

warmXtrophic Project: Flowering Phenology Analyses

Moriah Young

November 30, 2021

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"

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

# get rid of 'X' column that shows up
flwr_species$X <- NULL
flwr_plot$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; blue = ambient). First make it a factor
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"

# [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"

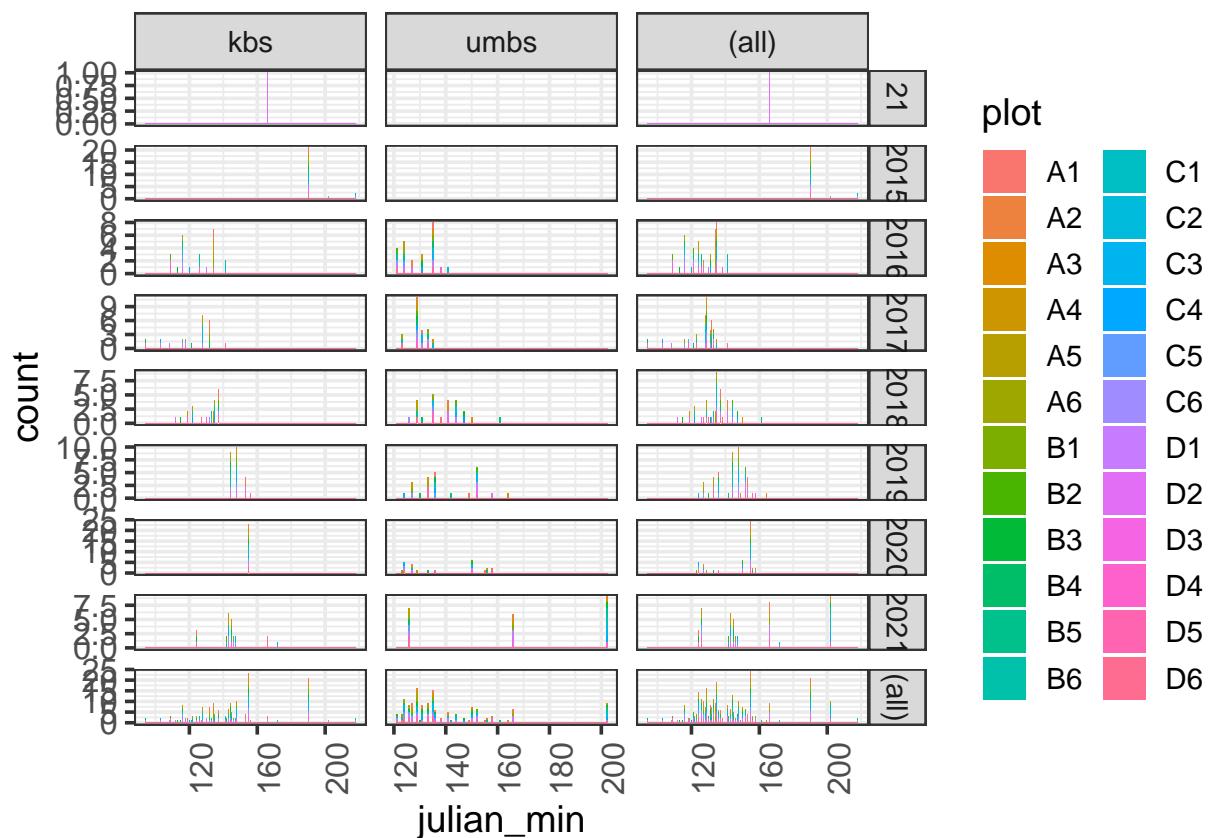
# [1] 'warmed' 'ambient'

umbs_flwr_plot <- subset(flwr_plot, site == "umbs") # pull out umbs only data at plot level
umbs_flwr_spp <- subset(flwr_species, site == "umbs") # pull out umbs only data at species level
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

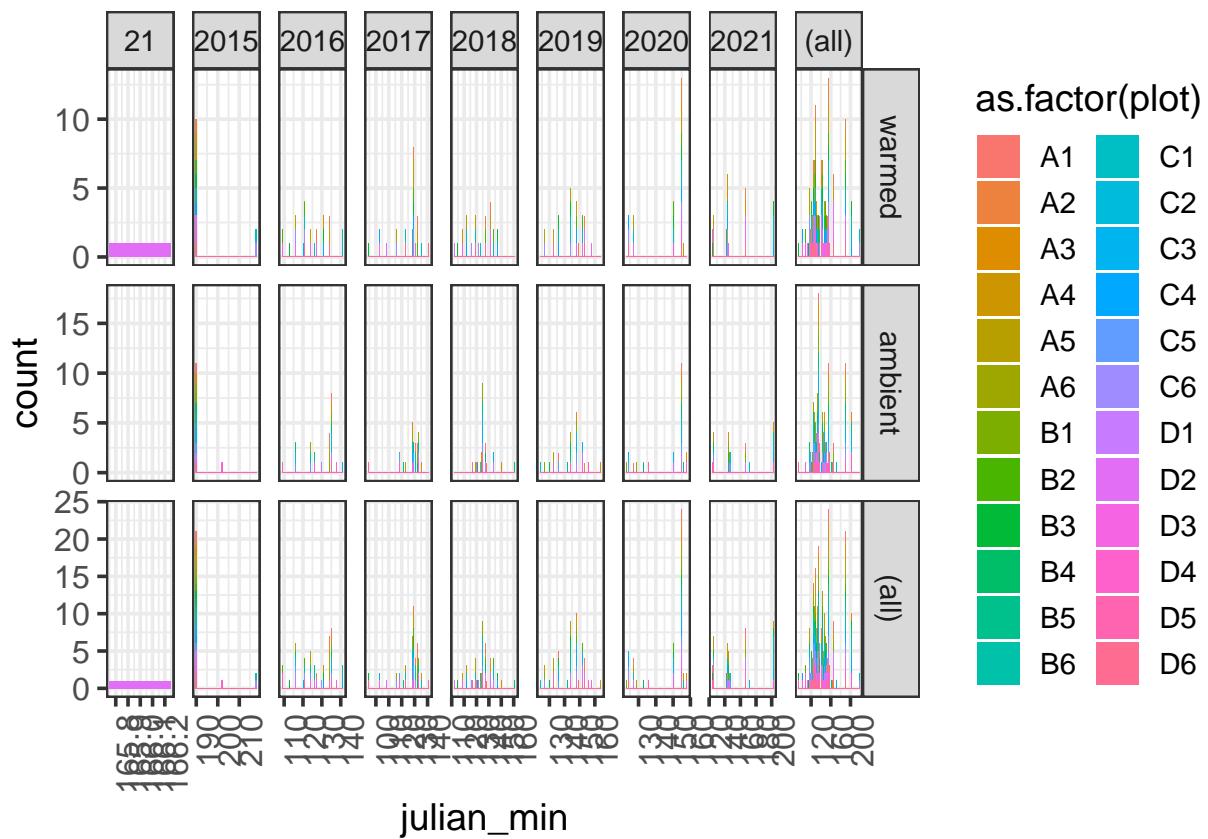
```

Data exploration for minimum (first) Julian date of flowering at the PLOT for both sites

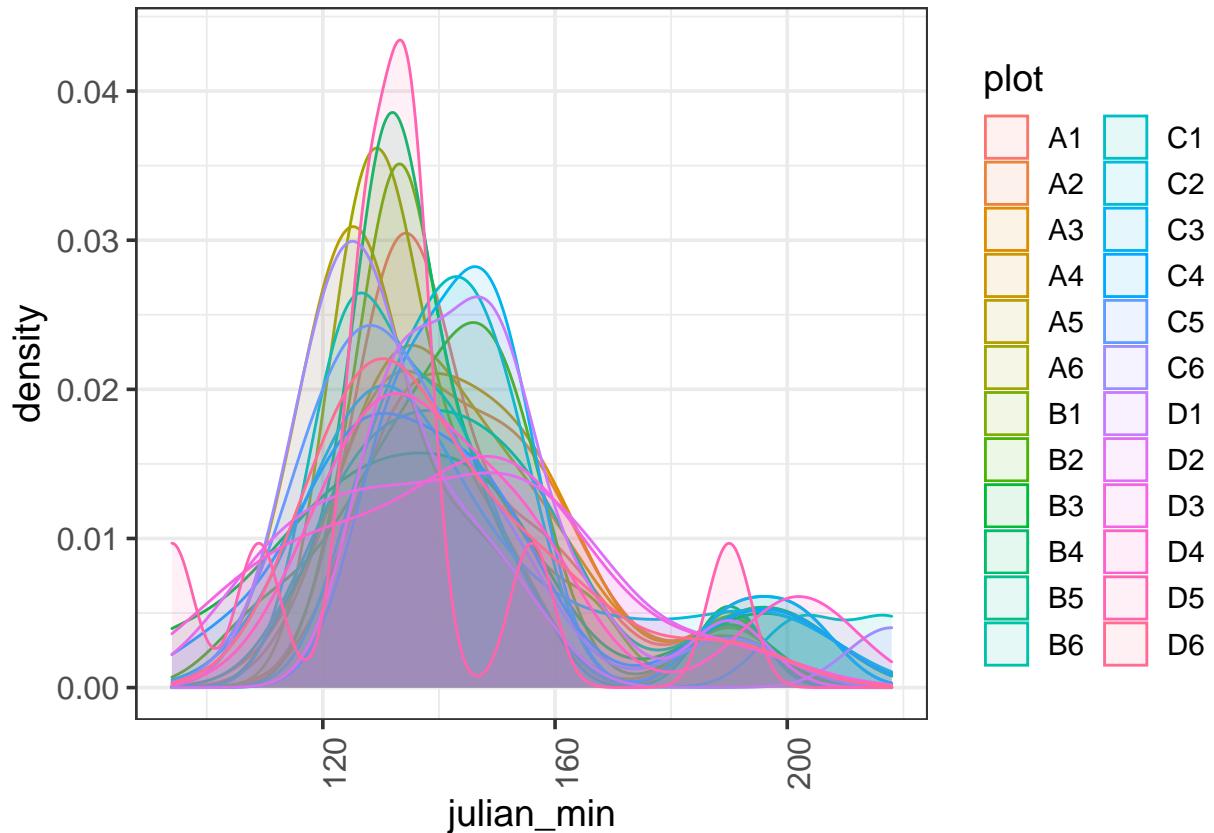
```
# Visualizing avg minimum Julian date for both sites at the PLOT LEVEL
ggplot(flwr_plot, aes(julian_min, fill = plot)) + geom_histogram(binwidth = 0.5) +
  facet_grid(year ~ site, margins = TRUE, scales = "free")
```



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



```
ggplot(fltrr_plot, aes(julian_min, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



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

```
## Warning: Groups with fewer than two data points have been dropped.
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```



```
## Warning in max(ids, na.rm = TRUE): no non-missing arguments to max; returning -
## Inf

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```

```

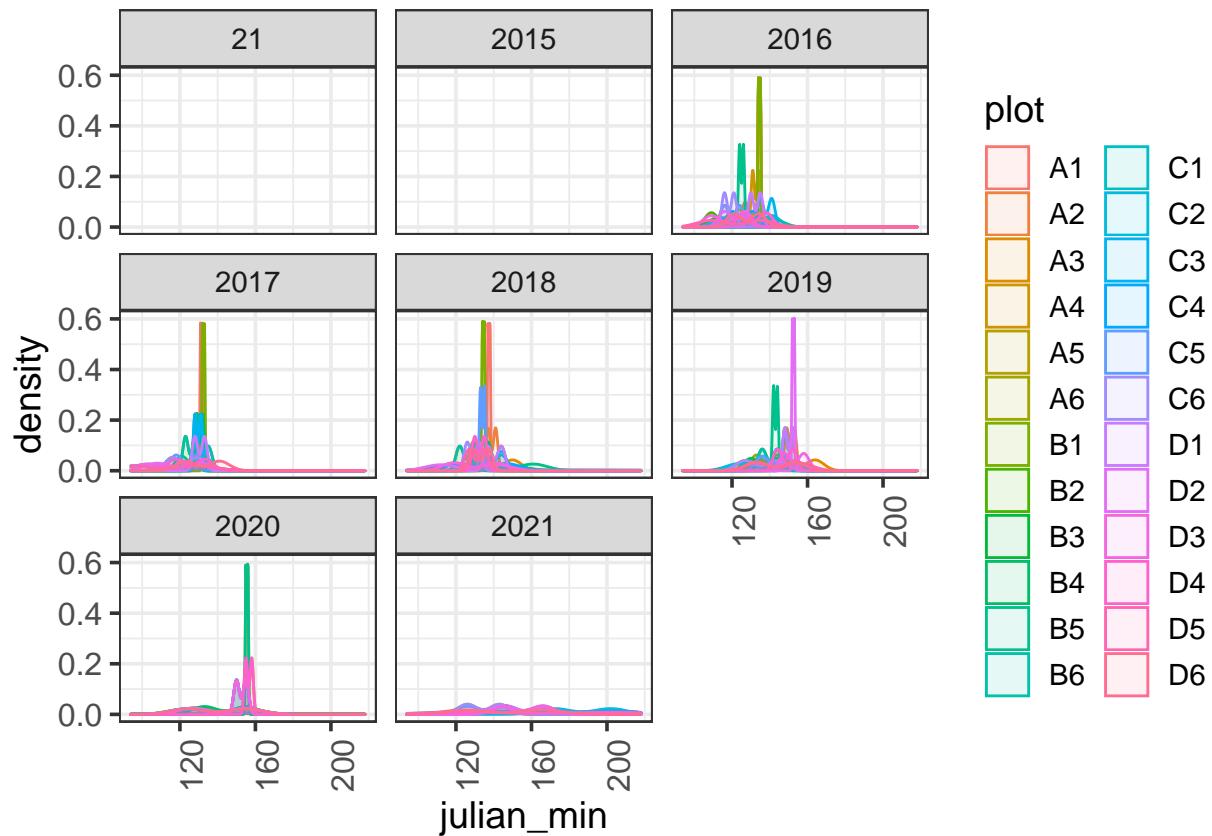
## Warning in max(ids, na.rm = TRUE): no non-missing arguments to max; returning -
## Inf

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## Warning in max(ids, na.rm = TRUE): no non-missing arguments to max; returning -
## Inf

```



```

ggplot(fltrr_plot, aes(julian_min, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
  facet_wrap(~year + plot)

```

```

## Warning: Groups with fewer than two data points have been dropped.

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```



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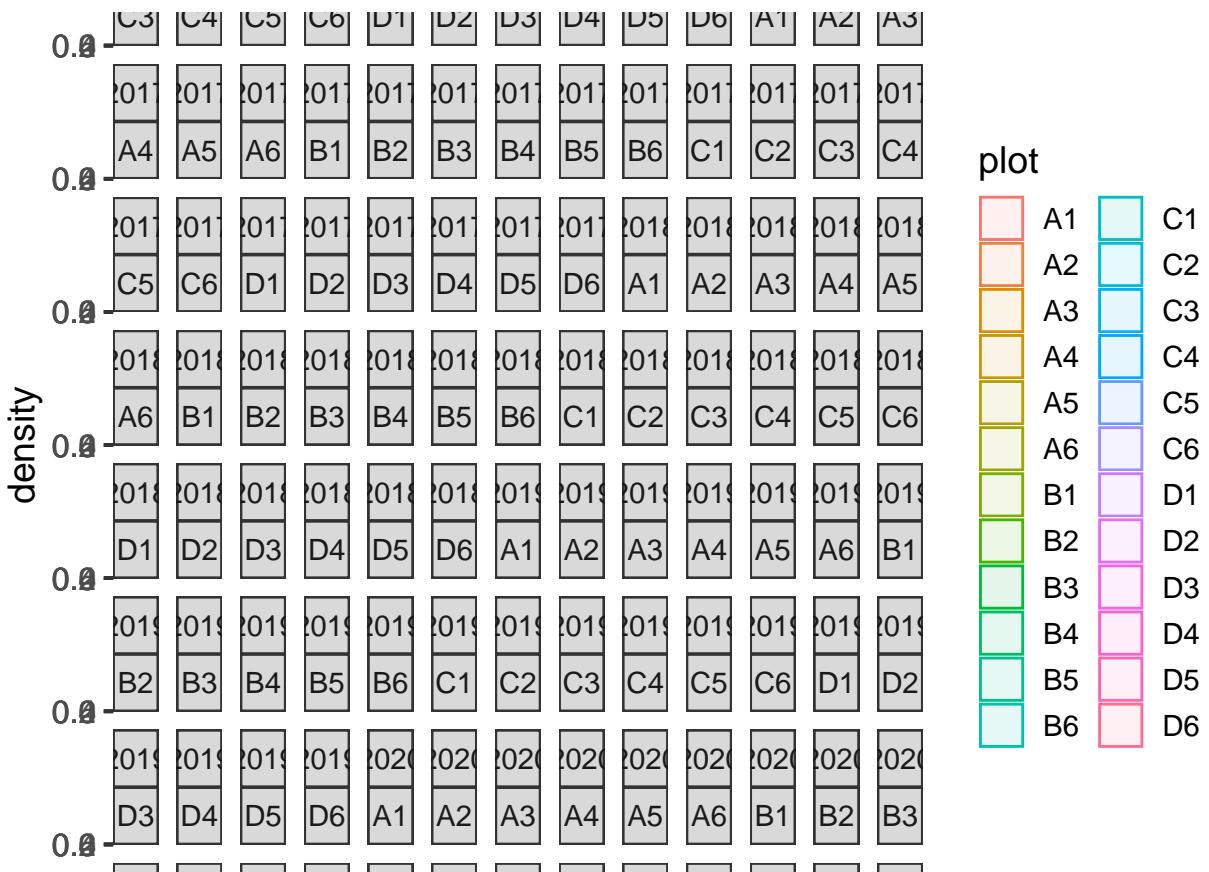
## Warning in max(ids, na.rm = TRUE): no non-missing arguments to max; returning -
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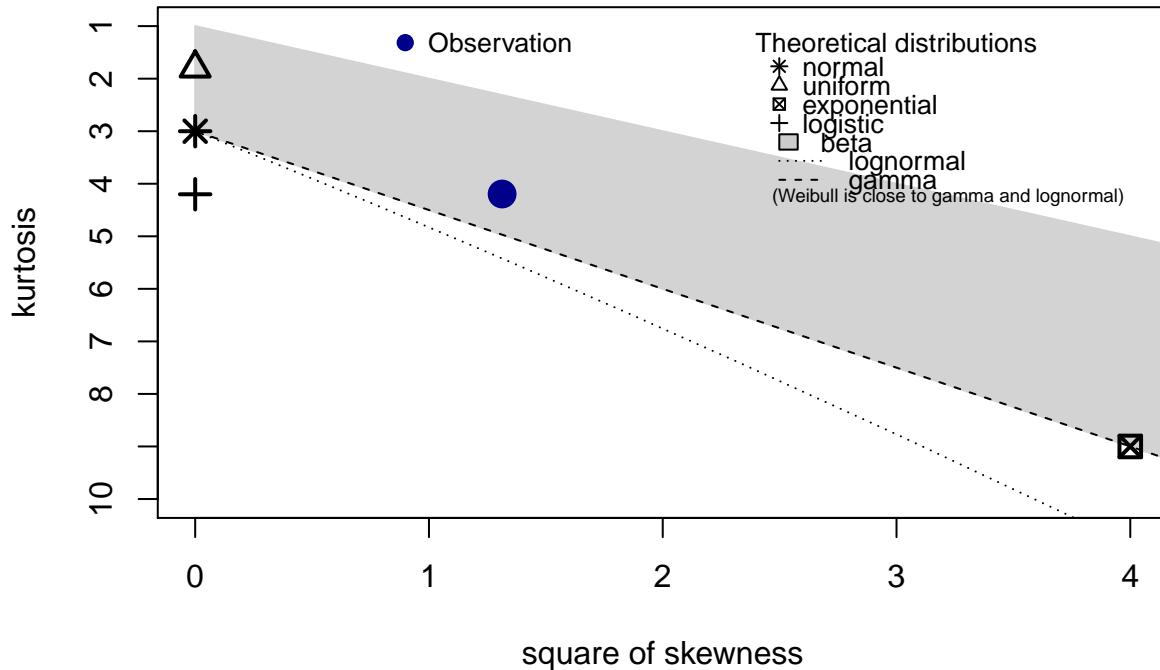
## Warning in max(ids, na.rm = TRUE): no non-missing arguments to max; returning -
## Inf

## Warning in max(ids, na.rm = TRUE): no non-missing arguments to max; returning -
## Inf
```



```
descdist(flwr_plot$julian_min, discrete = FALSE)
```

Cullen and Frey graph

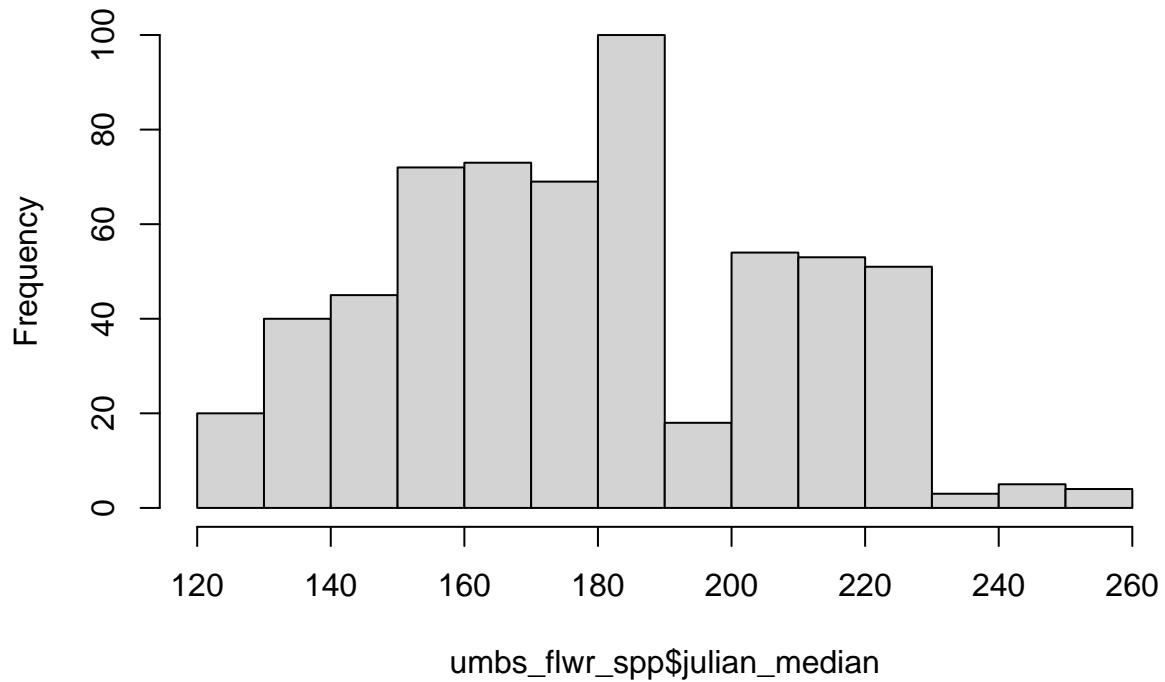


```
## summary statistics
## -----
## min: 94   max: 218
## median: 136
## mean: 143.0647
## estimated sd: 22.5183
## estimated skewness: 1.145825
## estimated kurtosis: 4.195345
```

UMBS SPECIES LEVEL - Looking at MEDIAN JULIAN DAY

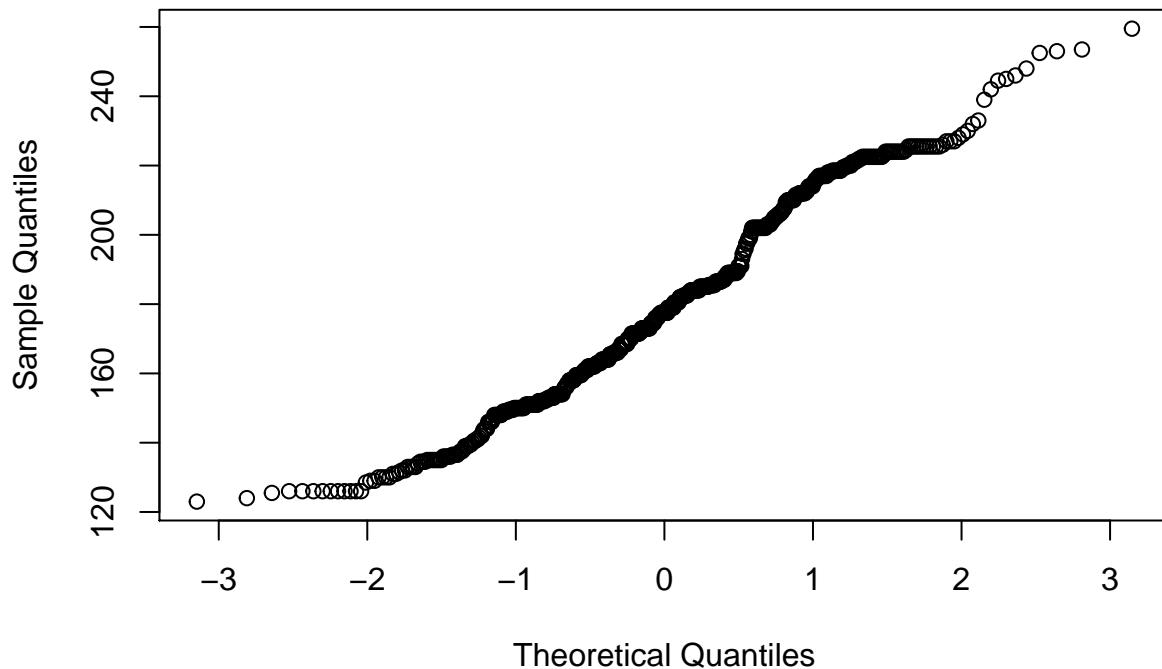
```
### UMBS ####
hist(umbs_flwr_spp$julian_median)
```

Histogram of umbs_flwr_spp\$julian_median



```
qqnorm(umbs_flwr_spp$julian_median)
```

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  

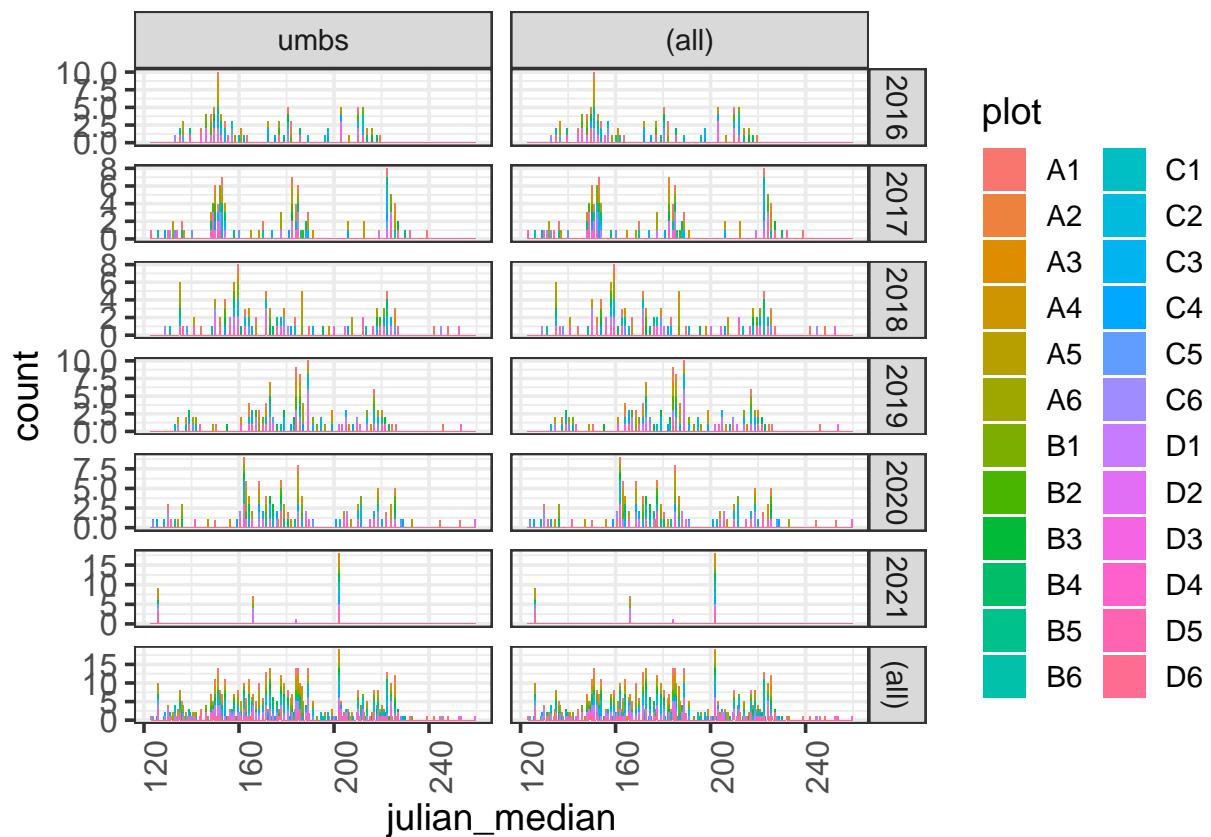
##  

## data: umbs_flwr_spp$julian_median  

## W = 0.9764, p-value = 2.552e-08

# 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")

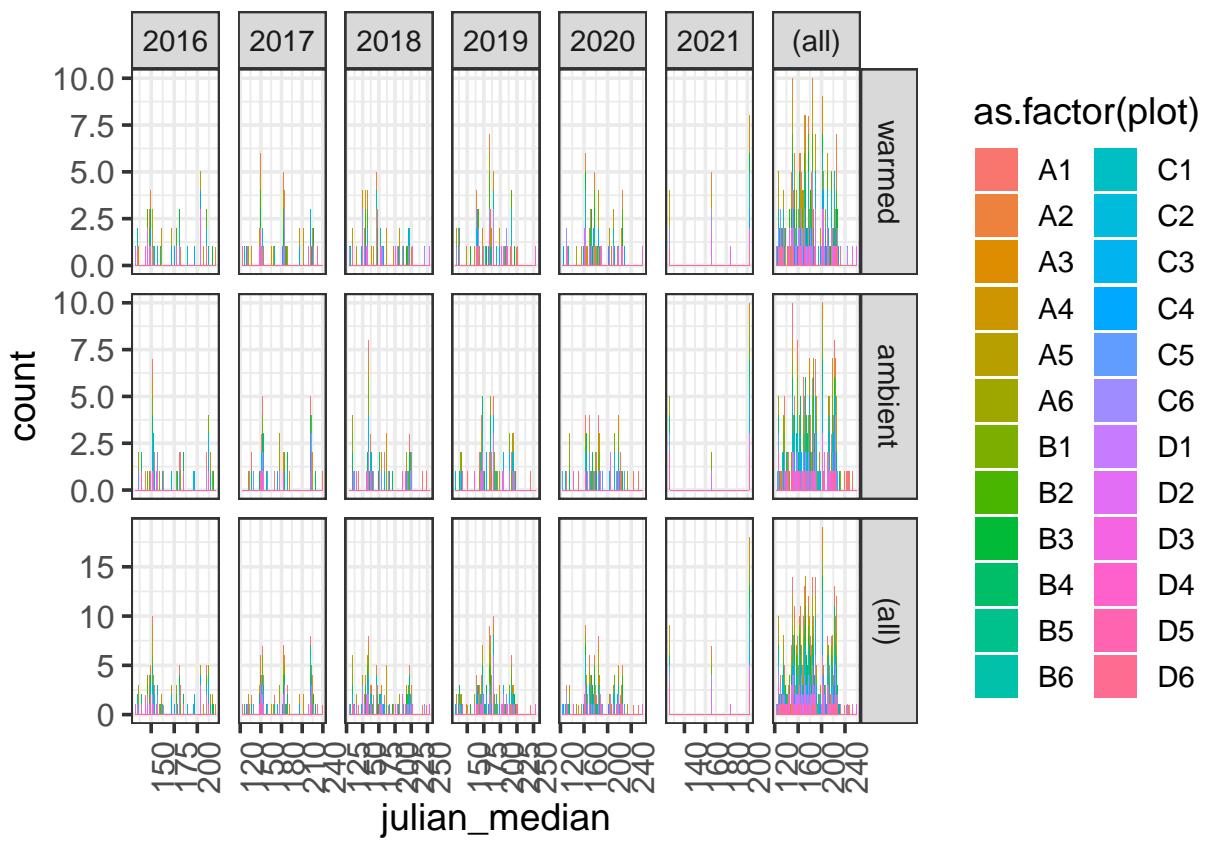
```



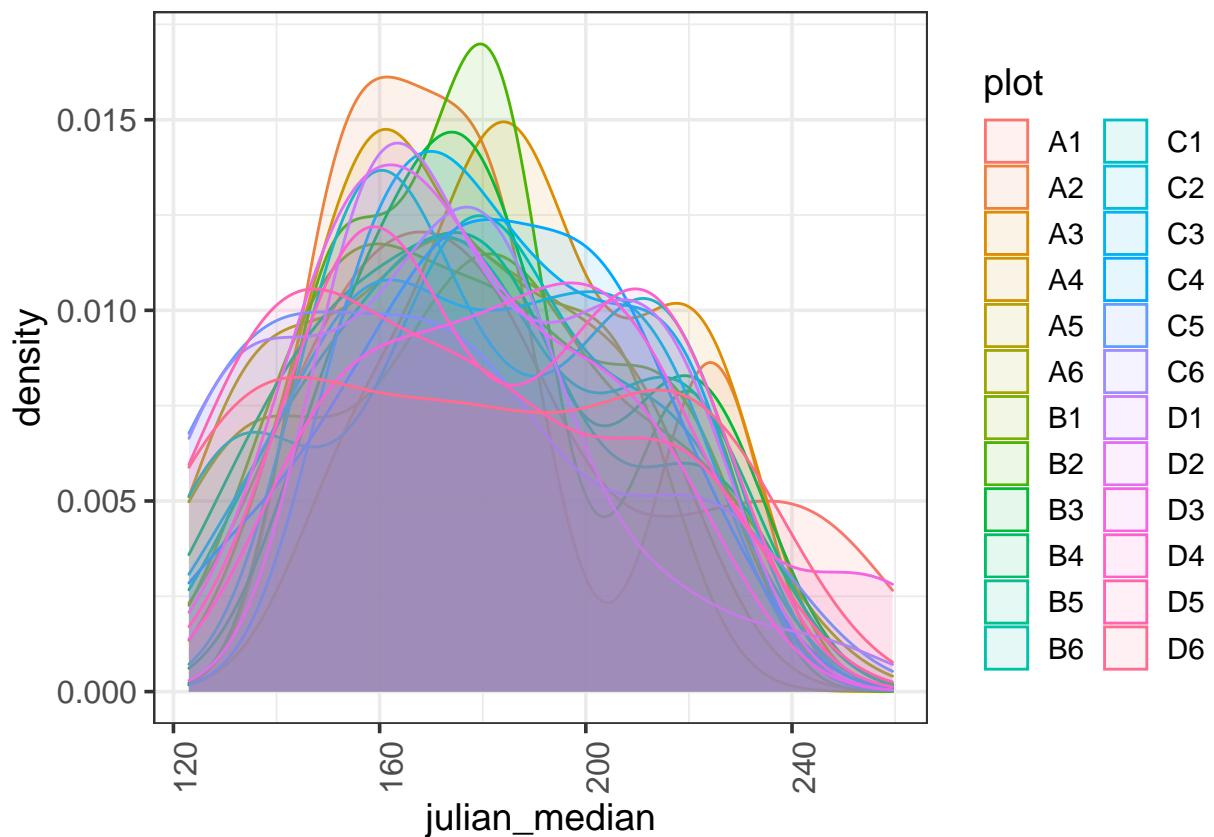
```

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

```



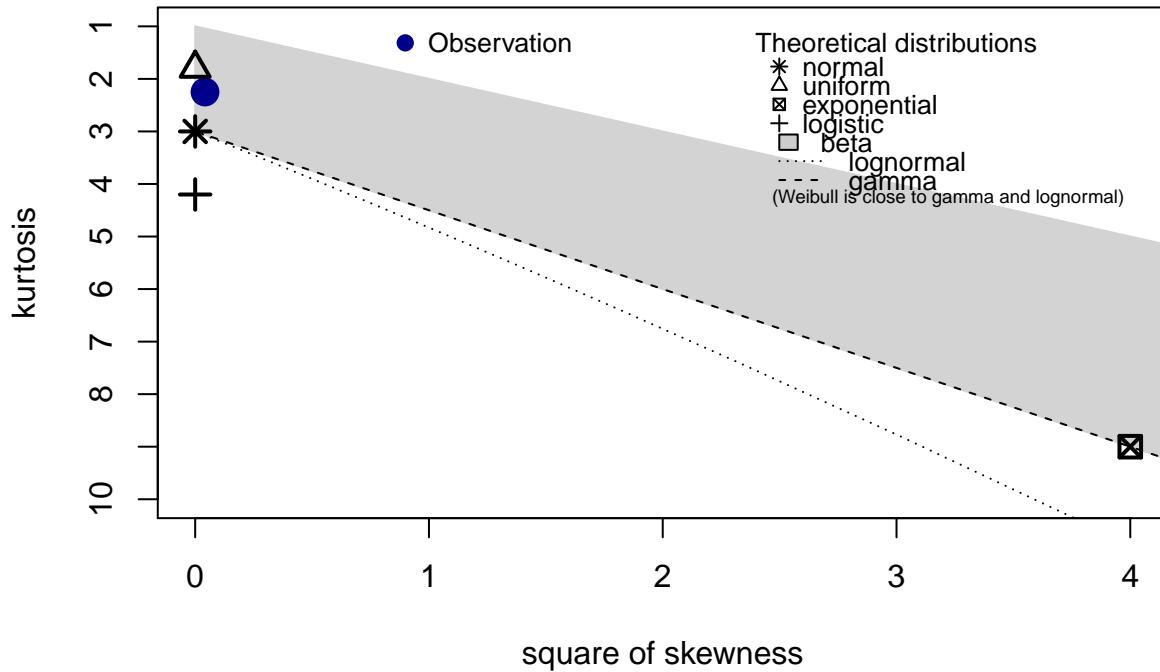
```
ggplot(umbs_flwr_spp, aes(julian_median, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



```
# ggplot(umbs_flwr_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_spp$julian_median, discrete = FALSE)
```

Cullen and Frey graph

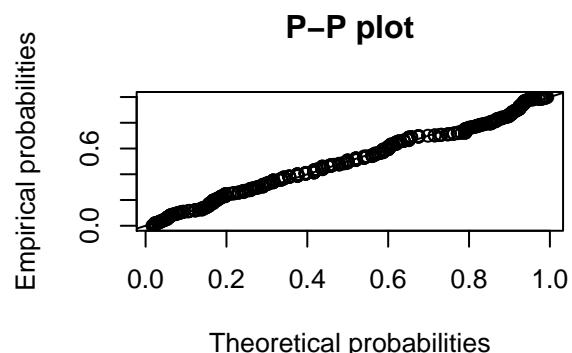
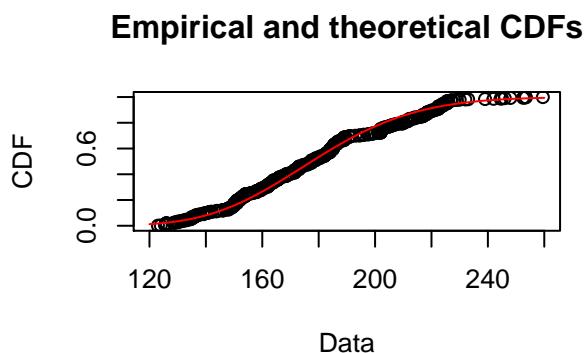
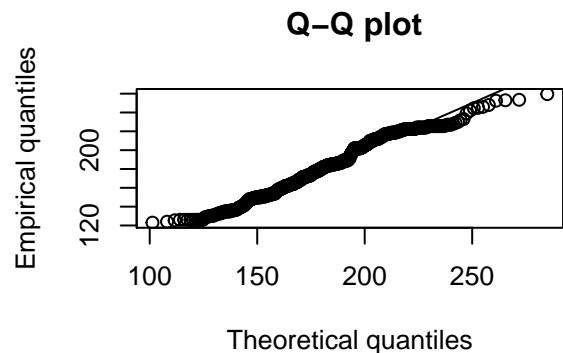
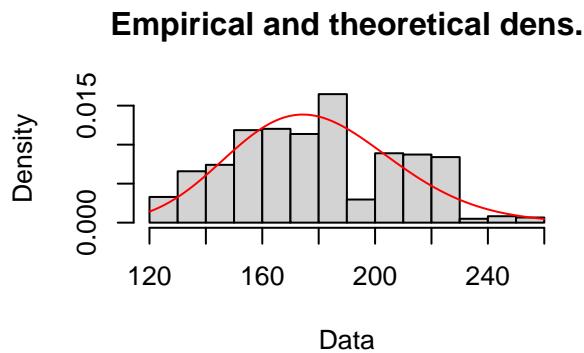


```

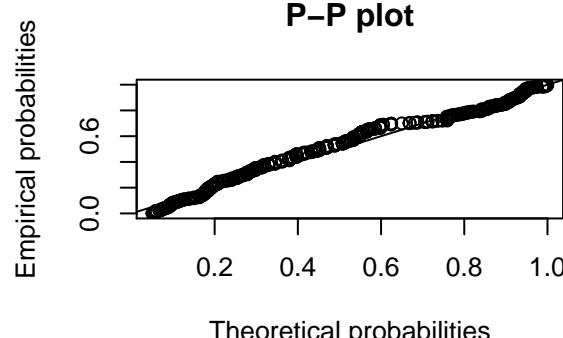
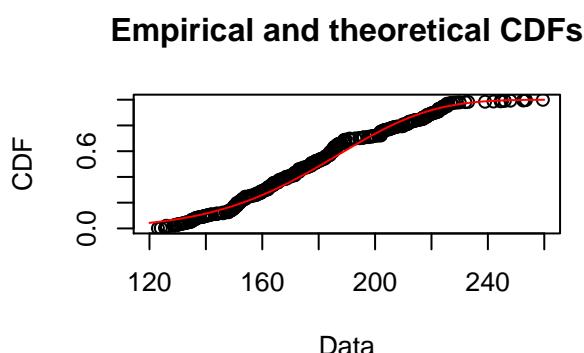
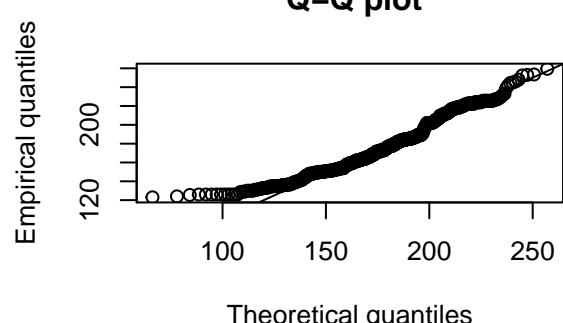
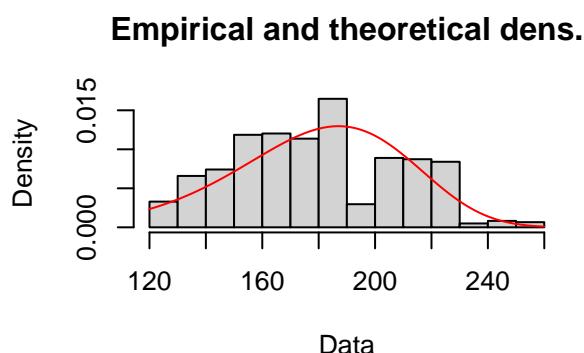
## summary statistics
## -----
## min: 123   max: 259.5
## median: 177.5
## mean: 179.1038
## estimated sd: 29.10271
## estimated skewness: 0.205113
## estimated kurtosis: 2.249624

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

```

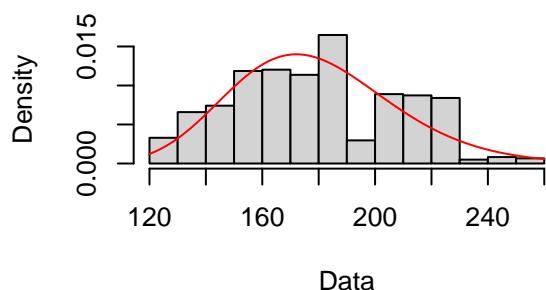


```
# Weibull distribution
fit.weibull <- fitdist(umbs_flwr_spp$julian_median, "weibull")
plot(fit.weibull)
```

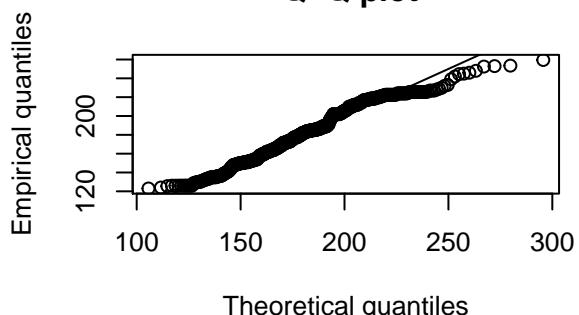


```
# Lognormal distribution
fit.ln <- fitdist(umbs_flwr_spp$julian_median, "lnorm")
plot(fit.ln)
```

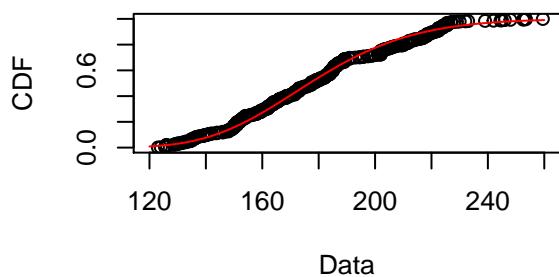
Empirical and theoretical dens.



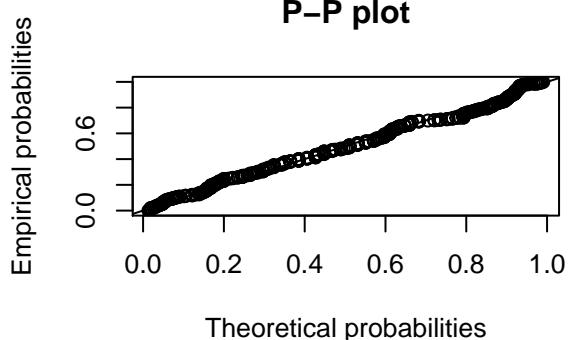
Q–Q plot



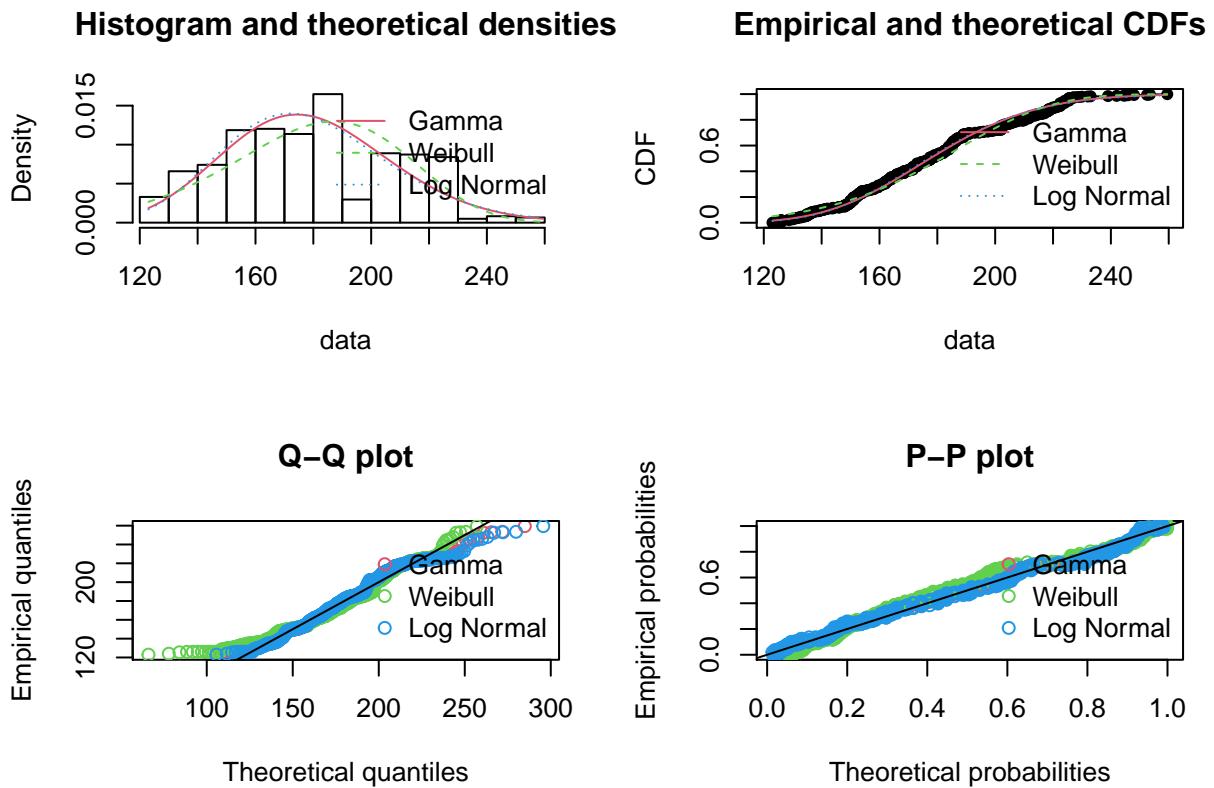
Empirical and theoretical CDFs



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 values)
gofstat(list(fit.gamma, fit.weibull, fit.ln), fitnames = c("Gamma", "Weibull", "Log Normal"))

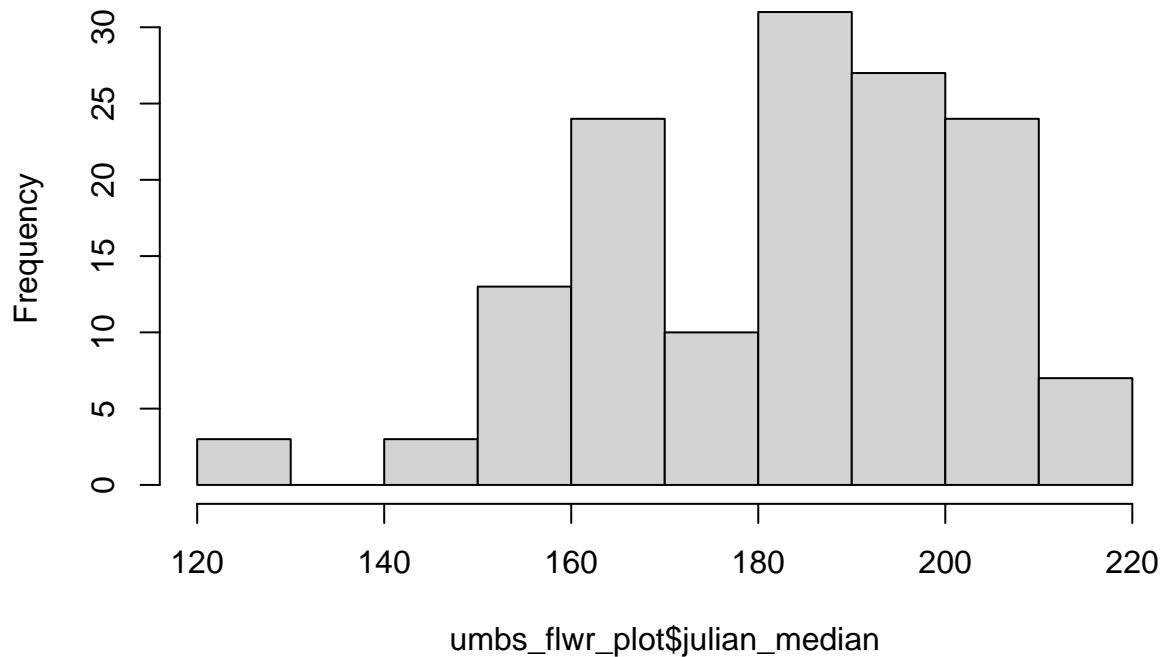
## Goodness-of-fit statistics
##                                     Gamma   Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.06912253 0.08866138 0.07150638
## Cramer-von Mises statistic   0.41231389 0.99385497 0.38676243
## Anderson-Darling statistic   3.15802349 6.29116186 3.08894826
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 5808.542 5850.567 5809.860
## Bayesian Information Criterion 5817.359 5859.384 5818.678

# Lognormal and gamma are very close, gamma slightly better, but going to go with
# log transforming
```

UMBS PLOT LEVEL - Looking at MEDIAN JULIAN DAY

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

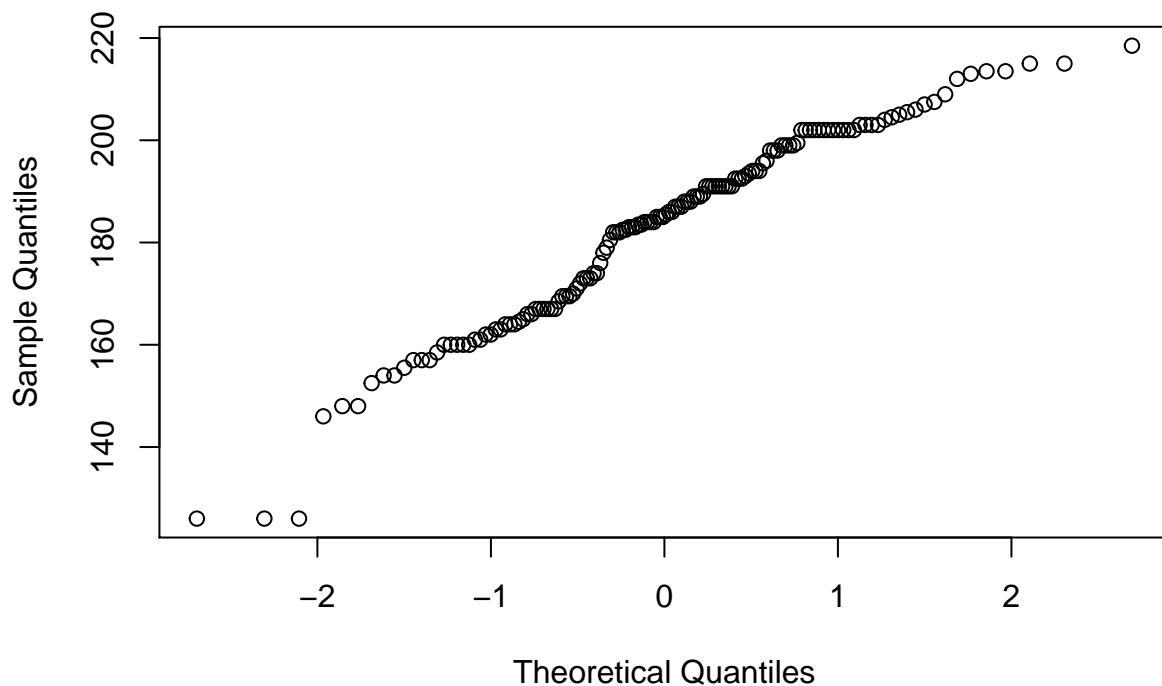
Histogram of umbs_flwr_plot\$julian_median



umbs_flwr_plot\$julian_median

```
qqnorm(umb...)
```

Normal Q-Q Plot



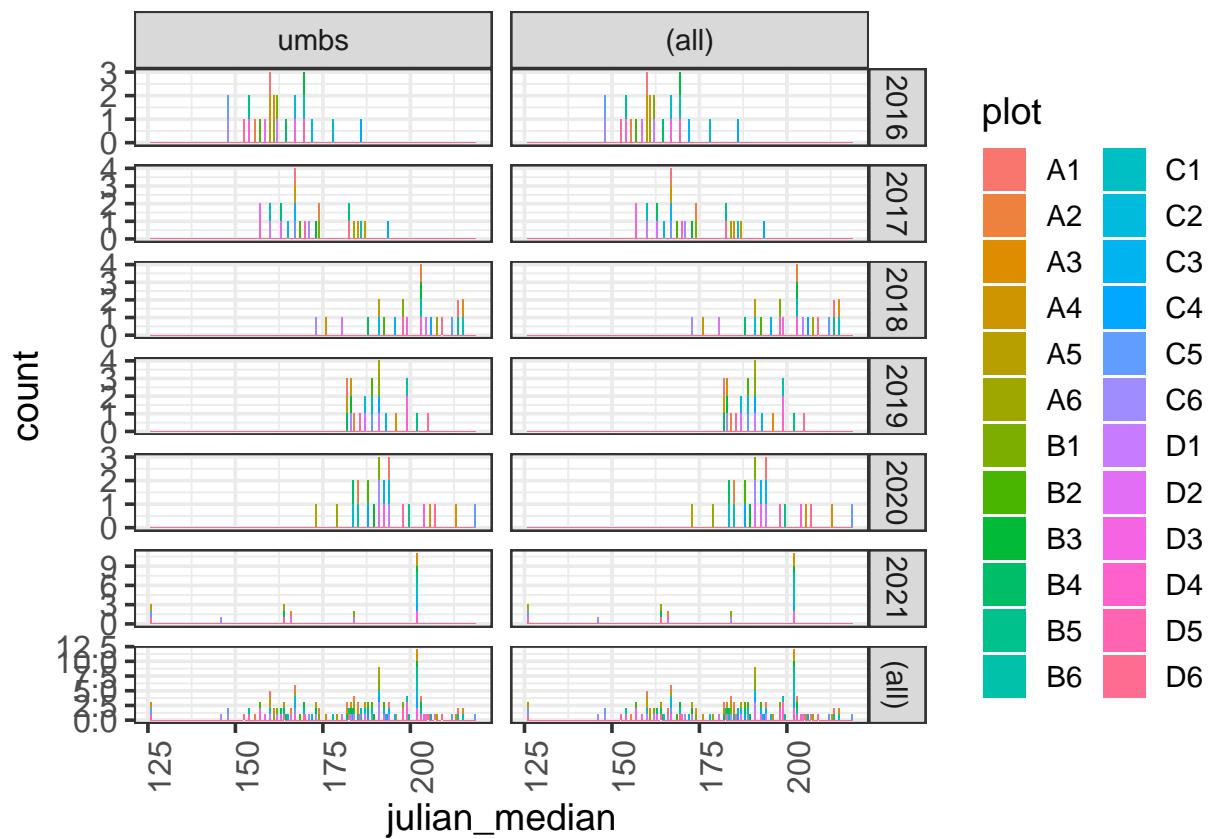
```

shapiro.test(umbs_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: umbs_flwr_plot$julian_median
## W = 0.96305, p-value = 0.0007095

# 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")

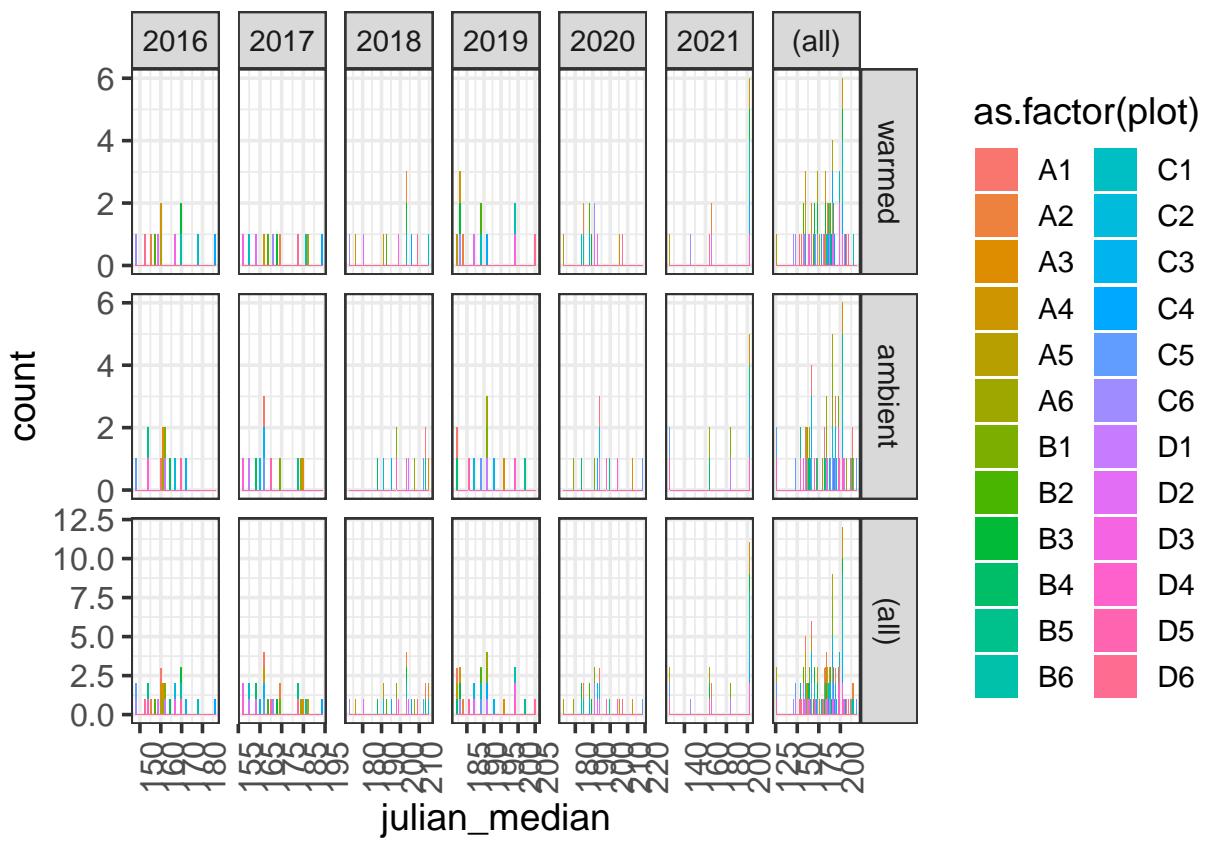
```



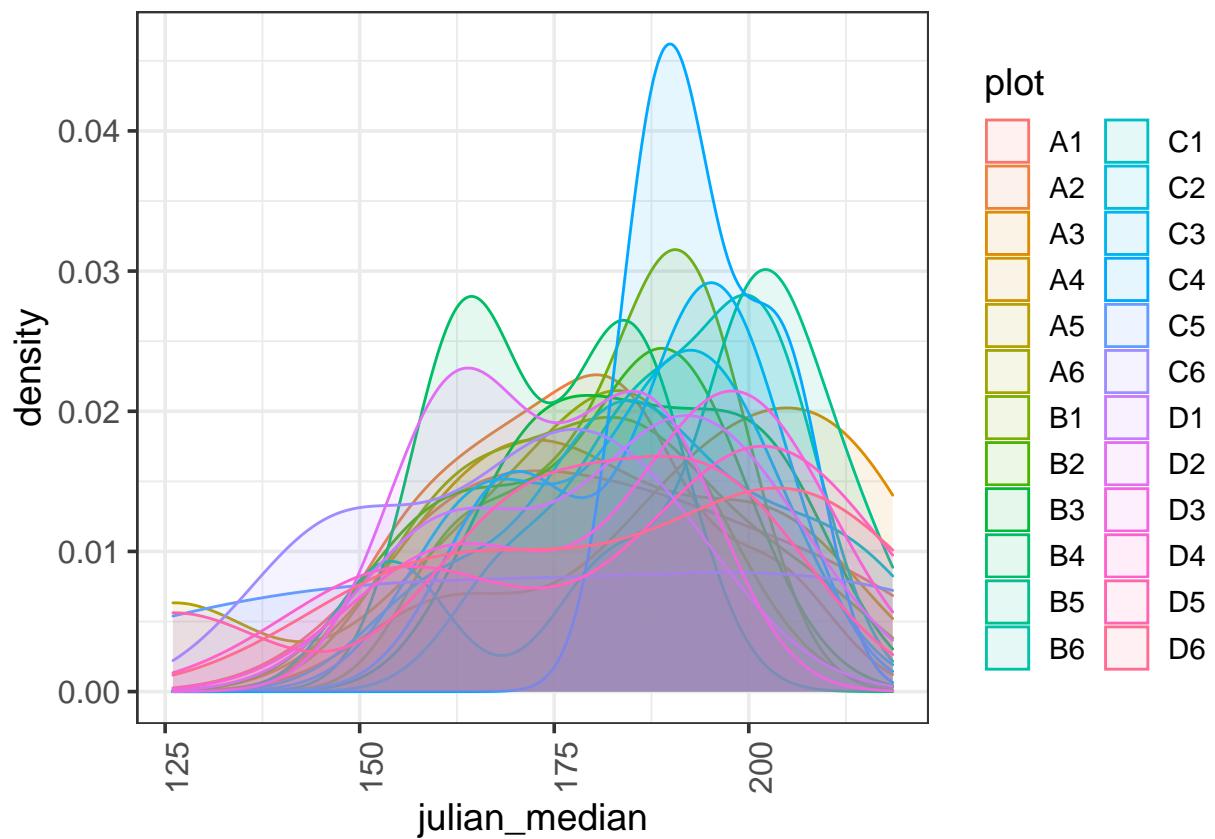
```

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

```



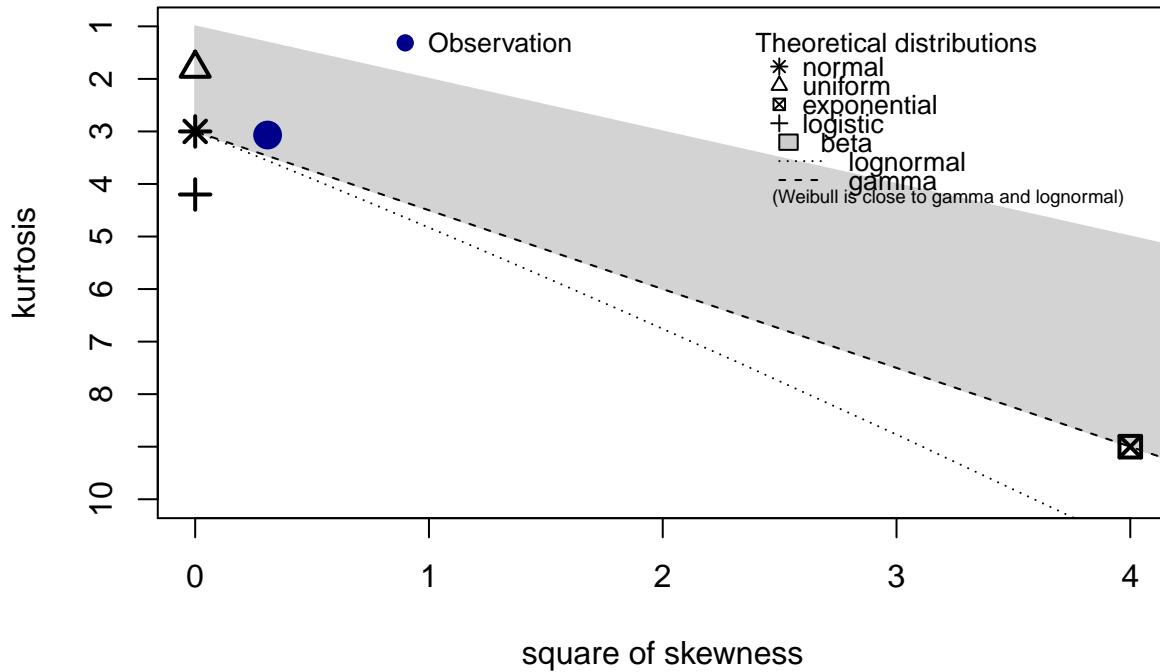
```
ggplot(umbs_flwr_plot, aes(julian_median, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



```
# 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

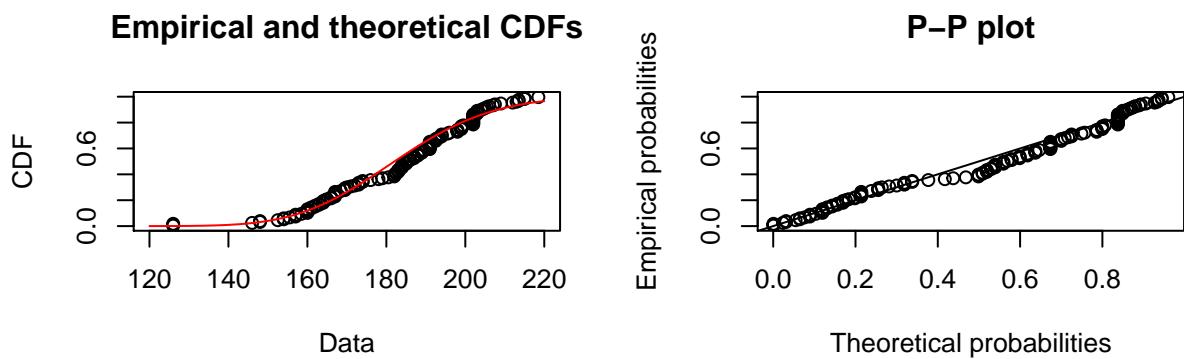
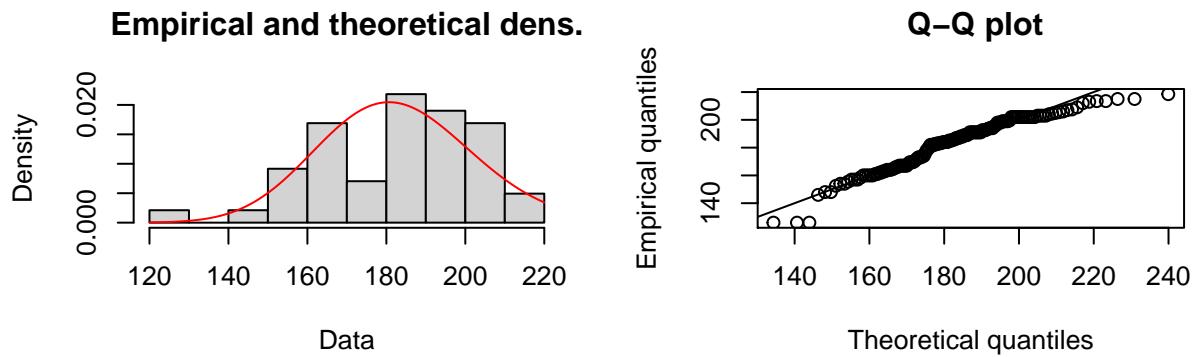


```

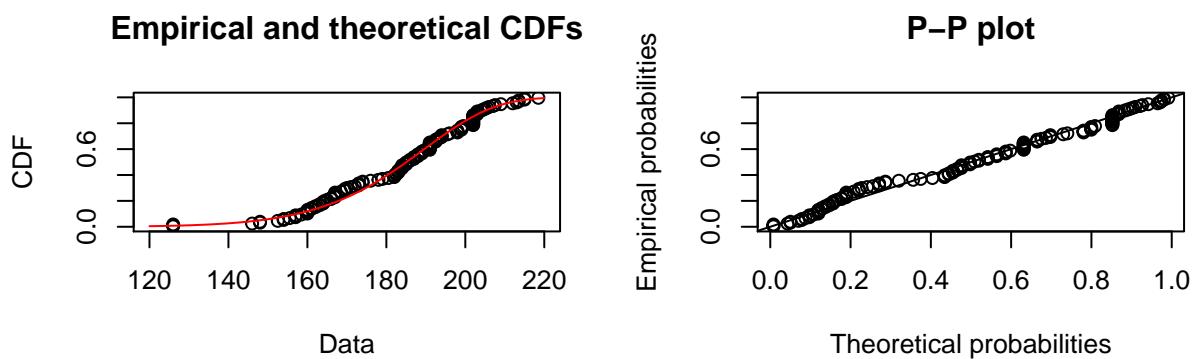
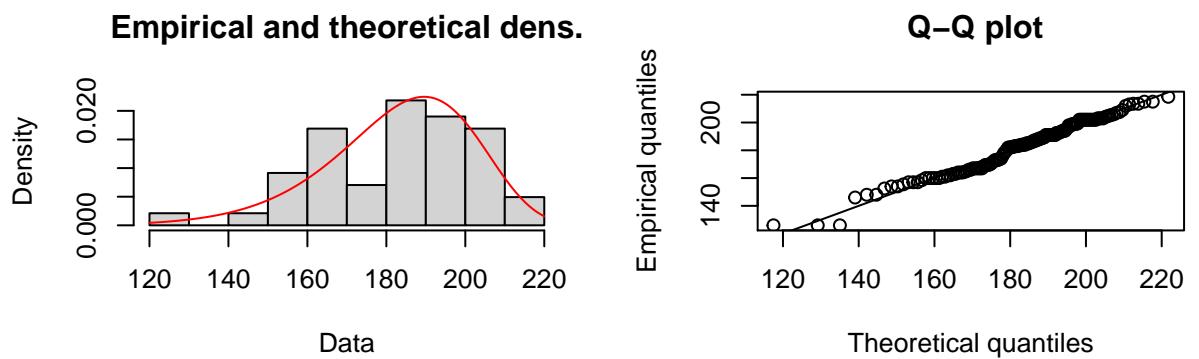
## summary statistics
## -----
## min: 126   max: 218.5
## median: 185.25
## mean: 182.757
## estimated sd: 19.13231
## estimated skewness: -0.5566556
## estimated kurtosis: 3.068298

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

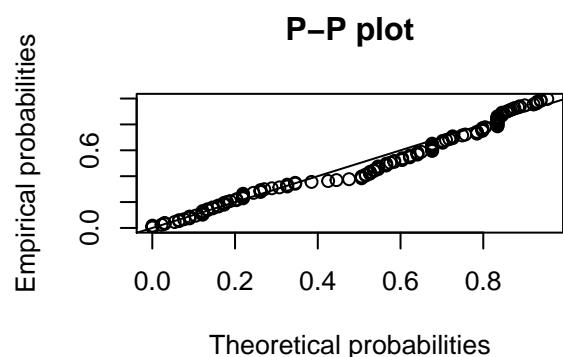
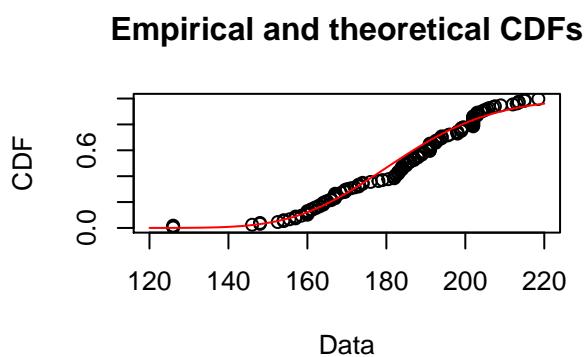
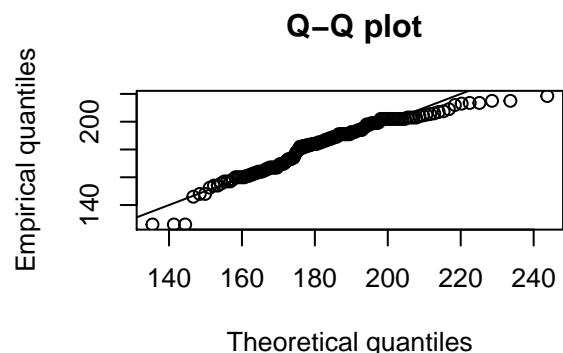
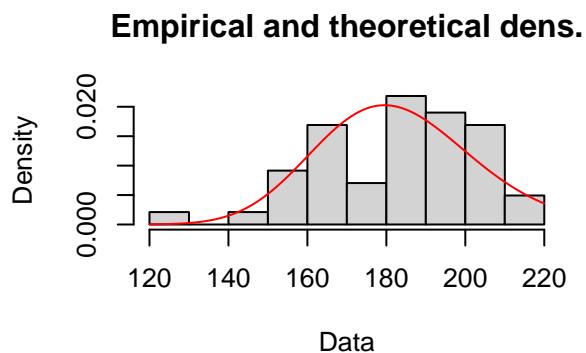
```



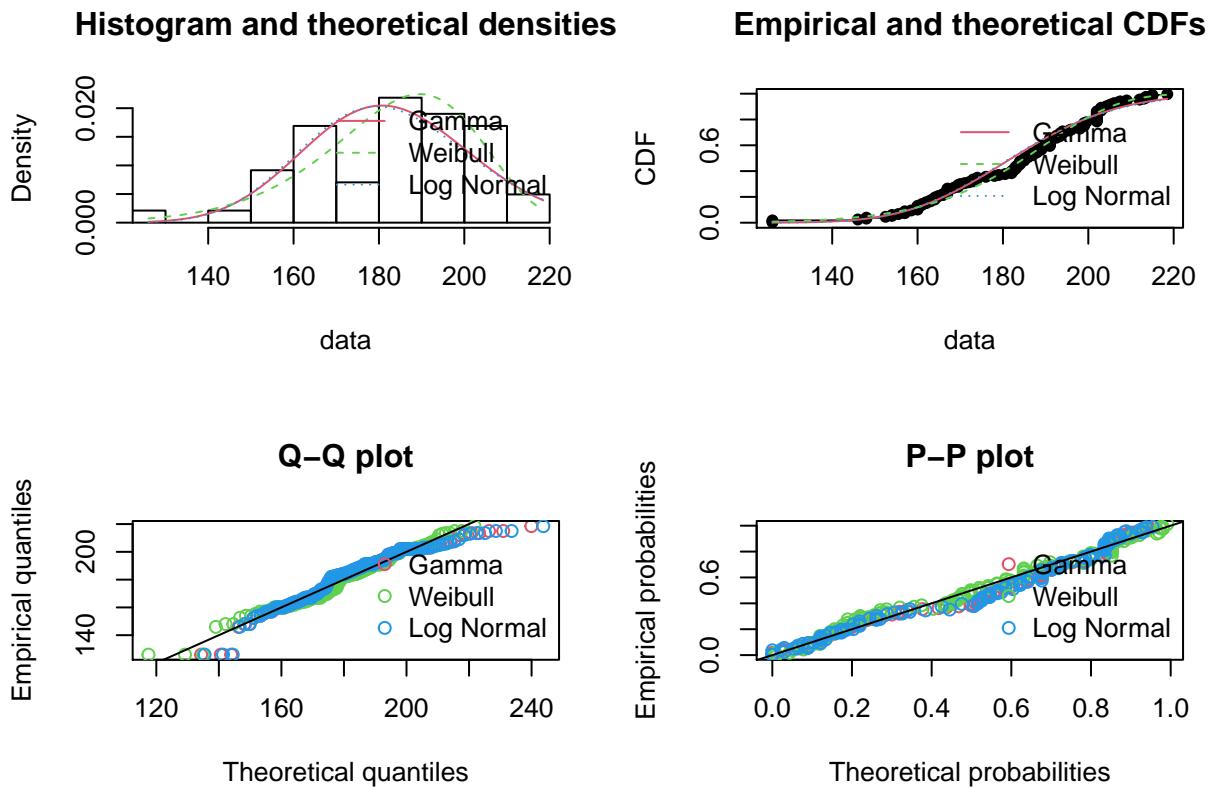
```
# Weibull distribution
fit.weibull <- fitdist(umbs_flwr_plot$julian_median, "weibull")
plot(fit.weibull)
```



```
# Lognormal distribution
fit.ln <- fitdist(umbs_flwr_plot$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 values)
gofstat(list(fit.gamma, fit.weibull, fit.ln), fitnames = c("Gamma", "Weibull", "Log Normal"))
```

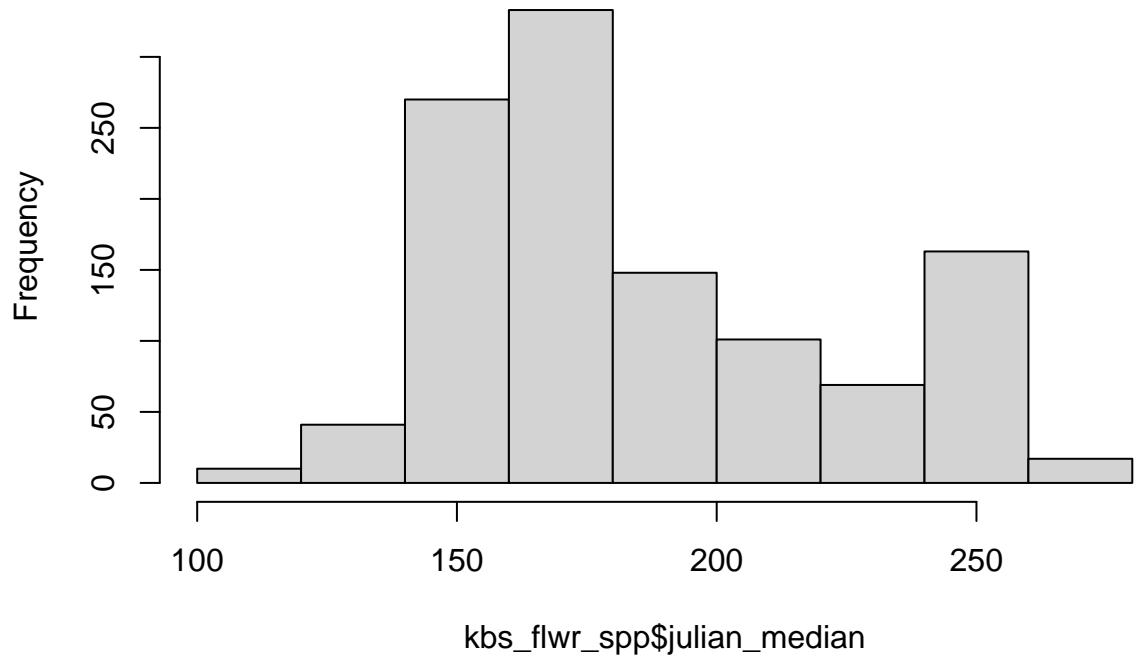
```
## Goodness-of-fit statistics
##                                     Gamma    Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.1184945 0.07844555 0.1255950
## Cramer-von Mises statistic   0.3117018 0.13714803 0.3469399
## Anderson-Darling statistic   1.8271082 0.86581300 2.0495794
##
## Goodness-of-fit criteria
##                                     Gamma    Weibull Log Normal
## Akaike's Information Criterion 1250.803 1234.193 1254.958
## Bayesian Information Criterion 1256.714 1240.104 1260.870
```

```
# Weibull the best...
```

KBS SPECIES LEVEL - Looking at MEDIAN JULIAN DAY

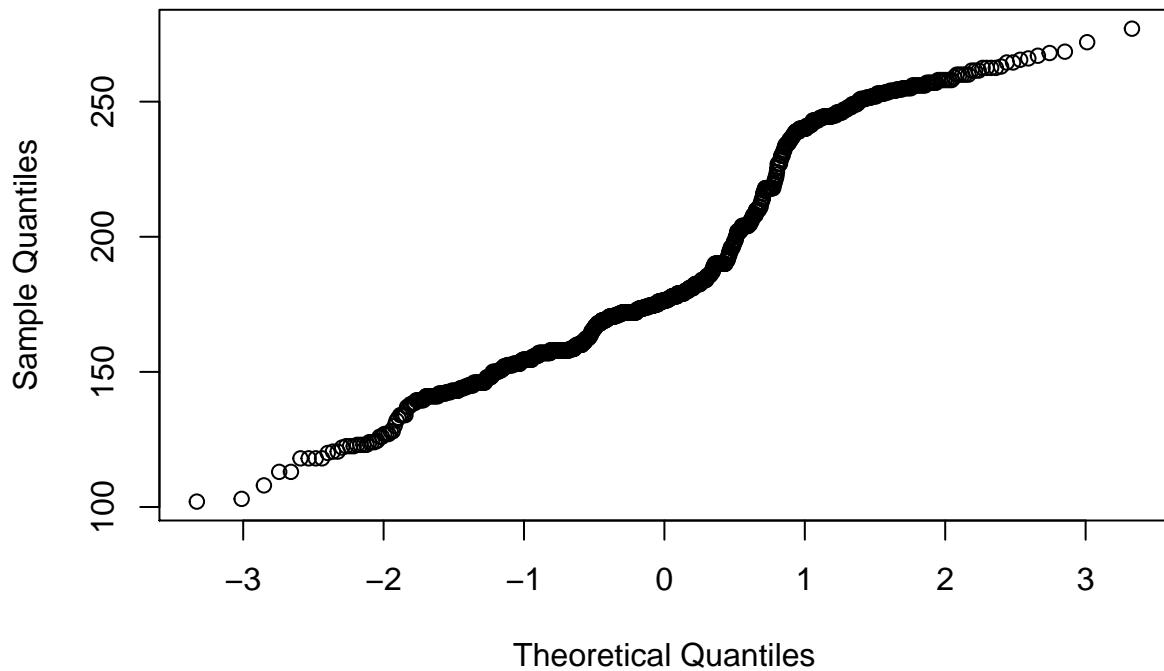
```
### KBS ####
hist(kbs_flwr_spp$julian_median)
```

Histogram of kbs_flwr_spp\$julian_median



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

Normal Q-Q Plot



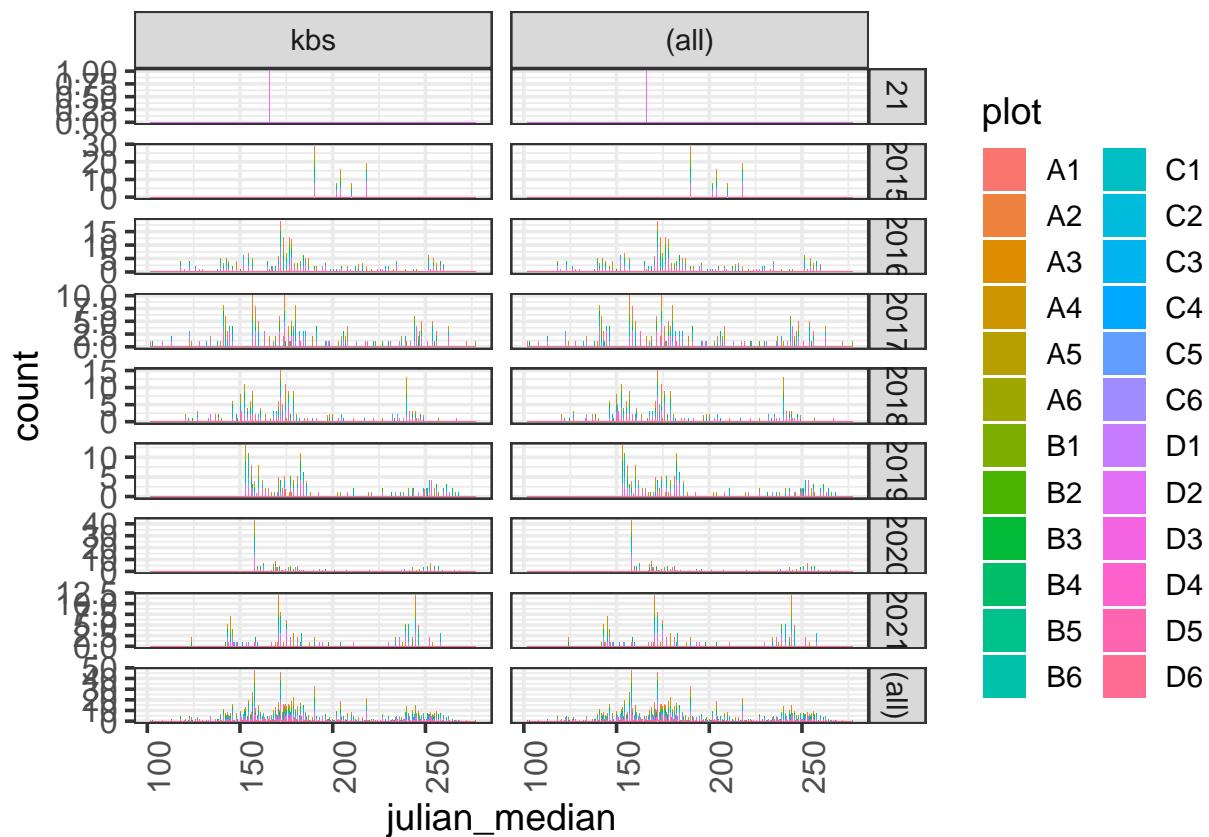
```

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

##
## Shapiro-Wilk normality test
##
## data: kbs_flwr_spp$julian_median
## W = 0.92791, p-value < 2.2e-16

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

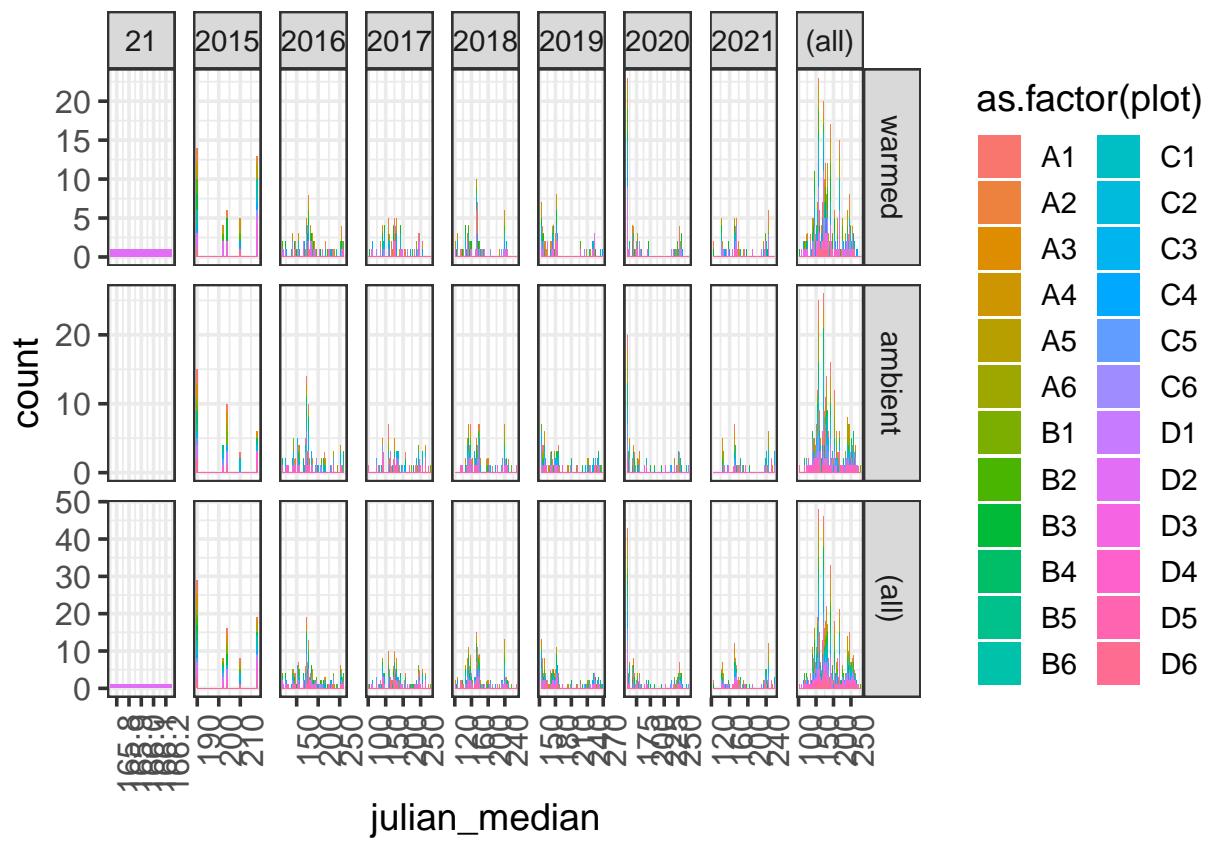
```



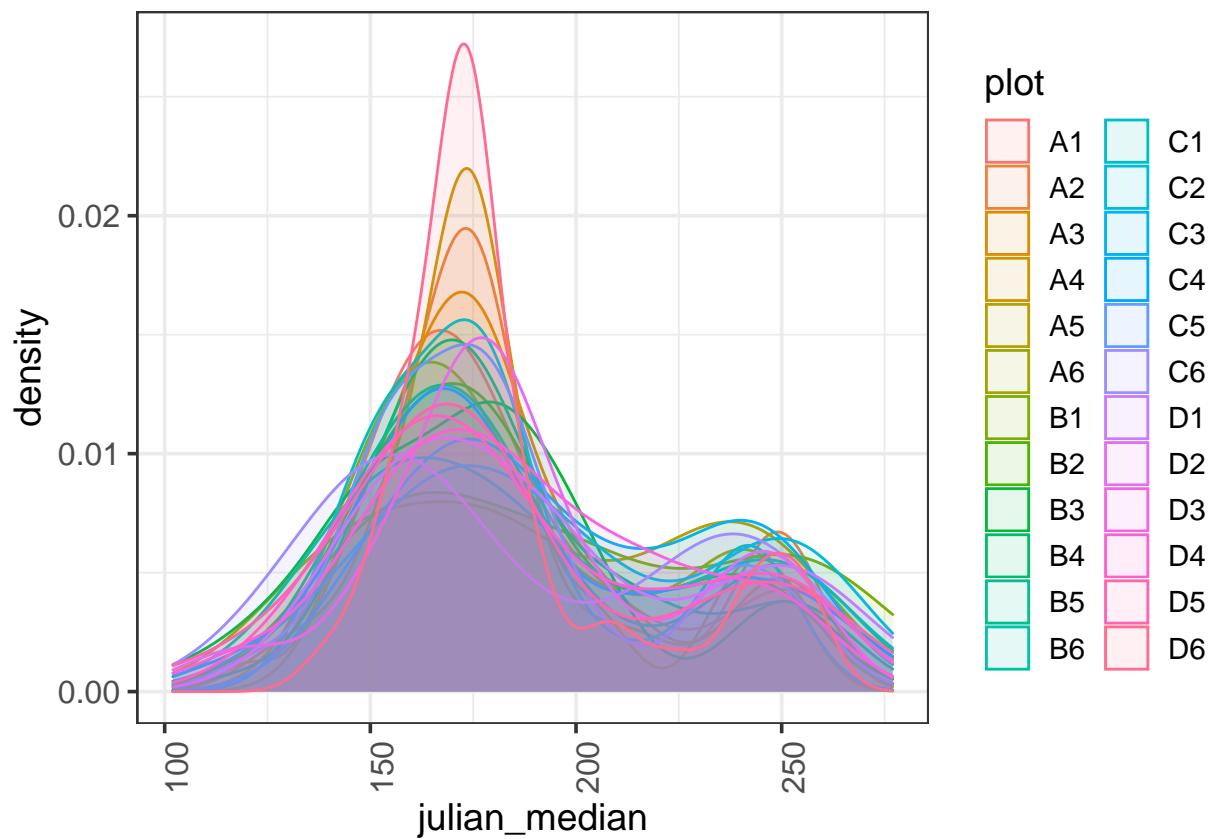
```

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

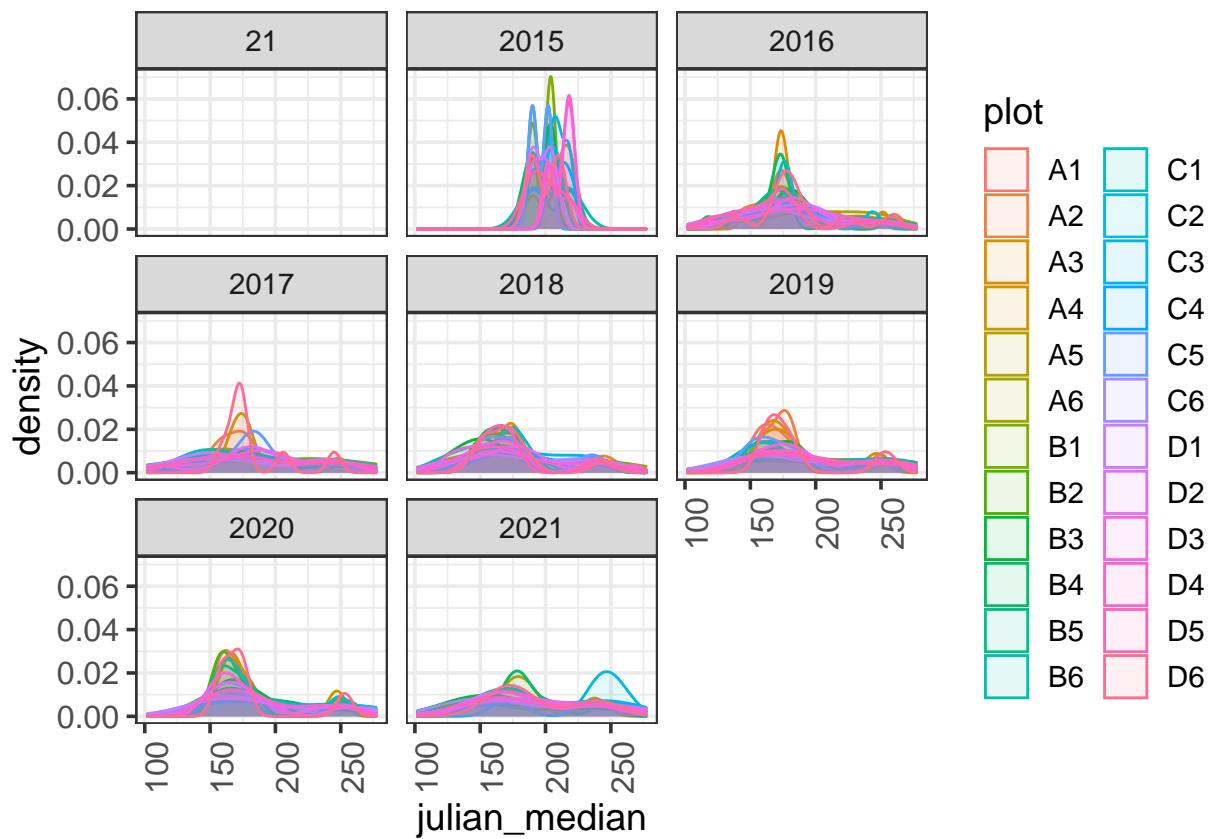
```



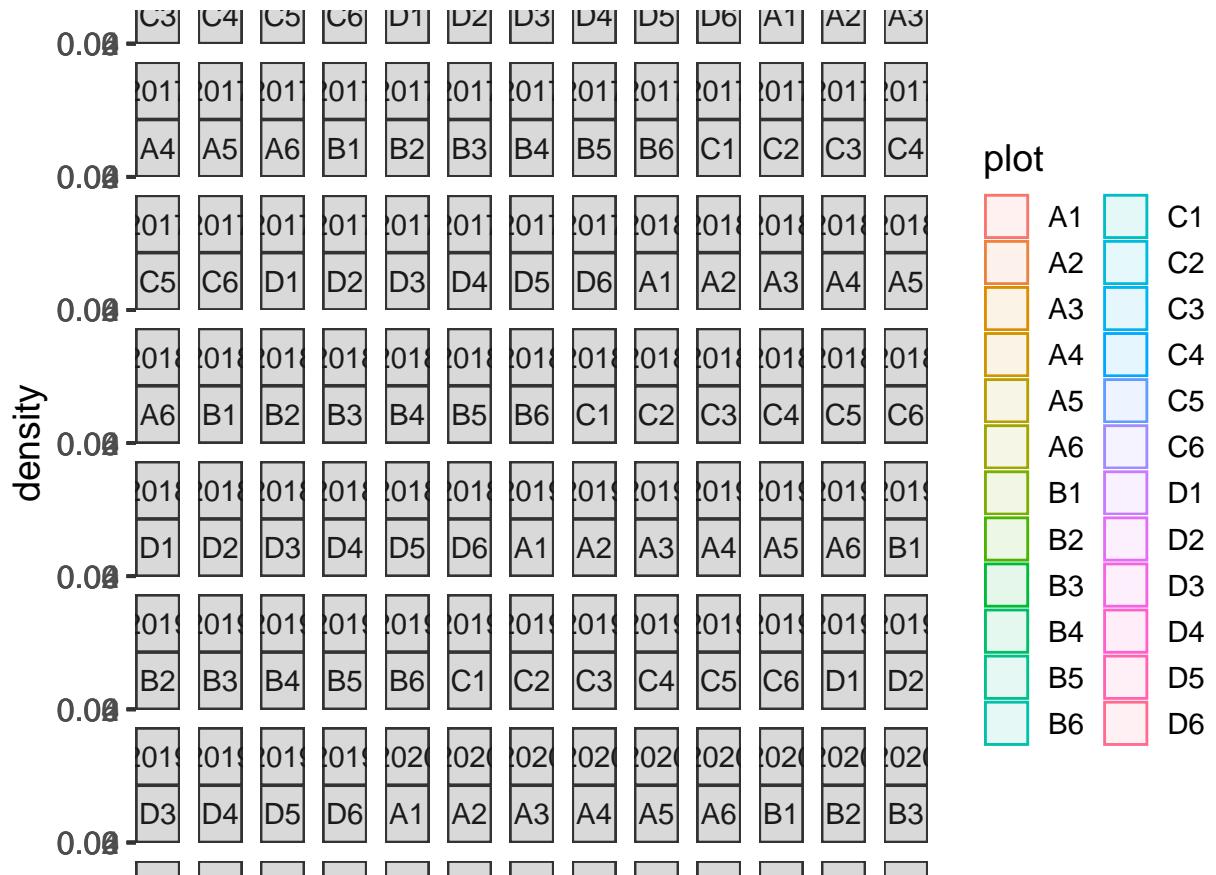
```
ggplot(kbs_flwr_spp, aes(julian_median, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



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

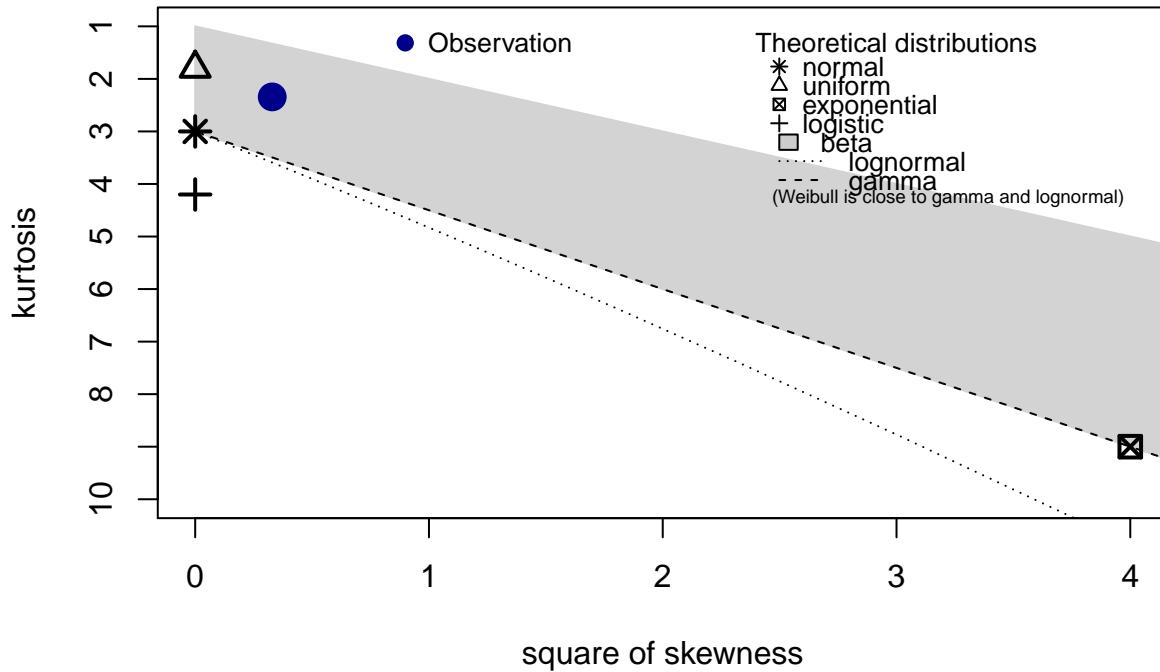


```
ggplot(kbs_flwr_spp, aes(julian_median, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
  facet_wrap(~year + plot)
```



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

Cullen and Frey graph

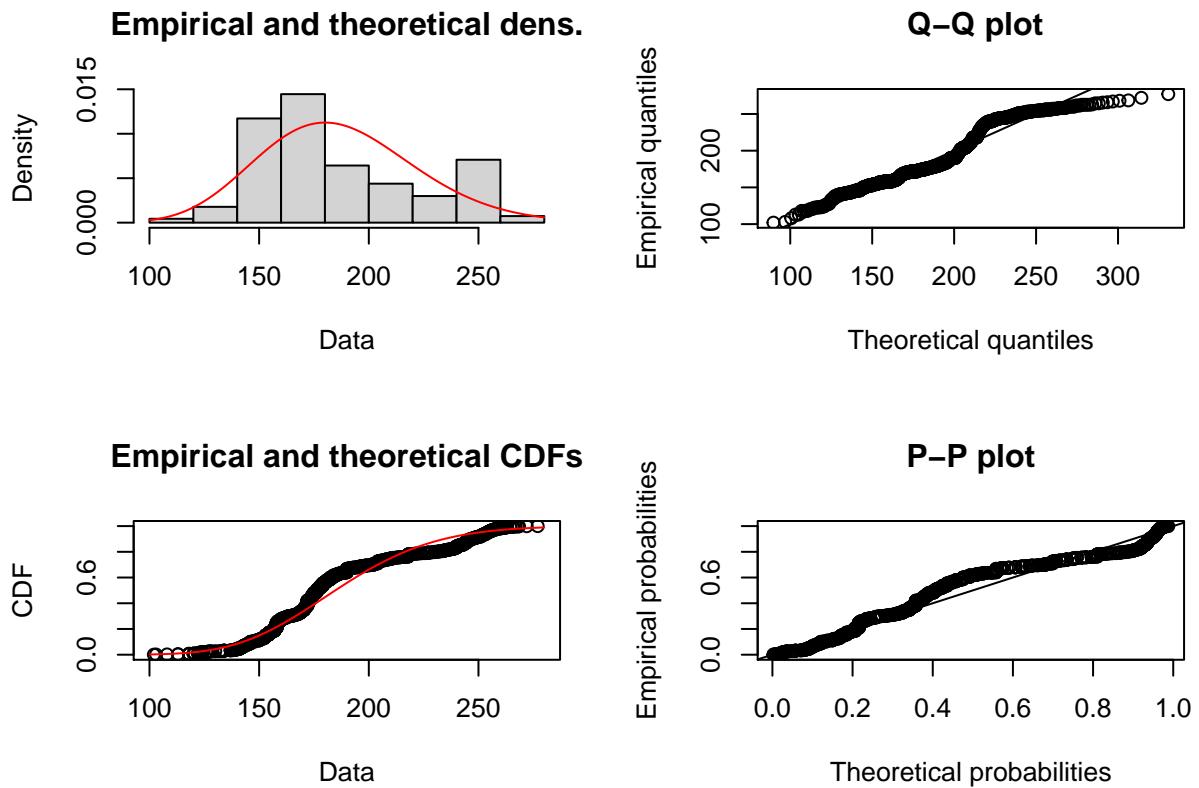


```

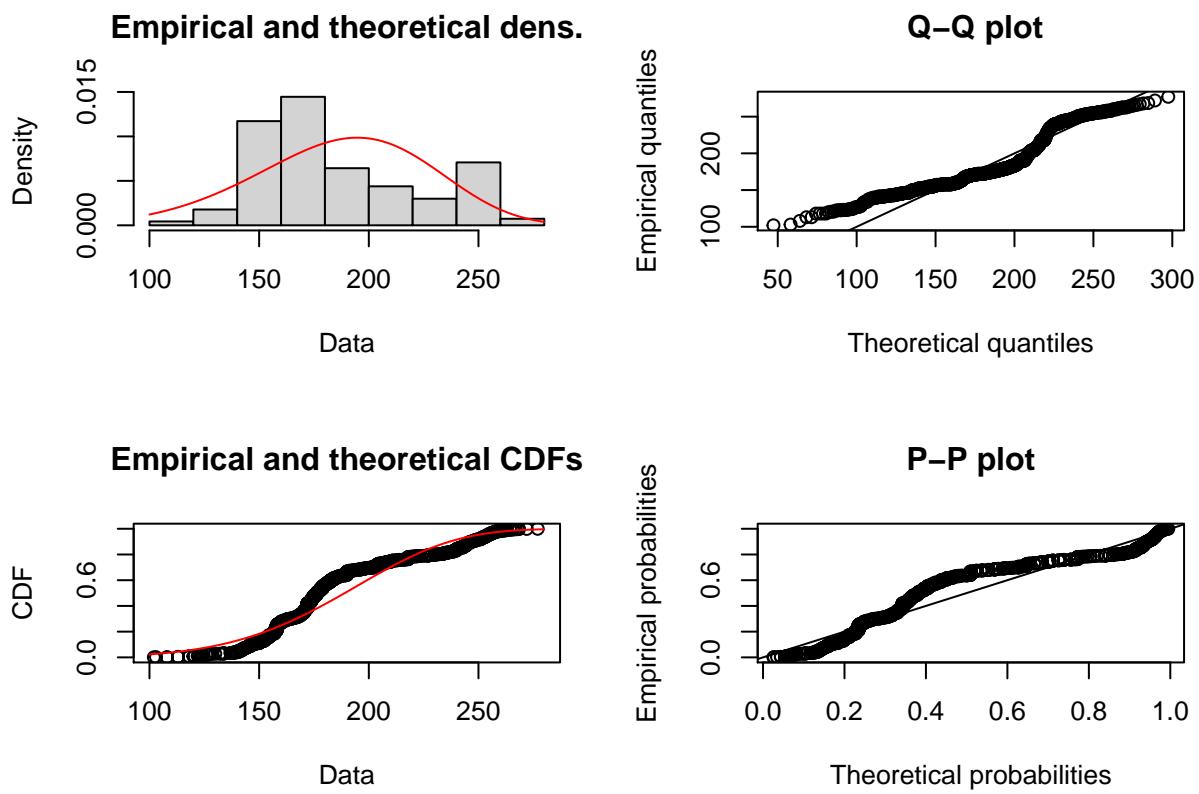
## summary statistics
## -----
## min: 102   max: 277
## median: 176.5
## mean: 187.0304
## estimated sd: 36.75702
## estimated skewness: 0.5740771
## estimated kurtosis: 2.342844

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

```

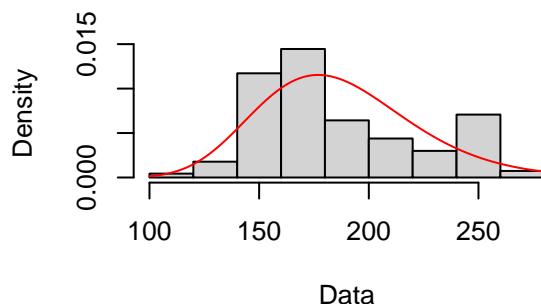


```
# Weibull distribution
fit.weibull <- fitdist(kbs_flwr_spp$julian_median, "weibull")
plot(fit.weibull)
```

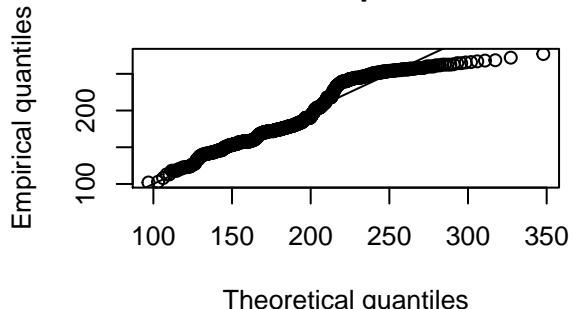


```
# Lognormal distribution
fit.ln <- fitdist(kbs_flwr_spp$julian_median, "lnorm")
plot(fit.ln)
```

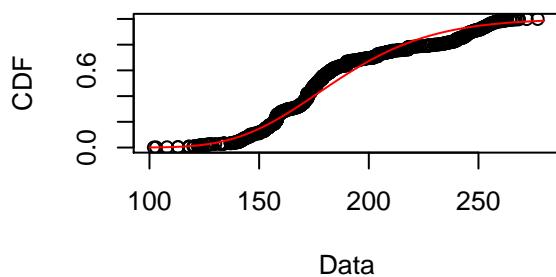
Empirical and theoretical dens.



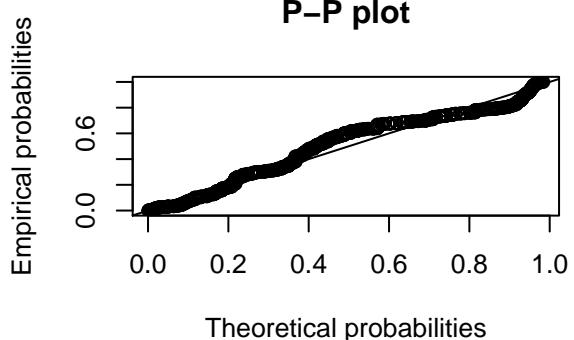
Q-Q plot



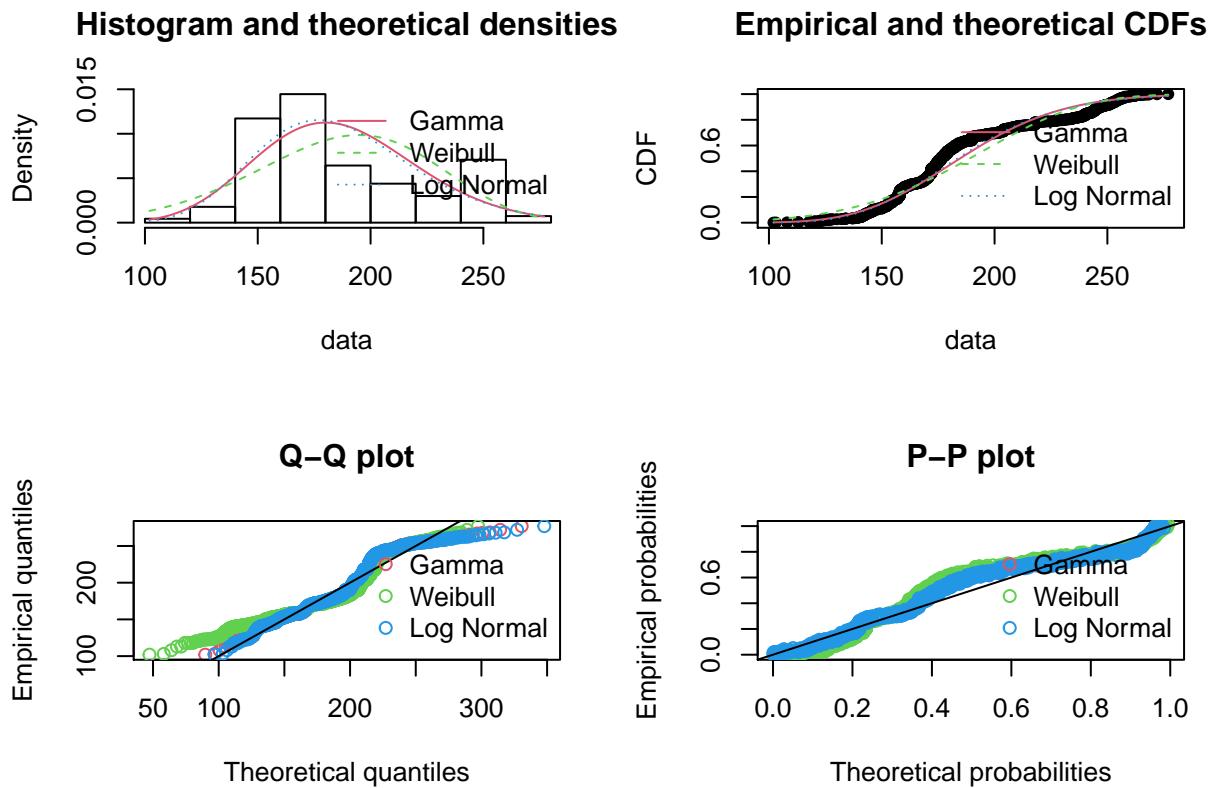
Empirical and theoretical CDFs



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)
```



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

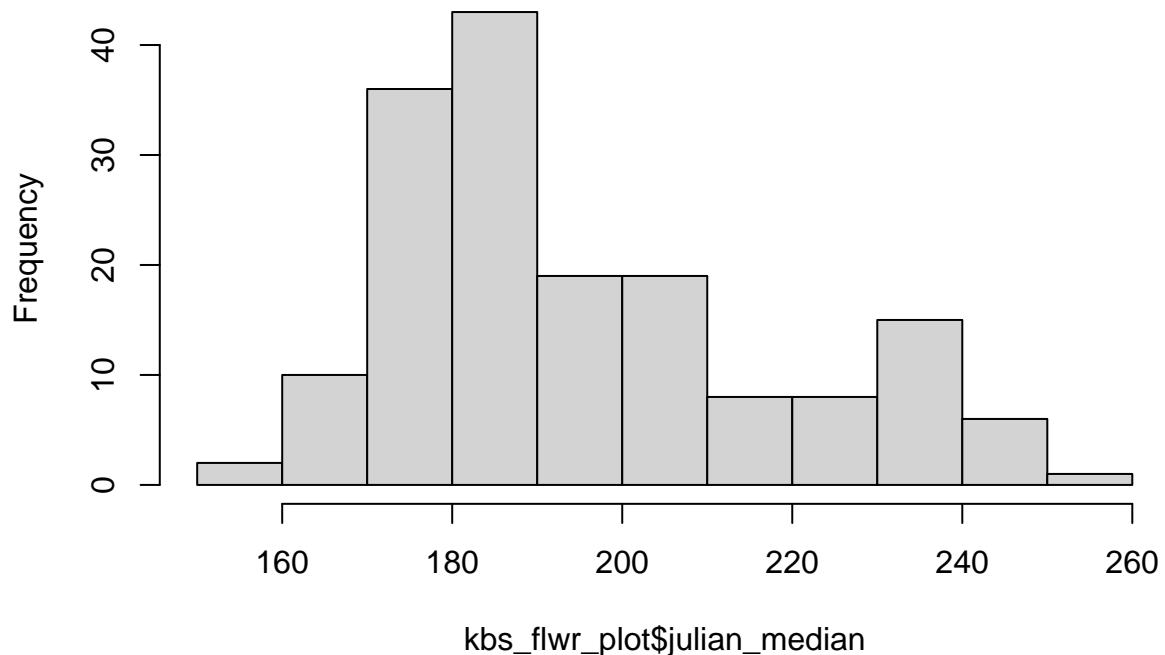
```
## Goodness-of-fit statistics
##                               Gamma   Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.1255364 0.1657855 0.112895
## Cramer-von Mises statistic   4.2217015 7.6018720 3.401248
## Anderson-Darling statistic  24.6691234 42.0641014 20.431315
##
## Goodness-of-fit criteria
##                               Gamma   Weibull Log Normal
## Akaike's Information Criterion 11501.63 11668.78 11480.01
## Bayesian Information Criterion 11511.73 11678.88 11490.10
```

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

KBS PLOT LEVEL - Looking at MEDIAN JULIAN DAY

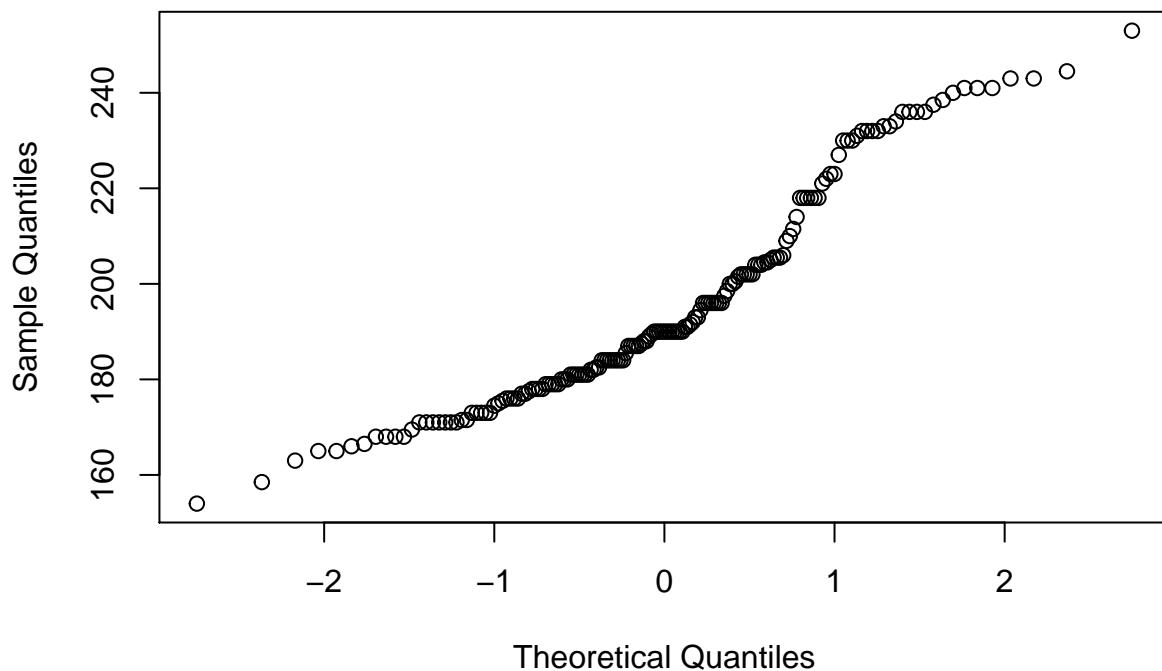
```
### UMBS ####
hist(kbs_flwr_plot$julian_median)
```

Histogram of kbs_flwr_plot\$julian_median



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

Normal Q-Q Plot



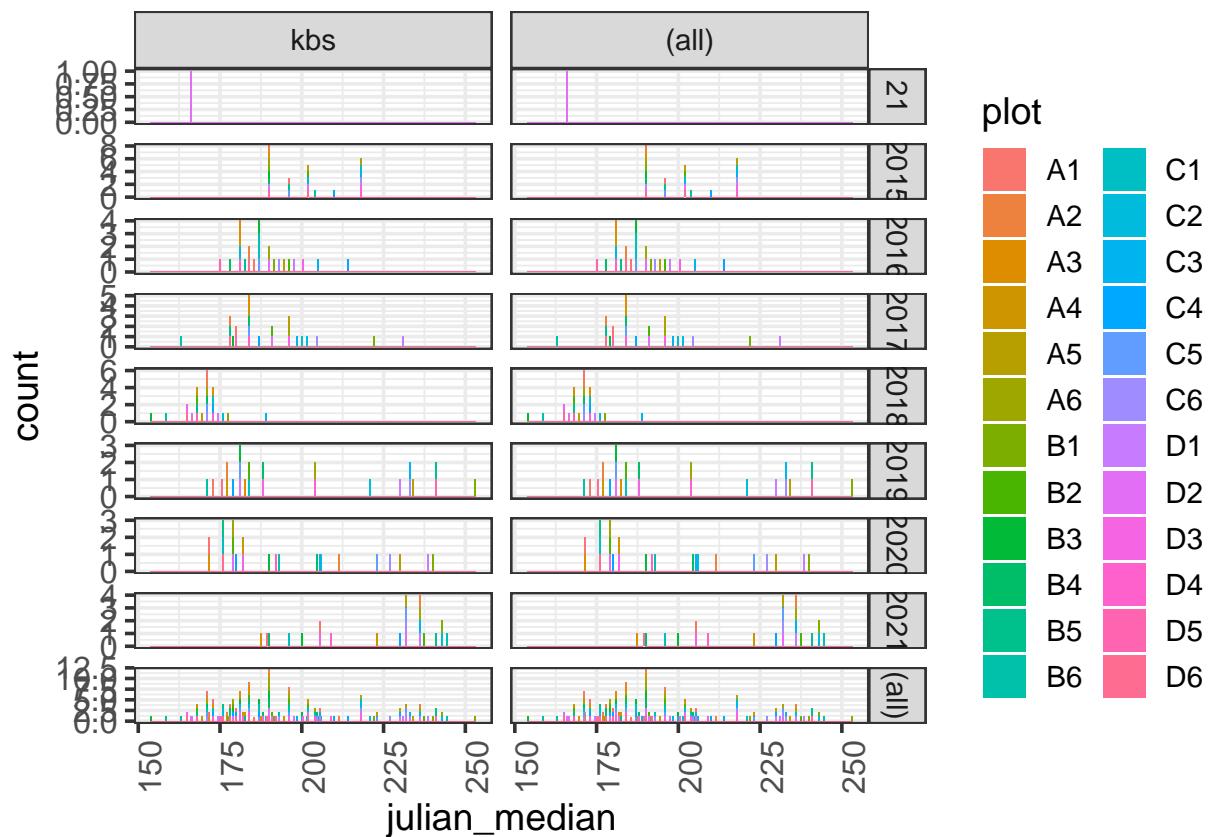
```

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 = 0.92754, p-value = 1.982e-07

# Visualizing median Julian date for umbs 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")

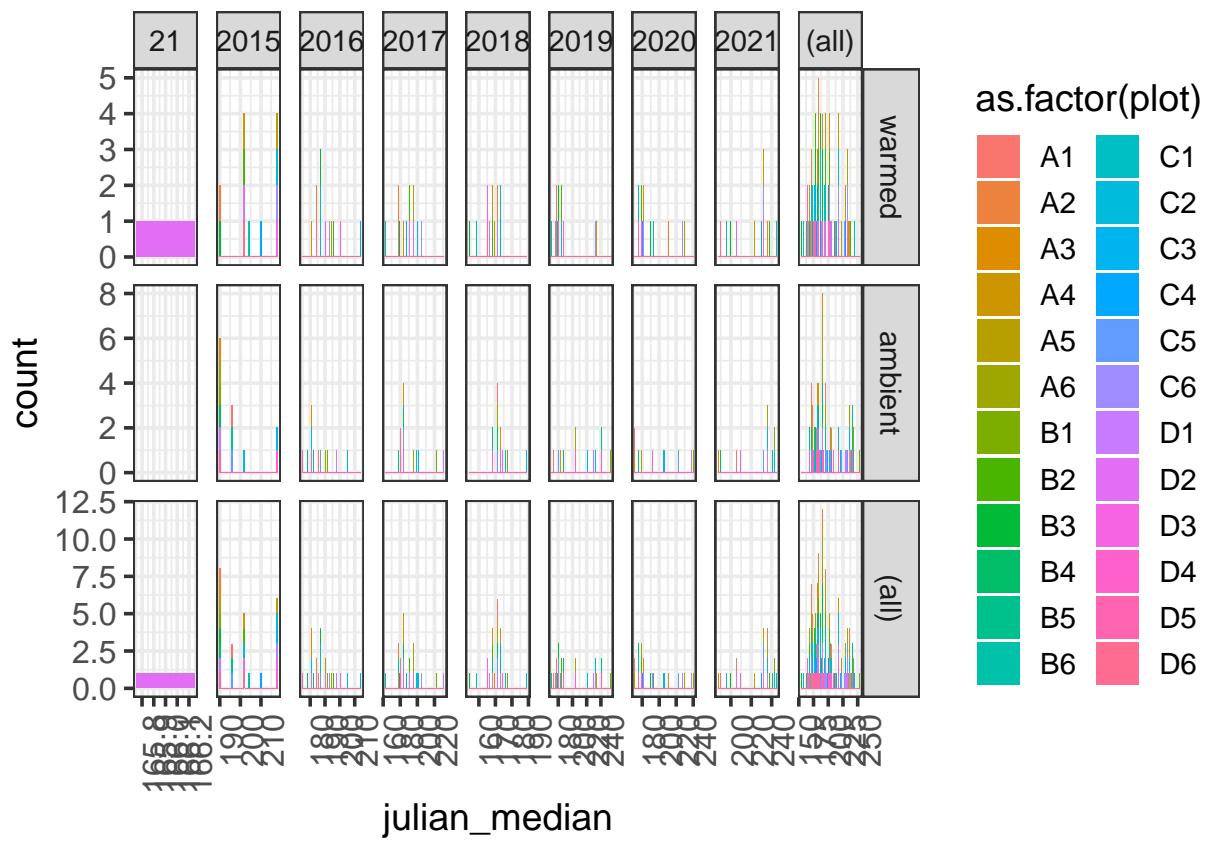
```



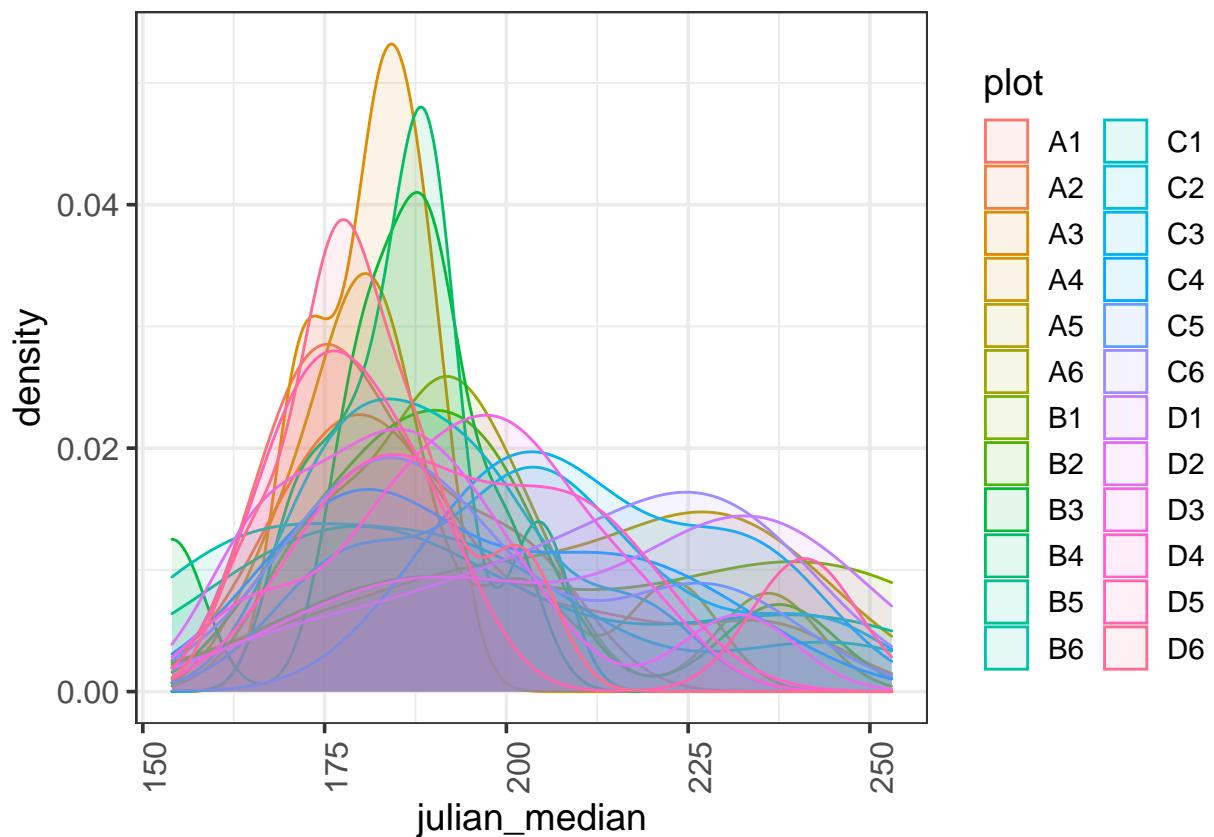
```

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

```



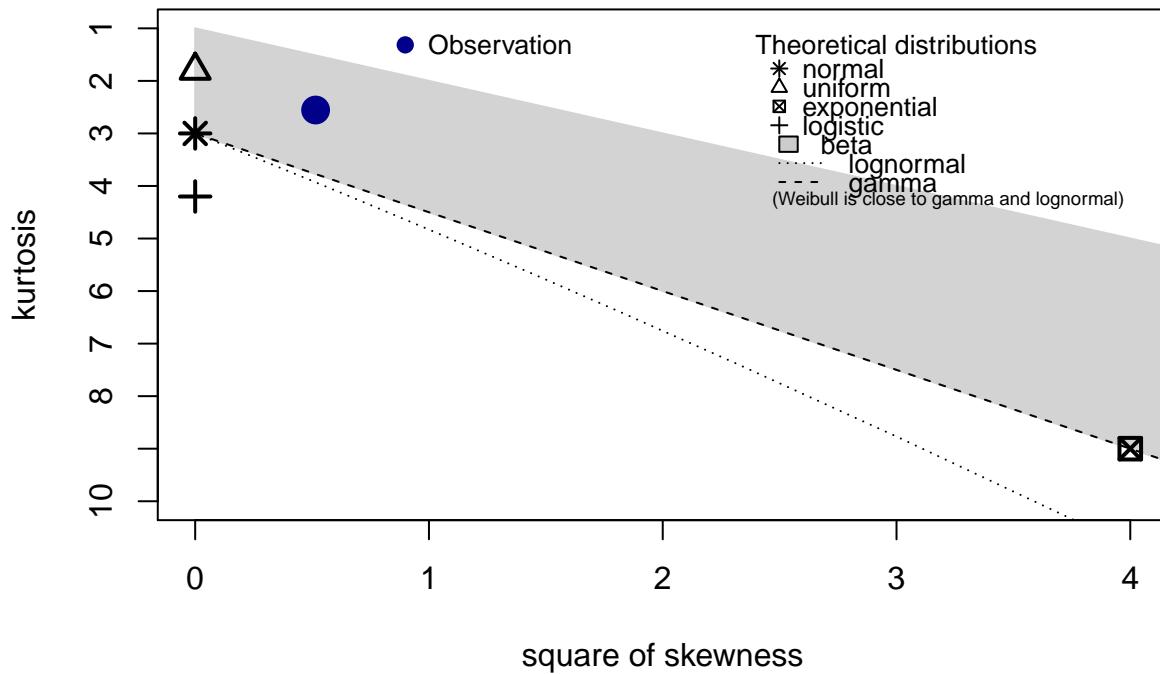
```
ggplot(kbs_flwr_plot, aes(julian_median, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



```
# 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

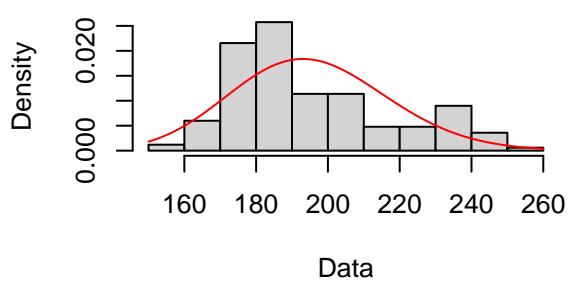
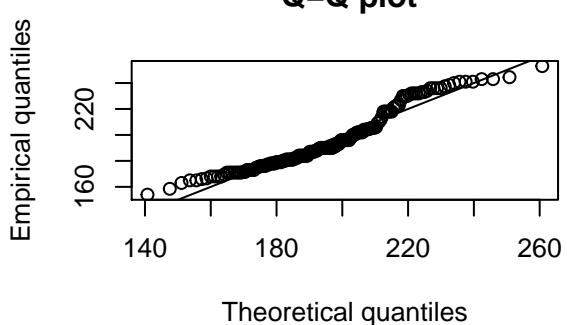
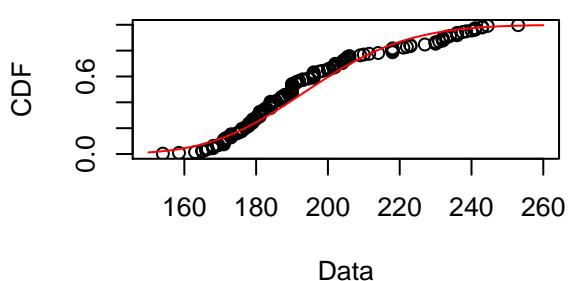
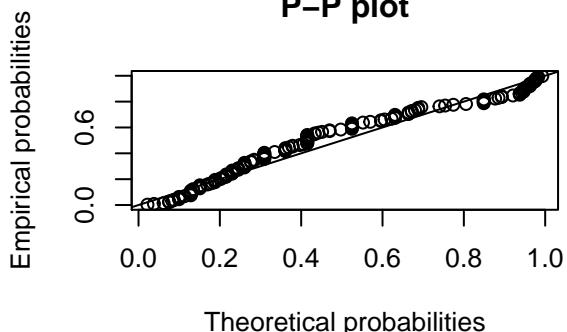


```

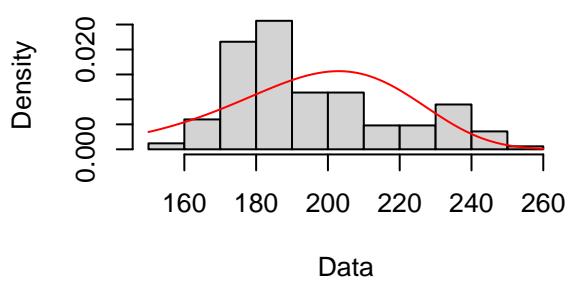
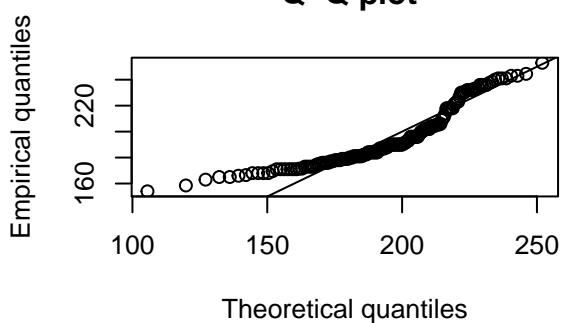
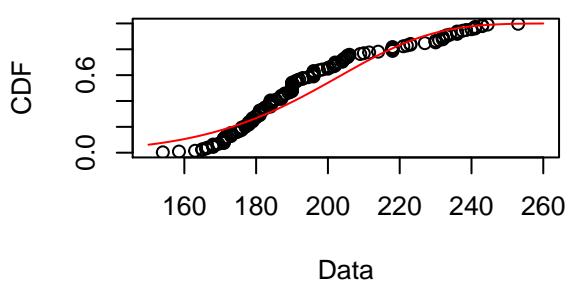
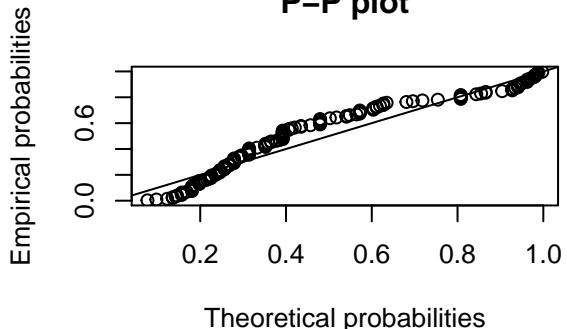
## summary statistics
## -----
## min: 154   max: 253
## median: 190
## mean: 195.4551
## estimated sd: 22.36882
## estimated skewness: 0.7177672
## estimated kurtosis: 2.554227

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

```

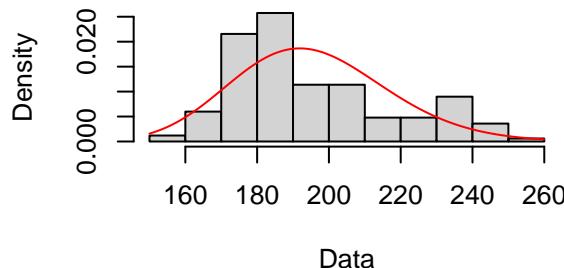
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

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

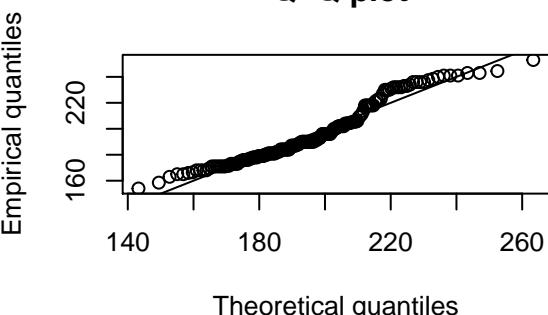
Empirical and theoretical dens.**Q-Q plot****Empirical and theoretical CDFs****P-P plot**

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

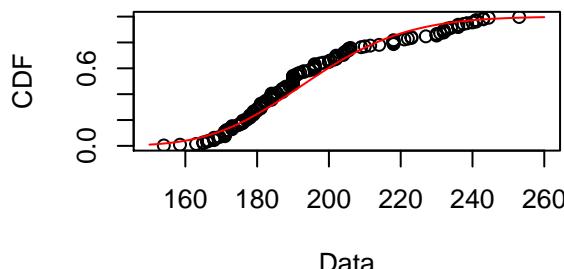
Empirical and theoretical dens.



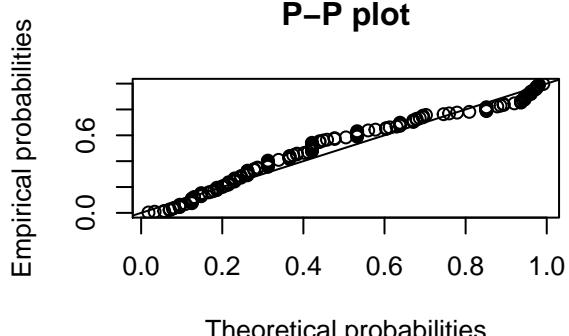
Q–Q plot



Empirical and theoretical CDFs

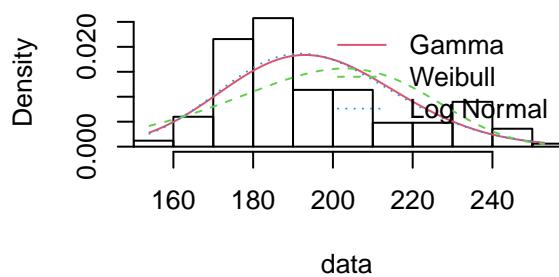


P–P plot

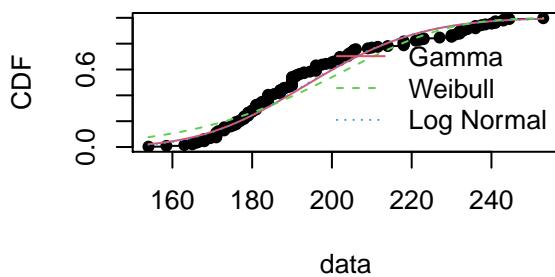


```
par(mfrow = c(2, 2))
plot.legend <- c("Gamma", "Weibull", "Log Normal")
denscomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
cdfcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
qqcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
ppcomp(list(fit.gamma,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

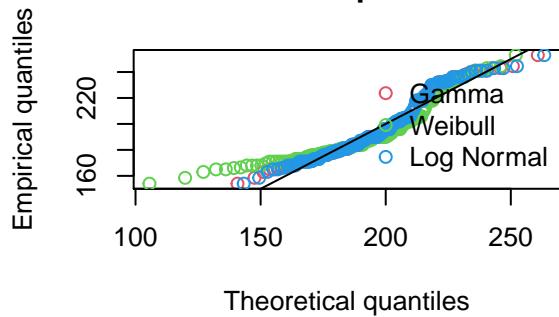
Histogram and theoretical densities



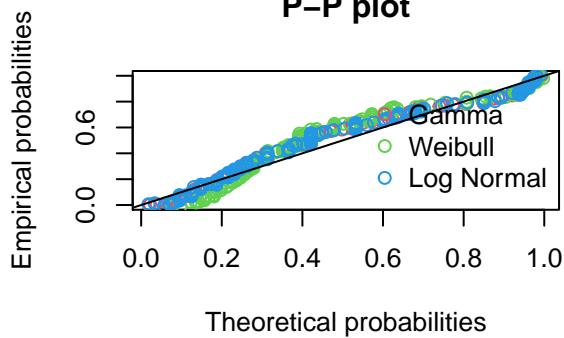
Empirical and theoretical CDFs



Q-Q plot



P-P plot



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

```
## Goodness-of-fit statistics
##                                     Gamma   Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.1300085 0.1552035 0.1237967
## Cramer-von Mises statistic  0.5865903 1.1490303 0.5144716
## Anderson-Darling statistic  3.6124147 6.6542134 3.2100022
##
## Goodness-of-fit criteria
##                                     Gamma   Weibull Log Normal
## Akaike's Information Criterion 1506.460 1543.903 1502.958
## Bayesian Information Criterion 1512.696 1550.139 1509.194
```

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

Centering and transforming data - Ignore right now!!

```
# umbs_flwr_plot$log_julian_min <- log(umb_flwr_plot$julian_min)
# umbs_flwr_plot$log_julianMin_centered = umbs_flwr_plot$log_julian_min -
# mean(umb_flwr_plot$log_julian_min) hist(umb_flwr_plot$log_julianMin_centered)
```

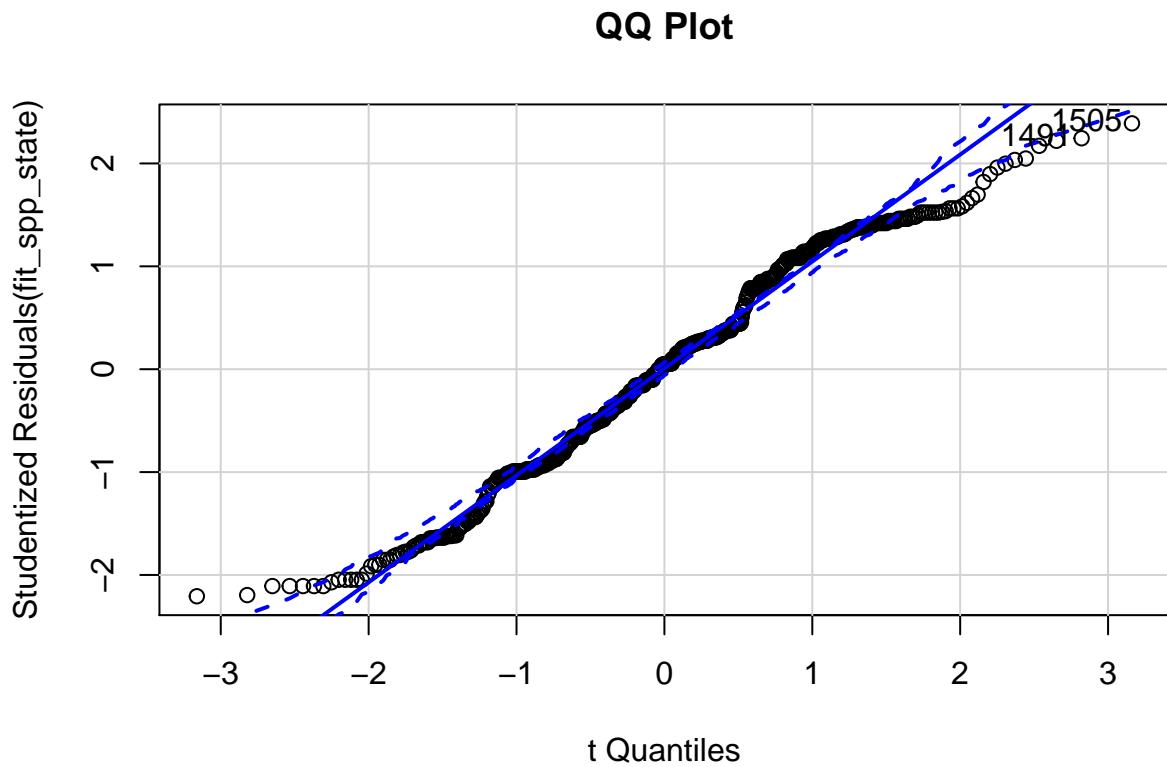
Leverage plots and detecting Outliers. <https://www.statmethods.net/stats/rdiagnostics.html>

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>

```
# 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
## 1505  2.389871          0.01716           NA
```

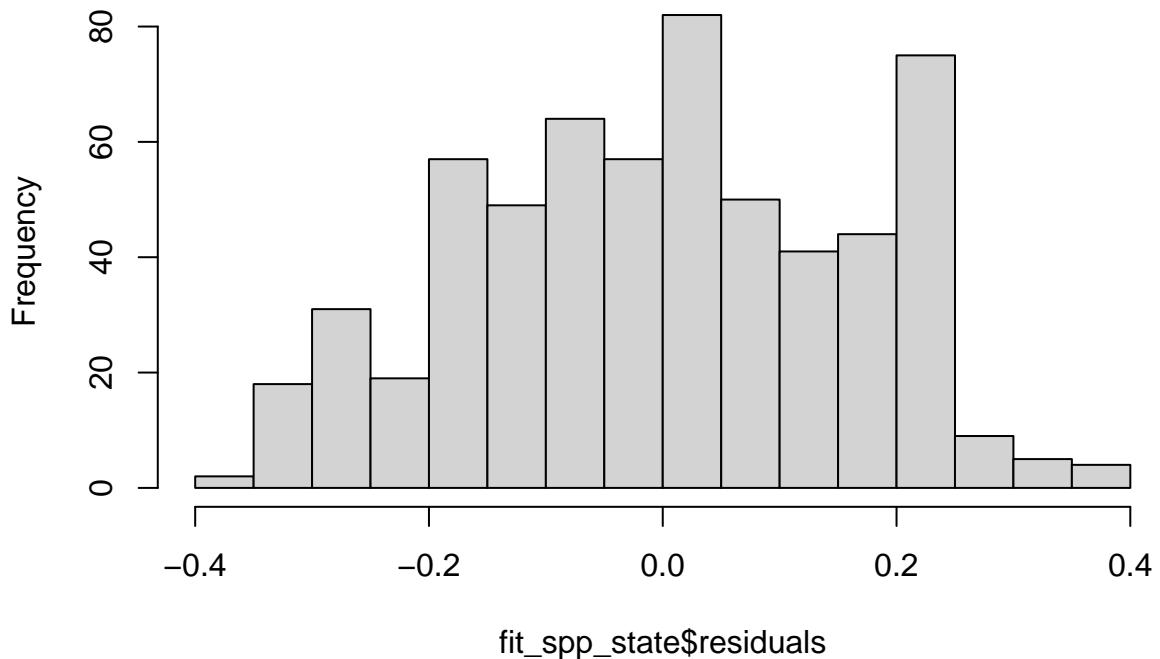
```
qqPlot(fit_spp_state, main = "QQ Plot")
```



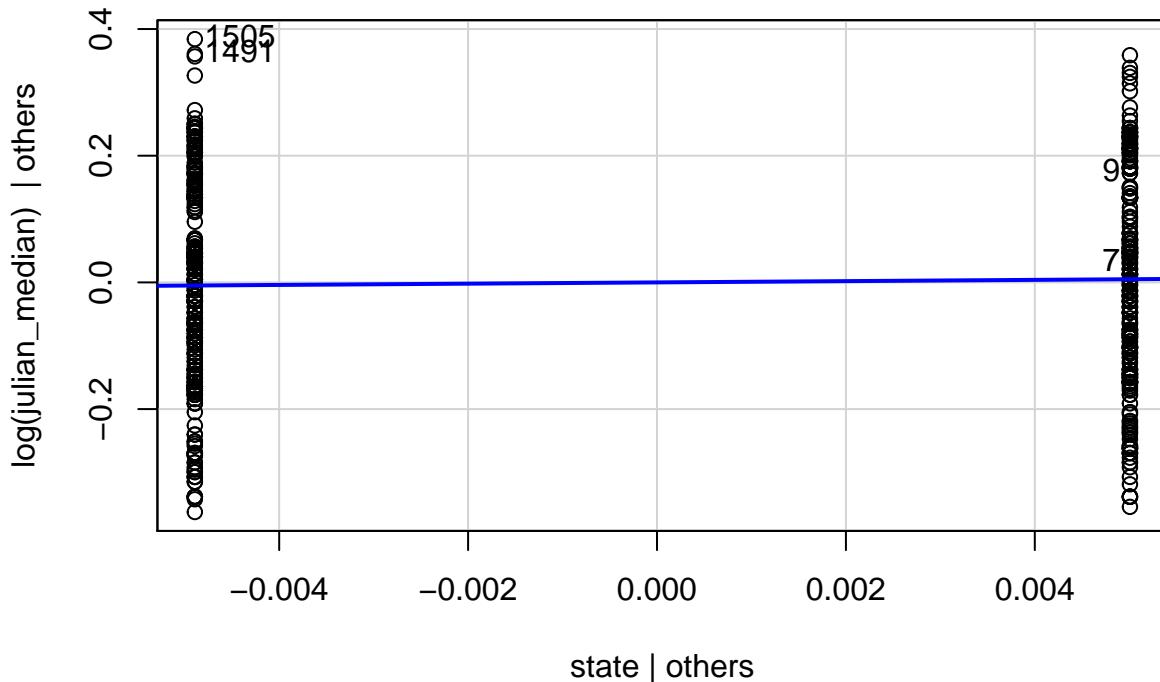
```
## 1491 1505
## 529 534
```

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

Histogram of fit_spp_state\$residuals



```
leveragePlots(fit_spp_state)
```



```
ols_test_normality(fit_spp_state)
```

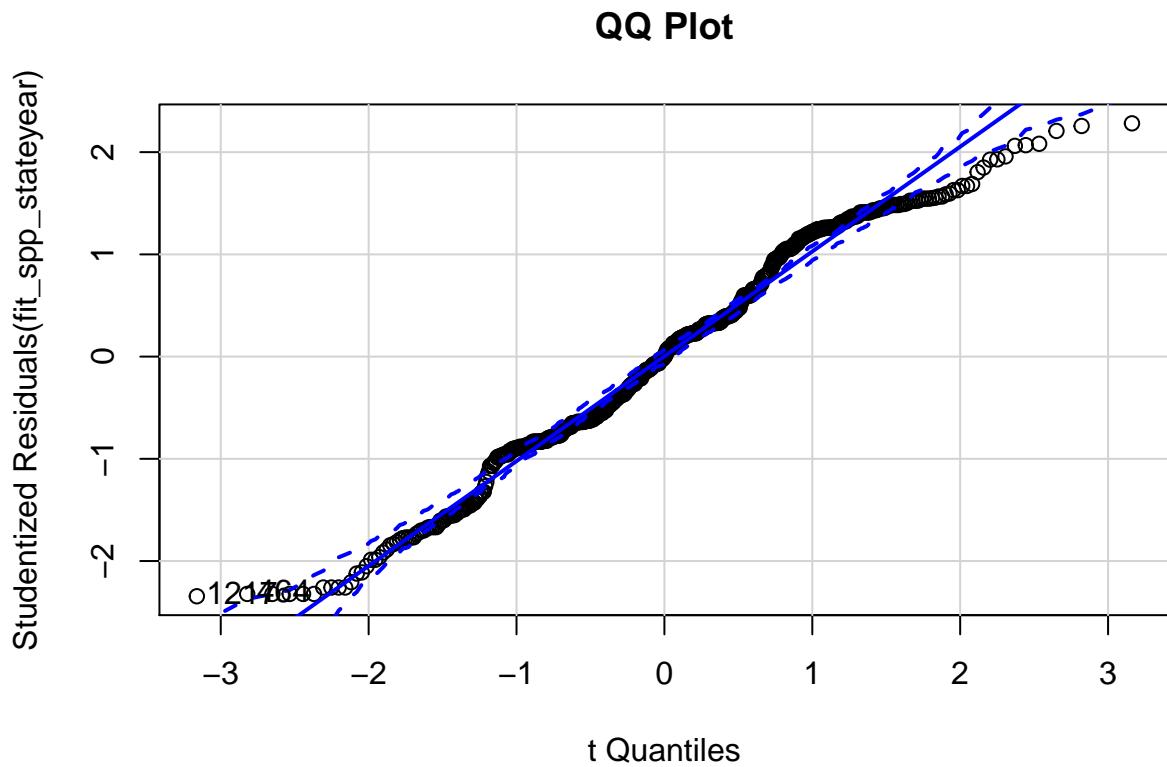
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----
##          Test      Statistic     pvalue
## -----
## Shapiro-Wilk      0.98    0.0000
## Kolmogorov-Smirnov 0.0658  0.0105
## Cramer-von Mises 140.9679 0.0000
## Anderson-Darling   3.1247  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 -2.344594          0.019371        NA
```

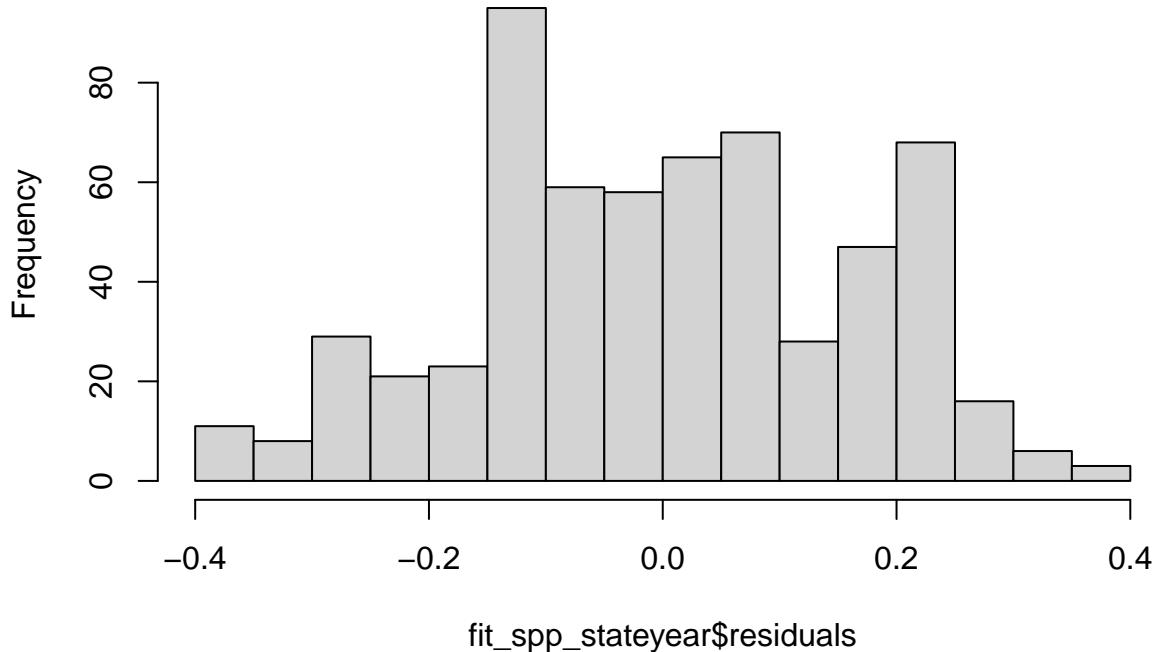
```
qqPlot(fit_spp_stateyear, main = "QQ Plot")
```



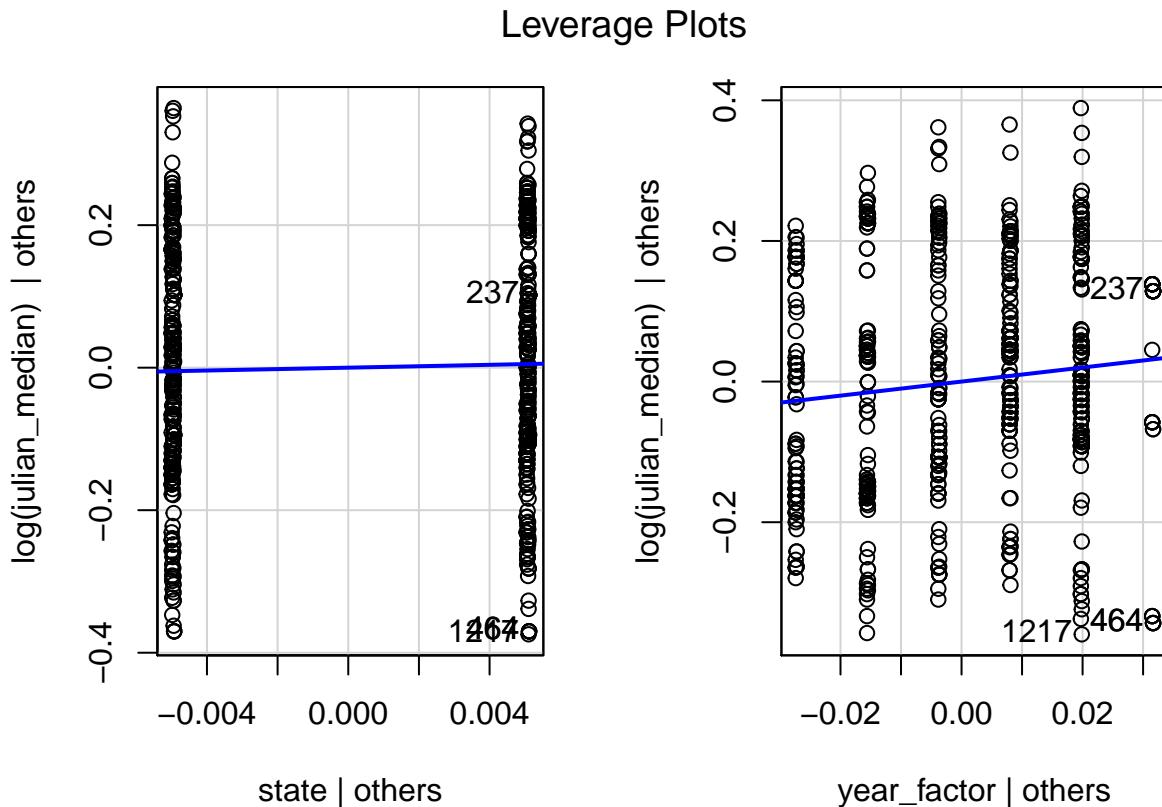
```
##   464 1217
##   175 434
```

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

Histogram of fit_spp_stateyear\$residuals



```
leveragePlots(fit_spp_stateyear)
```



```
ols_test_normality(fit_spp_stateyear)
```

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

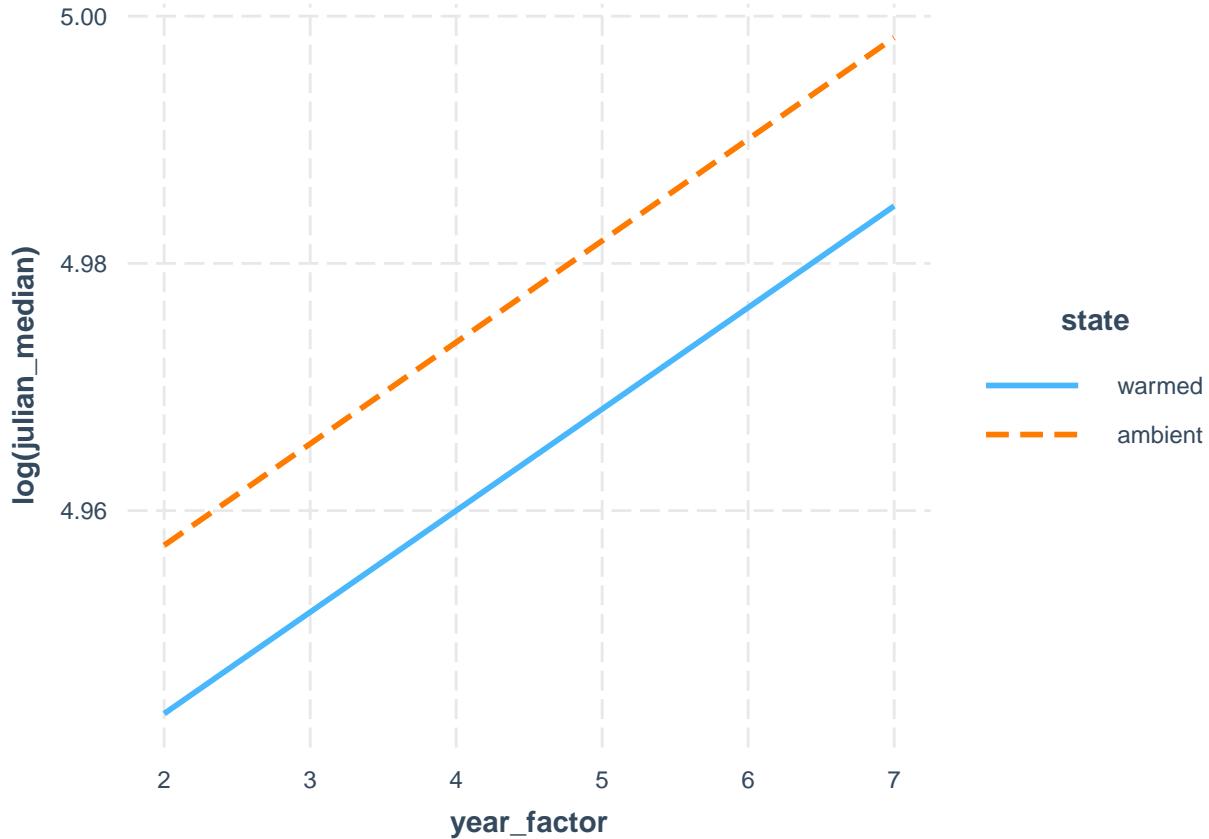
```
## -----
##      Test          Statistic       pvalue
## -----
## Shapiro-Wilk      0.9825       0.0000
## Kolmogorov-Smirnov 0.0604       0.0239
## Cramer-von Mises 141.3001      0.0000
## Anderson-Darling   2.866        0.0000
## -----
```

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

```
fit3 <- lm(log(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.
```

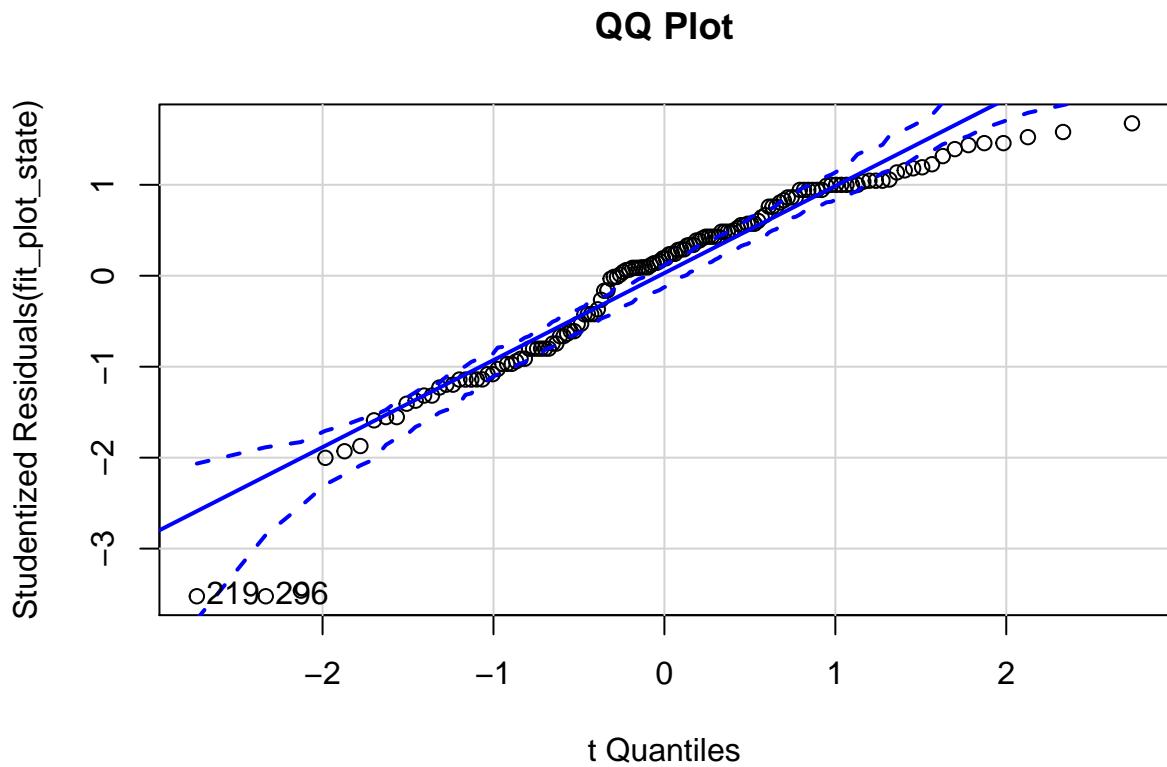


state —— dashed blue = warmed —— solid orange = ambient

```
# 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
```

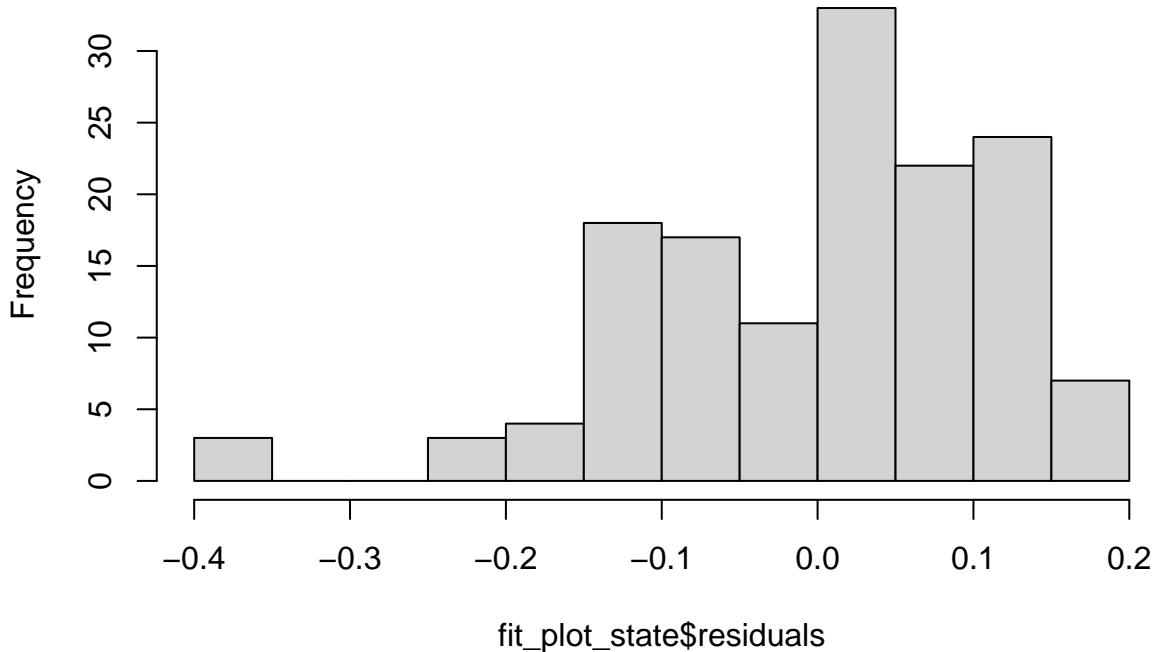
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 219 -3.52376          0.00057635     0.081842
```

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

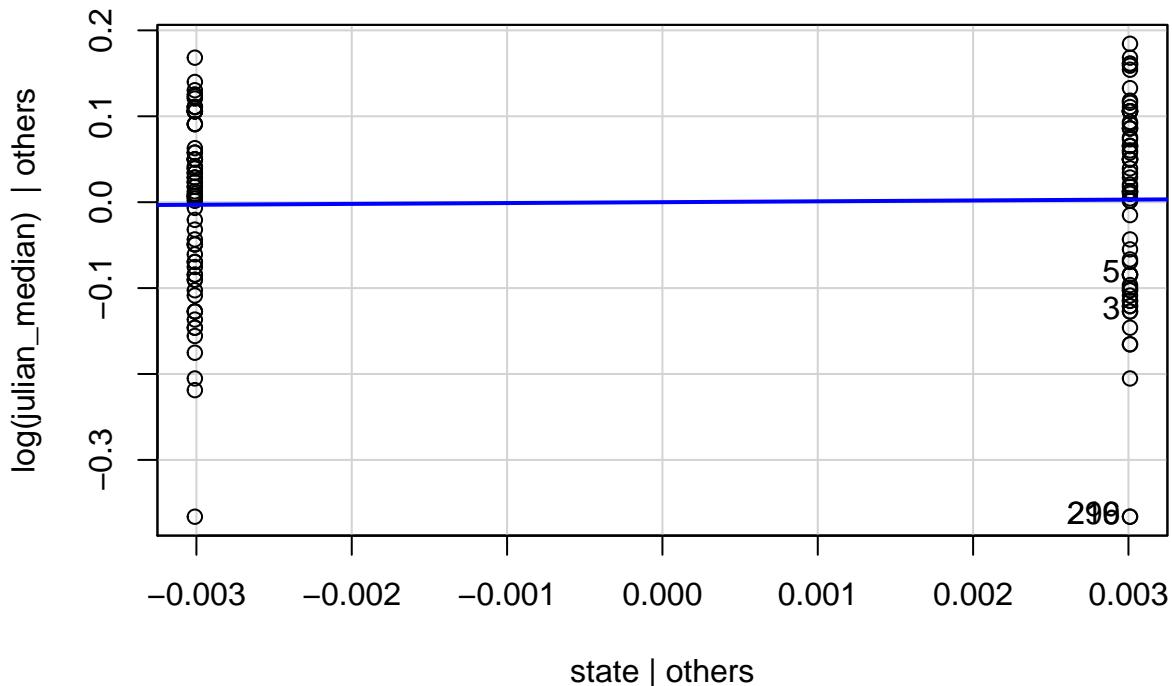


```
hist(fit_plot_state$residuals)
```

Histogram of fit_plot_state\$residuals



```
leveragePlots(fit_plot_state)
```



```
ols_test_normality(fit_plot_state)
```

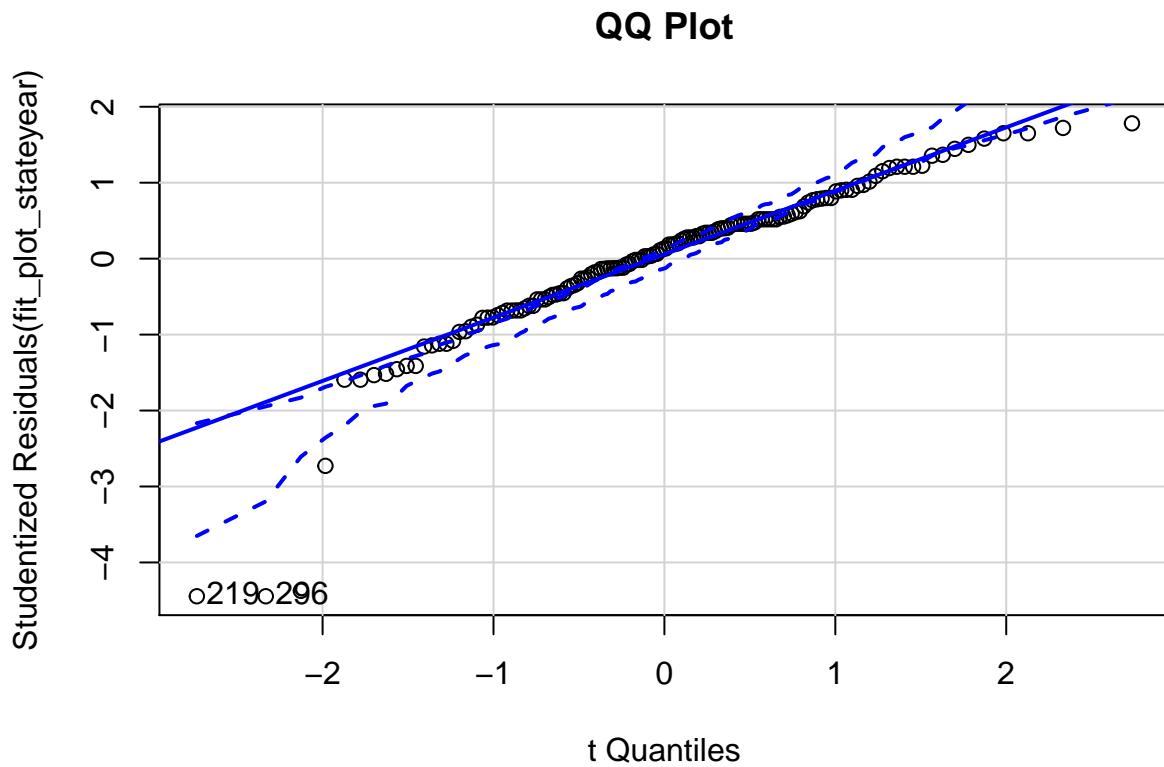
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----
##           Test          Statistic       pvalue
## -----
## Shapiro-Wilk      0.9388       0.0000
## Kolmogorov-Smirnov 0.1164       0.0428
## Cramer-von Mises   37.869       0.0000
## Anderson-Darling    2.0465       0.0000
## -----
```

```
# UMBS State and year model
fit_plot_stateyear <- lm(log(julian_median) ~ state + year_factor, data = umbs_flwr_plot)
outlierTest(fit_plot_stateyear) # outliers
```

```
##          rstudent unadjusted p-value Bonferroni p
## 219 -4.445205     1.7895e-05   0.0025411
## 296 -4.445205     1.7895e-05   0.0025411
## 64  -4.373452     2.3921e-05   0.0033968
```

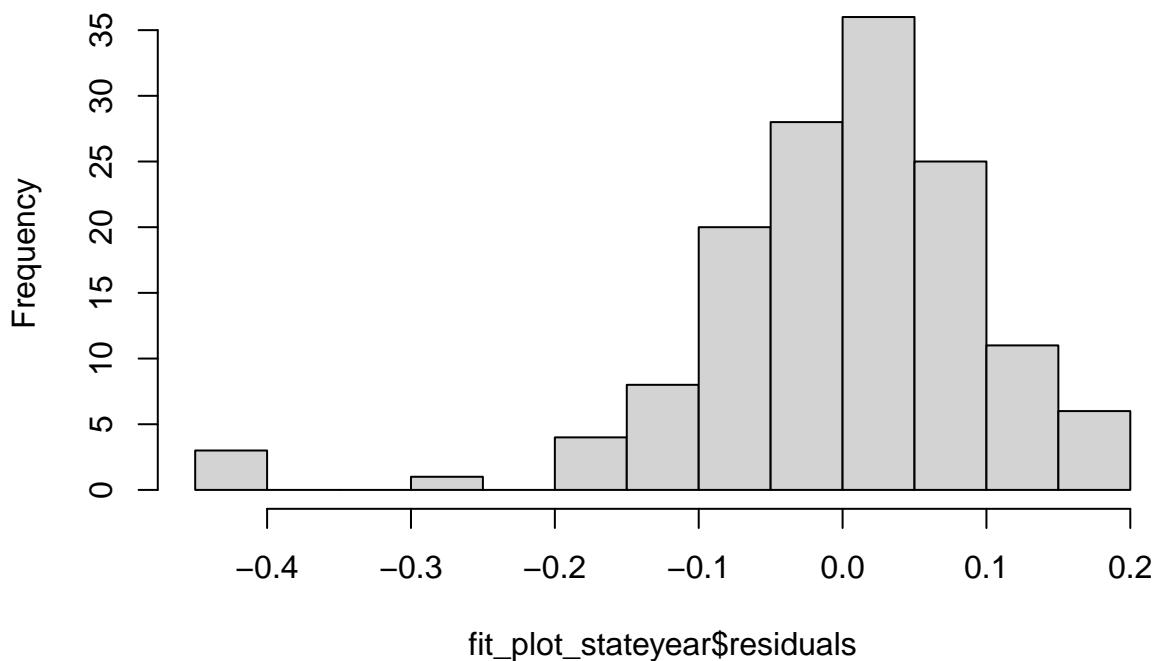
```
qqPlot(fit_plot_stateyear, main = "QQ Plot")
```



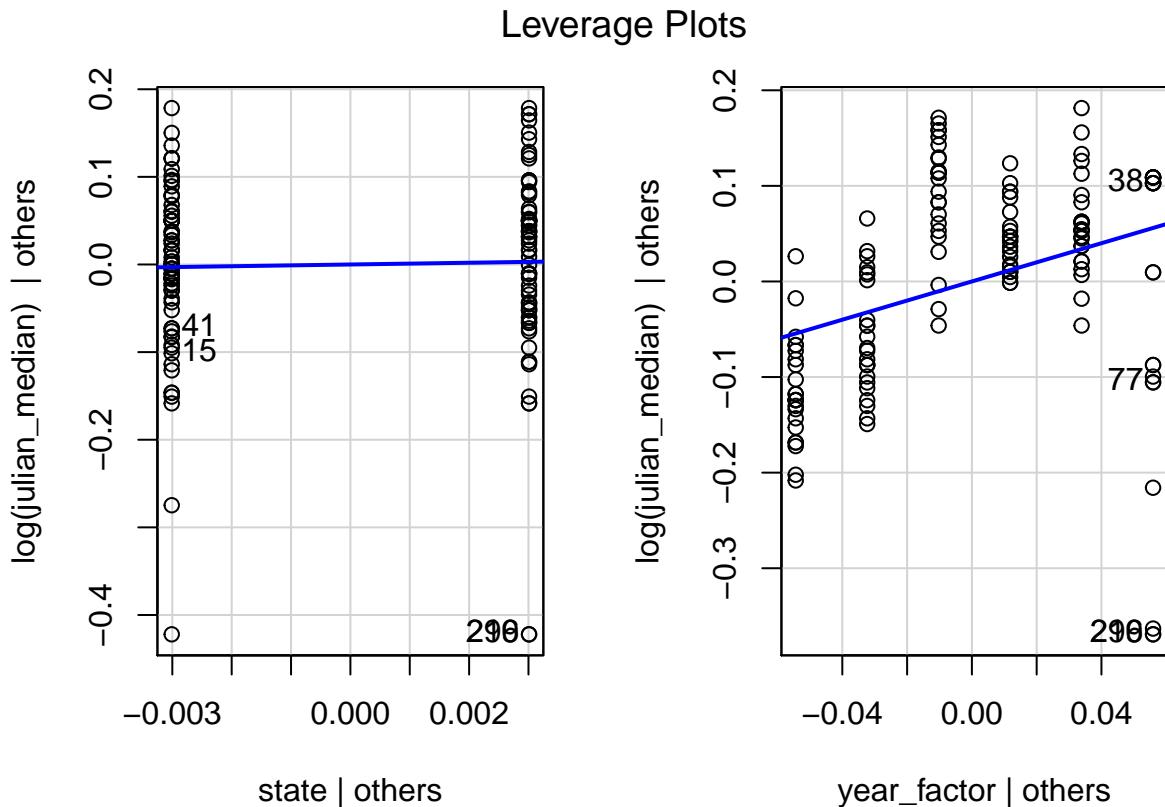
```
## 219 296
## 100 136
```

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

Histogram of fit_plot_stateyear\$residuals



```
leveragePlots(fit_plot_stateyear)
```



```
ols_test_normality(fit_plot_stateyear)
```

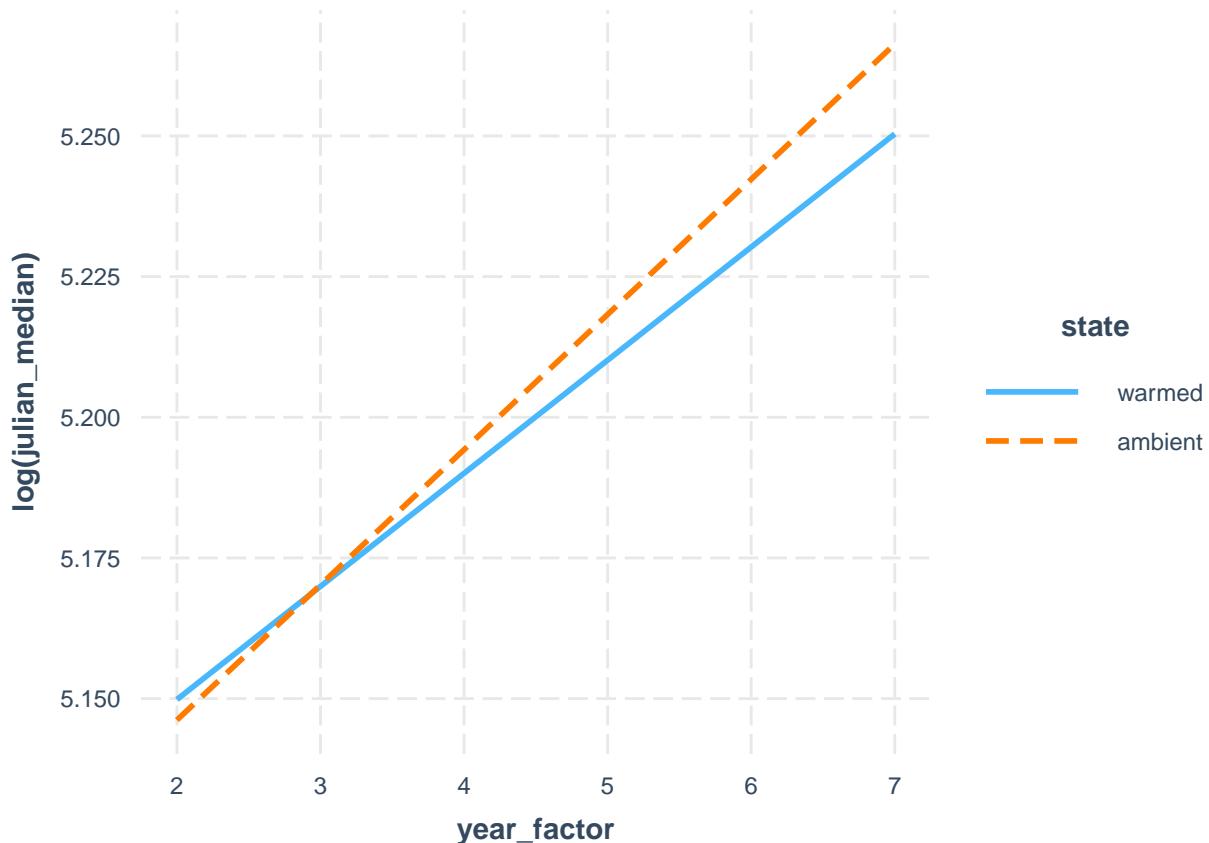
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----
##      Test          Statistic       pvalue
## -----
## Shapiro-Wilk      0.898       0.0000
## Kolmogorov-Smirnov 0.0935      0.1666
## Cramer-von Mises  39.1561      0.0000
## Anderson-Darling   2.2113      0.0000
## -----
```

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

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

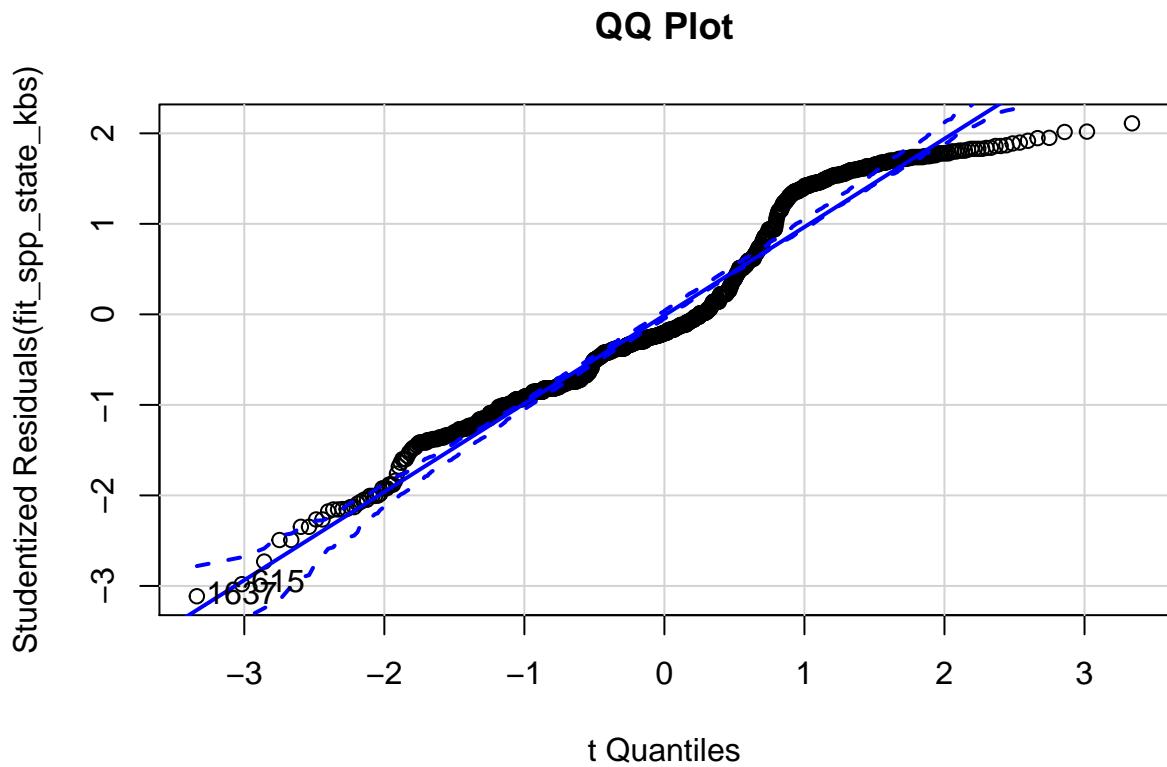
```
## Using data umbs_flwr_plot from global environment. This could cause
## incorrect results if umbs_flwr_plot has been altered since the model was
## fit. You can manually provide the data to the "data =" argument.
```



```
# 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) # outliers
```

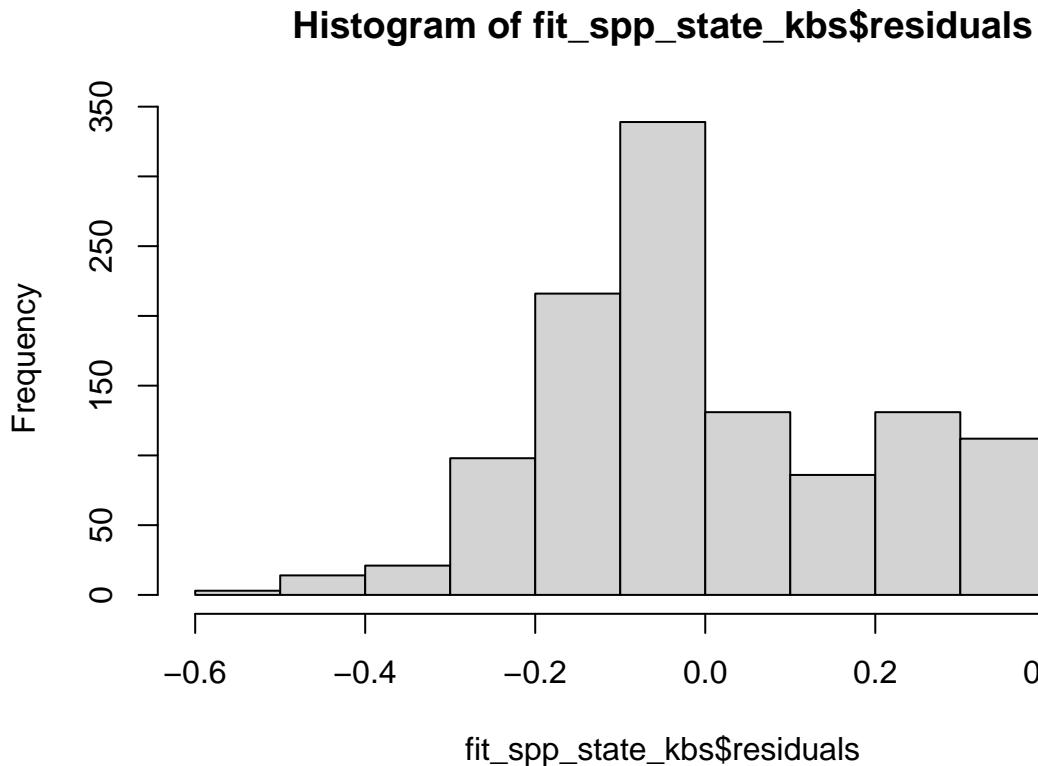
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstUDENT unadjusted p-value Bonferroni p
## 1637 -3.11402          0.0018912        NA

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

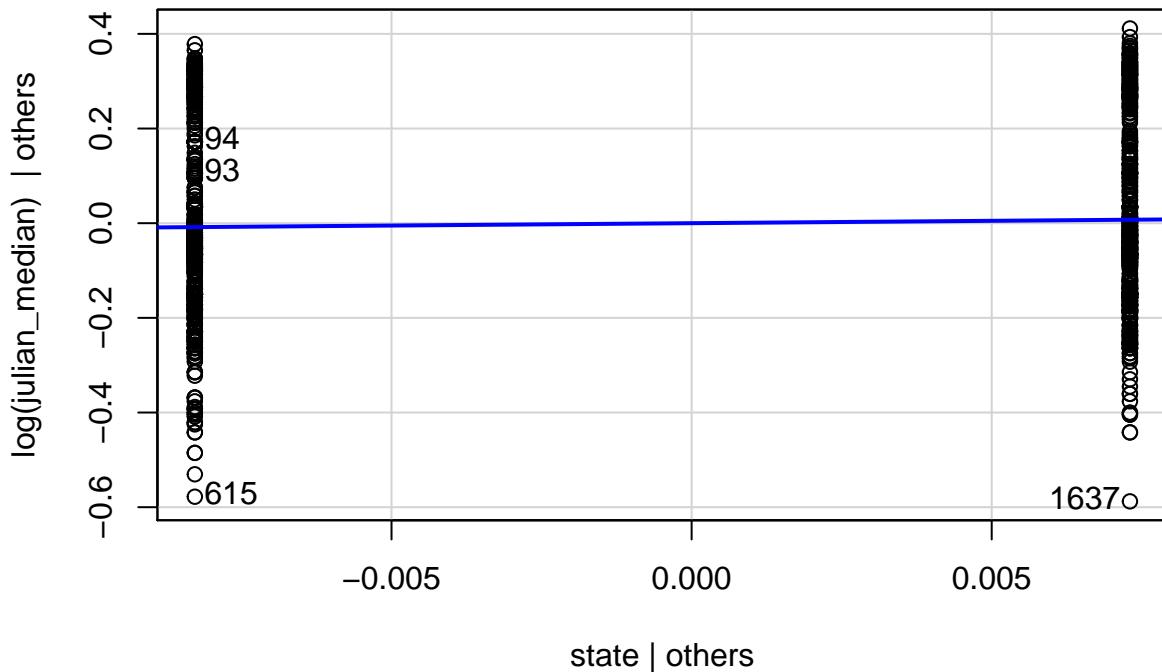


```
##   615 1637
##   383 1077
```

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



```
leveragePlots(fit_spp_state_kbs)
```



```
ols_test_normality(fit_spp_state_kbs)
```

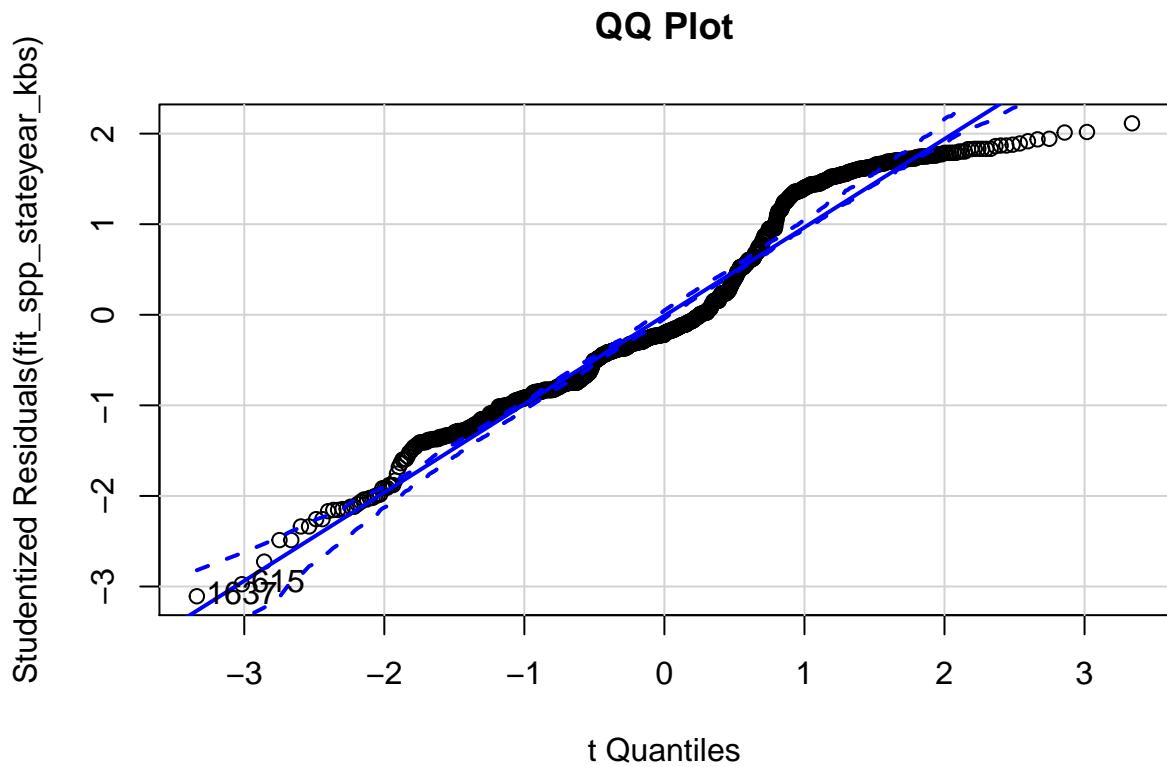
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----
##           Test          Statistic      pvalue
## -----
## Shapiro-Wilk       0.9563      0.0000
## Kolmogorov-Smirnov 0.1089      0.0000
## Cramer-von Mises   251.7392     0.0000
## Anderson-Darling    19.9905     0.0000
## -----
```

```
# UMBS 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
```

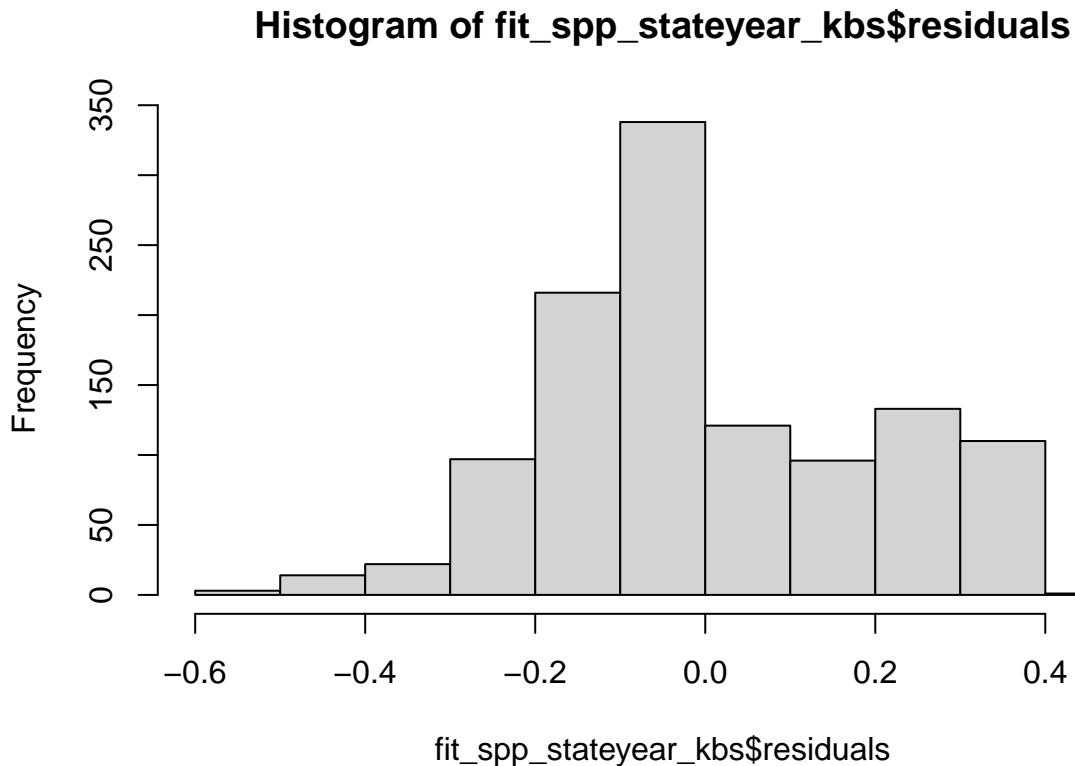
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 1637 -3.10761        0.0019324         NA
```

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



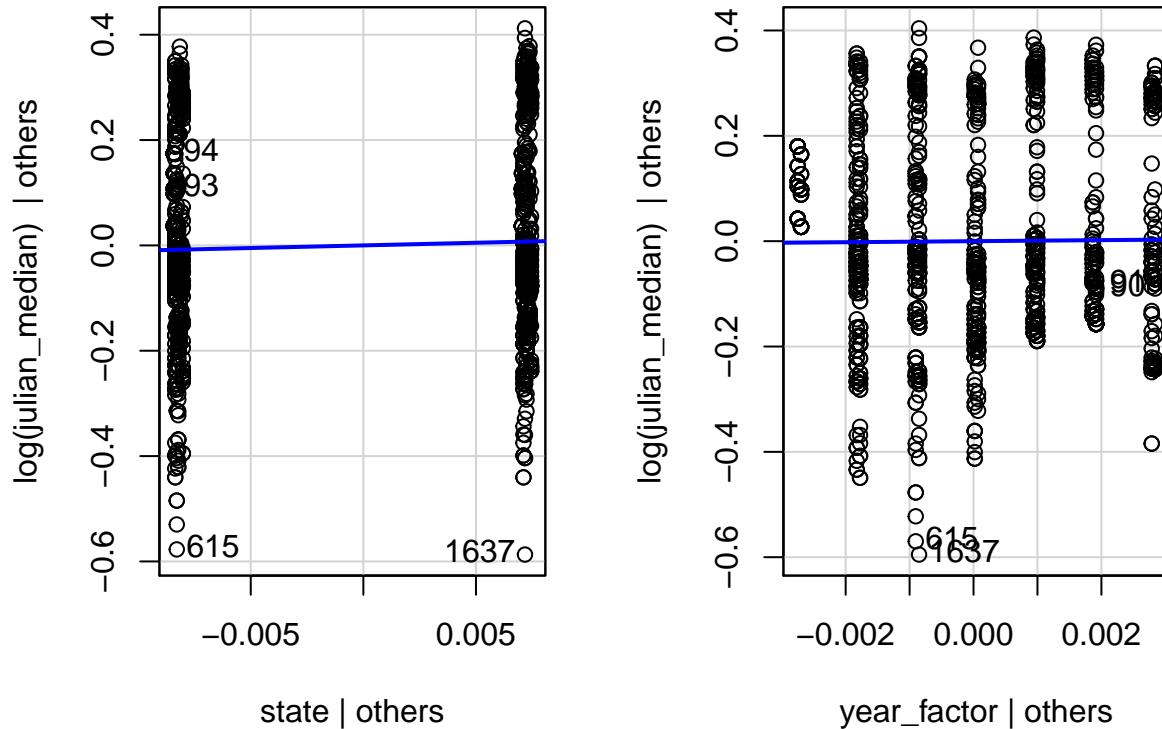
```
##   615 1637
##   383 1077
```

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



```
leveragePlots(fit_spp_stateyear_kbs)
```

Leverage Plots



```
ols_test_normality(fit_spp_stateyear_kbs)
```

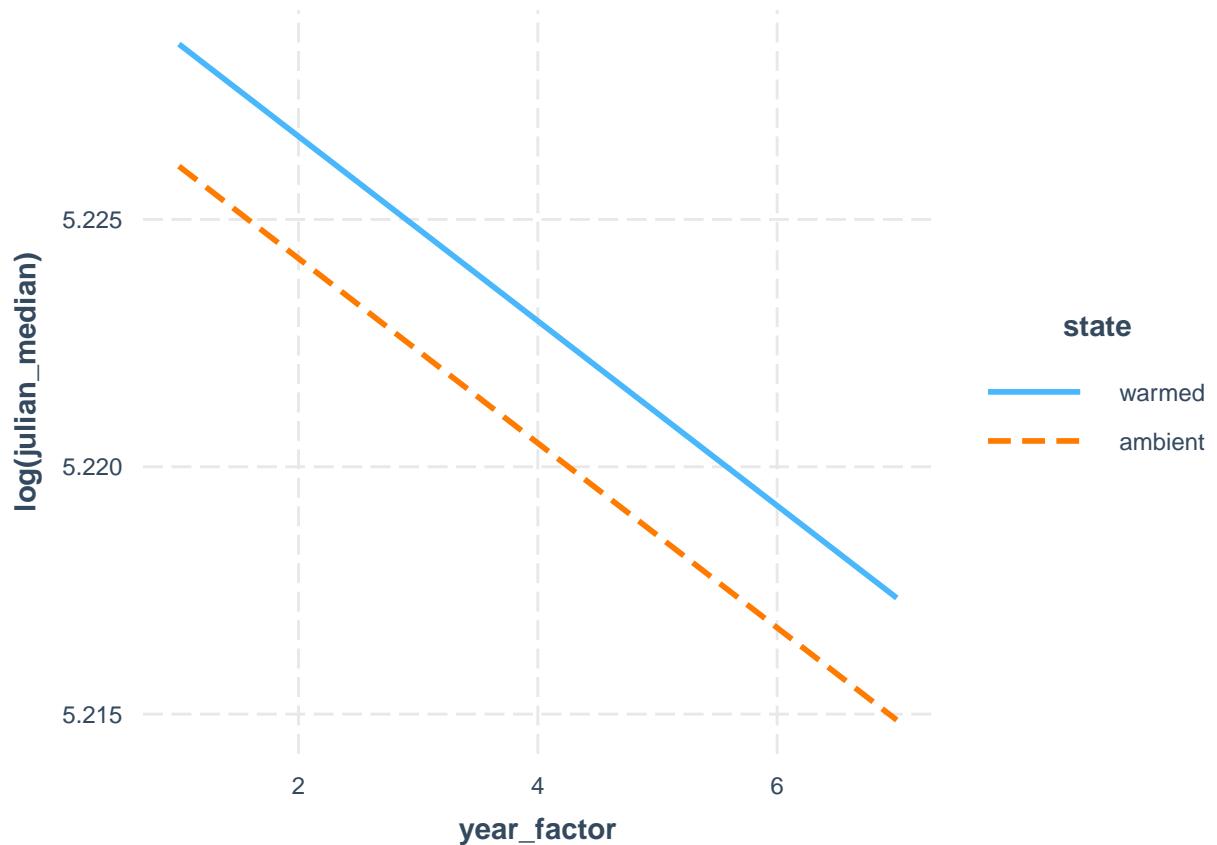
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----
##          Test      Statistic     pvalue
## -----
## Shapiro-Wilk      0.9565    0.0000
## Kolmogorov-Smirnov 0.1101    0.0000
## Cramer-von Mises   251.3042   0.0000
## Anderson-Darling    19.7878   0.0000
## -----
```

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

```
fit3_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.
```

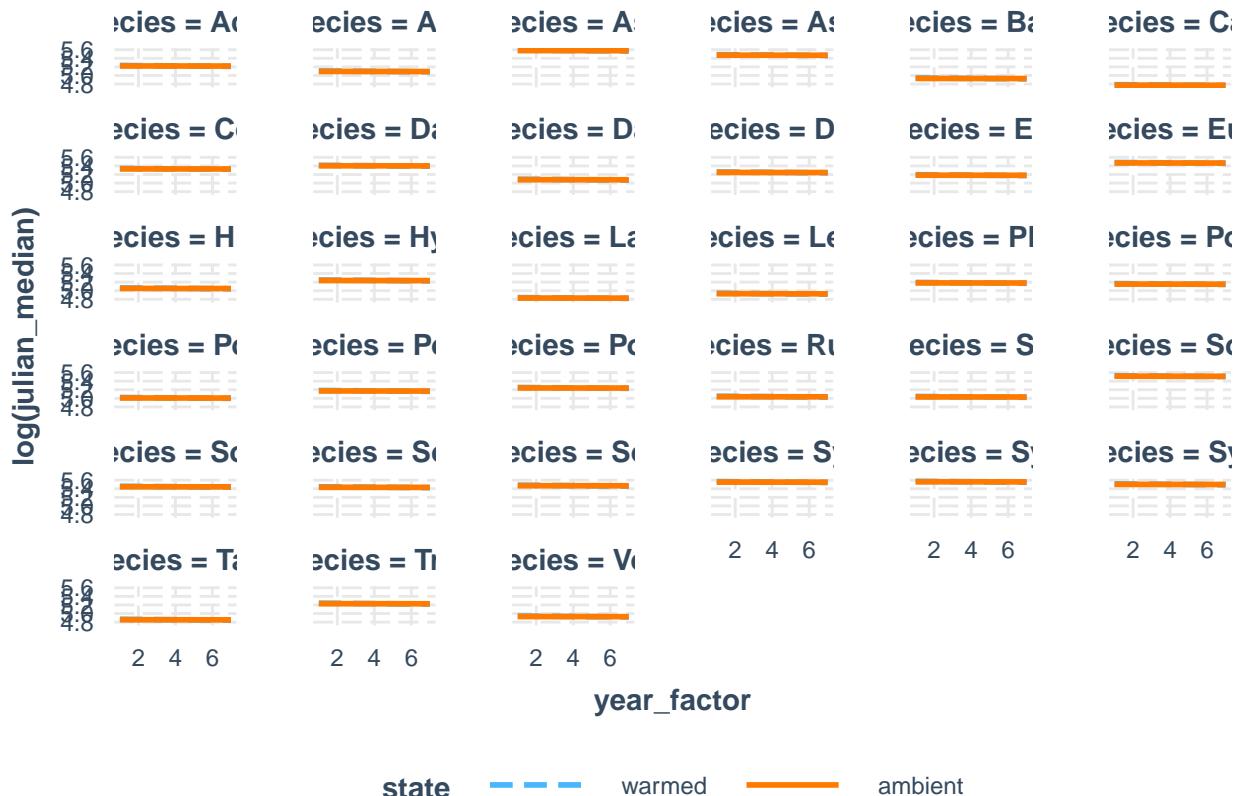


```

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.

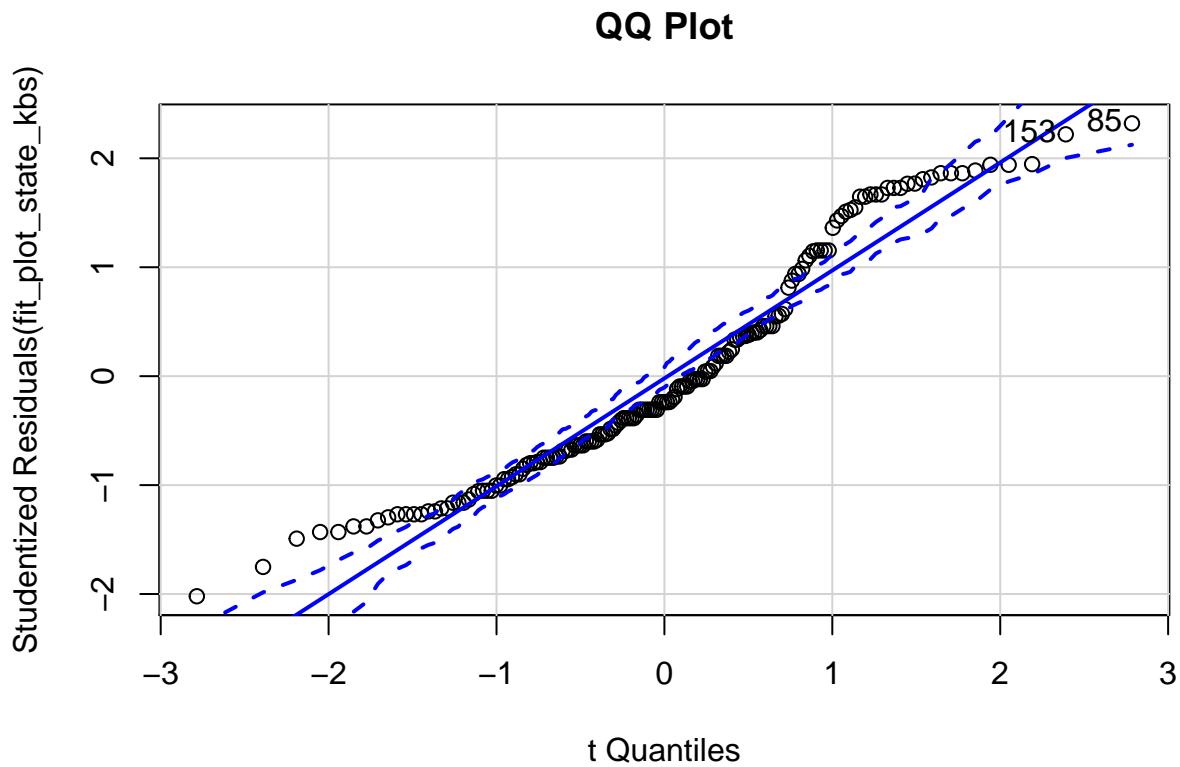
```



```
# 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
## 85 2.320858          0.021526         NA
```

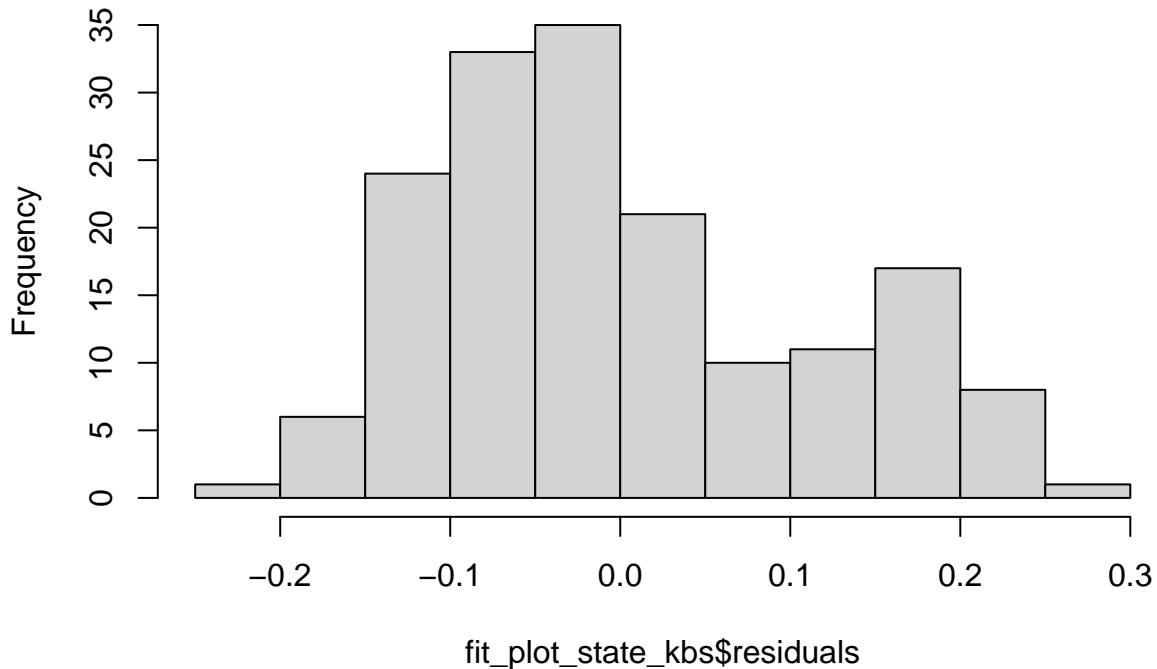
```
qqPlot(fit_plot_state_kbs, main = "QQ Plot")
```



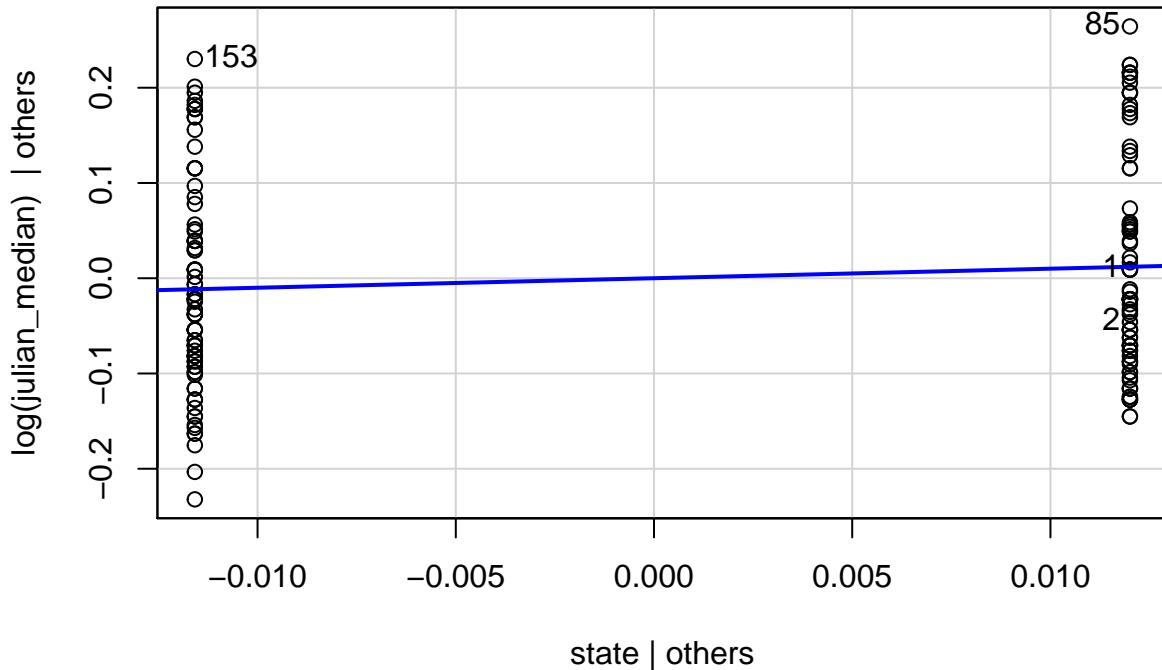
```
##   85 153
##   47 84
```

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

Histogram of fit_plot_state_kbs\$residuals



```
leveragePlots(fit_plot_state_kbs)
```



```
ols_test_normality(fit_plot_state_kbs)
```

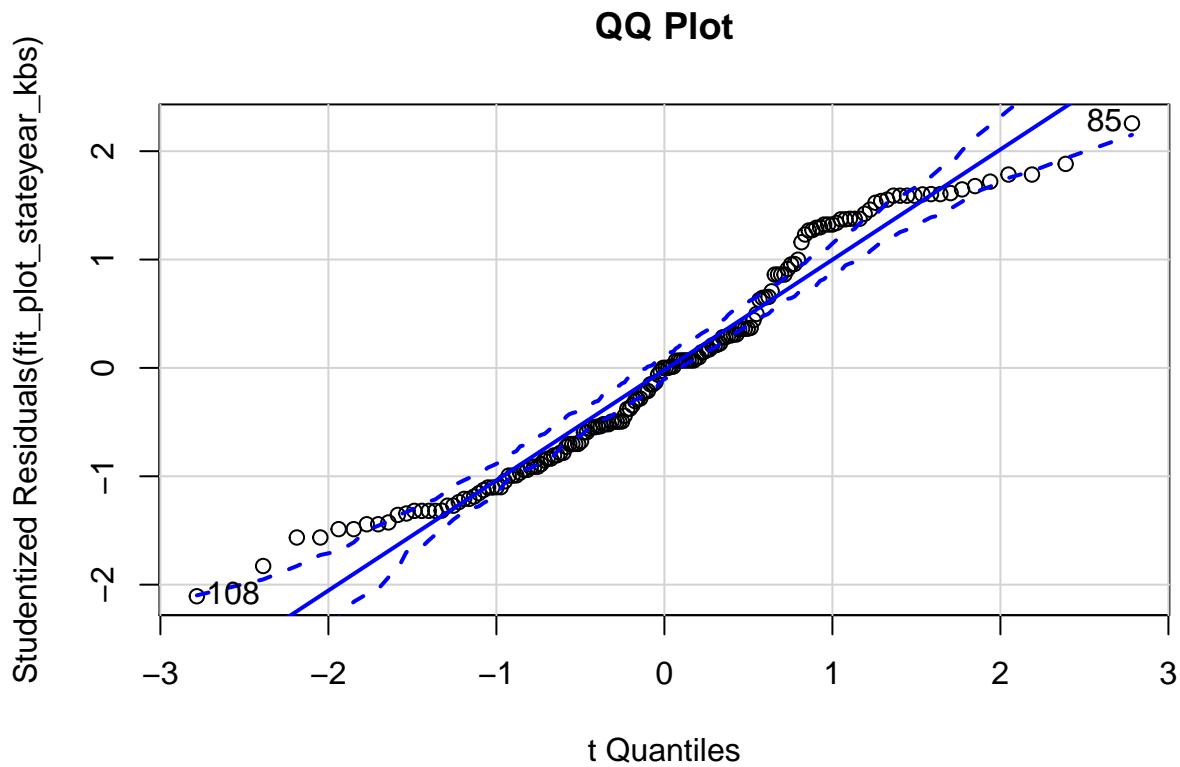
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----
##      Test          Statistic       pvalue
## -----
## Shapiro-Wilk      0.9441       0.0000
## Kolmogorov-Smirnov 0.1087       0.0387
## Cramer-von Mises  43.6201       0.0000
## Anderson-Darling   3.2161       0.0000
## -----
```

```
# UMBS 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
## 85  2.256773          0.025359           NA
```

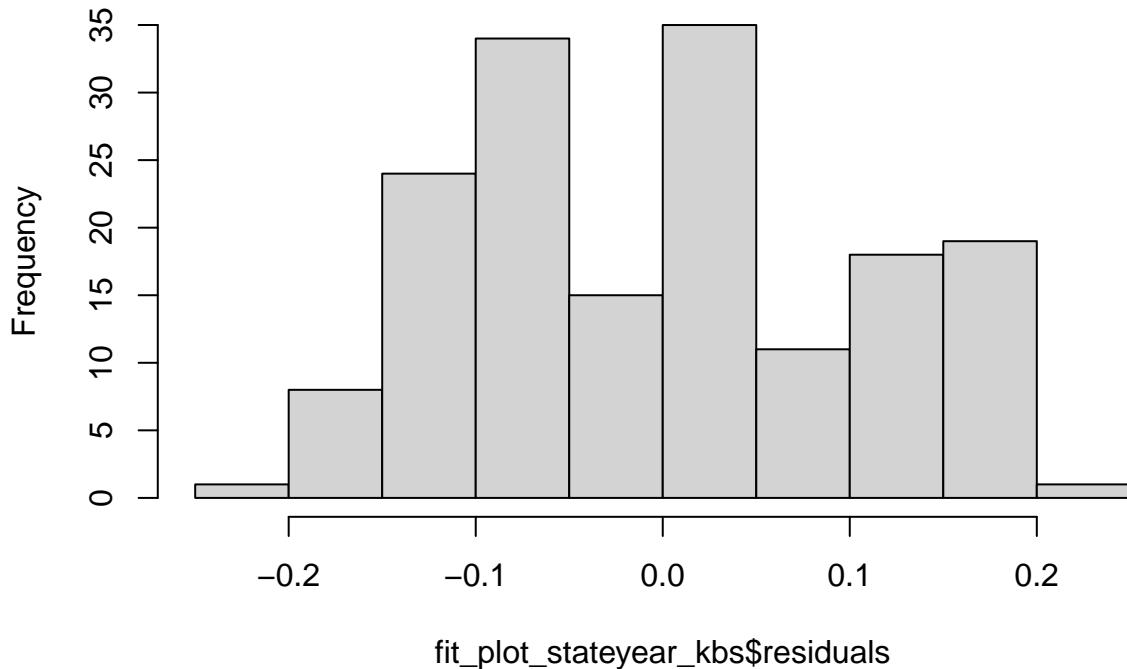
```
qqPlot(fit_plot_stateyear_kbs, main = "QQ Plot")
```



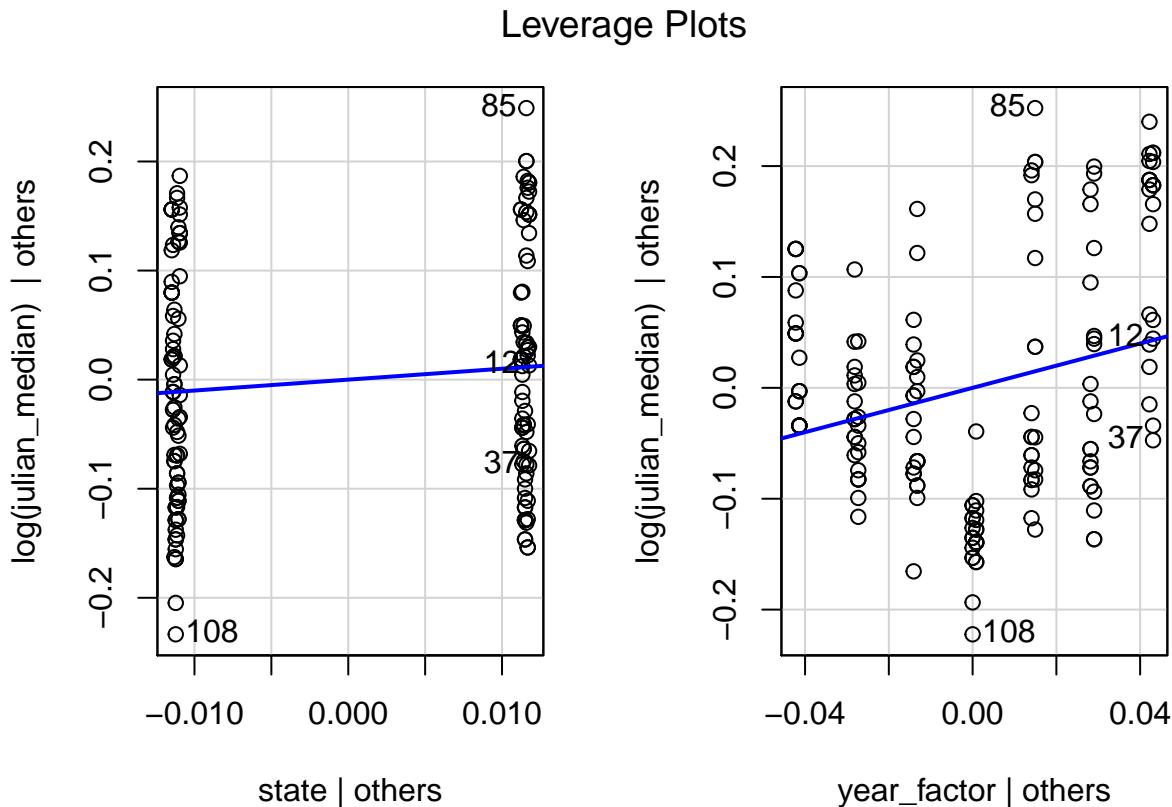
```
##   85 108
##   47 60
```

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

Histogram of fit_plot_stateyear_kbs\$residuals



```
leveragePlots(fit_plot_stateyear_kbs)
```



```
ols_test_normality(fit_plot_stateyear_kbs)
```

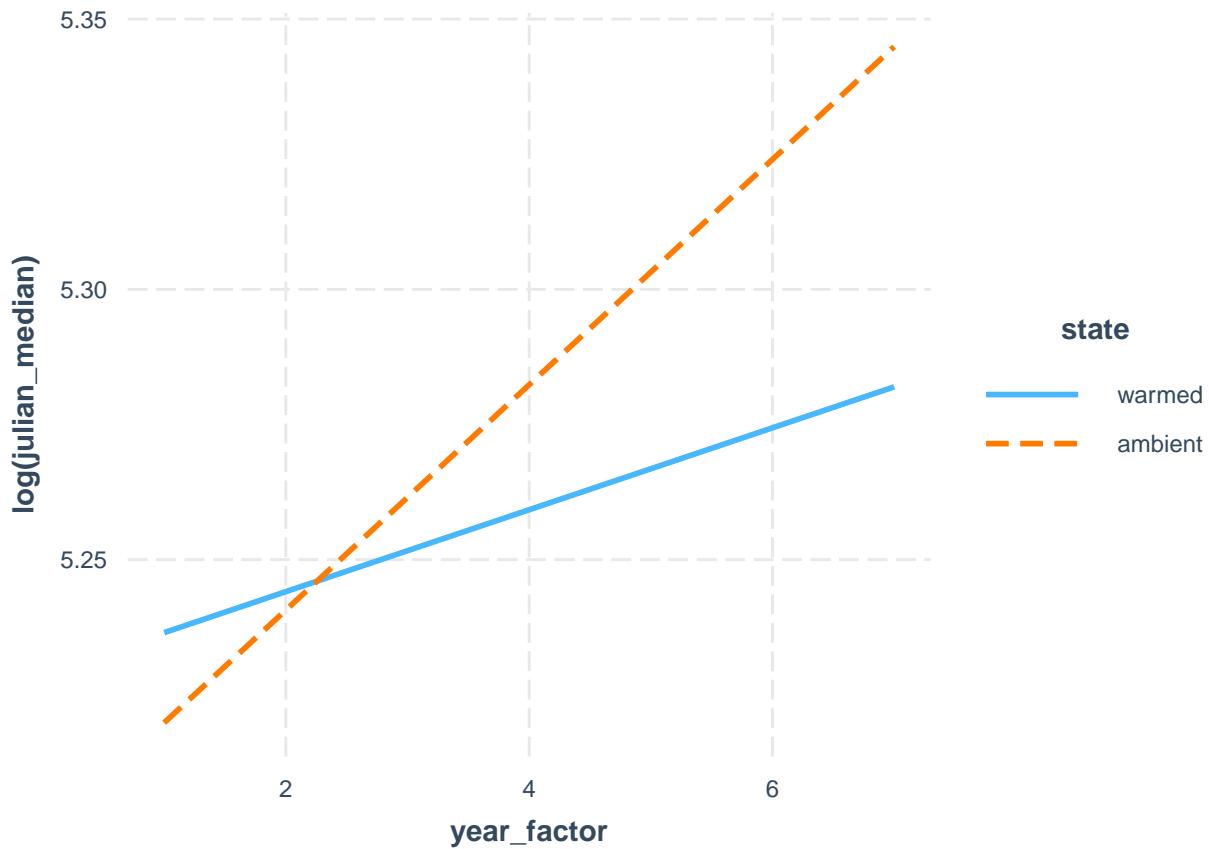
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----
##      Test          Statistic       pvalue
## -----
## Shapiro-Wilk      0.9581      1e-04
## Kolmogorov-Smirnov 0.0958     0.0949
## Cramer-von Mises  43.6796     0.0000
## Anderson-Darling   2.1902     0.0000
## -----
```

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

```
fit3_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

UMBS Species-level Mixed Effects Models

```
# Including year as a fixed effect and as an interactive term. Our goal here is
# to find a model that is the best fit to the data. We also want to find a model
# that is the most parsimonious (one that has the fewest parameters).

# 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), umbs_flwr_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

mod2 <- lmer(log(julian_median) ~ state * year_factor + insecticide * year_factor +
  (1 | species), umbs_flwr_spp, REML = FALSE)
# Run analysis of variance on each model (see this for more explanation on how
# anova on a linear mixed effects model is similar to an anova on a regular
# linear model: https://m-clark.github.io/docs/mixedModels/anovamixed.html)
anova(mod1)

## Type III Analysis of Variance Table with Satterthwaite's method
##          Sum Sq  Mean Sq NumDF DenDF F value    Pr(>F)
## state      0.010517 0.010517     1 592.99  3.1644  0.07577 .
## year_factor 0.086164 0.086164     1 593.53 25.9254 4.772e-07 ***
## insecticide 0.007921 0.007921     1 593.12  2.3832  0.12318
```

```

## state:year_factor      0.002477 0.002477      1 592.98  0.7452  0.38833
## year_factor:insecticide 0.006556 0.006556      1 593.18  1.9726  0.16070
## ---
## 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                      0.010517 0.010517      1 592.99  3.1644  0.07577 .
## year_factor                 0.086164 0.086164      1 593.53 25.9254 4.772e-07 ***
## insecticide                  0.007921 0.007921      1 593.12  2.3832  0.12318
## state:year_factor          0.002477 0.002477      1 592.98  0.7452  0.38833
## year_factor:insecticide    0.006556 0.006556      1 593.18  1.9726  0.16070
## ---
## 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 capturing the data than the simpler model. If the
# resulting p-value is sufficiently low (usually less than 0.05), we conclude
# that the more complex model is significantly better than the simpler model, and
# thus favor the more complex model. If the p-value is not sufficiently low
# (usually greater than 0.05), we should favor the simpler model.
# https://bookdown.org/ndphillips/YaRrr/comparing-regression-models-with-anova.html
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 | plot)
##       npar   AIC     BIC logLik deviance Chisq Df Pr(>Chisq)
## mod2    8 -1650.2 -1614.9 833.08 -1666.2
## mod1    9 -1648.2 -1608.5 833.08 -1666.2      0   1        1

```

```
summary(mod1)
```

```

## 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: umbs_flwr_spp
##
##       AIC     BIC logLik deviance df.resid
## -1648.2 -1608.5  833.1 -1666.2      598
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -5.6542 -0.5111  0.0670  0.6709  2.3200
##

```

```

## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0000000 0.00000
## species  (Intercept) 0.031094 0.17633
## Residual           0.003324 0.05765
## Number of obs: 607, groups: plot, 24; species, 14
##
## Fixed effects:
##                               Estimate Std. Error      df t value
## (Intercept)                5.143621  0.049041 15.971506 104.885
## stateambient               0.025410  0.014284 592.994827   1.779
## year_factor                 0.007309  0.002812 593.047313   2.599
## insecticideno_insects      -0.022183  0.014369 593.117789  -1.544
## stateambient:year_factor   -0.002700  0.003128 592.983665  -0.863
## year_factor:insecticideno_insects 0.004411  0.003141 593.182068   1.404
##                               Pr(>|t|)
## (Intercept)                < 2e-16 ***
## stateambient               0.07577 .
## year_factor                 0.00959 **
## insecticideno_insects      0.12318
## stateambient:year_factor   0.38833
## year_factor:insecticideno_insects 0.16070
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) sttmbn yr_fct insct_ sttm:_stateambint -0.151
## stateambint          -0.151
## year_factor          -0.247  0.548
## insctcdn_ns          -0.160  0.033  0.573
## sttmbnt:yr_          0.144 -0.943 -0.589 -0.046
## yr_fctr:ns_          0.149 -0.044 -0.610 -0.942  0.064
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

```

```
summary(mod2)
```

```

## 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: umbs_flwr_spp
##
##       AIC      BIC  logLik deviance df.resid
## -1650.2 -1614.9    833.1   -1666.2      599
##
## Scaled residuals:
##       Min     1Q Median     3Q    Max
## -5.6542 -0.5111  0.0670  0.6709  2.3200
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## species  (Intercept) 0.031094 0.17633

```

```

##  Residual           0.003324 0.05765
## Number of obs: 607, groups: species, 14
##
## Fixed effects:
##                               Estimate Std. Error      df t value
## (Intercept)             5.143621  0.049041 15.971641 104.885
## stateambient          0.025410  0.014284 592.994790   1.779
## year_factor            0.007309  0.002812 593.047276   2.599
## insecticideno_insects -0.022183  0.014369 593.117752  -1.544
## stateambient:year_factor -0.002700  0.003128 592.983627  -0.863
## year_factor:insecticideno_insects 0.004411  0.003141 593.182031   1.404
##                               Pr(>|t|)
## (Intercept)             < 2e-16 ***
## stateambient          0.07577 .
## year_factor            0.00959 **
## insecticideno_insects 0.12318
## stateambient:year_factor 0.38833
## year_factor:insecticideno_insects 0.16070
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) sttmbn yr_fct insct_ sttm:_
## stateambint -0.151
## year_factor -0.247  0.548
## insctcdn_ns -0.160  0.033  0.573
## sttmbnt:yr_  0.144 -0.943 -0.589 -0.046
## yr_fctr:ns_  0.149 -0.044 -0.610 -0.942  0.064

```

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

```

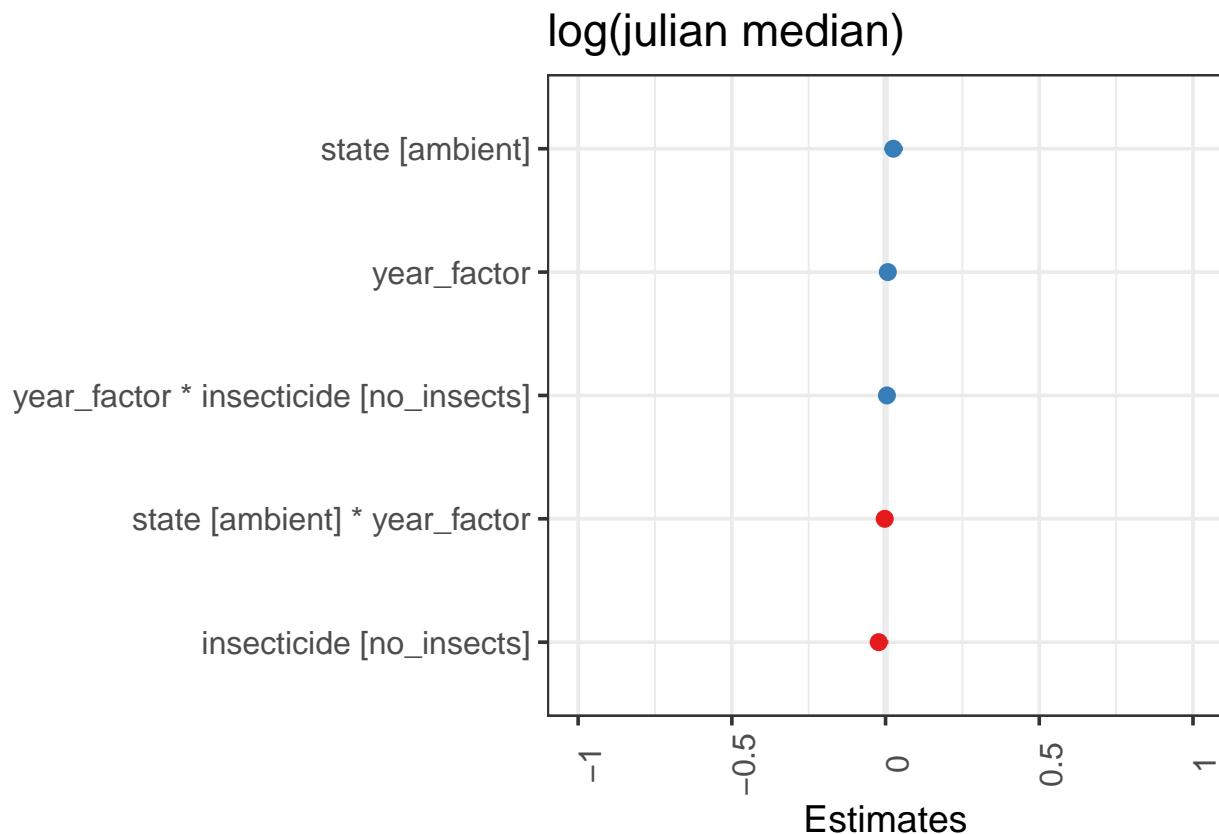
##      dAICc df weight
## mod2 0.0    8  0.74
## mod1 2.1    9  0.26

```

```

# Next, plot the model. There are multiple variables but here's one way to do it
# based on this package sjPlot:
# 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 the code to get warmed = red. I haven't figured this out
# yet. It does seem to work on some of the plots. hmm. ?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)

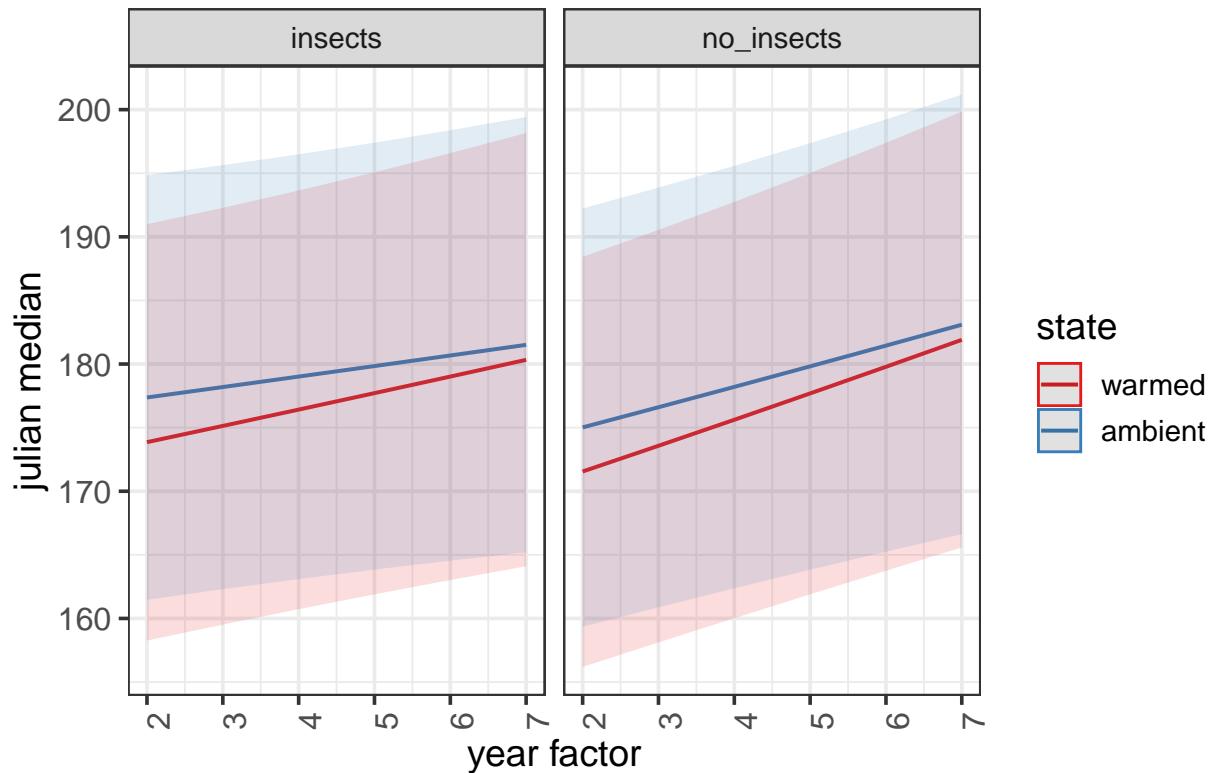
```



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

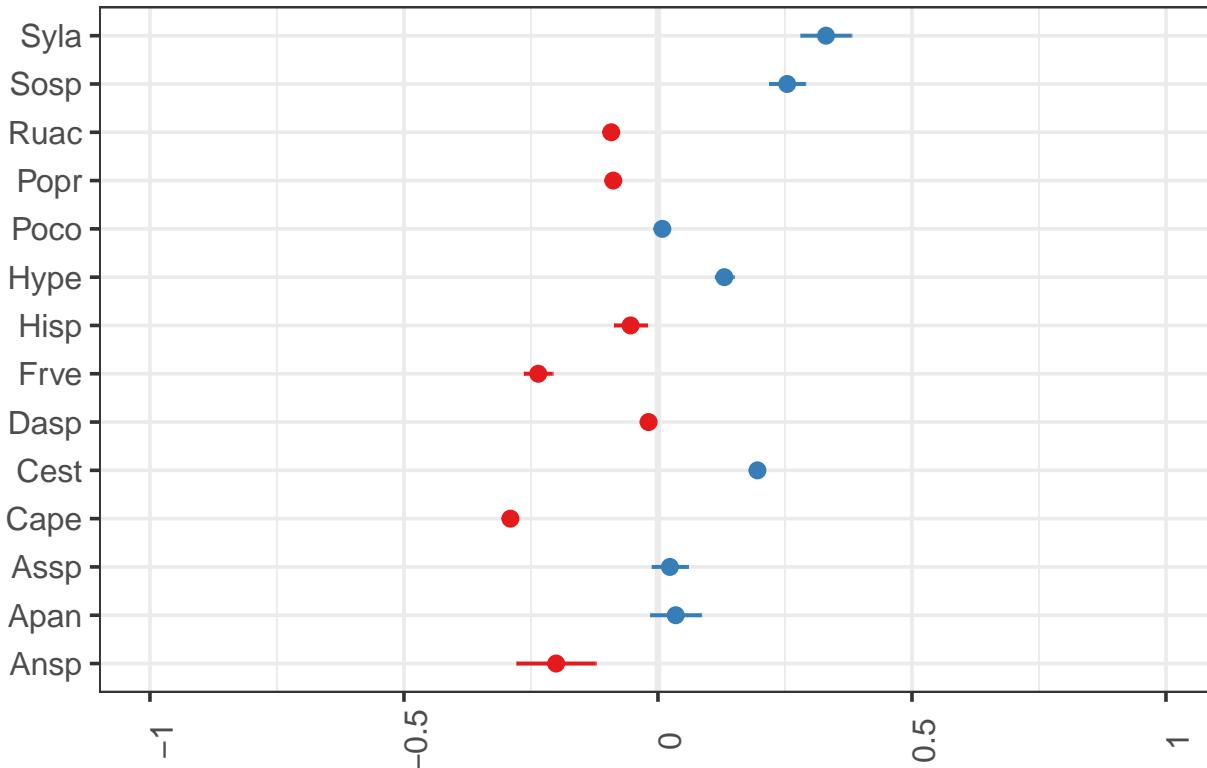
```
## Model has log-transformed response. Back-transforming predictions to original response scale. Standard
```

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)
```

```
## Data: umbs_flwr_spp
## Models:
## mod3: log(julian_median) ~ state * year_factor + (1 | species)
## mod2: log(julian_median) ~ state * year_factor + insecticide * year_factor +
## mod2: (1 | species)
##      npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod3     6 -1651.8 -1625.3  831.88   -1663.8
## mod2     8 -1650.2 -1614.9  833.08   -1666.2 2.4002  2     0.3012
```

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

```
##      dAICc df weight
## mod3  0.0   6  0.7
## mod2  1.7   8  0.3
```

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

```
# Does year need to be interactive with insecticide? - already removed
# insecticide mod4 <- lmer(log(julian_median) ~ state*year_factor + insecticide +
```

```

# (1/species) + (1/plot), umbs_flwr_spp, REML=FALSE)

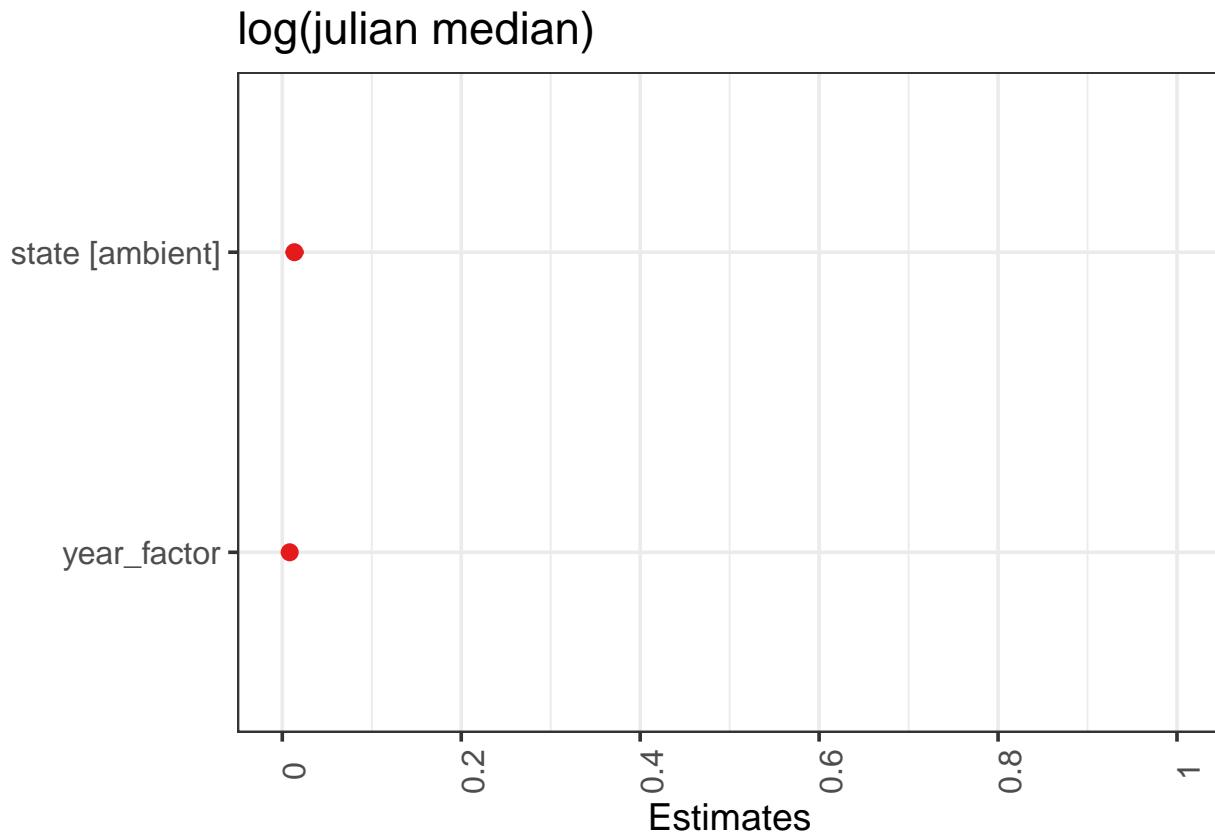
# Does year need to be interactive with state?
mod5 <- lmer(log(julian_median) ~ state + year_factor + (1 | species), umbs_flwr_spp,
             REML = FALSE)
anova(mod3, mod5)

## 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 -1652.9 -1630.9 831.45   -1662.9
## mod3     6 -1651.8 -1625.3 831.88   -1663.8 0.8578  1     0.3543

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

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

```



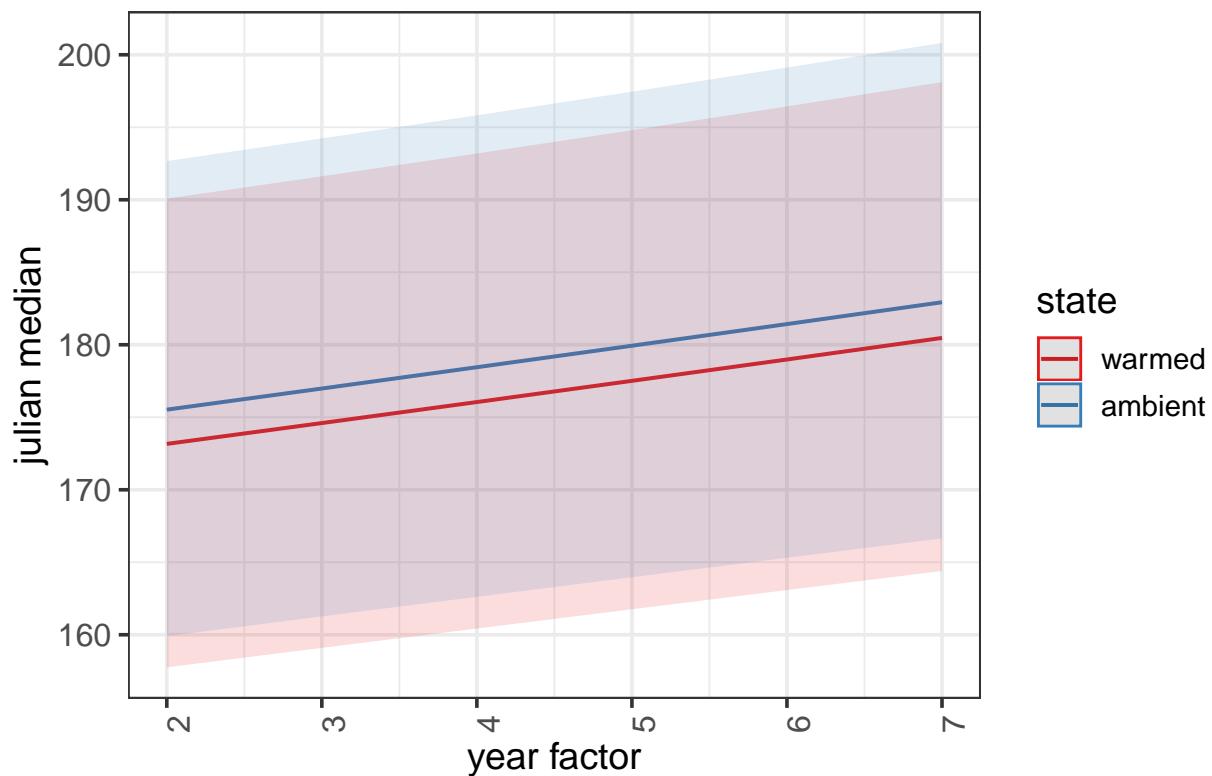
```

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

```

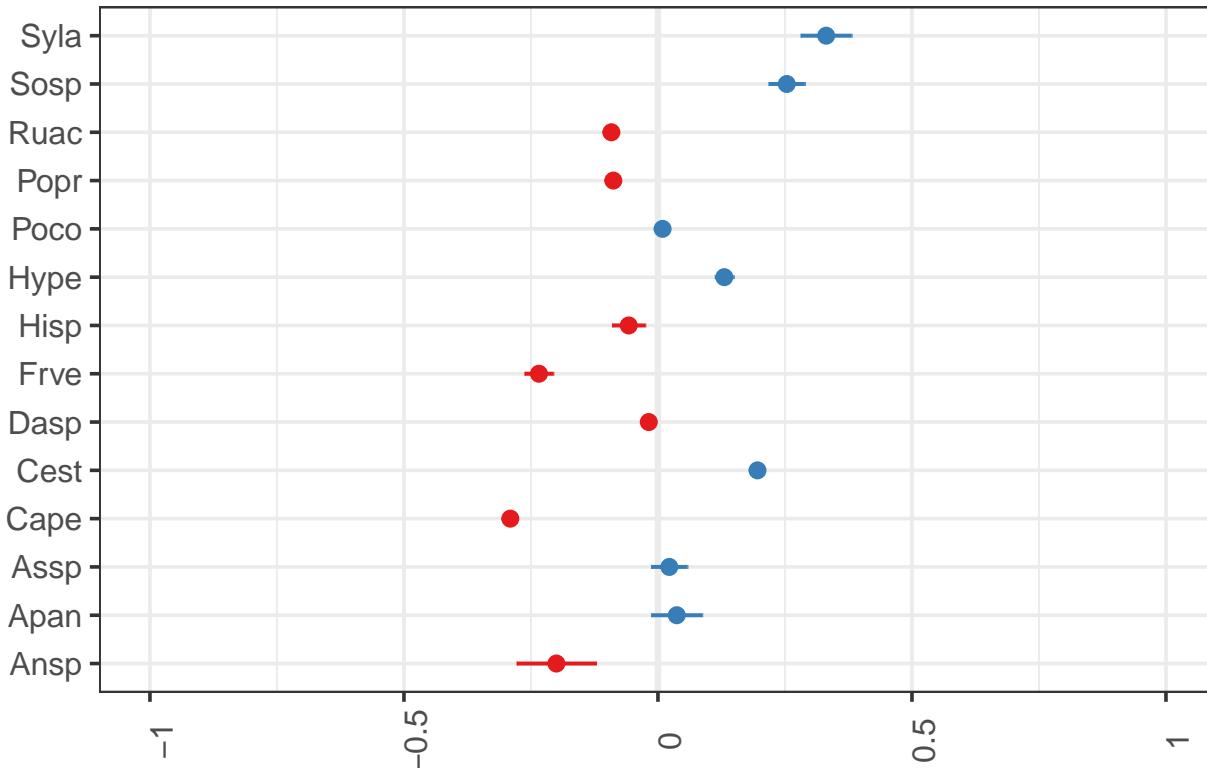
Model has log-transformed response. Back-transforming predictions to original response scale. Standardized residuals.

Predicted values of 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 = FALSE)
```

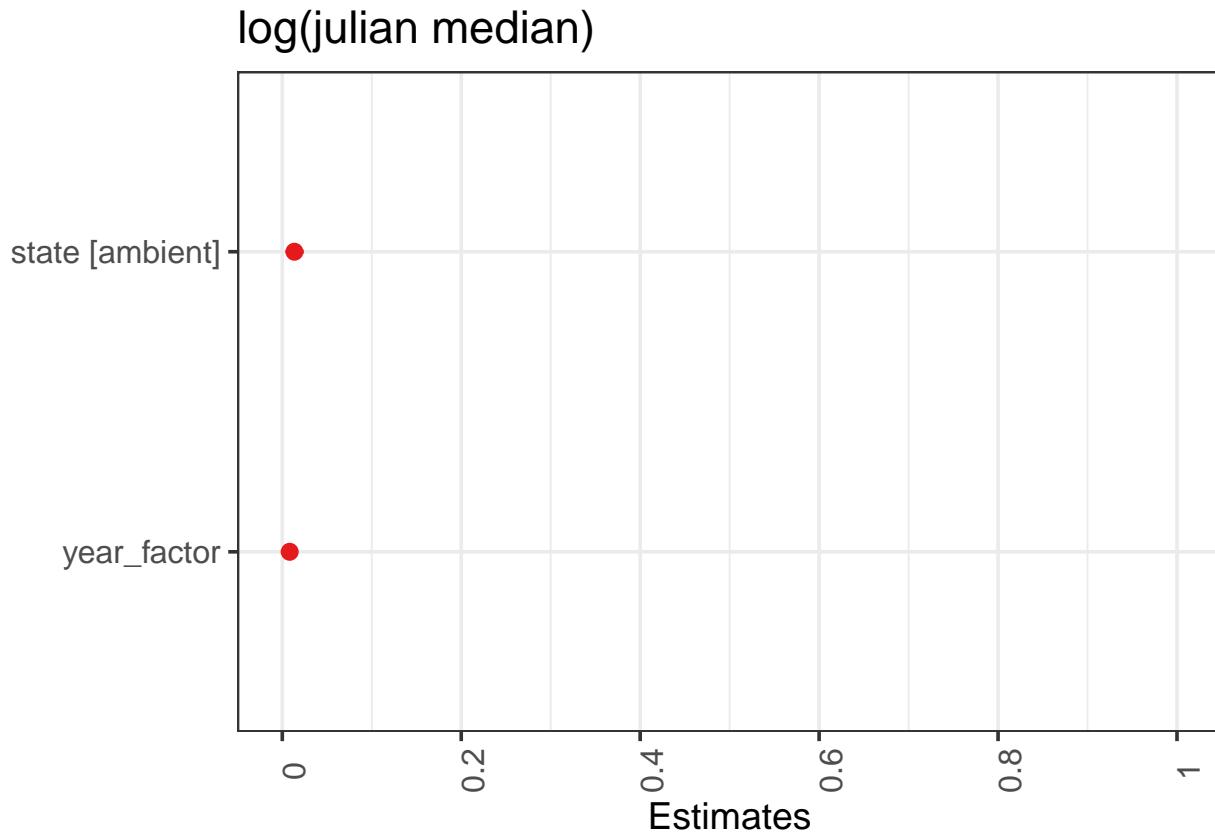
```
## boundary (singular) fit: see ?isSingular
## Warning: Model failed to converge with 1 negative eigenvalue: -2.7e-01
anova(mod5, mod6)
```

```
## Data: umbs_flwr_spp
## Models:
## mod5: log(julian_median) ~ state + year_factor + (1 | species)
## mod6: log(julian_median) ~ state + year_factor + (1 | species) + (1 +
## mod6:      year | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod5     5 -1652.9 -1630.9  831.45   -1662.9
## mod6     8 -1639.4 -1604.1  827.70   -1655.4      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      0.027151 0.027151      1 593.15  8.1242  0.00452 ***
## year_factor 0.088529 0.088529      1 593.54 26.4905 3.606e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ',' 1
```

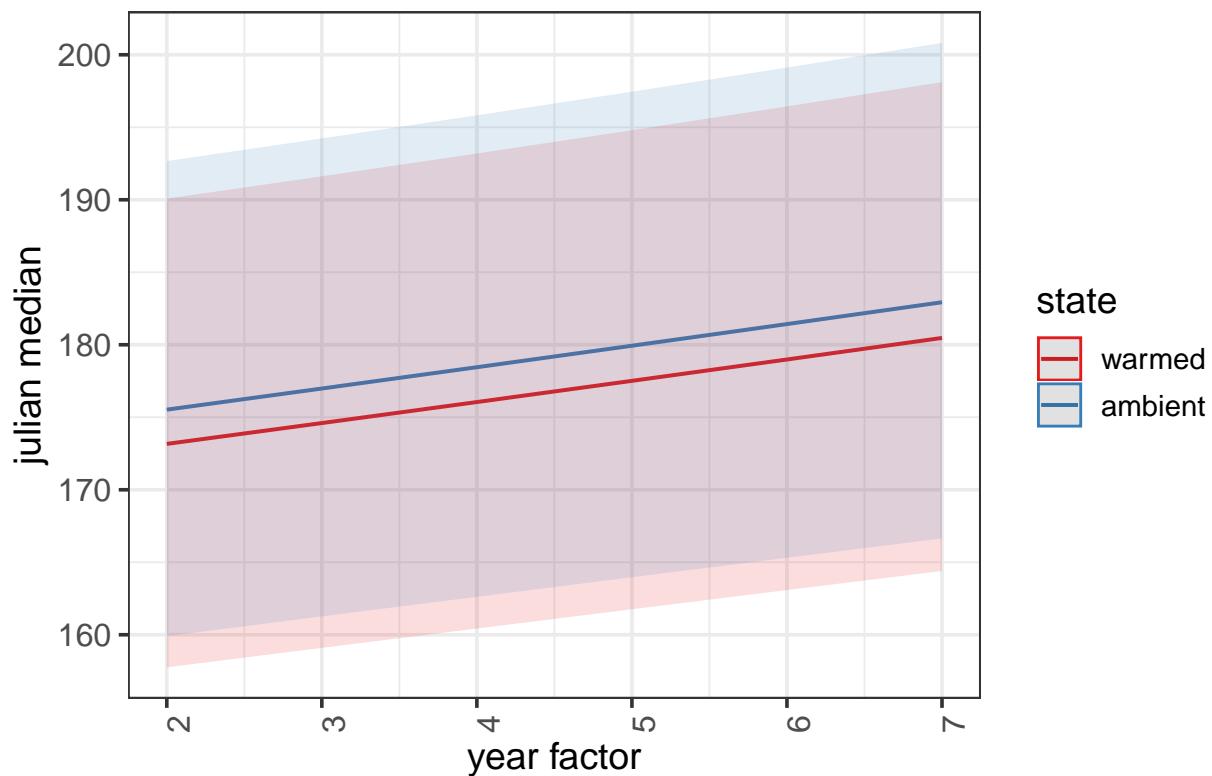
```
# Doesn't seem to matter  
plot_model(mod5, sort.est = TRUE)
```



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

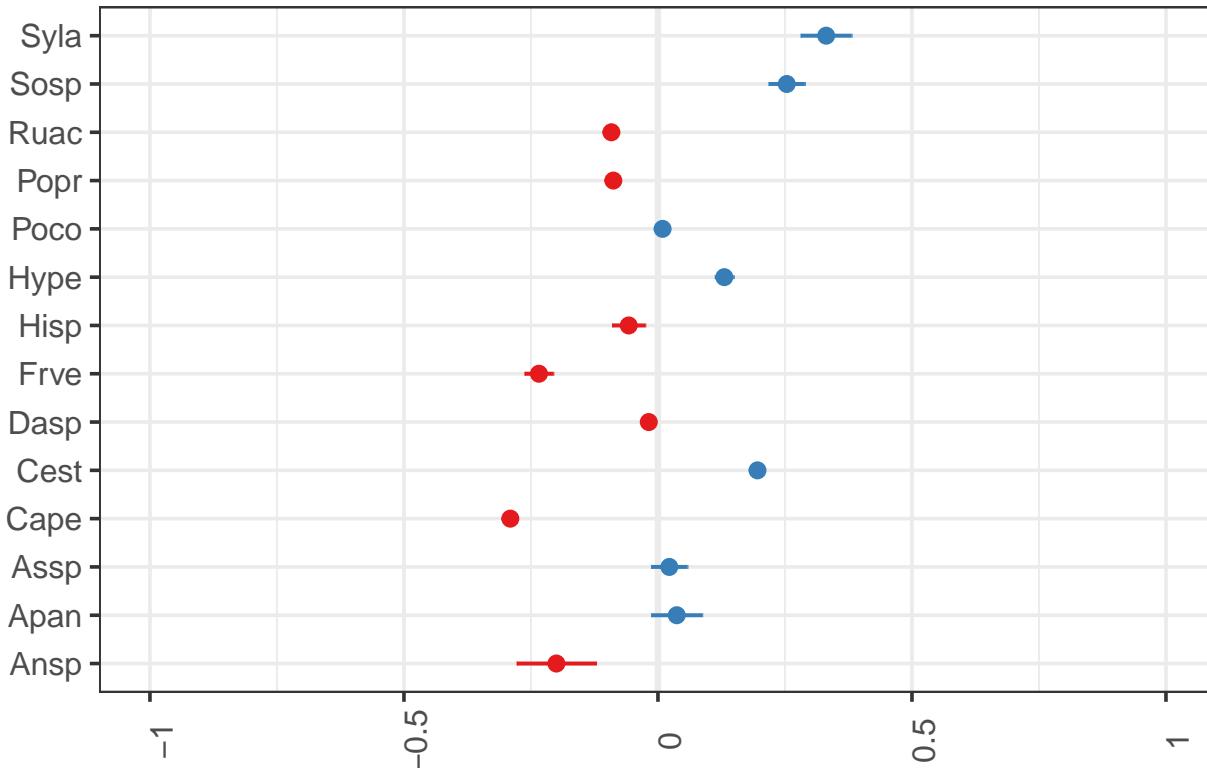
```
## Model has log-transformed response. Back-transforming predictions to original response scale. Standard
```

Predicted values of julian median



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

Random effects



```
# mod4 (and mod5) are pretty complex in terms of interpretation (they actually
# don't have many parameters though). We could consider an alternative model
# that's simpler to understand and also one that provides more insight about the
# species. That would be something like this:
```

```
mod7 <- lmer(log(julian_median) ~ state + species + (1 + factor(year_factor) | plot),
  umbs_flwr_spp, REML = FALSE)
```

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

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

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

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

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

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

```
## boundary (singular) fit: see ?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) |
## mod7:   plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod5     5 -1652.9 -1630.9 831.45   -1662.9
## mod7    37 -1743.9 -1580.8 908.95   -1817.9 154.99 32 < 2.2e-16 ***
## ---
## 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) +
## mod7a:   (1 | plot)
## mod7: log(julian_median) ~ state + species + (1 + factor(year_factor) |
## mod7:   plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod7a    22 -1826.1 -1729.2 935.07   -1870.1
## mod7    37 -1743.9 -1580.8 908.95   -1817.9      0 15           1
```

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

```
## Data: umbs_flwr_spp
## Models:
## mod7a: log(julian_median) ~ state + species + factor(year_factor) +
## mod7a:   (1 | plot)
## mod7b: log(julian_median) ~ state * factor(year_factor) + species +
## mod7b:   (1 | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod7a    22 -1826.1 -1729.2 935.07   -1870.1
## mod7b    27 -1825.9 -1706.8 939.93   -1879.9 9.7245  5   0.08343 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(mod7b, mod7c) #not sure what these results are telling me, no pvalue... but going with model 7c
```

```
## Data: umbs_flwr_spp
## Models:
## mod7c: log(julian_median) ~ state + species + factor(year_factor) +
## mod7c:   insecticide + (1 | plot)
## mod7b: log(julian_median) ~ state * factor(year_factor) + species +
## mod7b:   (1 | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod7c    23 -1825.6 -1724.2 935.79   -1871.6
## mod7b    27 -1825.9 -1706.8 939.93   -1879.9 8.2853  4   0.08167 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(mod7c)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + species + factor(year_factor) +
##           insecticide + (1 | plot)
## Data: umbs_flwr_spp
##
##          AIC      BIC  logLik deviance df.resid
## -1825.6 -1724.2    935.8 -1871.6      584
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -6.3533 -0.5399 -0.0579  0.5970  3.6199
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0000000 0.00000
## Residual            0.002682 0.05179
## Number of obs: 607, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept) 4.927883  0.037486 607.000000 131.460 < 2e-16 ***
## stateambient 0.012431  0.004264 607.000000  2.915  0.00369 **
## speciesApan  0.259967  0.043790 607.000000  5.937 4.90e-09 ***
## speciesAssp  0.244515  0.040586 607.000000  6.025 2.94e-09 ***
## speciesCape -0.074965  0.037580 607.000000 -1.995  0.04651 *
## speciesCest  0.412159  0.037189 607.000000 11.083 < 2e-16 ***
## speciesDasp  0.191427  0.037316 607.000000  5.130 3.91e-07 ***
## speciesFrve -0.017246  0.039169 607.000000 -0.440  0.65987
## speciesHisp  0.163749  0.039886 607.000000  4.105 4.59e-05 ***
## speciesHype  0.341821  0.037977 607.000000  9.001 < 2e-16 ***
## speciesPoco  0.212244  0.037458 607.000000  5.666 2.26e-08 ***
## speciesPopr  0.118605  0.037230 607.000000  3.186  0.00152 **
## speciesRuac  0.119059  0.037399 607.000000  3.183  0.00153 **
## speciesSosp  0.472702  0.040431 607.000000 11.691 < 2e-16 ***
## speciesSyla  0.541054  0.043717 607.000000 12.376 < 2e-16 ***
## factor(year_factor)3 0.027100  0.007434 607.000000  3.645  0.00029 ***
## factor(year_factor)4 0.035833  0.007418 607.000000  4.830 1.73e-06 ***
## factor(year_factor)5 0.073261  0.007219 607.000000 10.148 < 2e-16 ***
## factor(year_factor)6 0.054809  0.007222 607.000000  7.589 1.22e-13 ***
## factor(year_factor)7 -0.019474  0.010582 607.000000 -1.840  0.06620 .
## insecticideno_insects -0.005203  0.004335 607.000000 -1.200  0.23046
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 21 > 12.
## Use print(x, correlation=TRUE)  or
##      vcov(x)      if you need it

## optimizer (nloptwrap) convergence code: 0 (OK)
```

```

## boundary (singular) fit: see ?isSingular

anova(mod7c) # investigates whether at least one of the levels within each factor is significantly dif

## Type III Analysis of Variance Table with Satterthwaite's method
##                                     Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state                      0.0228 0.02279     1   607  8.4987  0.003685 ***
## species                    14.1272 1.08671    13   607 405.1876 < 2.2e-16 ***
## factor(year_factor)      0.4389 0.08777     5   607 32.7274 < 2.2e-16 ***
## insecticide                 0.0039 0.00386     1   607  1.4409  0.230464
## ---
## 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(mod7c, list(pairwise ~ state + year_factor), adjust = "tukey")

## boundary (singular) fit: see ?isSingular

## $`emmeans of state, year_factor`
##   state  year_factor emmean       SE   df lower.CL upper.CL
##   warmed          2  5.139 0.007196 335.9   5.124   5.153
##   ambient          2  5.151 0.007172 296.3   5.137   5.165
##   warmed          3  5.166 0.006750 274.1   5.152   5.179
##   ambient          3  5.178 0.006688 240.4   5.165   5.191
##   warmed          4  5.174 0.006759 261.5   5.161   5.188
##   ambient          4  5.187 0.006710 228.5   5.174   5.200
##   warmed          5  5.212 0.006568 256.3   5.199   5.225
##   ambient          5  5.224 0.006525 231.6   5.211   5.237
##   warmed          6  5.193 0.006484 242.1   5.181   5.206
##   ambient          6  5.206 0.006430 210.3   5.193   5.218
##   warmed          7  5.119 0.010026 512.0   5.099   5.139
##   ambient          7  5.131 0.010095 522.6   5.112   5.151
##
## Results are averaged over the levels of: species, insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, year_factor`
##   1           estimate       SE   df t.ratio p.value
##   warmed 2 - ambient 2 -0.01243 0.00436 20.5 -2.850 0.2297
##   warmed 2 - warmed 3 -0.02710 0.00757 612.3 -3.580 0.0190
##   warmed 2 - ambient 3 -0.03953 0.00871 253.2 -4.540 0.0005
##   warmed 2 - warmed 4 -0.03583 0.00756 617.0 -4.742 0.0002
##   warmed 2 - ambient 4 -0.04826 0.00871 246.8 -5.543 <.0001
##   warmed 2 - warmed 5 -0.07326 0.00735 616.0 -9.963 <.0001
##   warmed 2 - ambient 5 -0.08569 0.00854 240.0 -10.038 <.0001
##   warmed 2 - warmed 6 -0.05481 0.00736 616.8 -7.450 <.0001
##   warmed 2 - ambient 6 -0.06724 0.00853 234.5 -7.881 <.0001
##   warmed 2 - warmed 7  0.01947 0.01079 622.3  1.805 0.8149
##   warmed 2 - ambient 7  0.00704 0.01171 460.0  0.601 1.0000

```

```

## ambient 2 - warmed 3 -0.01467 0.00876 249.5 -1.674 0.8785
## ambient 2 - ambient 3 -0.02710 0.00757 612.3 -3.580 0.0190
## ambient 2 - warmed 4 -0.02340 0.00874 244.3 -2.676 0.2445
## ambient 2 - ambient 4 -0.03583 0.00756 617.0 -4.742 0.0002
## ambient 2 - warmed 5 -0.06083 0.00856 226.5 -7.104 <.0001
## ambient 2 - ambient 5 -0.07326 0.00735 616.0 -9.963 <.0001
## ambient 2 - warmed 6 -0.04238 0.00857 230.8 -4.943 0.0001
## ambient 2 - ambient 6 -0.05481 0.00736 616.8 -7.450 <.0001
## ambient 2 - warmed 7 0.03191 0.01156 405.2 2.760 0.2017
## ambient 2 - ambient 7 0.01947 0.01079 622.3 1.805 0.8149
## warmed 3 - ambient 3 -0.01243 0.00436 20.5 -2.850 0.2297
## warmed 3 - warmed 4 -0.00873 0.00717 610.6 -1.219 0.9874
## warmed 3 - ambient 4 -0.02116 0.00840 225.2 -2.520 0.3331
## warmed 3 - warmed 5 -0.04616 0.00696 609.8 -6.632 <.0001
## warmed 3 - ambient 5 -0.05859 0.00823 217.8 -7.119 <.0001
## warmed 3 - warmed 6 -0.02771 0.00694 610.3 -3.994 0.0042
## warmed 3 - ambient 6 -0.04014 0.00820 211.0 -4.893 0.0001
## warmed 3 - warmed 7 0.04657 0.01061 619.8 4.390 0.0008
## warmed 3 - ambient 7 0.03414 0.01157 455.4 2.951 0.1268
## ambient 3 - warmed 4 0.00370 0.00838 226.1 0.441 1.0000
## ambient 3 - ambient 4 -0.00873 0.00717 610.6 -1.219 0.9874
## ambient 3 - warmed 5 -0.03373 0.00820 207.8 -4.115 0.0032
## ambient 3 - ambient 5 -0.04616 0.00696 609.8 -6.632 <.0001
## ambient 3 - warmed 6 -0.01528 0.00819 210.6 -1.866 0.7784
## ambient 3 - ambient 6 -0.02771 0.00694 610.3 -3.994 0.0042
## ambient 3 - warmed 7 0.05900 0.01137 404.0 5.188 <.0001
## ambient 3 - ambient 7 0.04657 0.01061 619.8 4.390 0.0008
## warmed 4 - ambient 4 -0.01243 0.00436 20.5 -2.850 0.2297
## warmed 4 - warmed 5 -0.03743 0.00687 611.6 -5.445 <.0001
## warmed 4 - ambient 5 -0.04986 0.00815 211.1 -6.120 <.0001
## warmed 4 - warmed 6 -0.01898 0.00683 613.4 -2.778 0.1920
## warmed 4 - ambient 6 -0.03141 0.00810 202.3 -3.876 0.0078
## warmed 4 - warmed 7 0.05531 0.01048 620.5 5.278 <.0001
## warmed 4 - ambient 7 0.04288 0.01144 448.3 3.747 0.0108
## ambient 4 - warmed 5 -0.02500 0.00813 200.4 -3.073 0.0963
## ambient 4 - ambient 5 -0.03743 0.00687 611.6 -5.445 <.0001
## ambient 4 - warmed 6 -0.00655 0.00811 201.1 -0.807 0.9997
## ambient 4 - ambient 6 -0.01898 0.00683 613.4 -2.778 0.1920
## ambient 4 - warmed 7 0.06774 0.01126 394.4 6.016 <.0001
## ambient 4 - ambient 7 0.05531 0.01048 620.5 5.278 <.0001
## warmed 5 - ambient 5 -0.01243 0.00436 20.5 -2.850 0.2297
## warmed 5 - warmed 6 0.01845 0.00659 610.1 2.799 0.1830
## warmed 5 - ambient 6 0.00602 0.00790 184.4 0.762 0.9998
## warmed 5 - warmed 7 0.09274 0.01031 618.7 8.997 <.0001
## warmed 5 - ambient 7 0.08030 0.01128 438.7 7.119 <.0001
## ambient 5 - warmed 6 0.03088 0.00791 193.5 3.903 0.0071
## ambient 5 - ambient 6 0.01845 0.00659 610.1 2.799 0.1830
## ambient 5 - warmed 7 0.10517 0.01110 394.1 9.471 <.0001
## ambient 5 - ambient 7 0.09274 0.01031 618.7 8.997 <.0001
## warmed 6 - ambient 6 -0.01243 0.00436 20.5 -2.850 0.2297
## warmed 6 - warmed 7 0.07428 0.01030 620.9 7.209 <.0001
## warmed 6 - ambient 7 0.06185 0.01128 437.9 5.482 <.0001
## ambient 6 - warmed 7 0.08671 0.01110 384.2 7.815 <.0001
## ambient 6 - ambient 7 0.07428 0.01030 620.9 7.209 <.0001

```

```

##  warmed 7 - ambient 7  -0.01243 0.00436  20.5  -2.850 0.2297
##
## Results are averaged over the levels of: species, insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 12 estimates

emmeans(mod7c, list(pairwise ~ year_factor), adjust = "tukey")

## boundary (singular) fit: see ?isSingular

## $`emmeans of year_factor`
##   year_factor emmean      SE  df lower.CL upper.CL
##     2    5.145 0.006845 484.5   5.131   5.158
##     3    5.172 0.006355 420.5   5.159   5.184
##     4    5.181 0.006372 398.1   5.168   5.193
##     5    5.218 0.006173 408.5   5.206   5.230
##     6    5.200 0.006078 381.1   5.188   5.211
##     7    5.125 0.009821 599.9   5.106   5.145
##
## Results are averaged over the levels of: state, species, insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of year_factor`
##   1   estimate      SE  df t.ratio p.value
##   2 - 3 -0.02710 0.00757 612 -3.580  0.0050
##   2 - 4 -0.03583 0.00756 617 -4.742 <.0001
##   2 - 5 -0.07326 0.00735 616 -9.963 <.0001
##   2 - 6 -0.05481 0.00736 617 -7.450 <.0001
##   2 - 7  0.01947 0.01079 622  1.805  0.4632
##   3 - 4 -0.00873 0.00717 611 -1.219  0.8277
##   3 - 5 -0.04616 0.00696 610 -6.632 <.0001
##   3 - 6 -0.02771 0.00694 610 -3.994  0.0010
##   3 - 7  0.04657 0.01061 620  4.390  0.0002
##   4 - 5 -0.03743 0.00687 612 -5.445 <.0001
##   4 - 6 -0.01898 0.00683 613 -2.778  0.0624
##   4 - 7  0.05531 0.01048 620  5.278 <.0001
##   5 - 6  0.01845 0.00659 610  2.799  0.0590
##   5 - 7  0.09274 0.01031 619  8.997 <.0001
##   6 - 7  0.07428 0.01030 621  7.209 <.0001
##
## Results are averaged over the levels of: state, species, insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 6 estimates

emmeans(mod7c, list(pairwise ~ species), adjust = "tukey")

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

```

## $`emmeans of species`
##   species emmean      SE  df lower.CL upper.CL
##   Ansp     4.960 0.037739 628.1    4.886   5.034
##   Apan     5.220 0.023947 564.2    5.173   5.267
##   Assp     5.205 0.016986 583.6    5.171   5.238
##   Cape     4.885 0.007128 372.0    4.871   4.899
##   Cest     5.372 0.004679 314.1    5.363   5.381
##   Dasp     5.152 0.005976 445.1    5.140   5.163
##   Frve     4.943 0.013444 372.4    4.916   4.969
##   Hisp     5.124 0.015655 596.6    5.093   5.155
##   Hype     5.302 0.008849 518.5    5.285   5.319
##   Poco     5.172 0.006986 483.4    5.159   5.186
##   Popr     5.079 0.005393 411.1    5.068   5.089
##   Ruac     5.079 0.006306 368.6    5.067   5.092
##   Sosp     5.433 0.017121 373.0    5.399   5.466
##   Syla     5.501 0.023971 553.9    5.454   5.548
##
## Results are averaged over the levels of: state, year_factor, insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of species`
##   1           estimate      SE  df t.ratio p.value
##   Ansp - Apan -0.259967 0.04483 620  -5.799 <.0001
##   Ansp - Assp -0.244515 0.04153 625  -5.888 <.0001
##   Ansp - Cape  0.074966 0.03841 628   1.952 0.7967
##   Ansp - Cest -0.412159 0.03800 629  -10.847 <.0001
##   Ansp - Dasp -0.191427 0.03813 629  -5.021 0.0001
##   Ansp - Frve  0.017247 0.04011 620   0.430 1.0000
##   Ansp - Hisp -0.163749 0.04072 628  -4.021 0.0050
##   Ansp - Hype -0.341821 0.03882 628  -8.805 <.0001
##   Ansp - Poco -0.212244 0.03827 629  -5.545 <.0001
##   Ansp - Popr -0.118605 0.03804 629  -3.118 0.1032
##   Ansp - Ruac -0.119059 0.03820 629  -3.116 0.1036
##   Ansp - Sosp -0.472702 0.04144 611  -11.407 <.0001
##   Ansp - Syla -0.541054 0.04479 618  -12.081 <.0001
##   Apan - Assp  0.015451 0.02947 574   0.524 1.0000
##   Apan - Cape  0.334932 0.02495 574   13.426 <.0001
##   Apan - Cest -0.152193 0.02441 586  -6.235 <.0001
##   Apan - Dasp  0.068540 0.02475 585   2.769 0.2434
##   Apan - Frve  0.277213 0.02748 506  10.089 <.0001
##   Apan - Hisp  0.096217 0.02863 580   3.360 0.0512
##   Apan - Hype -0.081854 0.02543 579  -3.219 0.0780
##   Apan - Poco  0.047723 0.02498 562   1.911 0.8202
##   Apan - Popr  0.141361 0.02455 582   5.757 <.0001
##   Apan - Ruac  0.140907 0.02473 598   5.697 <.0001
##   Apan - Sosp -0.212735 0.02933 476  -7.254 <.0001
##   Apan - Syla -0.281087 0.03388 562  -8.297 <.0001
##   Assp - Cape  0.319481 0.01845 600  17.321 <.0001
##   Assp - Cest -0.167644 0.01762 612  -9.515 <.0001
##   Assp - Dasp  0.053088 0.01800 620   2.949 0.1600
##   Assp - Frve  0.261762 0.02153 582  12.157 <.0001
##   Assp - Hisp  0.080766 0.02318 628   3.484 0.0345

```

```

## Assp - Hype -0.097306 0.01921 615 -5.065 <.0001
## Assp - Poco  0.032271 0.01849 591  1.746 0.8986
## Assp - Popr  0.125910 0.01788 610  7.041 <.0001
## Assp - Ruac  0.125456 0.01815 621  6.914 <.0001
## Assp - Sosp -0.228186 0.02422 571 -9.422 <.0001
## Assp - Syla -0.296538 0.02939 598 -10.089 <.0001
## Cape - Cest -0.487125 0.00850 598 -57.275 <.0001
## Cape - Dasp -0.266393 0.00925 621 -28.793 <.0001
## Cape - Frve -0.057719 0.01520 461 -3.798 0.0120
## Cape - Hisp -0.238715 0.01719 611 -13.886 <.0001
## Cape - Hype -0.416787 0.01130 577 -36.897 <.0001
## Cape - Poco -0.287210 0.00988 625 -29.069 <.0001
## Cape - Popr -0.193571 0.00886 610 -21.850 <.0001
## Cape - Ruac -0.194025 0.00950 484 -20.428 <.0001
## Cape - Sosp -0.547667 0.01848 467 -29.630 <.0001
## Cape - Syla -0.616019 0.02500 544 -24.643 <.0001
## Cest - Dasp  0.220732 0.00749 622  29.487 <.0001
## Cest - Frve  0.429406 0.01422 465  30.205 <.0001
## Cest - Hisp  0.248410 0.01632 623  15.225 <.0001
## Cest - Hype  0.070338 0.00996 628   7.059 <.0001
## Cest - Poco  0.199915 0.00830 629  24.086 <.0001
## Cest - Popr  0.293554 0.00701 614  41.854 <.0001
## Cest - Ruac  0.293100 0.00777 628  37.699 <.0001
## Cest - Sosp -0.060542 0.01775 421 -3.411 0.0446
## Cest - Syla -0.128894 0.02438 575 -5.287 <.0001
## Dasp - Frve  0.208674 0.01468 479  14.217 <.0001
## Dasp - Hisp  0.027678 0.01653 627   1.674 0.9243
## Dasp - Hype -0.150394 0.01059 628 -14.200 <.0001
## Dasp - Poco -0.020817 0.00901 629 -2.311 0.5475
## Dasp - Popr  0.072822 0.00776 625   9.383 <.0001
## Dasp - Ruac  0.072368 0.00850 628   8.511 <.0001
## Dasp - Sosp -0.281274 0.01811 442 -15.535 <.0001
## Dasp - Syla -0.349626 0.02464 581 -14.190 <.0001
## Frve - Hisp -0.180996 0.02050 623 -8.827 <.0001
## Frve - Hype -0.359068 0.01609 473 -22.318 <.0001
## Frve - Poco -0.229491 0.01513 525 -15.166 <.0001
## Frve - Popr -0.135852 0.01445 484 -9.405 <.0001
## Frve - Ruac -0.136306 0.01484 439 -9.182 <.0001
## Frve - Sosp -0.489948 0.02169 486 -22.589 <.0001
## Frve - Syla -0.558300 0.02739 586 -20.382 <.0001
## Hisp - Hype -0.178072 0.01793 621 -9.930 <.0001
## Hisp - Poco -0.048495 0.01716 620 -2.826 0.2141
## Hisp - Popr  0.045144 0.01644 621   2.747 0.2552
## Hisp - Ruac  0.044690 0.01677 624   2.664 0.3023
## Hisp - Sosp -0.308952 0.02301 522 -13.425 <.0001
## Hisp - Syla -0.377304 0.02861 610 -13.189 <.0001
## Hype - Poco  0.129577 0.01114 600  11.627 <.0001
## Hype - Popr  0.223216 0.01022 626  21.839 <.0001
## Hype - Ruac  0.222762 0.01074 625  20.735 <.0001
## Hype - Sosp -0.130880 0.01923 380 -6.805 <.0001
## Hype - Syla -0.199232 0.02544 590 -7.833 <.0001
## Poco - Popr  0.093639 0.00852 626  10.991 <.0001
## Poco - Ruac  0.093185 0.00924 578  10.082 <.0001
## Poco - Sosp -0.260458 0.01842 474 -14.139 <.0001

```

```

##  Poco - Syla -0.328809 0.02482 565 -13.246 <.0001
##  Popr - Ruac -0.000454 0.00808 626 -0.056 1.0000
##  Popr - Sosp -0.354096 0.01788 438 -19.805 <.0001
##  Popr - Syla -0.422448 0.02446 574 -17.273 <.0001
##  Ruac - Sosp -0.353642 0.01820 402 -19.434 <.0001
##  Ruac - Syla -0.421994 0.02468 592 -17.102 <.0001
##  Sosp - Syla -0.068352 0.02931 582 -2.332 0.5319
##
## Results are averaged over the levels of: state, year_factor, insecticide
## 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(mod7c, list(pairwise ~ insecticide), adjust = "tukey")

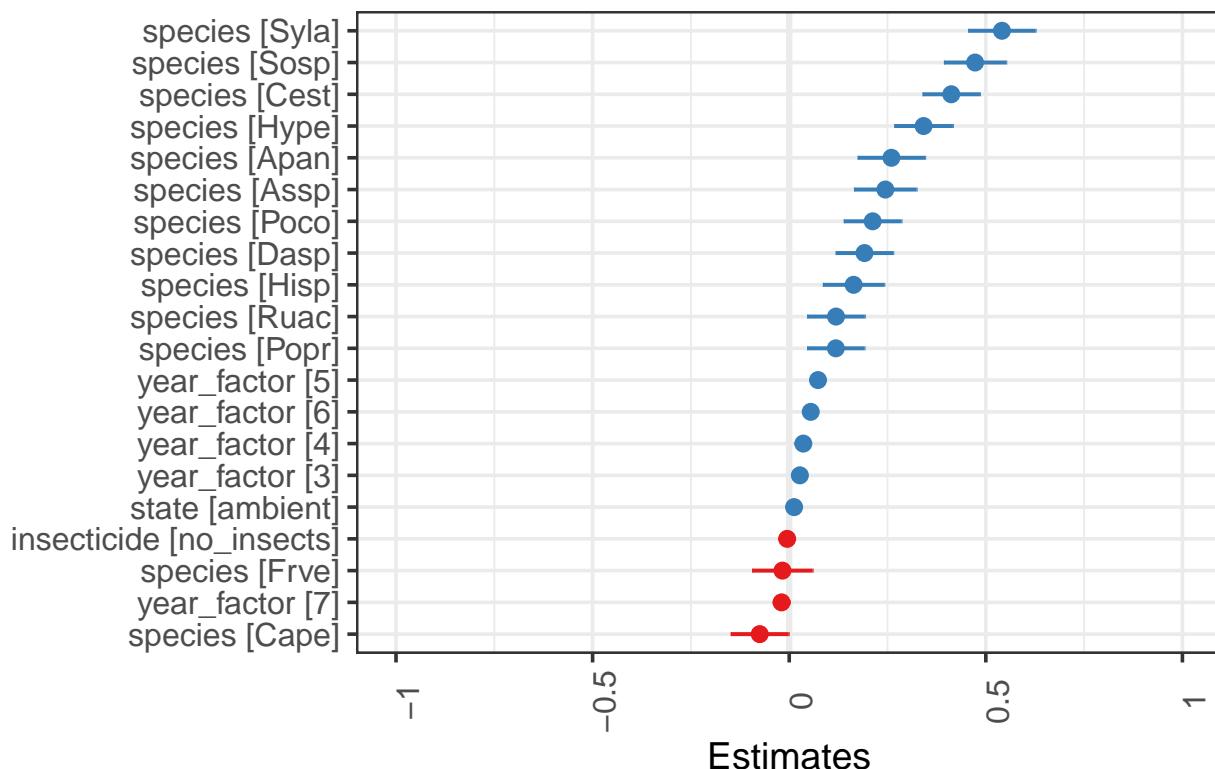
## boundary (singular) fit: see ?isSingular

## $`'emmeans of insecticide'
##   insecticide emmean      SE    df lower.CL upper.CL
##   insects      5.176 0.005183 120.92     5.166    5.186
##   no_insects   5.171 0.004886  87.18     5.161    5.180
##
## Results are averaged over the levels of: state, species, 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 insecticide'
##   1           estimate      SE    df t.ratio p.value
##   insects - no_insects  0.0052 0.00443 22.4 1.176   0.2521
##
## Results are averaged over the levels of: state, species, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.

# Take a look at the estimates for each fixed effect. These are the estimates
# from summary(mod7a). You'll see that species vary a lot - and many of them are
# different from zero (meaning their half cover date is significantly different
# from zero).
plot_model(mod7c, sort.est = TRUE)

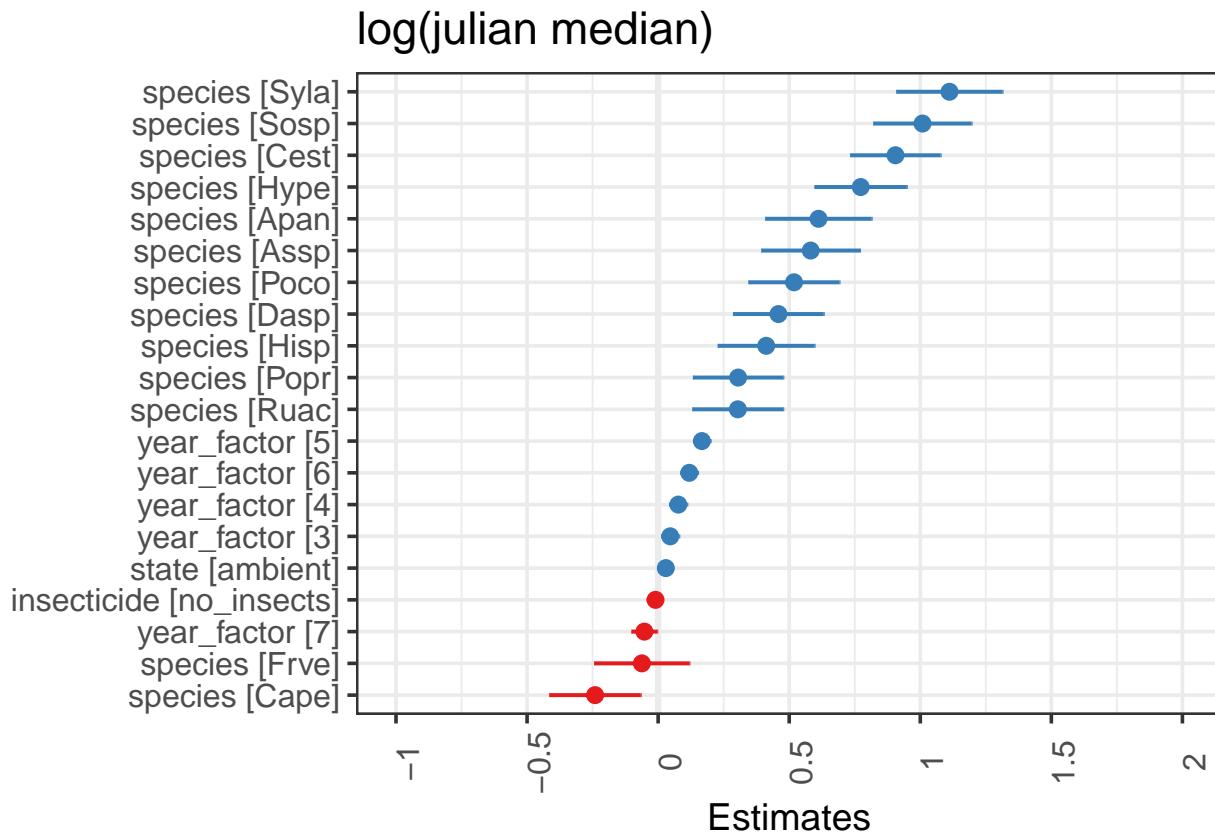
```

log(julian median)



```
# if you want to standardize the estimates:  
plot_model(mod7c, sort.est = TRUE, type = "std")
```

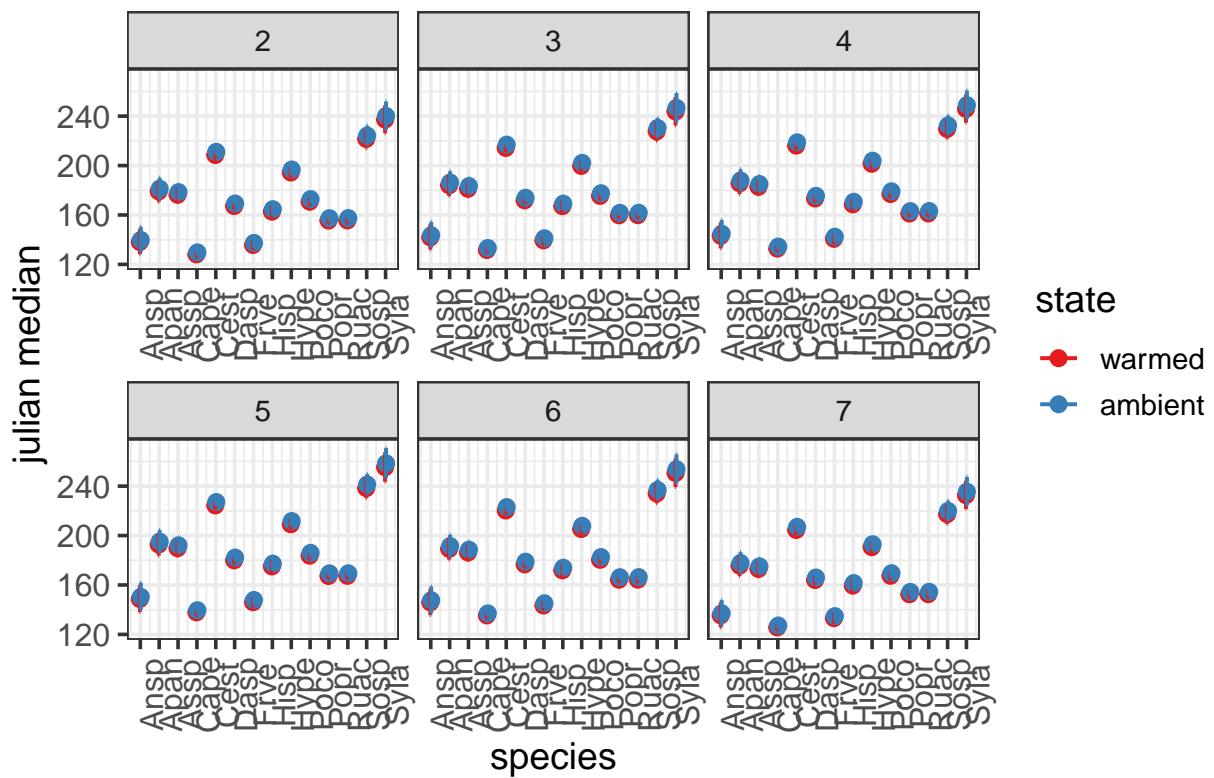
```
## Formula contains log- or sqrt-terms. See help("standardize") for how such terms are standardized.  
## boundary (singular) fit: see ?isSingular
```



```
# these are the fixed predicted values: - note this is a new plot
plot_model(mod7c, type = "pred", terms = c("species", "state", "year_factor"))
```

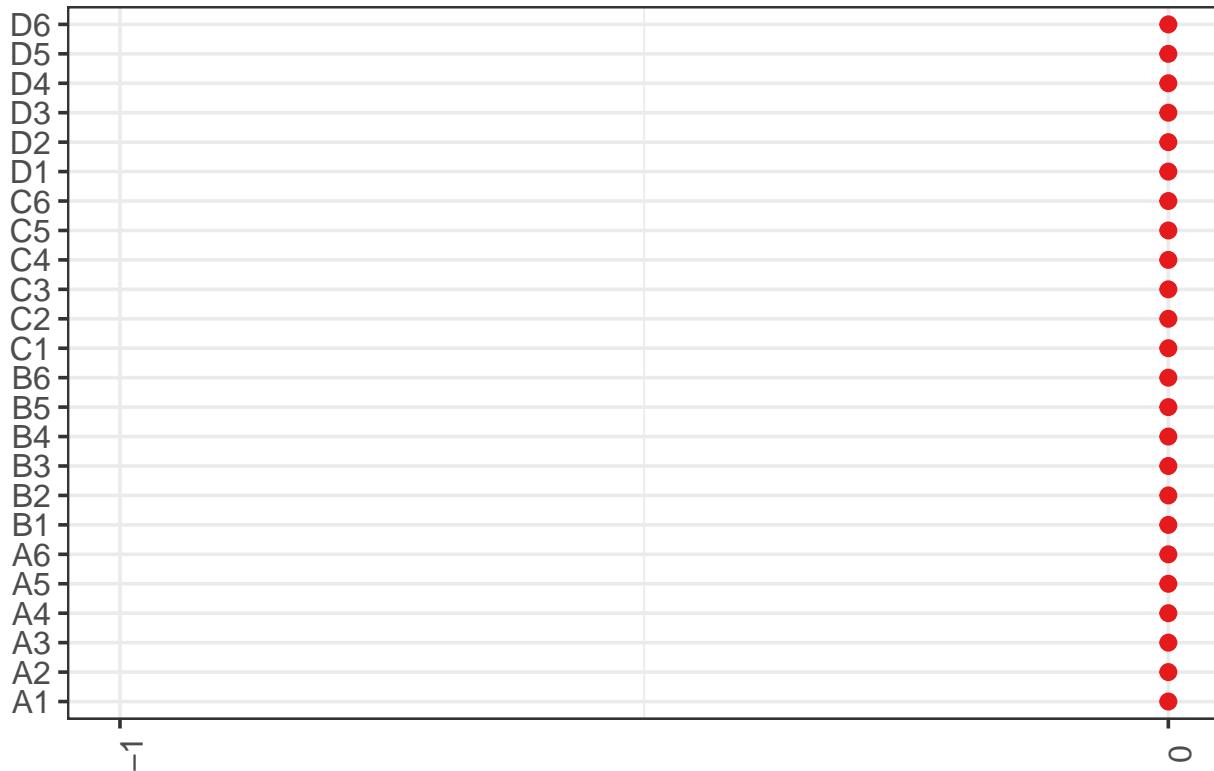
```
## Model has log-transformed response. Back-transforming predictions to original response scale. Standardized
```

Predicted values of julian median



```
# these are the random effects estimates  
plot_model(mod7c, 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 ?isSingular

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

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -7.8e-02

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

## boundary (singular) fit: see ?isSingular

anova(mod8, mod9) # model 8 is a better fit to data

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

```

## mod9:      plot)
## mod8: log(julian_median) ~ state * origin + (1 + factor(year_factor) |
## mod8:      plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod9   26 -519.35 -404.73 285.68  -571.35
## mod8   28 -516.81 -393.37 286.40  -572.81 1.4551  2     0.4831

anova(mod8, mod9a) # mod 8

## Data: umbs_flwr_spp
## Models:
## mod9a: log(julian_median) ~ state + origin + factor(year_factor) + (1 +
## mod9a:      plot)
## mod8: log(julian_median) ~ state * origin + (1 + factor(year_factor) +
## mod8:      plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod9a  11 -561.89 -513.39 291.94  -583.89
## mod8   28 -516.81 -393.37 286.40  -572.81     0 17           1

summary(mod8)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: log(julian_median) ~ state * origin + (1 + factor(year_factor) +
##      plot)
## Data: umbs_flwr_spp
##
##      AIC      BIC logLik deviance df.resid
## -516.8   -393.4   286.4   -572.8      579
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -1.8238 -0.8525 -0.1891  0.9181  3.0281
##
## Random effects:
## Groups   Name        Variance Std.Dev. Corr
## plot     (Intercept) 4.117e-06 0.002029
##          factor(year_factor)3 1.960e-05 0.004427 -1.00
##          factor(year_factor)4 2.957e-04 0.017195 -1.00  1.00
##          factor(year_factor)5 3.478e-04 0.018650 -1.00  1.00  1.00
##          factor(year_factor)6 3.606e-04 0.018989 -1.00  1.00  1.00  1.00
##          factor(year_factor)7 2.008e-03 0.044815 -1.00  1.00  1.00  1.00  1.00
## Residual            2.255e-02 0.150176
## Number of obs: 607, groups: plot, 24
##
## Fixed effects:
##                   Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)      5.085408  0.016513 259.693187 307.958 < 2e-16 ***
## stateambient    -0.009218  0.023101 277.558654 -0.399   0.690
## originBoth       0.038441  0.052668 597.238561  0.730   0.466
## originExotic     0.120568  0.019277 569.587803  6.255 7.83e-10 ***
## stateambient:originBoth 0.057361  0.069223 602.243514  0.829   0.408
## stateambient:originExotic 0.028966  0.027180 592.572342  1.066   0.287

```

```

## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) sttmbn orgnBt orgnEx sttm:B
## stateambient -0.715
## originBoth -0.308  0.220
## originExotic -0.823  0.588  0.256
## sttmbnt:rgB  0.234 -0.323 -0.761 -0.195
## sttmbnt:rgE  0.583 -0.816 -0.182 -0.709  0.272
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

anova(mod8)

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state      0.01498 0.01498     1 336.22 0.6641 0.4157
## origin     2.24131 1.12065     2 597.77 49.6902 <2e-16 ***
## state:origin 0.03269 0.01635     2 597.77 0.7248 0.4848
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

emmeans(mod8, list(pairwise ~ state * origin), adjust = "tukey")

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 2 negative eigenvalues: -8.0e-03 -1.5e+01

## $`emmeans of state, origin`
##   state origin emmean      SE    df lower.CL upper.CL
##   warmed Native  5.085 0.01870 133.88    5.048   5.122
##   ambient Native  5.076 0.01822 143.05    5.040   5.112
##   warmed Both    5.124 0.05468 299.80    5.016   5.231
##   ambient Both    5.172 0.04733 318.32    5.079   5.265
##   warmed Exotic  5.206 0.01307 43.85    5.180   5.232
##   ambient Exotic  5.226 0.01326 49.18    5.199   5.252
##
## 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  0.00922 0.0261 139.0  0.353  0.9993
##   warmed Native - warmed Both    -0.03844 0.0566 402.1 -0.679  0.9842
##   warmed Native - ambient Both   -0.08658 0.0509 304.7 -1.701  0.5318
##   warmed Native - warmed Exotic -0.12057 0.0203 504.9 -5.941 <.0001
##   warmed Native - ambient Exotic -0.14032 0.0229 94.5 -6.121 <.0001
##   ambient Native - warmed Both   -0.04766 0.0576 303.4 -0.827  0.9624
##   ambient Native - ambient Both   -0.09580 0.0489 462.6 -1.960  0.3670
##   ambient Native - warmed Exotic -0.12979 0.0224 93.4 -5.788 <.0001

```

```

## ambient Native - ambient Exotic -0.14953 0.0199 539.3 -7.522 <.0001
## warmed Both - ambient Both -0.04814 0.0723 338.5 -0.666 0.9855
## warmed Both - warmed Exotic -0.08213 0.0553 379.9 -1.484 0.6745
## warmed Both - ambient Exotic -0.10188 0.0563 296.2 -1.811 0.4604
## ambient Both - warmed Exotic -0.03398 0.0491 299.6 -0.692 0.9827
## ambient Both - ambient Exotic -0.05373 0.0477 433.2 -1.126 0.8702
## warmed Exotic - ambient Exotic -0.01975 0.0186 46.5 -1.061 0.8942
##
## 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
umbs_flwr_spp <- within(umbs_flwr_spp, growth_habit <- relevel(factor(growth_habit),
  ref = "Forb")) # releveling so forb is the reference
mod10 <- lmer(log(julian_median) ~ state * growth_habit + (1 + factor(year_factor) |
  plot), umbs_flwr_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -2.8e-01

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

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -4.8e-02

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

## boundary (singular) fit: see ?isSingular

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

## Data: umbs_flwr_spp
## Models:
## mod11: log(julian_median) ~ state + growth_habit + (1 + factor(year_factor) |
## mod11:   plot)
## mod10: log(julian_median) ~ state * growth_habit + (1 + factor(year_factor) |
## mod10:   plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod11    26 -627.01 -512.38  339.5   -679.01
## mod10    28 -623.40 -499.96  339.7   -679.40 0.3931  2     0.8216

anova(mod10, mod11a) # model 10 is still a better fit to data

```

```

## Data: umbs_flwr_spp
## Models:
## mod11a: log(julian_median) ~ state + growth_habit + factor(year_factor) +
## mod11a:      (1 | plot)
## mod10: log(julian_median) ~ state * growth_habit + (1 + factor(year_factor) | 
## mod10:      plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod11a   11 -679.84 -631.34 350.92  -701.84
## mod10    28 -623.40 -499.96 339.70  -679.40      0 17          1

summary(mod10)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula:
## log(julian_median) ~ state * growth_habit + (1 + factor(year_factor) | 
##      plot)
## Data: umbs_flwr_spp
##
##      AIC      BIC      logLik deviance df.resid
## -623.4   -500.0     339.7    -679.4      579
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -2.6026 -0.6329  0.2840  0.8351  2.0747
##
## Random effects:
## Groups   Name        Variance Std.Dev. Corr
## plot     (Intercept) 0.0011270 0.03357
##          factor(year_factor)3 0.0004142 0.02035 -1.00
##          factor(year_factor)4 0.0004077 0.02019 -0.99  0.99
##          factor(year_factor)5 0.0016369 0.04046 -1.00  1.00  1.00
##          factor(year_factor)6 0.0007891 0.02809 -0.99  0.99  1.00  1.00
##          factor(year_factor)7 0.0040388 0.06355  0.97 -0.97 -0.93 -0.95 -0.93
## Residual           0.0185775 0.13630
## Number of obs: 607, groups: plot, 24
##
## Fixed effects:
##                               Estimate Std. Error      df t value
## (Intercept)                  5.277416  0.012418 150.940456 424.971
## stateambient                 -0.005447  0.017230 139.572924 -0.316
## growth_habit                 -0.154928  0.049930 572.728224 -3.103
## growth_habitGraminoid       -0.181065  0.016140 572.602463 -11.218
## stateambient:growth_habit      0.004497  0.086091 567.943720  0.052
## stateambient:growth_habitGraminoid 0.014291  0.022775 572.712181  0.627
##                               Pr(>|t|)
## (Intercept)                  < 2e-16 ***
## stateambient                   0.75238
## growth_habit                   0.00201 **
## growth_habitGraminoid        < 2e-16 ***
## stateambient:growth_habit      0.95836
## stateambient:growth_habitGraminoid 0.53059
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

## 
## Correlation of Fixed Effects:
##           (Intr) sttmbn grwth_ grwt_G sttm:_
## stateambint -0.721
## growth_habit -0.212  0.153
## grwth_hbtGr -0.723  0.521  0.165
## sttmbnt:gr_  0.123 -0.164 -0.580 -0.096
## sttmbnt:g_G  0.512 -0.707 -0.117 -0.709  0.127
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

anova(mod10)

## Type III Analysis of Variance Table with Satterthwaite's method
##          Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state        0.0000 0.00001     1 326.24  0.0008 0.9782
## growth_habit 4.3819 2.19097     2 567.86 117.9363 <2e-16 ***
## state:growth_habit 0.0073 0.00366     2 567.86  0.1973 0.8210
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

emmeans(mod10, list(pairwise ~ factor(year_factor) * growth_habit), adjust = "tukey")

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -4.5e-04

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

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

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.00620103 (tol = 0.002, component 1)

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

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

## boundary (singular) fit: see ?isSingular

```

```

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

## boundary (singular) fit: see ?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, REML = FALSE)

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -2.7e-01

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

## boundary (singular) fit: see ?isSingular

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

## boundary (singular) fit: see ?isSingular

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

## boundary (singular) fit: see ?isSingular

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

## boundary (singular) fit: see ?isSingular

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

## boundary (singular) fit: see ?isSingular

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

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -7.8e-02

```

```

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

## boundary (singular) fit: see ?isSingular

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

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -2.8e-01

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

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -4.8e-02

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

## boundary (singular) fit: see ?isSingular

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

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.00620103 (tol = 0.002, component 1)

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, mod13, weights = T) #mod7a is the best fitting model (took out mod12 bc it w

##          dAICc   df weight
## mod7a      0.0 22  0.44
## mod7c      0.7 23  0.31
## mod7b     1.2 27  0.25
## mod7      85.5 37 <0.001
## mod13    153.7 14 <0.001
## mod5     171.6  5 <0.001
## mod3     172.8  6 <0.001
## mod2     174.5  8 <0.001
## mod1     176.5  9 <0.001
## mod6     185.2  8 <0.001
## mod11a   1145.0 11 <0.001
## mod11   1199.8 26 <0.001
## mod10   1203.8 28 <0.001
## mod9a   1263.0 11 <0.001
## mod9    1307.5 26 <0.001
## mod8    1310.4 28 <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
## -1826.1 -1729.1    935.1   -1870.1      585
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -6.3926 -0.5590 -0.0510  0.6258  3.6608
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0000000 0.00000
## Residual            0.002688 0.05185
## Number of obs: 607, groups: plot, 24
##
## Fixed effects:
##             Estimate Std. Error      df t value Pr(>|t|)    
## (Intercept) 4.925312  0.037469 607.00000 131.451 < 2e-16 ***
## stateambient 0.012630  0.004266 607.00000  2.961 0.003189 **  
## speciesApan  0.257087  0.043776 607.00000  5.873 7.06e-09 ***
## speciesAssp  0.245742  0.040621 607.00000  6.050 2.54e-09 ***
## speciesCape -0.075436  0.037622 607.00000 -2.005 0.045397 *   
## speciesCest  0.412077  0.037233 607.00000 11.068 < 2e-16 ***
## speciesDasp  0.191356  0.037360 607.00000  5.122 4.07e-07 *** 
## speciesFrve -0.017816  0.039213 607.00000 -0.454 0.649745  
## speciesHisp  0.161513  0.039889 607.00000  4.049 5.81e-05 *** 
## speciesHype  0.340885  0.038014 607.00000  8.967 < 2e-16 *** 
## speciesPoco  0.212399  0.037502 607.00000  5.664 2.29e-08 *** 
## speciesPopr  0.118326  0.037274 607.00000  3.175 0.001577 **  
## speciesRuac  0.118672  0.037442 607.00000  3.169 0.001604 **  
## speciesSosp  0.469950  0.040414 607.00000 11.628 < 2e-16 *** 
## speciesSyla  0.541455  0.043768 607.00000 12.371 < 2e-16 *** 
## factor(year_factor)3 0.026969  0.007442 607.00000  3.624 0.000314 *** 
## factor(year_factor)4 0.035854  0.007427 607.00000  4.828 1.75e-06 *** 
## factor(year_factor)5 0.073256  0.007228 607.00000 10.136 < 2e-16 *** 
## factor(year_factor)6 0.054814  0.007231 607.00000  7.581 1.29e-13 *** 
## factor(year_factor)7 -0.018860  0.010582 607.00000 -1.782 0.075207 .  
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 20 > 12.
## Use print(x, correlation=TRUE)  or
##      vcov(x)       if you need it

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

```
anova(mod7a)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##          Sum Sq Mean Sq NumDF DenDF F value    Pr(>F)
## state       0.0236 0.02357     1   607  8.7661 0.003189 **
## species     14.1324 1.08711    13   607 404.3763 < 2.2e-16 ***
## factor(year_factor) 0.4371 0.08742     5   607 32.5162 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

UMBS Plot-level Mixed Effects Models:

```
mod1p <- lmer(log(julian_median) ~ state + (1 | plot), umbs_flwr_plot, REML = FALSE)
```

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

```
mod2p <- lmer(log(julian_median) ~ state + factor(year_factor) + (1 | plot), umbs_flwr_plot,
REML = FALSE)
mod3p <- lmer(log(julian_median) ~ state * factor(year_factor) + (1 | plot), umbs_flwr_plot,
REML = FALSE)
anova(mod1p, mod2p) #mod2p
```

```
## Data: umbs_flwr_plot
## Models:
## mod1p: log(julian_median) ~ state + (1 | plot)
## mod2p: log(julian_median) ~ state + factor(year_factor) + (1 | plot)
##      npar   AIC   BIC logLik deviance Chisq Df Pr(>Chisq)
## mod1p    4 -218.63 -206.81 113.32   -226.63
## mod2p    9 -294.93 -268.32 156.46   -312.93 86.294  5 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova(mod2p, mod3p) # pvalue > 0.05 so models do not differ, go with simpler model = mod2p (interaction)
```

```
## Data: umbs_flwr_plot
## Models:
## mod2p: log(julian_median) ~ state + factor(year_factor) + (1 | plot)
## mod3p: log(julian_median) ~ state * factor(year_factor) + (1 | plot)
##      npar   AIC   BIC logLik deviance Chisq Df Pr(>Chisq)
## mod2p    9 -294.93 -268.32 156.46   -312.93
## mod3p   14 -288.19 -246.81 158.10   -316.19 3.268  5      0.6588
```

```
emmeans(mod2p, list(pairwise ~ state + factor(year_factor)), adjust = "tukey")
```

```
## $`emmeans of state, year_factor`
## state  year_factor emmean      SE df lower.CL upper.CL
## warmed           2  5.09 0.0191 110      5.05     5.12
```

```

## ambient          2  5.09 0.0191 110    5.05   5.13
## warmed          3  5.14 0.0191 110    5.10   5.18
## ambient          3  5.15 0.0191 110    5.11   5.19
## warmed          4  5.29 0.0191 110    5.25   5.33
## ambient          4  5.30 0.0191 110    5.26   5.34
## warmed          5  5.24 0.0191 110    5.21   5.28
## ambient          5  5.25 0.0191 110    5.21   5.29
## warmed          6  5.26 0.0191 110    5.22   5.30
## ambient          6  5.27 0.0191 110    5.23   5.30
## warmed          7  5.17 0.0198 115    5.13   5.21
## ambient          7  5.18 0.0198 115    5.14   5.22
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $'pairwise differences of state, year_factor'
##   1           estimate      SE   df t.ratio p.value
## warmed 2 - ambient 2 -0.00610 0.0174 26.1 -0.351 1.0000
## warmed 2 - warmed 3 -0.05645 0.0227 123.2 -2.483 0.3604
## warmed 2 - ambient 3 -0.06255 0.0286 121.2 -2.187 0.5624
## warmed 2 - warmed 4 -0.20624 0.0227 123.2 -9.072 <.0001
## warmed 2 - ambient 4 -0.21233 0.0286 121.2 -7.423 <.0001
## warmed 2 - warmed 5 -0.15862 0.0227 123.2 -6.977 <.0001
## warmed 2 - ambient 5 -0.16472 0.0286 121.2 -5.758 <.0001
## warmed 2 - warmed 6 -0.17467 0.0227 123.2 -7.683 <.0001
## warmed 2 - ambient 6 -0.18076 0.0286 121.2 -6.319 <.0001
## warmed 2 - warmed 7 -0.08566 0.0233 124.5 -3.677 0.0174
## warmed 2 - ambient 7 -0.09176 0.0291 123.0 -3.158 0.0808
## ambient 2 - warmed 3 -0.05035 0.0286 121.2 -1.760 0.8357
## ambient 2 - ambient 3 -0.05645 0.0227 123.2 -2.483 0.3604
## ambient 2 - warmed 4 -0.20014 0.0286 121.2 -6.997 <.0001
## ambient 2 - ambient 4 -0.20624 0.0227 123.2 -9.072 <.0001
## ambient 2 - warmed 5 -0.15252 0.0286 121.2 -5.332 <.0001
## ambient 2 - ambient 5 -0.15862 0.0227 123.2 -6.977 <.0001
## ambient 2 - warmed 6 -0.16857 0.0286 121.2 -5.893 <.0001
## ambient 2 - ambient 6 -0.17467 0.0227 123.2 -7.683 <.0001
## ambient 2 - warmed 7 -0.07956 0.0291 123.0 -2.739 0.2205
## ambient 2 - ambient 7 -0.08566 0.0233 124.5 -3.677 0.0174
## warmed 3 - ambient 3 -0.00610 0.0174 26.1 -0.351 1.0000
## warmed 3 - warmed 4 -0.14979 0.0227 123.2 -6.589 <.0001
## warmed 3 - ambient 4 -0.15588 0.0286 121.2 -5.450 <.0001
## warmed 3 - warmed 5 -0.10217 0.0227 123.2 -4.494 0.0009
## warmed 3 - ambient 5 -0.10826 0.0286 121.2 -3.785 0.0123
## warmed 3 - warmed 6 -0.11821 0.0227 123.2 -5.200 0.0001
## warmed 3 - ambient 6 -0.12431 0.0286 121.2 -4.346 0.0017
## warmed 3 - warmed 7 -0.02921 0.0233 124.5 -1.254 0.9831
## warmed 3 - ambient 7 -0.03530 0.0291 123.0 -1.215 0.9868
## ambient 3 - warmed 4 -0.14369 0.0286 121.2 -5.023 0.0001
## ambient 3 - ambient 4 -0.14979 0.0227 123.2 -6.589 <.0001
## ambient 3 - warmed 5 -0.09607 0.0286 121.2 -3.359 0.0464
## ambient 3 - ambient 5 -0.10217 0.0227 123.2 -4.494 0.0009
## ambient 3 - warmed 6 -0.11212 0.0286 121.2 -3.920 0.0078
## ambient 3 - ambient 6 -0.11821 0.0227 123.2 -5.200 0.0001

```

```

## ambient 3 - warmed 7 -0.02311 0.0291 123.0 -0.795 0.9997
## ambient 3 - ambient 7 -0.02921 0.0233 124.5 -1.254 0.9831
## warmed 4 - ambient 4 -0.00610 0.0174 26.1 -0.351 1.0000
## warmed 4 - warmed 5 0.04762 0.0227 123.2 2.095 0.6275
## warmed 4 - ambient 5 0.04152 0.0286 121.2 1.452 0.9503
## warmed 4 - warmed 6 0.03157 0.0227 123.2 1.389 0.9636
## warmed 4 - ambient 6 0.02548 0.0286 121.2 0.891 0.9991
## warmed 4 - warmed 7 0.12058 0.0233 124.5 5.176 0.0001
## warmed 4 - ambient 7 0.11448 0.0291 123.0 3.941 0.0072
## ambient 4 - warmed 5 0.05372 0.0286 121.2 1.878 0.7704
## ambient 4 - ambient 5 0.04762 0.0227 123.2 2.095 0.6275
## ambient 4 - warmed 6 0.03767 0.0286 121.2 1.317 0.9754
## ambient 4 - ambient 6 0.03157 0.0227 123.2 1.389 0.9636
## ambient 4 - warmed 7 0.12668 0.0291 123.0 4.360 0.0016
## ambient 4 - ambient 7 0.12058 0.0233 124.5 5.176 0.0001
## warmed 5 - ambient 5 -0.00610 0.0174 26.1 -0.351 1.0000
## warmed 5 - warmed 6 -0.01605 0.0227 123.2 -0.706 0.9999
## warmed 5 - ambient 6 -0.02214 0.0286 121.2 -0.774 0.9998
## warmed 5 - warmed 7 0.07296 0.0233 124.5 3.132 0.0864
## warmed 5 - ambient 7 0.06686 0.0291 123.0 2.302 0.4812
## ambient 5 - warmed 6 -0.00995 0.0286 121.2 -0.348 1.0000
## ambient 5 - ambient 6 -0.01605 0.0227 123.2 -0.706 0.9999
## ambient 5 - warmed 7 0.07906 0.0291 123.0 2.721 0.2287
## ambient 5 - ambient 7 0.07296 0.0233 124.5 3.132 0.0864
## warmed 6 - ambient 6 -0.00610 0.0174 26.1 -0.351 1.0000
## warmed 6 - warmed 7 0.08901 0.0233 124.5 3.821 0.0108
## warmed 6 - ambient 7 0.08291 0.0291 123.0 2.854 0.1713
## ambient 6 - warmed 7 0.09510 0.0291 123.0 3.274 0.0590
## ambient 6 - ambient 7 0.08901 0.0233 124.5 3.821 0.0108
## warmed 7 - ambient 7 -0.00610 0.0174 26.1 -0.351 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 12 estimates

mod2p.2 <- lmer(log(julian_median) ~ state + factor(year_factor) + insecticide +
  (1 | plot), umbs_flwr_plot, REML = FALSE)
anova(mod2p, mod2p.2) #mod2p

## Data: umbs_flwr_plot
## Models:
## mod2p: log(julian_median) ~ state + factor(year_factor) + (1 | plot)
## mod2p.2: log(julian_median) ~ state + factor(year_factor) + insecticide +
## mod2p.2: (1 | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## mod2p     9 -294.93 -268.32 156.46 -312.93
## mod2p.2   10 -292.93 -263.37 156.47 -312.93 0.0056  1      0.9402

summary(mod2p)

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

```

```

##      Data: umbs_flwr_plot
##
##      AIC      BIC  logLik deviance df.resid
## -294.9   -268.3   156.5    -312.9      133
##
## Scaled residuals:
##      Min     1Q Median     3Q    Max
## -4.1697 -0.4464  0.0157  0.5220  1.8189
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0006532 0.02556
## Residual           0.0059387 0.07706
## Number of obs: 142, groups: plot, 24
##
## Fixed effects:
##                   Estimate Std. Error      df t value Pr(>|t|) 
## (Intercept)      5.085e+00 1.854e-02 274.285 < 2e-16 ***
## stateambient    6.097e-03 1.662e-02 2.432e+01  0.367 0.716952
## factor(year_factor)3 5.645e-02 2.225e-02 1.184e+02  2.538 0.012461 *
## factor(year_factor)4 2.062e-01 2.225e-02 1.184e+02  9.271 1.04e-15 ***
## factor(year_factor)5 1.586e-01 2.225e-02 1.184e+02  7.130 8.57e-11 ***
## factor(year_factor)6 1.747e-01 2.225e-02 1.184e+02  7.852 2.06e-12 ***
## factor(year_factor)7 8.566e-02 2.278e-02 1.195e+02  3.760 0.000264 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) sttmbn fc(_3) fc(_4) fc(_5) fc(_6)
## stateambient -0.448
## fctr(yr_f)3 -0.600  0.000
## fctr(yr_f)4 -0.600  0.000  0.500
## fctr(yr_f)5 -0.600  0.000  0.500  0.500
## fctr(yr_f)6 -0.600  0.000  0.500  0.500  0.500
## fctr(yr_f)7 -0.586  0.000  0.488  0.488  0.488

```

KBS Species-level Mixed Effects Models

```
kmod7 <- lmer(log(julian_median) ~ state + species + (1 + factor(year_factor) | plot),
  kbs_flwr_spp, REML = FALSE)
```

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

```
kmod7a <- lmer(log(julian_median) ~ state + species + factor(year_factor) + (1 |
  plot), kbs_flwr_spp, REML = FALSE)
kmod7b <- lmer(log(julian_median) ~ state * factor(year_factor) + species + (1 |
  plot), kbs_flwr_spp, REML = FALSE)
kmod7c <- lmer(log(julian_median) ~ state + species + factor(year_factor) + insecticide +
  (1 | plot), kbs_flwr_spp, REML = FALSE)
# anova(umod6, umod7) # umodel 7 is a better fit to data
anova(kmod7, kmod7a) #kmod 7a
```

```

## Data: kbs_flwr_spp
## Models:
## kmod7a: log(julian_median) ~ state + species + factor(year_factor) +
## kmod7a:      (1 | plot)
## kmod7: log(julian_median) ~ state + species + (1 + factor(year_factor) | 
## kmod7:      plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## kmod7a   42 -3917.8 -3705.8 2000.9  -4001.8
## kmod7    63 -3839.7 -3521.6 1982.8  -3965.7      0 21          1

```

```
anova(kmod7a, kmod7b) #kmod 7a but only slightly so (pvalue = 0.058)
```

```

## Data: kbs_flwr_spp
## Models:
## kmod7a: log(julian_median) ~ state + species + factor(year_factor) +
## kmod7a:      (1 | plot)
## kmod7b: log(julian_median) ~ state * factor(year_factor) + species +
## kmod7b:      (1 | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## kmod7a   42 -3917.8 -3705.8 2000.9  -4001.8
## kmod7b   48 -3917.9 -3675.6 2007.0  -4013.9 12.154 6  0.05862 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
anova(kmod7a, kmod7c) #kmod 7a
```

```

## Data: kbs_flwr_spp
## Models:
## kmod7a: log(julian_median) ~ state + species + factor(year_factor) +
## kmod7a:      (1 | plot)
## kmod7c: log(julian_median) ~ state + species + factor(year_factor) +
## kmod7c:      insecticide + (1 | plot)
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## kmod7a   42 -3917.8 -3705.8 2000.9  -4001.8
## kmod7c   43 -3918.0 -3700.9 2002.0  -4004.0 2.1794 1  0.1399

```

```
summary(kmod7a)
```

```

## 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
## -3917.8  -3705.8   2000.9  -4001.8      1109
##
## Scaled residuals:
##      Min      1Q Median      3Q      Max
## -6.6968 -0.5912 -0.0204  0.5359  4.4994
##
## Random effects:

```

```

## Groups     Name      Variance Std.Dev.
## plot      (Intercept) 1.535e-05 0.003918
## Residual           1.797e-03 0.042388
## Number of obs: 1151, groups: plot, 24
##
## Fixed effects:
##                               Estimate Std. Error    df t value Pr(>|t|)
## (Intercept)                5.274e+00 7.634e-03 9.249e+02 690.861 < 2e-16 ***
## stateambient             -1.121e-03 3.069e-03 2.272e+01 -0.365   0.718
## speciesArel              -1.292e-01 7.661e-03 1.149e+03 -16.865 < 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 16.952 < 2e-16 ***
## speciesBavu              -2.865e-01 1.367e-02 1.146e+03 -20.957 < 2e-16 ***
## speciesCahi              -4.363e-01 1.117e-02 1.145e+03 -39.050 < 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 17.146 < 2e-16 ***
## speciesDagl              -1.403e-01 8.164e-03 1.150e+03 -17.188 < 2e-16 ***
## speciesDlre               4.734e-02 4.299e-02 1.146e+03 1.101   0.271
## speciesElre              -3.841e-02 7.582e-03 1.150e+03 -5.066 4.73e-07 ***
## speciesEugr               2.391e-01 8.512e-03 1.150e+03 28.089 < 2e-16 ***
## speciesHisp               -1.642e-01 7.683e-03 1.147e+03 -21.370 < 2e-16 ***
## speciesHype               7.909e-03 9.513e-03 1.147e+03 0.831   0.406
## speciesLapu              -3.979e-01 4.314e-02 1.148e+03 -9.225 < 2e-16 ***
## speciesLesp              -2.758e-01 4.303e-02 1.148e+03 -6.410 2.12e-10 ***
## speciesPhpr              -4.332e-02 7.083e-03 1.146e+03 -6.116 1.32e-09 ***
## speciesPoco               -6.833e-02 8.483e-03 1.150e+03 -8.055 1.97e-15 ***
## speciesPopr              -2.109e-01 6.946e-03 1.146e+03 -30.364 < 2e-16 ***
## speciesPore              -4.862e-02 8.266e-03 1.148e+03 -5.883 5.29e-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 -15.758 < 2e-16 ***
## speciesSila              -1.818e-01 4.297e-02 1.146e+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 7.903 6.35e-15 ***
## speciesSogr              2.288e-01 1.476e-02 1.149e+03 15.508 < 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 7.829 1.11e-14 ***
## speciesSypi              3.383e-01 1.179e-02 1.150e+03 28.708 < 2e-16 ***
## speciesSyur              2.838e-01 4.312e-02 1.148e+03 6.583 7.01e-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 -1.179   0.239
## speciesVear              -2.763e-01 3.063e-02 1.146e+03 -9.018 < 2e-16 ***
## factor(year_factor)2 -4.998e-02 5.932e-03 1.143e+03 -8.424 < 2e-16 ***
## factor(year_factor)3 -6.703e-02 6.294e-03 1.143e+03 -10.648 < 2e-16 ***
## factor(year_factor)4 -6.659e-02 6.298e-03 1.146e+03 -10.573 < 2e-16 ***
## factor(year_factor)5 -4.218e-02 6.438e-03 1.145e+03 -6.551 8.59e-11 ***
## factor(year_factor)6 -4.371e-02 6.555e-03 1.146e+03 -6.669 3.99e-11 ***
## factor(year_factor)7 -5.933e-02 6.823e-03 1.147e+03 -8.696 < 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

```

```

anova(kmod7a) # 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        0.000 0.00024     1    22.72  0.1334 0.7183
## species      38.670 1.20845    32 1143.67 672.5861 <2e-16 ***
## factor(year_factor) 0.275 0.04591     6 1140.60 25.5533 <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 same
# half cover dates).
emmeans(kmod7a, list(pairwise ~ year_factor), adjust = "tukey")

## $`emmeans of year_factor`
##   year_factor emmean       SE   df lower.CL upper.CL
##   1      5.271 0.006572 1082.4  5.258   5.284
##   2      5.221 0.004814  862.2  5.212   5.231
##   3      5.204 0.004822  837.4  5.195   5.214
##   4      5.205 0.004825  837.4  5.195   5.214
##   5      5.229 0.005184  894.0  5.219   5.239
##   6      5.228 0.005344  945.8  5.217   5.238
##   7      5.212 0.005403  925.2  5.201   5.223
##
## Results are averaged over the levels of: state, species
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of year_factor`
##   1 estimate       SE   df t.ratio p.value
##   1 - 2  0.049976 0.00604 1183  8.274 <.0001
##   1 - 3  0.067025 0.00641 1183 10.459 <.0001
##   1 - 4  0.066589 0.00641 1186 10.382 <.0001
##   1 - 5  0.042177 0.00656 1185  6.433 <.0001
##   1 - 6  0.043715 0.00668 1186  6.548 <.0001
##   1 - 7  0.059333 0.00695 1188  8.537 <.0001
##   2 - 3  0.017049 0.00442 1176  3.859 0.0023
##   2 - 4  0.016613 0.00434 1176  3.831 0.0026
##   2 - 5 -0.007799 0.00458 1183 -1.705 0.6131
##   2 - 6 -0.006261 0.00470 1184 -1.331 0.8372
##   2 - 7  0.009357 0.00512 1188  1.827 0.5297
##   3 - 4 -0.000436 0.00452 1173 -0.096 1.0000
##   3 - 5 -0.024848 0.00479 1183 -5.188 <.0001
##   3 - 6 -0.023310 0.00494 1188 -4.719 0.0001
##   3 - 7 -0.007692 0.00532 1191 -1.445 0.7773
##   4 - 5 -0.024412 0.00461 1177 -5.297 <.0001
##   4 - 6 -0.022874 0.00476 1182 -4.806 <.0001
##   4 - 7 -0.007256 0.00516 1187 -1.406 0.7986
##   5 - 6  0.001538 0.00488 1174  0.315 0.9999
##   5 - 7  0.017156 0.00523 1176  3.281 0.0183
##   6 - 7  0.015618 0.00534 1173  2.927 0.0539

```

```

## 
## Results are averaged over the levels of: state, species
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 7 estimates

emmeans(kmod7a, list(pairwise ~ species), adjust = "tukey")

## $`emmmeans of species`
##   species emmean      SE    df lower.CL upper.CL
##   Acmi     5.227 0.005964 1044.1    5.215    5.238
##   Arel     5.097 0.005133  928.3    5.087    5.107
##   Aspi     5.597 0.017927 1191.3    5.562    5.632
##   Assp     5.487 0.014673 1192.2    5.459    5.516
##   Bavu     4.940 0.012735 1119.2    4.915    4.965
##   Cahi     4.790 0.009911 1175.3    4.771    4.810
##   Cest     5.326 0.005383  964.1    5.315    5.336
##   Daca     5.408 0.009158 1167.1    5.390    5.425
##   Dagl     5.086 0.006012 1015.4    5.074    5.098
##   Dlre     5.274 0.043447 1188.3    5.189    5.359
##   Elre     5.188 0.005004  922.5    5.178    5.198
##   Eugr     5.466 0.006353 1020.8    5.453    5.478
##   Hisp     5.062 0.005360  967.9    5.052    5.073
##   Hype     5.234 0.007799 1049.1    5.219    5.250
##   Lapu     4.829 0.043491 1188.9    4.743    4.914
##   Lesp     4.951 0.043450 1189.9    4.866    5.036
##   Phpr     5.183 0.004328  753.4    5.175    5.192
##   Poco     5.158 0.006274 1034.2    5.146    5.171
##   Popr     5.016 0.004024  708.2    5.008    5.024
##   Pore     5.178 0.006219 1057.3    5.166    5.190
##   Posp     5.201 0.022218 1191.5    5.157    5.244
##   Rusp     5.043 0.010395 1124.2    5.023    5.064
##   Sila     5.045 0.043427 1188.4    4.960    5.130
##   Soca     5.522 0.003824  644.7    5.514    5.529
##   Soga     5.470 0.030777 1189.8    5.409    5.530
##   Sogr     5.455 0.013910 1192.2    5.428    5.483
##   Sora     5.494 0.016683 1192.0    5.462    5.527
##   Syla     5.564 0.043509 1190.2    5.479    5.650
##   Sypi     5.565 0.010449 1183.2    5.544    5.585
##   Syur     5.510 0.043509 1190.2    5.425    5.596
##   Taof     4.871 0.011768 1175.2    4.848    4.894
##   Trsp     5.215 0.007934 1174.7    5.200    5.231
##   Vear     4.950 0.030706 1189.7    4.890    5.011
## 
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
## 
## $`pairwise differences of species`
##   1           estimate      SE    df t.ratio p.value
##   Acmi - Arel  0.129201 0.00781 1190  16.553 <.0001
##   Acmi - Aspi -0.370585 0.01874 1182 -19.777 <.0001
##   Acmi - Assp -0.260835 0.01566 1177 -16.657 <.0001

```

```

## Acmi - Bavu 0.286507 0.01396 1190 20.531 <.0001
## Acmi - Cahи 0.436297 0.01138 1185 38.347 <.0001
## Acmi - Cest -0.099010 0.00779 1184 -12.710 <.0001
## Acmi - Daca -0.180928 0.01075 1187 -16.833 <.0001
## Acmi - Dagl 0.140322 0.00832 1191 16.865 <.0001
## Acmi - Dlre -0.047343 0.04379 1186 -1.081 1.0000
## Acmi - Elre 0.038409 0.00773 1191 4.971 0.0004
## Acmi - Eugr -0.239102 0.00868 1191 -27.562 <.0001
## Acmi - Hisp 0.164184 0.00783 1187 20.982 <.0001
## Acmi - Hype -0.007909 0.00971 1191 -0.815 1.0000
## Acmi - Lapu 0.397908 0.04395 1189 9.054 <.0001
## Acmi - Lesp 0.275812 0.04383 1188 6.292 <.0001
## Acmi - Phpr 0.043317 0.00721 1186 6.005 <.0001
## Acmi - Poco 0.068334 0.00865 1191 7.904 <.0001
## Acmi - Popr 0.210899 0.00707 1186 29.812 <.0001
## Acmi - Pore 0.048622 0.00842 1189 5.774 <.0001
## Acmi - Posp 0.026026 0.02295 1189 1.134 1.0000
## Acmi - Rusp 0.183211 0.01187 1189 15.431 <.0001
## Acmi - Sila 0.181785 0.04378 1186 4.153 0.0140
## Acmi - Soca -0.295068 0.00697 1185 -42.314 <.0001
## Acmi - Soga -0.242981 0.03132 1188 -7.758 <.0001
## Acmi - Sogr -0.228835 0.01503 1189 -15.221 <.0001
## Acmi - Sora -0.267817 0.01754 1183 -15.268 <.0001
## Acmi - Syla -0.337567 0.04393 1189 -7.685 <.0001
## Acmi - Sypi -0.338310 0.01201 1190 -28.172 <.0001
## Acmi - Syur -0.283822 0.04393 1189 -6.461 <.0001
## Acmi - Taof 0.355575 0.01301 1193 27.322 <.0001
## Acmi - Trsp 0.011242 0.00971 1178 1.158 1.0000
## Acmi - Vear 0.276268 0.03120 1186 8.853 <.0001
## Arel - Aspi -0.499787 0.01865 1186 -26.801 <.0001
## Arel - Assp -0.390037 0.01551 1182 -25.141 <.0001
## Arel - Bavu 0.157305 0.01366 1162 11.512 <.0001
## Arel - Cahи 0.307095 0.01106 1191 27.774 <.0001
## Arel - Cest -0.228211 0.00744 1192 -30.687 <.0001
## Arel - Daca -0.310130 0.01041 1191 -29.805 <.0001
## Arel - Dagl 0.011121 0.00770 1191 1.444 1.0000
## Arel - Dlre -0.176545 0.04377 1188 -4.034 0.0221
## Arel - Elre -0.090793 0.00698 1189 -13.013 <.0001
## Arel - Eugr -0.368304 0.00802 1193 -45.941 <.0001
## Arel - Hisp 0.034982 0.00723 1190 4.836 0.0007
## Arel - Hype -0.137111 0.00929 1190 -14.764 <.0001
## Arel - Lapu 0.268707 0.04377 1188 6.139 <.0001
## Arel - Lesp 0.146611 0.04370 1188 3.355 0.1939
## Arel - Phpr -0.085885 0.00656 1191 -13.099 <.0001
## Arel - Poco -0.060867 0.00788 1192 -7.726 <.0001
## Arel - Popr 0.081697 0.00629 1184 12.994 <.0001
## Arel - Pore -0.080579 0.00793 1190 -10.163 <.0001
## Arel - Posp -0.103176 0.02293 1187 -4.500 0.0033
## Arel - Rusp 0.054010 0.01146 1182 4.711 0.0013
## Arel - Sila 0.052583 0.04370 1188 1.203 1.0000
## Arel - Soca -0.424270 0.00616 1184 -68.886 <.0001
## Arel - Soga -0.372182 0.03114 1187 -11.953 <.0001
## Arel - Sogr -0.358036 0.01475 1189 -24.272 <.0001
## Arel - Sora -0.397019 0.01749 1188 -22.705 <.0001

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## Arel - Syla -0.466768 0.04378 1189 -10.663 <.0001
## Arel - Sypi -0.467512 0.01144 1188 -40.870 <.0001
## Arel - Syur -0.413024 0.04378 1189 -9.435 <.0001
## Arel - Taof 0.226373 0.01275 1193 17.755 <.0001
## Arel - Trsp -0.117959 0.00948 1180 -12.445 <.0001
## Arel - Vear 0.147066 0.03111 1187 4.728 0.0012
## Aspi - Assp 0.109750 0.02279 1176 4.816 0.0008
## Aspi - Bavu 0.657092 0.02187 1191 30.043 <.0001
## Aspi - Cahí 0.806882 0.02042 1184 39.521 <.0001
## Aspi - Cest 0.271576 0.01868 1186 14.541 <.0001
## Aspi - Daca 0.189657 0.01996 1183 9.500 <.0001
## Aspi - Dagl 0.510907 0.01884 1186 27.120 <.0001
## Aspi - Dlre 0.323242 0.04684 1186 6.901 <.0001
## Aspi - Elre 0.408994 0.01860 1186 21.988 <.0001
## Aspi - Eogr 0.131483 0.01905 1188 6.902 <.0001
## Aspi - Hisp 0.534769 0.01857 1185 28.799 <.0001
## Aspi - Hype 0.362676 0.01952 1192 18.582 <.0001
## Aspi - Lapu 0.768494 0.04705 1187 16.335 <.0001
## Aspi - Lesp 0.646398 0.04704 1188 13.741 <.0001
## Aspi - Phpr 0.413902 0.01839 1185 22.505 <.0001
## Aspi - Poco 0.438920 0.01896 1185 23.155 <.0001
## Aspi - Popr 0.581484 0.01829 1185 31.794 <.0001
## Aspi - Pore 0.419208 0.01884 1187 22.246 <.0001
## Aspi - Posp 0.396611 0.02868 1190 13.831 <.0001
## Aspi - Rusp 0.553797 0.02057 1186 26.923 <.0001
## Aspi - Sila 0.552370 0.04701 1186 11.750 <.0001
## Aspi - Soca 0.075517 0.01825 1184 4.138 0.0148
## Aspi - Soga 0.127605 0.03565 1189 3.580 0.1031
## Aspi - Sogr 0.141751 0.02259 1188 6.275 <.0001
## Aspi - Sora 0.102768 0.02411 1182 4.262 0.0091
## Aspi - Syla 0.033019 0.04695 1186 0.703 1.0000
## Aspi - Sypi 0.032275 0.02066 1180 1.562 0.9998
## Aspi - Syur 0.086763 0.04695 1186 1.848 0.9960
## Aspi - Taof 0.726160 0.02124 1184 34.187 <.0001
## Aspi - Trsp 0.381827 0.01965 1182 19.429 <.0001
## Aspi - Vear 0.646853 0.03541 1184 18.268 <.0001
## Assp - Bavu 0.547342 0.01932 1193 28.335 <.0001
## Assp - Cahí 0.697132 0.01758 1178 39.652 <.0001
## Assp - Cest 0.161825 0.01557 1183 10.391 <.0001
## Assp - Daca 0.079907 0.01708 1178 4.678 0.0015
## Assp - Dagl 0.401157 0.01575 1181 25.467 <.0001
## Assp - Dlre 0.213492 0.04565 1183 4.677 0.0015
## Assp - Elre 0.299244 0.01546 1185 19.360 <.0001
## Assp - Eogr 0.021733 0.01602 1185 1.357 1.0000
## Assp - Hisp 0.425019 0.01546 1184 27.495 <.0001
## Assp - Hype 0.252926 0.01657 1191 15.266 <.0001
## Assp - Lapu 0.658744 0.04595 1188 14.335 <.0001
## Assp - Lesp 0.536648 0.04588 1189 11.696 <.0001
## Assp - Phpr 0.304152 0.01521 1181 19.993 <.0001
## Assp - Poco 0.329170 0.01591 1184 20.691 <.0001
## Assp - Popr 0.471734 0.01511 1183 31.223 <.0001
## Assp - Pore 0.309458 0.01577 1181 19.623 <.0001
## Assp - Posp 0.286861 0.02674 1188 10.729 <.0001
## Assp - Rusp 0.444047 0.01785 1190 24.881 <.0001

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## Assp - Sila  0.442620 0.04581 1183   9.662 <.0001
## Assp - Soca -0.034233 0.01507 1183  -2.272 0.9301
## Assp - Soga  0.017855 0.03412 1189   0.523 1.0000
## Assp - Sogr  0.032001 0.02010 1187   1.592 0.9997
## Assp - Sora -0.006982 0.02183 1181  -0.320 1.0000
## Assp - Syla -0.076731 0.04590 1187  -1.672 0.9993
## Assp - Sypi -0.077475 0.01790 1183  -4.327 0.0069
## Assp - Syur -0.022987 0.04590 1187  -0.501 1.0000
## Assp - Taof  0.616410 0.01862 1187  33.108 <.0001
## Assp - Trsp  0.272077 0.01673 1179  16.261 <.0001
## Assp - Vear  0.537103 0.03387 1182  15.859 <.0001
## Bavu - Cahia 0.149790 0.01597 1189   9.377 <.0001
## Bavu - Cest  -0.385517 0.01384 1168  -27.863 <.0001
## Bavu - Daca  -0.467435 0.01562 1185  -29.934 <.0001
## Bavu - Dagl  -0.146185 0.01400 1167  -10.443 <.0001
## Bavu - Dlre  -0.333850 0.04522 1191  -7.383 <.0001
## Bavu - Elre  -0.248098 0.01356 1175  -18.302 <.0001
## Bavu - Eogr  -0.525609 0.01414 1179  -37.170 <.0001
## Bavu - Hisp  -0.122323 0.01374 1166  -8.902 <.0001
## Bavu - Hype  -0.294416 0.01487 1177  -19.793 <.0001
## Bavu - Lapu  0.111402 0.04526 1191   2.462 0.8429
## Bavu - Lesp  -0.010694 0.04517 1188  -0.237 1.0000
## Bavu - Phpr  -0.243190 0.01339 1168  -18.164 <.0001
## Bavu - Poco  -0.218172 0.01410 1167  -15.478 <.0001
## Bavu - Popr  -0.075608 0.01324 1170  -5.710 <.0001
## Bavu - Pore  -0.237884 0.01413 1168  -16.832 <.0001
## Bavu - Posp  -0.260481 0.02577 1192  -10.109 <.0001
## Bavu - Rusp  -0.103295 0.01632 1185  -6.330 <.0001
## Bavu - Sila  -0.104722 0.04523 1191  -2.315 0.9142
## Bavu - Soca  -0.581575 0.01318 1171  -44.140 <.0001
## Bavu - Soga  -0.529487 0.03329 1192  -15.908 <.0001
## Bavu - Sogr  -0.515342 0.01876 1192  -27.475 <.0001
## Bavu - Sora  -0.554324 0.02081 1190  -26.635 <.0001
## Bavu - Syla  -0.624073 0.04530 1191  -13.776 <.0001
## Bavu - Sypi  -0.624817 0.01644 1185  -38.017 <.0001
## Bavu - Syur  -0.570329 0.04530 1191  -12.589 <.0001
## Bavu - Taof  0.069068 0.01726 1180   4.003 0.0248
## Bavu - Trsp  -0.275265 0.01509 1174  -18.247 <.0001
## Bavu - Vear  -0.010239 0.03320 1192  -0.308 1.0000
## Cahia - Cest -0.535307 0.01118 1191  -47.864 <.0001
## Cahia - Daca -0.617225 0.01338 1189  -46.124 <.0001
## Cahia - Dagl -0.295975 0.01139 1190  -25.986 <.0001
## Cahia - Dlre -0.483640 0.04443 1184  -10.885 <.0001
## Cahia - Elre -0.397888 0.01094 1189  -36.372 <.0001
## Cahia - Eogr -0.675399 0.01172 1190  -57.612 <.0001
## Cahia - Hisp -0.272113 0.01110 1191  -24.504 <.0001
## Cahia - Hype -0.444206 0.01255 1192  -35.409 <.0001
## Cahia - Lapu -0.038388 0.04463 1190  -0.860 1.0000
## Cahia - Lesp -0.160485 0.04442 1186  -3.613 0.0931
## Cahia - Phpr -0.392980 0.01068 1189  -36.804 <.0001
## Cahia - Poco -0.367963 0.01165 1190  -31.590 <.0001
## Cahia - Popr -0.225398 0.01056 1191  -21.355 <.0001
## Cahia - Pore -0.387674 0.01157 1190  -33.509 <.0001
## Cahia - Posp -0.410271 0.02444 1189  -16.790 <.0001

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## Cahi - Rusp -0.253085 0.01423 1192 -17.782 <.0001
## Cahi - Sila -0.254512 0.04439 1184 -5.733 <.0001
## Cahi - Soca -0.731365 0.01048 1190 -69.768 <.0001
## Cahi - Soga -0.679277 0.03224 1190 -21.066 <.0001
## Cahi - Sogr -0.665132 0.01688 1190 -39.410 <.0001
## Cahi - Sora -0.704114 0.01922 1182 -36.635 <.0001
## Cahi - Syla -0.773864 0.04468 1190 -17.319 <.0001
## Cahi - Sypi -0.774607 0.01441 1189 -53.752 <.0001
## Cahi - Syur -0.720119 0.04468 1190 -16.117 <.0001
## Cahi - Taof -0.080722 0.01519 1193 -5.313 0.0001
## Cahi - Trsp -0.425055 0.01262 1186 -33.681 <.0001
## Cahi - Vear -0.160029 0.03214 1186 -4.979 0.0004
## Cest - Daca -0.081918 0.01049 1187 -7.812 <.0001
## Cest - Dagl 0.239332 0.00800 1191 29.898 <.0001
## Cest - Dlre 0.051666 0.04376 1186 1.181 1.0000
## Cest - Elre 0.137418 0.00735 1190 18.688 <.0001
## Cest - Eogr -0.140092 0.00829 1192 -16.892 <.0001
## Cest - Hisp 0.263194 0.00750 1184 35.088 <.0001
## Cest - Hype 0.091101 0.00934 1187 9.751 <.0001
## Cest - Lapu 0.496918 0.04386 1188 11.328 <.0001
## Cest - Lesp 0.374822 0.04378 1189 8.561 <.0001
## Cest - Phpr 0.142326 0.00677 1184 21.029 <.0001
## Cest - Poco 0.167344 0.00832 1192 20.107 <.0001
## Cest - Popr 0.309909 0.00670 1184 46.289 <.0001
## Cest - Pore 0.147632 0.00807 1187 18.305 <.0001
## Cest - Posp 0.125036 0.02260 1187 5.533 <.0001
## Cest - Rusp 0.282221 0.01169 1173 24.135 <.0001
## Cest - Sila 0.280795 0.04371 1186 6.424 <.0001
## Cest - Soca -0.196058 0.00659 1185 -29.752 <.0001
## Cest - Soga -0.143971 0.03123 1188 -4.610 0.0020
## Cest - Sogr -0.129825 0.01488 1191 -8.724 <.0001
## Cest - Sora -0.168807 0.01749 1187 -9.650 <.0001
## Cest - Syla -0.238557 0.04386 1189 -5.439 <.0001
## Cest - Sypi -0.239300 0.01176 1191 -20.342 <.0001
## Cest - Syur -0.184813 0.04386 1189 -4.214 0.0110
## Cest - Taof 0.454585 0.01285 1192 35.370 <.0001
## Cest - Trsp 0.110252 0.00919 1175 11.992 <.0001
## Cest - Vear 0.375278 0.03114 1187 12.050 <.0001
## Daca - Dagl 0.321250 0.01082 1188 29.698 <.0001
## Daca - Dlre 0.133585 0.04432 1185 3.014 0.4172
## Daca - Elre 0.219337 0.01037 1191 21.144 <.0001
## Daca - Eogr -0.058174 0.01112 1193 -5.233 0.0001
## Daca - Hisp 0.345112 0.01045 1192 33.011 <.0001
## Daca - Hype 0.173019 0.01195 1193 14.481 <.0001
## Daca - Lapu 0.578837 0.04450 1189 13.008 <.0001
## Daca - Lesp 0.456741 0.04441 1190 10.284 <.0001
## Daca - Phpr 0.224245 0.01000 1188 22.416 <.0001
## Daca - Poco 0.249263 0.01104 1191 22.580 <.0001
## Daca - Popr 0.391827 0.00989 1190 39.631 <.0001
## Daca - Pore 0.229551 0.01090 1189 21.058 <.0001
## Daca - Posp 0.206954 0.02402 1186 8.617 <.0001
## Daca - Rusp 0.364140 0.01372 1191 26.534 <.0001
## Daca - Sila 0.362713 0.04432 1185 8.183 <.0001
## Daca - Soca -0.114140 0.00982 1190 -11.627 <.0001

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## Daca - Soga -0.062052 0.03210 1189 -1.933 0.9919
## Daca - Sogr -0.047906 0.01659 1191 -2.887 0.5206
## Daca - Sora -0.086889 0.01886 1184 -4.607 0.0021
## Daca - Syla -0.156638 0.04448 1190 -3.521 0.1226
## Daca - Sypi -0.157382 0.01379 1191 -11.417 <.0001
## Daca - Syur -0.102894 0.04448 1190 -2.313 0.9150
## Daca - Taof 0.536503 0.01478 1193 36.299 <.0001
## Daca - Trsp 0.192170 0.01203 1185 15.978 <.0001
## Daca - Vear 0.457196 0.03198 1187 14.296 <.0001
## Dagl - Dlre -0.187666 0.04381 1186 -4.284 0.0083
## Dagl - Elre -0.101914 0.00764 1190 -13.345 <.0001
## Dagl - Eugr -0.379424 0.00866 1193 -43.822 <.0001
## Dagl - Hisp 0.023862 0.00784 1193 3.042 0.3955
## Dagl - Hype -0.148231 0.00979 1189 -15.144 <.0001
## Dagl - Lapu 0.257586 0.04387 1186 5.871 <.0001
## Dagl - Lesp 0.135490 0.04382 1189 3.092 0.3580
## Dagl - Phpr -0.097005 0.00722 1182 -13.444 <.0001
## Dagl - Poco -0.071988 0.00851 1183 -8.462 <.0001
## Dagl - Popr 0.070577 0.00702 1192 10.047 <.0001
## Dagl - Pore -0.091700 0.00846 1183 -10.835 <.0001
## Dagl - Posp -0.114296 0.02313 1187 -4.942 0.0004
## Dagl - Rusp 0.042889 0.01186 1188 3.615 0.0924
## Dagl - Sila 0.041463 0.04377 1186 0.947 1.0000
## Dagl - Soca -0.435390 0.00691 1190 -62.984 <.0001
## Dagl - Soga -0.383303 0.03131 1189 -12.243 <.0001
## Dagl - Sogr -0.369157 0.01501 1188 -24.588 <.0001
## Dagl - Sora -0.408139 0.01764 1187 -23.134 <.0001
## Dagl - Syla -0.477889 0.04394 1190 -10.875 <.0001
## Dagl - Sypi -0.478632 0.01198 1192 -39.964 <.0001
## Dagl - Syur -0.424144 0.04394 1190 -9.652 <.0001
## Dagl - Taof 0.215253 0.01306 1193 16.480 <.0001
## Dagl - Trsp -0.129080 0.00994 1184 -12.986 <.0001
## Dagl - Vear 0.135946 0.03120 1185 4.357 0.0061
## Dlre - Elre 0.085752 0.04369 1187 1.963 0.9897
## Dlre - Eugr -0.191759 0.04391 1187 -4.367 0.0059
## Dlre - Hisp 0.211527 0.04372 1187 4.838 0.0007
## Dlre - Hype 0.039434 0.04408 1185 0.895 1.0000
## Dlre - Lapu 0.445252 0.06151 1189 7.239 <.0001
## Dlre - Lesp 0.323156 0.06143 1189 5.260 0.0001
## Dlre - Phpr 0.090660 0.04363 1187 2.078 0.9768
## Dlre - Poco 0.115678 0.04391 1189 2.634 0.7269
## Dlre - Popr 0.258242 0.04359 1187 5.924 <.0001
## Dlre - Pore 0.095966 0.04384 1186 2.189 0.9547
## Dlre - Posp 0.073369 0.04887 1188 1.501 0.9999
## Dlre - Rusp 0.230555 0.04466 1189 5.162 0.0001
## Dlre - Sila 0.229128 0.06112 1165 3.749 0.0604
## Dlre - Soca -0.247725 0.04358 1187 -5.685 <.0001
## Dlre - Soga -0.195637 0.05325 1188 -3.674 0.0769
## Dlre - Sogr -0.181491 0.04551 1185 -3.988 0.0262
## Dlre - Sora -0.220474 0.04625 1183 -4.767 0.0010
## Dlre - Syla -0.290223 0.06155 1189 -4.715 0.0013
## Dlre - Sypi -0.290967 0.04473 1188 -6.505 <.0001
## Dlre - Syur -0.236479 0.06155 1189 -3.842 0.0440
## Dlre - Taof 0.402918 0.04494 1188 8.966 <.0001

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## Dlre - Trsp  0.058585 0.04418 1186   1.326 1.0000
## Dlre - Vear  0.323611 0.05294 1174   6.113 <.0001
## Elre - Eugr -0.277511 0.00796 1192 -34.865 <.0001
## Elre - Hisp  0.125775 0.00718 1189  17.509 <.0001
## Elre - Hype -0.046318 0.00921 1186  -5.027 0.0003
## Elre - Lapu  0.359500 0.04373 1188  8.220 <.0001
## Elre - Lesp  0.237404 0.04368 1189  5.435 <.0001
## Elre - Phpr  0.004908 0.00646 1184  0.760 1.0000
## Elre - Poco  0.029926 0.00781 1189  3.831 0.0457
## Elre - Popr  0.172490 0.00620 1180  27.819 <.0001
## Elre - Pore  0.010214 0.00788 1185  1.296 1.0000
## Elre - Posp -0.012382 0.02288 1189  -0.541 1.0000
## Elre - Rusp  0.144803 0.01143 1191  12.668 <.0001
## Elre - Sila  0.143376 0.04368 1187  3.282 0.2329
## Elre - Soca -0.333477 0.00607 1179 -54.947 <.0001
## Elre - Soga -0.281389 0.03112 1188  -9.042 <.0001
## Elre - Sogr -0.267243 0.01466 1187 -18.226 <.0001
## Elre - Sora -0.306226 0.01734 1184 -17.656 <.0001
## Elre - Syla -0.375975 0.04379 1190  -8.585 <.0001
## Elre - Sypi -0.376719 0.01149 1188 -32.776 <.0001
## Elre - Syur -0.322231 0.04379 1190  -7.358 <.0001
## Elre - Taof  0.317166 0.01271 1193  24.955 <.0001
## Elre - Trsp -0.027167 0.00945 1182  -2.875 0.5306
## Elre - Vear  0.237859 0.03107 1188  7.656 <.0001
## Eugr - Hisp  0.403286 0.00825 1193  48.876 <.0001
## Eugr - Hype  0.231193 0.00997 1185  23.186 <.0001
## Eugr - Lapu  0.637010 0.04387 1188  14.519 <.0001
## Eugr - Lesp  0.514915 0.04394 1190  11.718 <.0001
## Eugr - Phpr  0.282419 0.00760 1192  37.174 <.0001
## Eugr - Poco  0.307436 0.00881 1192  34.905 <.0001
## Eugr - Popr  0.450001 0.00741 1193  60.733 <.0001
## Eugr - Pore  0.287725 0.00887 1193  32.441 <.0001
## Eugr - Posp  0.265128 0.02310 1189  11.476 <.0001
## Eugr - Rusp  0.422314 0.01207 1192  34.991 <.0001
## Eugr - Sila  0.420887 0.04384 1187  9.601 <.0001
## Eugr - Soca -0.055966 0.00728 1193  -7.683 <.0001
## Eugr - Soga -0.003879 0.03143 1186  -0.123 1.0000
## Eugr - Sogr  0.010267 0.01530 1182  0.671 1.0000
## Eugr - Sora -0.028715 0.01786 1178  -1.608 0.9997
## Eugr - Syla -0.098465 0.04393 1190  -2.242 0.9401
## Eugr - Sypi -0.099208 0.01218 1193  -8.146 <.0001
## Eugr - Syur -0.044720 0.04393 1190  -1.018 1.0000
## Eugr - Taof  0.594677 0.01335 1191  44.557 <.0001
## Eugr - Trsp  0.250344 0.01007 1186  24.853 <.0001
## Eugr - Vear  0.515370 0.03138 1188  16.422 <.0001
## Hisp - Hype -0.172093 0.00940 1187 -18.302 <.0001
## Hisp - Lapu  0.233725 0.04383 1188  5.332 0.0001
## Hisp - Lesp  0.111629 0.04374 1188  2.552 0.7858
## Hisp - Phpr -0.120867 0.00672 1191 -17.992 <.0001
## Hisp - Poco -0.095849 0.00813 1192 -11.792 <.0001
## Hisp - Popr  0.046715 0.00647 1183  7.222 <.0001
## Hisp - Pore -0.115561 0.00799 1186 -14.464 <.0001
## Hisp - Posp -0.138158 0.02298 1189  -6.012 <.0001
## Hisp - Rusp  0.019028 0.01155 1180  1.647 0.9995

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##  Hisp - Sila  0.017601 0.04371 1187   0.403 1.0000
##  Hisp - Soca -0.459252 0.00636 1184 -72.234 <.0001
##  Hisp - Soga -0.407164 0.03118 1186 -13.060 <.0001
##  Hisp - Sogr -0.393018 0.01477 1187 -26.611 <.0001
##  Hisp - Sora -0.432001 0.01737 1185 -24.864 <.0001
##  Hisp - Syla -0.501750 0.04384 1190 -11.445 <.0001
##  Hisp - Sypi -0.502494 0.01163 1191 -43.222 <.0001
##  Hisp - Syur -0.448006 0.04384 1190 -10.219 <.0001
##  Hisp - Taof  0.191391 0.01274 1192  15.018 <.0001
##  Hisp - Trsp -0.152942 0.00956 1176 -15.997 <.0001
##  Hisp - Vear  0.112084 0.03110 1187   3.604 0.0956
##  Hype - Lapu  0.405817 0.04417 1189   9.187 <.0001
##  Hype - Lesp  0.283722 0.04409 1185   6.436 <.0001
##  Hype - Phpr  0.051226 0.00883 1188   5.801 <.0001
##  Hype - Poco  0.076243 0.00998 1185   7.640 <.0001
##  Hype - Popr  0.218808 0.00872 1186  25.088 <.0001
##  Hype - Pore  0.056532 0.00991 1187   5.704 <.0001
##  Hype - Posp  0.033935 0.02340 1189   1.450 1.0000
##  Hype - Rusp  0.191121 0.01292 1189  14.795 <.0001
##  Hype - Sila  0.189694 0.04408 1186   4.304 0.0076
##  Hype - Soca -0.287159 0.00863 1187 -33.286 <.0001
##  Hype - Soga -0.235071 0.03173 1187  -7.408 <.0001
##  Hype - Sogr -0.220926 0.01592 1191 -13.881 <.0001
##  Hype - Sora -0.259908 0.01835 1189 -14.167 <.0001
##  Hype - Syla -0.329658 0.04420 1191  -7.458 <.0001
##  Hype - Sypi -0.330401 0.01304 1191 -25.329 <.0001
##  Hype - Syur -0.275913 0.04420 1191  -6.242 <.0001
##  Hype - Taof  0.363484 0.01408 1190  25.814 <.0001
##  Hype - Trsp  0.019151 0.01098 1193   1.744 0.9985
##  Hype - Vear  0.284177 0.03165 1188   8.978 <.0001
##  Lapu - Lesp -0.122096 0.06149 1190  -1.986 0.9878
##  Lapu - Phpr -0.354592 0.04370 1187  -8.113 <.0001
##  Lapu - Poco -0.329574 0.04386 1187  -7.515 <.0001
##  Lapu - Popr -0.187009 0.04365 1188  -4.284 0.0083
##  Lapu - Pore -0.349286 0.04395 1187  -7.947 <.0001
##  Lapu - Posp -0.371882 0.04895 1189  -7.598 <.0001
##  Lapu - Rusp -0.214697 0.04472 1189  -4.801 0.0008
##  Lapu - Sila -0.216123 0.06148 1189  -3.515 0.1247
##  Lapu - Soca -0.692976 0.04362 1188 -15.887 <.0001
##  Lapu - Soga -0.640889 0.05331 1189 -12.022 <.0001
##  Lapu - Sogr -0.626743 0.04566 1186 -13.727 <.0001
##  Lapu - Sora -0.665725 0.04663 1189 -14.277 <.0001
##  Lapu - Syla -0.735475 0.06130 1188 -11.998 <.0001
##  Lapu - Sypi -0.736218 0.04474 1188 -16.456 <.0001
##  Lapu - Syur -0.681731 0.06130 1188 -11.121 <.0001
##  Lapu - Taof -0.042333 0.04504 1185  -0.940 1.0000
##  Lapu - Trsp -0.386666 0.04427 1188  -8.734 <.0001
##  Lapu - Vear -0.121640 0.05328 1189  -2.283 0.9262
##  Lesp - Phpr -0.232496 0.04364 1189  -5.328 0.0001
##  Lesp - Poco -0.207478 0.04385 1189  -4.732 0.0012
##  Lesp - Popr -0.064914 0.04360 1189  -1.489 0.9999
##  Lesp - Pore -0.227190 0.04386 1189  -5.180 0.0001
##  Lesp - Posp -0.249786 0.04889 1190  -5.109 0.0002
##  Lesp - Rusp -0.092601 0.04468 1190  -2.073 0.9776

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##  Lesp - Sila -0.094027 0.06142 1189 -1.531 0.9999
##  Lesp - Soca -0.570881 0.04358 1189 -13.100 <.0001
##  Lesp - Soga -0.518793 0.05307 1189 -9.776 <.0001
##  Lesp - Sogr -0.504647 0.04548 1190 -11.096 <.0001
##  Lesp - Sora -0.543630 0.04655 1189 -11.679 <.0001
##  Lesp - Syla -0.613379 0.06154 1189 -9.967 <.0001
##  Lesp - Sypi -0.614123 0.04467 1189 -13.750 <.0001
##  Lesp - Syur -0.559635 0.06154 1189 -9.094 <.0001
##  Lesp - Taof  0.079763 0.04497 1190  1.774 0.9980
##  Lesp - Trsp -0.264570 0.04421 1189 -5.984 <.0001
##  Lesp - Vear  0.000455 0.05312 1189  0.009 1.0000
##  Phpr - Poco  0.025018 0.00748 1184  3.347 0.1980
##  Phpr - Popr  0.167582 0.00573 1185 29.246 <.0001
##  Phpr - Pore  0.005306 0.00741 1181  0.716 1.0000
##  Phpr - Posp -0.017291 0.02264 1189 -0.764 1.0000
##  Phpr - Rusp  0.139895 0.01115 1187 12.544 <.0001
##  Phpr - Sila  0.138468 0.04360 1187  3.176 0.2990
##  Phpr - Soca -0.338385 0.00559 1182 -60.488 <.0001
##  Phpr - Soga -0.286297 0.03105 1189 -9.220 <.0001
##  Phpr - Sogr -0.272151 0.01448 1189 -18.795 <.0001
##  Phpr - Sora -0.311134 0.01717 1186 -18.123 <.0001
##  Phpr - Syla -0.380883 0.04373 1189 -8.710 <.0001
##  Phpr - Sypi -0.381627 0.01122 1191 -34.002 <.0001
##  Phpr - Syur -0.327139 0.04373 1189 -7.481 <.0001
##  Phpr - Taof  0.312258 0.01244 1192 25.093 <.0001
##  Phpr - Trsp -0.032074 0.00895 1177 -3.585 0.1013
##  Phpr - Vear  0.232951 0.03096 1186  7.525 <.0001
##  Poco - Popr  0.142565 0.00724 1192 19.680 <.0001
##  Poco - Pore -0.019712 0.00872 1188 -2.262 0.9337
##  Poco - Posp -0.042308 0.02323 1188 -1.821 0.9969
##  Poco - Rusp  0.114877 0.01199 1193  9.584 <.0001
##  Poco - Sila  0.113451 0.04391 1189  2.584 0.7637
##  Poco - Soca -0.363402 0.00713 1192 -50.987 <.0001
##  Poco - Soga -0.311315 0.03134 1189 -9.933 <.0001
##  Poco - Sogr -0.297169 0.01515 1191 -19.613 <.0001
##  Poco - Sora -0.336151 0.01783 1189 -18.855 <.0001
##  Poco - Syla -0.405901 0.04389 1189 -9.247 <.0001
##  Poco - Sypi -0.406645 0.01200 1192 -33.897 <.0001
##  Poco - Syur -0.352157 0.04389 1189 -8.023 <.0001
##  Poco - Taof  0.287241 0.01328 1193 21.629 <.0001
##  Poco - Trsp -0.057092 0.01028 1186 -5.556 <.0001
##  Poco - Vear  0.207933 0.03131 1189  6.642 <.0001
##  Popr - Pore -0.162276 0.00724 1188 -22.402 <.0001
##  Popr - Posp -0.184873 0.02271 1187 -8.140 <.0001
##  Popr - Rusp -0.027687 0.01102 1182 -2.512 0.8121
##  Popr - Sila -0.029114 0.04358 1187 -0.668 1.0000
##  Popr - Soca -0.505967 0.00527 1167 -96.055 <.0001
##  Popr - Soga -0.453879 0.03098 1187 -14.650 <.0001
##  Popr - Sogr -0.439734 0.01436 1188 -30.617 <.0001
##  Popr - Sora -0.478716 0.01707 1186 -28.049 <.0001
##  Popr - Syla -0.548466 0.04367 1189 -12.560 <.0001
##  Popr - Sypi -0.549209 0.01105 1188 -49.696 <.0001
##  Popr - Syur -0.494721 0.04367 1189 -11.329 <.0001
##  Popr - Taof  0.144676 0.01232 1193 11.745 <.0001

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## Popr - Trsp -0.199657 0.00896 1175 -22.285 <.0001
## Popr - Vear  0.065369 0.03091 1187   2.115 0.9708
## Pore - Posp -0.022596 0.02310 1189  -0.978 1.0000
## Pore - Rusp  0.134589 0.01199 1185  11.225 <.0001
## Pore - Sila  0.133162 0.04383 1186   3.038 0.3986
## Pore - Soca -0.343691 0.00715 1188 -48.079 <.0001
## Pore - Soga -0.291603 0.03134 1189  -9.304 <.0001
## Pore - Sogr -0.277457 0.01509 1188 -18.381 <.0001
## Pore - Sora -0.316440 0.01769 1188 -17.885 <.0001
## Pore - Syla -0.386189 0.04396 1190  -8.786 <.0001
## Pore - Sypi -0.386933 0.01204 1193 -32.138 <.0001
## Pore - Syur -0.332445 0.04396 1190  -7.563 <.0001
## Pore - Taof  0.306952 0.01314 1193  23.354 <.0001
## Pore - Trsp -0.037380 0.01000 1182  -3.737 0.0627
## Pore - Vear  0.227645 0.03124 1185   7.287 <.0001
## Posp - Rusp  0.157186 0.02463 1191   6.381 <.0001
## Posp - Sila  0.155759 0.04883 1188   3.190 0.2897
## Posp - Soca -0.321094 0.02268 1188 -14.156 <.0001
## Posp - Soga -0.269007 0.03799 1183  -7.081 <.0001
## Posp - Sogr -0.254861 0.02634 1190  -9.675 <.0001
## Posp - Sora -0.293843 0.02791 1190 -10.527 <.0001
## Posp - Syla -0.363593 0.04895 1190  -7.428 <.0001
## Posp - Sypi -0.364336 0.02472 1191 -14.741 <.0001
## Posp - Syur -0.309849 0.04895 1190  -6.330 <.0001
## Posp - Taof  0.329549 0.02524 1191  13.058 <.0001
## Posp - Trsp -0.014784 0.02318 1188  -0.638 1.0000
## Posp - Vear  0.250242 0.03800 1189   6.585 <.0001
## Rusp - Sila -0.001427 0.04463 1189  -0.032 1.0000
## Rusp - Soca -0.478280 0.01095 1184 -43.693 <.0001
## Rusp - Soga -0.426192 0.03242 1187 -13.145 <.0001
## Rusp - Sogr -0.412046 0.01728 1192 -23.851 <.0001
## Rusp - Sora -0.451029 0.01954 1186 -23.087 <.0001
## Rusp - Syla -0.520778 0.04472 1191 -11.645 <.0001
## Rusp - Sypi -0.521522 0.01461 1191 -35.696 <.0001
## Rusp - Syur -0.467034 0.04472 1191 -10.443 <.0001
## Rusp - Taof  0.172363 0.01551 1191  11.113 <.0001
## Rusp - Trsp -0.171969 0.01307 1191 -13.159 <.0001
## Rusp - Vear  0.093056 0.03240 1191   2.872 0.5335
## Sila - Soca -0.476853 0.04356 1187 -10.946 <.0001
## Sila - Soga -0.424766 0.05323 1188  -7.979 <.0001
## Sila - Sogr -0.410620 0.04557 1185  -9.012 <.0001
## Sila - Sora -0.449602 0.04646 1183  -9.676 <.0001
## Sila - Syla -0.519352 0.06153 1189  -8.441 <.0001
## Sila - Sypi -0.520095 0.04471 1188 -11.632 <.0001
## Sila - Syur -0.465607 0.06153 1189  -7.567 <.0001
## Sila - Taof  0.173790 0.04493 1188   3.868 0.0402
## Sila - Trsp -0.170543 0.04404 1186  -3.873 0.0396
## Sila - Vear  0.094483 0.05302 1174   1.782 0.9978
## Soca - Soga  0.052088 0.03097 1188   1.682 0.9992
## Soca - Sogr  0.066233 0.01432 1188   4.625 0.0019
## Soca - Sora  0.027251 0.01703 1185   1.600 0.9997
## Soca - Syla -0.042499 0.04364 1189  -0.974 1.0000
## Soca - Sypi -0.043242 0.01099 1187  -3.936 0.0316
## Soca - Syur  0.011246 0.04364 1189   0.258 1.0000

```

```

##  Soca - Taof  0.650643 0.01226 1193  53.063 <.0001
##  Soca - Trsp  0.306310 0.00887 1175  34.520 <.0001
##  Soca - Vear  0.571336 0.03089 1187  18.494 <.0001
##  Soga - Sogr  0.014146 0.03351 1181   0.422 1.0000
##  Soga - Sora -0.024837 0.03499 1185  -0.710 1.0000
##  Soga - Syla -0.094586 0.05333 1190  -1.774 0.9980
##  Soga - Sypi -0.095330 0.03245 1190  -2.938 0.4789
##  Soga - Syur -0.040842 0.05333 1190  -0.766 1.0000
##  Soga - Taof  0.598556 0.03279 1180  18.255 <.0001
##  Soga - Trsp  0.254223 0.03182 1186   7.990 <.0001
##  Soga - Vear  0.519248 0.04338 1189  11.970 <.0001
##  Sogr - Sora -0.038983 0.02151 1176  -1.812 0.9971
##  Sogr - Syla -0.108732 0.04572 1190  -2.378 0.8868
##  Sogr - Sypi -0.109476 0.01731 1190  -6.323 <.0001
##  Sogr - Syur -0.054988 0.04572 1190  -1.203 1.0000
##  Sogr - Taof  0.584410 0.01797 1179  32.516 <.0001
##  Sogr - Trsp  0.240077 0.01608 1184  14.929 <.0001
##  Sogr - Vear  0.505103 0.03355 1187  15.055 <.0001
##  Sora - Syla -0.069749 0.04665 1190  -1.495 0.9999
##  Sora - Sypi -0.070493 0.01971 1186  -3.576 0.1042
##  Sora - Syur -0.016005 0.04665 1190  -0.343 1.0000
##  Sora - Taof  0.623392 0.02019 1185  30.876 <.0001
##  Sora - Trsp  0.279059 0.01853 1183  15.061 <.0001
##  Sora - Vear  0.544085 0.03477 1185  15.649 <.0001
##  Syla - Sypi -0.000744 0.04465 1186  -0.017 1.0000
##  Syla - Syur  0.053744 0.06096 1165   0.882 1.0000
##  Syla - Taof  0.693142 0.04505 1187  15.387 <.0001
##  Syla - Trsp  0.348809 0.04427 1188   7.879 <.0001
##  Syla - Vear  0.613834 0.05329 1190  11.518 <.0001
##  Sypi - Syur  0.054488 0.04465 1186   1.220 1.0000
##  Sypi - Taof  0.693885 0.01567 1192  44.279 <.0001
##  Sypi - Trsp  0.349552 0.01321 1185  26.454 <.0001
##  Sypi - Vear  0.614578 0.03241 1188  18.962 <.0001
##  Syur - Taof  0.639397 0.04505 1187  14.194 <.0001
##  Syur - Trsp  0.295064 0.04427 1188   6.665 <.0001
##  Syur - Vear  0.560090 0.05329 1190  10.510 <.0001
##  Taof - Trsp -0.344333 0.01412 1190 -24.383 <.0001
##  Taof - Vear -0.079307 0.03280 1190  -2.418 0.8669
##  Trsp - Vear  0.265026 0.03174 1185   8.351 <.0001
##
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 33 estimates

# including native vs. exotic - first with interaction term
kbs_flwr_spp <- within(kbs_flwr_spp, origin <- relevel(factor(origin), ref = "Native")) # releveling s
kmmod8 <- lmer(log(julian_median) ~ state * origin + (1 + factor(year_factor) | plot),
  kbs_flwr_spp, REML = FALSE)

## boundary (singular) fit: see ?isSingular

## Warning: Model failed to converge with 1 negative eigenvalue: -4.7e+00

```

```
kmod9 <- lmer(log(julian_median) ~ state + origin + (1 + factor(year_factor) | plot),  
  kbs_flwr_spp, REML = FALSE)
```

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

```
kmod9a <- lmer(log(julian_median) ~ state + origin + factor(year_factor) + (1 | plot),  
  kbs_flwr_spp, REML = FALSE)
```

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

```
anova(kmod8, kmod9) # kmodel 9 is a better fit to data
```

```
## Data: kbs_flwr_spp  
## Models:  
## kmod9: log(julian_median) ~ state + origin + (1 + factor(year_factor) |  
## kmod9:     plot)  
## kmod8: log(julian_median) ~ state * origin + (1 + factor(year_factor) |  
## kmod8:     plot)  
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)  
## kmod9    34 -1329.8 -1159.0 698.92   -1397.8  
## kmod8    37 -1326.7 -1140.7 700.33   -1400.7 2.8067  3      0.4224
```

```
anova(kmod9, kmod9a) # kmod 9a?
```

```
## Data: kbs_flwr_spp  
## Models:  
## kmod9a: log(julian_median) ~ state + origin + factor(year_factor) + (1 |  
## kmod9a:     plot)  
## kmod9: log(julian_median) ~ state + origin + (1 + factor(year_factor) |  
## kmod9:     plot)  
##      npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)  
## kmod9a   13 -1415.2 -1349.9 720.61   -1441.2  
## kmod9    34 -1329.8 -1159.0 698.92   -1397.8      0 21           1
```

```
summary(kmod9a)
```

```
## 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: kbs_flwr_spp  
##  
##      AIC      BIC      logLik deviance df.resid  
## -1415.2 -1349.9     720.6   -1441.2      1112  
##  
## Scaled residuals:  
##      Min      1Q Median      3Q      Max  
## -3.8470 -0.5993  0.1929  0.5541  3.5658  
##  
## Random effects:
```

```

## Groups      Name          Variance Std.Dev.
## plot      (Intercept) 0.00000  0.0000
## Residual           0.01626  0.1275
## Number of obs: 1125, groups: plot, 24
##
## Fixed effects:
##                               Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)            5.566e+00 1.678e-02 1.125e+03 331.792 < 2e-16 ***
## stateambient         1.438e-02 7.657e-03 1.125e+03  1.877  0.0607 .
## origin              -3.262e-01 6.583e-02 1.125e+03 -4.955 8.33e-07 ***
## originBoth           -3.291e-01 1.377e-02 1.125e+03 -23.903 < 2e-16 ***
## originExotic        -3.149e-01 9.173e-03 1.125e+03 -34.328 < 2e-16 ***
## factor(year_factor)2 -1.382e-01 1.689e-02 1.125e+03 -8.182 7.49e-16 ***
## factor(year_factor)3 -1.500e-01 1.745e-02 1.125e+03 -8.597 < 2e-16 ***
## factor(year_factor)4 -1.608e-01 1.732e-02 1.125e+03 -9.282 < 2e-16 ***
## factor(year_factor)5 -1.013e-01 1.768e-02 1.125e+03 -5.732 1.27e-08 ***
## factor(year_factor)6 -1.163e-01 1.797e-02 1.125e+03 -6.469 1.47e-10 ***
## factor(year_factor)7 -1.328e-01 1.877e-02 1.125e+03 -7.078 2.57e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) sttmbn origin orgnBt orgnEx fc(_)2 fc(_)3 fc(_)4 fc(_)5
## stateambint -0.216
## origin      -0.242 -0.003
## originBoth   -0.308 -0.054  0.082
## originExotc  -0.424  0.023  0.107  0.488
## fctr(yr_f)2 -0.758 -0.031  0.195  0.018  0.021
## fctr(yr_f)3 -0.734 -0.033  0.189  0.028  0.017  0.728
## fctr(yr_f)4 -0.733 -0.040  0.189  0.061 -0.013  0.733  0.711
## fctr(yr_f)5 -0.733 -0.045  0.189  0.076  0.028  0.719  0.697  0.705
## fctr(yr_f)6 -0.722 -0.014  0.185  0.063  0.018  0.706  0.684  0.692  0.679
## fctr(yr_f)7 -0.714 -0.007  0.182  0.104  0.058  0.677  0.657  0.664  0.653
##                 fc(_)6
## stateambint
## origin
## originBoth
## originExotc
## fctr(yr_f)2
## fctr(yr_f)3
## fctr(yr_f)4
## fctr(yr_f)5
## fctr(yr_f)6
## fctr(yr_f)7  0.641
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular

anova(kmod9)

```

```

## Type III Analysis of Variance Table with Satterthwaite's method
##           Sum Sq Mean Sq NumDF DenDF F value Pr(>F)
## state     0.028  0.0280     1  63.20  1.7308 0.1931
## origin   20.534  6.8448     3 676.87 422.9865 <2e-16 ***
## ---
##
```

```

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

emmeans(kmod9a, list(pairwise ~ state + origin), adjust = "tukey")

## $`emmmeans of state, origin`
##   state  origin emmean      SE    df lower.CL upper.CL
##   warmed Native  5.452 0.009086 166.61   5.434   5.470
##   ambient Native  5.466 0.008893 161.26   5.449   5.484
##   warmed          5.126 0.065648 1135.99   4.997   5.254
##   ambient          5.140 0.065619 1135.23   5.011   5.269
##   warmed Both     5.123 0.012471 442.37   5.098   5.147
##   ambient Both    5.137 0.011867 382.29   5.114   5.160
##   warmed Exotic   5.137 0.006473  44.06   5.124   5.150
##   ambient Exotic   5.151 0.006475  43.57   5.138   5.164
##
## 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 -0.014375 0.00800  25.4 -1.796  0.6279
##   warmed Native - warmed          0.326208 0.06627 1135.9  4.923 <.0001
##   warmed Native - ambient          0.311833 0.06675 1127.5  4.672  0.0001
##   warmed Native - warmed Both    0.329121 0.01385 1133.5 23.762 <.0001
##   warmed Native - ambient Both   0.314746 0.01564 311.7 20.124 <.0001
##   warmed Native - warmed Exotic  0.314901 0.00923 1136.0 34.106 <.0001
##   warmed Native - ambient Exotic 0.300526 0.01236 138.9 24.314 <.0001
##   ambient Native - warmed         0.340582 0.06675 1132.7  5.102 <.0001
##   ambient Native - ambient          0.326208 0.06627 1135.9  4.923 <.0001
##   ambient Native - warmed Both    0.343496 0.01634 372.9 21.017 <.0001
##   ambient Native - ambient Both   0.329121 0.01385 1133.5 23.762 <.0001
##   ambient Native - warmed Exotic  0.329275 0.01207 134.3 27.271 <.0001
##   ambient Native - ambient Exotic 0.314901 0.00923 1136.0 34.106 <.0001
##   warmed - ambient             -0.014375 0.00800  25.4 -1.796  0.6279
##   warmed - warmed Both          0.002913 0.06659 1136.0  0.044  1.0000
##   warmed - ambient Both         -0.011461 0.06698 1132.5 -0.171  1.0000
##   warmed - warmed Exotic       -0.011307 0.06591 1135.5 -0.172  1.0000
##   warmed - ambient Exotic      -0.025681 0.06643 1133.5 -0.387  0.9999
##   ambient - warmed Both        0.017288 0.06715 1127.9  0.257  1.0000
##   ambient - ambient Both       0.002913 0.06659 1136.0  0.044  1.0000
##   ambient - warmed Exotic     0.003068 0.06637 1129.2  0.046  1.0000
##   ambient - ambient Exotic    -0.011307 0.06591 1135.5 -0.172  1.0000
##   warmed Both - ambient Both   -0.014375 0.00800  25.4 -1.796  0.6279
##   warmed Both - warmed Exotic  -0.014220 0.01235 1135.9 -1.152  0.9450
##   warmed Both - ambient Exotic -0.028595 0.01521 289.1 -1.880  0.5655
##   ambient Both - warmed Exotic 0.000154 0.01420 229.2  0.011  1.0000
##   ambient Both - ambient Exotic -0.014220 0.01235 1135.9 -1.152  0.9450
##   warmed Exotic - ambient Exotic -0.014375 0.00800  25.4 -1.796  0.6279
##
## Results are averaged over the levels of: year_factor
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.

```

```

## P value adjustment: tukey method for comparing a family of 8 estimates

# including growth form - first with interaction term
kbs_flwr_spp <- within(kbs_flwr_spp, growth_habit <- relevel(factor(growth_habit),
  ref = "Forb")) # releveling so forb is the reference
kmod10 <- 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 ?isSingular

kmod11 <- lmer(log(julian_median) ~ state + growth_habit + (1 + year_factor | plot),
  kbs_flwr_spp, REML = FALSE)
anova(kmod10, kmod11) # kmodel 11 is a better fit to data

## boundary (singular) fit: see ?isSingular

kmod11a <- lmer(log(julian_median) ~ state + growth_habit + year_factor + (1 | plot),
  kbs_flwr_spp, REML = FALSE)
anova(kmod10, kmod11a) # kmodel 11 is a better fit to data

## Data: kbs_flwr_spp
## Models:
## kmod11: log(julian_median) ~ state + growth_habit + (1 + year_factor | plot)
## kmod10: log(julian_median) ~ state * growth_habit + (1 + year_factor | plot)
##          npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## kmod11     9 -1004.6 -959.41 511.32   -1022.6
## kmod10    11 -1003.9 -948.62 512.95   -1025.9 3.2552  2      0.1964

anova(kmod11, kmod11a)

## Data: kbs_flwr_spp
## Models:
## kmod11a: log(julian_median) ~ state + growth_habit + year_factor + (1 | plot)
## kmod11: log(julian_median) ~ state + growth_habit + (1 + year_factor | plot)
##          npar      AIC      BIC logLik deviance Chisq Df Pr(>Chisq)
## kmod11a    8 -1017.8 -977.57 516.89   -1033.8
## kmod11     9 -1004.6 -959.41 511.32   -1022.6      0  1           1

summary(kmod11a)

## 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
## -4.5492 -0.4798  0.0751  0.6355  2.0532
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.0001551 0.01246
## Residual           0.0232239 0.15239
## Number of obs: 1125, groups: plot, 24
##
## Fixed effects:
##                   Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)      5.297e+00  1.334e-02  2.087e+02 397.218 < 2e-16 ***
## stateambient    2.757e-03  1.051e-02  2.272e+01   0.262 0.795385
## growth_habit    -2.276e-01  1.547e-02  1.121e+03 -14.717 < 2e-16 ***
## growth_habitForb/herb -5.426e-01  1.532e-01  1.123e+03 -3.541 0.000415 ***
## growth_habitGraminoid -2.262e-01  9.804e-03  1.125e+03 -23.072 < 2e-16 ***
## year_factor      8.679e-03  2.575e-03  1.124e+03   3.371 0.000774 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) sttmbn grwth_ grw_F/ grwt_G
## stateambint -0.426
## growth_habt -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(kmod11a)
```

```

## 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  0.0688 0.7953853
## growth_habit 14.1323  4.7108     3 1122.82 202.8404 < 2.2e-16 ***
## year_factor  0.2639  0.2639     1 1123.59 11.3638 0.0007744 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
emmeans(kmod11a, list(pairwise ~ state + growth_habit), adjust = "tukey")
```

```

## $`emmeans of state, growth_habit`
##   state   growth_habit emmean      SE      df lower.CL upper.CL
##   warmed   Forb      5.332 0.009593  61.86    5.312   5.351
##   ambient   Forb      5.334 0.009088  50.04    5.316   5.353
##   warmed      Forb     5.104 0.015704 365.88    5.073   5.135
##   ambient      Forb     5.107 0.015044 322.78    5.077   5.136
##   warmed Forb/herb    4.789 0.153568 1129.32    4.488   5.090
##   ambient Forb/herb    4.792 0.153838 1129.19    4.490   5.094
##   warmed Graminoid    5.105 0.009267   54.31    5.087   5.124

```

```

##  ambient Graminoid      5.108 0.009462   59.11     5.089     5.127
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, growth_habit`
## 1                               estimate      SE    df t.ratio
## warmed Forb - ambient Forb   -0.00276 0.01104   26.4 -0.250
## warmed Forb - warmed          0.22761 0.01552 1126.3 14.668
## warmed Forb - ambient         0.22485 0.01876  214.2 11.989
## warmed Forb - (warmed Forb/herb) 0.54257 0.15378 1127.6  3.528
## warmed Forb - (ambient Forb/herb) 0.53982 0.15447 1130.4  3.495
## warmed Forb - warmed Graminoid 0.22620 0.00985 1130.8 22.974
## warmed Forb - ambient Graminoid 0.22344 0.01523   97.9 14.674
## ambient Forb - warmed         0.23037 0.01933 239.4 11.920
## ambient Forb - ambient         0.22761 0.01552 1126.3 14.668
## ambient Forb - (warmed Forb/herb) 0.54533 0.15387 1130.5  3.544
## ambient Forb - (ambient Forb/herb) 0.54257 0.15378 1127.6  3.528
## ambient Forb - warmed Graminoid 0.22895 0.01434   78.1 15.963
## ambient Forb - ambient Graminoid 0.22620 0.00985 1130.8 22.974
## warmed - ambient             -0.00276 0.01104   26.4 -0.250
## warmed - (warmed Forb/herb)   0.31496 0.15434 1127.7  2.041
## warmed - (ambient Forb/herb) 0.31220 0.15507 1130.4  2.013
## warmed - warmed Graminoid    -0.00142 0.01577 1130.1 -0.090
## warmed - ambient Graminoid   -0.00417 0.01987 255.9 -0.210
## ambient - (warmed Forb/herb) 0.31772 0.15440 1130.6  2.058
## ambient - (ambient Forb/herb) 0.31496 0.15434 1127.7  2.041
## ambient - warmed Graminoid   0.00134 0.01862 205.4  0.072
## ambient - ambient Graminoid  -0.00142 0.01577 1130.1 -0.090
## (warmed Forb/herb) - (ambient Forb/herb) -0.00276 0.01104   26.4 -0.250
## (warmed Forb/herb) - warmed Graminoid  -0.31638 0.15366 1127.2 -2.059
## (warmed Forb/herb) - ambient Graminoid -0.31913 0.15380 1130.4 -2.075
## (ambient Forb/herb) - warmed Graminoid -0.31362 0.15431 1130.2 -2.032
## (ambient Forb/herb) - ambient Graminoid -0.31638 0.15366 1127.2 -2.059
## warmed Graminoid - ambient Graminoid -0.00276 0.01104   26.4 -0.250
## p.value
## 1.0000
## <.0001
## <.0001
## 0.0103
## 0.0116
## <.0001
## <.0001
## <.0001
## <.0001
## 0.0097
## 0.0103
## <.0001
## <.0001
## 1.0000
## 0.4547
## 0.4732
## 1.0000

```

```

##  1.0000
##  0.4433
##  0.4547
##  1.0000
##  1.0000
##  1.0000
##  0.4425
##  0.4318
##  0.4603
##  0.4425
##  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

```

KBS Plot-level Mixed Effects Models:

```

mod1pk <- lmer(log(julian_median) ~ state + (1 | plot), kbs_flwr_plot, REML = FALSE)
mod2pk <- lmer(log(julian_median) ~ state + factor(year_factor) + (1 | plot), kbs_flwr_plot,
REML = FALSE)
mod3pk <- lmer(log(julian_median) ~ state * factor(year_factor) + (1 | plot), kbs_flwr_plot,
REML = FALSE)
anova(mod1pk, mod2pk)

## Error in anova.merMod(mod1pk, mod2pk): models were not all fitted to the same size of dataset

anova(mod2pk, mod3pk) #mod2pk

## Data: kbs_flwr_plot
## Models:
## mod2pk: log(julian_median) ~ state + factor(year_factor) + (1 | plot)
## mod3pk: log(julian_median) ~ state * factor(year_factor) + (1 | plot)
##      npar    AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod2pk   10 -363.38 -332.27 191.69   -383.38
## mod3pk   16 -373.94 -324.15 202.97   -405.94 22.556   6  0.0009597 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

summary(mod2pk)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + factor(year_factor) + (1 | plot)
## Data: kbs_flwr_plot
##
##      AIC      BIC logLik deviance df.resid
## -363.4   -332.3    191.7   -383.4      156
## 
```

```

## Scaled residuals:
##      Min     1Q Median     3Q    Max
## -1.90904 -0.66579 -0.04988  0.53054  2.70703
##
## Random effects:
##   Groups   Name        Variance Std.Dev.
##   plot     (Intercept) 0.001780 0.04219
##   Residual           0.004843 0.06959
## Number of obs: 166, groups: plot, 24
##
## Fixed effects:
##                     Estimate Std. Error      df t value Pr(>|t|)    
##   (Intercept)      5.29354   0.01948  72.57830 271.756 < 2e-16 ***
##   stateambient    0.02327   0.02034  24.16832   1.144  0.26395  
##   factor(year_factor)2 -0.06515   0.02009 142.17889  -3.243  0.00147 ** 
##   factor(year_factor)3 -0.05860   0.02009 142.17889  -2.917  0.00411 ** 
##   factor(year_factor)4 -0.16873   0.02009 142.17889  -8.399 4.18e-14 ***
##   factor(year_factor)5 -0.01183   0.02009 142.17889  -0.589  0.55688  
##   factor(year_factor)6 -0.03181   0.02034 142.54598  -1.564  0.12002  
##   factor(year_factor)7  0.09595   0.02034 142.54598   4.718 5.62e-06 ***
##   ---
##   Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##            (Intr) sttmbn fc(_2) fc(_3) fc(_4) fc(_5) fc(_6)
## stateambint -0.522
## fctr(yr_f)2 -0.516  0.000
## fctr(yr_f)3 -0.516  0.000  0.500
## fctr(yr_f)4 -0.516  0.000  0.500  0.500
## fctr(yr_f)5 -0.516  0.000  0.500  0.500  0.500
## fctr(yr_f)6 -0.513  0.008  0.494  0.494  0.494  0.494
## fctr(yr_f)7 -0.513  0.008  0.494  0.494  0.494  0.494  0.491

emmeans(mod2p, list(pairwise ~ state + factor(year_factor)), adjust = "tukey")

## $`emmeans of state, year_factor`
##   state year_factor emmean     SE   df lower.CL upper.CL
##   warmed          2  5.09 0.0191 110     5.05    5.12
##   ambient         2  5.09 0.0191 110     5.05    5.13
##   warmed          3  5.14 0.0191 110     5.10    5.18
##   ambient         3  5.15 0.0191 110     5.11    5.19
##   warmed          4  5.29 0.0191 110     5.25    5.33
##   ambient         4  5.30 0.0191 110     5.26    5.34
##   warmed          5  5.24 0.0191 110     5.21    5.28
##   ambient         5  5.25 0.0191 110     5.21    5.29
##   warmed          6  5.26 0.0191 110     5.22    5.30
##   ambient         6  5.27 0.0191 110     5.23    5.30
##   warmed          7  5.17 0.0198 115     5.13    5.21
##   ambient         7  5.18 0.0198 115     5.14    5.22
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##

```

```

## $`pairwise differences of state, year_factor`
## 1             estimate    SE   df t.ratio p.value
## warmed 2 - ambient 2 -0.00610 0.0174 26.1 -0.351 1.0000
## warmed 2 - warmed 3 -0.05645 0.0227 123.2 -2.483 0.3604
## warmed 2 - ambient 3 -0.06255 0.0286 121.2 -2.187 0.5624
## warmed 2 - warmed 4 -0.20624 0.0227 123.2 -9.072 <.0001
## warmed 2 - ambient 4 -0.21233 0.0286 121.2 -7.423 <.0001
## warmed 2 - warmed 5 -0.15862 0.0227 123.2 -6.977 <.0001
## warmed 2 - ambient 5 -0.16472 0.0286 121.2 -5.758 <.0001
## warmed 2 - warmed 6 -0.17467 0.0227 123.2 -7.683 <.0001
## warmed 2 - ambient 6 -0.18076 0.0286 121.2 -6.319 <.0001
## warmed 2 - warmed 7 -0.08566 0.0233 124.5 -3.677 0.0174
## warmed 2 - ambient 7 -0.09176 0.0291 123.0 -3.158 0.0808
## ambient 2 - warmed 3 -0.05035 0.0286 121.2 -1.760 0.8357
## ambient 2 - ambient 3 -0.05645 0.0227 123.2 -2.483 0.3604
## ambient 2 - warmed 4 -0.20014 0.0286 121.2 -6.997 <.0001
## ambient 2 - ambient 4 -0.20624 0.0227 123.2 -9.072 <.0001
## ambient 2 - warmed 5 -0.15252 0.0286 121.2 -5.332 <.0001
## ambient 2 - ambient 5 -0.15862 0.0227 123.2 -6.977 <.0001
## ambient 2 - warmed 6 -0.16857 0.0286 121.2 -5.893 <.0001
## ambient 2 - ambient 6 -0.17467 0.0227 123.2 -7.683 <.0001
## ambient 2 - warmed 7 -0.07956 0.0291 123.0 -2.739 0.2205
## ambient 2 - ambient 7 -0.08566 0.0233 124.5 -3.677 0.0174
## warmed 3 - ambient 3 -0.00610 0.0174 26.1 -0.351 1.0000
## warmed 3 - warmed 4 -0.14979 0.0227 123.2 -6.589 <.0001
## warmed 3 - ambient 4 -0.15588 0.0286 121.2 -5.450 <.0001
## warmed 3 - warmed 5 -0.10217 0.0227 123.2 -4.494 0.0009
## warmed 3 - ambient 5 -0.10826 0.0286 121.2 -3.785 0.0123
## warmed 3 - warmed 6 -0.11821 0.0227 123.2 -5.200 0.0001
## warmed 3 - ambient 6 -0.12431 0.0286 121.2 -4.346 0.0017
## warmed 3 - warmed 7 -0.02921 0.0233 124.5 -1.254 0.9831
## warmed 3 - ambient 7 -0.03530 0.0291 123.0 -1.215 0.9868
## ambient 3 - warmed 4 -0.14369 0.0286 121.2 -5.023 0.0001
## ambient 3 - ambient 4 -0.14979 0.0227 123.2 -6.589 <.0001
## ambient 3 - warmed 5 -0.09607 0.0286 121.2 -3.359 0.0464
## ambient 3 - ambient 5 -0.10217 0.0227 123.2 -4.494 0.0009
## ambient 3 - warmed 6 -0.11212 0.0286 121.2 -3.920 0.0078
## ambient 3 - ambient 6 -0.11821 0.0227 123.2 -5.200 0.0001
## ambient 3 - warmed 7 -0.02311 0.0291 123.0 -0.795 0.9997
## ambient 3 - ambient 7 -0.02921 0.0233 124.5 -1.254 0.9831
## warmed 4 - ambient 4 -0.00610 0.0174 26.1 -0.351 1.0000
## warmed 4 - warmed 5 0.04762 0.0227 123.2 2.095 0.6275
## warmed 4 - ambient 5 0.04152 0.0286 121.2 1.452 0.9503
## warmed 4 - warmed 6 0.03157 0.0227 123.2 1.389 0.9636
## warmed 4 - ambient 6 0.02548 0.0286 121.2 0.891 0.9991
## warmed 4 - warmed 7 0.12058 0.0233 124.5 5.176 0.0001
## warmed 4 - ambient 7 0.11448 0.0291 123.0 3.941 0.0072
## ambient 4 - warmed 5 0.05372 0.0286 121.2 1.878 0.7704
## ambient 4 - ambient 5 0.04762 0.0227 123.2 2.095 0.6275
## ambient 4 - warmed 6 0.03767 0.0286 121.2 1.317 0.9754
## ambient 4 - ambient 6 0.03157 0.0227 123.2 1.389 0.9636
## ambient 4 - warmed 7 0.12668 0.0291 123.0 4.360 0.0016
## ambient 4 - ambient 7 0.12058 0.0233 124.5 5.176 0.0001
## warmed 5 - ambient 5 -0.00610 0.0174 26.1 -0.351 1.0000

```

```

##  warmed 5 - warmed 6  -0.01605 0.0227 123.2 -0.706  0.9999
##  warmed 5 - ambient 6 -0.02214 0.0286 121.2 -0.774  0.9998
##  warmed 5 - warmed 7  0.07296 0.0233 124.5  3.132  0.0864
##  warmed 5 - ambient 7  0.06686 0.0291 123.0  2.302  0.4812
##  ambient 5 - warmed 6 -0.00995 0.0286 121.2 -0.348  1.0000
##  ambient 5 - ambient 6 -0.01605 0.0227 123.2 -0.706  0.9999
##  ambient 5 - warmed 7  0.07906 0.0291 123.0  2.721  0.2287
##  ambient 5 - ambient 7  0.07296 0.0233 124.5  3.132  0.0864
##  warmed 6 - ambient 6 -0.00610 0.0174 26.1 -0.351  1.0000
##  warmed 6 - warmed 7   0.08901 0.0233 124.5  3.821  0.0108
##  warmed 6 - ambient 7   0.08291 0.0291 123.0  2.854  0.1713
##  ambient 6 - warmed 7   0.09510 0.0291 123.0  3.274  0.0590
##  ambient 6 - ambient 7   0.08901 0.0233 124.5  3.821  0.0108
##  warmed 7 - ambient 7  -0.00610 0.0174 26.1 -0.351  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 12 estimates

mod2pk.2 <- lmer(log(julian_median) ~ state + factor(year_factor) + insecticide +
  (1 | plot), kbs_flwr_plot, REML = FALSE)
anova(mod2pk, mod2pk.2) #mod2pk

## Data: kbs_flwr_plot
## Models:
## mod2pk: log(julian_median) ~ state + factor(year_factor) + (1 | plot)
## mod2pk.2: log(julian_median) ~ state + factor(year_factor) + insecticide +
## mod2pk.2: (1 | plot)
##      npar     AIC     BIC logLik deviance Chisq Df Pr(>Chisq)
## mod2pk     10 -363.38 -332.27 191.69  -383.38
## mod2pk.2   11 -361.39 -327.16 191.69  -383.39 0.0029  1     0.9567

summary(mod2pk)

## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
## method [lmerModLmerTest]
## Formula: log(julian_median) ~ state + factor(year_factor) + (1 | plot)
## Data: kbs_flwr_plot
##
##      AIC      BIC logLik deviance df.resid
## -363.4   -332.3   191.7    -383.4      156
##
## Scaled residuals:
##      Min      1Q Median      3Q      Max
## -1.90904 -0.66579 -0.04988  0.53054  2.70703
##
## Random effects:
## Groups   Name        Variance Std.Dev.
## plot     (Intercept) 0.001780 0.04219
## Residual           0.004843 0.06959
## Number of obs: 166, groups: plot, 24
##
## Fixed effects:
```

```

##                               Estimate Std. Error      df t value Pr(>|t|) 
## (Intercept)                 5.29354   0.01948  72.57830 271.756 < 2e-16 ***
## stateambient                0.02327   0.02034  24.16832   1.144  0.26395
## factor(year_factor)2       -0.06515   0.02009 142.17889  -3.243  0.00147 ** 
## factor(year_factor)3       -0.05860   0.02009 142.17889  -2.917  0.00411 ** 
## factor(year_factor)4       -0.16873   0.02009 142.17889  -8.399 4.18e-14 ***
## factor(year_factor)5       -0.01183   0.02009 142.17889  -0.589  0.55688
## factor(year_factor)6       -0.03181   0.02034 142.54598  -1.564  0.12002
## factor(year_factor)7        0.09595   0.02034 142.54598   4.718 5.62e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr) sttmbn fc(_).2 fc(_).3 fc(_).4 fc(_).5 fc(_).6
## stateambint -0.522
## fctr(yr_f).2 -0.516  0.000
## fctr(yr_f).3 -0.516  0.000  0.500
## fctr(yr_f).4 -0.516  0.000  0.500  0.500
## fctr(yr_f).5 -0.516  0.000  0.500  0.500  0.500
## fctr(yr_f).6 -0.513  0.008  0.494  0.494  0.494  0.494
## fctr(yr_f).7 -0.513  0.008  0.494  0.494  0.494  0.494  0.491

```