils (Crotty *et al.* 2012),
365 and the exclusion treatments may have provided a shelter allowing protists present in the exclusion

366 microcosms to thrive. Accordingly, Erktan *et al.* (Erktan *et al.* 2020) suggested that soil pores of
367 contrasting sizes could provide refuges, leading to segregation between prey and predators, therefore
368 affecting top-down controls. Alternatively, the exclusion of competitors also feeding on bacteria such as
369 microarthropods (e.g. collembolans and oribatids) and nematodes (Thakur & Geisen 2019) could have
370 left a broader niche and larger food source to the phagotrophic protists, even though diet preference
371 between bacterivores are still unclear. The positive response of phagotrophic protists to exclusion was
372 mirrored by a decrease in relative abundance of the dominant bacterial and fungal OTUs, among which
373 70 % and 80 % of the OTUs, respectively, were negatively and significantly affected by the exclusion
374 treatments. Overall, the OTUs affected by the exclusion treatments accounted for 46 %, 35 % and 27 %
375 of the dominant bacterial fungal and protistan OTUs, respectively, which underlines the importance of
376 the interplay between different trophic levels in soil and top-down effects on the soil microbiome.

377 Our co-occurrence network approach provided additional information on which associations
378 between the soil organisms were directly related to the exclusion treatments. Thus, the inference of
379 networks using the exclusion treatments as covariate allowed us to exclude co-variation caused by
380 abiotic filtering and to identify co-variations specifically induced by exclusion (Chiquet *et al.* 2021).
381 Negative edges specifically induced by exclusion were numerous between cercozoans and bacteria with
382 90 % of these edges comprising Bacteroidetes. Interestingly, the soil bacterial community was
383 dominated by Proteobacteria (59 %), while Bacteroidetes represented only 12 %. Thus, our results
384 suggest that prey switching, where the predator preferentially consumes the most abundant type of prey
385 as it can be observed in simplified systems with a single prey, is not the feeding strategy of cercozoans.
386 Instead, our field exclusion experiment supports previous studies suggesting that Bacteroidetes are
387 preferred prey sources for protists (Asiloglu *et al.* 2021; Flues *et al.* 2017). In contrast, the number of
388 edges connecting protists and fungi was much smaller, which echoes the absence of a significant

389 relationship between the responses of the fungal and protistan community to the exclusion treatments.
390 However, the high number of edges between bacteria and fungi, as well as the high percentage of
391 variance in the response of the fungal community to exclusion explained by the bacterial communities
392 (50 %), suggest that fungal community assembly is mostly influenced by bacteria (Bahram *et al.* 2018).

393 In conclusion, our experimental approach showed that exclusion of the soil fauna according to
394 body size led to cascading effects through the food web with both direct and indirect interactions. In
395 particular, exclusion of larger soil fauna positively impacted phagotrophic protists with subsequent ef-
396 fects on microbial community composition. Overall, our findings provide unique information on the
397 driving factors governing soil microbiome assembly *in situ* by unveiling the contribution of the top-
398 down control by soil protists on the bacterial community composition with indirect effects on the fun-
399 gal community. Since our experimental approach aimed at controlling environmental filtering and
400 therefore resulted in a low variation in the resource level, future work is needed to assess the relative
401 contribution of top-down and bottom-up processes as well as of their interactions in shaping soil micro-
402 bial communities.

403

404 **Conflict of interest statement**

405 The authors declare no competing interests

406

407 **Funding**

408 This research was funded by the ISITE-UBFC senior fellowship, grant RA19016.AEC.IS.

409

410 **Figure and table legends**

411 **Figure 1. Effect of the mesh exclusion treatment on bacterial, fungal, protistan and metazoan**
412 **communities.** A) Bacterial, fungal, protistan and metazoan observed richness across exclusion treat-
413 ments at T3 ($n=9$ for treatment 31 μm , $n=12$ for treatments 50 to 1000 μm and $n=6$ for no-mesh).
414 Boxes show the inter-quartile range between the 1st and 3rd quartiles, with median indicated by the
415 line and whiskers indicate the maximum and minimum of the inter-quartile range. Different lowercase
416 letters indicates significant difference within each panel ($p < 0.05$) determined with one-way Kruskal-
417 Wallis test and post-hoc Dunn's test. B) Principal component ordinations of bacterial, fungal, protistan
418 and metazoan communities at T3 across exclusion treatments and no-mesh controls, based on Euclid-
419 ean distances of centered log-ratio transformed OTU abundances. The effects of exclusion treatment
420 for each organism group and sampling time were tested with PerMANOVA (** $p < 0.01$, *** $p <$
421 0.001) and are displayed above each ordination. Ellipses represent 95 % confidence level around each
422 treatment centroid. C) Significant linear relationships (ANOVA, $p < 0.05$) between the responses to ex-
423 clusion of the bacterial, fungal, protistan and metazoan communities, based on multiple regression
424 models. Community response to exclusion was quantified by the beta-diversity distances to the no-
425 mesh control centroid. The proportion of variance explained by the best predictors, as determined using
426 stepwise AIC, is shown for each group.

427

428 **Figure 2. Proportion and response magnitude of the bacterial, fungal and protistan OTUs af-**
429 **ected by the mesh exclusion treatment at T3 as identified using the GLM model.** A) Proportion of
430 dominant OTUs with significantly increasing (blue) or decreasing (red) relative abundances in each ex-
431 clusion treatment compared to no-mesh controls (fdr-adjusted $p < 0.05$). B) Log2-fold changes in the
432 relative abundances of significantly affected OTUs in each exclusion treatment, relative to the no-mesh

433 control. Log₂-fold change medians are represented by black lines. Only 5 metazoan OTUs were af-
434 fected by exclusion treatments, and therefore are not shown.

435

436 **Figure 3. Taxonomic assignment and distribution of significantly impacted protistan, metazoan**
437 **and fungal OTUs by the mesh exclusion treatment at T3.** Heatmap showing the log₂-fold changes
438 in the relative abundances of significantly increasing (blue shades) and decreasing (red shades) OTUs
439 for each exclusion treatment, relative to the no-mesh control. The outer ring shows the trophic modes
440 based on taxonomic assignments, where bacterivore, myzocytotic, omnivore and eukaryvore are de-
441 fined here as finer trophic assignments within phagotrophs. The OTU taxonomy is indicated by differ-
442 ent colors on the innermost ring.

443

444 **Figure 4 Taxonomic assignment and distribution of significantly impacted bacterial OTUs by the**
445 **mesh exclusion treatment at T3.** Heatmap showing the log₂-fold changes in the relative abundances
446 of significantly increasing (blue shades) and decreasing (red shades) OTUs for each exclusion treat-
447 ment, as compared to the no-mesh control. The OTU taxonomy is indicated by different colors on the
448 innermost ring.

449

450 **Figure 5. Network edges specifically induced by exclusion.** A) Number of positive and negative
451 edges occurring between the different groups and statistically related to the exclusion treatment in the
452 m₀ – m₁ network. B) Chord diagram showing the distribution of negative edges between protistan and
453 metazoan (blues shades) and bacterial nodes (orange shades). The node taxonomy is represented at the

454 phylum or class level. C) Number of positive and negative edges of the m0 – m1 network involving
455 Cercozoa and bacteria, sorted by phylum or class.

456

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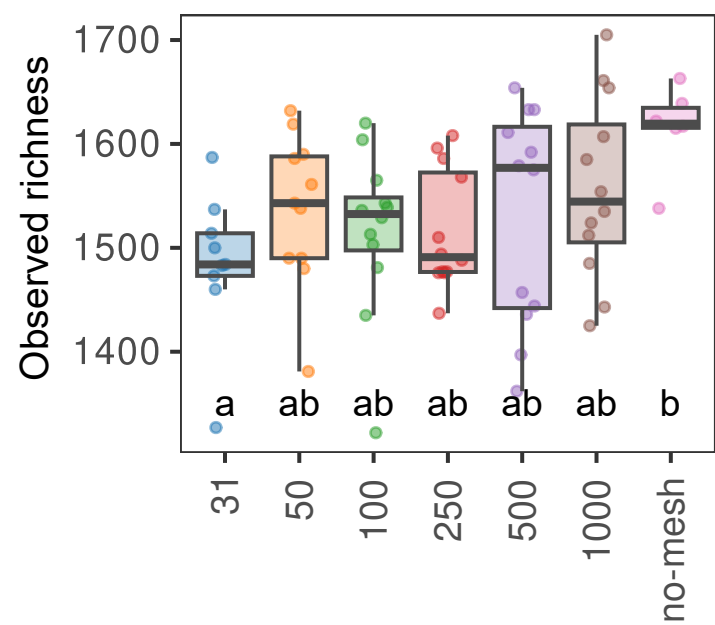
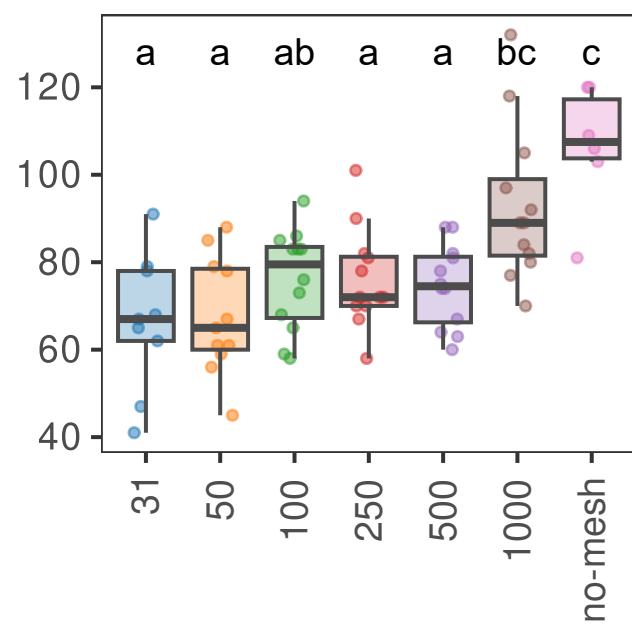
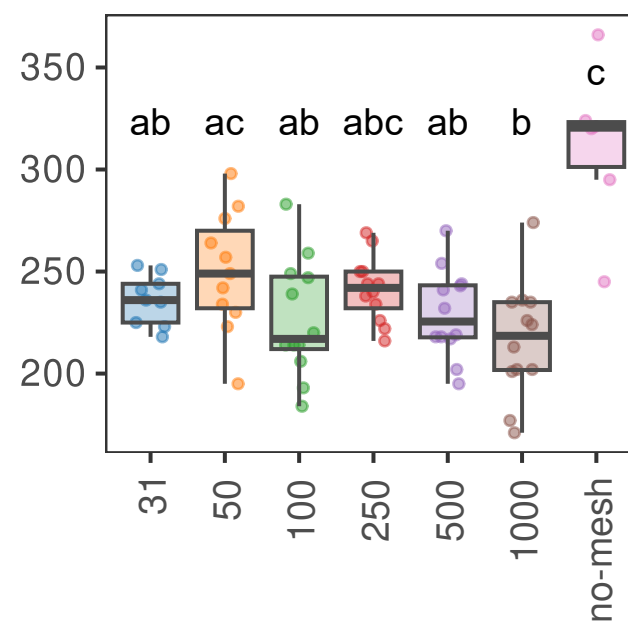
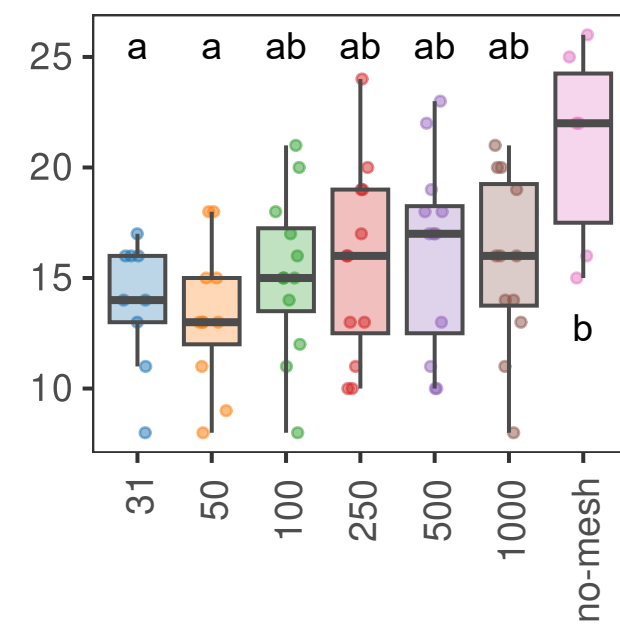
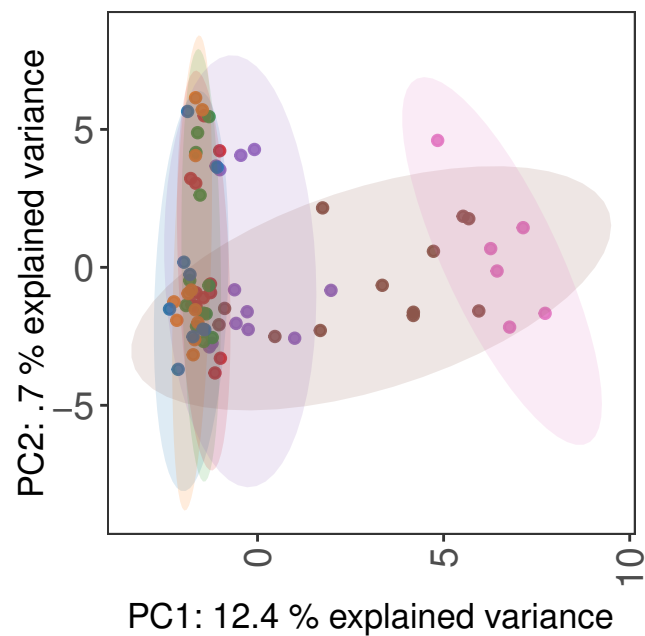
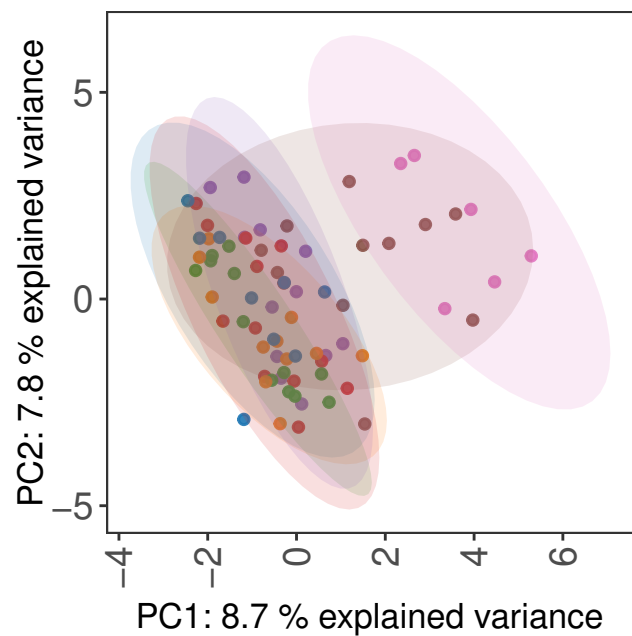
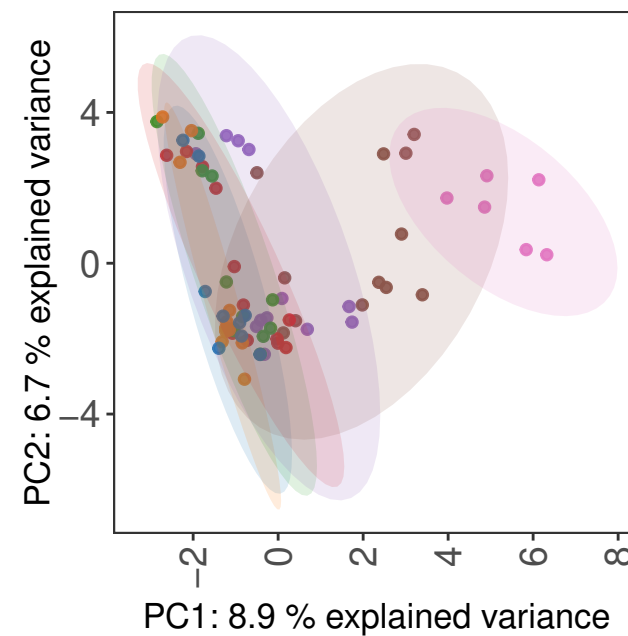
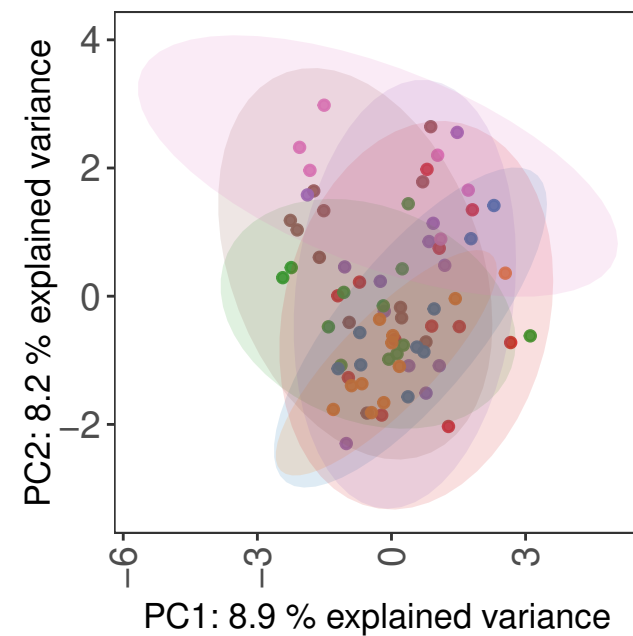
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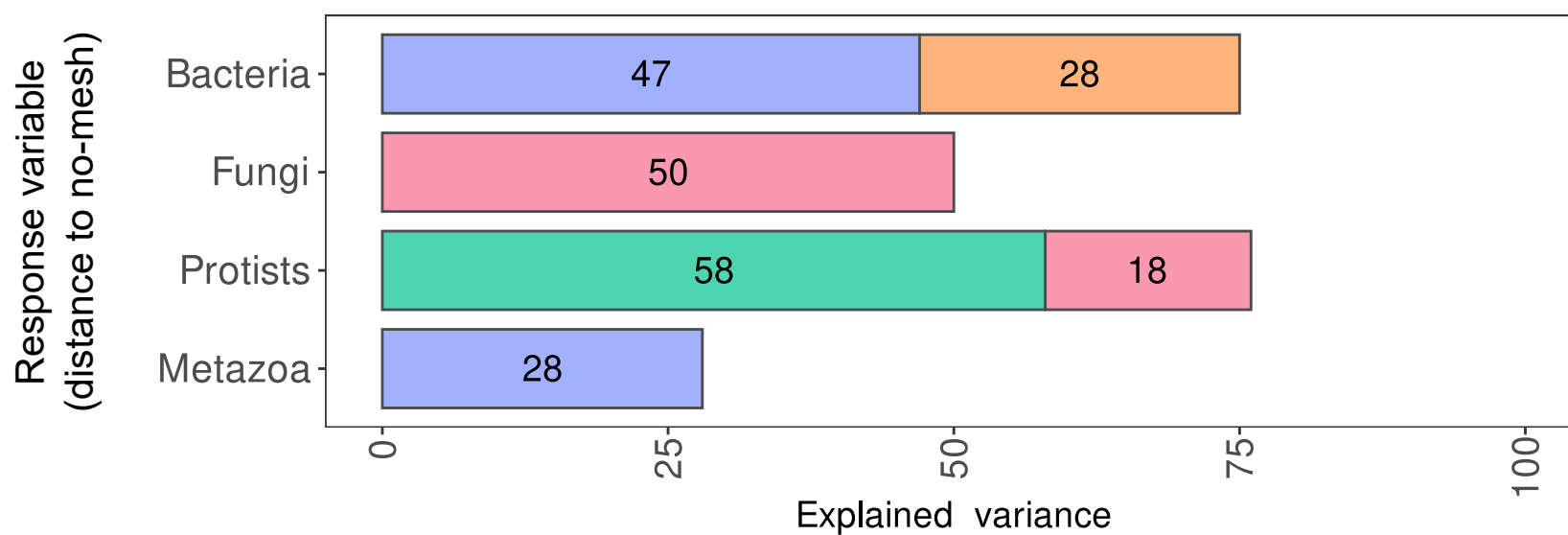
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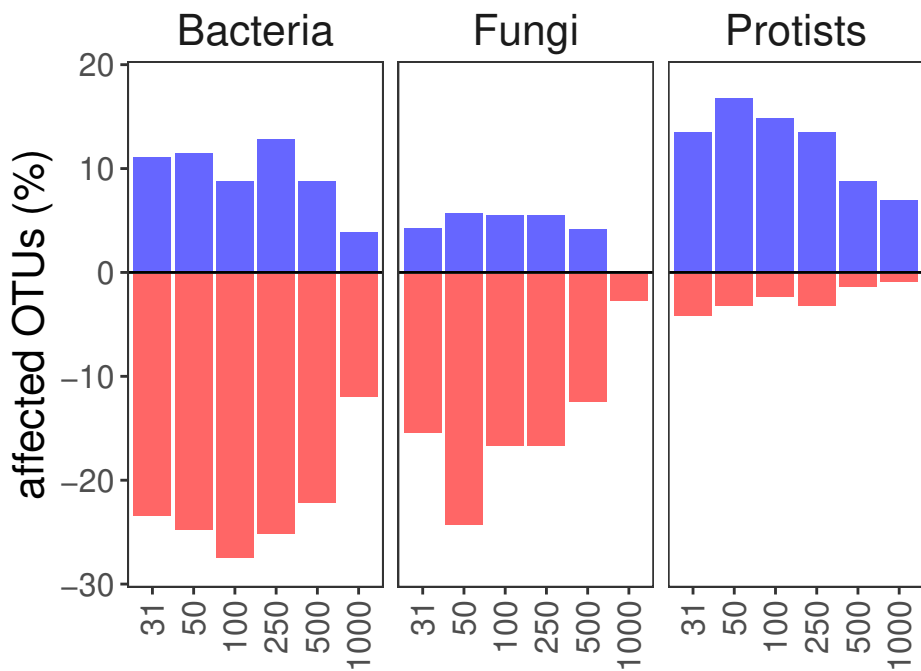
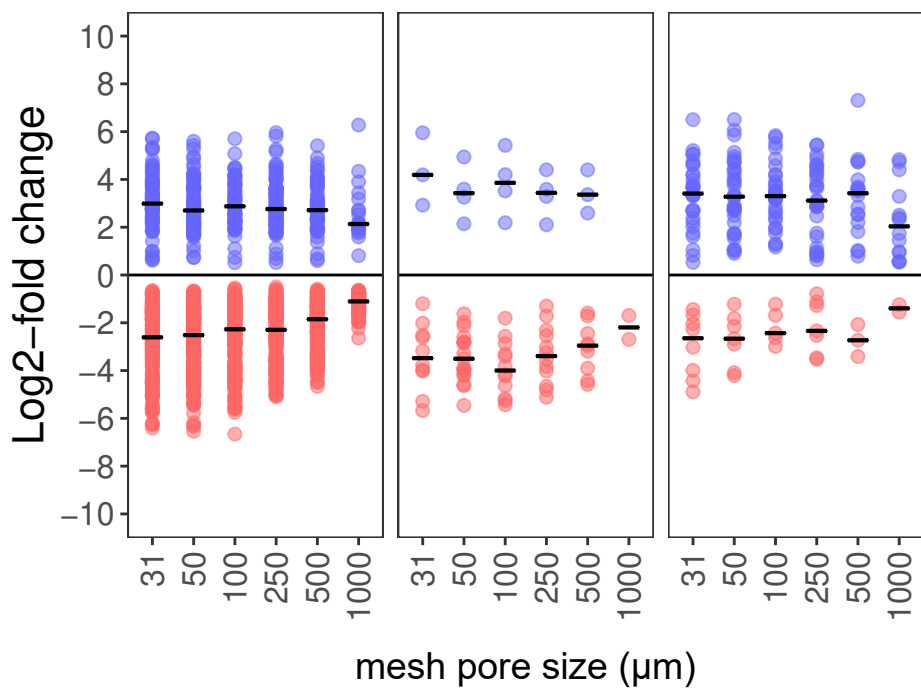
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A**Bacteria****Fungi****Protists****Metazoa****B** $F = 2.3, R^2 = 17\%^{***}$  $F = 1.8, R^2 = 14\%^{***}$  $F = 1.9, R^2 = 15\%^{***}$  $F = 1.5, R^2 = 12\%^{***}$ 

Mesh size (μm) ● 31 ● 50 ● 100 ● 250 ● 500 ● 1000 ● no-mesh

C

■ Bacteria
■ Fungi
■ Metazoa
■ Protists

A**B**

response ■ negative ■ positive

Taxonomy

Protists

- Cercozoa
- Telonema
- Stramenopiles
- Choanoflagellida
- Apusozoa
- Amoebozoa
- Ciliophora
- Unclassified

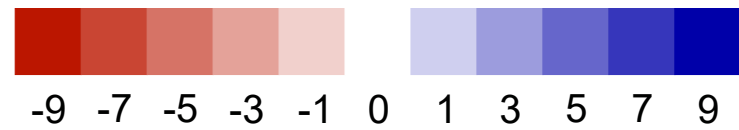
Metazoa

- Nematoda
- Annelida

Fungi

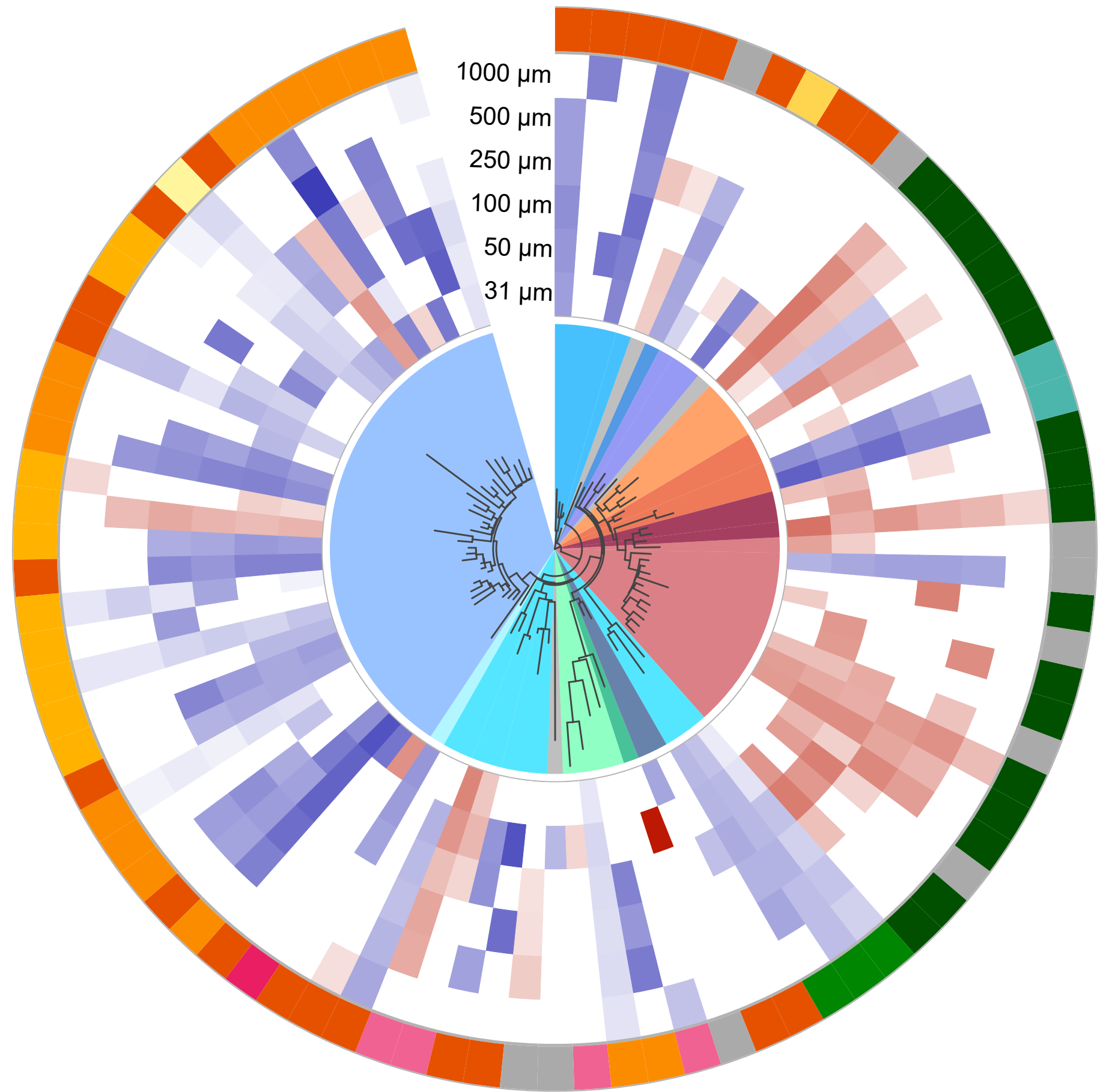
- Ascomycota
- Basidiomycota
- Chytridiomycota
- Mucromycota

Log2 Fold Change

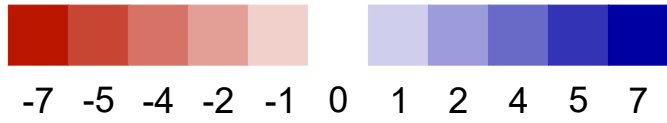


Trophic mode

- Phagotroph
- Bacterivore
- Myzocytotic
- Omnivore
- Eukaryvore
- Unclassified
- Osmotroph
- Saprotroph
- Symbiotroph
- Endoparasite
- Parasite

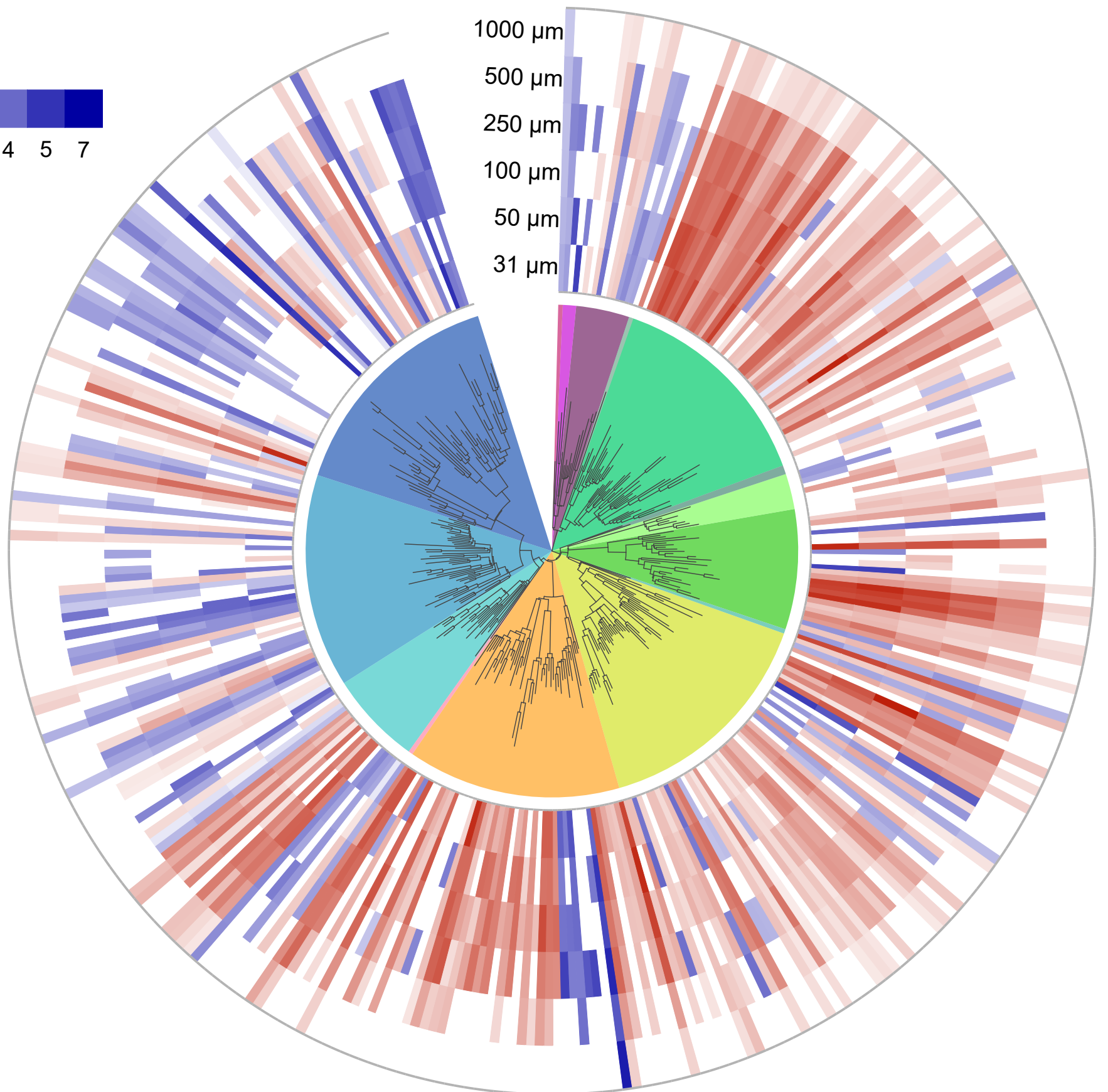


Log2 Fold Change

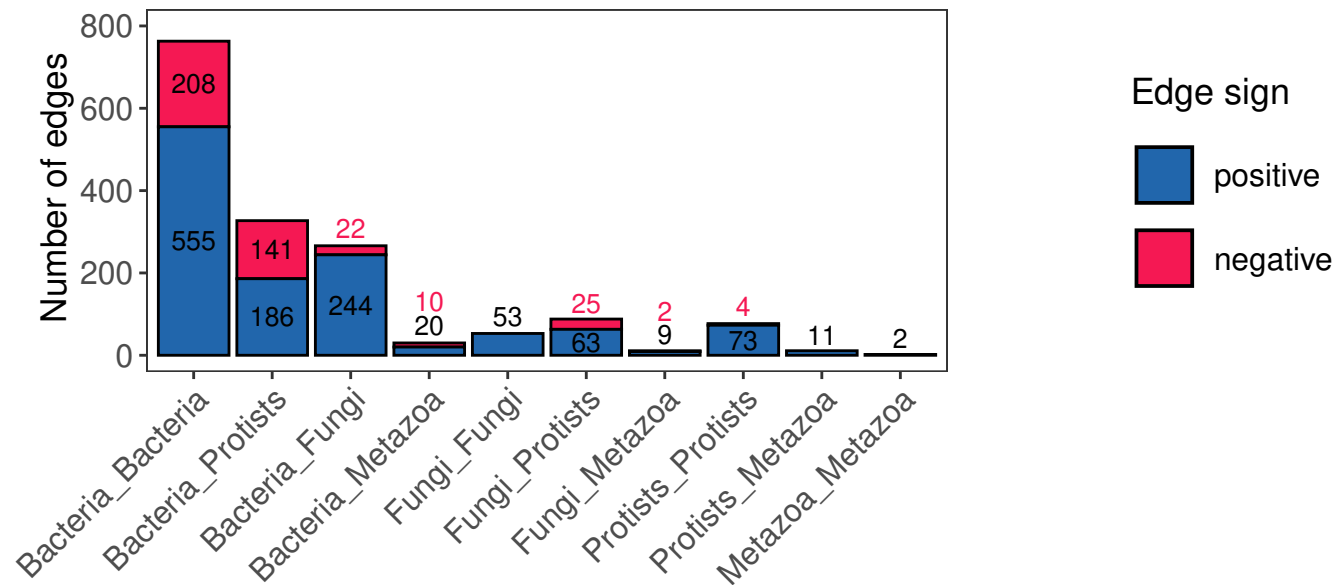


Taxonomy

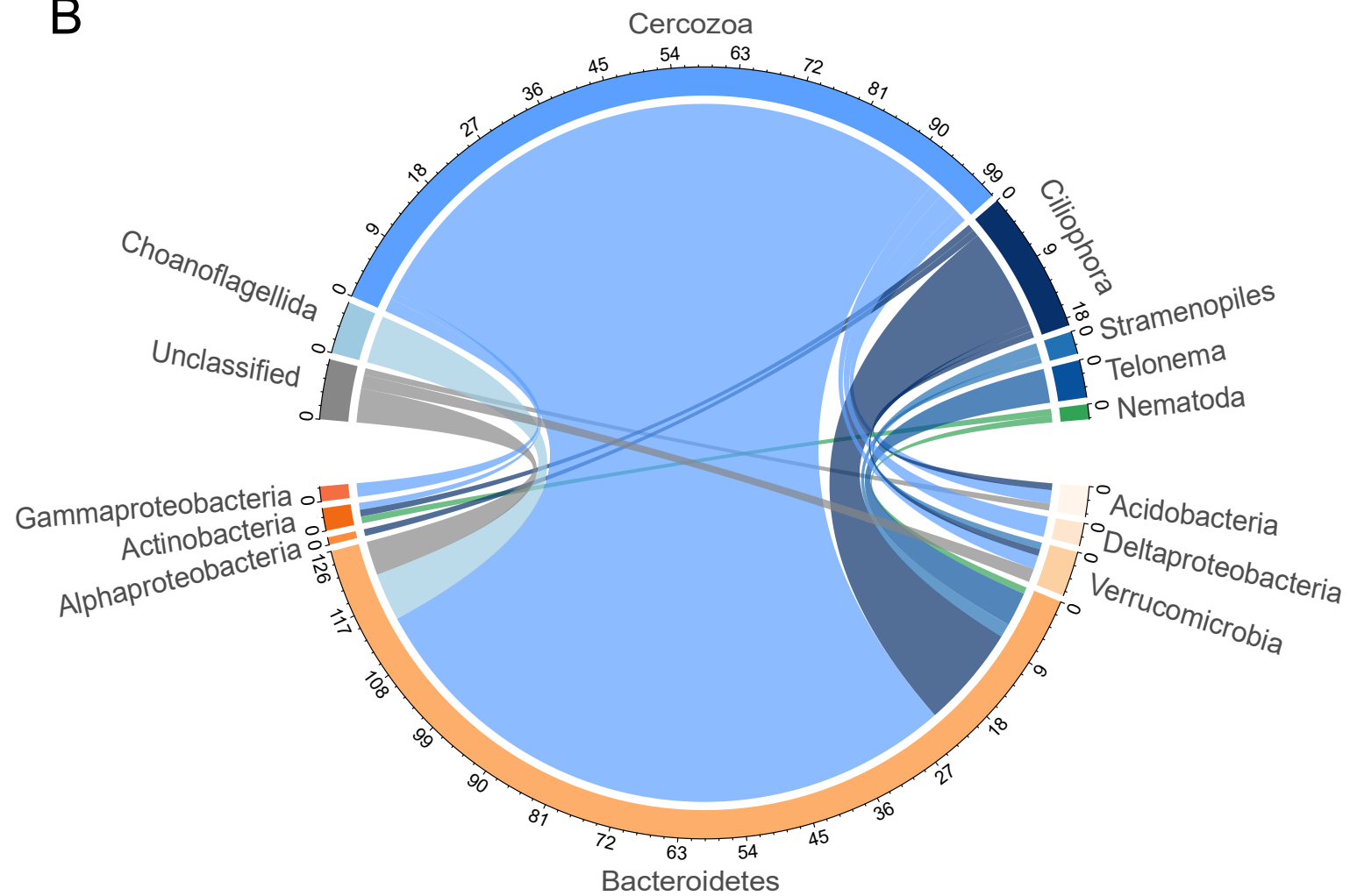
- Armatimonadetes
- Patescibacteria
- Chloroflexi
- Actinobacteria
- BRC1
- Gemmatimonadetes
- Verrucomicrobia
- Entotheonellaeota
- Acidobacteria
- Bacteroidetes
- Spirochaetes
- Deltaproteobacteria
- Gammaproteobacteria
- Alphaproteobacteria
- Unclassified



A



B



C

