warmXtrophic Project: Greenup Analyses

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Script Details:

```
# this portion of the script won't knit, so its set to eval=F

script_tbl <- data.frame(Item = c("OVERVIEW", "COLLABORATORS",
    "REQUIRES", "DATA INPUT", "DATA OUTPUT", "NOTES"), Details = c("This script explores and analyses t
    "Moriah Young, Mark Hammond, Pat Bills", "Prior to running this script, make sure plant_comp_clean_
    "Data imported as csv files from shared Google drive 'SpaCE_Lab_warmXtrophic' plant comp folder",
    "... a brief description of the data output from through the script, including what format it's in"
    "Each row in 'greenup' is the date at which spp_half_cover_date was recorded, per species. The 'gre

kbl(script_tbl) %>% kable_paper(full_width = F) %>% column_spec(1,
    bold = T, border_right = T) %>% column_spec(2, width = "30em",
    background = "lightblue")

metadata_tbl <- data.frame(Variable = c("spp_half_cover_date",
    "plot_half_cover_date", "state"), Definition = c("date at which 50% of a species max cover was reac
    "the date at which 50% of a plot's max cover was reached (per plot, per year)",
    "describes each treatment: warmed or ambient"))

kbl(metadata_tbl) %>% kable_paper(full_width = F) %>% column_spec(1,
    bold = T, border_right = T) %>% column_spec(2, width = "30em",
    background = "lightyellow")
```

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

# Load packages
library(tidyverse)
library(ggplot2)
library(lmerTest)
library(olsrr)
library(predictmeans)
library(car)
library(fitdistrplus)
library(ggpubr)
library(rstatix)
library(vegan)
library(interactions)
library(sjPlot)
library(effects)
library(glmmTMB)
```

```r
library(bbmle)
library(emmeans)
# install.packages('TMB',type='source')

# Set ggplot2 plots to bw: see here for more options:
# http://www.sthda.com/english/wiki/ggplot2-themes-and-background-colors-the-3-elements
theme_set(theme_bw(base_size = 14))

# Get data
L1_dir <- Sys.getenv("L1DIR")
L2_dir <- Sys.getenv("L2DIR")
greenup <- read.csv(file.path(L2_dir, "greenup/final_greenup_species_L2.csv"))  # spp level greenup dat
greenup <- greenup %>% dplyr::select(-X)  # get rid of 'X' column that shows up
greenupp <- read.csv(file.path(L2_dir, "greenup/final_greenup_plot_L2.csv"))  # plot level greenup date
greenupp <- greenupp %>% dplyr::select(-X)  # get rid of 'X' column that shows up

# check variable types
str(greenup)
```

```
## 'data.frame':    2408 obs. of  18 variables:
##  $ site               : chr  "kbs" "kbs" "kbs" "kbs" ...
##  $ plot               : chr  "A1" "A1" "A1" "A1" ...
##  $ year               : int  2016 2017 2018 2019 2020 2021 2016 2017 2016 2017 ...
##  $ species            : chr  "Acmi" "Acmi" "Acmi" "Acmi" ...
##  $ spp_half_cover_date: int  104 101 122 120 223 257 88 108 101 99 ...
##  $ min_green_date     : int  81 80 122 120 107 92 81 108 85 80 ...
##  $ treatment_key      : chr  "A0" "A0" "A0" "A0" ...
##  $ state              : chr  "ambient" "ambient" "ambient" "ambient" ...
##  $ insecticide        : chr  "no_insects" "no_insects" "no_insects" "no_insects" ...
##  $ scientific_name    : chr  "Achillea millefolium" "Achillea millefolium" "Achillea millefolium" "Ac
##  $ common_name        : chr  "common yarrow" "common yarrow" "common yarrow" "common yarrow" ...
##  $ USDA_species       : chr  "ACMI2" "ACMI2" "ACMI2" "ACMI2" ...
##  $ LTER_species       : chr  "ACHMI" "ACHMI" "ACHMI" "ACHMI" ...
##  $ origin             : chr  "Native" "Native" "Native" "Native" ...
##  $ group              : chr  "Dicot" "Dicot" "Dicot" "Dicot" ...
##  $ family             : chr  "Fabaceae" "Fabaceae" "Fabaceae" "Fabaceae" ...
##  $ duration           : chr  "Biennial" "Biennial" "Biennial" "Biennial" ...
##  $ growth_habit       : chr  "Forb" "Forb" "Forb" "Forb" ...
```

```r
# 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.
greenup$state <- as.factor(greenup$state)
levels(greenup$state)
```

```
## [1] "ambient" "warmed"
```

```r
greenup$state <- factor(greenup$state, levels(greenup$state)[c(2,
    1)])
levels(greenup$state)
```

```
## [1] "warmed"  "ambient"
```

```r
greenupp$state <- as.factor(greenupp$state)
levels(greenupp$state)
```

```
## [1] "ambient" "warmed"
```

```r
greenupp$state <- factor(greenupp$state, levels(greenupp$state)[c(2,
    1)])
levels(greenupp$state)
```

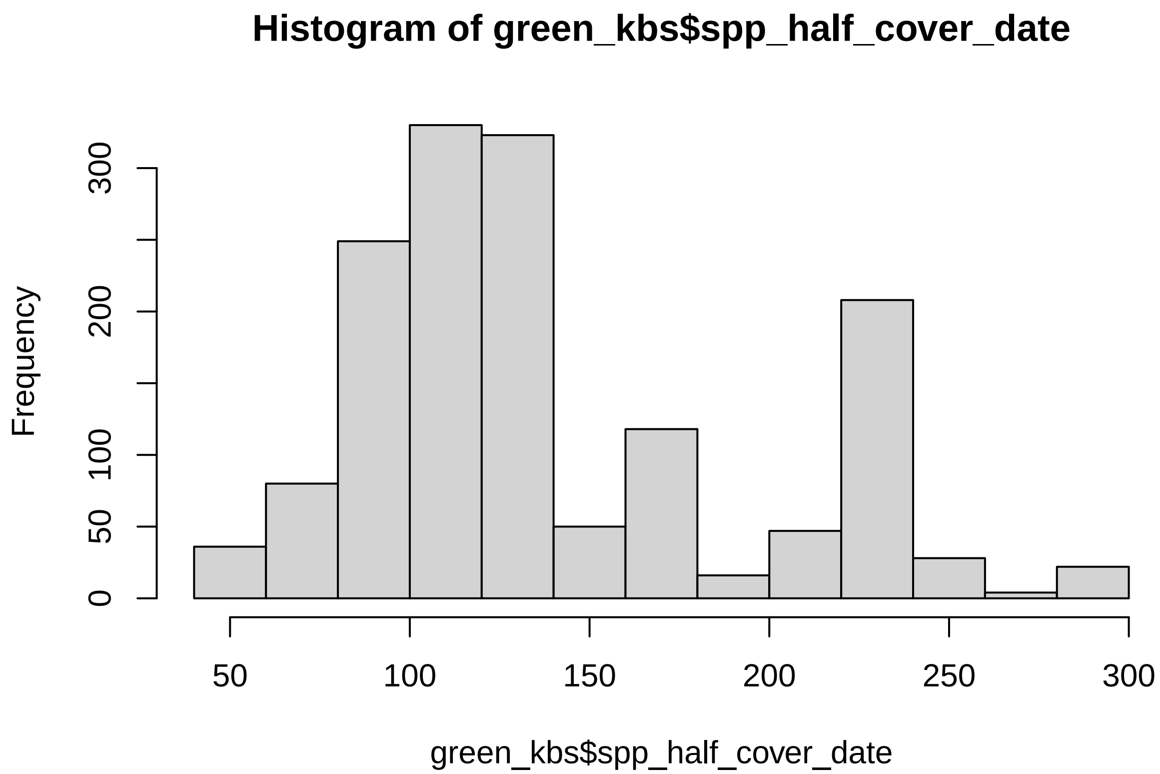
```
## [1] "warmed"  "ambient"
```

```r
# adding sequential year variable starting at 1: this is
# because 2016... are large numbers compare with other values
# in the dataset. We can always label axes with these real
# years.
greenup$year_factor[greenup$year == 2016] <- 1
greenup$year_factor[greenup$year == 2017] <- 2
greenup$year_factor[greenup$year == 2018] <- 3
greenup$year_factor[greenup$year == 2019] <- 4
greenup$year_factor[greenup$year == 2020] <- 5
greenup$year_factor[greenup$year == 2021] <- 6
greenup$year_factor <- as.factor(greenup$year_factor)  # having year as numerical was messing with some

greenupp$year_factor[greenupp$year == 2016] <- 1
greenupp$year_factor[greenupp$year == 2017] <- 2
greenupp$year_factor[greenupp$year == 2018] <- 3
greenupp$year_factor[greenupp$year == 2019] <- 4
greenupp$year_factor[greenupp$year == 2020] <- 5
greenupp$year_factor[greenupp$year == 2021] <- 6
greenupp$year_factor <- as.factor(greenupp$year_factor)

# create dataframes for kbs and umbs - remember that these
# contain species within plots
green_kbs <- subset(greenup, site == "kbs")
green_umbs <- subset(greenup, site == "umbs")

green_kbsp <- subset(greenupp, site == "kbs")
green_umbsp <- subset(greenupp, site == "umbs")
```

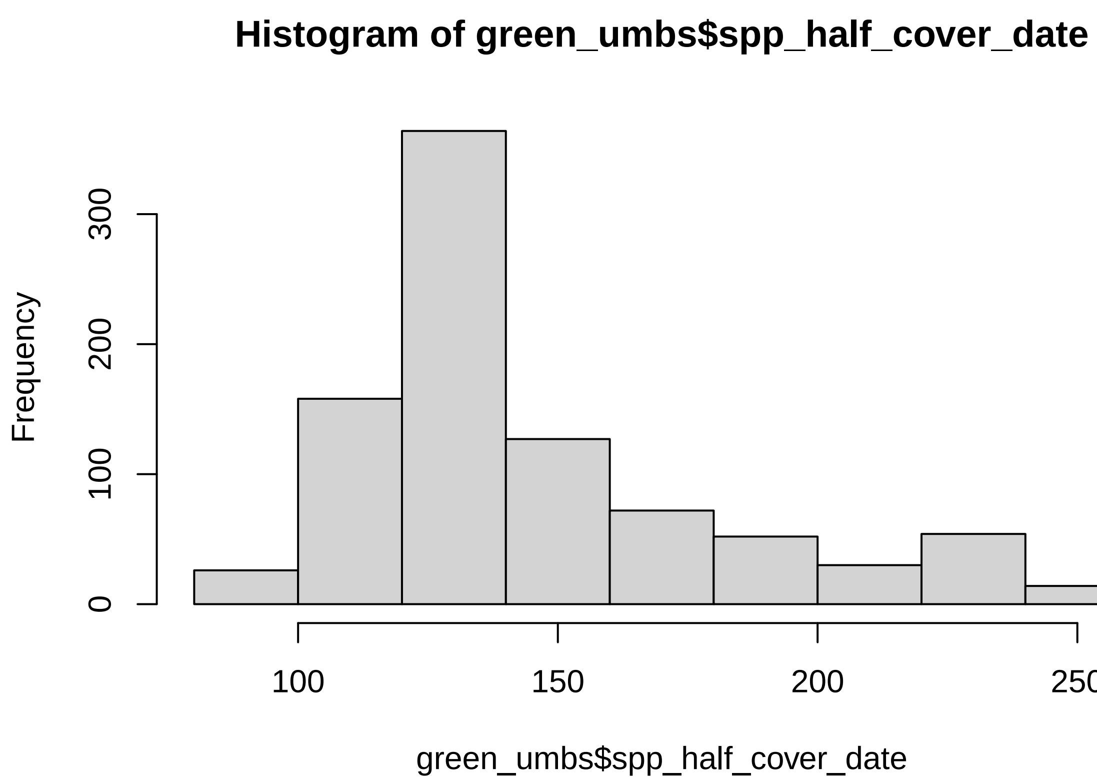
Data Exploration:

First, checking for normality in raw data. It's not going to tell you about normality once you fit a model to these data - that's when you really need to investigate the residuals.

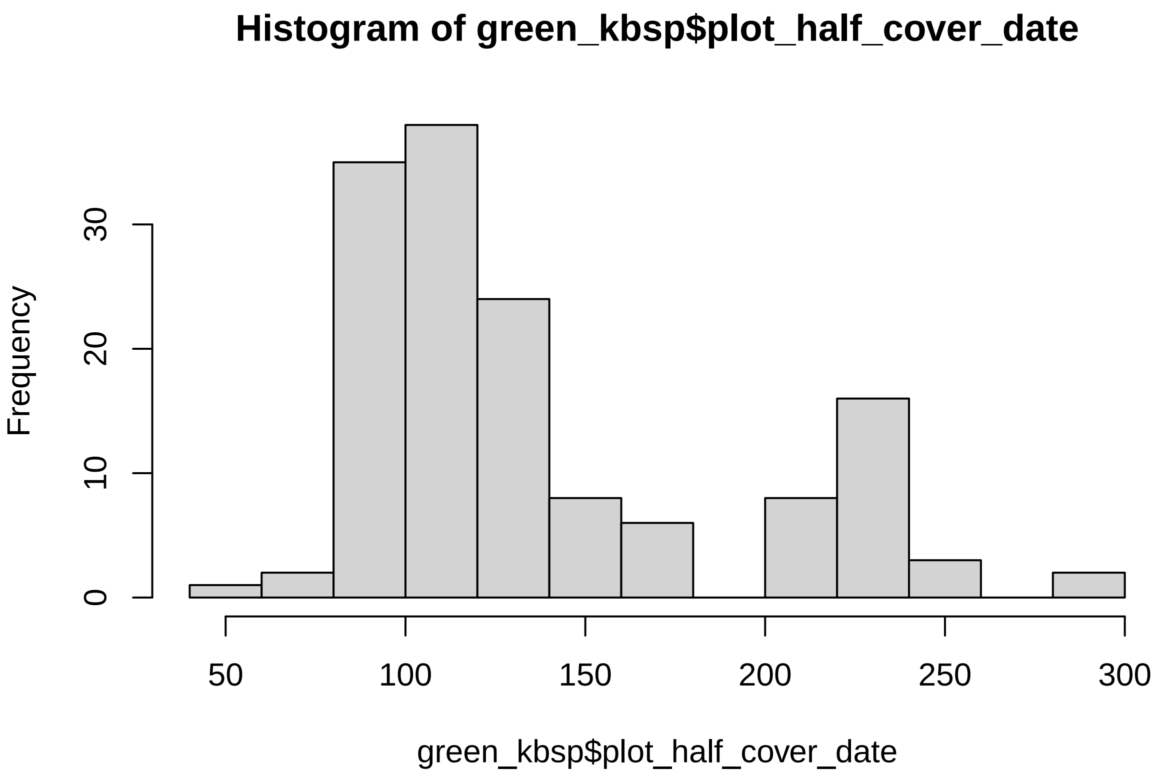
```r
# species level
hist(green_kbs$spp_half_cover_date)
```



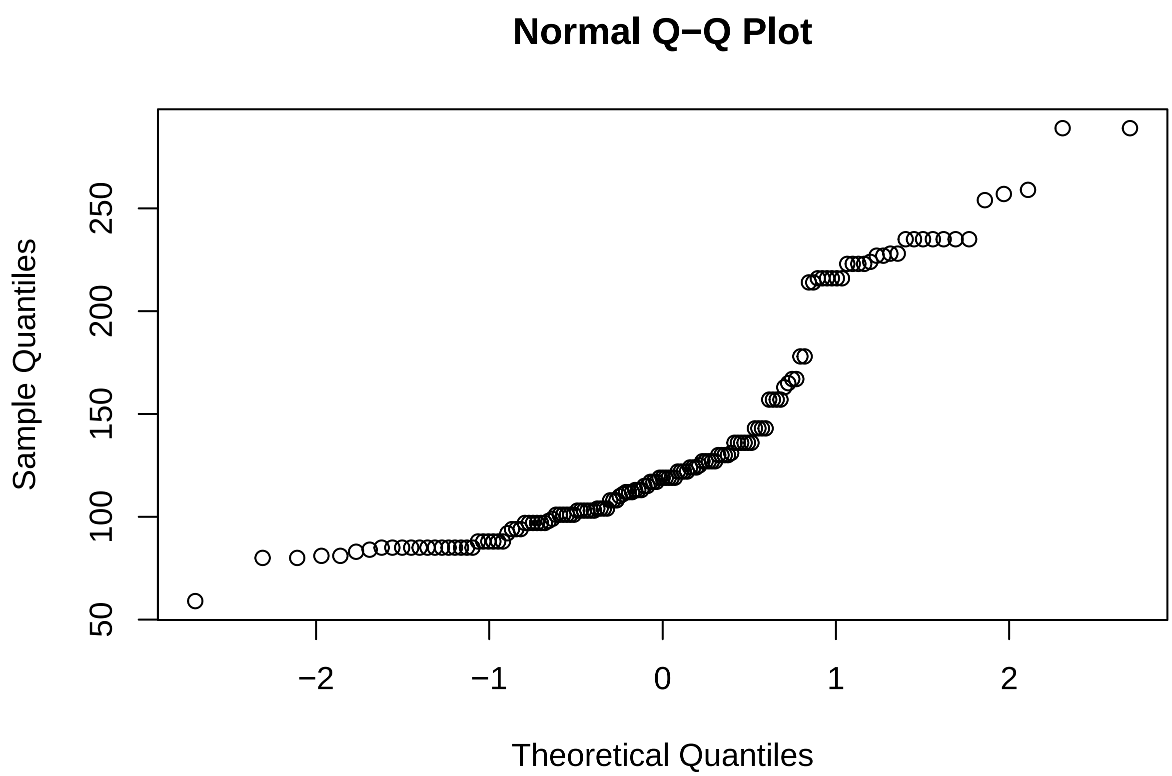

```r
hist(green_umbs$spp_half_cover_date)
```




```r
# plot level
hist(green_kbsp$plot_half_cover_date)
```




```
qqnorm(green_kbsp$plot_half_cover_date)
```

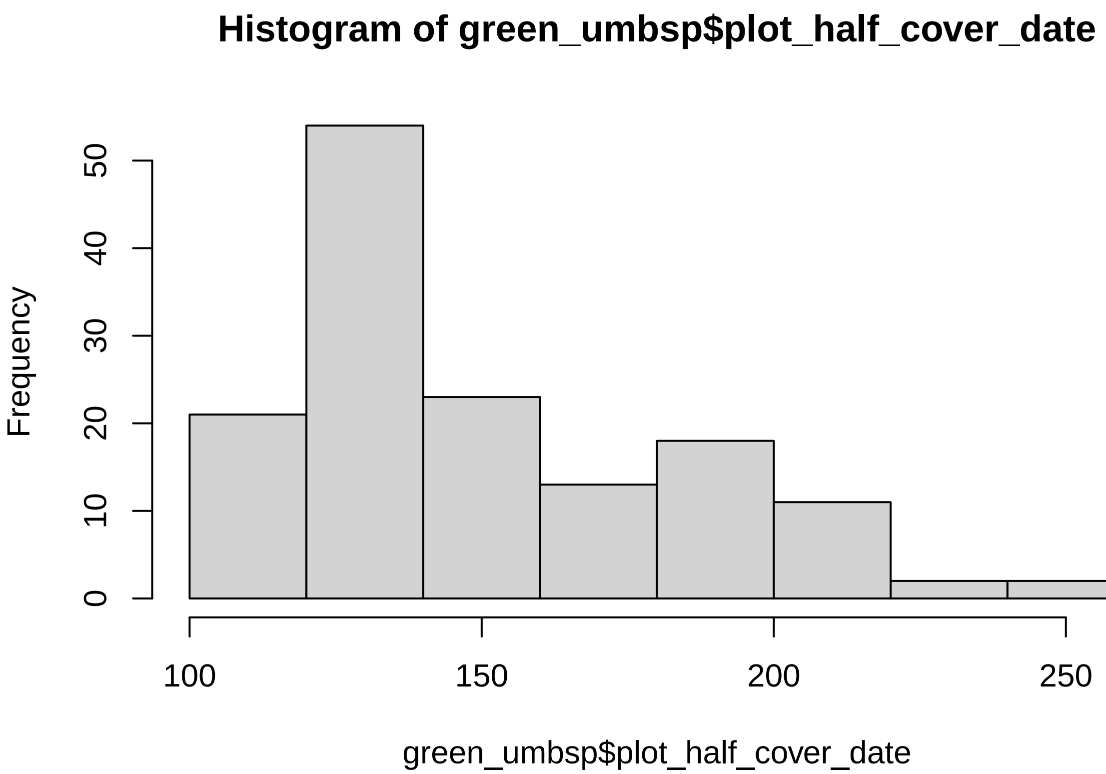



```
shapiro.test(green_kbsp$plot_half_cover_date)
```

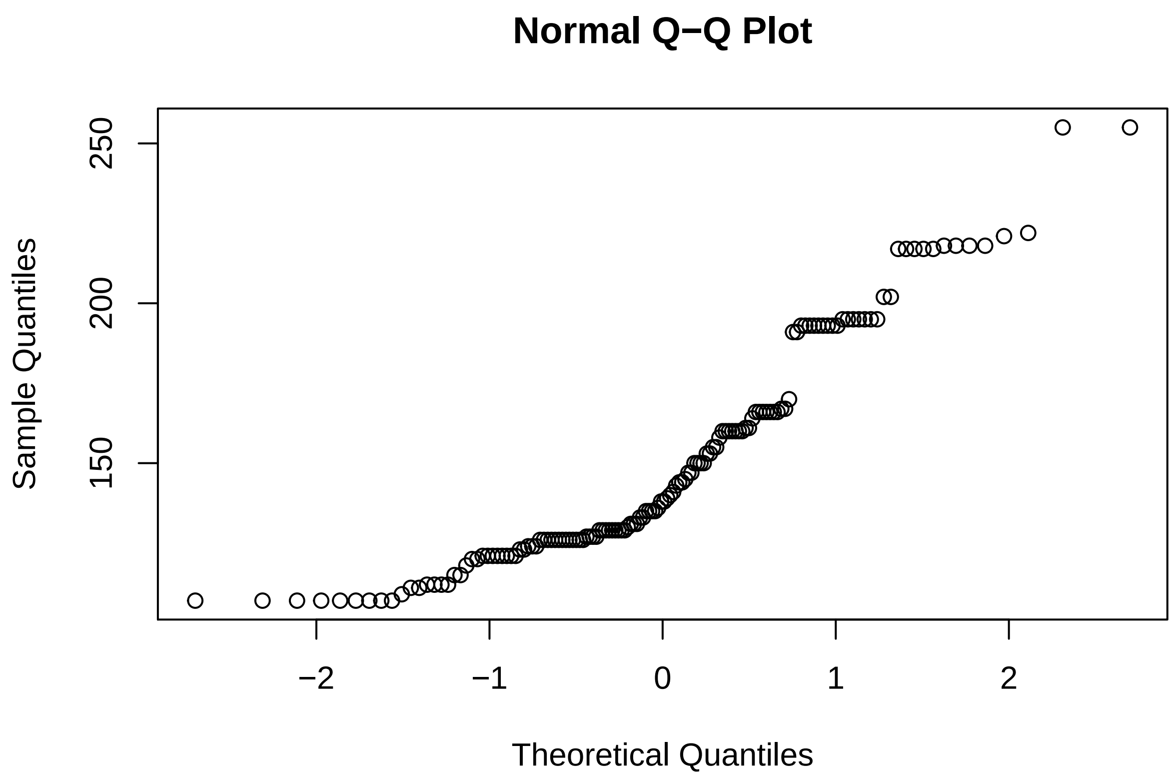
```
##
```

```
##  Shapiro-Wilk normality test
##
## data:  green_kbsp$plot_half_cover_date
## W = 0.84399, p-value = 5.136e-11
```

```r
hist(green_umbsp$plot_half_cover_date)
```



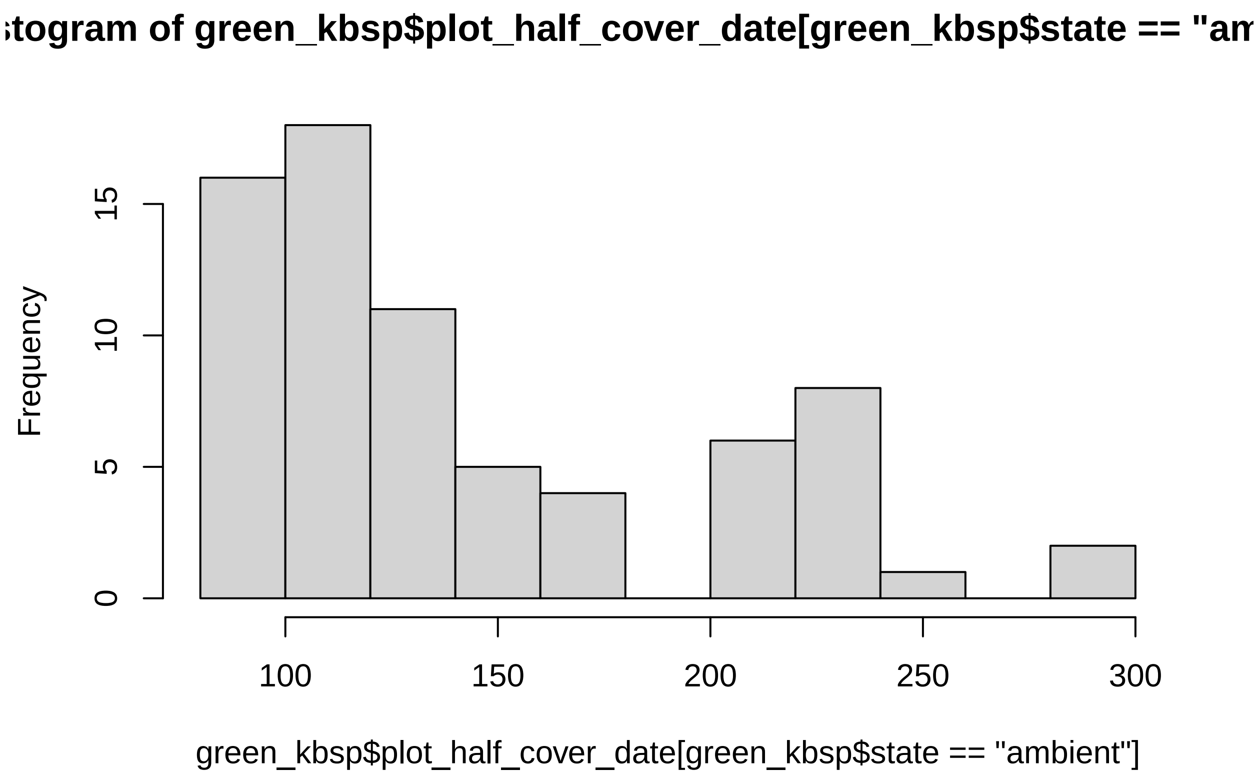

```r
qqnorm(green_umbsp$plot_half_cover_date)
```



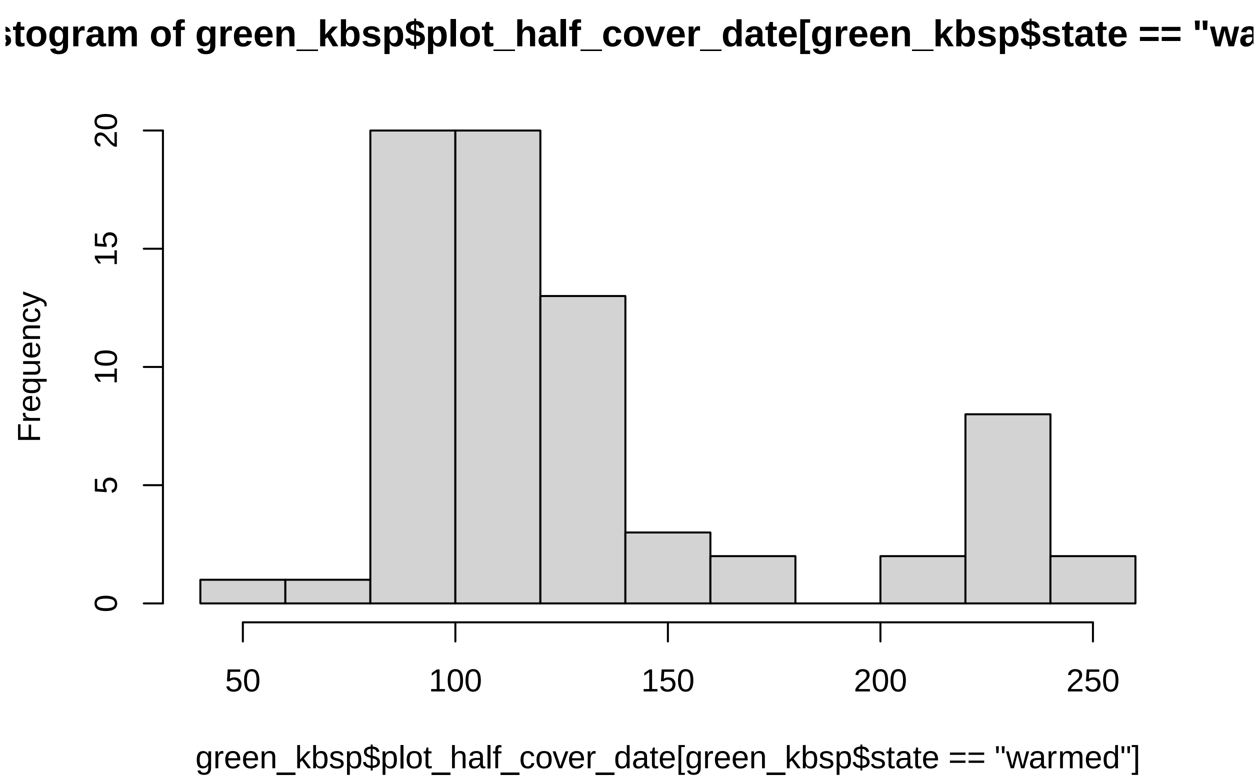

```
shapiro.test(green_umbsp$plot_half_cover_date)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  green_umbsp$plot_half_cover_date
## W = 0.89867, p-value = 1.874e-08
```

```
# histograms for each treatment separately - plot level
hist(green_kbsp$plot_half_cover_date[green_kbsp$state == "ambient"])
```

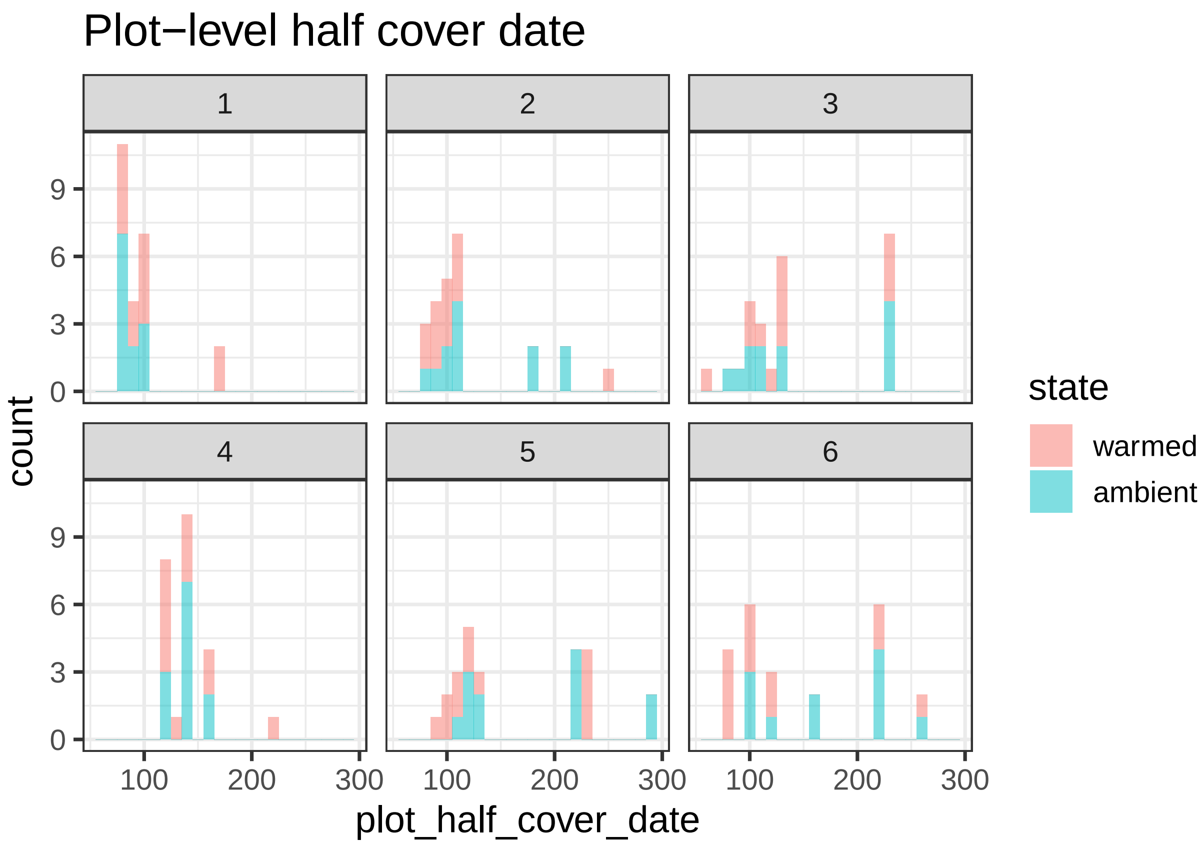



```
hist(green_kbsp$plot_half_cover_date[green_kbsp$state == "warmed"])
```

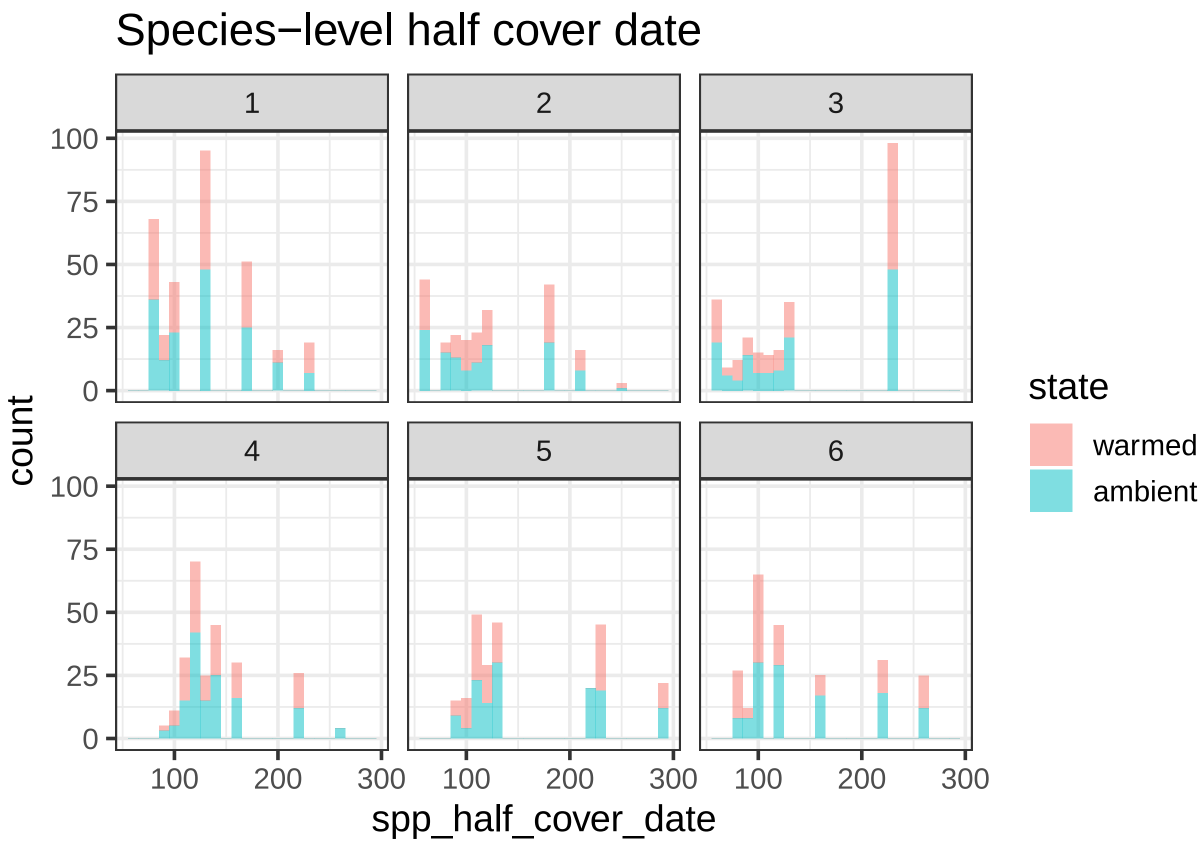



```
# histograms for each year - look at them together:
p1 <- ggplot(data = green_kbsp, aes(x = plot_half_cover_date,
    fill = state)) + geom_histogram(alpha = 0.5, binwidth = 10)
```

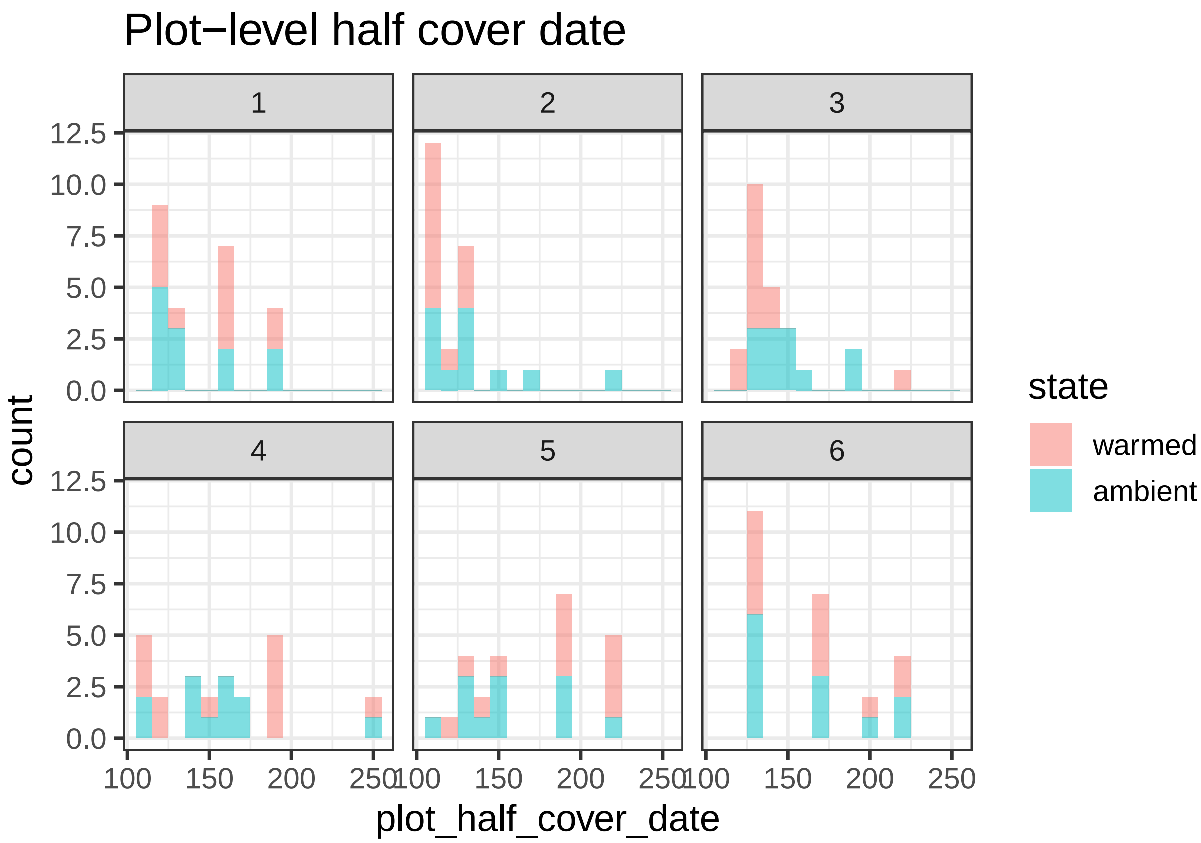
```r
p1 + facet_wrap(~year_factor) + labs(title = "Plot-level half cover date")
```



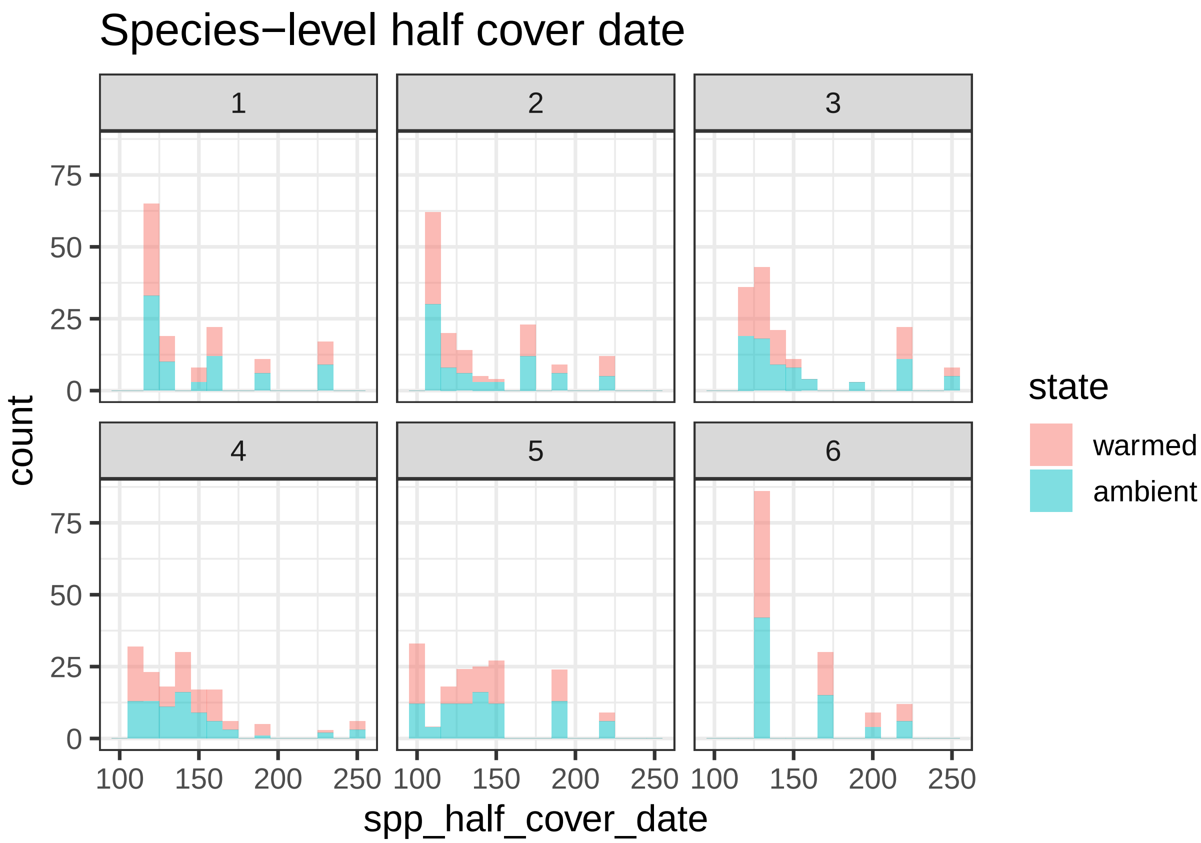

```r
p1.2 <- ggplot(data = green_kbs, aes(x = spp_half_cover_date,
    fill = state)) + geom_histogram(alpha = 0.5, binwidth = 10)
p1.2 + facet_wrap(~year_factor) + labs(title = "Species-level half cover date")
```



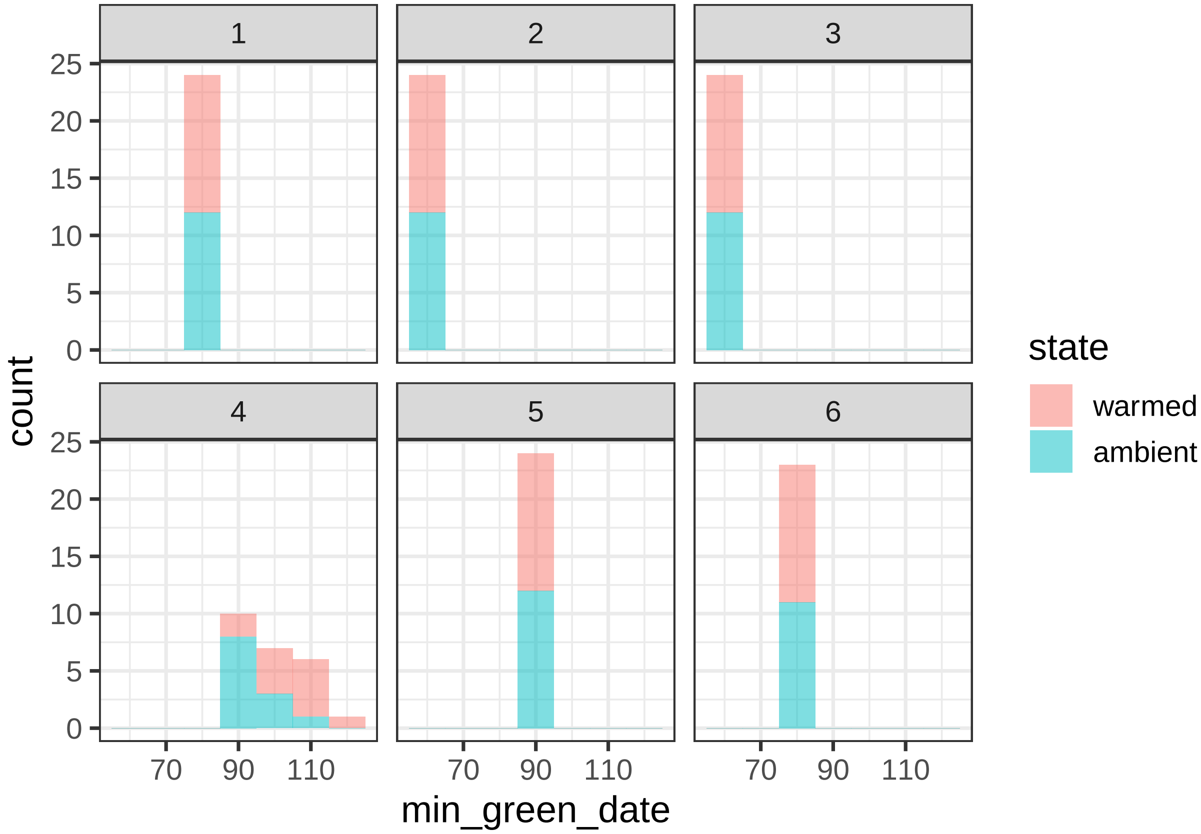

```r
p1u <- ggplot(data = green_umbsp, aes(x = plot_half_cover_date,
    fill = state)) + geom_histogram(alpha = 0.5, binwidth = 10)
p1u + facet_wrap(~year_factor) + labs(title = "Plot-level half cover date")
```



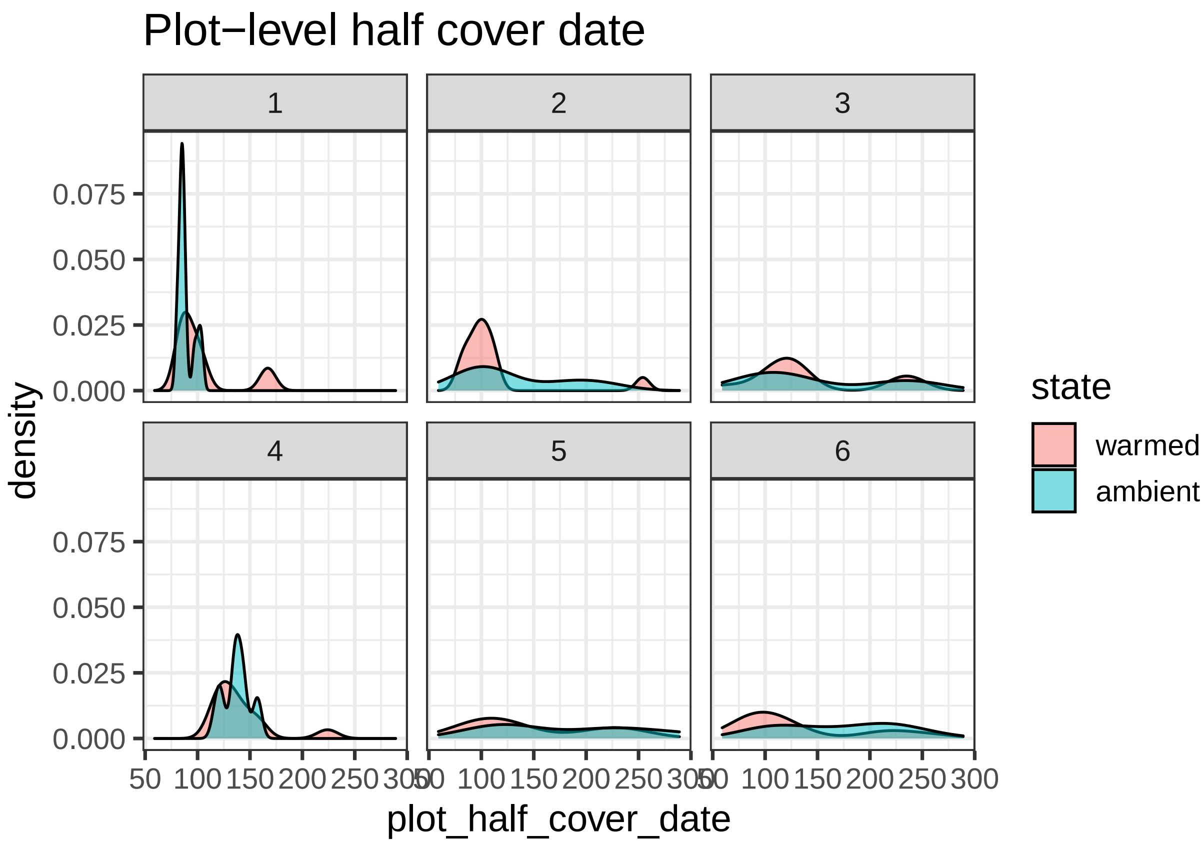

```r
p1.2u <- ggplot(data = green_umbs, aes(x = spp_half_cover_date,
    fill = state)) + geom_histogram(alpha = 0.5, binwidth = 10)
p1.2u + facet_wrap(~year_factor) + labs(title = "Species-level half cover date")
```



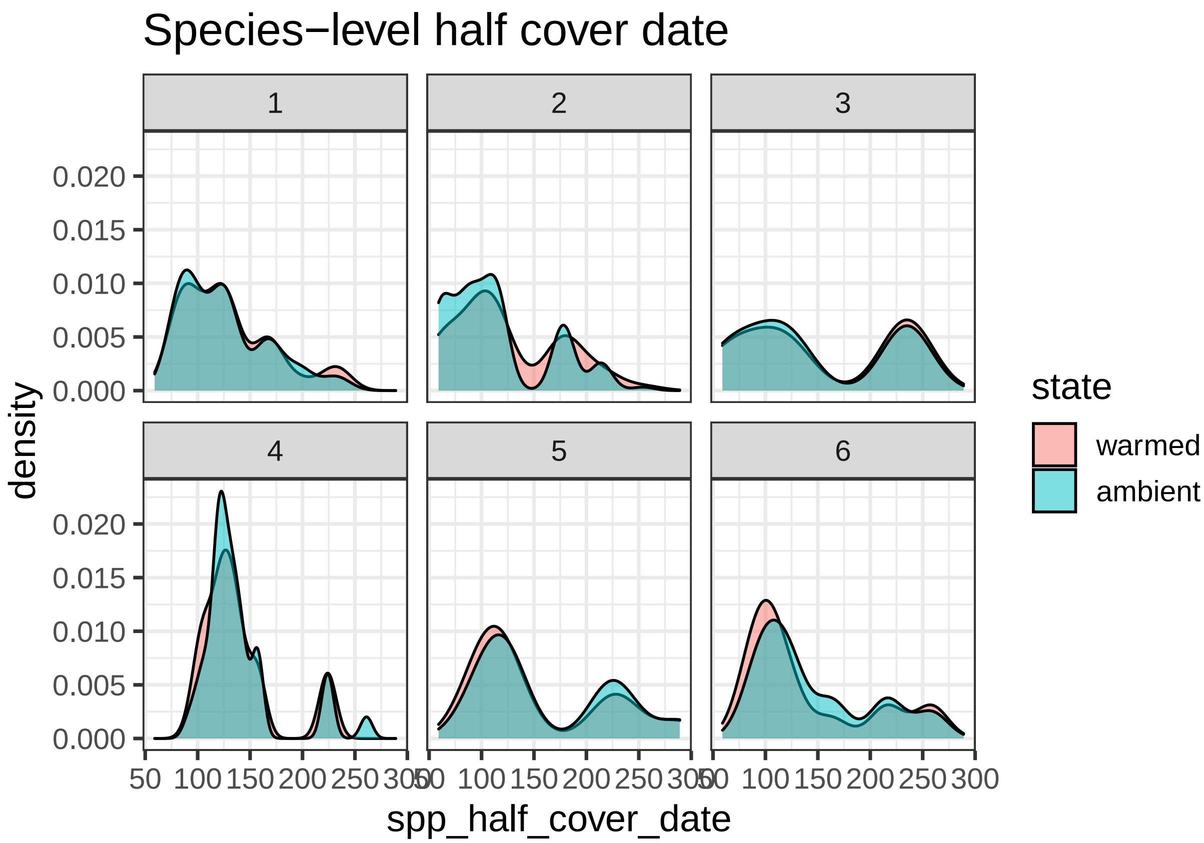

```r
# this will just show sampling date artifact
p2 <- ggplot(data = green_kbsp, aes(x = min_green_date, fill = state)) +
    geom_histogram(alpha = 0.5, binwidth = 10)
p2 + facet_wrap(~year_factor)
```



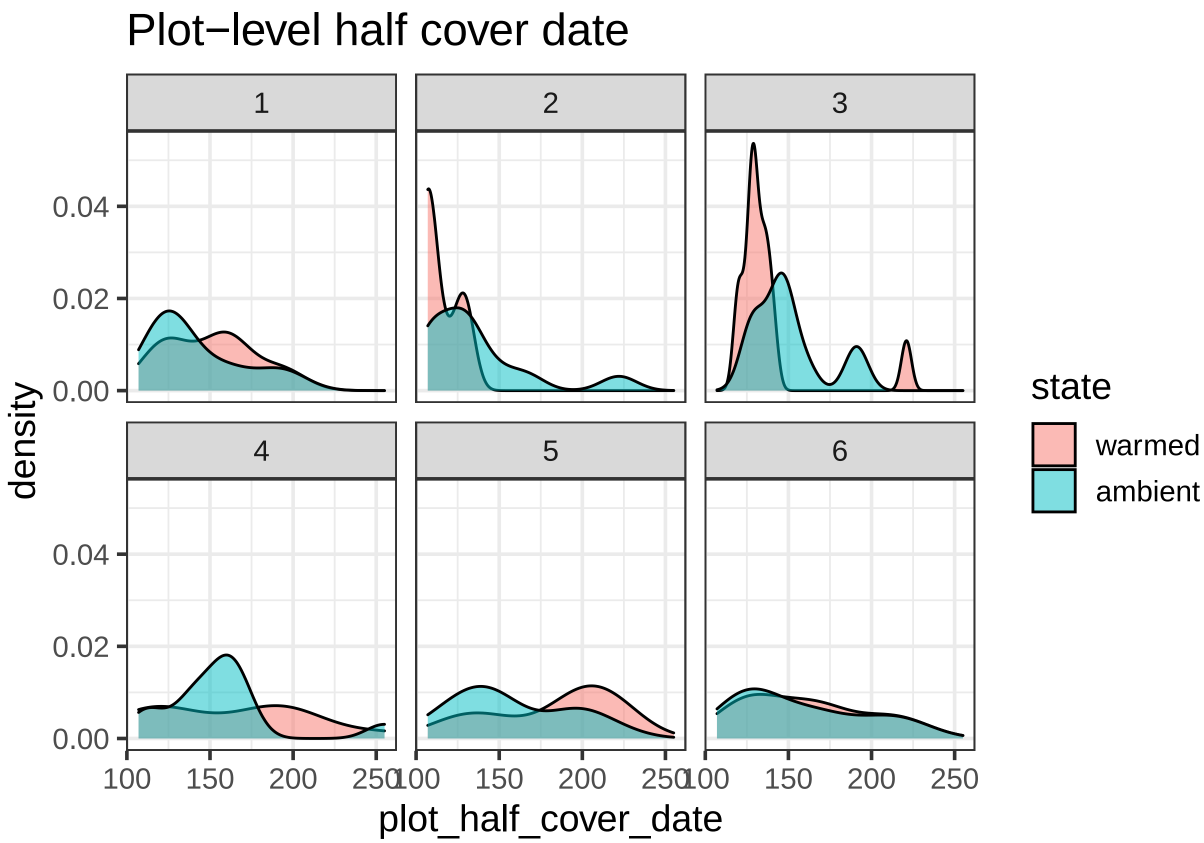

```r
# Density plot
p3 <- ggplot(data = green_kbsp, aes(x = plot_half_cover_date,
    fill = state)) + geom_density(alpha = 0.5)
p3 + facet_wrap(~year_factor) + labs(title = "Plot-level half cover date")
```



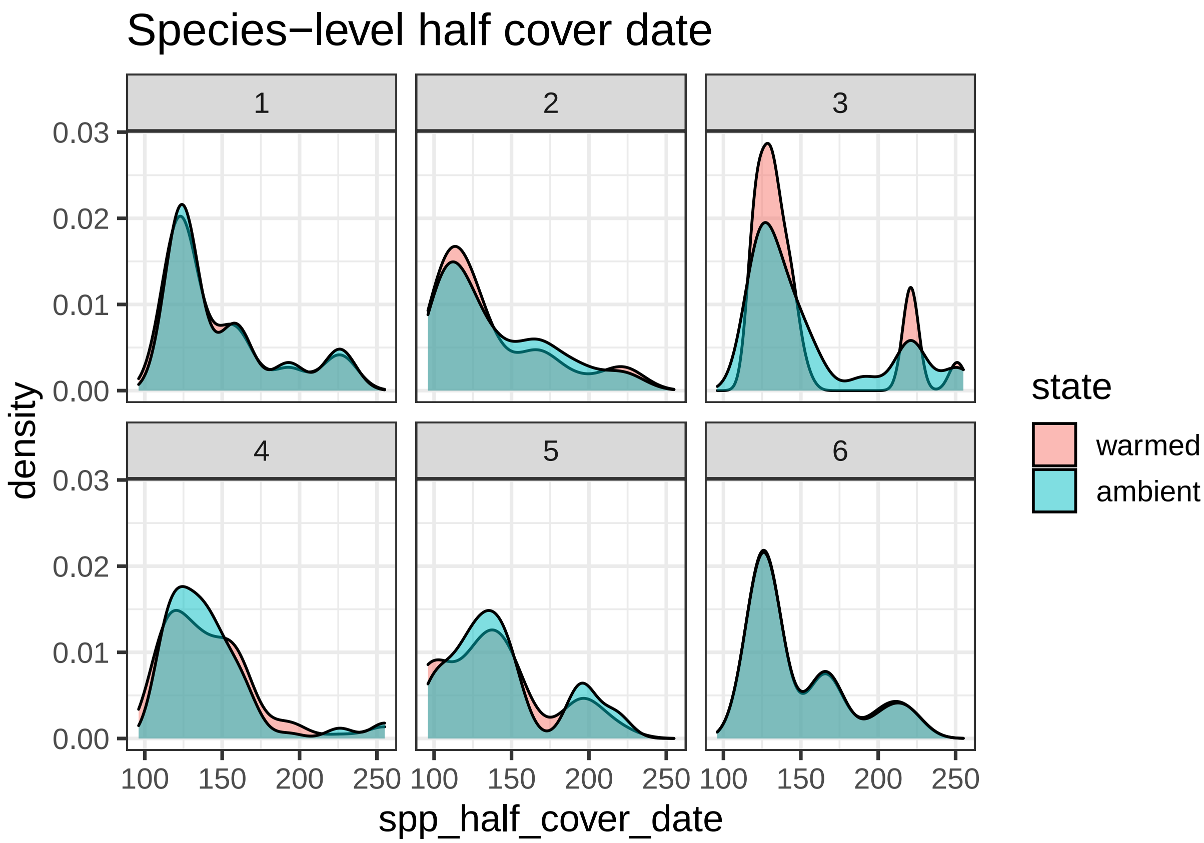

```
p3.2 <- ggplot(data = green_kbs, aes(x = spp_half_cover_date,
    fill = state)) + geom_density(alpha = 0.5)
p3.2 + facet_wrap(~year_factor) + labs(title = "Species-level half cover date")
```



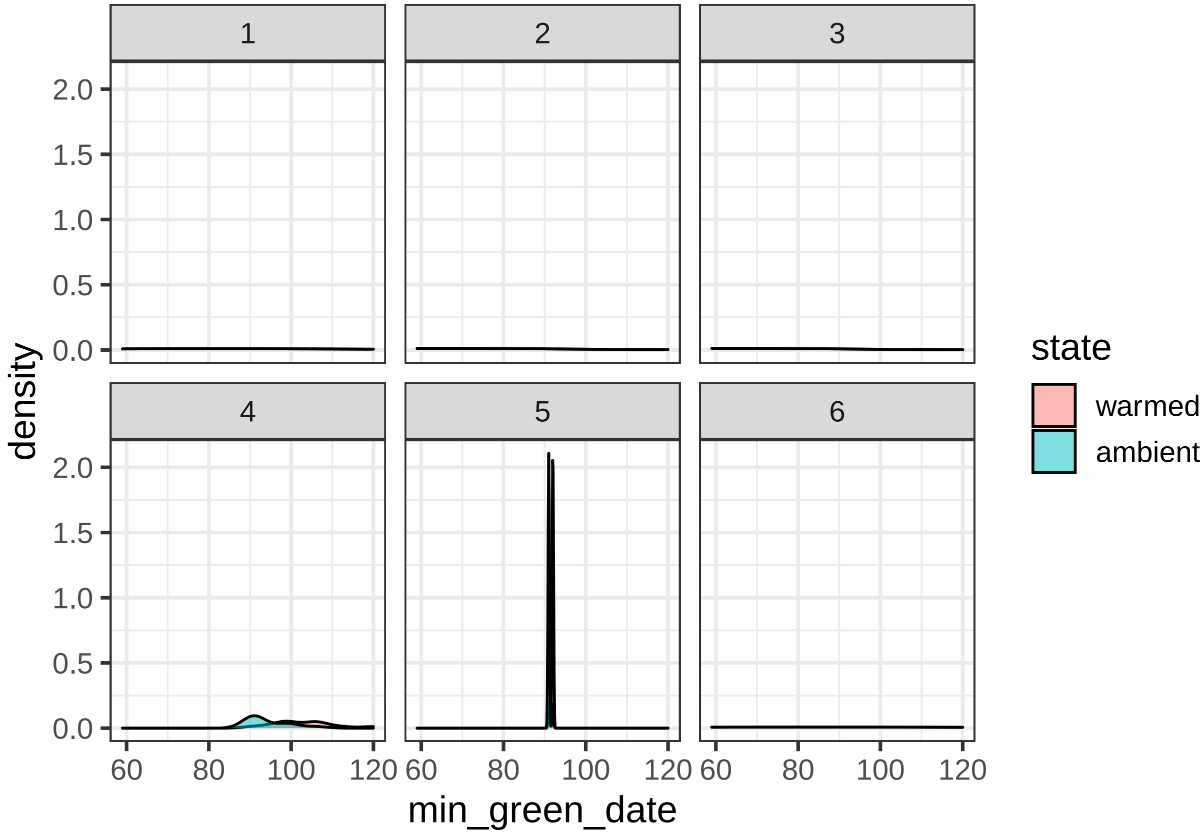

```
p3u <- ggplot(data = green_umbsp, aes(x = plot_half_cover_date,
    fill = state)) + geom_density(alpha = 0.5)
p3u + facet_wrap(~year_factor) + labs(title = "Plot-level half cover date")
```




```r
p3.2u <- ggplot(data = green_umbs, aes(x = spp_half_cover_date,
    fill = state)) + geom_density(alpha = 0.5)
p3.2u + facet_wrap(~year_factor) + labs(title = "Species-level half cover date")
```




```r
# this will just show sampling date artifact
p4 <- ggplot(data = green_kbsp, aes(x = min_green_date, fill = state)) +
    geom_density(alpha = 0.5)
p4 + facet_wrap(~year_factor)
```




```r
# code below won't run: Or try with tidyverse format
# green_kbsp.t<-as_tibble(green_kbsp) green_kbsp.t %>%
# gather(state, plot_half_cover_date, year_factor) %>%
# ggplot(aes(plot_half_cover_date, fill = state)) +
# geom_histogram() + facet_wrap(~year_factor)

# looks like the 225 spike is from 2018 and 2020 - what's
# going on here is that you are treating all species-plot
# records as independent observations, so the influence of
# species differences is likely coming through here.
kbs_2018 <- subset(green_kbs, year == 4)  # many records on 235
kbs_2020 <- subset(green_kbs, year == 6)  # records from 227 & 228
```

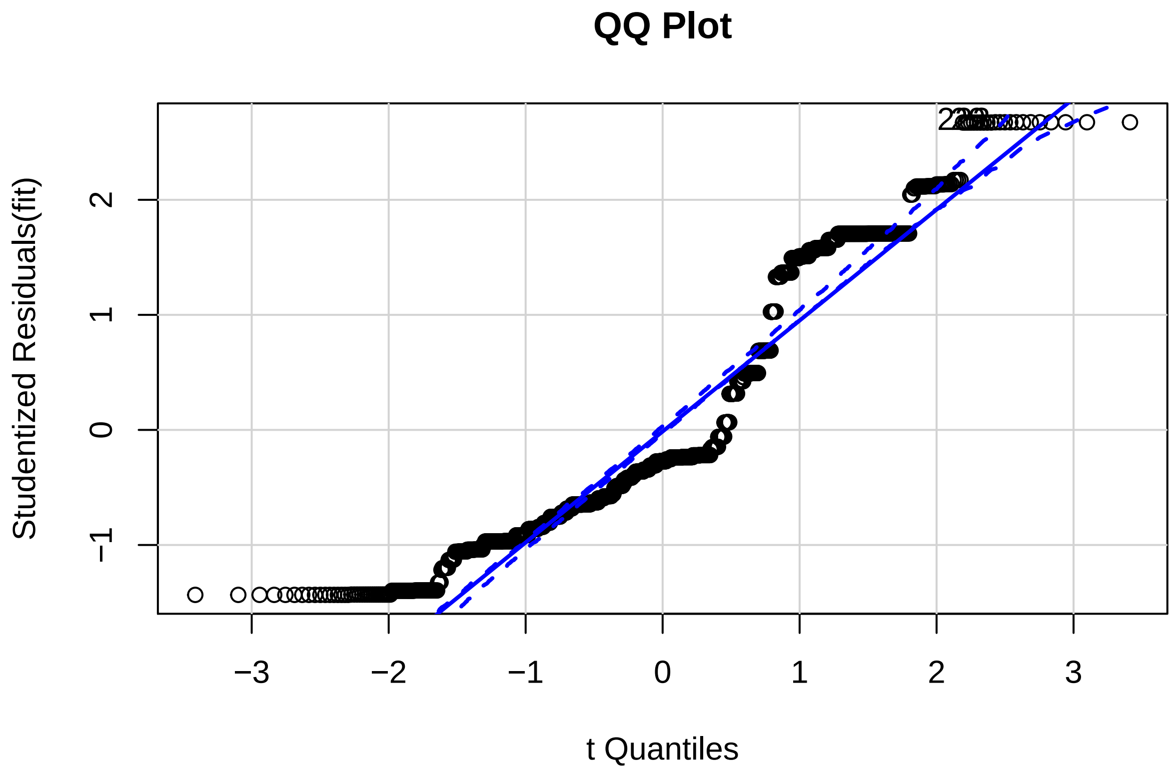
Leverage plots and detecting Outliers. https://www.statmethods.net/stats/rdiagnostics.html

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

```
# checking fit for date as a function of state and species -
# bringing in species here makes it obvious that that is
# explaining some of the variation compared with the
# state-only model you had previously.

# species-level data KBS State-only model
fit <- lm(spp_half_cover_date ~ state, data = green_kbs)
outlierTest(fit)  # no outliers
```

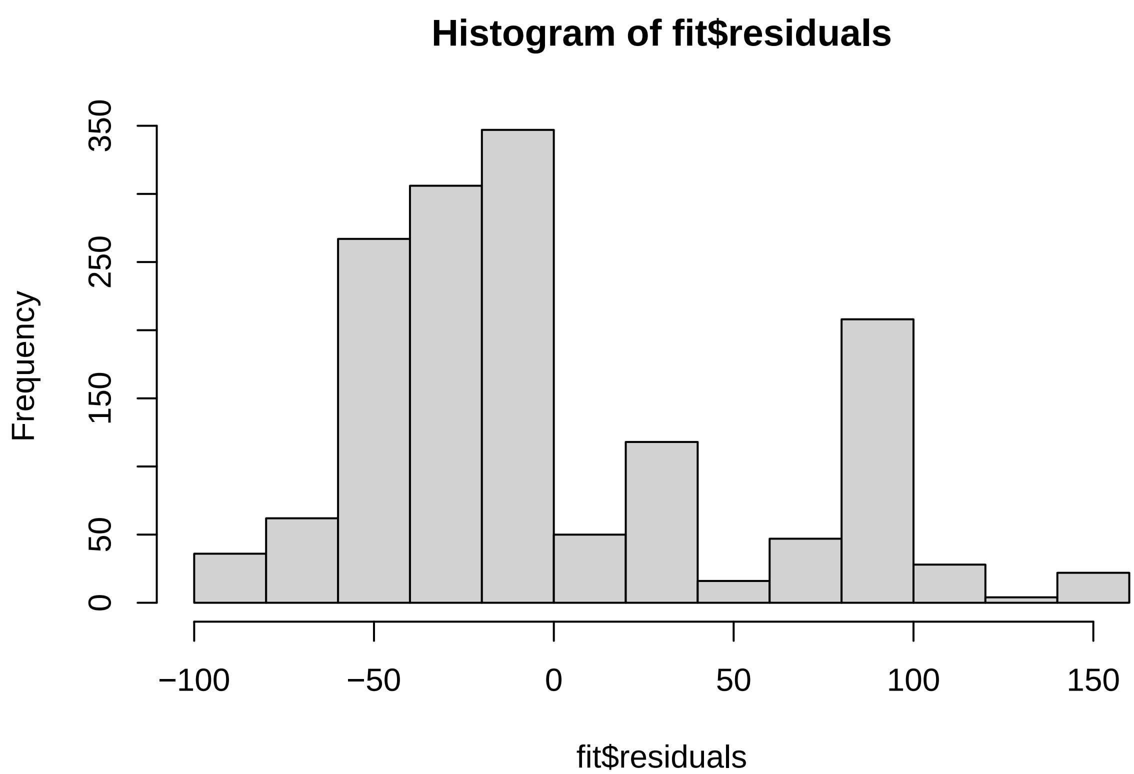
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##    rstudent unadjusted p-value Bonferroni p
## 29 2.673942          0.0075775           NA
```

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

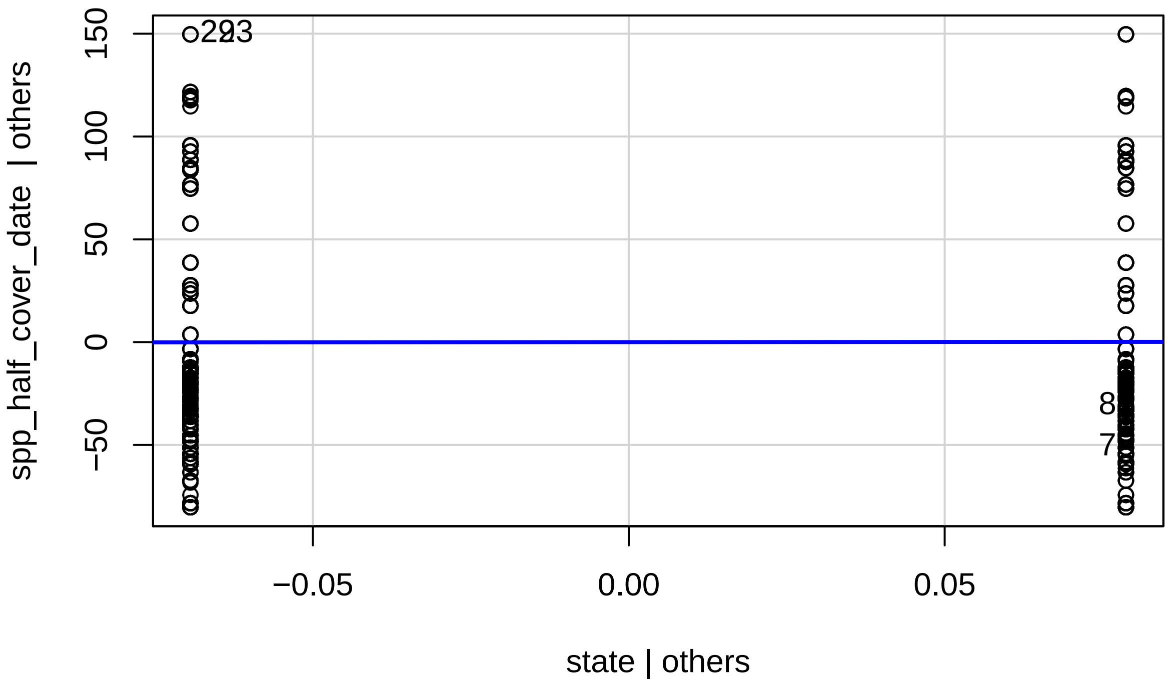



```
## 29 223
## 29 195
```

```
hist(fit$residuals)
```



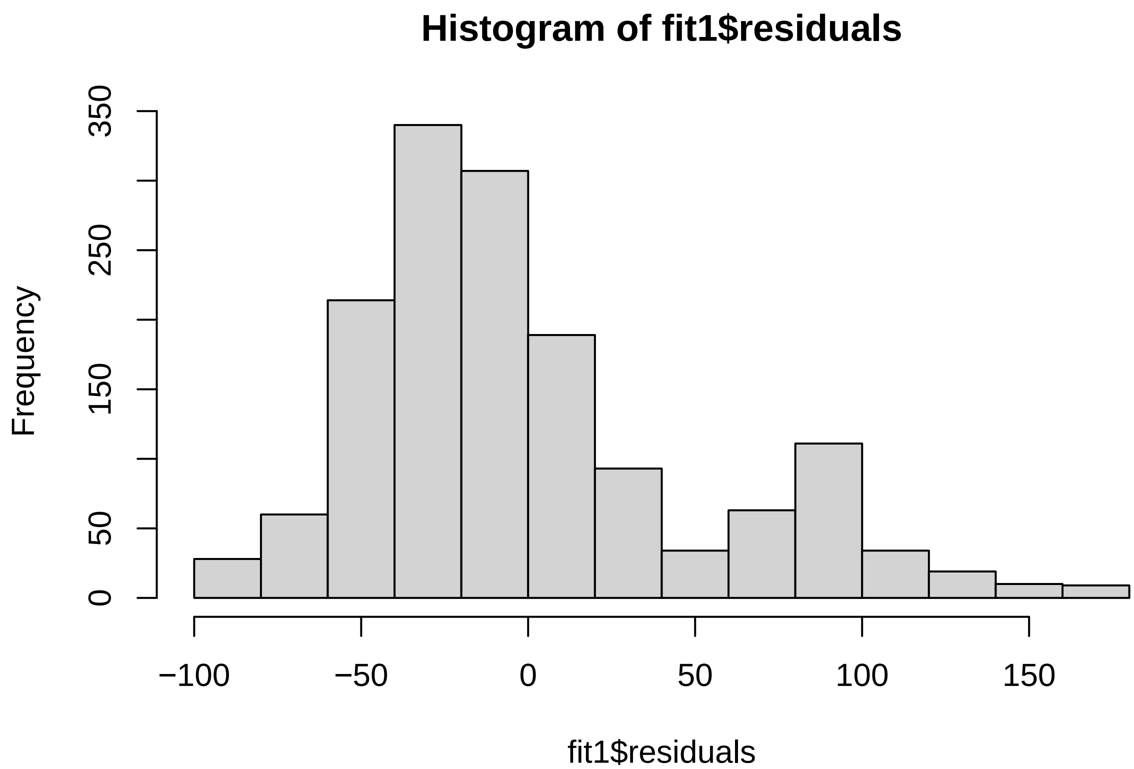
```r
leveragePlots(fit)
```



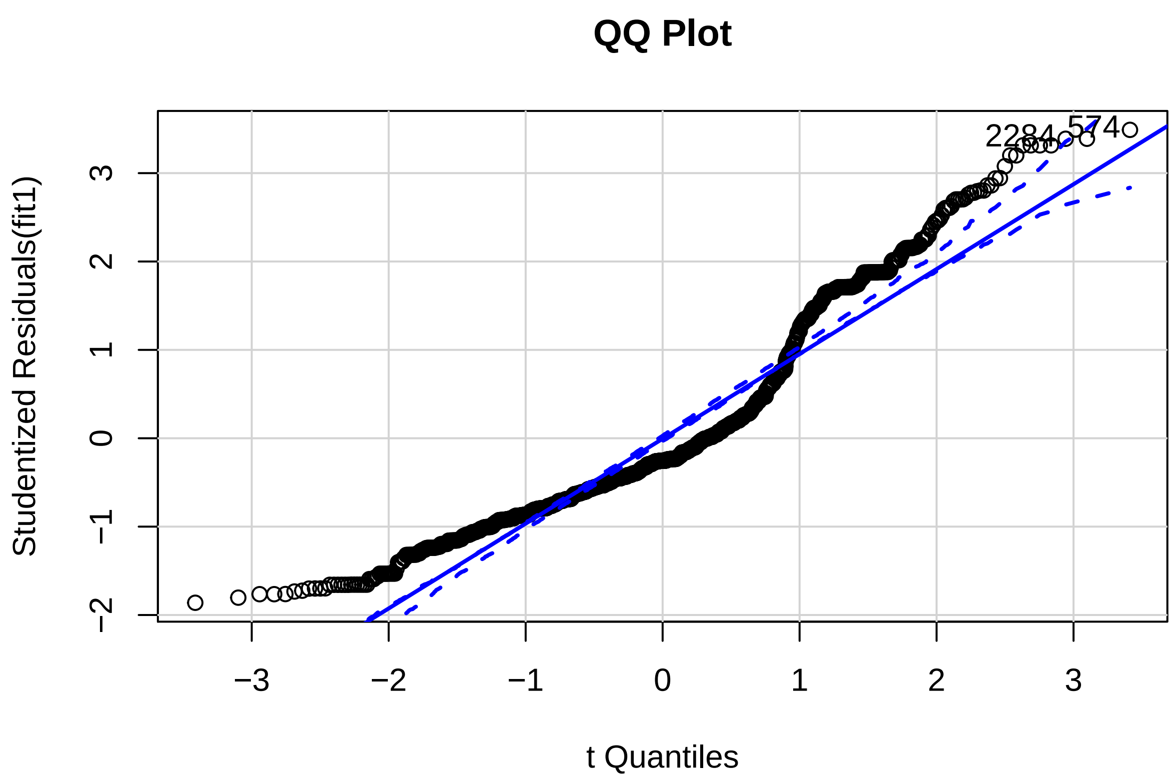

```r
# KBS State and species model
fit1 <- lm(spp_half_cover_date ~ state + species, data = green_kbs)
outlierTest(fit1)  # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##     rstudent unadjusted p-value Bonferroni p
## 574 3.489515         0.00049802      0.75251
```

```r
hist(fit1$residuals)
```

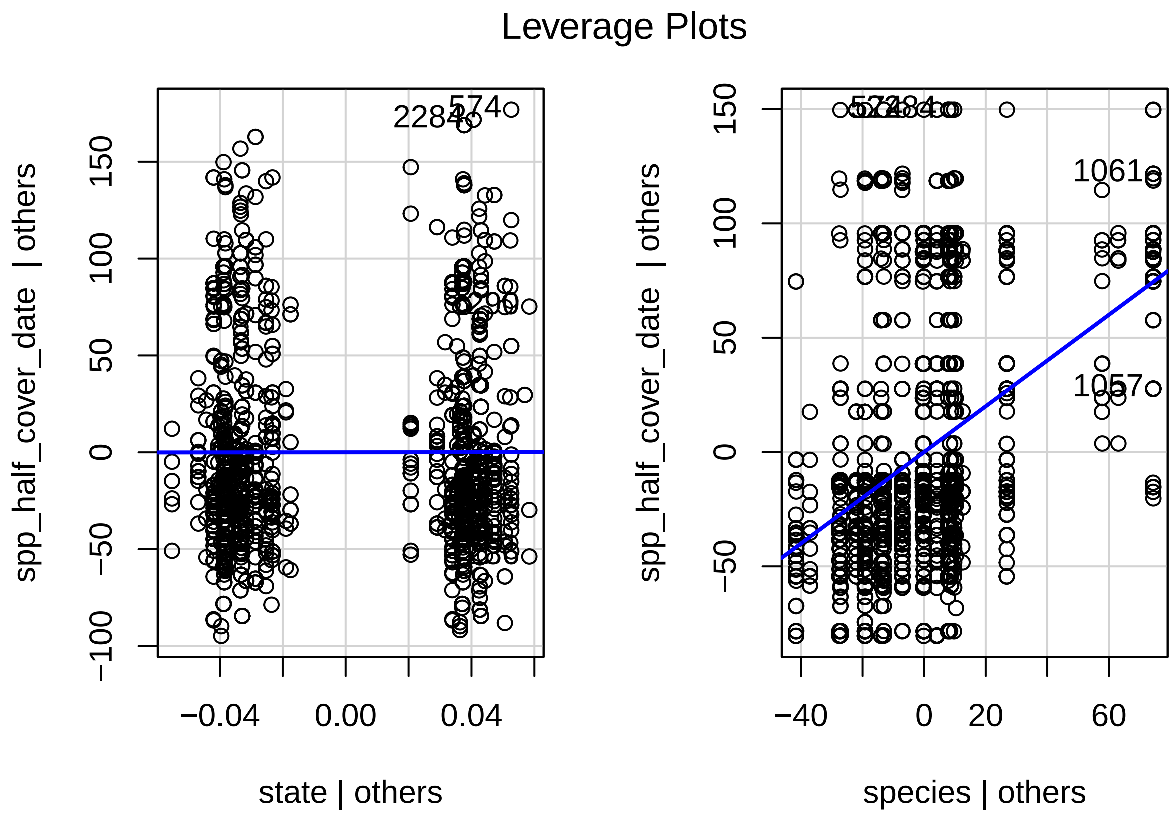



```r
qqPlot(fit1, main = "QQ Plot")
```




```
##  574 2284
##  345 1387
```

```r
leveragePlots(fit1)
```



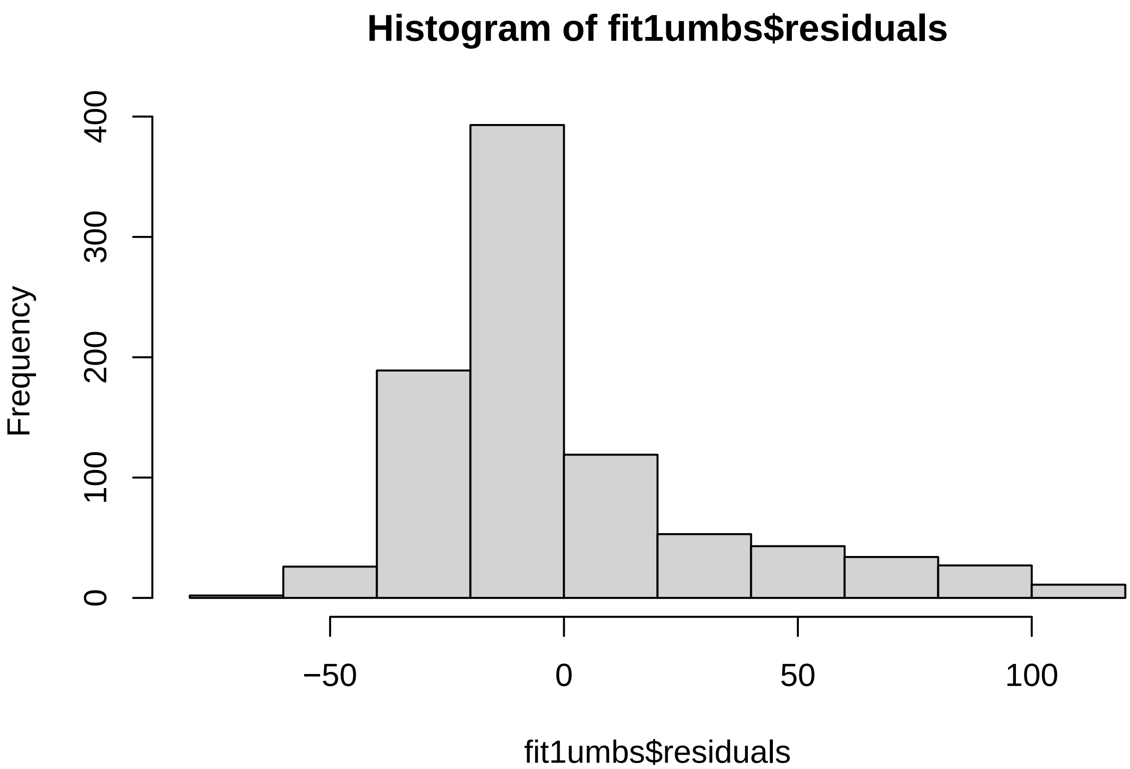

```r
ols_test_normality(fit1)  # p < 0.05 for all, so data is normal (I think)
```

```
## 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              0.9143         0.0000
## Kolmogorov-Smirnov        0.1372         0.0000
## Cramer-von Mises        149.3847         0.0000
## Anderson-Darling         48.7735         0.0000
## -----------------------------------------------
```

```r
# UMBS State and species model
fit1umbs <- lm(spp_half_cover_date ~ state + species, data = green_umbs)
outlierTest(fit1umbs)  # no outliers
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 2026 3.725776         0.00020715      0.18581
```

```r
hist(fit1umbs$residuals)
```



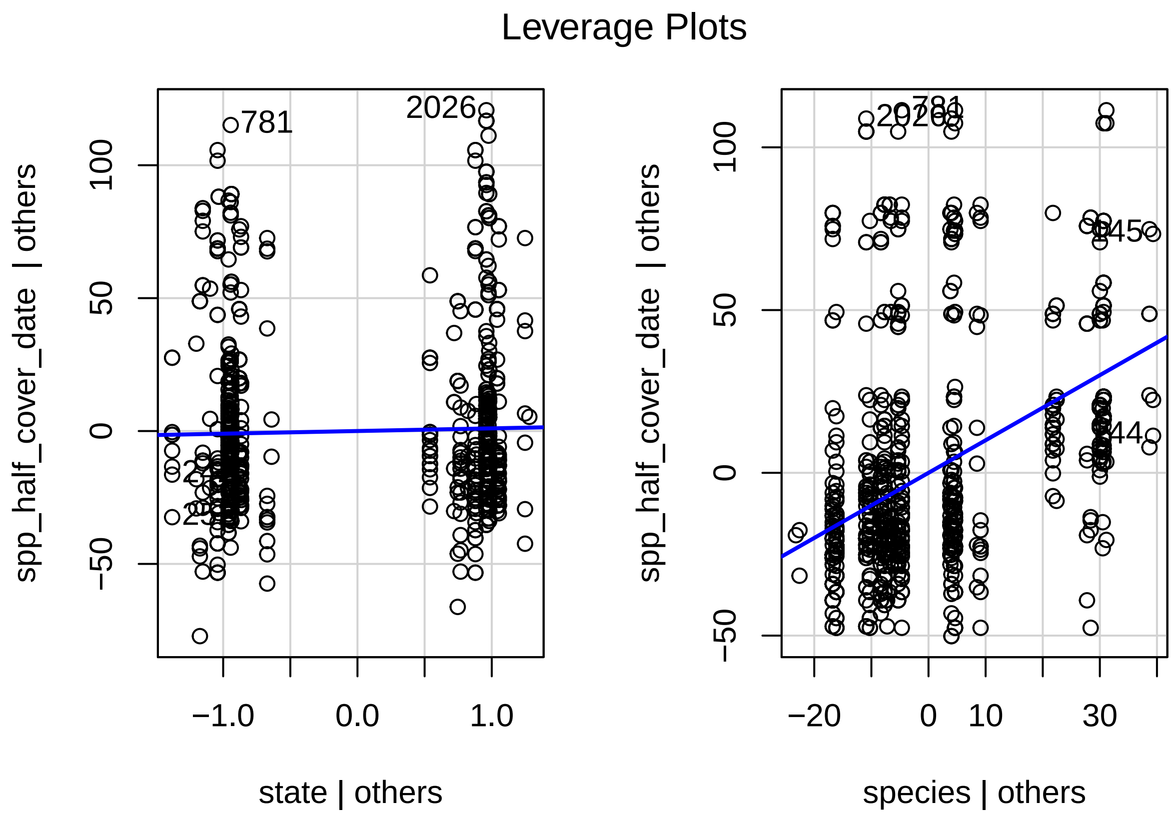

```
qqPlot(fit1umbs, main = "QQ Plot")
```

```
## Warning in rlm.default(x, y, weights, method = method, wt.method = wt.method, :
## 'rlm' failed to converge in 20 steps
```


```
##  781 2026
```

```
## 320 788
```

```r
leveragePlots(fit1umbs)
```



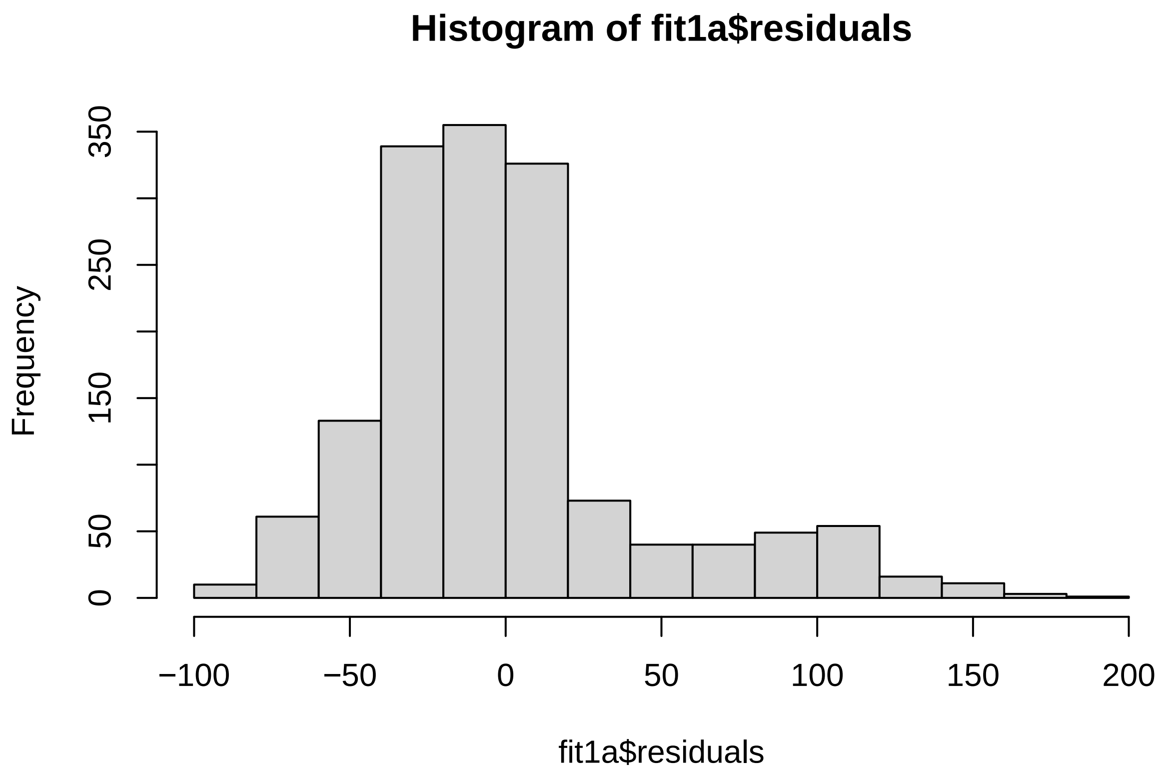

```r
ols_test_normality(fit1umbs)  # p < 0.05 for all, so data is normal (I think)
```

```
## 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              0.8553         0.0000
## Kolmogorov-Smirnov        0.1861         0.0000
## Cramer-von Mises        104.1103         0.0000
## Anderson-Darling         47.4699         0.0000
## -----------------------------------------------
```

```r
fit1a <- lm(min_green_date ~ state + species, data = green_kbs)
outlierTest(fit1a)  # no outliers
```

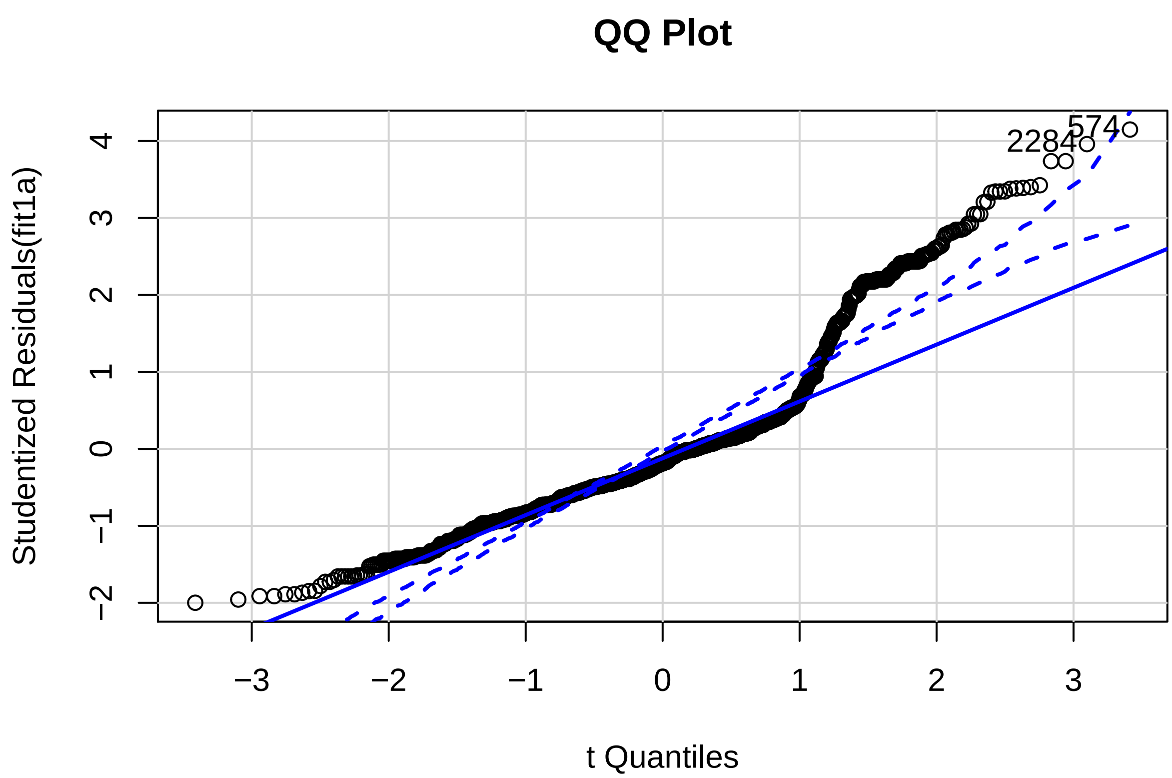
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##     rstudent unadjusted p-value Bonferroni p
## 574 4.148749         3.5322e-05     0.053372
```

```r
hist(fit1a$residuals)
```




```r
qqPlot(fit1a, main = "QQ Plot")
```

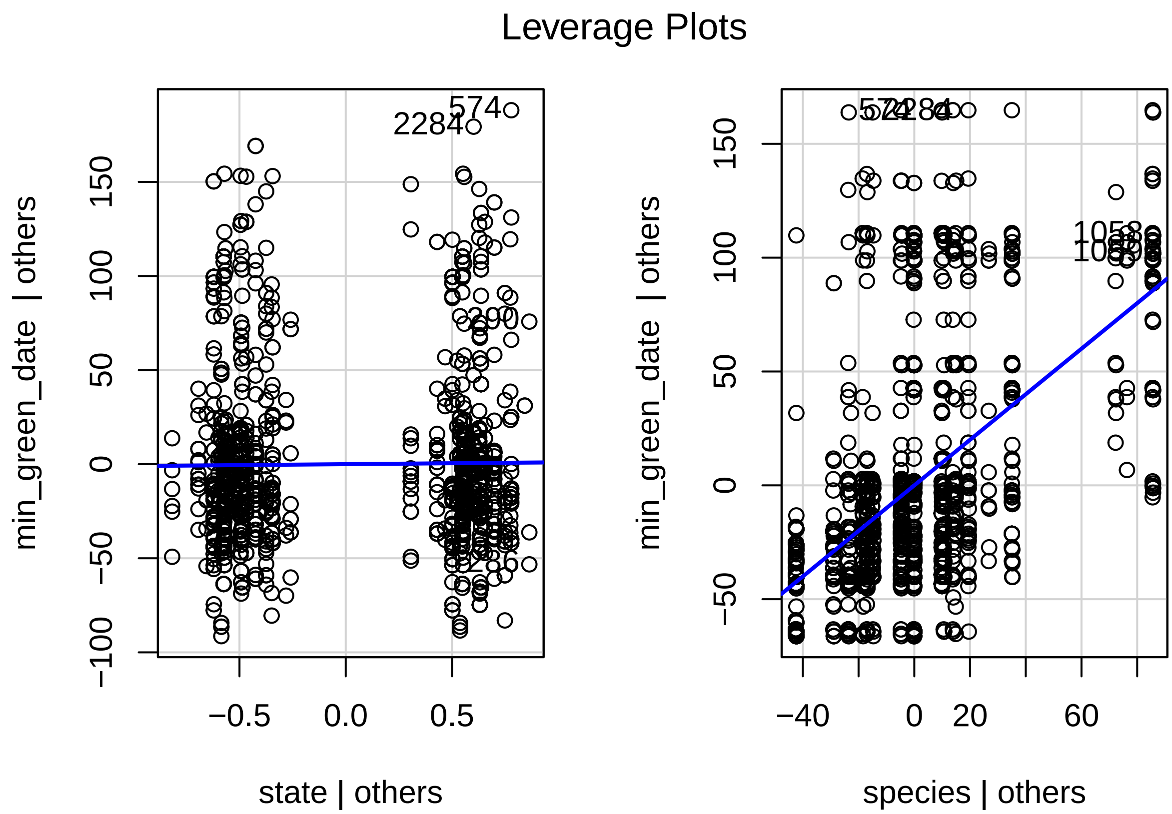
```
## Warning in rlm.default(x, y, weights, method = method, wt.method = wt.method, :
## 'rlm' failed to converge in 20 steps
```



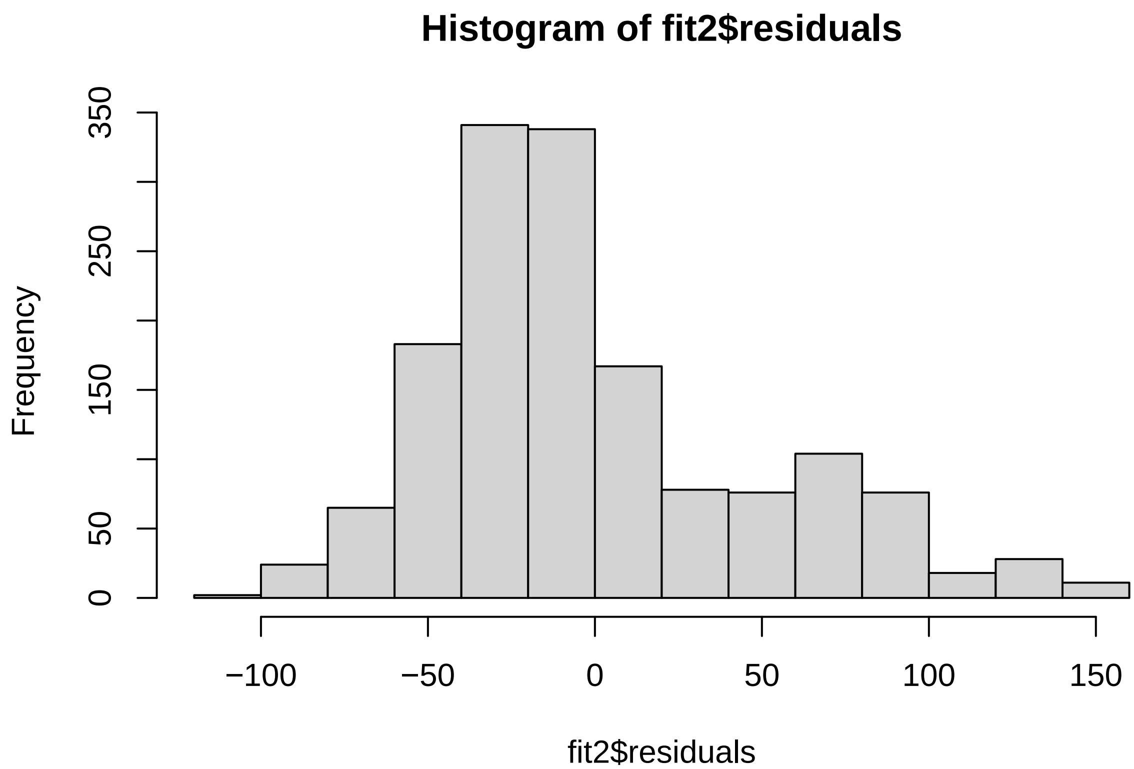

```
##  574 2284
```

```
##   345 1387
```

```r
leveragePlots(fit1a)
```



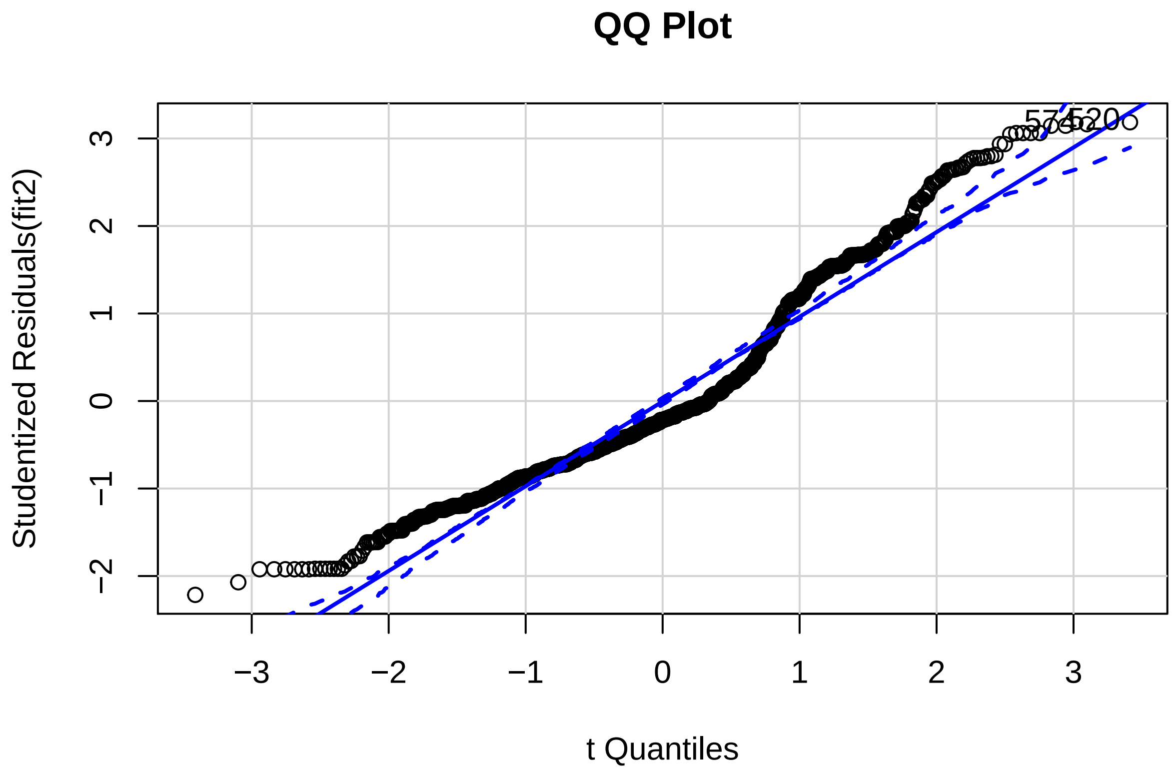

```r
# checking fit for date as a function of state and year
fit2 <- lm(spp_half_cover_date ~ state + species + year_factor,
    data = green_kbs)
hist(fit2$residuals)
```




```
outlierTest(fit2)  # no outliers
```

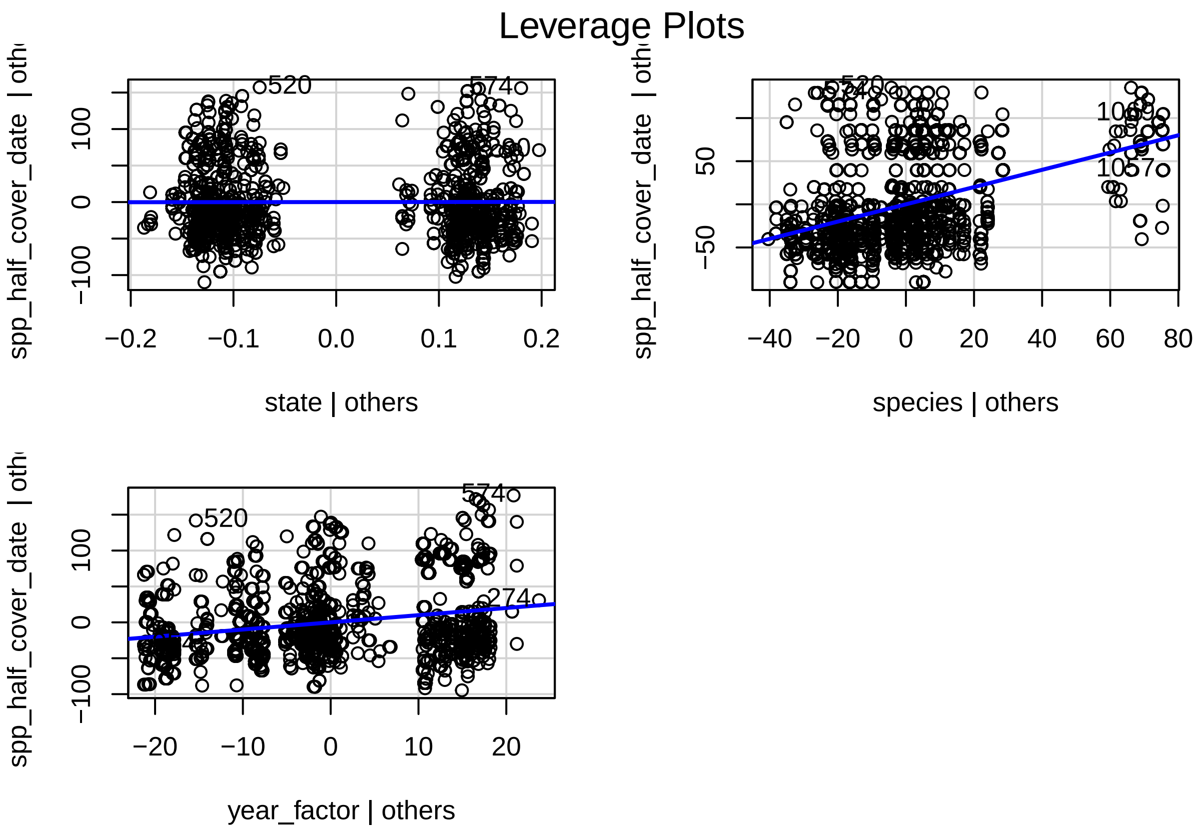
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##     rstudent unadjusted p-value Bonferroni p
## 520 3.185508          0.0014751           NA
```

```
qqPlot(fit2, main = "QQ Plot")
```




```
## 520 574
## 327 345
```

```r
leveragePlots(fit2)
```



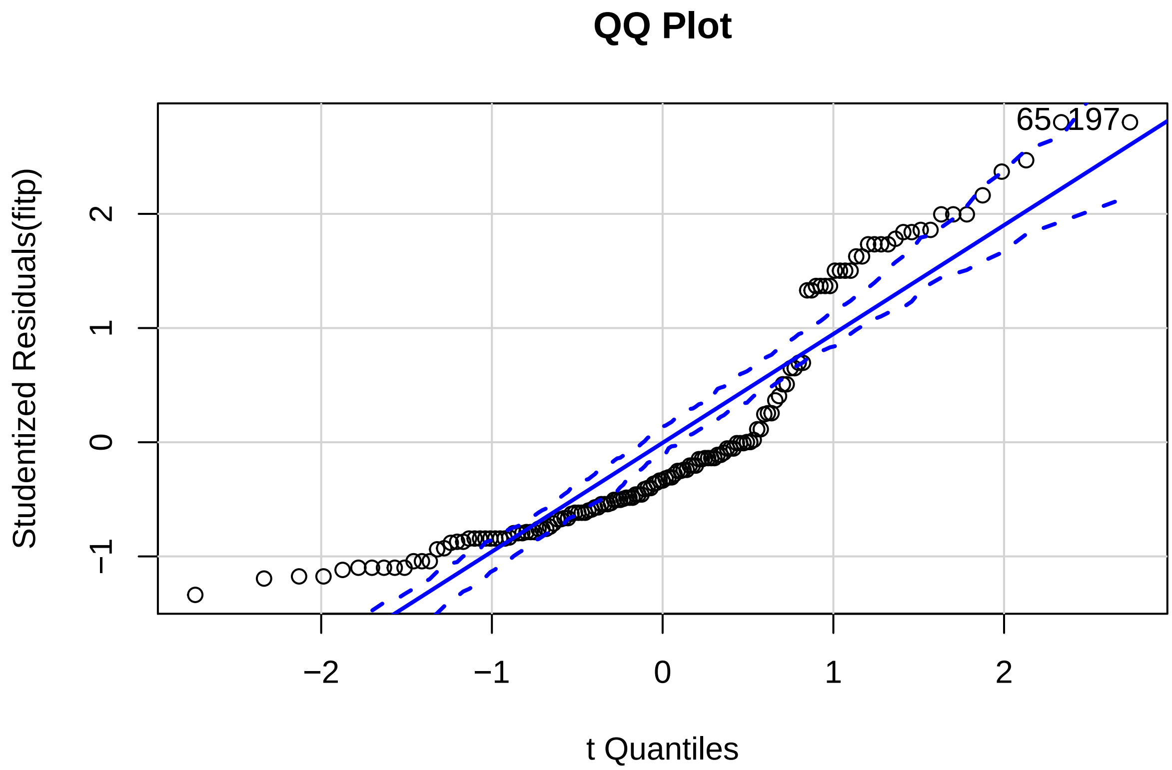

```r
ols_test_normality(fit2)  # p < 0.05 for all, so data is normal (I think)
```

```
## 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              0.9385         0.0000
## Kolmogorov-Smirnov        0.1351         0.0000
## Cramer-von Mises         151.8066        0.0000
## Anderson-Darling         35.3964         0.0000
## -----------------------------------------------
```

```r
# plot level data KBS State-only model
fitp <- lm(plot_half_cover_date ~ state, data = green_kbsp)
outlierTest(fitp)  # no outliers
```

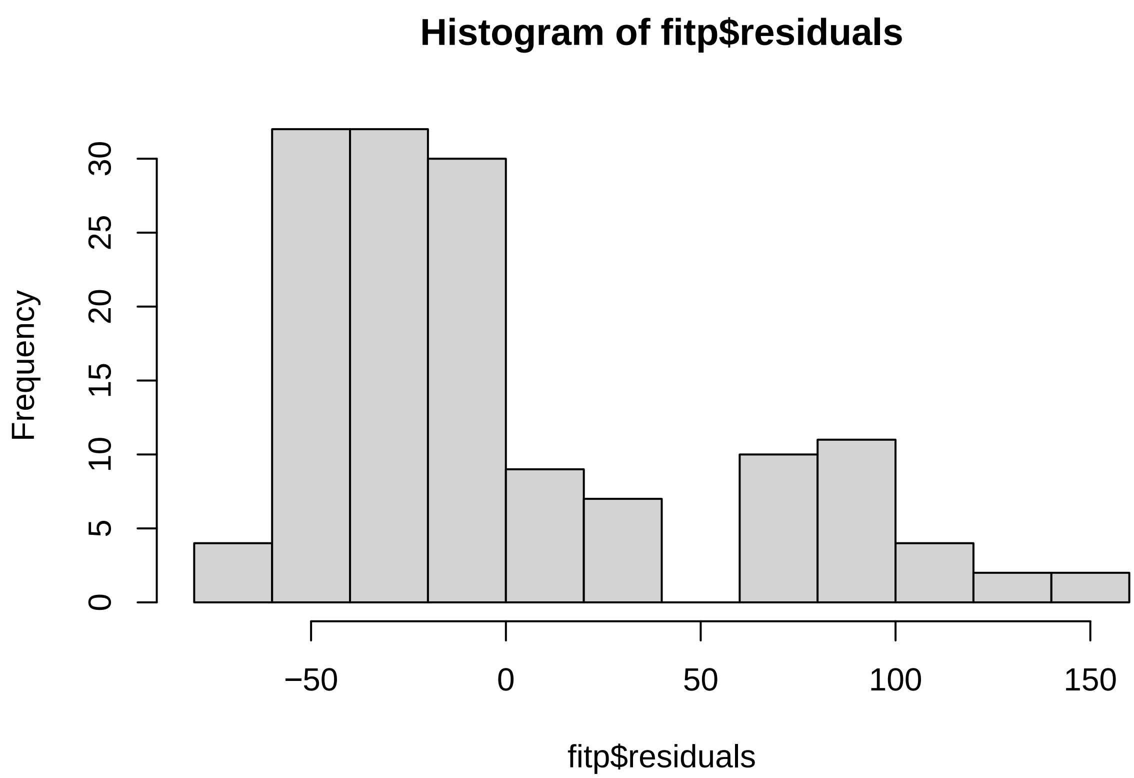
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##    rstudent unadjusted p-value Bonferroni p
## 65 2.802256          0.0057943      0.82858
```

```r
qqPlot(fitp, main = "QQ Plot")
```

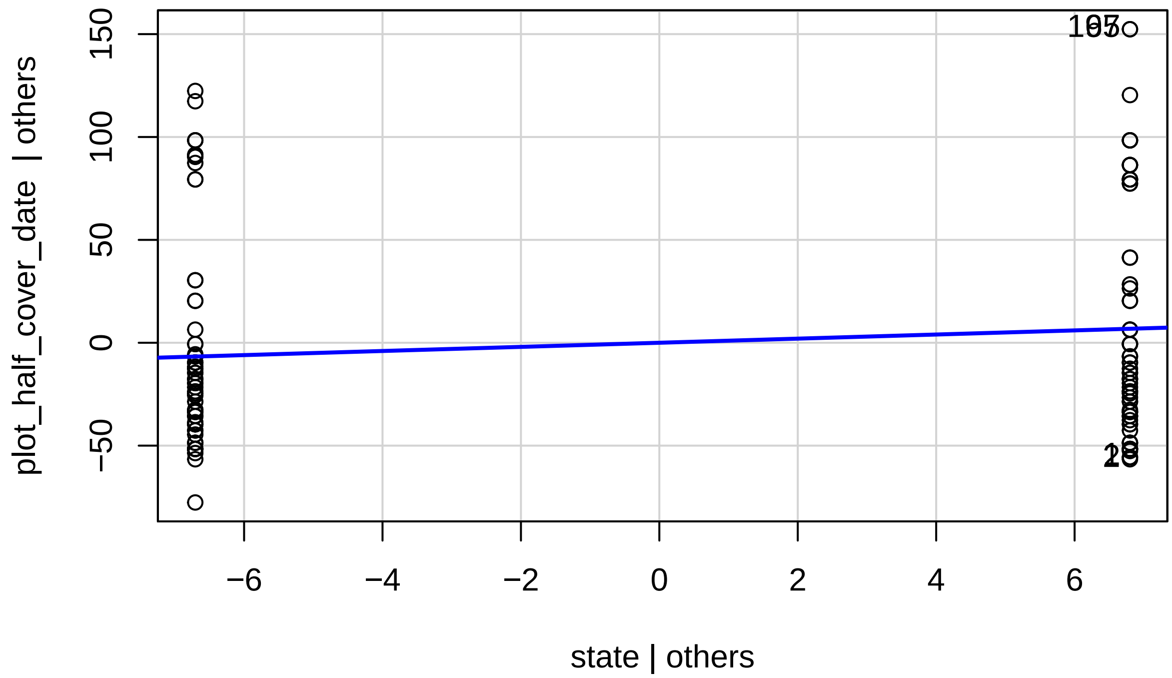



```
##  65 197
##  35 101
```

```
hist(fitp$residuals)
```



```r
leveragePlots(fitp)
```



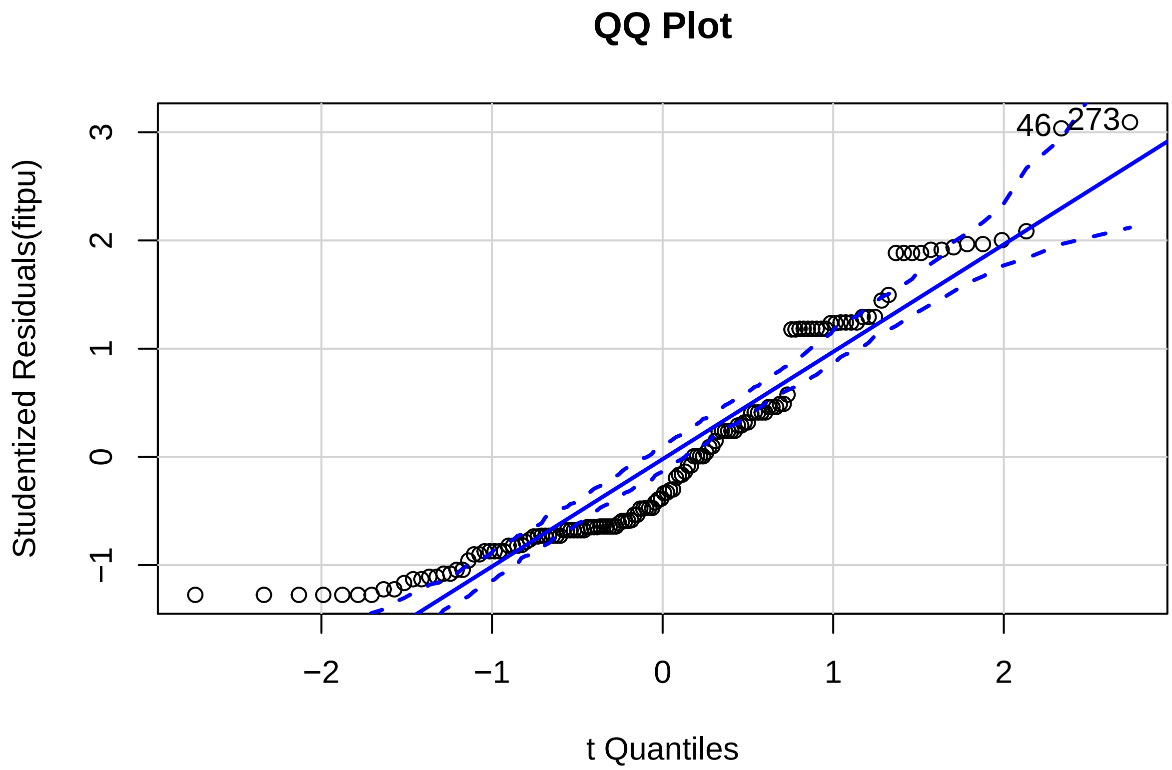

```r
ols_test_normality(fitp)
```

```
## 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              0.8578         0.0000
## Kolmogorov-Smirnov        0.1987         0.0000
## Cramer-von Mises         17.3799         0.0000
## Anderson-Darling          8.0711         0.0000
## -----------------------------------------------
```

```r
# UMBS State-only model
fitpu <- lm(plot_half_cover_date ~ state, data = green_umbsp)
outlierTest(fitpu)  # no outliers
```

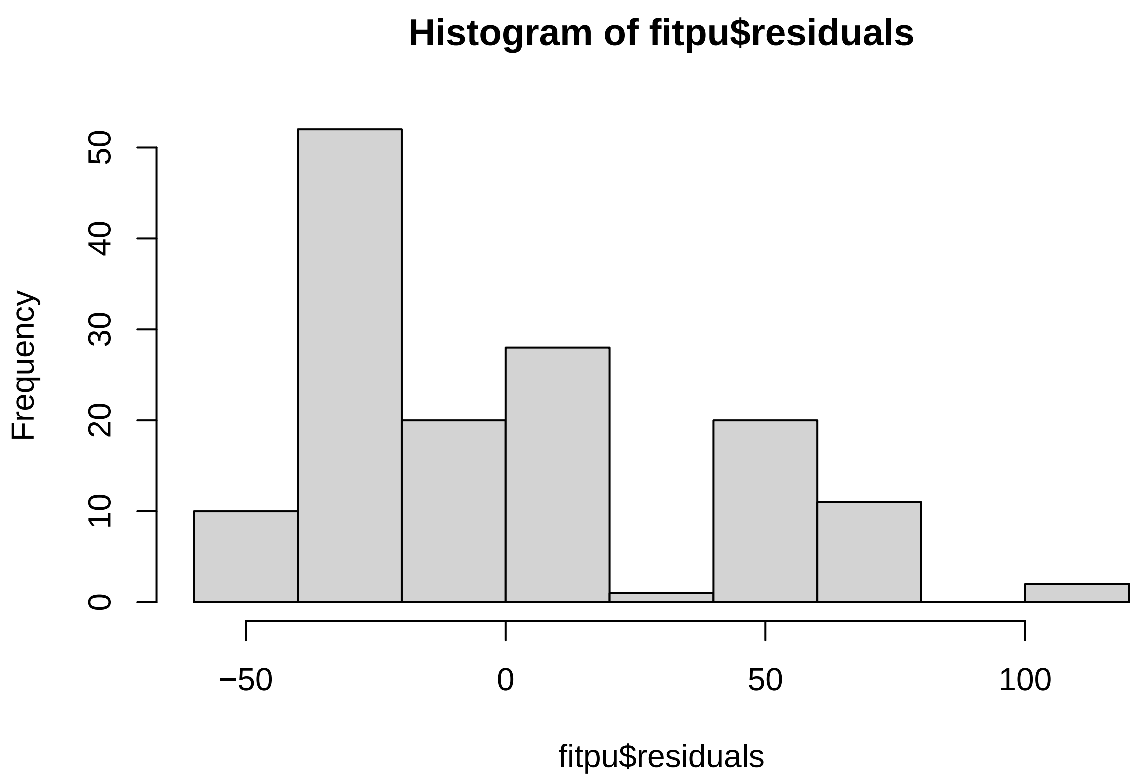
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##     rstudent unadjusted p-value Bonferroni p
## 273 3.091959          0.0023971      0.34519
```

```r
qqPlot(fitpu, main = "QQ Plot")
```

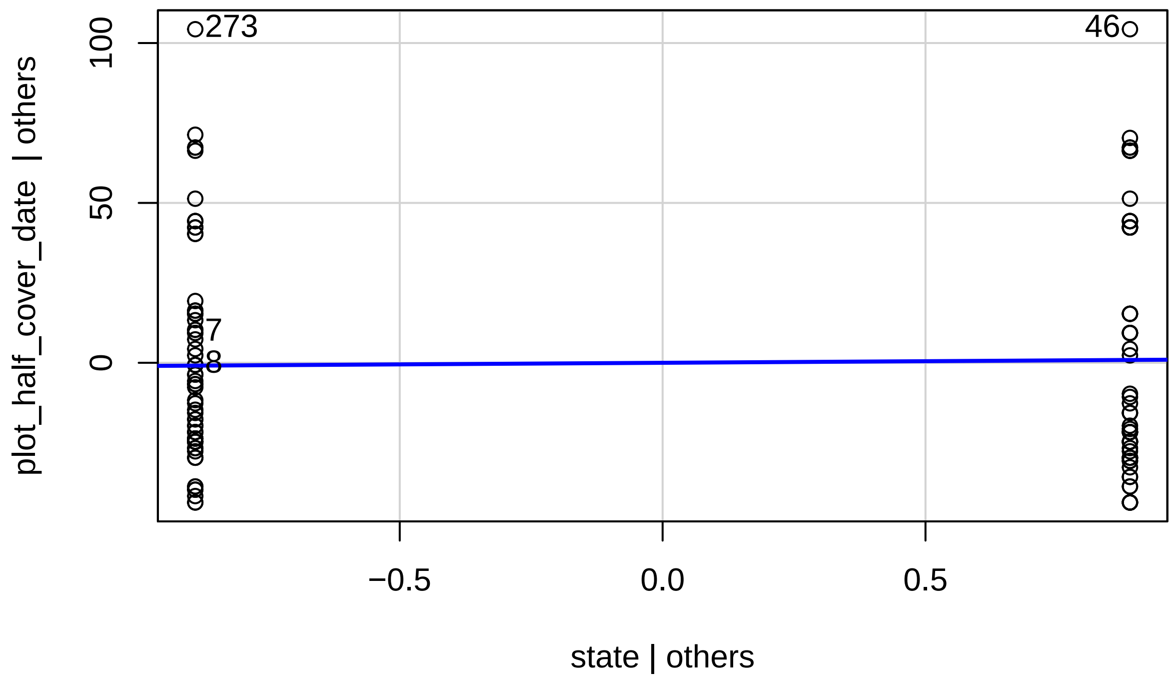



```
## 46 273
## 22 136
```

```r
hist(fitpu$residuals)
```



```r
leveragePlots(fitpu)
```



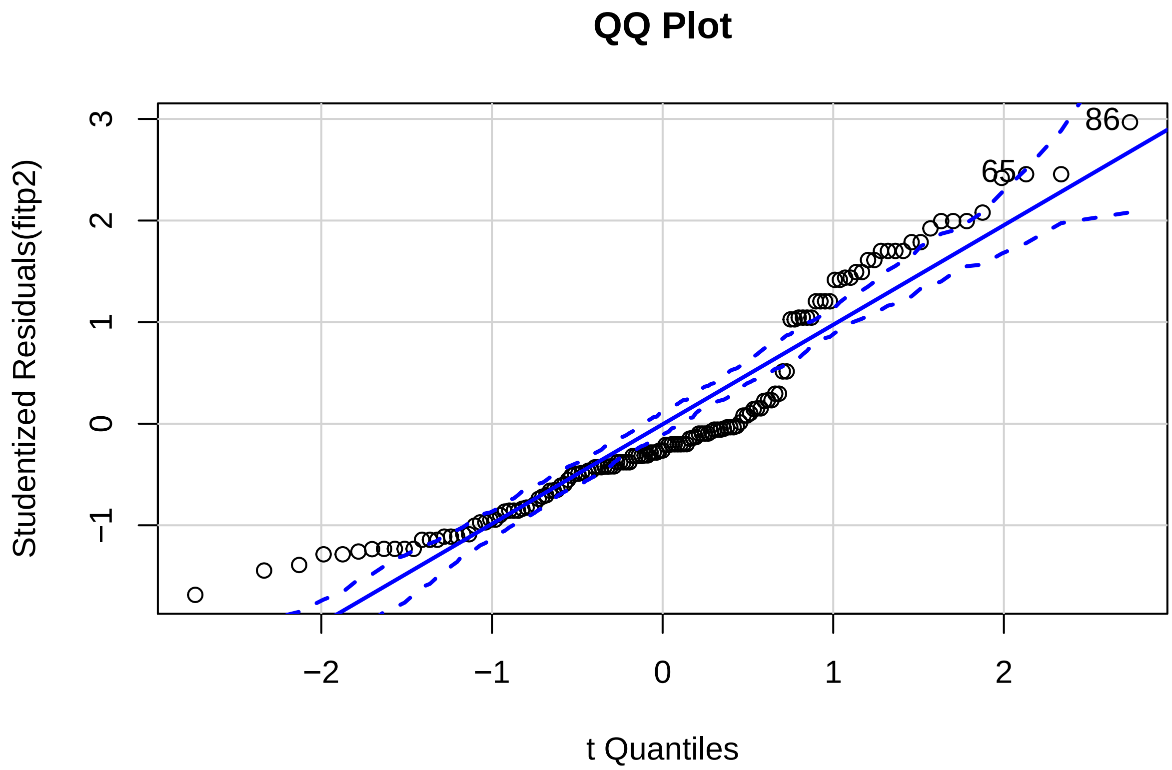

```r
ols_test_normality(fitpu)
```

```
## 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              0.9034         0.0000
## Kolmogorov-Smirnov        0.1604         0.0012
## Cramer-von Mises         12.5625         0.0000
## Anderson-Darling          4.9616         0.0000
## -----------------------------------------------
```

```r
# KBS State and year model
fitp2 <- lm(plot_half_cover_date ~ state + year_factor, data = green_kbsp)
outlierTest(fitp2)  # no outliers
```

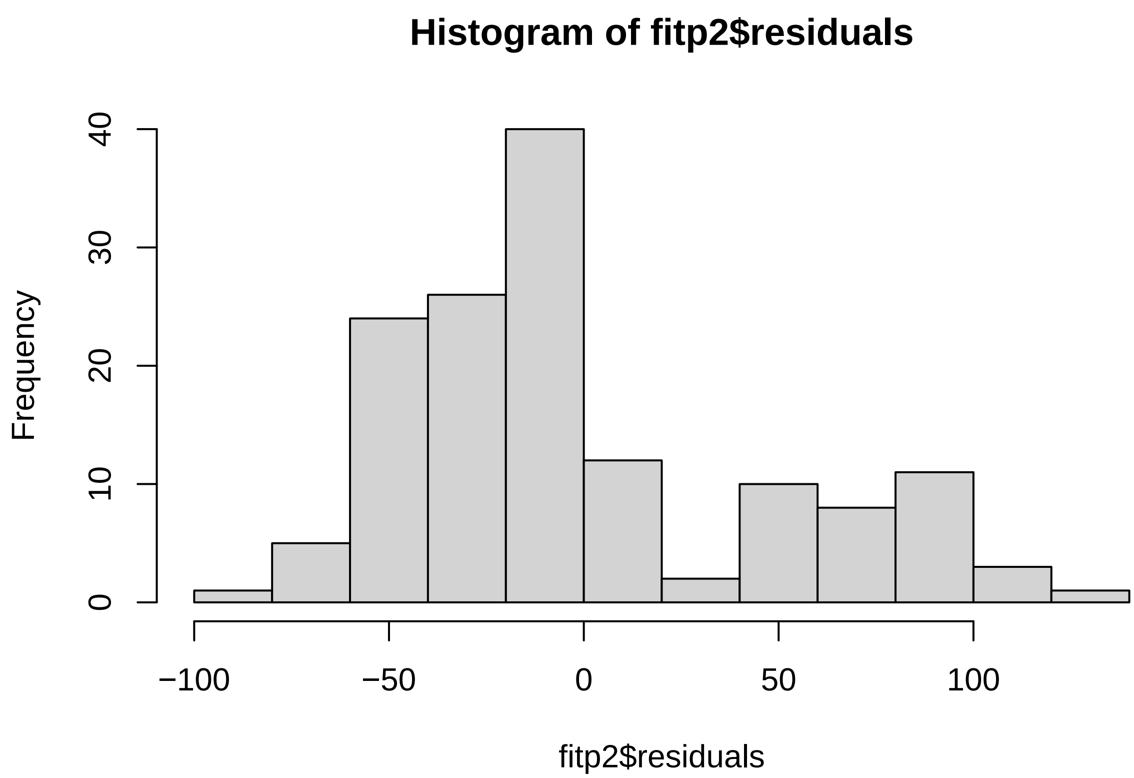
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##    rstudent unadjusted p-value Bonferroni p
## 86 2.967344          0.0035544      0.50827
```

```r
qqPlot(fitp2, main = "QQ Plot")
```

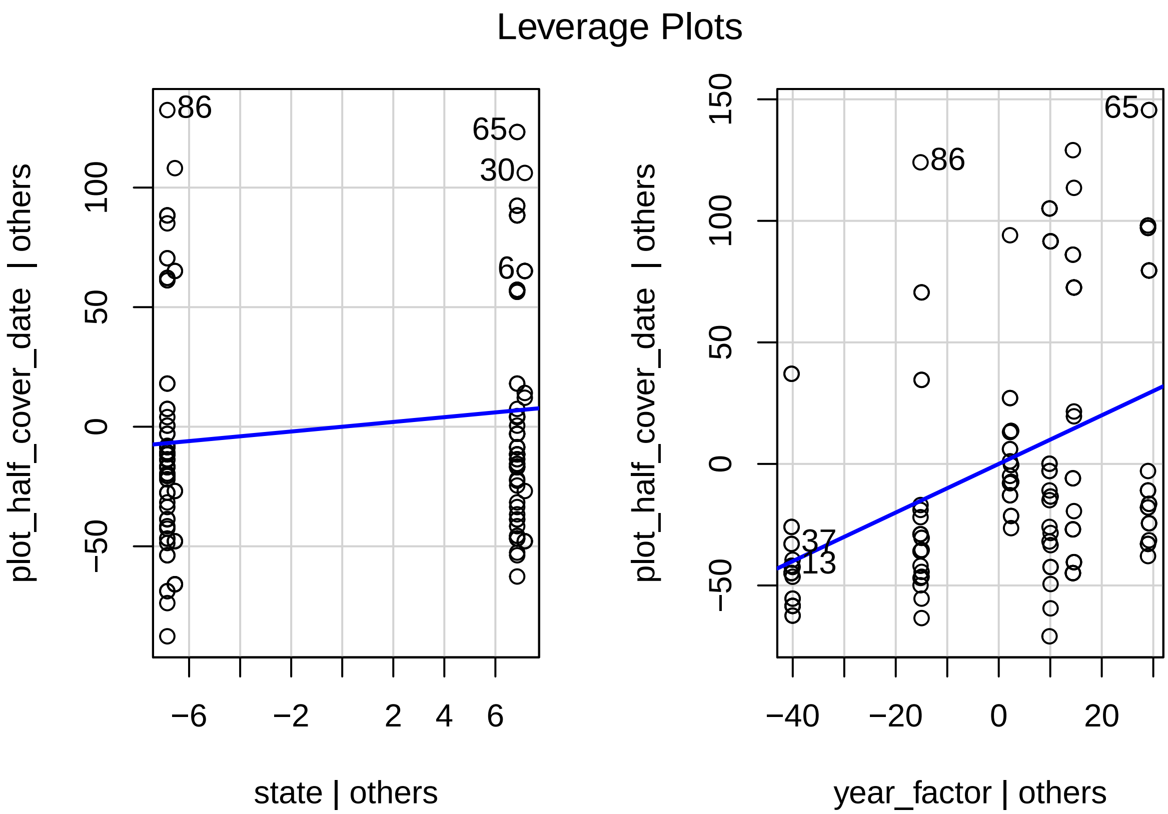



```
## 65 86
## 35 44
```

```r
hist(fitp2$residuals)
```



```r
leveragePlots(fitp2)
```



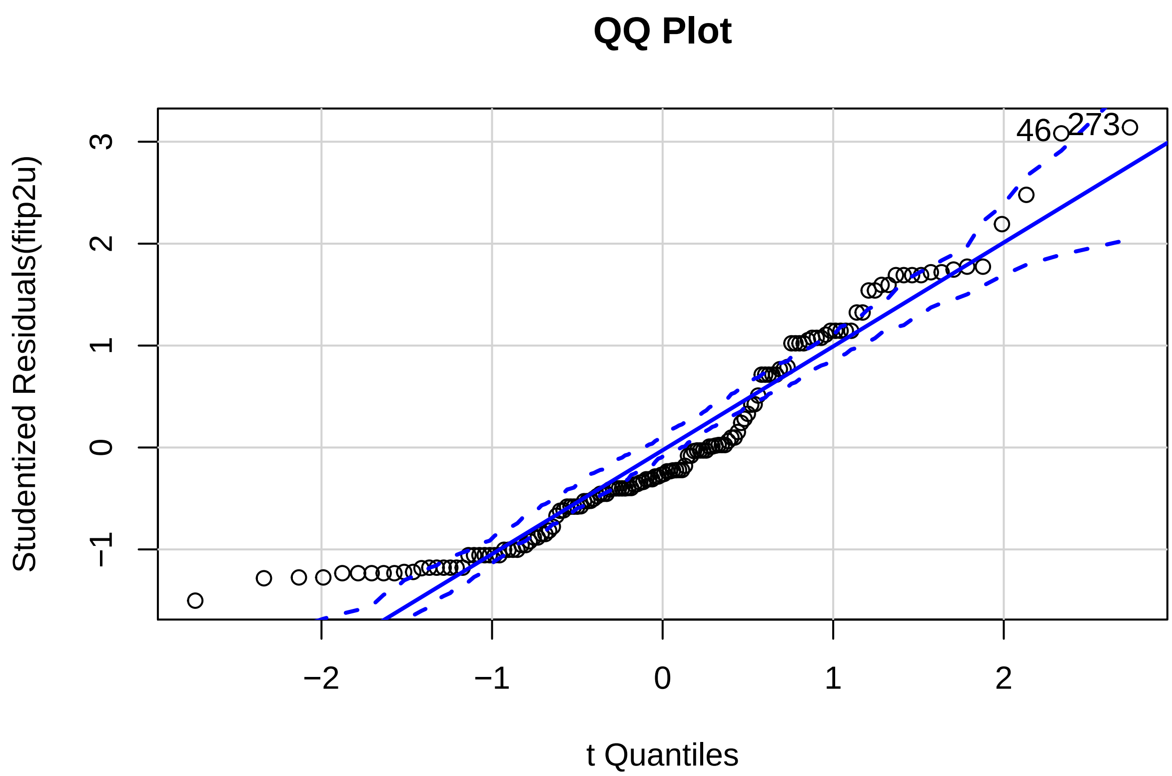

```r
ols_test_normality(fitp2)
```

```
## 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              0.91          0.0000
## Kolmogorov-Smirnov        0.1804         2e-04
## Cramer-von Mises         16.0135        0.0000
## Anderson-Darling          5.0934        0.0000
## -----------------------------------------------
```

```r
# UMBS State and year model
fitp2u <- lm(plot_half_cover_date ~ state + year, data = green_umbsp)
outlierTest(fitp2u)
```

```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##     rstudent unadjusted p-value Bonferroni p
## 273 3.140252          0.0020596      0.29659
```

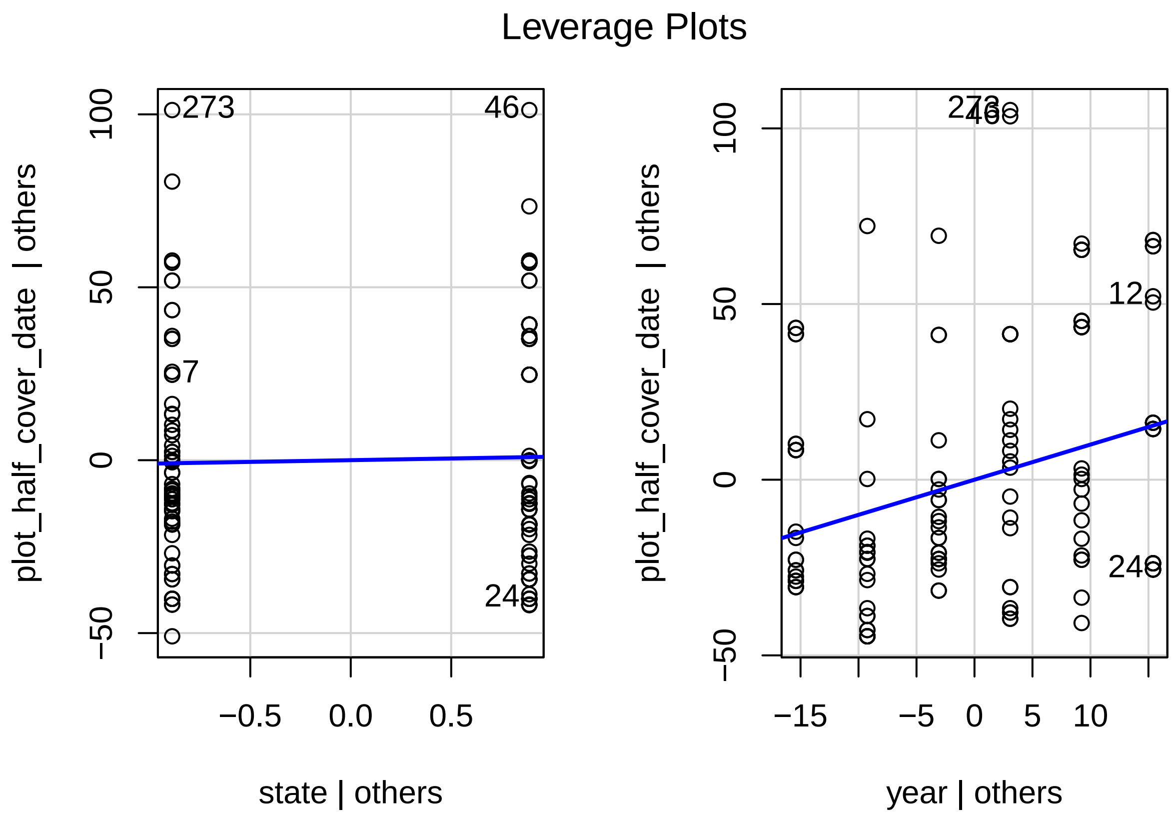
```r
qqPlot(fitp2u, main = "QQ Plot")
```




```
##  46 273
##  22 136
```

```
hist(fitp2u$residuals)
```

```r
leveragePlots(fitp2u)
```




```r
ols_test_normality(fitp2u)
```

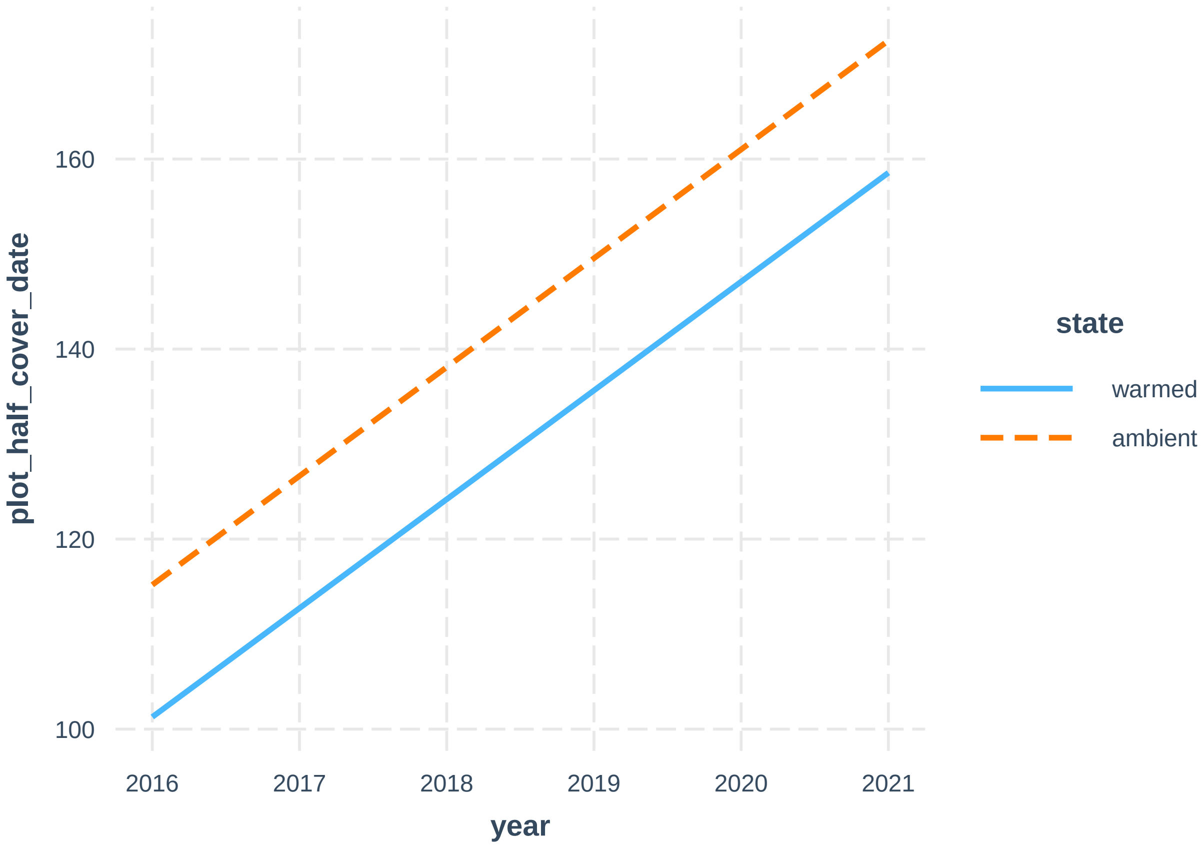
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test

## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9271         0.0000
## Kolmogorov-Smirnov        0.1362         0.0096
## Cramer-von Mises         12.9808         0.0000
## Anderson-Darling          3.3502         0.0000
## -----------------------------------------------
```

Normal distribution after accounting for species and/or year for each site and model. Set up some linear mixed effects models to evaluate. From Ben Bolker: "The traditional view of random effects is as a way to do correct statistical tests when some observations are correlated. . . . Random effects are especially useful when we have (1) lots of levels (e.g., many species or blocks), (2) relatively little data on each level (although we need multiple samples from most of the levels), and (3) uneven sampling across levels. People sometimes say that random effects are "factors that you aren't interested in." This is not always true. While it is often the case in ecological experiments (where variation among sites is usually just a nuisance), it is sometimes of great interest." In our case, variation among plots is a nuisance, and not something we're interested in. For some questions, variation among species is also a nuisance for us. It's possible that variation among years is a nuisance if we only care about warm vs. ambient, but I think time is an interesting variable to consider with this study.

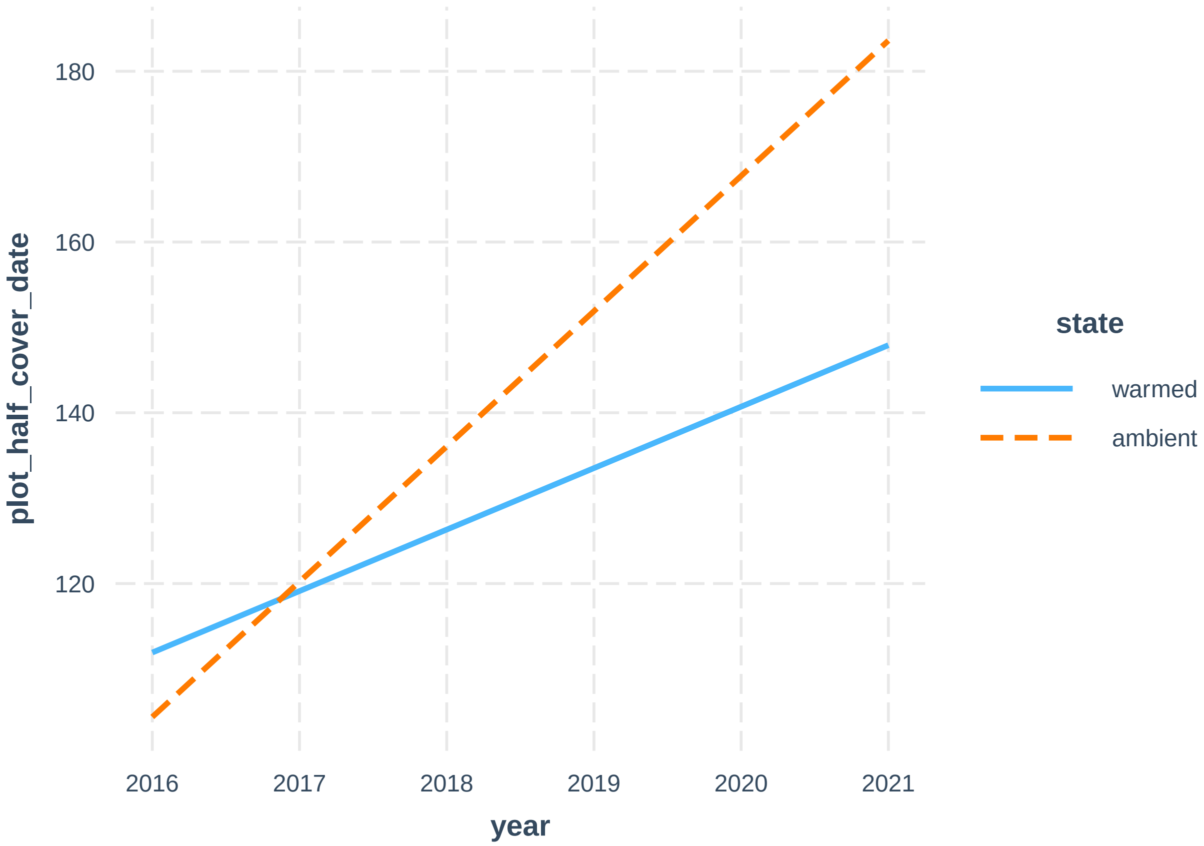
We should also think about how we're treating year. Some of the models have a state * year interaction as a fixed effect, which means that the warming or ambient treatment could affect the half_cover_date differently over time (there would be a different slope for each state in the relationship between half_cover_date (y) and year (x)). If we just had state + year, the states would have the same slope, indicating that they have no interaction in their effect on half_cover_date (but they could still have different intercepts).

```r
# 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/

# KBS
fit3 <- lm(plot_half_cover_date ~ state + year, data = green_kbsp)
interact_plot(fit3, pred = year, modx = state)
```

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

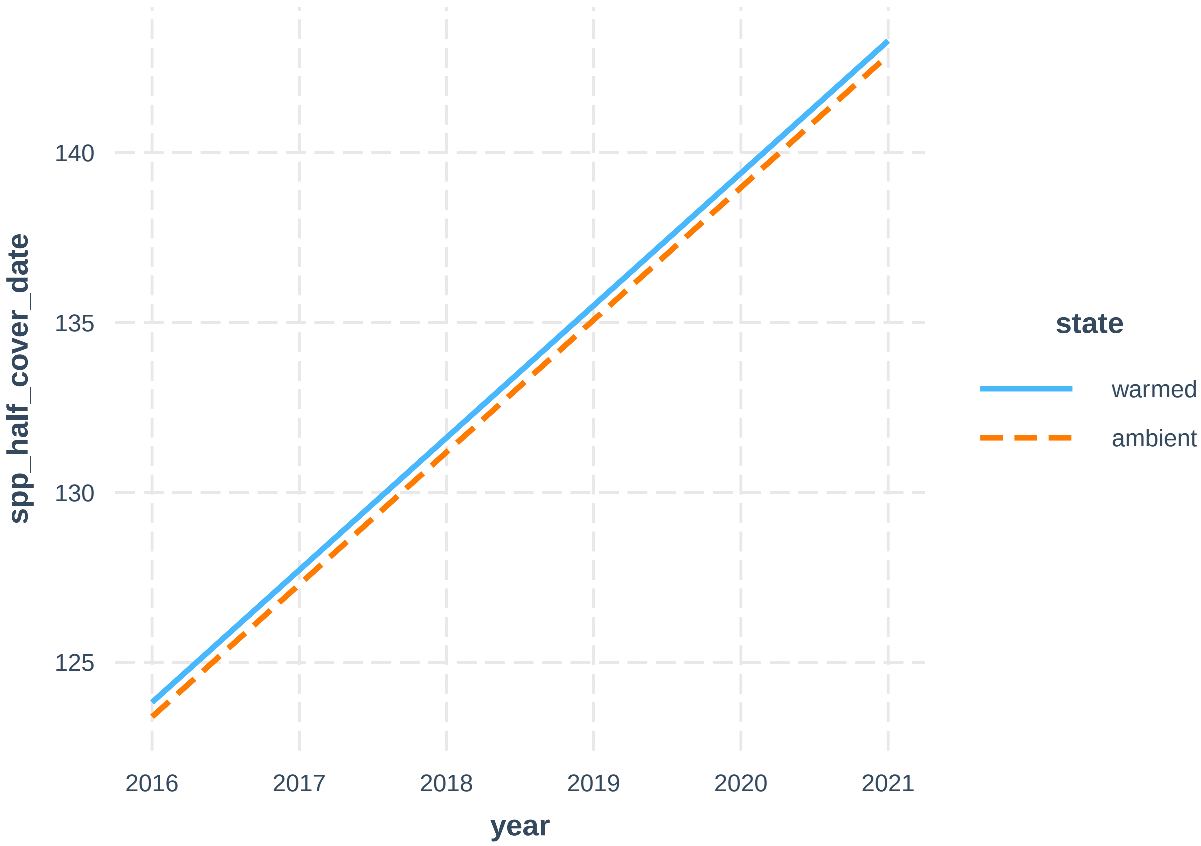



```
fit4 <- lm(plot_half_cover_date ~ state * year, data = green_kbsp)
interact_plot(fit4, pred = year, modx = state)
```



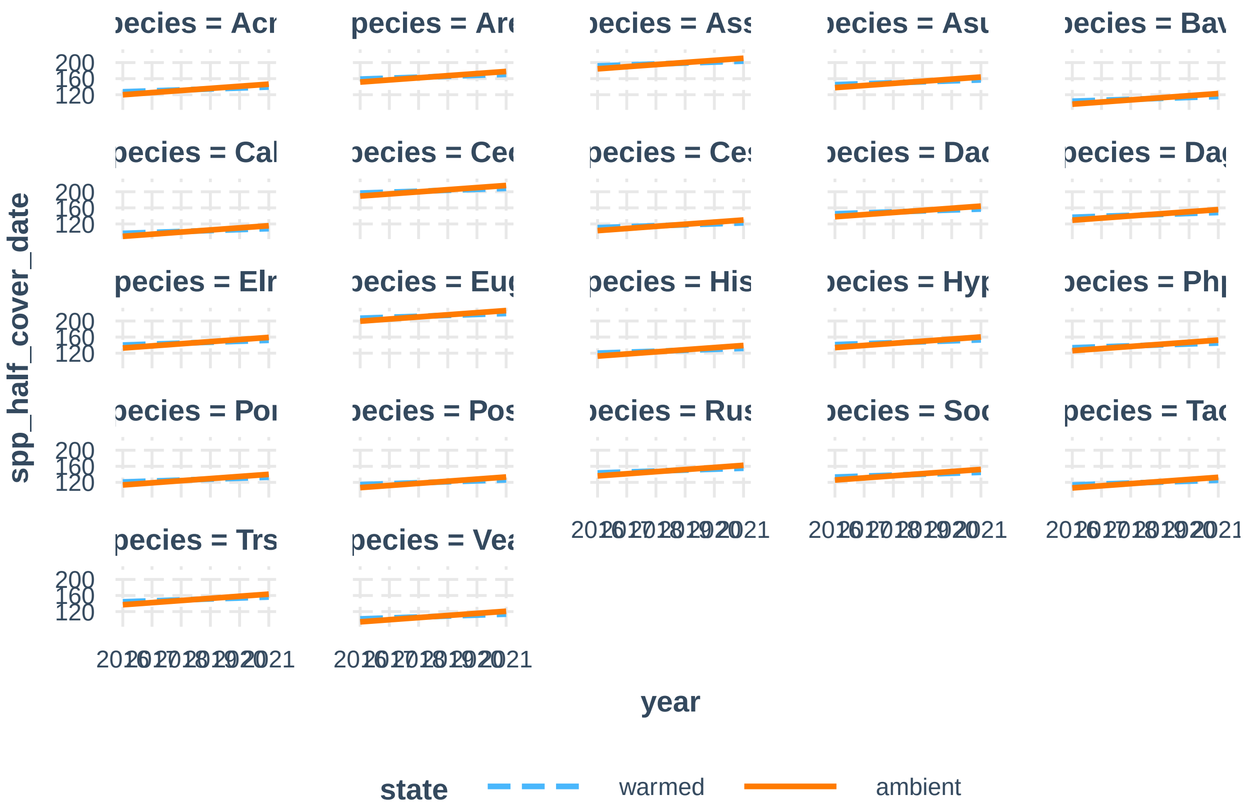

```
fit5 <- lm(spp_half_cover_date ~ state + year + species, data = green_kbs)
interact_plot(fit5, pred = year, modx = state)
```

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



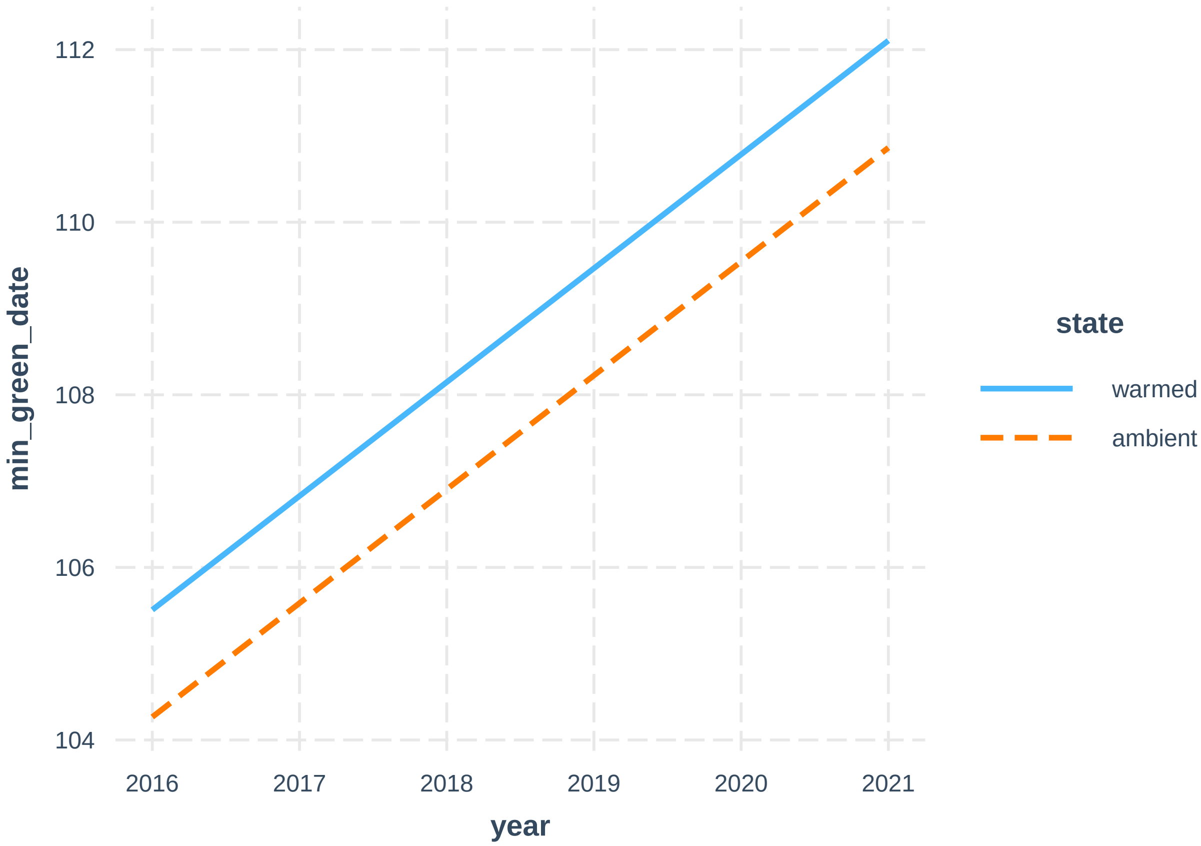

```
fit6 <- lm(spp_half_cover_date ~ state * year + species, data = green_kbs)
interact_plot(fit6, pred = year, modx = state, mod2 = species)
```

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



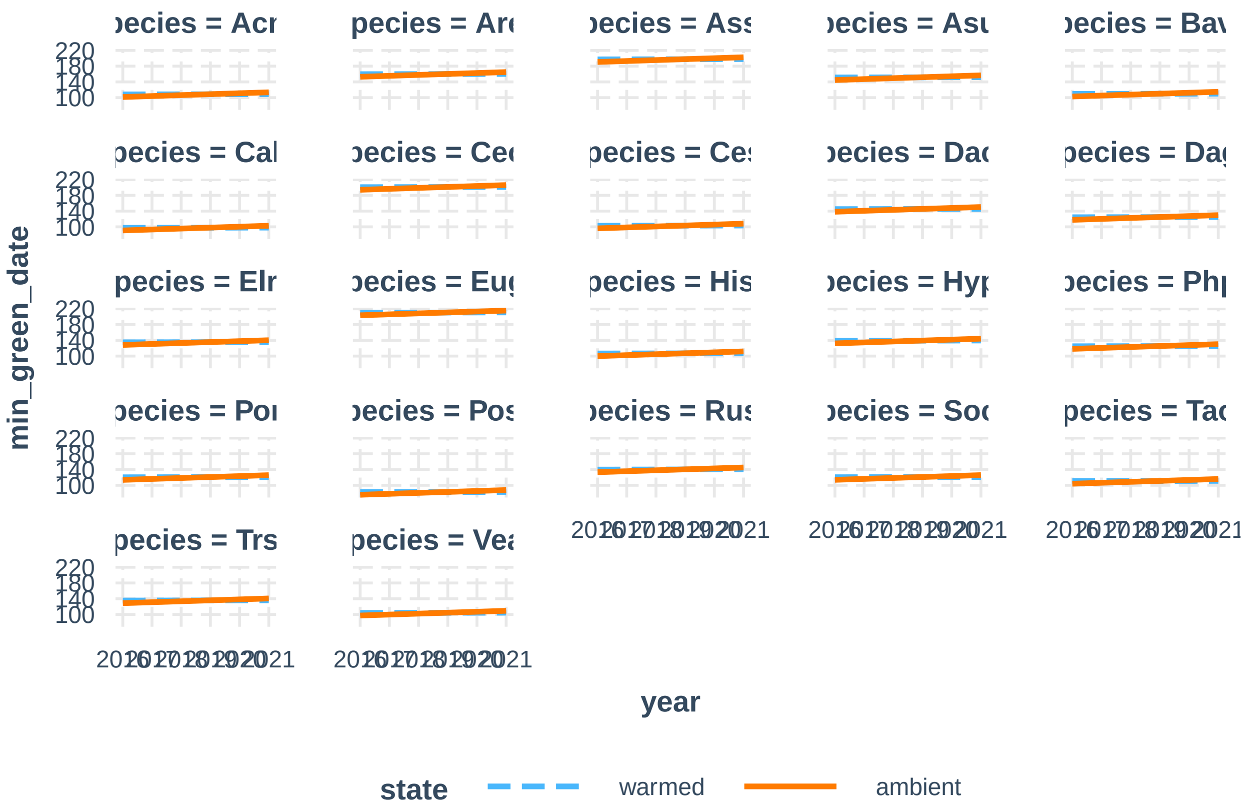

```r
fit7 <- lm(min_green_date ~ state + year + species, data = green_kbs)
interact_plot(fit7, pred = year, modx = state)
```

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



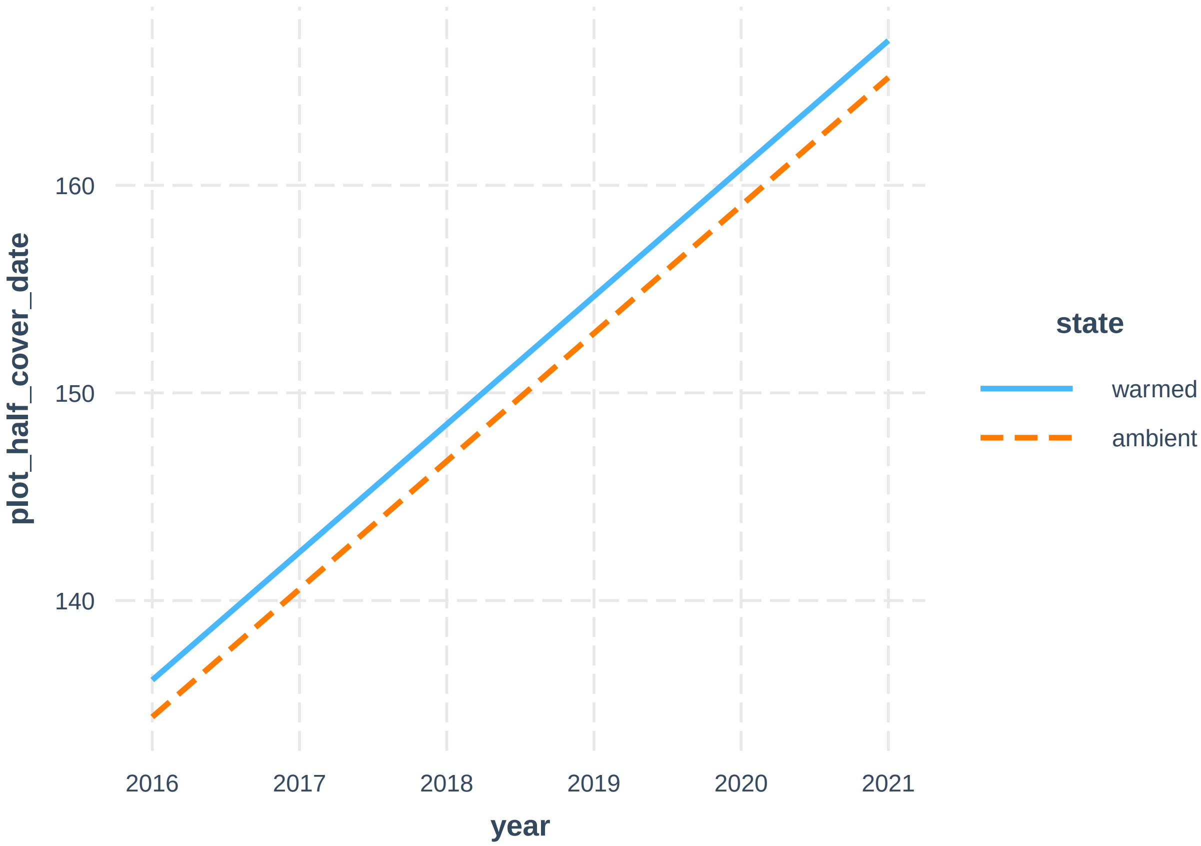

```
fit8 <- lm(min_green_date ~ state * year + species, data = green_kbs)
interact_plot(fit8, pred = year, modx = state, mod2 = species)
```

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

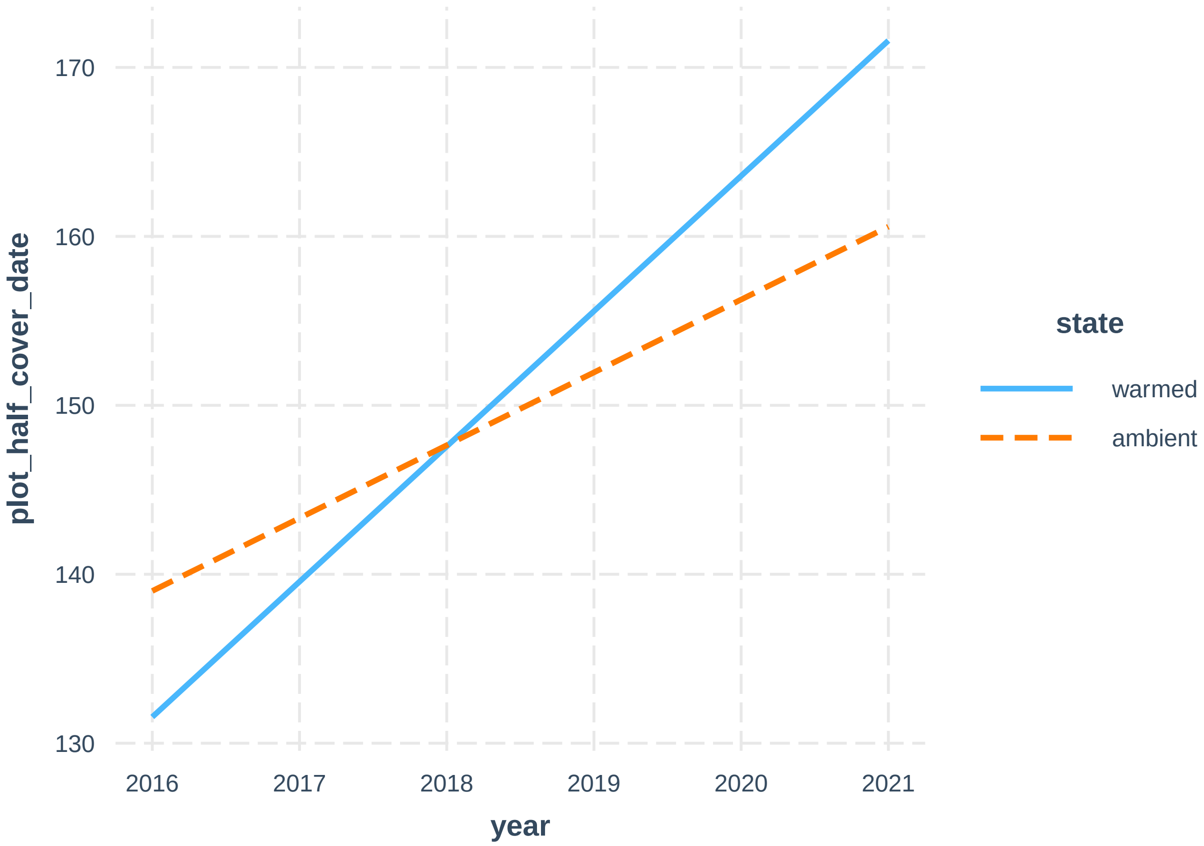



```r
# UMBS
fit3u <- lm(plot_half_cover_date ~ state + year, data = green_umbsp)
interact_plot(fit3u, pred = year, modx = state)
```

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

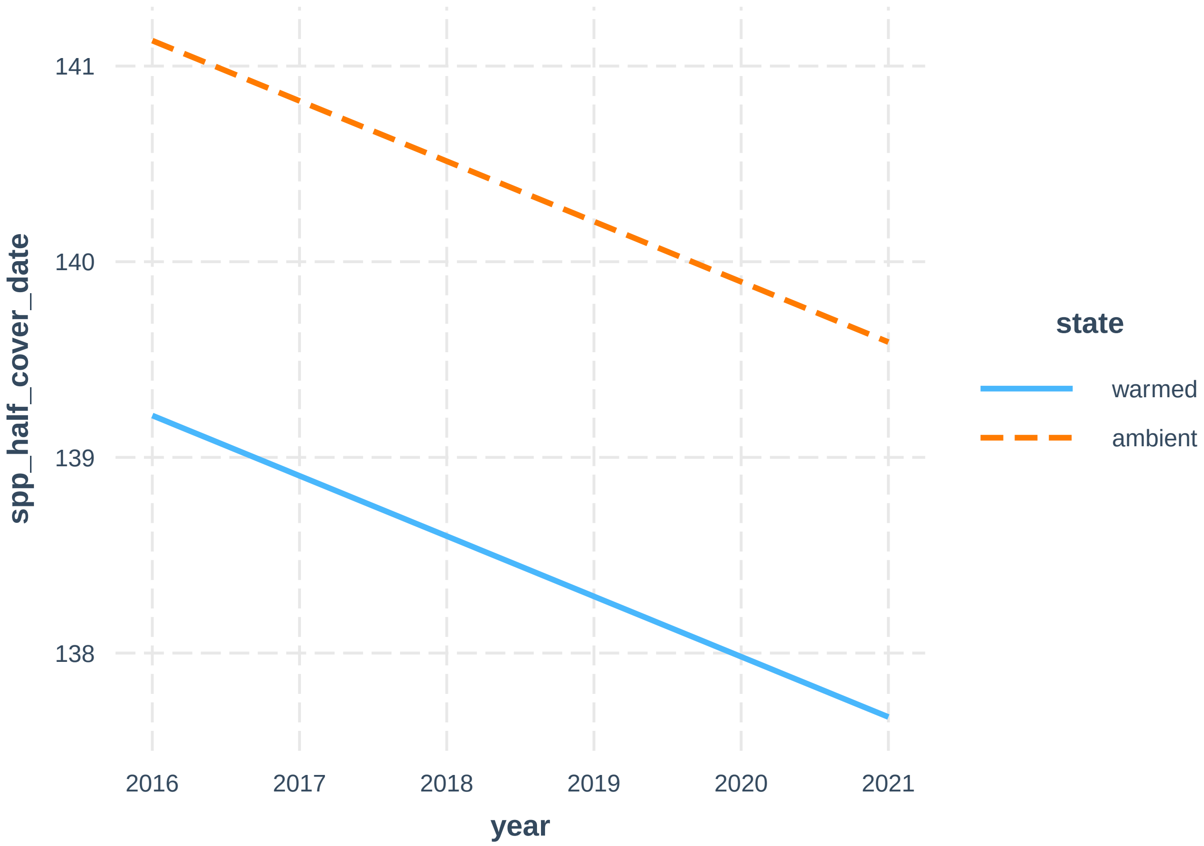



```
fit4u <- lm(plot_half_cover_date ~ state * year, data = green_umbsp)
interact_plot(fit4u, pred = year, modx = state)
```




```
fit5u <- lm(spp_half_cover_date ~ state + year + species, data = green_umbs)
interact_plot(fit5u, pred = year, modx = state)
```

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

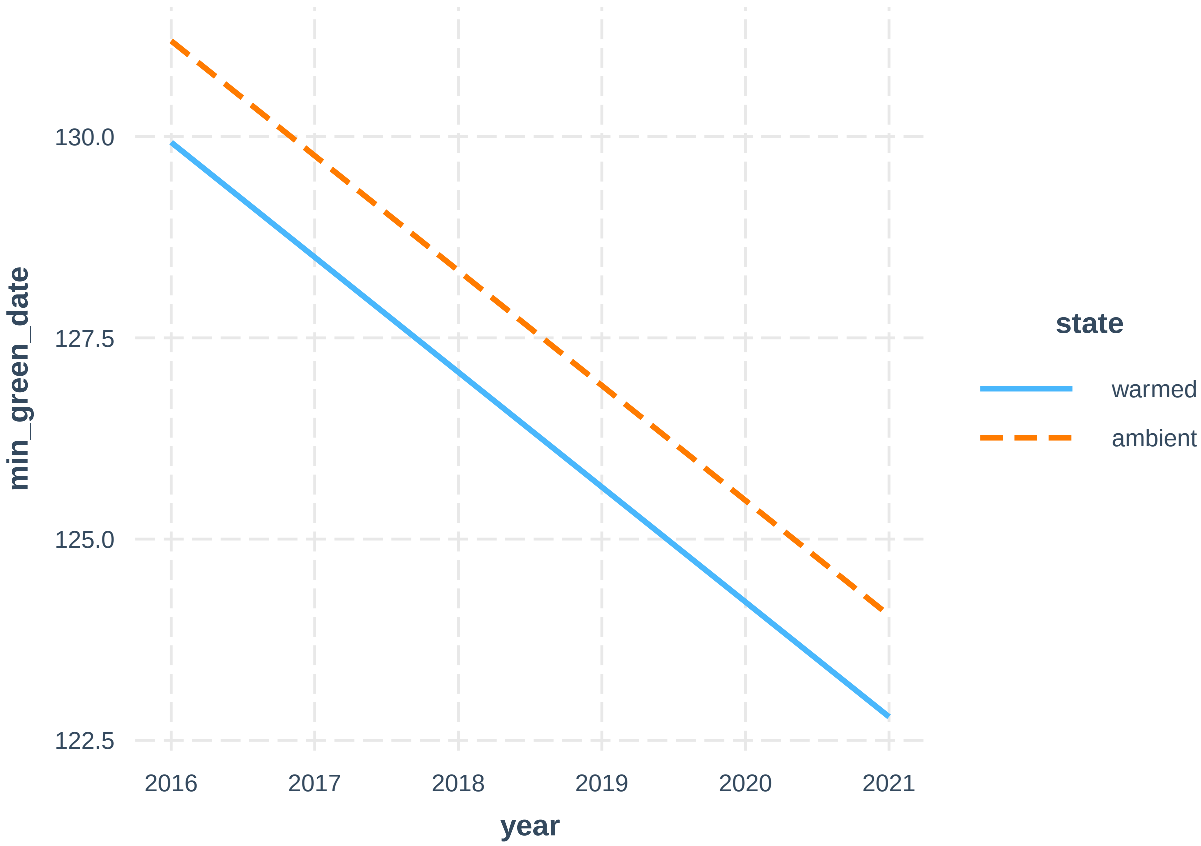



```
fit6u <- lm(spp_half_cover_date ~ state * year + species, data = green_umbs)
interact_plot(fit6u, pred = year, modx = state, mod2 = species)
```

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


```r
fit7u <- lm(min_green_date ~ state + year + species, data = green_umbs)
interact_plot(fit7u, pred = year, modx = state)
```

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




```
fit8u <- lm(min_green_date ~ state * year + species, data = green_umbs)
interact_plot(fit8u, pred = year, modx = state, mod2 = species)
```

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

KBS Species-level Mixed Effects Models:

```
# Start by replicating (almost) what we did in the Oecologia
# 2018 paper. The only difference here is that we have
# multiple years, so we are also 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).


## Note: KD re-ran different models below, these are models by
## PLZ Do we need to include plot as a random effect with the
## KBS models?
mod1 <- lmer(spp_half_cover_date ~ state * year_factor + insecticide *
    year_factor + (1 | species) + (1 | plot), green_kbs, REML = FALSE)
mod2 <- lmer(spp_half_cover_date ~ state * year_factor + insecticide *
    year_factor + (1 | species), green_kbs, 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 anove 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                      13      13     1   23.32  0.0051    0.9435
## year_factor            201178   40236     5 1481.69 16.3729 9.406e-16 ***
## insecticide                64      64     1   22.92  0.0260    0.8734
```

```
## state:year_factor        17353    3471     5 1476.94  1.4122    0.2168
## year_factor:insecticide   8290    1658     5 1476.73  0.6747    0.6427
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(mod2)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##                         Sum Sq Mean Sq NumDF  DenDF F value    Pr(>F)
## state                        1       1     1 1494.6  0.0004    0.9834
## year_factor             201128   40226     5 1493.7 16.2373 1.272e-15 ***
## insecticide                 38      38     1 1492.3  0.0153    0.9014
## state:year_factor        17392    3478     5 1488.7  1.4041    0.2198
## year_factor:insecticide   8167    1633     5 1489.1  0.6593    0.6544
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# Run an ANOVA to test if 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(mod2, mod1)  # favor mod 2
```

```
## Data: green_kbs
## Models:
## mod2: spp_half_cover_date ~ state * year_factor + insecticide * year_factor +
## mod2:     (1 | species)
## mod1: spp_half_cover_date ~ state * year_factor + insecticide * year_factor +
## mod1:     (1 | species) + (1 | plot)
##      npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod2   20 16198 16304 -8078.9    16158
## mod1   21 16197 16309 -8077.7    16155 2.351  1     0.1252
```

```r
summary(mod1)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula:
## spp_half_cover_date ~ state * year_factor + insecticide * year_factor +
##     (1 | species) + (1 | plot)
##    Data: green_kbs
##
##      AIC      BIC   logLik deviance df.resid
##  16197.4  16309.1  -8077.7  16155.4     1490
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.1401 -0.6679 -0.2290  0.4939  3.2472
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
```

```
##  plot     (Intercept)   21.19   4.604
##  species  (Intercept)  701.14  26.479
##  Residual             2457.46  49.573
## Number of obs: 1511, groups:  plot, 24; species, 22
##
## Fixed effects:
##                                    Estimate Std. Error        df t value
## (Intercept)                        132.5912     7.7803   57.5190  17.042
## stateambient                        -3.5259     5.9191  241.3907  -0.596
## year_factor2                        -7.0774     7.7297 1472.4624  -0.916
## year_factor3                        26.2075     7.3481 1474.5216   3.567
## year_factor4                         6.7615     7.2793 1478.4970   0.929
## year_factor5                        21.8553     7.3785 1478.4944   2.962
## year_factor6                         9.2088     7.4941 1484.7880   1.229
## insecticideno_insects                3.7585     5.9185  241.1836   0.635
## stateambient:year_factor2           -4.5737     8.7486 1473.8850  -0.523
## stateambient:year_factor3           -1.1482     8.3975 1477.4538  -0.137
## stateambient:year_factor4            2.0347     8.5280 1480.6286   0.239
## stateambient:year_factor5           15.3518     8.5364 1475.4692   1.798
## stateambient:year_factor6           10.8806     8.7035 1481.9963   1.250
## year_factor2:insecticideno_insects  -0.7372     8.7408 1474.0530  -0.084
## year_factor3:insecticideno_insects  -7.7324     8.3948 1477.9488  -0.921
## year_factor4:insecticideno_insects   1.7398     8.5364 1478.9656   0.204
## year_factor5:insecticideno_insects  -8.1151     8.5551 1473.6907  -0.949
## year_factor6:insecticideno_insects -10.8238     8.6939 1481.9730  -1.245
##                                    Pr(>|t|)
## (Intercept)                         < 2e-16 ***
## stateambient                       0.551948
## year_factor2                       0.360025
## year_factor3                       0.000373 ***
## year_factor4                       0.353109
## year_factor5                       0.003105 **
## year_factor6                       0.219339
## insecticideno_insects              0.525995
## stateambient:year_factor2          0.601201
## stateambient:year_factor3          0.891264
## stateambient:year_factor4          0.811455
## stateambient:year_factor5          0.072319 .
## stateambient:year_factor6          0.211445
## year_factor2:insecticideno_insects 0.932801
## year_factor3:insecticideno_insects 0.357152
## year_factor4:insecticideno_insects 0.838529
## year_factor5:insecticideno_insects 0.342992
## year_factor6:insecticideno_insects 0.213330
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation matrix not shown by default, as p = 18 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

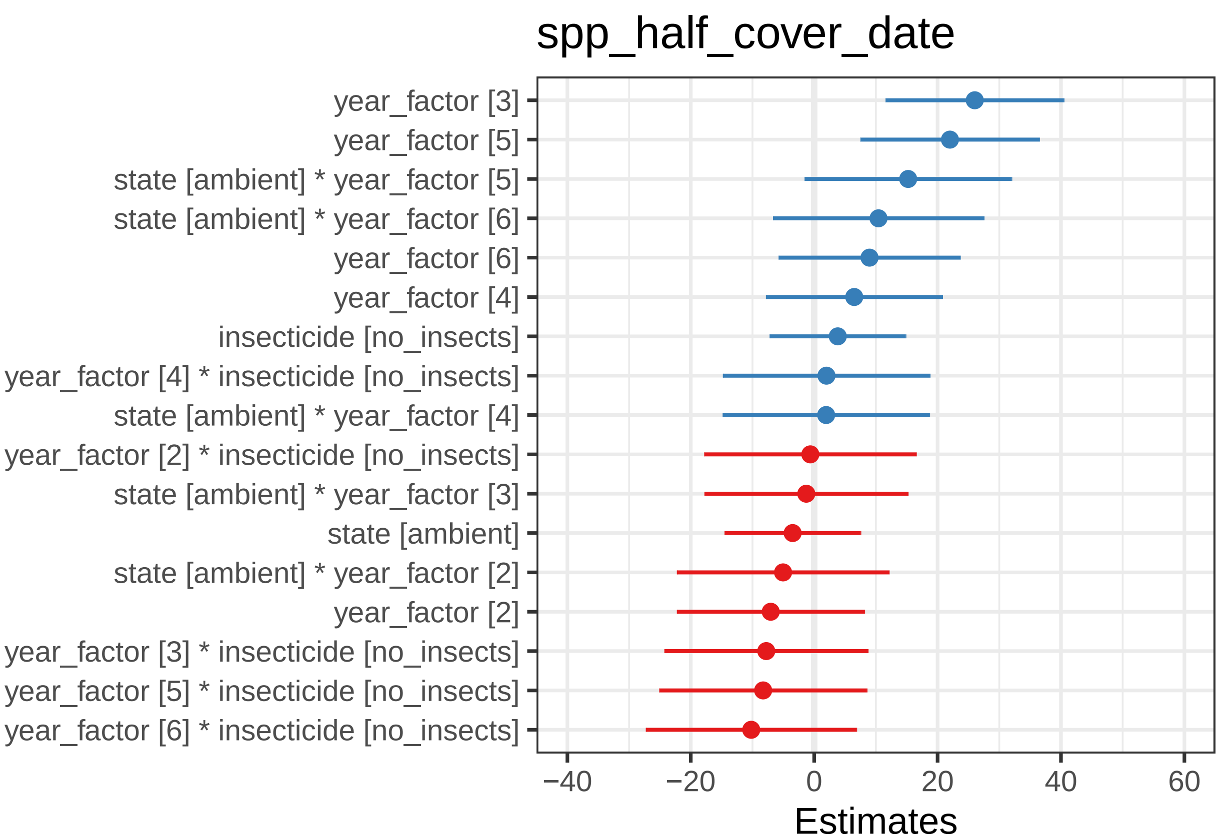
```
summary(mod2)
```

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

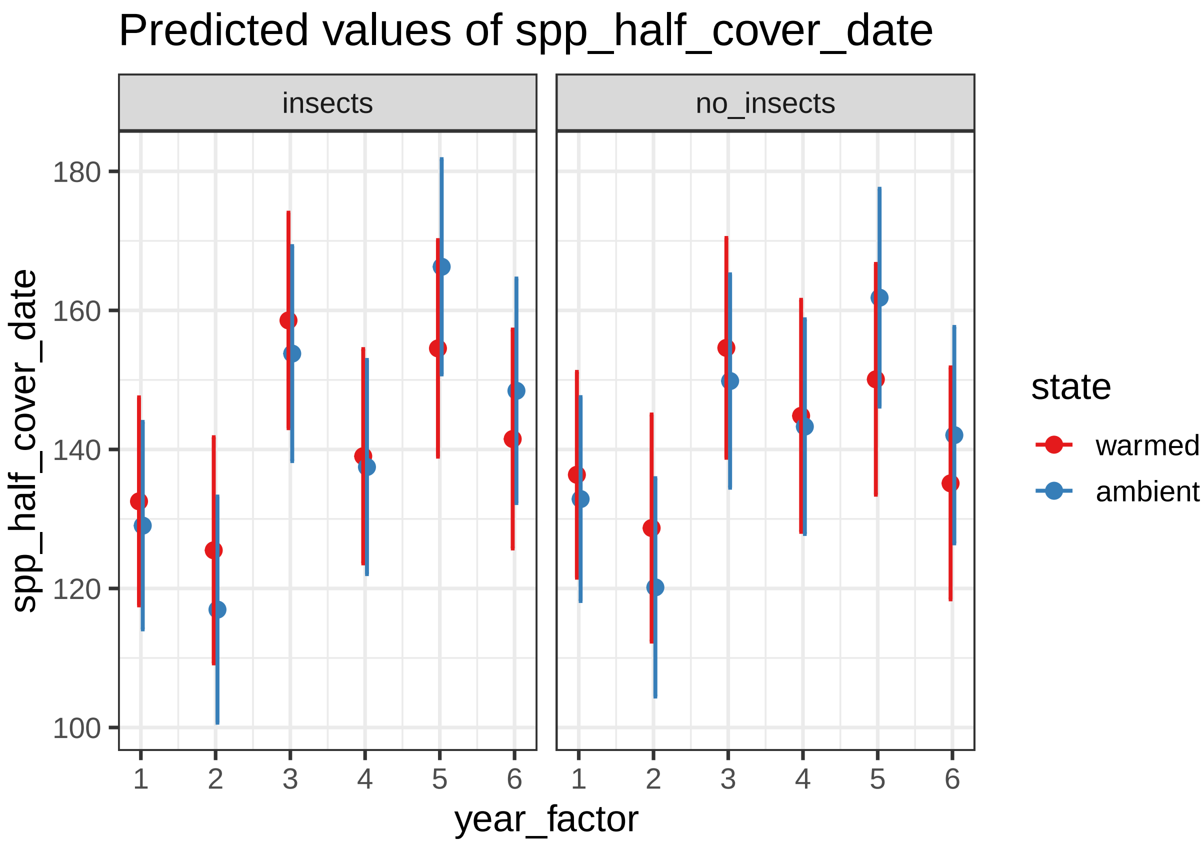
```
##   method [lmerModLmerTest]
## Formula:
## spp_half_cover_date ~ state * year_factor + insecticide * year_factor +
##     (1 | species)
##    Data: green_kbs
##
##      AIC      BIC   logLik deviance df.resid
##  16197.7  16304.2  -8078.9  16157.7     1491
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.1987 -0.6827 -0.2261  0.4740  3.2316
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  species  (Intercept)  706.2   26.57
##  Residual             2477.4   49.77
## Number of obs: 1511, groups:  species, 22
##
## Fixed effects:
##                                    Estimate Std. Error        df t value
## (Intercept)                        132.5308     7.6320   54.1583  17.365
## stateambient                        -3.4918     5.6309 1488.3923  -0.620
## year_factor2                        -7.0395     7.7573 1490.0939  -0.907
## year_factor3                        26.0247     7.3740 1491.7742   3.529
## year_factor4                         6.4911     7.2996 1488.8786   0.889
## year_factor5                        22.0036     7.4011 1491.2131   2.973
## year_factor6                         8.9698     7.5120 1492.7434   1.194
## insecticideno_insects                3.8211     5.6302 1487.8702   0.679
## stateambient:year_factor2           -5.0420     8.7766 1487.9825  -0.574
## stateambient:year_factor3           -1.2774     8.4232 1490.1563  -0.152
## stateambient:year_factor4            1.9401     8.5506 1490.2157   0.227
## stateambient:year_factor5           15.2331     8.5623 1488.1527   1.779
## stateambient:year_factor6           10.4250     8.7228 1488.9871   1.195
## year_factor2:insecticideno_insects  -0.6211     8.7688 1488.2688  -0.071
## year_factor3:insecticideno_insects  -7.7677     8.4203 1490.4370  -0.923
## year_factor4:insecticideno_insects   1.9900     8.5618 1491.0238   0.232
## year_factor5:insecticideno_insects  -8.2703     8.5830 1488.4535  -0.964
## year_factor6:insecticideno_insects -10.2006     8.7125 1488.4470  -1.171
##                                    Pr(>|t|)
## (Intercept)                         < 2e-16 ***
## stateambient                       0.535284
## year_factor2                       0.364307
## year_factor3                       0.000429 ***
## year_factor4                       0.374017
## year_factor5                       0.002996 **
## year_factor6                       0.232640
## insecticideno_insects              0.497449
## stateambient:year_factor2          0.565731
## stateambient:year_factor3          0.879485
## stateambient:year_factor4          0.820540
## stateambient:year_factor5          0.075430 .
## stateambient:year_factor6          0.232222
## year_factor2:insecticideno_insects 0.943545
```

```
## year_factor3:insecticideno_insects 0.356417
## year_factor4:insecticideno_insects 0.816236
## year_factor5:insecticideno_insects 0.335420
## year_factor6:insecticideno_insects 0.241864
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation matrix not shown by default, as p = 18 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

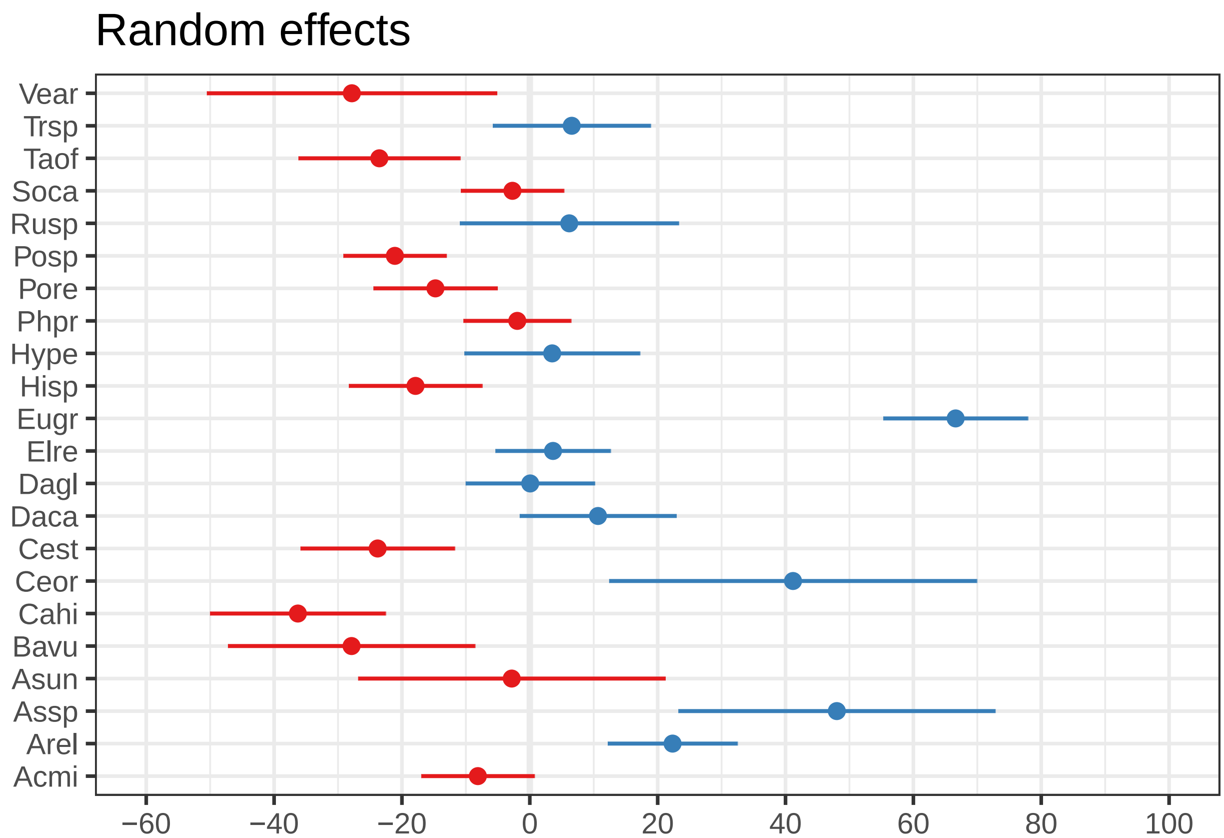
```r
# Next, plot the model. There are multiple variables but
# here's one way to do it based on this package sjPlot:
# https://strengejacke.github.io/sjPlot/articles/plot_model_estimates.html
# Annoyingly, this package somehow overwrites the factor
# order in its plotting so we will have to modify the 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(mod5)
plot_model(mod2, sort.est = TRUE)
```




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




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




```r
# Do we need to include insecticide?
mod3 <- lmer(spp_half_cover_date ~ state * year_factor + (1 |
    species), green_kbs, REML = FALSE)
anova(mod2, mod3)
```

```
## Data: green_kbs
## Models:
## mod3: spp_half_cover_date ~ state * year_factor + (1 | species)
## mod2: spp_half_cover_date ~ state * year_factor + insecticide * year_factor +
## mod2:     (1 | species)
##      npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod3   14 16189 16264 -8080.5    16161
## mod2   20 16198 16304 -8078.9    16158 3.2951  6      0.771
```

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

```
##      dAICc df weight
## mod3  0    14 0.989
## mod2  9    20 0.011
```

```r
# Dont' need insecticide, continue with mod3

# Does year need to be interactive with insecticide? -
# already removed insecticide mod4 <-
# lmer(spp_half_cover_date ~ state*year_factor + insecticide
# + (1|species) + (1|plot), green_kbs, #REML=FALSE)
# anova(mod1, mod4) No, P>0.05 so insecticide*year doesn't
# strongly improve model fit so we will shift to mod4
# anova(mod3, mod4) Yes, P<0.05 so insecticide still improves
```

```r
# model fit so we will stay with mod4

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

```
## Data: green_kbs
## Models:
## mod5: spp_half_cover_date ~ state + year_factor + (1 | species)
## mod3: spp_half_cover_date ~ state * year_factor + (1 | species)
##      npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod5    9 16186 16233 -8083.8    16168
## mod3   14 16189 16264 -8080.5    16161 6.4803  5     0.2622
```

```r
AICctab(mod3, mod5, weights = T)
```

```
##      dAICc df weight
## mod5  0.0  9  0.86
## mod3  3.7  14 0.14
```

```r
# state*year doesn't improve model fit so we could drop it
# and go with mod5, but note that the AIC values are super
# close
summary(mod5)
```

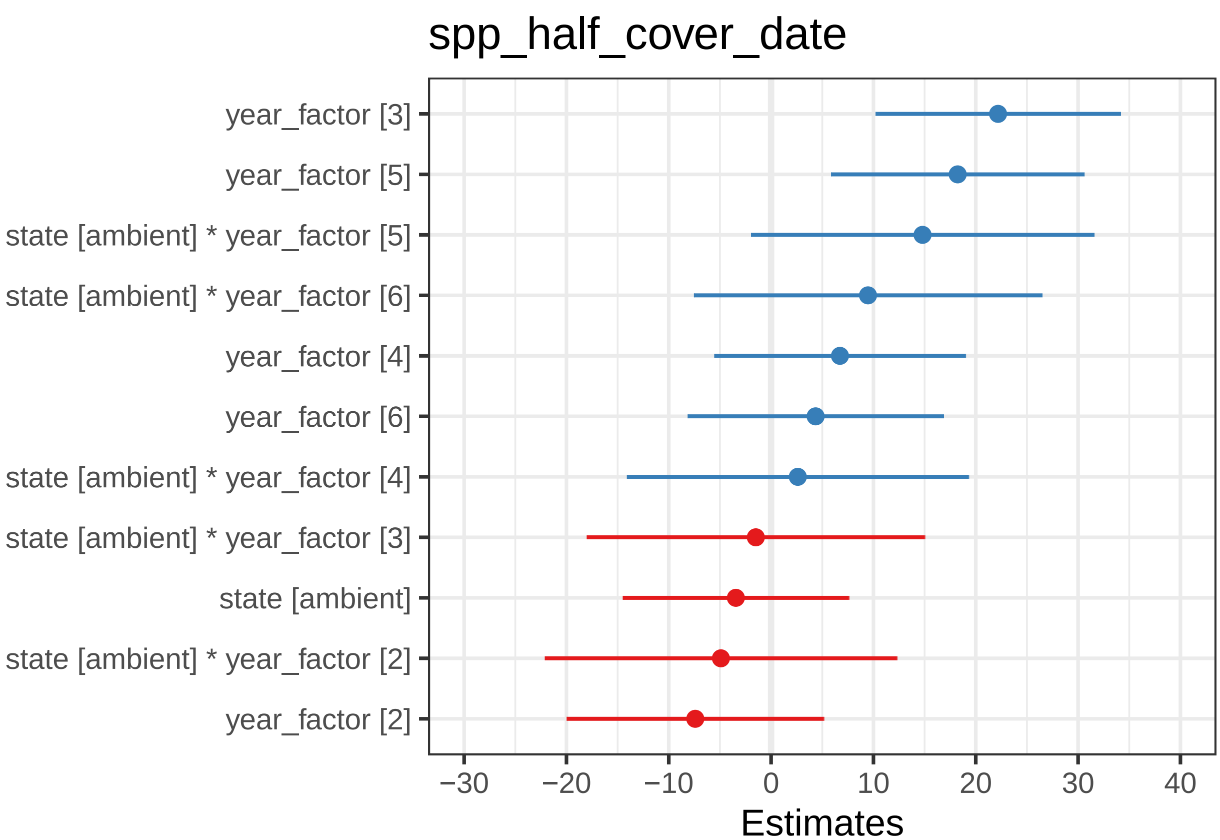
```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: spp_half_cover_date ~ state + year_factor + (1 | species)
##    Data: green_kbs
##
##      AIC      BIC   logLik deviance df.resid
##  16185.5  16233.4  -8083.8  16167.5     1502
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.1336 -0.6860 -0.2278  0.4745  3.1191
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  species  (Intercept)  709.2   26.63
##  Residual             2493.5   49.94
## Number of obs: 1511, groups:  species, 22
##
## Fixed effects:
##               Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)   132.8740     6.5879   29.8621  20.169  < 2e-16 ***
## stateambient   -0.1626     2.6097 1494.1996  -0.062   0.9503
## year_factor2  -10.0332     4.4619 1495.4833  -2.249   0.0247 *
## year_factor3   21.3776     4.2685 1498.0716   5.008 6.15e-07 ***
## year_factor4    8.0551     4.2861 1490.9749   1.879   0.0604 .
## year_factor5   26.1898     4.3838 1498.8556   5.974 2.88e-09 ***
## year_factor6    9.3321     4.4492 1498.6649   2.097   0.0361 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Correlation of Fixed Effects:
##              (Intr) sttmbn yr_fc2 yr_fc3 yr_fc4 yr_fc5
## stateambint -0.203
## year_factr2 -0.273 -0.015
## year_factr3 -0.292 -0.008  0.437
## year_factr4 -0.283 -0.030  0.433  0.451
## year_factr5 -0.281 -0.024  0.433  0.454  0.451
## year_factr6 -0.277 -0.020  0.431  0.446  0.446  0.453
```

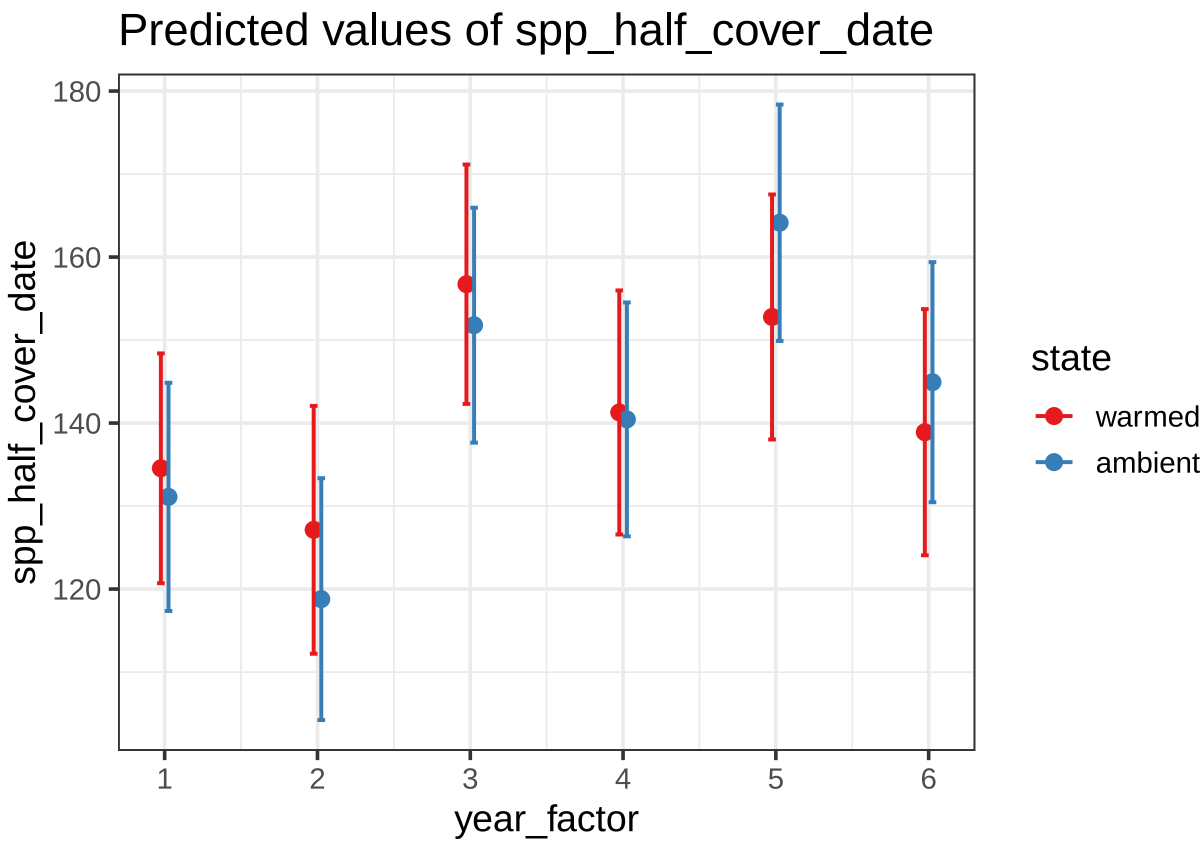
```
anova(mod3)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##                  Sum Sq Mean Sq NumDF  DenDF F value    Pr(>F)
## state                 0       0     1 1494.5  0.0001    0.9904
## year_factor      202859   40572     5 1493.7 16.3419 1.002e-15 ***
## state:year_factor  16124    3225     5 1488.6  1.2989    0.2617
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

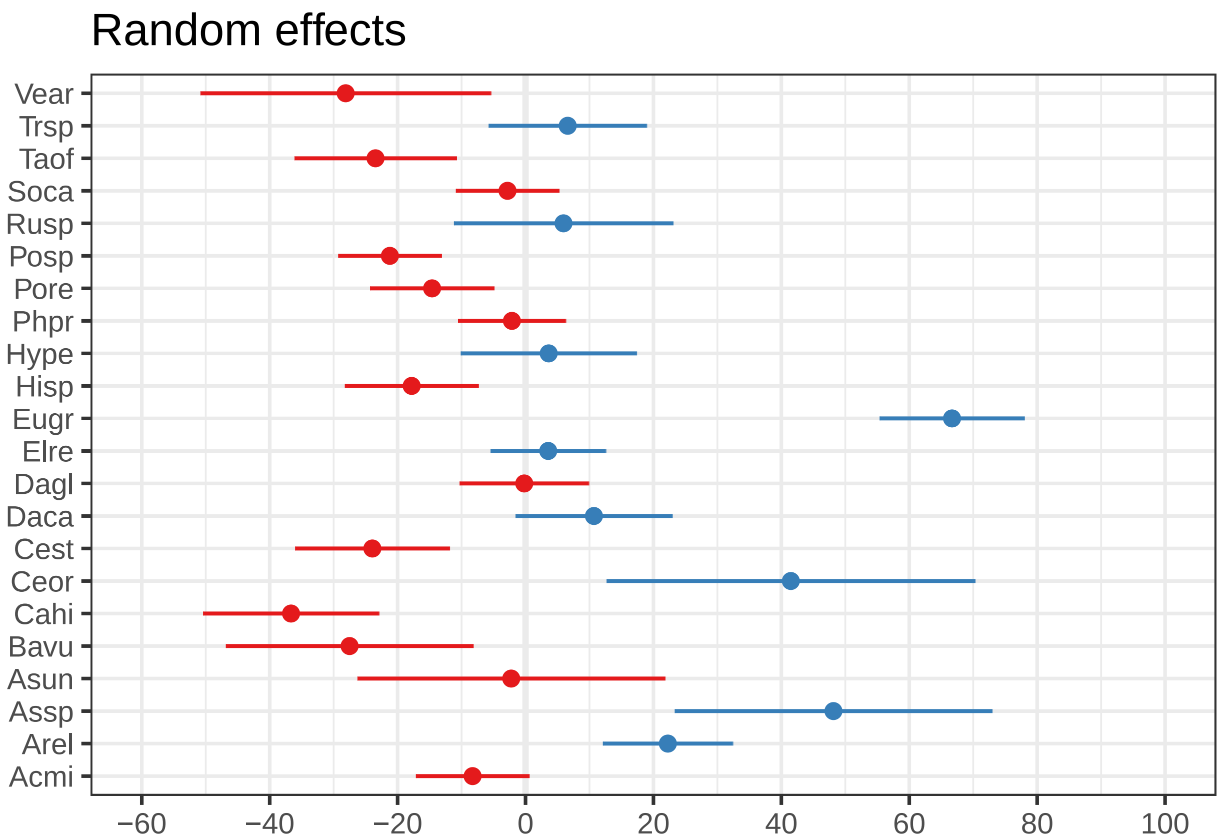
```
# these are the fixed effects estimates from summary(mod3)
plot_model(mod3, sort.est = TRUE)
```




```
# these are the fixed predicted values:
plot_model(mod3, type = "pred", terms = c("year_factor", "state"))
```




```r
# these are the random effects estimates
plot_model(mod3, type = "re", terms = c("species", "plot"))
```




```
# If we wanted to include plots nested within year it would
# look like this:
mod6 <- lmer(spp_half_cover_date ~ state * year_factor + (1 |
    species) + (1 + year | plot), green_kbs, REML = FALSE)
```

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

```
## Warning: Model failed to converge with 1 negative eigenvalue: -7.0e+00
```

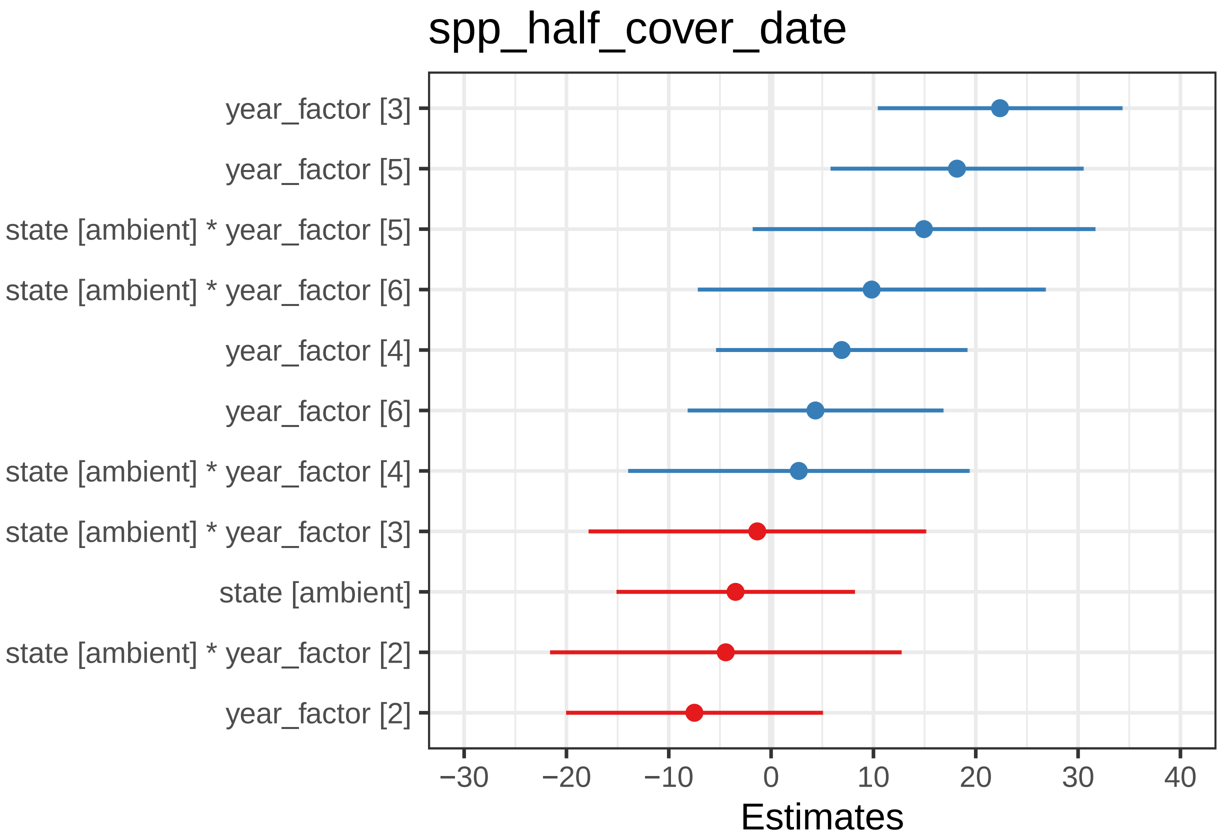
```
anova(mod3, mod6)
```

```
## Data: green_kbs
## Models:
## mod3: spp_half_cover_date ~ state * year_factor + (1 | species)
## mod6: spp_half_cover_date ~ state * year_factor + (1 | species) + (1 +
## mod6:     year | plot)
##      npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod3   14 16189 16264 -8080.5    16161
## mod6   17 16193 16283 -8079.4    16159 2.1868  3     0.5346
```

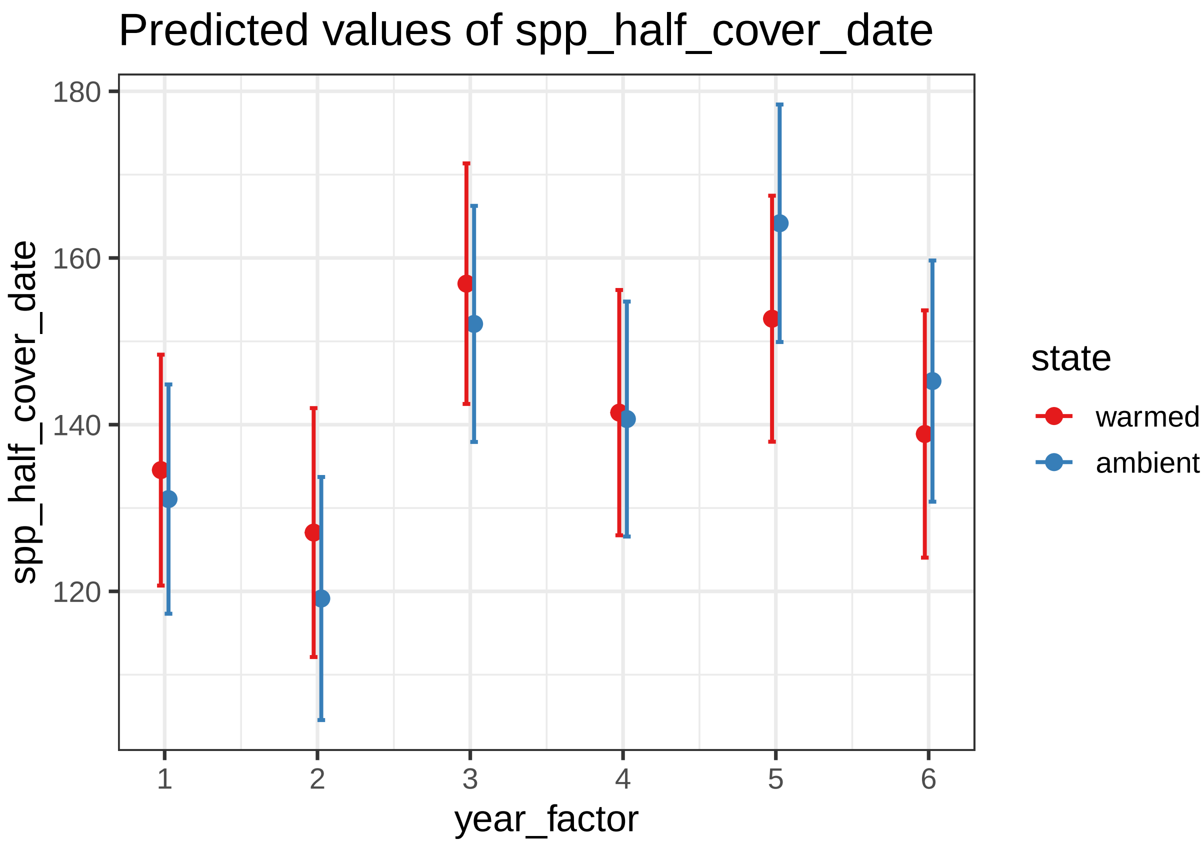
```
anova(mod6)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##                   Sum Sq Mean Sq NumDF   DenDF F value    Pr(>F)
## state                  4       4     1   22.65  0.0018    0.9667
## year_factor       202720   40544     5 1482.80 16.4503 7.876e-16 ***
## state:year_factor  15999    3200     5 1476.49  1.2983    0.2620
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# mod 3 still better fit
plot_model(mod6, sort.est = TRUE)
```



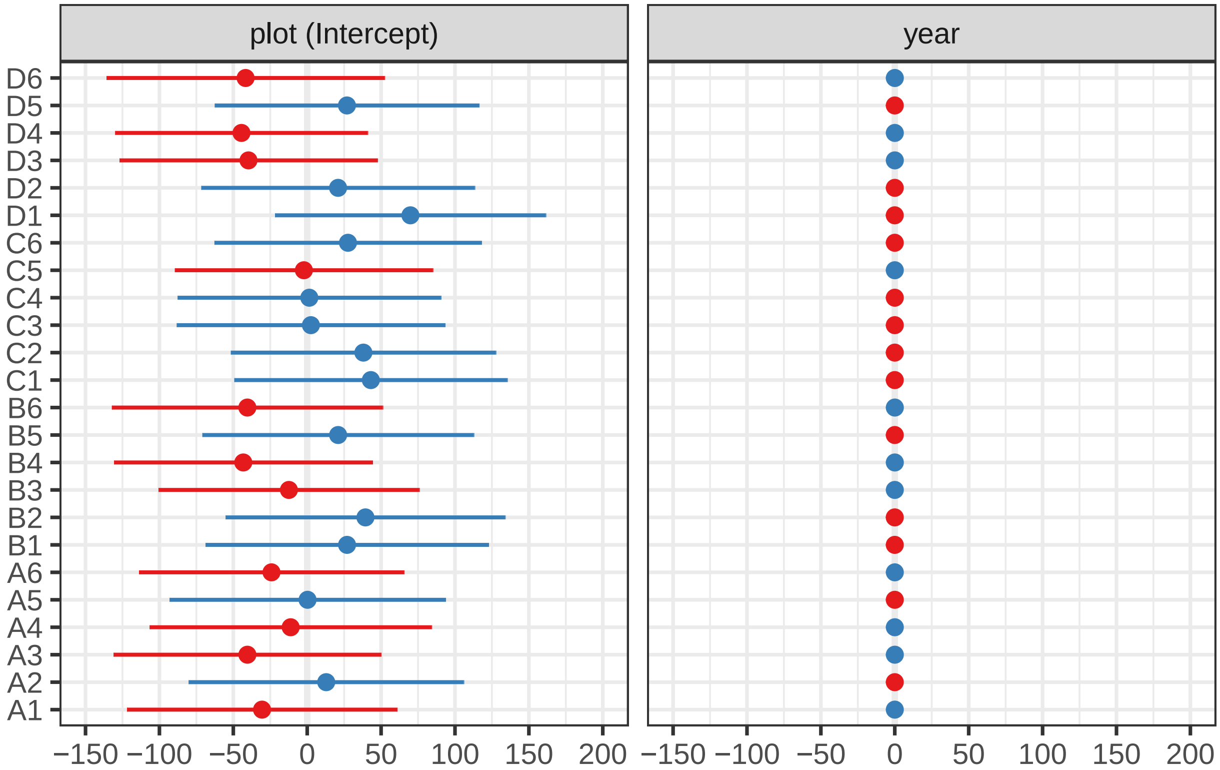

```r
# these are the fixed predicted values:
plot_model(mod6, type = "pred", terms = c("year_factor", "state"))
```



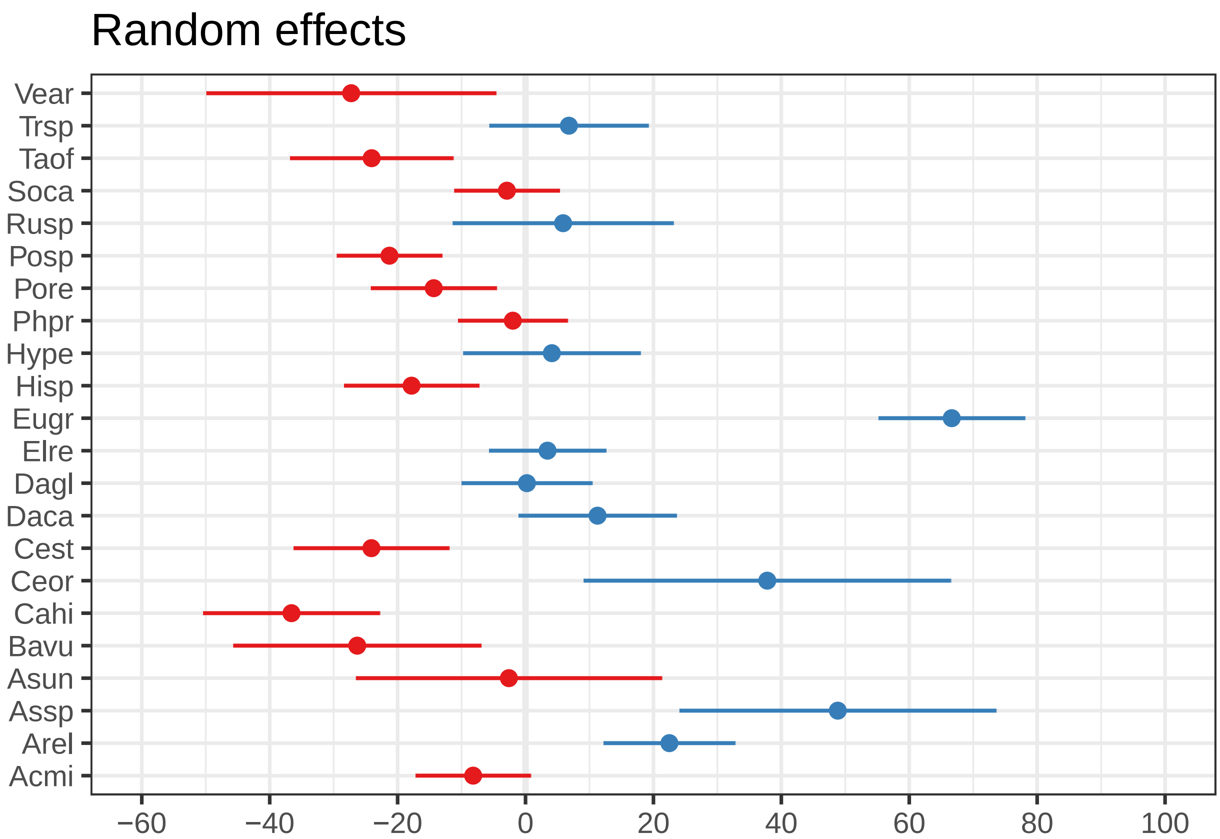

```
# these are the random effects estimates
plot_model(mod6, type = "re", terms = c("species", "plot"))
```

```
## [[1]]
```

Random effects




```
##
## [[2]]
```




```r
# mod3 (and mod6) 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.

# including species as fixed effect
mod7 <- lmer(spp_half_cover_date ~ state + species + (1 + year_factor |
    plot), green_kbs, REML = FALSE)
```

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

## Warning: Model failed to converge with 1 negative eigenvalue: -3.2e+00
```

```r
mod7a <- lmer(spp_half_cover_date ~ state + species + year_factor +
    (1 | plot), green_kbs, REML = FALSE)
mod7b <- lmer(spp_half_cover_date ~ state * year_factor + species +
    (1 | plot), green_kbs, REML = FALSE)
mod7c <- lmer(spp_half_cover_date ~ state + species + year_factor +
    insecticide + (1 | plot), green_kbs, REML = FALSE)
anova(mod6, mod7)  # model 7 is a better fit to data
```

```
## Data: green_kbs
## Models:
## mod6: spp_half_cover_date ~ state * year_factor + (1 | species) + (1 +
## mod6:     year | plot)
## mod7: spp_half_cover_date ~ state + species + (1 + year_factor | plot)
##      npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod6   17 16193 16283 -8079.4    16159
```

```
## mod7   45 16198 16437 -8054.0    16108 50.921 28   0.005095 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(mod7, mod7a)  #mod 7a
```

```
## Data: green_kbs
## Models:
## mod7a: spp_half_cover_date ~ state + species + year_factor + (1 | plot)
## mod7: spp_half_cover_date ~ state + species + (1 + year_factor | plot)
##       npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod7a   30 16141 16301 -8040.6    16081
## mod7    45 16198 16437 -8054.0    16108     0 15          1
```

```r
anova(mod7a, mod7b)  #mod 7a
```

```
## Data: green_kbs
## Models:
## mod7a: spp_half_cover_date ~ state + species + year_factor + (1 | plot)
## mod7b: spp_half_cover_date ~ state * year_factor + species + (1 | plot)
##       npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod7a   30 16141 16301 -8040.6    16081
## mod7b   35 16145 16331 -8037.3    16075 6.5812  5     0.2537
```

```r
anova(mod7a, mod7c)  #mod 7a
```

```
## Data: green_kbs
## Models:
## mod7a: spp_half_cover_date ~ state + species + year_factor + (1 | plot)
## mod7c: spp_half_cover_date ~ state + species + year_factor + insecticide +
## mod7c:     (1 | plot)
##       npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod7a   30 16141 16301 -8040.6    16081
## mod7c   31 16143 16308 -8040.6    16081 0.002  1      0.964
```

```r
summary(mod7a)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: spp_half_cover_date ~ state + species + year_factor + (1 | plot)
##    Data: green_kbs
##
##      AIC      BIC   logLik deviance df.resid
##  16141.1  16300.8  -8040.6  16081.1     1481
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.1580 -0.6793 -0.2178  0.4667  3.1466
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)   16.91   4.112
##  Residual             2438.42  49.380
## Number of obs: 1511, groups:  plot, 24
##
## Fixed effects:
##                Estimate Std. Error        df t value Pr(>|t|)
```

```
## (Intercept)   124.6679     5.5355  658.1208  22.522  < 2e-16 ***
## stateambient    -0.1218     3.0925   23.4606  -0.039 0.968910
## speciesArel    31.5237     6.9674 1502.0715   4.524 6.53e-06 ***
## speciesAssp    71.8944    15.0713 1504.7956   4.770 2.02e-06 ***
## speciesAsun     4.9822    14.5648 1497.4397   0.342 0.732343
## speciesBavu   -21.9349    11.5623 1510.9007  -1.897 0.058004 .
## speciesCahi   -30.8244     8.5743 1502.0958  -3.595 0.000335 ***
## speciesCeor    65.0746    18.2061 1473.6005   3.574 0.000362 ***
## speciesCest   -17.7608     7.7939 1499.7908  -2.279 0.022819 *
## speciesDaca    20.4666     7.8568 1502.9399   2.605 0.009279 **
## speciesDagl     8.5034     6.9340 1501.4392   1.226 0.220267
## speciesElre    12.0669     6.5205 1496.9446   1.851 0.064424 .
## speciesEugr    78.4509     7.4574 1509.7734  10.520  < 2e-16 ***
## speciesHisp   -10.1581     7.0897 1495.7777  -1.433 0.152123
## speciesHype    12.5225     8.5592 1510.9369   1.463 0.143660
## speciesPhpr     6.1822     6.2777 1493.4067   0.985 0.324886
## speciesPore    -6.5550     6.7603 1499.9341  -0.970 0.332387
## speciesPosp   -13.5300     6.1492 1491.2662  -2.200 0.027940 *
## speciesRusp    14.6457    10.3229 1478.7658   1.419 0.156182
## speciesSoca     5.3091     6.1492 1491.2662   0.863 0.388067
## speciesTaof   -17.2928     8.0633 1510.5669  -2.145 0.032142 *
## speciesTrsp    15.8169     7.9265 1499.7857   1.995 0.046174 *
## speciesVear   -25.8562    13.6356 1509.6798  -1.896 0.058121 .
## year_factor2  -10.0690     4.4226 1495.7614  -2.277 0.022943 *
## year_factor3   21.6909     4.2345 1498.3063   5.122 3.41e-07 ***
## year_factor4    7.9005     4.2476 1503.0642   1.860 0.063082 .
## year_factor5   25.8202     4.3513 1503.1515   5.934 3.67e-09 ***
## year_factor6    9.0605     4.4186 1507.1045   2.051 0.040484 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation matrix not shown by default, as p = 28 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

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

```
## Type III Analysis of Variance Table with Satterthwaite's method
##             Sum Sq Mean Sq NumDF   DenDF F value    Pr(>F)
## state            4       4     1   23.46  0.0016    0.9689
## species     779402   37114    21 1501.43 15.2207 < 2.2e-16 ***
## year_factor 207080   41416     5 1499.58 16.9847 2.297e-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(mod7a, list(pairwise ~ state + year_factor), adjust = "tukey")
```

```
## $`emmeans of state, year_factor`
##  state   year_factor emmean   SE  df lower.CL upper.CL
##  warmed  1              134 3.66 177      127      141
##  ambient 1              134 3.63 176      127      141
##  warmed  2              124 4.16 282      116      132
##  ambient 2              124 4.09 271      116      132
```

```
##  warmed  3              156 3.90 216      148      163
##  ambient 3              155 3.85 214      148      163
##  warmed  4              142 3.98 231      134      150
##  ambient 4              142 3.86 216      134      149
##  warmed  5              160 4.06 248      152      168
##  ambient 5              160 3.97 237      152      167
##  warmed  6              143 4.14 263      135      151
##  ambient 6              143 4.05 256      135      151
##
## Results are averaged over the levels of: species
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $`pairwise differences of state, year_factor`
##  1                    estimate   SE     df t.ratio p.value
##  warmed 1 - ambient 1     0.122 3.26   27.2  0.037  1.0000
##  warmed 1 - warmed 2     10.069 4.46 1522.7  2.256  0.5088
##  warmed 1 - ambient 2    10.191 5.49  226.9  1.855  0.7851
##  warmed 1 - warmed 3    -21.691 4.27 1525.2 -5.075  <.0001
##  warmed 1 - ambient 3   -21.569 5.36  207.8 -4.027  0.0044
##  warmed 1 - warmed 4     -7.900 4.29 1530.2 -1.842  0.7942
##  warmed 1 - ambient 4    -7.779 5.32  201.2 -1.463  0.9488
##  warmed 1 - warmed 5    -25.820 4.39 1530.2 -5.877  <.0001
##  warmed 1 - ambient 5   -25.698 5.42  214.8 -4.744  0.0002
##  warmed 1 - warmed 6     -9.061 4.46 1534.3 -2.030  0.6725
##  warmed 1 - ambient 6    -8.939 5.47  222.9 -1.633  0.8952
##  ambient 1 - warmed 2     9.947 5.56  236.6  1.789  0.8225
##  ambient 1 - ambient 2   10.069 4.46 1522.7  2.256  0.5088
##  ambient 1 - warmed 3   -21.813 5.39  208.8 -4.044  0.0042
##  ambient 1 - ambient 3  -21.691 4.27 1525.2 -5.075  <.0001
##  ambient 1 - warmed 4    -8.022 5.45  214.9 -1.471  0.9468
##  ambient 1 - ambient 4   -7.900 4.29 1530.2 -1.842  0.7942
##  ambient 1 - warmed 5   -25.942 5.52  225.5 -4.697  0.0003
##  ambient 1 - ambient 5  -25.820 4.39 1530.2 -5.877  <.0001
##  ambient 1 - warmed 6    -9.182 5.58  229.3 -1.647  0.8897
##  ambient 1 - ambient 6   -9.061 4.46 1534.3 -2.030  0.6725
##  warmed 2 - ambient 2     0.122 3.26   27.2  0.037  1.0000
##  warmed 2 - warmed 3    -31.760 4.64 1520.8 -6.851  <.0001
##  warmed 2 - ambient 3   -31.638 5.68  259.3 -5.568  <.0001
##  warmed 2 - warmed 4    -17.969 4.66 1523.0 -3.859  0.0066
##  warmed 2 - ambient 4   -17.848 5.65  254.4 -3.157  0.0752
##  warmed 2 - warmed 5    -35.889 4.71 1525.7 -7.617  <.0001
##  warmed 2 - ambient 5   -35.767 5.71  262.1 -6.263  <.0001
##  warmed 2 - warmed 6    -19.130 4.76 1533.4 -4.021  0.0035
##  warmed 2 - ambient 6   -19.008 5.75  265.9 -3.305  0.0488
##  ambient 2 - warmed 3   -31.882 5.65  250.0 -5.641  <.0001
##  ambient 2 - ambient 3  -31.760 4.64 1520.8 -6.851  <.0001
##  ambient 2 - warmed 4   -18.091 5.72  258.5 -3.166  0.0734
##  ambient 2 - ambient 4  -17.969 4.66 1523.0 -3.859  0.0066
##  ambient 2 - warmed 5   -36.011 5.75  263.0 -6.266  <.0001
##  ambient 2 - ambient 5  -35.889 4.71 1525.7 -7.617  <.0001
##  ambient 2 - warmed 6   -19.251 5.78  261.9 -3.329  0.0456
##  ambient 2 - ambient 6  -19.130 4.76 1533.4 -4.021  0.0035
##  warmed 3 - ambient 3     0.122 3.26   27.2  0.037  1.0000
```

```
##  warmed 3 - warmed 4     13.790 4.48 1522.6  3.077  0.0888
##  warmed 3 - ambient 4    13.912 5.49  227.6  2.532  0.3257
##  warmed 3 - warmed 5     -4.129 4.52 1526.1 -0.913  0.9990
##  warmed 3 - ambient 5    -4.008 5.54  232.5 -0.723  0.9999
##  warmed 3 - warmed 6     12.630 4.60 1532.3  2.747  0.2046
##  warmed 3 - ambient 6    12.752 5.60  241.3  2.275  0.4971
##  ambient 3 - warmed 4    13.669 5.59  240.7  2.446  0.3797
##  ambient 3 - ambient 4   13.790 4.48 1522.6  3.077  0.0888
##  ambient 3 - warmed 5    -4.251 5.61  242.6 -0.758  0.9998
##  ambient 3 - ambient 5   -4.129 4.52 1526.1 -0.913  0.9990
##  ambient 3 - warmed 6    12.509 5.67  246.8  2.207  0.5463
##  ambient 3 - ambient 6   12.630 4.60 1532.3  2.747  0.2046
##  warmed 4 - ambient 4     0.122 3.26   27.2  0.037  1.0000
##  warmed 4 - warmed 5    -17.920 4.54 1518.0 -3.950  0.0047
##  warmed 4 - ambient 5   -17.798 5.60  244.3 -3.179  0.0710
##  warmed 4 - warmed 6     -1.160 4.60 1526.3 -0.252  1.0000
##  warmed 4 - ambient 6    -1.038 5.65  251.2 -0.184  1.0000
##  ambient 4 - warmed 5   -18.042 5.57  241.2 -3.237  0.0602
##  ambient 4 - ambient 5  -17.920 4.54 1518.0 -3.950  0.0047
##  ambient 4 - warmed 6    -1.282 5.62  243.5 -0.228  1.0000
##  ambient 4 - ambient 6   -1.160 4.60 1526.3 -0.252  1.0000
##  warmed 5 - ambient 5     0.122 3.26   27.2  0.037  1.0000
##  warmed 5 - warmed 6     16.760 4.62 1526.0  3.630  0.0154
##  warmed 5 - ambient 6    16.882 5.65  252.2  2.986  0.1189
##  ambient 5 - warmed 6    16.638 5.65  247.6  2.945  0.1321
##  ambient 5 - ambient 6   16.760 4.62 1526.0  3.630  0.0154
##  warmed 6 - ambient 6     0.122 3.26   27.2  0.037  1.0000
##
## Results are averaged over the levels of: species
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 12 estimates
```

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

```
## $`emmeans of year_factor`
##  year_factor emmean   SE  df lower.CL upper.CL
##  1              134 3.26 402      127      140
##  2              124 3.79 617      116      131
##  3              156 3.52 482      149      162
##  4              142 3.56 499      135      149
##  5              160 3.67 538      152      167
##  6              143 3.75 572      136      150
##
## Results are averaged over the levels of: state, species
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $`pairwise differences of year_factor`
##  1      estimate   SE   df t.ratio p.value
##  1 - 2    10.07 4.46 1523  2.256  0.2130
##  1 - 3   -21.69 4.27 1525 -5.075  <.0001
##  1 - 4    -7.90 4.29 1530 -1.842  0.4387
##  1 - 5   -25.82 4.39 1530 -5.877  <.0001
##  1 - 6    -9.06 4.46 1534 -2.030  0.3255
##  2 - 3   -31.76 4.64 1521 -6.851  <.0001
```

```
##  2 - 4   -17.97 4.66 1523 -3.859  0.0017
##  2 - 5   -35.89 4.71 1526 -7.617  <.0001
##  2 - 6   -19.13 4.76 1533 -4.021  0.0009
##  3 - 4    13.79 4.48 1523  3.077  0.0259
##  3 - 5    -4.13 4.52 1526 -0.913  0.9432
##  3 - 6    12.63 4.60 1532  2.747  0.0670
##  4 - 5   -17.92 4.54 1518 -3.950  0.0011
##  4 - 6    -1.16 4.60 1526 -0.252  0.9999
##  5 - 6    16.76 4.62 1526  3.630  0.0040
##
## Results are averaged over the levels of: state, species
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

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

```
## $`emmeans of species`
##  species emmean    SE   df lower.CL upper.CL
##  Acmi       134  4.70 1009    124.5      143
##  Arel       165  5.40 1152    154.6      176
##  Assp       206 14.58 1507    177.0      234
##  Asun       139 14.01 1540    111.2      166
##  Bavu       112 10.79 1478     90.6      133
##  Cahi       103  7.42 1434     88.3      117
##  Ceor       199 17.88 1482    163.7      234
##  Cest       116  6.50 1358    103.2      129
##  Daca       154  6.57 1351    141.3      167
##  Dagl       142  5.36 1167    131.7      153
##  Elre       146  4.78 1047    136.4      155
##  Eugr       212  6.04 1213    200.3      224
##  Hisp       124  5.58 1226    112.6      134
##  Hype       146  7.40 1338    131.7      161
##  Phpr       140  4.46  936    131.1      149
##  Pore       127  5.15 1112    117.0      137
##  Posp       120  4.28  870    111.8      129
##  Rusp       148  9.43 1371    129.8      167
##  Soca       139  4.28  870    130.6      147
##  Taof       116  6.80 1337    103.0      130
##  Trsp       149  6.63 1378    136.5      163
##  Vear       108 13.04 1530     82.2      133
##
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $`pairwise differences of species`
##  1           estimate    SE   df t.ratio p.value
##  Acmi - Arel  -31.524  7.03 1529  -4.482 0.0016
##  Acmi - Assp  -71.894 15.25 1537  -4.714 0.0006
##  Acmi - Asun   -4.982 14.70 1524  -0.339 1.0000
##  Acmi - Bavu   21.935 11.69 1540   1.877 0.9612
##  Acmi - Cahi   30.824  8.66 1529   3.561 0.0567
##  Acmi - Ceor  -65.075 18.45 1510  -3.528 0.0629
##  Acmi - Cest   17.761  7.87 1527   2.258 0.8050
##  Acmi - Daca  -20.467  7.93 1530  -2.580 0.5690
```

```
##   Acmi - Dagl    -8.503  7.00 1529  -1.215 0.9999
##   Acmi - Elre   -12.067  6.58 1524  -1.834 0.9696
##   Acmi - Eugr   -78.451  7.53 1538 -10.413 <.0001
##   Acmi - Hisp    10.158  7.15 1523   1.420 0.9988
##   Acmi - Hype   -12.523  8.65 1540  -1.447 0.9984
##   Acmi - Phpr    -6.182  6.33 1520  -0.976 1.0000
##   Acmi - Pore     6.555  6.82 1527   0.961 1.0000
##   Acmi - Posp    13.530  6.20 1518   2.181 0.8493
##   Acmi - Rusp   -14.646 10.46 1516  -1.400 0.9990
##   Acmi - Soca    -5.309  6.20 1518  -0.856 1.0000
##   Acmi - Taof    17.293  8.15 1539   2.122 0.8786
##   Acmi - Trsp   -15.817  8.00 1527  -1.977 0.9351
##   Acmi - Vear    25.856 13.78 1537   1.877 0.9611
##   Arel - Assp   -40.371 15.50 1535  -2.605 0.5490
##   Arel - Asun    26.541 14.95 1527   1.775 0.9787
##   Arel - Bavu    53.459 11.98 1540   4.461 0.0018
##   Arel - Cahi    62.348  9.12 1537   6.837 <.0001
##   Arel - Ceor   -33.551 18.63 1514  -1.801 0.9749
##   Arel - Cest    49.285  8.37 1537   5.885 <.0001
##   Arel - Daca    11.057  8.39 1534   1.317 0.9996
##   Arel - Dagl    23.020  7.47 1531   3.080 0.2195
##   Arel - Elre    19.457  7.08 1531   2.748 0.4367
##   Arel - Eugr   -46.927  7.98 1540  -5.883 <.0001
##   Arel - Hisp    41.682  7.64 1531   5.456 <.0001
##   Arel - Hype    19.001  9.05 1540   2.100 0.8890
##   Arel - Phpr    25.341  6.87 1531   3.687 0.0373
##   Arel - Pore    38.079  7.33 1533   5.194 0.0001
##   Arel - Posp    45.054  6.76 1531   6.668 <.0001
##   Arel - Rusp    16.878 10.76 1529   1.568 0.9952
##   Arel - Soca    26.215  6.76 1531   3.880 0.0188
##   Arel - Taof    48.817  8.58 1538   5.693 <.0001
##   Arel - Trsp    15.707  8.44 1531   1.861 0.9645
##   Arel - Vear    57.380 14.05 1537   4.083 0.0087
##   Assp - Asun    66.912 20.25 1540   3.304 0.1226
##   Assp - Bavu    93.829 18.06 1538   5.195 0.0001
##   Assp - Cahi   102.719 16.25 1540   6.319 <.0001
##   Assp - Ceor     6.820 23.05 1519   0.296 1.0000
##   Assp - Cest    89.655 15.91 1537   5.635 <.0001
##   Assp - Daca    51.428 15.88 1540   3.239 0.1466
##   Assp - Dagl    63.391 15.48 1537   4.096 0.0083
##   Assp - Elre    59.827 15.28 1536   3.914 0.0166
##   Assp - Eugr    -6.557 15.69 1540  -0.418 1.0000
##   Assp - Hisp    82.052 15.56 1539   5.272 <.0001
##   Assp - Hype    59.372 16.29 1535   3.644 0.0432
##   Assp - Phpr    65.712 15.18 1537   4.329 0.0032
##   Assp - Pore    78.449 15.38 1539   5.100 0.0001
##   Assp - Posp    85.424 15.13 1536   5.646 <.0001
##   Assp - Rusp    57.249 17.27 1539   3.314 0.1191
##   Assp - Soca    66.585 15.13 1536   4.401 0.0023
##   Assp - Taof    89.187 16.02 1539   5.567 <.0001
##   Assp - Trsp    56.077 15.94 1540   3.518 0.0648
##   Assp - Vear    97.751 19.42 1533   5.033 0.0001
##   Asun - Bavu    26.917 17.65 1538   1.525 0.9967
##   Asun - Cahi    35.807 15.82 1528   2.264 0.8012
```

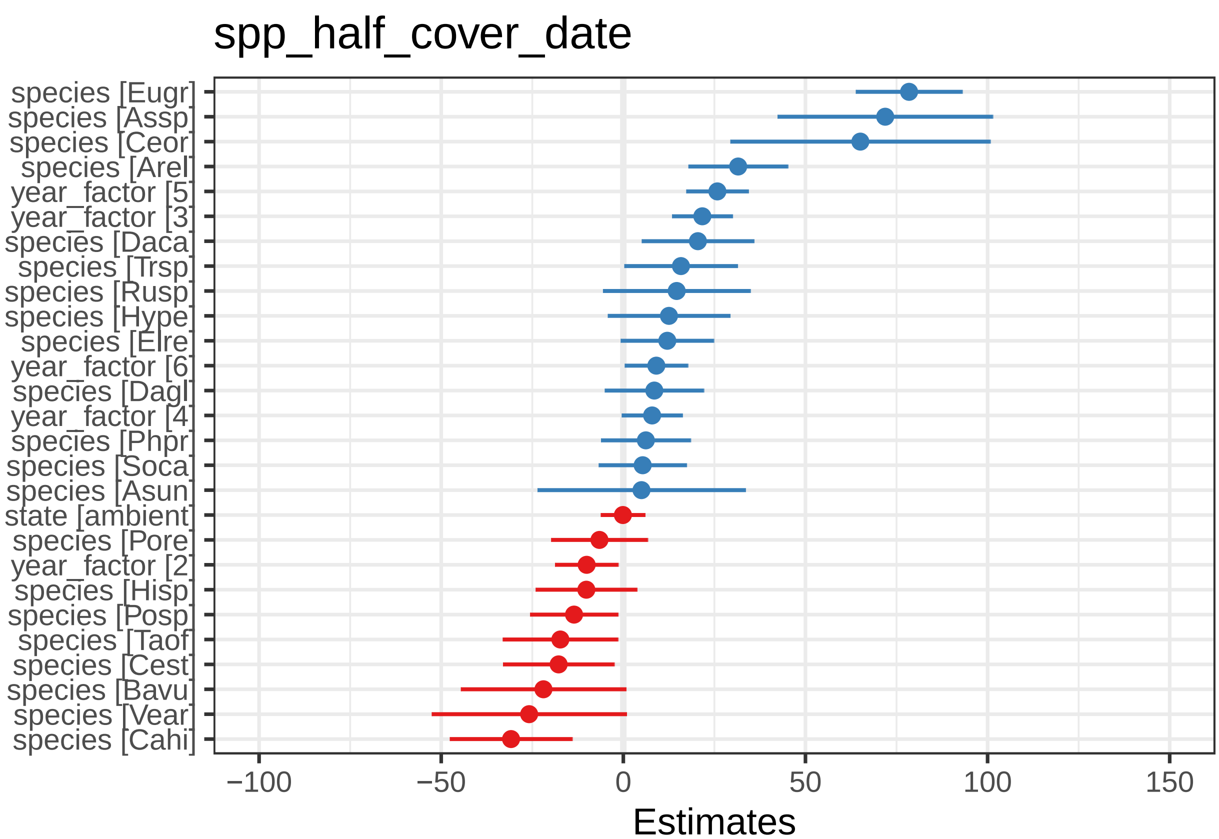
```
##   Asun - Ceor   -60.092 22.66 1536   -2.652 0.5117
##   Asun - Cest    22.743 15.34 1523    1.482 0.9977
##   Asun - Daca   -15.484 15.42 1527   -1.004 1.0000
##   Asun - Dagl    -3.521 14.92 1530   -0.236 1.0000
##   Asun - Elre    -7.085 14.73 1527   -0.481 1.0000
##   Asun - Eugr   -73.469 15.19 1530   -4.837 0.0003
##   Asun - Hisp    15.140 14.97 1524    1.011 1.0000
##   Asun - Hype    -7.540 15.77 1536   -0.478 1.0000
##   Asun - Phpr    -1.200 14.65 1527   -0.082 1.0000
##   Asun - Pore    11.537 14.85 1527    0.777 1.0000
##   Asun - Posp    18.512 14.58 1525    1.270 0.9998
##   Asun - Rusp    -9.663 16.83 1539   -0.574 1.0000
##   Asun - Soca    -0.327 14.58 1525   -0.022 1.0000
##   Asun - Taof    22.275 15.50 1530    1.437 0.9985
##   Asun - Trsp   -10.835 15.45 1527   -0.701 1.0000
##   Asun - Vear    30.838 19.11 1532    1.614 0.9931
##   Bavu - Cahi     8.889 13.02 1539    0.683 1.0000
##   Bavu - Ceor   -87.010 20.91 1507   -4.161 0.0064
##   Bavu - Cest    -4.174 12.58 1539   -0.332 1.0000
##   Bavu - Daca   -42.402 12.58 1540   -3.371 0.1014
##   Bavu - Dagl   -30.438 11.97 1539   -2.543 0.5984
##   Bavu - Elre   -34.002 11.71 1538   -2.904 0.3249
##   Bavu - Eugr  -100.386 12.26 1539   -8.188 <.0001
##   Bavu - Hisp   -11.777 12.09 1539   -0.974 1.0000
##   Bavu - Hype   -34.457 13.00 1537   -2.651 0.5124
##   Bavu - Phpr   -28.117 11.59 1539   -2.425 0.6895
##   Bavu - Pore   -15.380 11.91 1537   -1.291 0.9997
##   Bavu - Posp    -8.405 11.53 1539   -0.729 1.0000
##   Bavu - Rusp   -36.581 14.28 1529   -2.562 0.5834
##   Bavu - Soca   -27.244 11.53 1539   -2.364 0.7346
##   Bavu - Taof    -4.642 12.73 1536   -0.365 1.0000
##   Bavu - Trsp   -37.752 12.61 1539   -2.994 0.2681
##   Bavu - Vear     3.921 16.89 1539    0.232 1.0000
##   Cahi - Ceor   -95.899 19.28 1529   -4.974 0.0002
##   Cahi - Cest   -13.064  9.70 1532   -1.347 0.9994
##   Cahi - Daca   -51.291  9.77 1528   -5.252 <.0001
##   Cahi - Dagl   -39.328  9.08 1535   -4.330 0.0032
##   Cahi - Elre   -42.891  8.76 1533   -4.897 0.0002
##   Cahi - Eugr  -109.275  9.47 1533  -11.540 <.0001
##   Cahi - Hisp   -20.666  9.16 1532   -2.256 0.8059
##   Cahi - Hype   -43.347 10.37 1536   -4.182 0.0058
##   Cahi - Phpr   -37.007  8.55 1531   -4.328 0.0032
##   Cahi - Pore   -24.269  8.93 1536   -2.718 0.4602
##   Cahi - Posp   -17.294  8.46 1531   -2.045 0.9114
##   Cahi - Rusp   -45.470 11.94 1535   -3.808 0.0245
##   Cahi - Soca   -36.134  8.46 1531   -4.273 0.0040
##   Cahi - Taof   -13.532  9.94 1538   -1.361 0.9993
##   Cahi - Trsp   -46.641  9.79 1524   -4.765 0.0004
##   Cahi - Vear    -4.968 14.84 1531   -0.335 1.0000
##   Ceor - Cest    82.835 18.96 1514    4.370 0.0027
##   Ceor - Daca    44.608 18.98 1516    2.350 0.7443
##   Ceor - Dagl    56.571 18.64 1509    3.036 0.2437
##   Ceor - Elre    53.008 18.47 1519    2.870 0.3481
##   Ceor - Eugr   -13.376 18.84 1506   -0.710 1.0000
```

```
##  Ceor - Hisp   75.233 18.65 1518   4.035 0.0105
##  Ceor - Hype   52.552 19.35 1498   2.717 0.4612
##  Ceor - Phpr   58.892 18.40 1510   3.201 0.1619
##  Ceor - Pore   71.630 18.57 1505   3.858 0.0204
##  Ceor - Posp   78.605 18.34 1515   4.286 0.0038
##  Ceor - Rusp   50.429 20.14 1518   2.504 0.6293
##  Ceor - Soca   59.765 18.34 1515   3.259 0.1389
##  Ceor - Taof   82.367 19.05 1521   4.325 0.0032
##  Ceor - Trsp   49.258 18.97 1526   2.597 0.5559
##  Ceor - Vear   90.931 22.06 1525   4.123 0.0074
##  Cest - Daca  -38.227  9.06 1529  -4.219 0.0050
##  Cest - Dagl  -26.264  8.33 1535  -3.154 0.1829
##  Cest - Elre  -29.828  8.00 1530  -3.726 0.0326
##  Cest - Eugr  -96.212  8.79 1539 -10.942 <.0001
##  Cest - Hisp   -7.603  8.40 1523  -0.905 1.0000
##  Cest - Hype  -30.283  9.75 1540  -3.104 0.2069
##  Cest - Phpr  -23.943  7.77 1530  -3.082 0.2184
##  Cest - Pore  -11.206  8.14 1526  -1.377 0.9992
##  Cest - Posp   -4.231  7.66 1528  -0.552 1.0000
##  Cest - Rusp  -32.407 11.40 1508  -2.843 0.3666
##  Cest - Soca  -23.070  7.66 1528  -3.012 0.2574
##  Cest - Taof   -0.468  9.26 1537  -0.051 1.0000
##  Cest - Trsp  -33.578  9.13 1529  -3.678 0.0385
##  Cest - Vear    8.095 14.44 1538   0.561 1.0000
##  Daca - Dagl   11.963  8.37 1531   1.430 0.9986
##  Daca - Elre    8.400  8.04 1533   1.045 1.0000
##  Daca - Eugr  -57.984  8.82 1537  -6.574 <.0001
##  Daca - Hisp   30.625  8.48 1527   3.613 0.0479
##  Daca - Hype    7.944  9.80 1540   0.810 1.0000
##  Daca - Phpr   14.284  7.82 1531   1.827 0.9707
##  Daca - Pore   27.022  8.19 1527   3.297 0.1250
##  Daca - Posp   33.997  7.72 1532   4.406 0.0023
##  Daca - Rusp    5.821 11.41 1522   0.510 1.0000
##  Daca - Soca   15.158  7.72 1532   1.964 0.9390
##  Daca - Taof   37.759  9.34 1539   4.043 0.0102
##  Daca - Trsp    4.650  9.19 1525   0.506 1.0000
##  Daca - Vear   46.323 14.48 1534   3.200 0.1626
##  Dagl - Elre   -3.563  7.05 1524  -0.506 1.0000
##  Dagl - Eugr  -69.947  7.96 1539  -8.788 <.0001
##  Dagl - Hisp   18.661  7.61 1530   2.451 0.6705
##  Dagl - Hype   -4.019  9.03 1540  -0.445 1.0000
##  Dagl - Phpr    2.321  6.84 1523   0.340 1.0000
##  Dagl - Pore   15.058  7.30 1529   2.063 0.9045
##  Dagl - Posp   22.033  6.72 1526   3.277 0.1321
##  Dagl - Rusp   -6.142 10.75 1528  -0.571 1.0000
##  Dagl - Soca    3.194  6.72 1526   0.475 1.0000
##  Dagl - Taof   25.796  8.55 1537   3.017 0.2541
##  Dagl - Trsp   -7.314  8.43 1531  -0.868 1.0000
##  Dagl - Vear   34.360 14.05 1537   2.446 0.6739
##  Elre - Eugr  -66.384  7.58 1539  -8.761 <.0001
##  Elre - Hisp   22.225  7.24 1527   3.070 0.2248
##  Elre - Hype   -0.456  8.70 1539  -0.052 1.0000
##  Elre - Phpr    5.885  6.40 1517   0.920 1.0000
##  Elre - Pore   18.622  6.91 1527   2.695 0.4779
```

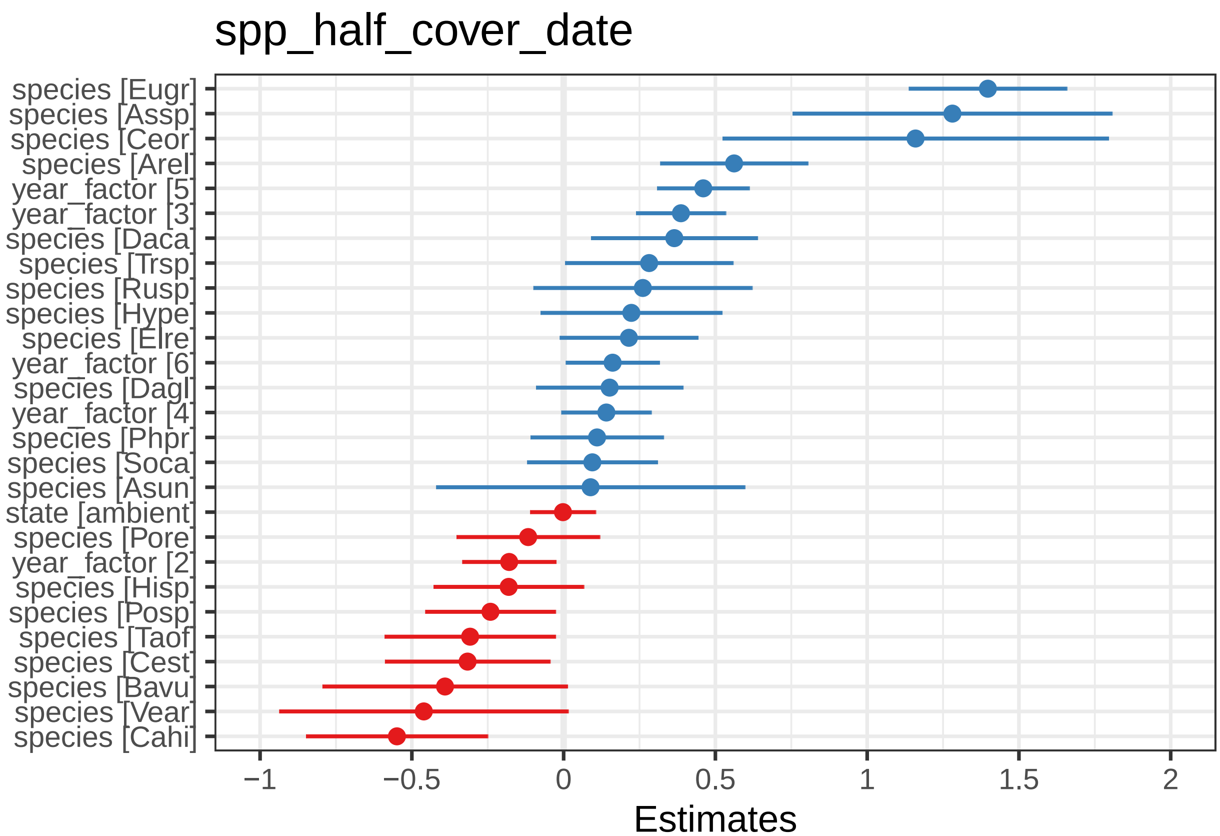
```
##  Elre - Posp   25.597  6.27 1516   4.084 0.0087
##  Elre - Rusp   -2.579 10.48 1531  -0.246 1.0000
##  Elre - Soca    6.758  6.27 1516   1.078 1.0000
##  Elre - Taof   29.360  8.22 1536   3.572 0.0547
##  Elre - Trsp   -3.750  8.09 1529  -0.464 1.0000
##  Elre - Vear   37.923 13.86 1539   2.737 0.4454
##  Eugr - Hisp   88.609  8.10 1539  10.944 <.0001
##  Eugr - Hype   65.928  9.44 1539   6.984 <.0001
##  Eugr - Phpr   72.269  7.38 1538   9.792 <.0001
##  Eugr - Pore   85.006  7.82 1539  10.868 <.0001
##  Eugr - Posp   91.981  7.27 1539  12.646 <.0001
##  Eugr - Rusp   63.805 11.08 1537   5.758 <.0001
##  Eugr - Soca   73.142  7.27 1539  10.056 <.0001
##  Eugr - Taof   95.744  8.96 1537  10.681 <.0001
##  Eugr - Trsp   62.634  8.85 1536   7.080 <.0001
##  Eugr - Vear  104.307 14.29 1537   7.300 <.0001
##  Hisp - Hype  -22.681  9.16 1540  -2.476 0.6509
##  Hisp - Phpr  -16.340  7.02 1527  -2.328 0.7595
##  Hisp - Pore   -3.603  7.44 1522  -0.484 1.0000
##  Hisp - Posp    3.372  6.90 1524   0.489 1.0000
##  Hisp - Rusp  -24.804 10.88 1515  -2.279 0.7914
##  Hisp - Soca  -15.467  6.90 1524  -2.243 0.8140
##  Hisp - Taof    7.135  8.65 1535   0.825 1.0000
##  Hisp - Trsp  -25.975  8.50 1523  -3.057 0.2316
##  Hisp - Vear   15.698 14.06 1536   1.116 1.0000
##  Hype - Phpr    6.340  8.53 1540   0.744 1.0000
##  Hype - Pore   19.078  8.91 1539   2.140 0.8700
##  Hype - Posp   26.053  8.43 1540   3.089 0.2146
##  Hype - Rusp   -2.123 11.91 1521  -0.178 1.0000
##  Hype - Soca    7.213  8.43 1540   0.855 1.0000
##  Hype - Taof   29.815  9.95 1539   2.996 0.2669
##  Hype - Trsp   -3.294  9.83 1539  -0.335 1.0000
##  Hype - Vear   38.379 14.91 1536   2.575 0.5733
##  Phpr - Pore   12.737  6.67 1525   1.909 0.9539
##  Phpr - Posp   19.712  6.03 1515   3.271 0.1346
##  Phpr - Rusp   -8.463 10.34 1527  -0.818 1.0000
##  Phpr - Soca    0.873  6.03 1515   0.145 1.0000
##  Phpr - Taof   23.475  8.02 1538   2.927 0.3095
##  Phpr - Trsp   -9.635  7.87 1529  -1.223 0.9999
##  Phpr - Vear   32.038 13.71 1537   2.337 0.7535
##  Pore - Posp    6.975  6.55 1526   1.064 1.0000
##  Pore - Rusp  -21.201 10.65 1524  -1.991 0.9307
##  Pore - Soca  -11.864  6.55 1526  -1.810 0.9735
##  Pore - Taof   10.738  8.40 1537   1.279 0.9997
##  Pore - Trsp  -22.372  8.26 1527  -2.708 0.4680
##  Pore - Vear   19.301 13.93 1536   1.386 0.9991
##  Posp - Rusp  -28.176 10.27 1523  -2.744 0.4402
##  Posp - Soca  -18.839  5.89 1513  -3.198 0.1634
##  Posp - Taof    3.763  7.92 1538   0.475 1.0000
##  Posp - Trsp  -29.347  7.77 1528  -3.776 0.0274
##  Posp - Vear   12.326 13.65 1538   0.903 1.0000
##  Rusp - Soca    9.337 10.27 1523   0.909 1.0000
##  Rusp - Taof   31.939 11.50 1539   2.777 0.4153
##  Rusp - Trsp   -1.171 11.45 1534  -0.102 1.0000
```

```
##   Rusp - Vear   40.502 16.03 1539   2.526 0.6121
##   Soca - Taof   22.602  7.92 1538   2.855 0.3585
##   Soca - Trsp  -10.508  7.77 1528  -1.352 0.9994
##   Soca - Vear   31.165 13.65 1538   2.282 0.7895
##   Taof - Trsp  -33.110  9.34 1536  -3.546 0.0595
##   Taof - Vear    8.563 14.58 1538   0.587 1.0000
##   Trsp - Vear   41.673 14.47 1534   2.881 0.3406
##
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 22 estimates
```

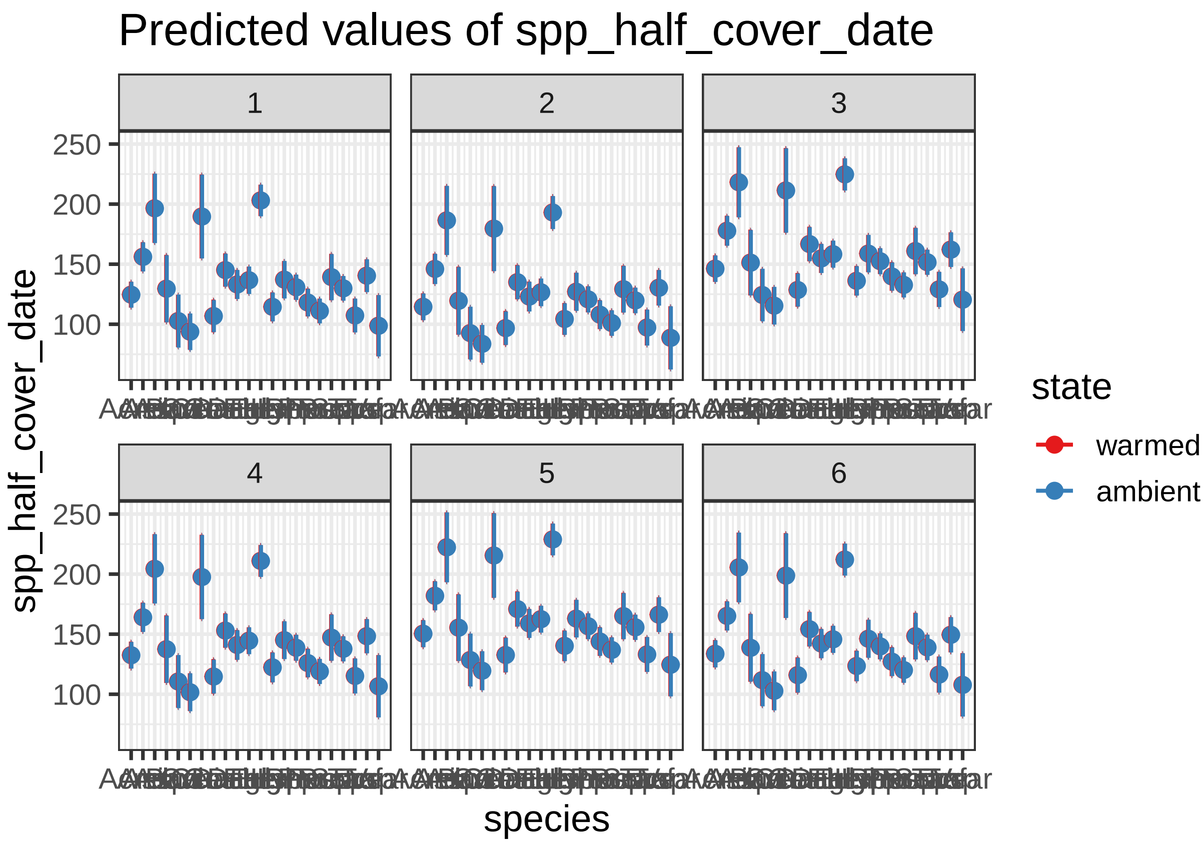
```
# using model 7a for overall species - level greenup model #

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



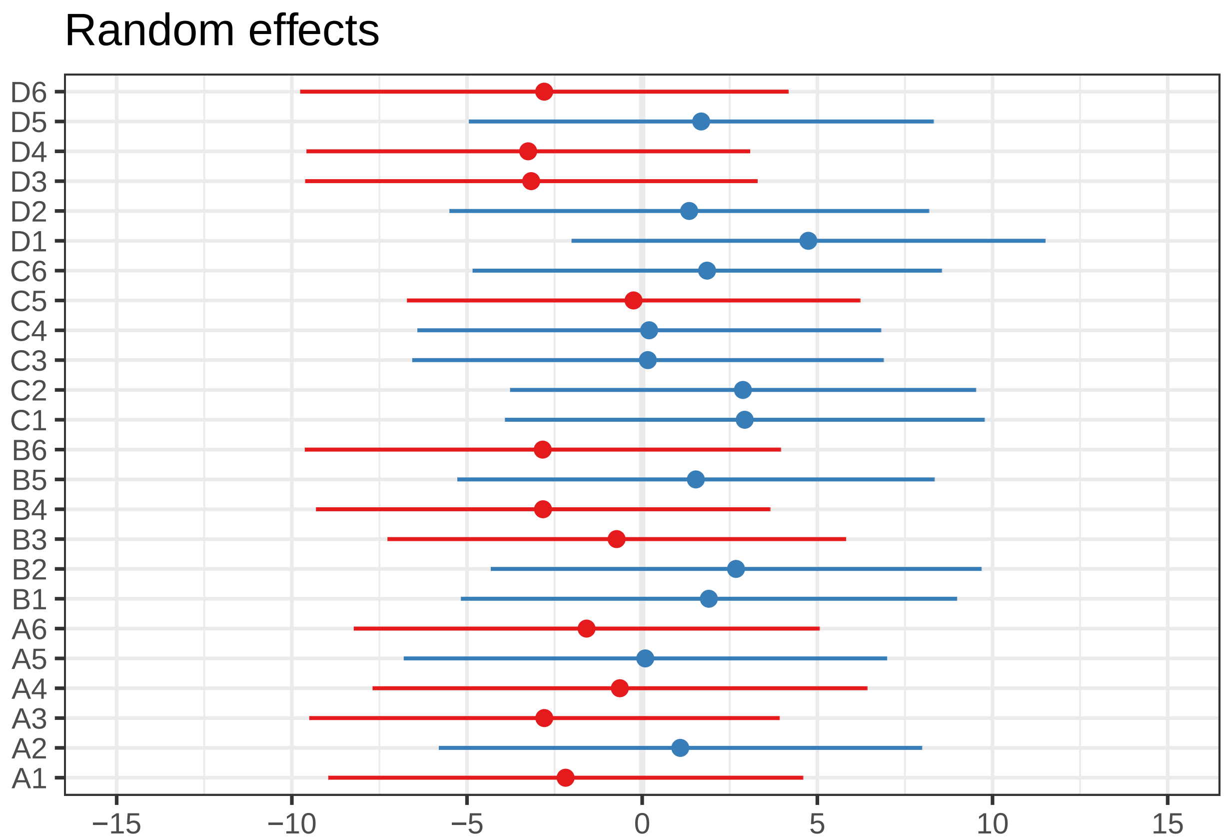

```
# if you want to standardize the estimates:
plot_model(mod7a, sort.est = TRUE, type = "std")
```




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




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




```r
# Start KD models - listed out possible models all at once,
# then compared (some of these are duplicates of models
# above):
mod_kd1 <- lmer(spp_half_cover_date ~ state + (1 | plot), green_kbs,
    REML = FALSE)
mod_kd2 <- lmer(spp_half_cover_date ~ state + (1 | year_factor),
    green_kbs, REML = FALSE)
mod_kd3 <- lmer(spp_half_cover_date ~ state + (1 + year_factor |
    plot), green_kbs, REML = FALSE)
```

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

## Warning: Model failed to converge with 1 negative eigenvalue: -1.1e+00
```

```r
mod_kd4 <- lmer(spp_half_cover_date ~ state + year_factor + (1 |
    plot), green_kbs, REML = FALSE)
mod_kd4 <- lmer(spp_half_cover_date ~ state * year_factor + (1 |
    plot), green_kbs, REML = FALSE)
mod_kd5 <- lmer(spp_half_cover_date ~ state + species + (1 |
    plot), green_kbs, REML = FALSE)
mod_kd6 <- lmer(spp_half_cover_date ~ state * species + (1 |
    plot), green_kbs, REML = FALSE)
mod_kd7 <- lmer(spp_half_cover_date ~ state + insecticide + (1 |
    plot), green_kbs, REML = FALSE)
mod_kd8 <- lmer(spp_half_cover_date ~ state * insecticide + (1 |
    plot), green_kbs, REML = FALSE)
mod_kd9 <- lmer(spp_half_cover_date ~ state + insecticide + species +
    (1 | plot), green_kbs, REML = FALSE)
mod_kd10 <- lmer(spp_half_cover_date ~ state + insecticide +
```

```r
    year_factor + (1 | plot), green_kbs, REML = FALSE)
mod_kd11 <- lmer(spp_half_cover_date ~ state + year_factor +
    species + (1 | plot), green_kbs, REML = FALSE)
mod_kd12 <- lmer(spp_half_cover_date ~ state + year_factor +
    species + insecticide + (1 | plot), green_kbs, REML = FALSE)
mod_kd13 <- lmer(spp_half_cover_date ~ insecticide + (1 | plot),
    green_kbs, REML = FALSE)
AICctab(mod_kd1, mod_kd2, mod_kd3, mod_kd4, mod_kd5, mod_kd6,
    mod_kd7, mod_kd8, mod_kd9, mod_kd10, mod_kd11, mod_kd12,
    mod_kd13, weights = T)
```

```
##          dAICc df weight
## mod_kd11   0.0 30 0.74
## mod_kd12   2.1 31 0.26
## mod_kd5   72.2 25 <0.001
## mod_kd9   74.2 26 <0.001
## mod_kd6   95.3 46 <0.001
## mod_kd10 248.3 10 <0.001
## mod_kd4  251.2 14 <0.001
## mod_kd2  259.5 4  <0.001
## mod_kd3  311.3 24 <0.001
## mod_kd13 323.9 4  <0.001
## mod_kd1  323.9 4  <0.001
## mod_kd7  325.9 5  <0.001
## mod_kd8  327.9 6  <0.001
```

```r
summary(mod_kd11)  # same as model 7a - confirm this model as the best
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: spp_half_cover_date ~ state + year_factor + species + (1 | plot)
##    Data: green_kbs
##
##      AIC      BIC   logLik deviance df.resid
##  16141.1  16300.8  -8040.6  16081.1     1481
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.1580 -0.6793 -0.2178  0.4667  3.1466
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)   16.91   4.112
##  Residual             2438.42  49.380
## Number of obs: 1511, groups:  plot, 24
##
## Fixed effects:
##                Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)    124.6679     5.5355  658.1208  22.522  < 2e-16 ***
## stateambient    -0.1218     3.0925   23.4606  -0.039 0.968910
## year_factor2   -10.0690     4.4226 1495.7614  -2.277 0.022943 *
## year_factor3    21.6909     4.2345 1498.3063   5.122 3.41e-07 ***
## year_factor4     7.9005     4.2476 1503.0642   1.860 0.063082 .
## year_factor5    25.8202     4.3513 1503.1515   5.934 3.67e-09 ***
```

```
## year_factor6    9.0605     4.4186 1507.1045   2.051 0.040484 *
## speciesArel    31.5237     6.9674 1502.0715   4.524 6.53e-06 ***
## speciesAssp    71.8944    15.0713 1504.7956   4.770 2.02e-06 ***
## speciesAsun     4.9822    14.5648 1497.4397   0.342 0.732343
## speciesBavu   -21.9349    11.5623 1510.9007  -1.897 0.058004 .
## speciesCahi   -30.8244     8.5743 1502.0958  -3.595 0.000335 ***
## speciesCeor    65.0746    18.2061 1473.6005   3.574 0.000362 ***
## speciesCest   -17.7608     7.7939 1499.7908  -2.279 0.022819 *
## speciesDaca    20.4666     7.8568 1502.9399   2.605 0.009279 **
## speciesDagl     8.5034     6.9340 1501.4392   1.226 0.220267
## speciesElre    12.0669     6.5205 1496.9446   1.851 0.064424 .
## speciesEugr    78.4509     7.4574 1509.7734  10.520  < 2e-16 ***
## speciesHisp   -10.1581     7.0897 1495.7777  -1.433 0.152123
## speciesHype    12.5225     8.5592 1510.9369   1.463 0.143660
## speciesPhpr     6.1822     6.2777 1493.4067   0.985 0.324886
## speciesPore    -6.5550     6.7603 1499.9341  -0.970 0.332387
## speciesPosp   -13.5300     6.1492 1491.2662  -2.200 0.027940 *
## speciesRusp    14.6457    10.3229 1478.7658   1.419 0.156182
## speciesSoca     5.3091     6.1492 1491.2662   0.863 0.388067
## speciesTaof   -17.2928     8.0633 1510.5669  -2.145 0.032142 *
## speciesTrsp    15.8169     7.9265 1499.7857   1.995 0.046174 *
## speciesVear   -25.8562    13.6356 1509.6798  -1.896 0.058121 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Correlation matrix not shown by default, as p = 28 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```r
# including native vs. exotic
green_kbs <- within(green_kbs, origin <- relevel(factor(origin),
    ref = "Native"))  # releveling so native is the reference
mod8 <- lmer(spp_half_cover_date ~ state * origin + (1 + year_factor |
    plot), green_kbs, REML = FALSE)
```

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

```
## Warning: Model failed to converge with 2 negative eigenvalues: -1.7e-02 -1.0e+00
```

```r
mod9 <- lmer(spp_half_cover_date ~ state + origin + (1 + year_factor |
    plot), green_kbs, REML = FALSE)
```

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

```
## Warning: Model failed to converge with 2 negative eigenvalues: -3.7e-02 -3.1e+00
```

```r
mod9a <- lmer(spp_half_cover_date ~ state + origin + factor(year_factor) +
    (1 | plot), green_kbs, REML = FALSE)
mod9b <- lmer(spp_half_cover_date ~ state + origin + insecticide +
    factor(year_factor) + (1 | plot), green_kbs, REML = FALSE)
anova(mod8, mod9)  # model 9 is a better fit to data
```

```
## Data: green_kbs
## Models:
## mod9: spp_half_cover_date ~ state + origin + (1 + year_factor | plot)
## mod8: spp_half_cover_date ~ state * origin + (1 + year_factor | plot)
##      npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
```

```
## mod9   27 16421 16564 -8183.3    16367
## mod8   30 16424 16583 -8181.8    16364 2.9482  3     0.3997
```

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

```
## Data: green_kbs
## Models:
## mod9a: spp_half_cover_date ~ state + origin + factor(year_factor) +
## mod9a:     (1 | plot)
## mod9: spp_half_cover_date ~ state + origin + (1 + year_factor | plot)
##       npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod9a   12 16357 16421 -8166.4    16333
## mod9    27 16421 16564 -8183.3    16367     0 15          1
```

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

```
## Data: green_kbs
## Models:
## mod9a: spp_half_cover_date ~ state + origin + factor(year_factor) +
## mod9a:     (1 | plot)
## mod9b: spp_half_cover_date ~ state + origin + insecticide + factor(year_factor) +
## mod9b:     (1 | plot)
##       npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod9a   12 16357 16421 -8166.4    16333
## mod9b   13 16359 16428 -8166.3    16333 0.2202  1     0.6389
```

```r
summary(mod9a)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: spp_half_cover_date ~ state + origin + factor(year_factor) +
##     (1 | plot)
##    Data: green_kbs
##
##      AIC      BIC   logLik deviance df.resid
##  16356.8  16420.7  -8166.4  16332.8     1499
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.7493 -0.7254 -0.3268  0.8091  2.7626
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)   11.86   3.444
##  Residual             2886.39  53.725
## Number of obs: 1511, groups:  plot, 24
##
## Fixed effects:
##                       Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)           140.3973     4.4045  332.1637  31.876  < 2e-16 ***
## stateambient           -0.2628     3.1160   23.7557  -0.084 0.933483
## origin                -30.9606     5.2195 1493.6401  -5.932 3.72e-09 ***
## originBoth            -11.3637     4.9735 1509.7461  -2.285 0.022459 *
## originExotic          -15.2916     3.4880 1503.3942  -4.384 1.25e-05 ***
## factor(year_factor)2   -8.4820     4.7478 1497.7707  -1.786 0.074221 .
## factor(year_factor)3   22.4346     4.5361 1498.9553   4.946 8.44e-07 ***
```

```
## factor(year_factor)4   12.3891     4.5725 1502.6179   2.710 0.006815 **
## factor(year_factor)5   32.5549     4.6117 1500.3453   7.059 2.55e-12 ***
## factor(year_factor)6   15.8772     4.6777 1506.5918   3.394 0.000706 ***
## ---
## 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 -0.352
## origin      -0.366 -0.002
## originBoth  -0.438 -0.023  0.334
## originExotc -0.577 -0.013  0.478  0.505
## fctr(yr_f)2 -0.461 -0.009 -0.009  0.097  0.016
## fctr(yr_f)3 -0.470 -0.006 -0.031  0.042  0.016  0.433
## fctr(yr_f)4 -0.463 -0.021 -0.009  0.031  0.021  0.428  0.447
## fctr(yr_f)5 -0.466 -0.015 -0.019  0.062  0.019  0.428  0.445  0.440
## fctr(yr_f)6 -0.462 -0.010 -0.005  0.057  0.019  0.421  0.437  0.433  0.432
```

```r
anova(mod9)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##        Sum Sq Mean Sq NumDF   DenDF F value   Pr(>F)
## state    3019    3019     1   42.21   1.056     0.31
## origin 110931   36977     3 1470.01  12.934 2.43e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```
## Warning in model.frame.default(formula, data = data, ...): variable
## 'year_factor' is not a factor
```

```
## $`emmeans of state, origin`
##  state   origin emmean   SE    df lower.CL upper.CL
##  warmed  Native    153 3.50 142.6      146      160
##  ambient Native    153 3.47 143.4      146      159
##  warmed            122 4.71 421.6      113      131
##  ambient           122 4.67 426.4      112      131
##  warmed  Both      141 4.49 324.2      133      150
##  ambient Both      141 4.38 310.6      133      150
##  warmed  Exotic    138 2.68  47.8      132      143
##  ambient Exotic    137 2.57  41.7      132      143
##
## Results are averaged over the levels of: year_factor
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $`pairwise differences of state, origin`
##  1                               estimate   SE     df t.ratio p.value
##  warmed Native - ambient Native     0.263 3.26   25.9   0.081  1.0000
##  warmed Native - warmed            30.961 5.23 1501.6   5.914  <.0001
##  warmed Native - ambient           31.223 6.17  325.2   5.065  <.0001
##  warmed Native - warmed Both       11.364 4.99 1519.0   2.275  0.3080
##  warmed Native - ambient Both      11.627 5.91  268.8   1.969  0.5052
##  warmed Native - warmed Exotic     15.292 3.50 1511.8   4.369  0.0004
##  warmed Native - ambient Exotic    15.554 4.76  121.8   3.270  0.0295
```

```
##  ambient Native - warmed          30.698 6.17  328.4  4.972  <.0001
##  ambient Native - ambient         30.961 5.23 1501.6  5.914  <.0001
##  ambient Native - warmed Both     11.101 6.03  287.7  1.842  0.5920
##  ambient Native - ambient Both    11.364 4.99 1519.0  2.275  0.3080
##  ambient Native - warmed Exotic   15.029 4.82  130.2  3.121  0.0447
##  ambient Native - ambient Exotic  15.292 3.50 1511.8  4.369  0.0004
##  warmed  - ambient                 0.263 3.26   25.9  0.081  1.0000
##  warmed  - warmed Both           -19.597 5.91 1517.6 -3.316  0.0209
##  warmed  - ambient Both          -19.334 6.70  409.8 -2.885  0.0783
##  warmed  - warmed Exotic         -15.669 4.71 1505.7 -3.329  0.0201
##  warmed  - ambient Exotic        -15.406 5.71  245.7 -2.699  0.1280
##  ambient  - warmed Both          -19.860 6.80  425.9 -2.920  0.0711
##  ambient  - ambient Both         -19.597 5.91 1517.6 -3.316  0.0209
##  ambient  - warmed Exotic        -15.932 5.75  254.7 -2.772  0.1069
##  ambient  - ambient Exotic       -15.669 4.71 1505.7 -3.329  0.0201
##  warmed Both - ambient Both        0.263 3.26   25.9  0.081  1.0000
##  warmed Both - warmed Exotic       3.928 4.42 1517.0  0.888  0.9871
##  warmed Both - ambient Exotic      4.191 5.54  213.5  0.757  0.9950
##  ambient Both - warmed Exotic      3.665 5.46  206.4  0.672  0.9976
##  ambient Both - ambient Exotic     3.928 4.42 1517.0  0.888  0.9871
##  warmed Exotic - ambient Exotic    0.263 3.26   25.9  0.081  1.0000
##
## Results are averaged over the levels of: year_factor
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 8 estimates
```

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

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

```
## Warning: Model failed to converge with 2 negative eigenvalues: -8.7e-02 -1.3e-01
```

```
mod11 <- lmer(spp_half_cover_date ~ state + growth_habit + (1 +
    year_factor | plot), green_kbs, REML = FALSE)
```

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

```
## Warning: Model failed to converge with 1 negative eigenvalue: -1.0e+00
```

```
mod11a <- lmer(spp_half_cover_date ~ state + growth_habit + factor(year_factor) +
    (1 | plot), green_kbs, REML = FALSE)
mod11b <- lmer(spp_half_cover_date ~ state + growth_habit + insecticide +
    factor(year_factor) + (1 | plot), green_kbs, REML = FALSE)
anova(mod10, mod11)  # model 11 is a better fit to data
```

```
## Data: green_kbs
## Models:
## mod11: spp_half_cover_date ~ state + growth_habit + (1 + year_factor |
## mod11:     plot)
## mod10: spp_half_cover_date ~ state * growth_habit + (1 + year_factor |
## mod10:     plot)
##       npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod11   27 16450 16593 -8197.9    16396
```

```
## mod10   30 16454 16614 -8197.0    16394 1.7173  3     0.6331
```

```r
anova(mod11, mod11a)  # model 11a
```

```
## Data: green_kbs
## Models:
## mod11a: spp_half_cover_date ~ state + growth_habit + factor(year_factor) +
## mod11a:     (1 | plot)
## mod11: spp_half_cover_date ~ state + growth_habit + (1 + year_factor |
## mod11:     plot)
##        npar   AIC   BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod11a   12 16384 16448 -8180.1    16360
## mod11    27 16450 16593 -8197.9    16396     0 15          1
```

```r
anova(mod11a, mod11b)  # model 11a
```

```
## Data: green_kbs
## Models:
## mod11a: spp_half_cover_date ~ state + growth_habit + factor(year_factor) +
## mod11a:     (1 | plot)
## mod11b: spp_half_cover_date ~ state + growth_habit + insecticide + factor(year_factor) +
## mod11b:     (1 | plot)
##        npar   AIC   BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod11a   12 16384 16448 -8180.1    16360
## mod11b   13 16386 16455 -8179.8    16360 0.4348  1     0.5096
```

```r
summary(mod11a)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: spp_half_cover_date ~ state + growth_habit + factor(year_factor) +
##     (1 | plot)
##    Data: green_kbs
##
##      AIC      BIC   logLik deviance df.resid
##  16384.1  16448.0  -8180.1  16360.1     1499
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.6850 -0.7388 -0.3369  0.7388  2.5016
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)    3.749  1.936
##  Residual             2946.114 54.278
## Number of obs: 1511, groups:  plot, 24
##
## Fixed effects:
##                          Estimate Std. Error        df t value Pr(>|t|)
## (Intercept)              127.2983     3.6569  215.2995  34.811  < 2e-16 ***
## stateambient              -0.5924     2.9167   23.4387  -0.203 0.840797
## growth_habit              -2.1183     4.4885 1505.1769  -0.472 0.637038
## growth_habitGraminoid      0.7180     3.0515 1510.8513   0.235 0.814020
## growth_habitVine          62.9345    19.3561 1421.6557   3.251 0.001175 **
## factor(year_factor)2      -8.6078     4.8090 1497.5236  -1.790 0.073668 .
## factor(year_factor)3      21.9800     4.5792 1500.4925   4.800 1.74e-06 ***
```

```
## factor(year_factor)4    12.1910     4.6253 1505.2357   2.636 0.008482 **
## factor(year_factor)5    32.2552     4.6818 1503.5078   6.889 8.21e-12 ***
## factor(year_factor)6    15.7438     4.7531 1509.5846   3.312 0.000947 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) sttmbn grwth_ grwt_G grwt_V fc(_)2 fc(_)3 fc(_)4 fc(_)5
## stateambint -0.409
## growth_habt -0.255 -0.030
## grwth_hbtGr -0.291  0.029  0.284
## grwth_hbtVn -0.062 -0.030  0.051  0.064
## fctr(yr_f)2 -0.539 -0.015  0.099 -0.048  0.039
## fctr(yr_f)3 -0.546 -0.007 -0.005 -0.051  0.020  0.431
## fctr(yr_f)4 -0.532 -0.025  0.008 -0.065  0.003  0.429  0.447
## fctr(yr_f)5 -0.518 -0.021  0.013 -0.115  0.017  0.429  0.445  0.443
## fctr(yr_f)6 -0.515 -0.015  0.026 -0.113  0.016  0.424  0.438  0.437  0.438
```

```r
anova(mod11a)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##                     Sum Sq Mean Sq NumDF   DenDF F value  Pr(>F)
## state                  122     122     1   23.44  0.0413 0.84080
## growth_habit         32481   10827     3 1477.69  3.6750 0.01179 *
## factor(year_factor) 264166   52833     5 1502.21 17.9332 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
emmeans(mod11a, list(pairwise ~ year_factor + growth_habit),
    adjust = "tukey")
```

```
## Warning in model.frame.default(formula, data = data, ...): variable
## 'year_factor' is not a factor
```

```
## $`emmeans of year_factor, growth_habit`
##  year_factor growth_habit emmean    SE   df lower.CL upper.CL
##  1           Forb            127  3.38  543      120      134
##  2           Forb            118  3.93  753      111      126
##  3           Forb            149  3.75  661      142      156
##  4           Forb            139  3.81  672      132      147
##  5           Forb            159  3.92  737      152      167
##  6           Forb            143  4.00  720      135      151
##  1                           125  4.78 1082      116      134
##  2                           116  5.58 1255      105      127
##  3                           147  5.03 1128      137      157
##  4                           137  5.13 1123      127      147
##  5                           157  5.23 1155      147      167
##  6                           141  5.34 1178      130      151
##  1           Graminoid       128  3.81  714      120      135
##  2           Graminoid       119  4.13  850      111      127
##  3           Graminoid       150  3.96  798      142      157
##  4           Graminoid       140  3.96  805      132      148
##  5           Graminoid       160  3.89  774      152      168
##  6           Graminoid       143  3.97  775      136      151
##  1           Vine            190 19.54 1420      152      228
##  2           Vine            181 19.81 1444      142      220
```

```
##  3           Vine            212 19.69 1435      173      251
##  4           Vine            202 19.63 1432      164      241
##  5           Vine            222 19.72 1422      184      261
##  6           Vine            206 19.72 1431      167      244
##
## Results are averaged over the levels of: state
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $`pairwise differences of year_factor, growth_habit`
##  1                          estimate    SE   df t.ratio p.value
##  1 Forb - 2 Forb               8.608  4.82 1506   1.784  0.9851
##  1 Forb - 3 Forb             -21.980  4.59 1509  -4.784  0.0005
##  1 Forb - 4 Forb             -12.191  4.64 1514  -2.626  0.5761
##  1 Forb - 5 Forb             -32.255  4.70 1512  -6.865  <.0001
##  1 Forb - 6 Forb             -15.744  4.77 1519  -3.298  0.1420
##  1 Forb - 1                    2.118  4.50 1514   0.470  1.0000
##  1 Forb - 2                   10.726  6.92 1509   1.550  0.9977
##  1 Forb - 3                  -19.862  6.42 1509  -3.095  0.2382
##  1 Forb - 4                  -10.073  6.49 1514  -1.551  0.9977
##  1 Forb - 5                  -30.137  6.55 1515  -4.600  0.0011
##  1 Forb - 6                  -13.626  6.65 1514  -2.050  0.9315
##  1 Forb - 1 Graminoid         -0.718  3.07 1521  -0.234  1.0000
##  1 Forb - 2 Graminoid          7.890  5.59 1508   1.411  0.9994
##  1 Forb - 3 Graminoid        -22.698  5.39 1504  -4.214  0.0060
##  1 Forb - 4 Graminoid        -12.909  5.39 1504  -2.396  0.7525
##  1 Forb - 5 Graminoid        -32.973  5.30 1506  -6.216  <.0001
##  1 Forb - 6 Graminoid        -16.462  5.37 1510  -3.066  0.2550
##  1 Forb - 1 Vine             -62.934 19.52 1444  -3.224  0.1732
##  1 Forb - 2 Vine             -54.327 20.28 1473  -2.679  0.5335
##  1 Forb - 3 Vine             -84.914 20.14 1466  -4.217  0.0060
##  1 Forb - 4 Vine             -75.126 20.07 1464  -3.743  0.0359
##  1 Forb - 5 Vine             -95.190 20.15 1455  -4.723  0.0006
##  1 Forb - 6 Vine             -78.678 20.16 1462  -3.902  0.0203
##  2 Forb - 3 Forb             -30.588  5.03 1505  -6.084  <.0001
##  2 Forb - 4 Forb             -20.799  5.06 1508  -4.110  0.0092
##  2 Forb - 5 Forb             -40.863  5.09 1508  -8.029  <.0001
##  2 Forb - 6 Forb             -24.352  5.15 1518  -4.725  0.0006
##  2 Forb - 1                   -6.490  6.27 1510  -1.036  1.0000
##  2 Forb - 2                    2.118  4.50 1514   0.470  1.0000
##  2 Forb - 3                  -28.470  6.41 1507  -4.444  0.0023
##  2 Forb - 4                  -18.681  6.48 1512  -2.884  0.3746
##  2 Forb - 5                  -38.745  6.52 1513  -5.946  <.0001
##  2 Forb - 6                  -22.233  6.61 1515  -3.365  0.1179
##  2 Forb - 1 Graminoid         -9.326  5.84 1517  -1.597  0.9965
##  2 Forb - 2 Graminoid         -0.718  3.07 1521  -0.234  1.0000
##  2 Forb - 3 Graminoid        -31.306  5.88 1507  -5.321  <.0001
##  2 Forb - 4 Graminoid        -21.517  5.88 1506  -3.662  0.0471
##  2 Forb - 5 Graminoid        -41.581  5.78 1509  -7.196  <.0001
##  2 Forb - 6 Graminoid        -25.070  5.83 1515  -4.297  0.0043
##  2 Forb - 1 Vine             -71.542 19.93 1435  -3.589  0.0599
##  2 Forb - 2 Vine             -62.934 19.52 1444  -3.224  0.1732
##  2 Forb - 3 Vine             -93.522 20.07 1450  -4.660  0.0009
##  2 Forb - 4 Vine             -83.733 20.00 1448  -4.186  0.0068
```

```
##  2 Forb - 5 Vine          -103.797 20.08 1437 -5.170  0.0001
##  2 Forb - 6 Vine           -87.286 20.08 1445 -4.346  0.0035
##  3 Forb - 4 Forb             9.789  4.85 1507  2.016  0.9419
##  3 Forb - 5 Forb           -10.275  4.90 1510 -2.098  0.9145
##  3 Forb - 6 Forb             6.236  4.97 1516  1.255  0.9999
##  3 Forb - 1                 24.098  6.45 1513  3.735  0.0368
##  3 Forb - 2                 32.706  7.08 1511  4.621  0.0010
##  3 Forb - 3                  2.118  4.50 1514  0.470  1.0000
##  3 Forb - 4                 11.907  6.67 1513  1.786  0.9849
##  3 Forb - 5                 -8.157  6.71 1515 -1.215  1.0000
##  3 Forb - 6                  8.354  6.80 1514  1.228  0.9999
##  3 Forb - 1 Graminoid       21.262  5.66 1520  3.759  0.0339
##  3 Forb - 2 Graminoid       29.870  5.89 1516  5.068  0.0001
##  3 Forb - 3 Graminoid       -0.718  3.07 1521 -0.234  1.0000
##  3 Forb - 4 Graminoid        9.071  5.70 1511  1.590  0.9967
##  3 Forb - 5 Graminoid      -10.993  5.62 1515 -1.958  0.9571
##  3 Forb - 6 Graminoid        5.518  5.68 1517  0.972  1.0000
##  3 Forb - 1 Vine           -40.955 19.97 1441 -2.051  0.9312
##  3 Forb - 2 Vine           -32.347 20.24 1463 -1.598  0.9965
##  3 Forb - 3 Vine           -62.934 19.52 1444 -3.224  0.1732
##  3 Forb - 4 Vine           -53.146 20.04 1454 -2.652  0.5551
##  3 Forb - 5 Vine           -73.210 20.12 1443 -3.639  0.0508
##  3 Forb - 6 Vine           -56.698 20.12 1451 -2.817  0.4245
##  4 Forb - 5 Forb           -20.064  4.93 1501 -4.073  0.0106
##  4 Forb - 6 Forb            -3.553  5.00 1512 -0.711  1.0000
##  4 Forb - 1                 14.309  6.44 1513  2.221  0.8594
##  4 Forb - 2                 22.917  7.06 1509  3.245  0.1638
##  4 Forb - 3                 -7.671  6.58 1507 -1.166  1.0000
##  4 Forb - 4                  2.118  4.50 1514  0.470  1.0000
##  4 Forb - 5                -17.946  6.69 1509 -2.682  0.5313
##  4 Forb - 6                 -1.435  6.78 1509 -0.211  1.0000
##  4 Forb - 1 Graminoid       11.473  5.73 1521  2.001  0.9461
##  4 Forb - 2 Graminoid       20.081  5.96 1519  3.370  0.1162
##  4 Forb - 3 Graminoid      -10.507  5.78 1516 -1.818  0.9813
##  4 Forb - 4 Graminoid       -0.718  3.07 1521 -0.234  1.0000
##  4 Forb - 5 Graminoid      -20.782  5.68 1513 -3.660  0.0474
##  4 Forb - 6 Graminoid       -4.271  5.74 1516 -0.744  1.0000
##  4 Forb - 1 Vine           -50.743 20.05 1443 -2.530  0.6524
##  4 Forb - 2 Vine           -42.136 20.33 1464 -2.073  0.9238
##  4 Forb - 3 Vine           -72.723 20.19 1457 -3.602  0.0574
##  4 Forb - 4 Vine           -62.934 19.52 1444 -3.224  0.1732
##  4 Forb - 5 Vine           -82.999 20.20 1447 -4.109  0.0092
##  4 Forb - 6 Vine           -66.487 20.21 1454 -3.290  0.1454
##  5 Forb - 6 Forb            16.511  5.02 1512  3.290  0.1453
##  5 Forb - 1                 34.373  6.47 1511  5.316  <.0001
##  5 Forb - 2                 42.981  7.07 1509  6.082  <.0001
##  5 Forb - 3                 12.393  6.59 1508  1.879  0.9726
##  5 Forb - 4                 22.182  6.66 1506  3.331  0.1299
##  5 Forb - 5                  2.118  4.50 1514  0.470  1.0000
##  5 Forb - 6                 18.630  6.78 1508  2.747  0.4796
##  5 Forb - 1 Graminoid       31.537  5.90 1521  5.345  <.0001
##  5 Forb - 2 Graminoid       40.145  6.10 1518  6.581  <.0001
##  5 Forb - 3 Graminoid        9.557  5.94 1515  1.610  0.9961
##  5 Forb - 4 Graminoid       19.346  5.92 1508  3.266  0.1552
```

```
##  5 Forb - 5 Graminoid        -0.718  3.07 1521 -0.234  1.0000
##  5 Forb - 6 Graminoid        15.793  5.88 1514  2.686  0.5278
##  5 Forb - 1 Vine            -30.679 20.00 1453 -1.534  0.9980
##  5 Forb - 2 Vine            -22.071 20.27 1473 -1.089  1.0000
##  5 Forb - 3 Vine            -52.659 20.13 1466 -2.616  0.5846
##  5 Forb - 4 Vine            -42.870 20.06 1466 -2.137  0.8991
##  5 Forb - 5 Vine            -62.934 19.52 1444 -3.224  0.1732
##  5 Forb - 6 Vine            -46.423 20.14 1464 -2.304  0.8122
##  6 Forb - 1                  17.862  6.48 1519  2.757  0.4716
##  6 Forb - 2                  26.470  7.08 1518  3.741  0.0361
##  6 Forb - 3                  -4.118  6.61 1516 -0.623  1.0000
##  6 Forb - 4                   5.671  6.67 1516  0.850  1.0000
##  6 Forb - 5                 -14.393  6.70 1517 -2.147  0.8948
##  6 Forb - 6                   2.118  4.50 1514  0.470  1.0000
##  6 Forb - 1 Graminoid        15.026  5.96 1521  2.521  0.6600
##  6 Forb - 2 Graminoid        23.634  6.16 1521  3.840  0.0255
##  6 Forb - 3 Graminoid        -6.954  6.00 1520 -1.160  1.0000
##  6 Forb - 4 Graminoid         2.835  5.98 1516  0.474  1.0000
##  6 Forb - 5 Graminoid       -17.229  5.88 1518 -2.929  0.3428
##  6 Forb - 6 Graminoid        -0.718  3.07 1521 -0.234  1.0000
##  6 Forb - 1 Vine            -47.191 20.03 1444 -2.356  0.7791
##  6 Forb - 2 Vine            -38.583 20.29 1464 -1.902  0.9688
##  6 Forb - 3 Vine            -69.171 20.16 1458 -3.431  0.0974
##  6 Forb - 4 Vine            -59.382 20.09 1457 -2.956  0.3245
##  6 Forb - 5 Vine            -79.446 20.16 1447 -3.940  0.0177
##  6 Forb - 6 Vine            -62.934 19.52 1444 -3.224  0.1732
##  1   - 2                      8.608  4.82 1506  1.784  0.9851
##  1   - 3                    -21.980  4.59 1509 -4.784  0.0005
##  1   - 4                    -12.191  4.64 1514 -2.626  0.5761
##  1   - 5                    -32.255  4.70 1512 -6.865  <.0001
##  1   - 6                    -15.744  4.77 1519 -3.298  0.1420
##  1   - 1 Graminoid           -2.836  4.67 1519 -0.607  1.0000
##  1   - 2 Graminoid            5.772  6.28 1511  0.920  1.0000
##  1   - 3 Graminoid          -24.816  6.46 1509 -3.843  0.0251
##  1   - 4 Graminoid          -15.027  6.41 1506 -2.343  0.7880
##  1   - 5 Graminoid          -35.091  6.33 1506 -5.547  <.0001
##  1   - 6 Graminoid          -18.580  6.34 1515 -2.931  0.3415
##  1   - 1 Vine               -65.053 19.80 1467 -3.286  0.1472
##  1   - 2 Vine               -56.445 20.44 1488 -2.761  0.4681
##  1   - 3 Vine               -87.033 20.42 1484 -4.263  0.0049
##  1   - 4 Vine               -77.244 20.34 1483 -3.798  0.0295
##  1   - 5 Vine               -97.308 20.41 1475 -4.767  0.0005
##  1   - 6 Vine               -80.797 20.41 1480 -3.959  0.0164
##  2   - 3                    -30.588  5.03 1505 -6.084  <.0001
##  2   - 4                    -20.799  5.06 1508 -4.110  0.0092
##  2   - 5                    -40.863  5.09 1508 -8.029  <.0001
##  2   - 6                    -24.352  5.15 1518 -4.725  0.0006
##  2   - 1 Graminoid          -11.444  7.13 1515 -1.605  0.9963
##  2   - 2 Graminoid           -2.836  4.67 1519 -0.607  1.0000
##  2   - 3 Graminoid          -33.424  7.18 1510 -4.654  0.0009
##  2   - 4 Graminoid          -23.635  7.14 1507 -3.312  0.1369
##  2   - 5 Graminoid          -43.699  7.04 1508 -6.206  <.0001
##  2   - 6 Graminoid          -27.188  7.05 1516 -3.857  0.0239
##  2   - 1 Vine               -73.661 20.31 1461 -3.626  0.0531
```

```
##  2  - 2 Vine               -65.053 19.80 1467 -3.286  0.1472
##  2  - 3 Vine               -95.641 20.45 1472 -4.676  0.0008
##  2  - 4 Vine               -85.852 20.37 1471 -4.214  0.0060
##  2  - 5 Vine              -105.916 20.44 1462 -5.181  0.0001
##  2  - 6 Vine               -89.404 20.44 1467 -4.375  0.0031
##  3  - 4                      9.789  4.85 1507  2.016  0.9419
##  3  - 5                    -10.275  4.90 1510 -2.098  0.9145
##  3  - 6                      6.236  4.97 1516  1.255  0.9999
##  3  - 1 Graminoid           19.144  6.65 1518  2.879  0.3785
##  3  - 2 Graminoid           27.752  6.53 1515  4.249  0.0052
##  3  - 3 Graminoid           -2.836  4.67 1519 -0.607  1.0000
##  3  - 4 Graminoid            6.953  6.67 1509  1.043  1.0000
##  3  - 5 Graminoid          -13.111  6.57 1511 -1.995  0.9478
##  3  - 6 Graminoid            3.400  6.58 1517  0.516  1.0000
##  3  - 1 Vine               -43.073 20.24 1464 -2.129  0.9026
##  3  - 2 Vine               -34.465 20.40 1481 -1.689  0.9926
##  3  - 3 Vine               -65.053 19.80 1467 -3.286  0.1472
##  3  - 4 Vine               -55.264 20.30 1475 -2.723  0.4985
##  3  - 5 Vine               -75.328 20.37 1466 -3.698  0.0418
##  3  - 6 Vine               -58.817 20.36 1471 -2.888  0.3718
##  4  - 5                    -20.064  4.93 1501 -4.073  0.0106
##  4  - 6                     -3.553  5.00 1512 -0.711  1.0000
##  4  - 1 Graminoid            9.355  6.76 1521  1.385  0.9996
##  4  - 2 Graminoid           17.963  6.63 1519  2.709  0.5099
##  4  - 3 Graminoid          -12.625  6.81 1517 -1.853  0.9767
##  4  - 4 Graminoid           -2.836  4.67 1519 -0.607  1.0000
##  4  - 5 Graminoid          -22.900  6.67 1512 -3.434  0.0966
##  4  - 6 Graminoid           -6.389  6.68 1518 -0.956  1.0000
##  4  - 1 Vine               -52.862 20.34 1465 -2.599  0.5976
##  4  - 2 Vine               -44.254 20.50 1481 -2.159  0.8895
##  4  - 3 Vine               -74.842 20.48 1476 -3.655  0.0482
##  4  - 4 Vine               -65.053 19.80 1467 -3.286  0.1472
##  4  - 5 Vine               -85.117 20.47 1468 -4.159  0.0075
##  4  - 6 Vine               -68.606 20.46 1473 -3.353  0.1221
##  5  - 6                     16.511  5.02 1512  3.290  0.1453
##  5  - 1 Graminoid           29.419  6.91 1520  4.255  0.0051
##  5  - 2 Graminoid           38.027  6.78 1518  5.612  <.0001
##  5  - 3 Graminoid            7.439  6.96 1517  1.069  1.0000
##  5  - 4 Graminoid           17.228  6.91 1510  2.493  0.6812
##  5  - 5 Graminoid           -2.836  4.67 1519 -0.607  1.0000
##  5  - 6 Graminoid           13.675  6.82 1518  2.006  0.9449
##  5  - 1 Vine               -32.798 20.29 1474 -1.617  0.9959
##  5  - 2 Vine               -24.190 20.44 1488 -1.183  1.0000
##  5  - 3 Vine               -54.778 20.42 1484 -2.682  0.5311
##  5  - 4 Vine               -44.989 20.34 1484 -2.212  0.8642
##  5  - 5 Vine               -65.053 19.80 1467 -3.286  0.1472
##  5  - 6 Vine               -48.541 20.40 1481 -2.379  0.7640
##  6  - 1 Graminoid           12.908  7.00 1521  1.843  0.9782
##  6  - 2 Graminoid           21.515  6.86 1520  3.134  0.2169
##  6  - 3 Graminoid           -9.072  7.05 1518 -1.287  0.9999
##  6  - 4 Graminoid            0.717  7.00 1513  0.102  1.0000
##  6  - 5 Graminoid          -19.348  6.90 1513 -2.805  0.4339
##  6  - 6 Graminoid           -2.836  4.67 1519 -0.607  1.0000
##  6  - 1 Vine               -49.309 20.33 1467 -2.426  0.7311
```

```
##  6  - 2 Vine               -40.701 20.48 1482 -1.987  0.9499
##  6  - 3 Vine               -71.289 20.46 1478 -3.484  0.0832
##  6  - 4 Vine               -61.500 20.38 1478 -3.018  0.2843
##  6  - 5 Vine               -81.564 20.45 1470 -3.989  0.0147
##  6  - 6 Vine               -65.053 19.80 1467 -3.286  0.1472
##  1 Graminoid - 2 Graminoid   8.608  4.82 1506  1.784  0.9851
##  1 Graminoid - 3 Graminoid  -21.980  4.59 1509 -4.784  0.0005
##  1 Graminoid - 4 Graminoid  -12.191  4.64 1514 -2.626  0.5761
##  1 Graminoid - 5 Graminoid  -32.255  4.70 1512 -6.865  <.0001
##  1 Graminoid - 6 Graminoid  -15.744  4.77 1519 -3.298  0.1420
##  1 Graminoid - 1 Vine       -62.217 19.56 1451 -3.181  0.1935
##  1 Graminoid - 2 Vine       -53.609 20.35 1478 -2.634  0.5698
##  1 Graminoid - 3 Vine       -84.197 20.21 1470 -4.165  0.0074
##  1 Graminoid - 4 Vine       -74.408 20.16 1468 -3.691  0.0428
##  1 Graminoid - 5 Vine       -94.472 20.28 1460 -4.659  0.0009
##  1 Graminoid - 6 Vine       -77.960 20.29 1467 -3.843  0.0252
##  2 Graminoid - 3 Graminoid  -30.588  5.03 1505 -6.084  <.0001
##  2 Graminoid - 4 Graminoid  -20.799  5.06 1508 -4.110  0.0092
##  2 Graminoid - 5 Graminoid  -40.863  5.09 1508 -8.029  <.0001
##  2 Graminoid - 6 Graminoid  -24.352  5.15 1518 -4.725  0.0006
##  2 Graminoid - 1 Vine       -70.824 19.94 1442 -3.552  0.0673
##  2 Graminoid - 2 Vine       -62.217 19.56 1451 -3.181  0.1935
##  2 Graminoid - 3 Vine       -92.804 20.11 1455 -4.615  0.0011
##  2 Graminoid - 4 Vine       -83.015 20.05 1453 -4.140  0.0082
##  2 Graminoid - 5 Vine      -103.080 20.16 1444 -5.112  0.0001
##  2 Graminoid - 6 Vine       -86.568 20.17 1450 -4.291  0.0044
##  3 Graminoid - 4 Graminoid   9.789  4.85 1507  2.016  0.9419
##  3 Graminoid - 5 Graminoid  -10.275  4.90 1510 -2.098  0.9145
##  3 Graminoid - 6 Graminoid   6.236  4.97 1516  1.255  0.9999
##  3 Graminoid - 1 Vine       -40.237 19.97 1449 -2.015  0.9423
##  3 Graminoid - 2 Vine       -31.629 20.28 1470 -1.560  0.9975
##  3 Graminoid - 3 Vine       -62.217 19.56 1451 -3.181  0.1935
##  3 Graminoid - 4 Vine       -52.428 20.09 1460 -2.610  0.5892
##  3 Graminoid - 5 Vine       -72.492 20.20 1451 -3.588  0.0600
##  3 Graminoid - 6 Vine       -55.980 20.21 1458 -2.770  0.4613
##  4 Graminoid - 5 Graminoid  -20.064  4.93 1501 -4.073  0.0106
##  4 Graminoid - 6 Graminoid   -3.553  5.00 1512 -0.711  1.0000
##  4 Graminoid - 1 Vine       -50.026 20.05 1451 -2.495  0.6794
##  4 Graminoid - 2 Vine       -41.418 20.35 1471 -2.035  0.9363
##  4 Graminoid - 3 Vine       -72.005 20.22 1464 -3.561  0.0654
##  4 Graminoid - 4 Vine       -62.217 19.56 1451 -3.181  0.1935
##  4 Graminoid - 5 Vine       -82.281 20.27 1454 -4.058  0.0112
##  4 Graminoid - 6 Vine       -65.769 20.28 1461 -3.243  0.1651
##  5 Graminoid - 6 Graminoid  16.511  5.02 1512  3.290  0.1453
##  5 Graminoid - 1 Vine       -29.961 19.96 1460 -1.501  0.9986
##  5 Graminoid - 2 Vine       -21.354 20.26 1479 -1.054  1.0000
##  5 Graminoid - 3 Vine       -51.941 20.13 1471 -2.581  0.6125
##  5 Graminoid - 4 Vine       -42.152 20.07 1471 -2.101  0.9137
##  5 Graminoid - 5 Vine       -62.217 19.56 1451 -3.181  0.1935
##  5 Graminoid - 6 Vine       -45.705 20.18 1469 -2.264  0.8359
##  6 Graminoid - 1 Vine       -46.473 19.98 1452 -2.326  0.7990
##  6 Graminoid - 2 Vine       -37.865 20.28 1471 -1.867  0.9746
##  6 Graminoid - 3 Vine       -68.453 20.15 1464 -3.397  0.1078
##  6 Graminoid - 4 Vine       -58.664 20.09 1462 -2.920  0.3495
```

```
##  6 Graminoid - 5 Vine       -78.728 20.20 1454 -3.897  0.0207
##  6 Graminoid - 6 Vine       -62.217 19.56 1451 -3.181  0.1935
##  1 Vine - 2 Vine              8.608  4.82 1506  1.784  0.9851
##  1 Vine - 3 Vine            -21.980  4.59 1509 -4.784  0.0005
##  1 Vine - 4 Vine            -12.191  4.64 1514 -2.626  0.5761
##  1 Vine - 5 Vine            -32.255  4.70 1512 -6.865  <.0001
##  1 Vine - 6 Vine            -15.744  4.77 1519 -3.298  0.1420
##  2 Vine - 3 Vine            -30.588  5.03 1505 -6.084  <.0001
##  2 Vine - 4 Vine            -20.799  5.06 1508 -4.110  0.0092
##  2 Vine - 5 Vine            -40.863  5.09 1508 -8.029  <.0001
##  2 Vine - 6 Vine            -24.352  5.15 1518 -4.725  0.0006
##  3 Vine - 4 Vine              9.789  4.85 1507  2.016  0.9419
##  3 Vine - 5 Vine            -10.275  4.90 1510 -2.098  0.9145
##  3 Vine - 6 Vine              6.236  4.97 1516  1.255  0.9999
##  4 Vine - 5 Vine            -20.064  4.93 1501 -4.073  0.0106
##  4 Vine - 6 Vine             -3.553  5.00 1512 -0.711  1.0000
##  5 Vine - 6 Vine             16.511  5.02 1512  3.290  0.1453
##
## Results are averaged over the levels of: state
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 24 estimates
```

```r
# You could now run some post hoc tests on these (see:
# https://stats.stackexchange.com/questions/169543/output-of-fixed-effects-summary-in-lmertest-in-r-and

# Here are some other options for plotting these plots above:
# https://stackoverflow.com/questions/31075407/plot-mixed-effects-model-in-ggplot

# Here's another approach:
# https://stats.stackexchange.com/questions/98958/plots-to-illustrate-results-of-linear-mixed-effect-mo
# Not quite working yet: newdat <-
# expand.grid(state=unique(green_kbs$state),
# year=c(min(green_kbs$year), max(green_kbs$year)),
# insecticide=unique(green_kbs$insecticide)) p <-
# ggplot(green_kbs, aes(x=year, y=spp_half_cover_date,
# colour=state, shape=insecticide)) + geom_point(size=3) +
# geom_line(aes(y=predict(mod5), group=species,
# size='species')) + geom_line(data=newdat,
# aes(y=predict(mod5, level=0, newdata=newdat),
# size='Population')) + scale_size_manual(name='Predictions',
# values=c('species'=0.5, 'Population'=3)) +
# #facet_wrap(~insecticide) + theme_bw(base_size=22) print(p)

# 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(spp_half_cover_date ~ state * year + (1 + year |
    species), green_kbs)
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## unable to evaluate scaled gradient

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge: degenerate Hessian with 1 negative eigenvalues

## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Model failed to converge with 1 negative eigenvalue: -1.6e-02
```

```
# 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(spp_half_cover_date ~ state * year + (1 | species),
    green_kbs)
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

KBS Plot-level Mixed Effects Models:

```
mod1p <- lmer(plot_half_cover_date ~ state + (1 | plot), green_kbsp,
    REML = FALSE)
```

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

```
mod2p <- lmer(plot_half_cover_date ~ insecticide + (1 | plot),
    green_kbsp, REML = FALSE)
```

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

```
mod3p <- lmer(plot_half_cover_date ~ insecticide + state + (1 |
    plot), green_kbsp, REML = FALSE)
```

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

```
mod4p <- lmer(plot_half_cover_date ~ insecticide * state + (1 |
    plot), green_kbsp, REML = FALSE)
```

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

```
mod5p <- lmer(plot_half_cover_date ~ state + year_factor + (1 |
    plot), green_kbsp, REML = FALSE)
```

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

```
mod6p <- lmer(plot_half_cover_date ~ state + year_factor + insecticide +
    (1 | plot), green_kbsp, REML = FALSE)
```

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

```
mod7p <- lmer(plot_half_cover_date ~ state * year_factor + (1 |
    plot), green_kbsp, REML = FALSE)
mod8p <- lmer(plot_half_cover_date ~ state * year_factor + insecticide +
    (1 | plot), green_kbsp, REML = FALSE)
```

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

```r
mod9p <- lmer(plot_half_cover_date ~ state * insecticide + year_factor +
    (1 | plot), green_kbsp, REML = FALSE)
```

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

```r
mod10p <- lmer(plot_half_cover_date ~ state + insecticide * year_factor +
    (1 | plot), green_kbsp, REML = FALSE)
```

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

```r
mod11p <- lmer(plot_half_cover_date ~ state * year_factor * insecticide +
    (1 | plot), green_kbsp, REML = FALSE)
```

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

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

```
##        dAICc df weight
## mod5p   0.0  9  0.364
## mod6p   0.0  10 0.358
## mod9p   1.0  11 0.223
## mod7p   6.0  14 0.019
## mod8p   6.0  15 0.018
## mod10p  6.0  15 0.018
## mod1p  16.8  4  <0.001
## mod3p  17.2  5  <0.001
## mod2p  17.4  4  <0.001
## mod4p  18.3  6  <0.001
## mod11p 24.6  26 <0.001
```

```r
anova(mod10p, mod11p)  #11p just barely better, going with 10p because is simpler
```

```
## Data: green_kbsp
## Models:
## mod10p: plot_half_cover_date ~ state + insecticide * year_factor + (1 |
## mod10p:     plot)
## mod11p: plot_half_cover_date ~ state * year_factor * insecticide + (1 |
## mod11p:     plot)
##        npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod10p   15 1536.1 1580.5 -753.06   1506.1
## mod11p   26 1546.3 1623.3 -747.15   1494.3 11.808 11     0.3782
```

```r
summary(mod10p)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: plot_half_cover_date ~ state + insecticide * year_factor + (1 |
##     plot)
##    Data: green_kbsp
##
##      AIC      BIC   logLik deviance df.resid
##   1536.1   1580.6   -753.1   1506.1      128
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
```

```
## -1.6812 -0.6129 -0.2590  0.3212  2.8442
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)    0      0.00
##  Residual             2196     46.86
## Number of obs: 143, groups:  plot, 24
##
## Fixed effects:
##                                     Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)                           83.198     14.084 143.000   5.907 2.43e-08
## stateambient                          13.938      7.840 143.000   1.778 0.077564
## insecticideno_insects                 12.750     19.131 143.000   0.666 0.506189
## year_factor2                          23.750     19.131 143.000   1.241 0.216471
## year_factor3                          64.667     19.131 143.000   3.380 0.000934
## year_factor4                          58.750     19.131 143.000   3.071 0.002554
## year_factor5                          92.583     19.131 143.000   4.839 3.33e-06
## year_factor6                          77.376     19.564 143.000   3.955 0.000120
## insecticideno_insects:year_factor2    2.583     27.055 143.000   0.095 0.924064
## insecticideno_insects:year_factor3  -29.167     27.055 143.000  -1.078 0.282827
## insecticideno_insects:year_factor4  -32.667     27.055 143.000  -1.207 0.229266
## insecticideno_insects:year_factor5  -46.750     27.055 143.000  -1.728 0.086155
## insecticideno_insects:year_factor6  -44.126     27.363 143.000  -1.613 0.109035
##
## (Intercept)                         ***
## stateambient                        .
## insecticideno_insects
## year_factor2
## year_factor3                        ***
## year_factor4                        **
## year_factor5                        ***
## year_factor6                        ***
## insecticideno_insects:year_factor2
## insecticideno_insects:year_factor3
## insecticideno_insects:year_factor4
## insecticideno_insects:year_factor5 .
## insecticideno_insects:year_factor6
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 13 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it

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

```r
emmeans(mod10p, list(pairwise ~ state + insecticide * year_factor),
    adjust = "tukey")
```

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

## $`emmeans of state, insecticide, year_factor`
##  state   insecticide year_factor emmean   SE  df lower.CL upper.CL
##  warmed  insects     1             83.2 14.8 152     54.0      112
```

```
##  ambient insects     1             97.1 14.8 152     68.0      126
##  warmed  no_insects  1             95.9 14.8 152     66.8      125
##  ambient no_insects  1            109.9 14.8 152     80.7      139
##  warmed  insects     2            106.9 14.8 152     77.8      136
##  ambient insects     2            120.9 14.8 152     91.7      150
##  warmed  no_insects  2            122.3 14.8 152     93.1      151
##  ambient no_insects  2            136.2 14.8 152    107.0      165
##  warmed  insects     3            147.9 14.8 152    118.7      177
##  ambient insects     3            161.8 14.8 152    132.6      191
##  warmed  no_insects  3            131.4 14.8 152    102.3      161
##  ambient no_insects  3            145.4 14.8 152    116.2      175
##  warmed  insects     4            141.9 14.8 152    112.8      171
##  ambient insects     4            155.9 14.8 152    126.7      185
##  warmed  no_insects  4            122.0 14.8 152     92.8      151
##  ambient no_insects  4            136.0 14.8 152    106.8      165
##  warmed  insects     5            175.8 14.8 152    146.6      205
##  ambient insects     5            189.7 14.8 152    160.5      219
##  warmed  no_insects  5            141.8 14.8 152    112.6      171
##  ambient no_insects  5            155.7 14.8 152    126.5      185
##  warmed  insects     6            160.6 15.3 152    130.3      191
##  ambient insects     6            174.5 15.5 153    143.9      205
##  warmed  no_insects  6            129.2 14.8 152    100.0      158
##  ambient no_insects  6            143.1 14.8 152    114.0      172
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $`pairwise differences of state, insecticide, year_factor`
##  1                                         estimate    SE    df t.ratio
##  warmed insects 1 - ambient insects 1        -13.938  8.22  25.4 -1.695
##  warmed insects 1 - warmed no_insects 1      -12.750 20.06 157.2 -0.635
##  warmed insects 1 - ambient no_insects 1     -26.688 21.68 140.8 -1.231
##  warmed insects 1 - warmed insects 2         -23.750 20.06 131.9 -1.184
##  warmed insects 1 - ambient insects 2        -37.688 21.68 156.9 -1.738
##  warmed insects 1 - warmed no_insects 2      -39.083 20.06 157.2 -1.948
##  warmed insects 1 - ambient no_insects 2     -53.021 21.68 140.8 -2.445
##  warmed insects 1 - warmed insects 3         -64.667 20.06 131.9 -3.223
##  warmed insects 1 - ambient insects 3        -78.604 21.68 156.9 -3.625
##  warmed insects 1 - warmed no_insects 3      -48.250 20.06 157.2 -2.405
##  warmed insects 1 - ambient no_insects 3     -62.188 21.68 140.8 -2.868
##  warmed insects 1 - warmed insects 4         -58.750 20.06 131.9 -2.928
##  warmed insects 1 - ambient insects 4        -72.688 21.68 156.9 -3.352
##  warmed insects 1 - warmed no_insects 4      -38.833 20.06 157.2 -1.935
##  warmed insects 1 - ambient no_insects 4     -52.771 21.68 140.8 -2.434
##  warmed insects 1 - warmed insects 5         -92.583 20.06 131.9 -4.614
##  warmed insects 1 - ambient insects 5       -106.521 21.68 156.9 -4.912
##  warmed insects 1 - warmed no_insects 5      -58.583 20.06 157.2 -2.920
##  warmed insects 1 - ambient no_insects 5     -72.521 21.68 140.8 -3.344
##  warmed insects 1 - warmed insects 6         -77.376 20.53 133.8 -3.768
##  warmed insects 1 - ambient insects 6        -91.314 22.26 157.0 -4.102
##  warmed insects 1 - warmed no_insects 6      -46.000 20.06 157.2 -2.293
##  warmed insects 1 - ambient no_insects 6     -59.938 21.68 140.8 -2.764
##  ambient insects 1 - warmed no_insects 1       1.188 21.68 140.8  0.055
##  ambient insects 1 - ambient no_insects 1    -12.750 20.06 157.2 -0.635
```

```
## ambient insects 1 - warmed insects 2          -9.812 21.68 156.9 -0.453
## ambient insects 1 - ambient insects 2        -23.750 20.06 131.9 -1.184
## ambient insects 1 - warmed no_insects 2      -25.146 21.68 140.8 -1.160
## ambient insects 1 - ambient no_insects 2     -39.083 20.06 157.2 -1.948
## ambient insects 1 - warmed insects 3         -50.729 21.68 156.9 -2.339
## ambient insects 1 - ambient insects 3        -64.667 20.06 131.9 -3.223
## ambient insects 1 - warmed no_insects 3      -34.312 21.68 140.8 -1.582
## ambient insects 1 - ambient no_insects 3     -48.250 20.06 157.2 -2.405
## ambient insects 1 - warmed insects 4         -44.812 21.68 156.9 -2.067
## ambient insects 1 - ambient insects 4        -58.750 20.06 131.9 -2.928
## ambient insects 1 - warmed no_insects 4      -24.896 21.68 140.8 -1.148
## ambient insects 1 - ambient no_insects 4     -38.833 20.06 157.2 -1.935
## ambient insects 1 - warmed insects 5         -78.646 21.68 156.9 -3.627
## ambient insects 1 - ambient insects 5        -92.583 20.06 131.9 -4.614
## ambient insects 1 - warmed no_insects 5      -44.646 21.68 140.8 -2.059
## ambient insects 1 - ambient no_insects 5     -58.583 20.06 157.2 -2.920
## ambient insects 1 - warmed insects 6         -63.438 21.97 157.0 -2.887
## ambient insects 1 - ambient insects 6        -77.376 20.53 133.8 -3.768
## ambient insects 1 - warmed no_insects 6      -32.062 21.68 140.8 -1.479
## ambient insects 1 - ambient no_insects 6     -46.000 20.06 157.2 -2.293
## warmed no_insects 1 - ambient no_insects 1   -13.938  8.22  25.4 -1.695
## warmed no_insects 1 - warmed insects 2       -11.000 20.06 157.2 -0.548
## warmed no_insects 1 - ambient insects 2      -24.938 21.68 140.8 -1.150
## warmed no_insects 1 - warmed no_insects 2    -26.333 20.06 131.9 -1.312
## warmed no_insects 1 - ambient no_insects 2   -40.271 21.68 156.9 -1.857
## warmed no_insects 1 - warmed insects 3       -51.917 20.06 157.2 -2.587
## warmed no_insects 1 - ambient insects 3      -65.854 21.68 140.8 -3.037
## warmed no_insects 1 - warmed no_insects 3    -35.500 20.06 131.9 -1.769
## warmed no_insects 1 - ambient no_insects 3   -49.438 21.68 156.9 -2.280
## warmed no_insects 1 - warmed insects 4       -46.000 20.06 157.2 -2.293
## warmed no_insects 1 - ambient insects 4      -59.938 21.68 140.8 -2.764
## warmed no_insects 1 - warmed no_insects 4    -26.083 20.06 131.9 -1.300
## warmed no_insects 1 - ambient no_insects 4   -40.021 21.68 156.9 -1.846
## warmed no_insects 1 - warmed insects 5       -79.833 20.06 157.2 -3.979
## warmed no_insects 1 - ambient insects 5      -93.771 21.68 140.8 -4.324
## warmed no_insects 1 - warmed no_insects 5    -45.833 20.06 131.9 -2.284
## warmed no_insects 1 - ambient no_insects 5   -59.771 21.68 156.9 -2.756
## warmed no_insects 1 - warmed insects 6       -64.626 20.53 157.3 -3.147
## warmed no_insects 1 - ambient insects 6      -78.564 22.26 142.2 -3.529
## warmed no_insects 1 - warmed no_insects 6    -33.250 20.06 131.9 -1.657
## warmed no_insects 1 - ambient no_insects 6   -47.188 21.68 156.9 -2.176
## ambient no_insects 1 - warmed insects 2        2.938 21.68 140.8  0.135
## ambient no_insects 1 - ambient insects 2     -11.000 20.06 157.2 -0.548
## ambient no_insects 1 - warmed no_insects 2   -12.396 21.68 156.9 -0.572
## ambient no_insects 1 - ambient no_insects 2  -26.333 20.06 131.9 -1.312
## ambient no_insects 1 - warmed insects 3      -37.979 21.68 140.8 -1.751
## ambient no_insects 1 - ambient insects 3     -51.917 20.06 157.2 -2.587
## ambient no_insects 1 - warmed no_insects 3   -21.562 21.68 156.9 -0.994
## ambient no_insects 1 - ambient no_insects 3  -35.500 20.06 131.9 -1.769
## ambient no_insects 1 - warmed insects 4      -32.062 21.68 140.8 -1.479
## ambient no_insects 1 - ambient insects 4     -46.000 20.06 157.2 -2.293
## ambient no_insects 1 - warmed no_insects 4   -12.146 21.68 156.9 -0.560
## ambient no_insects 1 - ambient no_insects 4  -26.083 20.06 131.9 -1.300
## ambient no_insects 1 - warmed insects 5      -65.896 21.68 140.8 -3.039
```

```
##  ambient no_insects 1 - ambient insects 5     -79.833 20.06 157.2 -3.979
##  ambient no_insects 1 - warmed no_insects 5   -31.896 21.68 156.9 -1.471
##  ambient no_insects 1 - ambient no_insects 5  -45.833 20.06 131.9 -2.284
##  ambient no_insects 1 - warmed insects 6      -50.688 21.97 141.5 -2.307
##  ambient no_insects 1 - ambient insects 6     -64.626 20.53 157.3 -3.147
##  ambient no_insects 1 - warmed no_insects 6   -19.312 21.68 156.9 -0.891
##  ambient no_insects 1 - ambient no_insects 6  -33.250 20.06 131.9 -1.657
##  warmed insects 2 - ambient insects 2         -13.938  8.22  25.4 -1.695
##  warmed insects 2 - warmed no_insects 2       -15.333 20.06 157.2 -0.764
##  warmed insects 2 - ambient no_insects 2      -29.271 21.68 140.8 -1.350
##  warmed insects 2 - warmed insects 3          -40.917 20.06 131.9 -2.039
##  warmed insects 2 - ambient insects 3         -54.854 21.68 156.9 -2.530
##  warmed insects 2 - warmed no_insects 3       -24.500 20.06 157.2 -1.221
##  warmed insects 2 - ambient no_insects 3      -38.438 21.68 140.8 -1.773
##  warmed insects 2 - warmed insects 4          -35.000 20.06 131.9 -1.744
##  warmed insects 2 - ambient insects 4         -48.938 21.68 156.9 -2.257
##  warmed insects 2 - warmed no_insects 4       -15.083 20.06 157.2 -0.752
##  warmed insects 2 - ambient no_insects 4      -29.021 21.68 140.8 -1.338
##  warmed insects 2 - warmed insects 5          -68.833 20.06 131.9 -3.431
##  warmed insects 2 - ambient insects 5         -82.771 21.68 156.9 -3.817
##  warmed insects 2 - warmed no_insects 5       -34.833 20.06 157.2 -1.736
##  warmed insects 2 - ambient no_insects 5      -48.771 21.68 140.8 -2.249
##  warmed insects 2 - warmed insects 6          -53.626 20.53 133.8 -2.612
##  warmed insects 2 - ambient insects 6         -67.564 22.26 157.0 -3.035
##  warmed insects 2 - warmed no_insects 6       -22.250 20.06 157.2 -1.109
##  warmed insects 2 - ambient no_insects 6      -36.188 21.68 140.8 -1.669
##  ambient insects 2 - warmed no_insects 2       -1.396 21.68 140.8 -0.064
##  ambient insects 2 - ambient no_insects 2     -15.333 20.06 157.2 -0.764
##  ambient insects 2 - warmed insects 3         -26.979 21.68 156.9 -1.244
##  ambient insects 2 - ambient insects 3        -40.917 20.06 131.9 -2.039
##  ambient insects 2 - warmed no_insects 3      -10.562 21.68 140.8 -0.487
##  ambient insects 2 - ambient no_insects 3     -24.500 20.06 157.2 -1.221
##  ambient insects 2 - warmed insects 4         -21.062 21.68 156.9 -0.971
##  ambient insects 2 - ambient insects 4        -35.000 20.06 131.9 -1.744
##  ambient insects 2 - warmed no_insects 4       -1.146 21.68 140.8 -0.053
##  ambient insects 2 - ambient no_insects 4     -15.083 20.06 157.2 -0.752
##  ambient insects 2 - warmed insects 5         -54.896 21.68 156.9 -2.532
##  ambient insects 2 - ambient insects 5        -68.833 20.06 131.9 -3.431
##  ambient insects 2 - warmed no_insects 5      -20.896 21.68 140.8 -0.964
##  ambient insects 2 - ambient no_insects 5     -34.833 20.06 157.2 -1.736
##  ambient insects 2 - warmed insects 6         -39.688 21.97 157.0 -1.806
##  ambient insects 2 - ambient insects 6        -53.626 20.53 133.8 -2.612
##  ambient insects 2 - warmed no_insects 6       -8.312 21.68 140.8 -0.383
##  ambient insects 2 - ambient no_insects 6     -22.250 20.06 157.2 -1.109
##  warmed no_insects 2 - ambient no_insects 2   -13.938  8.22  25.4 -1.695
##  warmed no_insects 2 - warmed insects 3       -25.583 20.06 157.2 -1.275
##  warmed no_insects 2 - ambient insects 3      -39.521 21.68 140.8 -1.823
##  warmed no_insects 2 - warmed no_insects 3     -9.167 20.06 131.9 -0.457
##  warmed no_insects 2 - ambient no_insects 3   -23.104 21.68 156.9 -1.065
##  warmed no_insects 2 - warmed insects 4       -19.667 20.06 157.2 -0.980
##  warmed no_insects 2 - ambient insects 4      -33.604 21.68 140.8 -1.550
##  warmed no_insects 2 - warmed no_insects 4      0.250 20.06 131.9  0.012
##  warmed no_insects 2 - ambient no_insects 4   -13.688 21.68 156.9 -0.631
##  warmed no_insects 2 - warmed insects 5       -53.500 20.06 157.2 -2.666
```

```
##  warmed no_insects 2 - ambient insects 5      -67.438 21.68 140.8 -3.110
##  warmed no_insects 2 - warmed no_insects 5    -19.500 20.06 131.9 -0.972
##  warmed no_insects 2 - ambient no_insects 5   -33.438 21.68 156.9 -1.542
##  warmed no_insects 2 - warmed insects 6       -38.293 20.53 157.3 -1.865
##  warmed no_insects 2 - ambient insects 6      -52.230 22.26 142.2 -2.346
##  warmed no_insects 2 - warmed no_insects 6     -6.917 20.06 131.9 -0.345
##  warmed no_insects 2 - ambient no_insects 6   -20.854 21.68 156.9 -0.962
##  ambient no_insects 2 - warmed insects 3      -11.646 21.68 140.8 -0.537
##  ambient no_insects 2 - ambient insects 3     -25.583 20.06 157.2 -1.275
##  ambient no_insects 2 - warmed no_insects 3     4.771 21.68 156.9  0.220
##  ambient no_insects 2 - ambient no_insects 3   -9.167 20.06 131.9 -0.457
##  ambient no_insects 2 - warmed insects 4       -5.729 21.68 140.8 -0.264
##  ambient no_insects 2 - ambient insects 4     -19.667 20.06 157.2 -0.980
##  ambient no_insects 2 - warmed no_insects 4    14.188 21.68 156.9  0.654
##  ambient no_insects 2 - ambient no_insects 4    0.250 20.06 131.9  0.012
##  ambient no_insects 2 - warmed insects 5      -39.562 21.68 140.8 -1.824
##  ambient no_insects 2 - ambient insects 5     -53.500 20.06 157.2 -2.666
##  ambient no_insects 2 - warmed no_insects 5    -5.562 21.68 156.9 -0.257
##  ambient no_insects 2 - ambient no_insects 5  -19.500 20.06 131.9 -0.972
##  ambient no_insects 2 - warmed insects 6      -24.355 21.97 141.5 -1.108
##  ambient no_insects 2 - ambient insects 6     -38.293 20.53 157.3 -1.865
##  ambient no_insects 2 - warmed no_insects 6     7.021 21.68 156.9  0.324
##  ambient no_insects 2 - ambient no_insects 6   -6.917 20.06 131.9 -0.345
##  warmed insects 3 - ambient insects 3         -13.938  8.22  25.4 -1.695
##  warmed insects 3 - warmed no_insects 3        16.417 20.06 157.2  0.818
##  warmed insects 3 - ambient no_insects 3        2.479 21.68 140.8  0.114
##  warmed insects 3 - warmed insects 4            5.917 20.06 131.9  0.295
##  warmed insects 3 - ambient insects 4          -8.021 21.68 156.9 -0.370
##  warmed insects 3 - warmed no_insects 4        25.833 20.06 157.2  1.288
##  warmed insects 3 - ambient no_insects 4       11.896 21.68 140.8  0.549
##  warmed insects 3 - warmed insects 5          -27.917 20.06 131.9 -1.391
##  warmed insects 3 - ambient insects 5         -41.854 21.68 156.9 -1.930
##  warmed insects 3 - warmed no_insects 5         6.083 20.06 157.2  0.303
##  warmed insects 3 - ambient no_insects 5       -7.854 21.68 140.8 -0.362
##  warmed insects 3 - warmed insects 6          -12.709 20.53 133.8 -0.619
##  warmed insects 3 - ambient insects 6         -26.647 22.26 157.0 -1.197
##  warmed insects 3 - warmed no_insects 6        18.667 20.06 157.2  0.930
##  warmed insects 3 - ambient no_insects 6        4.729 21.68 140.8  0.218
##  ambient insects 3 - warmed no_insects 3       30.354 21.68 140.8  1.400
##  ambient insects 3 - ambient no_insects 3      16.417 20.06 157.2  0.818
##  ambient insects 3 - warmed insects 4          19.854 21.68 156.9  0.916
##  ambient insects 3 - ambient insects 4          5.917 20.06 131.9  0.295
##  ambient insects 3 - warmed no_insects 4       39.771 21.68 140.8  1.834
##  ambient insects 3 - ambient no_insects 4      25.833 20.06 157.2  1.288
##  ambient insects 3 - warmed insects 5         -13.979 21.68 156.9 -0.645
##  ambient insects 3 - ambient insects 5        -27.917 20.06 131.9 -1.391
##  ambient insects 3 - warmed no_insects 5       20.021 21.68 140.8  0.923
##  ambient insects 3 - ambient no_insects 5       6.083 20.06 157.2  0.303
##  ambient insects 3 - warmed insects 6           1.228 21.97 157.0  0.056
##  ambient insects 3 - ambient insects 6        -12.709 20.53 133.8 -0.619
##  ambient insects 3 - warmed no_insects 6       32.604 21.68 140.8  1.504
##  ambient insects 3 - ambient no_insects 6      18.667 20.06 157.2  0.930
##  warmed no_insects 3 - ambient no_insects 3   -13.938  8.22  25.4 -1.695
##  warmed no_insects 3 - warmed insects 4       -10.500 20.06 157.2 -0.523
```

```
##  warmed no_insects 3 - ambient insects 4      -24.438 21.68 140.8 -1.127
##  warmed no_insects 3 - warmed no_insects 4      9.417 20.06 131.9  0.469
##  warmed no_insects 3 - ambient no_insects 4    -4.521 21.68 156.9 -0.208
##  warmed no_insects 3 - warmed insects 5       -44.333 20.06 157.2 -2.210
##  warmed no_insects 3 - ambient insects 5      -58.271 21.68 140.8 -2.687
##  warmed no_insects 3 - warmed no_insects 5    -10.333 20.06 131.9 -0.515
##  warmed no_insects 3 - ambient no_insects 5   -24.271 21.68 156.9 -1.119
##  warmed no_insects 3 - warmed insects 6       -29.126 20.53 157.3 -1.419
##  warmed no_insects 3 - ambient insects 6      -43.064 22.26 142.2 -1.934
##  warmed no_insects 3 - warmed no_insects 6      2.250 20.06 131.9  0.112
##  warmed no_insects 3 - ambient no_insects 6   -11.688 21.68 156.9 -0.539
##  ambient no_insects 3 - warmed insects 4        3.438 21.68 140.8  0.159
##  ambient no_insects 3 - ambient insects 4     -10.500 20.06 157.2 -0.523
##  ambient no_insects 3 - warmed no_insects 4    23.354 21.68 156.9  1.077
##  ambient no_insects 3 - ambient no_insects 4    9.417 20.06 131.9  0.469
##  ambient no_insects 3 - warmed insects 5      -30.396 21.68 140.8 -1.402
##  ambient no_insects 3 - ambient insects 5     -44.333 20.06 157.2 -2.210
##  ambient no_insects 3 - warmed no_insects 5     3.604 21.68 156.9  0.166
##  ambient no_insects 3 - ambient no_insects 5  -10.333 20.06 131.9 -0.515
##  ambient no_insects 3 - warmed insects 6      -15.188 21.97 141.5 -0.691
##  ambient no_insects 3 - ambient insects 6     -29.126 20.53 157.3 -1.419
##  ambient no_insects 3 - warmed no_insects 6    16.188 21.68 156.9  0.747
##  ambient no_insects 3 - ambient no_insects 6    2.250 20.06 131.9  0.112
##  warmed insects 4 - ambient insects 4         -13.938  8.22  25.4 -1.695
##  warmed insects 4 - warmed no_insects 4        19.917 20.06 157.2  0.993
##  warmed insects 4 - ambient no_insects 4        5.979 21.68 140.8  0.276
##  warmed insects 4 - warmed insects 5          -33.833 20.06 131.9 -1.686
##  warmed insects 4 - ambient insects 5         -47.771 21.68 156.9 -2.203
##  warmed insects 4 - warmed no_insects 5         0.167 20.06 157.2  0.008
##  warmed insects 4 - ambient no_insects 5      -13.771 21.68 140.8 -0.635
##  warmed insects 4 - warmed insects 6          -18.626 20.53 133.8 -0.907
##  warmed insects 4 - ambient insects 6         -32.564 22.26 157.0 -1.463
##  warmed insects 4 - warmed no_insects 6        12.750 20.06 157.2  0.635
##  warmed insects 4 - ambient no_insects 6       -1.188 21.68 140.8 -0.055
##  ambient insects 4 - warmed no_insects 4       33.854 21.68 140.8  1.561
##  ambient insects 4 - ambient no_insects 4      19.917 20.06 157.2  0.993
##  ambient insects 4 - warmed insects 5         -19.896 21.68 156.9 -0.918
##  ambient insects 4 - ambient insects 5        -33.833 20.06 131.9 -1.686
##  ambient insects 4 - warmed no_insects 5       14.104 21.68 140.8  0.650
##  ambient insects 4 - ambient no_insects 5       0.167 20.06 157.2  0.008
##  ambient insects 4 - warmed insects 6          -4.688 21.97 157.0 -0.213
##  ambient insects 4 - ambient insects 6        -18.626 20.53 133.8 -0.907
##  ambient insects 4 - warmed no_insects 6       26.688 21.68 140.8  1.231
##  ambient insects 4 - ambient no_insects 6      12.750 20.06 157.2  0.635
##  warmed no_insects 4 - ambient no_insects 4   -13.938  8.22  25.4 -1.695
##  warmed no_insects 4 - warmed insects 5       -53.750 20.06 157.2 -2.679
##  warmed no_insects 4 - ambient insects 5      -67.688 21.68 140.8 -3.121
##  warmed no_insects 4 - warmed no_insects 5    -19.750 20.06 131.9 -0.984
##  warmed no_insects 4 - ambient no_insects 5   -33.688 21.68 156.9 -1.554
##  warmed no_insects 4 - warmed insects 6       -38.543 20.53 157.3 -1.877
##  warmed no_insects 4 - ambient insects 6      -52.480 22.26 142.2 -2.357
##  warmed no_insects 4 - warmed no_insects 6     -7.167 20.06 131.9 -0.357
##  warmed no_insects 4 - ambient no_insects 6   -21.104 21.68 156.9 -0.973
##  ambient no_insects 4 - warmed insects 5      -39.812 21.68 140.8 -1.836
```

```
##  ambient no_insects 4 - ambient insects 5     -53.750 20.06 157.2 -2.679
##  ambient no_insects 4 - warmed no_insects 5    -5.812 21.68 156.9 -0.268
##  ambient no_insects 4 - ambient no_insects 5  -19.750 20.06 131.9 -0.984
##  ambient no_insects 4 - warmed insects 6      -24.605 21.97 141.5 -1.120
##  ambient no_insects 4 - ambient insects 6     -38.543 20.53 157.3 -1.877
##  ambient no_insects 4 - warmed no_insects 6     6.771 21.68 156.9  0.312
##  ambient no_insects 4 - ambient no_insects 6   -7.167 20.06 131.9 -0.357
##  warmed insects 5 - ambient insects 5         -13.938  8.22  25.4 -1.695
##  warmed insects 5 - warmed no_insects 5        34.000 20.06 157.2  1.695
##  warmed insects 5 - ambient no_insects 5       20.062 21.68 140.8  0.925
##  warmed insects 5 - warmed insects 6           15.207 20.53 133.8  0.741
##  warmed insects 5 - ambient insects 6           1.270 22.26 157.0  0.057
##  warmed insects 5 - warmed no_insects 6        46.583 20.06 157.2  2.322
##  warmed insects 5 - ambient no_insects 6       32.646 21.68 140.8  1.505
##  ambient insects 5 - warmed no_insects 5       47.938 21.68 140.8  2.211
##  ambient insects 5 - ambient no_insects 5      34.000 20.06 157.2  1.695
##  ambient insects 5 - warmed insects 6          29.145 21.97 157.0  1.326
##  ambient insects 5 - ambient insects 6         15.207 20.53 133.8  0.741
##  ambient insects 5 - warmed no_insects 6       60.521 21.68 140.8  2.791
##  ambient insects 5 - ambient no_insects 6      46.583 20.06 157.2  2.322
##  warmed no_insects 5 - ambient no_insects 5   -13.938  8.22  25.4 -1.695
##  warmed no_insects 5 - warmed insects 6       -18.793 20.53 157.3 -0.915
##  warmed no_insects 5 - ambient insects 6      -32.730 22.26 142.2 -1.470
##  warmed no_insects 5 - warmed no_insects 6     12.583 20.06 131.9  0.627
##  warmed no_insects 5 - ambient no_insects 6    -1.354 21.68 156.9 -0.062
##  ambient no_insects 5 - warmed insects 6       -4.855 21.97 141.5 -0.221
##  ambient no_insects 5 - ambient insects 6     -18.793 20.53 157.3 -0.915
##  ambient no_insects 5 - warmed no_insects 6    26.521 21.68 156.9  1.223
##  ambient no_insects 5 - ambient no_insects 6   12.583 20.06 131.9  0.627
##  warmed insects 6 - ambient insects 6         -13.938  8.22  25.4 -1.695
##  warmed insects 6 - warmed no_insects 6        31.376 20.53 157.3  1.528
##  warmed insects 6 - ambient no_insects 6       17.438 21.97 141.5  0.794
##  ambient insects 6 - warmed no_insects 6       45.314 22.26 142.2  2.036
##  ambient insects 6 - ambient no_insects 6      31.376 20.53 157.3  1.528
##  warmed no_insects 6 - ambient no_insects 6   -13.938  8.22  25.4 -1.695
##  p.value
##  0.9818
##  1.0000
##  0.9999
##  1.0000
##  0.9875
##  0.9552
##  0.7136
##  0.1908
##  0.0634
##  0.7422
##  0.3973
##  0.3567
##  0.1360
##  0.9580
##  0.7217
##  0.0021
##  0.0005
##  0.3601
```

```
## 0.1405
## 0.0424
## 0.0133
## 0.8138
## 0.4731
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9552
## 0.7852
## 0.1908
## 0.9961
## 0.7422
## 0.9205
## 0.3567
## 1.0000
## 0.9580
## 0.0631
## 0.0021
## 0.9225
## 0.3601
## 0.3828
## 0.0424
## 0.9985
## 0.8138
## 0.9818
## 1.0000
## 1.0000
## 0.9998
## 0.9730
## 0.6080
## 0.2869
## 0.9840
## 0.8212
## 0.8138
## 0.4731
## 0.9998
## 0.9748
## 0.0204
## 0.0062
## 0.8175
## 0.4781
## 0.2241
## 0.0852
## 0.9928
## 0.8756
## 1.0000
## 1.0000
## 1.0000
## 0.9998
## 0.9860
## 0.6080
```

```
## 1.0000
## 0.9840
## 0.9985
## 0.8138
## 1.0000
## 0.9998
## 0.2858
## 0.0204
## 0.9987
## 0.8175
## 0.8048
## 0.2241
## 1.0000
## 0.9928
## 0.9818
## 1.0000
## 0.9996
## 0.9287
## 0.6520
## 0.9999
## 0.9838
## 0.9865
## 0.8342
## 1.0000
## 0.9997
## 0.1131
## 0.0349
## 0.9876
## 0.8377
## 0.5896
## 0.2865
## 1.0000
## 0.9923
## 1.0000
## 1.0000
## 0.9999
## 0.9287
## 1.0000
## 0.9999
## 1.0000
## 0.9865
## 1.0000
## 1.0000
## 0.6505
## 0.1131
## 1.0000
## 0.9876
## 0.9802
## 0.5896
## 1.0000
## 1.0000
## 0.9818
## 0.9999
## 0.9777
```

```
## 1.0000
## 1.0000
## 1.0000
## 0.9971
## 1.0000
## 1.0000
## 0.5471
## 0.2455
## 1.0000
## 0.9974
## 0.9717
## 0.7803
## 1.0000
## 1.0000
## 1.0000
## 0.9999
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9775
## 0.5471
## 1.0000
## 1.0000
## 1.0000
## 0.9717
## 1.0000
## 1.0000
## 0.9818
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9998
## 1.0000
## 0.9994
## 0.9592
## 1.0000
## 1.0000
## 1.0000
## 0.9999
## 1.0000
## 1.0000
## 0.9993
## 1.0000
## 1.0000
## 1.0000
## 0.9761
## 0.9998
## 1.0000
## 0.9994
## 1.0000
```

```
## 1.0000
## 1.0000
## 1.0000
## 0.9981
## 1.0000
## 0.9818
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.8593
## 0.5315
## 1.0000
## 1.0000
## 0.9992
## 0.9578
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9993
## 0.8593
## 1.0000
## 1.0000
## 1.0000
## 0.9992
## 1.0000
## 1.0000
## 0.9818
## 1.0000
## 1.0000
## 0.9911
## 0.8625
## 1.0000
## 1.0000
## 1.0000
## 0.9988
## 1.0000
## 1.0000
## 0.9968
## 1.0000
## 1.0000
## 0.9911
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9999
## 1.0000
## 0.9818
## 0.5374
## 0.2394
```

```
## 1.0000
## 0.9971
## 0.9696
## 0.7731
## 1.0000
## 1.0000
## 0.9758
## 0.5374
## 1.0000
## 1.0000
## 1.0000
## 0.9696
## 1.0000
## 1.0000
## 0.9818
## 0.9908
## 1.0000
## 1.0000
## 1.0000
## 0.7963
## 0.9981
## 0.8579
## 0.9908
## 0.9997
## 1.0000
## 0.4530
## 0.7963
## 0.9818
## 1.0000
## 0.9986
## 1.0000
## 1.0000
## 1.0000
## 1.0000
## 0.9999
## 1.0000
## 0.9818
## 0.9977
## 1.0000
## 0.9303
## 0.9977
## 0.9818
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 24 estimates
```

Analyses for species who reached half cover within the green-up observation window

```
# Selecting species (these were determined in the
# half_cover_kbs dataframe made in the phenology_dates_L2.R
# script)
```

```r
species_kbs <- subset(green_kbs, species == "Taof")  # can change/add more species
mod_spp <- lmer(spp_half_cover_date ~ state + factor(year_factor) +
    (1 | plot), species_kbs, REML = FALSE)
mod_spp2 <- lmer(min_green_date ~ state + factor(year_factor) +
    (1 | plot), species_kbs, REML = FALSE)
summary(mod_spp)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: spp_half_cover_date ~ state + factor(year_factor) + (1 | plot)
##    Data: species_kbs
##
##      AIC      BIC   logLik deviance df.resid
##    567.7    585.9   -274.8    549.7       47
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.3148 -0.5539 -0.1129  0.2388  4.0379
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 155.9    12.49
##  Residual             941.5    30.68
## Number of obs: 56, groups:  plot, 21
##
## Fixed effects:
##                       Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)            120.052      9.287  45.084  12.927   <2e-16 ***
## stateambient           -18.032     10.395  20.860  -1.735   0.0975 .
## factor(year_factor)2    -6.455     15.941  50.140  -0.405   0.6872
## factor(year_factor)3     1.826     13.289  49.205   0.137   0.8913
## factor(year_factor)4    14.201     12.850  51.489   1.105   0.2742
## factor(year_factor)5    29.594     11.545  47.823   2.563   0.0136 *
## factor(year_factor)6   -23.750     19.956  52.047  -1.190   0.2394
## ---
## 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
## stateambint -0.576
## fctr(yr_f)2 -0.317 -0.033
## fctr(yr_f)3 -0.372 -0.053  0.277
## fctr(yr_f)4 -0.460  0.054  0.282  0.330
## fctr(yr_f)5 -0.446 -0.038  0.295  0.347  0.358
## fctr(yr_f)6 -0.317  0.066  0.190  0.207  0.240  0.242
```

```r
summary(mod_spp2)
```

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

```
##    544.5    562.7   -263.2    526.5       47
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -0.9957 -0.4769 -0.1362  0.4147  5.9393
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)  49.15    7.011
##  Residual             663.65   25.762
## Number of obs: 56, groups:  plot, 21
##
## Fixed effects:
##                      Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)           114.371      7.359  48.916  15.542   <2e-16 ***
## stateambient          -13.709      7.846  22.356  -1.747   0.0943 .
## factor(year_factor)2   -8.624     13.188  52.518  -0.654   0.5160
## factor(year_factor)3    4.476     11.021  51.089   0.406   0.6864
## factor(year_factor)4    8.045     10.614  52.700   0.758   0.4518
## factor(year_factor)5   12.390      9.599  49.693   1.291   0.2028
## factor(year_factor)6  -16.684     16.441  54.211  -1.015   0.3147
## ---
## 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
## stateambint -0.555
## fctr(yr_f)2 -0.340 -0.037
## fctr(yr_f)3 -0.399 -0.058  0.264
## fctr(yr_f)4 -0.485  0.055  0.269  0.317
## fctr(yr_f)5 -0.475 -0.040  0.290  0.343  0.353
## fctr(yr_f)6 -0.336  0.075  0.178  0.201  0.227  0.233
```

UMBS Mixed Effects Models

```r
# umod4 (and umod6) are pretty complex in terms of
# interpretation (they actually don't have many parameters
# though). We could consider an alternative umodel that's
# simpler to understand and also one that provides more
# insight about the species. That would be something like
# this:
umod7 <- lmer(spp_half_cover_date ~ state + species + (1 + year_factor |
    plot), green_umbs, REML = FALSE)
```

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

```
## Warning: Model failed to converge with 2 negative eigenvalues: -5.1e-03 -1.3e+01
```

```r
umod7a <- lmer(spp_half_cover_date ~ state + species + year_factor +
    (1 | plot), green_umbs, REML = FALSE)
umod7b <- lmer(spp_half_cover_date ~ state * year_factor + species +
    (1 | plot), green_umbs, REML = FALSE)
umod7c <- lmer(spp_half_cover_date ~ state + species + year_factor +
    insecticide + (1 | plot), green_umbs, REML = FALSE)
```

```r
# anova(umod6, umod7) # umodel 7 is a better fit to data
anova(umod7, umod7a)  #umod 7a
```

```
## Data: green_umbs
## Models:
## umod7a: spp_half_cover_date ~ state + species + year_factor + (1 | plot)
## umod7: spp_half_cover_date ~ state + species + (1 + year_factor | plot)
##        npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## umod7a   24 8792.4 8907.5 -4372.2   8744.4
## umod7    39 8833.2 9020.4 -4377.6   8755.2     0 15          1
```

```r
anova(umod7a, umod7b)  #umod 7a
```

```
## Data: green_umbs
## Models:
## umod7a: spp_half_cover_date ~ state + species + year_factor + (1 | plot)
## umod7b: spp_half_cover_date ~ state * year_factor + species + (1 | plot)
##        npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## umod7a   24 8792.4 8907.5 -4372.2   8744.4
## umod7b   29 8801.4 8940.6 -4371.7   8743.4 0.9563  5      0.966
```

```r
anova(umod7a, umod7c)  #umod 7a
```

```
## Data: green_umbs
## Models:
## umod7a: spp_half_cover_date ~ state + species + year_factor + (1 | plot)
## umod7c: spp_half_cover_date ~ state + species + year_factor + insecticide +
## umod7c:     (1 | plot)
##        npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## umod7a   24 8792.4 8907.5 -4372.2   8744.4
## umod7c   25 8794.1 8914.1 -4372.0   8744.1 0.2903  1       0.59
```

```r
summary(umod7a)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: spp_half_cover_date ~ state + species + year_factor + (1 | plot)
##    Data: green_umbs
##
##      AIC      BIC   logLik deviance df.resid
##   8792.4   8907.5  -4372.2   8744.4      873
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.4430 -0.6148 -0.3372  0.3114  3.8838
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)   6.832   2.614
##  Residual             996.756  31.571
## Number of obs: 897, groups:  plot, 24
##
## Fixed effects:
##              Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)  139.7663    12.4871 841.0321  11.193  < 2e-16 ***
## stateambient   2.0196     2.3879  21.2009   0.846 0.407116
```

```
## speciesAnsp    1.1563    15.0072 885.9950   0.077 0.938601
## speciesApan   47.5788    16.4350 891.6900   2.895 0.003885 **
## speciesAssp   30.0588    13.3287 856.5496   2.255 0.024373 *
## speciesAsun  -14.6516    21.9139 891.4896  -0.669 0.503924
## speciesCape   12.3747    12.4883 876.3550   0.991 0.322008
## speciesCest   -8.3557    12.3465 882.4998  -0.677 0.498733
## speciesDasp    3.2288    12.4073 882.4704   0.260 0.794741
## speciesFrve    1.4378    13.6708 857.9530   0.105 0.916262
## speciesHisp   42.9619    14.2965 895.1599   3.005 0.002729 **
## speciesHype   12.0091    12.6834 888.7625   0.947 0.343979
## speciesPosp    0.2736    12.3557 883.5200   0.022 0.982340
## speciesPtaq   39.0531    12.4926 888.0182   3.126 0.001829 **
## speciesRuac   -2.6753    12.4319 887.0693  -0.215 0.829664
## speciesSosp   18.4622    14.0177 890.2512   1.317 0.188155
## speciesSyla   38.6605    15.6647 893.2967   2.468 0.013774 *
## year_factor2 -12.6177     3.7673 879.8568  -3.349 0.000845 ***
## year_factor3   5.3407     3.7404 876.5303   1.428 0.153695
## year_factor4  -6.3800     3.7030 880.1806  -1.723 0.085256 .
## year_factor5  -9.1773     3.6624 877.4116  -2.506 0.012396 *
## year_factor6  -1.0631     3.8155 877.7303  -0.279 0.780605
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation matrix not shown by default, as p = 22 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```r
summary(umod7b)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: spp_half_cover_date ~ state * year_factor + species + (1 | plot)
##    Data: green_umbs
##
##      AIC      BIC   logLik deviance df.resid
##   8801.4   8940.6  -4371.7   8743.4      868
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.3943 -0.6317 -0.3500  0.3210  3.9300
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)   6.77    2.602
##  Residual             995.74   31.555
## Number of obs: 897, groups:  plot, 24
##
## Fixed effects:
##                         Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)             140.4319    12.7227 845.0322  11.038  < 2e-16 ***
## stateambient              0.5037     5.4202 396.0309   0.093  0.92601
## year_factor2            -13.5064     5.2853 881.4528  -2.555  0.01077 *
## year_factor3              3.3317     5.3561 876.8215   0.622  0.53408
## year_factor4             -5.8149     5.2195 876.8756  -1.114  0.26555
```

```
## year_factor5              -11.3986     5.2633 876.5891  -2.166  0.03061 *
## year_factor6               -1.1502     5.3856 878.8728  -0.214  0.83094
## speciesAnsp                 1.3393    15.0179 885.2280   0.089  0.92896
## speciesApan                47.1730    16.4343 891.6540   2.870  0.00420 **
## speciesAssp                30.1030    13.3260 855.5634   2.259  0.02414 *
## speciesAsun               -14.7552    21.9185 891.5777  -0.673  0.50100
## speciesCape                12.4965    12.4874 875.4285   1.001  0.31723
## speciesCest                -8.2251    12.3446 881.8502  -0.666  0.50540
## speciesDasp                 3.3185    12.4056 881.7157   0.267  0.78915
## speciesFrve                 1.4568    13.6681 856.8472   0.107  0.91514
## speciesHisp                42.9371    14.3101 894.8986   3.000  0.00277 **
## speciesHype                12.1382    12.6809 888.5194   0.957  0.33873
## speciesPosp                 0.3897    12.3536 882.9021   0.032  0.97484
## speciesPtaq                39.1805    12.4901 887.6035   3.137  0.00176 **
## speciesRuac                -2.5818    12.4295 886.5605  -0.208  0.83550
## speciesSosp                18.5936    14.0224 889.7611   1.326  0.18518
## speciesSyla                39.0210    15.6734 893.1282   2.490  0.01297 *
## stateambient:year_factor2   1.7607     7.4674 881.9032   0.236  0.81365
## stateambient:year_factor3   3.8944     7.4429 878.0562   0.523  0.60094
## stateambient:year_factor4  -1.2029     7.3289 880.4081  -0.164  0.86966
## stateambient:year_factor5   4.2573     7.2580 878.0013   0.587  0.55764
## stateambient:year_factor6   0.1136     7.5819 878.3505   0.015  0.98805
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation matrix not shown by default, as p = 27 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
summary(umod7c)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: spp_half_cover_date ~ state + species + year_factor + insecticide +
##     (1 | plot)
##    Data: green_umbs
##
##      AIC      BIC   logLik deviance df.resid
##   8794.1   8914.1  -4372.0   8744.1      872
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.4350 -0.6176 -0.3329  0.3062  3.8635
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)   5.921   2.433
##  Residual             997.165  31.578
## Number of obs: 897, groups:  plot, 24
##
## Fixed effects:
##                       Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)           140.3990    12.5203 804.9650  11.214  < 2e-16 ***
## stateambient            1.9991     2.3552  20.2602   0.849 0.405912
```

```
## speciesAnsp             1.2515    15.0027 884.1478   0.083 0.933540
## speciesApan            48.0310    16.4646 894.6716   2.917 0.003620 **
## speciesAssp            29.7904    13.3239 850.0062   2.236 0.025620 *
## speciesAsun           -14.7832    21.9148 891.6894  -0.675 0.500121
## speciesCape            12.3853    12.4829 873.0464   0.992 0.321387
## speciesCest            -8.3568    12.3417 879.9376  -0.677 0.498507
## speciesDasp             3.2283    12.4024 879.9108   0.260 0.794695
## speciesFrve             1.4587    13.6638 853.5382   0.107 0.915004
## speciesHisp            43.1791    14.3031 895.7486   3.019 0.002609 **
## speciesHype            12.0581    12.6799 887.3512   0.951 0.341883
## speciesPosp             0.2668    12.3509 881.0659   0.022 0.982770
## speciesPtaq            39.0541    12.4891 886.5146   3.127 0.001823 **
## speciesRuac            -2.6356    12.4285 885.4842  -0.212 0.832105
## speciesSosp            18.6585    14.0265 891.2903   1.330 0.183782
## speciesSyla            38.7245    15.6628 892.5958   2.472 0.013607 *
## year_factor2          -12.5950     3.7678 879.3405  -3.343 0.000864 ***
## year_factor3            5.3746     3.7412 875.6226   1.437 0.151192
## year_factor4           -6.3419     3.7039 879.3211  -1.712 0.087205 .
## year_factor5           -9.1548     3.6631 876.4639  -2.499 0.012629 *
## year_factor6           -1.0283     3.8164 876.7863  -0.269 0.787649
## insecticideno_insects  -1.2932     2.3671  20.7830  -0.546 0.590650
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation matrix not shown by default, as p = 23 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
anova(umod7a)  # investigates whether at least one of the levels within each factor is significantly di
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##              Sum Sq Mean Sq NumDF  DenDF F value    Pr(>F)
## state           713   713.0     1  21.20  0.7154    0.4071
## species      219437 14629.1    15 877.47 14.6767 < 2.2e-16 ***
## year_factor   31804  6360.8     5 876.74  6.3815 7.831e-06 ***
## ---
## 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(umod7a, list(pairwise ~ year_factor), adjust = "tukey")
```

```
## $`emmeans of year_factor`
##  year_factor emmean   SE  df lower.CL upper.CL
##  1              155 3.35 536      148      161
##  2              142 3.27 530      136      148
##  3              160 3.25 500      154      166
##  4              148 3.15 446      142      154
##  5              145 3.16 479      139      152
##  6              154 3.39 555      147      160
##
## Results are averaged over the levels of: state, species
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
```

```
## $`pairwise differences of year_factor`
##  1     estimate   SE  df t.ratio p.value
##  1 - 2    12.62 3.81 901  3.310  0.0124
##  1 - 3    -5.34 3.78 898 -1.411  0.7202
##  1 - 4     6.38 3.75 901  1.703  0.5304
##  1 - 5     9.18 3.71 899  2.477  0.1321
##  1 - 6     1.06 3.86 899  0.275  0.9998
##  2 - 3   -17.96 3.79 898 -4.734  <.0001
##  2 - 4    -6.24 3.75 898 -1.664  0.5560
##  2 - 5    -3.44 3.71 901 -0.928  0.9392
##  2 - 6   -11.55 3.87 897 -2.989  0.0341
##  3 - 4    11.72 3.68 896  3.187  0.0186
##  3 - 5    14.52 3.64 897  3.993  0.0010
##  3 - 6     6.40 3.81 897  1.679  0.5460
##  4 - 5     2.80 3.58 897  0.782  0.9706
##  4 - 6    -5.32 3.75 896 -1.417  0.7165
##  5 - 6    -8.11 3.71 897 -2.184  0.2461
##
## Results are averaged over the levels of: state, species
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 6 estimates
```

```
emmeans(umod7a, list(pairwise ~ species), adjust = "tukey")
```

```
## $`emmeans of species`
##  species emmean    SE  df lower.CL upper.CL
##  Amla       137 12.30 897    112.7      161
##  Ansp       138  9.00 918    120.3      156
##  Apan       184 11.49 893    161.8      207
##  Assp       167  5.80 780    155.5      178
##  Asun       122 18.67 920     85.5      159
##  Cape       149  3.39 620    142.5      156
##  Cest       128  2.74 468    123.1      134
##  Dasp       140  3.00 541    134.1      146
##  Frve       138  6.56 759    125.4      151
##  Hisp       180  7.77 908    164.5      195
##  Hype       149  4.17 739    140.6      157
##  Posp       137  2.81 492    131.5      143
##  Ptaq       176  3.35 589    169.3      182
##  Ruac       134  3.16 558    127.9      140
##  Sosp       155  7.33 802    140.9      170
##  Syla       175 10.33 845    155.2      196
##
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $`pairwise differences of species`
##  1           estimate    SE  df t.ratio p.value
##  Amla - Ansp   -1.156 15.27 914  -0.076 1.0000
##  Amla - Apan  -47.579 16.71 918  -2.848 0.2442
##  Amla - Assp  -30.059 13.59 894  -2.212 0.6887
##  Amla - Asun   14.652 22.21 912   0.660 1.0000
##  Amla - Cape  -12.375 12.72 908  -0.973 0.9999
##  Amla - Cest    8.356 12.57 912   0.665 1.0000
```

```
## Amla - Dasp   -3.229 12.63 912  -0.256 1.0000
## Amla - Frve   -1.438 13.94 895  -0.103 1.0000
## Amla - Hisp  -42.962 14.53 920  -2.958 0.1895
## Amla - Hype  -12.009 12.90 916  -0.931 0.9999
## Amla - Posp   -0.274 12.57 913  -0.022 1.0000
## Amla - Ptaq  -39.053 12.71 916  -3.073 0.1418
## Amla - Ruac    2.675 12.65 915   0.212 1.0000
## Amla - Sosp  -18.462 14.25 917  -1.295 0.9960
## Amla - Syla  -38.660 15.92 919  -2.428 0.5270
## Ansp - Apan  -46.422 14.59 920  -3.183 0.1057
## Ansp - Assp  -28.903 10.67 919  -2.709 0.3259
## Ansp - Asun   15.808 20.79 920   0.760 1.0000
## Ansp - Cape  -11.218  9.60 917  -1.168 0.9987
## Ansp - Cest    9.512  9.37 916   1.016 0.9998
## Ansp - Dasp   -2.073  9.42 915  -0.220 1.0000
## Ansp - Frve   -0.282 11.06 920  -0.025 1.0000
## Ansp - Hisp  -41.806 11.75 916  -3.557 0.0338
## Ansp - Hype  -10.853  9.91 914  -1.095 0.9994
## Ansp - Posp    0.883  9.39 916   0.094 1.0000
## Ansp - Ptaq  -37.897  9.58 919  -3.956 0.0081
## Ansp - Ruac    3.832  9.49 912   0.404 1.0000
## Ansp - Sosp  -17.306 11.54 913  -1.500 0.9825
## Ansp - Syla  -37.504 13.70 904  -2.738 0.3079
## Apan - Assp   17.520 12.84 897   1.364 0.9932
## Apan - Asun   62.230 21.91 918   2.840 0.2482
## Apan - Cape   35.204 11.93 908   2.950 0.1929
## Apan - Cest   55.934 11.78 911   4.749 0.0003
## Apan - Dasp   44.350 11.84 913   3.745 0.0177
## Apan - Frve   46.141 13.25 882   3.483 0.0430
## Apan - Hisp    4.617 13.87 917   0.333 1.0000
## Apan - Hype   35.570 12.14 916   2.929 0.2025
## Apan - Posp   47.305 11.79 911   4.011 0.0065
## Apan - Ptaq    8.526 11.92 916   0.715 1.0000
## Apan - Ruac   50.254 11.86 915   4.236 0.0026
## Apan - Sosp   29.117 13.62 906   2.138 0.7402
## Apan - Syla    8.918 15.42 896   0.579 1.0000
## Assp - Asun   44.710 19.52 920   2.291 0.6308
## Assp - Cape   17.684  6.64 901   2.662 0.3572
## Assp - Cest   38.415  6.34 908   6.056 <.0001
## Assp - Dasp   26.830  6.45 914   4.158 0.0036
## Assp - Frve   28.621  8.67 891   3.302 0.0753
## Assp - Hisp  -12.903  9.65 919  -1.337 0.9945
## Assp - Hype   18.050  7.06 916   2.556 0.4311
## Assp - Posp   29.785  6.38 907   4.671 0.0004
## Assp - Ptaq   -8.994  6.62 915  -1.359 0.9934
## Assp - Ruac   32.734  6.52 912   5.019 0.0001
## Assp - Sosp   11.597  9.31 890   1.246 0.9974
## Assp - Syla   -8.602 11.75 904  -0.732 1.0000
## Asun - Cape  -27.026 18.95 920  -1.426 0.9893
## Asun - Cest   -6.296 18.85 920  -0.334 1.0000
## Asun - Dasp  -17.880 18.89 920  -0.946 0.9999
## Asun - Frve  -16.089 19.74 920  -0.815 1.0000
## Asun - Hisp  -57.613 20.20 918  -2.852 0.2417
## Asun - Hype  -26.661 19.08 920  -1.398 0.9912
```

```
##  Asun - Posp  -14.925 18.85 920  -0.792 1.0000
##  Asun - Ptaq  -53.705 18.93 920  -2.837 0.2498
##  Asun - Ruac  -11.976 18.90 920  -0.634 1.0000
##  Asun - Sosp  -33.114 19.95 915  -1.660 0.9565
##  Asun - Syla  -53.312 21.11 899  -2.525 0.4539
##  Cape - Cest   20.730  4.25 909   4.872 0.0001
##  Cape - Dasp    9.146  4.44 916   2.061 0.7894
##  Cape - Frve   10.937  7.32 892   1.494 0.9832
##  Cape - Hisp  -30.587  8.44 919  -3.625 0.0269
##  Cape - Hype    0.366  5.28 920   0.069 1.0000
##  Cape - Posp   12.101  4.30 909   2.817 0.2609
##  Cape - Ptaq  -26.678  4.68 919  -5.705 <.0001
##  Cape - Ruac   15.050  4.55 919   3.310 0.0733
##  Cape - Sosp   -6.088  8.04 891  -0.757 1.0000
##  Cape - Syla  -26.286 10.84 875  -2.425 0.5287
##  Cest - Dasp  -11.585  3.95 901  -2.930 0.2025
##  Cest - Frve   -9.793  7.05 883  -1.389 0.9917
##  Cest - Hisp  -51.318  8.18 919  -6.271 <.0001
##  Cest - Hype  -20.365  4.90 918  -4.154 0.0037
##  Cest - Posp   -8.629  3.81 893  -2.264 0.6510
##  Cest - Ptaq  -47.409  4.23 915 -11.212 <.0001
##  Cest - Ruac   -5.680  4.08 910  -1.393 0.9915
##  Cest - Sosp  -26.818  7.77 890  -3.452 0.0475
##  Cest - Syla  -47.016 10.64 885  -4.418 0.0012
##  Dasp - Frve    1.791  7.15 881   0.251 1.0000
##  Dasp - Hisp  -39.733  8.25 917  -4.813 0.0002
##  Dasp - Hype   -8.780  5.05 917  -1.738 0.9362
##  Dasp - Posp    2.955  4.00 901   0.738 1.0000
##  Dasp - Ptaq  -35.824  4.40 915  -8.146 <.0001
##  Dasp - Ruac    5.904  4.25 906   1.389 0.9918
##  Dasp - Sosp  -15.233  7.86 887  -1.939 0.8569
##  Dasp - Syla  -35.432 10.71 887  -3.309 0.0738
##  Frve - Hisp  -41.524 10.06 919  -4.128 0.0041
##  Frve - Hype  -10.571  7.72 890  -1.369 0.9929
##  Frve - Posp    1.164  7.08 886   0.164 1.0000
##  Frve - Ptaq  -37.615  7.31 873  -5.145 <.0001
##  Frve - Ruac    4.113  7.22 884   0.570 1.0000
##  Frve - Sosp  -17.024  9.75 891  -1.746 0.9339
##  Frve - Syla  -37.223 12.11 910  -3.074 0.1416
##  Hisp - Hype   30.953  8.78 913   3.525 0.0376
##  Hisp - Posp   42.688  8.20 918   5.207 <.0001
##  Hisp - Ptaq    3.909  8.40 918   0.465 1.0000
##  Hisp - Ruac   45.637  8.33 915   5.482 <.0001
##  Hisp - Sosp   24.500 10.57 918   2.318 0.6104
##  Hisp - Syla    4.301 12.84 919   0.335 1.0000
##  Hype - Posp   11.736  4.94 918   2.378 0.5651
##  Hype - Ptaq  -27.044  5.27 920  -5.136 <.0001
##  Hype - Ruac   14.684  5.13 915   2.862 0.2363
##  Hype - Sosp   -6.453  8.40 884  -0.768 1.0000
##  Hype - Syla  -26.651 11.07 896  -2.407 0.5431
##  Posp - Ptaq  -38.779  4.28 916  -9.070 <.0001
##  Posp - Ruac    2.949  4.12 911   0.715 1.0000
##  Posp - Sosp  -18.189  7.79 892  -2.334 0.5982
##  Posp - Syla  -38.387 10.66 886  -3.601 0.0292
```

```
##  Ptaq - Ruac   41.728  4.51 918   9.260 <.0001
##  Ptaq - Sosp   20.591  8.00 893   2.575 0.4174
##  Ptaq - Syla    0.393 10.80 898   0.036 1.0000
##  Ruac - Sosp  -21.138  7.93 891  -2.666 0.3543
##  Ruac - Syla  -41.336 10.74 894  -3.848 0.0122
##  Sosp - Syla  -20.198 12.48 920  -1.618 0.9650
##
## Results are averaged over the levels of: state, year_factor
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 16 estimates
```

```r
# including native vs. exotic - first with interaction term
green_umbs <- within(green_umbs, origin <- relevel(factor(origin),
    ref = "Native"))  # releveling so native is the reference
umod8 <- lmer(spp_half_cover_date ~ state * origin + (1 + year_factor |
    plot), green_umbs, REML = FALSE)
```

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

## Warning: Model failed to converge with 3 negative eigenvalues: -8.3e-03 -4.6e+00
## -1.0e+01
```

```r
umod9 <- lmer(spp_half_cover_date ~ state + origin + (1 + year_factor |
    plot), green_umbs, REML = FALSE)
```

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

## Warning: Model failed to converge with 1 negative eigenvalue: -2.3e-01
```

```r
umod9a <- lmer(spp_half_cover_date ~ state + origin + factor(year_factor) +
    (1 | plot), green_umbs, REML = FALSE)
```

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

```r
anova(umod8, umod9)  # umodel 9 is a better fit to data
```

```
## Data: green_umbs
## Models:
## umod9: spp_half_cover_date ~ state + origin + (1 + year_factor | plot)
## umod8: spp_half_cover_date ~ state * origin + (1 + year_factor | plot)
##       npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## umod9   27 8918.5 9048.1 -4432.3   8864.5
## umod8   30 8917.9 9061.8 -4428.9   8857.9 6.6471  3    0.08404 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
anova(umod9, umod9a)  # umod 9a?
```

```
## Data: green_umbs
## Models:
## umod9a: spp_half_cover_date ~ state + origin + factor(year_factor) +
## umod9a:     (1 | plot)
## umod9: spp_half_cover_date ~ state + origin + (1 + year_factor | plot)
##        npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## umod9a   12 8875.2 8932.8 -4425.6   8851.2
## umod9    27 8918.5 9048.1 -4432.3   8864.5     0 15          1
```

```r
summary(umod9a)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: spp_half_cover_date ~ state + origin + factor(year_factor) +
##     (1 | plot)
##    Data: green_umbs
##
##      AIC      BIC   logLik deviance df.resid
##   8875.2   8932.8  -4425.6   8851.2      885
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.1090 -0.6546 -0.3354  0.2993  3.6228
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)    0      0.00
##  Residual             1130     33.61
## Number of obs: 897, groups:  plot, 24
##
## Fixed effects:
##                      Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)          155.6057     3.2586 897.0000  47.753  < 2e-16 ***
## stateambient           1.1163     2.2545 897.0000   0.495 0.620629
## origin               -16.5176     3.3127 897.0000  -4.986 7.40e-07 ***
## originBoth            18.2229     5.0828 897.0000   3.585 0.000355 ***
## originExotic         -18.8232     2.5475 897.0000  -7.389 3.39e-13 ***
## factor(year_factor)2 -12.3586     3.9553 897.0000  -3.125 0.001838 **
## factor(year_factor)3   5.7297     3.9516 897.0000   1.450 0.147420
## factor(year_factor)4  -4.6638     3.8963 897.0000  -1.197 0.231621
## factor(year_factor)5  -6.9443     3.8563 897.0000  -1.801 0.072078 .
## factor(year_factor)6   0.4909     4.0309 897.0000   0.122 0.903095
## ---
## 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 -0.355
## origin      -0.235  0.011
## originBoth  -0.117 -0.080  0.171
## originExotc -0.327  0.012  0.342  0.219
## fctr(yr_f)2 -0.616  0.020 -0.032 -0.075  0.001
## fctr(yr_f)3 -0.604 -0.005 -0.035  0.001 -0.029  0.509
## fctr(yr_f)4 -0.618  0.013 -0.039 -0.013 -0.028  0.518  0.518
## fctr(yr_f)5 -0.617 -0.008 -0.027 -0.031 -0.030  0.524  0.523  0.531
## fctr(yr_f)6 -0.594  0.014 -0.047 -0.023 -0.033  0.501  0.501  0.509  0.514
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

```r
anova(umod9)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##        Sum Sq Mean Sq NumDF  DenDF F value Pr(>F)
## state     510     510     1  64.67  0.4641 0.4982
## origin 103139   34380     3 843.94 31.2634 <2e-16 ***
## ---
```

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

```r
emmeans(umod9a, list(pairwise ~ state + origin), adjust = "tukey")
```

```
## Warning in model.frame.default(formula, data = data, ...): variable
## 'year_factor' is not a factor

## $`emmeans of state, origin`
##  state   origin emmean   SE    df lower.CL upper.CL
##  warmed  Native    153 2.10  64.0      148      157
##  ambient Native    154 2.10  61.1      150      158
##  warmed            136 3.09 280.8      130      142
##  ambient           137 3.12 289.1      131      143
##  warmed  Both      171 5.09 583.5      161      181
##  ambient Both      172 4.92 500.2      162      182
##  warmed  Exotic    134 2.26  85.8      129      138
##  ambient Exotic    135 2.28  90.2      130      139
##
## Results are averaged over the levels of: year_factor
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $`pairwise differences of state, origin`
##  1                                estimate   SE    df t.ratio p.value
##  warmed Native - ambient Native     -1.12 2.36  24.8 -0.473  0.9997
##  warmed Native - warmed             16.52 3.33 897.7  4.956  <.0001
##  warmed Native - ambient            15.40 4.10 218.3  3.755  0.0054
##  warmed Native - warmed Both       -18.22 5.14 895.8 -3.548  0.0097
##  warmed Native - ambient Both      -19.34 5.49 367.4 -3.520  0.0113
##  warmed Native - warmed Exotic      18.82 2.57 907.1  7.331  <.0001
##  warmed Native - ambient Exotic     17.71 3.50 120.8  5.054  <.0001
##  ambient Native - warmed            17.63 4.06 203.7  4.340  0.0006
##  ambient Native - ambient           16.52 3.33 897.7  4.956  <.0001
##  ambient Native - warmed Both      -17.11 5.81 475.3 -2.947  0.0659
##  ambient Native - ambient Both     -18.22 5.14 895.8 -3.548  0.0097
##  ambient Native - warmed Exotic     19.94 3.47 111.4  5.749  <.0001
##  ambient Native - ambient Exotic    18.82 2.57 907.1  7.331  <.0001
##  warmed  - ambient                  -1.12 2.36  24.8 -0.473  0.9997
##  warmed  - warmed Both             -34.74 5.63 894.9 -6.168  <.0001
##  warmed  - ambient Both            -35.86 5.95 425.5 -6.030  <.0001
##  warmed  - warmed Exotic             2.31 3.44 894.0  0.671  0.9977
##  warmed  - ambient Exotic            1.19 4.16 227.9  0.286  1.0000
##  ambient  - warmed Both            -33.62 6.26 538.1 -5.371  <.0001
##  ambient  - ambient Both           -34.74 5.63 894.9 -6.168  <.0001
##  ambient  - warmed Exotic            3.42 4.17 229.4  0.820  0.9918
##  ambient  - ambient Exotic           2.31 3.44 894.0  0.671  0.9977
##  warmed Both - ambient Both         -1.12 2.36  24.8 -0.473  0.9997
##  warmed Both - warmed Exotic        37.05 5.22 894.9  7.099  <.0001
##  warmed Both - ambient Exotic       35.93 5.89 490.2  6.102  <.0001
##  ambient Both - warmed Exotic       38.16 5.56 370.8  6.865  <.0001
##  ambient Both - ambient Exotic      37.05 5.22 894.9  7.099  <.0001
##  warmed Exotic - ambient Exotic     -1.12 2.36  24.8 -0.473  0.9997
##
## Results are averaged over the levels of: year_factor
## Degrees-of-freedom method: kenward-roger
```

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

```r
# including growth form - first with interaction term
green_umbs <- within(green_umbs, growth_habit <- relevel(factor(growth_habit),
    ref = "Forb"))  # releveling so forb is the reference
umod10 <- lmer(spp_half_cover_date ~ state * growth_habit + (1 +
    year_factor | plot), green_umbs, REML = FALSE)
```

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

```r
umod11 <- lmer(spp_half_cover_date ~ state + growth_habit + (1 +
    year_factor | plot), green_umbs, REML = FALSE)
```

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

```r
umod11a <- lmer(spp_half_cover_date ~ state + growth_habit +
    year_factor + (1 | plot), green_umbs, REML = FALSE)
```

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

```r
anova(umod10, umod11)  # umodel 11 is a better fit to data
```

```
## Data: green_umbs
## Models:
## umod11: spp_half_cover_date ~ state + growth_habit + (1 + year_factor |
## umod11:     plot)
## umod10: spp_half_cover_date ~ state * growth_habit + (1 + year_factor |
## umod10:     plot)
##        npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## umod11   27 8991.4 9121.0 -4468.7   8937.4
## umod10   30 8994.4 9138.4 -4467.2   8934.4 2.9817  3     0.3945
```

```r
anova(umod11, umod11a)
```

```
## Data: green_umbs
## Models:
## umod11a: spp_half_cover_date ~ state + growth_habit + year_factor + (1 |
## umod11a:     plot)
## umod11: spp_half_cover_date ~ state + growth_habit + (1 + year_factor |
## umod11:     plot)
##         npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## umod11a   12 8947.0 9004.6 -4461.5   8923.0
## umod11    27 8991.4 9121.0 -4468.7   8937.4     0 15          1
```

```r
summary(umod11a)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: spp_half_cover_date ~ state + growth_habit + year_factor + (1 |
##     plot)
##    Data: green_umbs
##
##      AIC      BIC   logLik deviance df.resid
##   8947.0   9004.6  -4461.5   8923.0      885
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.0153 -0.7074 -0.3967  0.4360  3.3480
```

```
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)    0      0.00
##  Residual             1224     34.98
## Number of obs: 897, groups:  plot, 24
##
## Fixed effects:
##                         Estimate Std. Error       df t value Pr(>|t|)
## (Intercept)             149.2638     3.2934 897.0000  45.322  < 2e-16 ***
## stateambient              2.2853     2.3383 897.0000   0.977  0.32867
## growth_habit             24.9558     7.9188 897.0000   3.151  0.00168 **
## growth_habitGraminoid    -5.3131     2.4203 897.0000  -2.195  0.02840 *
## growth_habitTree         -9.2509    13.3660 897.0000  -0.692  0.48904
## year_factor2            -12.9157     4.1539 897.0000  -3.109  0.00193 **
## year_factor3              4.7827     4.1203 897.0000   1.161  0.24605
## year_factor4             -6.0719     4.0617 897.0000  -1.495  0.13529
## year_factor5             -7.7178     4.0167 897.0000  -1.921  0.05500 .
## year_factor6             -0.8025     4.1926 897.0000  -0.191  0.84825
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) sttmbn grwth_ grwt_G grwt_T yr_fc2 yr_fc3 yr_fc4 yr_fc5
## stateambint -0.365
## growth_habt -0.025 -0.024
## grwth_hbtGr -0.269 -0.001  0.127
## grwth_hbtTr -0.016 -0.010  0.017  0.074
## year_factr2 -0.627  0.017 -0.156 -0.033 -0.004
## year_factr3 -0.625 -0.003 -0.004 -0.032 -0.068  0.505
## year_factr4 -0.643  0.015 -0.053 -0.027 -0.044  0.519  0.519
## year_factr5 -0.644 -0.008 -0.038 -0.018 -0.042  0.522  0.524  0.532
## year_factr6 -0.623  0.015 -0.030 -0.024 -0.002  0.500  0.500  0.508  0.513
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

```r
anova(umod11)
```

```
## Type III Analysis of Variance Table with Satterthwaite's method
##               Sum Sq Mean Sq NumDF  DenDF F value  Pr(>F)
## state         1368.7  1368.7     1  88.15  1.1374 0.28912
## growth_habit 17566.6  5855.5     3 835.64  4.8657 0.00232 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
emmeans(umod11a, list(pairwise ~ state + growth_habit), adjust = "tukey")
```

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

```
## $`emmeans of state, growth_habit`
##  state   growth_habit emmean   SE    df lower.CL upper.CL
##  warmed  Forb            145 1.96  38.7      142      149
##  ambient Forb            148 1.96  34.5      144      152
##  warmed                  170 7.96 778.9      155      186
##  ambient                 173 7.90 776.3      157      188
##  warmed  Graminoid       140 2.23  67.5      136      145
```

```
##  ambient Graminoid       142  2.22  66.5      138      147
##  warmed  Tree            136 13.51 805.0      110      163
##  ambient Tree            139 13.48 814.9      112      165
##
## Results are averaged over the levels of: year_factor
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $`pairwise differences of state, growth_habit`
##  1                                     estimate    SE    df t.ratio p.value
##  warmed Forb - ambient Forb               -2.29  2.36  20.8 -0.967  0.9744
##  warmed Forb - warmed                    -24.96  7.99 906.1 -3.123  0.0388
##  warmed Forb - ambient                   -27.24  8.28 698.0 -3.291  0.0232
##  warmed Forb - warmed Graminoid            5.31  2.44 904.3  2.176  0.3672
##  warmed Forb - ambient Graminoid           3.03  3.39  85.3  0.893  0.9860
##  warmed Forb - warmed Tree                 9.25 13.53 862.5  0.684  0.9974
##  warmed Forb - ambient Tree                6.97 13.70 787.0  0.508  0.9996
##  ambient Forb - warmed                   -22.67  8.39 689.3 -2.703  0.1234
##  ambient Forb - ambient                  -24.96  7.99 906.1 -3.123  0.0388
##  ambient Forb - warmed Graminoid           7.60  3.41  78.0  2.232  0.3449
##  ambient Forb - ambient Graminoid          5.31  2.44 904.3  2.176  0.3672
##  ambient Forb - warmed Tree               11.54 13.76 760.8  0.838  0.9909
##  ambient Forb - ambient Tree               9.25 13.53 862.5  0.684  0.9974
##  warmed  - ambient                        -2.29  2.36  20.8 -0.967  0.9744
##  warmed  - warmed Graminoid               30.27  8.06 897.4  3.754  0.0046
##  warmed  - ambient Graminoid              27.98  8.45 663.7  3.310  0.0219
##  warmed  - warmed Tree                    34.21 15.57 898.7  2.196  0.3549
##  warmed  - ambient Tree                   31.92 15.76 863.0  2.026  0.4648
##  ambient  - warmed Graminoid              32.55  8.35 655.8  3.899  0.0027
##  ambient  - ambient Graminoid             30.27  8.06 897.4  3.754  0.0046
##  ambient  - warmed Tree                   36.49 15.75 851.0  2.317  0.2855
##  ambient  - ambient Tree                  34.21 15.57 898.7  2.196  0.3549
##  warmed Graminoid - ambient Graminoid     -2.29  2.36  20.8 -0.967  0.9744
##  warmed Graminoid - warmed Tree            3.94 13.57 854.0  0.290  1.0000
##  warmed Graminoid - ambient Tree           1.65 13.74 773.2  0.120  1.0000
##  ambient Graminoid - warmed Tree           6.22 13.80 752.3  0.451  0.9998
##  ambient Graminoid - ambient Tree          3.94 13.57 854.0  0.290  1.0000
##  warmed Tree - ambient Tree               -2.29  2.36  20.8 -0.967  0.9744
##
## Results are averaged over the levels of: year_factor
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 8 estimates
```

UMBS Plot-level Mixed Effects Models:

```
mod1pu <- lmer(plot_half_cover_date ~ state + (1 | plot), green_umbsp,
    REML = FALSE)
```

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

```
mod2pu <- lmer(plot_half_cover_date ~ state + factor(year_factor) +
    (1 | plot), green_umbsp, REML = FALSE)
```

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

```r
mod3pu <- lmer(plot_half_cover_date ~ state * year_factor + (1 |
    plot), green_umbsp, REML = FALSE)
```

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

```r
anova(mod1pu, mod2pu, mod3pu)  #mod2pu
```

```
## Data: green_umbsp
## Models:
## mod1pu: plot_half_cover_date ~ state + (1 | plot)
## mod2pu: plot_half_cover_date ~ state + factor(year_factor) + (1 | plot)
## mod3pu: plot_half_cover_date ~ state * year_factor + (1 | plot)
##        npar    AIC    BIC  logLik deviance   Chisq Df Pr(>Chisq)
## mod1pu    4 1440.9 1452.8 -716.45   1432.9
## mod2pu    9 1424.0 1450.7 -702.99   1406.0 26.9273  5  5.893e-05 ***
## mod3pu   14 1426.1 1467.7 -699.05   1398.1  7.8726  5     0.1634
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod2pu)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's
##   method [lmerModLmerTest]
## Formula: plot_half_cover_date ~ state + factor(year_factor) + (1 | plot)
##    Data: green_umbsp
##
##      AIC      BIC   logLik deviance df.resid
##   1424.0   1450.7   -703.0   1406.0      135
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.8838 -0.6975 -0.1632  0.4816  3.0703
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept)    0      0.00
##  Residual             1018     31.91
## Number of obs: 144, groups:  plot, 24
##
## Fixed effects:
##                       Estimate Std. Error      df t value Pr(>|t|)
## (Intercept)            147.306      7.035 144.000  20.938   <2e-16 ***
## stateambient            -1.778      5.318 144.000  -0.334   0.7387
## factor(year_factor)2   -21.500      9.212 144.000  -2.334   0.0210 *
## factor(year_factor)3    -2.583      9.212 144.000  -0.280   0.7795
## factor(year_factor)4    13.167      9.212 144.000   1.429   0.1551
## factor(year_factor)5    23.583      9.212 144.000   2.560   0.0115 *
## factor(year_factor)6    12.917      9.212 144.000   1.402   0.1630
## ---
## 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
## stateambint -0.378
## fctr(yr_f)2 -0.655  0.000
```

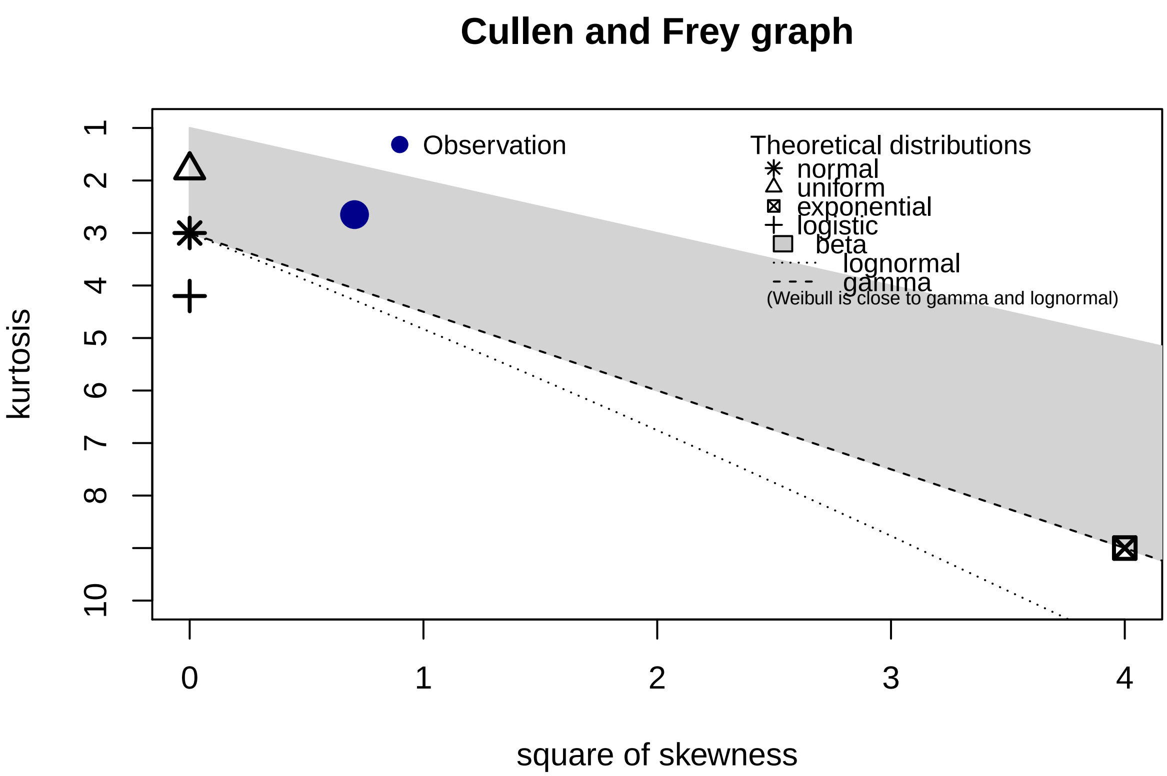
```
## fctr(yr_f)3 -0.655  0.000  0.500
## fctr(yr_f)4 -0.655  0.000  0.500  0.500
## fctr(yr_f)5 -0.655  0.000  0.500  0.500  0.500
## fctr(yr_f)6 -0.655  0.000  0.500  0.500  0.500  0.500
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

ORIGINAL CODE BELOW; not edited by Phoebe

can pretty much ignore everything below!

Seeing what other distribution could fit

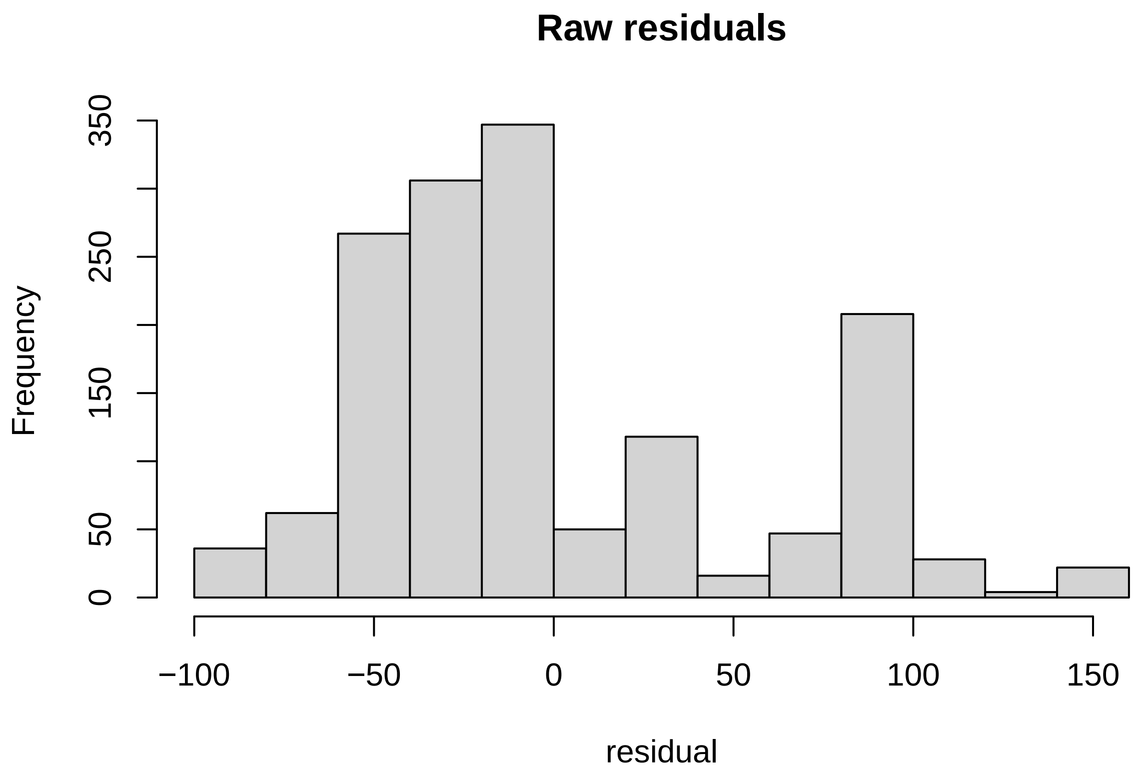
```
descdist(green_kbs$spp_half_cover_date, discrete = FALSE)
```



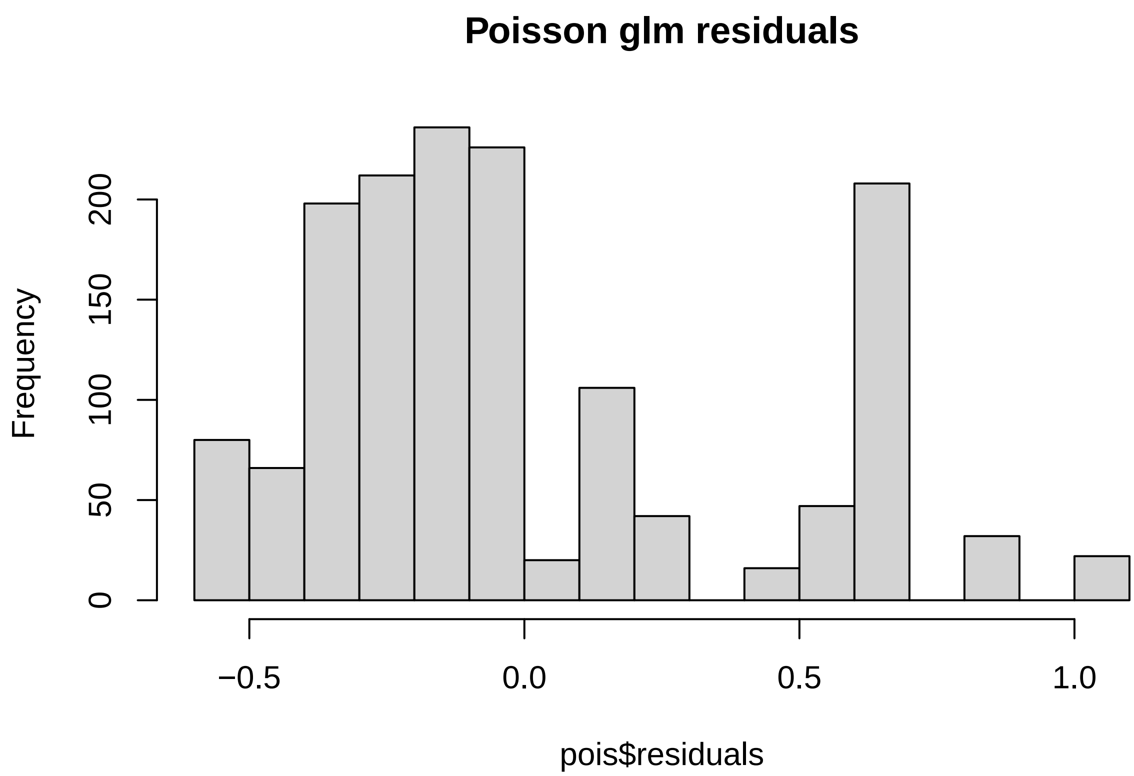

```
## summary statistics
## ------
## min:  59   max:  289
## median:  124
## mean:  139.3309
## estimated sd:  56.12957
## estimated skewness:  0.8397458
## estimated kurtosis:  2.650025
```

While uniform looks the closest, I'll try poisson

```r
fit <- lm(spp_half_cover_date ~ state, data = green_kbs)
residual <- fit$residuals
hist(residual, main = "Raw residuals")
```




```r
pois <- glm(spp_half_cover_date ~ state, data = green_kbs, family = "poisson")
hist(pois$residuals, main = "Poisson glm residuals")
```


Poisson glm residuals
Frequency
0
50
100
150
200
−0.5
0.0
0.5
1.0
pois$residuals

Below I try a few different generalized linear models with poisson distribution:

An interaction between state and year, plus insecticide as a fixed effect and species and plot as random effects

```
moda <- glmer(spp_half_cover_date ~ state * year + insecticide +
    (1 | species) + (1 | plot), data = green_kbs, family = poisson)
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.0128739 (tol = 0.002, component 1)

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model is nearly unider
##  - Rescale variables?;Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

```
summary(moda)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: poisson  ( log )
## Formula: spp_half_cover_date ~ state * year + insecticide + (1 | species) +
##     (1 | plot)
##    Data: green_kbs
##
##      AIC      BIC   logLik deviance df.resid
##  35773.3  35810.5 -17879.6  35759.3     1504
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -7.563 -2.897 -1.147  1.916 15.309
##
## Random effects:
##  Groups  Name        Variance Std.Dev.
##  plot    (Intercept) 0.003081 0.0555
##  species (Intercept) 0.035563 0.1886
## Number of obs: 1511, groups:  plot, 24; species, 22
##
## Fixed effects:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -28.182733   4.491500  -6.275 3.50e-10 ***
## stateambient        -43.588322   6.670109  -6.535 6.37e-11 ***
## year                  0.016413   0.002225   7.376 1.63e-13 ***
## insecticideno_insects -0.006946   0.023100  -0.301    0.764
## stateambient:year     0.021594   0.003304   6.535 6.37e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) sttmbn year   insct_
## stateambint -0.808
## year        -1.000  0.808
```

```
## insctcdn_ns -0.020  0.013  0.017
## statmbnt:yr  0.808 -1.000 -0.808 -0.013
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
## convergence code: 0
## Model failed to converge with max|grad| = 0.0128739 (tol = 0.002, component 1)
## Model is nearly unidentifiable: very large eigenvalue
##  - Rescale variables?
## Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

No interaction between state and year, but with state and insecticide as fixed effects and species and plot as random effects

```
modb <- glmer(spp_half_cover_date ~ state + year + insecticide +
    (1 | species) + (1 | plot), data = green_kbs, family = poisson)
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.00426111 (tol = 0.002, component 1)

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, : Model is nearly unider
##  - Rescale variables?;Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

```
summary(modb)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: poisson  ( log )
## Formula: spp_half_cover_date ~ state + year + insecticide + (1 | species) +
##     (1 | plot)
##    Data: green_kbs
##
##      AIC      BIC   logLik deviance df.resid
##  35843.8  35875.7 -17915.9  35831.8     1505
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -7.541 -2.891 -1.142  1.953 14.948
##
## Random effects:
##  Groups  Name        Variance Std.Dev.
##  plot    (Intercept) 0.003069 0.0554
##  species (Intercept) 0.035934 0.1896
## Number of obs: 1511, groups:  plot, 24; species, 22
##
## Fixed effects:
##                          Estimate Std. Error z value Pr(>|z|)
## (Intercept)            -5.122e+01  2.600e+00 -19.703   <2e-16 ***
## stateambient           -4.634e-04  2.306e-02  -0.020    0.984
## year                    2.783e-02  1.288e-03  21.608   <2e-16 ***
## insecticideno_insects -5.137e-03  2.306e-02  -0.223    0.824
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) sttmbn year
## stateambint  0.002
## year        -1.000 -0.007
## insctcdn_ns -0.016 -0.003  0.011
## convergence code: 0
## Model failed to converge with max|grad| = 0.00426111 (tol = 0.002, component 1)
## Model is nearly unidentifiable: very large eigenvalue
##  - Rescale variables?
## Model is nearly unidentifiable: large eigenvalue ratio
##  - Rescale variables?
```

State and insecticide as fixed effects & year, species and plot as random effects

```
modc <- glmer(spp_half_cover_date ~ state + insecticide + (1 |
    year) + (1 | species) + (1 | plot), data = green_kbs, family = poisson)
summary(modc)
```

Because no distributions seems to match well, I'll try a Friedman's test

```
# friedman_kbs <- green_kbs %>%
# friedman_test(spp_half_cover_date ~ state)
```

Error: Must extract column with a single valid subscript. x Subscript `var` can't be `NA`

Can't figure out what this means

If I include the blocks portion of the formula (from the documentation) I get this error

```
# friedman_kbs <- green_kbs %>%
# friedman_test(spp_half_cover_date ~ state | plot)
```

Error in friedman.test.default(c(141L, 202L, 122L, 101L, 127L, 120L, 197L, : not an unreplicated complete block design

Permanova?

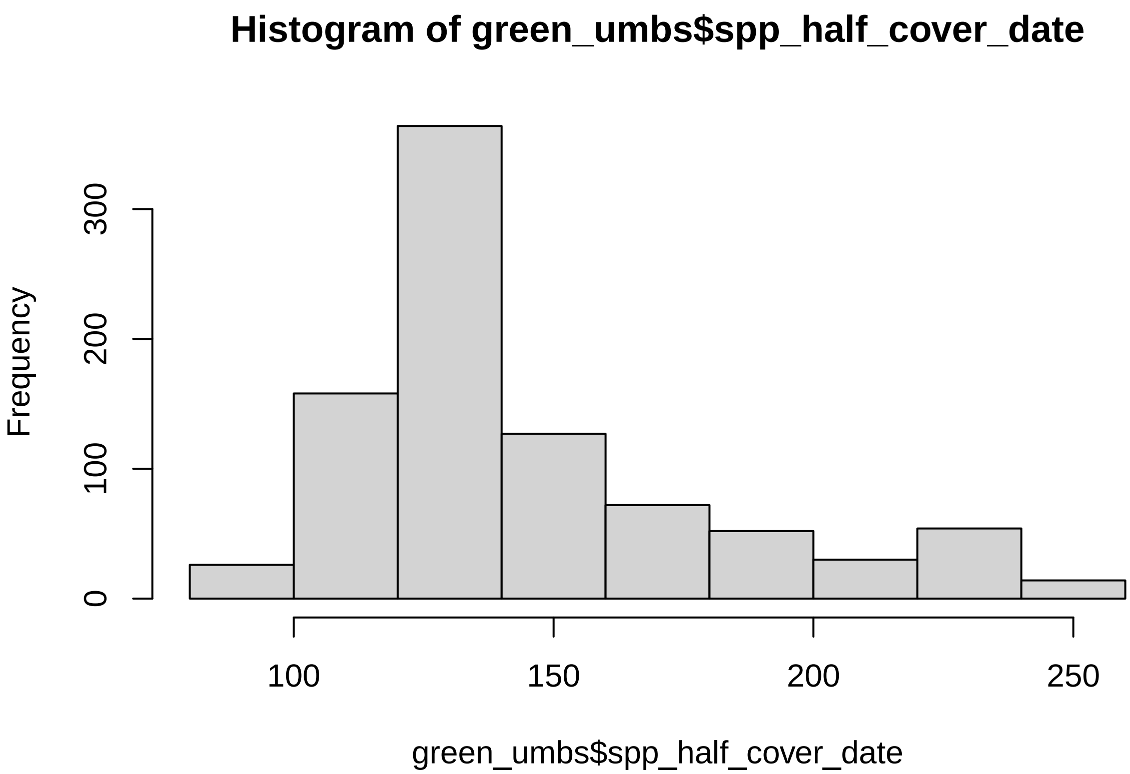
```
per1 <- adonis2(green_kbs$spp_half_cover_date ~ state * year +
    insecticide, data = green_kbs)
per1
per2 <- adonis(formula = green_kbs$spp_half_cover_date ~ state *
    year + insecticide, strata = green_kbs$plot, data = green_kbs)
per2
```

With per2, when controlling for "plot", there is a difference btwn treatments

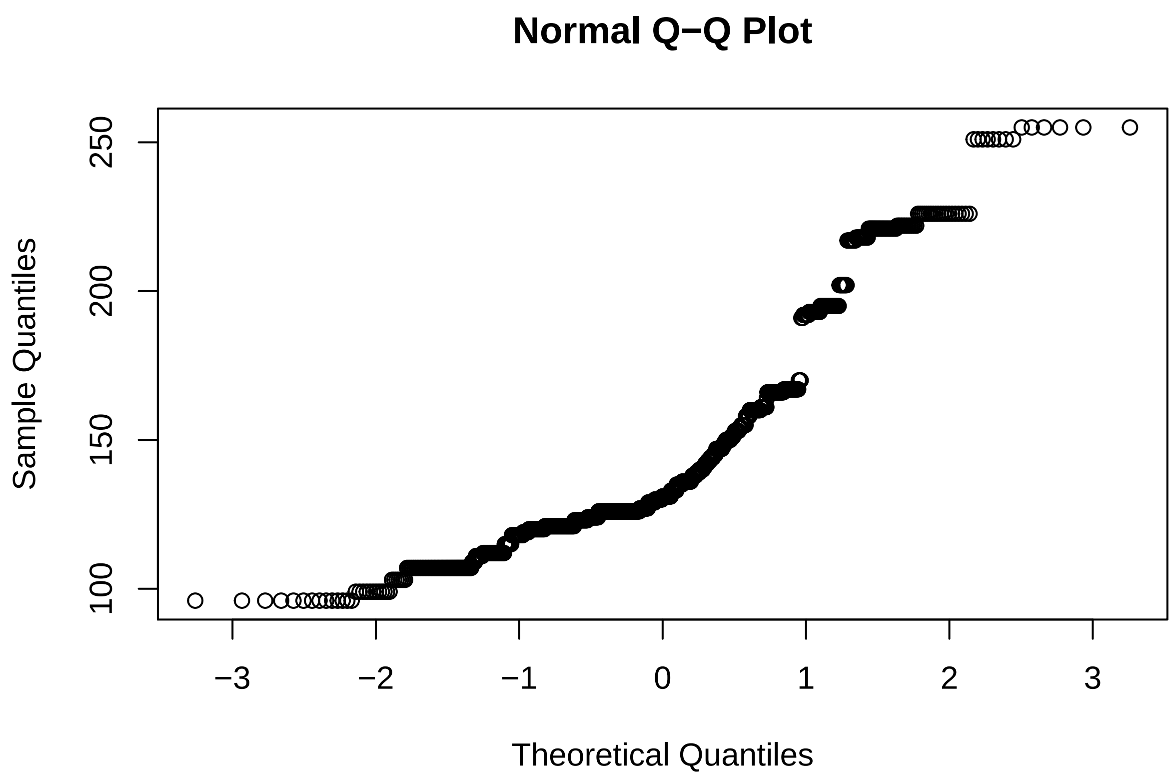
UMBS

Checking for normality

```r
hist(green_umbs$spp_half_cover_date)
```



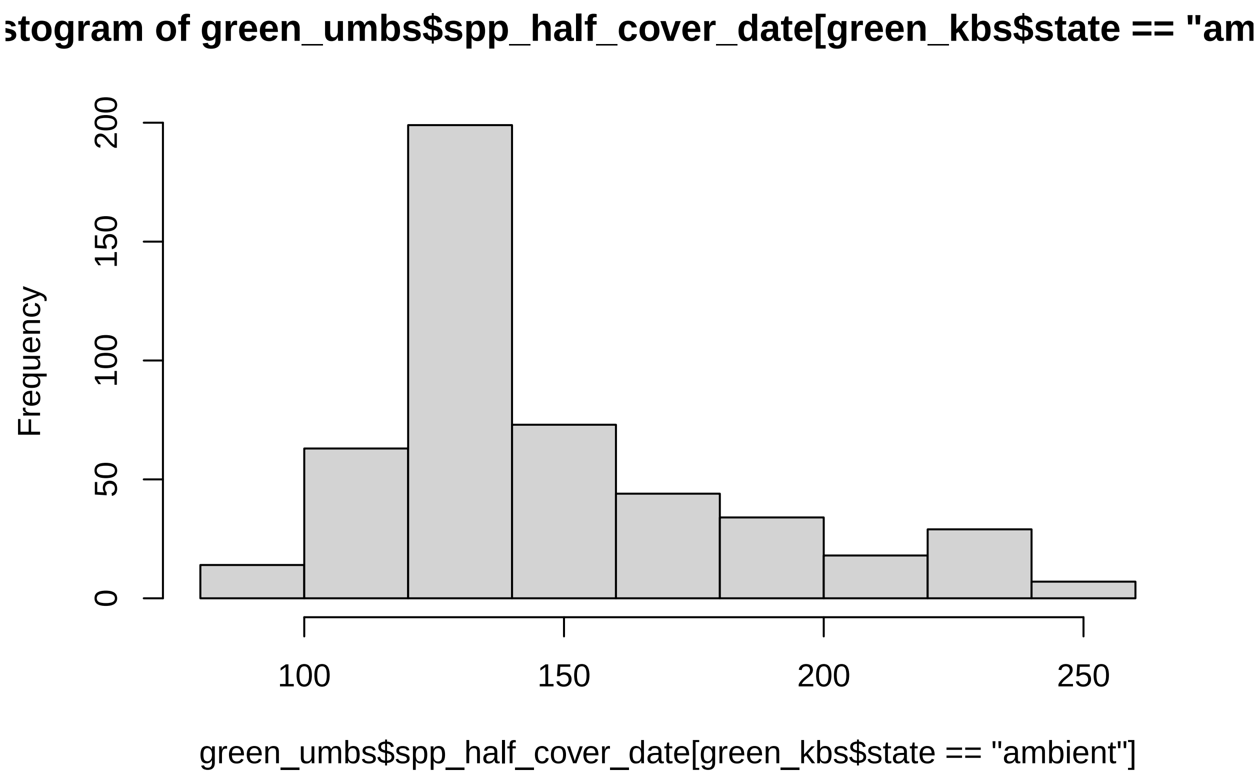

```r
qqnorm(green_umbs$spp_half_cover_date)
```



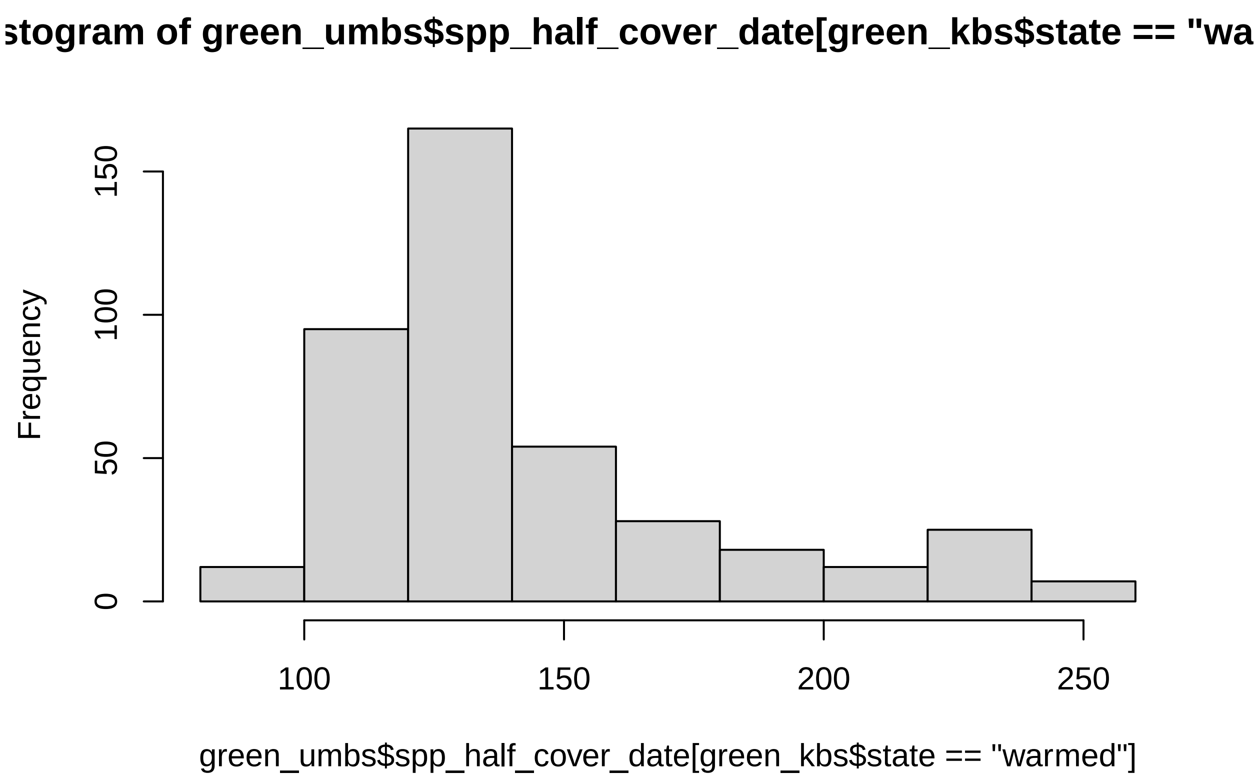

```r
shapiro.test(green_umbs$spp_half_cover_date)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  green_umbs$spp_half_cover_date
## W = 0.86297, p-value < 2.2e-16
```

```r
hist(green_umbs$spp_half_cover_date[green_kbs$state == "ambient"])
```



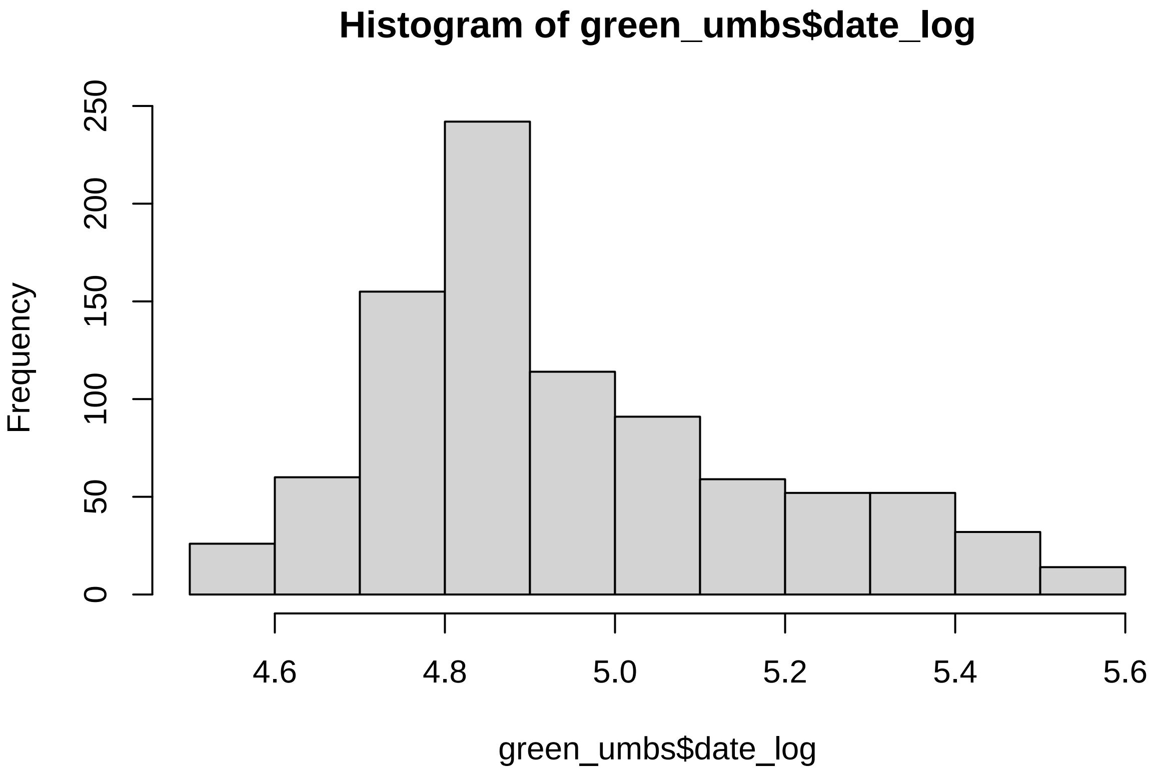

```r
hist(green_umbs$spp_half_cover_date[green_kbs$state == "warmed"])
```



These look pretty good

Trying log transformation

```
green_umbs$date_log <- log(green_umbs$spp_half_cover_date)
hist(green_umbs$date_log)
```



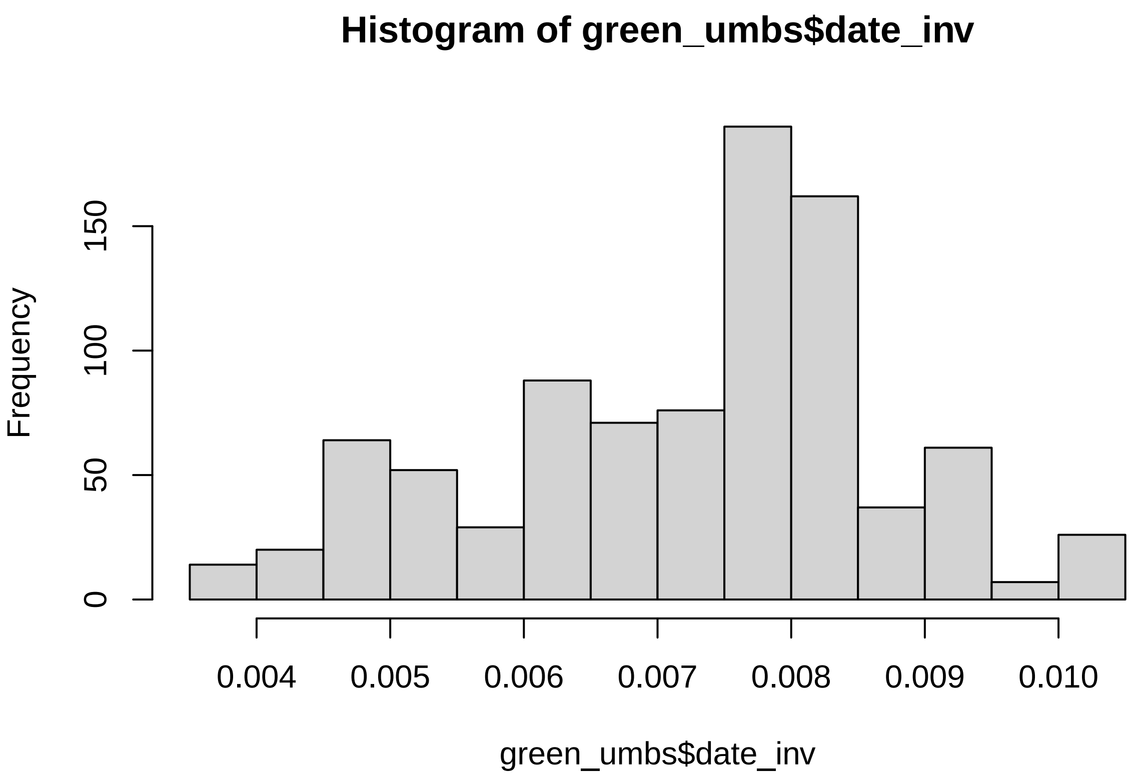

```
shapiro.test(green_umbs$date_log)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  green_umbs$date_log
## W = 0.9214, p-value < 2.2e-16
```

I think this looks good but shapiro-wilk is lower than 0.05

Trying inverse tranformation

```
green_umbs$date_inv <- 1/(green_umbs$spp_half_cover_date)
hist(green_umbs$date_inv)
```




```
shapiro.test(green_umbs$date_inv)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  green_umbs$date_inv
## W = 0.9592, p-value = 4.155e-15
```

This also looks good but is also still low for shapiro-wilk