### Analysis of BGC content across phylum Cyanobacteriota

#### Setup

#### Read in data

```
# Map antiSMASH classes to their categories
bgc_class <- read_tsv("./data/2025-01-16-1256-bgc_class_ref.tsv") %>% select(!owner_id)
class_to_cat <- bgc_class$bgc_category
names(class_to_cat) <- bgc_class$class_name

# NCBI Taxonomy data for Cyanobacteriota assemblies
cyano_asm_tax <- read_tsv("data/cyano_asm_tax.tsv")

# From SMC: All antiSMASH 'region's for Cyanobacteriota genomes
regions <- read_tsv("./data/2025-02-26-1456-cyano_as_regions.tsv")

# Table of NCBI assemblies at "chromosome" or "complete" quality levels
ncbi_hiq_meta <- read_tsv("data/ncbi_cyano_HiQualityGenomes_metadata.tsv")</pre>
```

#### Clean data

```
# Convert BGC 'class' to vector, add in BGC 'category' as vector, order levels of classes and categorie
regions <- regions %>%
  mutate(classes = map(region_class, function(class_string) {
      if (str_starts(class_string, fixed("["))) {
       fromJSON(class_string)
     } else {
       c(class_string)
     }
  })) %>%
  mutate(categories = classes %>% map(function(cls_vec) {
      map_vec(cls_vec, function(cls_str) class_to_cat[[cls_str]]) %>% unique() %>% sort())
  mutate(cats_str = categories %% map_chr(function(x) str_flatten(x, collapse = ", "))) %%
  add_count(cats_str) %>%
  mutate(
   cats_str = forcats::fct_reorder(cats_str, desc(n)),
   class_str = classes %>% map_chr(function(x) str_flatten(x, collapse = ", "))
```

regions

```
## # A tibble: 32,112 x 26
##
      region_gene_id bgc_id region_length contig_name region_start_nt region_end_nt
##
               <dbl> <dbl>
                                    <dbl> <chr>
                                                                <dbl>
##
          394444400 2.05e6
                                    20822 NZ_KK07376~
                                                              1448721
                                                                            1469542
  1
##
   2
          427693693 2.21e6
                                    6191 NZ NMQI010~
                                                                    1
                                                                               6191
                                    41152 NZ_NJHU010~
                                                                20319
## 3
          427830749 2.21e6
                                                                              61470
## 4
          427867799 2.21e6
                                    29334 NZ NJHW010~
                                                                 5515
                                                                              34848
          427879170 2.21e6
                                    5638 NZ NJHW010~
## 5
                                                                    1
                                                                               5638
## 6
          442232549 2.29e6
                                    27366 NZ VIKX010~
                                                                    1
                                                                              27366
## 7
          442951361 2.29e6
                                    61852 NZ BJCK010~
                                                               121631
                                                                             183482
##
  8
          444447386 2.30e6
                                    21923 NZ_WVIC010~
                                                                13038
                                                                              34960
          445057742 2.31e6
                                    40108 NZ_JAAGOGO~
                                                                26815
                                                                              66922
## 9
## 10
          446681012 2.31e6
                                    35928 NZ_QMEA010~
                                                                              35928
## # i 32,102 more rows
## # i 20 more variables: bgc_annotation_id <dbl>, region_class <chr>,
## #
       region_category <lgl>, contig_edge <lgl>, smc_id <dbl>, accession_id <chr>,
## #
      size_bp <dbl>, n_scaffolds <dbl>, data_source_description <chr>,
## #
      tax_phylum <chr>, tax_class <chr>, tax_order <chr>, tax_family <chr>,
## #
      tax_genus <chr>, tax_species <chr>, classes <list>, categories <list>,
## #
      cats_str <fct>, n <int>, class_str <chr>
```

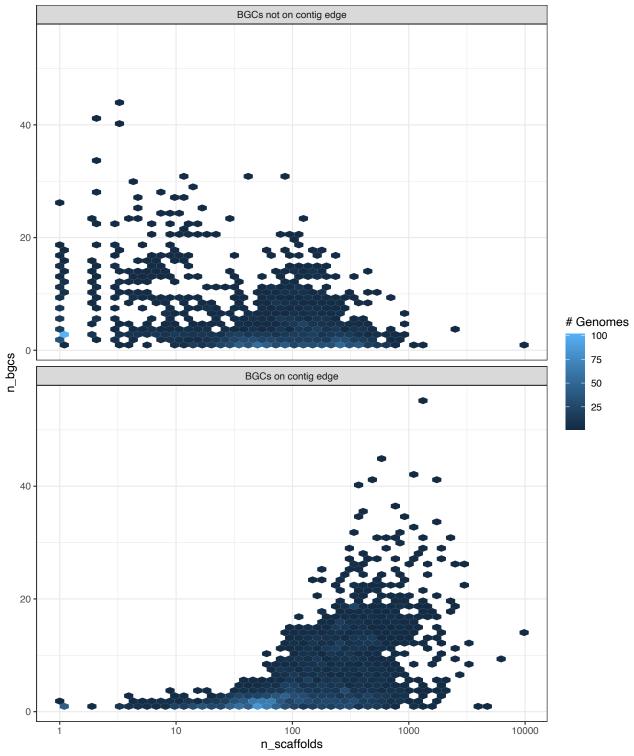
#### **Explore data**

The repetitive composition of many BGCs makes them a challenge during genome assembly, resulting in over-inflation of BGC counts when BGCs are split between the ends of two different contigs. Focusing on high-quality genomes can therefore ensure a higher-quality dataset.

#### How fragmented are the full set of genomes, and how does that impact BGC counts?

```
regions %>%
  group_by(smc_id, n_scaffolds, contig_edge) %>%
  summarize(n_bgcs = n()) %>%
  ungroup() %>%
  ggplot(aes(x = n_scaffolds, y = n_bgcs)) +
  stat_bin_hex(bins = 50) +
  scale_x_log10(breaks = breaks_log()) +
  guides(fill = guide_colorbar(title = "# Genomes")) +
  facet_wrap(. ~ contig_edge, ncol = 1, labeller = as_labeller(c("FALSE" = "BGCs not on contig edge", "theme_bw() +
  ggtitle("Fragmented genomes have inflated BGC counts", subtitle = "Full dataset")
```

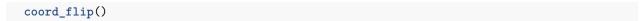
# Fragmented genomes have inflated BGC counts Full dataset

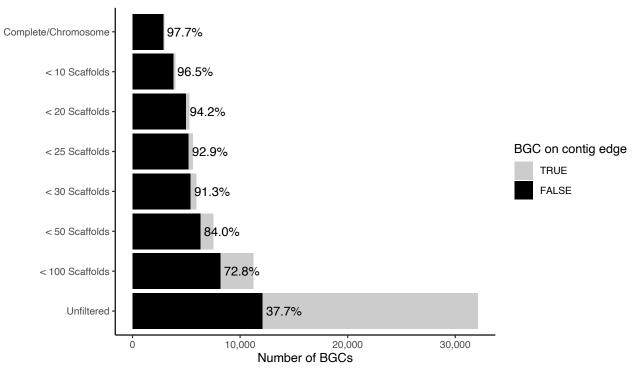


This figure depicts the number of BGCs against the number of scaffolds in a genome. To help avoid overplotting (i.e. many overlapping data points misrepresenting the distribution of the data), the colors of each spot in the figure correspond to how many data points overlap at those coordinates.

## How does the proportion of BGCs off/on a contig edge change if we filter for high-quality genomes in different ways?

```
filters_df <- bind_rows(</pre>
  regions %>%
    group_by(contig_edge) %>%
    summarize(filter = "Unfiltered", n = n()) %>%
   ungroup() %>%
   mutate(pct = 100 * n / sum(n)),
  regions %>%
    semi_join(ncbi_hiq_meta, by = join_by(accession_id == `Assembly Accession`)) %>%
    group_by(contig_edge) %>%
    summarize(filter = "Complete/Chromosome", n = n()) %>%
   mutate(pct = 100 * n / sum(n)),
 regions %>%
   filter(n_scaffolds < 10) %>%
   group by(contig edge) %>%
   summarize(filter = "< 10 Scaffolds", n = n()) %>%
    mutate(pct = 100 * n / sum(n)),
  regions %>%
   filter(n_scaffolds < 20) %>%
    group_by(contig_edge) %>%
    summarize(filter = "< 20 Scaffolds", n = n()) %>%
   mutate(pct = 100 * n / sum(n)),
  regions %>%
   filter(n_scaffolds < 25) %>%
    group_by(contig_edge) %>%
    summarize(filter = "< 25 Scaffolds", n = n()) %>%
   mutate(pct = 100 * n / sum(n)),
  regions %>%
   filter(n_scaffolds < 30) %>%
    group_by(contig_edge) %>%
   summarize(filter = "< 30 Scaffolds", n = n()) %>%
   mutate(pct = 100 * n / sum(n)),
  regions %>%
   filter(n scaffolds < 50) %>%
    group_by(contig_edge) %>%
    summarize(filter = "< 50 Scaffolds", n = n()) %>%
   mutate(pct = 100 * n / sum(n)),
  regions %>%
   filter(n_scaffolds < 100) %>%
    group_by(contig_edge) %>%
    summarize(filter = "< 100 Scaffolds", n = n()) %>%
   mutate(pct = 100 * n / sum(n)),
)
ggplot(filters_df, aes(x = filter, y = n)) +
  geom_col(aes(fill = fct_rev(as_factor(contig_edge))), position = position_stack()) +
  geom_text(aes(y = n, label = sprintf("%1.1f%%", pct)), data = filters_df %>% filter(contig_edge == FA
  scale_x_discrete(name = "", limits = c("Unfiltered", "< 100 Scaffolds", "< 50 Scaffolds", "< 30 Scaff</pre>
  scale_y_continuous(name = "Number of BGCs", labels = label_comma()) +
  scale_fill_manual(name = "BGC on contig edge", values = c("gray80", "black")) +
 theme classic() +
```





This figure depicts the counts of BGCs that are on a contig edge vs. those that are not, depending on how we define what a "high-quality genome" is. Complete/Chromosome refers to the genomes at the "Complete" or "Chromosome" assembly levels on NCBI.

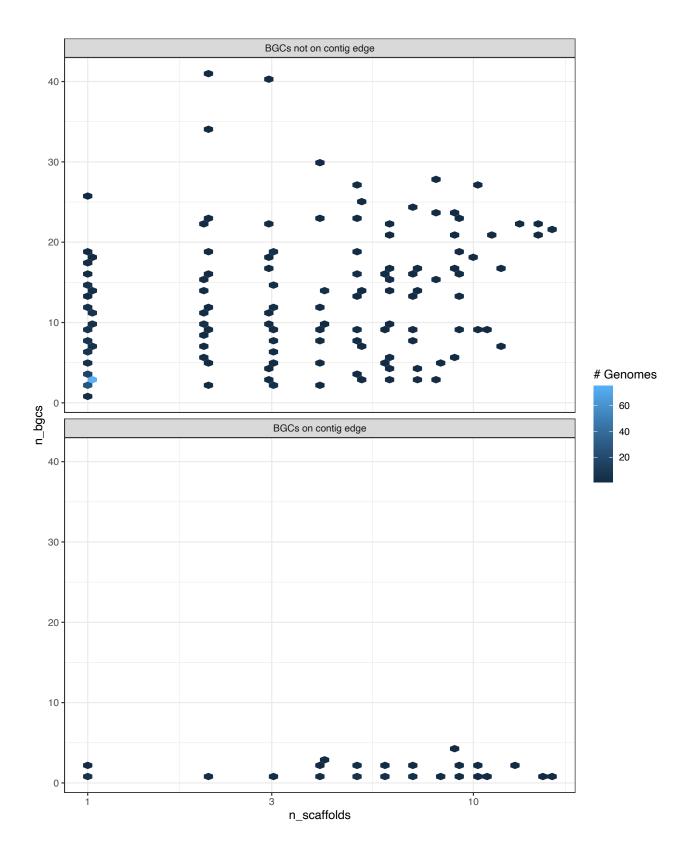
Based on this figure, and to be most conservative in this analysis, we will be going with the most restrictive criteria – using only genomes of "Chromosome" or "Complete" assembly quality as listed on NCBI.

#### Filter the dataset to high-quality genomes

Repeat the figure from above, and we should see that most BGCs are not on a contig edge.

```
regions <- regions %>%
  semi_join(ncbi_hiq_meta, by = join_by(accession_id == `Assembly Accession`))

regions %>%
  group_by(smc_id, tax_genus, n_scaffolds, contig_edge) %>%
  summarize(n_bgcs = n()) %>%
  ggplot(aes(x = n_scaffolds, y = n_bgcs)) +
  stat_bin_hex(bins = 50) +
  facet_wrap(. ~ contig_edge, ncol = 1, labeller = as_labeller(c("FALSE" = "BGCs not on contig edge", "scale_x_log10(breaks = breaks_log()) +
  guides(fill = guide_colorbar(title = "# Genomes")) +
  theme_bw()
```



#### Analyze data

Now we will proceed with our analysis, with the goal of looking at the BGC content of phylum Cyanobacteriota across the axes of length, BGC category, and taxonomy.

Note: AntiSMASH-annotated BGCs are assigned one or more of several dozen BGC "classes" based on the detection rule(s) triggered. These classes can also be grouped into one of 7 "categories" as defined by MIBiG – namely Polyketide, NRP, RiPP, Terpene, Saccharide, Alkaloid, and Other.

#### Summary statistics of BGC length across BGC categories

```
## # A tibble: 22 x 7
 ## # Groups: cats_str [22]
 ##
               cats_str
                                                                                n min_len max_len mean_len median_len
               <fct>
                                                                                           <dbl>
                                                                                                             <dbl>
                                                                                                                                <dbl> <dbl> <dbl>
 ##
                                                                      <int>
 ## 1 Terpene
                                                                                          13541
                                                                                                              39454
                                                                                                                                 20403.
                                                                                                                                                           20612. 2079.
                                                                           834
## 1 Terpene 834 13541 39454 20403. 20612. 2079.

## 2 RiPP 739 7553 76778 29623. 24133 10016.

## 3 NRP 500 20873 97395 47693. 43942. 10078.

## 4 Polyketide 307 22218 87362 46966. 46241 6996.

## 5 NRP, Polyketide 296 15761 190414 73530. 70899 24984.

## 6 Other 97 10034 60591 23411. 20762 10296.

## 7 NRP, RiPP 46 44214 131611 68485. 64902. 19801.

## 8 NRP, Other 32 43141 99576 76136. 78536. 20579.

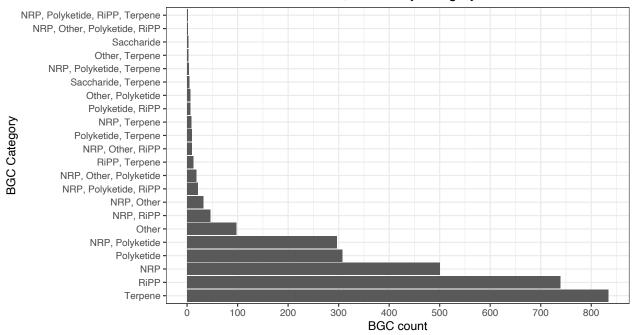
## 9 NRP, Polyketide, RiPP 21 58186 257631 124101. 91425 63076.

## 10 NRP, Other, Polyketide 18 47242 154012 80890. 73720. 33500.
 ## # i 12 more rows
```

#### How many BGCs in each category? (counting hybrids of categories as separate)

```
category_counts <- region_summary %>%
  ggplot(aes(y = reorder(cats_str, desc(n)))) +
  geom_col(aes(x = n)) +
  scale_x_continuous(name = "BGC count", breaks = breaks_width(100)) +
  scale_y_discrete(name = "BGC Category") +
  theme_bw() +
  ggtitle("Number of BGCs in dataset, divided by category")
category_counts
```

#### Number of BGCs in dataset, divided by category

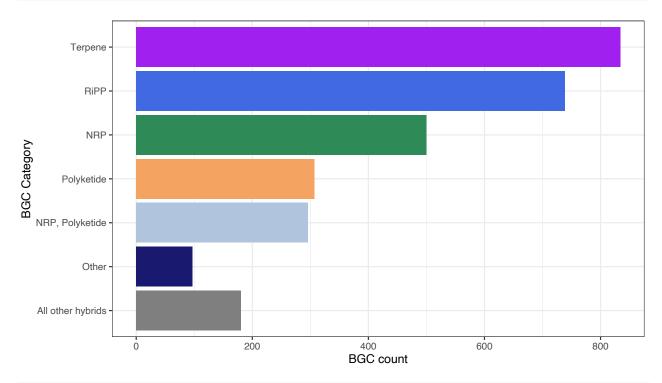


```
ggsave("./figs/svg/category_counts.svg", category_counts, device = "svg")
ggsave("./figs/png/category_counts.png", category_counts, device = "png")
```

#### How many BGCs in each category? (lumping all hybrids into one except NRPS-PKS)

```
# Lump any hybrid category with fewer than 80 BGCs into an "all other" category
# - Threshold determined arbitrarily to improve visualization
region_summary_lumped <- region_summary %>%
  mutate(
    group = if_else(n < 80, "All other hybrids", cats_str),</pre>
    group = group %>% fct_reorder(n)
  )
# Keep a reference DF handy for which categories got lumped
lump_groups <- region_summary_lumped %>% select(cats_str, group)
# Use the MIBiG / antiSMASH coloring scheme
cat_colors <- c(</pre>
  "Polyketide" = "#f4a460",
  "NRP" = "\#2e8b57",
  "RiPP" = "#4169e1".
  "Terpene" = "purple",
  "Saccharide" = "#deb887",
  "Other" = "#191970",
  "NRP, Polyketide" = "lightsteelblue",
  "All other hybrids" = "gray50"
# Plot it
```

```
lumped_category_counts <- region_summary_lumped %>%
    ggplot(aes(y = reorder(group, n))) +
    geom_col(aes(x = n, fill = group)) +
    scale_x_continuous(name = "BGC count", breaks = breaks_extended()) +
    scale_y_discrete(name = "BGC Category") +
    scale_fill_manual(values = cat_colors) +
    theme_bw() +
    guides(fill = "none")
lumped_category_counts
```



```
ggsave("./figs/svg/category_counts_lumped.svg", lumped_category_counts, device = "svg")
ggsave("./figs/png/category_counts_lumped.png", lumped_category_counts, device = "png")
```

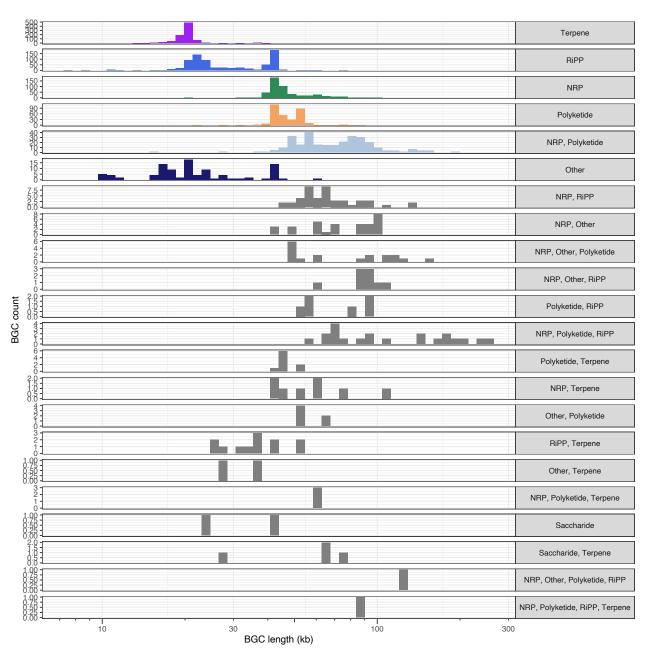
#### How do BGCs vary in length by category (or combination of categories)?

#### Un-lumped categories

```
regions_lumped <- regions %>% left_join(lump_groups, by = "cats_str")

region_hist <- ggplot(regions_lumped, aes(
    x = region_length / 1000,
)) +
    geom_histogram(aes(fill = group), bins = 50) +
    scale_x_log10(name = "BGC length (kb)", guide = "axis_logticks", breaks = breaks_log(), labels = labe
    scale_y_continuous(name = "BGC count", breaks = breaks_extended(), labels = label_comma()) +
    scale_fill_manual(values = cat_colors) +
    facet_grid(rows = vars(cats_str), scales = "free_y") +
    theme_bw() +
    theme(strip.text.y.right = element_text(angle = 0)) +</pre>
```

```
guides(fill = FALSE)
region_hist
```



```
ggsave("./figs/svg/region_hist.svg", region_hist, device = "svg")
ggsave("./figs/png/region_hist.png", region_hist, device = "png")
```

Lumped categories (again, except for NRPS-PKS hybrids)

```
region_hist_lumped <- regions_lumped %>%
filter(group != "All other hybrids") %>%
ggplot(aes(x = region_length / 1000)) +
```

```
geom_histogram(aes(fill = group), bins = 50) +
  scale_x_log10(name = "BGC length (kb)", guide = "axis_logticks", limits = c(1, NA), breaks = c(1, 5,
  scale_y_continuous(name = "BGC count", breaks = breaks_extended(n = 3)) +
  scale_fill_manual(values = cat_colors) +
  facet_wrap(vars(group), ncol = 1, scales = "free_y") +
  guides(fill = guide_legend(title = "BGC Category")) +
  theme_bw() +
  theme(
    strip.background = element_blank(),
    strip.text = element_blank()
region_hist_lumped
  600
  300
    0
  200
  100
                                                                                 BGC Category
    0
  200
                                                                                     Terpene
count
  100
                                                                                     RiPP
    0
                                                                                     NRP
DB 100
                                                                                     Polyketide
   50
                                                                                     NRP, Polyketide
    0
                                                                                     Other
   25
    0
   10
```

```
ggsave("./figs/svg/region_hist_lumped.svg", region_hist_lumped, device = "svg")
ggsave("./figs/png/region_hist_lumped.png", region_hist_lumped, device = "png")
```

BGC length (kb)

50

100

200

#### How does BGC count vary across genera and by category?

5

Table:

```
tax_count <- regions_lumped %>%
  group_by(tax_genus, cats_str) %>%
  summarize(num_bgcs = n()) %>%
  mutate(tax_genus = tax_genus %>% fct_reorder(num_bgcs)) %>%
  left_join(lump_groups, by = "cats_str") # %>%

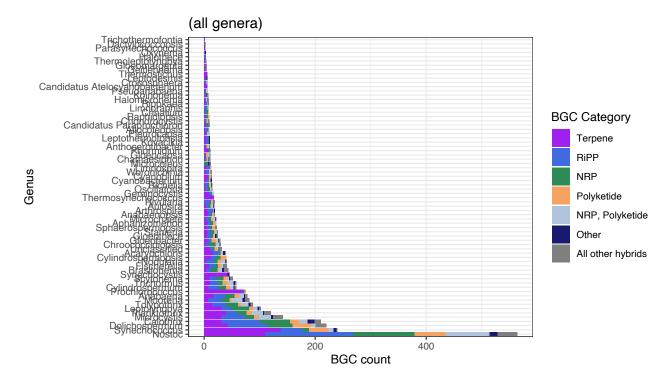
tax_count
```

## # A tibble: 388 x 4

```
## # Groups: tax_genus [70]
##
                                   num_bgcs group
     tax_genus
                   cats_str
      <fct>
##
                   <fct>
                                     <int> <fct>
                                         16 Terpene
## 1 Acaryochloris Terpene
## 2 Acaryochloris RiPP
                                         12 RiPP
## 3 Acaryochloris NRP
                                          2 NRP
## 4 Acaryochloris Polyketide
                                          2 Polyketide
## 5 Acaryochloris NRP, Polyketide
                                          2 NRP, Polyketide
## 6 Acaryochloris Other
                                          4 Other
## 7 Allocoleopsis Terpene
                                          2 Terpene
## 8 Allocoleopsis RiPP
                                          4 RiPP
## 9 Allocoleopsis NRP
                                          2 NRP
## 10 Allocoleopsis NRP, Polyketide
                                          1 NRP, Polyketide
## # i 378 more rows
```

#### Raw BGC counts by genus

```
p_all <- tax_count %>%
  group_by(tax_genus) %>%
  filter(sum(num_bgcs) > 0) %>%
  ggplot(aes(x = fct_infreq(tax_genus, w = num_bgcs))) +
  geom_col(aes(y = num_bgcs, fill = group), position = position_stack(reverse = TRUE)) +
  scale_y_continuous(name = "BGC count", breaks = breaks_extended()) +
  scale_x_discrete(name = "Genus") +
  scale_fill_manual(name = "BGC Category", values = cat_colors) +
  coord_flip() +
  theme_bw() +
  ggtitle("(all genera)")
p_all
```



```
ggsave("./figs/svg/genus_counts_all.svg", p_all, device = "svg")
ggsave("./figs/png/genus_counts_all.png", p_all, device = "png")
```

In order to normalize BGC counts to a per-genome basis, we must also know how many Cyano genomes *lacked* BGCs (as detected by antiSMASH).

```
# Plaintext file listing all the accessions that had no BGCs
cyano_nohits <- read_tsv("data/ncbi_cyano_nohit_accs.txt", col_names = c("accession_id")) %>%
  left_join(cyano_asm_tax, by = join_by(accession_id == assembly_accession))

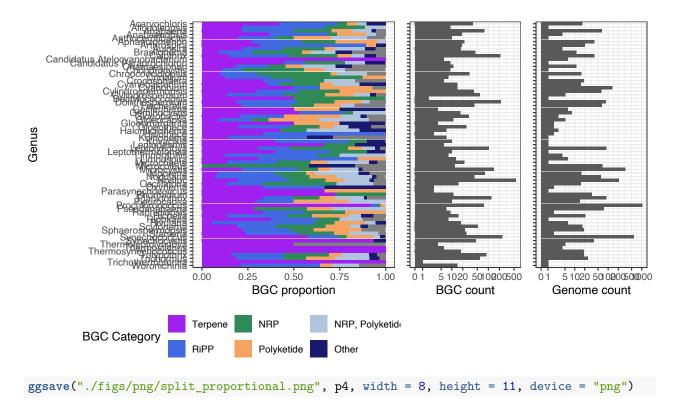
# Incorporate these into our genome counts
cyano_nohit_genus_counts <- cyano_nohits %>%
  group_by(genus) %>%
  summarize(n_nohits = n()) %>%
  mutate(genus = replace_na(genus, "Unclassified")) %>%
  arrange(genus)

genomes_by_genus <- read_tsv("data/2025-02-25-1442-cyano_smc_src_counts_by_genus.tsv")
genomes_by_genus <- genomes_by_genus %>%
  left_join(cyano_nohit_genus_counts, by = join_by(tax_genus == genus)) %>%
  mutate(n_nohits = replace_na(n_nohits, 0)) %>%
  mutate(tot_genomes = n_nohits + n_sources, .keep = "unused")
```

Plot the BGCs per genome (normalized to 100%) alongside number of BGCs per genus and genomes per genus

```
# Prepare the dataframe specific to this set of plots
df_plots <- tax_count %>%
 filter(tax_genus != "Unclassified") %>%
 left_join(genomes_by_genus, by = "tax_genus") %>%
  mutate(bgc_dens = num_bgcs / tot_genomes) %>%
  group_by(tax_genus) %>%
  mutate(tot_bgc_dens = sum(bgc_dens), tot_bgcs = sum(num_bgcs))
# Plot BGCs per genome, colored by category and divided by genus
p_bgc_dens <- df_plots %>%
  ggplot(aes(x = fct_rev(tax_genus))) +
  geom_col(aes(y = bgc_dens, fill = group), position = position_fill(reverse = TRUE)) +
  scale_y_continuous(name = "BGC proportion") +
  scale_x_discrete(name = "Genus") +
  scale_fill_manual(name = "BGC Category", values = cat_colors) +
  coord_flip() +
 theme_bw() +
  theme(legend.position = "bottom")
# p_bgc_dens
# Plot total BGC count by genus
p_bgc_ct <- df_plots %>%
  ggplot(aes(x = fct_rev(tax_genus))) +
  geom_col(aes(y = tot_bgcs), data = df_plots %% select(tax_genus, tot_bgcs, tot_bgc_dens) %% distinc
  scale_y_continuous(
   name = "BGC count",
   trans = transform_pseudo_log(base = 10),
```

```
breaks = c(0, 1, 5, 10, 20, 50, 100, 200, 500)
 ) +
  coord_flip() +
  theme_bw() +
  theme(
   axis.title.y = element_blank(),
   axis.text.y = element_blank()
  )
# Plot genome count by genus
genome_counts <- df_plots %>%
  group_by(tax_genus, tot_genomes) %>%
  summarize(tot_bgc_dens = sum(bgc_dens), tot_bgcs = sum(num_bgcs)) %>%
 arrange(tot_bgc_dens)
genome_counts
## # A tibble: 69 x 4
## # Groups: tax_genus [69]
##
     tax_genus tot_genomes tot_bgc_dens tot_bgcs
##
      <chr>>
                           <dbl>
                                        <dbl>
                                                 <int>
## 1 Prochlorococcus
                            1023
                                       0.0733
                                                    75
## 2 Pseudanabaena
                             75
                                       0.0933
                                                     7
                                       0.107
                                                    14
## 3 Cyanobium
                             131
## 4 Microcoleus
                             66
                                       0.182
                                                    12
## 5 Crocosphaera
                             19
                                       0.316
                                                     6
## 6 Phormidium
                              32
                                       0.344
                                                    11
                            579
                                       0.415
                                                   240
## 7 Synechococcus
## 8 Microcystis
                            329
                                       0.432
                                                   142
## 9 Aphanizomenon
                             38
                                       0.579
                                                    22
## 10 Fischerella
                              64
                                       0.641
## # i 59 more rows
p_genome_ct <- genome_counts %>%
  ggplot(aes(x = fct_rev(tax_genus))) +
  geom_col(aes(y = tot_genomes)) +
 scale_y_continuous(
   name = "Genome count",
   trans = transform pseudo log(base = 10),
   breaks = c(0, 1, 5, 10, 20, 50, 100, 200, 500, 1000)
  coord_flip() +
 theme bw() +
 theme(
   axis.title.y = element_blank(),
   axis.text.y = element_blank()
 )
# p_genome_ct
# Plot them all together
p4 <- plot_grid(p_bgc_dens, p_bgc_ct, p_genome_ct, align = "h", rel_widths = c(3, 1, 1), nrow = 1)
p4
```

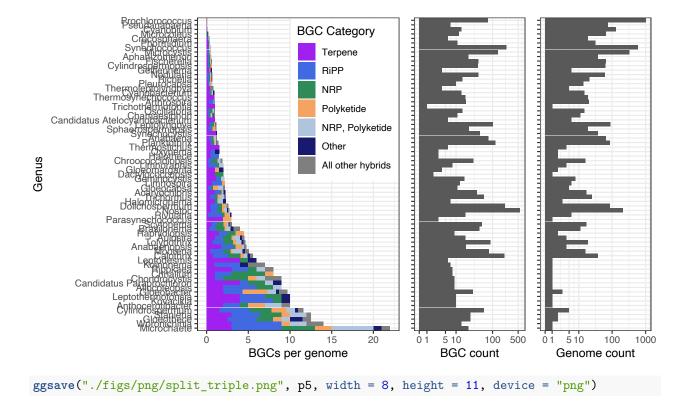


Plot the BGCs per genome (not normalized to 100%) alongside number of BGCs per genus and genomes per genus

```
# Prepare a dataframe specific to this set of plots
# df_plots <- tax_count %>%
  filter(tax_genus != "Unclassified") %>%
   left_join(genomes_by_genus, by = "tax_genus") %>%
  mutate(bgc_dens = num_bgcs / tot_genomes) %>%
  group_by(tax_genus) %>%
   mutate(tot_bgc_dens = sum(bgc_dens), tot_bgcs = sum(num_bgcs))
# Plot BGCs per genome, colored by category and divided by genus
p_bgc_dens <- df_plots %>%
  ggplot(aes(x = fct_reorder(tax_genus, tot_bgc_dens, .desc = T))) +
  geom_col(aes(y = bgc_dens, fill = group), position = position_stack(reverse = TRUE)) +
  scale_y_continuous(name = "BGCs per genome") +
  scale_x_discrete(name = "Genus") +
  scale_fill_manual(name = "BGC Category", values = cat_colors) +
  coord_flip() +
  guides(fill = guide_legend(position = "inside")) +
  theme_bw() +
  theme(legend.justification.inside = c(0.99, 0.99))
# p_bgc_dens
# Plot total BGC count by genus
p_bgc_ct <- df_plots %>%
  ggplot(aes(x = fct_reorder(tax_genus, tot_bgc_dens, .desc = T))) +
  geom col(aes(y = tot bgcs), data = df plots %% select(tax genus, tot bgcs, tot bgc dens) %% distinc
  scale_y_continuous(
```

```
name = "BGC count",
    trans = transform_pseudo_log(base = 10),
    breaks = c(0, 1, 5, 10, 100, 500)
  ) +
  coord_flip() +
  theme_bw() +
  theme(
    axis.title.y = element_blank(),
    axis.text.y = element_blank()
  )
# Plot genome count by genus
# genome_counts <- df_plots %>%
# group_by(tax_genus, tot_genomes) %>%
  summarize(tot_bgc_dens = sum(bgc_dens), tot_bgcs = sum(num_bgcs)) %>%
# arrange(tot_bgc_dens)
# genome_counts
p_genome_ct <- genome_counts %>%
  ggplot(aes(x = fct_reorder(tax_genus, tot_bgc_dens, .desc = T))) +
  geom_col(aes(y = tot_genomes)) +
  scale_y_continuous(name = "Genome count", trans = scales::transform_pseudo_log(base = 10), breaks = c
  coord_flip() +
  theme_bw() +
  theme(
    axis.title.y = element_blank(),
    axis.text.y = element_blank()
  )
# p_genome_ct
# Plot them all together
p5 <- plot_grid(p_bgc_dens, p_bgc_ct, p_genome_ct, align = "h", rel_widths = c(3, 1, 1), nrow = 1)
df_plots
## # A tibble: 378 x 8
## # Groups: tax_genus [69]
##
      tax_genus cats_str num_bgcs group tot_genomes bgc_dens tot_bgc_dens tot_bgcs
                             <int> <fct>
                                             <dbl>
                                                        <dbl>
                                                                     <dbl>
##
      <chr>
                 <fct>
                                                                              <int>
                               16 Terp~
                                                                      2.24
                                                        0.941
## 1 Acaryochl~ Terpene
                                                                                 38
                                                 17
                                                                      2.24
## 2 Acaryochl~ RiPP
                               12 RiPP
                                                  17
                                                        0.706
                                                                                 38
## 3 Acaryochl~ NRP
                                2 NRP
                                                  17
                                                                      2.24
                                                                                 38
                                                        0.118
## 4 Acaryochl~ Polyket~
                                2 Poly~
                                                  17
                                                       0.118
                                                                      2.24
                                                                                 38
## 5 Acaryochl~ NRP, Po~
                                2 NRP,~
                                                  17
                                                       0.118
                                                                      2.24
                                                                                 38
## 6 Acaryochl~ Other
                                4 Other
                                                  17
                                                       0.235
                                                                      2.24
                                                                                 38
## 7 Allocoleo~ Terpene
                                2 Terp~
                                                       2
                                                                      9
                                                  1
                                                                                  9
## 8 Allocoleo~ RiPP
                                4 RiPP
                                                  1
                                                       4
                                                                      9
                                                                                  9
                                                       2
                                                                      9
                                                                                  9
## 9 Allocoleo~ NRP
                                2 NRP
                                                   1
## 10 Allocoleo~ NRP, Po~
                               1 NRP,~
                                                   1
                                                        1
                                                                      9
                                                                                  9
## # i 368 more rows
```

p5



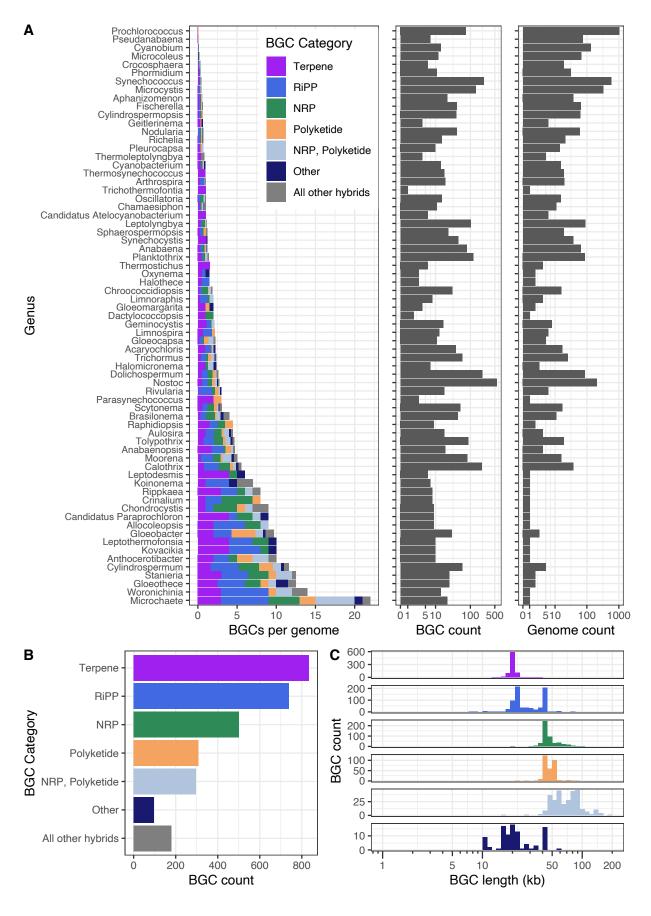
#### **Create Figure 2 for the manuscript**

```
p_a <- plot_grid(</pre>
    p_bgc_dens + theme(axis.text.y = element_text(size = 8)),
    p_bgc_ct,
    p_genome_ct,
    align = "h",
    rel_widths = c(3, 1, 1),
    nrow = 1
    )
p_b <- ggplot(</pre>
    region_summary_lumped,
    aes(y = reorder(group, n))
  geom_col(aes(x = n, fill = group)) +
  scale_x_continuous(name = "BGC count", breaks = breaks_extended()) +
  scale_y_discrete(name = "BGC Category") +
  scale_fill_manual(values = cat_colors) +
  theme_bw() +
  guides(fill = "none")
p_c <- regions_lumped %>%
  filter(group != "All other hybrids") %>%
  ggplot(aes(x = region_length / 1000)) +
      geom_histogram(aes(fill = group), bins = 50) +
      scale_x_log10(name = "BGC length (kb)", guide = "axis_logticks", limits = c(1, NA), breaks = c(1,
```

```
scale_y_continuous(name = "BGC count", breaks = breaks_extended(n = 3)) +
scale_fill_manual(values = cat_colors) +
facet_wrap(vars(group), ncol = 1, scales = "free_y") +
guides(fill = "none") +
theme_bw() +
theme(
    strip.background = element_blank(),
    strip.text = element_blank()
)

bottom_row <- plot_grid(p_b, p_c, nrow = 1, labels = c("B", "C"), label_size = 12)

fig2 <- plot_grid(p_a, bottom_row, nrow = 2, labels = c("A", ""), label_size = 12, rel_heights = c(2.5, fig2)</pre>
```



```
ggsave("./figs/_fig2.png", fig2, width = 7, height = 10, device = "png")
ggsave("./figs/_fig2.pdf", fig2, width = 7, height = 10, device = "pdf")
```