# warmXtrophic Project: Flowering Phenology Analysis

Moriah Young

July 09, 2021

### Load in packages & data

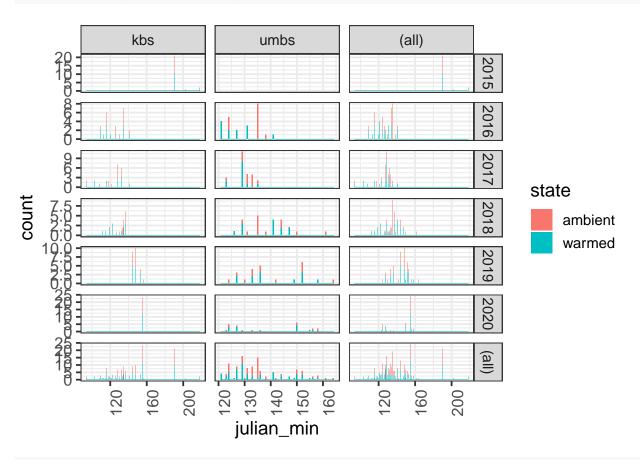
```
# clear all existing data
rm(list = ls())
# Load packages
library(tidyverse)
library(ggplot2)
library(lme4)
library(lmerTest)
library(emmeans)
library(vegan)
library(car)
library(rstatix)
library(scales)
library(fitdistrplus)
library(moments) # for calculating skewness of data
library(ggpubr)
library(jtools) # 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 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))
# Set working directory
Sys.getenv("L1DIR")
```

## [1] "/Volumes/GoogleDrive/Shared drives/SpaCE\_Lab\_warmXtrophic/data/L1/"

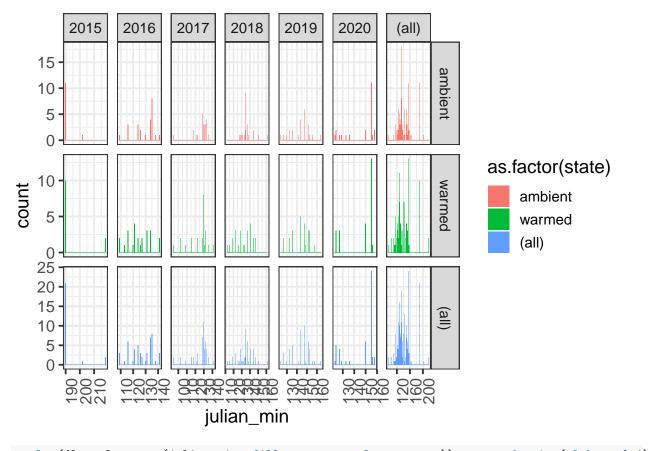
```
L1_dir <- Sys.getenv("L1DIR")
L2_dir <- Sys.getenv("L2DIR")
list.files(L1_dir)
                                                  "CN"
## [1] "ANPP"
                             "climate data"
                                                  "HOBO_data"
## [4] "greenup"
                             "herbivory"
## [7] "PAR"
                             "phenology"
                                                  "plant_composition"
## [10] "SLA"
# Set ggplot2 plotting This code for ggplot2 sets the theme to mostly black and
# white (Arial font, and large font, base size=24)
theme_set(theme_bw(14))
theme_update(axis.text.x = element_text(size = 12, angle = 90), axis.text.y = element_text(size = 12))
# Read in data cleaned phenology data from L1
phen_data <- read.csv(file.path(L1_dir, "phenology/final_flwr_sd_L1.csv"))</pre>
phen_data$X <- NULL # get rid of 'X' column that shows up</pre>
View(phen_data) # take a look at the data to see if looks good
# Order warm and ambient so that warm shows up first in plotting (and is default
# is red = warm; blue = ambient). First make it a factor
phen_data$state <- as.factor(phen_data$state)</pre>
levels(phen_data$state)
## [1] "ambient" "warmed"
# [1] 'ambient' 'warmed'
phen_data$state <- factor(phen_data$state, levels(phen_data$state)[c(2, 1)])</pre>
levels(phen_data$state)
## [1] "warmed" "ambient"
# [1] 'warmed' 'ambient'
# Flowering data species level data for flowering
flwr_spp <- read.csv(file.path(L1_dir, "phenology/final_flwr_species_L1.csv"))</pre>
flwr_spp$X <- NULL</pre>
# plot level data for flowering
flwr_plot <- read_csv(file.path(L1_dir, "phenology/final_flwr_plot_L1.csv"))</pre>
## Warning: Missing column names filled in: 'X1' [1]
flwr plot$X1 <- NULL</pre>
```

### Data exploration

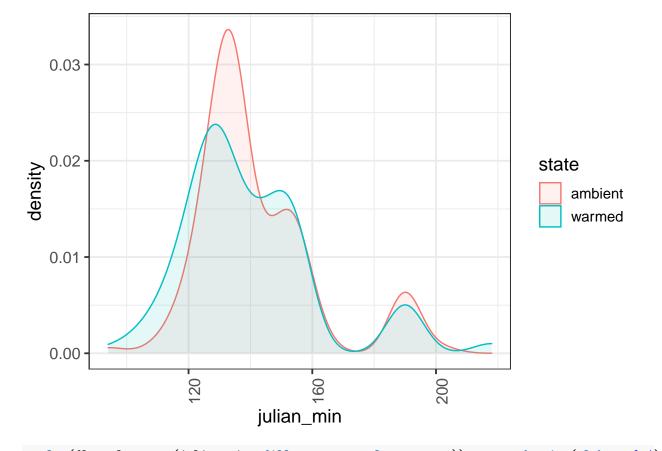
```
# Visualizing avg minimum julian date for both sites
ggplot(flwr_plot, aes(julian_min, fill = state)) + geom_histogram(binwidth = 0.5) +
    facet_grid(year ~ site, margins = TRUE, scales = "free")
```



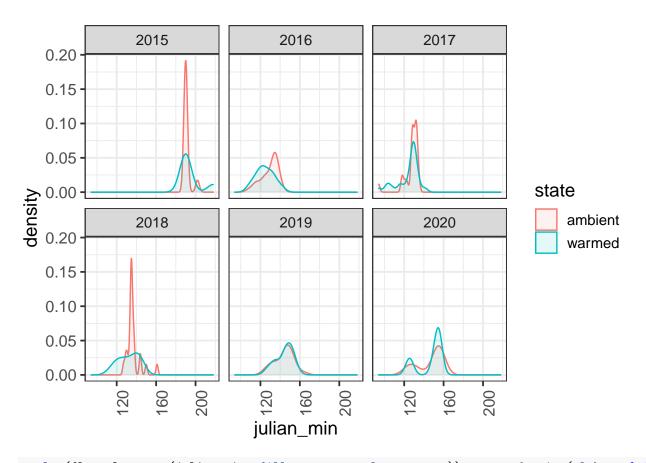
```
ggplot(flwr_plot, aes(julian_min, fill = as.factor(state))) + geom_histogram(binwidth = 0.5) +
    facet_grid(state ~ year, margins = TRUE, scales = "free")
```



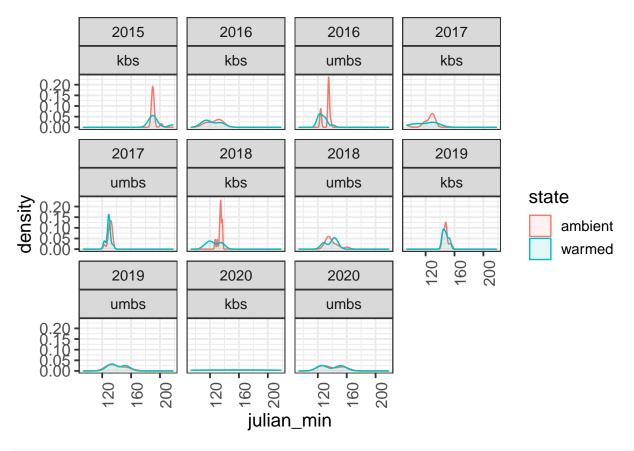
ggplot(flwr\_plot, aes(julian\_min, fill = state, color = state)) + geom\_density(alpha = 0.1)



ggplot(flwr\_plot, aes(julian\_min, fill = state, color = state)) + geom\_density(alpha = 0.1) +
 facet\_wrap(~year)

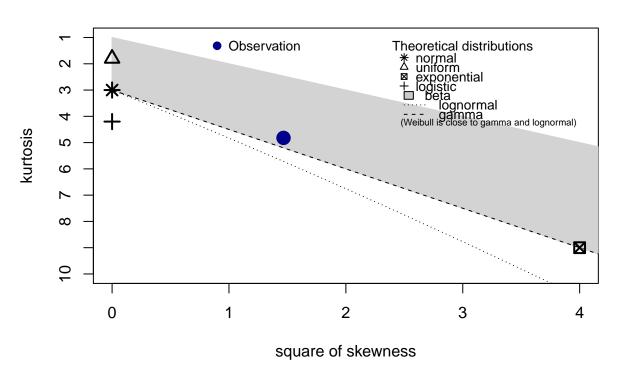


ggplot(flwr\_plot, aes(julian\_min, fill = state, color = state)) + geom\_density(alpha = 0.1) +
 facet\_wrap(~year + site)



descdist(flwr\_plot\$julian\_min, discrete = FALSE)

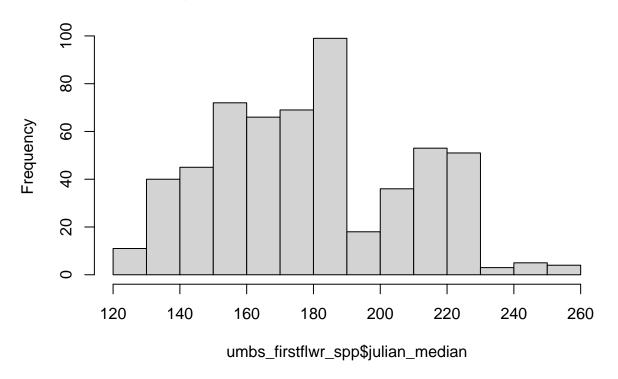
# **Cullen and Frey graph**



```
## summary statistics
## -----
## min: 94 max: 218
## median: 135
## mean: 140.7452
## estimated sd: 20.92644
## estimated skewness: 1.211022
## estimated kurtosis: 4.820602

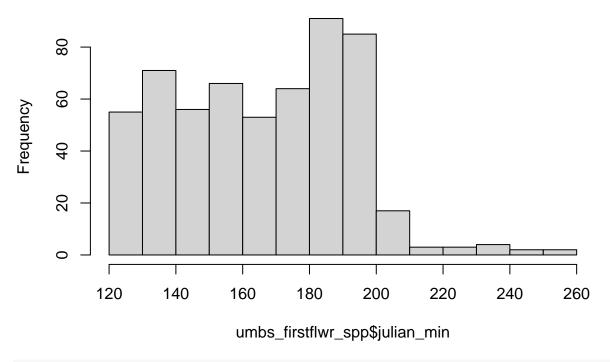
### UMBS ###
umbs_firstflwr_spp <- subset(flwr_spp, site == "umbs") # pull out umbs only data
hist(umbs_firstflwr_spp$julian_median)</pre>
```

# Histogram of umbs\_firstflwr\_spp\$julian\_median



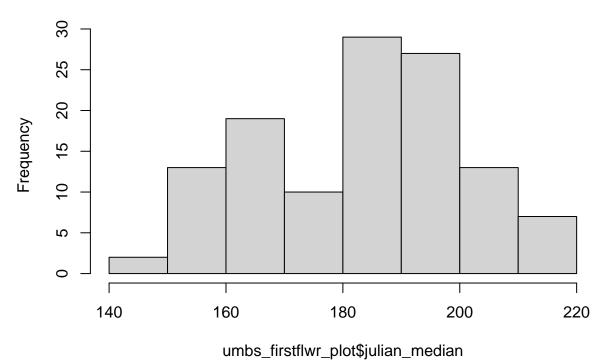
hist(umbs\_firstflwr\_spp\$julian\_min)

# Histogram of umbs\_firstflwr\_spp\$julian\_min

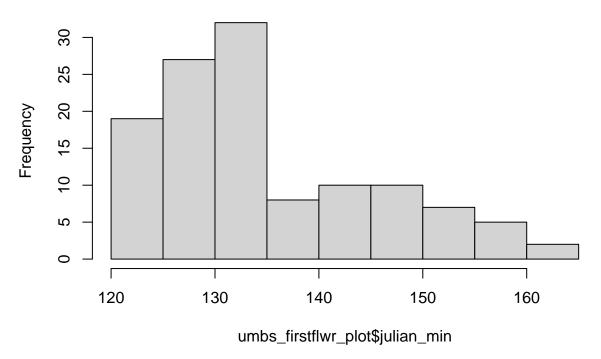


umbs\_firstflwr\_plot <- subset(flwr\_plot, site == "umbs") # pull out umbs only data
hist(umbs\_firstflwr\_plot\$julian\_median)</pre>

# Histogram of umbs\_firstflwr\_plot\$julian\_median

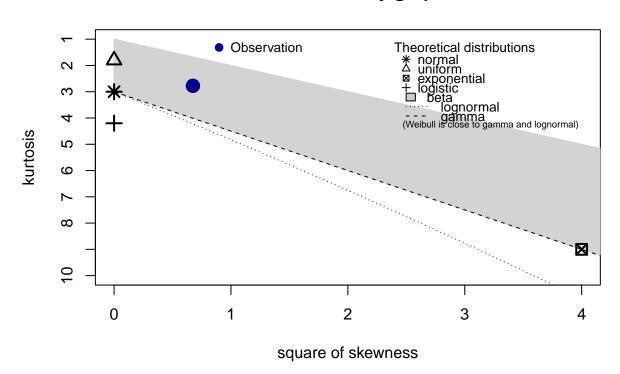


# Histogram of umbs\_firstflwr\_plot\$julian\_min

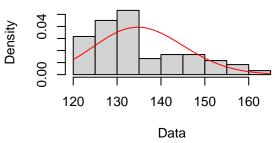


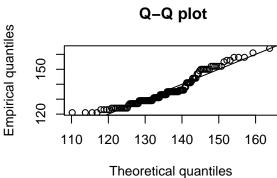
# Exploring distributions for these left-skewed data:
descdist(umbs\_firstflwr\_plot\$julian\_min, discrete = FALSE)

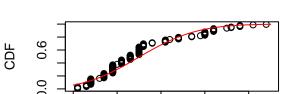
## **Cullen and Frey graph**

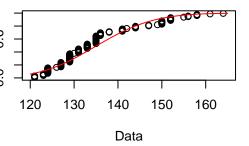


```
## summary statistics
## min: 121
              max: 164
## median: 133
## mean: 135.4917
## estimated sd: 10.38745
## estimated skewness: 0.8212294
## estimated kurtosis: 2.775374
# Beta distribution
fit.gamma <- fitdist(umbs_firstflwr_plot$julian_min, "gamma")</pre>
plot(fit.gamma)
                                                                Q-Q plot
       Empirical and theoretical dens.
```

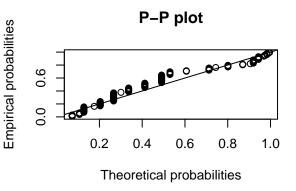






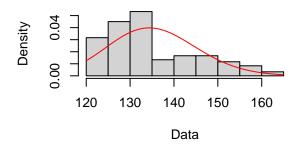


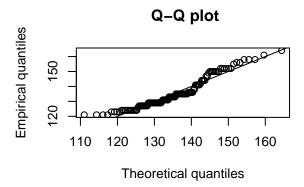
**Empirical and theoretical CDFs** 



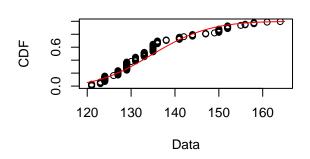
```
# Weibull distribution
fit.weibull <- fitdist(umbs_firstflwr_plot$julian_min, "weibull")</pre>
# Lognormal distribution
fit.ln <- fitdist(umbs_firstflwr_plot$julian_min, "lnorm")</pre>
plot(fit.ln)
```

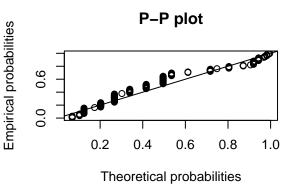
#### Empirical and theoretical dens.





### **Empirical and theoretical CDFs**

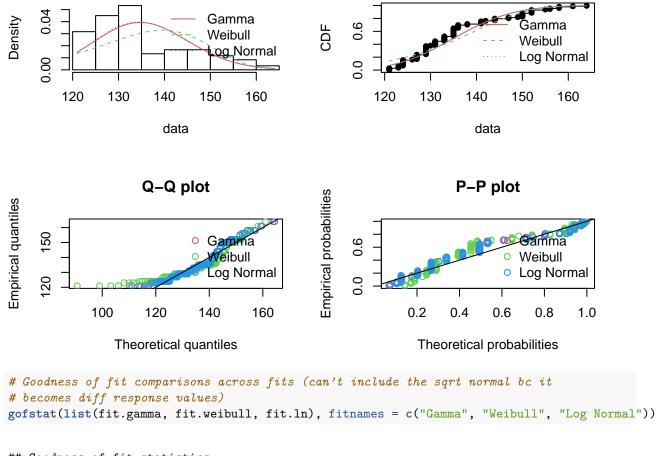




```
par(mfrow = c(2, 2))
plot.legend <- c("Gamma", "Weibull", "Log Normal")
denscomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
cdfcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
qqcomp(list(fit.gamma, fit.weibull, fit.ln), legendtext = plot.legend)
ppcomp(list(fit.gamma,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

#### Histogram and theoretical densities

#### **Empirical and theoretical CDFs**

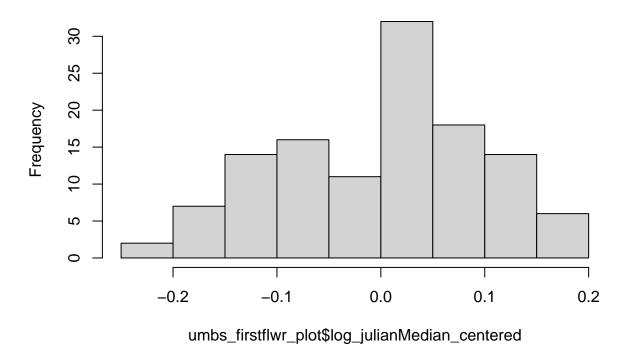


```
## Goodness-of-fit statistics
                                    Gamma
                                            Weibull Log Normal
## Kolmogorov-Smirnov statistic 0.1700250 0.2150911 0.1648747
## Cramer-von Mises statistic
                                0.5808497 1.0209433
                                                     0.5424176
## Anderson-Darling statistic
                                3.3369537 5.6394902 3.1360083
##
## Goodness-of-fit criteria
##
                                     Gamma Weibull Log Normal
## Akaike's Information Criterion 900.5729 933.5664
## Bayesian Information Criterion 906.1479 939.1413
                                                      904.0225
```

# Lognormal is slightly better than gamma

## Centering and transforming data

## Histogram of umbs\_firstflwr\_plot\$log\_julianMedian\_centered



### Determining appropriate distribution in mixed effects model

### **Avg Min Julian Date**

```
O
                                                              0
                                                                            0
      0.10
                                           0
                                                      0
                                                                0
resid(., type = "pearson")
                                                                          0
                                                     0
      0.05
                                                     O
                                                                                   O
                                               O
                                                                         000
                                                0
      0.00
                                                                   0
     -0.05
                                          0000
     -0.10
                                                        0
            4.80
                            4.85
                                            4.90
                                                            4.95
                                                                            5.00
                                              fitted(.)
# Homogeneity of variance is ok here (increasing variance in resids is not
# increasing with fitted values) Check for homogeneity of variances (true if
# p>0.05). If the result is not significant, the assumption of equal variances
# (homoscedasticity) is met (no significant difference between the group
# variances).
leveneTest(residuals(m1) ~ umbs_firstflwr_plot$state)
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.
## Levene's Test for Homogeneity of Variance (center = median)
          Df F value Pr(>F)
## group
          1
               0.001 0.9744
##
         118
# Assumption met
```

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

## Levene's Test for Homogeneity of Variance (center = median)
## Df F value Pr(>F)
## group 23  0.7084  0.8265
## 96
```

leveneTest(residuals(m1) ~ umbs\_firstflwr\_plot\$plot)

```
# Assumption met
leveneTest(residuals(m1) ~ umbs_firstflwr_plot$insecticide)

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

## Levene's Test for Homogeneity of Variance (center = median)
## Df F value Pr(>F)
## group 1 1.5017 0.2228
## 118

# Assumption met

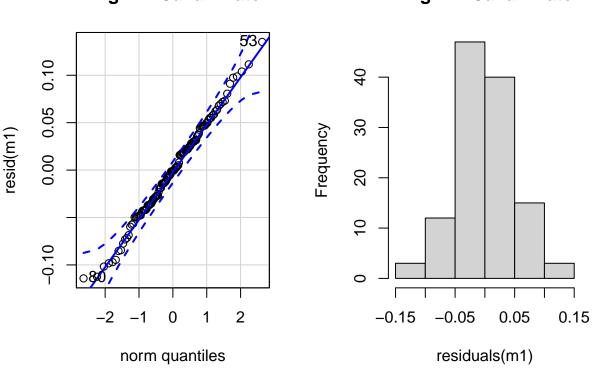
# (3) Normality of error term: need to check by histogram, QQplot of residuals,
# could do Kolmogorov-Smirnov test. Check for normal residuals
qqPlot(resid(m1), main = "Avg Min Julian Date")

## [1] 53 80
```

### **Avg Min Julian Date**

hist(residuals(m1), main = "Avg Min Julian Date")

# **Avg Min Julian Date**

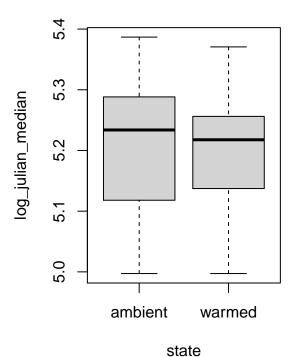


shapiro.test(resid(m1)) # not normally distributed resids bc p>0.05

```
##
## Shapiro-Wilk normality test
##
## data: resid(m1)
## W = 0.99448, p-value = 0.922
```

```
# Outliers sla[377,] sla[801,] Outlier test - yes, these are outliers bc p<0.05
outlierTest(m1)</pre>
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
     rstudent unadjusted p-value Bonferroni p
## 53 2.691335
                        0.0081977
                                       0.98372
# Remove these 2 points sla1<-sla[-c(377, 801),] m1.nooutlier <-
# lmer(log(area_cm2) ~ state + species + year + insecticide + (1/plot), data =
# sla1, REML=FALSE) shapiro.test(resid(m1.nooutlier)) # normally distributed
# resids - good!
# (4) Normality of random effect: Get the estimate of random effect (e.g., random
# intercepts), and check them as you would check the residual. [***need to do for
# final model]
# Plot key relationships '''{r} Convert all columns to factor first
umbs_firstflwr_plot <- as.data.frame(unclass(umbs_firstflwr_plot), stringsAsFactors = TRUE)
plot(log_julian_median ~ state, data = umbs_firstflwr_plot)
```



#### Fit models

```
m0 <- lmer(log_julian_median ~ 1, data = umbs_firstflwr_plot)
```

## Error: No random effects terms specified in formula

```
m1 <- lmer(log_julian_median ~ state, data = umbs_firstflwr_plot)</pre>
## Error: No random effects terms specified in formula
m2 <- lmer(log_julian_median ~ state + insecticide, data = umbs_firstflwr_plot)</pre>
## Error: No random effects terms specified in formula
m3 <- lmer(log_julian_median ~ state * insecticide, data = umbs_firstflwr_plot)
## Error: No random effects terms specified in formula
m4 <- lmer(log_julian_median ~ state * insecticide + (1 | species), data = umbs_firstflwr_plot)
## Error in eval(predvars, data, env): object 'species' not found
m5 <- lmer(log_julian_median ~ state + insecticide + (1 | species), data = umbs_firstflwr_plot)
## Error in eval(predvars, data, env): object 'species' not found
m6 <- lmer(log_julian_median ~ state * insecticide + (1 | species) + (1 | year_factor),
    data = umbs_firstflwr_plot)
## Error in eval(predvars, data, env): object 'species' not found
m7 <- lmer(log_julian_median ~ state + insecticide + (1 | species) + (1 | year_factor),
    data = umbs_firstflwr_plot)
## Error in eval(predvars, data, env): object 'species' not found
m8 <- lmer(log_julian_median ~ state + insecticide + origin + (1 | species) + (1 |
    year_factor), data = umbs_firstflwr_plot)
## Error in eval(predvars, data, env): object 'origin' not found
m9 <- lmer(log_julian_median ~ state + insecticide + origin + (1 | species) + (1 |
    year_factor) + (1 | plot), data = umbs_firstflwr_plot)
## Error in eval(predvars, data, env): object 'origin' not found
```

### Compare models

# AICtab(m0,m1,m2,m3,m4,m5, weights=TRUE)

# Evaluate models using residuals