zoopGAM.R

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```
#GAM analysis for FASTR zooplankton

library(tidyverse)
library(lubridate)
library(scales)
library(knitr)
library(mgcv)
library(lme4)
library(car)
library(emmeans)
library(gratia)
library(here)
library(forcats)
# Source functions
source(here("global_ndfa_funcs.R"))
source(here("Water_Quality/global_wq_funcs.R"))

#zooplankton data from Mallory and Nicole (biomass)
zoopNDFAv2<-read.csv("Zoop_code/zoop_NDFA_v2.csv", stringsAsFactors = FALSE)
#data organization and cleanup
#change to factors and organize sample period levels
zoopNDFAv2$SamplePeriod <- factor(zoopNDFAv2$SamplePeriod,levels = c("Before","During","After"
))
zoopNDFAv2$StationCode <- factor(zoopNDFAv2$StationCode)

#create regions for station groups
zoopNDFAv2$Region <- fct_collapse(zoopNDFAv2$StationCode,UpperYolo=c("RD22","I80"),
                                  MiddleSacRiver=c("SHR"),
                                  LowerYolo=c("LIS","STTD"),
                                  ColusaDrainRCS=c("RMB","RCS"),
                                  CacheSloughComplex=c("BL5","LIB"),
                                  LowerSac=c("RYI","RVB"))

#organize regions from north to south for facet plotting
zoopNDFAv2$Region <- factor(zoopNDFAv2$Region,levels = c("ColusaDrainRCS","UpperYolo","LowerYo
lo","CacheSloughComplex","MiddleSacRiver","LowerSac"))


#create regions for station groups
zoopNDFAv2$Regions2 <- fct_collapse(zoopNDFAv2$StationCode,Upstream=c("RCS","RD22","I80","LIS"
,"STTD"),
                                    Downstream=c("BL5","LIB","RYI","RVB"))

#organize regions from north to south for facet plotting
zoopNDFAv2$Regions2 <- factor(zoopNDFAv2$Regions2,levels = c("Upstream","Downstream"))
```

```
#remove macrozooplankton (incomplete dataset and not targeted by our gear)
zoopNDFAv2 <- zoopNDFAv2%>%filter(Classification!="Macrozooplankton")
glimpse(zoopNDFAv2)
```

```
## Rows: 6,309
## Columns: 53
## $ X              [3m [38;5;246m<int> [39m [23m 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26,
27, 28, 29, …
## $ Taxlife        [3m [38;5;246m<chr> [39m [23m "Acanthocyclops vernalis adult", "Acanthocyclops vernalis adult", "Acanthocyclop
s vernalis adult", "Acantho…
## $ Date           [3m [38;5;246m<chr> [39m [23m "2011-11-02", "2017-08-17", "2015-10-28", "2018-08-08", "2019-09-17", "2019-08
-07", "2019-10-15", "2016-07-…
## $ Year           [3m [38;5;246m<int> [39m [23m 2011, 2017, 2015, 2018, 2019, 2019, 2019, 2016, 2018, 2018, 2011, 2018, 2019, 201
8, 2016, 2011, 2015, 2017,…
## $ Month          [3m [38;5;246m<int> [39m [23m 11, 8, 10, 8, 9, 8, 10, 7, 9, 10, 11, 11, 8, 11, 7, 11, 9, 8, 8, 7, 10, 9, 10, 8, 6, 11, 10, 1
0, 5, 10, 8, …
## $ DateTime       [3m [38;5;246m<chr> [39m [23m "11/2/2011 4:15", "8/17/2017 4:44", "10/28/2015 6:19", "8/8/2018 9:08", "2019-
09-17 12:59:00", "2019-08-07 …
## $ Time           [3m [38;5;246m<chr> [39m [23m "8:15:00", "8:44:00", "10:19:00", "13:08:00", "12:59:00", "12:39:00", "10:49:00", "
9:15:00", "12:25:00", "1…
## $ StationCode    [3m [38;5;246m<fct> [39m [23m SHR, RCS, I80, BL5, RD22, STTD, RCS, RCS, I80, BL5, STTD, STTD, RMB,
SHR, SHR, STTD, LIS, RD22, I80, SHR, R…
## $ WaterTemp      [3m [38;5;246m<dbl> [39m [23m 13.60, 24.10, 17.37, 21.00, 21.60, 24.10, 15.80, 24.56, 20.30, 18.10, 11.90, 15.6
0, 26.60, 12.80, 20.77, 14…
## $ Secchi         [3m [38;5;246m<dbl> [39m [23m 1.69, 0.26, 0.33, 0.95, 0.24, 0.40, 0.24, 0.23, 0.35, 1.20, 0.29, 0.65, 0.23, 3.50, 1.30,
 0.26, 0.30, 0.23,…
## $ EC             [3m [38;5;246m<dbl> [39m [23m 94.0, 543.0, 918.0, 150.0, 488.0, 191.0, 493.0, 932.0, 538.0, 167.0, 412.0, 176.0, 588
.0, 106.0, 85.0, 526.…
## $ SpCnd          [3m [38;5;246m<dbl> [39m [23m NA, 553.0, 1074.0, 163.0, 522.0, 194.0, 598.0, 940.0, 591.0, 192.0, NA, 214.0, 57
1.0, 138.0, 93.0, NA, 679.…
## $ pH             [3m [38;5;246m<dbl> [39m [23m 8.18, 7.87, 8.15, 8.02, 7.65, 8.62, 7.58, 8.01, 7.81, 8.42, 7.91, 8.39, 7.64, 7.84, 7.21,
7.97, 7.62, 8.10,…
## $ DO             [3m [38;5;246m<dbl> [39m [23m 10.20, 5.27, 2.41, 7.51, 5.24, 7.87, 6.62, 4.71, 6.19, 8.68, 7.61, 8.53, 4.48, 9.87, 9.19
, 8.15, 5.18, 6.07…
## $ Turbidity      [3m [38;5;246m<dbl> [39m [23m NA, 28.20, 19.30, 8.50, 28.20, 21.10, 23.60, 28.40, 21.00, 5.60, NA, 12.00, 28.40,
4.60, 5.09, NA, 34.10, 3…
## $ FlowMeterSpeed [3m [38;5;246m<chr> [39m [23m "Regular", "Low", "Low", "Low", "Low", "Low", "Low", "Low", "Low", "Lo
w", "Low", "Low", "Low", "Low", "Regu…
## $ StartMeter     [3m [38;5;246m<int> [39m [23m 210000, 977364, 974646, 779207, 918869, 971346, 916166, 971721, 950295, 884
556, 1992, 569870, 935359, 56590…
## $ EndMeter       [3m [38;5;246m<int> [39m [23m 212717, 978000, 976000, 782453, 920245, 974965, 916690, 973000, 951761, 888
338, 4600, 574000, 936800, 56793…
## $ VolMeso        [3m [38;5;246m<int> [39m [23m 100, 80, 178, 92, 80, 74, 48, 72, 75, 92, 500, 117, 93, 53, 83, 1300, 90, 88, 78, 79,
46, 82, 155, 60, 80, …
## $ SubMeso        [3m [38;5;246m<dbl> [39m [23m 1.00, 8.00, 2.00, 0.20, 1.50, 4.00, 0.30, 0.04, 0.62, 0.40, 1.00, 0.40, 1.10, 4.00, 0.6
0, 1.00, 0.50, 7.00,…
## $ VolMicro       [3m [38;5;246m<dbl> [39m [23m 100, 80, 178, 92, 80, 74, 48, 72, 75, 92, 150, 117, 93, 53, 83, 1500, 90, 88, 78, 79,
 46, 82, 155, 60, 80, …
## $ SubMicro       [3m [38;5;246m<dbl> [39m [23m 1.00, 38.00, 4.00, 0.50, 5.40, 8.00, 0.08, 0.18, 0.62, 1.40, 1.00, 1.40, 2.60, 20.00,
20.00, 1.00, 1.50, 20…
## $ Subsample      [3m [38;5;246m<int> [39m [23m 5, 1, 1, 1, 1, 1, 1, 1, 1, 1, 5, 1, 1, 1, 1, 5, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
 1, 1, 1,…
## $ OrganismID     [3m [38;5;246m<int> [39m [23m 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10, 10
```

```
, 10, 10, 10, 10, 10,…
## $ Classification    [3m   [38;5;246m<chr>   [39m   [23m "Cyclopoids", "Cyclopoids", "Cyclopoids", "Cyclopoids", "Cyclopoids", "Cyclop
oids", "Cyclopoids", "Cyclopoi…
## $ Organism          [3m   [38;5;246m<chr>   [39m   [23m "Acanthocyclops vernalis adult", "Acanthocyclops vernalis adult", "Acanthocyclo
ps vernalis adult", "Acantho…
## $ Phylum            [3m   [38;5;246m<chr>   [39m   [23m "Arthropoda", "Arthropoda", "Arthropoda", "Arthropoda", "Arthropoda", "Arthrop
oda", "Arthropoda", "Arthropo…
## $ Subphylum         [3m   [38;5;246m<chr>   [39m   [23m "Crustacea", "Crustacea", "Crustacea", "Crustacea", "Crustacea", "Crustacea", "
Crustacea", "Crustacea", "Cr…
## $ Class             [3m   [38;5;246m<chr>   [39m   [23m "Hexanauplia", "Hexanauplia", "Hexanauplia", "Hexanauplia", "Hexanauplia", "He
xanauplia", "Hexanauplia", "H…
## $ Subclass          [3m   [38;5;246m<chr>   [39m   [23m "Copepoda", "Copepoda", "Copepoda", "Copepoda", "Copepoda", "Copepoda", "C
opepoda", "Copepoda", "Copepoda",…
## $ Infraclass        [3m   [38;5;246m<chr>   [39m   [23m "Neocopepoda", "Neocopepoda", "Neocopepoda", "Neocopepoda", "Neocopepoda
", "Neocopepoda", "Neocopepoda", "N…
## $ Superorder        [3m   [38;5;246m<chr>   [39m   [23m "Podoplea", "Podoplea", "Podoplea", "Podoplea", "Podoplea", "Podoplea", "Podo
plea", "Podoplea", "Podoplea",…
## $ Order             [3m   [38;5;246m<chr>   [39m   [23m "Cyclopoida", "Cyclopoida", "Cyclopoida", "Cyclopoida", "Cyclopoida", "Cyclopoi
da", "Cyclopoida", "Cyclopoi…
## $ Suborder          [3m   [38;5;246m<chr>   [39m   [23m NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,…
## $ Infraorder        [3m   [38;5;246m<chr>   [39m   [23m NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,…
## $ Superfamily       [3m   [38;5;246m<chr>   [39m   [23m NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA
, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,…
## $ Family            [3m   [38;5;246m<chr>   [39m   [23m "Cyclopidae", "Cyclopidae", "Cyclopidae", "Cyclopidae", "Cyclopidae", "Cyclopid
ae", "Cyclopidae", "Cyclopid…
## $ Genus             [3m   [38;5;246m<chr>   [39m   [23m "Acanthocyclops", "Acanthocyclops", "Acanthocyclops", "Acanthocyclops", "Aca
nthocyclops", "Acanthocyclops",…
## $ Species           [3m   [38;5;246m<chr>   [39m   [23m "vernalis", "vernalis", "vernalis", "vernalis", "vernalis", "vernalis", "vernalis", "ver
nalis", "vernalis",…
## $ TaxonName         [3m   [38;5;246m<chr>   [39m   [23m "Acanthocyclops vernalis", "Acanthocyclops vernalis", "Acanthocyclops vernal
is", "Acanthocyclops vernalis",…
## $ TaxonRank         [3m   [38;5;246m<chr>   [39m   [23m "Species", "Species", "Species", "Species", "Species", "Species", "Species", "Sp
ecies", "Species", "Species…
## $ CommonName        [3m   [38;5;246m<chr>   [39m   [23m "Acanthocyclops vernalis", "Acanthocyclops vernalis", "Acanthocyclops ver
nalis", "Acanthocyclops vernalis",…
## $ LifeStage         [3m   [38;5;246m<chr>   [39m   [23m "adult", "adult", "adult", "adult", "adult", "adult", "adult", "adult", "adult", "adult",
"adult", "adult",…
## $ Count             [3m   [38;5;246m<int>   [39m   [23m 2, 4, 9, 1, 9, 2, 3, 1, 5, 1, 4, 1, 1, 1, 1, 5, 8, 2, 8, 2, 1, 4, 1, 2, 1, 1, 1, 5, 8, 3, 1, 1, 1, 9,
 1, 10…
## $ CPUEZoop          [3m   [38;5;246m<dbl>   [39m   [23m 2.7915416, 5.5676508, 52.3700474, 12.5452243, 30.8810400, 0.9050702, 81.0
921968, 124.5865259, 36.5236963, 5…
## $ WYType            [3m   [38;5;246m<chr>   [39m   [23m "W", "W", "C", "BN", "W", "W", "W", "BN", "BN", "BN", "W", "BN", "W", "B
N", "BN", "W", "C", "W", "W", "BN",…
## $ FlowPulseType     [3m   [38;5;246m<chr>   [39m   [23m "NF", "CA", "NF", "MA-Ag", "MA-Ag", "MA-Ag", "MA-Ag", "MA-SR", "M
A-Ag", "MA-Ag", "NF", "MA-Ag", "MA-Ag", "M…
## $ NetFlowDays       [3m   [38;5;246m<int>   [39m   [23m 63, 12, 42, 30, 26, 26, 26, 19, 30, 30, 63, 30, 26, 30, 19, 63, 42, 12, 12, 19, 26, 2
6, 30, 26, 19, 30, 30,…
## $ SamplePeriod      [3m   [38;5;246m<fct>   [39m   [23m After, Before, After, Before, During, Before, After, Before, During, After, After,
 After, Before, After, Be…
## $ CarbonWeight      [3m   [38;5;246m<dbl>   [39m   [23m 3.36, 3.36, 3.36, 3.36, 3.36, 3.36, 3.36, 3.36, 3.36, 3.36, 3.36, 3.36, 3.36, 3.36,
3.36, 3.36, 3.36, 3.36,…
## $ BPUE              [3m   [38;5;246m<dbl>   [39m   [23m 9.379580, 18.707307, 175.963359, 42.151954, 103.760295, 3.041036, 272.469781
```

, 418.610727, 122.719620, 18.08…
$ Region [3m [38;5;246m<fct> [39m [23m MiddleSacRiver, ColusaDrainRCS, UpperYolo, CacheSloughComplex, UpperYolo, LowerYolo, ColusaDrainRCS, Colusa…
$ Regions2 [3m [38;5;246m<fct> [39m [23m NA, Upstream, Upstream, Downstream, Upstream, Upstream, Upstream, Upstream, Upstream, Downstream, Upstream,…

```
#read in data with additional flow parameters and create new data table joined with zoop data
flow_magnitude<-read.csv("Zoop_code/flow_magnitude.csv", stringsAsFactors = FALSE, na.strings=
"",header = TRUE)
flow_dates<-read.csv("Zoop_code/FlowDatesDesignations.csv", stringsAsFactors = FALSE, na.strin
gs="",header = TRUE)
flow_dates$PreFlowStart <- format(as.Date(flow_dates$PreFlowStart, format = "%m/%d/%Y"), "%Y-%
m-%d")
flow_dates$PreFlowEnd <- format(as.Date(flow_dates$PreFlowEnd, format = "%m/%d/%Y"), "%Y-%m-%d
")
flow_dates$PostFlowStart <- format(as.Date(flow_dates$PostFlowStart, format = "%m/%d/%Y"), "%Y
-%m-%d")
flow_dates$PostFlowEnd <- format(as.Date(flow_dates$PostFlowEnd, format = "%m/%d/%Y"), "%Y-%m-
%d")
flow_dates <- flow_dates %>% filter(Year!="2011")
flow_dates <- flow_dates %>% filter(Year!="2012")
flow_dates <- flow_dates %>% filter(Year!="2013")

zoopNDFAv3 <- zoopNDFAv2
zoopNDFAv3$Year <- as.character(zoopNDFAv3$Year)
flow_magnitude$Year<-as.character(flow_magnitude$Year)

zoopNDFAv3<-left_join(flow_magnitude,zoopNDFAv3)
```

```
## Joining, by = "Year"
```

```
#Remove years 2011 and 2012 with incomplete sampling and remove Sherwood (outside study area)
and Rominger Bridge (too few samples)
zoopNDFAv3 <-  zoopNDFAv3%>% filter(Year!="2011")
zoopNDFAv3 <-  zoopNDFAv3%>% filter(Year!="2012")
zoopNDFAv3 <- zoopNDFAv3 %>% filter(StationCode!="SHR")
zoopNDFAv3 <- zoopNDFAv3 %>% filter(StationCode!="RMB")

zoopNDFA4 <- zoopNDFAv3[,c("Year","Date","SamplePeriod","Region","Regions2","StationCode","CPU
EZoop")] #new table with relevant columns
zoopNDFA4$SamplePeriod <- as.character(zoopNDFA4$SamplePeriod)
zoopNDFA4$Regions2 <- as.character(zoopNDFA4$Regions2)
zoopNDFA4$StationCode <- as.character(zoopNDFA4$StationCode)



zoopNDFA4$scaleCPUE = scale(zoopNDFA4$CPUE) #may need to rescale data for certain analyses

#NOTE: added classification for individual taxa group analysis, but you need to remove this fo
r the original total zoop analysis

zoopNDFA4 <- zoopNDFA4 %>% group_by(Date,StationCode,Year, Regions2,SamplePeriod) %>%
```

```
  summarise(cpue=sum(CPUEZoop),
            scaled=sum(scaleCPUE))
```

```
## `summarise()` has grouped output by 'Date', 'StationCode', 'Year', 'Regions2'. You can over
ride using the `.groups` argument.
```

```
#2013 removed because only STTD sampled
zoopNDFA7=zoopNDFA4 %>% filter(Year!=2013) # this dataset excludes 2011-2013 and groups total
CPUE biomass for each sample

#remove data with bad flowmeter data affecting CPUE
zoopNDFA7 <- zoopNDFA7 %>%  filter(Date!="2016-07-07" | StationCode!="RVB")
zoopNDFA7 <- zoopNDFA7 %>% filter(Date!="2016-01-06" | StationCode!="STTD")

zoopNDFA7$SamplePeriod <- factor(zoopNDFA7$SamplePeriod,levels=c("Before","During","After"))


#the following is the model and post hoc from the original report#
######Two-way interactive model and station code as a random effect--THIS IS THE MODEL we ult
imately chose#####
model4.1 <- lmer(log(cpue) ~ Regions2*Year+Year*SamplePeriod+SamplePeriod*Regions2+(1|StationC
ode),data = zoopNDFA7,REML = TRUE)
summary(model4.1)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: log(cpue) ~ Regions2 * Year + Year * SamplePeriod + SamplePeriod *      Regions2 +
 (1 | StationCode)
##    Data: zoopNDFA7
##
## REML criterion at convergence: 1219.9
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5194 -0.5012 -0.0072  0.6401  3.0745
##
## Random effects:
##  Groups      Name        Variance Std.Dev.
##  StationCode (Intercept) 0.3042   0.5515
##  Residual                1.5325   1.2379
## Number of obs: 372, groups:  StationCode, 9
##
## Fixed effects:
##                                       Estimate Std. Error t value
## (Intercept)                            8.58720    0.45370  18.927
## Regions2Upstream                      -0.48107    0.53243  -0.904
## Year2015                              -0.56854    0.48288  -1.177
## Year2016                               1.95111    0.50218   3.885
## Year2017                              -0.87450    0.46314  -1.888
## Year2018                              -0.31307    0.42997  -0.728
## Year2019                              -1.30615    0.48972  -2.667
## SamplePeriodDuring                     0.13263    0.53483   0.248
## SamplePeriodAfter                     -0.16325    0.40940  -0.399
```

```
## Regions2Upstream:Year2015           -0.59910    0.46291  -1.294
## Regions2Upstream:Year2016           -0.13756    0.47208  -0.291
## Regions2Upstream:Year2017            1.46255    0.48820   2.996
## Regions2Upstream:Year2018           -0.29557    0.43022  -0.687
## Regions2Upstream:Year2019            1.17735    0.47956   2.455
## Year2015:SamplePeriodDuring          0.76600    0.63209   1.212
## Year2016:SamplePeriodDuring          0.01746    0.72402   0.024
## Year2017:SamplePeriodDuring          0.06818    0.62687   0.109
## Year2018:SamplePeriodDuring          0.17568    0.60151   0.292
## Year2019:SamplePeriodDuring         -0.56238    0.64912  -0.866
## Year2015:SamplePeriodAfter           0.66558    0.53275   1.249
## Year2016:SamplePeriodAfter          -0.91570    0.53568  -1.709
## Year2017:SamplePeriodAfter          -0.58336    0.62517  -0.933
## Year2018:SamplePeriodAfter          -0.45732    0.48210  -0.949
## Year2019:SamplePeriodAfter          -0.21785    0.55292  -0.394
## Regions2Upstream:SamplePeriodDuring -0.51267    0.33169  -1.546
## Regions2Upstream:SamplePeriodAfter   0.24541    0.31155   0.788
```

```
##
## Correlation matrix not shown by default, as p = 26 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
model4.1
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: log(cpue) ~ Regions2 * Year + Year * SamplePeriod + SamplePeriod *      Regions2 +
 (1 | StationCode)
##    Data: zoopNDFA7
## REML criterion at convergence: 1219.928
## Random effects:
##  Groups      Name        Std.Dev.
##  StationCode (Intercept) 0.5515
##  Residual                1.2379
## Number of obs: 372, groups:  StationCode, 9
## Fixed Effects:
##                          (Intercept)                     Regions2Upstream
         Year2015
##                              8.58720                             -0.48107
         -0.56854
##                             Year2016                             Year2017
         Year2018
##                              1.95111                             -0.87450
         -0.31307
##                             Year2019                   SamplePeriodDuring
 SamplePeriodAfter
##                             -1.30615                              0.13263
         -0.16325
##            Regions2Upstream:Year2015            Regions2Upstream:Year2016            Regions
2Upstream:Year2017
##                             -0.59910                             -0.13756
          1.46255
```

```
##           Regions2Upstream:Year2018            Regions2Upstream:Year2019          Year2015:
SamplePeriodDuring
##                             -0.29557                              1.17735
           0.76600
##           Year2016:SamplePeriodDuring          Year2017:SamplePeriodDuring          Year2018:
SamplePeriodDuring
##                              0.01746                              0.06818
           0.17568
##           Year2019:SamplePeriodDuring           Year2015:SamplePeriodAfter           Year2016
:SamplePeriodAfter
##                             -0.56238                              0.66558
          -0.91570
##            Year2017:SamplePeriodAfter           Year2018:SamplePeriodAfter           Year2019
:SamplePeriodAfter
##                             -0.58336                             -0.45732
          -0.21785
## Regions2Upstream:SamplePeriodDuring   Regions2Upstream:SamplePeriodAfter
##                             -0.51267                              0.24541
```

```
modtab <- Anova(model4.1, type = 3, test.statistic = "F") #this runs- year, regions:year, year
:sampleperiod, regions:sampleperiod are all significant
kable(modtab)
```

	F	Df	Df.res	Pr(>F)
(Intercept)	358.2249166	1	38.81165	0.0000000
Regions2	0.8163806	1	23.30296	0.3754865
Year	10.0582378	5	339.27879	0.0000000
SamplePeriod	0.1910946	2	339.02138	0.8261433
Regions2:Year	6.5141829	5	339.36170	0.0000084
Year:SamplePeriod	1.5048626	10	339.30267	0.1358657
Regions2:SamplePeriod	2.6001219	2	339.13176	0.0757446

```
summary(modtab)
```

```
##        F                  Df             Df.res          Pr(>F)
##  Min.   :  0.1911   Min.   : 1.000   Min.   : 23.3   Min.   :0.0000000
##  1st Qu.:  1.1606   1st Qu.: 1.500   1st Qu.:188.9   1st Qu.:0.0000042
##  Median :  2.6001   Median : 2.000   Median :339.1   Median :0.0757446
##  Mean   : 54.2728   Mean   : 3.714   Mean   :251.2   Mean   :0.2018926
##  3rd Qu.:  8.2862   3rd Qu.: 5.000   3rd Qu.:339.3   3rd Qu.:0.2556761
##  Max.   :358.2249   Max.   :10.000   Max.   :339.4   Max.   :0.8261433
```

```
#####Post-hoc with emmeans Sidak method - THIS IS THE POST HOC USED######
#use emmeans instead to get p value
lmer_emm <- emmeans(model4.1, specs = pairwise ~Regions2:Year,adjust="sidak")#post hoc test on
```

```
region and year (significant from anova) shows no significant differences of individual contr
asts within a year but significant differences between years
```

```
## Warning: You may have generated more contrasts than you really wanted. In the future,
## we suggest you avoid things like 'pairwise ~ fac1*fac2' when you have
## more than one factor. Instead, call emmeans() with just '~ fac1*fac2' and do the
## contrasts you need in a later step. See vignette("QuickStart", "emmeans").
```

```
phoc <- print(test(lmer_emm)$contrasts)
```

```
##  contrast                                   estimate    SE    df t.ratio p.value
##  Downstream Year2014 - Upstream Year2014      0.5702 0.502  18.5   1.136  1.0000
##  Downstream Year2014 - Downstream Year2015    0.0913 0.358 339.0   0.255  1.0000
##  Downstream Year2014 - Upstream Year2015      1.2606 0.501  18.3   2.518  0.7585
##  Downstream Year2014 - Downstream Year2016  -1.6517 0.370 339.1  -4.467  0.0007
##  Downstream Year2014 - Upstream Year2016    -0.9440 0.521  21.4  -1.812  0.9970
##  Downstream Year2014 - Downstream Year2017   1.0462 0.379 339.1   2.762  0.3303
##  Downstream Year2014 - Upstream Year2017     0.1538 0.521  21.3   0.295  1.0000
##  Downstream Year2014 - Downstream Year2018   0.4069 0.327 339.8   1.244  1.0000
##  Downstream Year2014 - Upstream Year2018     1.2727 0.495  17.4   2.573  0.7267
##  Downstream Year2014 - Downstream Year2019   1.5662 0.367 339.0   4.264  0.0017
##  Downstream Year2014 - Upstream Year2019     0.9590 0.509  19.6   1.884  0.9940
##  Upstream Year2014 - Downstream Year2015    -0.4788 0.498  17.9  -0.962  1.0000
##  Upstream Year2014 - Upstream Year2015       0.6904 0.312 339.1   2.215  0.8405
##  Upstream Year2014 - Downstream Year2016    -2.2219 0.512  20.1  -4.338  0.0208
##  Upstream Year2014 - Upstream Year2016      -1.5141 0.340 339.4  -4.459  0.0007
##  Upstream Year2014 - Downstream Year2017     0.4761 0.513  20.2   0.928  1.0000
##  Upstream Year2014 - Upstream Year2017      -0.4163 0.346 339.5  -1.202  1.0000
##  Upstream Year2014 - Downstream Year2018    -0.1632 0.479  15.3  -0.341  1.0000
##  Upstream Year2014 - Upstream Year2018       0.7025 0.302 339.4   2.330  0.7437
##  Upstream Year2014 - Downstream Year2019     0.9961 0.506  19.1   1.968  0.9871
##  Upstream Year2014 - Upstream Year2019       0.3889 0.326 339.0   1.191  1.0000
##  Downstream Year2015 - Upstream Year2015     1.1693 0.485  16.2   2.409  0.8488
##  Downstream Year2015 - Downstream Year2016  -1.7430 0.353 339.1  -4.931  0.0001
##  Downstream Year2015 - Upstream Year2016    -1.0353 0.504  18.8  -2.055  0.9745
##  Downstream Year2015 - Downstream Year2017   0.9549 0.357 339.1   2.674  0.4062
##  Downstream Year2015 - Upstream Year2017     0.0625 0.507  19.2   0.123  1.0000
##  Downstream Year2015 - Downstream Year2018   0.3156 0.304 339.9   1.037  1.0000
##  Downstream Year2015 - Upstream Year2018     1.1813 0.478  15.3   2.469  0.8213
##  Downstream Year2015 - Downstream Year2019   1.4749 0.346 339.0   4.262  0.0017
##  Downstream Year2015 - Upstream Year2019     0.8677 0.494  17.4   1.757  0.9988
##  Upstream Year2015 - Downstream Year2016    -2.9123 0.498  17.9  -5.850  0.0010
##  Upstream Year2015 - Upstream Year2016      -2.2046 0.320 339.2  -6.883  <.0001
##  Upstream Year2015 - Downstream Year2017    -0.2144 0.500  18.2  -0.429  1.0000
##  Upstream Year2015 - Upstream Year2017      -1.1068 0.325 339.4  -3.401  0.0484
##  Upstream Year2015 - Downstream Year2018    -0.8537 0.464  13.6  -1.838  0.9977
##  Upstream Year2015 - Upstream Year2018       0.0121 0.279 339.3   0.043  1.0000
##  Upstream Year2015 - Downstream Year2019     0.3056 0.493  17.2   0.620  1.0000
##  Upstream Year2015 - Upstream Year2019      -0.3016 0.306 339.2  -0.987  1.0000
##  Downstream Year2016 - Upstream Year2016     0.7077 0.503  18.6   1.408  1.0000
##  Downstream Year2016 - Downstream Year2017   2.6979 0.376 339.1   7.182  <.0001
##  Downstream Year2016 - Upstream Year2017     1.8055 0.517  20.8   3.491  0.1355
```

```
##  Downstream Year2016 - Downstream Year2018   2.0586 0.322 339.7   6.392  <.0001
##  Downstream Year2016 - Upstream Year2018     2.9244 0.491  17.0   5.951  0.0010
##  Downstream Year2016 - Downstream Year2019   3.2179 0.363 339.1   8.858  <.0001
##  Downstream Year2016 - Upstream Year2019     2.6107 0.506  19.1   5.159  0.0036
##  Upstream Year2016 - Downstream Year2017     1.9902 0.518  20.9   3.841  0.0610
##  Upstream Year2016 - Upstream Year2017       1.0978 0.354 339.4   3.097  0.1306
##  Upstream Year2016 - Downstream Year2018     1.3509 0.485  16.1   2.786  0.5829
##  Upstream Year2016 - Upstream Year2018       2.2167 0.310 339.4   7.142  <.0001
##  Upstream Year2016 - Downstream Year2019     2.5102 0.512  20.0   4.901  0.0057
##  Upstream Year2016 - Upstream Year2019       1.9030 0.336 339.6   5.669  <.0001
##  Downstream Year2017 - Upstream Year2017    -0.8924 0.507  19.3  -1.759  0.9986
##  Downstream Year2017 - Downstream Year2018  -0.6393 0.329 339.9  -1.945  0.9717
##  Downstream Year2017 - Upstream Year2018     0.2265 0.494  17.4   0.458  1.0000
##  Downstream Year2017 - Downstream Year2019   0.5200 0.368 339.1   1.413  1.0000
##  Downstream Year2017 - Upstream Year2019    -0.0872 0.510  19.6  -0.171  1.0000
##  Upstream Year2017 - Downstream Year2018     0.2531 0.487  16.4   0.519  1.0000
##  Upstream Year2017 - Upstream Year2018       1.1188 0.313 339.0   3.572  0.0264
##  Upstream Year2017 - Downstream Year2019     1.4124 0.515  20.4   2.743  0.5607
##  Upstream Year2017 - Upstream Year2019       0.8052 0.340 339.8   2.370  0.7056
##  Downstream Year2018 - Upstream Year2018     0.8657 0.457  12.8   1.893  0.9963
##  Downstream Year2018 - Downstream Year2019   1.1593 0.317 339.9   3.661  0.0190
##  Downstream Year2018 - Upstream Year2019     0.5521 0.474  14.7   1.166  1.0000
##  Upstream Year2018 - Downstream Year2019     0.2935 0.487  16.4   0.603  1.0000
##  Upstream Year2018 - Upstream Year2019      -0.3136 0.296 339.8  -1.061  1.0000
##  Downstream Year2019 - Upstream Year2019    -0.6072 0.502  18.5  -1.210  1.0000
##
## Results are averaged over the levels of: SamplePeriod
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: sidak method for 66 tests
```

```
kable(phoc)
```

contrast	estimate	SE	df	t.ratio	p.value
Downstream Year2014 - Upstream Year2014	0.5701628	0.5019185	18.51625	1.1359667	1.0000000
Downstream Year2014 - Downstream Year2015	0.0913436	0.3575355	339.00281	0.2554814	1.0000000
Downstream Year2014 - Upstream Year2015	1.2606056	0.5006444	18.32730	2.5179662	0.7585180
Downstream Year2014 - Downstream Year2016	-1.6516994	0.3697902	339.05784	-4.4665850	0.0007153
Downstream Year2014 - Upstream Year2016	-0.9439766	0.5208989	21.37195	-1.8122069	0.9969507
Downstream Year2014 - Downstream Year2017	1.0462248	0.3787772	339.06683	2.7621110	0.3302858
Downstream Year2014 - Upstream Year2017	0.1538404	0.5208343	21.34490	0.2953730	1.0000000
Downstream Year2014 - Downstream Year2018	0.4069489	0.3271289	339.83716	1.2440016	0.9999999
Downstream Year2014 - Upstream Year2018	1.2726796	0.4945718	17.44867	2.5732957	0.7267026
Downstream Year2014 - Downstream Year2019	1.5662254	0.3673432	339.00224	4.2636569	0.0017216
Downstream Year2014 - Upstream Year2019	0.9590338	0.5089682	19.55591	1.8842705	0.9939549

Upstream Year2014 - Downstream Year2015	-0.4788191	0.4975549	17.89296	-0.9623443	1.0000000
Upstream Year2014 - Upstream Year2015	0.6904428	0.3117172	339.06988	2.2149652	0.8404582
Upstream Year2014 - Downstream Year2016	-2.2218622	0.5122246	20.04520	-4.3376715	0.0207744
Upstream Year2014 - Upstream Year2016	-1.5141394	0.3396003	339.43563	-4.4585932	0.0007407
Upstream Year2014 - Downstream Year2017	0.4760620	0.5130859	20.18008	0.9278407	1.0000000
Upstream Year2014 - Upstream Year2017	-0.4163224	0.3464147	339.51689	-1.2018035	1.0000000
Upstream Year2014 - Downstream Year2018	-0.1632139	0.4786761	15.33345	-0.3409693	1.0000000
Upstream Year2014 - Upstream Year2018	0.7025168	0.3015708	339.43212	2.3295255	0.7437222
Upstream Year2014 - Downstream Year2019	0.9960626	0.5061594	19.13570	1.9678834	0.9870576
Upstream Year2014 - Upstream Year2019	0.3888710	0.3264173	339.03685	1.1913307	1.0000000
Downstream Year2015 - Upstream Year2015	1.1692619	0.4853666	16.22648	2.4090286	0.8487903
Downstream Year2015 - Downstream Year2016	-1.7430431	0.3534745	339.06008	-4.9311703	0.0000846
Downstream Year2015 - Upstream Year2016	-1.0353203	0.5037293	18.74824	-2.0553107	0.9744559
Downstream Year2015 - Downstream Year2017	0.9548811	0.3571456	339.09098	2.6736469	0.4062069
Downstream Year2015 - Upstream Year2017	0.0624967	0.5072576	19.25145	0.1232051	1.0000000
Downstream Year2015 - Downstream Year2018	0.3156053	0.3042419	339.94240	1.0373498	1.0000000
Downstream Year2015 - Upstream Year2018	1.1813359	0.4783887	15.30599	2.4694062	0.8213077
Downstream Year2015 - Downstream Year2019	1.4748817	0.3460661	339.00176	4.2618496	0.0017348
Downstream Year2015 - Upstream Year2019	0.8676901	0.4938313	17.37537	1.7570578	0.9987674
Upstream Year2015 - Downstream Year2016	-2.9123050	0.4978464	17.92496	-5.8498062	0.0010297
Upstream Year2015 - Upstream Year2016	-2.2045822	0.3203042	339.21474	-6.8827775	0.0000000
Upstream Year2015 - Downstream Year2017	-0.2143808	0.5000887	18.25325	-0.4286856	1.0000000
Upstream Year2015 - Upstream Year2017	-1.1067652	0.3254357	339.35885	-3.4008726	0.0484281
Upstream Year2015 - Downstream Year2018	-0.8536567	0.4643304	13.59224	-1.8384682	0.9977012
Upstream Year2015 - Upstream Year2018	0.0120740	0.2785586	339.28180	0.0433445	1.0000000
Upstream Year2015 - Downstream Year2019	0.3056198	0.4929444	17.24560	0.6199883	1.0000000
Upstream Year2015 - Upstream Year2019	-0.3015718	0.3055244	339.18389	-0.9870629	1.0000000
Downstream Year2016 - Upstream Year2016	0.7077228	0.5026290	18.58066	1.4080421	0.9999971
Downstream Year2016 - Downstream Year2017	2.6979242	0.3756263	339.09346	7.1824690	0.0000000
Downstream Year2016 - Upstream Year2017	1.8055398	0.5171480	20.76313	3.4913408	0.1355397
Downstream Year2016 - Downstream Year2018	2.0586483	0.3220754	339.73606	6.3918212	0.0000000

Downstream Year2016 - Upstream Year2018	2.9243790	0.4913867	17.01186	5.9512784	0.0010384
Downstream Year2016 - Downstream Year2019	3.2179248	0.3632708	339.05486	8.8581980	0.0000000
Downstream Year2016 - Upstream Year2019	2.6107332	0.5060368	19.11602	5.1591761	0.0036074
Upstream Year2016 - Downstream Year2017	1.9902014	0.5181991	20.95434	3.8406112	0.0610166
Upstream Year2016 - Upstream Year2017	1.0978170	0.3544825	339.39265	3.0969571	0.1305946
Upstream Year2016 - Downstream Year2018	1.3509255	0.4849742	16.11877	2.7855616	0.5828760
Upstream Year2016 - Upstream Year2018	2.2166562	0.3103480	339.42315	7.1424859	0.0000000
Upstream Year2016 - Downstream Year2019	2.5102020	0.5121903	20.01027	4.9009166	0.0056748
Upstream Year2016 - Upstream Year2019	1.9030104	0.3356931	339.58456	5.6688986	0.0000020
Downstream Year2017 - Upstream Year2017	-0.8923844	0.5074338	19.30500	-1.7586222	0.9985707
Downstream Year2017 - Downstream Year2018	-0.6392759	0.3286152	339.88646	-1.9453630	0.9716503
Downstream Year2017 - Upstream Year2018	0.2264548	0.4941785	17.41209	0.4582449	1.0000000
Downstream Year2017 - Downstream Year2019	0.5200006	0.3680927	339.07835	1.4126893	0.9999888
Downstream Year2017 - Upstream Year2019	-0.0871910	0.5095094	19.63214	-0.1711274	1.0000000
Upstream Year2017 - Downstream Year2018	0.2531085	0.4874433	16.42867	0.5192574	1.0000000
Upstream Year2017 - Upstream Year2018	1.1188392	0.3132274	339.02896	3.5719708	0.0264179
Upstream Year2017 - Downstream Year2019	1.4123850	0.5148746	20.40690	2.7431631	0.5607108
Upstream Year2017 - Upstream Year2019	0.8051934	0.3397747	339.81970	2.3697864	0.7055899
Downstream Year2018 - Upstream Year2018	0.8657307	0.4572303	12.77042	1.8934236	0.9962569
Downstream Year2018 - Downstream Year2019	1.1592765	0.3166198	339.87583	3.6614155	0.0190093
Downstream Year2018 - Upstream Year2019	0.5520849	0.4736620	14.71040	1.1655672	1.0000000
Upstream Year2018 - Downstream Year2019	0.2935458	0.4868504	16.40123	0.6029487	1.0000000
Upstream Year2018 - Upstream Year2019	-0.3136458	0.2955914	339.75741	-1.0610789	1.0000000
Downstream Year2019 - Upstream Year2019	-0.6071916	0.5018114	18.50230	-1.2099995	1.0000000

```
####GAM analysis####

#first some preliminary sample counts to assess study design

#counts by station, year and sample period
zoopNDFA7 %>%
  group_by(Year, SamplePeriod, StationCode) %>% summarise(n = n()) %>%
  arrange(StationCode) %>%
  pivot_wider(names_from = StationCode, values_from = n) %>%
  arrange(Year, SamplePeriod) %>%
  kable()
```

```
## `summarise()` has grouped output by 'Year', 'SamplePeriod'. You can override using the `.gr
oups` argument.
```

Year	SamplePeriod	BL5	I80	LIB	LIS	RCS	RD22	RVB	RYI	STTD
2014	Before	2	2	2	2	2	2	2	2	3
2014	During	1	1	1	1	1	1	1	1	1
2014	After	3	3	3	3	3	3	3	3	4
2015	Before	2	2	2	2	1	2	2	2	4
2015	During	3	2	3	2	2	2	3	3	3
2015	After	2	3	2	3	3	3	2	2	3
2016	Before	2	1	2	1	1	1	1	2	4
2016	During	1	1	1	1	1	1	1	1	1
2016	After	4	4	4	4	NA	4	4	4	4
2017	Before	3	3	3	3	3	3	3	3	3
2017	During	2	2	2	2	2	2	2	2	2
2017	After	1	NA	1	NA	NA	NA	1	1	4
2018	Before	5	3	3	3	3	3	3	5	5
2018	During	4	2	2	2	2	2	2	4	4
2018	After	6	2	2	2	2	2	2	6	7
2019	Before	2	2	2	2	2	2	2	2	2
2019	During	2	2	2	2	2	2	2	2	2
2019	After	2	2	2	2	2	2	2	2	2

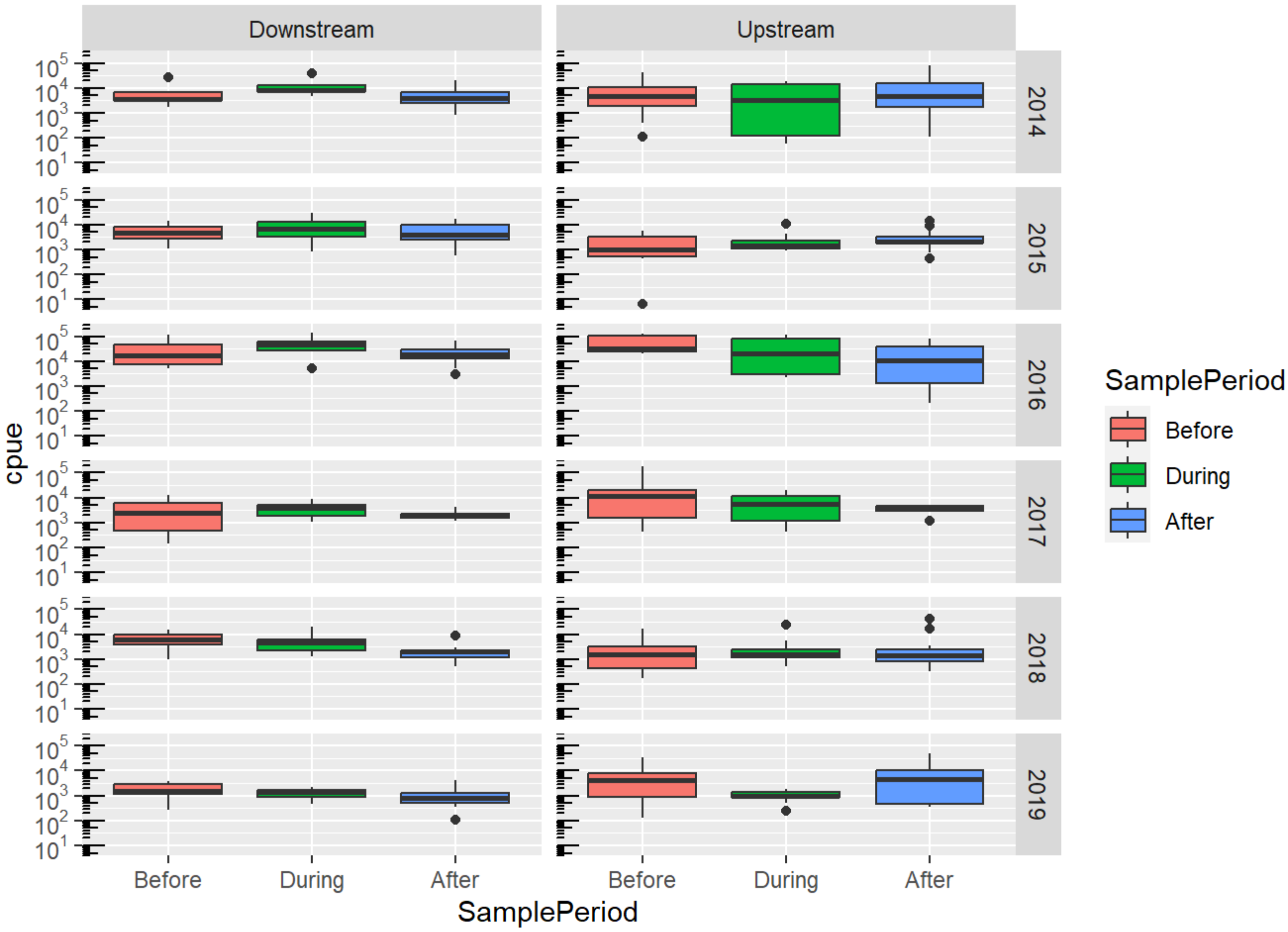
```
#counts by region, year and sample period
zoopNDFA7 %>%
  group_by(Year, SamplePeriod, Regions2) %>% summarise(n = n()) %>%
  pivot_wider(names_from = Regions2, values_from = n) %>%
  kable()
```

```
## `summarise()` has grouped output by 'Year', 'SamplePeriod'. You can override using the `.gr
oups` argument.
```

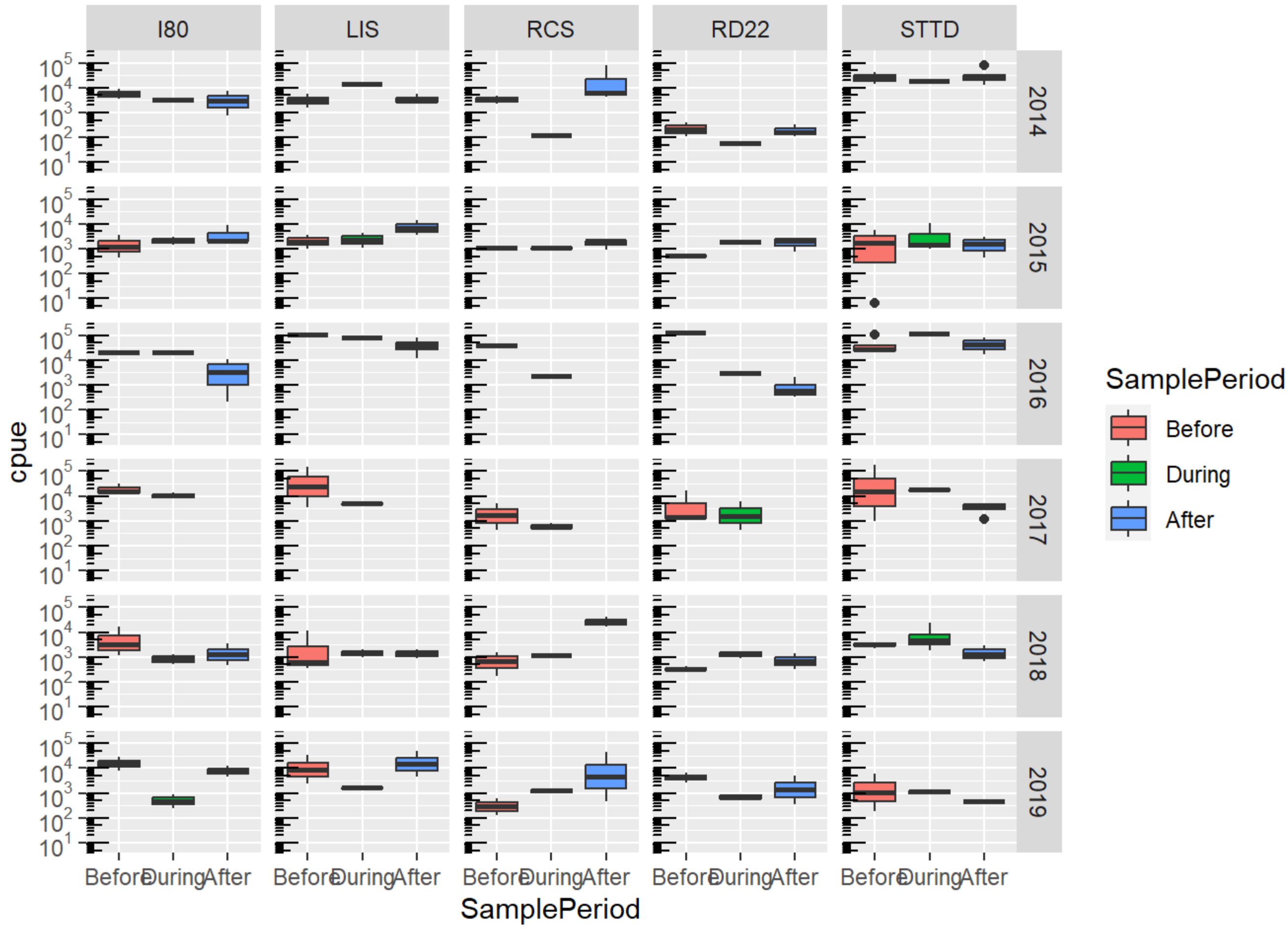
Year	SamplePeriod	Downstream	Upstream
2014	Before	8	11
2014	During	4	5

2014	After	12	16
2015	Before	8	11
2015	During	12	11
2015	After	8	15
2016	Before	7	8
2016	During	4	5
2016	After	16	16
2017	Before	12	15
2017	During	8	10
2017	After	4	4
2018	Before	16	17
2018	During	12	12
2018	After	16	15
2019	Before	8	10
2019	During	8	10
2019	After	8	10

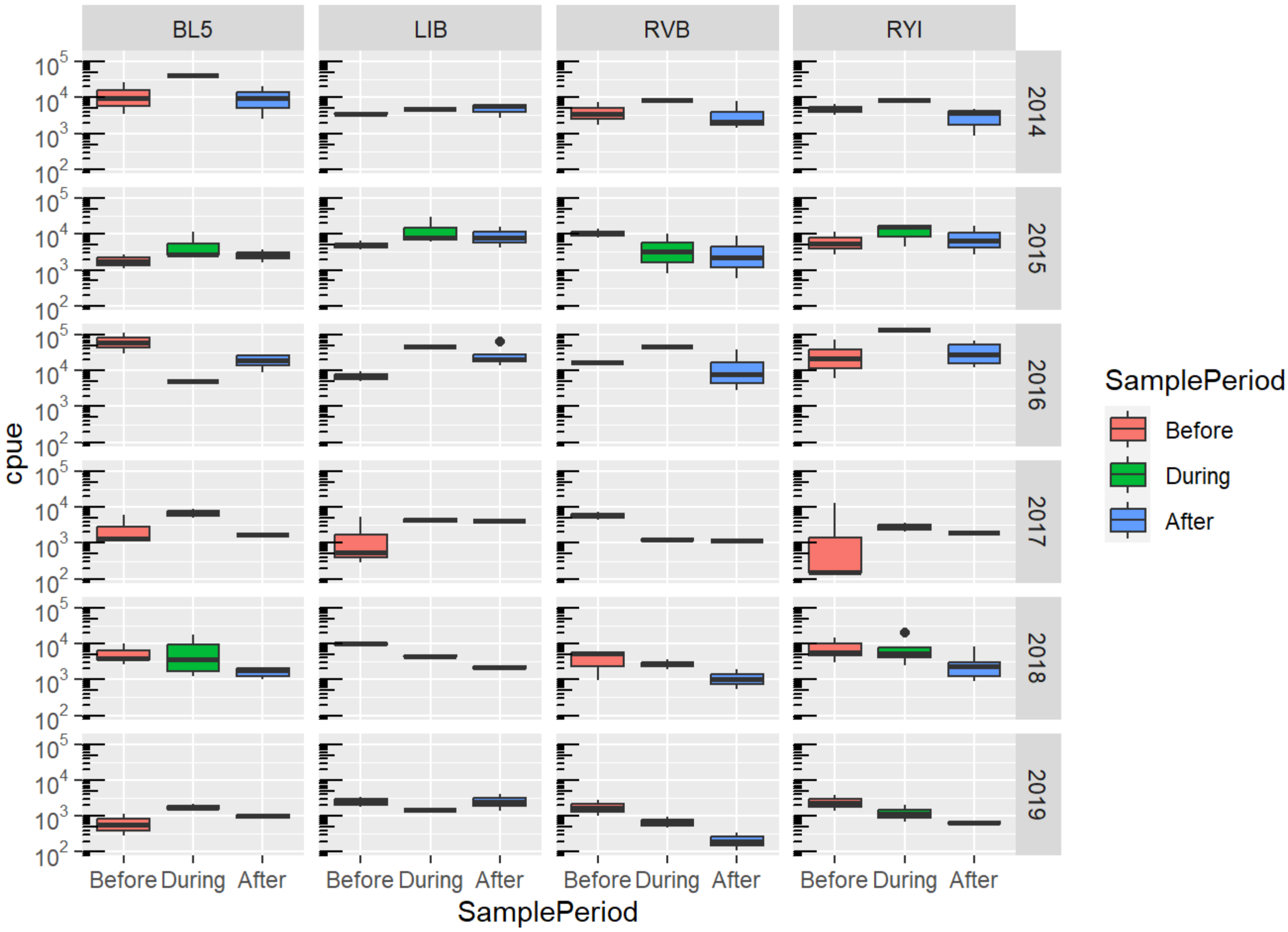
```
#boxplots by year and region

zoopNDFA7 %>%
  ggplot(aes(x = SamplePeriod, y = cpue, fill = SamplePeriod)) +
  geom_boxplot() +
  facet_grid(rows = vars(Year), cols = vars(Regions2)) +
  scale_y_log10(labels = trans_format("log10", math_format(10^.x))) +
  annotation_logticks(sides = "l")
```




```
#boxplots by station and region

zoopNDFA7 %>%
  filter(Regions2 == "Upstream") %>%
  ggplot(aes(x = SamplePeriod, y = cpue, fill = SamplePeriod)) +
  geom_boxplot() +
  facet_grid(rows = vars(Year), cols = vars(StationCode)) +
  scale_y_log10(labels = trans_format("log10", math_format(10^.x))) +
  annotation_logticks(sides = "l")
```



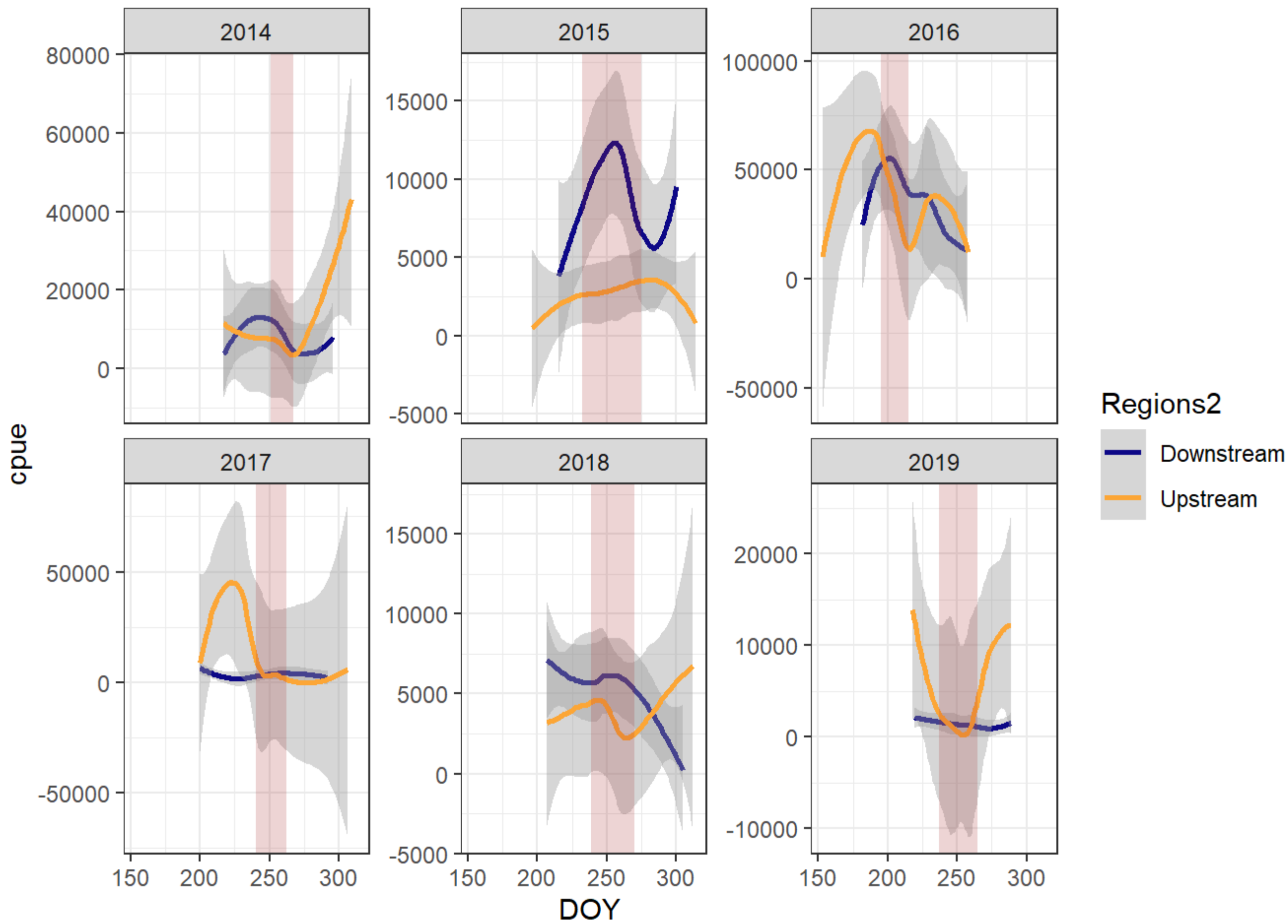

```
zoopNDFA7 %>%
  filter(Regions2 == "Downstream") %>%
  ggplot(aes(x = SamplePeriod, y = cpue, fill = SamplePeriod)) +
  geom_boxplot() +
  facet_grid(rows = vars(Year), cols = vars(StationCode)) +
  scale_y_log10(labels = trans_format("log10", math_format(10^.x))) +
  annotation_logticks(sides = "l")
```




```
#GAM smooth plots
zoopNDFA8 <- zoopNDFA7
zoopNDFA8$DOY <- yday(zoopNDFA8$Date)
zoopNDFA8$logcpue <- zoopNDFA8$cpue
zoopNDFA8$logcpue=log10(zoopNDFA8$cpue)
zoopNDFA8$StationCode <- factor(zoopNDFA8$StationCode)
zoopNDFA8$Regions2 <- factor(zoopNDFA8$Regions2)
zoopNDFA8$Year <- factor(zoopNDFA8$Year)


flow_dates$DOYpreEND <- yday(flow_dates$PreFlowEnd)
flow_dates$DOYpostSTART <- yday(flow_dates$PostFlowStart)

zoopNDFA8 %>%
  ggplot(aes(x = DOY, y = cpue, color = Regions2)) +
  geom_smooth() +
  scale_color_viridis_d(option = "plasma", end = 0.8) +
  facet_wrap(vars(Year), scales = "free_y") +
  geom_rect(
    data = flow_dates,
    aes(
      xmin = DOYpreEND,
      xmax = DOYpostSTART,
      ymin = -Inf,
      ymax = Inf
    ),
```

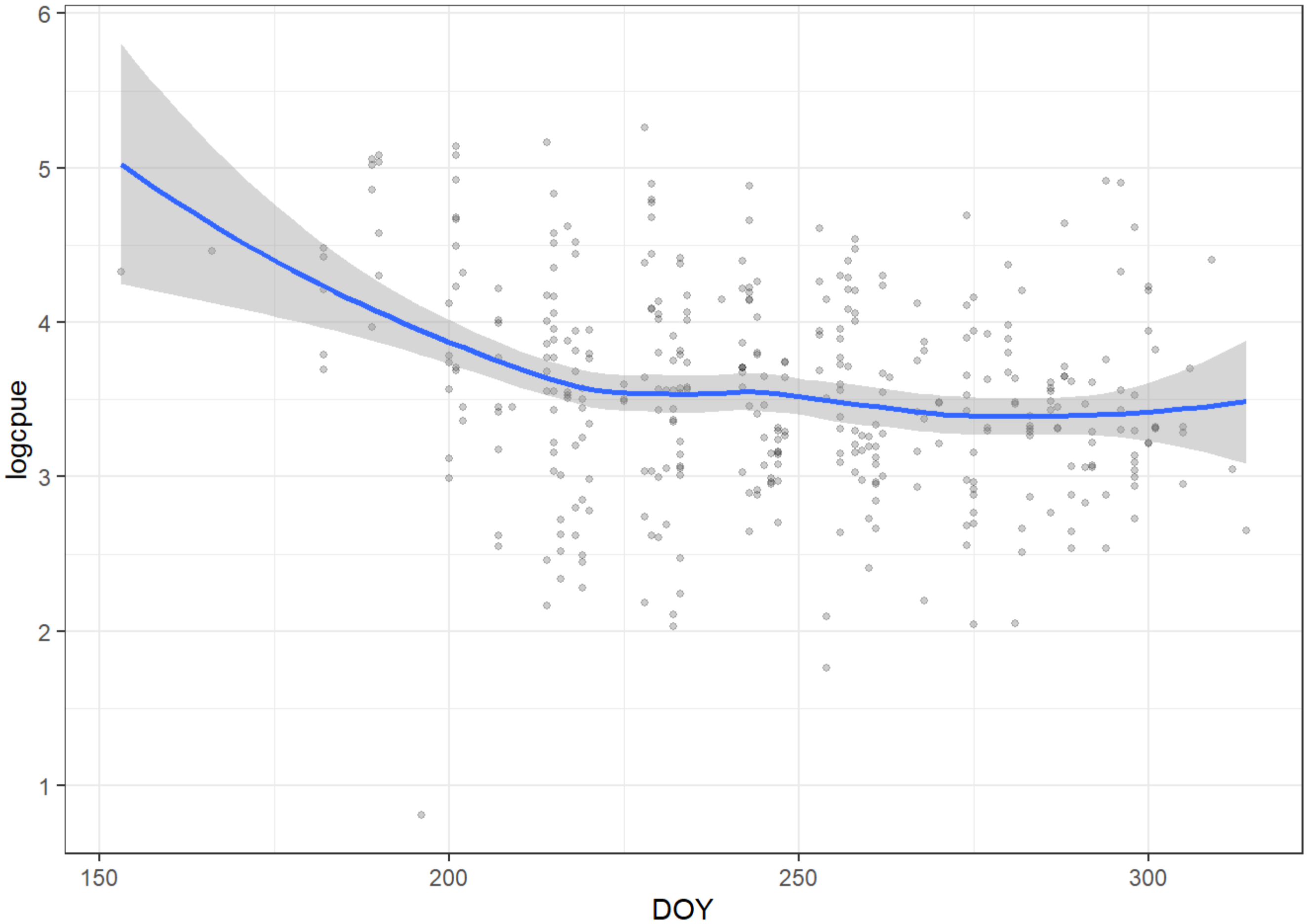
```
    inherit.aes = FALSE,
    alpha = 0.2,
    fill = "brown"
  ) +
  theme_bw()
```

```
## `geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```



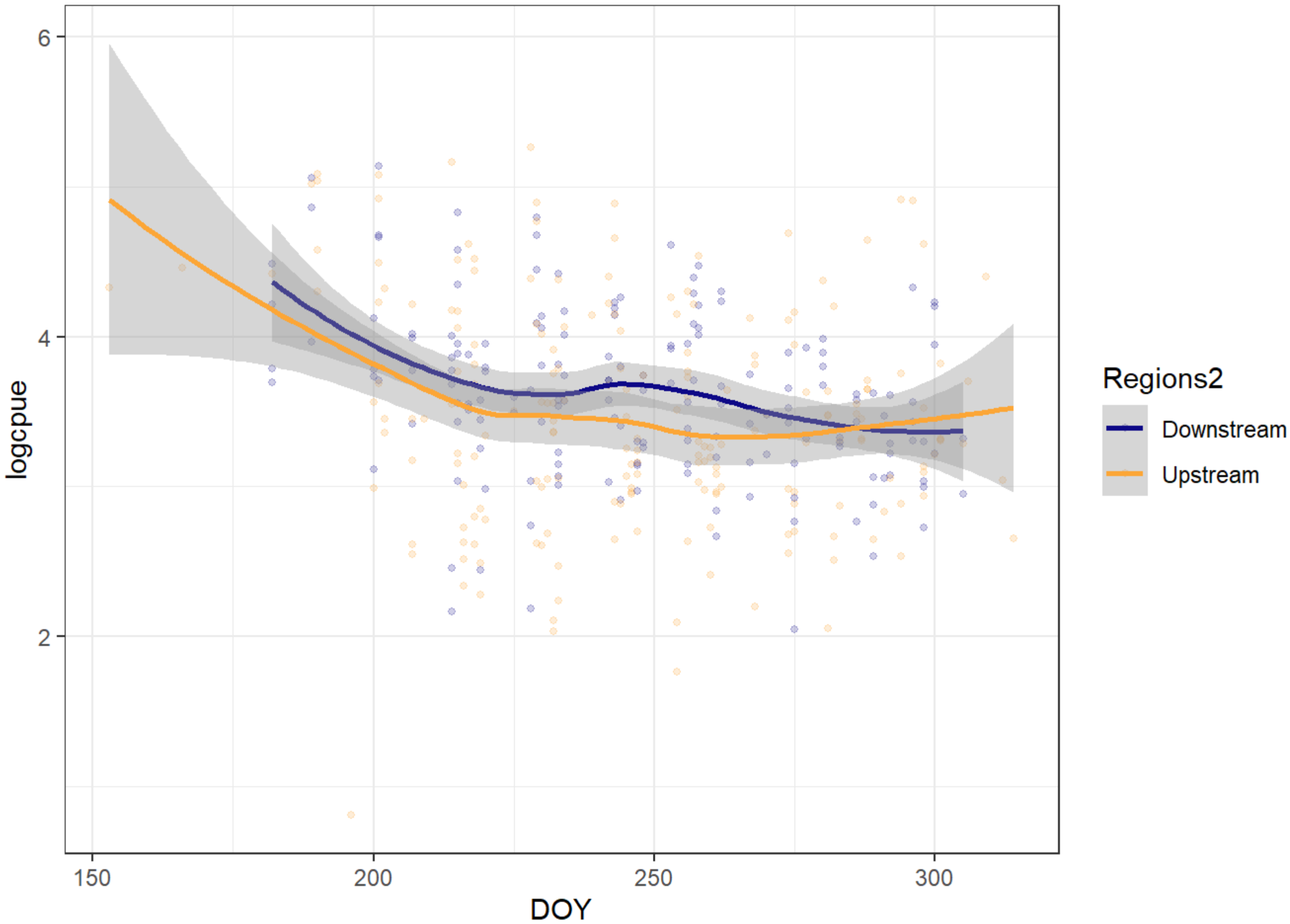

```
zoopNDFA8 %>%
  ggplot(aes(x = DOY, y = logcpue)) +
  geom_point(size = 1, alpha = 0.2) +
  geom_smooth() +
  theme_bw()
```

```
## `geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```




```
zoopNDFA8 %>%
  ggplot(aes(x = DOY, y = logcpue, color = Regions2)) +
  geom_point(size = 1, alpha = 0.2) +
  geom_smooth() +
  scale_color_viridis_d(option = "plasma", end = 0.8) +
  theme_bw()
```

```
## `geom_smooth()` using method = 'loess' and formula = 'y ~ x'
```

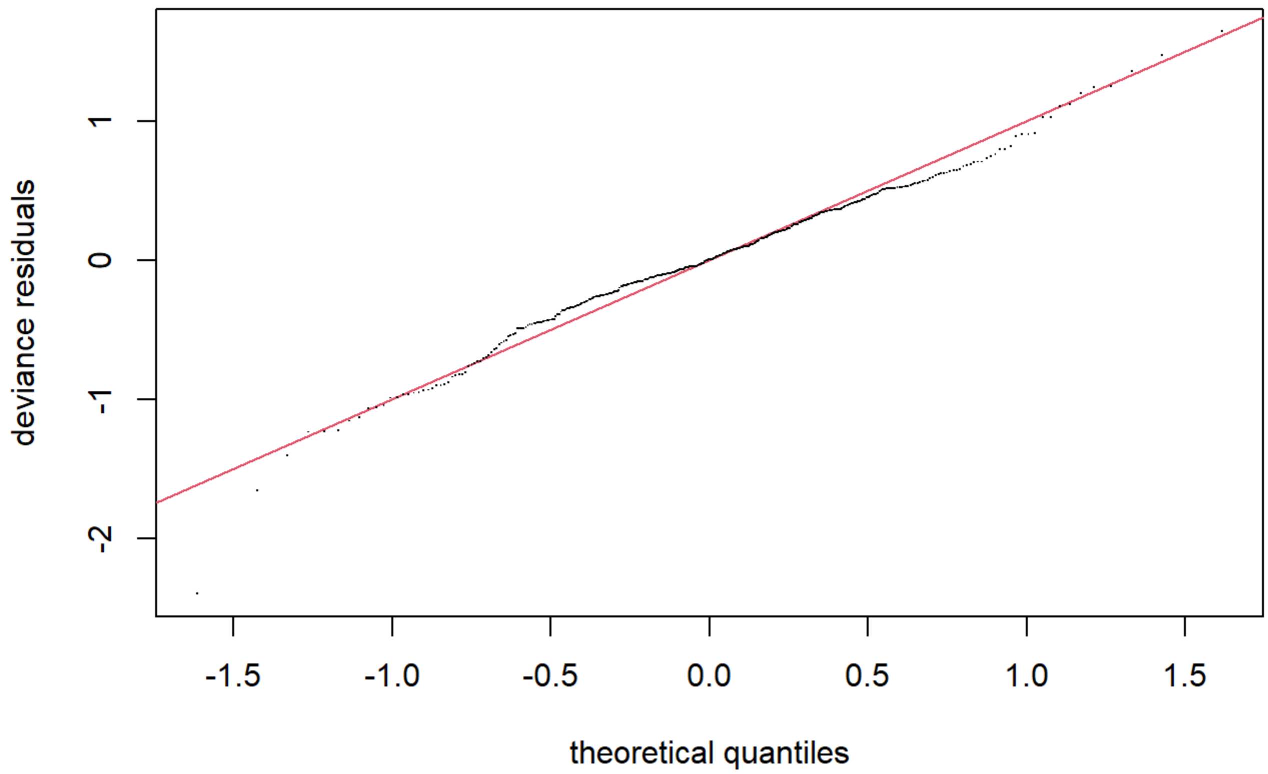


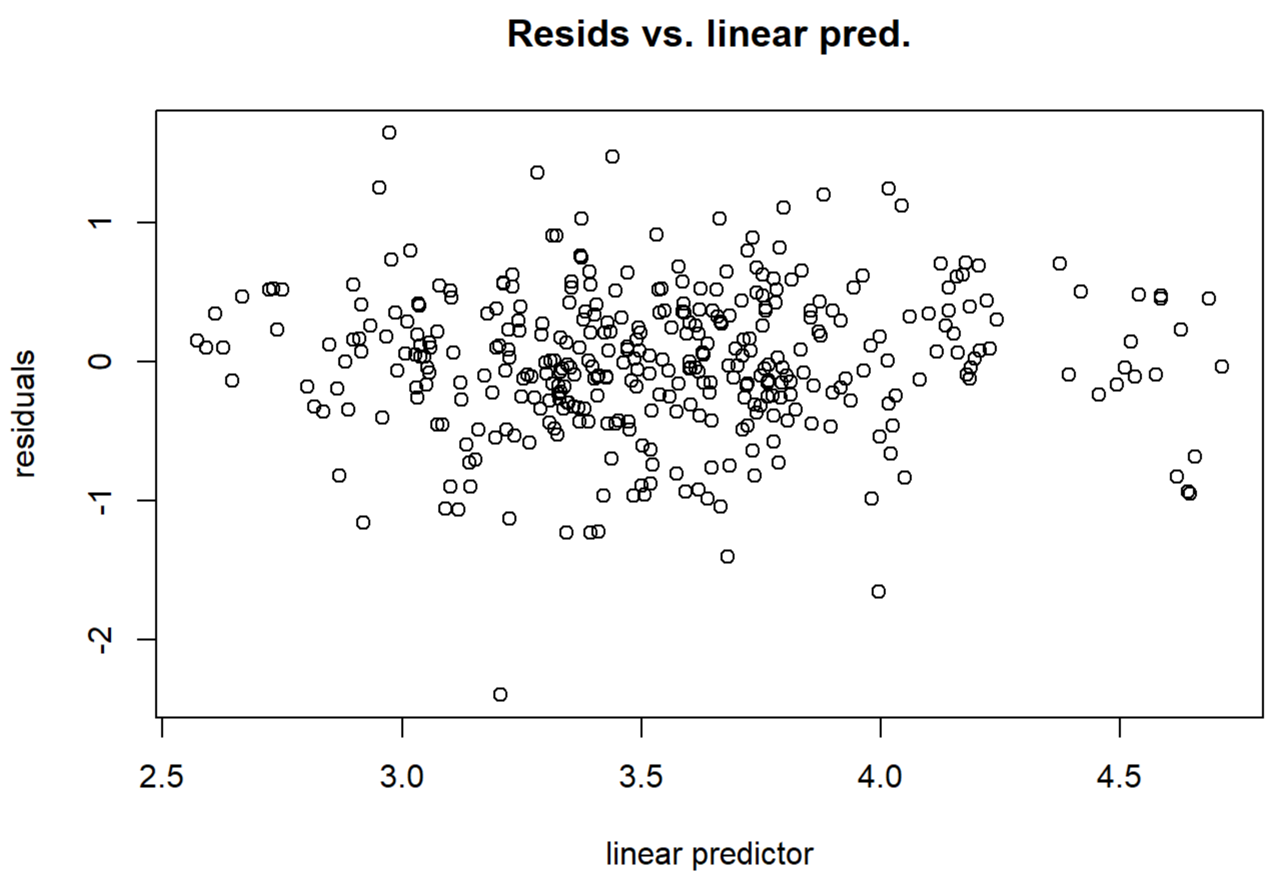

```
#model4.1 <- lmer(log(cpue) ~ Regions2*Year+Year*SamplePeriod+SamplePeriod*Regions2+(1|Station
Code),data = zoopNDFA7,REML = TRUE)

m_cpue_gam <- gam(
  logcpue ~ (Year+SamplePeriod+Regions2)^2 + s(DOY, k=20) + s(StationCode, bs = "re"),
  data = zoopNDFA8,
  method = "REML"
)

summary(m_cpue_gam)
```

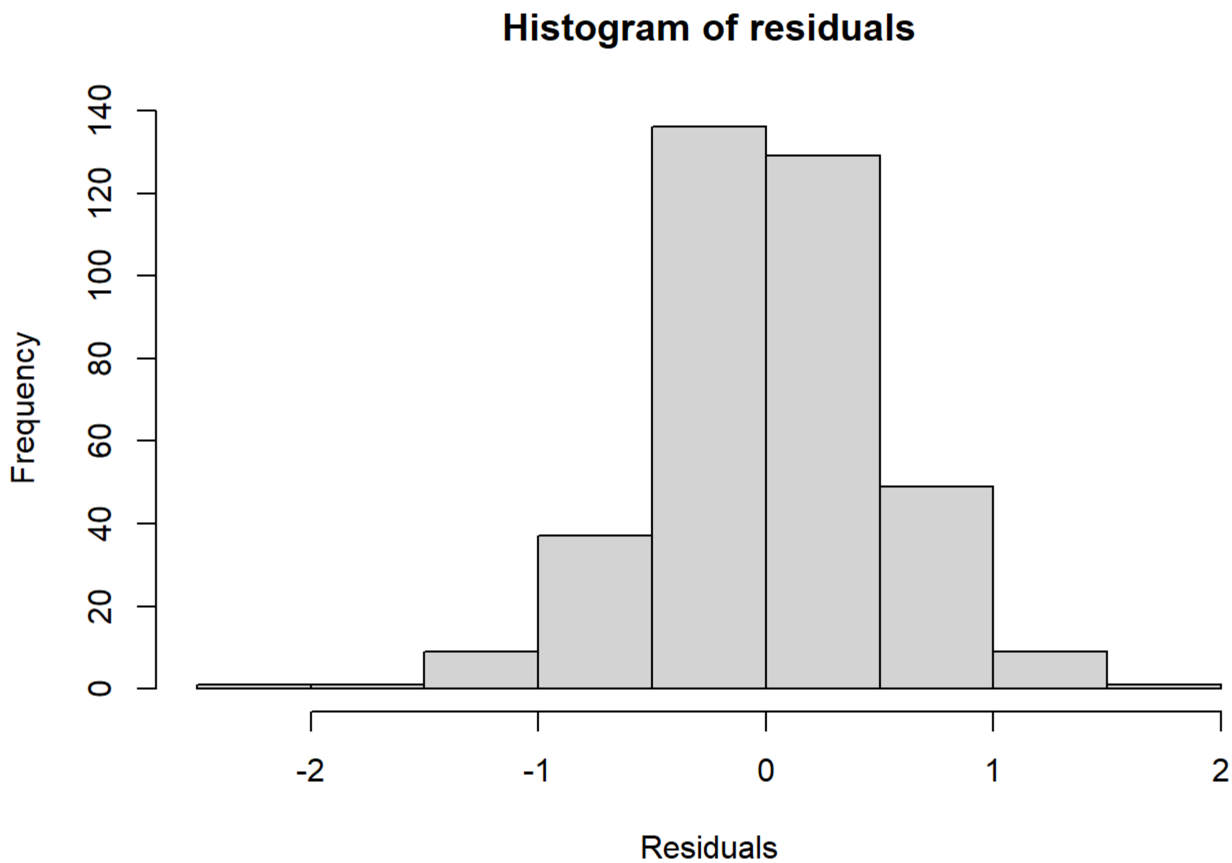
```
##
## Family: gaussian
## Link function: identity
##
## Formula:
## logcpue ~ (Year + SamplePeriod + Regions2)^2 + s(DOY, k = 20) +
##     s(StationCode, bs = "re")
##
## Parametric coefficients:
##                                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)                             3.75784    0.20626  18.219  < 2e-16 ***
## Year2015                               -0.24456    0.21001  -1.165 0.245025
## Year2016                                0.90105    0.24625   3.659 0.000293 ***
## Year2017                               -0.36649    0.20334  -1.802 0.072372 .
```

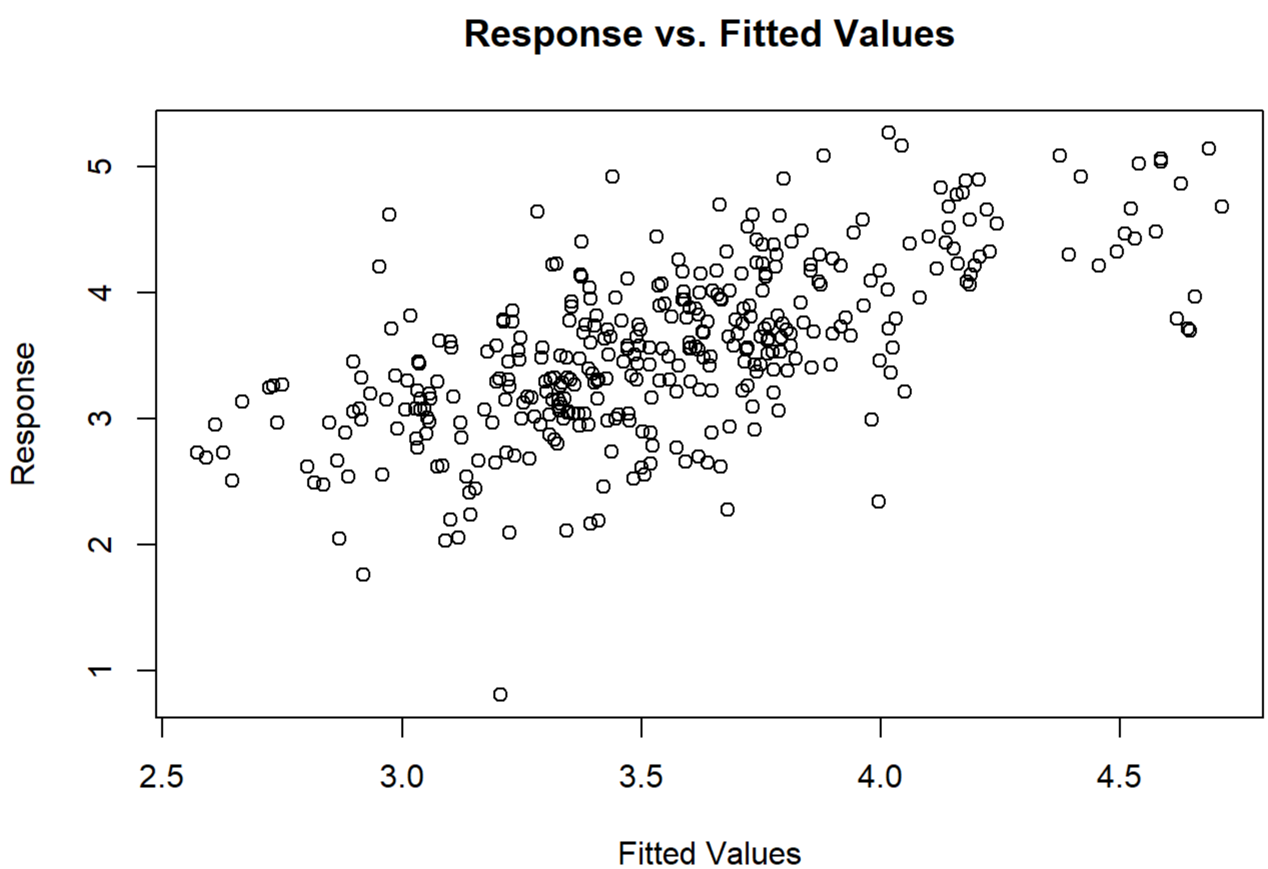
```
## Year2018                              -0.12904    0.18752  -0.688 0.491825
## Year2019                              -0.56858    0.21294  -2.670 0.007948 **
## SamplePeriodDuring                     0.02186    0.24461   0.089 0.928859
## SamplePeriodAfter                     -0.14299    0.23477  -0.609 0.542869
## Regions2Upstream                      -0.21037    0.23141  -0.909 0.363958
## Year2015:SamplePeriodDuring            0.32353    0.27551   1.174 0.241107
## Year2016:SamplePeriodDuring            0.01966    0.31586   0.062 0.950416
## Year2017:SamplePeriodDuring            0.02043    0.27325   0.075 0.940437
## Year2018:SamplePeriodDuring            0.06920    0.26196   0.264 0.791825
## Year2019:SamplePeriodDuring           -0.24458    0.28223  -0.867 0.386767
## Year2015:SamplePeriodAfter             0.27110    0.23475   1.155 0.248965
## Year2016:SamplePeriodAfter            -0.39392    0.23311  -1.690 0.091981 .
## Year2017:SamplePeriodAfter            -0.27617    0.27610  -1.000 0.317901
## Year2018:SamplePeriodAfter            -0.21550    0.21266  -1.013 0.311595
## Year2019:SamplePeriodAfter            -0.09427    0.24040  -0.392 0.695196
## Year2015:Regions2Upstream             -0.25393    0.20171  -1.259 0.208927
## Year2016:Regions2Upstream             -0.05708    0.20533  -0.278 0.781179
## Year2017:Regions2Upstream              0.63769    0.21233   3.003 0.002870 **
## Year2018:Regions2Upstream             -0.12765    0.18706  -0.682 0.495445
## Year2019:Regions2Upstream              0.51408    0.20859   2.465 0.014215 *
## SamplePeriodDuring:Regions2Upstream -0.22268    0.14422  -1.544 0.123501
## SamplePeriodAfter:Regions2Upstream   0.10576    0.13547   0.781 0.435526
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Approximate significance of smooth terms:
##                  edf Ref.df     F p-value
## s(DOY)         1.001  1.002 0.222   0.639
## s(StationCode) 6.210  7.000 7.720  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## R-sq.(adj) =   0.36   Deviance explained = 41.6%
## -REML =  322.8  Scale est. = 0.28971   n = 372
```

```
gam.check(m_cpue_gam)
```


deviance residuals
theoretical quantiles
-2
-1
0
1
-1.5
-1.0
-0.5
0.0
0.5
1.0
1.5

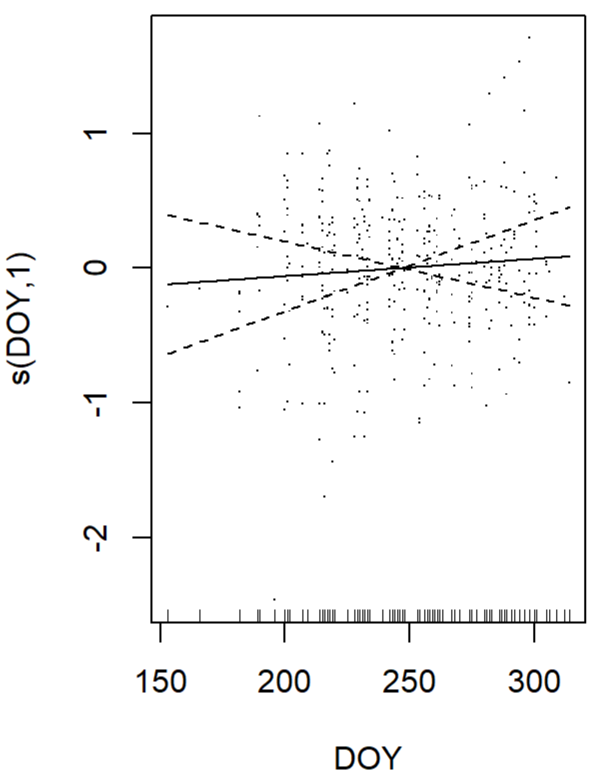

Resids vs. linear pred.
residuals
linear predictor
-2
-1
0
1
2.5
3.0
3.5
4.0
4.5

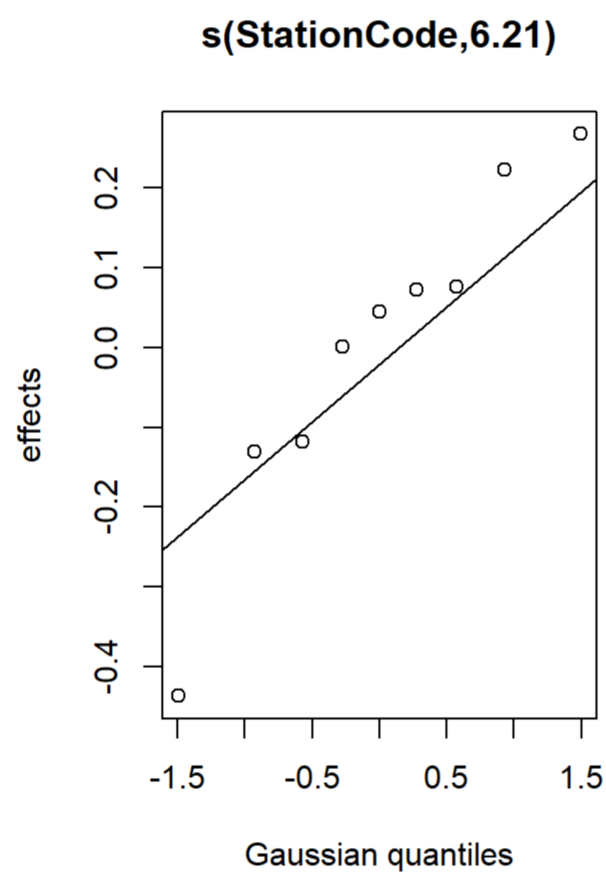

Histogram of residuals
Frequency
Residuals
0
20
40
60
80
100
120
140
-2
-1
0
1
2


Response vs. Fitted Values
Response
Fitted Values
1
2
3
4
5
2.5
3.0
3.5
4.0
4.5

```
##
## Method: REML   Optimizer: outer newton
## full convergence after 11 iterations.
## Gradient range [-0.0001881878,0.0002267279]
## (score 322.7969 & scale 0.2897056).
## Hessian positive definite, eigenvalue range [0.0001880989,172.5565].
## Model rank =  54 / 54
##
## Basis dimension (k) checking results. Low p-value (k-index<1) may
## indicate that k is too low, especially if edf is close to k'.
##
##                    k'   edf k-index p-value
## s(DOY)          19.00  1.00       1    0.48
## s(StationCode)   9.00  6.21      NA      NA
```

```
plot(m_cpue_gam, pages=1, residuals=TRUE)
```






```
#check out geom_quasirandom from the ggbeeswarm package
```