

Appendix S5: results after UPARSE clustering allowing unique sequences (Usearch function sortbysize with argument -minsize 1). Supplementary Materials of "Finding fungi in a needle stack: high alpha and low beta-diversity of foliar endophytic Ascomycetes revealed by metabarcoding in Corsican pine forests".

Adrien Taudiere*

CEFE - Centre d'Ecologie Fonctionnelle et Evolutive, Montpellier: France

November 9, 2017

Abstract

Plant leaves host highly diverse communities of foliar endophytic fungi (FEF). Compared to the other compartments of the plant microbiome, FEF diversity is poorly known. We here document the communities of FEF associated with the endemic Corsican black pine *Pinus nigra* subsp. *laricio* at three sites across its natural range and examine the effect of tree age and light exposure on FEF composition. Metabarcoding using next-generation sequencing provided 8243608 Ascomycota ITS2 sequences clustered into 642 FEF operational taxonomic units (OTUs). Site is the main determinant to explain the diversity and composition of FEF communities. Tree age somewhat affects FEF community composition, whereas needle location (shade vs canopy) has no effect. Results are robust against the various options of the bioinformatic pipeline specifically developed. This study provides the first picture of FEF diversity in a Mediterranean island and underlines the complementarity of forest massifs for fungal conservation.

Key words: foliar endophyte; fungi; community ecology; metabarcoding; *Cyclaneusma minus*, *Pinus nigra* subsp. *laricio*, Mediterranean, endemism, environmental sequencing

To set the filter parameter, see directly section 'Choice of filter parameters' [2.1](#).

To read a summary of this appendix, see directly section 'Summary' [7](#).

*adrien.taudiere@zaclys.net

Contents

1	Introduction	4
1.1	R requirements	4
1.2	System and session informations	4
1.3	Some usefull functions	6
2	Data	6
2.1	Choice of filter parameters	6
2.2	Load and convert loading	6
2.2.1	Otu table	6
2.2.2	Taxonomy	6
2.2.3	Add FUNguild information to taxonomy Table	7
2.2.4	Representative sequences	8
2.2.5	Samples information	8
2.2.6	Create the phyloseq object	8
2.2.7	Characteristics of the phyloseq data	8
2.3	Filter sample by number of sequences	8
2.4	Filter OTUs by number of samples	9
2.5	Filter OTUs by number of sequences	10
2.6	Summary of filtration workflow	11
3	Simple description of the dataset	11
3.1	Number of sequences and OTUs by samples	11
3.2	Number of sequences and samples for each OTUs	12
3.3	Distribution of sequences in the taxonomy	13
3.4	Focus on the 30 more abundant OTUs (number of sequences)	13
3.5	Focus on the 30 more frequent OTUs (number of samples)	16
4	Number of sequences and OTUs in function of putative ecology (using FUNGuild software; Nguyen et al, 2015)	18
5	Distribution of fungal endophytic alpha-biodiversity	19
5.1	Local diversity = Diversity by sites	19
5.2	Diversity by age of tree	19
5.3	Diversity by elevation of the sample	20
5.4	Which factor affect diversity?	20
6	Effect of site, age and elevation on fungal endophytic beta-diversity	28
6.1	Venn diagramm	28
6.2	Venn diagramm for OTUs present in at least 3 samples	28
6.3	Ordination	28
6.4	Permanova on sites, host ages and elevation	35
6.5	Permanova on sites, host ages and individual trees	35
6.6	Differences in abundances and OTUs number by Order.	36
6.7	Differences in abundances for each OTUs	40
6.7.1	Pairwise comparison of the OTUs composition by sites	40
6.7.2	Pairwise comparison of Order composition by sites	43
6.8	Distribution of OTUs abundance in the fungal phylogeny	43

7	Summary	46
7.1	Filtering summary	46
7.2	Alpha diversity	46
7.3	Beta diversity	47
7.4	Special case of <i>Cyclaneusma minus</i>	47

1 Introduction

This supplementary material presents the ecological analysis of endophytic fungal communities in *Pinus nigra* subsp. *laricio*, an endemic species of Corsica. The dataset analysed here was computed using UPARSE clustering allowing unique sequences (see main article and Sup. Mat. 1 for more details).

1.1 R requirements

First, set the working directory. In this directory, there is data folder and a R script "functions_for_phyloseq.R".

```
setwd("~/Nextcloud/GitHub/FEF_paper/")
```

Then, we may need to install packages.

```
# install.packages(c('ape', 'biom', 'optparse', 'RColorBrewer', 'randomForest', 'vegan',
#                    'VennDiagram', 'venneuler', 'xtable', 'schoRsch', 'ape',
#                    'ips', 'adeget', 'mvabund', 'rCharts', 'networkD3', 'data.tree'))
#
# # Upgrade Bioconductor to the latest version available for this version of R
# source("http://bioconductor.org/biocLite.R")
# biocLite(c("multtest", "DECIPHER", "edgeR", "phyloseq", "DESeq2", "metagenomeSeq"))
#
# require(devtools)
# install_github('ramnathu/rCharts')
# install_github("timelyportfolio/d3treeR")
```

```
## May be needed under windows
Sys.setenv(JAVA_HOME = "C:\\Program Files\\Java\\jdk1.8.0_73")

#Load the packages.
lapply(list("ggplot2", "phyloseq", "cluster", "plyr", "VennDiagram",
            "circlize", "xtable", "schoRsch", "DESeq2", "mvabund",
            "edgeR", "phangorn", "DECIPHER", "ips", "adeget", "multtest",
            "networkD3", "treemap", "data.tree", "d3treeR", "venneuler",
            "gridExtra"), library,
        character.only = TRUE)
library(vegan)
```

1.2 System and session informations

This document was created with R version 3.4.2 (2017-09-28) on Linux the 2017-11-09 15:49:27. See below for more information.

```
sessionInfo()

## R version 3.4.2 (2017-09-28)
## Platform: x86_64-pc-linux-gnu (64-bit)
## Running under: Ubuntu 16.04.3 LTS
##
## Matrix products: default
## BLAS: /usr/lib/libblas/libblas.so.3.6.0
## LAPACK: /usr/lib/lapack/liblapack.so.3.6.0
##
```

```

## locale:
## [1] LC_CTYPE=fr_FR.UTF-8          LC_NUMERIC=C
## [3] LC_TIME=fr_FR.UTF-8          LC_COLLATE=fr_FR.UTF-8
## [5] LC_MONETARY=fr_FR.UTF-8      LC_MESSAGES=fr_FR.UTF-8
## [7] LC_PAPER=fr_FR.UTF-8         LC_NAME=fr_FR.UTF-8
## [9] LC_ADDRESS=fr_FR.UTF-8       LC_TELEPHONE=fr_FR.UTF-8
## [11] LC_MEASUREMENT=fr_FR.UTF-8   LC_IDENTIFICATION=fr_FR.UTF-8
##
## attached base packages:
## [1] parallel stats4 grid stats graphics grDevices utils
## [8] datasets methods base
##
## other attached packages:
## [1] vegan_2.4-4 lattice_0.20-35
## [3] permute_0.9-4 gridExtra_2.2.1
## [5] venneuler_1.1-0 rJava_0.9-8
## [7] d3treeR_0.1 data.tree_0.7.0
## [9] treemap_2.4-2 networkD3_0.4
## [11] multtest_2.32.0 adegenet_2.1.0
## [13] ade4_1.7-8 ips_0.0-7
## [15] XML_3.98-1.9 colorspace_1.3-2
## [17] DECIPHER_2.4.0 RSQLite_2.0
## [19] Biostrings_2.44.2 XVector_0.16.0
## [21] phangorn_2.2.0 ape_4.1
## [23] edgeR_3.18.1 limma_3.32.5
## [25] mvabund_3.12.3 DESeq2_1.16.1
## [27] SummarizedExperiment_1.6.3 DelayedArray_0.2.7
## [29] matrixStats_0.52.2 Biobase_2.36.2
## [31] GenomicRanges_1.28.4 GenomeInfoDb_1.12.2
## [33] IRanges_2.10.3 S4Vectors_0.14.3
## [35] BiocGenerics_0.22.0 schoRsch_1.4
## [37] xtable_1.8-2 circlize_0.4.1
## [39] VennDiagram_1.6.17 futile.logger_1.4.3
## [41] plyr_1.8.4 cluster_2.0.6
## [43] phyloseq_1.20.0 ggplot2_2.2.1
## [45] knitr_1.17
##
## loaded via a namespace (and not attached):
## [1] backports_1.1.0 Hmisc_4.0-3
## [3] fastmatch_1.1-0 igraph_1.1.2
## [5] lazyeval_0.2.0 sp_1.2-5
## [7] splines_3.4.2 BiocParallel_1.10.1
## [9] gridBase_0.4-7 digest_0.6.12
## [11] foreach_1.4.3 htmltools_0.3.6
## [13] viridis_0.4.0 gdata_2.18.0
## [15] magrittr_1.5 checkmate_1.8.3
## [17] memoise_1.1.0 readr_1.1.1
## [19] annotate_1.54.0 gmodels_2.16.2
## [21] blob_1.1.0 dplyr_0.7.2
## [23] RCurl_1.95-4.8 jsonlite_1.5
## [25] genefilter_1.58.1 bindr_0.1
## [27] brew_1.0-6 survival_2.41-3
## [29] iterators_1.0.8 glue_1.1.1
## [31] gtable_0.2.0 zlibbioc_1.22.0
## [33] seqinr_3.4-5 Rook_1.1-1
## [35] shape_1.4.3 scales_0.5.0
## [37] futile.options_1.0.0 DBI_0.7
## [39] Rcpp_0.12.12 viridisLite_0.2.0
## [41] htmlTable_1.9 foreign_0.8-69
## [43] bit_1.1-12 spdep_0.6-15
## [45] Formula_1.2-2 tweedie_2.2.5
## [47] htmlwidgets_0.9 DiagrammeR_0.9.1
## [49] RColorBrewer_1.1-2 acepack_1.4.1
## [51] pkgconfig_2.0.1 nnet_7.3-12
## [53] deldir_0.1-14 locfit_1.5-9.1
## [55] rlang_0.1.2 reshape2_1.4.2
## [57] AnnotationDbi_1.38.2 visNetwork_2.0.1
## [59] munsell_0.4.3 tools_3.4.2
## [61] downloader_0.4 evaluate_0.10.1
## [63] biomformat_1.4.0 stringr_1.2.0
## [65] bit64_0.9-7 purrr_0.2.3
## [67] bindrcpp_0.2 nlme_3.1-131
## [69] mime_0.5 rstudioapi_0.6
## [71] compiler_3.4.2 rgexf_0.15.3
## [73] tibble_1.3.4 statmod_1.4.30
## [75] geneplotter_1.54.0 stringi_1.1.5
## [77] highr_0.6 Matrix_1.2-11
## [79] LearnBayes_2.15 GlobalOptions_0.0.12
## [81] data.table_1.10.4 bitops_1.0-6
## [83] httpuv_1.3.5 R6_2.2.2
## [85] latticeExtra_0.6-28 gridSVG_1.5-1
## [87] codetools_0.2-15 lambda.r_1.1.9
## [89] boot_1.3-20 MASS_7.3-47
## [91] gtools_3.5.0 assertthat_0.2.0
## [93] rhdf5_2.20.0 GenomeInfoDbData_0.99.0
## [95] mgcv_1.8-22 expm_0.999-2
## [97] hms_0.3 influenceR_0.1.0
## [99] quadprog_1.5-5 rpart_4.1-11
## [101] tidyr_0.7.1 coda_0.19-1
## [103] shiny_1.0.5 base64enc_0.1-3

```

1.3 Some usefull functions

The function `as.binaryOtuTable` converts a phyloseq object into a phyloseq object with binary (*i.e.* 0/1) OTU table. It allows to suppress effect due to the number of sequences wich may be the result of a lot of molecular artefact (Lindhal et al., 2013).

`funky.color` and `transpa` allow to create nice color palette.

`accu_plot` allows to plot accumulation curves in fonction of a factor in samples data (`@sam_data` of phyloseq object).

`otu_circle` uses the package `circlize` to plot circle of OTUs/sequences distributions in samples. `sankey_phyloseq` is an alternative using Sankey plot.

`phyloseq_to_edgeR`, wrote by Paul J. McMurdie, converts phyloseq OTU count data into DGEList for edgeR package.

`plot_deseq2_phyloseq` and `plot_edgeR_phyloseq` plot the result of differential analysis of count data (using either the package DESeq2 or edgeR).

```
source(file = "functions_for_phyloseq.R")
```

2 Data

2.1 Choice of filter parameters

```
#Choose the dataset folder
data_folder <- "Uparse_min1"

#Choose the minimum number of sequences by sample.
N_sam_min <- 20000

#Choose the minimum number of samples by OTU.
N_otu_sam_min <- 1

#Choose the minimum number of sequences by OTU.
N_seq_otu_min <- 5
```

2.2 Load and convert loading

2.2.1 Otu table

```
#Import biom data
dataBiom <- import_biom(paste("data/", data_folder, "/otu_table.biom", sep=""))
```

2.2.2 Taxonomy

```

#Import taxonomy data
taxRDP_brut <- readLines(paste("data/", data_folder, "/tax_assignments.txt", sep=""))
taxRDP_brut <- gsub(";", "\t", taxRDP_brut)
taxRDP_brut <- gsub(")", "", taxRDP_brut)
taxRDP_brut <- gsub("\\(", "\t", taxRDP_brut)
taxRDP_brut <- gsub("*_", "\t", taxRDP_brut)
taxRDP_brut <- read.table(textConnection(taxRDP_brut), sep = "\t", fill = TRUE)

```

```

# Sort taxonomy
sort_taxRDP_brut <- unlist(strsplit(unlist(strsplit(rownames(dataBiom), split = ";"))
                                [seq(1, length(rownames(dataBiom))*2, by = 2)],
                                split = "_"))[seq(2, length(rownames(dataBiom))*2,
                                                by = 2)]

taxRDP_brut <- taxRDP_brut[1:dim(taxRDP_brut)[1] %in% sort_taxRDP_brut,]

# Format taxonomy for phyloseq
taxRDP <- taxRDP_brut[match(taxa_names(dataBiom),
                           paste(taxRDP_brut[, 1], taxRDP_brut[, 2], "", sep = ";")),
                     c(5, 7, 9, 11, 13, 15, 17)]
taxRDP <- tax_table(as.matrix(taxRDP))
taxa_names(taxRDP) <- taxa_names(dataBiom)
colnames(taxRDP) <- c("Domain", "Phylum", "Class", "Order", "Family",
                     "Genus", "Species")

```

2.2.3 Add FUNguild information to taxonomy Table

```

taxRDP2 <- as.data.frame(taxRDP)
funguild <- read.delim(paste("data/", data_folder, "/FUNGUILD.guilds.txt", sep = ""))

match_interm <- match(paste(funguild$OTU_ID,";", sep = ""), gsub(";size=", "_",
                                                                rownames(taxRDP2)))

taxRDP2$Trophic_Mode <- NA
taxRDP2$Trophic_Mode[match_interm] <- as.character(funguild$Trophic.Mode)
taxRDP2$Guild <- NA
taxRDP2$Guild[match_interm] <- as.character(funguild$Guild)
taxRDP2$Confidence_Ranking <- NA
taxRDP2$Confidence_Ranking[match_interm] <- as.character(funguild$Confidence.Ranking)
taxRDP2$Growth_Morphology <- NA
taxRDP2$Growth_Morphology[match_interm] <- as.character(funguild$Growth.Morphology)
taxRDP2$Trait <- NA
taxRDP2$Trait[match_interm] <- as.character(funguild$Trait)

taxRDP2 <- tax_table(as.matrix(taxRDP2))
taxa_names(taxRDP2) <- taxa_names(dataBiom)
colnames(taxRDP2) <- c("Domain", "Phylum", "Class", "Order", "Family", "Genus", "Species",
                     "Trophic_Mode", "Guild", "Confidence_Ranking", "Growth_Morphology",
                     "Trait")

```

2.2.4 Representative sequences

```
map_endo <-  
  import_qiime(map = "data/map_qiimedata.txt")  
  
## Processing map file...  
  
map_endo <- map_endo[order(rownames(map_endo)),]
```

2.2.5 Samples information

```
repset <- import_qiime(refseqfilename = paste("data/", data_folder, "/seq.fasta",  
                                              sep = ""))  
  
## Processing Reference Sequences...
```

2.2.6 Create the phyloseq object

```
data_all <- merge_phyloseq(dataBiom, repset, taxRDP2)  
  
sample_data(data_all) <- map_endo  
  
data_all@tax_table[data_all@tax_table == ""] <- NA  
taxa_names(data_all) <-  
  unlist(strsplit(taxa_names(data_all) ,  
                  split = ";"))[seq(1, 2*length(taxa_names(data_all)), by=2)]
```

2.2.7 Characteristics of the phyloseq data

```
data_all  
  
## phyloseq-class experiment-level object  
## otu_table() OTU Table: [ 1667 taxa and 80 samples ]  
## sample_data() Sample Data: [ 80 samples by 6 sample variables ]  
## tax_table() Taxonomy Table: [ 1667 taxa by 12 taxonomic ranks ]  
## refseq() DNASTringSet: [ 1667 reference sequences ]
```

The data are made of 8.335341×10^6 sequences representing 1667 OTUs allocate to 80 samples.

2.3 Filter sample by number of sequences

```
N_sam_min  
  
## [1] 20000
```

If we discard samples with less than 2×10^4 sequences, we keep 72 on the 80 samples (90%).

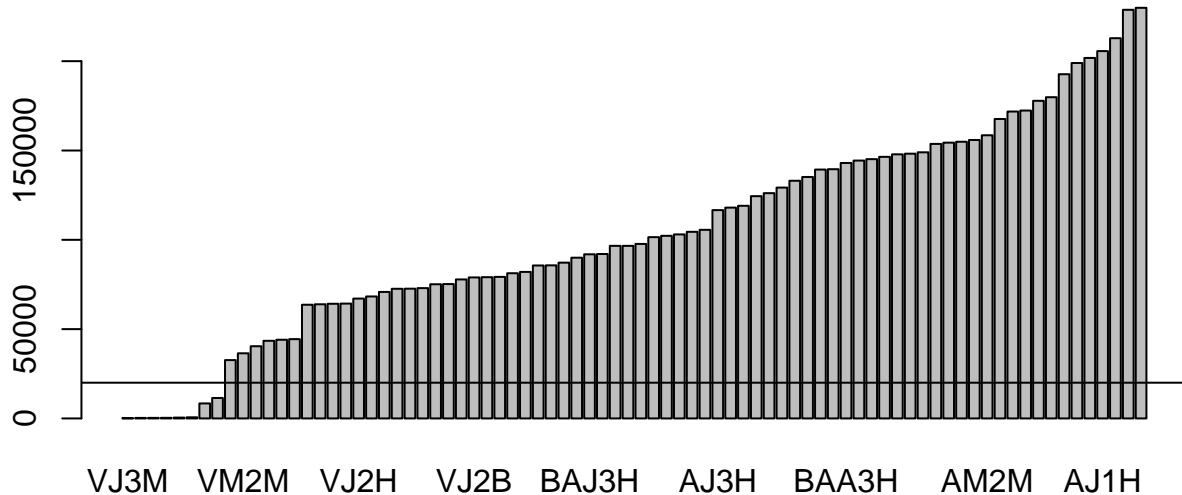


Figure 2.1: Number of sequences by sample. Horizontal line indicates the filtering parameter.

```
barplot(sort(sample_sums(data_all)))
abline(h = N_sam_min)
data.f1 <- prune_samples(sample_sums(data_all) > N_sam_min, data_all)
data.f1 <- prune_taxa(taxa_sums(data.f1) >= 1, data.f1)
```

2.4 Filter OTUs by number of samples

First, we can visualize the number of OTUs in a given number of samples (Figure 2.2).

```
df_nbOtu_sample <- data.frame("Nb of OTUs" = table(rowSums(as.binaryOtuTable(
  data.f1@otu_table)) [table(rowSums(as.binaryOtuTable(data.f1@otu_table)) > 1],
  "Nb samples" = as.numeric(names(table(rowSums(as.binaryOtuTable(data.f1@otu_table))
    [table(rowSums(as.binaryOtuTable(data.f1@otu_table)) > 1]))))

g <- ggplot(df_nbOtu_sample, aes(y = Nb.of.OTUs.Freq, x = Nb.samples))
g + geom_point(size = 4, col = rgb(0.1, 0.1, 0.1, 0.5)) +
  scale_y_continuous(trans = 'log10') +
  geom_smooth(size = 2, col = rgb(0.1, 0.1, 0.1, 0.5)) +
  geom_vline(xintercept= N_otu_sam_min)

## 'geom_smooth()' using method = 'loess'

summary(df_nbOtu_sample$Nb.samples)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      1.00  18.25   35.50   36.00  53.75   72.00
```

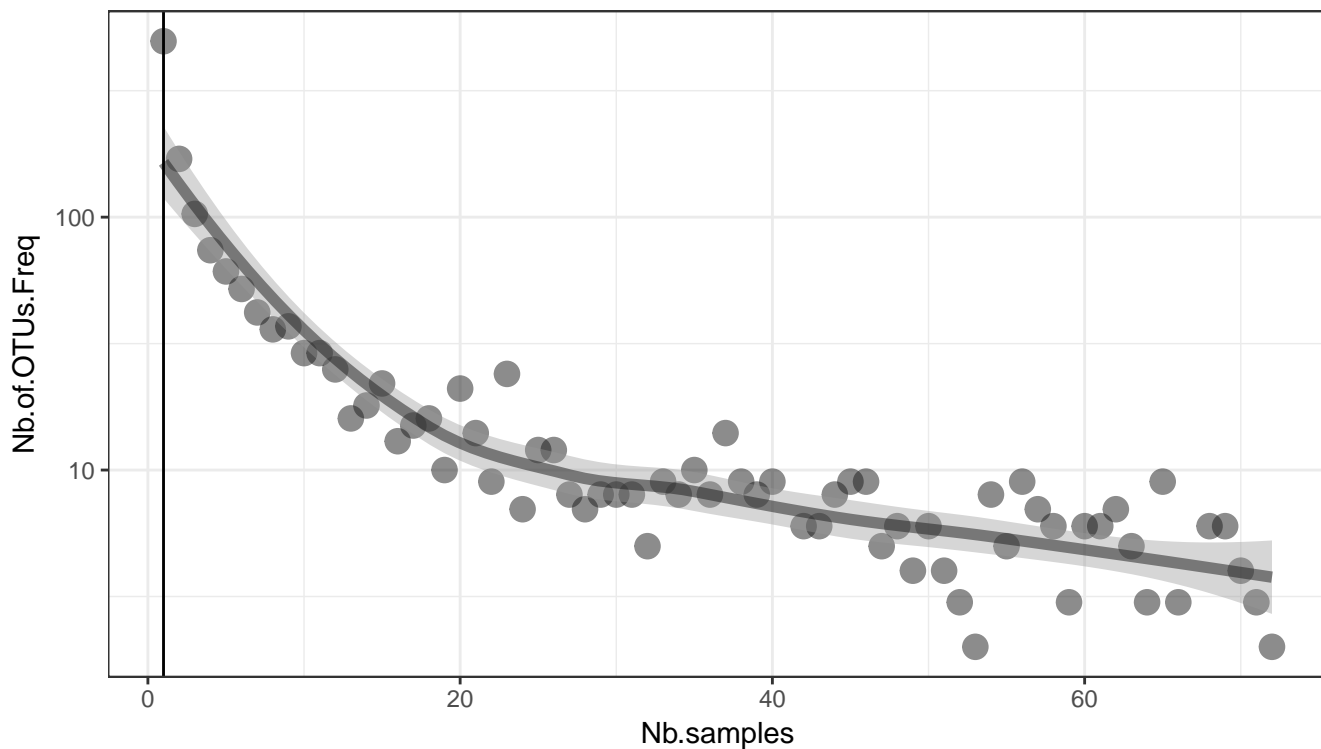


Figure 2.2: Number of OTU present in a given number of samples. Vertical bar illustrates the filtering parameter.

```
N_otu_sam_min
```

```
## [1] 1
```

```
data.f2 <- prune_taxa(rowSums(as.binaryOtuTable(data.f1)@otu_table) >=
                      N_otu_sam_min, data.f1)
```

If we discard OTUs present in less than 1 sample, we keep 1650 on the 1650 OTUs (100%).

2.5 Filter OTUs by number of sequences

We can visualize the number of sequences by OTU (Figure 2.3).

```
df_nbseq_Otu <- data.frame("Nb of sequences by OTUs" = rowSums(data.f2@otu_table))
g <- ggplot(df_nbseq_Otu, aes(x = Nb.of.sequences.by.OTUs))
g + geom_histogram(size = 2, col = rgb(0.8, 0.8, 0.8, 0.3)) +
  scale_x_continuous(trans = 'log10') +
  geom_vline(xintercept= N_seq_otu_min)
```

```
## 'stat_bin()' using 'bins = 30'. Pick better value with 'binwidth'.
```

```
summary(df_nbseq_Otu[, 1])
```

```
##      Min.   1st Qu.   Median     Mean   3rd Qu.    Max.
##      1.0      7.0     46.0    5038.3   337.8 1943171.0
```

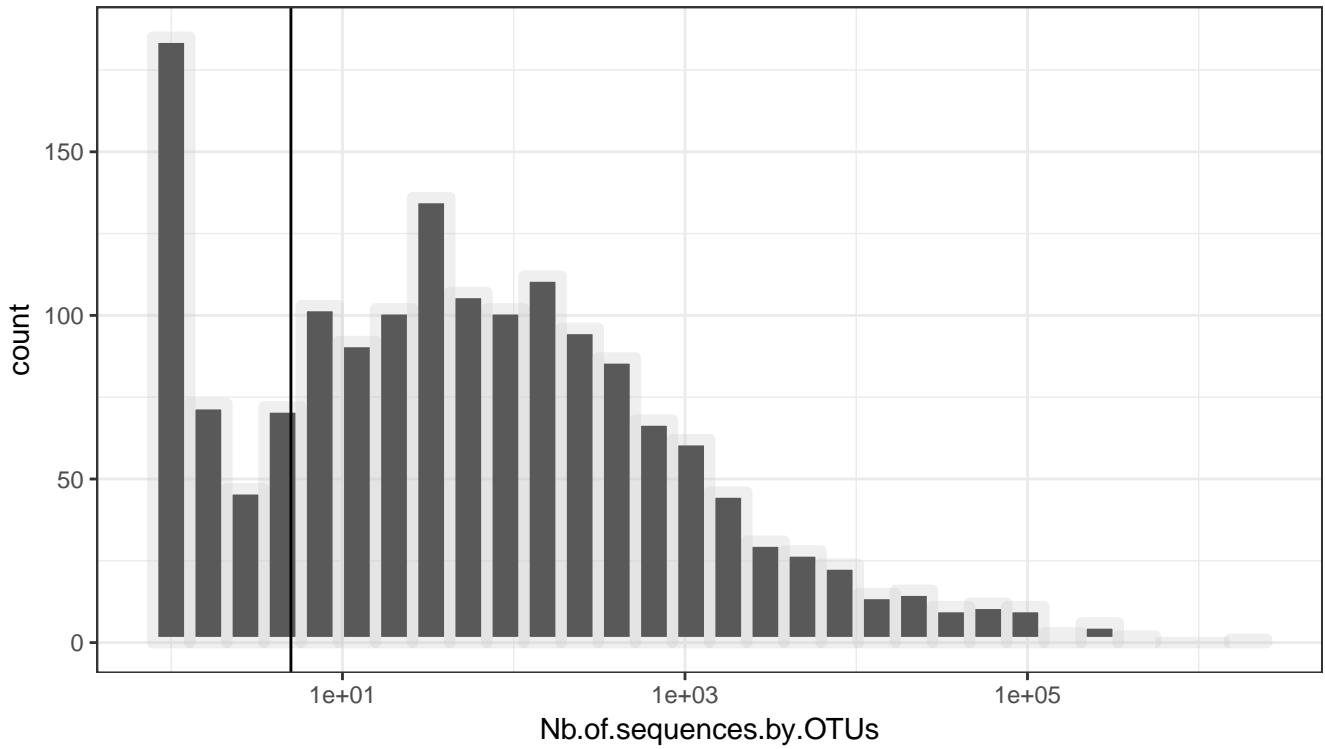


Figure 2.3: Number of sequences by OTU (log10 transformed). Horizontal bar illustrates the filtering parameter.

```
N_seq_otu_min
## [1] 5
```

If we discard OTUs with less than 1 sequences, we keep 1302 on the 1667 OTUs (78.1%).

```
data.f3 <- prune_taxa(rowSums(data.f2@otu_table) >= N_seq_otu_min, data.f2)
```

2.6 Summary of filtration workflow

The filtered data are made of 8.312594×10^6 sequences representing 1302 OTUs allocate to 72 samples.

	Nb.of.OTUs	Nb.of.samples	Nb.of.sequences
No filter	1667	80	8335341.00
Nb of sequences by sample ≥ 20000	1650	72	8313238.00
Nb of sample by OTUs ≥ 1	1650	72	8313238.00
Nb of sequences by OTUs ≥ 5	1302	72	8312594.00

Table 1: Number of OTUs, samples and sequences after filtering

3 Simple description of the dataset

3.1 Number of sequences and OTUs by samples

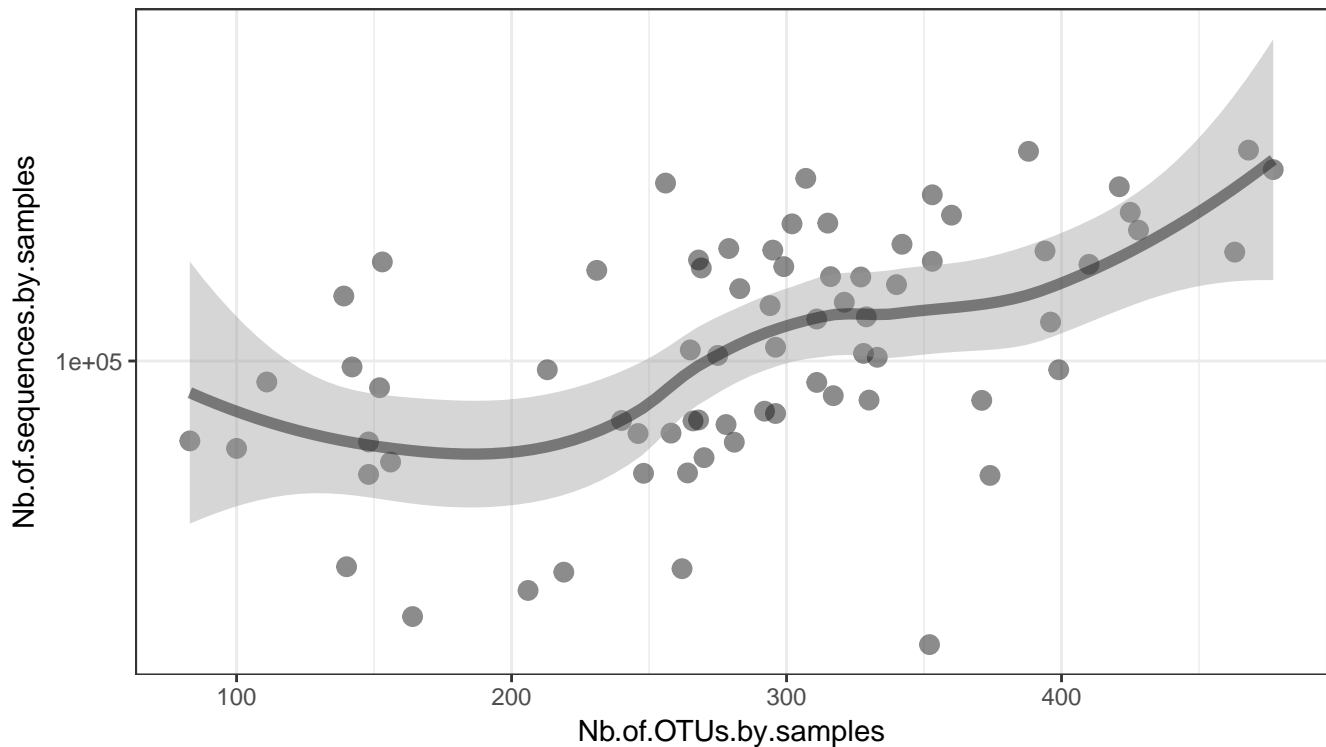


Figure 3.1: Number of OTUs by sample in fonction of the number of sequences by sample (log10 axe). The tendency is represented by the line obtained from loess (Local Polynomial Regression Fitting).

```
df_nbseq_nbotu <- data.frame("Nb of sequences by samples" = colSums(data.f3@otu_table),
                             "Nb of OTUs by samples" =
                               colSums(as.binaryOtuTable(data.f3@otu_table)))

g <- ggplot(df_nbseq_nbotu, aes(x = Nb.of.OTUs.by.samples,
                               y = Nb.of.sequences.by.samples))
g + geom_point(size = 3, col = rgb(0.1, 0.1, 0.1, 0.5)) +
  scale_y_continuous(trans = 'log10') +
  geom_smooth(size = 2, col = rgb(0.1, 0.1, 0.1, 0.5))

## 'geom_smooth()' using method = 'loess'
```

```
ggplot(as.data.frame(data.f3@refseq@ranges), aes(x = width)) + geom_density() +
  ylab("Reference sequences length")
```

3.2 Number of sequences and samples for each OTUs

```
df_nbseq_nbsam <- data.frame("Nb of sequences by OTUs" = rowSums(data.f3@otu_table)
                             [rowSums(data.f3@otu_table) > 0],
                             "Nb of samples by OTUs" =
                               rowSums(as.binaryOtuTable(data.f3@otu_table)
                                         [rowSums(data.f3@otu_table) > 0]))
```

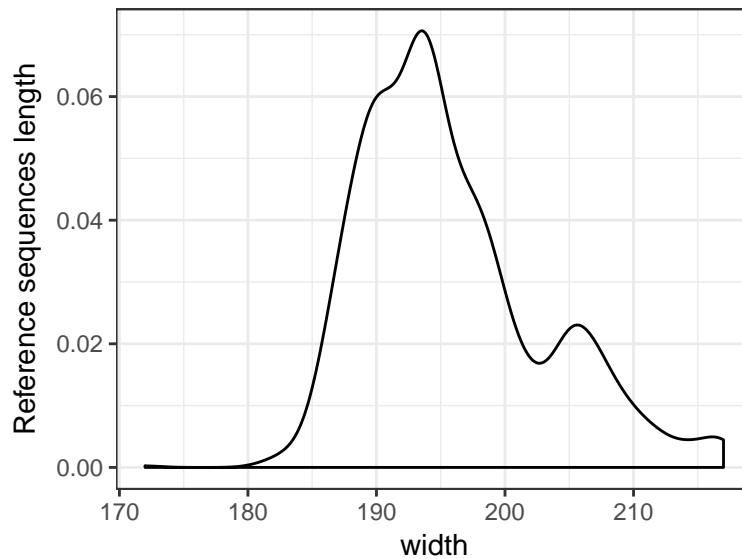


Figure 3.2: Distribution of reference sequences length.

```
g <- ggplot(df_nbseq_nbsam, aes(y = Nb.of.samples.by.OTUs,
                                x = Nb.of.sequences.by.OTUs))
g + geom_point(size = 3, col = rgb(0.1, 0.1, 0.1, 0.5)) +
  scale_x_continuous(trans = 'log10') +
  geom_smooth(size = 2, col = rgb(0.1, 0.1, 0.1, 0.5), method = "gam",
              formula = y ~ s(x, bs = "cs"))
```

3.3 Distribution of sequences in the taxonomy

```
df3 <- data.frame(as.data.frame(data.f3@tax_table), nb.seq = rowSums(data.f3@otu_table))
tm <- treemap(df3, index = c("Order", "Species"), vSize = "nb.seq", vColor = "Class",
              type = "categorical", palette = "Paired")
# For an interactive version in html
# d3tree(tm)
```

3.4 Focus on the 30 more abundant OTUs (number of sequences)

```
the30mostfrequents <- sort(decreasing = T, rowSums(data.f3@otu_table))[1:30]
barplot(the30mostfrequents, horiz = T, cex.names = 0.4, las = 2)
```

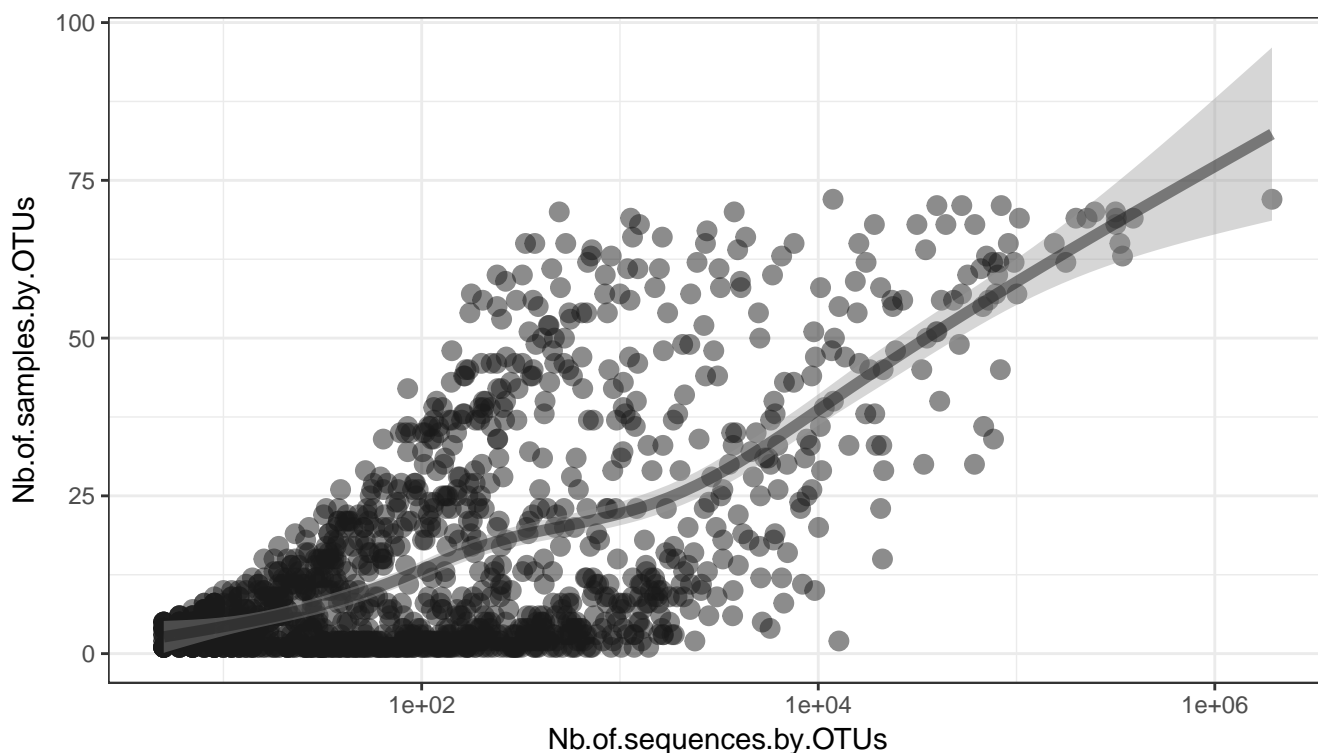


Figure 3.3: Number of sequences by OTUs (log10 axe) in fonction of the number of samples where OTUs were found. The tendency is represented by the line obtain from gam (Generalized additive models with integrated smoothness estimation).

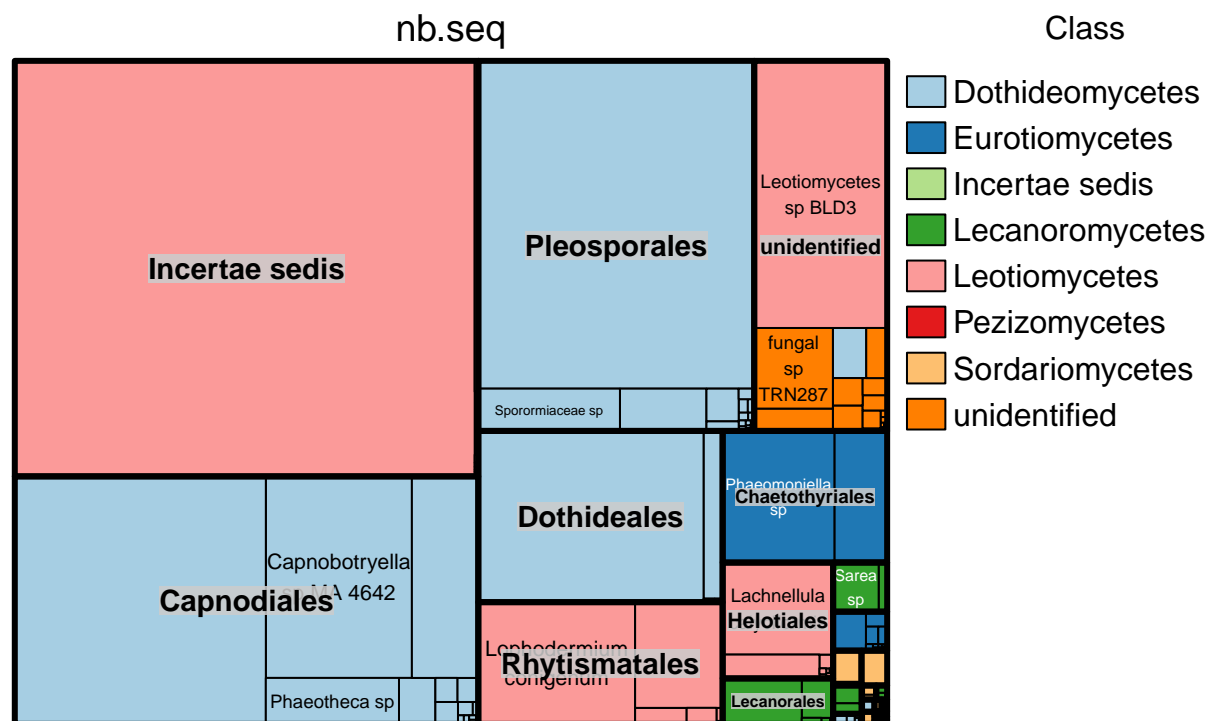


Figure 3.4: Distribution of the number of sequences in the Ascomycota taxonomy. Colors represent Class, bold lines delimit Order and thick line delimit species.

```
print(xtable(df_the30mostfrequents[, c(1:8, 12)], auto = T,
           caption = "Taxonomie of the 30 more
           abundant OTUs (number of sequences)",
           size = "\\tiny", include.rownames = FALSE)
```

Phylum	Class	Order	Family	Genus	Species	Trophic_Mode	Guild	Nb.sequences
Ascomycota	Leotiomyces	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	1943171
Ascomycota	Dothideomycetes	Pleosporales				-	-	387885
Ascomycota	Dothideomycetes	Capnodiales	Incertae sedis	Capnobotryella	Capnobotryella sp MA 4642	Saprotroph	Undefined Saprotroph	342517
Ascomycota	Dothideomycetes	Pleosporales	Incertae sedis			-	-	332263
Ascomycota	Leotiomyces	unidentified	unidentified	unidentified	Leotiomyces sp BLD3	-	-	318495
Ascomycota	Dothideomycetes	Dothideales	Dothioraceae	unidentified	Dothioraceae sp	-	-	317246
Ascomycota	Dothideomycetes	Capnodiales				-	-	315723
						-	-	247896
Ascomycota	Leotiomyces	Rhytismatales	Rhytismataceae	Lophodermium	Lophodermium conigenum	Pathotroph	Plant Pathogen	226872
Ascomycota	Dothideomycetes	Pleosporales				-	-	199465
						-	-	177383
Ascomycota	Dothideomycetes	Capnodiales	Mycosphaerellaceae	Phaeothecoidea	Phaeothecoidea sp	Saprotroph	Undefined Saprotroph	155089
Ascomycota	Leotiomyces	unidentified	unidentified	unidentified	Leotiomyces sp BLD3	-	-	103401
						-	-	100459
Ascomycota	Dothideomycetes	Dothideales	Dothioraceae	unidentified	Dothioraceae sp	-	-	97232
Ascomycota	Dothideomycetes	Pleosporales				-	-	90937
Ascomycota	Leotiomyces	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	83720
						-	-	82876
Ascomycota	Eurotiomyces	Chaetothyriales	Herpotrichiellaceae	Phaeomoniella	Phaeomoniella sp	Saprotroph	Undefined Saprotroph	81451
Ascomycota	Leotiomyces	Rhytismatales	Rhytismataceae	Lophodermium		Pathotroph	Plant Pathogen	80357
						-	-	78492
						-	-	76573
Ascomycota	Leotiomyces	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	75793
Ascomycota	unidentified	unidentified	unidentified	unidentified	fungal sp TRN287	-	-	72163
Ascomycota	Dothideomycetes	Capnodiales				-	-	70557
						-	-	68326
Ascomycota	Leotiomyces	Helotiales	Hyaloscyphaceae	Lachnellula	Lachnellula calyciformis	Saprotroph	Undefined Saprotroph	67576
Ascomycota	Eurotiomyces	Chaetothyriales	Herpotrichiellaceae	Phaeomoniella	Phaeomoniella sp	Saprotroph	Undefined Saprotroph	66072
Ascomycota	Dothideomycetes	Capnodiales	Davidiellaceae	Cladosporium		-	-	61649

Table 2: Taxonomie of the 30 more abundant OTUs (number of sequences)

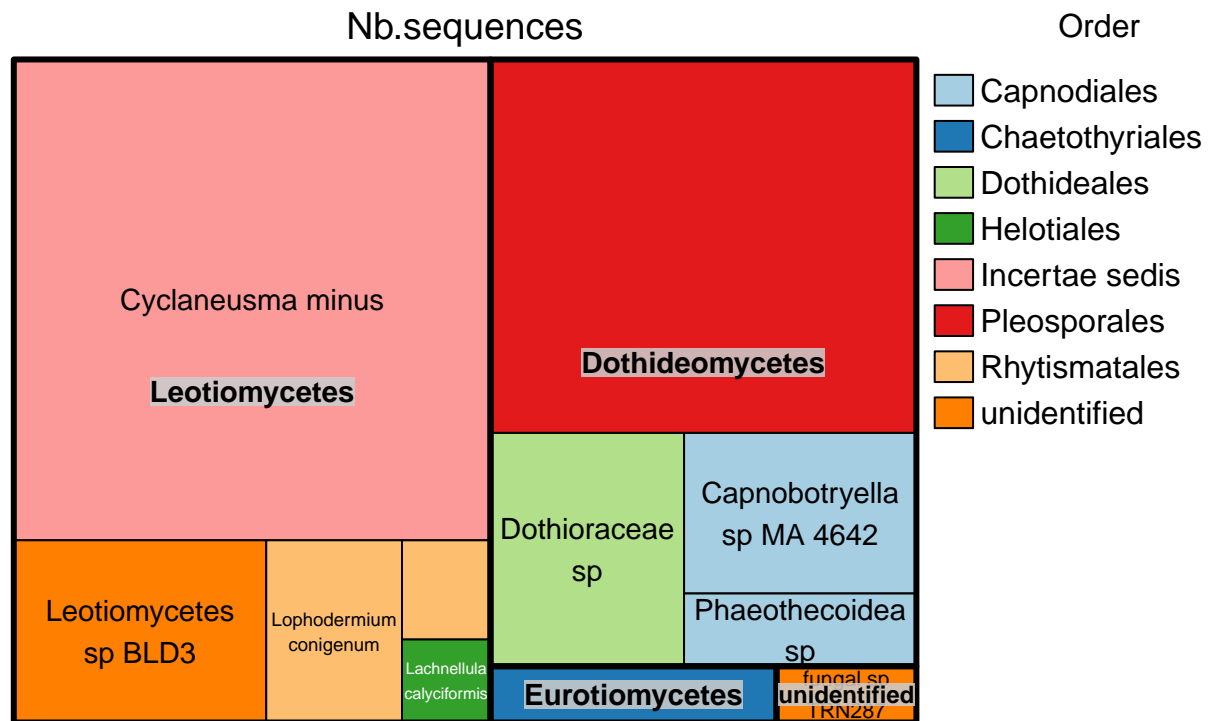


Figure 3.5: Number of sequences of the 30 most abundant OTUs (number of sequences). Colors indicate Order, bold lines delimit Class and thick lines delimit species.

```
treemap(df_the30mostfrequents, index = c("Class", "Species"), vSize = "Nb.sequences",
        vColor = "Order", type = "categorical", palette = "Paired")
```

3.5 Focus on the 30 more frequent OTUs (number of samples)

```
the30mostfrequents_samp <- sort(decreasing = T,
                                rowSums(as.binaryOtuTable(data.f3@otu_table))[1:30])
barplot(the30mostfrequents_samp, horiz = T, cex.names = 0.4, las = 2)
```



```
print(xtable(df_the30mostfrequents_samp[, c(1:8, 12)], auto = T,
  caption = "Taxonomie of the 30 more frequent OTUs (number of samples)",
  size = "\\tiny", include.rownames = FALSE)
```

Phylum	Class	Order	Family	Genus	Species	Trophic_Mode	Guild	Nb.samples
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	72
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	72
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	71
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	71
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	71
Ascomycota	Dothideomycetes	Capnodiales				-	-	70
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	70
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	70
Ascomycota	Leotiomycetes	Rhytismatales	Rhytismataceae	Lophodermium	Lophodermium conigenum	Pathotroph	Plant Pathogen	69
Ascomycota	Dothideomycetes	Pleosporales				-	-	69
Ascomycota	Leotiomycetes	unidentified	unidentified	unidentified	Leotiomycetes sp BLD3	-	-	69
Ascomycota	Leotiomycetes	unidentified	unidentified	unidentified	Leotiomycetes sp BLD3	-	-	69
Ascomycota	Dothideomycetes	Pleosporales				-	-	69
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	69
Ascomycota	Dothideomycetes	Dothideales	Dothioraceae	unidentified	Dothioraceae sp	-	-	68
Ascomycota	Dothideomycetes	Pleosporales	Incertae sedis	Ochrocladosporium	Ochrocladosporium sp	Saprotroph	Undefined Saprotroph	68
Ascomycota	Dothideomycetes	Capnodiales	Davidiellaceae	Cladosporium		-	-	68
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	68
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	68
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	68
Ascomycota	Leotiomycetes	unidentified	unidentified	unidentified	Leotiomycetes sp BLD3	-	-	67
Ascomycota	Dothideomycetes	Capnodiales				-	-	66
Ascomycota	Leotiomycetes	Incertae sedis	Incertae sedis	Cyclaneusma	Cyclaneusma minus	-	-	66

Table 3: Taxonomie of the 30 more frequent OTUs (number of samples)

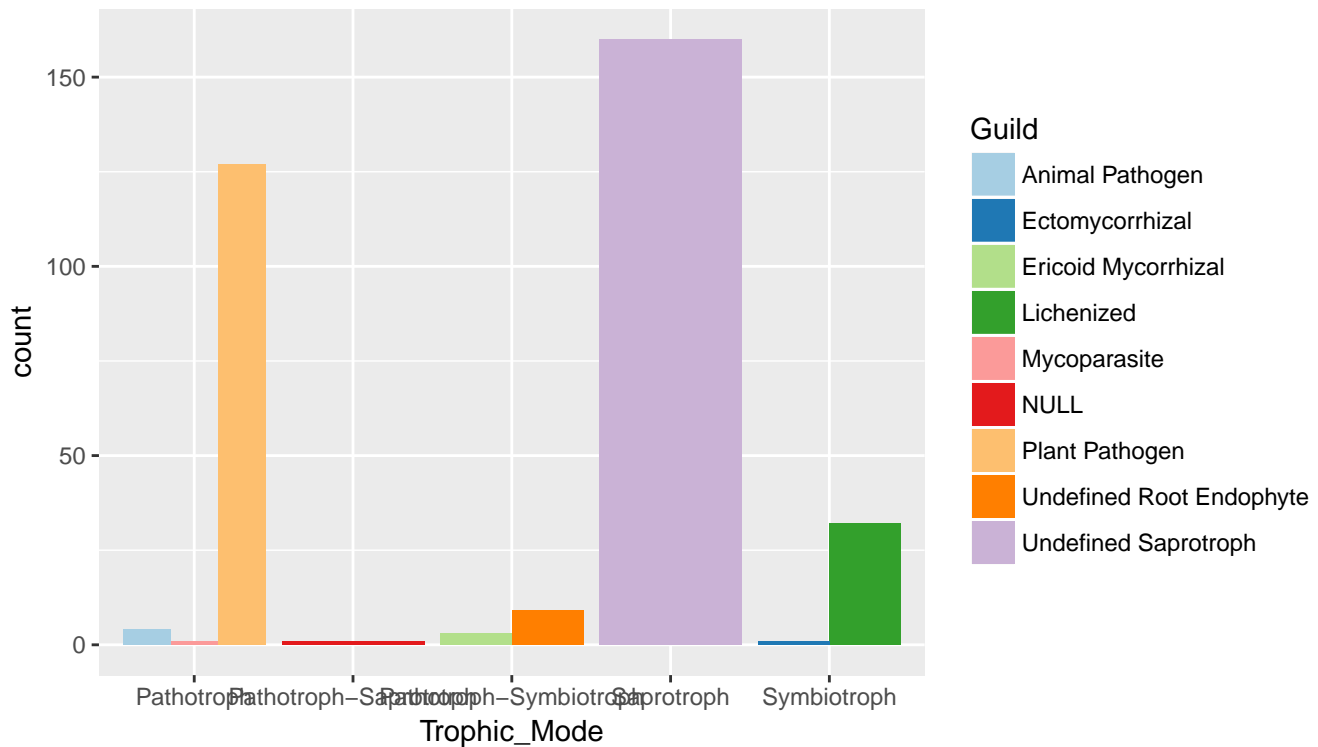


Figure 4.1: Distribution of OTUs into functional Guild.

4 Number of sequences and OTUs in function of putative ecology (using FUNGuild software; Nguyen et al, 2015)

```
tabPutativeEcology <- apply(data.f3@tax_table, 2, function(x) table(x))
tabPutativeEcology_percent <- apply(data.f3@tax_table, 2, function(x)
  round(table(x)/dim(data.f3@tax_table)[1]*100, 3))
sum(data.f3@otu_table[data.f3@tax_table[, "Trophic_Mode"] == "-"]) /
  sum(data.f3@otu_table)*100

## [1] 82.18797

tmdata <- as.data.frame(data.f3@tax_table[data.f3@tax_table[, "Trophic_Mode"] != "-"])
tmdata$Nb.sequences <- rowSums(data.f3@otu_table[data.f3@tax_table[, "Trophic_Mode"] != "-"])
tmdata$Nb.OTU <- rep(1, length(tmdata$Nb.sequences))
```

```
ggplot(tmdata) + geom_bar(aes(x = Trophic_Mode, fill=Guild), position = "dodge") +
  scale_fill_discrete("Paired") + theme_grey()
```

```
ggplot(tmdata, stat = "identity") +
  geom_bar(aes(x = Trophic_Mode, weight = Nb.sequences, fill = Guild), position = "dodge") +
  scale_fill_discrete("Paired") + scale_y_log10() + theme_grey()
```

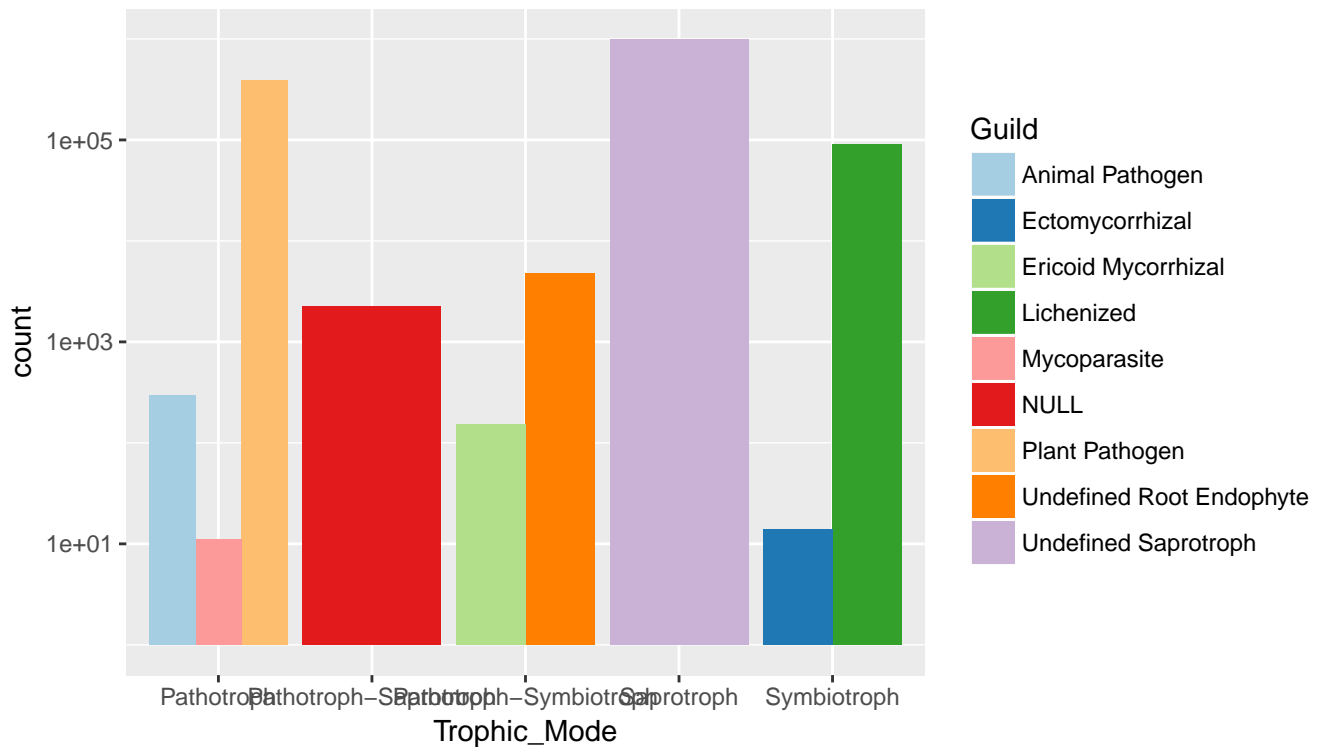


Figure 4.2: Distribution of sequences (log10 transformed) into functional Guild.

5 Distribution of fungal endophytic alpha-biodiversity

5.1 Local diversity = Diversity by sites

```
accu_plot(data.f3, "Sites", nbSeq = FALSE)
```

```
accu_plot(data.f3, "Sites", step = 5000)
```

```
measures_index <- c("Observed", "Chao1", "Shannon", "Simpson")
p <- plot_richness(data.f3, x = "Sites", color = "Sites", measures = measures_index)
p + geom_boxplot(data = p$data, alpha = 0.5)
```

5.2 Diversity by age of tree

```
accu_plot(data.f3, "Age", nbSeq = FALSE)
```

```
measures_index <- c("Observed", "Chao1", "Shannon", "Simpson")
p <- plot_richness(data.f3, x = "Age", color = "Sites", measures = measures_index)
p + geom_boxplot(data = p$data, aes(x = p$data$Age, y = value, color = NULL),
  alpha = 0.5)
```

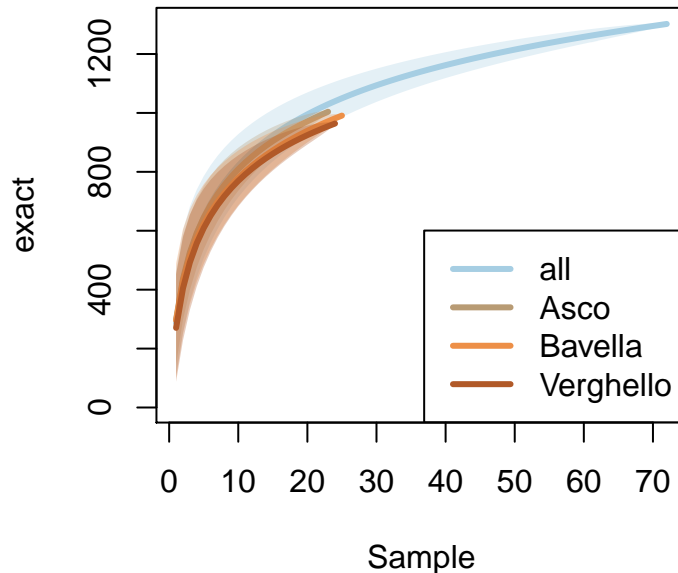


Figure 5.1: Rarefaction curves for each site. Note that if singletons were removed, these curves are biased.

5.3 Diversity by elevation of the sample

```
accu_plot(data.f3, "Elevation", nbSeq = FALSE)
```

```
measures_index <- c("Observed", "Chao1", "Shannon", "Simpson")
p <- plot_richness(data.f3, x = "Elevation", color = "Sites", measures = measures_index)
p + geom_boxplot(data = p$data, aes(x = p$data$Elevation, y = value, color = NULL),
  alpha = 0.5)
```

5.4 Which factor affect diversity?

```
## Uneven sequencing depth may have an impact
readNumbers = apply(t(data.f3@otu_table), 1, sum)

otuHill <- renyi(t(data.f3@otu_table), scale = c(0, 1, 2), hill = T)

hill.1 = otuHill$"0"
hill.2 = otuHill$"1"
hill.3 = otuHill$"2"

hill.1.m1 = lm(hill.1 ~ sqrt(readNumbers) + data.f3$sam_data$Sites +
  data.f3$sam_data$Age + data.f3$sam_data$Elevation)
```

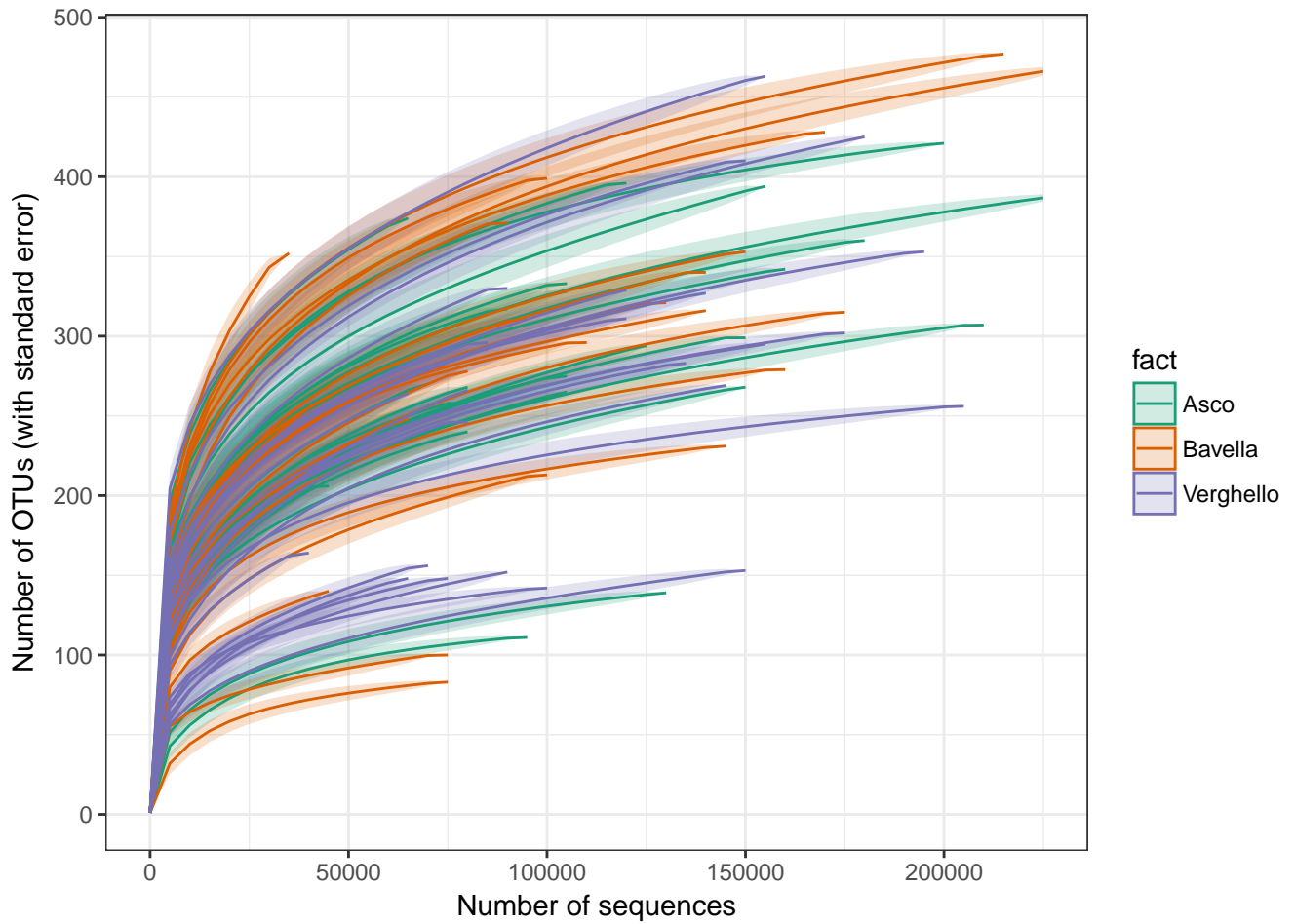


Figure 5.2: Rarefaction curves for each sample using sequences number on x-axes. Note that if singletons were removed, these curves are biased.

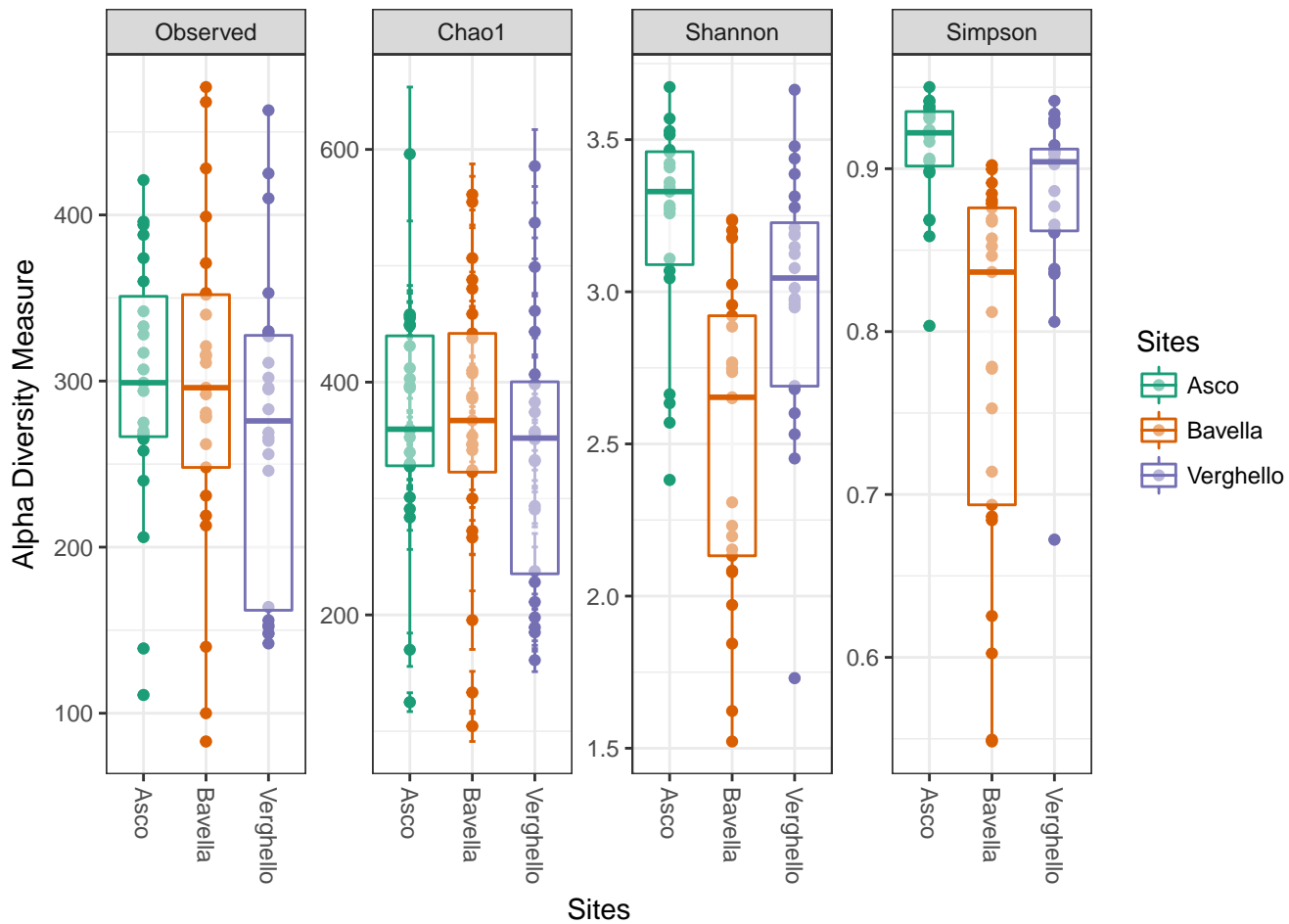


Figure 5.3: Diversity of each sites

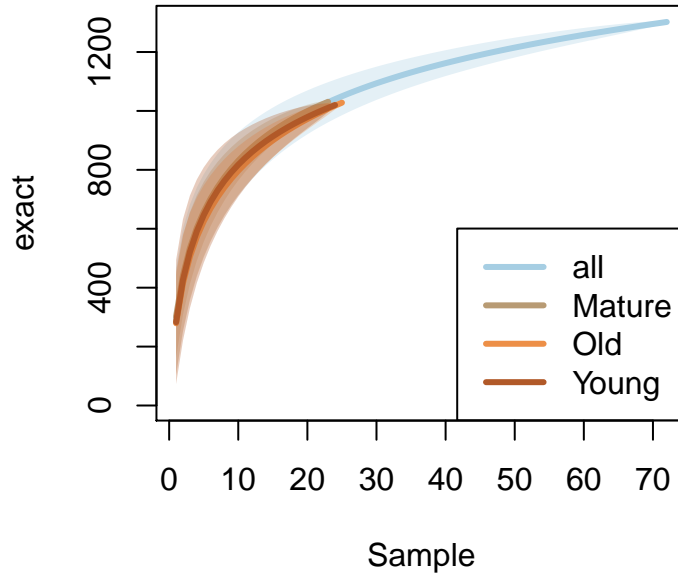


Figure 5.4: Rarefaction curves for each host age. Note that if singletons were removed, these curves are biased.

```
hill.2.m1 = lm(hill.2 ~ sqrt(readNumbers) + data.f3@sam_data$Sites +
               data.f3@sam_data$Age + data.f3@sam_data$Elevation)
hill.3.m1 = lm(hill.3 ~ sqrt(readNumbers) + data.f3@sam_data$Sites +
               data.f3@sam_data$Age + data.f3@sam_data$Elevation)
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	62.8502239	49.5872070	1.2674685	0.2095802
sqrt(readNumbers)	0.7288918	0.1267135	5.7522816	0.0000003
data.f3@sam_data\$SitesBavella	9.9500272	22.0573697	0.4510976	0.6534440
data.f3@sam_data\$SitesVerghello	-24.5733747	22.0808586	-1.1128813	0.2699220
data.f3@sam_data\$AgeOld	-13.7853535	21.9625265	-0.6276761	0.5324494
data.f3@sam_data\$AgeYoung	-37.0937028	22.4841290	-1.6497727	0.1038895
data.f3@sam_data\$ElevationMiddle	20.1789158	22.2394735	0.9073468	0.3676272
data.f3@sam_data\$ElevationTop	-5.5313782	21.9385577	-0.2521304	0.8017482

Table 4: Summary of the linear model of species richness (Hill number with $q = 0$)

Post-hoc Tukey tests among the three experimental treatments with partial residuals, after accounting for differential sequencing success.

```
tuk1 <- TukeyHSD(aov(lm(hill.1 ~ sqrt(readNumbers))$residuals ~ data.f3@sam_data$Site))
tuk2 <- TukeyHSD(aov(lm(hill.2 ~ sqrt(readNumbers))$residuals ~ data.f3@sam_data$Site))
tuk3 <- TukeyHSD(aov(lm(hill.3 ~ sqrt(readNumbers))$residuals ~ data.f3@sam_data$Site))
```

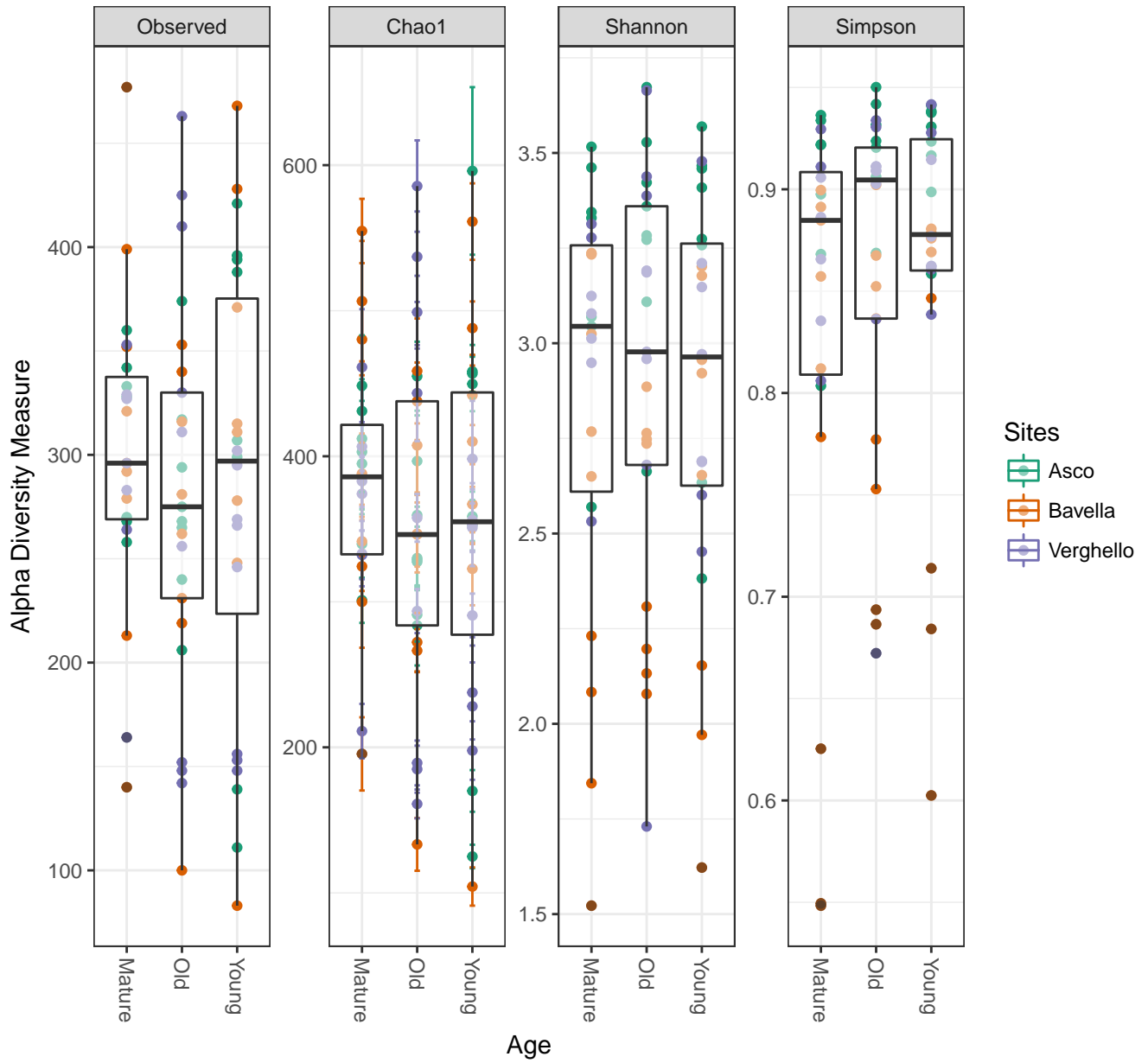


Figure 5.5: Diversity in function of tree age. Color represent sites.

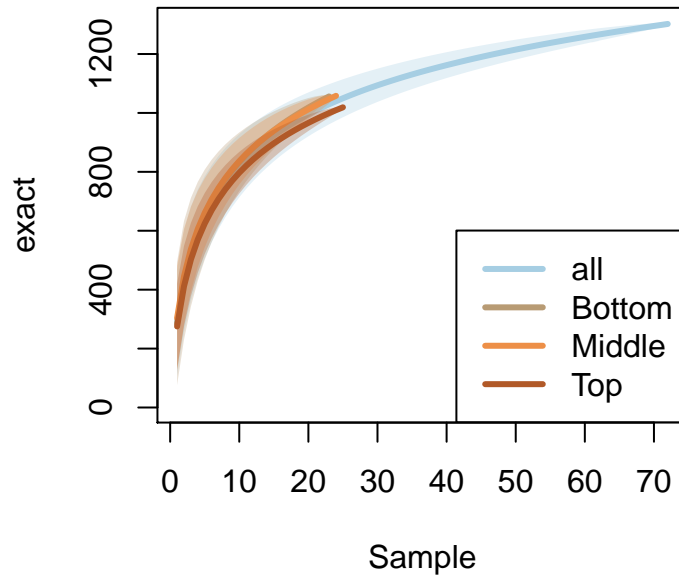


Figure 5.6: Rarefaction curves for each elevation. Notes that if singletons were removed, these curves are biased.

```
ggplot(data = df) + geom_linerange(aes(ymax = xSup, ymin = xInf, x = y), size = 2) +
  geom_point(aes(x=y, y=x), size=4, shape=21, fill="white") +
  coord_flip() + theme_gray() + geom_hline(yintercept = 0) +
  ylab("Differences in mean levels") + xlab("")
```

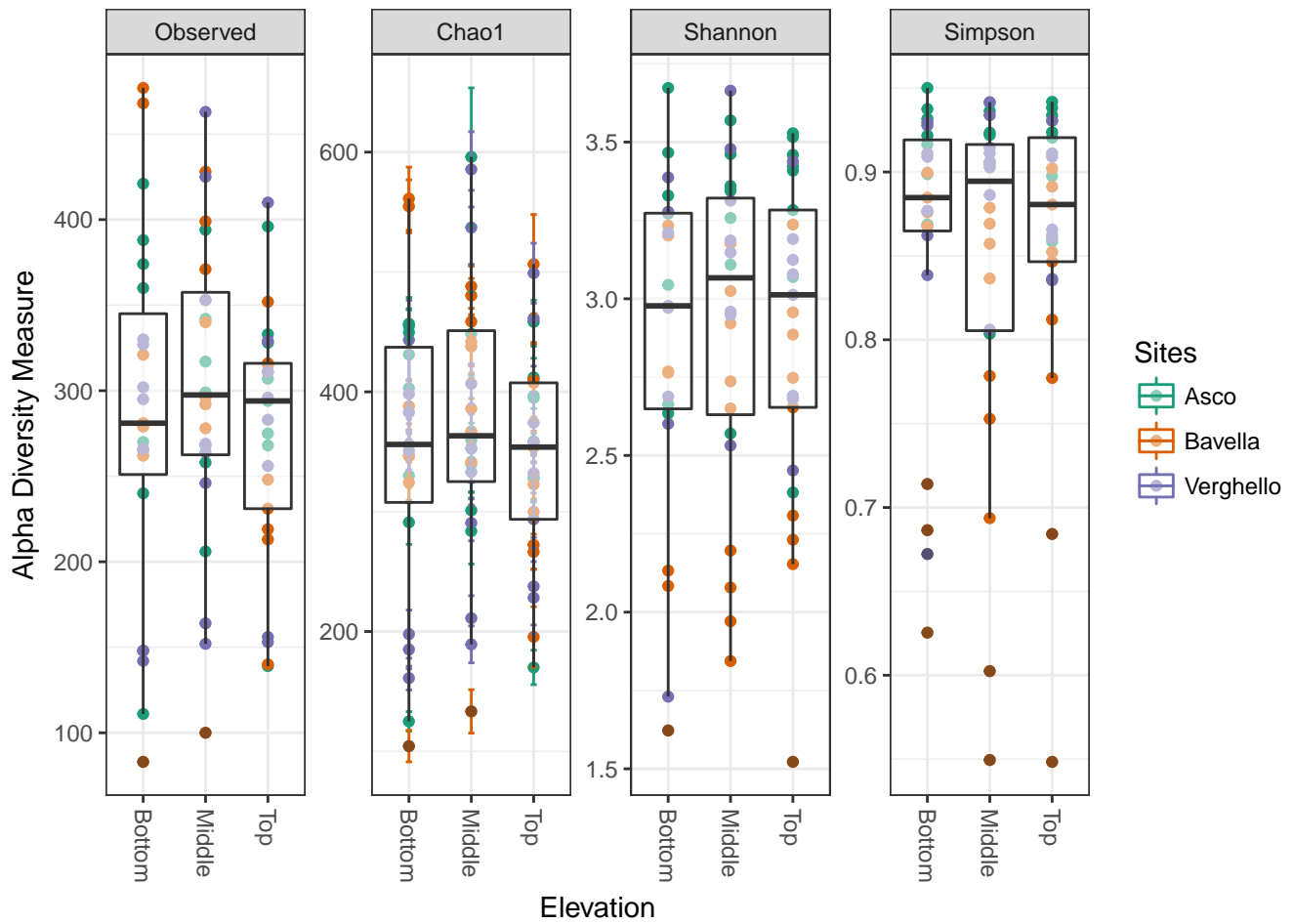


Figure 5.7: Diversity in function of elevation. Color represent sites.

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	15.9643217	4.7426774	3.3660990	0.0012932
sqrt(readNumbers)	0.0273900	0.0121193	2.2600329	0.0272300
data.f3@sam_data\$SitesBavella	-11.8649769	2.1096366	-5.6241804	0.0000004
data.f3@sam_data\$SitesVerghello	-4.9746545	2.1118832	-2.3555539	0.0215712
data.f3@sam_data\$AgeOld	1.0906065	2.1005655	0.5191966	0.6054145
data.f3@sam_data\$AgeYoung	-0.9054816	2.1504532	-0.4210655	0.6751180
data.f3@sam_data\$ElevationMiddle	2.1257168	2.1270536	0.9993715	0.3213784
data.f3@sam_data\$ElevationTop	1.0378518	2.0982731	0.4946219	0.6225607

Table 5: Summary of the linear model of the exponential of Shannon’s entropy index (Hill number with $q = 1$)

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	9.3970926	2.2046679	4.2623619	0.0000678
sqrt(readNumbers)	0.0071962	0.0056337	1.2773406	0.2060965
data.f3@sam_data\$SitesBavella	-6.6403487	0.9806799	-6.7711687	0.0000000
data.f3@sam_data\$SitesVerghello	-2.8126265	0.9817242	-2.8649865	0.0056353
data.f3@sam_data\$AgeOld	1.1277239	0.9764631	1.1549068	0.2524225
data.f3@sam_data\$AgeYoung	0.7541150	0.9996537	0.7543762	0.4533902
data.f3@sam_data\$ElevationMiddle	0.2513083	0.9887763	0.2541610	0.8001860
data.f3@sam_data\$ElevationTop	0.1848083	0.9753974	0.1894698	0.8503243

Table 6: Summary of the linear model of inverse of Simpson’s concentration index (Hill number with $q = 2$)

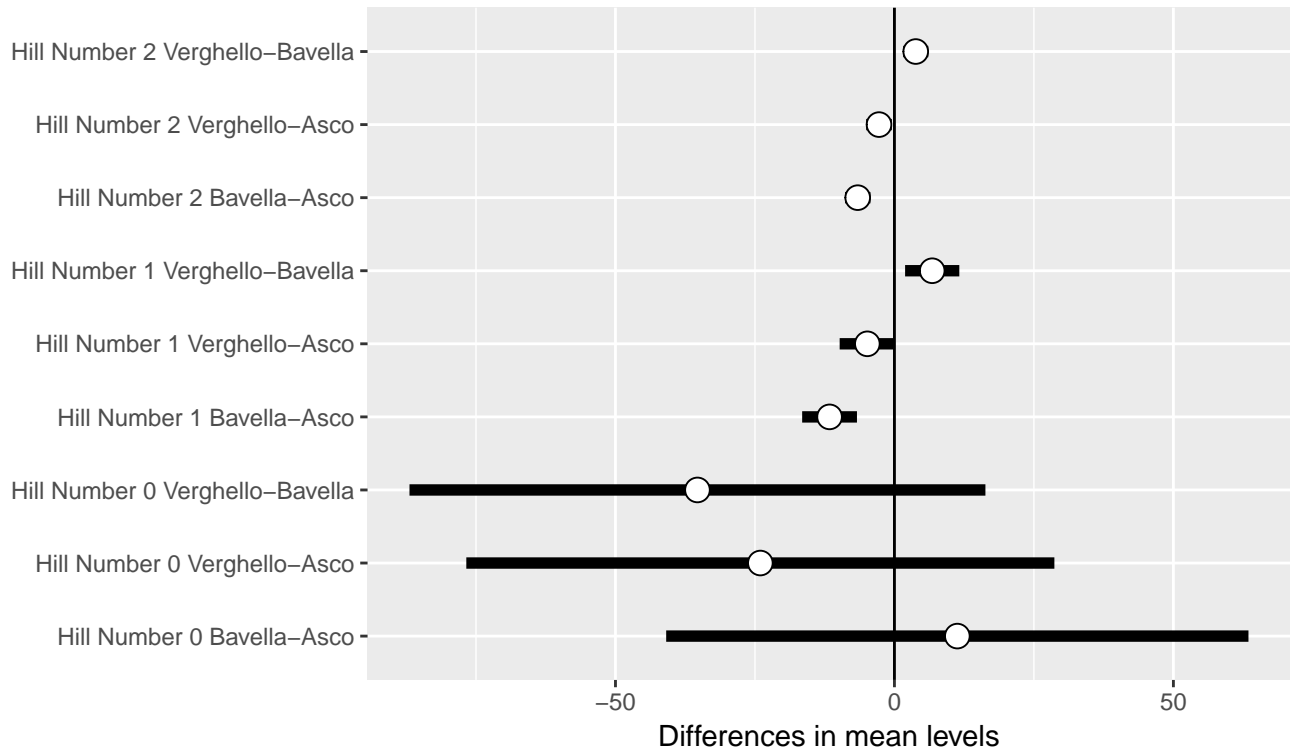


Figure 5.8: Results of the Tuckey HSD testing for differences in mean Hill numbers among pairs of modalities

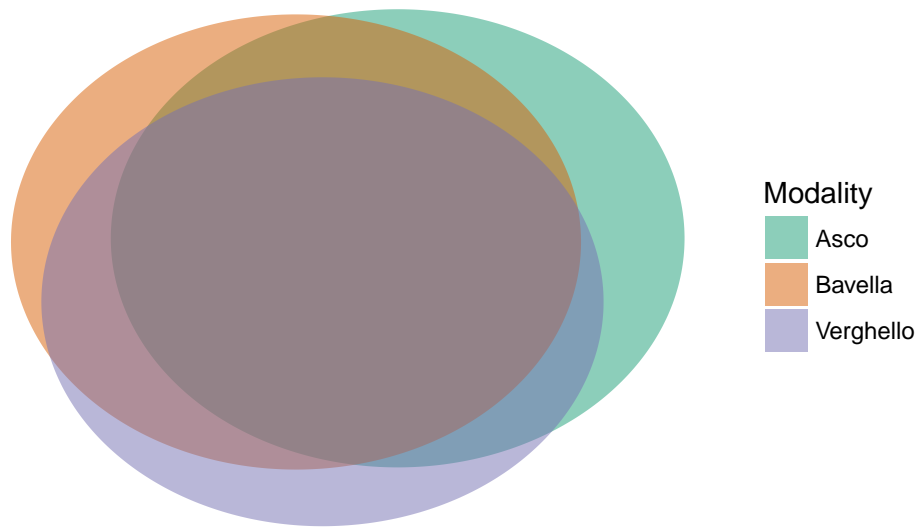


Figure 6.1: Venn diagramm of the distribution of OTUs among Sites

6 Effect of site, age and elevation on fungal endophytic beta-diversity

6.1 Venn diagramm

```
venn_phyloseq(data.f3, "Sites", printValues = F)
```

```
venn_phyloseq(data.f3, "Age", printValues = F)
```

```
venn_phyloseq(data.f3, "Elevation", printValues = F)
```

6.2 Venn diagramm for OTUs present in at least 3 samples

```
data.f3_3samp <- subset_taxa(data.f3, rowSums(data.f3@otu_table>0)>2)
venn_phyloseq(data.f3_3samp, "Sites", printValues = F)
```

```
venn_phyloseq(data.f3_3samp, "Age", printValues = F)
```

```
venn_phyloseq(data.f3_3samp, "Elevation", printValues = F)
```

6.3 Ordination

Ordination of the OTUs table using NMDS (Non-metric MultiDimensionstional Scaling).

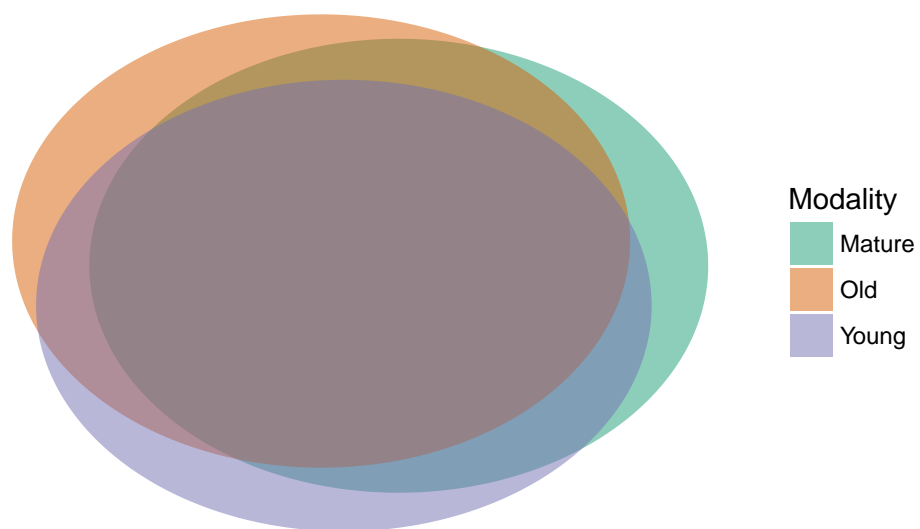


Figure 6.2: Venn diagramm of the distribution of OTUs among host age

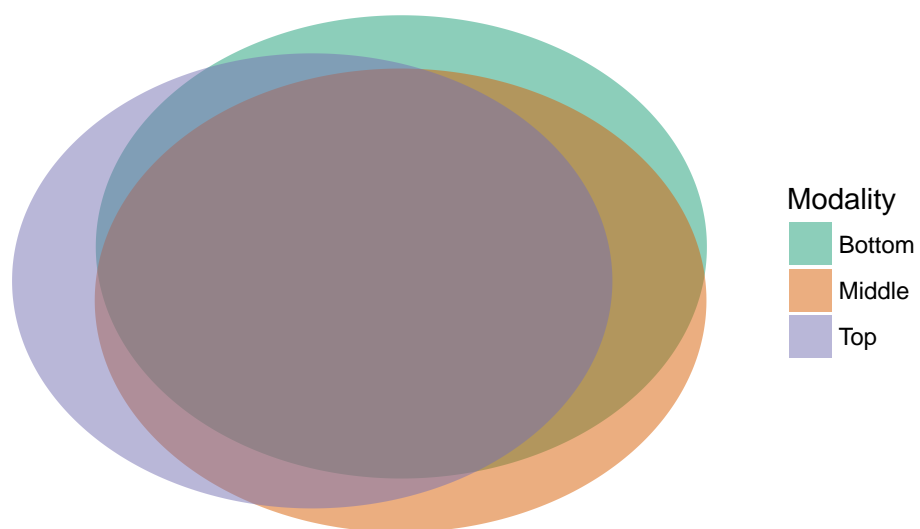


Figure 6.3: Venn diagramm of the distribution of OTUs among elevation of samples

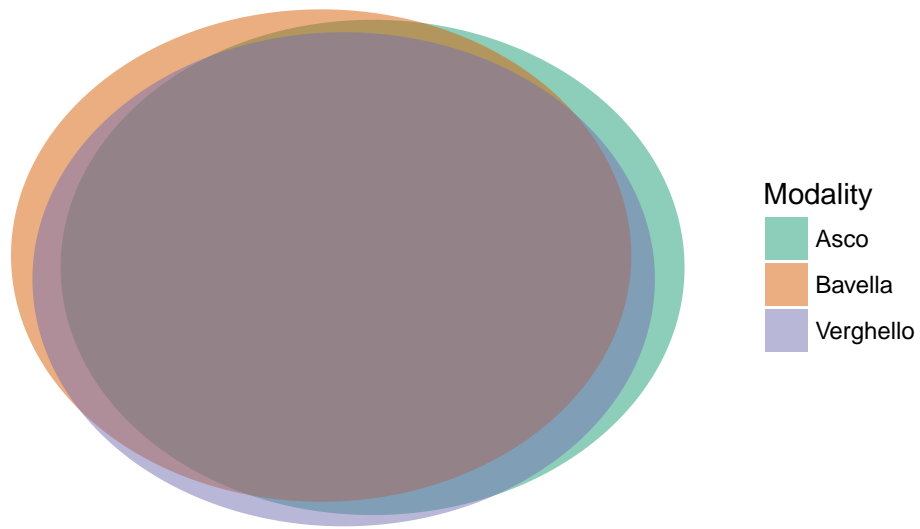


Figure 6.4: Venn diagramm of the distribution of OTUs among Sites

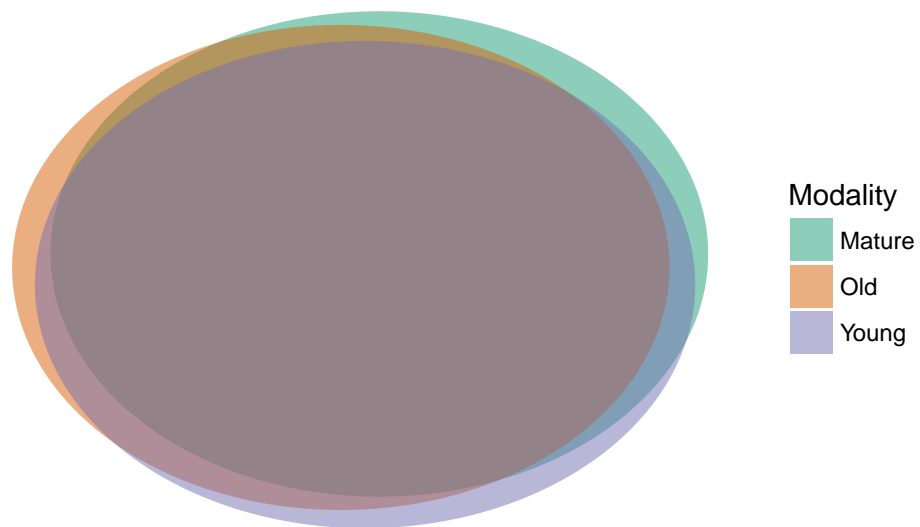


Figure 6.5: Venn diagramm of the distribution of OTUs among host age

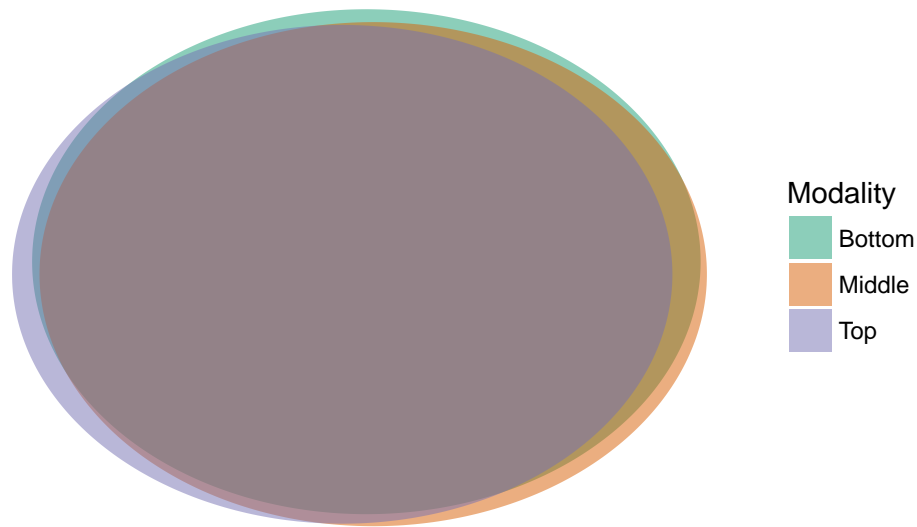


Figure 6.6: Venn diagramm of the distribution of OTUs among elevation of samples whitin the tree

```
my.ord.nmnds <- ordinate(data.f3, method = "NMDS")
my.ord.nmnds$stress
```

```
stressplot(my.ord.nmnds)
```

```
p <- plot_ordination(data.f3, my.ord.nmnds, color = "Sites", shape = "Age")
p + geom_point(size = 0) +
  geom_text(aes(x = p$data$NMDS1, y = p$data$NMDS2,
    label = as.character(as.vector(data.f3$sam_data[, "CODE"]$CODE))))
```

```
my.ord.nmnds_gower <- ordinate(data.f3, distance = "gower", method = "NMDS")
```

```
## Square root transformation
## Wisconsin double standardization
## Run 0 stress 0.2393401
## Run 1 stress 0.2438282
## Run 2 stress 0.4083443
## Run 3 stress 0.2425071
## Run 4 stress 0.4083585
## Run 5 stress 0.2406903
## Run 6 stress 0.2464409
## Run 7 stress 0.2394845
## ... Procrustes: rmse 0.01228488 max resid 0.07431725
## Run 8 stress 0.2394414
## ... Procrustes: rmse 0.01007789 max resid 0.06804078
## Run 9 stress 0.2452266
## Run 10 stress 0.239005
## ... New best solution
## ... Procrustes: rmse 0.0104553 max resid 0.07359731
```

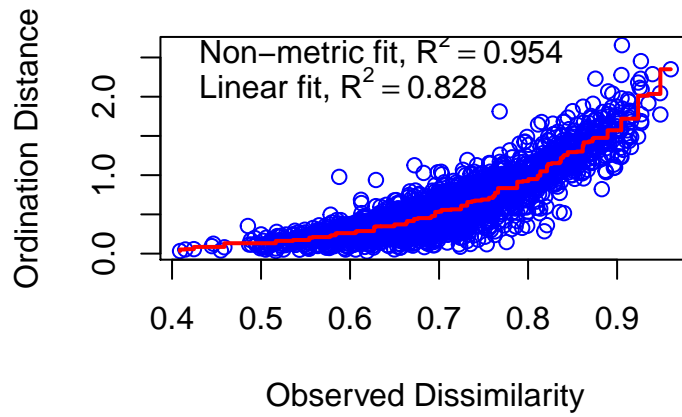


Figure 6.7: Stress plot of the NMDS

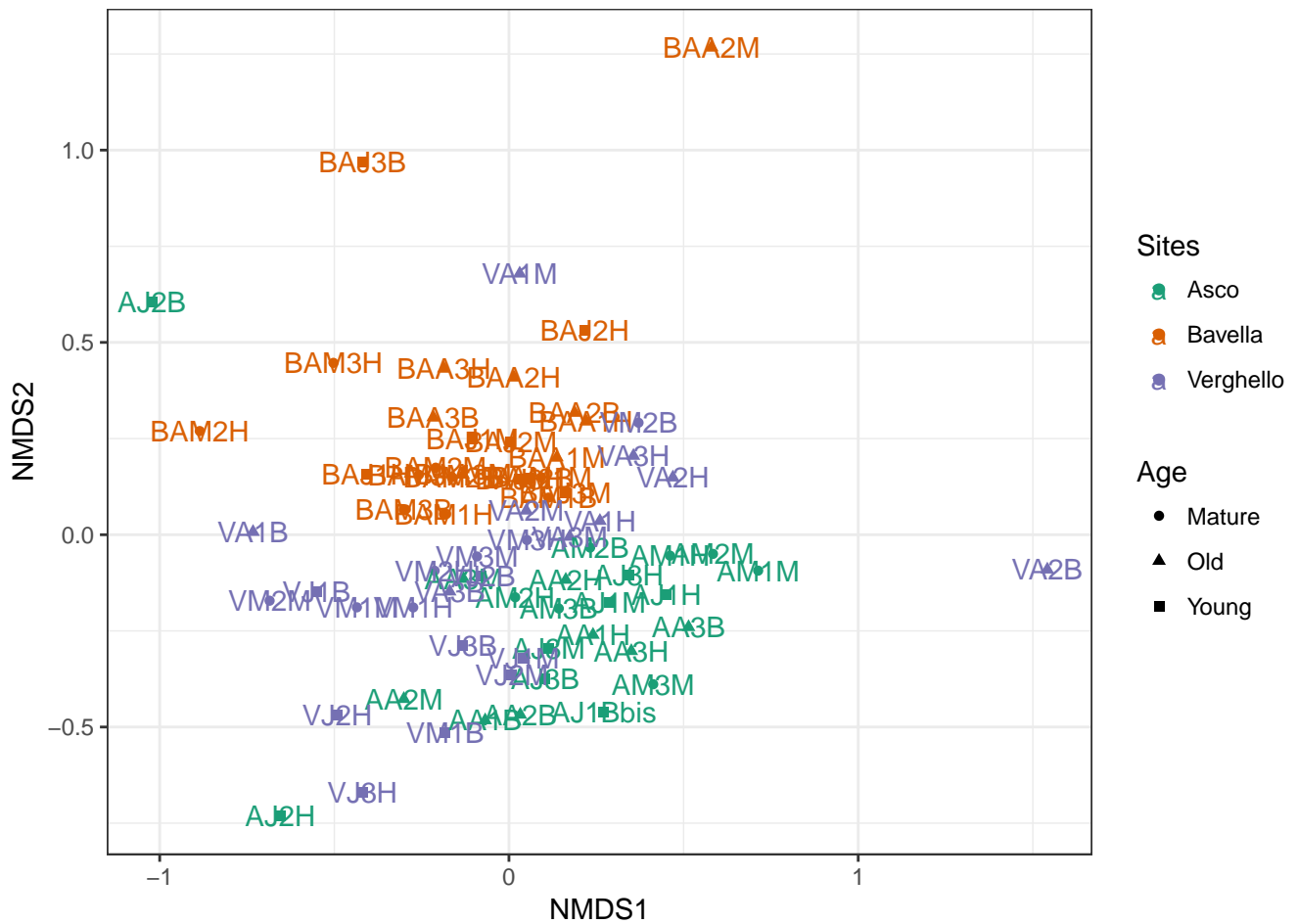


Figure 6.8: NMDS of OTU table. Colors represent sites and shape the age of tree.


```

## Run 11 stress 0.2399895
## Run 12 stress 0.2411228
## Run 13 stress 0.2424844
## Run 14 stress 0.2480004
## Run 15 stress 0.2418689
## Run 16 stress 0.2393749
## ... Procrustes: rmse 0.01189761 max resid 0.0778224
## Run 17 stress 0.2403961
## Run 18 stress 0.2448713
## Run 19 stress 0.2469104
## Run 20 stress 0.2480753
## *** No convergence -- monoMDS stopping criteria:
##      3: no. of iterations >= maxit
##     17: stress ratio > sratmax

my.ord.PCoA <- ordinate(data.f3, method = "PCoA")
my.ord.PCoA_gower <- ordinate(data.f3, distance = "gower", method = "PCoA")
my.ord.DCA <- ordinate(data.f3, method = "DCA")
my.ord.DCA_gower <- ordinate(data.f3, distance = "gower", method = "DCA")

p_NMDS_BRAY <- plot_ordination(data.f3, my.ord.nmds, color = "Sites",
                              shape = "Age", label = "CODE") + geom_point(size = 5)
p_NMDS_GOWER <- plot_ordination(data.f3, my.ord.nmds_gower, color = "Sites",
                              shape = "Age", label = "CODE") + geom_point(size = 5)
p_PCoA_BRAY <- plot_ordination(data.f3, my.ord.PCoA, color = "Sites",
                              shape = "Age", label = "CODE") + geom_point(size = 5)
p_PCoA_GOWER <- plot_ordination(data.f3, my.ord.PCoA_gower, color = "Sites",
                              shape = "Age", label = "CODE") + geom_point(size = 5)
p_DCA_BRAY <- plot_ordination(data.f3, my.ord.DCA, color = "Sites",
                              shape = "Age", label = "CODE") + geom_point(size = 5)
p_DCA_GOWER <- plot_ordination(data.f3, my.ord.DCA_gower, color = "Sites",
                              shape = "Age", label = "CODE") + geom_point(size = 5)

```

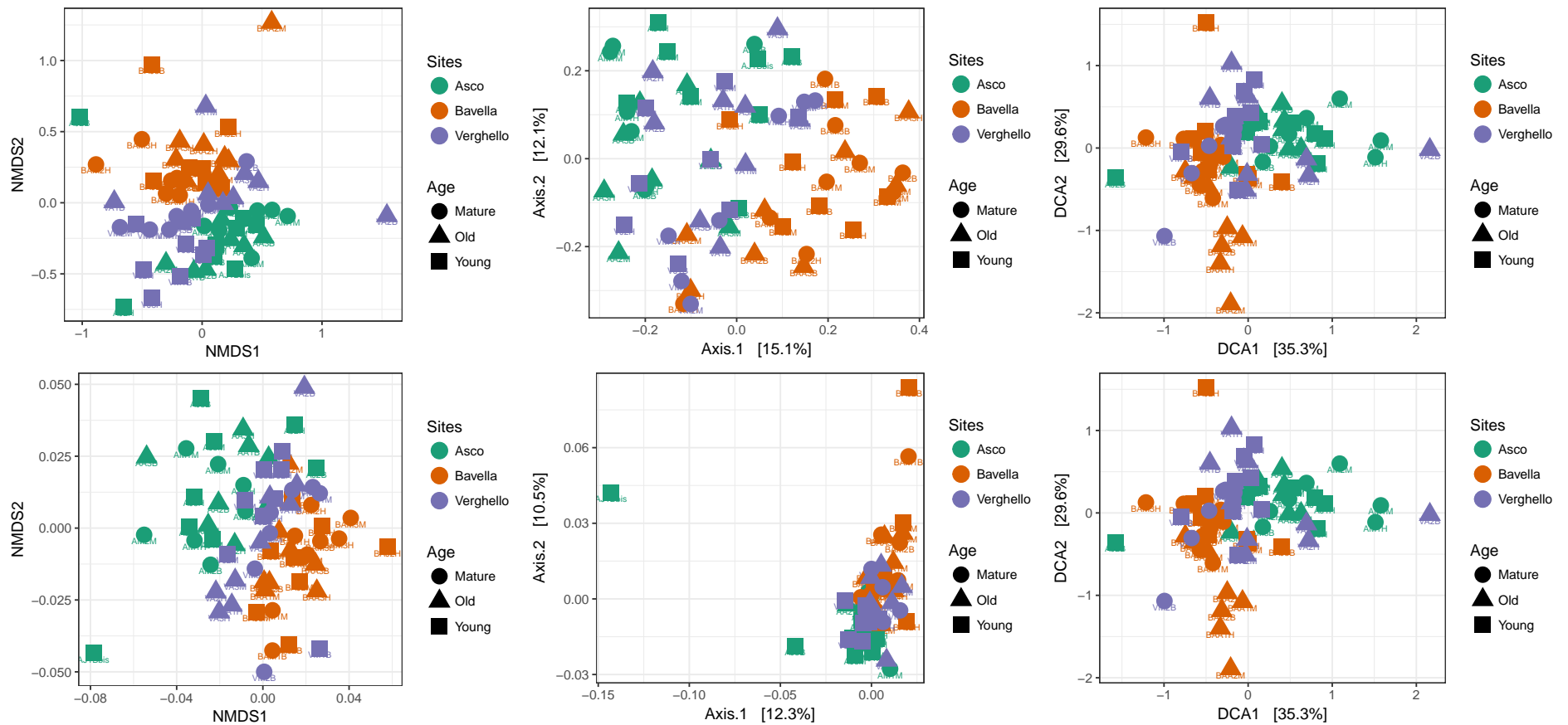


Figure 6.9: Comparison of different distances (bray (up) and gower (bottom)) and ordination methods (NMDS (left), PCoA (center) and DCA (right)).

```
multiplot(p_NMDS_BRAY, p_NMDS_GOWER, p_PCoA_BRAY, p_PCoA_GOWER, p_DCA_BRAY, p_DCA_GOWER,
          cols = 3)
```

6.4 Permanova on sites, host ages and elevation

```
sam_data <- as.data.frame(unclass(data.f3@sam_data))
sam_data$IndividualTree <- paste(sam_data$Sites, sam_data$Age, sam_data$Tree)
res.ado <- adonis(t(data.f3@otu_table) ~ Sites * Age * Elevation, sam_data,
  permutation = 9999)
```

If we only keep the 264 OTUs present in more than 30 sample, the Permanova results is the following:

```
res.ado_sampMin30 <- adonis(t(data.f3@otu_table[rowSums(data.f3@otu_table>0)>=30,]) ~
  Sites * Age * Elevation, sam_data, permutation = 9999)
```

```
data.f3_without_C_minus <- subset_taxa(data.f3, taxa_names(data.f3)!="OTU_1")
res.ado_without_C_minus <- adonis(t(data.f3_without_C_minus@otu_table) ~
  Sites * Age * Elevation, sam_data, permutation = 9999)
```

```
xtable(res.ado$aov.tab, caption = "Result of the permanova on abundances
(number of sequence).")
```

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
Sites	2	2.03	1.02	5.41	0.13	0.0001
Age	2	0.63	0.32	1.68	0.04	0.0122
Elevation	2	0.48	0.24	1.29	0.03	0.1195
Sites:Age	4	1.42	0.35	1.88	0.09	0.0002
Sites:Elevation	4	0.68	0.17	0.90	0.04	0.6973
Age:Elevation	4	0.81	0.20	1.07	0.05	0.3267
Sites:Age:Elevation	8	1.43	0.18	0.95	0.09	0.6260
Residuals	45	8.45	0.19		0.53	
Total	71	15.93			1.00	

Table 7: Result of the permanova on abundances (number of sequence).

```
xtable(res.ado_sampMin30$aov.tab, caption = "Result of the permanova on abundances
(number of sequence) using only OTUs present in more than 30 samples")
```

```
res.ado_bin <- adonis(t(as.binaryOtuTable(data.f3)@otu_table) ~ Sites * Age *
  Elevation, sam_data, permutation = 9999)
```

```
xtable(res.ado_bin$aov.tab, caption = "Result of the permanova on OTUs
(each OTU is representing by one sequence)).")
```

6.5 Permanova on sites, host ages and individual trees

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
Sites	2	1.98	0.99	5.59	0.13	0.0001
Age	2	0.61	0.30	1.71	0.04	0.0111
Elevation	2	0.47	0.23	1.32	0.03	0.1197
Sites:Age	4	1.37	0.34	1.93	0.09	0.0002
Sites:Elevation	4	0.64	0.16	0.90	0.04	0.6962
Age:Elevation	4	0.77	0.19	1.08	0.05	0.3080
Sites:Age:Elevation	8	1.33	0.17	0.94	0.09	0.6591
Residuals	45	7.98	0.18		0.53	
Total	71	15.14			1.00	

Table 8: Result of the permanova on abundances (number of sequence) using only OTUs present in more than 30 samples

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
Sites	2	0.88	0.44	3.66	0.09	0.0001
Age	2	0.44	0.22	1.83	0.05	0.0012
Elevation	2	0.25	0.13	1.04	0.03	0.3725
Sites:Age	4	0.69	0.17	1.43	0.07	0.0062
Sites:Elevation	4	0.39	0.10	0.82	0.04	0.9231
Age:Elevation	4	0.52	0.13	1.08	0.05	0.2686
Sites:Age:Elevation	8	0.88	0.11	0.92	0.09	0.7744
Residuals	45	5.42	0.12		0.57	
Total	71	9.47			1.00	

Table 9: Result of the permanova on OTUs (each OTU is representing by one sequence)).

```
res.ado_Tree <- adonis(t(data.f3@otu_table) ~ Sites*Age + Sites:Age:IndividualTree ,
                      sam_data, permutation = 9999)
res.ado_Tree_sampMin30 <- adonis(t(data.f3@otu_table[rowSums(data.f3@otu_table>0)>=30,]) ~
                                Sites*Age + Sites:Age:IndividualTree , sam_data,
                                permutation = 9999)
res.ado_Tree_bin <- adonis(t(as.binaryOtuTable(data.f3@otu_table) ~
                                Sites*Age + Sites:Age:IndividualTree , sam_data,
                                permutation = 9999)
```

```
xtable(res.ado_Tree$aov.tab, caption = "Result of the permanova on abundances
(number of sequence).")
```

```
xtable(res.ado_Tree_sampMin30$aov.tab, caption = "Result of the permanova on abundances
(number of sequence) using only OTUs present in more than 30 samples")
```

```
xtable(res.ado_Tree_bin$aov.tab, caption = "Result of the permanova on OTUs
(each OTU is representing by one sequence)).")
```

6.6 Differences in abundances and OTUs number by Order.

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
Sites	2	2.03	1.02	6.22	0.13	0.0001
Age	2	0.63	0.32	1.93	0.04	0.0024
Sites:Age	4	1.42	0.35	2.17	0.09	0.0001
Sites:Age:IndividualTree	18	4.49	0.25	1.53	0.28	0.0001
Residuals	45	7.35	0.16		0.46	
Total	71	15.93			1.00	

Table 10: Result of the permanova on abundances (number of sequence).

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
Sites	2	1.98	0.99	6.48	0.13	0.0001
Age	2	0.61	0.30	1.98	0.04	0.0035
Sites:Age	4	1.37	0.34	2.24	0.09	0.0001
Sites:Age:IndividualTree	18	4.30	0.24	1.56	0.28	0.0001
Residuals	45	6.88	0.15		0.45	
Total	71	15.14			1.00	

Table 11: Result of the permanova on abundances (number of sequence) using only OTUs present in more than 30 samples

	Df	SumsOfSqs	MeanSqs	F.Model	R2	Pr(>F)
Sites	2	0.88	0.44	4.13	0.09	0.0001
Age	2	0.44	0.22	2.07	0.05	0.0002
Sites:Age	4	0.70	0.18	1.65	0.07	0.0005
Sites:Age:IndividualTree	18	2.64	0.15	1.38	0.28	0.0001
Residuals	45	4.80	0.11		0.51	
Total	71	9.47			1.00	

Table 12: Result of the permanova on OTUs (each OTU is representing by one sequence)).

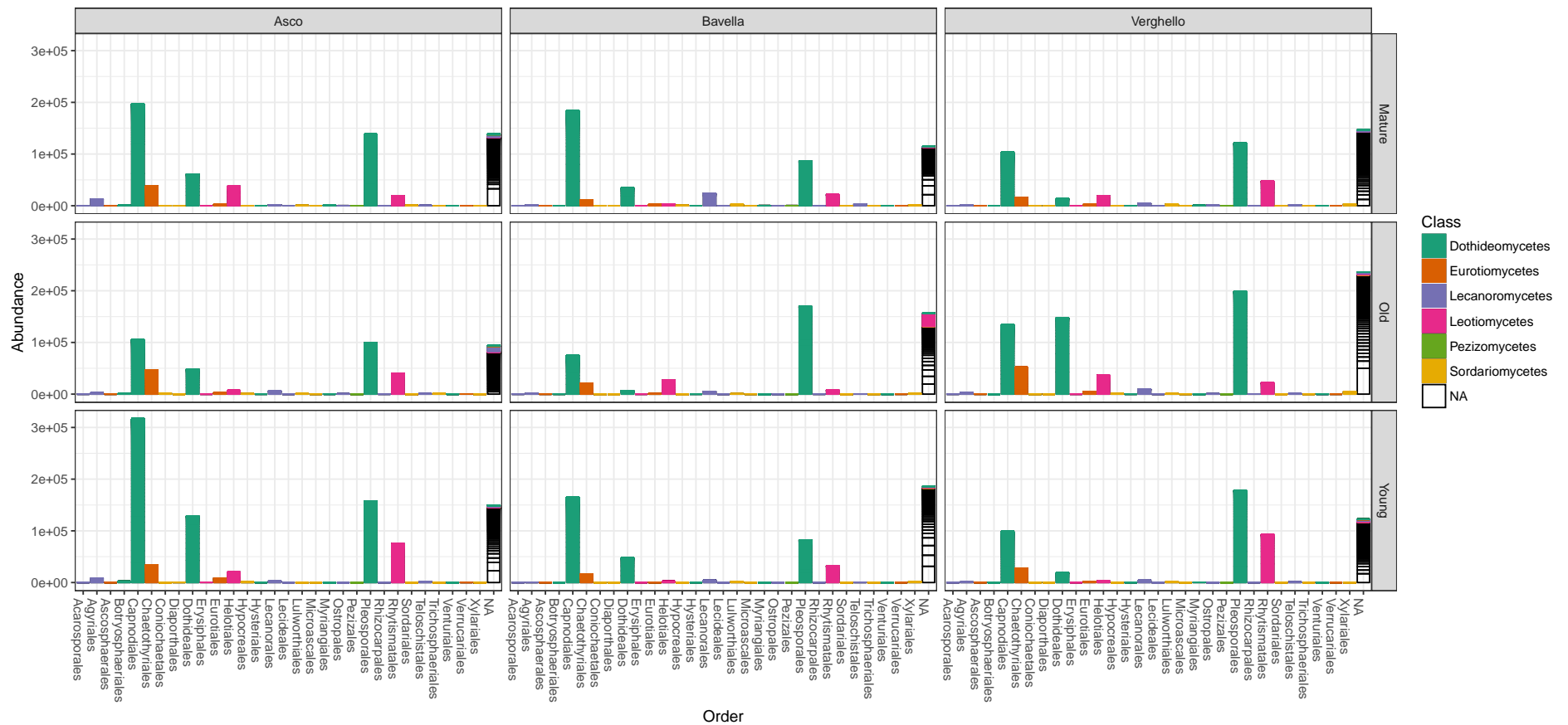


Figure 6.10: Taxonomic distribution of sequences in the different site * age combinaison.

```
data.f3_taxo_known <- prune_taxa(taxa_names(data.f3@tax_table)
  [!(data.f3@tax_table[, 4] %in% c("unidentified", "Incertae sedis"))], data.f3)
p <- plot_bar(data.f3_taxo_known, "Order", fill = "Class", facet_grid = Age ~ Sites)
p + geom_bar(aes(color = Class, fill = Class), stat = "identity", position = "stack")
```

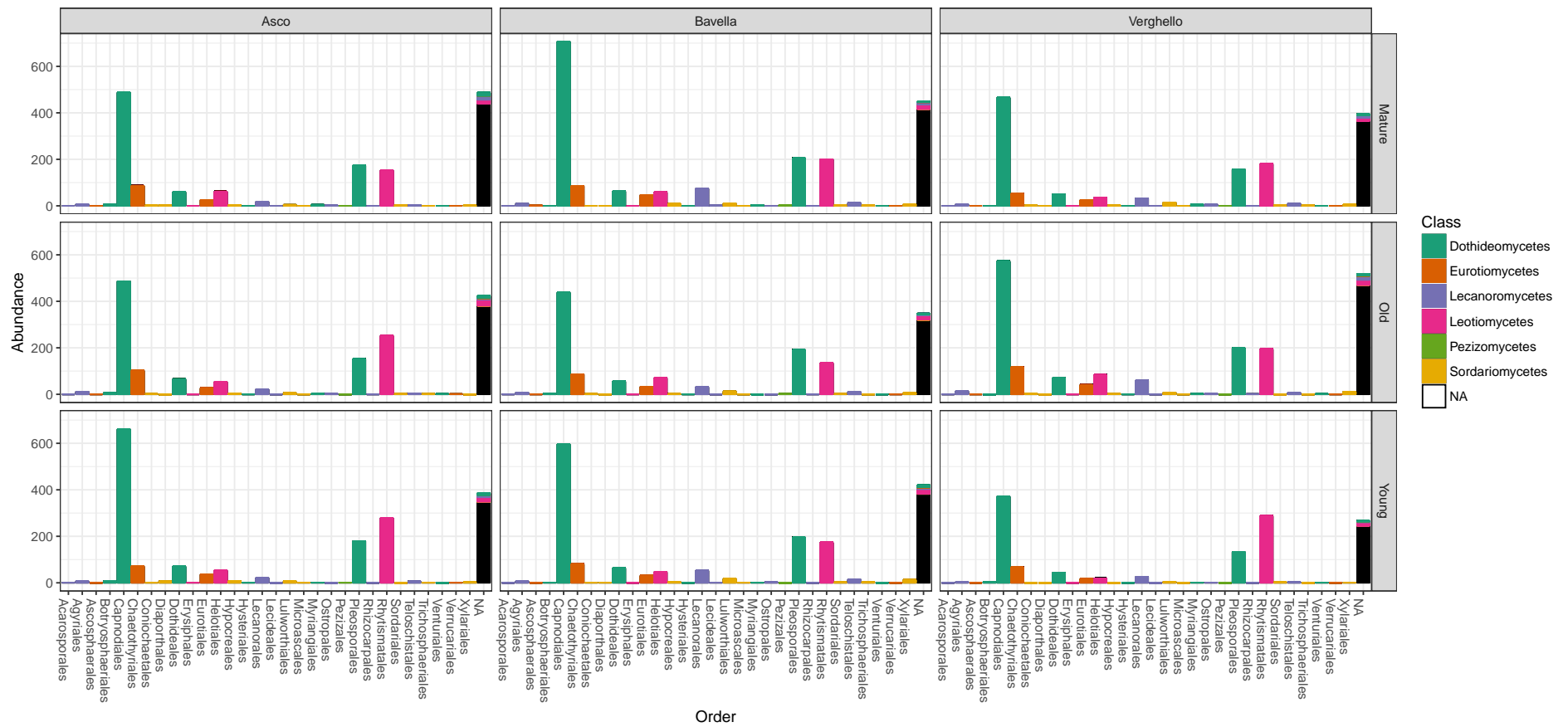


Figure 6.11: Taxonomic distribution of OTUs in the different site * age combinaison.

```
p <- plot_bar(as.binaryOtuTable(data.f3_taxo_known), "Order", fill = "Class",
              facet_grid = Age ~ Sites)
p + geom_bar(aes(color = Class, fill = Class), stat = "identity", position = "stack")
```

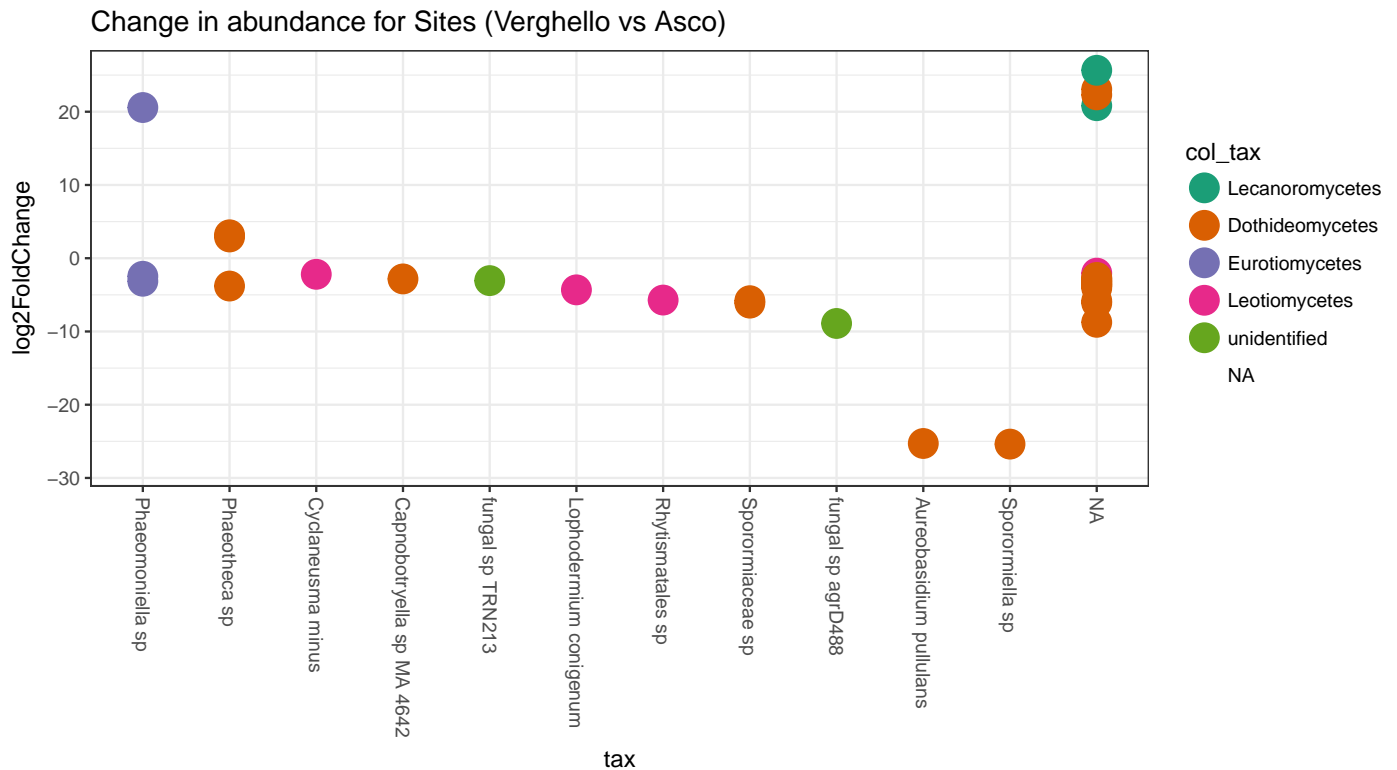


Figure 6.12: OTUs significantly different in terms of abundances between Verghello (positive values) and Asco (negative values)

6.7 Differences in abundances for each OTUs

6.7.1 Pairwise comparison of the OTUs composition by sites

```
library("DESeq2")
packageVersion("DESeq2")

## [1] '1.16.1'

data.f3_deseq2 <- phyloseq_to_deseq2(data.f3, ~ Sites)
data.f3_deseq2 <- DESeq(data.f3_deseq2, test = "Wald", fitType = "parametric")
res.f3_deseq2 <- results(data.f3_deseq2)
```

```
res_VA <- plot_deseq2_phyloseq(data.f3_deseq2, tax_table = data.f3@tax_table,
                               contrast = c("Sites", "Verghello", "Asco"),
                               taxa = "Species", color_tax = "Class")
res_VA
```

```
res_VB <- plot_deseq2_phyloseq(data.f3_deseq2, tax_table = data.f3@tax_table,
                               contrast = c("Sites", "Verghello", "Bavella"),
                               taxa = "Species", color_tax = "Class")
res_VB
```

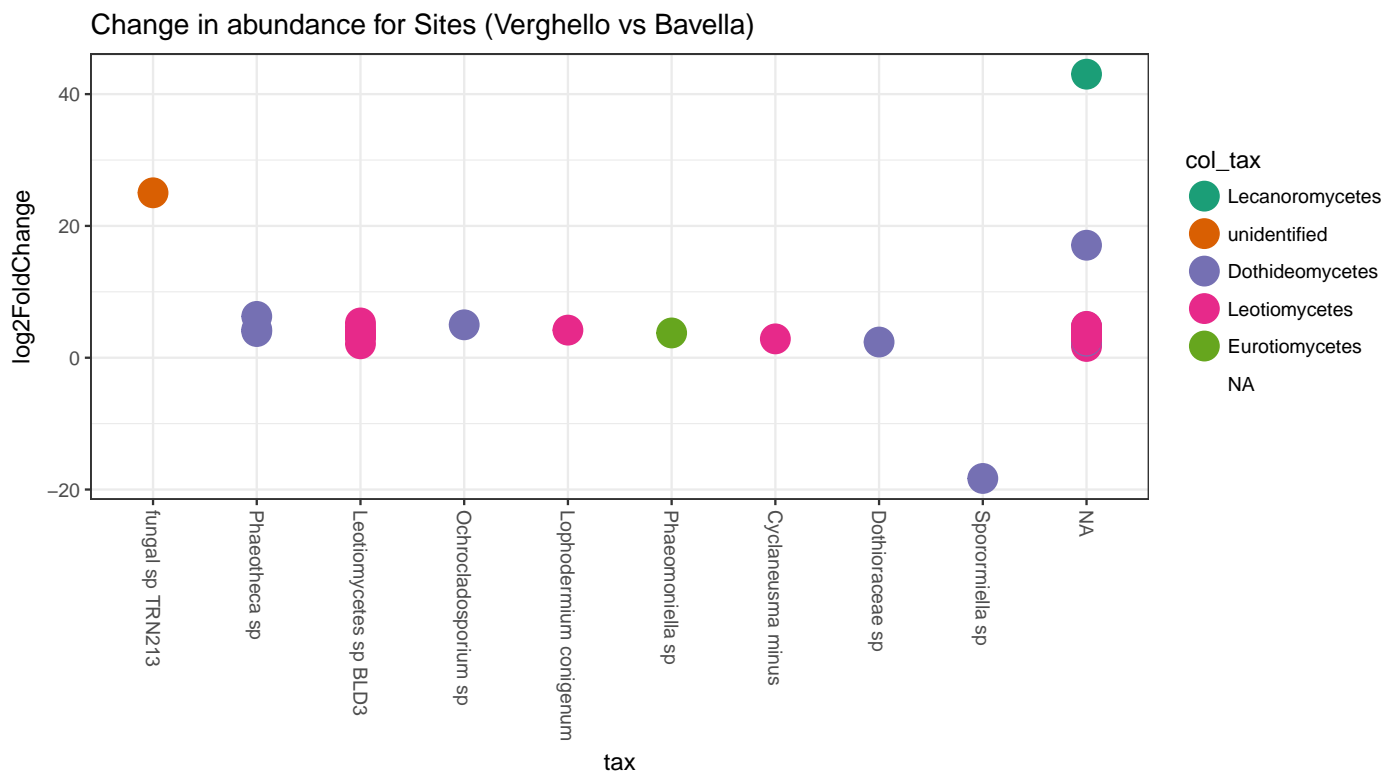



Figure 6.13: OTUs significantly different in terms of abundances between Verghello (positive values) and Bavella (negative values)

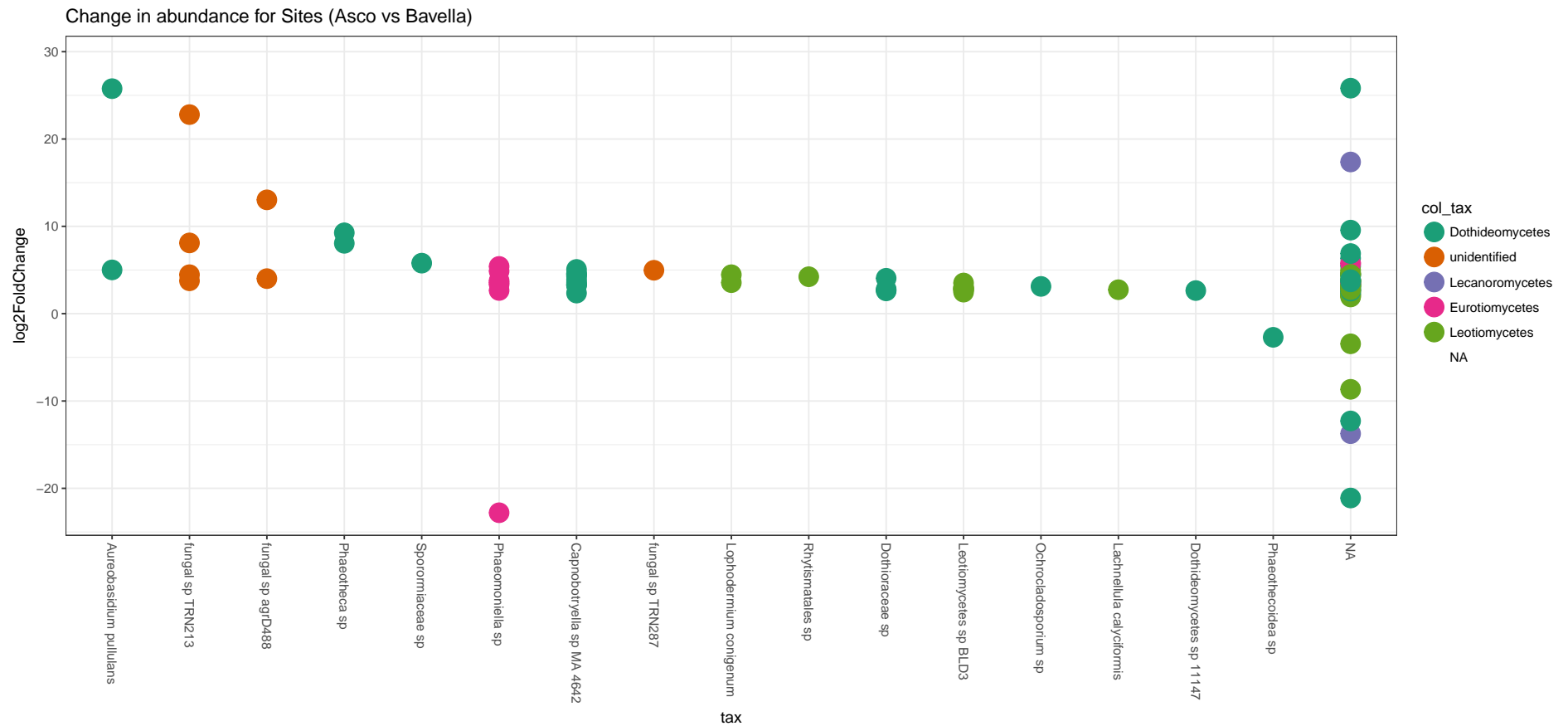


Figure 6.14: OTUs significantly different in terms of abundances between Asco (positive values) and Bavella (negative values)

```
res_AB <- plot_deseq2_phyloseq(data.f3_deseq2, tax_table = data.f3@tax_table,
                               contrast = c("Sites", "Asco", "Bavella"),
                               taxa = "Species", color_tax = "Class")
res_AB
```

6.7.2 Pairwise comparison of Order composition by sites

```
res_VA_o <- plot_deseq2_phyloseq(data.f3, contrast = c("Sites", "Verghello", "Asco"),
                                taxDepth = "Order", color_tax = "Class")
res_VB_o <- plot_deseq2_phyloseq(data.f3, contrast = c("Sites", "Verghello", "Bavella"),
                                taxDepth = "Order", color_tax = "Class")
res_AB_o <- plot_deseq2_phyloseq(data.f3, contrast = c("Sites", "Asco", "Bavella"),
                                taxDepth = "Order", color_tax = "Class")
```

6.8 Distribution of OTUs abundance in the fungal phylogeny

```
library("cluster")
library("phytools")

## Loading required package: maps
##
## Attaching package: 'maps'
## The following object is masked from 'package:plyr':
##
##   ozone
## The following object is masked from 'package:cluster':
##
##   votes.repub

data.f3_interm <- data.f3
data.f3_interm@otu_table <- otu_table(apply(data.f3@otu_table, 2, function(x) tapply(x, as.factor(data.f3@tax_table[, "Order"]), FUN = function(y) sum(y > 0))), MARGIN = 2)
data.f3_interm@tax_table <- tax_table(apply(data.f3@tax_table, 2, function(x) tapply(x, as.factor(data.f3@tax_table[, "Order"]), FUN = function(y) sum(y > 0))), MARGIN = 2)
data.f3_interm@refseq <- NULL

data.f3_interm <- subset_taxa(data.f3_interm, !grepl("uncultured", data.f3_interm@tax_table[, "Species"]))
data.f3_interm <- subset_taxa(data.f3_interm, !grepl("sp$", data.f3_interm@tax_table[, "Species"]))
data.f3_interm <- subset_taxa(data.f3_interm, !grepl("unidentified", data.f3_interm@tax_table[, "Family"]))
data.f3_interm <- subset_taxa(data.f3_interm, !grepl("unidentified", data.f3_interm@tax_table[, "Order"]))
data.f3_interm <- subset_taxa(data.f3_interm, !grepl("unidentified", data.f3_interm@tax_table[, "Class"]))
data.f3_interm <- subset_taxa(data.f3_interm, !grepl("Myxotrichaceae", data.f3_interm@tax_table[, "Species"]))
data.f3_interm <- subset_taxa(data.f3_interm, rowSums(data.f3_interm@otu_table) > 100)

tree_tax_interm <- as.data.frame(unclass(data.f3_interm@tax_table))
tree_tax_interm$OTUs <- rownames(tree_tax_interm)

tree_tax_interm <- as.data.frame(replace(as.matrix(tree_tax_interm), which(is.na(tree_tax_interm)), NA))

data.f3_interm@tax_table <- tax_table(as.matrix(tree_tax_interm))

tree_tax_interm$pathString <- paste("Fungi",
                                   tree_tax_interm$Phylum,
                                   tree_tax_interm$Class,
                                   tree_tax_interm$Order,
```

```

        tree_tax_interm$Family,
        tree_tax_interm$Genus,
        tree_tax_interm$OTUs,
        sep = "/" )

write(ToNewick(as.Node(tree_tax_interm, na.rm = TRUE)), file="tree.txt")
tree <- phytools::read.newick(file="tree.txt")
tree <- ape::collapse.singles(tree)

data.f3_interm@phy_tree <- tree
taxa_names(data.f3_interm@phy_tree) <- gsub("_", " ", taxa_names(data.f3_interm@phy_tree))
taxa_names(data.f3_interm@otu_table) <- gsub("_", " ", taxa_names(data.f3_interm@otu_table))
taxa_names(data.f3_interm@tax_table) <- gsub("_", " ", taxa_names(data.f3_interm@tax_table))
taxa_names(data.f3_interm@phy_tree) <- gsub(" ", "", taxa_names(data.f3_interm@phy_tree))
taxa_names(data.f3_interm@otu_table) <- gsub(" ", "", taxa_names(data.f3_interm@otu_table))
taxa_names(data.f3_interm@tax_table) <- gsub(" ", "", taxa_names(data.f3_interm@tax_table))

ptree <- plot_tree(data.f3_interm, color = "Class", shape = "Sites", ladderize = "left", justify = "left")

cond <- gsub(" ", "", rownames(data.f3_interm@otu_table)[rowSums(data.f3_interm@otu_table) >= 1])
df_cond <- as.data.frame(ptree$data)[ptree$data$OTU %in% cond,]
df_cond$Species <- data.f3_interm@tax_table[taxa_names(data.f3_interm) %in% cond, "OTUs"]

cond_Deseq <- levels(df_cond$Species)
df_cond_Deseq <- as.data.frame(ptree$data)[ptree$data$OTU %in% cond_Deseq,]
df_cond_Deseq$Species <- data.f3_interm@tax_table[gsub("_", " ", taxa_names(data.f3_interm)) %in% cond_Deseq, "OTUs"]

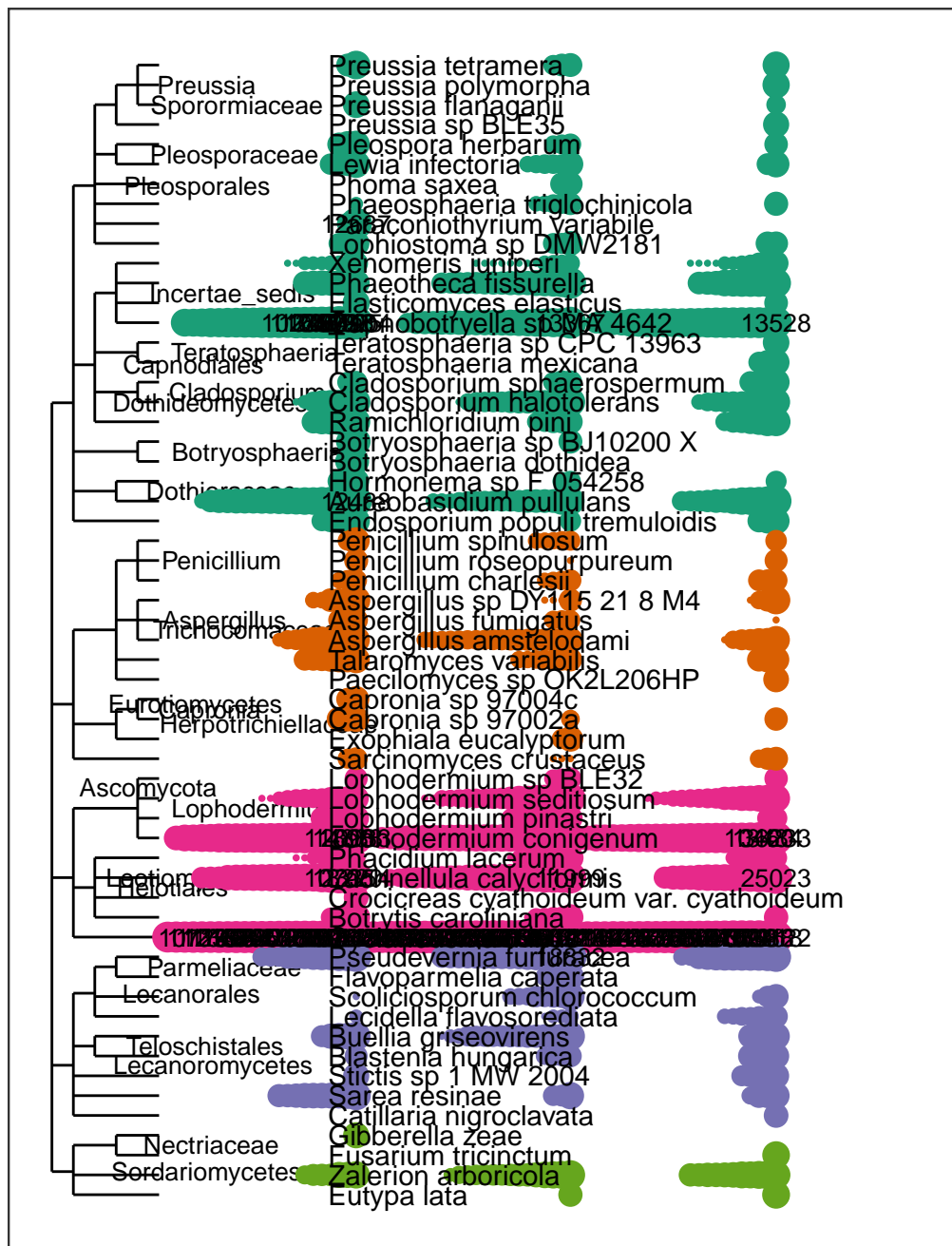
ptree + geom_text(data = df_cond, aes(x = 215, y = y, label = OTU), hjust = "left") + scale_shape_manual(values = c(1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100))

## [1] 269

sum(rowSums(data.f3@otu_table)[gsub("_", " ", data.f3@tax_table[, "Species"]) %in% gsub("_", " ", taxa_names(data.f3_interm@otu_table))])

## [1] 38.5203

```



Sites

- Asco
- Bavella
- Verghello

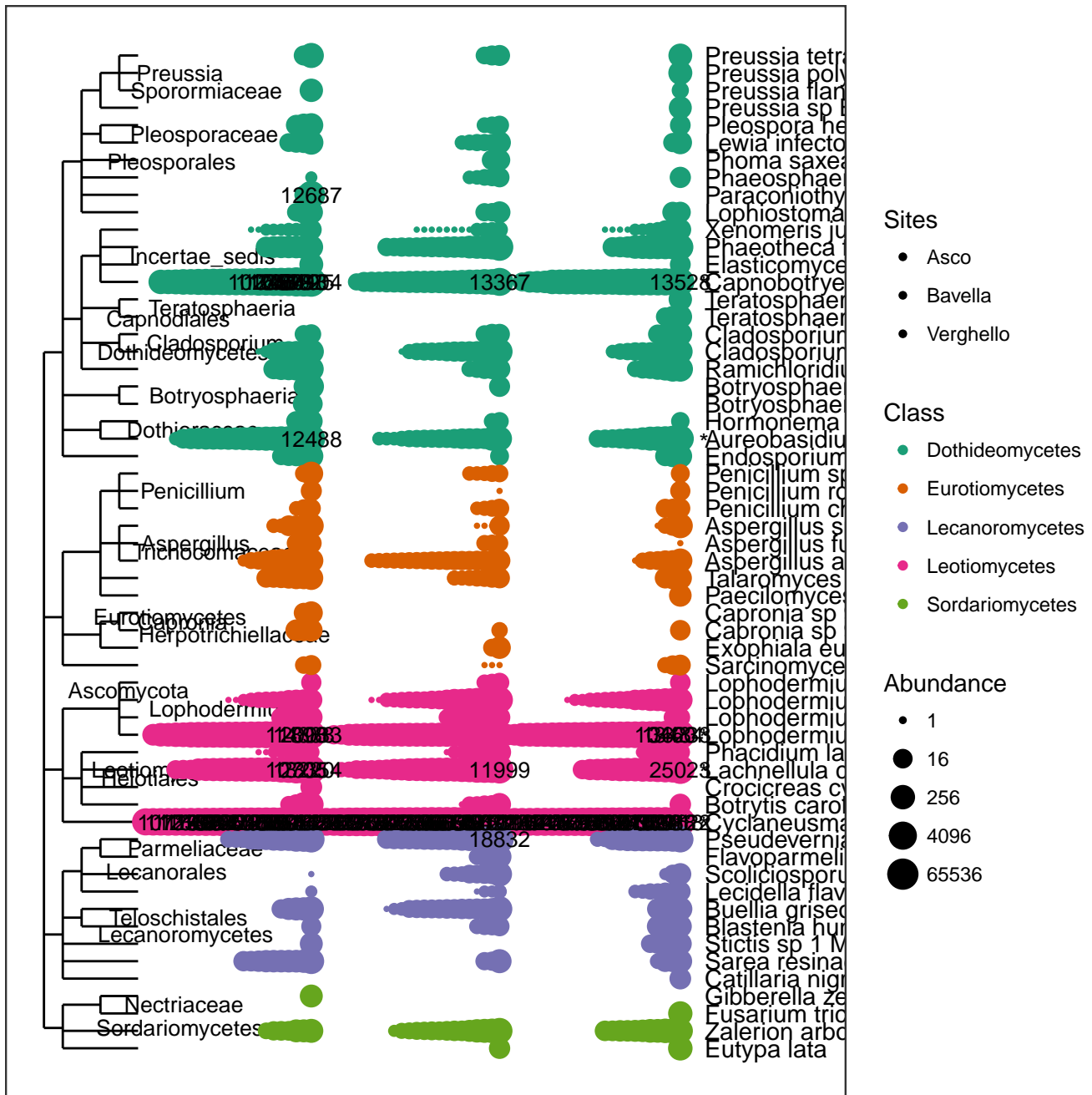
Class

- Dothideomycetes
- Eurotiomycetes
- Lecanoromycetes
- Leotiomycetes
- Sordariomycetes

Abundance

- 1
- 16
- 256
- 4096
- 65536

```
ptree + geom_text(data = df_cond, aes(x = 585, y = y, label = OTU), hjust = "left") + scale_shape_ma
ggsave("phylo_map.pdf", width = 20, height = 15)
```



7 Summary

7.1 Filtering summary

The raw data are made of 8.335341×10^6 sequences representing 1667 OTUs allocated to 80 samples.

After filtering, the dataset includes 8.312594×10^6 sequences representing 1302 OTUs allocated to 72 samples.

7.2 Alpha diversity

Host age and elevation within tree do not impact any aspect of fungal local diversity. Despite similar OTUs richness, Asco is a site more diverse than Verghello and Bavella.

7.3 Beta diversity

Site ($R^2 = 0.128$), age ($R^2 = 0.04$) and interaction age*site ($R^2 = 0.089$) statistically structured the fungal endophytic beta-diversity.

7.4 Special case of *Cyclaneusma minus*

Cyclaneusma minus account for 23.38% of total sequences.

```
cycla <- as.vector(data.f3@otu_table["OTU_1",]/ colSums(data.f3@otu_table) * 100)

par(mfrow=c(1,2))
boxplot(cycla~data.f3@sam_data$Age, ylab="% Cyclaneusma minus")
boxplot(cycla~data.f3@sam_data$Elevation, ylab="% Cyclaneusma minus")
boxplot(cycla~data.f3@sam_data$Sites, ylab="% Cyclaneusma minus")
par(mfrow=c(1,1))

tapply(cycla, data.f3@sam_data$Age, mean)

##      Mature      Old      Young
## 28.05235 22.51140 24.01578

tapply(cycla, data.f3@sam_data$Age, sd)

##      Mature      Old      Young
## 18.05840 13.30125 14.48586

tapply(cycla, data.f3@sam_data$Elevation, mean)

##      Bottom      Middle      Top
## 23.94633 27.48506 22.95842

tapply(cycla, data.f3@sam_data$Elevation, sd)

##      Bottom      Middle      Top
## 14.36857 16.84100 14.85478

tapply(cycla, data.f3@sam_data$Sites, mean)

##      Asco      Bavella Verghello
## 16.12246 36.73680 20.63047

tapply(cycla, data.f3@sam_data$Sites, sd)

##      Asco      Bavella Verghello
## 6.755436 17.731830 10.160594

wilcox.test(cycla[data.f3@sam_data$Sites=="Asco"], cycla[data.f3@sam_data$Sites=="Bavella"])

##
## Wilcoxon rank sum test
##
## data: cycla[data.f3@sam_data$Sites == "Asco"] and cycla[data.f3@sam_data$Sites == "Bavella"]
## W = 77, p-value = 3.837e-06
## alternative hypothesis: true location shift is not equal to 0
```

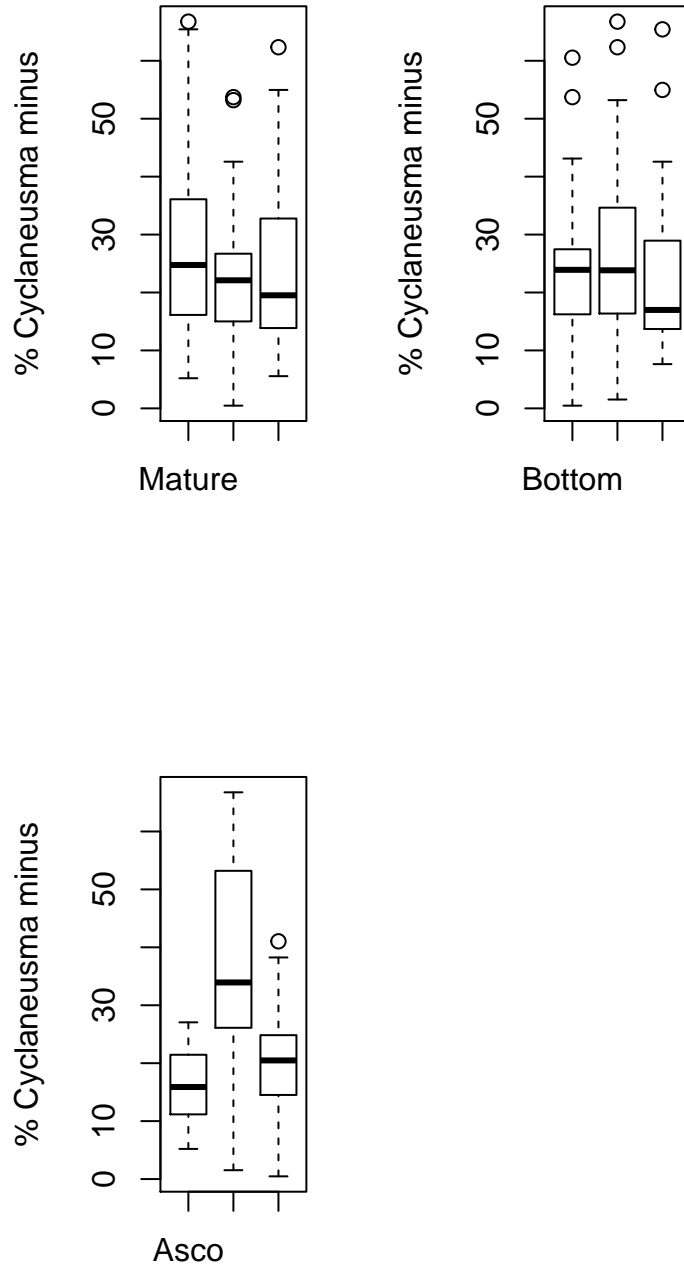


Figure 7.1: Number of sequences assigned to extitCyclaneusma minus across host age, elevation within tree and sites


```

wilcox.test(cycla[data.f3@sam_data$Sites=="Verghello"], cycla[data.f3@sam_data$Sites=="Bavella"])

##
## Wilcoxon rank sum test
##
## data: cycla[data.f3@sam_data$Sites == "Verghello"] and cycla[data.f3@sam_data$Sites == "Bavella"]
## W = 130, p-value = 0.000477
## alternative hypothesis: true location shift is not equal to 0

wilcox.test(cycla[data.f3@sam_data$Sites=="Asco"], cycla[data.f3@sam_data$Sites=="Verghello"])

##
## Wilcoxon rank sum test
##
## data: cycla[data.f3@sam_data$Sites == "Asco"] and cycla[data.f3@sam_data$Sites == "Verghello"]
## W = 204, p-value = 0.129
## alternative hypothesis: true location shift is not equal to 0

```

	Comparison	OTU_names	Species	Class	log2FoldChange (negative = more on second levels)
1	Verghello vs Asco	OTU.885	Phaeomoniella sp	Eurotiomycetes	-3.14180047934908
2	Verghello vs Asco	OTU.263			3.64844007621285
3	Verghello vs Asco	OTU.1192		Dothideomycetes	-4.06191788385273
4	Verghello vs Asco	OTU.805		Dothideomycetes	-3.74527277873544
5	Verghello vs Asco	OTU.688	fungal sp TRN213	unidentified	-3.05716134156103
6	Verghello vs Asco	OTU.35			3.45787058219993
7	Verghello vs Asco	OTU.861			-2.84255276977124
8	Verghello vs Asco	OTU.633	Phaeotheca sp	Dothideomycetes	-3.79929856510545
9	Verghello vs Asco	OTU.742			3.27422748242967
10	Verghello vs Asco	OTU.570		Dothideomycetes	-2.95237737337865
11	Verghello vs Asco	OTU.1203		Dothideomycetes	-3.37772312072497
12	Verghello vs Asco	OTU.1546	Capnobotryella sp MA 4642	Dothideomycetes	-2.8270261217971
13	Verghello vs Asco	OTU.399		Dothideomycetes	-3.24628121566645
14	Verghello vs Asco	OTU.669		Dothideomycetes	-6.11297624195951
15	Verghello vs Asco	OTU.1148	Phaeomoniella sp	Eurotiomycetes	-2.46378616499525
16	Verghello vs Asco	OTU.575			4.71085075476014
17	Verghello vs Asco	OTU.1168		Dothideomycetes	-3.13089568886969
18	Verghello vs Asco	OTU.809		Dothideomycetes	-2.80476330884076
19	Verghello vs Asco	OTU.1285		Leotiomycetes	-2.0352037582083
20	Verghello vs Asco	OTU.930			2.90203226388763
21	Verghello vs Asco	OTU.25	Phaeotheca sp	Dothideomycetes	3.20057595263818
22	Verghello vs Asco	OTU.18		Dothideomycetes	-5.82900067867463
23	Verghello vs Asco	OTU.1050	Cyclaneusma minus	Leotiomycetes	-2.1938663310028
24	Verghello vs Asco	OTU.895		Dothideomycetes	-3.59194016172022
25	Verghello vs Asco	OTU.1138			2.73811574455171
26	Verghello vs Asco	OTU.72	Rhytismatales sp	Leotiomycetes	-5.71309567878076
27	Verghello vs Asco	OTU.33	Aureobasidium pullulans	Dothideomycetes	-25.2920407676653
28	Verghello vs Asco	OTU.30	fungal sp agrD488	unidentified	-8.90732449255831
29	Verghello vs Asco	OTU.326	Phaeotheca sp	Dothideomycetes	2.90163549188653
30	Verghello vs Asco	OTU.379			-5.94480193488885
31	Verghello vs Asco	OTU.826		Dothideomycetes	-3.70188271469607
32	Verghello vs Asco	OTU.42			-28.4093647742594
33	Verghello vs Asco	OTU.21	Sporormiaceae sp	Dothideomycetes	-6.12827048914855
34	Verghello vs Asco	OTU.634			-24.9062387805127
35	Verghello vs Asco	OTU.1436		Dothideomycetes	-2.6205041473203
36	Verghello vs Asco	OTU.54	Sporormiella sp	Dothideomycetes	-25.378275998241
37	Verghello vs Asco	OTU.1078	Sporormiaceae sp	Dothideomycetes	-5.79837614995541
38	Verghello vs Asco	OTU.188			-24.7487110108513
39	Verghello vs Asco	OTU.159	Lophodermium conigenum	Leotiomycetes	-4.31908667235487
40	Verghello vs Asco	OTU.1369		Dothideomycetes	-8.74996839038013
41	Verghello vs Asco	OTU.149	Phaeomoniella sp	Eurotiomycetes	20.5726228422299
42	Verghello vs Asco	OTU.111		Dothideomycetes	23.052758808263
43	Verghello vs Asco	OTU.152		Lecanoromycetes	20.8234902163824
44	Verghello vs Asco	OTU.419		Dothideomycetes	22.303198860941
45	Verghello vs Asco	OTU.74			24.365344777204
46	Verghello vs Asco	OTU.105		Lecanoromycetes	25.6569833302234
47	Verghello vs Bavella	OTU.13	Phaeomoniella sp	Eurotiomycetes	3.759462667366
48	Verghello vs Bavella	OTU.9	Lophodermium conigenum	Leotiomycetes	4.188191232945
49	Verghello vs Bavella	OTU.1123		Dothideomycetes	2.60757748632336
50	Verghello vs Bavella	OTU.1102	Leotiomycetes sp BLD3	Leotiomycetes	3.40611194797604
51	Verghello vs Bavella	OTU.17			2.63932960489047
52	Verghello vs Bavella	OTU.189	Phaeotheca sp	Dothideomycetes	6.26969179588288
53	Verghello vs Bavella	OTU.11			5.77270198491659
54	Verghello vs Bavella	OTU.6	Dothioraceae sp	Dothideomycetes	2.38082031291577
55	Verghello vs Bavella	OTU.39	Leotiomycetes sp BLD3	Leotiomycetes	2.11331395697968
56	Verghello vs Bavella	OTU.46		Dothideomycetes	2.68995694269571
57	Verghello vs Bavella	OTU.20		Eurotiomycetes	4.49523983865664
58	Verghello vs Bavella	OTU.299	Ochrocladosporium sp	Dothideomycetes	4.99363124461955
59	Verghello vs Bavella	OTU.263			6.1863215387924
60	Verghello vs Bavella	OTU.756		Dothideomycetes	4.70424392971001
61	Verghello vs Bavella	OTU.227		Leotiomycetes	2.23867944260312
62	Verghello vs Bavella	OTU.935	Leotiomycetes sp BLD3	Leotiomycetes	3.4448021030654
63	Verghello vs Bavella	OTU.744	Cyclaneusma minus	Leotiomycetes	2.85886284279939
64	Verghello vs Bavella	OTU.1657	Leotiomycetes sp BLD3	Leotiomycetes	3.34719535552037
65	Verghello vs Bavella	OTU.35			7.99414113690649
66	Verghello vs Bavella	OTU.1527		Leotiomycetes	3.77565606014944
67	Verghello vs Bavella	OTU.503		Leotiomycetes	4.0707538748451
68	Verghello vs Bavella	OTU.861			3.99778432992676
69	Verghello vs Bavella	OTU.633	Phaeotheca sp	Dothideomycetes	4.25864744298029
70	Verghello vs Bavella	OTU.1120		Leotiomycetes	3.37101321682374
71	Verghello vs Bavella	OTU.1255		Leotiomycetes	3.47507576148164
72	Verghello vs Bavella	OTU.1121	Leotiomycetes sp BLD3	Leotiomycetes	3.21363087956089
73	Verghello vs Bavella	OTU.729		Leotiomycetes	4.7515217647916
74	Verghello vs Bavella	OTU.742			2.69179592736329
75	Verghello vs Bavella	OTU.1388		Leotiomycetes	1.7102831094592
76	Verghello vs Bavella	OTU.1232		Leotiomycetes	3.33173106215749
77	Verghello vs Bavella	OTU.457	fungal sp TRN213	unidentified	25.0251517044582
78	Verghello vs Bavella	OTU.1565	Leotiomycetes sp BLD3	Leotiomycetes	3.99810061312571
79	Verghello vs Bavella	OTU.1286		Leotiomycetes	3.44266738594465
80	Verghello vs Bavella	OTU.595		Leotiomycetes	2.44277599115821
81	Verghello vs Bavella	OTU.679		Leotiomycetes	4.53653641743523
82	Verghello vs Bavella	OTU.734		Dothideomycetes	2.5195236722982
83	Verghello vs Bavella	OTU.1292		Dothideomycetes	3.02284664254276
84	Verghello vs Bavella	OTU.669		Dothideomycetes	3.45549304491711
85	Verghello vs Bavella	OTU.640		Leotiomycetes	3.93876423355081
86	Verghello vs Bavella	OTU.575			4.63323931848402
87	Verghello vs Bavella	OTU.997		Eurotiomycetes	3.76739950320754
88	Verghello vs Bavella	OTU.1013		Dothideomycetes	2.76149108480107
89	Verghello vs Bavella	OTU.692	Leotiomycetes sp BLD3	Leotiomycetes	3.15138780696417
90	Verghello vs Bavella	OTU.930			2.70799737569365
91	Verghello vs Bavella	OTU.714	Leotiomycetes sp BLD3	Leotiomycetes	3.78172933086983
92	Verghello vs Bavella	OTU.25	Phaeotheca sp	Dothideomycetes	3.97275762815806
93	Verghello vs Bavella	OTU.1018		Leotiomycetes	2.6965257401675
94	Verghello vs Bavella	OTU.831		Leotiomycetes	4.10403849059408
95	Verghello vs Bavella	OTU.1064		Leotiomycetes	3.46003270070723
96	Verghello vs Bavella	OTU.267			4.1001095082275
97	Verghello vs Bavella	OTU.1180		Leotiomycetes	3.15223347765059
98	Verghello vs Bavella	OTU.616		Leotiomycetes	3.5551976152887
99	Verghello vs Bavella	OTU.1138			3.61854236763842
100	Verghello vs Bavella	OTU.1417		Leotiomycetes	4.61348516916332
101	Verghello vs Bavella	OTU.64			5.01883222005108
102	Verghello vs Bavella	OTU.34			5.25930283096
103	Verghello vs Bavella	OTU.1358	Leotiomycetes sp BLD3	Leotiomycetes	5.27490409917799
104	Verghello vs Bavella	OTU.862			3.15087972516567
105	Verghello vs Bavella	OTU.1104		Leotiomycetes	3.88500915389483
106	Verghello vs Bavella	OTU.1495	Leotiomycetes sp BLD3	Leotiomycetes	4.6302480280799
107	Verghello vs Bavella	OTU.873	Leotiomycetes sp BLD3	Leotiomycetes	3.56071879127986

	Comparison	Order	Class	log2FoldChange (negative = more on second levels)
1	Verghello vs Asco	Xylariales	Sordariomycetes	5.02800865384018
2	Verghello vs Bavella	Incertae sedis	Leotiomycetes	-1.36534813356438
3	Verghello vs Bavella	unidentified	unidentified	1.5926930618187
4	Asco vs Bavella	Botryosphaeriales	Dothideomycetes	7.33720699516155
5	Asco vs Bavella	Eurotiales	Eurotiomycetes	1.82573680514222
6	Asco vs Bavella	Incertae sedis	Leotiomycetes	-1.69236022105782
7	Asco vs Bavella	unidentified	unidentified	1.47100012610789
8	Asco vs Bavella	Xylariales	Sordariomycetes	-4.76720083284185

Table 14: Order showing differential abundances in the different sites.

	Nb.of.OTUs	Nb.of.samples	Nb.of.sequences
No filter	1667	80	8335341.00
Nb of sequences by sample ≥ 20000	1650	72	8313238.00
Nb of sample by OTUs ≥ 1	1650	72	8313238.00
Nb of sequences by OTUs ≥ 5	1302	72	8312594.00

Table 15: Number of OTUs, samples and sequences after filtering

List of Figures

2.1	Number of sequences by sample	9
2.2	Number of OTU present in a given number of samples	10
2.3	Number of sequences by OTU (log10 transformed)	11
3.1	Number of OTUs by sample in fonction of the number of sequences by sample (log10 axe)	12
3.2	Distribution of reference sequences length	13
3.3	Number of sequences by OTUs (log10 axe) in fonction of the number of samples where OTUs were found	14
3.4	Distribution of the number of sequences in the Ascomycota taxonomy	14
3.5	Number of sequences of the 30 most abundant OTUs (number of sequences)	16
4.1	Distribution of OTUs into functional Guild	18
4.2	Distribution of sequences (log10 transformed) into functional Guild	19
5.1	Rarefaction curves for each site	20
5.2	Rarefaction curves for each sample using sequences number on x-axes	21
5.3	Diversity of each sites	22
5.4	Rarefaction curves for each host age	23
5.5	Diversity in fonction of tree age	24
5.6	Rarefaction curves for each elevation	25
5.7	Diversity in fonction of elevation	26
5.8	Results of the Tuckey HSD testing for differences in mean Hill numbers among pairs of modalities	27
6.1	Venn diagramm of the distribution of OTUs among Sites	28
6.2	Venn diagramm of the distribution of OTUs among host age	29
6.3	Venn diagramm of the distribution of OTUs among elevation of samples	29
6.4	Venn diagramm of the distribution of OTUs among Sites	30
6.5	Venn diagramm of the distribution of OTUs among host age	30
6.6	Venn diagramm of the distribution of OTUs among elevation of samples whitin the tree	31
6.7	Stress plot of the NMDS	32
6.8	NMDS of OTU table	32
6.9	Comparison of different distances (bray (up) and gower (bottom)) and ordination methods (NMDS (left), PCoA (center) and DCA (right))	34
6.10	Taxonomic distribution of sequences in the different site * age combinaison	38
6.11	Taxonomic distribution of OTUs in the different site * age combinaison	39
6.12	OTUs significantly different in terms of abundances between Verghello (positive values) and Asco (negative values)	40
6.13	OTUs significantly different in terms of abundances between Verghello (positive values) and Bavella (negative values)	41
6.14	OTUs significantly different in terms of abundances between Asco (positive values) and Bavella (negative values)	42
7.1	Number of sequences assigned to extitCyclaneusma minus across host age, elevation whitin tree and sites	48

List of Tables

1	Number of OTUs, samples and sequences after filtering	11
2	Taxonomie of the 30 more abundant OTUs (number of sequences)	15
3	Taxonomie of the 30 more frequent OTUs (number of samples)	17

4	Summary of the linear model of species richness (Hill number with $q = 0$)	23
5	Summary of the linear model of the exponential of Shannon's entropy index (Hill number with $q = 1$)	27
6	Summary of the linear model of inverse of Simpson's concentration index (Hill number with $q = 2$)	27
7	Result of the permanova on abundances (number of sequence).	35
8	Result of the permanova on abundances (number of sequence) using only OTUs present in more than 30 samples	36
9	Result of the permanova on OTUs (each OTU is representing by one sequence)).	36
10	Result of the permanova on abundances (number of sequence).	37
11	Result of the permanova on abundances (number of sequence) using only OTUs present in more than 30 samples	37
12	Result of the permanova on OTUs (each OTU is representing by one sequence)).	37
13	OTUs showing differential abundances in the different sites.	50
14	Order showing differential abundances in the different sites.	51
15	Number of OTUs, samples and sequences after filtering	51