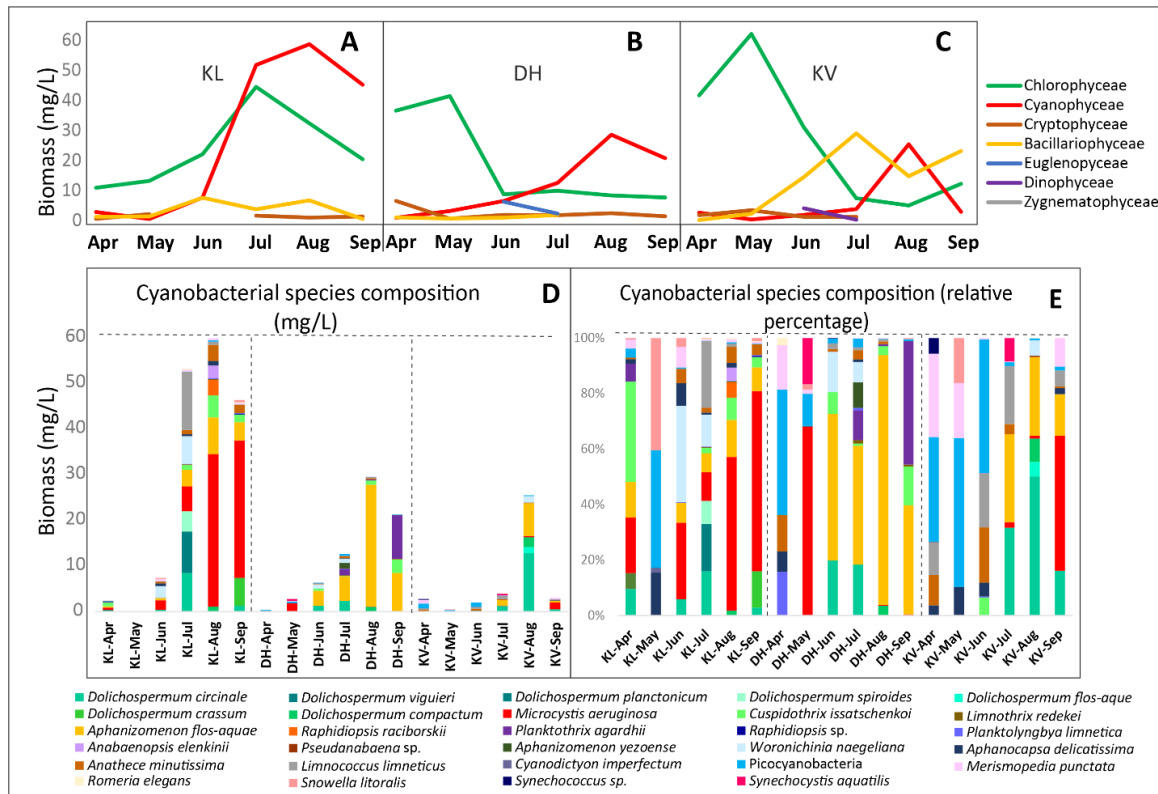


# Supplementary Materials: Insight into Unprecedented Diversity of Cyanopeptides in Eutrophic Ponds Using an MS/MS Networking Approach

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**Figure S1.** Phytoplankton composition of studied ponds throughout the sampling season. Biomass of phytoplankton among different sampling location A) KL B) DH, C) KV; D) biomass of cyanobacterial species; E) cyanobacterial relative species composition; KL: Klec, DH: Dehtář, KV: Kvítkovický.

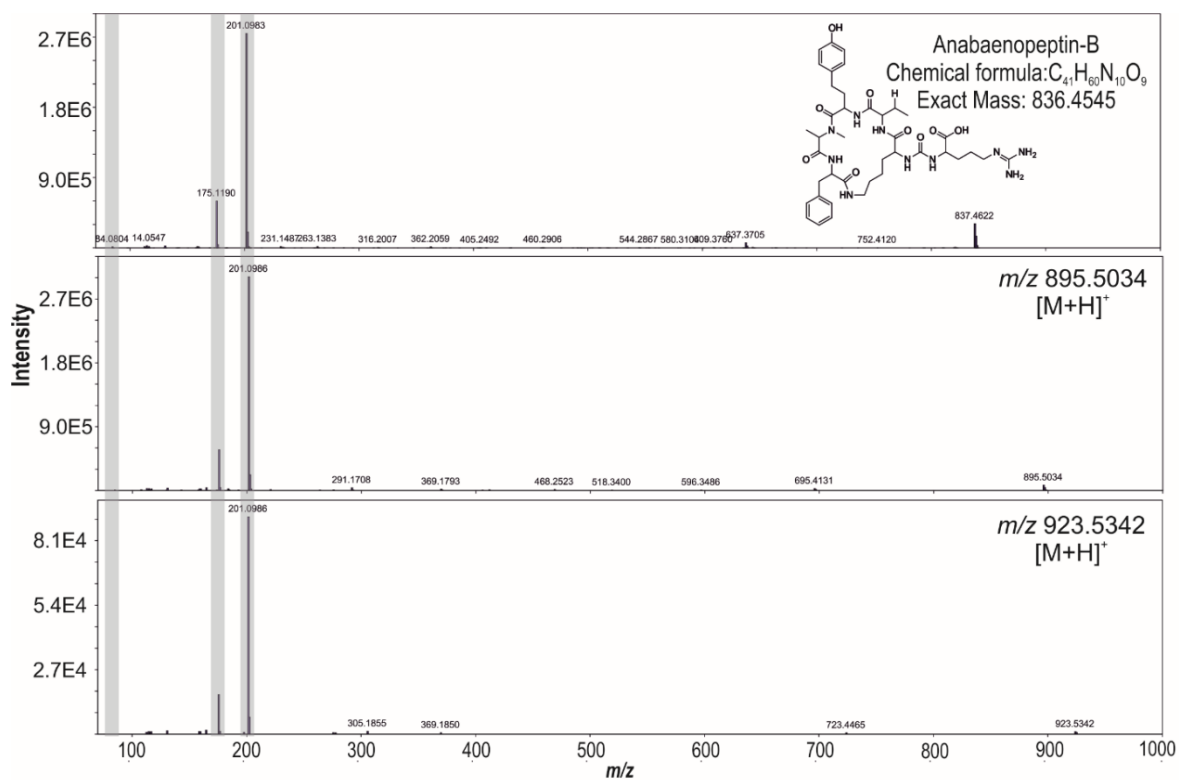


Chlorophyceae	10.80	13.18	22.37	45.59	32.99	20.62	38.00	43.15	8.69	9.91	8.26	7.56	41.81	62.25	31.14	7.58	5.14	12.32	
Cyanophyceae	2.43	0.03	7.40	53.11	60.30	46.33	0.43	2.79	6.28	12.65	29.57	21.33	2.77	0.49	2.01	3.90	25.51	3.06	
Cryptophyceae	0.10	1.70		1.17	0.51	0.87	6.34	0.13	1.43	1.33	2.05	0.99	1.88	3.56	1.34	1.39		1.16	
Bacillariophyceae	0.80	0.92	7.37	3.40	6.47	0.04	0.60	0.16	0.43	1.40			28.71	0.30	2.34	14.59	29.14	14.91	23.27
Euglenopyceae	0.06		1.69				2.01		6.06	1.90			2.47			0.38			0.26
Dinophyceae				1.14									0.32			4.21	0.40		4.38
Zygnematophyceae	0.44		0.38											2.29					
<b>Total phytoplankton biomass</b>	14.18	15.83	38.83	104.41	100.27	67.87	47.38	46.24	22.90	27.18	39.88	61.37	46.76	68.64	53.66	42.40	45.57	44.44	
% cyanobacteria	17.10	0.22	19.07	50.87	60.13	68.27	0.91	6.04	27.44	46.52	74.15	34.76	5.92	0.72	3.75	9.19	55.99	6.88	

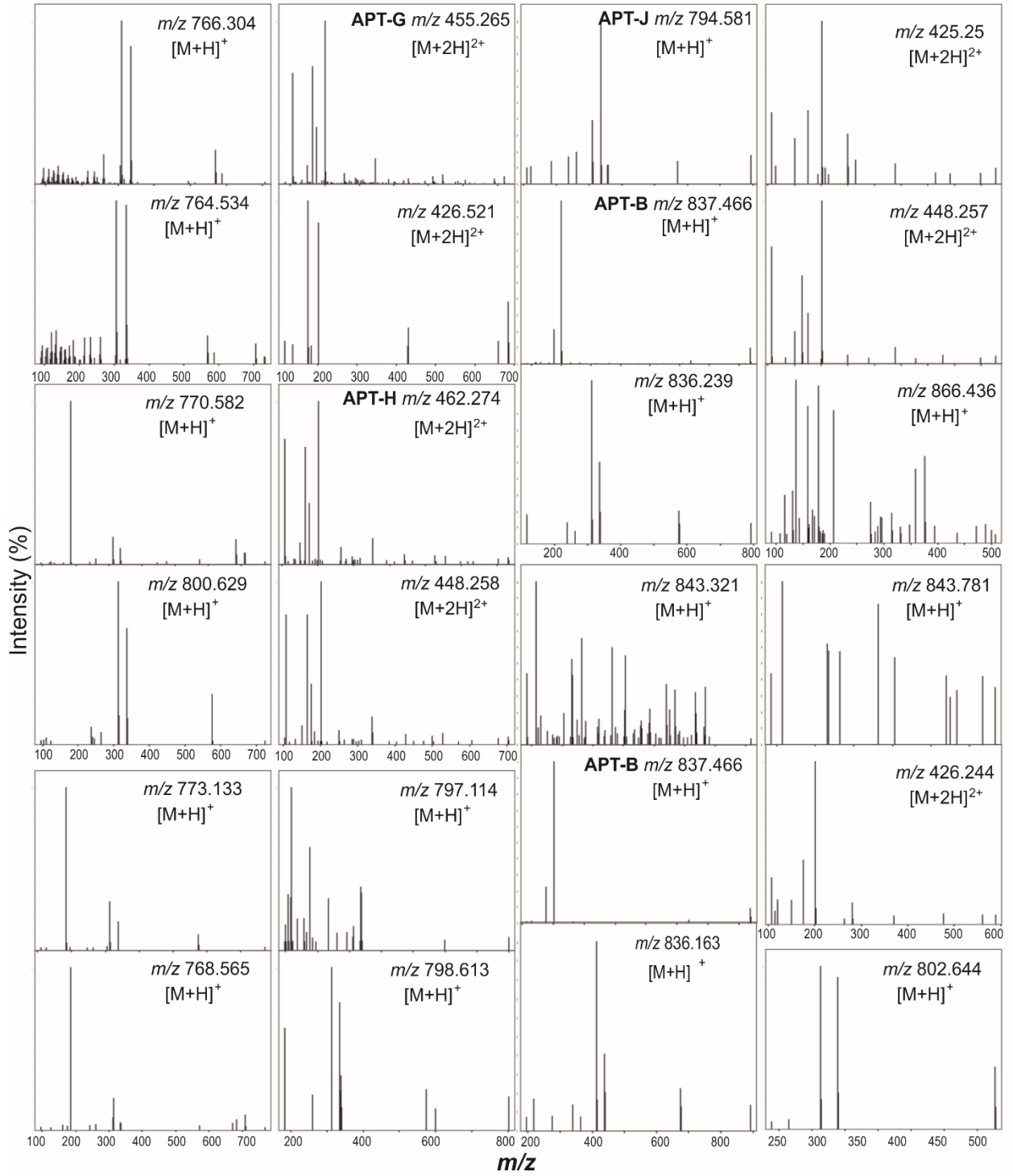
**Table S2.** Detected cyanopeptides (CNP) in all three studied ponds during the sampling season. KL: Klec, DH: Dehtář, KV: Kvítkovický.

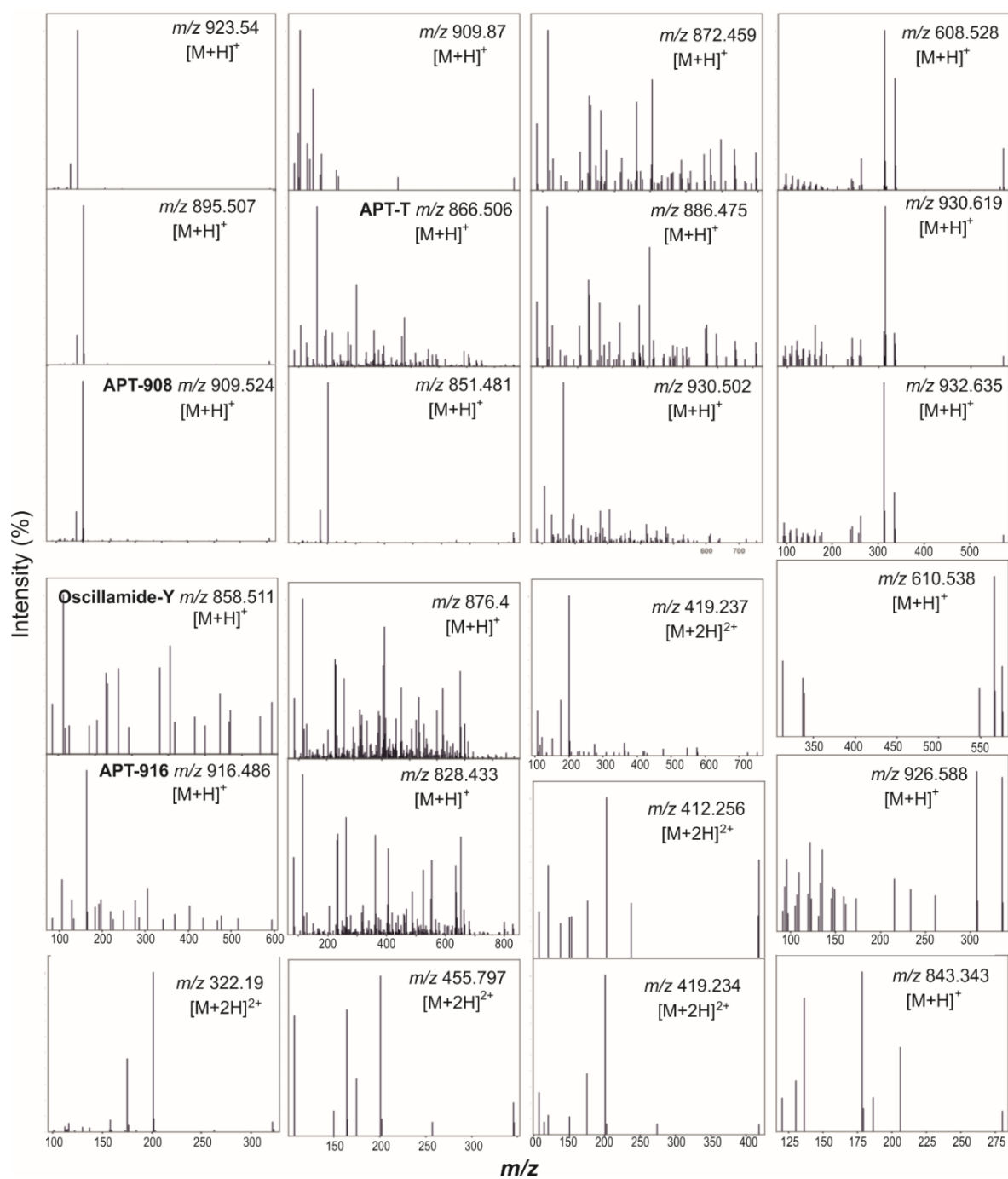
CNPs	KL			DH					KV					Total	Observed Mass (m/z)	Adduct	Error, ppm						
	Apr	May	Jun	Jul	Aug	Sep	Apr	May	Jun	Jul	Aug	Sep	Apr					May	Jun	Jul	Aug	Sep	
APT-908																			3	909.5190	M + H	0.2	
APT-915																				1	916.4857	M + H	-4.6
APT-der*																				2	930.4988	M + H	
APT-I																				1	760.4628	M + H	-3.2
APT-J																				1	794.4460	M + H	-1.5
APT-NZ841																				2	842.4466	M + H	-2.3
APT-T																				2	866.5049	M + H	-2.5
APT-A																				9	844.4252	M + H	-1.5
APT-B																				9	837.4621	M + H	-1.4
APT-C																				1	809.4555	M + H	0.1
APT-F																				7	851.4791	M + H	-2.0
APT-G*																				3	455.2625	M + 2H	
APT-H																				2	462.2727	M + 2H	-3.5
Oscillamide-Y																				10	858.4385	M + H	1.3
[D-Asp3]MC-RR																				3	512.7967	M + 2H	-2.4
[Dha7]MC-RR																				4	512.7813	M + 2H	2.1
[Dha7]MC-LR																				1	981.4770	M + H	-1.6
[DMAdda5]MC-LR*																				1	981.5156	M + H	
MC-LR																				12	995.5557	M + H	0.3
MC-RR																				15	1038.5754	M + H	-2.2
MC-FR																				1	1029.5437	M + H	-3.2



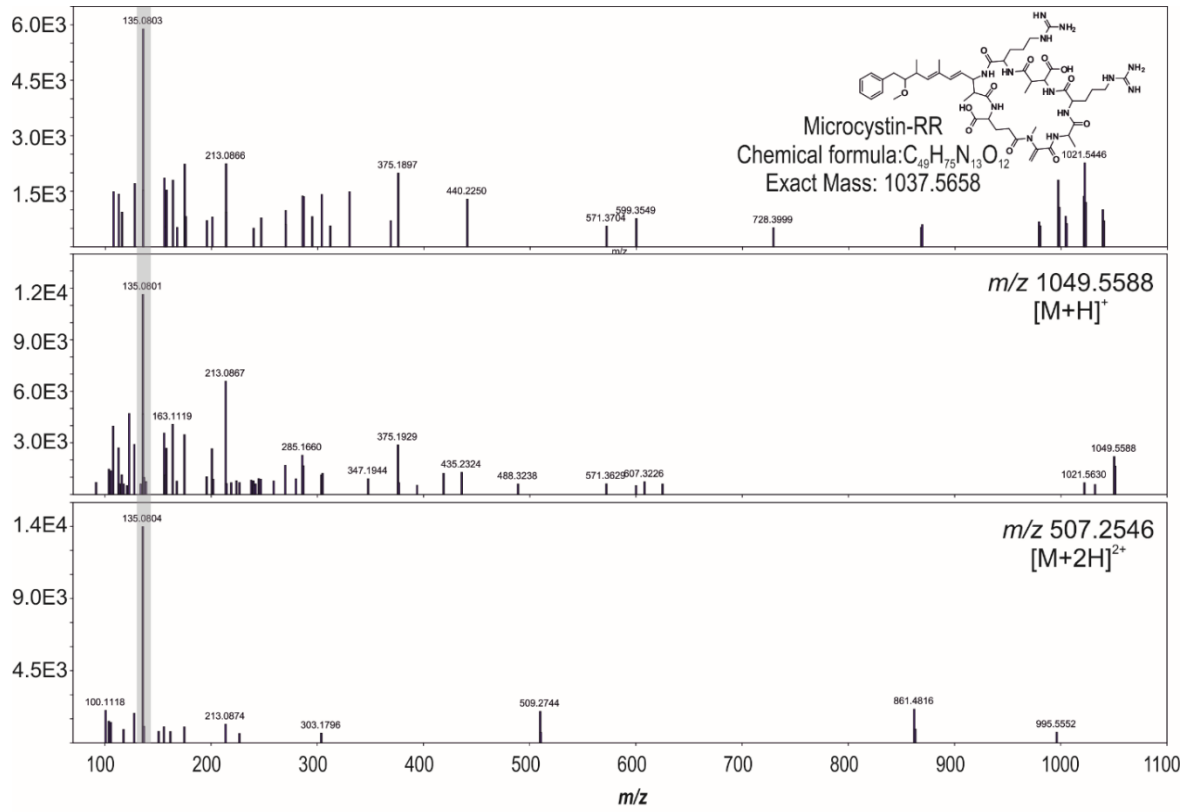


**Figure S2.** HR-MS/MS product ion spectra APT-B with comparison with two unknown variants highlighting the presence of diagnostic ion peak at  $m/z$  84.0810 (Lys immonium ion) together with other fragment ions of amino acids.



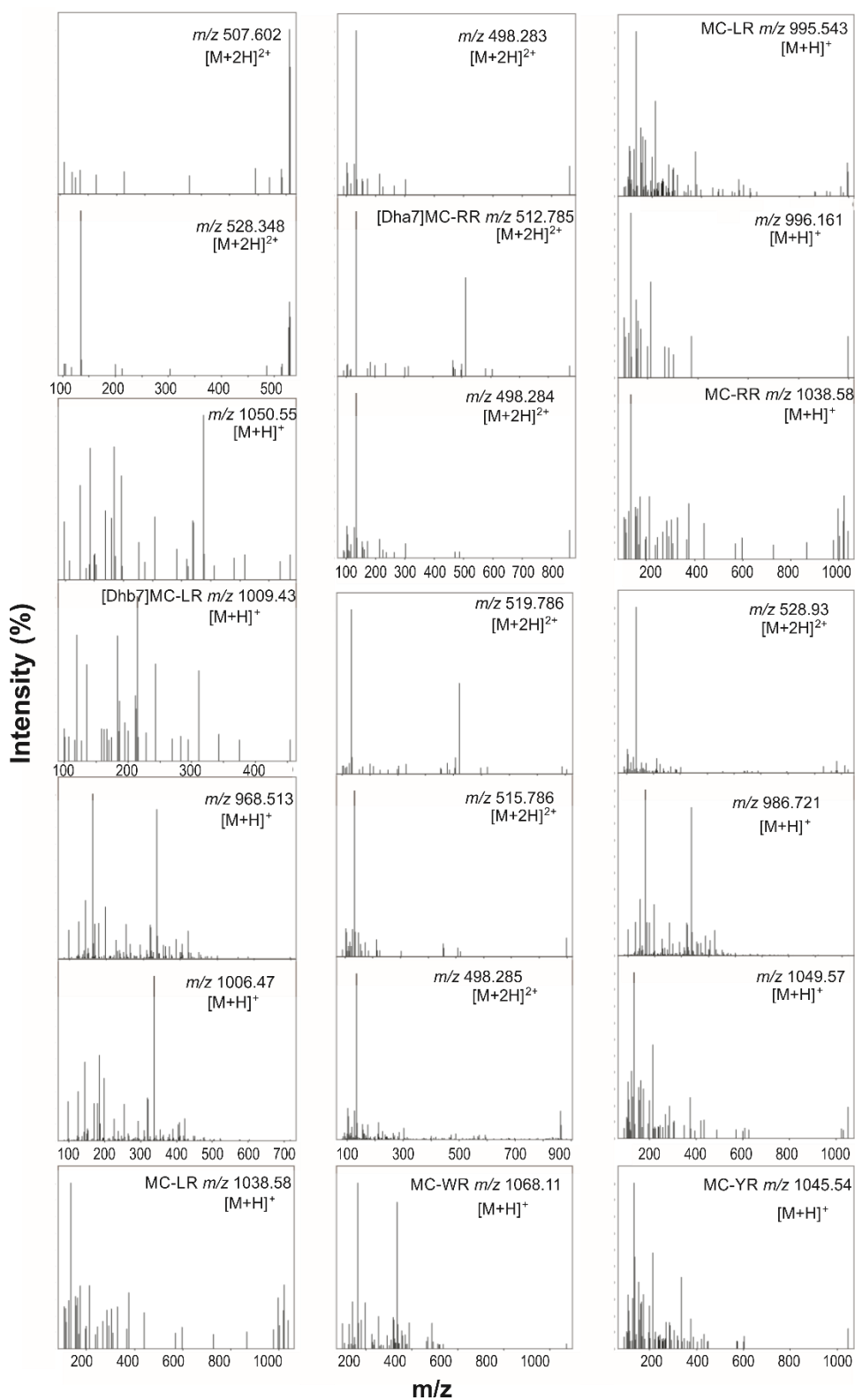


**Figure S3.** HR-MS/MS product ion spectra of protonated known/unknown APTs forming five clusters (Figure 2).



**Figure S4.** HR-MS/MS product ion spectra MC-RR with comparison with two unknown variants highlighting the presence of diagnostic ion peak originating from Adda moiety at  $m/z$  135.0804 Da.





**Figure S5.** HR-MS/MS product ion spectra of protonated known/unknown MCs forming two clusters (Figure 2).

**Code 1:** The R code developed for the entire analysis.

```
# Install/Load libraries
```

```
install.packages("ISLR")
```

```
install.packages("heatmaply")
```

```
library(ISLR)
```

```
library(ggplot2)
```

```
library(reshape2)
```

```
library(car)
```

```
library(heatmaply)
```

```
# Import data
```

```
cyanos <- read.table("cyanos.txt", header = T, sep = '\t', row.names = 1)
```

```
pept <- read.table("peptides.txt", header = T, sep = '\t', row.names = 1)
```

```
# Transpose data - the regression function is made for columns
```

```
cyanos_t1 <- t(cyanos)
```

```
pept_t <- as.data.frame(t(pept))
```

```
d <- as.data.frame(cbind(cyanos_t1, row.names(cyanos_t1)))
```

```
m_cya = melt(d, id.vars="V30")
```

```
m_cya$V30 = factor(m_cya$V30,
```

```
          levels=c("KL.Apr",      "KL.May",      "KL.Jun",      "KL.Jul","KL.Aug",
```

```
                  "KL.Sep",  "DH.Apr",      "DH.May",      "DH.Jun",      "DH.Jul",
```

```
                  "DH.Aug",  "DH.Sep",      "KV.Apr",      "KV.May",      "KV.Jun",
```

```
                  "KV.Jul",  "KV.Aug",      "KV.Sep"))
```

```
p <- ggplot(data=m_cya, aes(x=V30, y=as.numeric(value), fill=V30)) +
```

```
  geom_bar(stat="identity") +
```

```
  scale_fill_viridis_d() +
```

```
facet_wrap(~ variable, scales = "free", ncol=6) +
scale_y_continuous(name="Abundance") +
theme_minimal()

p + theme(legend.position = "none",
axis.text.x = element_text(angle = 90),
strip.text = element_text(face = "italic"))

# Explore and plot the cyano data
summary(cyanos_t1)

# Logistics Regression
res_pval <- matrix(NA, nrow = ncol(cyanos_t1), ncol = ncol(pept_t))
row.names(res_pval) <- colnames(cyanos_t1)
colnames(res_pval) <- colnames(pept_t)

for(i in 1:ncol(cyanos_t1)){
  for(j in 1:ncol(pept_t)){
    glm.fit <- glm(pept_t[,j] ~ as.numeric(cyanos_t1[,i]), family = binomial())
    fit <- Anova(glm.fit, type = 2)
    res_pval[i,j] <- fit$`Pr(>Chisq)` # gives the p-value for an asymptotic chi square statistic based
on the deviance
  }
}

# Plot the results as heatmap
# Remove insignificant values
filt_res <- matrix(NA, nrow = ncol(cyanos_t1), ncol = ncol(pept_t))
```

```
row.names(filt_res) <- colnames(cyanos_t1)

colnames(filt_res) <- colnames(pept_t)

for(i in 1:nrow(res_pval)){

  for(j in 1:ncol(res_pval)){

    if(res_pval[i,j]>=0.05){

      filt_res[i,j] <- NA

    }

    else{

      filt_res[i,j] <- res_pval[i,j]

    }

  }

}

# Make the species name italic

rownames(filt_res) <- paste("<i>", rownames(filt_res), "</i>")

# Plot raw p-values

heatmaply(filt_res, na.omit = T, na.value = "grey50", Rowv = F, Colv = F,

          grid_color = "grey50", key.title = "P - value", xlab = "Cyanopeptides",

          ylab = "Species")

# Save these results to a file

write.table(filt_res, "Logistic-regression_Cyanos_raw_Pval.txt", sep = '\t')

# Adjust these p-values using the Benjamini-Hochberg procedure

fdr_res <- matrix(NA, nrow = ncol(cyanos_t1), ncol = 1)

row.names(fdr_res) <- colnames(cyanos_t1)

for (i in 1:ncol(res_pval)){

  df <- res_pval[order(res_pval[,i]), i]

  v <- 1; s <- 1

  p_fdr <- c()
```

```
for(i in 2:length(df)){  
  if(df[i]==df[i-1]){  
    v <- c(v, s)  
  }  
  else{  
    s = s+1  
    v <- c(v, s)  
  }  
}  
df <- cbind(df, v)  
f <- df[row.names(res_pval),] # Reorder them as in the initial table (res_pval)  
for(i in 1:nrow(f)){  
  fdr <- f[i,1]*(nrow(f)/f[i,2])  
  if(fdr > 1){  
    p_fdr <- c(p_fdr, 1)  
  }  
  else{  
    p_fdr <- c(p_fdr, fdr)  
  }  
}  
#df <- cbind(df, p_fdr)  
fdr_res <- cbind(fdr_res, p_fdr)  
}  
  
fdr_res <- fdr_res[,-1]  
colnames(fdr_res) <- colnames(res_pval)  
  
# Remove insignificant values
```

```
filt_res_fdr <- matrix(NA, nrow = ncol(cyanos_t1), ncol = ncol(fdr_res))

row.names(filt_res_fdr) <- colnames(cyanos_t1)

colnames(filt_res_fdr) <- colnames(fdr_res)

for(i in 1:nrow(fdr_res)){

  for(j in 1:ncol(fdr_res)){

    if(fdr_res[i,j]>=0.2){

      filt_res_fdr[i,j] <- NA

    }

    else{

      filt_res_fdr[i,j] <- fdr_res[i,j]

    }

  }

}

# Make the species name italic

rownames(filt_res_fdr) <- paste("<i>", rownames(filt_res), "</i>")

# Plot raw p-values

heatmaply(filt_res_fdr, na.omit = T, na.value = "grey50", Rowv = F, Colv = F,

  grid_color = "grey50", key.title = "P - value", xlab = "Cyanopeptides",

  ylab = "Species")

# Save these results to a file

write.table(filt_res_fdr, "Logistic-regression_Cyanos_FDR_Pval.txt", sep = '\t')
```