

DspikeIn with Phyloseq

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2025-06-20

Required Packages

```
# INSTALL CRAN PACKAGES

# Install missing CRAN packages
install.packages(setdiff(
  c(
    "stats", "dplyr", "ggplot2", "flextable", "ggpubr",
    "randomForest", "ggribes", "ggalluvial", "tibble",
    "matrixStats", "RColorBrewer", "ape", "rlang",
    "scales", "magrittr", "phangorn", "igraph", "tidyr",
    "xml2", "data.table", "reshape2", "vegan", "patchwork", "officer"
  ),
  installed.packages()[, "Package"]
))

# Load CRAN packages
lapply(c(
  "stats", "dplyr", "ggplot2", "flextable", "ggpubr", "randomForest",
  "ggribes", "ggalluvial", "tibble", "matrixStats", "RColorBrewer",
  "ape", "rlang", "scales", "magrittr", "phangorn", "igraph", "tidyr",
  "xml2", "data.table", "reshape2", "vegan", "patchwork", "officer"
), library, character.only = TRUE)

# INSTALL BIOCONDUCTOR PACKAGES

# Install BiocManager if not installed
if (!requireNamespace("BiocManager", quietly = TRUE)) install.packages("BiocManager")

# Install missing Bioconductor packages
BiocManager::install(setdiff(
  c(
```

```

    "phyloseq", "msa", "DESeq2", "ggtree", "edgeR",
    "Biostrings", "DECIPHER", "microbiome", "limma",
    "S4Vectors", "SummarizedExperiment", "TreeSummarizedExperiment"
  ),
  installed.packages()[, "Package"]
))

# Load Bioconductor packages
lapply(
  c(
    "phyloseq", "msa", "DESeq2", "edgeR", "Biostrings", "ggtree", "DECIPHER",
    "microbiome", "limma", "S4Vectors", "SummarizedExperiment", "TreeSummarizedExperiment"
  ),
  library,
  character.only = TRUE
)

#                               INSTALL DspikeIn FROM GITHUB

# To access the DspikeIn vignette for a detailed tutorial, use vignette("DspikeIn"), or browse
devtools::install_github("mghotbi/DspikeIn", build_vignettes = TRUE, dependencies = TRUE)
library(DspikeIn)
browseVignettes("DspikeIn")
vignette("DspikeIn")

## or

if (!requireNamespace("devtools", quietly = TRUE)) install.packages("devtools")
devtools::install_github("mghotbi/DspikeIn")

# Load DspikeIn only if installed
if ("DspikeIn" %in% installed.packages()[, "Package"]) {
  library(DspikeIn)
} else {
  stop("DspikeIn installation failed. Check errors above.")
}

```

Acknowledgments

The development of the DspikeIn package was made possible through the generous and pioneering efforts of the R and Bioconductor communities. We gratefully acknowledge the developers and maintainers of the following open-source packages, whose tools and infrastructure underpin our work: **Core infrastructure & data manipulation:** methods, stats, utils, graphics, grDevices,

data.table, dplyr, tibble, tidyr, reshape2, matrixStats, rlang, S4Vectors, grid, officer, xml2 **Statistical analysis & modeling:** DESeq2, edgeR, limma, randomForest, microbiome **Phylogenetics & microbiome structure:** phyloseq, TreeSummarizedExperiment, SummarizedExperiment, phangorn, ape, DECIPHER, msa, Biostrings **Network and graph analysis:** igraph, ggraph **Visualization & layout design:** ggplot2, ggrepel, ggpubr, ggnewscale, ggalluvial, ggtree, ggtreeExtra, ggstar, ggribbles, patchwork, scales, RColorBrewer, flextable

These tools collectively empowered us to build a reproducible, modular, and extensible platform for robust absolute abundance quantification in microbial community analysis. We further acknowledge the broader scientific community working on absolute microbial quantification, spike-in calibration, and compositional data analysis, whose foundational insights directly informed the design and conceptual framework of DspikeIn.

DspikeIn

The DspikeIn package supports both phyloseq and TreeSummarizedExperiment formats to streamline microbial quantification across diverse experimental setups. It accommodates either a single spike-in taxon or synthetic community taxa with variable or equal spike-in volumes and copy numbers. The package offers a comprehensive suite of tools for AA quantification, addressing challenges through ten core functions: 1) validation of spiked species, 2) data preprocessing, 3) system-specific spiked species retrieval, 4) scaling factor calculation, 5) conversion to absolute abundance, 6) bias correction and normalization, 7) performance assessment, and 8) taxa exploration and filtering 9) network topology assessment 10) further analyses and visualization.

DspikeIn requirements

DspikeIn works with 7 taxonomic ranks

```
# To remove strain from the taxonomic ranks

# DspikeIn works with 7 taxonomic ranks
# colnames(taxmat) <- c("Kingdom", "Phylum", "Class", "Order", "Family", "Genus", "Species")

library(phyloseq)
# Function to remove strain information from taxonomy columns
remove_strain_info <- function(tax_table) {
  # Define the regex pattern for common strain identifiers
  pattern <- "Strain.*|strain.*|\\s*\\[.*\\]|\\s*\\(.*\\)" # Adjust the regex to match specific patterns
  # Apply the pattern to each column of the taxonomy table
  for (col in colnames(tax_table)) {
    tax_table[, col] <- gsub(pattern, "", tax_table[, col]) # Remove strain info
    tax_table[, col] <- trimws(tax_table[, col]) # Trim trailing whitespace
  }
  return(tax_table)
}
```

```

# Step 1: Extract the taxonomy table
taxonomy <- tax_table(ps)
# Step 2: Remove strain information (including the `Strain` column)
cleaned_taxonomy <- remove_strain_info(taxonomy)
# Remove the `Strain` column if it exists
if ("Strain" %in% colnames(cleaned_taxonomy)) {
  cleaned_taxonomy <- cleaned_taxonomy[, colnames(cleaned_taxonomy) != "Strain"]
}
# Step 3: Update the taxonomy table in the phyloseq object
tax_table(ps) <- cleaned_taxonomy
# Step 4: Verify the changes
print(head(tax_table(ps))) # Display the first few rows

#           To add species rank to the taxonomic ranks

library(phyloseq)

# Step 1: Extract taxonomy table safely
taxonomy <- as.data.frame(as.matrix(tax_table(ps)))
if (!"Genus" %in% colnames(taxonomy)) {
  stop("The 'Genus' column is missing in the taxonomy table.")
}

# Step 2: Handle potential missing genera (optional but recommended)
taxonomy$Genus[is.na(taxonomy$Genus) | taxonomy$Genus == ""] <- "Unknown"
# Step 3: Create a new 'species' column
taxonomy$species <- paste0(taxonomy$Genus, "_OTU", seq_len(nrow(taxonomy)))
# Step 4: Assign back to phyloseq object (must coerce back to matrix)
tax_table(ps) <- tax_table(as.matrix(taxonomy))

```

Build phyloseq or TreeSummarizedExperiment file

for more information please refer to <https://github.com/joey711/phyloseq> & <https://github.com/markrobinsonuzh/TreeSummarizedExperiment>

```

#           Build phyloseq

otu <- read.csv("otu.csv", header = TRUE, sep = ",", row.names = 1)
# taxonomic rank need to be capilalized, only the first letter of each rank
tax <- read.csv("tax.csv", header = TRUE, sep = ",", row.names = 1)
# Ensure 'spiked.volume' column is present and correctly formatted in metadata

```

```

meta <- read.csv("metadata.csv", header = TRUE, sep = ",")

# Convert data to appropriate formats
meta <- as.data.frame(meta)
taxmat <- as.matrix(tax)
otumat <- as.matrix(otu)
colnames(taxmat) <- c("Kingdom", "Phylum", "Class", "Order", "Family", "Genus", "Species")
OTU <- otu_table(otumat, taxa_are_rows = TRUE)
TAX <- phyloseq::tax_table(taxmat)

# Check
row.names(meta) <- sample_names(OTU)
metadata <- sample_data(meta)
# Build phyloseq obj
physeq <- phyloseq(OTU, TAX, metadata)

# Follow the next steps if tree and reference files are included
MyTree <- read.tree("tree.nwk")
reference_seqs <- readDNASTringSet(file = "dna-sequences.fasta", format = "fasta")

physeq_16SOTU <- merge_phyloseq(physeq, reference_seqs, MyTree)
physeq_16SOTU <- tidy_phyloseq_tse(physeq_16SOTU)

saveRDS(physeq_16SOTU, file = "physeq_16SOTU.rds")
physeq_16SOTU <- readRDS("physeq_16SOTU.rds")

#                               Build TreeSummarizedExperiment (TSE)

otu <- read.csv("otu.csv", header = TRUE, sep = ",", row.names = 1)
otu_mat <- as.matrix(otu) # Convert to matrix
tax <- read.csv("tax.csv", header = TRUE, sep = ",", row.names = 1)
colnames(tax) <- c("Kingdom", "Phylum", "Class", "Order", "Family", "Genus", "Species")
tax_mat <- as.matrix(tax) # Convert to matrix
meta <- read.csv("metadata.csv", header = TRUE, sep = ",", row.names = 1)
reference_seqs <- readDNASTringSet("dna-sequences.fasta", format = "fasta")
tse <- TreeSummarizedExperiment(
  assays = list(counts = otu_mat), # OTU table
  rowData = tax_mat, # Taxonomy information
  colData = meta, # Sample metadata
  rowTree = MyTree, # Phylogenetic tree
  rowSeqs = reference_seqs # Reference sequences
)

```

Do all detected sample spike-in sequences cluster with the reference, and are their branch lengths

statistically similar, supporting a common ancestor?

spike-in validation

All sample-derived sequences are forming a clade with the reference. We look for a monophyletic grouping of spike-in OTUs. The clade is strongly supported (bootstrap around 100 percentage). The branch lengths and distances are in a biologically plausible range.

```
# Use the Neighbor-Joining method based on a Jukes-Cantor distance matrix and plot the tree w  
# we compare the Sanger read of Tetragenococcus halophilus with the FASTA sequence of Tetragen
```

```
library(Biostrings)  
library(phyloseq)  
library(DspikeIn)  
  
# Get path to external data folder  
extdata_path <- system.file("extdata", package = "DspikeIn")  
list.files(extdata_path)
```

```
## [1] "Complete.graphml" "NoBasid.graphml" "NoHubs.graphml" "Ref.fasta" "Sample.fas
```

```
data("physeq_16SOTU", package = "DspikeIn")  
  
physeq_16SOTU <- tidy_phyloseq_tse(physeq_16SOTU)  
  
physeq_16SOTU <- phyloseq::prune_taxa(  
  get_tax_table(physeq_16SOTU)$Kingdom %in% c("Bacteria", "Archaea"),  
  physeq_16SOTU  
)  
  
# Subset the phyloseq object to include only Tetragenococcus species first  
# Tetragenococcus <- subset_taxa(physeq_16SOTU, Genus=="Tetragenococcus")  
# Tetragenococcus <- subset_taxa(Tetragenococcus, !is.na(taxa_names(Tetragenococcus)) & taxa_n  
# tree <- phy_tree(Tetragenococcus)  
# ref_sequences_Tetragenococcus <- refseq(Tetragenococcus)  
# library(Biostrings)  
# writeXStringSet(ref_sequences_Tetragenococcus, "Sample.fasta.fasta")  
  
ref_fasta <- system.file("extdata", "Ref.fasta", package = "DspikeIn")  
sample_fasta <- system.file("extdata", "Sample.fasta", package = "DspikeIn")
```

```
result <- validate_spikein_clade(
  reference_fasta = ref_fasta,
  sample_fasta = sample_fasta,
  bootstrap = 200,
  output_prefix = NULL)
```

```
## use default substitution matrix
```

```
# result$tree_plot
```

Did spike-ins behave as expected across all samples?

Tip labels= OTU/ASV names Branch length numbers= Actual evolutionary distances (small = very similar) Prevalence stars How frequently the OTU occurs across samples Blue bar ring= Log10 mean abundance Outer colored tiles= The metadata variable you choose (e.g., Animal.type)

```
data("physeq_16SOTU", package = "DspikeIn")
library(ggstar)
library(ggplot2)
# filter your object to only include spike-in taxa beforehand:
# change the OTU IDs for easy detection
# Big stars = detected in many samples
# Small stars = rarely detected
# log10(Mean Abundance) Bars= Color intensity reflects mean abundance.
# The log-transformed average abundance of each OTU across all samples where it appears.
# Extreme blue may signal unintended over-representation.
# Metadata Ring = factor of your interest e.g. Animal.type
# Each OTU is colored by where it was observed.
# Branch length numbers= Actual evolutionary distances (small = very similar)

spikein <- phyloseq::subset_taxa(physeq_16SOTU, Genus == "Tetragenococcus")
taxa_names(spikein) <- paste0("OTU", seq_len(ntaxa(spikein)))

# Visualize
ps <- plot_spikein_tree_diagnostic(
  obj = spikein,
  metadata_var = "Animal.type",
  output_prefix = "tetragenococcus_diag"
)
```

Pre_processing

merges monophyletic ASVs/OTUs

```

# merges monophyletic ASVs/OTUs

# The function Pre_processing_species() merges ASVs/OTUs
# of a species using "sum" or "max" methods, preserving taxonomic,
# phylogenetic, and sequencing data.

#                               Load the phyloseq objs/ TSE obj

library(phyloseq)
library(DspikeIn)
library(TreeSummarizedExperiment)
library(SummarizedExperiment)

data("physeq_16SOTU", package = "DspikeIn")

# TSE format
# tse_16SOTU <- convert_phyloseq_to_tse(physeq_16SOTU)
# physeq_16SOTU <- convert_tse_to_phyloseq(tse_16SOTU)

physeq_16SOTU <- DspikeIn::tidy_phyloseq_tse(physeq_16SOTU) # make it tidy

# for those prefer to use TSE format
tse_16SOTU <- convert_phyloseq_to_tse(physeq_16SOTU)

# Check if metadata contains spiked volumes with this format
colnames(sample_data(physeq_16SOTU))

```

```

## [1] "sample.id" "X16S.biosample"
## [3] "dna.biosample" "data.type"
## [5] "ampliconlibrary.quantification.ng.ul" "plate.ID"
## [7] "well.location" "Env.broad.scale"
## [9] "Host.taxon" "Host.genus"
## [11] "Host.species" "Animal.type"
## [13] "Animal.ecomode" "Clade.Order"
## [15] "Family" "Diet"
## [17] "Diet.Detailed" "Habitat"
## [19] "Metamorphosis" "Reproduction"
## [21] "Ecoregion.III" "Ecoregion.IV"
## [23] "Site" "sample.name"
## [25] "biosample.parent" "data.type.1"
## [27] "ampliconlibrary.quantification.ng.ul.1" "plate.ID.1"
## [29] "well.location.1" "sample.or.blank"
## [31] "sample.spiked.blank" "spiked.volume"
## [33] "swab.presence" "MK.spike"

```

Spiked species and related parameters for 16S (Phyloseq format)

```
#                               PREREQUISITE FOR 16S & CALCULATE SPIKED %

# Define spiked species and related parameters**

library(flextable)
library(DspikeIn)
# Define spike-in parameters
spiked_cells <- 1847
species_name <- spiked_species <- c("Tetragenococcus_halophilus", "Tetragenococcus_sp.")
merged_spiked_species <- "Tetragenococcus_halophilus"

# If you prefer Genus-level matching
# species_name <- spiked_species <- c("Tetragenococcus")
# merged_spiked_species <- "Tetragenococcus"

# Subset taxa for spiked species
Tetragenococcus <- phyloseq::subset_taxa(
  physeq_16SOTU,
  Species %in% species_name
)

# Get taxon hashcodes
hashcodes <- row.names(phyloseq::tax_table(Tetragenococcus))

# Subset samples based on spiked volume
spiked_16S_OTU_spiked <- phyloseq::subset_samples(
  physeq_16SOTU,
  spiked.volume %in% c("2", "1")
)

# Merge OTUs derived from spiked species
# File will be saved to tempdir() (no cleanup needed)
output_rds <- file.path(tempdir(), "merged_physeq_sum.rds")

Spiked_16S_sum_scaled <- Pre_processing_species(
  spiked_16S_OTU_spiked,
  species_name,
  merge_method = "sum",
  output_file = output_rds
)

# Calculate the spike-in percentage across samples
```

```
Perc <- calculate_spike_percentage(
  Spiked_16S_sum_scaled,
  merged_spiked_species,
  passed_range = c(0.1, 20)
)
```

Spiked species and related parameters for ITS

```
#                                     PREREQUISITE FOR ITS & CALCULATE SPIKED %

# Define spiked species and related parameters**

# Define the spiked species
# spiked_cells <- 733
# species_name <- spiked_species <- merged_spiked_species <- "Dekkera_bruuxellensis"

# Subset taxa for spiked species
# Dekkera <- phyloseq::subset_taxa(
# physeq_ITSOTU,
# Species %in% species_name)

# hashcodes <- row.names(phyloseq::tax_table(Dekkera))

# Subset samples based on spiked volume
# physeq_ITSOTU_spiked <- phyloseq::subset_samples(physeq_ITSOTU, spiked.volume %in% c("2", "1"))

# if TSE format
# tse_ITSOTU <- convert_phyloseq_to_tse(physeq_ITSOTU)
# physeq_ITSOTU_spiked <- tse_ITSOTU[, tse_ITSOTU$spiked.volume %in% c("2", "1")]
```

Calculating Scaling Factors (Phyloseq object)

```
#                                     CALCULATE SCALING FACTORS

# Calculate spike-in scaling factors
result <- calculate_spikeIn_factors(
  obj = Spiked_16S_sum_scaled,
  spiked_cells = spiked_cells,
```

```
merged_spiked_species = merged_spiked_species
)
```

```
# View extracted outputs
```

```
result$spiked_species_merged # Merged spiked species name
```

```
## phyloseq-class experiment-level object
## otu_table() OTU Table: [ 1 taxa and 264 samples ]
## sample_data() Sample Data: [ 264 samples by 34 sample variables ]
## tax_table() Taxonomy Table: [ 1 taxa by 7 taxonomic ranks ]
## refseq() DNASTringSet: [ 1 reference sequences ]
```

```
result$spiked_species_reads # Total reads detected for the spike
```

##	Sample	Spiked_Reads
##	spiked.blank.20433_S84	8
##	spiked.blank.20817_S84	47066
##	Std2uL.20625_S84	62433
##	StdSwab1uL.20624_S72	17639
##	STP1719.20422_S47	14549
##	STP213.20423_S59	83
##	STP268.20424_S71	17
##	STP544.20419_S11	2259
##	STP570.20420_S23	822
##	STP579.20421_S35	1759
##	STP614.20418_S94	0
##	UHM1000.20604_S22	118
##	UHM1001.20609_S82	93
##	UHM1007.20622_S48	118
##	UHM1009.20614_S47	116
##	UHM1010.20621_S36	979
##	UHM1011.20606_S46	130
##	UHM1024.20620_S24	994
##	UHM1026.20607_S58	396
##	UHM1028.20613_S35	898
##	UHM1032.20605_S34	1616
##	UHM1033.20619_S12	37416
##	UHM1034.20616_S71	4
##	UHM1035.20611_S11	210
##	UHM1036.20612_S23	249
##	UHM1052.20615_S59	150
##	UHM1060.20723_S1	24617
##	UHM1065.20724_S13	8179
##	UHM1068.20732_S14	243
##	UHM1069.20742_S39	343
##	UHM1070.20725_S25	1741

## UHM1071.20733_S26	UHM1071.20733_S26	56
## UHM1072.20734_S38	UHM1072.20734_S38	1486
## UHM1073.20735_S50	UHM1073.20735_S50	39
## UHM1075.20726_S37	UHM1075.20726_S37	1179
## UHM1077.20736_S62	UHM1077.20736_S62	73
## UHM1078.20727_S49	UHM1078.20727_S49	173
## UHM1080.20737_S74	UHM1080.20737_S74	69
## UHM1081.20728_S61	UHM1081.20728_S61	1772
## UHM1088.20738_S86	UHM1088.20738_S86	240
## UHM1090.20739_S3	UHM1090.20739_S3	5303
## UHM1093.20729_S73	UHM1093.20729_S73	333
## UHM1095.20730_S85	UHM1095.20730_S85	6219
## UHM1097.20623_S60	UHM1097.20623_S60	6050
## UHM1099.20608_S70	UHM1099.20608_S70	24
## UHM1100.20788_S21	UHM1100.20788_S21	75
## UHM1102.20789_S33	UHM1102.20789_S33	108
## UHM1104.20790_S45	UHM1104.20790_S45	83
## UHM1105.20791_S57	UHM1105.20791_S57	148
## UHM1109.20531_S1	UHM1109.20531_S1	116
## UHM1110.20568_S65	UHM1110.20568_S65	50
## UHM1113.20792_S69	UHM1113.20792_S69	79
## UHM1114.20793_S81	UHM1114.20793_S81	361
## UHM1115.20794_S93	UHM1115.20794_S93	181
## UHM1117.20795_S10	UHM1117.20795_S10	61
## UHM1118.20796_S22	UHM1118.20796_S22	248
## UHM1120.20797_S34	UHM1120.20797_S34	718
## UHM1124.20798_S46	UHM1124.20798_S46	583
## UHM1126.20799_S58	UHM1126.20799_S58	193
## UHM1128.20800_S70	UHM1128.20800_S70	183
## UHM1140.20555_S4	UHM1140.20555_S4	130
## UHM1145.20801_S82	UHM1145.20801_S82	45
## UHM1163.20405_S33	UHM1163.20405_S33	150
## UHM1164.20402_S92	UHM1164.20402_S92	3
## UHM1169.20552_S63	UHM1169.20552_S63	6591
## UHM1171.20579_S7	UHM1171.20579_S7	97
## UHM1176.20404_S21	UHM1176.20404_S21	67
## UHM1177.20546_S86	UHM1177.20546_S86	1558
## UHM1182.20576_S66	UHM1182.20576_S66	233
## UHM1210.20802_S94	UHM1210.20802_S94	98
## UHM1212.20803_S11	UHM1212.20803_S11	306
## UHM1217.20804_S23	UHM1217.20804_S23	188
## UHM1218.20805_S35	UHM1218.20805_S35	151
## UHM1219.20806_S47	UHM1219.20806_S47	57
## UHM1220.20807_S59	UHM1220.20807_S59	84
## UHM1221.20808_S71	UHM1221.20808_S71	105
## UHM1222.20809_S83	UHM1222.20809_S83	3039
## UHM1223.20810_S95	UHM1223.20810_S95	69
## UHM1225.20811_S12	UHM1225.20811_S12	229

## UHM1227.20812_S24	UHM1227.20812_S24	871
## UHM1228.20813_S36	UHM1228.20813_S36	69
## UHM1237.20814_S48	UHM1237.20814_S48	413
## UHM1240.20566_S41	UHM1240.20566_S41	683
## UHM1246.20815_S60	UHM1246.20815_S60	573
## UHM1247.20816_S72	UHM1247.20816_S72	235
## UHM1248.20575_S54	UHM1248.20575_S54	3287
## UHM1256.20570_S89	UHM1256.20570_S89	901
## UHM1260.20596_S21	UHM1260.20596_S21	614
## UHM1270.20577_S78	UHM1270.20577_S78	217
## UHM1271.20397_S32	UHM1271.20397_S32	893
## UHM1272.20398_S44	UHM1272.20398_S44	1529
## UHM1274.20554_S87	UHM1274.20554_S87	467
## UHM1275.20597_S33	UHM1275.20597_S33	1203
## UHM1282.20599_S57	UHM1282.20599_S57	3820
## UHM1287.20543_S50	UHM1287.20543_S50	1979
## UHM1291.20416_S70	UHM1291.20416_S70	261
## UHM1296.20550_S39	UHM1296.20550_S39	76
## UHM1319.20561_S76	UHM1319.20561_S76	1567
## UHM1324.20413_S34	UHM1324.20413_S34	433
## UHM1327.20545_S74	UHM1327.20545_S74	73
## UHM1328.20572_S18	UHM1328.20572_S18	3325
## UHM1334.20417_S82	UHM1334.20417_S82	155
## UHM1338.20399_S56	UHM1338.20399_S56	760
## UHM1341.20602_S93	UHM1341.20602_S93	8050
## UHM1356.20541_S26	UHM1356.20541_S26	810
## UHM1380.20580_S19	UHM1380.20580_S19	308
## UHM1383.20594_S92	UHM1383.20594_S92	421
## UHM1385.20563_S5	UHM1385.20563_S5	20431
## UHM1399.20756_S17	UHM1399.20756_S17	918
## UHM1400.20757_S29	UHM1400.20757_S29	316
## UHM1401.20758_S41	UHM1401.20758_S41	2414
## UHM1402.20759_S53	UHM1402.20759_S53	166
## UHM1403.20760_S65	UHM1403.20760_S65	303
## UHM1405.20761_S77	UHM1405.20761_S77	214
## UHM1406.20762_S89	UHM1406.20762_S89	213
## UHM1414.20763_S6	UHM1414.20763_S6	107
## UHM1419.20764_S18	UHM1419.20764_S18	488
## UHM1427.20389_S31	UHM1427.20389_S31	103
## UHM1428.20390_S43	UHM1428.20390_S43	0
## UHM1429.20391_S55	UHM1429.20391_S55	29
## UHM1430.20392_S67	UHM1430.20392_S67	11
## UHM1432.20393_S79	UHM1432.20393_S79	18
## UHM1435.20388_S19	UHM1435.20388_S19	0
## UHM162.20560_S64	UHM162.20560_S64	704
## UHM198.20585_S79	UHM198.20585_S79	3649
## UHM20.3314_S52	UHM20.3314_S52	43
## UHM20.3315_S64	UHM20.3315_S64	349

## UHM204.20409_S81	UHM204.20409_S81	66
## UHM206.20410_S93	UHM206.20410_S93	0
## UHM207.20593_S80	UHM207.20593_S80	200
## UHM208.20411_S10	UHM208.20411_S10	391
## UHM211.20406_S45	UHM211.20406_S45	164
## UHM215.20408_S69	UHM215.20408_S69	9
## UHM216.20429_S36	UHM216.20429_S36	63
## UHM219.20430_S48	UHM219.20430_S48	21041
## UHM236.20431_S60	UHM236.20431_S60	41
## UHM238.20407_S57	UHM238.20407_S57	120
## UHM245.20538_S85	UHM245.20538_S85	108
## UHM252.20558_S40	UHM252.20558_S40	1090
## UHM267.20400_S68	UHM267.20400_S68	127
## UHM274.20581_S31	UHM274.20581_S31	2025
## UHM276.20586_S91	UHM276.20586_S91	1169
## UHM280.20401_S80	UHM280.20401_S80	389
## UHM286.20425_S83	UHM286.20425_S83	30
## UHM289.20426_S95	UHM289.20426_S95	4
## UHM294.20427_S12	UHM294.20427_S12	610
## UHM298.20600_S69	UHM298.20600_S69	404
## UHM325.20548_S15	UHM325.20548_S15	584
## UHM337.20412_S22	UHM337.20412_S22	261
## UHM354.20535_S49	UHM354.20535_S49	355
## UHM356.20415_S58	UHM356.20415_S58	411
## UHM369.20773_S31	UHM369.20773_S31	233
## UHM370.20774_S43	UHM370.20774_S43	88
## UHM372.20775_S55	UHM372.20775_S55	30
## UHM373.20776_S67	UHM373.20776_S67	84
## UHM374.20777_S79	UHM374.20777_S79	69
## UHM375.20778_S91	UHM375.20778_S91	709
## UHM377.20779_S8	UHM377.20779_S8	477
## UHM38.3376_S36	UHM38.3376_S36	0
## UHM386.20781_S32	UHM386.20781_S32	234
## UHM387.20782_S44	UHM387.20782_S44	58
## UHM414.20583_S55	UHM414.20583_S55	85
## UHM418.20765_S30	UHM418.20765_S30	270
## UHM422.20766_S42	UHM422.20766_S42	1144
## UHM425.20767_S54	UHM425.20767_S54	118
## UHM426.20534_S37	UHM426.20534_S37	4598
## UHM428.20544_S62	UHM428.20544_S62	454
## UHM429.20559_S52	UHM429.20559_S52	1283
## UHM435.20547_S3	UHM435.20547_S3	1718
## UHM437.20768_S66	UHM437.20768_S66	49
## UHM439.20564_S17	UHM439.20564_S17	71
## UHM44.3526_S31	UHM44.3526_S31	1281
## UHM445.20569_S77	UHM445.20569_S77	26
## UHM447.20783_S56	UHM447.20783_S56	64
## UHM448.20769_S78	UHM448.20769_S78	424

## UHM45.3539_S92	UHM45.3539_S92	0
## UHM454.20770_S90	UHM454.20770_S90	278
## UHM455.20785_S80	UHM455.20785_S80	787
## UHM458.20786_S92	UHM458.20786_S92	64
## UHM459.20787_S9	UHM459.20787_S9	120
## UHM461.20771_S7	UHM461.20771_S7	242
## UHM467.20772_S19	UHM467.20772_S19	47
## UHM470.20533_S25	UHM470.20533_S25	1220
## UHM476.20414_S46	UHM476.20414_S46	1135
## UHM478.20549_S27	UHM478.20549_S27	429
## UHM479.20551_S51	UHM479.20551_S51	14412
## UHM481.20403_S9	UHM481.20403_S9	227
## UHM482.20590_S44	UHM482.20590_S44	233
## UHM483.20603_S10	UHM483.20603_S10	91
## UHM519.20582_S43	UHM519.20582_S43	136
## UHM520.20573_S30	UHM520.20573_S30	253
## UHM746.21478_S117	UHM746.21478_S117	85168
## UHM747.21477_S106	UHM747.21477_S106	82287
## UHM748.21467_S170	UHM748.21467_S170	55291
## UHM748.21487_S129	UHM748.21487_S129	36462
## UHM749.21479_S128	UHM749.21479_S128	62780
## UHM759.21466_S159	UHM759.21466_S159	76702
## UHM759.21486_S118	UHM759.21486_S118	16500
## UHM775.21485_S107	UHM775.21485_S107	43046
## UHM776.21482_S161	UHM776.21482_S161	58165
## UHM777.21484_S183	UHM777.21484_S183	23485
## UHM779.21468_S181	UHM779.21468_S181	80976
## UHM779.21488_S140	UHM779.21488_S140	9
## UHM782.21480_S139	UHM782.21480_S139	38354
## UHM810.21472_S138	UHM810.21472_S138	94712
## UHM811.21471_S127	UHM811.21471_S127	30104
## UHM813.21481_S150	UHM813.21481_S150	64962
## UHM818.21469_S105	UHM818.21469_S105	50417
## UHM818.21489_S151	UHM818.21489_S151	19
## UHM819.21473_S149	UHM819.21473_S149	83424
## UHM820.21470_S116	UHM820.21470_S116	66075
## UHM820.21490_S162	UHM820.21490_S162	515
## UHM827.21474_S160	UHM827.21474_S160	83467
## UHM829.21476_S182	UHM829.21476_S182	69357
## UHM832.21483_S172	UHM832.21483_S172	68494
## UHM836.20385_S78	UHM836.20385_S78	0
## UHM837.20386_S90	UHM837.20386_S90	0
## UHM838.20387_S7	UHM838.20387_S7	11
## UHM891.20384_S66	UHM891.20384_S66	85
## UHM892.20532_S13	UHM892.20532_S13	1164
## UHM893.20595_S9	UHM893.20595_S9	16
## UHM894.20540_S14	UHM894.20540_S14	36
## UHM895.20536_S61	UHM895.20536_S61	2116

## UHM896.20601_S81	UHM896.20601_S81	0
## UHM897.20591_S56	UHM897.20591_S56	0
## UHM898.20394_S91	UHM898.20394_S91	0
## UHM899.20588_S20	UHM899.20588_S20	24
## UHM900.20395_S8	UHM900.20395_S8	0
## UHM901.20542_S38	UHM901.20542_S38	95
## UHM902.20584_S67	UHM902.20584_S67	1217
## UHM903.20587_S8	UHM903.20587_S8	470
## UHM904.20567_S53	UHM904.20567_S53	45
## UHM905.20598_S45	UHM905.20598_S45	89
## UHM906.20565_S29	UHM906.20565_S29	0
## UHM907.20592_S68	UHM907.20592_S68	30
## UHM908.20396_S20	UHM908.20396_S20	0
## UHM909.20557_S28	UHM909.20557_S28	87
## UHM910.20562_S88	UHM910.20562_S88	34
## UHM965.20537_S73	UHM965.20537_S73	464
## UHM966.20743_S51	UHM966.20743_S51	461
## UHM967.20744_S63	UHM967.20744_S63	0
## UHM968.20571_S6	UHM968.20571_S6	33012
## UHM969.20745_S75	UHM969.20745_S75	30
## UHM971.20746_S87	UHM971.20746_S87	10
## UHM973.20578_S90	UHM973.20578_S90	46
## UHM974.20432_S72	UHM974.20432_S72	0
## UHM975.20747_S4	UHM975.20747_S4	33
## UHM977.20748_S16	UHM977.20748_S16	100
## UHM978.20749_S28	UHM978.20749_S28	91
## UHM979.20750_S40	UHM979.20750_S40	35
## UHM980.20731_S2	UHM980.20731_S2	248
## UHM981.20539_S2	UHM981.20539_S2	766
## UHM982.20740_S15	UHM982.20740_S15	161
## UHM983.20556_S16	UHM983.20556_S16	12547
## UHM984.20751_S52	UHM984.20751_S52	26
## UHM985.20752_S64	UHM985.20752_S64	797
## UHM988.20753_S76	UHM988.20753_S76	603
## UHM989.20754_S88	UHM989.20754_S88	17
## UHM991.20755_S5	UHM991.20755_S5	1864
## UHM993.20741_S27	UHM993.20741_S27	52
## UHM996.20610_S94	UHM996.20610_S94	0
## UHM997.20553_S75	UHM997.20553_S75	0
## UHM998.20618_S95	UHM998.20618_S95	2610
## UHM999.20617_S83	UHM999.20617_S83	72

```
scaling_factors <- result$scaling_factors
head(scaling_factors) # Vector of scaling factors per sample
```

## spiked.blank.20433_S84	spiked.blank.20817_S84	Std2uL.20625_S84	StdSwab1uL.20624_S72
## 230.87500000	0.03924277	0.02958371	0.05235558

```
##          STP213.20423_S59
##          22.25301205
```

Convert relative counts to absolute counts

```
#          Convert relative counts to absolute counts

# absolute counts=relative counts*sample-specific scaling factor

# Convert to absolute counts
absolute <- convert_to_absolute_counts(Spiked_16S_sum_scaled, scaling_factors)

# Extract processed data
absolute_counts <- absolute$absolute_counts
physeq_absolute <- absolute$obj_adj

physeq_absolute <- tidy_phyloseq_tse(physeq_absolute)

# View absolute count data
head(absolute_counts)
```

```
##          spiked.blank.20433_S84 spiked.blank.20817_S84 Std2uL.20625_
## 020e00d90ba97c5898944ab6f7b1b7c9          0          0
## b00466354053c9065c8aa3d6fbb33eaa          0          0
## f872c4bf84bcf44434fa2023788f6517          0          0
##          STP1719.20422_S47 STP213.20423_S59 STP268.20424_S71 STP544
## 020e00d90ba97c5898944ab6f7b1b7c9          0          0          0
## b00466354053c9065c8aa3d6fbb33eaa          0          0          0
## f872c4bf84bcf44434fa2023788f6517          0          0          0
##          STP579.20421_S35 STP614.20418_S94 UHM1000.20604_S22 UHM100
## 020e00d90ba97c5898944ab6f7b1b7c9          0          0          0
## b00466354053c9065c8aa3d6fbb33eaa          0          0          0
## f872c4bf84bcf44434fa2023788f6517          0          0          0
##          UHM1007.20622_S48 UHM1009.20614_S47 UHM1010.20621_S36 UHM1
## 020e00d90ba97c5898944ab6f7b1b7c9          0          0          0
## b00466354053c9065c8aa3d6fbb33eaa          0          0          0
## f872c4bf84bcf44434fa2023788f6517          0          0          0
##          UHM1024.20620_S24 UHM1026.20607_S58 UHM1028.20613_S35 UHM1
## 020e00d90ba97c5898944ab6f7b1b7c9          0          0          0
## b00466354053c9065c8aa3d6fbb33eaa          0          7          0
## f872c4bf84bcf44434fa2023788f6517          0          0          0
##          UHM1033.20619_S12 UHM1034.20616_S71 UHM1035.20611_S11 UHM1
## 020e00d90ba97c5898944ab6f7b1b7c9          0          462          0
```

## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	693	0
##	UHM1052.20615_S59	UHM1060.20723_S1	UHM1065.20724_S13
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1069.20742_S39	UHM1070.20725_S25	UHM1071.20733_S26
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1073.20735_S50	UHM1075.20726_S37	UHM1077.20736_S62
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1080.20737_S74	UHM1081.20728_S61	UHM1088.20738_S86
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1093.20729_S73	UHM1095.20730_S85	UHM1097.20623_S60
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1100.20788_S21	UHM1102.20789_S33	UHM1104.20790_S45
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1109.20531_S1	UHM1110.20568_S65	UHM1113.20792_S69
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1115.20794_S93	UHM1117.20795_S10	UHM1118.20796_S22
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1124.20798_S46	UHM1126.20799_S58	UHM1128.20800_S70
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1145.20801_S82	UHM1163.20405_S33	UHM1164.20402_S92
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1171.20579_S7	UHM1176.20404_S21	UHM1177.20546_S86
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
## b00466354053c9065c8aa3d6fbb33eaa	0	0	0
## f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1210.20802_S94	UHM1212.20803_S11	UHM1217.20804_S23
## 020e00d90ba97c5898944ab6f7b1b7c9	0	0	0

##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1219.20806_S47	UHM1220.20807_S59	UHM1221.20808_S71	UHM1222.20809_S82
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1223.20810_S95	UHM1225.20811_S12	UHM1227.20812_S24	UHM1228.20813_S35
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1237.20814_S48	UHM1240.20566_S41	UHM1246.20815_S60	UHM1252.20816_S67
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1248.20575_S54	UHM1256.20570_S89	UHM1260.20596_S21	UHM1264.20597_S25
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1271.20397_S32	UHM1272.20398_S44	UHM1274.20554_S87	UHM1275.20555_S88
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1282.20599_S57	UHM1287.20543_S50	UHM1291.20416_S70	UHM1292.20417_S71
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1319.20561_S76	UHM1324.20413_S34	UHM1327.20545_S74	UHM1328.20546_S75
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1334.20417_S82	UHM1338.20399_S56	UHM1341.20602_S93	UHM1342.20603_S94
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1380.20580_S19	UHM1383.20594_S92	UHM1385.20563_S5	UHM1386.20564_S6
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1400.20757_S29	UHM1401.20758_S41	UHM1402.20759_S53	UHM1403.20760_S54
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1405.20761_S77	UHM1406.20762_S89	UHM1414.20763_S6	UHM1415.20764_S7
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##	UHM1427.20389_S31	UHM1428.20390_S43	UHM1429.20391_S55	UHM1430.20392_S56
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0

##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM1432.20393_S79	UHM1435.20388_S19	UHM162.20560_S64
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM20.3315_S64	UHM204.20409_S81	UHM206.20410_S93
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM211.20406_S45	UHM215.20408_S69	UHM216.20429_S36
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM238.20407_S57	UHM245.20538_S85	UHM252.20558_S40
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM276.20586_S91	UHM280.20401_S80	UHM286.20425_S83
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM298.20600_S69	UHM325.20548_S15	UHM337.20412_S22
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM369.20773_S31	UHM370.20774_S43	UHM372.20775_S55
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM375.20778_S91	UHM377.20779_S8	UHM38.3376_S36
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM414.20583_S55	UHM418.20765_S30	UHM422.20766_S42
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM428.20544_S62	UHM429.20559_S52	UHM435.20547_S3
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM44.3526_S31	UHM445.20569_S77	UHM447.20783_S56
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM454.20770_S90	UHM455.20785_S80	UHM458.20786_S92
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0

##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM467.20772_S19	UHM470.20533_S25	UHM476.20414_S46 UHM478.20414_S46
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM481.20403_S9	UHM482.20590_S44	UHM483.20603_S10 UHM519.20603_S10
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM746.21478_S117	UHM747.21477_S106	UHM748.21467_S170 UHM749.21466_S159
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM749.21479_S128	UHM759.21466_S159	UHM759.21486_S118 UHM760.21485_S117
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM776.21482_S161	UHM777.21484_S183	UHM779.21468_S181 UHM780.21467_S170
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM782.21480_S139	UHM810.21472_S138	UHM811.21471_S127 UHM812.21470_S116
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM818.21469_S105	UHM818.21489_S151	UHM819.21473_S149 UHM820.21472_S138
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM820.21490_S162	UHM827.21474_S160	UHM829.21476_S182 UHM830.21475_S171
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM836.20385_S78	UHM837.20386_S90	UHM838.20387_S7 UHM891.20386_S89
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM893.20595_S9	UHM894.20540_S14	UHM895.20536_S61 UHM896.20535_S60
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM898.20394_S91	UHM899.20588_S20	UHM900.20395_S8 UHM901.20394_S7
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0
##	b00466354053c9065c8aa3d6fbb33eaa	0	0	0
##	f872c4bf84bcf44434fa2023788f6517	0	0	0
##		UHM903.20587_S8	UHM904.20567_S53	UHM905.20598_S45 UHM906.20597_S44
##	020e00d90ba97c5898944ab6f7b1b7c9	0	0	0

```
## b00466354053c9065c8aa3d6fbb33eaa      0      0      0
## f872c4bf84bcf44434fa2023788f6517      0      0      0
##                                UHM908.20396_S20 UHM909.20557_S28 UHM910.20562_S88 UHM965.1
## 020e00d90ba97c5898944ab6f7b1b7c9      0      0      0
## b00466354053c9065c8aa3d6fbb33eaa      0      0      0
## f872c4bf84bcf44434fa2023788f6517      0      0      0
##                                UHM967.20744_S63 UHM968.20571_S6  UHM969.20745_S75 UHM971.2
## 020e00d90ba97c5898944ab6f7b1b7c9      0      0      0
## b00466354053c9065c8aa3d6fbb33eaa      0      0      0
## f872c4bf84bcf44434fa2023788f6517      0      0      0
##                                UHM974.20432_S72 UHM975.20747_S4  UHM977.20748_S16 UHM978.2
## 020e00d90ba97c5898944ab6f7b1b7c9      0      0      0
## b00466354053c9065c8aa3d6fbb33eaa      0      0      0
## f872c4bf84bcf44434fa2023788f6517      0      0      0
##                                UHM980.20731_S2  UHM981.20539_S2  UHM982.20740_S15 UHM983.20
## 020e00d90ba97c5898944ab6f7b1b7c9      0      0      0
## b00466354053c9065c8aa3d6fbb33eaa      0      0      0
## f872c4bf84bcf44434fa2023788f6517      0      0      0
##                                UHM985.20752_S64 UHM988.20753_S76 UHM989.20754_S88 UHM991.1
## 020e00d90ba97c5898944ab6f7b1b7c9      0      0      0
## b00466354053c9065c8aa3d6fbb33eaa      0      0      0
## f872c4bf84bcf44434fa2023788f6517      0      0      0
##                                UHM996.20610_S94 UHM997.20553_S75 UHM998.20618_S95 UHM999.1
## 020e00d90ba97c5898944ab6f7b1b7c9      0      0      0
## b00466354053c9065c8aa3d6fbb33eaa      0      0      0
## f872c4bf84bcf44434fa2023788f6517      0      0      0
## [ reached 'max' / getOption("max.print") -- omitted 3 rows ]
```

Summary Stat

```
#                                CALCULATE SPIKE PERCENTAGE & summary stat

# ** Calculate spike percentage & Generate summary statistics for absolute counts**

# Generate summary statistics for absolute counts
post_eval_summary <- calculate_summary_stats_table(absolute_counts)

# You may want to Back normal to check calculation accuracy
# the scaling factor was computed based on spiked species reads and fixed cell count.
# Multiplying the spiked species read count by this scaling factor restores the exact spiked c
# lets check it
# BackNormal <- calculate_spike_percentage(
#   physeq_absolute,
#   merged_spiked_species,
```

```
# passed_range = c(0.1, 20)
# )
```

Filter unsuccessful spiked samples

```
# Optional, or you may do it at the end of the process
# ** Time to filter out unsuccessful spiked samples**

library(phyloseq)
library(dplyr)
library(tibble)
library(microbiome)

filtered_sample_data <- microbiome::meta(physeq_absolute) %>%
  as.data.frame() %>%
  tibble::rownames_to_column(var = "Sample") %>%
  dplyr::mutate(Sample = as.character(Sample)) %>%
  dplyr::left_join(Perc, by = "Sample")

filtered_sample_data <- tibble::column_to_rownames(filtered_sample_data, "Sample")

filtered_sample_data <- sample_data(as.data.frame(filtered_sample_data))

# Assign back to phyloseq obj
sample_data(physeq_absolute) <- filtered_sample_data
```

spiked species retrieval is system-dependent

The goal is to identify the range where, for example, the evenness of your community remains independent of spiked species retrieval—meaning the p-value should not be significant, and the R^2 value should be low, indicating minimal influence. Hill number is interpretable as “effective diversity” (number of abundant species).

```
# The acceptable range of spiked species retrieval is system-dependent
# Spiked species become centroid of the community (Distance to Centroid)
# Spiked species become dominant and imbalance the community (Evenness)

# What range of spiked species retrieval is appropriate for your system?
# Calculate Pielou's Evenness using Shannon index and species richness (Observed)
# Hill number  $q = 1 = \exp(\text{Shannon index})$ , representing the effective number of equally abundant
# Unlike Pielou's evenness, this metric is not normalized by richness and it shows Effective n
```

```

library(phyloseq)
library(vegan)
library(dplyr)
library(microbiome)
library(DspikeIn)

# 1. Alpha Diversity: Pielou's Evenness and Hill Number (q = 1)

# Estimate richness and Shannon index
alphab <- estimate_richness(
  physeq_absolute,
  measures = c("Observed", "Shannon")
)

# Calculate Pielou's Evenness = H' / S
alphab$Pielou_evenness <- alphab$Shannon / alphab$Observed

# Extract OTU matrix
otu_mat <- otu_table(physeq_absolute)
if (taxa_are_rows(physeq_absolute)) {
  otu_mat <- t(otu_mat)
}
otu_mat <- as(otu_mat, "matrix")

# Calculate Hill number q = 1
alphab$Hill_q1 <- exp(vegan::diversity(otu_mat, index = "shannon"))

# Add sample ID
alphab$Sample <- rownames(alphab)

# 2. Merge Alpha Diversity with Metadata
# =====

metadata <- as.data.frame(microbiome::meta(physeq_absolute))
metadata$Sample <- rownames(metadata)

metadata <- left_join(
  metadata,
  alphab[, c("Sample", "Observed", "Shannon", "Pielou_evenness", "Hill_q1")],
  by = "Sample"
)
metadata <- column_to_rownames(metadata, var = "Sample")
sample_data(physeq_absolute) <- sample_data(metadata)

# Check presence of spike-in reads
if (!"Spiked_Reads" %in% colnames(metadata)) {

```

```

    stop("Column 'Spiked_Reads' not found in metadata.")
  }

# 3. Beta Diversity: Distance to Global Centroid (Full Bray-Curtis)
# =====

# Convert OTU table to relative abundances
otu_mat_rel <- vegan::decostand(otu_mat, method = "total")

# centroid profile
centroid_profile <- colMeans(otu_mat_rel)

# Compute Bray-Curtis distance to centroid for each sample
dist_to_centroid <- apply(otu_mat_rel, 1, function(x) {
  vegan::vegdist(rbind(x, centroid_profile), method = "bray")[1]
})

# Add distance to metadata
metadata$Dist_to_Centroid <- dist_to_centroid[rownames(metadata)]

# Update phyloseq object
sample_data(physeq_absolute) <- sample_data(metadata)

# 4. Regression Plots: Diversity vs. Spike-in Reads
# =====

# Pielou's Evenness
plot_object_pielou <- regression_plot(
  data = metadata,
  x_var = "Pielou_evenness",
  y_var = "Spiked_Reads",
  custom_range = c(0.1, 20, 30, 40, 50, 60, 100),
  plot_title = NULL
)

# Hill Number (q = 1)
plot_object_hill <- regression_plot(
  data = metadata,
  x_var = "Hill_q1",
  y_var = "Spiked_Reads",
  custom_range = c(0.1, 10, 20, 30, 100),
  plot_title = NULL
)

# Distance to Global Centroid

```

```

plot_object_centroid <- regression_plot(
  data = metadata,
  x_var = "Dist_to_Centroid",
  y_var = "Spiked_Reads",
  custom_range = c(0.1, 20, 30, 40, 50, 60, 100),
  plot_title = NULL
)

# Interpretation
# =====
# - Pielou's evenness is normalized by richness; useful for detecting imbalance.
# - Hill number q = 1 gives effective number of common species; sensitive to dominance.
# - Distance to centroid in full Bray-Curtis space shows deviation from the average community.

```

Calculate the percentage of spiked species retrieval

```

# * Calculate the percentage of spiked species retrieval per sample*

absolute_abundance_16S_OTU_perc <- phyloseq::subset_samples(physeq_absolute, sample.or.blank != " ")

# Adjust the threshold range as needed based on system specifications

result_perc <- calculate_spike_percentage(
  absolute_abundance_16S_OTU_perc,
  merged_spiked_species,
  passed_range = c(0.1, 20)
)

# BackNormal
conc <- conclusion(absolute_abundance_16S_OTU_perc,
  merged_spiked_species,
  max_passed_range = 20,
  output_path
)

conc$full_report

```

##	Sample	Total_Reads	Spiked_Reads	Percentage	Result
## 1	STP1719.20422_S47	2429	1847	76.03952244	failed
## 2	STP213.20423_S59	188314	1847	0.98080865	passed
## 3	STP268.20424_S71	757488	1847	0.24383225	passed
## 4	STP544.20419_S11	1913	1847	96.54992159	failed
## 5	STP570.20420_S23	5948	1847	31.05245461	failed

## 6	STP579.20421_S35	5452	1847	33.87747616	failed
## 7	STP614.20418_S94	5	0	0.00000000	failed
## 8	UHM1000.20604_S22	43347	924	2.13163541	passed
## 9	UHM1001.20609_S82	39309	924	2.35060673	passed
## 10	UHM1007.20622_S48	86418	924	1.06922169	passed
## 11	UHM1009.20614_S47	181742	924	0.50841303	passed
## 12	UHM1010.20621_S36	6123	924	15.09064184	passed
## 13	UHM1011.20606_S46	81017	924	1.14050138	passed
## 14	UHM1024.20620_S24	2690	924	34.34944238	failed
## 15	UHM1026.20607_S58	7494	924	12.32986389	passed
## 16	UHM1028.20613_S35	2620	924	35.26717557	failed
## 17	UHM1032.20605_S34	1410	924	65.53191489	failed
## 18	UHM1033.20619_S12	966	924	95.65217391	failed
## 19	UHM1034.20616_S71	782439	924	0.11809227	passed
## 20	UHM1035.20611_S11	8082	924	11.43281366	passed
## 21	UHM1036.20612_S23	8625	924	10.71304348	passed
## 22	UHM1052.20615_S59	98557	924	0.93752854	passed
## 23	UHM1060.20723_S1	2074	1847	89.05496625	failed
## 24	UHM1065.20724_S13	2384	1847	77.47483221	failed
## 25	UHM1068.20732_S14	19198	1847	9.62079383	passed
## 26	UHM1069.20742_S39	88462	1847	2.08790215	passed
## 27	UHM1070.20725_S25	11119	1847	16.61120604	passed
## 28	UHM1071.20733_S26	66892	1847	2.76116725	passed
## 29	UHM1072.20734_S38	4254	1847	43.41795957	failed
## 30	UHM1073.20735_S50	129333	1847	1.42809646	passed
## 31	UHM1075.20726_S37	12116	1847	15.24430505	passed
## 32	UHM1077.20736_S62	240090	1847	0.76929485	passed
## 33	UHM1078.20727_S49	48860	1847	3.78018829	passed
## 34	UHM1080.20737_S74	237852	1847	0.77653331	passed
## 35	UHM1081.20728_S61	2118	1847	87.20491029	failed
## 36	UHM1088.20738_S86	48261	1847	3.82710677	passed
## 37	UHM1090.20739_S3	4260	1847	43.35680751	failed
## 38	UHM1093.20729_S73	11145	1847	16.57245402	passed
## 39	UHM1095.20730_S85	3475	1847	53.15107914	failed
## 40	UHM1097.20623_S60	1645	924	56.17021277	failed
## 41	UHM1099.20608_S70	141219	924	0.65430289	passed
## 42	UHM1100.20788_S21	120156	1847	1.53716835	passed
## 43	UHM1102.20789_S33	41207	1847	4.48224816	passed
## 44	UHM1104.20790_S45	75900	1847	2.43346509	passed
## 45	UHM1105.20791_S57	29445	1847	6.27271184	passed
## 46	UHM1109.20531_S1	49710	1847	3.71555019	passed
## 47	UHM1110.20568_S65	257312	1847	0.71780562	passed
## 48	UHM1113.20792_S69	374668	1847	0.49296978	passed
## 49	UHM1114.20793_S81	25789	1847	7.16196828	passed
## 50	UHM1115.20794_S93	53637	1847	3.44351847	passed
## 51	UHM1117.20795_S10	120412	1847	1.53390028	passed
## 52	UHM1118.20796_S22	39826	1847	4.63767388	passed
## 53	UHM1120.20797_S34	6447	1847	28.64898402	failed

## 54	UHM1124.20798_S46	19988	1847	9.24054433	passed
## 55	UHM1126.20799_S58	56862	1847	3.24821498	passed
## 56	UHM1128.20800_S70	75987	1847	2.43067893	passed
## 57	UHM1140.20555_S4	144876	1847	1.27488335	passed
## 58	UHM1145.20801_S82	136223	1847	1.35586502	passed
## 59	UHM1163.20405_S33	66525	1847	2.77639985	passed
## 60	UHM1164.20402_S92	560873	1847	0.32930806	passed
## 61	UHM1169.20552_S63	2087	1847	88.50023958	failed
## 62	UHM1171.20579_S7	94275	1847	1.95916203	passed
## 63	UHM1176.20404_S21	153994	1847	1.19939738	passed
## 64	UHM1177.20546_S86	7001	1847	26.38194544	failed
## 65	UHM1182.20576_S66	19322	1847	9.55905186	passed
## 66	UHM1210.20802_S94	107631	1847	1.71604835	passed
## 67	UHM1212.20803_S11	35517	1847	5.20032660	passed
## 68	UHM1217.20804_S23	66837	1847	2.76343941	passed
## 69	UHM1218.20805_S35	42728	1847	4.32269238	passed
## 70	UHM1219.20806_S47	73751	1847	2.50437282	passed
## 71	UHM1220.20807_S59	85890	1847	2.15042496	passed
## 72	UHM1221.20808_S71	37595	1847	4.91288735	passed
## 73	UHM1222.20809_S83	5442	1847	33.93972804	failed
## 74	UHM1223.20810_S95	114277	1847	1.61624824	passed
## 75	UHM1225.20811_S12	48275	1847	3.82599689	passed
## 76	UHM1227.20812_S24	20964	1847	8.81034154	passed
## 77	UHM1228.20813_S36	147297	1847	1.25392914	passed
## 78	UHM1237.20814_S48	24999	1847	7.38829553	passed
## 79	UHM1240.20566_S41	35116	1847	5.25971067	passed
## 80	UHM1246.20815_S60	16128	1847	11.45213294	passed
## 81	UHM1247.20816_S72	26551	1847	6.95642349	passed
## 82	UHM1248.20575_S54	7646	1847	24.15642166	failed
## 83	UHM1256.20570_S89	35459	1847	5.20883274	passed
## 84	UHM1260.20596_S21	34301	1847	5.38468266	passed
## 85	UHM1270.20577_S78	12183	1847	15.16046951	passed
## 86	UHM1271.20397_S32	19173	1847	9.63333855	passed
## 87	UHM1272.20398_S44	10447	1847	17.67971667	passed
## 88	UHM1274.20554_S87	32434	1847	5.69464143	passed
## 89	UHM1275.20597_S33	15061	1847	12.26346192	passed
## 90	UHM1282.20599_S57	6536	1847	28.25887393	failed
## 91	UHM1287.20543_S50	10739	1847	17.19899432	passed
## 92	UHM1291.20416_S70	74217	1847	2.48864815	passed
## 93	UHM1296.20550_S39	207620	1847	0.88960601	passed
## 94	UHM1319.20561_S76	11679	1847	15.81471016	passed
## 95	UHM1324.20413_S34	45204	1847	4.08592160	passed
## 96	UHM1327.20545_S74	272806	1847	0.67703790	passed
## 97	UHM1328.20572_S18	9273	1847	19.91804163	passed
## 98	UHM1334.20417_S82	76551	1847	2.41277057	passed
## 99	UHM1338.20399_S56	26305	1847	7.02147881	passed
## 100	UHM1341.20602_S93	4830	1847	38.24016563	failed
## 101	UHM1356.20541_S26	21082	1847	8.76102837	passed

## 102	UHM1380.20580_S19	71993	1847	2.56552720	passed
## 103	UHM1383.20594_S92	28316	1847	6.52281396	passed
## 104	UHM1385.20563_S5	2166	1847	85.27239151	failed
## 105	UHM1399.20756_S17	11403	1847	16.19749189	passed
## 106	UHM1400.20757_S29	49300	1847	3.74645030	passed
## 107	UHM1401.20758_S41	4984	1847	37.05858748	failed
## 108	UHM1402.20759_S53	78898	1847	2.34099724	passed
## 109	UHM1403.20760_S65	48278	1847	3.82575914	passed
## 110	UHM1405.20761_S77	51126	1847	3.61264327	passed
## 111	UHM1406.20762_S89	90444	1847	2.04214763	passed
## 112	UHM1414.20763_S6	113476	1847	1.62765695	passed
## 113	UHM1419.20764_S18	22182	1847	8.32657109	passed
## 114	UHM1427.20389_S31	93753	1847	1.97007029	passed
## 115	UHM1428.20390_S43	4532	0	0.00000000	failed
## 116	UHM1429.20391_S55	245778	1847	0.75149118	passed
## 117	UHM1430.20392_S67	846266	1847	0.21825289	passed
## 118	UHM1432.20393_S79	415264	1847	0.44477730	passed
## 119	UHM1435.20388_S19	9292	0	0.00000000	failed
## 120	UHM162.20560_S64	37088	1847	4.98004745	passed
## 121	UHM198.20585_S79	5610	1847	32.92335116	failed
## 122	UHM20.3314_S52	1335639	1847	0.13828587	passed
## 123	UHM20.3315_S64	352109	1847	0.52455348	passed
## 124	UHM204.20409_S81	160159	1847	1.15322898	passed
## 125	UHM206.20410_S93	523	0	0.00000000	failed
## 126	UHM207.20593_S80	76828	1847	2.40407143	passed
## 127	UHM208.20411_S10	34089	1847	5.41817008	passed
## 128	UHM211.20406_S45	87029	1847	2.12228108	passed
## 129	UHM215.20408_S69	3947656	1847	0.04678726	failed
## 130	UHM216.20429_S36	207601	1847	0.88968743	passed
## 131	UHM219.20430_S48	1897	1847	97.36425936	failed
## 132	UHM236.20431_S60	199471	1847	0.92594914	passed
## 133	UHM238.20407_S57	64050	1847	2.88368462	passed
## 134	UHM245.20538_S85	554868	1847	0.33287196	passed
## 135	UHM252.20558_S40	14250	1847	12.96140351	passed
## 136	UHM267.20400_S68	183380	1847	1.00719817	passed
## 137	UHM274.20581_S31	13695	1847	13.48667397	passed
## 138	UHM276.20586_S91	21560	1847	8.56679035	passed
## 139	UHM280.20401_S80	35352	1847	5.22459833	passed
## 140	UHM286.20425_S83	130953	1847	1.41042970	passed
## 141	UHM289.20426_S95	6003	1847	30.76794936	failed
## 142	UHM294.20427_S12	17177	1847	10.75275077	passed
## 143	UHM298.20600_S69	101173	1847	1.82558588	passed
## 144	UHM325.20548_S15	24562	1847	7.51974595	passed
## 145	UHM337.20412_S22	32632	1847	5.66008826	passed
## 146	UHM354.20535_S49	58805	1847	3.14088938	passed
## 147	UHM356.20415_S58	43688	1847	4.22770555	passed
## 148	UHM369.20773_S31	79551	1847	2.32178100	passed
## 149	UHM370.20774_S43	88455	1847	2.08806738	passed

## 150	UHM372.20775_S55	21119	1847	8.74567925	passed
## 151	UHM373.20776_S67	113026	1847	1.63413728	passed
## 152	UHM374.20777_S79	96042	1847	1.92311697	passed
## 153	UHM375.20778_S91	19019	1847	9.71134129	passed
## 154	UHM377.20779_S8	29234	1847	6.31798591	passed
## 155	UHM38.3376_S36	29112	0	0.00000000	failed
## 156	UHM386.20781_S32	54216	1847	3.40674340	passed
## 157	UHM387.20782_S44	68442	1847	2.69863534	passed
## 158	UHM414.20583_S55	278181	1847	0.66395620	passed
## 159	UHM418.20765_S30	46656	1847	3.95876200	passed
## 160	UHM422.20766_S42	10409	1847	17.74425978	passed
## 161	UHM425.20767_S54	66208	1847	2.78969309	passed
## 162	UHM426.20534_S37	5428	1847	34.02726603	failed
## 163	UHM428.20544_S62	13527	1847	13.65417314	passed
## 164	UHM429.20559_S52	21213	1847	8.70692500	passed
## 165	UHM435.20547_S3	13365	1847	13.81967826	passed
## 166	UHM437.20768_S66	148167	1847	1.24656637	passed
## 167	UHM439.20564_S17	96401	1847	1.91595523	passed
## 168	UHM44.3526_S31	5511	1847	33.51478860	failed
## 169	UHM445.20569_S77	90006	1847	2.05208542	passed
## 170	UHM447.20783_S56	168350	1847	1.09711910	passed
## 171	UHM448.20769_S78	28120	1847	6.56827881	passed
## 172	UHM45.3539_S92	35221	0	0.00000000	failed
## 173	UHM454.20770_S90	43632	1847	4.23313165	passed
## 174	UHM455.20785_S80	15021	1847	12.29611877	passed
## 175	UHM458.20786_S92	102573	1847	1.80066879	passed
## 176	UHM459.20787_S9	106958	1847	1.72684605	passed
## 177	UHM461.20771_S7	77653	1847	2.37853013	passed
## 178	UHM467.20772_S19	195315	1847	0.94565190	passed
## 179	UHM470.20533_S25	9215	1847	20.04340749	failed
## 180	UHM476.20414_S46	20143	1847	9.16943851	passed
## 181	UHM478.20549_S27	27792	1847	6.64579735	passed
## 182	UHM479.20551_S51	2119	1847	87.16375649	failed
## 183	UHM481.20403_S9	15762	1847	11.71805608	passed
## 184	UHM482.20590_S44	2014	1847	91.70804369	failed
## 185	UHM483.20603_S10	90381	1847	2.04357110	passed
## 186	UHM519.20582_S43	220582	1847	0.83733034	passed
## 187	UHM520.20573_S30	68381	1847	2.70104269	passed
## 188	UHM746.21478_S117	927	924	99.67637540	failed
## 189	UHM747.21477_S106	924	924	100.00000000	failed
## 190	UHM748.21467_S170	924	924	100.00000000	failed
## 191	UHM748.21487_S129	928	924	99.56896552	failed
## 192	UHM749.21479_S128	925	924	99.89189189	failed
## 193	UHM759.21466_S159	924	924	100.00000000	failed
## 194	UHM759.21486_S118	938	924	98.50746269	failed
## 195	UHM775.21485_S107	923	923	100.00000000	failed
## 196	UHM776.21482_S161	923	923	100.00000000	failed
## 197	UHM777.21484_S183	925	924	99.89189189	failed

```
## 198 UHM779.21468_S181          928          924 99.56896552 failed
## 199 UHM779.21488_S140          924          924 100.00000000 failed
## 200 UHM782.21480_S139          924          924 100.00000000 failed
## [ reached 'max' / getOption("max.print") -- omitted 60 rows ]
```

```
conc$summary_stats
```

Table 1: Summary Statistics of Spiked S

mean_total_reads_spiked	sd_total_reads_spiked	median_total_reads_spiked	mean_percentag
113,281.1	306,326.4	29,339.5	20.21071

```
# you may keep only passed data
# Filter to get only the samples that passed
passed_samples <- result_perc$Sample[result_perc$Result == "passed"]

# Subset the original phyloseq object to keep only the samples that passed
passed_physeq <- phyloseq::prune_samples(passed_samples, absolute_abundance_16S_OTU_perc)
```

Abundance-based Core microbiome

```
physeq_absolute <- absolute$obj_adj
pps_Abs <- DspikeIn::get_long_format_data(physeq_absolute)

# calculation for relative abundance needs sum of total reads
# total_reads <- sum(pps_Abs$Abundance)

# Generate an alluvial plot

alluvial_plot_abs <- alluvial_plot(
  data = pps_Abs,
  axes = c("Host.genus", "Ecoregion.III", "Diet", "Animal.ecomode"),
  abundance_threshold = 10000,
  fill_variable = "Class",
  silent = TRUE,
  abundance_type = "absolute",
  top_taxa = 15,
  text_size = 4,
  legend_ncol = 1,
  custom_colors = DspikeIn::color_palette$light_MG # Use the color palette from DspikeIn
)
```

Data transform & Normalization

you may select to transform your data before moving forward with Differential Abundance

```
# you may need to normalize/transform your data to reduce biases

ps <- physeq_16SOTU

# TC Normalization
result_TC <- normalization_set(ps, method = "TC", groups = "Host.species")
normalized_ps_TC <- result_TC$dat.normed
scaling_factors_TC <- result_TC$scaling.factor

# UQ Normalization
data("physeq_16SOTU", package = "DspikeIn")
ps <- physeq_16SOTU
result_UQ <- normalization_set(ps, method = "UQ", groups = "Host.species")
normalized_ps_UQ <- result_UQ$dat.normed
scaling_factors_UQ <- result_UQ$scaling.factor

# Median Normalization
data("physeq_16SOTU", package = "DspikeIn")
ps <- physeq_16SOTU
result_med <- normalization_set(ps, method = "med", groups = "Host.species")
normalized_ps_med <- result_med$dat.normed
scaling_factors_med <- result_med$scaling.factor

# DESeq Normalization
data("physeq_16SOTU", package = "DspikeIn")
ps <- physeq_16SOTU
ps_n <- remove_zero_negative_count_samples(ps)
result_DESeq <- normalization_set(ps_n, method = "DESeq", groups = "Animal.type")
normalized_ps_DESeq <- result_DESeq$dat.normed
scaling_factors_DESeq <- result_DESeq$scaling.factor

# Poisson Normalization
data("physeq_16SOTU", package = "DspikeIn")
ps <- physeq_16SOTU
result_Poisson <- normalization_set(ps, method = "Poisson", groups = "Host.genus")
normalized_ps_Poisson <- result_Poisson$dat.normed
scaling_factors_Poisson <- result_Poisson$scaling.factor

# Quantile Normalization
data("physeq_16SOTU", package = "DspikeIn")
ps <- physeq_16SOTU
result_QN <- normalization_set(ps, method = "QN")
normalized_ps_QN <- result_QN$dat.normed
```

```

scaling_factors_QN <- result_QN$scaling.factor

# TMM Normalization
data("physeq_16SOTU", package = "DspikeIn")
ps <- physeq_16SOTU
result_TMM <- normalization_set(ps, method = "TMM", groups = "Animal.type")
normalized_ps_TMM <- result_TMM$dat.normed
scaling_factors_TMM <- result_TMM$scaling.factor

# CLR Normalization
data("physeq_16SOTU", package = "DspikeIn")
ps <- physeq_16SOTU
result_clr <- normalization_set(ps, method = "clr")
normalized_ps_clr <- result_clr$dat.normed
scaling_factors_clr <- result_clr$scaling.factor

# Rarefying
data("physeq_16SOTU", package = "DspikeIn")
ps <- physeq_16SOTU
result_rar <- normalization_set(ps, method = "rar")
normalized_ps_rar <- result_rar$dat.normed
scaling_factors_rar <- result_rar$scaling.factor

# CSS Normalization
data("physeq_16SOTU", package = "DspikeIn")
ps <- physeq_16SOTU
result_css <- normalization_set(ps, method = "css")
normalized_ps_css <- result_css$dat.normed
scaling_factors_css <- result_css$scaling.factor

# TSS Normalization
data("physeq_16SOTU", package = "DspikeIn")
ps <- physeq_16SOTU
result_tss <- normalization_set(ps, method = "tss")
normalized_ps_tss <- result_tss$dat.normed
scaling_factors_tss <- result_tss$scaling.factor

# RLE Normalization
data("physeq_16SOTU", package = "DspikeIn")
ps <- physeq_16SOTU
result_rle <- normalization_set(ps, method = "rle")
normalized_ps_rle <- result_rle$dat.normed
scaling_factors_rle <- result_rle$scaling.factor

```

Ridge plot

```

rf_physeq <- RandomForest_selected(
  physeq_16SOTU,
  response_var = "Host.genus",
  na_vars = c("Habitat", "Ecoregion.III", "Host.genus", "Diet")
)

ridge_physeq <- ridge_plot_it(rf_physeq, taxrank = "Family", top_n = 10) + scale_fill_manual(v
# ridge_physeq

result_css <- normalization_set(rf_physeq, method = "css")
normalized_ps_css <- result_css$dat.normed

ridge_physeq <- ridge_plot_it(normalized_ps_css, taxrank = "Family", top_n = 10) + scale_fill_r
# ridge_physeq

```

Further analysis

remove the spike-in sp before further analysis

```

absolute <- phyloseq::subset_taxa(physeq_absolute, Genus != "Tetragenococcus")
absolute <- subset_taxa(absolute, Family != "Chloroplast" & Order != "Chloroplast")
Caudate_abs <- phyloseq::subset_samples(absolute, Clade.Order == "Caudate")
Three_Genara_abs <- phyloseq::subset_samples(Caudate_abs, Host.genus %in% c("Desmognathus", "P
Three_Genara_abs_BlueRidge <- phyloseq::subset_samples(Three_Genara_abs, Ecoregion.III == "Blue
Desmog_Blue_Ins_16_abs <- phyloseq::subset_samples(Three_Genara_abs_BlueRidge, Host.genus == "I

results_DESeq2 <- perform_and_visualize_DA(
  obj = Desmog_Blue_Ins_16_abs,
  method = "DESeq2",
  group_var = "Host.taxon",
  contrast = c("Desmognathus monticola", "Desmognathus imitator"),
  output_csv_path = "DA_DESeq2.csv",
  target_glom = "Genus",
  significance_level = 0.05
)

head(results_DESeq2$results)

```

##	baseMean	logFC	lfcSE	stat	pvalue	padj	FDR	Significance
## 1	10.000000	9.105617e-08	0.2413445	3.772871e-07	0.9999997	1	1	Not Significant Desmog
## 2	2.000000	1.334927e-07	0.5326085	2.506394e-07	0.9999998	1	1	Not Significant Desmog
## 3	1.357143	-1.055569e-06	0.7488460	-1.409594e-06	0.9999989	1	1	Not Significant Desmog
## 4	2.000000	1.334927e-07	0.5326085	2.506394e-07	0.9999998	1	1	Not Significant Desmog

```
## 5 12.000000 8.255739e-08 0.2212147 3.732003e-07 0.9999997 1 1 Not Significant Desmog
## 6 13.809524 -3.680398e-01 0.2446159 -1.504562e+00 0.1324366 1 1 Not Significant Desmog
##
## OTU Kingdom Phylum Class
## 1 b00466354053c9065c8aa3d6fbb33eaa Bacteria Armatimonadota uncultured uncl
## 2 f872c4bf84bcf44434fa2023788f6517 Bacteria Proteobacteria Gammaproteobacteria Chrom
## 3 df13f71584d4a579c81d909eaba11a74 Bacteria Firmicutes Syntrophomonadia Syntrophomon
## 4 ed285eb1aac505a1f062b482300b69f7 Bacteria Firmicutes Symbiobacteriia Symbiobacte
## 5 63f5509575600a9e7afb6847d6296976 Bacteria Gemmatimonadota Gemmatimonadetes Gemmatimon
## 6 fea92298310d6159915036da73e7a88a Bacteria Gemmatimonadota Gemmatimonadetes Gemmatimon
##
## Genus Species
## 1 uncultured <NA>
## 2 Thiophaeococcus <NA>
## 3 Syntrophomonas <NA>
## 4 uncultured <NA>
## 5 uncultured <NA>
## 6 Gemmatimonas <NA>
```

```
results_DESeq2$obj_significant
```

```
## phyloseq-class experiment-level object
## otu_table() OTU Table: [ 27 taxa and 42 samples ]
## sample_data() Sample Data: [ 42 samples by 34 sample variables ]
## tax_table() Taxonomy Table: [ 27 taxa by 7 taxonomic ranks ]
## phy_tree() Phylogenetic Tree: [ 27 tips and 26 internal nodes ]
## refseq() DNASTringSet: [ 27 reference sequences ]
```

```
# results_DESeq2$plot
# results_DESeq2$bar_plot
```

```
# Relative abundance
data("physeq_16SOTU", package = "DspikeIn")
physeq_16SOTU <- tidy_phyloseq_tse(physeq_16SOTU)

relative <- phyloseq::subset_taxa(physeq_16SOTU, Genus != "Tetragenococcus")
Caudate_rel <- phyloseq::subset_samples(relative, Clade.Order == "Caudate")
Three_Genara_rel <- phyloseq::subset_samples(Caudate_rel, Host.genus %in% c("Desmognathus", "P
Three_Genara_rel_BlueRidge <- phyloseq::subset_samples(Three_Genara_rel, Ecoregion.III == "Blue
Desmog_Blue_Ins_16_rel <- phyloseq::subset_samples(Three_Genara_rel_BlueRidge, Host.genus == "I

results_DESeq2_rel <- perform_and_visualize_DA(
  obj = Desmog_Blue_Ins_16_rel,
  method = "DESeq2",
  group_var = "Host.taxon",
  contrast = c("Desmognathus monticola", "Desmognathus imitator"),
  output_csv_path = "DA_DESeq2.csv",
  target_glom = "Genus",
```

```

    significance_level = 0.05
  )

# head(results_DESeq2_rel$results) # sig taxa
# results_DESeq2_rel$plot
# results_DESeq2_rel$bar_plot
# results_DESeq2_rel$obj_significant

```

Turnover (Presence/absence analysis)

taxonomic detection consistency between RA and AA OTU tables Presence/absence analysis to detect concordance between AA and RA profiles

```

# -----
# 1. Extract OTU tables
# -----
otu_rel <- otu_table(Desmog_Blue_Ins_16_rel)
otu_abs <- otu_table(Desmog_Blue_Ins_16_abs)

if (taxa_are_rows(Desmog_Blue_Ins_16_rel)) {
  otu_rel <- t(otu_rel)
  otu_abs <- t(otu_abs)
}

otu_rel <- as.matrix(otu_rel)
otu_abs <- as.matrix(otu_abs)

# -----
# 2. Convert to Presence/Absence
# -----
otu_rel_pa <- (otu_rel > 0) * 1
otu_abs_pa <- (otu_abs > 0) * 1

# -----
# 3. Identify common samples & taxa
# -----
shared_samples <- intersect(rownames(otu_rel_pa), rownames(otu_abs_pa))
shared_taxa <- intersect(colnames(otu_rel_pa), colnames(otu_abs_pa))

# Subset to common set
otu_rel_pa <- otu_rel_pa[shared_samples, shared_taxa]
otu_abs_pa <- otu_abs_pa[shared_samples, shared_taxa]

# -----
# 4. Compare presence/absence profiles

```

```
# -----
# Shared presence across both AA and RA
shared_pa <- (otu_rel_pa + otu_abs_pa) == 2
total_present <- (otu_rel_pa + otu_abs_pa) >= 1

# Calculate percent agreement (global)
percent_shared <- sum(shared_pa) / sum(total_present)

cat("percent of shared taxa detections (AA vs RA):",
    round(100 * percent_shared, 1), "%\n")
```

```
## percent of shared taxa detections (AA vs RA): 99.6 %
```

Differential abundance (Single and Multilayer Pairwise)

```
# DspikeIn: Differential Abundance Examples
# Using perform_and_visualize_DA() with multiple contrast scenarios
```

```
# Load example dataset from the package
data("physeq_16SOTU", package = "DspikeIn")
```

```
# 1. Single Contrast
```

```
res_single <- perform_and_visualize_DA(
  obj = physeq_16SOTU,
  method = "DESeq2",
  group_var = "Diet",
  contrast = c("Insectivore", "Carnivore"),
  target_glom = "Genus")
```

```
# 2. Single Factor - All Pairwise Contrasts
```

```
# level names for DESeq2 compatibility
```

```
sample_data(physeq_16SOTU)$Host.taxon <- factor(make.names(sample_data(physeq_16SOTU)$Host.taxon))
```

```
# Get unique levels
```

```
host_levels <- levels(sample_data(physeq_16SOTU)$Host.taxon)
```

```
# contrast list
```

```

contrast_named <- list(
  Host.taxon = combn(host_levels, 2, simplify = FALSE))

# multiple pairwise contrasts
res_multi <- perform_and_visualize_DA(
  obj = physeq_16SOTU,
  method = "DESeq2",
  group_var = "Host.taxon",
  contrast = contrast_named,
  target_glom = "Genus")

# 3. Single Factor - Selected Contrasts

contrast_list <- list(
  c("Insectivore", "Carnivore"),
  c("Omnivore", "Herbivore"))

res_selected <- perform_and_visualize_DA(
  obj = physeq_16SOTU,
  method = "DESeq2",
  group_var = "Diet",
  contrast = contrast_list,
  global_fdr = TRUE)

# 4. Multiple Factors - Selected Contrasts

contrast_named <- list(
  Diet = list(
    c("Insectivore", "Carnivore"),
    c("Omnivore", "Carnivore") ),
  Animal.type = list(
    c("Frog", "Salamander") ))

res_multi_factor <- perform_and_visualize_DA(
  obj = physeq_16SOTU,
  method = "DESeq2",
  contrast = contrast_named,
  target_glom = "Genus",
  significance_level = 0.01,
  global_fdr = TRUE)

```

```

# 5. Multiple Factors - all pairwise contrasts

# Ensure clean factor levels
sample_data(physeq_16SOTU)$Host.taxon <- droplevels(factor(sample_data(physeq_16SOTU)$Host.taxon))
sample_data(physeq_16SOTU)$Habitat <- droplevels(factor(sample_data(physeq_16SOTU)$Habitat))

# pairwise contrasts
host_levels <- levels(sample_data(physeq_16SOTU)$Host.taxon)
habitat_levels <- levels(sample_data(physeq_16SOTU)$Habitat)

contrast_named <- list(
  Host.taxon = combn(host_levels, 2, simplify = FALSE),
  Habitat = combn(habitat_levels, 2, simplify = FALSE))

results_multi_factor <- perform_and_visualize_DA(
  obj = physeq_16SOTU,
  method = "DESeq2",
  contrast = contrast_named,
  target_glom = "Genus",
  significance_level = 0.01)

# 6. Multiple Factors - combined group contrasts (interactions)

# Create a combined grouping variable
sample_data(physeq_16SOTU)$ComboGroup <- factor(interaction(
  sample_data(physeq_16SOTU)$Animal.type,
  sample_data(physeq_16SOTU)$Diet,
  drop = TRUE))

# selected contrasts
contrast_list <- list(
  c("Salamander.Insectivore", "Lizard.Insectivore"),
  c("Salamander.Carnivore", "Snake.Carnivore"),
  c("Salamander.Carnivore", "Frog.Carnivore"))

# multi-contrast analysis
res_combo <- perform_and_visualize_DA(
  obj = physeq_16SOTU,
  method = "DESeq2",
  group_var = "ComboGroup",
  contrast = contrast_list,
  target_glom = "Genus",
  global_fdr = TRUE)

```

Visualization

```
# Visualization of community composition

Rel <- phyloseq::subset_taxa(physeq_16SOTU, Genus != "Tetragenococcus")
Prok_OTU_spiked <- phyloseq::subset_samples(Rel, spiked.volume %in% c("2", "1"))
Prok_OTU_spiked <- phyloseq::subset_samples(Prok_OTU_spiked, sample.or.blank != "blank")
Prok_OTU_sal <- phyloseq::subset_samples(Prok_OTU_spiked, Animal.type == "Salamander")

Prok_OTU_sal <- tidy_phyloseq_tse(Prok_OTU_sal)

TB<-taxa_barplot(
  Prok_OTU_sal,
  target_glom = "Genus",
  custom_tax_names = NULL,
  normalize = TRUE,
  treatment_variable = "Habitat",
  abundance_type = "relative",
  x_angle = 25,
  fill_variable = "Family",
  facet_variable = "Diet",
  top_n_taxa = 20,
  palette = DspikeIn::color_palette$mix_MG,
  legend_size = 11,
  legend_columns = 1,
  x_scale = "free",
  xlab = NULL)
```

Microbial dynamics & NetWork comparision

```
# 1. Initialization and loading NetWorks for Comparision

# library(SpiecEasi)
# library(ggnet)
# library(igraph)
library(DspikeIn)
library(tidyr)
library(dplyr)
library(ggpubr)
library(igraph)
```

```

# To create a microbial co-occurrence network, you can refer to the SpiecEasi package available
# SpiecEasi GitHub Repository https://github.com/zdk123/SpiecEasi

# herp.Bas.rel.f is a merged phyloseq object for both bacterial and fungal domains
# spiec.easi(herp.Bas.rel.f, method='mb', lambda.min.ratio=1e-3, nlambda=250, pulsar.select=TRUE)

Complete <- load_graphml("Complete.graphml")
NoBasid <- load_graphml("NoBasid.graphml")
NoHubs <- load_graphml("NoHubs.graphml")

# result <- weight_Network(graph_path = "Complete.graphml")
# result

result_kk <- degree_network(
  graph_path = load_graphml("Complete.graphml"),
  save_metrics = TRUE,
  layout_type = "stress"
)
# print(result_kk$plot)

```

Network Topological Metrics

```

# 2. Metrics Calculation

result_Complete <- node_level_metrics(Complete)
result_NoHubs <- node_level_metrics(NoHubs)
result_NoBasid <- node_level_metrics(NoBasid)

Complete_metrics <- result_Complete$metrics
Nohub_metrics <- result_NoHubs$metrics
Nobasid_metrics <- result_NoBasid$metrics

Complete_metrics <- data.frame(lapply(Complete_metrics, as.character), stringsAsFactors = FALSE)
Nohub_metrics <- data.frame(lapply(Nohub_metrics, as.character), stringsAsFactors = FALSE)
Nobasid_metrics <- data.frame(lapply(Nobasid_metrics, as.character), stringsAsFactors = FALSE)

print(igraph::vcount(Complete)) # Number of nodes

```

```
## [1] 308
```

```
print(igraph::ecount(Complete)) # Number of edges
```

```
## [1] 1144
```

```
print(igraph::vcount(NoBasid))
```

```
## [1] 307
```

```
print(igraph::ecount(NoBasid))
```

```
## [1] 1187
```

```
print(igraph::vcount(NoHubs))
```

```
## [1] 286
```

```
print(igraph::ecount(NoHubs))
```

```
## [1] 916
```

```
metrics_scaled <- bind_rows(  
  Complete_metrics %>% mutate(Network = "Complete"),  
  Nohub_metrics %>% mutate(Network = "NoHubs"),  
  Nobasid_metrics %>% mutate(Network = "NoBasid")  
) %>%  
  dplyr::mutate(dplyr::across(where(is.numeric), scale))  
  
metrics_long_scaled <- metrics_scaled %>%  
  tidyr::pivot_longer(cols = -c(Node, Network), names_to = "Metric", values_to = "Value")
```

bind the metrics to plot them

```
# 3. Visualization
```

```
# Remove missing values
```

```
metrics_long_scaled <- na.omit(metrics_long_scaled)
```

```
# We visualize only six metrics
```

```
selected_metrics <- c(  
  "Degree", "Closeness", "Betweenness",  
  "EigenvectorCentrality", "PageRank", "Transitivity"  
)
```

```

metrics_long_filtered <- metrics_long_scaled %>%
  filter(Metric %in% selected_metrics) %>%
  mutate(
    Value = as.numeric(as.character(Value)),
    Network = recode(Network,
      "Complete" = "Complete Network",
      "NoHubs" = "Network & Module Hubs Removed",
      "NoBasid" = "Basidiobolus Subnetwork Removed" ) ) %>%
  na.omit() # Remove any NA if any

metrics_long_filtered$Network <- factor(metrics_long_filtered$Network,
  levels = c(
    "Complete Network",
    "Network & Module Hubs Removed",
    "Basidiobolus Subnetwork Removed" ))

# DspikeIn::color_palette$light_MG
network_colors <- c(
  "Complete Network" = "#F1E0C5",
  "Network & Module Hubs Removed" = "#D2A5A1",
  "Basidiobolus Subnetwork Removed" = "#B2C3A8")

# statistical comparisons a vs b
comparisons <- list(
  c("Complete Network", "Network & Module Hubs Removed"),
  c("Complete Network", "Basidiobolus Subnetwork Removed"),
  c("Network & Module Hubs Removed", "Basidiobolus Subnetwork Removed"))

networks_in_data <- unique(metrics_long_filtered$Network)
comparisons <- comparisons[sapply(comparisons, function(pair) all(pair %in% networks_in_data))]

met <- ggplot(metrics_long_filtered, aes(x = Network, y = Value, fill = Network)) +
  geom_boxplot(outlier.shape = NA) +
  geom_jitter(aes(color = Network),
    position = position_jitter(0.2), alpha = 0.2, size = 1.5 ) +
  scale_fill_manual(values = network_colors) +
  scale_color_manual(values = network_colors) +
  facet_wrap(~Metric, scales = "free_y", labeller = label_wrap_gen(width = 20)) +
  ggpubr::stat_compare_means(method = "wilcox.test", label = "p.signif", comparisons = comparisons) +
  theme_minimal() +
  theme(
    axis.title.x = element_blank(),
    axis.title.y = element_blank(),
    axis.text.x = element_text(size = 10, angle = 10, hjust = 0.8),
    strip.text = element_text(size = 12, margin = margin(t = 15, b = 5)),
    legend.position = "top",
    legend.text = element_text(size = 13),
  )

```

```

legend.title = element_text(size = 13, face = "bold"),
plot.title = element_text(size = 13, face = "bold")
) + labs(title = "Selected Node Metrics Across Networks", fill = "Network Type", color = "Ne

```

To find first and second neighbors your target node

```

Complete <- load_graphml("Complete.graphml")
result2 <- extract_neighbors(
  graph = Complete,
  target_node = "OTU69:Basidiobolus_sp", mode = "all")
head(result2$summary)

```

```

##           Type           Node
## 1 First Neighbor OTU8:Mortierella_sp
## 2 First Neighbor OTU13:Mortierella_sp
## 3 First Neighbor OTU15:Mortierella_sp
## 4 First Neighbor OTU16:Ascomycota_sp
## 5 First Neighbor OTU18:Helotiales_sp
## 6 First Neighbor OTU19:Margaritispora_monticola

```

Compute Node-Level Metrics

Metric	Description
'Node'	Node name (character format)
'Degree'	Number of edges connected to the node
'Strength'	Sum of edge weights connected to the node
'Closeness'	Closeness centrality (normalized, based on shortest paths)
'Betweenness'	Betweenness centrality (normalized, measures control over network flow)
'EigenvectorCentrality'	Eigenvector centrality (importance based on connections to influential nodes)
'PageRank'	PageRank score (importance based on incoming links)
'Transitivity'	Local clustering coefficient (tendency of a node to form triangles)
'Coreness'	Node's coreness (from k-core decomposition)
'Constraint'	Burt's constraint (measures structural holes in a node's ego network)
'EffectiveSize'	Inverse of constraint (larger values = more non-redundant connections)
'Redundancy'	Sum of constraint values of a node's alters
'Community'	Community assignment from Louvain clustering

Metric	Description
'Efficiency'	Global efficiency (average inverse shortest path length)
'Local_Efficiency'	Local efficiency (subgraph efficiency for a node's neighbors)
'Within_Module_Connectivity'	Proportion of neighbors in the same community
'Among_Module_Connectivity'	Proportion of neighbors in different communities

```

# Load required libraries
library(igraph)
library(dplyr)
library(tidyr)
library(ggplot2)
library(ggrepel)

# Compute Node-Level Metrics
completeMetrics <- node_level_metrics(Complete)
NoHubsMetrics <- node_level_metrics(NoHubs)
NoBasidMetrics <- node_level_metrics(NoBasid)

# completeMetrics$facet_plot

# Ensure each dataset has a "Network" column before combining
completeMetrics$metrics <- completeMetrics$metrics %>% mutate(Network = "Complete Network")
NoHubsMetrics$metrics <- NoHubsMetrics$metrics %>% mutate(Network = "Network & Module Hubs Rem
NoBasidMetrics$metrics <- NoBasidMetrics$metrics %>% mutate(Network = "Basidiobolus Subnetwork

# Combine All Data
combined_data <- bind_rows(
  completeMetrics$metrics,
  NoHubsMetrics$metrics,
  NoBasidMetrics$metrics
)

# Add Node Identifier if missing
if (!"Node" %in% colnames(combined_data)) {
  combined_data <- combined_data %>% mutate(Node = rownames(.))
}

# Convert `Network` into Factor
combined_data$Network <- factor(combined_data$Network, levels = c(
  "Complete Network",
  "Network & Module Hubs Removed",
  "Basidiobolus Subnetwork Removed"))

# Convert Data to Long Format
metrics_long <- combined_data %>%

```

```

pivot_longer(
  cols = c("Redundancy", "Efficiency", "Betweenness"),
  names_to = "Metric", values_to = "Value")

# Define Custom Colors and Shapes
network_colors <- c(
  "Complete Network" = "#F1E0C5",
  "Network & Module Hubs Removed" = "#D2A5A1",
  "Basidiobolus Subnetwork Removed" = "#B2C3A8")

network_shapes <- c(
  "Complete Network" = 21,
  "Network & Module Hubs Removed" = 22,
  "Basidiobolus Subnetwork Removed" = 23)

# Determine Top 30% of Nodes to Label/Optional
metrics_long <- metrics_long %>%
  group_by(Network, Metric) %>%
  mutate(Label = ifelse(rank(-Value, ties.method = "random") / n() <= 0.3, Node, NA))

# ?quadrant_plot() can creat plot for indivisual network
# plot <- quadrant_plot(metrics, x_metric = "Degree", y_metric = "Efficiency")

# Create comparision Plots
create_metric_plot <- function(metric_name, data, title) {
  data_filtered <- data %>% filter(Metric == metric_name)
  median_degree <- median(data_filtered$Degree, na.rm = TRUE)
  median_value <- median(data_filtered$Value, na.rm = TRUE)

  ggplot(data_filtered, aes(x = Degree, y = Value, fill = Network)) +
    geom_point(aes(shape = Network), size = 3, stroke = 1, color = "black") +
    geom_text_repel(aes(label = Label), size = 3, max.overlaps = 50) +
    scale_fill_manual(values = network_colors) +
    scale_shape_manual(values = network_shapes) +
    geom_vline(xintercept = median_degree, linetype = "dashed", color = "black", size = 1) +
    geom_hline(yintercept = median_value, linetype = "dashed", color = "black", size = 1) +
    labs(
      title = title,
      x = "Degree",
      y = metric_name,
      fill = "Network",
      shape = "Network" ) +
    theme_minimal() +
    theme(
      plot.title = element_text(
        hjust = 0.5, size = 16, face = "bold",

```

```

    margin = margin(t = 10, b = 20) # Moves the title downward
  ),
  axis.title = element_text(size = 14, face = "bold"),
  legend.position = "top",
  legend.title = element_text(size = 14, face = "bold"),
  legend.text = element_text(size = 12) )
}

# Generate Plots
plot_redundancy <- create_metric_plot("Redundancy", metrics_long, "Redundancy vs. Degree Across")
plot_efficiency <- create_metric_plot("Efficiency", metrics_long, "Efficiency vs. Degree Across")
plot_betweenness <- create_metric_plot("Betweenness", metrics_long, "Betweenness vs. Degree Across")

# Save Plots
# ggsave("plot_redundancy_20percent.png", plot_redundancy, width = 8, height = 6)
# ggsave("plot_efficiency_20percent.png", plot_efficiency, width = 8, height = 6)
# ggsave("plot_betweenness_20percent.png", plot_betweenness, width = 8, height = 6)

# Print Plots
# print(plot_redundancy)
# print(plot_efficiency)
# print(plot_betweenness)

```

Compute degree metrics and visualize the network

```

# Compute degree metrics and visualize the network
# Options: `"stress"` (default), `"graphopt"`, `"fr"`

result <- degree_network(graph_path = Complete, save_metrics = TRUE)
# print(result$metrics)
# print(result$plot)

# Compute network weights for different graph structures
NH <- weight_Network(graph_path = "NoHubs.graphml")
NB <- weight_Network(graph_path = "NoBasid.graphml")
C <- weight_Network(graph_path = "Complete.graphml")

# Extract metrics from the computed network weights
CompleteM <- C$metrics
NoHubsM <- NH$metrics
NoBasidM <- NB$metrics

```

```

# Combine metrics into a single dataframe for comparison
df <- bind_rows(
  CompleteM %>% mutate(Group = "CompleteM"),
  NoHubsM %>% mutate(Group = "NoHubsM"),
  NoBasidM %>% mutate(Group = "NoBasidM")) %>%
  pivot_longer(cols = -Group, names_to = "Metric", values_to = "Value")

# Aggregate the total values by metric and group
df_bar <- df %>%
  group_by(Metric, Group) %>%
  summarise(Total_Value = sum(Value), .groups = "drop")

# Plot the metrics comparison
pg<-ggplot(df_bar, aes(x = Metric, y = log1p(Total_Value), fill = Group)) +
  geom_bar(stat = "identity", position = "dodge", alpha = 0.8) +
  theme_minimal(base_size = 14) +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_fill_manual(values = c("#F1E0C5", "#D2A5A1", "#B2C3A8")) +
  labs(
    title = "Total Network Metrics Comparison",
    x = "Metric",
    y = "Total Value (log-scaled)",
    fill = "Group" )

```

Small-World Index Analysis

To determine whether the complete network exhibited small-world topology, we computed the Small-World Index (SWI; σ) following the quantitative framework established by Humphries M, Gurney K, 2008. PLoS ONE 4 (Eq.1) (SWI; σ) = (Global clustering coefficient real/Global clustering coefficient random)/(Avg Path real/Avg Path random))

```

library(igraph)
library(tidygraph)
library(ggraph)
library(DspikeIn)

# AA abundance
Complete<-load_graphml("Complete.graphml")
# NoHubs<-load_graphml("NoHubs.graphml")
# NoBasid<-load_graphml("NoBasid.graphml")

# RA abundance
# Complete_Rel<-load_graphml("~/Downloads/herp.spiecsym.Rel.graphml")

```

```

# Degree distribution
# deg <- degree(Complete_Rel)
deg <- degree(Complete)

hist(deg, breaks = 30, main = "Degree Distribution", xlab = "Degree")
fit <- fit_power_law(deg + 1) # Avoid zero degrees
print(fit)

# ---- empirical network ----
g_empirical = Complete
g_empirical = Complete_Rel

# ---- Calculate real network metrics ----
creal <- transitivity(g_empirical, type = "global")
E(g_empirical)$weight <- abs(E(g_empirical)$weight)
lreal <- mean_distance(g_empirical, directed = FALSE, unconnected = TRUE, weights = E(g_empirical)$weight)

# ---- Generate 1000 Erdős-Rényi random graphs with same size ----
set.seed(42) # for reproducibility
n_nodes <- vcount(g_empirical)
n_edges <- ecount(g_empirical)

crand_vals <- numeric(1000)
lrand_vals <- numeric(1000)

for (i in 1:1000) {
  g_rand <- sample_gnm(n = n_nodes, m = n_edges, directed = FALSE)
  if (!is_connected(g_rand)) next

  crand_vals[i] <- transitivity(g_rand, type = "global")
  lrand_vals[i] <- mean_distance(g_rand, directed = FALSE, unconnected = TRUE)
}

# ---- Calculate mean values across random graphs ----
crand <- mean(crand_vals, na.rm = TRUE)
lrand <- mean(lrand_vals, na.rm = TRUE)

# ---- Compute Small-World Index () ----
sigma <- (creal / crand) / (lreal / lrand)

cat("Global clustering coefficient (real):", creal, "\n")
cat("Average path length (real):", lreal, "\n")
cat("Mean clustering coefficient (random):", crand, "\n")

```

```
cat("Mean path length (random):", lrand, "\n")
cat("Small-World Index ():", round(sigma, 2), "\n")
```

```
sessionInfo()
```

```
## R version 4.5.0 (2025-04-11)
## Platform: aarch64-apple-darwin20
## Running under: macOS Sequoia 15.5
##
## Matrix products: default
## BLAS: /System/Library/Frameworks/Accelerate.framework/Versions/A/Frameworks/vecLib.framework
## LAPACK: /Library/Frameworks/R.framework/Versions/4.5-arm64/Resources/lib/libRlapack.dylib;
##
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
##
## time zone: Europe/Berlin
## tzcode source: internal
##
## attached base packages:
## [1] stats4 stats graphics grDevices utils datasets methods base
##
## other attached packages:
## [1] ggrepel_0.9.6 igraph_2.1.4 ggpubr_0.6.0
## [4] tidyr_1.3.1 DspikeIn_0.99.11 rmarkdown_2.29
## [7] mia_1.16.0 MultiAssayExperiment_1.34.0 vegan_2.7-1
## [10] permute_0.9-7 microbiome_1.30.0 tibble_3.3.0
## [13] dplyr_1.1.4 flextable_0.9.9 TreeSummarizedExperiment_1.28.0
## [16] SingleCellExperiment_1.30.1 SummarizedExperiment_1.38.1 Biobase_2.68.0
## [19] GenomicRanges_1.60.0 MatrixGenerics_1.20.0 matrixStats_1.5.0
## [22] ggplot2_3.5.2 ggstar_1.0.4 phyloseq_1.52.0
## [25] Biostrings_2.76.0 GenomeInfoDb_1.44.0 XVector_0.48.0
## [28] IRanges_2.42.0 S4Vectors_0.46.0 BiocGenerics_0.54.0
## [31] generics_0.1.4 BiocStyle_2.36.0
##
## loaded via a namespace (and not attached):
## [1] urlchecker_1.0.1 TH.data_1.1-3 vctrs_0.6.5 dplyr_1.1.4
## [5] BiocBaseUtils_1.10.0 rbiom_2.2.0 parallelly_1.45.0 munsell_0.5.0
## [9] MASS_7.3-65 fontLiberation_0.1.0 reshape2_1.4.4 ht_1.4.4
## [13] foreach_1.5.2 withr_3.0.2 xfun_0.52 ggplot2_3.5.2
## [17] ellipsis_0.3.2 survival_3.8-3 memoise_2.0.1 colorR_1.0.0
## [21] ggbeeswarm_0.7.2 emmeans_1.11.1 profvis_0.4.0 shiny_1.8.2
## [25] ragg_1.4.0 tidytree_0.4.6 zoo_1.8-14 ggplot2_3.5.2
## [29] Formula_1.2-5 sys_3.4.3 promises_1.3.3 ht_1.4.4
## [33] rstatix_0.7.2 rhdf5filters_1.20.0 ps_1.9.1 rlang_1.1.4
## [37] rstudioapi_0.17.1 UCSC.utils_1.4.0 miniUI_0.1.2 ggplot2_3.5.2
## [41] processx_3.8.6 curl_6.3.0 ScaledMatrix_1.16.0 ggplot2_3.5.2
```

## [45] polyclip_1.10-7	randomForest_4.7-1.2	GenomeInfoDbData_1.2.14	q
## [49] SparseArray_1.8.0	RBGL_1.84.0	xtable_1.8-4	s
## [53] desc_1.4.3	ade4_1.7-23	evaluate_1.0.4	S
## [57] BiocFileCache_2.16.0	hms_1.1.3	bookdown_0.43	i
## [61] filelock_1.0.3	readxl_1.4.5	readr_2.1.5	m
## [65] later_1.4.2	viridis_0.6.5	ggtree_3.16.0	l
## [69] DECIPHER_3.4.0	XML_3.99-0.18	scuttle_1.18.0	p
## [73] nlme_3.1-168	iterators_1.0.14	decontam_1.28.0	c
## [77] beachmat_2.24.0	stringi_1.8.7	biomformat_1.36.0	d
## [81] plyr_1.8.9	crayon_1.5.3	abind_1.4-8	s
## [85] ggtext_0.1.2	gridGraphics_0.5-1	locfit_1.5-9.12	g
## [89] bit_4.6.0	sandwich_3.1-1	fastmatch_1.1-6	c
## [93] multcomp_1.4-28	textshaping_1.0.1	BiocSingular_1.24.0	o
## [97] slam_0.1-55	bslib_0.9.0	multtest_2.64.0	m
## [101] splines_4.5.0	Rcpp_1.0.14	dbplyr_2.5.0	s
## [105] BiocCheck_1.44.2	cellranger_1.1.0	gridtext_0.1.5	k
## [109] blob_1.2.4	utf8_1.2.6	fs_1.6.6	D
## [113] pkgbuild_1.4.8	ggsignif_0.6.4	ggplotify_0.1.2	e
## [117] Matrix_1.7-3	callr_3.7.6	statmod_1.5.0	t
## [121] tweenr_2.0.3	pkgconfig_2.0.3	tools_4.5.0	c
## [125] RSQLite_2.4.1	viridisLite_0.4.2	DBI_1.2.3	f
## [129] scales_1.4.0	grid_4.5.0	credentials_2.0.2	u
## [133] fillpattern_1.0.2	broom_1.0.8	sass_0.4.10	o
## [137] patchwork_1.3.0	coda_0.19-4.1	BiocManager_1.30.26	g
## [141] carData_3.0-5	farver_2.1.2	tidygraph_1.3.1	m
## [145] biocViews_1.76.0	yaml_2.3.10	roxygen2_7.3.2	c
## [149] purrr_1.0.4	lifecycle_1.0.4	rsconnect_1.4.2	a
## [153] mvtnorm_1.3-3	bluster_1.18.0	sessioninfo_1.2.3	b
## [157] BiocParallel_1.42.1	gtable_0.3.6	ggribes_0.5.6	p
## [161] ape_5.8-1	testthat_3.2.3	limma_3.64.1	j
## [165] edgeR_4.6.2	bitops_1.0-9	bit64_4.6.0-1	b
## [169] Rtsne_0.17	yulab.utils_0.2.0	BiocNeighbors_2.2.0	z
## [173] jquerylib_0.1.4	lazyeval_0.2.2	shiny_1.10.0	h
## [177] rappdirs_0.3.3	tinytex_0.57	glue_1.8.0	h
## [181] gdtools_0.4.2	RCurl_1.98-1.17	rprojroot_2.0.4	t
## [185] gridExtra_2.3	R6_2.6.1	DESeq2_1.48.1	l
## [189] cluster_2.1.8.1	pkgload_1.4.0	Rhdf5lib_1.30.0	s
## [193] aplot_0.2.6	DirichletMultinomial_1.50.0	DelayedArray_0.34.1	t
## [197] vipor_0.4.7	ggforce_0.5.0	xml2_1.3.8	f
## [201] car_3.1-3	rsvd_1.0.5	fontquiver_0.2.1	d
## [205] htmlwidgets_1.6.4	RColorBrewer_1.1-3	rlang_1.1.6	g
## [209] uuid_1.2-1	remotes_2.5.0	RUnit_0.4.33.1	g
## [213] phangorn_2.12.1	beeswarm_0.4.0		

Dspikeln volume protocol

Spike-in volume Protocol;

The species *Tetragenococcus halophilus* (bacterial spike; ATCC33315) and *Dekkera bruxellensis* (fungal spike; WLP4642-White Labs) were selected as taxa to spike into gut microbiome samples as they were not found in an extensive collection of wildlife skin (GenBank BioProjects: PRJNA1114724, PRJNA 1114659) or gut microbiome samples. Stock cell suspensions of both microbes were grown in either static tryptic soy broth (*T. halophilus*) or potato dextrose broth (*D. bruxellensis*) for 72 hours then serially diluted and optical density (OD600) determined on a ClarioStar plate reader. Cell suspensions with an optical density of 1.0, 0.1, 0.01, 0.001 were DNA extracted using the Qiagen DNeasy Powersoil Pro Kit. These DNA isolations were used as standards to determine the proper spike in volume of cells to represent 0.1-10% of a sample (Rao et al., 2021b) Fecal pellets (3.1 ± 1.6 mg; range = 1 – 5.1 mg) from an ongoing live animal study using wood frogs (*Lithobates sylvaticus*) were used to standardize the input material for the development of this protocol. A total of (n=9) samples were used to validate the spike in protocol. Each fecal sample was homogenized in 1mL of sterile molecular grade water then 250uL of fecal slurry was DNA extracted as above with and without spiked cells. Two approaches were used to evaluate the target spike-in of 0.1-10%, the range of effective spike-in percentage described in (Rao et al., 2021b), including 1) an expected increase of qPCR cycle threshold (Ct) value that is proportional to the amount of spiked cells and 2) the expected increase in copy number of *T. halophilus* and *D. bruxellensis* in spiked vs. unspiked samples. A standard curve was generated using a synthetic fragment of DNA for the 16S-V4 rRNA and ITS1 rDNA regions of *T. halophilus* and *D. bruxellensis*, respectively. The standard curve was used to convert Ct values into log copy number for statistical analyses (detailed approach in [2, 3]) using the formula $y = -0.2426x + 10.584$ for *T. halophilus* and $y = -0.3071x + 10.349$ for *D. bruxellensis*, where x is the average Ct for each unknown sample. Quantitative PCR (qPCR) was used to compare known copy numbers from synthetic DNA sequences of *T. halophilus* and *D. bruxellensis* to DNA extractions of *T. halophilus* and *D. bruxellensis* independently, and wood frog fecal samples with and without spiked cells. SYBR qPCR assays were run at 20ul total volume including 10ul 2X Quantabio PerfeCTa SYBR Green Fastmix, 1ul of 10uM forward and reverse primers, 1ul of ArcticEnzymes dsDNAse master mix clean up kit, and either 1ul of DNA for *D. bruxellensis* or 3ul for *T. halophilus*. Different volumes of DNA were chosen for amplification of bacteria and fungi due to previous optimization of library preparation and sequencing steps [3]. The 515F [4] and 806R [5] primers were chosen to amplify bacteria and ITS1F12 [6] and ITS2 for fungi, as these are the same primers used during amplicon library preparation and sequencing. Cycling conditions on an Agilent AriaMX consisted of 95 C for 3 mins followed by 40 cycles of 95 C for 15 sec, 60 C for 30 sec and 72 C for 30 sec. Following amplification, a melt curve was generated under the following conditions including 95 C for 30 sec, and a melt from 60 C to 90 C increasing in resolution of 0.5 C in increments of a 5 sec soak time. To validate the spike in protocol we selected two sets of fecal samples including 360 samples from a diverse species pool of frogs, lizards, salamanders and snakes and a more targeted approach of 122 fecal samples from three genera of salamanders from the Plethodontidae. (Supplemental Table #). Fecal samples were not weighed in the field, rather, a complete fecal pellet was diluted in an equal volume of sterile water and standardized volume of fecal slurry (250uL) extracted for independent samples.. A volume of 1ul *T. halophilus* (1847 copies) and 1ul *D. bruxellensis* (733 copies) were spiked into each fecal sample then DNA was extracted as above, libraries constructed, and amplicon sequenced on an Illumina MiSeq as in [7] .

<https://github.com/mghotbi/DspikeIn>