Residence time structures microbial communities through niche partitioning

Emmi A. Mueller and Jay T. Lennon

2025-02-13

Initial Setup

Load packages

```
# devtools::install_github('BlakeRMills/MoMAColors')
library("MoMAColors")
library("vegan")
library("ggplot2")
library("lemon")
library("cowplot")
library("scales")
library("tidyr")
library("BiodiversityR")
library("dplyr")
library("mgcv")
library("tidymv")
library("spaa")
library("lsr")
library("table1")
library("caper")
library("ape")
```

Set up figure theme

```
my.cols <- RColorBrewer::brewer.pal(n = 4, name = "Greys")[3:4]

# Set theme for figures in the paper
theme_set(theme_classic() + theme(axis.title = element_text(size = 16),
    axis.title.x = element_text(margin = margin(t = 15, b = 15)),
    axis.title.y = element_text(margin = margin(l = 15, r = 15)),
    axis.text = element_text(size = 14), axis.text.x = element_text(margin = margin(t = 5)),
    axis.text.y = element_text(margin = margin(r = 5)), axis.line.x = element_blank(),
    axis.line.y = element_blank(), axis.ticks.x = element_line(linewidth = 1),
    axis.ticks.y = element_line(linewidth = 1), axis.ticks.length = unit(0.1,
        "in"), panel.border = element_rect(color = "black", fill = NA,
        linewidth = 1.5), legend.text = element_text(size = 10),
    strip.text = element_text(size = 14), strip.background = element_blank()))</pre>
```

Define inputs

```
# Tau = general design file for experiment, paired Day 0
# and 20
Tau <- read.csv("data/RTLC/2021_RTLC_Tau_Combined.csv", header = TRUE)
Tau.ctrl <- Tau[50:51, ]
Tau <- Tau[1:49, ]
Tau$Tau <- as.numeric(Tau$Tau)</pre>
Tau$Set <- as.character(Tau$Set)</pre>
Tau$Day_0_Seq[Tau$Day_0_Seq == ""] <- NA</pre>
Tau$Day_20_Seq[Tau$Day_20_Seq == ""] <- NA</pre>
# Tau.Seq = Full list of sequenced samples, non-paired Day
# 0 and 20
Tau.Seq <- read.csv("data/RTLC/2021 RTLC Tau Seq.csv", header = TRUE)
# Abundance (N) data
Tau <- N.fxn(read.csv("data/RTLC/RTLC S2/20210628 RTLC S2 N M1gate.csv",
   header = TRUE), Tau)
Tau <- N.fxn(read.csv("data/RTLC/RTLC S3/20210723 RTLC S3 N M1gate.csv",
   header = TRUE), Tau)
Tau <- N.fxn(read.csv("data/RTLC/RTLC_S4/20210904_RTLC_S4_N_M1gate.csv",
   header = TRUE), Tau)
# Biofilm data
Tau <- OT.fxn(read.csv("data/RTLC/RTLC_S1/20210602_RTLC_S1_Otoole.csv",
   header = TRUE), Tau)
Tau <- OT.fxn(read.csv("data/RTLC/RTLC_S2/20210628_RTLC_S2_Otoole.csv",</pre>
   header = TRUE), Tau)
Tau <- OT.fxn(read.csv("data/RTLC/RTLC_S3/20210723_RTLC_S3_Otoole.csv",</pre>
   header = TRUE), Tau)
Tau <- OT.fxn(read.csv("data/RTLC/RTLC S4/20210904 RTLC S4 Otoole.csv",
   header = TRUE), Tau)
# Bacterial Productivity (BP) data
print("Scintillation counter machine efficiency-")
## [1] "Scintillation counter machine efficiency-"
Tau <- as.data.frame(BP.fxn(read.csv("data/RTLC/RTLC S1/20210602 RTLC S1 BP.csv",
   header = FALSE), Tau, 1))
## [1] "Machine efficiency: 0.636787567178765"
Tau <- as.data.frame(BP.fxn(read.csv("data/RTLC/RTLC_S2/20210628_RTLC_S2_BP.csv",
   header = FALSE), Tau, 2))
## [1] "Machine efficiency: 0.638772848217168"
Tau <- as.data.frame(BP.fxn(read.csv("data/RTLC/RTLC_S3/20210723_RTLC_S3_BP.csv",
   header = FALSE), Tau, 3))
## [1] "Machine efficiency: 0.643492469287154"
Tau <- as.data.frame(BP.fxn(read.csv("data/RTLC/RTLC_S4/20210904_RTLC_S4_BP.csv",
header = FALSE), Tau, 4))
```

```
## [1] "Machine efficiency: 0.63773229695431"
Tau$ind_P <- Tau$uMChr/Tau$N
Tau$ind_P_g <- (Tau$gCLhr/1000)/Tau$N
Tau$turnover_t <- (2.6e-14)/Tau$ind_P_g

# Convert tau from min to h and categorize tau by flow rate
# manipulation method (Pump)
Tau$Set <- as.factor(Tau$Set)
Tau$Tau <- log(((10^Tau$Tau)/60), 10)
Tau$Pump <- Tau$Tau < 1.6

Tau.Seq$Tau <- as.numeric(Tau.Seq$Tau)
Tau.Seq$Tau <- log(((10^Tau.Seq$Tau)/60), 10)
Tau.Seq$Day <- as.factor(Tau.Seq$Day)

# Tau.20 = Tau subset to only samples with Day 20
# sequencing
Tau.20 <- subset(Tau[is.na(Tau$Day_20_Seq) == 0, ])</pre>
```

Load EcoPlate (EP) data (48 hours)

```
EP.S1 <- read.csv("data/RTLC/RTLC S1/eco.data rt S1 48.txt",
    header = TRUE, sep = "\t")
EP.S1 \leftarrow cbind(EP.S1[, 1:2], EP.S1[, 4:34])
EP.S2 <- read.csv("data/RTLC/RTLC_S2/eco.data_rt_S2_48.txt",</pre>
    header = TRUE, sep = "\t")
EP.S2 \leftarrow cbind(EP.S2[, 1:2], EP.S2[, 4:34])
EP.S3 <- read.csv("data/RTLC/RTLC_S3/eco.data_rt_S3_48.txt",</pre>
    header = TRUE, sep = "\t")
EP.S3 <- cbind(EP.S3[, 1:2], EP.S3[, 4:34])
EP.S4 <- read.csv("data/RTLC/RTLC S4/eco.data rt S4 48.txt",
    header = TRUE, sep = "\t")
EP.S4 \leftarrow cbind(EP.S4[, 1:2], EP.S4[, 4:34])
EP <- rbind(EP.S1, EP.S2, EP.S3, EP.S4)</pre>
rm(EP.S1, EP.S2, EP.S3, EP.S4)
ResType <- read.csv("code/resource_type.txt", header = TRUE,</pre>
    sep = "\t")
colnames(EP) <- c("Tau", "Set", "2-Hydroxy.Benzoic.Acid", "4-Hydroxy.Benzoic.Acid",</pre>
    "alpha-Cyclodextrin", "alpha-D-Lactose", "alpha-Ketobutyric.Acid",
    "beta-Methyl-D-Glucoside", "D-Cellobiose", "D-Galactonic.Acid.gamma-Lactone",
    "D-Galacturonic.Acid", "D-Glucosaminic.Acid", "D-Malic.Acid",
    "D-Mannitol", "D-Xylose", "D,L-alpha-Glycerol.Phosphate",
    "gamma-Hydroxybutyric.Acid", "Glucose-1-Phosphate", "Glycogen",
    "Glycyl-L-Glutamic.Acid", "i-Erythritol", "Itaconic.Acid",
```

```
"L-Arginine", "L-Asparagine", "L-Phenylalanine", "L-Serine",
    "L-Threonine", "N-Acetyl-D-Glucosamine", "Phenylethylamine",
    "Putrescine", "Pyruvic.Acid.Methyl.Ester", "Tween.40", "Tween.80")
EP$Tau \leftarrow log(((10^EP$Tau)/60), 10)
EP.long <- EP %>%
    gather(C_Source, OD_48, "2-Hydroxy.Benzoic.Acid":"Tween.80")
ResType <- distinct(ResType)</pre>
EP.long$Type <- NA
for (row in rownames(EP.long)) {
    EP.long[row, "Type"] <- ResType$Type[ResType$Resource ==</pre>
        EP.long[row, "C_Source"]]
}
x <- 1
while (x < nrow(EP) + 1) {
    EP[x, "NumRes"] <- sum(EP[x, 3:33] > 0.125)
    EP[x, "AvgRes"] <- mean(unlist(EP[x, 3:33]))</pre>
    x \leftarrow x + 1
}
Tau$NumRes <- EP$NumRes
Tau$AvgRes <- EP$AvgRes
# EP.env <- subset(EP, select = c(Tau, Set)) EP.env$Set <-</pre>
\# c(rep(1, 13), rep(2,12), rep(3,10), rep(4,14))
rownames(EP) <- EP$Tau</pre>
```

Clean and rarefy the OTU table

```
lows <- which(coverage < cutoff)</pre>
if (length(lows) > 0) {
   OTUs <- OTUs[-which(coverage < cutoff), ]
}
# Remove OTUs with less thatn 2 reads across all samples
OTUs <- OTUs[, which(colSums(OTUs) > 2)]
# Generate rarefacation plot
otu.min <- min(rowSums(OTUs))</pre>
asv.min <- min(rowSums(ASVs))
# rarefy OTUs and ASVs to the sample with the lowest number
# of reads then remove OTUs with O reads after rarefaction
set.seed(47405)
OTUs.r <- rrarefy(OTUs, otu.min)
OTUs.r <- OTUs.r[, -which(colSums(OTUs.r) == 0)]
rm(OTUs)
ASVs.r <- rrarefy(ASVs, asv.min)
ASVs.r <- ASVs.r[, -which(colSums(ASVs.r) == 0)]
rm(ASVs)
# Create dataframes of Day 20 samples rarified
OTUs.r.20 <- OTUs.r[rownames(OTUs.r) %in% unique(Tau$Day_20_Seq),
OTUs.r.20 <- OTUs.r.20[, which(colSums(OTUs.r.20) > 0)]
rownames(OTUs.r.20) <- subset(Tau.Seq, Day == 20)$Tau
ASVs.r.20 <- ASVs.r[rownames(ASVs.r) %in% unique(Tau$Day_20_Seq),
ASVs.r.20 <- ASVs.r.20[, which(colSums(ASVs.r.20) > 0)]
rownames(ASVs.r.20) <- subset(Tau.Seq, Day == 20)$Tau
# Generate OTU tables with p/a, relative abundance
OTUs.r.REL <- decostand(OTUs.r, method = "total")</pre>
OTUs.r.REL.20 <- OTUs.r.REL[rownames(OTUs.r.REL) %in% unique(Tau$Day_20_Seq),
OTUs.r.REL.20 <- OTUs.r.REL.20[, which(colSums(OTUs.r.REL.20) >
rownames(OTUs.r.REL.20) <- subset(Tau.Seq, Day == 20)$Tau
OTUs.r.PA <- decostand(OTUs.r, method = "pa")
OTUs.r.PA.20 <- OTUs.r.PA[rownames(OTUs.r.PA) %in% unique(Tau$Day_20_Seq),
OTUs.r.PA.20 <- OTUs.r.PA.20[, which(colSums(OTUs.r.PA.20) >
rownames(OTUs.r.PA.20) <- subset(Tau.Seq, Day == 20)$Tau
OTUs.tax.20 <- OTUs.tax[OTUs.tax$OTU %in% unique(colnames(OTUs.r.20)),
   ]
```

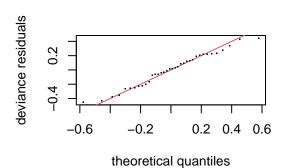
```
# Calculate richness (S) and evenness (SimpE) for OTUs (S \ensuremath{\mathfrak{C}}
# SimpE) and ASVs (S.ASV & SimpE.ASV)
S <- as.data.frame(cbind(row.names(OTUs.r), unname(S.cal(OTUs.r))))
S.ASV <- as.data.frame(cbind(row.names(ASVs.r), unname(S.cal(ASVs.r))))
SimpE <- as.data.frame(cbind(row.names(OTUs.r), unname(SimpE.cal(OTUs.r))))</pre>
SimpE.ASV <- as.data.frame(cbind(row.names(ASVs.r), unname(SimpE.cal(ASVs.r))))</pre>
```

Figure 1. Abundance, productivity, and resource consumption of microbial communities along a residence time gradient.

B. Microbial abundance

```
N.gam <- gam(log_N ~ s(Tau), family = gaussian(link = "identity"),
   data = Tau, method = "REML")
N.gam.re <- gam(log_N ~ s(Tau) + s(Set, bs = "re"), family = gaussian(link = "identity"),
   data = Tau, method = "REML")
AIC(N.gam, N.gam.re)
##
                        AIC
                df
## N.gam
          6.447302 33.06401
## N.gam.re 9.736133 16.89868
anova(N.gam, N.gam.re, test = "Chisq")
## Analysis of Deviance Table
## Model 1: log_N ~ s(Tau)
## Model 2: log_N ~ s(Tau) + s(Set, bs = "re")
## Resid. Df Resid. Dev
                           Df Deviance Pr(>Chi)
                3.6910
## 1
       29.684
       25.998
                 ## 2
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
# Random effect of set is significant
rm(N.gam)
summary(N.gam.re)
##
## Family: gaussian
## Link function: identity
##
## Formula:
## log_N ~ s(Tau) + s(Set, bs = "re")
## Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 7.115
                           0.153
                                 46.5 <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
```

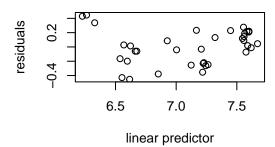
```
## Approximate significance of smooth terms:
##
            edf Ref.df
                          F p-value
## s(Tau) 4.693 5.771 17.04 < 2e-16 ***
## s(Set) 1.777 2.000 9.70 0.000235 ***
## Signif. codes:
                  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.759
                        Deviance explained = 80.3%
## -REML = 13.189 Scale est. = 0.068783 n = 36
mean(summary(N.gam.re)$s.table[, 4])
## [1] 0.0001177233
k.check(N.gam.re)
         k'
                 edf k-index p-value
## s(Tau) 9 4.693224 1.276555
                                 0.915
## s(Set) 3 1.776724
                                   NA
```



gam.check(N.gam.re)

NA

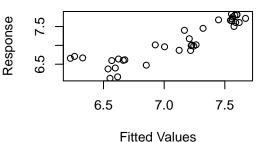
Resids vs. linear pred.



Histogram of residuals

Frequency \sim 0 -0.40.0 0.2 0.4 Residuals

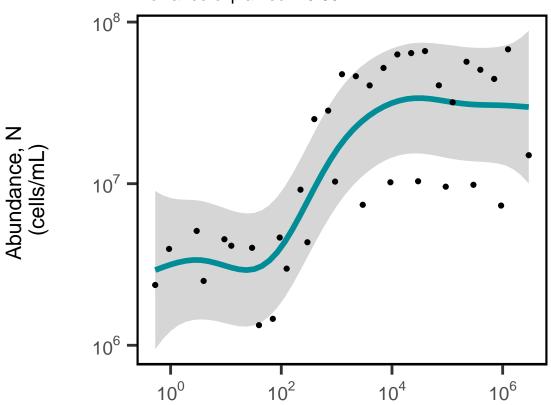
Response vs. Fitted Values



```
##
## Method: REML
                  Optimizer: outer newton
## full convergence after 5 iterations.
## Gradient range [-6.707242e-06,7.847398e-07]
## (score 13.18909 & scale 0.06878258).
## Hessian positive definite, eigenvalue range [0.4752446,17.25415].
```

```
## Model rank = 13 / 13
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
            k' edf k-index p-value
## s(Tau) 9.00 4.69
                       1.28
## s(Set) 3.00 1.78
                         NA
                                 NA
N_Tau <- tidymv::predict_gam(N.gam.re, exclude_terms = "s(Set)") %>%
    filter(Set == "2") %>%
    ggplot(aes(Tau, fit)) + geom_smooth_ci(color = "#008d98",
    cex = 2, ci_alpha = 0.2) + geom_point(data = Tau, aes(x = Tau,
    y = log_N)) + theme(axis.title.x = element_blank()) + ylab("Abundance, N \n(cells/mL)") +
    scale_x_continuous(labels = label_math(10^.x)) + scale_y_continuous(breaks = c(6,
    7, 8), labels = label_math(10^.x)) + labs(title = bquote("Deviance explained =" ~
    .(round_pad(summary(N.gam.re)$dev, 2)))) + theme(plot.margin = unit(c(0.2,
    0.2, 0.2, 0.8), "cm")) + theme(axis.title.y = element_text(vjust = 6))
N_Tau
```

Deviance explained = 0.80

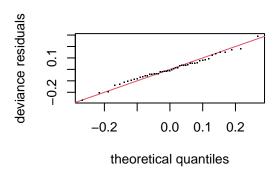


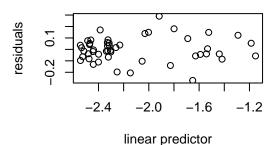
```
ggsave("./output/N_Tau.pdf")
ggsave("./output/N_Tau.png", width = 7, height = 5)
```

C. Biomass Production (uM C/hr)

```
BP.gam.re \leftarrow gam(log(uMChr, 10) \sim s(Tau) + s(Set, bs = "re"),
   family = gaussian(link = "identity"), data = Tau, method = "REML")
BP.gam <- gam(log(uMChr, 10) ~ s(Tau), family = gaussian(link = "identity"),
   data = Tau, method = "REML")
anova(BP.gam, BP.gam.re, test = "Chisq")
## Analysis of Deviance Table
## Model 1: log(uMChr, 10) ~ s(Tau)
## Model 2: log(uMChr, 10) ~ s(Tau) + s(Set, bs = "re")
    Resid. Df Resid. Dev
                             Df Deviance Pr(>Chi)
## 1
       41.310
                 0.89180
## 2
        38.089
                 0.53545 3.2212 0.35635 8.564e-06 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
AIC(BP.gam, BP.gam.re)
##
                   df
                            AIC
## BP.gam
             7.597687 -42.05894
## BP.gam.re 10.503073 -61.24511
anova(BP.gam, BP.gam.re, test = "Chisq")
## Analysis of Deviance Table
##
## Model 1: log(uMChr, 10) ~ s(Tau)
## Model 2: log(uMChr, 10) ~ s(Tau) + s(Set, bs = "re")
   Resid. Df Resid. Dev
                             Df Deviance Pr(>Chi)
## 1
       41.310
                 0.89180
        38.089
                 0.53545 3.2212 0.35635 8.564e-06 ***
## 2
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
# Random effect of set is significant
rm(BP.gam)
summary(BP.gam.re)
##
## Family: gaussian
## Link function: identity
##
## Formula:
## log(uMChr, 10) ~ s(Tau) + s(Set, bs = "re")
##
## Parametric coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.1159
                           0.0536 -39.48 <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
           edf Ref.df
                           F p-value
```

```
## s(Tau) 5.042 6.161 96.966 < 2e-16 ***
## s(Set) 2.666 3.000 8.319 7.24e-05 ***
                  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Signif. codes:
## R-sq.(adj) = 0.929
                        Deviance explained =
## -REML = -22.399 Scale est. = 0.013289
mean(summary(BP.gam.re)$s.table[, 4])
## [1] 3.622457e-05
k.check(BP.gam.re)
         k'
                  edf k-index p-value
## s(Tau)
          9 5.042344 1.137607
                                 0.765
## s(Set)
          4 2.666262
                            NA
                                    NA
gam.check(BP.gam.re)
```

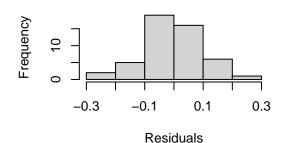


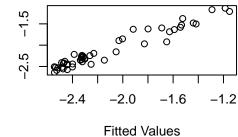


Resids vs. linear pred.

Histogram of residuals

Response vs. Fitted Values

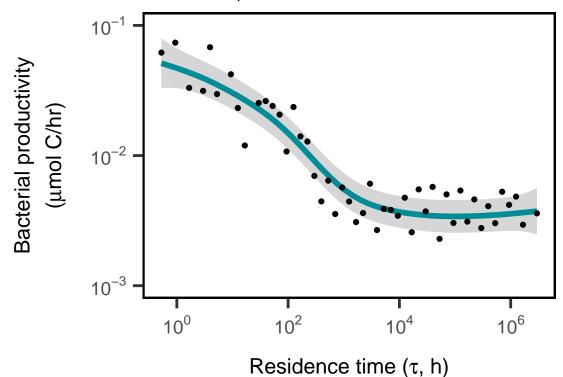




```
##
## Method: REML Optimizer: outer newton
## full convergence after 5 iterations.
## Gradient range [-2.109971e-09,7.289529e-10]
## (score -22.39941 & scale 0.01328936).
## Hessian positive definite, eigenvalue range [1.085797,23.76268].
## Model rank = 14 / 14
##
```

```
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##
            k'
               edf k-index p-value
## s(Tau) 9.00 5.04
                       1.14
## s(Set) 4.00 2.67
                         NA
                                 NA
BP_Tau <- predict_gam(BP.gam.re, exclude_terms = "s(Set)") %>%
   filter(Set == "1") %>%
    ggplot(aes(Tau, fit)) + geom_smooth_ci(color = "#008d98",
    cex = 2, ci_alpha = 0.2) + geom_point(data = Tau, aes(x = Tau,
   y = log(uMChr, 10))) + xlab(expression(paste("Residence time (",
   tau, ", h)"))) + ylab(expression(atop("Bacterial productivity",
   paste("(", mu, "mol C/hr)")))) + scale_x_continuous(labels = label_math(expr = 10^.x,
   format = force)) + scale_y_continuous(limits = c(-3, -1),
   breaks = c(-1, -2, -3), labels = label_math(expr = 10^{\circ}.x,
        format = force)) + labs(title = bquote("Deviance explained =" ~
    .(signif(summary(BP.gam.re)$dev, 2))))
BP_Tau
```

Deviance explained = 0.94



ggsave("./output/BP_Tau.pdf")
ggsave("./output/BP_Tau.png", width = 7, height = 5)

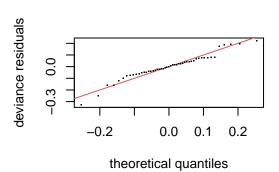
D. Average well response at 48 hours

```
Avg.gam <- gam(AvgRes ~ s(Tau), data = Tau, family = gaussian(link = "identity"),
   method = "REML")
Avg.gam.re <- gam(AvgRes ~ s(Tau) + s(Set, bs = "re"), data = Tau,
   family = gaussian(link = "identity"), method = "REML")
anova(Avg.gam, Avg.gam.re, test = "Chisq")
## Analysis of Deviance Table
##
## Model 1: AvgRes ~ s(Tau)
## Model 2: AvgRes ~ s(Tau) + s(Set, bs = "re")
## Resid. Df Resid. Dev
                             Df Deviance Pr(>Chi)
## 1
       47.000
                 1.0175
## 2
       43.836
                  0.5291 3.1639 0.48841 9.064e-09 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
AIC(Avg.gam, Avg.gam.re)
##
                   df
                            ATC
## Avg.gam
             3.000094 -44.79265
## Avg.gam.re 5.946984 -70.94147
# Random effect of set is significant
rm(Avg.gam)
summary(Avg.gam.re)
## Family: gaussian
## Link function: identity
##
## Formula:
## AvgRes \sim s(Tau) + s(Set, bs = "re")
## Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.60253
                          0.05653 10.66 8.42e-14 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
           edf Ref.df
                          F p-value
## s(Tau) 1.000
                1 13.00 0.000792 ***
## s(Set) 2.764
                    3 12.69 2.41e-06 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.509 Deviance explained = 54.7\%
## -REML = -29.608 Scale est. = 0.011961 n = 49
mean(summary(Avg.gam.re)$s.table[, 4])
```

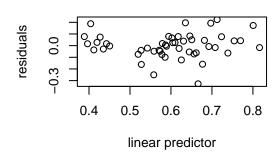
12

[1] 0.0003971892

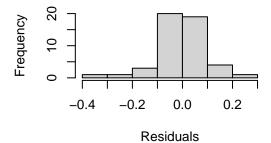
k.check(Avg.gam.re) k-index p-value k' edf 9 1.000047 0.9029773 0.1925 ## s(Tau) 4 2.764202 ## s(Set) NA NA gam.check(Avg.gam.re)



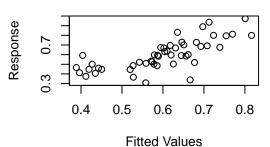
Resids vs. linear pred.



Histogram of residuals



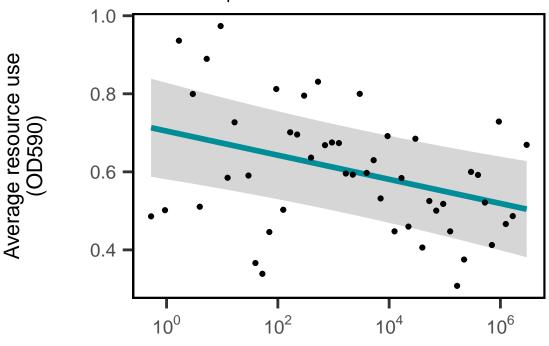
Response vs. Fitted Values



```
##
## Method: REML
                  Optimizer: outer newton
## full convergence after 10 iterations.
## Gradient range [-1.938184e-05,4.092839e-06]
## (score -29.60753 & scale 0.01196094).
## Hessian positive definite, eigenvalue range [1.938115e-05,23.58567].
## Model rank = 14 / 14
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
            k'
                edf k-index p-value
## s(Tau) 9.00 1.00
                        0.9
                               0.24
## s(Set) 4.00 2.76
                         NA
                                 NA
AvgRes_Tau <- predict_gam(Avg.gam.re, exclude_terms = "s(Set)") %>%
   filter(Set == "1") %>%
   ggplot(aes(Tau, fit)) + geom_smooth_ci(color = "#008d98",
    cex = 2, ci_alpha = 0.2) + geom_point(data = Tau, aes(x = Tau,
```

```
y = AvgRes)) + xlab(expression(paste("Residence time (",
    tau, ", h)"))) + ylab("Average resource use n(OD590)") +
    scale_x_continuous(labels = label_math(expr = 10^.x, format = force)) +
   labs(title = bquote("Deviance explained =" ~ .(signif(summary(Avg.gam.re)$dev,
        2)))) + theme(plot.margin = unit(c(0.2, 0.2, 0.2, 0.8),
    "cm")) + theme(axis.title.y = element_text(vjust = 6))
AvgRes_Tau
```

Deviance explained = 0.55

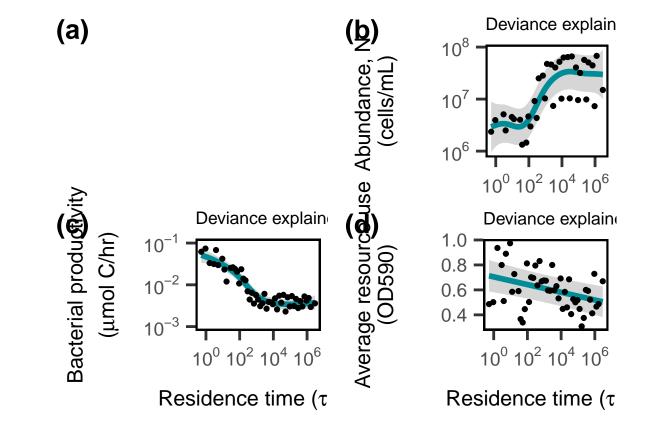


Residence time (τ, h)

```
ggsave("./output/AvgRes_Tau.pdf")
ggsave("./output/AvgRes_Tau.png", width = 7, height = 5)
```

Draw Figure

```
ggdraw() + draw_plot(N_Tau, x = 0.5, y = 0.55, width = 0.5, height = 0.45) +
    draw_plot(BP_Tau, x = 0, y = 0, width = 0.5, height = 0.55) +
    draw_plot(AvgRes_Tau, x = 0.5, y = 0, width = 0.5, height = 0.55) +
   draw_plot_label(label = c("(a)", "(b)", "(c)", "(d)"), size = 20,
        x = c(0, 0.5, 0, 0.5), y = c(1, 1, 0.55, 0.55)) + theme(plot.background = element_rect(fill = "
    color = NA))
```



```
ggsave("./output/RTLC_Fig1.pdf")
ggsave("./output/RTLC_Fig1.png", width = 12, height = 8, dpi = 800)
```

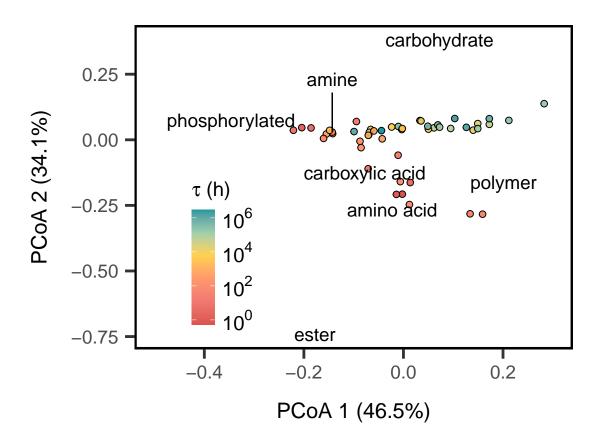
Figure 2. Resource use changed with residence time

Generate individual carbon source GAMs

A. Bray-Curtis distance Resource use

```
EP.rbys <- subset(EP, select = -c(Tau, NumRes, AvgRes, Set))</pre>
EP.db <- vegdist(EP.rbys, method = "bray")</pre>
EP.pcoa <- cmdscale(EP.db, eig = TRUE)</pre>
EP.REL <- EP.rbys
for (i in 1:nrow(EP.rbys)) {
    EP.REL[i, ] = EP.rbys[i, ]/sum(EP.rbys[i, ])
}
EP.pcoa <- add.spec.scores(EP.pcoa, EP.REL, method = "pcoa.scores")
explainvar1.ep <- round(EP.pcoa$eig[1]/sum(EP.pcoa$eig), 3) *
explainvar2.ep <- round(EP.pcoa$eig[2]/sum(EP.pcoa$eig), 3) *
explainvar3.ep <- round(EP.pcoa$eig[3]/sum(EP.pcoa$eig), 3) *
sum.eig.ep <- sum(explainvar3.ep, explainvar2.ep, explainvar1.ep)</pre>
types <- read.csv("data/RTLC/EcoPlate/Csourcetypes.csv", header = TRUE,</pre>
    sep = ",")
EP.plot <- as.data.frame(EP.pcoa$points)</pre>
EP.plot <- cbind(EP.plot, Tau$Tau, Tau$Pump, Tau$Set)</pre>
colnames(EP.plot) <- c("V1", "V2", "Tau", "Pump", "Set")</pre>
EP.plot$Pump <- factor(EP.plot$Pump, levels = c("TRUE", "FALSE"))</pre>
EP.cproj <- as.data.frame(EP.pcoa$cproj)</pre>
EP.cproj <- cbind(EP.cproj, as.data.frame(row.names(EP.pcoa$cproj)))</pre>
spe.corr.ep <- add.spec.scores(EP.pcoa, EP.REL, method = "cor.scores")$cproj</pre>
spe.corr.ep <- as.data.frame(cbind(spe.corr.ep, types$Type))</pre>
corrcut.ep <- 0.7</pre>
imp.spp.ep <- as.data.frame(spe.corr.ep[abs(as.numeric(spe.corr.ep[,</pre>
    1])) >= corrcut.ep | abs(as.numeric(spe.corr.ep[, 2])) >=
    corrcut.ep, ])
Dim1.ep <- c()
Dim2.ep <- c()</pre>
for (x in unique(spe.corr.ep$V3)) {
    Dim1.ep <- c(Dim1.ep, mean(as.numeric(subset(spe.corr.ep,</pre>
```

```
spe.corr.ep$V3 == x)$Dim1)))
    Dim2.ep <- c(Dim2.ep, mean(as.numeric(subset(spe.corr.ep,</pre>
        spe.corr.ep$V3 == x)$Dim2)))
}
spe.corr.ep.means <- as.data.frame(unique(spe.corr.ep$V3))</pre>
spe.corr.ep.means <- cbind(spe.corr.ep.means, as.vector(Dim1.ep),</pre>
    as.vector(Dim2.ep))
colnames(spe.corr.ep.means) <- c("C types", "Dim1", "Dim2")</pre>
EP.plot$Tau <- as.numeric(EP.plot$Tau)</pre>
spe.corr.ep <- spe.corr.ep[spe.corr.ep$C_source %in% c(gsub("-",</pre>
    ".", csource.sig$Resource), "X4.Hydroxy.Benzoic.Acid"), ]
spe.corr.ep$Dim1 <- as.numeric(spe.corr.ep$Dim1)</pre>
spe.corr.ep$Dim2 <- as.numeric(spe.corr.ep$Dim2)</pre>
spe.corr.ep$C_source <- rownames(spe.corr.ep)</pre>
ResUse_PCoA <- ggplot(EP.plot, aes(x = V1, y = V2)) + geom_point(shape = 21,
    cex = 2, aes(fill = as.numeric(Tau)), color = "black") +
    xlab(paste("PCoA 1 (", explainvar1.ep, "%)", sep = "")) +
    ylab(paste("PCoA 2 (", explainvar2.ep, "%)", sep = "")) +
    xlim(c(-0.5, 0.3)) + labs(fill = expression(paste(tau, "(h)"))) +
    scale fill gradientn(colors = alpha(moma.colors("ustwo"),
        0.9), labels = label math(expr = 10^.x, format = force)) +
    theme(legend.title = element text(size = 14)) + geom text(size = 5,
    data = subset(spe.corr.ep.means, spe.corr.ep.means$C_types !=
        "amine"), aes(x = Dim1, y = Dim2, label = C_types), color = "black") +
    geom_text(size = 5, data = subset(spe.corr.ep.means, spe.corr.ep.means$C_types ==
        "amine"), aes(x = Dim1, y = Dim2 + 0.2, label = C_types),
        color = "black") + geom_segment(aes(x = as.numeric(spe.corr.ep.means[6,
    "Dim1"]), y = as.numeric(spe.corr.ep.means[6, "Dim2"]), xend = as.numeric(spe.corr.ep.means[6,
    "Dim1"]), yend = as.numeric(spe.corr.ep.means[6, "Dim2"]) +
    0.15)) + theme(legend.title = element_text(size = 15), legend.position = c(0.2,
    0.3), legend.text = element_text(size = 15))
ResUse_PCoA
```



```
ggsave("./output/ResUse_PCoA.pdf")
ggsave("./output/ResUse_PCoA.png", width = 8, height = 5)
```

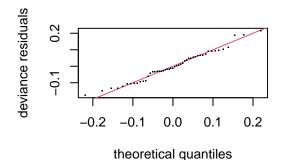
B. Resource Use PCoA1

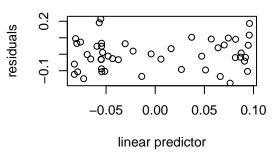
```
ResUse.PCoA1.gam <- gam(data = EP.plot, V1 ~ s(Tau), family = gaussian(link = "identity"),
    method = "REML")
ResUse.PCoA1.gam.re <- gam(data = EP.plot, V1 ~ s(Tau) + s(Set,</pre>
    bs = "re"), family = gaussian(link = "identity"), method = "REML")
anova(ResUse.PCoA1.gam, ResUse.PCoA1.gam.re, test = "Chisq")
## Analysis of Deviance Table
##
## Model 1: V1 ~ s(Tau)
## Model 2: V1 ~ s(Tau) + s(Set, bs = "re")
     Resid. Df Resid. Dev
                               Df Deviance Pr(>Chi)
## 1
        42.564
                  0.39463
                  0.22261 -1.2951 0.17202
        43.859
AIC(ResUse.PCoA1.gam, ResUse.PCoA1.gam.re)
## ResUse.PCoA1.gam
                       6.549076 -84.10591
## ResUse.PCoA1.gam.re 5.956827 -113.34358
```

```
\# Random effect of set is not significant
rm(ResUse.PCoA1.gam.re)
summary(ResUse.PCoA1.gam)
## Family: gaussian
## Link function: identity
##
## Formula:
## V1 ~ s(Tau)
##
## Parametric coefficients:
##
                Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.078e-17 1.348e-02
##
## Approximate significance of smooth terms:
          edf Ref.df
                       F p-value
## s(Tau) 3.662 4.549 5.446 0.000706 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.345 Deviance explained = 39.5%
## -REML = -37.513 Scale est. = 0.0089005 n = 49
mean(summary(ResUse.PCoA1.gam)$s.table[, 4])
## [1] 0.0007055848
k.check(ResUse.PCoA1.gam)
         k'
                 edf k-index p-value
## s(Tau) 9 3.662264 0.989424 0.3875
```

gam.check(ResUse.PCoA1.gam)

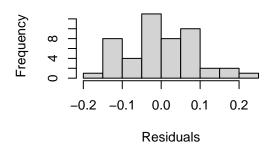
Resids vs. linear pred.

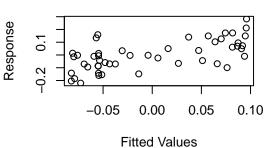




Histogram of residuals

Response vs. Fitted Values

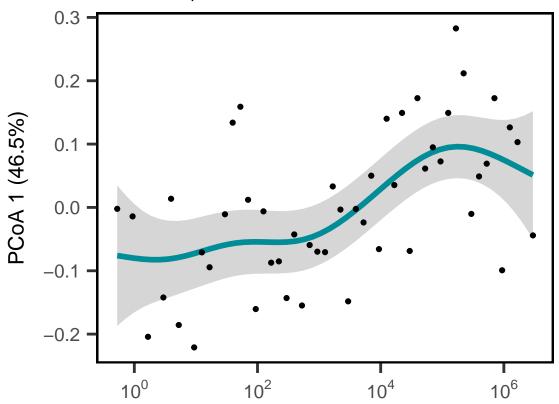




```
##
## Method: REML
                  Optimizer: outer newton
## full convergence after 6 iterations.
## Gradient range [-3.325556e-05,3.54571e-05]
## (score -37.51287 & scale 0.008900487).
## Hessian positive definite, eigenvalue range [0.1398772,23.57581].
## Model rank = 10 / 10
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##
            k' edf k-index p-value
## s(Tau) 9.00 3.66
                       0.99
                               0.38
```

```
ResUse_PCoA1 <- predict_gam(ResUse.PCoA1.gam) %>%
    ggplot(aes(Tau, fit)) + geom_smooth_ci(color = "#008d98",
    cex = 2, ci_alpha = 0.2) + geom_point(data = EP.plot, aes(x = Tau,
    y = V1)) + ylab(paste("PCoA 1 (", explainvar1.ep, "%)\n",
    sep = "")) + scale_x_continuous(labels = label_math(expr = 10^.x,
    format = force)) + theme(axis.title.y = element_text(margin = margin(t = 0,
        r = -6, b = 0, l = 12))) + labs(title = bquote("Deviance explained =" ~
        .(signif(summary(ResUse.PCoA1.gam)$dev, 2)))) + theme(axis.title.x = element_blank())
ResUse PCoA1
```

Deviance explained = 0.39



```
ggsave("./output/ResUse_PCoA1.pdf")
ggsave("./output/ResUse_PCoA1.png", width = 6.5, height = 5)
```

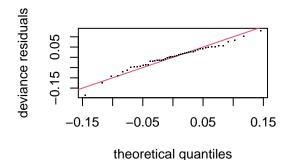
C. Resource Use PCoA2

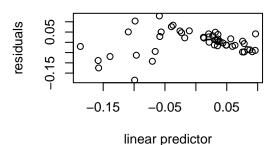
```
ResUse.PCoA2.gam <- gam(data = EP.plot, V2 ~ s(Tau), family = gaussian(link = "identity"),
   method = "REML")
ResUse.PCoA2.gam.re <- gam(data = EP.plot, V2 ~ s(Tau) + s(Set,</pre>
    bs = "re"), family = gaussian(link = "identity"), method = "REML")
anova(ResUse.PCoA2.gam, ResUse.PCoA2.gam.re, test = "Chisq")
## Analysis of Deviance Table
## Model 1: V2 ~ s(Tau)
## Model 2: V2 ~ s(Tau) + s(Set, bs = "re")
     Resid. Df Resid. Dev
                              Df Deviance Pr(>Chi)
## 1
        45.890
                  0.30490
                 0.15484 9.9228 0.15006 3.269e-05 ***
        35.967
## 2
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
AIC(ResUse.PCoA2.gam, ResUse.PCoA2.gam.re)
##
                              df
                                       AIC
## ResUse.PCoA2.gam
                        3.783514 -102.2766
## ResUse.PCoA2.gam.re 12.293564 -118.4579
```

```
# Random effect of set is significant
rm(ResUse.PCoA2.gam)
summary(ResUse.PCoA2.gam.re)
##
## Family: gaussian
## Link function: identity
##
## Formula:
## V2 \sim s(Tau) + s(Set, bs = "re")
## Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.001121 0.018245 0.061
##
## Approximate significance of smooth terms:
           edf Ref.df
                       F p-value
## s(Tau) 6.389 7.542 8.536 2.29e-06 ***
## s(Set) 2.165 3.000 2.844 0.0144 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) = 0.606 Deviance explained = 67.6\%
## -REML = -49.709 Scale est. = 0.0039255 n = 49
mean(summary(ResUse.PCoA2.gam.re)$s.table[, 4])
## [1] 0.007196484
k.check(ResUse.PCoA2.gam.re)
##
         k'
                 edf k-index p-value
## s(Tau) 9 6.388785 1.041467 0.5525
## s(Set) 4 2.165336
                                   NA
```

gam.check(ResUse.PCoA2.gam.re)

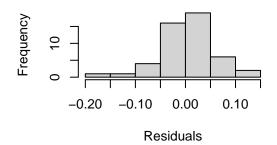
Resids vs. linear pred.



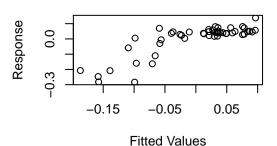


Histogram of residuals

Response vs. Fitted Values



##



```
## Method: REML
                  Optimizer: outer newton
## full convergence after 8 iterations.
## Gradient range [-7.662219e-07,1.587988e-08]
## (score -49.70925 & scale 0.003925458).
## Hessian positive definite, eigenvalue range [0.6970872,23.87046].
## Model rank = 14 / 14
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##
            k' edf k-index p-value
## s(Tau) 9.00 6.39
                       1.04
                               0.51
## s(Set) 4.00 2.17
                         NA
```

```
ResUse_PCoA2 <- predict_gam(ResUse.PCoA2.gam.re, exclude_terms = "s(Set)") %>%

filter(Set == "1") %>%

ggplot(aes(Tau, fit)) + geom_smooth_ci(color = "#008d98",

cex = 2, ci_alpha = 0.2) + geom_point(data = EP.plot, aes(x = Tau,

y = V2)) + ylab(paste("PCoA 2 (", explainvar2.ep, "%)\n",

sep = "")) + xlab(expression(paste("Residence time (", tau,

", h)"))) + scale_x_continuous(labels = label_math(expr = 10^.x,

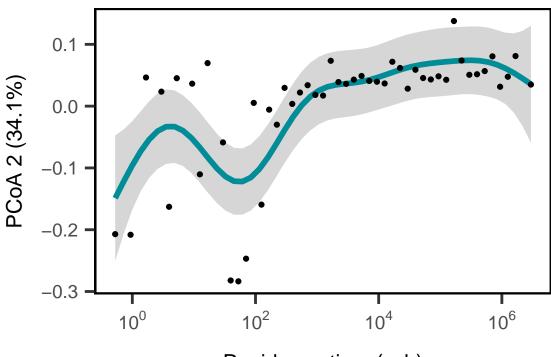
format = force)) + theme(axis.title.y = element_text(margin = margin(t = 0,

r = -6, b = 0, l = 12))) + labs(title = bquote("Deviance explained =" ~

.(signif(summary(ResUse.PCoA2.gam.re)$dev, 2))))

ResUse_PCoA2
```

Deviance explained = 0.68

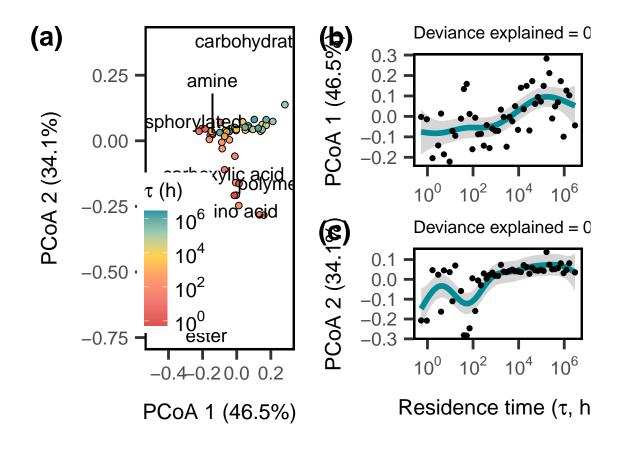


Residence time (τ, h)

```
ggsave("./output/ResUse_PCoA2.pdf")
ggsave("./output/ResUse_PCoA2.png", width = 6.5, height = 5)
```

Draw Figure

```
ggdraw() + draw_plot(ResUse_PCoA, x = 0, y = 0, width = 0.5,
height = 1) + draw_plot(ResUse_PCoA1, x = 0.5, y = 0.55,
width = 0.5, height = 0.45) + draw_plot(ResUse_PCoA2, x = 0.5,
y = 0, width = 0.5, height = 0.55) + draw_plot_label(label = c("(a)",
"(b)", "(c)"), size = 20, x = c(0, 0.5, 0.5), y = c(1.005,
1.005, 0.555)) + theme(plot.background = element_rect(fill = "white",
color = NA))
```



```
ggsave("./output/RTLC Fig2.pdf")
ggsave("./output/RTLC_Fig2.png", width = 12, height = 6, dpi = 800)
```

Figure 3. Microbial diversity increases with residence time Add OTU S and SimpE to Tau

```
Tau <- S.fxn(S, Tau)
Tau$Day_20.S <- as.numeric(Tau$Day_20.S)</pre>
Tau$Day_0.S <- as.numeric(Tau$Day_0.S)</pre>
Tau <- SimpE.fxn(SimpE, Tau)</pre>
Tau$Day_0.SimpE <- as.numeric(Tau$Day_0.SimpE)</pre>
Tau$Day_20.SimpE <- as.numeric(Tau$Day_20.SimpE)</pre>
```

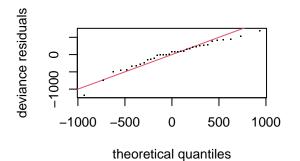
A. Observed Richness - OTUs

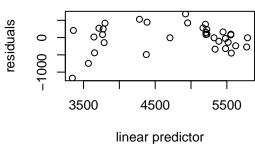
df

```
S.OTU.gam <- gam(Day_20.S ~ s(Tau, k = 14), family = gaussian(link = "identity"),
    data = Tau, method = "REML")
S.OTU.gam.re <- gam(Day_20.S ~ s(Tau) + s(Set, bs = "re"), family = gaussian(link = "identity"),
   data = Tau, method = "REML")
AIC(S.OTU.gam, S.OTU.gam.re)
##
                               AIC
```

```
## S.OTU.gam
                8.101273 541.8116
## S.OTU.gam.re 10.954306 535.4213
anova(S.OTU.gam, S.OTU.gam.re, test = "Chisq")
## Analysis of Deviance Table
##
## Model 1: Day_20.S \sim s(Tau, k = 14)
## Model 2: Day_20.S ~ s(Tau) + s(Set, bs = "re")
   Resid. Df Resid. Dev
                           Df Deviance Pr(>Chi)
## 1
       26.740 6816611
## 2
       23.449
                 4824718 3.2906 1991893 0.01517 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
# Random effect of set is significant
rm(S.OTU.gam)
summary(S.OTU.gam.re)
##
## Family: gaussian
## Link function: identity
## Formula:
## Day_20.S \sim s(Tau) + s(Set, bs = "re")
## Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 4790.2
                          161.7 29.62 <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
           edf Ref.df
                           F p-value
## s(Tau) 5.064 6.138 18.225 <2e-16 ***
## s(Set) 2.294 3.000 2.947 0.0186 *
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.792 Deviance explained = 83.7\%
## -REML = 257.71 Scale est. = 1.8109e+05 n = 35
k.check(S.OTU.gam.re)
         k'
                 edf k-index p-value
## s(Tau) 9 5.063830 1.204698
                               0.84
## s(Set) 4 2.294089
                                  NΑ
                           NA
gam.check(S.OTU.gam.re)
```

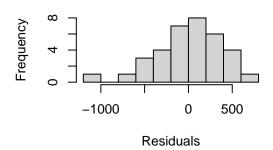
Resids vs. linear pred.

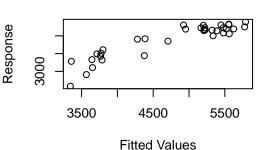




Histogram of residuals

Response vs. Fitted Values



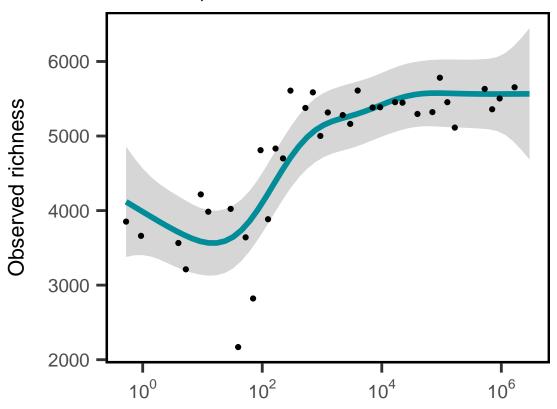


```
##
## Method: REML
                  Optimizer: outer newton
## full convergence after 4 iterations.
## Gradient range [-0.0001428268,1.919717e-05]
## (score 257.706 & scale 181093.9).
## Hessian positive definite, eigenvalue range [0.5611962,16.84203].
## Model rank = 14 / 14
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##
            k' edf k-index p-value
## s(Tau) 9.00 5.06
                        1.2
                               0.86
## s(Set) 4.00 2.29
                         NA
mean(summary(S.OTU.gam.re)$s.table[, 4])
```

[1] 0.009281618

S_OTU_Tau

Deviance explained = 0.84



```
ggsave("./output/S_OTU_Tau.pdf")
ggsave("./output/S_OTU_Tau.png", width = 7, height = 5)
```

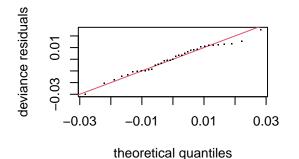
B. Simpson's Evenness (E[1/D]) - OTUs

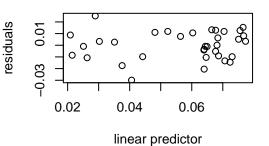
```
SimpE.OTU.gam <- gam(Day_20.SimpE ~ s(Tau, k = 15), family = gaussian(link = "identity"),
    data = Tau, method = "REML")
SimpE.OTU.gam.re <- gam(Day_20.SimpE ~ s(Tau) + s(Set, bs = "re"),</pre>
    family = gaussian(link = "identity"), data = Tau, method = "REML")
AIC(SimpE.OTU.gam, SimpE.OTU.gam.re)
##
                           df
## SimpE.OTU.gam
                    8.147650 -195.5583
## SimpE.OTU.gam.re 7.715705 -195.1028
anova(SimpE.OTU.gam, SimpE.OTU.gam.re, test = "Chisq")
## Analysis of Deviance Table
##
## Model 1: Day_20.SimpE \sim s(Tau, k = 15)
## Model 2: Day_20.SimpE ~ s(Tau) + s(Set, bs = "re")
     Resid. Df Resid. Dev
                                       Deviance Pr(>Chi)
                                 Df
```

```
## 1
       26.677 0.0048176
       27.253 0.0050026 -0.57592 -0.00018506 0.1612
# Random effect of set is not significant
rm(SimpE.OTU.gam.re)
summary(SimpE.OTU.gam)
##
## Family: gaussian
## Link function: identity
## Formula:
## Day_20.SimpE \sim s(Tau, k = 15)
## Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.056801 0.002178 26.09 <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
           edf Ref.df
                       F p-value
## s(Tau) 4.972 6.148 11.51 1.83e-06 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.674 Deviance explained = 72.2%
## -REML = -88.306 Scale est. = 0.00016596 n = 35
k.check(SimpE.OTU.gam)
         k'
                 edf k-index p-value
## s(Tau) 14 4.972393 0.963992 0.355
```

gam.check(SimpE.OTU.gam)

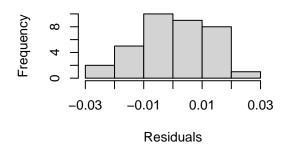
Resids vs. linear pred.

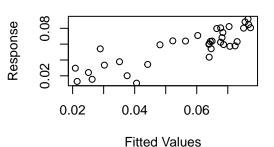




Histogram of residuals

Response vs. Fitted Values

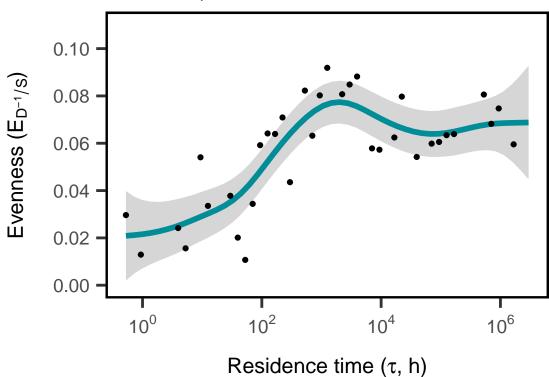




```
##
## Method: REML
                  Optimizer: outer newton
## full convergence after 7 iterations.
## Gradient range [-1.075916e-08,-8.738233e-09]
## (score -88.30582 & scale 0.0001659648).
## Hessian positive definite, eigenvalue range [0.7307918,16.75017].
## Model rank = 15 / 15
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##
             k'
                  edf k-index p-value
## s(Tau) 14.00
                4.97
                         0.96
                                 0.34
mean(summary(SimpE.OTU.gam)$s.table[, 4])
```

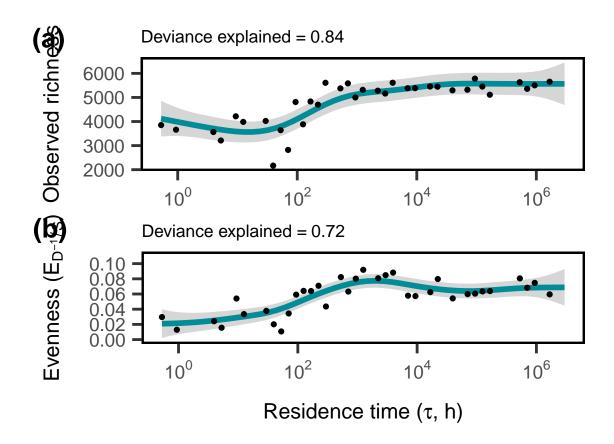
```
## [1] 1.832464e-06
```

Deviance explained = 0.72



```
ggsave("./output/SimpE_OTU_Tau.pdf")
ggsave("./output/SimpE_OTU_Tau.png", width = 7, height = 5)
```

Draw figure



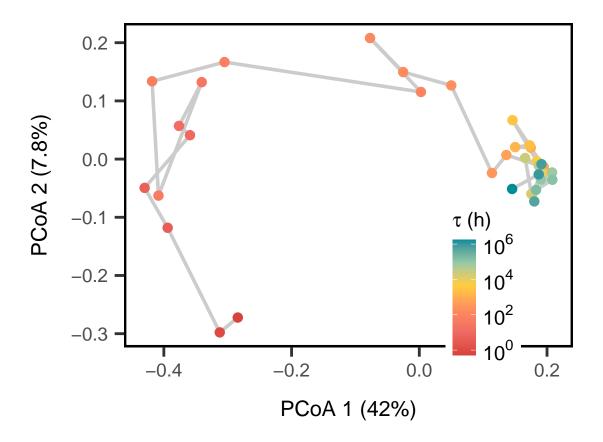
```
ggsave("./output/RTLC_Fig3.pdf")
ggsave("./output/RTLC_Fig3.png", width = 5, height = 6, dpi = 800)
```

Figure 4. Community assembly along a residence time gradient

A. Bray-Curtis Distance Community Composition PCoA

```
cor.test(x = CC.plot.order$Tau, y = CC.plot.order$V1)
```

```
##
## Pearson's product-moment correlation
##
## data: CC.plot.order$Tau and CC.plot.order$V1
## t = 8.3414, df = 33, p-value = 1.233e-09
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## 0.6758255 0.9077065
## sample estimates:
##
         cor
## 0.8235867
cor.test(x = CC.plot.order$Tau, y = CC.plot.order$V2)
##
## Pearson's product-moment correlation
##
## data: CC.plot.order$Tau and CC.plot.order$V2
## t = 0.14656, df = 33, p-value = 0.8844
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
## -0.3103807 0.3557270
## sample estimates:
##
          cor
## 0.02550377
CommComp_PCoA <- ggplot(CC.plot.order, aes(x = V1, y = V2)) +</pre>
    geom_path(linewidth = 1.25, color = alpha("black", 0.2)) +
   geom_point(cex = 3, aes(color = as.numeric(Tau))) + xlab(paste("PCoA 1 (",
    explainvar1, "%", sep = "")) + ylab(paste("PCoA 2 (", explainvar2,
    "%)", sep = "")) + labs(color = expression(paste(tau, " (h)"))) +
    scale_color_gradientn(colors = moma.colors("ustwo"), labels = label_math(expr = 10^.x,
        format = force)) + guides(color = guide_colorbar(position = "inside")) +
    theme(legend.title = element_text(size = 15), legend.position.inside = c(0.8,
        0.2), legend.text = element_text(size = 15))
CommComp_PCoA
```



```
ggsave("./output/CommComp_PCoA.pdf")
ggsave("./output/CommComp_PCoA.png", width = 10, height = 10)
```

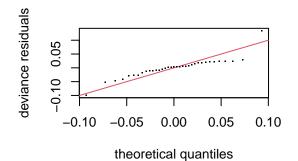
B. Community Composition - PCoA1

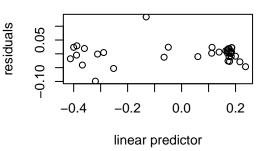
```
CommComp.PCoA1.gam <- gam(V1 ~ s(Tau), family = gaussian(link = "identity"),</pre>
   data = CC.plot, method = "REML")
CommComp.PCoA1.gam.re <- gam(V1 ~ s(Tau) + s(Set, bs = "re"),</pre>
    family = gaussian(link = "identity"), data = CC.plot, method = "REML")
AIC(CommComp.PCoA1.gam, CommComp.PCoA1.gam.re)
##
                                df
                                          AIC
## CommComp.PCoA1.gam
                          9.822328 -98.60803
## CommComp.PCoA1.gam.re 13.273815 -109.02901
anova(CommComp.PCoA1.gam, CommComp.PCoA1.gam.re, test = "Chisq")
## Analysis of Deviance Table
## Model 1: V1 ~ s(Tau)
## Model 2: V1 ~ s(Tau) + s(Set, bs = "re")
    Resid. Df Resid. Dev
                              Df Deviance Pr(>Chi)
## 1
        25.222
                 0.069866
        21.471
                 0.042590 3.7504 0.027276 0.00347 **
## 2
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

```
# Random effect of set is significant
rm(CommComp.PCoA1.gam)
summary(CommComp.PCoA1.gam.re)
##
## Family: gaussian
## Link function: identity
##
## Formula:
## V1 \sim s(Tau) + s(Set, bs = "re")
## Parametric coefficients:
               Estimate Std. Error t value Pr(>|t|)
##
## (Intercept) 0.0006728 0.0180653 0.037
##
## Approximate significance of smooth terms:
          edf Ref.df
                       F p-value
## s(Tau) 7.881 8.668 119.009 <2e-16 ***
## s(Set) 2.407 3.000 3.668 0.011 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) = 0.97 Deviance explained = 97.9\%
## -REML = -38.669 Scale est. = 0.0017961 n = 35
k.check(CommComp.PCoA1.gam.re)
##
         k'
                 edf k-index p-value
## s(Tau) 9 7.880743 1.098318 0.6725
## s(Set) 4 2.407351
```

gam.check(CommComp.PCoA1.gam.re)

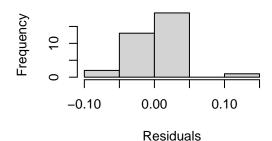
Resids vs. linear pred.

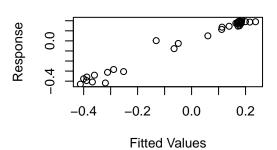




Histogram of residuals

Response vs. Fitted Values



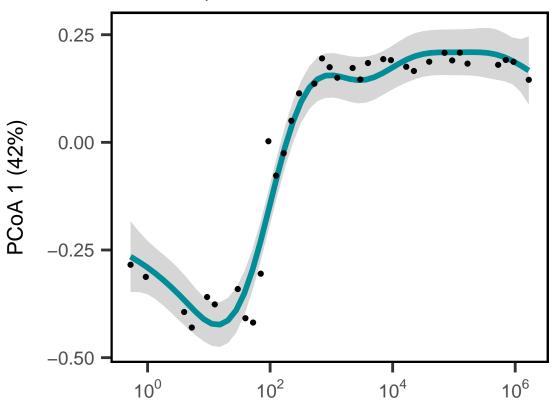


```
##
## Method: REML
                  Optimizer: outer newton
## full convergence after 7 iterations.
## Gradient range [-1.815658e-06,1.885777e-07]
## (score -38.66944 & scale 0.001796123).
## Hessian positive definite, eigenvalue range [0.7279977,17.40389].
## Model rank = 14 / 14
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##
            k'
                edf k-index p-value
## s(Tau) 9.00 7.88
                        1.1
                               0.72
## s(Set) 4.00 2.41
                         NA
mean(summary(CommComp.PCoA1.gam.re)$s.table[, 4])
```

[1] 0.005504149

```
CommComp_PCoA1 <- predict_gam(CommComp.PCoA1.gam.re, exclude_terms = "s(Set)") %>%
  filter(Set == "1") %>%
  ggplot(aes(Tau, fit)) + geom_smooth_ci(color = "#008d98",
  cex = 2, ci_alpha = 0.2) + geom_point(data = CC.plot, aes(x = Tau,
  y = V1)) + scale_x_continuous(labels = label_math(expr = 10^.x,
  format = force)) + ylab(paste("PCoA 1 (", explainvar1, "%)",
  sep = "")) + labs(title = bquote("Deviance explained =" ~
    .(signif(summary(CommComp.PCoA1.gam.re)$dev, 2)))) + theme(axis.title.x = element_blank())
```

Deviance explained = 0.98



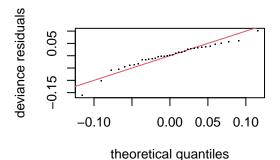
```
ggsave("./output/CommComp_PCoA1.pdf")
ggsave("./output/CommComp_PCoA1.png", width = 6.5, height = 5)
```

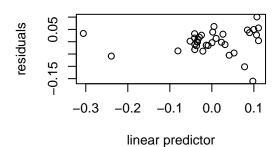
C. Community composition - PCoA2

```
CommComp.PCoA2.gam <- gam(V2 ~ s(Tau), family = gaussian(link = "identity"),
    data = CC.plot, method = "REML")
CommComp.PCoA2.gam.re <- gam(V2 ~ s(Tau) + s(Set, bs = "re"),</pre>
    family = gaussian(link = "identity"), data = CC.plot, method = "REML")
AIC(CommComp.PCoA2.gam.re, CommComp.PCoA2.gam)
##
                               df
## CommComp.PCoA2.gam.re 7.714415 -98.27226
## CommComp.PCoA2.gam
                         7.713969 -98.27299
anova(CommComp.PCoA2.gam, CommComp.PCoA2.gam.re, test = "Chisq")
## Analysis of Deviance Table
## Model 1: V2 ~ s(Tau)
## Model 2: V2 ~ s(Tau) + s(Set, bs = "re")
     Resid. Df Resid. Dev
                                  Df
                                       Deviance Pr(>Chi)
## 1
        27.185 0.079569
```

```
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
# Random effect of set is not significant (no difference in
# AIC)
rm(CommComp.PCoA2.gam.re)
summary(CommComp.PCoA2.gam)
## Family: gaussian
## Link function: identity
##
## Formula:
## V2 ~ s(Tau)
##
## Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.772e-17 8.908e-03
## Approximate significance of smooth terms:
          edf Ref.df F p-value
## s(Tau) 5.351 6.452 15.66 <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) = 0.746 Deviance explained = 78.6\%
## -REML = -40.918 Scale est. = 0.0027774 n = 35
k.check(CommComp.PCoA2.gam)
        k'
                edf k-index p-value
## s(Tau) 9 5.351009 0.9590669
                              0.37
gam.check(CommComp.PCoA2.gam)
```

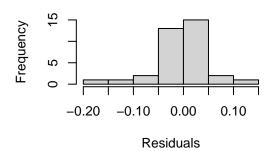
Resids vs. linear pred.

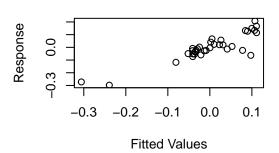




Histogram of residuals

Response vs. Fitted Values

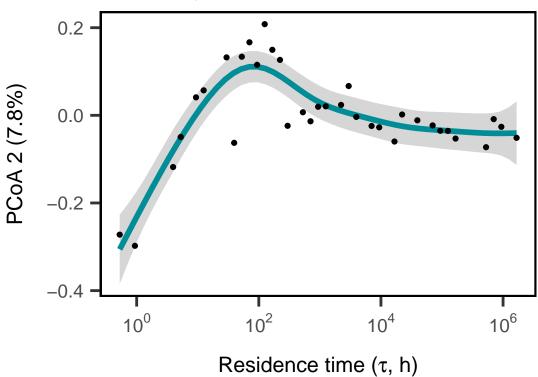




```
##
## Method: REML
                  Optimizer: outer newton
## full convergence after 6 iterations.
## Gradient range [-4.364615e-10,4.034817e-11]
## (score -40.91816 & scale 0.002777386).
## Hessian positive definite, eigenvalue range [1.626398,16.8182].
## Model rank = 10 / 10
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##
            k' edf k-index p-value
## s(Tau) 9.00 5.35
                       0.96
                               0.29
mean(summary(CommComp.PCoA2.gam)$s.table[, 4])
```

[1] 0

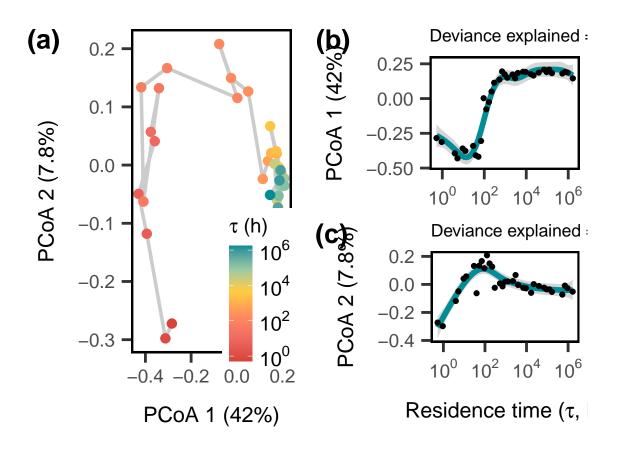
Deviance explained = 0.79



```
ggsave("./output/CommComp_PCoA2.pdf")
ggsave("./output/CommComp_PCoA2.png", width = 6.5, height = 5)
```

Draw Figure

```
ggdraw() + draw_plot(CommComp_PCoA, x = 0, y = 0, width = 0.5,
    height = 1) + draw_plot(CommComp_PCoA1, x = 0.5, y = 0.55,
    width = 0.5, height = 0.45) + draw_plot(CommComp_PCoA2, x = 0.5,
    y = 0, width = 0.5, height = 0.55) + draw_plot_label(label = c("(a)",
    "(b)", "(c)"), size = 20, x = c(0, 0.5, 0.5), y = c(1.005,
    1.005, 0.555)) + theme(plot.background = element_rect(fill = "white",
    color = NA))
```



```
ggsave("./output/RTLC_Fig4.pdf")
ggsave("./output/RTLC_Fig4.png", width = 12, height = 6, dpi = 800)
```

Figure 5. Niche partitioning along a residence time gradient.

Generate niche clusters

```
# } OTUs.70.corr[,paste0(otu1)] <- corr } OTUs.70.dist <-
\# ((1-OTUs.70.corr[,2:2205])/2) \ rownames(OTUs.70.dist) <-
# colnames(OTUs.70.corr[,2:2205]) OTUs.70.dist <-
# as.matrix(OTUs.70.dist) OTUs.70.dist <-
# as.dist(OTUs.70.dist, upper = TRUE, diag = TRUE)
# saveRDS(OTUs.70.dist, './data/OTUs.70.dist')
# Read in saved distance matrix
OTUs.70.dist <- readRDS("./data/OTUs.70.dist")</pre>
# Perform clustering with 6 clusters
set.seed(47401)
kmeans.clust <- kmeans(OTUs.70.dist, centers = 5)</pre>
# Calculate total abundance of each niche at each residence
# time
OTUs.niches <- data.frame()
OTUs.niches.sum <- as.data.frame(as.numeric(rownames(OTUs.70)))
n.cluster <- 1
while (n.cluster <= 5) {</pre>
    cond <- sapply(kmeans.clust$cluster, function(x) x == n.cluster)</pre>
    cluster <- names(kmeans.clust$cluster[cond])</pre>
    OTUs.cluster <- cbind(as.numeric(rownames(OTUs.70)), rep(n.cluster,
    colnames(OTUs.cluster) <- c("Tau", "Cluster")</pre>
    OTUs.cluster <- cbind(OTUs.cluster, OTUs.70[, colnames(OTUs.70) %in%
    OTUs.niches.sum <- cbind(OTUs.niches.sum, rowSums(OTUs.70[,
        colnames(OTUs.70) %in% cluster]))
    OTUs.cluster <- as.data.frame(OTUs.cluster) %>%
        gather(OTU, REL, cluster[1]:cluster[length(cluster)])
    colnames(OTUs.cluster) <- c("Tau", "Cluster", "OTU", "REL")</pre>
    OTUs.niches <- rbind(OTUs.niches, OTUs.cluster)
    n.cluster <- n.cluster + 1</pre>
}
colnames(OTUs.niches.sum) <- c("Tau", 1:(n.cluster - 1))</pre>
OTUs.niches.sum <- as.data.frame(OTUs.niches.sum) %>%
    gather(Cluster, REL, "1":paste(n.cluster - 1))
OTUs.niches.sum\Cluster <- as.numeric(OTUs.niches.sum\Cluster)
OTUs.niches.sum$Cluster <- as.factor(OTUs.niches.sum$Cluster)</pre>
```

Classify taxa by niche and determine proportion of each niche

```
colnames(niche.taxa) <- c("Niche", "Prop_num", "OTU", "Domain",</pre>
    "Phylum", "Class", "Order", "Family", "Genus")
niche.taxa$Niche <- as.factor(niche.taxa$Niche)</pre>
niche.taxa$Prop_num <- as.numeric(niche.taxa$Prop_num)</pre>
for (x in 1:5) {
    print(paste("Niche: ", x, " N:", nrow(subset(niche.taxa,
        niche.taxa$Niche == x)), " %:", round(nrow(subset(niche.taxa,
        niche.taxa$Niche == x))/nrow(niche.taxa), digits = 4)))
}
                               %: 0.3054"
## [1] "Niche: 1
                     N: 673
## [1] "Niche: 2
                     N: 427
                              %: 0.1937"
## [1] "Niche: 3
                     N: 336
                               %: 0.1525"
## [1] "Niche: 4
                     N: 287
                               %: 0.1302"
## [1] "Niche: 5
                               %: 0.2182"
                     N: 481
```

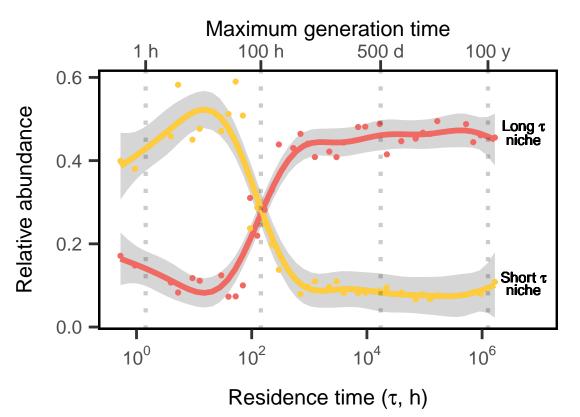
Fit total abundance of niches with gams and draw figure

```
##
## Family: gaussian
## Link function: identity
## Formula:
## REL ~ s(Tau)
##
## Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.335576  0.006688  50.17  <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
                        F p-value
         edf Ref.df
## s(Tau) 7.04 8.086 61.39 <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.936 Deviance explained = 94.9\%
## -REML = -46.42 Scale est. = 0.0015655 n = 35
## [1] 0
```

```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## REL ~ s(Tau)
## Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
           edf Ref.df
                      F p-value
## s(Tau) 3.346 4.153 11.8 5.57e-06 ***
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.587 Deviance explained = 62.8\%
## -REML = -59.924 Scale est. = 0.00108 n = 35
## [1] 5.568932e-06
##
## Family: gaussian
## Link function: identity
## Formula:
## REL ~ s(Tau)
## Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.08128
                        0.00248 32.78 <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
          edf Ref.df
                       F p-value
## s(Tau) 5.676 6.797 5.224 0.000724 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.512 Deviance explained = 59.4\%
## -REML = -82.46 Scale est. = 0.00021521 n = 35
## [1] 0.000724011
## Family: gaussian
## Link function: identity
##
## Formula:
## REL ~ s(Tau)
## Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.220047 0.008547 25.75 <2e-16 ***
```

```
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
            edf Ref.df
                           F p-value
## s(Tau) 6.911 7.98 49.65 <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) = 0.921 Deviance explained = 93.7\%
## -REML = -38.689 Scale est. = 0.0025567 n = 35
## [1] 0
##
## Family: gaussian
## Link function: identity
##
## Formula:
## REL ~ s(Tau)
## Parametric coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.074524 0.002968 25.11
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
            edf Ref.df
                           F p-value
## s(Tau) 4.111 5.057 9.058 2.39e-05 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.571 Deviance explained = 62.3%
## -REML = -79.423 Scale est. = 0.00030832 n = 35
## [1] 2.390613e-05
colnames(niche.gams) <- c("Cluster", "Tau", "fit", "se.fit")</pre>
niche.gams$Cluster <- as.numeric(niche.gams$Cluster)</pre>
niche.gams$Cluster <- as.factor(niche.gams$Cluster)</pre>
niche.gams\$umin \leftarrow (\log(2)/(1/((10^niche.gams<math>\$Tau) * 60)))
niche.gams$umin <- na_if(niche.gams$umin, niche.gams$Tau < 3)
scale.factor <- max(subset(niche.gams, niche.gams$Cluster %in%
    c(1, 4)) $fit) / max(niche.gams $umin)
tau.1 \leftarrow log10(1/(log(2)))
tau.100 \leftarrow log10(100/(log(2)))
tau.12000 \leftarrow log10(12000/(log(2)))
tau.876000 \leftarrow log10(876000/(log(2)))
OTUs_major_niches <- ggplot(data = subset(niche.gams, niche.gams$Cluster %in%
    c(1, 4)), aes(x = Tau, y = fit, group = Cluster)) + geom_smooth_ci(cex = 2,
    ci_alpha = 0.2, color = "grey") + geom_line(aes(color = Cluster),
```

```
linewidth = 2) + scale_y_continuous(name = "Relative abundance") +
    geom_point(data = subset(OTUs.niches.sum, OTUs.niches.sum$Cluster %in%
        c(1, 4)), aes(x = Tau, y = REL, color = Cluster)) + geom_vline(xintercept = c(tau.1,
    tau.100, tau.12000, tau.876000), color = alpha("black", 0.2),
   linetype = "13", linewidth = 1.5) + scale_x_continuous(labels = label_math(expr = 10^.x,
    format = force), limits = c(-0.3, 6.95), sec.axis = sec_axis(\sim log10(log(2)/(1/(10^{\circ}.))),
   name = "Maximum generation time", breaks = c(0, 2, log10(12000),
        log10(876000)), labels = c("1 h", "100 h", "500 d", "100 y"))) +
    scale color manual(values = as.vector(c(moma.colors("ustwo",
        5)[1], moma.colors("ustwo", 5)[3]))) + xlab(expression(paste("Residence time (",
   tau, ", h)"))) + theme(legend.position = "none") + geom_text(x = 6.72,
   y = 0.48, label = expression(paste("Long ", tau))) + geom_text(x = 6.72,
   y = 0.45, label = "niche") + geom_text(x = 6.72, y = 0.12,
   label = expression(paste("Short ", tau))) + geom_text(x = 6.72,
   y = 0.09, label = "niche")
OTUs_major_niches
```



```
ggsave("./output/RTLC_Fig5.pdf")
ggsave("./output/RTLC_Fig5.png", width = 6, height = 4, dpi = 800)
```

Test phylogenetic clustering of Niche 1 and 4 and look at unique taxa in each

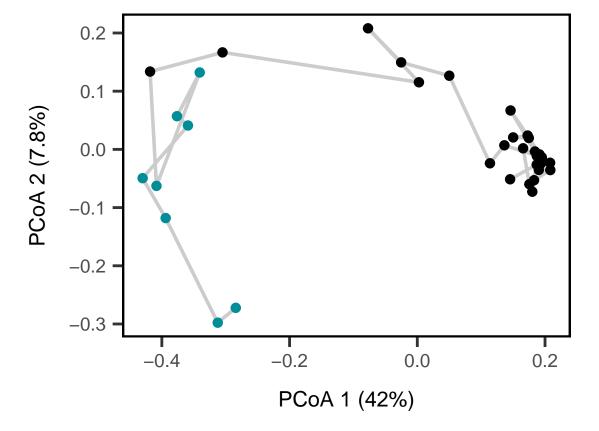
```
# Generate phylogenetic tree with niche as tip labels
niche1.otus <- subset(niche.taxa, niche.taxa$Niche == 1)$OTU</pre>
```

```
niche4.otus <- subset(niche.taxa, niche.taxa$Niche == 4)$OTU
niche3.otus <- subset(niche.taxa, niche.taxa$Niche == 3)$OTU
niche2.otus <- subset(niche.taxa, niche.taxa$Niche == 2)$OTU
niche5.otus <- subset(niche.taxa, niche.taxa$Niche == 5)$OTU
niche tree <- read.tree("./data/niche oturep.phylip.tre")</pre>
tip_otus <- read.csv("./data/seq_to_otu.csv", header = FALSE)</pre>
colnames(tip otus) <- c("Tips", "Otus")</pre>
tip_otus$Tips <- factor(tip_otus$Tips, levels = unique(as.character(niche_tree$tip.label)))</pre>
tip_otus <- tip_otus[order(tip_otus$Tips), ]</pre>
niche_tree$tip.label <- tip_otus$0tus</pre>
niche1 <- sapply(niche1.otus, grep, niche tree$tip.label)</pre>
niche4 <- sapply(niche4.otus, grep, niche_tree$tip.label)</pre>
niche3 <- sapply(niche3.otus, grep, niche_tree$tip.label)</pre>
niche2 <- sapply(niche2.otus, grep, niche_tree$tip.label)</pre>
niche5 <- sapply(niche5.otus, grep, niche_tree$tip.label)</pre>
niche_tree$edge.length[1] <- niche_tree$edge.length[296]</pre>
# Calculate Phylogenetic D and Cohen's D for Niche 1 and 4
niche.list <- as.data.frame(niche.taxa[, "Niche"])</pre>
rownames(niche.list) <- niche.taxa$OTU</pre>
colnames(niche.list) <- c("Niche")</pre>
niche.list$Niche <- as.numeric(niche.list$Niche)
niche.list <- as.data.frame((niche.list == 4) * 1)</pre>
niche.list$name <- rownames(niche.list)</pre>
rtlc.niche <- comparative.data(niche_tree, niche.list, "name")</pre>
D.otu.4 <- phylo.d(rtlc.niche, binvar = Niche)</pre>
niche.4.D <- D.otu.4$Permutations[["random"]]</pre>
cohensD(x = as.numeric(D.otu.4$Parameters[["Observed"]]), y = niche.4.D)
## [1] 19.14312
niche.list <- as.data.frame(niche.taxa[, "Niche"])</pre>
rownames(niche.list) <- niche.taxa$OTU</pre>
colnames(niche.list) <- c("Niche")</pre>
niche.list$Niche <- as.numeric(niche.list$Niche)</pre>
niche.list <- as.data.frame((niche.list == 1) * 1)</pre>
niche.list$name <- rownames(niche.list)</pre>
rtlc.niche <- comparative.data(niche tree, niche.list, "name")
D.otu.1 <- phylo.d(rtlc.niche, binvar = Niche)</pre>
niche.1.D <- D.otu.1$Permutations[["random"]]</pre>
cohensD(x = as.numeric(D.otu.1$Parameters[["Observed"]]), y = niche.1.D)
## [1] 15.36044
# Look at unique taxonomic orders between two major niches
n4.unique <- subset(niche.taxa, niche.taxa$Niche == 4)
```

Figure S1. Community composition and resource use do not reflect mode of flow-rate manipulation.

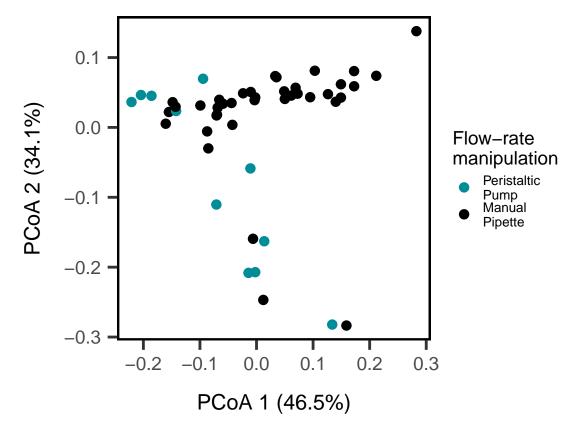
A. Community composition colored by pump/pipette

```
CommComp_pump <- ggplot(CC.plot.order, aes(x = V1, y = V2)) +
    geom_path(linewidth = 1.25, color = alpha("black", 0.2)) +
    xlab(paste("PCoA 1 (", explainvar1, "%)", sep = "")) + ylab(paste("PCoA 2 (",
    explainvar2, "%)", sep = "")) + geom_point(cex = 3, aes(color = Pump)) +
    labs(color = "Flow rate\nmanipulation") + scale_color_manual(values = c("#008d98",
    "black"), labels = c("Peristaltic \nPump", "Manual \nPipette")) +
    theme(legend.title = element_text(size = 14), legend.position = "none")</pre>
CommComp_pump
```



```
ggsave("./output/CommComp_PCoA_Pump.pdf")
ggsave("./output/CommComp_PCoA_Pump.png", width = 8, height = 5)
```

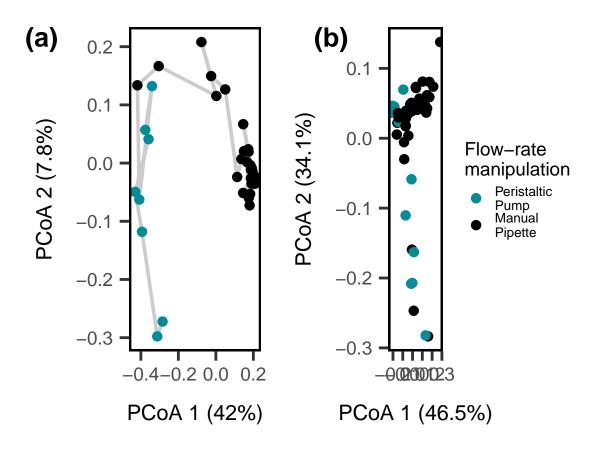
B. Resource use colored by pump/pipette



```
ggsave("./output/ResUse_PCoA_Pump.pdf")
ggsave("./output/ResUse_PCoA_Pump.png", width = 8, height = 5)
```

Draw Figure

```
ggdraw() + draw_plot(CommComp_pump, x = 0, y = 0, width = 0.45,
height = 1) + draw_plot(ResUse_pump, x = 0.45, y = 0, width = 0.55,
height = 1) + draw_plot_label(label = c("(a)", "(b)"), size = 20,
x = c(0, 0.5), y = c(1.005, 1.005)) + theme(plot.background = element_rect(fill = "white",
color = NA))
```



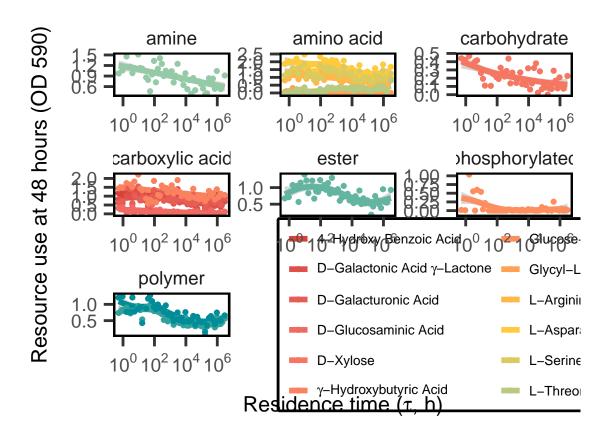
```
ggsave("./output/RTLC_FigS1.pdf")
ggsave("./output/RTLC_FigS1.png", width = 12, height = 6, dpi = 800)
```

Figure S3. Use of individual carbon sources mainly decreases with increased residence time.

```
Ind_ResUse <- ggplot(data = csource.gams, aes(x = Tau, y = fit,</pre>
    group = C_Source)) + geom_smooth_ci(cex = 2, ci_alpha = 0.2,
    color = "grey") + geom_line(cex = 2, aes(color = C_Source)) +
    facet_wrap(~Type, scales = "free") + geom_point(data = subset(EP.long,
   EP.long$C_Source %in% csource.sig$Resource), aes(x = Tau,
   y = OD_48, color = C_Source, group = C_Source)) + scale_x_continuous(labels = label_math(expr = 10^
   format = force)) + ylab("Resource use at 48 hours (OD 590)") +
    scale_color_discrete(type = moma.colors("ustwo", 16, type = "continuous"),
        labels = c("4-Hydroxy Benzoic Acid", expression(paste("D-Galactonic Acid ",
            gamma, "-Lactone")), "D-Galacturonic Acid", "D-Glucosaminic Acid",
            "D-Xylose", expression(paste(gamma, "-Hydroxybutyric Acid")),
            "Glucose-1-Phosphate", "Glycyl-L-Glutamic Acid",
            "L-Arginine", "L-Asparagine", "L-Serine", "L-Threonine",
            "Putrescine", "Pyruvic Acid Methyl Ester", "Tween 40",
            "Tween 80")) + xlab(expression(paste("Residence time (",
   tau, ", h)"))) + guides(color = guide_legend(nrow = 6)) +
    theme(legend.position = "bottom", legend.title = element_blank(),
        legend.box.background = element_rect(color = "black",
```

```
size = 2))
Ind_ResUse
                   10^{0} 10^{2} 10^{4} 10^{6} 10^{0} 10^{2} 10^{4} 10^{6} 10^{0} 10^{2} 10^{4} 10^{6}
       Resource use at 48 hours
             Q.6 carboxylic acid 0.6 ester 0.26 2hosphorylated 10^0 10^2 10^4 10^6 10^0 10^2 10^4 10^6 10^0 10^2 10^4 10^6
                   10^0 10^2 10^4 10^6
                                        Residence time (\tau, h)
              4–Hydroxy Benzoic Acid
                                          Glucose-1-Phosphate Putrescine
               D-Galactonic Acid γ-Lactone — Glycyl-L-Glutamic Acid — Pyruvic Acid Meth
                                      L–Arginine
               D-Galacturonic Acid
                                                                          Tween 40
                D-Glucosaminic Acid
                                     L-Asparagine
                                                                        Tween 80
                                            L-Serine
                D-Xylose
ggsave("./output/RTLC_FigS3.pdf", plot = reposition_legend(Ind_ResUse,
```

"left", panel = "panel-3-2"))



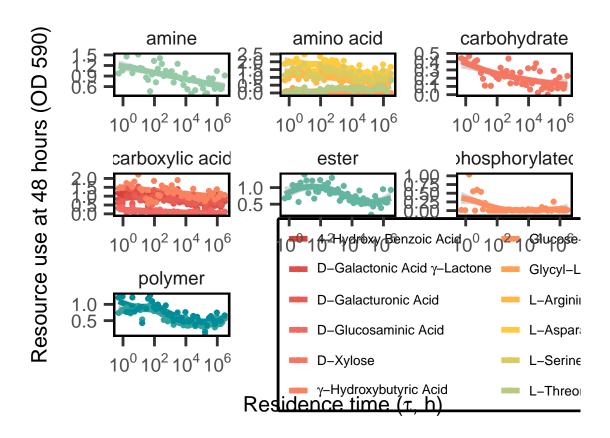


Figure S4. Phylum level changes across the residence time gradient.

```
# Generate total relative abundance for each phylum - time
# consuming, commented out to save time
# taxa \leftarrow as.data.frame(Tau.20$Tau) for(x in
# unique(OTUs.tax.20$Phylum)){ list <- data.frame(rep(0,</pre>
\# 35)) colnames(list) <- c(as.character(x)) for(y in
# OTUs.tax.20$OTU){ if(subset(OTUs.tax.20, OTUs.tax.20$OTU
\# == y)$Phylum == x){ list[,x] <- list[,x] +
# as.data.frame(OTUs.r.20[,y]) } taxa[,as.character(x)]
\# \leftarrow list[,x] } rownames(taxa) \leftarrow taxa\$`Tau.20\$Tau` taxa.20
# <- taxa[,-1] write.csv(taxa.20, './data/phyla.20.csv')
# Read in phylum abundance data generated above
phyla.20 <- read.csv("./data/phyla.20.csv", header = TRUE)</pre>
rownames(phyla.20) <- phyla.20$X
phyla.20 <- phyla.20[, -1]
phyla.20.rel <- decostand(phyla.20, method = "total")</pre>
phyla.20.rel <- cbind(Tau.20$Tau, phyla.20.rel)</pre>
colnames(phyla.20.rel) <- c("Tau", unique(OTUs.tax.20$Phylum))</pre>
phyla.20.long <- gather(phyla.20.rel, phylum, REL, Proteobacteria: Modulibacteria)
phyla.20.long$Tau <- as.numeric(phyla.20.long$Tau)</pre>
```

```
Phylum_Tau <- ggplot(phyla.20.long, aes(x = Tau, y = REL, group = phylum)) +
   geom_smooth(method = "loess", se = F, aes(color = phylum,
      group = phylum)) + ylab("Relative abundance") + scale_x_continuous(labels = label_math(expr = 1)
   format = force)) + labs(color = "Phylum") + xlab(expression(paste("Residence time (",
   tau, ", h)"))) + theme(legend.title = element_text(size = 20),
   legend.text = element_text(size = 15), axis.title = element_text(size = 20)) +
   guides(color = guide_legend(ncol = 3))
Phylum Tau

    Acidobacteriota

    Elusimicrobiota

                                                        Nitrospire

    Entotheonellaeota

    Actinobacteriota

                                                        Patesciba
                                Euryarchaeota
       AncK6
                                                        Planctor
      Archaea_unclassifiedFCPU426
                                                        Proteoba

    Armatimonadota

    Fibrobacterota

                                                        - RCP2-5
      Asgardarchaeota
                                Firmicutes
                                                        SAR324

    Bacteria unclassified — Fusobacteriota

                                                        Spirocha

    Bacteroidota

                                                        Sumerlae
                                — GAL15

    Bdellovibrionota

    Gemmatimonadota — Sva0485

                                                        Synergis

    Calditrichota

    Halobacterota

    Campylobacterota

    Hydrogenedentes

                                                        — TA06
      Chloroflexi

    Latescibacterota

                                                        Thermop

    Margulisbacteria

    Cloacimonadota

                                                        Verrucon
      Crenarchaeota
                                — MBNT15
                                                        — WPS-2
      Cyanobacteria

    Methylomirabilota

                                                        — WS1

    Dadabacteria

    Modulibacteria

                                                        — WS2
                                Myxococcota

    Deferrisomatota

                                                        — WS4
        Deinococcota
                                                        Zixibacte

    Nanoarchaeota

ggsave("./output/RTLC_FigS4.pdf")
```

```
ggsave("./output/RTLC_FigS4.pdf")
ggsave("./output/RTLC_FigS4.png", width = 12, height = 8, dpi = 800)
```

Figure S5. Amplicon sequence variant richness and evenness reflect operational taxonomic unit richness and evenness.

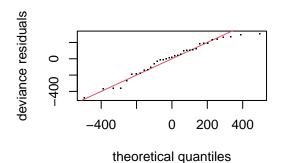
Add ASV S and SimpE to Tau

```
Tau <- ASV.S.fxn(S.ASV, Tau)
Tau$ASV_Day_20.S <- as.numeric(Tau$ASV_Day_20.S)
Tau$ASV_Day_0.S <- as.numeric(Tau$ASV_Day_0.S)

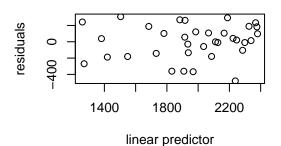
Tau <- ASV.SimpE.fxn(SimpE.ASV, Tau)
Tau$ASV_Day_0.SimpE <- as.numeric(Tau$ASV_Day_0.SimpE)
Tau$ASV_Day_20.SimpE <- as.numeric(Tau$ASV_Day_20.SimpE)
```

A. Species Richness - ASVs

```
S.ASV.gam <- gam(ASV_Day_20.S ~ s(Tau, k = 14), family = gaussian(link = "identity"),
    data = Tau, method = "REML")
S.ASV.gam.re <- gam(ASV_Day_20.S ~ s(Tau) + s(Set, bs = "re"),
    family = gaussian(link = "identity"), data = Tau, method = "REML")
AIC(S.ASV.gam, S.ASV.gam.re)
##
                      df
## S.ASV.gam
               8.390120 488.3867
## S.ASV.gam.re 8.155298 488.2937
anova(S.ASV.gam, S.ASV.gam.re, test = "Chisq")
## Analysis of Deviance Table
##
## Model 1: ASV_Day_20.S \sim s(Tau, k = 14)
## Model 2: ASV_Day_20.S ~ s(Tau) + s(Set, bs = "re")
   Resid. Df Resid. Dev
                               Df Deviance Pr(>Chi)
## 1
        26.340
                 1457077
## 2
        26.744
                 1472838 -0.40446
                                              0.272
                                    -15762
# Random effect of set is not significant
rm(S.ASV.gam.re)
summary(S.ASV.gam)
##
## Family: gaussian
## Link function: identity
##
## Formula:
## ASV_Day_20.S \sim s(Tau, k = 14)
## Parametric coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1963.31
                            38.23 51.35 <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
          edf Ref.df
                         F p-value
## s(Tau) 5.52 6.79 10.96 2.32e-06 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.684 Deviance explained = 73.5%
## -REML = 235.18 Scale est. = 51162
k.check(S.ASV.gam)
##
                  edf k-index p-value
          k'
## s(Tau) 13 5.520123 1.510897
```



Resids vs. linear pred.

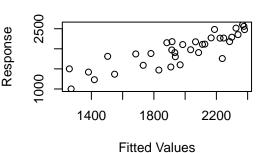


Histogram of residuals

Residuals

-400 0 200 400

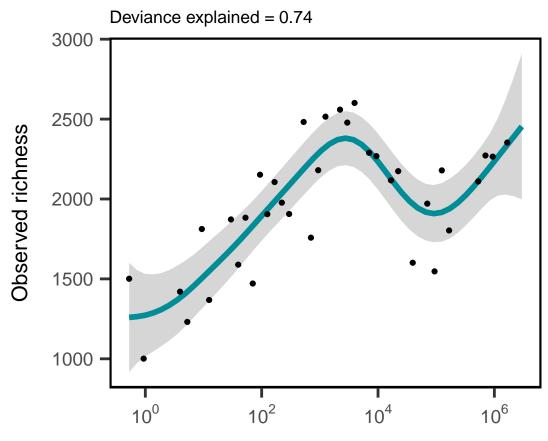
Response vs. Fitted Values



```
##
## Method: REML
                  Optimizer: outer newton
## full convergence after 5 iterations.
## Gradient range [-4.287254e-06,-6.357866e-07]
## (score 235.1819 & scale 51161.62).
## Hessian positive definite, eigenvalue range [1.108322,16.83186].
## Model rank = 14 / 14
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##
             k'
                  edf k-index p-value
## s(Tau) 13.00
                5.52
mean(summary(S.ASV.gam)$s.table[, 4])
```

```
## [1] 2.31524e-06
```

```
"cm"))
S.ob_ASV_Tau
```



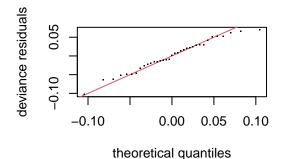
```
ggsave("./output/S.ob_ASV_Tau.pdf")
ggsave("./output/S.ob_ASV_Tau.png", width = 7, height = 5)
```

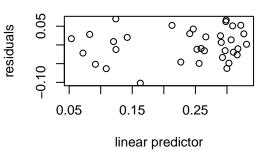
B. Species evenness - ASVs

```
## Resid. Df Resid. Dev
                        Df Deviance Pr(>Chi)
## 1
       26.810 0.094940
       ## 2
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
# Random effect of set is significant
rm(SimpE.ASV.gam)
summary(SimpE.ASV.gam.re)
##
## Family: gaussian
## Link function: identity
## Formula:
## ASV_Day_20.SimpE ~ s(Tau) + s(Set, bs = "re")
## Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.23700
                      0.01959
                                  12.1 3.37e-12 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
          edf Ref.df
                     F p-value
## s(Tau) 5.551 6.668 13.59 9.53e-07 ***
## s(Set) 2.386 3.000 3.56 0.0105 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.78 Deviance explained = 83.1%
## -REML = -41.309 Scale est. = 0.0022735 n = 35
k.check(SimpE.ASV.gam.re)
        k'
                edf k-index p-value
## s(Tau) 9 5.551311 1.055007 0.5625
## s(Set) 4 2.385561
                         NA
                                NA
```

gam.check(SimpE.ASV.gam.re)

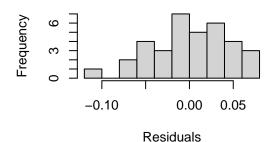
Resids vs. linear pred.

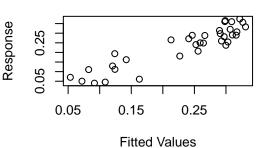




Histogram of residuals

Response vs. Fitted Values





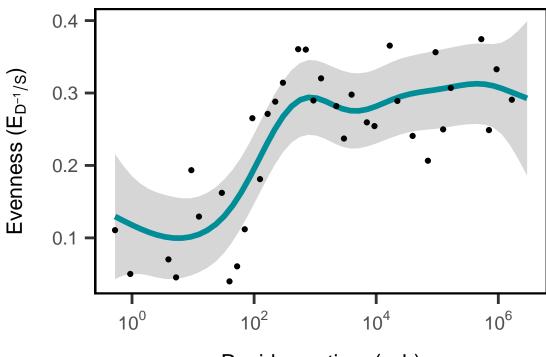
```
##
## Method: REML
                  Optimizer: outer newton
## full convergence after 5 iterations.
## Gradient range [-3.039985e-08,1.816935e-08]
## (score -41.30925 & scale 0.002273465).
## Hessian positive definite, eigenvalue range [0.3848146,16.90965].
## Model rank = 14 / 14
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##
            k'
                edf k-index p-value
## s(Tau) 9.00 5.55
                       1.06
                                0.5
## s(Set) 4.00 2.39
                         NA
mean(summary(SimpE.ASV.gam.re)$s.table[, 4])
```

[1] 0.005267034

```
SimpE_ASV_Tau <- predict_gam(SimpE.ASV.gam.re, exclude_terms = "s(Set)") %>%
  filter(Set == "1") %>%
  ggplot(aes(Tau, fit)) + geom_smooth_ci(color = "#008d98",
  cex = 2, ci_alpha = 0.2) + geom_point(data = Tau, aes(x = Tau,
  y = ASV_Day_20.SimpE)) + scale_x_continuous(labels = label_math(expr = 10^.x,
  format = force)) + ylab(expression(paste("Evenness", " (E"[D^"-1"/S],
  ")"))) + xlab(expression(paste("Residence time (", tau, ", h)"))) +
  labs(title = bquote("Deviance explained =" ~ .(signif(summary(SimpE.ASV.gam.re)$dev,
```

```
2))))
SimpE_ASV_Tau
```

Deviance explained = 0.83

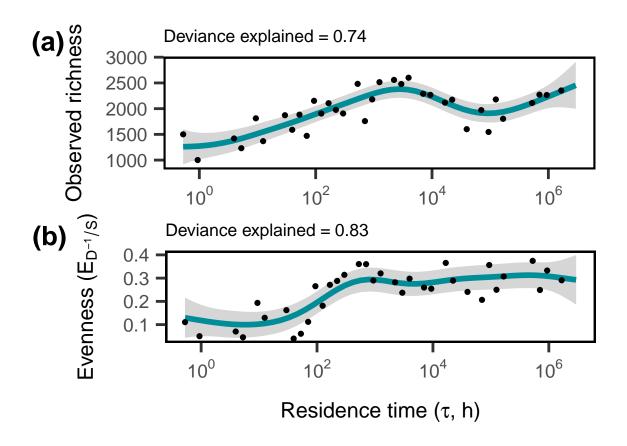


Residence time (τ, h)

```
ggsave("./output/SimpE_ASV_Tau.pdf")
ggsave("./output/SimpE_ASV_Tau.png", width = 7, height = 5)
```

Draw figure

```
ggdraw() + draw_plot(S.ob_ASV_Tau, x = 0, y = 0.55, width = 1,
height = 0.45) + draw_plot(SimpE_ASV_Tau, x = 0.04, y = 0,
width = 0.96, height = 0.55) + draw_plot_label(label = c("(a)",
"(b)"), size = 20, x = c(-0.02, -0.02), y = c(1, 0.55)) +
theme(plot.background = element_rect(fill = "white", color = NA))
```



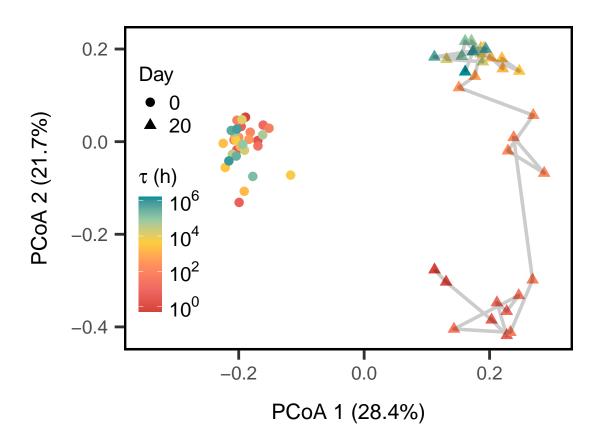
```
ggsave("./output/RTLC_FigS5.pdf")
ggsave("./output/RTLC_FigS5.png", width = 5, height = 6, dpi = 800)
```

Figure S6. Community composition over time.

A. Community composition data with Day 0 samples

```
tau.db.d0 <- vegdist(OTUs.r.REL, method = "bray", upper = TRUE,</pre>
    diag = TRUE)
adonis2(tau.db.d0 ~ Tau.Seq$Day)
## Permutation test for adonis under reduced model
## Terms added sequentially (first to last)
## Permutation: free
## Number of permutations: 999
##
## adonis2(formula = tau.db.d0 ~ Tau.Seq$Day)
              Df SumOfSqs
                                       F Pr(>F)
##
                               R2
## Tau.Seq$Day 1
                    2.6197 0.27559 26.25 0.001 ***
## Residual
               69
                    6.8861 0.72441
## Total
               70
                    9.5058 1.00000
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
tau.pcoa.d0 <- cmdscale(tau.db.d0, eig = TRUE, k = 3)
explainvar1.d0 <- round(tau.pcoa.d0$eig[1]/sum(tau.pcoa.d0$eig),
```

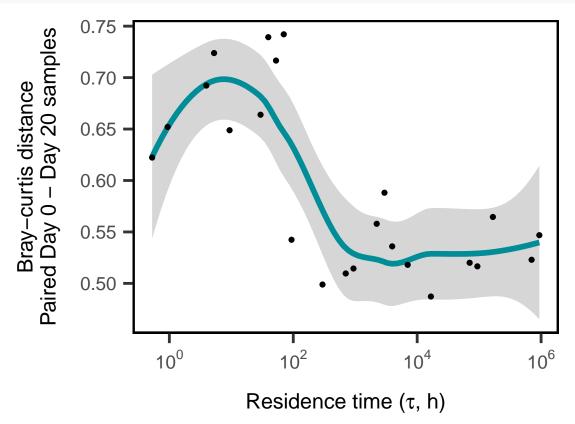
```
3) * 100
explainvar2.d0 <- round(tau.pcoa.d0$eig[2]/sum(tau.pcoa.d0$eig),
    3) * 100
explainvar3.d0 <- round(tau.pcoa.d0$eig[3]/sum(tau.pcoa.d0$eig),
    3) * 100
sum.eig.d0 <- sum(explainvar3.d0, explainvar2.d0, explainvar1.d0)</pre>
tau.plot.d0 <- as.data.frame(tau.pcoa.d0$points)</pre>
tau.plot.d0 <- cbind(tau.plot.d0, Tau.Seq)</pre>
tau.plot.d0.order <- tau.plot.d0[order(as.numeric(tau.plot.d0$Tau)),</pre>
tau.plot.d0.order <- subset(tau.plot.d0.order, is.na(tau.plot.d0.order$Tau) ==
    FALSE)
CommComp_D0_PCoA <- ggplot(tau.plot.d0.order, aes(x = V1, y = V2)) +</pre>
    geom_point(cex = 3, aes(color = as.numeric(Tau), shape = Day)) +
    geom_path(data = subset(tau.plot.d0.order, tau.plot.d0.order$Day ==
        20), aes(x = V1, y = V2), linewidth = 1.25, color = alpha("black",
        0.2)) + xlab(paste("PCoA 1 (", explainvar1.d0, "%)",
    sep = "")) + ylab(paste("PCoA 2 (", explainvar2.d0, "%)",
    sep = "")) + labs(color = expression(paste(tau, " (h)"))) +
    scale_color_gradientn(colors = moma.colors("ustwo"), labels = label_math(expr = 10^.x,
        format = force)) + xlim(c(-0.35, 0.3)) + guides(color = guide_colorbar(position = "inside"),
    shape = guide_legend(position = "inside")) + theme(legend.title = element_text(size = 15),
    legend.position.inside = c(0.1, 0.5), legend.text = element_text(size = 15))
CommComp_DO_PCoA
```



```
ggsave("./output/CommComp_D0_PCoA.pdf")
ggsave("./output/CommComp_D0_PCoA.png", width = 6, height = 6)
```

B. Paired Day 0 - Day 20 Bray-curtis distances

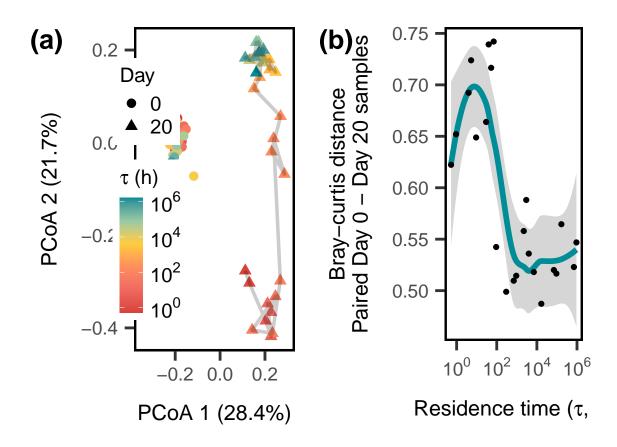
```
Tau.paired <- Tau
Tau.paired <- subset(Tau.paired, !is.na(Tau.paired$Day_0_Seq) &</pre>
    !is.na(Tau.paired$Day_20_Seq))
Tau.paired$BC <- NA
tau <- 1
while (tau <= nrow(Tau.paired)) {</pre>
    pair <- subset(OTUs.r.REL, rownames(OTUs.r.REL) %in% c(Tau.paired[tau,</pre>
        "Day_0_Seq"], Tau.paired[tau, "Day_20_Seq"]))
    Tau.paired[tau, "BC"] <- as.numeric(vegdist(pair, method = "bray"))</pre>
    tau <- tau + 1
}
PairedBC_Tau <- ggplot(data = Tau.paired, aes(x = Tau, y = BC)) +</pre>
    geom_smooth(method = "loess", color = "#008d98", linewidth = 2) +
    geom point() + scale x continuous(labels = label math(expr = 10^.x,
    format = force)) + xlab(expression(paste("Residence time (",
    tau, ", h)"))) + ylab("Bray-curtis distance\nPaired Day 0 - Day 20 samples")
```



```
ggsave("./output/PairedBC_Tau.pdf")
ggsave("./output/PairedBC_Tau.png", width = 7, height = 5)
```

Draw figure

```
ggdraw() + draw_plot(CommComp_D0_PCoA, x = 0, y = 0, width = 0.5,
height = 1) + draw_plot(PairedBC_Tau, x = 0.5, y = 0, width = 0.5,
height = 1) + draw_plot_label(label = c("(a)", "(b)"), size = 20,
x = c(0, 0.5), y = c(1, 1)) + theme(plot.background = element_rect(fill = "white",
color = NA))
```



```
ggsave("./output/RTLC_FigS6.pdf")
ggsave("./output/RTLC_FigS6.png", width = 12, height = 5, dpi = 800)
```

#Figure S7. Observed niche overlap was lower than expected from null models. ## Null model 1 - Uniform distribution, no fixed zeros

```
# A.niche.overlap <-c() x <-1 while(x < 100){ for(col in }
# 1:ncol(OTUs.70)){ OTUs.70[,col] <-runif(35, min = 0, max }
# = 1) } OTUs.70 <-decostand(OTUs.70, method = 'total') A.p
# <- mean(niche.overlap(OTUs.70, method = 'pianka'))
# print(paste(x, ' : ', A.p)) A.niche.overlap <-
# c(A.niche.overlap, A.p) x = x + 1 } all.niche.overlap <-
# as.data.frame(A.niche.overlap)
# write.csv(all.niche.overlap, file =
# './data/uniform_nicheoverlap.csv')
```

Null model 2 - Uniform distribution with fixed zeros

```
# A.niche.overlap <-c() x <-1 while(x < 100){ for(col in # 1:ncol(OTUs.70)){ n.zeros <- colSums(OTUs.70 == 0)[[col]] # + 1 OTUs.70 <- OTUs.70[order(OTUs.70[,col]),] # OTUs.70[,col] <- c(rep(0, n.zeros-1), runif(36-n.zeros, # min = 0, max = 1)) } OTUs.70 <-decostand(OTUs.70, method # = 'total') <math>A.p <- mean(niche.overlap(OTUs.70, method = # 'pianka')) print(paste(x, ': ', A.p)) A.niche.overlap <- # c(A.niche.overlap, A.p) x = x + 1 } all.niche.overlap <-
```

```
# as.data.frame(A.niche.overlap)
# write.csv(all.niche.overlap, file =
# './data/uniform_fixedzeros_nicheoverlap.csv')
```

Calculate actual niche overlap, Cohen's D for null models, and draw figure

```
initial.overlap <- mean(niche.overlap(as.data.frame(OTUs.70),</pre>
    method = "pianka"))
# Read in previously generated null model data
uniform.niche.overlap <- data.frame(Pianka = read.csv("./data/uniform_nicheoverlap.csv",
   header = TRUE)[, -1])
uniform.fixedzero.niche.overlap <- data.frame(Pianka = read.csv("./data/uniform fixedzeros nicheoverlap
   header = TRUE)[, -1])
cohensD(x = initial.overlap, y = uniform.fixedzero.niche.overlap$Pianka)
## [1] 45.439
cohensD(x = initial.overlap, y = uniform.niche.overlap$Pianka)
## [1] 175.1867
niche.overlap.uniform.long <- as.data.frame(uniform.niche.overlap$Pianka)</pre>
niche.overlap.uniform.long <- cbind(niche.overlap.uniform.long,</pre>
    uniform.fixedzero.niche.overlap$Pianka)
colnames(niche.overlap.uniform.long) <- c("uniform", "uniform.fixedzero")</pre>
niche.overlap.uniform.long <- gather(niche.overlap.uniform.long,</pre>
    key = "Null_model", value = "Pianka")
niche_uniform_nullmodels <- ggplot() + geom_hline(yintercept = initial.overlap,</pre>
   linetype = "dotted", color = "#008d98", cex = 2) + annotate("rect",
   xmin = 1.25, xmax = 1.75, ymin = initial.overlap - 0.01,
   ymax = initial.overlap + 0.01, fill = "white") + geom_violin(data = niche.overlap.uniform.long,
   aes(x = Null_model, y = Pianka), fill = "#95caa6", color = "white",
   cex = 1.5) + geom_jitter(data = niche.overlap.uniform.long,
   width = 0.1, color = alpha("black", 0.1), aes(x = Null_model,
        y = Pianka), cex = 0.3) + ylab("Niche overlap") + scale_x_discrete(labels = c("Null model 1",
    "Null model 2")) + theme(legend.position = "none", axis.title.x = element_blank()) +
    annotate("text", x = 1.5, y = initial.overlap, label = "Observed",
        color = "#008d98")
niche_uniform_nullmodels
```

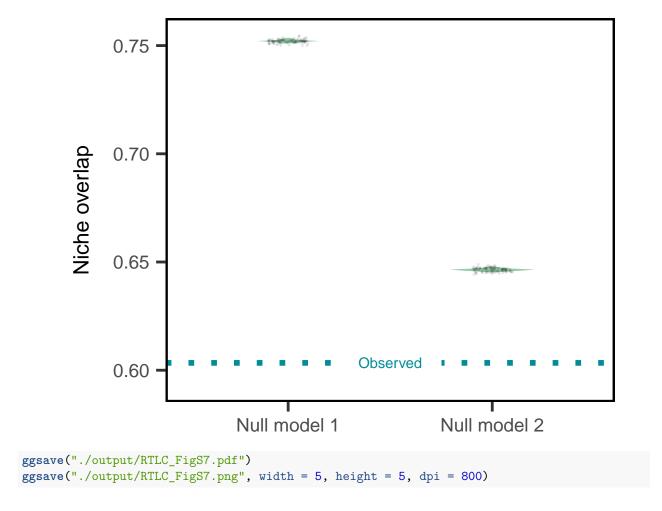
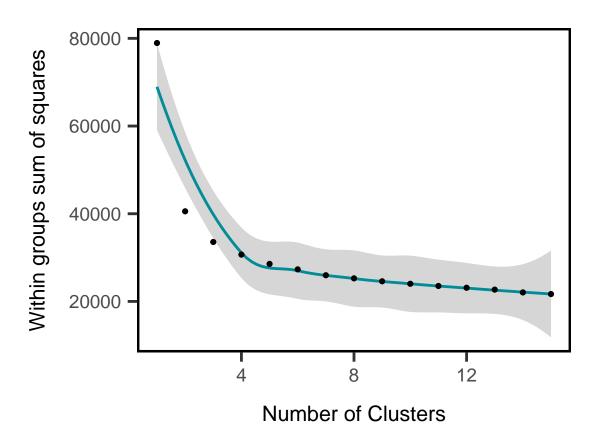


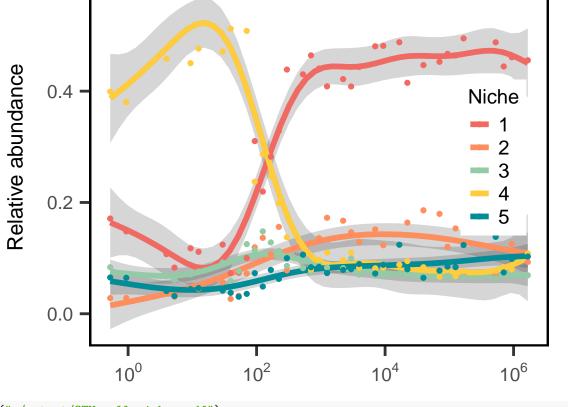
Figure S8. Five niches were identified across the residence time gradient using k-means clustering.

A. Within-group sum of squares for number of clusters



```
ggsave("./output/Nclust_Niches.pdf")
ggsave("./output/Nclust_niches.png", width = 6, height = 4)
```

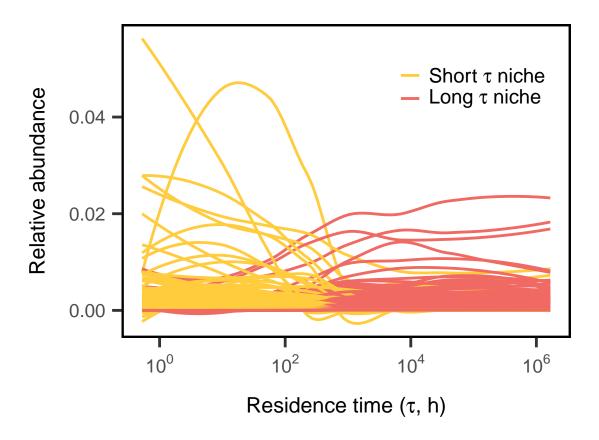
B. Total relative abundance of all niches



```
ggsave("./output/OTUs_all_niches.pdf")
ggsave("./output/OTUs_all_niches.png", width = 6, height = 4)
```

C. Individual relative abundance of OTUs in Niche 1 and 4

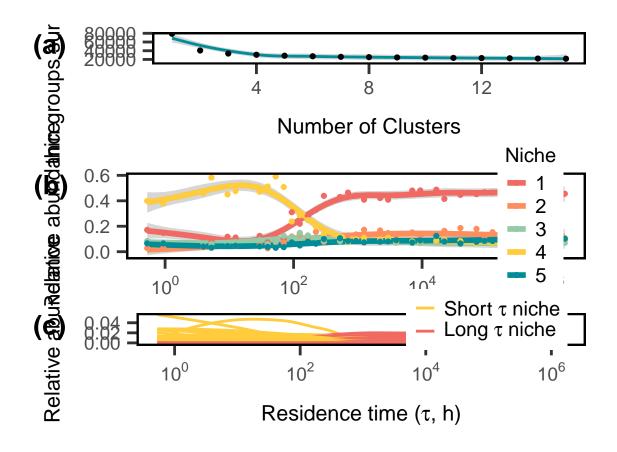
0.6



```
ggsave("./output/OTUs_ind_major_niches.pdf")
ggsave("./output/OTUs_ind_major_niches.png", width = 6, height = 4)
```

Draw Figure

```
ggdraw() + draw_plot(Nclust_Niches, x = 0, y = 0.675, width = 1,
height = 0.325) + draw_plot(OTUs_all_niches, x = 0, y = 0.35,
width = 1, height = 0.325) + draw_plot(OTUs_ind_major_niches,
x = 0, y = 0, width = 1, height = 0.35) + draw_plot_label(label = c("(a)",
"(b)", "(c)"), size = 20, x = c(0, 0, 0), y = c(1, 0.675,
0.35)) + theme(plot.background = element_rect(fill = "white",
color = NA))
```



```
ggsave("./output/RTLC_FigS8.pdf")
ggsave("./output/RTLC_FigS8.png", width = 10, height = 15, dpi = 800)
```

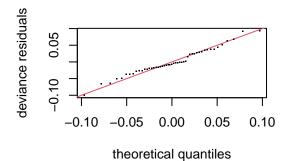
Figure S9. Biofilm production across the residence time gradient.

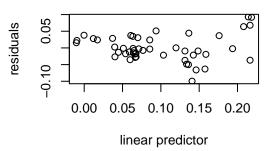
A. Total biofilm production

```
TotOT.gam.re <- gam(OT ~ s(Tau) + s(Set, bs = "re"), data = Tau,
    family = gaussian(link = "identity"), method = "REML")
TotOT.gam <- gam(OT ~ s(Tau), data = Tau, family = gaussian(link = "identity"),
   method = "REML")
AIC(TotOT.gam, TotOT.gam.re)
##
                      df
                               AIC
## TotOT.gam
                3.000080 -114.2994
## TotOT.gam.re 9.102045 -161.7488
anova(TotOT.gam, TotOT.gam.re, test = "Chisq")
## Analysis of Deviance Table
## Model 1: OT ~ s(Tau)
## Model 2: OT ~ s(Tau) + s(Set, bs = "re")
                              Df Deviance Pr(>Chi)
    Resid. Df Resid. Dev
       47.000 0.246314
## 1
```

```
39.968  0.072907 7.0317  0.17341 < 2.2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
# Random effect of set is significant
rm(TotOT.gam)
summary(TotOT.gam.re)
## Family: gaussian
## Link function: identity
## Formula:
## OT \sim s(Tau) + s(Set, bs = "re")
## Parametric coefficients:
             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.09732 0.03270 2.976 0.00484 **
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
          edf Ref.df
                      F p-value
## s(Tau) 3.287 4.109 6.142 0.000519 ***
## s(Set) 2.885 3.000 30.374 < 2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.698 Deviance explained = 73.7%
## -REML = -71.365 Scale est. = 0.001743 n = 49
k.check(TotOT.gam.re)
         k'
                 edf k-index p-value
## s(Tau) 9 3.287071 1.24012 0.935
## s(Set) 4 2.885161
                         NA
                                 NA
gam.check(TotOT.gam.re)
```

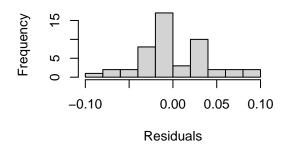
Resids vs. linear pred.

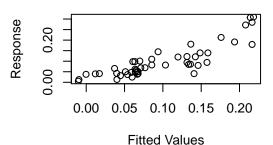




Histogram of residuals

Response vs. Fitted Values



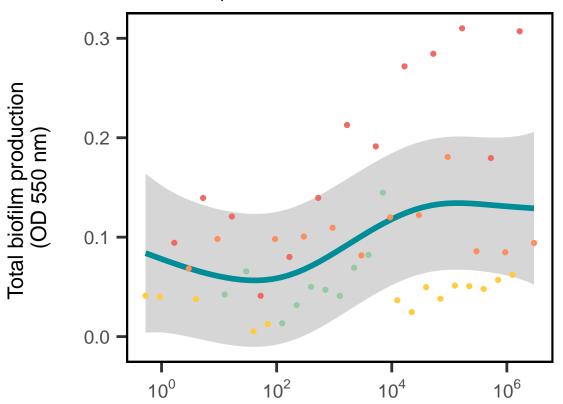


```
##
## Method: REML
                  Optimizer: outer newton
## full convergence after 7 iterations.
## Gradient range [-7.128326e-07,6.345747e-07]
## (score -71.36517 & scale 0.00174304).
## Hessian positive definite, eigenvalue range [0.6636435,23.65044].
## Model rank = 14 / 14
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##
            k'
                edf k-index p-value
## s(Tau) 9.00 3.29
                       1.24
                               0.96
## s(Set) 4.00 2.89
                         NA
```

```
## [1] 0.0002595414
```

mean(summary(TotOT.gam.re)\$s.table[, 4])

Deviance explained = 0.74

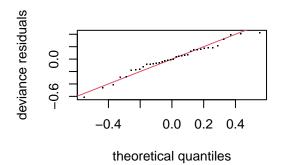


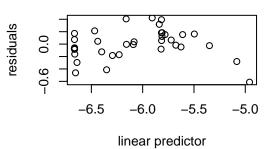
```
ggsave("./output/Total_OT_Tau.pdf")
ggsave("./output/Total_OT_Tau.png")
```

B. Per cell biofilm production

```
anova(PC.OT.gam, PC.OT.gam.re, test = "Chisq")
## Analysis of Deviance Table
##
## Model 1: log(OT/(N * 0.005), 10) ~ s(Tau)
## Model 2: log(OT/(N * 0.005), 10) \sim s(Tau) + s(Set, bs = "re")
## Resid. Df Resid. Dev
                            Df Deviance Pr(>Chi)
       32.483
                  7.3669
## 1
       28.808
                  1.9061 3.6754 5.4608 < 2.2e-16 ***
## 2
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
# Random effect of set is significant
rm(PC.OT.gam)
summary(PC.OT.gam.re)
##
## Family: gaussian
## Link function: identity
##
## Formula:
## log(OT/(N * 0.005), 10) \sim s(Tau) + s(Set, bs = "re")
## Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -6.0626
                         0.2687 -22.56 <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Approximate significance of smooth terms:
           edf Ref.df
                         F p-value
## s(Tau) 2.732 3.437 17.66 9.69e-07 ***
## s(Set) 1.939 2.000 40.26 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## R-sq.(adj) = 0.788 Deviance explained = 81.6\%
## -REML = 9.9783 Scale est. = 0.062846 n = 36
k.check(PC.OT.gam.re)
##
         k'
                 edf k-index p-value
## s(Tau) 9 2.731798 1.100471
                                 0.66
## s(Set) 3 1.938628
                                   NA
gam.check(PC.OT.gam.re)
```

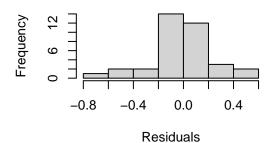
Resids vs. linear pred.

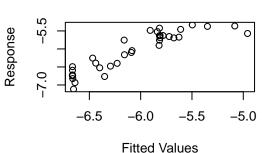




Histogram of residuals

Response vs. Fitted Values



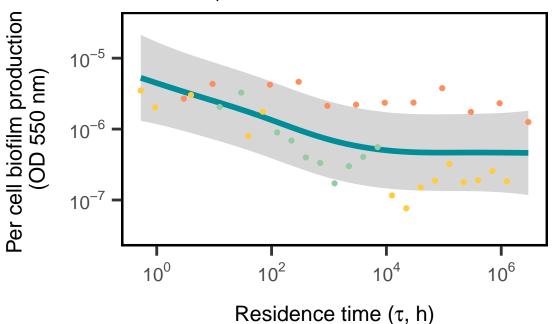


```
##
## Method: REML
                  Optimizer: outer newton
## full convergence after 6 iterations.
## Gradient range [-1.494689e-06,1.392979e-06]
## (score 9.97834 & scale 0.06284554).
## Hessian positive definite, eigenvalue range [0.4618004,17.10335].
## Model rank = 13 / 13
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##
            k'
                edf k-index p-value
## s(Tau) 9.00 2.73
                        1.1
                               0.68
## s(Set) 3.00 1.94
                         NA
mean(summary(PC.OT.gam.re)$s.table[, 4])
```

```
## [1] 4.845389e-07
```

```
5)[4], moma.colors("ustwo", 5)[3])), ) + scale_x_continuous(labels = label_math(expr = 10^.x,
    format = force)) + scale_y_continuous(limits = c(-7.5, -4.5),
    breaks = c(-7, -6, -5), labels = label_math(expr = 10^.x,
        format = force)) + labs(title = bquote("Deviance explained =" ~
        (signif(summary(PC.OT.gam.re)$dev, 2)))) + theme(legend.position = "bottom") +
        guides(color = guide_legend(title = "Experimental block"))
PC_OT_Tau
```

Deviance explained = 0.82

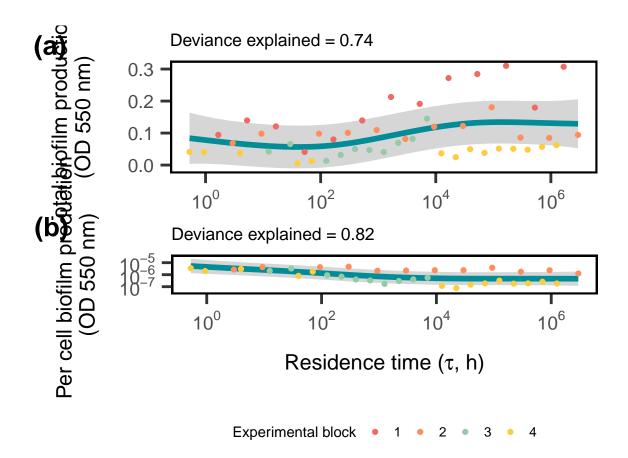


Experimental block • 1 • 2 • 3 • 4

```
ggsave("./output/PC_OT_Tau.pdf")
ggsave("./output/PC_OT_Tau.png")
```

Draw Figure

```
ggdraw() + draw_plot(Total_OT_Tau, x = 0, y = 0.55, width = 1,
    height = 0.45) + draw_plot(PC_OT_Tau, x = 0, y = 0, width = 1,
    height = 0.55) + draw_plot_label(label = c("(a)", "(b)"),
    size = 20, x = c(-0.02, -0.02), y = c(1, 0.58)) + theme(plot.background = element_rect(fill = "whit color = NA))
```



```
ggsave("./output/RTLC_FigS9.pdf")
ggsave("./output/RTLC_FigS9.png", width = 5, height = 8, dpi = 800)
```