

warmXtrophic Project: Phenology - Flowering Median Day 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(emmeans)
library(vegan)
library(car)
library(rstatix)
library(scales)
library(fitdistrplus)
library(moments) # for calculating skewness of data
library(ggpubr)
library(jtools) # summ() function
library(predictmeans)
library(olsrr)
library(car)
library(fitdistrplus)
library(ggpubr)
library(interactions)
library(sjPlot)
library(effects)
library(glmmTMB)
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")

# 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 data
flwr_species <- read.csv(file.path(L2_dir, "phenology/final_flwr_species_L2.csv")) # species level data
flwr_plot <- read.csv(file.path(L2_dir, "phenology/final_flwr_plot_L2.csv")) # plot level data
flwr_plot_origin <- read.csv(file.path(L2_dir, "phenology/final_flwr_plot_origin_L2.csv")) # plot level
flwr_plot_growthhabit <- read.csv(file.path(L2_dir, "phenology/final_flwr_plot_growthhabit_L2.csv")) # 

# get rid of "X" column that shows up
# In order for the "X" column not to show up, when you write.csv in the clean script, make sure you add
flwr_species$X <- NULL
flwr_plot$X <- NULL
flwr_plot_origin$X <- NULL
flwr_plot_growthhabit$X <- NULL
# take a look at the data to see if looks good
View(flwr_species)
View(flwr_plot)

# Order warmed and ambient so that warmed shows up first in plotting (and is default is red = warmed; b
flwr_species$state <- as.factor(flwr_species$state)
levels(flwr_species$state)

## [1] "ambient" "warmed"

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

## [1] "warmed"   "ambient"

# again for plot level data
flwr_plot$state <- as.factor(flwr_plot$state)
levels(flwr_plot$state)

## [1] "ambient" "warmed"

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

```

```

## [1] "warmed"   "ambient"

# [1] "warmed"   "ambient"

umbss_flwr_plot <- subset(flwr_plot, site == "umbss") # pull out umbs only data at plot level
# delete 2021 data from umbs dataframe (doesn't make sense to have bc we can't get min flower/sd, median)
umbss_flwr_plot <- subset(umbss_flwr_plot, year!="2021")
umbss_flwr_spp <- subset(flwr_species, site == "umbss") # pull out umbs only data at species level
umbss_flwr_spp <- subset(umbss_flwr_spp, year!="2021") # delete 2021 data
kbs_flwr_plot <- subset(flwr_plot, site == "kbs") # pull out kbs only data at plot level
kbs_flwr_spp <- subset(flwr_species, site == "kbs") # pull out kbs only data at species level
kbs_flwr_plot_origin <- subset(flwr_plot_origin, site == "kbs")
kbs_flwr_plot_growthhabit <- subset(flwr_plot_growthhabit, site == "kbs")
umbss_flwr_plot_origin <- subset(flwr_plot_origin, site == "umbss")
umbss_flwr_plot_origin <- subset(flwr_plot_origin, year != "2021") # delete 2021 data
umbss_flwr_plot_growthhabit <- subset(flwr_plot_growthhabit, site == "umbss")
umbss_flwr_plot_growthhabit <- subset(flwr_plot_growthhabit, year != "2021") # delete 2021 data

```

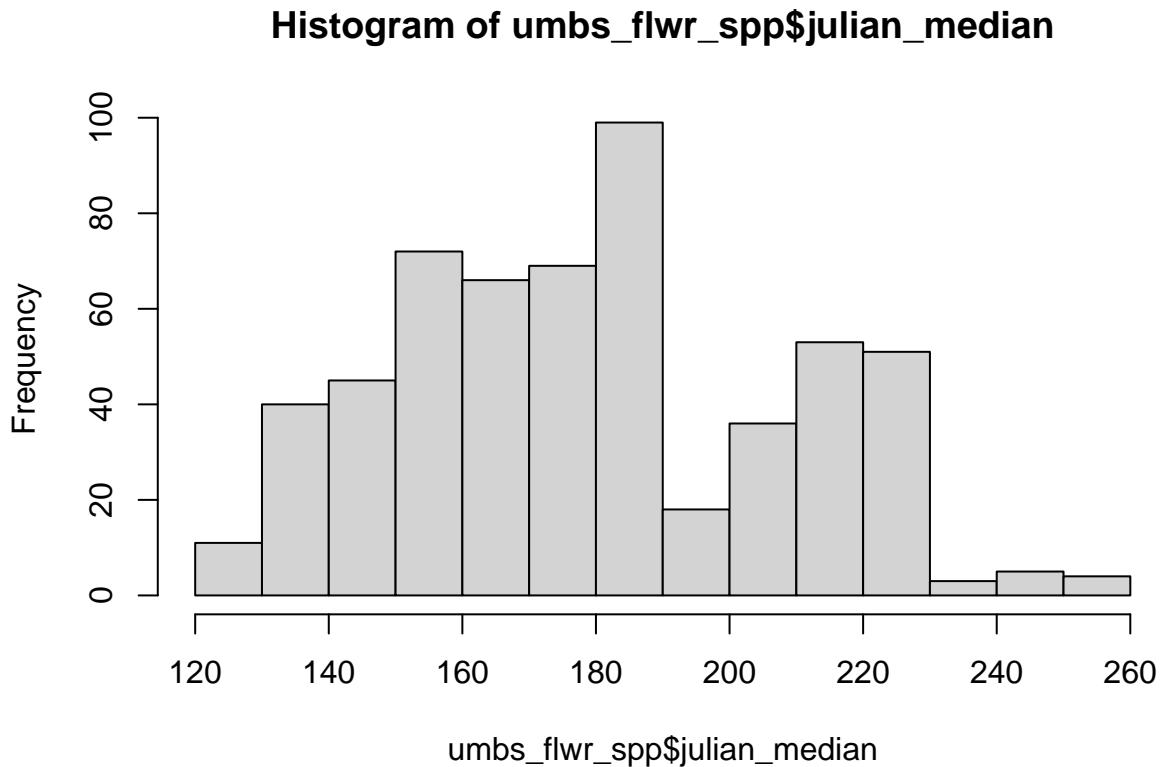
Phoebe

UMBS SPECIES LEVEL - Looking at MEDIAN JULIAN DAY

```

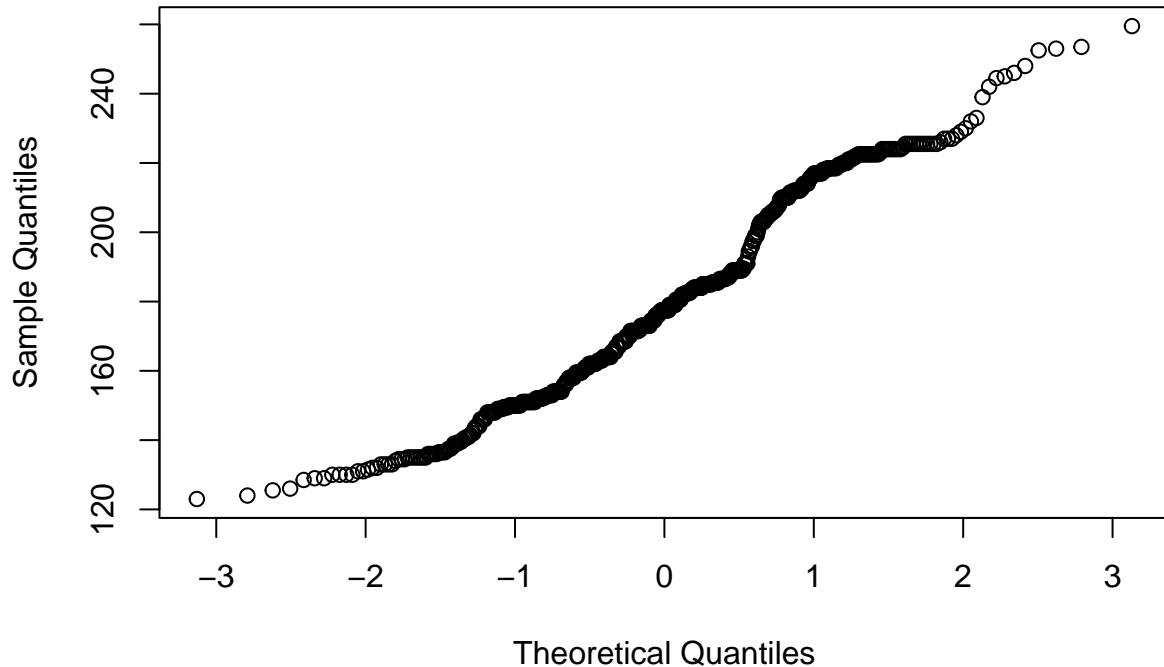
### UMBS ####
hist(umbss_flwr_spp$julian_median)

```



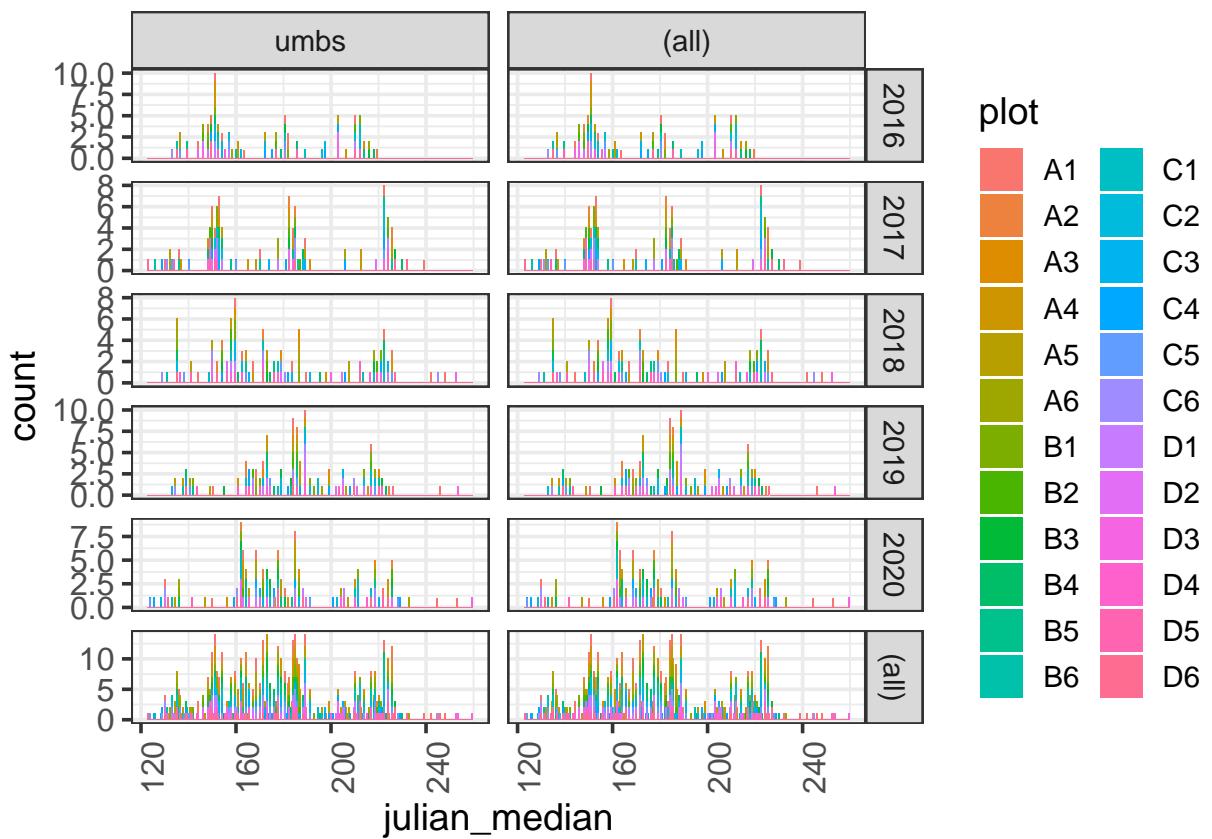
```
qqnorm(umbs_flwr_spp$julian_median) # this looks ok
```

Normal Q-Q Plot

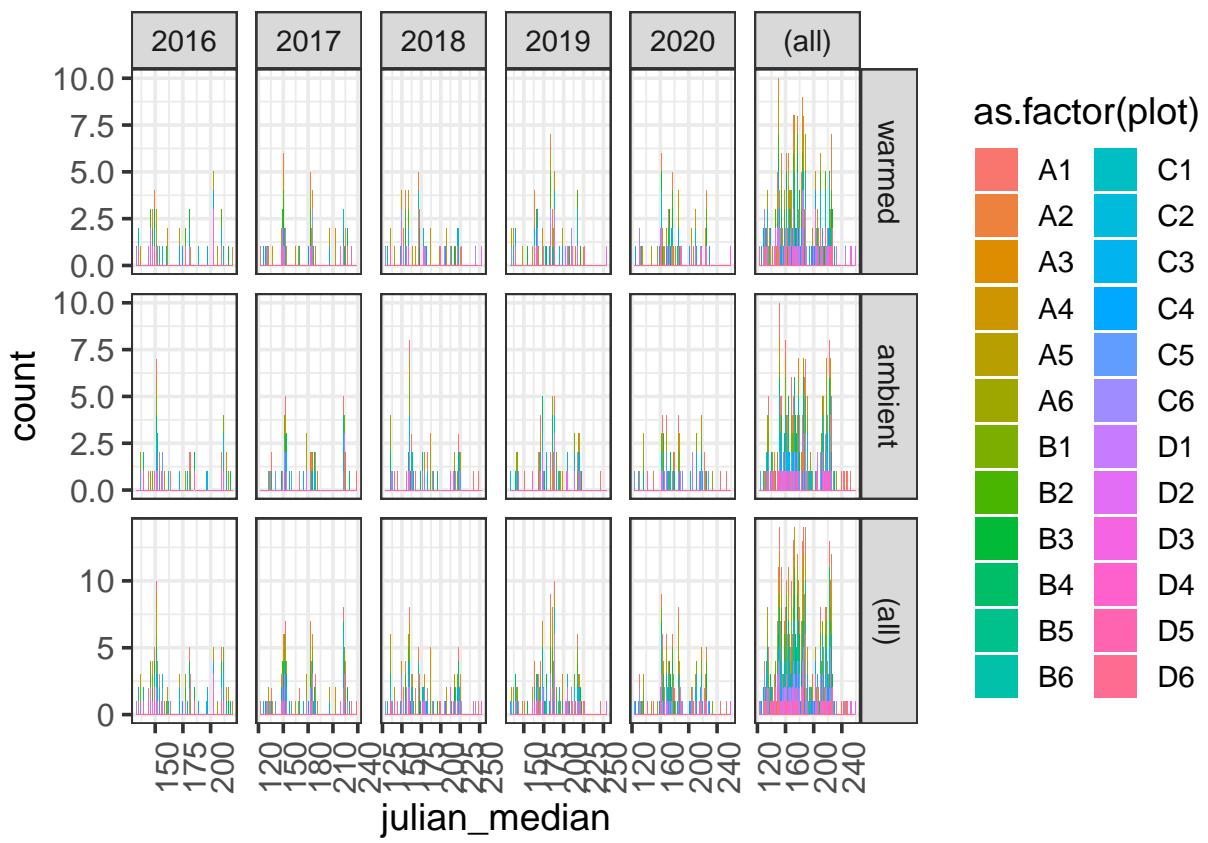


```
shapiro.test(umbs_flwr_spp$julian_median) # pvalue is < 0.05 so we reject the null hypothesis that the
```

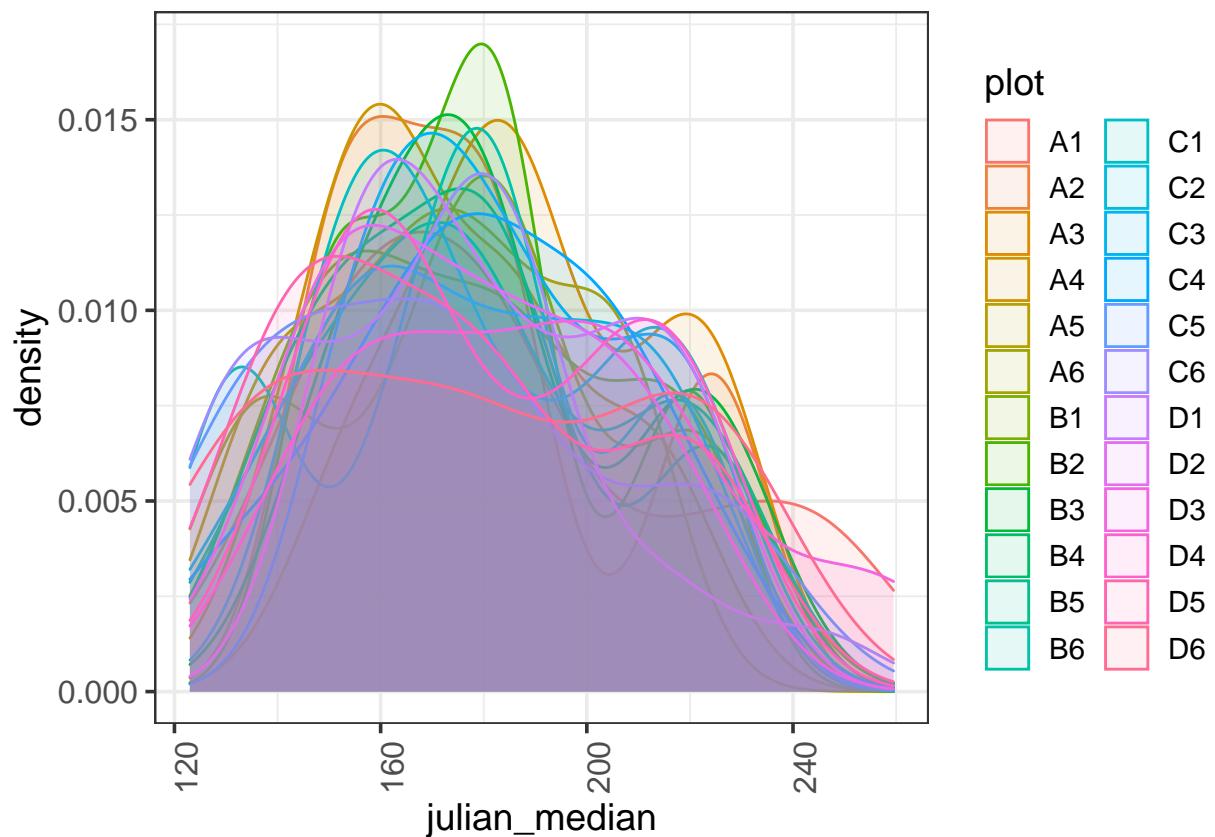
```
##  
## Shapiro-Wilk normality test  
##  
## data: umbs_flwr_spp$julian_median  
## W = 0.9706, p-value = 2.693e-09  
  
# Visualizing median Julian date for umbs at the PLOT LEVEL  
ggplot(umbs_flwr_spp, aes(julian_median, fill = plot)) +  
  geom_histogram(binwidth = 0.5) +  
  facet_grid(year ~ site, margins = TRUE, scales = "free")
```



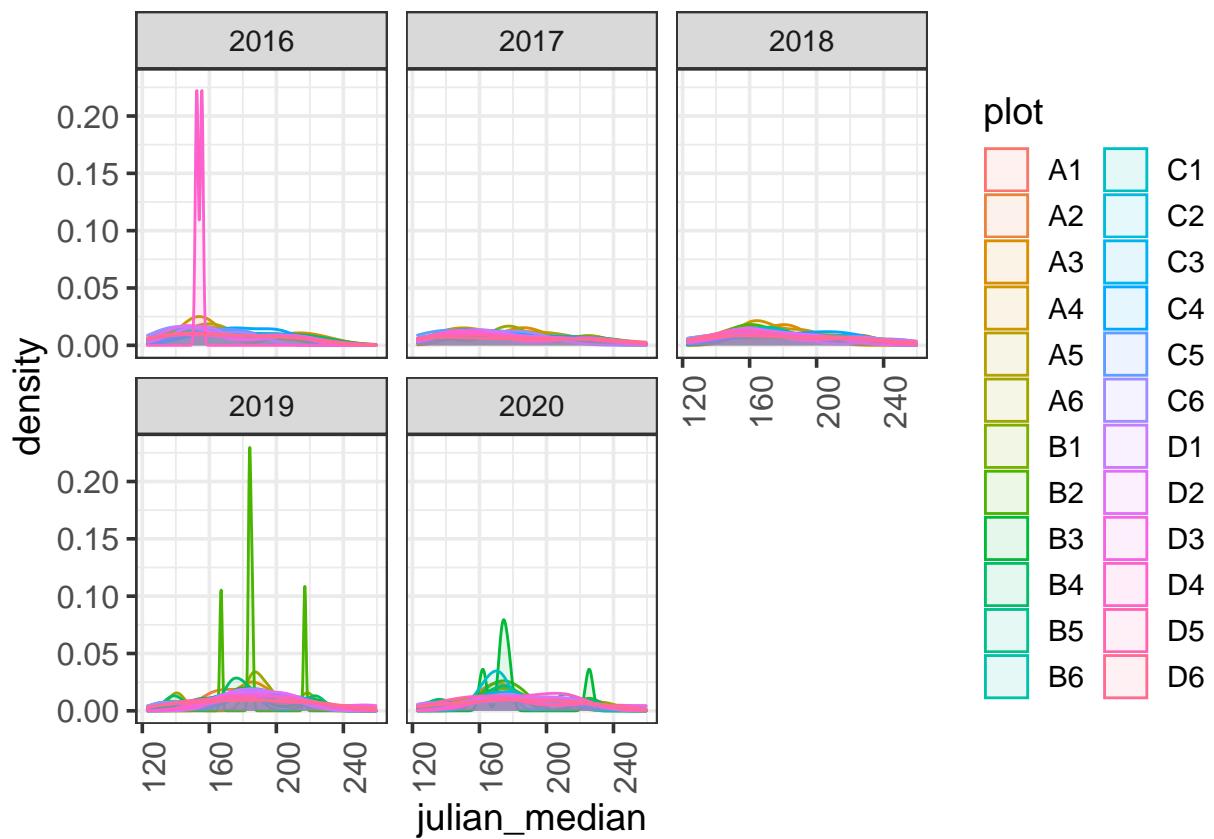
```
ggplot(umbs_flwr_spp, aes(julian_median, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
  facet_grid(state~year, margins = TRUE, scales = "free")
```



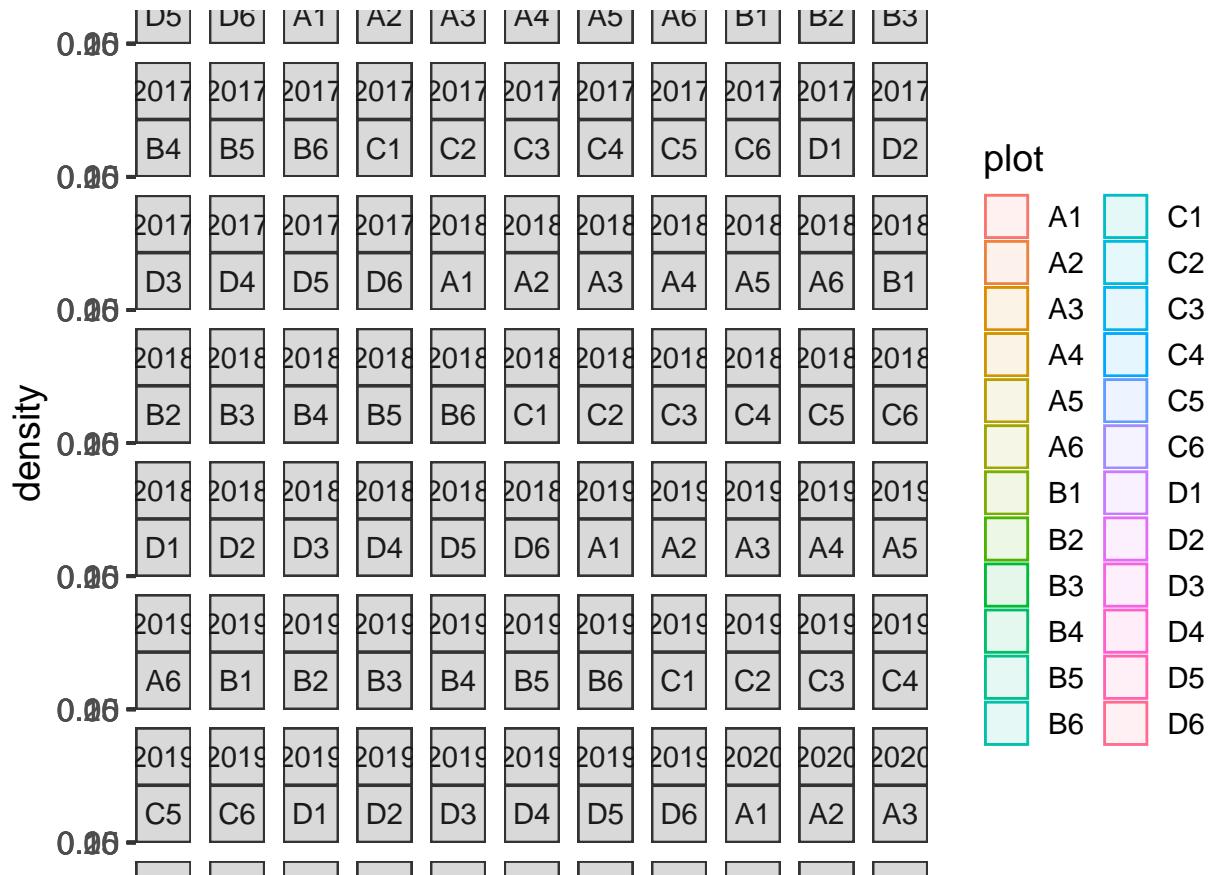
```
ggplot(umbs_flwr_spp, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1)
```



```
ggplot(umbs_flwr_spp, aes(julian_median, fill = plot, color=plot)) +  
  geom_density(alpha = 0.1) +  
  facet_wrap(~year)
```

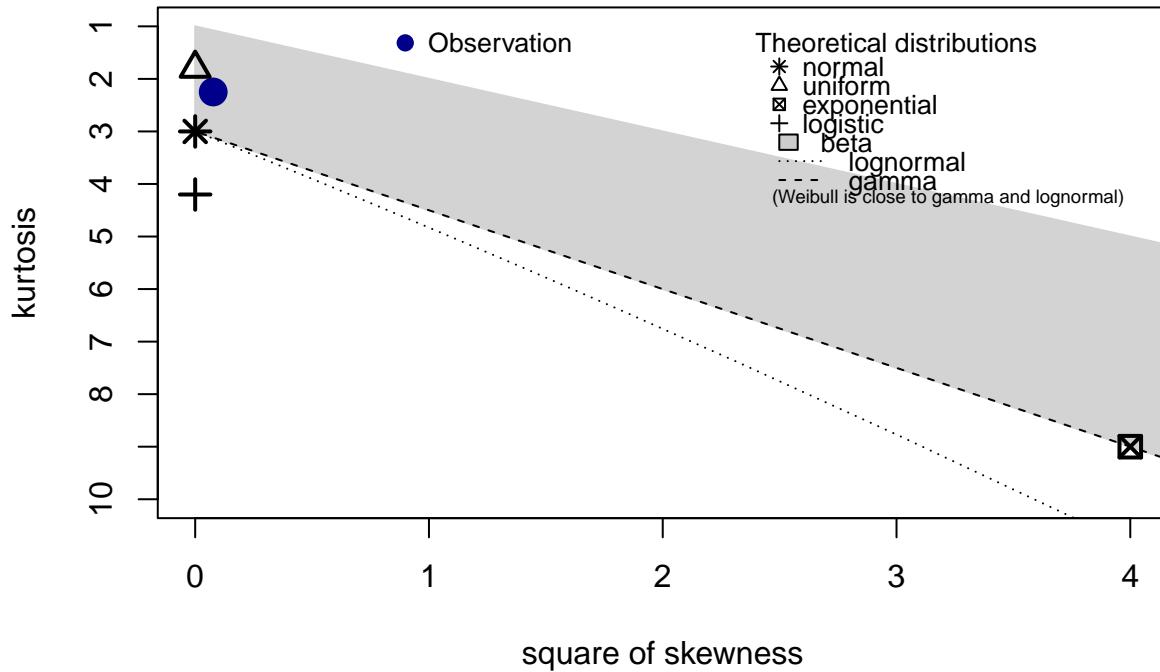


```
ggplot(umbs_flwr_spp, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year + plot)
```



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

Cullen and Frey graph

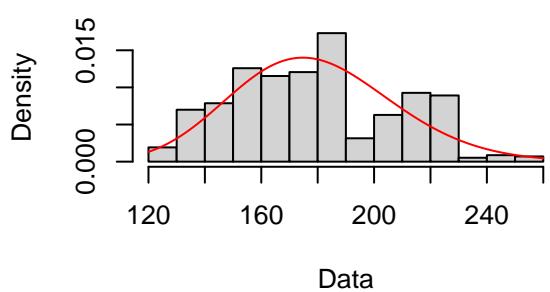
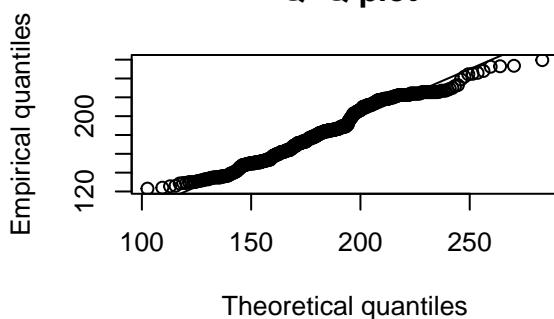
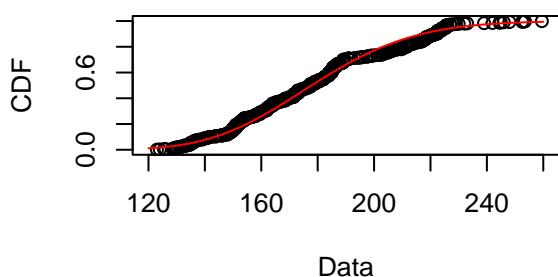
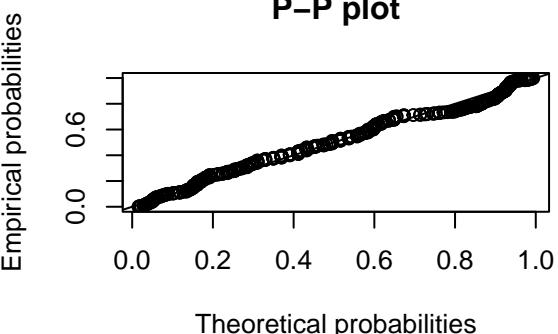


```

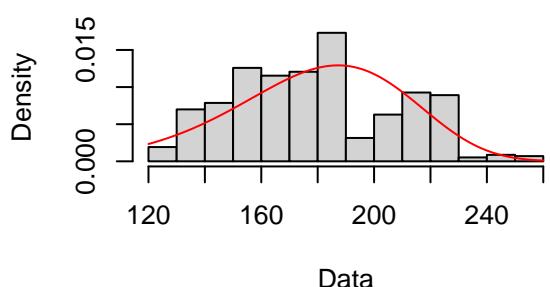
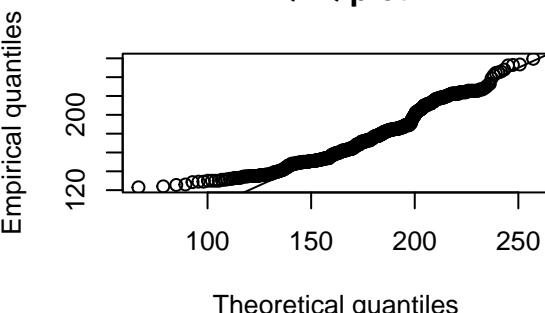
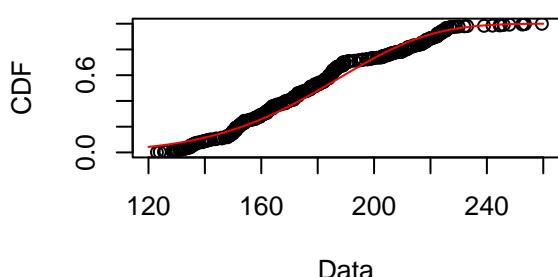
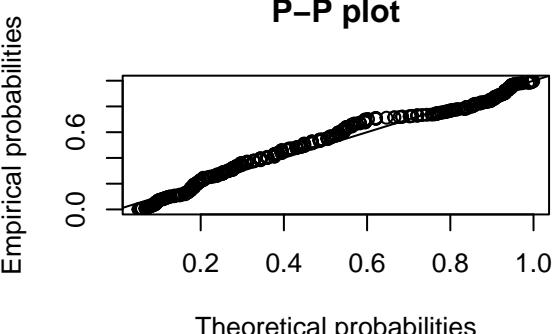
## summary statistics
## -----
## min: 123   max: 259.5
## median: 177.5
## mean: 179.3706
## estimated sd: 28.90832
## estimated skewness: 0.2778292
## estimated kurtosis: 2.249028

# Gamma distribution
fit.gamma <- fitdist(umbs_flwr_spp$julian_median, "gamma")
plot(fit.gamma)

```

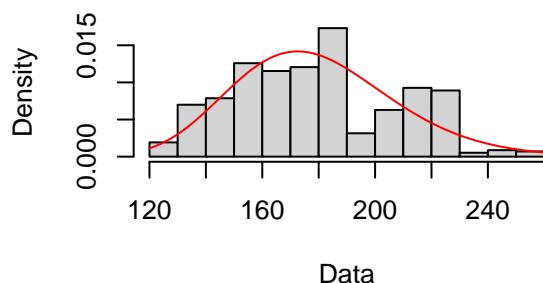
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

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

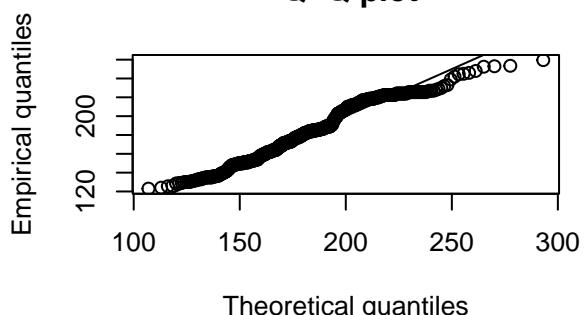
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

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

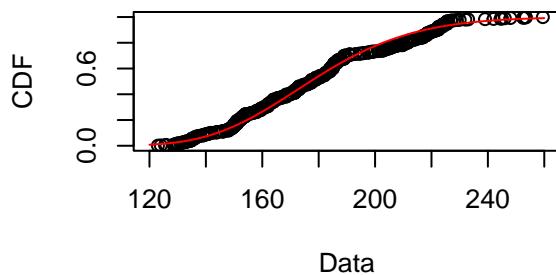
Empirical and theoretical dens.



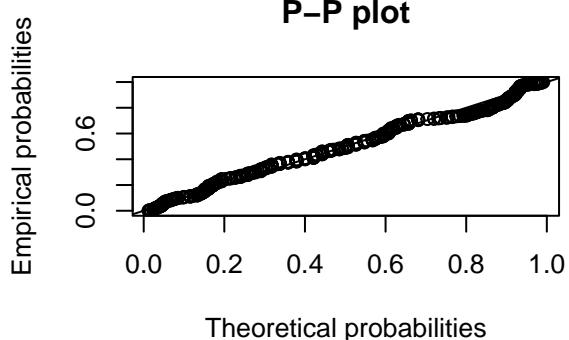
Q–Q plot



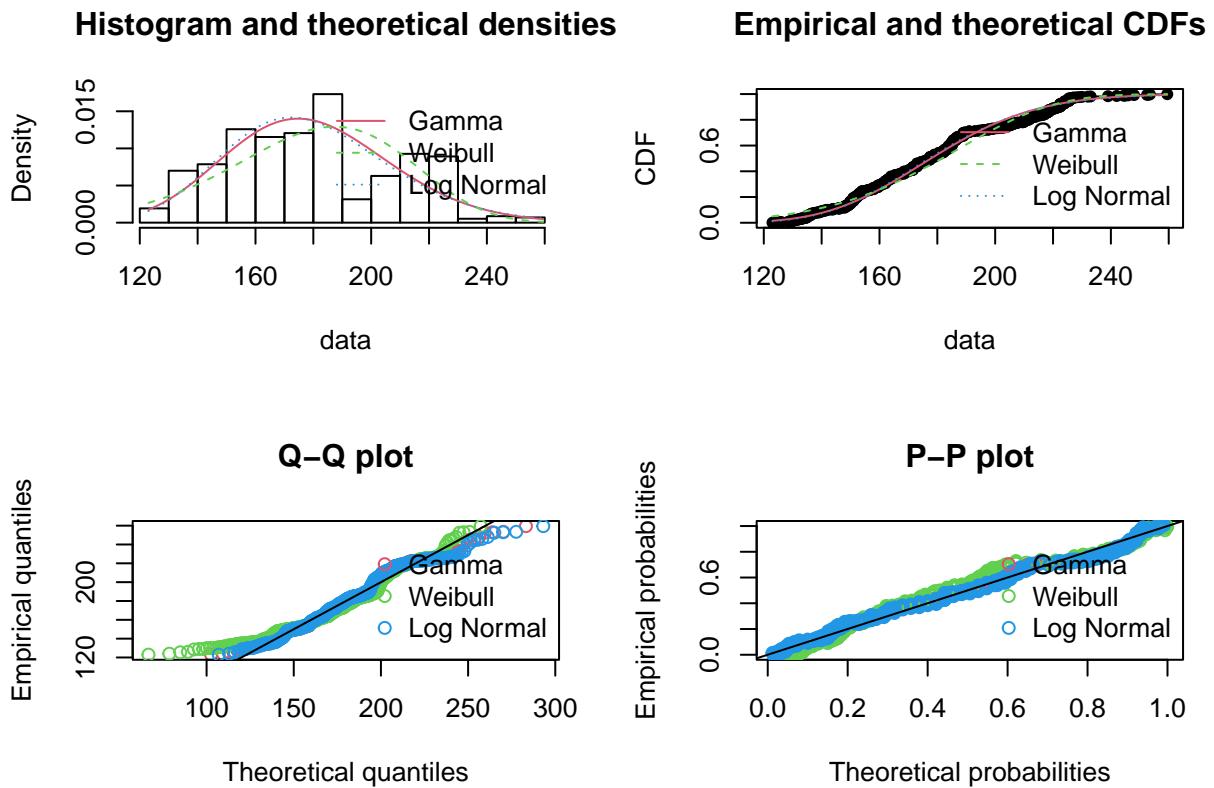
Empirical and theoretical CDFs



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)
```



```
# Goodness of fit comparisons across fits (can't include the sqrt normal bc it becomes diff response va
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 0.07251101 0.1040666 0.07215405
## Cramer-von Mises statistic   0.52738159 1.2693500 0.46115964
## Anderson-Darling statistic   3.91501557 7.8885552 3.58465528
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 5461.481 5512.411 5460.162
## Bayesian Information Criterion 5470.180 5521.109 5468.860
```

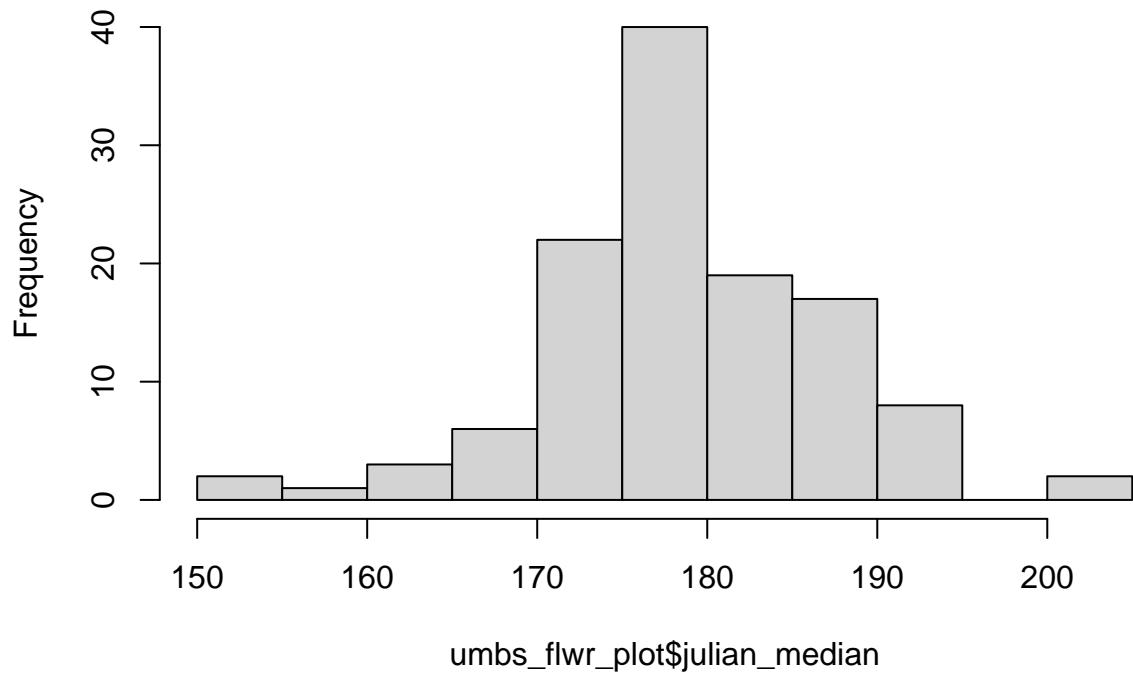
```
# Lognormal and gamma are very close, log normal slightly better, so going with log transforming
```

Phoebe

UMBS PLOT LEVEL - Looking at MEDIAN JULIAN DAY

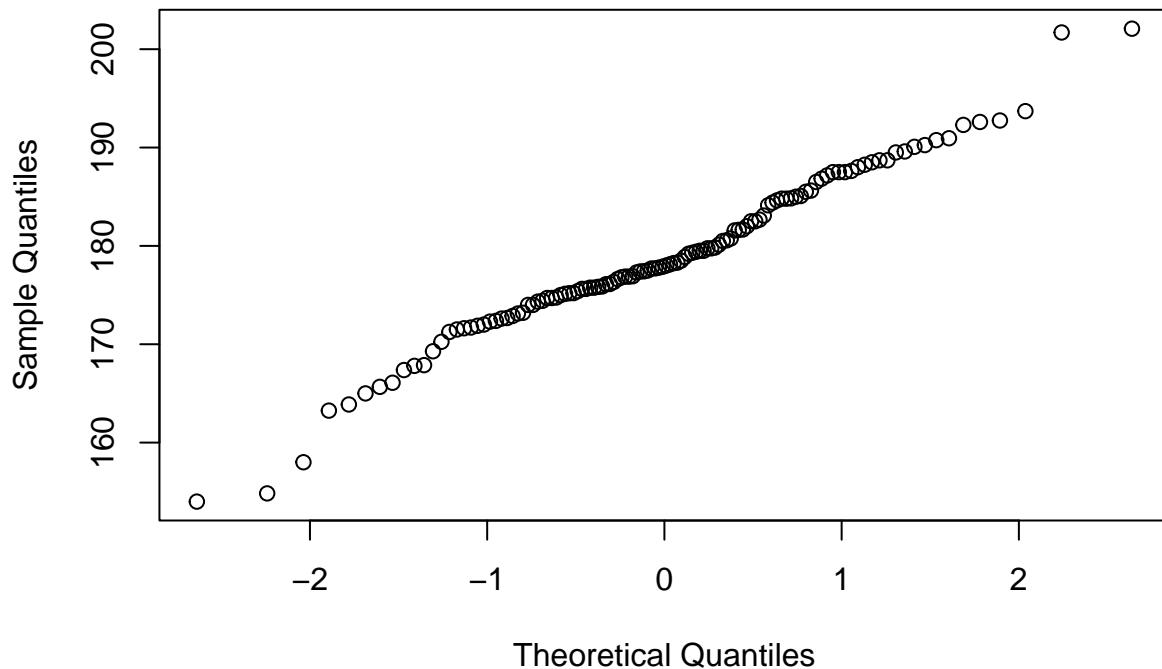
```
### UMBS ####
hist(umbs_flwr_plot$julian_median)
```

Histogram of umbs_flwr_plot\$julian_median



```
qqnorm(umbs_flwr_plot$julian_median)
```

Normal Q-Q Plot



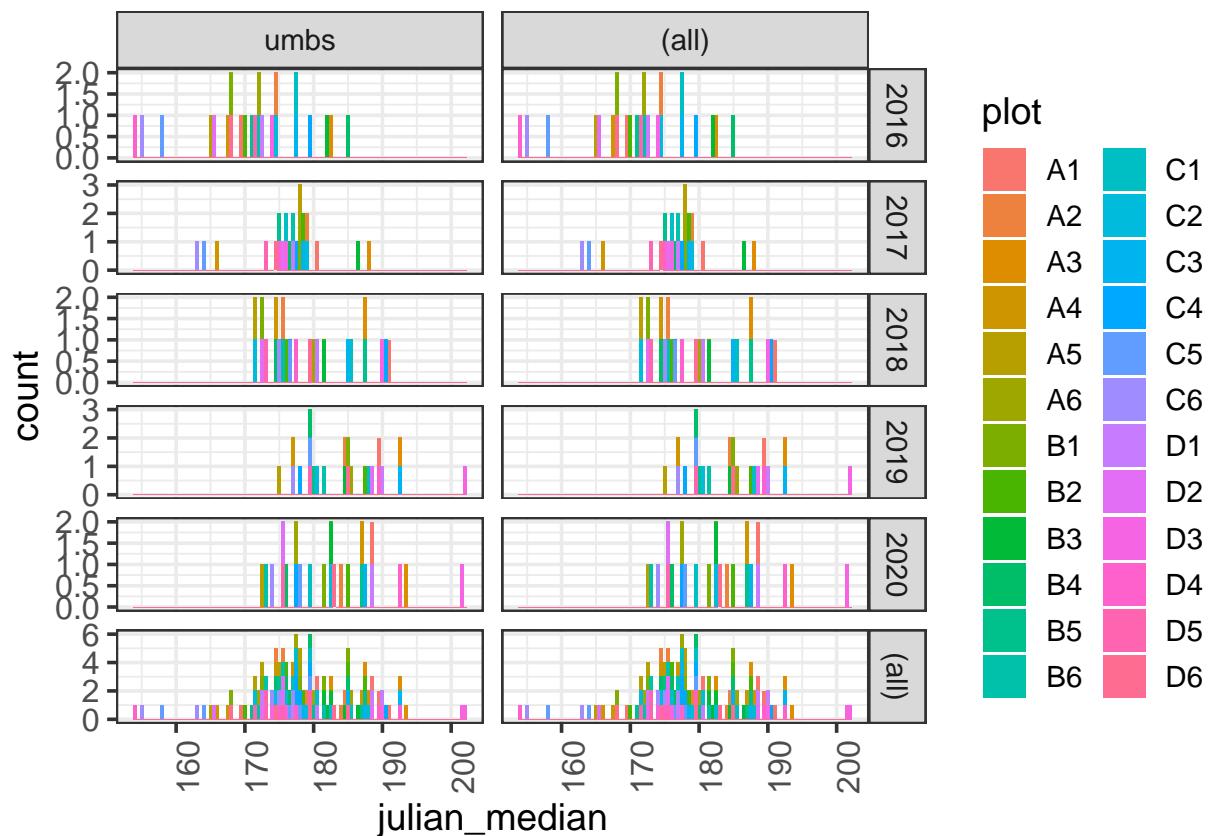
```

shapiro.test(umbs_flwr_plot$julian_median) # pvalue is > 0.05 so we accept the null hypothesis that the

##
## Shapiro-Wilk normality test
##
## data: umbs_flwr_plot$julian_median
## W = 0.9798, p-value = 0.0682

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

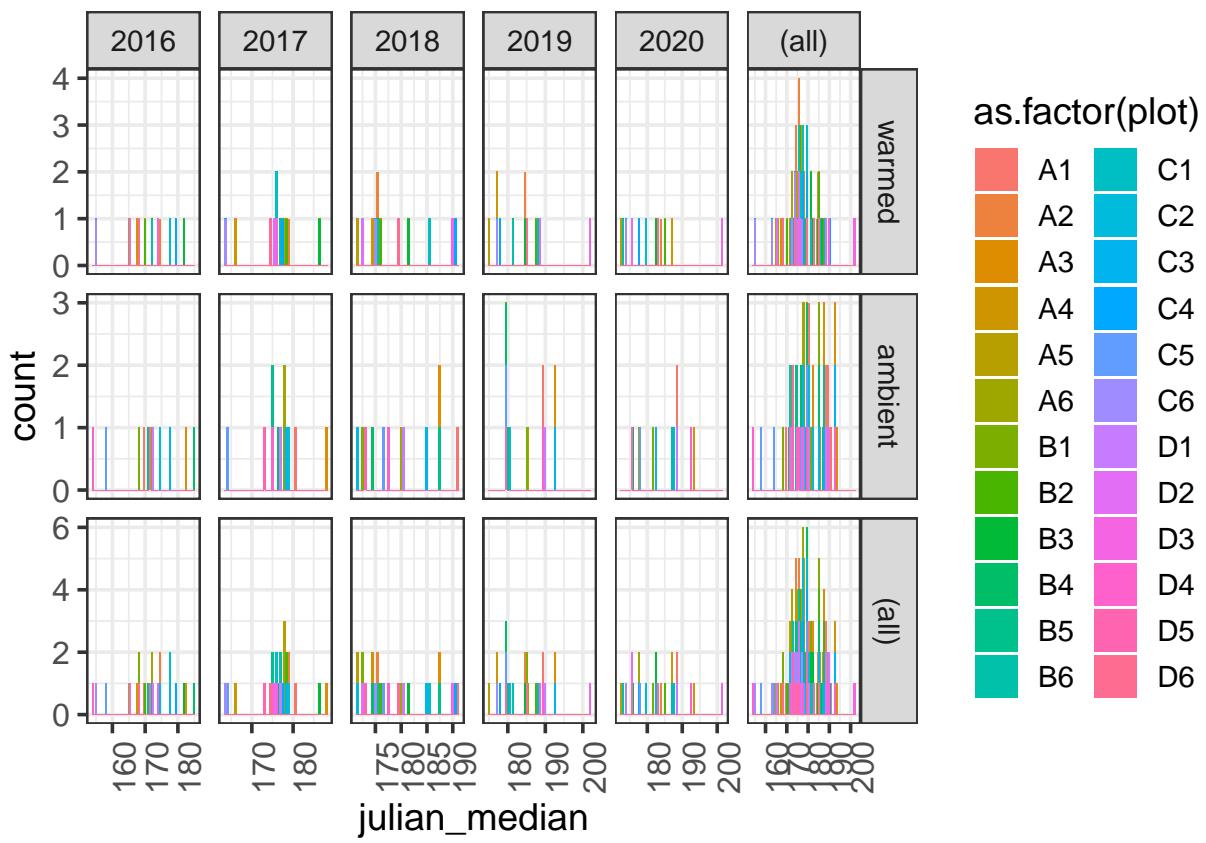
```



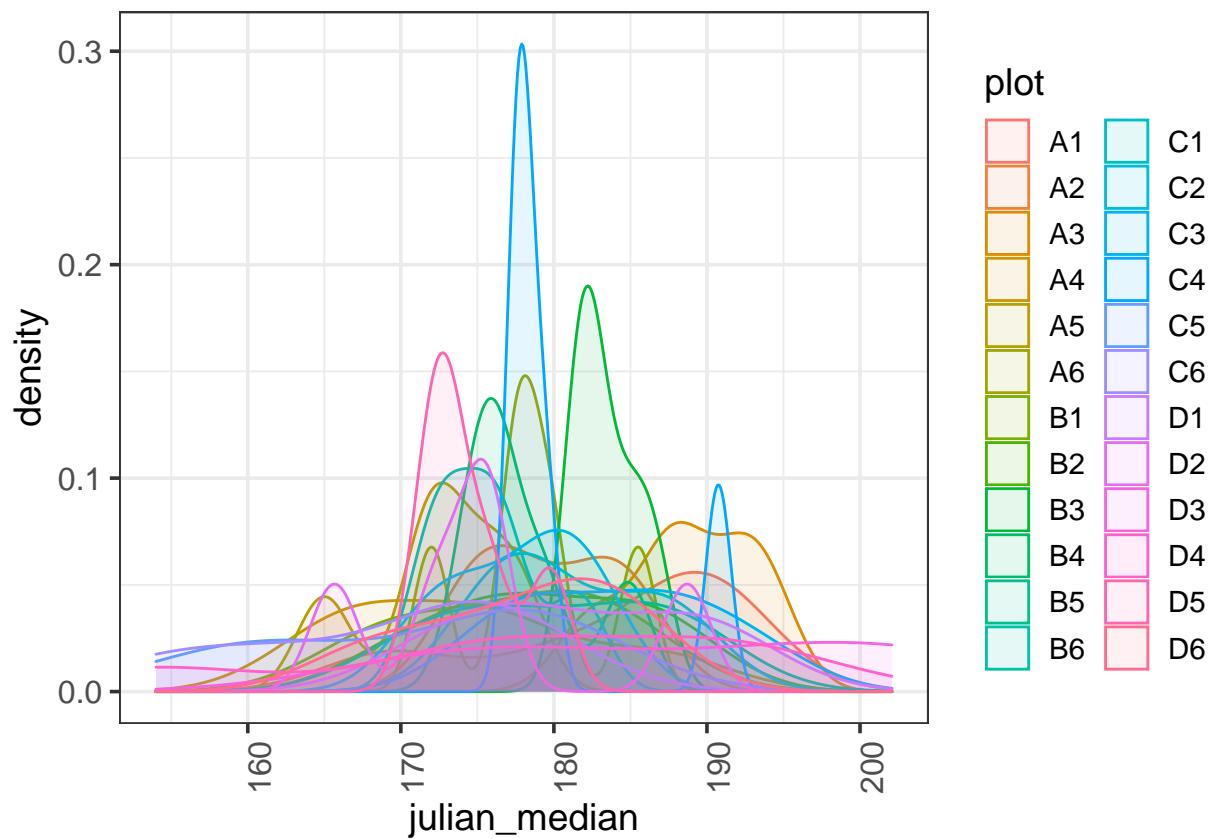
```

ggplot(umbs_flwr_plot, aes(julian_median, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
  facet_grid(state~year, margins = TRUE, scales = "free")

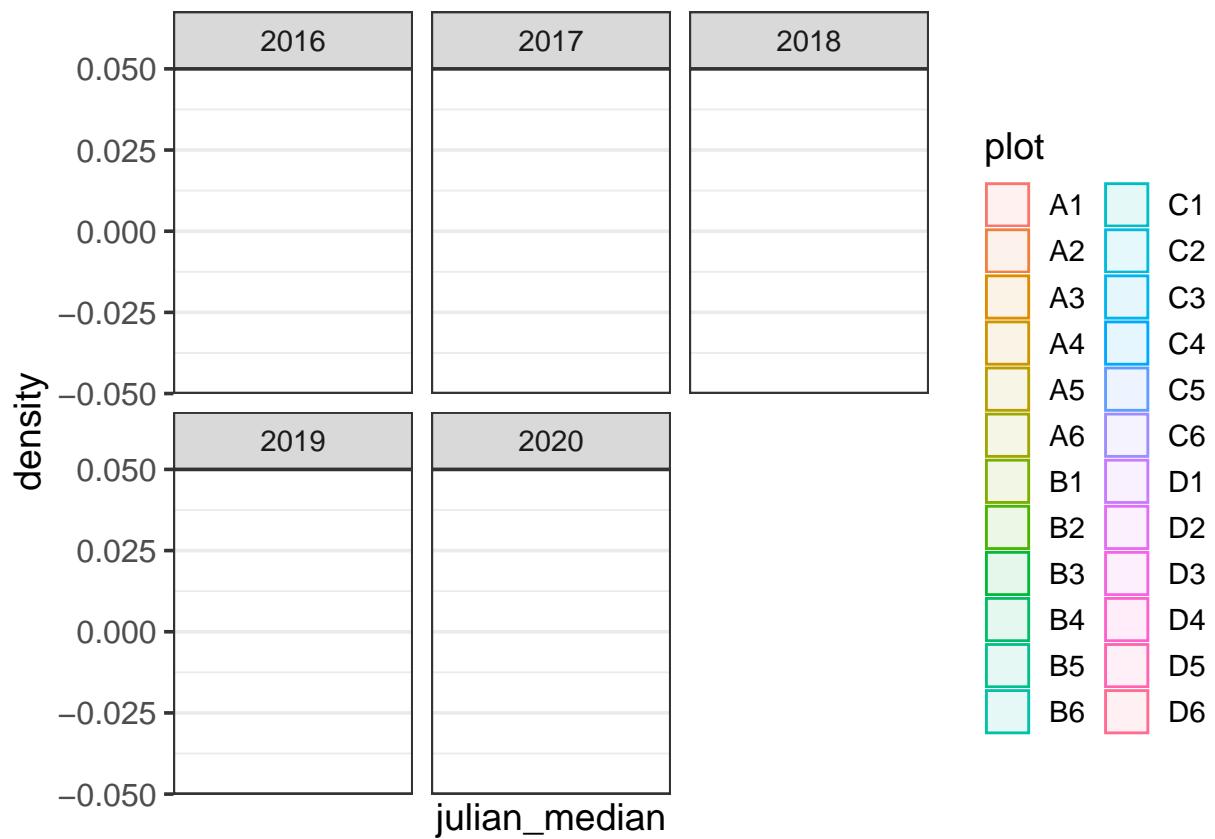
```



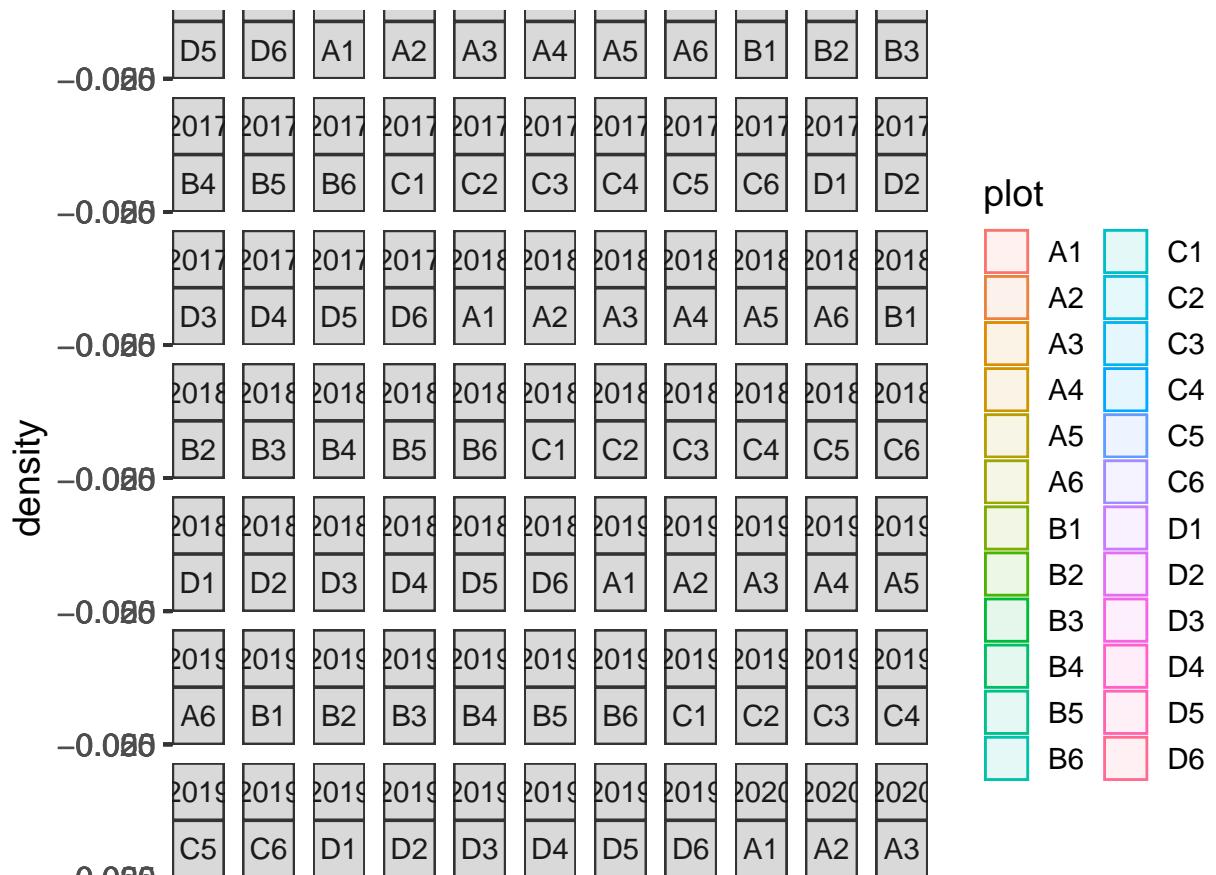
```
ggplot(umbs_flwr_plot, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1)
```



```
ggplot(umbs_flwr_plot, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year)
```

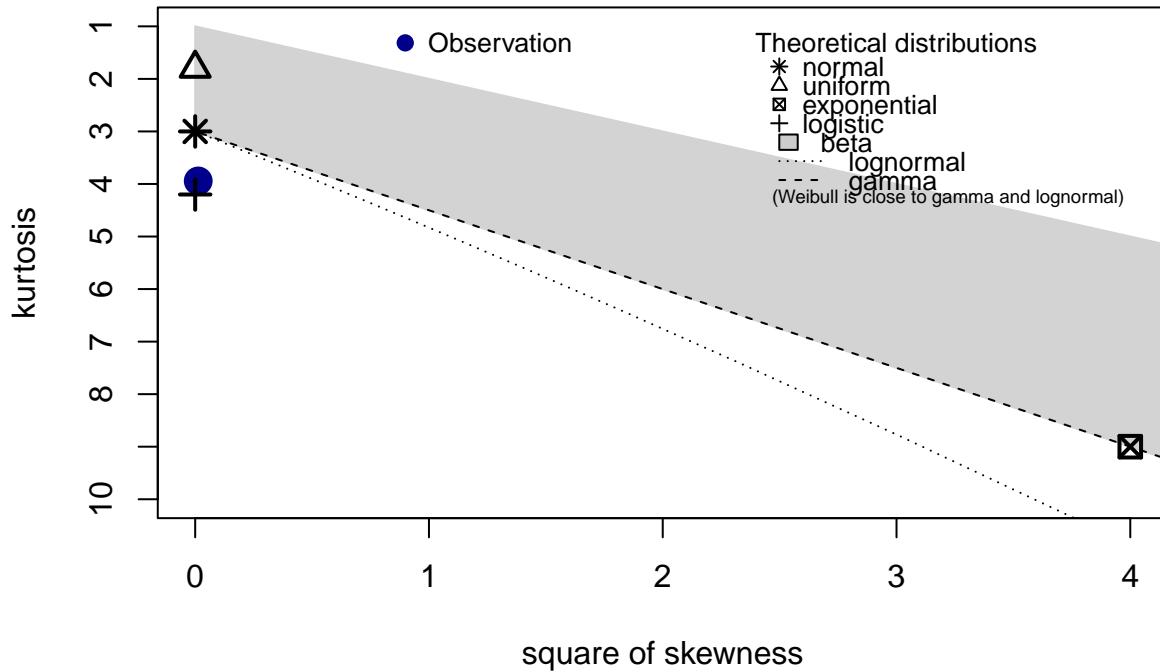


```
ggplot(umbs_flwr_plot, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year + plot)
```



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

Cullen and Frey graph



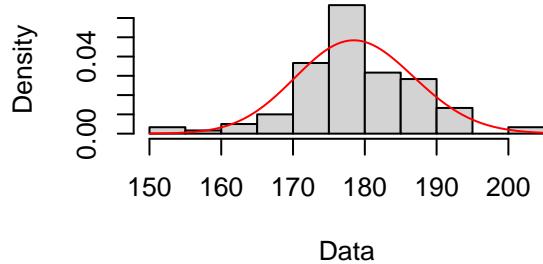
```

## summary statistics
## -----
## min: 154   max: 202.0833
## median: 177.9375
## mean: 178.8387
## estimated sd: 8.251076
## estimated skewness: -0.1139959
## estimated kurtosis: 3.94229

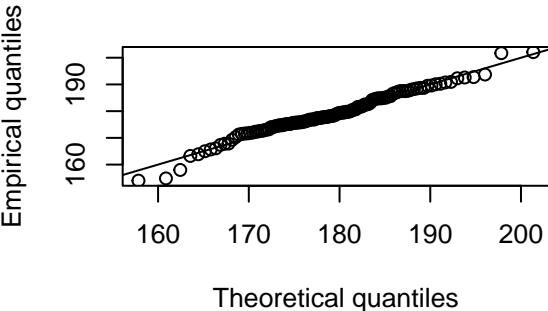
# Gamma distribution
fit.gamma <- fitdist(umbs_flwr_plot$julian_median, "gamma")
plot(fit.gamma)

```

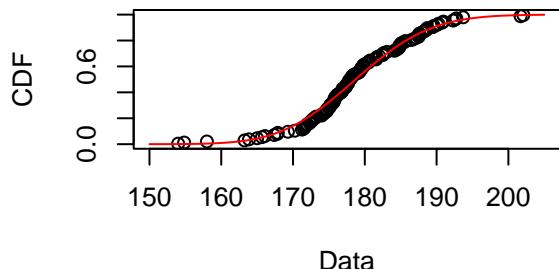
Empirical and theoretical dens.



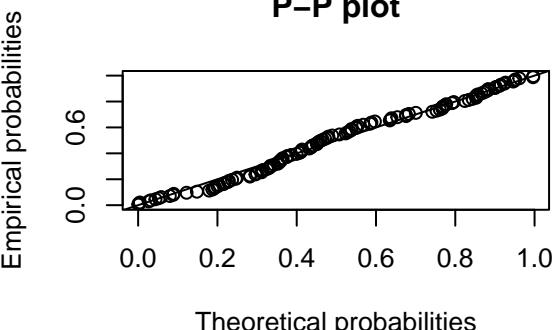
Q-Q plot



Empirical and theoretical CDFs

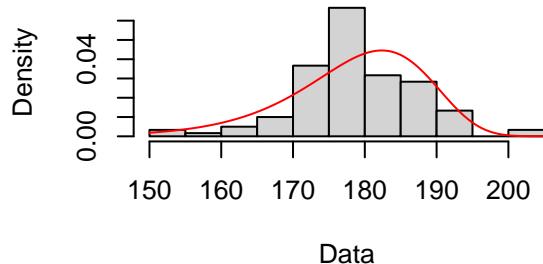


P-P plot

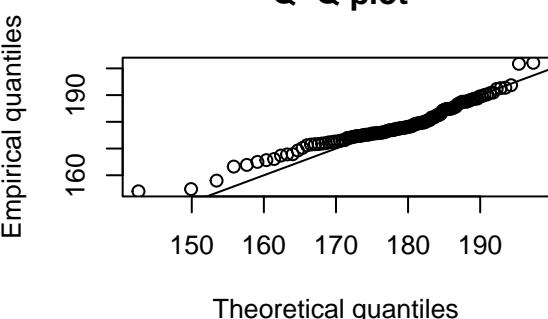


```
# Weibull distribution
fit.weibull <- fitdist(umbss_flwr_plot$julian_median, "weibull")
plot(fit.weibull)
```

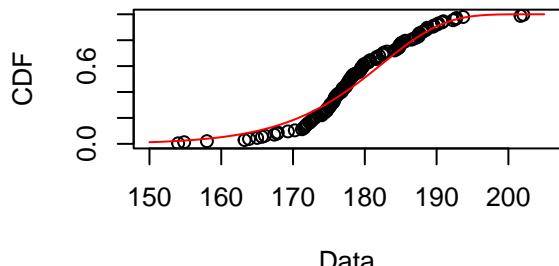
Empirical and theoretical dens.



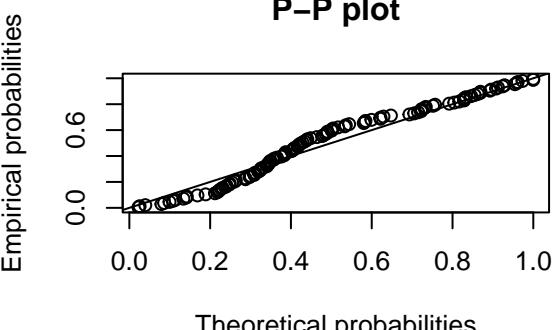
Q-Q plot



Empirical and theoretical CDFs

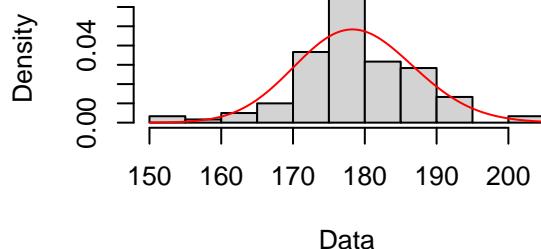


P-P plot

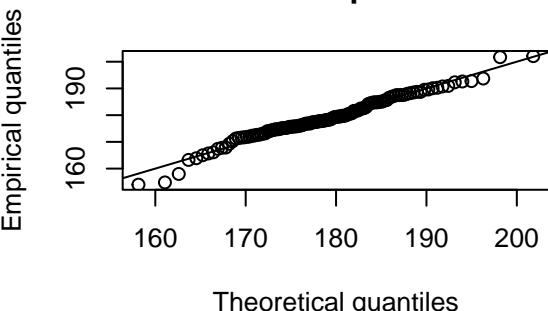


```
# Lognormal distribution
fit.ln <- fitdist(umbs_flwr_plot$julian_median, "lnorm")
plot(fit.ln)
```

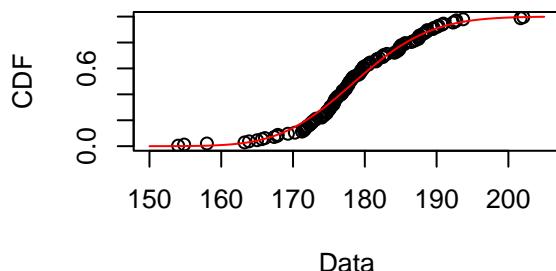
Empirical and theoretical dens.



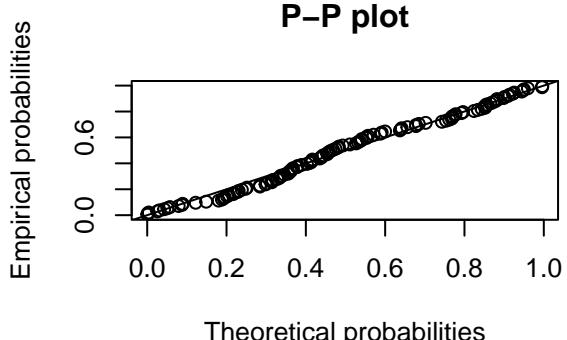
Q–Q plot



Empirical and theoretical CDFs

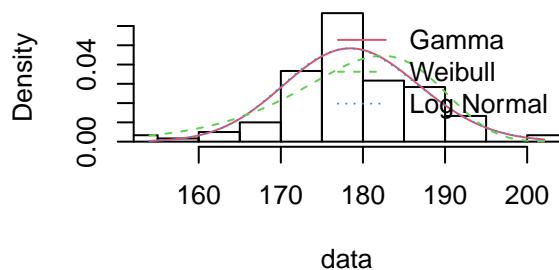


P–P plot

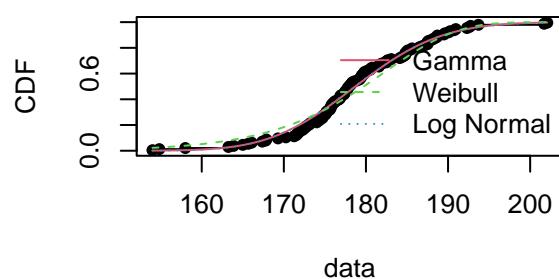


```
par(mfrow=c(2,2))
plot.legend <- c("Gamma", "Weibull", "Log Normal")
denscomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
cdfcomp (list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
qqcomp (list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
ppcomp (list(fit.gamma,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

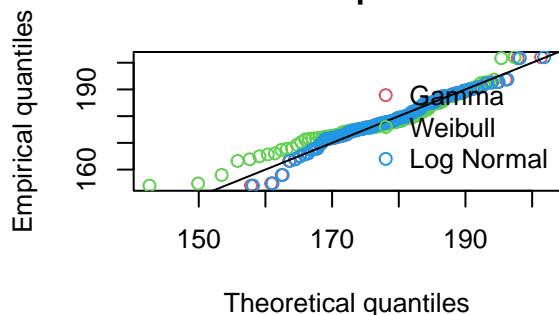
Histogram and theoretical densities



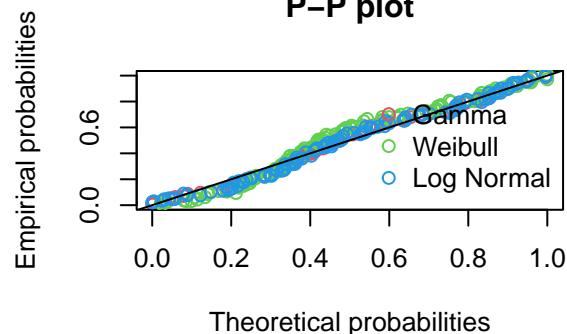
Empirical and theoretical CDFs



Q-Q plot



P-P plot



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

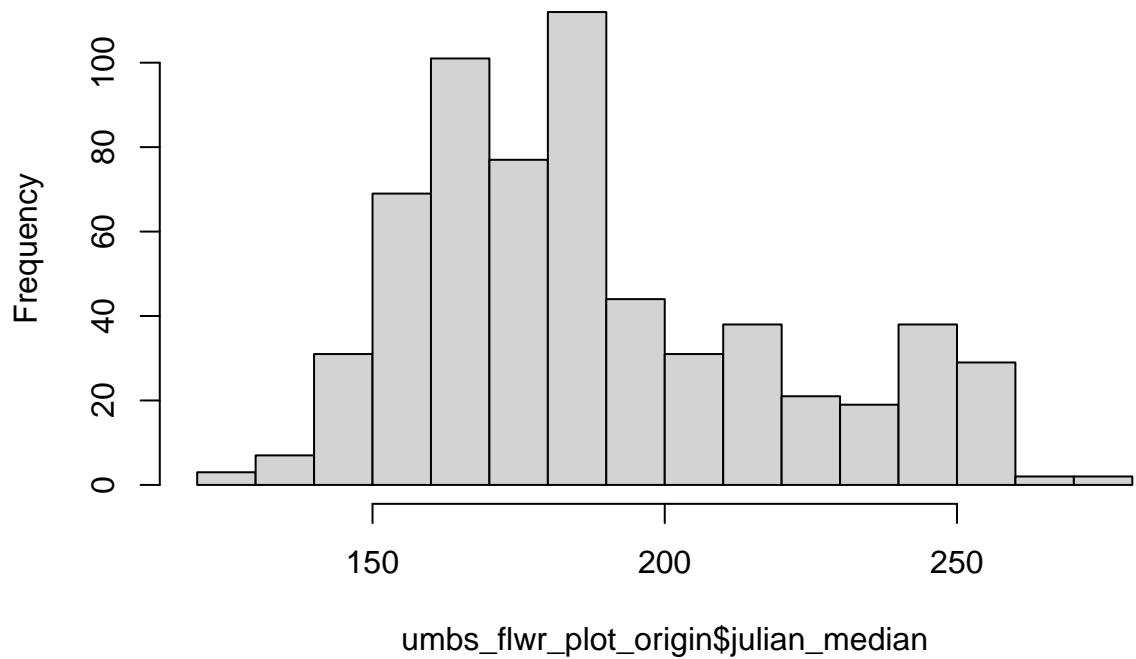
```
## Goodness-of-fit statistics
##                                     Gamma   Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.07087173 0.1123078 0.07183673
## Cramer-von Mises statistic   0.12153497 0.3827918 0.12108114
## Anderson-Darling statistic   0.76301381 2.1930729 0.78012312
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 850.722 865.6707    851.238
## Bayesian Information Criterion 856.297 871.2457    856.813
```

```
# Gamma is the best fit based on this function with log normal really close or we could go with normal
```

UMBS PLOT LEVEL ORIGIN - Looking at MEDIAN JULIAN DAY

```
### UMBS ####
hist(umbs_flwr_plot_origin$julian_median)
```

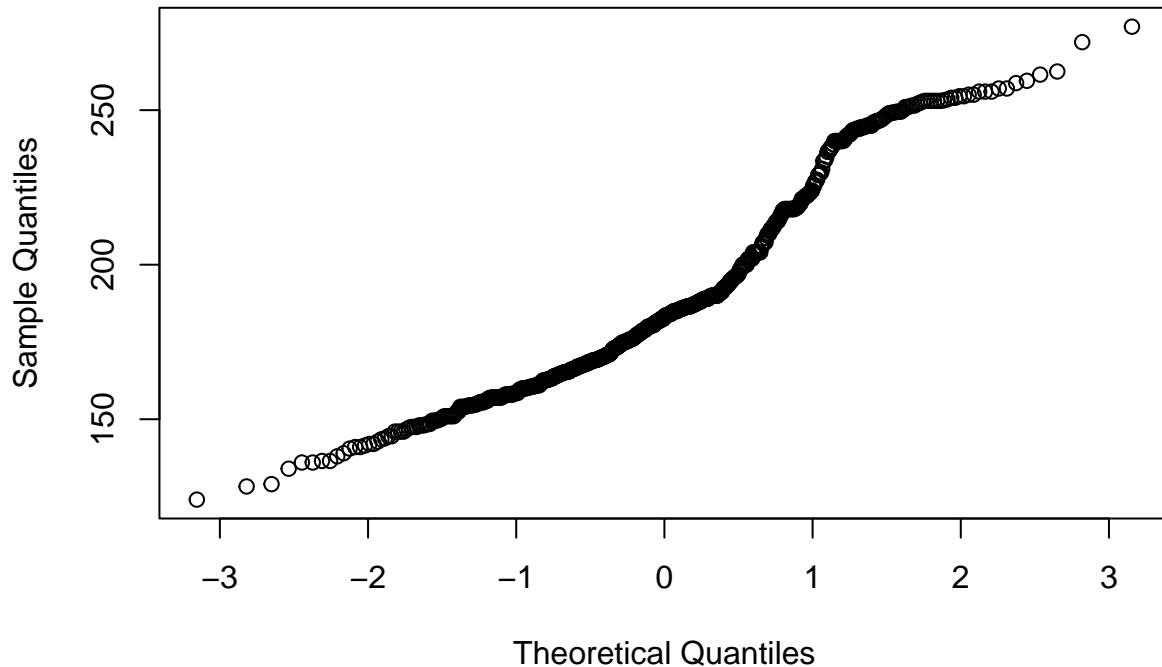
Histogram of umbs_flwr_plot_origin\$julian_median



```
umbs_flwr_plot_origin$julian_median
```

```
qqnorm(umbs_flwr_plot_origin$julian_median)
```

Normal Q-Q Plot



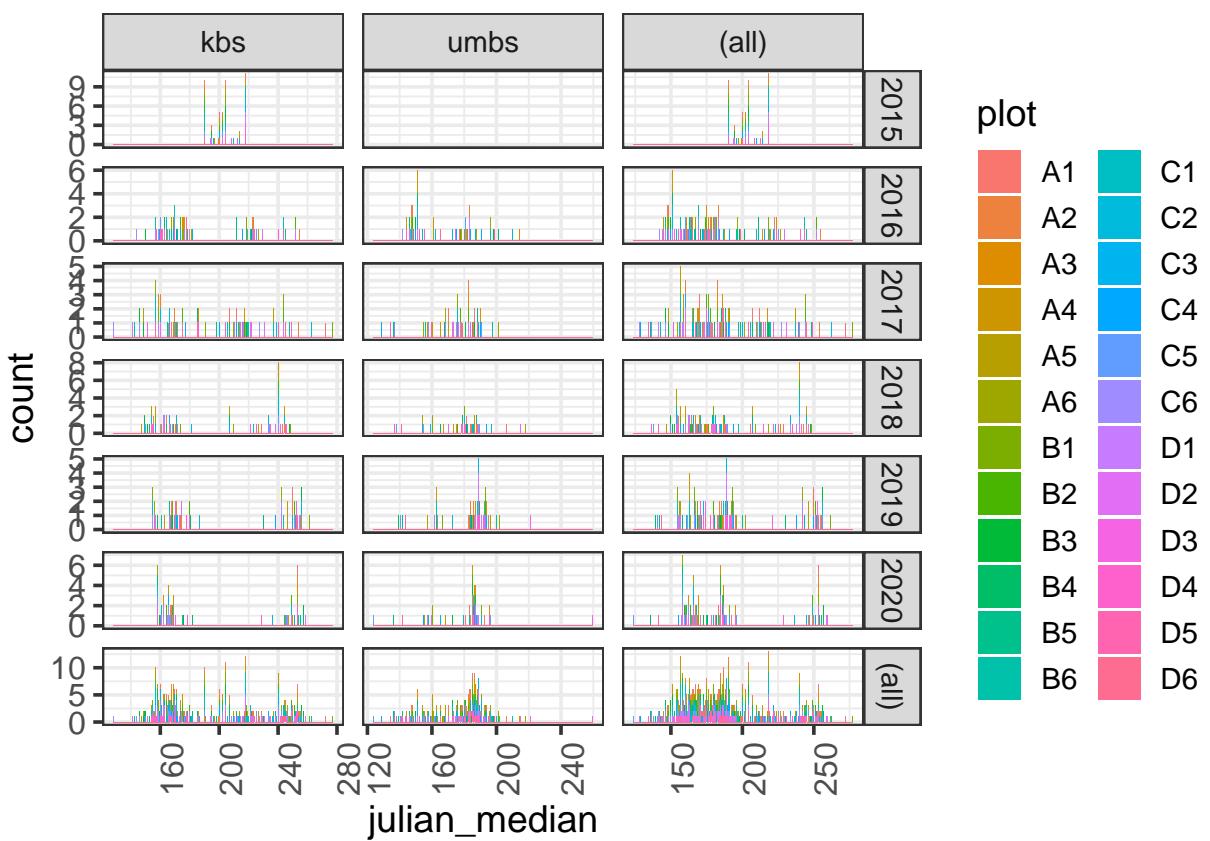
```

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

## 
## Shapiro-Wilk normality test
## 
## data: umbs_flwr_plot_origin$julian_median
## W = 0.93959, p-value = 3.173e-15

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

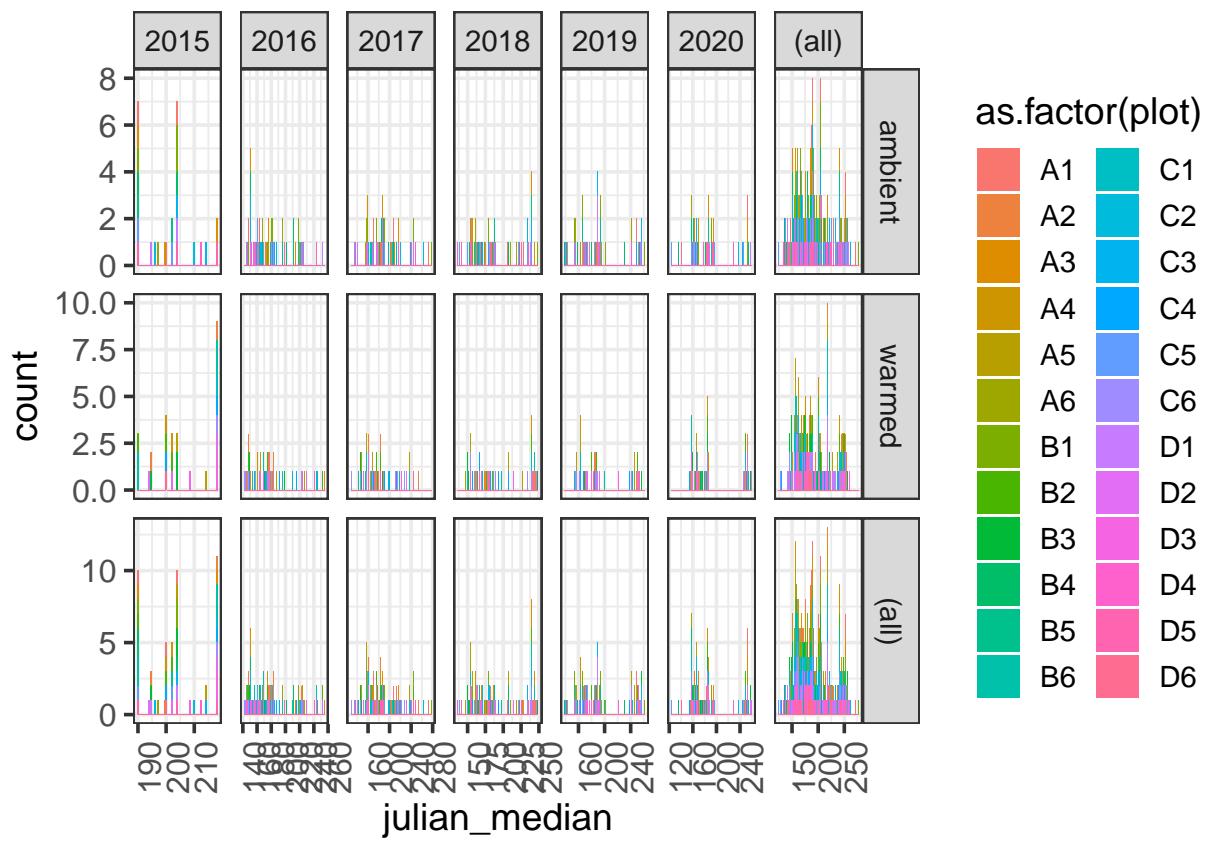
```



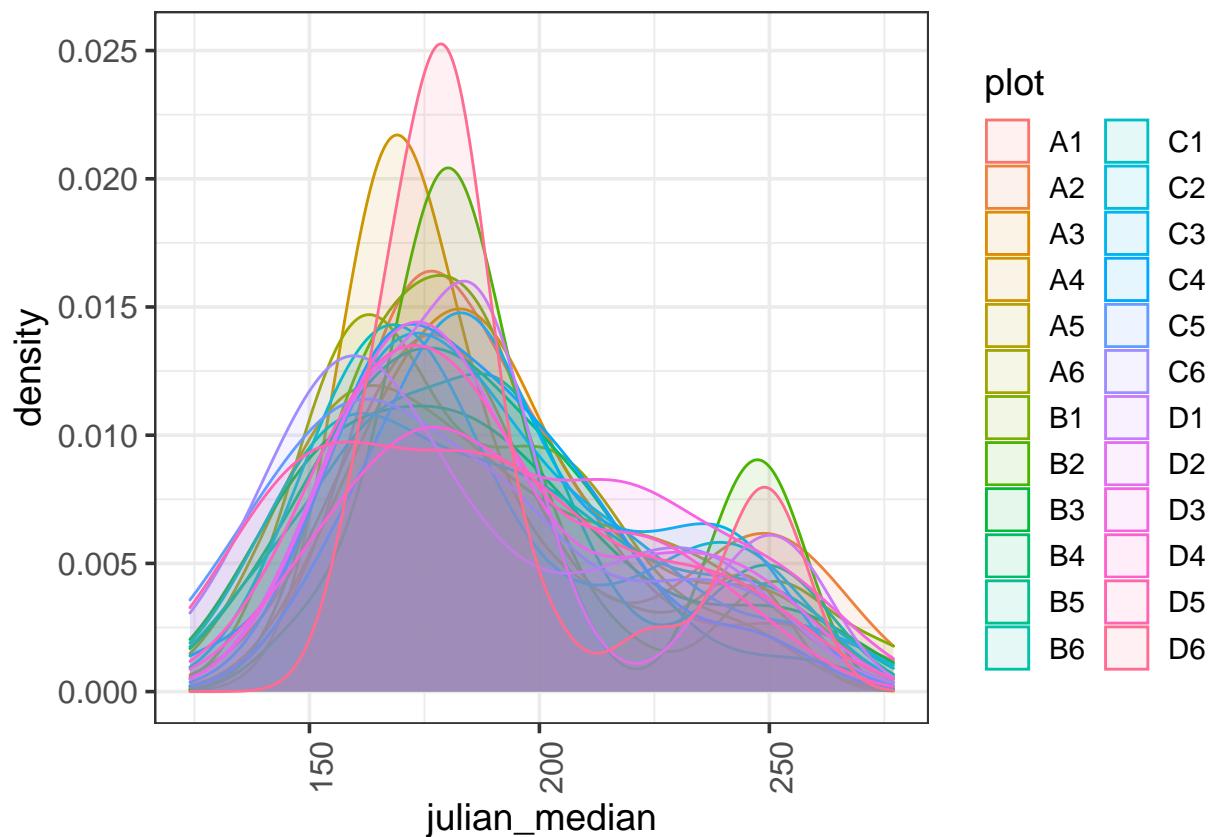
```

ggplot(umbs_flwr_plot_origin, aes(julian_median, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5)
  facet_grid(state~year, margins = TRUE, scales = "free")

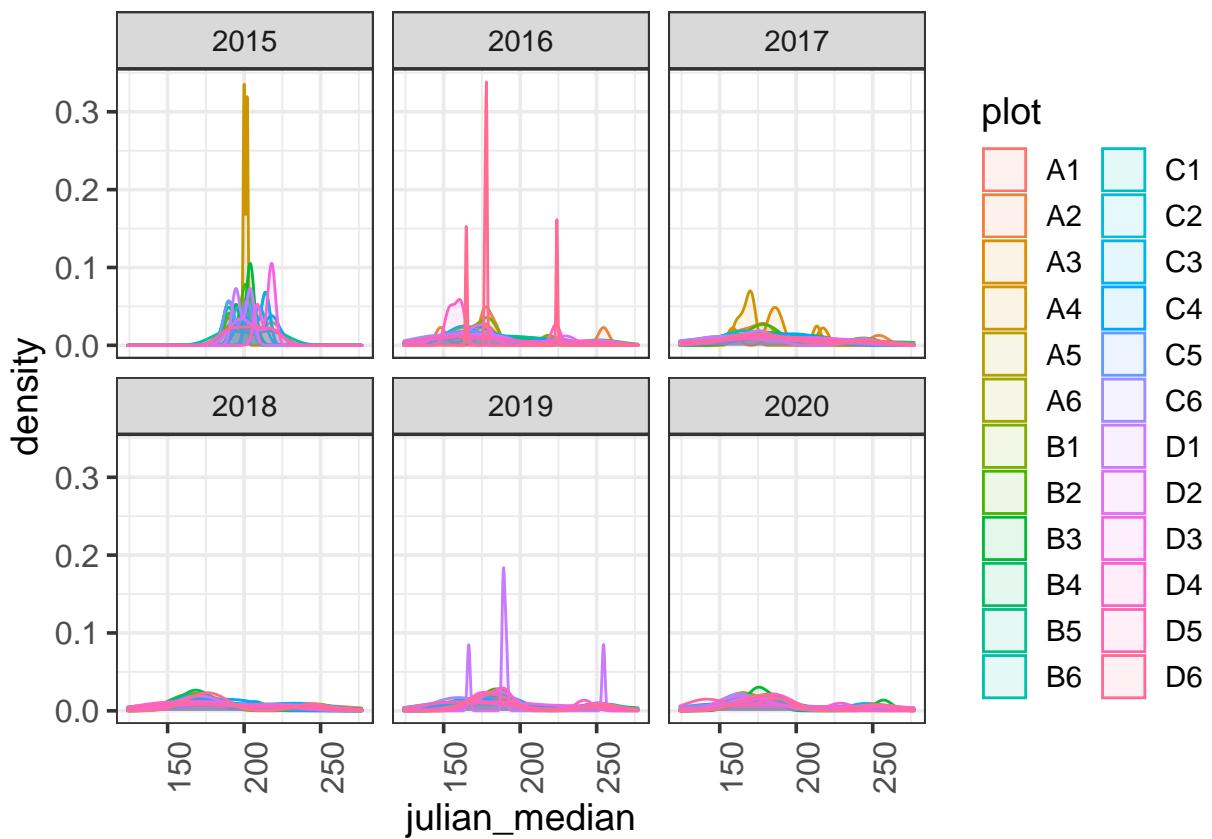
```



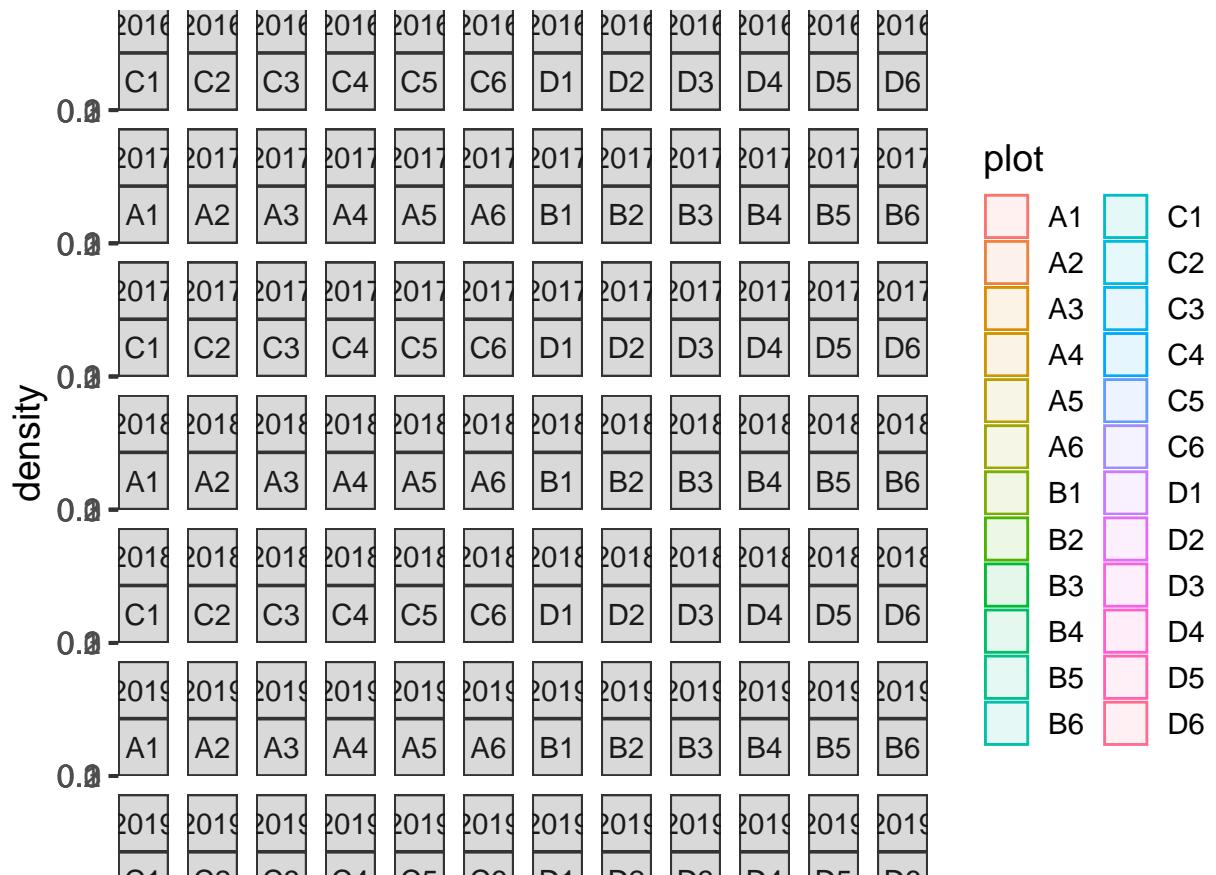
```
ggplot(umbs_flwr_plot_origin, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1)
```



```
ggplot(umbs_flwr_plot_origin, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year)
```

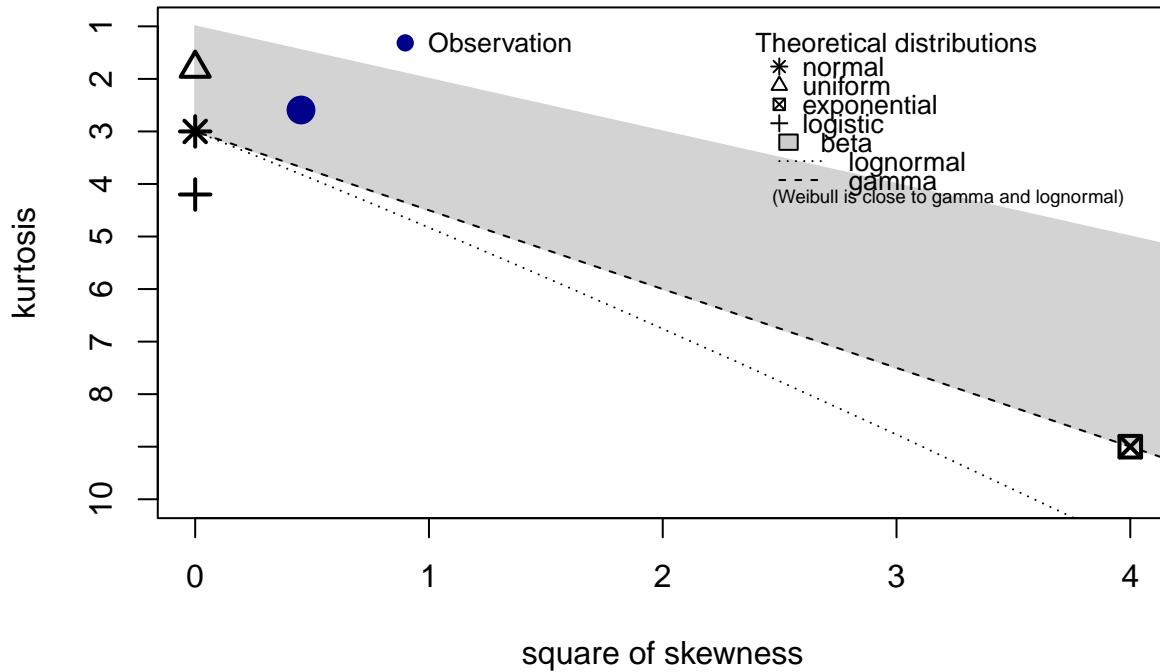


```
ggplot(umbs_flwr_plot_origin, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year + plot)
```



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

Cullen and Frey graph

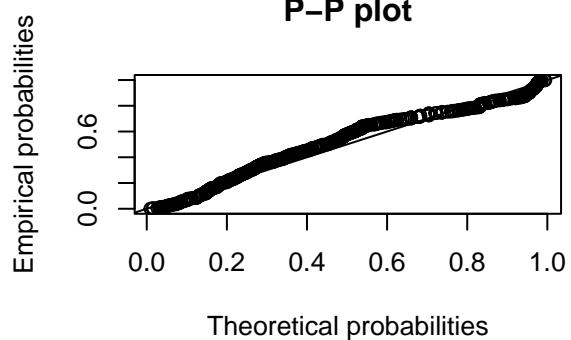
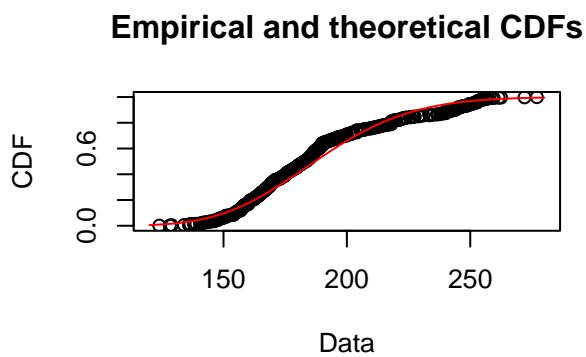
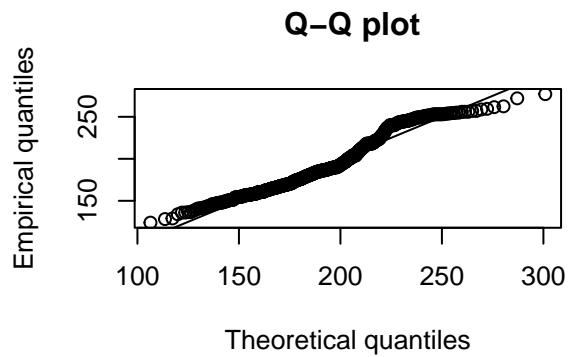
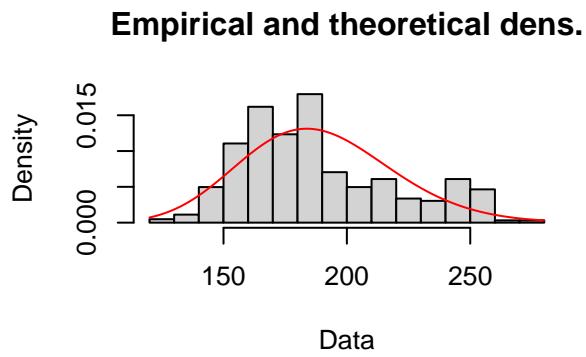


```

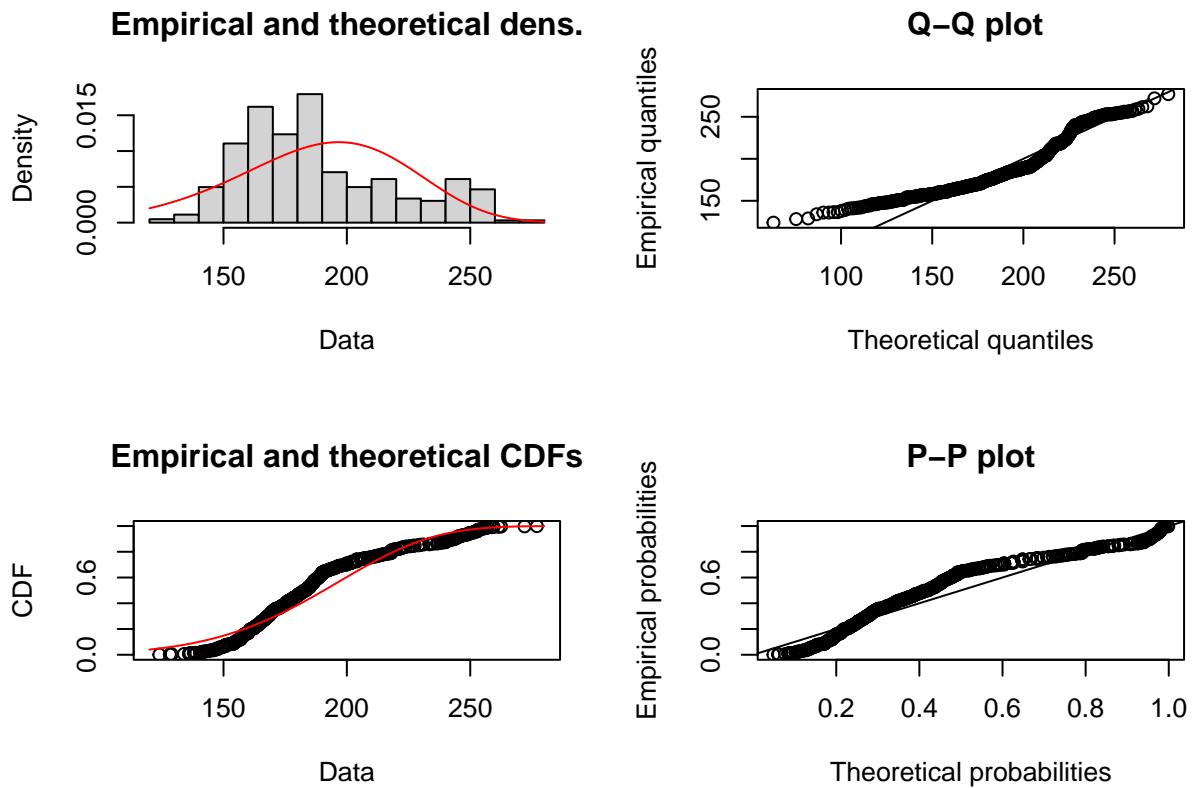
## summary statistics
## -----
## min: 124   max: 277
## median: 183.25
## mean: 188.7646
## estimated sd: 31.52303
## estimated skewness: 0.6727891
## estimated kurtosis: 2.59167

# Gamma distribution
fit.gamma <- fitdist(umbs_flwr_plot_origin$julian_median, "gamma")
plot(fit.gamma)

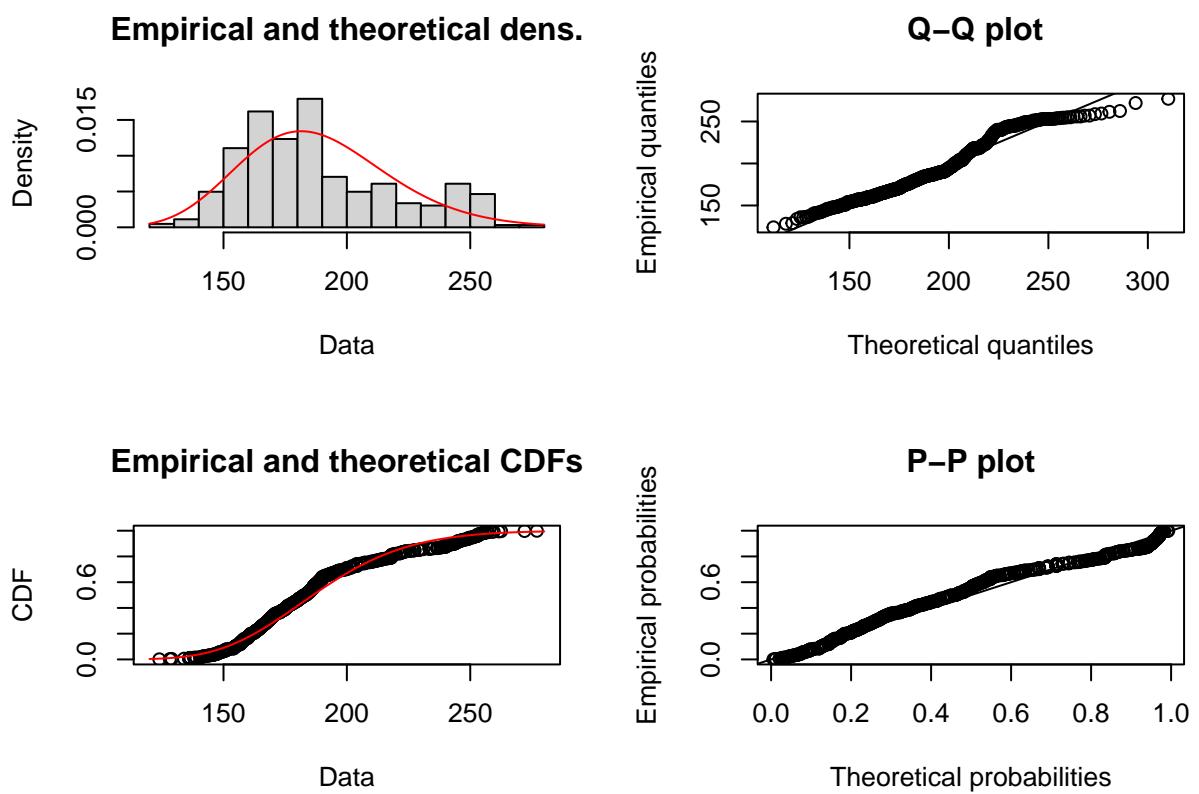
```



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



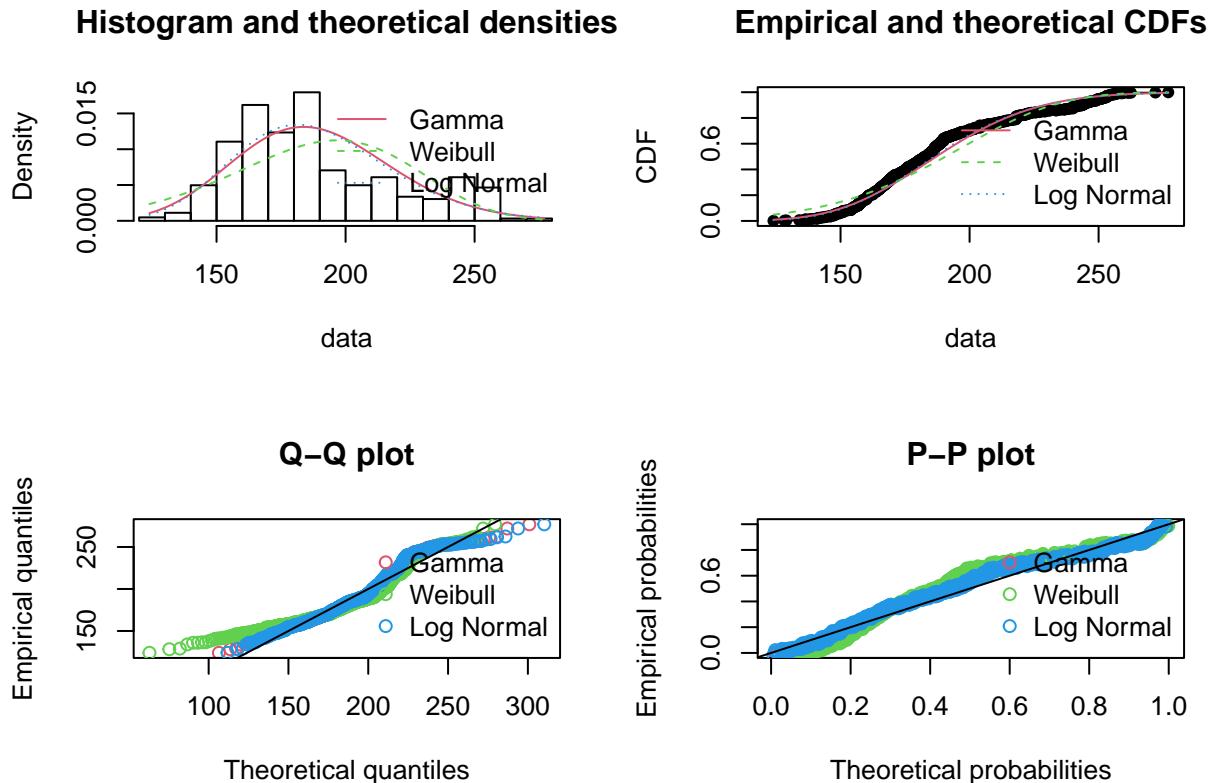
```
# Lognormal distribution
fit.ln <- fitdist(umbs_flwr_plot_origin$julian_median, "lnorm")
plot(fit.ln)
```



```

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)

```



```

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

```

```

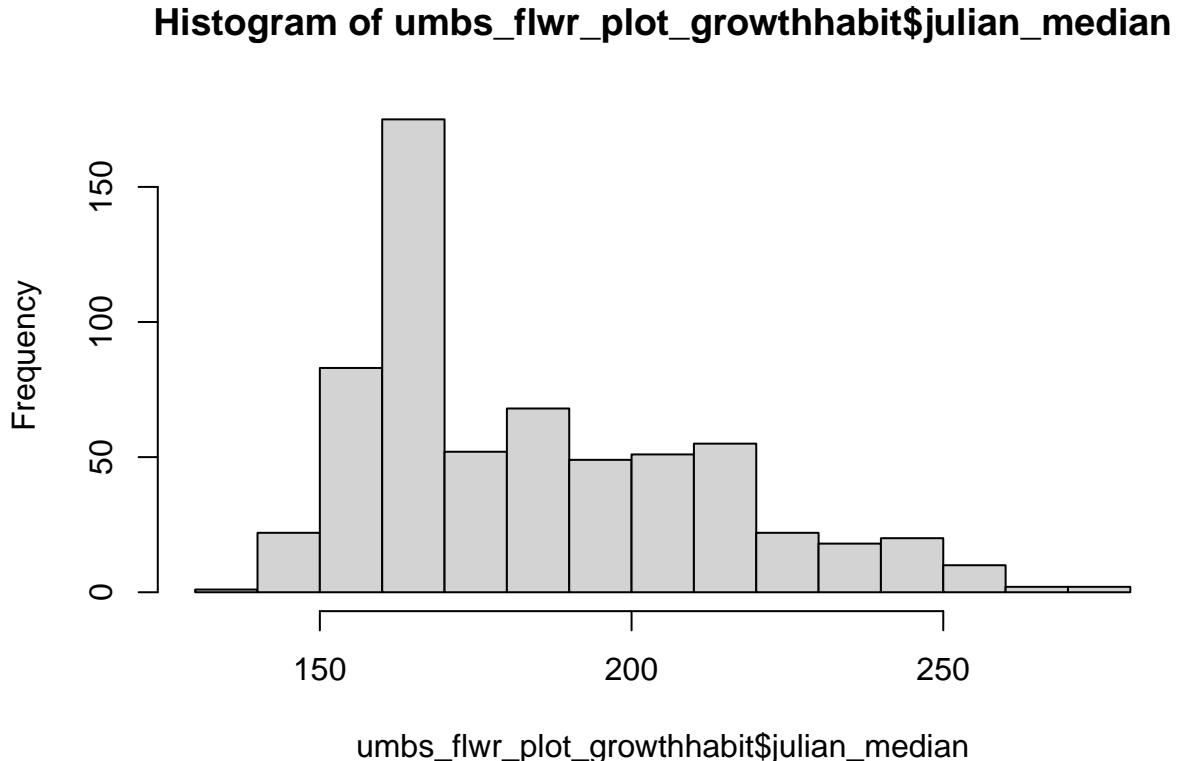
## Goodness-of-fit statistics
##                                     Gamma    Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.1034768 0.1489233 0.09218264
## Cramer-von Mises statistic   1.4384752 3.2757811 1.11486210
## Anderson-Darling statistic   9.0703276 19.4311214 7.23511209
##
## Goodness-of-fit criteria
##                                     Gamma    Weibull Log Normal
## Akaike's Information Criterion 6039.109 6155.551 6024.535
## Bayesian Information Criterion 6047.981 6164.423 6033.407

```

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

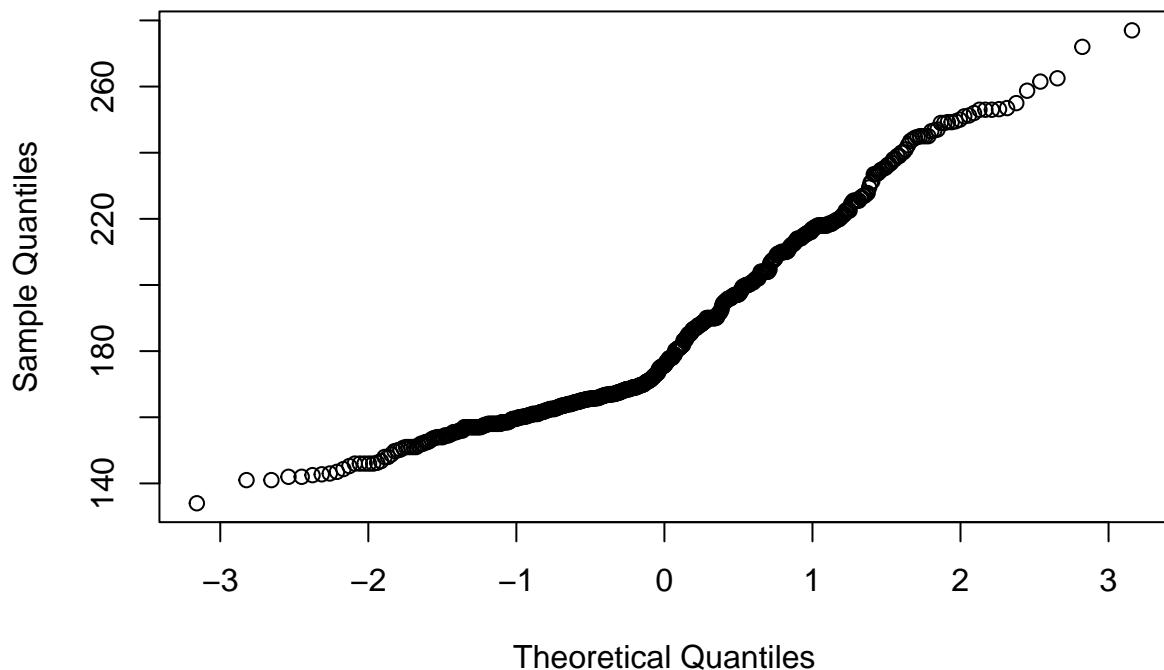
UMBS PLOT LEVEL GROWTH HABIT - Looking at MEDIAN JULIAN DAY

```
### UMBS ###
hist(umbs_flwr_plot_growthhabit$julian_median)
```



```
qqnorm(umbs_flwr_plot_growthhabit$julian_median)
```

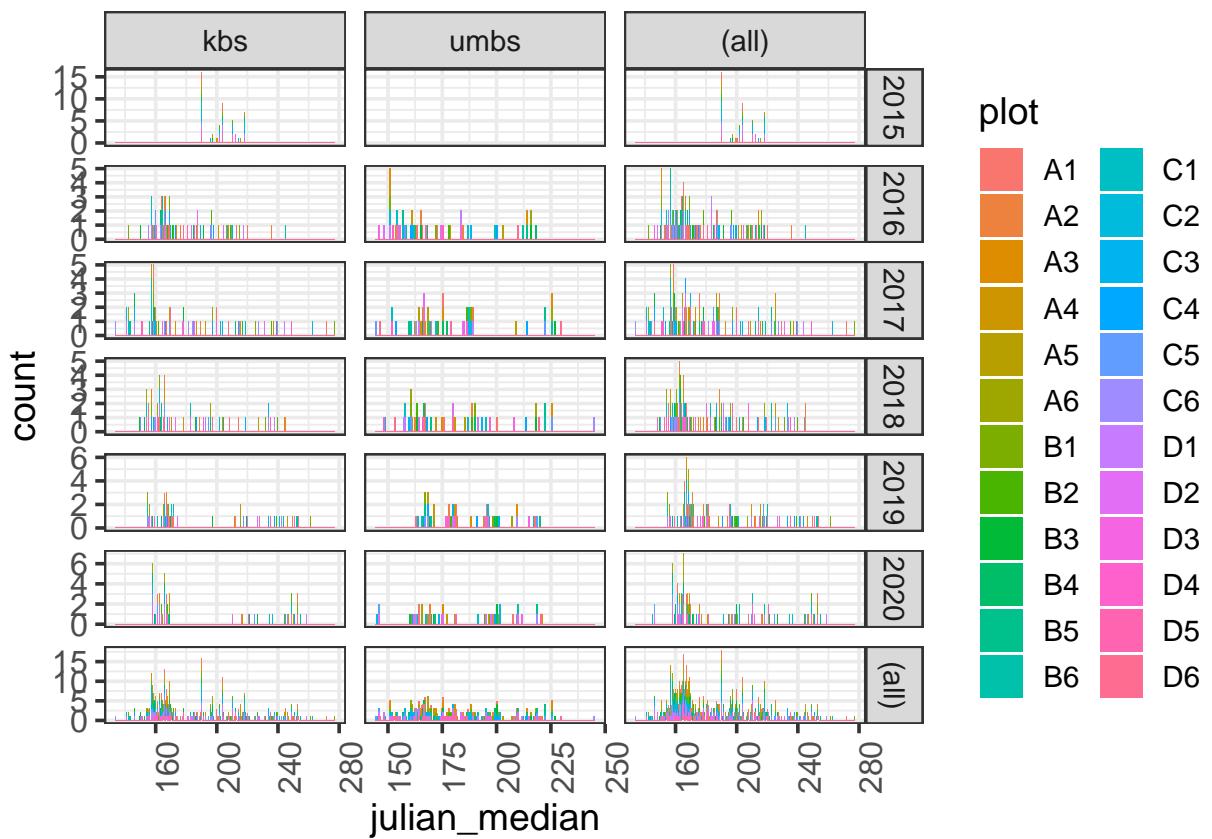
Normal Q-Q Plot



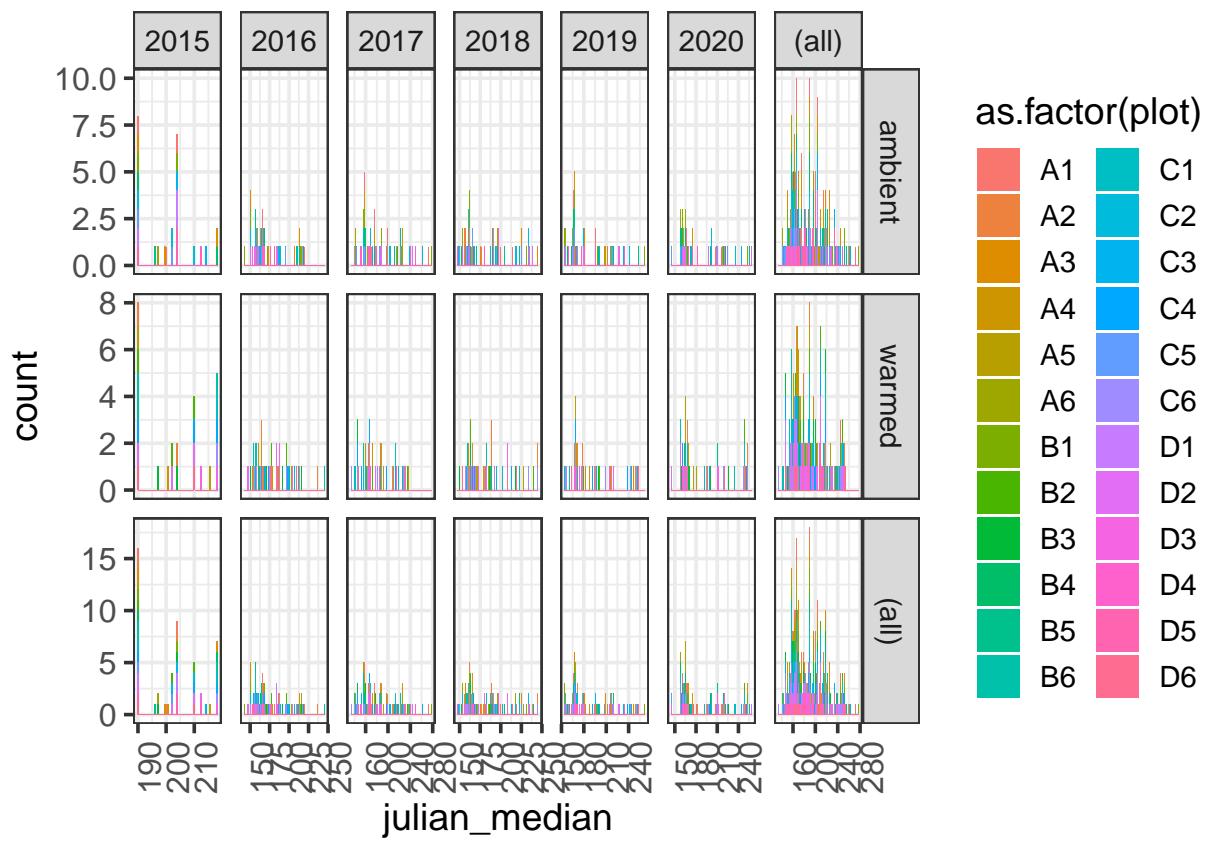
```
shapiro.test(umbs_flwr_plot_growthhabit$julian_median) # pvalue is < 0.05 so we reject the null hypothesis

##
## Shapiro-Wilk normality test
##
## data: umbs_flwr_plot_growthhabit$julian_median
## W = 0.92666, p-value < 2.2e-16

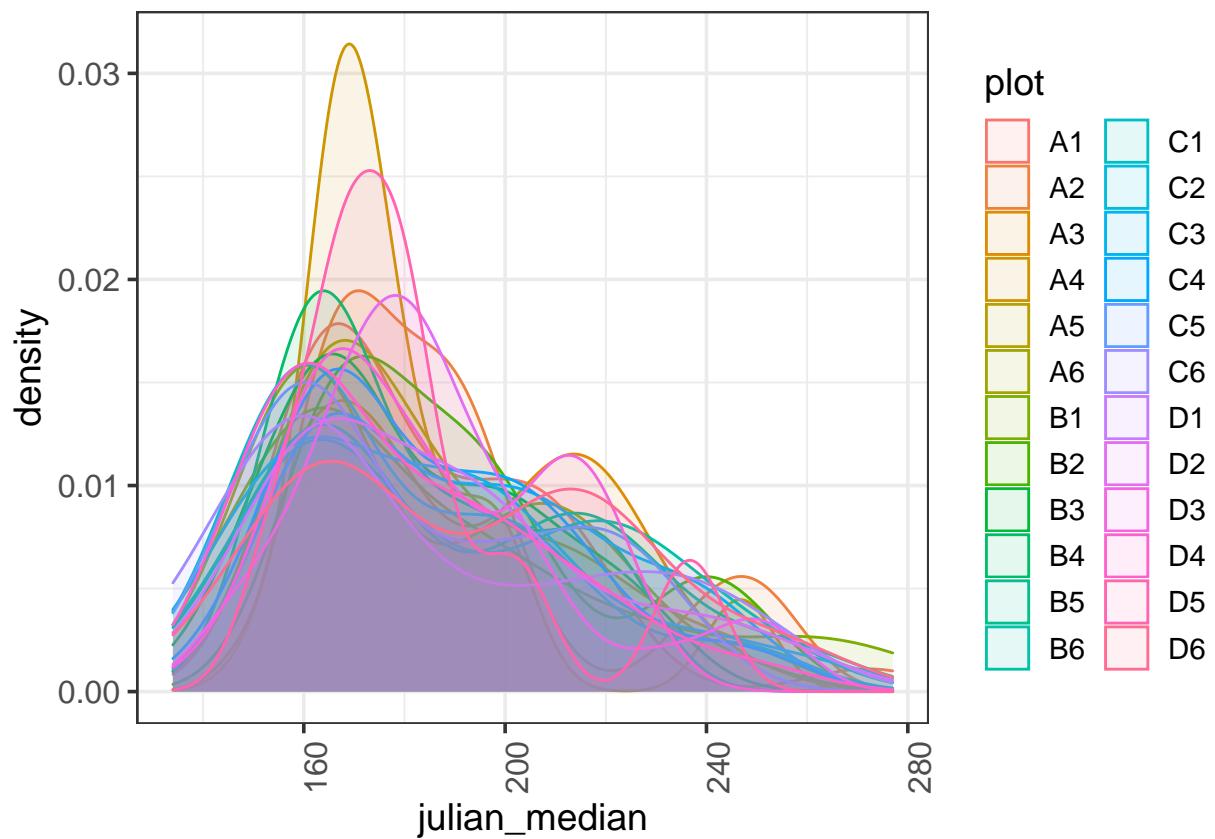
# Visualizing median Julian date for umbs at the PLOT LEVEL
ggplot(umbs_flwr_plot_growthhabit, aes(julian_median, fill = plot)) +
  geom_histogram(binwidth = 0.5) +
  facet_grid(year ~ site, margins = TRUE, scales = "free")
```



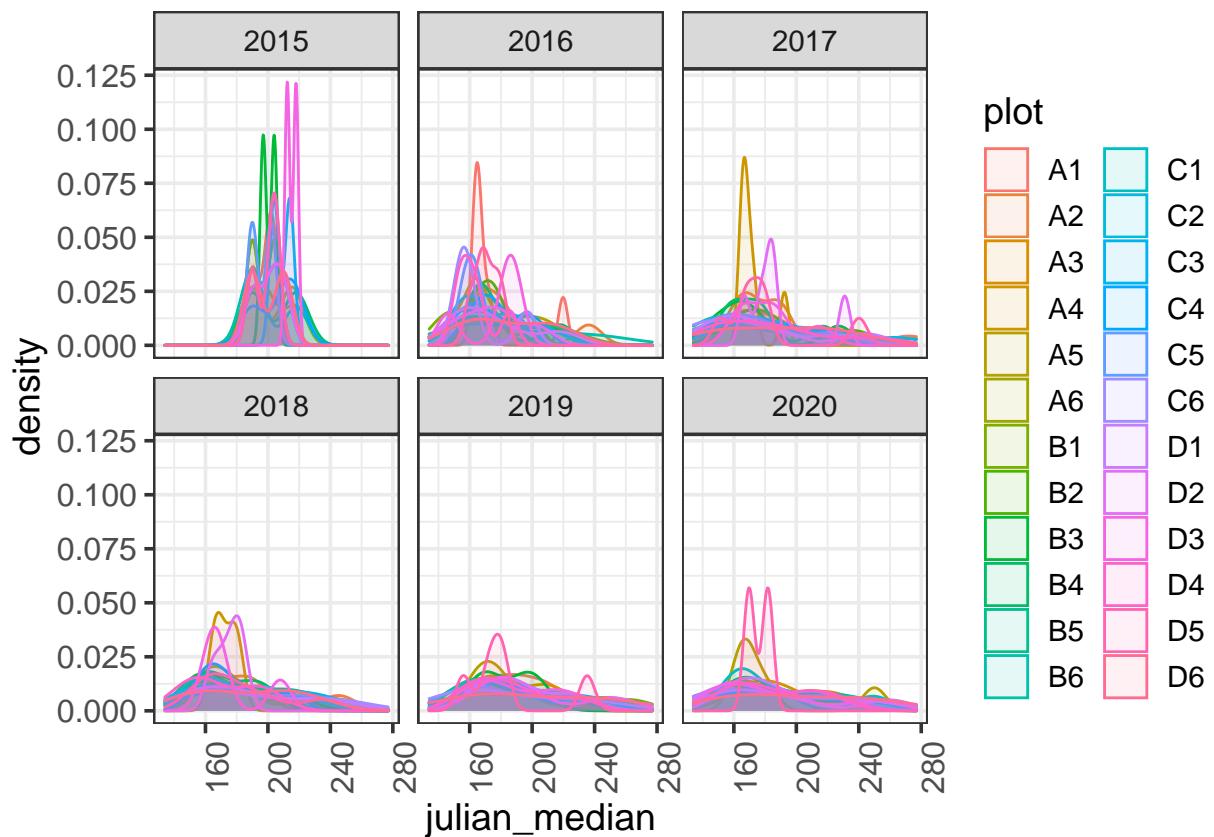
```
ggplot(umbs_flwr_plot_growthhabit, aes(julian_median, fill = as.factor(plot))) + geom_histogram(binwidth = 1)
  facet_grid(state~year, margins = TRUE, scales = "free")
```



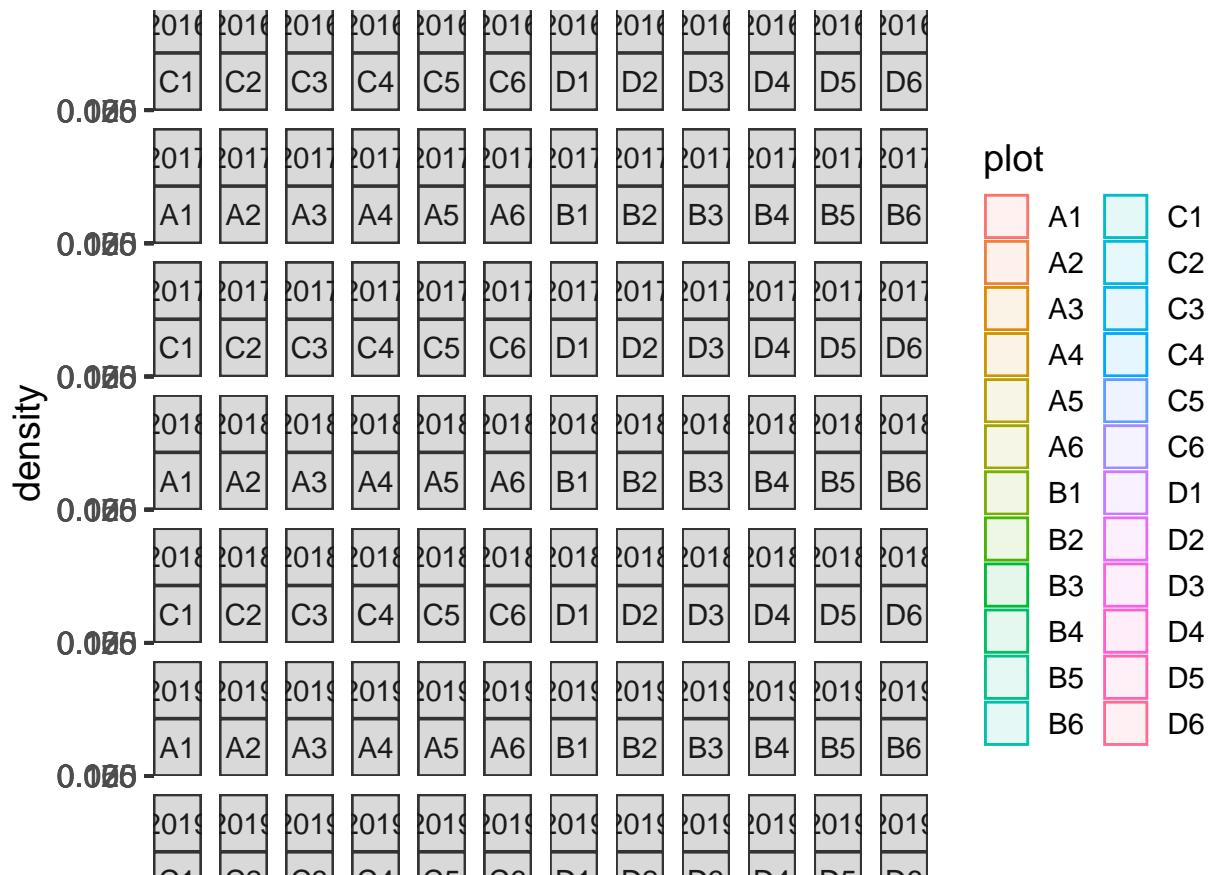
```
ggplot(umbs_flwr_plot_growthhabit, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1)
```



```
ggplot(umbs_flwr_plot_growthhabit, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year)
```

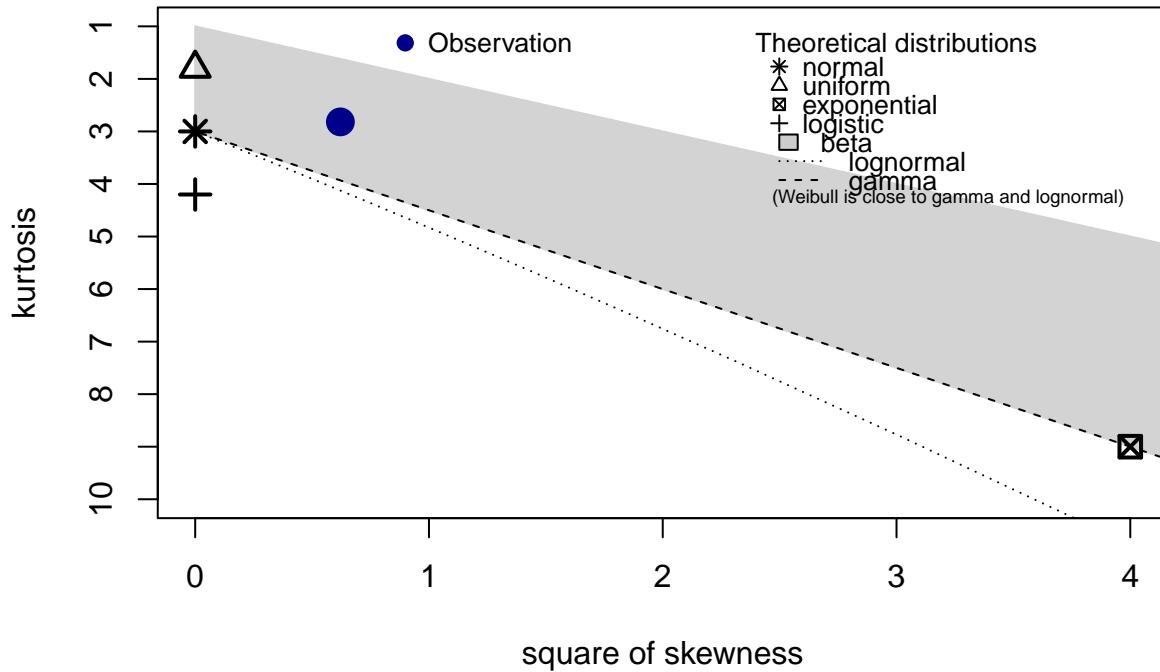


```
ggplot(umbs_flwr_plot_growthhabit, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year + plot)
```



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

Cullen and Frey graph



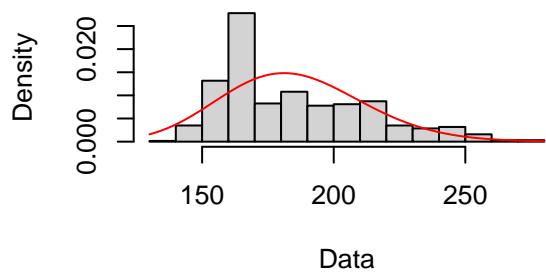
```

## summary statistics
## -----
## min: 134   max: 277
## median: 175.7083
## mean: 185.1005
## estimated sd: 27.99197
## estimated skewness: 0.7881167
## estimated kurtosis: 2.818375

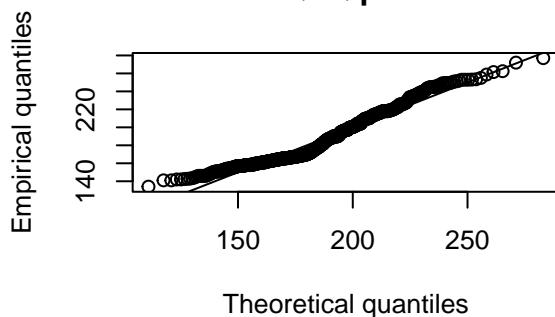
# Gamma distribution
fit.gamma <- fitdist(umbs_flwr_plot_growthhabit$julian_median, "gamma")
plot(fit.gamma)

```

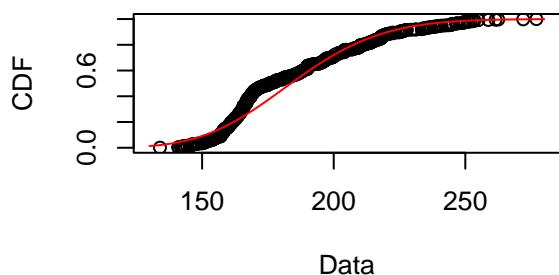
Empirical and theoretical dens.



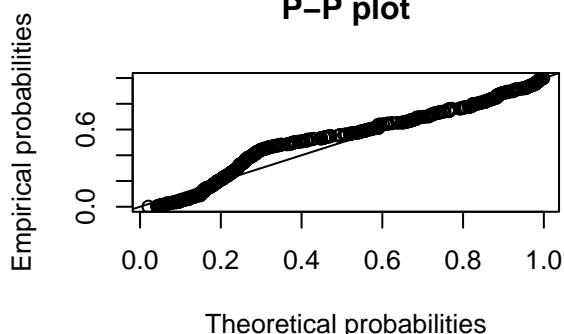
Q–Q plot



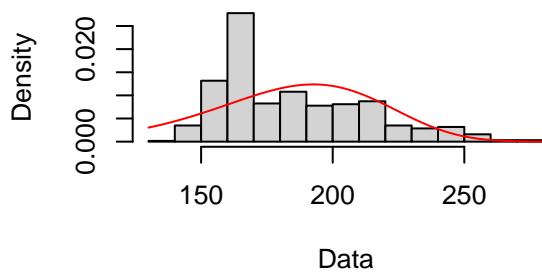
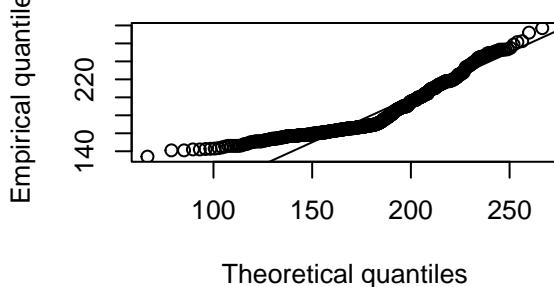
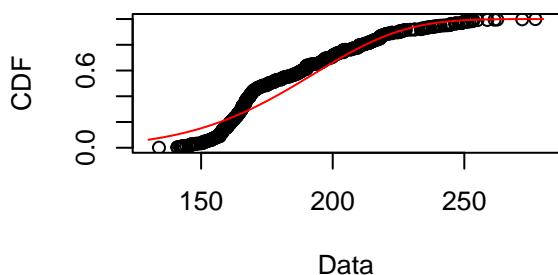
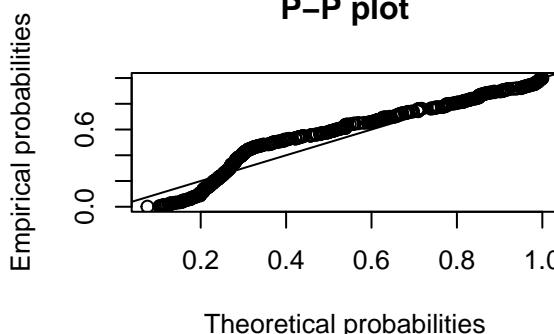
Empirical and theoretical CDFs



P–P plot

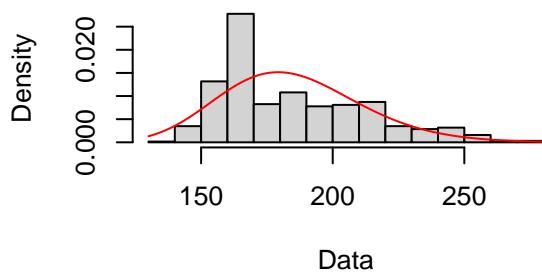
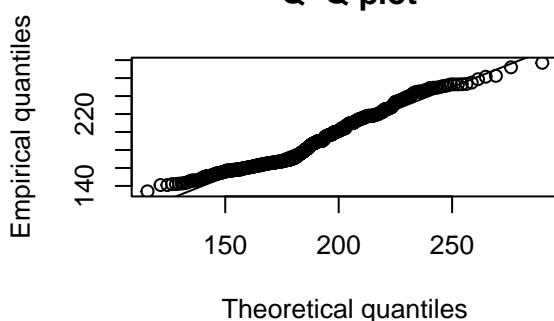
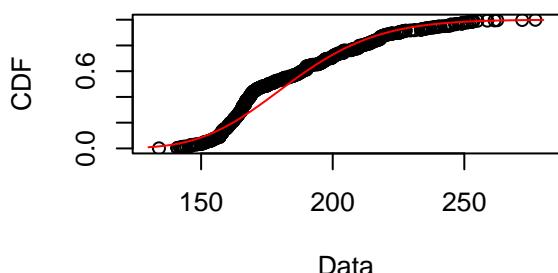
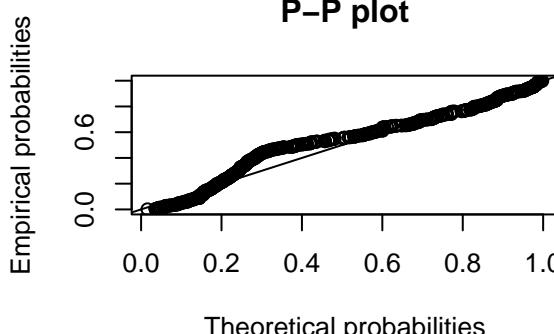


```
#  
# Weibull distribution  
fit.weibull <- fitdist(umbs_flwr_plot_growthhabit$julian_median, "weibull")  
plot(fit.weibull)
```

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

```
# Lognormal distribution
```

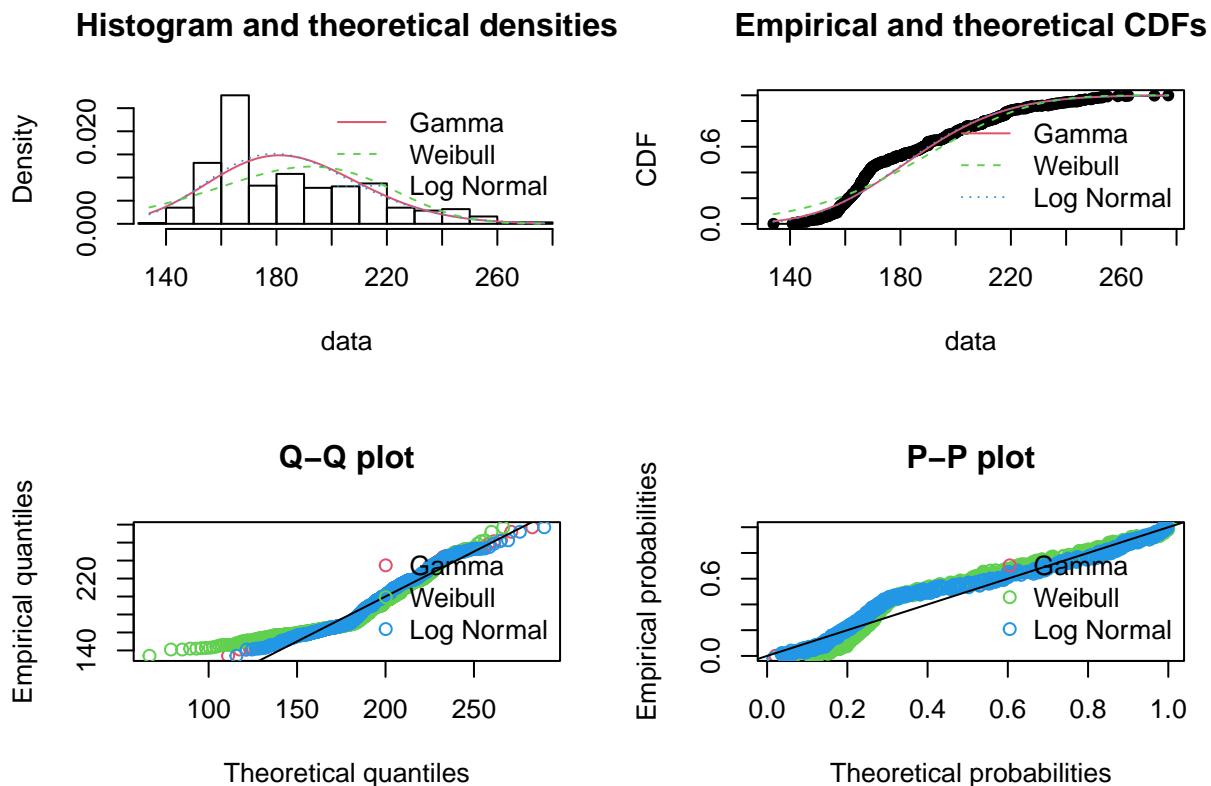
```
fit.ln <- fitdist(umbs_flwr_plot_growthhabit$julian_median, "lnorm")  
plot(fit.ln)
```

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)

```



```

# Goodness of fit comparisons across fits (can't include the sqrt normal bc it becomes diff response var)
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 0.1451735 0.138714 0.1414238
## Cramer-von Mises statistic   2.4663275 3.536763 2.2617767
## Anderson-Darling statistic  13.7523569 21.343517 12.4611085
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 5943.971 6086.608 5926.132
## Bayesian Information Criterion 5952.862 6095.500 5935.024

```

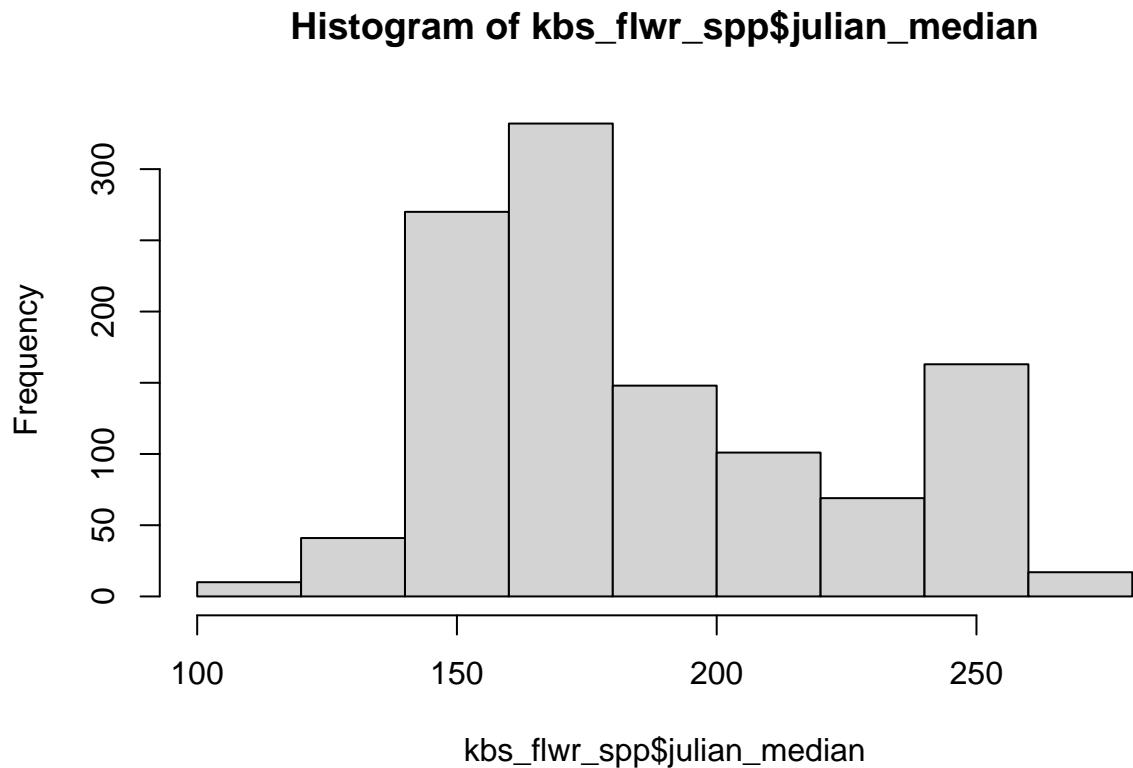
```

# Log normal looks like it's the best fit

```

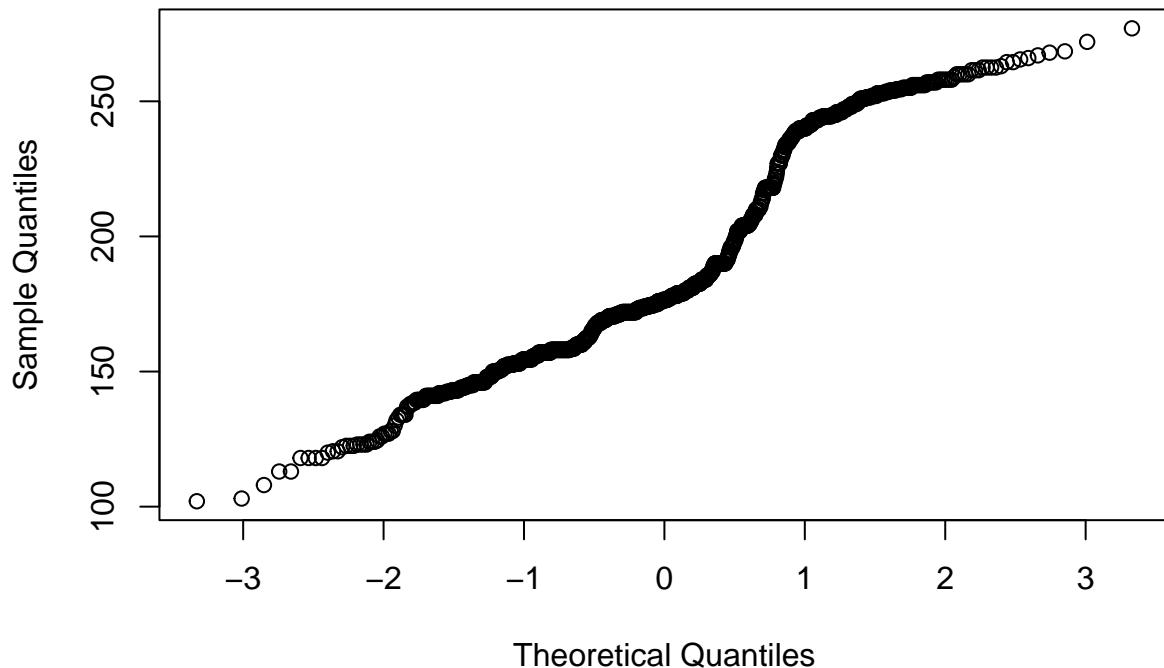
KBS SPECIES LEVEL - Looking at MEDIAN JULIAN DAY

```
### KBS ###
hist(kbs_flwr_spp$julian_median)
```



```
qqnorm(kbs_flwr_spp$julian_median)
```

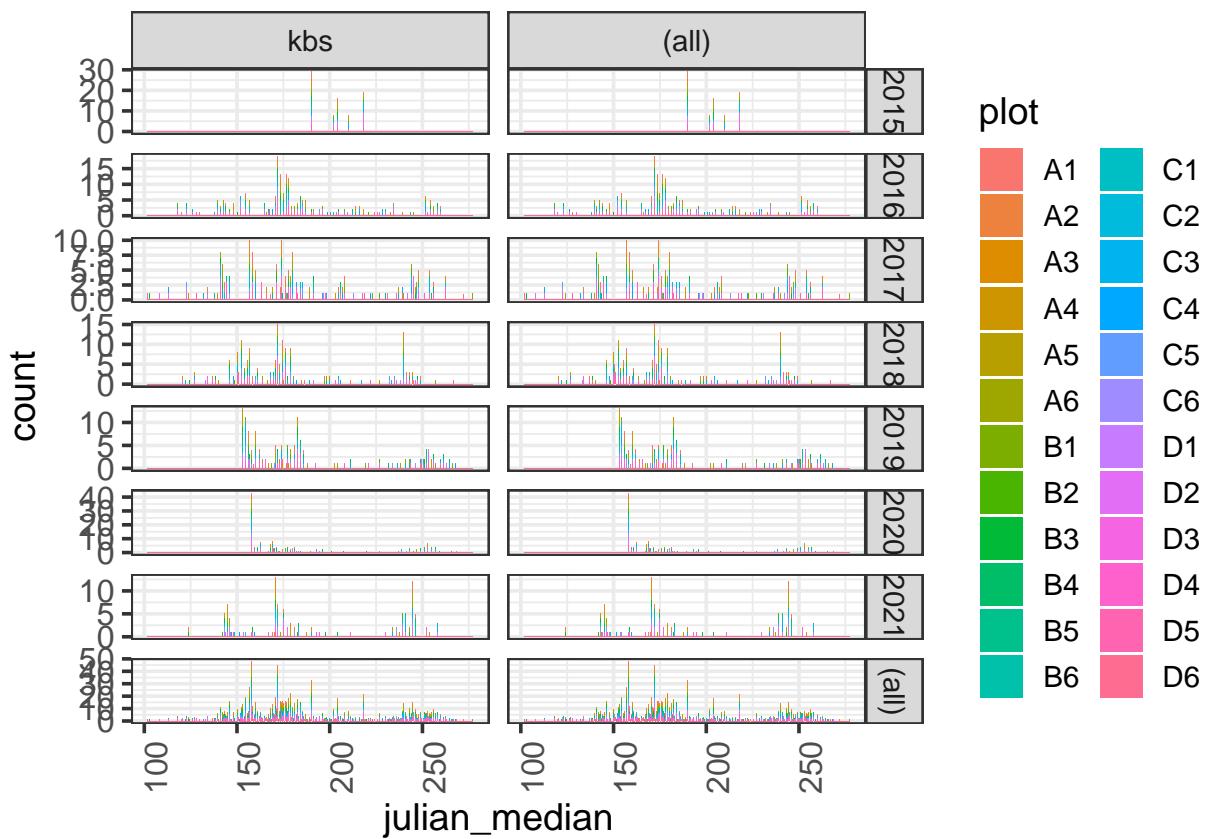
Normal Q-Q Plot



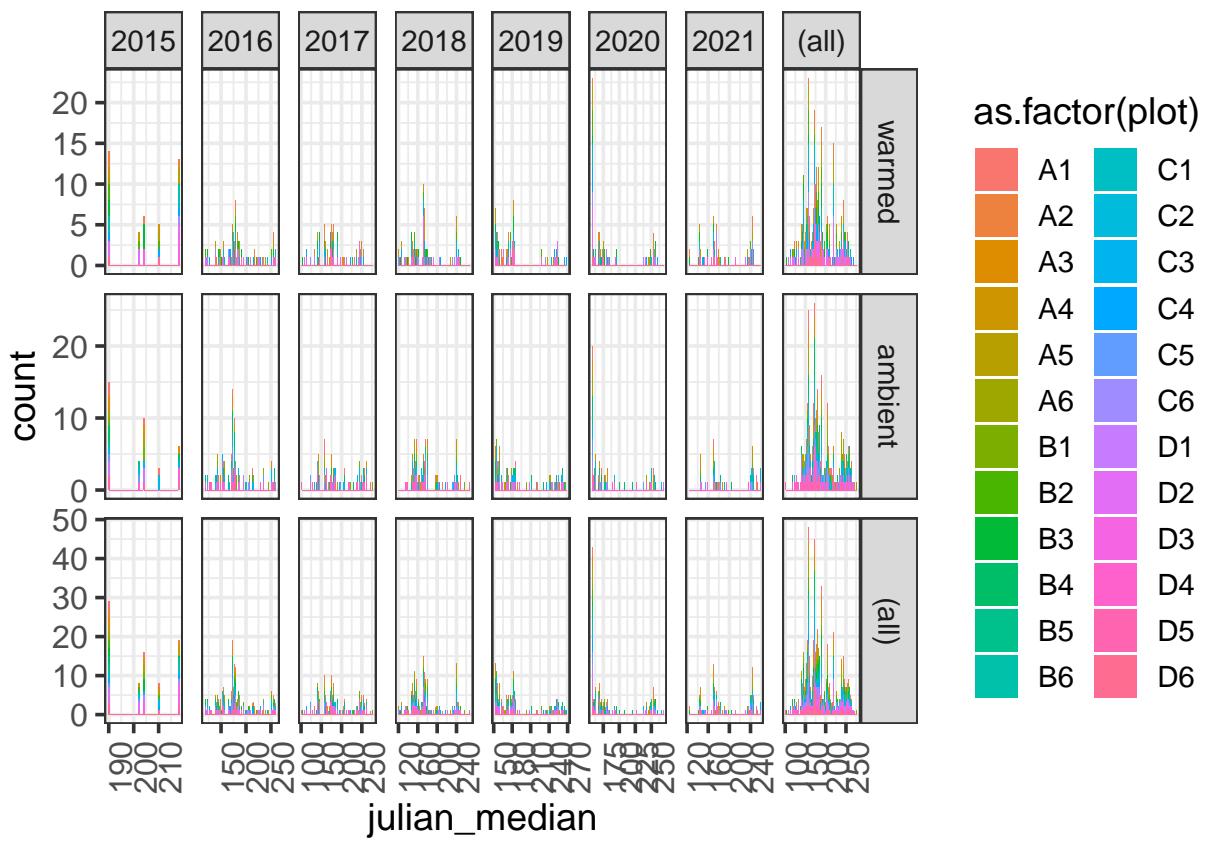
```
shapiro.test(kbs_flwr_spp$julian_median) # pvalue is < 0.05 so we reject the null hypothesis that the data is normally distributed

## 
## Shapiro-Wilk normality test
##
## data: kbs_flwr_spp$julian_median
## W = 0.92802, p-value < 2.2e-16

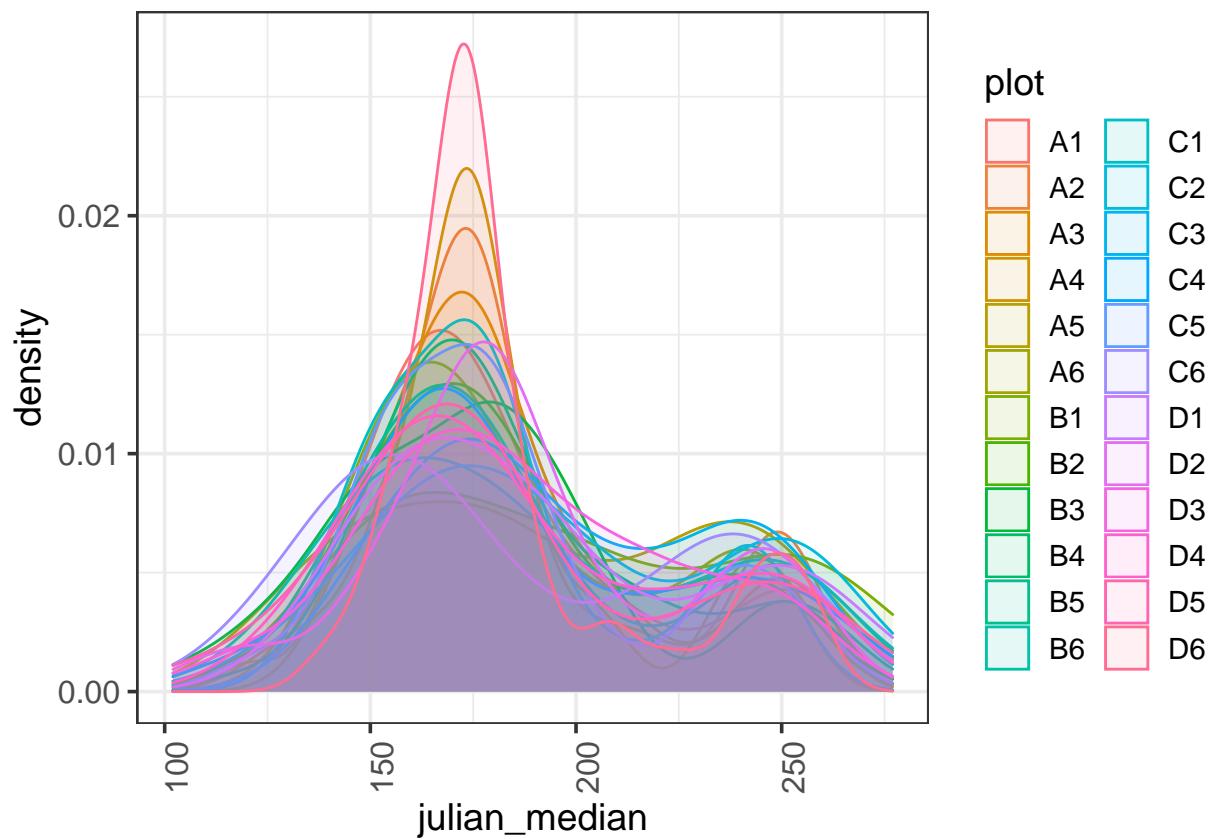
# Visualizing median Julian date for kbs at the SPECIES LEVEL
ggplot(kbs_flwr_spp, aes(julian_median, fill = plot)) +
  geom_histogram(binwidth = 0.5) +
  facet_grid(year ~ site, margins = TRUE, scales = "free")
```



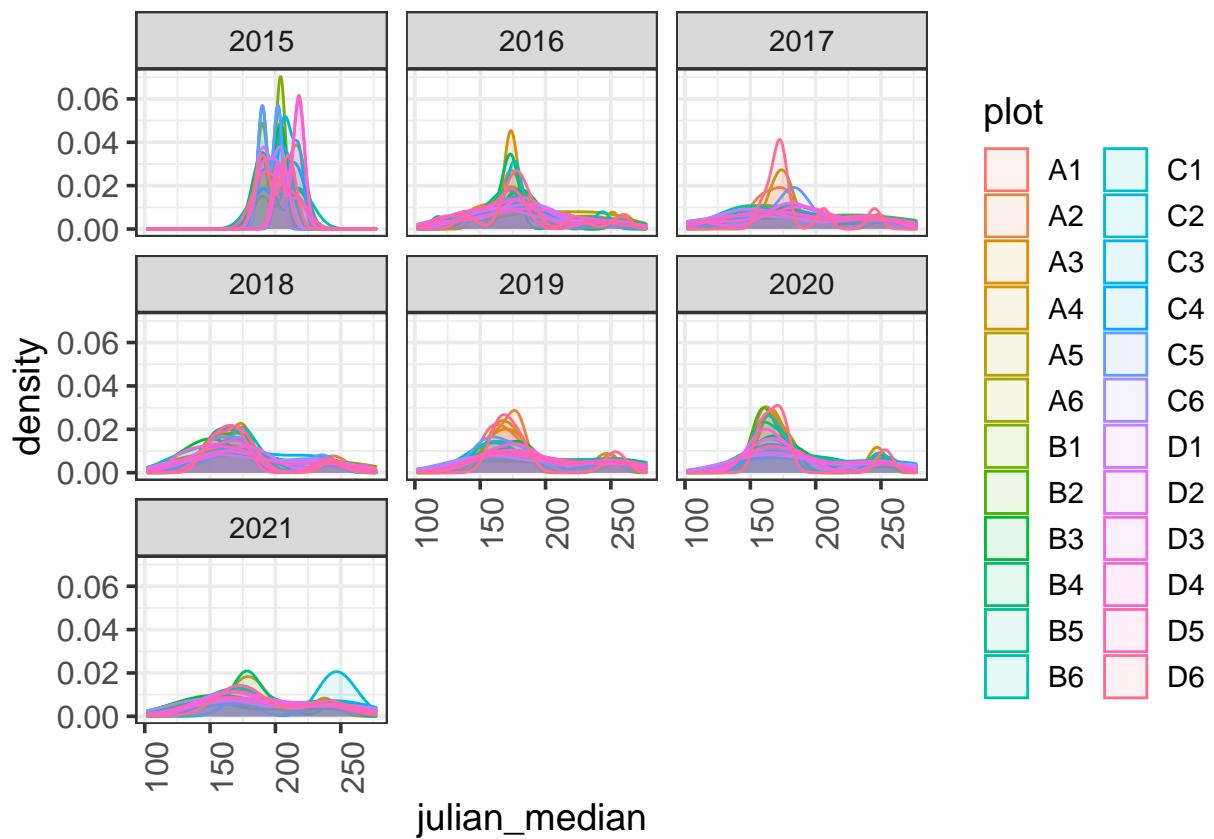
```
ggplot(kbs_flwr_spp, aes(julian_median, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
  facet_grid(state~year, margins = TRUE, scales = "free")
```



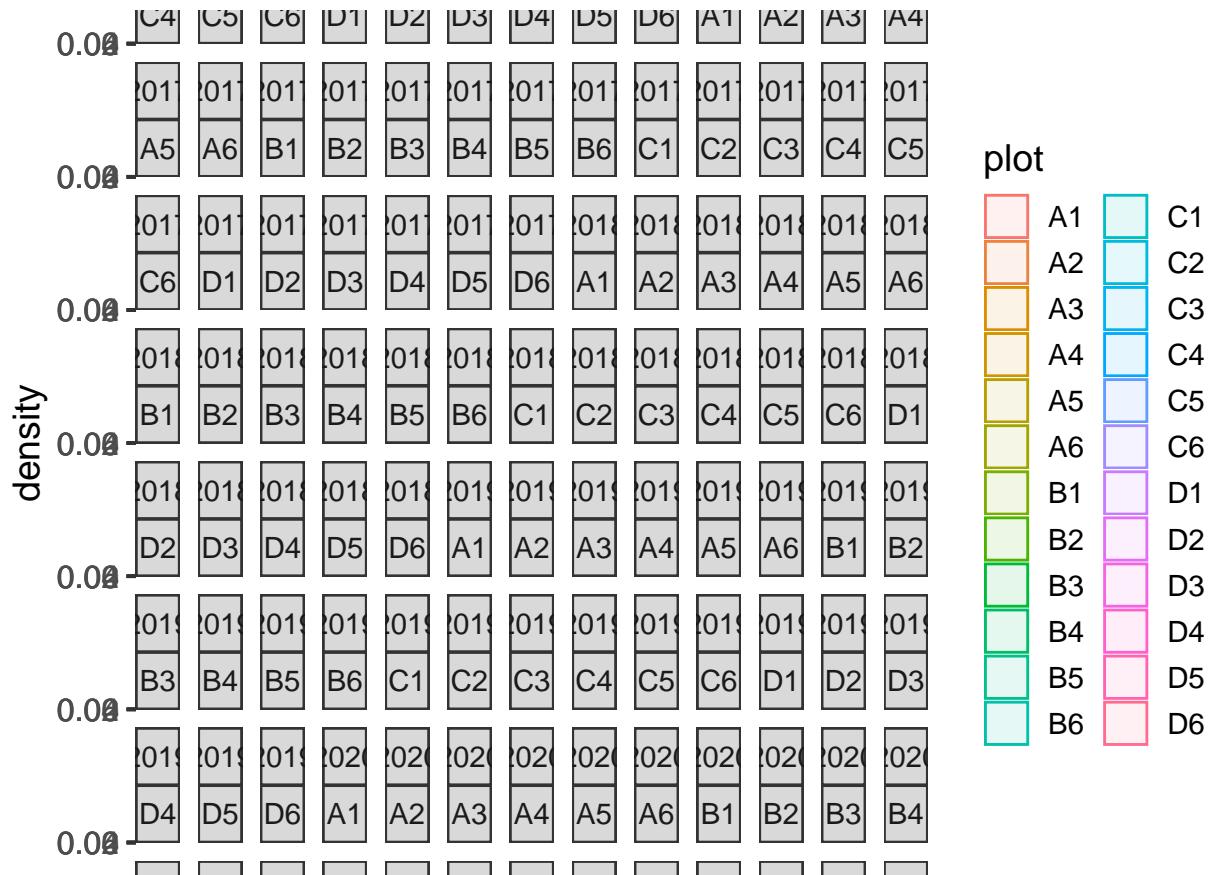
```
ggplot(kbs_flwr_spp, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1)
```



```
ggplot(kbs_flwr_spp, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year)
```

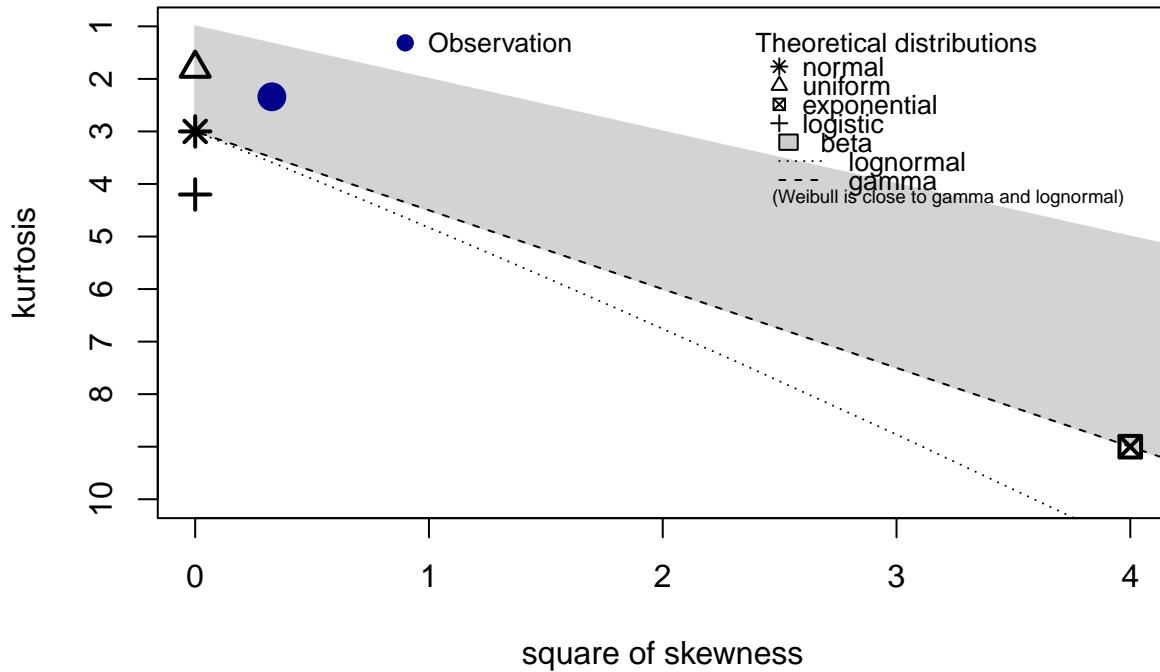


```
ggplot(kbs_flwr_spp, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year + plot)
```



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

Cullen and Frey graph

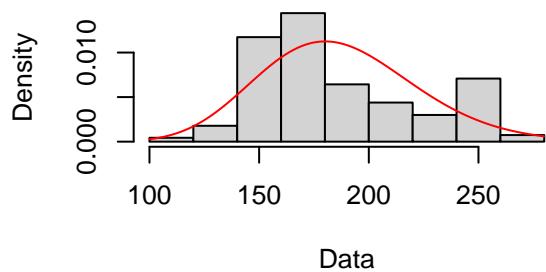
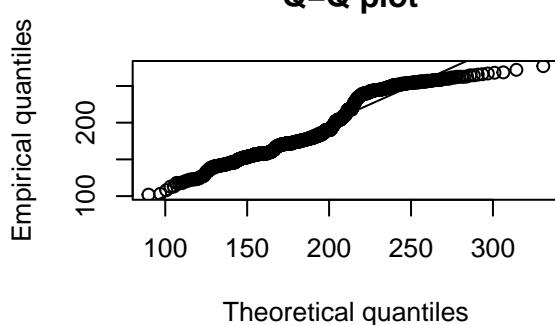
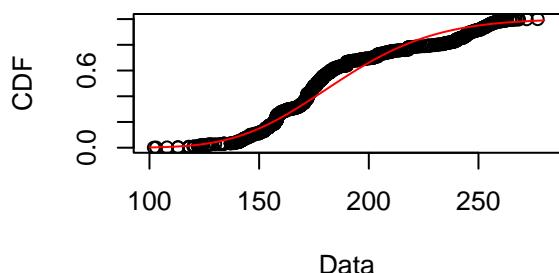
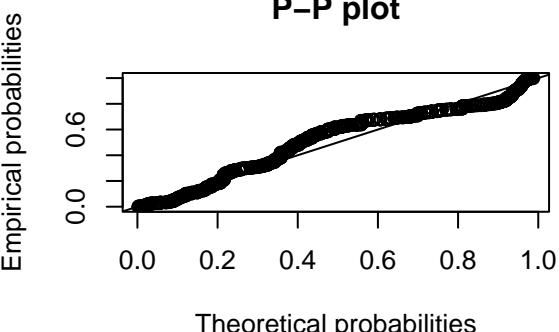


```

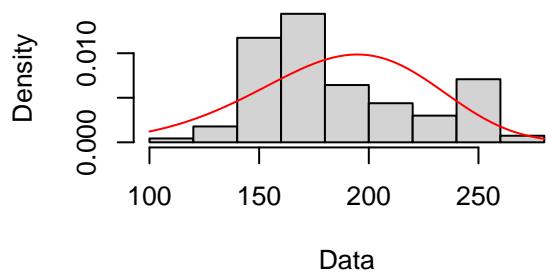
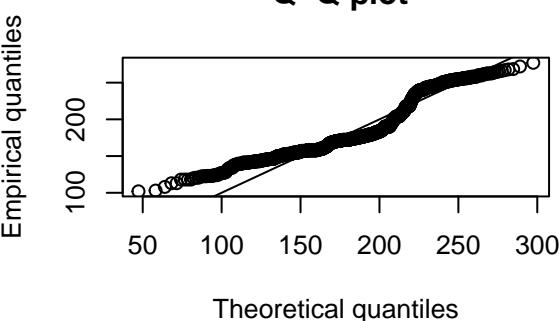
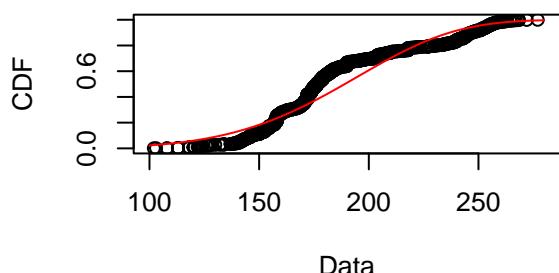
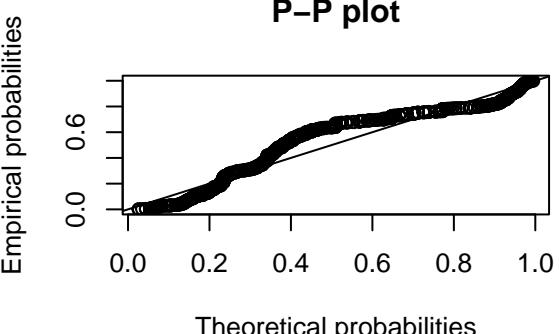
## summary statistics
## -----
## min: 102   max: 277
## median: 176.5
## mean: 187.0474
## estimated sd: 36.76832
## estimated skewness: 0.5728039
## estimated kurtosis: 2.340856

# Gamma distribution
fit.gamma <- fitdist(kbs_flwr_spp$julian_median, "gamma")
plot(fit.gamma)

```

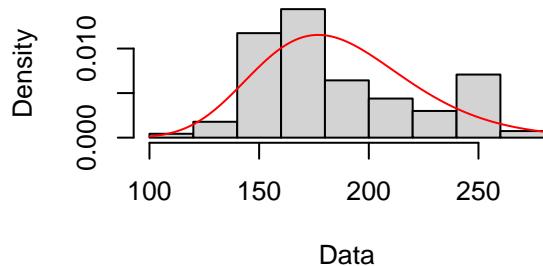
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

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

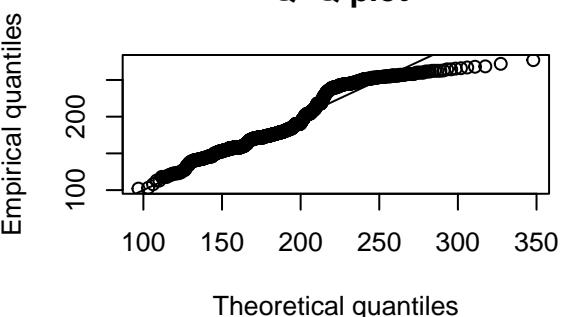
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

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

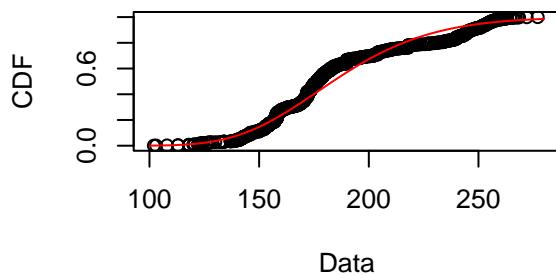
Empirical and theoretical dens.



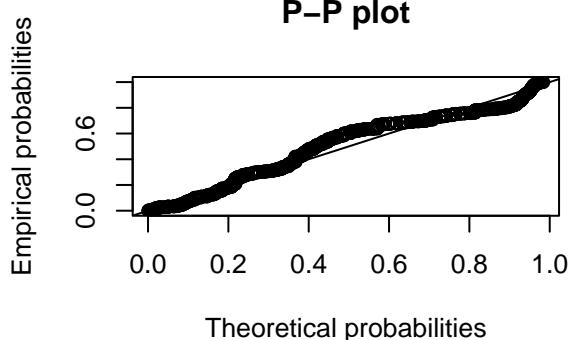
Q-Q plot



Empirical and theoretical CDFs

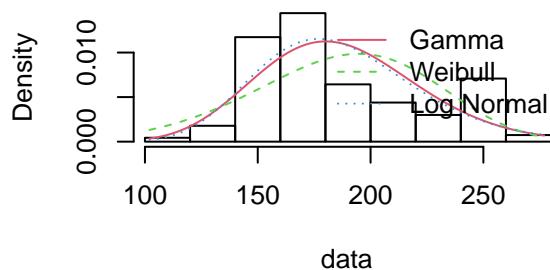


P-P plot

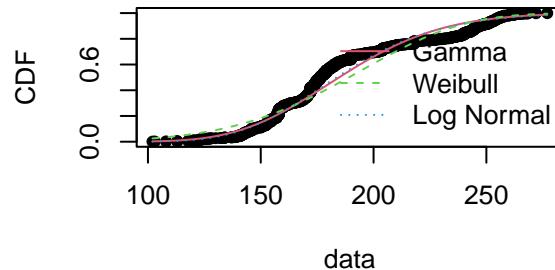


```
par(mfrow=c(2,2))
plot.legend <- c("Gamma", "Weibull", "Log Normal")
denscomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
cdfcomp (list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
qqcomp (list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
ppcomp (list(fit.gamma,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

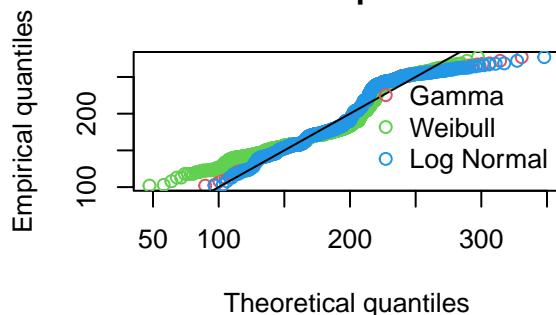
Histogram and theoretical densities



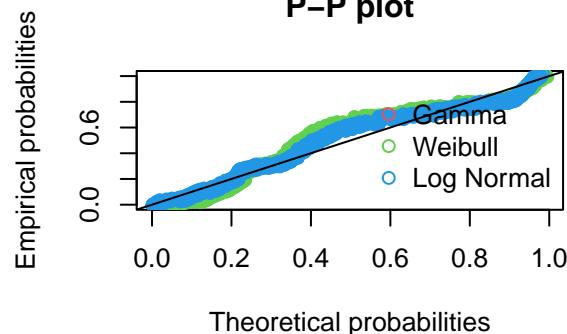
Empirical and theoretical CDFs



Q-Q plot



P-P plot



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

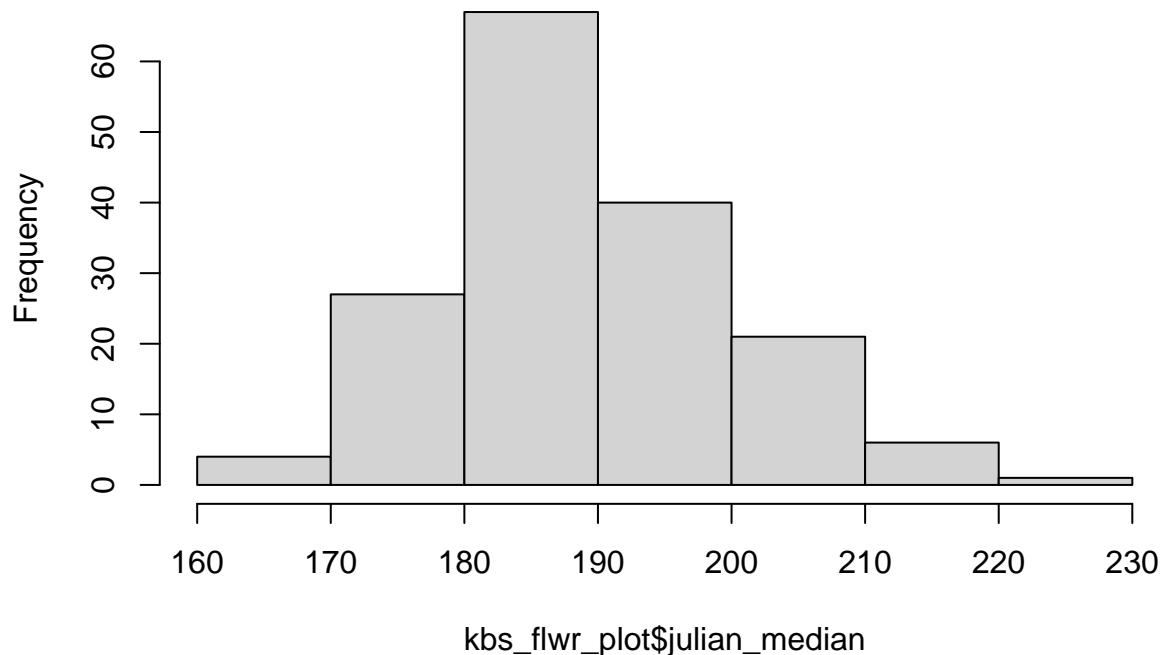
```
## Goodness-of-fit statistics
##                                     Gamma   Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.1253516 0.1655749 0.1127099
## Cramer-von Mises statistic   4.2072498 7.5748584 3.3888786
## Anderson-Darling statistic  24.5983693 41.9370913 20.3691810
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 11492.51 11659.13 11470.99
## Bayesian Information Criterion 11502.60 11669.22 11481.08
```

```
# Lognormal is the best so going to log transform response variable julian_median
```

KBS PLOT LEVEL - Looking at MEDIAN JULIAN DAY

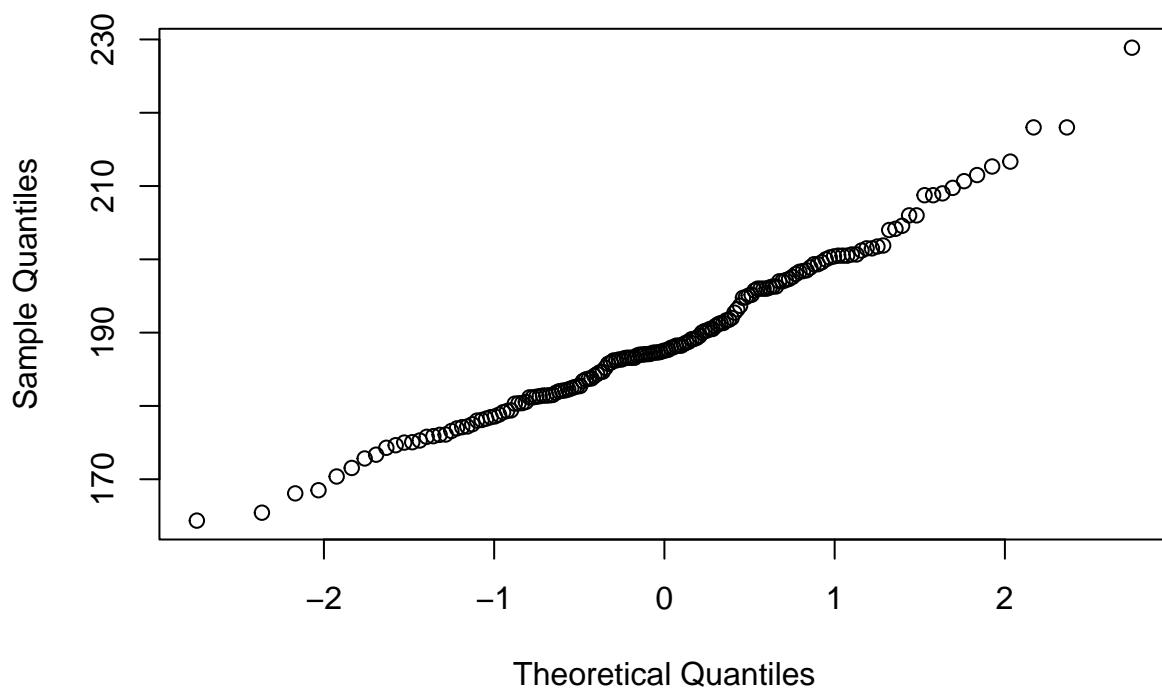
```
### UMBS ####
hist(kbs_flwr_plot$julian_median)
```

Histogram of kbs_flwr_plot\$julian_median



```
qqnorm(kbs_flwr_plot$julian_median)
```

Normal Q-Q Plot



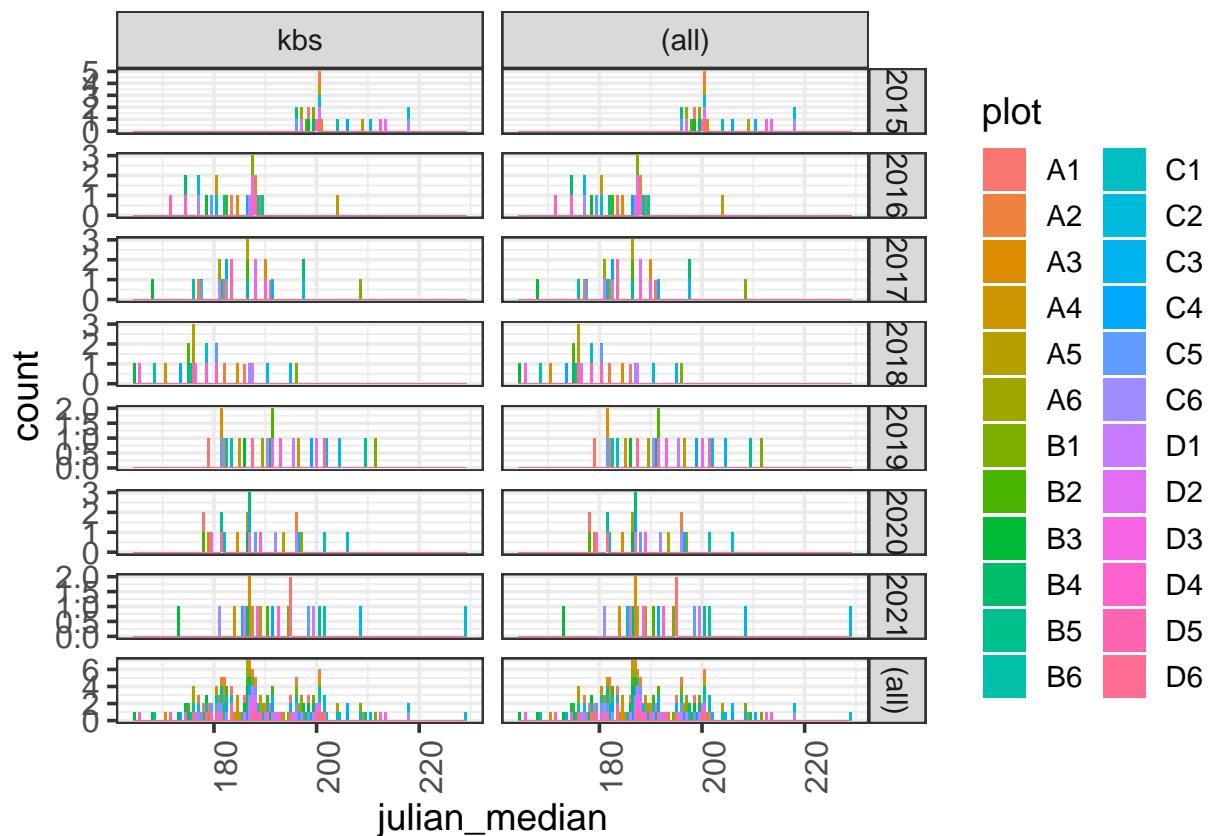
```

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

## 
## Shapiro-Wilk normality test
## 
## data: kbs_flwr_plot$julian_median
## W = 0.98056, p-value = 0.01976

# Visualizing median Julian date for kbs at the PLOT LEVEL
ggplot(kbs_flwr_plot, aes(julian_median, fill = plot)) +
  geom_histogram(binwidth = 0.5) +
  facet_grid(year ~ site, margins = TRUE, scales = "free")

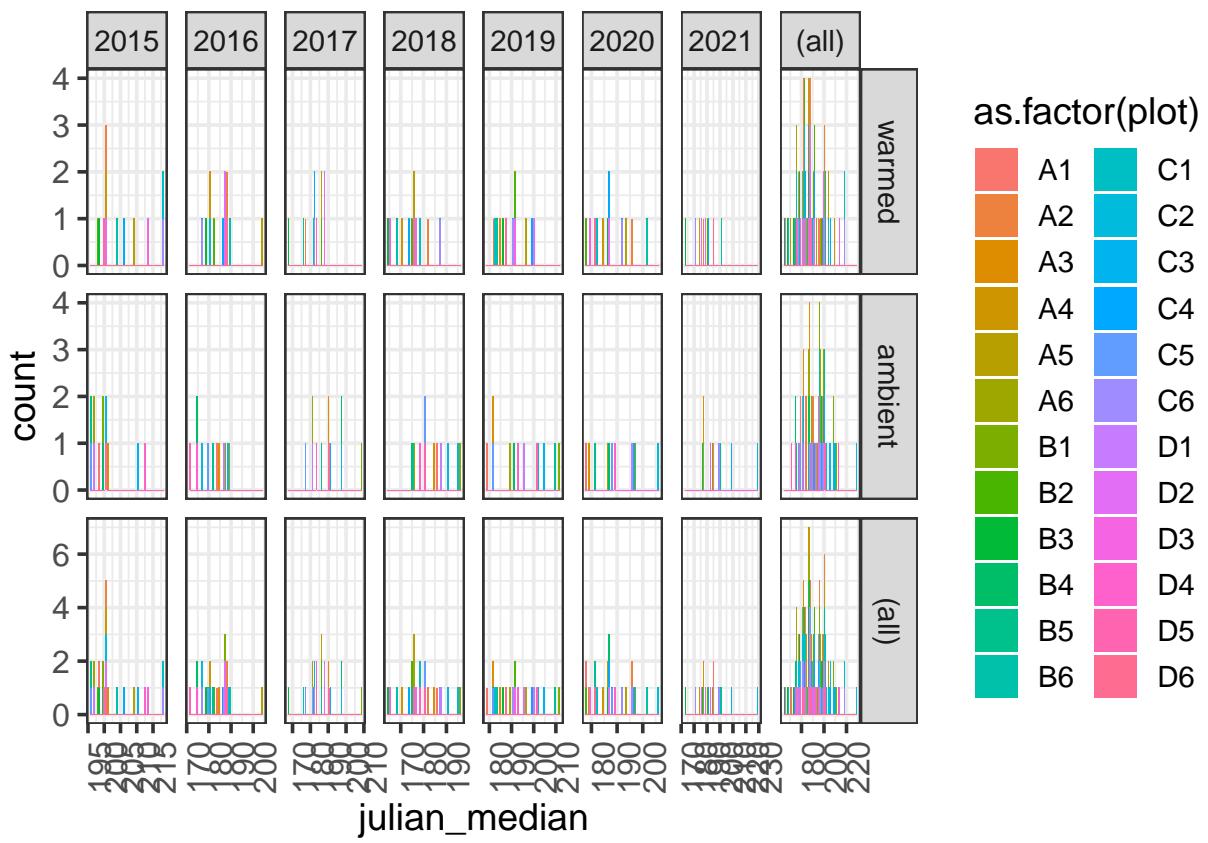
```



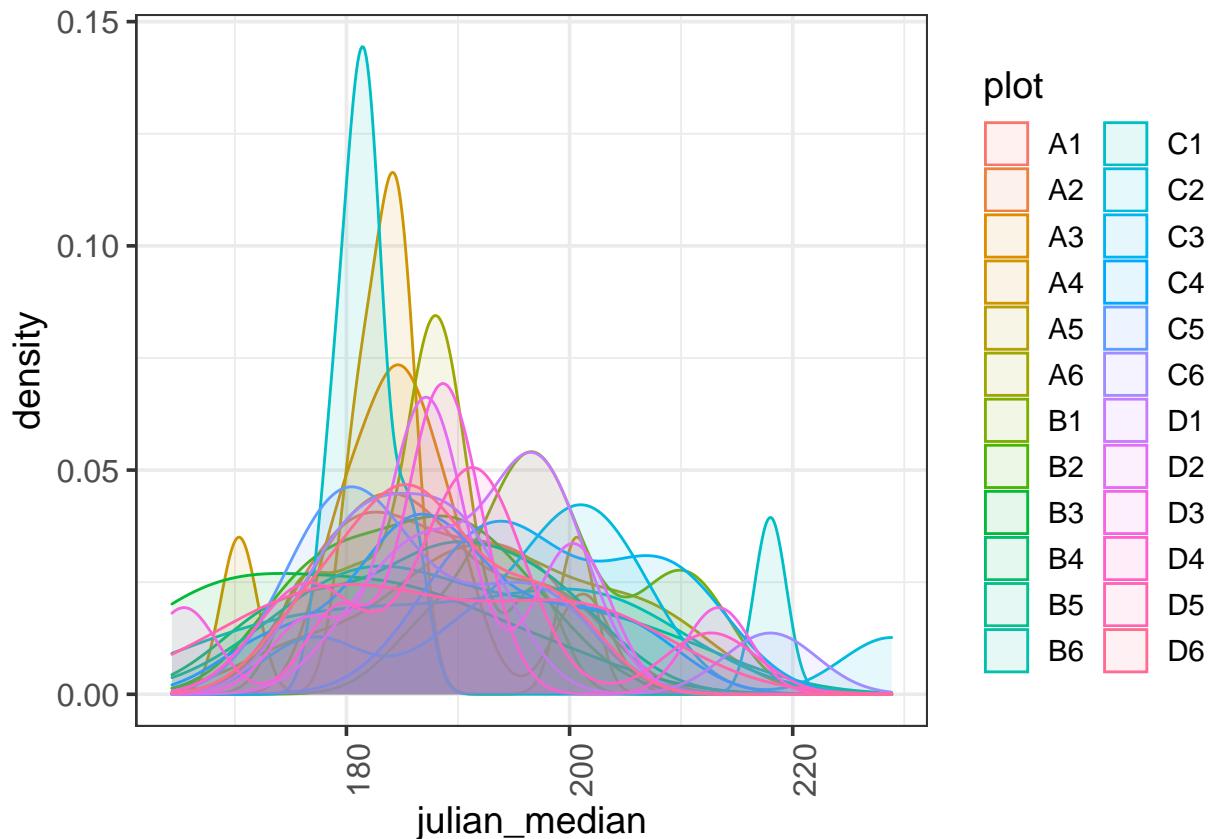
```

ggplot(kbs_flwr_plot, aes(julian_median, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
  facet_grid(state~year, margins = TRUE, scales = "free")

```



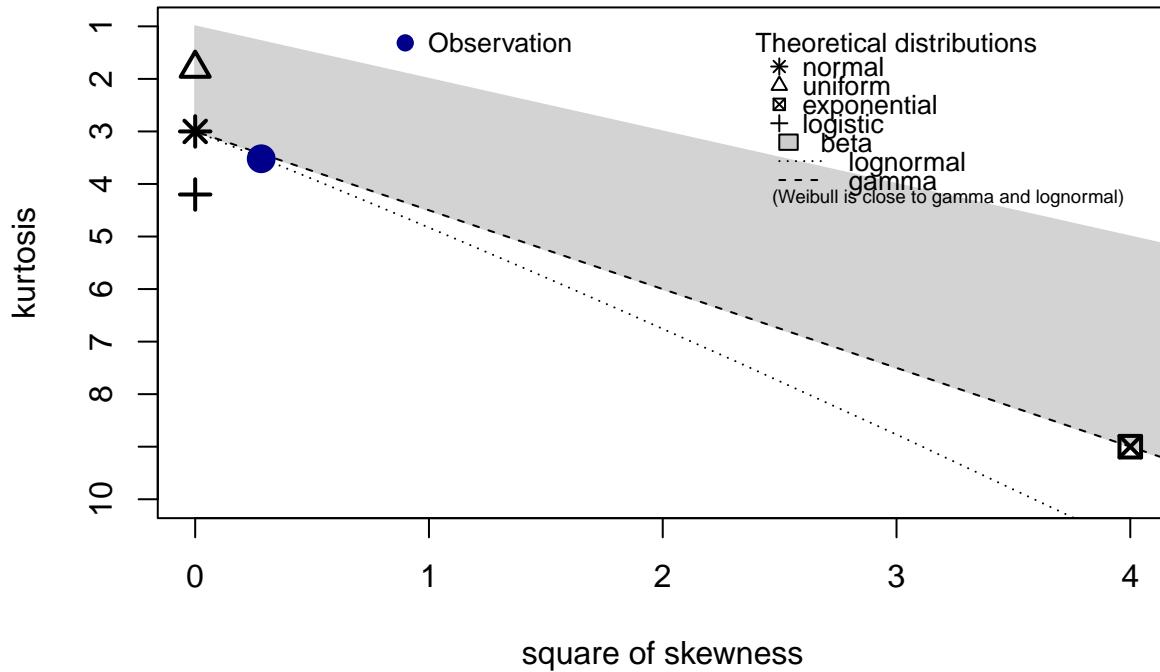
```
ggplot(kbs_flwr_plot, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1)
```



```
#ggplot(umbs_flwr_plot, aes(julian_median, fill = plot, color=plot)) +
#      geom_density(alpha = 0.1) +
#      facet_wrap(~year)
#
#ggplot(umbs_flwr_plot, aes(julian_median, fill = plot, color=plot)) +
#      geom_density(alpha = 0.1) +
#      facet_wrap(~year + plot)

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

Cullen and Frey graph

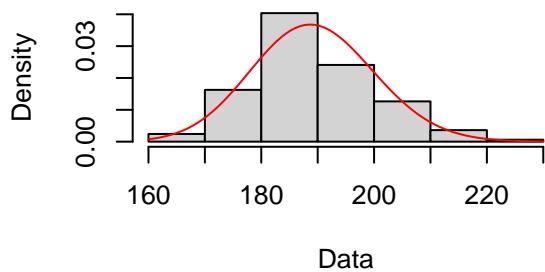
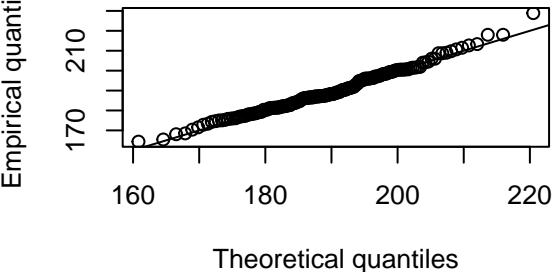
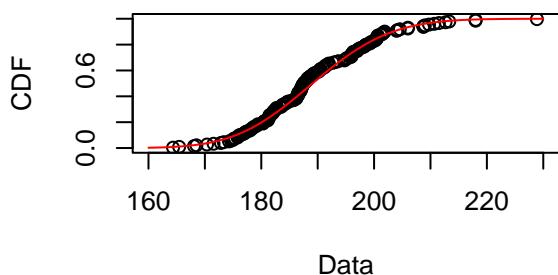
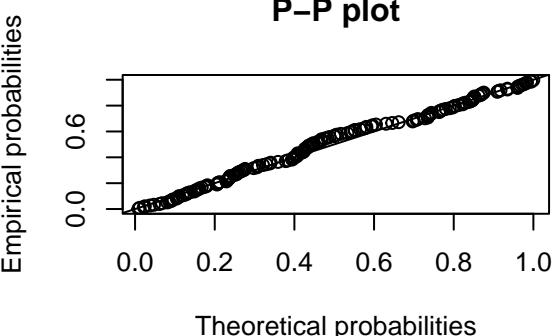


```

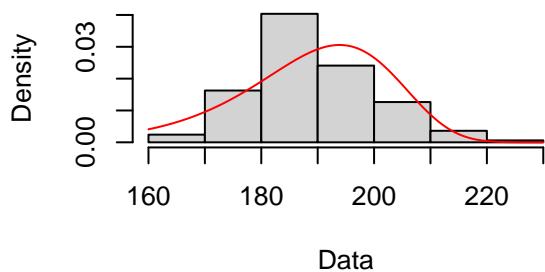
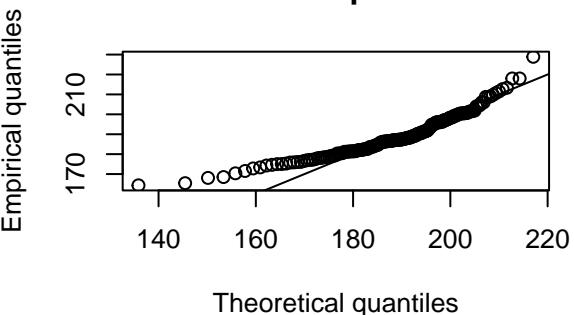
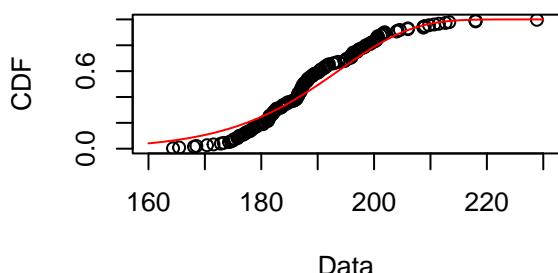
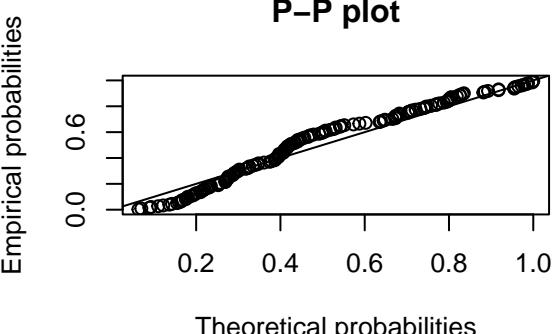
## summary statistics
## -----
## min: 164.3571   max: 228.875
## median: 187.5417
## mean: 189.305
## estimated sd: 10.98433
## estimated skewness: 0.5314459
## estimated kurtosis: 3.520081

# Gamma distribution
fit.gamma <- fitdist(kbs_flwr_plot$julian_median, "gamma")
plot(fit.gamma)

```

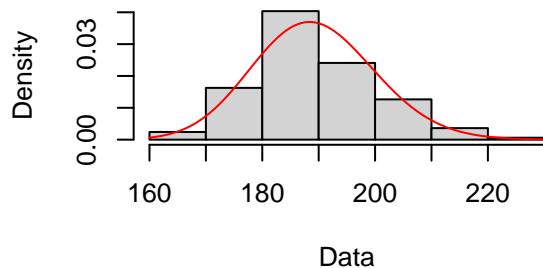
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

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

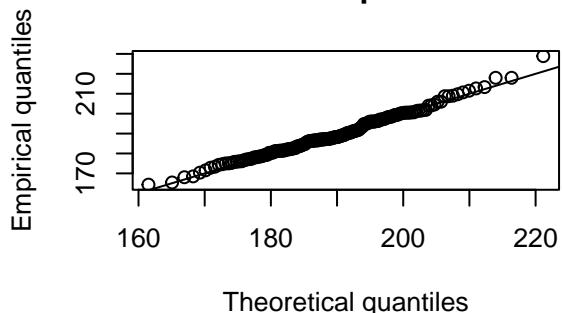
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

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

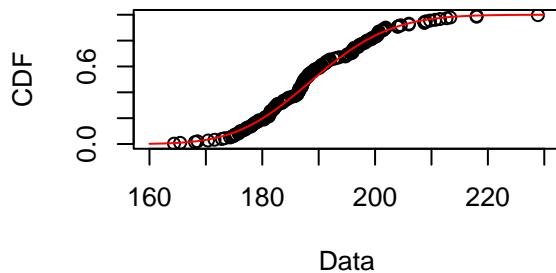
Empirical and theoretical dens.



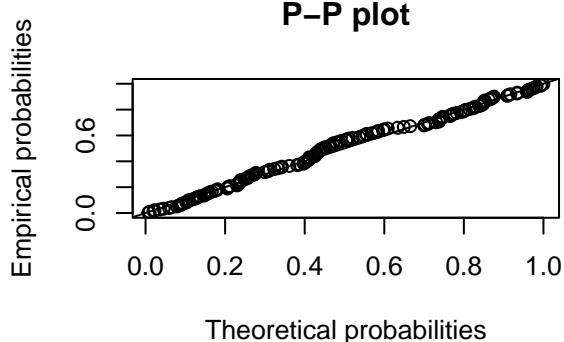
Q–Q plot



Empirical and theoretical CDFs

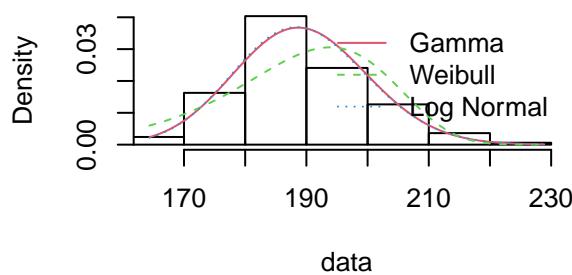


P–P plot

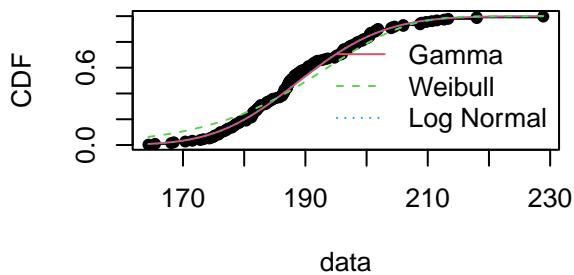


```
par(mfrow=c(2,2))
plot.legend <- c("Gamma", "Weibull", "Log Normal")
denscomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
cdfcomp (list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
qqcomp (list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
ppcomp (list(fit.gamma,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

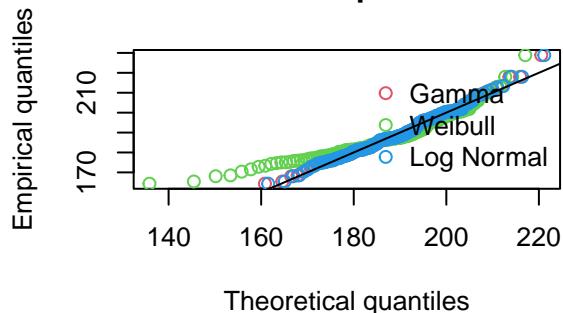
Histogram and theoretical densities



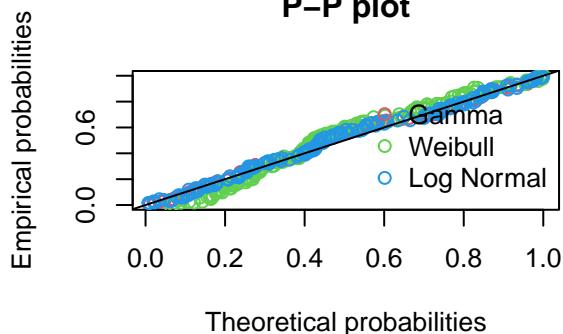
Empirical and theoretical CDFs



Q-Q plot



P-P plot



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

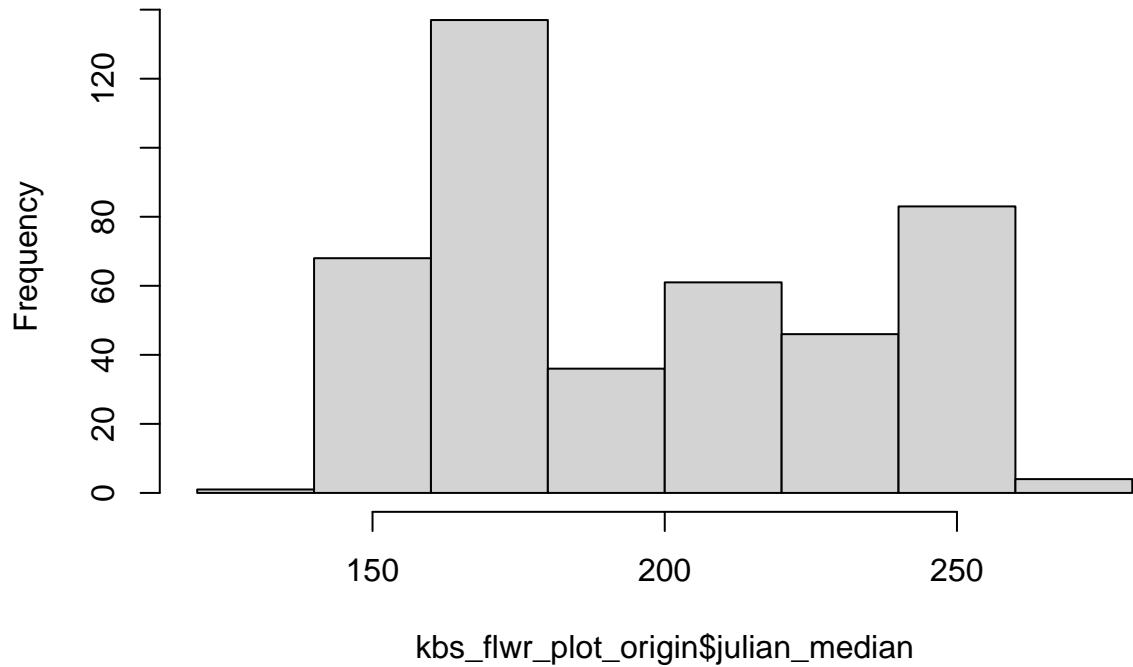
```
## Goodness-of-fit statistics
##                                     Gamma   Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.07431279 0.1078864 0.07064005
## Cramer-von Mises statistic   0.13811983 0.6267161 0.12249521
## Anderson-Darling statistic   0.72695322 4.0378415 0.63824442
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 1266.773 1310.745 1265.586
## Bayesian Information Criterion 1272.997 1316.969 1271.810
```

```
# Log normal is the best first so going to log transform response variable julian_median
```

KBS PLOT LEVEL ORIGIN - Looking at MEDIAN JULIAN DAY

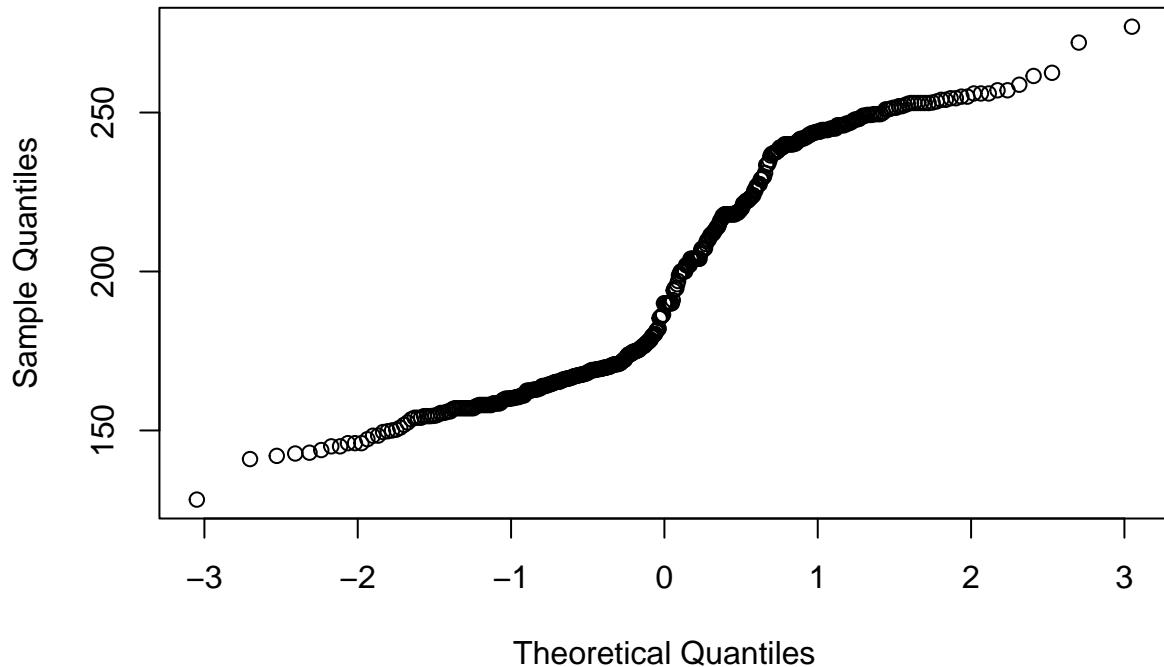
```
### KBS ####
hist(kbs_flwr_plot_origin$julian_median)
```

Histogram of kbs_flwr_plot_origin\$julian_median



```
qqnorm(kbs_flwr_plot_origin$julian_median)
```

Normal Q-Q Plot



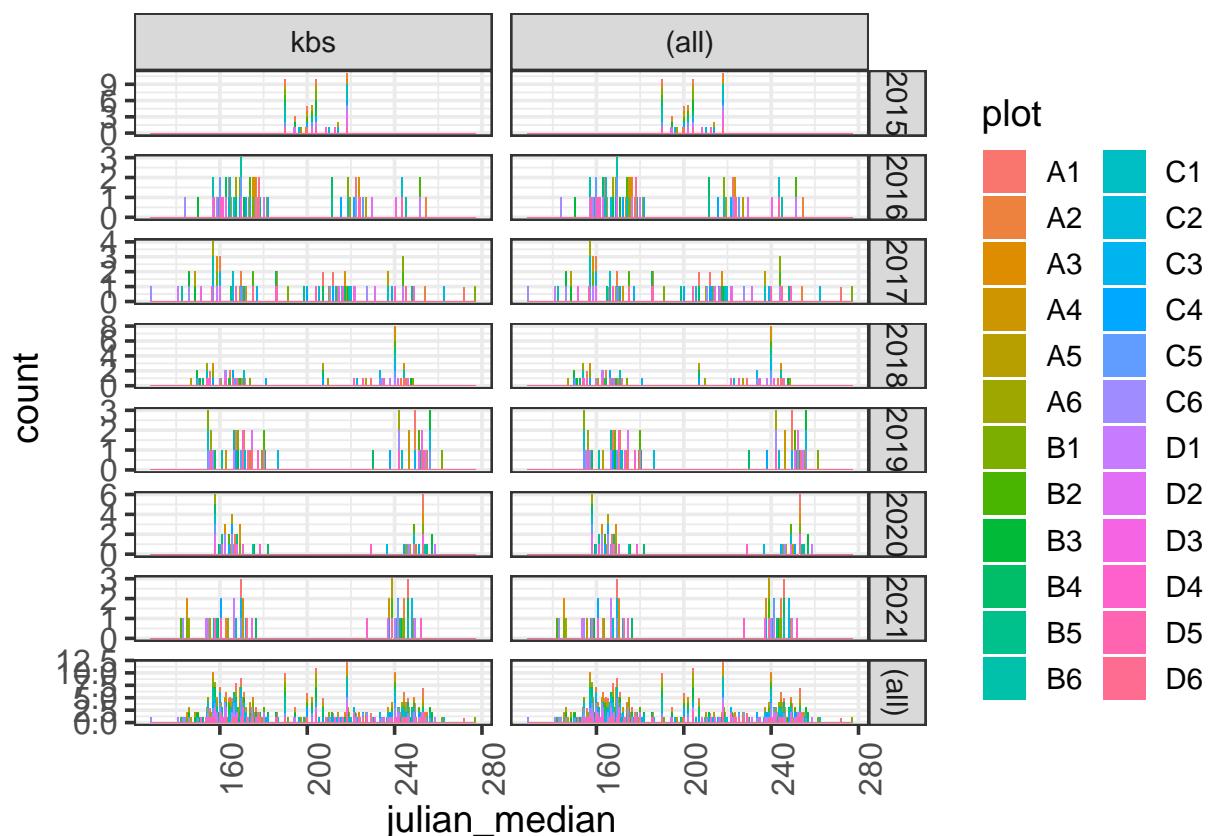
```

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

## 
## Shapiro-Wilk normality test
## 
## data: umbs_flwr_plot_origin$julian_median
## W = 0.93959, p-value = 3.173e-15

# Visualizing median Julian date for kbs at the PLOT LEVEL
ggplot(kbs_flwr_plot_origin, aes(julian_median, fill = plot)) +
  geom_histogram(binwidth = 0.5) +
  facet_grid(year ~ site, margins = TRUE, scales = "free")

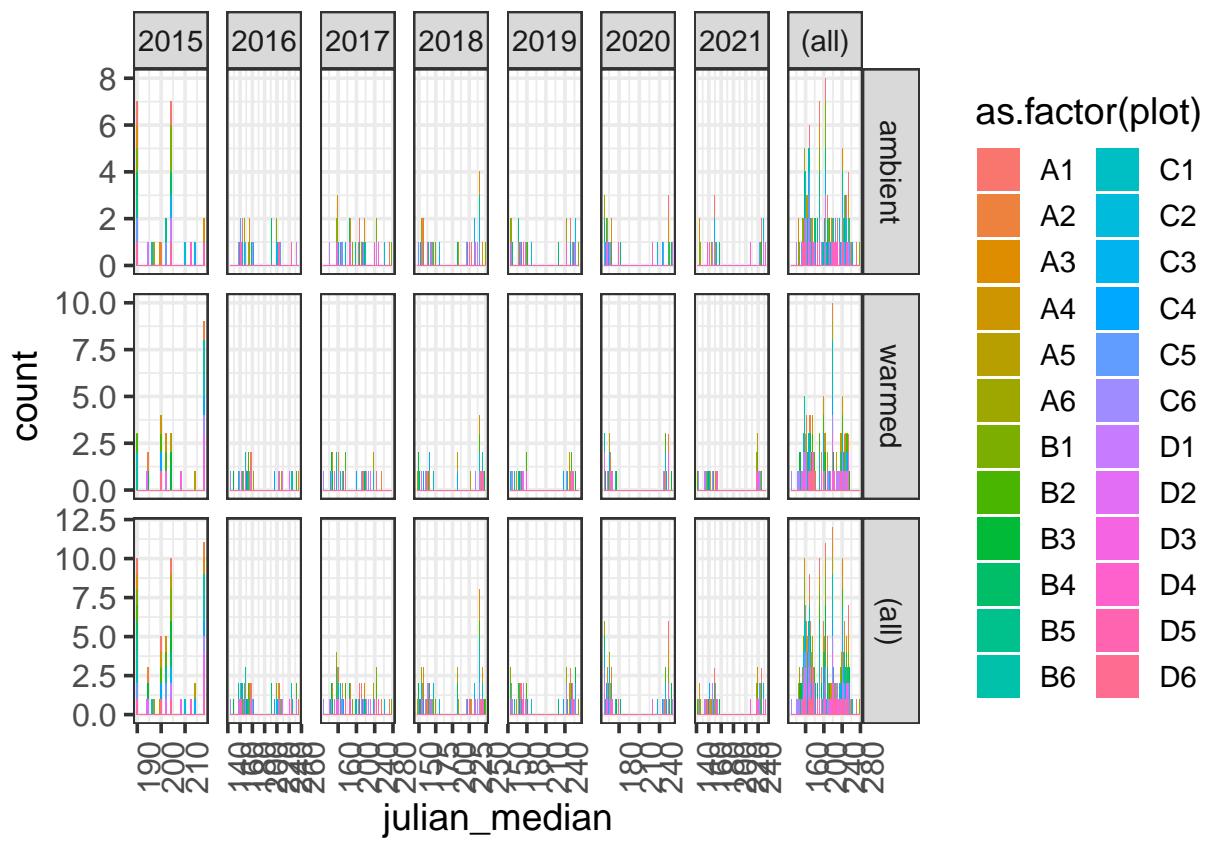
```



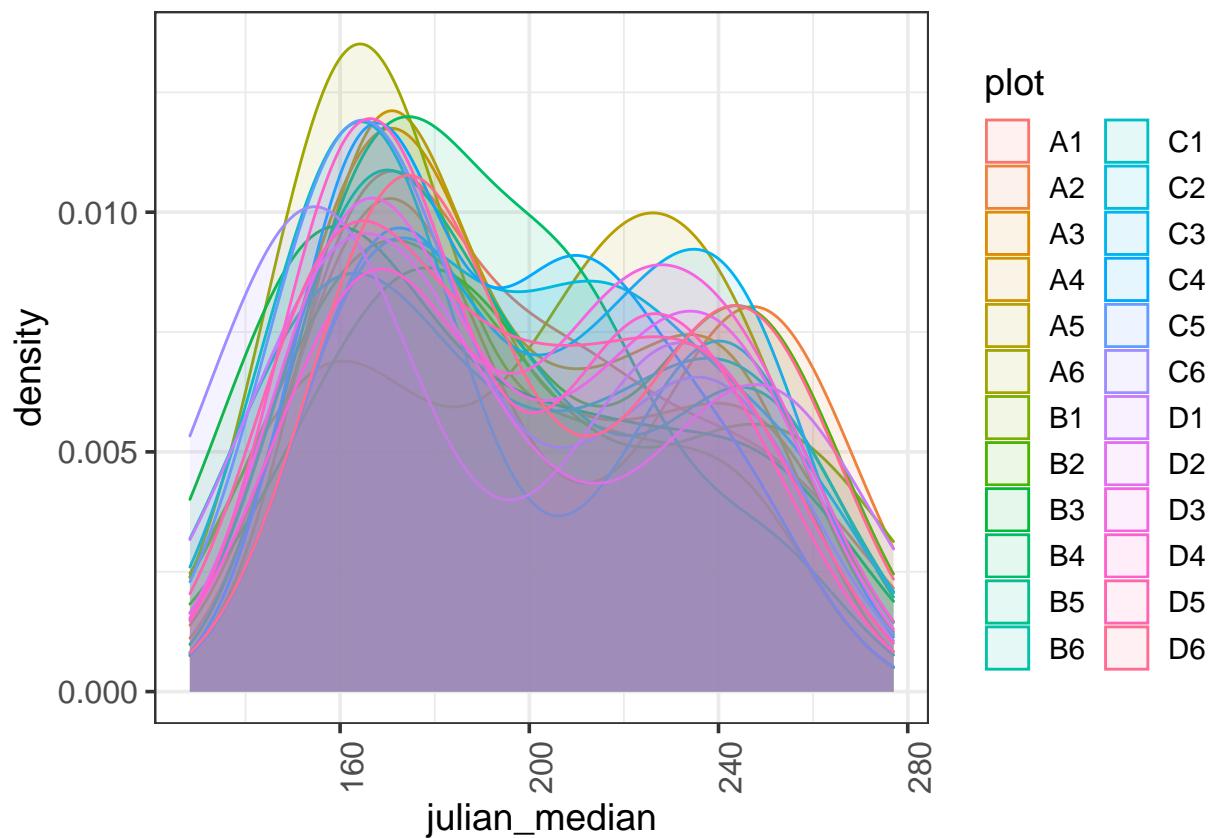
```

ggplot(kbs_flwr_plot_origin, aes(julian_median, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5)
  facet_grid(state~year, margins = TRUE, scales = "free")

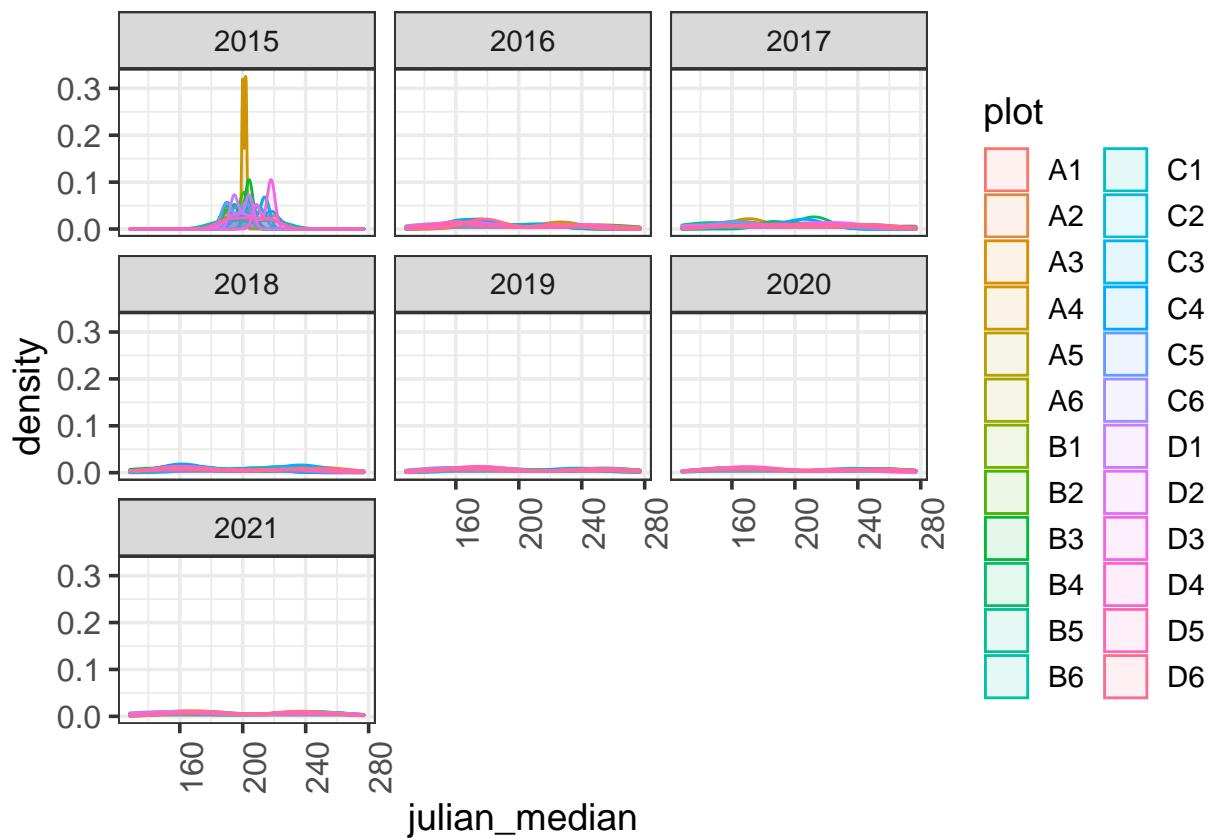
```



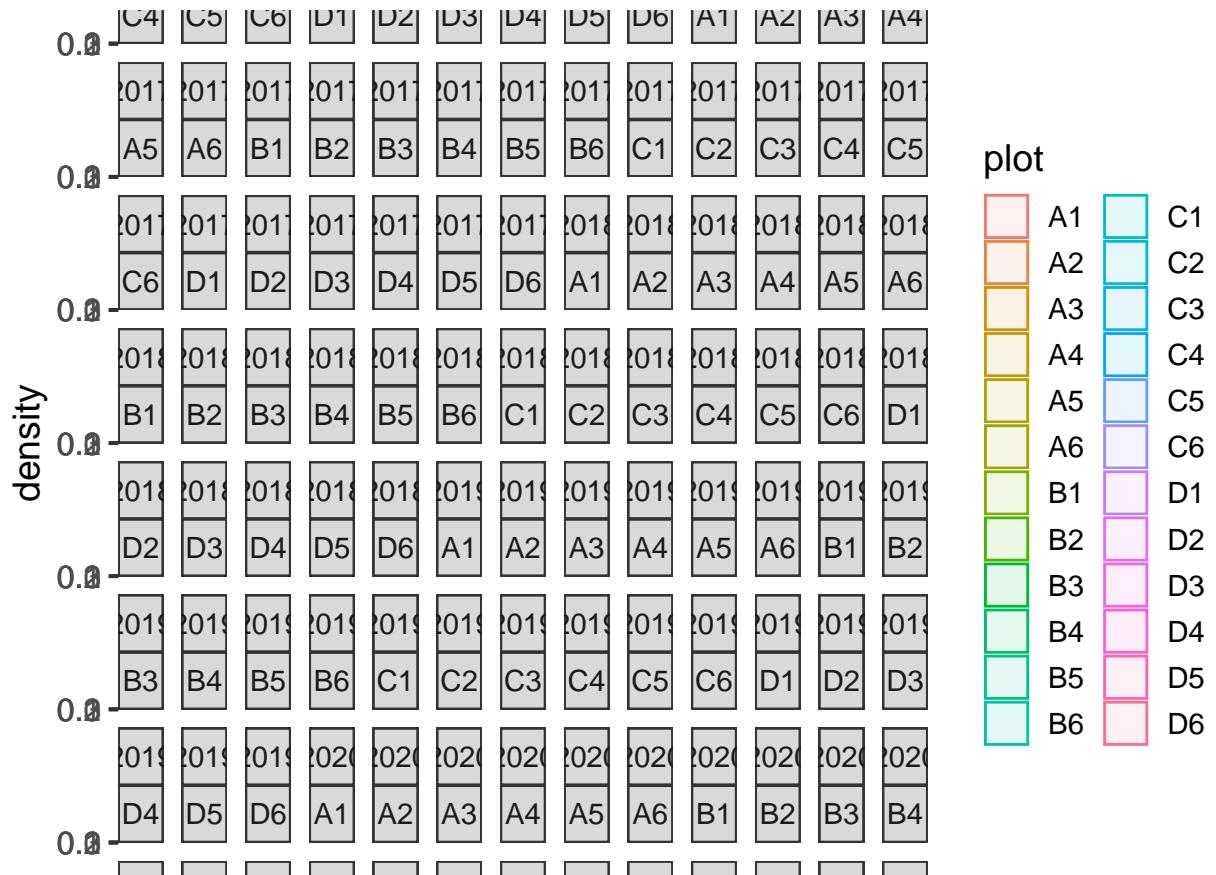
```
ggplot(kbs_flwr_plot_origin, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1)
```



```
ggplot(kbs_flwr_plot_origin, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year)
```

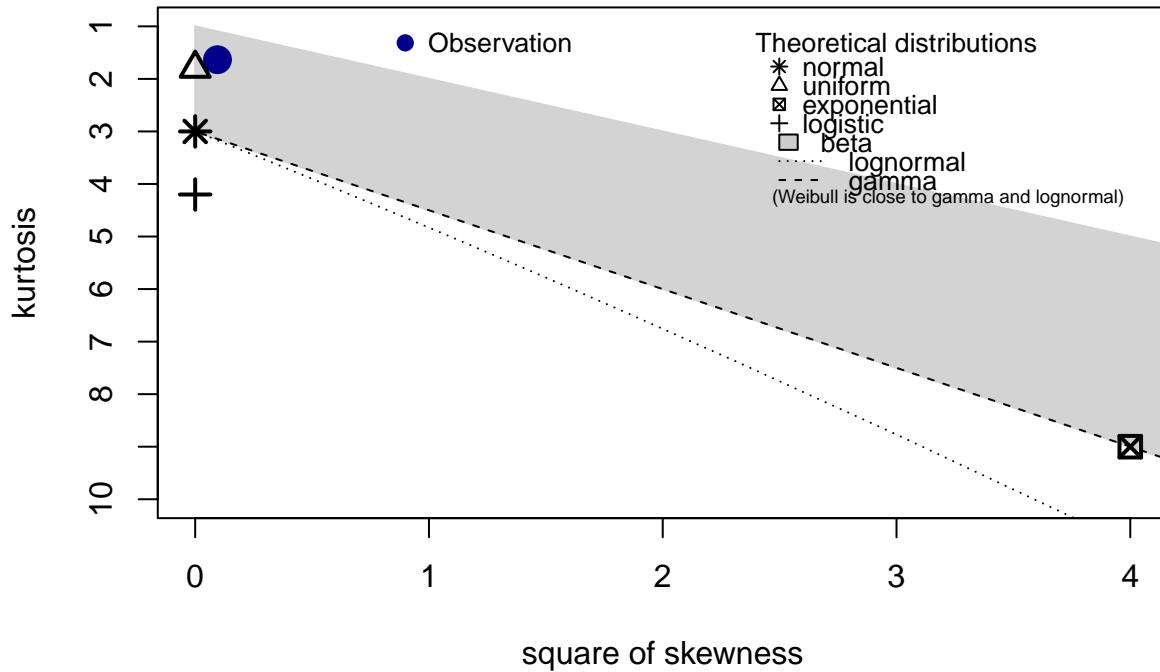


```
ggplot(kbs_flwr_plot_origin, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year + plot)
```



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

Cullen and Frey graph

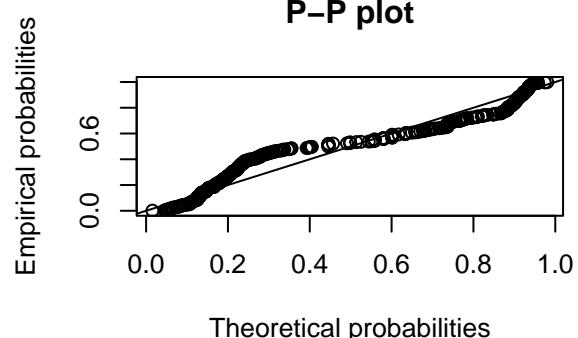
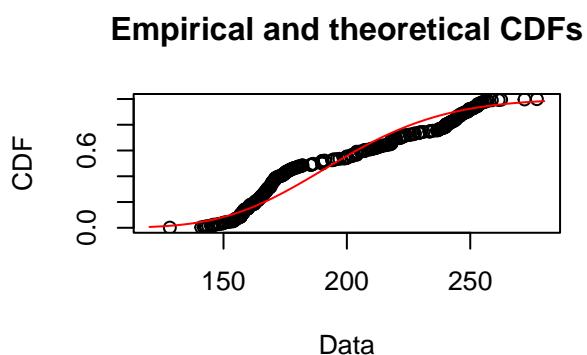
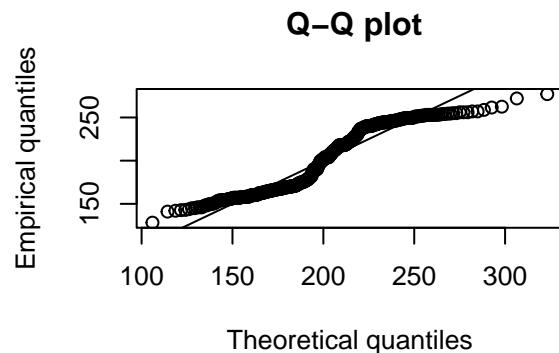
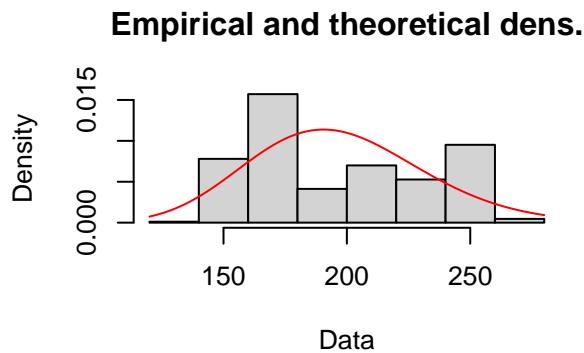


```

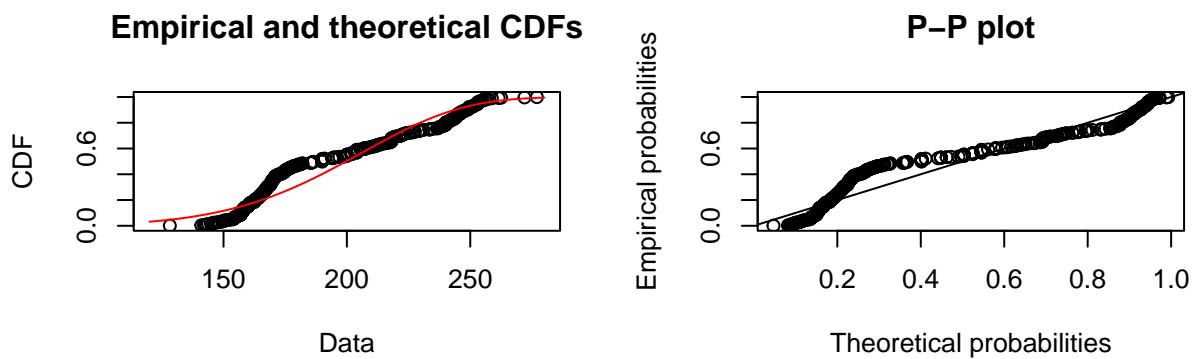
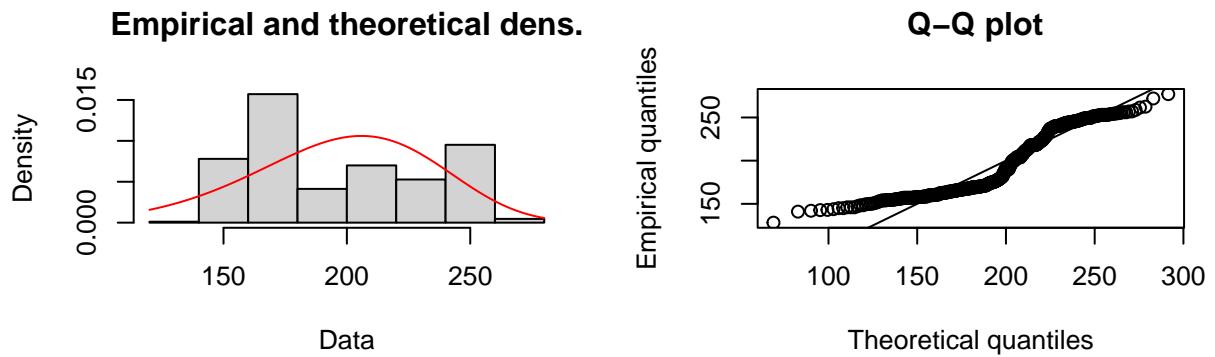
## summary statistics
## -----
## min: 128.25   max: 277
## median: 190
## mean: 196.9276
## estimated sd: 35.89503
## estimated skewness: 0.3090875
## estimated kurtosis: 1.634518

# Gamma distribution
fit.gamma <- fitdist(kbs_flwr_plot_origin$julian_median, "gamma")
plot(fit.gamma)

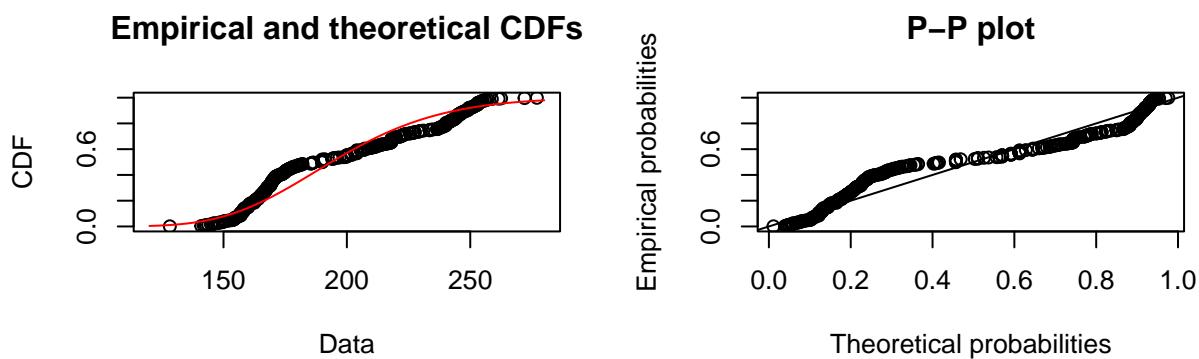
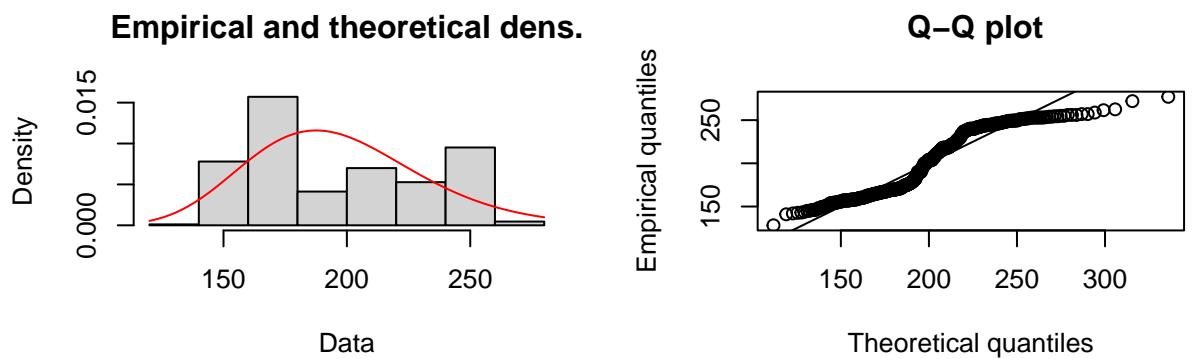
```



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



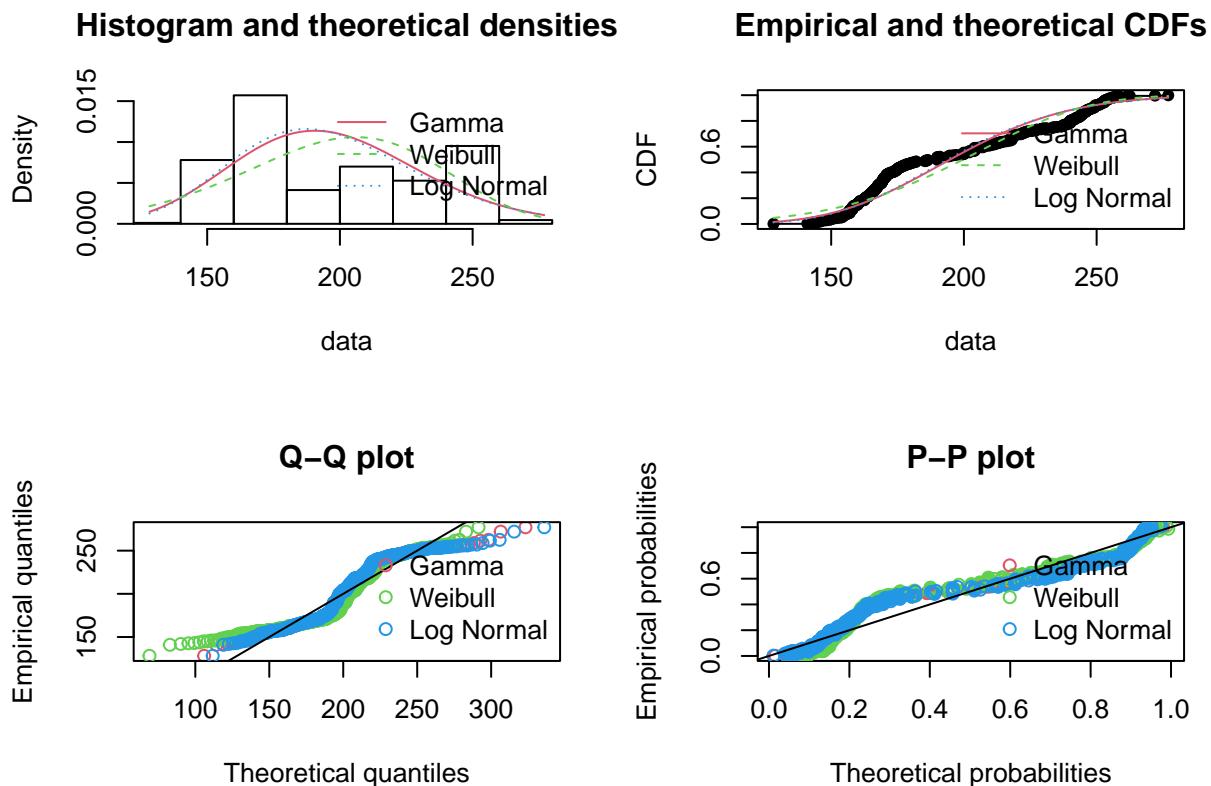
```
# Lognormal distribution
fit.ln <- fitdist(kbs_flwr_plot_origin$julian_median, "lnorm")
plot(fit.ln)
```



```

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)

```



```

# Goodness of fit comparisons across fits (can't include the sqrt normal bc it becomes diff response var)
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 0.1514862 0.1679864 0.1448371
## Cramer-von Mises statistic   2.4543715 2.6629609 2.3693302
## Anderson-Darling statistic 14.6913607 16.0876004 14.1458389
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 4345.563 4380.937 4340.755
## Bayesian Information Criterion 4353.718 4389.092 4348.910

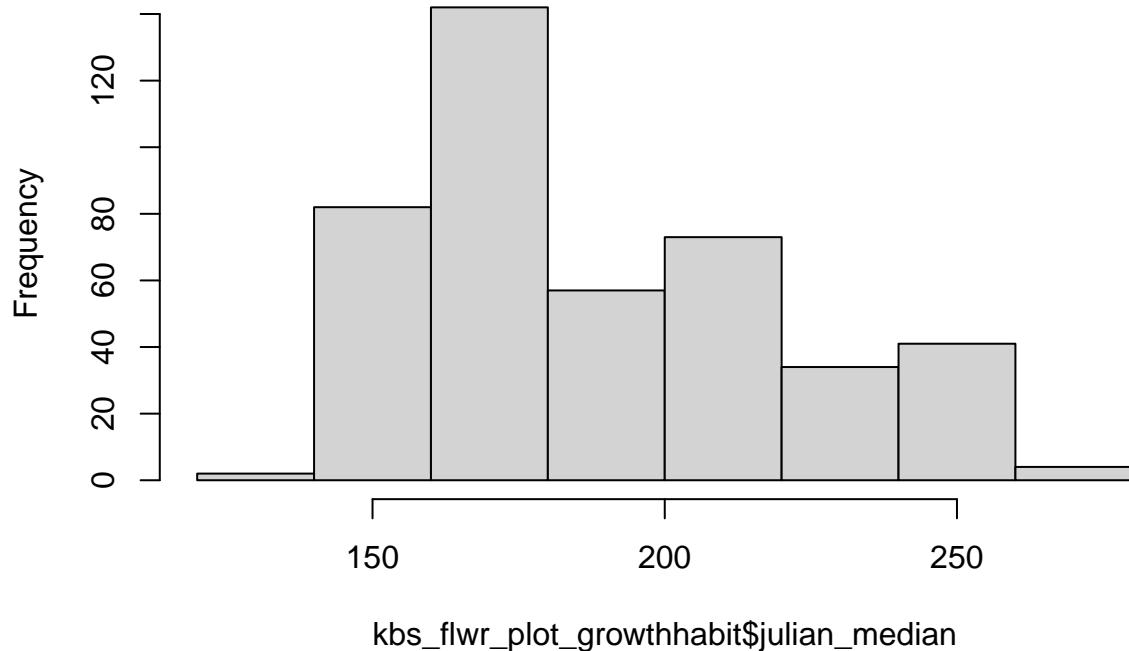
```

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

KBS PLOT LEVEL GROWTH HABIT - Looking at MEDIAN JULIAN DAY

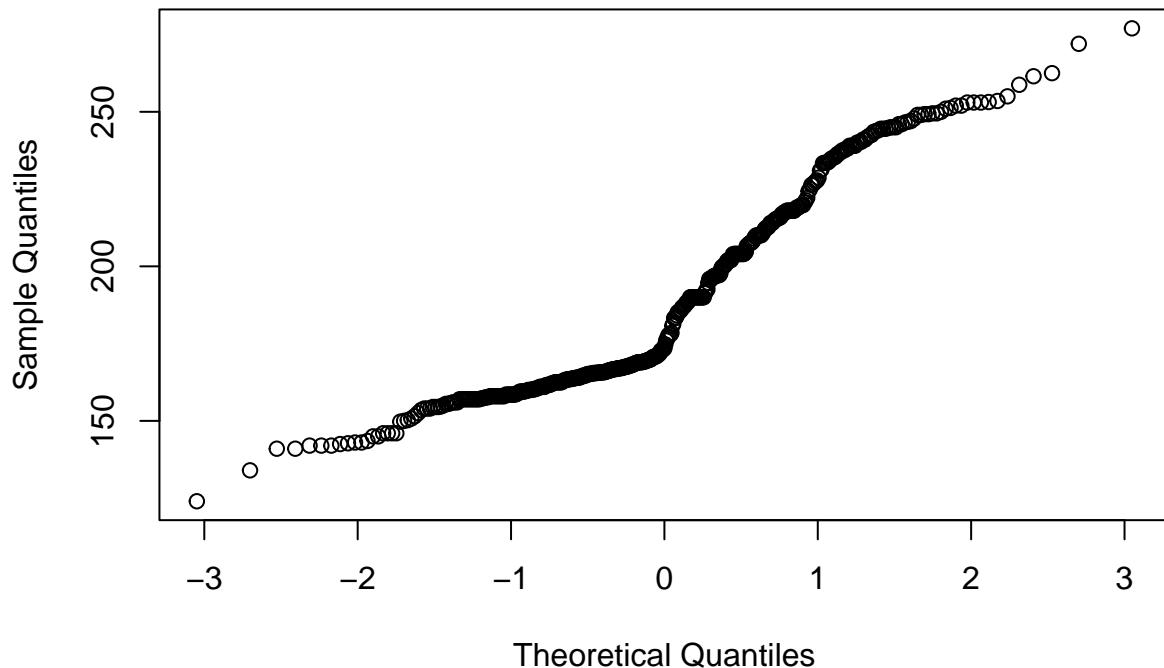
```
### KBS ###
hist(kbs_flwr_plot_growthhabit$julian_median)
```

Histogram of kbs_flwr_plot_growthhabit\$julian_median



```
qqnorm(kbs_flwr_plot_growthhabit$julian_median)
```

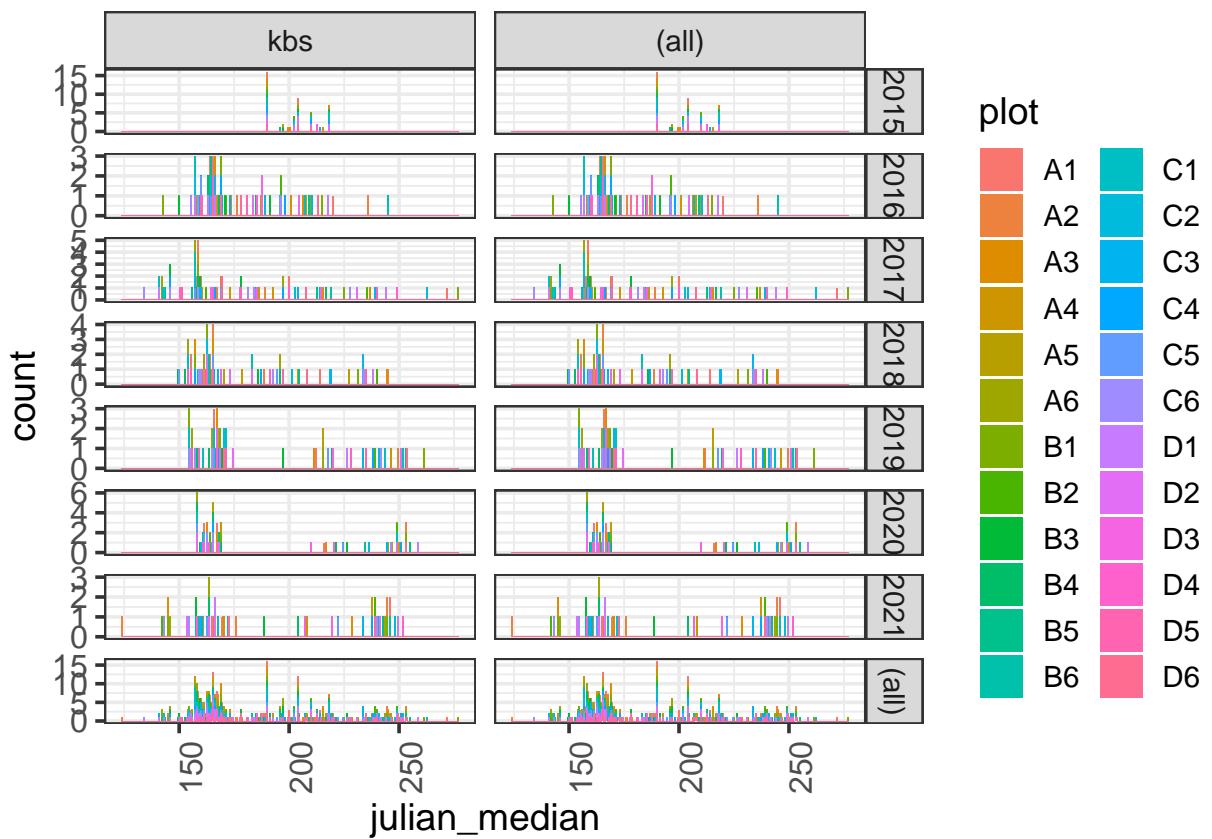
Normal Q-Q Plot



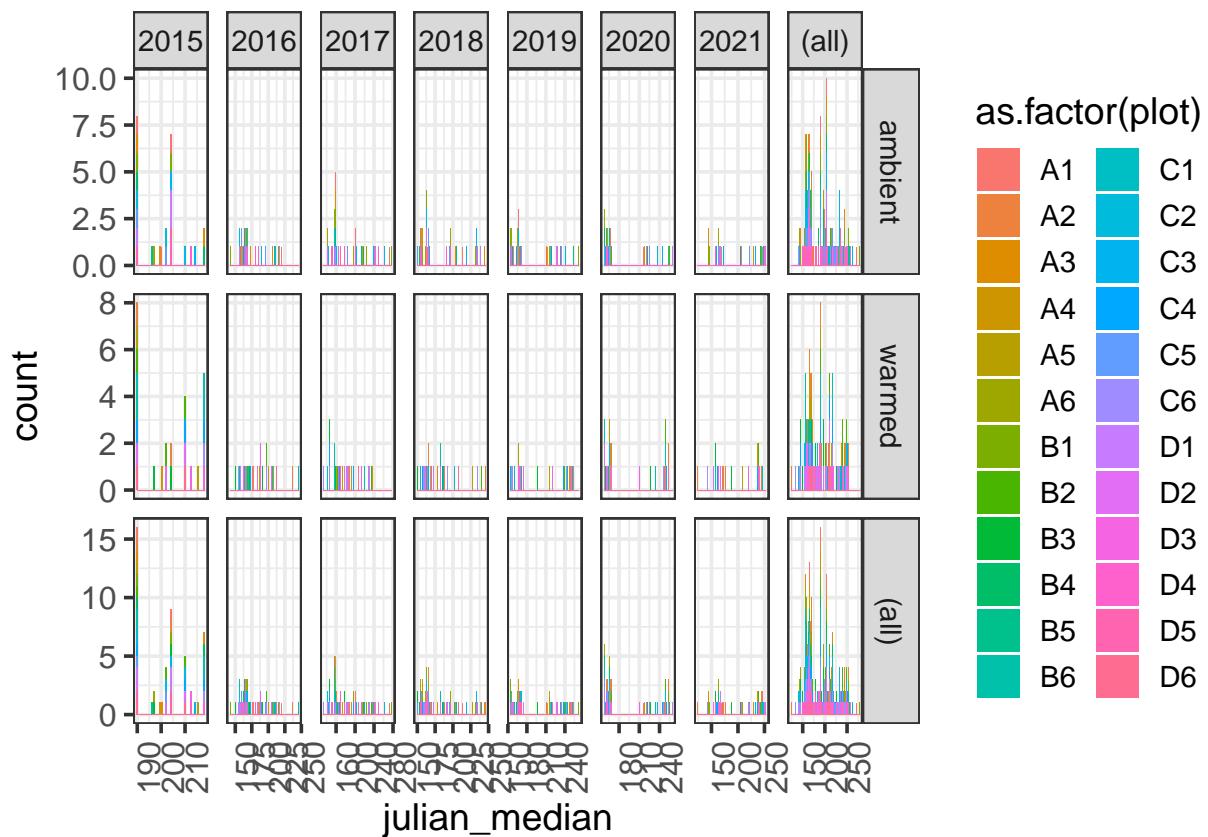
```
shapiro.test(kbs_flwr_plot_growthhabit$julian_median) # pvalue is < 0.05 so we reject the null hypothesis

## 
## Shapiro-Wilk normality test
##
## data: kbs_flwr_plot_growthhabit$julian_median
## W = 0.91448, p-value = 5.591e-15

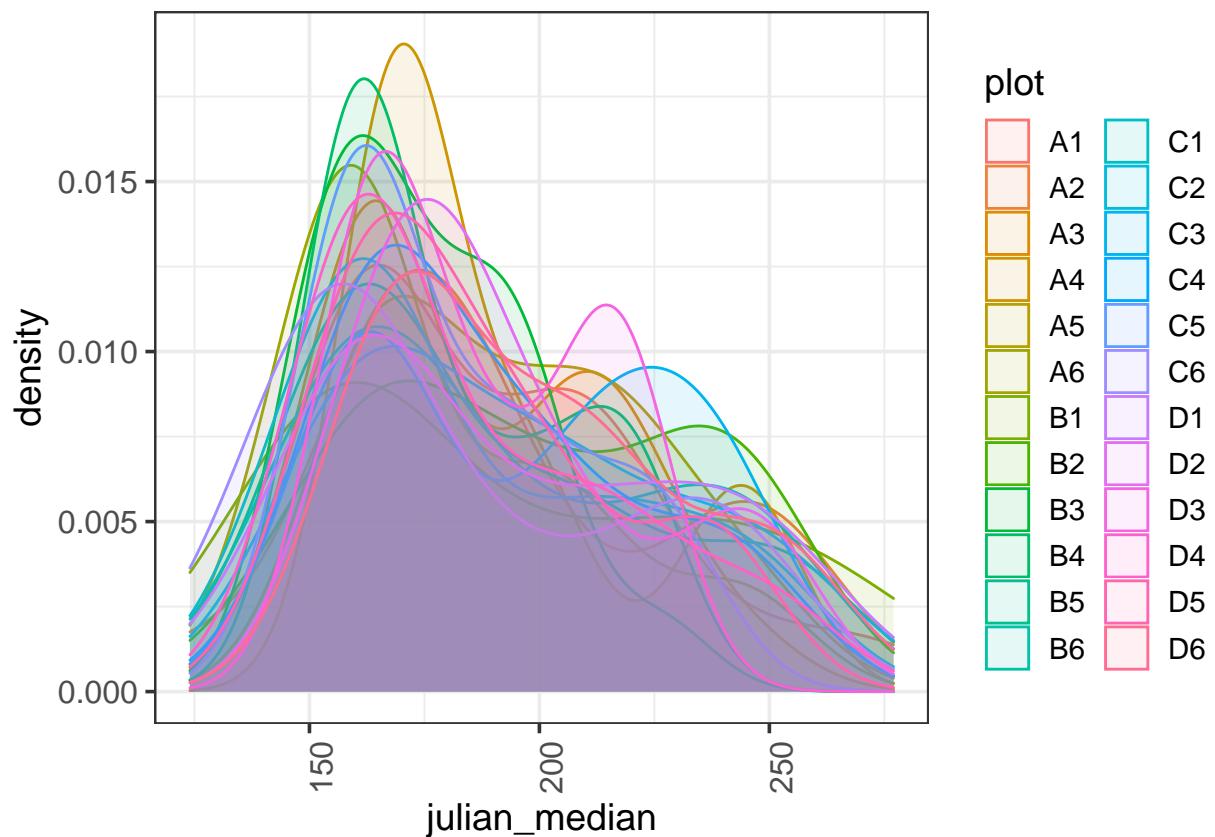
# Visualizing median Julian date for kbs at the PLOT LEVEL
ggplot(kbs_flwr_plot_growthhabit, aes(julian_median, fill = plot)) +
  geom_histogram(binwidth = 0.5) +
  facet_grid(year ~ site, margins = TRUE, scales = "free")
```



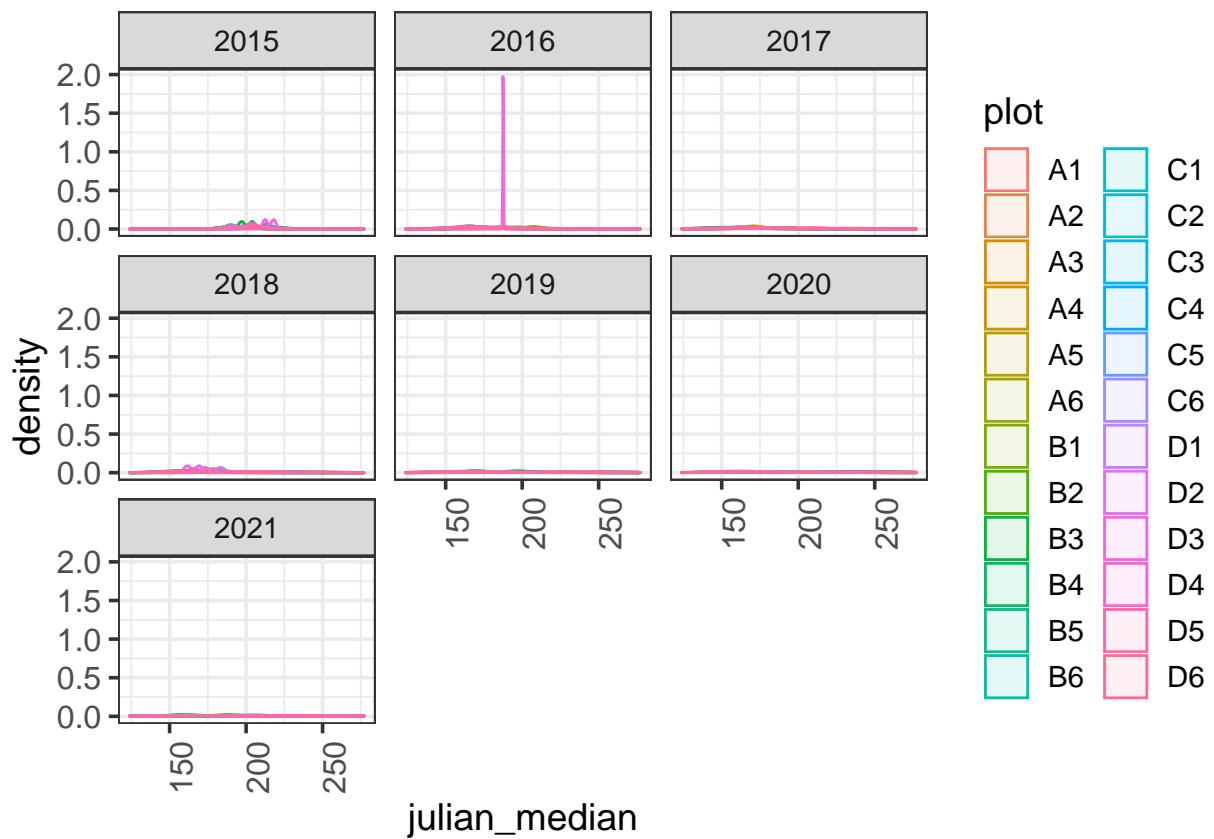
```
ggplot(kbs_flwr_plot_growthhabit, aes(julian_median, fill = as.factor(plot))) + geom_histogram(binwidth = 5)
  facet_grid(state~year, margins = TRUE, scales = "free")
```



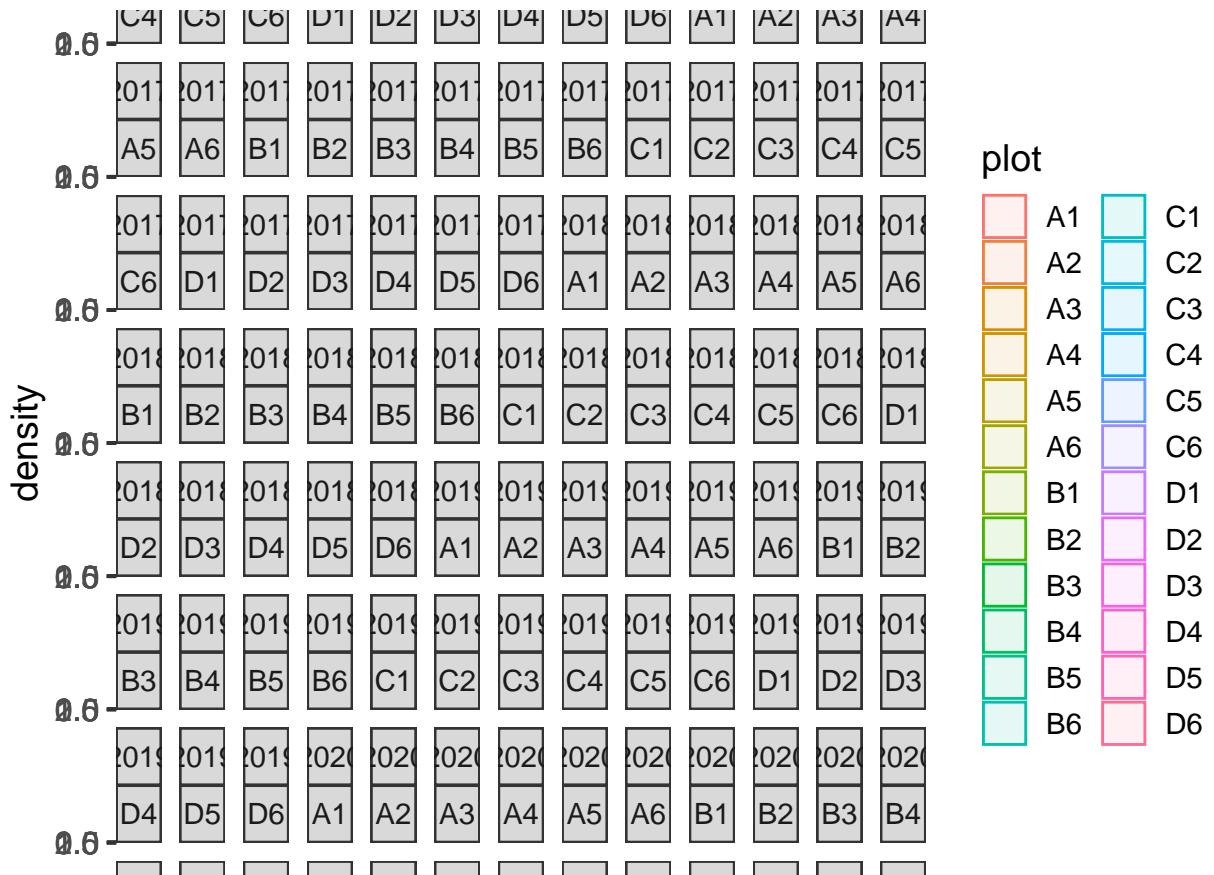
```
ggplot(kbs_flwr_plot_growthhabit, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1)
```



```
ggplot(kbs_flwr_plot_growthhabit, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year)
```

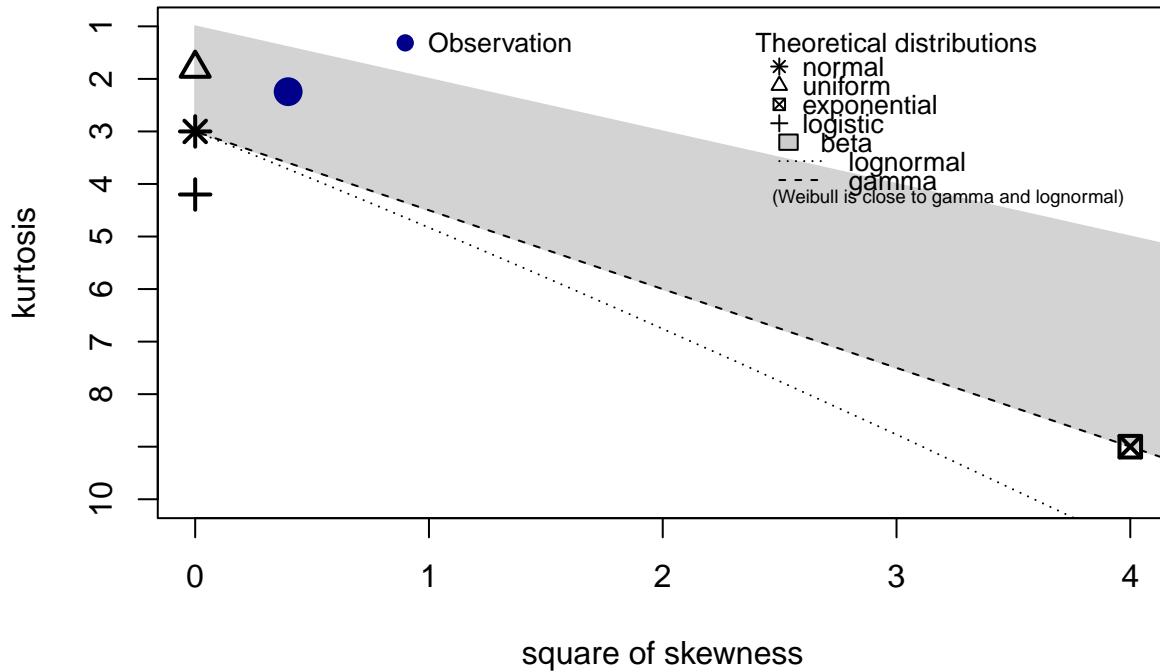


```
ggplot(kbs_flwr_plot_growthhabit, aes(julian_median, fill = plot, color=plot)) +
  geom_density(alpha = 0.1) +
  facet_wrap(~year + plot)
```



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

Cullen and Frey graph



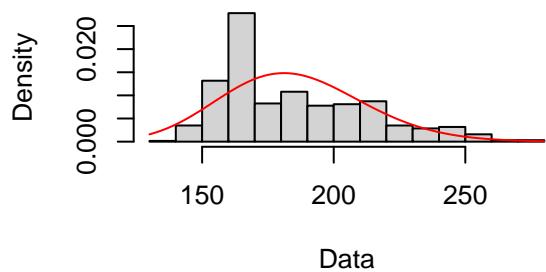
```

## summary statistics
## -----
## min: 124   max: 277
## median: 173.5
## mean: 188.3475
## estimated sd: 32.2652
## estimated skewness: 0.6305941
## estimated kurtosis: 2.243498

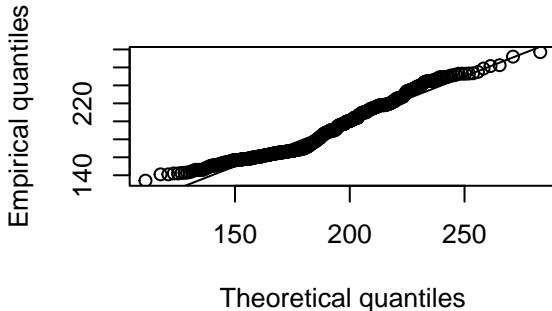
# Gamma distribution
fit.gamma <- fitdist(umbs_flwr_plot_growthhabit$julian_median, "gamma")
plot(fit.gamma)

```

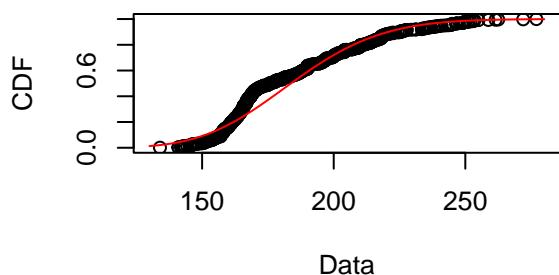
Empirical and theoretical dens.



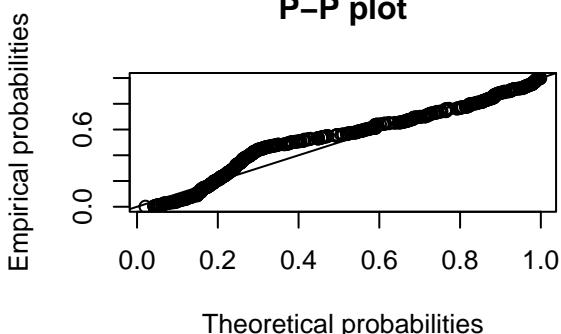
Q–Q plot



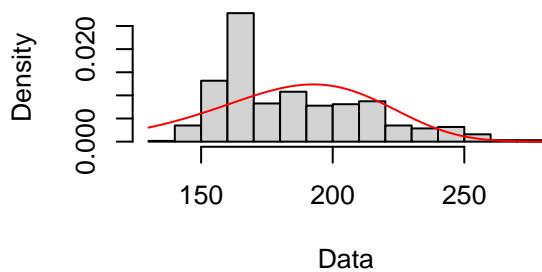
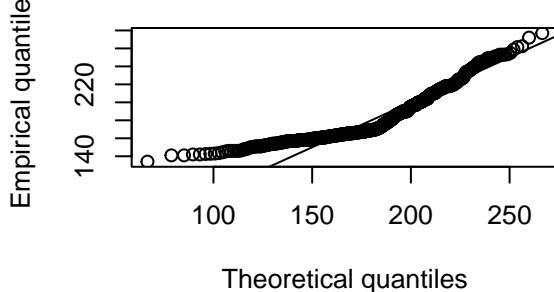
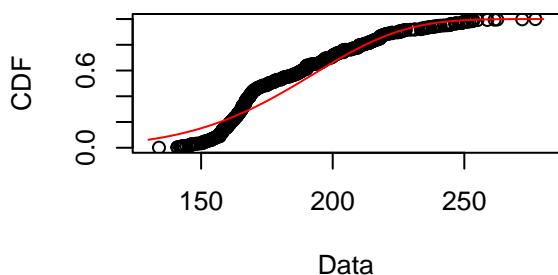
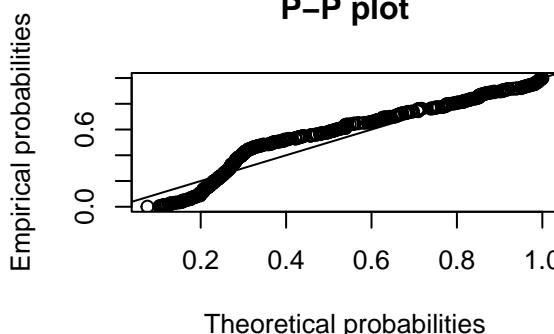
Empirical and theoretical CDFs



P–P plot

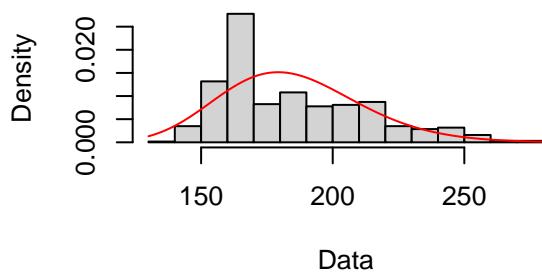
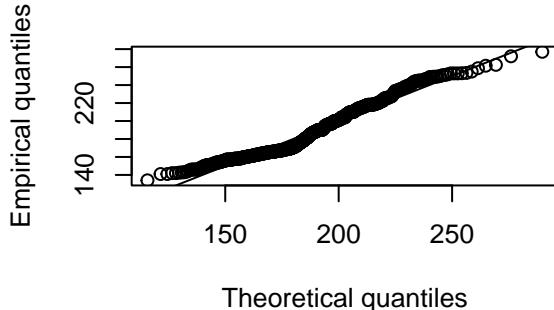
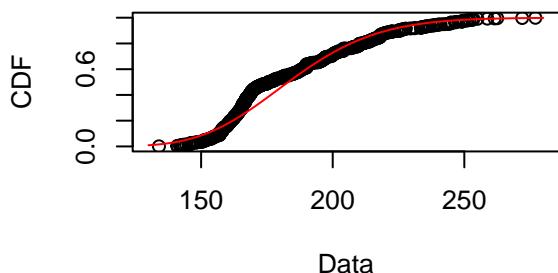
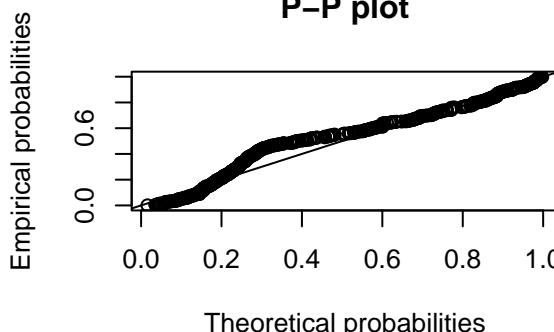


```
#  
# Weibull distribution  
fit.weibull <- fitdist(umbs_flwr_plot_growthhabit$julian_median, "weibull")  
plot(fit.weibull)
```

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

```
# Lognormal distribution
```

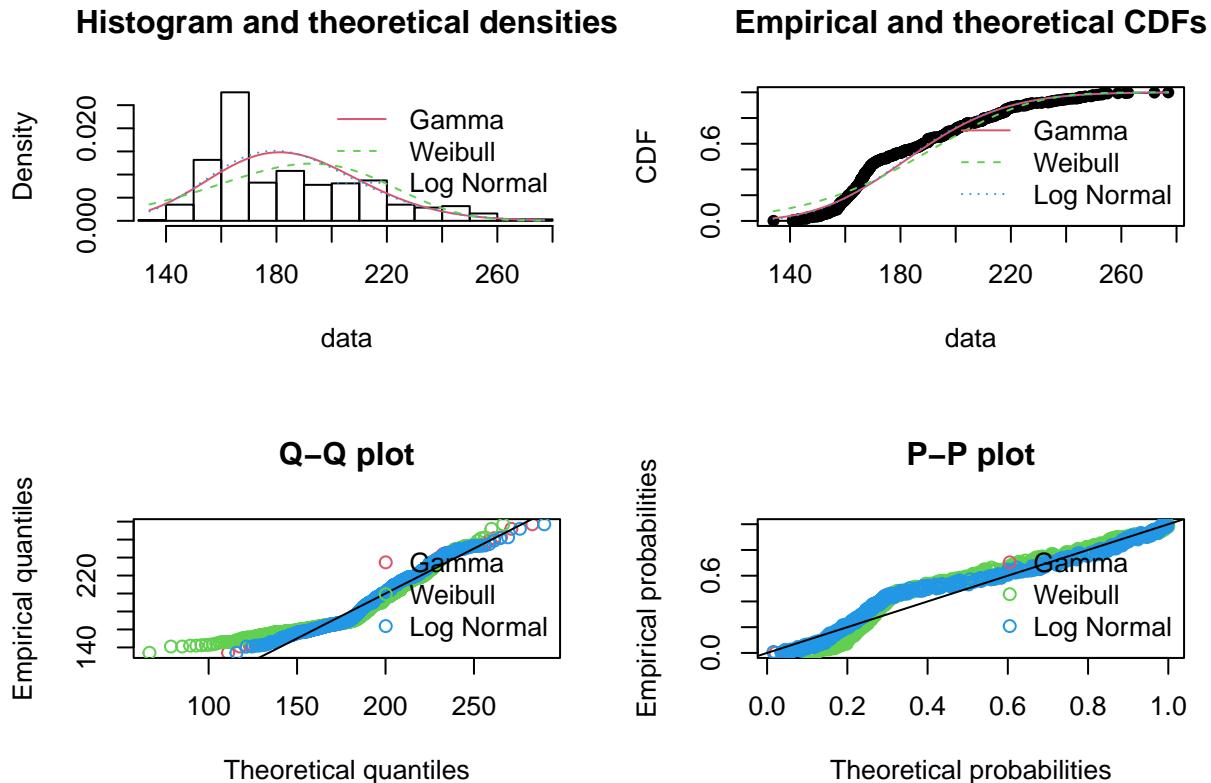
```
fit.ln <- fitdist(umbs_flwr_plot_growthhabit$julian_median, "lnorm")  
plot(fit.ln)
```

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)

```



```

# Goodness of fit comparisons across fits (can't include the sqrt normal bc it becomes diff response var)
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 0.1451735 0.138714 0.1414238
## Cramer-von Mises statistic   2.4663275 3.536763 2.2617767
## Anderson-Darling statistic  13.7523569 21.343517 12.4611085
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 5943.971 6086.608 5926.132
## Bayesian Information Criterion 5952.862 6095.500 5935.024

```

```

# Log normal looks like it's the best fit

```

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

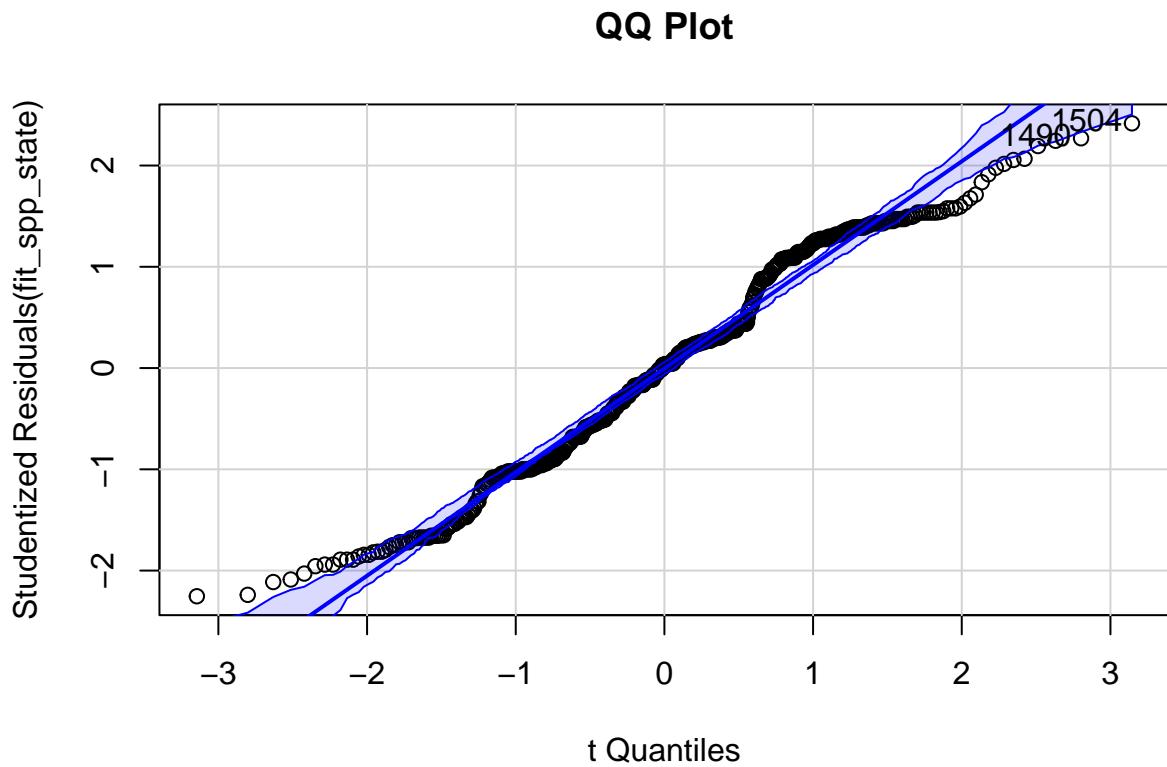
These illustrate whether certain data points have more leverage (more influence), and thus could be outliers. It's a way of detecting outliers. Leverage plots can help identify whether a point has high or low influence, based on its leverage and residual and determining model fit with and without the 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>

Phoebe

```
# species level data
# UMBS State-only model
fit_spp_state <- lm(log(julian_median) ~ state, data = umbs_flwr_spp)
outlierTest(fit_spp_state) # no outliers

## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 1504  2.416487          0.015985        NA

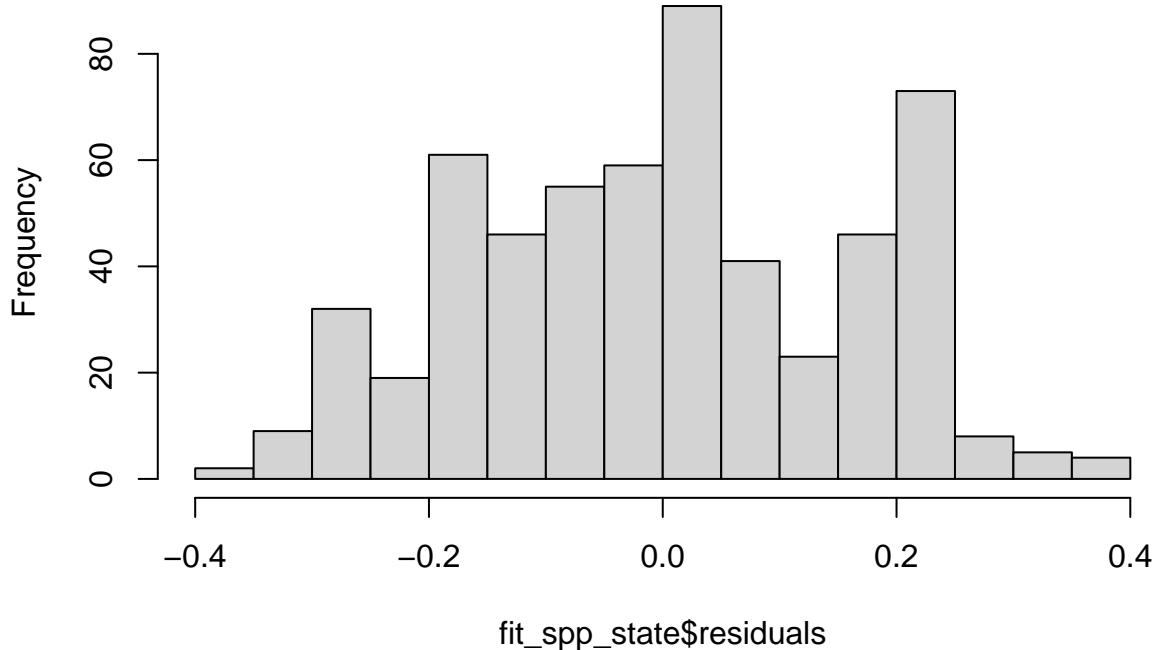
qqPlot(fit_spp_state, main="QQ Plot")
```



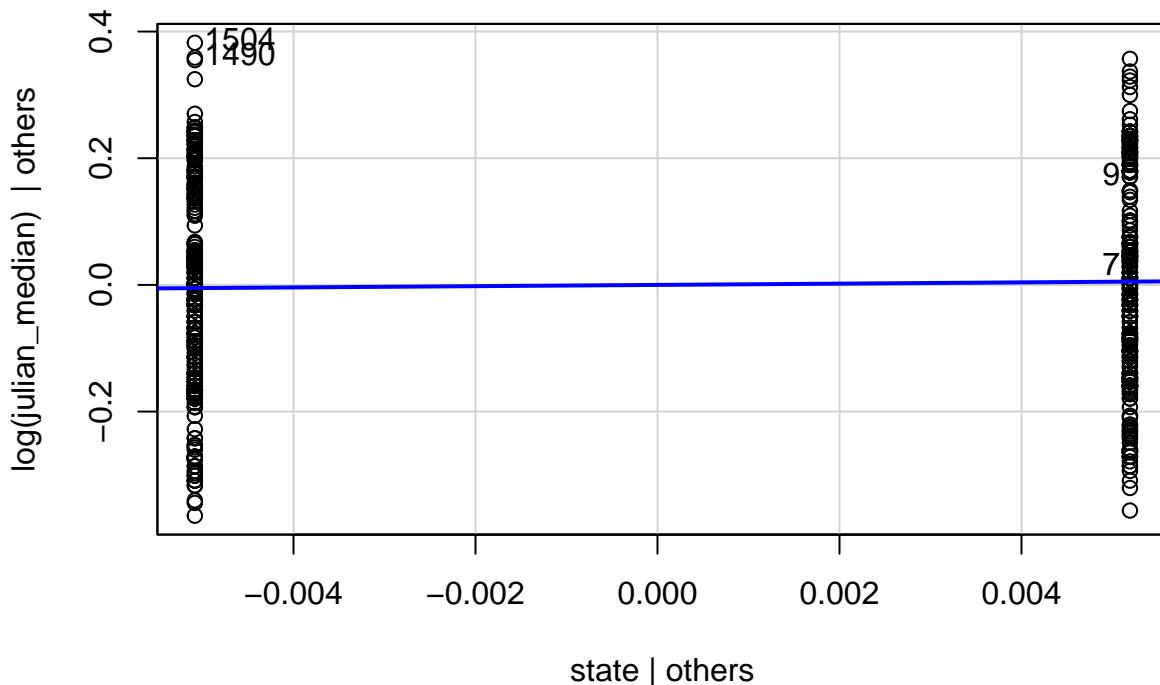
```
## 1490 1504
## 502 507
```

```
hist(fit_spp_state$residuals)
```

Histogram of fit_spp_state\$residuals



```
leveragePlots(fit_spp_state)
```



```
ols_test_normality(fit_spp_state)
```

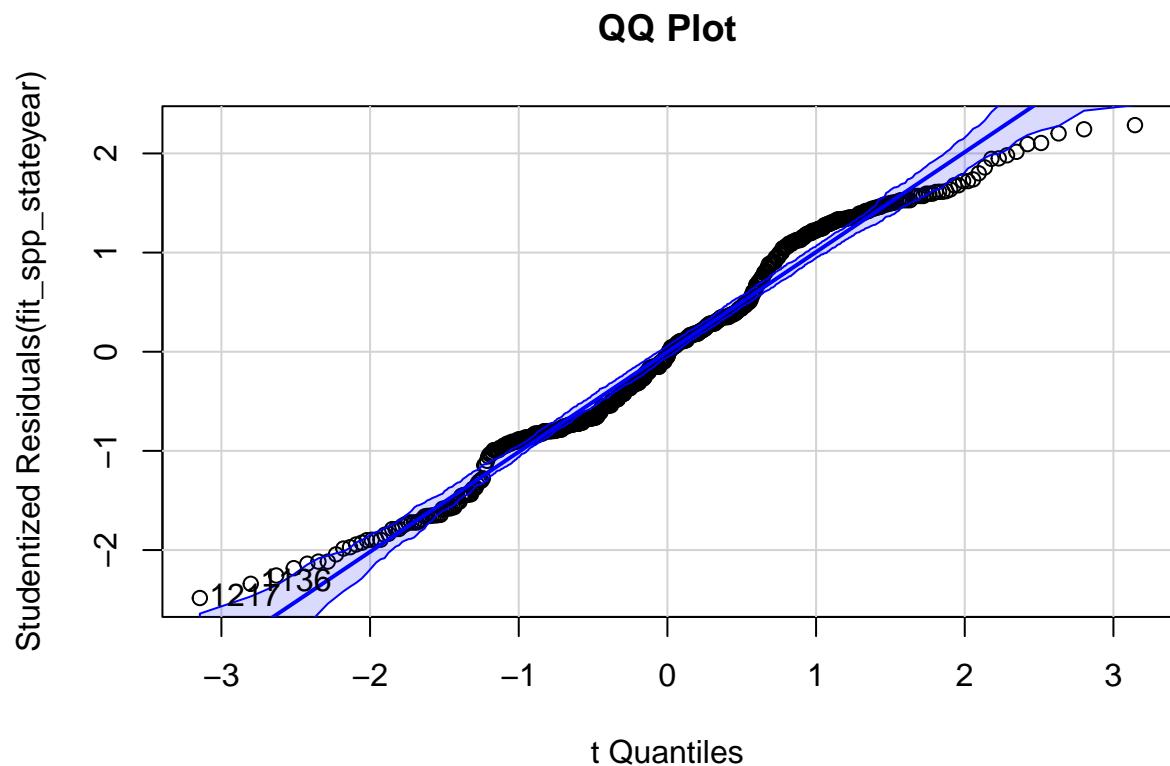
```
## Warning in ks.test.default(y, "pnorm", mean(y), sd(y)): ties should not be  
## present for the Kolmogorov-Smirnov test
```

```
## -----  
## Test Statistic pvalue  
## -----  
## Shapiro-Wilk 0.9777 0.0000  
## Kolmogorov-Smirnov 0.0747 0.0034  
## Cramer-von Mises 133.5002 0.0000  
## Anderson-Darling 3.6609 0.0000  
## -----
```

```
# UMBS State and year model  
fit_spp_stateyear <- lm(log(julian_median) ~ state + year_factor, data = umbs_flwr_spp)  
outlierTest(fit_spp_stateyear) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05  
## Largest |rstudent|:  
## rstudent unadjusted p-value Bonferroni p  
## 1217 -2.483867 0.013284 NA
```

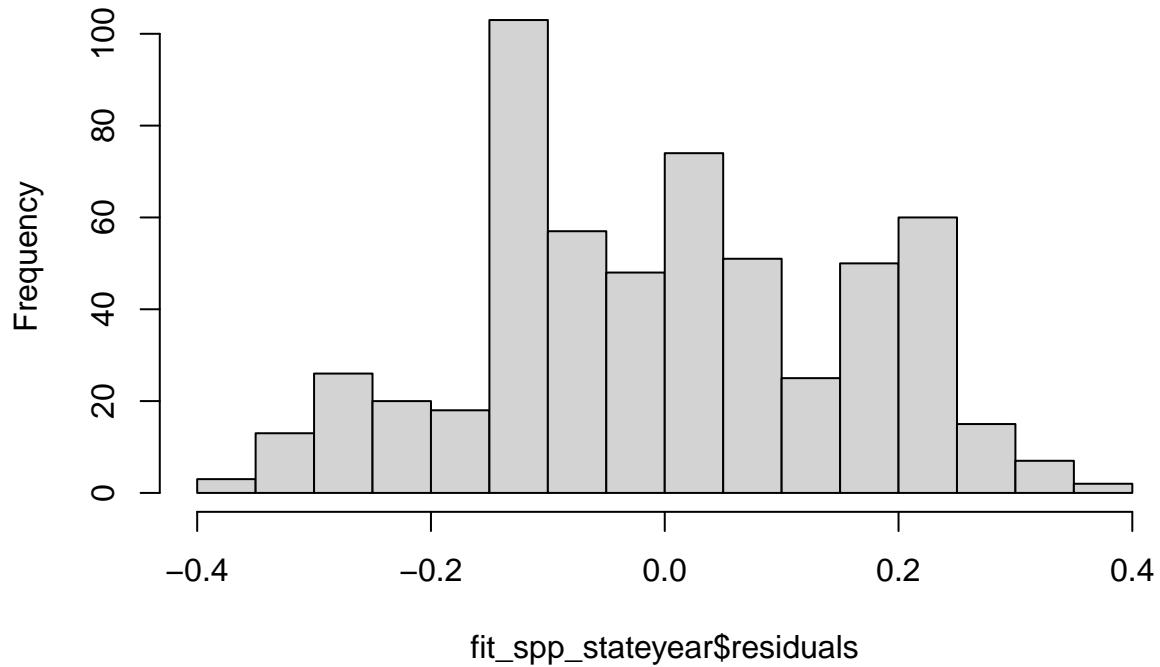
```
qqPlot(fit_spp_stateyear, main="QQ Plot")
```



```
## 1136 1217  
## 392 414
```

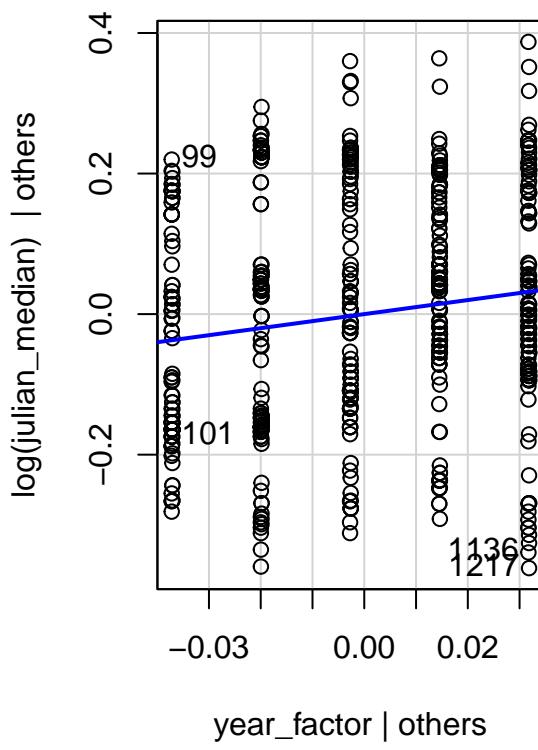
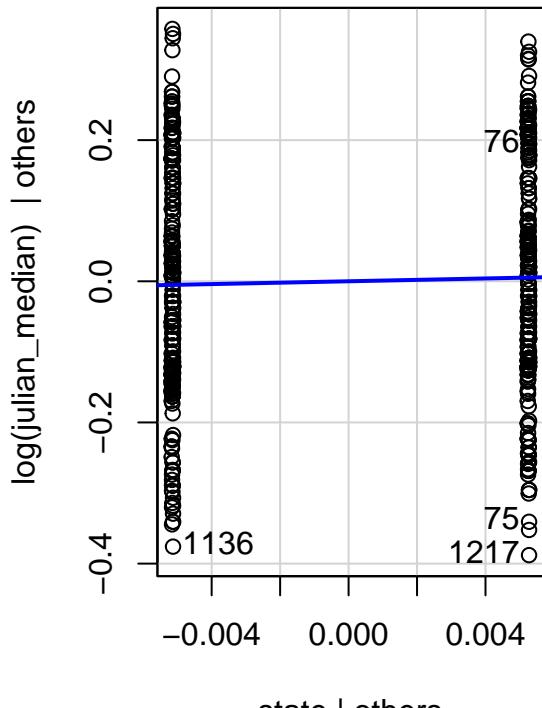
```
hist(fit_spp_stateyear$residuals)
```

Histogram of fit_spp_stateyear\$residuals



```
leveragePlots(fit_spp_stateyear)
```

Leverage Plots



```

ols_test_normality(fit_spp_stateyear)

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

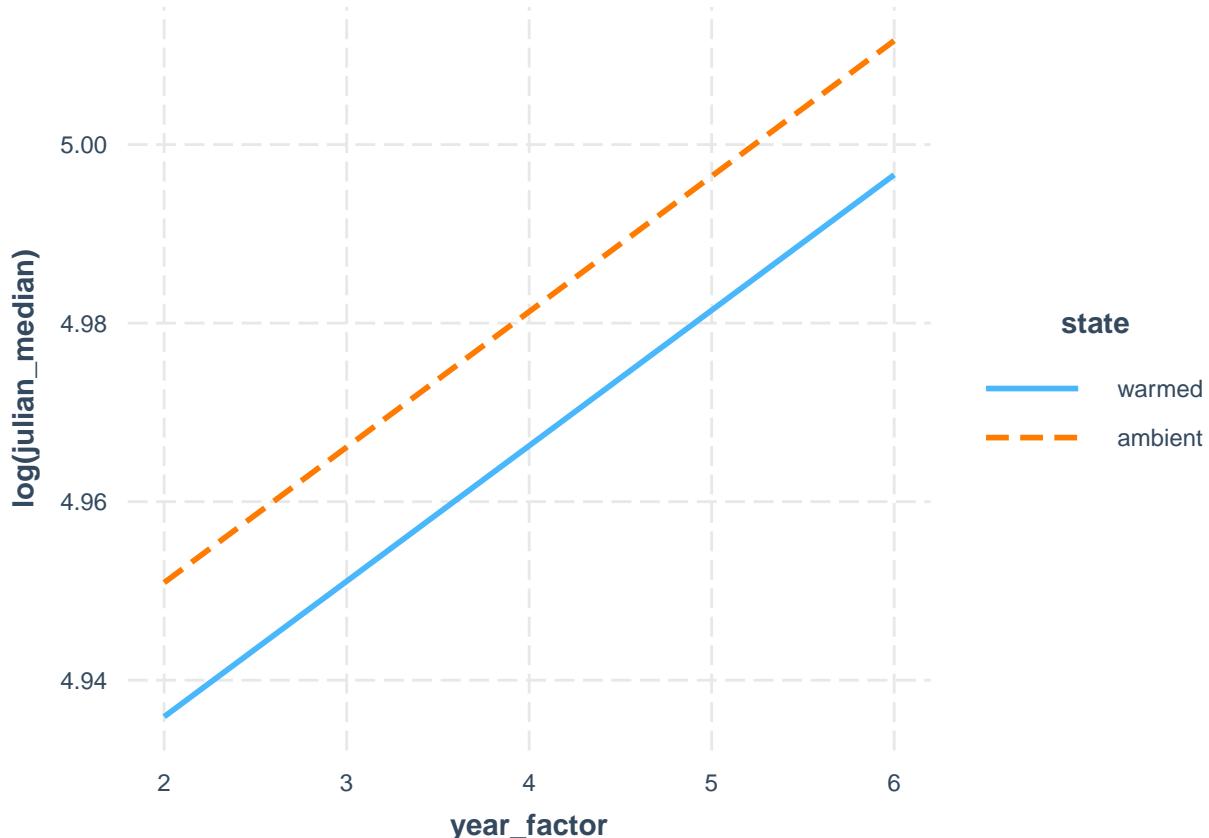
## -----
##          Test      Statistic     pvalue
## -----
## Shapiro-Wilk      0.9794    0.0000
## Kolmogorov-Smirnov   0.0715    0.0057
## Cramer-von Mises    133.7468   0.0000
## Anderson-Darling     3.8514    0.0000
## -----
# Interaction plot (ignore for now the repeated measures with species); see: https://cran.r-project.org

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

## Using data umbs_flwr_spp from global environment. This could cause
## incorrect results if umbs_flwr_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.

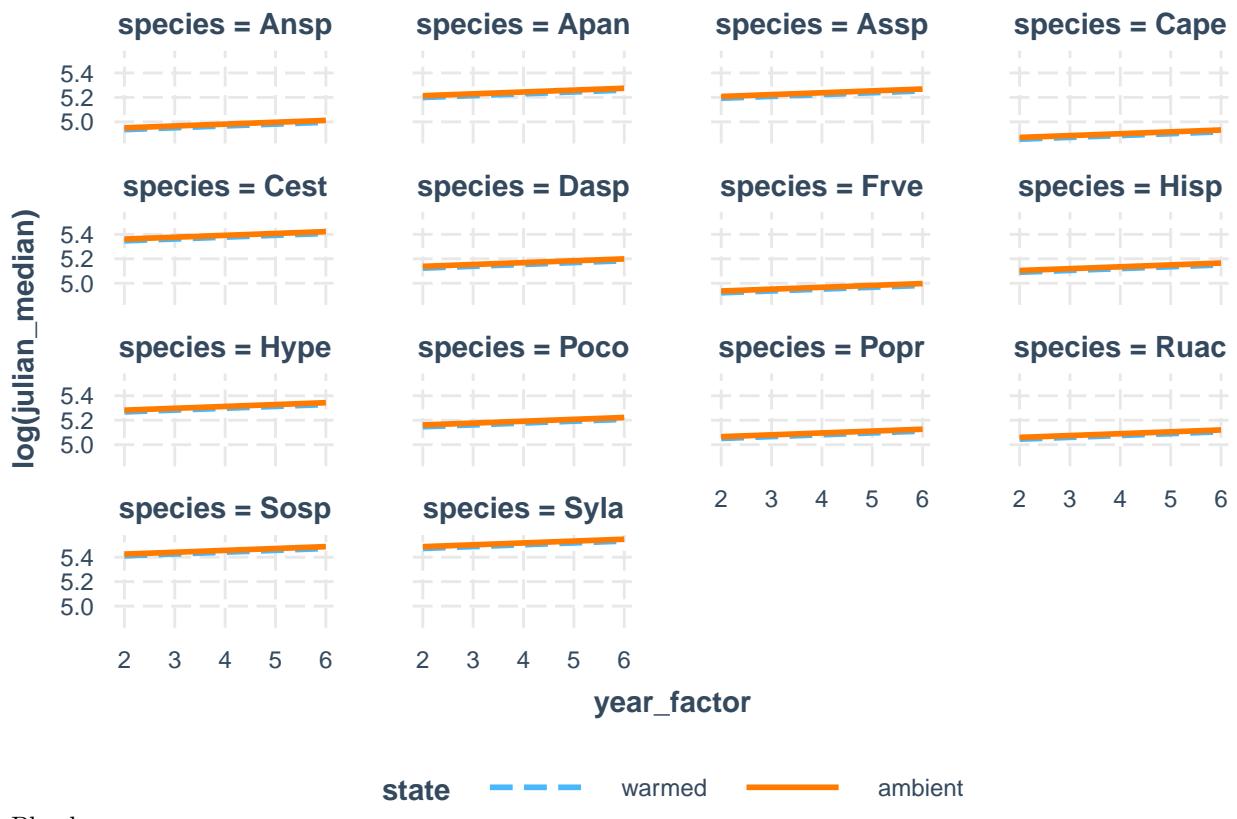
```



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

Using data umbs_flwr_spp from global environment. This could cause
 ## incorrect results if umbs_flwr_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.

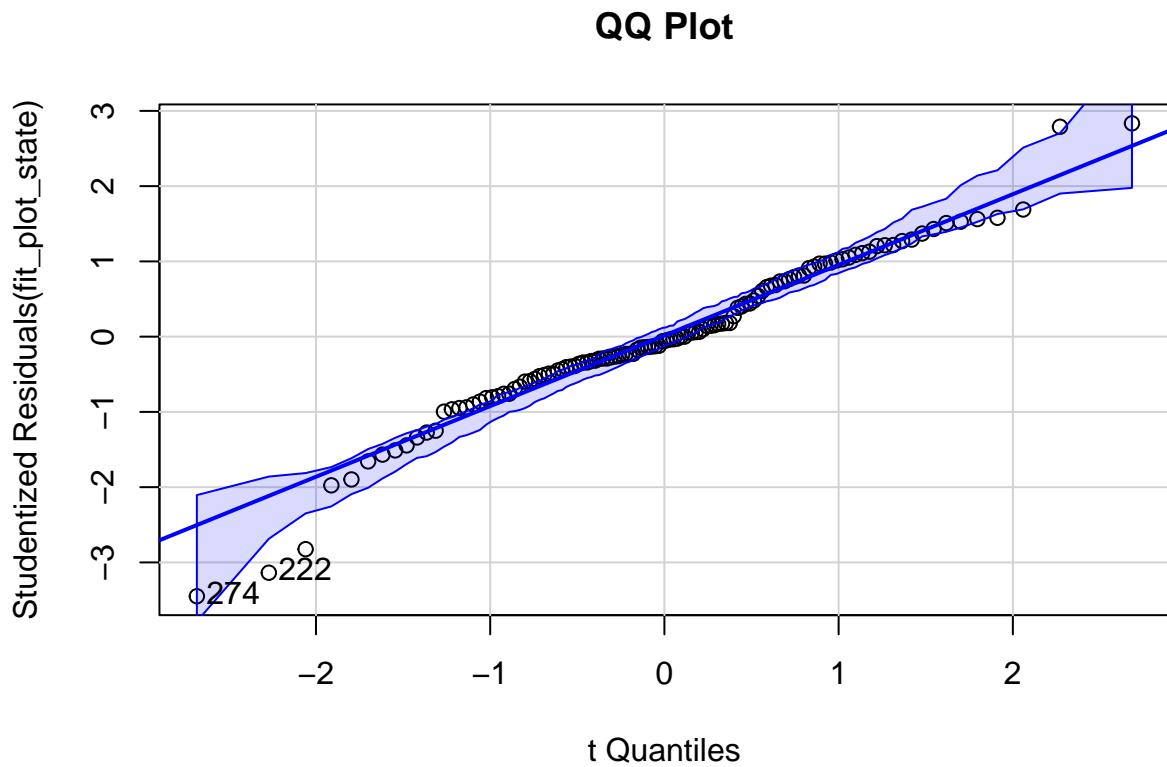


Phoebe

```
# Plot level data
# UMBS State-only model
fit_plot_state <- lm(log(julian_median) ~ state, data = umbs_flwr_plot)
outlierTest(fit_plot_state) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 274 -3.449752      0.00078104     0.093725
```

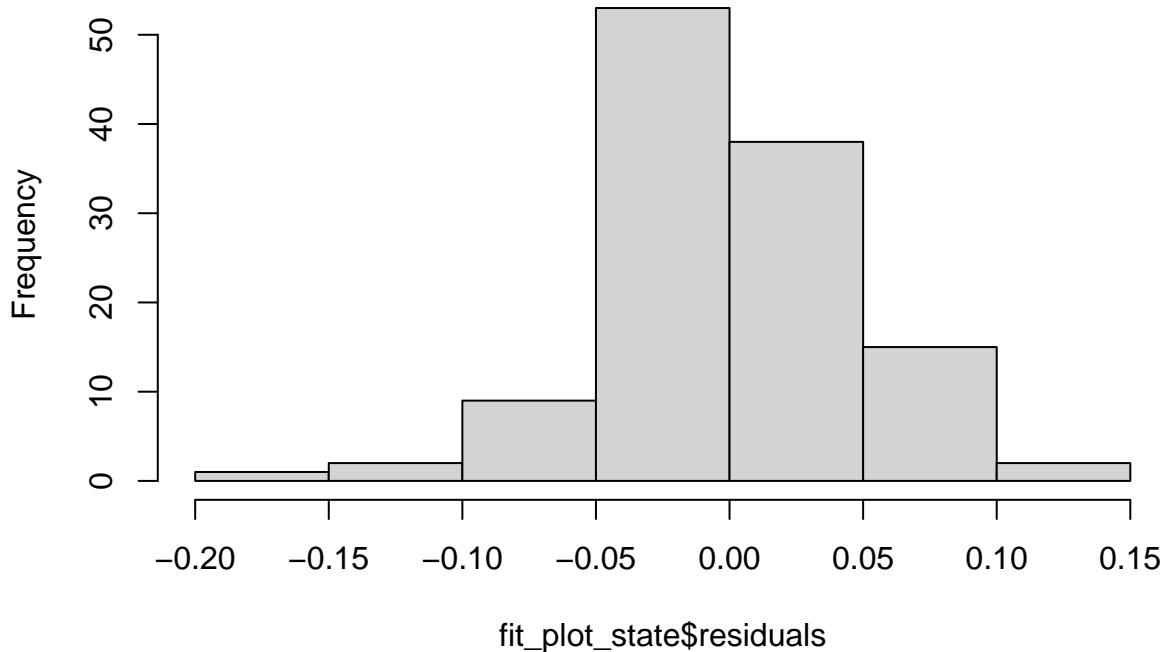
```
qqPlot(fit_plot_state, main="QQ Plot")
```



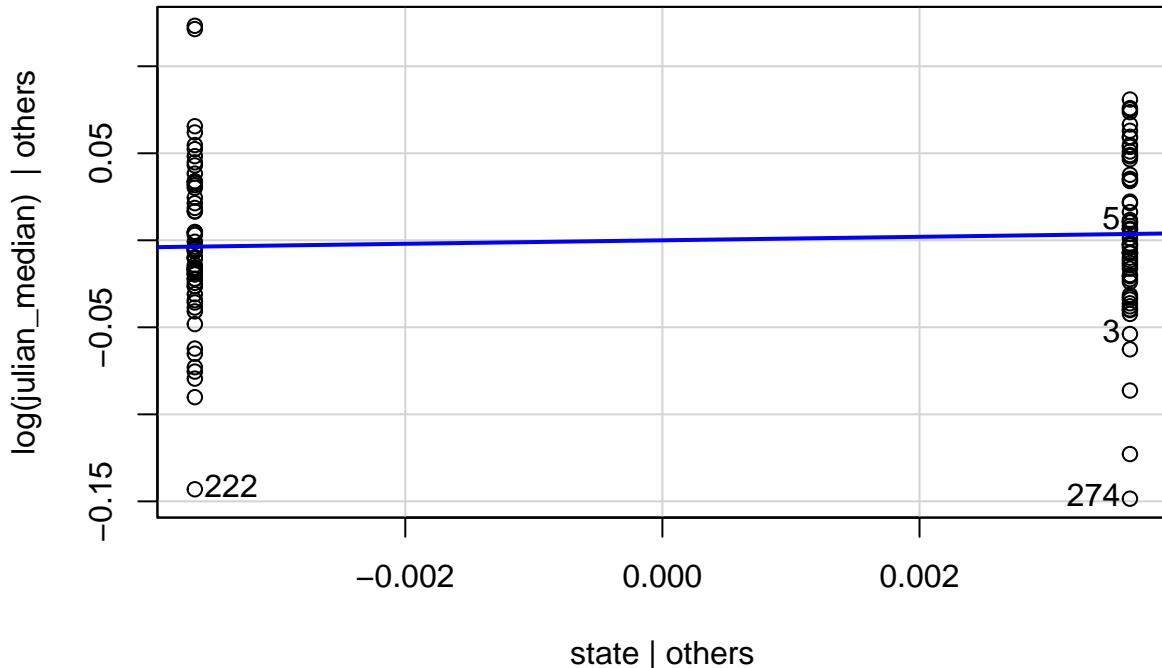
```
## 222 274
## 86 106
```

```
hist(fit_plot_state$residuals)
```

Histogram of fit_plot_state\$residuals



```
leveragePlots(fit_plot_state)
```



```
ols_test_normality(fit_plot_state) # looks ok besides Kolmogorov-Smirnov test
```

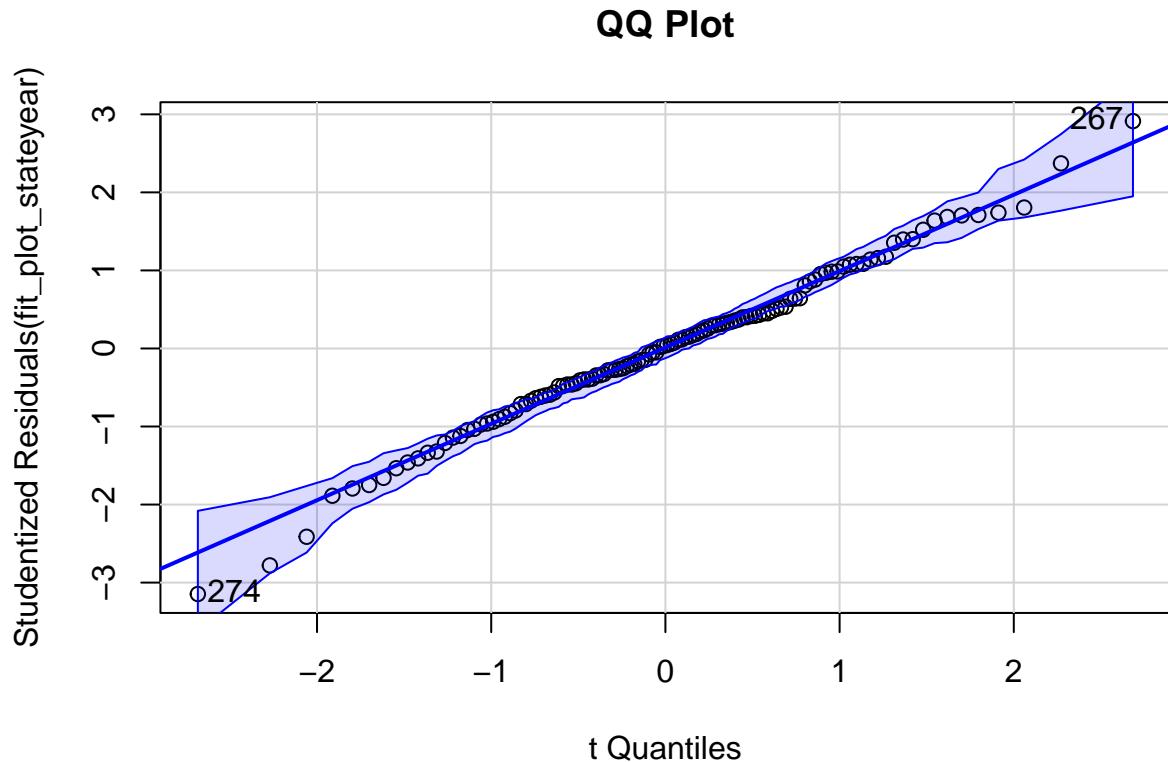
```
## Warning in ks.test.default(y, "pnorm", mean(y), sd(y)): ties should not be
## present for the Kolmogorov-Smirnov test
```

```
## -----
##      Test       Statistic     pvalue
## -----
## Shapiro-Wilk      0.9733    0.0172
## Kolmogorov-Smirnov 0.0781    0.4577
## Cramer-von Mises  36.5315   0.0000
## Anderson-Darling   0.8575    0.0268
## -----
```

```
# UMBS State and year model
fit_plot_stateyear <- lm(log(julian_median) ~ state + year_factor, data = umbs_flwr_plot)
outlierTest(fit_plot_stateyear) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##          rstudent unadjusted p-value Bonferroni p
## 274 -3.146336           0.0021011      0.25213
```

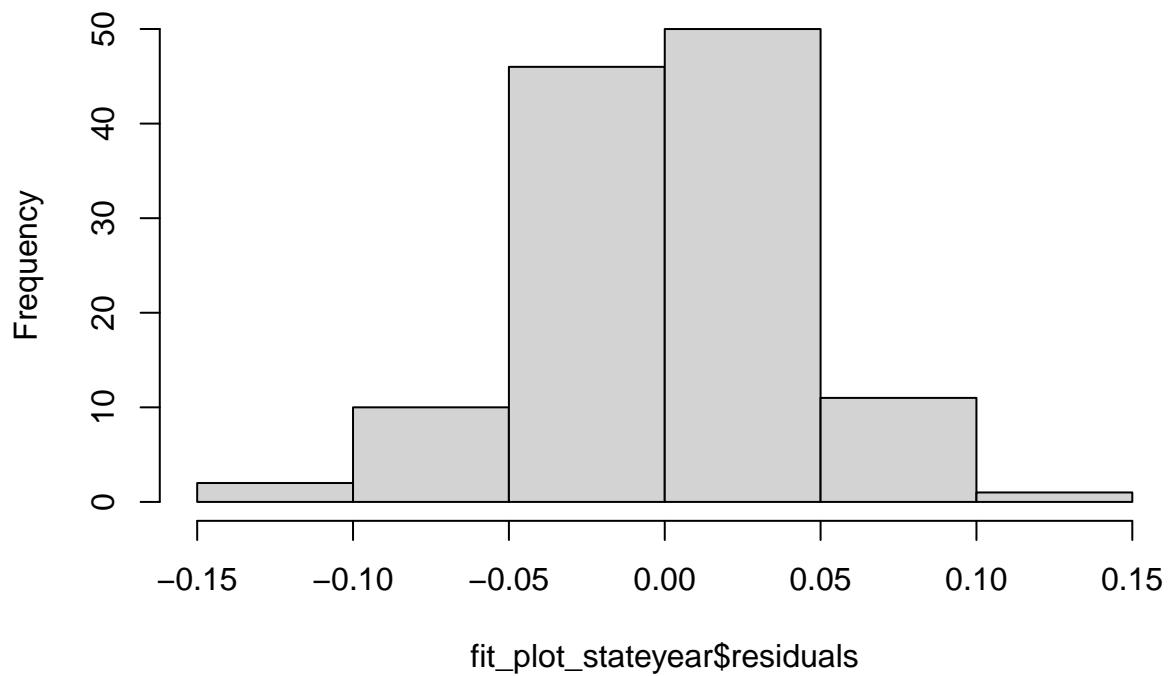
```
qqPlot(fit_plot_stateyear, main="QQ Plot")
```



```
## 267 274  
## 104 106
```

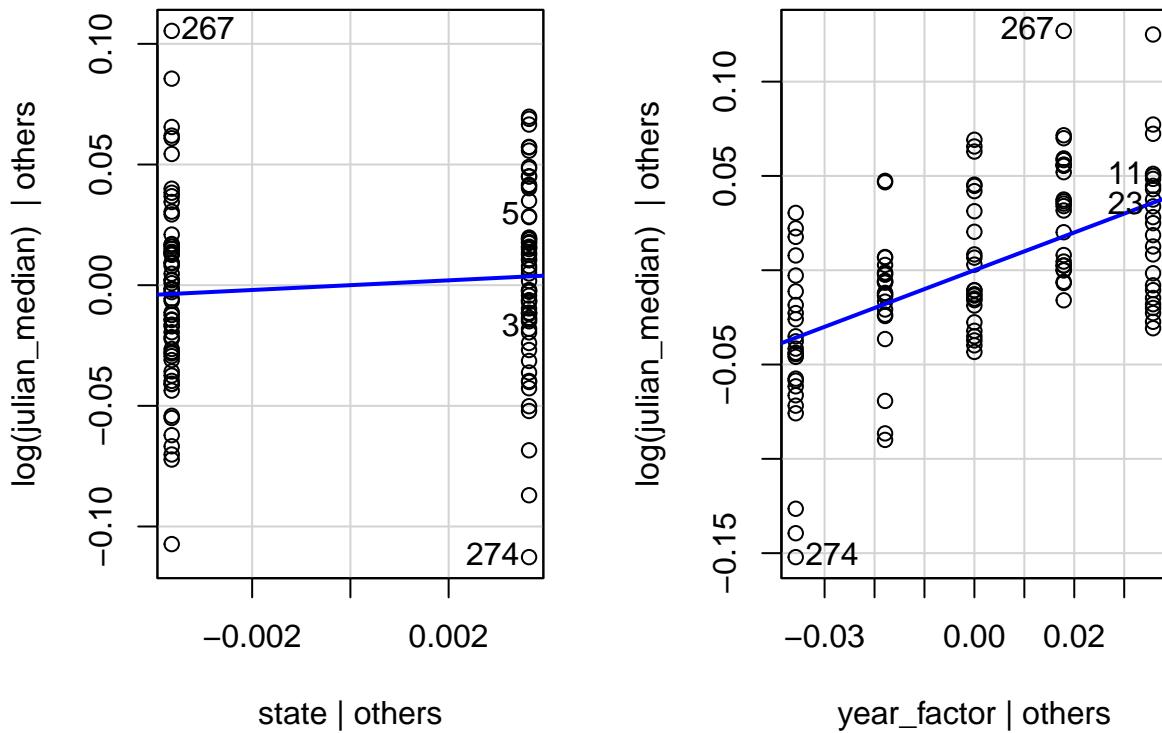
```
hist(fit_plot_stateyear$residuals)
```

Histogram of fit_plot_stateyear\$residuals



```
leveragePlots(fit_plot_stateyear)
```

Leverage Plots



```

ols_test_normality(fit_plot_stateyear) # not good

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

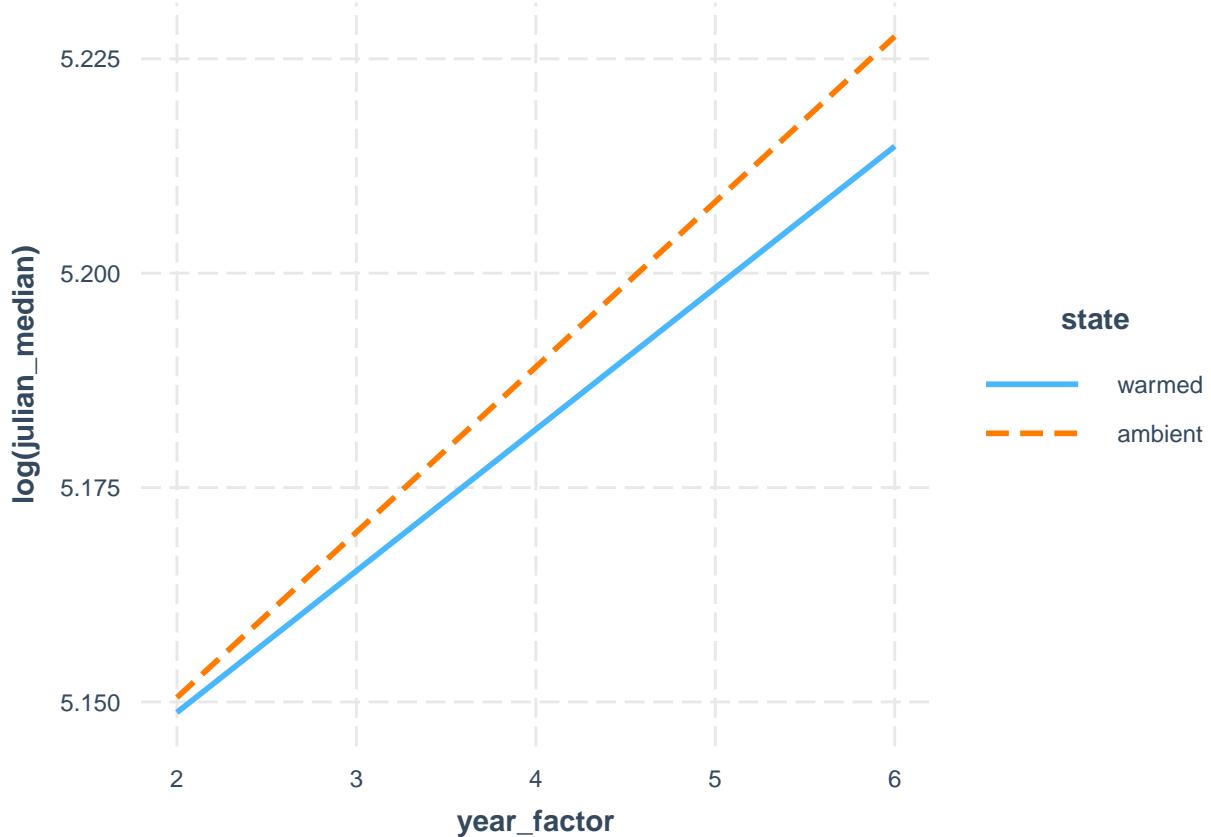
## -----
##          Test      Statistic     pvalue
## -----
## Shapiro-Wilk      0.9929    0.8000
## Kolmogorov-Smirnov   0.0546    0.8662
## Cramer-von Mises    37.0156   0.0000
## Anderson-Darling     0.2734    0.6606
## -----


# Interaction plot (ignore for now the repeated measures with species); see: https://cran.r-project.org

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

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

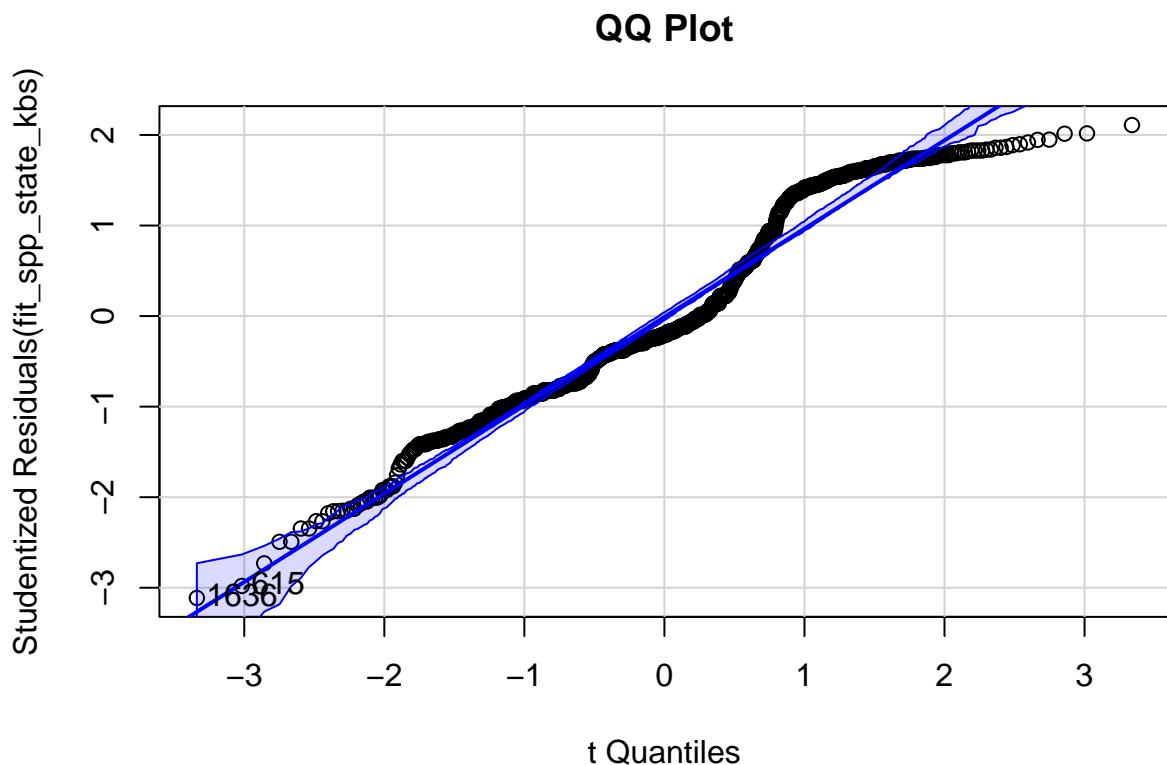
```



```
# species level data
# KBS State-only model
fit_spp_state_kbs <- lm(log(julian_median) ~ state, data = kbs_flwr_spp)
outlierTest(fit_spp_state_kbs) # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 1636 -3.112942          0.0018981       NA
```

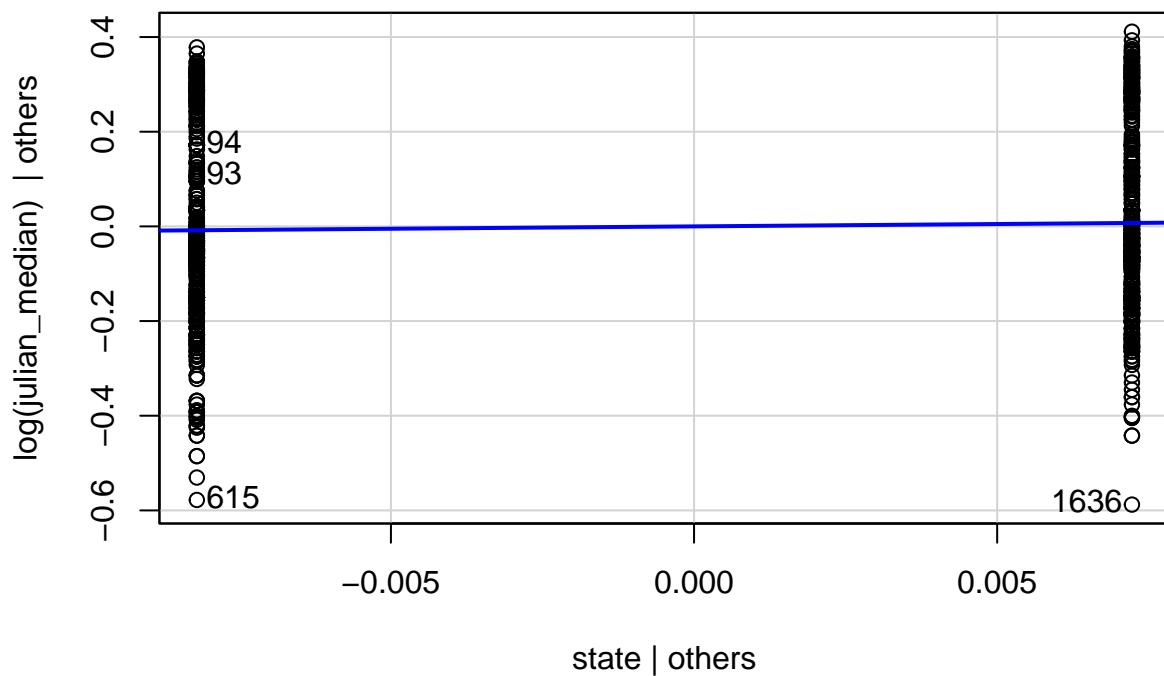
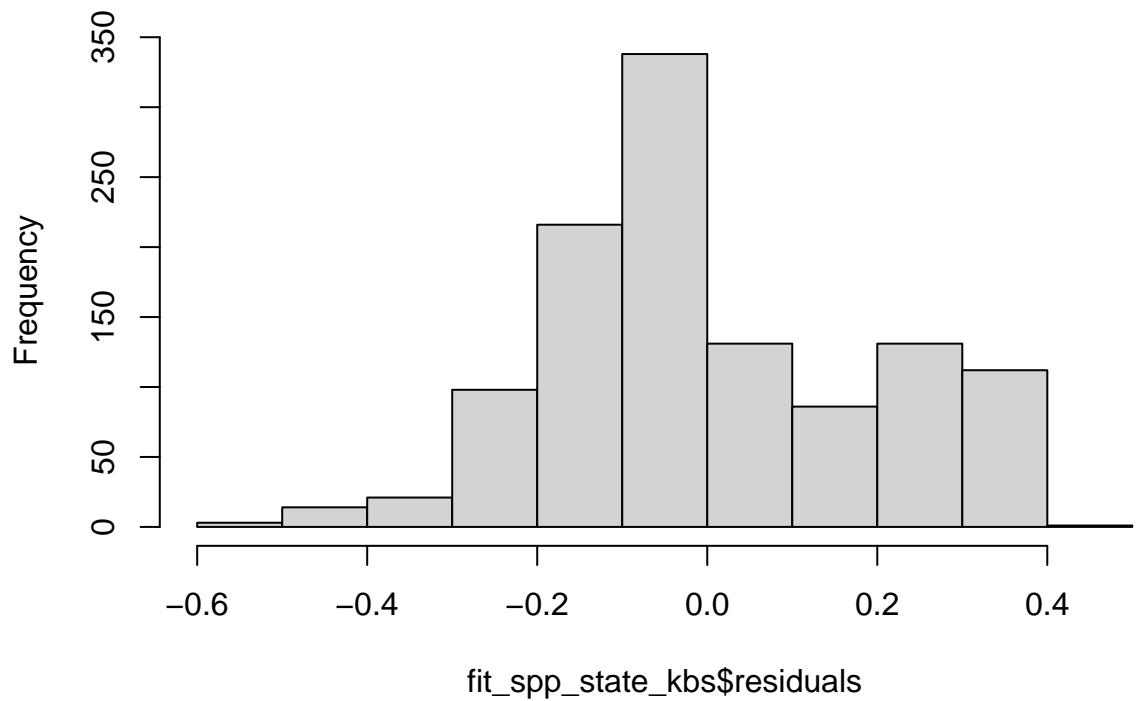
```
qqPlot(fit_spp_state_kbs, main="QQ Plot")
```



```
## 615 1636
## 383 1076
```

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

Histogram of fit_spp_state_kbs\$residuals



```

ols_test_normality(fit_spp_state_kbs)

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

## -----
##          Test      Statistic     pvalue
## -----
## Shapiro-Wilk      0.9563    0.0000
## Kolmogorov-Smirnov   0.1086    0.0000
## Cramer-von Mises    251.4677   0.0000
## Anderson-Darling     19.9373   0.0000
## -----
# KBS State and year model
fit_spp_stateyear_kbs <- lm(log(julian_median) ~ state + year_factor, data = kbs_flwr_spp)
outlierTest(fit_spp_stateyear_kbs) # no outliers

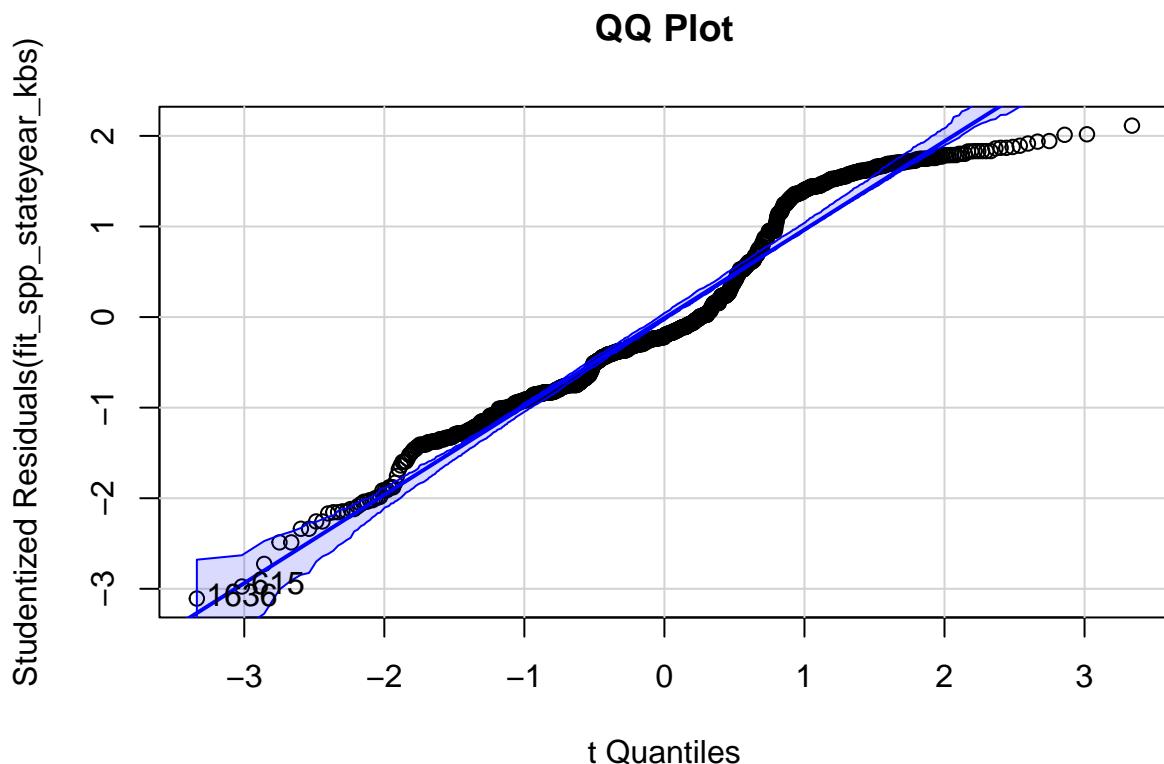
```

```

## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##           rstudent unadjusted p-value Bonferroni p
## 1636 -3.107604            0.0019325       NA

```

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

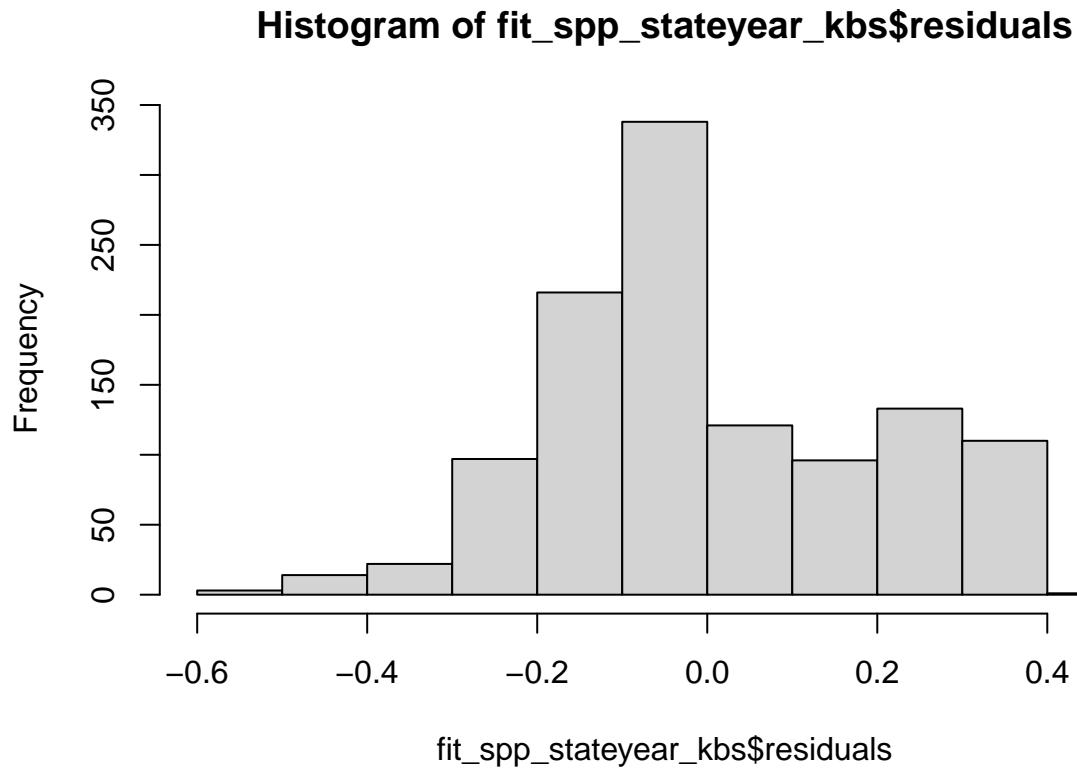


```

## 615 1636
## 383 1076

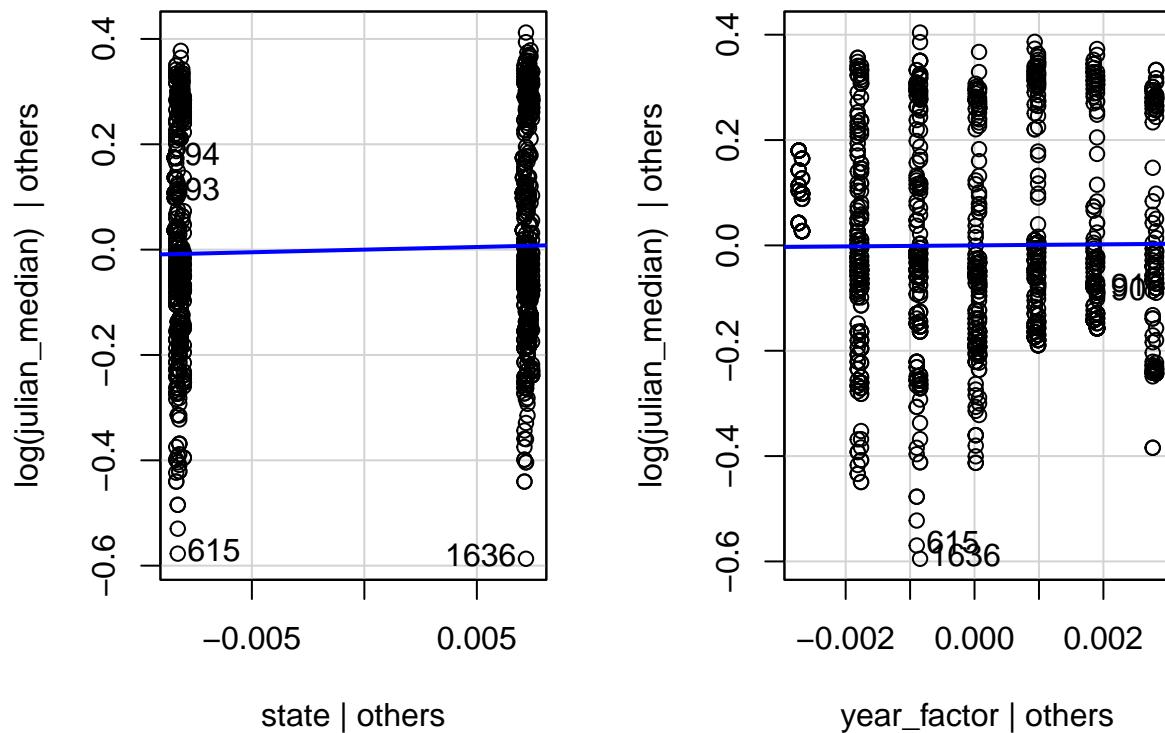
```

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



```
leveragePlots(fit_spp_stateyear_kbs)
```

Leverage Plots



```
ols_test_normality(fit_spp_stateyear_kbs)
```

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

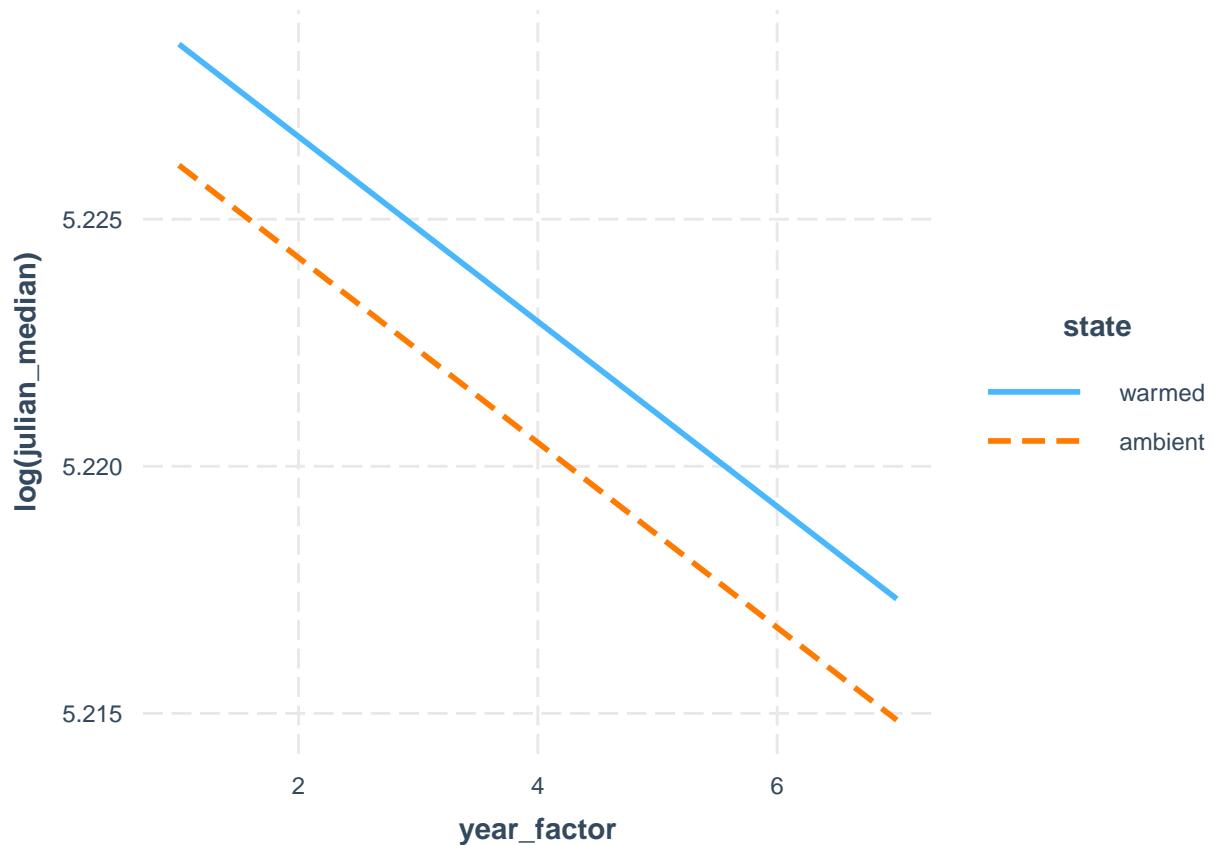
```

## -----
##      Test           Statistic      pvalue
## -----
## Shapiro-Wilk          0.9565      0.0000
## Kolmogorov-Smirnov    0.1102      0.0000
## Cramer-von Mises     251.3012     0.0000
## Anderson-Darling      19.791       0.0000
## -----

```

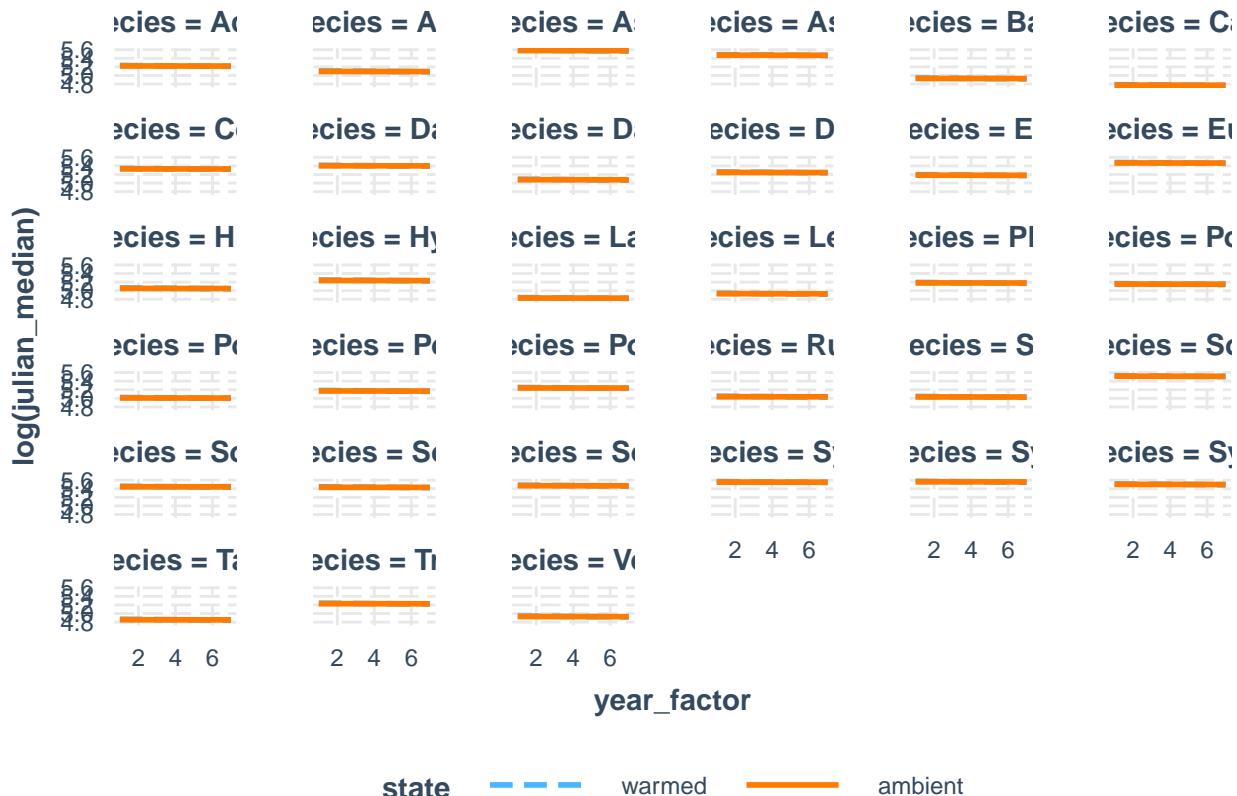
```
# Interaction plot (ignore for now the repeated measures with species); see: https://cran.r-project.org
fit3_spp_kbs <- lm(log(julian_median) ~ state + year_factor + species, data = kbs_flwr_spp)
interact_plot(fit3_spp_kbs, pred = year_factor, modx = state, data = kbs_flwr_spp)
```

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



```
fit4_spp_kbs <- lm(log(julian_median) ~ state * year_factor + species, data = kbs_flwr_spp)
interact_plot(fit4_spp_kbs, pred = year_factor, modx = state, mod2 = species, data = kbs_flwr_spp)
```

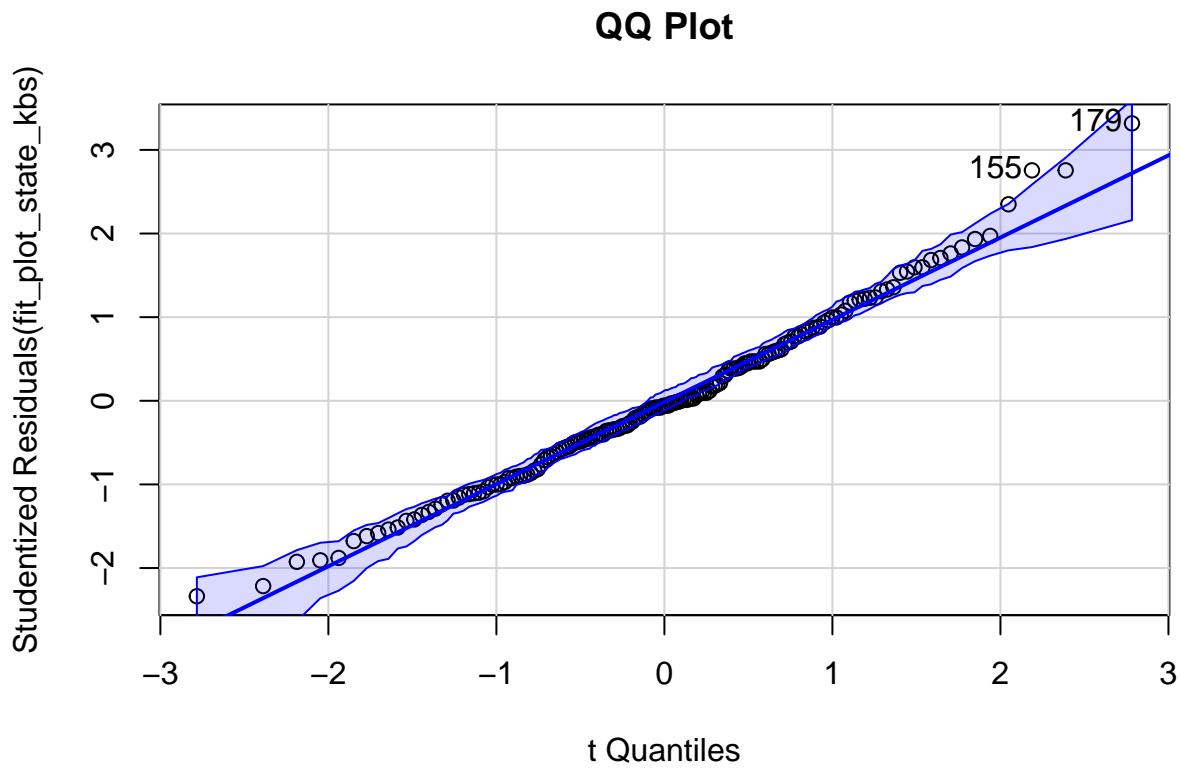
```
## Warning: year_factor and state and species are not included in an interaction with
## one another in the model.
```



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

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 179   3.31756          0.0011199        0.1859
```

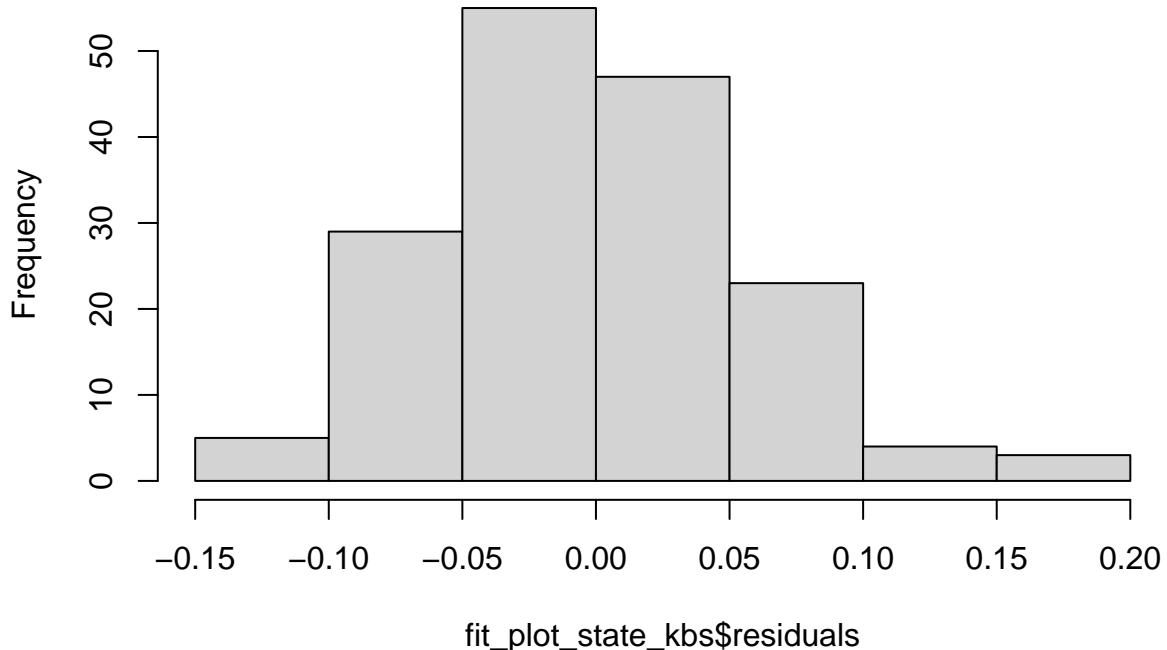
```
qqPlot(fit_plot_state_kbs, main="QQ Plot")
```



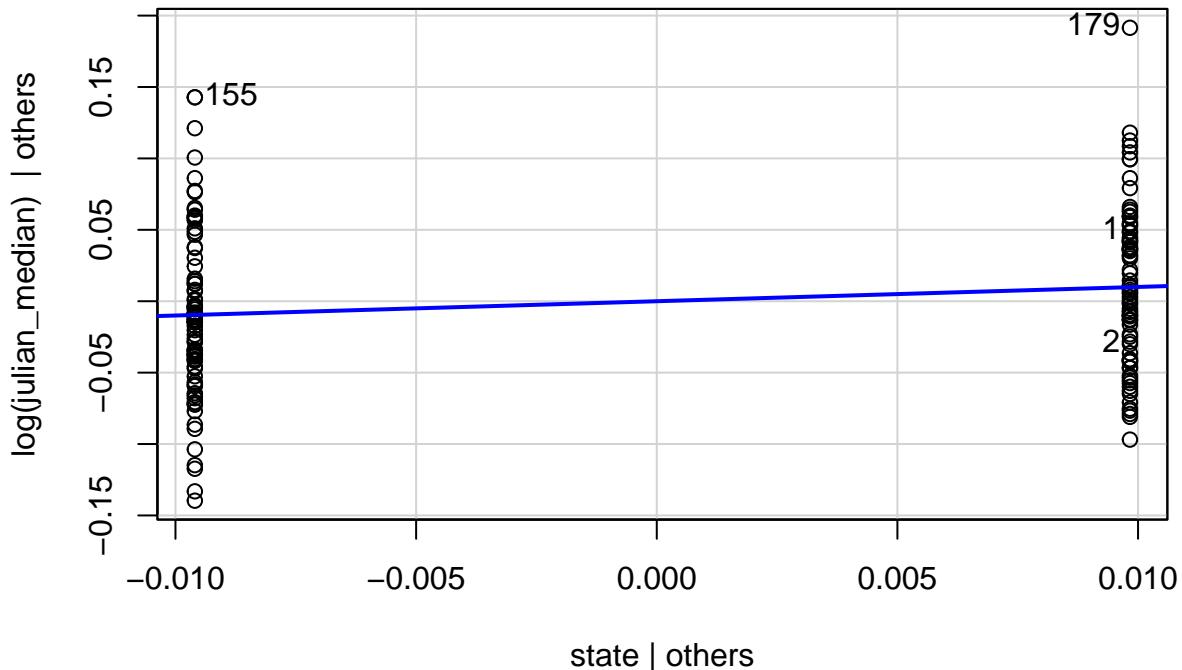
```
## 155 179
## 85 98
```

```
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)
```

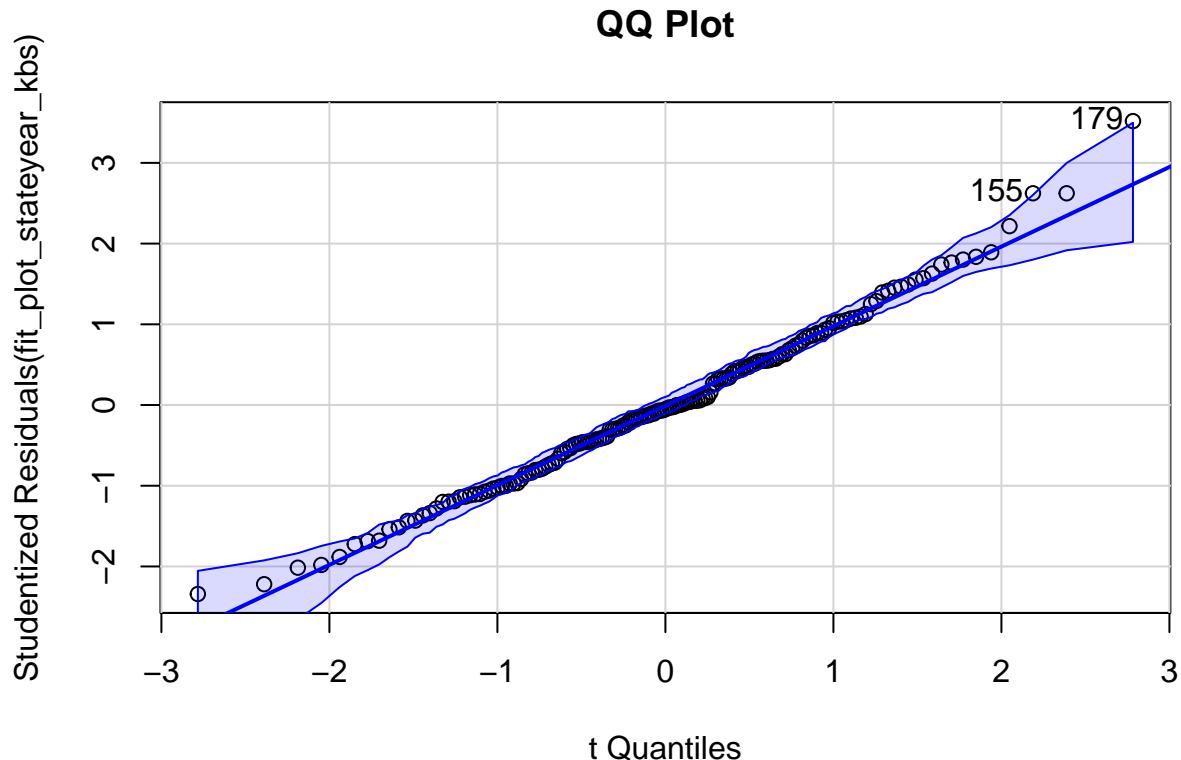
```
## Warning in ks.test.default(y, "pnorm", mean(y), sd(y)): ties should not be  
## present for the Kolmogorov-Smirnov test
```

```
## -----  
## Test Statistic pvalue  
## -----  
## Shapiro-Wilk 0.9896 0.2612  
## Kolmogorov-Smirnov 0.0636 0.5126  
## Cramer-von Mises 49.2333 0.0000  
## Anderson-Darling 0.4033 0.3526  
## -----
```

```
# KBS State and year model  
fit_plot_stateyear_kbs <- lm(log(julian_median) ~ state + year_factor, data = kbs_flwr_plot)  
outlierTest(fit_plot_stateyear_kbs) # outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05  
## Largest |rstudent|:  
##      rstudent unadjusted p-value Bonferroni p  
## 179 3.517401      0.0005656     0.09389
```

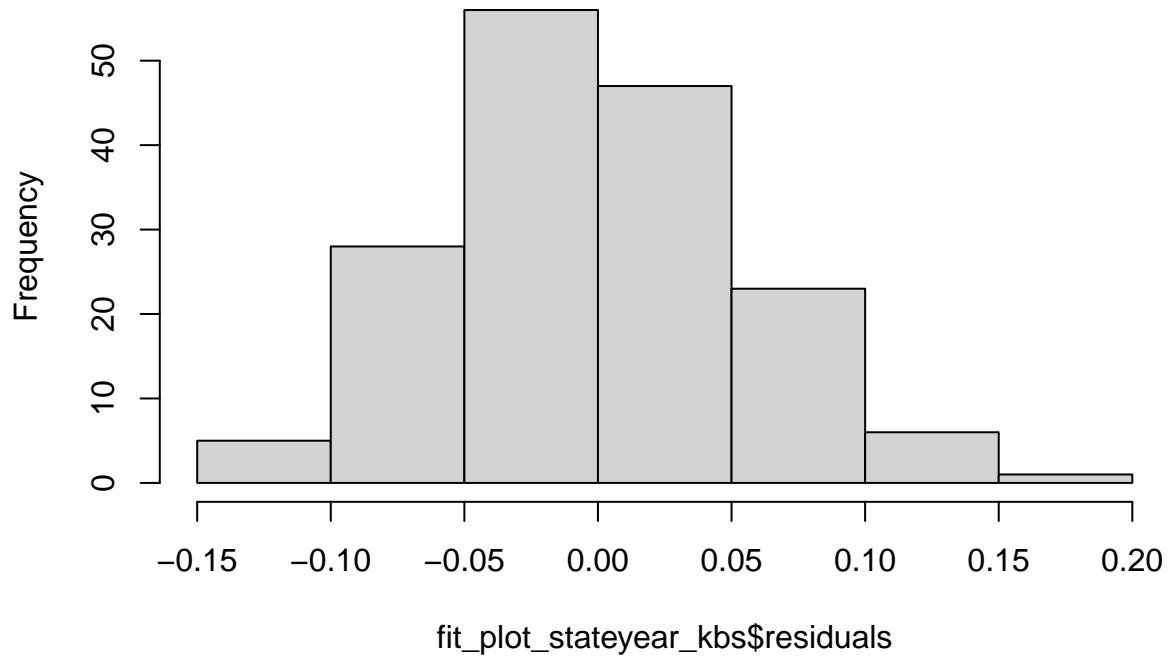
```
qqPlot(fit_plot_stateyear_kbs, main="QQ Plot")
```



```
## 155 179  
## 85 98
```

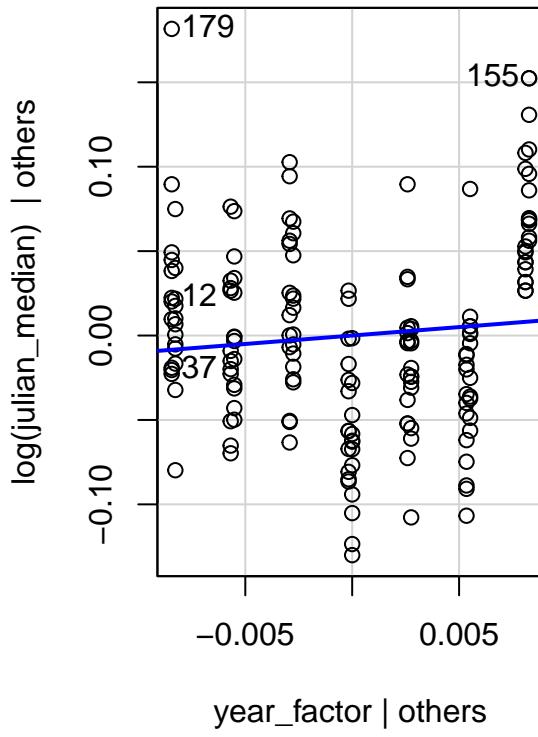
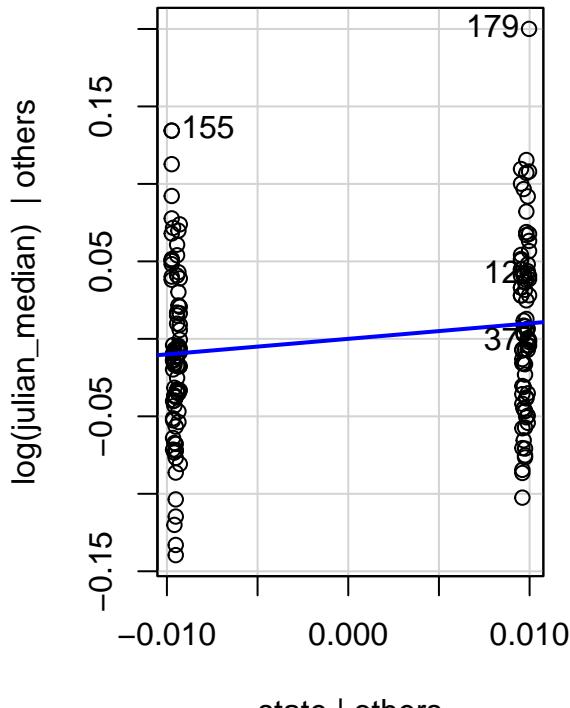
```
hist(fit_plot_stateyear_kbs$residuals)
```

Histogram of fit_plot_stateyear_kbs\$residuals



```
leveragePlots(fit_plot_stateyear_kbs)
```

Leverage Plots



```

ols_test_normality(fit_plot_stateyear_kbs)

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

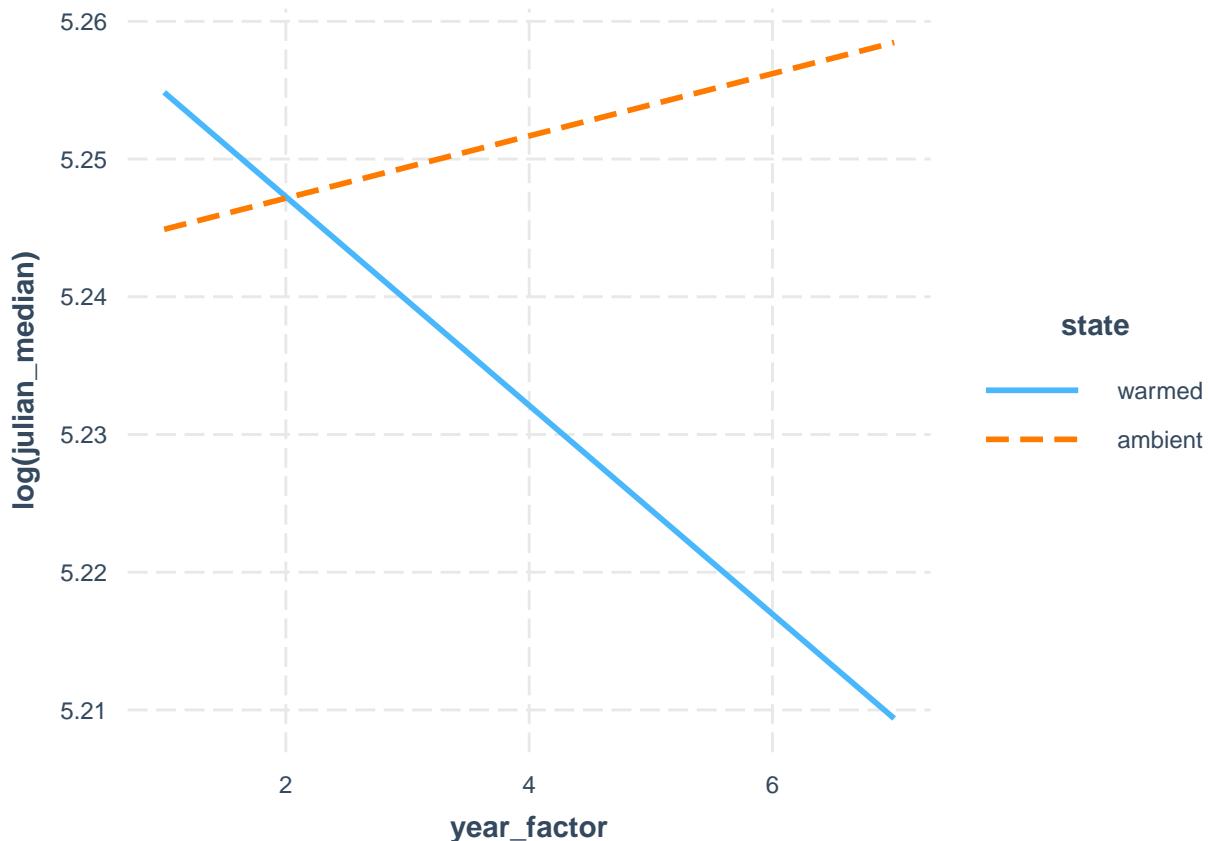
## -----
##          Test      Statistic     pvalue
## -----
## Shapiro-Wilk      0.9918    0.4607
## Kolmogorov-Smirnov   0.0626    0.5338
## Cramer-von Mises    49.2708   0.0000
## Anderson-Darling     0.2951    0.5928
## -----
```

Interaction plot (ignore for now the repeated measures with species); see: <https://cran.r-project.org>

```

fit3_plot_kbs <- lm(log(julian_median) ~ state * year_factor, data = kbs_flwr_plot)
interact_plot(fit3_plot_kbs, pred = year_factor, modx = state)
```

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

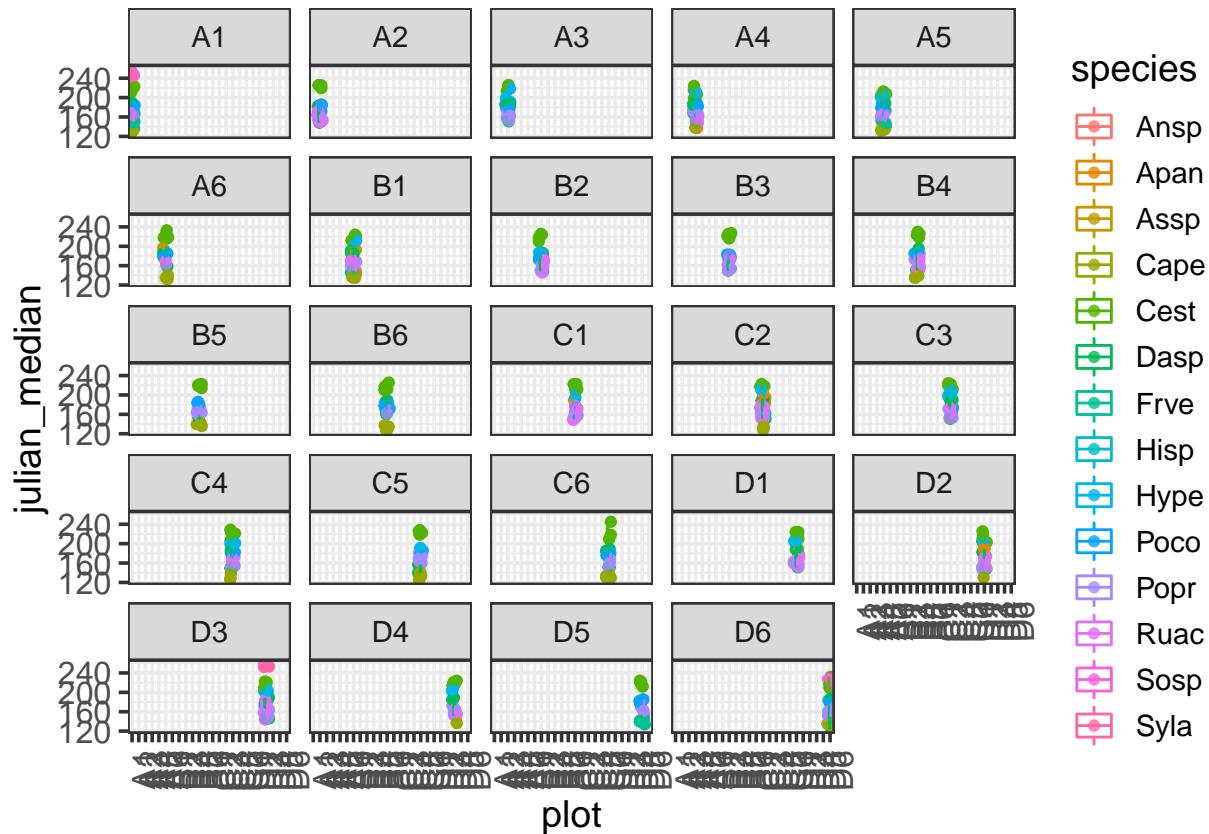


MIXED EFFECT MODELS

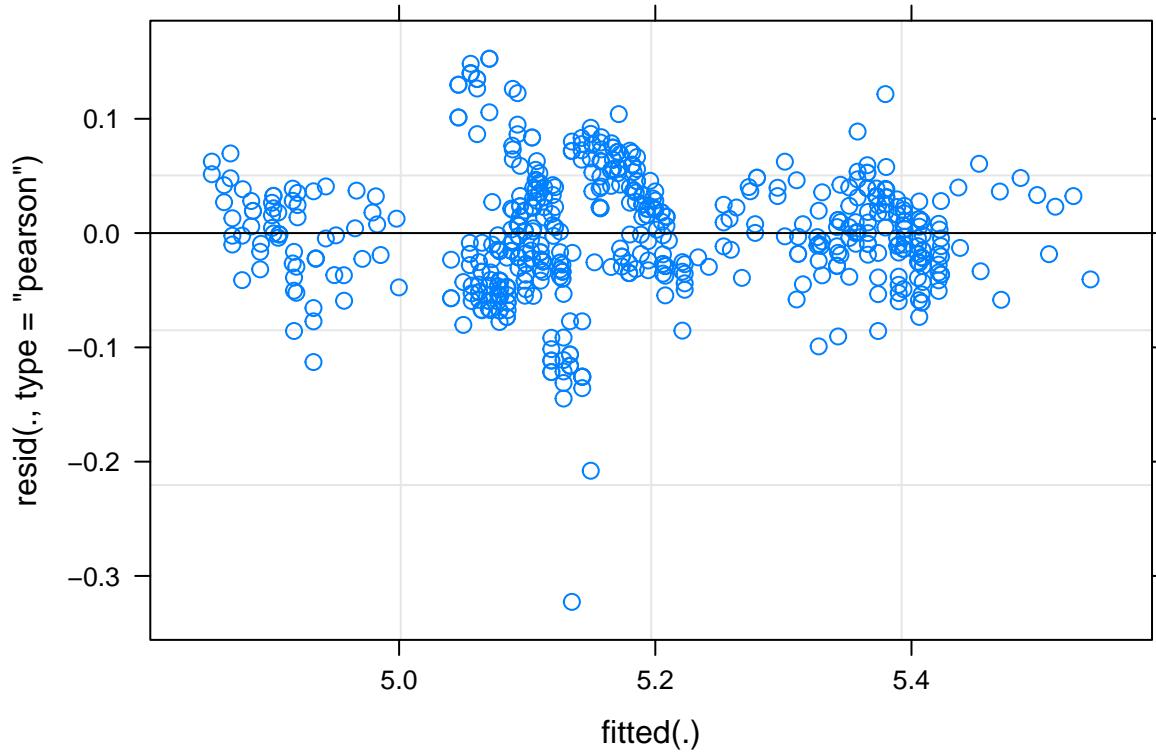
Phoebe

UMBS Species-level Mixed Effects Models

```
# UMBS SPECIES LEVEL - Looking at DURATION of flowering
mod1 <- lmer(log(julian_median) ~ state*year_factor + insecticide*year_factor + (1|species) + (1|plot),  
  
## boundary (singular) fit: see help('isSingular')  
  
ggplot(umbs_flwr_spp,aes(x=plot,y=julian_median,col=species)) + geom_jitter() + geom_boxplot(alpha=0.2)
```



```
# 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) # this looks ok?
```



```

# Homogeneity of variance looks weird here
# Check for homogeneity of variances (true if p>0.05). If the result is not significant, the assumption
# *****Levene's Test - tests whether or not the variance among two or more groups is equal - If the p-value
# is less than 0.05, then the null hypothesis is rejected.

leveneTest(residuals(mod1) ~ umbs_flwr_spp$state)

## Levene's Test for Homogeneity of Variance (center = median)
##          Df F value    Pr(>F)
## group     1  5.6956 0.01733 *
##          570
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Assumption not met
leveneTest(residuals(mod1) ~ umbs_flwr_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    13  5.363 3.768e-09 ***
##          558
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

# Assumption not met
leveneTest(residuals(mod1) ~ umbs_flwr_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 0.9965
##         570

# Assumption met
leveneTest(residuals(mod1) ~ umbs_flwr_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  0.7362 0.8096
##         548

# Assumption met

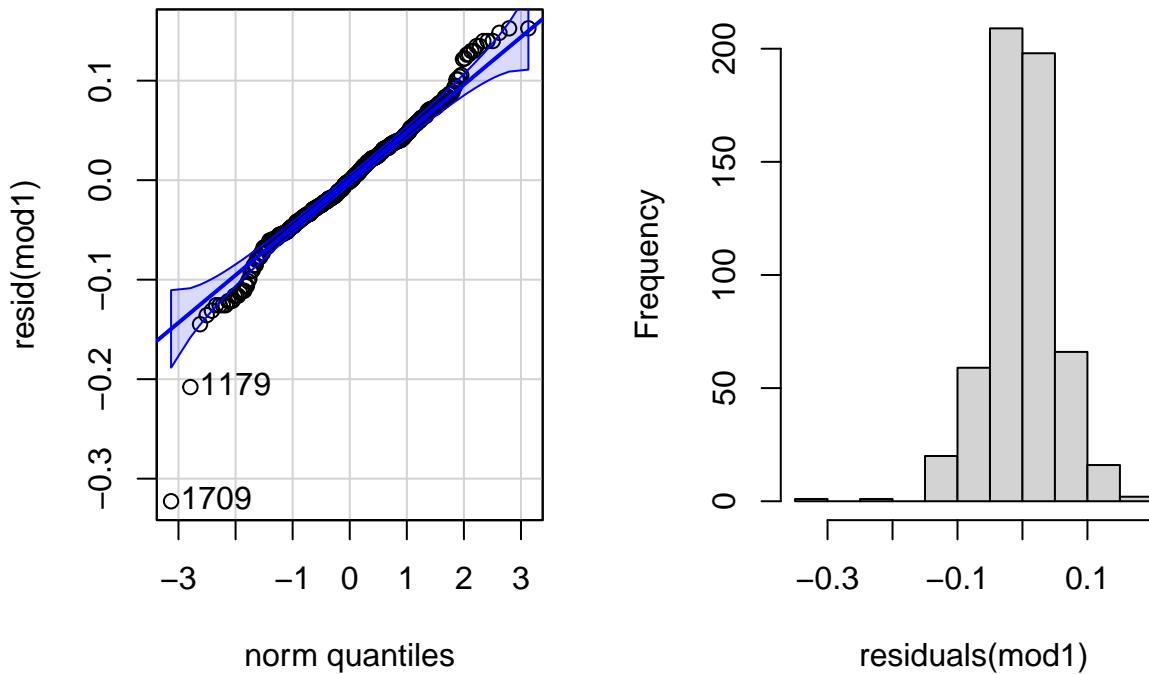
# (3) Normality of error term: need to check by histogram, QQplot of residuals, could do Kolmogorov-Smi
# Check for normal residuals
qqPlot(resid(mod1))

## 1709 1179
## 553  404

hist(residuals(mod1))

```

Histogram of residuals(mod1)



```
shapiro.test(resid(mod1)) # not normally distributed resids bc p<0.05
```

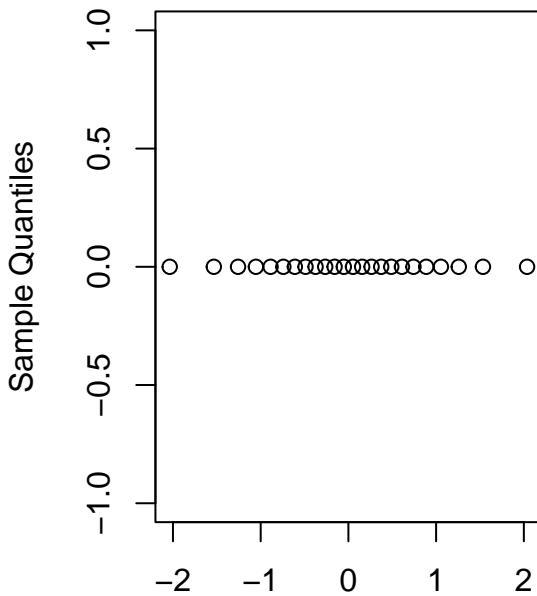
```
##  
## Shapiro-Wilk normality test  
##  
## data: resid(mod1)  
## W = 0.97432, p-value = 1.811e-08
```

```
outlierTest(mod1) # 1676 outlier
```

```
##          rstudent unadjusted p-value Bonferroni p  
## 1709 -6.073333      2.309e-09  1.3207e-06
```

```
# (4) Normality of random effect: Get the estimate of random effect (e.g., random intercepts), and check  
require(lme4)  
r_int<- ranef(mod1)$plot$`Intercept`  
qqnorm(r_int)  
# qqline(r_int) #doesn't work  
# shapiro.test(r_int) #this doesn't run
```

Normal Q–Q Plot



Theoretical Quantiles # Phoebe

```
# Do we need to include plot as a random effect with the UMBS models?
mod1 <- lmer(log(julian_median) ~ state*year_factor + insecticide*year_factor + (1|species) + (1|plot),  
# Run analysis of variance on each model (see this for more explanation on how anova on a linear mixed  
anova(mod1)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##                                     Sum Sq  Mean Sq NumDF DenDF F value Pr(>F)
## state                           0.002935 0.002935     1 558.00  1.0207 0.3128
## year_factor                     0.240534 0.240534     1 558.43 83.6531 <2e-16 ***
## insecticide                      0.002560 0.002560     1 558.09  0.8904 0.3458
## state:year_factor                0.000006 0.000006     1 557.98  0.0021 0.9635
## year_factor:insecticide          0.001030 0.001030     1 558.11  0.3581 0.5498
## ---
## 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                           0.002935 0.002935     1 558.00  1.0207 0.3128
## year_factor                     0.240534 0.240534     1 558.43 83.6531 <2e-16 ***
## insecticide                      0.002560 0.002560     1 558.09  0.8904 0.3458
## state:year_factor                0.000006 0.000006     1 557.98  0.0021 0.9635
```

```

## year_factor:insecticide 0.001030 0.001030      1 558.11  0.3581 0.5498
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Run an ANOVA to test the 2 models to test whether the more complex model is significantly better at c
anova(mod1, mod2) # Go with model 2 since pvalue >0.05, aka more complex model does not have something

## Data: umbs_flwr_spp
## Models:
## mod2: log(julian_median) ~ state * year_factor + insecticide * year_factor + (1 | species)
## mod1: log(julian_median) ~ state * year_factor + insecticide * year_factor + (1 | species) + (1 | pl
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod2     8 -1631.8 -1597.0 823.91  -1647.8
## mod1     9 -1629.8 -1590.7 823.91  -1647.8      0  1           1

summ(mod1)

## MODEL INFO:
## Observations: 572
## Dependent Variable: log(julian_median)
## Type: Mixed effects linear regression
##
## MODEL FIT:
## AIC = -1629.82, BIC = -1590.68
## Pseudo-R2 (fixed effects) = 0.02
## Pseudo-R2 (total) = 0.92
##
## FIXED EFFECTS:
## -----
##                               Est.   S.E.   t val.   d.f.   p
## -----
## (Intercept)                  5.12   0.05  105.12  558.00  0.00
## stateambient                 0.01   0.01    1.01  558.00  0.31
## year_factor                  0.01   0.00    4.84  558.06  0.00
## insecticideno_insects       -0.01   0.01   -0.94  558.09  0.35
## stateambient:year_factor     0.00   0.00    0.05  557.98  0.96
## year_factor:insecticideno_insects  0.00   0.00    0.60  558.11  0.55
## -----
## 
## 
## p values calculated using Satterthwaite d.f.
##
## RANDOM EFFECTS:
## -----
##      Group      Parameter   Std. Dev.
## -----
## plot      (Intercept)    0.00
## species   (Intercept)    0.18
## Residual            0.05
## -----
## 
## 
## Grouping variables:
## -----
##      Group   # groups   ICC

```

```

## -----
##   plot      24     0.00
##   species    14     0.91
## -----
## summ(mod2)

## MODEL INFO:
## Observations: 572
## Dependent Variable: log(julian_median)
## Type: Mixed effects linear regression
##
## MODEL FIT:
## AIC = -1631.82, BIC = -1597.03
## Pseudo-R2 (fixed effects) = 0.02
## Pseudo-R2 (total) = 0.92
##
## FIXED EFFECTS:
## -----
##                               Est.   S.E.   t val.   d.f.   p
## -----
## (Intercept)                  5.12   0.05  105.12  15.97  0.00
## stateambient                 0.01   0.01   1.01  558.00  0.31
## year_factor                  0.01   0.00   4.84  558.06  0.00
## insecticideno_insects       -0.01   0.01  -0.94  558.09  0.35
## stateambient:year_factor     0.00   0.00   0.05  557.98  0.96
## year_factor:insecticideno_insects  0.00   0.00   0.60  558.11  0.55
## -----
## 
## p values calculated using Satterthwaite d.f.
##
## RANDOM EFFECTS:
## -----
##   Group      Parameter   Std. Dev.
## -----
##   species  (Intercept)   0.18
##   Residual           0.05
## -----
## 
## Grouping variables:
## -----
##   Group # groups   ICC
## -----
##   species      14     0.91
## -----

```

```
AICctab(mod1, mod2, weights=T) # yup, model 2
```

```

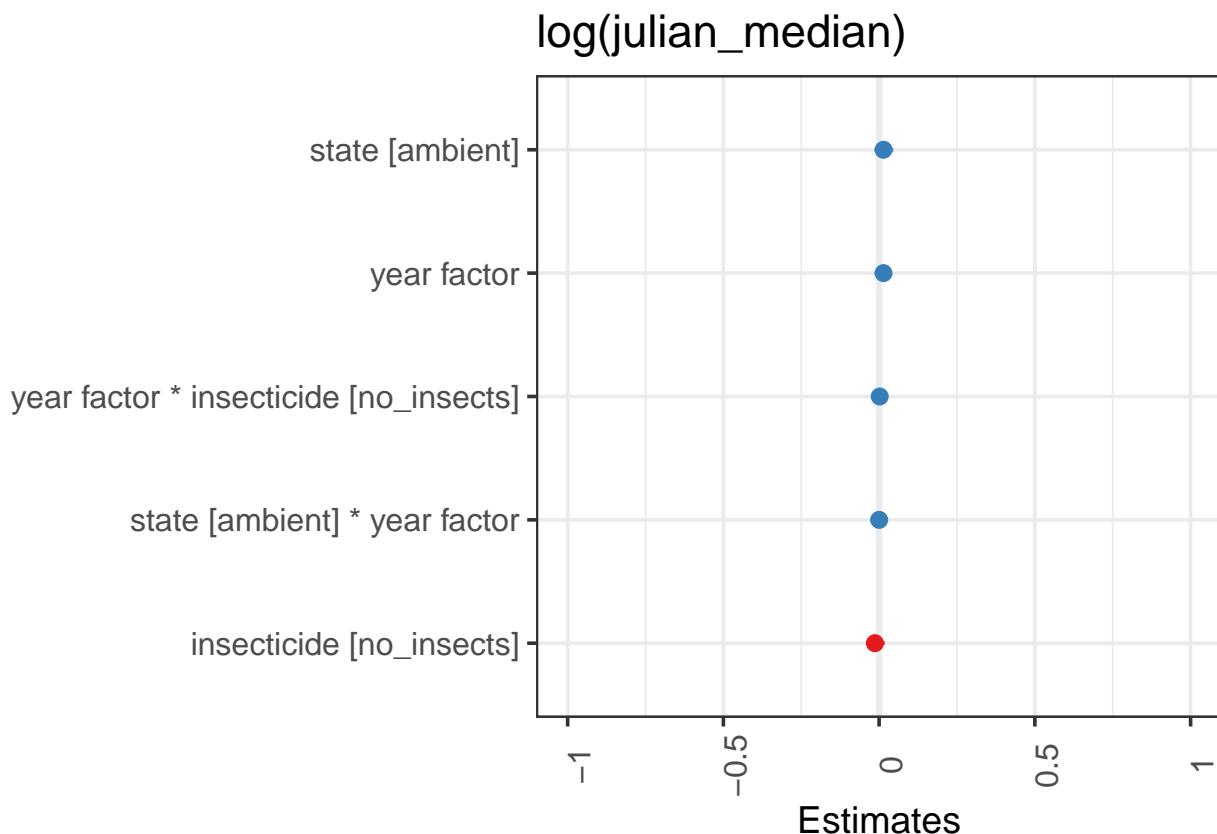
##      dAICc df weight
## mod2 0.0   8   0.74
## mod1 2.1   9   0.26

```

```

# Next, plot the model. There are multiple variables but here's one way to do it based on this package .
# https://strengejacke.github.io/sjPlot/articles/plot_model_estimates.html
# Annoyingly, this package somehow overwrites the factor order in its plotting so we will have to modify
#?plot_model
# 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"))

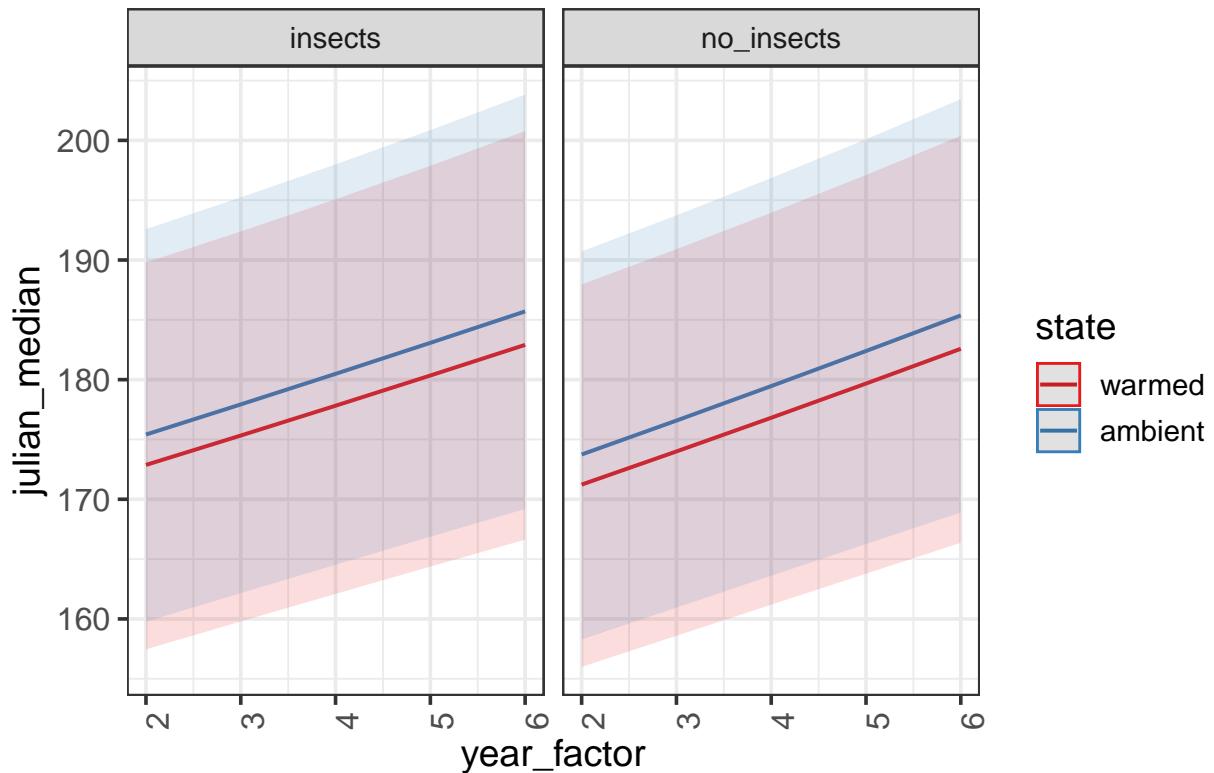
```

```

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

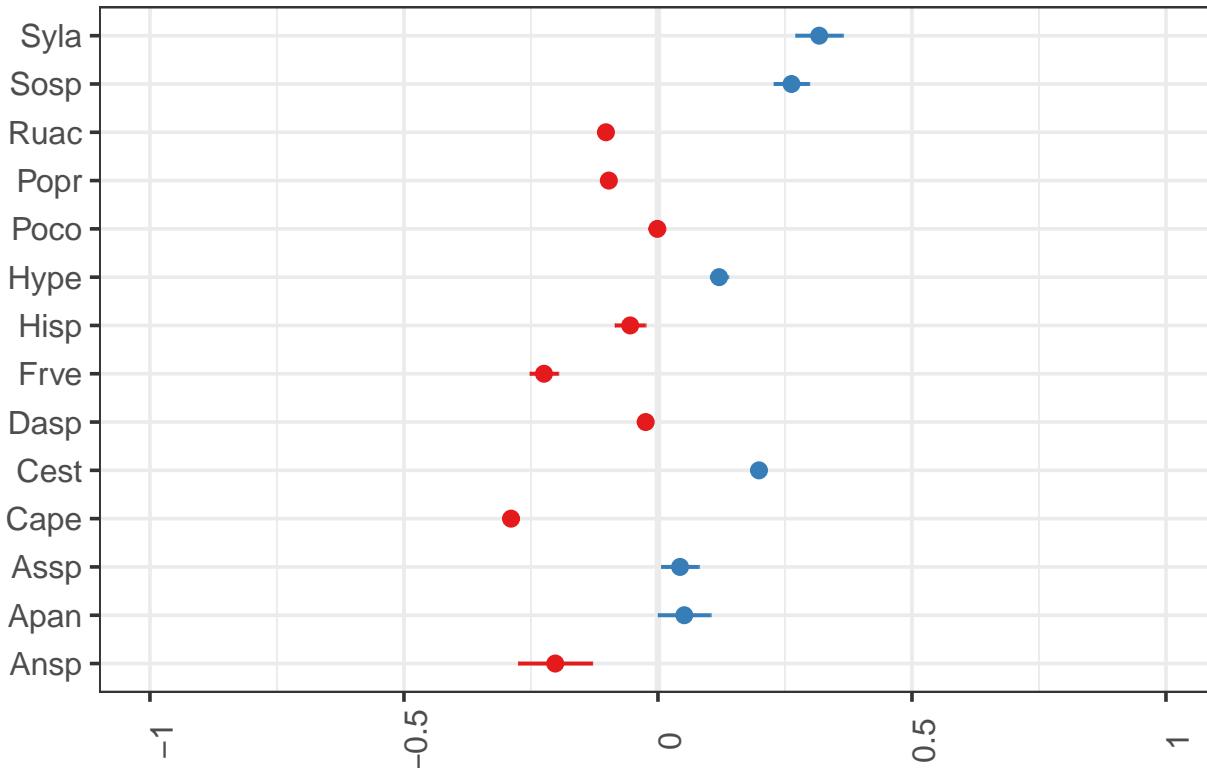
```

Predicted values of julian_median



```
# 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)
mod3 <- lmer(log(julian_median) ~ state*year_factor + (1|species), umbs_flwr_spp, REML=FALSE)
anova(mod2, mod3) # Looks like no pvalue > 0.05, so insecticide does not improve model fit so we will g
```

```
## Data: umbs_flwr_spp
## Models:
## mod3: log(julian_median) ~ state * year_factor + (1 | species)
## mod2: log(julian_median) ~ state * year_factor + insecticide * year_factor + (1 | species)
##      npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod3     6 -1634.1 -1608 823.05   -1646.1
## mod2     8 -1631.8 -1597 823.91   -1647.8 1.7163  2     0.4239
```

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

```
##      dAICc df weight
## mod3  0.0   6  0.77
## mod2  2.4   8  0.23
```

```
# Does year need to be interactive with insecticide? - already removed insecticide
# mod4 <- lmer(log(julian_median) ~ state*year_factor + insecticide + (1/species) + (1/plot), umbs_flwr_spp, REML=FALSE)

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

```

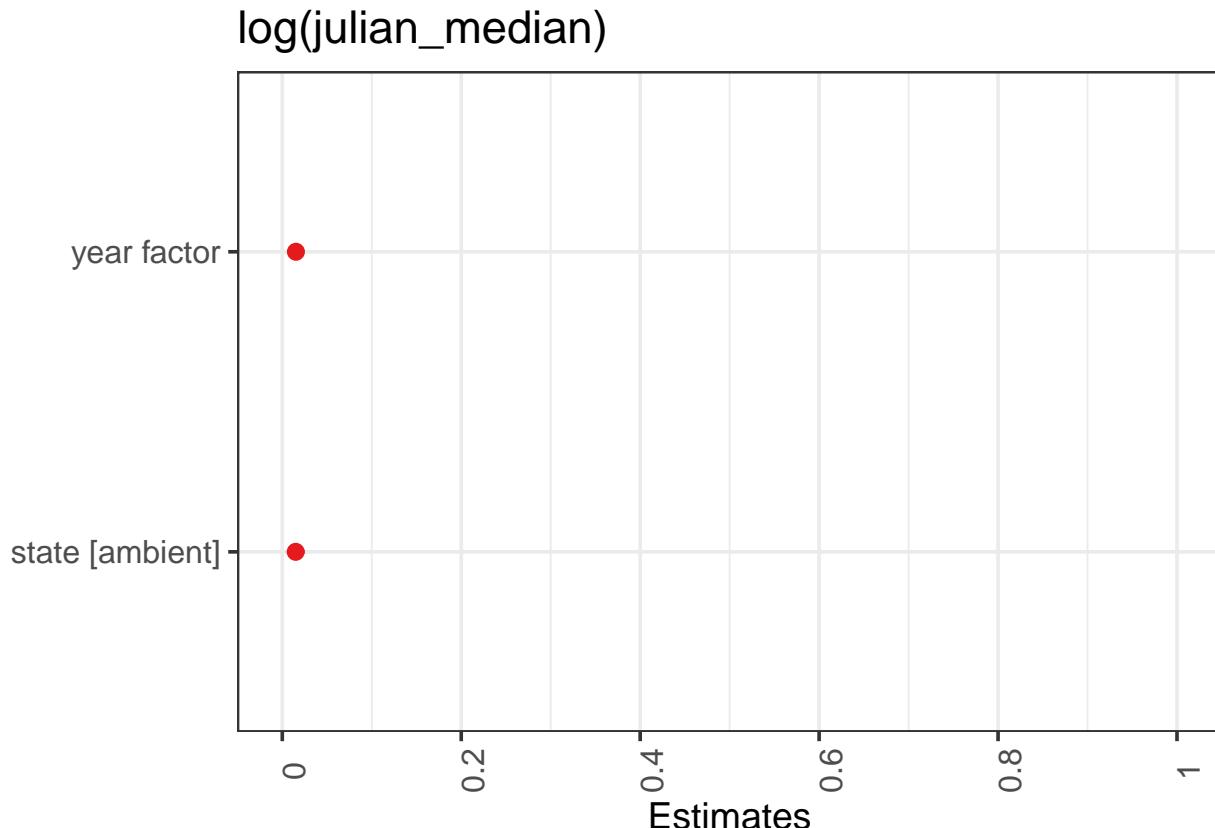
## Data: umbs_flwr_spp
## Models:
## mod5: log(julian_median) ~ state + year_factor + (1 | species)
## mod3: log(julian_median) ~ state * year_factor + (1 | species)
##      npar     AIC     BIC logLik deviance Chisq Df Pr(>Chisq)
## mod5     5 -1636.1 -1614.3 823.05   -1646.1
## mod3     6 -1634.1 -1608.0 823.05   -1646.1 0.0045  1     0.9463

```

```

# No, P>0.05 so state*year_factor doesn't strongly improve model fit so we will shift to mod5, but AIC is lower
# 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"))

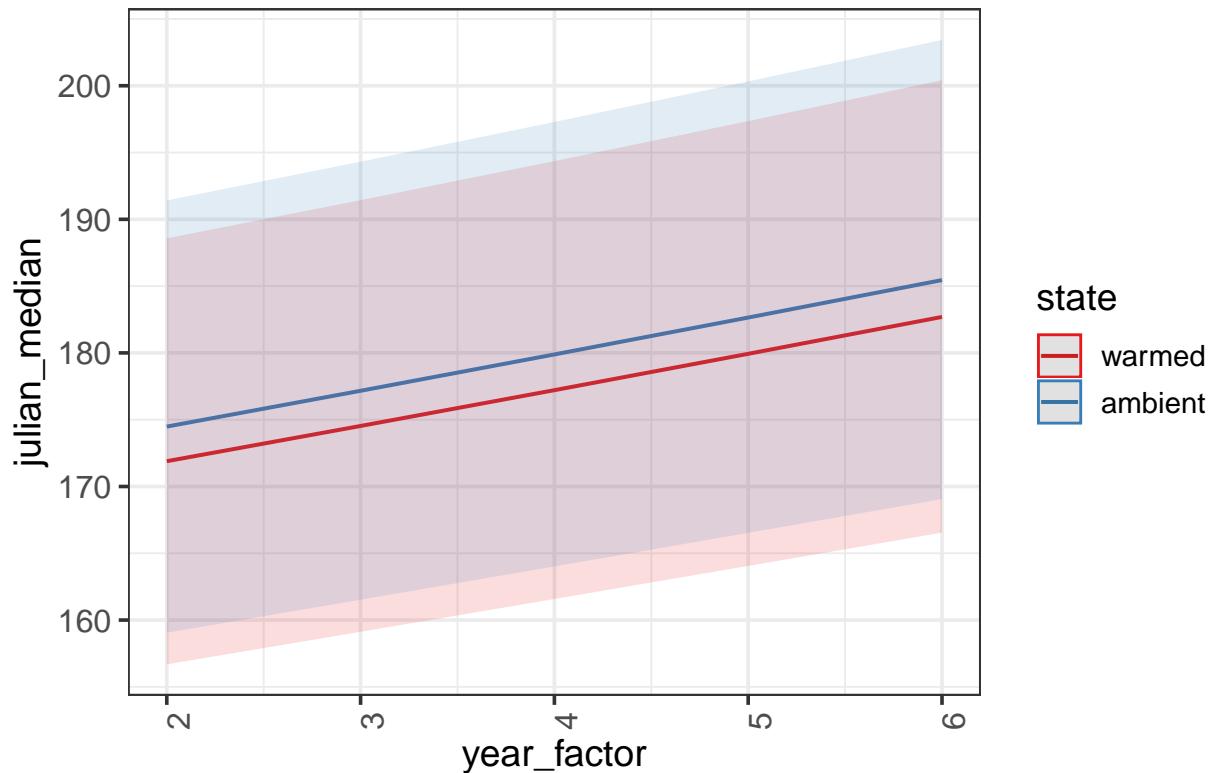
```

```

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

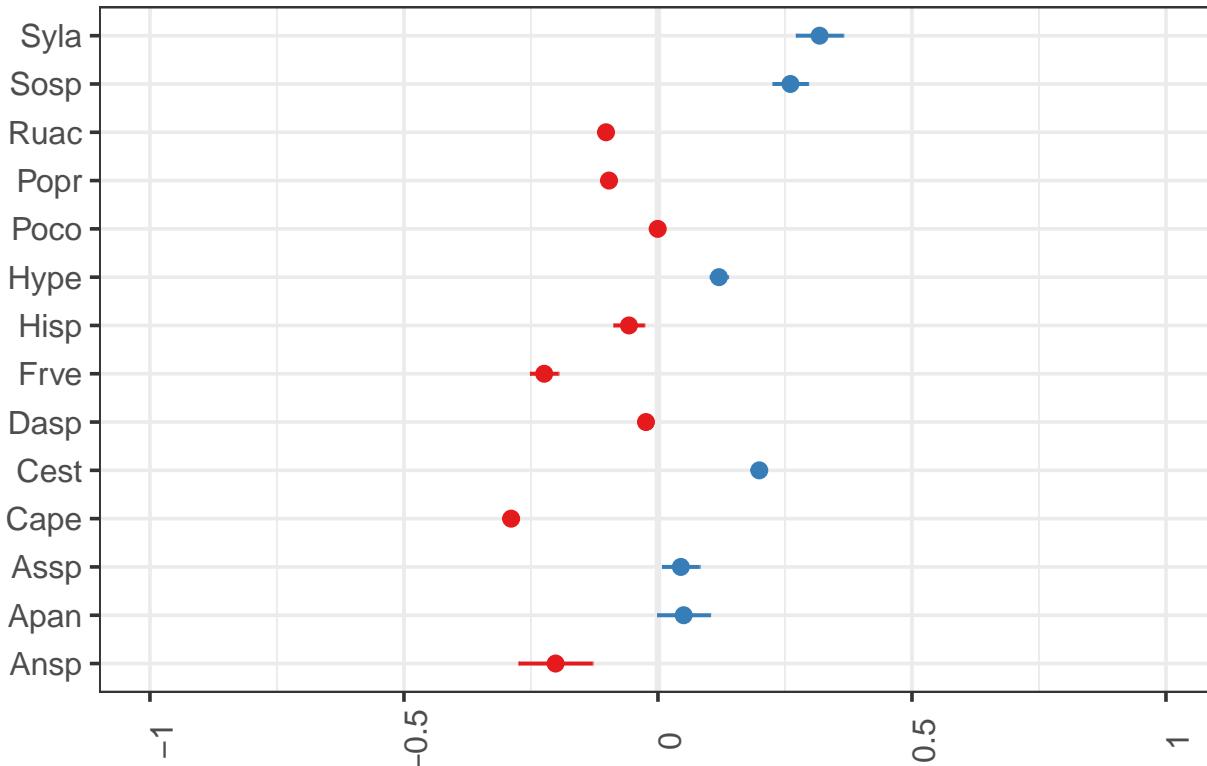
```

Predicted values of julian_median



```
# 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(julian_median) ~ state + year_factor + (1|species) + (1 + year|plot), umbs_flwr_spp, REML = TRUE)

## boundary (singular) fit: see help('isSingular')

## Warning: Model failed to converge with 1 negative eigenvalue: -9.0e-02

# model failed to converge...
anova(mod5, mod6)

## Data: umbs_flwr_spp
## Models:
## mod5: log(julian_median) ~ state + year_factor + (1 | species)
## mod6: log(julian_median) ~ state + year_factor + (1 | species) + (1 + year | plot)
##      npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod5     5 -1636.1 -1614.3  823.05   -1646.1
## mod6     8 -1620.1 -1585.3  818.04   -1636.1      0  3          1

anova(mod5)

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq  Mean Sq NumDF DenDF F value    Pr(>F)
## state       0.031325 0.031325     1  558.16 10.860 0.001045 ***
## year_factor 0.244442 0.244442     1  558.46 84.747 < 2.2e-16 ***
## ---
## 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)
mod7 <- lmer(log(julian_median) ~ state + species + (1+factor(year_factor)|plot), umbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod7a <- lmer(log(julian_median) ~ state + species + factor(year_factor) + (1|plot), umbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod7b <- lmer(log(julian_median) ~ state * factor(year_factor) + species + (1|plot), umbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod7c <- lmer(log(julian_median) ~ state + species + factor(year_factor) + insecticide + (1|plot), umbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

anova(mod5, mod7) # model 7 is a better fit to data

## Data: umbs_flwr_spp
## Models:
## mod5: log(julian_median) ~ state + year_factor + (1 | species)
## mod7: log(julian_median) ~ state + species + (1 + factor(year_factor) | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod5     5 -1636.1 -1614.3 823.05   -1646.1
## mod7    31 -1661.8 -1527.0 861.91  -1723.8 77.714 26  4.696e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(mod7, mod7a) #mod 7a

## Data: umbs_flwr_spp
## Models:
## mod7a: log(julian_median) ~ state + species + factor(year_factor) + (1 | plot)
## mod7: log(julian_median) ~ state + species + (1 + factor(year_factor) | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod7a    21 -1724.2 -1632.9 883.11   -1766.2
## mod7    31 -1661.8 -1527.0 861.91  -1723.8      0 10          1

anova(mod7a, mod7b) #mod 7a - interaction between state and year does not improve model, but pvalue = 0

## Data: umbs_flwr_spp
## Models:
## mod7a: log(julian_median) ~ state + species + factor(year_factor) + (1 | plot)
## mod7b: log(julian_median) ~ state * factor(year_factor) + species + (1 | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod7a    21 -1724.2 -1632.9 883.11   -1766.2
## mod7b    25 -1717.2 -1608.5 883.60  -1767.2 0.9783  4      0.9131

```

```

anova(mod7a, mod7c) # model 7a

## Data: umbs_flwr_spp
## Models:
## mod7a: log(julian_median) ~ state + species + factor(year_factor) + (1 | plot)
## mod7c: log(julian_median) ~ state + species + factor(year_factor) + insecticide + (1 | plot)
##      npar     AIC     BIC logLik deviance Chisq Df Pr(>Chisq)
## mod7a    21 -1724.2 -1632.9 883.11   -1766.2
## mod7c    22 -1723.8 -1628.1 883.89   -1767.8 1.5511   1      0.213

summ(mod7a)

## MODEL INFO:
## Observations: 572
## Dependent Variable: log(julian_median)
## Type: Mixed effects linear regression
##
## MODEL FIT:
## AIC = -1724.23, BIC = -1632.90
## Pseudo-R2 (fixed effects) = 0.90
## Pseudo-R2 (total) = 0.90
##
## FIXED EFFECTS:
## -----
##          Est.    S.E.    t val.    d.f.      p
## -----
## (Intercept) 4.92  0.04  131.84  572.00  0.00
## stateambient 0.02  0.00   3.44  572.00  0.00
## speciesApan  0.27  0.05   5.97  572.00  0.00
## speciesAssp  0.26  0.04   6.25  572.00  0.00
## speciesCape -0.08  0.04  -2.00  572.00  0.05
## speciesCest  0.41  0.04  11.16  572.00  0.00
## speciesDasp  0.19  0.04   5.14  572.00  0.00
## speciesFrve -0.01  0.04  -0.26  572.00  0.80
## speciesHisp  0.16  0.04   4.08  572.00  0.00
## speciesHype  0.34  0.04   8.84  572.00  0.00
## speciesPoco  0.21  0.04   5.69  572.00  0.00
## speciesPopr  0.12  0.04   3.19  572.00  0.00
## speciesRuac  0.11  0.04   3.00  572.00  0.00
## speciesSosp  0.48  0.04  11.76  572.00  0.00
## speciesSyla  0.54  0.04  12.42  572.00  0.00
## factor(year_factor)3 0.03  0.01   3.68  572.00  0.00
## factor(year_factor)4 0.04  0.01   4.87  572.00  0.00
## factor(year_factor)5 0.07  0.01  10.22  572.00  0.00
## factor(year_factor)6 0.06  0.01   7.67  572.00  0.00
## -----
## 
## p values calculated using Satterthwaite d.f.
##
## RANDOM EFFECTS:
## -----
##      Group     Parameter     Std. Dev.
## -----

```

```

##      plot      (Intercept)    0.00
##  Residual                      0.05
## -----
## 
## Grouping variables:
## -----
##   Group # groups   ICC
## -----
##   plot      24     0.00
## -----
```

anova(mod7a) # investigates whether at least one of the levels within each factor is significantly different from the others.

```

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state        0.0316 0.03162     1    572 11.844 0.0006208 ***
## species      12.8865 0.99127    13    572 371.266 < 2.2e-16 ***
## factor(year_factor) 0.3246 0.08114     4    572 30.391 < 2.2e-16 ***
## ---
## 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 median first flwr dates).

```

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

```

## boundary (singular) fit: see help('isSingular')

## $`emmeans of state, year_factor`
##   state  year_factor emmean       SE   df lower.CL upper.CL
##   warmed          2  5.139 0.007277 313.4   5.124   5.153
##   ambient          2  5.154 0.007218 273.1   5.139   5.168
##   warmed          3  5.166 0.006848 254.7   5.152   5.179
##   ambient          3  5.181 0.006755 219.1   5.168   5.194
##   warmed          4  5.175 0.006843 246.3   5.161   5.188
##   ambient          4  5.190 0.006766 209.8   5.176   5.203
##   warmed          5  5.212 0.006645 240.3   5.199   5.225
##   ambient          5  5.227 0.006577 212.6   5.214   5.240
##   warmed          6  5.194 0.006561 226.6   5.181   5.207
##   ambient          6  5.209 0.006488 192.4   5.196   5.222
## 
## 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
##   warmed year_factor2 - ambient year_factor2 -0.01505 0.00447 21.2 -3.366
##   warmed year_factor2 - warmed year_factor3 -0.02732 0.00755 574.5 -3.617
##   warmed year_factor2 - ambient year_factor3 -0.04237 0.00875 242.1 -4.840
##   warmed year_factor2 - warmed year_factor4 -0.03608 0.00754 579.1 -4.785
##   warmed year_factor2 - ambient year_factor4 -0.05112 0.00875 235.1 -5.840
##   warmed year_factor2 - warmed year_factor5 -0.07361 0.00733 577.9 -10.037
```

```

##  warmed year_factor2 - ambient year_factor5 -0.08866 0.00859 229.9 -10.325
##  warmed year_factor2 - warmed year_factor6 -0.05535 0.00734 578.9 -7.538
##  warmed year_factor2 - ambient year_factor6 -0.07040 0.00859 224.6 -8.194
##  ambient year_factor2 - warmed year_factor3 -0.01227 0.00880 239.6 -1.394
##  ambient year_factor2 - ambient year_factor3 -0.02732 0.00755 574.5 -3.617
##  ambient year_factor2 - warmed year_factor4 -0.02103 0.00878 235.5 -2.396
##  ambient year_factor2 - ambient year_factor4 -0.03608 0.00754 579.1 -4.785
##  ambient year_factor2 - warmed year_factor5 -0.05857 0.00859 217.9 -6.816
##  ambient year_factor2 - ambient year_factor5 -0.07361 0.00733 577.9 -10.037
##  ambient year_factor2 - warmed year_factor6 -0.04031 0.00860 222.3 -4.685
##  ambient year_factor2 - ambient year_factor6 -0.05535 0.00734 578.9 -7.538
##  warmed year_factor3 - ambient year_factor3 -0.01505 0.00447 21.2 -3.366
##  warmed year_factor3 - warmed year_factor4 -0.00876 0.00715 572.8 -1.226
##  warmed year_factor3 - ambient year_factor4 -0.02381 0.00844 215.0 -2.820
##  warmed year_factor3 - warmed year_factor5 -0.04630 0.00694 572.0 -6.667
##  warmed year_factor3 - ambient year_factor5 -0.06134 0.00828 209.2 -7.407
##  warmed year_factor3 - warmed year_factor6 -0.02804 0.00692 572.5 -4.051
##  warmed year_factor3 - ambient year_factor6 -0.04308 0.00826 202.7 -5.216
##  ambient year_factor3 - warmed year_factor4 0.00629 0.00842 217.7 0.747
##  ambient year_factor3 - ambient year_factor4 -0.00876 0.00715 572.8 -1.226
##  ambient year_factor3 - warmed year_factor5 -0.03125 0.00824 199.6 -3.794
##  ambient year_factor3 - ambient year_factor5 -0.04630 0.00694 572.0 -6.667
##  ambient year_factor3 - warmed year_factor6 -0.01299 0.00822 202.5 -1.580
##  ambient year_factor3 - ambient year_factor6 -0.02804 0.00692 572.5 -4.051
##  warmed year_factor4 - ambient year_factor4 -0.01505 0.00447 21.2 -3.366
##  warmed year_factor4 - warmed year_factor5 -0.03754 0.00686 573.7 -5.476
##  warmed year_factor4 - ambient year_factor5 -0.05258 0.00819 203.7 -6.418
##  warmed year_factor4 - warmed year_factor6 -0.01928 0.00681 575.5 -2.830
##  warmed year_factor4 - ambient year_factor6 -0.03432 0.00815 195.2 -4.209
##  ambient year_factor4 - warmed year_factor5 -0.02249 0.00818 191.8 -2.751
##  ambient year_factor4 - ambient year_factor5 -0.03754 0.00686 573.7 -5.476
##  ambient year_factor4 - warmed year_factor6 -0.00423 0.00814 192.5 -0.519
##  ambient year_factor4 - ambient year_factor6 -0.01928 0.00681 575.5 -2.830
##  warmed year_factor5 - ambient year_factor5 -0.01505 0.00447 21.2 -3.366
##  warmed year_factor5 - warmed year_factor6 0.01826 0.00658 572.3 2.777
##  warmed year_factor5 - ambient year_factor6 0.00321 0.00795 177.5 0.404
##  ambient year_factor5 - warmed year_factor6 0.03331 0.00795 186.4 4.187
##  ambient year_factor5 - ambient year_factor6 0.01826 0.00658 572.3 2.777
##  warmed year_factor6 - ambient year_factor6 -0.01505 0.00447 21.2 -3.366
## p.value
##  0.0683
##  0.0119
##  0.0001
##  0.0001
##  <.0001
##  <.0001
##  <.0001
##  <.0001
##  <.0001
##  0.9280
##  0.0119
##  0.3329
##  0.0001
##  <.0001

```

```

##  <.0001
##  0.0002
##  <.0001
##  0.0683
##  0.9681
##  0.1364
##  <.0001
##  <.0001
##  0.0023
##  <.0001
##  0.9991
##  0.9681
##  0.0074
##  <.0001
##  0.8564
##  0.0023
##  0.0683
##  <.0001
##  <.0001
##  0.1290
##  0.0016
##  0.1614
##  <.0001
##  1.0000
##  0.1290
##  0.0683
##  0.1467
##  1.0000
##  0.0017
##  0.1467
##  0.0683
##
## 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 10 estimates

```

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

```
## boundary (singular) fit: see help('isSingular')
```

```

## $`emmeans of year_factor`
##   year_factor emmean      SE    df lower.CL upper.CL
##       2  5.146 0.006894 445.6    5.133    5.160
##       3  5.173 0.006424 380.4    5.161    5.186
##       4  5.182 0.006427 364.5    5.170    5.195
##       5  5.220 0.006221 373.0    5.208    5.232
##       6  5.202 0.006130 346.2    5.189    5.214
##

```

```

## 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
## year_factor2 - year_factor3 -0.02732 0.00755 575 -3.617  0.0030
## year_factor2 - year_factor4 -0.03608 0.00754 579 -4.785 <.0001
## year_factor2 - year_factor5 -0.07361 0.00733 578 -10.037 <.0001
## year_factor2 - year_factor6 -0.05535 0.00734 579 -7.538 <.0001
## year_factor3 - year_factor4 -0.00876 0.00715 573 -1.226  0.7363
## year_factor3 - year_factor5 -0.04630 0.00694 572 -6.667 <.0001
## year_factor3 - year_factor6 -0.02804 0.00692 573 -4.051  0.0006
## year_factor4 - year_factor5 -0.03754 0.00686 574 -5.476 <.0001
## year_factor4 - year_factor6 -0.01928 0.00681 575 -2.830  0.0386
## year_factor5 - year_factor6  0.01826 0.00658 572  2.777  0.0447
##
## 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 5 estimates

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

## boundary (singular) fit: see help('isSingular')

## $'emmmeans of species'
##   species emmean      SE  df lower.CL upper.CL
## Ansp     4.970 0.037582 591.4    4.896  5.044
## Apan     5.239 0.026624 530.3    5.187  5.291
## Assp     5.228 0.018847 573.3    5.191  5.265
## Cape     4.895 0.007577 399.5    4.880  4.910
## Cest     5.384 0.004904 336.4    5.375  5.394
## Dasp     5.161 0.005742 397.7    5.150  5.173
## Frve     4.960 0.014315 398.6    4.932  4.988
## Hisp     5.132 0.015477 527.3    5.101  5.162
## Hype     5.305 0.009155 485.1    5.287  5.323
## Poco     5.182 0.006874 450.5    5.169  5.196
## Popr     5.088 0.005144 360.2    5.078  5.098
## Ruac     5.082 0.006370 363.0    5.069  5.094
## Sosp     5.447 0.017854 357.1    5.412  5.483
## Syla     5.511 0.023853 520.0    5.465  5.558
##
## 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
## Ansp - Apan -0.26930 0.04618 583 -5.831 <.0001
## Ansp - Assp -0.25816 0.04220 590 -6.118 <.0001
## Ansp - Cape  0.07511 0.03836 592  1.958  0.7932
## Ansp - Cest -0.41446 0.03790 592 -10.936 <.0001
## Ansp - Dasp -0.19148 0.03801 592 -5.038  0.0001
## Ansp - Frve  0.01007 0.04029 585  0.250  1.0000

```

```

## Ansp - Hisp -0.16210 0.04058 591 -3.995 0.0056
## Ansp - Hype -0.33557 0.03879 591 -8.651 <.0001
## Ansp - Poco -0.21266 0.03816 592 -5.572 <.0001
## Ansp - Popr -0.11837 0.03792 592 -3.121 0.1025
## Ansp - Ruac -0.11220 0.03811 592 -2.944 0.1623
## Ansp - Sosp -0.47768 0.04162 576 -11.476 <.0001
## Ansp - Syla -0.54167 0.04465 583 -12.131 <.0001
## Apan - Assp 0.01114 0.03263 537 0.341 1.0000
## Apan - Cape 0.34441 0.02764 548 12.461 <.0001
## Apan - Cest -0.14516 0.02706 547 -5.364 <.0001
## Apan - Dasp 0.07782 0.02728 545 2.853 0.2019
## Apan - Frve 0.27937 0.03022 495 9.246 <.0001
## Apan - Hisp 0.10721 0.03092 556 3.467 0.0366
## Apan - Hype -0.06627 0.02807 551 -2.361 0.5102
## Apan - Poco 0.05664 0.02748 528 2.062 0.7273
## Apan - Popr 0.15094 0.02710 545 5.570 <.0001
## Apan - Ruac 0.15711 0.02734 558 5.747 <.0001
## Apan - Sosp -0.20837 0.03208 479 -6.495 <.0001
## Apan - Syla -0.27236 0.03568 526 -7.633 <.0001
## Assp - Cape 0.33327 0.02032 583 16.405 <.0001
## Assp - Cest -0.15629 0.01948 588 -8.024 <.0001
## Assp - Dasp 0.06668 0.01966 590 3.391 0.0465
## Assp - Frve 0.26823 0.02349 577 11.418 <.0001
## Assp - Hisp 0.09607 0.02435 590 3.945 0.0068
## Assp - Hype -0.07741 0.02095 583 -3.695 0.0170
## Assp - Poco 0.04550 0.02017 580 2.256 0.5881
## Assp - Popr 0.13980 0.01956 586 7.147 <.0001
## Assp - Ruac 0.14597 0.01988 590 7.343 <.0001
## Assp - Sosp -0.21951 0.02592 552 -8.468 <.0001
## Assp - Syla -0.28350 0.03039 577 -9.328 <.0001
## Cape - Cest -0.48957 0.00902 580 -54.265 <.0001
## Cape - Dasp -0.26659 0.00952 588 -28.003 <.0001
## Cape - Frve -0.06504 0.01620 463 -4.015 0.0053
## Cape - Hisp -0.23720 0.01728 562 -13.730 <.0001
## Cape - Hype -0.41068 0.01184 552 -34.675 <.0001
## Cape - Poco -0.28777 0.01017 588 -28.285 <.0001
## Cape - Popr -0.19347 0.00915 580 -21.153 <.0001
## Cape - Ruac -0.18730 0.00992 498 -18.887 <.0001
## Cape - Sosp -0.55278 0.01937 446 -28.540 <.0001
## Cape - Syla -0.61677 0.02503 515 -24.642 <.0001
## Cest - Dasp 0.22298 0.00756 583 29.482 <.0001
## Cest - Frve 0.42453 0.01513 481 28.062 <.0001
## Cest - Hisp 0.25236 0.01625 570 15.527 <.0001
## Cest - Hype 0.07889 0.01037 588 7.605 <.0001
## Cest - Poco 0.20180 0.00842 590 23.963 <.0001
## Cest - Popr 0.29609 0.00710 575 41.703 <.0001
## Cest - Ruac 0.30226 0.00803 592 37.637 <.0001
## Cest - Sosp -0.06322 0.01851 407 -3.414 0.0441
## Cest - Syla -0.12721 0.02434 543 -5.226 <.0001
## Dasp - Frve 0.20155 0.01542 485 13.070 <.0001
## Dasp - Hisp 0.02939 0.01643 579 1.789 0.8805
## Dasp - Hype -0.14409 0.01083 590 -13.301 <.0001
## Dasp - Poco -0.02118 0.00902 592 -2.348 0.5202
## Dasp - Popr 0.07311 0.00774 587 9.451 <.0001

```

```

##  Dasp - Ruac  0.07929 0.00858 591   9.236 <.0001
##  Dasp - Sosp -0.28620 0.01876 422  -15.255 <.0001
##  Dasp - Syla -0.35019 0.02456 548  -14.256 <.0001
##  Frve - Hisp -0.17216 0.02097 588  -8.209 <.0001
##  Frve - Hype -0.34564 0.01699 479  -20.341 <.0001
##  Frve - Poco -0.22273 0.01589 518  -14.017 <.0001
##  Frve - Popr -0.12843 0.01521 491  -8.446 <.0001
##  Frve - Ruac -0.12226 0.01567 463  -7.802 <.0001
##  Frve - Sosp -0.48774 0.02276 514  -21.429 <.0001
##  Frve - Syla -0.55173 0.02772 563  -19.903 <.0001
##  Hisp - Hype -0.17348 0.01806 577  -9.605 <.0001
##  Hisp - Poco -0.05057 0.01706 565  -2.964 0.1545
##  Hisp - Popr  0.04373 0.01635 570  2.675 0.2962
##  Hisp - Ruac  0.04990 0.01675 577  2.979 0.1489
##  Hisp - Sosp -0.31558 0.02357 524  -13.389 <.0001
##  Hisp - Syla -0.37957 0.02846 566  -13.336 <.0001
##  Hype - Poco  0.12291 0.01140 559  10.783 <.0001
##  Hype - Popr  0.21720 0.01048 588  20.731 <.0001
##  Hype - Ruac  0.22338 0.01111 590  20.105 <.0001
##  Hype - Sosp -0.14210 0.02010 384  -7.069 <.0001
##  Hype - Syla -0.20610 0.02546 557  -8.095 <.0001
##  Poco - Popr  0.09429 0.00853 589  11.055 <.0001
##  Poco - Ruac  0.10047 0.00936 556  10.739 <.0001
##  Poco - Sosp -0.26502 0.01907 444  -13.896 <.0001
##  Poco - Syla -0.32901 0.02477 534  -13.285 <.0001
##  Popr - Ruac  0.00617 0.00818 591  0.755 1.0000
##  Popr - Sosp -0.35931 0.01856 421  -19.357 <.0001
##  Popr - Syla -0.42330 0.02438 542  -17.362 <.0001
##  Ruac - Sosp -0.36548 0.01895 399  -19.286 <.0001
##  Ruac - Syla -0.42947 0.02464 557  -17.429 <.0001
##  Sosp - Syla -0.06399 0.02962 550  -2.160 0.6586
##
## 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 14 estimates

```

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

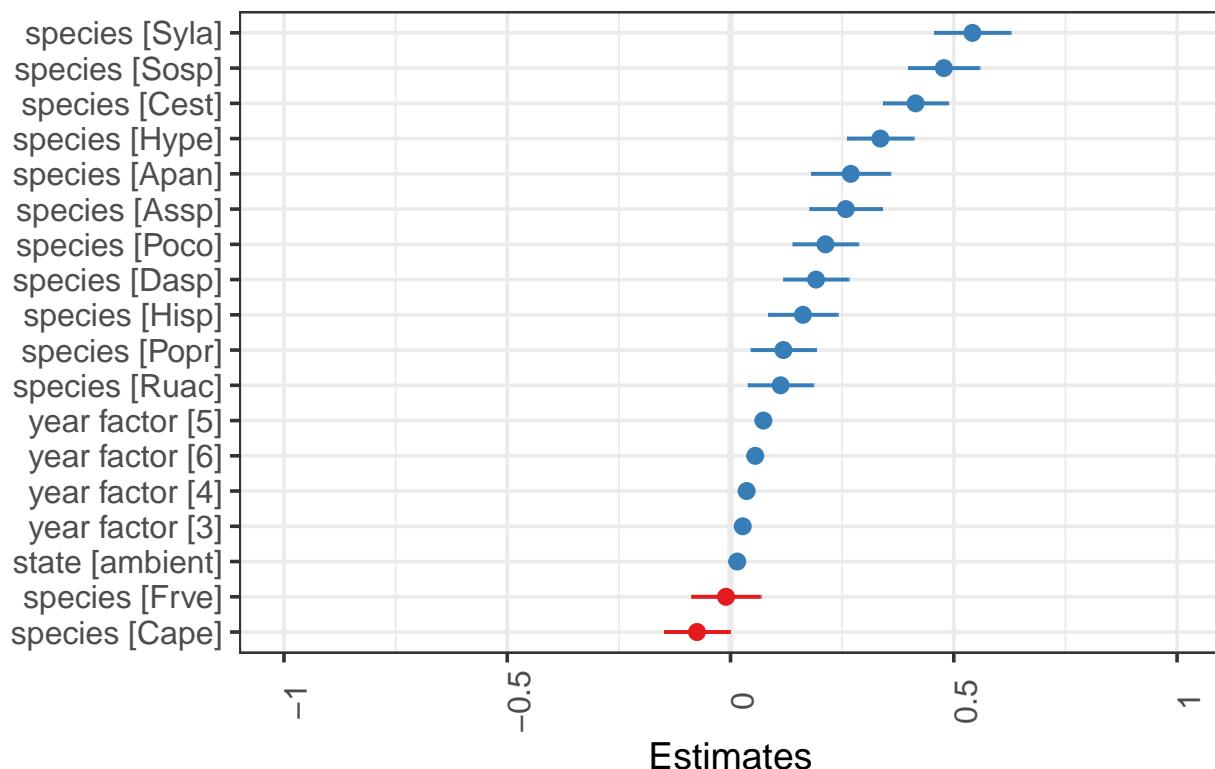
```
## boundary (singular) fit: see help('isSingular')
```

```
## Error in emmeans(object = object, specs = specs[[i]], name = contr.name, : No variable named insectici
```

Take a look at the estimates for each fixed effect. These are the estimates from summary(mod7a). You can plot them.

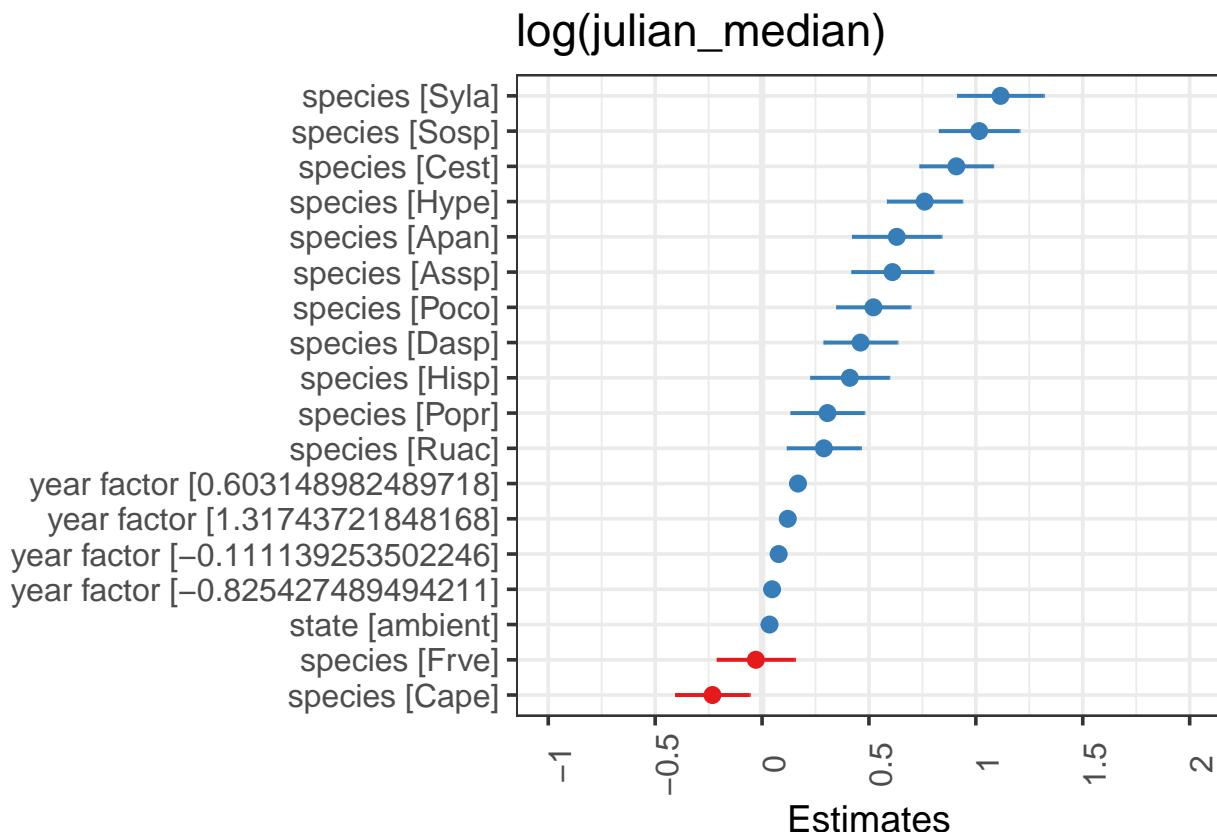
```
plot_model(mod7a, sort.est = TRUE)
```

log(julian_median)



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

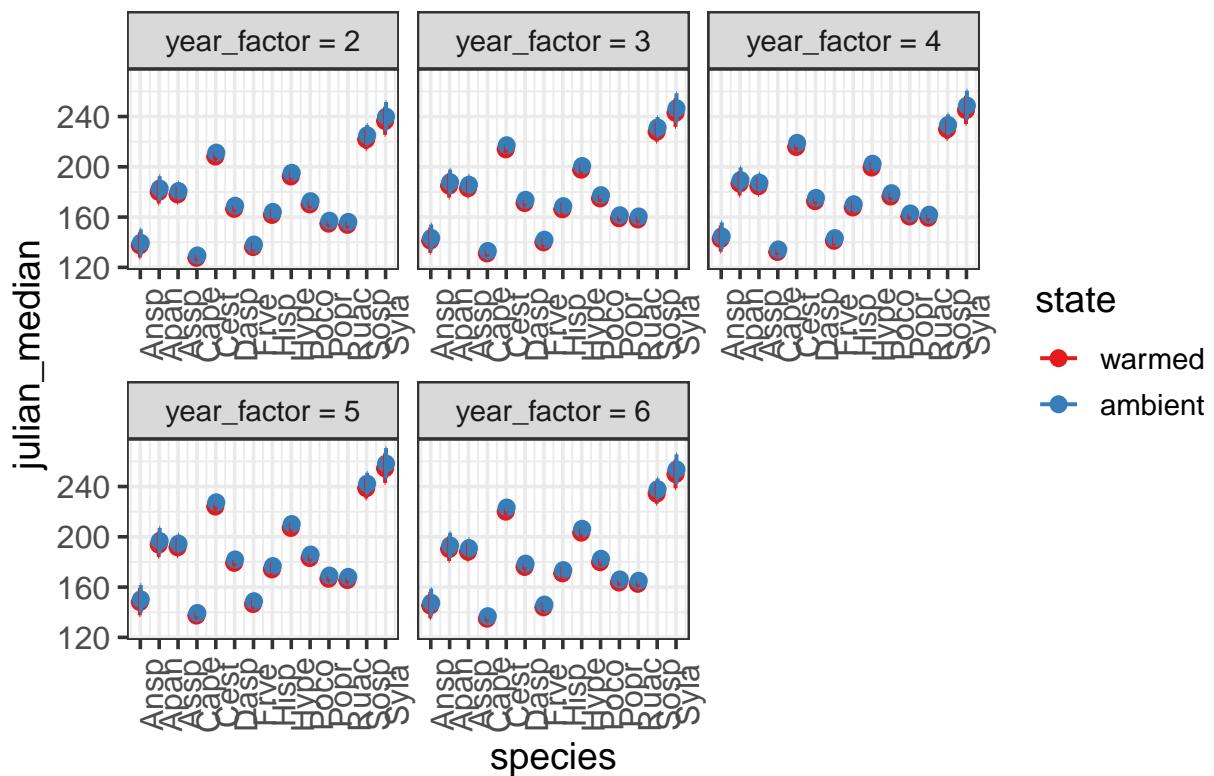
```
## Formula contains log- or sqrt-terms. See help("standardize") for how  
##   such terms are standardized.  
## boundary (singular) fit: see help('isSingular')
```



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

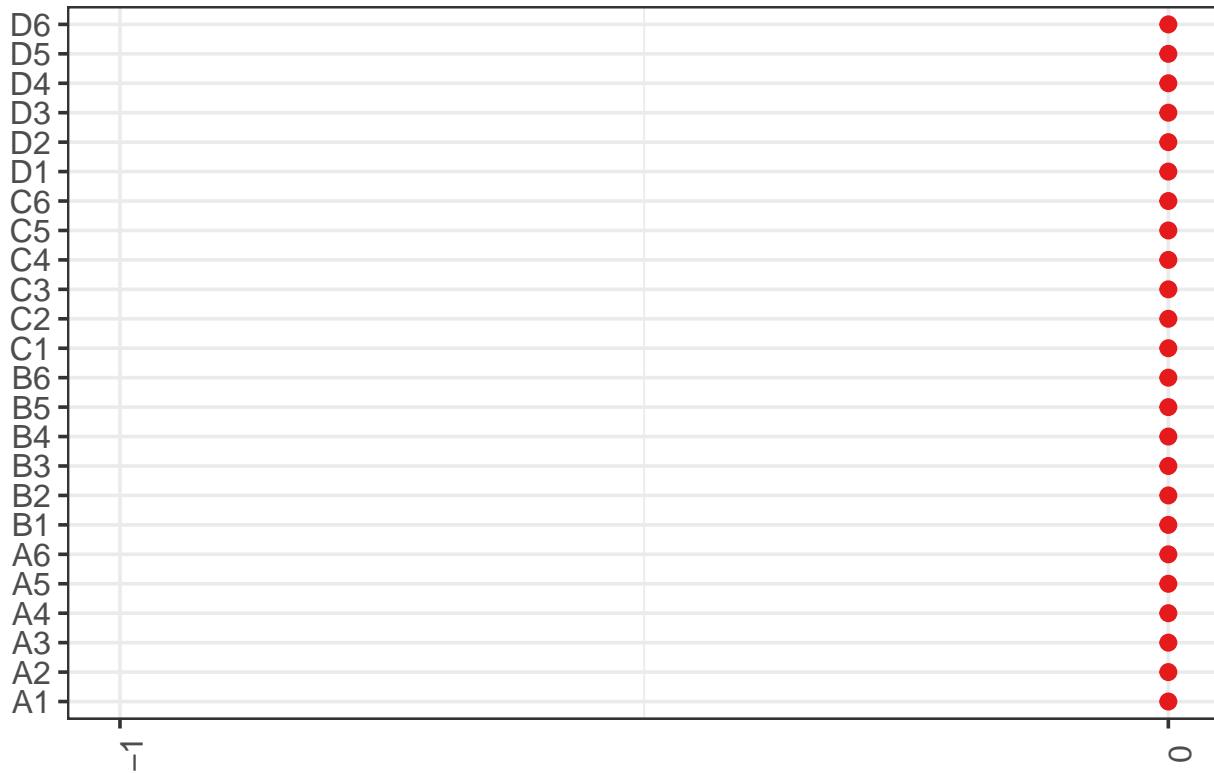
```
## Model has log-transformed response. Back-transforming predictions to original response scale. Standard
```

Predicted values of julian_median



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

Random effects



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

## boundary (singular) fit: see help('isSingular')

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

## boundary (singular) fit: see help('isSingular')

mod9a <- lmer(log(julian_median) ~ state + origin + factor(year_factor) + (1|plot), umbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod9b <- lmer(log(julian_median) ~ state + origin + insecticide + factor(year_factor) + (1|plot), umbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

anova(mod8, mod9) # model 9 is a better fit to data

## Data: umbs_flwr_spp
## Models:
## mod9: log(julian_median) ~ state + origin + (1 + factor(year_factor) | plot)
```

```

## mod8: log(julian_median) ~ state * origin + (1 + factor(year_factor) | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod9     20 -497.84 -410.85 268.92   -537.84
## mod8     22 -494.95 -399.26 269.47   -538.95 1.1094  2      0.5742

```

```
anova(mod9, mod9a) # mod 9a
```

```

## Data: umbs_flwr_spp
## Models:
## mod9a: log(julian_median) ~ state + origin + factor(year_factor) + (1 | plot)
## mod9: log(julian_median) ~ state + origin + (1 + factor(year_factor) | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod9a    10 -530.70 -487.21 275.35   -550.70
## mod9     20 -497.84 -410.85 268.92   -537.84      0 10          1

```

```
anova(mod9a, mod9b) # mod 9a
```

```

## Data: umbs_flwr_spp
## Models:
## mod9a: log(julian_median) ~ state + origin + factor(year_factor) + (1 | plot)
## mod9b: log(julian_median) ~ state + origin + insecticide + factor(year_factor) + (1 | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod9a    10 -530.70 -487.21 275.35   -550.70
## mod9b    11 -528.83 -480.99 275.41   -550.83 0.1286  1      0.7199

```

```
summary(mod9a)
```

```

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + origin + factor(year_factor) + (1 |
##   plot)
## Data: umbs_flwr_spp
##
##      AIC      BIC      logLik deviance df.resid
##    -530.7    -487.2     275.3    -550.7      562
##
## Scaled residuals:
##    Min      1Q  Median      3Q      Max
## -1.9687 -0.9202 -0.1915  0.8779  3.0575
##
## Random effects:
##   Groups   Name        Variance Std.Dev.
##   plot     (Intercept) 0.000000 0.0000
##   Residual           0.022360 0.1495
## Number of obs: 572, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)
## (Intercept) 5.05556  0.01892 572.00000 267.204 < 2e-16 ***
## stateambient 0.01304  0.01251 572.00000  1.042  0.29770
## originBoth   0.07581  0.03562 572.00000  2.128  0.03375 *
## originExotic 0.11855  0.01390 572.00000  8.527 < 2e-16 ***

```

```

## factor(year_factor)3 0.01108 0.02118 572.00000 0.523 0.60099
## factor(year_factor)4 0.02887 0.02116 572.00000 1.364 0.17308
## factor(year_factor)5 0.06335 0.02056 572.00000 3.082 0.00216 **
## factor(year_factor)6 0.04603 0.02051 572.00000 2.244 0.02520 *
##
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) sttmbn orgnBt orgnEx fc(_)3 fc(_)4 fc(_)5
## stateambint -0.338
## originBoth -0.276 -0.013
## originExotc -0.445 0.025 0.257
## fctr(yr_f)3 -0.583 0.001 0.090 -0.069
## fctr(yr_f)4 -0.577 -0.002 0.087 -0.082 0.549
## fctr(yr_f)5 -0.598 -0.002 0.097 -0.077 0.565 0.567
## fctr(yr_f)6 -0.598 0.000 0.108 -0.088 0.568 0.570 0.587
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')

```

```
anova(mod9a)
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state       0.02429 0.02429     1   572  1.0864  0.2977
## origin      1.62573 0.81287     2   572 36.3592 1.366e-15 ***
## factor(year_factor) 0.29150 0.07288     4   572  3.2597  0.0117 *
##
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

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

```
## boundary (singular) fit: see help('isSingular')
```

```

## $`emmeans of state, origin`
##   state  origin emmean      SE   df lower.CL upper.CL
##   warmed Native  5.085 0.013383  82.27   5.059   5.112
##   ambient Native  5.098 0.013272  75.69   5.072   5.125
##   warmed Both    5.161 0.034968 438.54   5.093   5.230
##   ambient Both   5.174 0.034798 409.14   5.106   5.243
##   warmed Exotic  5.204 0.009929  32.60   5.184   5.224
##   ambient Exotic 5.217 0.010184  35.42   5.196   5.238
##
## 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 -0.0130 0.0127 21.0 -1.029  0.9028
##   warmed Native - warmed Both   -0.0758 0.0361 571.6 -2.100  0.2889
##   warmed Native - ambient Both  -0.0888 0.0381 377.8 -2.329  0.1850

```

```

## warmed Native - warmed Exotic      -0.1186 0.0141 561.4   -8.409 <.0001
## warmed Native - ambient Exotic    -0.1316 0.0192 90.4    -6.865 <.0001
## ambient Native - warmed Both      -0.0628 0.0384 418.7   -1.635 0.5755
## ambient Native - ambient Both     -0.0758 0.0361 571.6   -2.100 0.2889
## ambient Native - warmed Exotic    -0.1055 0.0187 80.0    -5.630 <.0001
## ambient Native - ambient Exotic    -0.1186 0.0141 561.4   -8.409 <.0001
## warmed Both - ambient Both        -0.0130 0.0127 21.0    -1.029 0.9028
## warmed Both - warmed Exotic       -0.0427 0.0353 550.8   -1.210 0.8319
## warmed Both - ambient Exotic      -0.0558 0.0377 379.4   -1.478 0.6787
## ambient Both - warmed Exotic      -0.0297 0.0373 330.5   -0.796 0.9680
## ambient Both - ambient Exotic     -0.0427 0.0353 550.8   -1.210 0.8319
## warmed Exotic - ambient Exotic    -0.0130 0.0127 21.0    -1.029 0.9028
##
## 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 6 estimates

# including growth form - first with interaction term
umbss_flwr_spp <- within(umbss_flwr_spp, growth_habit <- relevel(factor(growth_habit), ref = "Forb")) # r
mod10 <- lmer(log(julian_median) ~ state * growth_habit + (1+factor(year_factor)|plot), umbs_flwr_spp, l

## boundary (singular) fit: see help('isSingular')

mod11 <- lmer(log(julian_median) ~ state + growth_habit + (1+factor(year_factor)|plot), umbs_flwr_spp, l

## boundary (singular) fit: see help('isSingular')

mod11a <- lmer(log(julian_median) ~ state + growth_habit + factor(year_factor) + (1|plot), umbs_flwr_spp, l

## boundary (singular) fit: see help('isSingular')

mod11b <- lmer(log(julian_median) ~ state + growth_habit + factor(year_factor) + insecticide + (1|plot))

## boundary (singular) fit: see help('isSingular')

anova(mod10, mod11) # model 11 is a better fit to data

## Data: umbs_flwr_spp
## Models:
## mod11: log(julian_median) ~ state + growth_habit + (1 + factor(year_factor) | plot)
## mod10: log(julian_median) ~ state * growth_habit + (1 + factor(year_factor) | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod11    20 -610.61 -523.62 325.30   -650.61
## mod10    22 -607.47 -511.79 325.74   -651.47 0.8678  2      0.648

anova(mod11, mod11a) # model 11a is still a better fit to data

```

```

## Data: umbs_flwr_spp
## Models:
## mod11a: log(julian_median) ~ state + growth_habit + factor(year_factor) + (1 | plot)
## mod11: log(julian_median) ~ state + growth_habit + (1 + factor(year_factor) | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod11a   10 -648.44 -604.95 334.22 -668.44
## mod11    20 -610.61 -523.62 325.30 -650.61      0 10          1

anova(mod11a, mod11b) # model 11a still a better fit to data

## Data: umbs_flwr_spp
## Models:
## mod11a: log(julian_median) ~ state + growth_habit + factor(year_factor) + (1 | plot)
## mod11b: log(julian_median) ~ state + growth_habit + factor(year_factor) + insecticide + (1 | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod11a   10 -648.44 -604.95 334.22 -668.44
## mod11b   11 -647.84 -600.00 334.92 -669.84 1.4004 1     0.2367

summary(mod11a)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + growth_habit + factor(year_factor) +
##           (1 | plot)
## Data: umbs_flwr_spp
##
##      AIC      BIC      logLik deviance df.resid
## -648.4   -605.0    334.2    -668.4      562
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -2.6685 -0.5723  0.1949  0.8177  2.0564
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0000   0.0000
## Residual            0.0182   0.1349
## Number of obs: 572, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)
## (Intercept) 5.222936  0.016510 572.000000 316.344 < 2e-16 ***
## stateambient 0.002125  0.011307 572.000000  0.188 0.850983
## growth_habit -0.135338  0.040330 572.000000 -3.356 0.000844 ***
## growth_habitGraminoid -0.169526  0.011457 572.000000 -14.796 < 2e-16 ***
## factor(year_factor)3  0.032751  0.019018 572.000000  1.722 0.085589 .
## factor(year_factor)4  0.041751  0.018997 572.000000  2.198 0.028361 *
## factor(year_factor)5  0.074759  0.018530 572.000000  4.035 6.21e-05 ***
## factor(year_factor)6  0.058423  0.018401 572.000000  3.175 0.001579 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
```

```

##          (Intr) sttmbn grwth_G fc(_)
## stateambint -0.366
## growth_habt -0.227  0.055
## grwth_hbtGr -0.379  0.046  0.155
## fctr(yr_f)3 -0.617  0.007  0.070 -0.038
## fctr(yr_f)4 -0.635  0.007  0.095  0.001  0.543
## fctr(yr_f)5 -0.656  0.009  0.135 -0.002  0.560  0.563
## fctr(yr_f)6 -0.661  0.011  0.121  0.003  0.562  0.566  0.584
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')

anova(mod11a)

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state        0.0006 0.00064     1    572  0.0353  0.850983
## growth_habit 4.0049 2.00243     2    572 110.0400 < 2.2e-16 ***
## factor(year_factor) 0.3363 0.08408     4    572  4.6207  0.001117 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

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

## boundary (singular) fit: see help('isSingular')

## $`emmeans of year_factor, growth_habit`
##   year_factor growth_habit emmean      SE   df lower.CL upper.CL
##   2 Forb       5.224 0.01551 421.9   5.194  5.254
##   3 Forb       5.257 0.01470 389.6   5.228  5.286
##   4 Forb       5.266 0.01431 355.3   5.238  5.294
##   5 Forb       5.299 0.01354 331.4   5.272  5.325
##   6 Forb       5.282 0.01338 320.9   5.256  5.309
##   2            5.089 0.04043 535.4   5.009  5.168
##   3            5.121 0.04150 531.3   5.040  5.203
##   4            5.130 0.04184 531.7   5.048  5.213
##   5            5.163 0.04225 537.5   5.080  5.246
##   6            5.147 0.04194 531.0   5.065  5.229
##   2 Graminoid  5.054 0.01528 437.0   5.024  5.085
##   3 Graminoid  5.087 0.01386 371.1   5.060  5.114
##   4 Graminoid  5.096 0.01406 381.8   5.069  5.124
##   5 Graminoid  5.129 0.01325 351.4   5.103  5.155
##   6 Graminoid  5.113 0.01317 335.3   5.087  5.139
##
## 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
##   year_factor2 Forb - year_factor3 Forb -0.03275 0.0192 564 -1.709
##   year_factor2 Forb - year_factor4 Forb -0.04175 0.0191 567 -2.181

```

```

## year_factor2 Forb - year_factor5 Forb      -0.07476 0.0187 564  -4.004
## year_factor2 Forb - year_factor6 Forb      -0.05842 0.0185 564  -3.151
## year_factor2 Forb - year_factor2           0.13534 0.0409 570  3.308
## year_factor2 Forb - year_factor3           0.10259 0.0464 575  2.211
## year_factor2 Forb - year_factor4           0.09359 0.0468 575  1.999
## year_factor2 Forb - year_factor5           0.06058 0.0472 576  1.283
## year_factor2 Forb - year_factor6           0.07692 0.0469 575  1.639
## year_factor2 Forb - year_factor2 Graminoid 0.16953 0.0116 564  14.605
## year_factor2 Forb - year_factor3 Graminoid 0.13678 0.0220 577  6.209
## year_factor2 Forb - year_factor4 Graminoid 0.12778 0.0224 576  5.707
## year_factor2 Forb - year_factor5 Graminoid 0.09477 0.0220 576  4.314
## year_factor2 Forb - year_factor6 Graminoid 0.11110 0.0219 577  5.072
## year_factor3 Forb - year_factor4 Forb      -0.00900 0.0183 563  -0.492
## year_factor3 Forb - year_factor5 Forb      -0.04201 0.0177 563  -2.367
## year_factor3 Forb - year_factor6 Forb      -0.02567 0.0176 563  -1.455
## year_factor3 Forb - year_factor2           0.16809 0.0439 578  3.827
## year_factor3 Forb - year_factor3           0.13534 0.0409 570  3.308
## year_factor3 Forb - year_factor4           0.12634 0.0453 577  2.792
## year_factor3 Forb - year_factor5           0.09333 0.0457 577  2.044
## year_factor3 Forb - year_factor6           0.10967 0.0454 576  2.417
## year_factor3 Forb - year_factor2 Graminoid 0.20228 0.0228 575  8.882
## year_factor3 Forb - year_factor3 Graminoid 0.16953 0.0116 564  14.605
## year_factor3 Forb - year_factor4 Graminoid 0.16053 0.0221 574  7.278
## year_factor3 Forb - year_factor5 Graminoid 0.12752 0.0216 575  5.910
## year_factor3 Forb - year_factor6 Graminoid 0.14385 0.0215 576  6.678
## year_factor4 Forb - year_factor5 Forb      -0.03301 0.0177 564  -1.867
## year_factor4 Forb - year_factor6 Forb      -0.01667 0.0176 565  -0.949
## year_factor4 Forb - year_factor2           0.17709 0.0435 577  4.074
## year_factor4 Forb - year_factor3           0.14434 0.0444 576  3.252
## year_factor4 Forb - year_factor4           0.13534 0.0409 570  3.308
## year_factor4 Forb - year_factor5           0.10233 0.0452 577  2.264
## year_factor4 Forb - year_factor6           0.11867 0.0449 575  2.642
## year_factor4 Forb - year_factor2 Graminoid 0.21128 0.0224 578  9.436
## year_factor4 Forb - year_factor3 Graminoid 0.17853 0.0213 579  8.387
## year_factor4 Forb - year_factor4 Graminoid 0.16953 0.0116 564  14.605
## year_factor4 Forb - year_factor5 Graminoid 0.13652 0.0211 578  6.462
## year_factor4 Forb - year_factor6 Graminoid 0.15285 0.0211 579  7.247
## year_factor5 Forb - year_factor6 Forb      0.01634 0.0170 561  0.963
## year_factor5 Forb - year_factor2           0.21010 0.0426 576  4.932
## year_factor5 Forb - year_factor3           0.17735 0.0435 574  4.076
## year_factor5 Forb - year_factor4           0.16835 0.0439 574  3.832
## year_factor5 Forb - year_factor5           0.13534 0.0409 570  3.308
## year_factor5 Forb - year_factor6           0.15167 0.0440 574  3.444
## year_factor5 Forb - year_factor2 Graminoid 0.24429 0.0220 578  11.102
## year_factor5 Forb - year_factor3 Graminoid 0.21153 0.0208 579  10.154
## year_factor5 Forb - year_factor4 Graminoid 0.20253 0.0212 577  9.568
## year_factor5 Forb - year_factor5 Graminoid 0.16953 0.0116 564  14.605
## year_factor5 Forb - year_factor6 Graminoid 0.18586 0.0206 578  9.021
## year_factor6 Forb - year_factor2           0.19376 0.0428 578  4.527
## year_factor6 Forb - year_factor3           0.16101 0.0437 576  3.682
## year_factor6 Forb - year_factor4           0.15201 0.0441 576  3.444
## year_factor6 Forb - year_factor5           0.11900 0.0445 577  2.672
## year_factor6 Forb - year_factor6           0.13534 0.0409 570  3.308
## year_factor6 Forb - year_factor2 Graminoid 0.22795 0.0218 577  10.436

```

```

##  year_factor6 Forb - year_factor3 Graminoid      0.19520 0.0207 578   9.436
##  year_factor6 Forb - year_factor4 Graminoid      0.18620 0.0210 576   8.855
##  year_factor6 Forb - year_factor5 Graminoid      0.15319 0.0205 576   7.475
##  year_factor6 Forb - year_factor6 Graminoid      0.16953 0.0116 564  14.605
##  year_factor2 - year_factor3                   -0.03275 0.0192 564  -1.709
##  year_factor2 - year_factor4                   -0.04175 0.0191 567  -2.181
##  year_factor2 - year_factor5                   -0.07476 0.0187 564  -4.004
##  year_factor2 - year_factor6                   -0.05842 0.0185 564  -3.151
##  year_factor2 - year_factor2 Graminoid        0.03419 0.0408 557   0.838
##  year_factor2 - year_factor3 Graminoid        0.00144 0.0436 572   0.033
##  year_factor2 - year_factor4 Graminoid        -0.00756 0.0434 571  -0.174
##  year_factor2 - year_factor5 Graminoid        -0.04057 0.0425 569  -0.955
##  year_factor2 - year_factor6 Graminoid        -0.02423 0.0427 571  -0.567
##  year_factor3 - year_factor4                   -0.00900 0.0183 563  -0.492
##  year_factor3 - year_factor5                   -0.04201 0.0177 563  -2.367
##  year_factor3 - year_factor6                   -0.02567 0.0176 563  -1.455
##  year_factor3 - year_factor2 Graminoid        0.06694 0.0465 568   1.440
##  year_factor3 - year_factor3 Graminoid        0.03419 0.0408 557   0.838
##  year_factor3 - year_factor4 Graminoid        0.02519 0.0445 570   0.566
##  year_factor3 - year_factor5 Graminoid        -0.00782 0.0436 566  -0.179
##  year_factor3 - year_factor6 Graminoid        0.00852 0.0438 569   0.194
##  year_factor4 - year_factor5                   -0.03301 0.0177 564  -1.867
##  year_factor4 - year_factor6                   -0.01667 0.0176 565  -0.949
##  year_factor4 - year_factor2 Graminoid        0.07594 0.0467 568   1.625
##  year_factor4 - year_factor3 Graminoid        0.04319 0.0450 569   0.960
##  year_factor4 - year_factor4 Graminoid        0.03419 0.0408 557   0.838
##  year_factor4 - year_factor5 Graminoid        0.00118 0.0438 566   0.027
##  year_factor4 - year_factor6 Graminoid        0.01752 0.0441 568   0.398
##  year_factor5 - year_factor6                   0.01634 0.0170 561   0.963
##  year_factor5 - year_factor2 Graminoid        0.10895 0.0471 570   2.311
##  year_factor5 - year_factor3 Graminoid        0.07620 0.0454 571   1.679
##  year_factor5 - year_factor4 Graminoid        0.06720 0.0451 571   1.489
##  year_factor5 - year_factor5 Graminoid        0.03419 0.0408 557   0.838
##  year_factor5 - year_factor6 Graminoid        0.05052 0.0445 571   1.136
##  year_factor6 - year_factor2 Graminoid        0.09261 0.0468 568   1.977
##  year_factor6 - year_factor3 Graminoid        0.05986 0.0451 569   1.328
##  year_factor6 - year_factor4 Graminoid        0.05086 0.0448 569   1.135
##  year_factor6 - year_factor5 Graminoid        0.01785 0.0439 566   0.406
##  year_factor6 - year_factor6 Graminoid        0.03419 0.0408 557   0.838
##  year_factor2 Graminoid - year_factor3 Graminoid -0.03275 0.0192 564  -1.709
##  year_factor2 Graminoid - year_factor4 Graminoid -0.04175 0.0191 567  -2.181
##  year_factor2 Graminoid - year_factor5 Graminoid -0.07476 0.0187 564  -4.004
##  year_factor2 Graminoid - year_factor6 Graminoid -0.05842 0.0185 564  -3.151
##  year_factor3 Graminoid - year_factor4 Graminoid -0.00900 0.0183 563  -0.492
##  year_factor3 Graminoid - year_factor5 Graminoid -0.04201 0.0177 563  -2.367
##  year_factor3 Graminoid - year_factor6 Graminoid -0.02567 0.0176 563  -1.455
##  year_factor4 Graminoid - year_factor5 Graminoid -0.03301 0.0177 564  -1.867
##  year_factor4 Graminoid - year_factor6 Graminoid -0.01667 0.0176 565  -0.949
##  year_factor5 Graminoid - year_factor6 Graminoid  0.01634 0.0170 561   0.963

##  p.value
##  0.9298
##  0.6787
##  0.0062
##  0.1055

```

```
## 0.0675
## 0.6570
## 0.7984
## 0.9945
## 0.9495
## <.0001
## <.0001
## <.0001
## 0.0018
## 0.0001
## 1.0000
## 0.5408
## 0.9817
## 0.0120
## 0.0675
## 0.2543
## 0.7709
## 0.5032
## <.0001
## <.0001
## <.0001
## <.0001
## <.0001
## 0.8684
## 0.9998
## 0.0047
## 0.0794
## 0.0675
## 0.6179
## 0.3441
## <.0001
## <.0001
## <.0001
## <.0001
## <.0001
## <.0001
## 0.9998
## 0.0001
## 0.0047
## 0.0118
## 0.0675
## 0.0444
## <.0001
## <.0001
## <.0001
## <.0001
## <.0001
## 0.0007
## 0.0201
## 0.0444
## 0.3249
## 0.0675
## <.0001
## <.0001
## <.0001
```

```

## <.0001
## <.0001
## 0.9298
## 0.6787
## 0.0062
## 0.1055
## 1.0000
## 1.0000
## 1.0000
## 0.9998
## 1.0000
## 1.0000
## 1.0000
## 0.5408
## 0.9817
## 0.9834
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.8684
## 0.9998
## 0.9527
## 0.9998
## 1.0000
## 1.0000
## 1.0000
## 0.9998
## 0.5829
## 0.9389
## 0.9774
## 1.0000
## 0.9985
## 0.8111
## 0.9923
## 0.9985
## 1.0000
## 1.0000
## 0.9298
## 0.6787
## 0.0062
## 0.1055
## 1.0000
## 0.5408
## 0.9817
## 0.8684
## 0.9998
## 0.9998
##
## 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 15 estimates

```

```

# New version of our model incorporating interaction term and species within year so that there is a se
# updated mod4
mod12 <- lmer(log(julian_median) ~ state * factor(year_factor) + (1+factor(year_factor)|species), umbs_1

## boundary (singular) fit: see help('isSingular')

# So another version of this model would include the interaction but not include the nesting (and thus i
# updated mod5
mod13 <- lmer(log(julian_median) ~ state * factor(year_factor) + (1|species), umbs_flwr_spp)

# All the models:
mod1 <- lmer(log(julian_median) ~ state*year_factor + insecticide*year_factor + (1|species) + (1|plot),

## boundary (singular) fit: see help('isSingular')

mod2 <- lmer(log(julian_median) ~ state*year_factor + insecticide*year_factor + (1|species), umbs_flwr_s
mod3 <- lmer(log(julian_median) ~ state*year_factor + (1|species), umbs_flwr_spp, REML=FALSE)
mod4 <- lmer(log(julian_median) ~ state*year_factor + insecticide + (1|species) + (1|plot), umbs_flwr_s

## boundary (singular) fit: see help('isSingular')

mod5 <- lmer(log(julian_median) ~ state + year_factor + (1|species), umbs_flwr_spp, REML=FALSE)
mod6 <- lmer(log(julian_median) ~ state + year_factor + (1|species) + (1 + year|plot), umbs_flwr_spp, R

## boundary (singular) fit: see help('isSingular')

## Warning: Model failed to converge with 1 negative eigenvalue: -9.0e-02

mod7 <- lmer(log(julian_median) ~ state + species + (1+factor(year_factor)|plot), umbs_flwr_spp, REM

## boundary (singular) fit: see help('isSingular')

mod7a <- lmer(log(julian_median) ~ state + species + factor(year_factor) + (1|plot), umbs_flwr_spp, REM

## boundary (singular) fit: see help('isSingular')

mod7b <- lmer(log(julian_median) ~ state * factor(year_factor) + species + (1|plot), umbs_flwr_spp, REM

## boundary (singular) fit: see help('isSingular')

mod7c <- lmer(log(julian_median) ~ state + species + factor(year_factor) + insecticide + (1|plot), umbs_1

## boundary (singular) fit: see help('isSingular')

mod8 <- lmer(log(julian_median) ~ state * origin + (1+factor(year_factor)|plot), umbs_flwr_spp, REM=FA

## boundary (singular) fit: see help('isSingular')

```

```

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

## boundary (singular) fit: see help('isSingular')

mod9a <- lmer(log(julian_median) ~ state + origin + factor(year_factor) + (1|plot), umbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod10 <- lmer(log(julian_median) ~ state * growth_habit + (1+factor(year_factor)|plot), umbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

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

## boundary (singular) fit: see help('isSingular')

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

## boundary (singular) fit: see help('isSingular')

mod12 <- lmer(log(julian_median) ~ state * factor(year_factor) + (1+factor(year_factor)|species), umbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod13 <- lmer(log(julian_median) ~ state * factor(year_factor) + (1|species), umbs_flwr_spp)
AICctab(mod1, mod2, mod3, mod5, mod6, mod7, mod7a, mod7b, mod7c, mod8, mod9, mod9a, mod10, mod11, mod11a, mod12, mod13)

##      dAICc  df weight
## mod7a     0.0 21  0.569
## mod7c     0.6 22  0.419
## mod7b     7.7 25  0.012
## mod7     64.4 31 <0.001
## mod5     86.6  5 <0.001
## mod3     88.6  6 <0.001
## mod2     91.0  8 <0.001
## mod1     93.0  9 <0.001
## mod6    102.7  8 <0.001
## mod13   145.5 12 <0.001
## mod11a  1074.5 10 <0.001
## mod11   1113.5 20 <0.001
## mod10   1116.9 22 <0.001
## mod9a   1192.2 10 <0.001
## mod9    1226.2 20 <0.001
## mod8    1229.4 22 <0.001

summary(mod7a)

```

```

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + species + factor(year_factor) +
##           (1 | plot)
## Data: umbs_flwr_spp
##
##      AIC      BIC  logLik deviance df.resid
## -1724.2 -1632.9    883.1   -1766.2      551
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -6.3936 -0.5403 -0.0484  0.6020  3.2104
##
## Random effects:
##   Groups   Name        Variance Std.Dev.
##   plot      (Intercept) 0.00000  0.00000
##   Residual            0.00267  0.05167
## Number of obs: 572, groups: plot, 24
##
## Fixed effects:
##                               Estimate Std. Error      df t value Pr(>|t|) 
## (Intercept)                4.923754  0.037345 572.000000 131.844 < 2e-16 ***
## stateambient               0.015047  0.004372 572.000000  3.441 0.000621 ***
## speciesApan                 0.269304  0.045135 572.000000  5.967 4.25e-09 ***
## speciesAssp                 0.258165  0.041286 572.000000  6.253 7.88e-10 ***
## speciesCape                -0.075106  0.037567 572.000000 -1.999 0.046051 *
## speciesCest                 0.414459  0.037123 572.000000 11.165 < 2e-16 ***
## speciesDasp                 0.191482  0.037233 572.000000  5.143 3.72e-07 ***
## speciesFrve                -0.010067  0.039373 572.000000 -0.256 0.798296
## speciesHisp                 0.162096  0.039753 572.000000  4.078 5.20e-05 ***
## speciesHype                 0.335573  0.037967 572.000000  8.838 < 2e-16 ***
## speciesPoco                 0.212661  0.037383 572.000000  5.689 2.04e-08 ***
## speciesPopr                 0.118368  0.037146 572.000000  3.187 0.001518 **
## speciesRuac                 0.112195  0.037338 572.000000  3.005 0.002774 **
## speciesSosp                 0.477677  0.040627 572.000000 11.757 < 2e-16 ***
## speciesSyla                 0.541668  0.043618 572.000000 12.418 < 2e-16 ***
## factor(year_factor)3         0.027319  0.007423 572.000000  3.680 0.000255 ***
## factor(year_factor)4         0.036078  0.007406 572.000000  4.871 1.44e-06 ***
## factor(year_factor)5         0.073615  0.007206 572.000000 10.216 < 2e-16 ***
## factor(year_factor)6         0.055354  0.007214 572.000000  7.673 7.27e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 19 > 12.
## Use print(x, correlation=TRUE)  or
##   vcov(x)      if you need it

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

anova(mod7a)

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

```

```

##                               Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state                      0.0316 0.03162     1    572 11.844 0.0006208 ***
## species                     12.8865 0.99127    13    572 371.266 < 2.2e-16 ***
## factor(year_factor)        0.3246 0.08114     4    572 30.391 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

Phoebe

UMBS Plot-level Mixed Effects Models:

```

mod1p <- lmer(log(julian_median) ~ state + (1|plot), umbs_flwr_plot, REML=FALSE)
mod2p <- lmer(log(julian_median) ~ insecticide + (1|plot), umbs_flwr_plot, REML=FALSE)
mod3p <- lmer(log(julian_median) ~ insecticide + state + (1|plot), umbs_flwr_plot, REML=FALSE)
mod4p <- lmer(log(julian_median) ~ insecticide * state + (1|plot), umbs_flwr_plot, REML=FALSE)
mod5p <- lmer(log(julian_median) ~ state + year_factor + (1|plot), umbs_flwr_plot, REML=FALSE)
mod6p <- lmer(log(julian_median) ~ state + year_factor + insecticide + (1|plot), umbs_flwr_plot, REML=FALSE)
mod7p <- lmer(log(julian_median) ~ state * year_factor + (1|plot), umbs_flwr_plot, REML=FALSE)
mod8p <- lmer(log(julian_median) ~ state * year_factor + insecticide + (1|plot), umbs_flwr_plot, REML=FALSE)
mod9p <- lmer(log(julian_median) ~ state * insecticide + year_factor + (1|plot), umbs_flwr_plot, REML=FALSE)
mod10p <- lmer(log(julian_median) ~ state + insecticide * year_factor + (1|plot), umbs_flwr_plot, REML=FALSE)
mod11p <- lmer(log(julian_median) ~ state * year_factor * insecticide + (1|plot), umbs_flwr_plot, REML=FALSE)
AICctab(mod1p, mod2p, mod3p, mod4p, mod5p, mod6p, mod7p, mod8p, mod9p, mod10p, mod11p, weights=T) # mod5p is best

##          dAICc df weight
## mod5p    0.0  5  0.278
## mod10p   0.1  7  0.258
## mod6p    1.3  6  0.143
## mod7p    1.7  6  0.116
## mod11p   2.2 10  0.093
## mod8p    3.1  7  0.059
## mod9p    3.3  7  0.053
## mod2p   55.4  4 <0.001
## mod1p   55.9  4 <0.001
## mod3p   57.2  5 <0.001
## mod4p   59.1  6 <0.001

anova(mod5p, mod7p) # go with simpler model 5p

```

```

## Data: umbs_flwr_plot
## Models:
## mod5p: log(julian_median) ~ state + year_factor + (1 | plot)
## mod7p: log(julian_median) ~ state * year_factor + (1 | plot)
##      npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod5p     5 -451.46 -437.52 230.73 -461.46
## mod7p     6 -449.94 -433.21 230.97 -461.94 0.4777  1     0.4895

```

```
AICctab(mod5p, mod7p, weights=T)
```

```
##      dAICc df weight
## mod5p 0.0   5  0.7
## mod7p 1.7   6  0.3
```

```
summ(mod5p)
```

```
## MODEL INFO:
## Observations: 120
## Dependent Variable: log(julian_median)
## Type: Mixed effects linear regression
##
```

```
## MODEL FIT:
## AIC = -451.46, BIC = -437.52
## Pseudo-R2 (fixed effects) = 0.31
## Pseudo-R2 (total) = 0.55
##
```

```
## FIXED EFFECTS:
## -----
```

	Est.	S.E.	t val.	d.f.	p
## (Intercept)	5.11	0.01	459.60	80.45	0.00
## stateambient	0.01	0.01	0.67	24.00	0.51
## year_factor	0.02	0.00	8.93	96.00	0.00

```
## -----
```

```
##
```

```
## p values calculated using Satterthwaite d.f.
```

```
##
```

```
## RANDOM EFFECTS:
## -----
```

Group	Parameter	Std. Dev.
## plot	(Intercept)	0.02
## Residual		0.03

```
## -----
```

```
##
```

```
## Grouping variables:
## -----
```

Group	# groups	ICC
## plot	24	0.35

```
## -----
```

```
summary(mod5p)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + year_factor + (1 | plot)
## Data: umbs_flwr_plot
##
```

```

##      AIC      BIC  logLik deviance df.resid
## -451.5   -437.5    230.7    -461.5      115
##
## Scaled residuals:
##      Min      1Q  Median      3Q     Max
## -3.4711 -0.5205 -0.0592  0.6232  2.2821
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0005201 0.02281
## Residual           0.0009634 0.03104
## Number of obs: 120, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)
## (Intercept) 5.110223  0.011119 80.446797 459.601 < 2e-16 ***
## stateambient 0.007274  0.010900 23.999999  0.667   0.511
## year_factor  0.017890  0.002004 96.000000  8.929 2.97e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) sttmbn
## stateambint -0.490
## year_factor -0.721  0.000

emmeans(mod5p, list(pairwise ~ state+year_factor), adjust = "tukey")

## $`emmeans of state, year_factor`
## state  year_factor emmean      SE      df lower.CL upper.CL
## warmed            4  5.182 0.00805 26.18    5.165   5.198
## ambient           4  5.189 0.00805 26.18    5.173   5.206
##
## 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
## warmed year_factor4 - ambient year_factor4 -0.00727 0.0114 26.2  -0.639
## p.value
## 0.5284
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.

# including native vs. exotic
umbs_flwr_plot_origin <- within(umbs_flwr_plot_origin, origin <- relevel(factor(origin), ref = "Native"))
mod12p <- lmer(log(julian_median) ~ state * origin + (1+year_factor|plot), umbs_flwr_plot_origin, REML=TRUE)

## boundary (singular) fit: see help('isSingular')

```

```

mod13p <- lmer(log(julian_median) ~ state + origin + (1+year_factor|plot), umbs_flwr_plot_origin, REML=TRUE)

## boundary (singular) fit: see help('isSingular')

mod14p <- lmer(log(julian_median) ~ state + origin + year_factor + (1|plot), umbs_flwr_plot_origin, REML=TRUE)

## boundary (singular) fit: see help('isSingular')

anova(mod12p, mod13p) # go with model 13p

## Data: umbs_flwr_plot_origin
## Models:
## mod13p: log(julian_median) ~ state + origin + (1 + year_factor | plot)
## mod12p: log(julian_median) ~ state * origin + (1 + year_factor | plot)
##      npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod13p     9 -606.74 -567.06 312.37   -624.74
## mod12p    12 -606.66 -553.75 315.33   -630.66 5.9171   3      0.1157

anova(mod13p, mod14p) # mod 14p

## Data: umbs_flwr_plot_origin
## Models:
## mod14p: log(julian_median) ~ state + origin + year_factor + (1 | plot)
## mod13p: log(julian_median) ~ state + origin + (1 + year_factor | plot)
##      npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod14p     8 -608.90 -573.63 312.45   -624.90
## mod13p     9 -606.74 -567.06 312.37   -624.74      0   1           1

summary(mod14p)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + origin + year_factor + (1 | plot)
## Data: umbs_flwr_plot_origin
##
##      AIC      BIC logLik deviance df.resid
##     -608.9   -573.6    312.5   -624.9      599
##
## Scaled residuals:
##      Min      1Q Median      3Q      Max
## -3.2499 -0.5014  0.0136  0.6508  1.8993
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.00000  0.0000
## Residual            0.02091  0.1446
## Number of obs: 607, groups:  plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)

```

```

## (Intercept) 5.299293 0.018166 607.000000 291.708 <2e-16 ***
## statewarmed 0.003932 0.011780 607.000000 0.334 0.739
## origin -0.052729 0.073673 607.000000 -0.716 0.474
## originBoth -0.159738 0.017073 607.000000 -9.356 <2e-16 ***
## originExotic -0.109924 0.012996 607.000000 -8.458 <2e-16 ***
## year_factor -0.001506 0.003741 607.000000 -0.403 0.687
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) sttwrm origin orgnBt orgnEx
## statewarmed -0.340
## origin -0.179 0.003
## originBoth -0.400 0.064 0.088
## originExotic -0.393 -0.005 0.096 0.403
## year_factor -0.792 0.025 0.143 0.119 0.023
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')

```

```
anova(mod14p)
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
## Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state 0.00233 0.00233 1 607 0.1114 0.7387
## origin 2.38287 0.79429 3 607 37.9800 <2e-16 ***
## year_factor 0.00339 0.00339 1 607 0.1620 0.6875
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

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

```
## boundary (singular) fit: see help('isSingular')
```

```

## $`emmeans of state, origin, year_factor`
## state origin year_factor emmean SE df lower.CL upper.CL
## ambient Native 3.662 5.294 0.01116 68.83 5.272 5.316
## warmed Native 3.662 5.298 0.01123 70.15 5.275 5.320
## ambient 3.662 5.241 0.07379 611.44 5.096 5.386
## warmed 3.662 5.245 0.07383 611.76 5.100 5.390
## ambient Both 3.662 5.134 0.01500 175.37 5.104 5.164
## warmed Both 3.662 5.138 0.01588 209.87 5.107 5.169
## ambient Exotic 3.662 5.184 0.01076 60.65 5.162 5.205
## warmed Exotic 3.662 5.188 0.01076 60.62 5.166 5.209
##
## 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, year_factor`
## 1
## ambient Native year_factor3.66227347611203 - warmed Native year_factor3.66227347611203
## ambient Native year_factor3.66227347611203 - ambient year_factor3.66227347611203

```

```

## ambient Native year_factor3.66227347611203 - warmed year_factor3.66227347611203
## ambient Native year_factor3.66227347611203 - ambient Both year_factor3.66227347611203
## ambient Native year_factor3.66227347611203 - warmed Both year_factor3.66227347611203
## ambient Native year_factor3.66227347611203 - ambient Exotic year_factor3.66227347611203
## ambient Native year_factor3.66227347611203 - warmed Exotic year_factor3.66227347611203
## warmed Native year_factor3.66227347611203 - ambient year_factor3.66227347611203
## warmed Native year_factor3.66227347611203 - warmed year_factor3.66227347611203
## warmed Native year_factor3.66227347611203 - ambient Both year_factor3.66227347611203
## warmed Native year_factor3.66227347611203 - warmed Both year_factor3.66227347611203
## warmed Native year_factor3.66227347611203 - ambient Exotic year_factor3.66227347611203
## warmed Native year_factor3.66227347611203 - warmed Exotic year_factor3.66227347611203
## ambient year_factor3.66227347611203 - warmed year_factor3.66227347611203
## ambient year_factor3.66227347611203 - ambient Both year_factor3.66227347611203
## ambient year_factor3.66227347611203 - warmed Both year_factor3.66227347611203
## ambient year_factor3.66227347611203 - ambient Exotic year_factor3.66227347611203
## ambient year_factor3.66227347611203 - warmed Exotic year_factor3.66227347611203
## warmed year_factor3.66227347611203 - ambient Both year_factor3.66227347611203
## warmed year_factor3.66227347611203 - warmed Both year_factor3.66227347611203
## warmed year_factor3.66227347611203 - ambient Exotic year_factor3.66227347611203
## warmed year_factor3.66227347611203 - warmed Exotic year_factor3.66227347611203
## ambient Both year_factor3.66227347611203 - warmed Both year_factor3.66227347611203
## ambient Both year_factor3.66227347611203 - ambient Exotic year_factor3.66227347611203
## ambient Both year_factor3.66227347611203 - warmed Exotic year_factor3.66227347611203
## warmed Both year_factor3.66227347611203 - ambient Exotic year_factor3.66227347611203
## warmed Both year_factor3.66227347611203 - warmed Exotic year_factor3.66227347611203
## ambient Exotic year_factor3.66227347611203 - warmed Exotic year_factor3.66227347611203
## estimate SE df t.ratio p.value
## -0.00393 0.0118 22.5 -0.332 1.0000
## 0.05273 0.0743 612.8 0.710 0.9967
## 0.04880 0.0752 606.7 0.649 0.9981
## 0.15974 0.0172 606.9 9.296 <.0001
## 0.15581 0.0215 191.6 7.253 <.0001
## 0.10992 0.0131 594.6 8.414 <.0001
## 0.10599 0.0176 103.1 6.026 <.0001
## 0.05666 0.0752 605.3 0.754 0.9952
## 0.05273 0.0743 612.8 0.710 0.9967
## 0.16367 0.0202 157.6 8.085 <.0001
## 0.15974 0.0172 606.9 9.296 <.0001
## 0.11386 0.0177 104.5 6.439 <.0001
## 0.10992 0.0131 594.6 8.414 <.0001
## -0.00393 0.0118 22.5 -0.332 1.0000
## 0.10701 0.0748 613.0 1.431 0.8425
## 0.10308 0.0758 603.9 1.359 0.8752
## 0.05719 0.0742 612.8 0.771 0.9945
## 0.05326 0.0751 605.5 0.710 0.9967
## 0.11094 0.0755 604.9 1.468 0.8240
## 0.10701 0.0748 613.0 1.431 0.8425
## 0.06113 0.0751 606.8 0.814 0.9924
## 0.05719 0.0742 612.8 0.771 0.9945
## -0.00393 0.0118 22.5 -0.332 1.0000
## -0.04981 0.0169 607.0 -2.950 0.0647
## -0.05375 0.0199 150.6 -2.694 0.1325
## -0.04588 0.0213 185.9 -2.156 0.3833
## -0.04981 0.0169 607.0 -2.950 0.0647

```

```

## -0.00393 0.0118 22.5 -0.332 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

# Phoebe ignore
# including growth form - first with interaction term
umbs_flwr_plot_growthhabit <- within(umbs_flwr_plot_growthhabit, growth_habit <- relevel(factor(growth_habit), "deciduous"))
mod15p <- lmer(log(julian_median) ~ state * growth_habit + (1+year_factor|plot), umbs_flwr_plot_growthhabit)

## boundary (singular) fit: see help('isSingular')

mod16p <- lmer(log(julian_median) ~ state + growth_habit + (1+year_factor|plot), umbs_flwr_plot_growthhabit)

## boundary (singular) fit: see help('isSingular')

mod17p <- lmer(log(julian_median) ~ state + growth_habit + year_factor + (1|plot), umbs_flwr_plot_growthhabit)
anova(mod15p, mod16p) # go with model 16pu

## Data: umbs_flwr_plot_growthhabit
## Models:
## mod16p: log(julian_median) ~ state + growth_habit + (1 + year_factor | plot)
## mod15p: log(julian_median) ~ state * growth_habit + (1 + year_factor | plot)
##      npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod16p     8 -1259.6 -1224.3 637.81   -1275.6
## mod15p    10 -1256.4 -1212.2 638.19   -1276.4 0.7531   2      0.6862

anova(mod16p, mod17p) # mod 17pu

## Data: umbs_flwr_plot_growthhabit
## Models:
## mod17p: log(julian_median) ~ state + growth_habit + year_factor + (1 | plot)
## mod16p: log(julian_median) ~ state + growth_habit + (1 + year_factor | plot)
##      npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod17p     7 -1262.5 -1231.6 638.26   -1276.5
## mod16p     8 -1259.6 -1224.3 637.81   -1275.6      0  1      1

summary(mod17p)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + growth_habit + year_factor + (1 |
##      plot)
## Data: umbs_flwr_plot_growthhabit
##
##      AIC      BIC logLik deviance df.resid
## -1262.5 -1231.6   638.3   -1276.5      606
##
## Scaled residuals:
```

```

##      Min     1Q   Median     3Q    Max
## -3.2072 -0.5881 -0.0492  0.4711  3.2640
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 3.925e-05 0.006265
## Residual           7.260e-03 0.085206
## Number of obs: 613, groups: plot, 24
##
## Fixed effects:
##                               Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)             5.318954  0.010535 279.429978 504.873 <2e-16 ***
## statewarmed            0.005897  0.007356 23.828948  0.802   0.431
## growth_habit          -0.219484  0.010089 604.507276 -21.755 <2e-16 ***
## growth_habitGraminoid -0.223689  0.007534 589.779435 -29.689 <2e-16 ***
## year_factor            0.002480  0.002194 598.154763   1.131   0.259
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) sttwrm grwth_ grwt_G
## statewarmed -0.352
## growth_habit -0.372  0.047
## grwth_hbtGr -0.334 -0.004  0.366
## year_factor  -0.782  0.006  0.118 -0.024

```

```
anova(mod17p)
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##                   Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state          0.0047  0.0047     1   23.83  0.6426 0.4307
## growth_habit  7.3938  3.6969     2  598.85 509.2054 <2e-16 ***
## year_factor   0.0093  0.0093     1  598.15  1.2782 0.2587
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

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

```

## $`emmeans of state, growth_habit, year_factor`
## state  growth_habit year_factor emmean       SE      df lower.CL upper.CL
## ambient Forb            3.69  5.328 0.006763 66.27   5.315  5.342
## warmed  Forb            3.69  5.334 0.006776 65.90   5.320  5.348
## ambient
## warmed            3.69  5.109 0.009392 202.23   5.090  5.127
## warmed            3.69  5.115 0.009770 224.53   5.095  5.134
## ambient Graminoid       3.69  5.104 0.006833 68.97   5.091  5.118
## warmed Graminoid       3.69  5.110 0.006815 67.66   5.097  5.124
##
## 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 year_factor3.69004893964111 - warmed Forb year_factor3.69004893964111
## ambient Forb year_factor3.69004893964111 - ambient year_factor3.69004893964111
## ambient Forb year_factor3.69004893964111 - warmed year_factor3.69004893964111
## ambient Forb year_factor3.69004893964111 - ambient Graminoid year_factor3.69004893964111
## ambient Forb year_factor3.69004893964111 - warmed Graminoid year_factor3.69004893964111
## warmed Forb year_factor3.69004893964111 - ambient year_factor3.69004893964111
## warmed Forb year_factor3.69004893964111 - warmed year_factor3.69004893964111
## warmed Forb year_factor3.69004893964111 - ambient Graminoid year_factor3.69004893964111
## warmed Forb year_factor3.69004893964111 - warmed Graminoid year_factor3.69004893964111
## ambient year_factor3.69004893964111 - warmed year_factor3.69004893964111
## ambient year_factor3.69004893964111 - ambient Graminoid year_factor3.69004893964111
## ambient year_factor3.69004893964111 - warmed Graminoid year_factor3.69004893964111
## warmed year_factor3.69004893964111 - ambient Graminoid year_factor3.69004893964111
## warmed year_factor3.69004893964111 - warmed Graminoid year_factor3.69004893964111
## ambient Graminoid year_factor3.69004893964111 - warmed Graminoid year_factor3.69004893964111
## estimate SE df t.ratio p.value
## -0.00590 0.00769 26.3 -0.767 0.9708
## 0.21948 0.01013 608.0 21.657 <.0001
## 0.21359 0.01300 192.2 16.432 <.0001
## 0.22369 0.00755 593.0 29.612 <.0001
## 0.21779 0.01076 104.8 20.237 <.0001
## 0.22538 0.01244 167.7 18.114 <.0001
## 0.21948 0.01013 608.0 21.657 <.0001
## 0.22959 0.01080 105.8 21.257 <.0001
## 0.22369 0.00755 593.0 29.612 <.0001
## -0.00590 0.00769 26.3 -0.767 0.9708
## 0.00421 0.01019 607.4 0.413 0.9985
## -0.00169 0.01247 169.6 -0.136 1.0000
## 0.01010 0.01306 195.1 0.774 0.9716
## 0.00421 0.01019 607.4 0.413 0.9985
## -0.00590 0.00769 26.3 -0.767 0.9708
##
## 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

```

KBS Species-level Mixed Effects Models

```

# Do we need to include plot as a random effect with the KBS models?
mod1k <- lmer(log(julian_median) ~ state*year_factor + insecticide*year_factor + (1|species) + (1|plot))
mod2k <- lmer(log(julian_median) ~ state*year_factor + insecticide*year_factor + (1|species), kbs_flwr_...
# Run analysis of variance on each model (see this for more explanation on how anova on a linear mixed
anova(mod1k)

## Type III Analysis of Variance Table with Satterthwaite's method
##          Sum Sq  Mean Sq NumDF DenDF F value    Pr(>F)
## state        0.0073318 0.0073318     1   291.58  3.5310 0.06123 .
## year_factor  0.0091266 0.0091266     1  1119.41  4.3953 0.03626 *
## insecticide  0.0005393 0.0005393     1   287.09  0.2597 0.61070
## state:year_factor 0.0068239 0.0068239     1  1115.45  3.2864 0.07013 .
## year_factor:insecticide 0.0000036 0.0000036     1  1113.40  0.0017 0.96666
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

anova(mod2k)

## Type III Analysis of Variance Table with Satterthwaite's method
##                                     Sum Sq  Mean Sq NumDF DenDF F value Pr(>F)
## state                      0.0085799 0.0085799     1 1118.3 4.0890 0.04340 *
## year_factor                 0.0097571 0.0097571     1 1119.5 4.6500 0.03127 *
## insecticide                  0.0004796 0.0004796     1 1118.3 0.2286 0.63267
## state:year_factor           0.0071248 0.0071248     1 1118.5 3.3955 0.06564 .
## year_factor:insecticide    0.0000016 0.0000016     1 1118.5 0.0008 0.97764
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Run an ANOVA to test the 2 models to test whether the more complex model is significantly better at c
anova(mod1k, mod2k) # models are not that different from each other so go with simpler model = model 2

## Data: kbs_flwr_spp
## Models:
## mod2k: log(julian_median) ~ state * year_factor + insecticide * year_factor + (1 | species)
## mod1k: log(julian_median) ~ state * year_factor + insecticide * year_factor + (1 | species) + (1 | p
##      npar   AIC   BIC logLik deviance Chisq Df Pr(>Chisq)
## mod2k    8 -3622.0 -3581.6 1819.0   -3638.0
## mod1k    9 -3622.1 -3576.7 1820.1   -3640.1 2.1026  1     0.1471

summary(mod1k)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## log(julian_median) ~ state * year_factor + insecticide * year_factor +
##   (1 | species) + (1 | plot)
## Data: kbs_flwr_spp
##
##      AIC      BIC logLik deviance df.resid
## -3622.1 -3576.7 1820.1   -3640.1     1142
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -5.7100 -0.5898 -0.0652  0.5671  4.0833
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## species  (Intercept) 5.308e-02 0.23039
## plot     (Intercept) 2.333e-05 0.00483
## Residual            2.076e-03 0.04557
## Number of obs: 1151, groups: species, 33; plot, 24
##
## Fixed effects:
##                               Estimate Std. Error      df t value
## (Intercept)                5.229e+00  4.072e-02 3.416e+01 128.402
## stateambient              -1.293e-02  6.881e-03 2.916e+02 -1.879
## year_factor                -3.117e-03  1.350e-03 1.114e+03 -2.309
## insecticideno_insects     3.499e-03  6.867e-03 2.871e+02  0.510

```

```

## stateambient:year_factor           2.755e-03  1.520e-03  1.115e+03  1.813
## year_factor:insecticideno_insects -6.346e-05  1.518e-03  1.113e+03 -0.042
##
##                                     Pr(>|t|)
## (Intercept)                      <2e-16 ***
## stateambient                      0.0612 .
## year_factor                        0.0211 *
## insecticideno_insects              0.6107
## stateambient:year_factor          0.0701 .
## year_factor:insecticideno_insects  0.9667
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) sttmbn yr_fct insct_ sttm:_
## stateambint -0.081
## year_factor -0.128  0.480
## insctcdn_ns -0.082 -0.007  0.484
## sttmbnt:yr_  0.069 -0.866 -0.549  0.014
## yr_fctr:ns_  0.069  0.010 -0.541 -0.869 -0.024

summary(mod2k)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## log(julian_median) ~ state * year_factor + insecticide * year_factor +
##   (1 | species)
## Data: kbs_flwr_spp
##
##      AIC      BIC      logLik deviance df.resid
## -3622.0 -3581.6    1819.0    -3638.0     1143
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -5.6930 -0.5948 -0.0669  0.5695  4.1365
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## species (Intercept) 0.052985 0.23019
## Residual            0.002098 0.04581
## Number of obs: 1151, groups: species, 33
##
## Fixed effects:
##                               Estimate Std. Error      df t value
## (Intercept)                  5.230e+00  4.066e-02 3.405e+01 128.633
## stateambient                 -1.336e-02  6.606e-03 1.118e+03 -2.022
## year_factor                  -3.203e-03  1.353e-03 1.119e+03 -2.367
## insecticideno_insects         3.150e-03  6.589e-03 1.118e+03  0.478
## stateambient:year_factor     2.805e-03  1.522e-03 1.119e+03  1.843
## year_factor:insecticideno_insects -4.265e-05  1.521e-03 1.119e+03 -0.028
##
##                                     Pr(>|t|)
## (Intercept)                      <2e-16 ***
## stateambient                      0.0434 *
## year_factor                        0.0181 *

```

```

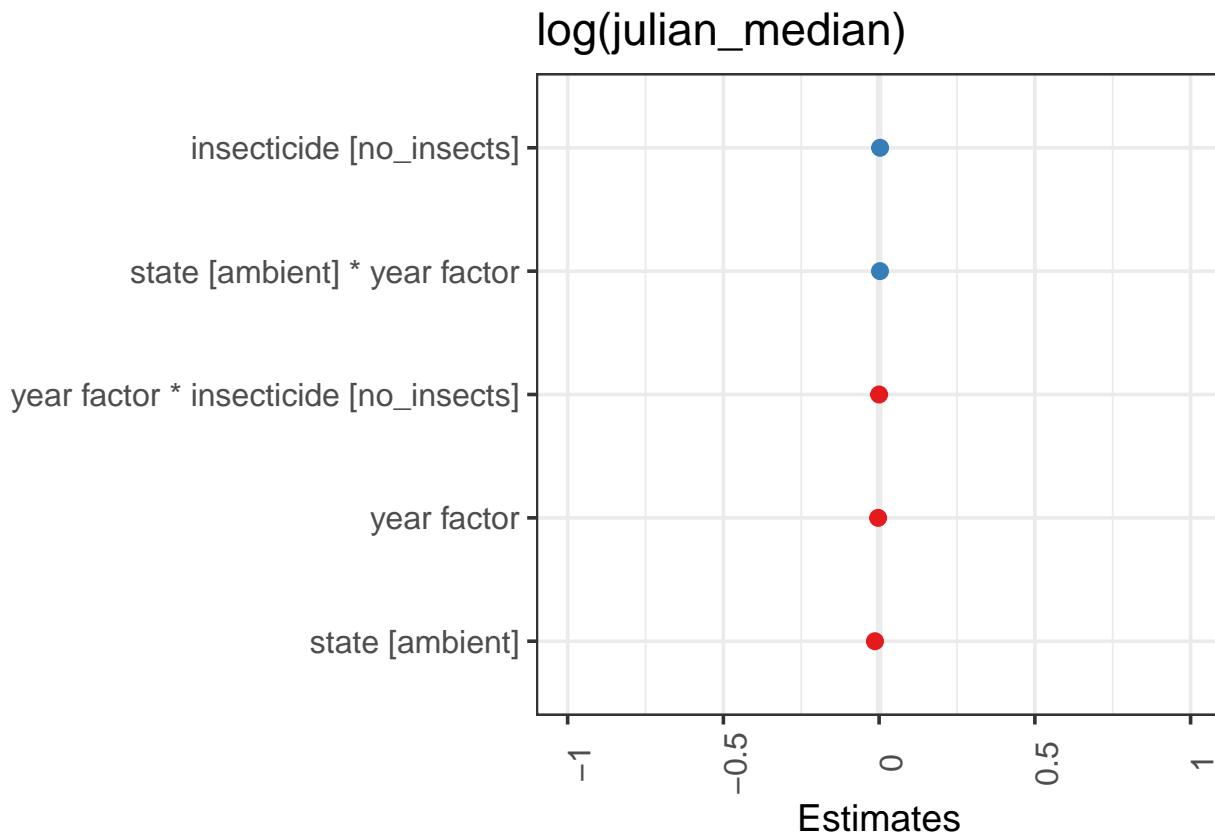
## insecticideno_insects          0.6327
## stateambient:year_factor       0.0656 .
## year_factor:insecticideno_insects  0.9776
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr) sttmbn yr_fct insct_ sttm:_
## stateambint -0.079
## year_factor -0.129  0.505
## insctcdn_ns -0.079 -0.004  0.505
## sttmbnt:yr_  0.070 -0.905 -0.554  0.011
## yr_fctr:ns_  0.069  0.007 -0.540 -0.908 -0.020

```

```

# Next, plot the model. There are multiple variables but here's one way to do it based on this package .
# https://strengejacke.github.io/sjPlot/articles/plot_model_estimates.html
# Annoyingly, this package somehow overwrites the factor order in its plotting so we will have to modify
#?plot_model
# Plot the fixed effects estimates for different models
# these are the fixed effects estimates
plot_model(mod2k, sort.est = TRUE)

```



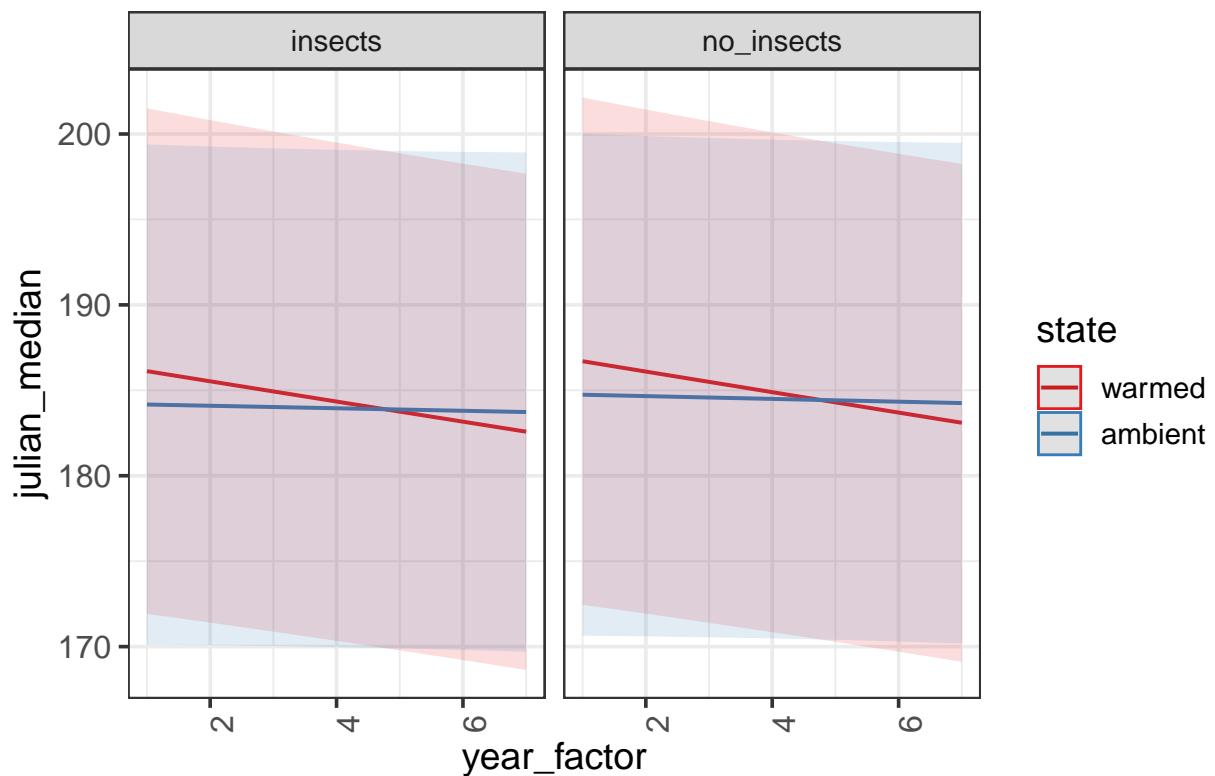
```

# these are the fixed predicted values:
plot_model(mod2k, type = "pred", terms = c("year_factor", "state", "insecticide"))

```

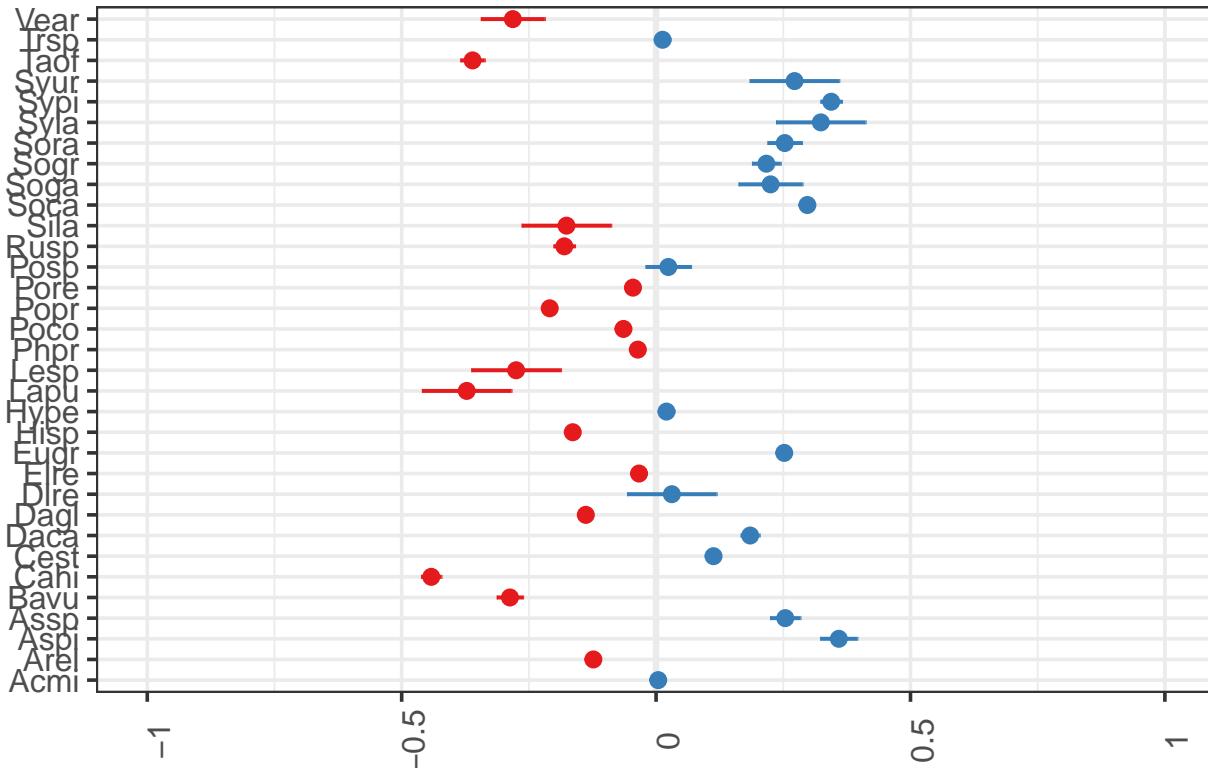
Model has log-transformed response. Back-transforming predictions to original response scale. Standardized residuals are back-transformed as well.

Predicted values of julian_median



```
# these are the random effects estimates  
plot_model(mod2k, type = "re", terms = c("species"))
```

Random effects



Do we need to include insecticide?

```
mod3k <- lmer(log(julian_median) ~ state*year_factor + (1|species), kbs_flwr_spp, REML=FALSE)
anova(mod2k, mod3k) # Don't need insecticide, continue with mod3 - the simpler model
```

Data: kbs_flwr_spp

Models:

mod3k: log(julian_median) ~ state * year_factor + (1 | species)

mod2k: log(julian_median) ~ state * year_factor + insecticide * year_factor + (1 | species)

npar AIC BIC logLik deviance Chisq Df Pr(>Chisq)

mod3k 6 -3624.8 -3594.6 1818.4 -3636.8

mod2k 8 -3622.0 -3581.6 1819.0 -3638.0 1.1718 2 0.5566

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

```
# mod4k <- lmer(log(julian_median) ~ state*year_factor + insecticide + (1/species) + (1/plot), kbs_flwr_spp, REML=FALSE)
```

Does year need to be interactive with state?

```
mod5k <- lmer(log(julian_median) ~ state + year_factor + (1|species) + (1|plot), kbs_flwr_spp, REML=FALSE)
anova(mod3k, mod5k) # models are pretty similar
```

Data: kbs_flwr_spp

Models:

mod3k: log(julian_median) ~ state * year_factor + (1 | species)

mod5k: log(julian_median) ~ state + year_factor + (1 | species) + (1 | plot)

npar AIC BIC logLik deviance Chisq Df Pr(>Chisq)

mod3k 6 -3624.8 -3594.6 1818.4 -3636.8

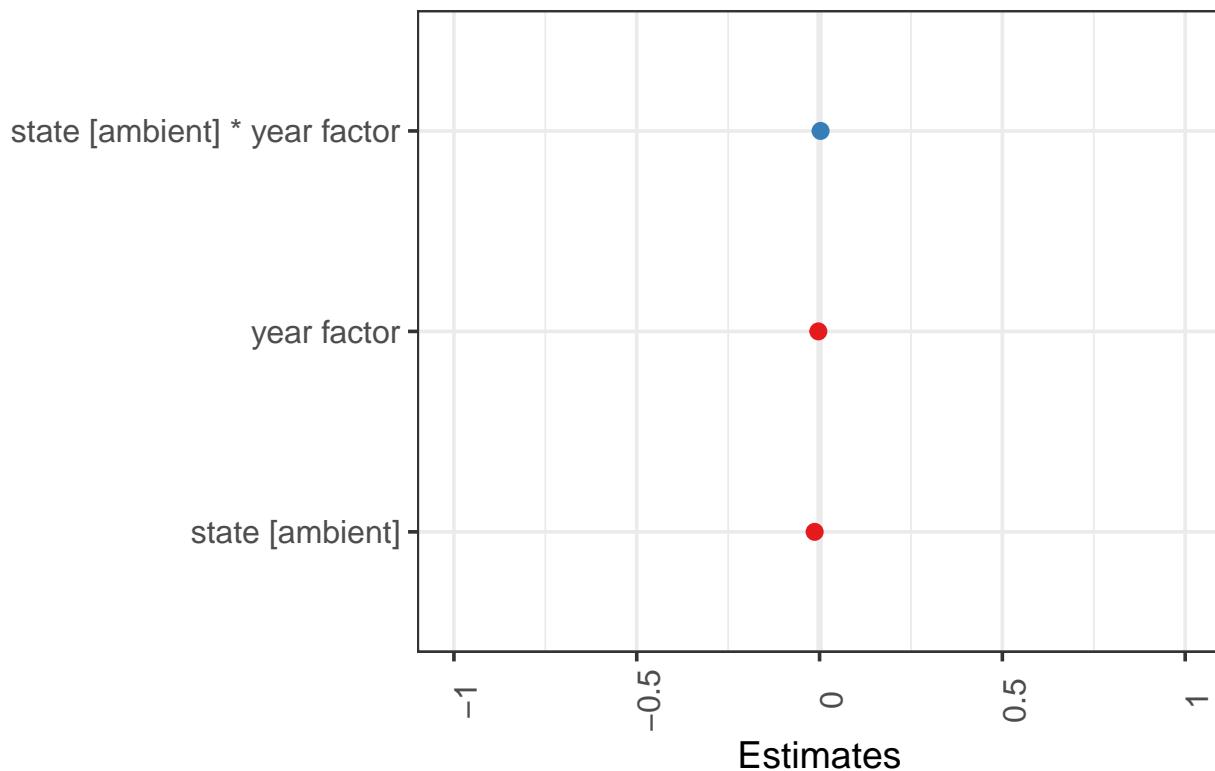
mod5k 6 -3623.9 -3593.6 1818.0 -3635.9 0 0

```
AICctab(mod3k, mod5k, weights=T) # go with mod3k
```

```
##      dAICc df weight
## mod3k 0.0    6  0.62
## mod5k 1.0    6  0.38
```

```
# Plot the fixed effects estimates for different models
# these are the fixed effects estimates from summary(mod3k)
plot_model(mod3k, sort.est = TRUE)
```

log(julian_median)

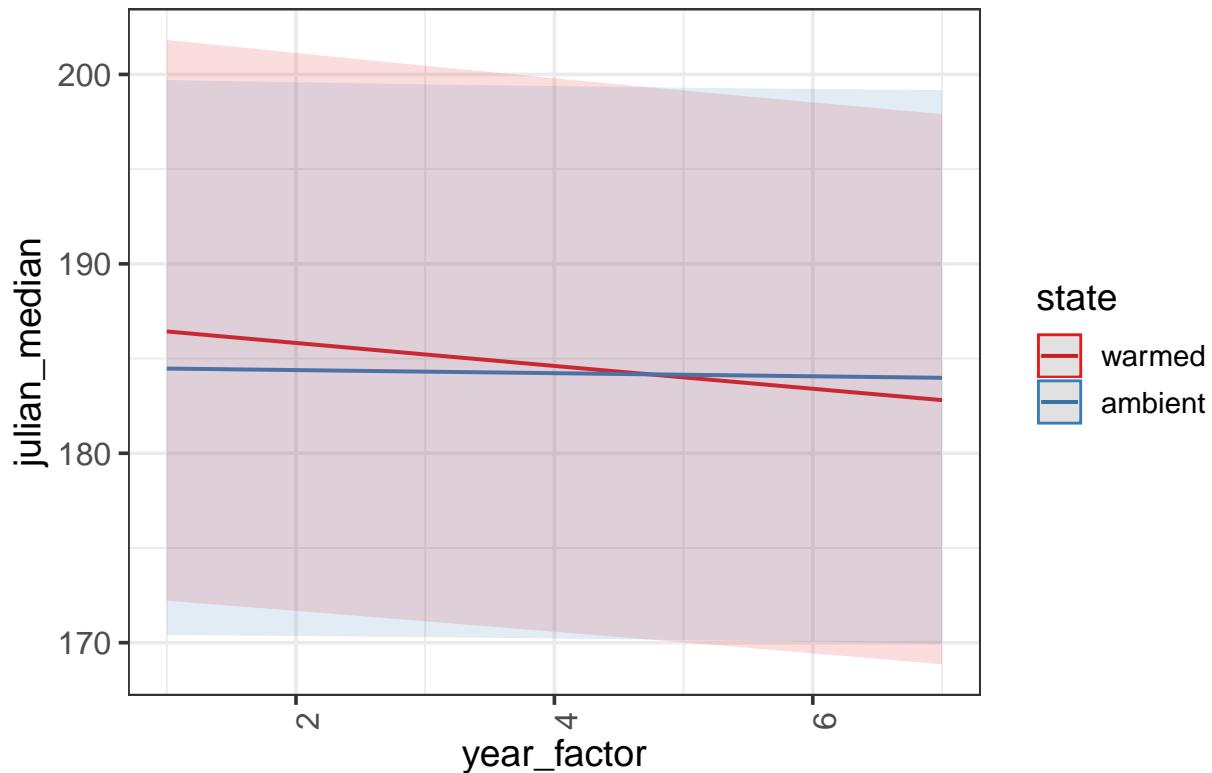


```
# these are the fixed predicted values:
```

```
plot_model(mod3k, type = "pred", terms = c("year_factor", "state"))
```

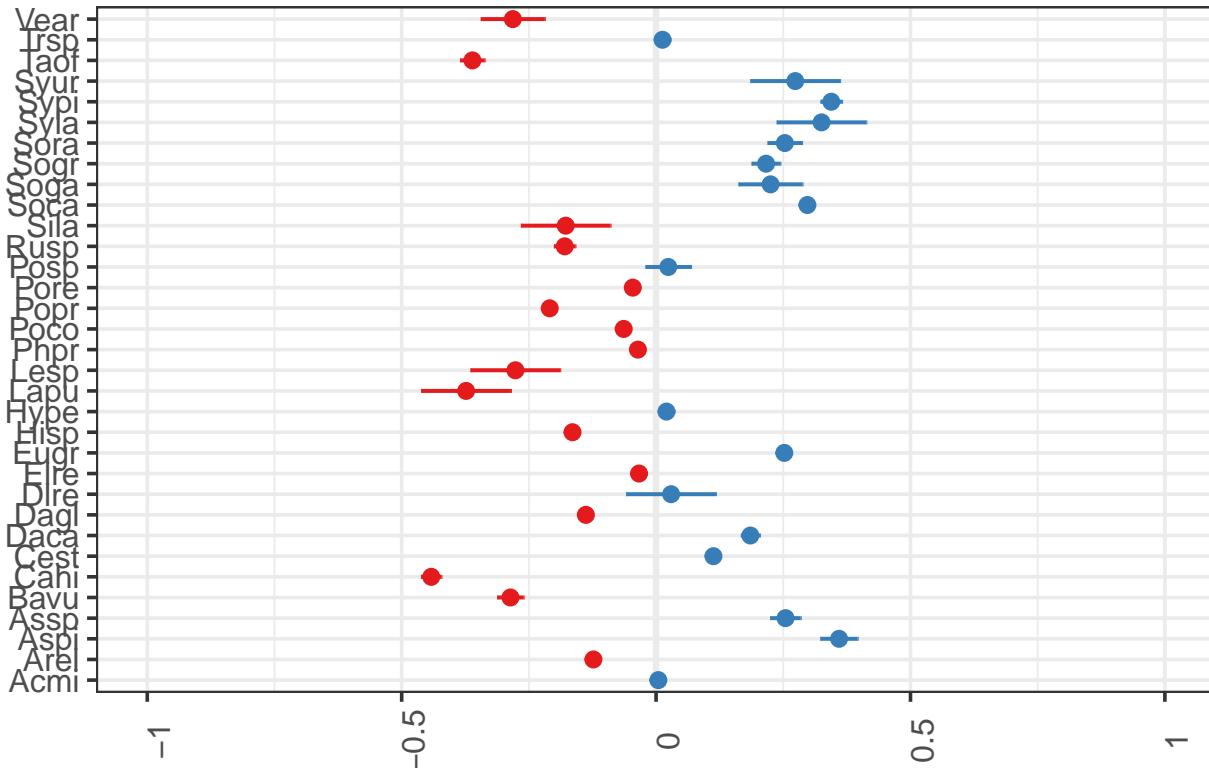
```
## Model has log-transformed response. Back-transforming predictions to original response scale. Standard
```

Predicted values of julian_median



```
# these are the random effects estimates
plot_model(mod3k, type = "re", terms = c("species"))
```

Random effects



```
# If we wanted to include plots nested within year it would look like this:
mod6k <- lmer(log(julian_median) ~ state + year_factor + (1|species) + (1 + year|plot), kbs_flwr_spp, REML = TRUE)

## boundary (singular) fit: see help('isSingular')

## Warning: Model failed to converge with 1 negative eigenvalue: -8.6e+08

anova(mod3k, mod6k) #stick with mod3k

## Data: kbs_flwr_spp
## Models:
## mod3k: log(julian_median) ~ state * year_factor + (1 | species)
## mod6k: log(julian_median) ~ state + year_factor + (1 | species) + (1 + year | plot)
##      npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod3k     6 -3624.8 -3594.6 1818.4   -3636.8
## mod6k     8 -3592.3 -3551.9 1804.2   -3608.3      0    2          1

anova(mod3k)

## Type III Analysis of Variance Table with Satterthwaite's method
##              Sum Sq  Mean Sq NumDF DenDF F value  Pr(>F)
## state           0.0086366 0.0086366     1 1118.4  4.1119 0.04282 *
## year_factor     0.0101664 0.0101664     1 1119.5  4.8403 0.02801 *
## state:year_factor 0.0072665 0.0072665     1 1118.6  3.4596 0.06315 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```

# We could consider an alternative model that's simpler to understand and also one that provides more information
mod7k <- lmer(log(julian_median) ~ state + species + (1+year_factor|plot), kbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod7ak <- lmer(log(julian_median) ~ state + species + year_factor + (1|plot), kbs_flwr_spp, REML=FALSE)
mod7bk <- lmer(log(julian_median) ~ state * year_factor + species + (1|plot), kbs_flwr_spp, REML=FALSE)
mod7ck <- lmer(log(julian_median) ~ state + species + year_factor + insecticide + (1|plot), kbs_flwr_spp, REML=FALSE)
anova(mod5k, mod7k) # model 7k is a better fit to data

## Data: kbs_flwr_spp
## Models:
## mod5k: log(julian_median) ~ state + year_factor + (1 | species) + (1 | plot)
## mod7k: log(julian_median) ~ state + species + (1 + year_factor | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod5k     6 -3623.9 -3593.6 1818.0   -3635.9
## mod7k    38 -3784.5 -3592.7 1930.3   -3860.5 224.64 32   < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(mod7k, mod7ak) #mod 7ak

## Data: kbs_flwr_spp
## Models:
## mod7ak: log(julian_median) ~ state + species + year_factor + (1 | plot)
## mod7k: log(julian_median) ~ state + species + (1 + year_factor | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod7ak    37 -3788.6 -3601.8 1931.3   -3862.6
## mod7k    38 -3784.5 -3592.7 1930.3   -3860.5      0  1           1

anova(mod7ak, mod7bk) #mod 7ak

## Data: kbs_flwr_spp
## Models:
## mod7ak: log(julian_median) ~ state + species + year_factor + (1 | plot)
## mod7bk: log(julian_median) ~ state * year_factor + species + (1 | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod7ak    37 -3788.6 -3601.8 1931.3   -3862.6
## mod7bk    38 -3789.9 -3598.0 1932.9   -3865.9 3.2529  1      0.0713 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

anova(mod7ak, mod7ck) #mod7ak

## Data: kbs_flwr_spp
## Models:
## mod7ak: log(julian_median) ~ state + species + year_factor + (1 | plot)
## mod7ck: log(julian_median) ~ state + species + year_factor + insecticide + (1 | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod7ak    37 -3788.6 -3601.8 1931.3   -3862.6
## mod7ck    38 -3787.6 -3595.7 1931.8   -3863.6 0.939  1      0.3325

```

```

summary(mod7ak)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + species + year_factor + (1 | plot)
## Data: kbs_flwr_spp
##
##      AIC      BIC  logLik deviance df.resid
## -3788.6 -3601.8  1931.3 -3862.6     1114
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -5.8540 -0.5924 -0.0494  0.5871  4.2201
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 2.299e-05 0.004795
## Residual           2.024e-03 0.044987
## Number of obs: 1151, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept) 5.230e+00 6.824e-03 7.077e+02 766.411 < 2e-16 ***
## stateambient -2.247e-03 3.399e-03 2.270e+01 -0.661  0.5152  
## speciesArel -1.272e-01 8.066e-03 1.148e+03 -15.768 < 2e-16 ***
## speciesAspi  3.567e-01 1.941e-02 1.141e+03 18.375 < 2e-16 ***
## speciesAssp  2.506e-01 1.620e-02 1.136e+03 15.474 < 2e-16 ***
## speciesBavu -2.928e-01 1.450e-02 1.148e+03 -20.193 < 2e-16 ***
## speciesCahi -4.469e-01 1.180e-02 1.143e+03 -37.865 < 2e-16 ***
## speciesCest  1.084e-01 8.062e-03 1.142e+03 13.445 < 2e-16 ***
## speciesDaca  1.820e-01 1.119e-02 1.145e+03 16.271 < 2e-16 ***
## speciesDagl -1.436e-01 8.630e-03 1.149e+03 -16.638 < 2e-16 ***
## speciesDlre  2.914e-02 4.556e-02 1.145e+03  0.640  0.5226  
## speciesElre -3.870e-02 8.034e-03 1.149e+03 -4.816 1.66e-06 ***
## speciesEugr  2.484e-01 8.970e-03 1.149e+03 27.697 < 2e-16 ***
## speciesHisp -1.681e-01 8.134e-03 1.146e+03 -20.664 < 2e-16 ***
## speciesHype  1.657e-02 1.007e-02 1.149e+03  1.645  0.1003  
## speciesLapu -4.010e-01 4.571e-02 1.147e+03 -8.771 < 2e-16 ***
## speciesLesp -2.915e-01 4.558e-02 1.147e+03 -6.395 2.34e-10 ***
## speciesPhpr -4.052e-02 7.503e-03 1.144e+03 -5.401 8.07e-08 ***
## speciesPoco -6.896e-02 8.979e-03 1.149e+03 -7.680 3.40e-14 ***
## speciesPopr -2.135e-01 7.356e-03 1.145e+03 -29.023 < 2e-16 ***
## speciesPore -5.001e-02 8.766e-03 1.147e+03 -5.706 1.47e-08 ***
## speciesPosp  2.077e-02 2.341e-02 1.147e+03  0.887  0.3752  
## speciesRusp -1.838e-01 1.234e-02 1.147e+03 -14.899 < 2e-16 ***
## speciesSila -1.848e-01 4.557e-02 1.145e+03 -4.055 5.36e-05 ***
## speciesSoca  2.930e-01 7.253e-03 1.144e+03 40.391 < 2e-16 ***
## speciesSoga  2.300e-01 3.250e-02 1.147e+03  7.076 2.59e-12 ***
## speciesSogr  2.139e-01 1.552e-02 1.148e+03 13.777 < 2e-16 ***
## speciesSora  2.508e-01 1.808e-02 1.141e+03 13.872 < 2e-16 ***
## speciesSyla  3.357e-01 4.568e-02 1.147e+03  7.349 3.78e-13 ***
## speciesSypi  3.414e-01 1.241e-02 1.149e+03 27.510 < 2e-16 ***
## speciesSyur  2.820e-01 4.568e-02 1.147e+03  6.173 9.30e-10 ***

```

```

## speciesTaof -3.656e-01 1.352e-02 1.151e+03 -27.038 < 2e-16 ***
## speciesTrsp 7.969e-03 9.937e-03 1.137e+03 0.802 0.4227
## speciesYear -2.927e-01 3.248e-02 1.145e+03 -9.011 < 2e-16 ***
## year_factor -1.817e-03 8.338e-04 1.151e+03 -2.179 0.0296 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

##
## Correlation matrix not shown by default, as p = 35 > 12.
## Use print(x, correlation=TRUE) or
##      vcov(x)      if you need it

```

`anova(mod7ak) # investigates whether at least one of the levels within each factor is significantly different.`

```

## Type III Analysis of Variance Table with Satterthwaite's method
##          Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state      0.001 0.00088     1    22.7 0.4371 0.51518
## species    39.819 1.24434    32 1144.2 614.8559 < 2e-16 ***
## year_factor 0.010 0.00961     1 1151.0  4.7466 0.02956 *
## ---
## 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 min first seed dates).`

`emmeans(mod7ak, list(pairwise ~ state + year_factor), adjust = "tukey")`

```

## $`emmeans of state, year_factor`
##   state  year_factor emmean       SE   df lower.CL upper.CL
##   warmed            3.95 5.219 0.004585 262.9    5.210    5.228
##   ambient            3.95 5.216 0.004551 264.6    5.207    5.225
## 
## 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
##   warmed year_factor3.9496090356212 - ambient year_factor3.9496090356212
##   estimate       SE   df t.ratio p.value
##   0.00225 0.00361 29.1   0.623  0.5381
## 
## Results are averaged over the levels of: species
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.

```

`emmeans(mod7ak, list(pairwise ~ year_factor), adjust = "tukey")`

`## 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

```

```

##          3.95  5.217 0.004197 533.9     5.209     5.226
##
## 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
##
## $` 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, species
## Note: contrasts are still on the log scale
## Degrees-of-freedom method: kenward-roger

emmeans(mod7ak, list(pairwise ~ species), adjust = "tukey")

## $`emmeans of species`
##   species emmean      SE   df lower.CL upper.CL
##   Acmi    5.222 0.006312 1015.8    5.209    5.234
##   Arel    5.095 0.005379  873.0    5.084    5.105
##   Aspi    5.578 0.018800 1185.9    5.542    5.615
##   Assp    5.472 0.015340 1187.1    5.442    5.502
##   Bavu    4.929 0.013465 1124.2    4.902    4.955
##   Cahi    4.775 0.010400 1169.5    4.754    4.795
##   Cest    5.330 0.005690  927.1    5.319    5.341
##   Daca    5.404 0.009677 1159.2    5.385    5.423
##   Dagl    5.078 0.006303  984.0    5.066    5.091
##   Dlre    5.251 0.045904 1181.4    5.161    5.341
##   Elre    5.183 0.005292  879.5    5.173    5.193
##   Eugr    5.470 0.006703  999.8    5.457    5.483
##   Hisp    5.054 0.005611  919.0    5.043    5.065
##   Hype    5.238 0.008266 1044.0    5.222    5.255
##   Lapu    4.821 0.045981 1182.7    4.731    4.911
##   Lesp    4.930 0.045915 1183.5    4.840    5.020
##   Phpr    5.181 0.004595  699.7    5.172    5.190
##   Poco    5.153 0.006639 1007.0    5.140    5.166
##   Popr    5.008 0.004220  630.6    5.000    5.017
##   Pore    5.172 0.006573 1031.4    5.159    5.185
##   Posp    5.242 0.023091 1185.5    5.197    5.288
##   Rusp    5.038 0.010998 1122.5    5.016    5.059
##   Sila    5.037 0.045931 1181.7    4.947    5.127
##   Soca    5.515 0.004015  568.0    5.507    5.523
##   Soga    5.452 0.032459 1184.4    5.388    5.515
##   Sogr    5.436 0.014558 1186.4    5.407    5.464
##   Sora    5.473 0.017376 1186.6    5.438    5.507
##   Syla    5.557 0.045993 1183.7    5.467    5.648
##   Sypi    5.563 0.010984 1176.4    5.542    5.585
##   Syur    5.504 0.045993 1183.7    5.413    5.594
##   Taof    4.856 0.012404 1167.4    4.832    4.880
##   Trsp    5.230 0.008266 1160.5    5.213    5.246
##   Vear    4.929 0.032455 1183.3    4.865    4.993
##
## 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 species’
##   estimate      SE   df t.ratio p.value
## Acmi - Arel  0.127183 0.00820 1183  15.514 <.0001
## Acmi - Aspi -0.356668 0.01972 1176 -18.091 <.0001
## Acmi - Assp -0.250598 0.01644 1171 -15.239 <.0001
## Acmi - Bavu  0.292834 0.01476 1186  19.833 <.0001
## Acmi - Cahи  0.446879 0.01199 1177  37.273 <.0001
## Acmi - Cest  -0.108400 0.00819 1177 -13.236 <.0001
## Acmi - Daca -0.182031 0.01137 1180 -16.012 <.0001
## Acmi - Dagл  0.143595 0.00877 1184  16.366 <.0001
## Acmi - Dlre -0.029136 0.04629 1179 -0.629 1.0000
## Acmi - Elre  0.038698 0.00817 1184  4.738 0.0011
## Acmi - Eugر -0.248449 0.00912 1184 -27.244 <.0001
## Acmi - Hisp  0.168076 0.00826 1181  20.336 <.0001
## Acmi - Hype -0.016570 0.01026 1187 -1.616 0.9996
## Acmi - Lapu  0.400970 0.04646 1182  8.630 <.0001
## Acmi - Lesp  0.291457 0.04632 1182  6.292 <.0001
## Acmi - Phpr  0.040520 0.00762 1179  5.316 0.0001
## Acmi - Poco  0.068958 0.00913 1184  7.554 <.0001
## Acmi - Popr  0.213495 0.00747 1180  28.564 <.0001
## Acmi - Pore  0.050013 0.00891 1182  5.614 <.0001
## Acmi - Posp -0.020772 0.02380 1182 -0.873 1.0000
## Acmi - Rusp  0.183809 0.01257 1186  14.628 <.0001
## Acmi - Sila  0.184760 0.04630 1180  3.990 0.0259
## Acmi - Soca -0.292971 0.00737 1179 -39.757 <.0001
## Acmi - Soga -0.229969 0.03303 1182 -6.962 <.0001
## Acmi - Sogr -0.213874 0.01578 1183 -13.553 <.0001
## Acmi - Sora -0.250833 0.01837 1176 -13.657 <.0001
## Acmi - Syla -0.335740 0.04643 1182 -7.231 <.0001
## Acmi - Sypi -0.341382 0.01262 1184 -27.061 <.0001
## Acmi - Syur -0.281996 0.04643 1182 -6.074 <.0001
## Acmi - Taof  0.365603 0.01376 1187  26.572 <.0001
## Acmi - Trsp -0.007969 0.01009 1172 -0.790 1.0000
## Acmi - Vear  0.292656 0.03300 1179  8.868 <.0001
## Arel - Aspi -0.483851 0.01949 1180 -24.825 <.0001
## Arel - Assp -0.377781 0.01618 1176 -23.354 <.0001
## Arel - Bavu  0.165651 0.01443 1166  11.480 <.0001
## Arel - Cahи  0.319696 0.01165 1184  27.439 <.0001
## Arel - Cest -0.235583 0.00776 1186 -30.370 <.0001
## Arel - Daca -0.309214 0.01097 1184 -28.186 <.0001
## Arel - Dagл  0.016413 0.00813 1184  2.019 0.9845
## Arel - Dlre -0.156319 0.04621 1180 -3.383 0.1803
## Arel - Elre -0.088485 0.00736 1183 -12.019 <.0001
## Arel - Eugر -0.375632 0.00842 1187 -44.610 <.0001
## Arel - Hisp  0.040893 0.00761 1183  5.376 <.0001
## Arel - Hype -0.143753 0.00973 1186 -14.774 <.0001
## Arel - Lapu  0.273787 0.04625 1182  5.920 <.0001
## Arel - Lesp  0.164274 0.04619 1181  3.556 0.1105
## Arel - Phpr -0.086663 0.00691 1185 -12.539 <.0001
## Arel - Poco -0.058225 0.00832 1186 -7.000 <.0001

```

```

## Arel - Popr  0.086312 0.00662 1177  13.040 <.0001
## Arel - Pore -0.077170 0.00835 1184  -9.238 <.0001
## Arel - Posp -0.147955 0.02370 1179  -6.242 <.0001
## Arel - Rusp  0.056626 0.01214 1181   4.666 0.0016
## Arel - Sila  0.057577 0.04625 1181   1.245 1.0000
## Arel - Soca -0.420154 0.00649 1177 -64.786 <.0001
## Arel - Soga -0.357152 0.03285 1181 -10.872 <.0001
## Arel - Sogr -0.341057 0.01545 1183 -22.076 <.0001
## Arel - Sora -0.378016 0.01816 1181 -20.818 <.0001
## Arel - Syla -0.462923 0.04624 1182 -10.012 <.0001
## Arel - Sypi -0.468565 0.01206 1182 -38.838 <.0001
## Arel - Syur -0.409178 0.04624 1182  -8.849 <.0001
## Arel - Taof  0.238420 0.01345 1187  17.730 <.0001
## Arel - Trsp -0.135152 0.00984 1175 -13.731 <.0001
## Arel - Vear  0.165474 0.03286 1180   5.035 0.0003
## Aspi - Assp  0.106071 0.02411 1170   4.399 0.0051
## Aspi - Bavu  0.649503 0.02307 1185  28.153 <.0001
## Aspi - Cahi  0.803547 0.02146 1178  37.452 <.0001
## Aspi - Cest  0.248268 0.01955 1180  12.699 <.0001
## Aspi - Daca  0.174637 0.02102 1177   8.308 <.0001
## Aspi - Dagl  0.500264 0.01976 1179  25.315 <.0001
## Aspi - Dlre  0.327532 0.04961 1179   6.602 <.0001
## Aspi - Elre  0.395366 0.01952 1180  20.252 <.0001
## Aspi - Eugr  0.108219 0.01993 1182   5.431 <.0001
## Aspi - Hisp  0.524744 0.01953 1179  26.875 <.0001
## Aspi - Hype  0.340098 0.02050 1186  16.587 <.0001
## Aspi - Lapu  0.757638 0.04970 1181  15.245 <.0001
## Aspi - Lesp  0.648126 0.04963 1182  13.059 <.0001
## Aspi - Phpr  0.397188 0.01929 1179  20.595 <.0001
## Aspi - Poco  0.425626 0.01988 1179  21.413 <.0001
## Aspi - Popr  0.570163 0.01921 1179  29.681 <.0001
## Aspi - Pore  0.406681 0.01981 1181  20.532 <.0001
## Aspi - Posp  0.335896 0.02975 1183  11.290 <.0001
## Aspi - Rusp  0.540478 0.02163 1180  24.990 <.0001
## Aspi - Sila  0.541428 0.04963 1180  10.909 <.0001
## Aspi - Soca  0.063697 0.01917 1178   3.323 0.2102
## Aspi - Soga  0.126699 0.03750 1183   3.378 0.1823
## Aspi - Sogr  0.142794 0.02373 1181   6.017 <.0001
## Aspi - Sora  0.105835 0.02553 1175   4.146 0.0144
## Aspi - Syla  0.020929 0.04959 1179   0.422 1.0000
## Aspi - Sypi  0.015286 0.02161 1174   0.707 1.0000
## Aspi - Syur  0.074673 0.04959 1179   1.506 0.9999
## Aspi - Taof  0.722271 0.02239 1178  32.264 <.0001
## Aspi - Trsp  0.348700 0.02044 1176  17.061 <.0001
## Aspi - Vear  0.649325 0.03744 1178  17.342 <.0001
## Assp - Bavu  0.543432 0.02037 1187  26.684 <.0001
## Assp - Cahi  0.697477 0.01844 1172  37.826 <.0001
## Assp - Cest  0.142198 0.01624 1177   8.758 <.0001
## Assp - Daca  0.068567 0.01799 1173   3.811 0.0490
## Assp - Dagl  0.394193 0.01649 1174  23.909 <.0001
## Assp - Dlre  0.221462 0.04834 1176   4.581 0.0023
## Assp - Elre  0.289295 0.01620 1179  17.861 <.0001
## Assp - Eugr  0.002148 0.01669 1179   0.129 1.0000
## Assp - Hisp  0.418674 0.01624 1178  25.788 <.0001

```

```

## Assp - Hype 0.234027 0.01736 1185 13.483 <.0001
## Assp - Lapu 0.651568 0.04850 1181 13.434 <.0001
## Assp - Lesp 0.542055 0.04842 1182 11.196 <.0001
## Assp - Phpr 0.291118 0.01592 1174 18.288 <.0001
## Assp - Poco 0.319556 0.01665 1177 19.188 <.0001
## Assp - Popr 0.464093 0.01584 1178 29.290 <.0001
## Assp - Pore 0.300611 0.01656 1175 18.158 <.0001
## Assp - Posp 0.229826 0.02765 1181 8.312 <.0001
## Assp - Rusp 0.434407 0.01876 1183 23.162 <.0001
## Assp - Sila 0.435358 0.04836 1177 9.003 <.0001
## Assp - Soca -0.042373 0.01579 1177 -2.683 0.6891
## Assp - Soga 0.020628 0.03589 1183 0.575 1.0000
## Assp - Sogr 0.036723 0.02109 1181 1.741 0.9986
## Assp - Sora -0.000235 0.02309 1175 -0.010 1.0000
## Assp - Syla -0.085142 0.04843 1180 -1.758 0.9983
## Assp - Sypi -0.090785 0.01875 1176 -4.841 0.0007
## Assp - Syur -0.031398 0.04843 1180 -0.648 1.0000
## Assp - Taof 0.616201 0.01960 1181 31.432 <.0001
## Assp - Trsp 0.242629 0.01729 1173 14.033 <.0001
## Assp - Vear 0.543254 0.03581 1175 15.170 <.0001
## Bavu - Cahи 0.154045 0.01690 1185 9.117 <.0001
## Bavu - Cest -0.401234 0.01458 1171 -27.512 <.0001
## Bavu - Daca -0.474866 0.01652 1182 -28.741 <.0001
## Bavu - Dagl -0.149239 0.01479 1170 -10.088 <.0001
## Bavu - Dlre -0.321971 0.04783 1184 -6.732 <.0001
## Bavu - Elre -0.254137 0.01434 1175 -17.724 <.0001
## Bavu - Eogr -0.541284 0.01491 1180 -36.304 <.0001
## Bavu - Hisp -0.124758 0.01454 1168 -8.581 <.0001
## Bavu - Hype -0.309405 0.01569 1178 -19.716 <.0001
## Bavu - Lapu 0.108136 0.04788 1185 2.259 0.9346
## Bavu - Lesp -0.001377 0.04775 1182 -0.029 1.0000
## Bavu - Phpr -0.252314 0.01415 1171 -17.834 <.0001
## Bavu - Poco -0.223876 0.01492 1170 -15.010 <.0001
## Bavu - Popr -0.079339 0.01402 1172 -5.660 <.0001
## Bavu - Pore -0.242821 0.01496 1170 -16.232 <.0001
## Bavu - Posp -0.313606 0.02675 1187 -11.725 <.0001
## Bavu - Rusp -0.109025 0.01727 1183 -6.313 <.0001
## Bavu - Sila -0.108075 0.04786 1184 -2.258 0.9348
## Bavu - Soca -0.585805 0.01395 1173 -41.994 <.0001
## Bavu - Soga -0.522804 0.03513 1187 -14.881 <.0001
## Bavu - Sogr -0.506709 0.01976 1187 -25.639 <.0001
## Bavu - Sora -0.543667 0.02187 1184 -24.854 <.0001
## Bavu - Syla -0.628574 0.04791 1185 -13.119 <.0001
## Bavu - Sypi -0.634217 0.01735 1182 -36.562 <.0001
## Bavu - Syur -0.574830 0.04791 1185 -11.997 <.0001
## Bavu - Taof 0.072769 0.01827 1179 3.982 0.0268
## Bavu - Trsp -0.300803 0.01580 1176 -19.038 <.0001
## Bavu - Vear -0.000178 0.03513 1186 -0.005 1.0000
## Cahи - Cest -0.555279 0.01168 1184 -47.521 <.0001
## Cahи - Daca -0.628910 0.01410 1182 -44.599 <.0001
## Cahи - Dagl -0.303283 0.01204 1183 -25.187 <.0001
## Cahи - Dlre -0.476015 0.04696 1177 -10.136 <.0001
## Cahи - Elre -0.408181 0.01155 1182 -35.351 <.0001
## Cahи - Eogr -0.695328 0.01226 1182 -56.693 <.0001

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## Cah - Hisp -0.278803 0.01173 1184 -23.760 <.0001
## Cah - Hype -0.463449 0.01314 1185 -35.268 <.0001
## Cah - Lapu -0.045909 0.04717 1183 -0.973 1.0000
## Cah - Lesp -0.155421 0.04699 1180 -3.308 0.2186
## Cah - Phpr -0.406359 0.01124 1181 -36.150 <.0001
## Cah - Poco -0.377921 0.01230 1183 -30.733 <.0001
## Cah - Popr -0.233384 0.01115 1184 -20.932 <.0001
## Cah - Pore -0.396866 0.01222 1183 -32.485 <.0001
## Cah - Posp -0.467651 0.02519 1181 -18.564 <.0001
## Cah - Rusp -0.263070 0.01504 1185 -17.493 <.0001
## Cah - Sila -0.262119 0.04697 1178 -5.580 <.0001
## Cah - Soca -0.739850 0.01107 1183 -66.837 <.0001
## Cah - Soga -0.676848 0.03407 1184 -19.864 <.0001
## Cah - Sogr -0.660753 0.01781 1184 -37.095 <.0001
## Cah - Sora -0.697712 0.02012 1175 -34.685 <.0001
## Cah - Syla -0.782618 0.04721 1183 -16.578 <.0001
## Cah - Sypi -0.788261 0.01516 1183 -52.003 <.0001
## Cah - Syur -0.728874 0.04721 1183 -15.440 <.0001
## Cah - Taof -0.081276 0.01609 1187 -5.050 0.0003
## Cah - Trsp -0.454848 0.01307 1178 -34.812 <.0001
## Cah - Vear -0.154222 0.03401 1179 -4.534 0.0029
## Cest - Daca -0.073631 0.01103 1180 -6.677 <.0001
## Cest - Dagl 0.251995 0.00834 1185 30.223 <.0001
## Cest - Dlre 0.079264 0.04621 1179 1.715 0.9989
## Cest - Elre 0.147098 0.00771 1184 19.086 <.0001
## Cest - Eogr -0.140049 0.00874 1187 -16.024 <.0001
## Cest - Hisp 0.276476 0.00779 1178 35.480 <.0001
## Cest - Hype 0.091830 0.00989 1184 9.282 <.0001
## Cest - Lapu 0.509370 0.04638 1181 10.983 <.0001
## Cest - Lesp 0.399857 0.04625 1182 8.645 <.0001
## Cest - Phpr 0.148920 0.00711 1178 20.942 <.0001
## Cest - Poco 0.177358 0.00875 1187 20.270 <.0001
## Cest - Popr 0.321895 0.00696 1178 46.218 <.0001
## Cest - Pore 0.158413 0.00846 1180 18.716 <.0001
## Cest - Posp 0.087628 0.02360 1180 3.714 0.0678
## Cest - Rusp 0.292209 0.01232 1173 23.720 <.0001
## Cest - Sila 0.293160 0.04621 1179 6.344 <.0001
## Cest - Soca -0.184571 0.00686 1178 -26.912 <.0001
## Cest - Soga -0.121569 0.03293 1183 -3.692 0.0726
## Cest - Sogr -0.105474 0.01555 1185 -6.782 <.0001
## Cest - Sora -0.142433 0.01818 1181 -7.835 <.0001
## Cest - Syla -0.227340 0.04636 1182 -4.903 0.0005
## Cest - Sypi -0.232982 0.01234 1185 -18.884 <.0001
## Cest - Syur -0.173595 0.04636 1182 -3.744 0.0613
## Cest - Taof 0.474003 0.01349 1187 35.125 <.0001
## Cest - Trsp 0.100431 0.00966 1169 10.392 <.0001
## Cest - Vear 0.401057 0.03289 1180 12.194 <.0001
## Daca - Dagl 0.325627 0.01141 1180 28.528 <.0001
## Daca - Dlre 0.152895 0.04686 1178 3.263 0.2442
## Daca - Elre 0.220729 0.01097 1185 20.123 <.0001
## Daca - Eogr -0.066418 0.01170 1187 -5.677 <.0001
## Daca - Hisp 0.350107 0.01105 1186 31.671 <.0001
## Daca - Hype 0.165461 0.01261 1187 13.123 <.0001
## Daca - Lapu 0.583001 0.04702 1182 12.400 <.0001

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## Daca - Lesp 0.473489 0.04693 1183 10.090 <.0001
## Daca - Phpr 0.222551 0.01057 1181 21.046 <.0001
## Daca - Poco 0.250989 0.01166 1184 21.527 <.0001
## Daca - Popr 0.395526 0.01045 1183 37.834 <.0001
## Daca - Pore 0.232044 0.01153 1183 20.124 <.0001
## Daca - Posp 0.161259 0.02491 1178 6.473 <.0001
## Daca - Rusp 0.365841 0.01453 1187 25.184 <.0001
## Daca - Sila 0.366791 0.04688 1178 7.825 <.0001
## Daca - Soca -0.110940 0.01038 1183 -10.689 <.0001
## Daca - Soga -0.047938 0.03385 1183 -1.416 1.0000
## Daca - Sogr -0.031843 0.01742 1186 -1.828 0.9967
## Daca - Sora -0.068802 0.01979 1178 -3.476 0.1396
## Daca - Syla -0.153708 0.04699 1183 -3.271 0.2395
## Daca - Sypi -0.159351 0.01454 1185 -10.957 <.0001
## Daca - Syur -0.099964 0.04699 1183 -2.127 0.9684
## Daca - Taof 0.547634 0.01562 1187 35.062 <.0001
## Daca - Trsp 0.174063 0.01254 1178 13.878 <.0001
## Daca - Vear 0.474688 0.03382 1180 14.036 <.0001
## Dagl - Dlre -0.172732 0.04629 1179 -3.731 0.0639
## Dagl - Elre -0.104898 0.00807 1184 -12.996 <.0001
## Dagl - Eogr -0.392045 0.00906 1187 -43.262 <.0001
## Dagl - Hisp 0.024481 0.00830 1187 2.949 0.4697
## Dagl - Hype -0.160166 0.01026 1186 -15.605 <.0001
## Dagl - Lapu 0.257374 0.04635 1179 5.553 <.0001
## Dagl - Lesp 0.147862 0.04633 1183 3.192 0.2886
## Dagl - Phpr -0.103076 0.00761 1175 -13.546 <.0001
## Dagl - Poco -0.074637 0.00897 1176 -8.317 <.0001
## Dagl - Popr 0.069899 0.00742 1185 9.415 <.0001
## Dagl - Pore -0.093583 0.00894 1177 -10.470 <.0001
## Dagl - Posp -0.164368 0.02387 1179 -6.886 <.0001
## Dagl - Rusp 0.040214 0.01256 1186 3.201 0.2823
## Dagl - Sila 0.041164 0.04632 1179 0.889 1.0000
## Dagl - Soca -0.436566 0.00731 1184 -59.762 <.0001
## Dagl - Soga -0.373565 0.03304 1183 -11.305 <.0001
## Dagl - Sogr -0.357470 0.01578 1183 -22.659 <.0001
## Dagl - Sora -0.394428 0.01842 1180 -21.418 <.0001
## Dagl - Syla -0.479335 0.04642 1184 -10.327 <.0001
## Dagl - Sypi -0.484978 0.01259 1187 -38.526 <.0001
## Dagl - Syur -0.425591 0.04642 1184 -9.169 <.0001
## Dagl - Taof 0.222008 0.01382 1187 16.062 <.0001
## Dagl - Trsp -0.151564 0.01027 1178 -14.758 <.0001
## Dagl - Vear 0.149061 0.03300 1178 4.518 0.0031
## Dlre - Elre 0.067834 0.04617 1180 1.469 0.9999
## Dlre - Eogr -0.219313 0.04635 1179 -4.731 0.0012
## Dlre - Hisp 0.197212 0.04623 1180 4.266 0.0089
## Dlre - Hype 0.012566 0.04657 1178 0.270 1.0000
## Dlre - Lapu 0.430106 0.06500 1182 6.617 <.0001
## Dlre - Lesp 0.320594 0.06491 1182 4.939 0.0004
## Dlre - Phpr 0.069656 0.04610 1179 1.511 0.9999
## Dlre - Poco 0.098094 0.04640 1181 2.114 0.9708
## Dlre - Popr 0.242631 0.04608 1180 5.265 0.0001
## Dlre - Pore 0.079149 0.04634 1178 1.708 0.9990
## Dlre - Posp 0.008364 0.05133 1180 0.163 1.0000
## Dlre - Rusp 0.212946 0.04720 1182 4.511 0.0032

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## Dlre - Sila  0.213896 0.06456 1160   3.313  0.2157
## Dlre - Soca -0.263835 0.04606 1180  -5.728 <.0001
## Dlre - Soga -0.200833 0.05621 1181  -3.573  0.1053
## Dlre - Sogr -0.184738 0.04810 1178  -3.841  0.0442
## Dlre - Sora -0.221697 0.04899 1177  -4.525  0.0030
## Dlre - Syla -0.306603 0.06503 1182  -4.715  0.0013
## Dlre - Sypi -0.312246 0.04723 1180  -6.611 <.0001
## Dlre - Syur -0.252859 0.06503 1182  -3.888  0.0375
## Dlre - Taof  0.394739 0.04753 1181   8.305 <.0001
## Dlre - Trsp  0.021168 0.04657 1178   0.455  1.0000
## Dlre - Vear  0.321793 0.05601 1168   5.745 <.0001
## Elre - Eugr -0.287147 0.00834 1186  -34.419 <.0001
## Elre - Hisp  0.129378 0.00759 1183   17.043 <.0001
## Elre - Hype -0.055268 0.00970 1184  -5.698 <.0001
## Elre - Lapu  0.362272 0.04621 1181   7.839 <.0001
## Elre - Lesp  0.252760 0.04618 1182   5.474 <.0001
## Elre - Phpr  0.001822 0.00683 1178   0.267  1.0000
## Elre - Poco  0.030260 0.00827 1183   3.660  0.0805
## Elre - Popr  0.174797 0.00656 1174  26.645 <.0001
## Elre - Pore  0.011315 0.00835 1179   1.356  1.0000
## Elre - Posp -0.059470 0.02369 1181  -2.511  0.8131
## Elre - Rusp  0.145112 0.01210 1187  11.992 <.0001
## Elre - Sila  0.146062 0.04621 1180   3.161  0.3091
## Elre - Soca -0.331669 0.00642 1173  -51.670 <.0001
## Elre - Soga -0.268667 0.03285 1182  -8.178 <.0001
## Elre - Sogr -0.252572 0.01541 1182  -16.389 <.0001
## Elre - Sora -0.289531 0.01811 1178  -15.991 <.0001
## Elre - Syla -0.374437 0.04627 1183  -8.093 <.0001
## Elre - Sypi -0.380080 0.01211 1181  -31.381 <.0001
## Elre - Syur -0.320693 0.04627 1183  -6.931 <.0001
## Elre - Taof  0.326905 0.01344 1187  24.326 <.0001
## Elre - Trsp -0.046666 0.00979 1175  -4.767  0.0010
## Elre - Vear  0.253959 0.03286 1181   7.728 <.0001
## Eugr - Hisp  0.416525 0.00862 1187  48.338 <.0001
## Eugr - Hype  0.231879 0.01053 1184  22.026 <.0001
## Eugr - Lapu  0.649419 0.04640 1181  13.997 <.0001
## Eugr - Lesp  0.539907 0.04639 1184  11.638 <.0001
## Eugr - Phpr  0.288969 0.00798 1187  36.198 <.0001
## Eugr - Poco  0.317407 0.00925 1187  34.331 <.0001
## Eugr - Popr  0.461944 0.00774 1187  59.655 <.0001
## Eugr - Pore  0.298462 0.00930 1187  32.098 <.0001
## Eugr - Posp  0.227677 0.02405 1182  9.468 <.0001
## Eugr - Rusp  0.432259 0.01274 1187  33.916 <.0001
## Eugr - Sila  0.433209 0.04639 1180  9.339 <.0001
## Eugr - Soca -0.044522 0.00762 1187  -5.840 <.0001
## Eugr - Soga  0.018480 0.03308 1180  0.559  1.0000
## Eugr - Sogr  0.034575 0.01591 1176  2.173  0.9587
## Eugr - Sora -0.002384 0.01853 1170  -0.129  1.0000
## Eugr - Syla -0.087290 0.04645 1184  -1.879  0.9948
## Eugr - Sypi -0.092933 0.01277 1187  -7.276 <.0001
## Eugr - Syur -0.033546 0.04645 1184  -0.722  1.0000
## Eugr - Taof  0.614053 0.01402 1186  43.806 <.0001
## Eugr - Trsp  0.240481 0.01062 1180  22.649 <.0001
## Eugr - Vear  0.541106 0.03311 1181  16.342 <.0001

```

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##  Hisp - Hype -0.184646 0.00987 1184 -18.717 <.0001
##  Hisp - Lapu  0.232894 0.04631 1181   5.029  0.0003
##  Hisp - Lesp  0.123381 0.04623 1181   2.669  0.7002
##  Hisp - Phpr -0.127556 0.00708 1185 -18.013 <.0001
##  Hisp - Poco -0.099118 0.00857 1187 -11.562 <.0001
##  Hisp - Popr  0.045419 0.00684 1177   6.638 <.0001
##  Hisp - Pore -0.118063 0.00845 1179 -13.978 <.0001
##  Hisp - Posp -0.188848 0.02371 1181   -7.966 <.0001
##  Hisp - Rusp  0.015733 0.01224 1180   1.286  1.0000
##  Hisp - Sila  0.016684 0.04625 1180   0.361  1.0000
##  Hisp - Soca -0.461047 0.00672 1178 -68.571 <.0001
##  Hisp - Soga -0.398045 0.03289 1180 -12.104 <.0001
##  Hisp - Sogr -0.381951 0.01551 1182 -24.620 <.0001
##  Hisp - Sora -0.418909 0.01819 1179 -23.026 <.0001
##  Hisp - Syla -0.503816 0.04631 1183 -10.879 <.0001
##  Hisp - Sypi -0.509459 0.01221 1185 -41.716 <.0001
##  Hisp - Syur -0.450072 0.04631 1183   -9.718 <.0001
##  Hisp - Taof  0.197527 0.01349 1187  14.641 <.0001
##  Hisp - Trsp -0.176045 0.00983 1169 -17.905 <.0001
##  Hisp - Vear  0.124580 0.03290 1180   3.787  0.0531
##  Hype - Lapu  0.417540 0.04670 1182   8.940 <.0001
##  Hype - Lesp  0.308028 0.04655 1178   6.617 <.0001
##  Hype - Phpr  0.057090 0.00932 1185   6.129 <.0001
##  Hype - Poco  0.085528 0.01051 1182   8.141 <.0001
##  Hype - Popr  0.230065 0.00915 1184  25.132 <.0001
##  Hype - Pore  0.066583 0.01044 1184   6.376 <.0001
##  Hype - Posp -0.004202 0.02444 1182  -0.172  1.0000
##  Hype - Rusp  0.200380 0.01363 1185  14.702 <.0001
##  Hype - Sila  0.201330 0.04660 1178   4.321  0.0071
##  Hype - Soca -0.276401 0.00906 1184 -30.511 <.0001
##  Hype - Soga -0.213399 0.03343 1182  -6.383 <.0001
##  Hype - Sogr -0.197304 0.01664 1185 -11.854 <.0001
##  Hype - Sora -0.234263 0.01916 1183 -12.226 <.0001
##  Hype - Syla -0.319169 0.04673 1184  -6.830 <.0001
##  Hype - Sypi -0.324812 0.01369 1187 -23.730 <.0001
##  Hype - Syur -0.265425 0.04673 1184  -5.680 <.0001
##  Hype - Taof  0.382173 0.01482 1185  25.789 <.0001
##  Hype - Trsp  0.008602 0.01156 1187   0.744  1.0000
##  Hype - Vear  0.309227 0.03344 1181   9.248 <.0001
##  Lapu - Lesp -0.109512 0.06496 1183  -1.686  0.9992
##  Lapu - Phpr -0.360450 0.04618 1181  -7.805 <.0001
##  Lapu - Poco -0.332012 0.04635 1180  -7.164 <.0001
##  Lapu - Popr -0.187475 0.04613 1182  -4.064  0.0197
##  Lapu - Pore -0.350957 0.04644 1180  -7.557 <.0001
##  Lapu - Posp -0.421742 0.05157 1182  -8.178 <.0001
##  Lapu - Rusp -0.217161 0.04726 1183  -4.595  0.0022
##  Lapu - Sila -0.216210 0.06505 1182  -3.324  0.2100
##  Lapu - Soca -0.693941 0.04610 1181 -15.052 <.0001
##  Lapu - Soga -0.630939 0.05628 1182 -11.212 <.0001
##  Lapu - Sogr -0.614844 0.04819 1180 -12.760 <.0001
##  Lapu - Sora -0.651803 0.04919 1182 -13.251 <.0001
##  Lapu - Syla -0.736710 0.06494 1182 -11.344 <.0001
##  Lapu - Sypi -0.742352 0.04723 1181 -15.716 <.0001
##  Lapu - Syur -0.682965 0.06494 1182 -10.516 <.0001

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## Lapu - Taof -0.035367 0.04760 1179 -0.743 1.0000
## Lapu - Trsp -0.408939 0.04681 1181 -8.737 <.0001
## Lapu - Vear -0.108313 0.05630 1182 -1.924 0.9924
## Lesp - Phpr -0.250937 0.04612 1182 -5.440 <.0001
## Lesp - Poco -0.222499 0.04637 1183 -4.798 0.0009
## Lesp - Popr -0.077963 0.04609 1182 -1.692 0.9991
## Lesp - Pore -0.241445 0.04638 1182 -5.206 0.0001
## Lesp - Posp -0.312229 0.05139 1183 -6.076 <.0001
## Lesp - Rusp -0.107648 0.04721 1184 -2.280 0.9274
## Lesp - Sila -0.106698 0.06493 1182 -1.643 0.9995
## Lesp - Soca -0.584428 0.04606 1182 -12.688 <.0001
## Lesp - Soga -0.521427 0.05622 1183 -9.274 <.0001
## Lesp - Sogr -0.505332 0.04816 1183 -10.492 <.0001
## Lesp - Sora -0.542290 0.04908 1183 -11.048 <.0001
## Lesp - Syla -0.627197 0.06500 1182 -9.649 <.0001
## Lesp - Sypi -0.632840 0.04722 1182 -13.401 <.0001
## Lesp - Syur -0.573453 0.06500 1182 -8.823 <.0001
## Lesp - Taof 0.074146 0.04756 1184 1.559 0.9998
## Lesp - Trsp -0.299426 0.04664 1182 -6.420 <.0001
## Lesp - Vear 0.001199 0.05622 1182 0.021 1.0000
## Phpr - Poco 0.028438 0.00790 1177 3.599 0.0971
## Phpr - Popr 0.172975 0.00605 1178 28.614 <.0001
## Phpr - Pore 0.009493 0.00783 1175 1.212 1.0000
## Phpr - Posp -0.061292 0.02349 1182 -2.610 0.7451
## Phpr - Rusp 0.143289 0.01180 1185 12.140 <.0001
## Phpr - Sila 0.144240 0.04612 1180 3.127 0.3324
## Phpr - Soca -0.333491 0.00590 1175 -56.510 <.0001
## Phpr - Soga -0.270489 0.03276 1183 -8.256 <.0001
## Phpr - Sogr -0.254394 0.01519 1184 -16.749 <.0001
## Phpr - Sora -0.291353 0.01790 1179 -16.278 <.0001
## Phpr - Syla -0.376260 0.04620 1183 -8.144 <.0001
## Phpr - Sypi -0.381902 0.01182 1185 -32.317 <.0001
## Phpr - Syur -0.322515 0.04620 1183 -6.981 <.0001
## Phpr - Taof 0.325083 0.01314 1187 24.743 <.0001
## Phpr - Trsp -0.048489 0.00930 1171 -5.215 0.0001
## Phpr - Vear 0.252137 0.03273 1180 7.704 <.0001
## Poco - Popr 0.144537 0.00766 1186 18.874 <.0001
## Poco - Pore -0.018945 0.00922 1181 -2.054 0.9802
## Poco - Posp -0.089730 0.02409 1181 -3.725 0.0652
## Poco - Rusp 0.114851 0.01267 1187 9.062 <.0001
## Poco - Sila 0.115802 0.04645 1182 2.493 0.8240
## Poco - Soca -0.361929 0.00753 1185 -48.060 <.0001
## Poco - Soga -0.298927 0.03310 1183 -9.031 <.0001
## Poco - Sogr -0.282832 0.01595 1185 -17.736 <.0001
## Poco - Sora -0.319791 0.01859 1182 -17.199 <.0001
## Poco - Syla -0.404697 0.04638 1183 -8.726 <.0001
## Poco - Sypi -0.410340 0.01267 1186 -32.398 <.0001
## Poco - Syur -0.350953 0.04638 1183 -7.567 <.0001
## Poco - Taof 0.296645 0.01403 1187 21.137 <.0001
## Poco - Trsp -0.076927 0.01069 1181 -7.197 <.0001
## Poco - Vear 0.223699 0.03311 1182 6.756 <.0001
## Popr - Pore -0.163482 0.00767 1182 -21.324 <.0001
## Popr - Posp -0.234267 0.02345 1180 -9.989 <.0001
## Popr - Rusp -0.029686 0.01168 1181 -2.543 0.7923

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## Popr - Sila -0.028735 0.04611 1180 -0.623 1.0000
## Popr - Soca -0.506466 0.00558 1161 -90.814 <.0001
## Popr - Soga -0.443464 0.03269 1181 -13.566 <.0001
## Popr - Sogr -0.427369 0.01508 1183 -28.333 <.0001
## Popr - Sora -0.464328 0.01783 1179 -26.036 <.0001
## Popr - Syla -0.549234 0.04614 1182 -11.904 <.0001
## Popr - Sypi -0.554877 0.01163 1182 -47.711 <.0001
## Popr - Syur -0.495490 0.04614 1182 -10.739 <.0001
## Popr - Taof 0.152108 0.01304 1187 11.669 <.0001
## Popr - Trsp -0.221464 0.00922 1168 -24.013 <.0001
## Popr - Vear 0.079162 0.03270 1181 2.421 0.8653
## Pore - Posp -0.070785 0.02392 1182 -2.959 0.4617
## Pore - Rusp 0.133796 0.01269 1183 10.544 <.0001
## Pore - Sila 0.134747 0.04636 1179 2.907 0.5045
## Pore - Soca -0.342984 0.00756 1182 -45.355 <.0001
## Pore - Soga -0.279982 0.03309 1183 -8.461 <.0001
## Pore - Sogr -0.263887 0.01589 1183 -16.611 <.0001
## Pore - Sora -0.300846 0.01851 1181 -16.251 <.0001
## Pore - Syla -0.385752 0.04644 1183 -8.306 <.0001
## Pore - Sypi -0.391395 0.01269 1187 -30.842 <.0001
## Pore - Syur -0.332008 0.04644 1183 -7.149 <.0001
## Pore - Taof 0.315590 0.01390 1187 22.698 <.0001
## Pore - Trsp -0.057982 0.01037 1175 -5.594 <.0001
## Pore - Vear 0.242644 0.03305 1179 7.342 <.0001
## Posp - Rusp 0.204581 0.02554 1185 8.011 <.0001
## Posp - Sila 0.205532 0.05131 1181 4.006 0.0245
## Posp - Soca -0.272199 0.02343 1180 -11.618 <.0001
## Posp - Soga -0.209197 0.03976 1178 -5.262 0.0001
## Posp - Sogr -0.193102 0.02725 1183 -7.087 <.0001
## Posp - Sora -0.230061 0.02882 1183 -7.984 <.0001
## Posp - Syla -0.314968 0.05159 1183 -6.106 <.0001
## Posp - Sypi -0.320610 0.02565 1184 -12.501 <.0001
## Posp - Syur -0.261223 0.05159 1183 -5.064 0.0002
## Posp - Taof 0.386375 0.02609 1185 14.808 <.0001
## Posp - Trsp 0.012803 0.02429 1181 0.527 1.0000
## Posp - Vear 0.313429 0.03979 1182 7.876 <.0001
## Rusp - Sila 0.000950 0.04723 1182 0.020 1.0000
## Rusp - Soca -0.476780 0.01160 1183 -41.107 <.0001
## Rusp - Soga -0.413779 0.03419 1181 -12.102 <.0001
## Rusp - Sogr -0.397684 0.01815 1186 -21.916 <.0001
## Rusp - Sora -0.434642 0.02046 1179 -21.246 <.0001
## Rusp - Syla -0.519549 0.04726 1185 -10.993 <.0001
## Rusp - Sypi -0.525192 0.01541 1187 -34.075 <.0001
## Rusp - Syur -0.465805 0.04726 1185 -9.856 <.0001
## Rusp - Taof 0.181794 0.01641 1185 11.082 <.0001
## Rusp - Trsp -0.191778 0.01369 1187 -14.007 <.0001
## Rusp - Vear 0.108847 0.03426 1185 3.177 0.2981
## Sila - Soca -0.477731 0.04610 1180 -10.364 <.0001
## Sila - Soga -0.414729 0.05624 1181 -7.375 <.0001
## Sila - Sogr -0.398634 0.04812 1179 -8.284 <.0001
## Sila - Sora -0.435593 0.04900 1177 -8.889 <.0001
## Sila - Syla -0.520499 0.06509 1182 -7.997 <.0001
## Sila - Sypi -0.526142 0.04727 1181 -11.130 <.0001
## Sila - Syur -0.466755 0.06509 1182 -7.171 <.0001

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##  Sila - Taof  0.180843 0.04754 1182   3.804  0.0502
##  Sila - Trsp -0.192728 0.04656 1179  -4.140  0.0147
##  Sila - Vear  0.107897 0.05603 1168   1.926  0.9923
##  Soca - Soga  0.063002 0.03267 1182   1.929  0.9921
##  Soca - Sogr  0.079097 0.01503 1183   5.264  0.0001
##  Soca - Sora  0.042138 0.01779 1178   2.369  0.8910
##  Soca - Syla -0.042769 0.04612 1182  -0.927  1.0000
##  Soca - Sypi -0.048411 0.01155 1181  -4.190  0.0121
##  Soca - Syur  0.010976 0.04612 1182   0.238  1.0000
##  Soca - Taof  0.658574 0.01297 1187  50.764 <.0001
##  Soca - Trsp  0.285002 0.00915 1168  31.162 <.0001
##  Soca - Vear  0.585628 0.03267 1180  17.925 <.0001
##  Soga - Sogr  0.016095 0.03547 1175   0.454  1.0000
##  Soga - Sora -0.020864 0.03676 1179  -0.568  1.0000
##  Soga - Syla -0.105770 0.05629 1183  -1.879  0.9948
##  Soga - Sypi -0.111413 0.03426 1184  -3.252  0.2507
##  Soga - Syur -0.052026 0.05629 1183  -0.924  1.0000
##  Soga - Taof  0.595572 0.03462 1174  17.204 <.0001
##  Soga - Trsp  0.222001 0.03346 1181   6.636 <.0001
##  Soga - Vear  0.522626 0.04590 1182  11.387 <.0001
##  Sogr - Sora -0.036959 0.02254 1169  -1.639  0.9995
##  Sogr - Syla -0.121865 0.04825 1183  -2.526  0.8033
##  Sogr - Sypi -0.127508 0.01819 1185  -7.009 <.0001
##  Sogr - Syur -0.068121 0.04825 1183  -1.412  1.0000
##  Sogr - Taof  0.579477 0.01896 1172  30.561 <.0001
##  Sogr - Trsp  0.205906 0.01663 1179  12.378 <.0001
##  Sogr - Vear  0.506531 0.03553 1181  14.257 <.0001
##  Sora - Syla -0.084907 0.04921 1183  -1.726  0.9988
##  Sora - Sypi -0.090549 0.02054 1179  -4.409  0.0049
##  Sora - Syur -0.031162 0.04921 1183  -0.633  1.0000
##  Sora - Taof  0.616436 0.02122 1178  29.053 <.0001
##  Sora - Trsp  0.242864 0.01909 1175  12.723 <.0001
##  Sora - Vear  0.543490 0.03675 1178  14.788 <.0001
##  Syla - Sypi -0.005643 0.04712 1179  -0.120  1.0000
##  Syla - Syur  0.053744 0.06455 1160   0.833  1.0000
##  Syla - Taof  0.701343 0.04760 1180  14.735 <.0001
##  Syla - Trsp  0.327771 0.04680 1182   7.004 <.0001
##  Syla - Vear  0.628396 0.05631 1183  11.160 <.0001
##  Sypi - Syur  0.059387 0.04712 1179   1.260  1.0000
##  Sypi - Taof  0.706986 0.01650 1186  42.855 <.0001
##  Sypi - Trsp  0.333414 0.01377 1178  24.213 <.0001
##  Sypi - Vear  0.634039 0.03425 1182  18.514 <.0001
##  Syur - Taof  0.647598 0.04760 1180  13.606 <.0001
##  Syur - Trsp  0.274027 0.04680 1182   5.856 <.0001
##  Syur - Vear  0.574652 0.05631 1183  10.206 <.0001
##  Taof - Trsp -0.373572 0.01470 1186 -25.411 <.0001
##  Taof - Vear -0.072946 0.03472 1184  -2.101  0.9732
##  Trsp - Vear  0.300625 0.03341 1178   8.997 <.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 33 estimates

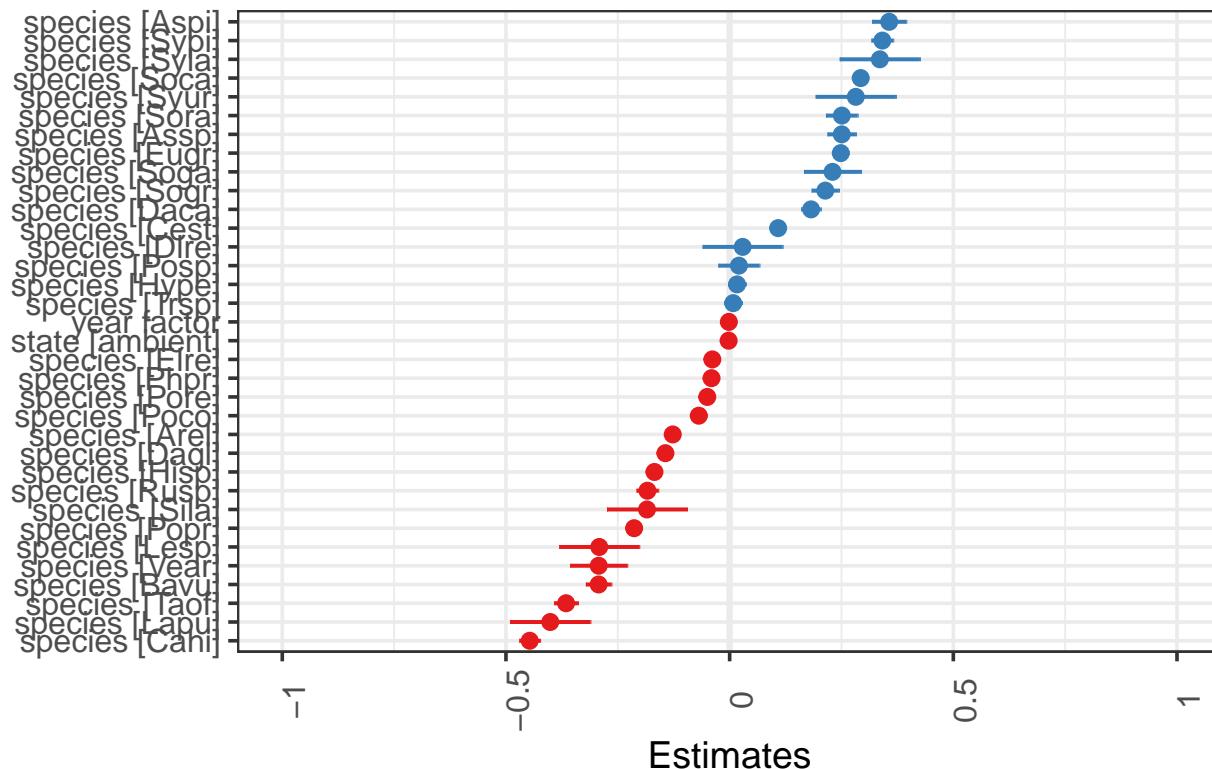
```

```
emmeans(mod7ak, list(pairwise ~ insecticide), adjust = "tukey")
```

```
## Error in emmeans(object = object, specs = specs[[i]], name = contr.name, : No variable named insecticid
```

```
# Take a look at the estimates for each fixed effect. These are the estimates from summary(mod7a). You can plot them like this:
```

log(julian_median)

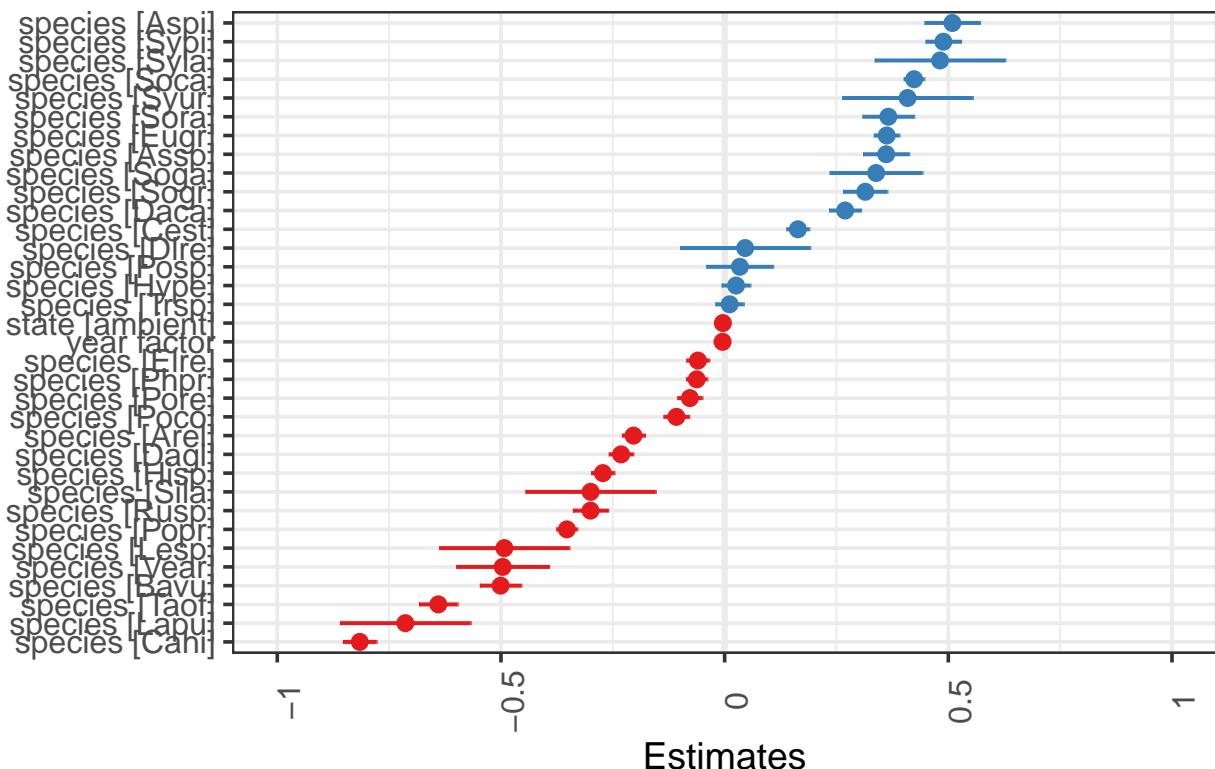


```
# if you want to standardize the estimates:
```

```
plot_model(mod7ak, sort.est = TRUE, type="std")
```

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

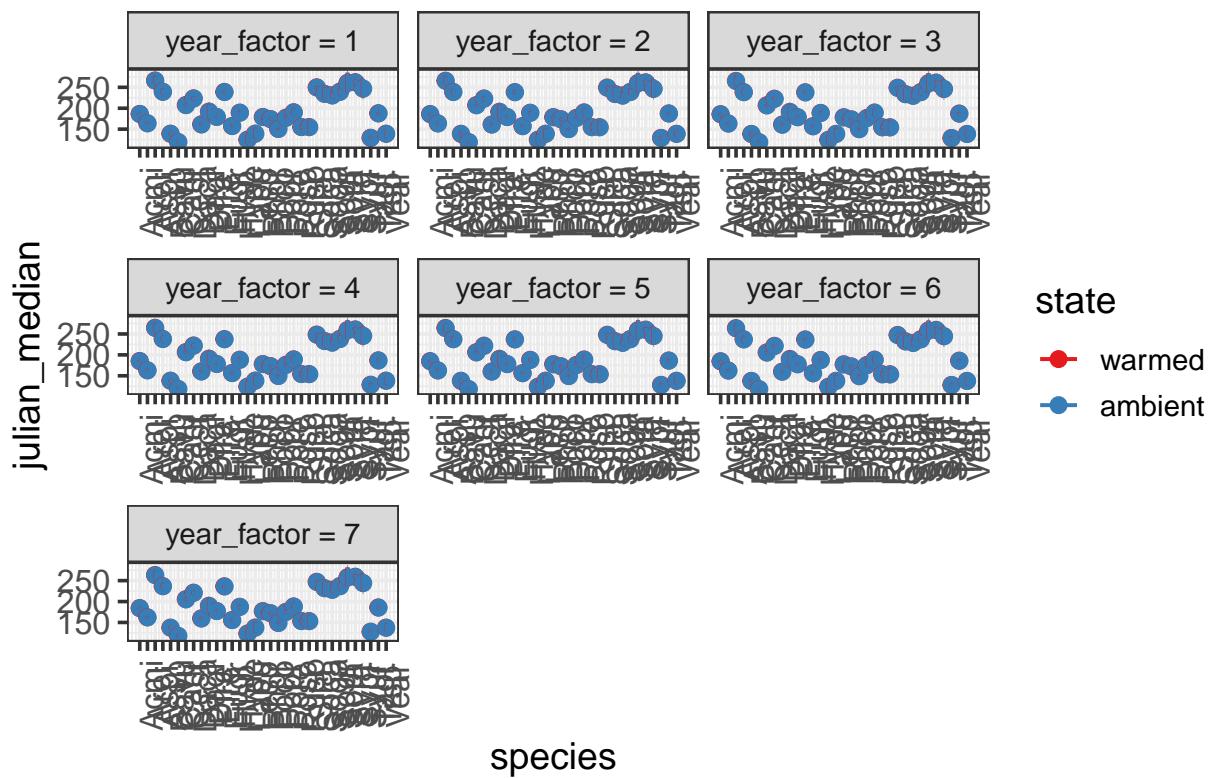
log(julian_median)



```
# these are the fixed predicted values: - note this is a new plot
plot_model(mod7ak, type = "pred", terms = c("species", "state", "year_factor"))
```

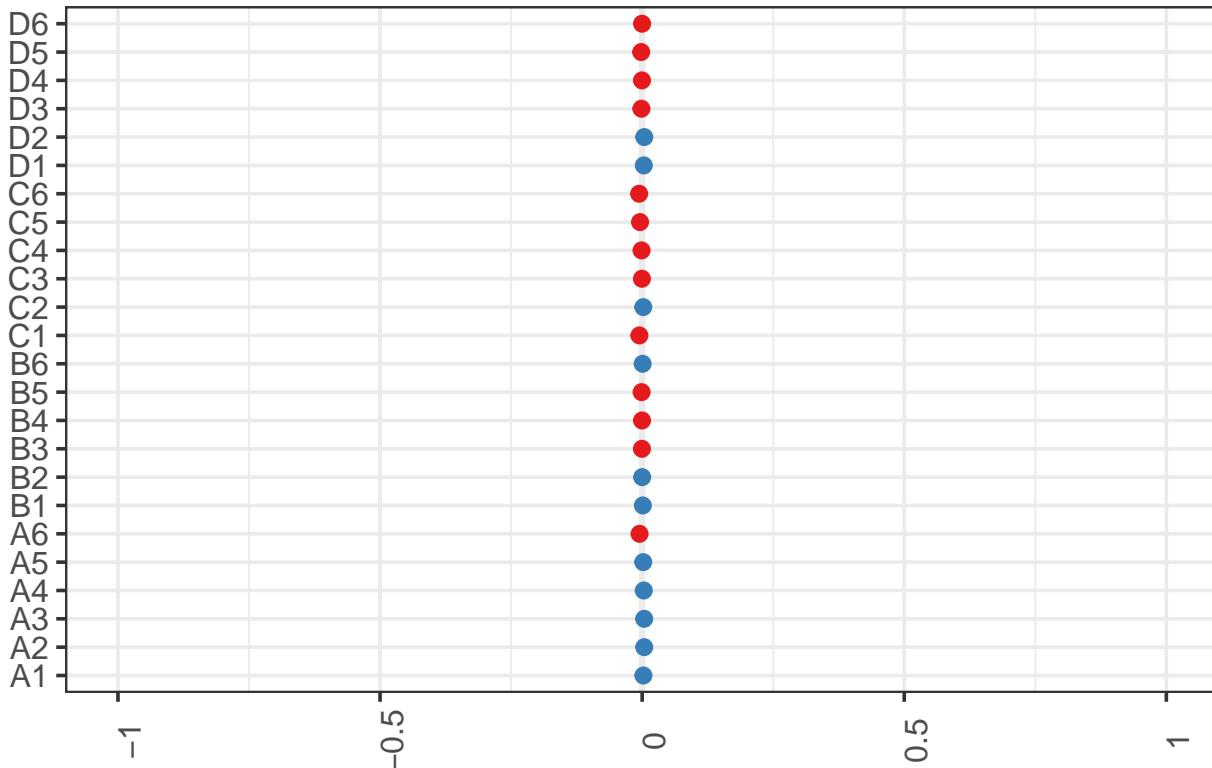
```
## Model has log-transformed response. Back-transforming predictions to original response scale. Standard
```

Predicted values of julian_median



```
# these are the random effects estimates  
plot_model(mod7ak, type = "re")
```

Random effects



```
AICctab(mod3k, mod7ak, weights=T)
```

```
##          dAICc df weight
## mod7ak    0.0 37  1
## mod3k   161.3 6 <0.001

# including native vs. exotic
kbs_flwr_spp <- within(kbs_flwr_spp, origin <- relevel(factor(origin), ref = "Native")) # releveling so
mod8k <- lmer(log(julian_median) ~ state * origin + (1+year_factor|plot), kbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod9k <- lmer(log(julian_median) ~ state + origin + (1+year_factor|plot), kbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod9ak <- lmer(log(julian_median) ~ state + origin + year_factor + (1|plot), kbs_flwr_spp, REML=FALSE)
anova(mod8k, mod9k) # model 9k is a better fit to data

## Data: kbs_flwr_spp
## Models:
## mod9k: log(julian_median) ~ state + origin + (1 + year_factor | plot)
## mod8k: log(julian_median) ~ state * origin + (1 + year_factor | plot)
##      npar     AIC     BIC logLik deviance Chisq Df Pr(>Chisq)
## mod9k     9 -1323.7 -1278.5 670.85 -1341.7
## mod8k    12 -1321.2 -1261.0 672.63 -1345.2 3.5596  3      0.3131
```

```

anova(mod9k, mod9ak) # mod 9ak

## Data: kbs_flwr_spp
## Models:
## mod9ak: log(julian_median) ~ state + origin + year_factor + (1 | plot)
## mod9k: log(julian_median) ~ state + origin + (1 + year_factor | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod9ak     8 -1328.5 -1288.2 672.23   -1344.5
## mod9k     9 -1323.7 -1278.5 670.85   -1341.7      0  1       1

```

```
AICctab(mod8k, mod9k, mod9ak, weights=T)
```

```

##      dAICc df weight
## mod9ak  0.0  8  0.896
## mod9k   4.8  9  0.081
## mod8k   7.4 12  0.023

```

```
summary(mod9ak)
```

```

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + origin + year_factor + (1 | plot)
## Data: kbs_flwr_spp
##
##      AIC      BIC logLik deviance df.resid
## -1328.5 -1288.3  672.2   -1344.5      1117
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -3.8677 -0.5420  0.1599  0.5617  3.2104
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 2.399e-05 0.004897
## Residual           1.770e-02 0.133037
## Number of obs: 1125, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept) 5.458e+00 1.323e-02 4.040e+02 412.486 < 2e-16 ***
## stateambient 1.190e-02 8.228e-03 2.130e+01  1.446  0.16277  
## origin      -2.132e-01 6.743e-02 1.124e+03 -3.162  0.00161 ** 
## originBoth   -3.283e-01 1.436e-02 1.122e+03 -22.871 < 2e-16 ***
## originExotic -3.162e-01 9.546e-03 1.125e+03 -33.124 < 2e-16 ***
## year_factor -3.903e-03 2.228e-03 1.124e+03  -1.752  0.08004 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) sttmbn origin orgnBt orgnEx
## stateambint -0.338
## origin      -0.151  0.006

```

```

## originBoth -0.430 -0.051  0.083
## originExotc -0.566  0.021  0.109  0.489
## year_factor -0.711  0.009  0.106  0.138  0.048

anova(mod9ak)

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state      0.0370 0.0370     1    21.3 2.0905 0.16277
## origin     20.4592 6.8197     3 1123.7 385.3230 < 2e-16 ***
## year_factor 0.0543 0.0543     1 1124.2 3.0695 0.08004 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

emmeans(mod9ak, list(pairwise ~ state * origin), adjust = "tukey")

## $`emmeans of state, origin`
##   state origin emmean       SE   df lower.CL upper.CL
##   warmed Native  5.443 0.009539 157.54   5.424   5.461
##   ambient Native  5.455 0.009293 149.49   5.436   5.473
##   warmed        5.229 0.067282 1131.24   5.097   5.361
##   ambient        5.241 0.067314 1131.17   5.109   5.373
##   warmed Both    5.114 0.013016 421.60   5.089   5.140
##   ambient Both   5.126 0.012367 362.93   5.102   5.150
##   warmed Exotic 5.126 0.006850  41.76   5.113   5.140
##   ambient Exotic 5.138 0.006774  39.48   5.125   5.152
##
## 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 -0.011897 0.00868 26.4 -1.371  0.8620
##   warmed Native - warmed          0.213224 0.06770 1129.5  3.150  0.0357
##   warmed Native - ambient          0.201327 0.06832 1126.0  2.947  0.0646
##   warmed Native - warmed Both    0.328350 0.01441 1127.2 22.792 <.0001
##   warmed Native - ambient Both   0.316453 0.01646 303.0 19.224 <.0001
##   warmed Native - warmed Exotic 0.316196 0.00958 1130.3 32.990 <.0001
##   warmed Native - ambient Exotic 0.304299 0.01307 135.0 23.286 <.0001
##   ambient Native - warmed          0.225122 0.06819 1129.1  3.302  0.0221
##   ambient Native - ambient          0.213224 0.06770 1129.5  3.150  0.0357
##   ambient Native - warmed Both    0.340247 0.01717 359.4 19.820 <.0001
##   ambient Native - ambient Both   0.328350 0.01441 1127.2 22.792 <.0001
##   ambient Native - warmed Exotic 0.328093 0.01279 130.5 25.654 <.0001
##   ambient Native - ambient Exotic 0.316196 0.00958 1130.3 32.990 <.0001
##   warmed - ambient              -0.011897 0.00868 26.4 -1.371  0.8620
##   warmed - warmed Both          0.115126 0.06804 1129.8  1.692  0.6926
##   warmed - ambient Both         0.103229 0.06844 1128.7  1.508  0.8031
##   warmed - warmed Exotic       0.102972 0.06733 1128.8  1.529  0.7915
##   warmed - ambient Exotic      0.091075 0.06784 1129.6  1.342  0.8824
##   ambient - warmed Both        0.127023 0.06874 1125.9  1.848  0.5874
##   ambient - ambient Both       0.115126 0.06804 1129.8  1.692  0.6926

```

```

## ambient - warmed Exotic      0.114869 0.06792 1127.0   1.691  0.6931
## ambient - ambient Exotic    0.102972 0.06733 1128.8   1.529  0.7915
## warmed Both - ambient Both -0.011897 0.00868   26.4  -1.371  0.8620
## warmed Both - warmed Exotic -0.012154 0.01282 1130.1  -0.948  0.9812
## warmed Both - ambient Exotic -0.024051 0.01597   278.2  -1.506  0.8039
## ambient Both - warmed Exotic -0.000257 0.01497  222.8  -0.017  1.0000
## ambient Both - ambient Exotic -0.012154 0.01282 1130.1  -0.948  0.9812
## warmed Exotic - ambient Exotic -0.011897 0.00868   26.4  -1.371  0.8620
##
## 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_flwr_spp <- within(kbs_flwr_spp, growth_habit <- relevel(factor(growth_habit), ref = "Forb")) # rel
mod10k <- lmer(log(julian_median) ~ state * growth_habit + (1+year_factor|plot), kbs_flwr_spp, REML=FALSE)

## fixed-effect model matrix is rank deficient so dropping 1 column / coefficient

## boundary (singular) fit: see help('isSingular')

mod11k <- lmer(log(julian_median) ~ state + growth_habit + (1+year_factor|plot), kbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod11ak <- lmer(log(julian_median) ~ state + growth_habit + year_factor + (1|plot), kbs_flwr_spp, REML=FALSE)
anova(mod10k, mod11k) # model 11k is a better fit to data

## Data: kbs_flwr_spp
## Models:
## mod11k: log(julian_median) ~ state + growth_habit + (1 + year_factor | plot)
## mod10k: log(julian_median) ~ state * growth_habit + (1 + year_factor | plot)
##          npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod11k     9 -1004.7 -959.44 511.33  -1022.7
## mod10k    11 -1003.9 -948.64 512.96  -1025.9 3.251  2      0.1968

anova(mod11k, mod11ak) # model 11ak is a better fit to data

## Data: kbs_flwr_spp
## Models:
## mod11ak: log(julian_median) ~ state + growth_habit + year_factor + (1 | plot)
## mod11k: log(julian_median) ~ state + growth_habit + (1 + year_factor | plot)
##          npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod11ak     8 -1017.8 -977.57 516.89  -1033.8
## mod11k     9 -1004.7 -959.44 511.33  -1022.7      0  1
##          dAICc df weight
## mod11ak  0.0  8  0.9977
## mod11k 13.1  9  0.0014
## mod10k 14.0 11 <0.001

```

```

summary(mod11ak)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + growth_habit + year_factor + (1 |
##   plot)
## Data: kbs_flwr_spp
##
##      AIC      BIC  logLik deviance df.resid
## -1017.8   -977.6    516.9   -1033.8     1117
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -4.5493 -0.4799  0.0751  0.6356  2.0530
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0001547 0.01244
## Residual           0.0232242 0.15239
## Number of obs: 1125, groups: plot, 24
##
## Fixed effects:
##                   Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)      5.297e+00  1.333e-02 2.088e+02 397.261 < 2e-16 ***
## stateambient    2.770e-03  1.050e-02 2.272e+01   0.264 0.794363
## growth_habit    -2.276e-01  1.547e-02 1.121e+03 -14.717 < 2e-16 ***
## growth_habitForb/herb -5.425e-01  1.532e-01 1.123e+03  -3.541 0.000415 ***
## growth_habitGraminoid -2.262e-01  9.804e-03 1.125e+03 -23.073 < 2e-16 ***
## year_factor      8.673e-03  2.575e-03 1.124e+03   3.368 0.000782 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) sttmbn grwth_ grwt_G
## stateambient -0.426
## growth_habit -0.263 -0.034
## grwth_hbtF/  0.004  0.029  0.014
## grwth_hbtGr -0.270  0.063  0.292  0.043
## year_factor  -0.720 -0.003  0.073 -0.055 -0.158

```

```
anova(mod11ak)
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state       0.0016  0.0016     1   22.72  0.0696 0.7943631
## growth_habit 14.1334  4.7111     3 1122.83 202.8547 < 2.2e-16 ***
## year_factor  0.2635  0.2635     1 1123.60 11.3459 0.0007818 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
emmeans(mod11ak, 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
##       3.96 Forb        5.333 0.007538  94.11     5.318    5.348
##       3.96          5.105 0.014352 667.52     5.077    5.134
##       3.96 Forb/herb   4.790 0.153604 1128.47     4.489    5.092
##       3.96 Graminoid   5.107 0.007565  96.40     5.092    5.122
##
## 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
##   year_factor3.96 Forb - year_factor3.96           estimate      SE      df
##   year_factor3.96 Forb - (year_factor3.96 Forb/herb) 0.54253 0.15378 1128
##   year_factor3.96 Forb - year_factor3.96 Graminoid   0.22620 0.00985 1131
##   year_factor3.96 - (year_factor3.96 Forb/herb)      0.31492 0.15434 1128
##   year_factor3.96 - year_factor3.96 Graminoid      -0.00141 0.01577 1130
##   (year_factor3.96 Forb/herb) - year_factor3.96 Graminoid -0.31633 0.15366 1127
##   t.ratio p.value
##   14.668 <.0001
##   3.528 0.0025
##   22.975 <.0001
##   2.040 0.1739
##   -0.089 0.9997
##   -2.059 0.1675
##
## 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

# New version of our model incorporating interaction term and species within year so that there is a se
# updated mod4
mod12k <- lmer(log(julian_median) ~ state * factor(year_factor) + (1+factor(year_factor)|species), kbs_)

## boundary (singular) fit: see help('isSingular')

# So another version of this model would include the interaction but not include the nesting (and thus
# updated mod5
mod13k <- lmer(log(julian_median) ~ state * factor(year_factor) + (1|species), kbs_flwr_spp)

# All the models ran:
mod1k <- lmer(log(julian_median) ~ state*year_factor + insecticide*year_factor + (1|species) + (1|plot)
mod2k <- lmer(log(julian_median) ~ state*year_factor + insecticide*year_factor + (1|species), kbs_flwr_spp, REML=TRUE)
mod3k <- lmer(log(julian_median) ~ state*year_factor + (1|species), kbs_flwr_spp, REML=FALSE)
mod4k <- lmer(log(julian_median) ~ state*year_factor + insecticide + (1|species) + (1|plot), kbs_flwr_spp, REML=TRUE)
mod5k <- lmer(log(julian_median) ~ state + year_factor + (1|species), kbs_flwr_spp, REML=FALSE)
mod6k <- lmer(log(julian_median) ~ state + year_factor + (1|species) + (1 + year|plot), kbs_flwr_spp, REML=TRUE)

## boundary (singular) fit: see help('isSingular')

```

```

## Warning: Model failed to converge with 1 negative eigenvalue: -8.6e+08

mod7k <- lmer(log(julian_median) ~ state + species + (1+factor(year_factor)|plot), kbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod7ak <- lmer(log(julian_median) ~ state + species + factor(year_factor) + (1|plot), kbs_flwr_spp, REML=FALSE)
mod7bk <- lmer(log(julian_median) ~ state * factor(year_factor) + species + (1|plot), kbs_flwr_spp, REML=FALSE)
mod7ck <- lmer(log(julian_median) ~ state + species + factor(year_factor) + insecticide + (1|plot), kbs_flwr_spp, REML=FALSE)
mod8k <- lmer(log(julian_median) ~ state * origin + (1+factor(year_factor)|plot), kbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

## Warning: Model failed to converge with 1 negative eigenvalue: -8.7e+00

mod9k <- lmer(log(julian_median) ~ state + origin + (1+factor(year_factor)|plot), kbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod9ak <- lmer(log(julian_median) ~ state + origin + factor(year_factor) + (1|plot), kbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod10k <- lmer(log(julian_median) ~ state * growth_habit + (1+factor(year_factor)|plot), kbs_flwr_spp, REML=FALSE)

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

mod11k <- lmer(log(julian_median) ~ state + growth_habit + (1+factor(year_factor)|plot), kbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod11ak <- lmer(log(julian_median) ~ state + growth_habit + factor(year_factor) + (1|plot), kbs_flwr_spp, REML=FALSE)
mod12k <- lmer(log(julian_median) ~ state * factor(year_factor) + (1+factor(year_factor)|species), kbs_flwr_spp, REML=FALSE)

## boundary (singular) fit: see help('isSingular')

mod13k <- lmer(log(julian_median) ~ state * factor(year_factor) + (1|species), kbs_flwr_spp, REML=FALSE)
AICctab(mod1k, mod2k, mod3k, mod5k, mod6k, mod7k, mod7ak, mod7bk, mod7ck, mod8k, mod9k, mod9ak, mod10k, mod11k, mod12k, mod13k)

## Error in ICtab(..., mnames = mnames, type = "AICc"): nobs different: must have identical data for all models

summary(mod7ak)

```

```

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + species + factor(year_factor) +
##           (1 | plot)
## Data: kbs_flwr_spp
##
##      AIC      BIC  logLik deviance df.resid
## -3917.7 -3705.7  2000.9 -4001.7     1109
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -6.6966 -0.5906 -0.0202  0.5356  4.5007
##
## Random effects:
##   Groups   Name        Variance Std.Dev.
##   plot     (Intercept) 1.522e-05 0.003902
##   Residual            1.797e-03 0.042390
## Number of obs: 1151, groups: plot, 24
##
## Fixed effects:
##                               Estimate Std. Error      df t value Pr(>|t|)    
##   (Intercept)             5.274e+00 7.634e-03 9.256e+02 690.898 < 2e-16 ***
##   stateambient          -1.106e-03 3.065e-03 2.271e+01 -0.361   0.722    
##   speciesArel           -1.292e-01 7.661e-03 1.149e+03 -16.864 < 2e-16 ***
##   speciesAspi            3.706e-01 1.841e-02 1.142e+03  20.135 < 2e-16 ***
##   speciesAssp            2.608e-01 1.539e-02 1.137e+03  16.951 < 2e-16 ***
##   speciesBavu            -2.865e-01 1.367e-02 1.145e+03 -20.955 < 2e-16 ***
##   speciesCahi            -4.363e-01 1.117e-02 1.145e+03 -39.048 < 2e-16 ***
##   speciesCest            9.901e-02 7.651e-03 1.143e+03  12.941 < 2e-16 ***
##   speciesDaca            1.809e-01 1.055e-02 1.146e+03  17.144 < 2e-16 ***
##   speciesDagl            -1.403e-01 8.164e-03 1.150e+03 -17.187 < 2e-16 ***
##   speciesDlre            4.734e-02 4.299e-02 1.147e+03   1.101   0.271    
##   speciesElre            -3.840e-02 7.582e-03 1.150e+03 -5.064  4.77e-07 ***
##   speciesEugr            2.391e-01 8.512e-03 1.150e+03  28.091 < 2e-16 ***
##   speciesHisp            -1.642e-01 7.683e-03 1.147e+03 -21.369 < 2e-16 ***
##   speciesHype            7.914e-03 9.513e-03 1.147e+03   0.832   0.406    
##   speciesLapu            -3.978e-01 4.314e-02 1.148e+03 -9.222 < 2e-16 ***
##   speciesLesp            -2.758e-01 4.303e-02 1.148e+03 -6.410  2.12e-10 ***
##   speciesPhpr            -4.331e-02 7.083e-03 1.146e+03 -6.115  1.32e-09 ***
##   speciesPoco            -6.849e-02 8.484e-03 1.150e+03 -8.073  1.72e-15 ***
##   speciesPopr            -2.109e-01 6.946e-03 1.146e+03 -30.362 < 2e-16 ***
##   speciesPore            -4.863e-02 8.266e-03 1.148e+03 -5.883  5.28e-09 ***
##   speciesPosp            -2.603e-02 2.252e-02 1.149e+03 -1.156   0.248    
##   speciesRusp            -1.832e-01 1.163e-02 1.143e+03 -15.757 < 2e-16 ***
##   speciesSila            -1.818e-01 4.297e-02 1.147e+03 -4.230  2.52e-05 ***
##   speciesSoca            2.951e-01 6.848e-03 1.145e+03  43.091 < 2e-16 ***
##   speciesSoga            2.430e-01 3.075e-02 1.148e+03  7.902  6.40e-15 ***
##   speciesSogr            2.288e-01 1.476e-02 1.149e+03  15.507 < 2e-16 ***
##   speciesSora            2.678e-01 1.723e-02 1.142e+03  15.545 < 2e-16 ***
##   speciesSyla            3.376e-01 4.312e-02 1.148e+03  7.830  1.10e-14 ***
##   speciesSypi            3.383e-01 1.179e-02 1.150e+03  28.707 < 2e-16 ***
##   speciesSyur            2.839e-01 4.312e-02 1.148e+03   6.584  6.95e-11 ***
##   speciesTaof            -3.556e-01 1.276e-02 1.151e+03 -27.867 < 2e-16 ***
##   speciesTrsp            -1.124e-02 9.539e-03 1.138e+03 -1.178   0.239

```

```

## speciesYear      -2.763e-01 3.064e-02 1.146e+03 -9.018 < 2e-16 ***
## factor(year_factor)2 -4.998e-02 5.933e-03 1.143e+03 -8.425 < 2e-16 ***
## factor(year_factor)3 -6.703e-02 6.295e-03 1.143e+03 -10.648 < 2e-16 ***
## factor(year_factor)4 -6.659e-02 6.298e-03 1.146e+03 -10.572 < 2e-16 ***
## factor(year_factor)5 -4.217e-02 6.438e-03 1.145e+03 -6.551 8.63e-11 ***
## factor(year_factor)6 -4.371e-02 6.555e-03 1.146e+03 -6.668 4.01e-11 ***
## factor(year_factor)7 -5.940e-02 6.823e-03 1.147e+03 -8.706 < 2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 40 > 12.
## Use print(x, correlation=TRUE) or
##      vcov(x) if you need it

summ(mod7ak)

## MODEL INFO:
## Observations: 1151
## Dependent Variable: log(julian_median)
## Type: Mixed effects linear regression
##
## MODEL FIT:
## AIC = -3917.73, BIC = -3705.70
## Pseudo-R2 (fixed effects) = 0.95
## Pseudo-R2 (total) = 0.95
##
## FIXED EFFECTS:
## -----
##             Est.   S.E.   t val.   d.f.    p
## -----
## (Intercept) 5.27  0.01  690.90  925.63  0.00
## stateambient -0.00  0.00  -0.36   22.71  0.72
## speciesArel -0.13  0.01  -16.86  1148.95  0.00
## speciesAspi  0.37  0.02  20.13  1141.58  0.00
## speciesAssp  0.26  0.02  16.95  1136.53  0.00
## speciesBavu -0.29  0.01  -20.95  1145.44  0.00
## speciesCahi -0.44  0.01  -39.05  1144.53  0.00
## speciesCest  0.10  0.01  12.94  1143.32  0.00
## speciesDaca  0.18  0.01  17.14  1146.40  0.00
## speciesDagl -0.14  0.01  -17.19  1150.19  0.00
## speciesDlre  0.05  0.04   1.10  1146.50  0.27
## speciesElre -0.04  0.01  -5.06  1150.00  0.00
## speciesEugr  0.24  0.01  28.09  1150.01  0.00
## speciesHisp -0.16  0.01  -21.37  1146.56  0.00
## speciesHype  0.01  0.01   0.83  1147.00  0.41
## speciesLapu -0.40  0.04  -9.22  1148.41  0.00
## speciesLesp -0.28  0.04  -6.41  1147.89  0.00
## speciesPhpr -0.04  0.01  -6.11  1145.58  0.00
## speciesPoco -0.07  0.01  -8.07  1150.07  0.00
## speciesPopr -0.21  0.01  -30.36  1146.18  0.00
## speciesPore -0.05  0.01  -5.88  1148.26  0.00
## speciesPosp -0.03  0.02  -1.16  1148.79  0.25

```

```

## speciesRusp          -0.18  0.01  -15.76  1143.11  0.00
## speciesSila          -0.18  0.04   -4.23  1146.52  0.00
## speciesSoca          0.30  0.01   43.09  1144.96  0.00
## speciesSoga          0.24  0.03   7.90  1147.71  0.00
## speciesSogr          0.23  0.01  15.51  1148.69  0.00
## speciesSora          0.27  0.02  15.54  1142.48  0.00
## speciesSyla          0.34  0.04   7.83  1148.26  0.00
## speciesSypi          0.34  0.01  28.71  1149.80  0.00
## speciesSyur          0.28  0.04   6.58  1148.26  0.00
## speciesTaof          -0.36  0.01  -27.87  1150.64  0.00
## speciesTrsp          -0.01  0.01  -1.18  1138.00  0.24
## speciesVear          -0.28  0.03  -9.02  1146.23  0.00
## factor(year_factor)2 -0.05  0.01  -8.42  1143.16  0.00
## factor(year_factor)3 -0.07  0.01  -10.65  1142.87  0.00
## factor(year_factor)4 -0.07  0.01  -10.57  1145.91  0.00
## factor(year_factor)5 -0.04  0.01  -6.55  1144.76  0.00
## factor(year_factor)6 -0.04  0.01  -6.67  1145.96  0.00
## factor(year_factor)7 -0.06  0.01  -8.71  1147.27  0.00
## -----
## 
## p values calculated using Satterthwaite d.f.
##
## RANDOM EFFECTS:
## -----
##   Group      Parameter    Std. Dev.
## -----
##   plot      (Intercept)  0.00
##   Residual                         0.04
## -----
## 
## Grouping variables:
## -----
##   Group # groups   ICC
## -----
##   plot      24     0.01
## -----
```

```
anova(mod7ak)
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state        0.000 0.00023     1   22.71  0.1302 0.7216
## species      38.673 1.20852    32 1143.66 672.5562 <2e-16 ***
## factor(year_factor) 0.276 0.04593     6 1140.62  25.5629 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

KBS Plot-level Mixed Effects Models:

```

mod1pk <- lmer(log(julian_median) ~ state + (1|plot), kbs_flwr_plot, REML=FALSE)
mod2pk <- lmer(log(julian_median) ~ insecticide + (1|plot), kbs_flwr_plot, REML=FALSE)
```

```

mod3pk <- lmer(log(julian_median) ~ insecticide + state + (1|plot), kbs_flwr_plot, REML=FALSE)
mod4pk <- lmer(log(julian_median) ~ insecticide * state + (1|plot), kbs_flwr_plot, REML=FALSE)
mod5pk <- lmer(log(julian_median) ~ state + year_factor + (1|plot), kbs_flwr_plot, REML=FALSE)
mod6pk <- lmer(log(julian_median) ~ state + year_factor + insecticide + (1|plot), kbs_flwr_plot, REML=FALSE)
mod7pk <- lmer(log(julian_median) ~ state * year_factor + (1|plot), kbs_flwr_plot, REML=FALSE)
mod8pk <- lmer(log(julian_median) ~ state * year_factor + insecticide + (1|plot), kbs_flwr_plot, REML=FALSE)
mod9pk <- lmer(log(julian_median) ~ state * insecticide + year_factor + (1|plot), kbs_flwr_plot, REML=FALSE)
mod10pk <- lmer(log(julian_median) ~ state + insecticide * year_factor + (1|plot), kbs_flwr_plot, REML=FALSE)
mod11pk <- lmer(log(julian_median) ~ state * year_factor * insecticide + (1|plot), kbs_flwr_plot, REML=FALSE)
AICctab(mod1pk, mod2pk, mod3pk, mod4pk, mod5pk, mod6pk, mod7pk, mod8pk, mod9pk, mod10pk, mod11pk, weights=T)

```

```

##          dAICc df weight
## mod7pk    0.0   6  0.380
## mod8pk    1.1   7  0.223
## mod1pk    2.6   4  0.102
## mod5pk    3.1   5  0.080
## mod3pk    3.6   5  0.062
## mod6pk    4.1   6  0.049
## mod10pk   5.3   7  0.027
## mod2pk    5.5   4  0.024
## mod4pk    5.8   6  0.021
## mod9pk    6.2   7  0.017
## mod11pk   6.6  10  0.014

```

```
anova(mod5pk, mod7pk) # go with more complex model mod7pk
```

```

## Data: kbs_flwr_plot
## Models:
## mod5pk: log(julian_median) ~ state + year_factor + (1 | plot)
## mod7pk: log(julian_median) ~ state * year_factor + (1 | plot)
##          npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod5pk     5 -475.50 -459.94  242.75   -485.50
## mod7pk     6 -478.76 -460.08  245.38   -490.76 5.2585  1     0.02184 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
AICctab(mod5pk, mod7pk, weights=T)
```

```

##          dAICc df weight
## mod7pk  0.0   6  0.83
## mod5pk  3.1   5  0.17

```

```
summ(mod5pk)
```

```

## MODEL INFO:
## Observations: 166
## Dependent Variable: log(julian_median)
## Type: Mixed effects linear regression
##
## MODEL FIT:
## AIC = -475.50, BIC = -459.94

```

```

## Pseudo-R2 (fixed effects) = 0.04
## Pseudo-R2 (total) = 0.07
##
## FIXED EFFECTS:
## -----
##          Est.   S.E.   t val.   d.f.    p
## -----
## (Intercept) 5.24  0.01  481.60 114.96  0.00
## stateambient 0.02  0.01   2.03  24.06  0.05
## year_factor -0.00  0.00  -1.29 143.51  0.20
## -----
## 
## p values calculated using Satterthwaite d.f.
##
## RANDOM EFFECTS:
## -----
##   Group   Parameter   Std. Dev.
## -----
##   plot   (Intercept) 0.01
## Residual           0.06
## -----
## 
## Grouping variables:
## -----
##   Group # groups   ICC
## -----
##   plot      24     0.03
## -----


summary(mod5pk)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + year_factor + (1 | plot)
## Data: kbs_flwr_plot
##
##      AIC      BIC   logLik deviance df.resid
## -475.5  -459.9   242.7   -485.5      161
## 
## Scaled residuals:
##   Min    1Q  Median    3Q   Max
## -2.2341 -0.6811 -0.0614  0.6005  3.2924
## 
## Random effects:
##   Groups   Name       Variance Std.Dev.
##   plot     (Intercept) 9.376e-05 0.009683
##   Residual            3.057e-03 0.055289
## Number of obs: 166, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept) 5.243235  0.010887 114.963396 481.60 <2e-16 ***
## stateambient 0.019188  0.009453  24.058062   2.03  0.0536 .
## year_factor -0.002780  0.002155 143.505655  -1.29  0.1991

```

```

## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr) sttmbn
## stateambient -0.441
## year_factor -0.792  0.015

emmeans(mod5pk, list(pairwise ~ state+year_factor), adjust = "tukey")

## $`emmeans of state, year_factor`
##   state   year_factor emmean      SE    df lower.CL upper.CL
##   warmed        3.97  5.232 0.006947 25.75     5.218    5.246
##   ambient        3.97  5.251 0.007018 26.48     5.237    5.266
##
## 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
##   warmed year_factor3.96987951807229 - ambient year_factor3.96987951807229
##   estimate      SE   df t.ratio p.value
##   -0.0192 0.00988 26.1  -1.943  0.0629
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.

# including native vs. exotic
kbs_flwr_plot_origin <- within(kbs_flwr_plot_origin, origin <- relevel(factor(origin), ref = "Native"))
mod12pk <- lmer(log(julian_median) ~ state * origin + (1+year_factor|plot), kbs_flwr_plot_origin, REML=TRUE)

## boundary (singular) fit: see help('isSingular')

mod13pk <- lmer(log(julian_median) ~ state + origin + (1+year_factor|plot), kbs_flwr_plot_origin, REML=TRUE)

## boundary (singular) fit: see help('isSingular')

mod14pk <- lmer(log(julian_median) ~ state + origin + year_factor + (1|plot), kbs_flwr_plot_origin, REML=TRUE)

## boundary (singular) fit: see help('isSingular')

anova(mod12pk, mod13pk) # go with model 12pk

## Data: kbs_flwr_plot_origin
## Models:
## mod13pk: log(julian_median) ~ state + origin + (1 + year_factor | plot)
## mod12pk: log(julian_median) ~ state * origin + (1 + year_factor | plot)
##          npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod13pk     9 -834.72 -798.40 426.36  -852.72
## mod12pk    12 -833.05 -784.63 428.53  -857.05 4.3374  3     0.2273

```

```

anova(mod12pk, mod14pk) # mod 14pk

## Data: kbs_flwr_plot_origin
## Models:
## mod14pk: log(julian_median) ~ state + origin + year_factor + (1 | plot)
## mod12pk: log(julian_median) ~ state * origin + (1 + year_factor | plot)
##          npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod14pk     8 -849.87 -817.59 432.94   -865.87
## mod12pk    12 -833.05 -784.63 428.53   -857.05      0  4           1

AICctab(mod12pk, mod13pk, mod14pk, weights=T)

##          dAICc df weight
## mod14pk  0.0   8   1
## mod13pk 15.2   9 <0.001
## mod12pk 17.2  12 <0.001

summary(mod14pk)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + origin + year_factor + (1 | plot)
## Data: kbs_flwr_plot_origin
##
##          AIC      BIC logLik deviance df.resid
## -849.9   -817.6   432.9   -865.9      410
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -3.4492 -0.7076 -0.0138  0.6231  2.8178
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 6.544e-21 8.089e-11
## Residual            7.377e-03 8.589e-02
## Number of obs: 418, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept) 5.495478  0.012365 418.000000 444.423 < 2e-16 ***
## statewarmed -0.004478  0.008442 418.000000 -0.530 0.596099  
## origin      -0.238119  0.044070 418.000000 -5.403 1.1e-07 ***
## originBoth   -0.340431  0.011357 418.000000 -29.975 < 2e-16 ***
## originExotic -0.316477  0.009636 418.000000 -32.845 < 2e-16 ***
## year_factor -0.008096  0.002207 418.000000 -3.668 0.000276 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) sttwrm origin orgnBt orgnEx
## statewarmed -0.353

```

```

## origin      -0.209  0.003
## originBoth  -0.475  0.084  0.118
## originExotc -0.442  0.009  0.121  0.445
## year_factor -0.751  0.003  0.160  0.140  0.049
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')

summ(mod14pk)

## MODEL INFO:
## Observations: 418
## Dependent Variable: log(julian_median)
## Type: Mixed effects linear regression
##
## MODEL FIT:
## AIC = -849.87, BIC = -817.59
## Pseudo-R2 (fixed effects) = 0.77
## Pseudo-R2 (total) = 0.77
##
## FIXED EFFECTS:
## -----
##           Est.   S.E.   t val.   d.f.    p
## -----
## (Intercept) 5.50  0.01  444.42  418.00  0.00
## statewarmed -0.00  0.01  -0.53  418.00  0.60
## origin      -0.24  0.04  -5.40  418.00  0.00
## originBoth   -0.34  0.01  -29.97 418.00  0.00
## originExotic -0.32  0.01  -32.84 418.00  0.00
## year_factor  -0.01  0.00  -3.67  418.00  0.00
## -----
## 
## p values calculated using Satterthwaite d.f.
##
## RANDOM EFFECTS:
## -----
##     Group   Parameter   Std. Dev.
## -----
## plot   (Intercept)  0.00
## Residual                      0.09
## -----
## 
## Grouping variables:
## -----
##   Group # groups   ICC
## -----
## plot      24       0.00
## -----

```

```

anova(mod14pk)

## Type III Analysis of Variance Table with Satterthwaite's method
##          Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state      0.0021  0.0021     1     418   0.2814  0.5960989
```

```

## origin      10.1266  3.3755      3   418 457.5558 < 2.2e-16 ***
## year_factor  0.0993  0.0993      1   418   13.4558 0.0002758 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

emmeans(mod14pk, list(pairwise ~ state + origin + year_factor), adjust = "tukey")

## boundary (singular) fit: see help('isSingular')

## $`emmeans of state, origin, year_factor`
##   state  origin year_factor emmean       SE    df lower.CL upper.CL
##   ambient Native      3.923  5.464 0.008253  76.41   5.447  5.480
##   warmed  Native      3.923  5.459 0.008134  73.12   5.443  5.475
##   ambient          3.923  5.226 0.044143 422.50   5.139  5.312
##   warmed           3.923  5.221 0.044140 422.89   5.134  5.308
##   ambient Both       3.923  5.123 0.009582 114.33   5.104  5.142
##   warmed  Both       3.923  5.119 0.010322 137.30   5.098  5.139
##   ambient Exotic     3.923  5.147 0.007984  67.82   5.131  5.163
##   warmed  Exotic     3.923  5.143 0.007954  67.73   5.127  5.159
##
## 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, year_factor`
## 1
## ambient Native year_factor3.92344497607656 - warmed Native year_factor3.92344497607656
## ambient Native year_factor3.92344497607656 - ambient year_factor3.92344497607656
## ambient Native year_factor3.92344497607656 - warmed year_factor3.92344497607656
## ambient Native year_factor3.92344497607656 - ambient Both year_factor3.92344497607656
## ambient Native year_factor3.92344497607656 - warmed Both year_factor3.92344497607656
## ambient Native year_factor3.92344497607656 - ambient Exotic year_factor3.92344497607656
## ambient Native year_factor3.92344497607656 - warmed Exotic year_factor3.92344497607656
## warmed Native year_factor3.92344497607656 - ambient year_factor3.92344497607656
## warmed Native year_factor3.92344497607656 - warmed year_factor3.92344497607656
## warmed Native year_factor3.92344497607656 - ambient Both year_factor3.92344497607656
## warmed Native year_factor3.92344497607656 - warmed Both year_factor3.92344497607656
## warmed Native year_factor3.92344497607656 - ambient Exotic year_factor3.92344497607656
## warmed Native year_factor3.92344497607656 - warmed Exotic year_factor3.92344497607656
## ambient year_factor3.92344497607656 - warmed year_factor3.92344497607656
## ambient year_factor3.92344497607656 - ambient Both year_factor3.92344497607656
## ambient year_factor3.92344497607656 - warmed Both year_factor3.92344497607656
## ambient year_factor3.92344497607656 - ambient Exotic year_factor3.92344497607656
## ambient year_factor3.92344497607656 - warmed Exotic year_factor3.92344497607656
## warmed year_factor3.92344497607656 - ambient Both year_factor3.92344497607656
## warmed year_factor3.92344497607656 - warmed Both year_factor3.92344497607656
## warmed year_factor3.92344497607656 - ambient Exotic year_factor3.92344497607656
## warmed year_factor3.92344497607656 - warmed Exotic year_factor3.92344497607656
## ambient Both year_factor3.92344497607656 - warmed Both year_factor3.92344497607656
## ambient Both year_factor3.92344497607656 - ambient Exotic year_factor3.92344497607656
## ambient Both year_factor3.92344497607656 - warmed Exotic year_factor3.92344497607656
## warmed Both year_factor3.92344497607656 - ambient Exotic year_factor3.92344497607656
## warmed Both year_factor3.92344497607656 - warmed Exotic year_factor3.92344497607656

```

```

## ambient Exotic year_factor3.92344497607656 - warmed Exotic year_factor3.92344497607656
## estimate      SE   df t.ratio p.value
## 0.00448 0.00851 22.6  0.526  0.9994
## 0.23812 0.04458 423.8  5.341 <.0001
## 0.24260 0.04541 418.5  5.343 <.0001
## 0.34043 0.01147 419.0 29.683 <.0001
## 0.34491 0.01485 152.2 23.219 <.0001
## 0.31648 0.00971 402.6 32.604 <.0001
## 0.32095 0.01297 110.7 24.754 <.0001
## 0.23364 0.04537 416.9  5.150 <.0001
## 0.23812 0.04458 423.8  5.341 <.0001
## 0.33595 0.01369 125.7 24.548 <.0001
## 0.34043 0.01147 419.0 29.683 <.0001
## 0.31200 0.01285 107.1 24.274 <.0001
## 0.31648 0.00971 402.6 32.604 <.0001
## 0.00448 0.00851 22.6  0.526  0.9994
## 0.10231 0.04471 424.0  2.288  0.3025
## 0.10679 0.04568 416.0  2.338  0.2757
## 0.07836 0.04447 423.7  1.762  0.6461
## 0.08284 0.04527 417.3  1.830  0.6001
## 0.09783 0.04535 417.7  2.157  0.3801
## 0.10231 0.04471 424.0  2.288  0.3025
## 0.07388 0.04528 418.7  1.632  0.7309
## 0.07836 0.04447 423.7  1.762  0.6461
## 0.00448 0.00851 22.6  0.526  0.9994
## -0.02395 0.01126 419.2 -2.127  0.3992
## -0.01948 0.01357 122.6 -1.436  0.8389
## -0.02843 0.01465 145.8 -1.941  0.5251
## -0.02395 0.01126 419.2 -2.127  0.3992
## 0.00448 0.00851 22.6  0.526  0.9994
##
## 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_flwr_plot_growthhabit <- within(kbs_flwr_plot_growthhabit, growth_habit <- relevel(factor(growth_habit), ref = "W"))
mod15pk <- lmer(log(julian_median) ~ state * growth_habit + (1+year_factor|plot), kbs_flwr_plot_growthhabit)

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

mod16pk <- lmer(log(julian_median) ~ state + growth_habit + (1+year_factor|plot), kbs_flwr_plot_growthhabit)

## boundary (singular) fit: see help('isSingular')

mod17pk <- lmer(log(julian_median) ~ state + growth_habit + year_factor + (1|plot), kbs_flwr_plot_growthhabit)
anova(mod15pk, mod16pk) # go with model 16pk

## Data: kbs_flwr_plot_growthhabit
## Models:
## mod16pk: log(julian_median) ~ state + growth_habit + (1 + year_factor | plot)

```

```

## mod15pk: log(julian_median) ~ state * growth_habit + (1 + year_factor | plot)
##          npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod16pk     9 -802.52 -766.22 410.26  -820.52
## mod15pk    11 -799.78 -755.41 410.89  -821.78 1.2589  2      0.5329

anova(mod16pk, mod17pk) # mod 17pk

## Data: kbs_flwr_plot_growthhabit
## Models:
## mod17pk: log(julian_median) ~ state + growth_habit + year_factor + (1 | plot)
## mod16pk: log(julian_median) ~ state + growth_habit + (1 + year_factor | plot)
##          npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod17pk     8 -805.09 -772.82 410.54  -821.09
## mod16pk     9 -802.52 -766.22 410.26  -820.52      0  1           1

AICctab(mod15pk, mod16pk, mod17pk, weights=T)

##          dAICc df weight
## mod17pk  0.0   8  0.754
## mod16pk  2.7   9  0.200
## mod15pk  5.6  11  0.046

summary(mod17pk)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + growth_habit + year_factor + (1 |
##          plot)
## Data: kbs_flwr_plot_growthhabit
##
##          AIC      BIC      logLik deviance df.resid
## -805.1   -772.8    410.5    -821.1      409
##
## Scaled residuals:
##       Min     1Q Median     3Q    Max
## -2.7027 -0.5557 -0.0874  0.3594  3.2117
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0001644 0.01282
## Residual            0.0080313 0.08962
## Number of obs: 417, groups: plot, 24
##
## Fixed effects:
##                   Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept)      5.362036  0.012861 179.763840 416.930 < 2e-16 ***
## statewarmed      0.009296  0.010274  24.023653  0.905   0.375    
## growth_habit     -0.265909  0.011680 407.525460 -22.767 < 2e-16 ***
## growth_habitForb/herb -0.569840  0.090874 414.160706 -6.271 9.05e-10 ***
## growth_habitGraminoid -0.262877  0.010017 393.598685 -26.242 < 2e-16 ***
## year_factor       0.001748  0.002294 404.022893  0.762   0.447    
## ---

```

```

## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) sttwrm grwth_ grw_F/ grwt_G
## statewarmed -0.398
## growth_habit -0.424  0.068
## grwth_hbtF/  0.029 -0.041  0.034
## grwth_hbtGr -0.348 -0.003  0.412  0.057
## year_factor -0.709 -0.005  0.101 -0.076 -0.040

```

```
summ(mod17pk)
```

```

## MODEL INFO:
## Observations: 417
## Dependent Variable: log(julian_median)
## Type: Mixed effects linear regression
##
## MODEL FIT:
## AIC = -805.09, BIC = -772.82
## Pseudo-R2 (fixed effects) = 0.68
## Pseudo-R2 (total) = 0.68
##
## FIXED EFFECTS:
## -----
##           Est.   S.E.    t val.    d.f.      p
## -----
## (Intercept) 5.36  0.01  416.93  179.76  0.00
## statewarmed 0.01  0.01   0.90   24.02  0.37
## growth_habit -0.27 0.01 -22.77  407.53  0.00
## growth_habitForb/herb -0.57 0.09 -6.27  414.16  0.00
## growth_habitGraminoid -0.26 0.01 -26.24  393.60  0.00
## year_factor  0.00  0.00   0.76  404.02  0.45
## -----
## 
## p values calculated using Satterthwaite d.f.
##
## RANDOM EFFECTS:
## -----
##     Group   Parameter   Std. Dev.
## -----
## plot     (Intercept)  0.01
## Residual          0.09
## 
## 
## Grouping variables:
## -----
##     Group # groups   ICC
## -----
## plot       24      0.02
## 
```

```
anova(mod17pk)
```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state      0.0066 0.00657     1  24.02  0.8187 0.3746
## growth_habit 7.0871 2.36237     3 406.65 294.1450 <2e-16 ***
## year_factor  0.0047 0.00466     1 404.02  0.5805 0.4466
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

emmeans(mod17pk, list(pairwise ~ state + growth_habit + year_factor), adjust = "tukey")

## $`emmeans of state, growth_habit, year_factor`
##   state  growth_habit year_factor emmean       SE    df lower.CL upper.CL
##   ambient   Forb          3.945 5.369 0.009359 63.47  5.350  5.388
##   warmed    Forb          3.945 5.378 0.009327 62.13  5.360  5.397
##   ambient          3.945 5.103 0.010903 105.20 5.081  5.125
##   warmed          3.945 5.112 0.011627 125.56 5.089  5.135
##   ambient   Forb/herb    3.945 4.799 0.091933 420.96 4.618  4.980
##   warmed   Forb/herb    3.945 4.808 0.091510 421.09 4.629  4.988
##   ambient  Graminoid    3.945 5.106 0.009538  68.14 5.087  5.125
##   warmed  Graminoid    3.945 5.115 0.009479  66.13 5.096  5.134
##
## 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 year_factor3.94484412470024 - warmed Forb year_factor3.94484412470024
##   ambient Forb year_factor3.94484412470024 - ambient year_factor3.94484412470024
##   ambient Forb year_factor3.94484412470024 - warmed year_factor3.94484412470024
##   ambient Forb year_factor3.94484412470024 - (ambient Forb/herb year_factor3.94484412470024)
##   ambient Forb year_factor3.94484412470024 - (warmed Forb/herb year_factor3.94484412470024)
##   ambient Forb year_factor3.94484412470024 - ambient Graminoid year_factor3.94484412470024
##   ambient Forb year_factor3.94484412470024 - warmed Graminoid year_factor3.94484412470024
##   warmed Forb year_factor3.94484412470024 - ambient year_factor3.94484412470024
##   warmed Forb year_factor3.94484412470024 - warmed year_factor3.94484412470024
##   warmed Forb year_factor3.94484412470024 - (ambient Forb/herb year_factor3.94484412470024)
##   warmed Forb year_factor3.94484412470024 - (warmed Forb/herb year_factor3.94484412470024)
##   warmed Forb year_factor3.94484412470024 - ambient Graminoid year_factor3.94484412470024
##   warmed Forb year_factor3.94484412470024 - warmed Graminoid year_factor3.94484412470024
##   ambient year_factor3.94484412470024 - warmed year_factor3.94484412470024
##   ambient year_factor3.94484412470024 - (ambient Forb/herb year_factor3.94484412470024)
##   ambient year_factor3.94484412470024 - (warmed Forb/herb year_factor3.94484412470024)
##   ambient year_factor3.94484412470024 - ambient Graminoid year_factor3.94484412470024
##   ambient year_factor3.94484412470024 - warmed Graminoid year_factor3.94484412470024
##   warmed year_factor3.94484412470024 - (ambient Forb/herb year_factor3.94484412470024)
##   warmed year_factor3.94484412470024 - (warmed Forb/herb year_factor3.94484412470024)
##   warmed year_factor3.94484412470024 - ambient Graminoid year_factor3.94484412470024
##   warmed year_factor3.94484412470024 - warmed Graminoid year_factor3.94484412470024
##   (ambient Forb/herb year_factor3.94484412470024) - (warmed Forb/herb year_factor3.94484412470024)
##   (ambient Forb/herb year_factor3.94484412470024) - ambient Graminoid year_factor3.94484412470024
##   (ambient Forb/herb year_factor3.94484412470024) - warmed Graminoid year_factor3.94484412470024
##   (warmed Forb/herb year_factor3.94484412470024) - ambient Graminoid year_factor3.94484412470024
##   (warmed Forb/herb year_factor3.94484412470024) - warmed Graminoid year_factor3.94484412470024

```

```

## ambient Graminoid year_factor3.94484412470024 - warmed Graminoid year_factor3.94484412470024
## estimate     SE   df t.ratio p.value
## -0.00930 0.0108 26.5  -0.864  0.9869
##  0.26591 0.0118 412.0  22.591 <.0001
##  0.25661 0.0165 130.8  15.583 <.0001
##  0.56984 0.0918 419.1   6.209 <.0001
##  0.56054 0.0920 422.3   6.094 <.0001
##  0.26288 0.0101 397.7  26.108 <.0001
##  0.25358 0.0147  94.7  17.232 <.0001
##  0.27520 0.0154 108.3  17.864 <.0001
##  0.26591 0.0118 412.0  22.591 <.0001
##  0.57914 0.0928 422.1   6.240 <.0001
##  0.56984 0.0918 419.1   6.209 <.0001
##  0.27217 0.0148  95.4  18.450 <.0001
##  0.26288 0.0101 397.7  26.108 <.0001
## -0.00930 0.0108  26.5  -0.864  0.9869
##  0.30393 0.0921 419.2   3.299  0.0233
##  0.29464 0.0922 422.4   3.194  0.0322
## -0.00303 0.0119 412.7  -0.254  1.0000
## -0.01233 0.0155 110.8  -0.794  0.9931
##  0.31323 0.0933 422.2   3.359  0.0192
##  0.30393 0.0921 419.2   3.299  0.0233
##  0.00626 0.0166 133.8   0.377  0.9999
## -0.00303 0.0119 412.7  -0.254  1.0000
## -0.00930 0.0108  26.5  -0.864  0.9869
## -0.30696 0.0918 419.1  -3.346  0.0200
## -0.31626 0.0928 422.1  -3.408  0.0163
## -0.29767 0.0920 422.3  -3.237  0.0283
## -0.30696 0.0918 419.1  -3.346  0.0200
## -0.00930 0.0108  26.5  -0.864  0.9869
##
## 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

```