

Beta diversity ITS2 DINO analyses for Pocillopora species across the Indo-Pacific, 29 Sep 2021

```
rm(list = ls())  
library(tidyr)  
library(purrr)  
library(dplyr)
```

```
##  
## Attaching package: 'dplyr'  
  
## The following objects are masked from 'package:stats':  
##  
##   filter, lag  
  
## The following objects are masked from 'package:base':  
##  
##   intersect, setdiff, setequal, union
```

```
library(metagMisc)
```

```
##  
## Attaching package: 'metagMisc'  
  
## The following object is masked from 'package:purrr':  
##  
##   some
```

```
library(kableExtra)
```

```
##  
## Attaching package: 'kableExtra'  
  
## The following object is masked from 'package:dplyr':  
##  
##   group_rows
```

```
library(reshape2)
```

```
##  
## Attaching package: 'reshape2'  
  
## The following object is masked from 'package:tidyr':  
##  
##   smiths
```

```

library(stringr)
library(tidyverse)

## -- Attaching packages ----- tidyverse 1.3.1 --

## v ggplot2 3.3.5      v readr  2.0.2
## v tibble  3.1.4      v forcats 0.5.1

## -- Conflicts ----- tidyverse_conflicts() --
## x dplyr::filter()      masks stats::filter()
## x kableExtra::group_rows() masks dplyr::group_rows()
## x dplyr::lag()         masks stats::lag()
## x metagMisc::some()    masks purrr::some()

library(phyloseq)
library(magrittr)

##
## Attaching package: 'magrittr'

## The following object is masked from 'package:purrr':
##
##   set_names

## The following object is masked from 'package:tidyr':
##
##   extract

library(metagMisc)
library(randomForest)

## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##   margin

## The following object is masked from 'package:dplyr':
##
##   combine

library(knitr)
library(seqinr)

```

```

##
## Attaching package: 'seqinr'

## The following object is masked from 'package:dplyr':
##
##      count

library(ggplot2)
library(gridExtra)

##
## Attaching package: 'gridExtra'

## The following object is masked from 'package:randomForest':
##
##      combine

## The following object is masked from 'package:dplyr':
##
##      combine

library(vegan)

## Loading required package: permute

##
## Attaching package: 'permute'

## The following object is masked from 'package:seqinr':
##
##      getType

## Loading required package: lattice

## This is vegan 2.5-7

library(DESeq2)

## Loading required package: S4Vectors

## Loading required package: stats4

## Loading required package: BiocGenerics

## Loading required package: parallel

##
## Attaching package: 'BiocGenerics'

```

```

## The following objects are masked from 'package:parallel':
##
##   clusterApply, clusterApplyLB, clusterCall, clusterEvalQ,
##   clusterExport, clusterMap, parApply, parCapply, parLapply,
##   parLapplyLB, parRapply, parSapply, parSapplyLB

## The following object is masked from 'package:gridExtra':
##
##   combine

## The following object is masked from 'package:randomForest':
##
##   combine

## The following objects are masked from 'package:dplyr':
##
##   combine, intersect, setdiff, union

## The following objects are masked from 'package:stats':
##
##   IQR, mad, sd, var, xtabs

## The following objects are masked from 'package:base':
##
##   anyDuplicated, append, as.data.frame, basename, cbind, colnames,
##   dirname, do.call, duplicated, eval, evalq, Filter, Find, get, grep,
##   grepl, intersect, is.unsorted, lapply, Map, mapply, match, mget,
##   order, paste, pmax, pmax.int, pmin, pmin.int, Position, rank,
##   rbind, Reduce, rownames, sapply, setdiff, sort, table, tapply,
##   union, unique, unsplit, which.max, which.min

##
## Attaching package: 'S4Vectors'

## The following objects are masked from 'package:dplyr':
##
##   first, rename

## The following object is masked from 'package:tidyr':
##
##   expand

## The following objects are masked from 'package:base':
##
##   expand.grid, I, unname

## Loading required package: IRanges

##
## Attaching package: 'IRanges'

```

```

## The following object is masked from 'package:phyloseq':
##
## distance

## The following objects are masked from 'package:dplyr':
##
## collapse, desc, slice

## The following object is masked from 'package:purrr':
##
## reduce

## Loading required package: GenomicRanges

## Loading required package: GenomeInfoDb

## Loading required package: SummarizedExperiment

## Loading required package: MatrixGenerics

## Loading required package: matrixStats

##
## Attaching package: 'matrixStats'

## The following object is masked from 'package:seqinr':
##
## count

## The following object is masked from 'package:dplyr':
##
## count

##
## Attaching package: 'MatrixGenerics'

## The following objects are masked from 'package:matrixStats':
##
## colAlls, colAnyNAs, colAnys, colAveragesPerRowSet, colCollapse,
## colCounts, colCummaxs, colCummins, colCumprods, colCumsums,
## colDiffs, colIQRDiffs, colIQRs, colLogSumExps, colMadDiffs,
## colMads, colMaxs, colMeans2, colMedians, colMins, colOrderStats,
## colProds, colQuantiles, colRanges, colRanks, colSdDiffs, colSds,
## colSums2, colTabulates, colVarDiffs, colVars, colWeightedMads,
## colWeightedMeans, colWeightedMedians, colWeightedSds,
## colWeightedVars, rowAlls, rowAnyNAs, rowAnys, rowAveragesPerColSet,
## rowCollapse, rowCounts, rowCummaxs, rowCummins, rowCumprods,
## rowCumsums, rowDiffs, rowIQRDiffs, rowIQRs, rowLogSumExps,
## rowMadDiffs, rowMads, rowMaxs, rowMeans2, rowMedians, rowMins,
## rowOrderStats, rowProds, rowQuantiles, rowRanges, rowRanks,
## rowSdDiffs, rowSds, rowSums2, rowTabulates, rowVarDiffs, rowVars,
## rowWeightedMads, rowWeightedMeans, rowWeightedMedians,
## rowWeightedSds, rowWeightedVars

```

```

## Loading required package: Biobase

## Welcome to Bioconductor
##
##     Vignettes contain introductory material; view with
##     'browseVignettes()'. To cite Bioconductor, see
##     'citation("Biobase")', and for packages 'citation("pkgname)".

##
## Attaching package: 'Biobase'

## The following object is masked from 'package:MatrixGenerics':
##
##     rowMedians

## The following objects are masked from 'package:matrixStats':
##
##     anyMissing, rowMedians

## The following object is masked from 'package:phyloseq':
##
##     sampleNames

library(picante)

## Loading required package: ape

##
## Attaching package: 'ape'

## The following objects are masked from 'package:seqinr':
##
##     as.alignment, consensus

## Loading required package: nlme

##
## Attaching package: 'nlme'

## The following object is masked from 'package:IRanges':
##
##     collapse

## The following object is masked from 'package:seqinr':
##
##     gls

## The following object is masked from 'package:dplyr':
##
##     collapse

```

```
library(remotes)
```

```
##  
## Attaching package: 'remotes'  
  
## The following object is masked from 'package:metagMisc':  
##  
##   add_metadata
```

```
library(ggrepel)  
library(igraph)
```

```
##  
## Attaching package: 'igraph'  
  
## The following objects are masked from 'package:ape':  
##  
##   edges, mst, ring  
  
## The following object is masked from 'package:GenomicRanges':  
##  
##   union  
  
## The following object is masked from 'package:IRanges':  
##  
##   union  
  
## The following object is masked from 'package:S4Vectors':  
##  
##   union  
  
## The following objects are masked from 'package:BiocGenerics':  
##  
##   normalize, path, union  
  
## The following object is masked from 'package:vegan':  
##  
##   diversity  
  
## The following object is masked from 'package:permute':  
##  
##   permute  
  
## The following object is masked from 'package:tibble':  
##  
##   as_data_frame  
  
## The following objects are masked from 'package:dplyr':  
##  
##   as_data_frame, groups, union
```

```

## The following objects are masked from 'package:purrr':
##
##   compose, simplify

## The following object is masked from 'package:tidyr':
##
##   crossing

## The following objects are masked from 'package:stats':
##
##   decompose, spectrum

## The following object is masked from 'package:base':
##
##   union

library(ellipse)

##
## Attaching package: 'ellipse'

## The following object is masked from 'package:graphics':
##
##   pairs

library(dplyr)
library(indicspecies)

##
## Attaching package: 'indicspecies'

## The following object is masked from 'package:SummarizedExperiment':
##
##   coverage

## The following object is masked from 'package:GenomicRanges':
##
##   coverage

## The following object is masked from 'package:IRanges':
##
##   coverage

library(yhat)

## Registered S3 methods overwritten by 'yacca':
##   method          from
##   plot.cca         vegan
##   print.cca        vegan
##   print.summary.cca vegan
##   summary.cca      vegan

```



```
library("dunn.test")
library(metagenomeSeq)
```

```
## Loading required package: limma

##
## Attaching package: 'limma'

## The following object is masked from 'package:DESeq2':
##
##      plotMA

## The following object is masked from 'package:BiocGenerics':
##
##      plotMA

## The following object is masked from 'package:seqinr':
##
##      zscore

## Loading required package: glmnet

## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following object is masked from 'package:S4Vectors':
##
##      expand

## The following objects are masked from 'package:tidyr':
##
##      expand, pack, unpack

## Loaded glmnet 4.1-2

## Loading required package: RColorBrewer
```

```
library(phyloseq)
```

```
## Remember to setwd to where rds files are found
##setwd("~/Users/victoriamarieglynn/Desktop/Desktop_May2021/CC_11May2021_DINOenv")
```

```
##Read rds file generated from DADA2
```

```
ps <- readRDS("/Users/victoriamarieglynn/Desktop/Desktop_May2021/CC_11May2021_DINOenv/symITSps_may2021..")
ps
```

```
## phyloseq-class experiment-level object
## otu_table() OTU Table: [ 11374 taxa and 416 samples ]
## sample_data() Sample Data: [ 416 samples by 21 sample variables ]
## phy_tree() Phylogenetic Tree: [ 11374 tips and 11372 internal nodes ]
```

```
taxa_names(ps) <- paste0("asv", seq(ntaxa(ps)))
# explicitly rename taxa to asvs
```

```
otu <- otu_table(ps)
tre <- phy_tree(ps)
sam <- sample_data(ps)
```

```
##Taxa import, below is for the NCBI search, which was as follows on our Compute Canada clusters:
```

```
###blastn \
###-query uniqueSeqs_F-asv.fasta \
###-db nt \
###-out SymPortal_NCBICrossref_Fb5.csv \
###-evalue 1e-5 \
###-outfmt "6 qseqid sseqid sscinames scomnames sskindoms stitle qstart qend mismatch evalue length" \
###-max_target_seqs 5
```

```
## For NCBI, I manually looked through the generated table to assign clade and type level identification
```

```
##I also used SymPortal for taxonomic assignment, but this did not result in ITS clades being grouped together
```

```
##vsearch --usearch_global uniqueSeqs_DINO_Stewart.fasta --db refSeqDB.fa --blast6out DINOSt_taxa.txt
```

```
taxtable<-read.csv("/Users/victoriamarieglynn/Desktop/Desktop_May2021/CC_11May2021_DINOenv/DINO_NCBICrossref_Fb5.csv")
summary(taxtable)
```

```
##      ASV                ITSclade          ITStype
## Length:882          Length:882          Length:882
## Class :character    Class :character    Class :character
## Mode :character     Mode :character     Mode :character
```

```
##This CSVs has all N sequences removed, as not informative
```

```
## taxonomy table into matrix
taxmat<-as.matrix(taxtable[,2:3])
rownames(taxmat)<-taxtable$ASV
```

```
##Combine the taxonomy matrix and the otu_table (otus) into a phyloseq object
```

```
TAX = tax_table(taxmat)
```

```
## Check if any duplicated row names
```

```
duplicated(TAX)
```

```
## asv1001 asv1074 asv1188 asv1235 asv1261 asv1341 asv137 asv148 asv1488 asv149
## FALSE FALSE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## asv1617 asv1660 asv1689 asv1997 asv2005 asv221 asv224 asv228 asv2280 asv2357
## TRUE TRUE FALSE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## asv2378 asv25 asv2553 asv2754 asv2830 asv3083 asv3798 asv4369 asv4370 asv448
## TRUE TRUE TRUE TRUE FALSE TRUE TRUE TRUE TRUE TRUE
```

##	asv449	asv454	asv492	asv547	asv604	asv606	asv618	asv625	asv640	asv693
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv756	asv765	asv779	asv790	asv793	asv809	asv831	asv838	asv860	asv1
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE
##	asv1005	asv101	asv1019	asv102	asv1023	asv1033	asv1037	asv1039	asv1042	asv1046
##	FALSE	TRUE	FALSE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE	TRUE
##	asv105	asv1055	asv106	asv1060	asv1067	asv107	asv1078	asv108	asv1085	asv1090
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1093	asv1098	asv1108	asv1110	asv112	asv1124	asv114	asv1144	asv1149	asv1153
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1156	asv1158	asv1167	asv117	asv1172	asv1175	asv1185	asv119	asv12	asv120
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1202	asv1205	asv1209	asv121	asv1216	asv1227	asv1228	asv123	asv1236	asv1239
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1247	asv125	asv1252	asv1256	asv1265	asv127	asv128	asv1284	asv1285	asv1293
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1295	asv1296	asv13	asv1302	asv1309	asv131	asv1310	asv132	asv133	asv134
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv135	asv136	asv1360	asv1363	asv1378	asv138	asv1389	asv139	asv1405	asv1408
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1426	asv1436	asv144	asv1441	asv1448	asv1457	asv146	asv147	asv1476	asv1482
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1497	asv15	asv150	asv1502	asv1505	asv1511	asv1517	asv1519	asv152	asv1523
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv153	asv154	asv1544	asv1545	asv155	asv1561	asv157	asv159	asv1594	asv1595
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1599	asv160	asv1601	asv161	asv1610	asv1616	asv163	asv1633	asv164	asv1653
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1668	asv167	asv1678	asv1686	asv1687	asv1690	asv1693	asv1696	asv17	asv1704
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv171	asv1711	asv1715	asv1719	asv1729	asv173	asv1737	asv175	asv176	asv1762
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1768	asv177	asv178	asv1784	asv1786	asv179	asv1792	asv1799	asv18	asv180
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1809	asv1810	asv182	asv1827	asv1828	asv1843	asv185	asv1854	asv1858	asv1863
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv187	asv1870	asv1875	asv188	asv1886	asv1896	asv1897	asv19	asv1903	asv1904
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1905	asv1906	asv191	asv1913	asv192	asv1920	asv1921	asv193	asv1938	asv194
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1952	asv1960	asv1969	asv1970	asv1982	asv1983	asv1990	asv1995	asv2	asv200
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv2013	asv202	asv2023	asv204	asv2043	asv2049	asv2051	asv2052	asv206	asv2071
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv2075	asv2076	asv209	asv2095	asv211	asv2117	asv215	asv2151	asv2157	asv2158
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv218	asv2187	asv22	asv2226	asv223	asv2248	asv2255	asv226	asv2268	asv227
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv229	asv2309	asv232	asv2329	asv233	asv2330	asv2339	asv2340	asv2341	asv235
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv2356	asv236	asv2367	asv2368	asv2377	asv239	asv2399	asv24	asv240	asv2400
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv2402	asv2403	asv241	asv242	asv2427	asv243	asv2441	asv246	asv248	asv2486
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

##	asv2488	asv250	asv254	asv2552	asv2564	asv257	asv258	asv26	asv2600	asv2608
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv2609	asv2610	asv2622	asv2629	asv2631	asv2632	asv264	asv2648	asv2649	asv265
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv2662	asv2663	asv2665	asv267	asv2682	asv269	asv2698	asv2699	asv2701	asv271
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv2717	asv2718	asv272	asv273	asv2744	asv2755	asv276	asv280	asv2804	asv2805
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv2806	asv281	asv2815	asv2825	asv2826	asv2827	asv283	asv284	asv288	asv2881
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv29	asv290	asv2915	asv2916	asv2918	asv2938	asv295	asv296	asv2965	asv298
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv2987	asv3	asv30	asv300	asv3003	asv301	asv302	asv3033	asv3049	asv305
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv3068	asv31	asv310	asv3104	asv3106	asv3107	asv312	asv3134	asv3135	asv3138
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv314	asv3160	asv317	asv3180	asv3181	asv3200	asv3201	asv321	asv3217	asv3219
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv322	asv323	asv3245	asv3246	asv3247	asv3249	asv325	asv3251	asv328	asv33
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv3304	asv3306	asv3307	asv332	asv3329	asv3331	asv334	asv335	asv3357	asv3358
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv336	asv337	asv340	asv341	asv3413	asv3414	asv343	asv3442	asv3443	asv3444
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv347	asv3474	asv348	asv35	asv351	asv3512	asv3539	asv355	asv3577	asv3578
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv3580	asv3581	asv3582	asv3583	asv3584	asv3608	asv361	asv362	asv3638	asv3640
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv365	asv367	asv3670	asv368	asv3698	asv37	asv3705	asv371	asv375	asv3753
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv377	asv378	asv3795	asv3796	asv3799	asv38	asv381	asv3828	asv3829	asv383
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv3830	asv3831	asv3832	asv3871	asv388	asv39	asv3925	asv393	asv395	asv399
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv4	asv4005	asv4006	asv402	asv404	asv4048	asv4049	asv405	asv406	asv4094
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv4095	asv4096	asv4097	asv41	asv410	asv411	asv414	asv4154	asv4157	asv4159
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv42	asv4204	asv4208	asv4209	asv423	asv424	asv4253	asv4254	asv426	asv427
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv428	asv43	asv4307	asv4308	asv4310	asv4311	asv433	asv4367	asv4368	asv4371
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv44	asv440	asv4428	asv4429	asv4430	asv4433	asv4434	asv444	asv445	asv446
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv45	asv450	asv46	asv460	asv462	asv468	asv47	asv471	asv472	asv475
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv476	asv477	asv479	asv48	asv486	asv490	asv491	asv493	asv495	asv498
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv499	asv50	asv500	asv505	asv507	asv51	asv514	asv516	asv519	asv52
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv53	asv531	asv532	asv535	asv537	asv54	asv540	asv543	asv554	asv556
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv56	asv561	asv562	asv563	asv565	asv587	asv60	asv605	asv607	asv609
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

##	asv611	asv613	asv63	asv630	asv632	asv633	asv638	asv649	asv653	asv654
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv657	asv660	asv661	asv666	asv67	asv68	asv691	asv699	asv70	asv700
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv703	asv706	asv71	asv714	asv715	asv718	asv73	asv732	asv735	asv742
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv746	asv75	asv752	asv753	asv76	asv764	asv77	asv770	asv772	asv774
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv777	asv78	asv784	asv787	asv788	asv789	asv79	asv792	asv799	asv8
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv80	asv801	asv806	asv807	asv808	asv818	asv82	asv825	asv827	asv83
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv834	asv837	asv85	asv859	asv86	asv863	asv864	asv87	asv873	asv874
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv877	asv88	asv884	asv887	asv89	asv899	asv9	asv90	asv902	asv905
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv911	asv914	asv916	asv92	asv922	asv925	asv929	asv934	asv94	asv940
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv943	asv945	asv946	asv948	asv950	asv956	asv961	asv967	asv968	asv970
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv976	asv977	asv985	asv989	asv992	asv999	asv1031	asv104	asv1049	asv1050
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	FALSE	TRUE
##	asv109	asv110	asv111	asv1131	asv1171	asv1194	asv1203	asv1204	asv1221	asv1258
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1286	asv129	asv1319	asv1342	asv1354	asv1359	asv1364	asv1391	asv14	asv142
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1420	asv145	asv1460	asv1465	asv1466	asv1471	asv1475	asv1498	asv1532	asv1533
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv156	asv1581	asv1589	asv16	asv1600	asv1609	asv166	asv1661	asv1667	asv1738
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1749	asv1757	asv1763	asv1777	asv1778	asv1785	asv1791	asv1805	asv183	asv1852
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv1853	asv1864	asv1874	asv1879	asv1931	asv1948	asv1973	asv201	asv2026	asv2032
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv2044	asv205	asv2063	asv2105	asv2124	asv2150	asv2169	asv2213	asv2290	asv23
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv231	asv2310	asv2312	asv2328	asv237	asv238	asv2401	asv245	asv2487	asv249
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	FALSE	TRUE	TRUE
##	asv2523	asv2524	asv2525	asv259	asv2599	asv260	asv2621	asv2630	asv2664	asv27
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv270	asv2700	asv279	asv2828	asv2829	asv286	asv2862	asv293	asv2937	asv294
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv297	asv2985	asv2986	asv3008	asv3084	asv3105	asv3136	asv3137	asv318	asv3248
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv327	asv3279	asv3305	asv3328	asv345	asv357	asv3579	asv359	asv3639	asv3702
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv3797	asv390	asv3926	asv396	asv40	asv4003	asv4004	asv415	asv4155	asv4156
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv417	asv422	asv429	asv4309	asv431	asv437	asv4431	asv4432	asv447	asv453
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv459	asv463	asv467	asv474	asv49	asv501	asv504	asv529	asv533	asv538
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
##	asv542	asv55	asv553	asv558	asv559	asv567	asv571	asv574	asv575	asv585
##	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE

```
## asv598 asv6 asv62 asv639 asv66 asv674 asv675 asv680 asv682 asv7
## TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## asv702 asv730 asv738 asv74 asv767 asv780 asv81 asv816 asv820 asv822
## TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## asv836 asv84 asv848 asv857 asv862 asv904 asv91 asv920 asv95 asv952
## TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE TRUE
## asv955 asv984 asv1059 asv1305 asv2311 asv2342 asv3330 asv385 asv461 asv489
## TRUE TRUE FALSE TRUE TRUE FALSE TRUE TRUE TRUE TRUE
## asv791 asv928
## TRUE TRUE
```

```
taxa_are_rows(TAX)
```

```
## NULL
```

```
any(duplicated(rownames(TAX)))
```

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

```
which(duplicated(rownames(TAX)))
```

```
## integer(0)
```

```
## If no duplicated row names:
```

```
ps_tax = phyloseq(otu, TAX, sam, tre)
```

```
ps_tax
```

```
## phyloseq-class experiment-level object
```

```
## otu_table() OTU Table: [ 882 taxa and 416 samples ]
```

```
## sample_data() Sample Data: [ 416 samples by 21 sample variables ]
```

```
## tax_table() Taxonomy Table: [ 882 taxa by 2 taxonomic ranks ]
```

```
## phy_tree() Phylogenetic Tree: [ 882 tips and 881 internal nodes ]
```

```
# Compare phyloseq's raw and now SymPortal amended ps's
```

```
ps_tax
```

```
## phyloseq-class experiment-level object
```

```
## otu_table() OTU Table: [ 882 taxa and 416 samples ]
```

```
## sample_data() Sample Data: [ 416 samples by 21 sample variables ]
```

```
## tax_table() Taxonomy Table: [ 882 taxa by 2 taxonomic ranks ]
```

```
## phy_tree() Phylogenetic Tree: [ 882 tips and 881 internal nodes ]
```

```
ps
```

```
## phyloseq-class experiment-level object
```

```
## otu_table() OTU Table: [ 11374 taxa and 416 samples ]
```

```
## sample_data() Sample Data: [ 416 samples by 21 sample variables ]
```

```
## phy_tree() Phylogenetic Tree: [ 11374 tips and 11372 internal nodes ]
```

```
## Only 52.6% of taxa kept from ps to ps_tax
```

```
#Remove samples less 1000 reads
```

```
ps1 = prune_samples(sample_sums(ps_tax) > 1000, ps_tax)
ps1
```

```
## phyloseq-class experiment-level object
## otu_table() OTU Table: [ 882 taxa and 343 samples ]
## sample_data() Sample Data: [ 343 samples by 21 sample variables ]
## tax_table() Taxonomy Table: [ 882 taxa by 2 taxonomic ranks ]
## phy_tree() Phylogenetic Tree: [ 882 tips and 881 internal nodes ]
```

```
#Remove taxa not seen more than 1 times in at least 5% of the samples
```

```
ps2 = filter_taxa(ps1, function(x) sum(x > 1) > (0.05*length(x)), TRUE)
ps2
```

```
## phyloseq-class experiment-level object
## otu_table() OTU Table: [ 435 taxa and 343 samples ]
## sample_data() Sample Data: [ 343 samples by 21 sample variables ]
## tax_table() Taxonomy Table: [ 435 taxa by 2 taxonomic ranks ]
## phy_tree() Phylogenetic Tree: [ 435 tips and 434 internal nodes ]
```

```
# keep only taxa that were observed at least twice
```

```
ps3 = prune_taxa(taxa_sums(ps2) >= 2, ps2)
ps3
```

```
## phyloseq-class experiment-level object
## otu_table() OTU Table: [ 435 taxa and 343 samples ]
## sample_data() Sample Data: [ 343 samples by 21 sample variables ]
## tax_table() Taxonomy Table: [ 435 taxa by 2 taxonomic ranks ]
## phy_tree() Phylogenetic Tree: [ 435 tips and 434 internal nodes ]
```

```
# remove taxonomy samples that were Ns
```

```
ps4 = subset_samples(ps3, Spec != "P_spp")
```

```
## Remove Fr Poly as ASVs all = 0
```

```
ps5 = subset_samples(ps4, Loc != "FrenPoly")
```

```
## Assign ASV numeric values to replace sequences
```

```
##n_seqs <- seq(ntaxa(ps5))
##len_n_seqs <- nchar(max(n_seqs))
##taxa_seqs <- taxa_names(ps5)
##asvs <- paste("ASV", formatC(n_seqs,
##width = len_n_seqs,
##flag = "0"), sep = "_")
##taxa_names(ps5) <- asvs
```

```

## remove samples with otu = 0
ps6 <- prune_samples(sample_sums(ps5) >= 1, ps5)
ps6

## phyloseq-class experiment-level object
## otu_table() OTU Table: [ 435 taxa and 338 samples ]
## sample_data() Sample Data: [ 338 samples by 21 sample variables ]
## tax_table() Taxonomy Table: [ 435 taxa by 2 taxonomic ranks ]
## phy_tree() Phylogenetic Tree: [ 435 tips and 434 internal nodes ]

##dfASV_seq <- data.frame(asv=asvs, seq=taxa_seqs, stringsAsFactors = FALSE)
##write.csv(dfASV_seq, file="dfASV_seq.csv", row.names = FALSE)
##write.fasta(as.list(taxa_seqs), asvs, "asv_seq.fasta", open = "w", nbchar = 60, as.string =TRUE)

##saveRDS(dfASV_seq, file="dfASV_Seq.rds")

## Remove singletons
ps6_filt <- filter_taxa(ps6, function(x) sum(x > 1) > 1, TRUE)
ps6_filt

## phyloseq-class experiment-level object
## otu_table() OTU Table: [ 435 taxa and 338 samples ]
## sample_data() Sample Data: [ 338 samples by 21 sample variables ]
## tax_table() Taxonomy Table: [ 435 taxa by 2 taxonomic ranks ]
## phy_tree() Phylogenetic Tree: [ 435 tips and 434 internal nodes ]

## CSS transformation

ps6_filt_css <- phyloseq_transform_css(ps6_filt, norm = TRUE, log = FALSE)
ps_normalized <- list()
normalization <- 'css'
ps_normalized[[normalization]] <- ps6_filt_css
ps_normalized[[normalization]]

## phyloseq-class experiment-level object
## otu_table() OTU Table: [ 435 taxa and 338 samples ]
## sample_data() Sample Data: [ 338 samples by 21 sample variables ]
## tax_table() Taxonomy Table: [ 435 taxa by 2 taxonomic ranks ]
## phy_tree() Phylogenetic Tree: [ 435 tips and 434 internal nodes ]

colnames(sample_data(ps6_filt_css))

## [1] "Loc" "Yr" "Spec" "Exp_cond" "Code"
## [6] "Repro" "Month" "Season" "S_region" "L_region"
## [11] "Exact.date" "Tbl_bin" "T_bleach" "DHW" "DHW_cat"
## [16] "SST_a" "Coord_X" "Coord_Y" "Primer" "Pub"
## [21] "Note"

```



```
saveRDS(ps6_filt_css, file="ps6_filt_css.rds")
```

```
## Set random seed for reproducibility
```

```
set.seed(8765)
```

```
##Alpha div
```

```
#Remove Panama
```

```
ps7 <- subset_samples(ps6_filt_css, Loc != "Panam")
```

```
#Remove P. me
```

```
ps8 <- subset_samples(ps7, Spec != "P_me")
```

```
ps9 = subset_samples(ps8, Spec == "P_dam")
```

```
ps10 = subset_samples(ps9, Loc != "Aus_GBR_Heron")
```

```
ps11 = subset_samples(ps10, Season != "Summer")
```

```
ps12 = subset_samples(ps11, Tbl_bin != "Bleaching")
```

```
ps13 = subset_samples(ps12, Loc != "NewCal")
```

```
ps13
```

```
## phyloseq-class experiment-level object
```

```
## otu_table() OTU Table: [ 435 taxa and 91 samples ]
```

```
## sample_data() Sample Data: [ 91 samples by 21 sample variables ]
```

```
## tax_table() Taxonomy Table: [ 435 taxa by 2 taxonomic ranks ]
```

```
## phy_tree() Phylogenetic Tree: [ 435 tips and 434 internal nodes ]
```

```
colnames(sample_data(ps13))
```

```
## [1] "Loc"      "Yr"      "Spec"    "Exp_cond" "Code"
## [6] "Repro"    "Month"   "Season"  "S_region" "L_region"
## [11] "Exact.date" "Tbl_bin" "T_bleach" "DHW"      "DHW_cat"
## [16] "SST_a"    "Coord_X" "Coord_Y" "Primer"   "Pub"
## [21] "Note"
```

```
head(sample_data(ps13))
```

```
##           Loc   Yr  Spec Exp_cond Code  Repro Month Season S_region L_region
## SRR5963024 Oman 2014 P_dam    31C  Om2    B   June Winter IndianOc IndianOc
## SRR5963025 Oman 2014 P_dam    31C  Om2    B   June Winter IndianOc IndianOc
## SRR5963026 Oman 2014 P_dam    31C  Om3    B   June Winter IndianOc IndianOc
## SRR5963027 Oman 2014 P_dam    31C  Om2    B   June Winter IndianOc IndianOc
## SRR5963028 Oman 2014 P_dam    31C  Om3    B   June Winter IndianOc IndianOc
## SRR5963029 Oman 2014 P_dam    31C  Om3    B   June Winter IndianOc IndianOc
##           Exact.date Tbl_bin T_bleach DHW DHW_cat SST_a Coord_X Coord_Y
## SRR5963024      <NA>   Long    15y 4.24   Mod  30.8  23.52  58.74
## SRR5963025      <NA>   Long    15y 4.24   Mod  30.8  23.52  58.74
## SRR5963026      <NA>   Long    15y 3.79   Mod  30.8  23.62  58.60
## SRR5963027      <NA>   Long    15y 4.24   Mod  30.8  23.52  58.74
```

```
## SRR5963028      <NA>      Long      15y 3.79      Mod 30.8    23.62    58.60
## SRR5963029      <NA>      Long      15y 3.79      Mod 30.8    23.62    58.60
##               Primer
## SRR5963024 ITS-DINO https://www.biorxiv.org/content/10.1101/398602v4.full.pdf
## SRR5963025 ITS-DINO https://www.biorxiv.org/content/10.1101/398602v4.full.pdf
## SRR5963026 ITS-DINO https://www.biorxiv.org/content/10.1101/398602v4.full.pdf
## SRR5963027 ITS-DINO https://www.biorxiv.org/content/10.1101/398602v4.full.pdf
## SRR5963028 ITS-DINO https://www.biorxiv.org/content/10.1101/398602v4.full.pdf
## SRR5963029 ITS-DINO https://www.biorxiv.org/content/10.1101/398602v4.full.pdf
##
## SRR5963024 Colonies said to be "Pocillopora damicornis-like"; based on ORF and microsatellites, all
## SRR5963025 Colonies said to be "Pocillopora damicornis-like"; based on ORF and microsatellites, all
## SRR5963026 Colonies said to be "Pocillopora damicornis-like"; based on ORF and microsatellites, all
## SRR5963027 Colonies said to be "Pocillopora damicornis-like"; based on ORF and microsatellites, all
## SRR5963028 Colonies said to be "Pocillopora damicornis-like"; based on ORF and microsatellites, all
## SRR5963029 Colonies said to be "Pocillopora damicornis-like"; based on ORF and microsatellites, all
```

```
Locs <- c("Djib", "Oman", "Aus_GBR_Heron", "NewCal", "Taiwan", "Moorea", "Tahiti", "Tahaa", "Raia")
DHW <- c("N", "Mod")
T_bl <- c("Recent", "Long")
Season <- c("Winter", "Spring")
S_region <- c("IndianOc", "Taiwan", "Aus", "NewCal", "FrPoly")
L_region <- c("IndianOc", "WPac", "NPac", "EPac")
```

```
##Dot plots
```

```
##Dot plots ITS type
```

```
library(ggplot2)
```

```
## Get relative abundances
```

```
ps.rel = transform_sample_counts(ps13, function(x) x/sum(x)*100)
```

```
# agglomerate taxa
```

```
glom <- tax_glom(ps.rel, taxrank = "ITStype", NArm = FALSE)
```

```
ps.melt <- psmelt(glom)
```

```
# change to character for easy-adjusted level
```

```
ps.melt$ITStype <- as.character(ps.melt$ITStype)
```

```
ps.melt <- ps.melt %>%
```

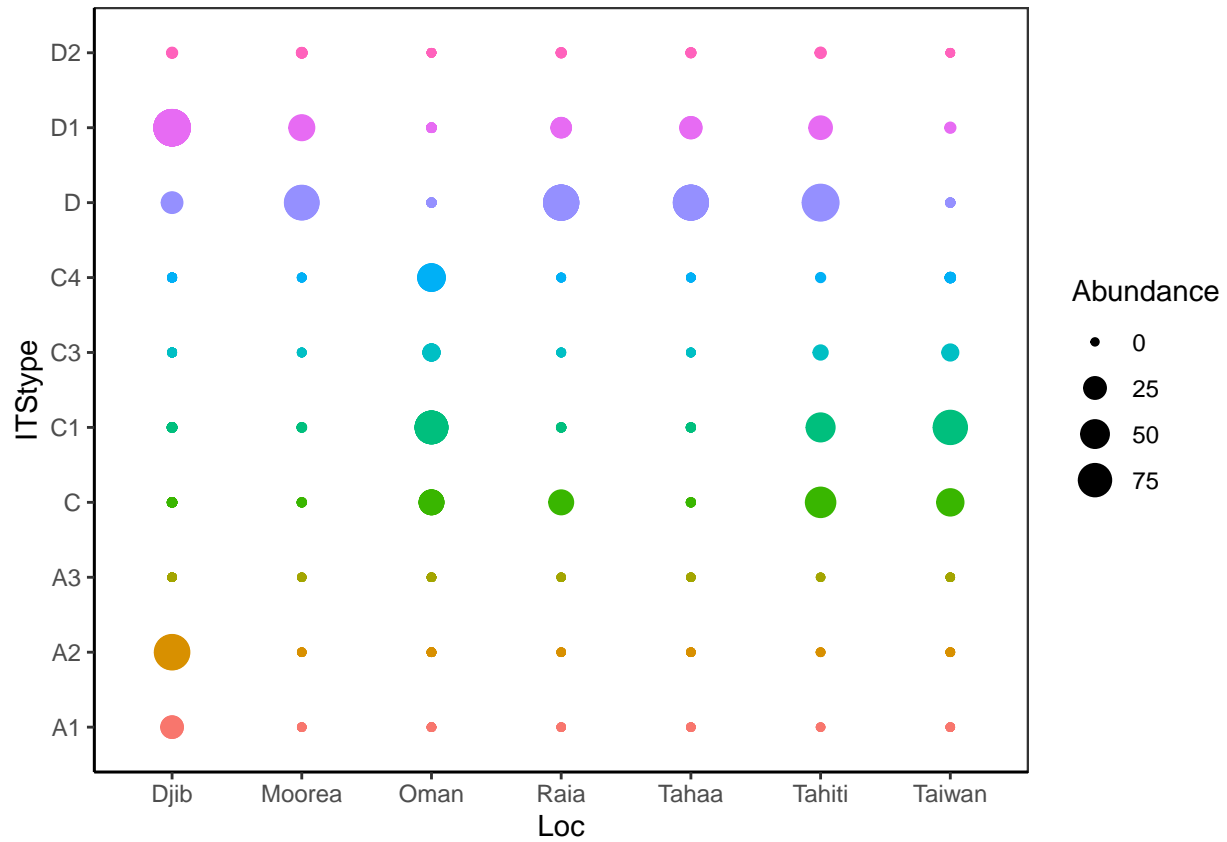
```
  group_by(Loc, ITStype) %>%
```

```
  mutate(median=median(Abundance))
```

```
##ITS type across locations
```

```
ITStype_loc <- ggplot(ps.melt, aes(x = Loc, y = ITStype, color = ITStype)) + geom_point(aes(size = Abund
```

```
ITStype_loc
```



```
ggsave("ITStype_loc_pdam_16Sept2021.pdf")
```

```
## Saving 6.5 x 4.5 in image
```

```
##ITS type across seasons
```

```
##ITStype_Season <- ggplot(ps13, aes(x = Season, y = ITStype, color = ITStype)) + geom_point(aes(size = Abundance)) +
##panel.background = element_blank(), axis.line = element_line(colour = "black")) + scale_x_discrete(1)
```

```
##print(ITStype_Season)
##ggsave("ITStype_Season_pdam.png")
```

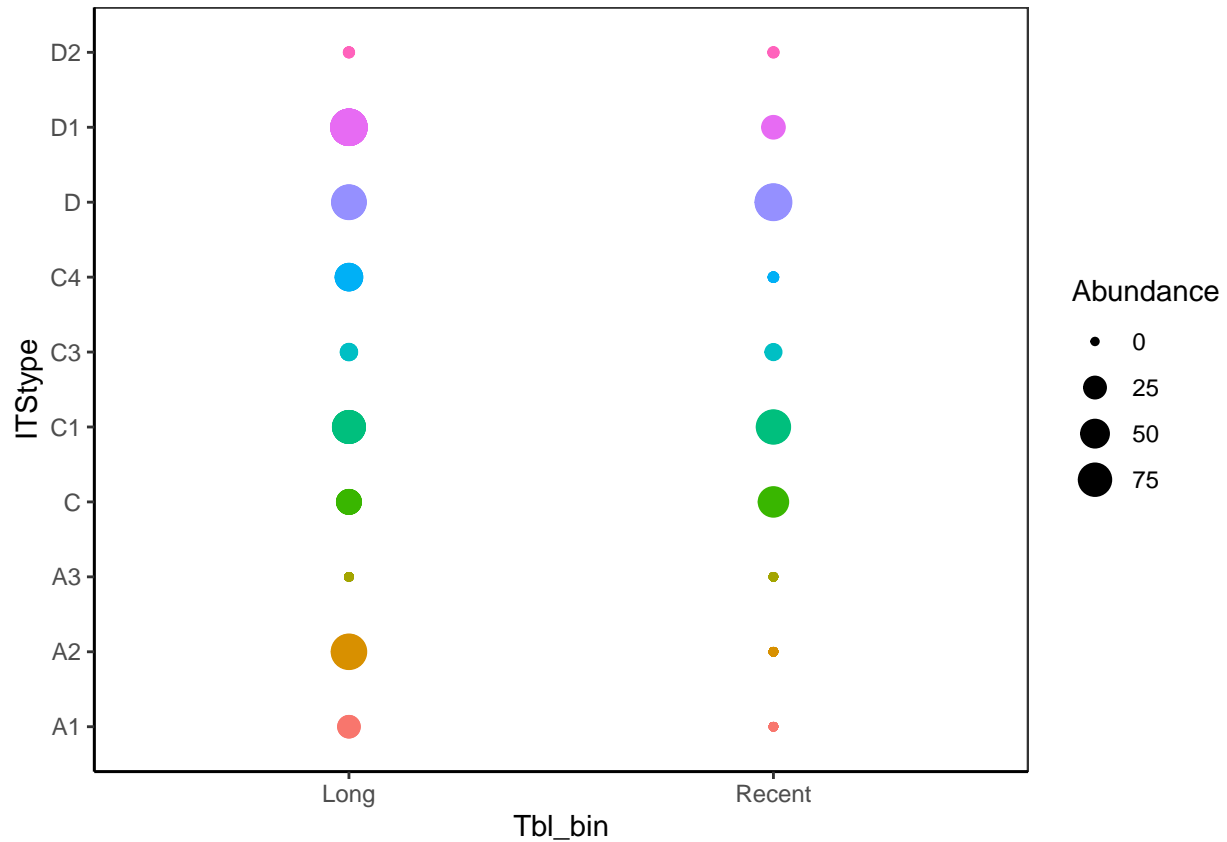
```
##ITS type across DHW
```

```
##ITStype_DHW <- ggplot(ps13, aes(x = DHW_cat, y = ITStype, color = ITStype)) + geom_point(aes(size = Abundance)) +
##panel.background = element_blank(), axis.line = element_line(colour = "black"))
```

```
##print(ITStype_DHW)
##ggsave("ITStype_DHW_pdam.png")
```

```
##ITS type across time mass bleaching
```

```
ITStype_blc <- ggplot(ps.melt, aes(x = Tbl_bin, y = ITStype, color = ITStype)) + geom_point(aes(size = Abundance))
ITStype_blc
```



```
ggsave("ITStype_blc_pdam_16Sep2021.pdf")
```

```
## Saving 6.5 x 4.5 in image
```

```
##Set random seed for reproducibility, calculate distance metrics
set.seed(423542)
```

```
bray.dist = phyloseq::distance(ps13, "bray")
jacc.dist = phyloseq::distance(ps13, "jaccard")
wuni.dist = phyloseq::distance(ps13, "wunifrac")
```

```
##Move into Vegan
```

```
asv_css <- t(otu_table(ps13))
asv_css_hell <- decostand(asv_css, "hell") #not sure we are going to do this.
meta = as(sample_data(ps13), "data.frame")
```

```
perm_css = adonis(asv_css ~ S_region/Loc + SST_a + Tbl_bin, meta) #uses bray internally.
perm_css$ao.v.tab
```

```
## Permutation: free
## Number of permutations: 999
##
## Terms added sequentially (first to last)
##
##          Df SumsOfSqs MeanSqs F.Model      R2 Pr(>F)
## S_region    2   12.991   6.4956  51.626 0.40081  0.001 ***
## SST_a        1    7.723   7.7234  61.384 0.23829  0.001 ***
## Tbl_bin       1    0.311   0.3113   2.474 0.00960  0.060 .
## S_region:Loc  3    0.943   0.3144   2.499 0.02910  0.007 **
## Residuals    83   10.443   0.1258          0.32220
## Total        90   32.412          1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
perm_css2 = adonis2(asv_css ~ S_region/Loc + SST_a + Tbl_bin, meta, method = "bray", sqrt.dist = FALSE)
perm_css2
```

```
## Permutation test for adonis under reduced model
## Terms added sequentially (first to last)
## Permutation: free
## Number of permutations: 999
##
## adonis2(formula = asv_css ~ S_region/Loc + SST_a + Tbl_bin, data = meta, method = "bray", sqrt.dist = FALSE)
##          Df SumOfSqs      R2      F Pr(>F)
## S_region    2   12.991 0.40081 51.6259  0.001 ***
## SST_a        1    7.723 0.23829 61.3842  0.001 ***
## Tbl_bin       1    0.311 0.00960  2.4742  0.031 *
## S_region:Loc  3    0.943 0.02910  2.4986  0.003 **
## Residual    83   10.443 0.32220
## Total       90   32.412 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#Remove loc as know may be masking abiotic differences, as per Mantel test showing a distance between loc and SST
perm_css3 = adonis2(asv_css ~ SST_a + Tbl_bin, meta, method = "bray", sqrt.dist = FALSE, by = "terms")
perm_css3
```

```
## Permutation test for adonis under reduced model
## Terms added sequentially (first to last)
## Permutation: free
## Number of permutations: 999
##
## adonis2(formula = asv_css ~ SST_a + Tbl_bin, data = meta, method = "bray", sqrt.dist = FALSE, by = "terms")
##          Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    8.678 0.26774 38.838  0.001 ***
## Tbl_bin     1    4.071 0.12561 18.221  0.001 ***
## Residual   88   19.663 0.60665
## Total     90   32.412 1.00000
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Pairwise differences - locations

library(pairwiseAdonis)

## Loading required package: cluster

pairwise.adonis2(asv_css ~ Loc, data = meta, sim.method = "bray", p.adjust.m = "BH",
  permutations = 999)

## $parent_call
## [1] "asv_css ~ Loc , strata = Null , permutations 999"
##
## $Oman_vs_Moorea
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  4.7766 0.62426 44.859  0.001 ***
## Residual 27  2.8750 0.37574
## Total    28  7.6515 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.3995 0.11634  4.0813  0.02 *
## Residual 31  3.0346 0.88366
## Total    32  3.4341 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Djib
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  8.0918 0.51525 48.895  0.001 ***
## Residual 46  7.6127 0.48475
## Total    47 15.7046 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Tahaa
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  5.6989 0.66865 58.519  0.001 ***
## Residual 29  2.8242 0.33135
## Total    30  8.5231 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  1.8377 0.32689 11.656  0.001 ***
## Residual 24  3.7839 0.67311
## Total    25  5.6216 1.00000
## ---
```

```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  4.9391 0.65069 50.296  0.001 ***
## Residual 27  2.6515 0.34931
## Total    28  7.5906 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  4.2849 0.81122 77.348  0.001 ***
## Residual 18  0.9972 0.18878
## Total    19  5.2821 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Djib
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  3.8454 0.40819 22.761  0.001 ***
## Residual 33  5.5753 0.59181
## Total    34  9.4207 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Tahaa
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.25581 0.24537 5.2024  0.003 **
## Residual 16  0.78673 0.75463
## Total    17  1.04253 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.40877 0.18966 2.5746  0.006 **
## Residual 11  1.74649 0.81034
## Total    12  2.15526 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.23498 0.27677 5.3577  0.002 **
## Residual 14  0.61402 0.72323
## Total    15  0.84899 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Djib
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  6.2600 0.52189 40.387  0.001 ***
## Residual 37  5.7349 0.47811

```

```

## Total      38  11.9949 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Tahaa
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   4.9609 0.8398 104.84  0.001 ***
## Residual 20   0.9464 0.1602
## Total    21   5.9073 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   1.8160 0.48789 14.291  0.002 **
## Residual 15   1.9061 0.51211
## Total    16   3.7221 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   4.4161 0.85093 102.75  0.001 ***
## Residual 18   0.7737 0.14907
## Total    19   5.1898 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Tahaa
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   4.5582 0.45208 28.878  0.001 ***
## Residual 35   5.5245 0.54792
## Total    36  10.0827 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   1.8458 0.22158 8.5396  0.001 ***
## Residual 30   6.4843 0.77842
## Total    31   8.3300 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   3.9998 0.42771 24.663  0.001 ***
## Residual 33   5.3518 0.57229
## Total    34   9.3516 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Tahaa_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)

```



```

## Loc      1  0.39949 0.19067 3.0627  0.005 **
## Residual 13  1.69569 0.80933
## Total    14  2.09518 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Tahaa_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.06429 0.10246 1.8265  0.126
## Residual 16  0.56322 0.89754
## Total    17  0.62751 1.00000
##
## $Tahiti_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.37316 0.1968 2.6952  0.011 *
## Residual 11  1.52298 0.8032
## Total    12  1.89614 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## attr("class")
## [1] "pwadstrata" "list"

pairwise.adonis2(asv_css ~ S_region, data = meta, sim.method = "bray", p.adjust.m = "BH",
  permutations = 999)

## $parent_call
## [1] "asv_css ~ S_region , strata = Null , permutations 999"
##
## $IndianOc_vs_FrPoly
##      Df SumOfSqs      R2      F Pr(>F)
## S_region  1   9.0872 0.32536 37.135  0.001 ***
## Residual 77  18.8426 0.67464
## Total    78  27.9299 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $IndianOc_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## S_region  1   2.6704 0.14089 9.5118  0.001 ***
## Residual 58  16.2830 0.85911
## Total    59  18.9533 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $FrPoly_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## S_region  1   7.0719 0.65551 78.018  0.001 ***
## Residual 41   3.7165 0.34449
## Total    42  10.7884 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## attr("class")

```

```
## [1] "pwadstrata" "list"
```

```
#Pairwise differences - SST
```

```
pairwise.adonis2(asv_css ~ SST_a, data = meta, sim.method = "bray", p.adjust.m = "BH",  
  permutations = 999)
```

```
## Set of permutations < 'minperm'. Generating entire set.
```

```
## 'nperm' >= set of all permutations: complete enumeration.
```

```
## Set of permutations < 'minperm'. Generating entire set.
```

```
## $parent_call
```

```
## [1] "asv_css ~ SST_a , strata = Null , permutations 999"
```

```
##
```

```
## $`30.8_vs_27.04`
```

```
##           Df SumOfSqs      R2      F Pr(>F)  
## SST_a      1   4.7766 0.62426 44.859  0.001 ***  
## Residual  27   2.8750 0.37574  
## Total     28   7.6515 1.00000
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## $`30.8_vs_28.59`
```

```
##           Df SumOfSqs      R2      F Pr(>F)  
## SST_a      1   0.3498 0.10705 3.4765  0.034 *  
## Residual  29   2.9179 0.89295  
## Total     30   3.2677 1.00000
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## $`30.8_vs_29.37`
```

```
##           Df SumOfSqs      R2      F Pr(>F)  
## SST_a      1   5.4194 0.54916 37.761  0.001 ***  
## Residual  31   4.4491 0.45084  
## Total     32   9.8684 1.00000
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## $`30.8_vs_27.19`
```

```
##           Df SumOfSqs      R2      F Pr(>F)  
## SST_a      1   3.9359 0.59642 36.946  0.001 ***  
## Residual  25   2.6633 0.40358  
## Total     26   6.5992 1.00000
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## $`30.8_vs_26.86`
```

```
##           Df SumOfSqs      R2      F Pr(>F)  
## SST_a      1   1.8377 0.32689 11.656  0.001 ***  
## Residual  24   3.7839 0.67311  
## Total     25   5.6216 1.00000
```

```
## ---
```

```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_29.11`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  4.3225 0.55244 33.327 0.001 ***
## Residual 27  3.5019 0.44756
## Total    28  7.8244 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.19616 0.07359 1.6681 0.097 .
## Residual 21  2.46946 0.92641
## Total    22  2.66562 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  4.9391 0.65069 50.296 0.001 ***
## Residual 27  2.6515 0.34931
## Total    28  7.5906 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  2.8301 0.52118 25.034 0.001 ***
## Residual 23  2.6001 0.47882
## Total    24  5.4302 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  3.2671 0.43589 20.09 0.001 ***
## Residual 26  4.2283 0.56411
## Total    27  7.4954 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_28.59`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  3.9759 0.81869 72.247 0.001 ***
## Residual 16  0.8805 0.18131
## Total    17  4.8564 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_29.37`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  3.1255 0.56446 23.328 0.001 ***
## Residual 18  2.4116 0.43554

```

```

## Total      19      5.5371 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_27.19`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.19517 0.23771 3.7421  0.014 *
## Residual  12  0.62587 0.76229
## Total      13  0.82104 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_26.86`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.40877 0.18966 2.5746  0.01 **
## Residual  11  1.74649 0.81034
## Total      12  2.15526 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_29.11`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  2.7223 0.65022 26.025  0.002 **
## Residual  14  1.4644 0.34978
## Total      15  4.1868 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  1.49594 0.77592 27.701  0.027 *
## Residual   8  0.43202 0.22408
## Total       9  1.92796 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.23498 0.27677 5.3577  0.001 ***
## Residual  14  0.61402 0.72323
## Total      15  0.84899 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.16731 0.2292 2.9735  0.03 *
## Residual  10  0.56267 0.7708
## Total      11  0.72998 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)

```

```

## SST_a      1    2.0860 0.48775 12.378  0.001 ***
## Residual 13    2.1908 0.51225
## Total     14    4.2768 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_29.37`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    4.2552 0.63418 34.671  0.001 ***
## Residual 20    2.4546 0.36582
## Total     21    6.7098 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_27.19`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    3.4256 0.83664 71.703  0.001 ***
## Residual 14    0.6689 0.16336
## Total     15    4.0944 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_26.86`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    1.7231 0.49055 12.518  0.002 **
## Residual 13    1.7895 0.50945
## Total     14    3.5125 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_29.11`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    3.6289 0.70652 38.518  0.001 ***
## Residual 16    1.5074 0.29348
## Total     17    5.1364 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    0.10339 0.17876 2.1766  0.13
## Residual 10    0.47501 0.82124
## Total     11    0.57840 1.00000
##
## $`28.59_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    4.1011 0.86192 99.874  0.001 ***
## Residual 16    0.6570 0.13808
## Total     17    4.7581 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)

```

```

## SST_a      1    2.6073 0.8115 51.659  0.002 **
## Residual 12    0.6057 0.1885
## Total     13    3.2129 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    2.8532 0.56088 19.159  0.001 ***
## Residual 15    2.2338 0.43912
## Total     16    5.0870 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.19`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    2.6283 0.54436 19.115  0.001 ***
## Residual 16    2.2000 0.45564
## Total     17    4.8283 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_26.86`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    1.6397 0.33057  7.4071  0.001 ***
## Residual 15    3.3206 0.66943
## Total     16    4.9603 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_29.11`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    0.02178 0.00712  0.129  0.938
## Residual 18    3.03853 0.99288
## Total     19    3.06031 1.00000
##
## $`29.37_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    1.4059 0.41205  8.4097  0.01 **
## Residual 12    2.0061 0.58795
## Total     13    3.4120 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    3.2455 0.5973 26.699  0.001 ***
## Residual 18    2.1881 0.4027
## Total     19    5.4336 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)

```

```

## SST_a      1    1.9501 0.47717 12.777  0.002 **
## Residual 14    2.1368 0.52283
## Total     15    4.0869 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    0.2755 0.06818 1.2439  0.297
## Residual 17    3.7649 0.93182
## Total     18    4.0404 1.00000
##
## $`27.19_vs_26.86`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    0.32225 0.17352 1.8896  0.05 *
## Residual  9    1.53483 0.82648
## Total     10    1.85708 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.19_vs_29.11`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    2.3545 0.65271 22.553  0.002 **
## Residual 12    1.2528 0.34729
## Total     13    3.6073 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.19_vs_28.67`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    1.43066 0.86653 38.953  0.035 *
## Residual  6    0.22037 0.13347
## Total      7    1.65102 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.19_vs_27.25`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    0.04146 0.09341 1.2364  0.25
## Residual 12    0.40236 0.90659
## Total     13    0.44382 1.00000
##
## $`27.19_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    0.01695 0.04607 0.3863  0.653
## Residual  8    0.35102 0.95393
## Total      9    0.36797 1.00000
##
## $`27.19_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    1.8220 0.47932 10.126  0.002 **
## Residual 11    1.9792 0.52068
## Total     12    3.8011 1.00000
## ---

```

```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_29.11`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   1.5264 0.3914 7.0743 0.004 **
## Residual 11   2.3734 0.6086
## Total    12   3.8998 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.79182 0.37126 2.9524 0.048 *
## Residual  5  1.34099 0.62874
## Total     6  2.13281 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.37316 0.1968 2.6952 0.01 **
## Residual 11  1.52298 0.8032
## Total    12  1.89614 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.28137 0.16051 1.3384 0.192
## Residual  7  1.47164 0.83949
## Total     8  1.75301 1.00000
##
## $`26.86_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   1.0897 0.2601 3.5153 0.012 *
## Residual 10   3.0998 0.7399
## Total    11   4.1895 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   1.3702 0.56408 10.352 0.019 *
## Residual  8   1.0589 0.43592
## Total     9   2.4292 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   2.8215 0.69454 31.832 0.001 ***
## Residual 14   1.2409 0.30546
## Total    15   4.0625 1.00000
## ---

```



```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   1.8185 0.60454 15.287  0.006 **
## Residual 10   1.1896 0.39546
## Total    11   3.0081 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   0.24474 0.07992  1.1291  0.345
## Residual 13   2.81774 0.92008
## Total    14   3.06248 1.00000
##
## $`28.67_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   1.53306 0.88027 58.818  0.019 *
## Residual  8   0.20851 0.11973
## Total     9   1.74158 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.67_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   1.27017 0.88989 32.326 0.06667 .
## Residual  4   0.15717 0.11011
## Total     5   1.42734 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.67_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   1.1398 0.38966  4.4689  0.025 *
## Residual  7   1.7853 0.61034
## Total     8   2.9251 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.25_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   0.05938 0.14898  1.7507  0.173
## Residual 10   0.33916 0.85102
## Total    11   0.39854 1.00000
##
## $`27.25_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   2.1803 0.52568 14.408  0.001 ***
## Residual 13   1.9673 0.47432
## Total    14   4.1476 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

```

```
## $`27.22_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   1.4169 0.42514 6.6559 0.006 **
## Residual    9   1.9160 0.57486
## Total     10   3.3329 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## attr("class")
## [1] "pwadstrata" "list"

#Pairwise differences - time since last mass bleaching event
pairwise.adonis2(asv_css ~ Tbl_bin, data = meta, sim.method = "bray", p.adjust.m = "BH",
  permutations = 999)
```

```
## $parent_call
## [1] "asv_css ~ Tbl_bin , strata = Null , permutations 999"
##
## $Long_vs_Recent
##           Df SumOfSqs      R2      F Pr(>F)
## Tbl_bin      1    3.232 0.09971 9.8572 0.001 ***
## Residual   89   29.180 0.90029
## Total     90   32.412 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## attr("class")
## [1] "pwadstrata" "list"
```

```
ano = anosim(asv_css, meta$Loc, distance = "bray", permutations = 9999)
ano
```

```
##
## Call:
## anosim(x = asv_css, grouping = meta$Loc, permutations = 9999,      distance = "bray")
## Dissimilarity: bray
##
## ANOSIM statistic R: 0.7507
##      Significance: 1e-04
##
## Permutation: free
## Number of permutations: 9999
```

```
ano1 = anosim(asv_css, meta$Season, distance = "bray", permutations = 9999)
ano1
```

```
##
## Call:
## anosim(x = asv_css, grouping = meta$Season, permutations = 9999,      distance = "bray")
## Dissimilarity: bray
##
## ANOSIM statistic R: 0.162
```

```
##      Significance: 1e-04
##
## Permutation: free
## Number of permutations: 9999
```

```
ano2 = anosim(asv_css, meta$Tbl_bin, distance = "bray", permutations = 9999)
ano2
```

```
##
## Call:
## anosim(x = asv_css, grouping = meta$Tbl_bin, permutations = 9999,      distance = "bray")
## Dissimilarity: bray
##
## ANOSIM statistic R: 0.08469
##      Significance: 0.005
##
## Permutation: free
## Number of permutations: 9999
```

```
ano3 = anosim(asv_css, meta$DHW_cat, distance = "bray", permutations = 9999)
ano3
```

```
##
## Call:
## anosim(x = asv_css, grouping = meta$DHW_cat, permutations = 9999,      distance = "bray")
## Dissimilarity: bray
##
## ANOSIM statistic R: 0.4796
##      Significance: 1e-04
##
## Permutation: free
## Number of permutations: 9999
```

```
ano4 = anosim(asv_css, meta$SST_a, distance = "bray", permutations = 9999)
ano4
```

```
##
## Call:
## anosim(x = asv_css, grouping = meta$SST_a, permutations = 9999,      distance = "bray")
## Dissimilarity: bray
##
## ANOSIM statistic R: 0.7304
##      Significance: 1e-04
##
## Permutation: free
## Number of permutations: 9999
```

```
#BC and NMDs
```

```
MDSbray <- ordinate(ps13, "NMDS", "bray", autotransform = FALSE, parallel = 48)
```

```
## Run 0 stress 0.04456561
```

```

## Run 1 stress 0.04456555
## ... New best solution
## ... Procrustes: rmse 0.0001326623  max resid 0.00098373
## ... Similar to previous best
## Run 2 stress 0.04493539
## ... Procrustes: rmse 0.009844637  max resid 0.03846779
## Run 3 stress 0.04493573
## ... Procrustes: rmse 0.009850276  max resid 0.03847498
## Run 4 stress 0.04456577
## ... Procrustes: rmse 0.0001858612  max resid 0.001087807
## ... Similar to previous best
## Run 5 stress 0.04456562
## ... Procrustes: rmse 0.0001273412  max resid 0.0009093265
## ... Similar to previous best
## Run 6 stress 0.07847378
## Run 7 stress 0.04456577
## ... Procrustes: rmse 0.0001094518  max resid 0.0007431928
## ... Similar to previous best
## Run 8 stress 0.04493802
## ... Procrustes: rmse 0.009861326  max resid 0.03846342
## Run 9 stress 0.04456578
## ... Procrustes: rmse 0.0001089732  max resid 0.0007324545
## ... Similar to previous best
## Run 10 stress 0.0445656
## ... Procrustes: rmse 6.589543e-05  max resid 0.00044703
## ... Similar to previous best
## Run 11 stress 0.04493532
## ... Procrustes: rmse 0.009845916  max resid 0.03847095
## Run 12 stress 0.07750406
## Run 13 stress 0.0787962
## Run 14 stress 0.04493641
## ... Procrustes: rmse 0.009840101  max resid 0.03846092
## Run 15 stress 0.04493795
## ... Procrustes: rmse 0.009866225  max resid 0.03846492
## Run 16 stress 0.04493539
## ... Procrustes: rmse 0.00984494  max resid 0.0384683
## Run 17 stress 0.04456575
## ... Procrustes: rmse 0.0001815277  max resid 0.001107512
## ... Similar to previous best
## Run 18 stress 0.04493572
## ... Procrustes: rmse 0.009850437  max resid 0.03847517
## Run 19 stress 0.04456562
## ... Procrustes: rmse 0.000130659  max resid 0.0009597634
## ... Similar to previous best
## Run 20 stress 0.04606561
## Run 21 stress 0.04456561
## ... Procrustes: rmse 0.0001348173  max resid 0.001015346
## ... Similar to previous best
## Run 22 stress 0.04456584
## ... Procrustes: rmse 0.0001367073  max resid 0.0007568961
## ... Similar to previous best
## Run 23 stress 0.04456578
## ... Procrustes: rmse 0.0001103917  max resid 0.0007595952
## ... Similar to previous best

```

```

## Run 24 stress 0.04456577
## ... Procrustes: rmse 0.000193339 max resid 0.0010716
## ... Similar to previous best
## Run 25 stress 0.04493724
## ... Procrustes: rmse 0.009861967 max resid 0.03846777
## Run 26 stress 0.04493538
## ... Procrustes: rmse 0.009844909 max resid 0.03846785
## Run 27 stress 0.04493977
## ... Procrustes: rmse 0.009877413 max resid 0.03847094
## Run 28 stress 0.0445656
## ... Procrustes: rmse 6.521118e-05 max resid 0.0004420611
## ... Similar to previous best
## Run 29 stress 0.07899086
## Run 30 stress 0.04456563
## ... Procrustes: rmse 0.0001259577 max resid 0.0008873855
## ... Similar to previous best
## Run 31 stress 0.0445658
## ... Procrustes: rmse 0.000117221 max resid 0.0007523223
## ... Similar to previous best
## Run 32 stress 0.07900047
## Run 33 stress 0.04493532
## ... Procrustes: rmse 0.009846248 max resid 0.03847123
## Run 34 stress 0.0787594
## Run 35 stress 0.04456562
## ... Procrustes: rmse 0.0001325707 max resid 0.0009866156
## ... Similar to previous best
## Run 36 stress 0.04456566
## ... Procrustes: rmse 0.0001525704 max resid 0.001034378
## ... Similar to previous best
## Run 37 stress 0.04456565
## ... Procrustes: rmse 0.0001476982 max resid 0.0009861435
## ... Similar to previous best
## Run 38 stress 0.04456562
## ... Procrustes: rmse 0.0001292296 max resid 0.0009372756
## ... Similar to previous best
## Run 39 stress 0.04456556
## ... Procrustes: rmse 1.521678e-05 max resid 8.320319e-05
## ... Similar to previous best
## Run 40 stress 0.04456556
## ... Procrustes: rmse 1.254994e-05 max resid 7.93294e-05
## ... Similar to previous best
## Run 41 stress 0.04456576
## ... Procrustes: rmse 0.0001809359 max resid 0.001090513
## ... Similar to previous best
## Run 42 stress 0.04456581
## ... Procrustes: rmse 0.0001324979 max resid 0.0007544023
## ... Similar to previous best
## Run 43 stress 0.04456576
## ... Procrustes: rmse 0.0001789633 max resid 0.00106577
## ... Similar to previous best
## Run 44 stress 0.04456561
## ... Procrustes: rmse 0.0001321434 max resid 0.0009774651
## ... Similar to previous best
## Run 45 stress 0.04456576

```

```
## ... Procrustes: rmse 0.0001823114 max resid 0.00109351
## ... Similar to previous best
## Run 46 stress 0.04539162
## Run 47 stress 0.04456575
## ... Procrustes: rmse 0.0001809748 max resid 0.001101382
## ... Similar to previous best
## Run 48 stress 0.04456555
## ... New best solution
## ... Procrustes: rmse 2.931123e-06 max resid 1.412157e-05
## ... Similar to previous best
## *** Solution reached
```

##Wunifrac and NMDS

```
MDSwuni <- ordinate(ps13, "NMDS", "unifrac", weighted = TRUE)
```

```
## Run 0 stress 9.931406e-05
## Run 1 stress 0.0002384287
## ... Procrustes: rmse 0.04922234 max resid 0.1645062
## Run 2 stress 0.0001793283
## ... Procrustes: rmse 0.04673508 max resid 0.152194
## Run 3 stress 0.0003249687
## ... Procrustes: rmse 0.04697159 max resid 0.1550795
## Run 4 stress 9.830611e-05
## ... New best solution
## ... Procrustes: rmse 0.04553518 max resid 0.1499965
## Run 5 stress 9.876233e-05
## ... Procrustes: rmse 0.001464196 max resid 0.006741422
## ... Similar to previous best
## Run 6 stress 9.797608e-05
## ... New best solution
## ... Procrustes: rmse 0.04044753 max resid 0.1352146
## Run 7 stress 0.0002525925
## ... Procrustes: rmse 0.03824358 max resid 0.1284796
## Run 8 stress 9.927441e-05
## ... Procrustes: rmse 0.04676491 max resid 0.1569664
## Run 9 stress 0.0001076674
## ... Procrustes: rmse 0.04630559 max resid 0.1554655
## Run 10 stress 0.0003764819
## ... Procrustes: rmse 0.04811834 max resid 0.1614708
## Run 11 stress 0.0007281039
## Run 12 stress 0.000507688
## ... Procrustes: rmse 0.04660333 max resid 0.1559861
## Run 13 stress 0.05411661
## Run 14 stress 0.0001478077
## ... Procrustes: rmse 0.04392056 max resid 0.1471097
## Run 15 stress 0.001315121
## Run 16 stress 0.0001962829
## ... Procrustes: rmse 0.04585003 max resid 0.1537805
## Run 17 stress 0.0001748006
## ... Procrustes: rmse 0.04268096 max resid 0.1429906
## Run 18 stress 0.0007254158
## Run 19 stress 0.0005738995
## ... Procrustes: rmse 0.04797309 max resid 0.1605292
```

```
## Run 20 stress 0.0006246007
## *** No convergence -- monoMDS stopping criteria:
##    11: no. of iterations >= maxit
##     4: stress < smin
##     1: stress ratio > sratmax
##     4: scale factor of the gradient < sfgrmin

## Warning in metaMDS(ps.dist): stress is (nearly) zero: you may have insufficient
## data
```

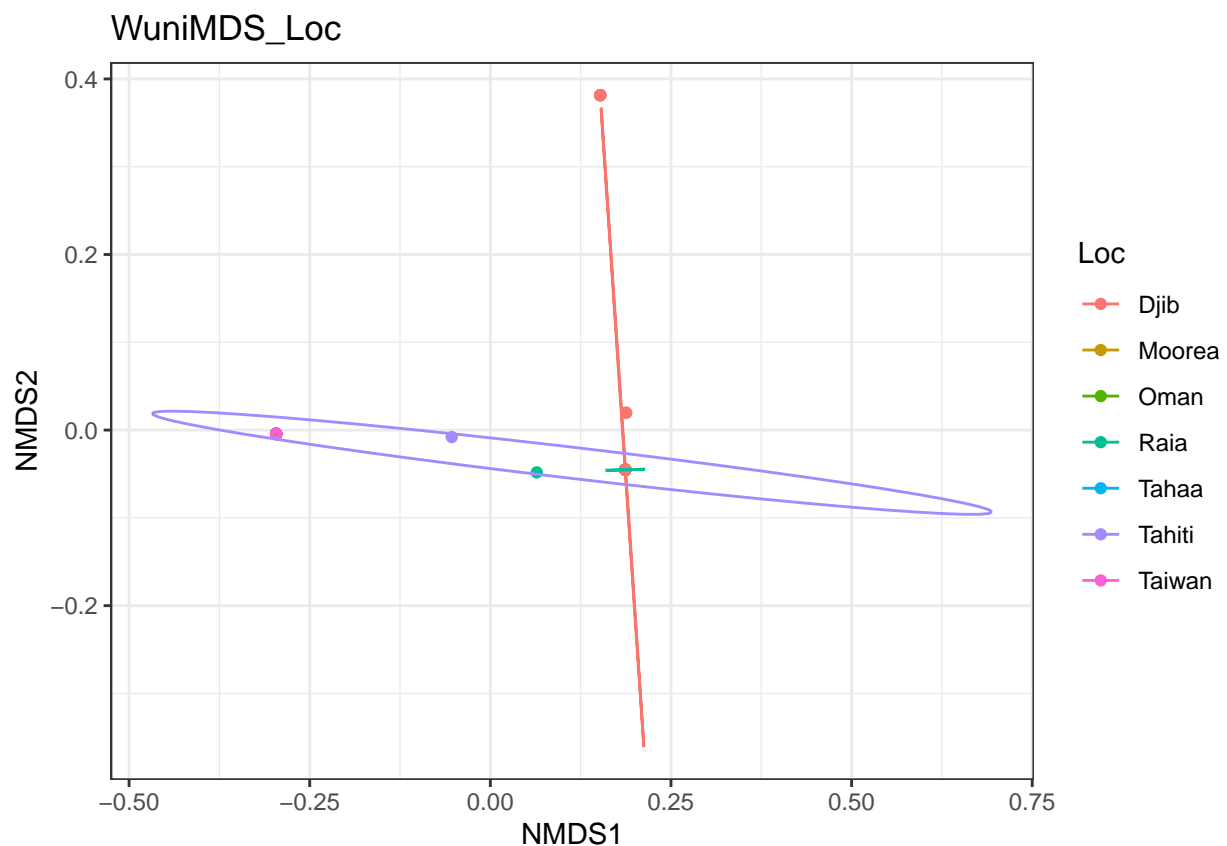
```
##Wunifrac NMDS trial
#Loc only

NMDSplot_loc <- plot_ordination(ps13, MDSwuni, type="samples", color="Loc") +
  theme_bw() +
  stat_ellipse() +
  ggtitle("WuniMDS_Loc")

NMDSplot_loc
```

```
## Warning in MASS::cov.trob(data[, vars]): Probable convergence failure
```

```
## Warning in MASS::cov.trob(data[, vars]): Probable convergence failure
```



```
ggsave("wuniNMDSplot_loc.png")
```

```
## Saving 6.5 x 4.5 in image
```

```
## Warning in MASS::cov.trob(data[, vars]): Probable convergence failure
```

```
## Warning in MASS::cov.trob(data[, vars]): Probable convergence failure
```

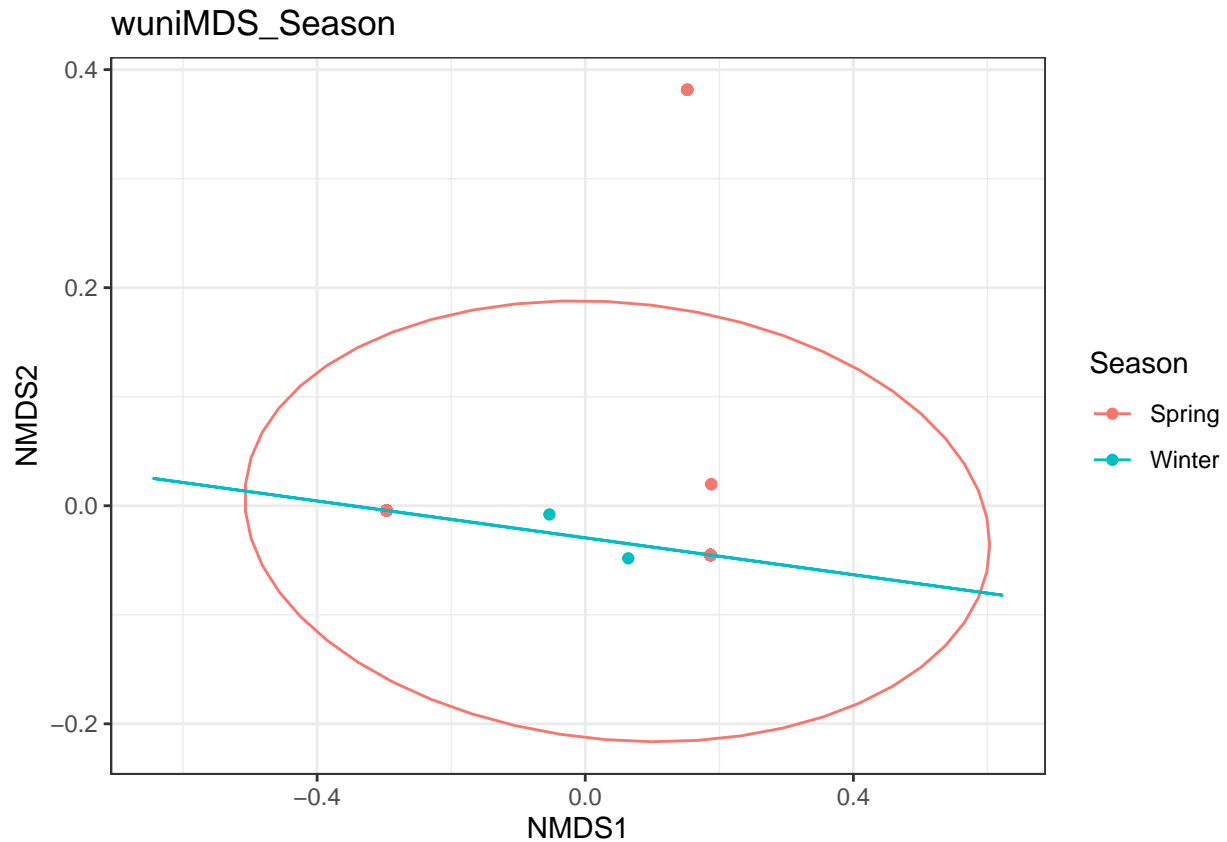
```
# Wuni Season
```

```
NMDSplot_Season <- plot_ordination(ps13, MDSwuni, type="samples", color="Season") +  
  theme_bw() +  
  stat_ellipse() +  
  ggtitle("wuniMDS_Season")
```

```
NMDSplot_Season
```

```
## Warning in MASS::cov.trob(data[, vars]): Probable convergence failure
```

```
## Warning in MASS::cov.trob(data[, vars]): Probable convergence failure
```



```
ggsave("wuniNMDSplot_Season.png")
```

```
## Saving 6.5 x 4.5 in image
```



```

## Warning in MASS::cov.trob(data[, vars]): Probable convergence failure

## Warning in MASS::cov.trob(data[, vars]): Probable convergence failure

Locs <- c("Djib", "Oman", "Taiwan", "Moorea", "Tahiti", "Tahaa", "Raia")
MDSbray$Loc <- factor(MDSbray$Loc, levels = c("Djib", "Oman", "Taiwan", "Moorea", "Tahiti", "Tahaa", "Raia"))

DHW <- c("N", "Mod")
MDSbray$DHW_cat <- factor(MDSbray$DHW_cat, levels = c("N", "Mod"))

T_bl <- c("Recent", "Long")
MDSbray$Tbl_bin <- factor(MDSbray$Tbl_bin, levels = c("Recent", "Long"))

Season <- c("Winter", "Spring")
MDSbray$Season <- factor(MDSbray$Season, levels = c("Winter", "Spring"))

S_region <- c("IndianOc", "Aus", "NewCal", "FrPoly")
MDSbray$S_region <- factor(MDSbray$S_region, levels = c("IndianOc", "Aus", "NewCal", "FrPoly"))

L_region <- c("IndianOc", "WPac", "NPac", "EPac")
MDSbray$L_region <- factor(MDSbray$L_region, levels = c("IndianOc", "WPac", "NPac", "EPac"))

NMDSplot_loc <- plot_ordination(ps13, MDSbray, type="samples", color="Loc", shape = "S_region") +
  theme_bw() +
  stat_ellipse() +
  ggtitle("BrayMDS_Loc_pdam")

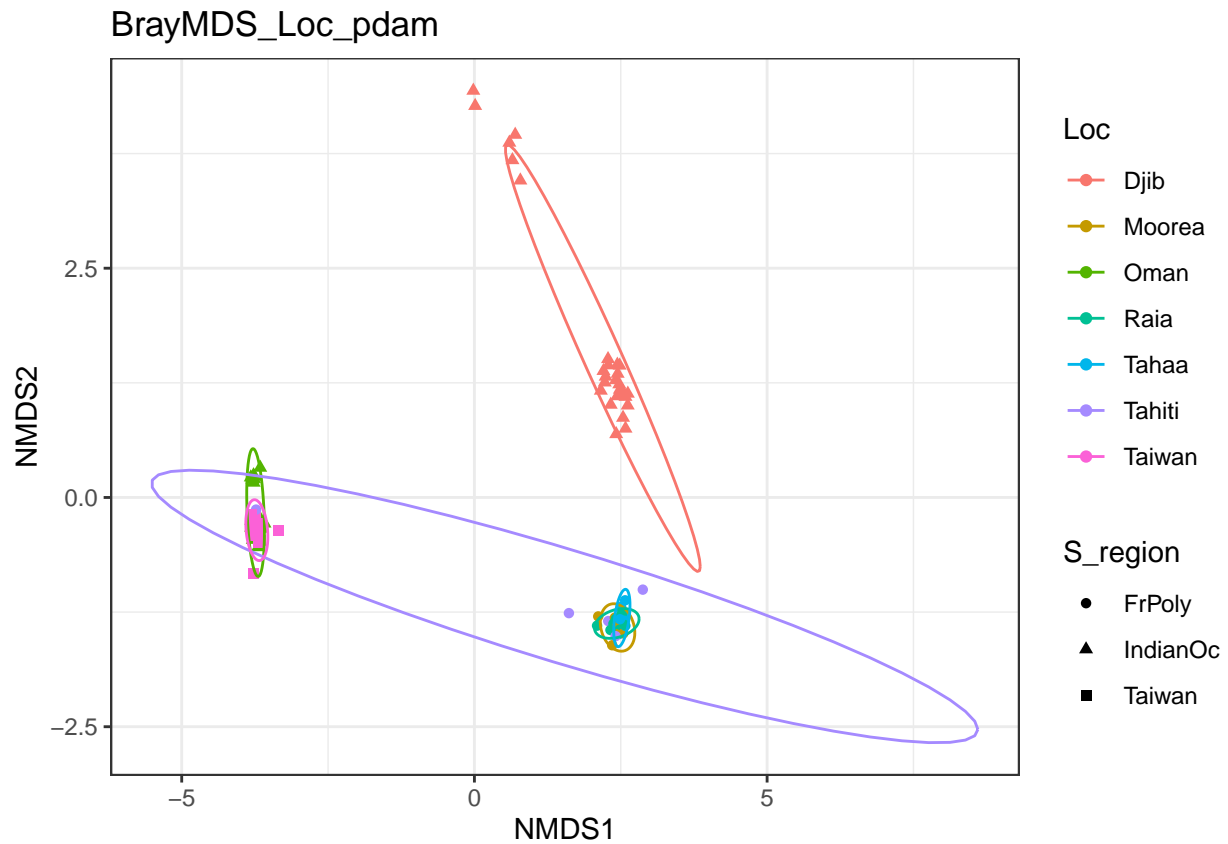
summary (NMDSplot_loc)

## data: NMDS1, NMDS2, Loc, Yr, Spec, Exp_cond, Code, Repro, Month,
##   Season, S_region, L_region, Exact.date, Tbl_bin, T_bleach, DHW,
##   DHW_cat, SST_a, Coord_X, Coord_Y, Primer, Pub, Note [91x23]
## mapping: colour = ~Loc, shape = ~S_region, na.rm = TRUE, x = ~NMDS1, y = ~NMDS2
## faceting: <ggproto object: Class FacetNull, Facet, gg>
##   compute_layout: function
##   draw_back: function
##   draw_front: function
##   draw_labels: function
##   draw_panels: function
##   finish_data: function
##   init_scales: function
##   map_data: function
##   params: list
##   setup_data: function
##   setup_params: function
##   shrink: TRUE
##   train_scales: function
##   vars: function
##   super: <ggproto object: Class FacetNull, Facet, gg>
## -----
## geom_point: na.rm = TRUE
## stat_identity: na.rm = TRUE
## position_identity

```

```
##
## geom_path: na.rm = FALSE
## stat_ellipse: type = t, level = 0.95, segments = 51, na.rm = FALSE
## position_identity
```

```
NMDSplot_loc
```



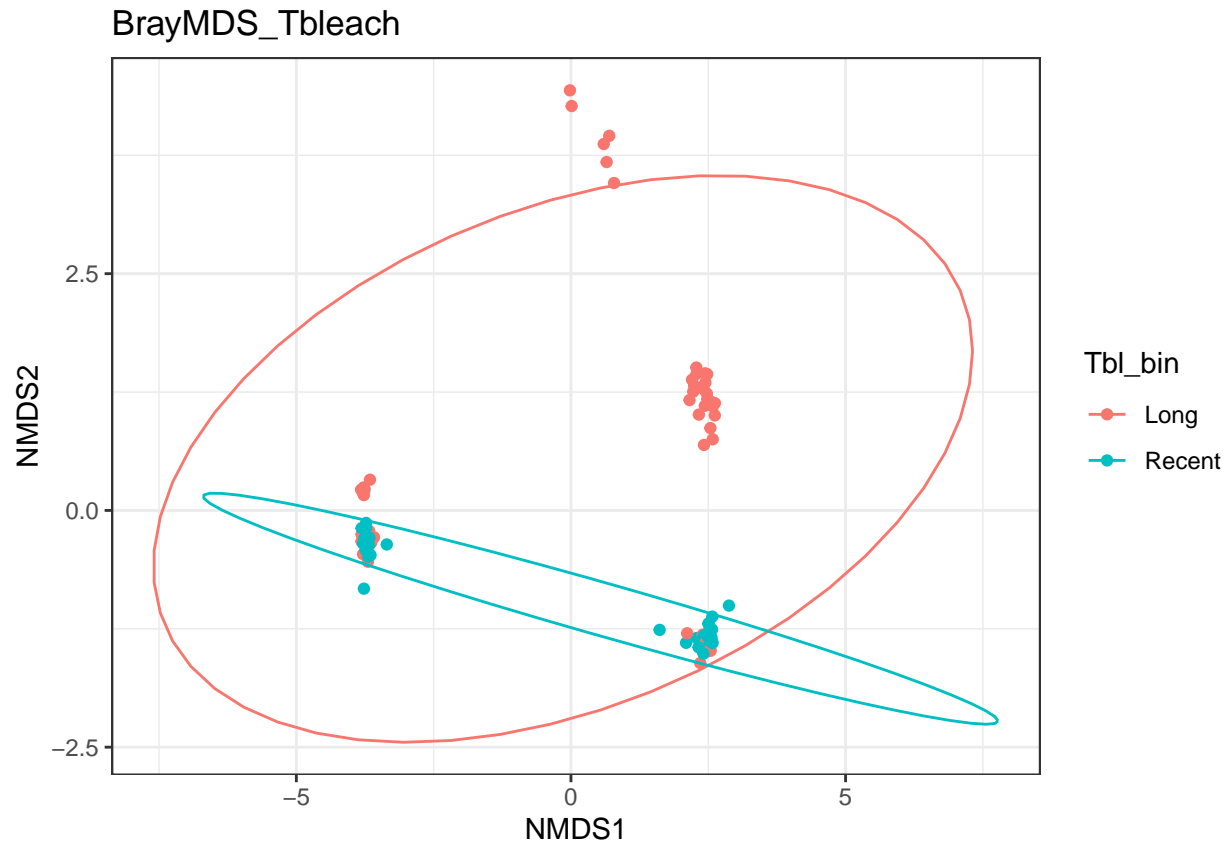
```
ggsave("NMDSplot_loc_pdam_1Nov2021.pdf")
```

```
## Saving 6.5 x 4.5 in image
```

```
# Tbleach

NMDSplot_Tbleach <- plot_ordination(ps13, MDSbray, type="samples", color="Tbl_bin") +
  theme_bw() +
  stat_ellipse() +
  ggtitle("BrayMDS_Tbleach")

NMDSplot_Tbleach
```



```
ggsave("NMDSplot_Tbleach_pdam_1Nov2021.pdf")
```

```
## Saving 6.5 x 4.5 in image
```

```
## Test dispersion/homoscedascity
```

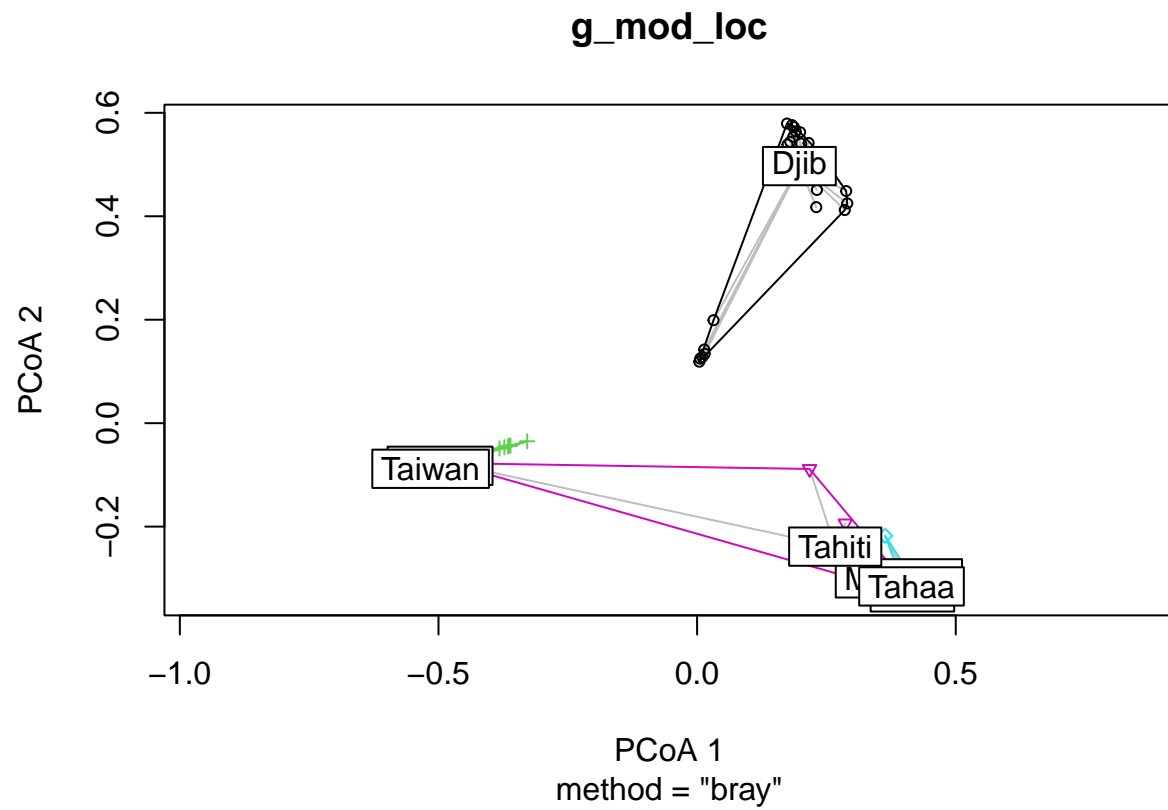
```
##by location
```

```
g_mod_loc <- with(meta, betadisper(bray.dist, Loc))
g_mod_loc
```

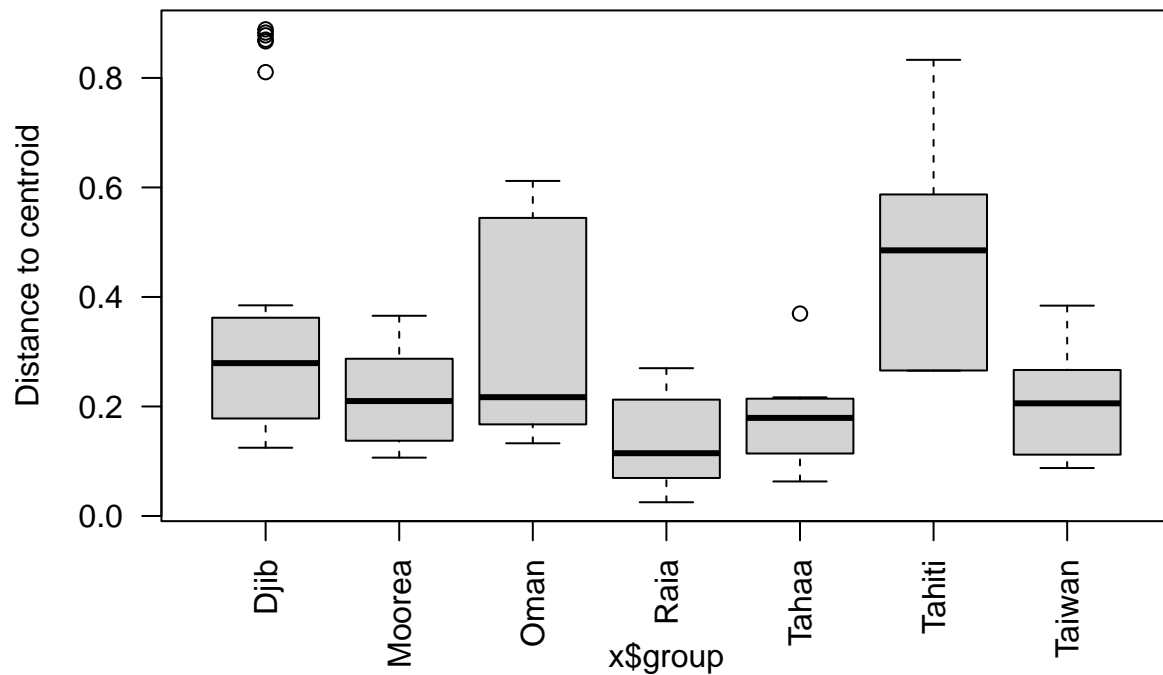
```
##
## Homogeneity of multivariate dispersions
##
## Call: betadisper(d = bray.dist, group = Loc)
##
## No. of Positive Eigenvalues: 55
## No. of Negative Eigenvalues: 35
##
## Average distance to median:
## Djib Moorea Oman Raia Tahaa Tahiti Taiwan
## 0.3726 0.2176 0.3134 0.1360 0.1751 0.4873 0.2016
##
## Eigenvalues for PCoA axes:
## (Showing 8 of 90 eigenvalues)
## PCoA1 PCoA2 PCoA3 PCoA4 PCoA5 PCoA6 PCoA7 PCoA8
```

```
## 13.6789  8.6777  3.4738  2.1797  0.8579  0.6863  0.4543  0.4404
```

```
plot(g_mod_loc)
```



```
boxplot(g_mod_loc, las=2)
```



```
anova(g_mod_loc)
```

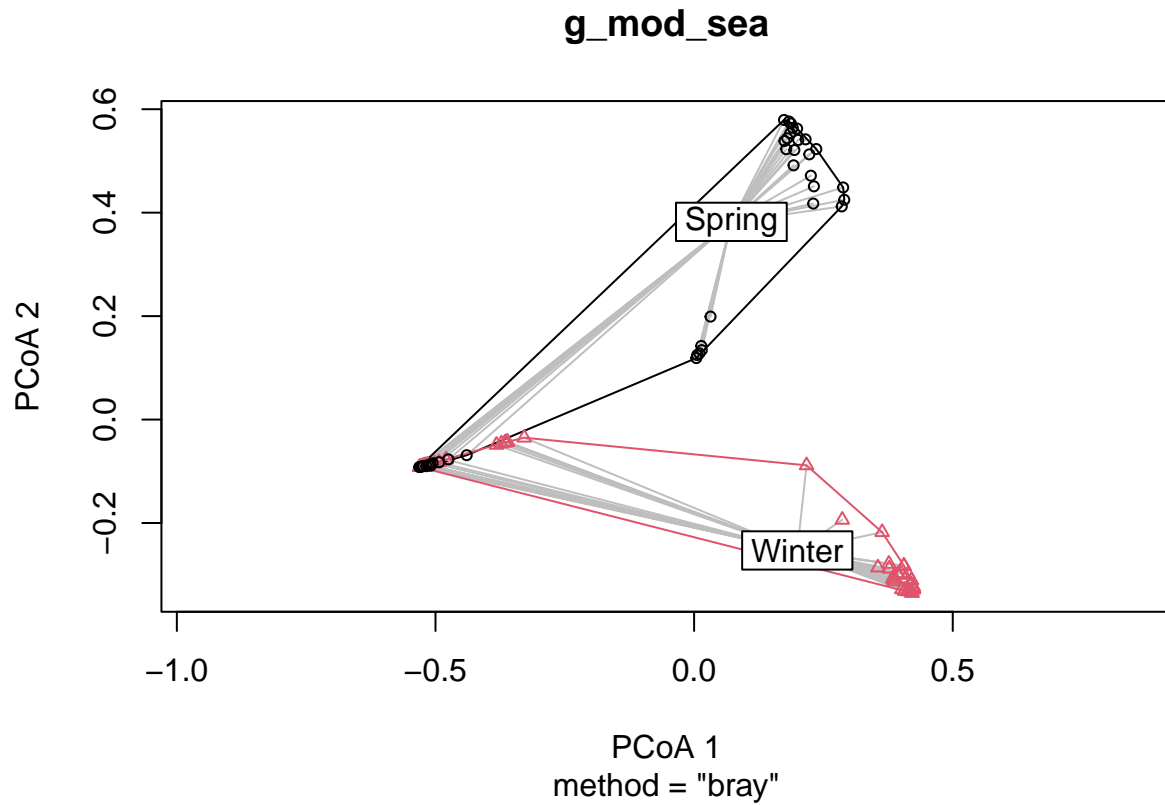
```
## Analysis of Variance Table
##
## Response: Distances
##          Df Sum Sq Mean Sq F value    Pr(>F)
## Groups      6  0.8466  0.141095   3.7104 0.002546 **
## Residuals  84  3.1943  0.038027
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##by season
g_mod_sea <- with(meta, betadisper(bray.dist, Season))
g_mod_sea
```

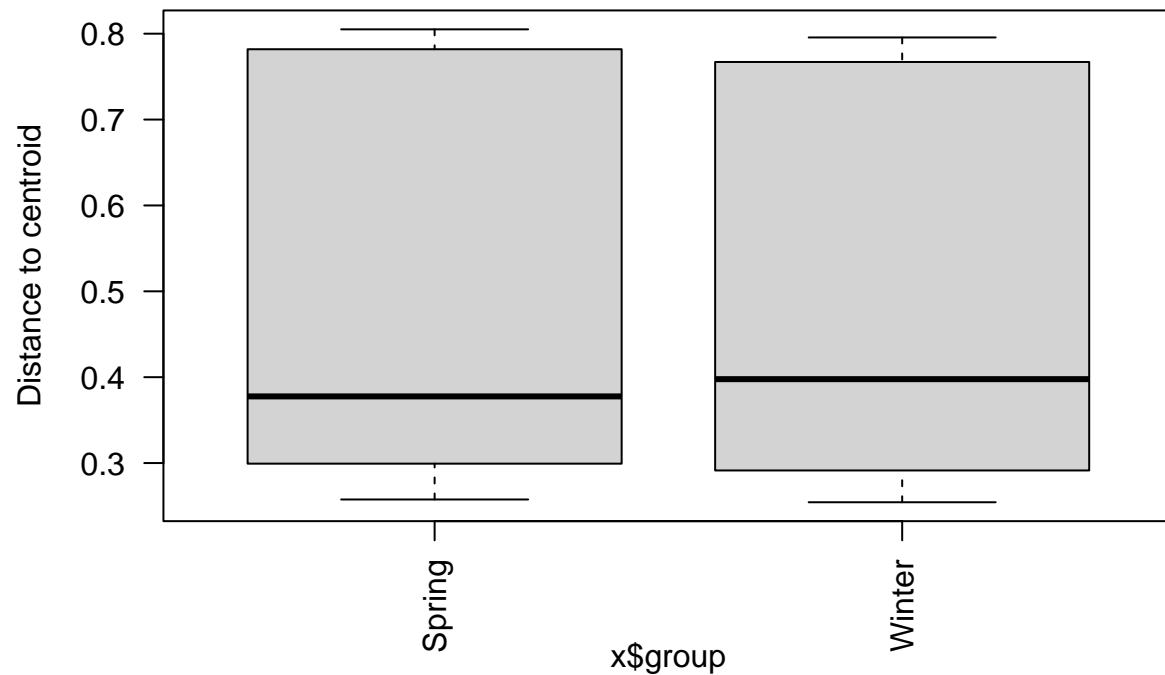
```
##
## Homogeneity of multivariate dispersions
##
## Call: betadisper(d = bray.dist, group = Season)
##
## No. of Positive Eigenvalues: 55
## No. of Negative Eigenvalues: 35
##
## Average distance to median:
## Spring Winter
```

```
## 0.529 0.517
##
## Eigenvalues for PCoA axes:
## (Showing 8 of 90 eigenvalues)
##   PCoA1   PCoA2   PCoA3   PCoA4   PCoA5   PCoA6   PCoA7   PCoA8
## 13.6789  8.6777  3.4738  2.1797  0.8579  0.6863  0.4543  0.4404
```

```
plot(g_mod_sea)
```



```
boxplot(g_mod_sea, las=2)
```



```
anova(g_mod_sea)
```

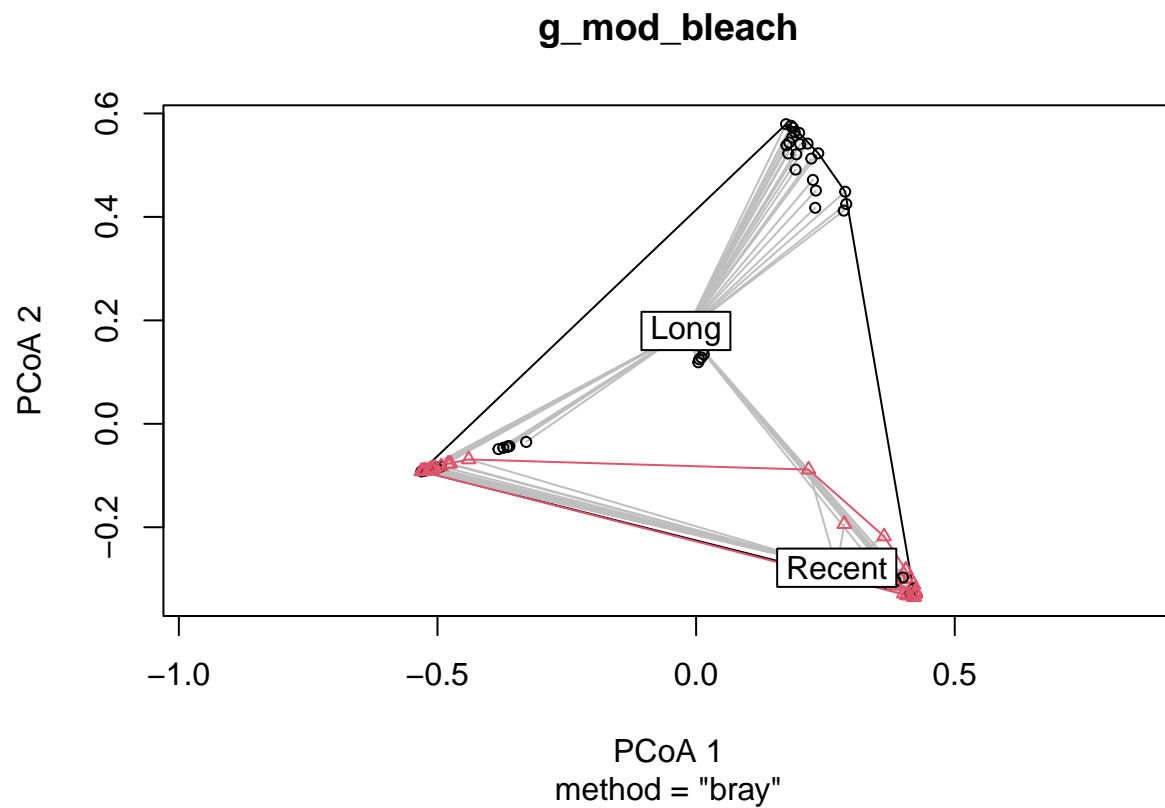
```
## Analysis of Variance Table
##
## Response: Distances
##           Df Sum Sq Mean Sq F value Pr(>F)
## Groups      1  0.0032  0.003203   0.0575  0.811
## Residuals  89  4.9569  0.055695
```

```
##by tbleaching
g_mod_bleach <- with(meta, betadisper(bray.dist, Tbl_bin))
g_mod_bleach
```

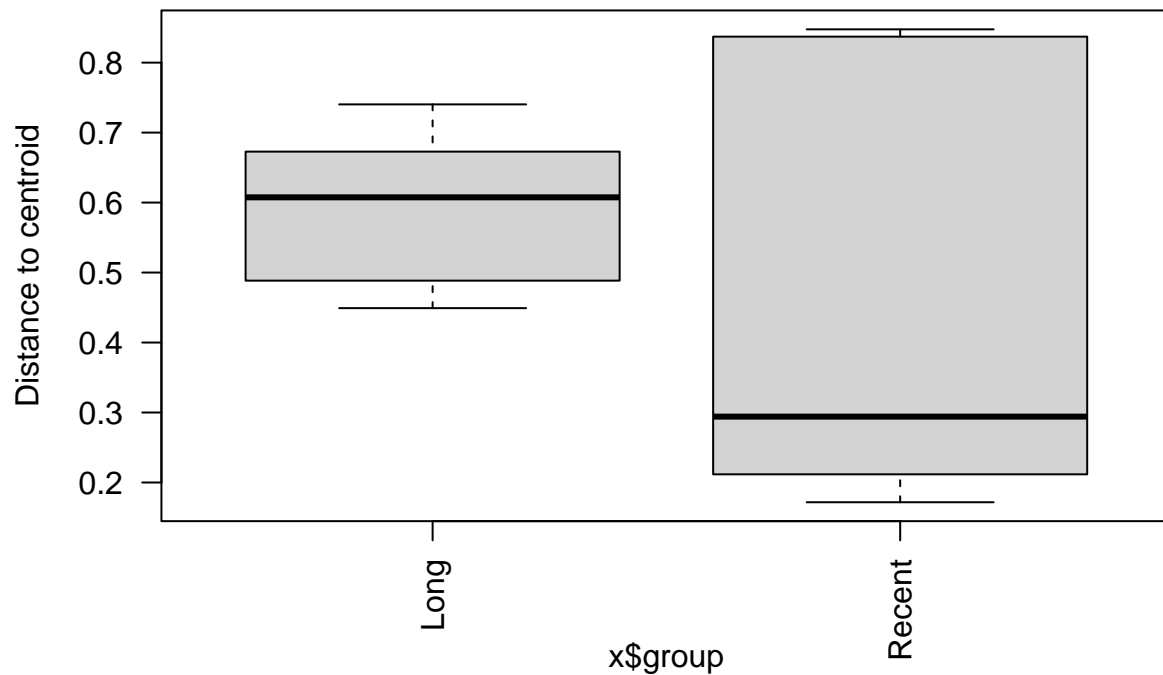
```
##
## Homogeneity of multivariate dispersions
##
## Call: betadisper(d = bray.dist, group = Tbl_bin)
##
## No. of Positive Eigenvalues: 55
## No. of Negative Eigenvalues: 35
##
## Average distance to median:
##   Long Recent
## 0.5903 0.4801
##
```

```
## Eigenvalues for PCoA axes:
## (Showing 8 of 90 eigenvalues)
##   PCoA1  PCoA2  PCoA3  PCoA4  PCoA5  PCoA6  PCoA7  PCoA8
## 13.6789  8.6777  3.4738  2.1797  0.8579  0.6863  0.4543  0.4404
```

```
plot(g_mod_bleach)
```



```
boxplot(g_mod_bleach, las=2)
```

```
anova(g_mod_bleach)
```

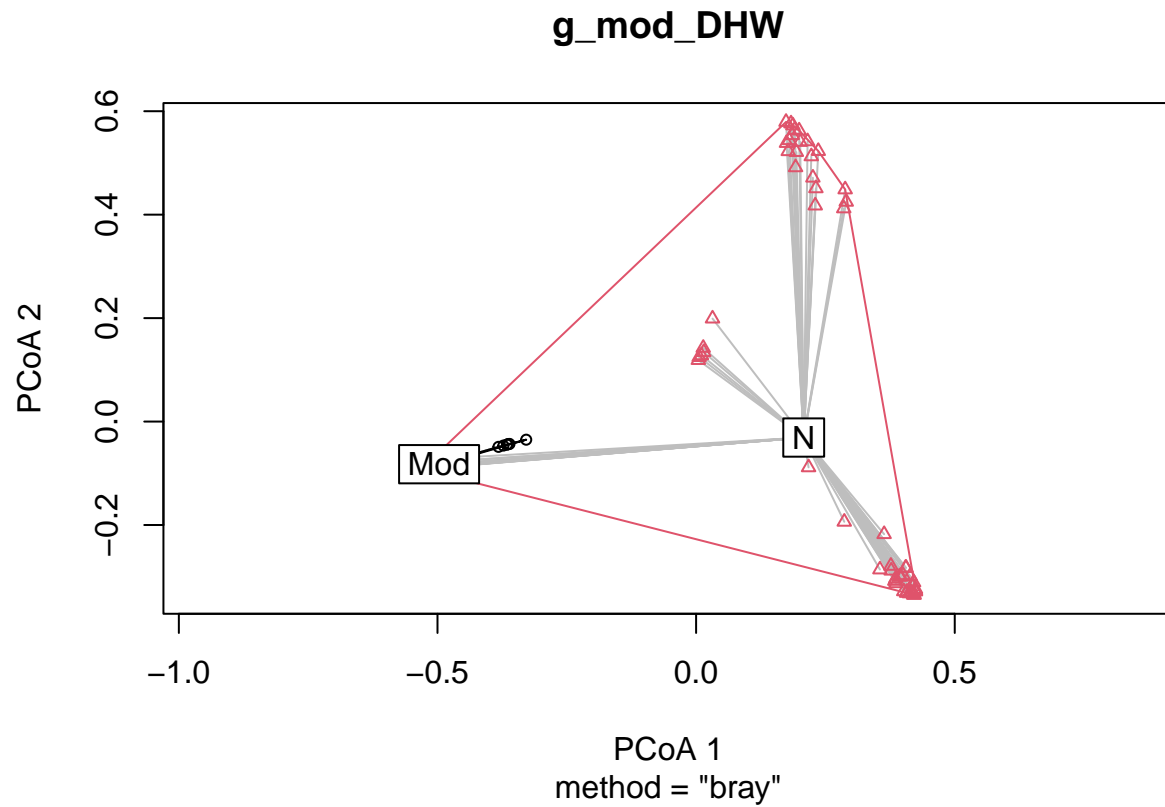
```
## Analysis of Variance Table
##
## Response: Distances
##           Df Sum Sq Mean Sq F value    Pr(>F)
## Groups      1  0.2619   0.26192    6.7142 0.01118 *
## Residuals  89  3.4719   0.03901
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##by DHW
g_mod_DHW <- with(meta, betadisper(bray.dist, DHW_cat))
g_mod_DHW
```

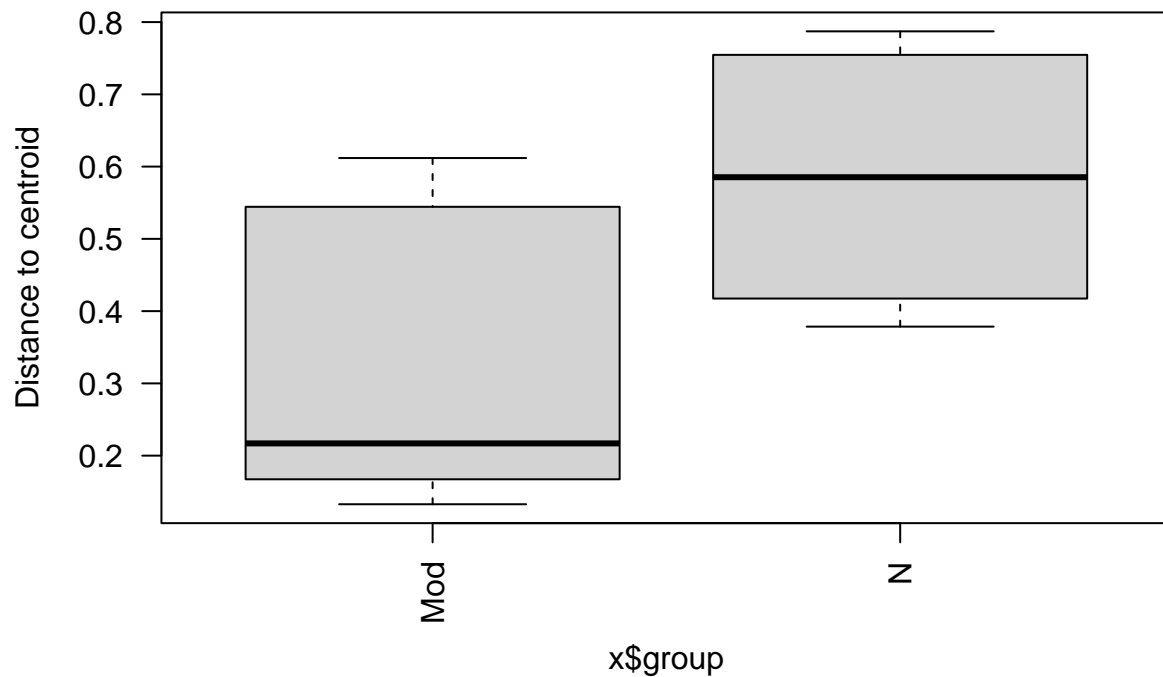
```
##
## Homogeneity of multivariate dispersions
##
## Call: betadisper(d = bray.dist, group = DHW_cat)
##
## No. of Positive Eigenvalues: 55
## No. of Negative Eigenvalues: 35
##
## Average distance to median:
##      Mod      N
```

```
## 0.3134 0.5683
##
## Eigenvalues for PCoA axes:
## (Showing 8 of 90 eigenvalues)
##   PCoA1   PCoA2   PCoA3   PCoA4   PCoA5   PCoA6   PCoA7   PCoA8
## 13.6789  8.6777  3.4738  2.1797  0.8579  0.6863  0.4543  0.4404
```

```
plot(g_mod_DHW)
```



```
boxplot(g_mod_DHW, las=2)
```



```
anova(g_mod_DHW)
```

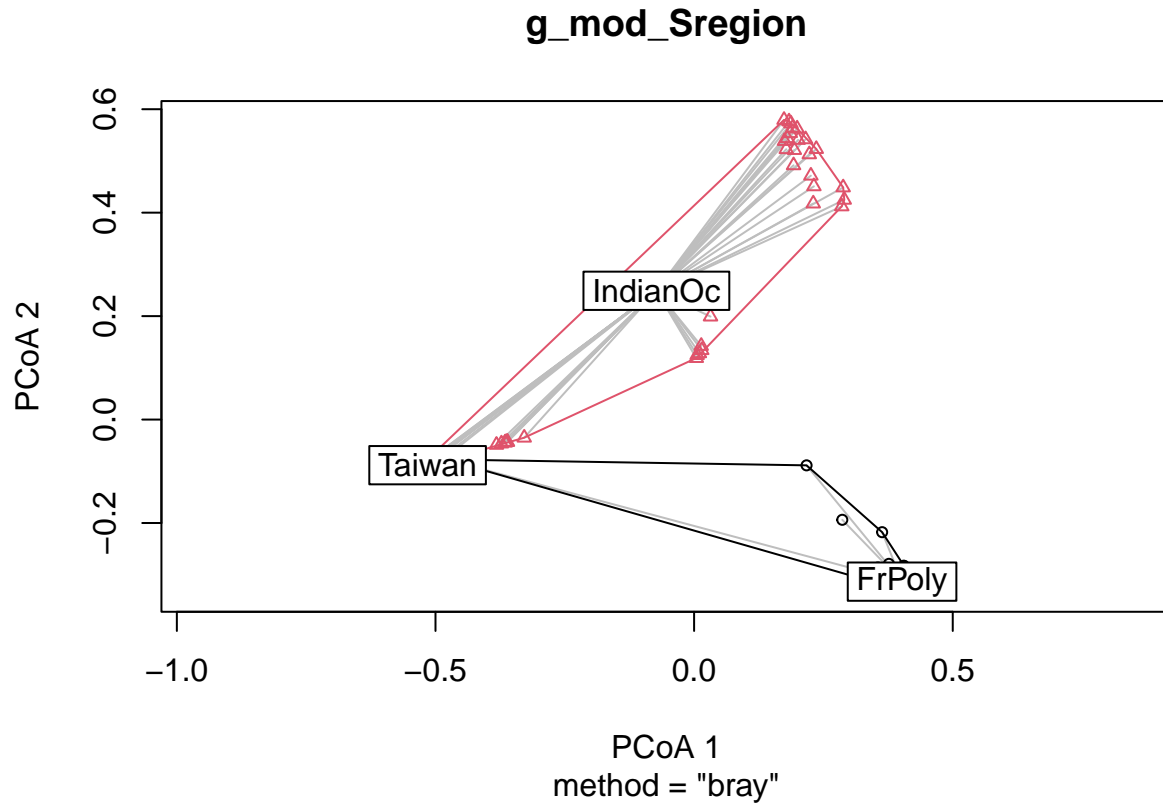
```
## Analysis of Variance Table
##
## Response: Distances
##          Df Sum Sq Mean Sq F value    Pr(>F)
## Groups      1  1.0492   1.04916   42.904 3.605e-09 ***
## Residuals  89  2.1764   0.02445
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
#by S_region
g_mod_Sregion <- with(meta, betadisper(bray.dist, S_region))
g_mod_Sregion
```

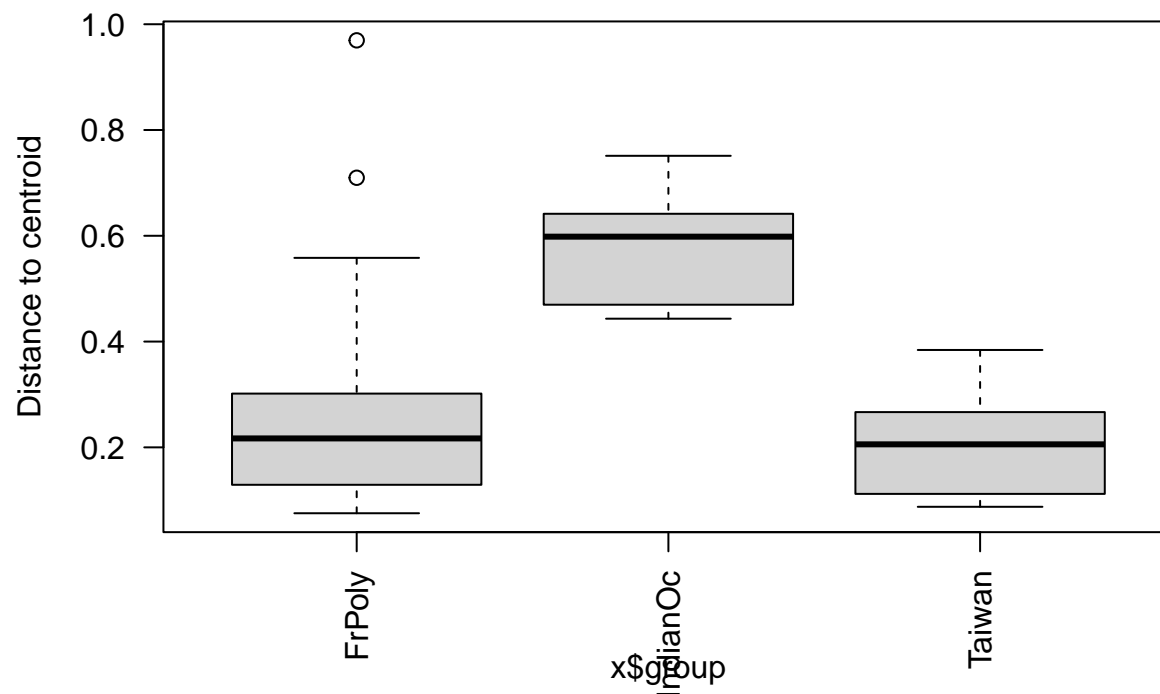
```
##
## Homogeneity of multivariate dispersions
##
## Call: betadisper(d = bray.dist, group = S_region)
##
## No. of Positive Eigenvalues: 55
## No. of Negative Eigenvalues: 35
##
## Average distance to median:
##   FrPoly IndianOc   Taiwan
```

```
## 0.2598 0.5669 0.2016
##
## Eigenvalues for PCoA axes:
## (Showing 8 of 90 eigenvalues)
## PCoA1 PCoA2 PCoA3 PCoA4 PCoA5 PCoA6 PCoA7 PCoA8
## 13.6789 8.6777 3.4738 2.1797 0.8579 0.6863 0.4543 0.4404
```

```
plot(g_mod_Sregion)
```



```
boxplot(g_mod_Sregion, las=2)
```



```
anova(g_mod_Sregion)
```

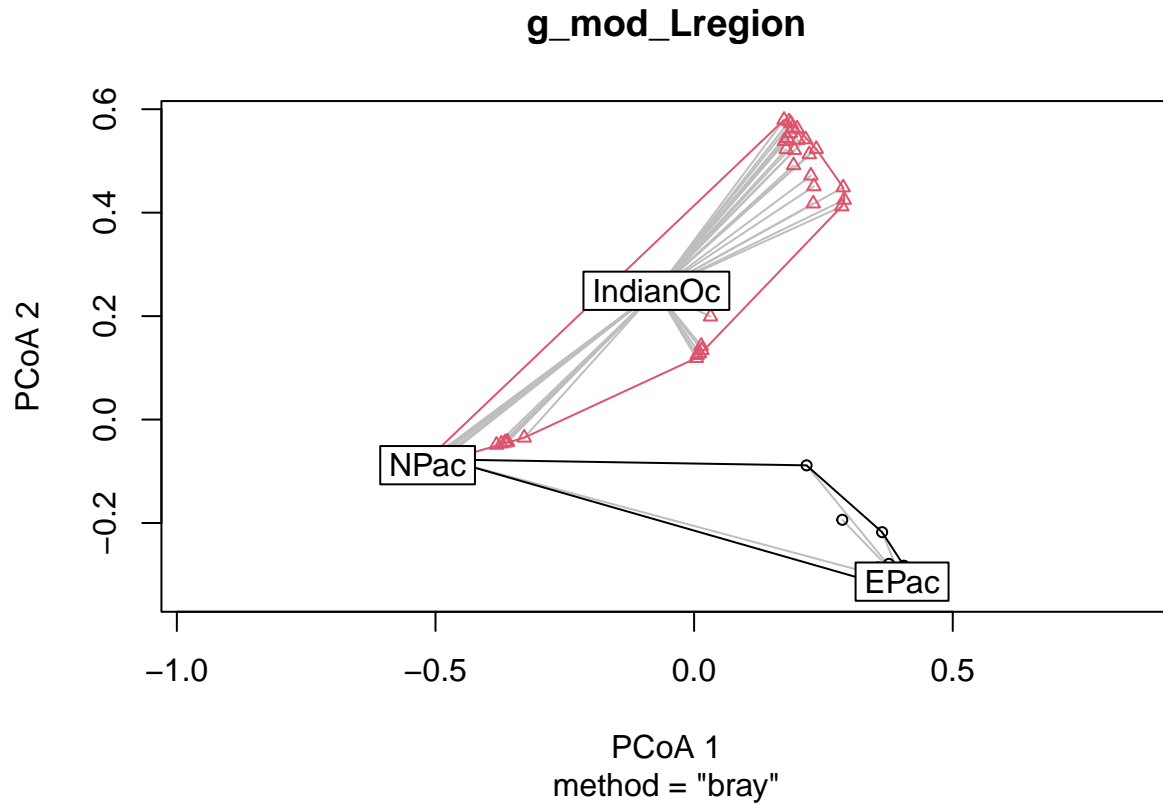
```
## Analysis of Variance Table
##
## Response: Distances
##          Df Sum Sq Mean Sq F value    Pr(>F)
## Groups      2  2.4002   1.20010   61.408 < 2.2e-16 ***
## Residuals  88  1.7198   0.01954
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##by L_region
g_mod_Lregion <- with(meta, betadisper(bray.dist, L_region))
g_mod_Lregion
```

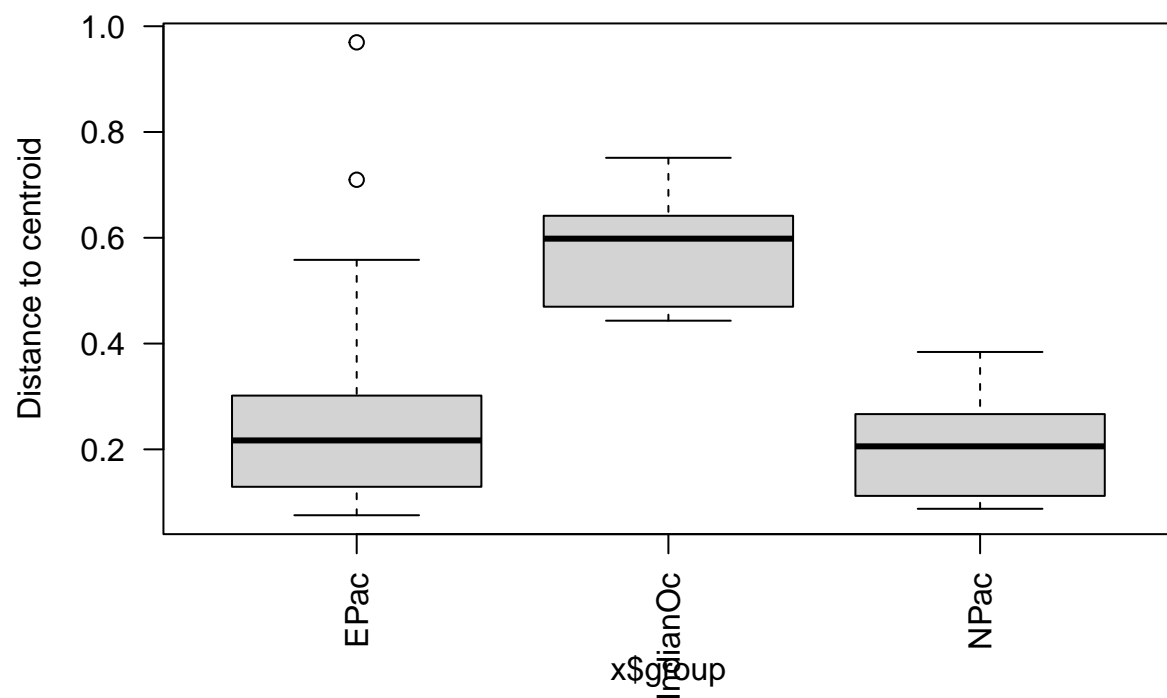
```
##
## Homogeneity of multivariate dispersions
##
## Call: betadisper(d = bray.dist, group = L_region)
##
## No. of Positive Eigenvalues: 55
## No. of Negative Eigenvalues: 35
##
## Average distance to median:
##      EPac IndianOc      NPac
```

```
## 0.2598 0.5669 0.2016
##
## Eigenvalues for PCoA axes:
## (Showing 8 of 90 eigenvalues)
## PCoA1 PCoA2 PCoA3 PCoA4 PCoA5 PCoA6 PCoA7 PCoA8
## 13.6789 8.6777 3.4738 2.1797 0.8579 0.6863 0.4543 0.4404
```

```
plot(g_mod_Lregion)
```



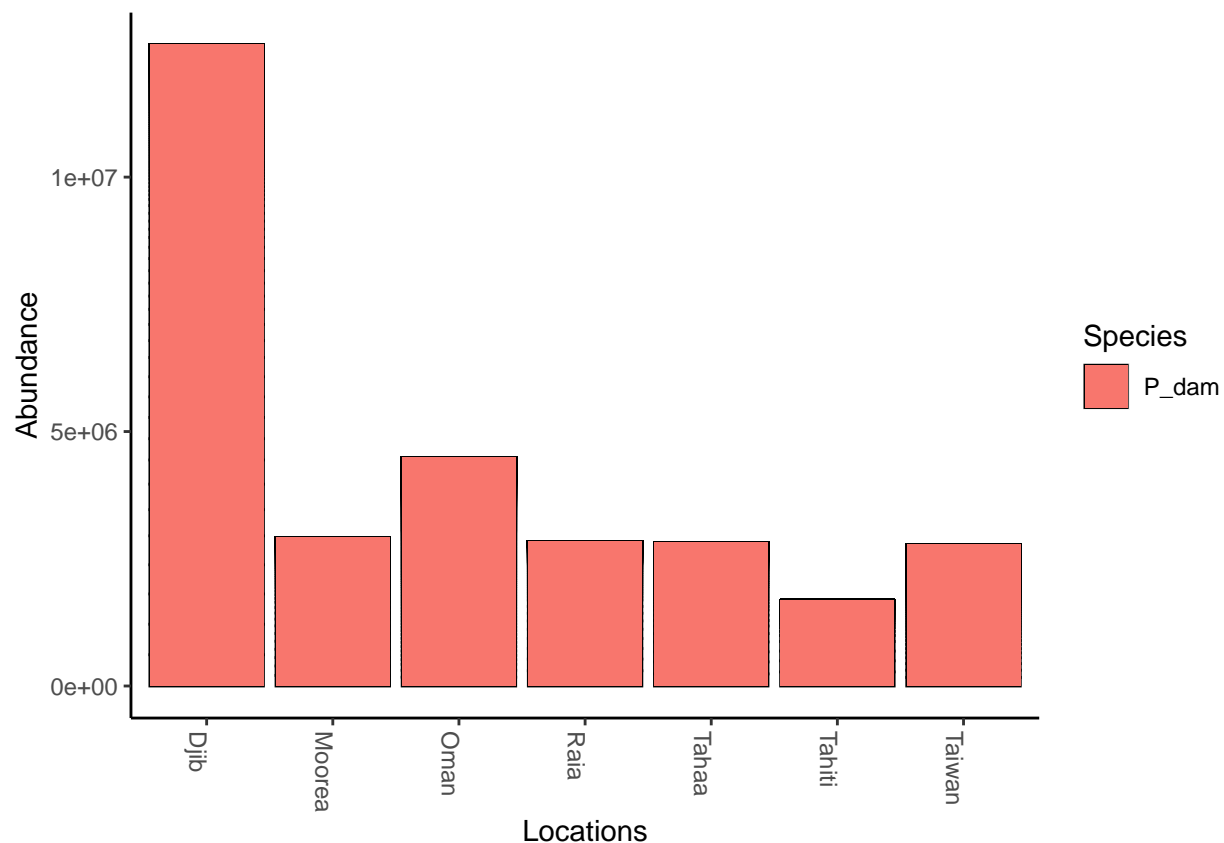
```
boxplot(g_mod_Lregion, las=2)
```



```
anova(g_mod_Lregion)
```

```
## Analysis of Variance Table
##
## Response: Distances
##          Df Sum Sq Mean Sq F value    Pr(>F)
## Groups      2  2.4002   1.20010   61.408 < 2.2e-16 ***
## Residuals  88  1.7198   0.01954
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
specloc <- plot_bar(ps13, x="Loc", fill="Spec") + labs(x = "Locations", y = "Abundance") + geom_bar(position = "stack")
panel.background = element_blank(), axis.line = element_line(colour = "black"))
specloc
```



```
ggsave("specloc.png")
```

```
## Saving 6.5 x 4.5 in image
```

```
##Mantel test
##Set random seed for reproducibility
set.seed(5462)

library(geosphere)

#longitude and latitude
sam_ps13 <- sample_data(ps13)
sam_ps13
```

```
##      Loc   Yr  Spec Exp_cond Code  Repro Month Season S_region L_region
## SRR5963024 Oman 2014 P_dam    31C  Om2    B   June Winter IndianOc IndianOc
## SRR5963025 Oman 2014 P_dam    31C  Om2    B   June Winter IndianOc IndianOc
## SRR5963026 Oman 2014 P_dam    31C  Om3    B   June Winter IndianOc IndianOc
## SRR5963027 Oman 2014 P_dam    31C  Om2    B   June Winter IndianOc IndianOc
## SRR5963028 Oman 2014 P_dam    31C  Om3    B   June Winter IndianOc IndianOc
## SRR5963029 Oman 2014 P_dam    31C  Om3    B   June Winter IndianOc IndianOc
## SRR5963042 Oman 2014 P_dam    31C  Om1    B   June Winter IndianOc IndianOc
## SRR5963043 Oman 2014 P_dam    31C  Om1    B   June Winter IndianOc IndianOc
## SRR5963049 Oman 2014 P_dam    31C  Om1    B   June Winter IndianOc IndianOc
## SRR5963092 Oman 2014 P_dam    34C  Om2    B   June Winter IndianOc IndianOc
```


##	SRR5963093	Oman	2014	P_dam	34C	Om2	B	June	Winter	IndianOc	IndianOc
##	SRR5963099	Oman	2014	P_dam	34C	Om1	B	June	Winter	IndianOc	IndianOc
##	SRR5963100	Oman	2014	P_dam	34C	Om1	B	June	Winter	IndianOc	IndianOc
##	SRR5963101	Oman	2014	P_dam	34C	Om1	B	June	Winter	IndianOc	IndianOc
##	SRR5963102	Oman	2014	P_dam	surface	Om1	B	June	Winter	IndianOc	IndianOc
##	SRR5963106	Oman	2014	P_dam	34C	Om3	B	June	Winter	IndianOc	IndianOc
##	SRR5963107	Oman	2014	P_dam	34C	Om3	B	June	Winter	IndianOc	IndianOc
##	SRR5963108	Oman	2014	P_dam	34C	Om3	B	June	Winter	IndianOc	IndianOc
##	SRR5963109	Oman	2014	P_dam	34C	Om3	B	June	Winter	IndianOc	IndianOc
##	SRR5963110	Oman	2014	P_dam	surface	Om3	B	June	Winter	IndianOc	IndianOc
##	SRR5963111	Oman	2014	P_dam	surface	Om2	B	June	Winter	IndianOc	IndianOc
##	SRR5970158	Moorea	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970160	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970162	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970164	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970166	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970168	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970169	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970174	Tahaa	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970176	Tahaa	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970178	Tahaa	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970181	Tahaa	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970182	Tahiti	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970185	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970187	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970189	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970191	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970193	Tahiti	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970197	Tahaa	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970199	Tahiti	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970201	Tahaa	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970204	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970206	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970208	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970210	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970211	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970213	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970215	Taiwan	2012	P_dam	Nat	<NA>	B	Sep	Spring	Taiwan	NPac
##	SRR5970221	Moorea	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970223	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970230	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970232	Raia	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970234	Moorea	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970236	Raia	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970238	Raia	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970241	Raia	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970243	Moorea	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970245	Moorea	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970247	Tahiti	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970250	Raia	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970252	Raia	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970254	Moorea	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970256	Moorea	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970259	Raia	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac

##	SRR5970262	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970263	Tahiti	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970264	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970266	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970274	Tahaa	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970276	Tahaa	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970278	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970280	Raia	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970282	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970284	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970286	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970288	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970290	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970296	Tahaa	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970300	Tahaa	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970303	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970304	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970306	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970308	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970310	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970312	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970325	Moorea	2008	P_dam	Nat	<NA>	B	June	Winter	FrPoly	EPac
##	SRR5970327	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970329	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970331	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970333	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##	SRR5970335	Djib	2014	P_dam	Nat	<NA>	B	Nov	Spring	IndianOc	IndianOc
##		Exact.date	Tbl_bin	T_bleach	DHW	DHW_cat	SST_a	Coord_X	Coord_Y		
##	SRR5963024	<NA>	Long	15y	4.24	Mod	30.80	23.52000	58.74000		
##	SRR5963025	<NA>	Long	15y	4.24	Mod	30.80	23.52000	58.74000		
##	SRR5963026	<NA>	Long	15y	3.79	Mod	30.80	23.62000	58.60000		
##	SRR5963027	<NA>	Long	15y	4.24	Mod	30.80	23.52000	58.74000		
##	SRR5963028	<NA>	Long	15y	3.79	Mod	30.80	23.62000	58.60000		
##	SRR5963029	<NA>	Long	15y	3.79	Mod	30.80	23.62000	58.60000		
##	SRR5963042	<NA>	Long	15y	4.28	Mod	30.80	23.50000	58.75000		
##	SRR5963043	<NA>	Long	15y	4.28	Mod	30.80	23.50000	58.75000		
##	SRR5963049	<NA>	Long	15y	4.28	Mod	30.80	23.50000	58.75000		
##	SRR5963092	<NA>	Long	15y	4.24	Mod	30.80	23.52000	58.74000		
##	SRR5963093	<NA>	Long	15y	4.24	Mod	30.80	23.52000	58.74000		
##	SRR5963099	<NA>	Long	15y	4.28	Mod	30.80	23.50000	58.75000		
##	SRR5963100	<NA>	Long	15y	4.28	Mod	30.80	23.50000	58.75000		
##	SRR5963101	<NA>	Long	15y	4.28	Mod	30.80	23.50000	58.75000		
##	SRR5963102	<NA>	Long	15y	4.28	Mod	30.80	23.50000	58.75000		
##	SRR5963106	<NA>	Long	15y	3.79	Mod	30.80	23.62000	58.60000		
##	SRR5963107	<NA>	Long	15y	3.79	Mod	30.80	23.62000	58.60000		
##	SRR5963108	<NA>	Long	15y	3.79	Mod	30.80	23.62000	58.60000		
##	SRR5963109	<NA>	Long	15y	3.79	Mod	30.80	23.62000	58.60000		
##	SRR5963110	<NA>	Long	15y	3.79	Mod	30.80	23.62000	58.60000		
##	SRR5963111	<NA>	Long	15y	4.24	Mod	30.80	23.52000	58.74000		
##	SRR5970158	<NA>	Long	10y	0.00	N	27.04	-17.48969	-149.89685		
##	SRR5970160	24_Sep	Recent	5y	0.00	N	28.59	21.93020	120.74497		
##	SRR5970162	24_Sep	Recent	5y	0.00	N	28.59	21.93010	120.74497		
##	SRR5970164	24_Sep	Recent	5y	0.00	N	28.59	21.93040	120.74497		
##	SRR5970166	24_Sep	Recent	5y	0.00	N	28.59	21.93030	120.74497		

## SRR5970168	24_Sep	Recent	5y	0.00	N	28.59	21.93050	120.74497
## SRR5970169	23_Nov	Long	>15y	0.00	N	29.37	11.77949	42.92435
## SRR5970174	<NA>	Recent	5y	0.00	N	27.19	-16.67674	-151.45526
## SRR5970176	<NA>	Recent	5y	0.00	N	27.19	-16.61418	-151.54275
## SRR5970178	<NA>	Recent	5y	0.00	N	27.19	-16.61418	-151.54275
## SRR5970181	<NA>	Recent	5y	0.00	N	27.19	-16.67674	-151.45526
## SRR5970182	<NA>	Recent	5y	0.00	N	26.86	-17.57443	-149.61974
## SRR5970185	24_Sep	Recent	5y	0.00	N	28.59	21.94544	120.74802
## SRR5970187	24_Sep	Recent	5y	0.00	N	28.59	21.94544	120.74803
## SRR5970189	24_Sep	Recent	5y	0.00	N	28.59	21.94544	120.74803
## SRR5970191	24_Sep	Recent	5y	0.00	N	28.59	21.94544	120.74803
## SRR5970193	<NA>	Recent	5y	0.00	N	26.86	-17.57443	-149.61974
## SRR5970197	<NA>	Recent	5y	0.00	N	27.19	-16.61417	-151.54275
## SRR5970199	<NA>	Recent	5y	0.00	N	26.86	-17.57443	-149.61974
## SRR5970201	<NA>	Recent	5y	0.00	N	27.19	-16.61418	-151.54275
## SRR5970204	23_Nov	Long	>15y	0.00	N	29.11	11.73035	43.22408
## SRR5970206	23_Nov	Long	>15y	0.00	N	29.11	11.73035	43.22408
## SRR5970208	23_Nov	Long	>15y	0.00	N	29.11	11.73035	43.22408
## SRR5970210	23_Nov	Long	>15y	0.00	N	29.11	11.73035	43.22408
## SRR5970211	24_Sep	Recent	5y	0.00	N	28.67	21.99382	120.70630
## SRR5970213	24_Sep	Recent	5y	0.00	N	28.59	21.93060	120.74497
## SRR5970215	24_Sep	Recent	5y	0.00	N	28.67	21.99382	120.70650
## SRR5970221	<NA>	Long	10y	0.00	N	27.04	-17.49214	-149.86898
## SRR5970223	23_Nov	Long	>15y	0.00	N	29.37	11.77949	42.92435
## SRR5970230	23_Nov	Long	>15y	0.00	N	29.37	11.77949	42.92435
## SRR5970232	<NA>	Recent	5y	0.00	N	27.25	-16.78944	-151.39184
## SRR5970234	<NA>	Long	10y	0.00	N	27.04	-17.49214	-149.86898
## SRR5970236	<NA>	Recent	5y	0.00	N	27.25	-16.78945	-151.39184
## SRR5970238	<NA>	Recent	5y	0.00	N	27.25	-16.78944	-151.39184
## SRR5970241	<NA>	Recent	5y	0.00	N	27.25	-16.78945	-151.39184
## SRR5970243	<NA>	Long	10y	0.00	N	27.04	-17.49214	-149.86898
## SRR5970245	<NA>	Long	10y	0.00	N	27.04	-17.49214	-149.86898
## SRR5970247	<NA>	Recent	5y	0.00	N	26.86	-17.57443	-149.61974
## SRR5970250	<NA>	Recent	5y	0.00	N	27.25	-16.78944	-151.39184
## SRR5970252	<NA>	Recent	5y	0.00	N	27.25	-16.78944	-151.39184
## SRR5970254	<NA>	Long	10y	0.00	N	27.04	-17.48969	-149.89685
## SRR5970256	<NA>	Long	10y	0.00	N	27.04	-17.48969	-149.89685
## SRR5970259	<NA>	Recent	5y	0.00	N	27.25	-16.78944	-151.39184
## SRR5970262	23_Nov	Long	>15y	0.00	N	29.37	11.77949	42.92435
## SRR5970263	<NA>	Recent	5y	0.00	N	26.86	-17.57443	-149.61974
## SRR5970264	23_Nov	Long	>15y	0.00	N	29.37	11.77949	42.92435
## SRR5970266	23_Nov	Long	>15y	0.00	N	29.37	11.77949	42.92435
## SRR5970274	<NA>	Recent	5y	0.00	N	27.22	-16.67674	-151.45526
## SRR5970276	<NA>	Recent	5y	0.00	N	27.22	-16.67674	-151.45526
## SRR5970278	23_Nov	Long	>15y	0.00	N	29.37	11.77949	42.92435
## SRR5970280	<NA>	Recent	5y	0.00	N	27.25	-16.78944	-151.39184
## SRR5970282	23_Nov	Long	>15y	0.00	N	29.11	11.73035	43.22408
## SRR5970284	23_Nov	Long	>15y	0.00	N	29.35	11.58261	42.79607
## SRR5970286	23_Nov	Long	>15y	0.00	N	29.11	11.73035	43.22408
## SRR5970288	23_Nov	Long	>15y	0.00	N	29.11	11.73035	43.22408
## SRR5970290	23_Nov	Long	>15y	0.00	N	29.35	11.58261	42.79607
## SRR5970296	<NA>	Recent	5y	0.00	N	27.22	-16.67674	-151.45526
## SRR5970300	<NA>	Recent	5y	0.00	N	27.22	-16.67674	-151.45526
## SRR5970303	23_Nov	Long	>15y	0.00	N	29.11	11.73035	43.22408

##	SRR5970304	23_Nov	Long	>15y 0.00	N 29.35	11.58261	42.79607
##	SRR5970306	23_Nov	Long	>15y 0.00	N 29.35	11.58261	42.79607
##	SRR5970308	23_Nov	Long	>15y 0.00	N 29.35	11.58261	42.79607
##	SRR5970310	23_Nov	Long	>15y 0.00	N 29.35	11.58261	42.79607
##	SRR5970312	23_Nov	Long	>15y 0.00	N 29.35	11.58261	42.79607
##	SRR5970325	<NA>	Long	10y 0.00	N 27.04	-17.48969	-149.89685
##	SRR5970327	23_Nov	Long	>15y 0.00	N 29.37	11.77949	42.92435
##	SRR5970329	23_Nov	Long	>15y 0.00	N 29.37	11.77949	42.92435
##	SRR5970331	23_Nov	Long	>15y 0.00	N 29.37	11.77949	42.92435
##	SRR5970333	23_Nov	Long	>15y 0.00	N 29.37	11.77949	42.92435
##	SRR5970335	23_Nov	Long	>15y 0.00	N 29.37	11.77949	42.92435
##	Primer						
##	SRR5963024	ITS-DINO					
##	SRR5963025	ITS-DINO					
##	SRR5963026	ITS-DINO					
##	SRR5963027	ITS-DINO					
##	SRR5963028	ITS-DINO					
##	SRR5963029	ITS-DINO					
##	SRR5963042	ITS-DINO					
##	SRR5963043	ITS-DINO					
##	SRR5963049	ITS-DINO					
##	SRR5963092	ITS-DINO					
##	SRR5963093	ITS-DINO					
##	SRR5963099	ITS-DINO					
##	SRR5963100	ITS-DINO					
##	SRR5963101	ITS-DINO					
##	SRR5963102	ITS-DINO					
##	SRR5963106	ITS-DINO					
##	SRR5963107	ITS-DINO					
##	SRR5963108	ITS-DINO					
##	SRR5963109	ITS-DINO					
##	SRR5963110	ITS-DINO					
##	SRR5963111	ITS-DINO					
##	SRR5970158	ITS-DINO					
##	SRR5970160	ITS-DINO					
##	SRR5970162	ITS-DINO					
##	SRR5970164	ITS-DINO					
##	SRR5970166	ITS-DINO					
##	SRR5970168	ITS-DINO					
##	SRR5970169	ITS-DINO					
##	SRR5970174	ITS-DINO					
##	SRR5970176	ITS-DINO					
##	SRR5970178	ITS-DINO					
##	SRR5970181	ITS-DINO					
##	SRR5970182	ITS-DINO					
##	SRR5970185	ITS-DINO					
##	SRR5970187	ITS-DINO					
##	SRR5970189	ITS-DINO					
##	SRR5970191	ITS-DINO					
##	SRR5970193	ITS-DINO					
##	SRR5970197	ITS-DINO					
##	SRR5970199	ITS-DINO					
##	SRR5970201	ITS-DINO					
##	SRR5970204	ITS-DINO					

SRR5970206 ITS-DINO
 ## SRR5970208 ITS-DINO
 ## SRR5970210 ITS-DINO
 ## SRR5970211 ITS-DINO
 ## SRR5970213 ITS-DINO
 ## SRR5970215 ITS-DINO
 ## SRR5970221 ITS-DINO
 ## SRR5970223 ITS-DINO
 ## SRR5970230 ITS-DINO
 ## SRR5970232 ITS-DINO
 ## SRR5970234 ITS-DINO
 ## SRR5970236 ITS-DINO
 ## SRR5970238 ITS-DINO
 ## SRR5970241 ITS-DINO
 ## SRR5970243 ITS-DINO
 ## SRR5970245 ITS-DINO
 ## SRR5970247 ITS-DINO
 ## SRR5970250 ITS-DINO
 ## SRR5970252 ITS-DINO
 ## SRR5970254 ITS-DINO
 ## SRR5970256 ITS-DINO
 ## SRR5970259 ITS-DINO
 ## SRR5970262 ITS-DINO
 ## SRR5970263 ITS-DINO
 ## SRR5970264 ITS-DINO
 ## SRR5970266 ITS-DINO
 ## SRR5970274 ITS-DINO
 ## SRR5970276 ITS-DINO
 ## SRR5970278 ITS-DINO
 ## SRR5970280 ITS-DINO
 ## SRR5970282 ITS-DINO
 ## SRR5970284 ITS-DINO
 ## SRR5970286 ITS-DINO
 ## SRR5970288 ITS-DINO
 ## SRR5970290 ITS-DINO
 ## SRR5970296 ITS-DINO
 ## SRR5970300 ITS-DINO
 ## SRR5970303 ITS-DINO
 ## SRR5970304 ITS-DINO
 ## SRR5970306 ITS-DINO
 ## SRR5970308 ITS-DINO
 ## SRR5970310 ITS-DINO
 ## SRR5970312 ITS-DINO
 ## SRR5970325 ITS-DINO
 ## SRR5970327 ITS-DINO
 ## SRR5970329 ITS-DINO
 ## SRR5970331 ITS-DINO
 ## SRR5970333 ITS-DINO
 ## SRR5970335 ITS-DINO
 ##

Pub

SRR5963024 <https://www.biorxiv.org/content/10.1101/398602v4.full.pdf>
 ## SRR5963025 <https://www.biorxiv.org/content/10.1101/398602v4.full.pdf>
 ## SRR5963026 <https://www.biorxiv.org/content/10.1101/398602v4.full.pdf>
 ## SRR5963027 <https://www.biorxiv.org/content/10.1101/398602v4.full.pdf>

[illegible]

[illegible]

SRR5963111 Colonies said to be "Pocillopora damicornis-like"; based on ORF and microsatellites, all
 ## SRR5970158
 ## SRR5970160
 ## SRR5970162
 ## SRR5970164
 ## SRR5970166
 ## SRR5970168
 ## SRR5970169 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970174 Last mas
 ## SRR5970176 Last mas
 ## SRR5970178 Last mas
 ## SRR5970181 Last mas
 ## SRR5970182 Last mas
 ## SRR5970185
 ## SRR5970187
 ## SRR5970189
 ## SRR5970191
 ## SRR5970193 Last mas
 ## SRR5970197 Last mas
 ## SRR5970199 Last mas
 ## SRR5970201 Last mas
 ## SRR5970204 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970206 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970208 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970210 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970211
 ## SRR5970213
 ## SRR5970215
 ## SRR5970221
 ## SRR5970223 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970230 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970232 Last mas
 ## SRR5970234
 ## SRR5970236 Last mas
 ## SRR5970238 Last mas
 ## SRR5970241 Last mas
 ## SRR5970243
 ## SRR5970245
 ## SRR5970247 Last mas
 ## SRR5970250 Last mas
 ## SRR5970252 Last mas
 ## SRR5970254
 ## SRR5970256
 ## SRR5970259 Last mas
 ## SRR5970262 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970263 Last mas
 ## SRR5970264 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970266 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970274 Last mas
 ## SRR5970276 Last mas
 ## SRR5970278 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970280 Last mas
 ## SRR5970282 Last mass bleaching event in 1998 after ENSO; no p
 ## SRR5970284 Last mass bleaching event in 1998 after ENSO; no p


```

## SRR5970286 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970288 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970290 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970296 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970300 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970303 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970304 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970306 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970308 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970310 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970312 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970325 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970327 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970329 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970331 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970333 Last mass bleaching event in 1998 after ENSO; no p
## SRR5970335 Last mass bleaching event in 1998 after ENSO; no p

```

```

geo = data.frame(sam_ps13$Coord_Y, sam_ps13$Coord_X)
geo

```

```

##      sam_ps13.Coord_Y sam_ps13.Coord_X
## 1      58.74000      23.52000
## 2      58.74000      23.52000
## 3      58.60000      23.62000
## 4      58.74000      23.52000
## 5      58.60000      23.62000
## 6      58.60000      23.62000
## 7      58.75000      23.50000
## 8      58.75000      23.50000
## 9      58.75000      23.50000
## 10     58.74000      23.52000
## 11     58.74000      23.52000
## 12     58.75000      23.50000
## 13     58.75000      23.50000
## 14     58.75000      23.50000
## 15     58.75000      23.50000
## 16     58.60000      23.62000
## 17     58.60000      23.62000
## 18     58.60000      23.62000
## 19     58.60000      23.62000
## 20     58.60000      23.62000
## 21     58.74000      23.52000
## 22    -149.89685    -17.48969
## 23     120.74497     21.93020
## 24     120.74497     21.93010
## 25     120.74497     21.93040
## 26     120.74497     21.93030
## 27     120.74497     21.93050
## 28      42.92435      11.77949
## 29    -151.45526    -16.67674
## 30    -151.54275    -16.61418
## 31    -151.54275    -16.61418
## 32    -151.45526    -16.67674

```

## 33	-149.61974	-17.57443
## 34	120.74802	21.94544
## 35	120.74803	21.94544
## 36	120.74803	21.94544
## 37	120.74803	21.94544
## 38	-149.61974	-17.57443
## 39	-151.54275	-16.61417
## 40	-149.61974	-17.57443
## 41	-151.54275	-16.61418
## 42	43.22408	11.73035
## 43	43.22408	11.73035
## 44	43.22408	11.73035
## 45	43.22408	11.73035
## 46	120.70630	21.99382
## 47	120.74497	21.93060
## 48	120.70650	21.99382
## 49	-149.86898	-17.49214
## 50	42.92435	11.77949
## 51	42.92435	11.77949
## 52	-151.39184	-16.78944
## 53	-149.86898	-17.49214
## 54	-151.39184	-16.78945
## 55	-151.39184	-16.78944
## 56	-151.39184	-16.78945
## 57	-149.86898	-17.49214
## 58	-149.86898	-17.49214
## 59	-149.61974	-17.57443
## 60	-151.39184	-16.78944
## 61	-151.39184	-16.78944
## 62	-149.89685	-17.48969
## 63	-149.89685	-17.48969
## 64	-151.39184	-16.78944
## 65	42.92435	11.77949
## 66	-149.61974	-17.57443
## 67	42.92435	11.77949
## 68	42.92435	11.77949
## 69	-151.45526	-16.67674
## 70	-151.45526	-16.67674
## 71	42.92435	11.77949
## 72	-151.39184	-16.78944
## 73	43.22408	11.73035
## 74	42.79607	11.58261
## 75	43.22408	11.73035
## 76	43.22408	11.73035
## 77	42.79607	11.58261
## 78	-151.45526	-16.67674
## 79	-151.45526	-16.67674
## 80	43.22408	11.73035
## 81	42.79607	11.58261
## 82	42.79607	11.58261
## 83	42.79607	11.58261
## 84	42.79607	11.58261
## 85	42.79607	11.58261
## 86	-149.89685	-17.48969

```
## 87      42.92435      11.77949
## 88      42.92435      11.77949
## 89      42.92435      11.77949
## 90      42.92435      11.77949
## 91      42.92435      11.77949
```

```
#geographic data frame - haversine distance
d.geo = distm(geo, fun = distVincentyEllipsoid)
dist.geo = as.dist(d.geo)
```

```
##Bray-Curtis
bray.dist = phyloseq::distance(ps13, "bray")
```

```
#bray vs geographic
bray_geo = mantel(bray.dist, dist.geo, method = "spearman", permutations = 9999, na.rm = TRUE)
bray_geo
```

```
##
## Mantel statistic based on Spearman's rank correlation rho
##
## Call:
## mantel(xdis = bray.dist, ydis = dist.geo, method = "spearman",      permutations = 9999, na.rm = TRUE)
##
## Mantel statistic r: 0.3712
##      Significance: 1e-04
##
## Upper quantiles of permutations (null model):
##      90%      95%      97.5%      99%
## 0.0201 0.0313 0.0421 0.0570
## Permutation: free
## Number of permutations: 9999
```

```
#Bray vs environ
```

```
temp = sam_ps13$SST_a
##bleach = sam_ps13$Tb1_bin
```

```
#environmental vectors - euclidean distance
dist.temp = dist(temp, method = "euclidean")
##dist.bleach = dist(bleach, method = "euclidean")
```

```
bray_temp = mantel(bray.dist, dist.temp, method = "spearman", permutations = 9999, na.rm = TRUE)
#bray_bleach = mantel(bray.dist, dist.bleach, method = "spearman", permutations = 9999, na.rm = TRUE)
```

```
##summary results
```

```
bray_temp
```

```
##
## Mantel statistic based on Spearman's rank correlation rho
##
## Call:
```

```
## mantel(xdis = bray.dist, ydis = dist.temp, method = "spearman",      permutations = 9999, na.rm = TR
##
## Mantel statistic r: 0.409
##      Significance: 1e-04
##
## Upper quantiles of permutations (null model):
##      90%      95%  97.5%      99%
## 0.0220 0.0326 0.0438 0.0582
## Permutation: free
## Number of permutations: 9999
```

```
#bray_Bleach
```

```
##Prepare for network analysis; plot only top200TU as too complicated to visualize with full dataset
```

```
##Set random seed for reproducibility
set.seed(711L)
```

```
#Sort the OTUs by abundance and pick the top 20
top200TU.names = names(sort(taxa_sums(ps13), TRUE)[1:20])
```

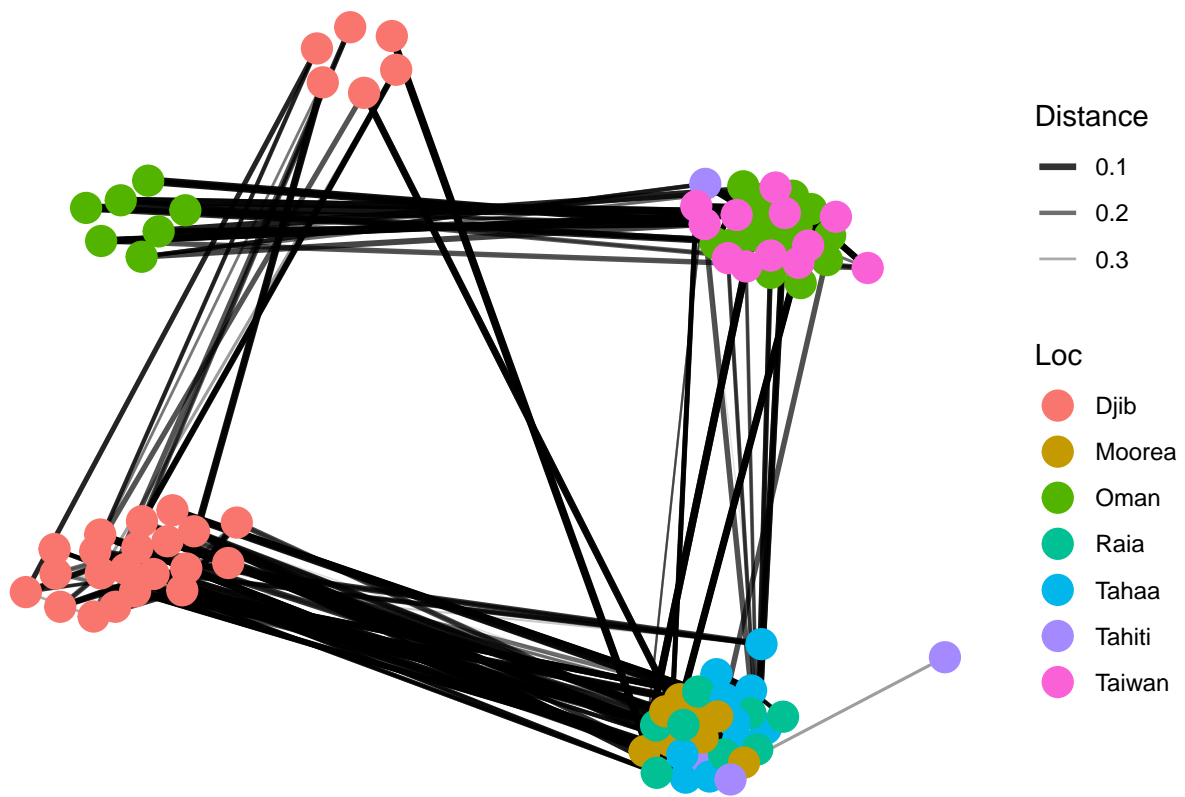
```
#Cut down the physeq.tree data to only the top 20
top200TU = prune_taxa(top200TU.names, ps13)
```

```
top200TU
```

```
## phyloseq-class experiment-level object
## otu_table() OTU Table:      [ 20 taxa and 91 samples ]
## sample_data() Sample Data:  [ 91 samples by 21 sample variables ]
## tax_table() Taxonomy Table:  [ 20 taxa by 2 taxonomic ranks ]
## phy_tree() Phylogenetic Tree: [ 20 tips and 19 internal nodes ]
```

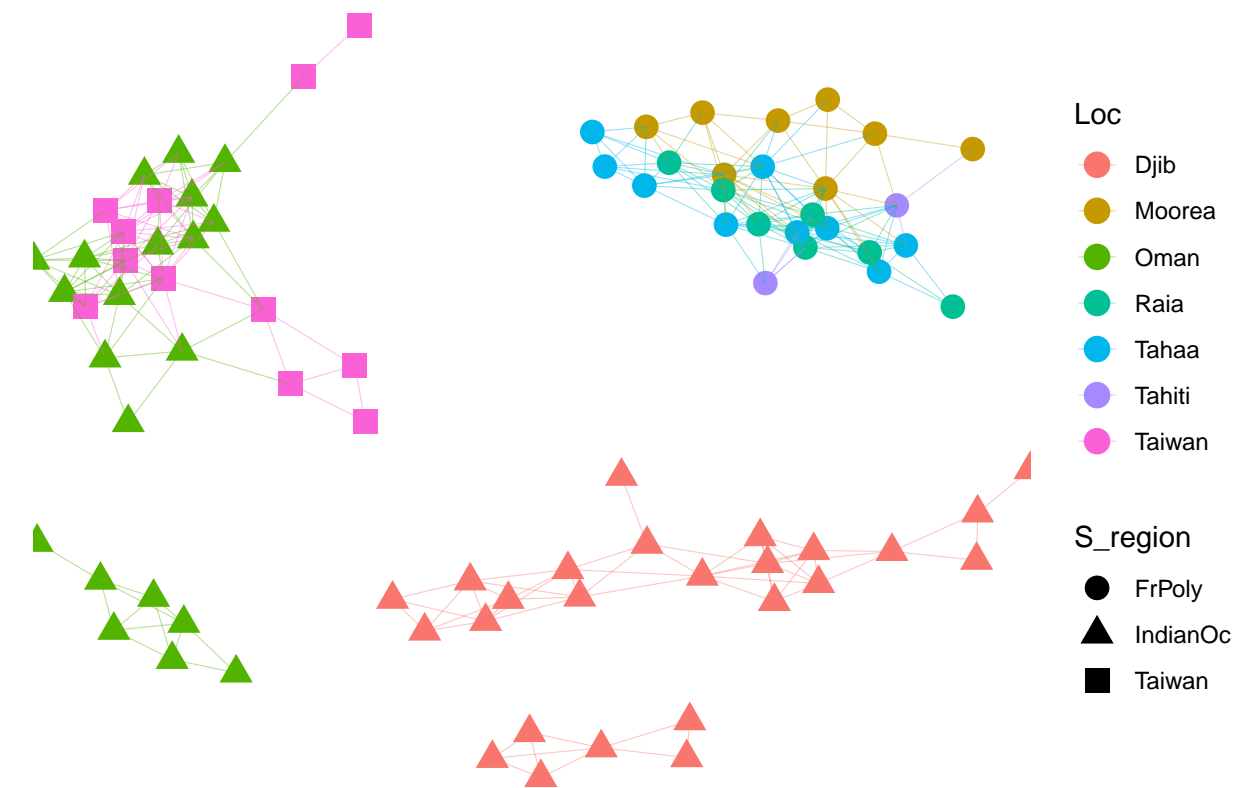
```
#Default settings as a trial
```

```
plot_net(top200TU, maxdist = 0.4, point_label = "Loc")
```

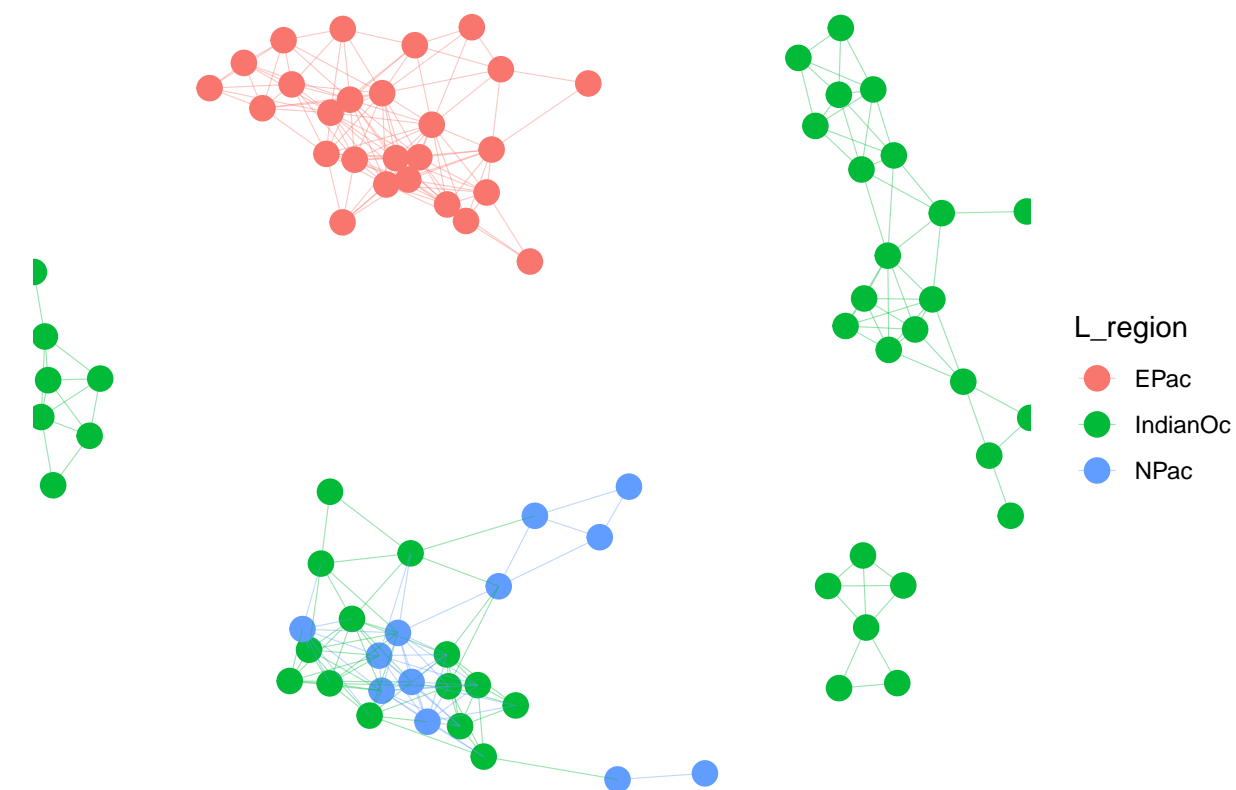
```
## Now explicitly include Bray-Curtis distances
```

```
ig <- make_network(top200TU, dist.fun="bray", max.dist=0.3)
ig2 <- plot_network(ig, top200TU, color="Loc", shape = "S_region", line_weight=0.2, label=NULL) + scale_x("Distance")
par(mar=c(1,1,1,1))
ig2
```



```
ggsave("network_pdam_16Sep2021.pdf", width = 30, height = 20, dpi = 300)
```

```
ig3 <- plot_network(ig, top200TU, color="L_region", line_weight=0.2, label=NULL) + scale_x_discrete(lim=c(1, 100))
ig3
```

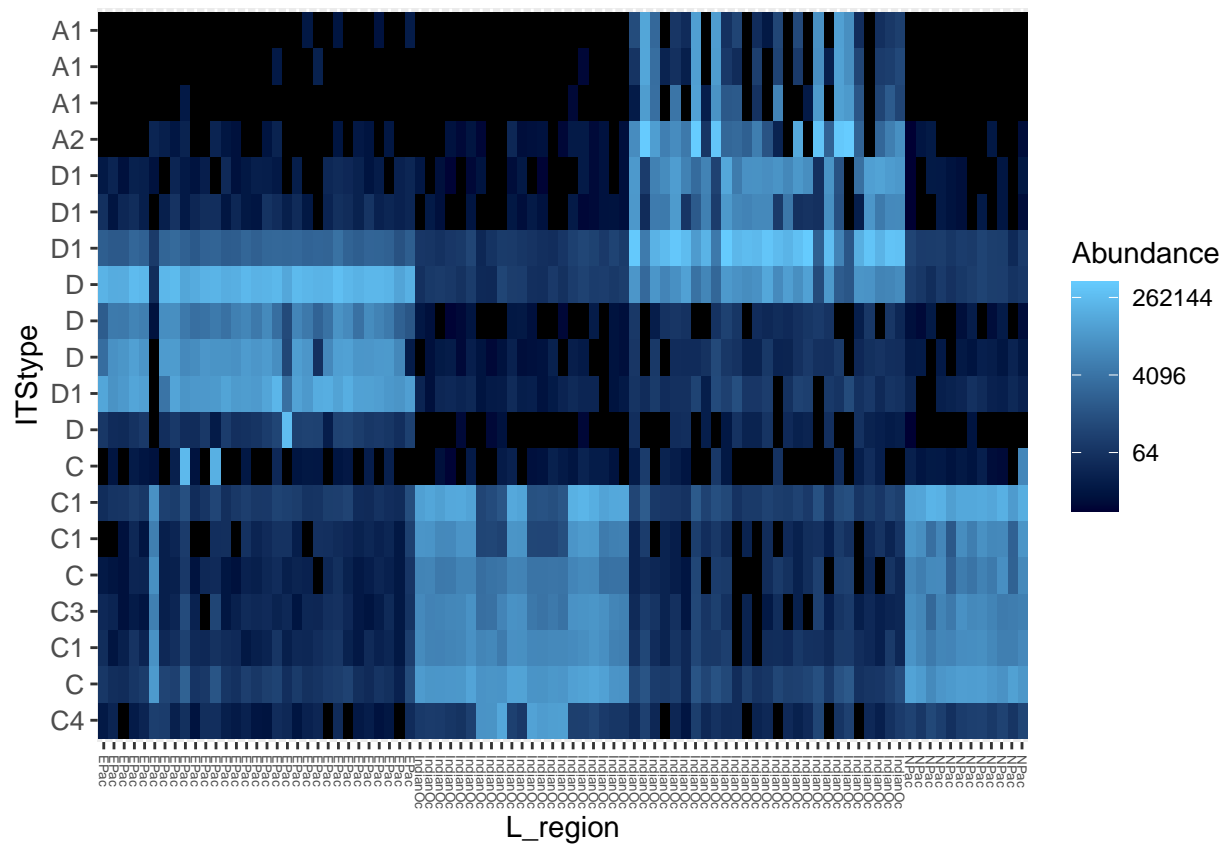


```
ggsave("network_pdam_lregion.pdf", width = 30, height = 20, dpi = 600)
```

```
##Heatmap
```

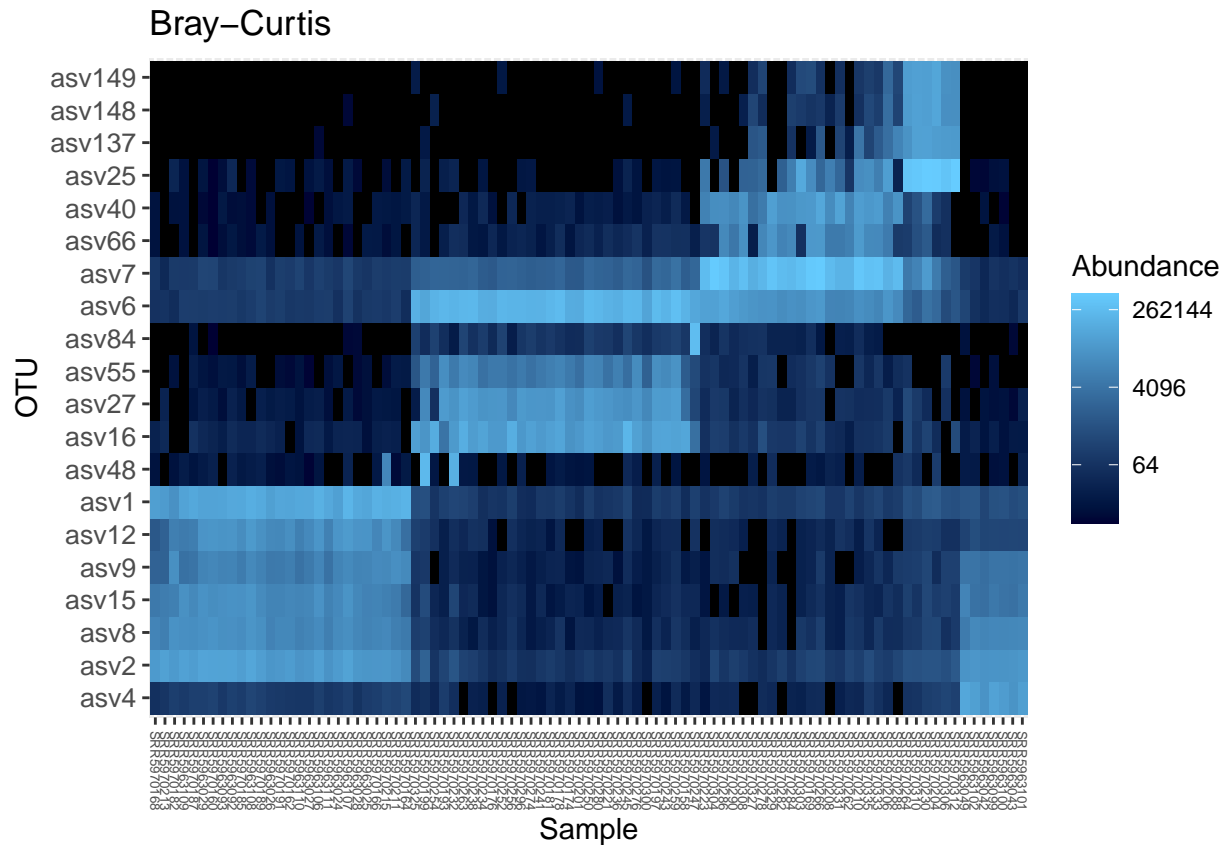
```
plot_heatmap(top200TU, sample.label="L_region", sample.order="L_region", taxa.label="ITStype")
```

```
## Warning: Transformation introduced infinite values in discrete y-axis
```

```
plot_heatmap(top200TU, "NMDS", "bray", title="Bray-Curtis")
```

```
## Warning: Transformation introduced infinite values in discrete y-axis
```



```
##IndicSpecies
```

```
##s_loc <- simper(asv_css, meta$Loc, permutations=100)
#3s_season <- simper(asv_css, meta$Season, permutations=100)
##s_dhw <- simper(asv_css, meta$DHW, permutations=100)
##s_sregion <- simper(asv_css, meta$Loc, permutations=100)
##s_lregion <- simper(asv_css, meta$Season, permutations=100)
```

```
set.seed(15673)
library(xlsx)
library(data.table)
```

```
##
## Attaching package: 'data.table'

## The following object is masked from 'package:SummarizedExperiment':
##
##   shift

## The following object is masked from 'package:GenomicRanges':
##
##   shift

## The following object is masked from 'package:IRanges':
##
##   shift
```

```
## The following objects are masked from 'package:S4Vectors':
##
##   first, second
```

```
## The following objects are masked from 'package:reshape2':
##
##   dcast, melt
```

```
## The following objects are masked from 'package:dplyr':
##
##   between, first, last
```

```
## The following object is masked from 'package:purrr':
##
##   transpose
```

```
inv_loc = multipatt(asv_css, meta$Loc, func = "IndVal.g", control = how(nperm=999))
summary(inv_loc)
```

```
##
## Multilevel pattern analysis
## -----
##
## Association function: IndVal.g
## Significance level (alpha): 0.05
##
## Total number of species: 435
## Selected number of species: 330
## Number of species associated to 1 group: 108
## Number of species associated to 2 groups: 114
## Number of species associated to 3 groups: 62
## Number of species associated to 4 groups: 39
## Number of species associated to 5 groups: 5
## Number of species associated to 6 groups: 2
##
## List of species associated to each combination:
##
## Group Djib #sps. 23
##          stat p.value
## asv40    0.980  0.001 ***
## asv145   0.948  0.001 ***
## asv25    0.943  0.001 ***
## asv474   0.924  0.001 ***
## asv459   0.918  0.001 ***
## asv553   0.914  0.001 ***
## asv529   0.914  0.001 ***
## asv501   0.901  0.001 ***
## asv1471  0.899  0.001 ***
## asv1203  0.893  0.001 ***
## asv1050  0.890  0.001 ***
## asv453   0.888  0.001 ***
## asv1194  0.885  0.001 ***
## asv148   0.882  0.001 ***
```

```

## asv449 0.882 0.001 ***
## asv1600 0.875 0.001 ***
## asv2105 0.873 0.001 ***
## asv149 0.860 0.001 ***
## asv156 0.854 0.001 ***
## asv137 0.839 0.001 ***
## asv201 0.837 0.001 ***
## asv598 0.767 0.004 **
## asv780 0.766 0.001 ***
##
## Group Moorea #sps. 6
##      stat p.value
## asv74 0.999 0.001 ***
## asv533 0.961 0.001 ***
## asv1777 0.707 0.001 ***
## asv816 0.701 0.002 **
## asv857 0.700 0.003 **
## asv318 0.620 0.005 **
##
## Group Oman #sps. 51
##      stat p.value
## asv351 0.872 0.001 ***
## asv516 0.814 0.001 ***
## asv535 0.769 0.001 ***
## asv328 0.759 0.001 ***
## asv139 0.753 0.001 ***
## asv348 0.750 0.001 ***
## asv477 0.716 0.002 **
## asv191 0.706 0.003 **
## asv383 0.695 0.002 **
## asv1897 0.690 0.002 **
## asv3104 0.690 0.001 ***
## asv305 0.689 0.003 **
## asv3329 0.657 0.002 **
## asv177 0.648 0.003 **
## asv2341 0.647 0.004 **
## asv899 0.641 0.002 **
## asv121 0.617 0.003 **
## asv486 0.617 0.008 **
## asv161 0.614 0.010 **
## asv450 0.614 0.006 **
## asv784 0.613 0.004 **
## asv414 0.613 0.005 **
## asv160 0.610 0.009 **
## asv317 0.594 0.010 **
## asv150 0.577 0.006 **
## asv288 0.577 0.006 **
## asv295 0.577 0.005 **
## asv388 0.577 0.005 **
## asv462 0.577 0.006 **
## asv468 0.577 0.006 **
## asv1037 0.577 0.005 **
## asv1039 0.577 0.005 **
## asv1982 0.577 0.004 **

```

```

## asv428 0.576 0.011 *
## asv479 0.571 0.009 **
## asv1799 0.569 0.007 **
## asv460 0.563 0.009 **
## asv248 0.557 0.017 *
## asv47 0.535 0.015 *
## asv138 0.535 0.009 **
## asv1686 0.535 0.020 *
## asv1693 0.535 0.010 **
## asv335 0.533 0.009 **
## asv147 0.528 0.030 *
## asv1265 0.519 0.026 *
## asv426 0.488 0.029 *
## asv703 0.488 0.034 *
## asv2051 0.488 0.025 *
## asv2631 0.488 0.035 *
## asv3414 0.488 0.032 *
## asv280 0.436 0.038 *
##
## Group Taiwan #sps. 28
##      stat p.value
## asv105 0.996 0.001 ***
## asv164 0.986 0.001 ***
## asv78 0.966 0.001 ***
## asv70 0.962 0.001 ***
## asv159 0.947 0.001 ***
## asv235 0.933 0.001 ***
## asv187 0.929 0.001 ***
## asv223 0.926 0.001 ***
## asv60 0.912 0.001 ***
## asv154 0.905 0.001 ***
## asv233 0.904 0.001 ***
## asv236 0.904 0.001 ***
## asv68 0.902 0.001 ***
## asv232 0.900 0.001 ***
## asv200 0.898 0.001 ***
## asv243 0.897 0.001 ***
## asv39 0.887 0.001 ***
## asv444 0.876 0.001 ***
## asv80 0.722 0.001 ***
## asv1149 0.719 0.001 ***
## asv42 0.681 0.002 **
## asv101 0.645 0.001 ***
## asv1594 0.619 0.008 **
## asv943 0.589 0.003 **
## asv215 0.577 0.008 **
## asv1093 0.548 0.006 **
## asv192 0.500 0.008 **
## asv613 0.442 0.035 *
##
## Group Djib+Raia #sps. 1
##      stat p.value
## asv952 0.866 0.001 ***
##

```

```

## Group Djib+Tahiti #sps. 1
##      stat p.value
## asv848 0.828 0.002 **
##
## Group Moorea+Tahiti #sps. 5
##      stat p.value
## asv249 0.996 0.001 ***
## asv95 0.911 0.001 ***
## asv415 0.827 0.001 ***
## asv463 0.650 0.006 **
## asv585 0.452 0.041 *
##
## Group Oman+Tahiti #sps. 6
##      stat p.value
## asv531 0.782 0.006 **
## asv519 0.760 0.001 ***
## asv52 0.679 0.002 **
## asv1544 0.604 0.008 **
## asv2663 0.588 0.008 **
## asv254 0.542 0.049 *
##
## Group Oman+Taiwan #sps. 95
##      stat p.value
## asv133 0.991 0.001 ***
## asv67 0.990 0.001 ***
## asv19 0.987 0.001 ***
## asv89 0.987 0.001 ***
## asv30 0.986 0.001 ***
## asv117 0.983 0.001 ***
## asv38 0.982 0.001 ***
## asv112 0.982 0.001 ***
## asv267 0.981 0.001 ***
## asv176 0.980 0.001 ***
## asv35 0.979 0.001 ***
## asv152 0.977 0.001 ***
## asv88 0.976 0.001 ***
## asv26 0.974 0.001 ***
## asv211 0.972 0.001 ***
## asv46 0.971 0.001 ***
## asv54 0.970 0.001 ***
## asv476 0.969 0.001 ***
## asv239 0.968 0.001 ***
## asv106 0.965 0.001 ***
## asv119 0.962 0.001 ***
## asv611 0.962 0.001 ***
## asv332 0.954 0.001 ***
## asv271 0.954 0.001 ***
## asv399 0.953 0.001 ***
## asv605 0.953 0.001 ***
## asv73 0.952 0.001 ***
## asv94 0.951 0.001 ***
## asv498 0.951 0.001 ***
## asv153 0.947 0.001 ***
## asv312 0.946 0.001 ***

```

##	asv163	0.944	0.001	***
##	asv302	0.942	0.001	***
##	asv127	0.941	0.001	***
##	asv41	0.941	0.001	***
##	asv85	0.935	0.001	***
##	asv123	0.935	0.001	***
##	asv51	0.934	0.001	***
##	asv746	0.928	0.001	***
##	asv440	0.927	0.001	***
##	asv22	0.926	0.001	***
##	asv2013	0.921	0.001	***
##	asv226	0.918	0.001	***
##	asv107	0.916	0.001	***
##	asv90	0.913	0.001	***
##	asv128	0.896	0.001	***
##	asv556	0.890	0.001	***
##	asv240	0.889	0.001	***
##	asv71	0.881	0.001	***
##	asv322	0.870	0.001	***
##	asv155	0.862	0.001	***
##	asv946	0.862	0.001	***
##	asv368	0.862	0.001	***
##	asv1252	0.856	0.001	***
##	asv543	0.853	0.001	***
##	asv1310	0.853	0.001	***
##	asv406	0.846	0.001	***
##	asv772	0.843	0.001	***
##	asv132	0.836	0.001	***
##	asv227	0.835	0.001	***
##	asv157	0.833	0.001	***
##	asv1601	0.824	0.001	***
##	asv202	0.822	0.001	***
##	asv1360	0.821	0.001	***
##	asv179	0.816	0.001	***
##	asv381	0.816	0.001	***
##	asv402	0.816	0.001	***
##	asv323	0.814	0.001	***
##	asv144	0.813	0.001	***
##	asv393	0.798	0.001	***
##	asv1886	0.787	0.001	***
##	asv2248	0.778	0.001	***
##	asv180	0.754	0.003	**
##	asv1729	0.754	0.002	**
##	asv827	0.748	0.001	***
##	asv940	0.739	0.001	***
##	asv1124	0.739	0.001	***
##	asv2157	0.739	0.001	***
##	asv1216	0.730	0.001	***
##	asv2075	0.718	0.002	**
##	asv2356	0.718	0.001	***
##	asv2805	0.718	0.001	***
##	asv2486	0.696	0.002	**
##	asv2916	0.696	0.001	***
##	asv654	0.651	0.001	***

```

## asv2701 0.651 0.002 **
## asv82 0.603 0.005 **
## asv188 0.603 0.009 **
## asv1085 0.603 0.005 **
## asv3304 0.603 0.006 **
## asv265 0.577 0.010 **
## asv427 0.577 0.008 **
## asv321 0.550 0.014 *
## asv1256 0.550 0.014 *
## asv1019 0.492 0.027 *
##
## Group Raia+Tahaa #sps. 3
##      stat p.value
## asv286 0.996 0.001 ***
## asv270 0.969 0.001 ***
## asv1359 0.848 0.001 ***
##
## Group Raia+Tahiti #sps. 1
##      stat p.value
## asv1131 0.516 0.019 *
##
## Group Tahiti+Taiwan #sps. 2
##      stat p.value
## asv753 0.733 0.001 ***
## asv770 0.692 0.004 **
##
## Group Djib+Moorea+Tahiti #sps. 1
##      stat p.value
## asv639 0.842 0.001 ***
##
## Group Djib+Raia+Tahaa #sps. 1
##      stat p.value
## asv66 0.986 0.001 ***
##
## Group Moorea+Raia+Tahaa #sps. 6
##      stat p.value
## asv91 0.999 0.001 ***
## asv166 0.996 0.001 ***
## asv205 0.994 0.001 ***
## asv129 0.990 0.001 ***
## asv559 0.985 0.001 ***
## asv1864 0.858 0.001 ***
##
## Group Moorea+Raia+Tahiti #sps. 1
##      stat p.value
## asv836 0.535 0.029 *
##
## Group Oman+Raia+Taiwan #sps. 2
##      stat p.value
## asv4 0.995 0.001 ***
## asv3180 0.541 0.016 *
##
## Group Oman+Tahiti+Taiwan #sps. 50
##      stat p.value

```



```

## asv33 0.999 0.001 ***
## asv12 0.998 0.001 ***
## asv24 0.972 0.001 ***
## asv44 0.971 0.001 ***
## asv37 0.957 0.001 ***
## asv131 0.956 0.001 ***
## asv863 0.956 0.001 ***
## asv79 0.956 0.001 ***
## asv87 0.953 0.001 ***
## asv136 0.946 0.001 ***
## asv167 0.946 0.001 ***
## asv537 0.946 0.001 ***
## asv609 0.946 0.001 ***
## asv1476 0.932 0.001 ***
## asv607 0.926 0.001 ***
## asv108 0.913 0.001 ***
## asv229 0.903 0.001 ***
## asv563 0.903 0.001 ***
## asv347 0.889 0.001 ***
## asv13 0.882 0.001 ***
## asv1448 0.863 0.001 ***
## asv1156 0.843 0.001 ***
## asv283 0.843 0.001 ***
## asv859 0.843 0.001 ***
## asv1863 0.843 0.001 ***
## asv17 0.827 0.001 ***
## asv185 0.827 0.002 **
## asv269 0.827 0.001 ***
## asv788 0.827 0.001 ***
## asv134 0.811 0.001 ***
## asv125 0.798 0.001 ***
## asv182 0.778 0.002 **
## asv209 0.778 0.001 ***
## asv1108 0.775 0.001 ***
## asv371 0.769 0.001 ***
## asv264 0.761 0.001 ***
## asv922 0.743 0.001 ***
## asv2804 0.743 0.001 ***
## asv405 0.707 0.001 ***
## asv735 0.707 0.001 ***
## asv1247 0.707 0.001 ***
## asv1810 0.707 0.001 ***
## asv505 0.688 0.005 **
## asv825 0.669 0.005 **
## asv2329 0.669 0.003 **
## asv175 0.607 0.014 *
## asv1784 0.607 0.007 **
## asv2718 0.607 0.008 **
## asv446 0.513 0.015 *
## asv242 0.487 0.046 *
##
## Group Raia+Tahiti+Taiwan #sps. 1
##      stat p.value
## asv48 0.872 0.03 *

```

```

##
## Group Djib+Moorea+Raia+Tahiti #sps. 1
##      stat p.value
## asv49 0.959    0.001 ***
##
## Group Djib+Oman+Tahiti+Taiwan #sps. 1
##      stat p.value
## asv43 0.804    0.01 **
##
## Group Moorea+Raia+Tahaa+Tahiti #sps. 37
##      stat p.value
## asv81 1.000    0.001 ***
## asv55 0.999    0.001 ***
## asv62 0.999    0.001 ***
## asv84 0.984    0.017 *
## asv16 0.983    0.003 **
## asv27 0.983    0.001 ***
## asv110 0.983    0.001 ***
## asv417 0.983    0.001 ***
## asv260 0.980    0.001 ***
## asv558 0.975    0.001 ***
## asv431 0.972    0.001 ***
## asv245 0.972    0.001 ***
## asv237 0.968    0.001 ***
## asv862 0.967    0.001 ***
## asv429 0.967    0.001 ***
## asv447 0.967    0.001 ***
## asv467 0.967    0.001 ***
## asv109 0.966    0.001 ***
## asv1031 0.965    0.001 ***
## asv1258 0.964    0.001 ***
## asv327 0.964    0.001 ***
## asv1475 0.963    0.001 ***
## asv820 0.963    0.001 ***
## asv955 0.960    0.001 ***
## asv1778 0.957    0.001 ***
## asv293 0.955    0.001 ***
## asv1785 0.951    0.001 ***
## asv767 0.950    0.001 ***
## asv396 0.948    0.001 ***
## asv1931 0.944    0.001 ***
## asv1465 0.933    0.001 ***
## asv357 0.933    0.001 ***
## asv730 0.904    0.001 ***
## asv297 0.898    0.001 ***
## asv2828 0.880    0.001 ***
## asv142 0.880    0.001 ***
## asv2150 0.835    0.001 ***
##
## Group Djib+Moorea+Raia+Tahaa+Tahiti #sps. 3
##      stat p.value
## asv359 0.937    0.001 ***
## asv682 0.927    0.001 ***
## asv1749 0.861    0.001 ***

```

```
##
## Group Oman+Raia+Tahaa+Tahiti+Taiwan #sps. 2
##      stat p.value
## asv15 0.998 0.001 ***
## asv9 0.998 0.001 ***
##
## Group Djib+Moorea+Raia+Tahaa+Tahiti+Taiwan #sps. 1
##      stat p.value
## asv23 0.999 0.001 ***
##
## Group Moorea+Oman+Raia+Tahaa+Tahiti+Taiwan #sps. 1
##      stat p.value
## asv8 0.999 0.001 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
indisp.sign<-as.data.table(inv_loc$sign, keep.rownames=TRUE)
#add adjusted p-value
indisp.sign[,p.value.bh:=p.adjust(p.value, method="BH")]
#now can select only the indicators with adjusted significant p-values

IndVal_loc = indisp.sign[p.value.bh<=0.05, ]
IndVal_loc
```

```
##          rn s.Djib s.Moorea s.Oman s.Raia s.Tahaa s.Tahiti s.Taiwan index
## 1:   asv4      0      0      1      1      0      0      1     56
## 2:   asv8      0      1      1      1      1      1      1    126
## 3:   asv9      0      0      1      1      1      1      1    119
## 4:  asv12      0      0      1      0      0      1      1     59
## 5:  asv13      0      0      1      0      0      1      1     59
## ---
## 324: asv3104      0      0      1      0      0      0      0      3
## 325: asv3180      0      0      1      1      0      0      1     56
## 326: asv3304      0      0      1      0      0      0      1     22
## 327: asv3329      0      0      1      0      0      0      0      3
## 328: asv3414      0      0      1      0      0      0      0      3
##          stat p.value p.value.bh
## 1: 0.9953327 0.001 0.001574468
## 2: 0.9990148 0.001 0.001574468
## 3: 0.9980955 0.001 0.001574468
## 4: 0.9979479 0.001 0.001574468
## 5: 0.8816859 0.001 0.001574468
## ---
## 324: 0.6900656 0.001 0.001574468
## 325: 0.5410018 0.016 0.019035370
## 326: 0.6030227 0.006 0.007844523
## 327: 0.6574373 0.002 0.002960000
## 328: 0.4879500 0.032 0.036656347
```

```
write.xlsx(IndVal_loc, file = "IndVal_loc_16Sep2021.xlsx")
```

```
inv_blc = multipatt(asv_css, meta$Tbl_bin, func = "IndVal.g", control = how(nperm=999))
summary(inv_blc)
```

```
##
## Multilevel pattern analysis
## -----
##
## Association function: IndVal.g
## Significance level (alpha): 0.05
##
## Total number of species: 435
## Selected number of species: 96
## Number of species associated to 1 group: 96
##
## List of species associated to each combination:
##
## Group Long #sps. 51
##          stat p.value
## asv40    0.896  0.002 **
## asv25    0.856  0.001 ***
## asv145   0.740  0.001 ***
## asv201   0.707  0.001 ***
## asv553   0.705  0.001 ***
## asv156   0.694  0.002 **
## asv639   0.682  0.002 **
## asv453   0.665  0.002 **
## asv952   0.664  0.002 **
## asv474   0.661  0.022 *
## asv1050  0.658  0.002 **
## asv148   0.655  0.001 ***
## asv1203  0.653  0.001 ***
## asv459   0.653  0.002 **
## asv529   0.652  0.003 **
## asv501   0.640  0.003 **
## asv88    0.638  0.023 *
## asv1471  0.635  0.001 ***
## asv1600  0.635  0.002 **
## asv2105  0.632  0.001 ***
## asv1194  0.622  0.003 **
## asv149   0.612  0.003 **
## asv449   0.612  0.002 **
## asv137   0.598  0.003 **
## asv598   0.566  0.006 **
## asv780   0.566  0.005 **
## asv351   0.554  0.018 *
## asv191   0.514  0.025 *
## asv516   0.499  0.005 **
## asv535   0.497  0.002 **
## asv139   0.481  0.030 *
## asv348   0.480  0.015 *
## asv519   0.471  0.011 *
## asv328   0.468  0.031 *
## asv477   0.439  0.023 *
```

```

## asv1897 0.423 0.011 *
## asv3104 0.423 0.008 **
## asv305 0.422 0.035 *
## asv160 0.401 0.020 *
## asv784 0.401 0.026 *
## asv899 0.398 0.033 *
## asv121 0.378 0.030 *
## asv460 0.378 0.031 *
## asv486 0.378 0.035 *
## asv150 0.354 0.041 *
## asv288 0.354 0.047 *
## asv462 0.354 0.049 *
## asv468 0.354 0.045 *
## asv1037 0.354 0.046 *
## asv1039 0.354 0.046 *
## asv1982 0.354 0.048 *
##
## Group Recent #sps. 45
##          stat p.value
## asv55 0.897 0.001 ***
## asv48 0.861 0.004 **
## asv84 0.827 0.030 *
## asv286 0.809 0.001 ***
## asv129 0.802 0.001 ***
## asv109 0.800 0.001 ***
## asv81 0.798 0.001 ***
## asv205 0.787 0.001 ***
## asv270 0.773 0.001 ***
## asv142 0.760 0.001 ***
## asv1465 0.746 0.001 ***
## asv1778 0.745 0.001 ***
## asv767 0.734 0.001 ***
## asv558 0.731 0.001 ***
## asv1931 0.705 0.001 ***
## asv396 0.704 0.002 **
## asv1031 0.704 0.002 **
## asv1785 0.696 0.001 ***
## asv2828 0.685 0.001 ***
## asv862 0.665 0.003 **
## asv357 0.662 0.004 **
## asv1359 0.634 0.001 ***
## asv297 0.614 0.003 **
## asv105 0.608 0.001 ***
## asv78 0.592 0.005 **
## asv70 0.588 0.002 **
## asv187 0.587 0.006 **
## asv235 0.586 0.002 **
## asv159 0.584 0.001 ***
## asv164 0.577 0.005 **
## asv232 0.570 0.009 **
## asv200 0.569 0.007 **
## asv154 0.563 0.025 *
## asv68 0.555 0.011 *
## asv444 0.552 0.011 *

```

```
## asv39 0.546 0.021 *
## asv223 0.538 0.023 *
## asv60 0.530 0.022 *
## asv753 0.510 0.010 **
## asv264 0.509 0.027 *
## asv42 0.477 0.002 **
## asv80 0.421 0.019 *
## asv101 0.378 0.009 **
## asv1131 0.350 0.024 *
## asv215 0.338 0.018 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
indisp.sign<-as.data.table(inv_blc$sign, keep.rownames=TRUE)
#add adjusted p-value
indisp.sign[,p.value.bh:=p.adjust(p.value, method="BH")]
#now can select only the indicators with adjusted significant p-values

IndVal_blc = indispsign[p.value.bh<=0.05, ]
IndVal_blc
```

##	rn	s.Long	s.Recent	index	stat	p.value	p.value.bh
## 1:	asv25	1	0	1	0.8556200	0.001	0.006000000
## 2:	asv39	0	1	2	0.5464411	0.021	0.046140845
## 3:	asv40	1	0	1	0.8960228	0.002	0.007609756
## 4:	asv42	0	1	2	0.4773189	0.002	0.007609756
## 5:	asv48	0	1	2	0.8614219	0.004	0.012480000
## 6:	asv55	0	1	2	0.8968675	0.001	0.006000000
## 7:	asv60	0	1	2	0.5297407	0.022	0.047013699
## 8:	asv68	0	1	2	0.5548573	0.011	0.026400000
## 9:	asv70	0	1	2	0.5879262	0.002	0.007609756
## 10:	asv78	0	1	2	0.5921531	0.005	0.014444444
## 11:	asv80	0	1	2	0.4208911	0.019	0.042956522
## 12:	asv81	0	1	2	0.7983603	0.001	0.006000000
## 13:	asv88	1	0	1	0.6376096	0.023	0.047210526
## 14:	asv101	0	1	2	0.3779645	0.009	0.023400000
## 15:	asv105	0	1	2	0.6077233	0.001	0.006000000
## 16:	asv109	0	1	2	0.8002843	0.001	0.006000000
## 17:	asv129	0	1	2	0.8022506	0.001	0.006000000
## 18:	asv137	1	0	1	0.5975967	0.003	0.009750000
## 19:	asv142	0	1	2	0.7598660	0.001	0.006000000
## 20:	asv145	1	0	1	0.7400631	0.001	0.006000000
## 21:	asv148	1	0	1	0.6546537	0.001	0.006000000
## 22:	asv149	1	0	1	0.6123310	0.003	0.009750000
## 23:	asv154	0	1	2	0.5630697	0.025	0.049367089
## 24:	asv156	1	0	1	0.6941641	0.002	0.007609756
## 25:	asv159	0	1	2	0.5841520	0.001	0.006000000
## 26:	asv160	1	0	1	0.4008919	0.020	0.044571429
## 27:	asv164	0	1	2	0.5768880	0.005	0.014444444
## 28:	asv187	0	1	2	0.5868317	0.006	0.016714286
## 29:	asv191	1	0	1	0.5142148	0.025	0.049367089
## 30:	asv200	0	1	2	0.5688478	0.007	0.019157895
## 31:	asv201	1	0	1	0.7067211	0.001	0.006000000
## 32:	asv205	0	1	2	0.7873764	0.001	0.006000000

## 33:	asv215	0	1	2	0.3380617	0.018	0.041294118
## 34:	asv223	0	1	2	0.5384108	0.023	0.047210526
## 35:	asv232	0	1	2	0.5704446	0.009	0.023400000
## 36:	asv235	0	1	2	0.5856639	0.002	0.007609756
## 37:	asv270	0	1	2	0.7728419	0.001	0.006000000
## 38:	asv286	0	1	2	0.8093620	0.001	0.006000000
## 39:	asv297	0	1	2	0.6138627	0.003	0.009750000
## 40:	asv348	1	0	1	0.4802149	0.015	0.035454545
## 41:	asv351	1	0	1	0.5539321	0.018	0.041294118
## 42:	asv357	0	1	2	0.6617079	0.004	0.012480000
## 43:	asv396	0	1	2	0.7041406	0.002	0.007609756
## 44:	asv444	0	1	2	0.5522738	0.011	0.026400000
## 45:	asv449	1	0	1	0.6122777	0.002	0.007609756
## 46:	asv453	1	0	1	0.6648085	0.002	0.007609756
## 47:	asv459	1	0	1	0.6529337	0.002	0.007609756
## 48:	asv474	1	0	1	0.6613430	0.022	0.047013699
## 49:	asv477	1	0	1	0.4389702	0.023	0.047210526
## 50:	asv501	1	0	1	0.6402061	0.003	0.009750000
## 51:	asv516	1	0	1	0.4989422	0.005	0.014444444
## 52:	asv519	1	0	1	0.4712941	0.011	0.026400000
## 53:	asv529	1	0	1	0.6523065	0.003	0.009750000
## 54:	asv535	1	0	1	0.4968256	0.002	0.007609756
## 55:	asv553	1	0	1	0.7052576	0.001	0.006000000
## 56:	asv558	0	1	2	0.7312706	0.001	0.006000000
## 57:	asv598	1	0	1	0.5664184	0.006	0.016714286
## 58:	asv639	1	0	1	0.6822422	0.002	0.007609756
## 59:	asv753	0	1	2	0.5104382	0.010	0.025573770
## 60:	asv767	0	1	2	0.7343698	0.001	0.006000000
## 61:	asv780	1	0	1	0.5660152	0.005	0.014444444
## 62:	asv862	0	1	2	0.6651863	0.003	0.009750000
## 63:	asv952	1	0	1	0.6641044	0.002	0.007609756
## 64:	asv1031	0	1	2	0.7035375	0.002	0.007609756
## 65:	asv1050	1	0	1	0.6583165	0.002	0.007609756
## 66:	asv1131	0	1	2	0.3504492	0.024	0.048623377
## 67:	asv1194	1	0	1	0.6218406	0.003	0.009750000
## 68:	asv1203	1	0	1	0.6532600	0.001	0.006000000
## 69:	asv1359	0	1	2	0.6339334	0.001	0.006000000
## 70:	asv1465	0	1	2	0.7455714	0.001	0.006000000
## 71:	asv1471	1	0	1	0.6351243	0.001	0.006000000
## 72:	asv1600	1	0	1	0.6347221	0.002	0.007609756
## 73:	asv1778	0	1	2	0.7450212	0.001	0.006000000
## 74:	asv1785	0	1	2	0.6959315	0.001	0.006000000
## 75:	asv1897	1	0	1	0.4225771	0.011	0.026400000
## 76:	asv1931	0	1	2	0.7045757	0.001	0.006000000
## 77:	asv2105	1	0	1	0.6324148	0.001	0.006000000
## 78:	asv2828	0	1	2	0.6851706	0.001	0.006000000
## 79:	asv3104	1	0	1	0.4225771	0.008	0.021517241
##	rn	s.Long	s.Recent	index	stat	p.value	p.value.bh

```
write.xlsx(IndVal_blc, file = "IndVal_blc_16Sep2021.xlsx")
```

```
inv_sregion = multipatt(asv_css, meta$S_region, func = "IndVal.g", control = how(nperm=999))
summary(inv_sregion)
```

```

##
## Multilevel pattern analysis
## -----
##
## Association function: IndVal.g
## Significance level (alpha): 0.05
##
## Total number of species: 435
## Selected number of species: 278
## Number of species associated to 1 group: 204
## Number of species associated to 2 groups: 74
##
## List of species associated to each combination:
##
## Group FrPoly #sps. 56
##      stat p.value
## asv81  0.999  0.001 ***
## asv55  0.998  0.001 ***
## asv62  0.997  0.001 ***
## asv84  0.983  0.001 ***
## asv16  0.983  0.001 ***
## asv27  0.983  0.001 ***
## asv110 0.981  0.001 ***
## asv205 0.981  0.001 ***
## asv129 0.979  0.001 ***
## asv260 0.974  0.001 ***
## asv862 0.967  0.001 ***
## asv109 0.965  0.001 ***
## asv166 0.965  0.001 ***
## asv558 0.963  0.001 ***
## asv417 0.963  0.001 ***
## asv431 0.959  0.001 ***
## asv237 0.951  0.001 ***
## asv559 0.950  0.001 ***
## asv767 0.950  0.001 ***
## asv429 0.948  0.001 ***
## asv447 0.948  0.001 ***
## asv467 0.947  0.001 ***
## asv1778 0.946  0.001 ***
## asv1031 0.945  0.001 ***
## asv1475 0.942  0.001 ***
## asv327 0.941  0.001 ***
## asv1258 0.941  0.001 ***
## asv293 0.940  0.001 ***
## asv820 0.938  0.001 ***
## asv245 0.937  0.001 ***
## asv955 0.935  0.001 ***
## asv1465 0.933  0.001 ***
## asv91  0.932  0.001 ***
## asv357 0.932  0.001 ***
## asv1785 0.928  0.001 ***
## asv396 0.924  0.001 ***
## asv1931 0.918  0.001 ***
## asv533 0.916  0.001 ***

```



```

## asv297 0.898 0.001 ***
## asv95 0.898 0.001 ***
## asv2828 0.880 0.001 ***
## asv142 0.879 0.001 ***
## asv270 0.878 0.001 ***
## asv730 0.871 0.001 ***
## asv249 0.860 0.001 ***
## asv286 0.860 0.001 ***
## asv682 0.843 0.001 ***
## asv2150 0.806 0.001 ***
## asv1864 0.777 0.001 ***
## asv74 0.761 0.009 **
## asv415 0.752 0.001 ***
## asv1359 0.673 0.001 ***
## asv463 0.569 0.009 **
## asv816 0.468 0.010 **
## asv836 0.440 0.020 *
## asv1777 0.432 0.034 *
##
## Group IndianOc #sps. 36
##      stat p.value
## asv25 0.890 0.001 ***
## asv145 0.772 0.002 **
## asv553 0.733 0.001 ***
## asv201 0.721 0.002 **
## asv1050 0.711 0.002 **
## asv459 0.705 0.001 ***
## asv156 0.702 0.002 **
## asv501 0.692 0.004 **
## asv529 0.689 0.003 **
## asv453 0.688 0.001 ***
## asv1471 0.686 0.001 ***
## asv2105 0.683 0.001 ***
## asv148 0.677 0.004 **
## asv1203 0.673 0.001 ***
## asv1194 0.671 0.001 ***
## asv1600 0.667 0.001 ***
## asv449 0.661 0.004 **
## asv137 0.645 0.003 **
## asv149 0.645 0.003 **
## asv598 0.594 0.023 *
## asv780 0.594 0.013 *
## asv191 0.552 0.029 *
## asv516 0.538 0.015 *
## asv535 0.537 0.010 **
## asv139 0.518 0.039 *
## asv348 0.518 0.017 *
## asv519 0.510 0.017 *
## asv477 0.468 0.028 *
## asv1897 0.456 0.026 *
## asv3104 0.456 0.024 *
## asv305 0.456 0.049 *
## asv160 0.433 0.047 *
## asv784 0.433 0.042 *

```

```

## asv899 0.430 0.044 *
## asv121 0.408 0.049 *
## asv486 0.408 0.048 *
##
## Group Taiwan #sps. 112
##          stat p.value
## asv105 0.998 0.001 ***
## asv164 0.994 0.001 ***
## asv78 0.987 0.001 ***
## asv70 0.984 0.001 ***
## asv235 0.978 0.001 ***
## asv187 0.968 0.001 ***
## asv223 0.965 0.001 ***
## asv154 0.962 0.001 ***
## asv22 0.962 0.001 ***
## asv60 0.958 0.001 ***
## asv68 0.958 0.001 ***
## asv236 0.956 0.001 ***
## asv226 0.955 0.001 ***
## asv159 0.955 0.001 ***
## asv232 0.955 0.001 ***
## asv233 0.954 0.001 ***
## asv200 0.954 0.001 ***
## asv243 0.951 0.001 ***
## asv85 0.948 0.001 ***
## asv67 0.948 0.001 ***
## asv136 0.941 0.001 ***
## asv211 0.940 0.001 ***
## asv39 0.928 0.001 ***
## asv444 0.903 0.001 ***
## asv71 0.898 0.001 ***
## asv33 0.891 0.001 ***
## asv46 0.876 0.001 ***
## asv605 0.871 0.001 ***
## asv112 0.869 0.001 ***
## asv35 0.865 0.001 ***
## asv127 0.860 0.001 ***
## asv332 0.860 0.001 ***
## asv41 0.858 0.001 ***
## asv1310 0.856 0.001 ***
## asv537 0.843 0.001 ***
## asv17 0.838 0.001 ***
## asv283 0.836 0.001 ***
## asv240 0.832 0.001 ***
## asv264 0.830 0.001 ***
## asv1360 0.827 0.001 ***
## asv611 0.814 0.001 ***
## asv153 0.814 0.001 ***
## asv179 0.812 0.001 ***
## asv167 0.811 0.001 ***
## asv128 0.810 0.001 ***
## asv607 0.806 0.001 ***
## asv772 0.806 0.001 ***
## asv753 0.805 0.001 ***

```

##	asv609	0.805	0.001	***
##	asv498	0.802	0.001	***
##	asv90	0.799	0.001	***
##	asv157	0.794	0.001	***
##	asv863	0.793	0.001	***
##	asv543	0.783	0.001	***
##	asv229	0.783	0.001	***
##	asv38	0.782	0.002	**
##	asv770	0.778	0.001	***
##	asv371	0.775	0.002	**
##	asv393	0.773	0.001	***
##	asv1476	0.771	0.001	***
##	asv1149	0.769	0.001	***
##	asv51	0.769	0.001	***
##	asv119	0.766	0.001	***
##	asv134	0.765	0.002	**
##	asv155	0.761	0.002	**
##	asv922	0.750	0.001	***
##	asv271	0.747	0.001	***
##	asv123	0.746	0.001	***
##	asv80	0.745	0.001	***
##	asv180	0.736	0.001	***
##	asv827	0.727	0.001	***
##	asv2013	0.726	0.001	***
##	asv132	0.725	0.001	***
##	asv125	0.723	0.002	**
##	asv322	0.723	0.001	***
##	asv399	0.720	0.001	***
##	asv381	0.715	0.001	***
##	asv1601	0.715	0.001	***
##	asv1886	0.706	0.001	***
##	asv940	0.705	0.002	**
##	asv42	0.702	0.001	***
##	asv2916	0.690	0.001	***
##	asv2329	0.687	0.001	***
##	asv227	0.678	0.001	***
##	asv2356	0.671	0.001	***
##	asv1156	0.670	0.004	**
##	asv1594	0.664	0.001	***
##	asv144	0.646	0.001	***
##	asv209	0.646	0.001	***
##	asv101	0.645	0.001	***
##	asv202	0.640	0.001	***
##	asv735	0.637	0.002	**
##	asv788	0.637	0.006	**
##	asv1729	0.635	0.001	***
##	asv1784	0.628	0.001	***
##	asv82	0.621	0.002	**
##	asv943	0.619	0.001	***
##	asv1093	0.597	0.001	***
##	asv215	0.577	0.002	**
##	asv1216	0.574	0.011	*
##	asv1810	0.570	0.012	*
##	asv1124	0.562	0.011	*

```

## asv175 0.518 0.013 *
## asv192 0.500 0.005 **
## asv3304 0.489 0.015 *
## asv613 0.472 0.009 **
## asv1256 0.446 0.026 *
## asv806 0.444 0.015 *
## asv265 0.443 0.040 *
## asv404 0.441 0.017 *
## asv493 0.408 0.018 *
## asv1952 0.362 0.037 *
##
## Group FrPoly+IndianOc #sps. 8
##      stat p.value
## asv66 0.927 0.001 ***
## asv49 0.905 0.003 **
## asv40 0.893 0.005 **
## asv359 0.819 0.003 **
## asv1749 0.738 0.002 **
## asv474 0.703 0.015 *
## asv952 0.701 0.004 **
## asv639 0.675 0.014 *
##
## Group IndianOc+Taiwan #sps. 66
##      stat p.value
## asv12 0.942 0.003 **
## asv19 0.937 0.001 ***
## asv26 0.870 0.001 ***
## asv30 0.862 0.015 *
## asv24 0.859 0.001 ***
## asv43 0.832 0.001 ***
## asv44 0.826 0.001 ***
## asv106 0.820 0.001 ***
## asv87 0.818 0.003 **
## asv94 0.806 0.001 ***
## asv89 0.794 0.001 ***
## asv133 0.793 0.001 ***
## asv267 0.771 0.001 ***
## asv176 0.771 0.001 ***
## asv73 0.766 0.003 **
## asv88 0.762 0.001 ***
## asv37 0.759 0.010 **
## asv312 0.754 0.002 **
## asv440 0.751 0.001 ***
## asv117 0.749 0.002 **
## asv239 0.746 0.001 ***
## asv152 0.736 0.001 ***
## asv54 0.735 0.001 ***
## asv476 0.719 0.001 ***
## asv302 0.718 0.007 **
## asv746 0.717 0.001 ***
## asv163 0.716 0.009 **
## asv13 0.715 0.002 **
## asv79 0.709 0.011 *
## asv347 0.705 0.005 **

```

```

## asv108 0.705 0.006 **
## asv131 0.704 0.005 **
## asv563 0.695 0.001 ***
## asv107 0.694 0.002 **
## asv1448 0.668 0.001 ***
## asv556 0.668 0.003 **
## asv368 0.659 0.005 **
## asv1252 0.658 0.005 **
## asv946 0.653 0.004 **
## asv859 0.647 0.006 **
## asv1863 0.643 0.003 **
## asv406 0.640 0.008 **
## asv351 0.631 0.012 *
## asv185 0.622 0.007 **
## asv323 0.615 0.006 **
## asv402 0.606 0.014 *
## asv269 0.591 0.017 *
## asv1108 0.579 0.027 *
## asv2248 0.577 0.010 **
## asv182 0.572 0.018 *
## asv2804 0.561 0.014 *
## asv2157 0.548 0.014 *
## asv383 0.540 0.025 *
## asv405 0.538 0.024 *
## asv1247 0.533 0.017 *
## asv2075 0.532 0.012 *
## asv2805 0.532 0.014 *
## asv505 0.524 0.042 *
## asv328 0.516 0.031 *
## asv2486 0.516 0.023 *
## asv825 0.506 0.034 *
## asv654 0.483 0.019 *
## asv2701 0.483 0.035 *
## asv3329 0.483 0.029 *
## asv2341 0.465 0.043 *
## asv1085 0.447 0.044 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

indisp.sign<-as.data.table(inv_sregion$sign, keep.rownames=TRUE)
#add adjusted p-value
indisp.sign[,p.value.bh:=p.adjust(p.value, method="BH")]
#now can select only the indicators with adjusted significant p-values
IndVal_sregion = indispc.sign[p.value.bh<=0.05, ]
IndVal_sregion

```

```

##          rn s.FrPoly s.IndianOc s.Taiwan index      stat p.value  p.value.bh
## 1:  asv12          0          1          1      6 0.9422385  0.003 0.005482234
## 2:  asv13          0          1          1      6 0.7149152  0.002 0.003850267
## 3:  asv16          1          0          0      1 0.9829279  0.001 0.002130178
## 4:  asv17          0          0          1      3 0.8380529  0.001 0.002130178
## 5:  asv19          0          1          1      6 0.9367926  0.001 0.002130178
## ---
## 263: asv2828          1          0          0      1 0.8798827  0.001 0.002130178

```

```
## 264: asv2916      0      0      1      3 0.6903017  0.001 0.002130178
## 265: asv3104      0      1      0      2 0.4564355  0.024 0.033882353
## 266: asv3304      0      0      1      3 0.4885800  0.015 0.022314050
## 267: asv3329      0      1      1      6 0.4830459  0.029 0.039847328
```

```
write.xlsx(IndVal_sregion, file = "IndVal_sregion_16Sep2021.xlsx")
```

```
inv_lregion = multipatt(asv_css, meta$L_region, func = "IndVal.g", control = how(nperm=999))
summary(inv_lregion)
```

```
##
## Multilevel pattern analysis
## -----
##
## Association function: IndVal.g
## Significance level (alpha): 0.05
##
## Total number of species: 435
## Selected number of species: 279
## Number of species associated to 1 group: 204
## Number of species associated to 2 groups: 75
##
## List of species associated to each combination:
##
## Group EPac #sps. 57
##          stat p.value
## asv81    0.999  0.001 ***
## asv55    0.998  0.001 ***
## asv62    0.997  0.001 ***
## asv84    0.983  0.001 ***
## asv16    0.983  0.001 ***
## asv27    0.983  0.001 ***
## asv110   0.981  0.001 ***
## asv205   0.981  0.001 ***
## asv129   0.979  0.001 ***
## asv260   0.974  0.001 ***
## asv862   0.967  0.001 ***
## asv109   0.965  0.001 ***
## asv166   0.965  0.001 ***
## asv558   0.963  0.001 ***
## asv417   0.963  0.001 ***
## asv431   0.959  0.001 ***
## asv237   0.951  0.001 ***
## asv559   0.950  0.001 ***
## asv767   0.950  0.001 ***
## asv429   0.948  0.001 ***
## asv447   0.948  0.001 ***
## asv467   0.947  0.001 ***
## asv1778  0.946  0.001 ***
## asv1031  0.945  0.001 ***
## asv1475  0.942  0.001 ***
## asv327   0.941  0.001 ***
## asv1258  0.941  0.001 ***
```

```

## asv293 0.940 0.001 ***
## asv820 0.938 0.001 ***
## asv245 0.937 0.001 ***
## asv955 0.935 0.001 ***
## asv1465 0.933 0.001 ***
## asv91 0.932 0.001 ***
## asv357 0.932 0.001 ***
## asv1785 0.928 0.001 ***
## asv396 0.924 0.001 ***
## asv1931 0.918 0.001 ***
## asv533 0.916 0.001 ***
## asv297 0.898 0.001 ***
## asv95 0.898 0.001 ***
## asv2828 0.880 0.001 ***
## asv142 0.879 0.001 ***
## asv270 0.878 0.001 ***
## asv730 0.871 0.001 ***
## asv249 0.860 0.001 ***
## asv286 0.860 0.001 ***
## asv682 0.843 0.001 ***
## asv2150 0.806 0.001 ***
## asv1864 0.777 0.001 ***
## asv74 0.761 0.013 *
## asv415 0.752 0.001 ***
## asv1359 0.673 0.002 **
## asv463 0.569 0.010 **
## asv816 0.468 0.010 **
## asv836 0.440 0.015 *
## asv1777 0.432 0.023 *
## asv1131 0.372 0.048 *
##
## Group IndianOc #sps. 35
##      stat p.value
## asv25 0.890 0.001 ***
## asv145 0.772 0.002 **
## asv553 0.733 0.001 ***
## asv201 0.721 0.004 **
## asv1050 0.711 0.001 ***
## asv459 0.705 0.001 ***
## asv156 0.702 0.001 ***
## asv501 0.692 0.003 **
## asv529 0.689 0.001 ***
## asv453 0.688 0.002 **
## asv1471 0.686 0.001 ***
## asv2105 0.683 0.002 **
## asv148 0.677 0.002 **
## asv1203 0.673 0.001 ***
## asv1194 0.671 0.001 ***
## asv1600 0.667 0.002 **
## asv449 0.661 0.004 **
## asv137 0.645 0.002 **
## asv149 0.645 0.006 **
## asv598 0.594 0.017 *
## asv780 0.594 0.014 *

```

```

## asv191 0.552 0.020 *
## asv516 0.538 0.015 *
## asv535 0.537 0.013 *
## asv139 0.518 0.042 *
## asv348 0.518 0.017 *
## asv519 0.510 0.023 *
## asv477 0.468 0.029 *
## asv1897 0.456 0.023 *
## asv3104 0.456 0.028 *
## asv305 0.456 0.044 *
## asv160 0.433 0.038 *
## asv784 0.433 0.035 *
## asv899 0.430 0.044 *
## asv486 0.408 0.045 *
##
## Group NPac #sps. 112
##      stat p.value
## asv105 0.998 0.001 ***
## asv164 0.994 0.001 ***
## asv78 0.987 0.001 ***
## asv70 0.984 0.001 ***
## asv235 0.978 0.001 ***
## asv187 0.968 0.001 ***
## asv223 0.965 0.001 ***
## asv154 0.962 0.001 ***
## asv22 0.962 0.001 ***
## asv60 0.958 0.001 ***
## asv68 0.958 0.001 ***
## asv236 0.956 0.001 ***
## asv226 0.955 0.001 ***
## asv159 0.955 0.001 ***
## asv232 0.955 0.001 ***
## asv233 0.954 0.001 ***
## asv200 0.954 0.001 ***
## asv243 0.951 0.001 ***
## asv85 0.948 0.001 ***
## asv67 0.948 0.001 ***
## asv136 0.941 0.001 ***
## asv211 0.940 0.001 ***
## asv39 0.928 0.001 ***
## asv444 0.903 0.001 ***
## asv71 0.898 0.001 ***
## asv33 0.891 0.001 ***
## asv46 0.876 0.001 ***
## asv605 0.871 0.001 ***
## asv112 0.869 0.001 ***
## asv35 0.865 0.001 ***
## asv127 0.860 0.001 ***
## asv332 0.860 0.001 ***
## asv41 0.858 0.001 ***
## asv1310 0.856 0.001 ***
## asv537 0.843 0.001 ***
## asv17 0.838 0.001 ***
## asv283 0.836 0.001 ***

```


##	asv240	0.832	0.001	***
##	asv264	0.830	0.001	***
##	asv1360	0.827	0.001	***
##	asv611	0.814	0.001	***
##	asv153	0.814	0.001	***
##	asv179	0.812	0.001	***
##	asv167	0.811	0.001	***
##	asv128	0.810	0.001	***
##	asv607	0.806	0.001	***
##	asv772	0.806	0.001	***
##	asv753	0.805	0.001	***
##	asv609	0.805	0.001	***
##	asv498	0.802	0.001	***
##	asv90	0.799	0.001	***
##	asv157	0.794	0.001	***
##	asv863	0.793	0.001	***
##	asv543	0.783	0.001	***
##	asv229	0.783	0.001	***
##	asv38	0.782	0.001	***
##	asv770	0.778	0.001	***
##	asv371	0.775	0.001	***
##	asv393	0.773	0.001	***
##	asv1476	0.771	0.001	***
##	asv1149	0.769	0.001	***
##	asv51	0.769	0.001	***
##	asv119	0.766	0.001	***
##	asv134	0.765	0.001	***
##	asv155	0.761	0.001	***
##	asv922	0.750	0.001	***
##	asv271	0.747	0.001	***
##	asv123	0.746	0.001	***
##	asv80	0.745	0.001	***
##	asv180	0.736	0.003	**
##	asv827	0.727	0.001	***
##	asv2013	0.726	0.001	***
##	asv132	0.725	0.001	***
##	asv125	0.723	0.001	***
##	asv322	0.723	0.001	***
##	asv399	0.720	0.001	***
##	asv381	0.715	0.001	***
##	asv1601	0.715	0.001	***
##	asv1886	0.706	0.001	***
##	asv940	0.705	0.001	***
##	asv42	0.702	0.001	***
##	asv2916	0.690	0.001	***
##	asv2329	0.687	0.001	***
##	asv227	0.678	0.001	***
##	asv2356	0.671	0.001	***
##	asv1156	0.670	0.001	***
##	asv1594	0.664	0.001	***
##	asv144	0.646	0.004	**
##	asv209	0.646	0.001	***
##	asv101	0.645	0.001	***
##	asv202	0.640	0.004	**

```

## asv735 0.637 0.001 ***
## asv788 0.637 0.003 **
## asv1729 0.635 0.002 **
## asv1784 0.628 0.001 ***
## asv82 0.621 0.004 **
## asv943 0.619 0.002 **
## asv1093 0.597 0.001 ***
## asv215 0.577 0.001 ***
## asv1216 0.574 0.006 **
## asv1810 0.570 0.005 **
## asv1124 0.562 0.003 **
## asv175 0.518 0.022 *
## asv192 0.500 0.001 ***
## asv3304 0.489 0.020 *
## asv613 0.472 0.007 **
## asv1256 0.446 0.023 *
## asv806 0.444 0.010 **
## asv265 0.443 0.050 *
## asv404 0.441 0.015 *
## asv493 0.408 0.019 *
## asv1952 0.362 0.036 *
##
## Group EPac+IndianOc #sps. 8
##      stat p.value
## asv66 0.927 0.002 **
## asv49 0.905 0.002 **
## asv40 0.893 0.007 **
## asv359 0.819 0.002 **
## asv1749 0.738 0.003 **
## asv474 0.703 0.019 *
## asv952 0.701 0.009 **
## asv639 0.675 0.014 *
##
## Group IndianOc+NPac #sps. 67
##      stat p.value
## asv12 0.942 0.003 **
## asv19 0.937 0.001 ***
## asv26 0.870 0.001 ***
## asv30 0.862 0.009 **
## asv24 0.859 0.001 ***
## asv43 0.832 0.001 ***
## asv44 0.826 0.001 ***
## asv106 0.820 0.001 ***
## asv87 0.818 0.002 **
## asv94 0.806 0.001 ***
## asv89 0.794 0.001 ***
## asv133 0.793 0.001 ***
## asv267 0.771 0.002 **
## asv176 0.771 0.001 ***
## asv73 0.766 0.002 **
## asv88 0.762 0.001 ***
## asv37 0.759 0.012 *
## asv312 0.754 0.001 ***
## asv440 0.751 0.001 ***

```

```

## asv117 0.749 0.002 **
## asv239 0.746 0.002 **
## asv152 0.736 0.001 ***
## asv54 0.735 0.002 **
## asv476 0.719 0.001 ***
## asv302 0.718 0.003 **
## asv746 0.717 0.002 **
## asv163 0.716 0.012 *
## asv13 0.715 0.001 ***
## asv79 0.709 0.008 **
## asv347 0.705 0.002 **
## asv108 0.705 0.004 **
## asv131 0.704 0.003 **
## asv563 0.695 0.001 ***
## asv107 0.694 0.003 **
## asv1448 0.668 0.003 **
## asv556 0.668 0.002 **
## asv368 0.659 0.004 **
## asv1252 0.658 0.003 **
## asv946 0.653 0.002 **
## asv859 0.647 0.003 **
## asv1863 0.643 0.002 **
## asv406 0.640 0.003 **
## asv351 0.631 0.007 **
## asv185 0.622 0.006 **
## asv323 0.615 0.005 **
## asv402 0.606 0.012 *
## asv269 0.591 0.022 *
## asv1108 0.579 0.030 *
## asv2248 0.577 0.014 *
## asv182 0.572 0.013 *
## asv2804 0.561 0.013 *
## asv2157 0.548 0.017 *
## asv383 0.540 0.024 *
## asv405 0.538 0.019 *
## asv1247 0.533 0.025 *
## asv2075 0.532 0.012 *
## asv2805 0.532 0.018 *
## asv505 0.524 0.036 *
## asv328 0.516 0.031 *
## asv2486 0.516 0.021 *
## asv825 0.506 0.038 *
## asv654 0.483 0.024 *
## asv2701 0.483 0.036 *
## asv3329 0.483 0.023 *
## asv2341 0.465 0.035 *
## asv188 0.447 0.050 *
## asv1085 0.447 0.040 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

indisp.sign<-as.data.table(inv_lregion$sign, keep.rownames=TRUE)
#add adjusted p-value
indisp.sign[,p.value.bh:=p.adjust(p.value, method="BH")]

```

```
#now can select only the indicators with adjusted significant p-values
```

```
IndVal_lregion = indisp.sign[p.value.bh<=0.05, ]
IndVal_lregion
```

```
##          rn s.EPac s.IndianOc s.NPac index      stat p.value  p.value.bh
##  1:  asv12      0          1      1      6 0.9422385   0.003 0.005268293
##  2:  asv13      0          1      1      6 0.7149152   0.001 0.002130178
##  3:  asv16      1          0      0      1 0.9829279   0.001 0.002130178
##  4:  asv17      0          0      1      3 0.8380529   0.001 0.002130178
##  5:  asv19      0          1      1      6 0.9367926   0.001 0.002130178
##  ---
## 265: asv2828      1          0      0      1 0.8798827   0.001 0.002130178
## 266: asv2916      0          0      1      3 0.6903017   0.001 0.002130178
## 267: asv3104      0          1      0      2 0.4564355   0.028 0.038620690
## 268: asv3304      0          0      1      3 0.4885800   0.020 0.028915663
## 269: asv3329      0          1      1      6 0.4830459   0.023 0.032217899
```

```
write.xlsx(IndVal_lregion, file = "IndVal_lregion_16Sep2021.xlsx")
```

```
inv_temp = multipatt(asv_css, meta$SST_a, func = "IndVal.g", control = how(nperm=999))
summary(inv_temp)
```

```
##
## Multilevel pattern analysis
## -----
##
## Association function: IndVal.g
## Significance level (alpha): 0.05
##
## Total number of species: 435
## Selected number of species: 312
## Number of species associated to 1 group: 50
## Number of species associated to 2 groups: 49
## Number of species associated to 3 groups: 126
## Number of species associated to 4 groups: 38
## Number of species associated to 5 groups: 29
## Number of species associated to 6 groups: 7
## Number of species associated to 7 groups: 8
## Number of species associated to 8 groups: 3
## Number of species associated to 9 groups: 1
## Number of species associated to 10 groups: 1
##
## List of species associated to each combination:
##
## Group 27.04 #sps. 4
##          stat p.value
## asv74   0.998   0.001 ***
## asv1777 0.707   0.005 **
## asv816   0.701   0.009 **
## asv857   0.698   0.008 **
##
## Group 28.59 #sps. 3
```

```

##          stat p.value
## asv101  0.707   0.003 **
## asv943  0.655   0.007 **
## asv1093 0.615   0.012 *
##
## Group 28.67 #sps. 15
##          stat p.value
## asv192  0.959   0.001 ***
## asv215  0.942   0.001 ***
## asv42   0.917   0.001 ***
## asv1594 0.905   0.001 ***
## asv806  0.904   0.001 ***
## asv371  0.900   0.001 ***
## asv264  0.828   0.002 **
## asv80   0.774   0.004 **
## asv940  0.765   0.001 ***
## asv3180 0.763   0.002 **
## asv175  0.720   0.007 **
## asv325  0.704   0.005 **
## asv2881 0.636   0.007 **
## asv1952 0.617   0.013 *
## asv404  0.613   0.009 **
##
## Group 30.8 #sps. 28
##          stat p.value
## asv351  0.866   0.001 ***
## asv516  0.811   0.001 ***
## asv535  0.757   0.004 **
## asv139  0.752   0.009 **
## asv328  0.749   0.003 **
## asv348  0.747   0.009 **
## asv1897 0.690   0.008 **
## asv3104 0.690   0.013 *
## asv305  0.689   0.011 *
## asv899  0.641   0.013 *
## asv121  0.617   0.012 *
## asv486  0.617   0.010 **
## asv784  0.608   0.017 *
## asv160  0.601   0.040 *
## asv150  0.577   0.015 *
## asv288  0.577   0.017 *
## asv295  0.577   0.035 *
## asv388  0.577   0.030 *
## asv462  0.577   0.019 *
## asv468  0.577   0.017 *
## asv1037 0.577   0.019 *
## asv1039 0.577   0.020 *
## asv1982 0.577   0.019 *
## asv428  0.575   0.048 *
## asv479  0.570   0.036 *
## asv1799 0.568   0.039 *
## asv460  0.563   0.048 *
## asv138  0.535   0.048 *
##

```

```

## Group 26.86+27.04 #sps. 1
##      stat p.value
## asv249 0.994 0.001 ***
##
## Group 26.86+30.8 #sps. 3
##      stat p.value
## asv519 0.760 0.003 **
## asv52 0.679 0.018 *
## asv2663 0.588 0.015 *
##
## Group 28.59+28.67 #sps. 25
##      stat p.value
## asv105 0.998 0.001 ***
## asv164 0.993 0.001 ***
## asv78 0.983 0.001 ***
## asv70 0.980 0.001 ***
## asv235 0.978 0.001 ***
## asv154 0.964 0.001 ***
## asv223 0.960 0.001 ***
## asv187 0.957 0.001 ***
## asv22 0.955 0.001 ***
## asv60 0.951 0.001 ***
## asv233 0.950 0.001 ***
## asv159 0.949 0.001 ***
## asv236 0.949 0.001 ***
## asv226 0.949 0.001 ***
## asv200 0.949 0.001 ***
## asv243 0.946 0.001 ***
## asv232 0.945 0.001 ***
## asv68 0.943 0.001 ***
## asv39 0.922 0.001 ***
## asv444 0.890 0.001 ***
## asv1360 0.829 0.001 ***
## asv753 0.772 0.001 ***
## asv1149 0.769 0.003 **
## asv770 0.745 0.003 **
## asv82 0.631 0.019 *
##
## Group 28.59+30.8 #sps. 10
##      stat p.value
## asv227 0.861 0.001 ***
## asv2075 0.741 0.002 **
## asv2916 0.718 0.003 **
## asv383 0.705 0.013 *
## asv3329 0.672 0.010 **
## asv2341 0.648 0.017 *
## asv188 0.622 0.018 *
## asv265 0.596 0.025 *
## asv427 0.596 0.026 *
## asv1256 0.568 0.041 *
##
## Group 28.67+30.8 #sps. 9
##      stat p.value
## asv2248 0.806 0.001 ***

```

```

## asv477 0.722 0.008 **
## asv191 0.695 0.015 *
## asv177 0.656 0.008 **
## asv414 0.626 0.012 *
## asv161 0.624 0.017 *
## asv450 0.623 0.016 *
## asv1265 0.616 0.022 *
## asv317 0.613 0.014 *
##
## Group 29.11+29.37 #sps. 1
##      stat p.value
## asv201 0.846 0.004 **
##
## Group 26.86+27.04+27.19 #sps. 1
##      stat p.value
## asv95 0.944 0.001 ***
##
## Group 26.86+27.04+27.22 #sps. 2
##      stat p.value
## asv415 0.832 0.002 **
## asv463 0.629 0.030 *
##
## Group 26.86+28.59+30.8 #sps. 6
##      stat p.value
## asv209 0.799 0.001 ***
## asv1108 0.793 0.001 ***
## asv1247 0.726 0.004 **
## asv505 0.707 0.014 *
## asv825 0.687 0.008 **
## asv2718 0.624 0.018 *
##
## Group 26.86+28.67+30.8 #sps. 1
##      stat p.value
## asv531 0.778 0.026 *
##
## Group 27.04+27.19+27.22 #sps. 1
##      stat p.value
## asv533 0.959 0.009 **
##
## Group 27.19+27.22+27.25 #sps. 4
##      stat p.value
## asv286 0.996 0.001 ***
## asv270 0.968 0.001 ***
## asv142 0.900 0.001 ***
## asv1359 0.834 0.001 ***
##
## Group 28.59+28.67+30.8 #sps. 90
##      stat p.value
## asv67 0.991 0.001 ***
## asv133 0.988 0.001 ***
## asv89 0.988 0.001 ***
## asv112 0.986 0.001 ***
## asv19 0.985 0.001 ***
## asv35 0.983 0.001 ***

```

```

## asv117 0.983 0.001 ***
## asv38 0.982 0.001 ***
## asv211 0.981 0.001 ***
## asv30 0.980 0.001 ***
## asv26 0.979 0.001 ***
## asv152 0.978 0.001 ***
## asv267 0.978 0.001 ***
## asv176 0.974 0.001 ***
## asv46 0.973 0.001 ***
## asv54 0.973 0.001 ***
## asv239 0.972 0.001 ***
## asv88 0.971 0.001 ***
## asv106 0.970 0.001 ***
## asv476 0.969 0.001 ***
## asv332 0.968 0.001 ***
## asv611 0.964 0.001 ***
## asv119 0.963 0.001 ***
## asv271 0.961 0.001 ***
## asv153 0.961 0.001 ***
## asv605 0.957 0.001 ***
## asv167 0.956 0.001 ***
## asv498 0.956 0.001 ***
## asv399 0.956 0.001 ***
## asv863 0.956 0.001 ***
## asv41 0.953 0.001 ***
## asv94 0.951 0.001 ***
## asv537 0.950 0.001 ***
## asv73 0.948 0.001 ***
## asv51 0.948 0.001 ***
## asv312 0.943 0.001 ***
## asv127 0.942 0.001 ***
## asv163 0.940 0.001 ***
## asv123 0.935 0.001 ***
## asv1476 0.935 0.001 ***
## asv85 0.933 0.001 ***
## asv607 0.930 0.001 ***
## asv302 0.928 0.001 ***
## asv746 0.923 0.001 ***
## asv2013 0.921 0.001 ***
## asv107 0.917 0.001 ***
## asv90 0.917 0.001 ***
## asv128 0.911 0.001 ***
## asv440 0.907 0.001 ***
## asv556 0.894 0.001 ***
## asv240 0.893 0.001 ***
## asv71 0.882 0.001 ***
## asv13 0.875 0.001 ***
## asv946 0.872 0.001 ***
## asv322 0.870 0.001 ***
## asv155 0.869 0.001 ***
## asv1448 0.868 0.001 ***
## asv283 0.855 0.001 ***
## asv543 0.853 0.001 ***
## asv1310 0.853 0.001 ***

```



```

## asv406 0.852 0.002 **
## asv772 0.847 0.001 ***
## asv859 0.845 0.001 ***
## asv132 0.838 0.001 ***
## asv1156 0.834 0.001 ***
## asv157 0.833 0.001 ***
## asv1252 0.833 0.001 ***
## asv202 0.825 0.001 ***
## asv323 0.821 0.001 ***
## asv1601 0.821 0.001 ***
## asv179 0.816 0.001 ***
## asv381 0.816 0.001 ***
## asv402 0.816 0.004 **
## asv144 0.813 0.001 ***
## asv393 0.798 0.001 ***
## asv125 0.795 0.001 ***
## asv1886 0.778 0.001 ***
## asv827 0.762 0.002 **
## asv1729 0.762 0.001 ***
## asv180 0.758 0.018 *
## asv1216 0.739 0.001 ***
## asv1124 0.739 0.003 **
## asv2157 0.739 0.007 **
## asv2356 0.718 0.006 **
## asv2805 0.718 0.002 **
## asv2486 0.696 0.012 *
## asv654 0.651 0.014 *
## asv2701 0.651 0.010 **
## asv1085 0.603 0.019 *
## asv3304 0.603 0.025 *
##
## Group 29.11+29.35+29.37 #sps. 21
##      stat p.value
## asv145 0.956 0.001 ***
## asv25 0.943 0.001 ***
## asv459 0.921 0.001 ***
## asv529 0.920 0.001 ***
## asv553 0.919 0.001 ***
## asv1471 0.914 0.001 ***
## asv1050 0.908 0.001 ***
## asv501 0.902 0.001 ***
## asv1203 0.899 0.001 ***
## asv453 0.898 0.001 ***
## asv1194 0.896 0.001 ***
## asv1600 0.892 0.001 ***
## asv2105 0.890 0.001 ***
## asv148 0.882 0.002 **
## asv449 0.882 0.001 ***
## asv156 0.879 0.001 ***
## asv639 0.873 0.001 ***
## asv149 0.861 0.002 **
## asv137 0.839 0.005 **
## asv598 0.769 0.012 *
## asv780 0.768 0.008 **

```

```

##
## Group 26.86+28.59+28.67+30.8 #sps. 27
##      stat p.value
## asv33  0.998  0.001 ***
## asv24  0.970  0.001 ***
## asv44  0.969  0.001 ***
## asv37  0.956  0.001 ***
## asv79  0.955  0.001 ***
## asv131 0.953  0.001 ***
## asv136 0.946  0.001 ***
## asv609 0.946  0.001 ***
## asv87  0.938  0.001 ***
## asv563 0.904  0.001 ***
## asv229 0.903  0.001 ***
## asv108 0.903  0.001 ***
## asv347 0.867  0.001 ***
## asv1863 0.843  0.001 ***
## asv17  0.827  0.001 ***
## asv185 0.827  0.001 ***
## asv269 0.827  0.001 ***
## asv788 0.827  0.001 ***
## asv134 0.811  0.001 ***
## asv182 0.778  0.001 ***
## asv922 0.743  0.002 **
## asv2804 0.743  0.001 ***
## asv405 0.707  0.005 **
## asv735 0.707  0.001 ***
## asv1810 0.707  0.004 **
## asv2329 0.669  0.011 *
## asv1784 0.607  0.026 *
##
## Group 26.86+28.67+29.11+30.8 #sps. 1
##      stat p.value
## asv254 0.606  0.032 *
##
## Group 26.86+29.11+29.35+29.37 #sps. 1
##      stat p.value
## asv848 0.828  0.013 *
##
## Group 27.04+27.19+27.22+27.25 #sps. 6
##      stat p.value
## asv91  0.999  0.001 ***
## asv166 0.995  0.001 ***
## asv205 0.994  0.001 ***
## asv129 0.990  0.001 ***
## asv559 0.986  0.001 ***
## asv1864 0.810  0.002 **
##
## Group 27.22+28.59+28.67+30.8 #sps. 1
##      stat p.value
## asv368 0.853  0.001 ***
##
## Group 27.22+29.11+29.35+29.37 #sps. 1
##      stat p.value

```

```

## asv474 0.944 0.001 ***
##
## Group 27.25+28.59+28.67+30.8 #sps. 1
## stat p.value
## asv4 0.992 0.001 ***
##
## Group 26.86+27.04+27.19+27.22+27.25 #sps. 26
## stat p.value
## asv81 0.999 0.001 ***
## asv84 0.983 0.038 *
## asv110 0.980 0.001 ***
## asv260 0.971 0.001 ***
## asv862 0.967 0.001 ***
## asv109 0.966 0.001 ***
## asv558 0.962 0.001 ***
## asv767 0.950 0.001 ***
## asv1778 0.948 0.001 ***
## asv429 0.944 0.001 ***
## asv447 0.943 0.001 ***
## asv245 0.941 0.001 ***
## asv1475 0.940 0.001 ***
## asv1258 0.938 0.001 ***
## asv820 0.936 0.001 ***
## asv293 0.935 0.001 ***
## asv327 0.934 0.001 ***
## asv1465 0.933 0.001 ***
## asv357 0.932 0.001 ***
## asv955 0.930 0.001 ***
## asv396 0.928 0.001 ***
## asv1785 0.926 0.001 ***
## asv1931 0.912 0.001 ***
## asv297 0.898 0.001 ***
## asv2828 0.880 0.001 ***
## asv2150 0.804 0.001 ***
##
## Group 26.86+27.22+28.59+28.67+30.8 #sps. 1
## stat p.value
## asv12 0.998 0.001 ***
##
## Group 27.19+28.67+29.11+29.35+29.37 #sps. 1
## stat p.value
## asv40 0.985 0.001 ***
##
## Group 27.22+27.25+29.11+29.35+29.37 #sps. 1
## stat p.value
## asv952 0.89 0.001 ***
##
## Group 26.86+27.04+27.19+27.22+27.25+28.67 #sps. 1
## stat p.value
## asv55 0.998 0.001 ***
##
## Group 26.86+27.04+27.19+27.22+27.25+29.11 #sps. 2
## stat p.value
## asv431 0.955 0.001 ***

```

```

## asv467 0.943    0.001 ***
##
## Group 26.86+27.04+27.19+27.22+27.25+29.35 #sps. 1
##      stat p.value
## asv1031 0.941    0.001 ***
##
## Group 26.86+27.04+27.19+27.22+27.25+29.37 #sps. 1
##      stat p.value
## asv62 0.998    0.001 ***
##
## Group 26.86+27.04+27.25+29.11+29.35+29.37 #sps. 1
##      stat p.value
## asv49 0.962    0.001 ***
##
## Group 27.04+27.19+27.22+27.25+29.11+29.37 #sps. 1
##      stat p.value
## asv1749 0.879    0.001 ***
##
## Group 26.86+27.04+27.19+27.22+27.25+28.67+29.37 #sps. 2
##      stat p.value
## asv27 0.988    0.001 ***
## asv16 0.988    0.001 ***
##
## Group 26.86+27.04+27.19+27.22+27.25+29.11+29.37 #sps. 3
##      stat p.value
## asv417 0.963    0.001 ***
## asv237 0.959    0.001 ***
## asv359 0.944    0.001 ***
##
## Group 26.86+27.19+27.22+27.25+28.59+28.67+30.8 #sps. 1
##      stat p.value
## asv9 0.997    0.001 ***
##
## Group 26.86+28.59+28.67+29.11+29.35+29.37+30.8 #sps. 1
##      stat p.value
## asv43 0.817    0.016 *
##
## Group 27.19+27.22+27.25+28.67+29.11+29.35+29.37 #sps. 1
##      stat p.value
## asv66 0.988    0.001 ***
##
## Group 26.86+27.04+27.19+27.22+27.25+29.11+29.35+29.37 #sps. 2
##      stat p.value
## asv682 0.925    0.001 ***
## asv730 0.900    0.001 ***
##
## Group 26.86+27.19+27.22+27.25+28.59+28.67+29.11+30.8 #sps. 1
##      stat p.value
## asv15 0.998    0.001 ***
##
## Group 26.86+27.04+27.19+27.22+27.25+28.59+28.67+29.11+30.8 #sps. 1
##      stat p.value
## asv8 0.999    0.009 **
##

```

```
## Group 26.86+27.04+27.19+27.22+27.25+28.59+28.67+29.11+29.35+29.37 #sps. 1
## stat p.value
## asv23 0.999 0.001 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
indisp.sign<-as.data.table(inv_temp$sign, keep.rownames=TRUE)
#add adjusted p-value
indisp.sign[,p.value.bh:=p.adjust(p.value, method="BH")]
#now can select only the indicators with adjusted significant p-values
IndVal_temp = indisp.sign[p.value.bh<=0.05, ]
IndVal_temp
```

```
##          rn s.26.86 s.27.04 s.27.19 s.27.22 s.27.25 s.28.59 s.28.67 s.29.11
## 1:   asv4      0      0      0      0      1      1      1      0
## 2:   asv8      1      1      1      1      1      1      1      1
## 3:   asv9      1      0      1      1      1      1      1      0
## 4:  asv12      1      0      0      1      0      1      1      0
## 5:  asv13      0      0      0      0      0      1      1      0
## ---
## 305: asv2916      0      0      0      0      0      1      0      0
## 306: asv3104      0      0      0      0      0      0      0      0
## 307: asv3180      0      0      0      0      0      0      1      0
## 308: asv3304      0      0      0      0      0      1      1      0
## 309: asv3329      0      0      0      0      0      1      0      0
##      s.29.35 s.29.37 s.30.8 index      stat p.value  p.value.bh
## 1:      0      0      1   530 0.9919628  0.001 0.001758294
## 2:      0      0      1  1983 0.9986101  0.009 0.013042969
## 3:      0      0      1  1615 0.9974249  0.001 0.001758294
## 4:      0      0      1   720 0.9980285  0.001 0.001758294
## 5:      0      0      1   215 0.8746931  0.001 0.001758294
## ---
## 305:      0      0      1    56 0.7184212  0.003 0.004860262
## 306:      0      0      1    11 0.6900656  0.013 0.017797048
## 307:      0      0      0     7 0.7628160  0.002 0.003342342
## 308:      0      0      1   215 0.6030227  0.025 0.031228956
## 309:      0      0      1    56 0.6720215  0.010 0.014324324
```

```
write.xlsx(IndVal_temp, file = "IndVal_temp_16Sep2021.xlsx")
```

##GLM by clade

```
ps13_CladeA = subset_taxa(ps13, ITSclade=="A")
ps13_CladeC = subset_taxa(ps13, ITSclade=="C")
ps13_CladeD = subset_taxa(ps13, ITSclade=="D")
```

```
set.seed(199932)
```

#Clade A

```
ps13_CladeA_n2 = prune_samples(sample_sums(ps13_CladeA) >= 1, ps13_CladeA)
asv_css_A <- t(otu_table(ps13_CladeA_n2))
meta_A = as(sample_data(ps13_CladeA_n2), "data.frame")
```

```

#Clade C
asv_css_C <- t(otu_table(ps13_CladeC))
meta_C = as(sample_data(ps13_CladeC), "data.frame")

#Clade D
asv_css_D <- t(otu_table(ps13_CladeD))
meta_D = as(sample_data(ps13_CladeD), "data.frame")

perm_css_A = adonis2(asv_css_A ~ S_region/Loc + SST_a + Tbl_bin, meta_A, method = "bray", sqrt.dist = F)
perm_css_A

## Permutation test for adonis under reduced model
## Terms added sequentially (first to last)
## Permutation: free
## Number of permutations: 999
##
## adonis2(formula = asv_css_A ~ S_region/Loc + SST_a + Tbl_bin, data = meta_A, method = "bray", sqrt.d
##
##          Df SumOfSqs      R2      F Pr(>F)
## S_region    2   2.5064 0.11108  5.1774 0.001 ***
## SST_a        1   5.0493 0.22379 20.8606 0.001 ***
## Tbl_bin       1   0.2207 0.00978  0.9118 0.444
## S_region:Loc  3   1.4738 0.06532  2.0296 0.014 *
## Residual     55  13.3128 0.59003
## Total        62  22.5631 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

perm_css_C = adonis2(asv_css_C ~ S_region/Loc + SST_a + Tbl_bin, meta_C, method = "bray", sqrt.dist = F)
perm_css_C

## Permutation test for adonis under reduced model
## Terms added sequentially (first to last)
## Permutation: free
## Number of permutations: 999
##
## adonis2(formula = asv_css_C ~ S_region/Loc + SST_a + Tbl_bin, data = meta_C, method = "bray", sqrt.d
##
##          Df SumOfSqs      R2      F Pr(>F)
## S_region    2   7.2496 0.25521 25.7169 0.001 ***
## SST_a        1   7.8701 0.27706 55.8362 0.001 ***
## Tbl_bin       1   0.2128 0.00749  1.5097 0.180
## S_region:Loc  3   1.3747 0.04840  3.2511 0.005 **
## Residual     83  11.6989 0.41184
## Total        90  28.4061 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

perm_css_D = adonis2(asv_css_D ~ S_region/Loc + SST_a + Tbl_bin, meta_D, method = "bray", sqrt.dist = F)
perm_css_D

## Permutation test for adonis under reduced model
## Terms added sequentially (first to last)

```

```
## Permutation: free
## Number of permutations: 999
##
## adonis2(formula = asv_css_D ~ S_region/Loc + SST_a + Tbl_bin, data = meta_D, method = "bray", sqrt.d = FALSE)
##           Df SumOfSqs      R2      F Pr(>F)
## S_region    2  12.7427 0.40306 53.4274  0.001 ***
## SST_a       1   7.8263 0.24755 65.6281  0.001 ***
## Tbl_bin     1   0.3052 0.00965  2.5591  0.062 .
## S_region:Loc 3   0.8427 0.02665  2.3554  0.016 *
## Residual    83   9.8980 0.31308
## Total      90  31.6149 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Pairwise differences - Clade A
```

```
library(pairwiseAdonis)
```

```
pairwise.adonis2(asv_css_A ~ Loc, data = meta_A, sim.method = "bray", p.adjust.m = "BH", permutations = 999)
```

```
## $parent_call
## [1] "asv_css_A ~ Loc , strata = Null , permutations 999"
##
## $Oman_vs_Taiwan
##           Df SumOfSqs      R2      F Pr(>F)
## Loc       1   0.1001 0.04843 0.9161  0.454
## Residual  18   1.9670 0.95157
## Total    19   2.0671 1.00000
##
## $Oman_vs_Djib
##           Df SumOfSqs      R2      F Pr(>F)
## Loc       1   5.2509 0.36419 21.193  0.001 ***
## Residual  37   9.1671 0.63581
## Total    38  14.4180 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Tahaa
##           Df SumOfSqs      R2      F Pr(>F)
## Loc       1   0.16553 0.08748 1.6297  0.185
## Residual  17   1.72667 0.91252
## Total    18   1.89220 1.00000
##
## $Oman_vs_Tahiti
##           Df SumOfSqs      R2      F Pr(>F)
## Loc       1   0.61711 0.3841  9.3547  0.003 **
## Residual  15   0.98952 0.6159
## Total    16   1.60664 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Raia
##           Df SumOfSqs      R2      F Pr(>F)
## Loc       1   0.9558 0.32586 8.2174  0.003 **
## Residual  17   1.9773 0.67414
```

```

## Total      18      2.9331 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Moorea
##           Df SumOfSqs      R2      F Pr(>F)
## Loc        1  0.60951 0.20722 4.4435  0.013 *
## Residual  17  2.33188 0.79278
## Total      18  2.94140 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Djib
##           Df SumOfSqs      R2      F Pr(>F)
## Loc        1   2.3240 0.19991 7.2458  0.001 ***
## Residual  29   9.3015 0.80009
## Total     30  11.6255 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Tahaa
##           Df SumOfSqs      R2      F Pr(>F)
## Loc        1  0.03635 0.01916 0.1758  0.668
## Residual   9  1.86103 0.98084
## Total     10  1.89738 1.00000
##
## $Taiwan_vs_Tahiti
##           Df SumOfSqs      R2      F Pr(>F)
## Loc        1  0.46923 0.29454 2.9225  0.042 *
## Residual   7  1.12388 0.70546
## Total      8  1.59311 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Raia
##           Df SumOfSqs      R2      F Pr(>F)
## Loc        1  0.59496 0.21981 2.5357  0.092 .
## Residual   9  2.11169 0.78019
## Total     10  2.70664 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Moorea
##           Df SumOfSqs      R2      F Pr(>F)
## Loc        1  0.36632 0.12933 1.3368  0.214
## Residual   9  2.46624 0.87067
## Total     10  2.83256 1.00000
##
## $Djib_vs_Tahaa
##           Df SumOfSqs      R2      F Pr(>F)
## Loc        1   2.0453 0.18415 6.3201  0.001 ***
## Residual  28   9.0612 0.81585
## Total     29  11.1065 1.00000
## ---

```



```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   1.5842 0.15988 4.9481  0.001 ***
## Residual 26   8.3241 0.84012
## Total    27   9.9082 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   1.8306 0.16429 5.5044  0.001 ***
## Residual 28   9.3119 0.83571
## Total    29  11.1425 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Moorea
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   1.5307 0.1367 4.4338  0.001 ***
## Residual 28   9.6664 0.8633
## Total    29  11.1971 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Tahaa_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.35332 0.28565 2.3992  0.038 *
## Residual  6  0.88360 0.71435
## Total     7  1.23692 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Tahaa_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.52743 0.21987 2.2547  0.131
## Residual  8  1.87141 0.78013
## Total     9  2.39883 1.00000
##
## $Tahaa_vs_Moorea
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.32509 0.12743 1.1684  0.371
## Residual  8  2.22596 0.87257
## Total     9  2.55104 1.00000
##
## $Tahiti_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.59336 0.34345 3.1387  0.091 .
## Residual  6  1.13426 0.65655
## Total     7  1.72761 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

```

```
## $Tahiti_vs_Moorea
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.39944 0.21154 1.6098  0.199
## Residual  6  1.48881 0.78846
## Total      7  1.88824 1.00000
##
## $Raia_vs_Moorea
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1  0.28056 0.10176 0.9063  0.526
## Residual  8  2.47661 0.89824
## Total      9  2.75718 1.00000
##
## attr("class")
## [1] "pwadstrata" "list"
```

```
pairwise.adonis2(asv_css_A ~ S_region, data = meta_A, sim.method = "bray", p.adjust.m = "BH", permutat.
```

```
## $parent_call
## [1] "asv_css_A ~ S_region , strata = Null , permutations 999"
##
## $IndianOc_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## S_region  1   0.9454 0.05759 2.6279  0.024 *
## Residual 43  15.4687 0.94241
## Total    44  16.4140 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $IndianOc_vs_FrPoly
##      Df SumOfSqs      R2      F Pr(>F)
## S_region  1   1.8865 0.0903 5.4593  0.003 **
## Residual 55  19.0060 0.9097
## Total    56  20.8925 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_FrPoly
##      Df SumOfSqs      R2      F Pr(>F)
## S_region  1   0.3263 0.0547 1.273  0.291
## Residual 22   5.6386 0.9453
## Total    23   5.9649 1.0000
##
## attr("class")
## [1] "pwadstrata" "list"
```

```
pairwise.adonis2(asv_css_A ~ SST_a, data = meta_A, sim.method = "bray", p.adjust.m = "BH", permutat.
```

```
## 'nperm' >= set of all permutations: complete enumeration.
```

```
## Set of permutations < 'minperm'. Generating entire set.
```

```
## Set of permutations < 'minperm'. Generating entire set.
```

```
## 'nperm' >= set of all permutations: complete enumeration.
```

```

## Set of permutations < 'minperm'. Generating entire set.
## Set of permutations < 'minperm'. Generating entire set.

## 'nperm' >= set of all permutations: complete enumeration.

## Set of permutations < 'minperm'. Generating entire set.

## 'nperm' >= set of all permutations: complete enumeration.

## Set of permutations < 'minperm'. Generating entire set.
## Set of permutations < 'minperm'. Generating entire set.
## Set of permutations < 'minperm'. Generating entire set.

## 'nperm' >= set of all permutations: complete enumeration.

## Set of permutations < 'minperm'. Generating entire set.

## 'nperm' >= set of all permutations: complete enumeration.

## Set of permutations < 'minperm'. Generating entire set.

## 'nperm' >= set of all permutations: complete enumeration.

## Set of permutations < 'minperm'. Generating entire set.

## $parent_call
## [1] "asv_css_A ~ SST_a , strata = Null , permutations 999"
##
## $`30.8_vs_28.59`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.00749 0.00652 0.1049  0.963
## Residual  16  1.14261 0.99348
## Total     17  1.15011 1.00000
##
## $`30.8_vs_29.37`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   3.8602 0.49338 22.399  0.001 ***
## Residual  23   3.9637 0.50662
## Total     24   7.8239 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_27.19`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.3996 0.22006  3.95  0.086 .

```

```

## Residual 14    1.4163 0.77994
## Total      15    1.8159 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## `$30.8_vs_26.86`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.61711 0.3841 9.3547 0.004 **
## Residual 15  0.98952 0.6159
## Total     16  1.60664 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## `$30.8_vs_29.11`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  3.0572 0.46602 17.455 0.001 ***
## Residual 20  3.5030 0.53398
## Total     21  6.5602 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## `$30.8_vs_28.67`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.4005 0.22044 3.9589 0.067 .
## Residual 14  1.4163 0.77956
## Total     15  1.8168 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## `$30.8_vs_27.25`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.9558 0.32586 8.2174 0.002 **
## Residual 17  1.9773 0.67414
## Total     18  2.9331 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## `$30.8_vs_27.04`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.60951 0.20722 4.4435 0.009 **
## Residual 17  2.33188 0.79278
## Total     18  2.94140 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## `$30.8_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.05387 0.05479 0.8695 0.43
## Residual 15  0.92922 0.94521
## Total     16  0.98309 1.00000
##
## `$30.8_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  2.5563 0.47626 16.369 0.001 ***

```

```

## Residual 18 2.8112 0.52374
## Total 19 5.3675 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_29.37`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 1.8633 0.36272 7.399 0.002 **
## Residual 13 3.2737 0.63728
## Total 14 5.1370 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_27.19`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.30311 0.29445 1.6693 0.2667
## Residual 4 0.72631 0.70555
## Total 5 1.02943 1.00000
##
## $`28.59_vs_26.86`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.36313 0.54798 6.0615 0.029 *
## Residual 5 0.29954 0.45202
## Total 6 0.66267 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_29.11`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 1.625 0.36615 5.7766 0.003 **
## Residual 10 2.813 0.63385
## Total 11 4.438 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_28.67`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.32434 0.3087 1.7862 0.2667
## Residual 4 0.72631 0.6913
## Total 5 1.05066 1.0000
##
## $`28.59_vs_27.25`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.56138 0.30366 3.0526 0.11
## Residual 7 1.28735 0.69634
## Total 8 1.84873 1.00000
##
## $`28.59_vs_27.04`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.36831 0.18322 1.5702 0.195
## Residual 7 1.64190 0.81678
## Total 8 2.01021 1.00000
##
## $`28.59_vs_27.22`

```

```

##          Df SumOfSqs      R2      F Pr(>F)
## SST_a      1 0.018593 0.07211 0.3886 0.878
## Residual    5 0.239238 0.92789
## Total       6 0.257832 1.00000
##
## $`28.59_vs_29.35`
##          Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  1.4965 0.41366 5.644 0.007 **
## Residual    8  2.1212 0.58634
## Total       9  3.6176 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.19`
##          Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.7687 0.1781 2.3836 0.044 *
## Residual   11  3.5474 0.8219
## Total      12  4.3161 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_26.86`
##          Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  1.4704 0.32028 5.6543 0.004 **
## Residual   12  3.1206 0.67972
## Total      13  4.5911 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_29.11`
##          Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.2720 0.04606 0.8208 0.516
## Residual   17  5.6341 0.95394
## Total      18  5.9062 1.00000
##
## $`29.37_vs_28.67`
##          Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.7814 0.18051 2.423 0.033 *
## Residual   11  3.5474 0.81949
## Total      12  4.3288 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.25`
##          Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  1.6556 0.28723 5.6416 0.001 ***
## Residual   14  4.1085 0.71277
## Total      15  5.7640 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.04`
##          Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  1.4039 0.23929 4.404 0.001 ***

```

```

## Residual 14 4.4630 0.76071
## Total 15 5.8669 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.22`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 1.6123 0.34505 6.3219 0.005 **
## Residual 12 3.0603 0.65495
## Total 13 4.6726 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_29.35`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.4454 0.08268 1.3519 0.241
## Residual 15 4.9423 0.91732
## Total 16 5.3877 1.00000
##
## $`27.19_vs_26.86`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.40270 0.41263 2.1075 0.1
## Residual 3 0.57322 0.58737
## Total 4 0.97592 1.00000
##
## $`27.19_vs_29.11`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.6667 0.17763 1.7279 0.048 *
## Residual 8 3.0867 0.82237
## Total 9 3.7534 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.19_vs_28.67`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.03037 0.02948 0.0607 1
## Residual 2 1.00000 0.97052
## Total 3 1.03037 1.00000
##
## $`27.19_vs_27.25`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.39664 0.20261 1.2705 0.426
## Residual 5 1.56103 0.79739
## Total 6 1.95767 1.00000
##
## $`27.19_vs_27.04`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.28707 0.13033 0.7493 0.712
## Residual 5 1.91558 0.86967
## Total 6 2.20265 1.00000
##
## $`27.19_vs_27.22`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.29745 0.36705 1.7397 0.4

```

```

## Residual 3 0.51292 0.63295
## Total 4 0.81037 1.00000
##
## $`27.19_vs_29.35`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.64552 0.21232 1.6173 0.157
## Residual 6 2.39485 0.78768
## Total 7 3.04037 1.00000
##
## $`26.86_vs_29.11`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 1.3633 0.33886 4.6128 0.006 **
## Residual 9 2.6599 0.66114
## Total 10 4.0232 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_28.67`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.53083 0.4808 2.7781 0.1
## Residual 3 0.57322 0.5192
## Total 4 1.10405 1.0000
##
## $`26.86_vs_27.25`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.59336 0.34345 3.1387 0.097 .
## Residual 6 1.13426 0.65655
## Total 7 1.72761 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_27.04`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.39944 0.21154 1.6098 0.206
## Residual 6 1.48881 0.78846
## Total 7 1.88824 1.00000
##
## $`26.86_vs_27.22`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.28424 0.76741 13.198 0.1
## Residual 4 0.08615 0.23259
## Total 5 0.37039 1.00000
##
## $`26.86_vs_29.35`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 1.2156 0.38182 4.3235 0.029 *
## Residual 7 1.9681 0.61818
## Total 8 3.1837 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_28.67`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.6730 0.179 1.7442 0.06 .

```



```

## Residual 8 3.0867 0.821
## Total 9 3.7597 1.000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_27.25`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 1.3851 0.27521 4.1769 0.001 ***
## Residual 11 3.6477 0.72479
## Total 12 5.0329 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_27.04`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 1.1724 0.22656 3.2221 0.001 ***
## Residual 11 4.0023 0.77344
## Total 12 5.1747 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_27.22`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 1.4410 0.35663 4.9888 0.006 **
## Residual 9 2.5996 0.64337
## Total 10 4.0407 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_29.35`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.3789 0.07796 1.0146 0.4
## Residual 12 4.4816 0.92204
## Total 13 4.8605 1.00000
##
## $`28.67_vs_27.25`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.44482 0.22176 1.4248 0.362
## Residual 5 1.56103 0.77824
## Total 6 2.00585 1.00000
##
## $`28.67_vs_27.04`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.33378 0.14839 0.8712 0.422
## Residual 5 1.91558 0.85161
## Total 6 2.24936 1.00000
##
## $`28.67_vs_27.22`
## Df SumOfSqs R2 F Pr(>F)
## SST_a 1 0.34718 0.40365 2.0306 0.1
## Residual 3 0.51292 0.59635
## Total 4 0.86011 1.00000
##
## $`28.67_vs_29.35`

```

```

##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.6478 0.21291 1.623  0.142
## Residual    6   2.3948 0.78709
## Total       7   3.0427 1.00000
##
## $`27.25_vs_27.04`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.28056 0.10176 0.9063  0.497
## Residual    8   2.47661 0.89824
## Total       9   2.75718 1.00000
##
## $`27.25_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.49813 0.31686 2.783  0.189
## Residual    6   1.07396 0.68314
## Total       7   1.57208 1.00000
##
## $`27.25_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   1.2756 0.30145 3.8839  0.002 **
## Residual    9   2.9559 0.69855
## Total      10   4.2315 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.34108 0.19275 1.4326  0.339
## Residual    6   1.42851 0.80725
## Total       7   1.76959 1.00000
##
## $`27.04_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   1.0751 0.24515 2.9229  0.008 **
## Residual    9   3.3104 0.75485
## Total      10   4.3856 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.22_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   1.3507 0.41452 4.956  0.015 *
## Residual    7   1.9078 0.58548
## Total       8   3.2585 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## attr("class")
## [1] "pwadstrata" "list"

```

```
# Pairwise differences - Clade C
```

```
library(pairwiseAdonis)
```

```
pairwise.adonis2(asv_css_C ~ Loc, data = meta_C, sim.method = "bray", p.adjust.m = "BH",
```

```
permutations = 999)
```

```
## $parent_call
## [1] "asv_css_C ~ Loc , strata = Null , permutations 999"
##
## $Oman_vs_Moorea
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1      4.501 0.58326 37.788 0.001 ***
## Residual 27      3.216 0.41674
## Total    28      7.717 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1      0.3998 0.1164 4.0838 0.026 *
## Residual 31      3.0351 0.8836
## Total    32      3.4350 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Djib
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1      8.3368 0.55312 56.937 0.001 ***
## Residual 46      6.7354 0.44688
## Total    47     15.0722 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Tahaa
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1      5.2693 0.60431 44.289 0.001 ***
## Residual 29      3.4502 0.39569
## Total    30      8.7195 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1      1.6991 0.30156 10.362 0.001 ***
## Residual 24      3.9352 0.69844
## Total    25      5.6343 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1      4.1027 0.52052 29.311 0.001 ***
## Residual 27      3.7793 0.47948
## Total    28      7.8820 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```

## $Moorea_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   4.0682 0.75301 54.877  0.001 ***
## Residual 18   1.3344 0.24699
## Total    19   5.4027 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Djib
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   0.2209 0.04203 1.4479  0.165
## Residual 33   5.0347 0.95797
## Total    34   5.2556 1.00000
##
## $Moorea_vs_Tahaa
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   0.3280 0.15788 2.9997  0.016 *
## Residual 16   1.7495 0.84212
## Total    17   2.0775 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   0.41951 0.15807 2.0652  0.029 *
## Residual 11   2.23449 0.84193
## Total    12   2.65400 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   0.14202 0.06396 0.9566  0.452
## Residual 14   2.07857 0.93604
## Total    15   2.22059 1.00000
##
## $Taiwan_vs_Djib
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   6.4576 0.57089 49.225  0.001 ***
## Residual 37   4.8538 0.42911
## Total    38  11.3114 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Tahaa
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1   4.6236 0.74667 58.95  0.001 ***
## Residual 20   1.5687 0.25333
## Total    21   6.1922 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)

```

```

## Loc      1    1.7001 0.4529 12.418  0.002 **
## Residual 15    2.0536 0.5471
## Total    16    3.7537 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1    3.7299 0.66279 35.378  0.001 ***
## Residual 18    1.8977 0.33721
## Total    19    5.6276 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Tahaa
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1    0.9015 0.1461 5.9886  0.003 **
## Residual 35    5.2689 0.8539
## Total    36    6.1704 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1    0.4158 0.06739 2.1677  0.063 .
## Residual 30    5.7539 0.93261
## Total    31    6.1696 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1    0.3646 0.06116 2.1496  0.042 *
## Residual 33    5.5980 0.93884
## Total    34    5.9626 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Tahaa_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1    0.61323 0.19897 3.2292  0.002 **
## Residual 13    2.46873 0.80103
## Total    14    3.08196 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Tahaa_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc      1    0.18615 0.07449 1.2878  0.203
## Residual 16    2.31282 0.92551
## Total    17    2.49897 1.00000
##
## $Tahiti_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)

```

```

## Loc      1  0.27608 0.08982 1.0855  0.37
## Residual 11  2.79779 0.91018
## Total    12  3.07387 1.00000
##
## attr("class")
## [1] "pwadstrata" "list"

pairwise.adonis2(asv_css_C ~ S_region, data = meta_C, sim.method = "bray", p.adjust.m = "BH",
  permutations = 999)

## $parent_call
## [1] "asv_css_C ~ S_region , strata = Null , permutations 999"
##
## $IndianOc_vs_FrPoly
##      Df SumOfSqs      R2      F Pr(>F)
## S_region  1   2.7804 0.11902 10.403  0.001 ***
## Residual 77  20.5797 0.88098
## Total    78  23.3602 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $IndianOc_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## S_region  1   2.750 0.14946 10.192  0.001 ***
## Residual 58  15.649 0.85054
## Total    59  18.399 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $FrPoly_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## S_region  1   6.3967 0.51251 43.105  0.001 ***
## Residual 41   6.0843 0.48749
## Total    42  12.4811 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## attr("class")
## [1] "pwadstrata" "list"

pairwise.adonis2(asv_css_C ~ SST_a, data = meta_C, sim.method = "bray", p.adjust.m = "BH",
  permutations = 999)

## Set of permutations < 'minperm'. Generating entire set.

## 'nperm' >= set of all permutations: complete enumeration.

## Set of permutations < 'minperm'. Generating entire set.

## $parent_call
## [1] "asv_css_C ~ SST_a , strata = Null , permutations 999"
##

```

```

## $`30.8_vs_27.04`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    4.501 0.58326 37.788 0.001 ***
## Residual 27    3.216 0.41674
## Total    28    7.717 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_28.59`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    0.3500 0.10708 3.4776 0.053 .
## Residual 29    2.9184 0.89292
## Total    30    3.2684 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_29.37`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    5.3431 0.54668 37.384 0.001 ***
## Residual 31    4.4307 0.45332
## Total    32    9.7738 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_27.19`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    3.7394 0.56254 32.148 0.001 ***
## Residual 25    2.9080 0.43746
## Total    26    6.6474 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_26.86`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    1.6991 0.30156 10.362 0.001 ***
## Residual 24    3.9352 0.69844
## Total    25    5.6343 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_29.11`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    4.3705 0.56513 35.087 0.001 ***
## Residual 27    3.3632 0.43487
## Total    28    7.7337 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    0.19646 0.07364 1.6693 0.108
## Residual 21    2.47161 0.92636
## Total    22    2.66807 1.00000
##

```

```

## $`30.8_vs_27.25`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   4.1027 0.52052 29.311  0.001 ***
## Residual 27   3.7793 0.47948
## Total     28   7.8820 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   2.6946 0.49368 22.426  0.001 ***
## Residual 23   2.7635 0.50632
## Total     24   5.4581 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   3.6638 0.50461 26.484  0.001 ***
## Residual 26   3.5968 0.49539
## Total     27   7.2606 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_28.59`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   3.7755 0.75613 49.609  0.002 **
## Residual 16   1.2177 0.24387
## Total     17   4.9932 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_29.37`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.1861 0.06382  1.227  0.257
## Residual 18   2.7300 0.93618
## Total     19   2.9161 1.00000
##
## $`27.04_vs_27.19`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.18184 0.13091  1.8075  0.089 .
## Residual 12   1.20724 0.86909
## Total     13   1.38908 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_26.86`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.41951 0.15807  2.0652  0.036 *
## Residual 11   2.23449 0.84193
## Total     12   2.65400 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

```



```

## $`27.04_vs_29.11`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.11509 0.06475 0.9692  0.399
## Residual 14  1.66242 0.93525
## Total     15  1.77751 1.00000
##
## $`27.04_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  1.42332 0.64868 14.771  0.019 *
## Residual  8  0.77087 0.35132
## Total      9  2.19419 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.14202 0.06396 0.9566  0.443
## Residual 14  2.07857 0.93604
## Total     15  2.22059 1.00000
##
## $`27.04_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.43795 0.29183 4.1208  0.002 **
## Residual 10  1.06276 0.70817
## Total     11  1.50070 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.28398 0.13026 1.947  0.103
## Residual 13  1.89611 0.86974
## Total     14  2.18009 1.00000
##
## $`28.59_vs_29.37`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  4.2174 0.63422 34.677  0.001 ***
## Residual 20  2.4324 0.36578
## Total     21  6.6498 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_27.19`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  3.2745 0.7826 50.396  0.001 ***
## Residual 14  0.9097 0.2174
## Total     15  4.1842 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_26.86`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  1.6152 0.45471 10.841  0.002 **
## Residual 13  1.9369 0.54529

```

```

## Total      14      3.5521 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_29.11`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   3.6759 0.72924 43.092  0.001 ***
## Residual  16   1.3648 0.27076
## Total     17   5.0407 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_28.67`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.10349 0.17942 2.1865  0.114
## Residual  10   0.47329 0.82058
## Total     11   0.57678 1.00000
##
## $`28.59_vs_27.25`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   3.4684 0.66072 31.159  0.001 ***
## Residual  16   1.7810 0.33928
## Total     17   5.2493 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   2.4960 0.76537 39.145  0.002 **
## Residual  12   0.7652 0.23463
## Total     13   3.2612 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   3.1793 0.66543 29.833  0.001 ***
## Residual  15   1.5985 0.33457
## Total     16   4.7778 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.19`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.37054 0.13269 2.4479  0.061 .
## Residual  16   2.42194 0.86731
## Total     17   2.79248 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_26.86`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.3332 0.0881 1.4491  0.147
## Residual  15   3.4492 0.9119

```

```

## Total      16      3.7824 1.0000
##
## $`29.37_vs_29.11`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.13439 0.04463 0.8408  0.46
## Residual  18  2.87712 0.95537
## Total     19  3.01151 1.00000
##
## $`29.37_vs_28.67`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   1.3949 0.41263 8.43  0.011 *
## Residual  12   1.9856 0.58737
## Total     13   3.3804 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.25`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.2964 0.08257 1.62  0.108
## Residual  18   3.2933 0.91743
## Total     19   3.5897 1.00000
##
## $`29.37_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.65946 0.22454 4.0538  0.008 **
## Residual  14  2.27746 0.77546
## Total     15  2.93692 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.0951 0.02967 0.5198  0.807
## Residual  17   3.1108 0.97033
## Total     18   3.2059 1.00000
##
## $`27.19_vs_26.86`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.4733 0.19723 2.2111  0.007 **
## Residual   9   1.9265 0.80277
## Total     10   2.3998 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.19_vs_29.11`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.28095 0.1718 2.4892  0.015 *
## Residual  12  1.35440 0.8282
## Total     13  1.63535 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.19_vs_28.67`
##           Df SumOfSqs      R2      F Pr(>F)

```

```

## SST_a      1  1.36956 0.74741 17.754  0.035 *
## Residual   6  0.46285 0.25259
## Total      7  1.83241 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.19_vs_27.25`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.10415 0.05555 0.7059  0.802
## Residual  12  1.77055 0.94445
## Total     13  1.87469 1.00000
##
## $`27.19_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.23714 0.23908 2.5137  0.033 *
## Residual   8  0.75474 0.76092
## Total      9  0.99188 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.19_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.46752 0.22744 3.2383  0.035 *
## Residual  11  1.58809 0.77256
## Total     12  2.05561 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_29.11`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.36729 0.13361 1.6964  0.053 .
## Residual  11  2.38165 0.86639
## Total     12  2.74894 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_28.67`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.74157 0.3323 2.4883  0.047 *
## Residual   5  1.49009 0.6677
## Total      6  2.23167 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_27.25`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.27608 0.08982 1.0855  0.38
## Residual  11  2.79779 0.91018
## Total     12  3.07387 1.00000
##
## $`26.86_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.57532 0.24406 2.26  0.011 *
## Residual   7  1.78198 0.75594

```

```

## Total      8  2.35730 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.34767 0.11734 1.3293  0.197
## Residual 10  2.61533 0.88266
## Total    11  2.96300 1.00000
##
## $`29.11_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  1.38762 0.60183 12.092  0.021 *
## Residual  8  0.91803 0.39817
## Total     9  2.30565 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.19715 0.08137 1.2401  0.21
## Residual 14  2.22573 0.91863
## Total    15  2.42288 1.00000
##
## $`29.11_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.57751 0.3231 4.7732  0.003 **
## Residual 10  1.20992 0.6769
## Total    11  1.78743 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.1709 0.07718 1.0873  0.32
## Residual 13  2.0433 0.92282
## Total    14  2.2142 1.00000
##
## $`28.67_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  1.2995 0.49342 7.7923  0.02 *
## Residual  8  1.3342 0.50658
## Total     9  2.6337 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.67_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  1.21766 0.79273 15.299 0.06667 .
## Residual  4  0.31837 0.20727
## Total     5  1.53602 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

```

```
## $`28.67_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   1.2641 0.52326 7.683  0.028 *
## Residual    7   1.1517 0.47674
## Total       8   2.4158 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.25_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.31581 0.16263 1.9422  0.04 *
## Residual   10  1.62606 0.83737
## Total      11  1.94188 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.25_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.38477 0.13528 2.0338  0.061 .
## Residual   13  2.45942 0.86472
## Total      14  2.84419 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.22_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.74647 0.34084 4.6538  0.015 *
## Residual    9  1.44361 0.65916
## Total      10  2.19008 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## attr("class")
## [1] "pwadstrata" "list"
```

```
# Pairwise differences - Clade D
```

```
pairwise.adonis2(asv_css_D ~ Loc, data = meta_D, sim.method = "bray", p.adjust.m = "BH",
  permutations = 999)
```

```
## $parent_call
## [1] "asv_css_D ~ Loc , strata = Null , permutations 999"
##
## $Oman_vs_Moorea
##           Df SumOfSqs      R2      F Pr(>F)
## Loc        1   5.0305 0.71524 67.817  0.001 ***
## Residual   27   2.0028 0.28476
## Total      28   7.0333 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Taiwan
##           Df SumOfSqs      R2      F Pr(>F)
## Loc        1  0.09222 0.03296 1.0565  0.36
```

```

## Residual 31 2.70593 0.96704
## Total 32 2.79814 1.00000
##
## $Oman_vs_Djib
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 8.1598 0.54955 56.121 0.001 ***
## Residual 46 6.6883 0.45045
## Total 47 14.8481 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Tahaa
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 5.9771 0.75382 88.801 0.001 ***
## Residual 29 1.9520 0.24618
## Total 30 7.9291 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 2.0569 0.42128 17.471 0.001 ***
## Residual 24 2.8255 0.57872
## Total 25 4.8824 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Oman_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 5.2334 0.75263 82.146 0.001 ***
## Residual 27 1.7201 0.24737
## Total 28 6.9535 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 4.0749 0.72575 47.633 0.001 ***
## Residual 18 1.5398 0.27425
## Total 19 5.6147 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Djib
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 3.8188 0.40882 22.821 0.001 ***
## Residual 33 5.5222 0.59118
## Total 34 9.3410 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Tahaa
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 0.25554 0.24538 5.2026 0.002 **

```

```

## Residual 16 0.78589 0.75462
## Total 17 1.04144 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 0.35915 0.17792 2.3807 0.009 **
## Residual 11 1.65943 0.82208
## Total 12 2.01858 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Moorea_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 0.22063 0.2848 5.575 0.001 ***
## Residual 14 0.55404 0.7152
## Total 15 0.77467 1.0000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Djib
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 5.5678 0.47212 33.092 0.001 ***
## Residual 37 6.2253 0.52788
## Total 38 11.7931 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Tahaa
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 4.707 0.75968 63.223 0.001 ***
## Residual 20 1.489 0.24032
## Total 21 6.196 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Tahiti
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 1.7371 0.42373 11.029 0.002 **
## Residual 15 2.3625 0.57627
## Total 16 4.0997 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Taiwan_vs_Raia
##      Df SumOfSqs      R2      F Pr(>F)
## Loc    1 4.2436 0.77146 60.76 0.001 ***
## Residual 18 1.2572 0.22854
## Total 19 5.5008 1.00000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Tahaa

```



```

##           Df SumOfSqs      R2      F Pr(>F)
## Loc           1   4.5028 0.45145 28.804  0.001 ***
## Residual    35   5.4713 0.54855
## Total       36   9.9741 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Tahiti
##           Df SumOfSqs      R2      F Pr(>F)
## Loc           1   1.8363 0.22445  8.6822  0.001 ***
## Residual     30   6.3449 0.77555
## Total        31   8.1811 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Djib_vs_Raia
##           Df SumOfSqs      R2      F Pr(>F)
## Loc           1   3.9935 0.43252 25.152  0.001 ***
## Residual     33   5.2395 0.56748
## Total        34   9.2330 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Tahaa_vs_Tahiti
##           Df SumOfSqs      R2      F Pr(>F)
## Loc           1   0.32408 0.16768  2.6191  0.023 *
## Residual     13   1.60860 0.83232
## Total        14   1.93268 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $Tahaa_vs_Raia
##           Df SumOfSqs      R2      F Pr(>F)
## Loc           1   0.04881 0.08841  1.5518  0.207
## Residual     16   0.50321 0.91159
## Total        17   0.55202 1.00000
##
## $Tahiti_vs_Raia
##           Df SumOfSqs      R2      F Pr(>F)
## Loc           1   0.33852 0.19736  2.7047  0.011 *
## Residual     11   1.37675 0.80264
## Total        12   1.71527 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## attr("class")
## [1] "pwadstrata" "list"

pairwise.adonis2(asv_css_D ~ S_region, data = meta_D, sim.method = "bray", p.adjust.m = "BH",
  permutations = 999)

## $parent_call
## [1] "asv_css_D ~ S_region , strata = Null , permutations 999"
##

```

```

## $IndianOc_vs_FrPoly
##      Df SumOfSqs      R2      F Pr(>F)
## S_region 1   9.4525 0.34748 41.003  0.001 ***
## Residual 77  17.7507 0.65252
## Total    78  27.2031 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $IndianOc_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## S_region 1   2.0378 0.11317  7.4012  0.002 **
## Residual 58  15.9695 0.88683
## Total    59  18.0074 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $FrPoly_vs_Taiwan
##      Df SumOfSqs      R2      F Pr(>F)
## S_region 1   6.7576 0.62677 68.85  0.001 ***
## Residual 41   4.0241 0.37323
## Total    42  10.7817 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## attr("class")
## [1] "pwadstrata" "list"

pairwise.adonis2(asv_css_D ~ SST_a, data = meta_D, sim.method = "bray", p.adjust.m = "BH",
  permutations = 999)

## Set of permutations < 'minperm'. Generating entire set.

## 'nperm' >= set of all permutations: complete enumeration.

## Set of permutations < 'minperm'. Generating entire set.

## $parent_call
## [1] "asv_css_D ~ SST_a , strata = Null , permutations 999"
##
## $`30.8_vs_27.04`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   5.0305 0.71524 67.817  0.001 ***
## Residual 27   2.0028 0.28476
## Total    28   7.0333 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_28.59`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   0.09316 0.03396 1.0195  0.375
## Residual 29   2.65000 0.96604
## Total    30   2.74317 1.00000
##

```

```

## $`30.8_vs_29.37`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   5.8092 0.63395 53.688 0.001 ***
## Residual  31   3.3543 0.36605
## Total     32   9.1636 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_27.19`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   4.1297 0.69746 57.634 0.001 ***
## Residual  25   1.7914 0.30254
## Total     26   5.9211 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_26.86`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   2.0569 0.42128 17.471 0.001 ***
## Residual  24   2.8255 0.57872
## Total     25   4.8824 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_29.11`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   4.5201 0.63543 47.061 0.001 ***
## Residual  27   2.5933 0.36457
## Total     28   7.1134 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_28.67`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.03322 0.0202 0.4329 0.895
## Residual  21   1.61137 0.9798
## Total     22   1.64459 1.0000
##
## $`30.8_vs_27.25`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   5.2334 0.75263 82.146 0.001 ***
## Residual  27   1.7201 0.24737
## Total     28   6.9535 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`30.8_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   2.9657 0.63181 39.468 0.001 ***
## Residual  23   1.7282 0.36819
## Total     24   4.6939 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

```

```

## $`30.8_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    2.7789 0.44368 20.735  0.001 ***
## Residual 26    3.4844 0.55632
## Total    27    6.2633 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_28.59`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    3.7138 0.7145 40.043  0.001 ***
## Residual 16    1.4839 0.2855
## Total    17    5.1977 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_29.37`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    3.1892 0.59307 26.234  0.001 ***
## Residual 18    2.1883 0.40693
## Total    19    5.3775 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_27.19`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    0.19506 0.23778 3.7436  0.016 *
## Residual 12    0.62528 0.76222
## Total    13    0.82034 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_26.86`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    0.35915 0.17792 2.3807  0.006 **
## Residual 11    1.65943 0.82208
## Total    12    2.01858 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_29.11`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    2.7111 0.65512 26.594  0.001 ***
## Residual 14    1.4272 0.34488
## Total    15    4.1383 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1    1.48819 0.7697 26.737  0.024 *
## Residual  8    0.44529 0.2303
## Total     9    1.93347 1.0000
## ---

```

```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.22063 0.2848 5.575  0.002 **
## Residual 14  0.55404 0.7152
## Total    15  0.77467 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.16696 0.22898 2.9699  0.026 *
## Residual 10  0.56216 0.77102
## Total    11  0.72911 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.04_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  1.9931 0.46228 11.176  0.001 ***
## Residual 13  2.3183 0.53772
## Total    14  4.3114 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_29.37`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  3.9697 0.58334 28  0.001 ***
## Residual 20  2.8355 0.41666
## Total    21  6.8052 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_27.19`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  3.1956 0.71521 35.159  0.001 ***
## Residual 14  1.2725 0.28479
## Total    15  4.4681 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_26.86`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  1.6054 0.41037 9.0478  0.001 ***
## Residual 13  2.3066 0.58963
## Total    14  3.9120 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_29.11`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  3.3204 0.61548 25.61  0.001 ***
## Residual 16  2.0744 0.38452

```

```

## Total      17      5.3948 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_28.67`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.0290 0.02586 0.2655  0.959
## Residual  10   1.0925 0.97414
## Total     11   1.1215 1.00000
##
## $`28.59_vs_27.25`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   3.8702 0.76314 51.549  0.001 ***
## Residual  16   1.2012 0.23686
## Total     17   5.0714 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   2.4288 0.66759 24.1  0.002 **
## Residual  12   1.2093 0.33241
## Total     13   3.6381 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.59_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   2.0404 0.4076 10.321  0.001 ***
## Residual  15   2.9655 0.5924
## Total     16   5.0060 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.19`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   2.6718 0.57476 21.625  0.001 ***
## Residual  16   1.9768 0.42524
## Total     17   4.6487 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_26.86`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   1.7078 0.36192 8.508  0.002 **
## Residual  15   3.0110 0.63808
## Total     16   4.7188 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_29.11`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.02955 0.01052 0.1914  0.898
## Residual  18   2.77877 0.98948

```

```

## Total      19  2.80832 1.00000
##
## $`29.37_vs_28.67`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   1.4080 0.43933 9.4029  0.015 *
## Residual  12   1.7968 0.56067
## Total     13   3.2048 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.25`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   3.3252 0.6357 31.409  0.001 ***
## Residual  18   1.9056 0.3643
## Total     19   5.2308 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   1.9783 0.5083 14.473  0.002 **
## Residual  14   1.9137 0.4917
## Total     15   3.8920 1.0000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.37_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.3335 0.0833 1.5449  0.203
## Residual  17   3.6699 0.9167
## Total     18   4.0034 1.0000
##
## $`27.19_vs_26.86`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   0.26412 0.15427 1.6417  0.094 .
## Residual   9   1.44798 0.84573
## Total     10   1.71210 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.19_vs_29.11`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   2.3357 0.65767 23.054  0.001 ***
## Residual  12   1.2158 0.34233
## Total     13   3.5515 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.19_vs_28.67`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1   1.41985 0.8586 36.431  0.041 *
## Residual   6   0.23384 0.1414
## Total      7   1.65369 1.0000
## ---

```

```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`27.19_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.02891 0.07783 1.0128  0.322
## Residual 12  0.34260 0.92217
## Total    13  0.37151 1.00000
##
## $`27.19_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.01682 0.04577 0.3838  0.645
## Residual  8  0.35071 0.95423
## Total     9  0.36753 1.00000
##
## $`27.19_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   1.7321 0.45118 9.0431  0.002 **
## Residual 11   2.1069 0.54882
## Total    12   3.8390 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_29.11`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1   1.5378 0.40599 7.5182  0.002 **
## Residual 11   2.2499 0.59401
## Total    12   3.7877 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.79941 0.38667 3.1523  0.041 *
## Residual  5  1.26799 0.61333
## Total     6  2.06740 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.33852 0.19736 2.7047  0.018 *
## Residual 11  1.37675 0.80264
## Total    12  1.71527 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`26.86_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a    1  0.22666 0.14065 1.1457  0.325
## Residual  7  1.38486 0.85935
## Total     8  1.61152 1.00000
##
## $`26.86_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)

```



```

## SST_a      1    0.9884 0.23936 3.1469  0.013 *
## Residual  10    3.1410 0.76064
## Total     11    4.1295 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_28.67`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    1.3450 0.56494 10.388  0.026 *
## Residual    8    1.0358 0.43506
## Total      9    2.3808 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    2.8238 0.71158 34.541  0.001 ***
## Residual  14    1.1445 0.28842
## Total     15    3.9684 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    1.7993 0.60952 15.61  0.002 **
## Residual  10    1.1527 0.39048
## Total     11    2.9519 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`29.11_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    0.3033 0.09442  1.3554  0.204
## Residual  13    2.9088 0.90558
## Total     14    3.2121 1.00000
##
## $`28.67_vs_27.25`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    1.5441 0.90473 75.971  0.016 *
## Residual    8    0.1626 0.09527
## Total      9    1.7067 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.67_vs_27.22`
##      Df SumOfSqs      R2      F Pr(>F)
## SST_a      1    1.25898 0.88059 29.499 0.06667 .
## Residual    4    0.17071 0.11941
## Total      5    1.42969 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## $`28.67_vs_29.35`
##      Df SumOfSqs      R2      F Pr(>F)

```

```

## SST_a      1  0.8977 0.31781 3.2611  0.029 *
## Residual    7  1.9269 0.68219
## Total       8  2.8246 1.00000
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## `$27.25_vs_27.22`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  0.05069 0.15353 1.8138  0.192
## Residual   10  0.27947 0.84647
## Total      11  0.33016 1.00000
##
## `$27.25_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  2.0991 0.50768 13.405  0.001 ***
## Residual   13  2.0357 0.49232
## Total      14  4.1348 1.00000
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## `$27.22_vs_29.35`
##           Df SumOfSqs      R2      F Pr(>F)
## SST_a      1  1.3412 0.39623 5.9062  0.003 **
## Residual    9  2.0438 0.60377
## Total      10  3.3850 1.00000
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## attr("class")
## [1] "pwadstrata" "list"

pairwise.adonis2(asv_css_D ~ Tbl_bin, data = meta_D, sim.method = "bray", p.adjust.m = "BH",
  permutations = 999)

## $parent_call
## [1] "asv_css_D ~ Tbl_bin , strata = Null , permutations 999"
##
## $Long_vs_Recent
##           Df SumOfSqs      R2      F Pr(>F)
## Tbl_bin    1  3.1394 0.0993 9.8123  0.001 ***
## Residual   89 28.4755 0.9007
## Total      90 31.6149 1.0000
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## attr("class")
## [1] "pwadstrata" "list"

#EXTRA CODE FOR MANTEL TESTS -- NOT USED

##scatterplots

##aa = as.vector(bray.dist)

```

```
##tt = as.vector(dist.temp)
##dd = as.vector(dist.DHW)
##gg = as.vector(dist.geo)
```

```
#new data frame with vectorized distance matrices
##mat = data.frame(aa,tt,dd, gg)
```

```
##mm_temp = ggplot(mat, aes(y = aa, x = tt)) +
  ## geom_point(size = 4, alpha = 0.75, colour = "black",shape = 21, aes(fill=tt)) +
  ## geom_smooth(method = "lm", colour = "black", alpha = 0.2) +
  ## labs(x = "Difference in Temperature (C)", y = "Bray-Curtis Dissimilarity", fill = "Difference in
  ## theme( axis.text.x = element_text(face = "bold",colour = "black", size = 12),
  ##       axis.text.y = element_text(face = "bold", size = 11, colour = "black"),
  ##       axis.title= element_text(face = "bold", size = 14, colour = "black"),
  ##       panel.background = element_blank(),
  ##       panel.border = element_rect(fill = NA, colour = "black"),
  ##       legend.position = "top",
  ##       legend.text = element_text(size = 10, face = "bold"),
  ##       legend.title = element_text(size = 11, face = "bold")) +
  ##       scale_fill_continuous(high = "navy", low = "skyblue")
```

```
##mm_temp
```

```
##mm_dhw = ggplot(mat, aes(y = aa, x = dd)) +
  ## geom_point(size = 4, alpha = 0.75, colour = "black",shape = 21, aes(fill=dd)) +
  ## geom_smooth(method = "lm", colour = "black", alpha = 0.2) +
  ## labs(x = "Difference in DHW", y = "Bray-Curtis Dissimilarity", fill = "Difference in DHW") +
  ## theme( axis.text.x = element_text(face = "bold",colour = "black", size = 12),
  ##       axis.text.y = element_text(face = "bold", size = 11, colour = "black"),
  ##       axis.title= element_text(face = "bold", size = 14, colour = "black"),
  ##       panel.background = element_blank(),
  ##       panel.border = element_rect(fill = NA, colour = "black"),
  ##       legend.position = "top",
  ##       legend.text = element_text(size = 10, face = "bold"),
  ##       # legend.title = element_text(size = 11, face = "bold")) +
  ##       scale_fill_continuous(high = "navy", low = "skyblue")
```

```
##mm_dhw
```

```
##mm_dist = ggplot(mat, aes(y = aa, x = gg)) +
  ## geom_point(size = 4, alpha = 0.75, colour = "black",shape = 21, aes(fill = gg/1000)) +
  ## geom_smooth(method = "lm", colour = "black", alpha = 0.2) +
  ## labs(x = "Physical Separation (m)", y = "Bray-Curtis Dissimilarity", fill = "Physical Separation
  ## theme( axis.text.x = element_text(face = "bold",colour = "black", size = 12),
  ##       axis.text.y = element_text(face = "bold", size = 11, colour = "black"),
  ##       axis.title= element_text(face = "bold", size = 14, colour = "black"),
  ##       panel.background = element_blank(),
  ##       panel.border = element_rect(fill = NA, colour = "black"),
  ##       legend.position = "top",
  ##       legend.text = element_text(size = 10, face = "bold"),
  ##       legend.title = element_text(size = 11, face = "bold")) +
  ##       scale_fill_continuous(high = "navy", low = "skyblue")
```

```
##mm_dist
```