

warmXtrophic Project: Plant Composition Data Analyses

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Load in packages & data

```
# Clear all existing data
rm(list = ls())

# Load packages
library(tidyverse)
library(ggplot2)
library(lme4)
library(lmerTest)
library(olsrr)
library(predictmeans)
library(car)
library(fitdistrplus)
library(ggpubr)
library(rstatix)
library(vegan)
library(interactions)
library(sjPlot)
library(effects)
library(glmmTMB)
library(labdsrv) # used with Vegan package, the matrify() and matrify2() functions
library(agricolae) # HSD.test() function
library(emmeans)
library(scales)
library(fitdistrplus)
library(moments) # for calculating skewness of data
library(jtools) # summ() function
library(GGally) # ggpairs() function
library(bbmle) # AICtab() function

# Set working directory
Sys.getenv("L1DIR")

## [1] "/Volumes/GoogleDrive/Shared drives/SpaCE_Lab_warmXtrophic/data/L1"

L0_dir <- Sys.getenv("LODIR")
L1_dir <- Sys.getenv("L1DIR")
L2_dir <- Sys.getenv("L2DIR")
list.files(L1_dir)
```

```

## [1] "ANPP"           "climate_data"      "CN"
## [4] "Greenness"       "herbivory"        "HOB0_data"
## [7] "PAR"             "phenology"        "plant_composition"
## [10] "SLA"

# Set ggplot2 plotting This code for ggplot2 sets the theme to mostly black and
# white (Arial font, and large font, base size=24)
theme_set(theme_bw(14))
theme_update(axis.text.x = element_text(size = 12, angle = 90), axis.text.y = element_text(size = 12))

# read in plant comp data
comp_species <- read.csv(file.path(L2_dir, "plant_composition/final_plant_comp_species_L2.csv"))
comp_plot <- read.csv(file.path(L2_dir, "plant_composition/final_plant_comp_plot_L2.csv"))
comp_plot_origin <- read.csv(file.path(L2_dir, "plant_composition/final_plant_comp_plot_origin_L2.csv"))
comp_plot_growthhabit <- read.csv(file.path(L2_dir, "plant_composition/final_plant_comp_plot_growthhabit"))

comp_species <- comp_species %>% select(-X) # get rid of 'X' column that shows up
comp_plot <- comp_plot %>% select(-X) # get rid of 'X' column that shows up
comp_plot_origin <- comp_plot_origin %>% select(-X)
comp_plot_growthhabit <- comp_plot_growthhabit %>% select(-X)

# Order warmed and ambient so that warmed shows up first in plotting (and is
# default is red = warmed; blue = ambient). First make it a factor
comp_species$state <- as.factor(comp_species$state)
levels(comp_species$state)

## [1] "ambient" "warmed"

# [1] 'ambient' 'warmed'
comp_species$state <- factor(comp_species$state, levels(comp_species$state)[c(2,
  1)])
levels(comp_species$state)

## [1] "warmed"   "ambient"

# [1] 'warmed' 'ambient'

comp_plot$state <- as.factor(comp_plot$state)
levels(comp_plot$state)

## [1] "ambient" "warmed"

# [1] 'ambient' 'warmed'
comp_plot$state <- factor(comp_plot$state, levels(comp_plot$state)[c(2, 1)])
levels(comp_plot$state)

## [1] "warmed"   "ambient"

```

```

# [1] 'warmed' 'ambient'

# create dataframes for kbs and umbs - remember that these contain species within
# plots
comp_kbs_spp <- subset(comp_species, site == "kbs")
comp_umbs_spp <- subset(comp_species, site == "umbs")
comp_umbs_spp <- subset(comp_umbs_spp, year_factor != "7") # delete 2021 data from umbs dataframe (does

# create dataframes for kbs and umbs
comp_kbs_plot <- subset(comp_plot, site == "kbs")
comp_umbs_plot <- subset(comp_plot, site == "umbs")
comp_umbs_plot <- subset(comp_umbs_plot, year_factor != "7") # delete 2021 data from umbs dataframe (d

kbs_comp_plot_origin <- subset(comp_plot_origin, site == "kbs")
kbs_comp_plot_growthhabit <- subset(comp_plot_growthhabit, site == "kbs")
umbs_comp_plot_origin <- subset(comp_plot_origin, site == "umbs")
umbs_comp_plot_origin <- subset(umbs_comp_plot_origin, year_factor != "7") # delete 2021 data
umbs_comp_plot_growthhabit <- subset(comp_plot_growthhabit, site == "umbs")
umbs_comp_plot_growthhabit <- subset(umbs_comp_plot_growthhabit, year_factor != "7") # delete 2021 dat

```

Data exploration - some different ways of visualizing these data

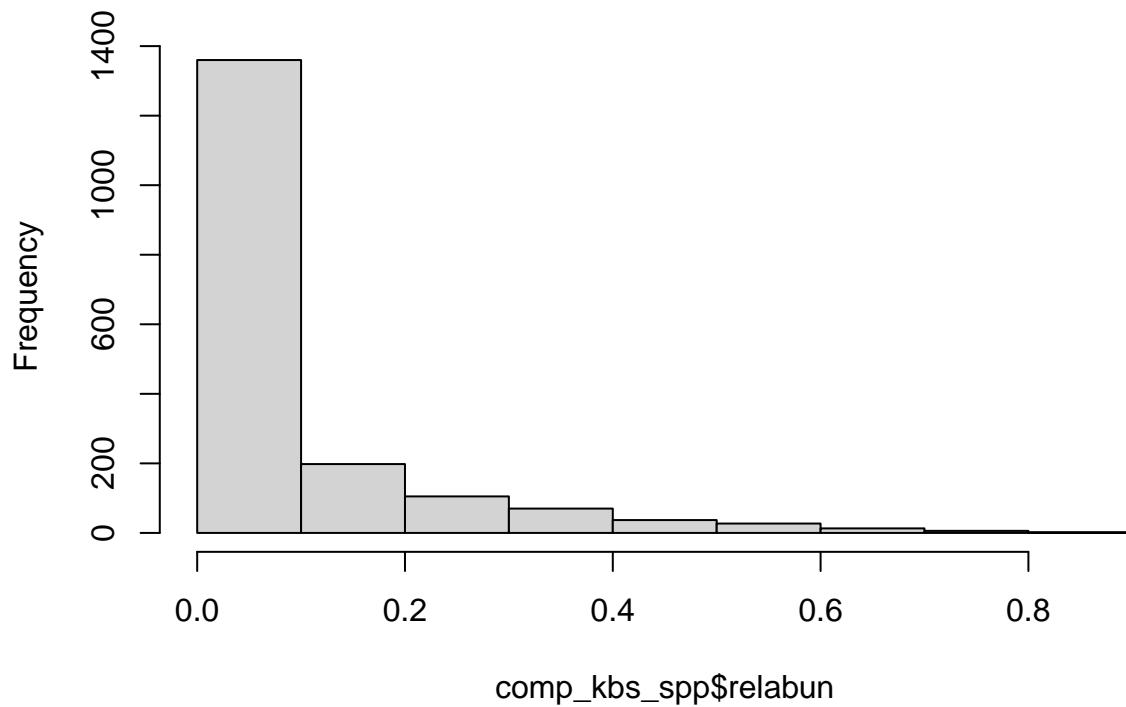
KBS SPECIES LEVEL - Looking at RELATIVE ABUNDANCE

```

### KBS ####
hist(comp_kbs_spp$relabun) # very skewed to the right

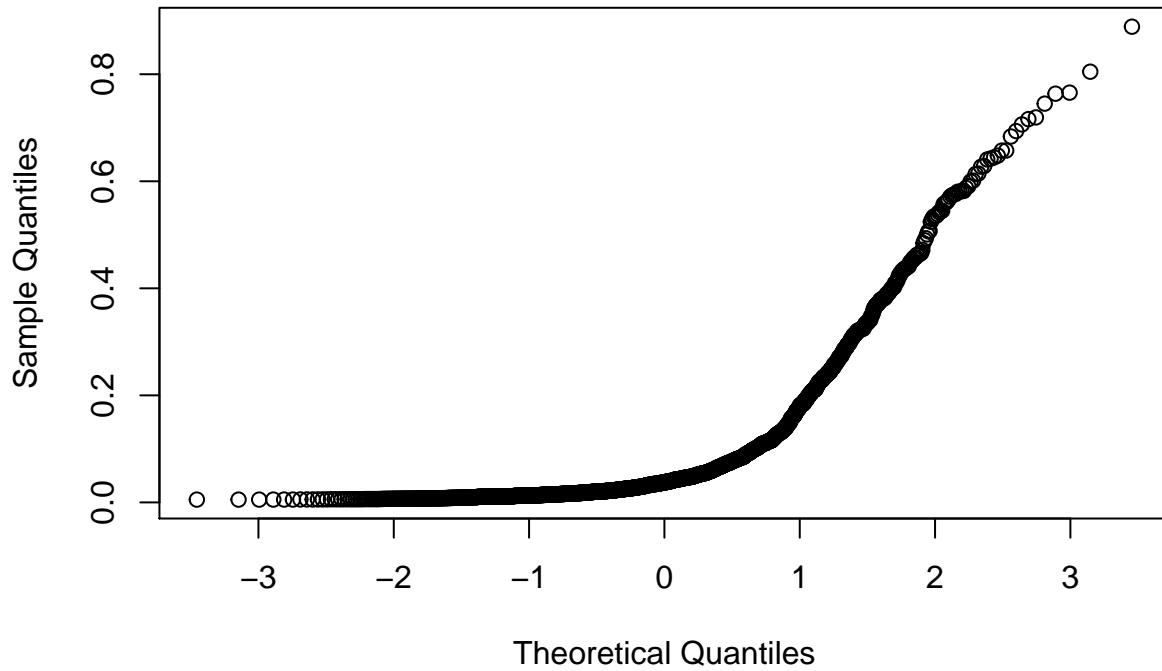
```

Histogram of comp_kbs_spp\$relabun



```
qqnorm(comp_kbs_spp$relabun)
```

Normal Q-Q Plot



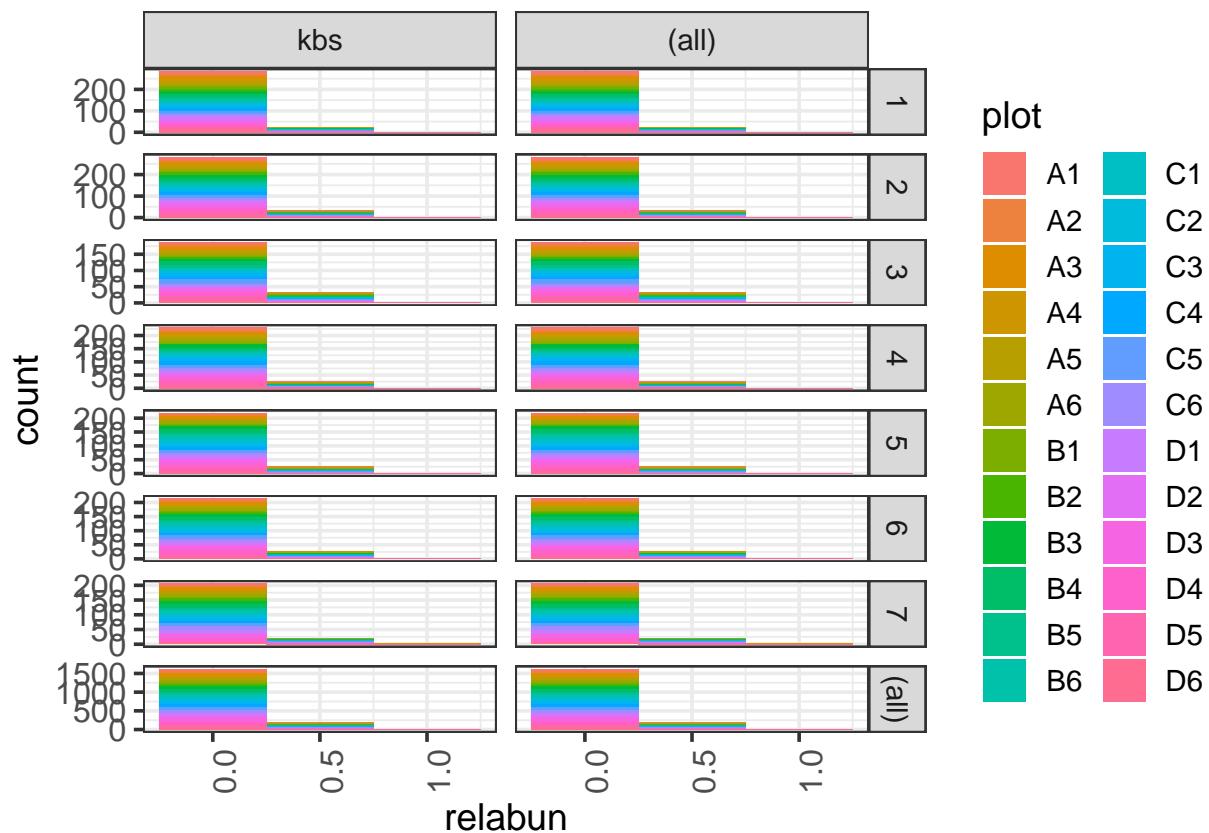
```

shapiro.test(comp_kbs_spp$relabun) # pvalue is < 0.05 so we reject the null hypothesis that the data is normal

## 
## Shapiro-Wilk normality test
## 
## data: comp_kbs_spp$relabun
## W = 0.65236, p-value < 2.2e-16

# Visualizing relative abundance for kbs at the SPECIES LEVEL
ggplot(comp_kbs_spp, aes(relabun, fill = plot)) + geom_histogram(binwidth = 0.5) +
  facet_grid(year_factor ~ site, margins = TRUE, scales = "free")

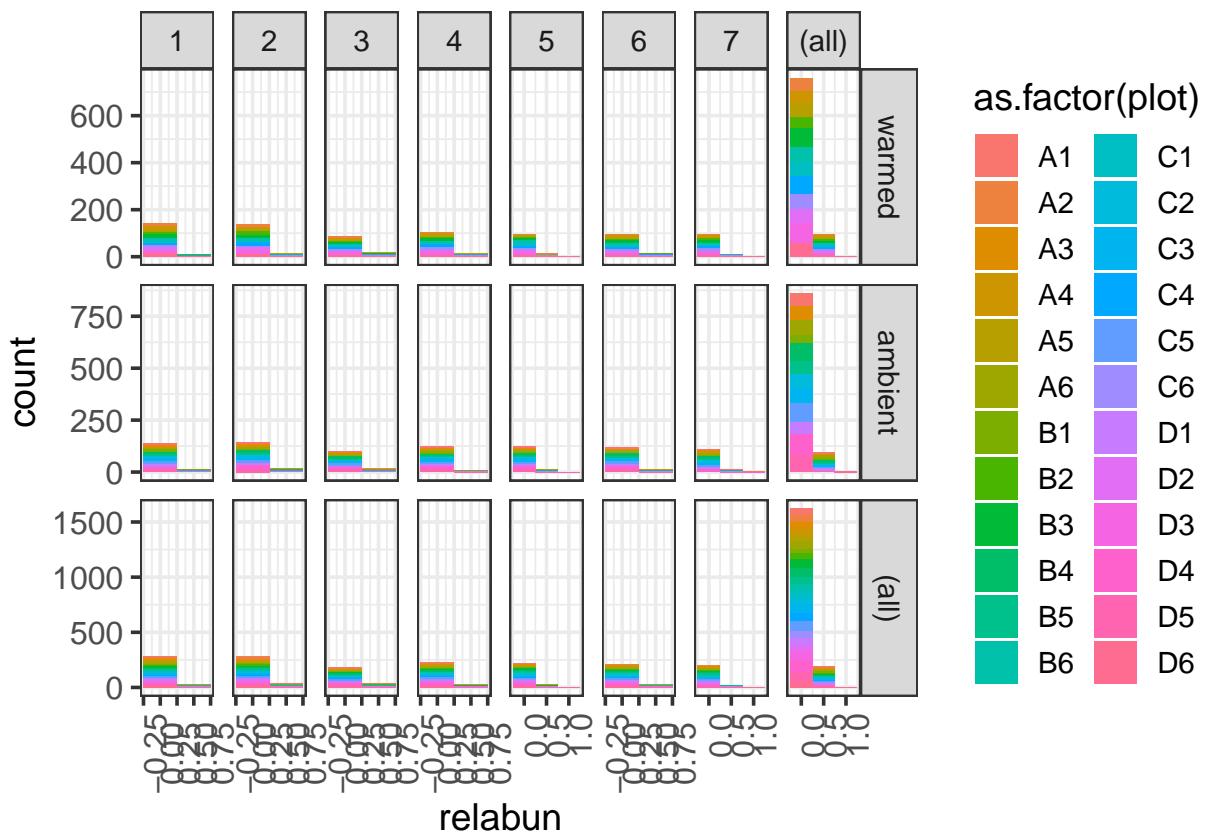
```



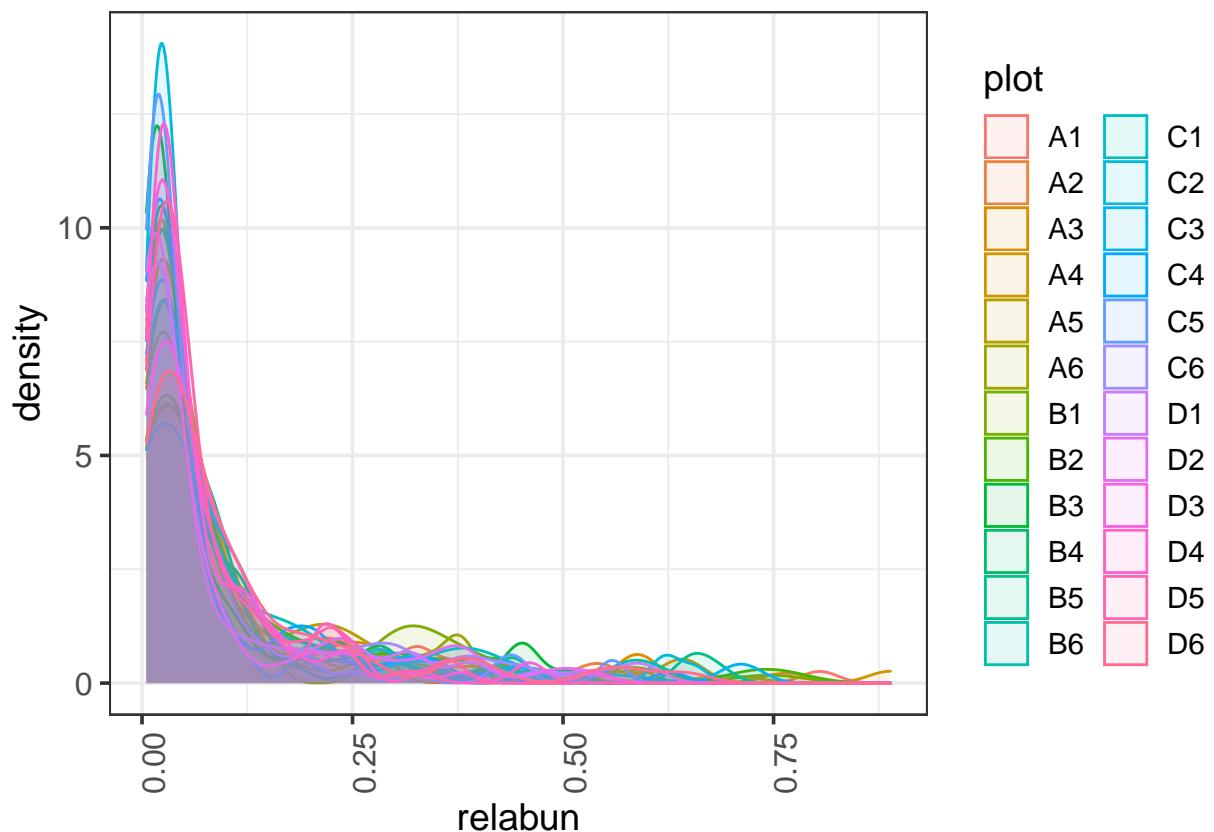
```

ggplot(comp_kbs_spp, aes(relabun, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
  facet_grid(state ~ year_factor, margins = TRUE, scales = "free")

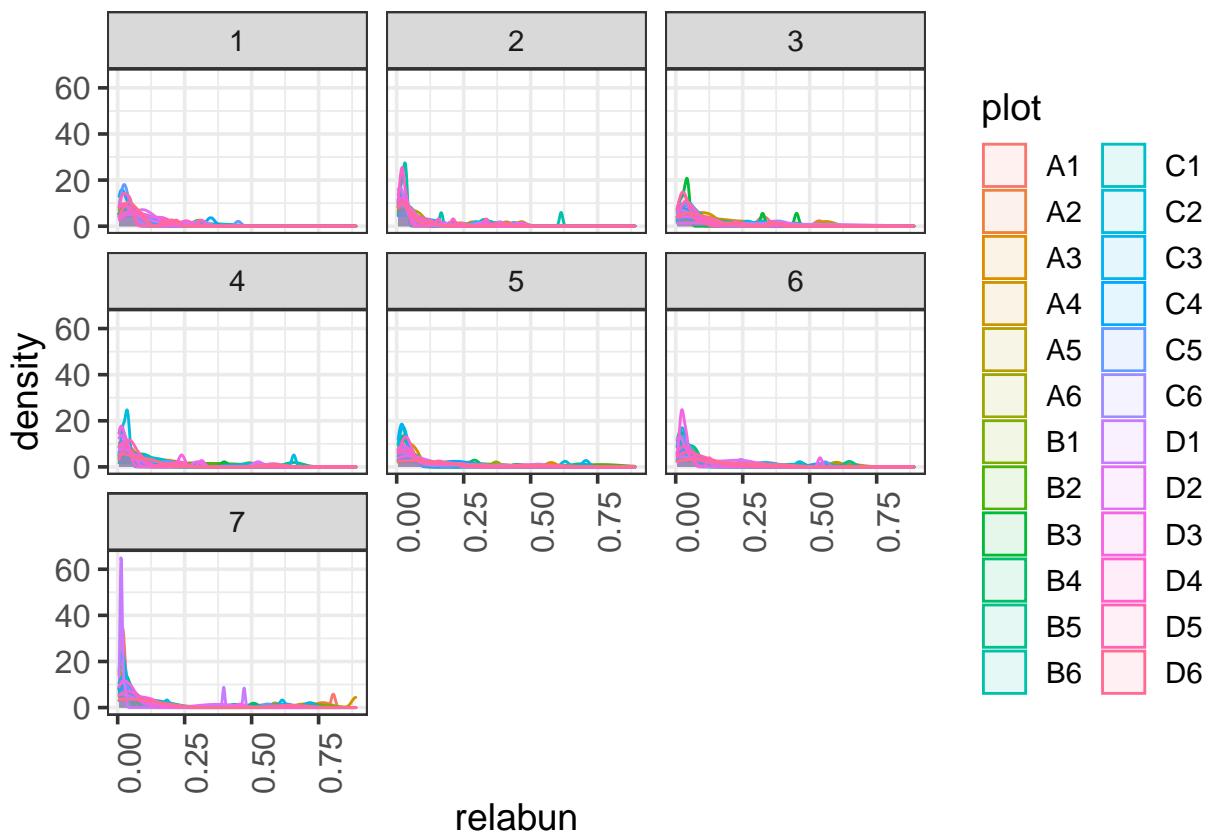
```



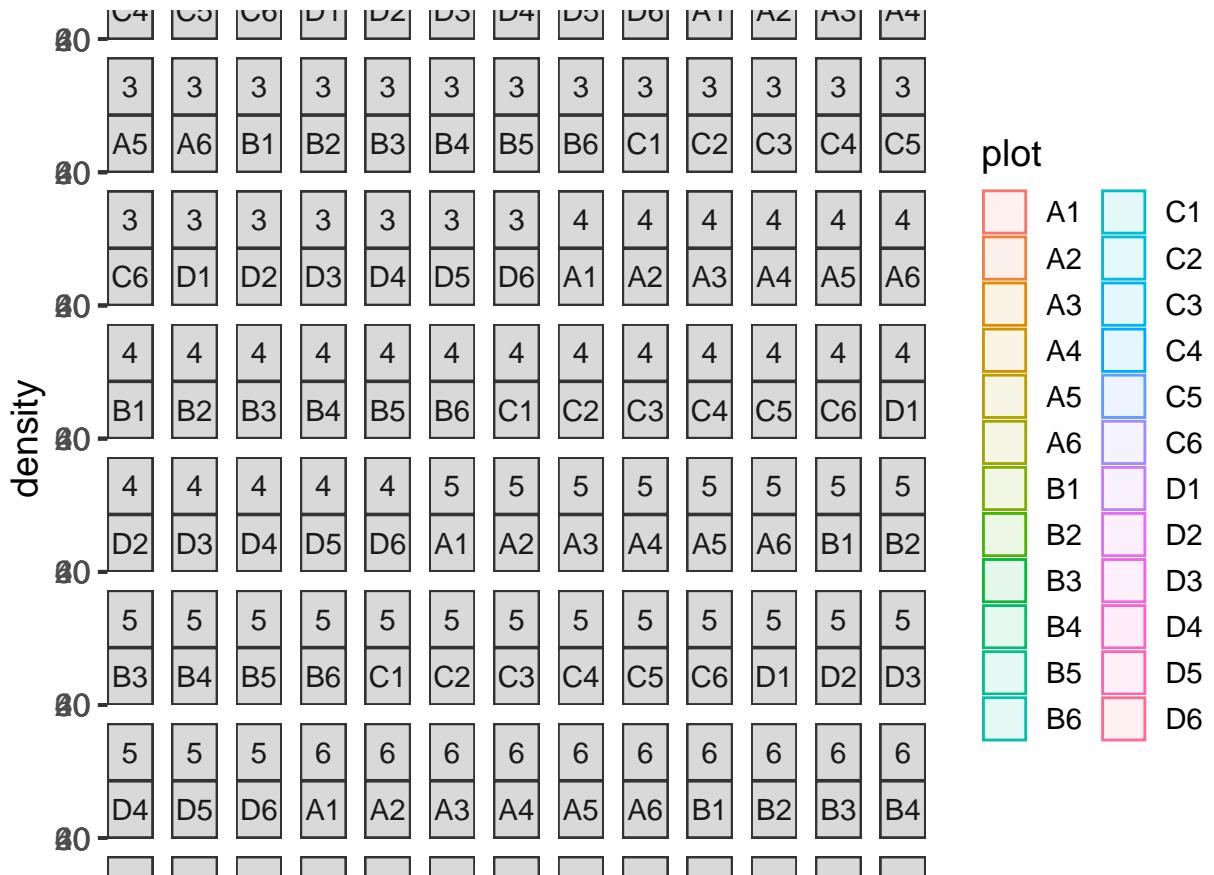
```
ggplot(comp_kbs_spp, aes(relabun, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



```
ggplot(comp_kbs_spp, aes(relabun, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
  facet_wrap(~year_factor)
```

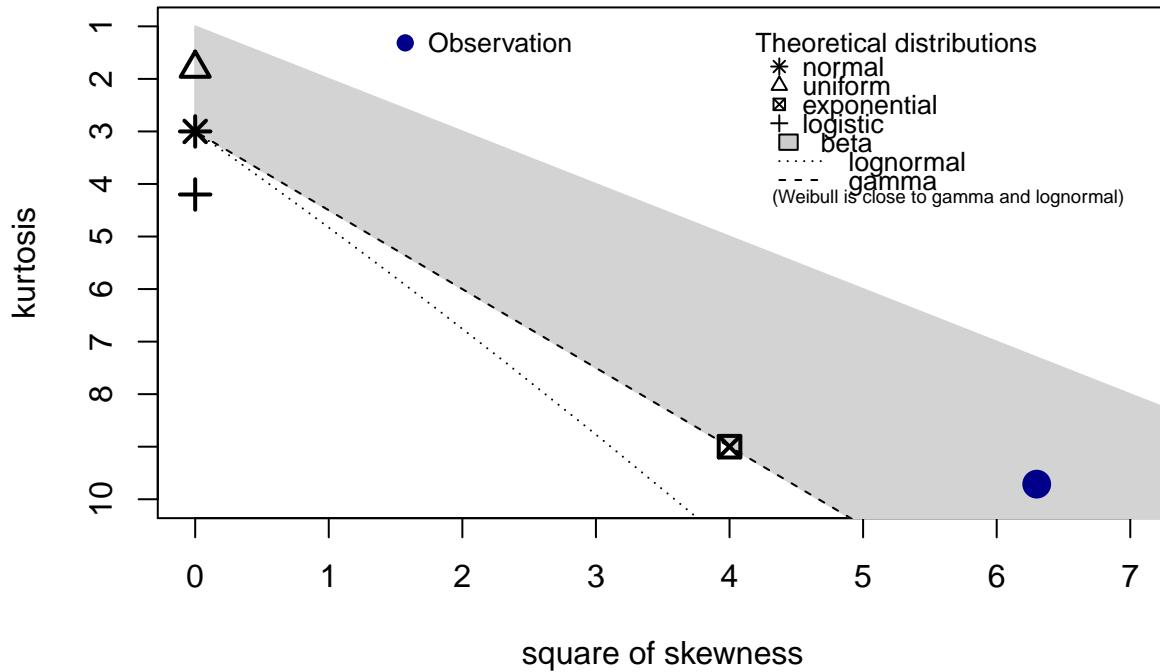


```
ggplot(comp_kbs_spp, aes(relabun, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
  facet_wrap(~year_factor + plot)
```



```
# Exploring distributions for these right-skewed data:  
descdist(comp_kbs_spp$relabun, discrete = FALSE)
```

Cullen and Frey graph



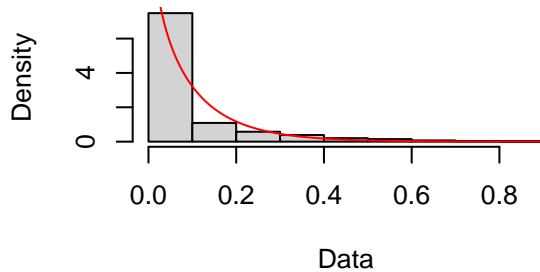
```

## summary statistics
## -----
## min:  0.005242388  max:  0.8888504
## median:  0.03707022
## mean:  0.09185919
## estimated sd:  0.1308706
## estimated skewness:  2.509919
## estimated kurtosis:  9.712586

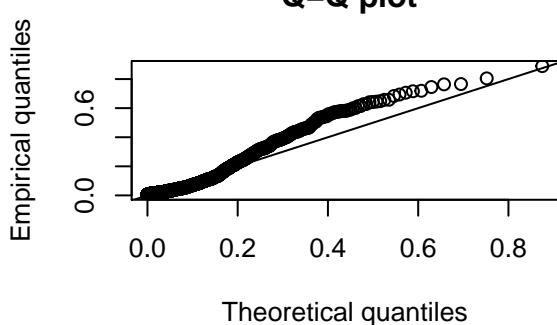
# Gamma distribution
fit.gamma <- fitdist(comp_kbs_spp$relabun, "gamma")
plot(fit.gamma)

```

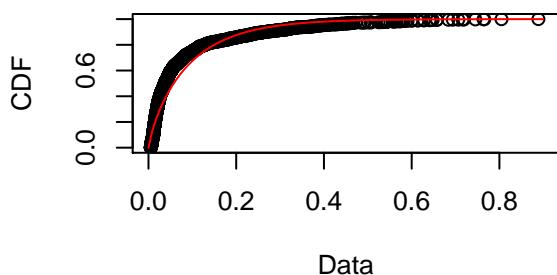
Empirical and theoretical dens.



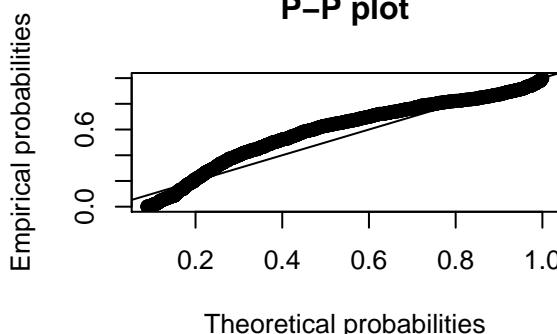
Q-Q plot



Empirical and theoretical CDFs

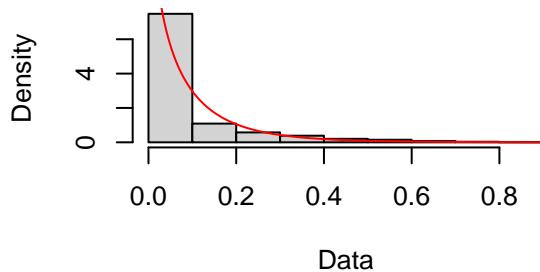


P-P plot

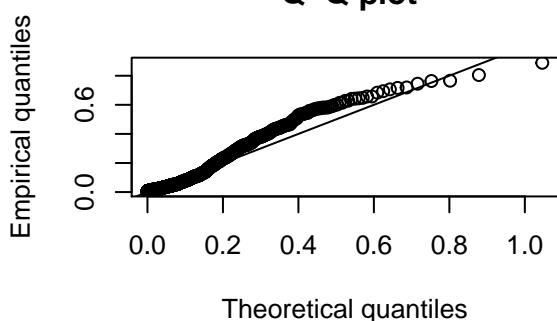


```
# Weibull distribution
fit.weibull <- fitdist(comp_kbs_spp$relabun, "weibull")
plot(fit.weibull)
```

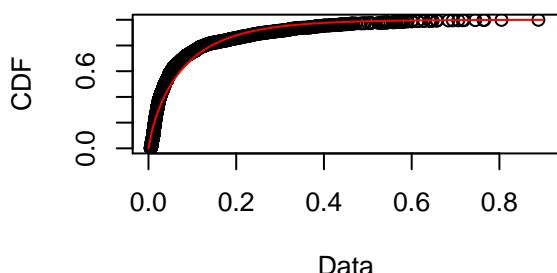
Empirical and theoretical dens.



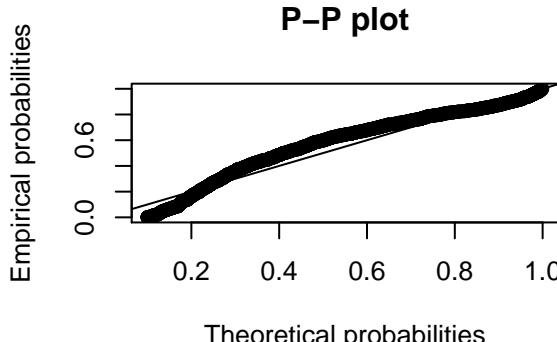
Q-Q plot



Empirical and theoretical CDFs

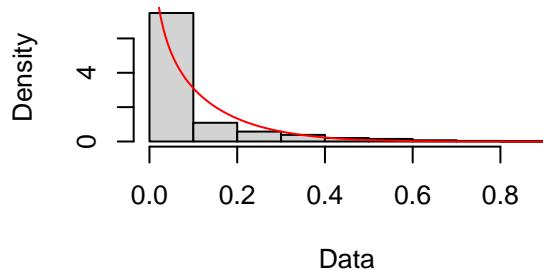


P-P plot

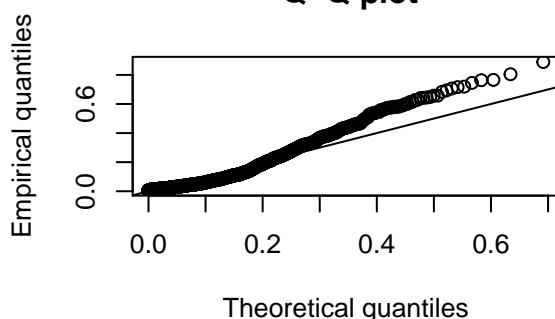


```
# Beta distribution
fit.beta <- fitdist(comp_kbs_spp$relabun, "beta")
plot(fit.beta)
```

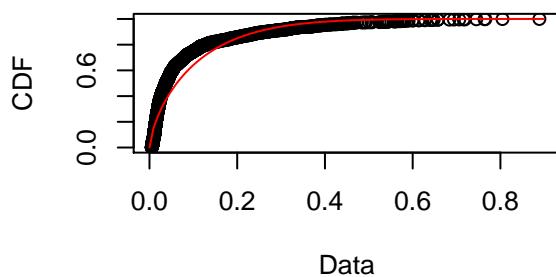
Empirical and theoretical dens.



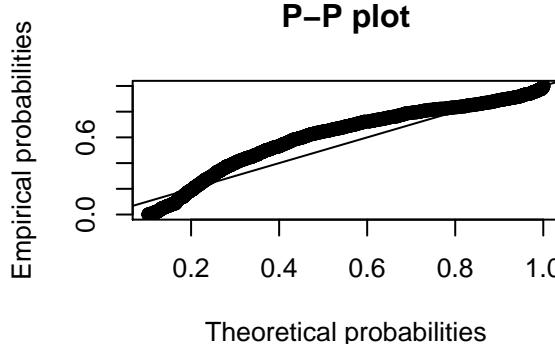
Q–Q plot



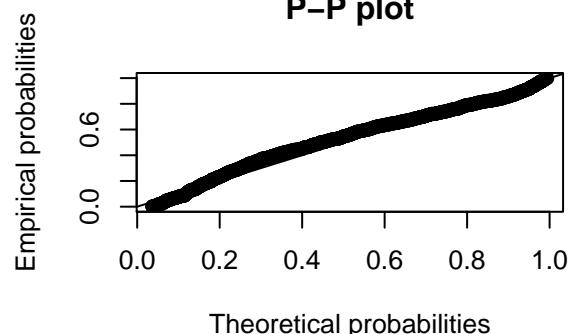
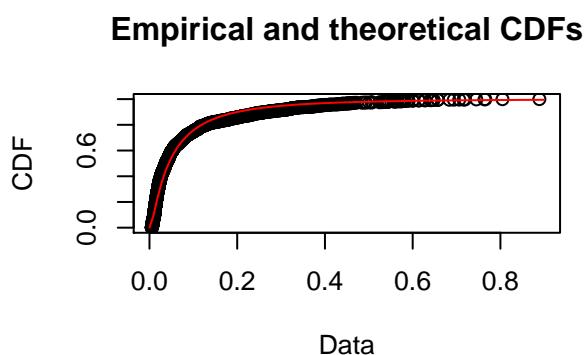
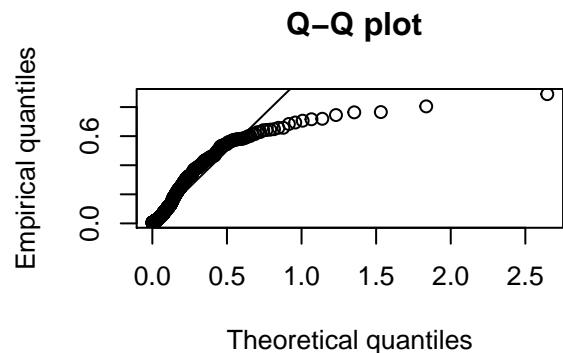
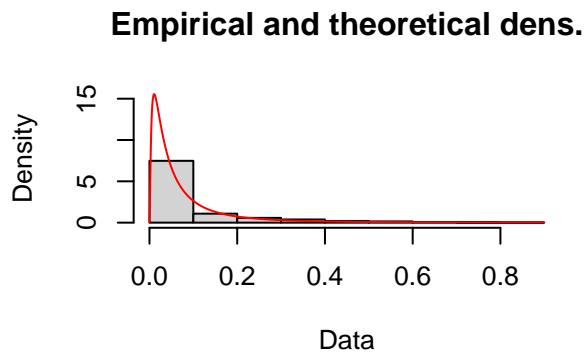
Empirical and theoretical CDFs



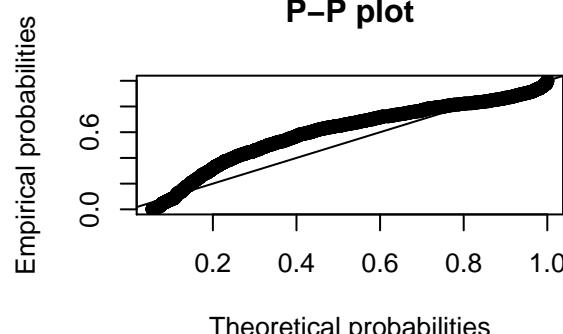
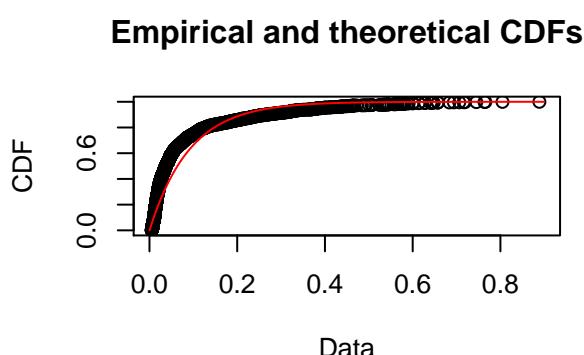
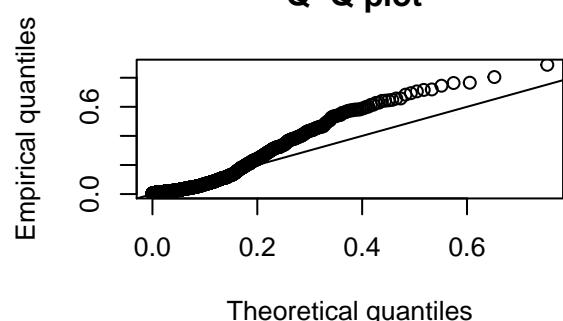
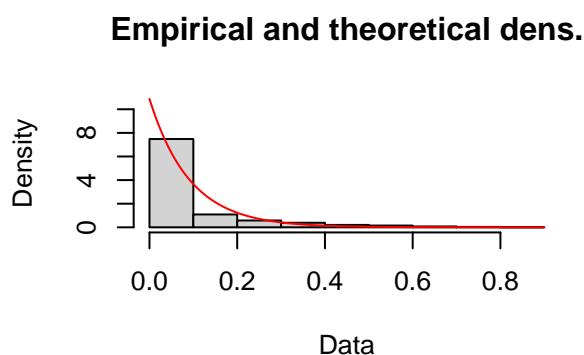
P–P plot



```
# Lognormal distribution
fit.ln <- fitdist(comp_kbs_spp$relabun, "lnorm")
plot(fit.ln)
```



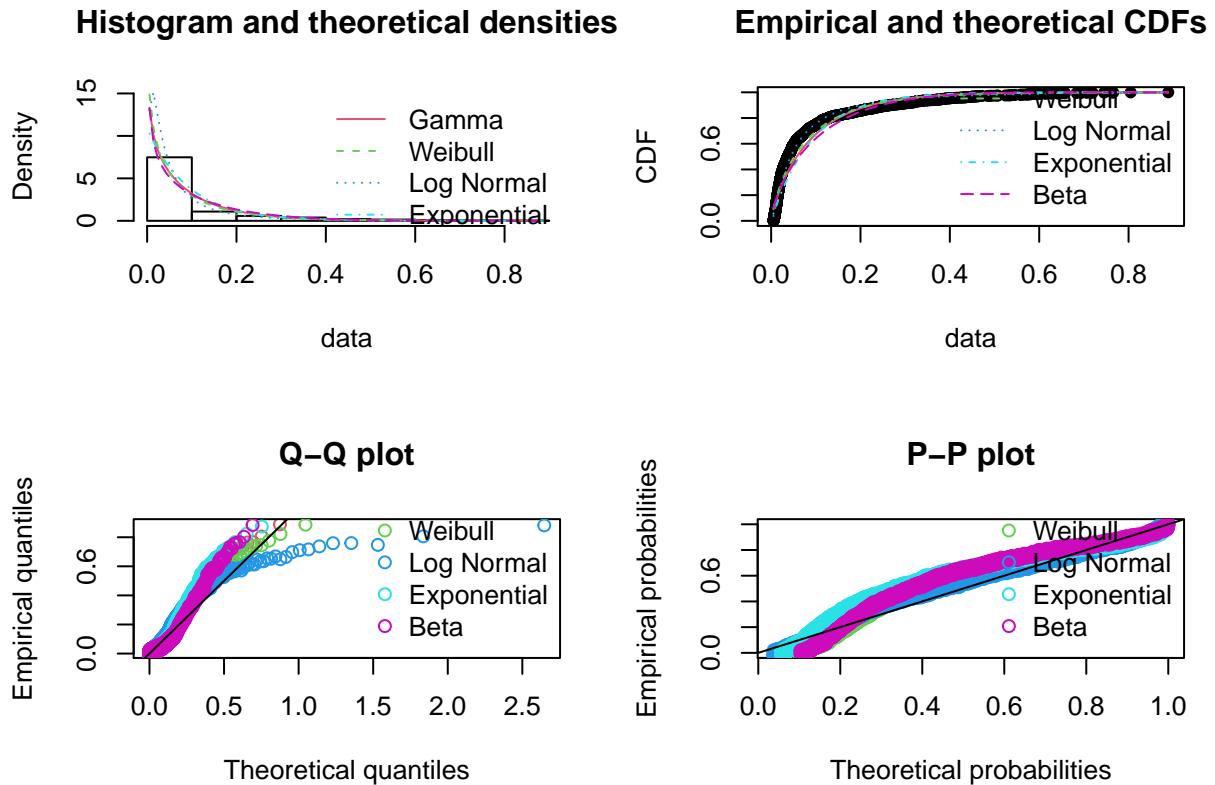
```
# Exponential distribution is another option
fit.exp <- fitdist(comp_kbs_spp$relabun, "exp")
plot(fit.exp)
```



```

par(mfrow = c(2, 2))
plot.legend <- c("Gamma", "Weibull", "Log Normal", "Exponential", "Beta")
denscomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp, fit.beta), legendtext = plot.legend)
cdfcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp, fit.beta), legendtext = plot.legend)
qqcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp, fit.beta), legendtext = plot.legend)
ppcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp, fit.beta), legendtext = plot.legend)

```



```

# Goodness of fit comparisons across fits (can't include the sqrt normal bc it
# becomes diff response values)
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp, fit.beta), fitnames = c("Gamma",
    "Weibull", "Log Normal", "Exp", "Beta"))

```

```

## Goodness-of-fit statistics
##                                     Gamma   Weibull  Log Normal      Exp
## Kolmogorov-Smirnov statistic 0.1344308 0.1033437 0.07028364 0.1745875
## Cramer-von Mises statistic  11.5969326 7.4683494 2.61728997 20.4114453
## Anderson-Darling statistic  63.7686160 46.8700036 17.18469890 105.2325017
##                                     Beta
## Kolmogorov-Smirnov statistic 0.1528005
## Cramer-von Mises statistic 15.1430209
## Anderson-Darling statistic 80.6642522
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull  Log Normal      Exp
## Akaike's Information Criterion -5106.036 -5187.224 -5591.800 -5042.944
## Bayesian Information Criterion -5095.025 -5176.213 -5580.789 -5037.439
##                                     Beta

```

```

## Akaike's Information Criterion -4939.073
## Bayesian Information Criterion -4928.062

# Beta and exp distributions look to be the best based on AIC and BIC values

```

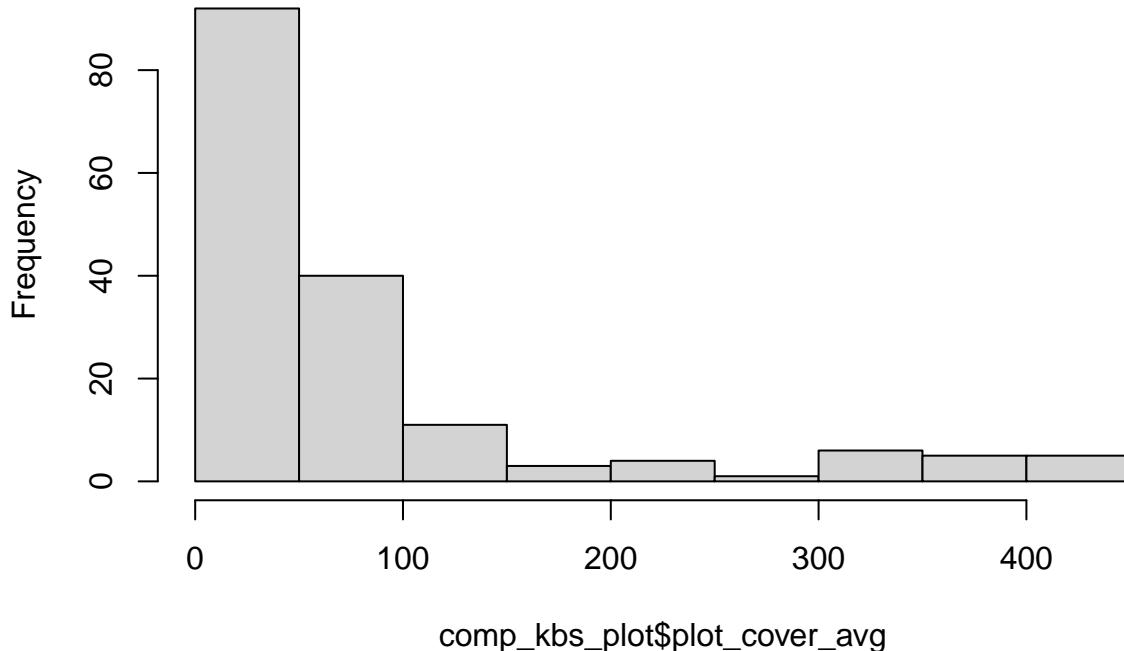
KBS PLOT LEVEL - Looking at PLOT AVG TOTALS

```

### KBS ####
hist(comp_kbs_plot$plot_cover_avg) # skewed to the right

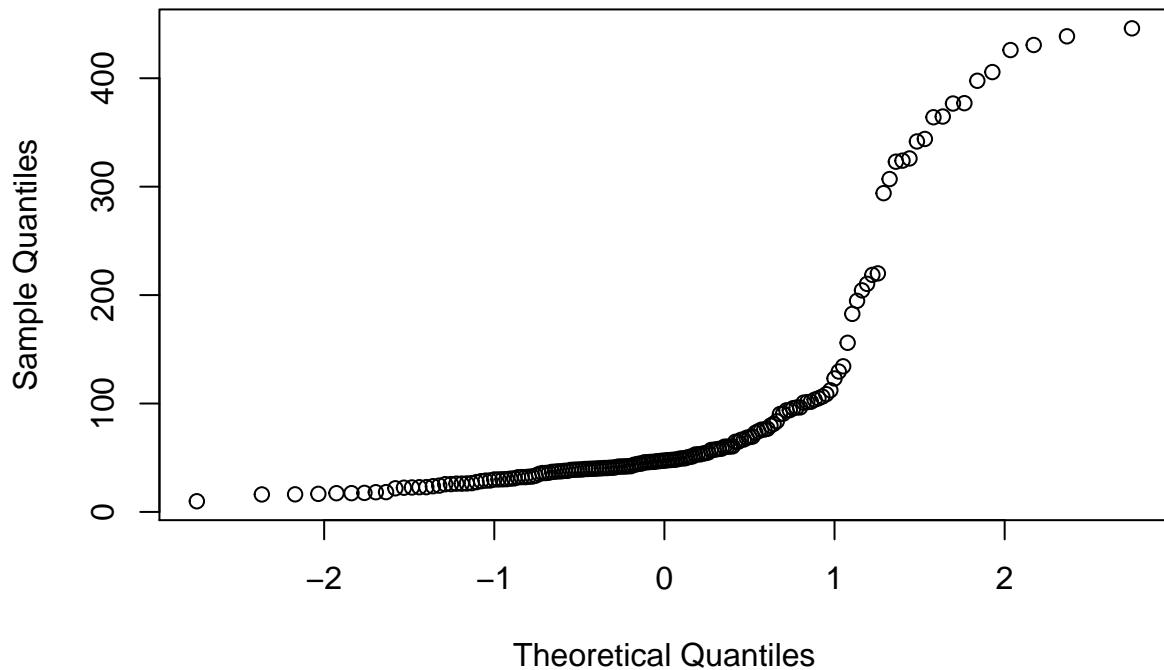
```

Histogram of comp_kbs_plot\$plot_cover_avg



```
qqnorm(comp_kbs_plot$plot_cover_avg)
```

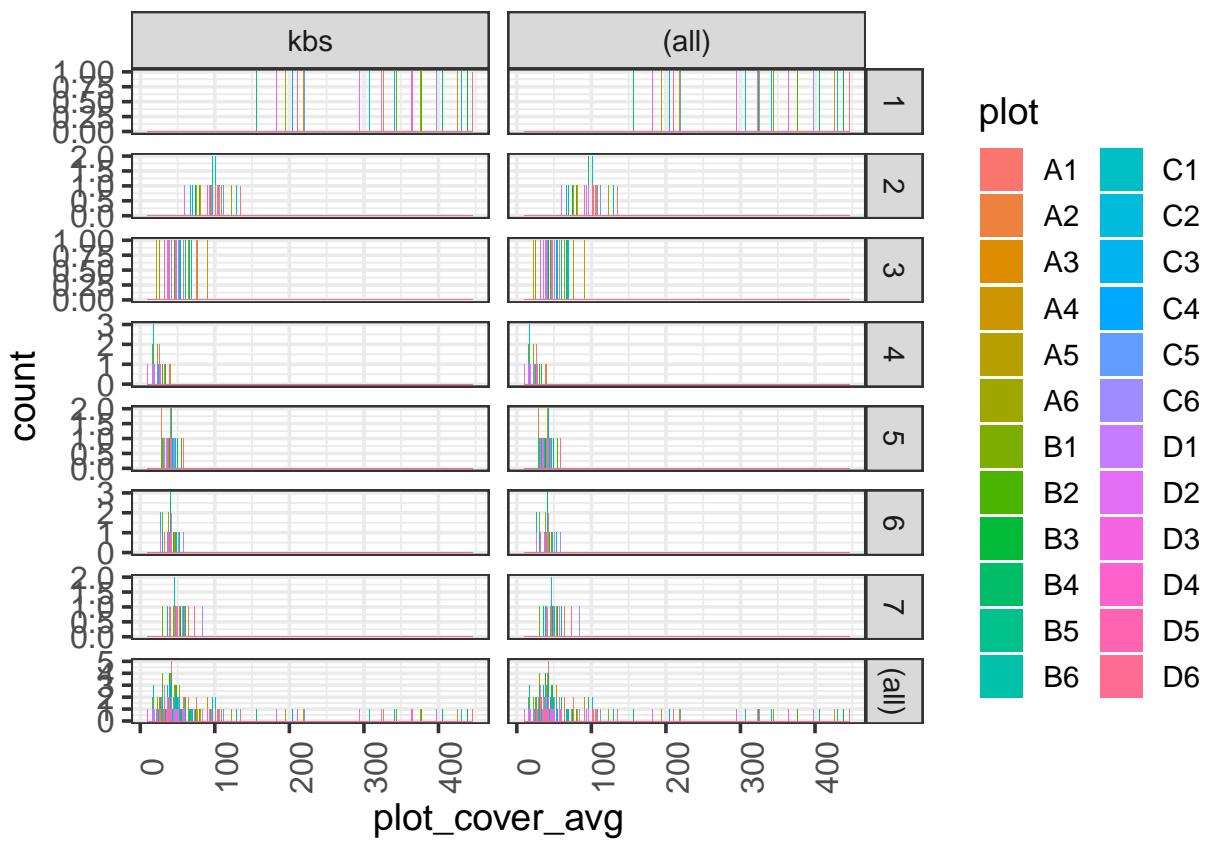
Normal Q-Q Plot



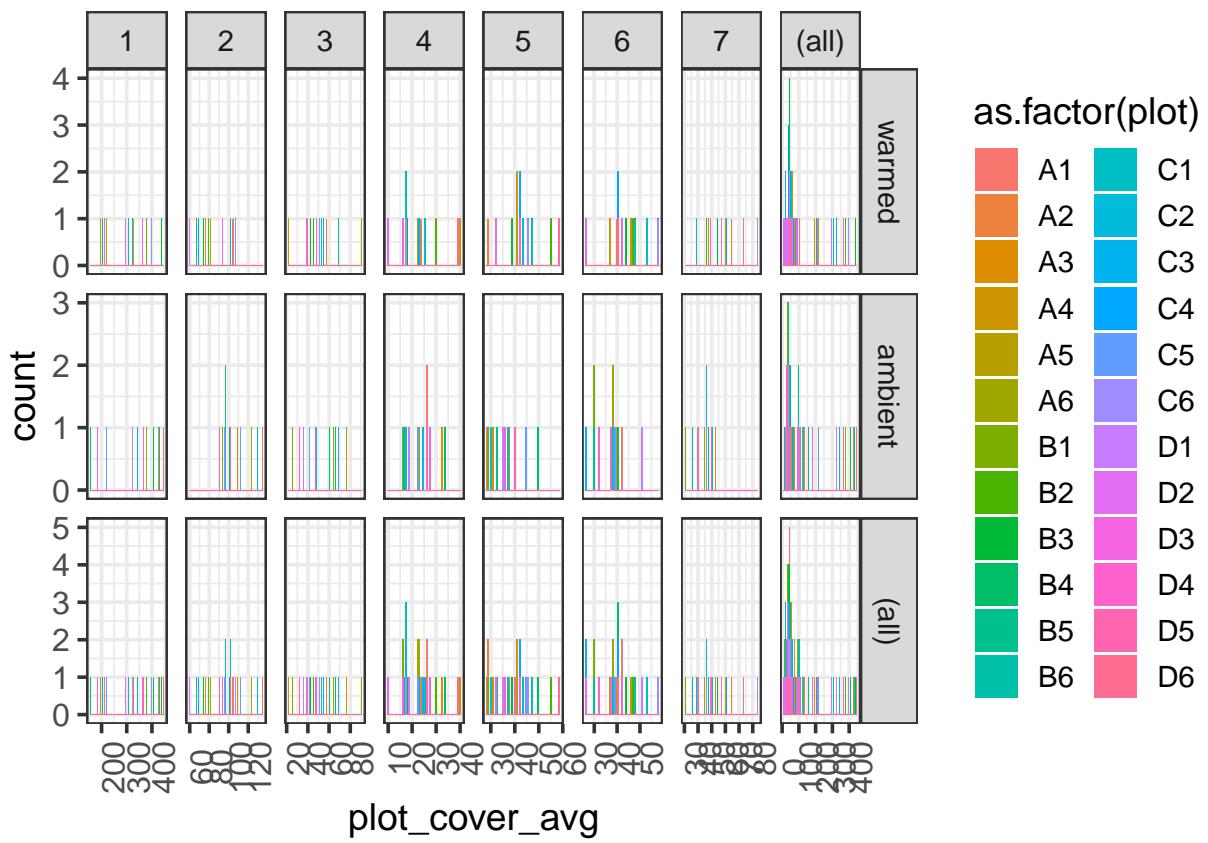
```
shapiro.test(comp_kbs_plot$plot_cover_avg) # pvalue is < 0.05 so we reject the null hypothesis that the data is normally distributed

## 
## Shapiro-Wilk normality test
##
## data: comp_kbs_plot$plot_cover_avg
## W = 0.62827, p-value < 2.2e-16

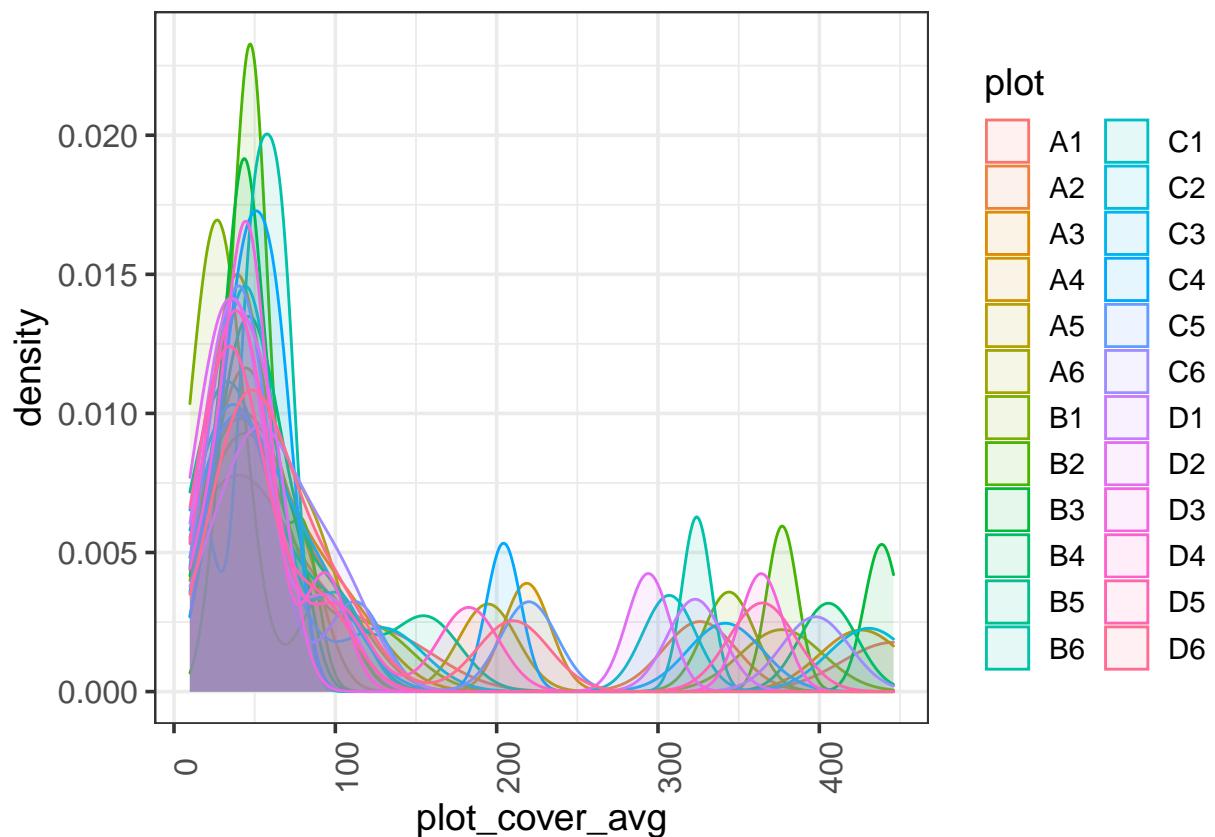
# Visualizing plot average totals for kbs at the PLOT LEVEL
ggplot(comp_kbs_plot, aes(plot_cover_avg, fill = plot)) + geom_histogram(binwidth = 0.5) +
  facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



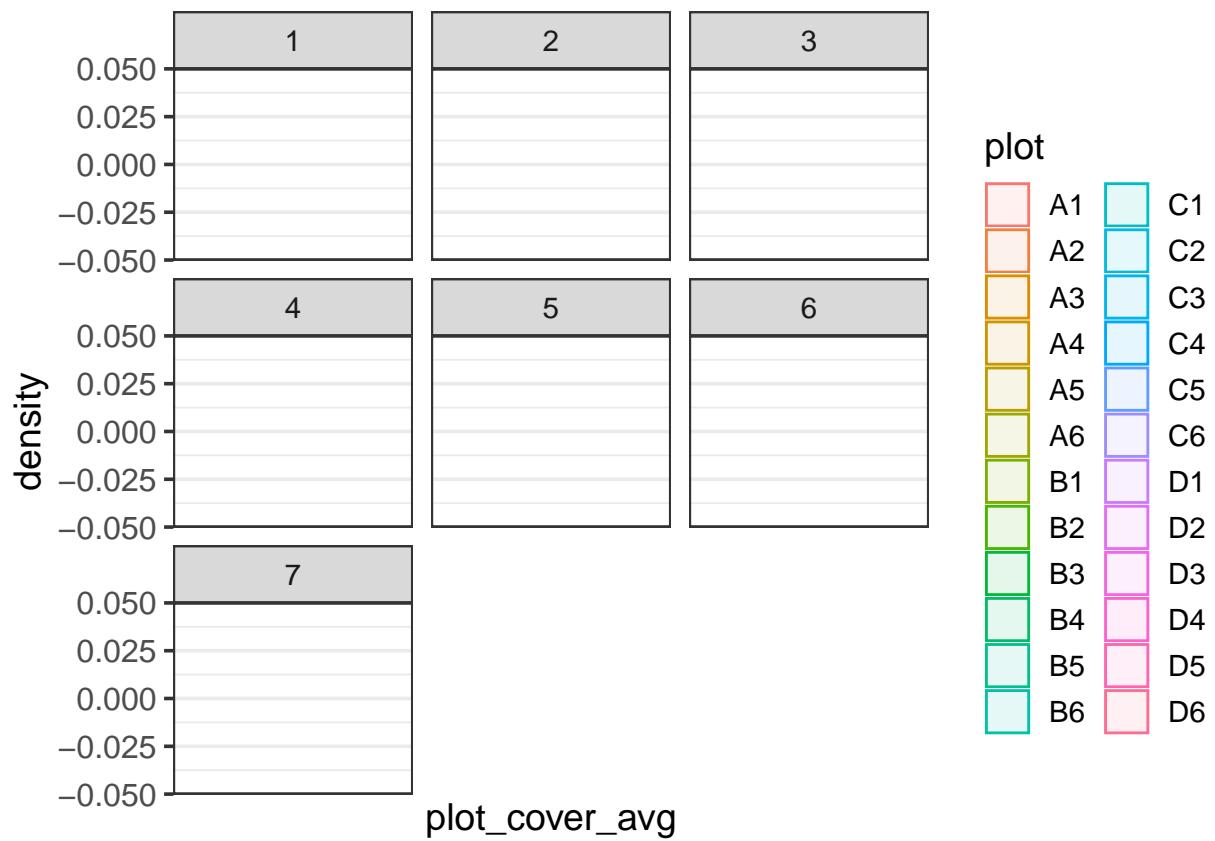
```
ggplot(comp_kbs_plot, aes(plot_cover_avg, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
  facet_grid(state ~ year_factor, margins = TRUE, scales = "free")
```



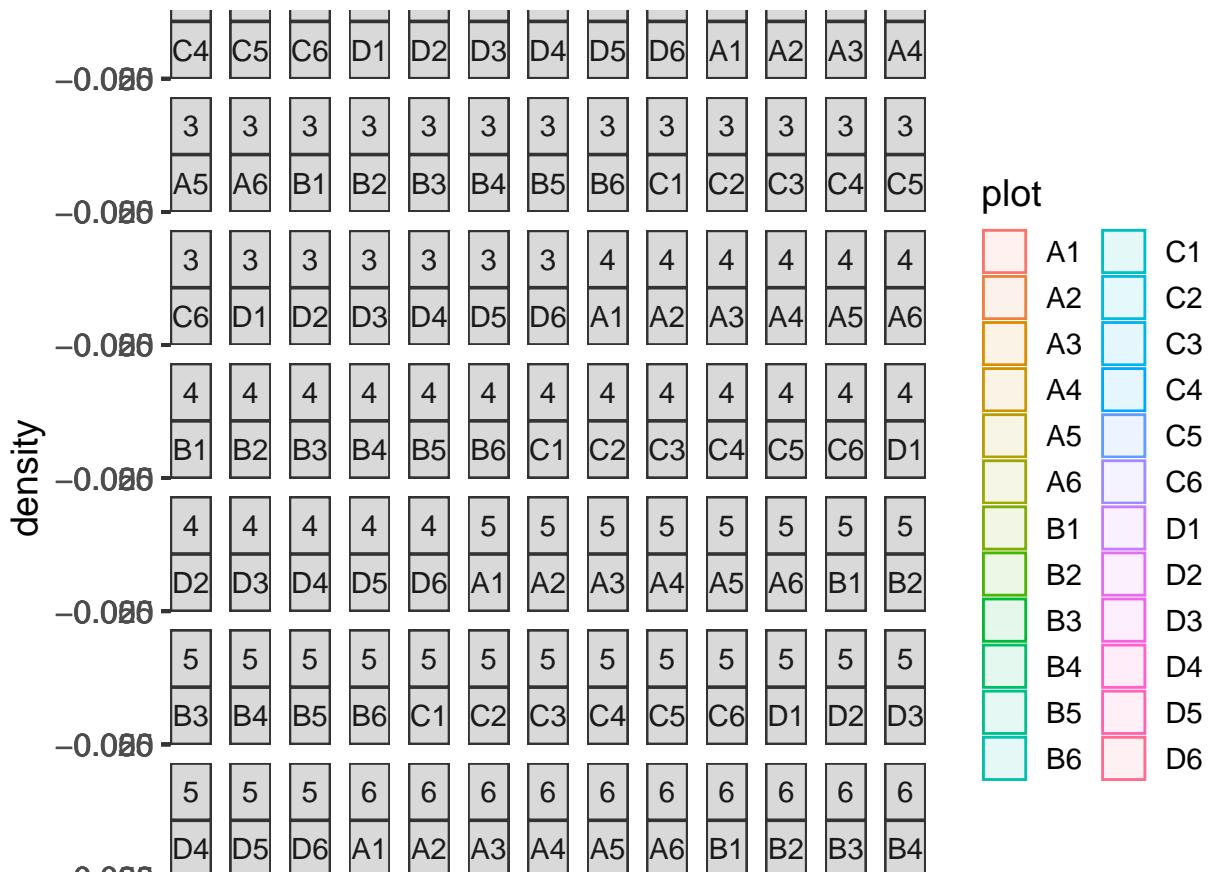
```
ggplot(comp_kbs_plot, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



```
ggplot(comp_kbs_plot, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
  facet_wrap(~year_factor)
```

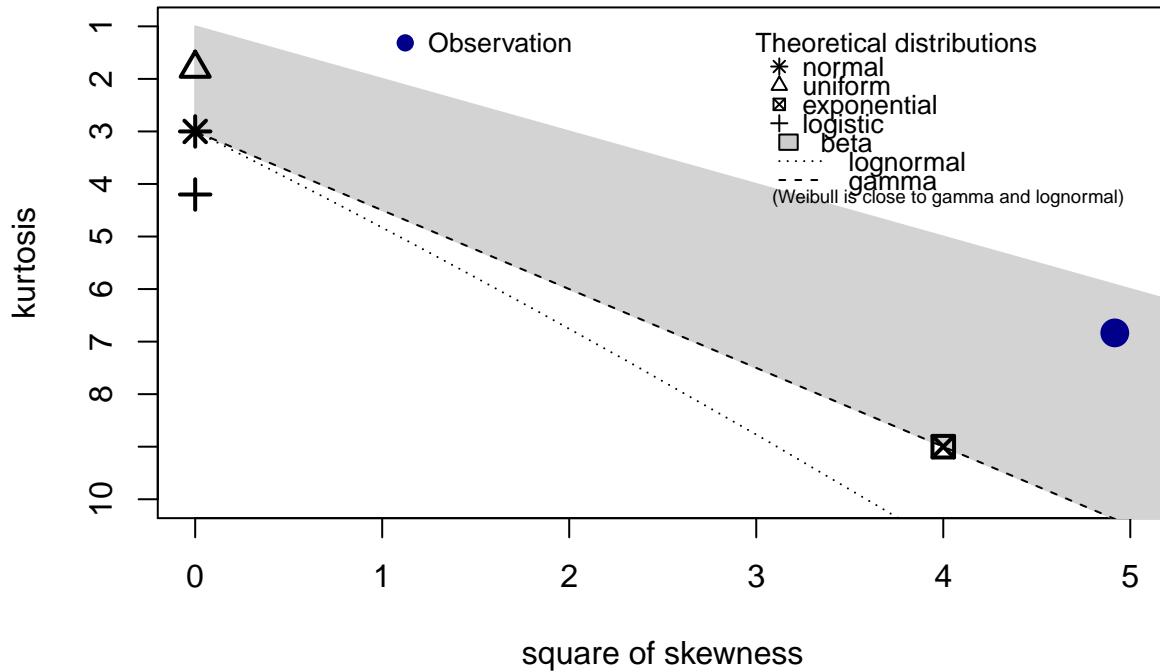


```
ggplot(comp_kbs_plot, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
  facet_wrap(~year_factor + plot)
```



```
# Exploring distributions for these right-skewed data:  
descdist(comp_kbs_plot$plot_cover_avg, discrete = FALSE)
```

Cullen and Frey graph



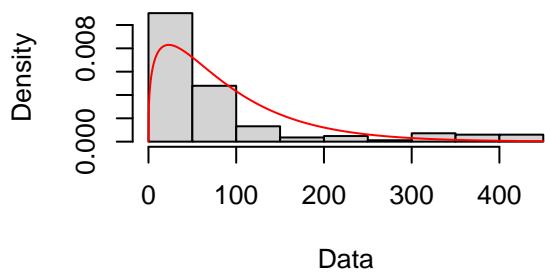
```

## summary statistics
## -----
## min:  9.857143  max:  446
## median: 47.23077
## mean:  89.1331
## estimated sd: 103.2916
## estimated skewness: 2.217462
## estimated kurtosis: 6.834041

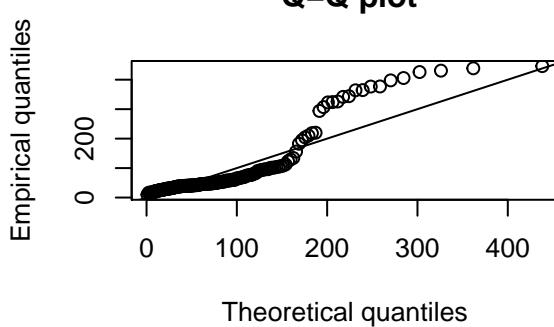
# Gamma distribution
fit.gamma <- fitdist(comp_kbs_plot$plot_cover_avg, "gamma")
plot(fit.gamma)

```

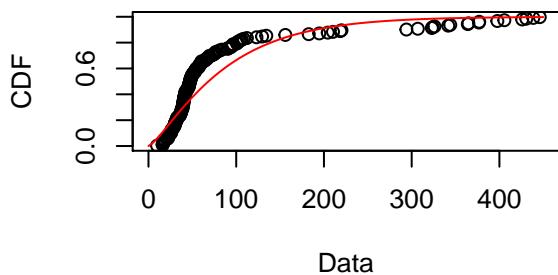
Empirical and theoretical dens.



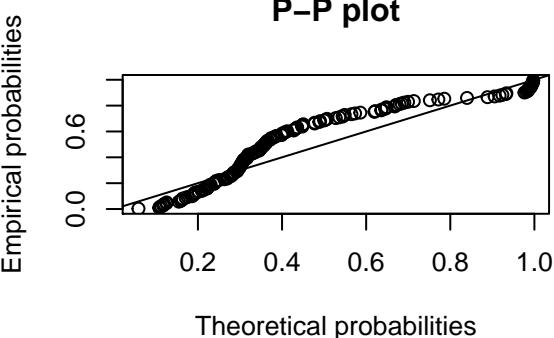
Q-Q plot



Empirical and theoretical CDFs

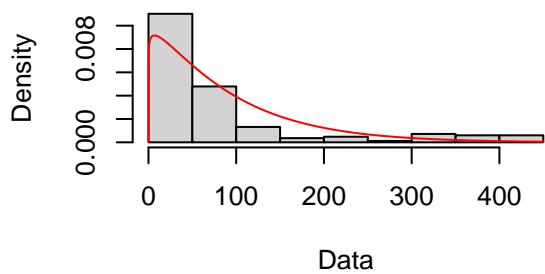


P-P plot

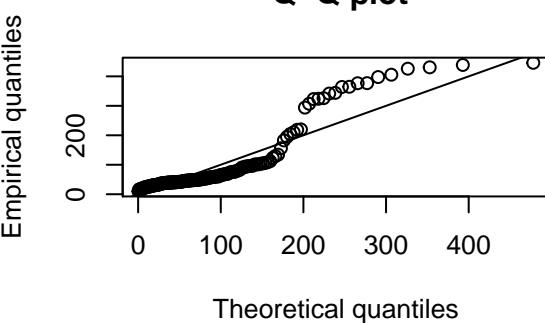


```
# Weibull distribution
fit.weibull <- fitdist(comp_kbs_plot$plot_cover_avg, "weibull")
plot(fit.weibull)
```

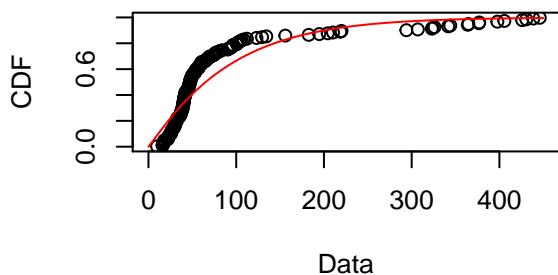
Empirical and theoretical dens.



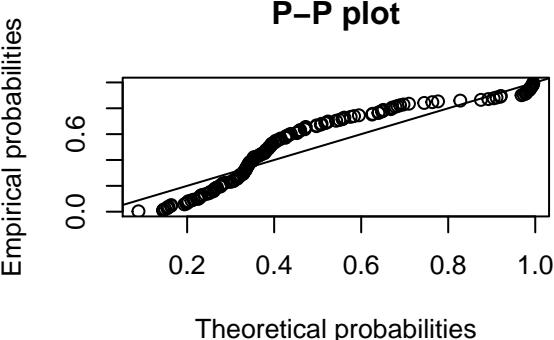
Q-Q plot



Empirical and theoretical CDFs

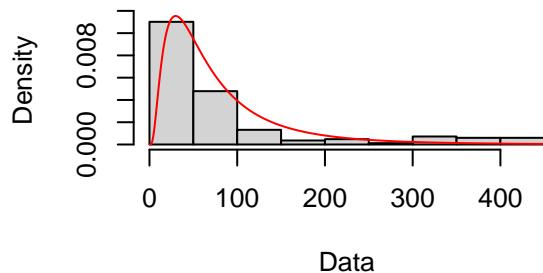


P-P plot

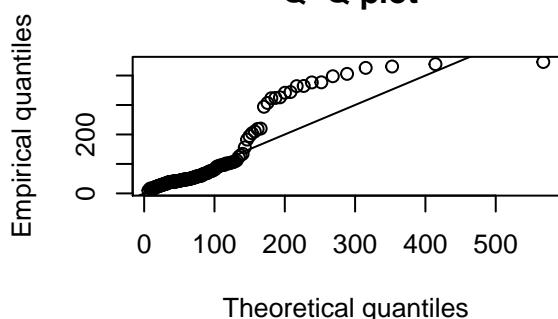


```
# Lognormal distribution
fit.ln <- fitdist(comp_kbs_plot$plot_cover_avg, "lnorm")
plot(fit.ln)
```

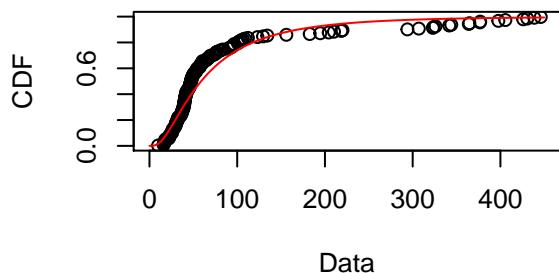
Empirical and theoretical dens.



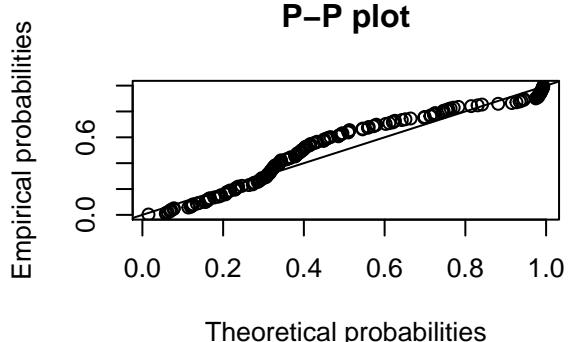
Q-Q plot



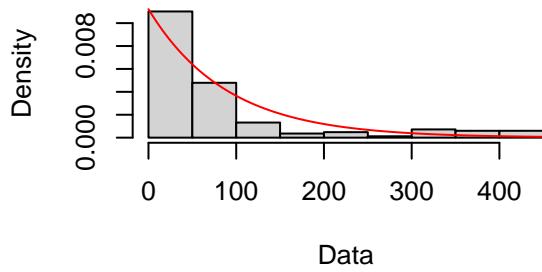
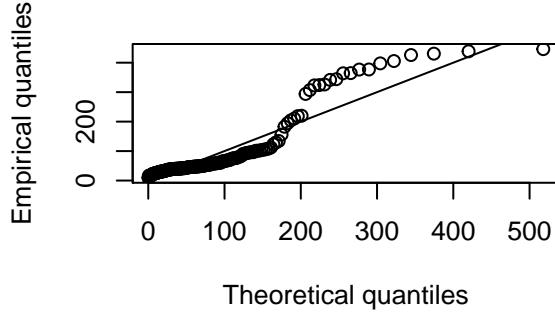
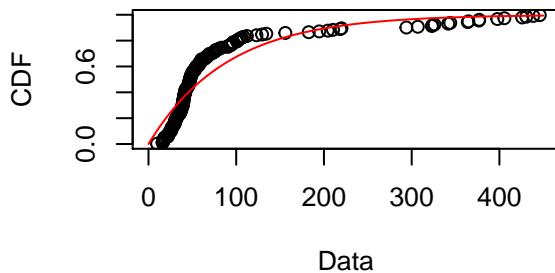
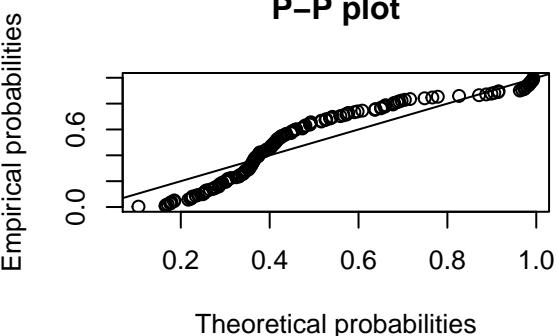
Empirical and theoretical CDFs



P-P plot

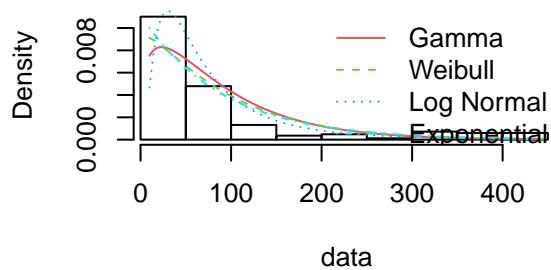


```
# Exponential distribution is another option
fit.exp <- fitdist(comp_kbs_plot$plot_cover_avg, "exp")
plot(fit.exp)
```

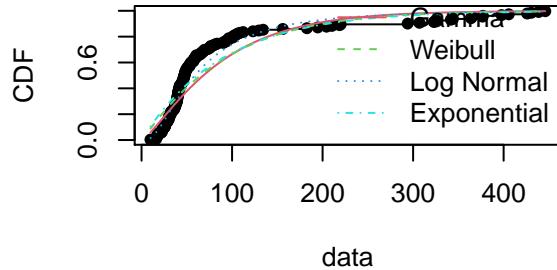
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

```
par(mfrow = c(2, 2))
plot.legend <- c("Gamma", "Weibull", "Log Normal", "Exponential")
denscomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp), legendtext = plot.legend)
cdfcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp), legendtext = plot.legend)
qqcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp), legendtext = plot.legend)
ppcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp), legendtext = plot.legend)
```

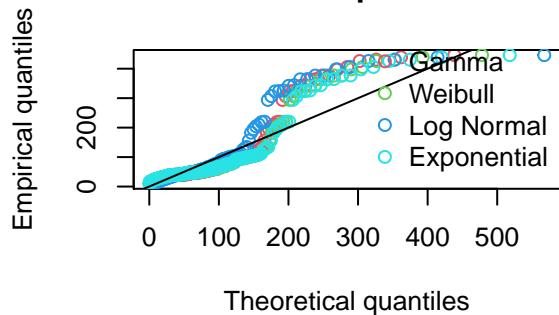
Histogram and theoretical densities



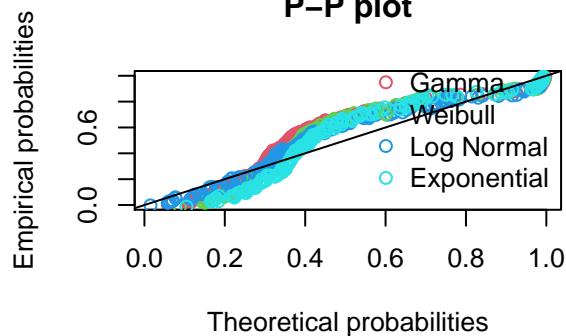
Empirical and theoretical CDFs



Q-Q plot



P-P plot



```
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull",
  "Log Normal", "Exp"))
```

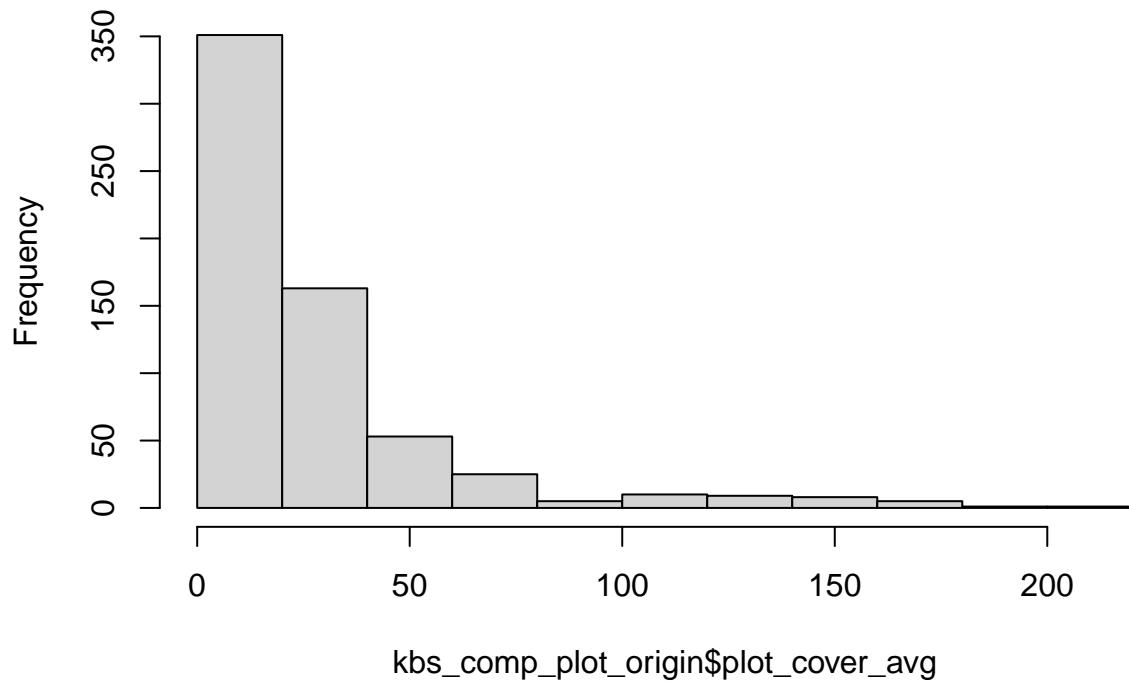
```
## Goodness-of-fit statistics
##                                     Gamma   Weibull Log Normal      Exp
## Kolmogorov-Smirnov statistic 0.2084312 0.1860727 0.1457357 0.1659281
## Cramer-von Mises statistic  2.1039134 1.9334703 0.9063833 1.8481234
## Anderson-Darling statistic 11.5222610 10.9721217 5.3825803 10.7379076
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal      Exp
## Akaike's Information Criterion 1829.221 1836.325 1774.742 1835.704
## Bayesian Information Criterion 1835.457 1842.561 1780.978 1838.822
```

```
# log normal distribution looks to be the best based on AIC and BIC values
```

KBS PLOT LEVEL ORIGIN - Looking at PLOT AVG TOTALS

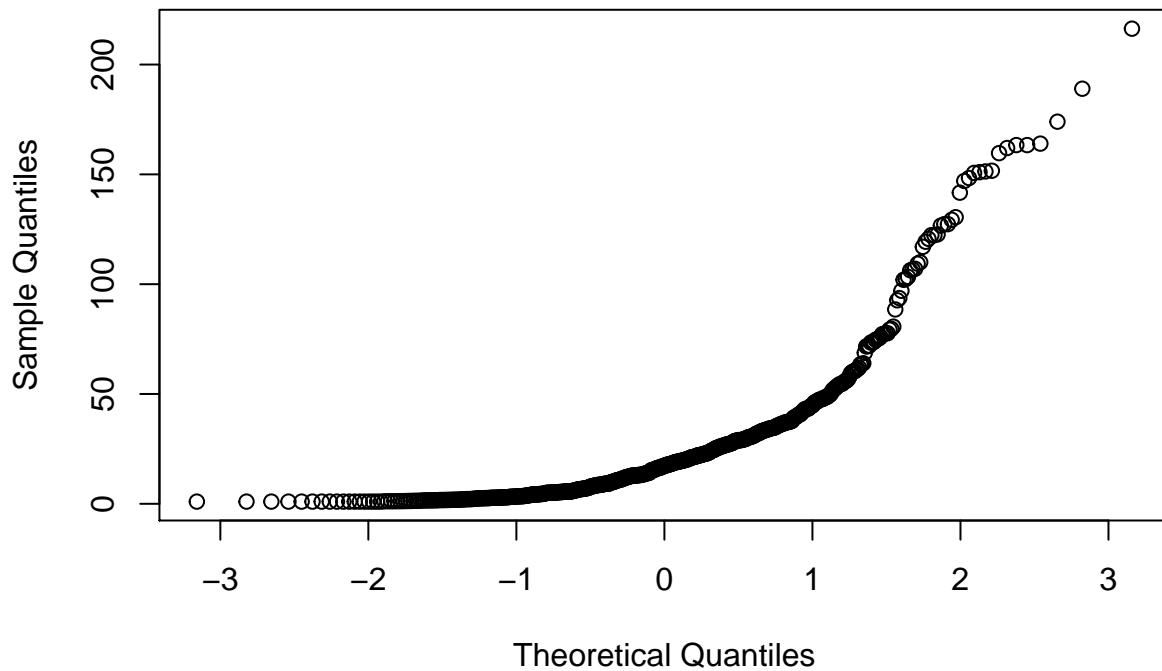
```
### KBS ####
hist(kbs_comp_plot_origin$plot_cover_avg) # skewed to the right
```

Histogram of kbs_comp_plot_origin\$plot_cover_avg



```
qqnorm(kbs_comp_plot_origin$plot_cover_avg)
```

Normal Q-Q Plot



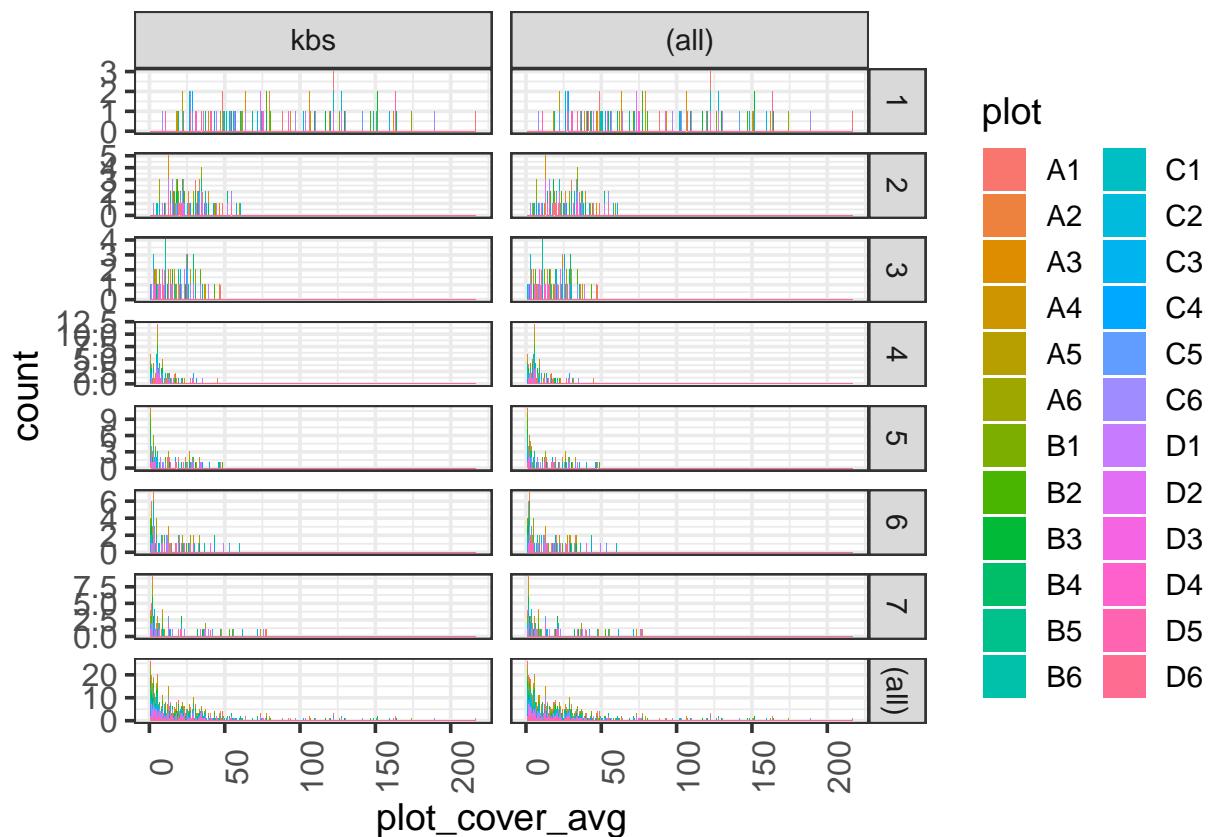
```

shapiro.test(kbs_comp_plot_origin$plot_cover_avg) # pvalue is < 0.05 so we reject the null hypothesis

## 
## Shapiro-Wilk normality test
## 
## data: kbs_comp_plot_origin$plot_cover_avg
## W = 0.71214, p-value < 2.2e-16

# Visualizing plot average totals for kbs at the PLOT LEVEL
ggplot(kbs_comp_plot_origin, aes(plot_cover_avg, fill = plot)) + geom_histogram(binwidth = 0.5) +
  facet_grid(year_factor ~ site, margins = TRUE, scales = "free")

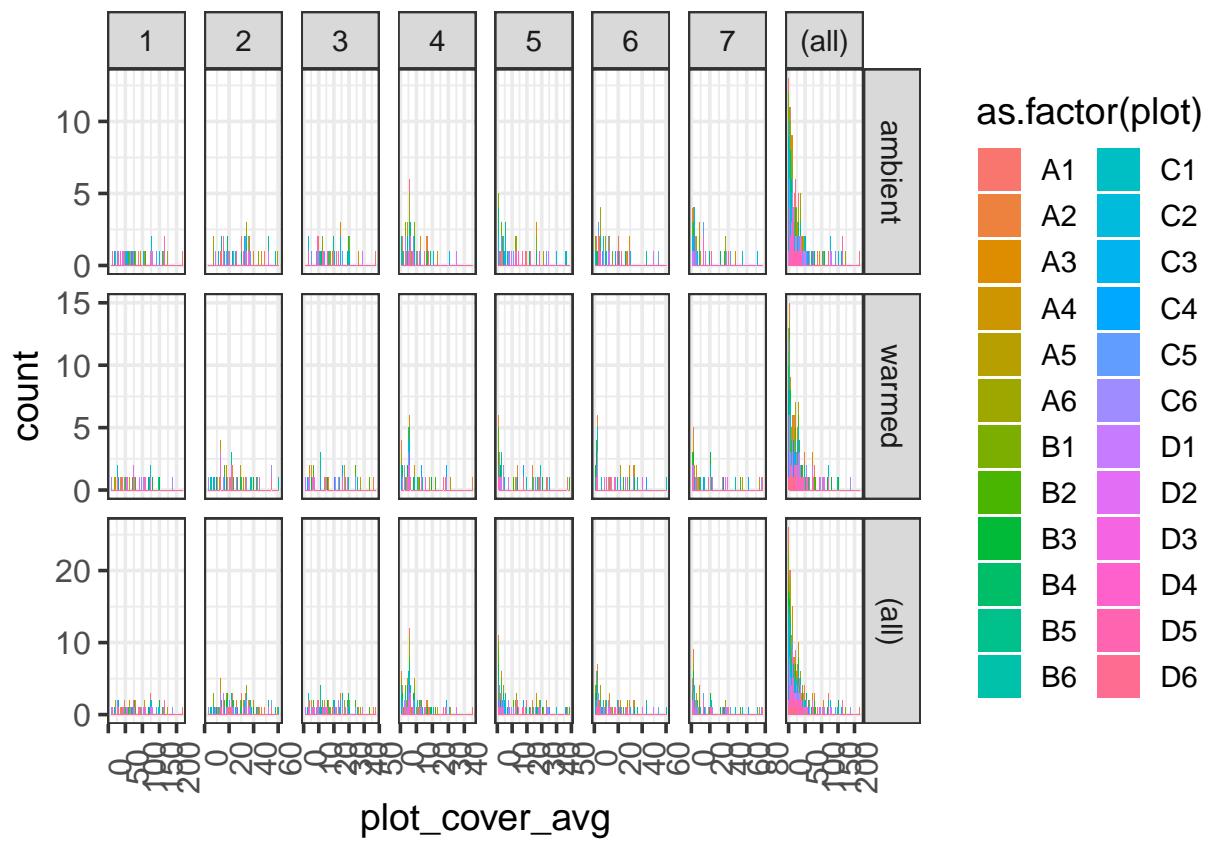
```



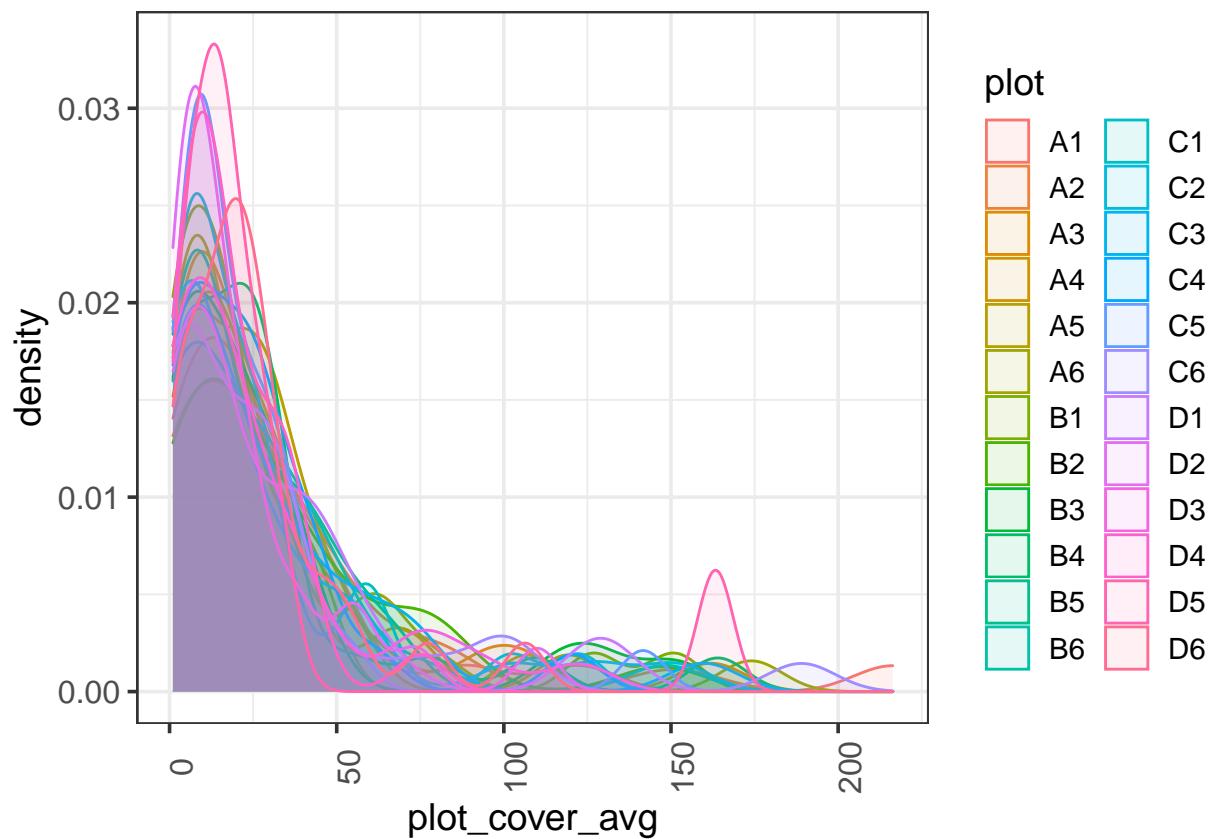
```

ggplot(kbs_comp_plot_origin, aes(plot_cover_avg, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
  facet_grid(state ~ year_factor, margins = TRUE, scales = "free")

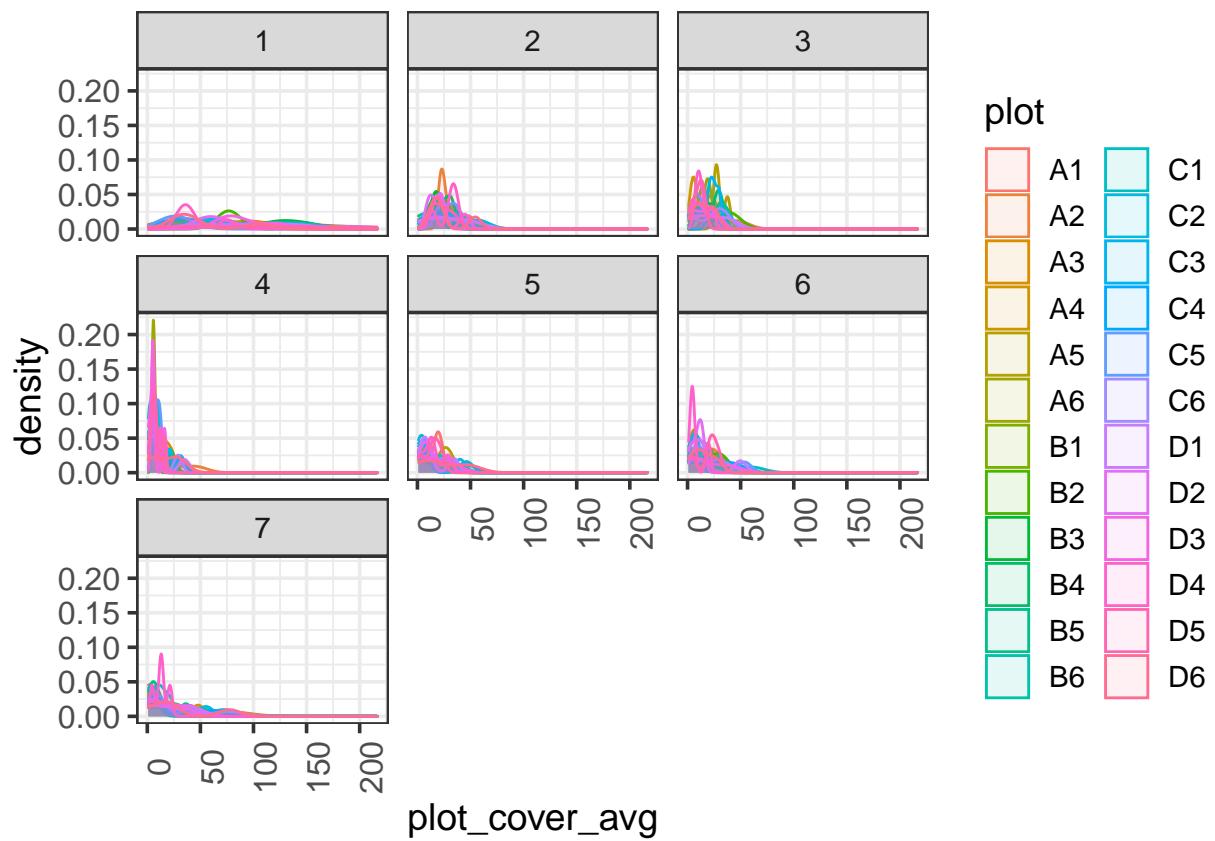
```



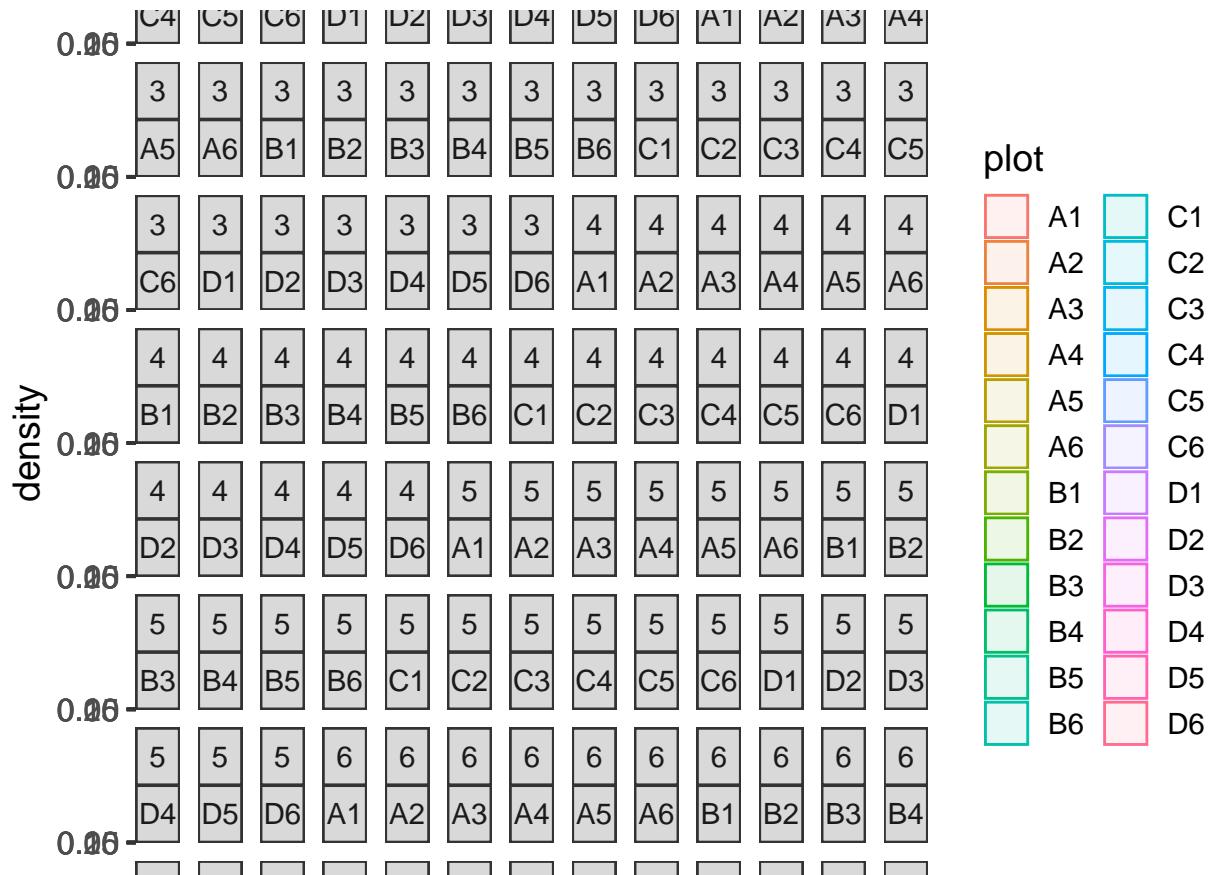
```
ggplot(kbs_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



```
ggplot(kbs_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1)  
  facet_wrap(~year_factor)
```

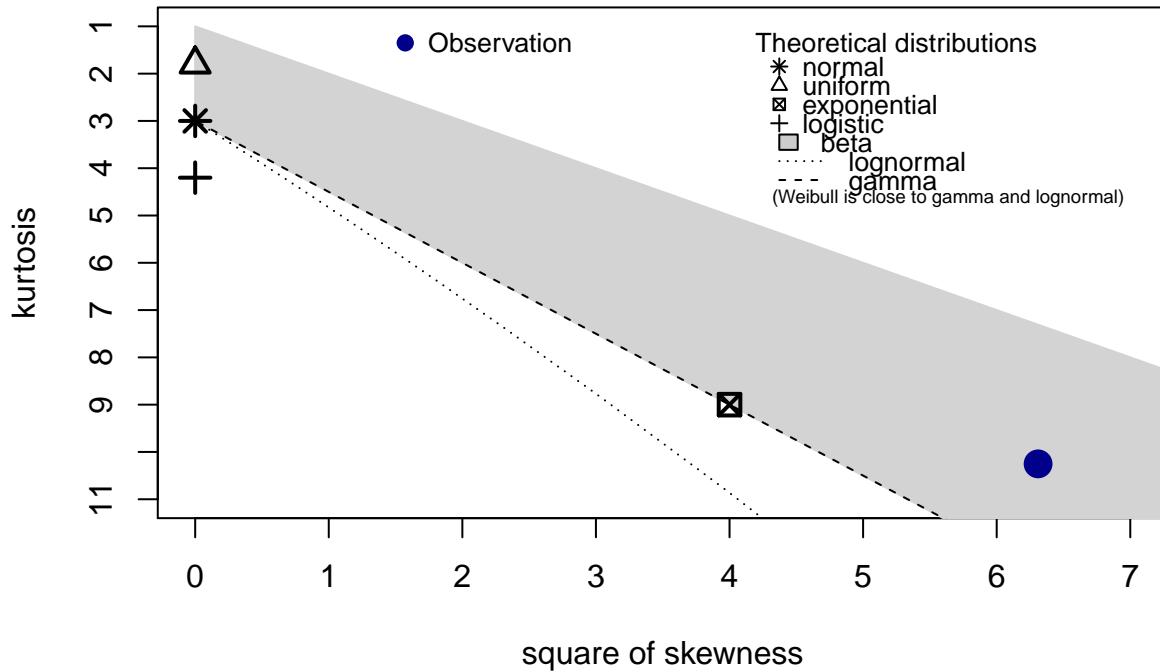


```
ggplot(kbs_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1)
  facet_wrap(~year_factor + plot)
```



```
# Exploring distributions for these data:  
descdist(kbs_comp_plot_origin$plot_cover_avg, discrete = FALSE)
```

Cullen and Frey graph

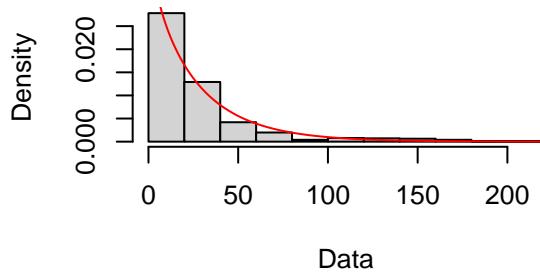
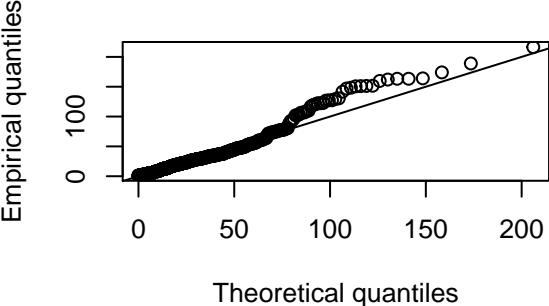
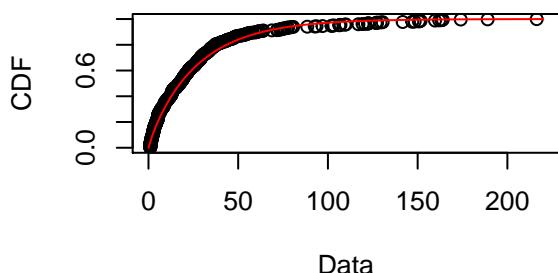
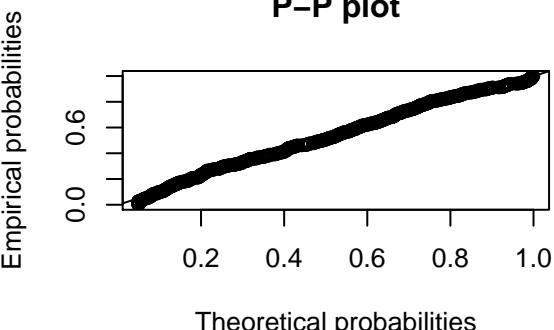


```

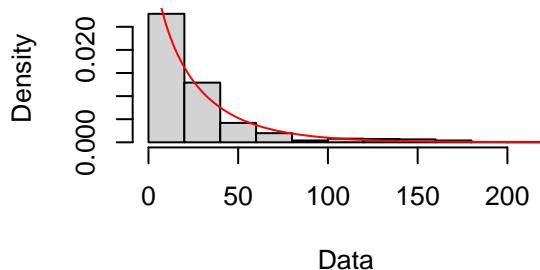
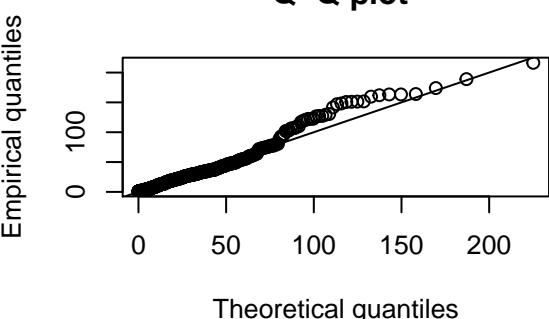
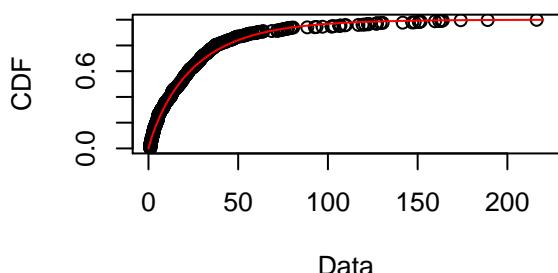
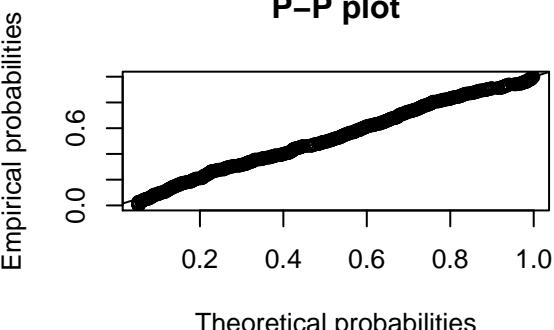
## summary statistics
## -----
## min: 1   max: 216.3333
## median: 17.28571
## mean: 26.83611
## estimated sd: 32.6559
## estimated skewness: 2.511938
## estimated kurtosis: 10.25197

# Gamma distribution
fit.gamma <- fitdist(kbs_comp_plot_origin$plot_cover_avg, "gamma")
plot(fit.gamma)

```

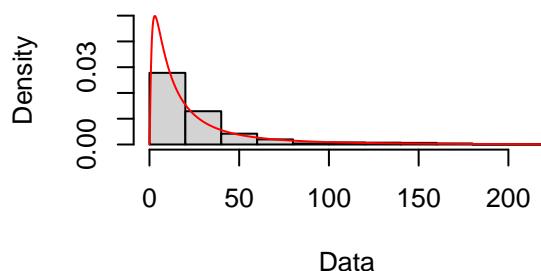
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

```
# Weibull distribution
fit.weibull <- fitdist(kbs_comp_plot_origin$plot_cover_avg, "weibull")
plot(fit.weibull)
```

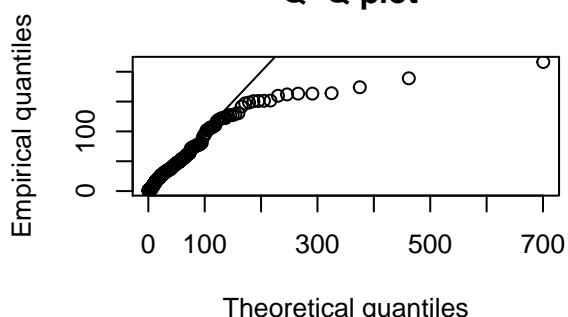
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

```
# Lognormal distribution
fit.ln <- fitdist(kbs_comp_plot_origin$plot_cover_avg, "lnorm")
plot(fit.ln)
```

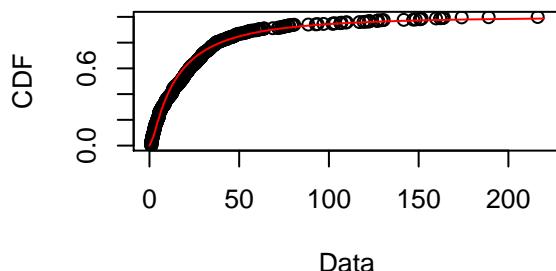
Empirical and theoretical dens.



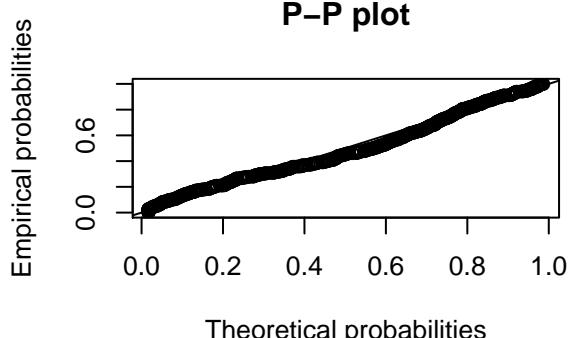
Q-Q plot



Empirical and theoretical CDFs

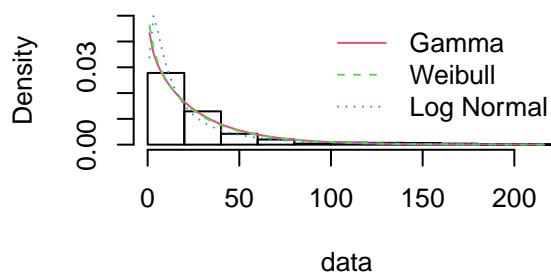


P-P plot

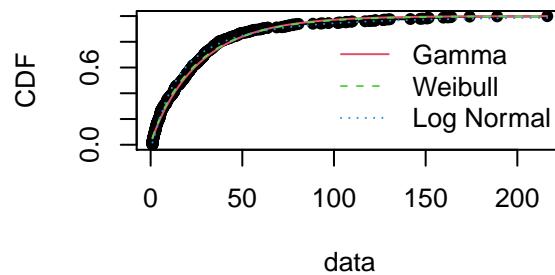


```
par(mfrow = c(2, 2))
plot.legend <- c("Gamma", "Weibull", "Log Normal")
denscomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
cdfcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
qqcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
ppcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
```

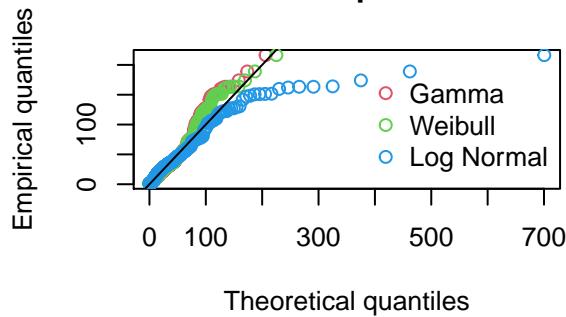
Histogram and theoretical densities



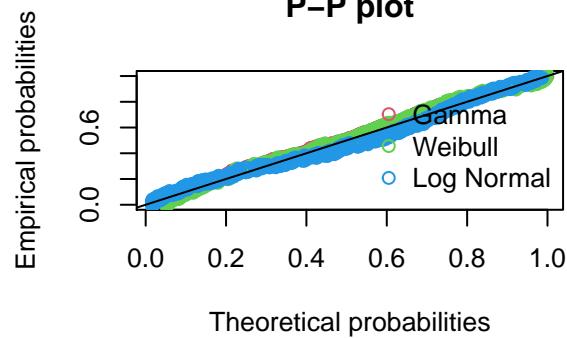
Empirical and theoretical CDFs



Q-Q plot



P-P plot



```
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln), fitnames = c("Gamma", "Weibull", "Log Normal"))
```

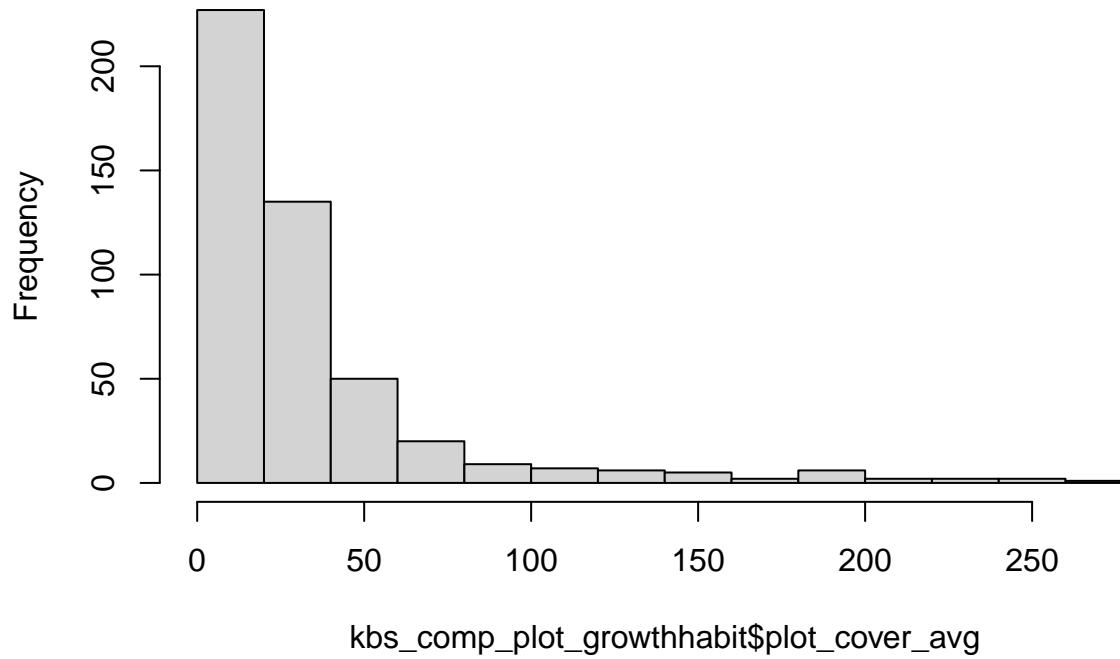
```
## Goodness-of-fit statistics
##                                     Gamma   Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.05150168 0.05273026 0.07179812
## Cramer-von Mises statistic   0.43058339 0.24636972 0.75485282
## Anderson-Darling statistic   3.60928359 2.60647008 4.19051306
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 5411.983 5404.915 5389.716
## Bayesian Information Criterion 5420.878 5413.809 5398.611
```

```
# log normal looks like it's the best fit
```

KBS PLOT LEVEL GROWTH HABIT - Looking at PLOT AVG TOTALS

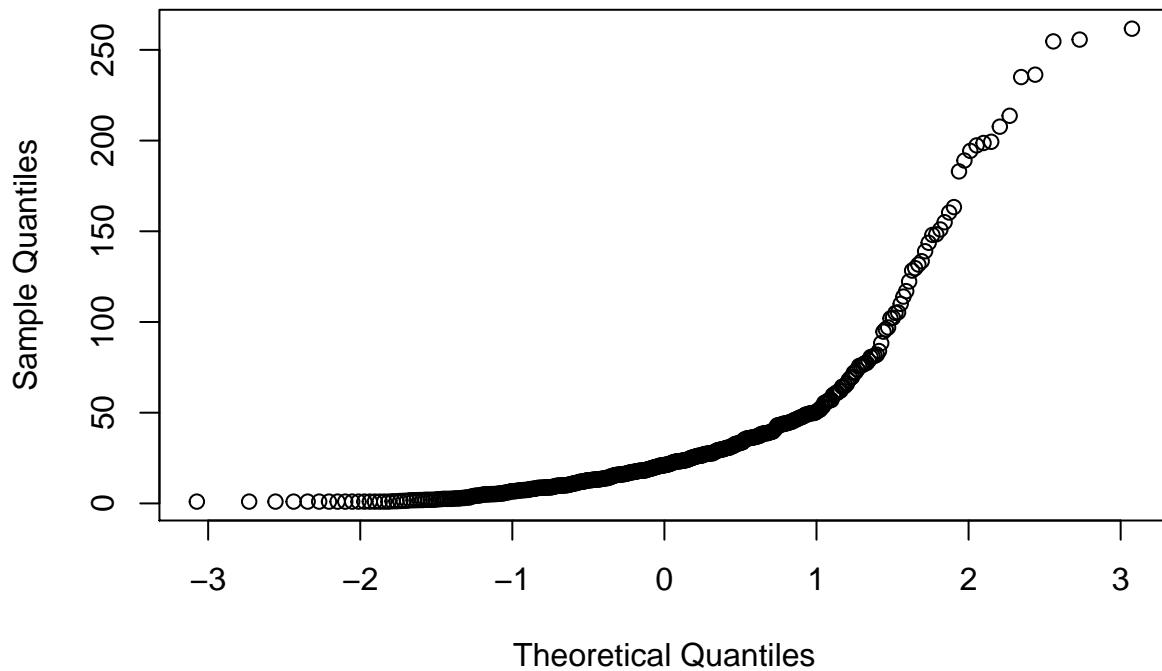
```
### KBS ####
hist(kbs_comp_plot_growthhabit$plot_cover_avg) # skewed to the right
```

Histogram of kbs_comp_plot_growthhabit\$plot_cover_avg



```
qqnorm(kbs_comp_plot_growthhabit$plot_cover_avg)
```

Normal Q-Q Plot



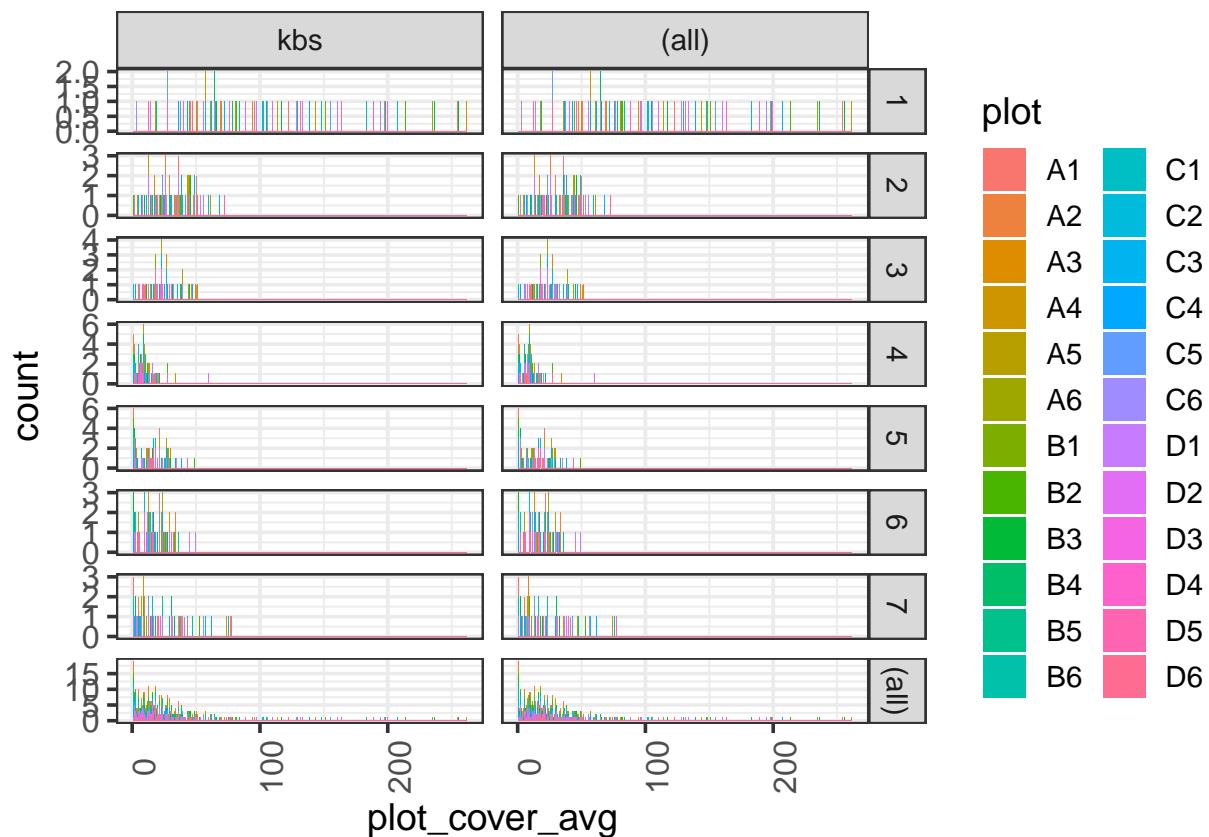
```

shapiro.test(kbs_comp_plot_growthhabit$plot_cover_avg) # pvalue is < 0.05 so we reject the null hypothesis

## 
## Shapiro-Wilk normality test
## 
## data: kbs_comp_plot_growthhabit$plot_cover_avg
## W = 0.6636, p-value < 2.2e-16

# Visualizing plot average totals for kbs at the PLOT LEVEL
ggplot(kbs_comp_plot_growthhabit, aes(plot_cover_avg, fill = plot)) + geom_histogram(binwidth = 0.5) +
  facet_grid(year_factor ~ site, margins = TRUE, scales = "free")

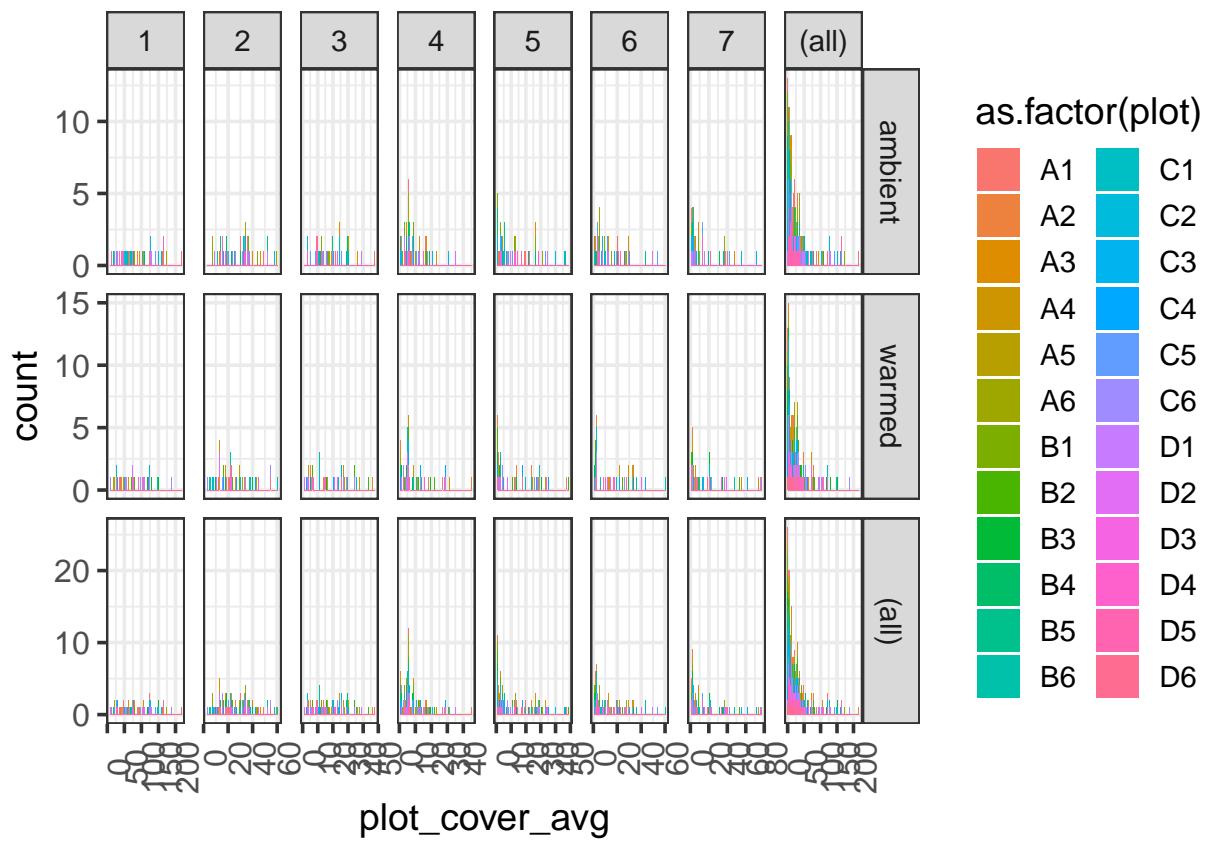
```



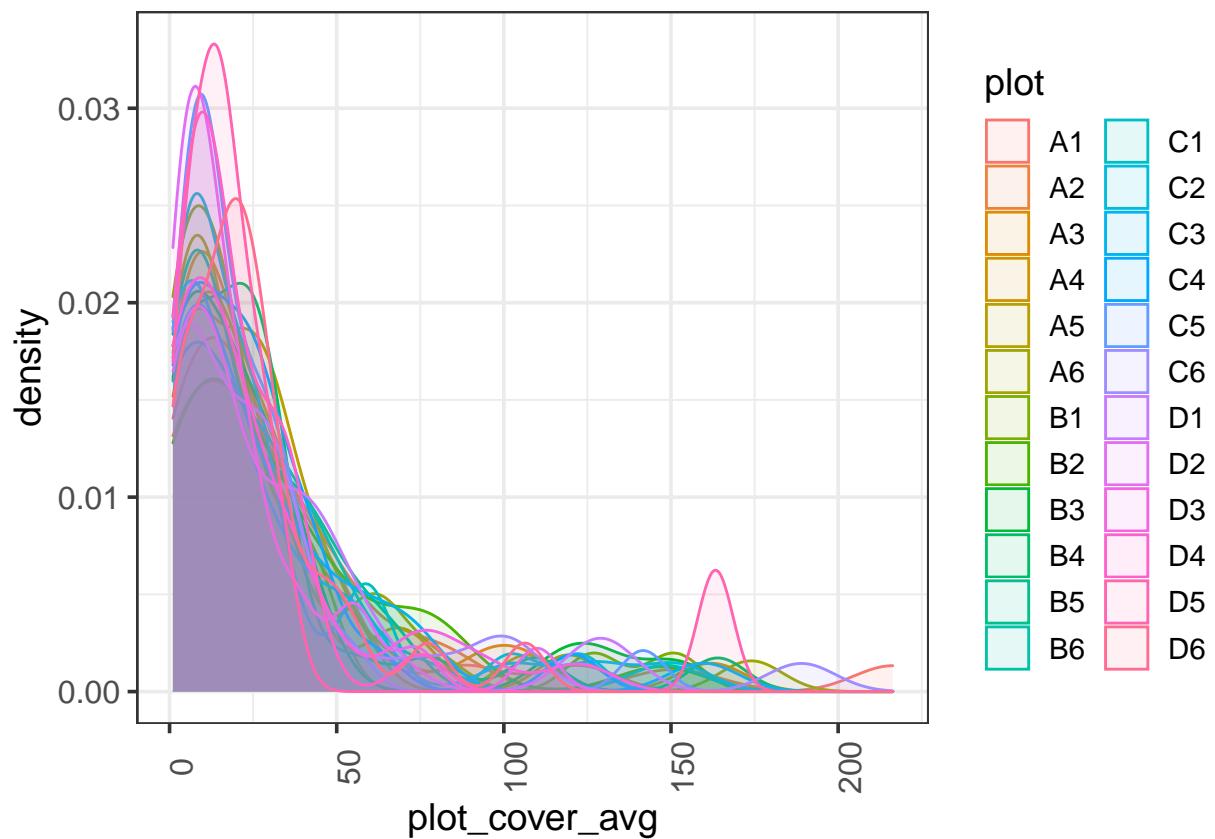
```

ggplot(kbs_comp_plot_origin, aes(plot_cover_avg, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
  facet_grid(state ~ year_factor, margins = TRUE, scales = "free")

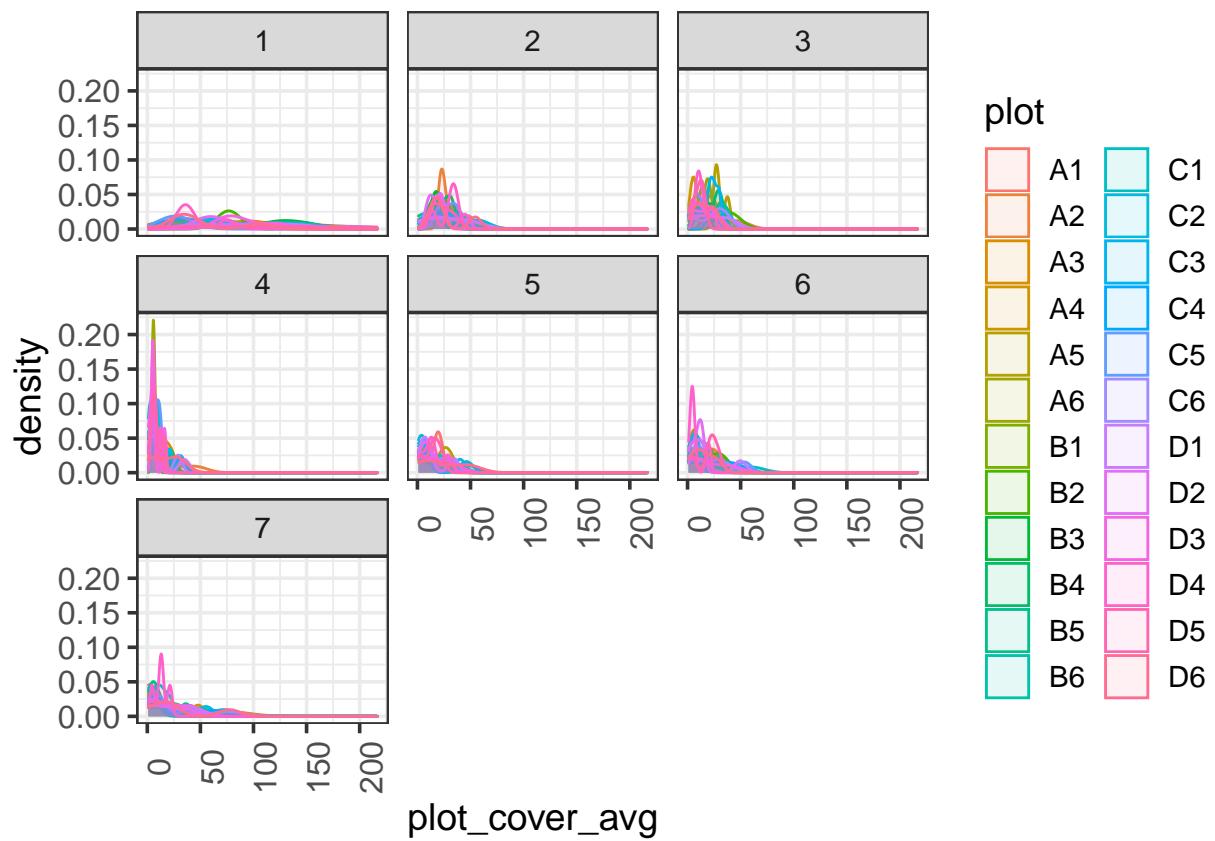
```



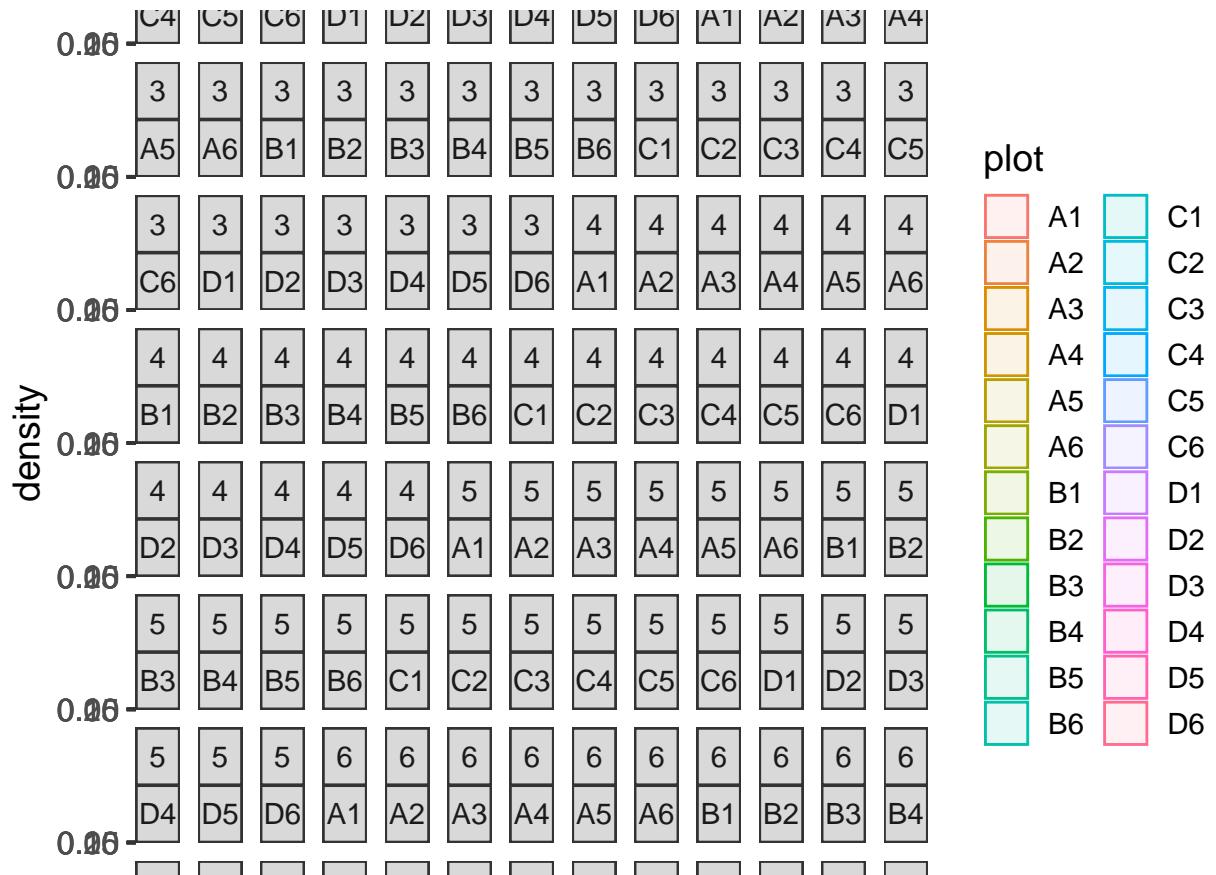
```
ggplot(kbs_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



```
ggplot(kbs_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1)  
  facet_wrap(~year_factor)
```

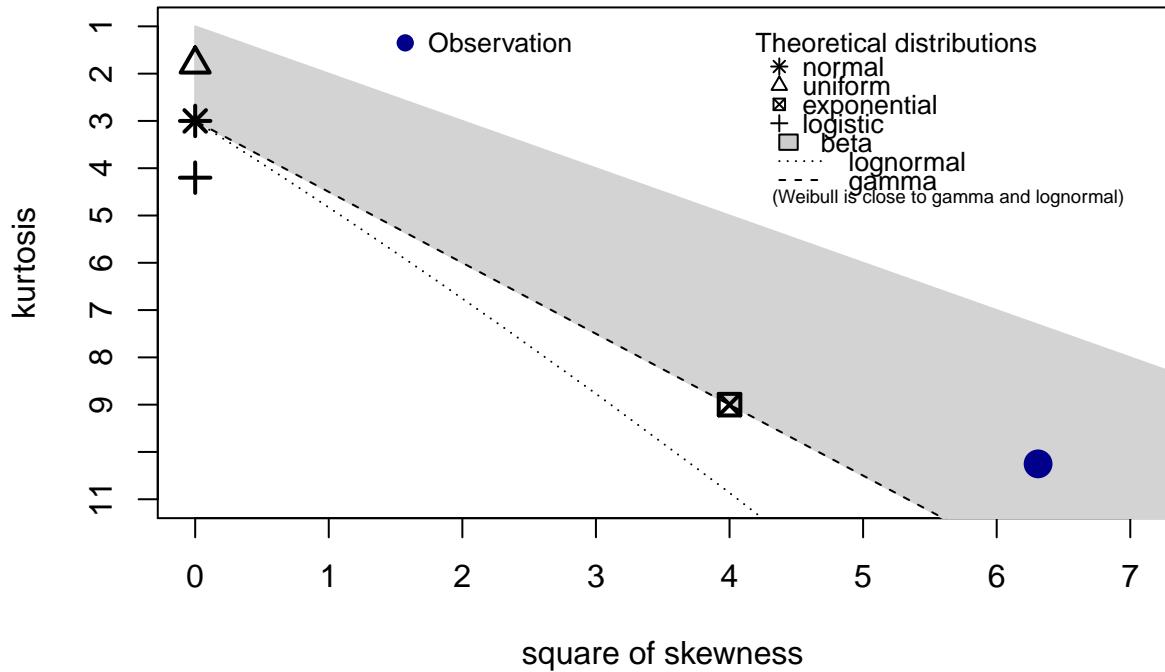


```
ggplot(kbs_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1)
  facet_wrap(~year_factor + plot)
```



```
# Exploring distributions for these data:  
descdist(kbs_comp_plot_origin$plot_cover_avg, discrete = FALSE)
```

Cullen and Frey graph

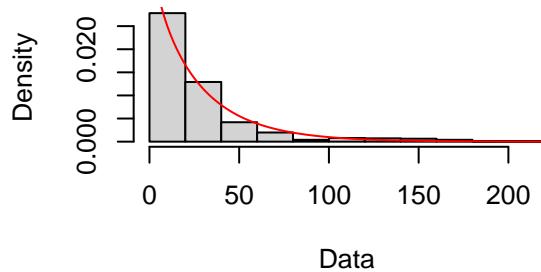
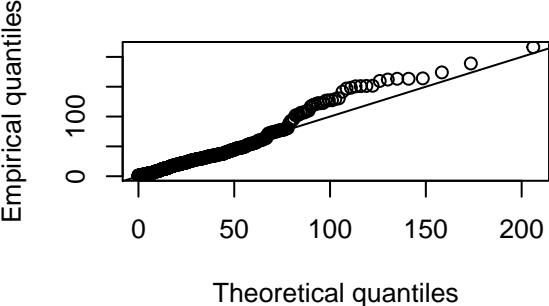
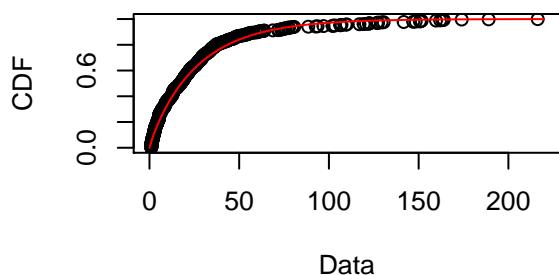
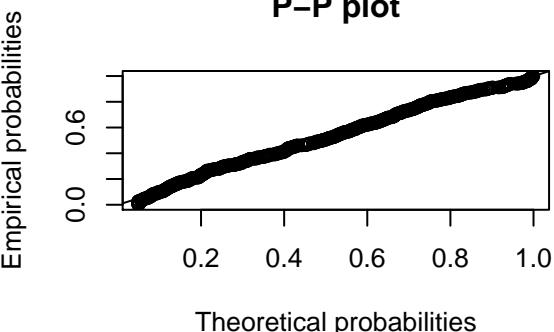


```

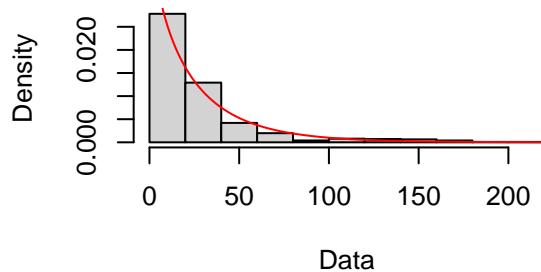
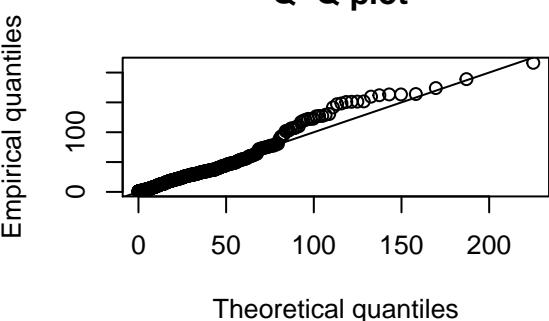
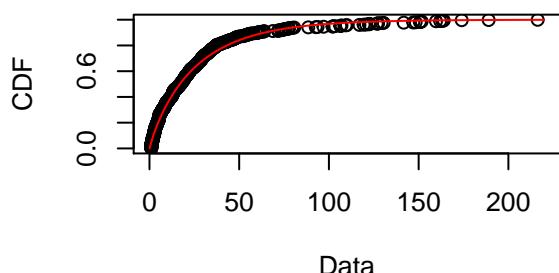
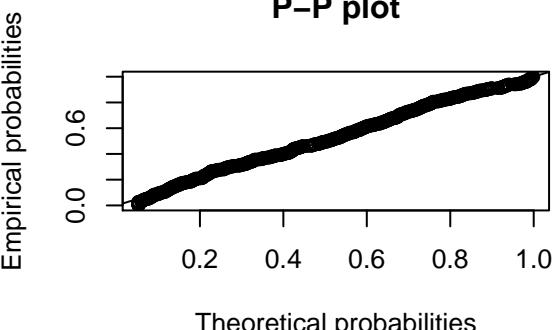
## summary statistics
## -----
## min: 1   max: 216.3333
## median: 17.28571
## mean: 26.83611
## estimated sd: 32.6559
## estimated skewness: 2.511938
## estimated kurtosis: 10.25197

# Gamma distribution
fit.gamma <- fitdist(kbs_comp_plot_origin$plot_cover_avg, "gamma")
plot(fit.gamma)

```

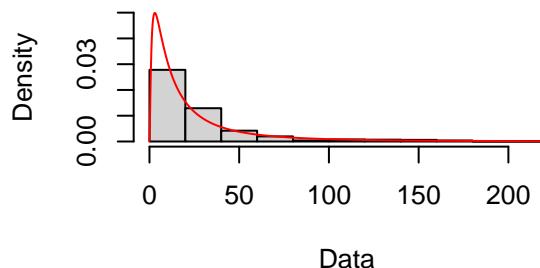
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

```
# Weibull distribution
fit.weibull <- fitdist(kbs_comp_plot_origin$plot_cover_avg, "weibull")
plot(fit.weibull)
```

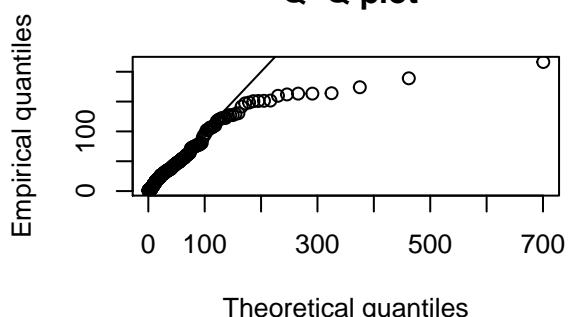
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

```
# Lognormal distribution
fit.ln <- fitdist(kbs_comp_plot_origin$plot_cover_avg, "lnorm")
plot(fit.ln)
```

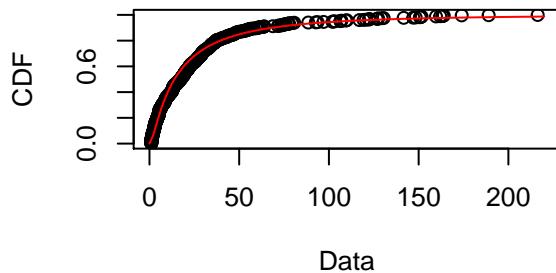
Empirical and theoretical dens.



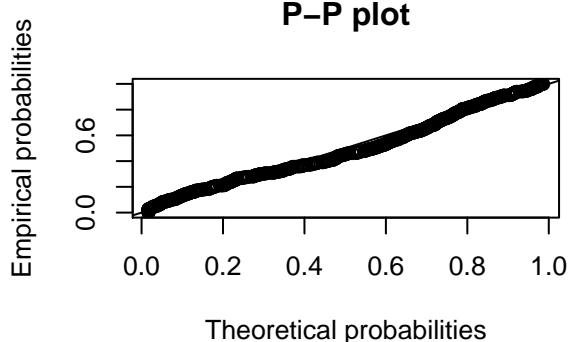
Q-Q plot



Empirical and theoretical CDFs

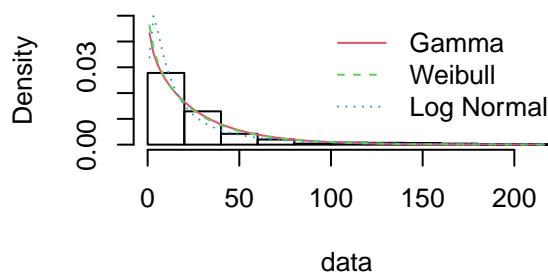


P-P plot

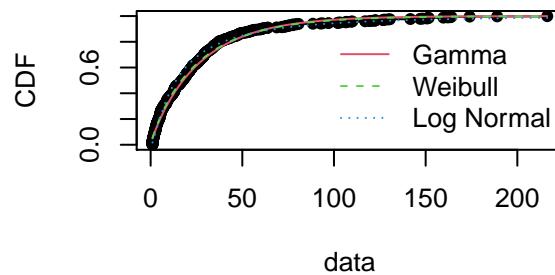


```
par(mfrow = c(2, 2))
plot.legend <- c("Gamma", "Weibull", "Log Normal")
denscomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
cdfcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
qqcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
ppcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
```

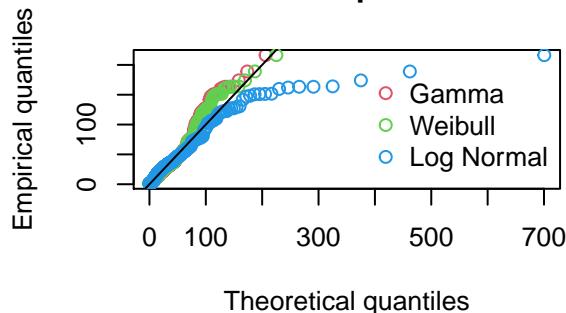
Histogram and theoretical densities



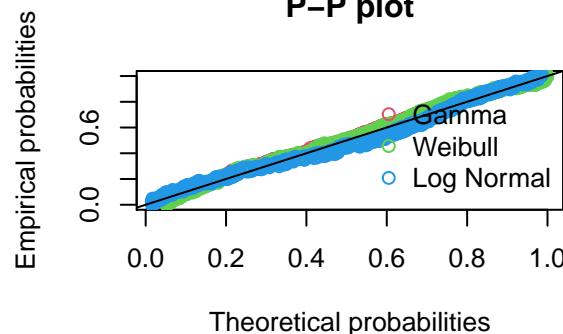
Empirical and theoretical CDFs



Q-Q plot



P-P plot



```
# Goodness of fit comparisons across fits (can't include the sqrt normal bc it
# becomes diff response values)
gofstat(list(fit.gamma, fit.weibull, fit.ln), fitnames = c("Gamma", "Weibull", "Log Normal"))
```

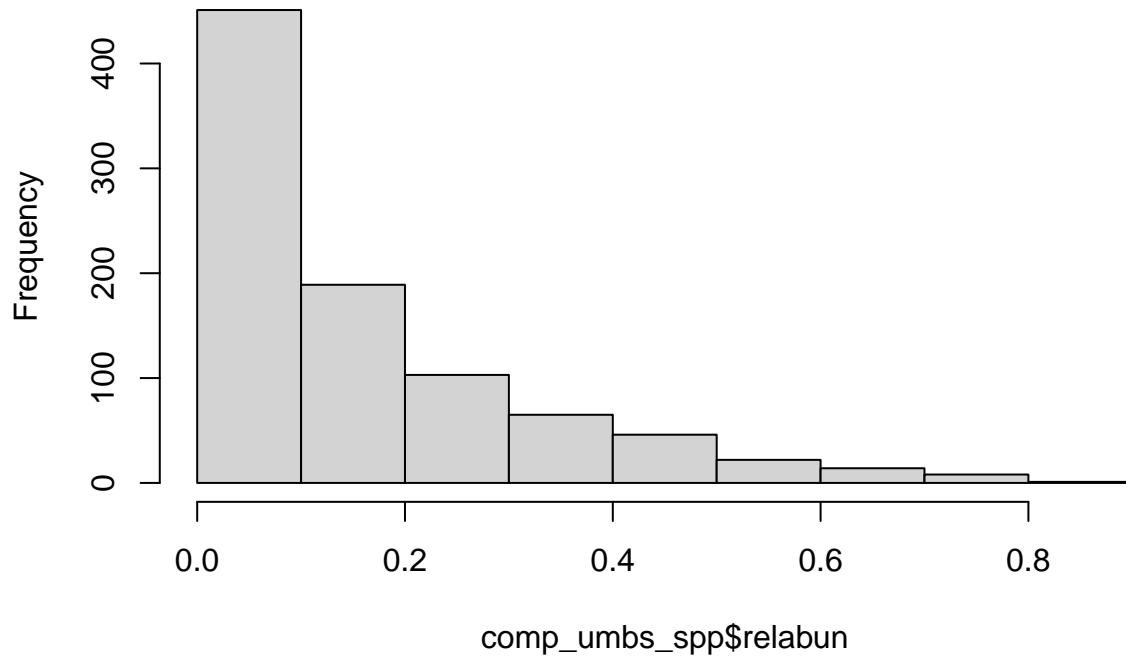
```
## Goodness-of-fit statistics
##                                     Gamma   Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.05150168 0.05273026 0.07179812
## Cramer-von Mises statistic   0.43058339 0.24636972 0.75485282
## Anderson-Darling statistic   3.60928359 2.60647008 4.19051306
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 5411.983 5404.915 5389.716
## Bayesian Information Criterion 5420.878 5413.809 5398.611
```

log normal looks like it's the best fit

UMBS SPECIES LEVEL - Looking at RELATIVE ABUNDANCE

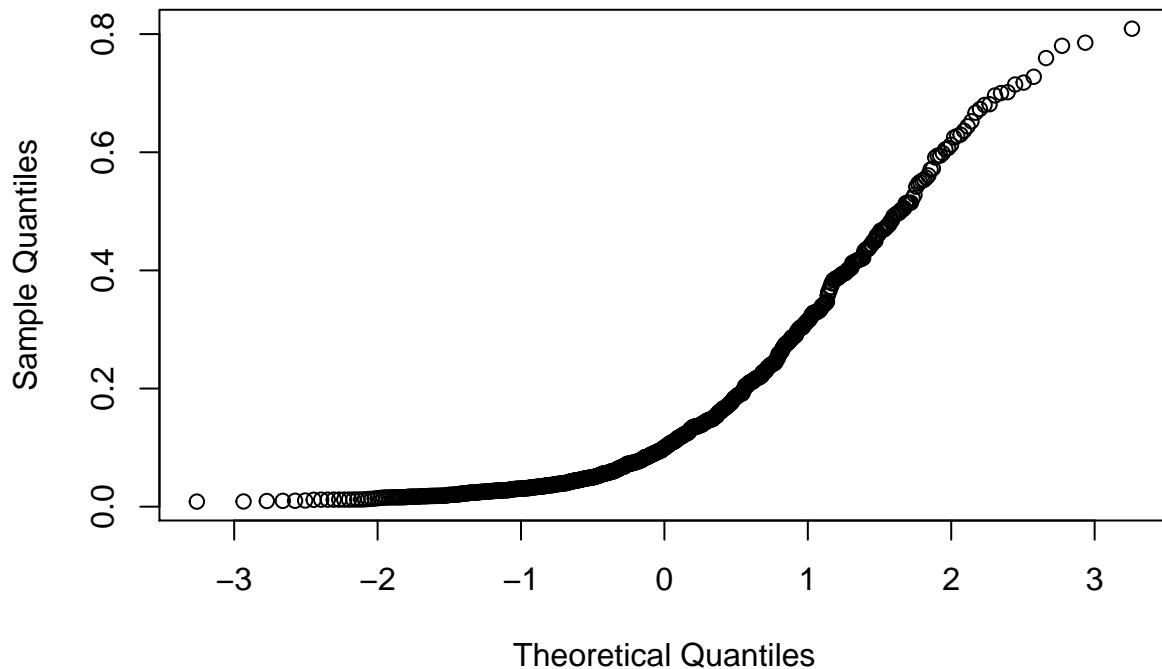
```
### UMBS ####
hist(comp_umbs_spp$relabun) # skewed to the right
```

Histogram of comp_umbs_spp\$relabun



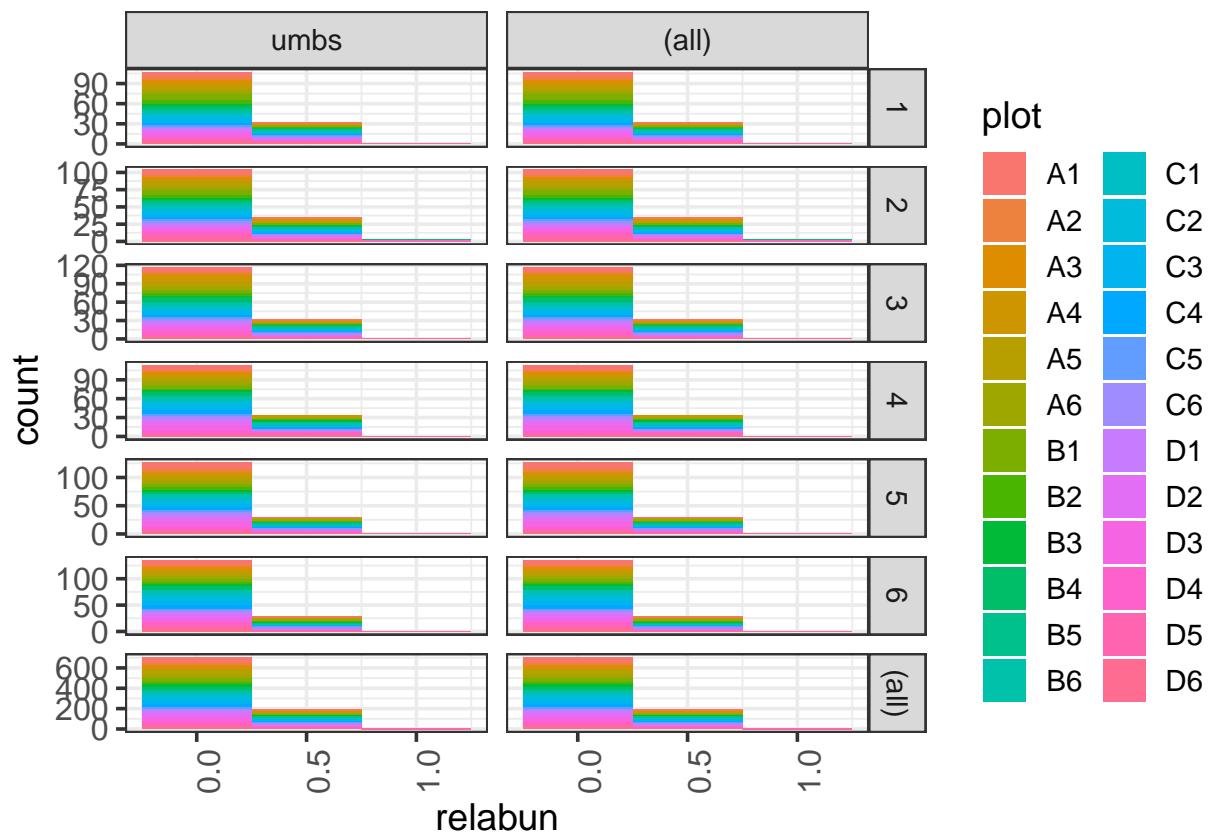
```
qqnorm(comp_umbs_spp$relabun)
```

Normal Q-Q Plot

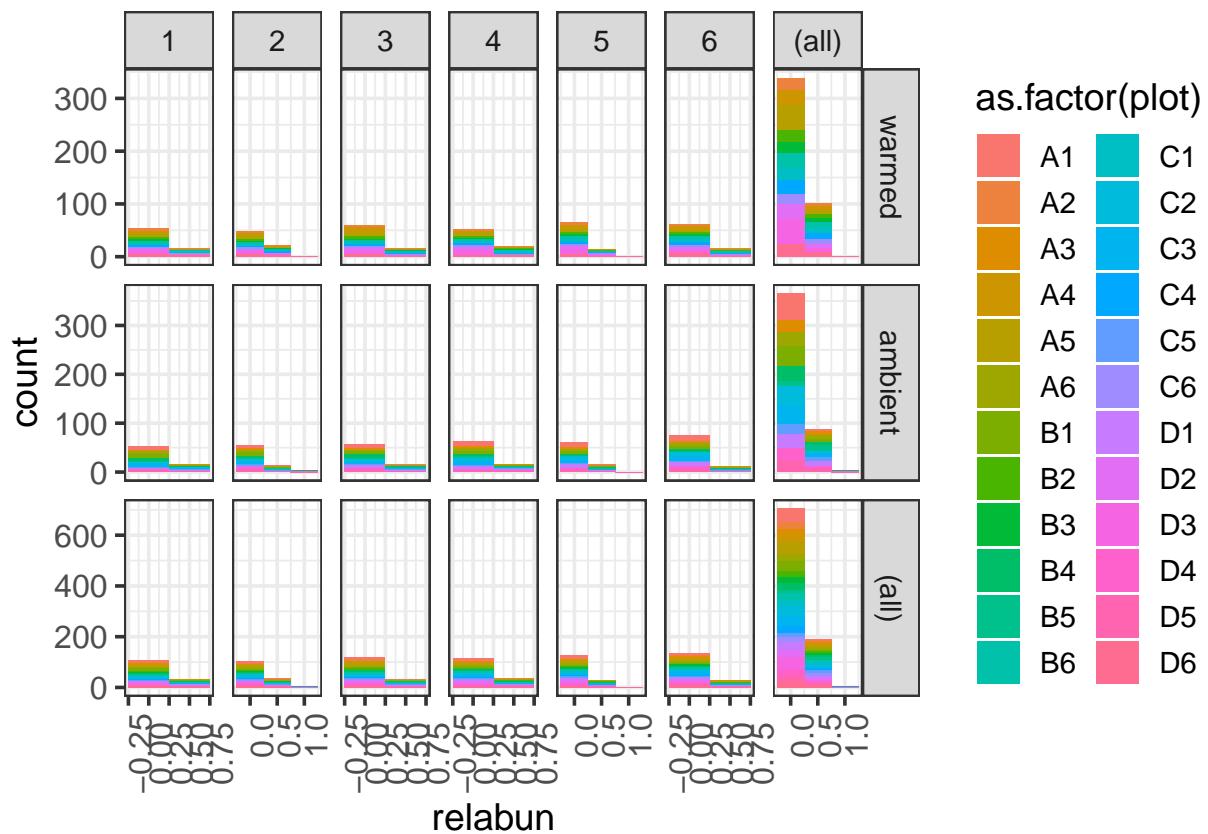


```
shapiro.test(comp_umbs_spp$relabun) # pvalue is < 0.05 so we reject the null hypothesis that the data
```

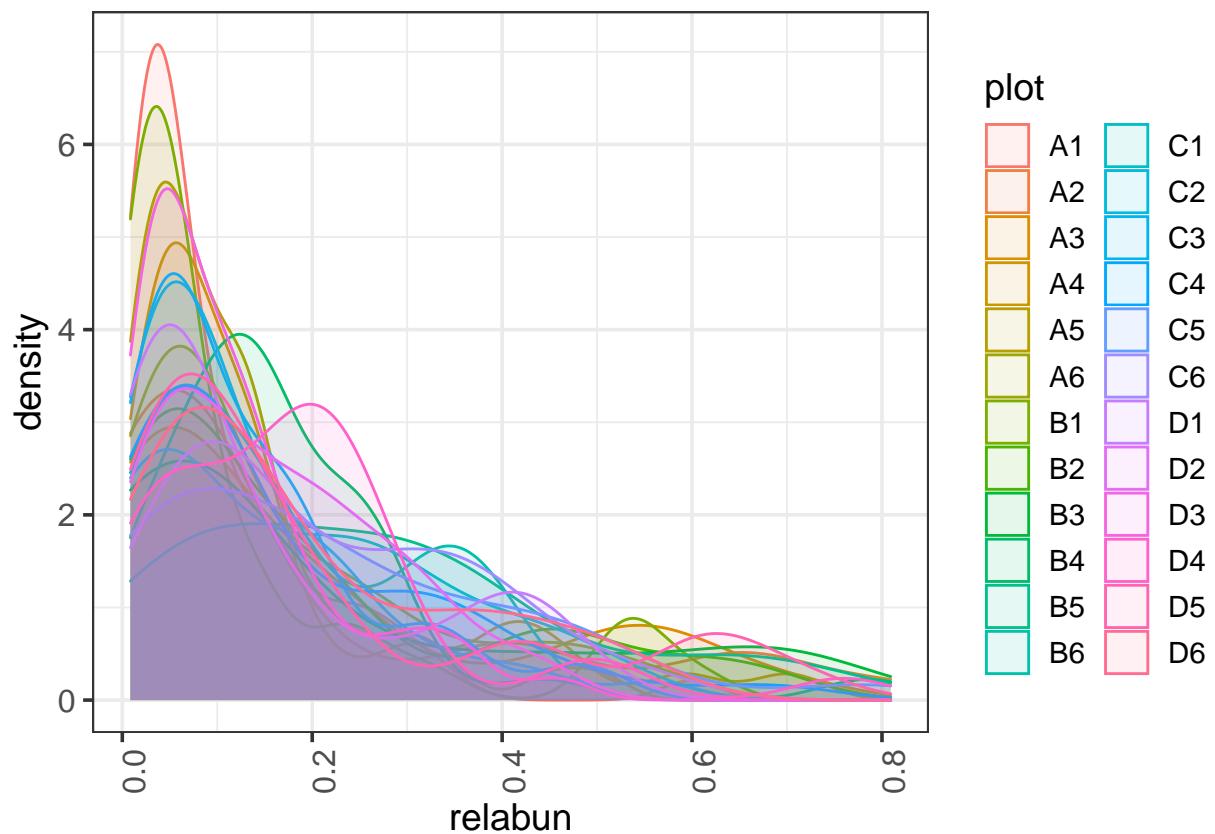
```
##  
## Shapiro-Wilk normality test  
##  
## data: comp_umbs_spp$relabun  
## W = 0.81681, p-value < 2.2e-16  
  
# Visualizing median Julian date for umbs at the SPECIES LEVEL  
ggplot(comp_umbs_spp, aes(relabun, fill = plot)) + geom_histogram(binwidth = 0.5) +  
  facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



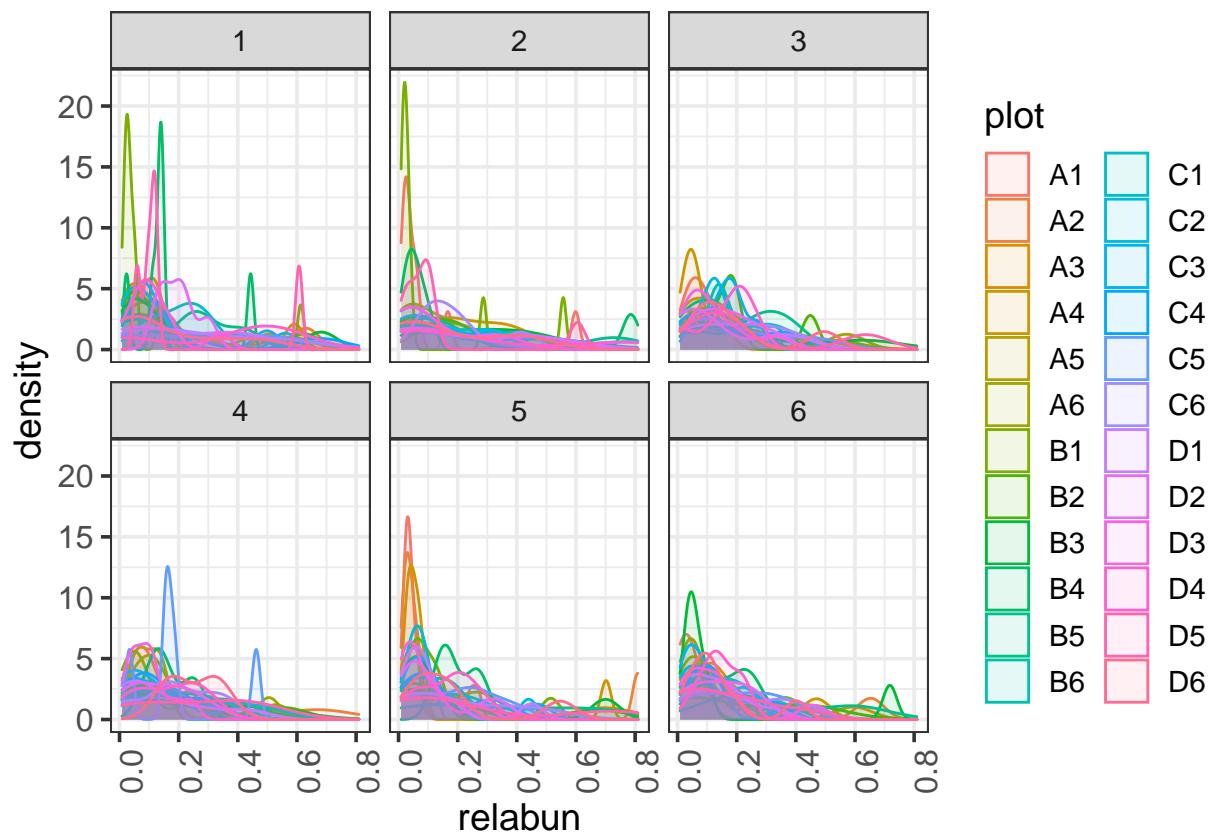
```
ggplot(comp_umbs_spp, aes(relabun, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +  
  facet_grid(state ~ year_factor, margins = TRUE, scales = "free")
```



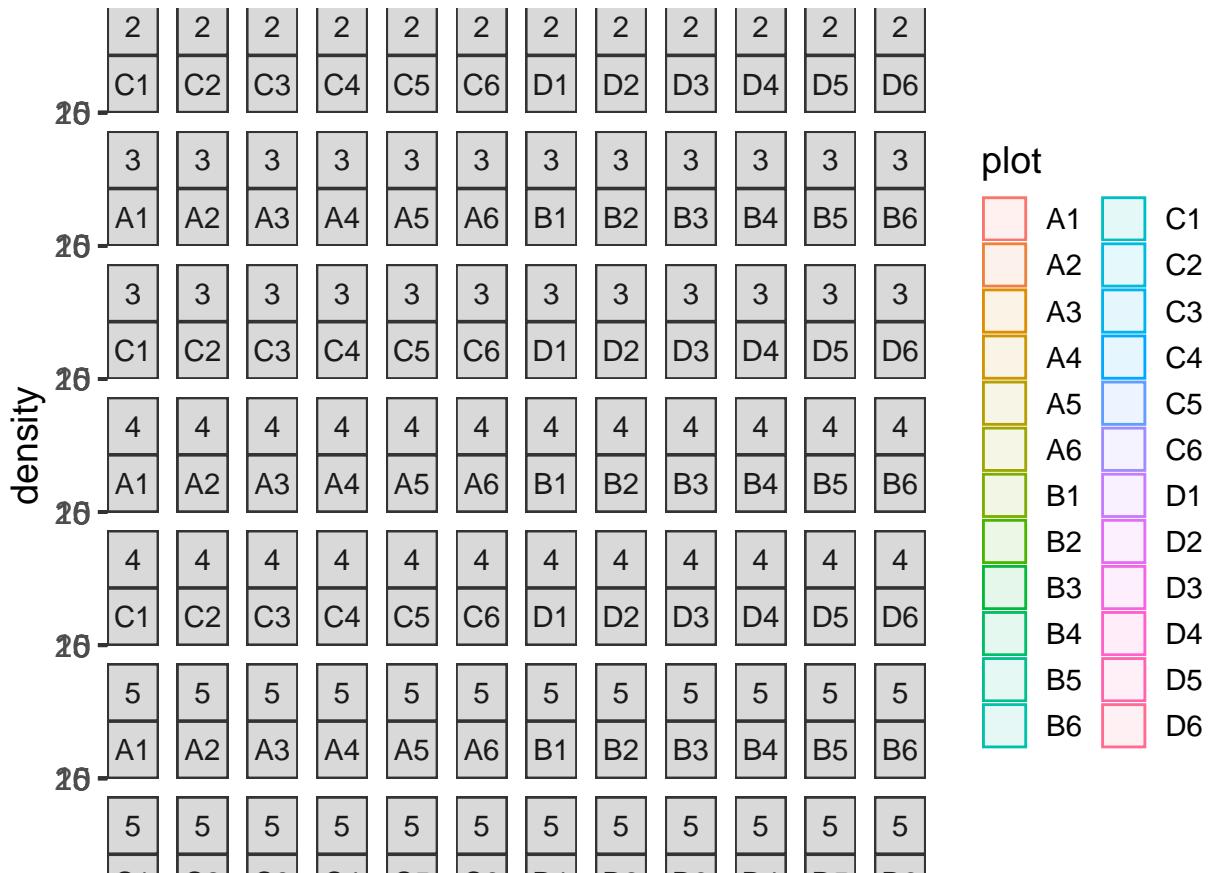
```
ggplot(comp_umbs_spp, aes(relabun, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



```
ggplot(comp_umbs_spp, aes(relabun, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
  facet_wrap(~year_factor)
```

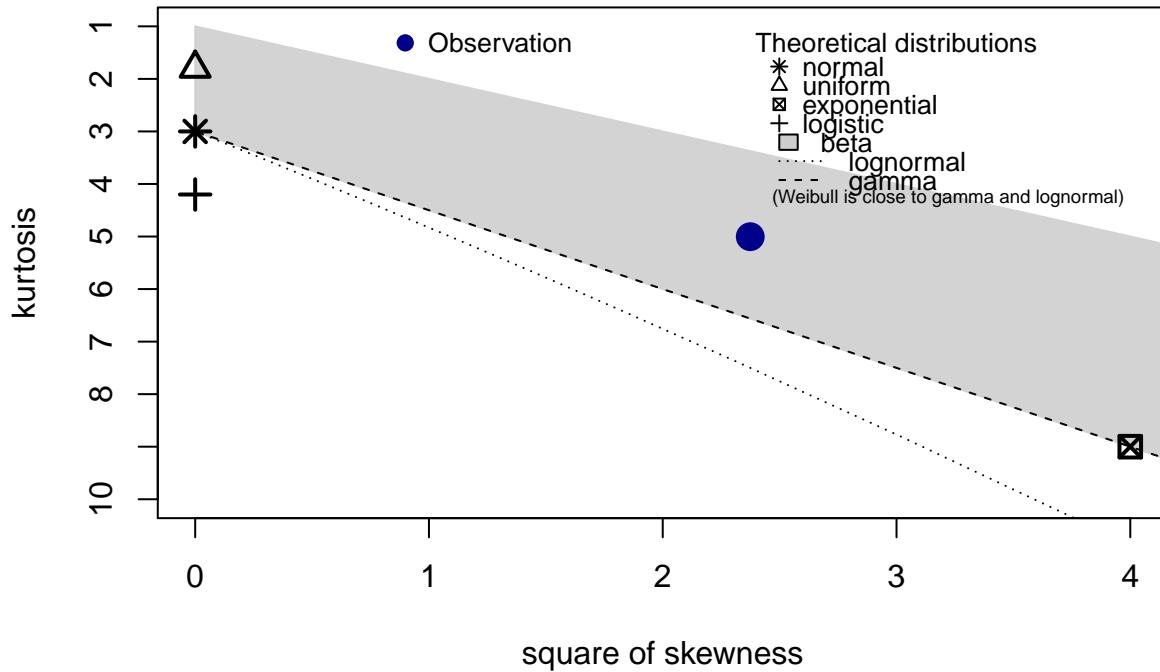


```
ggplot(comp_umbs_spp, aes(relabun, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
  facet_wrap(~year_factor + plot)
```



```
# Exploring distributions for these right-skewed data:  
descdist(comp_umbs_spp$relabun, discrete = FALSE)
```

Cullen and Frey graph



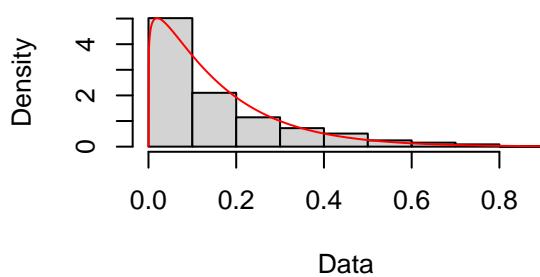
```

## summary statistics
## -----
## min:  0.008576329  max:  0.8091703
## median:  0.09957567
## mean:  0.160178
## estimated sd:  0.1594335
## estimated skewness:  1.540918
## estimated kurtosis:  5.003079

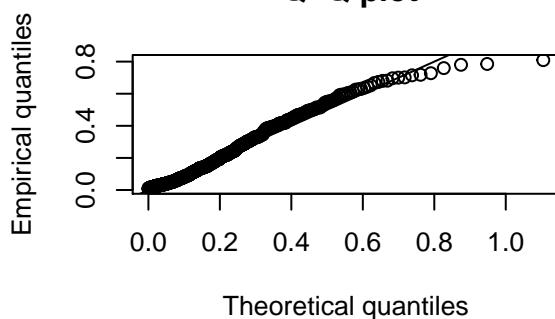
# Gamma distribution
fit.gamma <- fitdist(comp_umbs_spp$relabun, "gamma")
plot(fit.gamma)

```

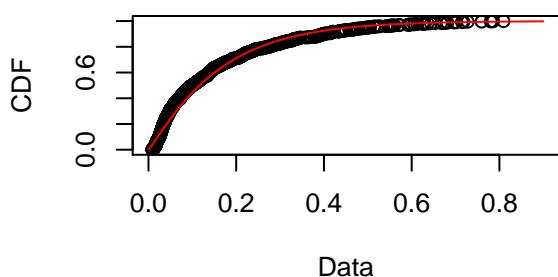
Empirical and theoretical dens.



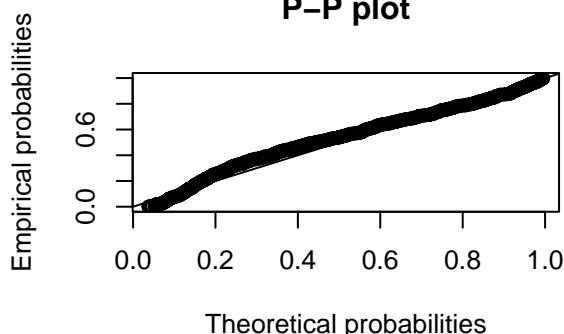
Q-Q plot



Empirical and theoretical CDFs

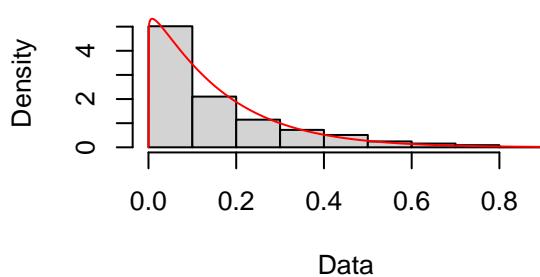


P-P plot

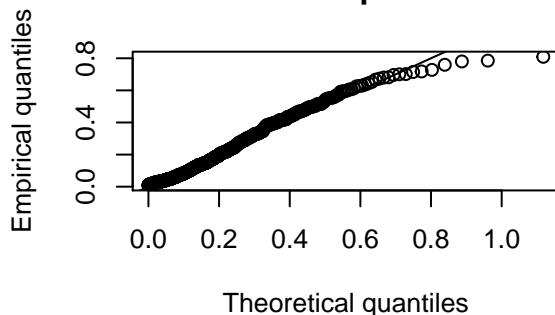


```
# Weibull distribution
fit.weibull <- fitdist(comp_umbs_spp$relabun, "weibull")
plot(fit.weibull)
```

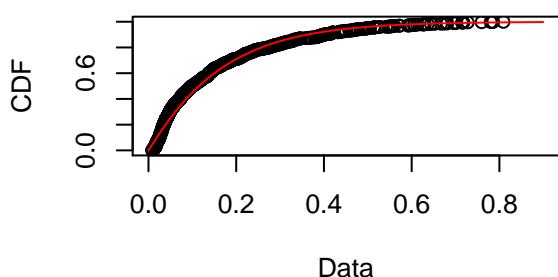
Empirical and theoretical dens.



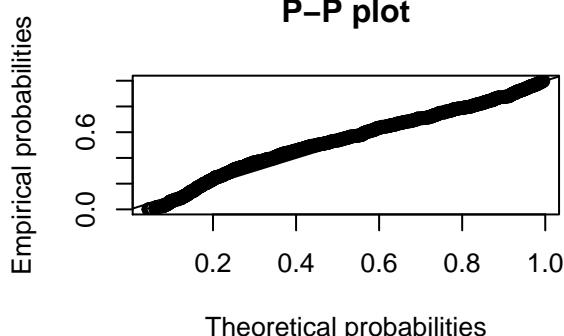
Q-Q plot



Empirical and theoretical CDFs

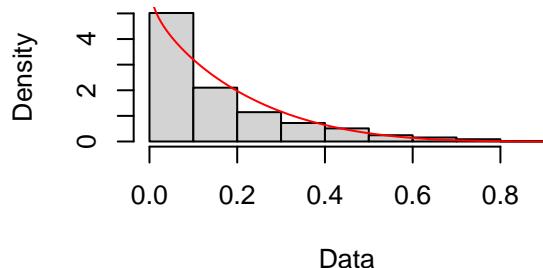


P-P plot

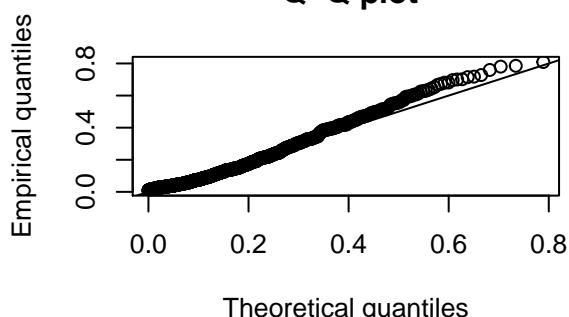


```
# Beta
fit.beta <- fitdist(comp_umbs_spp$relabun, "beta")
plot(fit.beta)
```

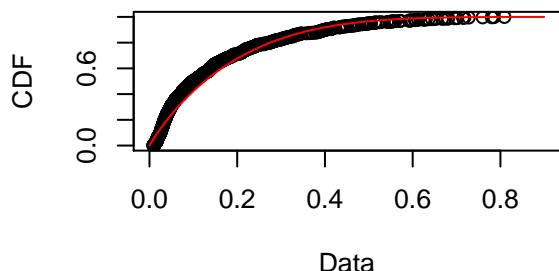
Empirical and theoretical dens.



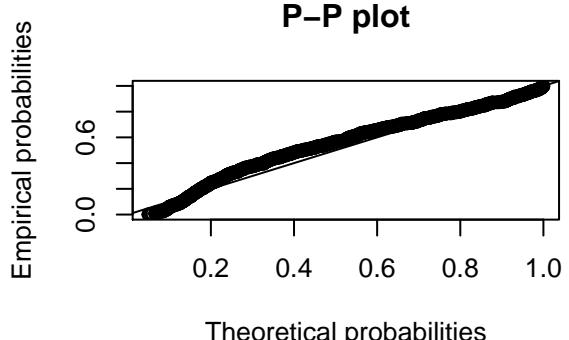
Q–Q plot



Empirical and theoretical CDFs

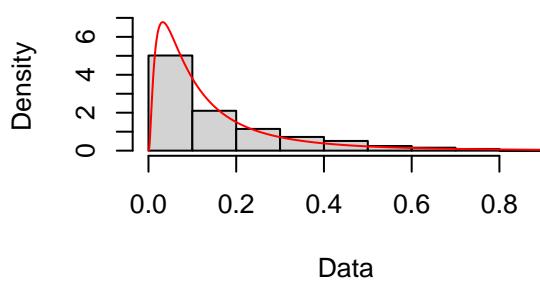


P–P plot

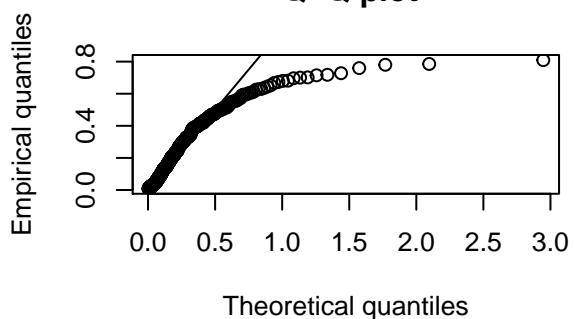


```
# Lognormal distribution
fit.ln <- fitdist(comp_umbs_spp$relabun, "lnorm")
plot(fit.ln)
```

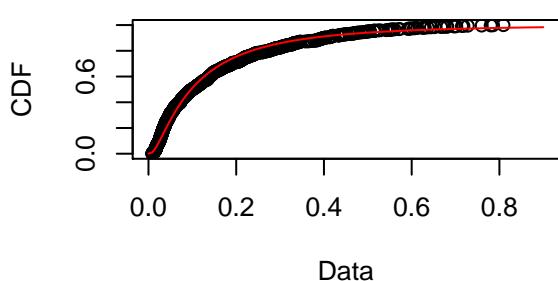
Empirical and theoretical dens.



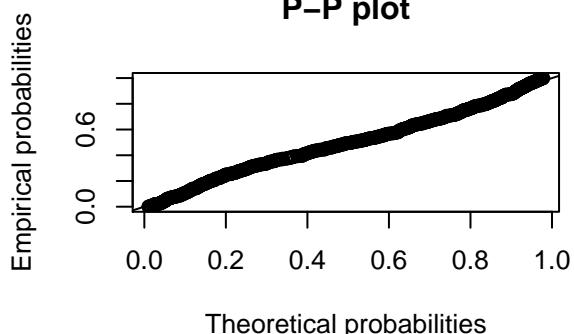
Q-Q plot



Empirical and theoretical CDFs

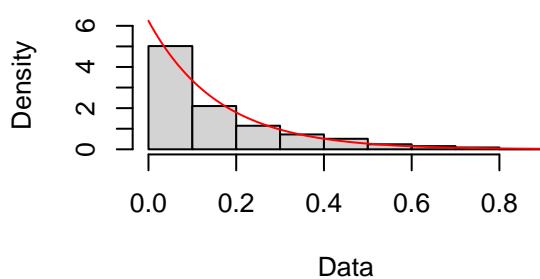


P-P plot

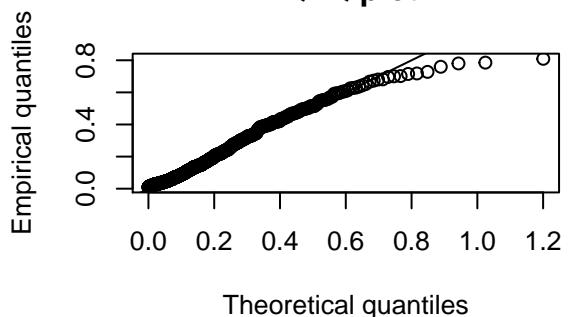


```
# Exponential distribution is another option  
fit.exp <- fitdist(comp_umbs_spp$relabun, "exp")  
plot(fit.exp)
```

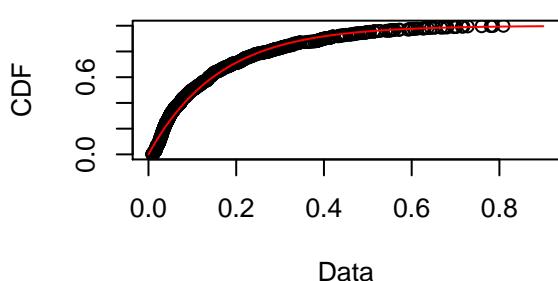
Empirical and theoretical dens.



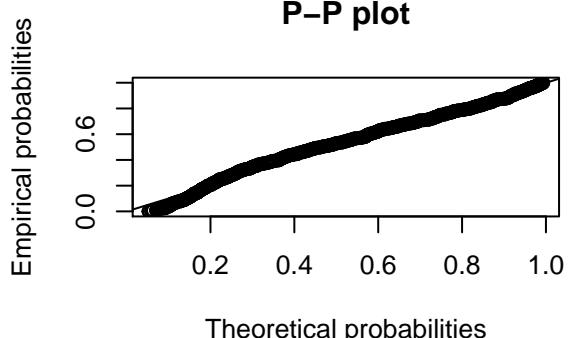
Q-Q plot



Empirical and theoretical CDFs



P-P plot

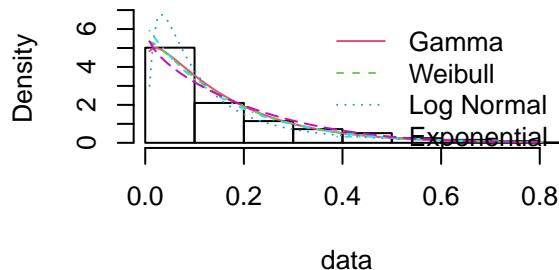


```

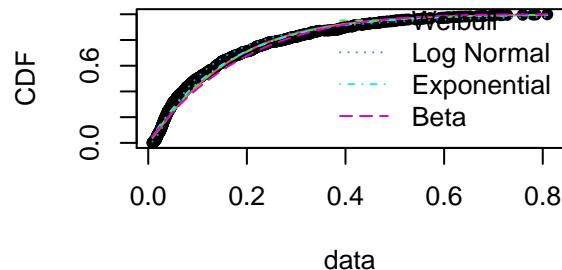
par(mfrow = c(2, 2))
plot.legend <- c("Gamma", "Weibull", "Log Normal", "Exponential", "Beta")
denscomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp, fit.beta), legendtext = plot.legend)
cdfcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp, fit.beta), legendtext = plot.legend)
qqcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp, fit.beta), legendtext = plot.legend)
ppcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp, fit.beta), legendtext = plot.legend)

```

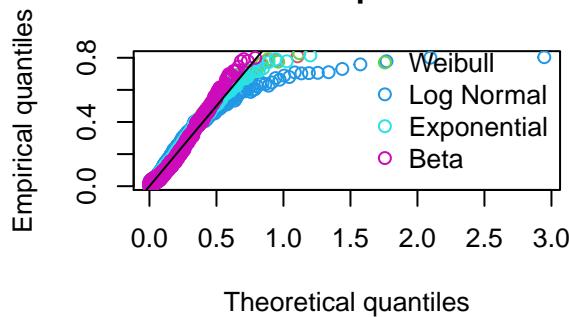
Histogram and theoretical densities



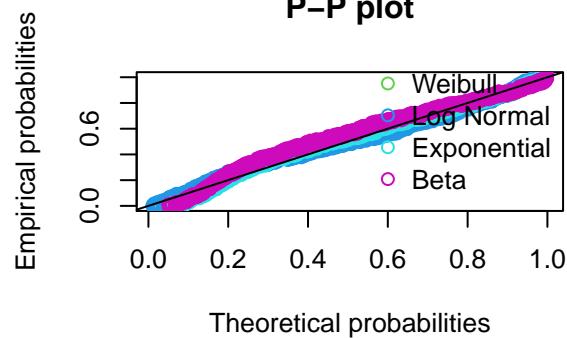
Empirical and theoretical CDFs



Q-Q plot



P-P plot



```

# Goodness of fit comparisons across fits (can't include the sqrt normal bc it
# becomes diff response values)
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp, fit.beta), fitnames = c("Gamma",
    "Weibull", "Log Normal", "Exp", "Beta"))

```

```

## Goodness-of-fit statistics
##                                     Gamma     Weibull   Log Normal      Exp
## Kolmogorov-Smirnov statistic 0.07776196 0.06720039 0.05018519 0.0666861
## Cramer-von Mises statistic   1.50231036 1.20082631 0.74429208 0.8263555
## Anderson-Darling statistic   9.33691935 8.24847329 4.80014789 7.1414656
##                                     Beta
## Kolmogorov-Smirnov statistic  0.0857168
## Cramer-von Mises statistic   2.3253269
## Anderson-Darling statistic   13.7081247
##
## Goodness-of-fit criteria
##                                     Gamma     Weibull   Log Normal      Exp
## Akaike's Information Criterion -1500.418 -1494.224 -1553.369 -1492.983
## Bayesian Information Criterion -1490.815 -1484.622 -1543.767 -1488.181
##                                     Beta

```

```

## Akaike's Information Criterion -1459.308
## Bayesian Information Criterion -1449.705

# Beta and exp distributions look to be the best based on AIC and BIC values

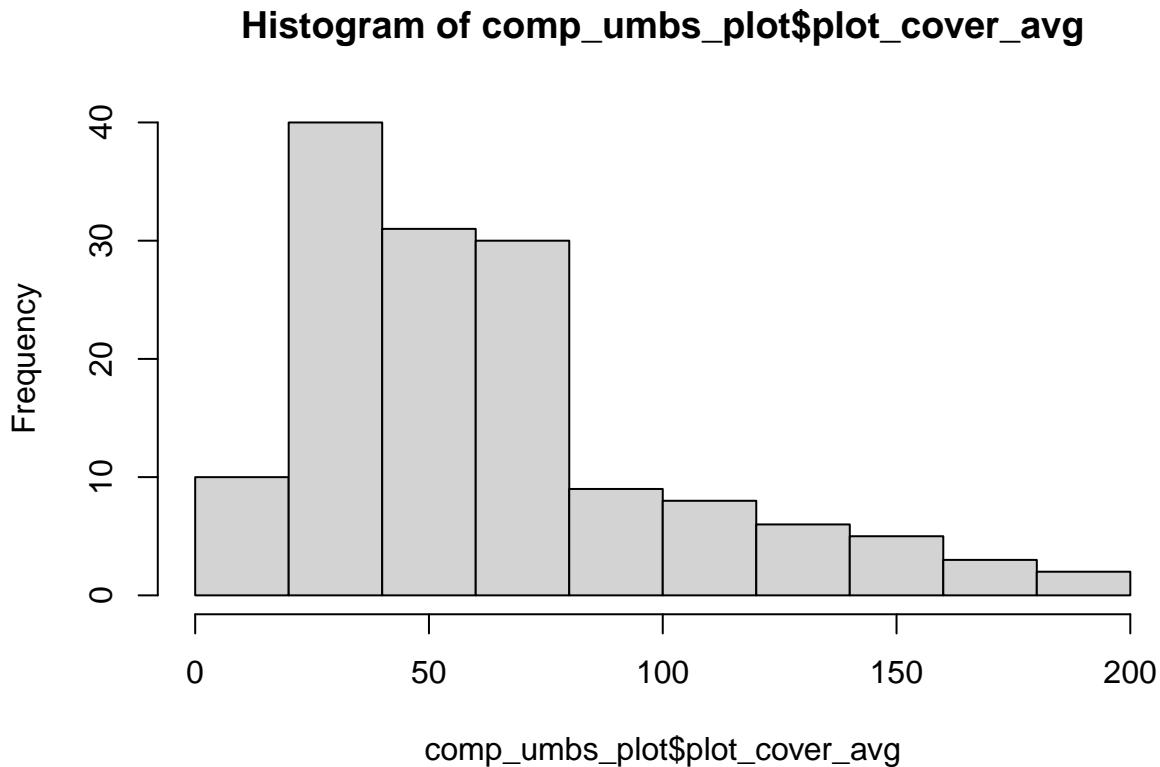
```

UMBS PLOT LEVEL - Looking at PLOT AVG TOTALS

```

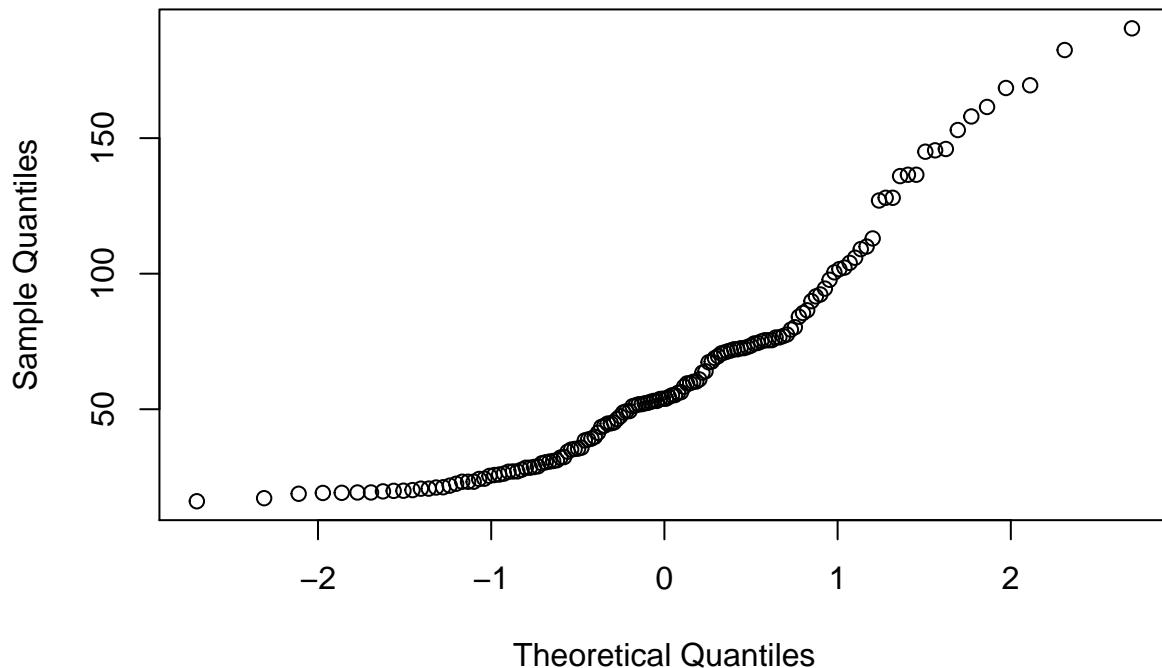
### UMBS ####
hist(comp_umbs_plot$plot_cover_avg) # skewed to the right

```



```
qqnorm(comp_umbs_plot$plot_cover_avg)
```

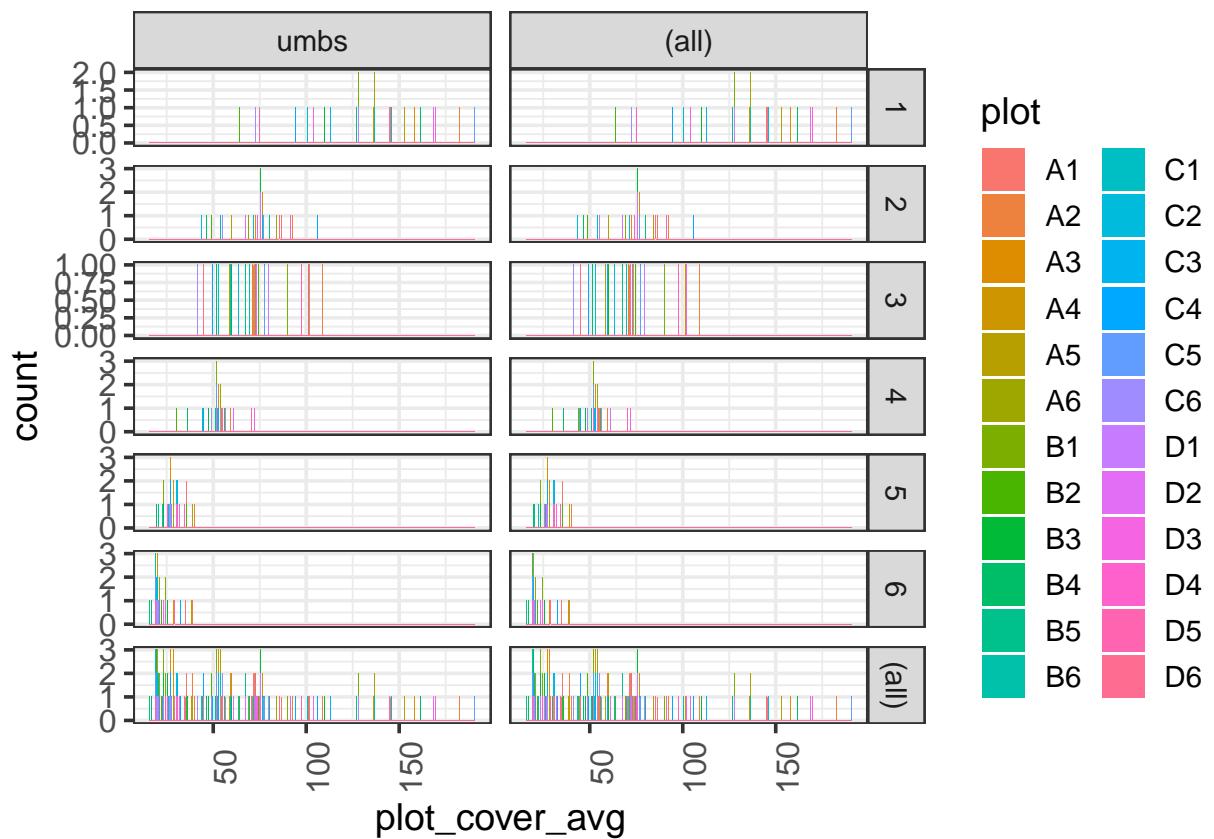
Normal Q-Q Plot



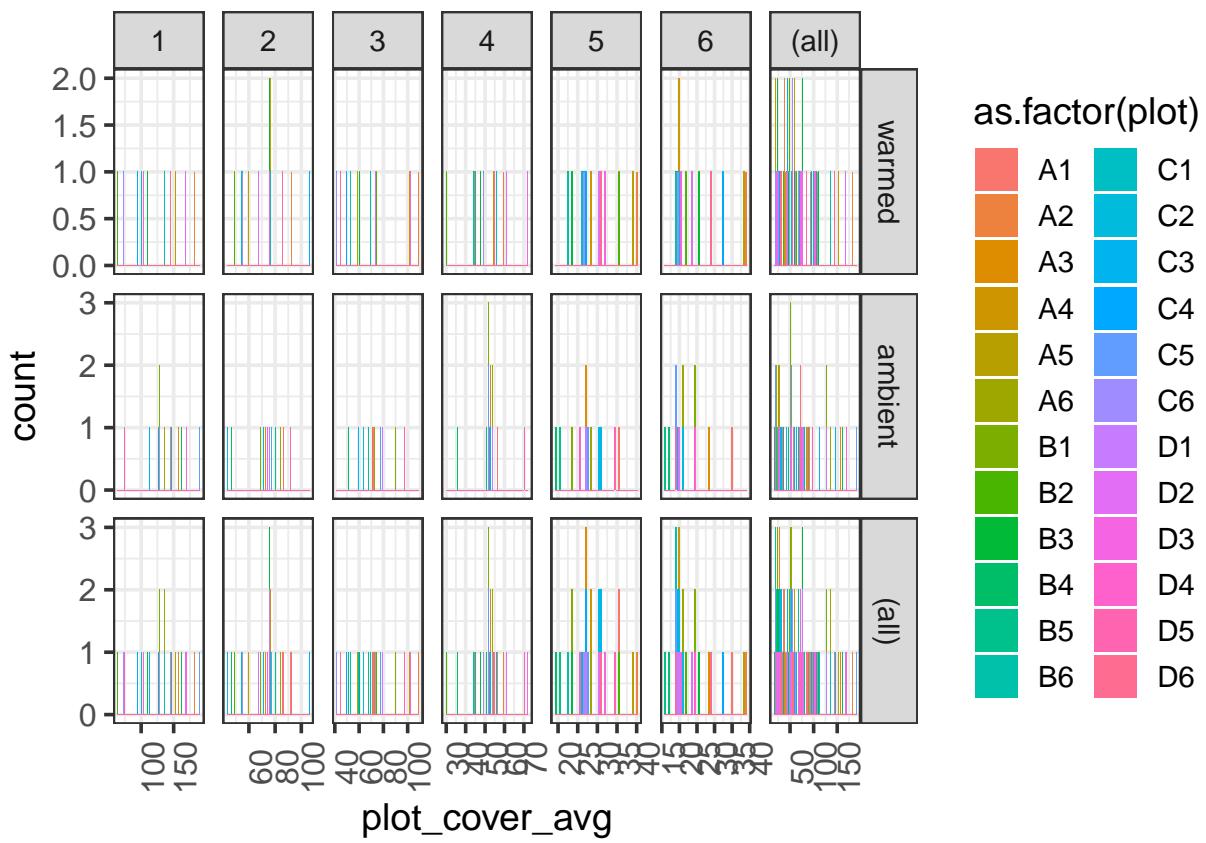
```
shapiro.test(comp_umbs_plot$plot_cover_avg) # pvalue is < 0.05 so we reject the null hypothesis that the data is normally distributed

## 
## Shapiro-Wilk normality test
##
## data: comp_umbs_plot$plot_cover_avg
## W = 0.888888, p-value = 5.615e-09

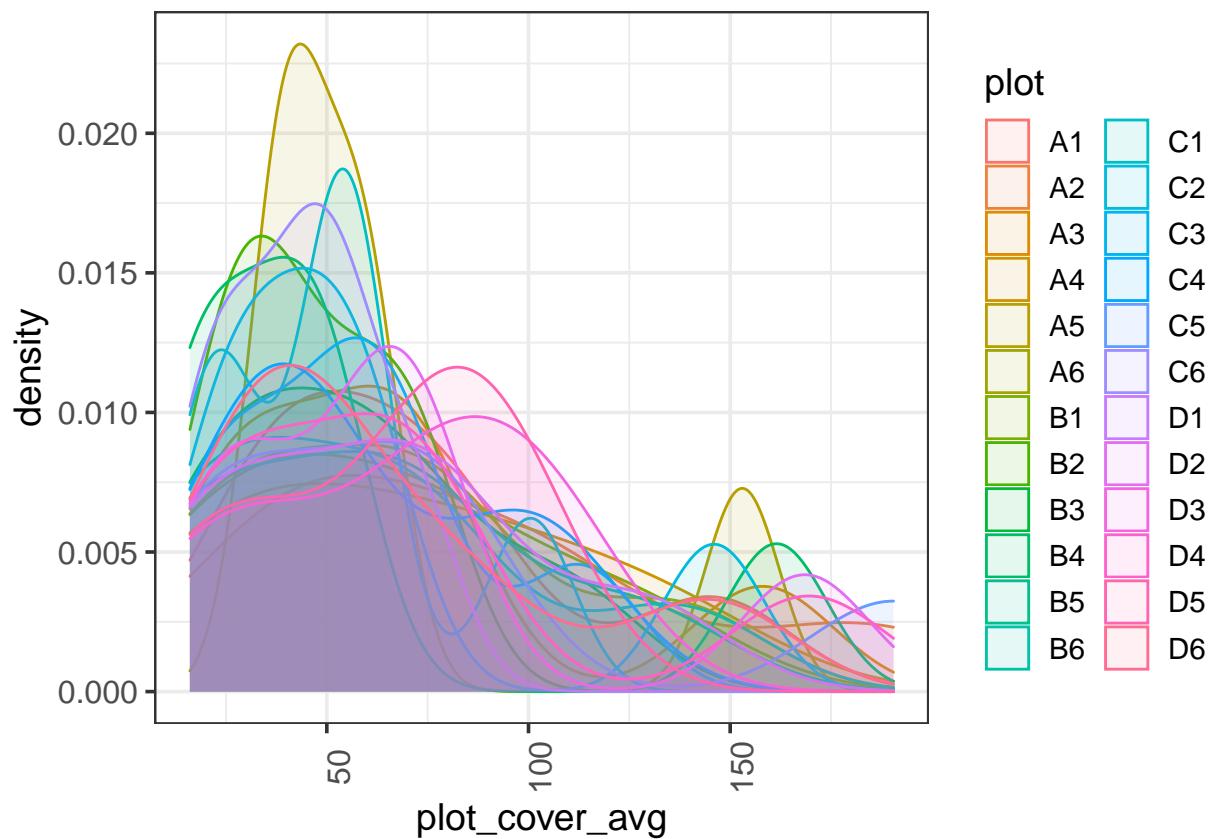
# Visualizing median Julian date for umbs at the PLOT LEVEL
ggplot(comp_umbs_plot, aes(plot_cover_avg, fill = plot)) + geom_histogram(binwidth = 0.5) +
  facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



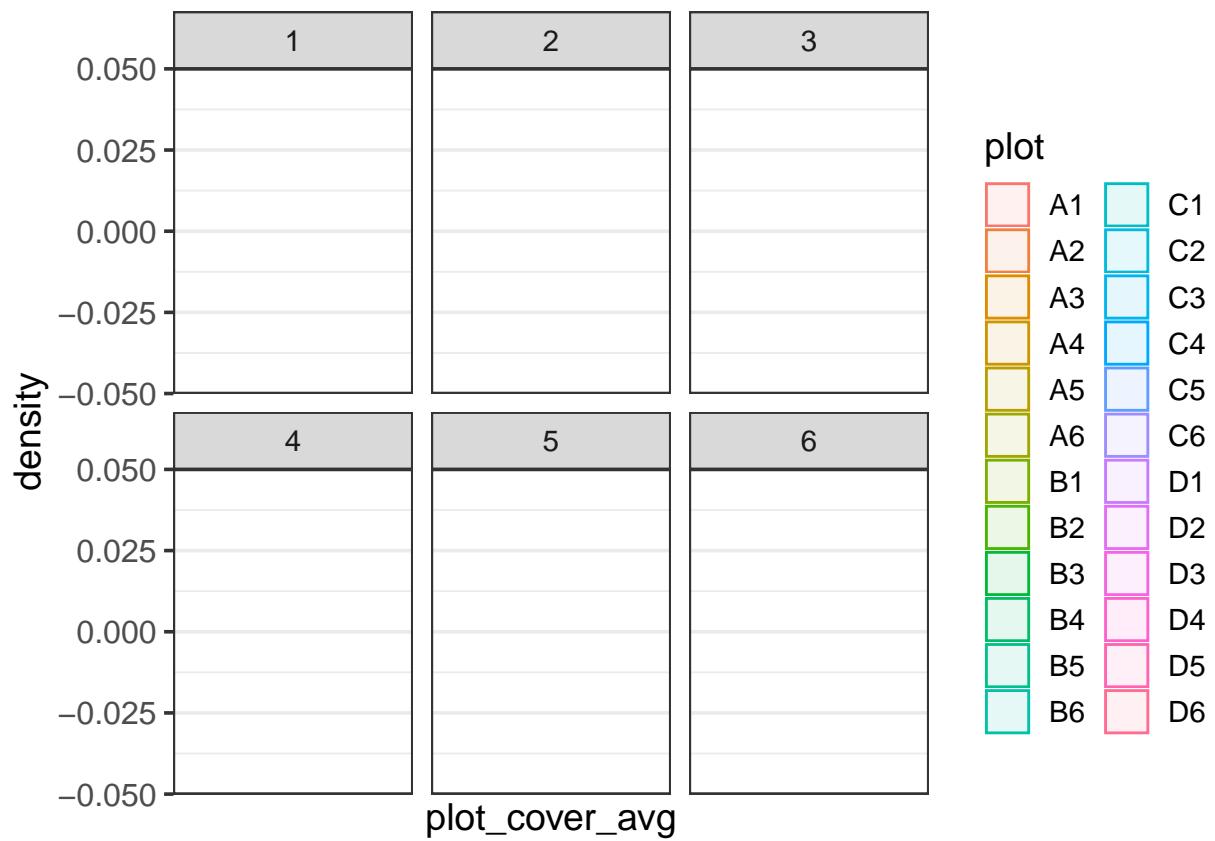
```
ggplot(comp_umbs_plot, aes(plot_cover_avg, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
  facet_grid(state ~ year_factor, margins = TRUE, scales = "free")
```



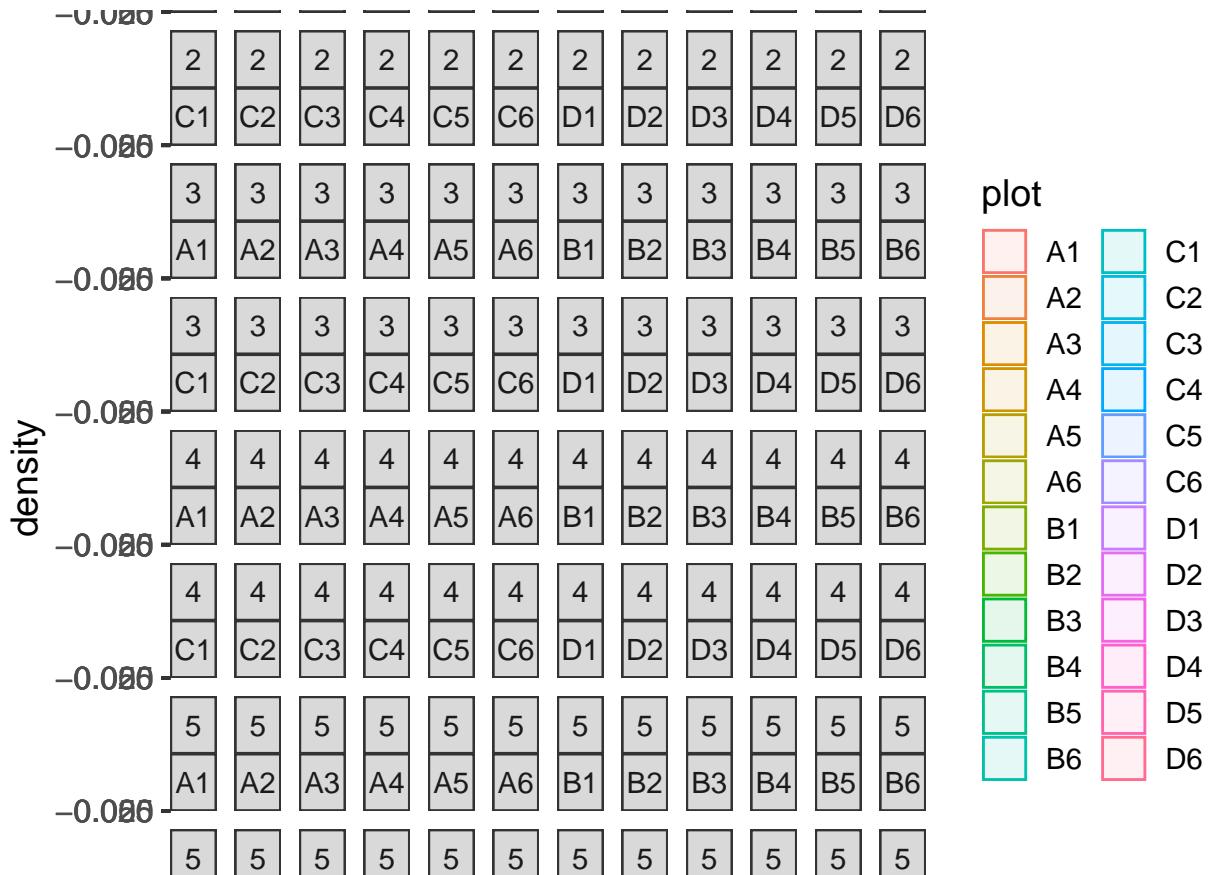
```
ggplot(comp_umbs_plot, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



```
ggplot(comp_umbs_plot, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
  facet_wrap(~year_factor)
```

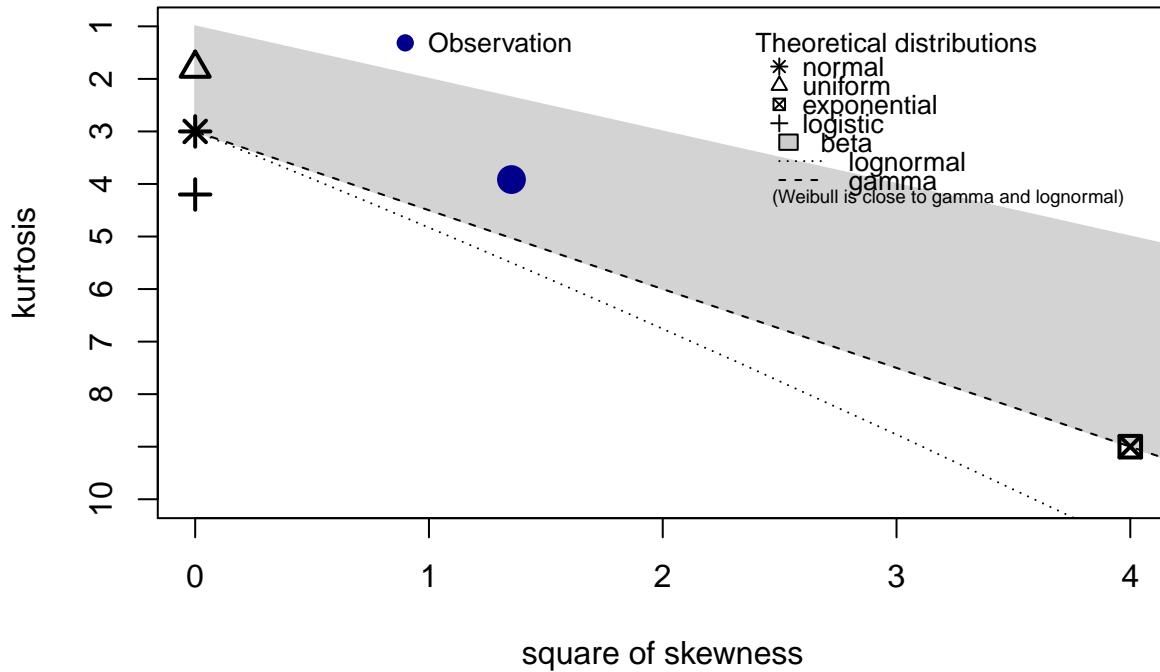


```
ggplot(comp_umbs_plot, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
  facet_wrap(~year_factor + plot)
```



```
# Exploring distributions for these right-skewed data:  
descdist(comp_umbs_plot$plot_cover_avg, discrete = FALSE)
```

Cullen and Frey graph

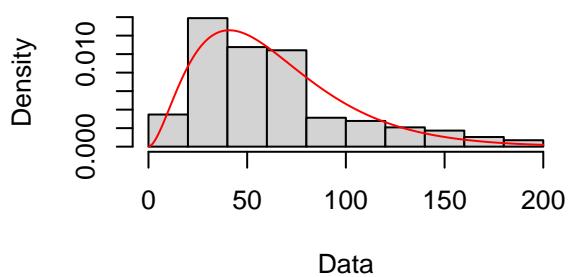
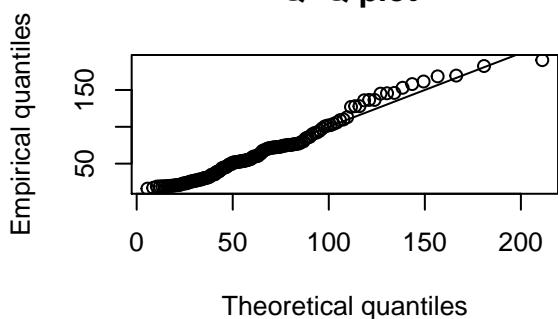
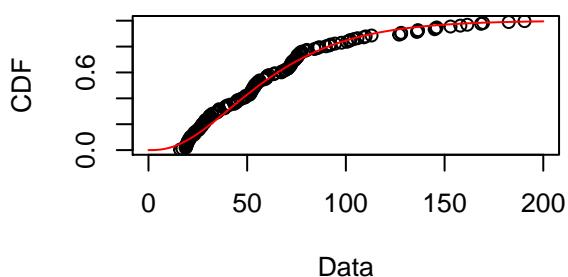
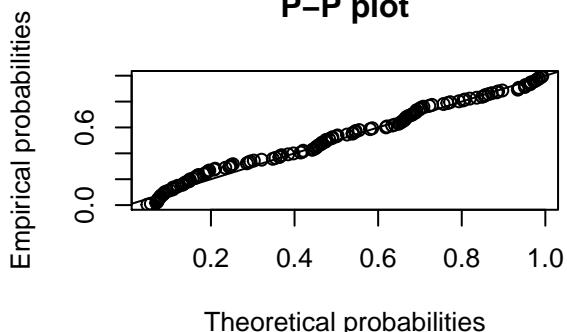


```

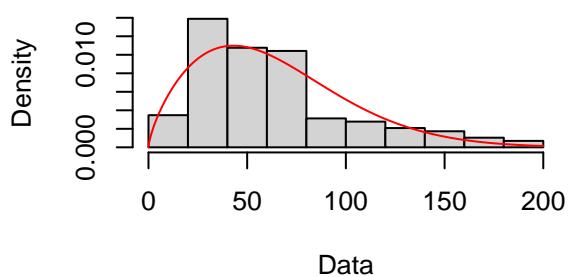
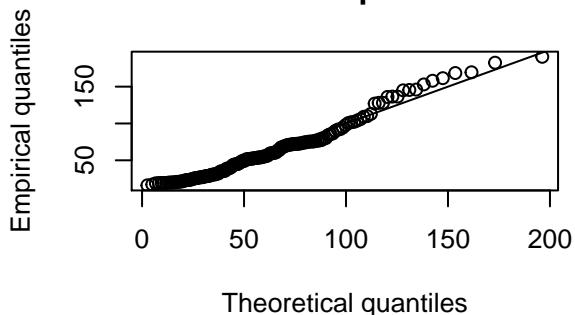
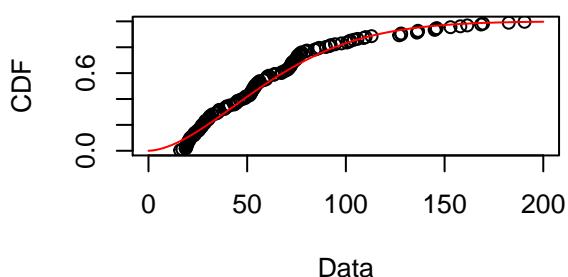
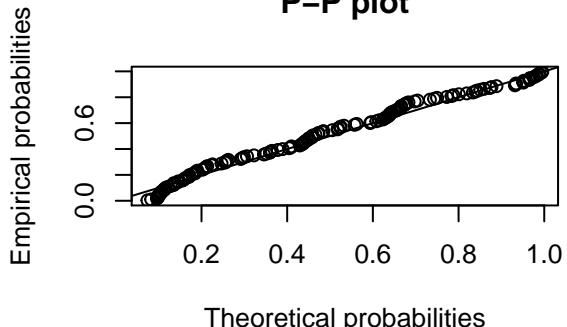
## summary statistics
## -----
## min: 16.05882  max: 190.5
## median: 53.88562
## mean: 63.35173
## estimated sd: 39.75901
## estimated skewness: 1.163142
## estimated kurtosis: 3.915878

# Gamma distribution
fit.gamma <- fitdist(comp_umbs_plot$plot_cover_avg, "gamma")
plot(fit.gamma)

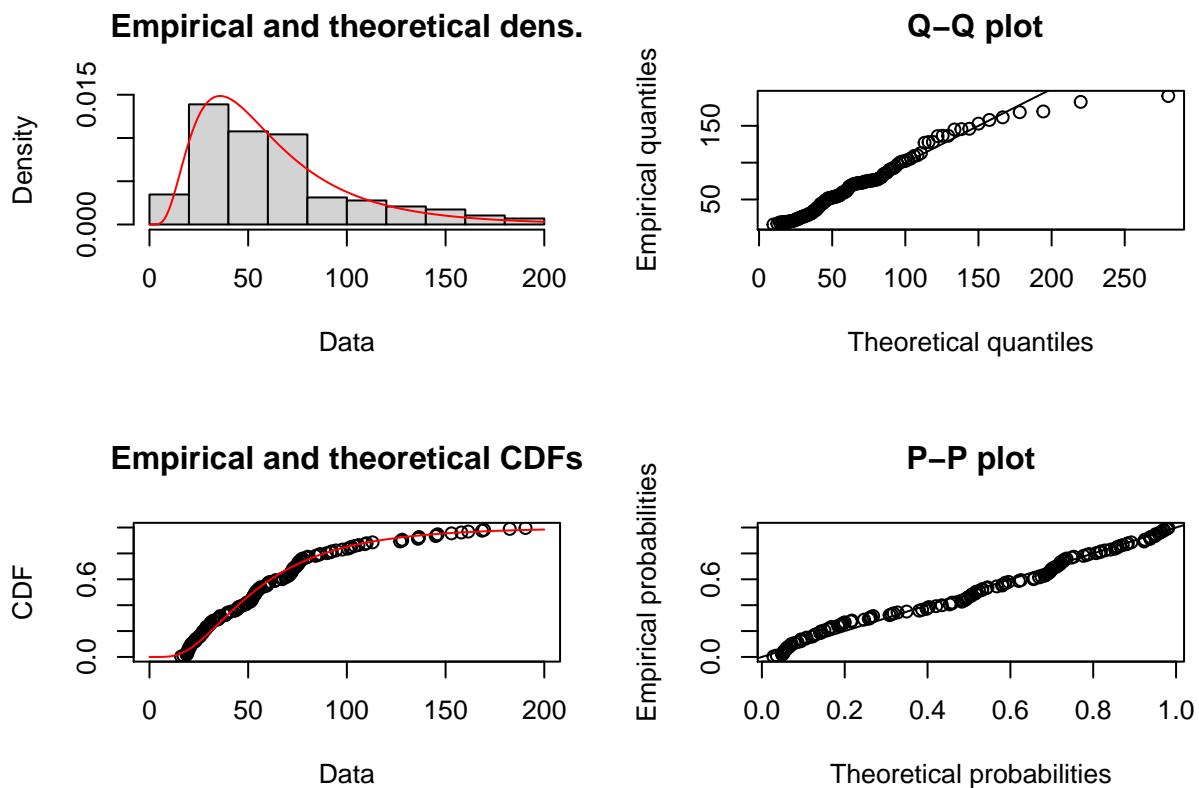
```

Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

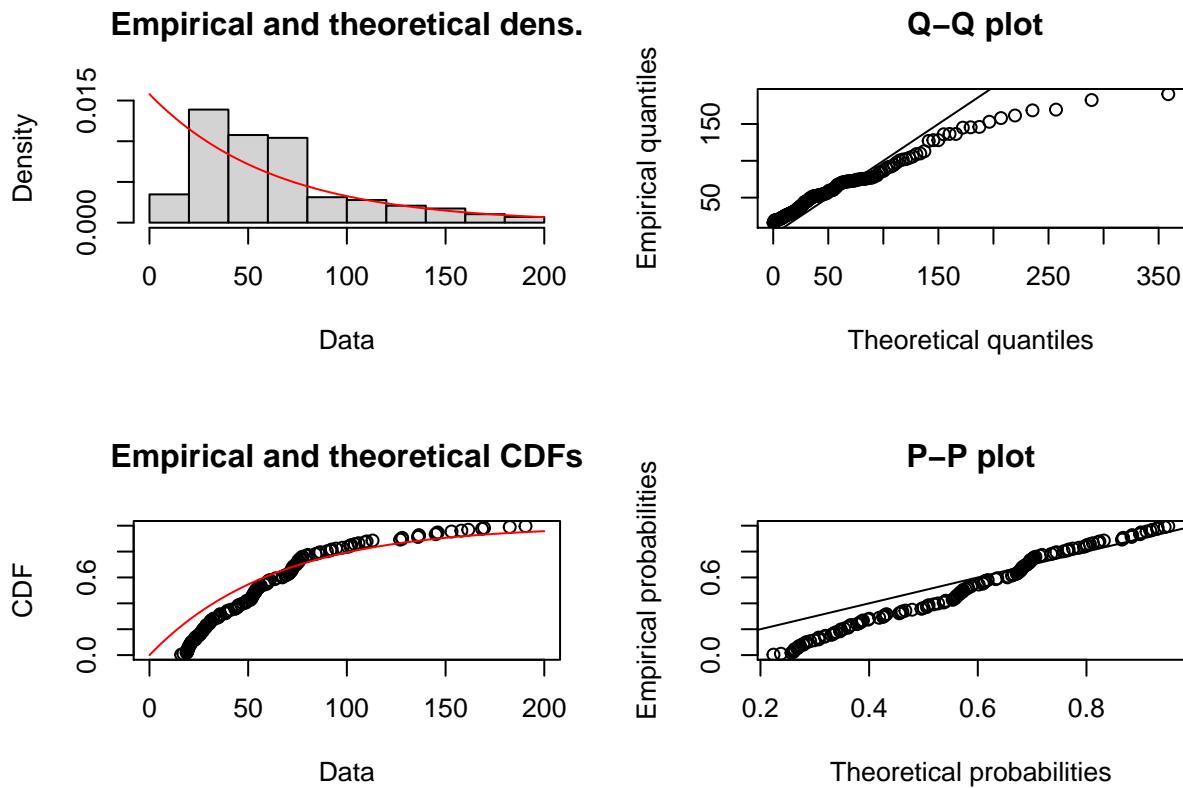
```
# Weibull distribution
fit.weibull <- fitdist(comp_umbs_plot$plot_cover_avg, "weibull")
plot(fit.weibull)
```

Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

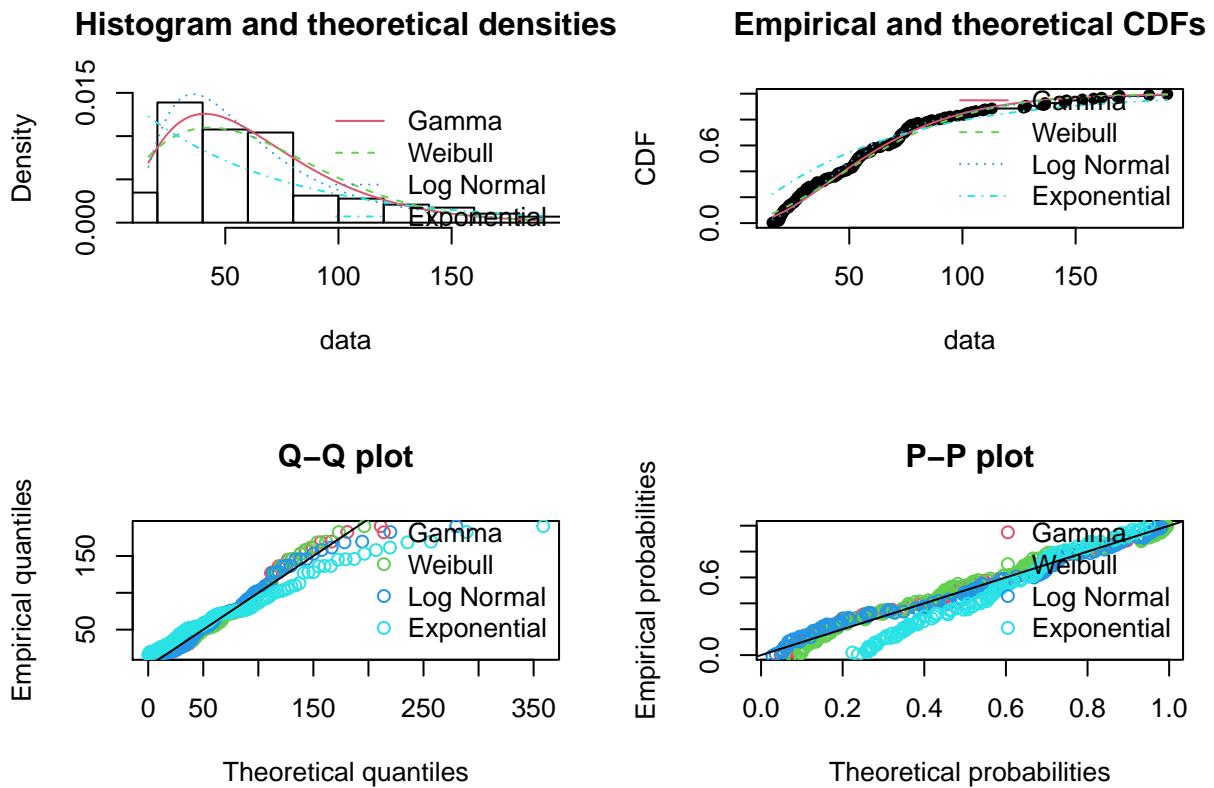
```
# Lognormal distribution
fit.ln <- fitdist(comp_umbs_plot$plot_cover_avg, "lnorm")
plot(fit.ln)
```



```
# Exponential distribution is another option
fit.exp <- fitdist(comp_umbs_plot$plot_cover_avg, "exp")
plot(fit.exp)
```



```
par(mfrow = c(2, 2))
plot.legend <- c("Gamma", "Weibull", "Log Normal", "Exponential")
denscomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp), legendtext = plot.legend)
cdfcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp), legendtext = plot.legend)
qqcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp), legendtext = plot.legend)
ppcomp(list(fit.gamma, fit.weibull, fit.ln, fit.exp), legendtext = plot.legend)
```



```
# Goodness of fit comparisons across fits (can't include the sqrt normal bc it
# becomes diff response values)
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull",
  "Log Normal", "Exp"))
```

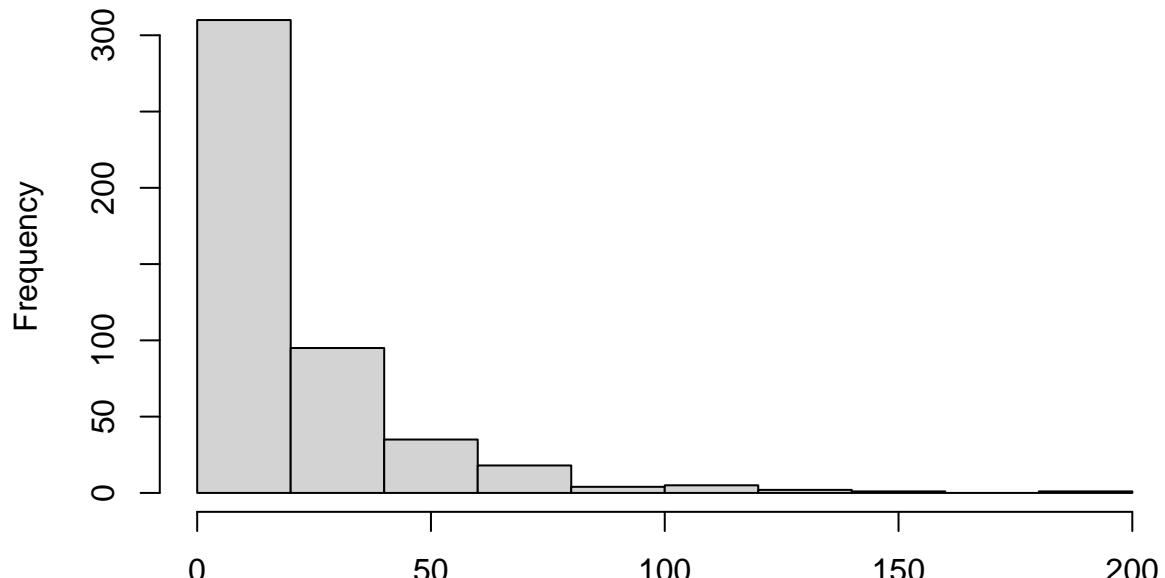
```
## Goodness-of-fit statistics
##                                     Gamma   Weibull Log Normal      Exp
## Kolmogorov-Smirnov statistic 0.07479574 0.08203544 0.07074297 0.2431617
## Cramer-von Mises statistic  0.13935488 0.19248423 0.14807679 1.8922613
## Anderson-Darling statistic  1.16877890 1.59146091 1.03119165 10.9587774
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal      Exp
## Akaike's Information Criterion 1421.071 1429.938 1415.615 1484.826
## Bayesian Information Criterion 1427.011 1435.878 1421.555 1487.796

# log normal distribution looks to be the best based on AIC and BIC values
```

UMBS PLOT LEVEL ORIGIN - Looking at PLOT AVG TOTALS

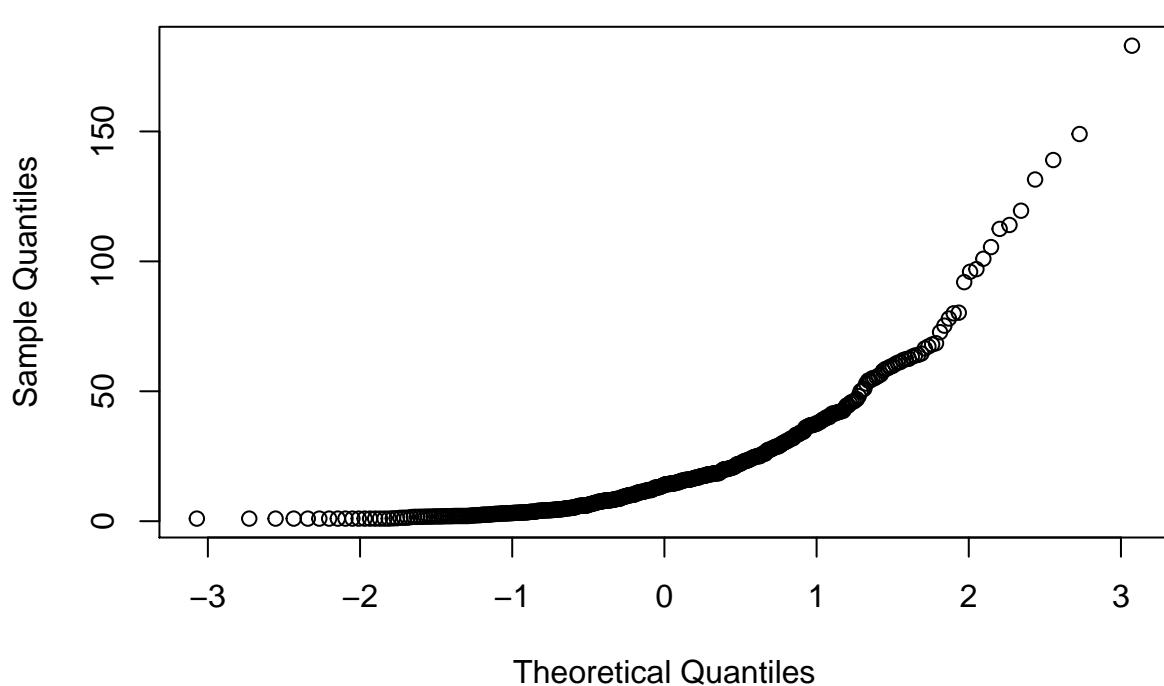
```
### UMBS ####
hist(umbs_comp_plot_origin$plot_cover_avg) # skewed to the right
```

Histogram of umbs_comp_plot_origin\$plot_cover_avg



```
qqnorm(umbc_comp_plot_origin$plot_cover_avg)
```

Normal Q-Q Plot



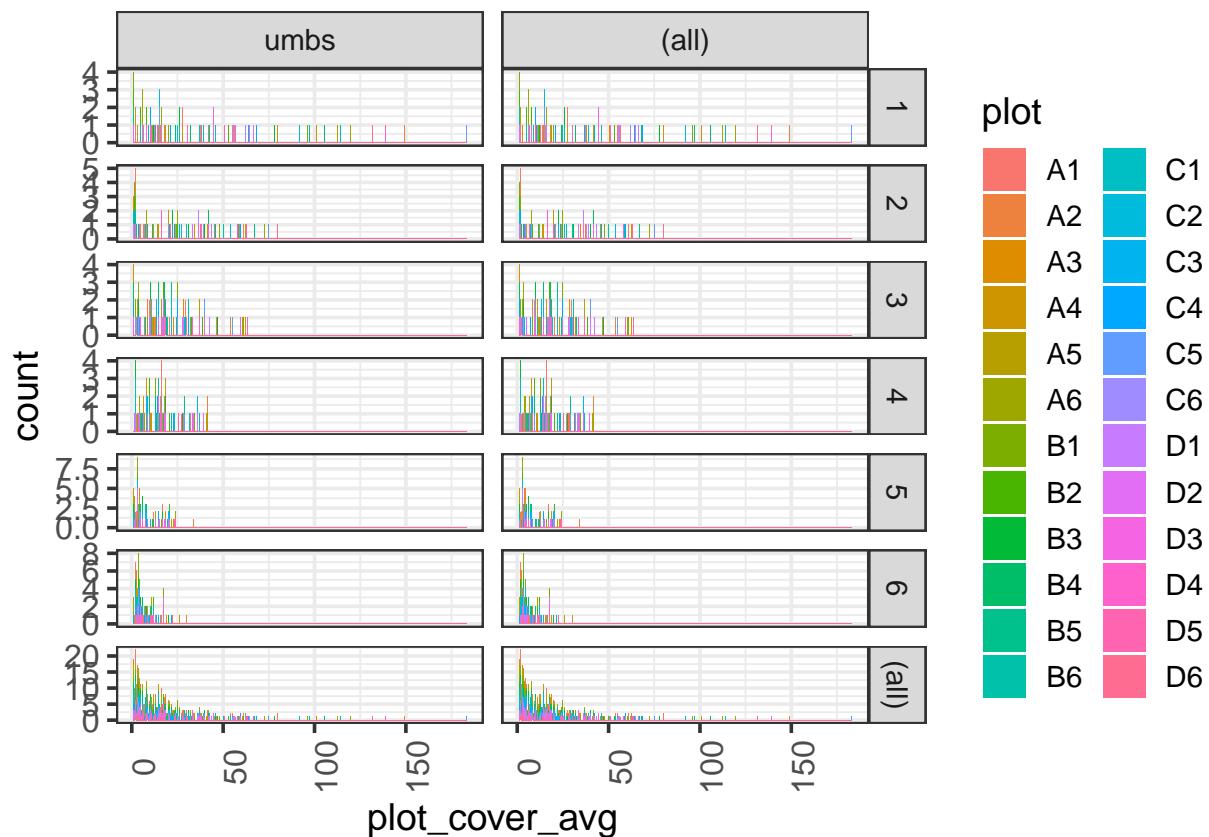
```

shapiro.test(umbs_comp_plot_origin$plot_cover_avg) # pvalue is < 0.05 so we reject the null hypothesis

## 
## Shapiro-Wilk normality test
## 
## data: umbs_comp_plot_origin$plot_cover_avg
## W = 0.73533, p-value < 2.2e-16

# Visualizing plot average totals for umbs at the PLOT LEVEL
ggplot(umbs_comp_plot_origin, aes(plot_cover_avg, fill = plot)) + geom_histogram(binwidth = 0.5) +
  facet_grid(year_factor ~ site, margins = TRUE, scales = "free")

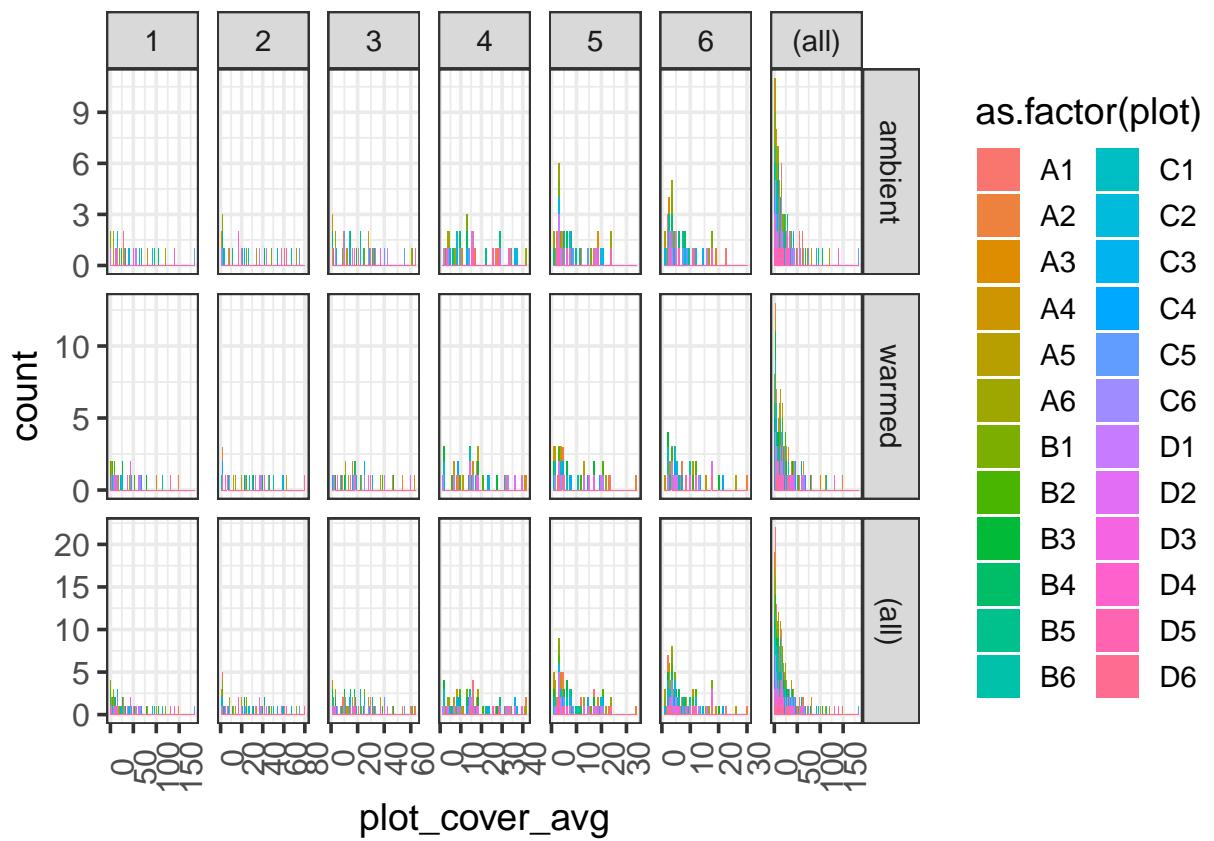
```



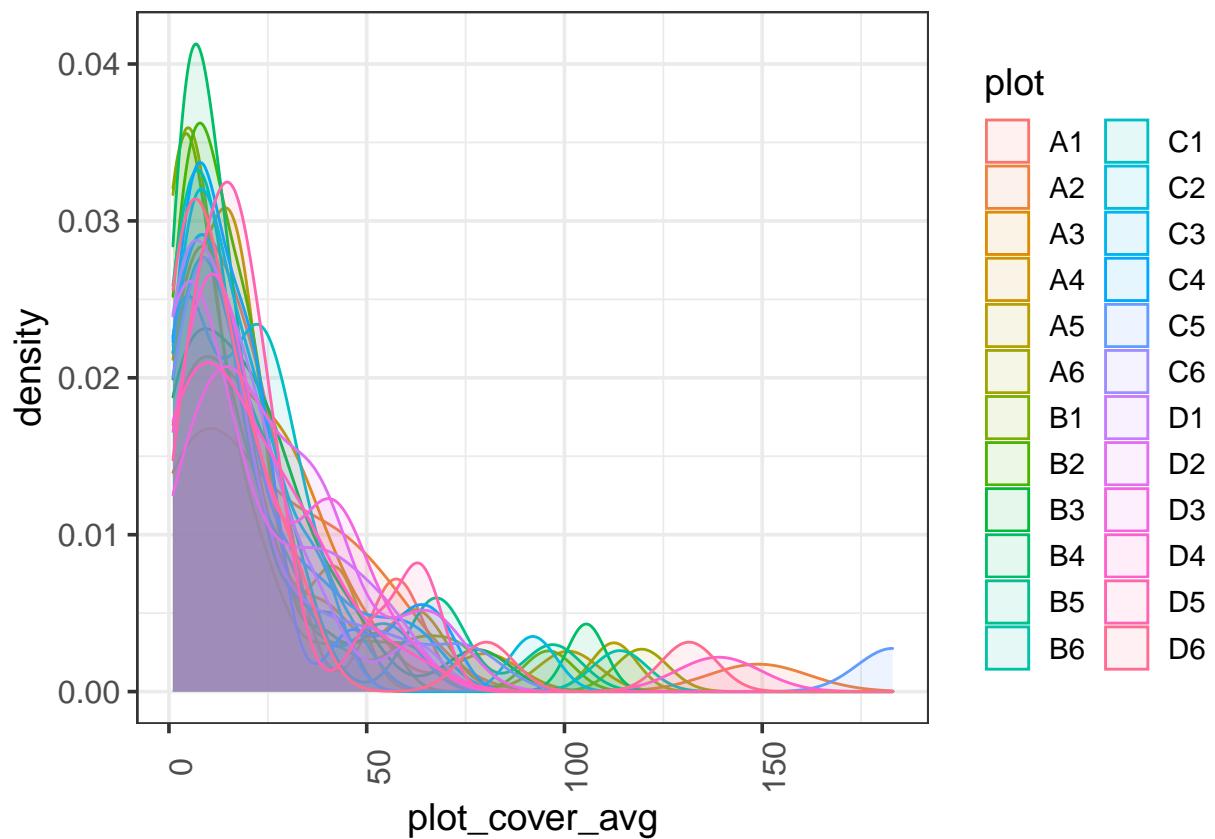
```

ggplot(umbs_comp_plot_origin, aes(plot_cover_avg, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
  facet_grid(state ~ year_factor, margins = TRUE, scales = "free")

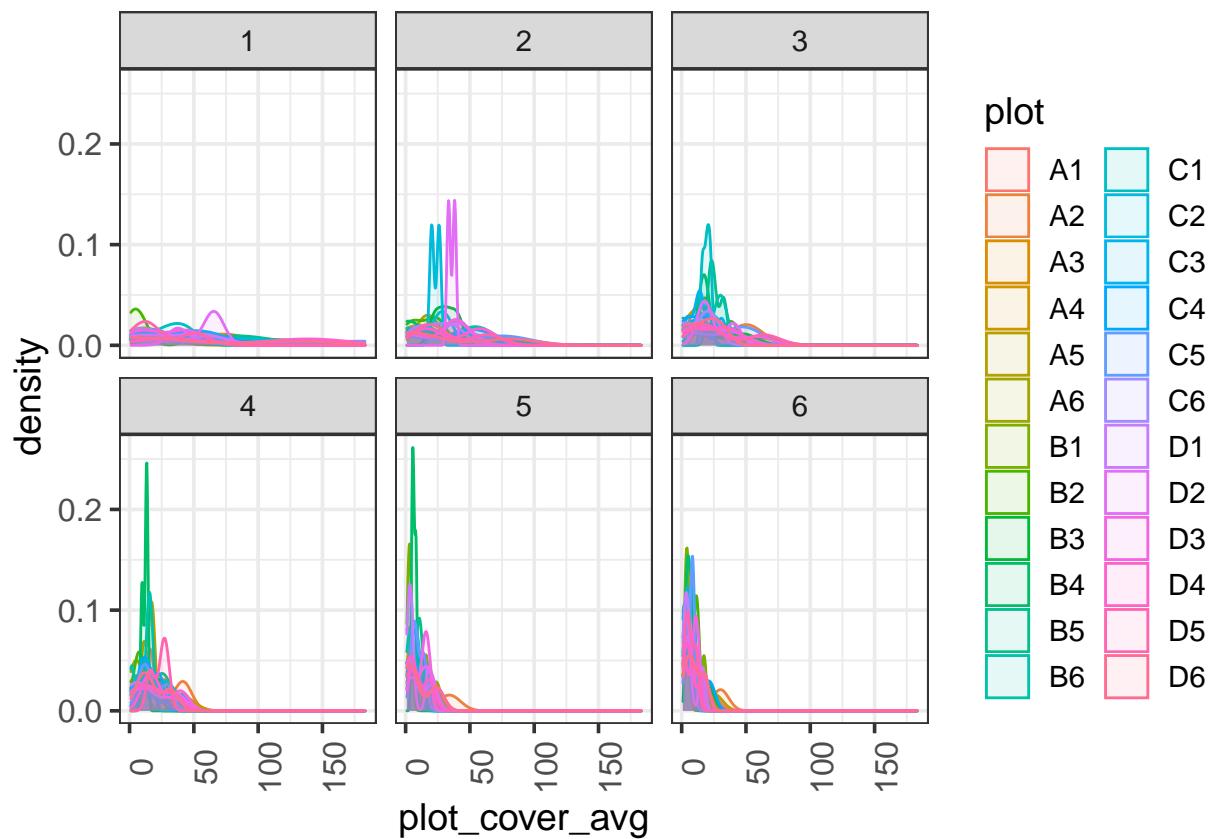
```



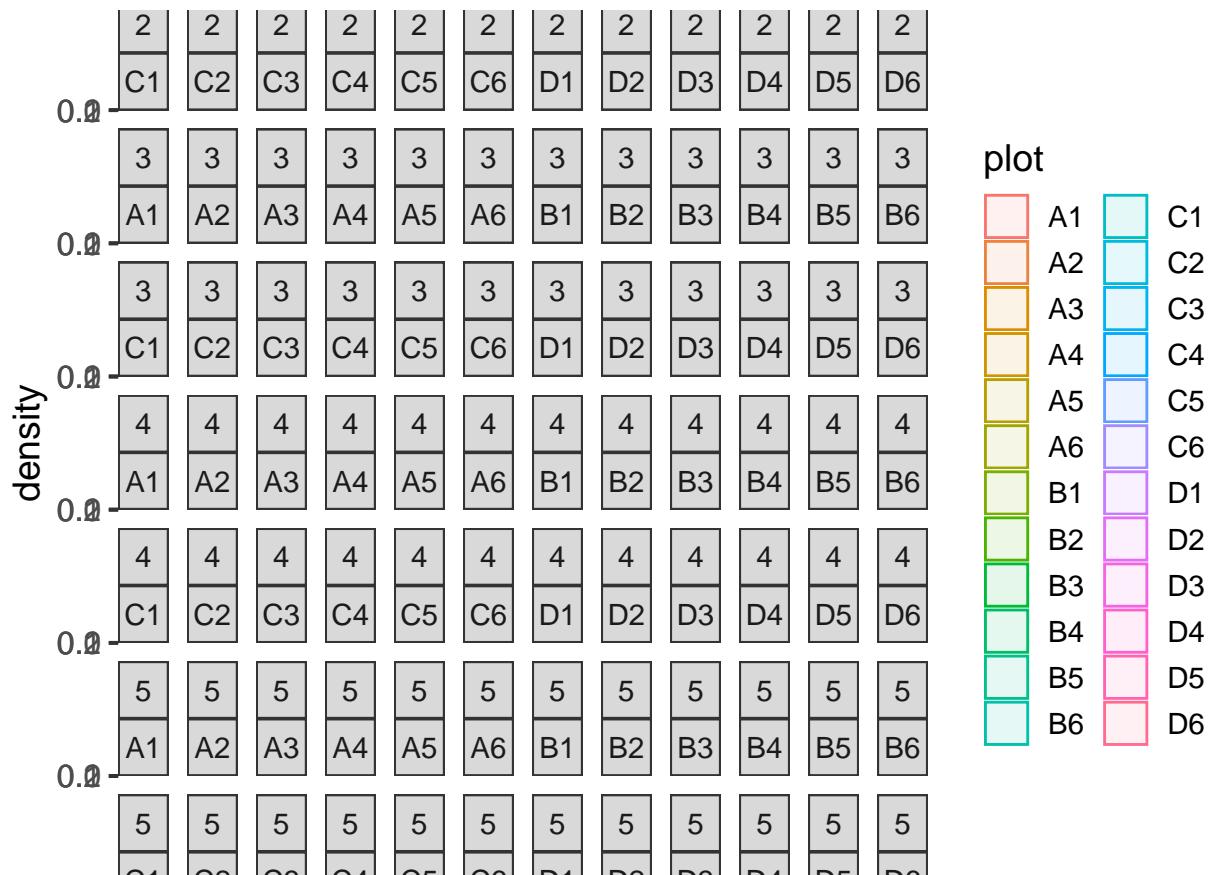
```
ggplot(umbs_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.5)
```



```
ggplot(umbs_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.5)
  facet_wrap(~year_factor)
```

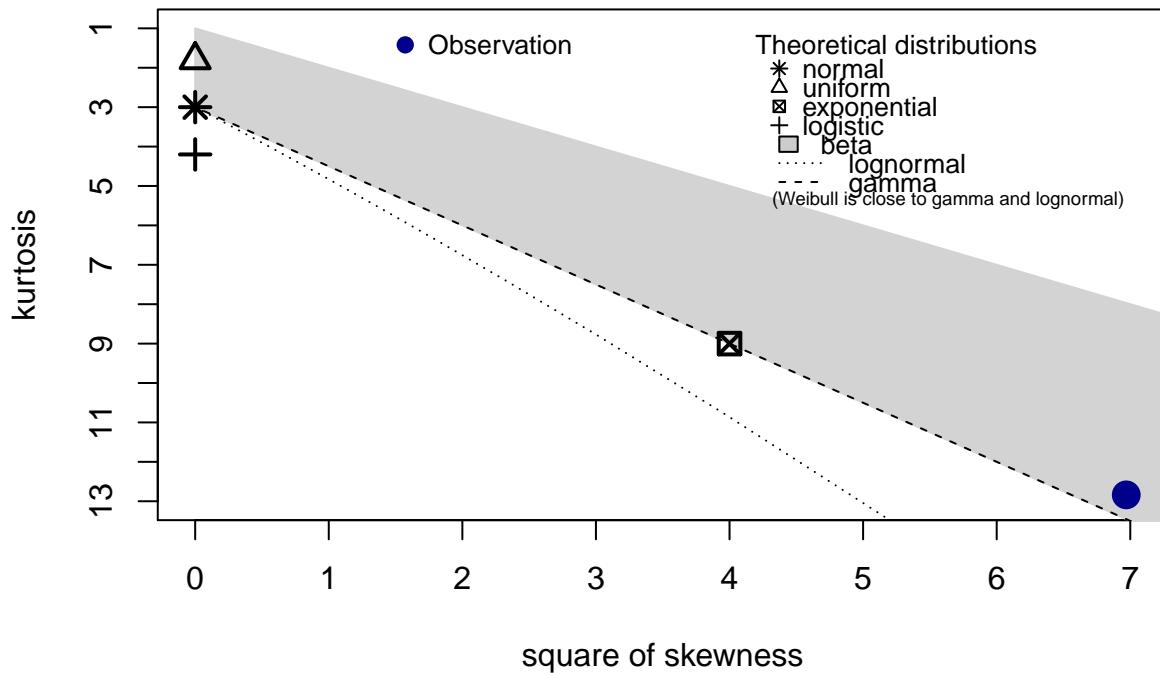


```
ggplot(umbs_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.5)
  facet_wrap(~year_factor + plot)
```



```
# Exploring distributions for these data:  
descdist(umbs_comp_plot_origin$plot_cover_avg, discrete = FALSE)
```

Cullen and Frey graph

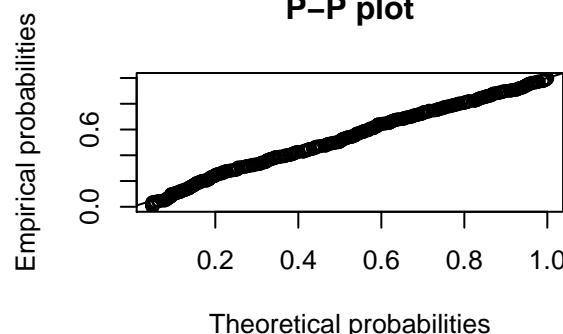
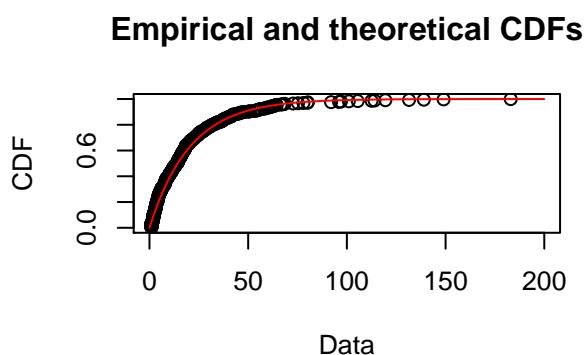
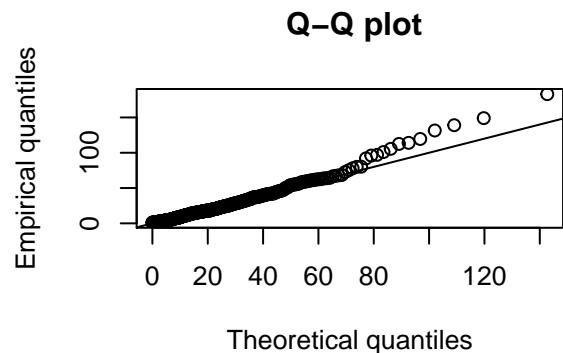
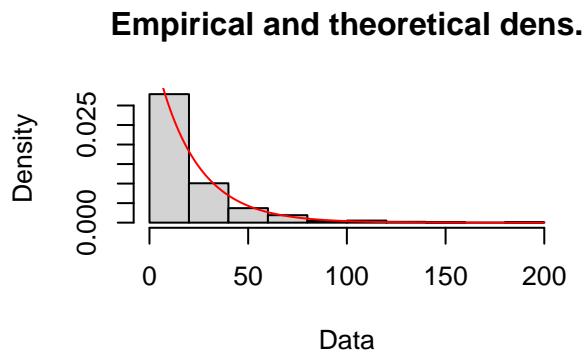


```

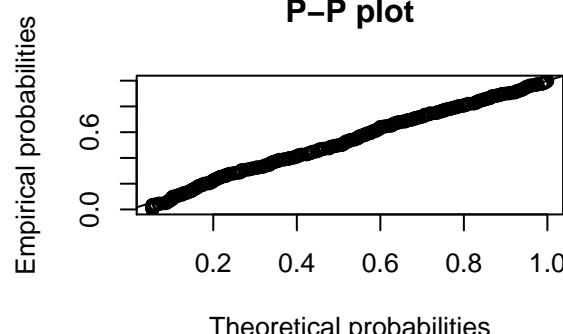
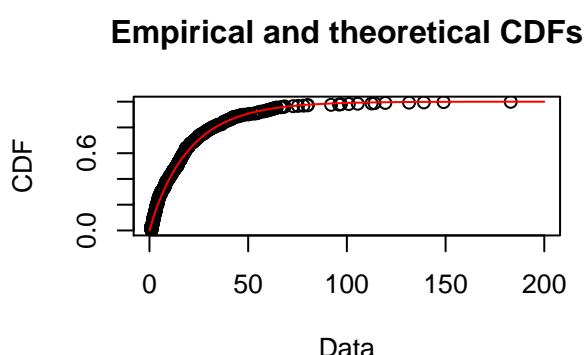
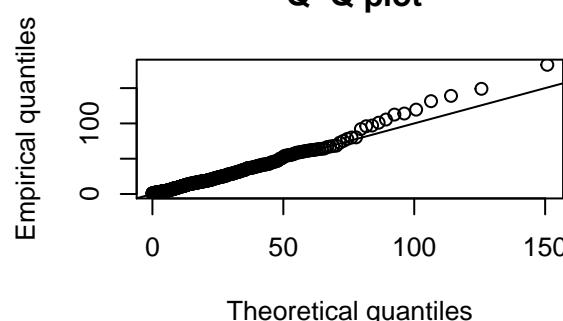
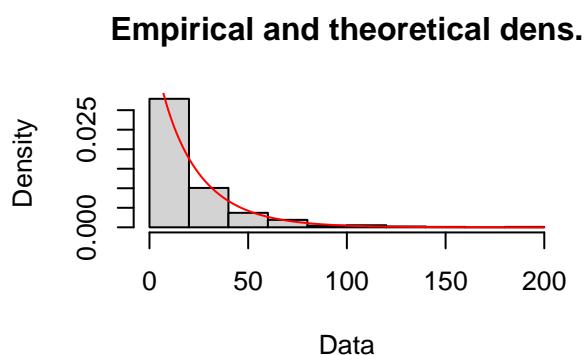
## summary statistics
## -----
## min: 1   max: 183
## median: 14
## mean: 20.69013
## estimated sd: 23.71993
## estimated skewness: 2.640043
## estimated kurtosis: 12.83848

# Gamma distribution
fit.gamma <- fitdist(umbs_comp_plot_origin$plot_cover_avg, "gamma")
plot(fit.gamma)

```

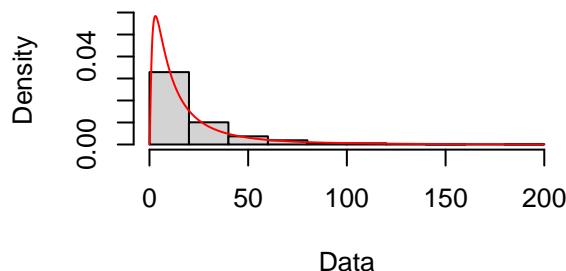


```
# Weibull distribution
fit.weibull <- fitdist(umbc_comp_plot_origin$plot_cover_avg, "weibull")
plot(fit.weibull)
```

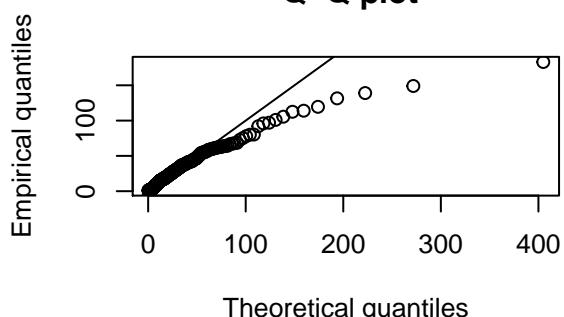


```
# Lognormal distribution
fit.ln <- fitdist(umbs_comp_plot_origin$plot_cover_avg, "lnorm")
plot(fit.ln)
```

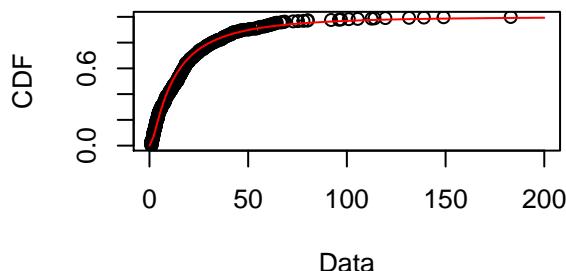
Empirical and theoretical dens.



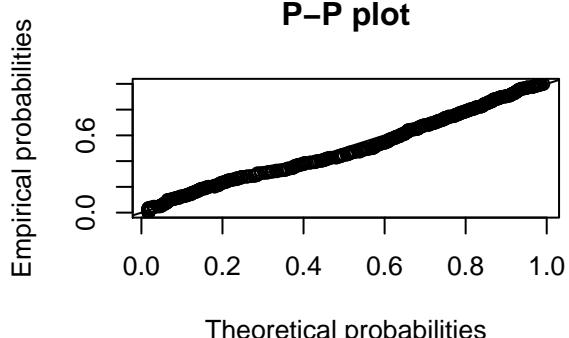
Q–Q plot



Empirical and theoretical CDFs

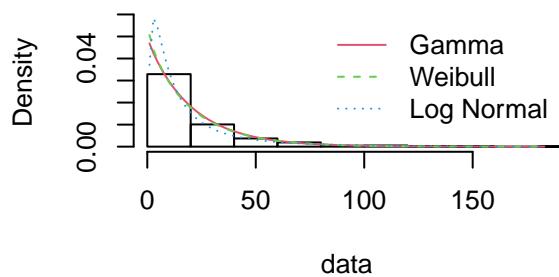


P–P plot

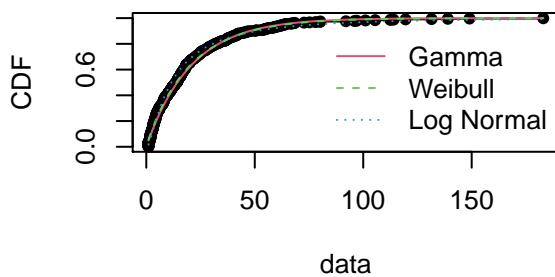


```
par(mfrow = c(2, 2))
plot.legend <- c("Gamma", "Weibull", "Log Normal")
denscomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
cdfcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
qqcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
ppcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
```

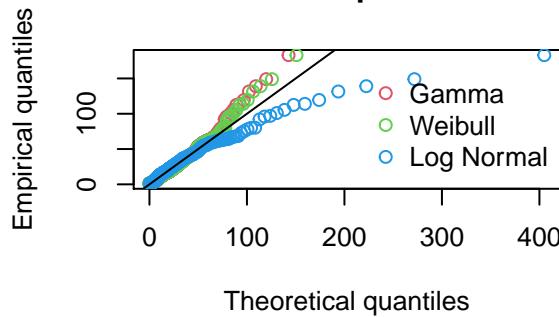
Histogram and theoretical densities



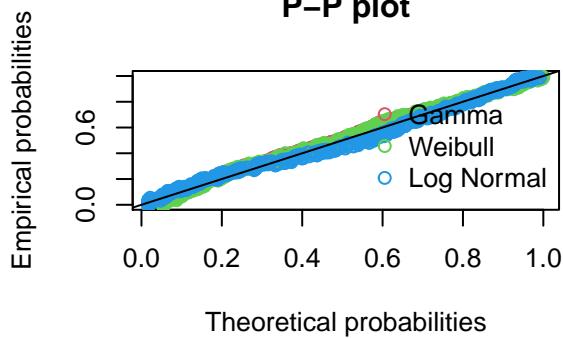
Empirical and theoretical CDFs



Q-Q plot



P-P plot



```
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln), fitnames = c("Gamma", "Weibull", "Log Normal"))
```

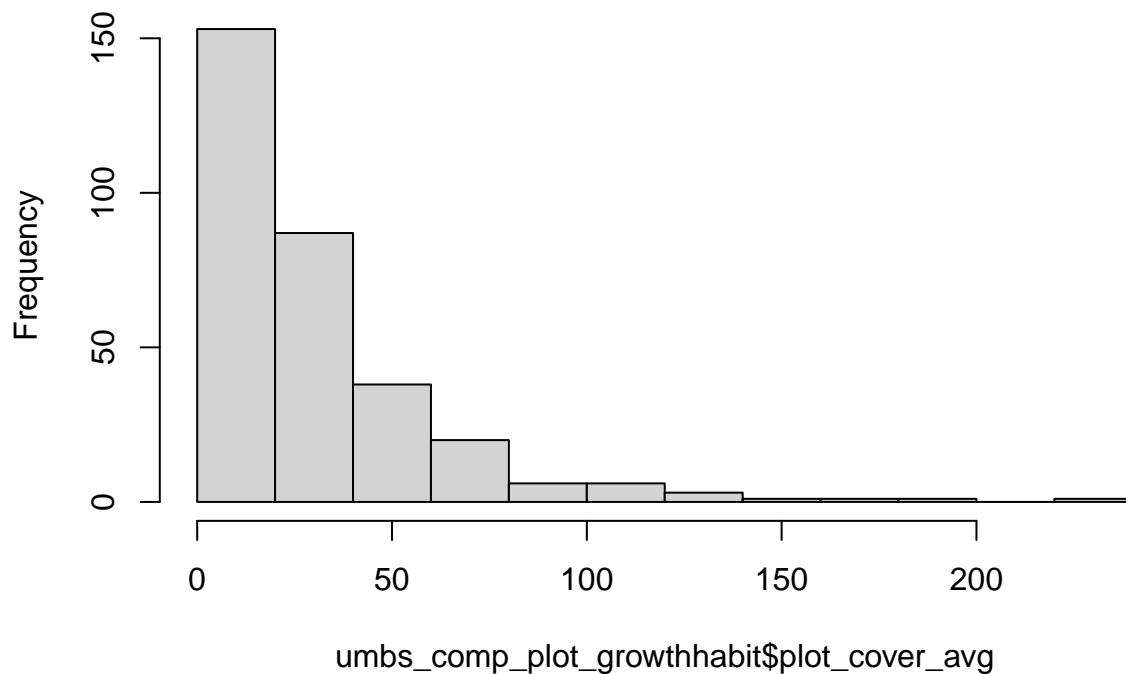
```
## Goodness-of-fit statistics
##                                     Gamma    Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.05144002 0.05435059 0.06972493
## Cramer-von Mises statistic   0.31034696 0.18376774 0.42240938
## Anderson-Darling statistic   2.26233406 1.74799931 2.44661427
##
## Goodness-of-fit criteria
##                                     Gamma    Weibull Log Normal
## Akaike's Information Criterion 3799.896 3798.425 3782.243
## Bayesian Information Criterion 3808.206 3806.735 3790.553
```

```
# log normal looks like it's the best fit
```

UMBS PLOT LEVEL GROWTH HABIT - Looking at PLOT AVG TOTALS

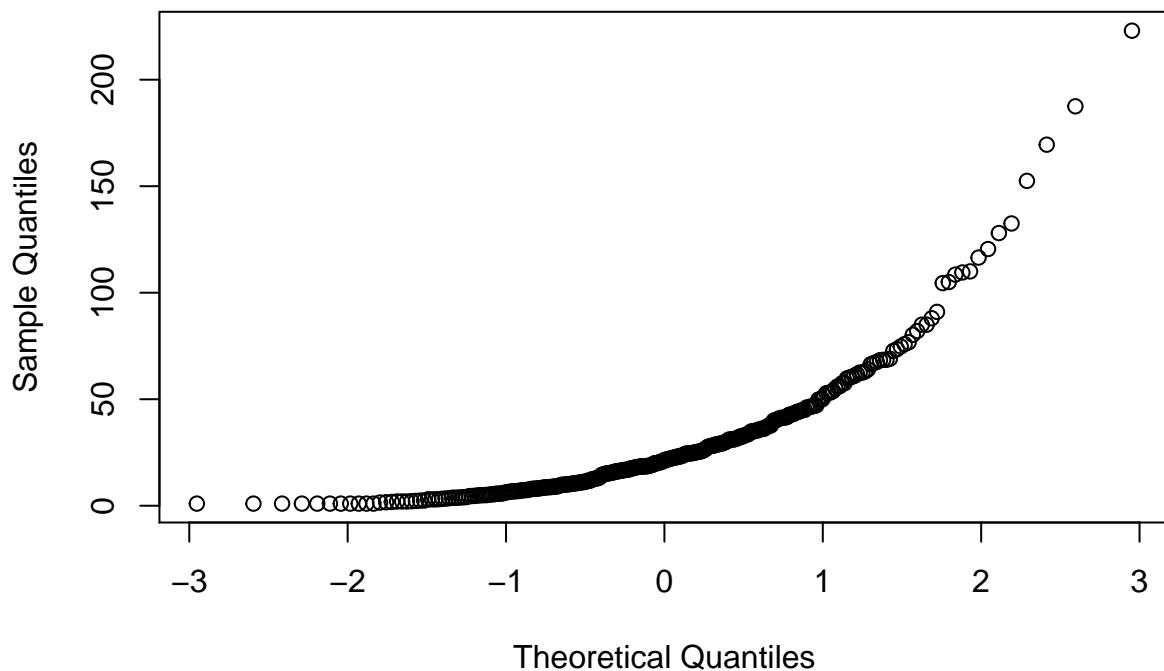
```
### UMBS ####
hist(umbs_comp_plot_growthhabit$plot_cover_avg)
```

Histogram of umbs_comp_plot_growthhabit\$plot_cover_avg



```
qqnorm(umbc_comp_plot_growthhabit$plot_cover_avg)
```

Normal Q-Q Plot



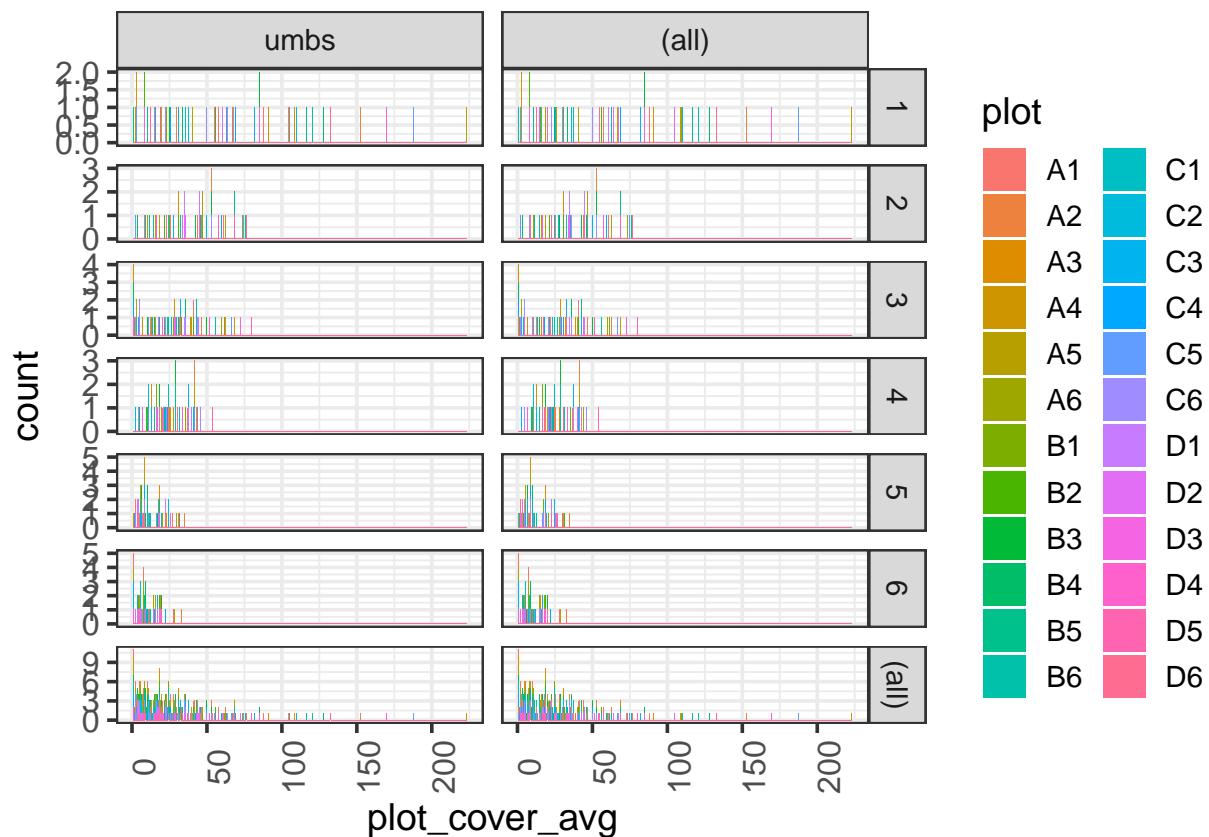
```

shapiro.test(umbs_comp_plot_growthhabit$plot_cover_avg) # pvalue is < 0.05 so we reject the null hypothesis

## 
## Shapiro-Wilk normality test
## 
## data: umbs_comp_plot_growthhabit$plot_cover_avg
## W = 0.76384, p-value < 2.2e-16

# Visualizing plot average totals for umbs at the PLOT LEVEL
ggplot(umbs_comp_plot_growthhabit, aes(plot_cover_avg, fill = plot)) + geom_histogram(binwidth = 0.5) +
  facet_grid(year_factor ~ site, margins = TRUE, scales = "free")

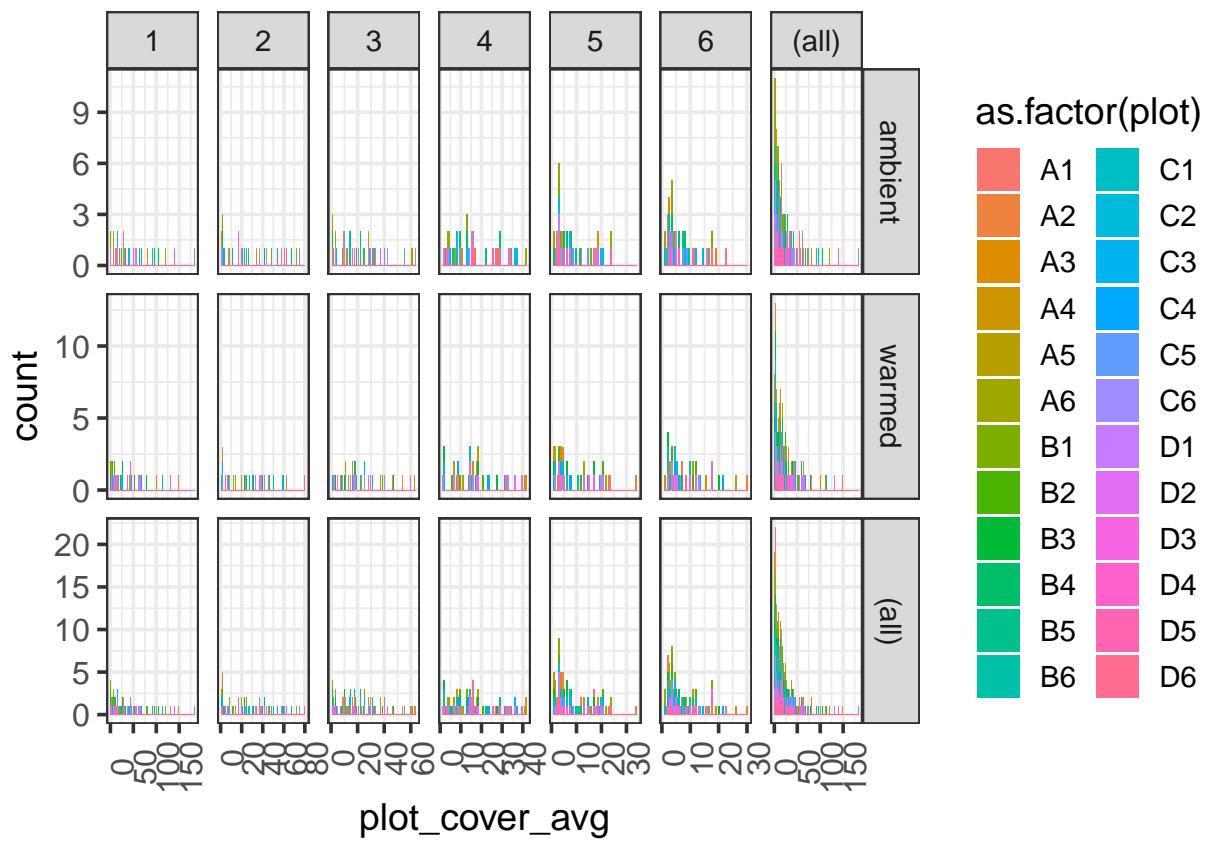
```



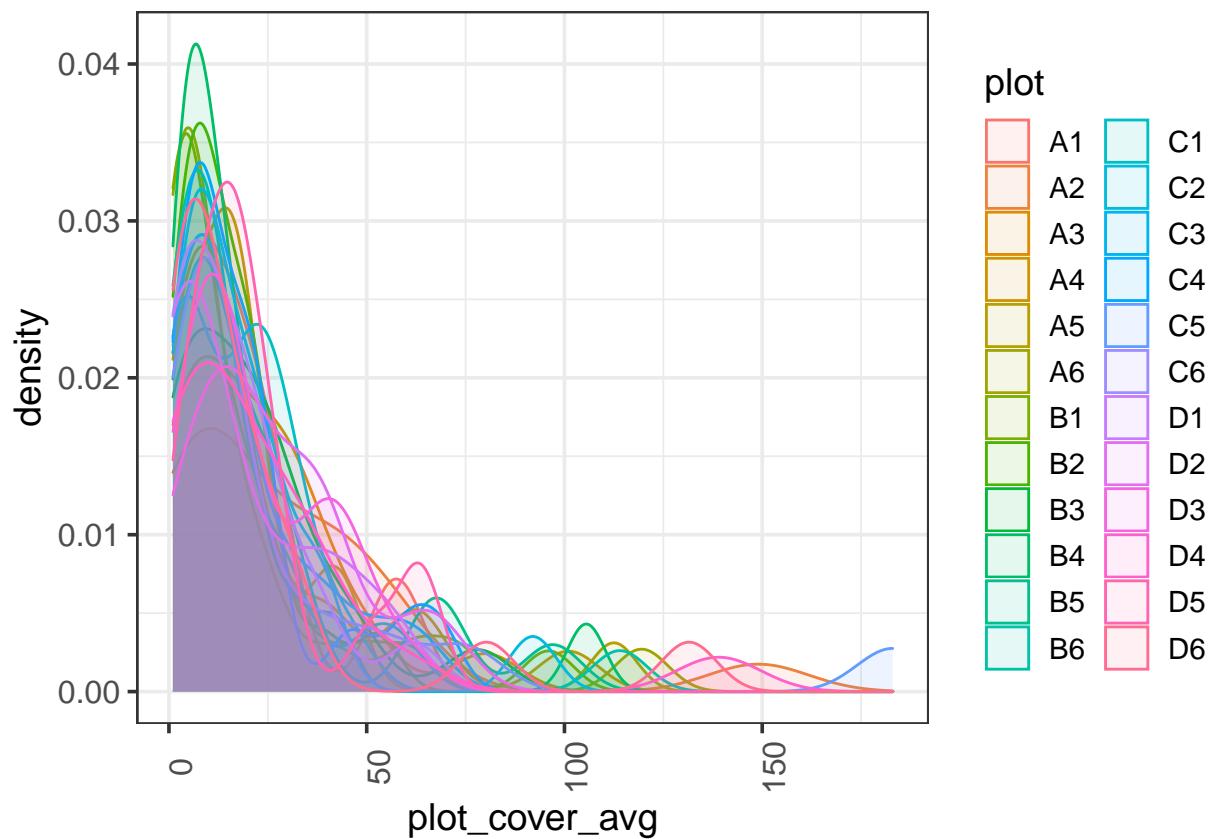
```

ggplot(umbs_comp_plot_origin, aes(plot_cover_avg, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
  facet_grid(state ~ year_factor, margins = TRUE, scales = "free")

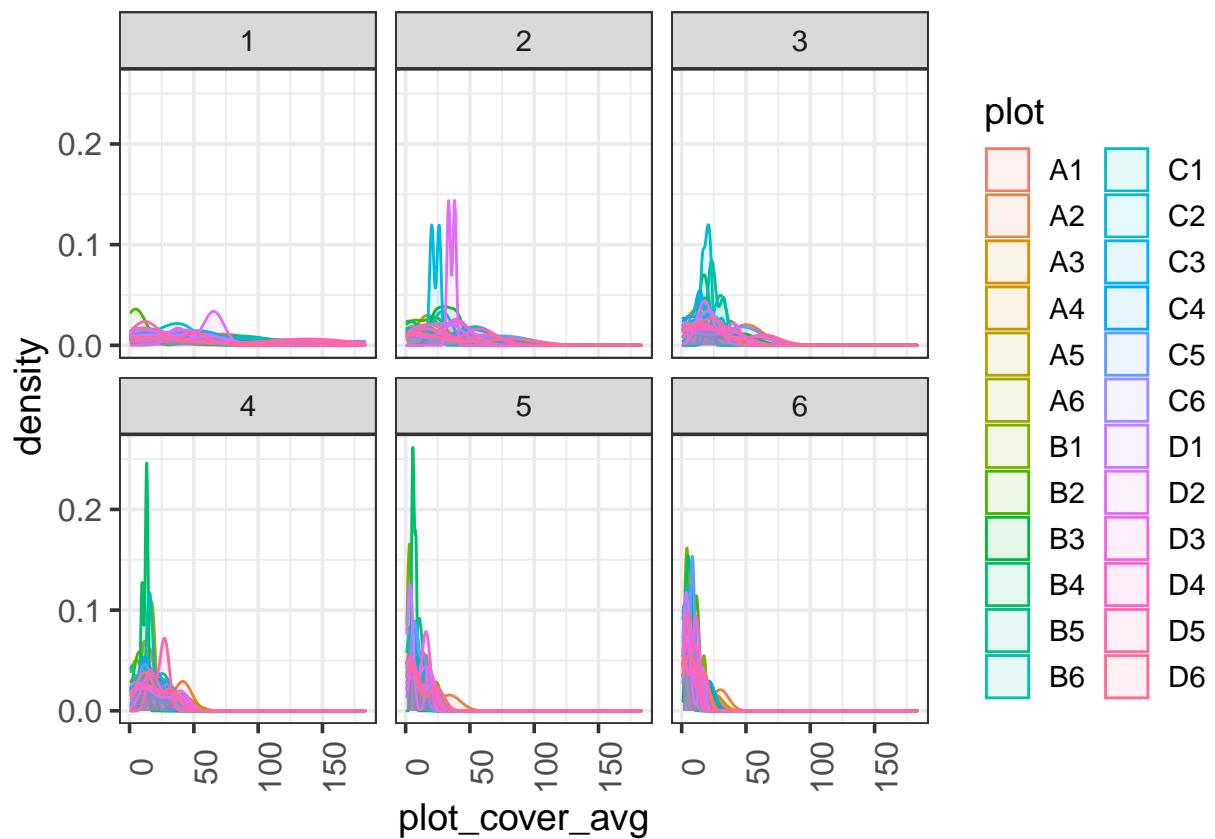
```



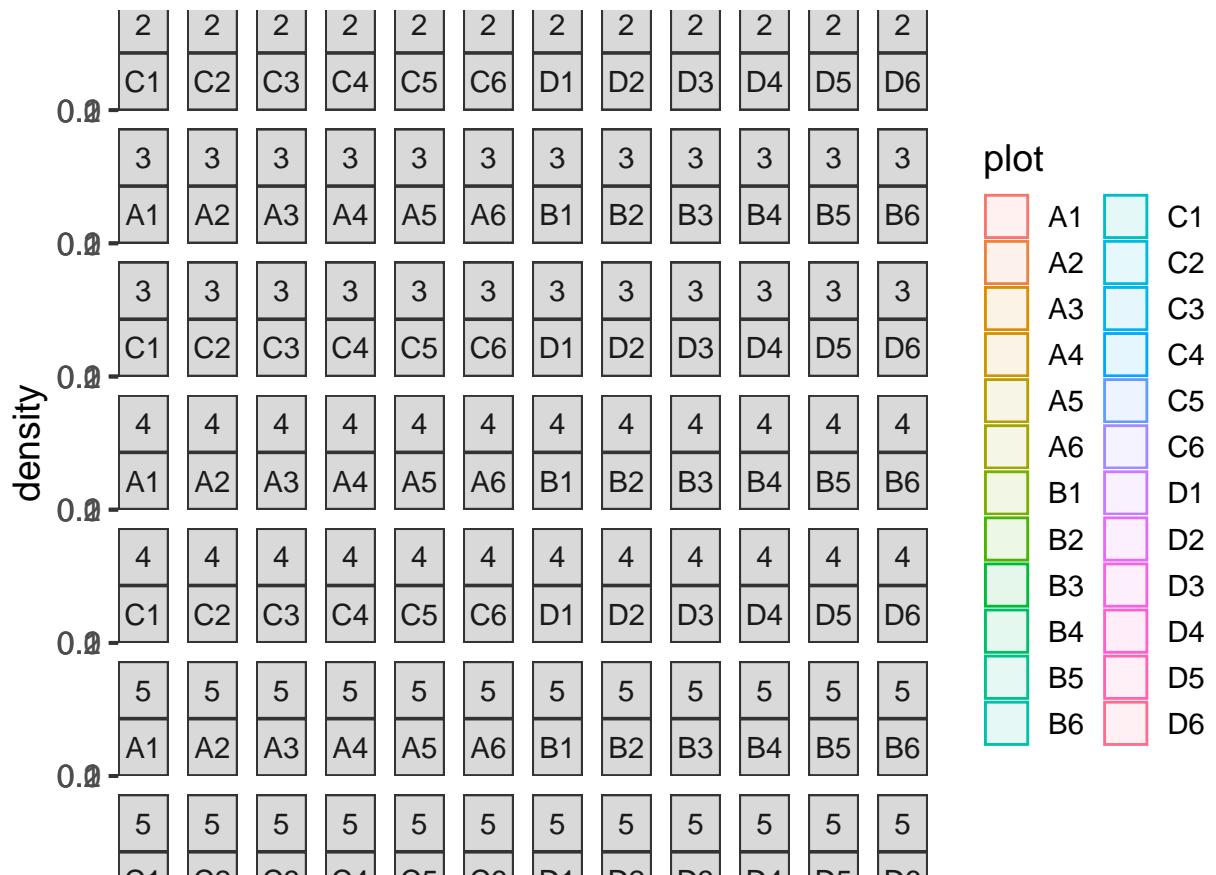
```
ggplot(umbc_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.5)
```



```
ggplot(umbs_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.5)
  facet_wrap(~year_factor)
```

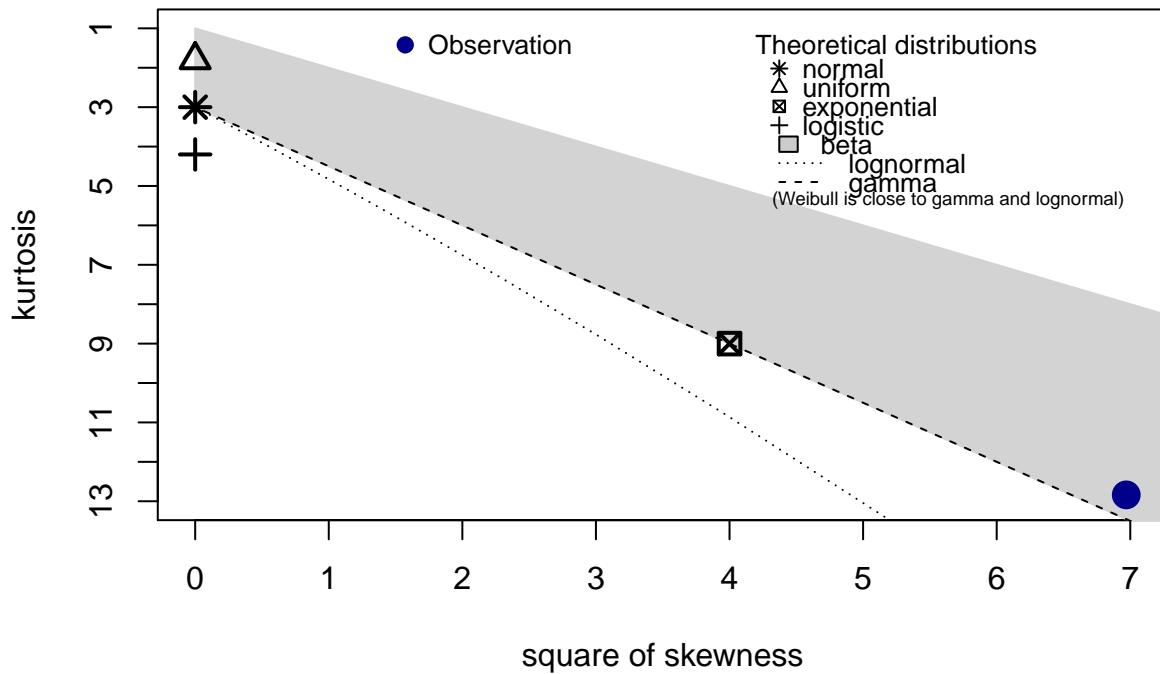


```
ggplot(umbs_comp_plot_origin, aes(plot_cover_avg, fill = plot, color = plot)) + geom_density(alpha = 0.5)
  facet_wrap(~year_factor + plot)
```



```
# Exploring distributions for these data:  
descdist(umbs_comp_plot_origin$plot_cover_avg, discrete = FALSE)
```

Cullen and Frey graph

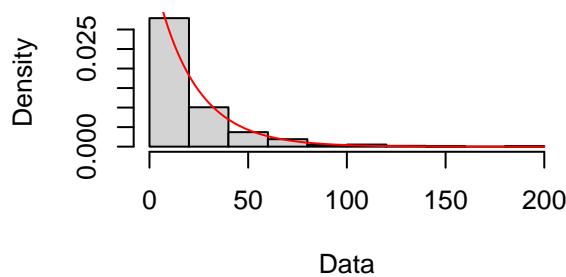
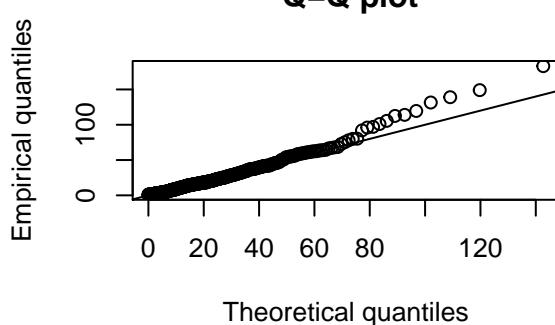
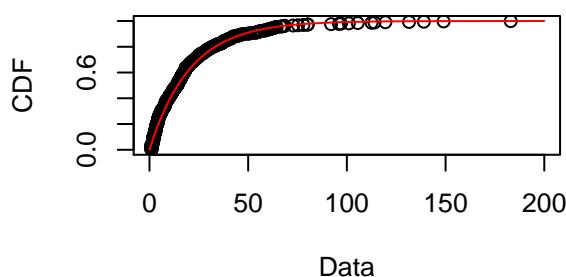
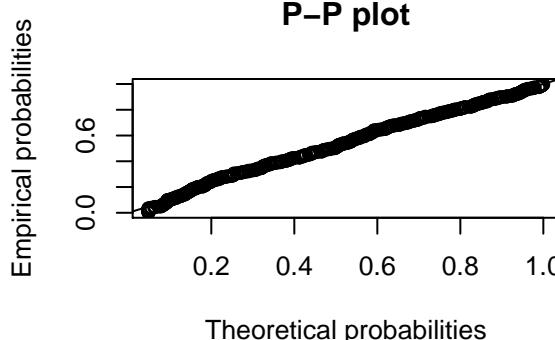


```

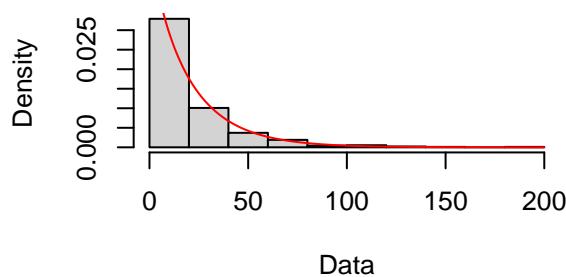
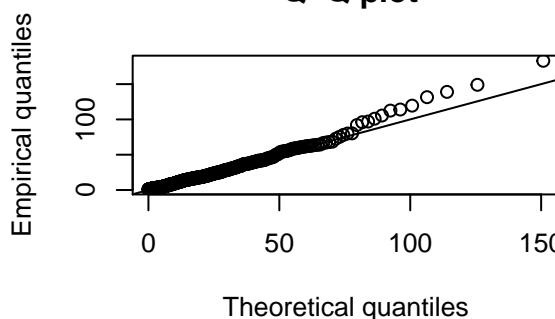
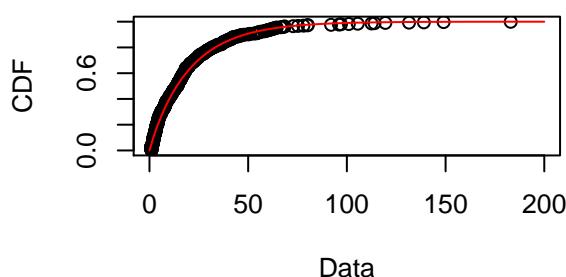
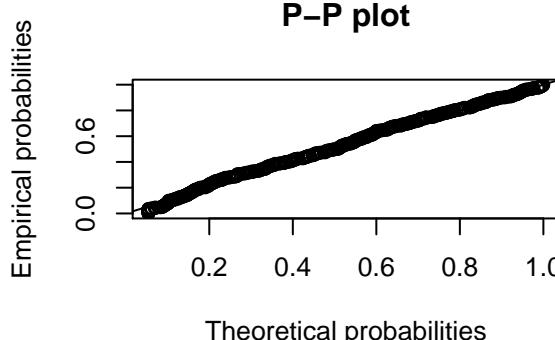
## summary statistics
## -----
## min: 1   max: 183
## median: 14
## mean: 20.69013
## estimated sd: 23.71993
## estimated skewness: 2.640043
## estimated kurtosis: 12.83848

# Gamma distribution
fit.gamma <- fitdist(umbs_comp_plot_origin$plot_cover_avg, "gamma")
plot(fit.gamma)

```

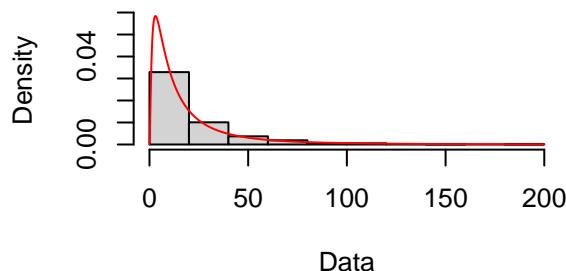
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

```
# Weibull distribution
fit.weibull <- fitdist(umbc_comp_plot_origin$plot_cover_avg, "weibull")
plot(fit.weibull)
```

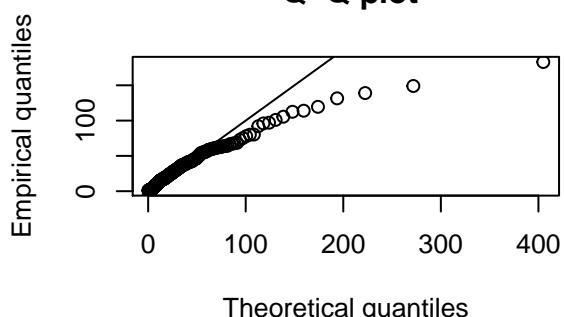
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

```
# Lognormal distribution
fit.ln <- fitdist(umbs_comp_plot_origin$plot_cover_avg, "lnorm")
plot(fit.ln)
```

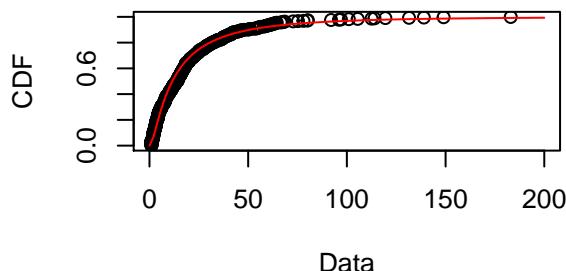
Empirical and theoretical dens.



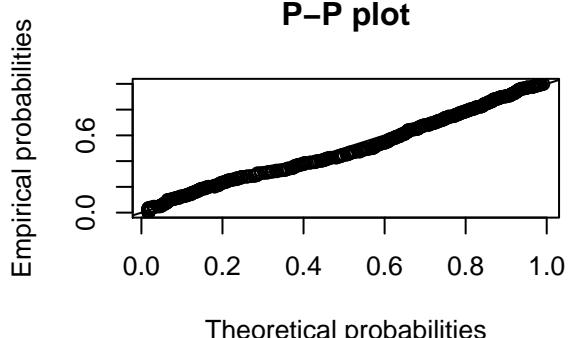
Q–Q plot



Empirical and theoretical CDFs

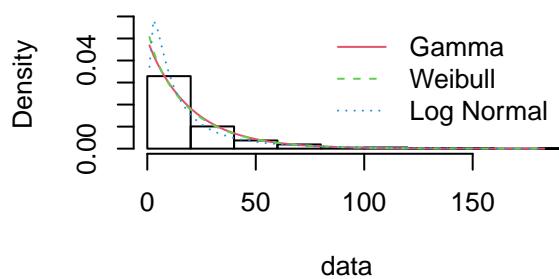


P–P plot

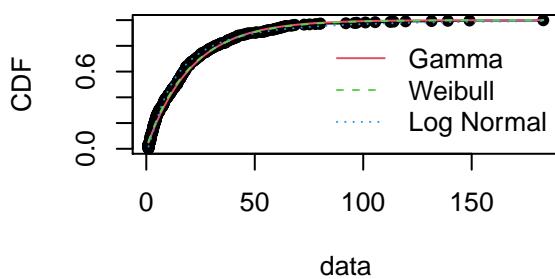


```
par(mfrow = c(2, 2))
plot.legend <- c("Gamma", "Weibull", "Log Normal")
denscomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
cdfcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
qqcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
ppcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
```

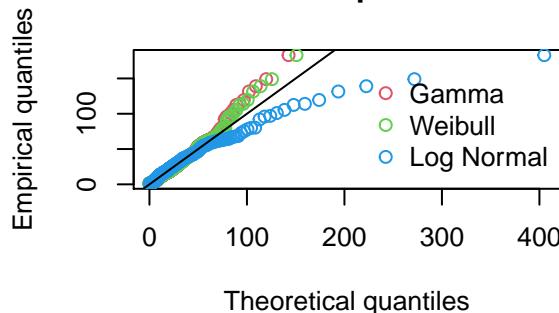
Histogram and theoretical densities



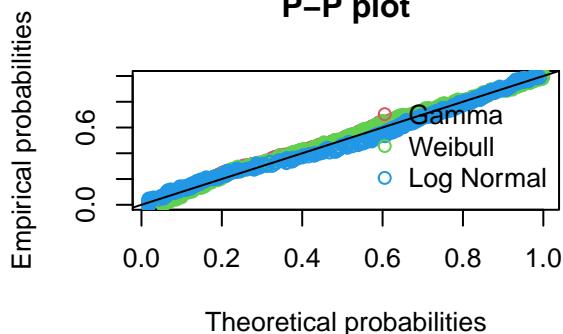
Empirical and theoretical CDFs



Q-Q plot



P-P plot



```
# Goodness of fit comparisons across fits (can't include the sqrt normal bc it
# becomes diff response values)
gofstat(list(fit.gamma, fit.weibull, fit.ln), fitnames = c("Gamma", "Weibull", "Log Normal"))
```

```
## Goodness-of-fit statistics
##                                     Gamma   Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.05144002 0.05435059 0.06972493
## Cramer-von Mises statistic  0.31034696 0.18376774 0.42240938
## Anderson-Darling statistic  2.26233406 1.74799931 2.44661427
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 3799.896 3798.425 3782.243
## Bayesian Information Criterion 3808.206 3806.735 3790.553

# log normal looks like it's the best fit
```

Leverage plots and detecting Outliers. <https://www.statmethods.net/stats/rdiagnostics.html>

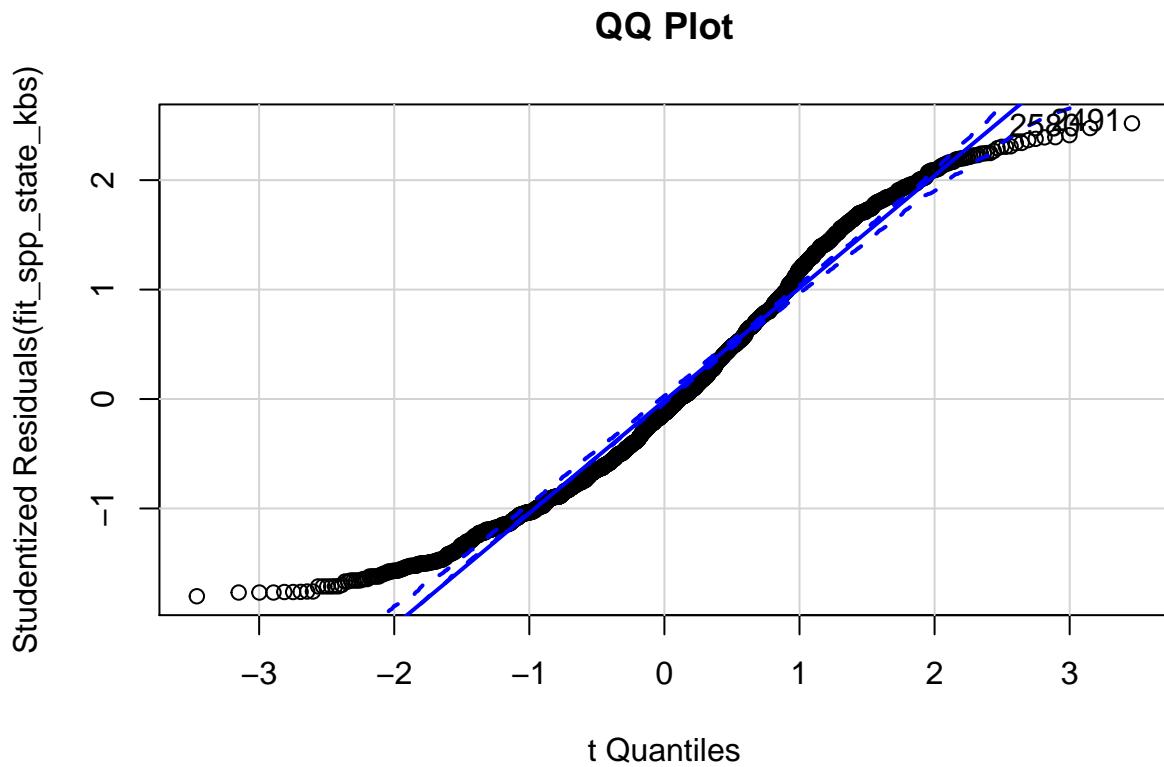
These illustrate whether certain data points have more leverage (more influence), and thus could be outliers. It's a way of detecting outliers. Leverage plots can help identify whether a point has high or low influence, based on its leverage and residual and determining model fit with and without the point in question. Ultimately you decide whether the points are outliers or not, based on the knowledge of the system and how much it changes the model when included vs. excluded from the data used to fit the model. Here is a good overview of the combination of leverage and residual: scroll down to sections beginning at “13.3 Unusual Observations”: <https://daviddalpiaz.github.io/appliedstats/model-diagnostics.html>

KBS

```
# species level data KBS State-only model
fit_spp_state_kbs <- lm(log(relabun) ~ state, data = comp_kbs_spp)
outlierTest(fit_spp_state_kbs)

## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 2491  2.518923          0.011857         NA

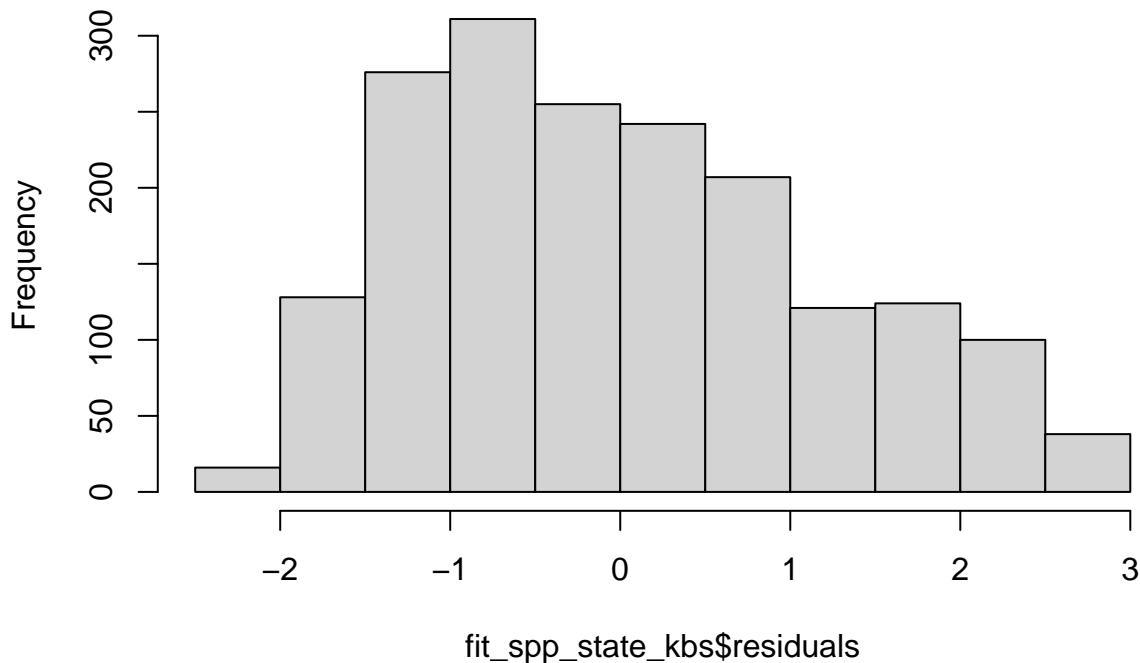
qqPlot(fit_spp_state_kbs, main = "QQ Plot")
```



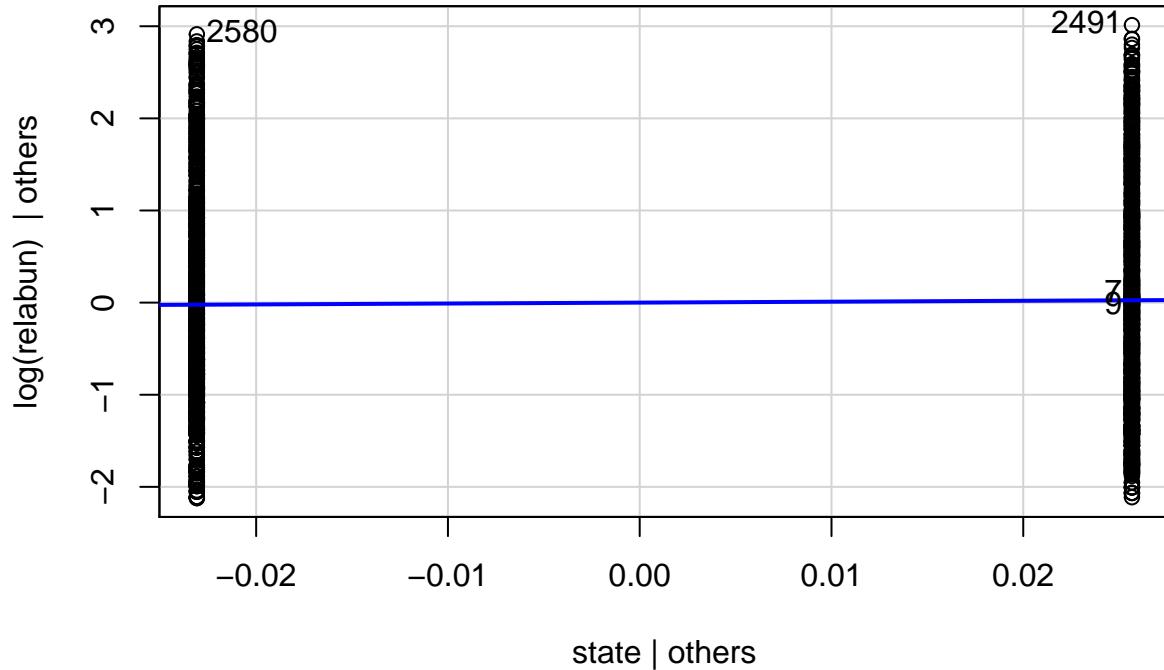
```
## 2491 2580
## 1491 1580
```

```
hist(fit_spp_state_kbs$residuals)
```

Histogram of fit_spp_state_kbs\$residuals



```
leveragePlots(fit_spp_state_kbs)
```



```
ols_test_normality(fit_spp_state_kbs)
```

```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

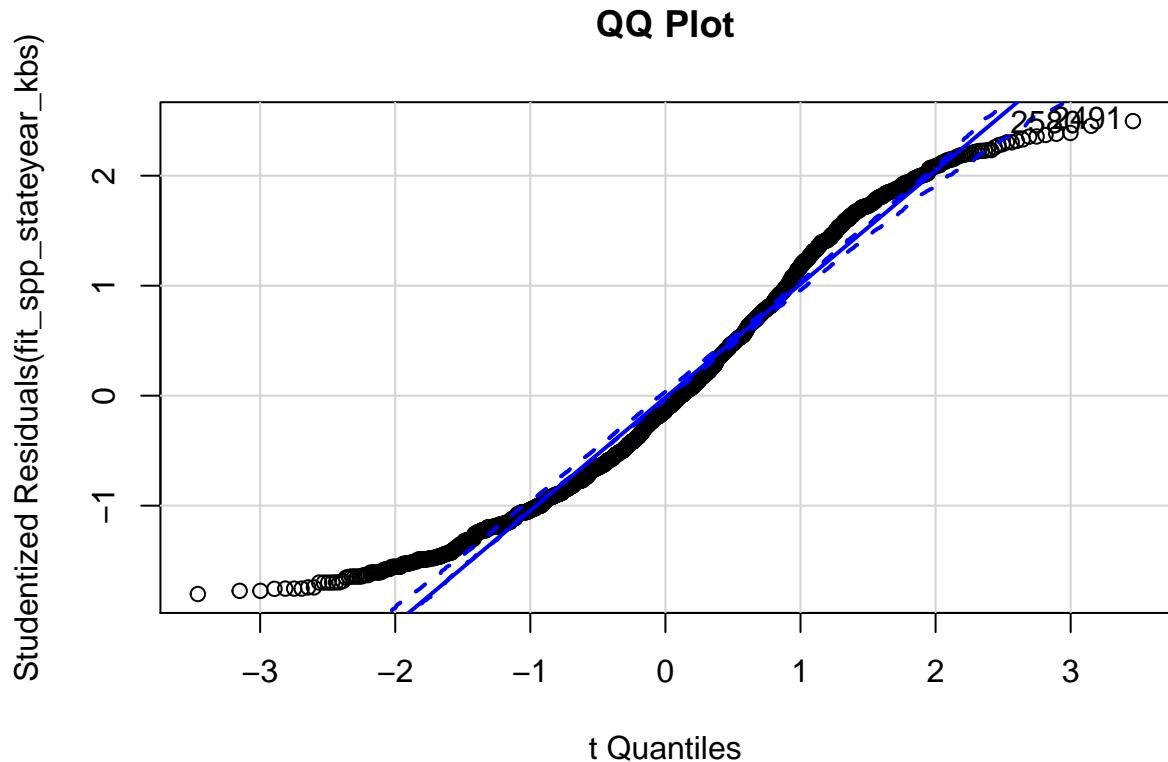
```
## -----
##          Test      Statistic     pvalue
## -----
## Shapiro-Wilk      0.9664     0.0000
## Kolmogorov-Smirnov 0.0678     0.0000
## Cramer-von Mises   144.9267    0.0000
## Anderson-Darling    16.7536    0.0000
## -----
```

```
# comp_kbs_spp_no_outliers <- comp_kbs_spp[-449,] # remove outliers
# fit_spp_state_kbs1 <- lm(log(relabun) ~ state, data = comp_kbs_spp_no_outliers)
# outlierTest(fit_spp_state_kbs1) # outliers - row 449 qqPlot(fit_spp_state_kbs1,
# main='QQ Plot') hist(fit_spp_state_kbs1$residuals)
# leveragePlots(fit_spp_state_kbs1) ols_test_normality(fit_spp_state_kbs1)

# KBS State and year model
fit_spp_stateyear_kbs <- lm(log(relabun) ~ state + year_factor, data = comp_kbs_spp)
outlierTest(fit_spp_stateyear_kbs) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##           rstudent unadjusted p-value Bonferroni p
## 2491 2.496313             0.012637        NA
```

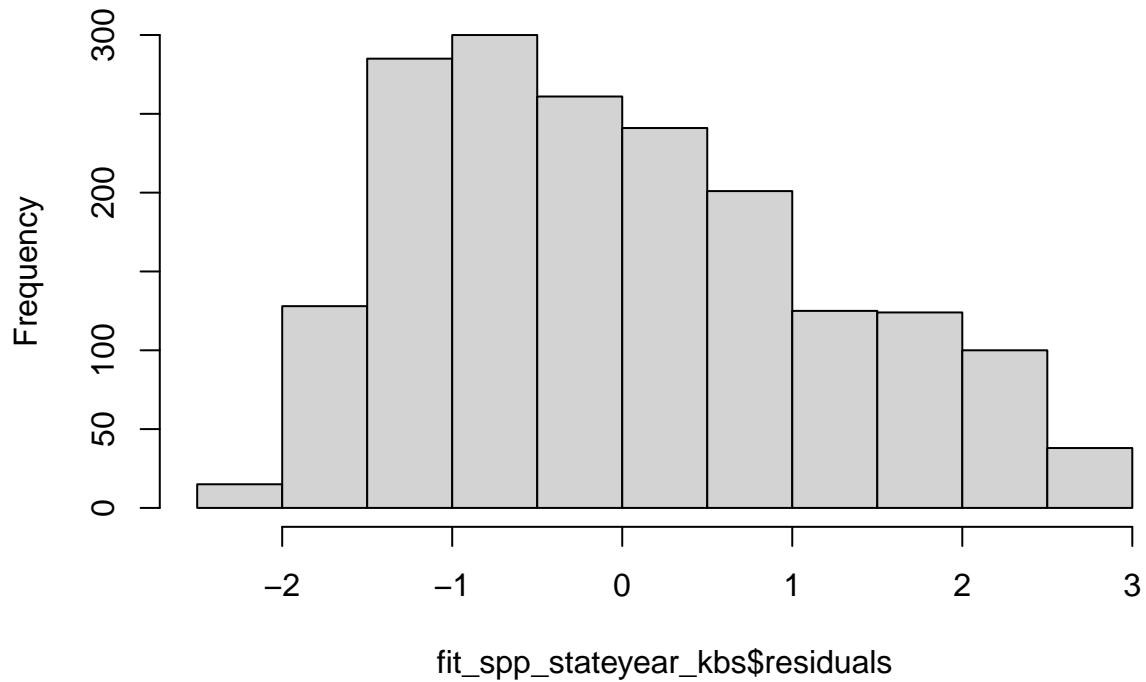
```
qqPlot(fit_spp_stateyear_kbs, main = "QQ Plot")
```



```
## 2491 2580  
## 1491 1580
```

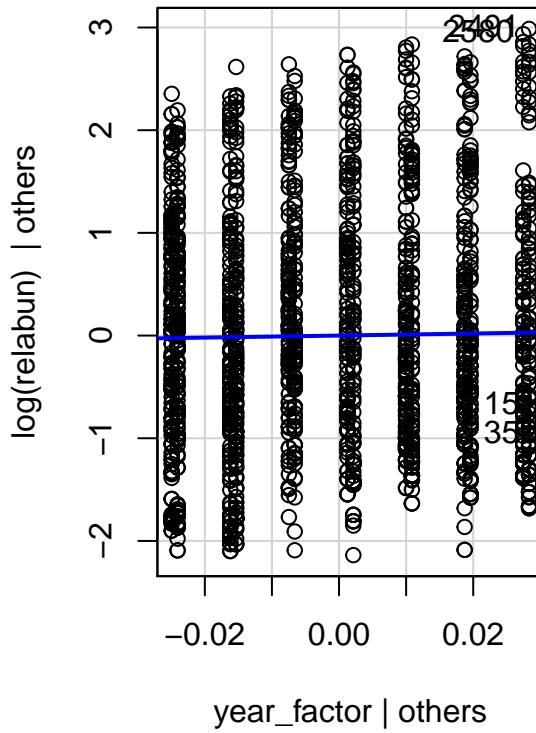
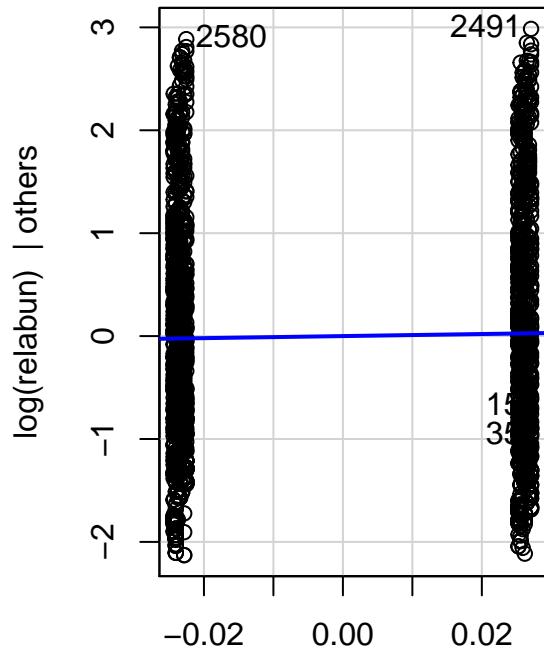
```
hist(fit_spp_stateyear_kbs$residuals)
```

Histogram of fit_spp_stateyear_kbs\$residuals



```
leveragePlots(fit_spp_stateyear_kbs)
```

Leverage Plots



```

ols_test_normality(fit_spp_stateyear_kbs)

## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test

## -----
##          Test       Statistic      pvalue
## -----
## Shapiro-Wilk      0.9656      0.0000
## Kolmogorov-Smirnov 0.0685      0.0000
## Cramer-von Mises   144.8202     0.0000
## Anderson-Darling    17.0611     0.0000
## -----

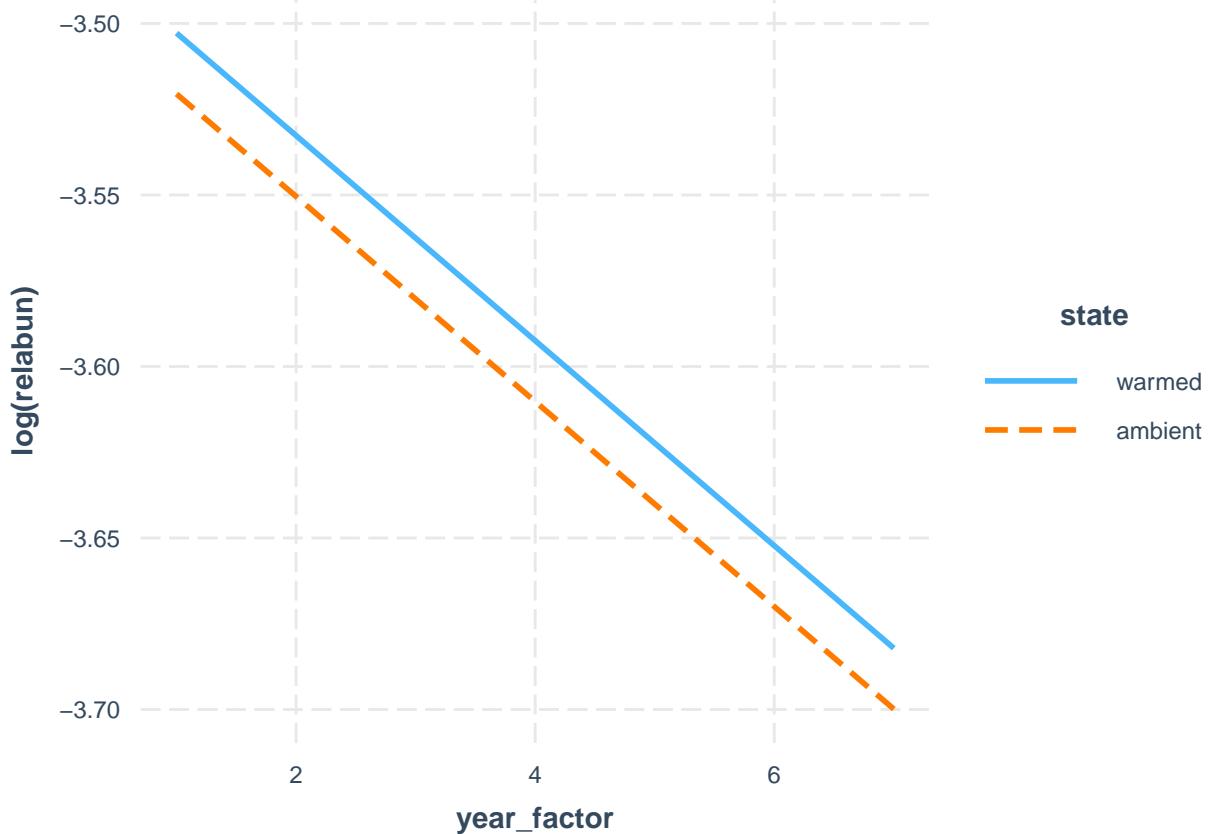

# Interaction plot (ignore for now the repeated measures with species); see:
# https://cran.r-project.org/web/packages/interactions/vignettes/interactions.html
# and: https://interactions.jacob-long.com/

fit3 <- lm(log(relabun) ~ state + year_factor + species, data = comp_kbs_spp)
interact_plot(fit3, pred = year_factor, modx = state)

## Using data comp_kbs_spp from global environment. This could cause incorrect
## results if comp_kbs_spp has been altered since the model was fit. You can
## manually provide the data to the "data =" argument.

## Warning: year_factor and state are not included in an interaction with one another
## in the model.

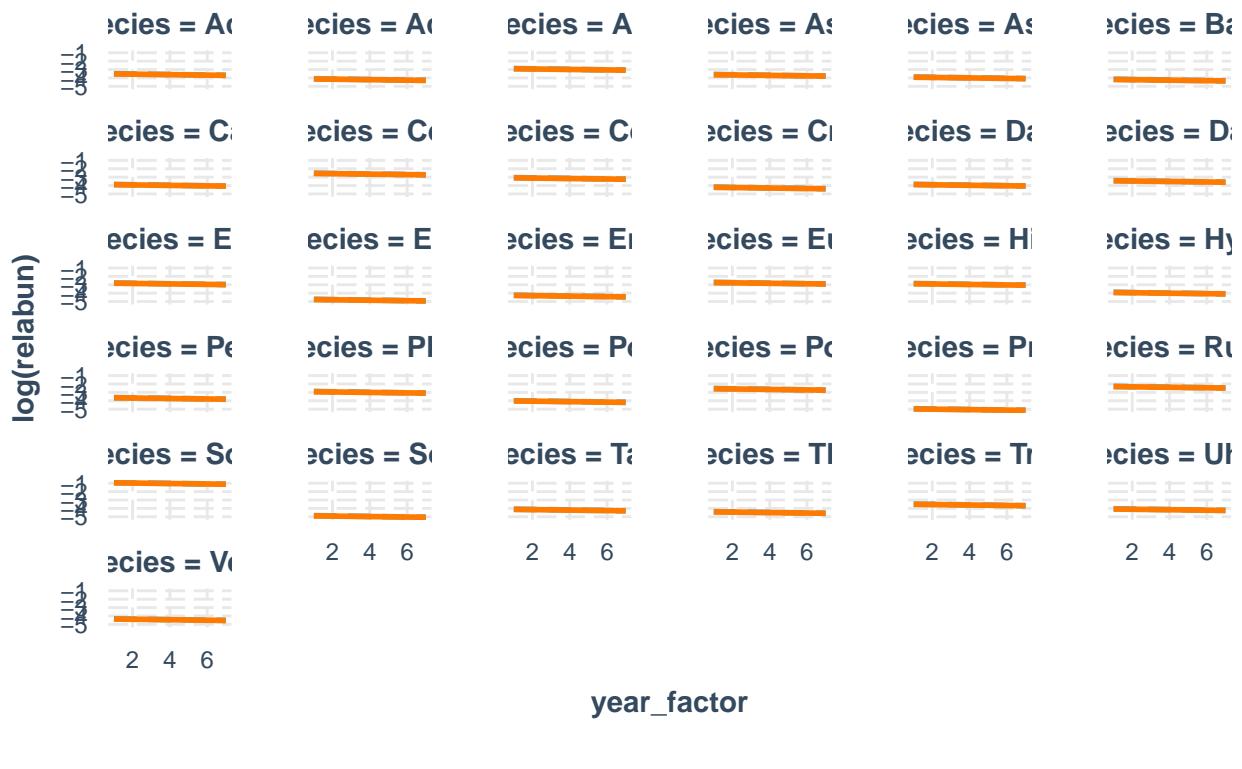
```



```
fit4 <- lm(log(relabun) ~ state * year_factor + species, data = comp_kbs_spp)
interact_plot(fit4, pred = year_factor, modx = state, mod2 = species)
```

Using data comp_kbs_spp from global environment. This could cause incorrect
results if comp_kbs_spp has been altered since the model was fit. You can
manually provide the data to the "data =" argument.

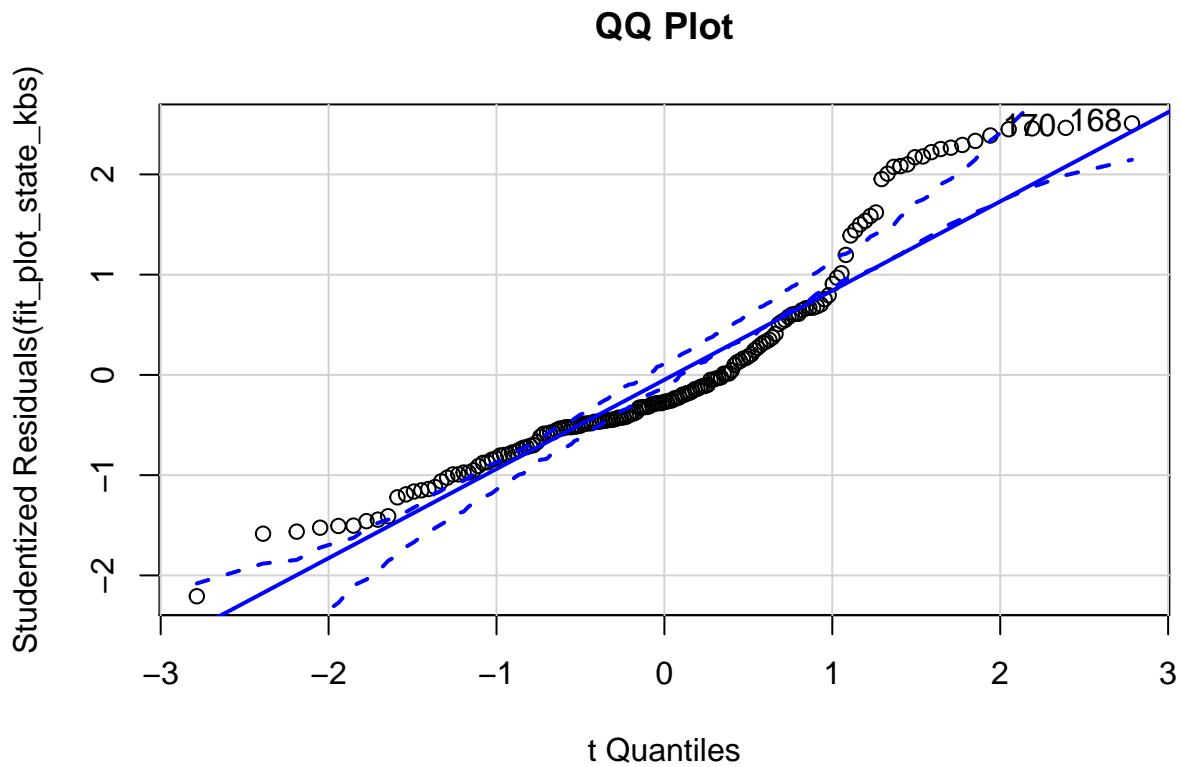
Warning: year_factor and state and species are not included in an interaction with
one another in the model.



```
# Plot level data KBS State-only model
fit_plot_state_kbs <- lm(log(plot_cover_avg) ~ state, data = comp_kbs_plot)
outlierTest(fit_plot_state_kbs) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 168 2.509288          0.013068        NA
```

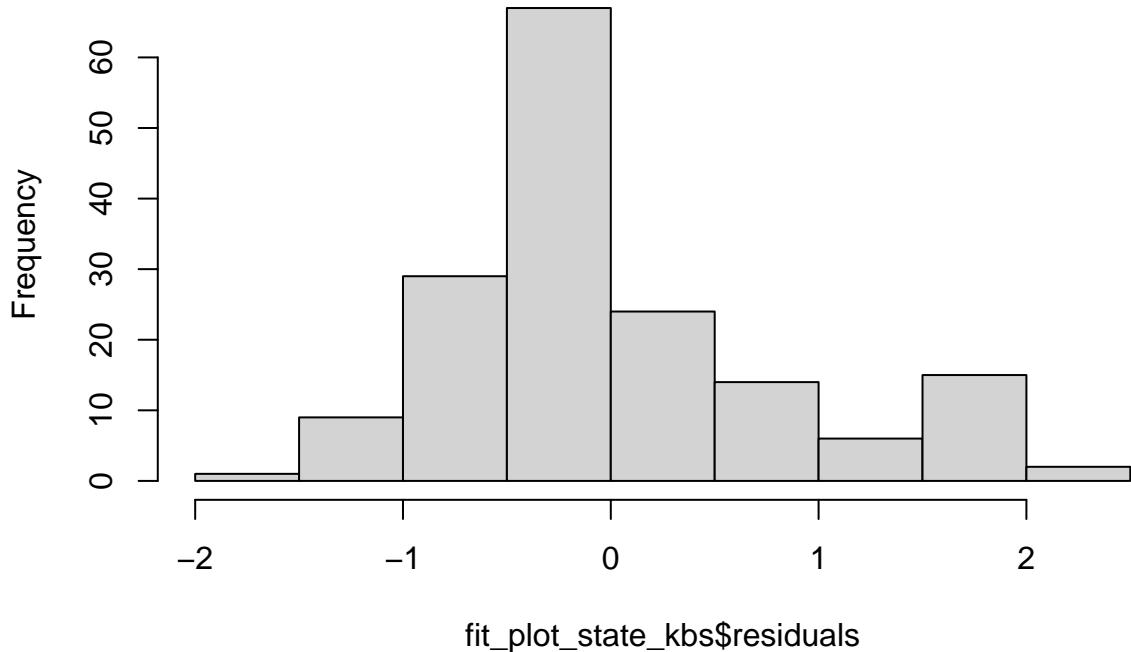
```
# comp_kbs_plot_no_outliers <- comp_kbs_plot[-252,] # remove outliers
qqPlot(fit_plot_state_kbs, main = "QQ Plot")
```



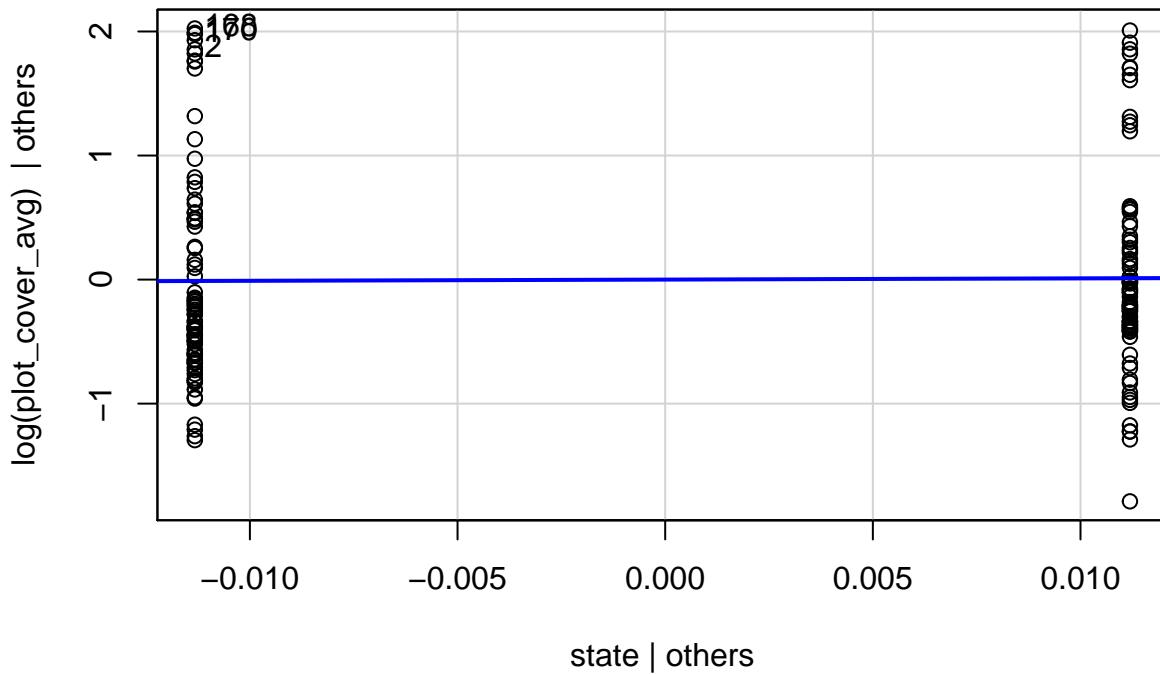
```
## 168 170
## 84 86
```

```
hist(fit_plot_state_kbs$residuals)
```

Histogram of fit_plot_state_kbs\$residuals



```
leveragePlots(fit_plot_state_kbs)
```



```
ols_test_normality(fit_plot_state_kbs)
```

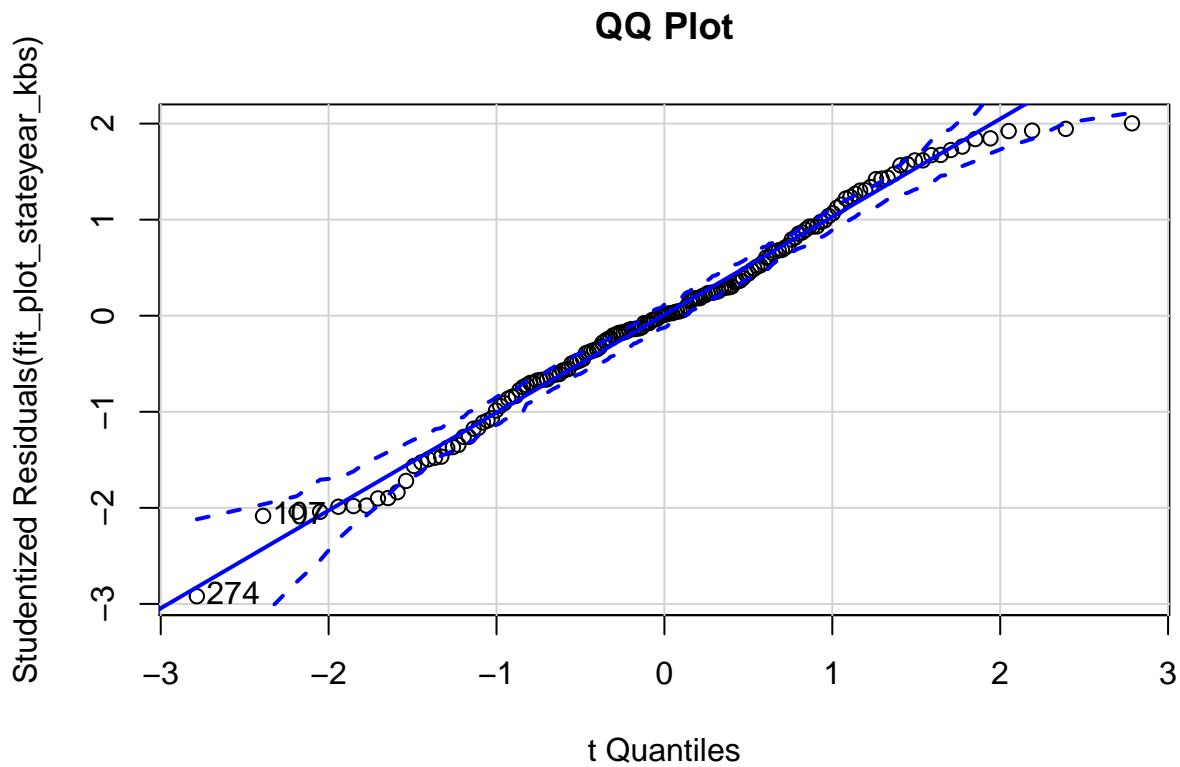
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----
##      Test          Statistic       pvalue
## -----
## Shapiro-Wilk      0.9122       0.0000
## Kolmogorov-Smirnov 0.1469       0.0015
## Cramer-von Mises  20.8792       0.0000
## Anderson-Darling   5.4727       0.0000
## -----
```

```
# KBS State and year model
fit_plot_stateyear_kbs <- lm(log(plot_cover_avg) ~ state + year_factor, data = comp_kbs_plot)
outlierTest(fit_plot_stateyear_kbs) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 274 -2.920104        0.0039949      0.66716
```

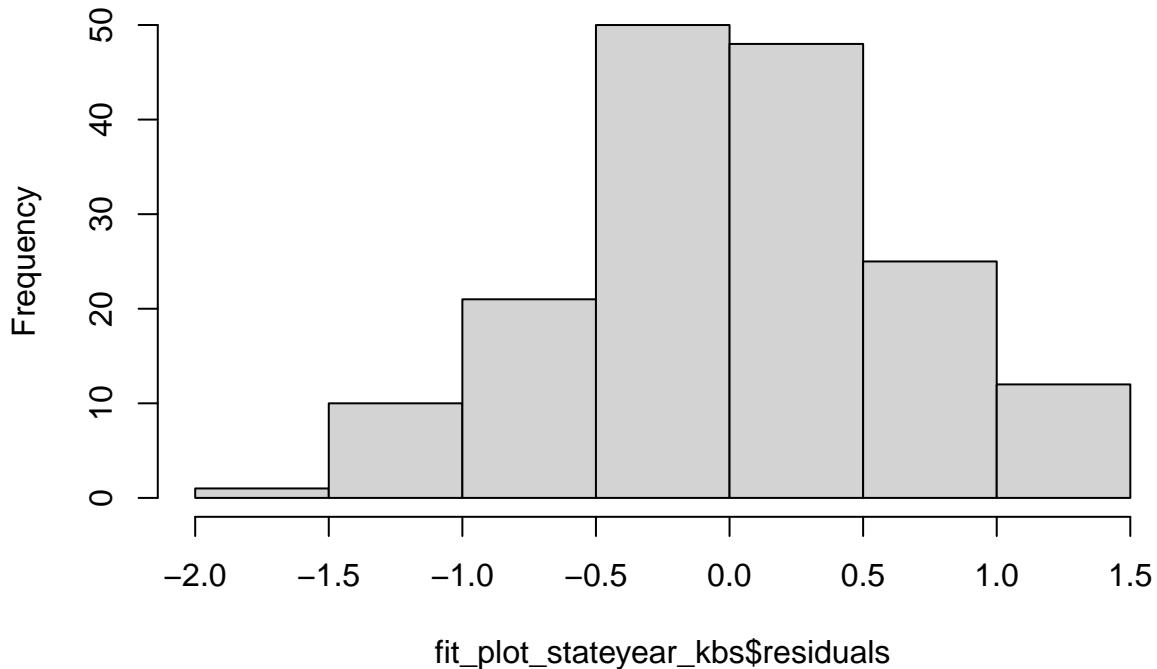
```
# comp_kbs_plot_no_outliers <- comp_kbs_plot[-190,] # remove outliers
qqPlot(fit_plot_stateyear_kbs, main = "QQ Plot")
```



```
## 107 274
## 65 148
```

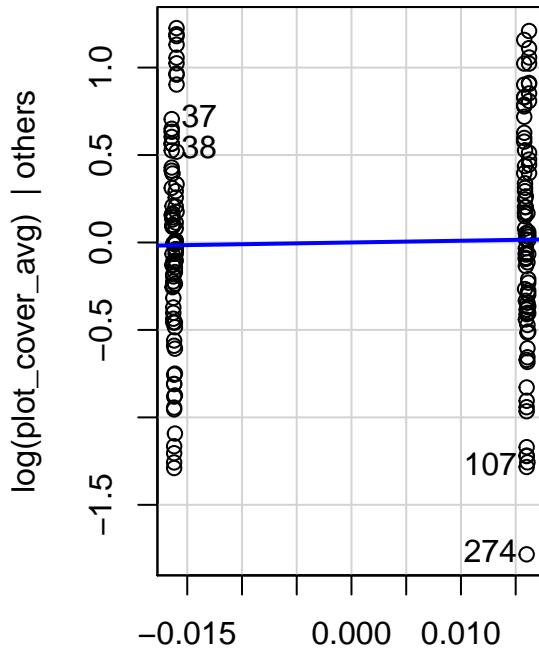
```
hist(fit_plot_stateyear_kbs$residuals)
```

Histogram of fit_plot_stateyear_kbs\$residuals

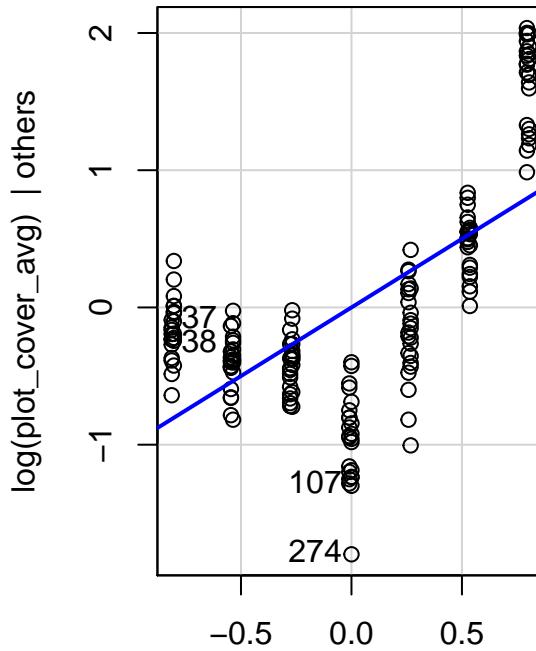


```
leveragePlots(fit_plot_stateyear_kbs)
```

Leverage Plots



state | others



year_factor | others

```
ols_test_normality(fit_plot_stateyear_kbs) # not all are under 0.05 but I think we can move forward wi
```

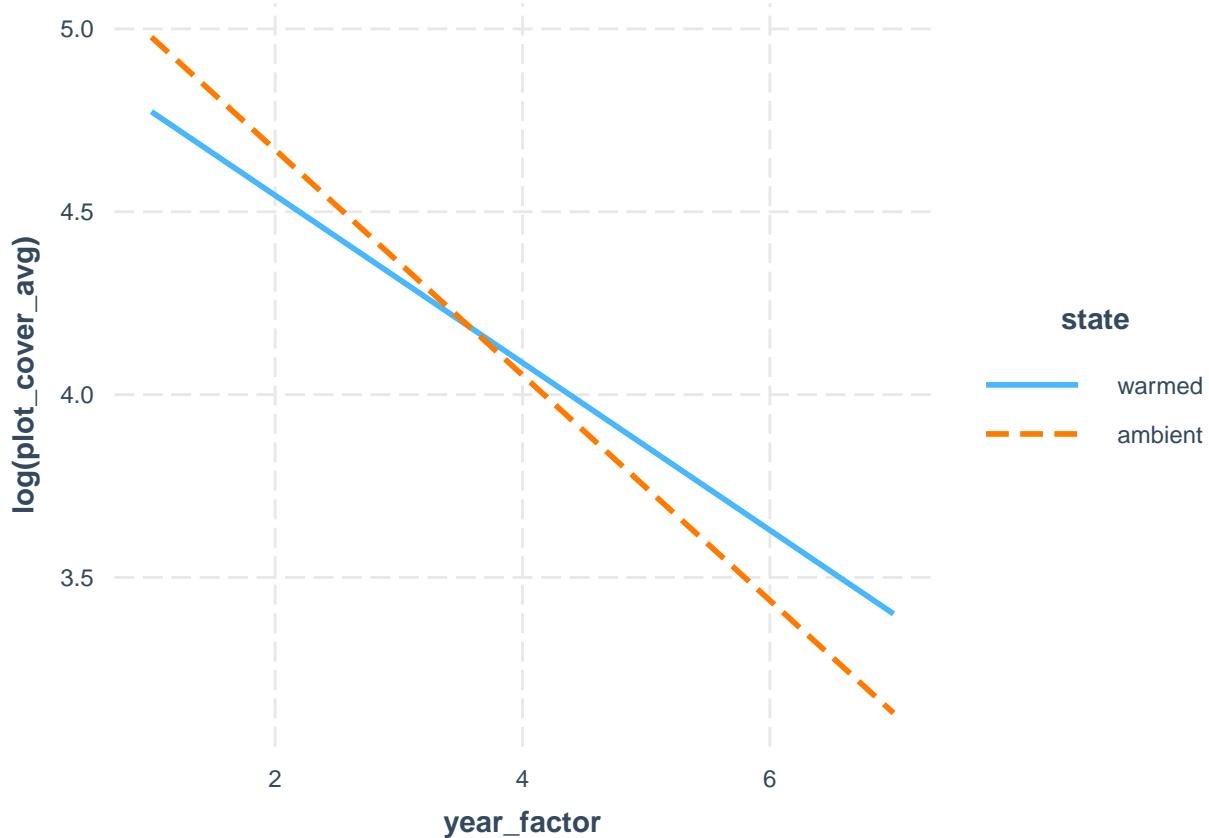
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----
##      Test       Statistic     pvalue
## -----
## Shapiro-Wilk      0.9869    0.1200
## Kolmogorov-Smirnov 0.0413    0.9387
## Cramer-von Mises   16.4303   0.0000
## Anderson-Darling    0.4221    0.3183
## -----
```

```
# Interaction plot (ignore for now the repeated measures with species); see:
# https://cran.r-project.org/web/packages/interactions/vignettes/interactions.html
# and: https://interactions.jacob-long.com/
```

```
fit3 <- lm(log(plot_cover_avg) ~ state * year_factor, data = comp_kbs_plot)
interact_plot(fit3, pred = year_factor, modx = state)
```

```
## Using data comp_kbs_plot from global environment. This could cause
## incorrect results if comp_kbs_plot has been altered since the model was
## fit. You can manually provide the data to the "data =" argument.
```

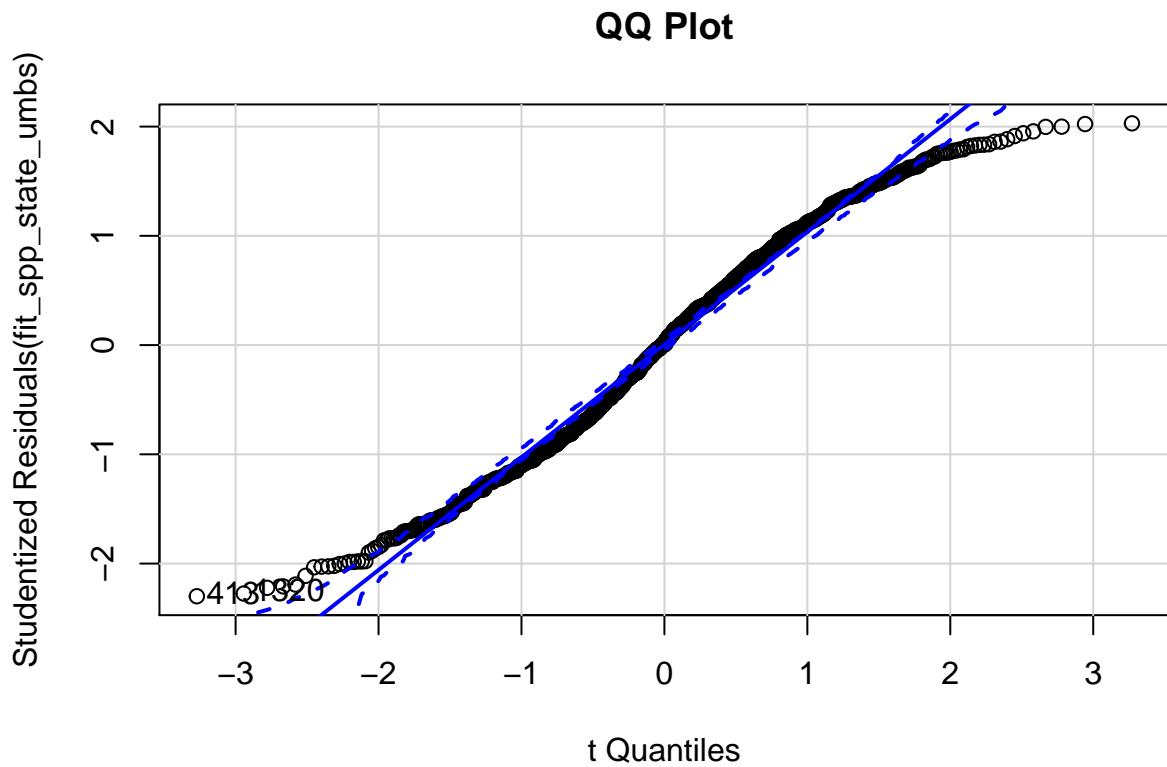


UMBS

```
# species level data UMBS State-only model
fit_spp_state_umbs <- lm(log(relabun) ~ state, data = comp_umbs_spp)
outlierTest(fit_spp_state_umbs) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 413 -2.299237          0.021721           NA
```

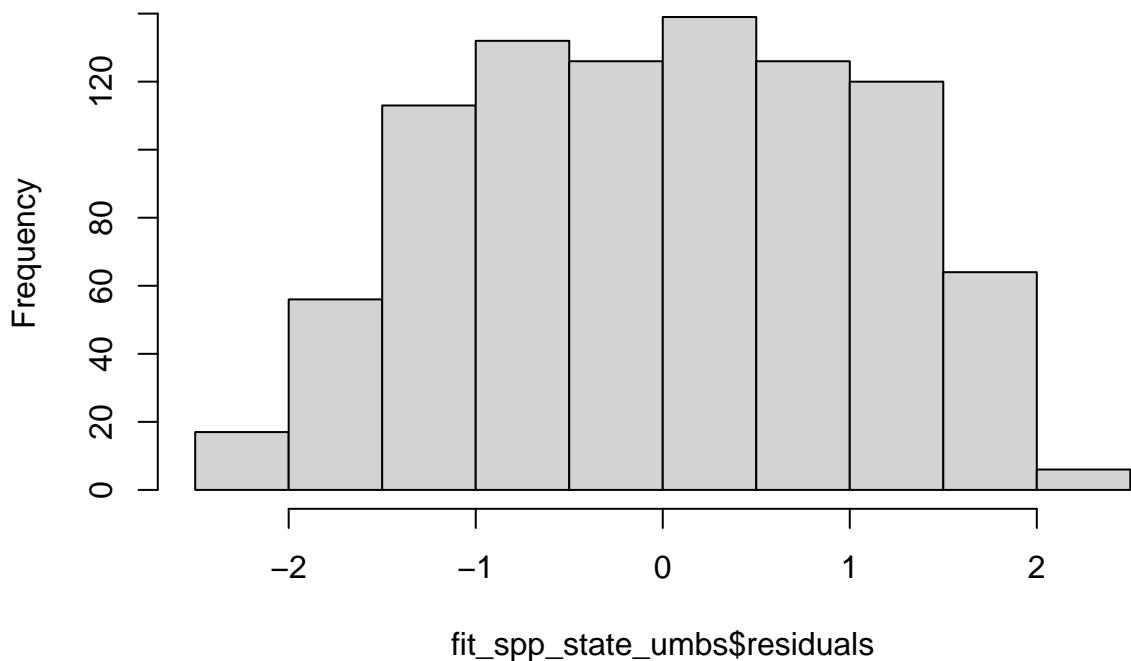
```
qqPlot(fit_spp_state_umbs, main = "QQ Plot")
```



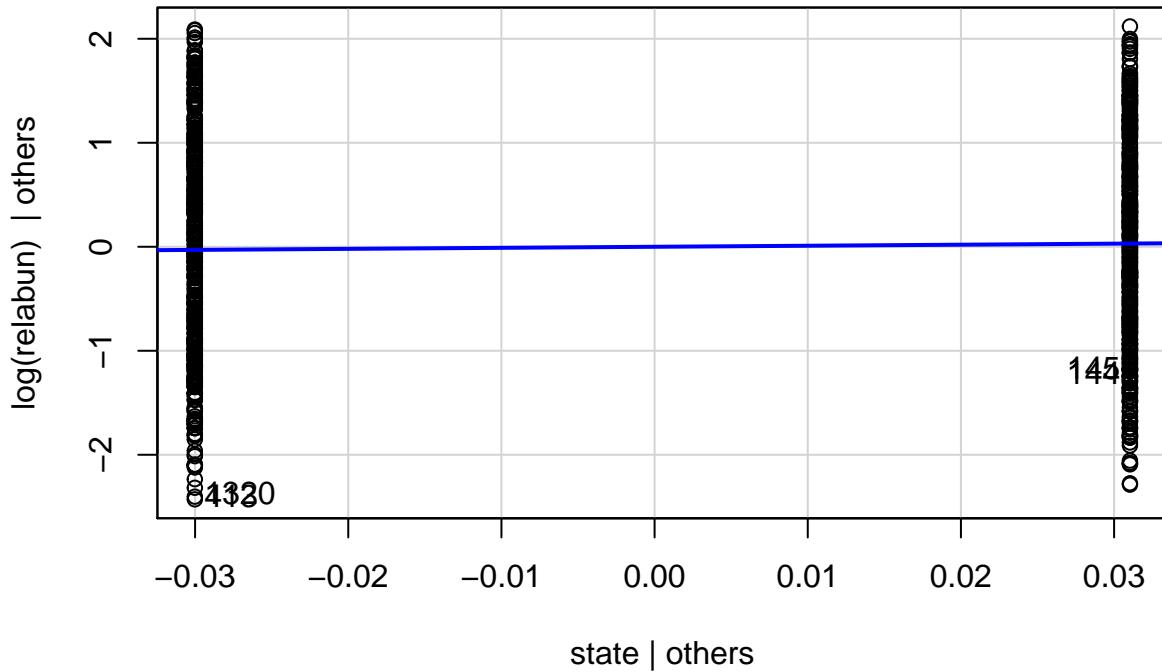
```
##   413 1320
##    64  425
```

```
hist(fit_spp_state_umbs$residuals)
```

Histogram of fit_spp_state_umbs\$residuals



```
leveragePlots(fit_spp_state_umbs)
```



```
ols_test_normality(fit_spp_state_umbs)
```

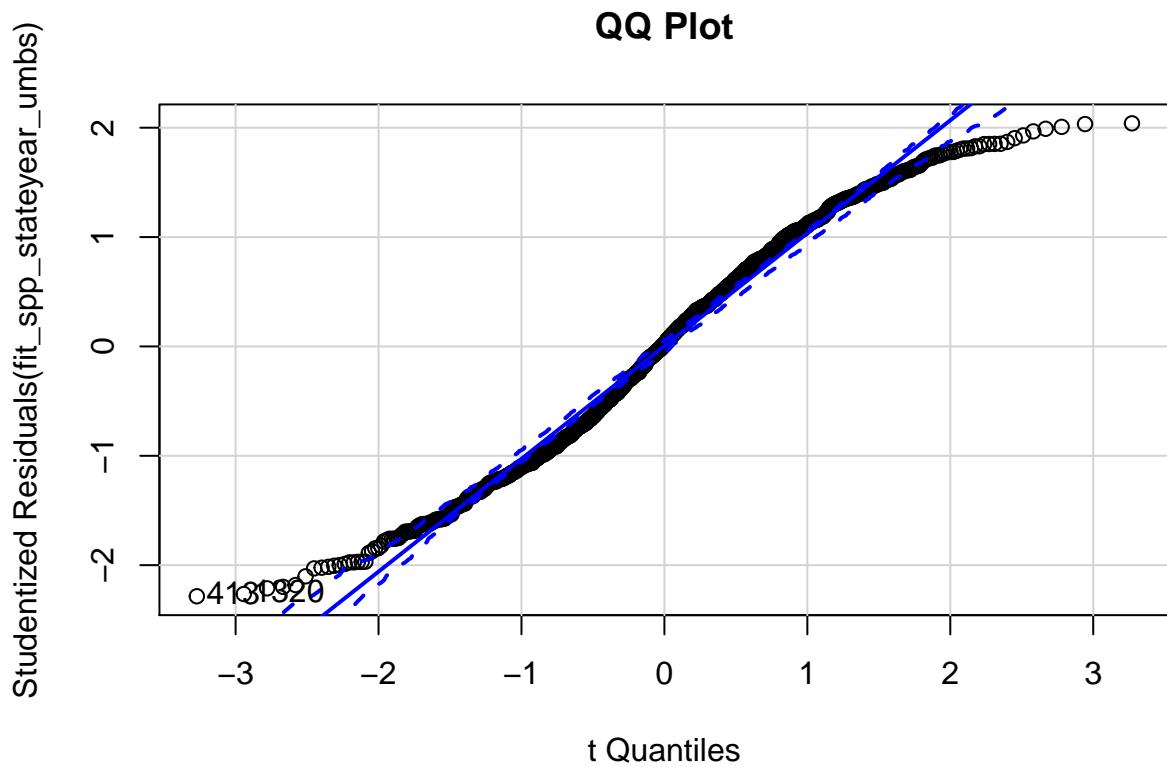
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----
##      Test          Statistic       pvalue
## -----
## Shapiro-Wilk      0.9795       0.0000
## Kolmogorov-Smirnov 0.0487       0.0279
## Cramer-von Mises  54.5597       0.0000
## Anderson-Darling   4.7484       0.0000
## -----
```

```
# UMBS State and year model
fit_spp_stateyear_umbs <- lm(log(relabun) ~ state + year_factor, data = comp_umbs_spp)
outlierTest(fit_spp_stateyear_umbs) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 413 -2.284325           0.022586        NA
```

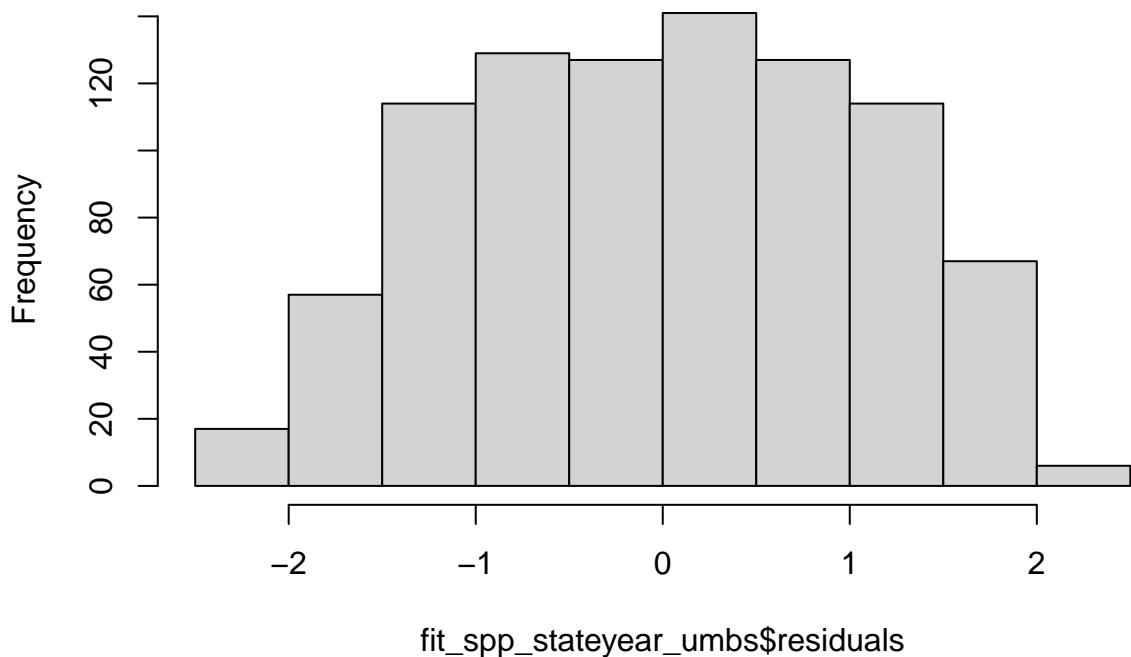
```
qqPlot(fit_spp_stateyear_umbs, main = "QQ Plot")
```



```
##   413 1320
##    64   425
```

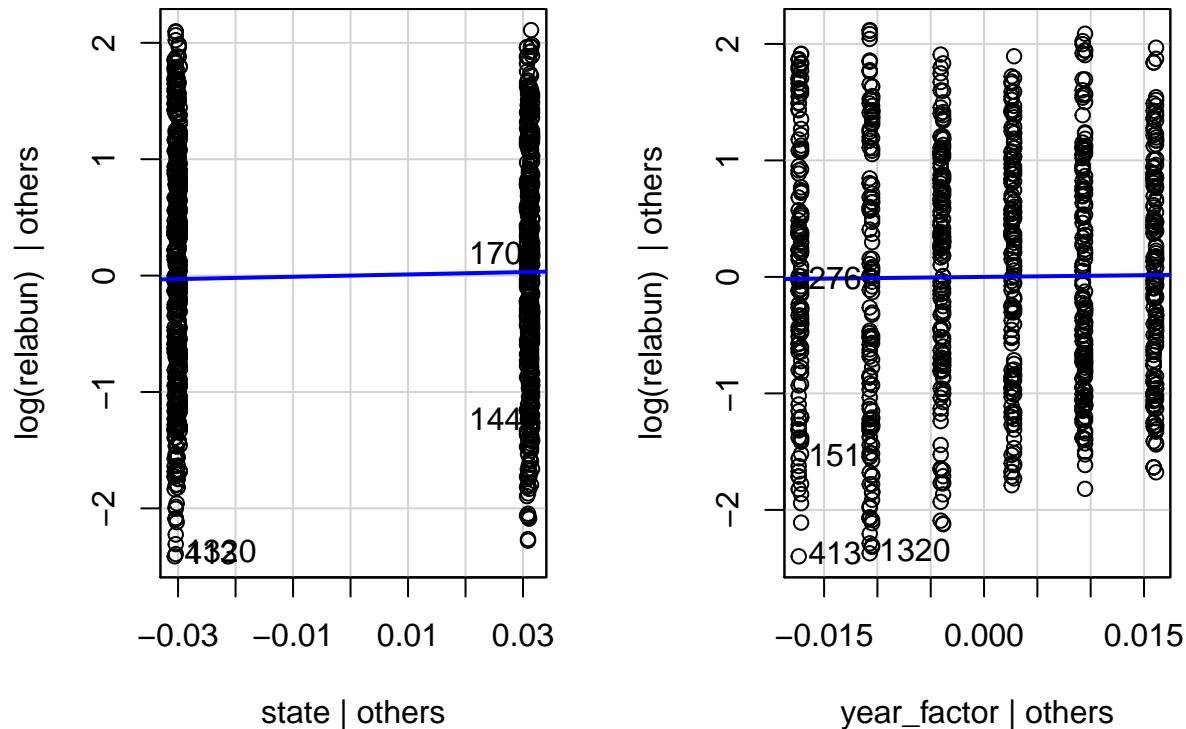
```
hist(fit_spp_stateyear_umbs$residuals)
```

Histogram of fit_spp_stateyear_umbs\$residuals



```
leveragePlots(fit_spp_stateyear_umbs)
```

Leverage Plots



```
ols_test_normality(fit_spp_stateyear_umbs)
```

```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

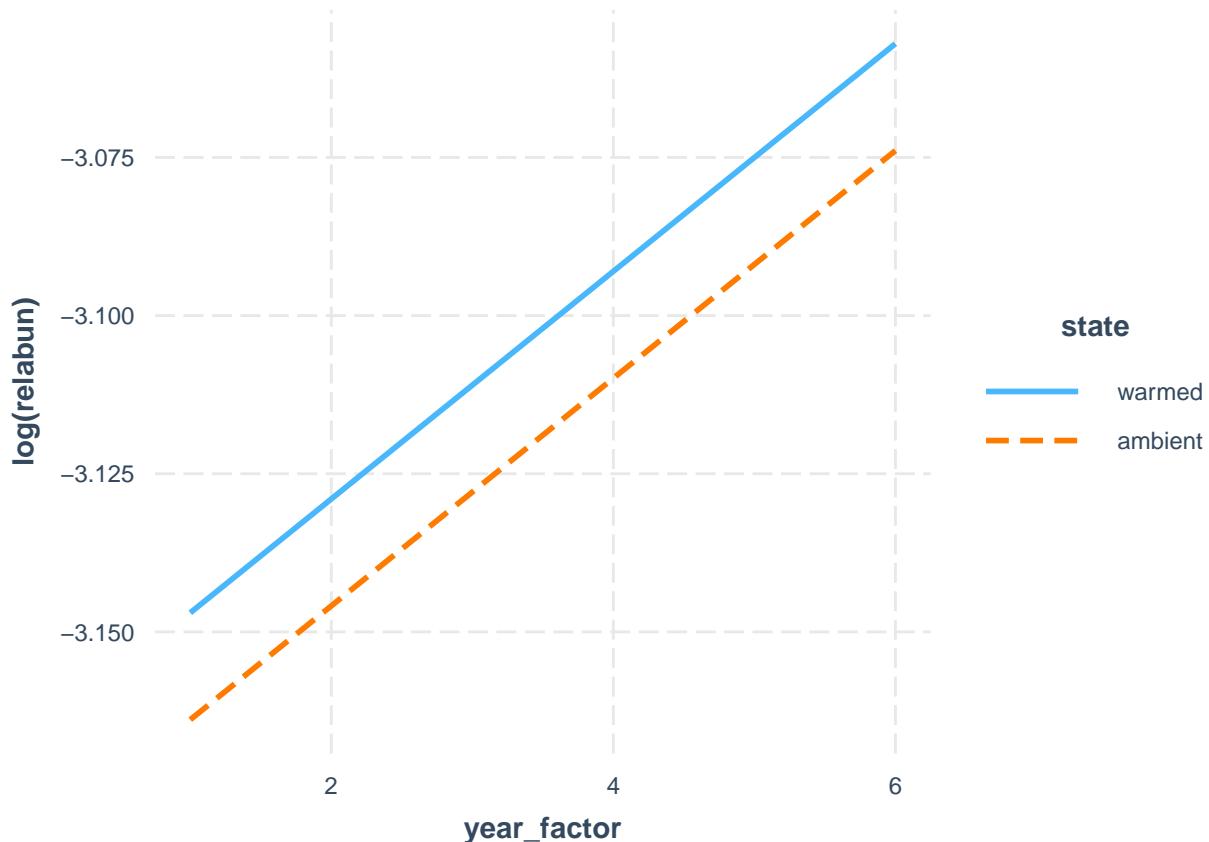
```
## -----
##      Test          Statistic       pvalue
## -----
## Shapiro-Wilk      0.9794      0.0000
## Kolmogorov-Smirnov   0.05      0.0225
## Cramer-von Mises    54.4927      0.0000
## Anderson-Darling     4.7891      0.0000
## -----
```

```
# Interaction plot (ignore for now the repeated measures with species); see:
# https://cran.r-project.org/web/packages/interactions/vignettes/interactions.html
# and: https://interactions.jacob-long.com/
```

```
fit3 <- lm(log(relabun) ~ state + year_factor + species, data = comp_umbs_spp)
interact_plot(fit3, pred = year_factor, modx = state)
```

```
## Using data comp_umbs_spp from global environment. This could cause
## incorrect results if comp_umbs_spp has been altered since the model was
## fit. You can manually provide the data to the "data =" argument.
```

```
## Warning: year_factor and state are not included in an interaction with one another
## in the model.
```



```
fit4 <- lm(log(relabun) ~ state * year_factor + species, data = comp_umbs_spp)
interact_plot(fit4, pred = year_factor, modx = state, mod2 = species)
```

```
## Using data comp_umbs_spp from global environment. This could cause
## incorrect results if comp_umbs_spp has been altered since the model was
## fit. You can manually provide the data to the "data =" argument.
```

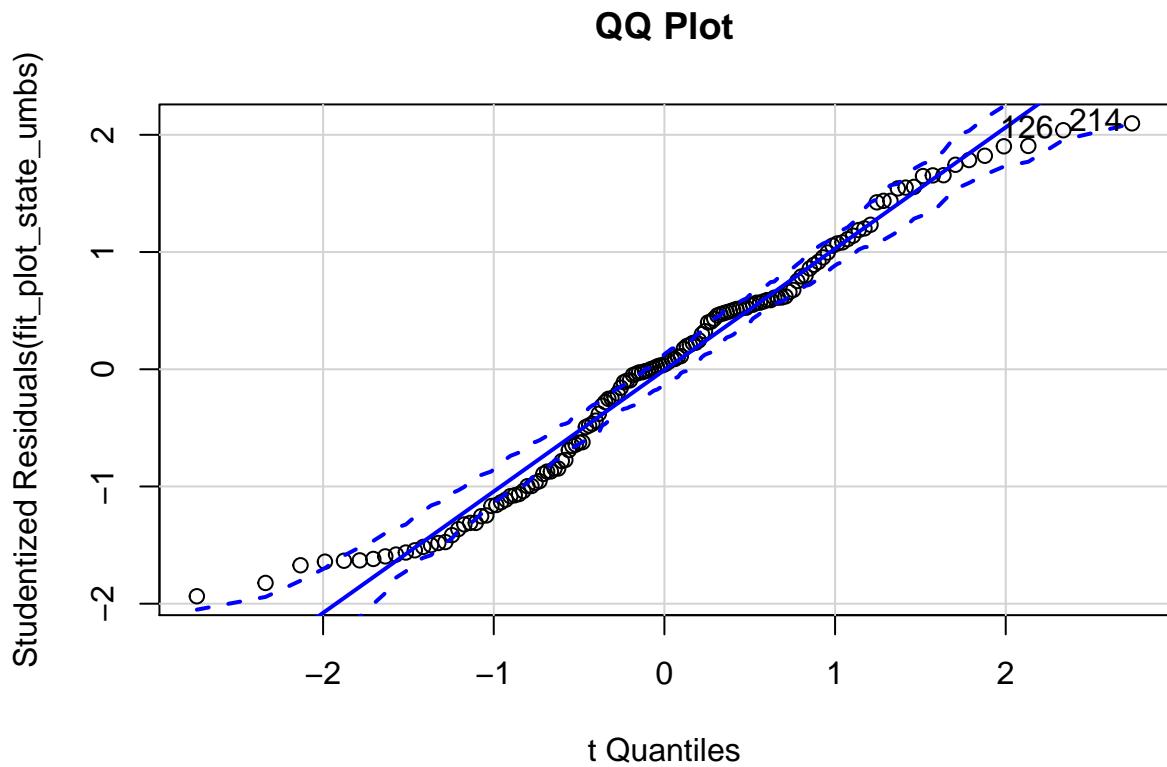
```
## Warning: year_factor and state and species are not included in an interaction with
## one another in the model.
```



```
# Plot level data UMBS State-only model
fit_plot_state_umbs <- lm(log(plot_cover_avg) ~ state, data = comp_umbs_plot)
outlierTest(fit_plot_state_umbs) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 214 2.097798          0.037707         NA
```

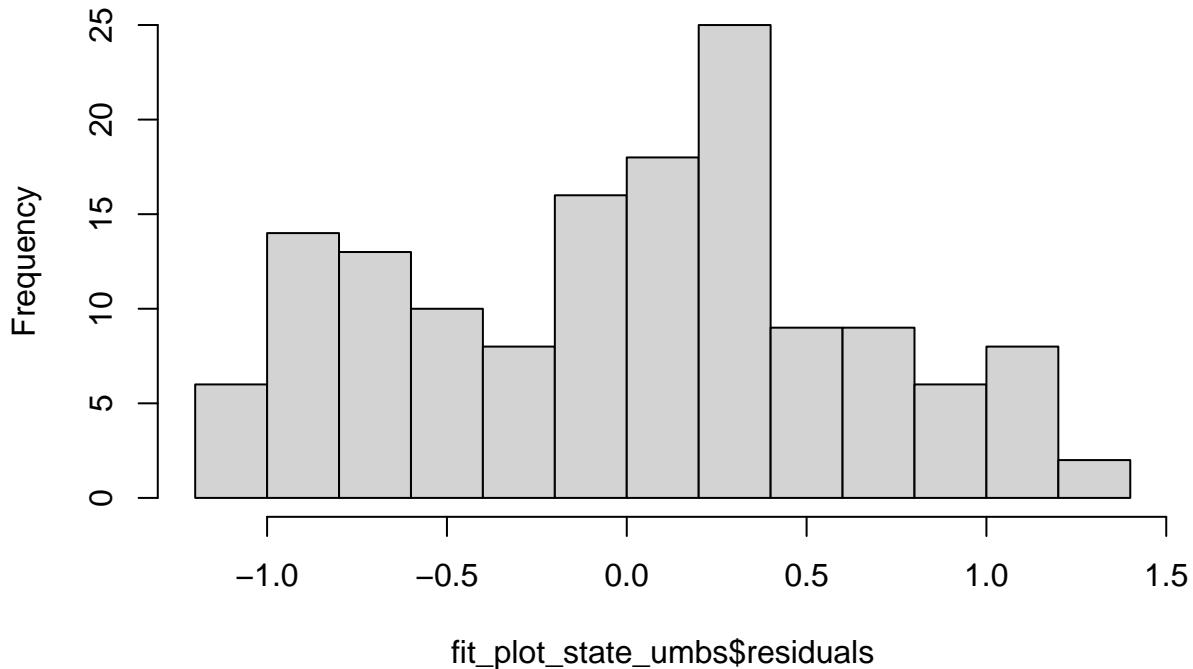
```
qqPlot(fit_plot_state_umbs, main = "QQ Plot")
```



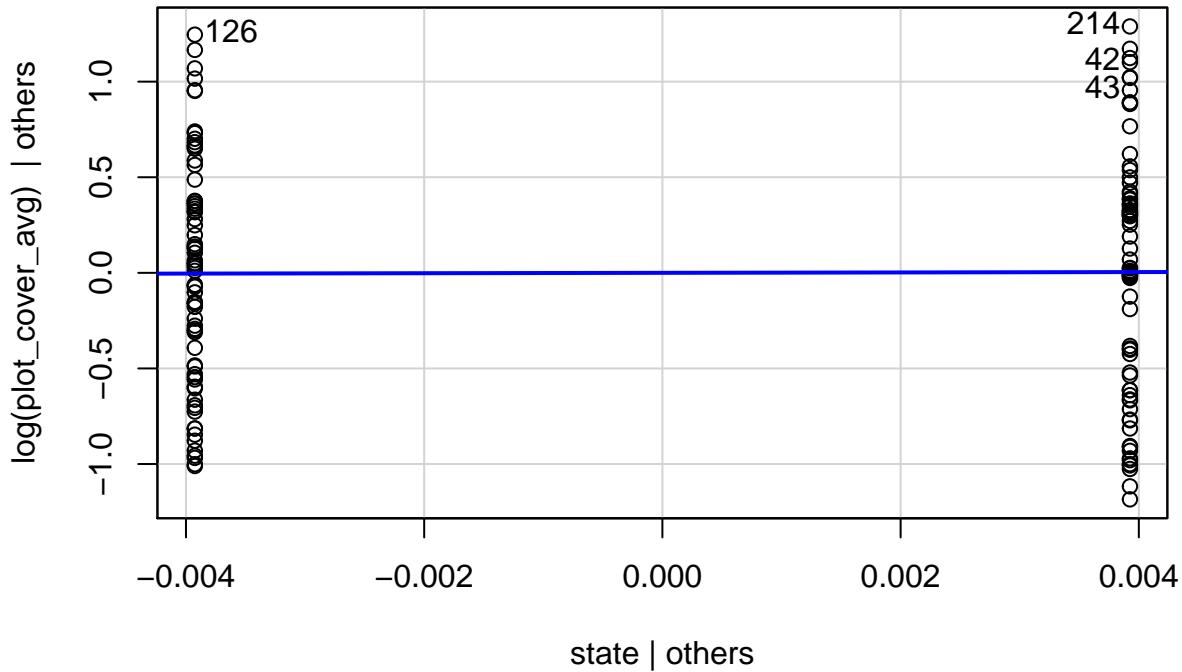
```
## 126 214
## 37 77
```

```
hist(fit_plot_state_umbs$residuals)
```

Histogram of fit_plot_state_umbs\$residuals



```
leveragePlots(fit_plot_state_umbs)
```



```
ols_test_normality(fit_plot_state_umbs)
```

```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

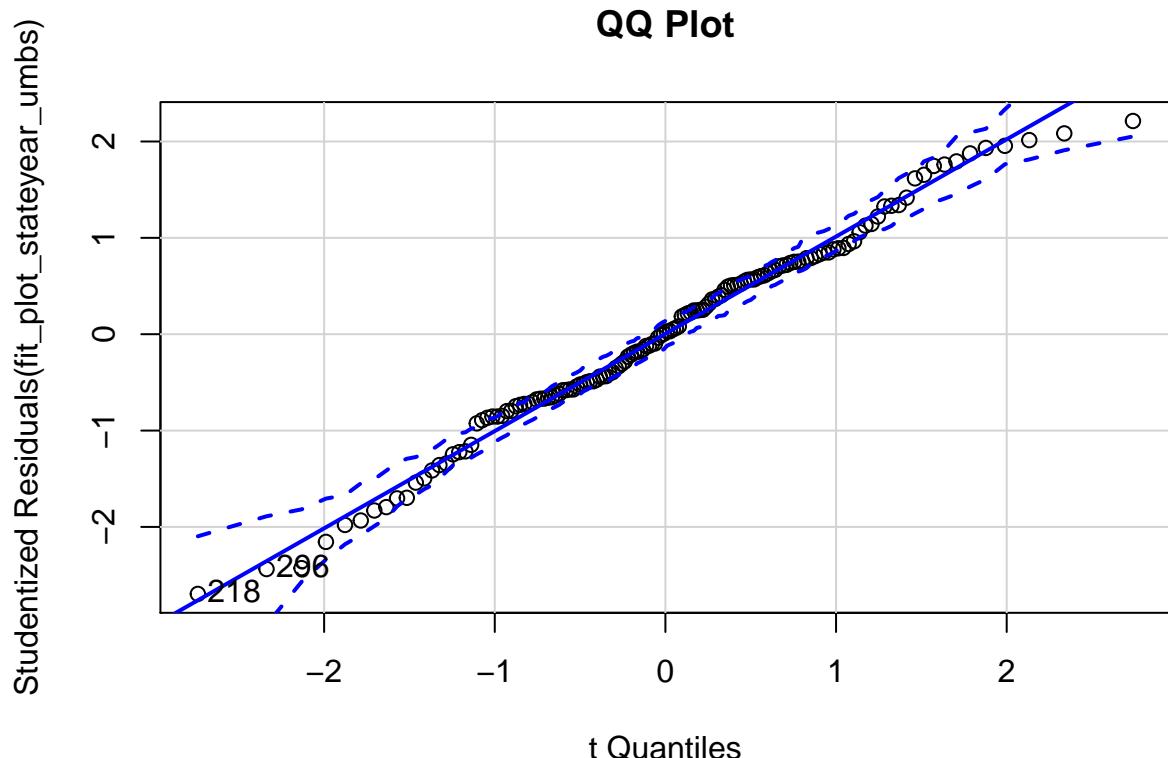
```
## -----
##      Test          Statistic       pvalue
## -----
## Shapiro-Wilk      0.9722      0.0049
## Kolmogorov-Smirnov 0.0717      0.4498
## Cramer-von Mises 12.7256      0.0000
## Anderson-Darling   1.0016      0.0118
## -----
```

```
# comp_umbs_plot_no_outliers <- comp_umbs_plot[-298,] # remove outliers
```

```
# KBS State and year model
fit_plot_stateyear_umbs <- lm(log(plot_cover_avg) ~ state + year_factor, data = comp_umbs_plot)
outlierTest(fit_plot_stateyear_umbs) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 218 -2.695146           0.0078978        NA
```

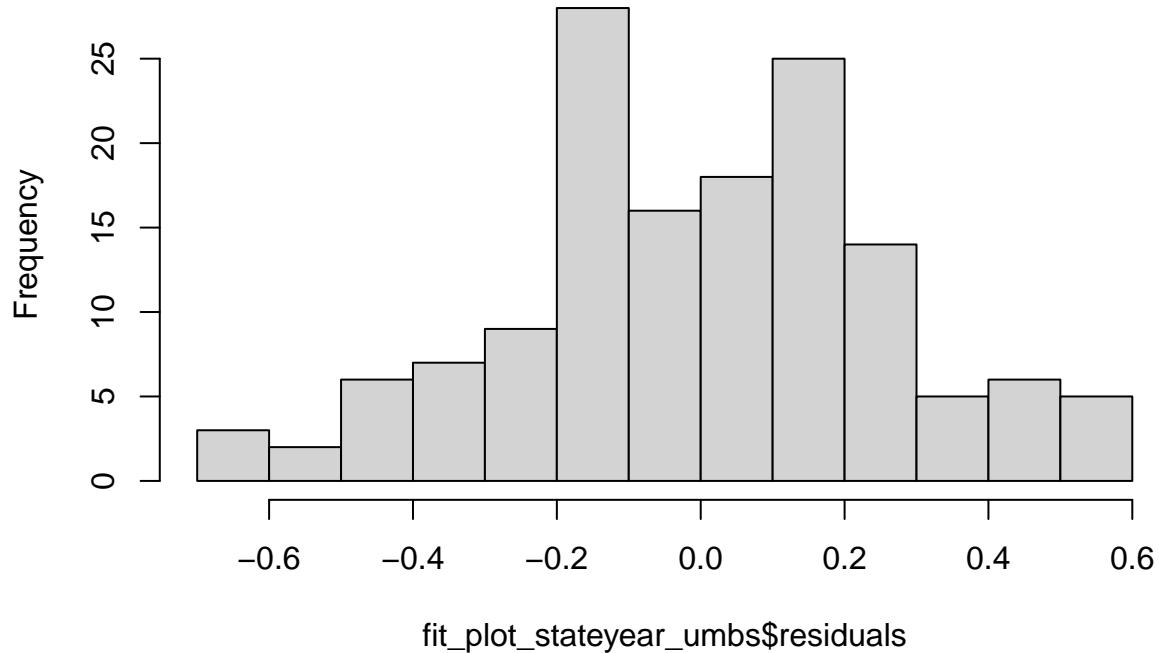
```
# comp_umbs_plot_no_outliers <- comp_umbs_plot[-190,] # remove outliers
qqPlot(fit_plot_stateyear_umbs, main = "QQ Plot")
```



```
## 218 296
## 81 111
```

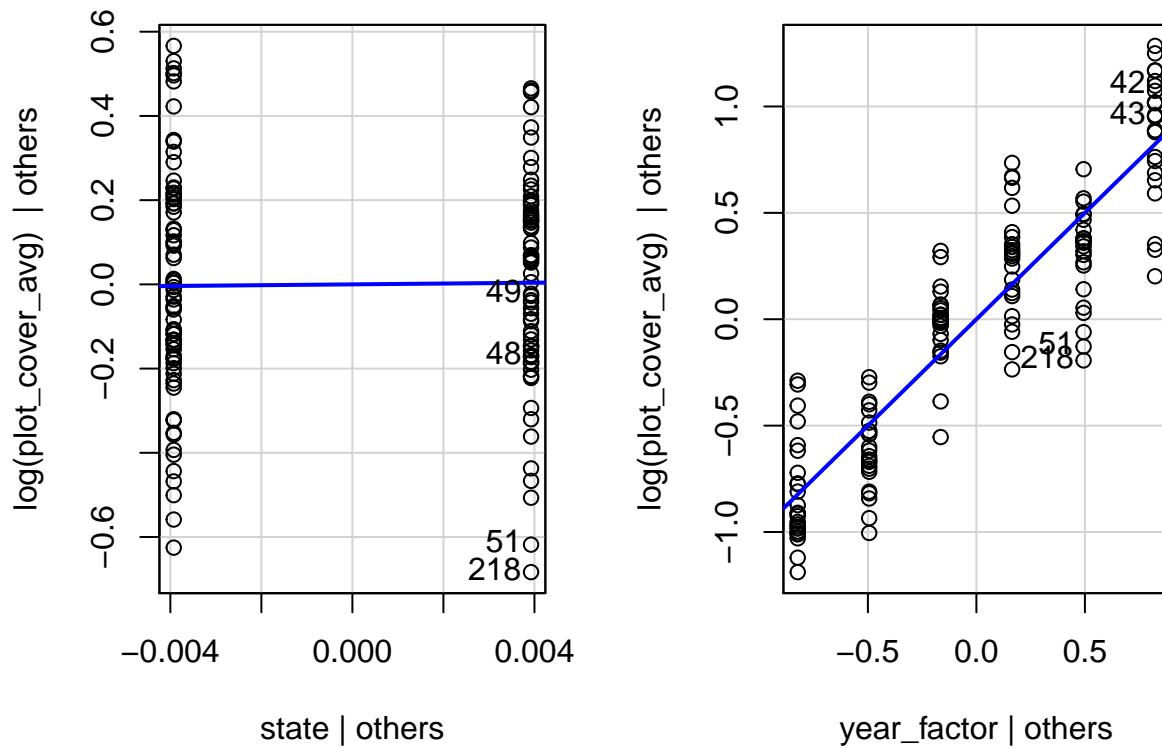
```
hist(fit_plot_stateyear_umbs$residuals)
```

Histogram of fit_plot_stateyear_umbs\$residuals



```
leveragePlots(fit_plot_stateyear_umbs)
```

Leverage Plots



```

ols_test_normality(fit_plot_stateyear_umbs) # not all are under 0.05 but I think we can move forward w

## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test

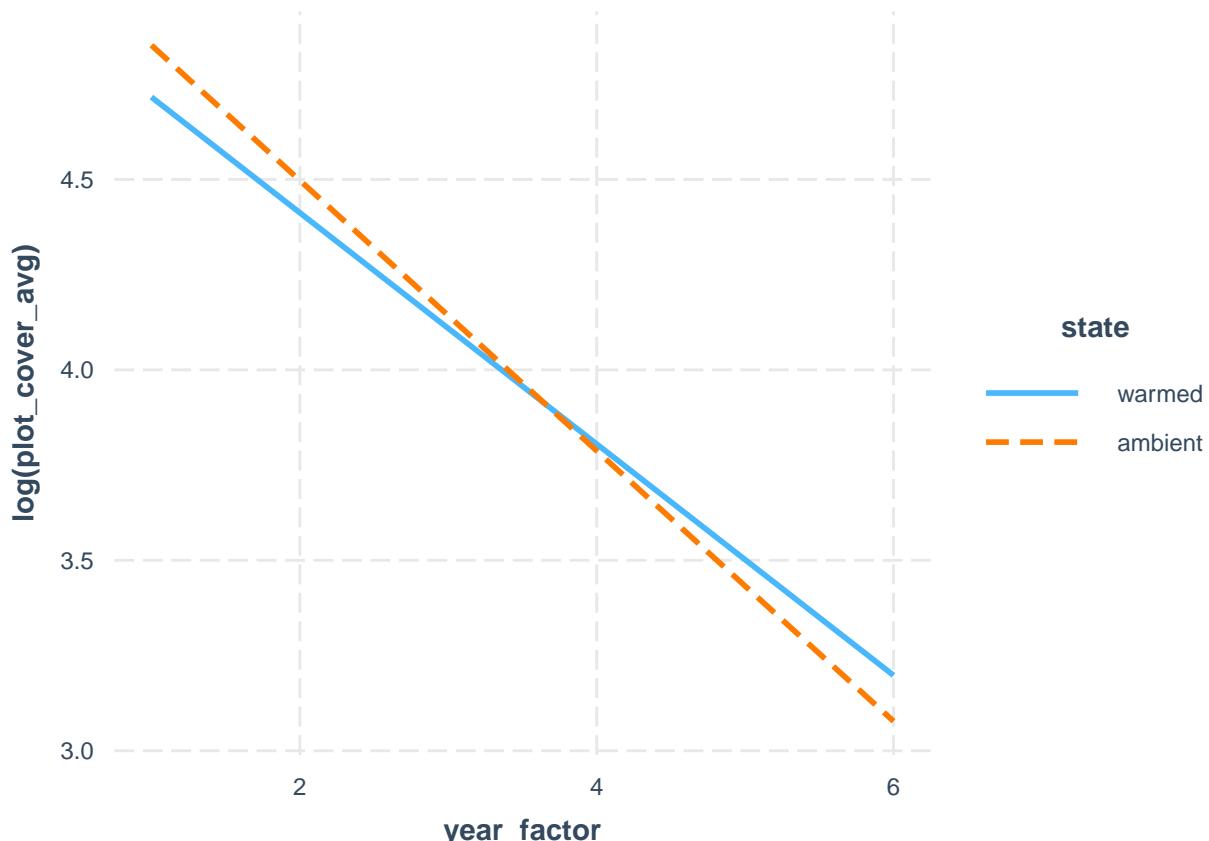
## -----
##          Test      Statistic     pvalue
## -----
## Shapiro-Wilk      0.9893    0.3354
## Kolmogorov-Smirnov   0.0493    0.8753
## Cramer-von Mises     27.072   0.0000
## Anderson-Darling     0.4069    0.3452
## -----
```

Interaction plot (ignore for now the repeated measures with species); see:
<https://cran.r-project.org/web/packages/interactions/vignettes/interactions.html>
and: <https://interactions.jacob-long.com/>

```

fit3 <- lm(log(plot_cover_avg) ~ state * year_factor, data = comp_umbs_plot)
interact_plot(fit3, pred = year_factor, modx = state)

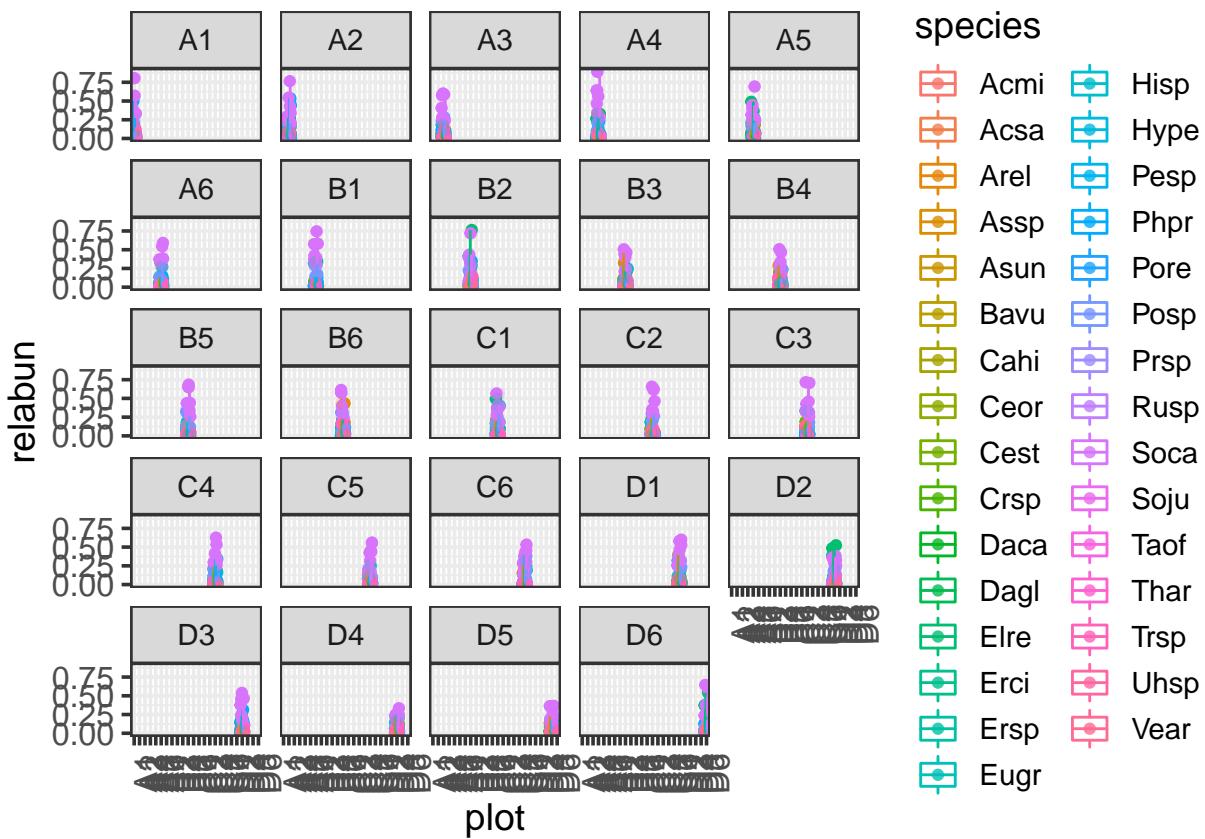
## Using data comp_umbs_plot from global environment. This could cause
## incorrect results if comp_umbs_plot has been altered since the model was
## fit. You can manually provide the data to the "data =" argument.
```



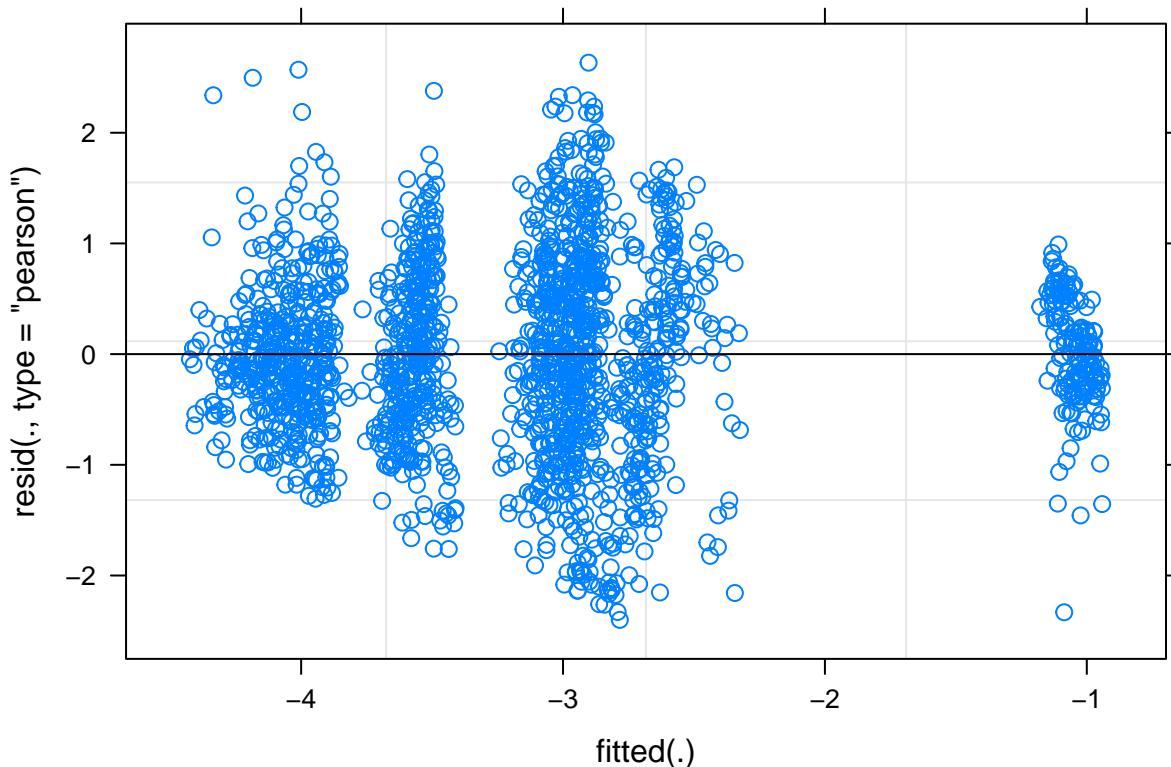
MIXED EFFECT MODELS

KBS species level data

```
# KBS SPECIES LEVEL - Looking at RELATIVE ABUNDANCE
mod1 <- lmer(log(relabun) ~ state * year_factor + insecticide * year_factor + (1 | species) + (1 | plot), comp_kbs_spp, REML = FALSE)
ggplot(comp_kbs_spp, aes(x = plot, y = relabun, col = species)) + geom_jitter() +
  geom_boxplot(alpha = 0.2) + facet_wrap(~plot)
```



```
# Check Assumptions: (1) Linearity: if covariates are not categorical (year # isn't) (2) Homogeneity: Need to Check by plotting residuals vs predicted # values.
par(mfrow = c(1, 2))
plot(mod1)
```



```
# Homogeneity of variance is weird Check for homogeneity of variances (true if
# p>0.05). If the result is not significant, the assumption of equal variances
# (homoscedasticity) is met (no significant difference between the group
# variances). *****Levene's Test - tests whether or not the variance among two
# or more groups is equal - If the p-value is less than our chosen significance
# level, we can reject the null hypothesis and conclude that we have enough
# evidence to state that the variance among the groups is not equal (which we
# want).
```

```
leveneTest(residuals(mod1) ~ comp_kbs_spp$state)
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##          Df F value    Pr(>F)
## group     1 8.1274 0.004409 **
##          1816
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Assumption met
leveneTest(residuals(mod1) ~ comp_kbs_spp$species)
```

```
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##          Df F value    Pr(>F)
## group     30 9.5894 < 2.2e-16 ***
##
```

```

##      1787
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Assumption met
leveneTest(residuals(mod1) ~ comp_kbs_spp$insecticide)

## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.

## Levene's Test for Homogeneity of Variance (center = median)
##          Df F value Pr(>F)
## group     1  0.7224 0.3955
##          1816

# Assumption not met - this seems weird
leveneTest(residuals(mod1) ~ comp_kbs_spp$plot)

## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.

## Levene's Test for Homogeneity of Variance (center = median)
##          Df F value  Pr(>F)
## group    23  1.7568 0.01463 *
##          1794
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Assumption met

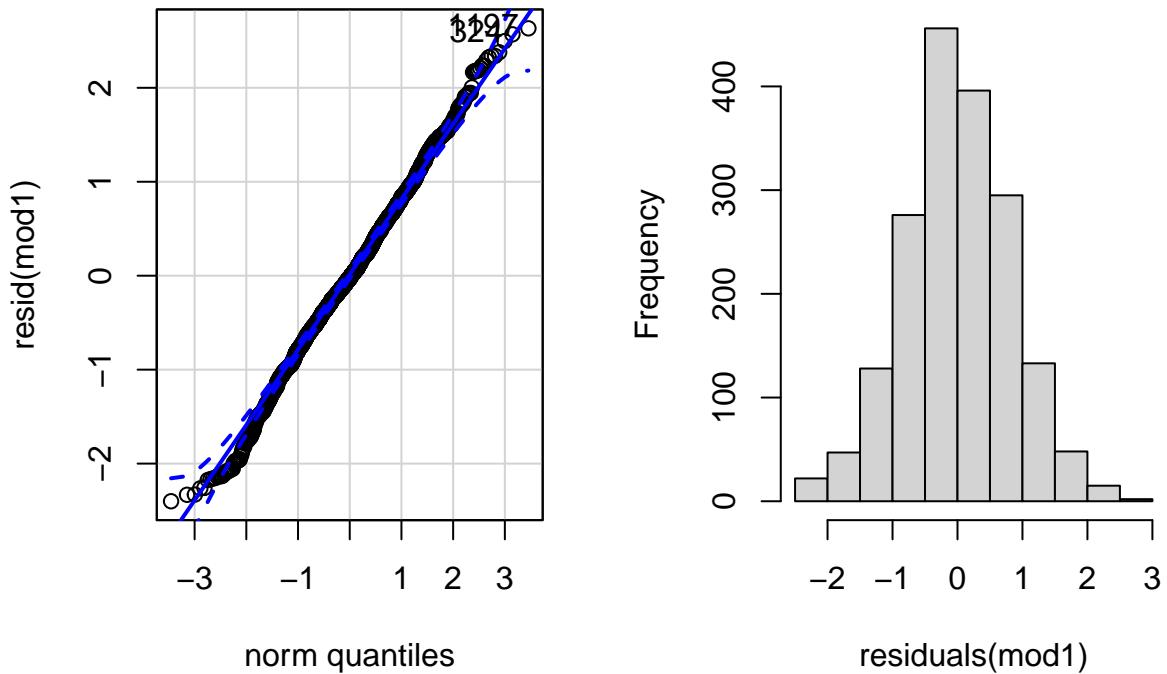
# (3) Normality of error term: need to check by histogram, QQplot of residuals,
# could do Kolmogorov-Smirnov test. Check for normal residuals
qqPlot(resid(mod1))

## 1197 324
## 713 257

hist(residuals(mod1))

```

Histogram of residuals(mod1)



```
shapiro.test(resid(mod1)) # not normally distributed resids bc p<0.05 but its not horrible - histogram
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: resid(mod1)  
## W = 0.99775, p-value = 0.01176
```

```
outlierTest(mod1) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05  
## Largest |rstudent|:  
##      rstudent unadjusted p-value Bonferroni p  
## 324 3.182167          0.0014866       NA
```

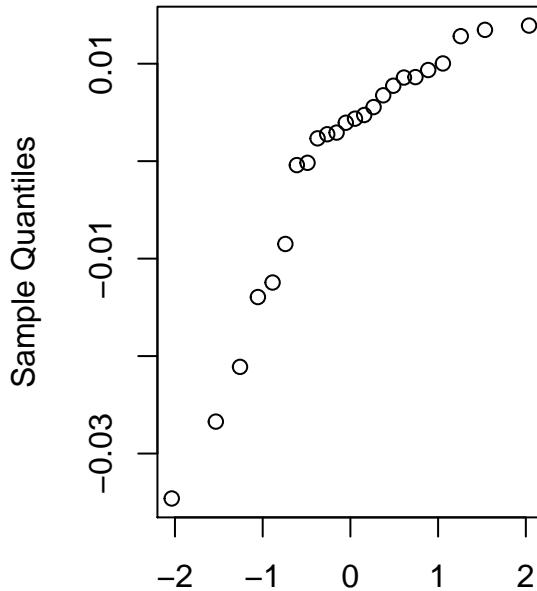
(4) Normality of random effect: Get the estimate of random effect (e.g., random intercepts), and check them as you would check the residual.

```
require(lme4)  
r_int <- ranef(mod1)$plot$`Intercept`  
qnorm(r_int)  
# qqline(r_int) doesn't work  
shapiro.test(r_int)
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: r_int  
## W = 0.84158, p-value = 0.001532
```

```
# Not normally distributed random effect - p-value = 0.0015
```

Normal Q–Q Plot



Theoretical Quantiles

```
# Do we need to include plot as a random effect with the KBS models?
mod1 <- lmer(log(relabun) ~ state * year_factor + insecticide * year_factor + (1 |
  species) + (1 | plot), comp_kbs_spp, REML = FALSE)
mod2 <- lmer(log(relabun) ~ state * year_factor + insecticide * year_factor + (1 |
  species), comp_kbs_spp, REML = FALSE)
# Run analysis of variance on each model (see this for more explanation on how
# anova on a linear mixed effects model is similar to an anova on a regular
# linear model: https://m-clark.github.io/docs/mixedModels/anovamixed.html)
anova(mod1)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##                                     Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state                           0.0745 0.0745     1   346.29  0.1057 0.745233
## year_factor                     5.1615 5.1615     1 1803.74  7.3298 0.006846 ***
## insecticide                      0.0028 0.0028     1   352.08  0.0040 0.949833
## state:year_factor                0.0108 0.0108     1 1795.30  0.0154 0.901364
## year_factor:insecticide          0.0232 0.0232     1 1797.80  0.0329 0.856061
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(mod2)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##                                     Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state                           0.0756 0.0756     1 1798.8  0.1072 0.743362
```

```

## year_factor      5.2202  5.2202      1 1803.8  7.3994 0.006587 **
## insecticide     0.0048  0.0048      1 1804.0  0.0068 0.934314
## state:year_factor 0.0126  0.0126      1 1796.4  0.0179 0.893691
## year_factor:insecticide 0.0254  0.0254      1 1800.3  0.0359 0.849641
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
anova(mod1, mod2) # Go with model 2 since pvalue >0.05, aka more complex model does not have something
```

```

## Data: comp_kbs_spp
## Models:
## mod2: log(relabun) ~ state * year_factor + insecticide * year_factor +
## mod2:          (1 | species)
## mod1: log(relabun) ~ state * year_factor + insecticide * year_factor +
## mod1:          (1 | species) + (1 | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod2    8 4636.7 4680.7 -2310.3   4620.7
## mod1    9 4638.4 4688.0 -2310.2   4620.4 0.2303  1     0.6313

```

```
summ(mod1)
```

Observations	1818
Dependent variable	log(relabun)
Type	Mixed effects linear regression

AIC	4638.44
BIC	4687.99
Pseudo-R ² (fixed effects)	0.00
Pseudo-R ² (total)	0.47

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	-3.42	0.17	-20.24	43.88	0.00
stateambient	-0.03	0.09	-0.33	346.29	0.75
year_factor	-0.03	0.02	-1.78	1800.47	0.08
insecticideno_insects	-0.01	0.09	-0.06	352.08	0.95
stateambient:year_factor	0.00	0.02	0.12	1795.30	0.90
year_factor:insecticideno_insects	0.00	0.02	0.18	1797.80	0.86

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
species	(Intercept)	0.79
plot	(Intercept)	0.04
Residual		0.84

Grouping Variables		
Group	# groups	ICC
species	31	0.47
plot	24	0.00

```
summ(mod2)
```

Observations	1818
Dependent variable	log(relabun)
Type	Mixed effects linear regression
AIC	4636.67
BIC	4680.71
Pseudo-R ² (fixed effects)	0.00
Pseudo-R ² (total)	0.47

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	-3.42	0.17	-20.31	43.61	0.00
stateambient	-0.03	0.08	-0.33	1798.79	0.74
year_factor	-0.03	0.02	-1.80	1800.92	0.07
insecticideno_insects	-0.01	0.08	-0.08	1804.05	0.93
stateambient:year_factor	0.00	0.02	0.13	1796.41	0.89
year_factor:insecticideno_insects	0.00	0.02	0.19	1800.29	0.85

p values calculated using Satterthwaite d.f.

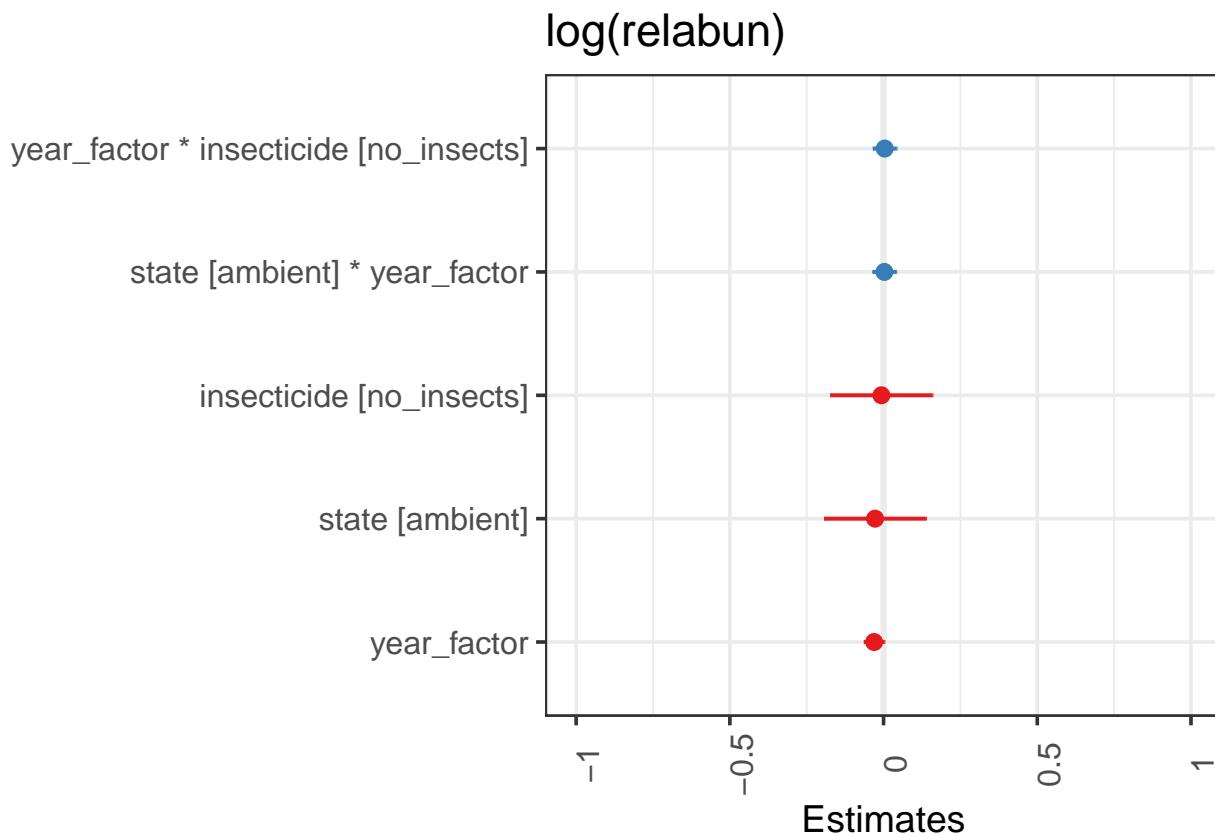
Random Effects		
Group	Parameter	Std. Dev.
species	(Intercept)	0.79
	Residual	0.84

Grouping Variables		
Group	# groups	ICC
species	31	0.47

```
AICctab(mod1, mod2, weights = T)
```

```
##      dAICc df weight
## mod2  0.0   8  0.71
## mod1 1.8   9  0.29
```

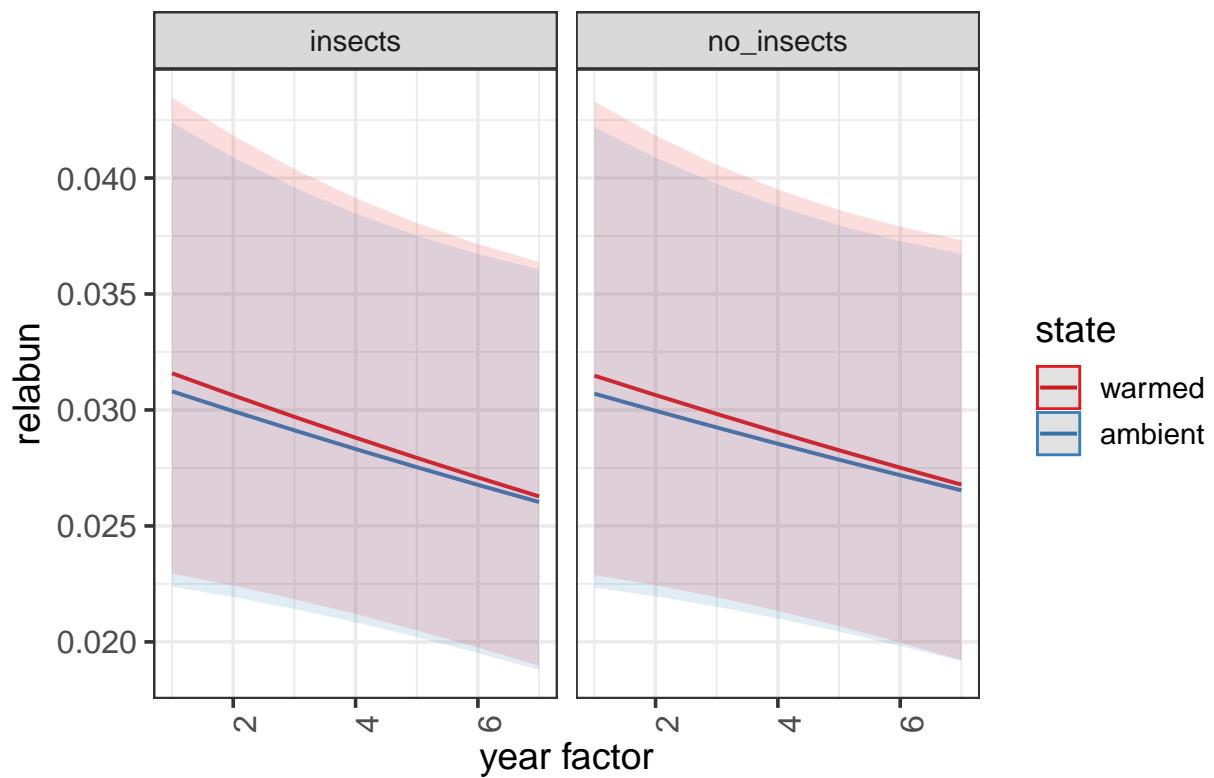
```
# Plot the fixed effects estimates for different models these are the fixed  
# effects estimates from summary(mod1)  
plot_model(mod2, sort.est = TRUE)
```



```
# these are the fixed predicted values:  
plot_model(mod2, type = "pred", terms = c("year_factor", "state", "insecticide"))
```

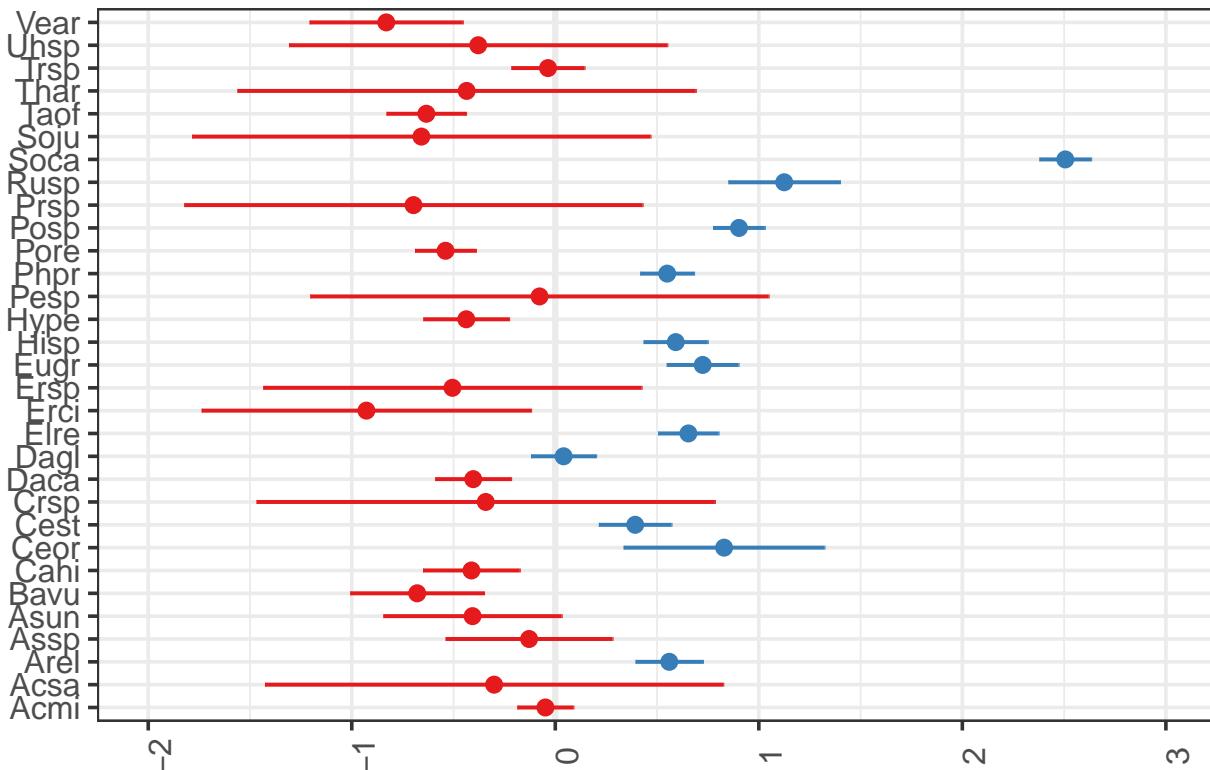
Model has log-transformed response. Back-transforming predictions to original response scale. Standard

Predicted values of relabun



```
# these are the random effects estimates
plot_model(mod2, type = "re", terms = c("species"))
```

Random effects



```
# Do we need to include insecticide? (dropping insecticide from the model) mod2
# <- lmer(log(relabun) ~ state*year_factor + insecticide*year_factor +
# (1/species), comp_kbs_spp, REML=FALSE)
mod3 <- lmer(log(relabun) ~ state * year_factor + (1 | species), comp_kbs_spp, REML = FALSE)
anova(mod2, mod3)
```

```
## Data: comp_kbs_spp
## Models:
## mod3: log(relabun) ~ state * year_factor + (1 | species)
## mod2: log(relabun) ~ state * year_factor + insecticide * year_factor +
## mod2: (1 | species)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod3     6 4632.7 4665.8 -2310.4    4620.7
## mod2     8 4636.7 4680.7 -2310.3    4620.7 0.0684  2      0.9664
```

```
AICctab(mod2, mod3, weights = T)
```

```
##      dAICc df weight
## mod3  0.0   6  0.88
## mod2  4.0   8  0.12
```

```
# Looks like no, pvalue > 0.05, so insecticide does not improve model fit so we
# will go with mod 3
```

```
# Does year need to be interactive with insecticide? - already removed
```

```

# insecticide mod4 <- lmer(log(relabun) ~ state*year_factor + insecticide +
# (1/species) + (1/plot), comp_kbs_spp, REML=FALSE)

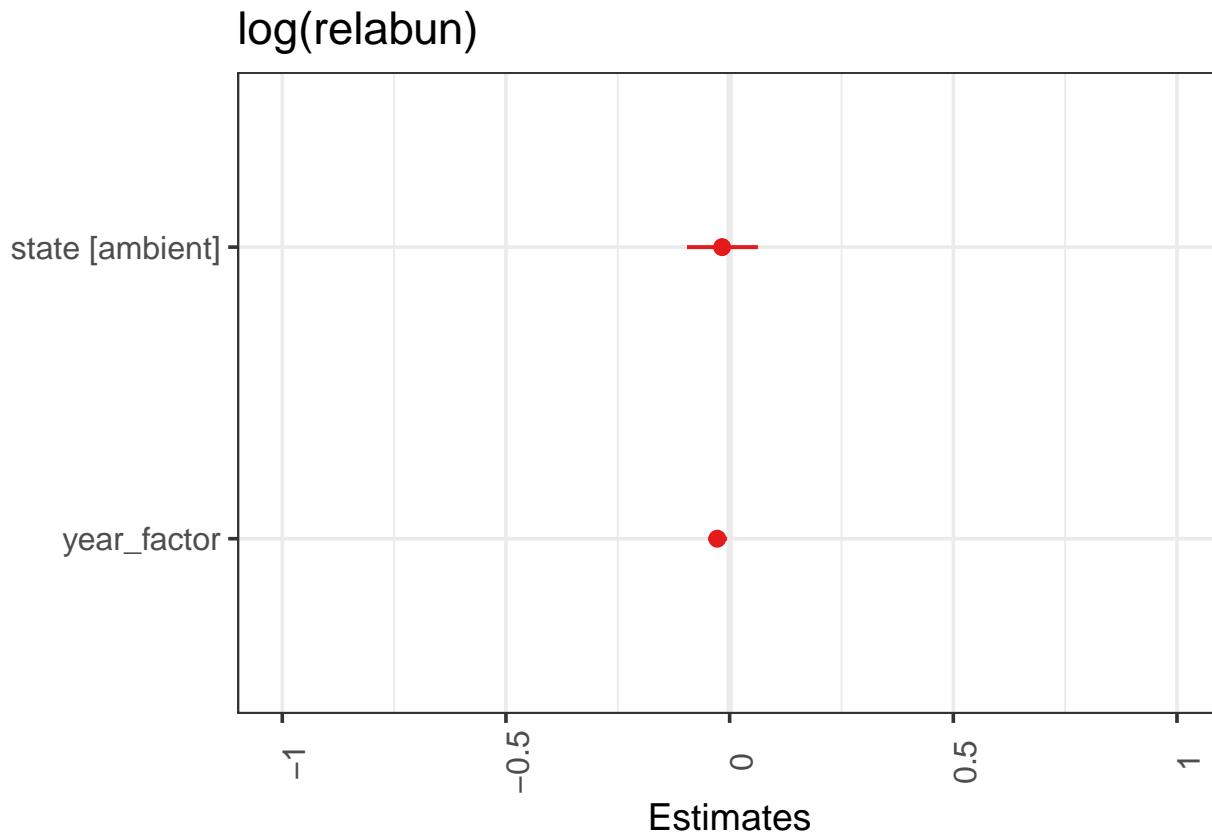
# Does year need to be interactive with state?
mod5 <- lmer(log(relabun) ~ state + year_factor + (1 | species), comp_kbs_spp, REML = FALSE)
anova(mod3, mod5)

## Data: comp_kbs_spp
## Models:
## mod5: log(relabun) ~ state + year_factor + (1 | species)
## mod3: log(relabun) ~ state * year_factor + (1 | species)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod5     5 4630.8 4658.3 -2310.4    4620.8
## mod3     6 4632.7 4665.8 -2310.4    4620.7  0.0244  1    0.8758

# No, P>0.05 so state*year_factor doesn't strongly improve model fit so we will
# shift to mod5, but AIC values are super close!!

# Plot the fixed effects estimates for different models these are the fixed
# effects estimates from summary(mod5)
plot_model(mod5, sort.est = TRUE)

```



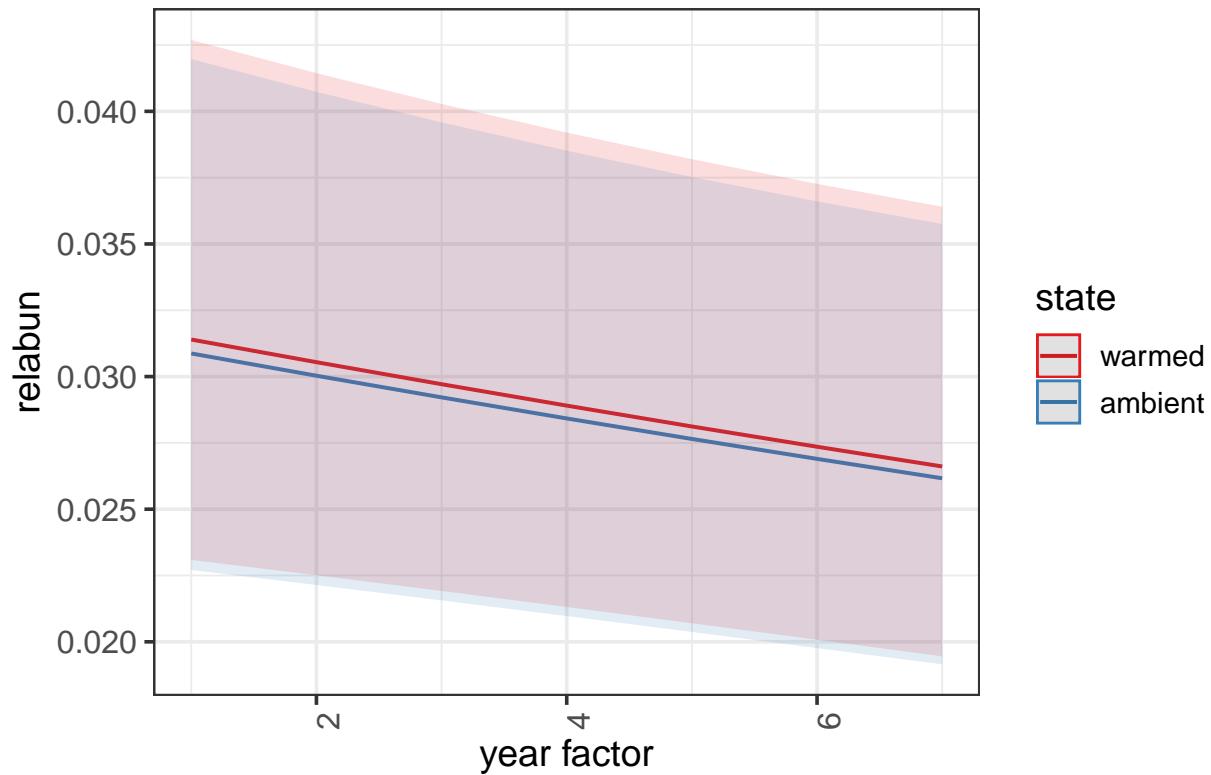
```

# these are the fixed predicted values:
plot_model(mod5, type = "pred", terms = c("year_factor", "state"))

```

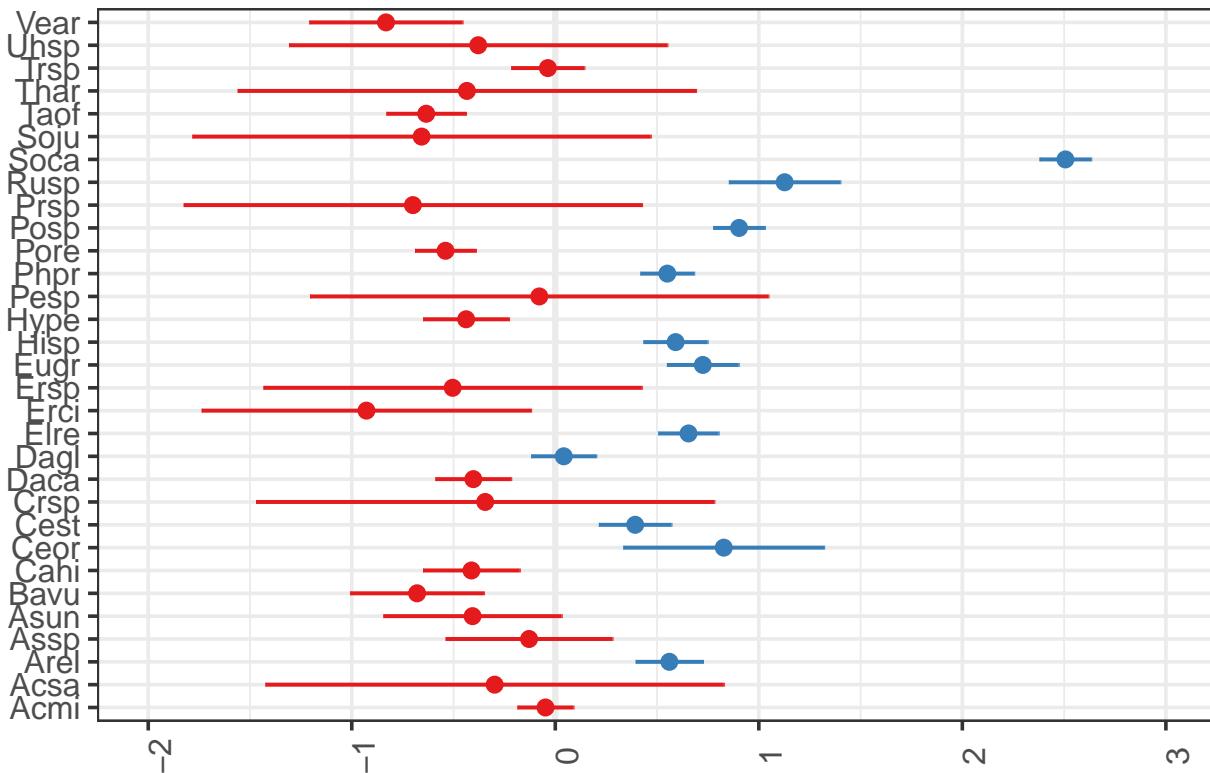
Model has log-transformed response. Back-transforming predictions to original response scale. Standardized residuals.

Predicted values of relabun



```
# these are the random effects estimates
plot_model(mod5, type = "re", terms = c("species"))
```

Random effects



```
# If we wanted to include plots nested within year it would look like this:
```

```
mod6 <- lmer(log(relabun) ~ state + year_factor + (1 | species) + (1 + year_factor | plot), comp_kbs_spp, REML = FALSE)
```

```
## boundary (singular) fit: see ?isSingular
```

```
## Warning: Model failed to converge with 1 negative eigenvalue: -1.9e+01
```

```
# Model failed to converge with 1 negative eigenvalue: -1.9e+00
anova(mod5, mod6)
```

```
## Data: comp_kbs_spp
```

```
## Models:
```

```
## mod5: log(relabun) ~ state + year_factor + (1 | species)
## mod6: log(relabun) ~ state + year_factor + (1 | species) + (1 + year_factor | plot)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod5     5 4630.8 4658.3 -2310.4    4620.8
## mod6     8 4636.5 4680.5 -2310.2    4620.5 0.2722  3    0.9652
```

```
anova(mod5)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
```

	Sum Sq	Mean Sq	NumDF	DenDF	F value	Pr(>F)
## state	0.1259	0.1259	1	1794.9	0.1784	0.672798

```

## year_factor 5.2852 5.2852      1 1803.5 7.4912 0.006261 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# mod4 (and mod5) are pretty complex in terms of interpretation (they actually
# don't have many parameters though). We could consider an alternative model
# that's simpler to understand and also one that provides more insight about the
# species. That would be something like this:
mod7 <- lmer(log(relabun) ~ state + species + (1 + factor(year_factor) | plot), comp_kbs_spp,
              REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod7a <- lmer(log(relabun) ~ state + species + factor(year_factor) + (1 | plot),
               comp_kbs_spp, REML = FALSE)
mod7b <- lmer(log(relabun) ~ state * factor(year_factor) + species + (1 | plot),
               comp_kbs_spp, REML = FALSE)
mod7c <- lmer(log(relabun) ~ state + species + factor(year_factor) + insecticide +
               (1 | plot), comp_kbs_spp, REML = FALSE)
anova(mod5, mod7) # model 7 is a better fit to data

## Data: comp_kbs_spp
## Models:
## mod5: log(relabun) ~ state + year_factor + (1 | species)
## mod7: log(relabun) ~ state + species + (1 + factor(year_factor) | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod5    5 4630.8 4658.3 -2310.4   4620.8
## mod7   61 4599.4 4935.2 -2238.7  4477.4 143.4 56  1.326e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(mod7, mod7a) #mod 7a

## Data: comp_kbs_spp
## Models:
## mod7a: log(relabun) ~ state + species + factor(year_factor) + (1 | plot)
## mod7b: log(relabun) ~ state * factor(year_factor) + species + (1 | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod7a   40 4526.0 4746.2 -2223.0   4446.0
## mod7b   61 4599.4 4935.2 -2238.7  4477.4      0 21           1

anova(mod7a, mod7b) #mod 7a - interaction between state and year does not improve model go with simple

## Data: comp_kbs_spp
## Models:
## mod7a: log(relabun) ~ state + species + factor(year_factor) + (1 | plot)
## mod7b: log(relabun) ~ state * factor(year_factor) + species + (1 | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod7a   40 4526 4746.2 -2223.0   4446
## mod7b   46 4533 4786.2 -2220.5  4441 4.9698  6     0.5477

```

```

anova(mod7a, mod7c)  #models are not different than one another, go with simpler model = mod7a

## Data: comp_kbs_spp
## Models:
## mod7a: log(relabun) ~ state + species + factor(year_factor) + (1 | plot)
## mod7c: log(relabun) ~ state + species + factor(year_factor) + insecticide +
## mod7c:      (1 | plot)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod7a    40 4526.0 4746.2 -2223.0   4446.0
## mod7c    41 4527.9 4753.6 -2222.9   4445.9  0.0743  1     0.7852

summary(mod7a)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(relabun) ~ state + species + factor(year_factor) + (1 | plot)
## Data: comp_kbs_spp
##
##      AIC      BIC  logLik deviance df.resid
## 4526.0 4746.2 -2223.0   4446.0     1778
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -2.8999 -0.6322 -0.0266  0.6582  3.2129
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.001051 0.03242
## Residual           0.674474 0.82126
## Number of obs: 1818, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept) -3.49208  0.08482 991.66088 -41.170 < 2e-16 ***
## stateambient -0.02111  0.04132 25.14843 -0.511 0.613795  
## speciesAcsa  -0.58737  0.82609 1817.09558 -0.711 0.477160  
## speciesArel   0.63389  0.10833 1811.85043  5.852 5.76e-09 ***
## speciesAssp  -0.12894  0.22370 1768.43494 -0.576 0.564410  
## speciesAsun  -0.40312  0.24020 1808.16036 -1.678 0.093466 .
## speciesBavu  -0.66849  0.18219 1816.18706 -3.669 0.000250 ***
## speciesCahi  -0.34196  0.13928 1812.42590 -2.455 0.014176 *  
## speciesCeor   1.05516  0.26968 1718.47460  3.913 9.48e-05 ***
## speciesCest   0.46134  0.11357 1808.59624  4.062 5.07e-05 ***
## speciesCrsp  -0.71193  0.82605 1816.56947 -0.862 0.388890  
## speciesDaca  -0.34892  0.11645 1812.41139 -2.996 0.002770 ** 
## speciesDagl   0.09496  0.10594 1811.04506  0.896 0.370162  
## speciesElre   0.69972  0.10197 1806.27959  6.862 9.31e-12 ***
## speciesErci  -1.25286  0.48151 1817.00942 -2.602 0.009345 ** 
## speciesErsp  -0.74372  0.58684 1817.36081 -1.267 0.205201  
## speciesEugr   0.80724  0.11258 1817.99980  7.170 1.08e-12 ***
## speciesHisp   0.69927  0.10532 1803.72462  6.640 4.15e-11 ***
## speciesHype  -0.39850  0.12673 1816.45240 -3.144 0.001691 **
```

```

## speciesPesp      -0.14053   0.82609 1817.55278 -0.170 0.864939
## speciesPhpr      0.60546   0.09565 1802.00193  6.330 3.09e-10 ***
## speciesPore     -0.48846   0.10192 1808.38590 -4.793 1.78e-06 ***
## speciesPosp      0.95873   0.09383 1799.61063 10.218 < 2e-16 ***
## speciesPrsp     -1.43795   0.82605 1816.56091 -1.741 0.081895 .
## speciesRusp      1.21613   0.15554 1718.13879  7.819 9.24e-15 ***
## speciesSoca      2.57299   0.09383 1799.61063 27.421 < 2e-16 ***
## speciesSoju     -1.38323   0.82612 1817.56258 -1.674 0.094229 .
## speciesTaof     -0.55969   0.12036 1817.98387 -4.650 3.56e-06 ***
## speciesThar     -0.88670   0.82609 1816.97798 -1.073 0.283248
## speciesTrsp      0.06316   0.11413 1806.83812  0.553 0.580073
## speciesUhsp     -0.57186   0.58683 1817.23884 -0.974 0.329945
## speciesVear     -0.76051   0.20647 1817.54411 -3.683 0.000237 ***
## factor(year_factor)2 -0.25667   0.06719 1799.77733 -3.820 0.000138 ***
## factor(year_factor)3  0.19701   0.07426 1807.20791  2.653 0.008046 **
## factor(year_factor)4 -0.10085   0.07125 1808.64692 -1.415 0.157108
## factor(year_factor)5 -0.12596   0.07150 1814.15732 -1.762 0.078301 .
## factor(year_factor)6 -0.10747   0.07254 1815.10992 -1.482 0.138644
## factor(year_factor)7 -0.30491   0.07361 1817.31191 -4.142 3.60e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 38 > 12.
## Use print(x, correlation=TRUE)  or
##      vcov(x)      if you need it

```

```
summ(mod7a)
```

Observations	1818
Dependent variable	log(relabun)
Type	Mixed effects linear regression

AIC	4525.97
BIC	4746.19
Pseudo-R ² (fixed effects)	0.52
Pseudo-R ² (total)	0.52

```
anova(mod7a) # investigates whether at least one of the levels within each factor is significantly dif
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##          Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state        0.18   0.176     1   25.15  0.2611   0.6138
## species     1287.05  42.902    30 1807.33 63.6078 < 2.2e-16 ***
## factor(year_factor) 39.41   6.568      6 1809.89  9.7383 1.401e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	-3.49	0.08	-41.17	991.66	0.00
stateambient	-0.02	0.04	-0.51	25.15	0.61
speciesAcsa	-0.59	0.83	-0.71	1817.10	0.48
speciesArel	0.63	0.11	5.85	1811.85	0.00
speciesAssp	-0.13	0.22	-0.58	1768.43	0.56
speciesAsun	-0.40	0.24	-1.68	1808.16	0.09
speciesBavu	-0.67	0.18	-3.67	1816.19	0.00
speciesCahi	-0.34	0.14	-2.46	1812.43	0.01
speciesCeor	1.06	0.27	3.91	1718.47	0.00
speciesCest	0.46	0.11	4.06	1808.60	0.00
speciesCrsp	-0.71	0.83	-0.86	1816.57	0.39
speciesDaca	-0.35	0.12	-3.00	1812.41	0.00
speciesDagl	0.09	0.11	0.90	1811.05	0.37
speciesElre	0.70	0.10	6.86	1806.28	0.00
speciesErci	-1.25	0.48	-2.60	1817.01	0.01
speciesErsp	-0.74	0.59	-1.27	1817.36	0.21
speciesEugr	0.81	0.11	7.17	1818.00	0.00
speciesHisp	0.70	0.11	6.64	1803.72	0.00
speciesHype	-0.40	0.13	-3.14	1816.45	0.00
speciesPesp	-0.14	0.83	-0.17	1817.55	0.86
speciesPhpr	0.61	0.10	6.33	1802.00	0.00
speciesPore	-0.49	0.10	-4.79	1808.39	0.00
speciesPosp	0.96	0.09	10.22	1799.61	0.00
speciesPrsp	-1.44	0.83	-1.74	1816.56	0.08
speciesRusp	1.22	0.16	7.82	1718.14	0.00
speciesSoca	2.57	0.09	27.42	1799.61	0.00
speciesSoju	-1.38	0.83	-1.67	1817.56	0.09
speciesTaof	-0.56	0.12	-4.65	1817.98	0.00
speciesThar	-0.89	0.83	-1.07	1816.98	0.28
speciesTrsp	0.06	0.11	0.55	1806.84	0.58
speciesUhsp	-0.57	0.59	-0.97	1817.24	0.33
speciesVear	-0.76	0.21	-3.68	1817.54	0.00
factor(year_factor)2	-0.26	0.07	-3.82	1799.78	0.00
factor(year_factor)3	0.20	0.07	2.65	1807.21	0.01
factor(year_factor)4	-0.10	0.07	-1.42	1808.65	0.16
factor(year_factor)5	-0.13	0.07	-1.76	1814.16	0.08
factor(year_factor)6	-0.11	0.07	-1.48	1815.11	0.14
factor(year_factor)7	-0.30	0.07	-4.14	1817.31	0.00

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.03
	Residual	0.82

Grouping Variables		
Group	# groups	ICC
plot	24	0.00

```
# Yes, at least one of the species is different (they do not all have the same
# relative abundances).
emmeans(mod7a, list(pairwise ~ state + year_factor), adjust = "tukey")
```

```
## $`emmmeans of state, year_factor`
##   state  year_factor emmean      SE   df lower.CL upper.CL
##   warmed          1 -3.55 0.0851  976   -3.72   -3.39
##   ambient          1 -3.58 0.0851  977   -3.74   -3.41
##   warmed          2 -3.81 0.0921 1126   -3.99   -3.63
##   ambient          2 -3.83 0.0917 1123   -4.01   -3.65
##   warmed          3 -3.36 0.0976 1227   -3.55   -3.17
##   ambient          3 -3.38 0.0969 1214   -3.57   -3.19
##   warmed          4 -3.66 0.0948 1161   -3.84   -3.47
##   ambient          4 -3.68 0.0942 1165   -3.86   -3.49
##   warmed          5 -3.68 0.0956 1172   -3.87   -3.49
##   ambient          5 -3.70 0.0944 1166   -3.89   -3.52
##   warmed          6 -3.66 0.0963 1179   -3.85   -3.47
##   ambient          6 -3.68 0.0954 1176   -3.87   -3.50
##   warmed          7 -3.86 0.0972 1180   -4.05   -3.67
##   ambient          7 -3.88 0.0964 1187   -4.07   -3.69
##
## Results are averaged over the levels of: species
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, year_factor`
##   estimate      SE   df t.ratio p.value
##   warmed 1 - ambient 1  0.02111 0.0436  27.1  0.485  1.0000
##   warmed 1 - warmed 2  0.25667 0.0679 1835.7  3.781  0.0118
##   warmed 1 - ambient 2  0.27778 0.0802  318.5  3.465  0.0384
##   warmed 1 - warmed 3 -0.19701 0.0750 1843.8 -2.625  0.3248
##   warmed 1 - ambient 3 -0.17590 0.0859  397.2 -2.048  0.7364
##   warmed 1 - warmed 4  0.10085 0.0720 1845.3  1.400  0.9820
##   warmed 1 - ambient 4  0.12197 0.0835  364.7  1.460  0.9735
##   warmed 1 - warmed 5  0.12596 0.0723 1851.6  1.742  0.9005
##   warmed 1 - ambient 5  0.14707 0.0831  352.8  1.770  0.8878
##   warmed 1 - warmed 6  0.10747 0.0733 1852.7  1.465  0.9735
##   warmed 1 - ambient 6  0.12858 0.0843  367.7  1.526  0.9621
##   warmed 1 - warmed 7  0.30491 0.0745 1855.5  4.095  0.0035
##   warmed 1 - ambient 7  0.32602 0.0852  381.0  3.825  0.0111
##   ambient 1 - warmed 2  0.23556 0.0811  328.4  2.903  0.1815
##   ambient 1 - ambient 2  0.25667 0.0679 1835.7  3.781  0.0118
##   ambient 1 - warmed 3 -0.21813 0.0876  422.9 -2.489  0.4180
##   ambient 1 - ambient 3 -0.19701 0.0750 1843.8 -2.625  0.3248
##   ambient 1 - warmed 4  0.07974 0.0848  372.8  0.940  0.9996
##   ambient 1 - ambient 4  0.10085 0.0720 1845.3  1.400  0.9820
```

```

## ambient 1 - warmed 5  0.10484 0.0857  379.5  1.223  0.9946
## ambient 1 - ambient 5 0.12596 0.0723 1851.6  1.742  0.9005
## ambient 1 - warmed 6  0.08635 0.0864  388.6  1.000  0.9993
## ambient 1 - ambient 6 0.10747 0.0733 1852.7  1.465  0.9735
## ambient 1 - warmed 7  0.28380 0.0873  393.6  3.252  0.0722
## ambient 1 - ambient 7 0.30491 0.0745 1855.5  4.095  0.0035
## warmed 2 - ambient 2  0.02111 0.0436   27.1  0.485  1.0000
## warmed 2 - warmed 3  -0.45369 0.0740 1841.4 -6.131 <.0001
## warmed 2 - ambient 3 -0.43257 0.0855  390.0 -5.062  0.0001
## warmed 2 - warmed 4  -0.15582 0.0710 1844.3 -2.195  0.6331
## warmed 2 - ambient 4 -0.13470 0.0831  357.1 -1.621  0.9396
## warmed 2 - warmed 5  -0.13072 0.0712 1849.5 -1.836  0.8598
## warmed 2 - ambient 5 -0.10960 0.0826  346.4 -1.327  0.9885
## warmed 2 - warmed 6  -0.14920 0.0728 1849.4 -2.050  0.7355
## warmed 2 - ambient 6 -0.12809 0.0842  369.2 -1.521  0.9632
## warmed 2 - warmed 7  0.04824 0.0739 1854.4  0.653  1.0000
## warmed 2 - ambient 7 0.06935 0.0852  380.6  0.814  0.9999
## ambient 2 - warmed 3 -0.47480 0.0863  405.9 -5.502 <.0001
## ambient 2 - ambient 3 -0.45369 0.0740 1841.4 -6.131 <.0001
## ambient 2 - warmed 4 -0.17693 0.0835  355.6 -2.120  0.6872
## ambient 2 - ambient 4 -0.15582 0.0710 1844.3 -2.195  0.6331
## ambient 2 - warmed 5 -0.15183 0.0843  363.6 -1.800  0.8750
## ambient 2 - ambient 5 -0.13072 0.0712 1849.5 -1.836  0.8598
## ambient 2 - warmed 6 -0.17032 0.0854  380.5 -1.994  0.7708
## ambient 2 - ambient 6 -0.14920 0.0728 1849.4 -2.050  0.7355
## ambient 2 - warmed 7  0.02712 0.0863  383.7  0.314  1.0000
## ambient 2 - ambient 7 0.04824 0.0739 1854.4  0.653  1.0000
## warmed 3 - ambient 3  0.02111 0.0436   27.1  0.485  1.0000
## warmed 3 - warmed 4  0.29787 0.0770 1839.8  3.866  0.0086
## warmed 3 - ambient 4 0.31898 0.0887  450.8  3.595  0.0244
## warmed 3 - warmed 5  0.32297 0.0774 1842.9  4.174  0.0025
## warmed 3 - ambient 5 0.34408 0.0884  442.9  3.893  0.0085
## warmed 3 - warmed 6  0.30448 0.0782 1845.8  3.892  0.0078
## warmed 3 - ambient 6 0.32560 0.0894  455.1  3.643  0.0207
## warmed 3 - warmed 7  0.50192 0.0790 1854.3  6.354 <.0001
## warmed 3 - ambient 7 0.52304 0.0900  457.6  5.808 <.0001
## ambient 3 - warmed 4 0.27675 0.0883  432.0  3.135  0.0997
## ambient 3 - ambient 4 0.29787 0.0770 1839.8  3.866  0.0086
## ambient 3 - warmed 5 0.30186 0.0892  443.3  3.384  0.0483
## ambient 3 - ambient 5 0.32297 0.0774 1842.9  4.174  0.0025
## ambient 3 - warmed 6 0.28337 0.0897  449.7  3.159  0.0933
## ambient 3 - ambient 6 0.30448 0.0782 1845.8  3.892  0.0078
## ambient 3 - warmed 7 0.48081 0.0904  443.2  5.321 <.0001
## ambient 3 - ambient 7 0.50192 0.0790 1854.3  6.354 <.0001
## warmed 4 - ambient 4  0.02111 0.0436   27.1  0.485  1.0000
## warmed 4 - warmed 5  0.02510 0.0745 1841.8  0.337  1.0000
## warmed 4 - ambient 5 0.04622 0.0857  395.3  0.539  1.0000
## warmed 4 - warmed 6  0.00662 0.0751 1845.8  0.088  1.0000
## warmed 4 - ambient 6 0.02773 0.0864  402.6  0.321  1.0000
## warmed 4 - warmed 7  0.20406 0.0764 1852.7  2.671  0.2963
## warmed 4 - ambient 7 0.22517 0.0875  415.6  2.572  0.3617
## ambient 4 - warmed 5  0.00399 0.0870  414.4  0.046  1.0000
## ambient 4 - ambient 5 0.02510 0.0745 1841.8  0.337  1.0000
## ambient 4 - warmed 6 -0.01450 0.0872  415.9 -0.166  1.0000

```

```

##  ambient 4 - ambient 6  0.00662 0.0751 1845.8  0.088  1.0000
##  ambient 4 - warmed 7   0.18294 0.0883  420.1  2.071  0.7206
##  ambient 4 - ambient 7   0.20406 0.0764 1852.7  2.671  0.2963
##  warmed 5 - ambient 5   0.02111 0.0436   27.1  0.485  1.0000
##  warmed 5 - warmed 6   -0.01849 0.0755 1836.3 -0.245  1.0000
##  warmed 5 - ambient 6   0.00263 0.0874  424.5  0.030  1.0000
##  warmed 5 - warmed 7    0.17895 0.0765 1846.9  2.341  0.5246
##  warmed 5 - ambient 7   0.20007 0.0883  433.5  2.267  0.5804
##  ambient 5 - warmed 6   -0.03960 0.0869  418.8 -0.456  1.0000
##  ambient 5 - ambient 6   -0.01849 0.0755 1836.3 -0.245  1.0000
##  ambient 5 - warmed 7    0.15784 0.0877  419.0  1.799  0.8757
##  ambient 5 - ambient 7   0.17895 0.0765 1846.9  2.341  0.5246
##  warmed 6 - ambient 6   0.02111 0.0436   27.1  0.485  1.0000
##  warmed 6 - warmed 7    0.19744 0.0768 1846.3  2.571  0.3599
##  warmed 6 - ambient 7   0.21855 0.0883  436.0  2.475  0.4278
##  ambient 6 - warmed 7    0.17633 0.0883  427.1  1.997  0.7687
##  ambient 6 - ambient 7   0.19744 0.0768 1846.3  2.571  0.3599
##  warmed 7 - ambient 7   0.02111 0.0436   27.1  0.485  1.0000
##
## Results are averaged over the levels of: species
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 14 estimates

```

```
emmeans(mod7a, list(pairwise ~ year_factor), adjust = "tukey")
```

```

## $`emmeans of year_factor`
##   year_factor emmean     SE   df lower.CL upper.CL
##       1      -3.57 0.0822 1512    -3.73    -3.40
##       2      -3.82 0.0892 1602    -4.00    -3.65
##       3      -3.37 0.0948 1648    -3.55    -3.18
##       4      -3.67 0.0920 1616    -3.85    -3.49
##       5      -3.69 0.0925 1617    -3.87    -3.51
##       6      -3.67 0.0934 1618    -3.86    -3.49
##       7      -3.87 0.0943 1616    -4.06    -3.69
##
## Results are averaged over the levels of: state, species
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of year_factor`
##   1   estimate     SE   df t.ratio p.value
##   1 - 2  0.25667 0.0679 1836   3.781  0.0031
##   1 - 3 -0.19701 0.0750 1844  -2.625  0.1190
##   1 - 4  0.10085 0.0720 1845   1.400  0.8018
##   1 - 5  0.12596 0.0723 1852   1.742  0.5874
##   1 - 6  0.10747 0.0733 1853   1.465  0.7655
##   1 - 7  0.30491 0.0745 1855   4.095  0.0009
##   2 - 3 -0.45369 0.0740 1841  -6.131 <.0001
##   2 - 4 -0.15582 0.0710 1844  -2.195  0.2984
##   2 - 5 -0.13072 0.0712 1850  -1.836  0.5240
##   2 - 6 -0.14920 0.0728 1849  -2.050  0.3834
##   2 - 7  0.04824 0.0739 1854   0.653  0.9949

```

```

## 3 - 4  0.29787 0.0770 1840  3.866  0.0022
## 3 - 5  0.32297 0.0774 1843  4.174  0.0006
## 3 - 6  0.30448 0.0782 1846  3.892  0.0020
## 3 - 7  0.50192 0.0790 1854  6.354  <.0001
## 4 - 5  0.02510 0.0745 1842  0.337  0.9999
## 4 - 6  0.00662 0.0751 1846  0.088  1.0000
## 4 - 7  0.20406 0.0764 1853  2.671  0.1061
## 5 - 6 -0.01849 0.0755 1836 -0.245  1.0000
## 5 - 7  0.17895 0.0765 1847  2.341  0.2252
## 6 - 7  0.19744 0.0768 1846  2.571  0.1355
##
## Results are averaged over the levels of: state, species
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 7 estimates

emmeans(mod7a, list(pairwise ~ species), adjust = "tukey")

## $`emmeans of species`
##   species emmean    SE  df lower.CL upper.CL
##   Acmi     -3.60 0.0703 1327   -3.74   -3.464
##   Acsa     -4.19 0.8328 1856   -5.82   -2.557
##   Arel     -2.97 0.0848 1510   -3.13   -2.802
##   Assp     -3.73 0.2162 1745   -4.16   -3.307
##   Asun     -4.01 0.2327 1857   -4.46   -3.549
##   Bavu     -4.27 0.1709 1790   -4.61   -3.936
##   Cahi     -3.94 0.1229 1787   -4.19   -3.703
##   Ceor     -2.55 0.2649 1714   -3.07   -2.028
##   Cest     -3.14 0.0922 1632   -3.32   -2.960
##   Crsp     -4.31 0.8328 1855   -5.95   -2.681
##   Daca     -3.95 0.0957 1634   -4.14   -3.764
##   Dagl     -3.51 0.0817 1496   -3.67   -3.347
##   Elre     -2.90 0.0760 1459   -3.05   -2.754
##   Erci     -4.86 0.4822 1856   -5.80   -3.910
##   Ersp     -4.35 0.5896 1856   -5.50   -3.190
##   Eugr     -2.80 0.0904 1490   -2.97   -2.618
##   Hisp     -2.90 0.0811 1515   -3.06   -2.744
##   Hype     -4.00 0.1081 1614   -4.21   -3.789
##   Pesp     -3.74 0.8328 1857   -5.38   -2.110
##   Phpr     -3.00 0.0675 1263   -3.13   -2.865
##   Pore     -4.09 0.0766 1420   -4.24   -3.941
##   Posp     -2.64 0.0648 1199   -2.77   -2.517
##   Prsp     -5.04 0.8328 1855   -6.67   -3.407
##   Rusp     -2.39 0.1419 1556   -2.66   -2.108
##   Soca     -1.03 0.0648 1199   -1.16   -0.902
##   Soju     -4.99 0.8327 1856   -6.62   -3.353
##   Taof     -4.16 0.1004 1623   -4.36   -3.965
##   Thar     -4.49 0.8327 1856   -6.12   -2.856
##   Trsp     -3.54 0.0926 1650   -3.72   -3.358
##   Uhsp     -4.17 0.5896 1856   -5.33   -3.018
##   Vear     -4.36 0.1972 1846   -4.75   -3.976
##
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger

```

```

## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $'pairwise differences of species'
##   1           estimate    SE  df t.ratio p.value
## Acmi - Acsa  0.587373 0.8355 1855   0.703 1.0000
## Acmi - Arel -0.633887 0.1095 1849  -5.789 <.0001
## Acmi - Assp  0.128943 0.2269 1818   0.568 1.0000
## Acmi - Asun  0.403123 0.2428 1845   1.661 0.9990
## Acmi - Bavu  0.668493 0.1844 1856   3.625 0.0806
## Acmi - Cahi  0.341964 0.1408 1850   2.429 0.8390
## Acmi - Ceor -1.055158 0.2737 1765  -3.854 0.0375
## Acmi - Cest -0.461344 0.1148 1845  -4.019 0.0205
## Acmi - Crsp  0.711927 0.8356 1854   0.852 1.0000
## Acmi - Daca  0.348916 0.1177 1849   2.964 0.4280
## Acmi - Dagl -0.094964 0.1071 1848  -0.887 1.0000
## Acmi - Elre -0.699721 0.1030 1843  -6.790 <.0001
## Acmi - Erci  1.252857 0.4870 1855   2.573 0.7439
## Acmi - Ersp  0.743720 0.5936 1856   1.253 1.0000
## Acmi - Eugr -0.807237 0.1139 1857  -7.087 <.0001
## Acmi - Hisp -0.699273 0.1064 1840  -6.571 <.0001
## Acmi - Hype  0.398498 0.1283 1856   3.107 0.3216
## Acmi - Pesp  0.140530 0.8355 1856   0.168 1.0000
## Acmi - Phpr -0.605460 0.0966 1838  -6.265 <.0001
## Acmi - Pore  0.488459 0.1030 1845   4.742 0.0009
## Acmi - Posp -0.958730 0.0948 1836 -10.114 <.0001
## Acmi - Prsp  1.437955 0.8355 1854   1.721 0.9982
## Acmi - Rusp -1.216127 0.1579 1768  -7.701 <.0001
## Acmi - Soca -2.572992 0.0948 1836 -27.143 <.0001
## Acmi - Soju  1.383233 0.8355 1856   1.656 0.9991
## Acmi - Taof  0.559692 0.1218 1857   4.596 0.0019
## Acmi - Thar  0.886698 0.8356 1855   1.061 1.0000
## Acmi - Trsp -0.063156 0.1153 1843  -0.548 1.0000
## Acmi - Uhsp  0.571862 0.5935 1856   0.964 1.0000
## Acmi - Vear  0.760508 0.2089 1856   3.641 0.0765
## Acsa - Arel -1.221260 0.8371 1855  -1.459 0.9999
## Acsa - Assp -0.458430 0.8602 1857  -0.533 1.0000
## Acsa - Asun -0.184251 0.8650 1854  -0.213 1.0000
## Acsa - Bavu  0.081120 0.8500 1855   0.095 1.0000
## Acsa - Cahi -0.245409 0.8420 1856  -0.291 1.0000
## Acsa - Ceor -1.642532 0.8738 1857  -1.880 0.9925
## Acsa - Cest -1.048717 0.8375 1856  -1.252 1.0000
## Acsa - Crsp  0.124554 1.1761 1854   0.106 1.0000
## Acsa - Daca -0.238457 0.8380 1856  -0.285 1.0000
## Acsa - Dagl -0.682338 0.8367 1856  -0.815 1.0000
## Acsa - Elre -1.287094 0.8364 1856  -1.539 0.9998
## Acsa - Erci  0.665484 0.9602 1856   0.693 1.0000
## Acsa - Ersp  0.156347 1.0183 1856   0.154 1.0000
## Acsa - Eugr -1.394611 0.8373 1855  -1.666 0.9990
## Acsa - Hisp -1.286647 0.8363 1855  -1.538 0.9998
## Acsa - Hype -0.188876 0.8394 1856  -0.225 1.0000
## Acsa - Pesp -0.446843 1.1762 1856  -0.380 1.0000
## Acsa - Phpr -1.192833 0.8354 1856  -1.428 0.9999
## Acsa - Pore -0.098914 0.8362 1856  -0.118 1.0000

```

```

##  Acsa - Posp -1.546103 0.8352 1855 -1.851 0.9940
##  Acsa - Prsp  0.850581 1.1761 1855  0.723 1.0000
##  Acsa - Rusp -1.803500 0.8447 1856 -2.135 0.9578
##  Acsa - Soca -3.160366 0.8352 1855 -3.784 0.0478
##  Acsa - Soju  0.795860 1.1757 1856  0.677 1.0000
##  Acsa - Taof  -0.027681 0.8383 1854 -0.033 1.0000
##  Acsa - Thar  0.299325 1.1757 1856  0.255 1.0000
##  Acsa - Trsp  -0.650530 0.8373 1855 -0.777 1.0000
##  Acsa - Uhsp  -0.015511 1.0183 1856 -0.015 1.0000
##  Acsa - Vear  0.173135 0.8556 1856  0.202 1.0000
##  Arel - Assp  0.762830 0.2321 1806  3.287 0.2106
##  Arel - Asun  1.037010 0.2474 1848  4.192 0.0105
##  Arel - Bavu  1.302380 0.1902 1856  6.849 <.0001
##  Arel - Cahí  0.975851 0.1492 1856  6.541 <.0001
##  Arel - Ceor  -0.421271 0.2778 1764 -1.516 0.9998
##  Arel - Cest  0.172543 0.1251 1857  1.379 1.0000
##  Arel - Crsp  1.345814 0.8371 1854  1.608 0.9994
##  Arel - Daca  0.982803 0.1273 1855  7.718 <.0001
##  Arel - Dagl  0.538922 0.1168 1849  4.613 0.0017
##  Arel - Elre  -0.065834 0.1129 1852 -0.583 1.0000
##  Arel - Ercí  1.886744 0.4897 1855  3.853 0.0376
##  Arel - Ersp  1.377607 0.5957 1855  2.313 0.8984
##  Arel - Eugr  -0.173350 0.1232 1855 -1.408 1.0000
##  Arel - Hisp  -0.065386 0.1167 1853 -0.560 1.0000
##  Arel - Hype  1.032385 0.1368 1857  7.548 <.0001
##  Arel - Pesp  0.774417 0.8371 1857  0.925 1.0000
##  Arel - Phpr  0.028427 0.1076 1851  0.264 1.0000
##  Arel - Pore  1.122346 0.1135 1853  9.890 <.0001
##  Arel - Posp  -0.324843 0.1060 1851 -3.066 0.3505
##  Arel - Prsp  2.071842 0.8370 1854  2.475 0.8106
##  Arel - Rusp  -0.582240 0.1646 1807 -3.537 0.1055
##  Arel - Soca -1.939105 0.1060 1851 -18.301 <.0001
##  Arel - Soju  2.017120 0.8371 1856  2.410 0.8499
##  Arel - Taof  1.193579 0.1308 1857  9.123 <.0001
##  Arel - Thar  1.520585 0.8371 1855  1.817 0.9956
##  Arel - Trsp  0.570731 0.1250 1852  4.564 0.0021
##  Arel - Uhsp  1.205749 0.5958 1856  2.024 0.9786
##  Arel - Vear  1.394395 0.2145 1856  6.501 <.0001
##  Assp - Asun  0.274180 0.3186 1850  0.861 1.0000
##  Assp - Bavu  0.539550 0.2751 1838  1.961 0.9861
##  Assp - Cahí  0.213021 0.2479 1850  0.859 1.0000
##  Assp - Ceor  -1.184101 0.3420 1756 -3.462 0.1314
##  Assp - Cest  -0.590287 0.2346 1821 -2.516 0.7839
##  Assp - Crsp  0.582984 0.8594 1849  0.678 1.0000
##  Assp - Daca  0.219973 0.2354 1849  0.934 1.0000
##  Assp - Dagl  -0.223907 0.2309 1821 -0.970 1.0000
##  Assp - Elre  -0.828664 0.2290 1812 -3.619 0.0822
##  Assp - Ercí  1.123915 0.5280 1857  2.129 0.9594
##  Assp - Ersp  0.614777 0.6278 1857  0.979 1.0000
##  Assp - Eugr  -0.936180 0.2338 1836 -4.004 0.0218
##  Assp - Hisp  -0.828216 0.2307 1829 -3.590 0.0897
##  Assp - Hype  0.269555 0.2413 1824  1.117 1.0000
##  Assp - Pesp  0.011587 0.8602 1857  0.013 1.0000
##  Assp - Phpr  -0.734403 0.2261 1818 -3.248 0.2321

```

```

## Assp - Pore 0.359516 0.2289 1830 1.571 0.9996
## Assp - Posp -1.087672 0.2254 1813 -4.826 0.0006
## Assp - Prsp 1.309012 0.8603 1856 1.522 0.9998
## Assp - Rusp -1.345070 0.2580 1826 -5.214 0.0001
## Assp - Soca -2.701935 0.2254 1813 -11.988 <.0001
## Assp - Soju 1.254290 0.8601 1857 1.458 0.9999
## Assp - Taof 0.430749 0.2380 1827 1.810 0.9958
## Assp - Thar 0.757756 0.8600 1856 0.881 1.0000
## Assp - Trsp -0.192099 0.2346 1839 -0.819 1.0000
## Assp - Uhsp 0.442919 0.6278 1857 0.705 1.0000
## Assp - Vear 0.631565 0.2915 1856 2.166 0.9499
## Asun - Bavu 0.265371 0.2886 1857 0.919 1.0000
## Asun - Cahi -0.061159 0.2631 1849 -0.232 1.0000
## Asun - Ceor -1.458281 0.3523 1840 -4.139 0.0129
## Asun - Cest -0.864467 0.2499 1844 -3.459 0.1325
## Asun - Crsp 0.308804 0.8651 1855 0.357 1.0000
## Asun - Daca -0.054207 0.2517 1848 -0.215 1.0000
## Asun - Dagl -0.498087 0.2461 1850 -2.024 0.9786
## Asun - Elre -1.102844 0.2443 1848 -4.514 0.0027
## Asun - Erci 0.849735 0.5358 1854 1.586 0.9996
## Asun - Ersp 0.340598 0.6341 1853 0.537 1.0000
## Asun - Eugr -1.210360 0.2494 1850 -4.852 0.0006
## Asun - Hisp -1.102396 0.2458 1845 -4.485 0.0031
## Asun - Hype -0.004625 0.2563 1856 -0.018 1.0000
## Asun - Pesp -0.262592 0.8646 1855 -0.304 1.0000
## Asun - Phpr -1.008583 0.2422 1847 -4.165 0.0117
## Asun - Pore 0.085336 0.2446 1847 0.349 1.0000
## Asun - Posp -1.361852 0.2413 1846 -5.645 <.0001
## Asun - Prsp 1.034832 0.8650 1855 1.196 1.0000
## Asun - Rusp -1.619250 0.2723 1849 -5.948 <.0001
## Asun - Soca -2.976115 0.2413 1846 -12.336 <.0001
## Asun - Soju 0.980110 0.8652 1856 1.133 1.0000
## Asun - Taof 0.156569 0.2531 1850 0.619 1.0000
## Asun - Thar 0.483576 0.8650 1853 0.559 1.0000
## Asun - Trsp -0.466279 0.2506 1847 -1.860 0.9936
## Asun - Uhsp 0.168739 0.6343 1855 0.266 1.0000
## Asun - Vear 0.357386 0.3053 1851 1.170 1.0000
## Bavu - Cahi -0.326529 0.2100 1857 -1.555 0.9997
## Bavu - Ceor -1.723652 0.3156 1782 -5.461 <.0001
## Bavu - Cest -1.129837 0.1945 1852 -5.809 <.0001
## Bavu - Crsp 0.043434 0.8500 1850 0.051 1.0000
## Bavu - Daca -0.319577 0.1957 1856 -1.633 0.9993
## Bavu - Dagl -0.763458 0.1889 1855 -4.042 0.0188
## Bavu - Elre -1.368214 0.1863 1851 -7.344 <.0001
## Bavu - Erci 0.584364 0.5121 1857 1.141 1.0000
## Bavu - Ersp 0.075227 0.6141 1856 0.123 1.0000
## Bavu - Eugr -1.475731 0.1927 1856 -7.659 <.0001
## Bavu - Hisp -1.367767 0.1890 1854 -7.236 <.0001
## Bavu - Hype -0.269996 0.2017 1851 -1.339 1.0000
## Bavu - Pesp -0.527963 0.8505 1857 -0.621 1.0000
## Bavu - Phpr -1.273953 0.1832 1853 -6.952 <.0001
## Bavu - Pore -0.180034 0.1872 1849 -0.962 1.0000
## Bavu - Posp -1.627223 0.1823 1853 -8.925 <.0001
## Bavu - Prsp 0.769462 0.8505 1855 0.905 1.0000

```

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##  Bavu - Rusp -1.884620 0.2220 1817 -8.489 <.0001
##  Bavu - Soca -3.241486 0.1823 1853 -17.779 <.0001
##  Bavu - Soju  0.714740 0.8501 1857  0.841 1.0000
##  Bavu - Taof -0.108801 0.1985 1843 -0.548 1.0000
##  Bavu - Thar  0.218205 0.8499 1855  0.257 1.0000
##  Bavu - Trsp -0.731650 0.1944 1857 -3.764 0.0512
##  Bavu - Uhsp -0.096631 0.6142 1857 -0.157 1.0000
##  Bavu - Vear  0.092015 0.2611 1857  0.352 1.0000
##  Cahi - Ceor -1.397122 0.2914 1819 -4.795 0.0007
##  Cahi - Cest -0.803308 0.1524 1852 -5.269 0.0001
##  Cahi - Crsp  0.369963 0.8422 1854  0.439 1.0000
##  Cahi - Daca  0.006952 0.1548 1847  0.045 1.0000
##  Cahi - Dagl -0.436928 0.1474 1855 -2.964 0.4278
##  Cahi - Elre -1.041685 0.1442 1853 -7.221 <.0001
##  Cahi - Erci  0.910894 0.4981 1854  1.829 0.9951
##  Cahi - Ersp  0.401756 0.6026 1855  0.667 1.0000
##  Cahi - Eugr -1.149201 0.1522 1854 -7.552 <.0001
##  Cahi - Hisp -1.041237 0.1466 1852 -7.104 <.0001
##  Cahi - Hype  0.056534 0.1631 1854  0.347 1.0000
##  Cahi - Pesp -0.201433 0.8422 1856 -0.239 1.0000
##  Cahi - Phpr -0.947424 0.1396 1852 -6.786 <.0001
##  Cahi - Pore  0.146495 0.1443 1855  1.015 1.0000
##  Cahi - Posp -1.300693 0.1383 1851 -9.403 <.0001
##  Cahi - Prsp  1.095991 0.8422 1854  1.301 1.0000
##  Cahi - Rusp -1.558091 0.1877 1829 -8.302 <.0001
##  Cahi - Soca -2.914956 0.1383 1851 -21.073 <.0001
##  Cahi - Soju  1.041269 0.8419 1856  1.237 1.0000
##  Cahi - Taof  0.217728 0.1580 1857  1.378 1.0000
##  Cahi - Thar  0.544735 0.8419 1855  0.647 1.0000
##  Cahi - Trsp -0.405120 0.1529 1844 -2.649 0.6856
##  Cahi - Uhsp  0.229898 0.6027 1856  0.381 1.0000
##  Cahi - Vear  0.418545 0.2307 1849  1.815 0.9956
##  Ceor - Cest  0.593814 0.2798 1771  2.122 0.9608
##  Ceor - Crsp  1.767085 0.8737 1857  2.023 0.9787
##  Ceor - Daca  1.404074 0.2811 1768  4.994 0.0003
##  Ceor - Dagl  0.960194 0.2771 1760  3.466 0.1301
##  Ceor - Elre  0.355437 0.2754 1788  1.290 1.0000
##  Ceor - Erci  2.308016 0.5497 1855  4.199 0.0102
##  Ceor - Ersp  1.798879 0.6448 1848  2.790 0.5707
##  Ceor - Eugr  0.247921 0.2796 1754  0.887 1.0000
##  Ceor - Hisp  0.355885 0.2763 1777  1.288 1.0000
##  Ceor - Hype  1.453656 0.2862 1731  5.080 0.0002
##  Ceor - Pesp  1.195689 0.8735 1856  1.369 1.0000
##  Ceor - Phpr  0.449698 0.2732 1755  1.646 0.9992
##  Ceor - Pore  1.543617 0.2754 1747  5.605 <.0001
##  Ceor - Posp  0.096429 0.2724 1773  0.354 1.0000
##  Ceor - Prsp  2.493113 0.8736 1857  2.854 0.5176
##  Ceor - Rusp -0.160969 0.3000 1761 -0.537 1.0000
##  Ceor - Soca -1.517834 0.2724 1773 -5.572 <.0001
##  Ceor - Soju  2.438391 0.8735 1857  2.792 0.5693
##  Ceor - Taof  1.614850 0.2826 1772  5.714 <.0001
##  Ceor - Thar  1.941857 0.8738 1857  2.222 0.9331
##  Ceor - Trsp  0.992002 0.2797 1794  3.547 0.1025
##  Ceor - Uhsp  1.627020 0.6459 1857  2.519 0.7819

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##  Ceor - Vear  1.815667 0.3296 1810  5.509 <.0001
##  Cest - Crsp  1.173271 0.8373 1854  1.401 1.0000
##  Cest - Daca  0.810260 0.1313 1850  6.173 <.0001
##  Cest - Dagl  0.366380 0.1227 1854  2.986 0.4103
##  Cest - Elre  -0.238377 0.1197 1849 -1.992 0.9827
##  Cest - Erci   1.714202 0.4900 1854  3.498 0.1184
##  Cest - Ersp   1.205064 0.5961 1856  2.022 0.9789
##  Cest - Eugr  -0.345893 0.1287 1856 -2.687 0.6553
##  Cest - Hisp  -0.237929 0.1213 1843 -1.961 0.9861
##  Cest - Hype   0.859842 0.1414 1856  6.082 <.0001
##  Cest - Pesp   0.601875 0.8372 1856  0.719 1.0000
##  Cest - Phpr  -0.1444116 0.1136 1848 -1.269 1.0000
##  Cest - Pore   0.949803 0.1186 1845  8.010 <.0001
##  Cest - Posp  -0.497385 0.1120 1846 -4.442 0.0037
##  Cest - Prsp   1.899299 0.8373 1854  2.268 0.9166
##  Cest - Rusp  -0.754783 0.1689 1748 -4.470 0.0033
##  Cest - Soca  -2.111648 0.1120 1846 -18.857 <.0001
##  Cest - Soju   1.844577 0.8375 1856  2.203 0.9394
##  Cest - Taof   1.021036 0.1350 1857  7.564 <.0001
##  Cest - Thar   1.348043 0.8374 1855  1.610 0.9994
##  Cest - Trsp   0.398188 0.1290 1847  3.086 0.3357
##  Cest - Uhsp   1.033206 0.5961 1856  1.733 0.9979
##  Cest - Vear   1.221853 0.2166 1857  5.640 <.0001
##  Crsp - Daca  -0.363011 0.8377 1853 -0.433 1.0000
##  Crsp - Dagl  -0.806891 0.8366 1854 -0.964 1.0000
##  Crsp - Elre  -1.411648 0.8365 1854 -1.688 0.9987
##  Crsp - Erci   0.540931 0.9601 1855  0.563 1.0000
##  Crsp - Ersp   0.031793 1.0183 1855  0.031 1.0000
##  Crsp - Eugr  -1.519164 0.8375 1854 -1.814 0.9957
##  Crsp - Hisp  -1.411200 0.8363 1854 -1.687 0.9987
##  Crsp - Hype  -0.313429 0.8396 1854 -0.373 1.0000
##  Crsp - Pesp  -0.571396 1.1757 1856 -0.486 1.0000
##  Crsp - Phpr  -1.317387 0.8355 1854 -1.577 0.9996
##  Crsp - Pore  -0.223468 0.8360 1854 -0.267 1.0000
##  Crsp - Posp  -1.670656 0.8353 1854 -2.000 0.9817
##  Crsp - Prsp   0.726028 1.1758 1855  0.617 1.0000
##  Crsp - Rusp  -1.928054 0.8440 1852 -2.284 0.9103
##  Crsp - Soca  -3.284919 0.8353 1854 -3.933 0.0283
##  Crsp - Soju   0.671306 1.1761 1855  0.571 1.0000
##  Crsp - Taof  -0.152235 0.8384 1854 -0.182 1.0000
##  Crsp - Thar   0.174772 1.1761 1854  0.149 1.0000
##  Crsp - Trsp  -0.775083 0.8373 1853 -0.926 1.0000
##  Crsp - Uhsp  -0.140065 1.0183 1855 -0.138 1.0000
##  Crsp - Vear   0.048582 0.8556 1853  0.057 1.0000
##  Daca - Dagl  -0.443880 0.1252 1851 -3.546 0.1029
##  Daca - Elre  -1.048637 0.1221 1854 -8.590 <.0001
##  Daca - Erci   0.903942 0.4910 1855  1.841 0.9945
##  Daca - Ersp   0.394804 0.5969 1856  0.661 1.0000
##  Daca - Eugr  -1.156153 0.1310 1857 -8.823 <.0001
##  Daca - Hisp  -1.048189 0.1243 1848 -8.431 <.0001
##  Daca - Hype   0.049582 0.1437 1857  0.345 1.0000
##  Daca - Pesp  -0.208385 0.8379 1857 -0.249 1.0000
##  Daca - Phpr  -0.954376 0.1163 1850 -8.204 <.0001
##  Daca - Pore  0.139543 0.1214 1849  1.149 1.0000

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## Daca - Posp -1.307645 0.1148 1852 -11.386 <.0001
## Daca - Prsp  1.089039 0.8379 1855   1.300 1.0000
## Daca - Rusp -1.565043 0.1706 1787  -9.172 <.0001
## Daca - Soca -2.921908 0.1148 1852 -25.441 <.0001
## Daca - Soju  1.034317 0.8379 1856   1.234 1.0000
## Daca - Taof  0.210776 0.1378 1857   1.530 0.9998
## Daca - Thar  0.537783 0.8378 1854   0.642 1.0000
## Daca - Trsp  -0.412072 0.1318 1844  -3.126 0.3082
## Daca - Uhsp  0.222946 0.5968 1855   0.374 1.0000
## Daca - Vear  0.411593 0.2182 1852   1.886 0.9921
## Dagl - Elre -0.604757 0.1108 1845  -5.458 <.0001
## Dagl - Erci  1.347822 0.4889 1855   2.757 0.5983
## Dagl - Ersp  0.838685 0.5952 1856   1.409 1.0000
## Dagl - Eugr -0.712273 0.1212 1856  -5.878 <.0001
## Dagl - Hisp -0.604309 0.1144 1850  -5.282 0.0001
## Dagl - Hype  0.493462 0.1348 1857   3.660 0.0720
## Dagl - Pesp  0.235495 0.8368 1857   0.281 1.0000
## Dagl - Phpr  -0.510496 0.1052 1843  -4.854 0.0006
## Dagl - Pore  0.583423 0.1112 1849   5.248 0.0001
## Dagl - Posp -0.863765 0.1035 1847  -8.343 <.0001
## Dagl - Prsp  1.532919 0.8366 1854   1.832 0.9949
## Dagl - Rusp -1.121163 0.1631 1803  -6.875 <.0001
## Dagl - Soca -2.478028 0.1035 1847  -23.934 <.0001
## Dagl - Soju  1.478197 0.8366 1856   1.767 0.9972
## Dagl - Taof  0.654656 0.1288 1856   5.083 0.0002
## Dagl - Thar  0.981663 0.8367 1855   1.173 1.0000
## Dagl - Trsp  0.031808 0.1229 1850   0.259 1.0000
## Dagl - Uhsp  0.666827 0.5951 1855   1.121 1.0000
## Dagl - Vear  0.855473 0.2134 1856   4.009 0.0213
## Elre - Erci  1.952578 0.4885 1855   3.997 0.0223
## Elre - Ersp  1.443441 0.5947 1855   2.427 0.8399
## Elre - Eugr -0.107516 0.1175 1857  -0.915 1.0000
## Elre - Hisp  0.000448 0.1108 1847   0.004 1.0000
## Elre - Hype  1.098219 0.1316 1855   8.343 <.0001
## Elre - Pesp  0.840251 0.8364 1856   1.005 1.0000
## Elre - Phpr  0.094261 0.1009 1837   0.934 1.0000
## Elre - Pore  1.188180 0.1074 1847  11.061 <.0001
## Elre - Posp -0.259008 0.0991 1835  -2.614 0.7132
## Elre - Prsp  2.137676 0.8364 1854   2.556 0.7561
## Elre - Rusp -0.516406 0.1605 1812  -3.218 0.2496
## Elre - Soca -1.873271 0.0991 1835  -18.903 <.0001
## Elre - Soju  2.082954 0.8362 1856   2.491 0.8005
## Elre - Taof  1.259413 0.1257 1856  10.020 <.0001
## Elre - Thar  1.586419 0.8363 1855   1.897 0.9914
## Elre - Trsp  0.636565 0.1198 1847   5.314 0.0001
## Elre - Uhsp  1.271583 0.5947 1855   2.138 0.9570
## Elre - Vear  1.460229 0.2114 1856   6.906 <.0001
## Erci - Ersp -0.509137 0.7589 1856  -0.671 1.0000
## Erci - Eugr -2.060095 0.4904 1856  -4.201 0.0101
## Erci - Hisp -1.952131 0.4883 1854  -3.998 0.0222
## Erci - Hype -0.854360 0.4937 1855  -1.731 0.9980
## Erci - Pesp -1.112327 0.9600 1857  -1.159 1.0000
## Erci - Phpr -1.858317 0.4867 1855  -3.818 0.0426
## Erci - Pore -0.764399 0.4878 1854  -1.567 0.9997

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## Erci - Posp -2.211587 0.4864 1855 -4.547 0.0023
## Erci - Prsp  0.185097 0.9601 1855  0.193 1.0000
## Erci - Rusp -2.468984 0.5022 1857 -4.916 0.0004
## Erci - Soca -3.825850 0.4864 1855 -7.865 <.0001
## Erci - Soju  0.130375 0.9602 1856  0.136 1.0000
## Erci - Taof  -0.693165 0.4919 1854 -1.409 1.0000
## Erci - Thar  -0.366159 0.9602 1855 -0.381 1.0000
## Erci - Trsp  -1.316014 0.4900 1854 -2.686 0.6564
## Erci - Uhsp  -0.680995 0.7589 1856 -0.897 1.0000
## Erci - Vear  -0.492349 0.5205 1852 -0.946 1.0000
## Ersp - Eugr  -1.550958 0.5963 1856 -2.601 0.7228
## Ersp - Hisp  -1.442994 0.5946 1855 -2.427 0.8401
## Ersp - Hype  -0.345223 0.5991 1856 -0.576 1.0000
## Ersp - Pesp  -0.603190 1.0183 1857 -0.592 1.0000
## Ersp - Phpr  -1.349180 0.5934 1856 -2.274 0.9145
## Ersp - Pore  -0.255261 0.5943 1856 -0.429 1.0000
## Ersp - Posp  -1.702450 0.5930 1856 -2.871 0.5035
## Ersp - Prsp  0.694235 1.0183 1855  0.682 1.0000
## Ersp - Rusp  -1.959847 0.6063 1857 -3.232 0.2412
## Ersp - Soca  -3.316713 0.5930 1856 -5.593 <.0001
## Ersp - Soju  0.639513 1.0183 1856  0.628 1.0000
## Ersp - Taof  -0.184028 0.5977 1856 -0.308 1.0000
## Ersp - Thar  0.142978 1.0183 1856  0.140 1.0000
## Ersp - Trsp  -0.806877 0.5960 1855 -1.354 1.0000
## Ersp - Uhsp  -0.171858 0.8313 1856 -0.207 1.0000
## Ersp - Vear  0.016788 0.6215 1856  0.027 1.0000
## Eugr - Hisp  0.107964 0.1206 1857  0.895 1.0000
## Eugr - Hype  1.205735 0.1402 1854  8.603 <.0001
## Eugr - Pesp  0.947768 0.8376 1857  1.132 1.0000
## Eugr - Phpr  0.201777 0.1121 1857  1.801 0.9961
## Eugr - Pore  1.295696 0.1178 1856 10.998 <.0001
## Eugr - Posp  -0.151492 0.1105 1857 -1.371 1.0000
## Eugr - Prsp  2.245192 0.8374 1853  2.681 0.6602
## Eugr - Rusp  -0.408890 0.1675 1829 -2.441 0.8315
## Eugr - Soca  -1.765755 0.1105 1857 -15.977 <.0001
## Eugr - Soju  2.190470 0.8375 1857  2.615 0.7118
## Eugr - Taof  1.366929 0.1342 1857 10.183 <.0001
## Eugr - Thar  1.693936 0.8373 1855  2.023 0.9787
## Eugr - Trsp  0.744081 0.1285 1856  5.791 <.0001
## Eugr - Uhsp  1.379099 0.5963 1857  2.313 0.8984
## Eugr - Vear  1.567746 0.2164 1856  7.245 <.0001
## Hisp - Hype  1.097771 0.1344 1856  8.170 <.0001
## Hisp - Pesp  0.839804 0.8363 1856  1.004 1.0000
## Hisp - Phpr  0.093813 0.1048 1846  0.895 1.0000
## Hisp - Pore  1.187732 0.1104 1840 10.755 <.0001
## Hisp - Posp  -0.259456 0.1030 1842 -2.518 0.7824
## Hisp - Prsp  2.137228 0.8364 1855  2.555 0.7564
## Hisp - Rusp  -0.516854 0.1629 1768 -3.172 0.2781
## Hisp - Soca  -1.873719 0.1030 1842 -18.185 <.0001
## Hisp - Soju  2.082506 0.8364 1856  2.490 0.8012
## Hisp - Taof  1.258965 0.1278 1855  9.851 <.0001
## Hisp - Thar  1.585972 0.8364 1855  1.896 0.9914
## Hisp - Trsp  0.636117 0.1214 1840  5.238 0.0001
## Hisp - Uhsp  1.271136 0.5946 1856  2.138 0.9572

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##  Hisp - Vear  1.459782 0.2123 1855   6.877 <.0001
##  Hype - Pesp -0.257967 0.8396 1857  -0.307 1.0000
##  Hype - Phpr -1.003958 0.1267 1857  -7.922 <.0001
##  Hype - Pore  0.089961 0.1318 1855   0.682 1.0000
##  Hype - Posp -1.357227 0.1254 1855 -10.825 <.0001
##  Hype - Prsp  1.039457 0.8392 1852   1.239 1.0000
##  Hype - Rusp -1.614625 0.1779 1802  -9.078 <.0001
##  Hype - Soca -2.971490 0.1254 1855 -23.701 <.0001
##  Hype - Soju  0.984735 0.8394 1857   1.173 1.0000
##  Hype - Taof  0.161194 0.1469 1852   1.098 1.0000
##  Hype - Thar  0.488201 0.8395 1856   0.582 1.0000
##  Hype - Trsp -0.461654 0.1415 1857  -3.263 0.2236
##  Hype - Uhsp  0.173364 0.5991 1857   0.289 1.0000
##  Hype - Vear  0.362011 0.2244 1856   1.614 0.9994
##  Pesp - Phpr -0.745990 0.8354 1856  -0.893 1.0000
##  Pesp - Pore  0.347928 0.8359 1856   0.416 1.0000
##  Pesp - Posp -1.099260 0.8352 1856  -1.316 1.0000
##  Pesp - Prsp  1.297424 1.1757 1856   1.104 1.0000
##  Pesp - Rusp -1.356657 0.8446 1857  -1.606 0.9995
##  Pesp - Soca -2.713523 0.8352 1856  -3.249 0.2316
##  Pesp - Soju  1.242702 1.1762 1856   1.057 1.0000
##  Pesp - Taof  0.419162 0.8385 1857   0.500 1.0000
##  Pesp - Thar  0.746168 1.1762 1856   0.634 1.0000
##  Pesp - Trsp -0.203687 0.8374 1856  -0.243 1.0000
##  Pesp - Uhsp  0.431332 1.0183 1857   0.424 1.0000
##  Pesp - Vear  0.619978 0.8558 1857   0.724 1.0000
##  Phpr - Pore  1.093919 0.1012 1842  10.805 <.0001
##  Phpr - Posp -0.353270 0.0927 1834  -3.810 0.0437
##  Phpr - Prsp  2.043415 0.8354 1854   2.446 0.8287
##  Phpr - Rusp -0.610667 0.1566 1796  -3.899 0.0320
##  Phpr - Soca -1.967532 0.0927 1834 -21.222 <.0001
##  Phpr - Soju  1.988693 0.8353 1856   2.381 0.8655
##  Phpr - Taof  1.165152 0.1203 1857   9.686 <.0001
##  Phpr - Thar  1.492158 0.8353 1855   1.786 0.9966
##  Phpr - Trsp  0.542304 0.1138 1846   4.764 0.0009
##  Phpr - Uhsp  1.177322 0.5933 1856   1.984 0.9836
##  Phpr - Vear  1.365968 0.2080 1856   6.566 <.0001
##  Pore - Posp -1.447188 0.0995 1844 -14.544 <.0001
##  Pore - Prsp  0.949496 0.8360 1854   1.136 1.0000
##  Pore - Rusp -1.704586 0.1605 1792 -10.617 <.0001
##  Pore - Soca -3.061451 0.0995 1844 -30.768 <.0001
##  Pore - Soju  0.894774 0.8361 1856   1.070 1.0000
##  Pore - Taof  0.071233 0.1253 1855   0.569 1.0000
##  Pore - Thar  0.398240 0.8361 1855   0.476 1.0000
##  Pore - Trsp -0.551615 0.1191 1844 -4.633 0.0016
##  Pore - Uhsp  0.083403 0.5942 1856   0.140 1.0000
##  Pore - Vear  0.272050 0.2110 1855   1.289 1.0000
##  Posp - Prsp  2.396684 0.8352 1854   2.870 0.5045
##  Posp - Rusp -0.257398 0.1555 1784  -1.655 0.9991
##  Posp - Soca -1.614263 0.0908 1830 -17.782 <.0001
##  Posp - Soju  2.341962 0.8351 1856   2.804 0.5586
##  Posp - Taof  1.518422 0.1188 1857  12.779 <.0001
##  Posp - Thar  1.845428 0.8352 1855   2.210 0.9372
##  Posp - Trsp  0.895573 0.1123 1845   7.975 <.0001

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##  Posp - Uhsp  1.530592 0.5930 1856   2.581 0.7377
##  Posp - Vear  1.719238 0.2072 1856   8.297 <.0001
##  Prsp - Rusp -2.654082 0.8440 1851  -3.145 0.2957
##  Prsp - Soca -4.010947 0.8352 1854  -4.802 0.0007
##  Prsp - Soju -0.054722 1.1762 1855  -0.047 1.0000
##  Prsp - Taof -0.878263 0.8383 1853  -1.048 1.0000
##  Prsp - Thar -0.551256 1.1761 1854  -0.469 1.0000
##  Prsp - Trsp -1.501111 0.8374 1854  -1.793 0.9964
##  Prsp - Uhsp -0.866093 1.0183 1856  -0.850 1.0000
##  Prsp - Vear -0.677446 0.8558 1855  -0.792 1.0000
##  Rusp - Soca -1.356865 0.1555 1784  -8.724 <.0001
##  Rusp - Soju  2.599360 0.8448 1857  3.077 0.3424
##  Rusp - Taof  1.775819 0.1729 1842  10.271 <.0001
##  Rusp - Thar  2.102826 0.8448 1856  2.489 0.8017
##  Rusp - Trsp  1.152971 0.1689 1813  6.826 <.0001
##  Rusp - Uhsp  1.787989 0.6064 1857  2.949 0.4401
##  Rusp - Vear  1.976635 0.2427 1853  8.144 <.0001
##  Soca - Soju 3.956225 0.8351 1856  4.737 0.0010
##  Soca - Taof  3.132684 0.1188 1857  26.365 <.0001
##  Soca - Thar  3.459691 0.8352 1855  4.143 0.0128
##  Soca - Trsp  2.509836 0.1123 1845  22.351 <.0001
##  Soca - Uhsp  3.144855 0.5930 1856  5.303 0.0001
##  Soca - Vear  3.333501 0.2072 1856  16.087 <.0001
##  Soju - Taof -0.823541 0.8386 1856  -0.982 1.0000
##  Soju - Thar -0.496534 1.1757 1856  -0.422 1.0000
##  Soju - Trsp -1.446389 0.8373 1856  -1.727 0.9980
##  Soju - Uhsp -0.811371 1.0169 1843  -0.798 1.0000
##  Soju - Vear -0.622724 0.8554 1856  -0.728 1.0000
##  Taof - Thar  0.327006 0.8385 1855  0.390 1.0000
##  Taof - Trsp -0.622848 0.1351 1856  -4.610 0.0017
##  Taof - Uhsp  0.012170 0.5978 1856  0.020 1.0000
##  Taof - Vear  0.200816 0.2203 1857  0.912 1.0000
##  Thar - Trsp -0.949855 0.8372 1854  -1.135 1.0000
##  Thar - Uhsp -0.314836 1.0183 1856  -0.309 1.0000
##  Thar - Vear -0.126190 0.8552 1854  -0.148 1.0000
##  Trsp - Uhsp  0.635019 0.5960 1856  1.065 1.0000
##  Trsp - Vear  0.823665 0.2164 1852  3.806 0.0443
##  Uhsp - Vear  0.188646 0.6215 1856  0.304 1.0000
##
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 31 estimates

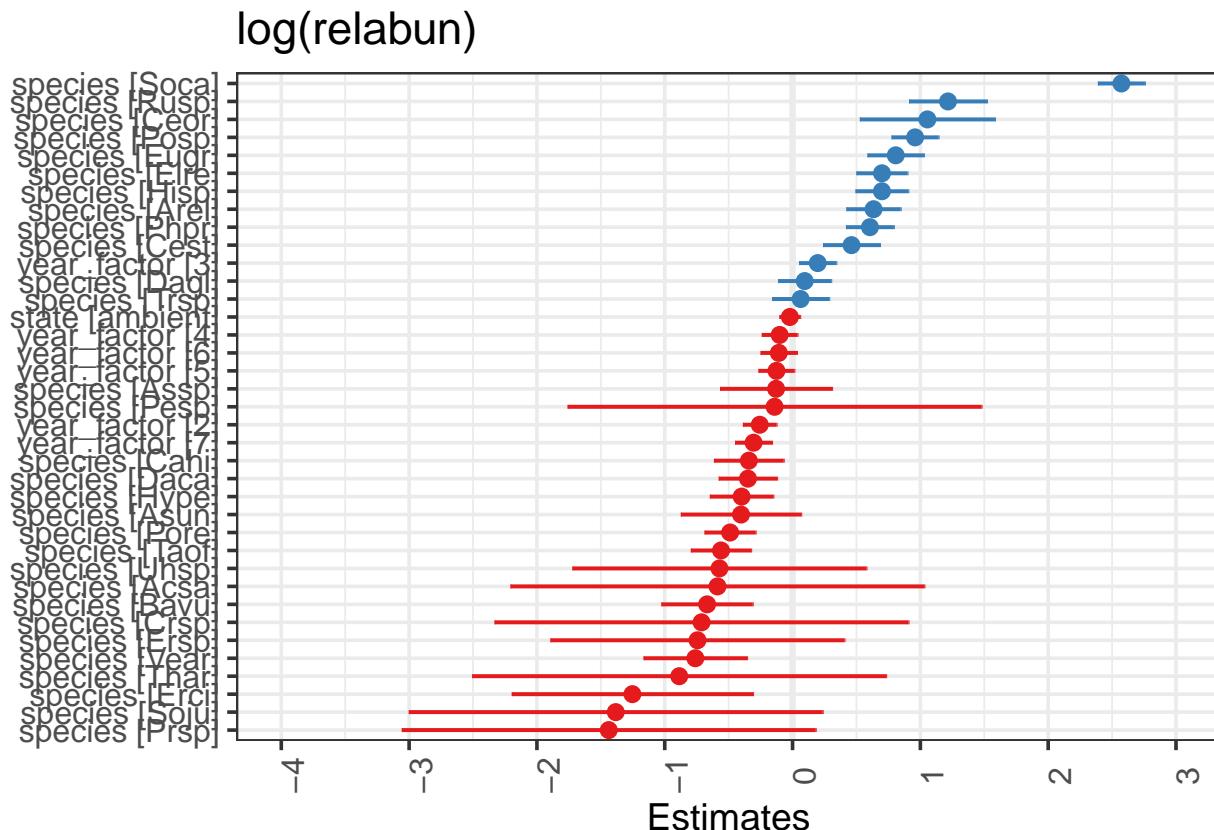
```

```

# Take a look at the estimates for each fixed effect. These are the estimates
# from summary(mod7a). You'll see that species vary a lot - and many of them are
# different from zero (meaning their half cover date is significantly different
# from zero).

```

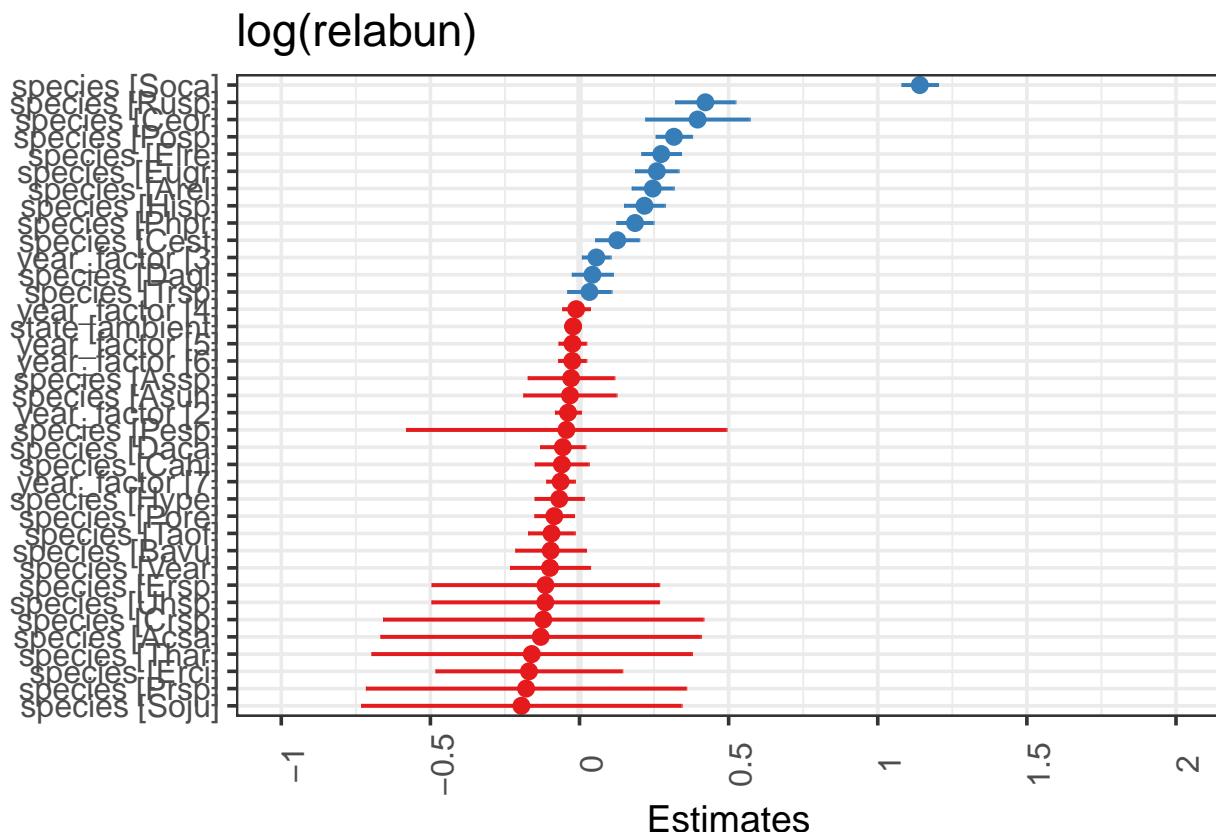
```
plot_model(mod7a, sort.est = TRUE)
```



```
# if you want to standardize the estimates:
plot_model(mod7a, sort.est = TRUE, type = "std")
```

```
## Formula contains log- or sqrt-terms. See help("standardize") for how such terms are standardized.

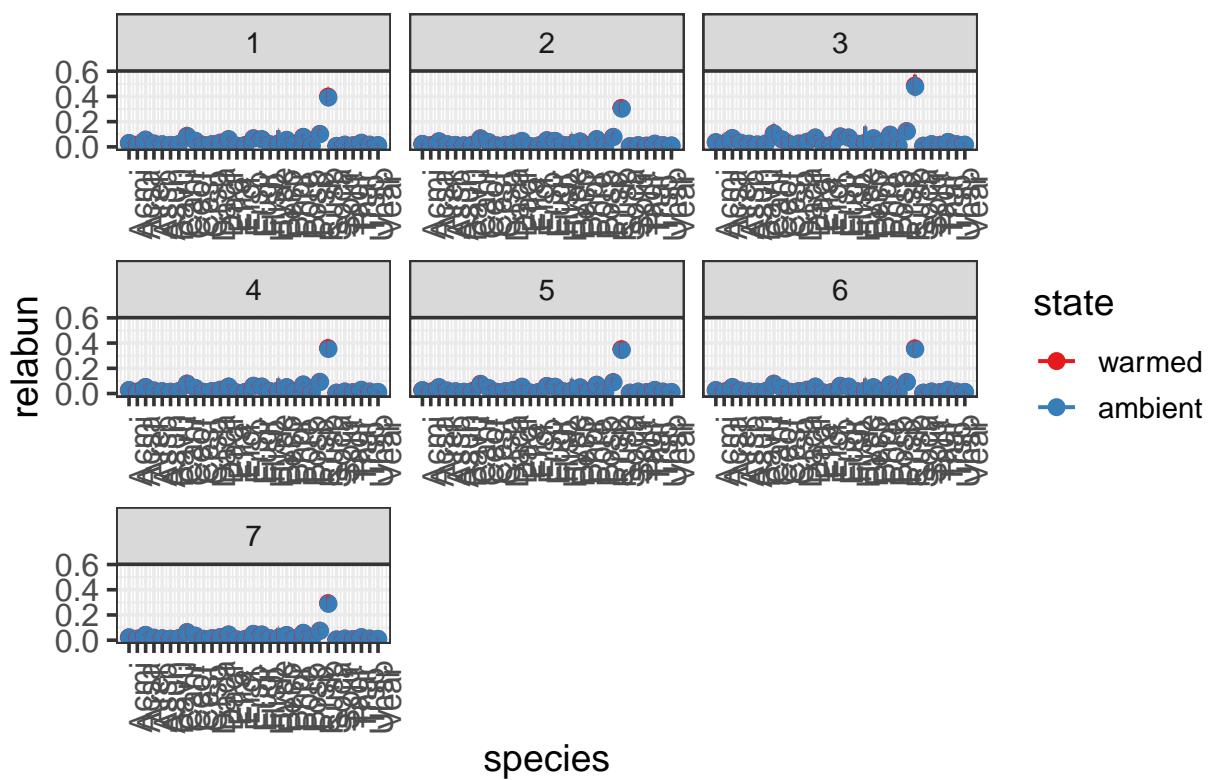
## boundary (singular) fit: see ?isSingular
```



```
# these are the fixed predicted values: - note this is a new plot
plot_model(mod7a, type = "pred", terms = c("species", "state", "year_factor"))
```

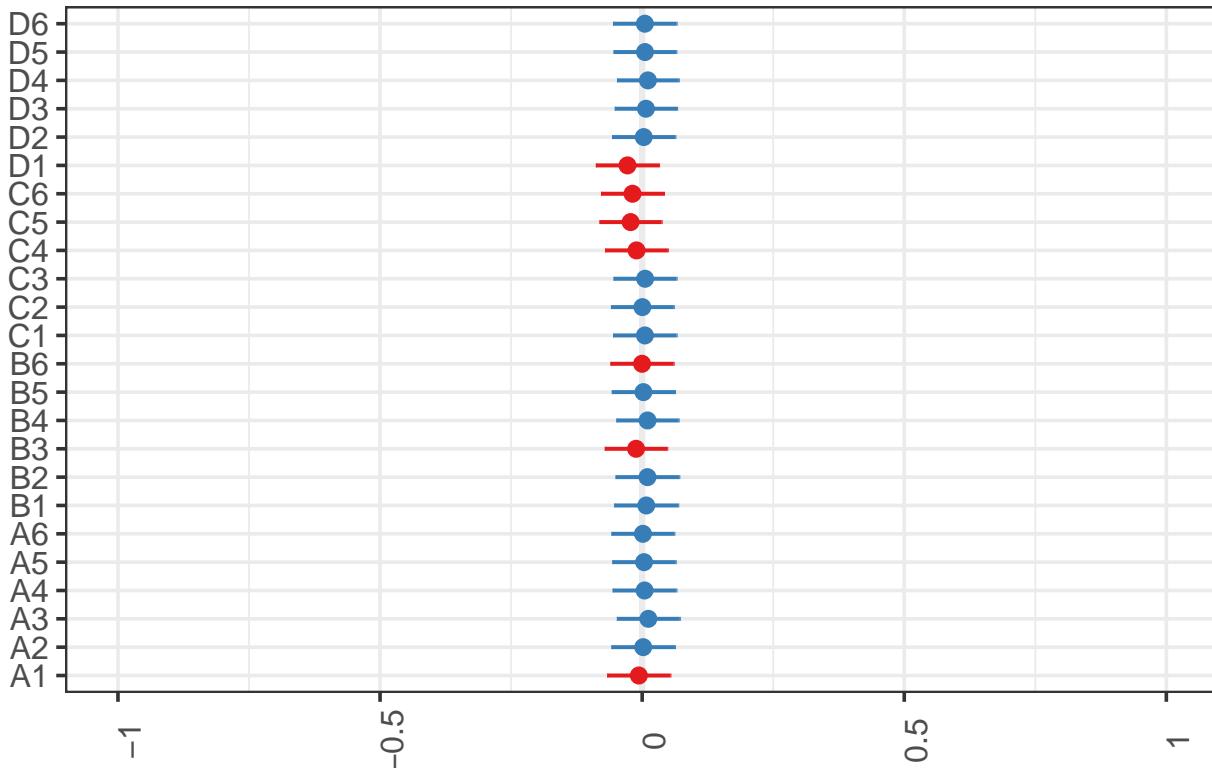
```
## Model has log-transformed response. Back-transforming predictions to original response scale. Standardized
```

Predicted values of relabun



```
# these are the random effects estimates  
plot_model(mod7a, type = "re")
```

Random effects



```
# including native vs. exotic
comp_kbs_spp <- within(comp_kbs_spp, origin <- relevel(factor(origin), ref = "Native")) # releveling s
mod8 <- lmer(log(relabun) ~ state * origin + (1 + factor(year_factor) | plot), comp_kbs_spp,
             REML = FALSE)

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -1.5e+01

mod9 <- lmer(log(relabun) ~ state + origin + (1 + factor(year_factor) | plot), comp_kbs_spp,
              REML = FALSE)

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -7.4e+00

mod9a <- lmer(log(relabun) ~ state + origin + factor(year_factor) + (1 | plot), comp_kbs_spp,
               REML = FALSE)
anova(mod8, mod9) # model 8 is a better fit to data

## Data: comp_kbs_spp
## Models:
## mod9: log(relabun) ~ state + origin + (1 + factor(year_factor) | plot)
## mod8: log(relabun) ~ state * origin + (1 + factor(year_factor) | plot)
```

```

##      npar     AIC     BIC logLik deviance Chisq Df Pr(>Chisq)
## mod9    34 5536.0 5723.2 -2734.0    5468.0
## mod8    37 5533.3 5737.0 -2729.6    5459.3 8.7886  3     0.03224 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(mod8, mod9a)  # mod 9a

## Data: comp_kbs_spp
## Models:
## mod9a: log(relabun) ~ state + origin + factor(year_factor) + (1 | plot)
## mod8: log(relabun) ~ state * origin + (1 + factor(year_factor) | plot)
##      npar     AIC     BIC logLik deviance Chisq Df Pr(>Chisq)
## mod9a    13 5463.6 5535.2 -2718.8    5437.6
## mod8     37 5533.3 5737.0 -2729.6    5459.3      0 24             1

AICctab(mod8, mod9a, weights = T)  # mod 9a

##      dAICc df weight
## mod9a   0    13  1
## mod8   71    37 <0.001

summary(mod9a)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(relabun) ~ state + origin + factor(year_factor) + (1 | plot)
## Data: comp_kbs_spp
##
##      AIC      BIC logLik deviance df.resid
## 5463.6 5535.2 -2718.8    5437.6      1805
##
## Scaled residuals:
##      Min      1Q Median      3Q      Max
## -2.6925 -0.8002 -0.1102  0.8065  2.9608
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.00038  0.01949
## Residual           1.16508  1.07939
## Number of obs: 1818, groups: plot, 24
##
## Fixed effects:
##                  Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept)      -2.34809   0.08230 484.57449 -28.530 < 2e-16 ***
## stateambient    -0.03636   0.05138  22.27356 -0.708 0.486521  
## origin          -0.43964   0.09596 1802.01365 -4.581 4.93e-06 ***
## originBoth       -0.73514   0.08859 1817.97150 -8.298 < 2e-16 ***
## originExotic    -1.14875   0.06413 1813.91677 -17.913 < 2e-16 ***
## factor(year_factor)2 -0.21361   0.08669 1799.51136 -2.464 0.013832 *  
## factor(year_factor)3  0.33043   0.09578 1806.72053  3.450 0.000573 *** 
## factor(year_factor)4  0.00706   0.09151 1808.28498  0.077 0.938511 

```

```

## factor(year_factor)5    0.02754    0.09226 1813.65959    0.298 0.765397
## factor(year_factor)6    0.08353    0.09305 1812.27608    0.898 0.369424
## factor(year_factor)7   -0.08879    0.09435 1816.40687   -0.941 0.346809
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) sttmbn origin orgnBt orgnEx fc(_)2 fc(_)3 fc(_)4 fc(_)5
## stateambint -0.299
## origin      -0.368 -0.008
## originBoth   -0.436 -0.029  0.345
## originExotc  -0.545 -0.018  0.477  0.518
## fctr(yr_f)2 -0.523 -0.008  0.010  0.004 -0.021
## fctr(yr_f)3 -0.493 -0.017  0.002  0.088 -0.004  0.459
## fctr(yr_f)4 -0.504 -0.013 -0.018  0.040 -0.005  0.479  0.439
## fctr(yr_f)5 -0.497 -0.029  0.001  0.031 -0.001  0.475  0.434  0.452
## fctr(yr_f)6 -0.498 -0.023 -0.007  0.057 -0.002  0.472  0.434  0.450  0.445
## fctr(yr_f)7 -0.494 -0.017  0.005  0.054 -0.002  0.465  0.427  0.443  0.439
##           fc(_)6
## stateambint
## origin
## originBoth
## originExotc
## fctr(yr_f)2
## fctr(yr_f)3
## fctr(yr_f)4
## fctr(yr_f)5
## fctr(yr_f)6
## fctr(yr_f)7  0.437

```

```
anova(mod9a)
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##             Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state          0.58   0.583     1   22.27  0.5007  0.4865
## origin        397.85 132.616     3 1813.20 113.8257 < 2.2e-16 ***
## factor(year_factor) 41.68   6.946     6 1809.21  5.9619 3.508e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
emmeans(mod9a, list(pairwise ~ state + origin), adjust = "tukey")
```

```

## $`emmeans of state, origin`
##   state origin emmean    SE df lower.CL upper.CL
##   warmed Native -2.33 0.0615 183.6   -2.45   -2.21
##   ambient Native -2.36 0.0612 188.7   -2.48   -2.24
##   warmed       -2.77 0.0847 573.0   -2.93   -2.60
##   ambient       -2.80 0.0840 580.5   -2.97   -2.64
##   warmed Both   -3.06 0.0772 382.8   -3.21   -2.91
##   ambient Both   -3.10 0.0752 359.6   -3.25   -2.95
##   warmed Exotic -3.48 0.0456  54.8   -3.57   -3.38
##   ambient Exotic -3.51 0.0439  47.7   -3.60   -3.42
## 

```

```

## Results are averaged over the levels of: year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $'pairwise differences of state, origin'
##   1           estimate      SE    df t.ratio p.value
## warmed Native - ambient Native  0.0364 0.0540  26.2  0.673  0.9971
## warmed Native - warmed          0.4396 0.0962 1811.8  4.569  0.0001
## warmed Native - ambient         0.4760 0.1100  437.2  4.327  0.0005
## warmed Native - warmed Both    0.7351 0.0890 1828.8  8.264 <.0001
## warmed Native - ambient Both   0.7715 0.1028  327.5  7.505 <.0001
## warmed Native - warmed Exotic  1.1488 0.0644 1823.8 17.851 <.0001
## warmed Native - ambient Exotic 1.1851 0.0833  154.8 14.220 <.0001
## ambient Native - warmed        0.4033 0.1107 446.4  3.643  0.0072
## ambient Native - ambient       0.4396 0.0962 1811.8  4.569  0.0001
## ambient Native - warmed Both   0.6988 0.1053  361.4  6.636 <.0001
## ambient Native - ambient Both   0.7351 0.0890 1828.8  8.264 <.0001
## ambient Native - warmed Exotic 1.1124 0.0847 169.1 13.138 <.0001
## ambient Native - ambient Exotic 1.1488 0.0644 1823.8 17.851 <.0001
## warmed - ambient              0.0364 0.0540  26.2  0.673  0.9971
## warmed - warmed Both           0.2955 0.1062 1827.6  2.782  0.1002
## warmed - ambient Both          0.3319 0.1184  519.7  2.803  0.0964
## warmed - warmed Exotic         0.7091 0.0866 1817.3  8.189 <.0001
## warmed - ambient Exotic        0.7455 0.1019  329.7  7.317 <.0001
## ambient - warmed Both          0.2591 0.1199  547.6  2.161  0.3774
## ambient - ambient Both         0.2955 0.1062 1827.6  2.782  0.1002
## ambient - warmed Exotic        0.6728 0.1022  341.4  6.581 <.0001
## ambient - ambient Exotic       0.7091 0.0866 1817.3  8.189 <.0001
## warmed Both - ambient Both     0.0364 0.0540  26.2  0.673  0.9971
## warmed Both - warmed Exotic    0.4136 0.0782 1827.8  5.286 <.0001
## warmed Both - ambient Exotic   0.4500 0.0958  260.1  4.695  0.0001
## ambient Both - warmed Exotic   0.3773 0.0943  246.9  4.001  0.0021
## ambient Both - ambient Exotic   0.4136 0.0782 1827.8  5.286 <.0001
## warmed Exotic - ambient Exotic 0.0364 0.0540  26.2  0.673  0.9971
##
## Results are averaged over the levels of: year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 8 estimates

# including growth form - first with interaction term
comp_kbs_spp <- within(comp_kbs_spp, growth_habit <- relevel(factor(growth_habit),
  ref = "Forb")) # releveling so forb is the reference
mod10 <- lmer(log(relabun) ~ state * growth_habit + (1 + factor(year_factor) | plot),
  comp_kbs_spp, REML = FALSE)

## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient
## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -1.3e+00

```

```

mod11 <- lmer(log(relabun) ~ state + growth_habit + (1 + factor(year_factor) | plot),
  comp_kbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -1.0e+01

mod11a <- lmer(log(relabun) ~ state + growth_habit + factor(year_factor) + (1 | plot),
  comp_kbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

anova(mod10, mod11) # model 10 is a better fit to data

## Data: comp_kbs_spp
## Models:
## mod11: log(relabun) ~ state + growth_habit + (1 + factor(year_factor) |
## mod11:   plot)
## mod10: log(relabun) ~ state * growth_habit + (1 + factor(year_factor) |
## mod10:   plot)
##       npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod11   35 5830.1 6022.8 -2880.0   5760.1
## mod10   38 5827.5 6036.7 -2875.8   5751.5 8.5415  3   0.03605 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(mod10, mod11a) # model 11a is a better fit to data

## Data: comp_kbs_spp
## Models:
## mod11a: log(relabun) ~ state + growth_habit + factor(year_factor) + (1 |
## mod11a:   plot)
## mod10: log(relabun) ~ state * growth_habit + (1 + factor(year_factor) |
## mod10:   plot)
##       npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod11a   14 5760.3 5837.3 -2866.1   5732.3
## mod10    38 5827.5 6036.7 -2875.8   5751.5      0 24           1

summary(mod11a)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(relabun) ~ state + growth_habit + factor(year_factor) + (1 |
##   plot)
## Data: comp_kbs_spp
##
##       AIC      BIC  logLik deviance df.resid
##   5760.3  5837.3 -2866.1   5732.3     1804
##
## Scaled residuals:
```

```

##      Min      1Q Median      3Q     Max
## -1.9771 -0.7893 -0.1534  0.6579  2.7358
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.000    0.000
## Residual           1.371    1.171
## Number of obs: 1818, groups: plot, 24
##
## Fixed effects:
##                               Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)            -3.183e+00 7.718e-02 1.818e+03 -41.245 < 2e-16 ***
## stateambient          -5.077e-02 5.511e-02 1.818e+03 -0.921 0.356990
## growth_habit          9.928e-02 8.474e-02 1.818e+03  1.171 0.241563
## growth_habitGraminoid 2.359e-01 6.074e-02 1.818e+03  3.884 0.000106 ***
## growth_habitTree       -9.147e-01 1.173e+00 1.818e+03 -0.780 0.435697
## growth_habitVine       6.863e-01 3.726e-01 1.818e+03  1.842 0.065660 .
## factor(year_factor)2  -2.560e-01 9.410e-02 1.818e+03 -2.721 0.006578 **
## factor(year_factor)3   3.027e-01 1.043e-01 1.818e+03  2.902 0.003753 **
## factor(year_factor)4  -1.160e-02 9.930e-02 1.818e+03 -0.117 0.907011
## factor(year_factor)5   9.927e-04 1.003e-01 1.818e+03  0.010 0.992105
## factor(year_factor)6   4.062e-02 1.014e-01 1.818e+03  0.401 0.688808
## factor(year_factor)7  -1.374e-01 1.029e-01 1.818e+03 -1.335 0.182118
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##                (Intr) sttmbn grwth_G grwt_T grwt_V fc(_)
## stateambint -0.356
## growth_habt -0.269 -0.033
## grwth_hbtGr -0.283  0.021  0.287
## grwth_hbtTr -0.066  0.023  0.018  0.019
## grwth_hbtVn -0.047 -0.026  0.052  0.064  0.003
## fctr(yr_f)2 -0.623 -0.008  0.031  0.012  0.041 -0.010
## fctr(yr_f)3 -0.567 -0.020  0.113 -0.034  0.037  0.026  0.459
## fctr(yr_f)4 -0.578 -0.014  0.024 -0.035  0.038  0.009  0.480  0.439
## fctr(yr_f)5 -0.565 -0.030  0.035 -0.048  0.037 -0.006  0.476  0.437  0.453
## fctr(yr_f)6 -0.552 -0.026  0.038 -0.094  0.036  0.006  0.470  0.436  0.451
## fctr(yr_f)7 -0.548 -0.020  0.049 -0.093  0.036  0.005  0.464  0.431  0.445
##                  fc(_)
## stateambint
## growth_habt
## grwth_hbtGr
## grwth_hbtTr
## grwth_hbtVn
## fctr(yr_f)2
## fctr(yr_f)3
## fctr(yr_f)4
## fctr(yr_f)5
## fctr(yr_f)6  0.449
## fctr(yr_f)7  0.443  0.443
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

```

```
anova(mod11a)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state          1.163  1.1634      1   1818  0.8489  0.356990
## growth_habit   25.167  6.2918      4   1818  4.5908  0.001087 **
## factor(year_factor) 44.391  7.3985      6   1818  5.3984  1.534e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

emmeans(mod11a, list(pairwise ~ factor(year_factor) * growth_habit), adjust = "tukey")

## $`emmeans of year_factor, growth_habit`
##   year_factor growth_habit emmean       SE   df lower.CL upper.CL
##   1 Forb        -3.21 0.0725  752    -3.35    -3.07
##   2 Forb        -3.46 0.0709  704    -3.60    -3.33
##   3 Forb        -2.91 0.0831  963    -3.07    -2.74
##   4 Forb        -3.22 0.0788  842    -3.37    -3.07
##   5 Forb        -3.21 0.0802  854    -3.36    -3.05
##   6 Forb        -3.17 0.0824  934    -3.33    -3.01
##   7 Forb        -3.35 0.0841  904    -3.51    -3.18
##   1            -3.11 0.0938 1240    -3.29    -2.93
##   2            -3.37 0.0952 1241    -3.55    -3.18
##   3            -2.81 0.1116 1462    -3.03    -2.59
##   4            -3.12 0.1008 1306    -3.32    -2.92
##   5            -3.11 0.1028 1300    -3.31    -2.91
##   6            -3.07 0.1048 1341    -3.27    -2.86
##   7            -3.25 0.1071 1364    -3.46    -3.04
##   1 Graminoid   -2.97 0.0799  905    -3.13    -2.82
##   2 Graminoid   -3.23 0.0792  905    -3.38    -3.07
##   3 Graminoid   -2.67 0.0871 1077    -2.84    -2.50
##   4 Graminoid   -2.98 0.0830 1007    -3.15    -2.82
##   5 Graminoid   -2.97 0.0833 1011    -3.14    -2.81
##   6 Graminoid   -2.93 0.0820  985    -3.09    -2.77
##   7 Graminoid   -3.11 0.0837  984    -3.27    -2.95
##   1 Tree         -4.12 1.1761 1830    -6.43    -1.82
##   2 Tree         -4.38 1.1799 1830    -6.69    -2.07
##   3 Tree         -3.82 1.1808 1830    -6.14    -1.50
##   4 Tree         -4.13 1.1804 1830    -6.45    -1.82
##   5 Tree         -4.12 1.1804 1830    -6.44    -1.81
##   6 Tree         -4.08 1.1805 1830    -6.40    -1.77
##   7 Tree         -4.26 1.1807 1830    -6.58    -1.95
##   1 Vine         -2.52 0.3781 1647    -3.26    -1.78
##   2 Vine         -2.78 0.3769 1633    -3.52    -2.04
##   3 Vine         -2.22 0.3828 1675    -2.97    -1.47
##   4 Vine         -2.53 0.3802 1655    -3.28    -1.79
##   5 Vine         -2.52 0.3790 1652    -3.26    -1.78
##   6 Vine         -2.48 0.3807 1634    -3.23    -1.73
##   7 Vine         -2.66 0.3810 1648    -3.41    -1.91
##
## Results are averaged over the levels of: state
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
```

```

## Confidence level used: 0.95
##
## $`pairwise differences of year_factor, growth_habit`
##   1                      estimate      SE    df t.ratio p.value
## 1 Forb - 2 Forb          0.255998 0.0944 1813  2.712  0.6952
## 1 Forb - 3 Forb         -0.302699 0.1047 1819 -2.892  0.5458
## 1 Forb - 4 Forb          0.011600 0.0997 1822  0.116  1.0000
## 1 Forb - 5 Forb         -0.000993 0.1007 1828 -0.010  1.0000
## 1 Forb - 6 Forb         -0.040623 0.1018 1827 -0.399  1.0000
## 1 Forb - 7 Forb          0.137411 0.1034 1830  1.329  1.0000
## 1 Forb - 1               -0.099275 0.0851 1826 -1.167  1.0000
## 1 Forb - 2               0.156723 0.1291 1823  1.214  1.0000
## 1 Forb - 3               -0.401974 0.1422 1823 -2.827  0.6002
## 1 Forb - 4               -0.087675 0.1326 1824 -0.661  1.0000
## 1 Forb - 5               -0.100268 0.1341 1828 -0.748  1.0000
## 1 Forb - 6               -0.139898 0.1352 1828 -1.035  1.0000
## 1 Forb - 7               0.038136 0.1371 1828  0.278  1.0000
## 1 Forb - 1 Graminoid     -0.235896 0.0610 1830 -3.866  0.0441
## 1 Forb - 2 Graminoid     0.020102 0.1130 1820  0.178  1.0000
## 1 Forb - 3 Graminoid     -0.538595 0.1193 1818 -4.514  0.0034
## 1 Forb - 4 Graminoid     -0.224296 0.1149 1814 -1.952  0.9933
## 1 Forb - 5 Graminoid     -0.236889 0.1151 1818 -2.058  0.9849
## 1 Forb - 6 Graminoid     -0.276519 0.1136 1820 -2.434  0.8787
## 1 Forb - 7 Graminoid     -0.098485 0.1150 1822 -0.856  1.0000
## 1 Forb - 1 Tree          0.914712 1.1784 1830  0.776  1.0000
## 1 Forb - 2 Tree          1.170710 1.1860 1830  0.987  1.0000
## 1 Forb - 3 Tree          0.612013 1.1869 1830  0.516  1.0000
## 1 Forb - 4 Tree          0.926312 1.1864 1830  0.781  1.0000
## 1 Forb - 5 Tree          0.913719 1.1864 1830  0.770  1.0000
## 1 Forb - 6 Tree          0.874089 1.1865 1830  0.737  1.0000
## 1 Forb - 7 Tree          1.052123 1.1867 1830  0.887  1.0000
## 1 Forb - 1 Vine          -0.686336 0.3755 1666 -1.828  0.9978
## 1 Forb - 2 Vine          -0.430337 0.3863 1677 -1.114  1.0000
## 1 Forb - 3 Vine          -0.989034 0.3923 1714 -2.521  0.8304
## 1 Forb - 4 Vine          -0.674735 0.3894 1697 -1.733  0.9992
## 1 Forb - 5 Vine          -0.687328 0.3882 1694 -1.771  0.9988
## 1 Forb - 6 Vine          -0.726958 0.3897 1676 -1.865  0.9969
## 1 Forb - 7 Vine          -0.548924 0.3900 1689 -1.408  1.0000
## 2 Forb - 3 Forb          -0.558697 0.1039 1818 -5.379 <.0001
## 2 Forb - 4 Forb          -0.244398 0.0991 1821 -2.467  0.8615
## 2 Forb - 5 Forb          -0.256991 0.1001 1825 -2.568  0.8003
## 2 Forb - 6 Forb          -0.296621 0.1012 1823 -2.931  0.5126
## 2 Forb - 7 Forb          -0.118587 0.1028 1829 -1.154  1.0000
## 2 Forb - 1               -0.355274 0.1251 1817 -2.840  0.5892
## 2 Forb - 2               -0.099275 0.0851 1826 -1.167  1.0000
## 2 Forb - 3               -0.657972 0.1398 1821 -4.707  0.0014
## 2 Forb - 4               -0.343673 0.1302 1821 -2.639  0.7508
## 2 Forb - 5               -0.356266 0.1317 1826 -2.705  0.7008
## 2 Forb - 6               -0.395896 0.1328 1826 -2.981  0.4712
## 2 Forb - 7               -0.217862 0.1347 1826 -1.617  0.9998
## 2 Forb - 1 Graminoid     -0.491895 0.1118 1825 -4.400  0.0055
## 2 Forb - 2 Graminoid     -0.235896 0.0610 1830 -3.866  0.0441
## 2 Forb - 3 Graminoid     -0.794593 0.1180 1820 -6.732 <.0001
## 2 Forb - 4 Graminoid     -0.480294 0.1138 1816 -4.220  0.0117

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## 2 Forb - 5 Graminoid	-0.492887	0.1140	1818	-4.325	0.0076
## 2 Forb - 6 Graminoid	-0.532517	0.1125	1819	-4.735	0.0012
## 2 Forb - 7 Graminoid	-0.354483	0.1138	1823	-3.114	0.3654
## 2 Forb - 1 Tree	0.658714	1.1783	1830	0.559	1.0000
## 2 Forb - 2 Tree	0.914712	1.1784	1830	0.776	1.0000
## 2 Forb - 3 Tree	0.356015	1.1830	1830	0.301	1.0000
## 2 Forb - 4 Tree	0.670314	1.1825	1830	0.567	1.0000
## 2 Forb - 5 Tree	0.657721	1.1825	1830	0.556	1.0000
## 2 Forb - 6 Tree	0.618091	1.1826	1830	0.523	1.0000
## 2 Forb - 7 Tree	0.796125	1.1828	1830	0.673	1.0000
## 2 Forb - 1 Vine	-0.942334	0.3881	1700	-2.428	0.8815
## 2 Forb - 2 Vine	-0.686336	0.3755	1666	-1.828	0.9978
## 2 Forb - 3 Vine	-1.245033	0.3930	1723	-3.168	0.3260
## 2 Forb - 4 Vine	-0.930733	0.3901	1707	-2.386	0.9011
## 2 Forb - 5 Vine	-0.943327	0.3888	1705	-2.426	0.8826
## 2 Forb - 6 Vine	-0.982957	0.3904	1688	-2.518	0.8322
## 2 Forb - 7 Vine	-0.804922	0.3907	1700	-2.060	0.9846
## 3 Forb - 4 Forb	0.314299	0.1083	1817	2.901	0.5375
## 3 Forb - 5 Forb	0.301706	0.1091	1820	2.767	0.6508
## 3 Forb - 6 Forb	0.262076	0.1097	1820	2.389	0.8998
## 3 Forb - 7 Forb	0.440110	0.1110	1829	3.964	0.0312
## 3 Forb - 1	0.203424	0.1272	1822	1.599	0.9998
## 3 Forb - 2	0.459422	0.1285	1823	3.575	0.1135
## 3 Forb - 3	-0.099275	0.0851	1826	-1.167	1.0000
## 3 Forb - 4	0.215024	0.1318	1820	1.632	0.9998
## 3 Forb - 5	0.202431	0.1331	1824	1.521	0.9999
## 3 Forb - 6	0.162801	0.1339	1825	1.216	1.0000
## 3 Forb - 7	0.340835	0.1357	1827	2.512	0.8359
## 3 Forb - 1 Graminoid	0.066803	0.1230	1829	0.543	1.0000
## 3 Forb - 2 Graminoid	0.322801	0.1229	1827	2.628	0.7591
## 3 Forb - 3 Graminoid	-0.235896	0.0610	1830	-3.866	0.0441
## 3 Forb - 4 Graminoid	0.078403	0.1243	1819	0.631	1.0000
## 3 Forb - 5 Graminoid	0.065810	0.1243	1818	0.529	1.0000
## 3 Forb - 6 Graminoid	0.026180	0.1225	1822	0.214	1.0000
## 3 Forb - 7 Graminoid	0.204214	0.1237	1827	1.651	0.9997
## 3 Forb - 1 Tree	1.217411	1.1791	1830	1.032	1.0000
## 3 Forb - 2 Tree	1.473409	1.1829	1830	1.246	1.0000
## 3 Forb - 3 Tree	0.914712	1.1784	1830	0.776	1.0000
## 3 Forb - 4 Tree	1.229011	1.1832	1830	1.039	1.0000
## 3 Forb - 5 Tree	1.216418	1.1833	1830	1.028	1.0000
## 3 Forb - 6 Tree	1.176788	1.1833	1830	0.995	1.0000
## 3 Forb - 7 Tree	1.354822	1.1835	1830	1.145	1.0000
## 3 Forb - 1 Vine	-0.383637	0.3873	1669	-0.990	1.0000
## 3 Forb - 2 Vine	-0.127638	0.3862	1657	-0.330	1.0000
## 3 Forb - 3 Vine	-0.686336	0.3755	1666	-1.828	0.9978
## 3 Forb - 4 Vine	-0.372036	0.3892	1679	-0.956	1.0000
## 3 Forb - 5 Vine	-0.384630	0.3879	1677	-0.992	1.0000
## 3 Forb - 6 Vine	-0.424259	0.3893	1658	-1.090	1.0000
## 3 Forb - 7 Vine	-0.246225	0.3896	1670	-0.632	1.0000
## 4 Forb - 5 Forb	-0.012593	0.1047	1819	-0.120	1.0000
## 4 Forb - 6 Forb	-0.052223	0.1056	1822	-0.495	1.0000
## 4 Forb - 7 Forb	0.125811	0.1071	1828	1.175	1.0000
## 4 Forb - 1	-0.110876	0.1295	1825	-0.857	1.0000
## 4 Forb - 2	0.145123	0.1309	1826	1.108	1.0000

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## 4 Forb - 3      -0.413574 0.1434 1822 -2.883 0.5531
## 4 Forb - 4      -0.099275 0.0851 1826 -1.167 1.0000
## 4 Forb - 5      -0.111868 0.1356 1825 -0.825 1.0000
## 4 Forb - 6      -0.151498 0.1365 1827 -1.110 1.0000
## 4 Forb - 7      0.026536 0.1384 1826 0.192 1.0000
## 4 Forb - 1 Graminoid -0.247497 0.1187 1830 -2.084 0.9818
## 4 Forb - 2 Graminoid 0.008502 0.1188 1830 0.072 1.0000
## 4 Forb - 3 Graminoid -0.550195 0.1243 1827 -4.425 0.0050
## 4 Forb - 4 Graminoid -0.235896 0.0610 1830 -3.866 0.0441
## 4 Forb - 5 Graminoid -0.248489 0.1205 1823 -2.062 0.9844
## 4 Forb - 6 Graminoid -0.288119 0.1189 1826 -2.424 0.8838
## 4 Forb - 7 Graminoid -0.110085 0.1202 1828 -0.916 1.0000
## 4 Forb - 1 Tree   0.903112 1.1788 1830 0.766 1.0000
## 4 Forb - 2 Tree   1.159110 1.1826 1830 0.980 1.0000
## 4 Forb - 3 Tree   0.600413 1.1835 1830 0.507 1.0000
## 4 Forb - 4 Tree   0.914712 1.1784 1830 0.776 1.0000
## 4 Forb - 5 Tree   0.902119 1.1830 1830 0.763 1.0000
## 4 Forb - 6 Tree   0.862489 1.1830 1830 0.729 1.0000
## 4 Forb - 7 Tree   1.040523 1.1832 1830 0.879 1.0000
## 4 Forb - 1 Vine   -0.697936 0.3877 1682 -1.800 0.9983
## 4 Forb - 2 Vine   -0.441938 0.3867 1670 -1.143 1.0000
## 4 Forb - 3 Vine   -1.000635 0.3925 1709 -2.549 0.8125
## 4 Forb - 4 Vine   -0.686336 0.3755 1666 -1.828 0.9978
## 4 Forb - 5 Vine   -0.698929 0.3884 1691 -1.800 0.9983
## 4 Forb - 6 Vine   -0.738559 0.3899 1672 -1.894 0.9959
## 4 Forb - 7 Vine   -0.560525 0.3901 1685 -1.437 1.0000
## 5 Forb - 6 Forb   -0.039630 0.1063 1813 -0.373 1.0000
## 5 Forb - 7 Forb   0.138404 0.1077 1824 1.285 1.0000
## 5 Forb - 1          -0.098282 0.1295 1826 -0.759 1.0000
## 5 Forb - 2          0.157716 0.1310 1826 1.204 1.0000
## 5 Forb - 3          -0.400981 0.1433 1822 -2.798 0.6250
## 5 Forb - 4          -0.086682 0.1342 1820 -0.646 1.0000
## 5 Forb - 5          -0.099275 0.0851 1826 -1.167 1.0000
## 5 Forb - 6          -0.138905 0.1363 1821 -1.019 1.0000
## 5 Forb - 7          0.039129 0.1382 1822 0.283 1.0000
## 5 Forb - 1 Graminoid -0.234903 0.1203 1828 -1.952 0.9933
## 5 Forb - 2 Graminoid 0.021095 0.1203 1830 0.175 1.0000
## 5 Forb - 3 Graminoid -0.537602 0.1256 1829 -4.279 0.0092
## 5 Forb - 4 Graminoid -0.223303 0.1219 1826 -1.832 0.9977
## 5 Forb - 5 Graminoid -0.235896 0.0610 1830 -3.866 0.0441
## 5 Forb - 6 Graminoid -0.275526 0.1202 1824 -2.293 0.9367
## 5 Forb - 7 Graminoid -0.097492 0.1215 1827 -0.803 1.0000
## 5 Forb - 1 Tree     0.915705 1.1789 1830 0.777 1.0000
## 5 Forb - 2 Tree     1.171703 1.1827 1830 0.991 1.0000
## 5 Forb - 3 Tree     0.613006 1.1836 1830 0.518 1.0000
## 5 Forb - 4 Tree     0.927305 1.1830 1830 0.784 1.0000
## 5 Forb - 5 Tree     0.914712 1.1784 1830 0.776 1.0000
## 5 Forb - 6 Tree     0.875082 1.1831 1830 0.740 1.0000
## 5 Forb - 7 Tree     1.053116 1.1833 1830 0.890 1.0000
## 5 Forb - 1 Vine     -0.685343 0.3894 1682 -1.760 0.9989
## 5 Forb - 2 Vine     -0.429345 0.3884 1671 -1.105 1.0000
## 5 Forb - 3 Vine     -0.988042 0.3942 1710 -2.507 0.8389
## 5 Forb - 4 Vine     -0.673743 0.3913 1694 -1.722 0.9993
## 5 Forb - 5 Vine     -0.686336 0.3755 1666 -1.828 0.9978

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## 5 Forb - 6 Vine	-0.725966	0.3915	1676	-1.854	0.9972
## 5 Forb - 7 Vine	-0.547932	0.3918	1688	-1.399	1.0000
## 6 Forb - 7 Forb	0.178034	0.1082	1824	1.645	0.9997
## 6 Forb - 1	-0.058653	0.1301	1824	-0.451	1.0000
## 6 Forb - 2	0.197346	0.1316	1824	1.500	1.0000
## 6 Forb - 3	-0.361351	0.1436	1821	-2.516	0.8331
## 6 Forb - 4	-0.047052	0.1346	1820	-0.349	1.0000
## 6 Forb - 5	-0.059645	0.1359	1818	-0.439	1.0000
## 6 Forb - 6	-0.099275	0.0851	1826	-1.167	1.0000
## 6 Forb - 7	0.078759	0.1384	1820	0.569	1.0000
## 6 Forb - 1 Graminoid	-0.195274	0.1236	1830	-1.580	0.9999
## 6 Forb - 2 Graminoid	0.060725	0.1236	1830	0.491	1.0000
## 6 Forb - 3 Graminoid	-0.497972	0.1284	1827	-3.878	0.0424
## 6 Forb - 4 Graminoid	-0.183673	0.1249	1825	-1.470	1.0000
## 6 Forb - 5 Graminoid	-0.196266	0.1248	1818	-1.572	0.9999
## 6 Forb - 6 Graminoid	-0.235896	0.0610	1830	-3.866	0.0441
## 6 Forb - 7 Graminoid	-0.057862	0.1242	1825	-0.466	1.0000
## 6 Forb - 1 Tree	0.955335	1.1790	1830	0.810	1.0000
## 6 Forb - 2 Tree	1.211333	1.1828	1830	1.024	1.0000
## 6 Forb - 3 Tree	0.652636	1.1837	1830	0.551	1.0000
## 6 Forb - 4 Tree	0.966935	1.1832	1830	0.817	1.0000
## 6 Forb - 5 Tree	0.954342	1.1832	1830	0.807	1.0000
## 6 Forb - 6 Tree	0.914712	1.1784	1830	0.776	1.0000
## 6 Forb - 7 Tree	1.092746	1.1834	1830	0.923	1.0000
## 6 Forb - 1 Vine	-0.645713	0.3885	1701	-1.662	0.9996
## 6 Forb - 2 Vine	-0.389715	0.3875	1691	-1.006	1.0000
## 6 Forb - 3 Vine	-0.948412	0.3931	1726	-2.413	0.8890
## 6 Forb - 4 Vine	-0.634113	0.3903	1711	-1.625	0.9998
## 6 Forb - 5 Vine	-0.646706	0.3890	1712	-1.662	0.9996
## 6 Forb - 6 Vine	-0.686336	0.3755	1666	-1.828	0.9978
## 6 Forb - 7 Vine	-0.508302	0.3907	1706	-1.301	1.0000
## 7 Forb - 1	-0.236687	0.1306	1830	-1.812	0.9981
## 7 Forb - 2	0.019312	0.1321	1830	0.146	1.0000
## 7 Forb - 3	-0.539385	0.1440	1829	-3.747	0.0662
## 7 Forb - 4	-0.225086	0.1351	1828	-1.666	0.9996
## 7 Forb - 5	-0.237679	0.1363	1828	-1.743	0.9991
## 7 Forb - 6	-0.277309	0.1370	1829	-2.025	0.9881
## 7 Forb - 7	-0.099275	0.0851	1826	-1.167	1.0000
## 7 Forb - 1 Graminoid	-0.373308	0.1249	1826	-2.989	0.4646
## 7 Forb - 2 Graminoid	-0.117309	0.1249	1828	-0.939	1.0000
## 7 Forb - 3 Graminoid	-0.676006	0.1296	1830	-5.216	0.0001
## 7 Forb - 4 Graminoid	-0.361707	0.1262	1830	-2.866	0.5676
## 7 Forb - 5 Graminoid	-0.374300	0.1261	1828	-2.968	0.4821
## 7 Forb - 6 Graminoid	-0.413930	0.1243	1829	-3.331	0.2225
## 7 Forb - 7 Graminoid	-0.235896	0.0610	1830	-3.866	0.0441
## 7 Forb - 1 Tree	0.777301	1.1791	1830	0.659	1.0000
## 7 Forb - 2 Tree	1.033299	1.1829	1830	0.874	1.0000
## 7 Forb - 3 Tree	0.474602	1.1837	1830	0.401	1.0000
## 7 Forb - 4 Tree	0.788901	1.1832	1830	0.667	1.0000
## 7 Forb - 5 Tree	0.776308	1.1833	1830	0.656	1.0000
## 7 Forb - 6 Tree	0.736678	1.1833	1830	0.623	1.0000
## 7 Forb - 7 Tree	0.914712	1.1784	1830	0.776	1.0000
## 7 Forb - 1 Vine	-0.823747	0.3890	1685	-2.118	0.9772
## 7 Forb - 2 Vine	-0.567749	0.3880	1674	-1.463	1.0000

##	7	Forb	-	3	Vine	-1.126446	0.3936	1711	-2.862	0.5711
##	7	Forb	-	4	Vine	-0.812147	0.3908	1696	-2.078	0.9826
##	7	Forb	-	5	Vine	-0.824740	0.3895	1696	-2.117	0.9772
##	7	Forb	-	6	Vine	-0.864370	0.3909	1678	-2.211	0.9594
##	7	Forb	-	7	Vine	-0.686336	0.3755	1666	-1.828	0.9978
##	1	-	2			0.255998	0.0944	1813	2.712	0.6952
##	1	-	3			-0.302699	0.1047	1819	-2.892	0.5458
##	1	-	4			0.011600	0.0997	1822	0.116	1.0000
##	1	-	5			-0.000993	0.1007	1828	-0.010	1.0000
##	1	-	6			-0.040623	0.1018	1827	-0.399	1.0000
##	1	-	7			0.137411	0.1034	1830	1.329	1.0000
##	1	-	1	Graminoid		-0.136621	0.0894	1829	-1.529	0.9999
##	1	-	2	Graminoid		0.119377	0.1286	1819	0.928	1.0000
##	1	-	3	Graminoid		-0.439320	0.1284	1819	-3.422	0.1755
##	1	-	4	Graminoid		-0.125021	0.1306	1818	-0.957	1.0000
##	1	-	5	Graminoid		-0.137614	0.1300	1817	-1.058	1.0000
##	1	-	6	Graminoid		-0.177244	0.1285	1817	-1.380	1.0000
##	1	-	7	Graminoid		0.000790	0.1289	1825	0.006	1.0000
##	1	-	1	Tree		1.013987	1.1799	1830	0.859	1.0000
##	1	-	2	Tree		1.269985	1.1873	1830	1.070	1.0000
##	1	-	3	Tree		0.711288	1.1876	1830	0.599	1.0000
##	1	-	4	Tree		1.025588	1.1877	1830	0.863	1.0000
##	1	-	5	Tree		1.012995	1.1877	1830	0.853	1.0000
##	1	-	6	Tree		0.973365	1.1877	1830	0.820	1.0000
##	1	-	7	Tree		1.151399	1.1878	1830	0.969	1.0000
##	1	-	1	Vine		-0.587060	0.3806	1704	-1.542	0.9999
##	1	-	2	Vine		-0.331062	0.3906	1712	-0.847	1.0000
##	1	-	3	Vine		-0.889759	0.3947	1740	-2.254	0.9482
##	1	-	4	Vine		-0.575460	0.3937	1728	-1.462	1.0000
##	1	-	5	Vine		-0.588053	0.3923	1726	-1.499	1.0000
##	1	-	6	Vine		-0.627683	0.3937	1711	-1.594	0.9998
##	1	-	7	Vine		-0.449649	0.3938	1720	-1.142	1.0000
##	2	-	3			-0.558697	0.1039	1818	-5.379	<.0001
##	2	-	4			-0.244398	0.0991	1821	-2.467	0.8615
##	2	-	5			-0.256991	0.1001	1825	-2.568	0.8003
##	2	-	6			-0.296621	0.1012	1823	-2.931	0.5126
##	2	-	7			-0.118587	0.1028	1829	-1.154	1.0000
##	2	-	1	Graminoid		-0.392619	0.1314	1827	-2.988	0.4653
##	2	-	2	Graminoid		-0.136621	0.0894	1829	-1.529	0.9999
##	2	-	3	Graminoid		-0.695318	0.1292	1822	-5.383	<.0001
##	2	-	4	Graminoid		-0.381019	0.1316	1822	-2.896	0.5424
##	2	-	5	Graminoid		-0.393612	0.1310	1820	-3.006	0.4507
##	2	-	6	Graminoid		-0.433242	0.1294	1819	-3.348	0.2131
##	2	-	7	Graminoid		-0.255208	0.1299	1827	-1.965	0.9926
##	2	-	1	Tree		0.757989	1.1801	1830	0.642	1.0000
##	2	-	2	Tree		1.013987	1.1799	1830	0.859	1.0000
##	2	-	3	Tree		0.455290	1.1839	1830	0.385	1.0000
##	2	-	4	Tree		0.769589	1.1841	1830	0.650	1.0000
##	2	-	5	Tree		0.756996	1.1840	1830	0.639	1.0000
##	2	-	6	Tree		0.717366	1.1841	1830	0.606	1.0000
##	2	-	7	Tree		0.895400	1.1842	1830	0.756	1.0000
##	2	-	1	Vine		-0.843059	0.3936	1731	-2.142	0.9733
##	2	-	2	Vine		-0.587060	0.3806	1704	-1.542	0.9999
##	2	-	3	Vine		-1.145757	0.3959	1749	-2.894	0.5440

##	2	-	4	Vine	-0.831458	0.3951	1737	-2.105	0.9791
##	2	-	5	Vine	-0.844051	0.3936	1736	-2.144	0.9729
##	2	-	6	Vine	-0.883681	0.3951	1721	-2.237	0.9530
##	2	-	7	Vine	-0.705647	0.3951	1729	-1.786	0.9986
##	3	-	4		0.314299	0.1083	1817	2.901	0.5375
##	3	-	5		0.301706	0.1091	1820	2.767	0.6508
##	3	-	6		0.262076	0.1097	1820	2.389	0.8998
##	3	-	7		0.440110	0.1110	1829	3.964	0.0312
##	3	-	1	Graminoid	0.166078	0.1463	1828	1.135	1.0000
##	3	-	2	Graminoid	0.422076	0.1445	1825	2.922	0.5204
##	3	-	3	Graminoid	-0.136621	0.0894	1829	-1.529	0.9999
##	3	-	4	Graminoid	0.177678	0.1460	1821	1.217	1.0000
##	3	-	5	Graminoid	0.165085	0.1453	1819	1.136	1.0000
##	3	-	6	Graminoid	0.125455	0.1436	1820	0.873	1.0000
##	3	-	7	Graminoid	0.303489	0.1440	1828	2.108	0.9786
##	3	-	1	Tree	1.316686	1.1815	1830	1.114	1.0000
##	3	-	2	Tree	1.572684	1.1850	1830	1.327	1.0000
##	3	-	3	Tree	1.013987	1.1799	1830	0.859	1.0000
##	3	-	4	Tree	1.328286	1.1854	1830	1.121	1.0000
##	3	-	5	Tree	1.315693	1.1854	1830	1.110	1.0000
##	3	-	6	Tree	1.276063	1.1854	1830	1.076	1.0000
##	3	-	7	Tree	1.454097	1.1855	1830	1.227	1.0000
##	3	-	1	Vine	-0.284362	0.3948	1708	-0.720	1.0000
##	3	-	2	Vine	-0.028363	0.3931	1697	-0.072	1.0000
##	3	-	3	Vine	-0.587060	0.3806	1704	-1.542	0.9999
##	3	-	4	Vine	-0.272761	0.3961	1715	-0.689	1.0000
##	3	-	5	Vine	-0.285354	0.3946	1714	-0.723	1.0000
##	3	-	6	Vine	-0.324984	0.3959	1698	-0.821	1.0000
##	3	-	7	Vine	-0.146950	0.3959	1706	-0.371	1.0000
##	4	-	5		-0.012593	0.1047	1819	-0.120	1.0000
##	4	-	6		-0.052223	0.1056	1822	-0.495	1.0000
##	4	-	7		0.125811	0.1071	1828	1.175	1.0000
##	4	-	1	Graminoid	-0.148221	0.1370	1830	-1.082	1.0000
##	4	-	2	Graminoid	0.107777	0.1352	1828	0.797	1.0000
##	4	-	3	Graminoid	-0.450920	0.1346	1826	-3.350	0.2120
##	4	-	4	Graminoid	-0.136621	0.0894	1829	-1.529	0.9999
##	4	-	5	Graminoid	-0.149214	0.1364	1821	-1.094	1.0000
##	4	-	6	Graminoid	-0.188844	0.1347	1823	-1.402	1.0000
##	4	-	7	Graminoid	-0.010810	0.1351	1828	-0.080	1.0000
##	4	-	1	Tree	1.002387	1.1805	1830	0.849	1.0000
##	4	-	2	Tree	1.258385	1.1841	1830	1.063	1.0000
##	4	-	3	Tree	0.699688	1.1843	1830	0.591	1.0000
##	4	-	4	Tree	1.013987	1.1799	1830	0.859	1.0000
##	4	-	5	Tree	1.001394	1.1844	1830	0.845	1.0000
##	4	-	6	Tree	0.961764	1.1845	1830	0.812	1.0000
##	4	-	7	Tree	1.139798	1.1846	1830	0.962	1.0000
##	4	-	1	Vine	-0.598661	0.3931	1717	-1.523	0.9999
##	4	-	2	Vine	-0.342663	0.3915	1706	-0.875	1.0000
##	4	-	3	Vine	-0.901360	0.3953	1737	-2.280	0.9407
##	4	-	4	Vine	-0.587060	0.3806	1704	-1.542	0.9999
##	4	-	5	Vine	-0.599654	0.3930	1724	-1.526	0.9999
##	4	-	6	Vine	-0.639284	0.3944	1708	-1.621	0.9998
##	4	-	7	Vine	-0.461249	0.3945	1717	-1.169	1.0000
##	5	-	6		-0.039630	0.1063	1813	-0.373	1.0000

##	5	-	7		0.138404	0.1077	1824	1.285	1.0000
##	5	-	1	Graminoid	-0.135628	0.1391	1830	-0.975	1.0000
##	5	-	2	Graminoid	0.120370	0.1373	1830	0.877	1.0000
##	5	-	3	Graminoid	-0.438327	0.1365	1829	-3.211	0.2965
##	5	-	4	Graminoid	-0.124028	0.1390	1827	-0.892	1.0000
##	5	-	5	Graminoid	-0.136621	0.0894	1829	-1.529	0.9999
##	5	-	6	Graminoid	-0.176251	0.1365	1823	-1.291	1.0000
##	5	-	7	Graminoid	0.001783	0.1370	1829	0.013	1.0000
##	5	-	1	Tree	1.014980	1.1807	1830	0.860	1.0000
##	5	-	2	Tree	1.270978	1.1843	1830	1.073	1.0000
##	5	-	3	Tree	0.712281	1.1845	1830	0.601	1.0000
##	5	-	4	Tree	1.026580	1.1847	1830	0.867	1.0000
##	5	-	5	Tree	1.013987	1.1799	1830	0.859	1.0000
##	5	-	6	Tree	0.974357	1.1846	1830	0.823	1.0000
##	5	-	7	Tree	1.152391	1.1847	1830	0.973	1.0000
##	5	-	1	Vine	-0.586068	0.3951	1716	-1.483	1.0000
##	5	-	2	Vine	-0.330069	0.3935	1706	-0.839	1.0000
##	5	-	3	Vine	-0.888767	0.3972	1737	-2.237	0.9529
##	5	-	4	Vine	-0.574467	0.3965	1725	-1.449	1.0000
##	5	-	5	Vine	-0.587060	0.3806	1704	-1.542	0.9999
##	5	-	6	Vine	-0.626690	0.3963	1710	-1.581	0.9999
##	5	-	7	Vine	-0.448656	0.3963	1719	-1.132	1.0000
##	6	-	7		0.178034	0.1082	1824	1.645	0.9997
##	6	-	1	Graminoid	-0.095998	0.1421	1830	-0.675	1.0000
##	6	-	2	Graminoid	0.160000	0.1404	1830	1.140	1.0000
##	6	-	3	Graminoid	-0.398697	0.1393	1829	-2.862	0.5710
##	6	-	4	Graminoid	-0.084398	0.1419	1828	-0.595	1.0000
##	6	-	5	Graminoid	-0.096991	0.1411	1821	-0.687	1.0000
##	6	-	6	Graminoid	-0.136621	0.0894	1829	-1.529	0.9999
##	6	-	7	Graminoid	0.041413	0.1396	1828	0.297	1.0000
##	6	-	1	Tree	1.054610	1.1809	1830	0.893	1.0000
##	6	-	2	Tree	1.310608	1.1844	1830	1.107	1.0000
##	6	-	3	Tree	0.751911	1.1846	1830	0.635	1.0000
##	6	-	4	Tree	1.066210	1.1848	1830	0.900	1.0000
##	6	-	5	Tree	1.053617	1.1848	1830	0.889	1.0000
##	6	-	6	Tree	1.013987	1.1799	1830	0.859	1.0000
##	6	-	7	Tree	1.192021	1.1848	1830	1.006	1.0000
##	6	-	1	Vine	-0.546438	0.3942	1732	-1.386	1.0000
##	6	-	2	Vine	-0.290440	0.3926	1723	-0.740	1.0000
##	6	-	3	Vine	-0.849137	0.3963	1751	-2.143	0.9731
##	6	-	4	Vine	-0.534837	0.3955	1740	-1.352	1.0000
##	6	-	5	Vine	-0.547431	0.3940	1741	-1.389	1.0000
##	6	-	6	Vine	-0.587060	0.3806	1704	-1.542	0.9999
##	6	-	7	Vine	-0.409027	0.3953	1734	-1.035	1.0000
##	7	-	1	Graminoid	-0.274032	0.1440	1830	-1.903	0.9956
##	7	-	2	Graminoid	-0.018034	0.1422	1830	-0.127	1.0000
##	7	-	3	Graminoid	-0.576731	0.1411	1830	-4.088	0.0196
##	7	-	4	Graminoid	-0.262432	0.1437	1829	-1.827	0.9978
##	7	-	5	Graminoid	-0.275025	0.1429	1825	-1.924	0.9947
##	7	-	6	Graminoid	-0.314655	0.1411	1825	-2.230	0.9547
##	7	-	7	Graminoid	-0.136621	0.0894	1829	-1.529	0.9999
##	7	-	1	Tree	0.876576	1.1810	1830	0.742	1.0000
##	7	-	2	Tree	1.132574	1.1846	1830	0.956	1.0000
##	7	-	3	Tree	0.573877	1.1848	1830	0.484	1.0000

##	7	- 4	Tree	0.888176	1.1850	1830	0.750	1.0000
##	7	- 5	Tree	0.875583	1.1849	1830	0.739	1.0000
##	7	- 6	Tree	0.835953	1.1849	1830	0.706	1.0000
##	7	- 7	Tree	1.013987	1.1799	1830	0.859	1.0000
##	7	- 1	Vine	-0.724472	0.3950	1721	-1.834	0.9977
##	7	- 2	Vine	-0.468474	0.3934	1711	-1.191	1.0000
##	7	- 3	Vine	-1.027171	0.3970	1739	-2.587	0.7874
##	7	- 4	Vine	-0.712871	0.3963	1729	-1.799	0.9984
##	7	- 5	Vine	-0.725465	0.3948	1730	-1.838	0.9976
##	7	- 6	Vine	-0.765094	0.3961	1714	-1.932	0.9944
##	7	- 7	Vine	-0.587060	0.3806	1704	-1.542	0.9999
##	1	Graminoid	- 2 Graminoid	0.255998	0.0944	1813	2.712	0.6952
##	1	Graminoid	- 3 Graminoid	-0.302699	0.1047	1819	-2.892	0.5458
##	1	Graminoid	- 4 Graminoid	0.011600	0.0997	1822	0.116	1.0000
##	1	Graminoid	- 5 Graminoid	-0.000993	0.1007	1828	-0.010	1.0000
##	1	Graminoid	- 6 Graminoid	-0.040623	0.1018	1827	-0.399	1.0000
##	1	Graminoid	- 7 Graminoid	0.137411	0.1034	1830	1.329	1.0000
##	1	Graminoid	- 1 Tree	1.150608	1.1788	1830	0.976	1.0000
##	1	Graminoid	- 2 Tree	1.406607	1.1864	1830	1.186	1.0000
##	1	Graminoid	- 3 Tree	0.847909	1.1876	1830	0.714	1.0000
##	1	Graminoid	- 4 Tree	1.162209	1.1870	1830	0.979	1.0000
##	1	Graminoid	- 5 Tree	1.149616	1.1872	1830	0.968	1.0000
##	1	Graminoid	- 6 Tree	1.109986	1.1874	1830	0.935	1.0000
##	1	Graminoid	- 7 Tree	1.288020	1.1876	1830	1.085	1.0000
##	1	Graminoid	- 1 Vine	-0.450439	0.3765	1677	-1.196	1.0000
##	1	Graminoid	- 2 Vine	-0.194441	0.3871	1687	-0.502	1.0000
##	1	Graminoid	- 3 Vine	-0.753138	0.3939	1721	-1.912	0.9952
##	1	Graminoid	- 4 Vine	-0.438839	0.3909	1703	-1.123	1.0000
##	1	Graminoid	- 5 Vine	-0.451432	0.3899	1700	-1.158	1.0000
##	1	Graminoid	- 6 Vine	-0.491062	0.3922	1685	-1.252	1.0000
##	1	Graminoid	- 7 Vine	-0.313028	0.3925	1697	-0.798	1.0000
##	2	Graminoid	- 3 Graminoid	-0.558697	0.1039	1818	-5.379	<.0001
##	2	Graminoid	- 4 Graminoid	-0.244398	0.0991	1821	-2.467	0.8615
##	2	Graminoid	- 5 Graminoid	-0.256991	0.1001	1825	-2.568	0.8003
##	2	Graminoid	- 6 Graminoid	-0.296621	0.1012	1823	-2.931	0.5126
##	2	Graminoid	- 7 Graminoid	-0.118587	0.1028	1829	-1.154	1.0000
##	2	Graminoid	- 1 Tree	0.894610	1.1788	1830	0.759	1.0000
##	2	Graminoid	- 2 Tree	1.150608	1.1788	1830	0.976	1.0000
##	2	Graminoid	- 3 Tree	0.591911	1.1837	1830	0.500	1.0000
##	2	Graminoid	- 4 Tree	0.906210	1.1832	1830	0.766	1.0000
##	2	Graminoid	- 5 Tree	0.893617	1.1833	1830	0.755	1.0000
##	2	Graminoid	- 6 Tree	0.853987	1.1836	1830	0.722	1.0000
##	2	Graminoid	- 7 Tree	1.032021	1.1838	1830	0.872	1.0000
##	2	Graminoid	- 1 Vine	-0.706438	0.3892	1711	-1.815	0.9981
##	2	Graminoid	- 2 Vine	-0.450439	0.3765	1677	-1.196	1.0000
##	2	Graminoid	- 3 Vine	-1.009137	0.3947	1732	-2.557	0.8077
##	2	Graminoid	- 4 Vine	-0.694837	0.3918	1715	-1.774	0.9987
##	2	Graminoid	- 5 Vine	-0.707430	0.3908	1712	-1.810	0.9982
##	2	Graminoid	- 6 Vine	-0.747060	0.3930	1698	-1.901	0.9957
##	2	Graminoid	- 7 Vine	-0.569026	0.3933	1708	-1.447	1.0000
##	3	Graminoid	- 4 Graminoid	0.314299	0.1083	1817	2.901	0.5375
##	3	Graminoid	- 5 Graminoid	0.301706	0.1091	1820	2.767	0.6508
##	3	Graminoid	- 6 Graminoid	0.262076	0.1097	1820	2.389	0.8998
##	3	Graminoid	- 7 Graminoid	0.440110	0.1110	1829	3.964	0.0312

## 3 Graminoid - 1 Tree	1.453307	1.1794	1830	1.232	1.0000
## 3 Graminoid - 2 Tree	1.709305	1.1831	1830	1.445	1.0000
## 3 Graminoid - 3 Tree	1.150608	1.1788	1830	0.976	1.0000
## 3 Graminoid - 4 Tree	1.464908	1.1837	1830	1.238	1.0000
## 3 Graminoid - 5 Tree	1.452314	1.1838	1830	1.227	1.0000
## 3 Graminoid - 6 Tree	1.412684	1.1841	1830	1.193	1.0000
## 3 Graminoid - 7 Tree	1.590718	1.1842	1830	1.343	1.0000
## 3 Graminoid - 1 Vine	-0.147741	0.3877	1681	-0.381	1.0000
## 3 Graminoid - 2 Vine	0.108258	0.3865	1668	0.280	1.0000
## 3 Graminoid - 3 Vine	-0.450439	0.3765	1677	-1.196	1.0000
## 3 Graminoid - 4 Vine	-0.136140	0.3901	1688	-0.349	1.0000
## 3 Graminoid - 5 Vine	-0.148733	0.3891	1685	-0.382	1.0000
## 3 Graminoid - 6 Vine	-0.188363	0.3912	1669	-0.481	1.0000
## 3 Graminoid - 7 Vine	-0.010329	0.3915	1679	-0.026	1.0000
## 4 Graminoid - 5 Graminoid	-0.012593	0.1047	1819	-0.120	1.0000
## 4 Graminoid - 6 Graminoid	-0.052223	0.1056	1822	-0.495	1.0000
## 4 Graminoid - 7 Graminoid	0.125811	0.1071	1828	1.175	1.0000
## 4 Graminoid - 1 Tree	1.139008	1.1791	1830	0.966	1.0000
## 4 Graminoid - 2 Tree	1.395006	1.1828	1830	1.179	1.0000
## 4 Graminoid - 3 Tree	0.836309	1.1839	1830	0.706	1.0000
## 4 Graminoid - 4 Tree	1.150608	1.1788	1830	0.976	1.0000
## 4 Graminoid - 5 Tree	1.138015	1.1835	1830	0.962	1.0000
## 4 Graminoid - 6 Tree	1.098385	1.1838	1830	0.928	1.0000
## 4 Graminoid - 7 Tree	1.276419	1.1840	1830	1.078	1.0000
## 4 Graminoid - 1 Vine	-0.462040	0.3881	1695	-1.191	1.0000
## 4 Graminoid - 2 Vine	-0.206041	0.3869	1683	-0.533	1.0000
## 4 Graminoid - 3 Vine	-0.764739	0.3935	1720	-1.944	0.9938
## 4 Graminoid - 4 Vine	-0.450439	0.3765	1677	-1.196	1.0000
## 4 Graminoid - 5 Vine	-0.463033	0.3896	1700	-1.189	1.0000
## 4 Graminoid - 6 Vine	-0.502662	0.3918	1684	-1.283	1.0000
## 4 Graminoid - 7 Vine	-0.324628	0.3921	1695	-0.828	1.0000
## 5 Graminoid - 6 Graminoid	-0.039630	0.1063	1813	-0.373	1.0000
## 5 Graminoid - 7 Graminoid	0.138404	0.1077	1824	1.285	1.0000
## 5 Graminoid - 1 Tree	1.151601	1.1791	1830	0.977	1.0000
## 5 Graminoid - 2 Tree	1.407599	1.1829	1830	1.190	1.0000
## 5 Graminoid - 3 Tree	0.848902	1.1840	1830	0.717	1.0000
## 5 Graminoid - 4 Tree	1.163201	1.1835	1830	0.983	1.0000
## 5 Graminoid - 5 Tree	1.150608	1.1788	1830	0.976	1.0000
## 5 Graminoid - 6 Tree	1.110978	1.1838	1830	0.938	1.0000
## 5 Graminoid - 7 Tree	1.289012	1.1840	1830	1.089	1.0000
## 5 Graminoid - 1 Vine	-0.449447	0.3896	1696	-1.154	1.0000
## 5 Graminoid - 2 Vine	-0.193448	0.3884	1684	-0.498	1.0000
## 5 Graminoid - 3 Vine	-0.752146	0.3949	1721	-1.905	0.9955
## 5 Graminoid - 4 Vine	-0.437846	0.3921	1704	-1.117	1.0000
## 5 Graminoid - 5 Vine	-0.450439	0.3765	1677	-1.196	1.0000
## 5 Graminoid - 6 Vine	-0.490069	0.3932	1689	-1.246	1.0000
## 5 Graminoid - 7 Vine	-0.312035	0.3935	1699	-0.793	1.0000
## 6 Graminoid - 7 Graminoid	0.178034	0.1082	1824	1.645	0.9997
## 6 Graminoid - 1 Tree	1.191231	1.1790	1830	1.010	1.0000
## 6 Graminoid - 2 Tree	1.447229	1.1827	1830	1.224	1.0000
## 6 Graminoid - 3 Tree	0.888532	1.1838	1830	0.751	1.0000
## 6 Graminoid - 4 Tree	1.202831	1.1833	1830	1.016	1.0000
## 6 Graminoid - 5 Tree	1.190238	1.1834	1830	1.006	1.0000
## 6 Graminoid - 6 Tree	1.150608	1.1788	1830	0.976	1.0000

## 6 Graminoid - 7 Tree	1.328642	1.1839	1830	1.122	1.0000
## 6 Graminoid - 1 Vine	-0.409817	0.3879	1712	-1.056	1.0000
## 6 Graminoid - 2 Vine	-0.153818	0.3867	1701	-0.398	1.0000
## 6 Graminoid - 3 Vine	-0.712516	0.3931	1735	-1.812	0.9981
## 6 Graminoid - 4 Vine	-0.398216	0.3903	1719	-1.020	1.0000
## 6 Graminoid - 5 Vine	-0.410809	0.3893	1719	-1.055	1.0000
## 6 Graminoid - 6 Vine	-0.450439	0.3765	1677	-1.196	1.0000
## 6 Graminoid - 7 Vine	-0.272405	0.3917	1714	-0.696	1.0000
## 7 Graminoid - 1 Tree	1.013197	1.1791	1830	0.859	1.0000
## 7 Graminoid - 2 Tree	1.269195	1.1828	1830	1.073	1.0000
## 7 Graminoid - 3 Tree	0.710498	1.1839	1830	0.600	1.0000
## 7 Graminoid - 4 Tree	1.024797	1.1834	1830	0.866	1.0000
## 7 Graminoid - 5 Tree	1.012204	1.1835	1830	0.855	1.0000
## 7 Graminoid - 6 Tree	0.972574	1.1837	1830	0.822	1.0000
## 7 Graminoid - 7 Tree	1.150608	1.1788	1830	0.976	1.0000
## 7 Graminoid - 1 Vine	-0.587851	0.3885	1698	-1.513	1.0000
## 7 Graminoid - 2 Vine	-0.331852	0.3873	1686	-0.857	1.0000
## 7 Graminoid - 3 Vine	-0.890550	0.3936	1721	-2.262	0.9459
## 7 Graminoid - 4 Vine	-0.576250	0.3909	1705	-1.474	1.0000
## 7 Graminoid - 5 Vine	-0.588843	0.3898	1705	-1.511	1.0000
## 7 Graminoid - 6 Vine	-0.628473	0.3919	1690	-1.604	0.9998
## 7 Graminoid - 7 Vine	-0.450439	0.3765	1677	-1.196	1.0000
## 1 Tree - 2 Tree	0.255998	0.0944	1813	2.712	0.6952
## 1 Tree - 3 Tree	-0.302699	0.1047	1819	-2.892	0.5458
## 1 Tree - 4 Tree	0.011600	0.0997	1822	0.116	1.0000
## 1 Tree - 5 Tree	-0.000993	0.1007	1828	-0.010	1.0000
## 1 Tree - 6 Tree	-0.040623	0.1018	1827	-0.399	1.0000
## 1 Tree - 7 Tree	0.137411	0.1034	1830	1.329	1.0000
## 1 Tree - 1 Vine	-1.601048	1.2357	1829	-1.296	1.0000
## 1 Tree - 2 Vine	-1.345049	1.2354	1829	-1.089	1.0000
## 1 Tree - 3 Vine	-1.903747	1.2372	1829	-1.539	0.9999
## 1 Tree - 4 Vine	-1.589447	1.2364	1829	-1.286	1.0000
## 1 Tree - 5 Vine	-1.602040	1.2360	1829	-1.296	1.0000
## 1 Tree - 6 Vine	-1.641670	1.2365	1829	-1.328	1.0000
## 1 Tree - 7 Vine	-1.463636	1.2366	1829	-1.184	1.0000
## 2 Tree - 3 Tree	-0.558697	0.1039	1818	-5.379	<.0001
## 2 Tree - 4 Tree	-0.2444398	0.0991	1821	-2.467	0.8615
## 2 Tree - 5 Tree	-0.256991	0.1001	1825	-2.568	0.8003
## 2 Tree - 6 Tree	-0.296621	0.1012	1823	-2.931	0.5126
## 2 Tree - 7 Tree	-0.118587	0.1028	1829	-1.154	1.0000
## 2 Tree - 1 Vine	-1.857046	1.2432	1829	-1.494	1.0000
## 2 Tree - 2 Vine	-1.601048	1.2357	1829	-1.296	1.0000
## 2 Tree - 3 Vine	-2.159745	1.2411	1829	-1.740	0.9991
## 2 Tree - 4 Vine	-1.845446	1.2403	1829	-1.488	1.0000
## 2 Tree - 5 Vine	-1.858039	1.2399	1829	-1.499	1.0000
## 2 Tree - 6 Vine	-1.897669	1.2404	1829	-1.530	0.9999
## 2 Tree - 7 Vine	-1.719635	1.2405	1829	-1.386	1.0000
## 3 Tree - 4 Tree	0.314299	0.1083	1817	2.901	0.5375
## 3 Tree - 5 Tree	0.301706	0.1091	1820	2.767	0.6508
## 3 Tree - 6 Tree	0.262076	0.1097	1820	2.389	0.8998
## 3 Tree - 7 Tree	0.440110	0.1110	1829	3.964	0.0312
## 3 Tree - 1 Vine	-1.298349	1.2431	1828	-1.044	1.0000
## 3 Tree - 2 Vine	-1.042351	1.2391	1828	-0.841	1.0000
## 3 Tree - 3 Vine	-1.601048	1.2357	1829	-1.296	1.0000

## 3 Tree - 4 Vine	-1.286749	1.2400	1829	-1.038	1.0000
## 3 Tree - 5 Vine	-1.299342	1.2397	1829	-1.048	1.0000
## 3 Tree - 6 Vine	-1.338971	1.2402	1829	-1.080	1.0000
## 3 Tree - 7 Vine	-1.160937	1.2402	1829	-0.936	1.0000
## 4 Tree - 5 Tree	-0.012593	0.1047	1819	-0.120	1.0000
## 4 Tree - 6 Tree	-0.052223	0.1056	1822	-0.495	1.0000
## 4 Tree - 7 Tree	0.125811	0.1071	1828	1.175	1.0000
## 4 Tree - 1 Vine	-1.612648	1.2431	1829	-1.297	1.0000
## 4 Tree - 2 Vine	-1.356650	1.2391	1828	-1.095	1.0000
## 4 Tree - 3 Vine	-1.915347	1.2409	1829	-1.544	0.9999
## 4 Tree - 4 Vine	-1.601048	1.2357	1829	-1.296	1.0000
## 4 Tree - 5 Vine	-1.613641	1.2397	1829	-1.302	1.0000
## 4 Tree - 6 Vine	-1.653271	1.2402	1829	-1.333	1.0000
## 4 Tree - 7 Vine	-1.475237	1.2402	1829	-1.189	1.0000
## 5 Tree - 6 Tree	-0.039630	0.1063	1813	-0.373	1.0000
## 5 Tree - 7 Tree	0.138404	0.1077	1824	1.285	1.0000
## 5 Tree - 1 Vine	-1.600055	1.2436	1828	-1.287	1.0000
## 5 Tree - 2 Vine	-1.344057	1.2396	1828	-1.084	1.0000
## 5 Tree - 3 Vine	-1.902754	1.2414	1829	-1.533	0.9999
## 5 Tree - 4 Vine	-1.588455	1.2406	1829	-1.280	1.0000
## 5 Tree - 5 Vine	-1.601048	1.2357	1829	-1.296	1.0000
## 5 Tree - 6 Vine	-1.640678	1.2407	1829	-1.322	1.0000
## 5 Tree - 7 Vine	-1.462644	1.2407	1829	-1.179	1.0000
## 6 Tree - 7 Tree	0.178034	0.1082	1824	1.645	0.9997
## 6 Tree - 1 Vine	-1.560425	1.2432	1829	-1.255	1.0000
## 6 Tree - 2 Vine	-1.304427	1.2393	1828	-1.053	1.0000
## 6 Tree - 3 Vine	-1.863124	1.2410	1829	-1.501	1.0000
## 6 Tree - 4 Vine	-1.548825	1.2402	1829	-1.249	1.0000
## 6 Tree - 5 Vine	-1.561418	1.2398	1829	-1.259	1.0000
## 6 Tree - 6 Vine	-1.601048	1.2357	1829	-1.296	1.0000
## 6 Tree - 7 Vine	-1.423014	1.2403	1829	-1.147	1.0000
## 7 Tree - 1 Vine	-1.738459	1.2435	1828	-1.398	1.0000
## 7 Tree - 2 Vine	-1.482461	1.2395	1828	-1.196	1.0000
## 7 Tree - 3 Vine	-2.041158	1.2412	1829	-1.645	0.9997
## 7 Tree - 4 Vine	-1.726859	1.2404	1828	-1.392	1.0000
## 7 Tree - 5 Vine	-1.739452	1.2401	1829	-1.403	1.0000
## 7 Tree - 6 Vine	-1.779082	1.2405	1828	-1.434	1.0000
## 7 Tree - 7 Vine	-1.601048	1.2357	1829	-1.296	1.0000
## 1 Vine - 2 Vine	0.255998	0.0944	1813	2.712	0.6952
## 1 Vine - 3 Vine	-0.302699	0.1047	1819	-2.892	0.5458
## 1 Vine - 4 Vine	0.011600	0.0997	1822	0.116	1.0000
## 1 Vine - 5 Vine	-0.000993	0.1007	1828	-0.010	1.0000
## 1 Vine - 6 Vine	-0.040623	0.1018	1827	-0.399	1.0000
## 1 Vine - 7 Vine	0.137411	0.1034	1830	1.329	1.0000
## 2 Vine - 3 Vine	-0.558697	0.1039	1818	-5.379	<.0001
## 2 Vine - 4 Vine	-0.244398	0.0991	1821	-2.467	0.8615
## 2 Vine - 5 Vine	-0.256991	0.1001	1825	-2.568	0.8003
## 2 Vine - 6 Vine	-0.296621	0.1012	1823	-2.931	0.5126
## 2 Vine - 7 Vine	-0.118587	0.1028	1829	-1.154	1.0000
## 3 Vine - 4 Vine	0.314299	0.1083	1817	2.901	0.5375
## 3 Vine - 5 Vine	0.301706	0.1091	1820	2.767	0.6508
## 3 Vine - 6 Vine	0.262076	0.1097	1820	2.389	0.8998
## 3 Vine - 7 Vine	0.440110	0.1110	1829	3.964	0.0312
## 4 Vine - 5 Vine	-0.012593	0.1047	1819	-0.120	1.0000

```

## 4 Vine - 6 Vine      -0.052223 0.1056 1822 -0.495  1.0000
## 4 Vine - 7 Vine      0.125811 0.1071 1828  1.175  1.0000
## 5 Vine - 6 Vine     -0.039630 0.1063 1813 -0.373  1.0000
## 5 Vine - 7 Vine      0.138404 0.1077 1824  1.285  1.0000
## 6 Vine - 7 Vine      0.178034 0.1082 1824  1.645  0.9997
##
## Results are averaged over the levels of: state
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 35 estimates

# New version of our model incorporating interaction term and species within year
# so that there is a separate intercept and slope for each species. The issue
# here is that there are some species that are not found each year. Easiest to
# remove those from another version of this dataframe before running below.
# Otherwise, it's not a balanced design. updated mod4
mod12 <- lmer(log(relabun) ~ state * factor(year_factor) + (1 + factor(year_factor) |
  species), comp_kbs_spp)

## boundary (singular) fit: see ?isSingular

# So another version of this model would include the interaction but not include
# the nesting (and thus would assume that species aren't observed ea yr) updated
# mod5
mod13 <- lmer(log(relabun) ~ state * factor(year_factor) + (1 | species), comp_kbs_spp)

# All the models ran:
mod1 <- lmer(log(relabun) ~ state * year_factor + insecticide * year_factor + (1 |
  species) + (1 | plot), comp_kbs_spp, REML = FALSE)
mod2 <- lmer(log(relabun) ~ state * year_factor + insecticide * year_factor + (1 |
  species), comp_kbs_spp, REML = FALSE)
mod3 <- lmer(log(relabun) ~ state * year_factor + (1 | species), comp_kbs_spp, REML = FALSE)
mod4 <- lmer(log(relabun) ~ state * year_factor + insecticide + (1 | species) + (1 |
  plot), comp_kbs_spp, REML = FALSE)
mod5 <- lmer(log(relabun) ~ state + year_factor + (1 | species), comp_kbs_spp, REML = FALSE)
# mod6 <- lmer(log(relabun) ~ state + year_factor + (1/species) + (1 +
# year_factor|plot), comp_kbs_spp, REML=FALSE)
mod7 <- lmer(log(relabun) ~ state + species + (1 + factor(year_factor) | plot), comp_kbs_spp,
  REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod7a <- lmer(log(relabun) ~ state + species + factor(year_factor) + (1 | plot),
  comp_kbs_spp, REML = FALSE)
mod7b <- lmer(log(relabun) ~ state * factor(year_factor) + species + (1 | plot),
  comp_kbs_spp, REML = FALSE)
mod7c <- lmer(log(relabun) ~ state + species + factor(year_factor) + insecticide +
  (1 | plot), comp_kbs_spp, REML = FALSE)
mod8 <- lmer(log(relabun) ~ state * origin + (1 + factor(year_factor) | plot), comp_kbs_spp,
  REML = FALSE)

## boundary (singular) fit: see ?isSingular

```

```

## Warning: Model failed to converge with 1 negative eigenvalue: -1.5e+01

mod9 <- lmer(log(relabun) ~ state + origin + (1 + factor(year_factor) | plot), comp_kbs_spp,
             REML = FALSE)

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -7.4e+00

mod9a <- lmer(log(relabun) ~ state + origin + factor(year_factor) + (1 | plot), comp_kbs_spp,
               REML = FALSE)
mod10 <- lmer(log(relabun) ~ state * growth_habit + (1 + factor(year_factor) | plot),
               comp_kbs_spp, REML = FALSE)

## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient
## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -1.3e+00

mod11 <- lmer(log(relabun) ~ state + growth_habit + (1 + factor(year_factor) | plot),
               comp_kbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -1.0e+01

mod11a <- lmer(log(relabun) ~ state + growth_habit + factor(year_factor) + (1 | plot),
                 comp_kbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod12 <- lmer(log(relabun) ~ state * factor(year_factor) + (1 + factor(year_factor) |
               species), comp_kbs_spp)

## boundary (singular) fit: see ?isSingular

mod13 <- lmer(log(relabun) ~ state * factor(year_factor) + (1 | species), comp_kbs_spp)
AICctab(mod1, mod2, mod3, mod5, mod6, mod7, mod7a, mod7b, mod7c, mod8, mod9, mod9a,
        mod10, mod11, mod11a, mod13, weights = T) #mod7a is the best fitting model (took out mod12 bc it w

##          dAICc  df weight
## mod7a      0.0 40  0.721
## mod7c      2.0 41  0.263
## mod7b      7.6 46  0.016
## mod7      75.9 61 <0.001
## mod5     103.0 5  <0.001
## mod3     105.0 6  <0.001
## mod6     108.8 8  <0.001
## mod2     108.9 8  <0.001

```

```

## mod1    110.7 9 <0.001
## mod13   115.8 16 <0.001
## mod9a   936.0 13 <0.001
## mod8    1007.0 37 <0.001
## mod9    1009.6 34 <0.001
## mod11a  1232.7 14 <0.001
## mod10   1301.4 38 <0.001
## mod11   1303.7 35 <0.001

summary(mod7a)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(relabun) ~ state + species + factor(year_factor) + (1 | plot)
## Data: comp_kbs_spp
##
##      AIC      BIC  logLik deviance df.resid
## 4526.0 4746.2 -2223.0   4446.0     1778
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -2.8999 -0.6322 -0.0266  0.6582  3.2129
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.001051 0.03242
## Residual           0.674474 0.82126
## Number of obs: 1818, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept) -3.49208  0.08482 991.66088 -41.170 < 2e-16 ***
## stateambient -0.02111  0.04132 25.14843 -0.511 0.613795    
## speciesAcsa  -0.58737  0.82609 1817.09558 -0.711 0.477160    
## speciesArel   0.63389  0.10833 1811.85043  5.852 5.76e-09 ***
## speciesAssp  -0.12894  0.22370 1768.43494 -0.576 0.564410    
## speciesAsun  -0.40312  0.24020 1808.16036 -1.678 0.093466 .  
## speciesBavu  -0.66849  0.18219 1816.18706 -3.669 0.000250 *** 
## speciesCahi  -0.34196  0.13928 1812.42590 -2.455 0.014176 *  
## speciesCeor   1.05516  0.26968 1718.47460  3.913 9.48e-05 *** 
## speciesCest   0.46134  0.11357 1808.59624  4.062 5.07e-05 *** 
## speciesCrsp  -0.71193  0.82605 1816.56947 -0.862 0.388890    
## speciesDaca  -0.34892  0.11645 1812.41139 -2.996 0.002770 ** 
## speciesDagl   0.09496  0.10594 1811.04506  0.896 0.370162    
## speciesElre   0.69972  0.10197 1806.27959  6.862 9.31e-12 *** 
## speciesErci  -1.25286  0.48151 1817.00942 -2.602 0.009345 ** 
## speciesErsp  -0.74372  0.58684 1817.36081 -1.267 0.205201    
## speciesEugr   0.80724  0.11258 1817.99980  7.170 1.08e-12 *** 
## speciesHisp   0.69927  0.10532 1803.72462  6.640 4.15e-11 *** 
## speciesHype  -0.39850  0.12673 1816.45240 -3.144 0.001691 ** 
## speciesPesp  -0.14053  0.82609 1817.55278 -0.170 0.864939    
## speciesPhpr   0.60546  0.09565 1802.00193  6.330 3.09e-10 *** 
## speciesPore  -0.48846  0.10192 1808.38590 -4.793 1.78e-06 *** 
## speciesPosp   0.95873  0.09383 1799.61063 10.218 < 2e-16 ***

```

```

## speciesPrsp      -1.43795  0.82605 1816.56091 -1.741 0.081895 .
## speciesRusp     1.21613  0.15554 1718.13879  7.819 9.24e-15 ***
## speciesSoca     2.57299  0.09383 1799.61063 27.421 < 2e-16 ***
## speciesSoju    -1.38323  0.82612 1817.56258 -1.674 0.094229 .
## speciesTaof    -0.55969  0.12036 1817.98387 -4.650 3.56e-06 ***
## speciesThar    -0.88670  0.82609 1816.97798 -1.073 0.283248
## speciesTrsp     0.06316  0.11413 1806.83812  0.553 0.580073
## speciesUhsp    -0.57186  0.58683 1817.23884 -0.974 0.329945
## speciesVear    -0.76051  0.20647 1817.54411 -3.683 0.000237 ***
## factor(year_factor)2 -0.25667  0.06719 1799.77733 -3.820 0.000138 ***
## factor(year_factor)3  0.19701  0.07426 1807.20791  2.653 0.008046 **
## factor(year_factor)4 -0.10085  0.07125 1808.64692 -1.415 0.157108
## factor(year_factor)5 -0.12596  0.07150 1814.15732 -1.762 0.078301 .
## factor(year_factor)6 -0.10747  0.07254 1815.10992 -1.482 0.138644
## factor(year_factor)7 -0.30491  0.07361 1817.31191 -4.142 3.60e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 38 > 12.
## Use print(x, correlation=TRUE)  or
##      vcov(x)      if you need it

```

```
anova(mod7a)
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##                               Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state                      0.18   0.176     1    25.15  0.2611   0.6138
## species                   1287.05  42.902    30 1807.33 63.6078 < 2.2e-16 ***
## factor(year_factor)     39.41    6.568     6 1809.89  9.7383 1.401e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

KBS Plot-level Mixed Effects Models:

```

mod1p <- lmer(log(plot_cover_avg) ~ state + (1 | plot), comp_kbs_plot, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod2p <- lmer(log(plot_cover_avg) ~ insecticide + (1 | plot), comp_kbs_plot, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod3p <- lmer(log(plot_cover_avg) ~ insecticide + state + (1 | plot), comp_kbs_plot,
REML = FALSE)

## boundary (singular) fit: see ?isSingular

```

```

mod4p <- lmer(log(plot_cover_avg) ~ insecticide * state + (1 | plot), comp_kbs_plot,
  REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod5p <- lmer(log(plot_cover_avg) ~ state + year_factor + (1 | plot), comp_kbs_plot,
  REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod6p <- lmer(log(plot_cover_avg) ~ state + year_factor + insecticide + (1 | plot),
  comp_kbs_plot, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod7p <- lmer(log(plot_cover_avg) ~ state * year_factor + (1 | plot), comp_kbs_plot,
  REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod8p <- lmer(log(plot_cover_avg) ~ state * year_factor + insecticide + (1 | plot),
  comp_kbs_plot, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod9p <- lmer(log(plot_cover_avg) ~ state * insecticide + year_factor + (1 | plot),
  comp_kbs_plot, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod10p <- lmer(log(plot_cover_avg) ~ state + insecticide * year_factor + (1 | plot),
  comp_kbs_plot, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod11p <- lmer(log(plot_cover_avg) ~ state * year_factor * insecticide + (1 | plot),
  comp_kbs_plot, REML = FALSE)

## boundary (singular) fit: see ?isSingular

AICctab(mod1p, mod2p, mod3p, mod4p, mod5p, mod6p, mod7p, mod8p, mod9p, mod10p, mod11p,
  weights = T) # model 11p and 10p the same

##      dAICc df weight
## mod7p    0.0  6  0.3654
## mod5p    0.5  5  0.2841
## mod8p   1.9  7  0.1419

```

```

## mod6p   2.4  6  0.1125
## mod10p   4.0  7  0.0495
## mod9p    4.5  7  0.0394
## mod11p   7.9 10  0.0071
## mod2p    88.9  4 <0.001
## mod1p    89.2  4 <0.001
## mod3p    91.0  5 <0.001
## mod4p    93.2  6 <0.001

anova(mod7p, mod5p)  #7p just barely better

## Data: comp_kbs_plot
## Models:
## mod5p: log(plot_cover_avg) ~ state + year_factor + (1 | plot)
## mod7p: log(plot_cover_avg) ~ state * year_factor + (1 | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod5p     5 328.58 344.17 -159.29   318.58
## mod7p     6 327.93 346.64 -157.97   315.93 2.6553  1      0.1032

summ(mod7p)

```

Observations	167
Dependent variable	log(plot_cover_avg)
Type	Mixed effects linear regression

AIC	327.93
BIC	346.64
Pseudo-R ² (fixed effects)	0.43
Pseudo-R ² (total)	0.43

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	5.00	0.15	32.91	167.00	0.00
stateambient	0.28	0.22	1.31	167.00	0.19
year_factor	-0.23	0.03	-6.73	167.00	0.00
stateambient:year_factor	-0.08	0.05	-1.64	167.00	0.10

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.00
Residual		0.62

```
summary(mod7p)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
```

Grouping Variables		
Group	# groups	ICC
plot	24	0.00

```

##   method [lmerModLmerTest]
## Formula: log(plot_cover_avg) ~ state * year_factor + (1 | plot)
##   Data: comp_kbs_plot
##
##      AIC      BIC  logLik deviance df.resid
##  327.9    346.6   -158.0     315.9      161
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -2.88697 -0.59256 -0.03461  0.71718  2.10258
##
## Random effects:
##   Groups   Name        Variance Std.Dev.
##   plot      (Intercept) 0.0000  0.0000
##   Residual           0.3883  0.6231
## Number of obs: 167, groups: plot, 24
##
## Fixed effects:
##                     Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)       5.00246   0.15202 167.00000 32.906 < 2e-16 ***
## stateambient     0.28313   0.21552 167.00000  1.314   0.191
## year_factor      -0.22885   0.03399 167.00000 -6.732 2.56e-10 ***
## stateambient:year_factor -0.07920   0.04841 167.00000 -1.636   0.104
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) sttmbn yr_fct
## stateambint -0.705
## year_factor -0.894  0.631
## sttmbnt:yr_  0.628 -0.894 -0.702
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

```

`anova(mod7p)`

```

## Type III Analysis of Variance Table with Satterthwaite's method
##              Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state          0.670  0.670     1    167  1.7258 0.1908
## year_factor    47.760 47.760     1    167 123.0123 <2e-16 ***
## state:year_factor 1.039  1.039     1    167   2.6766 0.1037
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

`emmeans(mod7p, list(pairwise ~ state * year_factor), adjust = "tukey")`

`## boundary (singular) fit: see ?isSingular`

```

## $`emmeans of state, year_factor`
##   state  year_factor emmean      SE   df lower.CL upper.CL
##   warmed          3.98  4.09 0.0688 22.8     3.95    4.23
##   ambient          3.98  4.06 0.0692 23.3     3.92    4.20
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, year_factor`
##   1                               estimate      SE   df
##   warmed 3.98203592814371 - ambient 3.98203592814371  0.0322 0.0976 23.1
##   t.ratio p.value
##   0.330   0.7443
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.

# including native vs. exotic
kbs_comp_plot_origin <- within(kbs_comp_plot_origin, origin <- relevel(factor(origin),
  ref = "Native")) # releveling so native is the reference
mod12p <- lmer(log(plot_cover_avg) ~ state * origin + (1 + year_factor | plot), kbs_comp_plot_origin,
  REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod13p <- lmer(log(plot_cover_avg) ~ state + origin + (1 + year_factor | plot), kbs_comp_plot_origin,
  REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod14p <- lmer(log(plot_cover_avg) ~ state + origin + year_factor + (1 | plot), kbs_comp_plot_origin,
  REML = FALSE)

## boundary (singular) fit: see ?isSingular

anova(mod12p, mod13p) # go with model 12pu

## Data: kbs_comp_plot_origin
## Models:
## mod13p: log(plot_cover_avg) ~ state + origin + (1 + year_factor | plot)
## mod12p: log(plot_cover_avg) ~ state * origin + (1 + year_factor | plot)
##   npar   AIC   BIC logLik deviance Chisq Df Pr(>Chisq)
## mod13p    9 1730.3 1770.3 -856.14    1712.3
## mod12p   12 1722.5 1775.8 -849.23    1698.5 13.825  3   0.003154 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(mod12p, mod14p) # mod 14pu

```

```

## Data: kbs_comp_plot_origin
## Models:
## mod14p: log(plot_cover_avg) ~ state + origin + year_factor + (1 | plot)
## mod12p: log(plot_cover_avg) ~ state * origin + (1 + year_factor | plot)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod14p     8 1660.7 1696.2 -822.32   1644.7
## mod12p    12 1722.5 1775.8 -849.23   1698.5      0  4          1
## 
```

`summ(mod14p)`

Observations	631
Dependent variable	log(plot_cover_avg)
Type	Mixed effects linear regression

AIC	1660.65
BIC	1696.22
Pseudo-R ² (fixed effects)	0.48
Pseudo-R ² (total)	0.48

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	4.80	0.11	45.66	631.00	0.00
statewarmed	-0.06	0.07	-0.79	631.00	0.43
origin	-1.38	0.10	-14.17	631.00	0.00
originBoth	-1.53	0.10	-14.68	631.00	0.00
originExotic	-0.78	0.10	-8.03	631.00	0.00
year_factor	-0.32	0.02	-17.89	631.00	0.00

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.00
Residual		0.89

Grouping Variables		
Group	# groups	ICC
plot	24	0.00

`anova(mod14p)`

```

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state        0.50   0.500     1   631   0.6307 0.4274
## origin      227.63  75.878     3   631  95.6399 <2e-16 ***
## 
```

```

## year_factor 253.91 253.915      1   631 320.0458 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

emmeans(mod14p, list(pairwise ~ state + origin), adjust = "tukey")

## boundary (singular) fit: see ?isSingular

## $`emmeans of state, origin`
##   state  origin emmean     SE df lower.CL upper.CL
##   ambient Native    3.55 0.0780 120     3.39    3.70
##   warmed   Native    3.49 0.0778 119     3.34    3.65
##   ambient          2.17 0.0780 120     2.01    2.32
##   warmed          2.11 0.0778 119     1.96    2.27
##   ambient Both     2.02 0.0852 156     1.85    2.19
##   warmed Both     1.96 0.0876 166     1.79    2.13
##   ambient Exotic   2.77 0.0780 120     2.61    2.92
##   warmed Exotic   2.71 0.0778 119     2.56    2.86
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, origin`
##   1                           estimate     SE   df t.ratio p.value
##   ambient Native - warmed Native  0.0564 0.0713 22.4  0.790  0.9920
##   ambient Native - ambient          1.3808 0.0979 614.7 14.098 <.0001
##   ambient Native - warmed          1.4371 0.1212 165.0 11.862 <.0001
##   ambient Native - ambient Both   1.5311 0.1049 622.9 14.600 <.0001
##   ambient Native - warmed Both   1.5874 0.1285 191.5 12.352 <.0001
##   ambient Native - ambient Exotic 0.7829 0.0979 614.7  7.994 <.0001
##   ambient Native - warmed Exotic 0.8393 0.1212 165.0  6.927 <.0001
##   warmed Native - ambient         1.3244 0.1212 165.0 10.931 <.0001
##   warmed Native - warmed          1.3808 0.0979 614.7 14.098 <.0001
##   warmed Native - ambient Both   1.4747 0.1251 180.8 11.788 <.0001
##   warmed Native - warmed Both   1.5311 0.1049 622.9 14.600 <.0001
##   warmed Native - ambient Exotic 0.7266 0.1212 165.0  5.997 <.0001
##   warmed Native - warmed Exotic 0.7829 0.0979 614.7  7.994 <.0001
##   ambient - warmed               0.0564 0.0713 22.4  0.790  0.9920
##   ambient - ambient Both          0.1503 0.1049 622.9  1.433  0.8416
##   ambient - warmed Both          0.2067 0.1285 191.5  1.608  0.7450
##   ambient - ambient Exotic      -0.5979 0.0979 614.7 -6.104 <.0001
##   ambient - warmed Exotic       -0.5415 0.1212 165.0 -4.469  0.0004
##   warmed - ambient Both          0.0939 0.1251 180.8  0.751  0.9952
##   warmed - warmed Both          0.1503 0.1049 622.9  1.433  0.8416
##   warmed - ambient Exotic      -0.6542 0.1212 165.0 -5.400 <.0001
##   warmed - warmed Exotic       -0.5979 0.0979 614.7 -6.104 <.0001
##   ambient Both - warmed Both    0.0564 0.0713 22.4  0.790  0.9920
##   ambient Both - ambient Exotic -0.7481 0.1049 622.9 -7.134 <.0001
##   ambient Both - warmed Exotic -0.6918 0.1251 180.8 -5.530 <.0001
##   warmed Both - ambient Exotic -0.8045 0.1285 191.5 -6.260 <.0001
##   warmed Both - warmed Exotic -0.7481 0.1049 622.9 -7.134 <.0001
##   ambient Exotic - warmed Exotic 0.0564 0.0713 22.4  0.790  0.9920

```

```

## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 8 estimates

# including growth form - first with interaction term
kbs_comp_plot_growthhabit <- within(kbs_comp_plot_growthhabit, growth_habit <- relevel(factor(growth_habit,
  ref = "Forb")) # releveling so forb is the reference
mod15p <- lmer(log(plot_cover_avg) ~ state * growth_habit + (1 + year_factor | plot),
  kbs_comp_plot_growthhabit, REML = FALSE)

## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient
## boundary (singular) fit: see ?isSingular

mod16p <- lmer(log(plot_cover_avg) ~ state + growth_habit + (1 + year_factor | plot),
  kbs_comp_plot_growthhabit, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod17p <- lmer(log(plot_cover_avg) ~ state + growth_habit + year_factor + (1 | plot),
  kbs_comp_plot_growthhabit, REML = FALSE)

## boundary (singular) fit: see ?isSingular

anova(mod15p, mod16p) # go with model 15pu

## Data: kbs_comp_plot_growthhabit
## Models:
## mod16p: log(plot_cover_avg) ~ state + growth_habit + (1 + year_factor | plot)
## mod15p: log(plot_cover_avg) ~ state * growth_habit + (1 + year_factor | plot)
## mod15p: npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod16p  10 1277.1 1318.8 -628.57    1257.1
## mod15p  13 1266.8 1320.9 -620.41    1240.8 16.321  3  0.0009746 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(mod15p, mod17p) # mod 17pu

## Data: kbs_comp_plot_growthhabit
## Models:
## mod17p: log(plot_cover_avg) ~ state + growth_habit + year_factor + (1 | plot)
## mod15p: log(plot_cover_avg) ~ state * growth_habit + (1 + year_factor | plot)
## mod15p: npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod17p   9 1216.5 1253.9 -599.23    1198.5
## mod15p  13 1266.8 1320.9 -620.41    1240.8      0  4          1

```

```
summ(mod17p)
```

Observations	474
Dependent variable	log(plot_cover_avg)
Type	Mixed effects linear regression
AIC	1216.45
BIC	1253.90
Pseudo-R ² (fixed effects)	0.47
Pseudo-R ² (total)	0.47
Fixed Effects	
	Est. S.E. t val. d.f. p
(Intercept)	4.64 0.11 42.04 474.00 0.00
statewarmed	-0.07 0.08 -0.84 474.00 0.40
growth_habit	-1.48 0.10 -14.76 474.00 0.00
growth_habitGraminoid	-0.40 0.09 -4.24 474.00 0.00
growth_habitTree	-3.20 0.86 -3.71 474.00 0.00
growth_habitVine	-1.38 0.28 -4.94 474.00 0.00
year_factor	-0.28 0.02 -14.38 474.00 0.00

p values calculated using Satterthwaite d.f.

	Random Effects	
Group	Parameter	Std. Dev.
plot	(Intercept)	0.00
Residual		0.86

	Grouping Variables	
Group	# groups	ICC
plot	24	0.00

```
anova(mod17p)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##          Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state      0.523   0.523     1    474   0.7123 0.3991
## growth_habit 179.550  44.888     4    474  61.1700 <2e-16 ***
## year_factor  151.719  151.719     1    474 206.7528 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
emmeans(mod17p, list(pairwise ~ state + growth_habit), adjust = "tukey")
```

```
## boundary (singular) fit: see ?isSingular
```

```

## $`emmeans of state, growth_habit`
##   state   growth_habit emmean      SE    df lower.CL upper.CL
## ambient     Forb      3.540 0.0779  79.1     3.38    3.69
## warmed     Forb      3.473 0.0776  78.2     3.32    3.63
## ambient     ambient   2.056 0.0846 102.6     1.89    2.22
## warmed     warmed   1.989 0.0873 110.7     1.82    2.16
## ambient     Graminoid 3.142 0.0779  79.1     2.99    3.30
## warmed     Graminoid 3.075 0.0776  78.2     2.92    3.23
## ambient     Tree      0.344 0.8724 481.0    -1.37   2.06
## warmed     Tree      0.277 0.8689 480.9    -1.43   1.98
## ambient     Vine      2.158 0.2792 284.2     1.61    2.71
## warmed     Vine      2.092 0.2835 304.9     1.53    2.65
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, growth_habit`
##   1                         estimate      SE    df t.ratio p.value
## ambient Forb - warmed Forb  0.0667 0.0796 22.3  0.837 0.9970
## ambient Forb - ambient     1.4838 0.1014 466.3 14.638 <.0001
## ambient Forb - warmed     1.5504 0.1308 137.1 11.851 <.0001
## ambient Forb - ambient Graminoid 0.3979 0.0944 458.6  4.213 0.0012
## ambient Forb - warmed Graminoid 0.4645 0.1235 118.2  3.761 0.0096
## ambient Forb - ambient Tree  3.1959 0.8724 481.1  3.663 0.0103
## ambient Forb - warmed Tree  3.2626 0.8725 480.4  3.739 0.0078
## ambient Forb - ambient Vine 1.3815 0.2865 363.0  4.822 0.0001
## ambient Forb - warmed Vine 1.4482 0.3015 293.6  4.804 0.0001
## warmed Forb - ambient     1.4171 0.1269 128.2 11.165 <.0001
## warmed Forb - warmed     1.4838 0.1014 466.3 14.638 <.0001
## warmed Forb - ambient Graminoid 0.3312 0.1235 118.2  2.681 0.1935
## warmed Forb - warmed Graminoid 0.3979 0.0944 458.6  4.213 0.0012
## warmed Forb - ambient Tree  3.1293 0.8795 480.6  3.558 0.0148
## warmed Forb - warmed Tree  3.1959 0.8724 481.1  3.663 0.0103
## warmed Forb - ambient Vine 1.3149 0.2932 257.4  4.485 0.0005
## warmed Forb - warmed Vine 1.3815 0.2865 363.0  4.822 0.0001
## ambient     - warmed     0.0667 0.0796 22.3  0.837 0.9970
## ambient     - ambient Graminoid -1.0859 0.1014 466.3 -10.713 <.0001
## ambient     - warmed Graminoid -1.0193 0.1269 128.2 -8.030 <.0001
## ambient     - ambient Tree  1.7121 0.8730 481.1  1.961 0.6267
## ambient     - warmed Tree  1.7788 0.8728 480.5  2.038 0.5725
## ambient     - ambient Vine -0.1023 0.2885 365.2 -0.354 1.0000
## ambient     - warmed Vine -0.0356 0.3026 295.6 -0.118 1.0000
## warmed     - ambient Graminoid -1.1526 0.1308 137.1 -8.810 <.0001
## warmed     - warmed Graminoid -1.0859 0.1014 466.3 -10.713 <.0001
## warmed     - ambient Tree  1.6455 0.8803 480.7  1.869 0.6900
## warmed     - warmed Tree  1.7121 0.8730 481.1  1.961 0.6267
## warmed     - ambient Vine -0.1689 0.2960 261.3 -0.571 0.9999
## warmed     - warmed Vine -0.1023 0.2885 365.2 -0.354 1.0000
## ambient Graminoid - warmed Graminoid 0.0667 0.0796 22.3  0.837 0.9970
## ambient Graminoid - ambient Tree 2.7981 0.8724 481.1  3.207 0.0459
## ambient Graminoid - warmed Tree 2.8647 0.8725 480.4  3.283 0.0364
## ambient Graminoid - ambient Vine 0.9837 0.2865 363.0  3.434 0.0230
## ambient Graminoid - warmed Vine 1.0503 0.3015 293.6  3.484 0.0199

```

```

## warmed Graminoid - ambient Tree          2.7314 0.8795 480.6   3.106 0.0618
## warmed Graminoid - warmed Tree          2.7981 0.8724 481.1   3.207 0.0459
## warmed Graminoid - ambient Vine         0.9170 0.2932 257.4   3.128 0.0601
## warmed Graminoid - warmed Vine          0.9837 0.2865 363.0   3.434 0.0230
## ambient Tree - warmed Tree              0.0667 0.0796 22.3    0.837 0.9970
## ambient Tree - ambient Vine             -1.8144 0.9135 479.2  -1.986 0.6092
## ambient Tree - warmed Vine              -1.7477 0.9216 477.3  -1.896 0.6716
## warmed Tree - ambient Vine              -1.8811 0.9123 475.9  -2.062 0.5555
## warmed Tree - warmed Vine              -1.8144 0.9135 479.2  -1.986 0.6092
## ambient Vine - warmed Vine              0.0667 0.0796 22.3    0.837 0.9970
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 10 estimates

```

UMBS Species Level Mixed Effects Models

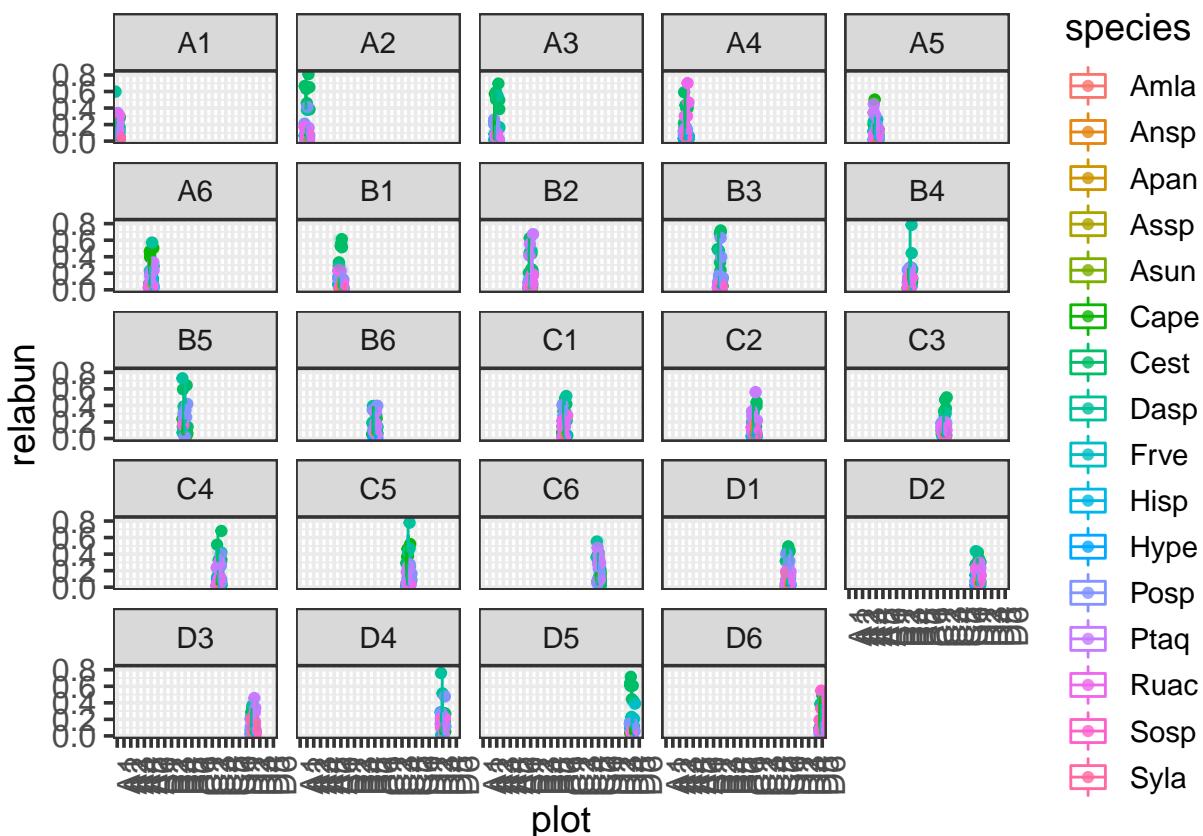
```

# UMBS SPECIES LEVEL - Looking at RELATIVE ABUNDANCE
mod1u <- lmer(log(relabun) ~ state * year_factor + insecticide * year_factor + (1 |
  species) + (1 | plot), comp_umbs_spp, REML = FALSE)

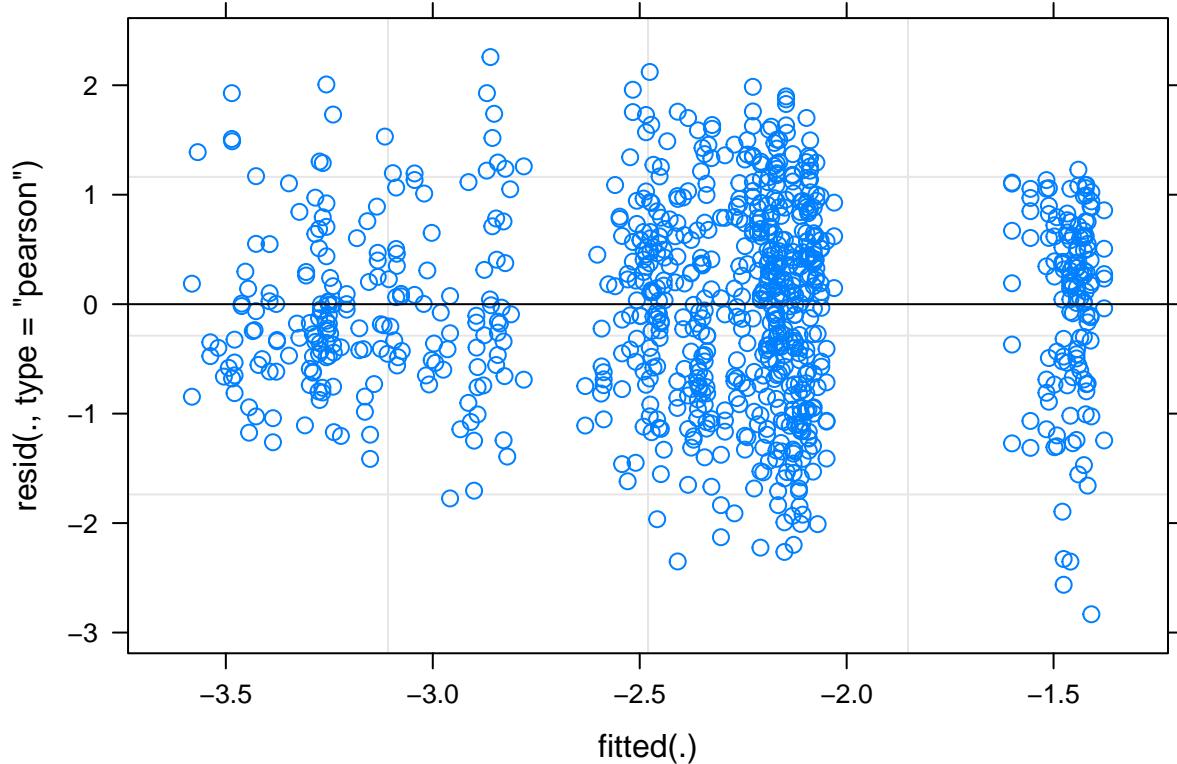
```

```
## boundary (singular) fit: see ?isSingular
```

```
ggplot(comp_umbs_spp, aes(x = plot, y = relabun, col = species)) + geom_jitter() +
  geom_boxplot(alpha = 0.2) + facet_wrap(~plot)
```



```
# Check Assumptions: (1) Linearity: if covariates are not categorical (year
# isn't) (2) Homogeneity: Need to Check by plotting residuals vs predicted
# values.
par(mfrow = c(1, 2))
plot(mod1u)
```



```
# Homogeneity of variance is ok here (increasing variance in resids is not
# increasing with fitted values) Check for homogeneity of variances (true if
# p>0.05). If the result is not significant, the assumption of equal variances
# (homoscedasticity) is met (no significant difference between the group
# variances). *****Levene's Test - tests whether or not the variance among two
# or more groups is equal - If the p-value is less than our chosen significance
# level, we can reject the null hypothesis and conclude that we have enough
# evidence to state that the variance among the groups is not equal (which we
# want).
```

```
leveneTest(residuals(mod1u) ~ comp_umbs_spp$state)
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##          Df F value Pr(>F)
## group     1  0.0505 0.8222
##          897
```

```
# Assumption not met
leveneTest(residuals(mod1u) ~ comp_umbs_spp$species)
```

```
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.
```

```

## Levene's Test for Homogeneity of Variance (center = median)
##          Df F value    Pr(>F)
## group    15 2.8451 0.0002262 ***
##             883
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Assumption met
leveneTest(residuals(mod1u) ~ comp_umbs_spp$insecticide)

## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.

## Levene's Test for Homogeneity of Variance (center = median)
##          Df F value    Pr(>F)
## group    1  1.9758 0.1602
##             897

# Assumption not met - but close
leveneTest(residuals(mod1u) ~ comp_umbs_spp$plot)

## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.

## Levene's Test for Homogeneity of Variance (center = median)
##          Df F value    Pr(>F)
## group   23 2.3561 0.0003437 ***
##             875
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

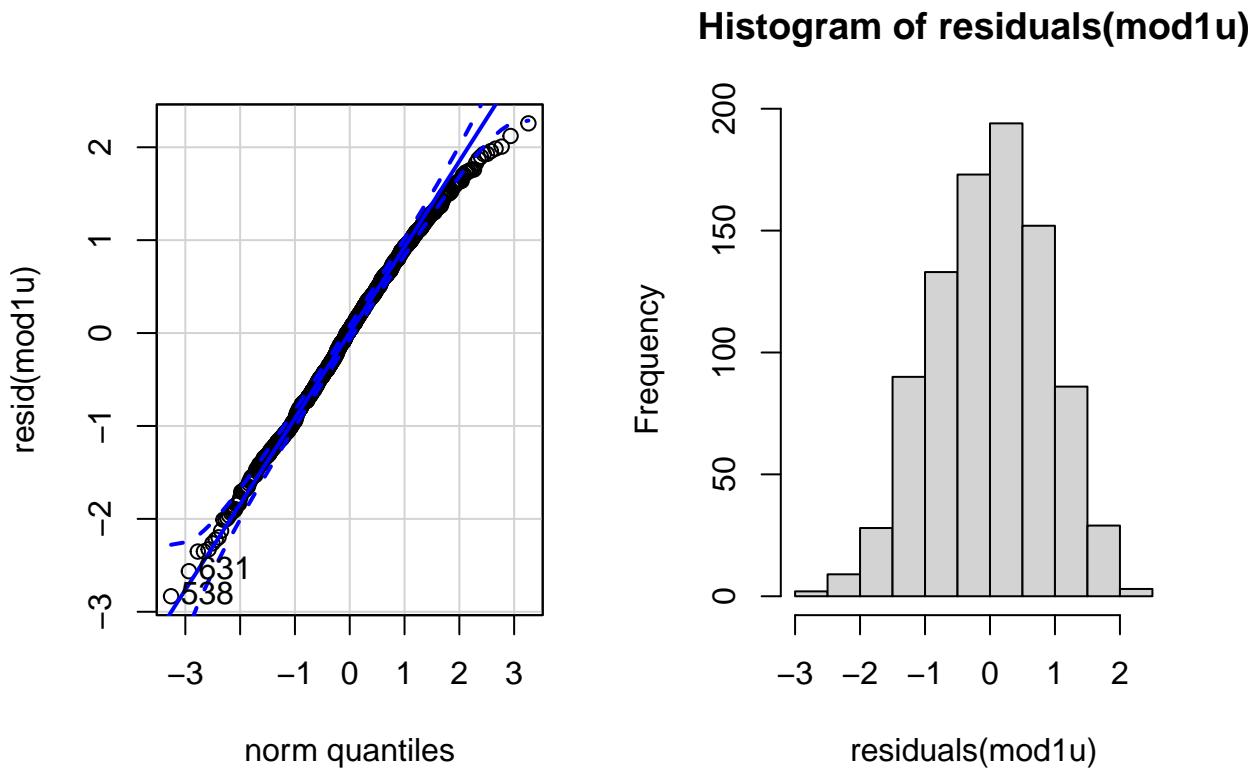
# Assumption met

# (3) Normality of error term: need to check by histogram, QQplot of residuals,
# could do Kolmogorov-Smirnov test. Check for normal residuals
qqPlot(resid(mod1u))

## 538 631
## 160 210

hist(residuals(mod1u))

```



```
shapiro.test(resid(mod1u)) # not normally distributed resids bc p<0.05 but close 0.01
```

```
##  
## Shapiro-Wilk normality test  
##  
## data: resid(mod1u)  
## W = 0.99584, p-value = 0.01617
```

```
outlierTest(mod1u) # no outliers
```

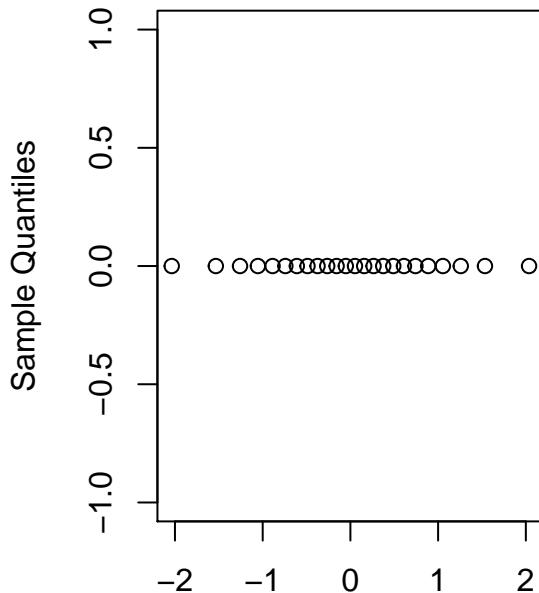
```
## No Studentized residuals with Bonferroni p < 0.05  
## Largest |rstudent|:  
##      rstudent unadjusted p-value Bonferroni p  
## 538 -3.236539          0.0012546        NA
```

```
# (4) Normality of random effect: Get the estimate of random effect (e.g., random  
# intercepts), and check them as you would check the residual.  
require(lme4)  
r_int <- ranef(mod1u)$plot$`  
qqnorm(r_int)  
# qline(r_int) #doesn't work  
shapiro.test(r_int)
```

```
## Error in shapiro.test(r_int): all 'x' values are identical
```

```
# Normally distributed random effect - p-value > 0.05
```

Normal Q–Q Plot



Theoretical Quantiles

```
# Do we need to include plot as a random effect with the KBS models?  
modiu <- lmer(log(relabun) ~ state * year_factor + insecticide * year_factor + (1 |  
    species) + (1 | plot), comp_umbs_spp, REML = FALSE)
```

```
## boundary (singular) fit: see ?isSingular
```

```
mod2u <- lmer(log(relabun) ~ state * year_factor + insecticide * year_factor + (1 |  
    species), comp_umbs_spp, REML = FALSE)  
# Run analysis of variance on each model (see this for more explanation on how  
# anova on a linear mixed effects model is similar to an anova on a regular  
# linear model: https://m-clark.github.io/docs/mixedModels/anovamixed.html)  
anova(modiu)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method  
##                                     Sum Sq Mean Sq NumDF DenDF F value Pr(>F)  
## state                      0.48531 0.48531     1  885.25  0.6229 0.4302  
## year_factor                 0.80199 0.80199     1  890.55  1.0293 0.3106  
## insecticide                  0.77081 0.77081     1  885.27  0.9893 0.3202  
## state:year_factor           0.41633 0.41633     1  885.26  0.5343 0.4650  
## year_factor:insecticide     0.51853 0.51853     1  886.95  0.6655 0.4148
```

```
anova(mod2u)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
```

```

##                                     Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state                           0.48531 0.48531      1 885.25  0.6229 0.4302
## year_factor                     0.80199 0.80199      1 890.55  1.0293 0.3106
## insecticide                      0.77081 0.77081      1 885.27  0.9893 0.3202
## state:year_factor               0.41633 0.41633      1 885.26  0.5343 0.4650
## year_factor:insecticide          0.51853 0.51853      1 886.95  0.6655 0.4148

```

```
anova(mod1u, mod2u) # Go with model 2 since pvalue >0.05, aka more complex model does not have something
```

```

## Data: comp_umbs_spp
## Models:
## mod2u: log(relabun) ~ state * year_factor + insecticide * year_factor +
## mod2u: (1 | species)
## mod1u: log(relabun) ~ state * year_factor + insecticide * year_factor +
## mod1u: (1 | species) + (1 | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod2u     8 2386.7 2425.1 -1185.4   2370.7
## mod1u     9 2388.7 2431.9 -1185.4   2370.7     0  1           1

```

```
summ(mod1u)
```

Observations	899
Dependent variable	log(relabun)
Type	Mixed effects linear regression

AIC	2388.72
BIC	2431.93
Pseudo-R ² (fixed effects)	0.00
Pseudo-R ² (total)	0.30

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	-2.80	0.19	-14.41	41.89	0.00
stateambient	-0.11	0.14	-0.79	885.25	0.43
year_factor	0.02	0.03	0.63	886.84	0.53
insecticideno_insects	0.14	0.14	0.99	885.27	0.32
stateambient:year_factor	0.03	0.03	0.73	885.26	0.46
year_factor:insecticideno_insects	-0.03	0.03	-0.82	886.95	0.41

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.00
species	(Intercept)	0.58
Residual		0.88

Grouping Variables		
Group	# groups	ICC
plot	24	0.00
species	16	0.30

```
summ(mod2u)
```

Observations	899
Dependent variable	log(relabun)
Type	Mixed effects linear regression

AIC	2386.72
BIC	2425.13
Pseudo-R ² (fixed effects)	0.00
Pseudo-R ² (total)	0.30

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	-2.80	0.19	-14.41	41.89	0.00
stateambient	-0.11	0.14	-0.79	885.25	0.43
year_factor	0.02	0.03	0.63	886.84	0.53
insecticideno_insects	0.14	0.14	0.99	885.27	0.32
stateambient:year_factor	0.03	0.03	0.73	885.26	0.46
year_factor:insecticideno_insects	-0.03	0.03	-0.82	886.95	0.41

p values calculated using Satterthwaite d.f.

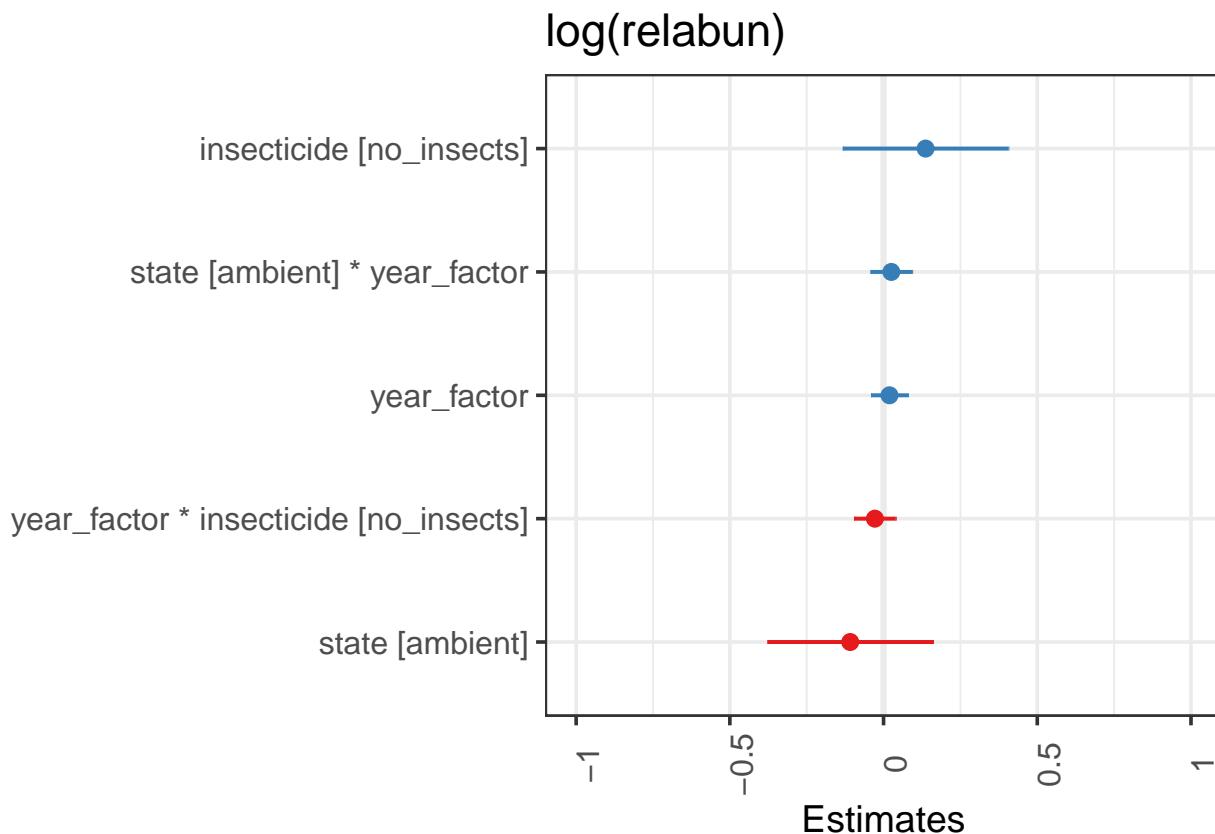
Random Effects		
Group	Parameter	Std. Dev.
species	(Intercept)	0.58
	Residual	0.88

Grouping Variables		
Group	# groups	ICC
species	16	0.30

```
AICctab(mod1u, mod2u, weights = T)
```

```
##      dAICc df weight
## mod2u  0.0   8  0.74
## mod1u  2.0   9  0.26
```

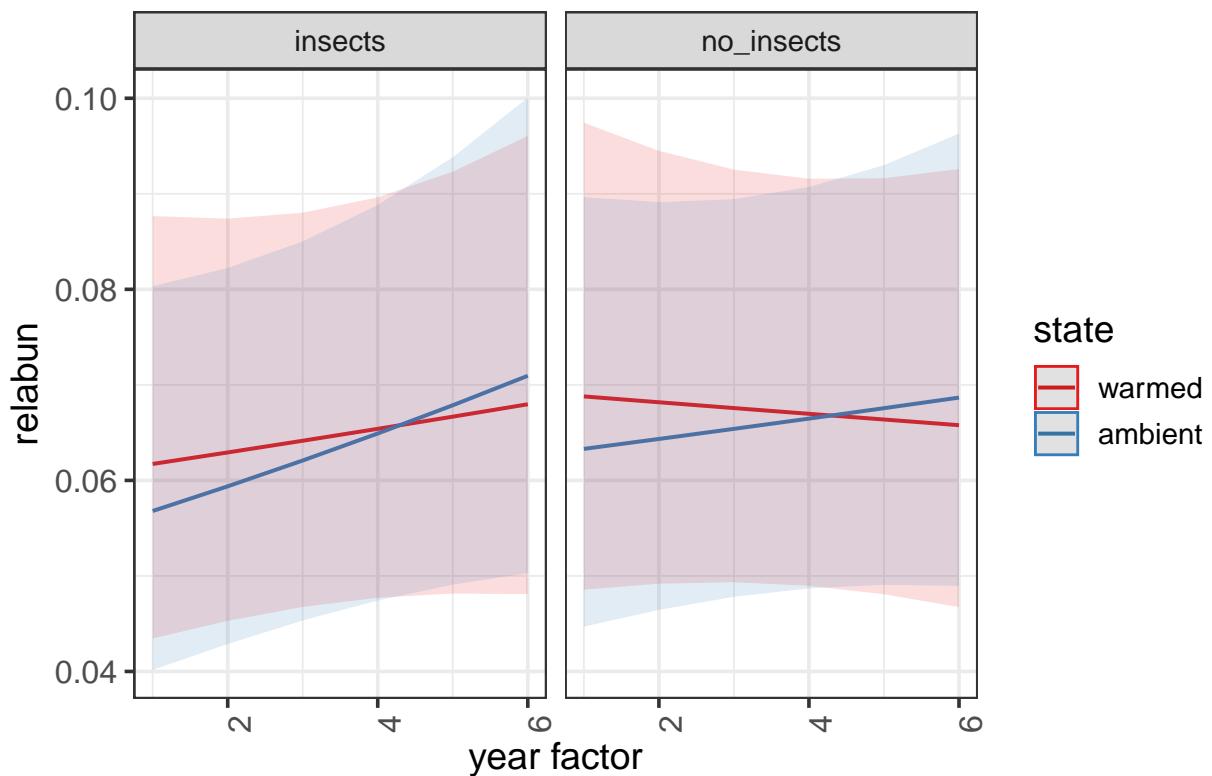
```
# Plot the fixed effects estimates for different models these are the fixed  
# effects estimates from summary(mod1)  
plot_model(mod2u, sort.est = TRUE)
```



```
# these are the fixed predicted values:  
plot_model(mod2u, type = "pred", terms = c("year_factor", "state", "insecticide"))
```

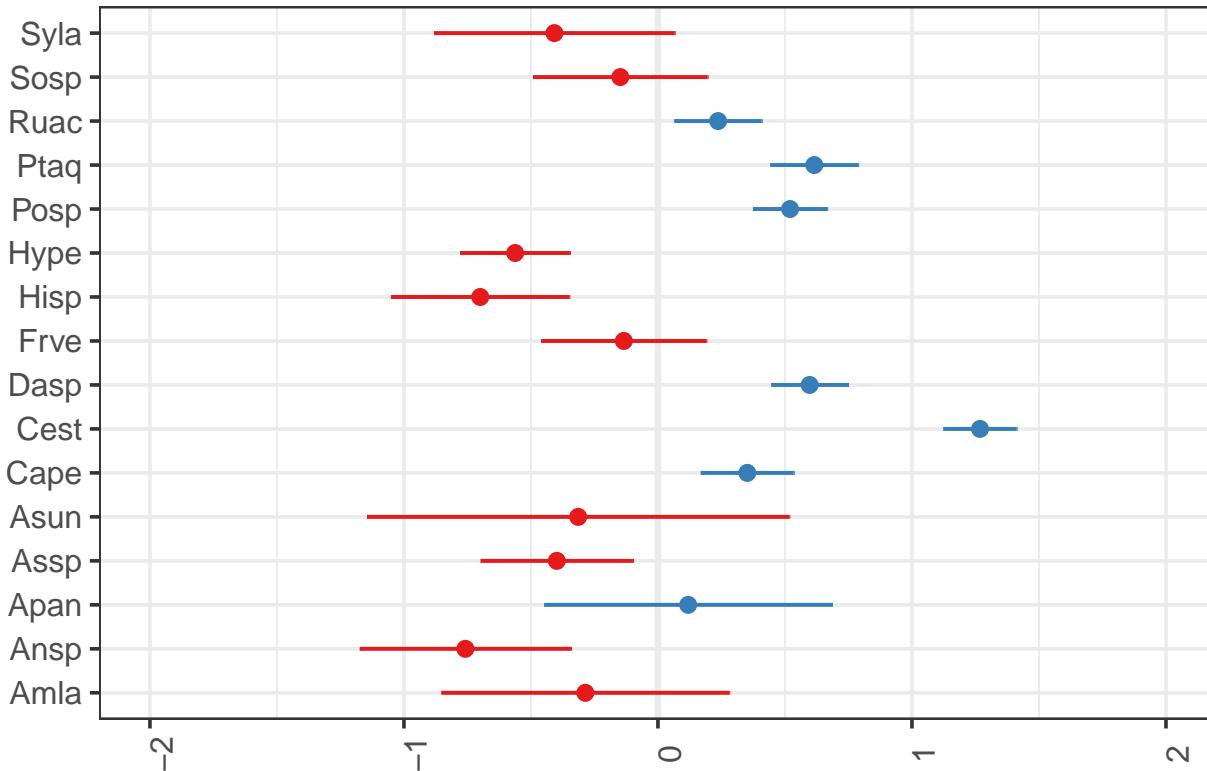
Model has log-transformed response. Back-transforming predictions to original response scale. Standard

Predicted values of relabun



```
# these are the random effects estimates
plot_model(mod2u, type = "re", terms = c("species"))
```

Random effects



```
# Does year need to be interactive with insecticide? - already removed
# insecticide
mod3u <- lmer(log(relabun) ~ state * year_factor + insecticide + (1 | species) +
  (1 | plot), comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

anova(mod2u, mod3u) # Looks like no, pvalue > 0.05, so year interactive with insecticide does not improve model fit so we will remove it

## Data: comp_umbs_spp
## Models:
## mod2u: log(relabun) ~ state * year_factor + insecticide * year_factor +
## mod2u:           (1 | species)
## mod3u: log(relabun) ~ state * year_factor + insecticide + (1 | species) +
## mod3u:           (1 | plot)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod2u     8 2386.7 2425.1 -1185.4    2370.7
## mod3u     8 2387.4 2425.8 -1185.7    2371.4      0   0

# Do we need to include insecticide? (dropping insecticide from the model)
mod4u <- lmer(log(relabun) ~ state * year_factor + (1 | species), comp_umbs_spp,
  REML = FALSE)
anova(mod2u, mod4u) # Looks like no, pvalue > 0.05, so insecticide does not improve model fit so we will remove it

## Data: comp_umbs_spp
```

```

## Models:
## mod4u: log(relabun) ~ state * year_factor + (1 | species)
## mod2u: log(relabun) ~ state * year_factor + insecticide * year_factor +
## mod2u:      (1 | species)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod4u     6 2383.7 2412.6 -1185.9   2371.7
## mod2u     8 2386.7 2425.1 -1185.4   2370.7 1.0233  2     0.5995

AICctab(mod2u, mod4u, weights = T)

##          dAICc df weight
## mod4u  0.0   6  0.82
## mod2u  3.0   8  0.18

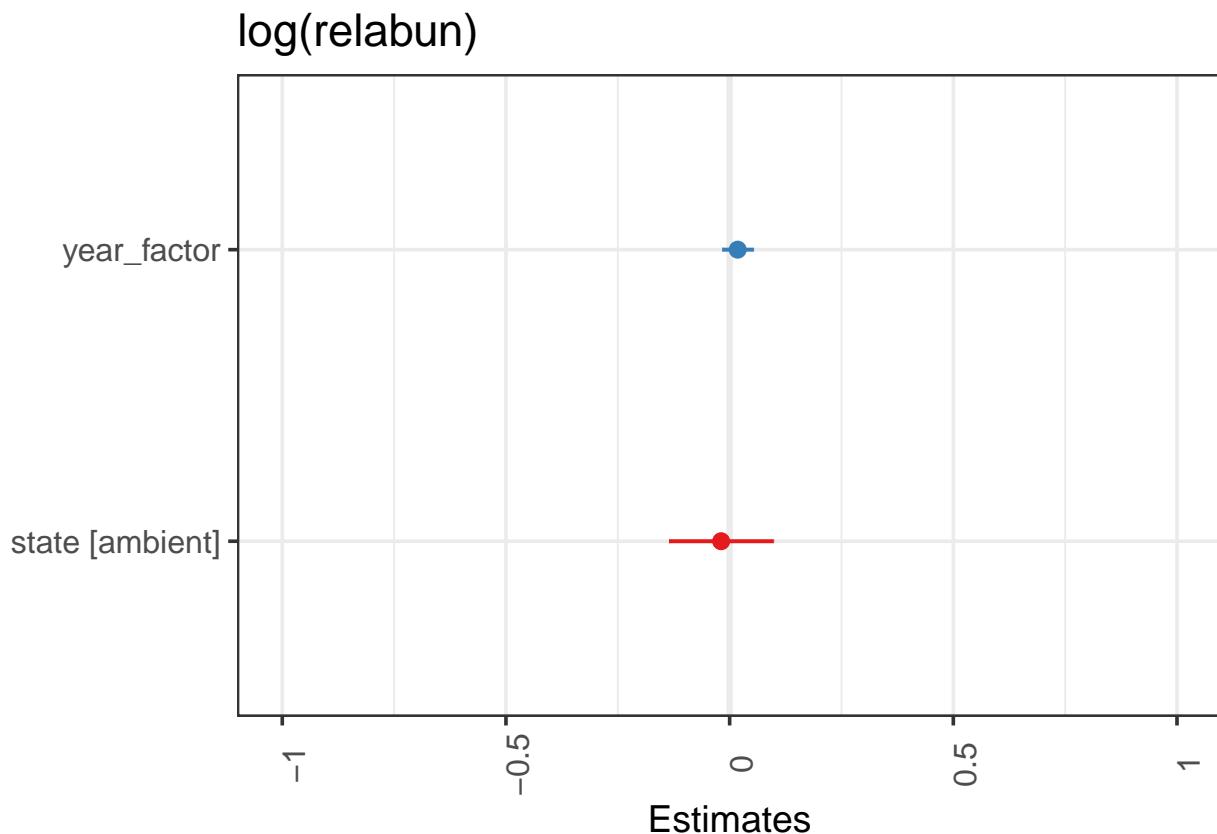
# Does year need to be interactive with state?
mod5u <- lmer(log(relabun) ~ state + year_factor + (1 | species), comp_umbs_spp,
               REML = FALSE)
anova(mod4u, mod5u)

## Data: comp_umbs_spp
## Models:
## mod5u: log(relabun) ~ state + year_factor + (1 | species)
## mod4u: log(relabun) ~ state * year_factor + (1 | species)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod5u     5 2382.3 2406.3 -1186.2   2372.3
## mod4u     6 2383.7 2412.6 -1185.9   2371.7 0.5743  1     0.4486

# No, P>0.05 so state*year_factor doesn't strongly improve model fit so we will
# shift to mod5u, but AIC values are close!!

# Plot the fixed effects estimates for different models these are the fixed
# effects estimates from summary(mod5)
plot_model(mod5u, sort.est = TRUE)

```

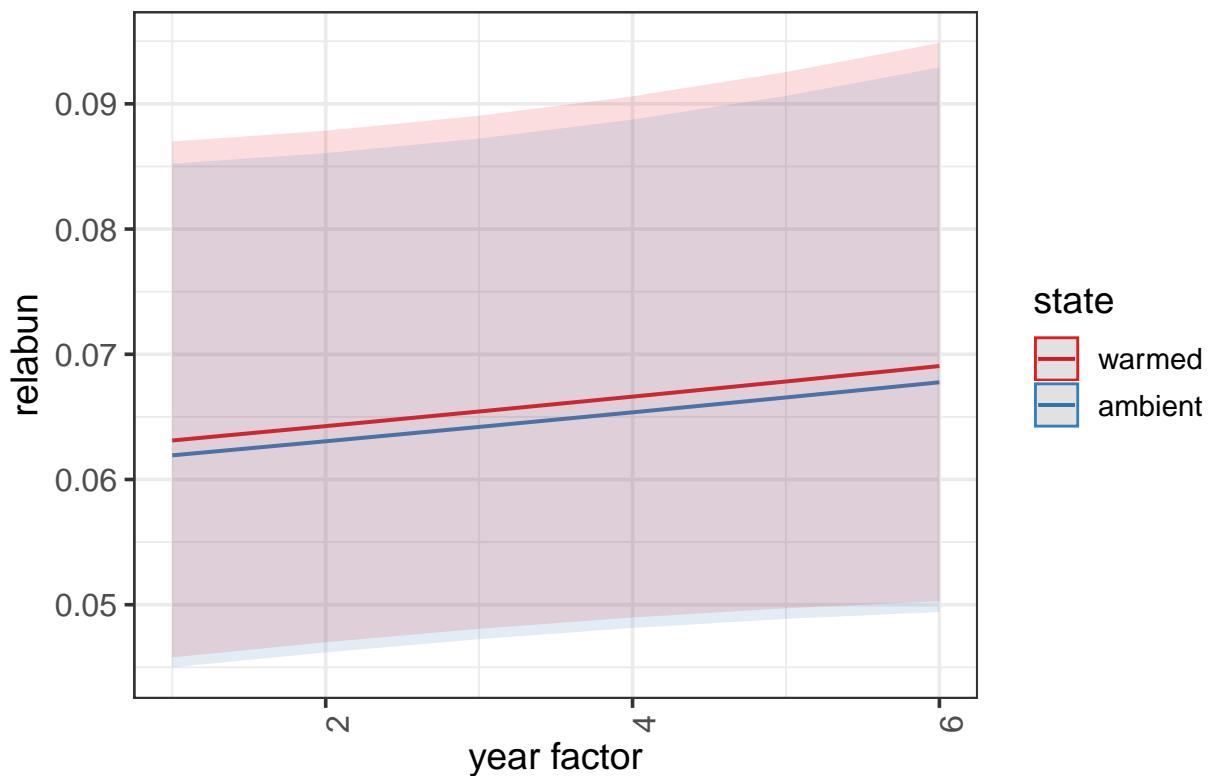


```
# these are the fixed predicted values:
```

```
plot_model(mod5u, type = "pred", terms = c("year_factor", "state"))
```

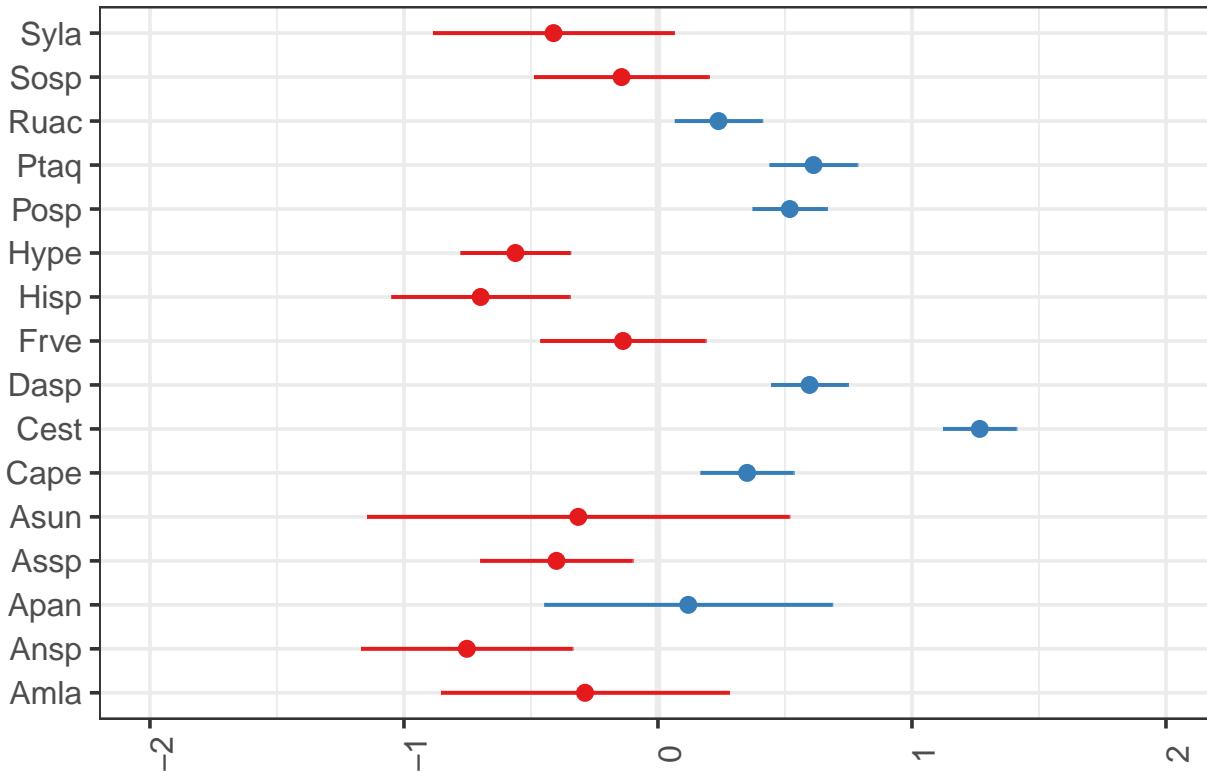
```
## Model has log-transformed response. Back-transforming predictions to original response scale. Standard
```

Predicted values of relabun



```
# these are the random effects estimates
plot_model(mod5u, type = "re", terms = c("species"))
```

Random effects



```
# If we wanted to include plots nested within year it would look like this:
mod6u <- lmer(log(relabun) ~ state + year_factor + (1 | species) + (1 + year_factor |
  plot), comp_umbs_spp, REML = FALSE)
```

```
## boundary (singular) fit: see ?isSingular
```

```
anova(mod5u, mod6u) # go with simpler model = mod5u
```

```
## Data: comp_umbs_spp
## Models:
## mod5u: log(relabun) ~ state + year_factor + (1 | species)
## mod6u: log(relabun) ~ state + year_factor + (1 | species) + (1 + year_factor |
## mod6u:   plot)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod5u     5 2382.3 2406.3 -1186.2    2372.3
## mod6u     8 2388.3 2426.7 -1186.2    2372.3      0  3          1
```

```
anova(mod5u)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state       0.08011 0.08011      1  885.97  0.1026 0.7488
## year_factor 0.82358 0.82358      1  890.68  1.0550 0.3046
```

```

# reminder what model 5u is: mod5u <- lmer(log(relabun) ~ state + year_factor +
# (1/species), comp_umbs_spp, REML=FALSE)

# mod5u (and mod6u) are pretty complex in terms of interpretation (they actually
# don't have many parameters though). We could consider an alternative model
# that's simpler to understand and also one that provides more insight about the
# species. That would be something like this:
mod7u <- lmer(log(relabun) ~ state + species + (1 + factor(year_factor) | plot),
  comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -8.0e+00

mod7au <- lmer(log(relabun) ~ state + species + factor(year_factor) + (1 | plot),
  comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod7bu <- lmer(log(relabun) ~ state * factor(year_factor) + species + (1 | plot),
  comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod7cu <- lmer(log(relabun) ~ state + species + factor(year_factor) + insecticide +
  (1 | plot), comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

anova(mod5u, mod7u) # model 7u is a better fit to data

## Data: comp_umbs_spp
## Models:
## mod5u: log(relabun) ~ state + year_factor + (1 | species)
## mod7u: log(relabun) ~ state + species + (1 + factor(year_factor) | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod5u    5 2382.3 2406.3 -1186.2   2372.3
## mod7u   39 2392.0 2579.3 -1157.0   2314.0 58.297 34   0.005881 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(mod7u, mod7au) #mod 7au

## Data: comp_umbs_spp
## Models:
## mod7au: log(relabun) ~ state + species + factor(year_factor) + (1 | plot)
## mod7u: log(relabun) ~ state + species + (1 + factor(year_factor) | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod7au   24 2346.9 2462.2 -1149.5   2298.9
## mod7u   39 2392.0 2579.3 -1157.0   2314.0      0 15          1

```

```

anova(mod7au, mod7bu)  #mod 7au - interaction between state and year does not improve model go with simpe

## Data: comp_umbs_spp
## Models:
## mod7au: log(relabun) ~ state + species + factor(year_factor) + (1 | plot)
## mod7bu: log(relabun) ~ state * factor(year_factor) + species + (1 | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod7au    24 2346.9 2462.2 -1149.5   2298.9
## mod7bu    29 2352.8 2492.1 -1147.4   2294.8 4.1234  5     0.5318

anova(mod7au, mod7cu)  #models are not different than one another, go with simpler model = mod7au

## Data: comp_umbs_spp
## Models:
## mod7au: log(relabun) ~ state + species + factor(year_factor) + (1 | plot)
## mod7cu: log(relabun) ~ state + species + factor(year_factor) + insecticide +
## mod7cu:      (1 | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod7au    24 2346.9 2462.2 -1149.5   2298.9
## mod7cu    25 2348.5 2468.6 -1149.3   2298.5 0.4019  1     0.5261

summary(mod7au)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(relabun) ~ state + species + factor(year_factor) + (1 | plot)
## Data: comp_umbs_spp
##
##      AIC      BIC  logLik deviance df.resid
##  2346.9  2462.2 -1149.5   2298.9     875
##
## Scaled residuals:
##    Min     1Q   Median     3Q    Max
## -3.2474 -0.7044  0.0280  0.7063  2.6539
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0000   0.0000
## Residual           0.7553   0.8691
## Number of obs: 899, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept) -3.10745  0.34107 899.00000 -9.111 < 2e-16 ***
## stateambient -0.01567  0.05839 899.00000 -0.268 0.78846  
## speciesAnsp  -0.49583  0.40091 899.00000 -1.237 0.21649  
## speciesApan  0.55769  0.46483 899.00000  1.200 0.23054  
## speciesAssp  -0.01418  0.36498 899.00000 -0.039 0.96903  
## speciesAsun  -0.22506  0.69954 899.00000 -0.322 0.74773  
## speciesCape  0.75918  0.34226 899.00000  2.218 0.02680 *  
## speciesCest  1.68795  0.33791 899.00000  4.995 7.06e-07 ***

```

```

## speciesDasp      1.00785   0.33901 899.00000  2.973  0.00303 **
## speciesFrve    0.27617   0.37191 899.00000  0.743  0.45793
## speciesHisp    -0.45271   0.38135 899.00000 -1.187  0.23549
## speciesHype    -0.17211   0.34724 899.00000 -0.496  0.62027
## speciesPosp     0.91835   0.33807 899.00000  2.716  0.00673 **
## speciesPtaq     1.03503   0.34184 899.00000  3.028  0.00253 **
## speciesRuac     0.64773   0.34103 899.00000  1.899  0.05784 .
## speciesSosp     0.23844   0.37741 899.00000  0.632  0.52770
## speciesSyla    -0.08720   0.42122 899.00000 -0.207  0.83605
## factor(year_factor)2 -0.24404  0.10419 899.00000 -2.342  0.01939 *
## factor(year_factor)3  0.11660   0.10324 899.00000  1.129  0.25905
## factor(year_factor)4  0.08689   0.10373 899.00000  0.838  0.40245
## factor(year_factor)5 -0.04077   0.10238 899.00000 -0.398  0.69055
## factor(year_factor)6  0.01253   0.10117 899.00000  0.124  0.90145
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

##
## Correlation matrix not shown by default, as p = 22 > 12.
## Use print(x, correlation=TRUE)  or
##      vcov(x)       if you need it

```

```

## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

```

```
anova(mod7au) # investigates whether at least one of the levels within each factor is significantly di
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##                               Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state                      0.054  0.0544     1     899  0.0720  0.788461
## species                    295.084 19.6722    15     899 26.0460 < 2.2e-16 ***
## factor(year_factor)     11.599  2.3197     5     899  3.0713  0.009337 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
# Yes, at least one of the species is different (they do not all have the same
# relative abundances).
```

```
emmeans(mod7au, list(pairwise ~ state + year_factor), adjust = "tukey")
```

```
## boundary (singular) fit: see ?isSingular
```

```

## $`emmeans of state, year_factor`
##   state  year_factor emmean      SE  df lower.CL upper.CL
##   warmed          1 -2.75 0.0987 338    -2.95   -2.56
##   ambient         1 -2.77 0.0973 303    -2.96   -2.58
##   warmed          2 -3.00 0.0981 331    -3.19   -2.80
##   ambient         2 -3.01 0.0964 300    -3.20   -2.82
##   warmed          3 -2.64 0.0961 326    -2.82   -2.45
##   ambient         3 -2.65 0.0951 301    -2.84   -2.46
##   warmed          4 -2.67 0.0956 301    -2.85   -2.48
##   ambient         4 -2.68 0.0937 272    -2.87   -2.50
##   warmed          5 -2.79 0.0911 253    -2.97   -2.61

```

```

## ambient          5 -2.81 0.0903 223    -2.99    -2.63
## warmed          6 -2.74 0.0933 295    -2.92    -2.56
## ambient          6 -2.76 0.0911 248    -2.94    -2.58
##
## Results are averaged over the levels of: species
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $'pairwise differences of state, year_factor'
##   1           estimate      SE   df t.ratio p.value
## warmed 1 - ambient 1  0.01567 0.0594 20.9  0.264  1.0000
## warmed 1 - warmed 2  0.24404 0.1055 903.2  2.313  0.4680
## warmed 1 - ambient 2  0.25971 0.1208 295.7  2.149  0.5879
## warmed 1 - warmed 3 -0.11660 0.1046 906.0 -1.115  0.9940
## warmed 1 - ambient 3 -0.10092 0.1207 291.4 -0.836  0.9995
## warmed 1 - warmed 4 -0.08689 0.1051 906.3 -0.827  0.9996
## warmed 1 - ambient 4 -0.07121 0.1204 290.9 -0.592  1.0000
## warmed 1 - warmed 5  0.04077 0.1037 908.3  0.393  1.0000
## warmed 1 - ambient 5  0.05644 0.1201 278.4  0.470  1.0000
## warmed 1 - warmed 6 -0.01253 0.1025 908.2 -0.122  1.0000
## warmed 1 - ambient 6  0.00314 0.1180 262.4  0.027  1.0000
## ambient 1 - warmed 2  0.22836 0.1214 292.3  1.882  0.7697
## ambient 1 - ambient 2  0.24404 0.1055 903.2  2.313  0.4680
## ambient 1 - warmed 3 -0.13227 0.1199 279.8 -1.103  0.9944
## ambient 1 - ambient 3 -0.11660 0.1046 906.0 -1.115  0.9940
## ambient 1 - warmed 4 -0.10256 0.1210 286.0 -0.847  0.9995
## ambient 1 - ambient 4 -0.08689 0.1051 906.3 -0.827  0.9996
## ambient 1 - warmed 5  0.02510 0.1190 278.1  0.211  1.0000
## ambient 1 - ambient 5  0.04077 0.1037 908.3  0.393  1.0000
## ambient 1 - warmed 6 -0.02820 0.1190 279.4 -0.237  1.0000
## ambient 1 - ambient 6 -0.01253 0.1025 908.2 -0.122  1.0000
## warmed 2 - ambient 2  0.01567 0.0594 20.9  0.264  1.0000
## warmed 2 - warmed 3 -0.36063 0.1047 908.5 -3.444  0.0294
## warmed 2 - ambient 3 -0.34496 0.1210 288.2 -2.850  0.1653
## warmed 2 - warmed 4 -0.33092 0.1043 906.1 -3.174  0.0678
## warmed 2 - ambient 4 -0.31525 0.1199 284.3 -2.628  0.2690
## warmed 2 - warmed 5 -0.20326 0.1033 910.2 -1.968  0.7152
## warmed 2 - ambient 5 -0.18759 0.1200 272.4 -1.563  0.9206
## warmed 2 - warmed 6 -0.25657 0.1020 907.0 -2.514  0.3321
## warmed 2 - ambient 6 -0.24089 0.1179 259.3 -2.044  0.6629
## ambient 2 - warmed 3 -0.37630 0.1197 280.0 -3.143  0.0778
## ambient 2 - ambient 3 -0.36063 0.1047 908.5 -3.444  0.0294
## ambient 2 - warmed 4 -0.34660 0.1201 282.8 -2.886  0.1515
## ambient 2 - ambient 4 -0.33092 0.1043 906.1 -3.174  0.0678
## ambient 2 - warmed 5 -0.21894 0.1183 275.1 -1.850  0.7886
## ambient 2 - ambient 5 -0.20326 0.1033 910.2 -1.968  0.7152
## ambient 2 - warmed 6 -0.27224 0.1183 279.4 -2.301  0.4784
## ambient 2 - ambient 6 -0.25657 0.1020 907.0 -2.514  0.3321
## warmed 3 - ambient 3  0.01567 0.0594 20.9  0.264  1.0000
## warmed 3 - warmed 4  0.02971 0.1042 905.1  0.285  1.0000
## warmed 3 - ambient 4  0.04538 0.1193 280.9  0.381  1.0000
## warmed 3 - warmed 5  0.15737 0.1031 906.0  1.526  0.9332
## warmed 3 - ambient 5  0.17304 0.1192 271.0  1.452  0.9517

```

```

##  warmed 3 - warmed 6  0.10407 0.1018 908.0  1.022  0.9972
##  warmed 3 - ambient 6 0.11974 0.1170 253.2  1.023  0.9971
##  ambient 3 - warmed 4 0.01404 0.1207 287.6  0.116  1.0000
##  ambient 3 - ambient 4 0.02971 0.1042 905.1  0.285  1.0000
##  ambient 3 - warmed 5 0.14170 0.1188 282.1  1.192  0.9892
##  ambient 3 - ambient 5 0.15737 0.1031 906.0  1.526  0.9332
##  ambient 3 - warmed 6 0.08839 0.1188 281.5  0.744  0.9999
##  ambient 3 - ambient 6 0.10407 0.1018 908.0  1.022  0.9972
##  warmed 4 - ambient 4 0.01567 0.0594 20.9   0.264  1.0000
##  warmed 4 - warmed 5 0.12766 0.1014 903.3  1.259  0.9838
##  warmed 4 - ambient 5 0.14333 0.1185 266.4  1.210  0.9878
##  warmed 4 - warmed 6 0.07436 0.1001 904.8  0.743  0.9999
##  warmed 4 - ambient 6 0.09003 0.1163 249.1  0.774  0.9998
##  ambient 4 - warmed 5 0.11199 0.1166 270.5  0.960  0.9983
##  ambient 4 - ambient 5 0.12766 0.1014 903.3  1.259  0.9838
##  ambient 4 - warmed 6 0.05868 0.1166 270.3  0.503  1.0000
##  ambient 4 - ambient 6 0.07436 0.1001 904.8  0.743  0.9999
##  warmed 5 - ambient 5 0.01567 0.0594 20.9   0.264  1.0000
##  warmed 5 - warmed 6 -0.05330 0.0987 904.5 -0.540  1.0000
##  warmed 5 - ambient 6 -0.03763 0.1141 242.4 -0.330  1.0000
##  ambient 5 - warmed 6 -0.06897 0.1163 259.8 -0.593  1.0000
##  ambient 5 - ambient 6 -0.05330 0.0987 904.5 -0.540  1.0000
##  warmed 6 - ambient 6 0.01567 0.0594 20.9   0.264  1.0000
##
## Results are averaged over the levels of: species
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 12 estimates

```

```
emmeans(mod7au, list(pairwise ~ year_factor), adjust = "tukey")
```

```

## boundary (singular) fit: see ?isSingular

## $`emmeans of year_factor`
##  year_factor emmean    SE  df lower.CL upper.CL
##    1     -2.76 0.0934 539    -2.94   -2.58
##    2     -3.00 0.0926 534    -3.19   -2.82
##    3     -2.64 0.0909 540    -2.82   -2.47
##    4     -2.67 0.0898 493    -2.85   -2.50
##    5     -2.80 0.0857 414    -2.97   -2.63
##    6     -2.75 0.0873 475    -2.92   -2.58
##
## Results are averaged over the levels of: state, species
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of year_factor`
##  1     estimate    SE  df t.ratio p.value
##  1 - 2    0.2440 0.1055 903   2.313  0.1898
##  1 - 3   -0.1166 0.1046 906  -1.115  0.8752
##  1 - 4   -0.0869 0.1051 906  -0.827  0.9625
##  1 - 5    0.0408 0.1037 908   0.393  0.9988

```

```

## 1 - 6 -0.0125 0.1025 908 -0.122 1.0000
## 2 - 3 -0.3606 0.1047 908 -3.444 0.0079
## 2 - 4 -0.3309 0.1043 906 -3.174 0.0193
## 2 - 5 -0.2033 0.1033 910 -1.968 0.3617
## 2 - 6 -0.2566 0.1020 907 -2.514 0.1209
## 3 - 4 0.0297 0.1042 905 0.285 0.9997
## 3 - 5 0.1574 0.1031 906 1.526 0.6473
## 3 - 6 0.1041 0.1018 908 1.022 0.9106
## 4 - 5 0.1277 0.1014 903 1.259 0.8073
## 4 - 6 0.0744 0.1001 905 0.743 0.9765
## 5 - 6 -0.0533 0.0987 905 -0.540 0.9945
##
## Results are averaged over the levels of: state, species
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 6 estimates

emmeans(mod7au, list(pairwise ~ species), adjust = "tukey")

## boundary (singular) fit: see ?isSingular

## $`emmeans of species`
##   species emmean    SE df lower.CL upper.CL
##   Amla     -3.13 0.3364 840    -3.79    -2.47
##   Ansp     -3.62 0.2291 912    -4.07    -3.17
##   Apan     -2.57 0.3361 870    -3.23    -1.91
##   Assp     -3.14 0.1598 705    -3.45    -2.83
##   Asun     -3.35 0.6273 922    -4.58    -2.12
##   Cape     -2.37 0.0950 657    -2.55    -2.18
##   Cest     -1.44 0.0738 525    -1.58    -1.29
##   Dasp     -2.12 0.0776 560    -2.27    -1.97
##   Frve     -2.85 0.1746 652    -3.19    -2.51
##   Hisp     -3.58 0.1913 887    -3.95    -3.20
##   Hype     -3.30 0.1130 714    -3.52    -3.08
##   Posp     -2.21 0.0750 539    -2.36    -2.06
##   Ptaq     -2.09 0.0893 603    -2.27    -1.92
##   Ruac     -2.48 0.0888 595    -2.65    -2.30
##   Sosp     -2.89 0.1856 664    -3.25    -2.52
##   Syla     -3.21 0.2683 734    -3.74    -2.69
##
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of species`
##   1           estimate    SE df t.ratio p.value
##   Amla - Ansp  0.4958 0.409 876  1.214  0.9981
##   Amla - Apan -0.5577 0.473 906 -1.179  0.9986
##   Amla - Assp  0.0142 0.373 815  0.038  1.0000
##   Amla - Asun  0.2251 0.710 920  0.317  1.0000
##   Amla - Cape -0.7592 0.349 859 -2.175  0.7144
##   Amla - Cest -1.6880 0.344 871 -4.901  0.0001

```

```

## Amla - Dasp -1.0079 0.346 871 -2.917 0.2088
## Amla - Frve -0.2762 0.380 820 -0.727 1.0000
## Amla - Hisp 0.4527 0.388 907 1.167 0.9988
## Amla - Hype 0.1721 0.354 891 0.487 1.0000
## Amla - Posp -0.9183 0.345 873 -2.665 0.3549
## Amla - Ptaq -1.0350 0.348 883 -2.972 0.1830
## Amla - Ruac -0.6477 0.347 885 -1.864 0.8913
## Amla - Sosp -0.2384 0.384 892 -0.620 1.0000
## Amla - Syla 0.0872 0.429 897 0.203 1.0000
## Ansp - Apan -1.0535 0.408 920 -2.585 0.4107
## Ansp - Assp -0.4817 0.280 916 -1.723 0.9407
## Ansp - Asun -0.2708 0.670 921 -0.404 1.0000
## Ansp - Cape -1.2550 0.249 921 -5.046 0.0001
## Ansp - Cest -2.1838 0.241 921 -9.071 <.0001
## Ansp - Dasp -1.5037 0.242 921 -6.222 <.0001
## Ansp - Frve -0.7720 0.288 908 -2.683 0.3430
## Ansp - Hisp -0.0431 0.297 922 -0.145 1.0000
## Ansp - Hype -0.3237 0.256 920 -1.262 0.9970
## Ansp - Posp -1.4142 0.241 921 -5.863 <.0001
## Ansp - Ptaq -1.5309 0.246 921 -6.219 <.0001
## Ansp - Ruac -1.1436 0.246 919 -4.655 0.0004
## Ansp - Sosp -0.7343 0.294 875 -2.494 0.4771
## Ansp - Syla -0.4086 0.353 856 -1.156 0.9989
## Apan - Assp 0.5719 0.372 844 1.537 0.9779
## Apan - Asun 0.7827 0.711 918 1.101 0.9994
## Apan - Cape -0.2015 0.348 883 -0.578 1.0000
## Apan - Cest -1.1303 0.344 894 -3.285 0.0791
## Apan - Dasp -0.4502 0.345 895 -1.304 0.9957
## Apan - Frve 0.2815 0.379 827 0.742 1.0000
## Apan - Hisp 1.0104 0.388 901 2.605 0.3961
## Apan - Hype 0.7298 0.353 907 2.066 0.7863
## Apan - Posp -0.3607 0.344 891 -1.048 0.9997
## Apan - Ptaq -0.4773 0.348 905 -1.373 0.9927
## Apan - Ruac -0.0900 0.347 903 -0.259 1.0000
## Apan - Sosp 0.3192 0.385 868 0.829 1.0000
## Apan - Syla 0.6449 0.430 843 1.500 0.9825
## Assp - Asun 0.2109 0.647 921 0.326 1.0000
## Assp - Cape -0.7734 0.186 823 -4.162 0.0036
## Assp - Cest -1.7021 0.176 872 -9.668 <.0001
## Assp - Dasp -1.0220 0.178 885 -5.754 <.0001
## Assp - Frve -0.2903 0.236 853 -1.232 0.9977
## Assp - Hisp 0.4385 0.250 910 1.757 0.9306
## Assp - Hype 0.1579 0.196 877 0.808 1.0000
## Assp - Posp -0.9325 0.177 869 -5.281 <.0001
## Assp - Ptaq -1.0492 0.183 888 -5.733 <.0001
## Assp - Ruac -0.6619 0.183 881 -3.624 0.0270
## Assp - Sosp -0.2526 0.245 843 -1.031 0.9997
## Assp - Syla 0.0730 0.311 871 0.235 1.0000
## Asun - Cape -0.9842 0.634 922 -1.552 0.9759
## Asun - Cest -1.9130 0.632 921 -3.029 0.1590
## Asun - Dasp -1.2329 0.632 921 -1.950 0.8516
## Asun - Frve -0.5012 0.651 921 -0.770 1.0000
## Asun - Hisp 0.2276 0.656 919 0.347 1.0000
## Asun - Hype -0.0530 0.637 921 -0.083 1.0000

```

```

##  Asun - Posp -1.1434 0.632 921 -1.810 0.9126
##  Asun - Ptaq -1.2601 0.634 921 -1.989 0.8311
##  Asun - Ruac -0.8728 0.633 921 -1.378 0.9924
##  Asun - Sosp -0.4635 0.653 914 -0.710 1.0000
##  Asun - Syla -0.1379 0.680 902 -0.203 1.0000
##  Cape - Cest -0.9288 0.120 920 -7.719 <.0001
##  Cape - Dasp -0.2487 0.123 921 -2.023 0.8121
##  Cape - Frve 0.4830 0.199 831 2.430 0.5253
##  Cape - Hisp 1.2119 0.214 920 5.661 <.0001
##  Cape - Hype 0.9313 0.147 911 6.337 <.0001
##  Cape - Posp -0.1592 0.121 919 -1.316 0.9953
##  Cape - Ptaq -0.2758 0.131 920 -2.112 0.7572
##  Cape - Ruac 0.1114 0.130 902 0.857 1.0000
##  Cape - Sosp 0.5207 0.209 797 2.489 0.4806
##  Cape - Syla 0.8464 0.285 771 2.972 0.1833
##  Cest - Dasp 0.6801 0.107 904 6.350 <.0001
##  Cest - Frve 1.4118 0.190 818 7.448 <.0001
##  Cest - Hisp 2.1407 0.205 921 10.438 <.0001
##  Cest - Hype 1.8601 0.135 921 13.784 <.0001
##  Cest - Posp 0.7696 0.105 900 7.313 <.0001
##  Cest - Ptaq 0.6529 0.116 919 5.634 <.0001
##  Cest - Ruac 1.0402 0.115 919 9.008 <.0001
##  Cest - Sosp 1.4495 0.200 811 7.256 <.0001
##  Cest - Syla 1.7752 0.278 805 6.379 <.0001
##  Dasp - Frve 0.7317 0.191 814 3.832 0.0130
##  Dasp - Hisp 1.4606 0.206 922 7.084 <.0001
##  Dasp - Hype 1.1800 0.137 922 8.596 <.0001
##  Dasp - Posp 0.0895 0.108 905 0.829 1.0000
##  Dasp - Ptaq -0.0272 0.118 918 -0.230 1.0000
##  Dasp - Ruac 0.3601 0.118 918 3.052 0.1500
##  Dasp - Sosp 0.7694 0.201 807 3.827 0.0132
##  Dasp - Syla 1.0950 0.279 809 3.921 0.0093
##  Frve - Hisp 0.7289 0.258 921 2.823 0.2578
##  Frve - Hype 0.4483 0.208 841 2.154 0.7289
##  Frve - Posp -0.6422 0.190 823 -3.378 0.0600
##  Frve - Ptaq -0.7589 0.196 805 -3.871 0.0112
##  Frve - Ruac -0.3716 0.196 825 -1.898 0.8766
##  Frve - Sosp 0.0377 0.254 840 0.148 1.0000
##  Frve - Syla 0.3634 0.319 879 1.140 0.9990
##  Hisp - Hype -0.2806 0.223 919 -1.258 0.9971
##  Hisp - Posp -1.3711 0.205 921 -6.680 <.0001
##  Hisp - Ptaq -1.4877 0.211 922 -7.054 <.0001
##  Hisp - Ruac -1.1004 0.211 921 -5.213 <.0001
##  Hisp - Sosp -0.6911 0.265 904 -2.605 0.3966
##  Hisp - Syla -0.3655 0.329 905 -1.110 0.9993
##  Hype - Posp -1.0905 0.135 921 -8.048 <.0001
##  Hype - Ptaq -1.2071 0.144 920 -8.382 <.0001
##  Hype - Ruac -0.8198 0.143 921 -5.723 <.0001
##  Hype - Sosp -0.4105 0.218 812 -1.884 0.8829
##  Hype - Syla -0.0849 0.291 835 -0.292 1.0000
##  Posp - Ptaq -0.1167 0.117 920 -1.001 0.9998
##  Posp - Ruac 0.2706 0.116 920 2.328 0.6030
##  Posp - Sosp 0.6799 0.200 814 3.396 0.0569
##  Posp - Syla 1.0055 0.279 806 3.610 0.0285

```

```

## Ptaq - Ruac  0.3873 0.126 922  3.073  0.1421
## Ptaq - Sosp  0.7966 0.206 827  3.872  0.0112
## Ptaq - Syla  1.1222 0.283 833  3.972  0.0076
## Ruac - Sosp  0.4093 0.206 831  1.989  0.8310
## Ruac - Syla  0.7349 0.282 835  2.603  0.3978
## Sosp - Syla  0.3256 0.324 922  1.005  0.9998
##
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 16 estimates

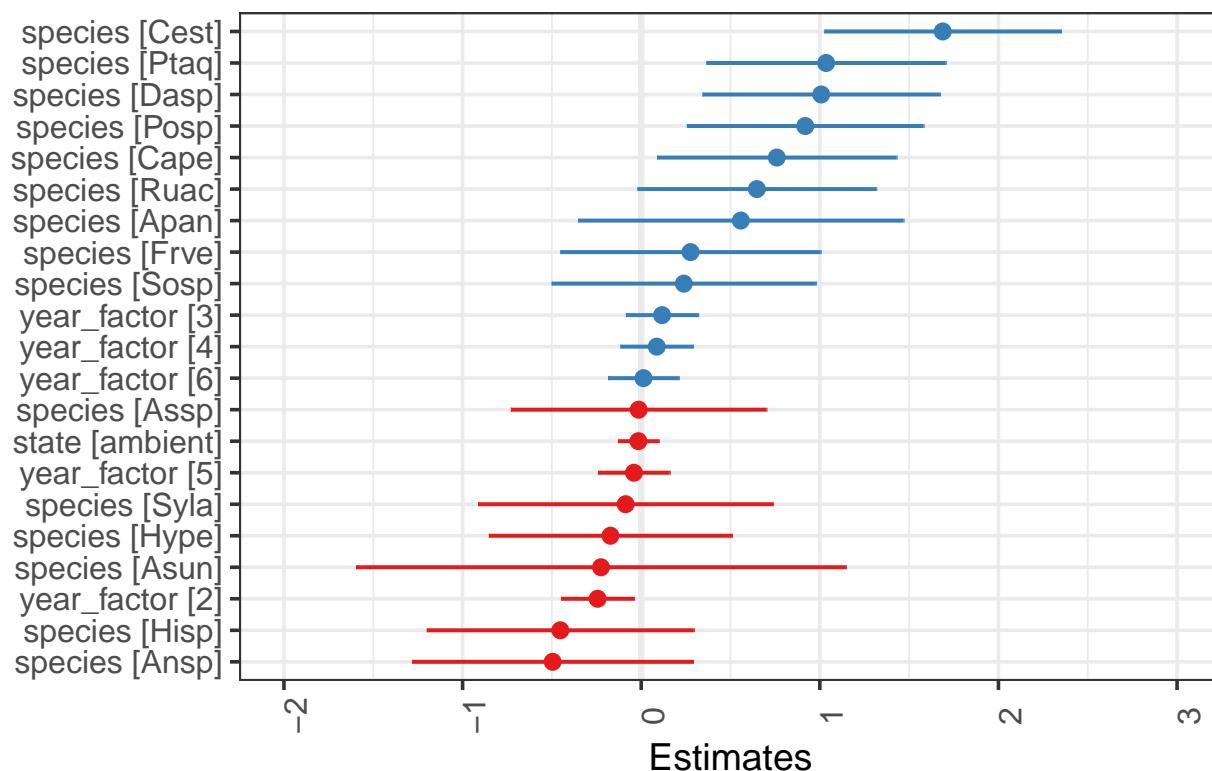
```

```

# Take a look at the estimates for each fixed effect. These are the estimates
# from summary(mod7au). You'll see that species vary a lot - and many of them are
# different from zero (meaning their half cover date is significantly different
# from zero).
plot_model(mod7au, sort.est = TRUE)

```

log(relabun)



```

# if you want to standardize the estimates:
plot_model(mod7au, sort.est = TRUE, type = "std")

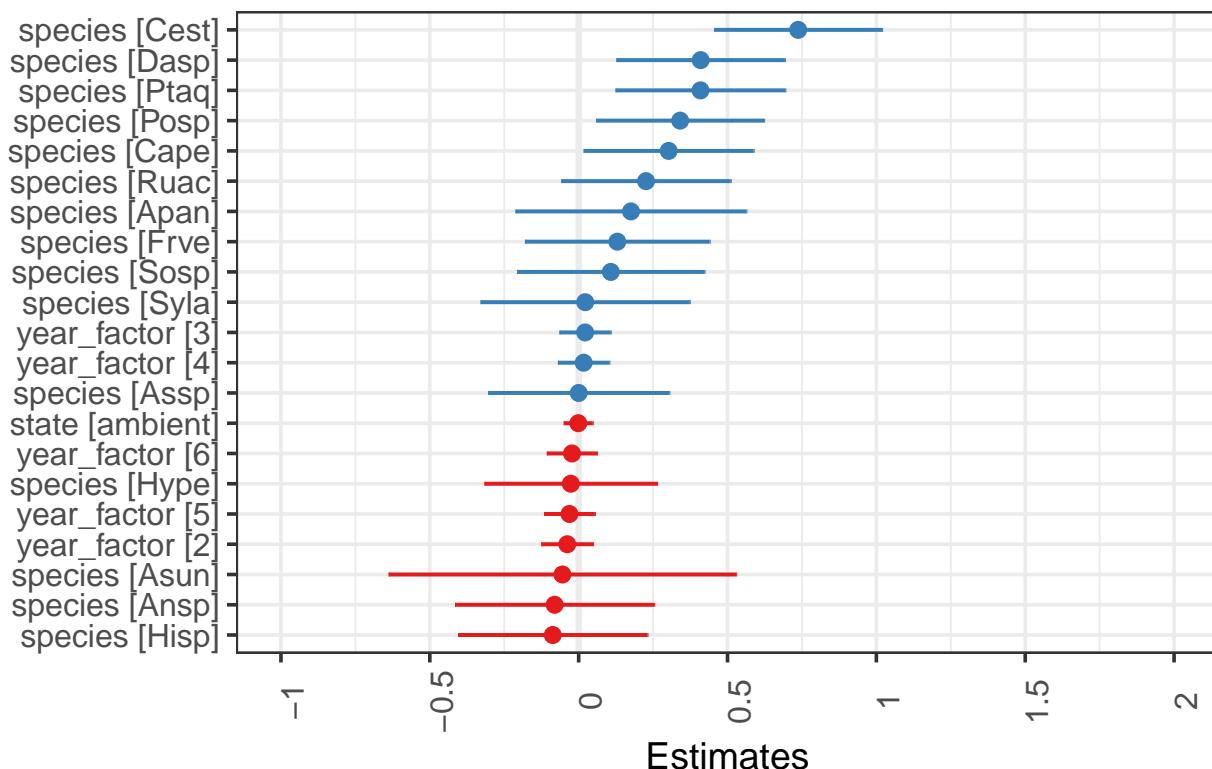
```

```

## Formula contains log- or sqrt-terms. See help("standardize") for how such terms are standardized.
## boundary (singular) fit: see ?isSingular

```

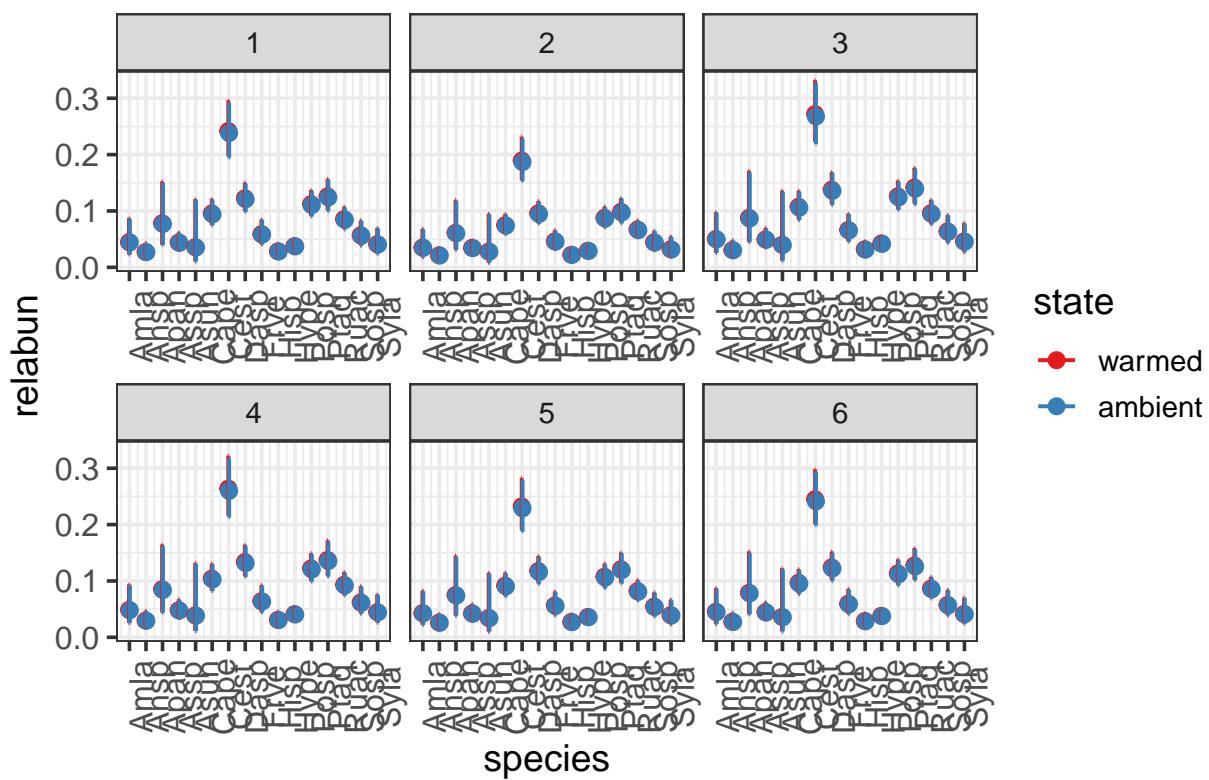
log(relabun)



```
# these are the fixed predicted values: - note this is a new plot
plot_model(mod7au, type = "pred", terms = c("species", "state", "year_factor"))
```

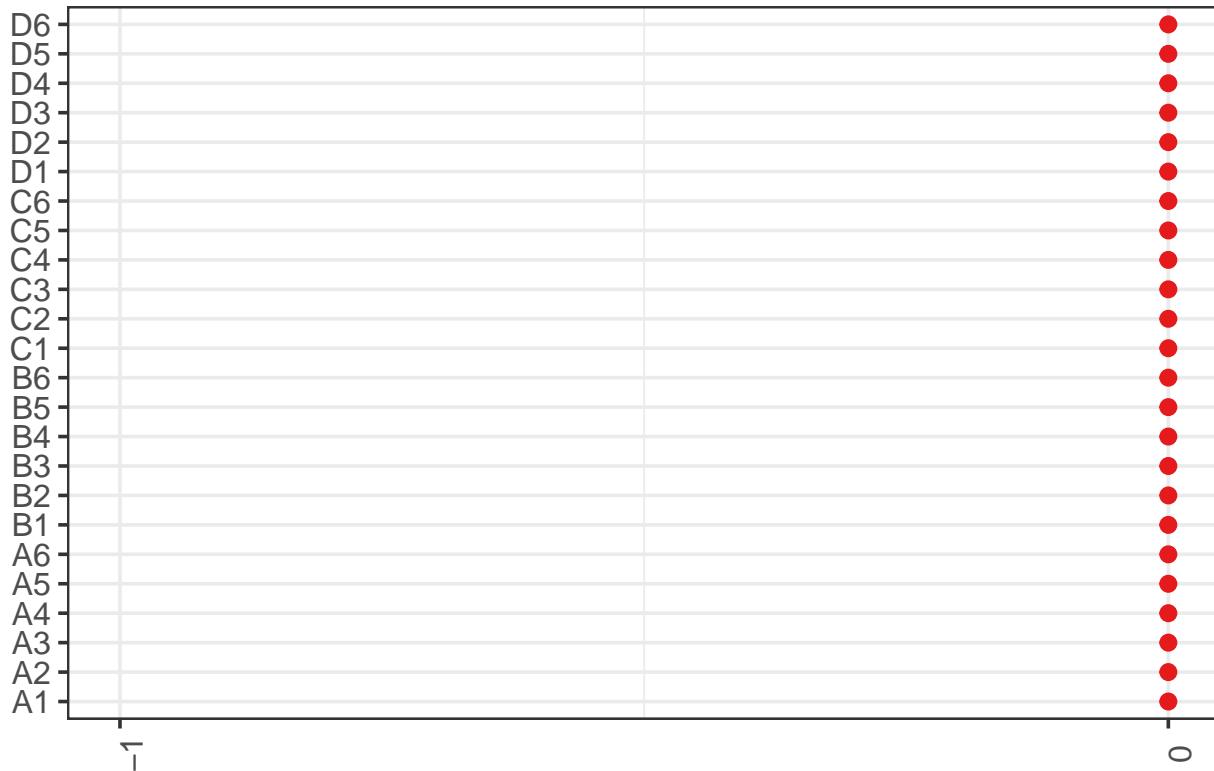
```
## Model has log-transformed response. Back-transforming predictions to original response scale. Standard
```

Predicted values of relabun



```
# these are the random effects estimates  
plot_model(mod7au, type = "re")
```

Random effects



```
# including native vs. exotic
comp_umbs_spp <- within(comp_umbs_spp, origin <- relevel(factor(origin), ref = "Native")) # releveling
mod8u <- lmer(log(relabun) ~ state * origin + (1 + factor(year_factor) | plot), comp_umbs_spp,
REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod9u <- lmer(log(relabun) ~ state + origin + (1 + factor(year_factor) | plot), comp_umbs_spp,
REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod9au <- lmer(log(relabun) ~ state + origin + factor(year_factor) + (1 | plot),
comp_umbs_spp, REML = FALSE)
anova(mod8u, mod9u) # model 9au is a better fit to data

## Data: comp_umbs_spp
## Models:
## mod9u: log(relabun) ~ state + origin + (1 + factor(year_factor) | plot)
## mod8u: log(relabun) ~ state * origin + (1 + factor(year_factor) | plot)
##      npar    AIC    BIC   logLik deviance Chisq Df Pr(>Chisq)
## mod9u    27 2621.8 2751.4 -1283.9    2567.8
## mod8u    30 2627.0 2771.1 -1283.5    2567.0 0.7828  3      0.8536
```

```

anova(mod9au, mod9au) # mod 9au

## Data: comp_umbs_spp
## Models:
## mod9au: log(relabun) ~ state + origin + factor(year_factor) + (1 | plot)
## mod9u: log(relabun) ~ state + origin + (1 + factor(year_factor) | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod9au    12 2583.7 2641.3 -1279.8   2559.7
## mod9u     27 2621.8 2751.4 -1283.9   2567.8      0 15          1

summary(mod9au)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(relabun) ~ state + origin + factor(year_factor) + (1 | plot)
## Data: comp_umbs_spp
##
##      AIC      BIC  logLik deviance df.resid
## 2583.7 2641.3 -1279.8   2559.7      887
##
## Scaled residuals:
##      Min      1Q      Median      3Q      Max
## -2.53037 -0.80643  0.02779  0.75061  2.26651
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.01676  0.1294
## Residual           0.99643  0.9982
## Number of obs: 899, groups: plot, 24
##
## Fixed effects:
##                   Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)      -2.277637  0.104842 193.052697 -21.724 < 2e-16 ***
## stateambient    -0.013732  0.085670  24.045502 -0.160  0.87399
## origin          0.133966  0.098199 884.240210  1.364  0.17284
## originBoth       -0.915855  0.147988 898.951040 -6.189 9.21e-10 ***
## originExotic    0.217616  0.076397 893.726835  2.849  0.00449 **
## factor(year_factor)2 -0.277550  0.119333 877.690322 -2.326  0.02025 *
## factor(year_factor)3  0.065374  0.117909 880.489235  0.554  0.57941
## factor(year_factor)4 -0.003281  0.118263 879.852006 -0.028  0.97787
## factor(year_factor)5 -0.132600  0.116568 881.205652 -1.138  0.25562
## factor(year_factor)6 -0.071020  0.115377 880.813842 -0.616  0.53835
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) sttmbn origin orgnBt orgnEx fc(_)2 fc(_)3 fc(_)4 fc(_)5
## stateambint -0.408
## origin      -0.252  0.007
## originBoth   -0.151 -0.043  0.169
## originExotc  -0.286  0.012  0.334  0.217
## fctr(yr_f)2 -0.576 -0.007  0.032  0.035 -0.016

```

```

## fctr(yr_f)3 -0.577  0.007  0.001 -0.038 -0.013  0.509
## fctr(yr_f)4 -0.568 -0.011 -0.003  0.036 -0.046  0.511  0.514
## fctr(yr_f)5 -0.581  0.004 -0.007  0.024 -0.045  0.518  0.522  0.525
## fctr(yr_f)6 -0.580 -0.013  0.005  0.006 -0.047  0.523  0.528  0.530  0.537

```

```
anova(mod9au)
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##                               Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state                      0.026  0.0256     1    24.05  0.0257  0.87399
## origin                     57.912 19.3040     3   893.78 19.3732 3.556e-12 ***
## factor(year_factor)      10.729  2.1458     5   880.38  2.1535  0.05721 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
emmeans(mod9au, list(pairwise ~ state), adjust = "tukey")
```

```

## $`emmeans of state`
##   state emmean    SE  df lower.CL upper.CL
##   warmed -2.49 0.0713 42.1    -2.63    -2.34
##   ambient -2.50 0.0695 36.7    -2.64    -2.36
## 
## Results are averaged over the levels of: origin, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
## 
## $`pairwise differences of state`
##   1           estimate    SE  df t.ratio p.value
##   warmed - ambient  0.0137 0.0897 25.9 0.153   0.8796
## 
## Results are averaged over the levels of: origin, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.

```

```
emmeans(mod9au, list(pairwise ~ origin), adjust = "tukey")
```

```

## $`emmeans of origin`
##   origin emmean    SE  df lower.CL upper.CL
##   Native -2.35 0.0584  76    -2.47    -2.24
##          -2.22 0.0898 364    -2.40    -2.04
##   Both   -3.27 0.1441 683    -3.55    -2.99
##   Exotic -2.14 0.0652 118    -2.27    -2.01
## 
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
## 
## $`pairwise differences of origin`
##   1           estimate    SE  df t.ratio p.value
##   Native - Exotic -0.1340 0.0987 892 -1.357   0.5268

```

```

##  Native - Both      0.9159 0.1492 909   6.139 <.0001
##  Native - Exotic   -0.2176 0.0769 902  -2.831  0.0245
##  - Both            1.0498 0.1645 909   6.383 <.0001
##  - Exotic          -0.0837 0.1029 893  -0.813  0.8483
##  Both - Exotic     -1.1335 0.1523 909  -7.442 <.0001
##
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 4 estimates

```

```
emmeans(mod9au, list(pairwise ~ state + origin), adjust = "tukey")
```

```

## $`emmeans of state, origin`
## state origin emmean    SE    df lower.CL upper.CL
## warmed Native  -2.35 0.0738 48.8   -2.50   -2.20
## ambient Native -2.36 0.0735 47.4   -2.51   -2.21
## warmed        -2.21 0.1002 166.8  -2.41   -2.02
## ambient        -2.23 0.1005 169.4  -2.43   -2.03
## warmed Both    -3.26 0.1527 472.6  -3.56   -2.96
## ambient Both   -3.28 0.1490 424.8  -3.57   -2.98
## warmed Exotic -2.13 0.0788 64.1   -2.29   -1.97
## ambient Exotic -2.14 0.0795 65.8   -2.30   -1.98
##
## Results are averaged over the levels of: year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, origin`
## 1
##   estimate    SE    df t.ratio p.value
##   warmed Native - ambient Native  0.0137 0.0897 25.9  0.153  1.0000
##   warmed Native - warmed           -0.1340 0.0987 892.1 -1.357  0.8763
##   warmed Native - ambient          -0.1202 0.1338 132.6 -0.898  0.9858
##   warmed Native - warmed Both    0.9159 0.1492 909.2  6.139 <.0001
##   warmed Native - ambient Both   0.9296 0.1710 265.4  5.436 <.0001
##   warmed Native - warmed Exotic -0.2176 0.0769 902.4 -2.831  0.0888
##   warmed Native - ambient Exotic -0.2039 0.1188 82.1  -1.716  0.6772
##   ambient Native - warmed         -0.1477 0.1330 127.8 -1.111  0.9534
##   ambient Native - ambient        -0.1340 0.0987 892.1 -1.357  0.8763
##   ambient Native - warmed Both   0.9021 0.1771 315.2  5.093 <.0001
##   ambient Native - ambient Both  0.9159 0.1492 909.2  6.139 <.0001
##   ambient Native - warmed Exotic -0.2313 0.1175 78.3  -1.969  0.5092
##   ambient Native - ambient Exotic -0.2176 0.0769 902.4 -2.831  0.0888
##   warmed - ambient             0.0137 0.0897 25.9  0.153  1.0000
##   warmed - warmed Both          1.0498 0.1645 909.2  6.383 <.0001
##   warmed - ambient Both         1.0636 0.1842 325.3  5.774 <.0001
##   warmed - warmed Exotic       -0.0837 0.1029 892.5 -0.813  0.9924
##   warmed - ambient Exotic      -0.0699 0.1367 141.6 -0.512  0.9996
##   ambient - warmed Both         1.0361 0.1905 381.4  5.439 <.0001
##   ambient - ambient Both        1.0498 0.1645 909.2  6.383 <.0001
##   ambient - warmed Exotic     -0.0974 0.1364 141.9 -0.714  0.9965
##   ambient - ambient Exotic    -0.0837 0.1029 892.5 -0.813  0.9924
##   warmed Both - ambient Both   0.0137 0.0897 25.9  0.153  1.0000

```

```

##  warmed Both - warmed Exotic      -1.1335 0.1523 909.2 -7.442 <.0001
##  warmed Both - ambient Exotic    -1.1197 0.1802 331.6 -6.213 <.0001
##  ambient Both - warmed Exotic    -1.1472 0.1733 276.4 -6.620 <.0001
##  ambient Both - ambient Exotic   -1.1335 0.1523 909.2 -7.442 <.0001
##  warmed Exotic - ambient Exotic  0.0137 0.0897 25.9  0.153  1.0000
##
## Results are averaged over the levels of: year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 8 estimates

# including growth form - first with interaction term
comp_umbs_spp <- within(comp_umbs_spp, growth_habit <- relevel(factor(growth_habit),
  ref = "Forb")) # releveling so forb is the reference
mod10u <- lmer(log(relabun) ~ state * growth_habit + (1 + factor(year_factor) | plot),
  comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod11u <- lmer(log(relabun) ~ state + growth_habit + (1 + factor(year_factor) | plot),
  comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod11au <- lmer(log(relabun) ~ state + growth_habit + factor(year_factor) + (1 |
  plot), comp_umbs_spp, REML = FALSE)
anova(mod10u, mod11u) # model 11u is a better fit to data

## Data: comp_umbs_spp
## Models:
## mod11u: log(relabun) ~ state + growth_habit + (1 + factor(year_factor) |
## mod11u:      plot)
## mod10u: log(relabun) ~ state * growth_habit + (1 + factor(year_factor) |
## mod10u:      plot)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod11u    27 2640.3 2770.0 -1293.2    2586.3
## mod10u    30 2645.4 2789.4 -1292.7    2585.4 0.9457   3     0.8144

anova(mod11u, mod11au) # model 11au is a better fit to data

## Data: comp_umbs_spp
## Models:
## mod11au: log(relabun) ~ state + growth_habit + factor(year_factor) + (1 |
## mod11au:      plot)
## mod11u: log(relabun) ~ state + growth_habit + (1 + factor(year_factor) |
## mod11u:      plot)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod11au    12 2601.0 2658.6 -1288.5    2577.0
## mod11u    27 2640.3 2770.0 -1293.2    2586.3      0 15           1

```

```
summary(mod11au)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(relabun) ~ state + growth_habit + factor(year_factor) + (1 |
##   plot)
## Data: comp_umbs_spp
##
##          AIC      BIC  logLik deviance df.resid
## 2601.0  2658.6 -1288.5   2577.0     887
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -2.62938 -0.81414  0.01516  0.76999  2.15772
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.01753  0.1324
## Residual           1.01553  1.0077
## Number of obs: 899, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)
## (Intercept) -2.24465  0.10458 179.96251 -21.463 < 2e-16 ***
## stateambient -0.03773  0.08684 23.75489 -0.435  0.6678
## growth_habit -1.19514  0.21448 892.34291 -5.572 3.33e-08 ***
## growth_habitGraminoid 0.09902  0.07023 898.90497  1.410  0.1589
## growth_habitTree -0.77483  0.38923 898.25957 -1.991  0.0468 *
## factor(year_factor)2 -0.28257  0.12062 877.64319 -2.343  0.0194 *
## factor(year_factor)3  0.09504  0.11932 880.11154  0.796  0.4260
## factor(year_factor)4  0.02161  0.11963 879.85909  0.181  0.8567
## factor(year_factor)5 -0.09189  0.11762 880.75256 -0.781  0.4349
## factor(year_factor)6 -0.05415  0.11650 880.71438 -0.465  0.6422
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) sttmbn grwth_ grwt_G grwt_T fc(_2 fc(_3 fc(_4 fc(_5
## stateambint -0.413
## growth_habit -0.103 -0.013
## grwth_hbtGr -0.293 -0.004  0.131
## grwth_hbtTr -0.015 -0.011  0.021  0.070
## fctr(yr_f)2 -0.593 -0.006  0.068  0.038  0.004
## fctr(yr_f)3 -0.585  0.006 -0.077  0.006 -0.001  0.503
## fctr(yr_f)4 -0.588 -0.009  0.064  0.007 -0.063  0.511  0.508
## fctr(yr_f)5 -0.602  0.006  0.021  0.011 -0.040  0.517  0.520  0.525
## fctr(yr_f)6 -0.605 -0.012  0.035  0.022 -0.039  0.523  0.524  0.530  0.537
```

```
anova(mod11au)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##              Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state          0.192  0.1917     1   23.75  0.1888  0.66783
```

```

## growth_habit      40.424 13.4748      3 896.28 13.2688 1.762e-08 ***
## factor(year_factor) 12.007  2.4013      5 880.03  2.3646   0.03817 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

emmeans(mod11au, list(pairwise ~ state + factor(year_factor) + growth_habit), adjust = "tukey")

## $`emmeans of state, year_factor, growth_habit`
## state  year_factor growth_habit emmean    SE df lower.CL upper.CL
## warmed     1 Forb      -2.24 0.107 193  -2.46  -2.03
## ambient    1 Forb      -2.28 0.107 189  -2.49  -2.07
## warmed     2 Forb      -2.53 0.105 181  -2.73  -2.32
## ambient    2 Forb      -2.56 0.104 174  -2.77  -2.36
## warmed     3 Forb      -2.15 0.105 183  -2.36  -1.94
## ambient    3 Forb      -2.19 0.106 184  -2.40  -1.98
## warmed     4 Forb      -2.22 0.105 181  -2.43  -2.02
## ambient    4 Forb      -2.26 0.104 174  -2.47  -2.06
## warmed     5 Forb      -2.34 0.102 162  -2.54  -2.14
## ambient    5 Forb      -2.37 0.103 162  -2.58  -2.17
## warmed     6 Forb      -2.30 0.101 160  -2.50  -2.10
## ambient    6 Forb      -2.34 0.100 148  -2.53  -2.14
## warmed     1          -3.44 0.231 808  -3.89  -2.99
## ambient    1          -3.48 0.230 807  -3.93  -3.03
## warmed     2          -3.72 0.238 821  -4.19  -3.26
## ambient    2          -3.76 0.237 821  -4.22  -3.30
## warmed     3          -3.34 0.221 784  -3.78  -2.91
## ambient    3          -3.38 0.221 784  -3.82  -2.95
## warmed     4          -3.42 0.237 818  -3.88  -2.95
## ambient    4          -3.46 0.236 818  -3.92  -2.99
## warmed     5          -3.53 0.231 801  -3.99  -3.08
## ambient    5          -3.57 0.231 800  -4.02  -3.12
## warmed     6          -3.49 0.232 811  -3.95  -3.04
## ambient    6          -3.53 0.231 808  -3.98  -3.08
## warmed     1 Graminoid -2.15 0.110 214  -2.36  -1.93
## ambient    1 Graminoid -2.18 0.110 216  -2.40  -1.97
## warmed     2 Graminoid -2.43 0.111 221  -2.65  -2.21
## ambient    2 Graminoid -2.47 0.110 220  -2.68  -2.25
## warmed     3 Graminoid -2.05 0.108 205  -2.26  -1.84
## ambient    3 Graminoid -2.09 0.109 212  -2.30  -1.87
## warmed     4 Graminoid -2.12 0.108 204  -2.34  -1.91
## ambient    4 Graminoid -2.16 0.107 203  -2.37  -1.95
## warmed     5 Graminoid -2.24 0.106 191  -2.45  -2.03
## ambient    5 Graminoid -2.28 0.106 196  -2.49  -2.07
## warmed     6 Graminoid -2.20 0.106 190  -2.41  -1.99
## ambient    6 Graminoid -2.24 0.105 183  -2.44  -2.03
## warmed     1 Tree      -3.02 0.405 888  -3.82  -2.22
## ambient    1 Tree      -3.06 0.404 889  -3.85  -2.26
## warmed     2 Tree      -3.30 0.405 887  -4.10  -2.51
## ambient    2 Tree      -3.34 0.404 888  -4.13  -2.55
## warmed     3 Tree      -2.92 0.405 889  -3.72  -2.13
## ambient    3 Tree      -2.96 0.404 890  -3.76  -2.17
## warmed     4 Tree      -3.00 0.398 884  -3.78  -2.22
## ambient    4 Tree      -3.04 0.396 885  -3.81  -2.26
## warmed     5 Tree      -3.11 0.400 886  -3.90  -2.33

```

```

## ambient      5 Tree      -3.15 0.399 887    -3.93    -2.37
## warmed      6 Tree      -3.07 0.400 887    -3.86    -2.29
## ambient      6 Tree      -3.11 0.398 888    -3.89    -2.33
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $'pairwise differences of state, year_factor, growth_habit'
## 1
## warmed 1 Forb - ambient 1 Forb
## warmed 1 Forb - warmed 2 Forb
## warmed 1 Forb - ambient 2 Forb
## warmed 1 Forb - warmed 3 Forb
## warmed 1 Forb - ambient 3 Forb
## warmed 1 Forb - warmed 4 Forb
## warmed 1 Forb - ambient 4 Forb
## warmed 1 Forb - warmed 5 Forb
## warmed 1 Forb - ambient 5 Forb
## warmed 1 Forb - warmed 6 Forb
## warmed 1 Forb - ambient 6 Forb
## warmed 1 Forb - warmed 1
## warmed 1 Forb - ambient 1
## warmed 1 Forb - warmed 2
## warmed 1 Forb - ambient 2
## warmed 1 Forb - warmed 3
## warmed 1 Forb - ambient 3
## warmed 1 Forb - warmed 4
## warmed 1 Forb - ambient 4
## warmed 1 Forb - warmed 5
## warmed 1 Forb - ambient 5
## warmed 1 Forb - warmed 6
## warmed 1 Forb - ambient 6
## warmed 1 Forb - warmed 1 Graminoid
## warmed 1 Forb - ambient 1 Graminoid
## warmed 1 Forb - warmed 2 Graminoid
## warmed 1 Forb - ambient 2 Graminoid
## warmed 1 Forb - warmed 3 Graminoid
## warmed 1 Forb - ambient 3 Graminoid
## warmed 1 Forb - warmed 4 Graminoid
## warmed 1 Forb - ambient 4 Graminoid
## warmed 1 Forb - warmed 5 Graminoid
## warmed 1 Forb - ambient 5 Graminoid
## warmed 1 Forb - warmed 6 Graminoid
## warmed 1 Forb - ambient 6 Graminoid
## warmed 1 Forb - warmed 1 Tree
## warmed 1 Forb - ambient 1 Tree
## warmed 1 Forb - warmed 2 Tree
## warmed 1 Forb - ambient 2 Tree
## warmed 1 Forb - warmed 3 Tree
## warmed 1 Forb - ambient 3 Tree
## warmed 1 Forb - warmed 4 Tree
## warmed 1 Forb - ambient 4 Tree
## warmed 1 Forb - warmed 5 Tree

```

	estimate	SE	df	t.ratio
## warmed 1 Forb - ambient 1 Forb	3.77e-02	0.0911	25.8	0.414
## warmed 1 Forb - warmed 2 Forb	2.83e-01	0.1212	885.3	2.332
## warmed 1 Forb - ambient 2 Forb	3.20e-01	0.1511	197.6	2.119
## warmed 1 Forb - warmed 3 Forb	-9.50e-02	0.1199	887.9	-0.793
## warmed 1 Forb - ambient 3 Forb	-5.73e-02	0.1510	195.9	-0.380
## warmed 1 Forb - warmed 4 Forb	-2.16e-02	0.1202	887.6	-0.180
## warmed 1 Forb - ambient 4 Forb	1.61e-02	0.1501	193.0	0.107
## warmed 1 Forb - warmed 5 Forb	9.19e-02	0.1182	888.5	0.777
## warmed 1 Forb - ambient 5 Forb	1.30e-01	0.1496	188.4	0.866
## warmed 1 Forb - warmed 6 Forb	5.42e-02	0.1171	888.5	0.463
## warmed 1 Forb - ambient 6 Forb	9.19e-02	0.1475	178.7	0.623
## warmed 1 Forb - warmed 1	1.20e+00	0.2158	900.6	5.538
## warmed 1 Forb - ambient 1	1.23e+00	0.2331	587.9	5.288
## warmed 1 Forb - warmed 2	1.48e+00	0.2546	897.3	5.805
## warmed 1 Forb - ambient 2	1.52e+00	0.2692	721.3	5.630
## warmed 1 Forb - warmed 3	1.10e+00	0.2386	898.8	4.610
## warmed 1 Forb - ambient 3	1.14e+00	0.2546	673.9	4.469
## warmed 1 Forb - warmed 4	1.17e+00	0.2537	898.6	4.626
## warmed 1 Forb - ambient 4	1.21e+00	0.2682	716.0	4.516
## warmed 1 Forb - warmed 5	1.29e+00	0.2483	899.7	5.183
## warmed 1 Forb - ambient 5	1.32e+00	0.2637	697.9	5.023
## warmed 1 Forb - warmed 6	1.25e+00	0.2491	898.2	5.016
## warmed 1 Forb - ambient 6	1.29e+00	0.2638	701.8	4.879
## warmed 1 Forb - warmed 1 Graminoid	-9.90e-02	0.0708	908.8	-1.399
## warmed 1 Forb - ambient 1 Graminoid	-6.13e-02	0.1150	68.4	-0.533
## warmed 1 Forb - warmed 2 Graminoid	1.84e-01	0.1426	894.5	1.287
## warmed 1 Forb - ambient 2 Graminoid	2.21e-01	0.1686	282.1	1.312
## warmed 1 Forb - warmed 3 Graminoid	-1.94e-01	0.1396	897.6	-1.390
## warmed 1 Forb - ambient 3 Graminoid	-1.56e-01	0.1668	270.7	-0.937
## warmed 1 Forb - warmed 4 Graminoid	-1.21e-01	0.1400	896.8	-0.862
## warmed 1 Forb - ambient 4 Graminoid	-8.29e-02	0.1661	268.7	-0.499
## warmed 1 Forb - warmed 5 Graminoid	-7.13e-03	0.1384	893.7	-0.051
## warmed 1 Forb - ambient 5 Graminoid	3.06e-02	0.1658	267.2	0.185
## warmed 1 Forb - warmed 6 Graminoid	-4.49e-02	0.1381	897.1	-0.325
## warmed 1 Forb - ambient 6 Graminoid	-7.13e-03	0.1645	257.1	-0.043
## warmed 1 Forb - warmed 1 Tree	7.75e-01	0.3926	909.2	1.973
## warmed 1 Forb - ambient 1 Tree	8.13e-01	0.4020	842.6	2.021
## warmed 1 Forb - warmed 2 Tree	1.06e+00	0.4114	909.3	2.570
## warmed 1 Forb - ambient 2 Tree	1.10e+00	0.4202	857.0	2.606
## warmed 1 Forb - warmed 3 Tree	6.80e-01	0.4104	909.3	1.656
## warmed 1 Forb - ambient 3 Tree	7.18e-01	0.4195	859.2	1.710
## warmed 1 Forb - warmed 4 Tree	7.53e-01	0.4034	909.3	1.867
## warmed 1 Forb - ambient 4 Tree	7.91e-01	0.4123	851.3	1.918
## warmed 1 Forb - warmed 5 Tree	8.67e-01	0.4054	909.3	2.138

```

## warmed 1 Forb - ambient 5 Tree          9.04e-01 0.4147 854.3  2.181
## warmed 1 Forb - warmed 6 Tree          8.29e-01 0.4053 909.3  2.045
## warmed 1 Forb - ambient 6 Tree          8.67e-01 0.4141 854.6  2.093
## ambient 1 Forb - warmed 2 Forb          2.45e-01 0.1520 199.8  1.611
## ambient 1 Forb - ambient 2 Forb          2.83e-01 0.1212 885.3  2.332
## ambient 1 Forb - warmed 3 Forb          -1.33e-01 0.1502 190.0  -0.884
## ambient 1 Forb - ambient 3 Forb          -9.50e-02 0.1199 887.9  -0.793
## ambient 1 Forb - warmed 4 Forb          -5.93e-02 0.1515 195.3  -0.392
## ambient 1 Forb - ambient 4 Forb          -2.16e-02 0.1202 887.6  -0.180
## ambient 1 Forb - warmed 5 Forb          5.42e-02 0.1488 185.0  0.364
## ambient 1 Forb - ambient 5 Forb          9.19e-02 0.1182 888.5  0.777
## ambient 1 Forb - warmed 6 Forb          1.64e-02 0.1491 186.8  0.110
## ambient 1 Forb - ambient 6 Forb          5.42e-02 0.1171 888.5  0.463
## ambient 1 Forb - warmed 1               1.16e+00 0.2353 586.4  4.918
## ambient 1 Forb - ambient 1              1.20e+00 0.2158 900.6  5.538
## ambient 1 Forb - warmed 2              1.44e+00 0.2716 717.9  5.302
## ambient 1 Forb - ambient 2              1.48e+00 0.2546 897.3  5.805
## ambient 1 Forb - warmed 3              1.06e+00 0.2562 666.9  4.147
## ambient 1 Forb - ambient 3              1.10e+00 0.2386 898.8  4.610
## ambient 1 Forb - warmed 4              1.14e+00 0.2709 711.4  4.193
## ambient 1 Forb - ambient 4              1.17e+00 0.2537 898.6  4.626
## ambient 1 Forb - warmed 5              1.25e+00 0.2652 694.0  4.711
## ambient 1 Forb - ambient 5              1.29e+00 0.2483 899.7  5.183
## ambient 1 Forb - warmed 6              1.21e+00 0.2666 703.1  4.545
## ambient 1 Forb - ambient 6              1.25e+00 0.2491 898.2  5.016
## ambient 1 Forb - warmed 1 Graminoid   -1.37e-01 0.1157 66.6   -1.182
## ambient 1 Forb - ambient 1 Graminoid   -9.90e-02 0.0708 908.8  -1.399
## ambient 1 Forb - warmed 2 Graminoid   1.46e-01 0.1698 276.0   0.859
## ambient 1 Forb - ambient 2 Graminoid   1.84e-01 0.1426 894.5  1.287
## ambient 1 Forb - warmed 3 Graminoid   -2.32e-01 0.1666 256.7  -1.391
## ambient 1 Forb - ambient 3 Graminoid   -1.94e-01 0.1396 897.6  -1.390
## ambient 1 Forb - warmed 4 Graminoid   -1.58e-01 0.1678 262.6  -0.944
## ambient 1 Forb - ambient 4 Graminoid   -1.21e-01 0.1400 896.8  -0.862
## ambient 1 Forb - warmed 5 Graminoid   -4.49e-02 0.1655 256.2  -0.271
## ambient 1 Forb - ambient 5 Graminoid   -7.13e-03 0.1384 893.7  -0.051
## ambient 1 Forb - warmed 6 Graminoid   -8.26e-02 0.1664 258.3  -0.497
## ambient 1 Forb - ambient 6 Graminoid   -4.49e-02 0.1381 897.1  -0.325
## ambient 1 Forb - warmed 1 Tree          7.37e-01 0.4041 836.5  1.824
## ambient 1 Forb - ambient 1 Tree          7.75e-01 0.3926 909.2  1.973
## ambient 1 Forb - warmed 2 Tree          1.02e+00 0.4226 851.5  2.413
## ambient 1 Forb - ambient 2 Tree          1.06e+00 0.4114 909.3  2.570
## ambient 1 Forb - warmed 3 Tree          6.42e-01 0.4212 853.1  1.524
## ambient 1 Forb - ambient 3 Tree          6.80e-01 0.4104 909.3  1.656
## ambient 1 Forb - warmed 4 Tree          7.15e-01 0.4148 845.0  1.725
## ambient 1 Forb - ambient 4 Tree          7.53e-01 0.4034 909.3  1.867
## ambient 1 Forb - warmed 5 Tree          8.29e-01 0.4164 848.8  1.991
## ambient 1 Forb - ambient 5 Tree          8.67e-01 0.4054 909.3  2.138
## ambient 1 Forb - warmed 6 Tree          7.91e-01 0.4167 850.0  1.899
## ambient 1 Forb - ambient 6 Tree          8.29e-01 0.4053 909.3  2.045
## warmed 2 Forb - ambient 2 Forb          3.77e-02 0.0911 25.8   0.414
## warmed 2 Forb - warmed 3 Forb          -3.78e-01 0.1202 889.8  -3.140
## warmed 2 Forb - ambient 3 Forb          -3.40e-01 0.1517 197.4  -2.241
## warmed 2 Forb - warmed 4 Forb          -3.04e-01 0.1194 888.1  -2.548
## warmed 2 Forb - ambient 4 Forb          -2.66e-01 0.1499 190.9  -1.777

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## warmed 2 Forb - warmed 5 Forb          -1.91e-01 0.1177 889.6 -1.620
## warmed 2 Forb - ambient 5 Forb         -1.53e-01 0.1497 187.4 -1.022
## warmed 2 Forb - warmed 6 Forb          -2.28e-01 0.1164 887.7 -1.963
## warmed 2 Forb - ambient 6 Forb         -1.91e-01 0.1474 177.7 -1.294
## warmed 2 Forb - warmed 1               9.13e-01 0.2402 898.0  3.799
## warmed 2 Forb - ambient 1              9.50e-01 0.2562 678.8  3.710
## warmed 2 Forb - warmed 2               1.20e+00 0.2158 900.6  5.538
## warmed 2 Forb - ambient 2              1.23e+00 0.2331 587.9  5.288
## warmed 2 Forb - warmed 3               8.18e-01 0.2313 899.6  3.535
## warmed 2 Forb - ambient 3              8.55e-01 0.2480 648.1  3.449
## warmed 2 Forb - warmed 4               8.91e-01 0.2462 899.1  3.619
## warmed 2 Forb - ambient 4              9.29e-01 0.2614 693.9  3.553
## warmed 2 Forb - warmed 5               1.00e+00 0.2408 900.4  4.171
## warmed 2 Forb - ambient 5              1.04e+00 0.2570 674.2  4.056
## warmed 2 Forb - warmed 6               9.67e-01 0.2415 898.5  4.003
## warmed 2 Forb - ambient 6              1.00e+00 0.2569 678.9  3.910
## warmed 2 Forb - warmed 1 Graminoid    -3.82e-01 0.1380 894.5 -2.765
## warmed 2 Forb - ambient 1 Graminoid   -3.44e-01 0.1655 264.2 -2.078
## warmed 2 Forb - warmed 2 Graminoid    -9.90e-02 0.0708 908.8 -1.399
## warmed 2 Forb - ambient 2 Graminoid   -6.13e-02 0.1150 68.4  -0.533
## warmed 2 Forb - warmed 3 Graminoid    -4.77e-01 0.1376 898.8 -3.464
## warmed 2 Forb - ambient 3 Graminoid   -4.39e-01 0.1655 262.0 -2.652
## warmed 2 Forb - warmed 4 Graminoid    -4.03e-01 0.1369 897.2 -2.946
## warmed 2 Forb - ambient 4 Graminoid   -3.65e-01 0.1640 256.4 -2.229
## warmed 2 Forb - warmed 5 Graminoid    -2.90e-01 0.1356 894.4 -2.136
## warmed 2 Forb - ambient 5 Graminoid   -2.52e-01 0.1639 256.0 -1.537
## warmed 2 Forb - warmed 6 Graminoid    -3.27e-01 0.1351 896.8 -2.423
## warmed 2 Forb - ambient 6 Graminoid   -2.90e-01 0.1624 246.1 -1.784
## warmed 2 Forb - warmed 1 Tree          4.92e-01 0.4103 909.2  1.200
## warmed 2 Forb - ambient 1 Tree         5.30e-01 0.4195 859.6  1.263
## warmed 2 Forb - warmed 2 Tree          7.75e-01 0.3926 909.2  1.973
## warmed 2 Forb - ambient 2 Tree         8.13e-01 0.4020 842.6  2.021
## warmed 2 Forb - warmed 3 Tree          3.97e-01 0.4099 909.2  0.969
## warmed 2 Forb - ambient 3 Tree         4.35e-01 0.4192 860.3  1.038
## warmed 2 Forb - warmed 4 Tree          4.71e-01 0.4026 909.3  1.169
## warmed 2 Forb - ambient 4 Tree         5.08e-01 0.4117 852.5  1.235
## warmed 2 Forb - warmed 5 Tree          5.84e-01 0.4047 909.3  1.443
## warmed 2 Forb - ambient 5 Tree         6.22e-01 0.4142 855.4  1.502
## warmed 2 Forb - warmed 6 Tree          5.46e-01 0.4046 909.3  1.351
## warmed 2 Forb - ambient 6 Tree         5.84e-01 0.4136 855.9  1.412
## ambient 2 Forb - warmed 3 Forb        -4.15e-01 0.1500 189.3 -2.769
## ambient 2 Forb - ambient 3 Forb       -3.78e-01 0.1202 889.8 -3.140
## ambient 2 Forb - warmed 4 Forb        -3.42e-01 0.1504 191.1 -2.274
## ambient 2 Forb - ambient 4 Forb       -3.04e-01 0.1194 888.1 -2.548
## ambient 2 Forb - warmed 5 Forb        -2.28e-01 0.1479 181.8 -1.544
## ambient 2 Forb - ambient 5 Forb       -1.91e-01 0.1177 889.6 -1.620
## ambient 2 Forb - warmed 6 Forb        -2.66e-01 0.1481 183.6 -1.797
## ambient 2 Forb - ambient 6 Forb       -2.28e-01 0.1164 887.7 -1.963
## ambient 2 Forb - warmed 1             8.75e-01 0.2577 676.3  3.395
## ambient 2 Forb - ambient 1            9.13e-01 0.2402 898.0  3.799
## ambient 2 Forb - warmed 2             1.16e+00 0.2353 586.4  4.918
## ambient 2 Forb - ambient 2            1.20e+00 0.2158 900.6  5.538
## ambient 2 Forb - warmed 3             7.80e-01 0.2491 641.2  3.131
## ambient 2 Forb - ambient 3            8.18e-01 0.2313 899.6  3.535

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## ambient 2 Forb - warmed 4          8.53e-01 0.2636 689.8  3.237
## ambient 2 Forb - ambient 4        8.91e-01 0.2462 899.1  3.619
## ambient 2 Forb - warmed 5          9.67e-01 0.2579 670.7  3.748
## ambient 2 Forb - ambient 5        1.00e+00 0.2408 900.4  4.171
## ambient 2 Forb - warmed 6          9.29e-01 0.2593 681.1  3.583
## ambient 2 Forb - ambient 6        9.67e-01 0.2415 898.5  4.003
## ambient 2 Forb - warmed 1 Graminoid -4.19e-01 0.1652 254.7 -2.539
## ambient 2 Forb - ambient 1 Graminoid -3.82e-01 0.1380 894.5 -2.765
## ambient 2 Forb - warmed 2 Graminoid -1.37e-01 0.1157 66.6 -1.182
## ambient 2 Forb - ambient 2 Graminoid -9.90e-02 0.0708 908.8 -1.399
## ambient 2 Forb - warmed 3 Graminoid -5.14e-01 0.1645 246.4 -3.127
## ambient 2 Forb - ambient 3 Graminoid -4.77e-01 0.1376 898.8 -3.464
## ambient 2 Forb - warmed 4 Graminoid -4.41e-01 0.1648 248.8 -2.675
## ambient 2 Forb - ambient 4 Graminoid -4.03e-01 0.1369 897.2 -2.946
## ambient 2 Forb - warmed 5 Graminoid -3.27e-01 0.1628 243.3 -2.012
## ambient 2 Forb - ambient 5 Graminoid -2.90e-01 0.1356 894.4 -2.136
## ambient 2 Forb - warmed 6 Graminoid -3.65e-01 0.1635 245.5 -2.234
## ambient 2 Forb - ambient 6 Graminoid -3.27e-01 0.1351 896.8 -2.423
## ambient 2 Forb - warmed 1 Tree      4.55e-01 0.4212 854.7  1.079
## ambient 2 Forb - ambient 1 Tree    4.92e-01 0.4103 909.2  1.200
## ambient 2 Forb - warmed 2 Tree     7.37e-01 0.4041 836.5  1.824
## ambient 2 Forb - ambient 2 Tree    7.75e-01 0.3926 909.2  1.973
## ambient 2 Forb - warmed 3 Tree     3.59e-01 0.4207 854.5  0.855
## ambient 2 Forb - ambient 3 Tree    3.97e-01 0.4099 909.2  0.969
## ambient 2 Forb - warmed 4 Tree     4.33e-01 0.4139 846.4  1.046
## ambient 2 Forb - ambient 4 Tree    4.71e-01 0.4026 909.3  1.169
## ambient 2 Forb - warmed 5 Tree     5.46e-01 0.4156 850.2  1.315
## ambient 2 Forb - ambient 5 Tree    5.84e-01 0.4047 909.3  1.443
## ambient 2 Forb - warmed 6 Tree     5.09e-01 0.4158 851.6  1.223
## ambient 2 Forb - ambient 6 Tree    5.46e-01 0.4046 909.3  1.351
## warmed 3 Forb - ambient 3 Forb   3.77e-02 0.0911 25.8  0.414
## warmed 3 Forb - warmed 4 Forb     7.34e-02 0.1191 887.5  0.616
## warmed 3 Forb - ambient 4 Forb    1.11e-01 0.1489 186.3  0.747
## warmed 3 Forb - warmed 5 Forb     1.87e-01 0.1166 888.2  1.603
## warmed 3 Forb - ambient 5 Forb    2.25e-01 0.1480 180.2  1.518
## warmed 3 Forb - warmed 6 Forb     1.49e-01 0.1157 889.1  1.290
## warmed 3 Forb - ambient 6 Forb    1.87e-01 0.1460 170.9  1.280
## warmed 3 Forb - warmed 1          1.29e+00 0.2549 897.5  5.062
## warmed 3 Forb - ambient 1         1.33e+00 0.2695 719.5  4.928
## warmed 3 Forb - warmed 2          1.57e+00 0.2619 897.5  6.005
## warmed 3 Forb - ambient 2         1.61e+00 0.2759 737.2  5.838
## warmed 3 Forb - warmed 3          1.20e+00 0.2158 900.6  5.538
## warmed 3 Forb - ambient 3         1.23e+00 0.2331 587.9  5.288
## warmed 3 Forb - warmed 4          1.27e+00 0.2610 898.0  4.861
## warmed 3 Forb - ambient 4         1.31e+00 0.2749 734.2  4.752
## warmed 3 Forb - warmed 5          1.38e+00 0.2555 899.0  5.409
## warmed 3 Forb - ambient 5         1.42e+00 0.2703 717.2  5.252
## warmed 3 Forb - warmed 6          1.34e+00 0.2563 897.7  5.244
## warmed 3 Forb - ambient 6         1.38e+00 0.2704 720.7  5.111
## warmed 3 Forb - warmed 1 Graminoid -3.98e-03 0.1388 894.5 -0.029
## warmed 3 Forb - ambient 1 Graminoid 3.37e-02 0.1654 263.4  0.204
## warmed 3 Forb - warmed 2 Graminoid 2.79e-01 0.1414 895.6  1.970
## warmed 3 Forb - ambient 2 Graminoid 3.16e-01 0.1672 272.6  1.892
## warmed 3 Forb - warmed 3 Graminoid -9.90e-02 0.0708 908.8 -1.399

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## warmed 3 Forb - ambient 3 Graminoid -6.13e-02 0.1150 68.4 -0.533
## warmed 3 Forb - warmed 4 Graminoid -2.56e-02 0.1386 895.2 -0.185
## warmed 3 Forb - ambient 4 Graminoid 1.21e-02 0.1646 261.1 0.074
## warmed 3 Forb - warmed 5 Graminoid 8.79e-02 0.1366 891.8 0.643
## warmed 3 Forb - ambient 5 Graminoid 1.26e-01 0.1640 258.1 0.766
## warmed 3 Forb - warmed 6 Graminoid 5.02e-02 0.1365 896.1 0.368
## warmed 3 Forb - ambient 6 Graminoid 8.79e-02 0.1628 248.1 0.540
## warmed 3 Forb - warmed 1 Tree 8.70e-01 0.4106 909.3 2.118
## warmed 3 Forb - ambient 1 Tree 9.08e-01 0.4195 856.2 2.164
## warmed 3 Forb - warmed 2 Tree 1.15e+00 0.4113 909.3 2.802
## warmed 3 Forb - ambient 2 Tree 1.19e+00 0.4199 854.7 2.834
## warmed 3 Forb - warmed 3 Tree 7.75e-01 0.3926 909.2 1.973
## warmed 3 Forb - ambient 3 Tree 8.13e-01 0.4020 842.6 2.021
## warmed 3 Forb - warmed 4 Tree 8.48e-01 0.4032 909.2 2.104
## warmed 3 Forb - ambient 4 Tree 8.86e-01 0.4120 849.4 2.151
## warmed 3 Forb - warmed 5 Tree 9.62e-01 0.4051 909.3 2.374
## warmed 3 Forb - ambient 5 Tree 9.99e-01 0.4142 852.4 2.413
## warmed 3 Forb - warmed 6 Tree 9.24e-01 0.4051 909.3 2.281
## warmed 3 Forb - ambient 6 Tree 9.62e-01 0.4137 852.6 2.325
## ambient 3 Forb - warmed 4 Forb 3.57e-02 0.1510 194.4 0.236
## ambient 3 Forb - ambient 4 Forb 7.34e-02 0.1191 887.5 0.616
## ambient 3 Forb - warmed 5 Forb 1.49e-01 0.1479 182.6 1.009
## ambient 3 Forb - ambient 5 Forb 1.87e-01 0.1166 888.2 1.603
## ambient 3 Forb - ambient 6 Forb 1.11e-01 0.1484 184.6 0.751
## ambient 3 Forb - ambient 1 1.49e-01 0.1157 889.1 1.290
## ambient 3 Forb - warmed 1 1.25e+00 0.2718 720.2 4.608
## ambient 3 Forb - ambient 1 1.29e+00 0.2549 897.5 5.062
## ambient 3 Forb - warmed 2 1.54e+00 0.2786 737.2 5.509
## ambient 3 Forb - ambient 2 1.57e+00 0.2619 897.5 6.005
## ambient 3 Forb - warmed 3 1.16e+00 0.2353 586.4 4.918
## ambient 3 Forb - ambient 3 1.20e+00 0.2158 900.6 5.538
## ambient 3 Forb - warmed 4 1.23e+00 0.2779 733.0 4.429
## ambient 3 Forb - ambient 4 1.27e+00 0.2610 898.0 4.861
## ambient 3 Forb - warmed 5 1.34e+00 0.2722 717.1 4.939
## ambient 3 Forb - ambient 5 1.38e+00 0.2555 899.0 5.409
## ambient 3 Forb - warmed 6 1.31e+00 0.2736 725.2 4.775
## ambient 3 Forb - ambient 6 1.34e+00 0.2563 897.7 5.244
## ambient 3 Forb - warmed 1 Graminoid -4.17e-02 0.1666 262.2 -0.250
## ambient 3 Forb - ambient 1 Graminoid -3.98e-03 0.1388 894.5 -0.029
## ambient 3 Forb - warmed 2 Graminoid 2.41e-01 0.1692 273.1 1.424
## ambient 3 Forb - ambient 2 Graminoid 2.79e-01 0.1414 895.6 1.970
## ambient 3 Forb - warmed 3 Graminoid -1.37e-01 0.1157 66.6 -1.182
## ambient 3 Forb - ambient 3 Graminoid -9.90e-02 0.0708 908.8 -1.399
## ambient 3 Forb - warmed 4 Graminoid -6.33e-02 0.1670 261.6 -0.379
## ambient 3 Forb - ambient 4 Graminoid -2.56e-02 0.1386 895.2 -0.185
## ambient 3 Forb - warmed 5 Graminoid 5.02e-02 0.1644 253.6 0.305
## ambient 3 Forb - ambient 5 Graminoid 8.79e-02 0.1366 891.8 0.643
## ambient 3 Forb - warmed 6 Graminoid 1.24e-02 0.1654 255.7 0.075
## ambient 3 Forb - ambient 6 Graminoid 5.02e-02 0.1365 896.1 0.368
## ambient 3 Forb - warmed 1 Tree 8.32e-01 0.4218 851.9 1.973
## ambient 3 Forb - ambient 1 Tree 8.70e-01 0.4106 909.3 2.118
## ambient 3 Forb - warmed 2 Tree 1.11e+00 0.4225 850.1 2.638
## ambient 3 Forb - ambient 2 Tree 1.15e+00 0.4113 909.3 2.802
## ambient 3 Forb - warmed 3 Tree 7.37e-01 0.4041 836.5 1.824

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## ambient 3 Forb - ambient 3 Tree	7.75e-01	0.3926	909.2	1.973
## ambient 3 Forb - warmed 4 Tree	8.11e-01	0.4148	844.1	1.954
## ambient 3 Forb - ambient 4 Tree	8.48e-01	0.4032	909.2	2.104
## ambient 3 Forb - warmed 5 Tree	9.24e-01	0.4162	847.8	2.220
## ambient 3 Forb - ambient 5 Tree	9.62e-01	0.4051	909.3	2.374
## ambient 3 Forb - warmed 6 Tree	8.86e-01	0.4166	849.0	2.127
## ambient 3 Forb - ambient 6 Tree	9.24e-01	0.4051	909.3	2.281
## warmed 4 Forb - ambient 4 Forb	3.77e-02	0.0911	25.8	0.414
## warmed 4 Forb - warmed 5 Forb	1.14e-01	0.1162	885.7	0.976
## warmed 4 Forb - ambient 5 Forb	1.51e-01	0.1488	183.8	1.017
## warmed 4 Forb - warmed 6 Forb	7.58e-02	0.1150	886.7	0.659
## warmed 4 Forb - ambient 6 Forb	1.13e-01	0.1466	173.5	0.774
## warmed 4 Forb - warmed 1	1.22e+00	0.2402	897.4	5.066
## warmed 4 Forb - ambient 1	1.25e+00	0.2562	679.5	4.896
## warmed 4 Forb - warmed 2	1.50e+00	0.2471	897.1	6.069
## warmed 4 Forb - ambient 2	1.54e+00	0.2624	700.4	5.857
## warmed 4 Forb - warmed 3	1.12e+00	0.2311	898.1	4.853
## warmed 4 Forb - ambient 3	1.16e+00	0.2480	651.1	4.675
## warmed 4 Forb - warmed 4	1.20e+00	0.2158	900.6	5.538
## warmed 4 Forb - ambient 4	1.23e+00	0.2331	587.9	5.288
## warmed 4 Forb - warmed 5	1.31e+00	0.2405	898.8	5.441
## warmed 4 Forb - ambient 5	1.35e+00	0.2568	677.1	5.243
## warmed 4 Forb - warmed 6	1.27e+00	0.2413	897.3	5.268
## warmed 4 Forb - ambient 6	1.31e+00	0.2568	680.6	5.096
## warmed 4 Forb - warmed 1 Graminoid	-7.74e-02	0.1390	895.0	-0.557
## warmed 4 Forb - ambient 1 Graminoid	-3.97e-02	0.1666	268.0	-0.238
## warmed 4 Forb - warmed 2 Graminoid	2.05e-01	0.1407	895.4	1.459
## warmed 4 Forb - ambient 2 Graminoid	2.43e-01	0.1675	273.6	1.450
## warmed 4 Forb - warmed 3 Graminoid	-1.72e-01	0.1385	896.6	-1.245
## warmed 4 Forb - ambient 3 Graminoid	-1.35e-01	0.1665	267.7	-0.809
## warmed 4 Forb - warmed 4 Graminoid	-9.90e-02	0.0708	908.8	-1.399
## warmed 4 Forb - ambient 4 Graminoid	-6.13e-02	0.1150	68.4	-0.533
## warmed 4 Forb - warmed 5 Graminoid	1.45e-02	0.1363	891.0	0.106
## warmed 4 Forb - ambient 5 Graminoid	5.22e-02	0.1646	261.1	0.317
## warmed 4 Forb - warmed 6 Graminoid	-2.33e-02	0.1359	895.4	-0.171
## warmed 4 Forb - ambient 6 Graminoid	1.45e-02	0.1632	250.2	0.089
## warmed 4 Forb - warmed 1 Tree	7.96e-01	0.4177	909.2	1.907
## warmed 4 Forb - ambient 1 Tree	8.34e-01	0.4267	863.6	1.955
## warmed 4 Forb - warmed 2 Tree	1.08e+00	0.4180	909.3	2.581
## warmed 4 Forb - ambient 2 Tree	1.12e+00	0.4269	862.1	2.616
## warmed 4 Forb - warmed 3 Tree	7.01e-01	0.4173	909.1	1.681
## warmed 4 Forb - ambient 3 Tree	7.39e-01	0.4265	864.7	1.733
## warmed 4 Forb - warmed 4 Tree	7.75e-01	0.3926	909.2	1.973
## warmed 4 Forb - ambient 4 Tree	8.13e-01	0.4020	842.6	2.021
## warmed 4 Forb - warmed 5 Tree	8.88e-01	0.4120	909.2	2.156
## warmed 4 Forb - ambient 5 Tree	9.26e-01	0.4214	860.4	2.198
## warmed 4 Forb - warmed 6 Tree	8.51e-01	0.4119	909.2	2.065
## warmed 4 Forb - ambient 6 Tree	8.88e-01	0.4208	860.5	2.111
## ambient 4 Forb - warmed 5 Forb	7.58e-02	0.1465	178.0	0.517
## ambient 4 Forb - ambient 5 Forb	1.14e-01	0.1162	885.7	0.976
## ambient 4 Forb - warmed 6 Forb	3.80e-02	0.1468	179.2	0.259
## ambient 4 Forb - ambient 6 Forb	7.58e-02	0.1150	886.7	0.659
## ambient 4 Forb - warmed 1	1.18e+00	0.2575	678.4	4.579
## ambient 4 Forb - ambient 1	1.22e+00	0.2402	897.4	5.066

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## ambient 4 Forb - warmed 2          1.46e+00 0.2642 698.9  5.533
## ambient 4 Forb - ambient 2        1.50e+00 0.2471 897.1  6.069
## ambient 4 Forb - warmed 3          1.08e+00 0.2488 645.6  4.356
## ambient 4 Forb - ambient 3        1.12e+00 0.2311 898.1  4.853
## ambient 4 Forb - warmed 4          1.16e+00 0.2353 586.4  4.918
## ambient 4 Forb - ambient 4        1.20e+00 0.2158 900.6  5.538
## ambient 4 Forb - warmed 5          1.27e+00 0.2575 675.0  4.935
## ambient 4 Forb - ambient 5        1.31e+00 0.2405 898.8  5.441
## ambient 4 Forb - warmed 6          1.23e+00 0.2589 684.2  4.762
## ambient 4 Forb - ambient 6        1.27e+00 0.2413 897.3  5.268
## ambient 4 Forb - warmed 1 Graminoid -1.15e-01 0.1658 258.7 -0.694
## ambient 4 Forb - ambient 1 Graminoid -7.74e-02 0.1390 895.0 -0.557
## ambient 4 Forb - warmed 2 Graminoid 1.67e-01 0.1676 266.1  0.999
## ambient 4 Forb - ambient 2 Graminoid 2.05e-01 0.1407 895.4  1.459
## ambient 4 Forb - warmed 3 Graminoid -2.10e-01 0.1650 252.1 -1.274
## ambient 4 Forb - ambient 3 Graminoid -1.72e-01 0.1385 896.6 -1.245
## ambient 4 Forb - warmed 4 Graminoid -1.37e-01 0.1157 66.6 -1.182
## ambient 4 Forb - ambient 4 Graminoid -9.90e-02 0.0708 908.8 -1.399
## ambient 4 Forb - warmed 5 Graminoid -2.33e-02 0.1631 248.5 -0.143
## ambient 4 Forb - ambient 5 Graminoid 1.45e-02 0.1363 891.0  0.106
## ambient 4 Forb - warmed 6 Graminoid -6.10e-02 0.1639 249.8 -0.372
## ambient 4 Forb - ambient 6 Graminoid -2.33e-02 0.1359 895.4 -0.171
## ambient 4 Forb - warmed 1 Tree      7.59e-01 0.4283 859.4  1.772
## ambient 4 Forb - ambient 1 Tree     7.96e-01 0.4177 909.2  1.907
## ambient 4 Forb - warmed 2 Tree      1.04e+00 0.4287 857.7  2.429
## ambient 4 Forb - ambient 2 Tree     1.08e+00 0.4180 909.3  2.581
## ambient 4 Forb - warmed 3 Tree      6.64e-01 0.4277 859.8  1.552
## ambient 4 Forb - ambient 3 Tree     7.01e-01 0.4173 909.1  1.681
## ambient 4 Forb - warmed 4 Tree      7.37e-01 0.4041 836.5  1.824
## ambient 4 Forb - ambient 4 Tree     7.75e-01 0.3926 909.2  1.973
## ambient 4 Forb - warmed 5 Tree      8.51e-01 0.4226 856.0  2.013
## ambient 4 Forb - ambient 5 Tree     8.88e-01 0.4120 909.2  2.156
## ambient 4 Forb - warmed 6 Tree      8.13e-01 0.4229 857.0  1.922
## ambient 4 Forb - ambient 6 Tree     8.51e-01 0.4119 909.2  2.065
## warmed 5 Forb - ambient 5 Forb    3.77e-02 0.0911 25.8  0.414
## warmed 5 Forb - warmed 6 Forb      -3.77e-02 0.1132 886.8 -0.333
## warmed 5 Forb - ambient 6 Forb     -6.40e-06 0.1440 164.6  0.000
## warmed 5 Forb - warmed 1           1.10e+00 0.2438 896.6  4.525
## warmed 5 Forb - ambient 1         1.14e+00 0.2590 692.6  4.405
## warmed 5 Forb - warmed 2           1.39e+00 0.2508 896.5  5.527
## warmed 5 Forb - ambient 2         1.42e+00 0.2653 712.6  5.366
## warmed 5 Forb - warmed 3           1.01e+00 0.2347 897.3  4.296
## warmed 5 Forb - ambient 3         1.05e+00 0.2507 665.0  4.173
## warmed 5 Forb - warmed 4           1.08e+00 0.2496 897.0  4.333
## warmed 5 Forb - ambient 4         1.12e+00 0.2641 709.2  4.238
## warmed 5 Forb - warmed 5           1.20e+00 0.2158 900.6  5.538
## warmed 5 Forb - ambient 5         1.23e+00 0.2331 587.9  5.288
## warmed 5 Forb - warmed 6           1.16e+00 0.2450 896.4  4.724
## warmed 5 Forb - ambient 6         1.20e+00 0.2597 694.4  4.602
## warmed 5 Forb - warmed 1 Graminoid -1.91e-01 0.1371 899.3 -1.392
## warmed 5 Forb - ambient 1 Graminoid -1.53e-01 0.1640 253.8 -0.934
## warmed 5 Forb - warmed 2 Graminoid 9.17e-02 0.1391 899.7  0.659
## warmed 5 Forb - ambient 2 Graminoid 1.29e-01 0.1652 260.4  0.783
## warmed 5 Forb - warmed 3 Graminoid -2.86e-01 0.1362 900.6 -2.099

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## warmed 5 Forb - ambient 3 Graminoid -2.48e-01 0.1636 252.0 -1.518
## warmed 5 Forb - warmed 4 Graminoid -2.13e-01 0.1359 898.9 -1.564
## warmed 5 Forb - ambient 4 Graminoid -1.75e-01 0.1623 248.4 -1.077
## warmed 5 Forb - warmed 5 Graminoid -9.90e-02 0.0708 908.8 -1.399
## warmed 5 Forb - ambient 5 Graminoid -6.13e-02 0.1150 68.4 -0.533
## warmed 5 Forb - warmed 6 Graminoid -1.37e-01 0.1342 899.4 -1.019
## warmed 5 Forb - ambient 6 Graminoid -9.90e-02 0.1608 237.6 -0.616
## warmed 5 Forb - warmed 1 Tree 6.83e-01 0.4146 909.3 1.647
## warmed 5 Forb - ambient 1 Tree 7.21e-01 0.4233 860.0 1.703
## warmed 5 Forb - warmed 2 Tree 9.66e-01 0.4150 909.3 2.327
## warmed 5 Forb - ambient 2 Tree 1.00e+00 0.4235 858.5 2.369
## warmed 5 Forb - warmed 3 Tree 5.88e-01 0.4140 909.3 1.420
## warmed 5 Forb - ambient 3 Tree 6.26e-01 0.4229 861.2 1.479
## warmed 5 Forb - warmed 4 Tree 6.61e-01 0.4069 909.3 1.625
## warmed 5 Forb - ambient 4 Tree 6.99e-01 0.4155 853.7 1.682
## warmed 5 Forb - warmed 5 Tree 7.75e-01 0.3926 909.2 1.973
## warmed 5 Forb - ambient 5 Tree 8.13e-01 0.4020 842.6 2.021
## warmed 5 Forb - warmed 6 Tree 7.37e-01 0.4088 909.3 1.803
## warmed 5 Forb - ambient 6 Tree 7.75e-01 0.4174 856.9 1.856
## ambient 5 Forb - warmed 6 Forb -7.55e-02 0.1465 175.9 -0.515
## ambient 5 Forb - ambient 6 Forb -3.77e-02 0.1132 886.8 -0.333
## ambient 5 Forb - warmed 1 1.07e+00 0.2615 690.8 4.075
## ambient 5 Forb - ambient 1 1.10e+00 0.2438 896.6 4.525
## ambient 5 Forb - warmed 2 1.35e+00 0.2682 710.2 5.026
## ambient 5 Forb - ambient 2 1.39e+00 0.2508 896.5 5.527
## ambient 5 Forb - warmed 3 9.70e-01 0.2528 659.1 3.839
## ambient 5 Forb - ambient 3 1.01e+00 0.2347 897.3 4.296
## ambient 5 Forb - warmed 4 1.04e+00 0.2673 705.6 3.905
## ambient 5 Forb - ambient 4 1.08e+00 0.2496 897.0 4.333
## ambient 5 Forb - warmed 5 1.16e+00 0.2353 586.4 4.918
## ambient 5 Forb - ambient 5 1.20e+00 0.2158 900.6 5.538
## ambient 5 Forb - warmed 6 1.12e+00 0.2631 697.0 4.256
## ambient 5 Forb - ambient 6 1.16e+00 0.2450 896.4 4.724
## ambient 5 Forb - warmed 1 Graminoid -2.29e-01 0.1652 249.9 -1.384
## ambient 5 Forb - ambient 1 Graminoid -1.91e-01 0.1371 899.3 -1.392
## ambient 5 Forb - warmed 2 Graminoid 5.39e-02 0.1673 258.2 0.322
## ambient 5 Forb - ambient 2 Graminoid 9.17e-02 0.1391 899.7 0.659
## ambient 5 Forb - warmed 3 Graminoid -3.24e-01 0.1641 241.9 -1.972
## ambient 5 Forb - ambient 3 Graminoid -2.86e-01 0.1362 900.6 -2.099
## ambient 5 Forb - warmed 4 Graminoid -2.50e-01 0.1648 246.3 -1.518
## ambient 5 Forb - ambient 4 Graminoid -2.13e-01 0.1359 898.9 -1.564
## ambient 5 Forb - warmed 5 Graminoid -1.37e-01 0.1157 66.6 -1.182
## ambient 5 Forb - ambient 5 Graminoid -9.90e-02 0.0708 908.8 -1.399
## ambient 5 Forb - warmed 6 Graminoid -1.74e-01 0.1635 242.4 -1.067
## ambient 5 Forb - ambient 6 Graminoid -1.37e-01 0.1342 899.4 -1.019
## ambient 5 Forb - warmed 1 Tree 6.45e-01 0.4256 855.1 1.516
## ambient 5 Forb - ambient 1 Tree 6.83e-01 0.4146 909.3 1.647
## ambient 5 Forb - warmed 2 Tree 9.28e-01 0.4261 853.3 2.177
## ambient 5 Forb - ambient 2 Tree 9.66e-01 0.4150 909.3 2.327
## ambient 5 Forb - warmed 3 Tree 5.50e-01 0.4249 855.4 1.295
## ambient 5 Forb - ambient 3 Tree 5.88e-01 0.4140 909.3 1.420
## ambient 5 Forb - warmed 4 Tree 6.24e-01 0.4183 847.7 1.491
## ambient 5 Forb - ambient 4 Tree 6.61e-01 0.4069 909.3 1.625
## ambient 5 Forb - warmed 5 Tree 7.37e-01 0.4041 836.5 1.824

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## ambient 5 Forb - ambient 5 Tree	7.75e-01	0.3926	909.2	1.973
## ambient 5 Forb - warmed 6 Tree	6.99e-01	0.4203	852.6	1.664
## ambient 5 Forb - ambient 6 Tree	7.37e-01	0.4088	909.3	1.803
## warmed 6 Forb - ambient 6 Forb	3.77e-02	0.0911	25.8	0.414
## warmed 6 Forb - warmed 1	1.14e+00	0.2419	898.4	4.716
## warmed 6 Forb - ambient 1	1.18e+00	0.2579	685.1	4.570
## warmed 6 Forb - warmed 2	1.42e+00	0.2488	897.9	5.721
## warmed 6 Forb - ambient 2	1.46e+00	0.2642	706.3	5.532
## warmed 6 Forb - warmed 3	1.05e+00	0.2328	899.3	4.493
## warmed 6 Forb - ambient 3	1.08e+00	0.2496	656.6	4.341
## warmed 6 Forb - warmed 4	1.12e+00	0.2478	898.8	4.518
## warmed 6 Forb - ambient 4	1.16e+00	0.2631	701.7	4.399
## warmed 6 Forb - warmed 5	1.23e+00	0.2424	899.8	5.087
## warmed 6 Forb - ambient 5	1.27e+00	0.2586	683.0	4.913
## warmed 6 Forb - warmed 6	1.20e+00	0.2158	900.6	5.538
## warmed 6 Forb - ambient 6	1.23e+00	0.2331	587.9	5.288
## warmed 6 Forb - warmed 1 Graminoid	-1.53e-01	0.1355	896.2	-1.131
## warmed 6 Forb - ambient 1 Graminoid	-1.15e-01	0.1637	255.8	-0.705
## warmed 6 Forb - warmed 2 Graminoid	1.29e-01	0.1373	895.8	0.943
## warmed 6 Forb - ambient 2 Graminoid	1.67e-01	0.1648	262.6	1.014
## warmed 6 Forb - warmed 3 Graminoid	-2.48e-01	0.1347	898.3	-1.843
## warmed 6 Forb - ambient 3 Graminoid	-2.10e-01	0.1634	254.1	-1.288
## warmed 6 Forb - warmed 4 Graminoid	-1.75e-01	0.1342	896.3	-1.303
## warmed 6 Forb - ambient 4 Graminoid	-1.37e-01	0.1620	249.5	-0.846
## warmed 6 Forb - warmed 5 Graminoid	-6.13e-02	0.1328	892.4	-0.461
## warmed 6 Forb - ambient 5 Graminoid	-2.35e-02	0.1619	249.4	-0.145
## warmed 6 Forb - warmed 6 Graminoid	-9.90e-02	0.0708	908.8	-1.399
## warmed 6 Forb - ambient 6 Graminoid	-6.13e-02	0.1150	68.4	-0.533
## warmed 6 Forb - warmed 1 Tree	7.21e-01	0.4140	909.3	1.741
## warmed 6 Forb - ambient 1 Tree	7.58e-01	0.4232	859.3	1.792
## warmed 6 Forb - warmed 2 Tree	1.00e+00	0.4144	909.3	2.421
## warmed 6 Forb - ambient 2 Tree	1.04e+00	0.4234	858.0	2.459
## warmed 6 Forb - warmed 3 Tree	6.26e-01	0.4135	909.3	1.513
## warmed 6 Forb - ambient 3 Tree	6.63e-01	0.4228	860.4	1.569
## warmed 6 Forb - warmed 4 Tree	6.99e-01	0.4063	909.3	1.721
## warmed 6 Forb - ambient 4 Tree	7.37e-01	0.4154	852.8	1.774
## warmed 6 Forb - warmed 5 Tree	8.13e-01	0.4084	909.3	1.990
## warmed 6 Forb - ambient 5 Tree	8.50e-01	0.4178	855.9	2.035
## warmed 6 Forb - warmed 6 Tree	7.75e-01	0.3926	909.2	1.973
## warmed 6 Forb - ambient 6 Tree	8.13e-01	0.4020	842.6	2.021
## ambient 6 Forb - warmed 1	1.10e+00	0.2590	677.8	4.259
## ambient 6 Forb - ambient 1	1.14e+00	0.2419	898.4	4.716
## ambient 6 Forb - warmed 2	1.39e+00	0.2657	698.8	5.215
## ambient 6 Forb - ambient 2	1.42e+00	0.2488	897.9	5.721
## ambient 6 Forb - warmed 3	1.01e+00	0.2503	644.4	4.028
## ambient 6 Forb - ambient 3	1.05e+00	0.2328	899.3	4.493
## ambient 6 Forb - warmed 4	1.08e+00	0.2649	692.9	4.083
## ambient 6 Forb - ambient 4	1.12e+00	0.2478	898.8	4.518
## ambient 6 Forb - warmed 5	1.20e+00	0.2592	674.5	4.611
## ambient 6 Forb - ambient 5	1.23e+00	0.2424	899.8	5.087
## ambient 6 Forb - warmed 6	1.16e+00	0.2353	586.4	4.918
## ambient 6 Forb - ambient 6	1.20e+00	0.2158	900.6	5.538
## ambient 6 Forb - warmed 1 Graminoid	-1.91e-01	0.1628	239.9	-1.173
## ambient 6 Forb - ambient 1 Graminoid	-1.53e-01	0.1355	896.2	-1.131

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## ambient 6 Forb - warmed 2 Graminoid
## ambient 6 Forb - ambient 2 Graminoid
## ambient 6 Forb - warmed 3 Graminoid
## ambient 6 Forb - ambient 3 Graminoid
## ambient 6 Forb - warmed 4 Graminoid
## ambient 6 Forb - ambient 4 Graminoid
## ambient 6 Forb - warmed 5 Graminoid
## ambient 6 Forb - ambient 5 Graminoid
## ambient 6 Forb - warmed 6 Graminoid
## ambient 6 Forb - ambient 6 Graminoid
## ambient 6 Forb - warmed 1 Tree
## ambient 6 Forb - ambient 1 Tree
## ambient 6 Forb - warmed 2 Tree
## ambient 6 Forb - ambient 2 Tree
## ambient 6 Forb - warmed 3 Tree
## ambient 6 Forb - ambient 3 Tree
## ambient 6 Forb - warmed 4 Tree
## ambient 6 Forb - ambient 4 Tree
## ambient 6 Forb - warmed 5 Tree
## ambient 6 Forb - ambient 5 Tree
## ambient 6 Forb - warmed 6 Tree
## ambient 6 Forb - ambient 6 Tree
## warmed 1 - ambient 1
## warmed 1 - warmed 2
## warmed 1 - ambient 2
## warmed 1 - warmed 3
## warmed 1 - ambient 3
## warmed 1 - warmed 4
## warmed 1 - ambient 4
## warmed 1 - warmed 5
## warmed 1 - ambient 5
## warmed 1 - warmed 6
## warmed 1 - ambient 6
## warmed 1 - warmed 1 Graminoid
## warmed 1 - ambient 1 Graminoid
## warmed 1 - warmed 2 Graminoid
## warmed 1 - ambient 2 Graminoid
## warmed 1 - warmed 3 Graminoid
## warmed 1 - ambient 3 Graminoid
## warmed 1 - warmed 4 Graminoid
## warmed 1 - ambient 4 Graminoid
## warmed 1 - warmed 5 Graminoid
## warmed 1 - ambient 5 Graminoid
## warmed 1 - warmed 6 Graminoid
## warmed 1 - ambient 6 Graminoid
## warmed 1 - warmed 1 Tree
## warmed 1 - ambient 1 Tree
## warmed 1 - warmed 2 Tree
## warmed 1 - ambient 2 Tree
## warmed 1 - warmed 3 Tree
## warmed 1 - ambient 3 Tree
## warmed 1 - warmed 4 Tree
## warmed 1 - ambient 4 Tree
## warmed 1 - warmed 5 Tree
9.17e-02 0.1647 248.4 0.557
1.29e-01 0.1373 895.8 0.943
-2.86e-01 0.1617 232.1 -1.768
-2.48e-01 0.1347 898.3 -1.843
-2.13e-01 0.1623 235.6 -1.310
-1.75e-01 0.1342 896.3 -1.303
-9.90e-02 0.1601 230.3 -0.618
-6.13e-02 0.1328 892.4 -0.461
-1.37e-01 0.1157 66.6 -1.182
-9.90e-02 0.0708 908.8 -1.399
6.83e-01 0.4246 853.5 1.608
7.21e-01 0.4140 909.3 1.741
9.66e-01 0.4251 851.8 2.271
1.00e+00 0.4144 909.3 2.421
5.88e-01 0.4240 853.6 1.387
6.26e-01 0.4135 909.3 1.513
6.61e-01 0.4173 845.7 1.585
6.99e-01 0.4063 909.3 1.721
7.75e-01 0.4190 849.6 1.849
8.13e-01 0.4084 909.3 1.990
7.37e-01 0.4041 836.5 1.824
7.75e-01 0.3926 909.2 1.973
3.77e-02 0.0911 25.8 0.414
2.83e-01 0.1212 885.3 2.332
3.20e-01 0.1511 197.6 2.119
-9.50e-02 0.1199 887.9 -0.793
-5.73e-02 0.1510 195.9 -0.380
-2.16e-02 0.1202 887.6 -0.180
1.61e-02 0.1501 193.0 0.107
9.19e-02 0.1182 888.5 0.777
1.30e-01 0.1496 188.4 0.866
5.42e-02 0.1171 888.5 0.463
9.19e-02 0.1475 178.7 0.623
-1.29e+00 0.2183 905.7 -5.929
-1.26e+00 0.2374 582.7 -5.292
-1.01e+00 0.2438 902.9 -4.150
-9.74e-01 0.2608 675.9 -3.734
-1.39e+00 0.2572 902.5 -5.402
-1.35e+00 0.2738 715.1 -4.935
-1.32e+00 0.2426 902.8 -5.423
-1.28e+00 0.2596 673.9 -4.923
-1.20e+00 0.2463 901.2 -4.881
-1.16e+00 0.2637 689.4 -4.416
-1.24e+00 0.2448 903.3 -5.064
-1.20e+00 0.2616 675.1 -4.595
-4.20e-01 0.4436 907.3 -0.947
-3.83e-01 0.4525 883.6 -0.845
-1.38e-01 0.4565 907.1 -0.302
-1.00e-01 0.4650 887.8 -0.215
-5.15e-01 0.4638 906.2 -1.111
-4.78e-01 0.4724 891.7 -1.011
-4.42e-01 0.4495 907.2 -0.983
-4.04e-01 0.4581 886.0 -0.882
-3.28e-01 0.4538 906.6 -0.724

```

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## warmed 1 - ambient 5 Tree          -2.91e-01 0.4626 888.5 -0.628
## warmed 1 - warmed 6 Tree          -3.66e-01 0.4530 906.7 -0.808
## warmed 1 - ambient 6 Tree          -3.28e-01 0.4615 887.8 -0.712
## ambient 1 - warmed 2              2.45e-01 0.1520 199.8  1.611
## ambient 1 - ambient 2             2.83e-01 0.1212 885.3  2.332
## ambient 1 - warmed 3              -1.33e-01 0.1502 190.0 -0.884
## ambient 1 - ambient 3             -9.50e-02 0.1199 887.9 -0.793
## ambient 1 - warmed 4              -5.93e-02 0.1515 195.3 -0.392
## ambient 1 - ambient 4             -2.16e-02 0.1202 887.6 -0.180
## ambient 1 - warmed 5              5.42e-02 0.1488 185.0  0.364
## ambient 1 - ambient 5             9.19e-02 0.1182 888.5  0.777
## ambient 1 - warmed 6              1.64e-02 0.1491 186.8  0.110
## ambient 1 - ambient 6             5.42e-02 0.1171 888.5  0.463
## ambient 1 - warmed 1 Graminoid   -1.33e+00 0.2356 574.4 -5.654
## ambient 1 - ambient 1 Graminoid   -1.29e+00 0.2183 905.7 -5.929
## ambient 1 - warmed 2 Graminoid   -1.05e+00 0.2596 669.7 -4.042
## ambient 1 - ambient 2 Graminoid   -1.01e+00 0.2438 902.9 -4.150
## ambient 1 - warmed 3 Graminoid   -1.43e+00 0.2718 706.4 -5.250
## ambient 1 - ambient 3 Graminoid   -1.39e+00 0.2572 902.5 -5.402
## ambient 1 - warmed 4 Graminoid   -1.35e+00 0.2587 666.3 -5.232
## ambient 1 - ambient 4 Graminoid   -1.32e+00 0.2426 902.8 -5.423
## ambient 1 - warmed 5 Graminoid   -1.24e+00 0.2615 682.7 -4.741
## ambient 1 - ambient 5 Graminoid   -1.20e+00 0.2463 901.2 -4.881
## ambient 1 - warmed 6 Graminoid   -1.28e+00 0.2608 673.8 -4.899
## ambient 1 - ambient 6 Graminoid   -1.24e+00 0.2448 903.3 -5.064
## ambient 1 - warmed 1 Tree         -4.58e-01 0.4533 881.2 -1.011
## ambient 1 - ambient 1 Tree        -4.20e-01 0.4436 907.3 -0.947
## ambient 1 - warmed 2 Tree         -1.75e-01 0.4660 885.5 -0.377
## ambient 1 - ambient 2 Tree        -1.38e-01 0.4565 907.1 -0.302
## ambient 1 - warmed 3 Tree         -5.53e-01 0.4729 889.4 -1.170
## ambient 1 - ambient 3 Tree        -5.15e-01 0.4638 906.2 -1.111
## ambient 1 - warmed 4 Tree         -4.80e-01 0.4592 883.3 -1.044
## ambient 1 - ambient 4 Tree        -4.42e-01 0.4495 907.2 -0.983
## ambient 1 - warmed 5 Tree         -3.66e-01 0.4631 886.4 -0.791
## ambient 1 - ambient 5 Tree        -3.28e-01 0.4538 906.6 -0.724
## ambient 1 - warmed 6 Tree         -4.04e-01 0.4627 886.1 -0.873
## ambient 1 - ambient 6 Tree        -3.66e-01 0.4530 906.7 -0.808
## warmed 2 - ambient 2             3.77e-02 0.0911 25.8  0.414
## warmed 2 - warmed 3              -3.78e-01 0.1202 889.8 -3.140
## warmed 2 - ambient 3             -3.40e-01 0.1517 197.4 -2.241
## warmed 2 - warmed 4              -3.04e-01 0.1194 888.1 -2.548
## warmed 2 - ambient 4             -2.66e-01 0.1499 190.9 -1.777
## warmed 2 - warmed 5              -1.91e-01 0.1177 889.6 -1.620
## warmed 2 - ambient 5             -1.53e-01 0.1497 187.4 -1.022
## warmed 2 - warmed 6              -2.28e-01 0.1164 887.7 -1.963
## warmed 2 - ambient 6             -1.91e-01 0.1474 177.7 -1.294
## warmed 2 - warmed 1 Graminoid   -1.58e+00 0.2554 902.1 -6.174
## warmed 2 - ambient 1 Graminoid   -1.54e+00 0.2722 709.9 -5.654
## warmed 2 - warmed 2 Graminoid   -1.29e+00 0.2183 905.7 -5.929
## warmed 2 - ambient 2 Graminoid   -1.26e+00 0.2374 582.7 -5.292
## warmed 2 - warmed 3 Graminoid   -1.67e+00 0.2629 902.3 -6.359
## warmed 2 - ambient 3 Graminoid   -1.63e+00 0.2794 729.1 -5.847
## warmed 2 - warmed 4 Graminoid   -1.60e+00 0.2481 902.4 -6.441
## warmed 2 - ambient 4 Graminoid   -1.56e+00 0.2650 690.5 -5.889

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## warmed 2 - warmed 5 Graminoid          -1.48e+00 0.2519 900.9 -5.894
## warmed 2 - ambient 5 Graminoid        -1.45e+00 0.2692 705.1 -5.376
## warmed 2 - warmed 6 Graminoid         -1.52e+00 0.2504 902.8 -6.082
## warmed 2 - ambient 6 Graminoid        -1.48e+00 0.2670 692.2 -5.560
## warmed 2 - warmed 1 Tree              -7.03e-01 0.4632 906.1 -1.517
## warmed 2 - ambient 1 Tree             -6.65e-01 0.4719 891.7 -1.409
## warmed 2 - warmed 2 Tree              -4.20e-01 0.4436 907.3 -0.947
## warmed 2 - ambient 2 Tree             -3.83e-01 0.4525 883.6 -0.845
## warmed 2 - warmed 3 Tree              -7.98e-01 0.4672 905.8 -1.708
## warmed 2 - ambient 3 Tree             -7.60e-01 0.4759 893.4 -1.597
## warmed 2 - warmed 4 Tree              -7.24e-01 0.4527 906.7 -1.600
## warmed 2 - ambient 4 Tree             -6.87e-01 0.4614 888.1 -1.488
## warmed 2 - warmed 5 Tree              -6.11e-01 0.4571 906.1 -1.337
## warmed 2 - ambient 5 Tree             -5.73e-01 0.4660 890.4 -1.230
## warmed 2 - warmed 6 Tree              -6.49e-01 0.4562 906.1 -1.422
## warmed 2 - ambient 6 Tree             -6.11e-01 0.4648 889.9 -1.315
## ambient 2 - warmed 3                 -4.15e-01 0.1500 189.3 -2.769
## ambient 2 - ambient 3                -3.78e-01 0.1202 889.8 -3.140
## ambient 2 - warmed 4                 -3.42e-01 0.1504 191.1 -2.274
## ambient 2 - ambient 4                -3.04e-01 0.1194 888.1 -2.548
## ambient 2 - warmed 5                 -2.28e-01 0.1479 181.8 -1.544
## ambient 2 - ambient 5                -1.91e-01 0.1177 889.6 -1.620
## ambient 2 - warmed 6                 -2.66e-01 0.1481 183.6 -1.797
## ambient 2 - ambient 6                -2.28e-01 0.1164 887.7 -1.963
## ambient 2 - warmed 1 Graminoid       -1.61e+00 0.2701 705.2 -5.978
## ambient 2 - ambient 1 Graminoid      -1.58e+00 0.2554 902.1 -6.174
## ambient 2 - warmed 2 Graminoid       -1.33e+00 0.2356 574.4 -5.654
## ambient 2 - ambient 2 Graminoid      -1.29e+00 0.2183 905.7 -5.929
## ambient 2 - warmed 3 Graminoid       -1.71e+00 0.2770 721.5 -6.172
## ambient 2 - ambient 3 Graminoid      -1.67e+00 0.2629 902.3 -6.359
## ambient 2 - warmed 4 Graminoid       -1.64e+00 0.2636 683.6 -6.206
## ambient 2 - ambient 4 Graminoid      -1.60e+00 0.2481 902.4 -6.441
## ambient 2 - warmed 5 Graminoid       -1.52e+00 0.2666 699.2 -5.712
## ambient 2 - ambient 5 Graminoid      -1.48e+00 0.2519 900.9 -5.894
## ambient 2 - warmed 6 Graminoid       -1.56e+00 0.2658 691.3 -5.871
## ambient 2 - ambient 6 Graminoid      -1.52e+00 0.2504 902.8 -6.082
## ambient 2 - warmed 1 Tree            -7.41e-01 0.4723 890.0 -1.568
## ambient 2 - ambient 1 Tree           -7.03e-01 0.4632 906.1 -1.517
## ambient 2 - warmed 2 Tree            -4.58e-01 0.4533 881.2 -1.011
## ambient 2 - ambient 2 Tree           -4.20e-01 0.4436 907.3 -0.947
## ambient 2 - warmed 3 Tree            -8.36e-01 0.4761 891.3 -1.755
## ambient 2 - ambient 3 Tree           -7.98e-01 0.4672 905.8 -1.708
## ambient 2 - warmed 4 Tree            -7.62e-01 0.4622 885.7 -1.649
## ambient 2 - ambient 4 Tree           -7.24e-01 0.4527 906.7 -1.600
## ambient 2 - warmed 5 Tree            -6.49e-01 0.4661 888.5 -1.392
## ambient 2 - ambient 5 Tree           -6.11e-01 0.4571 906.1 -1.337
## ambient 2 - warmed 6 Tree            -6.86e-01 0.4657 888.4 -1.474
## ambient 2 - ambient 6 Tree           -6.49e-01 0.4562 906.1 -1.422
## warmed 3 - ambient 3                 3.77e-02 0.0911 25.8  0.414
## warmed 3 - warmed 4                 7.34e-02 0.1191 887.5  0.616
## warmed 3 - ambient 4                 1.11e-01 0.1489 186.3  0.747
## warmed 3 - warmed 5                 1.87e-01 0.1166 888.2  1.603
## warmed 3 - ambient 5                 2.25e-01 0.1480 180.2  1.518
## warmed 3 - warmed 6                 1.49e-01 0.1157 889.1  1.290

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## warmed 3 - ambient 6          1.87e-01 0.1460 170.9  1.280
## warmed 3 - warmed 1 Graminoid -1.20e+00 0.2406 903.3 -4.984
## warmed 3 - ambient 1 Graminoid -1.16e+00 0.2579 662.9 -4.504
## warmed 3 - warmed 2 Graminoid -9.17e-01 0.2347 904.1 -3.905
## warmed 3 - ambient 2 Graminoid -8.79e-01 0.2521 642.1 -3.486
## warmed 3 - warmed 3 Graminoid -1.29e+00 0.2183 905.7 -5.929
## warmed 3 - ambient 3 Graminoid -1.26e+00 0.2374 582.7 -5.292
## warmed 3 - warmed 4 Graminoid -1.22e+00 0.2334 903.2 -5.229
## warmed 3 - ambient 4 Graminoid -1.18e+00 0.2508 641.9 -4.717
## warmed 3 - warmed 5 Graminoid -1.11e+00 0.2370 901.6 -4.671
## warmed 3 - ambient 5 Graminoid -1.07e+00 0.2548 658.7 -4.197
## warmed 3 - warmed 6 Graminoid -1.14e+00 0.2356 904.0 -4.860
## warmed 3 - ambient 6 Graminoid -1.11e+00 0.2527 642.7 -4.381
## warmed 3 - warmed 1 Tree       -3.25e-01 0.4553 907.1 -0.714
## warmed 3 - ambient 1 Tree     -2.88e-01 0.4638 887.2 -0.620
## warmed 3 - warmed 2 Tree      -4.27e-02 0.4520 907.6 -0.094
## warmed 3 - ambient 2 Tree     -4.96e-03 0.4604 884.9 -0.011
## warmed 3 - warmed 3 Tree      -4.20e-01 0.4436 907.3 -0.947
## warmed 3 - ambient 3 Tree     -3.83e-01 0.4525 883.6 -0.845
## warmed 3 - warmed 4 Tree      -3.47e-01 0.4449 907.6 -0.780
## warmed 3 - ambient 4 Tree     -3.09e-01 0.4534 883.2 -0.682
## warmed 3 - warmed 5 Tree      -2.33e-01 0.4491 907.0 -0.520
## warmed 3 - ambient 5 Tree     -1.96e-01 0.4579 885.9 -0.427
## warmed 3 - warmed 6 Tree      -2.71e-01 0.4483 907.1 -0.605
## warmed 3 - ambient 6 Tree     -2.33e-01 0.4567 885.1 -0.511
## ambient 3 - warmed 4          3.57e-02 0.1510 194.4  0.236
## ambient 3 - ambient 4         7.34e-02 0.1191 887.5  0.616
## ambient 3 - warmed 5          1.49e-01 0.1479 182.6  1.009
## ambient 3 - ambient 5         1.87e-01 0.1166 888.2  1.603
## ambient 3 - warmed 6          1.11e-01 0.1484 184.6  0.751
## ambient 3 - ambient 6         1.49e-01 0.1157 889.1  1.290
## ambient 3 - warmed 1 Graminoid -1.24e+00 0.2566 661.1 -4.819
## ambient 3 - ambient 1 Graminoid -1.20e+00 0.2406 903.3 -4.984
## ambient 3 - warmed 2 Graminoid -9.54e-01 0.2514 639.9 -3.797
## ambient 3 - ambient 2 Graminoid -9.17e-01 0.2347 904.1 -3.905
## ambient 3 - warmed 3 Graminoid -1.33e+00 0.2356 574.4 -5.654
## ambient 3 - ambient 3 Graminoid -1.29e+00 0.2183 905.7 -5.929
## ambient 3 - warmed 4 Graminoid -1.26e+00 0.2503 638.2 -5.027
## ambient 3 - ambient 4 Graminoid -1.22e+00 0.2334 903.2 -5.229
## ambient 3 - warmed 5 Graminoid -1.14e+00 0.2530 655.6 -4.525
## ambient 3 - ambient 5 Graminoid -1.11e+00 0.2370 901.6 -4.671
## ambient 3 - warmed 6 Graminoid -1.18e+00 0.2524 645.8 -4.686
## ambient 3 - ambient 6 Graminoid -1.14e+00 0.2356 904.0 -4.860
## ambient 3 - warmed 1 Tree     -3.63e-01 0.4648 885.5 -0.781
## ambient 3 - ambient 1 Tree    -3.25e-01 0.4553 907.1 -0.714
## ambient 3 - warmed 2 Tree     -8.04e-02 0.4617 882.9 -0.174
## ambient 3 - ambient 2 Tree    -4.27e-02 0.4520 907.6 -0.094
## ambient 3 - warmed 3 Tree     -4.58e-01 0.4533 881.2 -1.011
## ambient 3 - ambient 3 Tree    -4.20e-01 0.4436 907.3 -0.947
## ambient 3 - warmed 4 Tree     -3.85e-01 0.4548 880.8 -0.846
## ambient 3 - ambient 4 Tree    -3.47e-01 0.4449 907.6 -0.780
## ambient 3 - warmed 5 Tree     -2.71e-01 0.4586 884.1 -0.591
## ambient 3 - ambient 5 Tree    -2.33e-01 0.4491 907.0 -0.520
## ambient 3 - warmed 6 Tree     -3.09e-01 0.4582 883.8 -0.674

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## ambient 3 - ambient 6 Tree          -2.71e-01 0.4483 907.1 -0.605
## warmed 4 - ambient 4              3.77e-02 0.0911 25.8  0.414
## warmed 4 - warmed 5              1.14e-01 0.1162 885.7 0.976
## warmed 4 - ambient 5              1.51e-01 0.1488 183.8 1.017
## warmed 4 - warmed 6              7.58e-02 0.1150 886.7 0.659
## warmed 4 - ambient 6              1.13e-01 0.1466 173.5 0.774
## warmed 4 - warmed 1 Graminoid    -1.27e+00 0.2555 902.9 -4.980
## warmed 4 - ambient 1 Graminoid   -1.23e+00 0.2725 706.8 -4.532
## warmed 4 - warmed 2 Graminoid    -9.90e-01 0.2494 903.4 -3.969
## warmed 4 - ambient 2 Graminoid   -9.52e-01 0.2665 689.0 -3.574
## warmed 4 - warmed 3 Graminoid    -1.37e+00 0.2630 902.5 -5.200
## warmed 4 - ambient 3 Graminoid   -1.33e+00 0.2797 728.0 -4.755
## warmed 4 - warmed 4 Graminoid    -1.29e+00 0.2183 905.7 -5.929
## warmed 4 - ambient 4 Graminoid   -1.26e+00 0.2374 582.7 -5.292
## warmed 4 - warmed 5 Graminoid    -1.18e+00 0.2519 901.0 -4.688
## warmed 4 - ambient 5 Graminoid   -1.14e+00 0.2692 704.0 -4.245
## warmed 4 - warmed 6 Graminoid    -1.22e+00 0.2504 903.2 -4.866
## warmed 4 - ambient 6 Graminoid   -1.18e+00 0.2672 690.0 -4.419
## warmed 4 - warmed 1 Tree         -3.99e-01 0.4695 906.1 -0.849
## warmed 4 - ambient 1 Tree        -3.61e-01 0.4782 892.7 -0.755
## warmed 4 - warmed 2 Tree         -1.16e-01 0.4660 906.7 -0.249
## warmed 4 - ambient 2 Tree        -7.84e-02 0.4746 890.8 -0.165
## warmed 4 - warmed 3 Tree         -4.94e-01 0.4734 905.7 -1.043
## warmed 4 - ambient 3 Tree        -4.56e-01 0.4821 894.5 -0.946
## warmed 4 - warmed 4 Tree         -4.20e-01 0.4436 907.3 -0.947
## warmed 4 - ambient 4 Tree        -3.83e-01 0.4525 883.6 -0.845
## warmed 4 - warmed 5 Tree         -3.07e-01 0.4633 906.0 -0.662
## warmed 4 - ambient 5 Tree        -2.69e-01 0.4722 891.8 -0.570
## warmed 4 - warmed 6 Tree         -3.45e-01 0.4625 906.1 -0.745
## warmed 4 - ambient 6 Tree        -3.07e-01 0.4710 891.1 -0.651
## ambient 4 - warmed 5             7.58e-02 0.1465 178.0  0.517
## ambient 4 - ambient 5            1.14e-01 0.1162 885.7 0.976
## ambient 4 - warmed 6             3.80e-02 0.1468 179.2 0.259
## ambient 4 - ambient 6            7.58e-02 0.1150 886.7 0.659
## ambient 4 - warmed 1 Graminoid   -1.31e+00 0.2701 703.4 -4.851
## ambient 4 - ambient 1 Graminoid  -1.27e+00 0.2555 902.9 -4.980
## ambient 4 - warmed 2 Graminoid   -1.03e+00 0.2646 684.8 -3.885
## ambient 4 - ambient 2 Graminoid  -9.90e-01 0.2494 903.4 -3.969
## ambient 4 - warmed 3 Graminoid   -1.41e+00 0.2769 721.5 -5.074
## ambient 4 - ambient 3 Graminoid  -1.37e+00 0.2630 902.5 -5.200
## ambient 4 - warmed 4 Graminoid   -1.33e+00 0.2356 574.4 -5.654
## ambient 4 - ambient 4 Graminoid  -1.29e+00 0.2183 905.7 -5.929
## ambient 4 - warmed 5 Graminoid   -1.22e+00 0.2664 699.4 -4.574
## ambient 4 - ambient 5 Graminoid  -1.18e+00 0.2519 901.0 -4.688
## ambient 4 - warmed 6 Graminoid   -1.26e+00 0.2656 690.4 -4.729
## ambient 4 - ambient 6 Graminoid  -1.22e+00 0.2504 903.2 -4.866
## ambient 4 - warmed 1 Tree        -4.36e-01 0.4784 891.2 -0.912
## ambient 4 - ambient 1 Tree       -3.99e-01 0.4695 906.1 -0.849
## ambient 4 - warmed 2 Tree        -1.54e-01 0.4751 889.1 -0.324
## ambient 4 - ambient 2 Tree       -1.16e-01 0.4660 906.7 -0.249
## ambient 4 - warmed 3 Tree        -5.31e-01 0.4821 892.8 -1.102
## ambient 4 - ambient 3 Tree       -4.94e-01 0.4734 905.7 -1.043
## ambient 4 - warmed 4 Tree        -4.58e-01 0.4533 881.2 -1.011
## ambient 4 - ambient 4 Tree       -4.20e-01 0.4436 907.3 -0.947

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## ambient 4 - warmed 5 Tree          -3.45e-01 0.4722 890.2 -0.730
## ambient 4 - ambient 5 Tree        -3.07e-01 0.4633 906.0 -0.662
## ambient 4 - warmed 6 Tree         -3.82e-01 0.4718 890.0 -0.810
## ambient 4 - ambient 6 Tree        -3.45e-01 0.4625 906.1 -0.745
## warmed 5 - ambient 5              3.77e-02 0.0911 25.8  0.414
## warmed 5 - warmed 6               -3.77e-02 0.1132 886.8 -0.333
## warmed 5 - ambient 6              -6.40e-06 0.1440 164.6  0.000
## warmed 5 - warmed 1 Graminoid    -1.39e+00 0.2501 904.6 -5.542
## warmed 5 - ambient 1 Graminoid   -1.35e+00 0.2667 686.3 -5.055
## warmed 5 - warmed 2 Graminoid    -1.10e+00 0.2440 905.2 -4.523
## warmed 5 - ambient 2 Graminoid   -1.07e+00 0.2608 667.0 -4.087
## warmed 5 - warmed 3 Graminoid    -1.48e+00 0.2575 904.2 -5.752
## warmed 5 - ambient 3 Graminoid   -1.44e+00 0.2739 709.1 -5.270
## warmed 5 - warmed 4 Graminoid    -1.41e+00 0.2426 904.4 -5.802
## warmed 5 - ambient 4 Graminoid   -1.37e+00 0.2594 667.1 -5.282
## warmed 5 - warmed 5 Graminoid    -1.29e+00 0.2183 905.7 -5.929
## warmed 5 - ambient 5 Graminoid   -1.26e+00 0.2374 582.7 -5.292
## warmed 5 - warmed 6 Graminoid    -1.33e+00 0.2449 904.9 -5.438
## warmed 5 - ambient 6 Graminoid   -1.29e+00 0.2614 668.6 -4.950
## warmed 5 - warmed 1 Tree          -5.12e-01 0.4644 906.8 -1.103
## warmed 5 - ambient 1 Tree         -4.74e-01 0.4727 890.2 -1.004
## warmed 5 - warmed 2 Tree          -2.30e-01 0.4609 907.3 -0.498
## warmed 5 - ambient 2 Tree         -1.92e-01 0.4692 888.1 -0.409
## warmed 5 - warmed 3 Tree          -6.07e-01 0.4682 906.4 -1.297
## warmed 5 - ambient 3 Tree         -5.70e-01 0.4766 892.2 -1.195
## warmed 5 - warmed 4 Tree          -5.34e-01 0.4538 907.3 -1.176
## warmed 5 - ambient 4 Tree         -4.96e-01 0.4622 886.8 -1.073
## warmed 5 - warmed 5 Tree          -4.20e-01 0.4436 907.3 -0.947
## warmed 5 - ambient 5 Tree         -3.83e-01 0.4525 883.6 -0.845
## warmed 5 - warmed 6 Tree          -4.58e-01 0.4574 906.8 -1.002
## warmed 5 - ambient 6 Tree         -4.20e-01 0.4656 888.5 -0.903
## ambient 5 - warmed 6              -7.55e-02 0.1465 175.9 -0.515
## ambient 5 - ambient 6             -3.77e-02 0.1132 886.8 -0.333
## ambient 5 - warmed 1 Graminoid   -1.42e+00 0.2656 681.9 -5.361
## ambient 5 - ambient 1 Graminoid  -1.39e+00 0.2501 904.6 -5.542
## ambient 5 - warmed 2 Graminoid   -1.14e+00 0.2601 661.9 -4.388
## ambient 5 - ambient 2 Graminoid  -1.10e+00 0.2440 905.2 -4.523
## ambient 5 - warmed 3 Graminoid   -1.52e+00 0.2723 701.3 -5.577
## ambient 5 - ambient 3 Graminoid  -1.48e+00 0.2575 904.2 -5.752
## ambient 5 - warmed 4 Graminoid   -1.45e+00 0.2589 660.6 -5.582
## ambient 5 - ambient 4 Graminoid  -1.41e+00 0.2426 904.4 -5.802
## ambient 5 - warmed 5 Graminoid   -1.33e+00 0.2356 574.4 -5.654
## ambient 5 - ambient 5 Graminoid  -1.29e+00 0.2183 905.7 -5.929
## ambient 5 - warmed 6 Graminoid   -1.37e+00 0.2612 668.4 -5.245
## ambient 5 - ambient 6 Graminoid  -1.33e+00 0.2449 904.9 -5.438
## ambient 5 - warmed 1 Tree         -5.50e-01 0.4737 888.3 -1.161
## ambient 5 - ambient 1 Tree        -5.12e-01 0.4644 906.8 -1.103
## ambient 5 - warmed 2 Tree         -2.67e-01 0.4704 885.9 -0.568
## ambient 5 - ambient 2 Tree        -2.30e-01 0.4609 907.3 -0.498
## ambient 5 - warmed 3 Tree         -6.45e-01 0.4773 889.9 -1.351
## ambient 5 - ambient 3 Tree        -6.07e-01 0.4682 906.4 -1.297
## ambient 5 - warmed 4 Tree         -5.72e-01 0.4636 884.1 -1.233
## ambient 5 - ambient 4 Tree        -5.34e-01 0.4538 907.3 -1.176
## ambient 5 - warmed 5 Tree         -4.58e-01 0.4533 881.2 -1.011

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## ambient 5 - ambient 5 Tree          -4.20e-01 0.4436 907.3 -0.947
## ambient 5 - warmed 6 Tree          -4.96e-01 0.4671 886.8 -1.061
## ambient 5 - ambient 6 Tree          -4.58e-01 0.4574 906.8 -1.002
## warmed 6 - ambient 6              3.77e-02 0.0911 25.8  0.414
## warmed 6 - warmed 1 Graminoid     -1.35e+00 0.2505 902.8 -5.383
## warmed 6 - ambient 1 Graminoid    -1.31e+00 0.2678 696.8 -4.895
## warmed 6 - warmed 2 Graminoid     -1.07e+00 0.2443 903.2 -4.363
## warmed 6 - ambient 2 Graminoid    -1.03e+00 0.2617 678.7 -3.928
## warmed 6 - warmed 3 Graminoid     -1.44e+00 0.2579 902.5 -5.596
## warmed 6 - ambient 3 Graminoid    -1.41e+00 0.2750 718.6 -5.112
## warmed 6 - warmed 4 Graminoid     -1.37e+00 0.2430 902.6 -5.638
## warmed 6 - ambient 4 Graminoid    -1.33e+00 0.2604 677.8 -5.116
## warmed 6 - warmed 5 Graminoid     -1.26e+00 0.2468 900.9 -5.091
## warmed 6 - ambient 5 Graminoid    -1.22e+00 0.2646 693.8 -4.606
## warmed 6 - warmed 6 Graminoid     -1.29e+00 0.2183 905.7 -5.929
## warmed 6 - ambient 6 Graminoid    -1.26e+00 0.2374 582.7 -5.292
## warmed 6 - warmed 1 Tree          -4.74e-01 0.4646 906.8 -1.021
## warmed 6 - ambient 1 Tree          -4.37e-01 0.4733 890.6 -0.923
## warmed 6 - warmed 2 Tree          -1.92e-01 0.4610 907.2 -0.416
## warmed 6 - ambient 2 Tree          -1.54e-01 0.4697 888.7 -0.328
## warmed 6 - warmed 3 Tree          -5.69e-01 0.4684 906.4 -1.216
## warmed 6 - ambient 3 Tree          -5.32e-01 0.4772 892.5 -1.114
## warmed 6 - warmed 4 Tree          -4.96e-01 0.4540 907.2 -1.093
## warmed 6 - ambient 4 Tree          -4.58e-01 0.4628 887.2 -0.990
## warmed 6 - warmed 5 Tree          -3.83e-01 0.4584 906.6 -0.835
## warmed 6 - ambient 5 Tree          -3.45e-01 0.4673 889.6 -0.738
## warmed 6 - warmed 6 Tree          -4.20e-01 0.4436 907.3 -0.947
## warmed 6 - ambient 6 Tree          -3.83e-01 0.4525 883.6 -0.845
## ambient 6 - warmed 1 Graminoid    -1.39e+00 0.2652 687.2 -5.226
## ambient 6 - ambient 1 Graminoid   -1.35e+00 0.2505 902.8 -5.383
## ambient 6 - warmed 2 Graminoid    -1.10e+00 0.2597 668.0 -4.250
## ambient 6 - ambient 2 Graminoid   -1.07e+00 0.2443 903.2 -4.363
## ambient 6 - warmed 3 Graminoid    -1.48e+00 0.2721 706.1 -5.443
## ambient 6 - ambient 3 Graminoid   -1.44e+00 0.2579 902.5 -5.596
## ambient 6 - warmed 4 Graminoid    -1.41e+00 0.2586 665.5 -5.444
## ambient 6 - ambient 4 Graminoid   -1.37e+00 0.2430 902.6 -5.638
## ambient 6 - warmed 5 Graminoid    -1.29e+00 0.2615 682.7 -4.948
## ambient 6 - ambient 5 Graminoid   -1.26e+00 0.2468 900.9 -5.091
## ambient 6 - warmed 6 Graminoid    -1.33e+00 0.2356 574.4 -5.654
## ambient 6 - ambient 6 Graminoid   -1.29e+00 0.2183 905.7 -5.929
## ambient 6 - warmed 1 Tree          -5.12e-01 0.4735 888.3 -1.082
## ambient 6 - ambient 1 Tree          -4.74e-01 0.4646 906.8 -1.021
## ambient 6 - warmed 2 Tree          -2.30e-01 0.4702 886.1 -0.488
## ambient 6 - ambient 2 Tree          -1.92e-01 0.4610 907.2 -0.416
## ambient 6 - warmed 3 Tree          -6.07e-01 0.4772 889.9 -1.273
## ambient 6 - ambient 3 Tree          -5.69e-01 0.4684 906.4 -1.216
## ambient 6 - warmed 4 Tree          -5.34e-01 0.4634 884.1 -1.152
## ambient 6 - ambient 4 Tree          -4.96e-01 0.4540 907.2 -1.093
## ambient 6 - warmed 5 Tree          -4.20e-01 0.4673 887.1 -0.899
## ambient 6 - ambient 5 Tree          -3.83e-01 0.4584 906.6 -0.835
## ambient 6 - warmed 6 Tree          -4.58e-01 0.4533 881.2 -1.011
## ambient 6 - ambient 6 Tree          -4.20e-01 0.4436 907.3 -0.947
## warmed 1 Graminoid - ambient 1 Graminoid 3.77e-02 0.0911 25.8  0.414
## warmed 1 Graminoid - warmed 2 Graminoid 2.83e-01 0.1212 885.3  2.332

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## warmed 1 Graminoid - ambient 2 Graminoid      3.20e-01 0.1511 197.6  2.119
## warmed 1 Graminoid - warmed 3 Graminoid     -9.50e-02 0.1199 887.9 -0.793
## warmed 1 Graminoid - ambient 3 Graminoid     -5.73e-02 0.1510 195.9 -0.380
## warmed 1 Graminoid - warmed 4 Graminoid     -2.16e-02 0.1202 887.6 -0.180
## warmed 1 Graminoid - ambient 4 Graminoid      1.61e-02 0.1501 193.0  0.107
## warmed 1 Graminoid - warmed 5 Graminoid      9.19e-02 0.1182 888.5  0.777
## warmed 1 Graminoid - ambient 5 Graminoid     1.30e-01 0.1496 188.4  0.866
## warmed 1 Graminoid - warmed 6 Graminoid      5.42e-02 0.1171 888.5  0.463
## warmed 1 Graminoid - ambient 6 Graminoid     9.19e-02 0.1475 178.7  0.623
## warmed 1 Graminoid - warmed 1 Tree           8.74e-01 0.3942 908.8  2.217
## warmed 1 Graminoid - ambient 1 Tree          9.12e-01 0.4036 836.1  2.259
## warmed 1 Graminoid - warmed 2 Tree           1.16e+00 0.4121 909.1  2.806
## warmed 1 Graminoid - ambient 2 Tree          1.19e+00 0.4210 850.9  2.836
## warmed 1 Graminoid - warmed 3 Tree           7.79e-01 0.4117 909.3  1.892
## warmed 1 Graminoid - ambient 3 Tree          8.17e-01 0.4209 853.9  1.940
## warmed 1 Graminoid - warmed 4 Tree           8.52e-01 0.4048 909.0  2.106
## warmed 1 Graminoid - ambient 4 Tree          8.90e-01 0.4137 845.4  2.151
## warmed 1 Graminoid - warmed 5 Tree           9.66e-01 0.4067 909.1  2.374
## warmed 1 Graminoid - ambient 5 Tree          1.00e+00 0.4160 847.7  2.412
## warmed 1 Graminoid - warmed 6 Tree           9.28e-01 0.4064 909.2  2.283
## warmed 1 Graminoid - ambient 6 Tree          9.66e-01 0.4153 848.5  2.326
## ambient 1 Graminoid - warmed 2 Graminoid    2.45e-01 0.1520 199.8  1.611
## ambient 1 Graminoid - ambient 2 Graminoid   2.83e-01 0.1212 885.3  2.332
## ambient 1 Graminoid - warmed 3 Graminoid    -1.33e-01 0.1502 190.0 -0.884
## ambient 1 Graminoid - ambient 3 Graminoid   -9.50e-02 0.1199 887.9 -0.793
## ambient 1 Graminoid - warmed 4 Graminoid    -5.93e-02 0.1515 195.3 -0.392
## ambient 1 Graminoid - ambient 4 Graminoid   -2.16e-02 0.1202 887.6 -0.180
## ambient 1 Graminoid - warmed 5 Graminoid    5.42e-02 0.1488 185.0  0.364
## ambient 1 Graminoid - ambient 5 Graminoid   9.19e-02 0.1182 888.5  0.777
## ambient 1 Graminoid - warmed 6 Graminoid    1.64e-02 0.1491 186.8  0.110
## ambient 1 Graminoid - ambient 6 Graminoid   5.42e-02 0.1171 888.5  0.463
## ambient 1 Graminoid - warmed 1 Tree          8.36e-01 0.4055 832.8  2.062
## ambient 1 Graminoid - ambient 1 Tree         8.74e-01 0.3942 908.8  2.217
## ambient 1 Graminoid - warmed 2 Tree          1.12e+00 0.4231 847.6  2.644
## ambient 1 Graminoid - ambient 2 Tree         1.16e+00 0.4121 909.1  2.806
## ambient 1 Graminoid - warmed 3 Tree          7.41e-01 0.4225 850.1  1.754
## ambient 1 Graminoid - ambient 3 Tree         7.79e-01 0.4117 909.3  1.892
## ambient 1 Graminoid - warmed 4 Tree          8.15e-01 0.4160 841.6  1.958
## ambient 1 Graminoid - ambient 4 Tree         8.52e-01 0.4048 909.0  2.106
## ambient 1 Graminoid - warmed 5 Tree          9.28e-01 0.4176 844.5  2.222
## ambient 1 Graminoid - ambient 5 Tree         9.66e-01 0.4067 909.1  2.374
## ambient 1 Graminoid - warmed 6 Tree          8.90e-01 0.4177 846.4  2.131
## ambient 1 Graminoid - ambient 6 Tree         9.28e-01 0.4064 909.2  2.283
## warmed 2 Graminoid - ambient 2 Graminoid   3.77e-02 0.0911 25.8  0.414
## warmed 2 Graminoid - warmed 3 Graminoid    -3.78e-01 0.1202 889.8 -3.140
## warmed 2 Graminoid - ambient 3 Graminoid   -3.40e-01 0.1517 197.4 -2.241
## warmed 2 Graminoid - warmed 4 Graminoid    -3.04e-01 0.1194 888.1 -2.548
## warmed 2 Graminoid - ambient 4 Graminoid   -2.66e-01 0.1499 190.9 -1.777
## warmed 2 Graminoid - warmed 5 Graminoid    -1.91e-01 0.1177 889.6 -1.620
## warmed 2 Graminoid - ambient 5 Graminoid   -1.53e-01 0.1497 187.4 -1.022
## warmed 2 Graminoid - warmed 6 Graminoid    -2.28e-01 0.1164 887.7 -1.963
## warmed 2 Graminoid - ambient 6 Graminoid   -1.91e-01 0.1474 177.7 -1.294
## warmed 2 Graminoid - warmed 1 Tree          5.91e-01 0.4126 909.3  1.433
## warmed 2 Graminoid - ambient 1 Tree         6.29e-01 0.4218 854.7  1.491

```

## warmed 2 Graminoid - warmed 2 Tree	8.74e-01	0.3942	908.8	2.217
## warmed 2 Graminoid - ambient 2 Tree	9.12e-01	0.4036	836.1	2.259
## warmed 2 Graminoid - warmed 3 Tree	4.96e-01	0.4121	909.3	1.204
## warmed 2 Graminoid - ambient 3 Tree	5.34e-01	0.4214	855.7	1.267
## warmed 2 Graminoid - warmed 4 Tree	5.70e-01	0.4048	909.1	1.407
## warmed 2 Graminoid - ambient 4 Tree	6.07e-01	0.4139	847.3	1.468
## warmed 2 Graminoid - warmed 5 Tree	6.83e-01	0.4068	909.2	1.679
## warmed 2 Graminoid - ambient 5 Tree	7.21e-01	0.4163	849.5	1.732
## warmed 2 Graminoid - warmed 6 Tree	6.45e-01	0.4065	909.3	1.588
## warmed 2 Graminoid - ambient 6 Tree	6.83e-01	0.4155	850.5	1.644
## ambient 2 Graminoid - warmed 3 Graminoid	-4.15e-01	0.1500	189.3	-2.769
## ambient 2 Graminoid - ambient 3 Graminoid	-3.78e-01	0.1202	889.8	-3.140
## ambient 2 Graminoid - warmed 4 Graminoid	-3.42e-01	0.1504	191.1	-2.274
## ambient 2 Graminoid - ambient 4 Graminoid	-3.04e-01	0.1194	888.1	-2.548
## ambient 2 Graminoid - warmed 5 Graminoid	-2.28e-01	0.1479	181.8	-1.544
## ambient 2 Graminoid - ambient 5 Graminoid	-1.91e-01	0.1177	889.6	-1.620
## ambient 2 Graminoid - warmed 6 Graminoid	-2.66e-01	0.1481	183.6	-1.797
## ambient 2 Graminoid - ambient 6 Graminoid	-2.28e-01	0.1164	887.7	-1.963
## ambient 2 Graminoid - warmed 1 Tree	5.54e-01	0.4233	852.1	1.308
## ambient 2 Graminoid - ambient 1 Tree	5.91e-01	0.4126	909.3	1.433
## ambient 2 Graminoid - warmed 2 Tree	8.36e-01	0.4055	832.8	2.062
## ambient 2 Graminoid - ambient 2 Tree	8.74e-01	0.3942	908.8	2.217
## ambient 2 Graminoid - warmed 3 Tree	4.59e-01	0.4226	852.1	1.085
## ambient 2 Graminoid - ambient 3 Tree	4.96e-01	0.4121	909.3	1.204
## ambient 2 Graminoid - warmed 4 Tree	5.32e-01	0.4159	843.7	1.279
## ambient 2 Graminoid - ambient 4 Tree	5.70e-01	0.4048	909.1	1.407
## ambient 2 Graminoid - warmed 5 Tree	6.45e-01	0.4175	846.6	1.546
## ambient 2 Graminoid - ambient 5 Tree	6.83e-01	0.4068	909.2	1.679
## ambient 2 Graminoid - warmed 6 Tree	6.08e-01	0.4176	848.7	1.455
## ambient 2 Graminoid - ambient 6 Tree	6.45e-01	0.4065	909.3	1.588
## warmed 3 Graminoid - ambient 3 Graminoid	3.77e-02	0.0911	25.8	0.414
## warmed 3 Graminoid - warmed 4 Graminoid	7.34e-02	0.1191	887.5	0.616
## warmed 3 Graminoid - ambient 4 Graminoid	1.11e-01	0.1489	186.3	0.747
## warmed 3 Graminoid - warmed 5 Graminoid	1.87e-01	0.1166	888.2	1.603
## warmed 3 Graminoid - ambient 5 Graminoid	2.25e-01	0.1480	180.2	1.518
## warmed 3 Graminoid - warmed 6 Graminoid	1.49e-01	0.1157	889.1	1.290
## warmed 3 Graminoid - ambient 6 Graminoid	1.87e-01	0.1460	170.9	1.280
## warmed 3 Graminoid - warmed 1 Tree	9.69e-01	0.4123	909.2	2.350
## warmed 3 Graminoid - ambient 1 Tree	1.01e+00	0.4212	850.4	2.390
## warmed 3 Graminoid - warmed 2 Tree	1.25e+00	0.4121	909.0	3.037
## warmed 3 Graminoid - ambient 2 Tree	1.29e+00	0.4209	848.2	3.063
## warmed 3 Graminoid - warmed 3 Tree	8.74e-01	0.3942	908.8	2.217
## warmed 3 Graminoid - ambient 3 Tree	9.12e-01	0.4036	836.1	2.259
## warmed 3 Graminoid - warmed 4 Tree	9.47e-01	0.4047	908.9	2.341
## warmed 3 Graminoid - ambient 4 Tree	9.85e-01	0.4135	843.3	2.382
## warmed 3 Graminoid - warmed 5 Tree	1.06e+00	0.4065	909.0	2.609
## warmed 3 Graminoid - ambient 5 Tree	1.10e+00	0.4157	845.5	2.643
## warmed 3 Graminoid - warmed 6 Tree	1.02e+00	0.4063	909.1	2.518
## warmed 3 Graminoid - ambient 6 Tree	1.06e+00	0.4150	846.2	2.556
## ambient 3 Graminoid - warmed 4 Graminoid	3.57e-02	0.1510	194.4	0.236
## ambient 3 Graminoid - ambient 4 Graminoid	7.34e-02	0.1191	887.5	0.616
## ambient 3 Graminoid - warmed 5 Graminoid	1.49e-01	0.1479	182.6	1.009
## ambient 3 Graminoid - ambient 5 Graminoid	1.87e-01	0.1166	888.2	1.603
## ambient 3 Graminoid - warmed 6 Graminoid	1.11e-01	0.1484	184.6	0.751

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## ambient 3 Graminoid - ambient 6 Graminoid 1.49e-01 0.1157 889.1 1.290
## ambient 3 Graminoid - warmed 1 Tree 9.31e-01 0.4233 848.4 2.200
## ambient 3 Graminoid - ambient 1 Tree 9.69e-01 0.4123 909.2 2.350
## ambient 3 Graminoid - warmed 2 Tree 1.21e+00 0.4233 846.0 2.868
## ambient 3 Graminoid - ambient 2 Tree 1.25e+00 0.4121 909.0 3.037
## ambient 3 Graminoid - warmed 3 Tree 8.36e-01 0.4055 832.8 2.062
## ambient 3 Graminoid - ambient 3 Tree 8.74e-01 0.3942 908.8 2.217
## ambient 3 Graminoid - warmed 4 Tree 9.10e-01 0.4161 840.4 2.186
## ambient 3 Graminoid - ambient 4 Tree 9.47e-01 0.4047 908.9 2.341
## ambient 3 Graminoid - warmed 5 Tree 1.02e+00 0.4175 843.3 2.450
## ambient 3 Graminoid - ambient 5 Tree 1.06e+00 0.4065 909.0 2.609
## ambient 3 Graminoid - warmed 6 Tree 9.85e-01 0.4177 845.1 2.359
## ambient 3 Graminoid - ambient 6 Tree 1.02e+00 0.4063 909.1 2.518
## warmed 4 Graminoid - ambient 4 Graminoid 3.77e-02 0.0911 25.8 0.414
## warmed 4 Graminoid - warmed 5 Graminoid 1.14e-01 0.1162 885.7 0.976
## warmed 4 Graminoid - ambient 5 Graminoid 1.51e-01 0.1488 183.8 1.017
## warmed 4 Graminoid - warmed 6 Graminoid 7.58e-02 0.1150 886.7 0.659
## warmed 4 Graminoid - ambient 6 Graminoid 1.13e-01 0.1466 173.5 0.774
## warmed 4 Graminoid - warmed 1 Tree 8.95e-01 0.4193 909.3 2.136
## warmed 4 Graminoid - ambient 1 Tree 9.33e-01 0.4284 858.4 2.178
## warmed 4 Graminoid - warmed 2 Tree 1.18e+00 0.4188 909.3 2.813
## warmed 4 Graminoid - ambient 2 Tree 1.22e+00 0.4278 856.3 2.842
## warmed 4 Graminoid - warmed 3 Tree 8.00e-01 0.4187 909.3 1.912
## warmed 4 Graminoid - ambient 3 Tree 8.38e-01 0.4280 859.8 1.958
## warmed 4 Graminoid - warmed 4 Tree 8.74e-01 0.3942 908.8 2.217
## warmed 4 Graminoid - ambient 4 Tree 9.12e-01 0.4036 836.1 2.259
## warmed 4 Graminoid - warmed 5 Tree 9.87e-01 0.4135 909.3 2.388
## warmed 4 Graminoid - ambient 5 Tree 1.03e+00 0.4229 854.2 2.424
## warmed 4 Graminoid - warmed 6 Tree 9.50e-01 0.4131 909.3 2.299
## warmed 4 Graminoid - ambient 6 Tree 9.87e-01 0.4221 854.9 2.339
## ambient 4 Graminoid - warmed 5 Graminoid 7.58e-02 0.1465 178.0 0.517
## ambient 4 Graminoid - ambient 5 Graminoid 1.14e-01 0.1162 885.7 0.976
## ambient 4 Graminoid - warmed 6 Graminoid 3.80e-02 0.1468 179.2 0.259
## ambient 4 Graminoid - ambient 6 Graminoid 7.58e-02 0.1150 886.7 0.659
## ambient 4 Graminoid - warmed 1 Tree 8.58e-01 0.4297 856.3 1.996
## ambient 4 Graminoid - ambient 1 Tree 8.95e-01 0.4193 909.3 2.136
## ambient 4 Graminoid - warmed 2 Tree 1.14e+00 0.4294 854.0 2.655
## ambient 4 Graminoid - ambient 2 Tree 1.18e+00 0.4188 909.3 2.813
## ambient 4 Graminoid - warmed 3 Tree 7.63e-01 0.4290 856.9 1.778
## ambient 4 Graminoid - ambient 3 Tree 8.00e-01 0.4187 909.3 1.912
## ambient 4 Graminoid - warmed 4 Tree 8.36e-01 0.4055 832.8 2.062
## ambient 4 Graminoid - ambient 4 Tree 8.74e-01 0.3942 908.8 2.217
## ambient 4 Graminoid - warmed 5 Tree 9.50e-01 0.4239 851.9 2.240
## ambient 4 Graminoid - ambient 5 Tree 9.87e-01 0.4135 909.3 2.388
## ambient 4 Graminoid - warmed 6 Tree 9.12e-01 0.4240 853.5 2.151
## ambient 4 Graminoid - ambient 6 Tree 9.50e-01 0.4131 909.3 2.299
## warmed 5 Graminoid - ambient 5 Graminoid 3.77e-02 0.0911 25.8 0.414
## warmed 5 Graminoid - warmed 6 Graminoid -3.77e-02 0.1132 886.8 -0.333
## warmed 5 Graminoid - ambient 6 Graminoid -6.40e-06 0.1440 164.6 0.000
## warmed 5 Graminoid - warmed 1 Tree 7.82e-01 0.4162 909.3 1.879
## warmed 5 Graminoid - ambient 1 Tree 8.20e-01 0.4250 855.4 1.929
## warmed 5 Graminoid - warmed 2 Tree 1.06e+00 0.4159 909.2 2.560
## warmed 5 Graminoid - ambient 2 Tree 1.10e+00 0.4245 853.3 2.597
## warmed 5 Graminoid - warmed 3 Tree 6.87e-01 0.4155 909.3 1.653

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## warmed 5 Graminoid - ambient 3 Tree	7.25e-01	0.4245	856.8	1.707
## warmed 5 Graminoid - warmed 4 Tree	7.60e-01	0.4084	909.1	1.862
## warmed 5 Graminoid - ambient 4 Tree	7.98e-01	0.4171	848.8	1.913
## warmed 5 Graminoid - warmed 5 Tree	8.74e-01	0.3942	908.8	2.217
## warmed 5 Graminoid - ambient 5 Tree	9.12e-01	0.4036	836.1	2.259
## warmed 5 Graminoid - warmed 6 Tree	8.36e-01	0.4101	909.3	2.039
## warmed 5 Graminoid - ambient 6 Tree	8.74e-01	0.4187	851.8	2.087
## ambient 5 Graminoid - warmed 6 Graminoid	-7.55e-02	0.1465	175.9	-0.515
## ambient 5 Graminoid - ambient 6 Graminoid	-3.77e-02	0.1132	886.8	-0.333
## ambient 5 Graminoid - warmed 1 Tree	7.44e-01	0.4271	852.7	1.742
## ambient 5 Graminoid - ambient 1 Tree	7.82e-01	0.4162	909.3	1.879
## ambient 5 Graminoid - warmed 2 Tree	1.03e+00	0.4269	850.3	2.405
## ambient 5 Graminoid - ambient 2 Tree	1.06e+00	0.4159	909.2	2.560
## ambient 5 Graminoid - warmed 3 Tree	6.49e-01	0.4263	853.2	1.523
## ambient 5 Graminoid - ambient 3 Tree	6.87e-01	0.4155	909.3	1.653
## ambient 5 Graminoid - warmed 4 Tree	7.23e-01	0.4198	845.2	1.721
## ambient 5 Graminoid - ambient 4 Tree	7.60e-01	0.4084	909.1	1.862
## ambient 5 Graminoid - warmed 5 Tree	8.36e-01	0.4055	832.8	2.062
## ambient 5 Graminoid - ambient 5 Tree	8.74e-01	0.3942	908.8	2.217
## ambient 5 Graminoid - warmed 6 Tree	7.98e-01	0.4214	849.8	1.894
## ambient 5 Graminoid - ambient 6 Tree	8.36e-01	0.4101	909.3	2.039
## warmed 6 Graminoid - ambient 6 Graminoid	3.77e-02	0.0911	25.8	0.414
## warmed 6 Graminoid - warmed 1 Tree	8.20e-01	0.4159	909.2	1.971
## warmed 6 Graminoid - ambient 1 Tree	8.57e-01	0.4251	854.2	2.017
## warmed 6 Graminoid - warmed 2 Tree	1.10e+00	0.4155	909.1	2.653
## warmed 6 Graminoid - ambient 2 Tree	1.14e+00	0.4246	852.2	2.685
## warmed 6 Graminoid - warmed 3 Tree	7.25e-01	0.4153	909.3	1.745
## warmed 6 Graminoid - ambient 3 Tree	7.62e-01	0.4246	855.5	1.795
## warmed 6 Graminoid - warmed 4 Tree	7.98e-01	0.4081	909.0	1.956
## warmed 6 Graminoid - ambient 4 Tree	8.36e-01	0.4172	847.3	2.003
## warmed 6 Graminoid - warmed 5 Tree	9.12e-01	0.4101	909.1	2.223
## warmed 6 Graminoid - ambient 5 Tree	9.49e-01	0.4196	849.7	2.262
## warmed 6 Graminoid - warmed 6 Tree	8.74e-01	0.3942	908.8	2.217
## warmed 6 Graminoid - ambient 6 Tree	9.12e-01	0.4036	836.1	2.259
## ambient 6 Graminoid - warmed 1 Tree	7.82e-01	0.4264	850.5	1.834
## ambient 6 Graminoid - ambient 1 Tree	8.20e-01	0.4159	909.2	1.971
## ambient 6 Graminoid - warmed 2 Tree	1.06e+00	0.4261	848.2	2.498
## ambient 6 Graminoid - ambient 2 Tree	1.10e+00	0.4155	909.1	2.653
## ambient 6 Graminoid - warmed 3 Tree	6.87e-01	0.4256	850.9	1.614
## ambient 6 Graminoid - ambient 3 Tree	7.25e-01	0.4153	909.3	1.745
## ambient 6 Graminoid - warmed 4 Tree	7.60e-01	0.4190	842.6	1.815
## ambient 6 Graminoid - ambient 4 Tree	7.98e-01	0.4081	909.0	1.956
## ambient 6 Graminoid - warmed 5 Tree	8.74e-01	0.4206	845.7	2.078
## ambient 6 Graminoid - ambient 5 Tree	9.12e-01	0.4101	909.1	2.223
## ambient 6 Graminoid - warmed 6 Tree	8.36e-01	0.4055	832.8	2.062
## ambient 6 Graminoid - ambient 6 Tree	8.74e-01	0.3942	908.8	2.217
## warmed 1 Tree - ambient 1 Tree	3.77e-02	0.0911	25.8	0.414
## warmed 1 Tree - warmed 2 Tree	2.83e-01	0.1212	885.3	2.332
## warmed 1 Tree - ambient 2 Tree	3.20e-01	0.1511	197.6	2.119
## warmed 1 Tree - warmed 3 Tree	-9.50e-02	0.1199	887.9	-0.793
## warmed 1 Tree - ambient 3 Tree	-5.73e-02	0.1510	195.9	-0.380
## warmed 1 Tree - warmed 4 Tree	-2.16e-02	0.1202	887.6	-0.180
## warmed 1 Tree - ambient 4 Tree	1.61e-02	0.1501	193.0	0.107
## warmed 1 Tree - warmed 5 Tree	9.19e-02	0.1182	888.5	0.777

```

## warmed 1 Tree - ambient 5 Tree      1.30e-01 0.1496 188.4  0.866
## warmed 1 Tree - warmed 6 Tree     5.42e-02 0.1171 888.5  0.463
## warmed 1 Tree - ambient 6 Tree     9.19e-02 0.1475 178.7  0.623
## ambient 1 Tree - warmed 2 Tree    2.45e-01 0.1520 199.8  1.611
## ambient 1 Tree - ambient 2 Tree   2.83e-01 0.1212 885.3  2.332
## ambient 1 Tree - warmed 3 Tree   -1.33e-01 0.1502 190.0  -0.884
## ambient 1 Tree - ambient 3 Tree   -9.50e-02 0.1199 887.9  -0.793
## ambient 1 Tree - warmed 4 Tree   -5.93e-02 0.1515 195.3  -0.392
## ambient 1 Tree - ambient 4 Tree   -2.16e-02 0.1202 887.6  -0.180
## ambient 1 Tree - warmed 5 Tree   5.42e-02 0.1488 185.0  0.364
## ambient 1 Tree - ambient 5 Tree   9.19e-02 0.1182 888.5  0.777
## ambient 1 Tree - warmed 6 Tree   1.64e-02 0.1491 186.8  0.110
## ambient 1 Tree - ambient 6 Tree   5.42e-02 0.1171 888.5  0.463
## warmed 2 Tree - ambient 2 Tree   3.77e-02 0.0911 25.8   0.414
## warmed 2 Tree - warmed 3 Tree   -3.78e-01 0.1202 889.8  -3.140
## warmed 2 Tree - ambient 3 Tree   -3.40e-01 0.1517 197.4  -2.241
## warmed 2 Tree - warmed 4 Tree   -3.04e-01 0.1194 888.1  -2.548
## warmed 2 Tree - ambient 4 Tree   -2.66e-01 0.1499 190.9  -1.777
## warmed 2 Tree - warmed 5 Tree   -1.91e-01 0.1177 889.6  -1.620
## warmed 2 Tree - ambient 5 Tree   -1.53e-01 0.1497 187.4  -1.022
## warmed 2 Tree - warmed 6 Tree   -2.28e-01 0.1164 887.7  -1.963
## warmed 2 Tree - ambient 6 Tree   -1.91e-01 0.1474 177.7  -1.294
## ambient 2 Tree - warmed 3 Tree   -4.15e-01 0.1500 189.3  -2.769
## ambient 2 Tree - ambient 3 Tree   -3.78e-01 0.1202 889.8  -3.140
## ambient 2 Tree - warmed 4 Tree   -3.42e-01 0.1504 191.1  -2.274
## ambient 2 Tree - ambient 4 Tree   -3.04e-01 0.1194 888.1  -2.548
## ambient 2 Tree - warmed 5 Tree   -2.28e-01 0.1479 181.8  -1.544
## ambient 2 Tree - ambient 5 Tree   -1.91e-01 0.1177 889.6  -1.620
## ambient 2 Tree - warmed 6 Tree   -2.66e-01 0.1481 183.6  -1.797
## ambient 2 Tree - ambient 6 Tree   -2.28e-01 0.1164 887.7  -1.963
## warmed 3 Tree - ambient 3 Tree   3.77e-02 0.0911 25.8   0.414
## warmed 3 Tree - warmed 4 Tree   7.34e-02 0.1191 887.5  0.616
## warmed 3 Tree - ambient 4 Tree   1.11e-01 0.1489 186.3  0.747
## warmed 3 Tree - warmed 5 Tree   1.87e-01 0.1166 888.2  1.603
## warmed 3 Tree - ambient 5 Tree   2.25e-01 0.1480 180.2  1.518
## warmed 3 Tree - warmed 6 Tree   1.49e-01 0.1157 889.1  1.290
## warmed 3 Tree - ambient 6 Tree   1.87e-01 0.1460 170.9  1.280
## ambient 3 Tree - warmed 4 Tree   3.57e-02 0.1510 194.4  0.236
## ambient 3 Tree - ambient 4 Tree   7.34e-02 0.1191 887.5  0.616
## ambient 3 Tree - warmed 5 Tree   1.49e-01 0.1479 182.6  1.009
## ambient 3 Tree - ambient 5 Tree   1.87e-01 0.1166 888.2  1.603
## ambient 3 Tree - warmed 6 Tree   1.11e-01 0.1484 184.6  0.751
## ambient 3 Tree - ambient 6 Tree   1.49e-01 0.1157 889.1  1.290
## warmed 4 Tree - ambient 4 Tree   3.77e-02 0.0911 25.8   0.414
## warmed 4 Tree - warmed 5 Tree   1.14e-01 0.1162 885.7  0.976
## warmed 4 Tree - ambient 5 Tree   1.51e-01 0.1488 183.8  1.017
## warmed 4 Tree - warmed 6 Tree   7.58e-02 0.1150 886.7  0.659
## warmed 4 Tree - ambient 6 Tree   1.13e-01 0.1466 173.5  0.774
## ambient 4 Tree - warmed 5 Tree   7.58e-02 0.1465 178.0  0.517
## ambient 4 Tree - ambient 5 Tree   1.14e-01 0.1162 885.7  0.976
## ambient 4 Tree - warmed 6 Tree   3.80e-02 0.1468 179.2  0.259
## ambient 4 Tree - ambient 6 Tree   7.58e-02 0.1150 886.7  0.659
## warmed 5 Tree - ambient 5 Tree   3.77e-02 0.0911 25.8   0.414
## warmed 5 Tree - warmed 6 Tree   -3.77e-02 0.1132 886.8  -0.333

```

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## warmed 5 Tree - ambient 6 Tree          -6.40e-06 0.1440 164.6  0.000
## ambient 5 Tree - warmed 6 Tree         -7.55e-02 0.1465 175.9 -0.515
## ambient 5 Tree - ambient 6 Tree        -3.77e-02 0.1132 886.8 -0.333
## warmed 6 Tree - ambient 6 Tree         3.77e-02 0.0911 25.8  0.414
## p.value
## 1.0000
## 0.9763
## 0.9943
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## <.0001
## 0.0002
## <.0001
## 0.0042
## 0.0080
## 0.0040
## 0.0065
## 0.0003
## 0.0006
## 0.0006
## 0.0013
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9990
## 0.9983
## 0.9078
## 0.8911
## 1.0000
## 1.0000
## 0.9997
## 0.9995
## 0.9948
## 0.9924
## 0.9979
## 0.9966
## 1.0000
## 0.9763

```



```
##  0.1250
##  <.0001
##  0.0002
##  0.2030
##  0.2549
##  0.1615
##  0.1948
##  0.0256
##  0.0400
##  0.0474
##  0.0663
##  0.7970
##  0.9964
##  1.0000
##  1.0000
##  0.2438
##  0.8622
##  0.6564
##  0.9870
##  0.9949
##  1.0000
##  0.9576
##  0.9999
##  1.0000
##  1.0000
##  0.9990
##  0.9983
##  1.0000
##  1.0000
##  1.0000
##  1.0000
##  1.0000
##  1.0000
##  0.7877
##  0.4877
##  0.9809
##  0.9170
##  1.0000
##  1.0000
##  0.9998
##  0.9991
##  0.2895
##  0.0941
##  0.0011
##  <.0001
##  0.4966
##  0.2030
##  0.4080
##  0.1615
##  0.1115
##  0.0256
##  0.1797
```



```
## 1.0000
## 1.0000
## 0.9957
## 0.9935
## 0.7708
## 0.7467
## 0.9990
## 0.9983
## 0.9962
## 0.9942
## 0.9687
## 0.9601
## 0.9834
## 0.9774
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.0044
## 0.0005
## 0.0001
## <.0001
## 0.0011
## <.0001
## 0.0094
## 0.0014
## 0.0010
## 0.0001
## 0.0021
## 0.0002
## 1.0000
## 1.0000
## 1.0000
## 0.9990
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9990
## 0.9957
## 0.8748
## 0.7708
## 0.9998
## 0.9990
## 0.9992
## 0.9962
## 0.9896
## 0.9687
```



```
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9771
## 0.9697
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9990
## 0.9983
## 0.9999
## 0.9998
## 1.0000
## 1.0000
## 0.0373
## 0.0061
## 0.0006
## <.0001
## 0.0837
## 0.0158
## 0.0673
## 0.0136
## 0.0011
## <.0001
## 0.0189
## 0.0025
## 1.0000
## 1.0000
## 1.0000
## 0.9987
## 0.9964
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9927
## 0.9771
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9998
## 0.9990
## 1.0000
## 0.9999
## 1.0000
## 0.0026
```

```
## 0.0052
## <.0001
## <.0001
## 0.0070
## 0.0136
## 0.0063
## 0.0107
## 0.0005
## 0.0011
## <.0001
## 0.0002
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9998
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9999
## 0.9582
## 0.9479
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9999
## 0.9988
## 0.9981
## 0.9990
## 0.9983
## 0.0187
## 0.0026
## 0.0003
## <.0001
## 0.0444
## 0.0070
## 0.0362
## 0.0063
## 0.0044
## 0.0005
## 0.0011
## <.0001
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9999
## 0.9998
## 1.0000
```



```
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9899
## 0.9859
## 0.7680
## 0.7449
## 0.9996
## 0.9993
## 0.9961
## 0.9941
## 0.9686
## 0.9603
## 0.9831
## 0.9772
## 1.0000
## 0.9763
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9974
## 0.9899
## 0.8718
## 0.7680
## 0.9999
## 0.9996
## 0.9992
## 0.9961
## 0.9893
## 0.9686
## 0.9951
## 0.9831
## 1.0000
## 0.4877
## 0.9849
## 0.9170
## 0.9999
## 1.0000
## 1.0000
## 0.9991
## 1.0000
## 1.0000
## 1.0000
## 0.9899
## 0.9859
## 1.0000
## 1.0000
## 1.0000
```



```
## 0.9974
## 0.9899
## 0.9921
## 0.9749
## 0.9503
## 0.8896
## 0.9715
## 0.9285
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9949
## 0.9926
## 0.7629
## 0.7406
## 0.9995
## 0.9992
## 0.9899
## 0.9859
## 0.9658
## 0.9573
## 0.9812
## 0.9750
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9987
## 0.9949
## 0.8654
## 0.7629
## 0.9999
## 0.9995
## 0.9974
## 0.9899
## 0.9878
## 0.9658
## 0.9942
## 0.9812
## 1.0000
## 1.0000
## 1.0000
## 0.9997
## 0.9994
## 0.9121
## 0.8956
## 1.0000
## 1.0000
## 0.9997
## 0.9995
## 0.9899
## 0.9859
```

```
## 0.9980
## 0.9967
## 1.0000
## 1.0000
## 1.0000
## 0.9997
## 0.9619
## 0.9121
## 1.0000
## 1.0000
## 1.0000
## 0.9997
## 0.9974
## 0.9899
## 0.9996
## 0.9980
## 1.0000
## 0.9990
## 0.9984
## 0.8669
## 0.8484
## 0.9999
## 0.9999
## 0.9992
## 0.9986
## 0.9894
## 0.9855
## 0.9899
## 0.9859
## 0.9998
## 0.9990
## 0.9354
## 0.8669
## 1.0000
## 0.9999
## 0.9999
## 0.9992
## 0.9970
## 0.9894
## 0.9974
## 0.9899
## 1.0000
## 0.9763
## 0.9943
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9763
```



```

## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 48 estimates

```

```
emmeans(mod11au, list(pairwise ~ state), adjust = "tukey")
```

```

## $`emmeans of state`
##   state    emmean     SE  df lower.CL upper.CL
##   warmed    -2.76 0.126 276    -3.01    -2.52
##   ambient    -2.80 0.125 271    -3.05    -2.56
##
## Results are averaged over the levels of: growth_habit, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state`
##   1           estimate     SE  df t.ratio p.value
##   warmed - ambient    0.0377 0.0911 25.8 0.414   0.6820
##
## Results are averaged over the levels of: growth_habit, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.

```

```
emmeans(mod11au, list(pairwise ~ factor(year_factor)), adjust = "tukey")
```

```

## $`emmeans of year_factor`
##   year_factor    emmean     SE  df lower.CL upper.CL
##   1             -2.73 0.142 697    -3.01    -2.45
##   2             -3.01 0.145 704    -3.30    -2.73
##   3             -2.64 0.137 673    -2.91    -2.37
##   4             -2.71 0.138 667    -2.98    -2.44
##   5             -2.82 0.137 655    -3.09    -2.55
##   6             -2.79 0.136 664    -3.05    -2.52
##
## Results are averaged over the levels of: state, growth_habit
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of year_factor`
##   1   estimate     SE  df t.ratio p.value
##   1 - 2    0.2826 0.121 885   2.332  0.1824
##   1 - 3   -0.0950 0.120 888  -0.793  0.9688
##   1 - 4   -0.0216 0.120 888  -0.180  1.0000
##   1 - 5    0.0919 0.118 889   0.777  0.9713
##   1 - 6    0.0542 0.117 888   0.463  0.9974
##   2 - 3   -0.3776 0.120 890  -3.140  0.0215
##   2 - 4   -0.3042 0.119 888  -2.548  0.1116
##   2 - 5   -0.1907 0.118 890  -1.620  0.5857
##   2 - 6   -0.2284 0.116 888  -1.963  0.3647
##   3 - 4    0.0734 0.119 887   0.616  0.9899
##   3 - 5    0.1869 0.117 888   1.603  0.5970

```

```

## 3 - 6  0.1492 0.116 889  1.290  0.7906
## 4 - 5  0.1135 0.116 886  0.976  0.9254
## 4 - 6  0.0758 0.115 887  0.659  0.9863
## 5 - 6 -0.0377 0.113 887 -0.333  0.9995
##
## Results are averaged over the levels of: state, growth_habit
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 6 estimates

emmeans(mod11au, list(pairwise ~ growth_habit), adjust = "tukey")

## $`emmeans of growth_habit`
##   growth_habit emmean      SE   df lower.CL upper.CL
##   Forb        -2.32 0.0546 52.6   -2.43   -2.21
##   Graminoid   -3.51 0.2137 877.9   -3.93   -3.09
##   Tree        -2.22 0.0617 93.4   -2.34   -2.09
## 
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of growth_habit`
##   1           estimate      SE   df t.ratio p.value
##   Forb -          1.195 0.2158 901  5.538 <.0001
##   Forb - Graminoid -0.099 0.0708 909 -1.399  0.5001
##   Forb - Tree     0.775 0.3926 909  1.973  0.1988
##   - Graminoid   -1.294 0.2183 906 -5.929 <.0001
##   - Tree        -0.420 0.4436 907 -0.947  0.7792
##   Graminoid - Tree 0.874 0.3942 909  2.217  0.1194
## 
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 4 estimates

# New version of our model incorporating interaction term and species within year
# so that there is a separate intercept and slope for each species. The issue
# here is that there are some species that are not found each year. Easiest to
# remove those from another version of this dataframe before running below.
# Otherwise, it's not a balanced design. updated mod4
mod12u <- lmer(log(relabun) ~ state * factor(year_factor) + (1 + factor(year_factor) | species), comp_umbs_spp)

## boundary (singular) fit: see ?isSingular

# So another version of this model would include the interaction but not include
# the nesting (and thus would assume that species aren't observed ea yr) updated
# mod5
mod13u <- lmer(log(relabun) ~ state * factor(year_factor) + (1 | species), comp_umbs_spp)

```

```

# All the models ran:
mod1u <- lmer(log(relabun) ~ state * year_factor + insecticide * year_factor + (1 |
  species) + (1 | plot), comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod2u <- lmer(log(relabun) ~ state * year_factor + insecticide * year_factor + (1 |
  species), comp_umbs_spp, REML = FALSE)
mod3u <- lmer(log(relabun) ~ state * year_factor + (1 | species), comp_umbs_spp,
  REML = FALSE)
mod4u <- lmer(log(relabun) ~ state * year_factor + insecticide + (1 | species) +
  (1 | plot), comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod5u <- lmer(log(relabun) ~ state + year_factor + (1 | species), comp_umbs_spp,
  REML = FALSE)
mod6u <- lmer(log(relabun) ~ state + year_factor + (1 | species) + (1 + year_factor |
  plot), comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod7u <- lmer(log(relabun) ~ state + species + (1 + factor(year_factor) | plot),
  comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -8.0e+00

mod7au <- lmer(log(relabun) ~ state + species + factor(year_factor) + (1 | plot),
  comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod7bu <- lmer(log(relabun) ~ state * factor(year_factor) + species + (1 | plot),
  comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod7cu <- lmer(log(relabun) ~ state + species + factor(year_factor) + insecticide +
  (1 | plot), comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod8u <- lmer(log(relabun) ~ state * origin + (1 + factor(year_factor) | plot), comp_umbs_spp,
  REML = FALSE)

## boundary (singular) fit: see ?isSingular

```

```

mod9u <- lmer(log(relabun) ~ state + origin + (1 + factor(year_factor) | plot), comp_umbs_spp,
               REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod9au <- lmer(log(relabun) ~ state + origin + factor(year_factor) + (1 | plot),
                comp_umbs_spp, REML = FALSE)
mod10u <- lmer(log(relabun) ~ state * growth_habit + (1 + factor(year_factor) | plot),
                comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod11u <- lmer(log(relabun) ~ state + growth_habit + (1 + factor(year_factor) | plot),
                comp_umbs_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod11au <- lmer(log(relabun) ~ state + growth_habit + factor(year_factor) + (1 |
    plot), comp_umbs_spp, REML = FALSE)
mod12u <- lmer(log(relabun) ~ state * factor(year_factor) + (1 + factor(year_factor) |
    species), comp_umbs_spp)

## boundary (singular) fit: see ?isSingular

mod13u <- lmer(log(relabun) ~ state * factor(year_factor) + (1 | species), comp_umbs_spp)
AICctab(mod1u, mod2u, mod3u, mod4u, mod5u, mod6u, mod7u, mod7au, mod7bu, mod7cu,
        mod8u, mod9u, mod9au, mod10u, mod11u, mod11au, mod13u, weights = T) #mod7a is the best fitting model

##          dAICc df weight
## mod7au     0.0 24 0.684
## mod7cu     1.7 25 0.290
## mod7bu     6.5 29 0.026
## mod5u     34.1 5 <0.001
## mod3u     35.5 6 <0.001
## mod2u     38.6 8 <0.001
## mod4u     39.2 8 <0.001
## mod6u     40.2 8 <0.001
## mod1u     40.6 9 <0.001
## mod7u     47.3 39 <0.001
## mod13u    64.2 14 <0.001
## mod9au   235.7 12 <0.001
## mod11au   253.0 12 <0.001
## mod9u    275.2 27 <0.001
## mod8u    280.9 30 <0.001
## mod11u   293.8 27 <0.001
## mod10u   299.2 30 <0.001

AICctab(mod7au, mod7cu, weights = T)

```

```

##          dAICc df weight
## mod7au   0.0  24  0.7
## mod7cu   1.7  25  0.3

summary(mod7au)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(relabun) ~ state + species + factor(year_factor) + (1 | plot)
## Data: comp_umbs_spp
##
##          AIC      BIC  logLik deviance df.resid
## 2346.9  2462.2 -1149.5   2298.9     875
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -3.2474 -0.7044  0.0280  0.7063  2.6539
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0000   0.0000
## Residual           0.7553   0.8691
## Number of obs: 899, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept) -3.10745  0.34107 899.00000 -9.111 < 2e-16 ***
## stateambient -0.01567  0.05839 899.00000 -0.268 0.78846  
## speciesAnsp  -0.49583  0.40091 899.00000 -1.237 0.21649  
## speciesApan  0.55769  0.46483 899.00000  1.200 0.23054  
## speciesAssp  -0.01418  0.36498 899.00000 -0.039 0.96903  
## speciesAsun  -0.22506  0.69954 899.00000 -0.322 0.74773  
## speciesCape  0.75918  0.34226 899.00000  2.218 0.02680 *   
## speciesCest  1.68795  0.33791 899.00000  4.995 7.06e-07 ***
## speciesDasp  1.00785  0.33901 899.00000  2.973 0.00303 **  
## speciesFrve  0.27617  0.37191 899.00000  0.743 0.45793  
## speciesHisp  -0.45271  0.38135 899.00000 -1.187 0.23549  
## speciesHype  -0.17211  0.34724 899.00000 -0.496 0.62027  
## speciesPosp  0.91835  0.33807 899.00000  2.716 0.00673 **  
## speciesPtaq  1.03503  0.34184 899.00000  3.028 0.00253 **  
## speciesRuac  0.64773  0.34103 899.00000  1.899 0.05784 .  
## speciesSosp  0.23844  0.37741 899.00000  0.632 0.52770  
## speciesSyla  -0.08720  0.42122 899.00000 -0.207 0.83605  
## factor(year_factor)2 -0.24404  0.10419 899.00000 -2.342 0.01939 * 
## factor(year_factor)3  0.11660  0.10324 899.00000  1.129 0.25905  
## factor(year_factor)4  0.08689  0.10373 899.00000  0.838 0.40245  
## factor(year_factor)5 -0.04077  0.10238 899.00000 -0.398 0.69055  
## factor(year_factor)6  0.01253  0.10117 899.00000  0.124 0.90145  
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 22 > 12.

```

```

## Use print(x, correlation=TRUE) or
##      vcov(x)      if you need it

## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

anova(mod7au)

## Type III Analysis of Variance Table with Satterthwaite's method
##                               Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state                      0.054  0.0544     1     899  0.0720  0.788461
## species                   295.084 19.6722    15     899 26.0460 < 2.2e-16 ***
## factor(year_factor)   11.599  2.3197     5     899  3.0713  0.009337 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

UMBS Plot-level Mixed Effects Models:

```

mod1pu <- lmer(log(plot_cover_avg) ~ state + (1 | plot), comp_umbs_plot, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod2pu <- lmer(log(plot_cover_avg) ~ insecticide + (1 | plot), comp_umbs_plot, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod3pu <- lmer(log(plot_cover_avg) ~ insecticide + state + (1 | plot), comp_umbs_plot,
REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod4pu <- lmer(log(plot_cover_avg) ~ insecticide * state + (1 | plot), comp_umbs_plot,
REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod5pu <- lmer(log(plot_cover_avg) ~ state + year_factor + (1 | plot), comp_umbs_plot,
REML = FALSE)
mod6pu <- lmer(log(plot_cover_avg) ~ state + year_factor + insecticide + (1 | plot),
comp_umbs_plot, REML = FALSE)
mod7pu <- lmer(log(plot_cover_avg) ~ state * year_factor + (1 | plot), comp_umbs_plot,
REML = FALSE)
mod8pu <- lmer(log(plot_cover_avg) ~ state * year_factor + insecticide + (1 | plot),
comp_umbs_plot, REML = FALSE)
mod9pu <- lmer(log(plot_cover_avg) ~ state * insecticide + year_factor + (1 | plot),
comp_umbs_plot, REML = FALSE)
mod10pu <- lmer(log(plot_cover_avg) ~ state + insecticide * year_factor + (1 | plot),

```

```

comp_umbs_plot, REML = FALSE)
mod11pu <- lmer(log(plot_cover_avg) ~ state * year_factor * insecticide + (1 | plot),
comp_umbs_plot, REML = FALSE)
AICctab(mod1pu, mod2pu, mod3pu, mod4pu, mod5pu, mod6pu, mod7pu, mod8pu, mod9pu, mod10pu,
mod11pu, weights = T) # model 11p and 10p the same

```

```

##          dAICc df weight
## mod7pu     0.0  6  0.547
## mod8pu     2.0  7  0.202
## mod5pu     2.6  5  0.149
## mod6pu     4.6  6  0.056
## mod10pu    6.7  7  0.019
## mod9pu     6.8  7  0.019
## mod11pu    8.5 10  0.008
## mod2pu   254.8  4 <0.001
## mod1pu   254.9  4 <0.001
## mod3pu   257.0  5 <0.001
## mod4pu   259.2  6 <0.001

```

```
anova(mod7pu, mod8pu) #7p just barely better
```

```

## Data: comp_umbs_plot
## Models:
## mod7pu: log(plot_cover_avg) ~ state * year_factor + (1 | plot)
## mod8pu: log(plot_cover_avg) ~ state * year_factor + insecticide + (1 |
## mod8pu:      plot)
##      npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod7pu     6 23.621 41.440 -5.8104    11.621
## mod8pu     7 25.399 46.188 -5.6996    11.399 0.2216  1      0.6378

```

```
summ(mod7pu)
```

Observations	144
Dependent variable	log(plot_cover_avg)
Type	Mixed effects linear regression

AIC	23.62
BIC	41.44
Pseudo-R ² (fixed effects)	0.83
Pseudo-R ² (total)	0.85

```
summ(mod8pu)
```

```
anova(mod8pu)
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value Pr(>F)

```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	5.02	0.07	71.99	123.04	0.00
stateambient	0.19	0.10	1.90	123.04	0.06
year_factor	-0.30	0.02	-18.49	120.00	0.00
stateambient:year_factor	-0.05	0.02	-2.21	120.00	0.03

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.10
Residual		0.24

Grouping Variables		
Group	# groups	ICC
plot	24	0.14

Observations	144
Dependent variable	log(plot_cover_avg)
Type	Mixed effects linear regression

AIC	25.40
BIC	46.19
Pseudo-R ² (fixed effects)	0.83
Pseudo-R ² (total)	0.85

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	5.01	0.07	66.79	100.44	0.00
stateambient	0.19	0.10	1.90	123.50	0.06
year_factor	-0.30	0.02	-18.49	120.00	0.00
insecticideno_insects	0.03	0.06	0.47	24.00	0.64
stateambient:year_factor	-0.05	0.02	-2.21	120.00	0.03

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.10
Residual		0.24

Grouping Variables		
Group	# groups	ICC
plot	24	0.14

```

## state          0.205   0.205      1 123.5   3.6257 0.05922 .
## year_factor    45.539  45.539      1 120.0  804.0575 < 2e-16 ***
## insecticide     0.013   0.013      1 24.0    0.2226 0.64132
## state:year_factor 0.277   0.277      1 120.0   4.8838 0.02901 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
emmeans(mod8pu, list(pairwise ~ state * year_factor), adjust = "tukey")
```

```

## $`emmeans of state, year_factor`
## state  year_factor emmean    SE  df lower.CL upper.CL
## warmed        3.5  3.96 0.042 27.4     3.87    4.04
## ambient       3.5  3.96 0.042 27.4     3.88    4.05
##
## Results are averaged over the levels of: insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, year_factor`
## 1           estimate    SE  df t.ratio p.value
## warmed - ambient 3.5 -0.00785 0.0594 27.4 -0.132  0.8958
##
## Results are averaged over the levels of: insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.

```

```
emmeans(mod8pu, list(pairwise ~ state), adjust = "tukey")
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```

## $`emmeans of state`
## state  emmean    SE  df lower.CL upper.CL
## warmed    3.96 0.042 27.4     3.87    4.04
## ambient   3.96 0.042 27.4     3.88    4.05
##
## Results are averaged over the levels of: insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state`
## 1           estimate    SE  df t.ratio p.value
## warmed - ambient -0.00785 0.0594 27.4 -0.132  0.8958
##
## Results are averaged over the levels of: insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.

```

```
emmeans(mod8pu, list(pairwise ~ year_factor), adjust = "tukey")
```

```
## NOTE: Results may be misleading due to involvement in interactions
```

```

## Note: Use 'contrast(regrid(object), ...)' to obtain contrasts of back-transformed estimates

## $`emmeans of year_factor`
##   year_factor emmean    SE  df lower.CL upper.CL
##       3.5     3.96 0.0297 27.4      3.9     4.02
## 
## Results are averaged over the levels of: state, insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
## 
## $` of year_factor`
##   1          estimate SE df z.ratio p.value
##   (nothing)  nonEst NA NA NA      NA
## 
## Results are averaged over the levels of: state, insecticide
## Note: contrasts are still on the log scale
## Degrees-of-freedom method: kenward-roger

# including native vs. exotic
umbs_comp_plot_origin <- within(umbs_comp_plot_origin, origin <- relevel(factor(origin),
  ref = "Native")) # releveling so native is the reference
mod12pu <- lmer(log(plot_cover_avg) ~ state * origin + (1 + year_factor | plot),
  umbs_comp_plot_origin, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod13pu <- lmer(log(plot_cover_avg) ~ state + origin + (1 + year_factor | plot),
  umbs_comp_plot_origin, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod14pu <- lmer(log(plot_cover_avg) ~ state + origin + year_factor + (1 | plot),
  umbs_comp_plot_origin, REML = FALSE)

## boundary (singular) fit: see ?isSingular

anova(mod12pu, mod13pu) # go with model 13pu

## Data: umbs_comp_plot_origin
## Models:
## mod13pu: log(plot_cover_avg) ~ state + origin + (1 + year_factor | plot)
## mod12pu: log(plot_cover_avg) ~ state * origin + (1 + year_factor | plot)
##          npar   AIC   BIC logLik deviance Chisq Df Pr(>Chisq)
## mod13pu    9 1255.1 1292.5 -618.55    1237.1
## mod12pu   12 1257.9 1307.8 -616.95    1233.9 3.1883  3     0.3635

anova(mod13pu, mod14pu) # mod 14pu

```

```

## Data: umbs_comp_plot_origin
## Models:
## mod14pu: log(plot_cover_avg) ~ state + origin + year_factor + (1 | plot)
## mod13pu: log(plot_cover_avg) ~ state + origin + (1 + year_factor | plot)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod14pu     8 1196.0 1229.3 -590.01   1180.0
## mod13pu     9 1255.1 1292.5 -618.55   1237.1      0  1          1

summary(mod14pu)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(plot_cover_avg) ~ state + origin + year_factor + (1 | plot)
## Data: umbs_comp_plot_origin
##
##      AIC      BIC  logLik deviance df.resid
## 1196.0 1229.3  -590.0   1180.0      463
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -3.5201 -0.6139  0.1769  0.7356  2.3020
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0000   0.0000
## Residual           0.7171   0.8468
## Number of obs: 471, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|) 
## (Intercept)  3.72572  0.11430 471.00000 32.595 < 2e-16 ***
## statewarmed -0.02655  0.07826 471.00000 -0.339  0.73451
## origin       -0.45014  0.10107 471.00000 -4.454 1.05e-05 ***
## originBoth    -1.90785  0.14151 471.00000 -13.482 < 2e-16 ***
## originExotic  0.26540  0.10033 471.00000  2.645  0.00844 **
## year_factor   -0.29050  0.02279 471.00000 -12.748 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##            (Intr) sttwrm origin orgnBt orgnEx
## statewarmed -0.362
## origin       -0.420 -0.009
## originBoth    -0.344  0.056  0.350
## originExotic -0.428 -0.008  0.495  0.353
## year_factor   -0.708  0.031 -0.016  0.021 -0.009
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

summ(mod14pu)

```

Observations	471
Dependent variable	log(plot_cover_avg)
Type	Mixed effects linear regression

AIC	1196.02
BIC	1229.26
Pseudo-R ² (fixed effects)	0.47
Pseudo-R ² (total)	0.47

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	3.73	0.11	32.60	471.00	0.00
statewarmed	-0.03	0.08	-0.34	471.00	0.73
origin	-0.45	0.10	-4.45	471.00	0.00
originBoth	-1.91	0.14	-13.48	471.00	0.00
originExotic	0.27	0.10	2.65	471.00	0.01
year_factor	-0.29	0.02	-12.75	471.00	0.00

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.00
	Residual	0.85

Grouping Variables		
Group	# groups	ICC
plot	24	0.00

```
anova(mod14pu)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##          Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state      0.083  0.083     1    471  0.1151 0.7345
## origin     183.400 61.133     3    471  85.2490 <2e-16 ***
## year_factor 116.533 116.533     1    471 162.5035 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
emmeans(mod14pu, list(pairwise ~ state), adjust = "tukey")
```

```
## boundary (singular) fit: see ?isSingular
```

```
## $`emmeans of state`
##   state emmean    SE  df lower.CL upper.CL
##   ambient  2.18 0.0578 24.1     2.06    2.30
##   warmed   2.15 0.0602 29.2     2.03    2.28
```

```

## 
## Results are averaged over the levels of: origin
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $'pairwise differences of state'
##   1           estimate      SE   df t.ratio p.value
## ambient - warmed    0.0266  0.0788 22.4  0.337   0.7394
##
## Results are averaged over the levels of: origin
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.

emmeans(mod14pu, list(pairwise ~ origin), adjust = "tukey")

```

```

## boundary (singular) fit: see ?isSingular

## $'emmmeans of origin'
##   origin emmean      SE   df lower.CL upper.CL
##   Native  2.691  0.0713 194    2.550    2.83
##          2.241  0.0726 202    2.098    2.38
##   Both    0.783  0.1244 321    0.538    1.03
##   Exotic  2.956  0.0715 195    2.815    3.10
##
## Results are averaged over the levels of: state
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $'pairwise differences of origin'
##   1           estimate      SE   df t.ratio p.value
##   Native -          0.450  0.102 456    4.425  0.0001
##   Native - Both     1.908  0.143 472   13.309 <.0001
##   Native - Exotic   -0.265  0.101 455   -2.628  0.0438
##   - Both          1.458  0.144 472   10.117 <.0001
##   - Exotic         -0.716  0.102 455   -7.023 <.0001
##   Both - Exotic    -2.173  0.144 472  -15.142 <.0001
##
## Results are averaged over the levels of: state
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 4 estimates

```

```
emmeans(mod14pu, list(pairwise ~ state + origin), adjust = "tukey")
```

```

## boundary (singular) fit: see ?isSingular

## $'emmmeans of state, origin'
##   state origin emmean      SE   df lower.CL upper.CL
##   ambient Native  2.704  0.0813 96.4    2.543    2.87
##   warmed  Native  2.678  0.0816 97.4    2.516    2.84

```

```

## ambient      2.254 0.0829 102.3    2.090    2.42
## warmed      2.228 0.0823 100.3    2.064    2.39
## ambient Both 0.796 0.1280 210.9    0.544    1.05
## warmed Both  0.770 0.1329 242.9    0.508    1.03
## ambient Exotic 2.970 0.0820 98.5    2.807    3.13
## warmed Exotic 2.943 0.0814 97.0    2.782    3.10
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $'pairwise differences of state, origin'
## 1                           estimate     SE   df t.ratio p.value
## ambient Native - warmed Native  0.0266 0.0788 22.4  0.337 1.0000
## ambient Native - ambient        0.4501 0.1017 455.7 4.425 0.0003
## ambient Native - warmed        0.4767 0.1281 138.1 3.720 0.0068
## ambient Native - ambient Both  1.9079 0.1433 471.5 13.309 <.0001
## ambient Native - warmed Both   1.9344 0.1673 226.7 11.561 <.0001
## ambient Native - ambient Exotic -0.2654 0.1010 455.2 -2.628 0.1485
## ambient Native - warmed Exotic -0.2388 0.1276 136.6 -1.872 0.5722
## warmed Native - ambient       0.4236 0.1293 141.1 3.277 0.0281
## warmed Native - warmed        0.4501 0.1017 455.7 4.425 0.0003
## warmed Native - ambient Both  1.8813 0.1598 188.7 11.774 <.0001
## warmed Native - warmed Both   1.9079 0.1433 471.5 13.309 <.0001
## warmed Native - ambient Exotic -0.2920 0.1287 139.0 -2.269 0.3181
## warmed Native - warmed Exotic -0.2654 0.1010 455.2 -2.628 0.1485
## ambient - warmed              0.0266 0.0788 22.4  0.337 1.0000
## ambient - ambient Both         1.4577 0.1441 471.8 10.117 <.0001
## ambient - warmed Both          1.4843 0.1684 229.7 8.815 <.0001
## ambient - ambient Exotic      -0.7155 0.1019 455.3 -7.023 <.0001
## ambient - warmed Exotic       -0.6890 0.1288 140.6 -5.347 <.0001
## warmed - ambient Both          1.4312 0.1600 189.7 8.945 <.0001
## warmed - warmed Both           1.4577 0.1441 471.8 10.117 <.0001
## warmed - ambient Exotic       -0.7421 0.1288 139.9 -5.761 <.0001
## warmed - warmed Exotic        -0.7155 0.1019 455.3 -7.023 <.0001
## ambient Both - warmed Both    0.0266 0.0788 22.4  0.337 1.0000
## ambient Both - ambient Exotic -2.1733 0.1435 472.4 -15.142 <.0001
## ambient Both - warmed Exotic  -2.1467 0.1595 189.7 -13.458 <.0001
## warmed Both - ambient Exotic  -2.1998 0.1679 229.2 -13.103 <.0001
## warmed Both - warmed Exotic   -2.1733 0.1435 472.4 -15.142 <.0001
## ambient Exotic - warmed Exotic 0.0266 0.0788 22.4  0.337 1.0000
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 8 estimates

```

```

# including growth form - first with interaction term
umbs_comp_plot_growthhabit <- within(umbs_comp_plot_growthhabit, growth_habit <- relevel(factor(growth_habit),
  ref = "Forb")) # releveling so forb is the reference
mod15pu <- lmer(log(plot_cover_avg) ~ state * growth_habit + (1 + year_factor | plot),
  umbs_comp_plot_growthhabit, REML = FALSE)

```

```

## boundary (singular) fit: see ?isSingular

```

```

mod16pu <- lmer(log(plot_cover_avg) ~ state + growth_habit + (1 + year_factor | plot),
  umbs_comp_plot_growthhabit, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod17pu <- lmer(log(plot_cover_avg) ~ state + growth_habit + year_factor + (1 | plot),
  umbs_comp_plot_growthhabit, REML = FALSE)

## boundary (singular) fit: see ?isSingular

anova(mod15pu, mod16pu) # go with model 16pu

## Data: umbs_comp_plot_growthhabit
## Models:
## mod16pu: log(plot_cover_avg) ~ state + growth_habit + (1 + year_factor |
## mod16pu:      plot)
## mod15pu: log(plot_cover_avg) ~ state * growth_habit + (1 + year_factor |
## mod15pu:      plot)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod16pu     9 751.42 785.25 -366.71    733.42
## mod15pu    12 756.22 801.32 -366.11    732.22 1.202   3      0.7525

anova(mod16pu, mod17pu) # mod 17pu

## Data: umbs_comp_plot_growthhabit
## Models:
## mod17pu: log(plot_cover_avg) ~ state + growth_habit + year_factor + (1 |
## mod17pu:      plot)
## mod16pu: log(plot_cover_avg) ~ state + growth_habit + (1 + year_factor |
## mod16pu:      plot)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod17pu     8 688.55 718.62 -336.27    672.55
## mod16pu     9 751.42 785.25 -366.71    733.42      0   1          1

summary(mod17pu)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(plot_cover_avg) ~ state + growth_habit + year_factor + (1 |
##      plot)
## Data: umbs_comp_plot_growthhabit
##
##      AIC      BIC  logLik deviance df.resid
##      688.5    718.6   -336.3    672.5      309
##
## Scaled residuals:
##      Min      1Q  Median      3Q      Max
##      -4.1205 -0.6184  0.1987  0.6956  2.2908
##
## Random effects:
```

```

## Groups      Name          Variance Std.Dev.
## plot       (Intercept) 0.0000   0.000
## Residual           0.4886   0.699
## Number of obs: 317, groups: plot, 24
##
## Fixed effects:
##                               Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)             4.291700  0.108758 317.000000 39.461 < 2e-16 ***
## statewarmed            0.001112  0.078551 317.000000  0.014  0.9887
## growth_habit           -2.461517  0.157201 317.000000 -15.658 < 2e-16 ***
## growth_habitGraminoid -0.173923  0.082521 317.000000 -2.108  0.0358 *
## growth_habitTree        -1.972891  0.272433 317.000000 -7.242 3.38e-12 ***
## year_factor            -0.312931  0.023348 317.000000 -13.403 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) sttwrm grwth_ grwt_G grwt_T
## statewarmed -0.376
## growth_habt -0.238  0.013
## grwth_hbtGr -0.386  0.003  0.264
## grwth_hbtTr -0.036  0.020  0.075  0.151
## year_factor -0.761  0.016  0.045  0.005 -0.114
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

```

```
summ(mod17pu)
```

Observations	317
Dependent variable	log(plot_cover_avg)
Type	Mixed effects linear regression

AIC	688.55
BIC	718.62
Pseudo-R ² (fixed effects)	0.60
Pseudo-R ² (total)	0.60

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	4.29	0.11	39.46	317.00	0.00
statewarmed	0.00	0.08	0.01	317.00	0.99
growth_habit	-2.46	0.16	-15.66	317.00	0.00
growth_habitGraminoid	-0.17	0.08	-2.11	317.00	0.04
growth_habitTree	-1.97	0.27	-7.24	317.00	0.00
year_factor	-0.31	0.02	-13.40	317.00	0.00

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.00
Residual		0.70

Grouping Variables		
Group	# groups	ICC
plot	24	0.00

```
anova(mod17pu)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state        0.000  0.000     1    317  0.0002 0.9887
## growth_habit 142.153  47.384     3    317 96.9856 <2e-16 ***
## year_factor   87.766  87.766     1    317 179.6389 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

emmeans(mod17pu, list(pairwise ~ state + growth_habit + year_factor), adjust = "tukey")

## boundary (singular) fit: see ?isSingular

## $`emmeans of state, growth_habit, year_factor`
## state  growth_habit year_factor emmean      SE   df lower.CL upper.CL
## ambient Forb          3.52 3.191 0.0713  56.1  3.048  3.33
## warmed  Forb          3.52 3.192 0.0710  55.3  3.050  3.33
## ambient           3.52 0.729 0.1533 240.7  0.427  1.03
## warmed            3.52 0.731 0.1545 229.1  0.426  1.04
## ambient Graminoid    3.52 3.017 0.0710  55.3  2.875  3.16
## warmed  Graminoid    3.52 3.018 0.0710  55.3  2.876  3.16
## ambient Tree         3.52 1.218 0.2758 241.9  0.675  1.76
## warmed   Tree        3.52 1.219 0.2775 239.6  0.673  1.77
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, growth_habit, year_factor`
## 1
## ambient Forb 3.51735015772871 - warmed Forb 3.51735015772871
## ambient Forb 3.51735015772871 - ambient   3.51735015772871
## ambient Forb 3.51735015772871 - warmed   3.51735015772871
## ambient Forb 3.51735015772871 - ambient Graminoid 3.51735015772871
## ambient Forb 3.51735015772871 - warmed Graminoid 3.51735015772871
## ambient Forb 3.51735015772871 - ambient Tree 3.51735015772871
## ambient Forb 3.51735015772871 - warmed Tree 3.51735015772871
## warmed Forb 3.51735015772871 - ambient   3.51735015772871
## warmed Forb 3.51735015772871 - warmed   3.51735015772871
```

```

## warmed Forb 3.51735015772871 - ambient Graminoid 3.51735015772871
## warmed Forb 3.51735015772871 - warmed Graminoid 3.51735015772871
## warmed Forb 3.51735015772871 - ambient Tree 3.51735015772871
## warmed Forb 3.51735015772871 - warmed Tree 3.51735015772871
## ambient 3.51735015772871 - warmed 3.51735015772871
## ambient 3.51735015772871 - ambient Graminoid 3.51735015772871
## ambient 3.51735015772871 - warmed Graminoid 3.51735015772871
## ambient 3.51735015772871 - ambient Tree 3.51735015772871
## ambient 3.51735015772871 - warmed Tree 3.51735015772871
## warmed 3.51735015772871 - ambient Graminoid 3.51735015772871
## warmed 3.51735015772871 - warmed Graminoid 3.51735015772871
## warmed 3.51735015772871 - ambient Tree 3.51735015772871
## warmed 3.51735015772871 - warmed Tree 3.51735015772871
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## ambient Tree 3.51735015772871 - warmed Tree 3.51735015772871
## estimate SE df t.ratio p.value
## -0.00111 0.0795 21.8 -0.014 1.0000
## 2.46152 0.1600 322.2 15.384 <.0001
## 2.46041 0.1798 192.7 13.682 <.0001
## 0.17392 0.0833 300.6 2.088 0.4254
## 0.17281 0.1153 89.2 1.498 0.8063
## 1.97289 0.2801 279.1 7.045 <.0001
## 1.97178 0.2927 224.8 6.736 <.0001
## 2.46263 0.1775 207.7 13.876 <.0001
## 2.46152 0.1600 322.2 15.384 <.0001
## 0.17503 0.1149 88.4 1.523 0.7931
## 0.17392 0.0833 300.6 2.088 0.4254
## 1.97400 0.2895 228.6 6.820 <.0001
## 1.97289 0.2801 279.1 7.045 <.0001
## -0.00111 0.0795 21.8 -0.014 1.0000
## -2.28759 0.1599 322.3 -14.305 <.0001
## -2.28871 0.1775 207.8 -12.893 <.0001
## -0.48863 0.3109 313.8 -1.572 0.7670
## -0.48974 0.3217 280.4 -1.522 0.7950
## -2.28648 0.1796 192.4 -12.730 <.0001
## -2.28759 0.1599 322.3 -14.305 <.0001
## -0.48751 0.3201 278.9 -1.523 0.7944
## -0.48863 0.3109 313.8 -1.572 0.7670
## -0.00111 0.0795 21.8 -0.014 1.0000
## 1.79897 0.2801 278.8 6.423 <.0001
## 1.79786 0.2927 224.6 6.143 <.0001
## 1.80008 0.2895 228.4 6.217 <.0001
## 1.79897 0.2801 278.8 6.423 <.0001
## -0.00111 0.0795 21.8 -0.014 1.0000
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 8 estimates

```

```
emmeans(mod17pu, list(pairwise ~ state), adjust = "tukey")
```

```
## boundary (singular) fit: see ?isSingular
```

```
## $'emmeans of state'  
##   state    emmean      SE   df lower.CL upper.CL  
##   ambient    2.04 0.0892 69.6     1.86    2.22  
##   warmed    2.04 0.0909 68.3     1.86    2.22  
##  
## Results are averaged over the levels of: growth_habit  
## Degrees-of-freedom method: kenward-roger  
## Results are given on the log (not the response) scale.  
## Confidence level used: 0.95  
##  
## $'pairwise differences of state'  
##   1           estimate      SE   df t.ratio p.value  
##   ambient - warmed -0.00111 0.0795 21.8 -0.014  0.9890  
##  
## Results are averaged over the levels of: growth_habit  
## Degrees-of-freedom method: kenward-roger  
## Results are given on the log (not the response) scale.
```

```
emmeans(mod17pu, list(pairwise ~ growth_habit), adjust = "tukey")
```

```
## boundary (singular) fit: see ?isSingular
```

```
## $'emmeans of growth_habit'  
##   growth_habit    emmean      SE   df lower.CL upper.CL  
##   Forb          3.19 0.0590 99.3     3.074    3.31  
##             0.73 0.1487 280.8     0.437    1.02  
##   Graminoid     3.02 0.0588 98.4     2.901    3.13  
##   Tree          1.22 0.2738 255.1     0.680    1.76  
##  
## Results are averaged over the levels of: state  
## Degrees-of-freedom method: kenward-roger  
## Results are given on the log (not the response) scale.  
## Confidence level used: 0.95  
##  
## $'pairwise differences of growth_habit'  
##   1           estimate      SE   df t.ratio p.value  
##   Forb -          2.462 0.1600 322  15.384 <.0001  
##   Forb - Graminoid 0.174 0.0833 301   2.088 0.1595  
##   Forb - Tree     1.973 0.2801 279   7.045 <.0001  
##   - Graminoid    -2.288 0.1599 322 -14.305 <.0001  
##   - Tree         -0.489 0.3109 314  -1.572 0.3964  
##   Graminoid - Tree 1.799 0.2801 279   6.423 <.0001  
##  
## Results are averaged over the levels of: state  
## Degrees-of-freedom method: kenward-roger  
## Results are given on the log (not the response) scale.  
## P value adjustment: tukey method for comparing a family of 4 estimates
```

```
emmeans(mod17pu, list(pairwise ~ year_factor), adjust = "tukey")

## boundary (singular) fit: see ?isSingular
## Note: Use 'contrast(regrid(object), ...)' to obtain contrasts of back-transformed estimates

## $`emmeans of year_factor`
##   year_factor emmean    SE df lower.CL upper.CL
##       3.52    2.04 0.0808 102     1.88      2.2
##
## Results are averaged over the levels of: state, growth_habit
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $` of year_factor`
##   1   estimate SE df z.ratio p.value
##   (nothing)  nonEst NA NA NA      NA
##
## Results are averaged over the levels of: state, growth_habit
## Note: contrasts are still on the log scale
## Degrees-of-freedom method: kenward-roger
```