

02_Frequencies

2025-03-11

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```
library(CCA)
library(dplyr)
library(ggplot2)
library(reshape2)
library(ggribes)
library(gridExtra)
library(patchwork)
library(FactoMineR)
```

Load

Loading Pre-processed data provided

```
## load
load(here::here("Data", "ProcessedData", "processed_AnalysisData.Rdata"))
```

```
processed_data
```

```
## # A tibble: 14,575 x 484
##   fishNum dateSample dateTimeSample    dateProcessed species  spCode
##   <chr>    <date>      <dtm>          <date>        <chr>    <dbl>
## 1 LT001   2022-07-21 2022-07-21 16:56:00 2022-07-27 lakeTrout 81
## 2 LT001   2022-07-21 2022-07-21 16:56:00 2022-07-27 lakeTrout 81
## 3 LT001   2022-07-21 2022-07-21 16:56:00 2022-07-27 lakeTrout 81
## 4 LT001   2022-07-21 2022-07-21 16:56:00 2022-07-27 lakeTrout 81
## 5 LT001   2022-07-21 2022-07-21 16:56:00 2022-07-27 lakeTrout 81
## 6 LT001   2022-07-21 2022-07-21 16:56:00 2022-07-27 lakeTrout 81
## 7 LT001   2022-07-21 2022-07-21 16:56:00 2022-07-27 lakeTrout 81
## 8 LT001   2022-07-21 2022-07-21 16:56:00 2022-07-27 lakeTrout 81
## 9 LT001   2022-07-21 2022-07-21 16:56:00 2022-07-27 lakeTrout 81
## 10 LT001  2022-07-21 2022-07-21 16:56:00 2022-07-27 lakeTrout 81
## # i 14,565 more rows
## # i 478 more variables: totalLength <dbl>, forkLength <dbl>, weight <dbl>,
## #   girth <dbl>, dorsoLatHeight <dbl>, clipTag <chr>, sex <chr>, mat <dbl>,
## #   airBladderTotalLength <dbl>, airBladderWidth <dbl>, airBladderWeight <dbl>,
## #   airBladderWeightCond <dbl>, agingStructure <chr>, tissueSample <chr>,
## #   Region_name <chr>, FishTrack <chr>, MaxTSdiff <dbl>, Ping_time <chr>,
## #   deltaRange <dbl>, deltaMinAng <dbl>, deltaMajAng <dbl>, ...
## variable names in data
names(processed_data)
```

##	[1]	"fishNum"	"dateSample"
##	[3]	"dateTimeSample"	"dateProcessed"
##	[5]	"species"	"spCode"
##	[7]	"totalLength"	"forkLength"
##	[9]	"weight"	"girth"
##	[11]	"dorsoLatHeight"	"clipTag"
##	[13]	"sex"	"mat"
##	[15]	"airbladderTotalLength"	"airBladderWidth"
##	[17]	"airbladderWeight"	"airBladderWeightCond"
##	[19]	"agingStructure"	"tissueSample"
##	[21]	"Region_name"	"FishTrack"
##	[23]	"MaxTSdiff"	"Ping_time"
##	[25]	"deltaRange"	"deltaMinAng"
##	[27]	"deltaMajAng"	"aspectAngle"
##	[29]	"Target_range"	"Angle_minor_axis"
##	[31]	"Angle_major_axis"	"Distance_minor_axis"
##	[33]	"Distance_major_axis"	"StandDev_Angles_Minor_Axis"
##	[35]	"StandDev_Angles_Major_Axis"	"Target_true_depth"
##	[37]	"pingNumber"	"Ping_S"
##	[39]	"Ping_E"	"Num_targets"
##	[41]	"TS_mean"	"Target_range_mean"
##	[43]	"Speed_4D_mean_unsmoothed"	"Fish_track_change_in_range"
##	[45]	"Time_in_beam"	"Distance_3D_unsmoothed"
##	[47]	"Thickness_mean"	"Exclude_below_line_range_mean"
##	[49]	"Target_depth_mean"	"Target_depth_max"
##	[51]	"Target_depth_min"	"Fish_track_change_in_depth"
##	[53]	"Region_bottom_altitude_min"	"Region_bottom_altitude_max"
##	[55]	"Region_bottom_altitude_mean"	"Region_top_altitude_min"
##	[57]	"Region_top_altitude_max"	"Region_top_altitude_mean"
##	[59]	"F45"	"F45.5"
##	[61]	"F46"	"F46.5"
##	[63]	"F47"	"F47.5"
##	[65]	"F48"	"F48.5"
##	[67]	"F49"	"F49.5"
##	[69]	"F50"	"F50.5"
##	[71]	"F51"	"F51.5"
##	[73]	"F52"	"F52.5"
##	[75]	"F53"	"F53.5"
##	[77]	"F54"	"F54.5"
##	[79]	"F55"	"F55.5"
##	[81]	"F56"	"F56.5"
##	[83]	"F57"	"F57.5"
##	[85]	"F58"	"F58.5"
##	[87]	"F59"	"F59.5"
##	[89]	"F60"	"F60.5"
##	[91]	"F61"	"F61.5"
##	[93]	"F62"	"F62.5"
##	[95]	"F63"	"F63.5"
##	[97]	"F64"	"F64.5"
##	[99]	"F65"	"F65.5"
##	[101]	"F66"	"F66.5"
##	[103]	"F67"	"F67.5"
##	[105]	"F68"	"F68.5"
##	[107]	"F69"	"F69.5"

## [109]	"F70"	"F70.5"
## [111]	"F71"	"F71.5"
## [113]	"F72"	"F72.5"
## [115]	"F73"	"F73.5"
## [117]	"F74"	"F74.5"
## [119]	"F75"	"F75.5"
## [121]	"F76"	"F76.5"
## [123]	"F77"	"F77.5"
## [125]	"F78"	"F78.5"
## [127]	"F79"	"F79.5"
## [129]	"F80"	"F80.5"
## [131]	"F81"	"F81.5"
## [133]	"F82"	"F82.5"
## [135]	"F83"	"F83.5"
## [137]	"F84"	"F84.5"
## [139]	"F85"	"F85.5"
## [141]	"F86"	"F86.5"
## [143]	"F87"	"F87.5"
## [145]	"F88"	"F88.5"
## [147]	"F89"	"F89.5"
## [149]	"F90"	"F90.5"
## [151]	"F91"	"F91.5"
## [153]	"F92"	"F92.5"
## [155]	"F93"	"F93.5"
## [157]	"F94"	"F94.5"
## [159]	"F95"	"F95.5"
## [161]	"F96"	"F96.5"
## [163]	"F97"	"F97.5"
## [165]	"F98"	"F98.5"
## [167]	"F99"	"F99.5"
## [169]	"F100"	"F100.5"
## [171]	"F101"	"F101.5"
## [173]	"F102"	"F102.5"
## [175]	"F103"	"F103.5"
## [177]	"F104"	"F104.5"
## [179]	"F105"	"F105.5"
## [181]	"F106"	"F106.5"
## [183]	"F107"	"F107.5"
## [185]	"F108"	"F108.5"
## [187]	"F109"	"F109.5"
## [189]	"F110"	"F110.5"
## [191]	"F111"	"F111.5"
## [193]	"F112"	"F112.5"
## [195]	"F113"	"F113.5"
## [197]	"F114"	"F114.5"
## [199]	"F115"	"F115.5"
## [201]	"F116"	"F116.5"
## [203]	"F117"	"F117.5"
## [205]	"F118"	"F118.5"
## [207]	"F119"	"F119.5"
## [209]	"F120"	"F120.5"
## [211]	"F121"	"F121.5"
## [213]	"F122"	"F122.5"
## [215]	"F123"	"F123.5"

## [217]	"F124"	"F124.5"
## [219]	"F125"	"F125.5"
## [221]	"F126"	"F126.5"
## [223]	"F127"	"F127.5"
## [225]	"F128"	"F128.5"
## [227]	"F129"	"F129.5"
## [229]	"F130"	"F130.5"
## [231]	"F131"	"F131.5"
## [233]	"F132"	"F132.5"
## [235]	"F133"	"F133.5"
## [237]	"F134"	"F134.5"
## [239]	"F135"	"F135.5"
## [241]	"F136"	"F136.5"
## [243]	"F137"	"F137.5"
## [245]	"F138"	"F138.5"
## [247]	"F139"	"F139.5"
## [249]	"F140"	"F140.5"
## [251]	"F141"	"F141.5"
## [253]	"F142"	"F142.5"
## [255]	"F143"	"F143.5"
## [257]	"F144"	"F144.5"
## [259]	"F145"	"F145.5"
## [261]	"F146"	"F146.5"
## [263]	"F147"	"F147.5"
## [265]	"F148"	"F148.5"
## [267]	"F149"	"F149.5"
## [269]	"F150"	"F150.5"
## [271]	"F151"	"F151.5"
## [273]	"F152"	"F152.5"
## [275]	"F153"	"F153.5"
## [277]	"F154"	"F154.5"
## [279]	"F155"	"F155.5"
## [281]	"F156"	"F156.5"
## [283]	"F157"	"F157.5"
## [285]	"F158"	"F158.5"
## [287]	"F159"	"F159.5"
## [289]	"F160"	"F160.5"
## [291]	"F161"	"F161.5"
## [293]	"F162"	"F162.5"
## [295]	"F163"	"F163.5"
## [297]	"F164"	"F164.5"
## [299]	"F165"	"F165.5"
## [301]	"F166"	"F166.5"
## [303]	"F167"	"F167.5"
## [305]	"F168"	"F168.5"
## [307]	"F169"	"F169.5"
## [309]	"F170"	"F173"
## [311]	"F173.5"	"F174"
## [313]	"F174.5"	"F175"
## [315]	"F175.5"	"F176"
## [317]	"F176.5"	"F177"
## [319]	"F177.5"	"F178"
## [321]	"F178.5"	"F179"
## [323]	"F179.5"	"F180"

## [325]	"F180.5"	"F181"
## [327]	"F181.5"	"F182"
## [329]	"F182.5"	"F183"
## [331]	"F183.5"	"F184"
## [333]	"F184.5"	"F185"
## [335]	"F185.5"	"F186"
## [337]	"F186.5"	"F187"
## [339]	"F187.5"	"F188"
## [341]	"F188.5"	"F189"
## [343]	"F189.5"	"F190"
## [345]	"F190.5"	"F191"
## [347]	"F191.5"	"F192"
## [349]	"F192.5"	"F193"
## [351]	"F193.5"	"F194"
## [353]	"F194.5"	"F195"
## [355]	"F195.5"	"F196"
## [357]	"F196.5"	"F197"
## [359]	"F197.5"	"F198"
## [361]	"F198.5"	"F199"
## [363]	"F199.5"	"F200"
## [365]	"F200.5"	"F201"
## [367]	"F201.5"	"F202"
## [369]	"F202.5"	"F203"
## [371]	"F203.5"	"F204"
## [373]	"F204.5"	"F205"
## [375]	"F205.5"	"F206"
## [377]	"F206.5"	"F207"
## [379]	"F207.5"	"F208"
## [381]	"F208.5"	"F209"
## [383]	"F209.5"	"F210"
## [385]	"F210.5"	"F211"
## [387]	"F211.5"	"F212"
## [389]	"F212.5"	"F213"
## [391]	"F213.5"	"F214"
## [393]	"F214.5"	"F215"
## [395]	"F215.5"	"F216"
## [397]	"F216.5"	"F217"
## [399]	"F217.5"	"F218"
## [401]	"F218.5"	"F219"
## [403]	"F219.5"	"F220"
## [405]	"F220.5"	"F221"
## [407]	"F221.5"	"F222"
## [409]	"F222.5"	"F223"
## [411]	"F223.5"	"F224"
## [413]	"F224.5"	"F225"
## [415]	"F225.5"	"F226"
## [417]	"F226.5"	"F227"
## [419]	"F227.5"	"F228"
## [421]	"F228.5"	"F229"
## [423]	"F229.5"	"F230"
## [425]	"F230.5"	"F231"
## [427]	"F231.5"	"F232"
## [429]	"F232.5"	"F233"
## [431]	"F233.5"	"F234"

```
## [433] "F234.5"          "F235"
## [435] "F235.5"          "F236"
## [437] "F236.5"          "F237"
## [439] "F237.5"          "F238"
## [441] "F238.5"          "F239"
## [443] "F239.5"          "F240"
## [445] "F240.5"          "F241"
## [447] "F241.5"          "F242"
## [449] "F242.5"          "F243"
## [451] "F243.5"          "F244"
## [453] "F244.5"          "F245"
## [455] "F245.5"          "F246"
## [457] "F246.5"          "F247"
## [459] "F247.5"          "F248"
## [461] "F248.5"          "F249"
## [463] "F249.5"          "F250"
## [465] "F250.5"          "F251"
## [467] "F251.5"          "F252"
## [469] "F252.5"          "F253"
## [471] "F253.5"          "F254"
## [473] "F254.5"          "F255"
## [475] "F255.5"          "F256"
## [477] "F256.5"          "F257"
## [479] "F257.5"          "F258"
## [481] "F258.5"          "F259"
## [483] "F259.5"          "F260"
```

Create a dataframe only containing frequencies.

```
frequency_data <- (
  processed_data
  |> select(1, 5, 59:481)
)
frequency_data |> head()
```

```
## # A tibble: 6 x 425
##   fishNum species    F45 F45.5    F46 F46.5    F47 F47.5    F48 F48.5    F49 F49.5
##   <chr>   <chr>      <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 LT001 lakeTrout -48.9 -47.5 -45.9 -44.2 -43.0 -41.7 -40.6 -39.6 -38.6 -37.7
## 2 LT001 lakeTrout -47.4 -47.6 -47.1 -45.5 -43.6 -41.6 -40.1 -39.0 -38.0 -37.2
## 3 LT001 lakeTrout -47.9 -49.3 -49.3 -47.2 -44.9 -42.7 -41.0 -39.5 -38.3 -37.2
## 4 LT001 lakeTrout -44.3 -45.7 -47.6 -48.8 -48.6 -46.7 -44.7 -42.9 -41.5 -40.3
## 5 LT001 lakeTrout -41.4 -42.3 -43.6 -44.7 -45.9 -46.6 -46.9 -46.7 -46.0 -45.1
## 6 LT001 lakeTrout -33.8 -33.7 -33.7 -33.5 -33.7 -33.8 -34.0 -34.1 -34.2 -34.2
## # i 413 more variables: F50 <dbl>, F50.5 <dbl>, F51 <dbl>, F51.5 <dbl>,
## #   F52 <dbl>, F52.5 <dbl>, F53 <dbl>, F53.5 <dbl>, F54 <dbl>, F54.5 <dbl>,
## #   F55 <dbl>, F55.5 <dbl>, F56 <dbl>, F56.5 <dbl>, F57 <dbl>, F57.5 <dbl>,
## #   F58 <dbl>, F58.5 <dbl>, F59 <dbl>, F59.5 <dbl>, F60 <dbl>, F60.5 <dbl>,
## #   F61 <dbl>, F61.5 <dbl>, F62 <dbl>, F62.5 <dbl>, F63 <dbl>, F63.5 <dbl>,
## #   F64 <dbl>, F64.5 <dbl>, F65 <dbl>, F65.5 <dbl>, F66 <dbl>, F66.5 <dbl>,
## #   F67 <dbl>, F67.5 <dbl>, F68 <dbl>, F68.5 <dbl>, F69 <dbl>, F69.5 <dbl>, ...
```

Basic Frequencies

Data cleaning

Since we notice the data of F90 to F170 are missing, we want to remove these frequencies columns from our dataset.

```
## removing columns 93(F90) to 253(F170)
frequency_data <- frequency_data |> select(-c(93:253))
## name(frequency_data)
```

Separate into three dataset for each species

```
LakeTrout <- frequency_data[frequency_data$species == "lakeTrout", ]
LakeWhiteFish <- frequency_data[frequency_data$species == "lakeWhitefish", ]
SmallmouthBass <- frequency_data[frequency_data$species == "smallmouthBass", ]
```

TS Mean Between Fish Species

We want to use the mean of target strength across all ping times of each fish across all frequencies to explore the dataset by fish species. We first create a dataframe that contains all mean values as above.

```
ts_mean_allTime_data <- (
  frequency_data
  |> group_by(fishNum, species)
  |> mutate(species = recode(species,
    "lakeTrout" = "Lake Trout",
    "lakeWhitefish" = "Lake Whitefish",
    "smallmouthBass" = "Smallmouth Bass"))
  |> summarize(across(starts_with("F"), ~mean(., na.rm = TRUE), .names = "{.col}_mean"))
)
```

`summarise()` has grouped output by 'fishNum'. You can override using the
`.groups` argument.

```
ts_mean_allTime_data |> head()
```

```
## # A tibble: 6 x 264
## # Groups:   fishNum [6]
##   fishNum species    F45_mean F45.5_mean F46_mean F46.5_mean F47_mean F47.5_mean
##   <chr>   <chr>      <dbl>      <dbl>    <dbl>      <dbl>    <dbl>      <dbl>
## 1 LT001   Lake Trout  -46.3      -46.2    -46.3      -45.9    -45.4      -44.9
## 2 LT002   Lake Trout  -47.7      -47.3    -47.0      -46.6    -46.6      -46.4
## 3 LT003   Lake Trout  -47.3      -47.0    -46.8      -46.4    -46.3      -46.1
## 4 LT004   Lake Trout  -40.4      -40.3    -40.3      -40.0    -40.0      -39.8
## 5 LT005   Lake Trout  -60.5      -60.2    -60.1      -59.6    -59.7      -59.6
## 6 LT006   Lake Trout  -39.3      -39.2    -39.2      -38.9    -38.8      -38.6
## # i 256 more variables: F48_mean <dbl>, F48.5_mean <dbl>, F49_mean <dbl>,
## #   F49.5_mean <dbl>, F50_mean <dbl>, F50.5_mean <dbl>, F51_mean <dbl>,
## #   F51.5_mean <dbl>, F52_mean <dbl>, F52.5_mean <dbl>, F53_mean <dbl>,
## #   F53.5_mean <dbl>, F54_mean <dbl>, F54.5_mean <dbl>, F55_mean <dbl>,
## #   F55.5_mean <dbl>, F56_mean <dbl>, F56.5_mean <dbl>, F57_mean <dbl>,
## #   F57.5_mean <dbl>, F58_mean <dbl>, F58.5_mean <dbl>, F59_mean <dbl>,
## #   F59.5_mean <dbl>, F60_mean <dbl>, F60.5_mean <dbl>, F61_mean <dbl>, ...
```

We then melt the wide format dataframe into a long format dataframe for easy visualization.

```
ts_mean_allTime_data_long <- (
  ts_mean_allTime_data
```

```

|> melt(
  id.vars = c("fishNum", "species"),
  variable.name = "Frequency",
  value.name = "TS_mean_allTime"
)
)

ts_mean_allTime_data_long$Frequency <- as.numeric(gsub("F([0-9.]+)_mean", "\\1",
                                                    ts_mean_allTime_data_long$Frequency))
ts_mean_allTime_data_long <- ts_mean_allTime_data_long |> arrange(fishNum, Frequency)
ts_mean_allTime_data_long |> head()

```

```

##   fishNum   species Frequency TS_mean_allTime
## 1  LT001 Lake Trout    45.0      -46.26963
## 2  LT001 Lake Trout    45.5      -46.18908
## 3  LT001 Lake Trout    46.0      -46.33088
## 4  LT001 Lake Trout    46.5      -45.91361
## 5  LT001 Lake Trout    47.0      -45.44261
## 6  LT001 Lake Trout    47.5      -44.92863

```

Plots We want to show different type of plots to discover the frequency patterns of each fish species.

First we want to plot an frequency response plot showing the mean target strength across different frequencies for different fish species with each fish response in the background.

```

(
  ggplot(ts_mean_allTime_data_long, aes(x = Frequency, y = TS_mean_allTime, color = species))
  ## Individual fish (dotted lines)
  + geom_line(
    aes(group = interaction(fishNum, species)),
    linetype = "dotted",
    alpha = 0.3,
    linewidth = 0.5
  )
  ## Mean trends (bold lines)
  + stat_summary(
    fun = mean,
    geom = "line",
    aes(group = species),
    linewidth = 1.2
  )
  ## Aesthetics
  + scale_x_continuous(breaks = seq(40, 260, by = 20))
  + labs(
    x = "Frequency (Hz)",
    y = "Mean Target Strength (dB)",
    color = "Fish Type"
  )
  + theme(legend.position = "top")
)

```

```

## Warning: Removed 172 rows containing non-finite outside the scale range
## (`stat_summary()`).

```

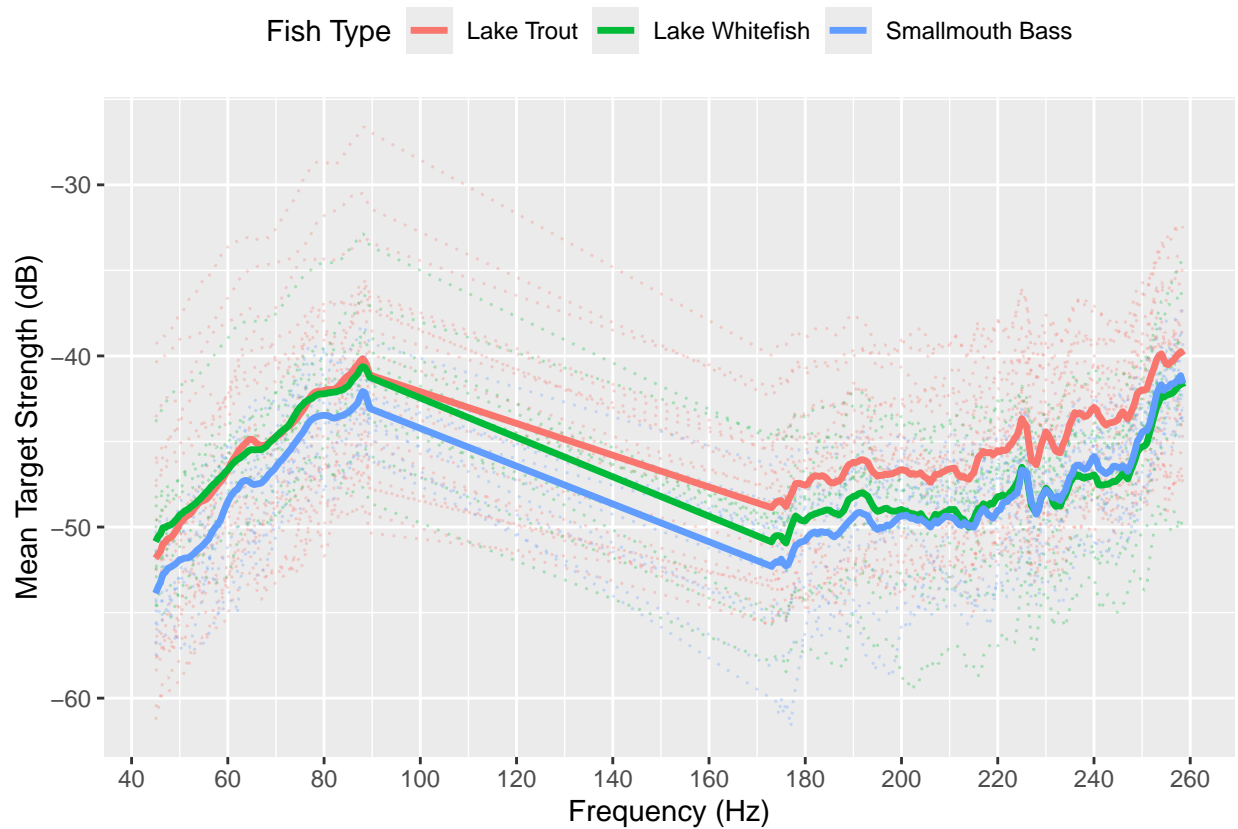
```

## Warning: Removed 172 rows containing missing values or values outside the scale range

```



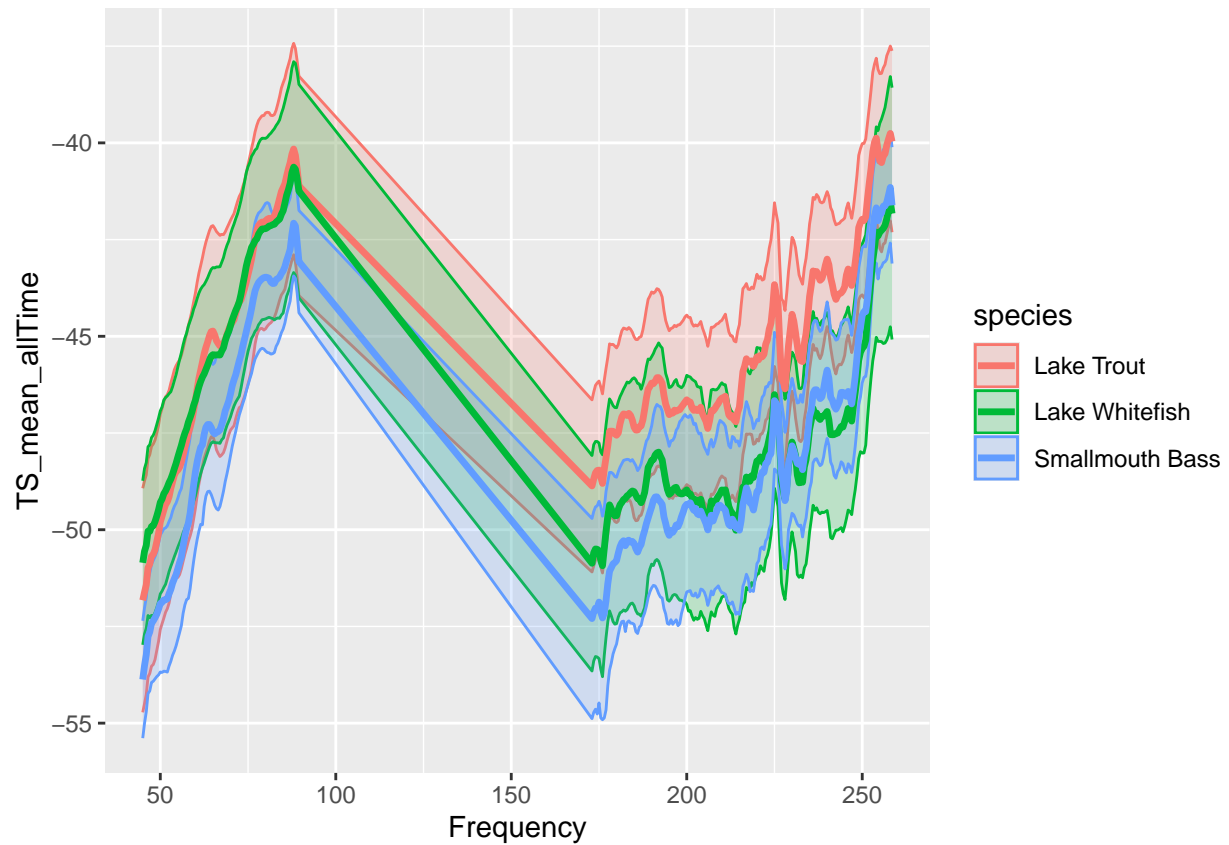
```
## (`geom_line()`).
```



Plot to observe the range of frequencies for each individual fish for each species.

```
(
  ggplot(ts_mean_allTime_data_long, aes(x = Frequency, y = TS_mean_allTime, color = species))
  + stat_summary(fun.data = mean_cl_normal, geom = "ribbon", alpha = 0.2, aes(fill = species))
  + stat_summary(fun = mean, geom = "line", linewidth = 1.2)
)
```

```
## Warning: Removed 172 rows containing non-finite outside the scale range
## (`stat_summary()`).
## Removed 172 rows containing non-finite outside the scale range
## (`stat_summary()`).
```

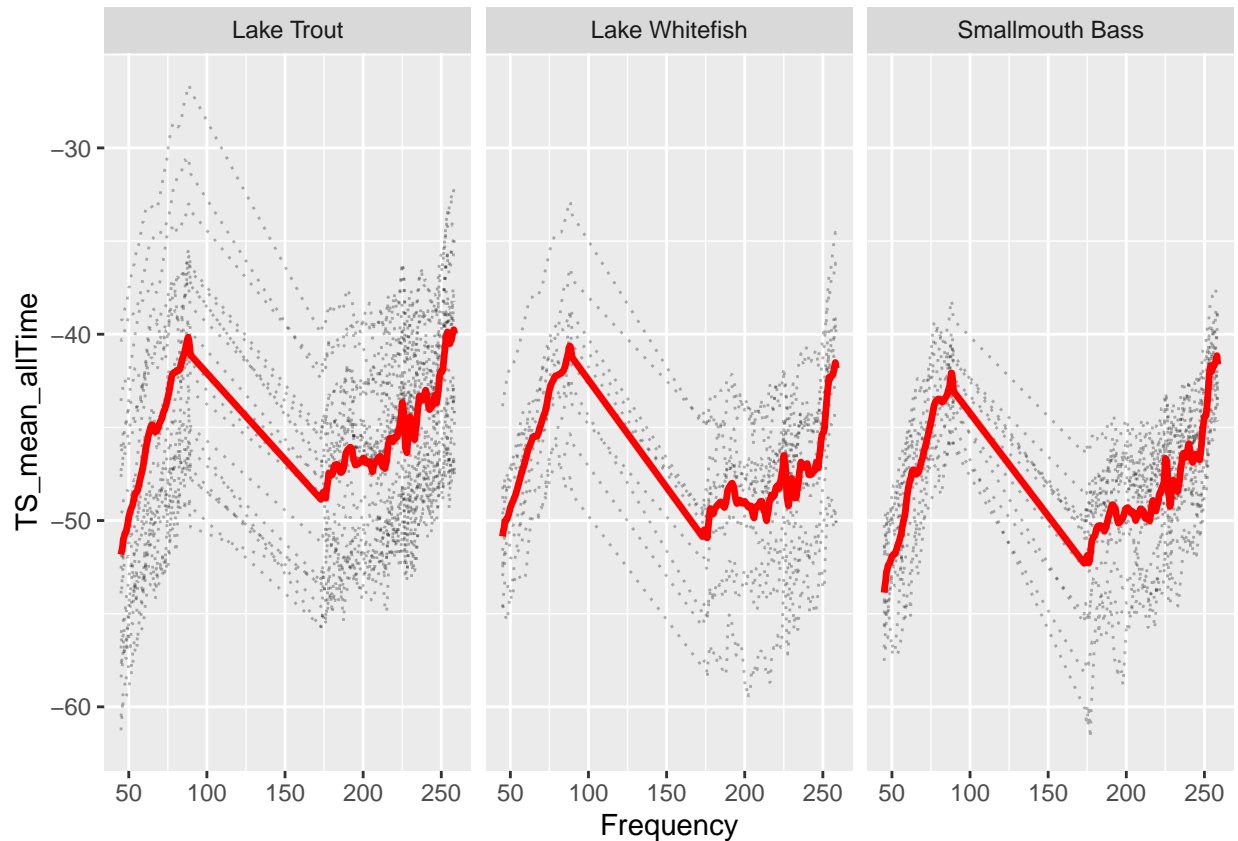


Plot to observe the range of frequencies of each species separately.

```
(
  ggplot(ts_mean_allTime_data_long, aes(x = Frequency, y = TS_mean_allTime))
  + geom_line(aes(group = fishNum), linetype = "dotted", alpha = 0.3)
  + stat_summary(fun = mean, geom = "line", color = "red", linewidth = 1.2)
  + facet_wrap(~species)
)
```

```
## Warning: Removed 172 rows containing non-finite outside the scale range
## (`stat_summary()`).
```

```
## Warning: Removed 172 rows containing missing values or values outside the scale range
## (`geom_line()`).
```



Density contour plot to show target strength measurements across different frequency ranges for each fish species.

```
## function to create density contour plot
create_frequency_density_plot <- function(data, title){
  #' Create Target Strength Frequency Response Plots
  #'
  #' This function creates visualization of acoustic target strength data across frequency ranges for fish
  #' The plot combines multiple visualization elements:
  #'   - Hexagonal binning to show data density distribution
  #'   - Individual fish measurements as dotted gray lines
  #'   - Mean target strength trend line in red
  #'
  #' @param data A long format data frame containing columns in this order: fishNum, species, Frequency, TS_mean
  #' @param title String for the plot title

  colnames(data)[4] <- "TS_mean"

  (
    ggplot(data, aes(x = Frequency, y = TS_mean))
    ## hexbin density layer
    + geom_hex(aes(fill = after_stat(count)), bins = 20, alpha = 0.7)
    ## Individual fish lines
    + geom_line(
      aes(group = interaction(fishNum, species)),
      linetype = "dotted",
      alpha = 0.2,
    )
  )
}
```

```

    color = "gray20"
  )
  ## mean trend
  + stat_summary(
    fun = mean,
    geom = "line",
    color = "red",
    linewidth = 1.2
  )
  ## facet by fish type
  + facet_wrap(~species, nrow = 1)
  ## Aesthetics
  + scale_fill_viridis_c(name = "Data Density")
  + scale_x_continuous(breaks = seq(0, 260, by = 20))
  + labs(title = title, x = "Frequency (Hz)", y = "TS_mean (dB)")
  # + theme_minimal()
  + theme(legend.position = "bottom")
)
}

## split data into two frequency groups
ts_mean_allTime_low_long <- ts_mean_allTime_data_long |> filter(Frequency >= 45 & Frequency <= 89.5)
ts_mean_allTime_high_long <- ts_mean_allTime_data_long |> filter(Frequency >= 173 & Frequency <= 260)

# Create plots for both frequency ranges
plot_frequency_density_low <- create_frequency_density_plot(ts_mean_allTime_low_long, "Frequency Range: Low")
plot_frequency_density_high <- create_frequency_density_plot(ts_mean_allTime_high_long, "Frequency Range: High")

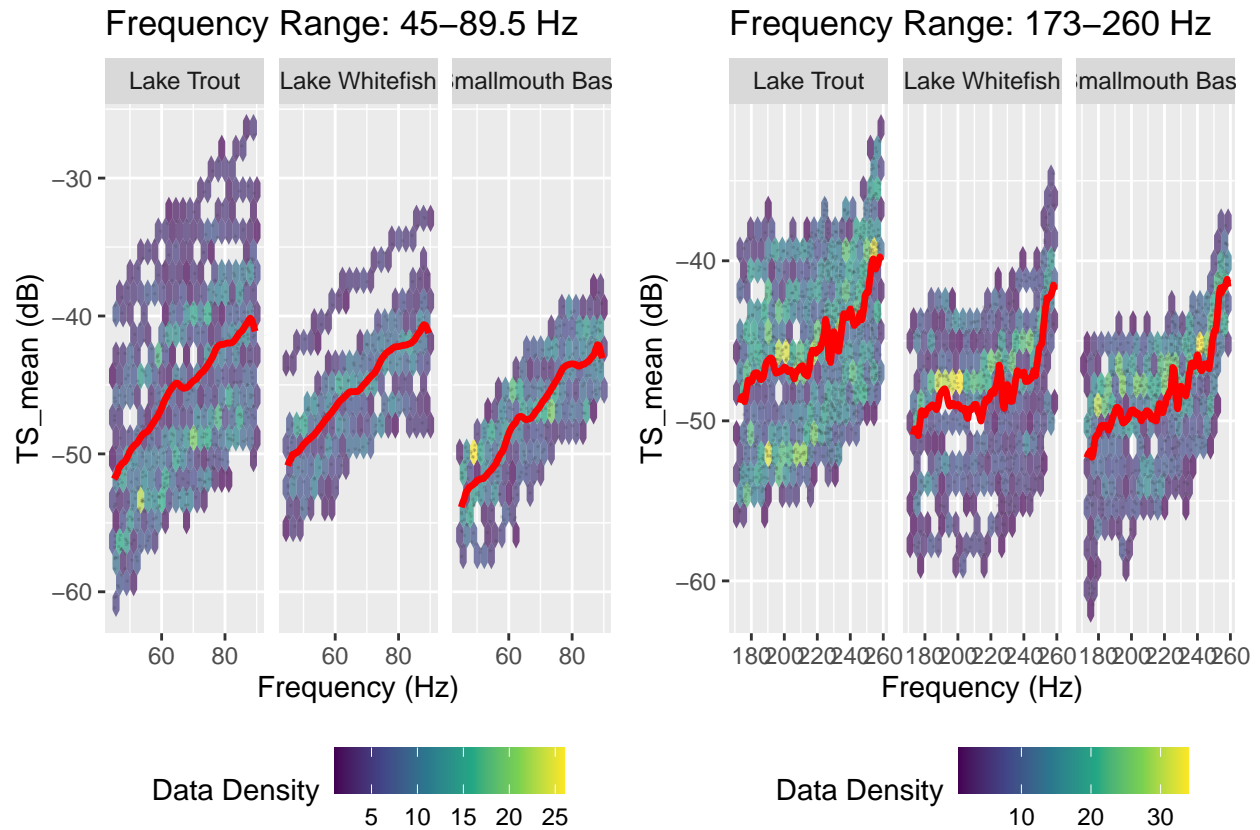
# Arrange side-by-side
grid.arrange(plot_frequency_density_low, plot_frequency_density_high, ncol = 2)

## Warning: Removed 172 rows containing non-finite outside the scale range
## (`stat_binhex()`).

## Warning: Removed 172 rows containing non-finite outside the scale range
## (`stat_summary()`).

## Warning: Removed 172 rows containing missing values or values outside the scale range
## (`geom_line()`).

```



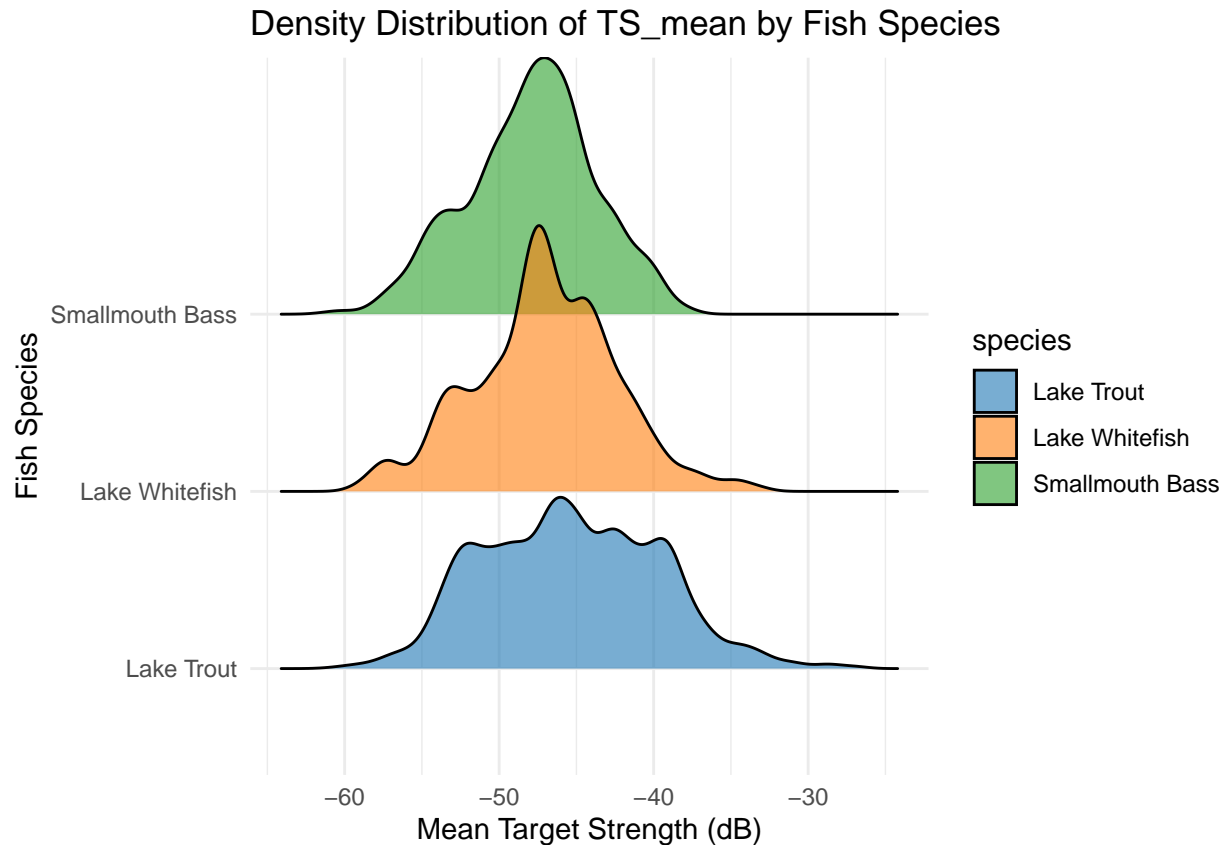
Create plot of density distribution of target strength by fish species.

```
(
  ggplot(ts_mean_allTime_data_long, aes(
    x = TS_mean_allTime,      # Numeric variable for density
    y = species,             # Categorical variable (fish species)
    fill = species           # Color by species
  ))
  ## density ridges
  + geom_density_ridges(alpha = 0.6, scale = 1.5)
  + labs(
    title = "Density Distribution of TS_mean by Fish Species",
    x = "Mean Target Strength (dB)",
    y = "Fish Species"
  )
  + theme_minimal()
  + scale_fill_manual(values = c("#1f77b4", "#ff7f0e", "#2ca02c"))
)
```

Picking joint bandwidth of 0.808

Warning: Removed 172 rows containing non-finite outside the scale range

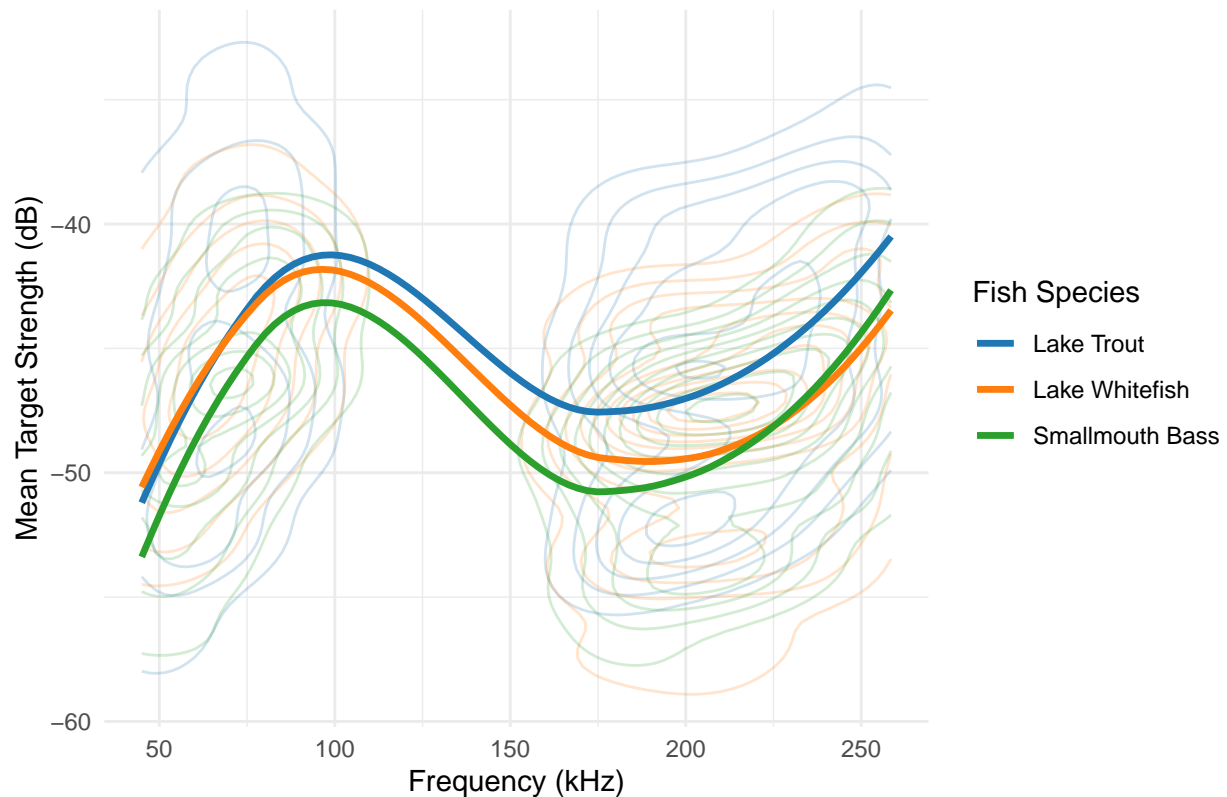
(`stat_density_ridges()`).



We create another density contour plot and we want to observe if there any potential dominant frequency response region by each fish species.

```
(
  ggplot(ts_mean_allTime_data_long, aes(x = Frequency, y = TS_mean_allTime, color = species))
  ## density contours
  + geom_density_2d(aes(fill = species), alpha = 0.2, contour_var = "density")
  ## frequency response trend lines
  + geom_smooth(
    method = "loess",
    formula = y ~ x,
    se = FALSE, # Remove confidence bands
    linewidth = 1.2
  )
  ## Aesthetics
  + labs(
    title = "Dominant Regions and Frequency Response by Fish Species",
    x = "Frequency (kHz)",
    y = "Mean Target Strength (dB)",
    color = "Fish Species"
  )
  + scale_color_manual(values = c("#1f77b4", "#ff7f0e", "#2ca02c"))
  + scale_fill_manual(values = c("#1f77b4", "#ff7f0e", "#2ca02c"))
  + theme(legend.position = "bottom")
  + theme_minimal()
)
```

Dominant Regions and Frequency Response by Fish Species



TS Mean In Fish Species

This section we want to investigate the potential trend / pattern in the frequency response in an individual fish species.

Lake Trout We first want to investigate the frequency response across different ping time for a single fish. We want to focus on `fishNum = LT001`.

```
LT001_frequency <- LakeTrout[LakeTrout$fishNum == "LT004", ]
# LT001_frequency <- LakeWhiteFish[LakeWhiteFish$fishNum == "LWF003", ]
# LT001_frequency <- SmallmouthBass[SmallmouthBass$fishNum == "SMB005", ]

## melt dataframe into plottable format
LT001_frequency$ping_id <- 1:nrow(LT001_frequency)
LT001_frequency_long <- melt(
  LT001_frequency,
  id.vars = c("fishNum", "species", "ping_id"),
  variable.name = "Frequency",
  value.name = "TS"
)
LT001_frequency_long$Frequency <- as.numeric(gsub("F", "",
  LT001_frequency_long$Frequency))
LT001_frequency_long |> head()
```

```
##   fishNum  species ping_id Frequency      TS
## 1   LT004 lakeTrout      1      45 -41.64990
## 2   LT004 lakeTrout      2      45 -44.13450
```

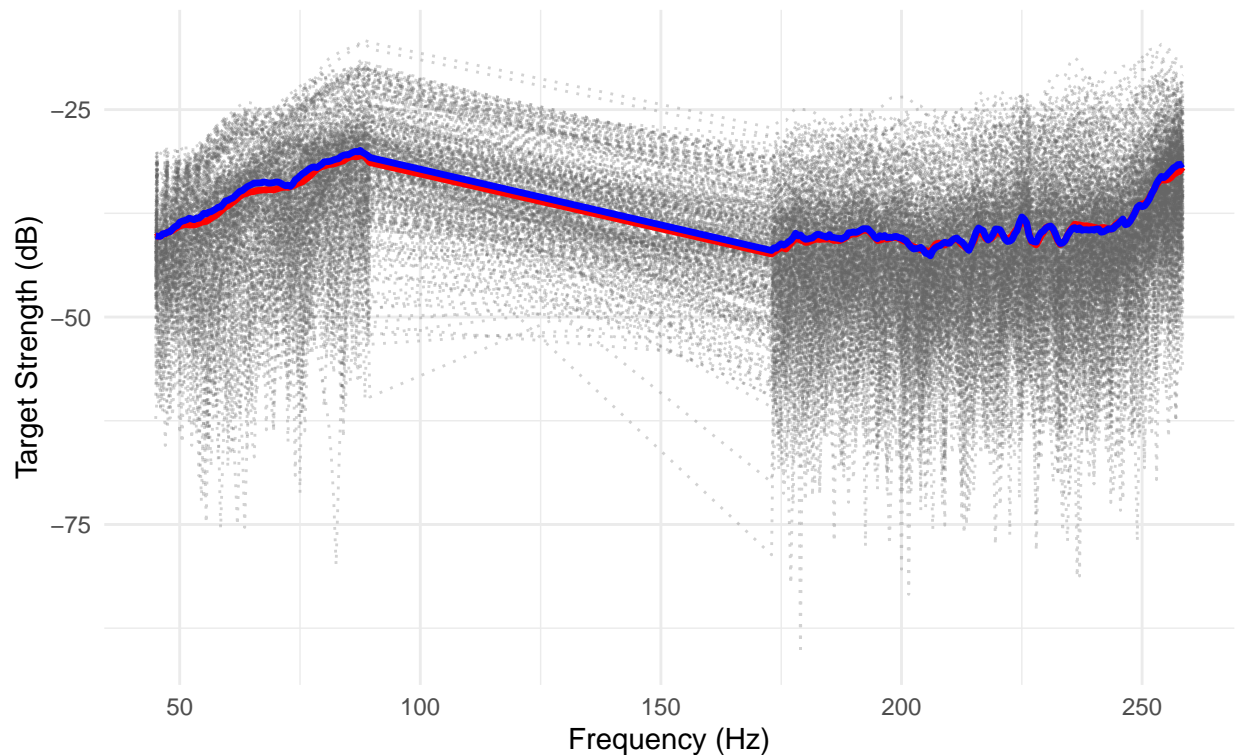
```
## 3   LT004 lakeTrout      3      45 -47.54812
## 4   LT004 lakeTrout      4      45 -36.01969
## 5   LT004 lakeTrout      5      45 -35.59207
## 6   LT004 lakeTrout      6      45 -34.82420
```

Plot to create visualization of frequency response of fish LT001 across ping time.

```
(
  ggplot(LT001_frequency_long, aes(x = Frequency, y = TS))
  ## Individual ping time response as dotted lines
  + geom_line(aes(group = ping_id), linetype = "dotted", alpha = 0.3, color = "gray40")
  ## mean response as solid line
  + stat_summary(fun = mean, geom = "line", color = "red", linewidth = 1.2)
  + stat_summary(fun = median, geom = "line", color = "blue", linewidth = 1.2)
  ## confidence interval for mean
  # + stat_summary(fun.data = mean_cl_normal, geom = "ribbon", alpha = 0.2, fill = "red")
  + labs(
    title = "Acoustic Frequency Response",
    subtitle = "Individual ping responses with mean trend",
    x = "Frequency (Hz)",
    y = "Target Strength (dB)"
  )
  + theme(
    panel.grid.minor = element_blank(),
    legend.position = "none"
  )
  + theme_minimal()
)
```


Acoustic Frequency Response

Individual ping responses with mean trend



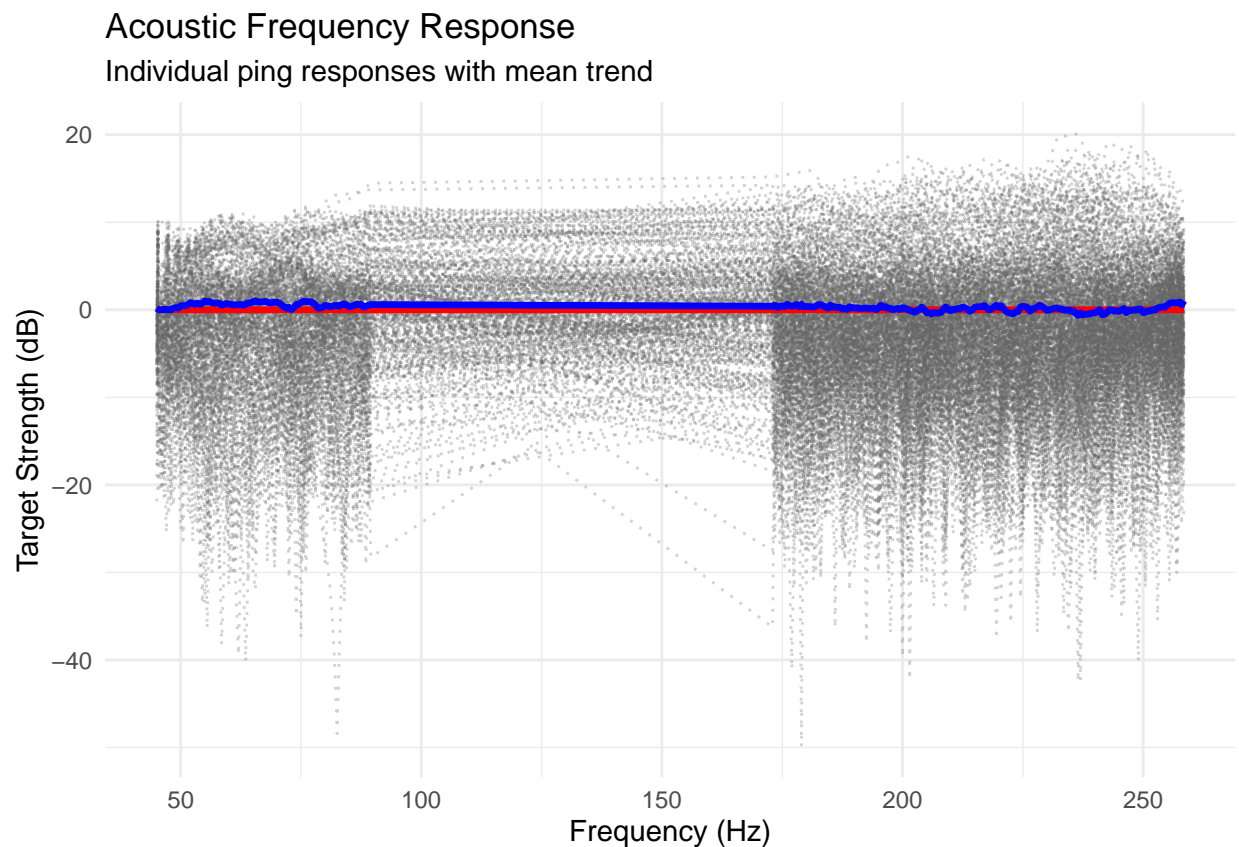
Next, we want to compute the difference between the frequency response from the mean from different ping time.

```
## compute mean
LT001_frequency_mean <- (
  LT001_frequency_long
  |> group_by(Frequency)
  |> summarize(TS_mean = mean(TS, na.rm = TRUE))
)

## left join and compute difference
LT001_frequency_long <- (
  LT001_frequency_long
  |> left_join(LT001_frequency_mean, by = "Frequency")
  |> mutate(diff_from_mean = TS - TS_mean)
)
LT001_frequency_long |> head()
```

##	fishNum	species	ping_id	Frequency	TS	TS_mean	diff_from_mean
## 1	LT004	lakeTrout	1	45	-41.64990	-40.39746	-1.252438
## 2	LT004	lakeTrout	2	45	-44.13450	-40.39746	-3.737038
## 3	LT004	lakeTrout	3	45	-47.54812	-40.39746	-7.150657
## 4	LT004	lakeTrout	4	45	-36.01969	-40.39746	4.377772
## 5	LT004	lakeTrout	5	45	-35.59207	-40.39746	4.805394
## 6	LT004	lakeTrout	6	45	-34.82420	-40.39746	5.573259

```
(
  ggplot(LT001_frequency_long, aes(x = Frequency, y = diff_from_mean))
  ## Individual ping time response as dotted lines
  + geom_line(aes(group = ping_id), linetype = "dotted", alpha = 0.3, color = "gray40")
  ## mean respinse as solid line
  + stat_summary(fun = mean, geom = "line", color = "red", linewidth = 1.2)
  + stat_summary(fun = median, geom = "line", color = "blue", linewidth = 1.2)
  ## confidence interval for mean
  # + stat_summary(fun.data = mean_cl_normal, geom = "ribbon", alpha = 0.2, fill = "red")
  + labs(
    title = "Acoustic Frequency Response",
    subtitle = "Individual ping responses with mean trend",
    x = "Frequency (Hz)",
    y = "Target Strength (dB)"
  )
)
+ theme(
  panel.grid.minor = element_blank(),
  legend.position = "none"
)
+ theme_minimal()
)
```



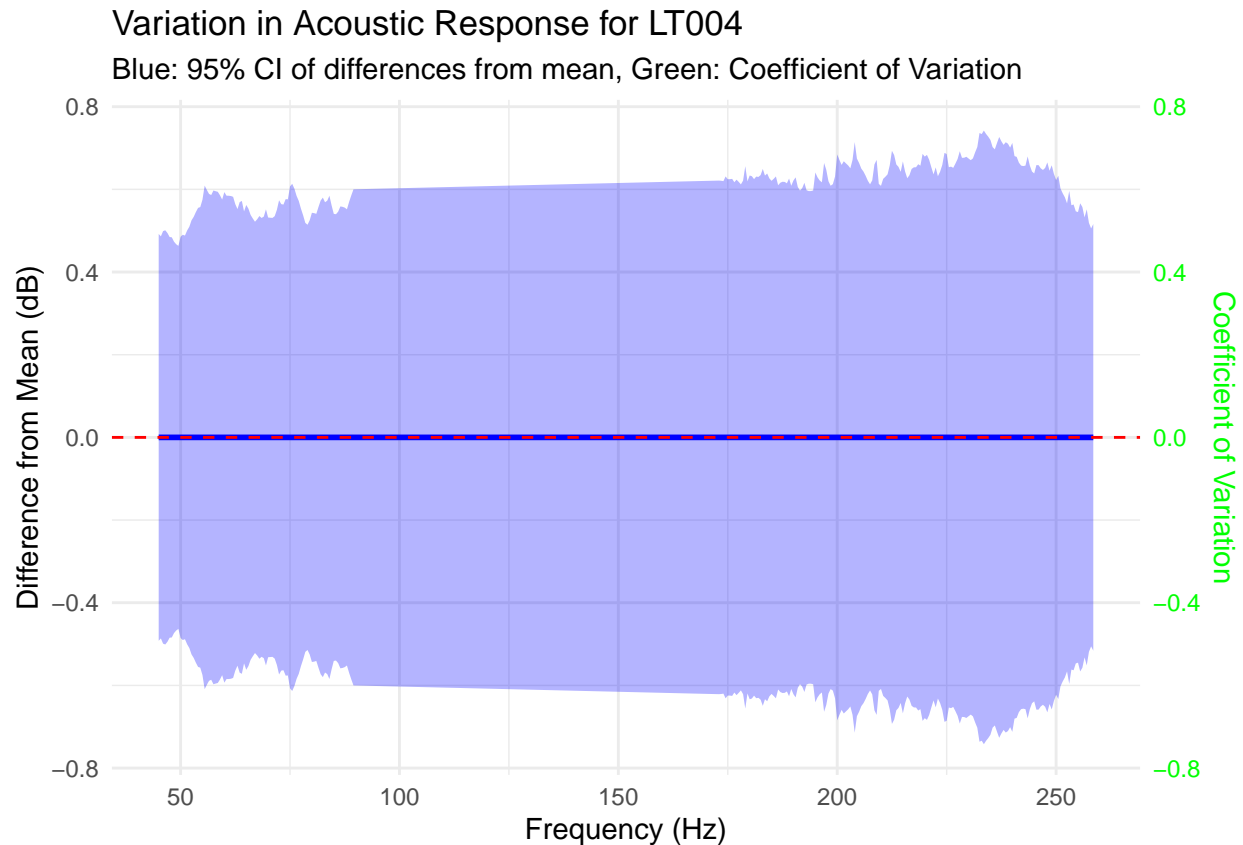
```
# Calculate confidence intervals for the differences from mean
ci_data <- LT001_frequency_long %>%
  group_by(Frequency) %>%
  summarize(
```

```

mean_diff = mean(diff_from_mean, na.rm = TRUE),
sd_diff = sd(diff_from_mean, na.rm = TRUE),
n = n(),
# Calculate 95% confidence interval
ci_lower = mean_diff - qt(0.975, n-1) * sd_diff / sqrt(n),
ci_upper = mean_diff + qt(0.975, n-1) * sd_diff / sqrt(n),
# Calculate variability metrics
cv = sd_diff / abs(mean_diff + 0.0001), # Coefficient of variation (adding small constant to avoid
range = max(diff_from_mean, na.rm = TRUE) - min(diff_from_mean, na.rm = TRUE)
)

# Create a visualization of the confidence intervals
ggplot(ci_data, aes(x = Frequency)) +
  # Add confidence interval as ribbon
  geom_ribbon(aes(ymin = ci_lower, ymax = ci_upper), alpha = 0.3, fill = "blue") +
  # Add mean line
  geom_line(aes(y = mean_diff), color = "blue", linewidth = 1) +
  # Add zero reference line
  geom_hline(yintercept = 0, linetype = "dashed", color = "red") +
  # Add variability plot
  # geom_line(aes(y = cv), color = "green", linewidth = 1) +
  # Create second y-axis for coefficient of variation
  scale_y_continuous(
    name = "Difference from Mean (dB)",
    sec.axis = sec_axis(~ ., name = "Coefficient of Variation")
  ) +
  labs(
    title = paste("Variation in Acoustic Response for", unique(LT001_frequency_long$fishNum)),
    subtitle = "Blue: 95% CI of differences from mean, Green: Coefficient of Variation",
    x = "Frequency (Hz)"
  ) +
  theme_minimal() +
  theme(
    axis.title.y.right = element_text(color = "green"),
    axis.text.y.right = element_text(color = "green")
  )

```



Principal Component Analysis We want to perform PCA in Lake Trout and we want to see if specified frequencies is contributing strongly to the variance of Lake Trout.

aggregating dataframe into mean frequencies by each fish and scale

```
LakeTrout_agg <- (
  LakeTrout
  |> group_by(fishNum)
  |> filter(fishNum != "LT008") ## contains missing bal
  |> summarise(across(starts_with("F"), mean, na.rm = TRUE))
  |> ungroup()
  |> dplyr::select(-fishNum)
  |> scale()
)
```

```
## Warning: There was 1 warning in `summarise()`.
## i In argument: `across(starts_with("F"), mean, na.rm = TRUE)`.
## i In group 1: `fishNum = "LT001"`.
## Caused by warning:
## ! The `...` argument of `across()` is deprecated as of dplyr 1.1.0.
## Supply arguments directly to `.fns` through an anonymous function instead.
##
## # Previously
##   across(a:b, mean, na.rm = TRUE)
##
## # Now
##   across(a:b, \(x) mean(x, na.rm = TRUE))
```

```
LakeTrout_pca <- PCA(LakeTrout_agg, graph = FALSE)
LakeTrout_pca$eig
```

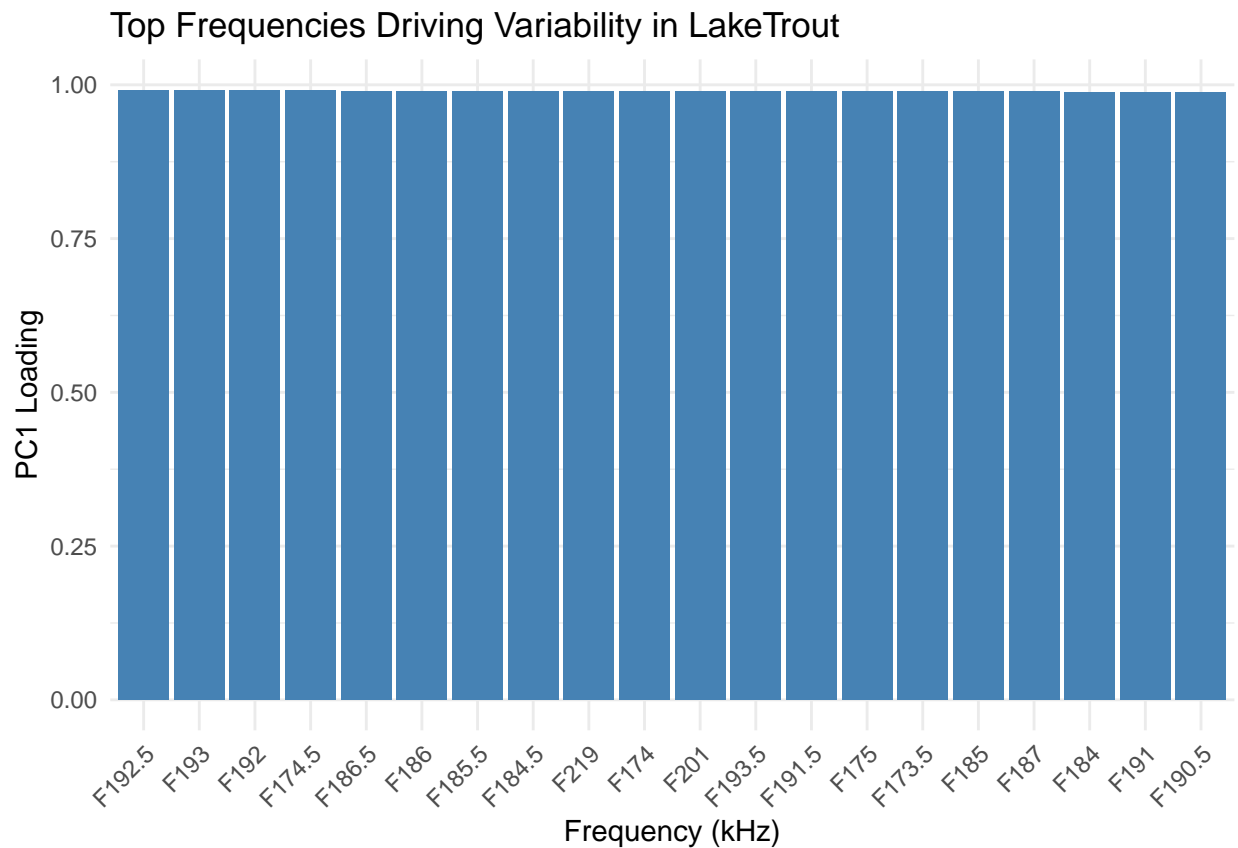
```
##          eigenvalue percentage of variance cumulative percentage of variance
## comp 1  244.21489472          93.211791879          93.21179
## comp 2   11.98462387           4.574283918          97.78608
## comp 3    1.27549045           0.486828415          98.27290
## comp 4    1.05141984           0.401305283          98.67421
## comp 5    0.91561696           0.349472122          99.02368
## comp 6    0.60554067           0.231122395          99.25480
## comp 7    0.41031229           0.156607745          99.41141
## comp 8    0.26497132           0.101134090          99.51255
## comp 9    0.23101183           0.088172453          99.60072
## comp 10   0.22164218           0.084596254          99.68531
## comp 11   0.17298864           0.066026199          99.75134
## comp 12   0.13547558           0.051708235          99.80305
## comp 13   0.12137783           0.046327415          99.84938
## comp 14   0.10342138           0.039473811          99.88885
## comp 15   0.09071791           0.034625156          99.92348
## comp 16   0.07759171           0.029615158          99.95309
## comp 17   0.06594847           0.025171171          99.97826
## comp 18   0.03107329           0.011860036          99.99012
## comp 19   0.02588105           0.009878265         100.00000
```

```
LakeTrout_loadings_pc1 <-(
  LakeTrout_pca$var$coord[, 1]
  |> as.data.frame()
  |> rename>Loading = "LakeTrout_pca$var$coord[, 1]"
  |> mutate(Frequency = rownames(LakeTrout_pca$var$coord))
  |> arrange(desc(abs>Loading)))
)
# loadings_pc1
LakeTrout_loadings_pc1_top_frequencies <- LakeTrout_loadings_pc1 |> head(20)
print(LakeTrout_loadings_pc1_top_frequencies)
```

```
##          Loading Frequency
## F192.5 0.9917246      F192.5
## F193   0.9911145      F193
## F192   0.9906835      F192
## F174.5 0.9906645      F174.5
## F186.5 0.9901207      F186.5
## F186   0.9898355      F186
## F185.5 0.9898325      F185.5
## F184.5 0.9898172      F184.5
## F219   0.9897545      F219
## F174   0.9895466      F174
## F201   0.9895126      F201
## F193.5 0.9894501      F193.5
## F191.5 0.9893288      F191.5
## F175   0.9888396      F175
## F173.5 0.9887690      F173.5
## F185   0.9887283      F185
## F187   0.9886458      F187
## F184   0.9884787      F184
```

```
## F191 0.9879446 F191
## F190.5 0.9878550 F190.5
```

```
ggplot(LakeTrout_loadings_pc1_top_frequencies, aes(x = reorder(Frequency, -abs>Loading)), y = Loading))
geom_bar(stat = "identity", fill = "steelblue") +
labs(title = "Top Frequencies Driving Variability in LakeTrout",
x = "Frequency (kHz)", y = "PC1 Loading") +
theme_minimal() +
theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



```
cor_mat <- cor(LakeTrout_agg) |> as.data.frame()
cor_mat |> head()
```

```
##          F45      F45.5      F46      F46.5      F47      F47.5      F48
## F45  1.0000000 0.9996056 0.9984781 0.9963892 0.9938490 0.9907588 0.9873195
## F45.5 0.9996056 1.0000000 0.9994420 0.9977076 0.9952274 0.9922555 0.9889508
## F46  0.9984781 0.9994420 1.0000000 0.9991627 0.9970995 0.9944152 0.9912062
## F46.5 0.9963892 0.9977076 0.9991627 1.0000000 0.9992304 0.9974915 0.9950857
## F47  0.9938490 0.9952274 0.9970995 0.9992304 1.0000000 0.9993983 0.9979255
## F47.5 0.9907588 0.9922555 0.9944152 0.9974915 0.9993983 1.0000000 0.9995045
##          F48.5      F49      F49.5      F50      F50.5      F51      F51.5
## F45  0.9854044 0.9867684 0.9875213 0.9879263 0.9864481 0.9846682 0.9823516
## F45.5 0.9872332 0.9884595 0.9890266 0.9890938 0.9875503 0.9859041 0.9838920
## F46  0.9899854 0.9910707 0.9913655 0.9911944 0.9896404 0.9880390 0.9861063
## F46.5 0.9942902 0.9948713 0.9945583 0.9936412 0.9917328 0.9898139 0.9879700
## F47  0.9972634 0.9976006 0.9969827 0.9954719 0.9931085 0.9906675 0.9892975
## F47.5 0.9990207 0.9990787 0.9982728 0.9964518 0.9938612 0.9912456 0.9897838
```

##		F52	F52.5	F53	F53.5	F54	F54.5	F55
##	F45	0.9784427	0.9752323	0.9749124	0.9758274	0.9793099	0.9835452	0.9865828
##	F45.5	0.9802075	0.9773009	0.9769559	0.9776729	0.9810197	0.9851049	0.9878685
##	F46	0.9829682	0.9805702	0.9800609	0.9805476	0.9836110	0.9872657	0.9894391
##	F46.5	0.9852680	0.9833675	0.9826165	0.9825025	0.9848524	0.9877872	0.9891125
##	F47	0.9868246	0.9849949	0.9844540	0.9838143	0.9851698	0.9869363	0.9871556
##	F47.5	0.9870537	0.9850853	0.9841743	0.9827655	0.9833158	0.9843635	0.9839844
##		F55.5	F56	F56.5	F57	F57.5	F58	F58.5
##	F45	0.9882379	0.9880204	0.9868946	0.9849491	0.9826938	0.9790282	0.9742466
##	F45.5	0.9893801	0.9891469	0.9880760	0.9865137	0.9845111	0.9811511	0.9767838
##	F46	0.9904948	0.9904018	0.9896441	0.9886293	0.9868956	0.9840928	0.9805374
##	F46.5	0.9894972	0.9889457	0.9883278	0.9880547	0.9869264	0.9850078	0.9824732
##	F47	0.9869529	0.9858366	0.9851733	0.9853552	0.9846066	0.9832537	0.9813668
##	F47.5	0.9833049	0.9818024	0.9810931	0.9815788	0.9811626	0.9803480	0.9789828
##		F59	F59.5	F60	F60.5	F61	F61.5	F62
##	F45	0.9726974	0.9729084	0.9747031	0.9755038	0.9760930	0.9759473	0.9755610
##	F45.5	0.9755277	0.9758662	0.9774892	0.9781902	0.9786538	0.9784071	0.9779916
##	F46	0.9798032	0.9803538	0.9819924	0.9827455	0.9832965	0.9831439	0.9827446
##	F46.5	0.9826682	0.9838174	0.9856276	0.9865472	0.9872740	0.9870454	0.9864016
##	F47	0.9822194	0.9841360	0.9863297	0.9876743	0.9888113	0.9887047	0.9880671
##	F47.5	0.9805389	0.9831913	0.9858067	0.9875771	0.9891117	0.9890382	0.9884401
##		F62.5	F63	F63.5	F64	F64.5	F65	F65.5
##	F45	0.9749474	0.9763192	0.9770825	0.9752035	0.9721714	0.9702102	0.9690829
##	F45.5	0.9773644	0.9785647	0.9791646	0.9773056	0.9743185	0.9721607	0.9707896
##	F46	0.9819044	0.9827168	0.9829475	0.9809075	0.9778756	0.9758360	0.9744647
##	F46.5	0.9853464	0.9856095	0.9853228	0.9830642	0.9798341	0.9779481	0.9766652
##	F47	0.9870246	0.9868557	0.9862236	0.9840216	0.9806383	0.9788223	0.9773040
##	F47.5	0.9876186	0.9873080	0.9864360	0.9839550	0.9801991	0.9782156	0.9766181
##		F66	F66.5	F67	F67.5	F68	F68.5	F69
##	F45	0.9693286	0.9694006	0.9693635	0.9701633	0.9729604	0.9749580	0.9735983
##	F45.5	0.9705929	0.9702044	0.9698984	0.9707058	0.9736817	0.9761107	0.9755301
##	F46	0.9743693	0.9737714	0.9735222	0.9744489	0.9774257	0.9796496	0.9793211
##	F46.5	0.9770049	0.9764910	0.9762480	0.9772222	0.9800893	0.9819148	0.9816792
##	F47	0.9775724	0.9774012	0.9769491	0.9778995	0.9807999	0.9823260	0.9818747
##	F47.5	0.9771173	0.9776056	0.9775672	0.9787093	0.9817307	0.9832829	0.9828455
##		F69.5	F70	F70.5	F71	F71.5	F72	F72.5
##	F45	0.9713382	0.9687595	0.9662977	0.9653687	0.9674539	0.9686952	0.9681880
##	F45.5	0.9738804	0.9715984	0.9692356	0.9684252	0.9705783	0.9715785	0.9708675
##	F46	0.9777119	0.9753733	0.9730581	0.9723520	0.9745443	0.9755351	0.9748343
##	F46.5	0.9798350	0.9772485	0.9749231	0.9742504	0.9764004	0.9774216	0.9770064
##	F47	0.9796851	0.9768184	0.9742553	0.9732771	0.9755322	0.9765071	0.9761753
##	F47.5	0.9804991	0.9774544	0.9747710	0.9737119	0.9758441	0.9766067	0.9762177
##		F73	F73.5	F74	F74.5	F75	F75.5	F76
##	F45	0.9643414	0.9665943	0.9708638	0.9712180	0.9683276	0.9643715	0.9647953
##	F45.5	0.9668647	0.9686072	0.9723308	0.9721909	0.9689943	0.9648905	0.9653424
##	F46	0.9709055	0.9720941	0.9751185	0.9743950	0.9712244	0.9674893	0.9683512
##	F46.5	0.9733277	0.9742328	0.9767563	0.9756761	0.9725105	0.9692312	0.9706053
##	F47	0.9720753	0.9730024	0.9757517	0.9748336	0.9720097	0.9691752	0.9708732
##	F47.5	0.9719202	0.9726238	0.9750131	0.9737850	0.9708668	0.9682587	0.9703683
##		F76.5	F77	F77.5	F78	F78.5	F79	F79.5
##	F45	0.9670242	0.9686722	0.9695534	0.9688760	0.9672709	0.9637791	0.9592755
##	F45.5	0.9680940	0.9699244	0.9710981	0.9702755	0.9682266	0.9642796	0.9592677
##	F46	0.9718798	0.9737178	0.9749261	0.9740485	0.9719117	0.9679660	0.9626831
##	F46.5	0.9742707	0.9756156	0.9766900	0.9757167	0.9735335	0.9697745	0.9645636

##	F47	0.9746522	0.9757820	0.9768712	0.9759442	0.9737483	0.9699725	0.9651319
##	F47.5	0.9742646	0.9754484	0.9765460	0.9756221	0.9733571	0.9695004	0.9644536
##		F80	F80.5	F81	F81.5	F82	F82.5	F83
##	F45	0.9532876	0.9511268	0.9517823	0.9556073	0.9574697	0.9581440	0.9602334
##	F45.5	0.9528631	0.9508473	0.9519910	0.9560693	0.9583415	0.9594043	0.9619342
##	F46	0.9556484	0.9535186	0.9545732	0.9583147	0.9600952	0.9605580	0.9625559
##	F46.5	0.9573167	0.9552776	0.9561451	0.9593051	0.9602870	0.9599690	0.9610987
##	F47	0.9582841	0.9566196	0.9573339	0.9599221	0.9599652	0.9587307	0.9587519
##	F47.5	0.9575909	0.9559968	0.9564101	0.9584435	0.9579054	0.9564316	0.9562671
##		F83.5	F84	F84.5	F85	F85.5	F86	F86.5
##	F45	0.9590305	0.9571245	0.9573435	0.9556413	0.9552736	0.9567014	0.9565901
##	F45.5	0.9612836	0.9596192	0.9601070	0.9586652	0.9583425	0.9598657	0.9597721
##	F46	0.9620461	0.9602928	0.9609014	0.9597421	0.9595353	0.9612628	0.9612409
##	F46.5	0.9603609	0.9585003	0.9593386	0.9586490	0.9585151	0.9606123	0.9607602
##	F47	0.9574204	0.9554590	0.9562851	0.9555293	0.9550756	0.9575098	0.9580271
##	F47.5	0.9549700	0.9530404	0.9540247	0.9535225	0.9531281	0.9556724	0.9565174
##		F87	F87.5	F88	F88.5	F89	F89.5	F173
##	F45	0.9574097	0.9598496	0.9656046	0.9687327	0.9695074	0.9686576	0.8813356
##	F45.5	0.9604769	0.9624892	0.9676919	0.9703363	0.9702609	0.9686341	0.8836910
##	F46	0.9620685	0.9640473	0.9690843	0.9719469	0.9715406	0.9696071	0.8889647
##	F46.5	0.9616690	0.9637103	0.9686105	0.9718969	0.9714925	0.9696770	0.8917619
##	F47	0.9591011	0.9610838	0.9665572	0.9701155	0.9699025	0.9681438	0.8913108
##	F47.5	0.9578091	0.9601245	0.9658643	0.9696870	0.9695886	0.9676789	0.8911367
##		F173.5	F174	F174.5	F175	F175.5	F176	F176.5
##	F45	0.8814772	0.8810421	0.8834045	0.8798306	0.8670267	0.8489260	0.8490983
##	F45.5	0.8839726	0.8833285	0.8849828	0.8815669	0.8688293	0.8506633	0.8509417
##	F46	0.8891655	0.8878578	0.8880548	0.8845918	0.8722406	0.8541429	0.8545605
##	F46.5	0.8915497	0.8893972	0.8882559	0.8849893	0.8730501	0.8546588	0.8552488
##	F47	0.8899080	0.8869906	0.8858323	0.8827736	0.8707320	0.8517708	0.8524922
##	F47.5	0.8891889	0.8856715	0.8842160	0.8813939	0.8693702	0.8499375	0.8507694
##		F177	F177.5	F178	F178.5	F179	F179.5	F180
##	F45	0.8640953	0.8766028	0.8846390	0.8806816	0.8717291	0.8623332	0.8631477
##	F45.5	0.8655766	0.8782449	0.8862591	0.8829334	0.8746567	0.8658677	0.8669211
##	F46	0.8685362	0.8809136	0.8886960	0.8864997	0.8795427	0.8717874	0.8733244
##	F46.5	0.8685224	0.8803432	0.8876107	0.8862746	0.8805027	0.8738929	0.8755586
##	F47	0.8650202	0.8762372	0.8834710	0.8823050	0.8766323	0.8703765	0.8722364
##	F47.5	0.8627065	0.8735401	0.8806376	0.8795769	0.8739760	0.8683094	0.8704206
##		F180.5	F181	F181.5	F182	F182.5	F183	F183.5
##	F45	0.8654168	0.8704839	0.8677580	0.8695321	0.8748813	0.8826885	0.8861074
##	F45.5	0.8691107	0.8734816	0.8702658	0.8715584	0.8764993	0.8842940	0.8875695
##	F46	0.8757515	0.8794224	0.8759184	0.8769556	0.8814191	0.8893540	0.8920466
##	F46.5	0.8779132	0.8808335	0.8775290	0.8784588	0.8828894	0.8914265	0.8936175
##	F47	0.8743899	0.8776247	0.8748340	0.8762460	0.8812647	0.8900543	0.8924706
##	F47.5	0.8724474	0.8753421	0.8726361	0.8740840	0.8792534	0.8882148	0.8909228
##		F184	F184.5	F185	F185.5	F186	F186.5	F187
##	F45	0.8902087	0.8899975	0.8860738	0.8879036	0.8827378	0.8788590	0.8749909
##	F45.5	0.8913532	0.8910028	0.8871659	0.8889536	0.8842905	0.8805274	0.8769116
##	F46	0.8955622	0.8951811	0.8913020	0.8928568	0.8886567	0.8848546	0.8813356
##	F46.5	0.8968817	0.8968364	0.8932051	0.8943968	0.8906447	0.8863434	0.8827183
##	F47	0.8954086	0.8951577	0.8910980	0.8922472	0.8889687	0.8847599	0.8815075
##	F47.5	0.8939633	0.8940610	0.8902659	0.8914994	0.8885209	0.8842388	0.8811923
##		F187.5	F188	F188.5	F189	F189.5	F190	F190.5
##	F45	0.8670948	0.8736199	0.8741425	0.8752081	0.8774032	0.8768977	0.8797257
##	F45.5	0.8688889	0.8750852	0.8753203	0.8762507	0.8786040	0.8783831	0.8814973

##	F46	0.8731630	0.8788583	0.8789595	0.8798426	0.8823442	0.8824717	0.8853695
##	F46.5	0.8743315	0.8797977	0.8801899	0.8811792	0.8840614	0.8852015	0.8881963
##	F47	0.8732634	0.8784382	0.8789759	0.8800912	0.8832836	0.8851057	0.8886781
##	F47.5	0.8730249	0.8782978	0.8790229	0.8801188	0.8835117	0.8858142	0.8896689
##	F191	F191.5	F192	F192.5	F193	F193.5	F194	
##	F45	0.8781818	0.8836352	0.8860715	0.8896868	0.8883366	0.8853000	0.8757910
##	F45.5	0.8801050	0.8854476	0.8875401	0.8909004	0.8897272	0.8869828	0.8776980
##	F46	0.8839128	0.8886737	0.8903256	0.8939006	0.8934861	0.8914922	0.8822523
##	F46.5	0.8867526	0.8911166	0.8924067	0.8961781	0.8963447	0.8947025	0.8854790
##	F47	0.8869798	0.8906492	0.8915331	0.8956676	0.8963286	0.8947016	0.8854759
##	F47.5	0.8879203	0.8911790	0.8916840	0.8957233	0.8961188	0.8939614	0.8850069
##	F194.5	F195	F195.5	F196	F196.5	F197	F197.5	
##	F45	0.8725687	0.8690538	0.8647146	0.8586165	0.8520763	0.8417781	0.8461424
##	F45.5	0.8740107	0.8700650	0.8657652	0.8592377	0.8529951	0.8426675	0.8470977
##	F46	0.8778125	0.8728617	0.8683224	0.8611408	0.8556435	0.8453604	0.8497123
##	F46.5	0.8805018	0.8747703	0.8699064	0.8619751	0.8569878	0.8464986	0.8506163
##	F47	0.8807893	0.8750064	0.8700973	0.8616713	0.8564983	0.8453100	0.8489539
##	F47.5	0.8805758	0.8749140	0.8702178	0.8616769	0.8562981	0.8446120	0.8480549
##	F198	F198.5	F199	F199.5	F200	F200.5	F201	
##	F45	0.8469048	0.8442648	0.8436048	0.8546200	0.8658122	0.8707601	0.8738943
##	F45.5	0.8479169	0.8452724	0.8445146	0.8554607	0.8666075	0.8718054	0.8750523
##	F46	0.8505671	0.8479337	0.8470889	0.8577636	0.8687639	0.8742796	0.8777576
##	F46.5	0.8514519	0.8481006	0.8466847	0.8567185	0.8680714	0.8745390	0.8786997
##	F47	0.8497251	0.8456834	0.8440536	0.8534941	0.8653302	0.8727755	0.8773325
##	F47.5	0.8488437	0.8443403	0.8425504	0.8515378	0.8633237	0.8711308	0.8757898
##	F201.5	F202	F202.5	F203	F203.5	F204	F204.5	
##	F45	0.8672311	0.8678472	0.8590229	0.8540326	0.8499832	0.8479032	0.8438723
##	F45.5	0.8683216	0.8689468	0.8602023	0.8549402	0.8508695	0.8486307	0.8442134
##	F46	0.8713431	0.8722081	0.8634012	0.8579811	0.8538991	0.8514670	0.8465810
##	F46.5	0.8730778	0.8743564	0.8651726	0.8597230	0.8556393	0.8530446	0.8477358
##	F47	0.8720325	0.8732063	0.8632490	0.8576906	0.8533077	0.8511095	0.8464261
##	F47.5	0.8705795	0.8716900	0.8613167	0.8558843	0.8515709	0.8492915	0.8446808
##	F205	F205.5	F206	F206.5	F207	F207.5	F208	
##	F45	0.8438744	0.8530104	0.8576317	0.8559934	0.8598971	0.8641325	0.8581053
##	F45.5	0.8439907	0.8531335	0.8576581	0.8560001	0.8596715	0.8641711	0.8584839
##	F46	0.8460521	0.8550152	0.8593349	0.8573716	0.8603399	0.8649209	0.8596328
##	F46.5	0.8472091	0.8558373	0.8594970	0.8572746	0.8601430	0.8653929	0.8607746
##	F47	0.8461299	0.8545386	0.8575653	0.8550196	0.8583274	0.8641634	0.8598480
##	F47.5	0.8445502	0.8526318	0.8553434	0.8526969	0.8560408	0.8622156	0.8585043
##	F208.5	F209	F209.5	F210	F210.5	F211	F211.5	
##	F45	0.8436658	0.8337528	0.8364794	0.8436289	0.8498493	0.8563687	0.8546032
##	F45.5	0.8439564	0.8338900	0.8366601	0.8440762	0.8505136	0.8573123	0.8558820
##	F46	0.8450302	0.8343373	0.8364582	0.8437715	0.8500952	0.8577998	0.8572976
##	F46.5	0.8463106	0.8345945	0.8351880	0.8421351	0.8485884	0.8575730	0.8581897
##	F47	0.8455187	0.8334624	0.8332370	0.8399656	0.8463606	0.8558189	0.8566819
##	F47.5	0.8445140	0.8322650	0.8314311	0.8379433	0.8444859	0.8542300	0.8552172
##	F212	F212.5	F213	F213.5	F214	F214.5	F215	
##	F45	0.8574469	0.8608665	0.8598258	0.8585295	0.8571250	0.8631257	0.8639994
##	F45.5	0.8588150	0.8621803	0.8606818	0.8591382	0.8575760	0.8634090	0.8644789
##	F46	0.8607082	0.8641004	0.8612378	0.8588554	0.8568647	0.8626664	0.8643587
##	F46.5	0.8621732	0.8654905	0.8610791	0.8572028	0.8542674	0.8596574	0.8617882
##	F47	0.8607755	0.8641384	0.8593709	0.8545897	0.8505908	0.8554287	0.8572417
##	F47.5	0.8594094	0.8626875	0.8575466	0.8520458	0.8470016	0.8509378	0.8524917
##	F215.5	F216	F216.5	F217	F217.5	F218	F218.5	

##	F45	0.8699774	0.8655652	0.8544398	0.8476136	0.8406149	0.8480860	0.8670758
##	F45.5	0.8707068	0.8665095	0.8552435	0.8485549	0.8418781	0.8490780	0.8675653
##	F46	0.8717291	0.8687689	0.8577830	0.8512354	0.8448554	0.8513976	0.8686805
##	F46.5	0.8706073	0.8692267	0.8585103	0.8521968	0.8458881	0.8520777	0.8686840
##	F47	0.8666128	0.8659400	0.8557386	0.8503158	0.8445178	0.8507204	0.8669878
##	F47.5	0.8624892	0.8628803	0.8533305	0.8485553	0.8432201	0.8493403	0.8651829
##	F219	F219.5	F220	F220.5	F221	F221.5	F222	
##	F45	0.8802872	0.8748360	0.8632657	0.8626737	0.8535032	0.8512038	0.8523668
##	F45.5	0.8805856	0.8748207	0.8630290	0.8624480	0.8539021	0.8517935	0.8532623
##	F46	0.8813972	0.8758788	0.8644312	0.8642142	0.8567709	0.8545042	0.8554348
##	F46.5	0.8816106	0.8763989	0.8651434	0.8653597	0.8588058	0.8562988	0.8565390
##	F47	0.8797898	0.8743640	0.8628216	0.8633505	0.8570355	0.8547846	0.8552688
##	F47.5	0.8778475	0.8722983	0.8607982	0.8617637	0.8557516	0.8537733	0.8541533
##	F222.5	F223	F223.5	F224	F224.5	F225	F225.5	
##	F45	0.8552939	0.8669005	0.8771203	0.8898932	0.8924879	0.8868608	0.8736940
##	F45.5	0.8557416	0.8663970	0.8763824	0.8891025	0.8920151	0.8866512	0.8738698
##	F46	0.8563034	0.8647374	0.8745288	0.8873953	0.8910152	0.8866663	0.8746342
##	F46.5	0.8559894	0.8623433	0.8719194	0.8852852	0.8901199	0.8873201	0.8760995
##	F47	0.8538928	0.8594401	0.8685292	0.8819444	0.8876229	0.8856241	0.8747964
##	F47.5	0.8521490	0.8565710	0.8649505	0.8786048	0.8846443	0.8830639	0.8725628
##	F226	F226.5	F227	F227.5	F228	F228.5	F229	
##	F45	0.8633489	0.8433197	0.8393526	0.8378730	0.8374162	0.8377274	0.8339260
##	F45.5	0.8635477	0.8433070	0.8394750	0.8382265	0.8373129	0.8372811	0.8334922
##	F46	0.8640279	0.8430699	0.8385424	0.8369201	0.8355700	0.8355429	0.8313964
##	F46.5	0.8648117	0.8424705	0.8368232	0.8350905	0.8342845	0.8352030	0.8308267
##	F47	0.8630437	0.8391946	0.8322364	0.8305419	0.8309879	0.8337894	0.8302466
##	F47.5	0.8607421	0.8363091	0.8290740	0.8277729	0.8288704	0.8322977	0.8287450
##	F229.5	F230	F230.5	F231	F231.5	F232	F232.5	
##	F45	0.8467275	0.8565762	0.8656352	0.8576426	0.8609871	0.8572262	0.8440392
##	F45.5	0.8463118	0.8562155	0.8656927	0.8583998	0.8618968	0.8579669	0.8445246
##	F46	0.8438914	0.8539772	0.8642258	0.8586509	0.8623284	0.8579843	0.8437248
##	F46.5	0.8424901	0.8525663	0.8632583	0.8591185	0.8628905	0.8585533	0.8429876
##	F47	0.8412986	0.8507444	0.8603071	0.8552141	0.8594089	0.8558589	0.8397491
##	F47.5	0.8391313	0.8481947	0.8577755	0.8530665	0.8572351	0.8538578	0.8377520
##	F233	F233.5	F234	F234.5	F235	F235.5	F236	
##	F45	0.8333317	0.8366802	0.8408595	0.8462262	0.8568916	0.8535567	0.8490322
##	F45.5	0.8338303	0.8366961	0.8407625	0.8457496	0.8561975	0.8528897	0.8481310
##	F46	0.8324186	0.8341979	0.8380735	0.8428337	0.8530254	0.8497737	0.8452907
##	F46.5	0.8300360	0.8302295	0.8338234	0.8393436	0.8500462	0.8474654	0.8438331
##	F47	0.8260897	0.8254907	0.8288292	0.8354098	0.8469268	0.8450107	0.8414716
##	F47.5	0.8236486	0.8222212	0.8251759	0.8324872	0.8442446	0.8426725	0.8393617
##	F236.5	F237	F237.5	F238	F238.5	F239	F239.5	
##	F45	0.8407288	0.8307361	0.8302941	0.8371227	0.8303338	0.8195819	0.8048591
##	F45.5	0.8398633	0.8299363	0.8297264	0.8370725	0.8308804	0.8199862	0.8049946
##	F46	0.8380717	0.8287120	0.8286068	0.8365459	0.8310531	0.8199924	0.8047792
##	F46.5	0.8373178	0.8286419	0.8283989	0.8363450	0.8307988	0.8195812	0.8042413
##	F47	0.8346809	0.8263534	0.8260764	0.8336427	0.8280510	0.8174253	0.8024139
##	F47.5	0.8325299	0.8244403	0.8244350	0.8318175	0.8260560	0.8151364	0.7999009
##	F240	F240.5	F241	F241.5	F242	F242.5	F243	
##	F45	0.8012034	0.8119111	0.8232119	0.8205556	0.8241461	0.8246914	0.8189326
##	F45.5	0.8008836	0.8112852	0.8221050	0.8196869	0.8238432	0.8253657	0.8195798
##	F46	0.7999548	0.8093506	0.8196557	0.8183505	0.8240588	0.8271032	0.8206720
##	F46.5	0.7987836	0.8072055	0.8173106	0.8170406	0.8239599	0.8282860	0.8207863
##	F47	0.7962648	0.8037351	0.8139576	0.8133122	0.8206538	0.8250512	0.8175594

```
## F47.5 0.7929423 0.7998048 0.8097374 0.8094554 0.8172251 0.8220156 0.8143599
##      F243.5      F244      F244.5      F245      F245.5      F246      F246.5
## F45  0.8008462 0.7913604 0.7917053 0.7797381 0.8038966 0.7972928 0.7809050
## F45.5 0.8018708 0.7921430 0.7922611 0.7796716 0.8041698 0.7975864 0.7815122
## F46  0.8036701 0.7936316 0.7927343 0.7795146 0.8037592 0.7972902 0.7816752
## F46.5 0.8044560 0.7945117 0.7924711 0.7785146 0.8018015 0.7952315 0.7799219
## F47  0.8011025 0.7901081 0.7875208 0.7741376 0.7977175 0.7916288 0.7761487
## F47.5 0.7981415 0.7873565 0.7845421 0.7708189 0.7941973 0.7884395 0.7729537
##      F247      F247.5      F248      F248.5      F249      F249.5      F250
## F45  0.7592057 0.7496167 0.7466897 0.7476320 0.7650295 0.7769755 0.7854903
## F45.5 0.7594649 0.7497131 0.7468825 0.7476831 0.7649499 0.7769557 0.7853718
## F46  0.7598120 0.7499402 0.7474876 0.7476179 0.7640064 0.7764159 0.7849735
## F46.5 0.7584944 0.7483636 0.7469218 0.7475968 0.7632353 0.7763789 0.7849754
## F47  0.7548691 0.7442494 0.7426250 0.7435024 0.7593330 0.7722924 0.7810309
## F47.5 0.7520089 0.7415516 0.7405823 0.7419201 0.7573149 0.7703213 0.7791222
##      F250.5      F251      F251.5      F252      F252.5      F253      F253.5
## F45  0.7966254 0.8005155 0.8128418 0.8139394 0.8129073 0.8135229 0.8364870
## F45.5 0.7967630 0.8008432 0.8132548 0.8152107 0.8139524 0.8146988 0.8372672
## F46  0.7972893 0.8017937 0.8140174 0.8158160 0.8140244 0.8146342 0.8359513
## F46.5 0.7978170 0.8019768 0.8136590 0.8152507 0.8135780 0.8144136 0.8344865
## F47  0.7940566 0.7976597 0.8100188 0.8120208 0.8101070 0.8116255 0.8323072
## F47.5 0.7925026 0.7959519 0.8081004 0.8105999 0.8087133 0.8106671 0.8311265
##      F254      F254.5      F255      F255.5      F256      F256.5      F257
## F45  0.8500803 0.8512987 0.8462635 0.8490578 0.8640935 0.8672562 0.8587325
## F45.5 0.8508589 0.8523015 0.8478659 0.8511738 0.8655596 0.8681721 0.8602313
## F46  0.8507433 0.8533112 0.8498270 0.8531286 0.8659914 0.8677359 0.8602365
## F46.5 0.8505427 0.8535687 0.8508017 0.8532012 0.8638956 0.8651321 0.8586462
## F47  0.8478591 0.8506880 0.8468212 0.8487535 0.8594512 0.8613242 0.8562778
## F47.5 0.8469944 0.8498602 0.8456638 0.8467361 0.8564972 0.8589619 0.8551134
##      F257.5      F258      F258.5
## F45  0.8309907 0.8401535 0.8497166
## F45.5 0.8328851 0.8414124 0.8504737
## F46  0.8333260 0.8414542 0.8501398
## F46.5 0.8323266 0.8405863 0.8494949
## F47  0.8315986 0.8391294 0.8475065
## F47.5 0.8312648 0.8386555 0.8468001
```

Lake White Fish

```
is.na(LakeWhiteFish) |> sum()
```

PCA

```
## [1] 0
```

```
## aggregating dataframe into mean frquencies by each fish and scale
LakeWhiteFish_agg <- (
  LakeWhiteFish
  |> group_by(fishNum)
  |> summarise(across(starts_with("F"), mean, na.rm = TRUE))
  |> ungroup()
  |> dplyr::select(-fishNum)
  |> scale()
)
```

```
LakeWhiteFish_pca <- PCA(LakeWhiteFish_agg, graph = FALSE)
LakeWhiteFish_pca$eig
```

```
##          eigenvalue percentage of variance cumulative percentage of variance
## comp 1    231.9991409             88.54929044             88.54929
## comp 2     22.5857938              8.62053199             97.16982
## comp 3       2.9915858              1.14182662             98.31165
## comp 4       1.2695144              0.48454748             98.79620
## comp 5       1.2381232              0.47256612             99.26876
## comp 6       0.6835889              0.26091178             99.52967
## comp 7       0.5099489              0.19463698             99.72431
## comp 8       0.3544067              0.13526972             99.85958
## comp 9       0.2432860              0.09285724             99.95244
## comp 10      0.1246115              0.04756163            100.00000
```

```
LakeWhiteFish_loadings_pc1 <-(
  LakeWhiteFish_pca$var$coord[, 1]
  |> as.data.frame()
  |> rename>Loading = "LakeWhiteFish_pca$var$coord[, 1]"
  |> mutate(Frequency = rownames(LakeWhiteFish_pca$var$coord))
  |> arrange(desc(abs>Loading)))
)
# loadings_pc1
LakeWhiteFish_loadings_pc1_top_frequencies <- LakeWhiteFish_loadings_pc1 |> head(20)
print(LakeWhiteFish_loadings_pc1_top_frequencies)
```

```
##          Loading Frequency
## F177    0.9925150      F177
## F177.5  0.9923810      F177.5
## F181.5  0.9917162      F181.5
## F179    0.9916320      F179
## F176.5  0.9913896      F176.5
## F179.5  0.9913677      F179.5
## F178    0.9911983      F178
## F191.5  0.9910568      F191.5
## F192    0.9909740      F192
## F178.5  0.9909690      F178.5
## F182    0.9903404      F182
## F181    0.9902244      F181
## F187    0.9899987      F187
## F192.5  0.9897638      F192.5
## F189    0.9895014      F189
## F191    0.9894162      F191
## F180    0.9893366      F180
## F189.5  0.9893036      F189.5
## F180.5  0.9886951      F180.5
## F176    0.9886713      F176
```

```
is.na(SmallmouthBass) |> sum()
```

Smallmouth Bass

```
## [1] 0
```

```

## aggregating dataframe into mean frquencies by each fish and scale
SmallmouthBass_agg <- (
  SmallmouthBass
  |> group_by(fishNum)
  |> summarise(across(starts_with("F"), mean, na.rm = TRUE))
  |> ungroup()
  |> dplyr::select(-fishNum)
  |> scale()
)

SmallmouthBass_pca <- PCA(SmallmouthBass_agg, graph = FALSE)
SmallmouthBass_pca$eig

##          eigenvalue percentage of variance cumulative percentage of variance
## comp 1    213.3640082             81.4366443             81.43664
## comp 2     23.9921634              9.1573143             90.59396
## comp 3     11.5097038              4.3930167             94.98698
## comp 4      3.9931711              1.5241111             96.51109
## comp 5      2.5775514              0.9837982             97.49488
## comp 6      2.0178735              0.7701807             98.26507
## comp 7      1.3838672              0.5281936             98.79326
## comp 8      1.1034893              0.4211791             99.21444
## comp 9      0.9147164              0.3491284             99.56357
## comp 10     0.6858171              0.2617623             99.82533
## comp 11     0.4576387              0.1746713             100.00000

SmallmouthBass_loadings_pc1 <-(
  SmallmouthBass_pca$var$coord[, 1]
  |> as.data.frame()
  |> rename>Loading = "SmallmouthBass_pca$var$coord[, 1]"
  |> mutate(Frequency = rownames(SmallmouthBass_pca$var$coord))
  |> arrange(desc(abs>Loading)))
)

# loadings_pc1
SmallmouthBass_loadings_pc1_top_frequencies <- SmallmouthBass_loadings_pc1 |> head(20)
print(SmallmouthBass_loadings_pc1_top_frequencies)

##          Loading Frequency
## F208    0.9897487      F208
## F209    0.9890043      F209
## F209.5  0.9878411      F209.5
## F208.5  0.9869398      F208.5
## F184.5  0.9859878      F184.5
## F210.5  0.9857557      F210.5
## F210    0.9845922      F210
## F212    0.9834752      F212
## F184    0.9829311      F184
## F212.5  0.9822498      F212.5
## F211    0.9818086      F211
## F185    0.9815360      F185
## F207.5  0.9813842      F207.5
## F183.5  0.9804217      F183.5
## F211.5  0.9798649      F211.5
## F205    0.9793735      F205

```

```
## F205.5 0.9790389 F205.5
## F213.5 0.9784301 F213.5
## F207 0.9775466 F207
## F214 0.9772022 F214
```

```
(SmallmouthBass
  |> group_by(fishNum)
  |> summarise(across(starts_with("F"), mean, na.rm = TRUE))
  |> ungroup()
  |> dplyr::select(-fishNum)
  |> summarise(across(starts_with("F"), mean, na.rm = TRUE))
)
```

```
## # A tibble: 1 x 262
##      F45 F45.5 F46 F46.5 F47 F47.5 F48 F48.5 F49 F49.5 F50 F50.5 F51
##    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 -53.9 -53.5 -53.2 -52.8 -52.6 -52.4 -52.4 -52.3 -52.2 -52.1 -51.9 -51.9 -51.8
## # i 249 more variables: F51.5 <dbl>, F52 <dbl>, F52.5 <dbl>, F53 <dbl>,
## # F53.5 <dbl>, F54 <dbl>, F54.5 <dbl>, F55 <dbl>, F55.5 <dbl>, F56 <dbl>,
## # F56.5 <dbl>, F57 <dbl>, F57.5 <dbl>, F58 <dbl>, F58.5 <dbl>, F59 <dbl>,
## # F59.5 <dbl>, F60 <dbl>, F60.5 <dbl>, F61 <dbl>, F61.5 <dbl>, F62 <dbl>,
## # F62.5 <dbl>, F63 <dbl>, F63.5 <dbl>, F64 <dbl>, F64.5 <dbl>, F65 <dbl>,
## # F65.5 <dbl>, F66 <dbl>, F66.5 <dbl>, F67 <dbl>, F67.5 <dbl>, F68 <dbl>,
## # F68.5 <dbl>, F69 <dbl>, F69.5 <dbl>, F70 <dbl>, F70.5 <dbl>, F71 <dbl>, ...
```

Overall PCA

```
LT_mean_frequency <- (
  LakeTrout
  |> group_by(fishNum)
  |> filter(fishNum != "LT008")
  |> dplyr::select(matches("^F(1[7-9][0-9](\\.[0-9])?|2[0-5][0-9](\\.[0-9])?|260(\\.[0-9])?)$"))
  |> summarise(across(starts_with("F"), mean, na.rm = TRUE))
  |> ungroup()
  |> dplyr::select(-fishNum)
  |> summarise(across(starts_with("F"), mean, na.rm = TRUE))
)
```

```
## Adding missing grouping variables: `fishNum`
```

```
LT_mean_frequency |> head()
```

```
## # A tibble: 1 x 172
##      F173 F173.5 F174 F174.5 F175 F175.5 F176 F176.5 F177 F177.5 F178 F178.5
##    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 -48.9 -48.7 -48.5 -48.5 -48.5 -48.6 -48.8 -48.4 -48.1 -47.8 -47.5 -47.5
## # i 160 more variables: F179 <dbl>, F179.5 <dbl>, F180 <dbl>, F180.5 <dbl>,
## # F181 <dbl>, F181.5 <dbl>, F182 <dbl>, F182.5 <dbl>, F183 <dbl>,
## # F183.5 <dbl>, F184 <dbl>, F184.5 <dbl>, F185 <dbl>, F185.5 <dbl>,
## # F186 <dbl>, F186.5 <dbl>, F187 <dbl>, F187.5 <dbl>, F188 <dbl>,
## # F188.5 <dbl>, F189 <dbl>, F189.5 <dbl>, F190 <dbl>, F190.5 <dbl>,
## # F191 <dbl>, F191.5 <dbl>, F192 <dbl>, F192.5 <dbl>, F193 <dbl>,
## # F193.5 <dbl>, F194 <dbl>, F194.5 <dbl>, F195 <dbl>, F195.5 <dbl>, ...
```

```
LWF_mean_frequency <- (
  LakeWhiteFish
```

```

|> group_by(fishNum)
|> dplyr::select(matches("^F(1[7-9][0-9](\\.[0-9])?|2[0-5][0-9](\\.[0-9])?|260(\\.[0-9])?)$"))
|> summarise(across(starts_with("F"), mean, na.rm = TRUE))
|> ungroup()
|> dplyr::select(-fishNum)
|> summarise(across(starts_with("F"), mean, na.rm = TRUE))
)

```

Adding missing grouping variables: `fishNum`

```
LWF_mean_frequency |> head()
```

```

## # A tibble: 1 x 172
##   F173 F173.5 F174 F174.5 F175 F175.5 F176 F176.5 F177 F177.5 F178 F178.5
##   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 -50.9 -50.6 -50.5 -50.5 -50.5 -50.8 -50.9 -50.5 -50.0 -49.7 -49.4 -49.5
## # i 160 more variables: F179 <dbl>, F179.5 <dbl>, F180 <dbl>, F180.5 <dbl>,
## #   F181 <dbl>, F181.5 <dbl>, F182 <dbl>, F182.5 <dbl>, F183 <dbl>,
## #   F183.5 <dbl>, F184 <dbl>, F184.5 <dbl>, F185 <dbl>, F185.5 <dbl>,
## #   F186 <dbl>, F186.5 <dbl>, F187 <dbl>, F187.5 <dbl>, F188 <dbl>,
## #   F188.5 <dbl>, F189 <dbl>, F189.5 <dbl>, F190 <dbl>, F190.5 <dbl>,
## #   F191 <dbl>, F191.5 <dbl>, F192 <dbl>, F192.5 <dbl>, F193 <dbl>,
## #   F193.5 <dbl>, F194 <dbl>, F194.5 <dbl>, F195 <dbl>, F195.5 <dbl>, ...

```

```

SB_mean_frequency <- (
  SmallmouthBass
|> group_by(fishNum)
|> dplyr::select(matches("^F(1[7-9][0-9](\\.[0-9])?|2[0-5][0-9](\\.[0-9])?|260(\\.[0-9])?)$"))
|> summarise(across(starts_with("F"), mean, na.rm = TRUE))
|> ungroup()
|> dplyr::select(-fishNum)
|> summarise(across(starts_with("F"), mean, na.rm = TRUE))
)

```

Adding missing grouping variables: `fishNum`

```
SB_mean_frequency |> head()
```

```

## # A tibble: 1 x 172
##   F173 F173.5 F174 F174.5 F175 F175.5 F176 F176.5 F177 F177.5 F178 F178.5
##   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 -52.3 -52.1 -52.0 -52.1 -51.9 -52.1 -52.3 -52.2 -51.8 -51.4 -51.1 -51.0
## # i 160 more variables: F179 <dbl>, F179.5 <dbl>, F180 <dbl>, F180.5 <dbl>,
## #   F181 <dbl>, F181.5 <dbl>, F182 <dbl>, F182.5 <dbl>, F183 <dbl>,
## #   F183.5 <dbl>, F184 <dbl>, F184.5 <dbl>, F185 <dbl>, F185.5 <dbl>,
## #   F186 <dbl>, F186.5 <dbl>, F187 <dbl>, F187.5 <dbl>, F188 <dbl>,
## #   F188.5 <dbl>, F189 <dbl>, F189.5 <dbl>, F190 <dbl>, F190.5 <dbl>,
## #   F191 <dbl>, F191.5 <dbl>, F192 <dbl>, F192.5 <dbl>, F193 <dbl>,
## #   F193.5 <dbl>, F194 <dbl>, F194.5 <dbl>, F195 <dbl>, F195.5 <dbl>, ...

```

prepare fish species PCA comparison data

```
prepare_species_PCA_data <- function(species, mean_freq_df, loadings_df) {
```

```

  ## convey mean frequency data to long format
  species_long <- melt(
    mean_freq_df,
    variable.name = "Frequency",

```

```

    value.name = "TS"

  )
  ## removing "F" from frequency and make it numerical
  species_long$Frequency <- as.numeric(gsub("F", "",
                                           species_long$Frequency))
  loadings_df$Frequency <- as.numeric(gsub("F", "",
                                           loadings_df$Frequency))

  ## Add species name
  species_long$Species <- species

  ## join with loadings
  species_combined <- merge(
    species_long,
    loadings_df[, c("Frequency", "Loading")],
    by = "Frequency",
    all.x = TRUE
  )

  return(species_combined)
}

```

```

## prepare PCA data for each species
LakeTrout_PCA_data <- prepare_species_PCA_data(
  "Lake Trout",
  LT_mean_frequency,
  LakeTrout_loadings_pc1
)

```

```

## No id variables; using all as measure variables
LakeWhiteFish_PCA_data <- prepare_species_PCA_data(
  "Lake Whitefish",
  LWF_mean_frequency,
  LakeWhiteFish_loadings_pc1
)

```

```

## No id variables; using all as measure variables
SmallmouthBass_PCA_data <- prepare_species_PCA_data(
  "Smallmouth Bass",
  SB_mean_frequency,
  SmallmouthBass_loadings_pc1
)

```

```

## No id variables; using all as measure variables
all_species_PCA_data <- rbind(
  LakeTrout_PCA_data,
  LakeWhiteFish_PCA_data,
  SmallmouthBass_PCA_data
)

```

```

all_species_PCA_data |> head()

```

```

##   Frequency      TS   Species   Loading

```



```

## 1      173.0 -48.86743 Lake Trout 0.9871391
## 2      173.5 -48.68770 Lake Trout 0.9887690
## 3      174.0 -48.53021 Lake Trout 0.9895466
## 4      174.5 -48.46775 Lake Trout 0.9906645
## 5      175.0 -48.45928 Lake Trout 0.9888396
## 6      175.5 -48.63499 Lake Trout 0.9829606

## create plots to show PCA loadings and TS_mean to visualize the PCA data
species_colors <- c(
  "Lake Trout" = "#1f77b4",
  "Lake Whitefish" = "#2ca02c",
  "Smallmouth Bass" = "#ff7f0e"
)

## PCA loading plots
all_species_PCA_plot <- (
  ggplot(all_species_PCA_data,
    aes(x = Frequency, y = Loading, color = Species))
  + geom_line(linewidth = 0.5)
  + scale_color_manual(values = species_colors)
  + labs(
    title = "PC1 Loadings by species",
    y = "PC1 Loading"
  )
  + theme(
    axis.title.x = element_blank(),
    axis.text.x = element_blank(),
    legend.position = "none"
  )
  + theme_minimal()
)

## TS_mean plots
all_species_TS_mean_plot <- (
  ggplot(all_species_PCA_data,
    aes(x = Frequency, y = TS, color = Species))
  + geom_line(linewidth = 0.8)
  + scale_color_manual(values = species_colors)
  + labs(
    title = "Mean Target Strength by Species",
    y = "Target Strength",
    x = "Frequency"
  )
  + theme(
    axis.text.x = element_text(angle = 45, hjust = 1),
    legend.position = "bottom"
  )
  + theme_minimal()
)

## combined plots
all_species_PCA_combined_plot <- (
  all_species_PCA_plot / all_species_TS_mean_plot
  + plot_layout(heights = c(1, 1.2))
)

```

```
)  
all_species_PCA_combined_plot
```

