warmXtrophic Project: Plant Composition Diversity Data Analyses

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Load in packages & data

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

# Load packages
library(tidyverse)
library(ggplot2)
library(lme4)
library(olsrr)
library(predictmeans)
library(car)
library(fitdistrplus)
library(ggpubr)
library(rstatix)
library(vegan)
library(interactions)
library(emmeans)
library(sjPlot)
library(effects)
library(glmmTMB)
library(labdsv)  # used with Vegan package, the matrify() and matrify2() functions
library(agricolae)  # HSD.test() function
library(bbmle)
library(jtools)  # summ() function

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

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

```
L0_dir <- Sys.getenv("L0DIR")
L1_dir <- Sys.getenv("L1DIR")
L2_dir <- Sys.getenv("L2DIR")
list.files(L1_dir)
```

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

```r
# read in plant comp data
comp <- read.csv(file.path(L1_dir, "plant_composition/final_plantcomp_L1.csv"))
comp <- comp %>% select(-X)  # get rid of 'X' column that shows up

# Remove non-plant data
comp <- comp[!(comp$species == "Bare_Ground" | comp$species == "Unknown" | comp$species ==
    "Brown" | comp$species == "Litter" | comp$species == "Vert_Litter" | comp$species ==
    "Animal_Disturbance"), ]

# read in meta data
meta <- read.csv(file.path(L0_dir, "plot.csv"))  # dataframe above already has meta data in it
```

Function to get data into wide format in order to work in the Vegan package

```r
# Function to get data in wide format to work in Vegan package - taken from link
# below
# https://stackoverflow.com/questions/50691393/transform-community-data-into-wide-format-for-vegan-pack

matrify2 <- function(data) {
    # Data must have columns: plot, SPEC, abundance measure,Year
    if (ncol(data) != 4)
        stop("data frame must have four column format")
    plt <- factor(data[, 1])
    spc <- factor(data[, 2])
    abu <- data[, 3]
    yrs <- factor(data[, 4])
    plt.codes <- sort(levels(factor(plt)))  ##object with sorted plot numbers
    spc.codes <- levels(factor(spc))  ##object with sorted SPEC names
    yrs.codes <- sort(levels(factor(yrs)))  ##object with sorted sampling Years
    taxa <- matrix(0, nrow = length(plt.codes) * length(yrs.codes), ncol = length(spc.codes))  ##Create
    plt.list <- rep(plt.codes, length(yrs.codes))  ##Create a list of all the plot numbers (in order of
    yrs.list <- rep(yrs.codes, each = length(plt.codes))  ##Create a list of all the Year numbers (in o
    col <- match(spc, spc.codes)  ##object that determines the alphabetical order ranking of each SPEC
    row.plt <- match(plt, plt.codes)  ##object that determines the rank order ranking of each plot of t
    row.yrs <- match(yrs, yrs.codes)  ##object that determines the rank order ranking of each Year of t
    for (i in 1:length(abu)) {
        row <- (row.plt[i]) + length(plt.codes) * (row.yrs[i] - 1)  ##Determine row number by assuming
        if (!is.na(abu[i])) {
            ## ONly use value if !is.na .. [ignore all is.NA values]
            taxa[row, col[i]] <- sum(taxa[row, col[i]], abu[i])  ##Add abundance measure of row i to th
        }
    }
    taxa <- data.frame(taxa)  ##Convert to data.frame for easier manipulation
    taxa <- cbind(yrs.list, plt.list, taxa)  ##Add ID columns for plot and Year to each row already rep
    names(taxa) <- c("Year", "Plot", spc.codes)
    taxa
}
```

Calculating Shannon and Simpsons Diversity and Species Richness

```r
# diversity_by_year <- function(comp, site, div_index = 'shannon'){ subset comp
# data by site
comp_kbs <- subset(comp, site == "kbs") %>% dplyr::select(plot, species, cover, year)
```

```r
comp_umbs <- subset(comp, site == "umbs") %>% dplyr::select(plot, species, cover,
    year)


# convert the abundance (cover) data to wide format for each species in columns
# for the vegan package kbs
comp_kbs$cover <- as.numeric(comp_kbs$cover)  # change cover data to numeric
comp_wide_kbs <- matrify2(comp_kbs)  # use matrify2 function
# umbs
comp_umbs$cover <- as.numeric(comp_umbs$cover)  # change cover data to numeric
```

```
## Warning: NAs introduced by coercion
```

```r
comp_wide_umbs <- matrify2(comp_umbs)  # use matrify2 function

# comp_wide_data assumes to have columns Year, Plot, and columns for each species
# found, e.g. for Vegan

# first, split up the wide data into a list of years.  Each list item is a year
# of data
comp_wide_by_year_kbs <- dplyr::group_by(comp_wide_kbs, Year) %>% dplyr::group_split()
comp_wide_by_year_umbs <- dplyr::group_by(comp_wide_umbs, Year) %>% dplyr::group_split()

# we need to add plot names.  Get those Plot names by taking a column from any
# one of the years since we are assuming the Plot column is the exact same across
# years and IN THE SAME ORDER Moriah - this might be a problem bc I know at kbs
# some data wasn't taken for one of plots in later years due to a groundhog hole
# in the plot
plot_names <- comp_wide_by_year_kbs[[1]]$Plot
plot_names <- comp_wide_by_year_umbs[[1]]$Plot

# remove the plot and year columns from each item in the list so that Vegan will
# work.  This assumes row order is the exact same for all years (each row a plot)
comp_wide_by_year_kbs <- lapply(comp_wide_by_year_kbs, dplyr::select, c(-Year, -Plot))
comp_wide_by_year_umbs <- lapply(comp_wide_by_year_umbs, dplyr::select, c(-Year,
    -Plot))

# apply the diversity function to each year - in this case the main index is
# plot, each year considered separately
shannon_by_year_list_kbs <- lapply(comp_wide_by_year_kbs, vegan::diversity, index = "shannon")
shannon_by_year_list_umbs <- lapply(comp_wide_by_year_umbs, vegan::diversity, index = "shannon")

simpson_by_year_list_kbs <- lapply(comp_wide_by_year_kbs, vegan::diversity, index = "simpson")
simpson_by_year_list_umbs <- lapply(comp_wide_by_year_umbs, vegan::diversity, index = "simpson")

richness_by_year_list_kbs <- lapply(comp_wide_by_year_kbs, vegan::specnumber)  # species richness
richness_by_year_list_umbs <- lapply(comp_wide_by_year_umbs, vegan::specnumber)  # species richness

# each item in the list is a year of diversity, so name those with the years we
# know we have
names(shannon_by_year_list_kbs) <- as.character(2015:2021)
names(shannon_by_year_list_umbs) <- as.character(2015:2021)
names(simpson_by_year_list_kbs) <- as.character(2015:2021)
```

```r
names(simpson_by_year_list_umbs) <- as.character(2015:2021)
names(richness_by_year_list_kbs) <- as.character(2015:2021)
names(richness_by_year_list_umbs) <- as.character(2015:2021)

# 'unlist' and create a new data frame, each year a column, each row a plot, and
# add a new row with the plot names
shannon_kbs <- do.call(cbind, shannon_by_year_list_kbs) %>% cbind(Plot = plot_names) %>%
    as.data.frame()
shannon_umbs <- do.call(cbind, shannon_by_year_list_umbs) %>% cbind(Plot = plot_names) %>%
    as.data.frame()
simpson_kbs <- do.call(cbind, simpson_by_year_list_kbs) %>% cbind(Plot = plot_names) %>%
    as.data.frame()
simpson_umbs <- do.call(cbind, simpson_by_year_list_umbs) %>% cbind(Plot = plot_names) %>%
    as.data.frame()
richness_kbs <- do.call(cbind, richness_by_year_list_kbs) %>% cbind(Plot = plot_names) %>%
    as.data.frame()
richness_umbs <- do.call(cbind, richness_by_year_list_umbs) %>% cbind(Plot = plot_names) %>%
    as.data.frame()
# an alternative tidyverse way x<- diversity_by_year(diversity_by_year_list)

## optional step!
shannon_kbs
```

```
##                2015             2016              2017             2018
## 1  1.74982308774477 1.89484825550382  1.46457885369235 1.79022612402249
## 2  1.90662337874857 1.84725215309623  1.13716030470414 1.36198444330393
## 3  1.98749299359934 1.61377593556905  1.71072749310064 1.67233412309495
## 4  1.76205160229741 1.77517711389533  1.32874743973109 1.03860433128686
## 5  1.75210718809553 1.66227443462069  1.69192914802754 1.90695858866473
## 6   1.6900850428406 1.43660622202068  1.39873211536317  1.8571841570528
## 7  1.49086543230336 1.47097168973964  1.21337363817196 1.28050329701639
## 8  1.80821328729531  1.9254070243331  1.14986934861213  1.2616299180373
## 9   2.1087845075131 1.80236101080512  1.56273408513826 1.83756938558579
## 10 1.98196568606134 1.90616309802705  1.91936048574866 1.96655841609062
## 11 1.84296460180767  1.8965200697777  1.25355451781611 1.26874311894322
## 12 1.76762986966693 1.34098707770158  1.28659495811355 1.56199705257429
## 13 1.43883353670948 1.44641730798802  1.26464841035831 1.49328461093835
## 14 1.75673653952927  1.6273811911906  1.59862659873349 1.57746303850457
## 15 1.93644517652882  1.9750616592266  1.60757066797302 1.53493741382157
## 16 1.58409303017981 1.79057866130084  1.84017946573311 1.96848518019582
## 17 1.60506299754593 1.91996670439262  1.83507553957834 1.61808366536974
## 18  1.4247004760432 1.27334741927488 0.988243173382032 1.46588240243596
## 19 1.72885447960798 1.50003663417278   0.7586338108316 1.21791312632341
## 20 2.14484946283764 1.92315942970564  1.01772685103368 1.68252998651447
## 21 2.10055052731924 1.81252205715579  1.57077556615872 1.86767543214417
## 22 1.89362827233848 1.86514077199398  2.13631841372597 2.17843467691095
## 23 1.73593769273967 2.12071598624058   1.7062450650214  1.9415443800649
## 24 2.03965289235968 1.56767987740433  1.60740329659913 1.52284566334068
##                 2019             2020              2021 Plot
## 1   1.63141828218805  1.40619117164602 0.780282286358405   A1
## 2   1.03501044156779  1.30464181679929 0.761966098342232   A2
## 3   1.40564143802668  1.52023377614068  1.46818923776404   A3
## 4  0.807186457770002  1.10403362311013 0.522975735072191   A4
```

```
## 5   1.29530398546089  1.47867329613074  1.12613740316083   A5
## 6   1.56587400893309    1.776898556231  1.59272035502521   A6
## 7  0.966220584181466 0.903368616352641 0.787741797532107   B1
## 8     0.6001886754368  1.32028023954065 0.804089503088995   B2
## 9   1.55079429713458  1.75134927146181  1.50101684634471   B3
## 10   1.9076117928339  1.85066103391479  1.82018142958166   B4
## 11  1.07712923504737  1.51478024391315  1.63669387518496   B5
## 12  1.70747374757789  1.35162942534084  1.17907511874716   B6
## 13  1.46913677234012  1.55507473988238  1.50836959659867   C1
## 14  1.27508655116576  1.55732962234086 0.950411775293582   C2
## 15 0.883992796139038  1.72599963232697 0.996523451248442   C3
## 16  1.59775101771005  1.56782535025894  1.25369833009911   C4
## 17  1.72425066783732  1.70780555305176  1.47888650241859   C5
## 18  1.59762443325548  1.56141444142399  1.48024946913317   C6
## 19  1.25325132142148  1.78617517426128  1.13570812589948   D1
## 20  1.34286442427345  1.61533909948124  1.36264400396897   D2
## 21  1.94852371633076   1.7075032751265  1.86430302721765   D3
## 22  2.27772535378833  2.07864562723304   2.3134678596367   D4
## 23  1.98707494159271  2.36198520777061                 0   D5
## 24  1.02058088927649  1.28140861968835  1.14514426526423   D6
```

```
shannon_umbs
```

```
##                 2015              2016              2017              2018
## 1   1.79750600753516  1.09884956681657  1.65427009762925  1.72338781506085
## 2   1.03103412684858   1.0510661759467  1.01847657461102 0.926553867333551
## 3   1.23108760738823 0.832986567666689  1.05822294906718   1.1308760877669
## 4   1.11379164827808  1.09649945437462  1.58403466753454  1.26981056014349
## 5   1.41499122544575  1.54066354734953  1.75670820671366  1.83315130300093
## 6    1.3233120828513  1.11575480079886 0.921037312752463  1.22171569425616
## 7   1.08343195035589  1.03279159363802 0.876057255954377  1.24419243607285
## 8   1.09147272846172  1.24329181475844  1.29855975285605  1.23947894561033
## 9    0.9085145936062 0.959769287477707 0.649404154675513  0.83871658655578
## 10    1.318924658555 0.450107654438585   1.5725829367254  1.57921265075159
## 11  1.26789311388011 0.770745734585134  1.18646068972002 0.773638703559191
## 12  1.30080601995319  1.20839564977282   1.4044265373131  1.38328133173653
## 13  1.36610720736298 0.842368707930785  1.26913274303141  1.11918161689174
## 14  1.37712670393695  1.50441888100153  1.69244837402528  1.45297259997684
## 15  1.50594110744263   1.4028839310817  1.48760307705478  1.44909606234782
## 16  0.80322481868332  0.83389395416706  1.14271822258295  1.51638798771447
## 17 0.627025432024711 0.606005414459172  1.16938338399709  1.09757402522846
## 18 0.973444495419564  1.35315156462733   1.1423956505593  1.23956352450531
## 19  1.07986059255333 0.879465952690604  1.24184224778392  1.31578039164066
## 20  1.44773174456628  1.00905352578159   1.4126219798077  1.40929473472627
## 21  1.69964939346275  1.46688269951968  1.45944936854917  1.75936201800645
## 22 0.486356026733479 0.588197569441821  1.56011268630929  1.49990768246823
## 23  1.03086631184147  1.07092560439311 0.907225455933764  1.10551205477812
## 24  1.21191539524654   1.1042823781343  1.21986566532071  1.35947699709629
##                 2019              2020              2021 Plot
## 1    2.0145918118242  1.96581039743491  1.62531304044023   A1
## 2  0.691995913183193 0.974169862064642   1.2163860305222   A2
## 3    0.9724493832543  1.06768390565336 0.627765100792579   A3
## 4  0.915646292742865  1.33900551463997  1.50133902689179   A4
## 5   1.94764990159352  1.89835885910774  1.44706286625285   A5
```

```
## 6   1.45054061735534  1.37183773873638   0.9114708169835   A6
## 7   1.43250053727084  1.60608516148779  1.81536751087183   B1
## 8   1.11587149404342  1.18251733489018 0.699678505406374   B2
## 9  0.857420615656224 0.863774981807558 0.845161671782528   B3
## 10  1.50784697421321  1.49837008041475  1.26916283332234   B4
## 11 0.705571885627956 0.785670252458899 0.749093258816757   B5
## 12  1.51929284719405  1.26323616766899  1.48810325489543   B6
## 13  1.22897033192299  1.42548312428012  1.50648093715665   C1
## 14  1.55447238564657  1.84837077356116  1.53050384901037   C2
## 15  1.47245049389592  1.58772129323631  1.41124646634374   C3
## 16  1.66601534933355  1.58346400146614   1.6069039235169   C4
## 17  1.36933451043502  1.19760885543397  1.14167338748084   C5
## 18    1.430726166755   1.4500169349134  1.43036518013435   C6
## 19  1.47812095926711  1.58341388787888  1.48823193587079   D1
## 20   1.5069193093977  1.56477969632959   1.6541529758687   D2
## 21  1.86897728881615  1.68447529694085  1.35856632476605   D3
## 22  1.53228686591738  1.61076832230645  0.99499394631327   D4
## 23 0.830686156562969   1.0913363381619 0.773326936854788   D5
## 24  1.20925855258584  1.57780388206066  1.32789605853908   D6
```

```
simpson_kbs
```

```
##                 2015              2016              2017              2018
## 1  0.766870884639189 0.823600379009441 0.669970612122163 0.792803292663434
## 2  0.824841816486214 0.805940862097132 0.499709133216987 0.623691553362043
## 3  0.828686254197066 0.728993484800695 0.778484724344667 0.761018567091786
## 4  0.738148795359905 0.779195685408527 0.674027859607777  0.46483341170387
## 5  0.756661662600863 0.759331717451524 0.794191531560507 0.826255563486254
## 6  0.762720651578041 0.686170490068043 0.682640602567073 0.820699003229588
## 7  0.700361681990265 0.695895867286818   0.6406304410362 0.620339189530199
## 8  0.783443210041582 0.796952728466453 0.568738391710711 0.629793171081865
## 9   0.85202580353101   0.7665662215285 0.686447730344905 0.802143581590417
## 10 0.833373281416579 0.804789855757118 0.818183051613997  0.83324261597826
## 11 0.770869288297173 0.806677816489445 0.639179017826651 0.687020408163265
## 12  0.76450490270792 0.646818638172756 0.678240740740741 0.696795149086659
## 13 0.709838359617137 0.725891639283279 0.667428159728074  0.75230700794084
## 14 0.785929607299984  0.72292899628807 0.743432883409502 0.744780076527052
## 15 0.823420345032719 0.832436597166027 0.763797078484721 0.726274509803922
## 16 0.654529777602729 0.777007401273226  0.79995353553853         0.8309375
## 17 0.625523415977961 0.792765655930173  0.76581878159848 0.746319144011822
## 18 0.704299809801377 0.639714299847363   0.5372249851279 0.675099625649076
## 19 0.777657431991318 0.707756409626478 0.511572448948445 0.621866861979167
## 20 0.864562605087386 0.795995629187316  0.55935445591551 0.743354570701767
## 21 0.860059507037529 0.781193869031822  0.70627921429947 0.795813589494414
## 22 0.784345196867175 0.777684767323901 0.844995601120368 0.845727421846003
## 23 0.752489062828992 0.836073675909881 0.738066374249671 0.813970728556539
## 24 0.805724317549936  0.68369595303304 0.736577662934252 0.671294957669714
##                 2019              2020              2021 Plot
## 1  0.744030963344864 0.681173628374357  0.31691061817816   A1
## 2  0.579995934976211 0.638810546280009 0.334507745761638   A2
## 3  0.584676661510214 0.669108061578879 0.618510810498323   A3
## 4  0.430735774702038 0.568853518348468 0.233219176149988   A4
## 5  0.658874440657044 0.712547258979206  0.54804761734017   A5
## 6  0.689000632886357 0.733239660599723 0.683305590306138   A6
```

```
## 7  0.559629533293698 0.542724815344088 0.454256354786371   B1
## 8  0.350685964365913 0.659569777777778 0.368562317051501   B2
## 9  0.697750611122558 0.779782631634483 0.648804958875388   B3
## 10 0.791674030547972 0.778692272519433 0.738644416099773   B4
## 11  0.51649312786339 0.675432006010518 0.717925112299805   B5
## 12 0.752039809440949 0.609829650868612 0.596963532986962   B6
## 13 0.673337608772195 0.697247947339858  0.73166150089227   C1
## 14 0.558333333333333 0.653639621387881 0.386258854201612   C2
## 15 0.379454448181556 0.784021274135738 0.413610537190083   C3
## 16 0.759107437439011 0.738078211449434 0.561981986029065   C4
## 17 0.712175547020406 0.724004532045851 0.647082589372988   C5
## 18 0.723685531726264 0.721988669210313 0.660308276718533   C6
## 19 0.611126332886096 0.767500619744093 0.582100639914504   D1
## 20 0.668075618532739 0.771916351606805         0.6670875   D2
## 21 0.799494908515558 0.719122023809524 0.748326798269335   D3
## 22 0.863004568664338 0.799644444444444 0.881920545290521   D4
## 23 0.820386553117797 0.894844444444444                 1   D5
## 24 0.555720538426452 0.604785855814662 0.582358370257467   D6
```

```
simpson_umbs
```

```
##                 2015              2016              2017              2018
## 1  0.803651350361947 0.518021818303318 0.749935581164312 0.780447431836471
## 2  0.513942578344905 0.594922099568322 0.580847119481778 0.537914590135762
## 3  0.651998878384874  0.51969353367307  0.62361000601603 0.621049060722415
## 4   0.53019571799308  0.63263595198428 0.719124757425875 0.679248576505622
## 5  0.659831688666752  0.71961166106126 0.791945676510559 0.821094182825485
## 6  0.663258597324531 0.581490697217445 0.486816473295548 0.583825155889476
## 7   0.47808837890625 0.540416233090531 0.485752310135581  0.60350368416452
## 8    0.5367431640625 0.653791866455371   0.6791560831622 0.659640549783434
## 9  0.466735537190083 0.576399929724254 0.358035710426563 0.516646244974109
## 10 0.660046583404422 0.194447875269723 0.761378886774374 0.759230049530712
## 11 0.697904395808792 0.404969866363875 0.676421684447795 0.506466832900534
## 12 0.672677749600826 0.611635512439156 0.720802667809737 0.716561919252198
## 13 0.696418405485013  0.52483366989053 0.685950768658756 0.627113362673129
## 14 0.683547569900544 0.742917694154277 0.792074834149668 0.671508647897993
## 15  0.72683843683922 0.704035286924622 0.755341077401123 0.704908843922949
## 16 0.439797318104196 0.529037132235587 0.614395337667324 0.728138720934779
## 17 0.318956193467943 0.335954629785799 0.599502233973408 0.614952310152146
## 18 0.524518430439952 0.685626839507872 0.577156968879958 0.672445928291479
## 19  0.61126708984375 0.535793386254989 0.650513981027962 0.667439154604523
## 20 0.744692653805176 0.583673713906044 0.708623992756904 0.706475637664839
## 21  0.77237426035503 0.714387657496839 0.701189913977081 0.777224837599696
## 22 0.296168672392339  0.35450464238343 0.777778445254093 0.753174057442528
## 23 0.505866666666667 0.500274526372213 0.518274834675336 0.654759722222222
## 24 0.640570749108204 0.599740090968161 0.626607455129365 0.737825595208942
##                 2019              2020              2021 Plot
## 1  0.827049377504845 0.819794112943276 0.754245304265574   A1
## 2  0.320281363818386 0.488362236109984 0.660249568204312   A2
## 3   0.52420395421436 0.560729395728045 0.305003664982061   A3
## 4  0.435078053259871 0.679325791124446 0.735691499343216   A4
## 5  0.832386773323435 0.816534755928695 0.711820118343195   A5
## 6    0.7242749862058 0.634818165594618 0.520850283833198   A6
## 7  0.646093108568434 0.752279165728469 0.807908483766449   B1
```

```
## 8  0.595468089196463 0.634898031836444 0.376185752371505   B2
## 9  0.480244562843916 0.429955418381344 0.454936762674035   B3
## 10  0.76584692800909 0.760568595041322 0.670657439446367   B4
## 11 0.500926841324765 0.515960230245945 0.426011342155009   B5
## 12 0.725153173029621 0.636572781065089 0.704939575871576   B6
## 13 0.655944552047205  0.72670137568765  0.70431447152118   C1
## 14 0.681283053391007 0.809777692497464            0.7268   C2
## 15  0.67519048258181  0.70870126977055 0.708750862103939   C3
## 16 0.759131936187591 0.740066115702479 0.783164752961049   C4
## 17 0.711271684135555 0.652132184124355 0.641611570247934   C5
## 18 0.727484540151748 0.726502082093992 0.724931188606348   C6
## 19 0.669370235153776 0.724783740656757 0.713416327870508   D1
## 20  0.70734693877551 0.749155422698143 0.770053025839576   D2
## 21 0.799890430971512 0.794255690761811 0.664751887286771   D3
## 22 0.767165814463112 0.773412228796844  0.49960664537924   D4
## 23 0.457231212946643     0.58333984375 0.412229403919155   D5
## 24 0.624235194977063 0.752106880824906 0.693237346417583   D6
```

```
richness_kbs
```

```
##    2015 2016 2017 2018 2019 2020 2021 Plot
## 1    12   14    9   11    9    8    9   A1
## 2    12   13   10   10    6    8    6   A2
## 3    13   13    9   10   11    9   12   A3
## 4    15   12    6    8    5    7    6   A4
## 5    13   10    8   11    8    8    8   A5
## 6    10   11    9   12   12   12   12   A6
## 7    12   10    6    9    6    6    6   B1
## 8    13   15    7    5    5    7    8   B2
## 9    13   15    9   14   13   12   12   B3
## 10   14   13   12   12   15   14   13   B4
## 11   13   13   10    6    9    9   11   B5
## 12   13   11    7   10   13    9    9   B6
## 13   10   10    8    6   11   13    8   C1
## 14   11   13    9   10   12   12   12   C2
## 15   13   13    8   13   11    8   10   C3
## 16   14   14   13   15   10    9    9   C4
## 17   17   16   14   13   13   12   12   C5
## 18   12   10    9   11   11   11   13   C6
## 19   11   14    4    9   10   13   11   D1
## 20   13   15    8   10    8    7    8   D2
## 21   11   15   10   13   15   13   15   D3
## 22   15   16   14   16   15   15   14   D4
## 23   13   16   13   13   14   13    0   D5
## 24   14   12    9    9    6    7    6   D6
```

```
richness_umbs
```

```
##    2015 2016 2017 2018 2019 2020 2021 Plot
## 1     9    9    9    9   13   12    9   A1
## 2     5    6    6    4    6    5    4   A2
## 3     5    5    5    6    4    6    4   A3
## 4     6    4   10    5    7    5    6   A4
```

```
## 5     8    9    9    8    9    9    8   A5
## 6     6    6    5    6    7    8    5   A6
## 7    10    9    7    7    7    7    8   B1
## 8     6    6    5    5    5    5    5   B2
## 9     5    4    4    5    5    6    4   B3
## 10    6    5    8    6    5    6    6   B4
## 11    4    4    4    5    3    3    4   B5
## 12    6    5    6    6    7    7    7   B6
## 13    5    6    6    5    5    7    7   C1
## 14    7    7    7    8    8    9    7   C2
## 15    6    8    6    8    7   10    5   C3
## 16    5    5    6    7    7    7    6   C4
## 17    4    4    5    5    5    5    4   C5
## 18    4    5    5    5    5    5    5   C6
## 19    5    5    7    7    8    8    6   D1
## 20    5    5    6    7    8    7    7   D2
## 21    8    8    8   10   11    7    6   D3
## 22    3    4    6    6    6    7    5   D4
## 23    5    7    4    4    4    6    4   D5
## 24    6    6    5    4    5    7    5   D6
```

```r
# this output has a column for each year 2015, 2016, and Plot, but if you need it
# narrow use 'melt' from reshape2:
library(reshape2)
```

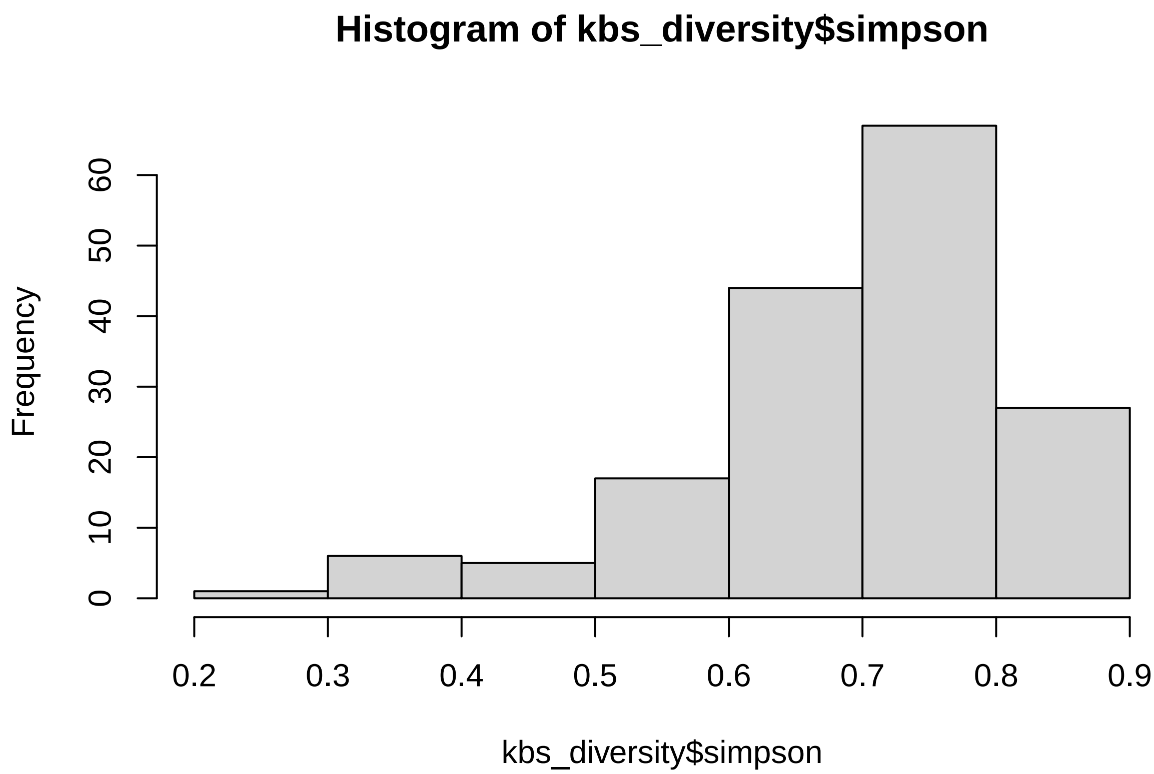
```
##
## Attaching package: 'reshape2'

## The following object is masked from 'package:tidyr':
##
##     smiths
```

```r
# calculate shannon diversity
shannon_by_plot_year_kbs <- reshape2::melt(shannon_kbs, id = "Plot", variable.name = c("Year"),
    value.name = "shannon")
shannon_by_plot_year_kbs$site <- "kbs"  # adding site column
shannon_by_plot_year_umbs <- reshape2::melt(shannon_umbs, id = "Plot", variable.name = c("Year"),
    value.name = "shannon")
shannon_by_plot_year_umbs$site <- "umbs"  # adding site column

# calculate simpson diversity
simpson_by_plot_year_kbs <- reshape2::melt(simpson_kbs, id = "Plot", variable.name = c("Year"),
    value.name = "simpson")
simpson_by_plot_year_kbs$site <- "kbs"  # adding site column
simpson_by_plot_year_umbs <- reshape2::melt(simpson_umbs, id = "Plot", variable.name = c("Year"),
    value.name = "simpson")
simpson_by_plot_year_umbs$site <- "umbs"  # adding site column

# calculate species richness
richness_by_plot_year_kbs <- reshape2::melt(richness_kbs, id = "Plot", variable.name = c("Year"),
    value.name = "richness")
richness_by_plot_year_kbs$site <- "kbs"  # adding site column
richness_by_plot_year_umbs <- reshape2::melt(richness_umbs, id = "Plot", variable.name = c("Year"),
```

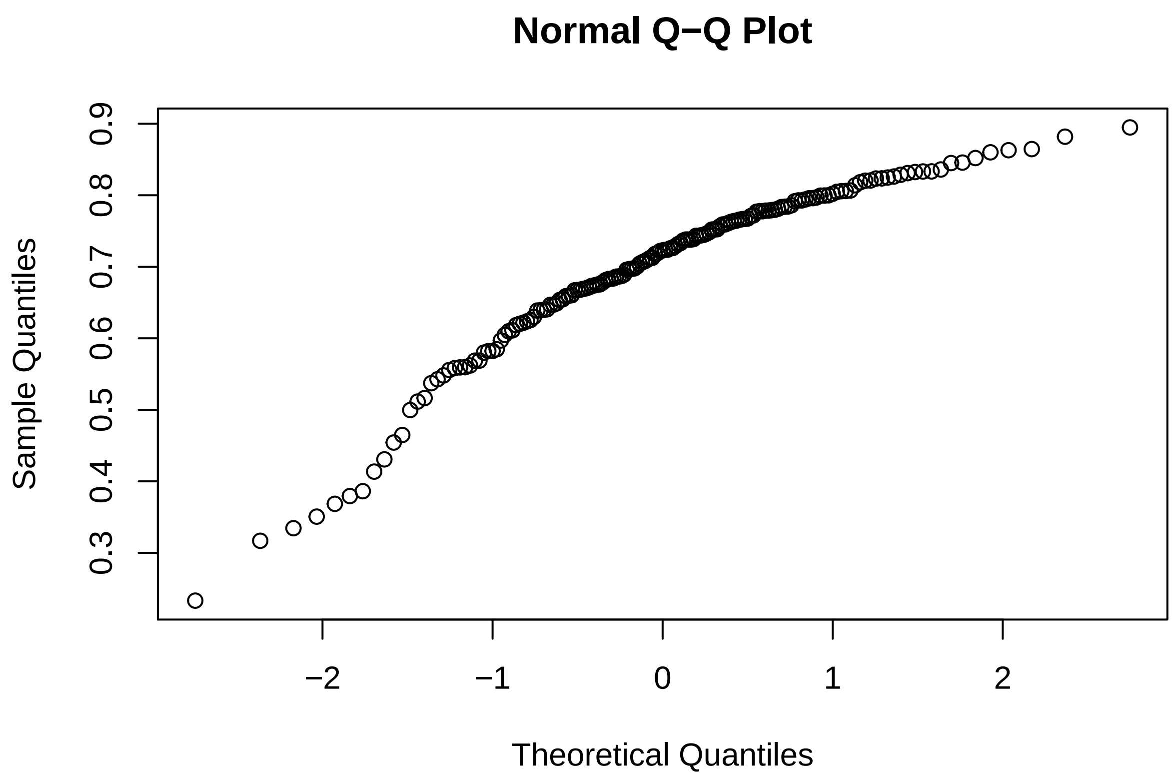
```r
    value.name = "richness")
richness_by_plot_year_umbs$site <- "umbs"  # adding site column

# combine umbs and kbs shannon diversity measures into 1 dataframe
shannon_diversity <- full_join(shannon_by_plot_year_kbs, shannon_by_plot_year_umbs,
    by = c("Plot", "Year", "shannon", "site"))

# combine umbs and kbs simpson diversity measures into 1 dataframe
simpson_diversity <- full_join(simpson_by_plot_year_kbs, simpson_by_plot_year_umbs,
    by = c("Plot", "Year", "simpson", "site"))

# combine umbs and kbs richness measures into 1 dataframe
richness <- full_join(richness_by_plot_year_kbs, richness_by_plot_year_umbs, by = c("Plot",
    "Year", "richness", "site"))

# combine simpson and shannon diversity data frames into 1
comp_diversity <- full_join(simpson_diversity, shannon_diversity, by = c("Plot",
    "Year", "site"))
# Looks like diversity and simpson diveristy measures are the same?? Need to look
# into this
comp_diversity <- full_join(comp_diversity, richness, by = c("Plot", "Year", "site"))

names(comp_diversity) <- tolower(names(comp_diversity))  # column names to lower case so I can combine

# merge meta data with comp_diversity
comp_diversity <- full_join(comp_diversity, meta, by = "plot")

comp_diversity$simpson <- as.numeric(comp_diversity$simpson)
comp_diversity$shannon <- as.numeric(comp_diversity$shannon)
comp_diversity$richness <- as.numeric(comp_diversity$richness)

# adding sequential year variable starting at 1: this is because the years (e.g.
# 2015, 2016, etc) are large numbers compared with other values in the dataset.
# We can always label axes with these real years.
comp_diversity$year_factor[comp_diversity$year == 2015] <- 1
comp_diversity$year_factor[comp_diversity$year == 2016] <- 2
comp_diversity$year_factor[comp_diversity$year == 2017] <- 3
comp_diversity$year_factor[comp_diversity$year == 2018] <- 4
comp_diversity$year_factor[comp_diversity$year == 2019] <- 5
comp_diversity$year_factor[comp_diversity$year == 2020] <- 6
comp_diversity$year_factor[comp_diversity$year == 2021] <- 7

comp_diversity <- comp_diversity[, c("site", "plot", "year", "year_factor", "treatment_key",
    "state", "insecticide", "simpson", "shannon", "richness")]  #reorder columns

# write a new csv with diversity indices and upload to the shared google drive L2
# data folder
write.csv(comp_diversity, file.path(L2_dir, "plant_composition/final_plant_comp_diversity_L2.csv"))

# create separate data frames for kbs and umbs sites
kbs_diversity <- subset(comp_diversity, site == "kbs")
kbs_diversity <- kbs_diversity[-167, ]  # remove this row with zero values for shannon diversity and sp
umbs_diversity <- subset(comp_diversity, site == "umbs")
```

Simpson's Index KBS

```r
### KBS ###
hist(kbs_diversity$simpson)  # skewed to the left
```



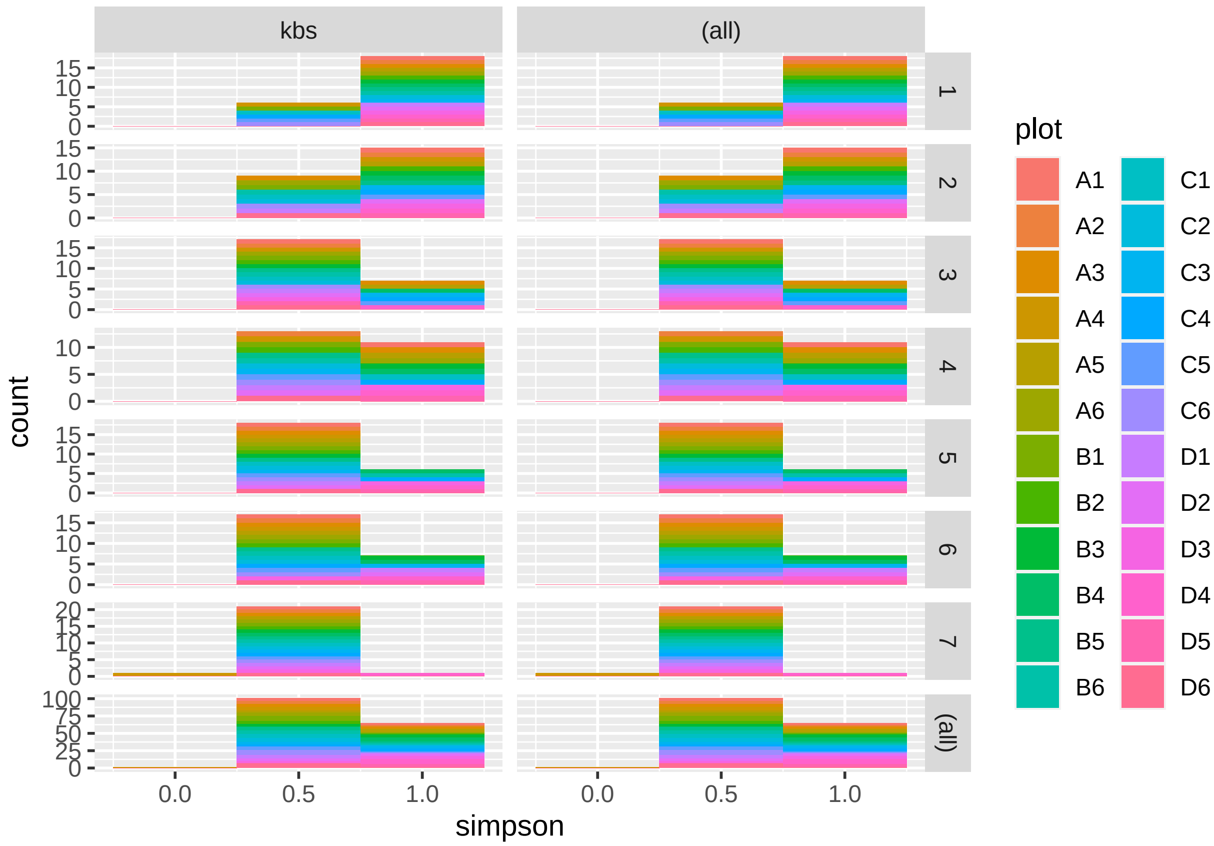

```r
qqnorm(kbs_diversity$simpson)
```



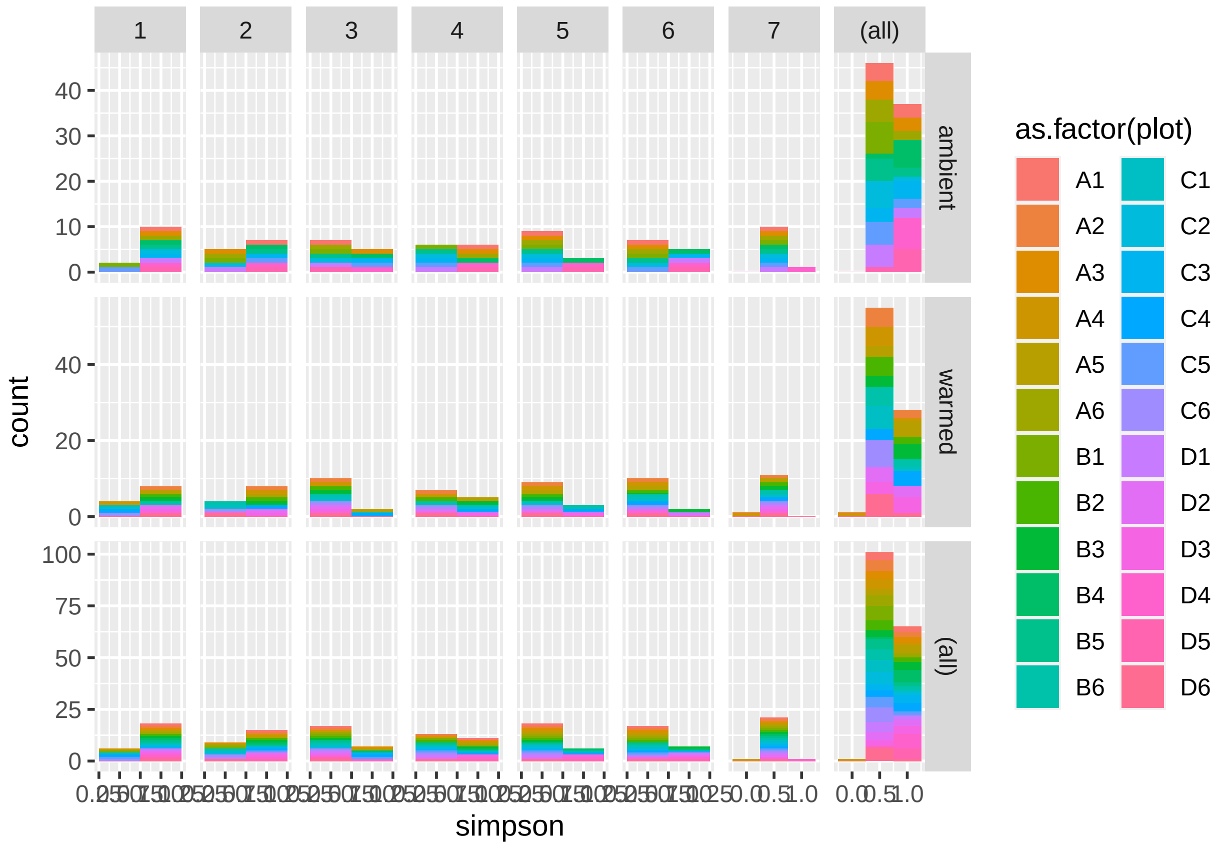

```r
shapiro.test(kbs_diversity$simpson)  # pvalue is < 0.05 so we reject the null hypothesis that the data
```

```
##
##  Shapiro-Wilk normality test
##
## data:  kbs_diversity$simpson
## W = 0.91068, p-value = 1.448e-08
```

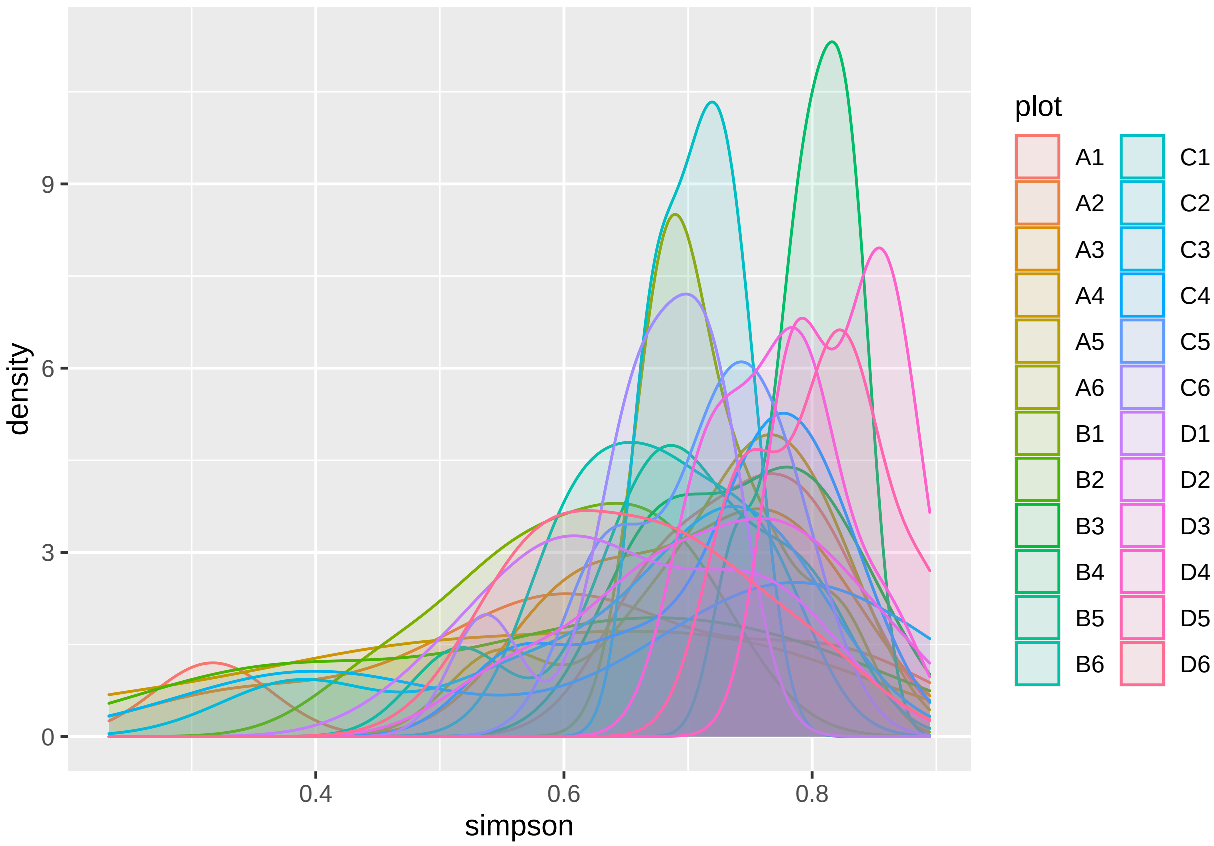
```r
# Visualizing plot average totals for kbs at the PLOT LEVEL
ggplot(kbs_diversity, aes(simpson, fill = plot)) + geom_histogram(binwidth = 0.5) +
    facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



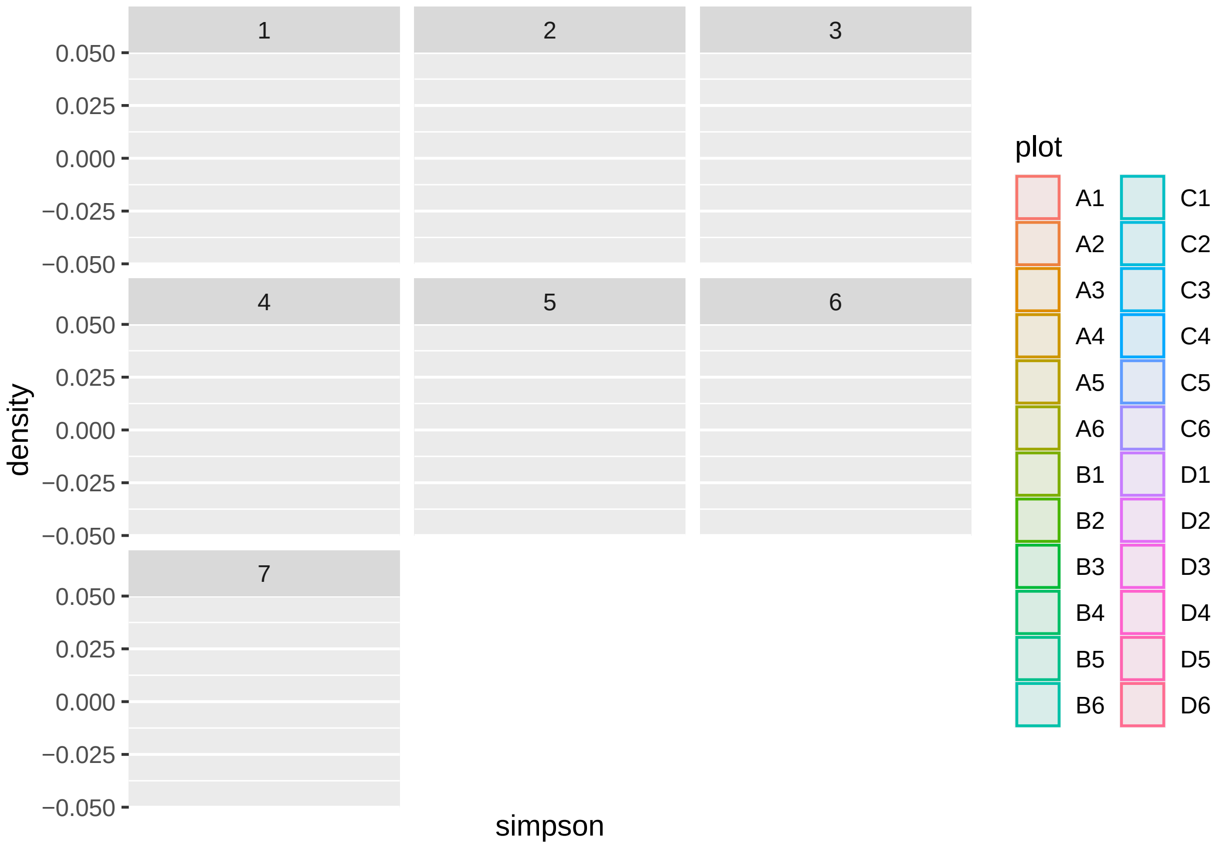

```r
ggplot(kbs_diversity, aes(simpson, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
    facet_grid(state ~ year_factor, margins = TRUE, scales = "free")
```



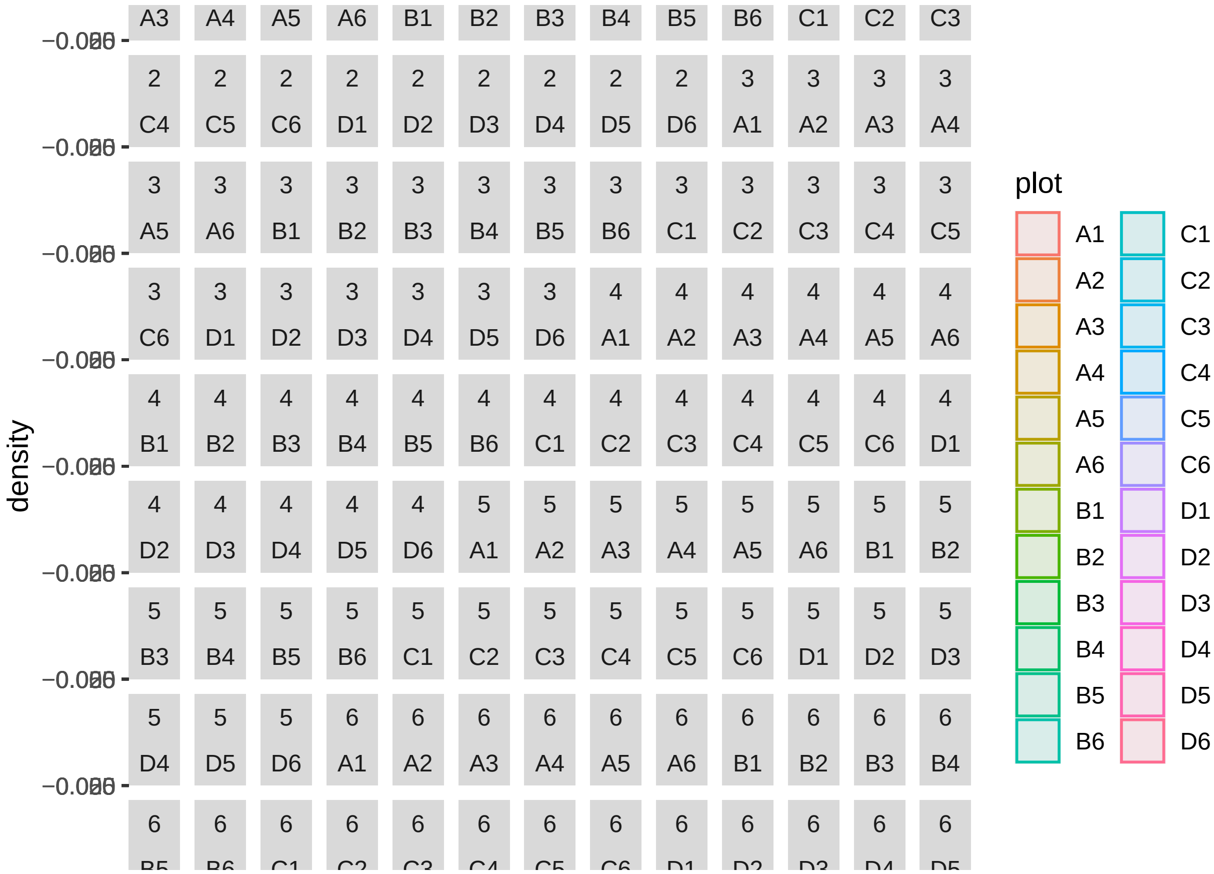

```
ggplot(kbs_diversity, aes(simpson, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



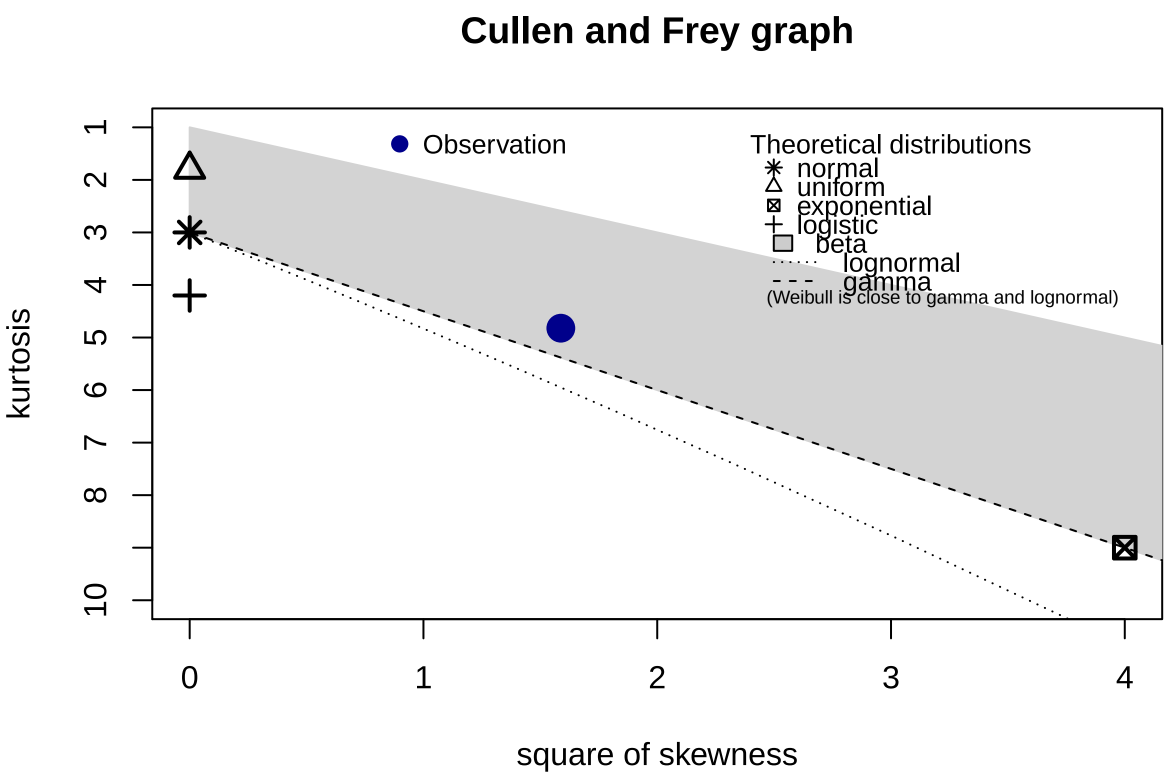

```
ggplot(kbs_diversity, aes(simpson, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
    facet_wrap(~year_factor)
```




```r
ggplot(kbs_diversity, aes(simpson, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
    facet_wrap(~year_factor + plot)
```

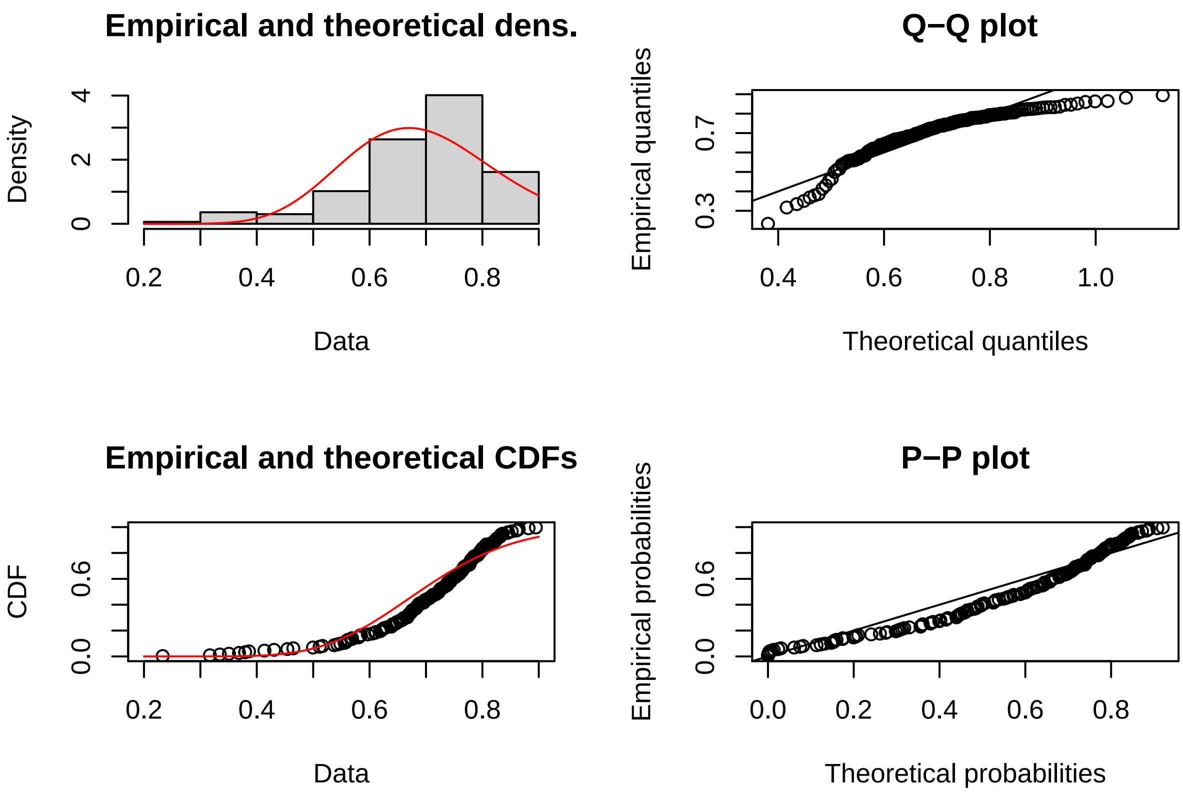



```r
# Exploring distributions for these right-skewed data:
descdist(kbs_diversity$simpson, discrete = FALSE)
```

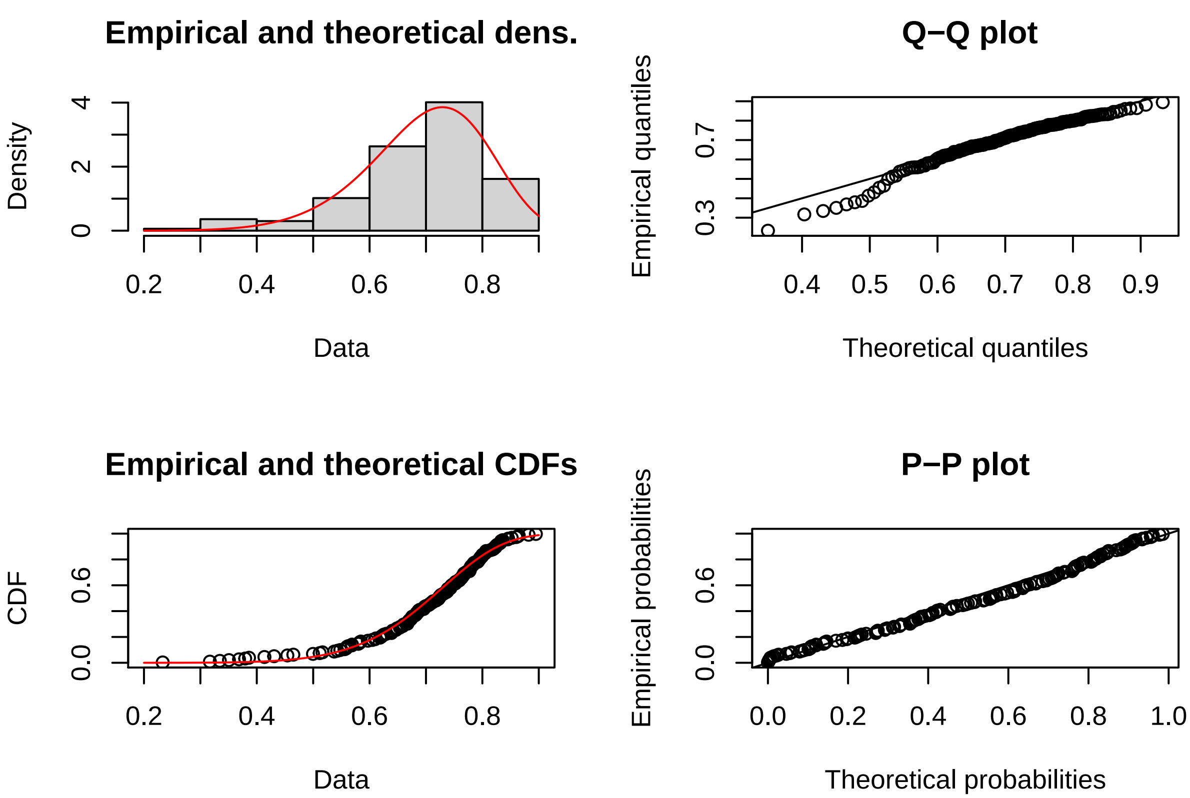



```
## summary statistics
## ------
## min:  0.2332192   max:  0.8948444
## median:  0.722929
## mean:  0.6961958
## estimated sd:  0.1212307
## estimated skewness:  -1.259996
## estimated kurtosis:  4.822646
```

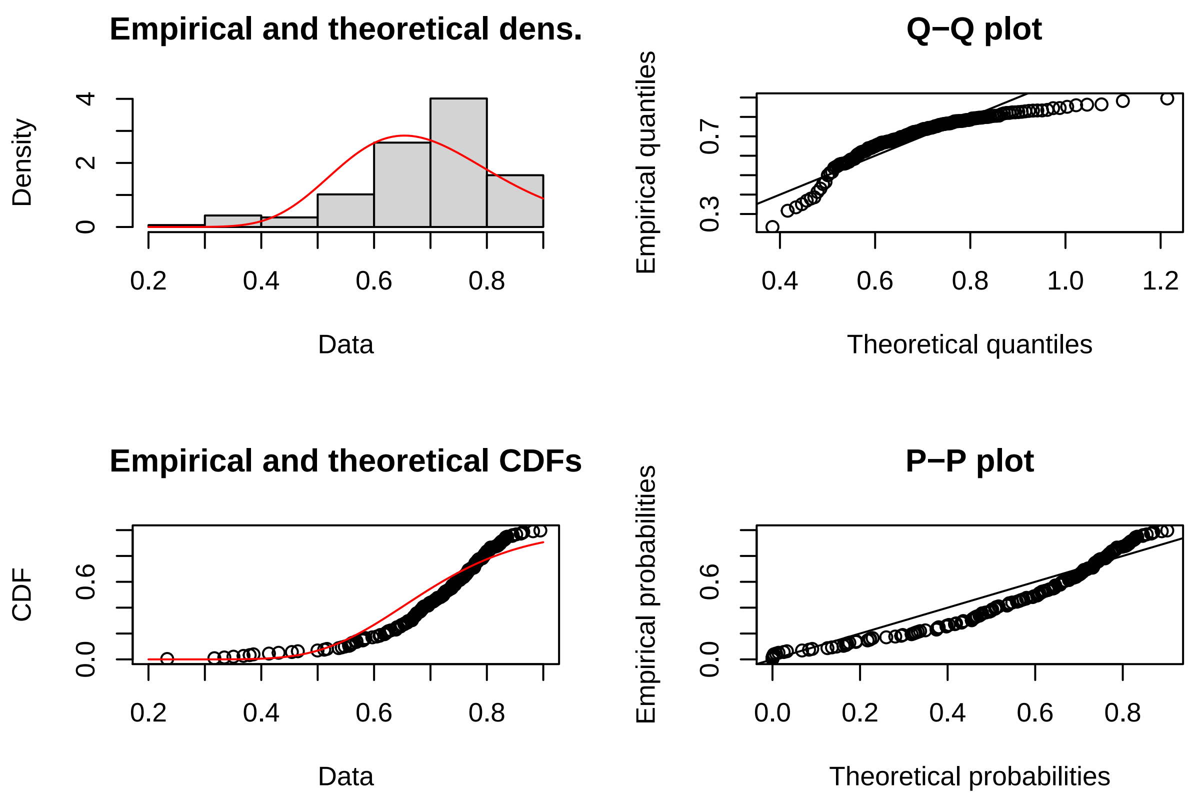
```
# Gamma distribution
fit.gamma <- fitdist(kbs_diversity$simpson, "gamma")
plot(fit.gamma)
```



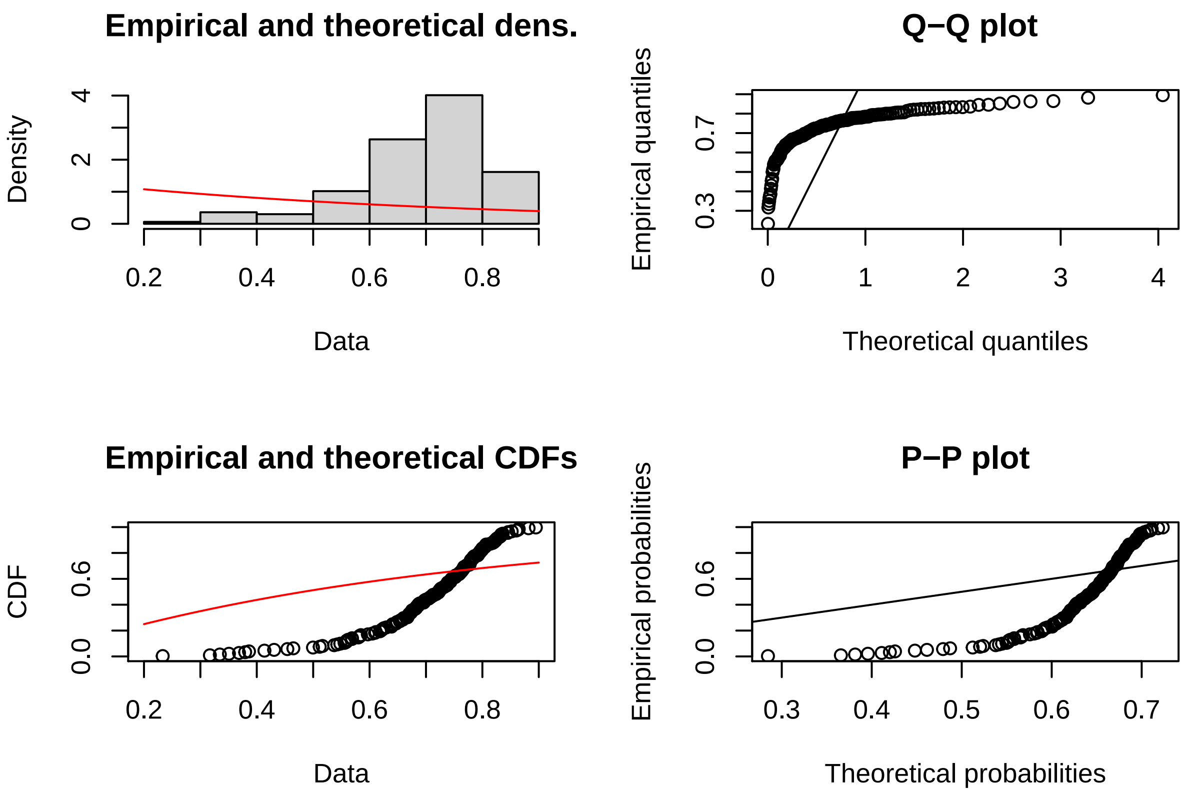

```r
# Weibull distribution
fit.weibull <- fitdist(kbs_diversity$simpson, "weibull")
plot(fit.weibull)
```



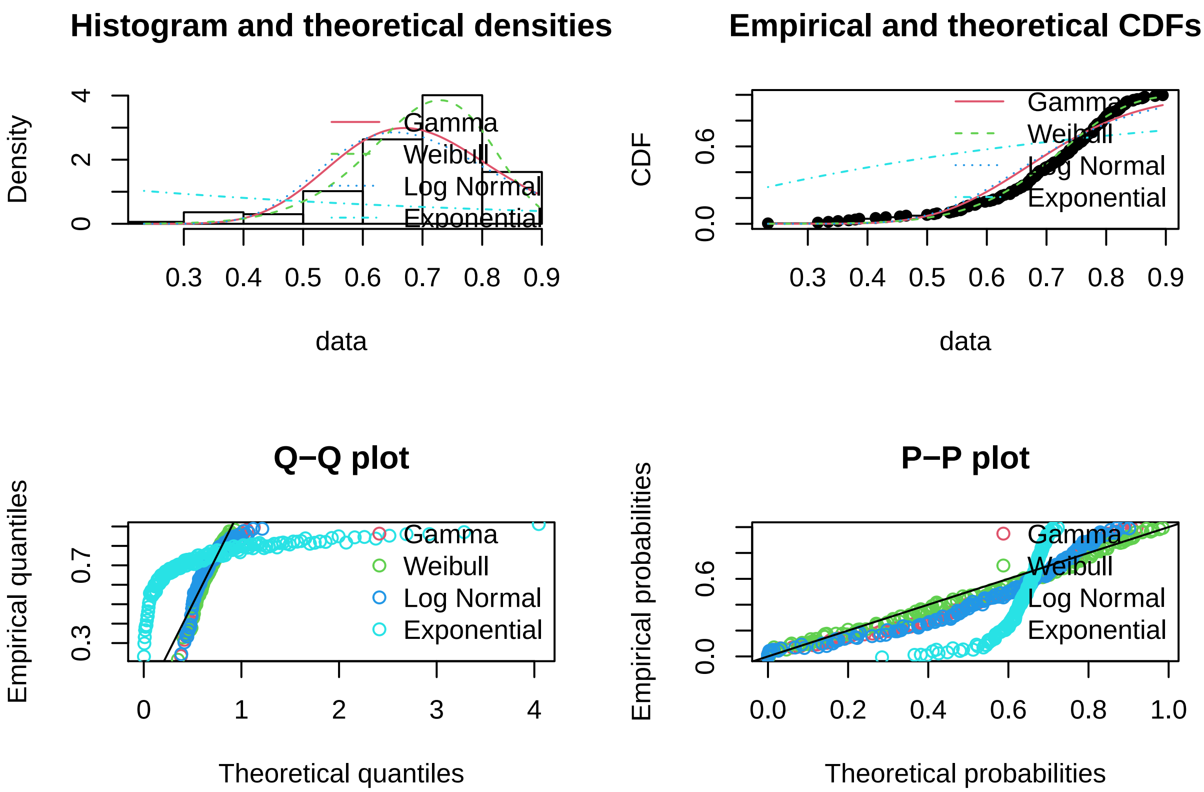
```r
# Lognormal distribution
fit.ln <- fitdist(kbs_diversity$simpson, "lnorm")
plot(fit.ln)
```




```r
# Exponential distribution is another option
fit.exp <- fitdist(kbs_diversity$simpson, "exp")
plot(fit.exp)
```




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



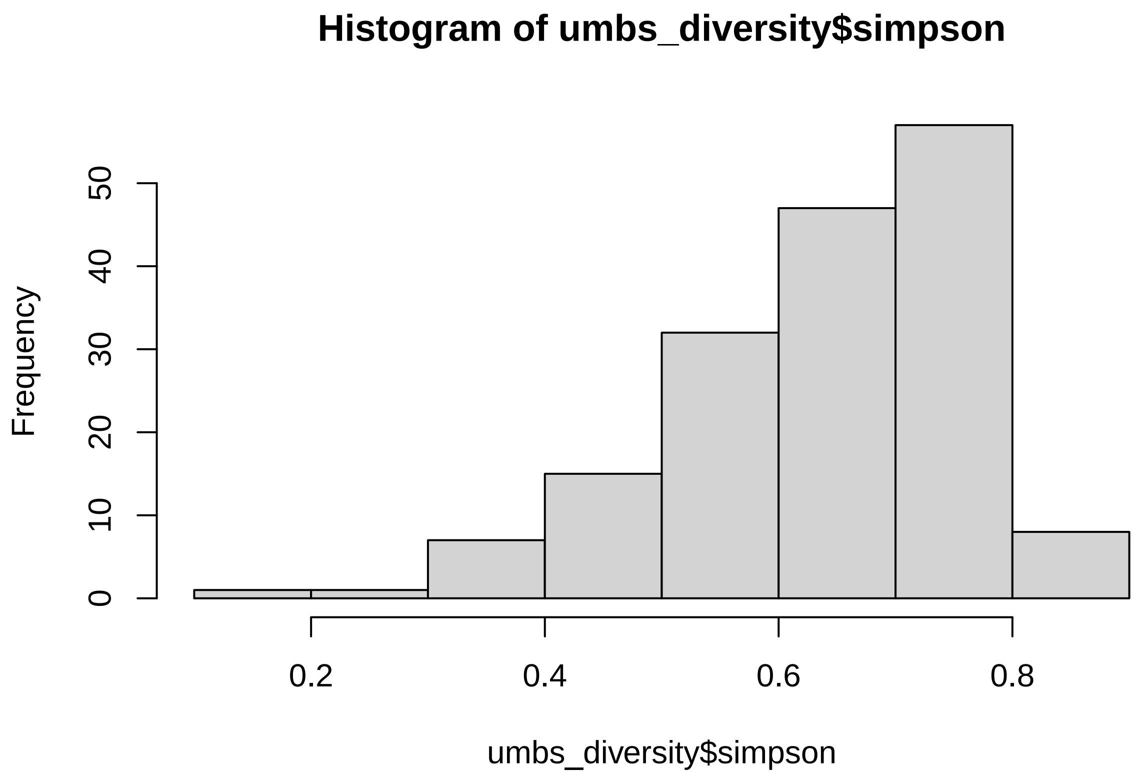

```r
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull",
    "Log Normal", "Exp"))
```

```
## Goodness-of-fit statistics
##                                  Gamma    Weibull Log Normal        Exp
## Kolmogorov-Smirnov statistic 0.1400265 0.06478399  0.1556896  0.4539216
## Cramer-von Mises statistic   1.0447969 0.18630187  1.3326522 11.3505327
## Anderson-Darling statistic   6.4420313 1.44401297  8.0592683 53.5448274
##
## Goodness-of-fit criteria
##                                   Gamma   Weibull Log Normal      Exp
## Akaike's Information Criterion -193.5478 -256.8517  -171.8578 215.0505
## Bayesian Information Criterion -187.3118 -250.6157  -165.6219 218.1685
```

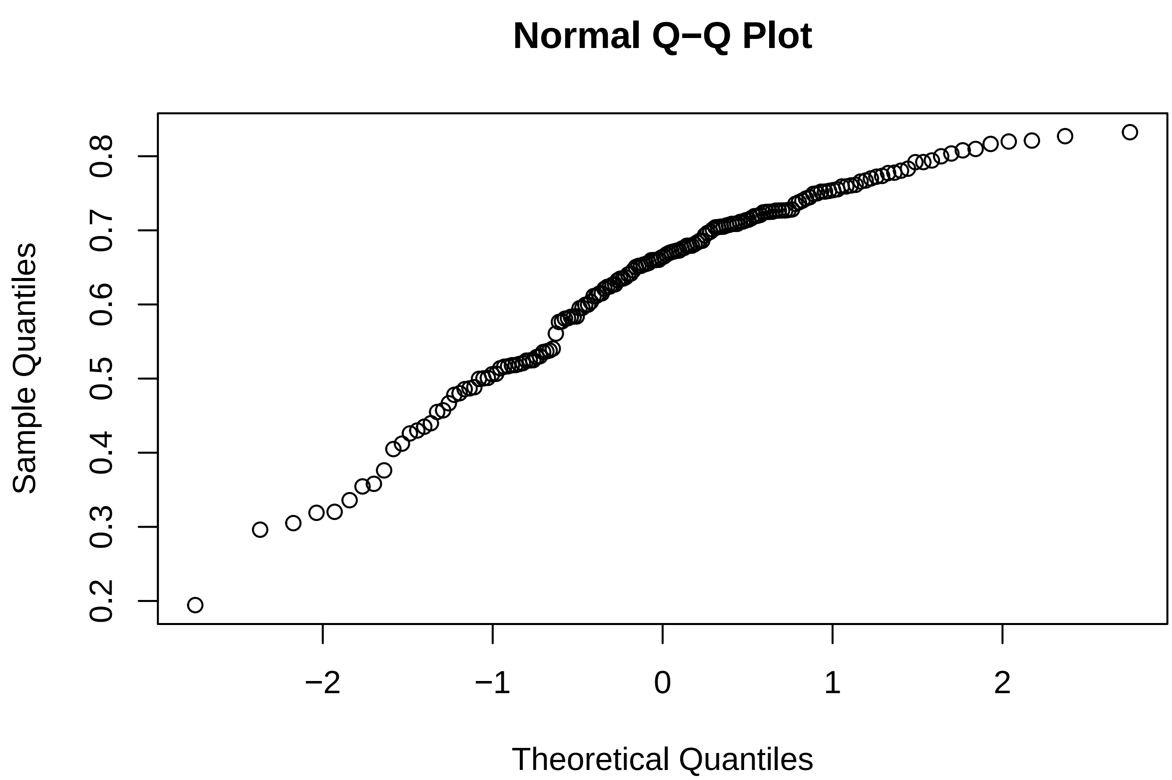
```r
# log normal distribution looks to be the best based on AIC and BIC values
```

UMBS

```r
### UMBS ###
hist(umbs_diversity$simpson)  # skewed to the left
```



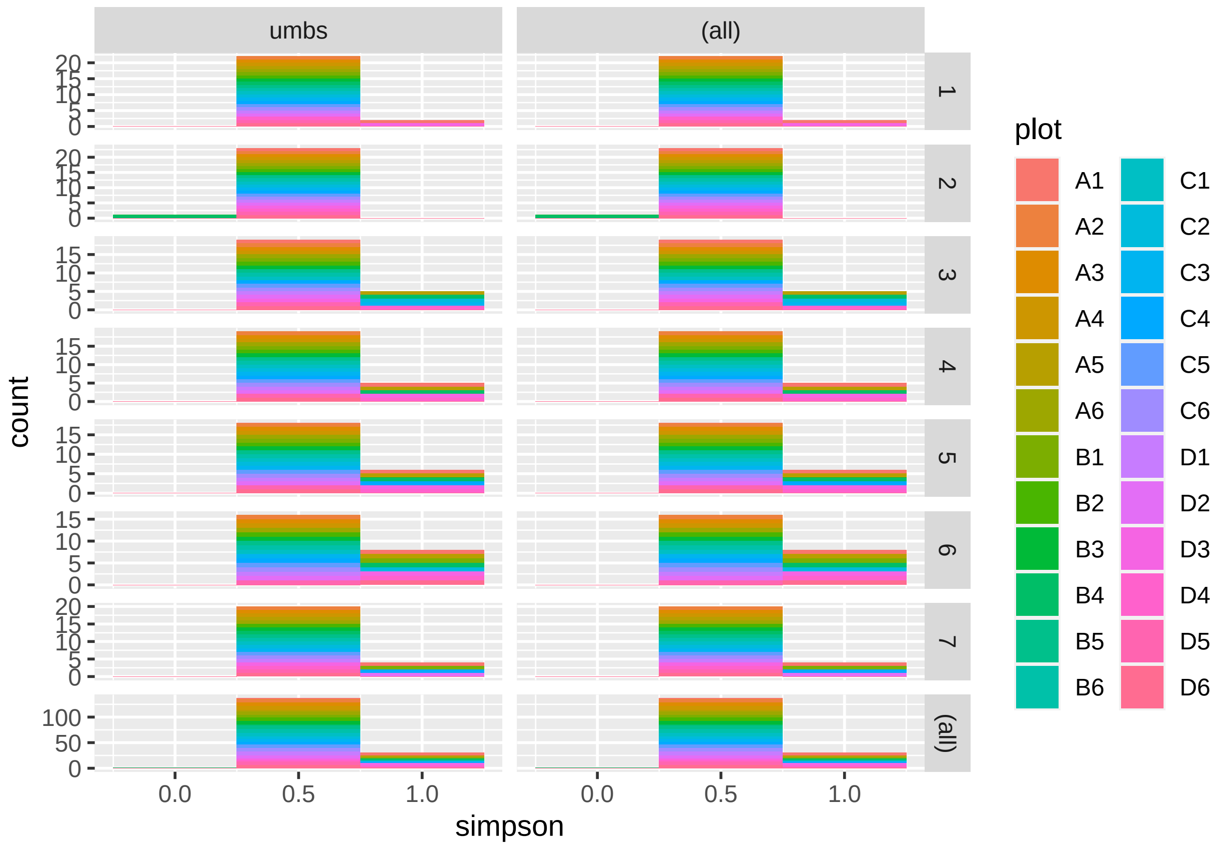

```r
qqnorm(umbs_diversity$simpson)
```



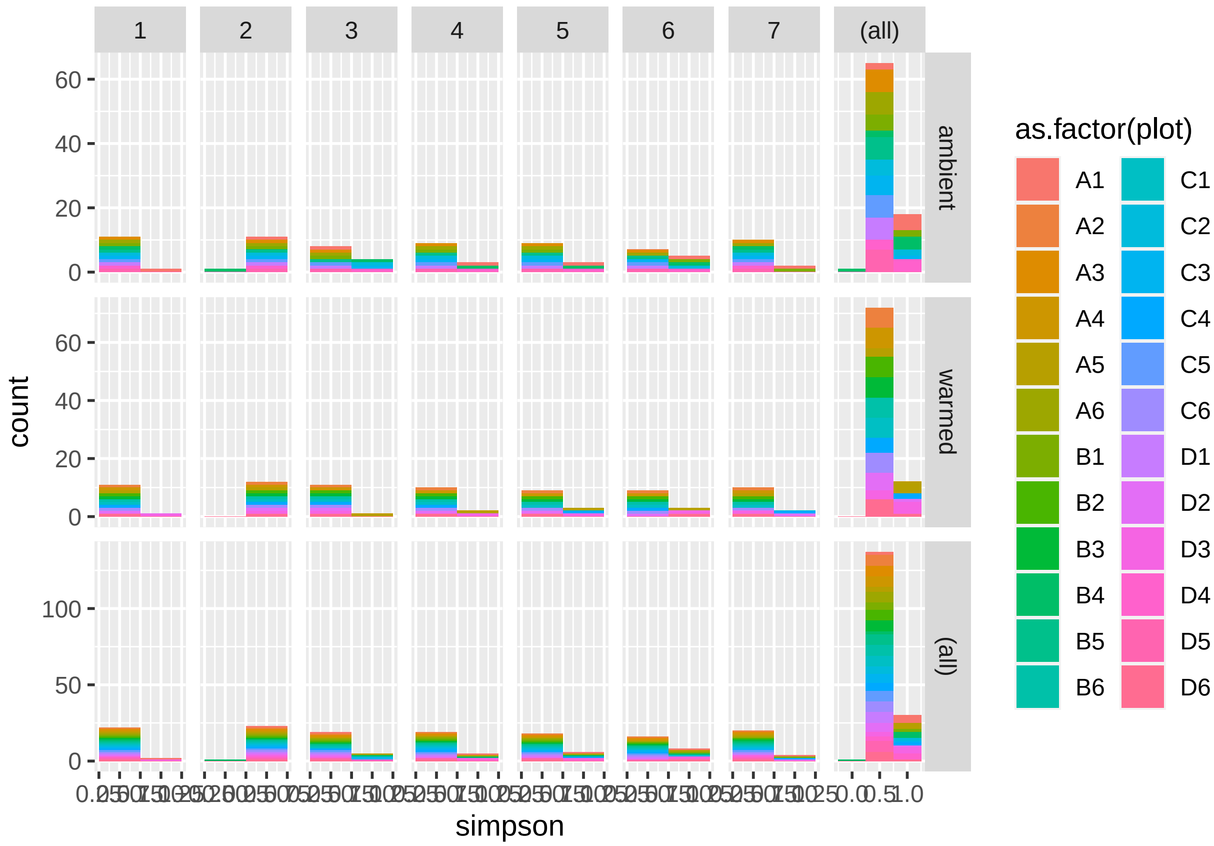
```r
shapiro.test(umbs_diversity$simpson)  # pvalue is < 0.05 so we reject the null hypothesis that the data
```

```
##
##  Shapiro-Wilk normality test
##
## data:  umbs_diversity$simpson
## W = 0.93887, p-value = 1.325e-06
```

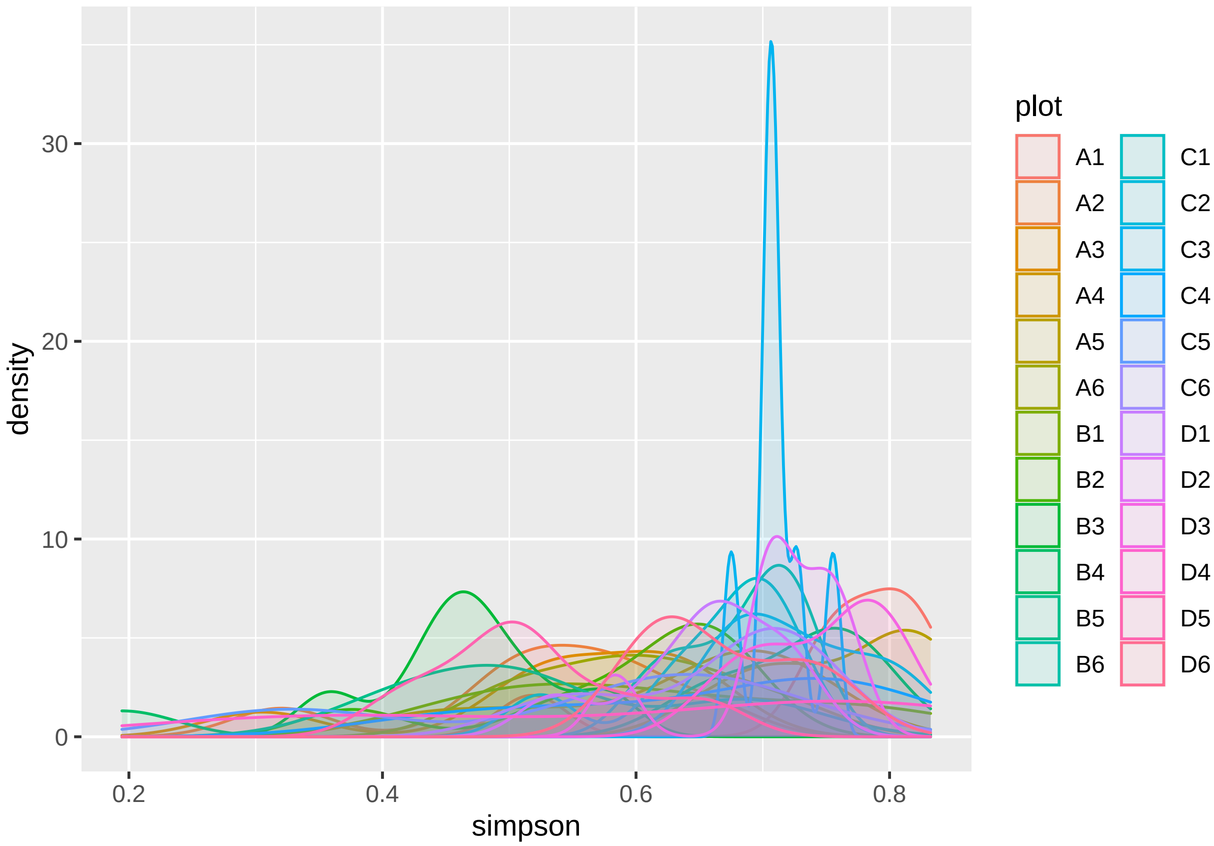
```r
# Visualizing plot average totals for umbs at the PLOT LEVEL
ggplot(umbs_diversity, aes(simpson, fill = plot)) + geom_histogram(binwidth = 0.5) +
    facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



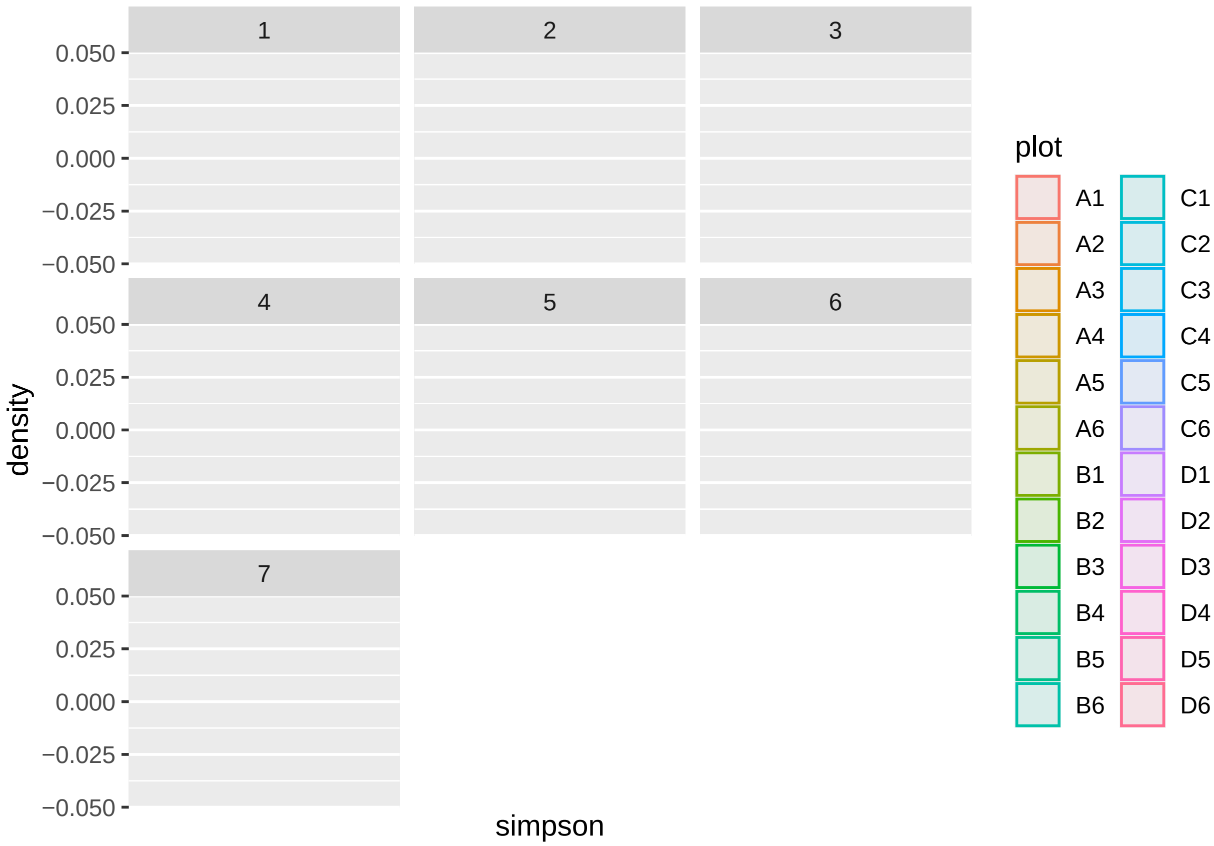

```r
ggplot(umbs_diversity, aes(simpson, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
    facet_grid(state ~ year_factor, margins = TRUE, scales = "free")
```



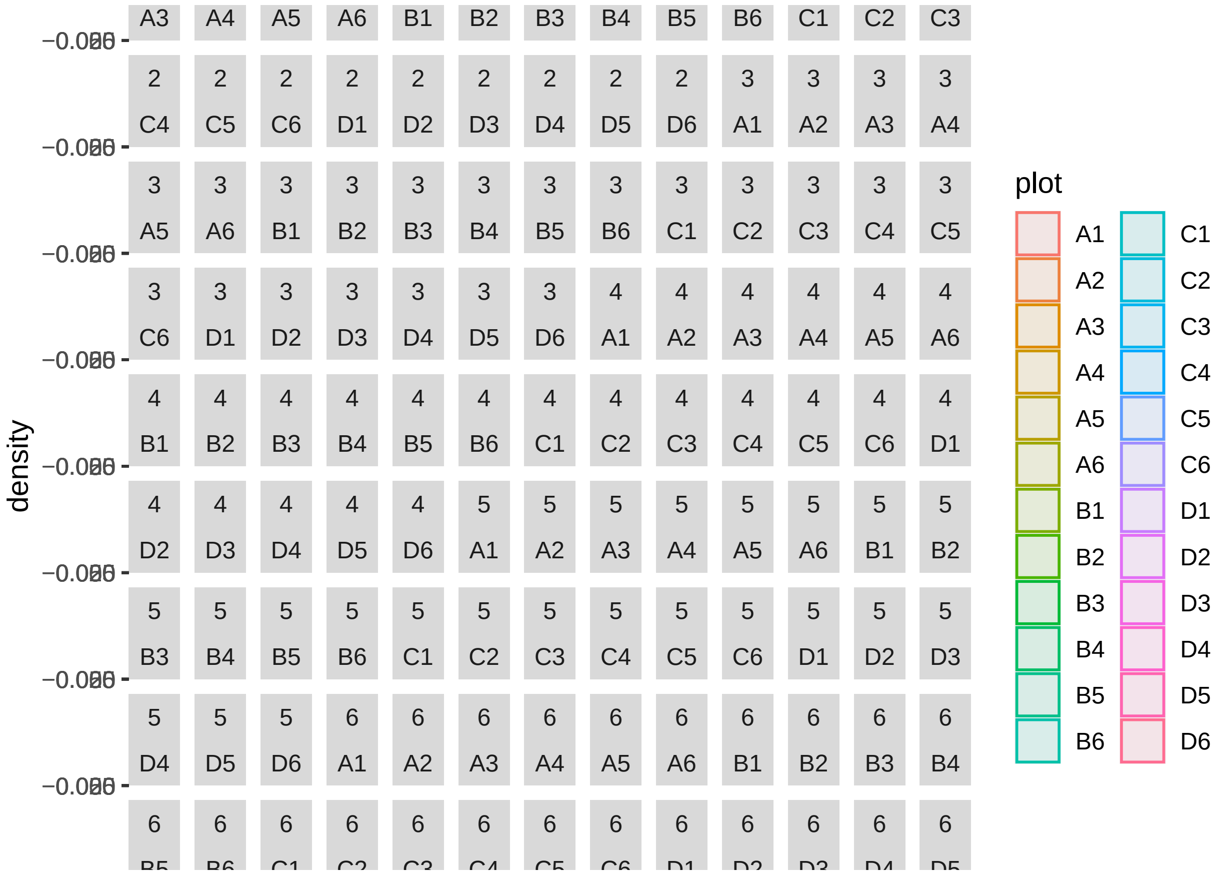

```r
ggplot(umbs_diversity, aes(simpson, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



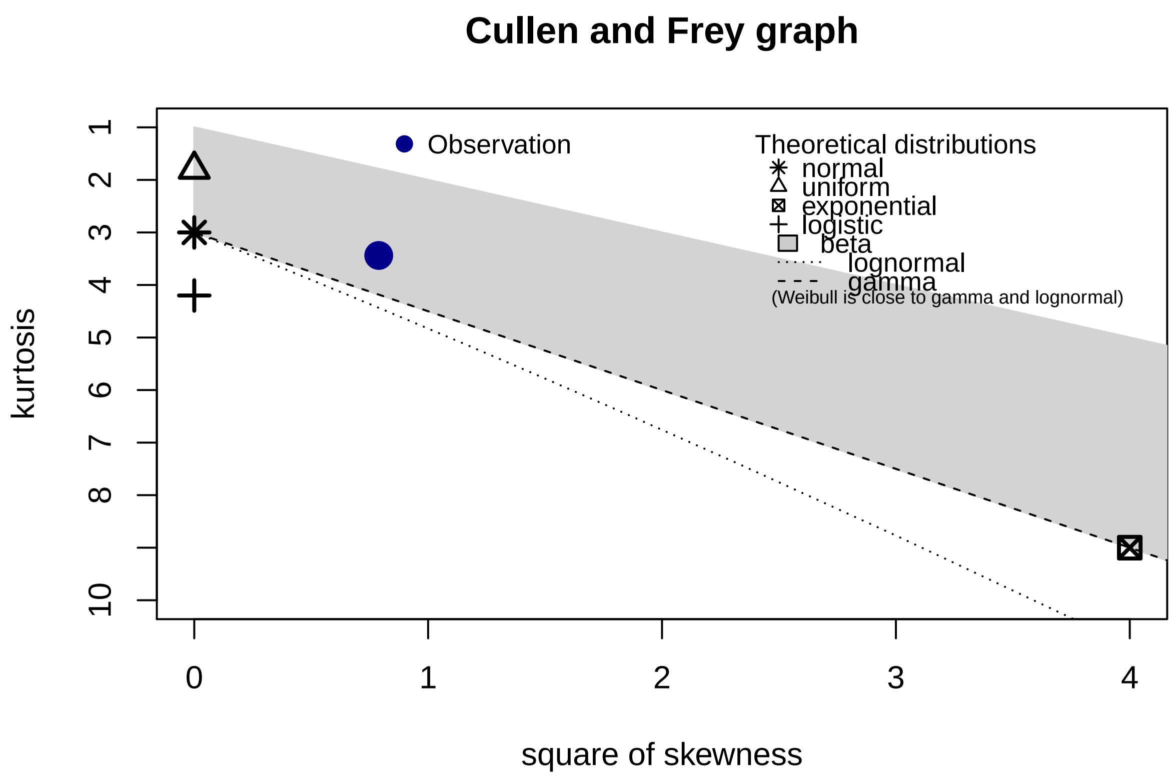

```
ggplot(umbs_diversity, aes(simpson, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
    facet_wrap(~year_factor)
```




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

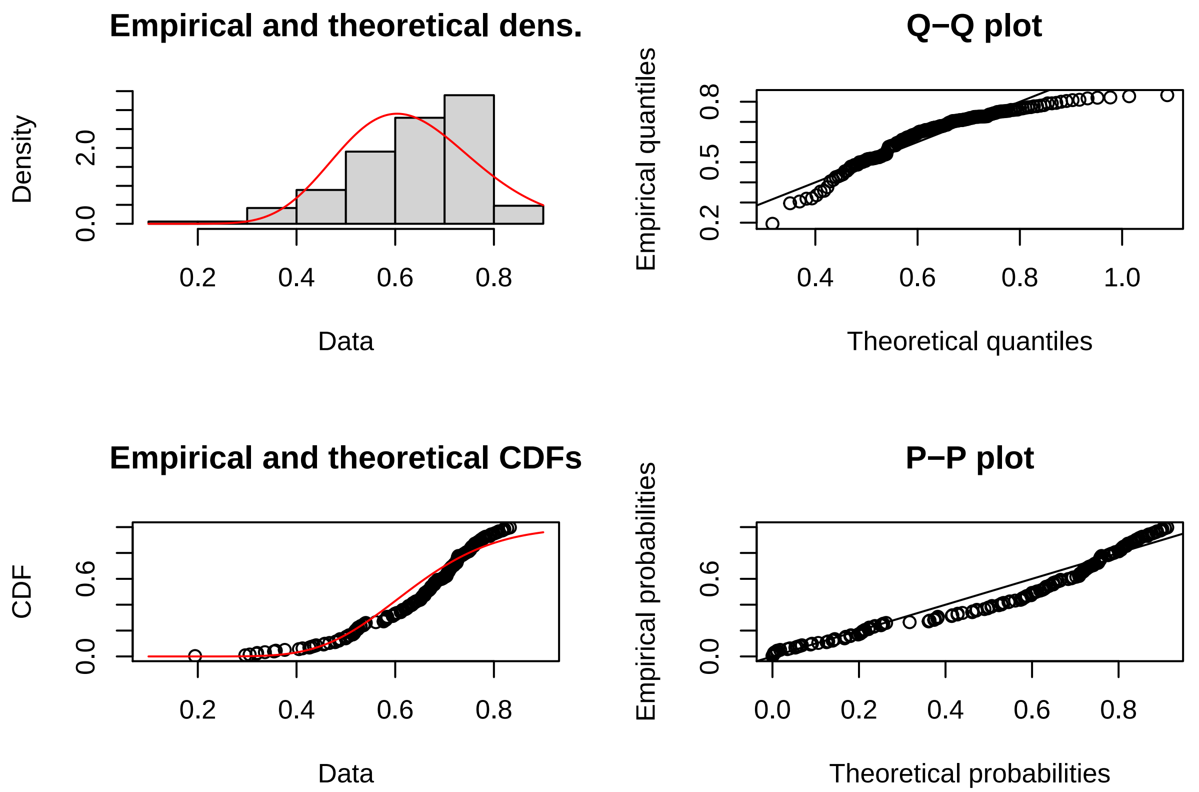



```r
# Exploring distributions for these right-skewed data:
descdist(umbs_diversity$simpson, discrete = FALSE)
```

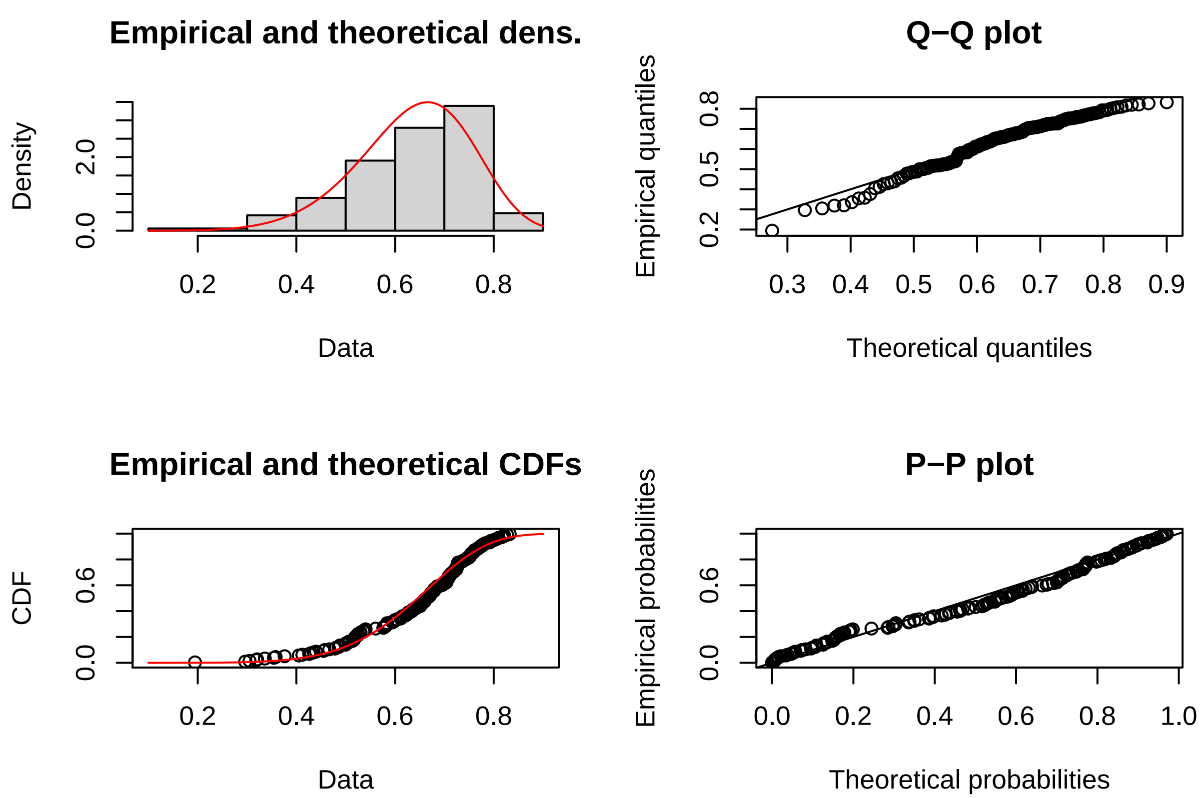



```
## summary statistics
## ------
## min:  0.1944479   max:  0.8323868
## median:  0.6640052
## mean:  0.6348357
## estimated sd:  0.1272632
## estimated skewness:  -0.8881556
## estimated kurtosis:  3.43863
```

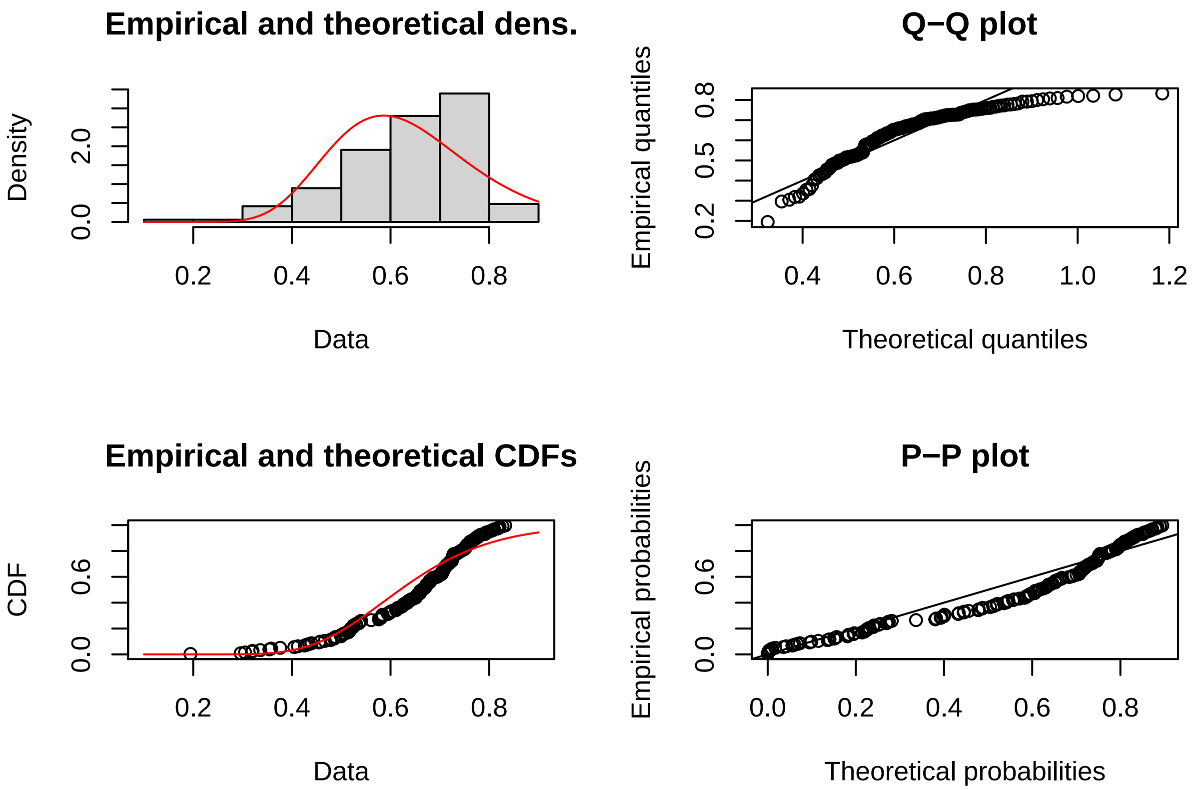
```
# Gamma distribution
fit.gamma <- fitdist(umbs_diversity$simpson, "gamma")
plot(fit.gamma)
```



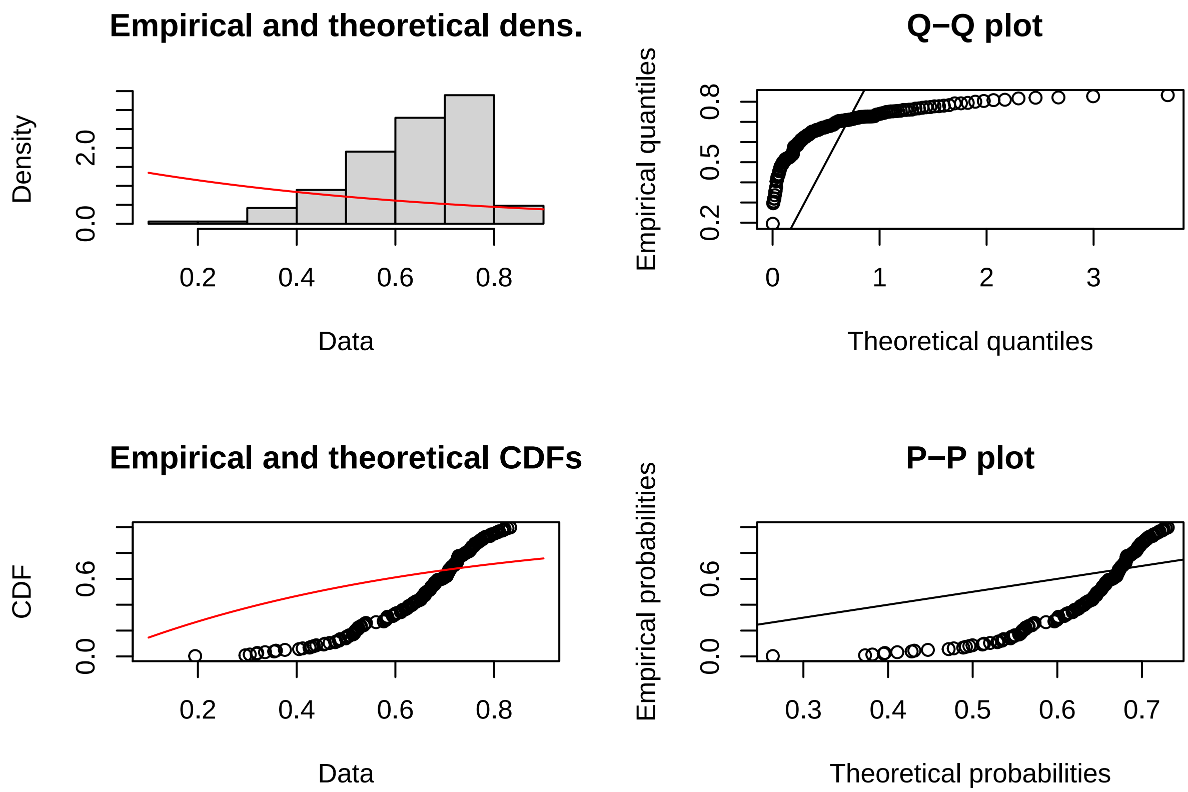

```r
# Weibull distribution
fit.weibull <- fitdist(umbs_diversity$simpson, "weibull")
plot(fit.weibull)
```



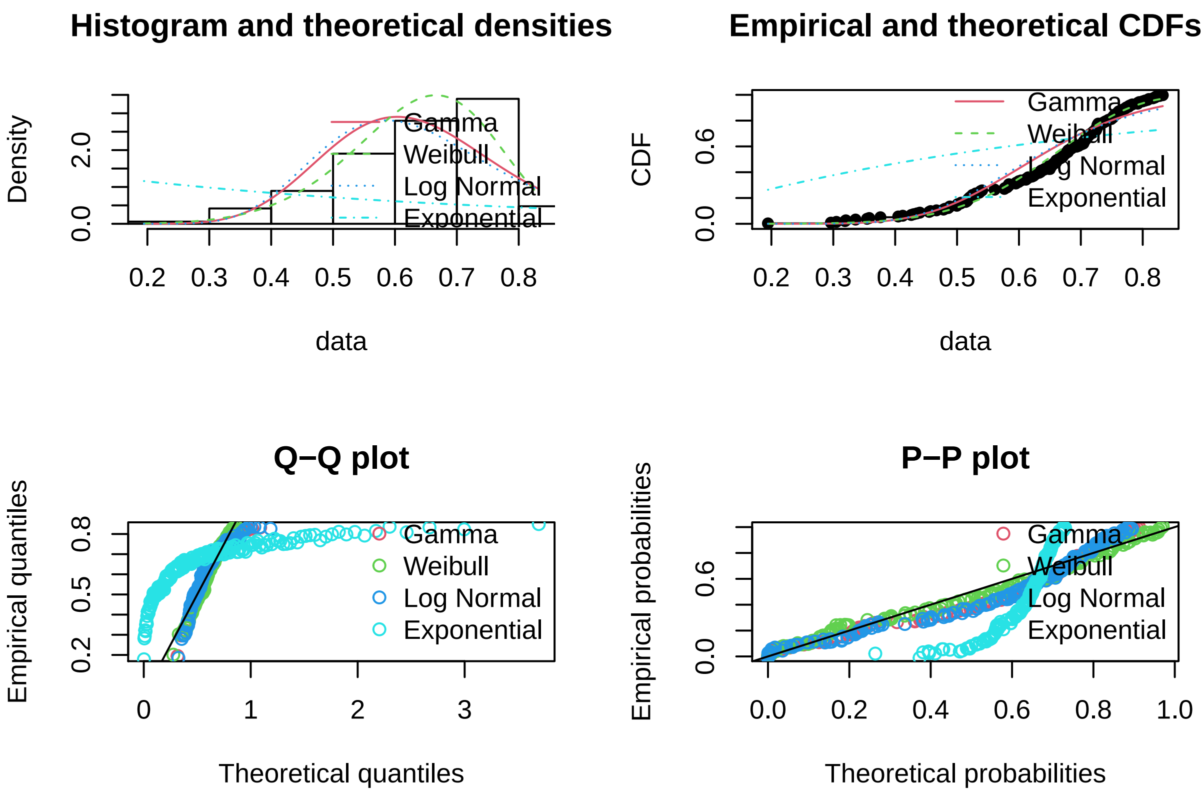
```
# Lognormal distribution
fit.ln <- fitdist(umbs_diversity$simpson, "lnorm")
plot(fit.ln)
```




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




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



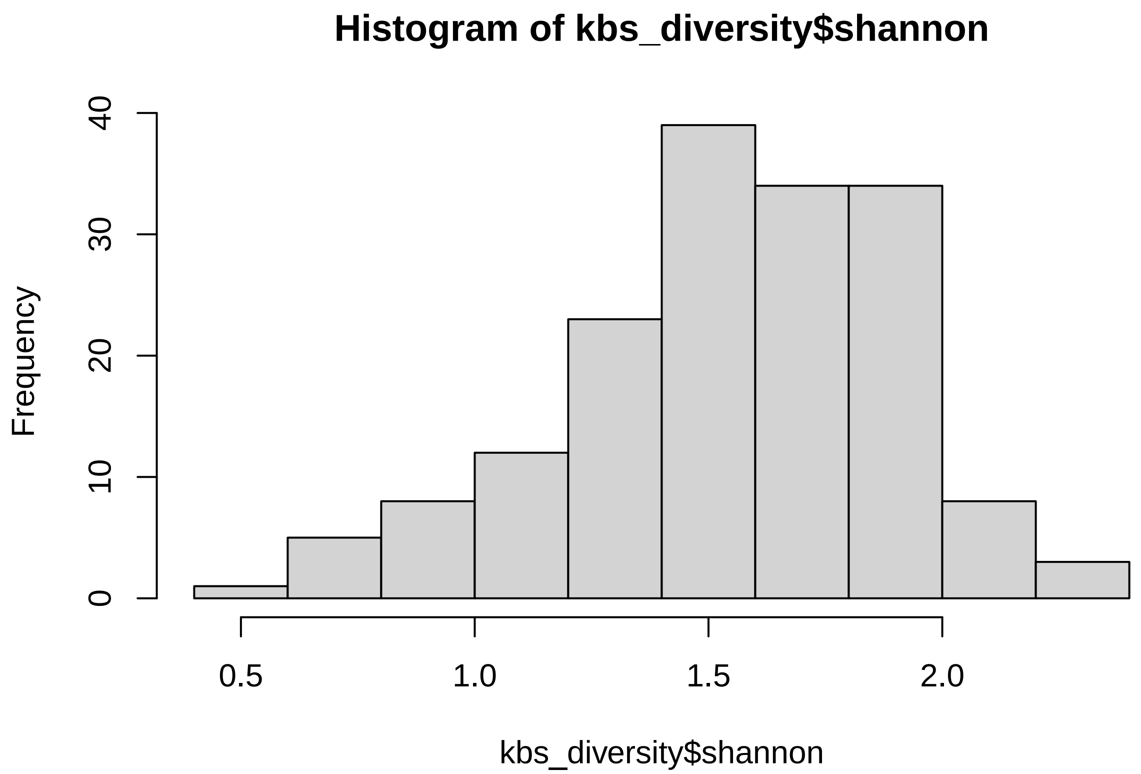

```r
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull",
    "Log Normal", "Exp"))
```

```
## Goodness-of-fit statistics
##                                  Gamma    Weibull Log Normal        Exp
## Kolmogorov-Smirnov statistic 0.1386796 0.08169643  0.1477967  0.4233562
## Cramer-von Mises statistic   0.8657611 0.28748472  1.0723870 10.4611503
## Anderson-Darling statistic   4.9892149 1.71943419  6.2102120 49.8375410
##
## Goodness-of-fit criteria
##                                    Gamma   Weibull Log Normal      Exp
## Akaike's Information Criterion -184.7834 -232.0070  -165.6780 185.3253
## Bayesian Information Criterion -178.5354 -225.7591  -159.4301 188.4492
```

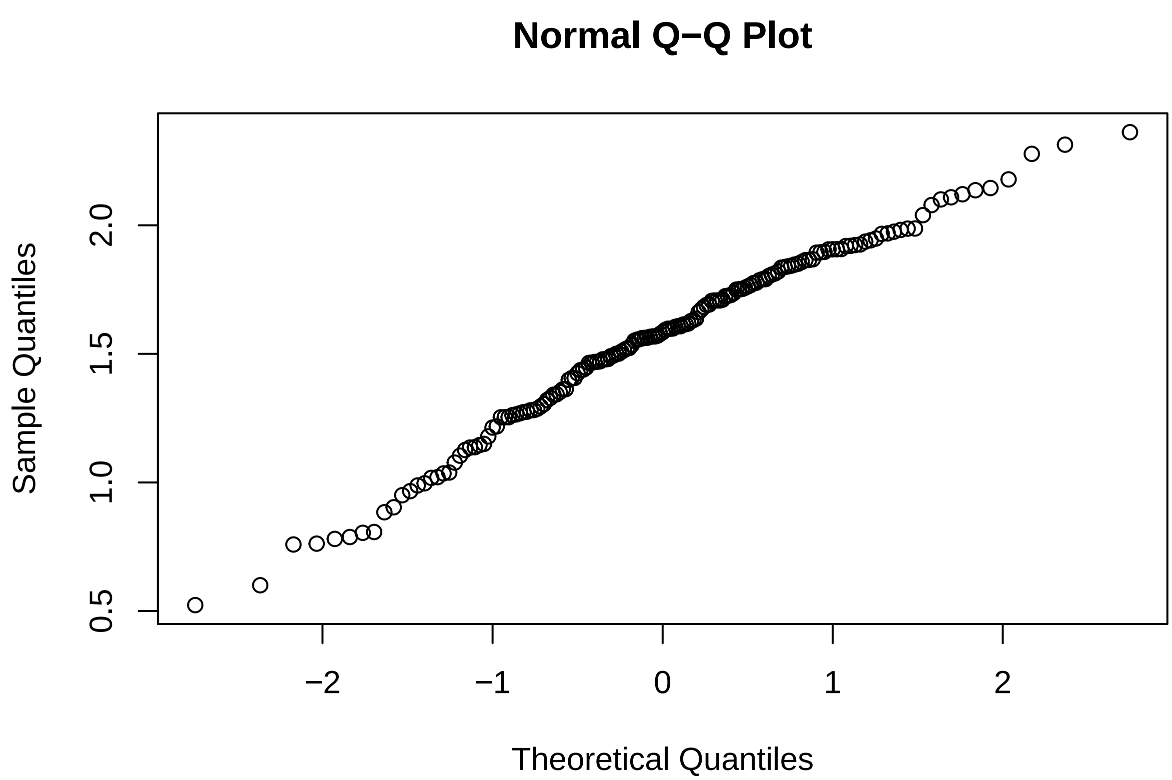
```r
# log normal distribution looks to be the best based on AIC and BIC values
```

Shannon Index KBS

```r
### KBS ###
hist(kbs_diversity$shannon)  # skewed to the left
```



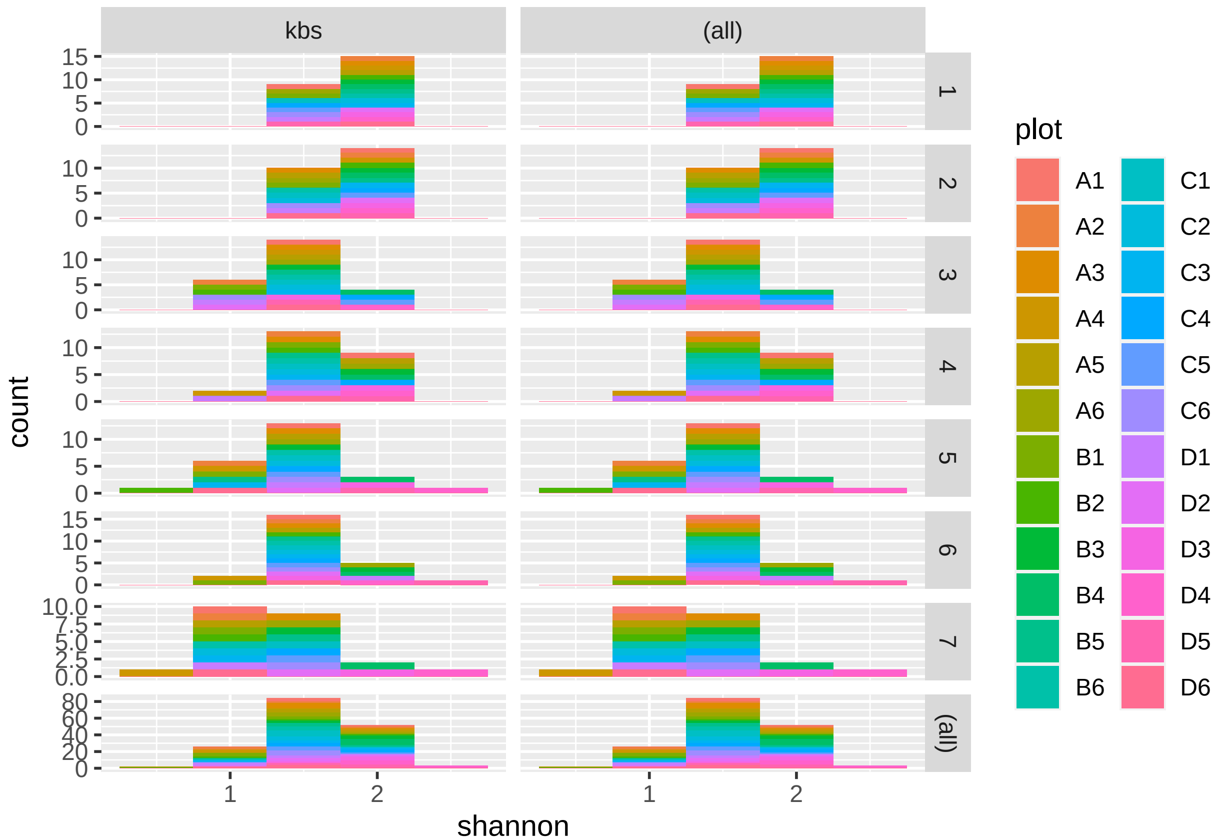

```
qqnorm(kbs_diversity$shannon)
```



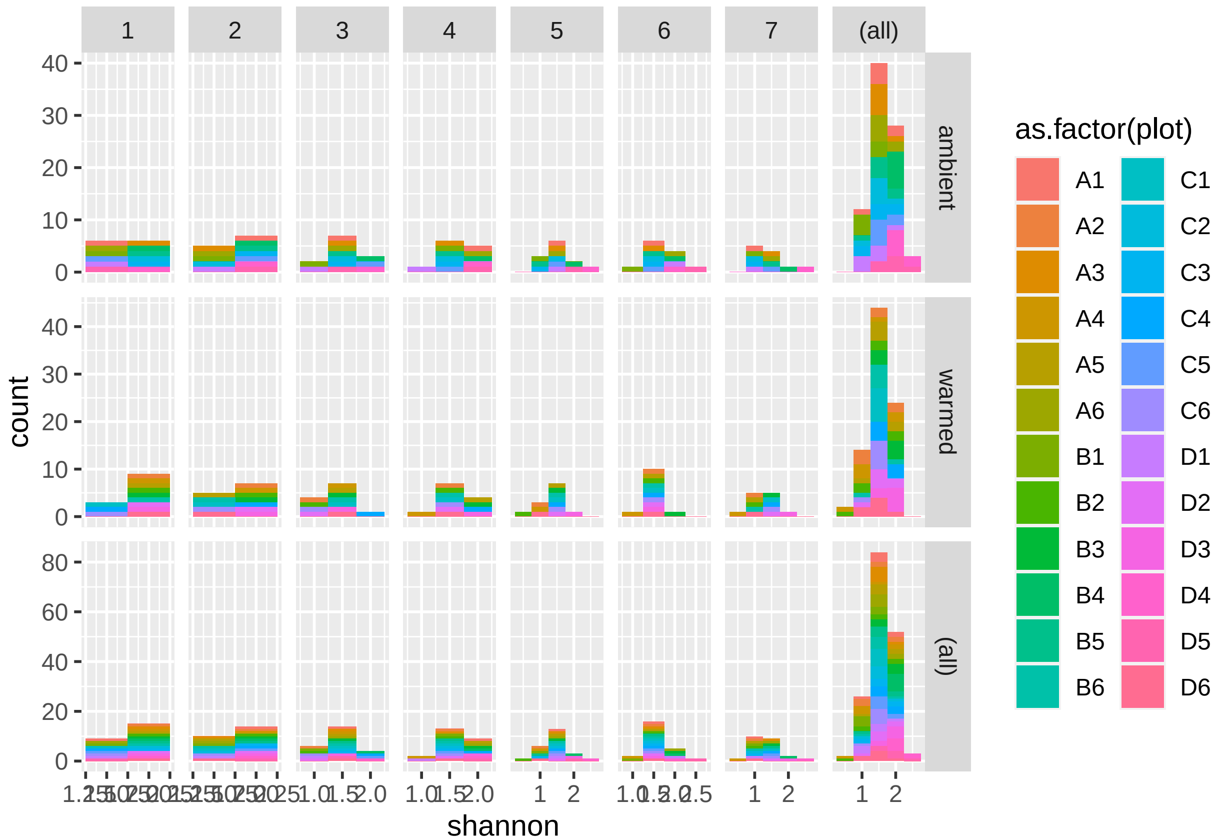
```r
shapiro.test(kbs_diversity$shannon)  # pvalue is < 0.05 so we reject the null hypothesis that the data
```

```
##
##  Shapiro-Wilk normality test
##
## data:  kbs_diversity$shannon
## W = 0.98203, p-value = 0.02923
```

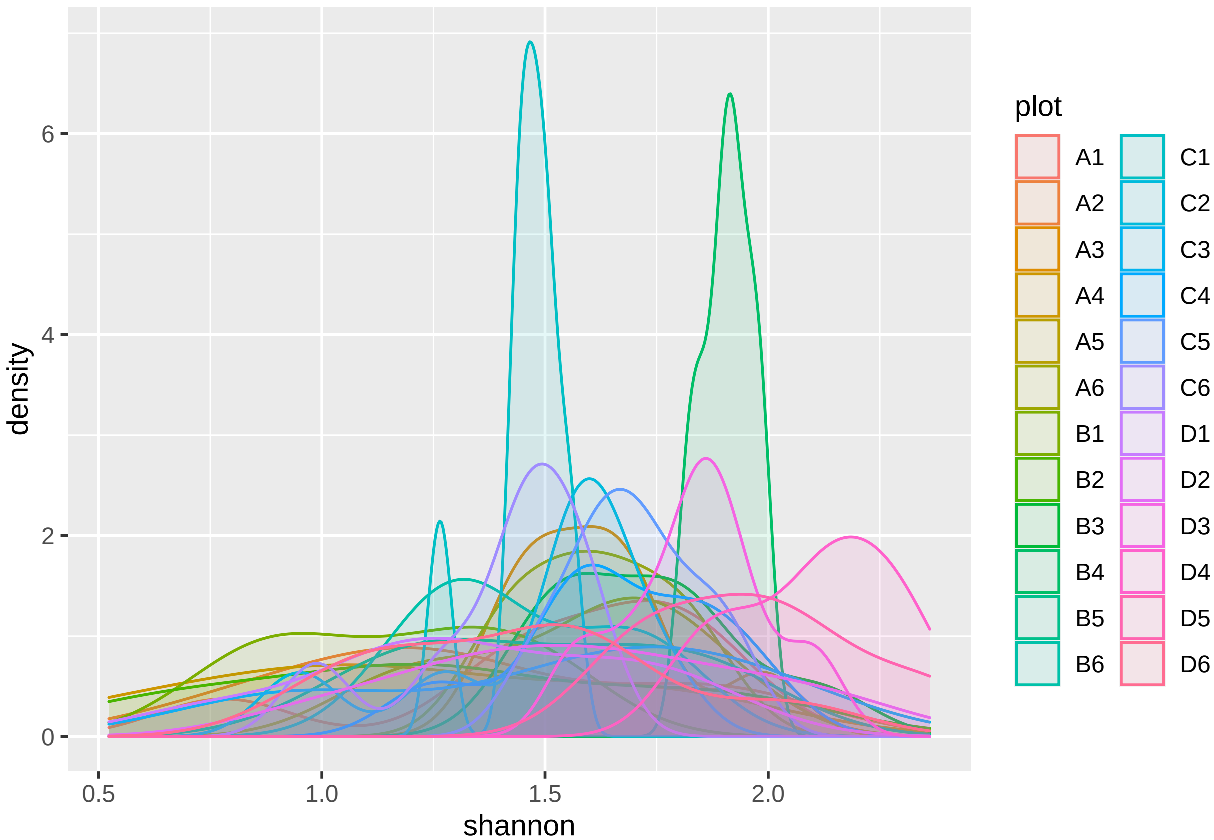
```r
# Visualizing plot average totals for kbs at the PLOT LEVEL
ggplot(kbs_diversity, aes(shannon, fill = plot)) + geom_histogram(binwidth = 0.5) +
    facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



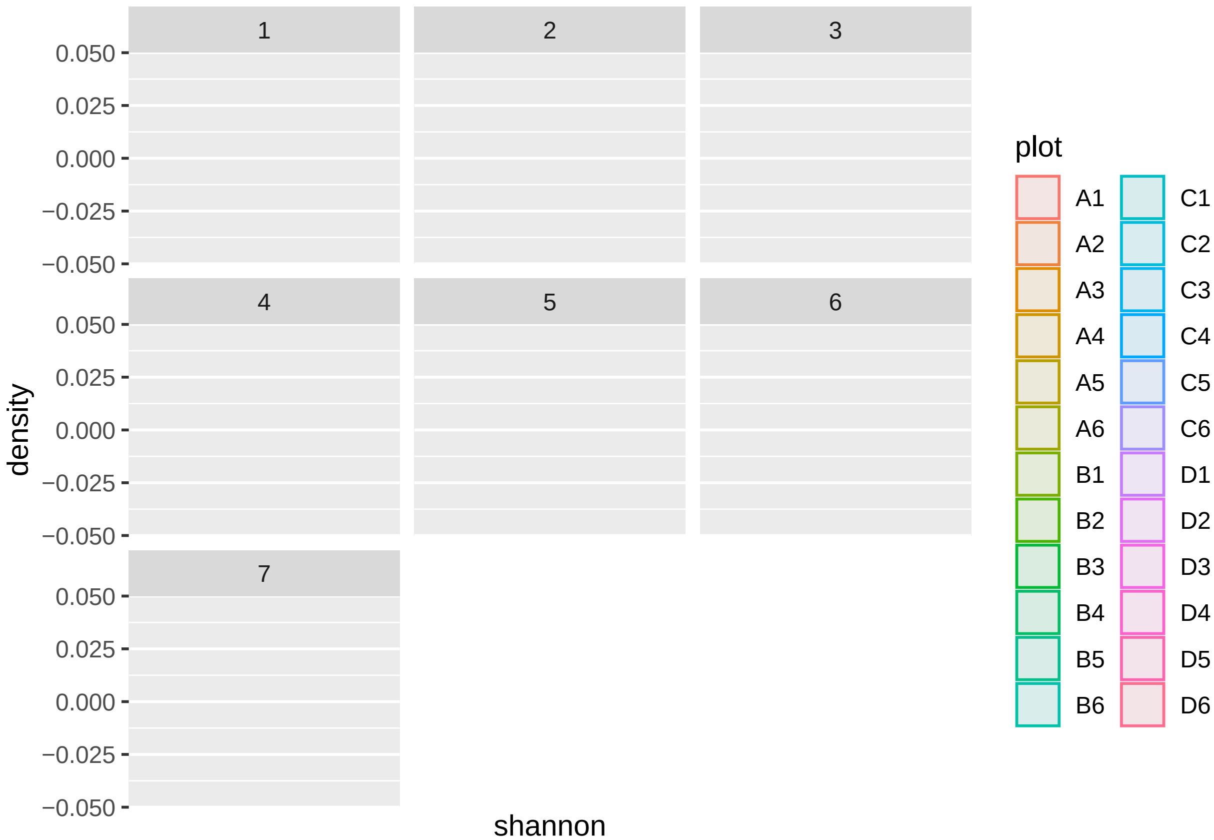

```r
ggplot(kbs_diversity, aes(shannon, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
    facet_grid(state ~ year_factor, margins = TRUE, scales = "free")
```



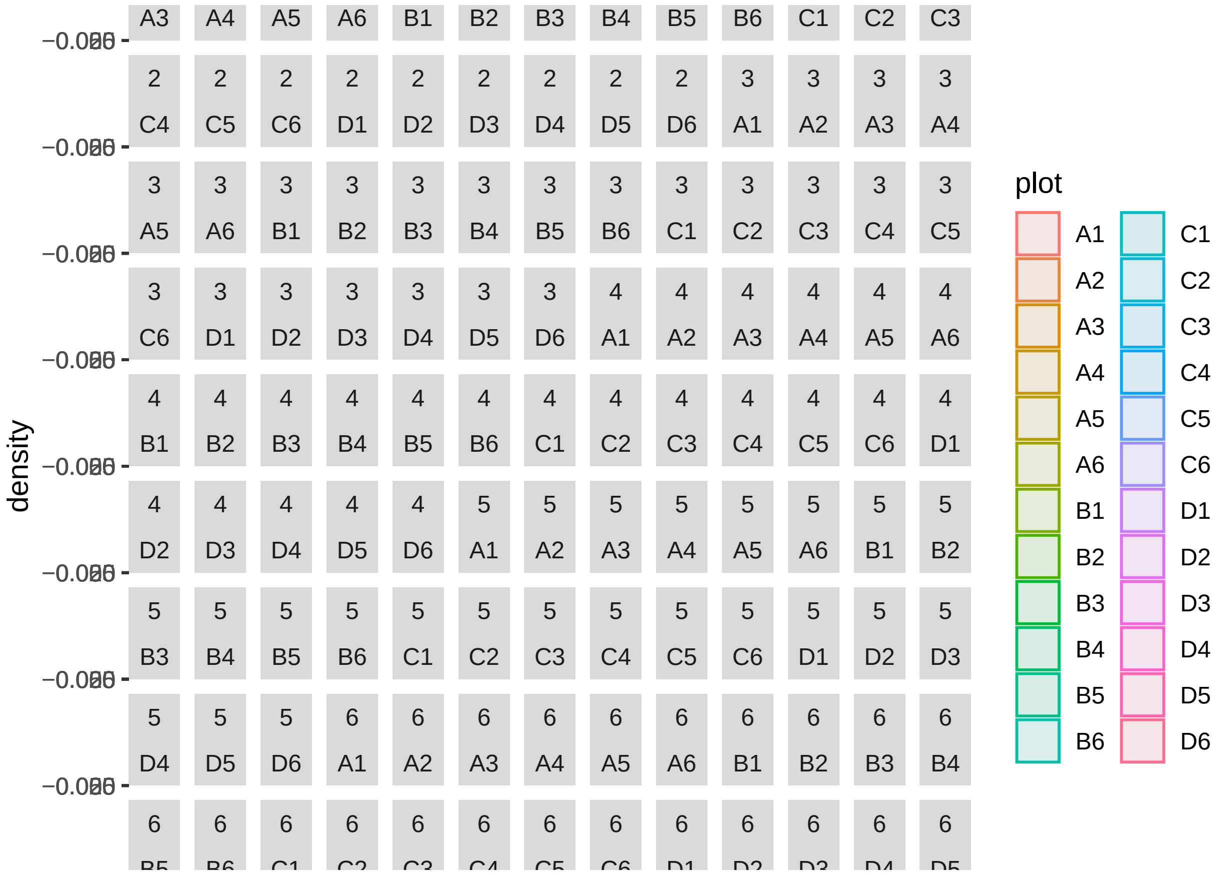

```
ggplot(kbs_diversity, aes(shannon, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



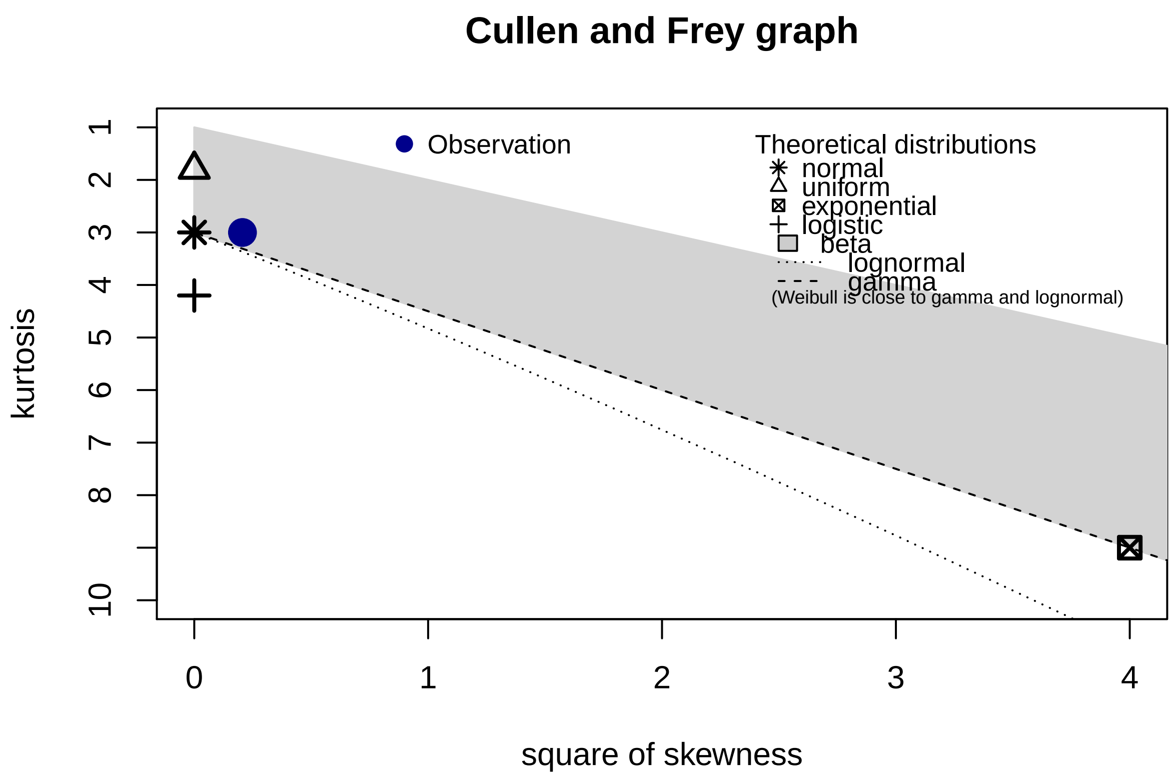

```
ggplot(kbs_diversity, aes(shannon, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
    facet_wrap(~year_factor)
```




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

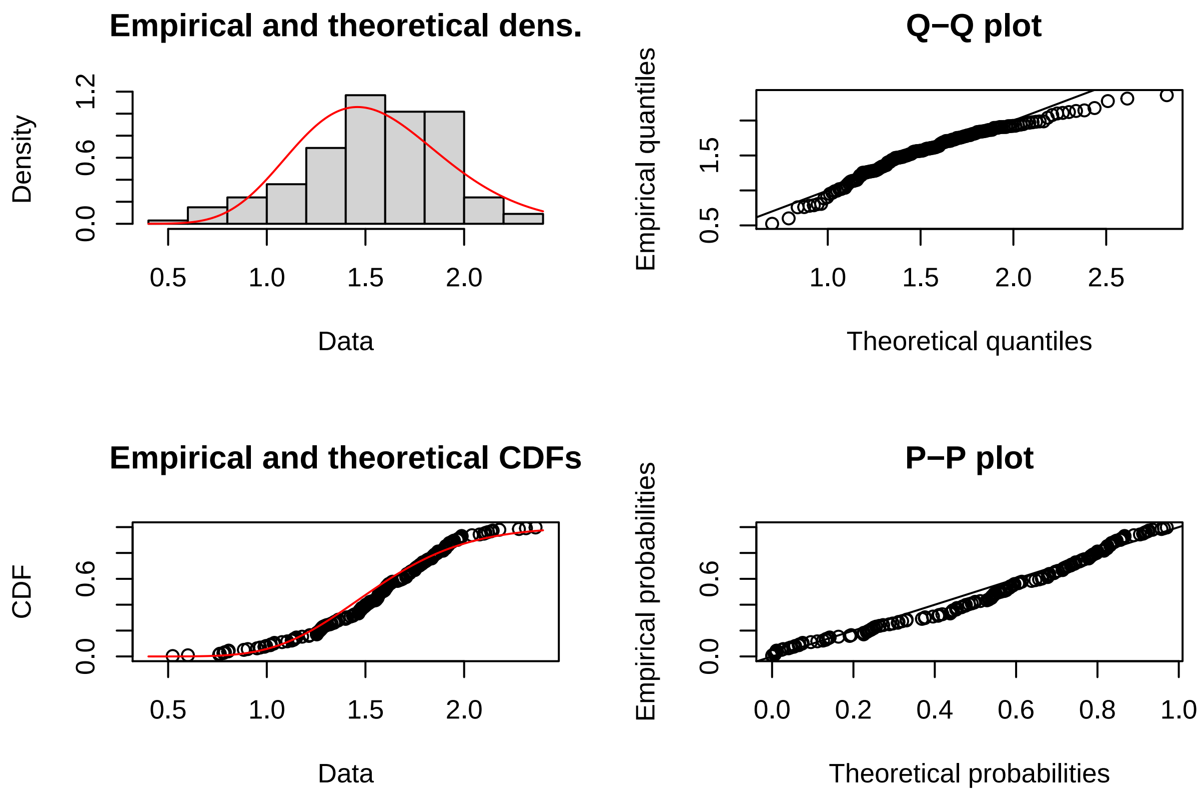



```
# Exploring distributions for these right-skewed data:
descdist(kbs_diversity$shannon, discrete = FALSE)
```

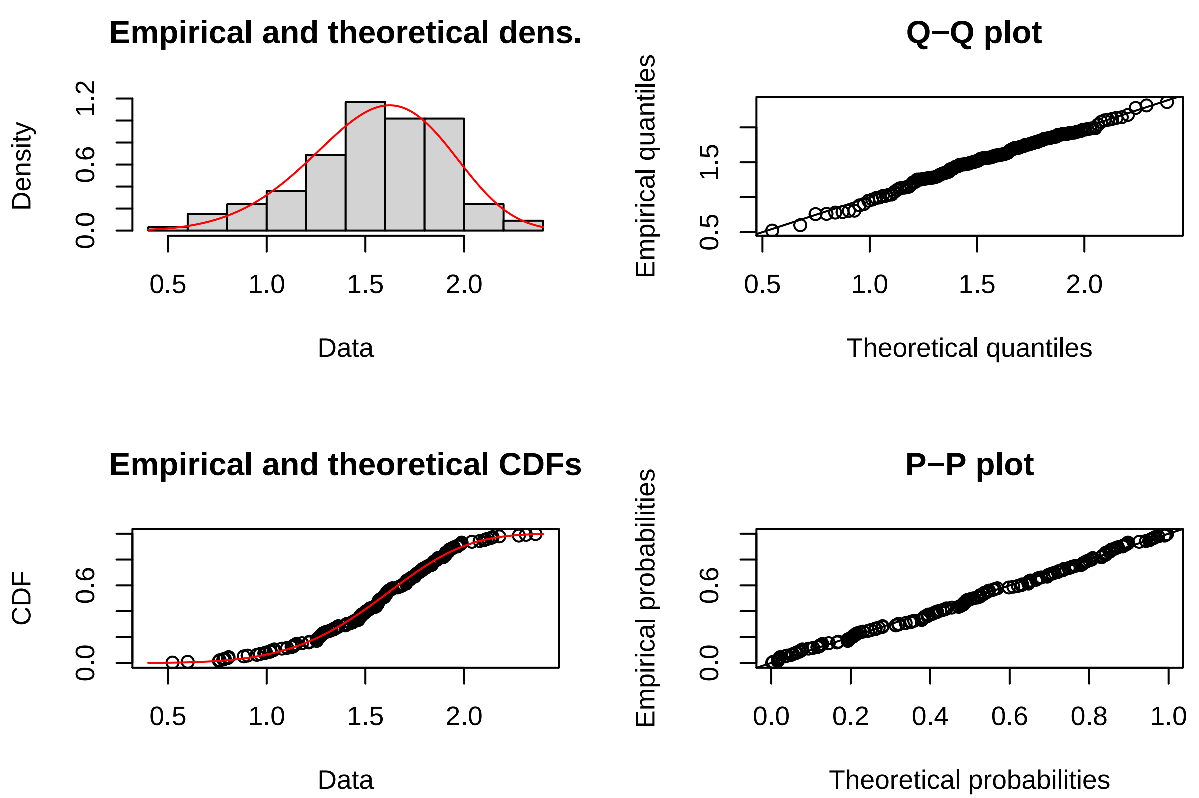



```
## summary statistics
## ------
## min:  0.5229757   max:  2.361985
## median:  1.584093
## mean:  1.555341
## estimated sd:  0.3579429
## estimated skewness:  -0.4540695
## estimated kurtosis:  3.00097
```

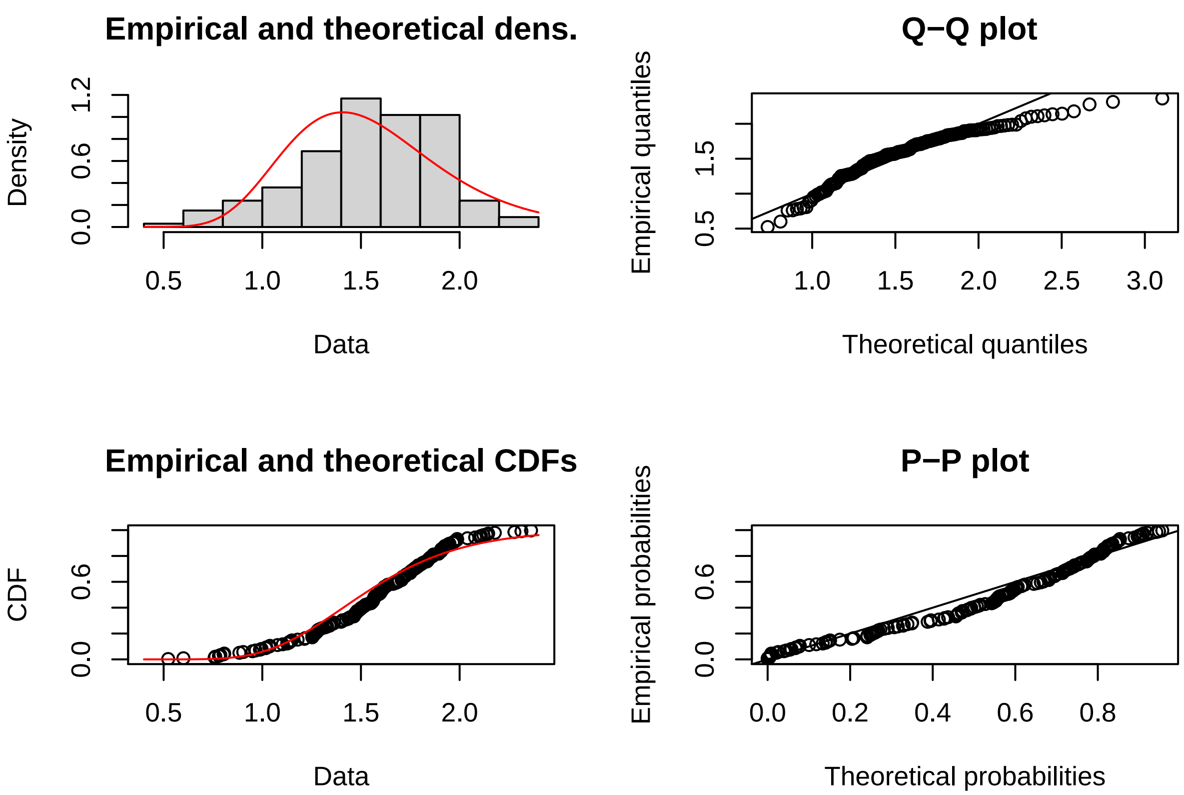
```r
# Gamma distribution
fit.gamma <- fitdist(kbs_diversity$shannon, "gamma")
plot(fit.gamma)
```



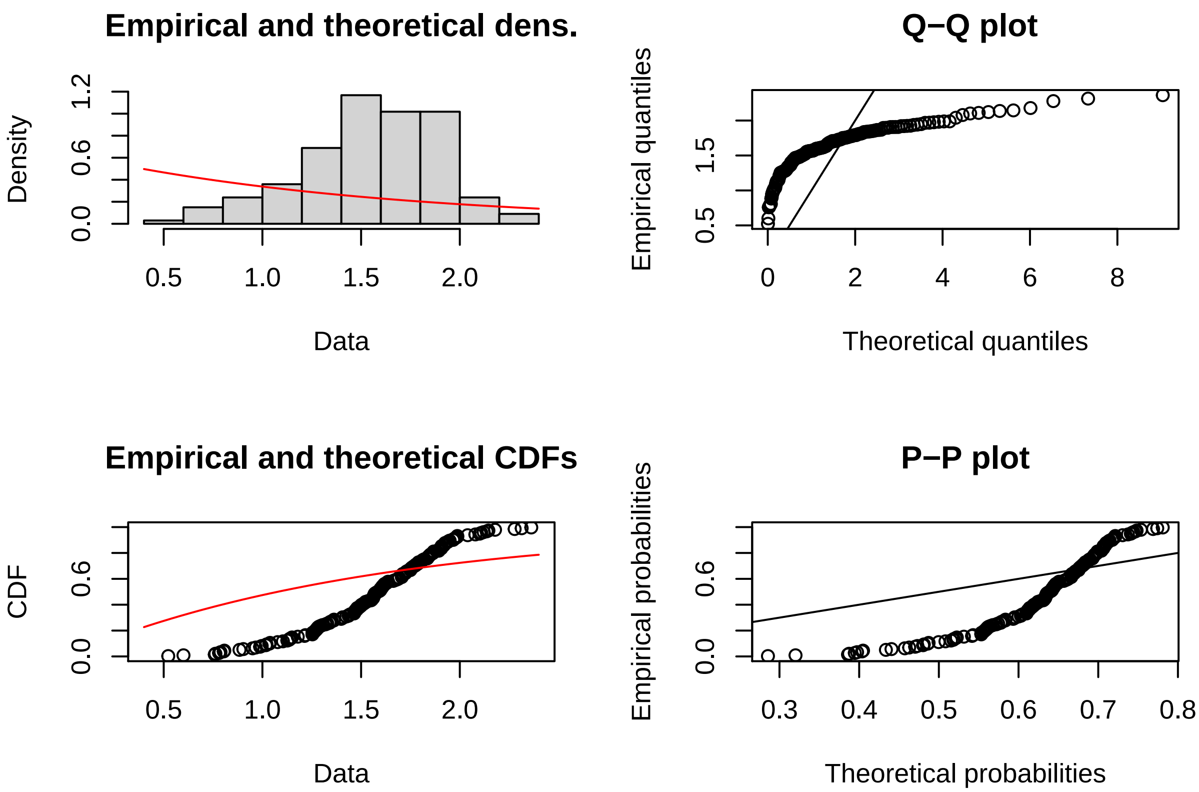

```r
# Weibull distribution
fit.weibull <- fitdist(kbs_diversity$shannon, "weibull")
plot(fit.weibull)
```



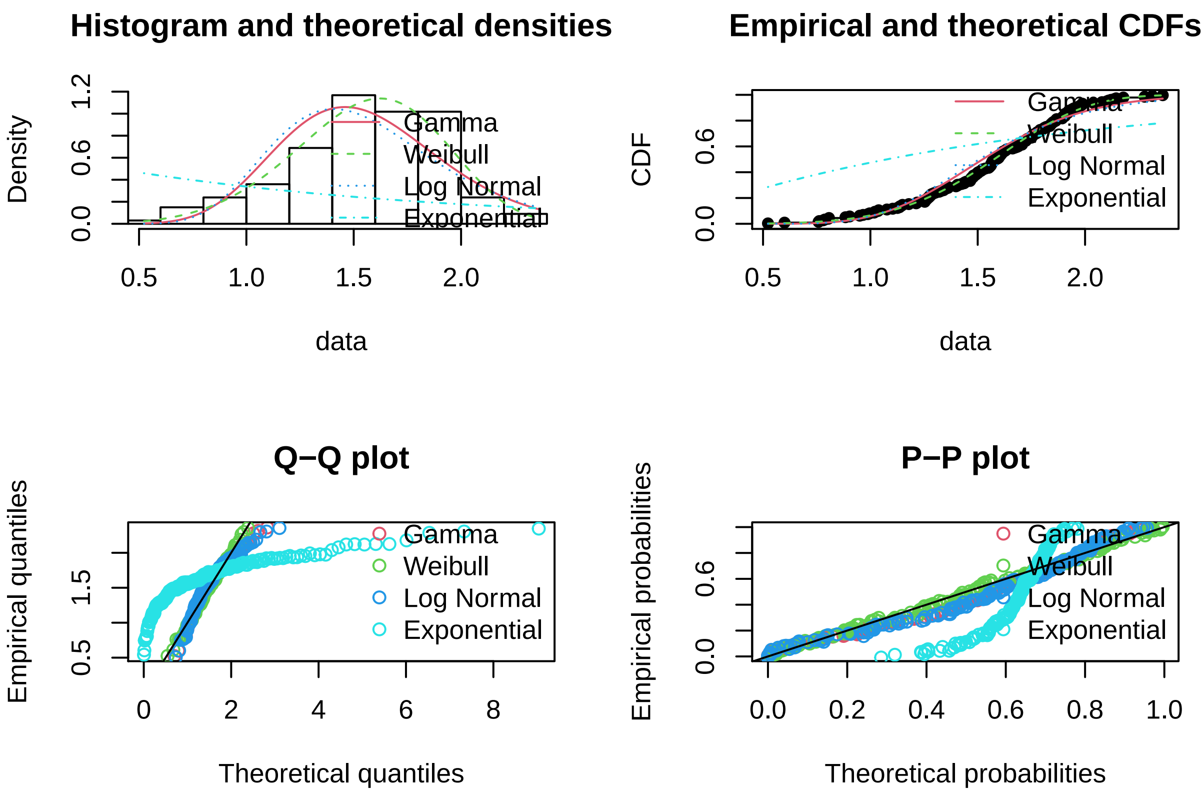
```r
# Lognormal distribution
fit.ln <- fitdist(kbs_diversity$shannon, "lnorm")
plot(fit.ln)
```




```r
# Exponential distribution is another option
fit.exp <- fitdist(kbs_diversity$shannon, "exp")
plot(fit.exp)
```




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



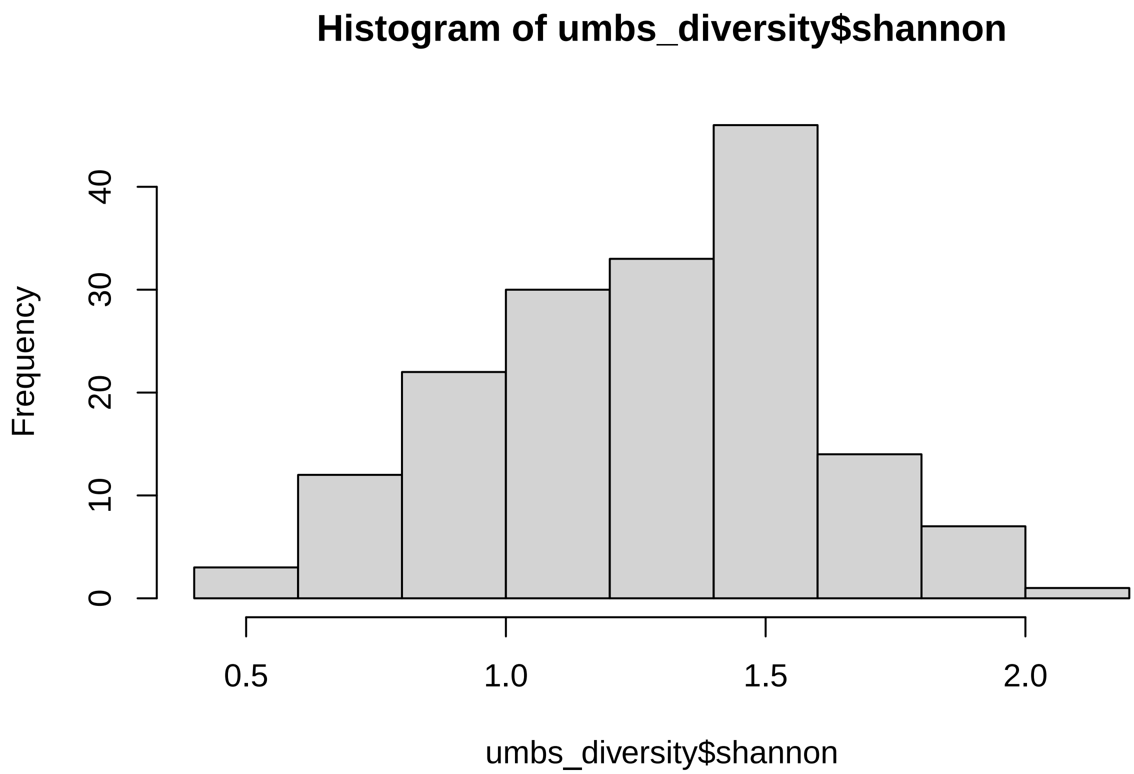

```r
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull",
    "Log Normal", "Exp"))
```

```
## Goodness-of-fit statistics
##                                  Gamma    Weibull Log Normal        Exp
## Kolmogorov-Smirnov statistic 0.1085337 0.04923548  0.1267870  0.3984132
## Cramer-von Mises statistic   0.4288512 0.05446699  0.6284122  9.4977889
## Anderson-Darling statistic   2.5904881 0.37827589  3.7721513 45.6029349
##
## Goodness-of-fit criteria
##                                   Gamma  Weibull Log Normal     Exp
## Akaike's Information Criterion 153.2781 127.3441   168.7664 483.526
## Bayesian Information Criterion 159.5141 133.5801   175.0023 486.644
```

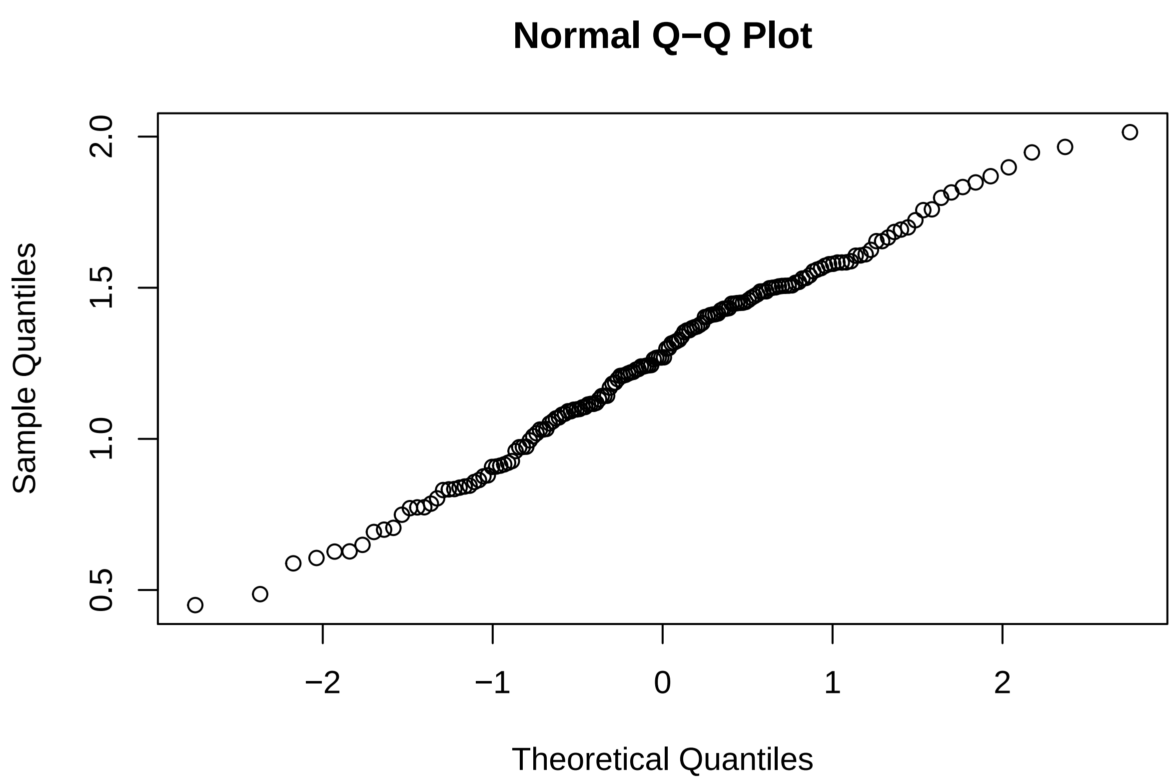
```r
# weibull distribution looks to be the best based on AIC and BIC values
```

UMBS

```r
### UMBS ###
hist(umbs_diversity$shannon)
```



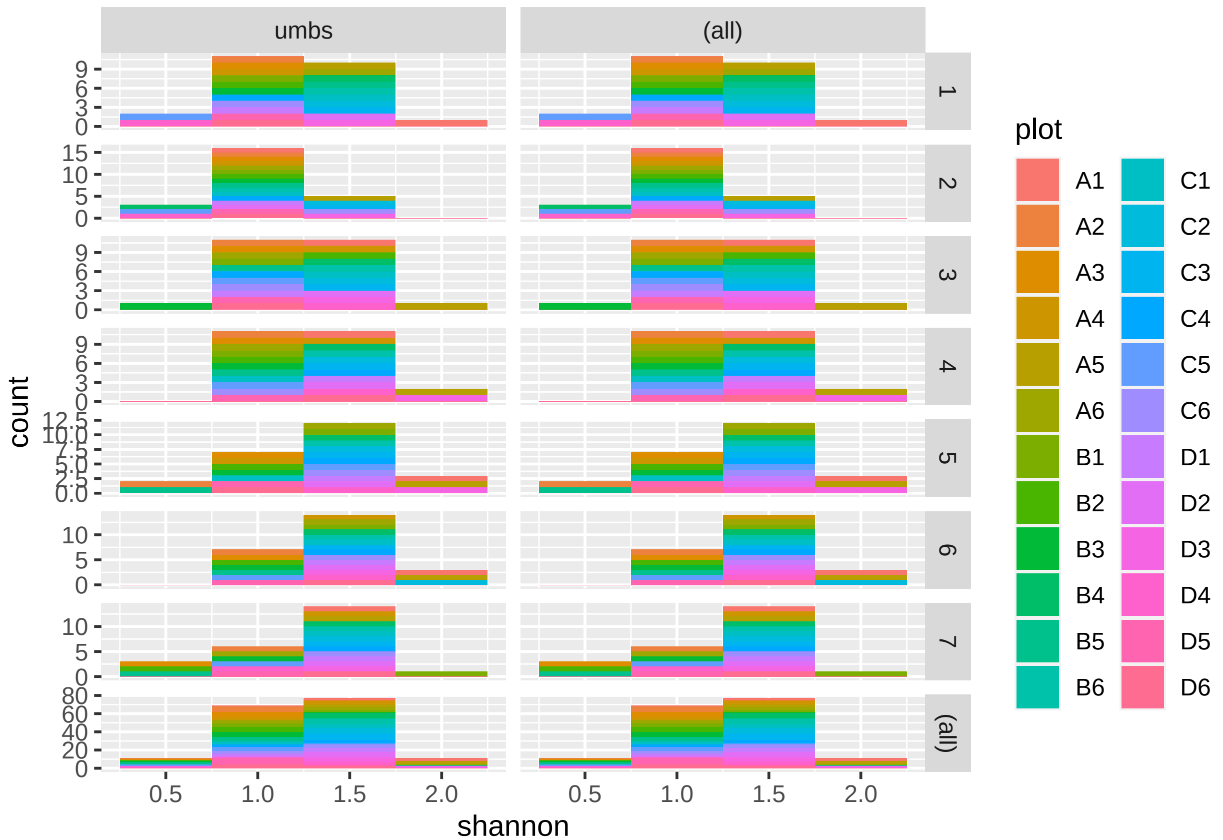

```
qqnorm(umbs_diversity$shannon)
```



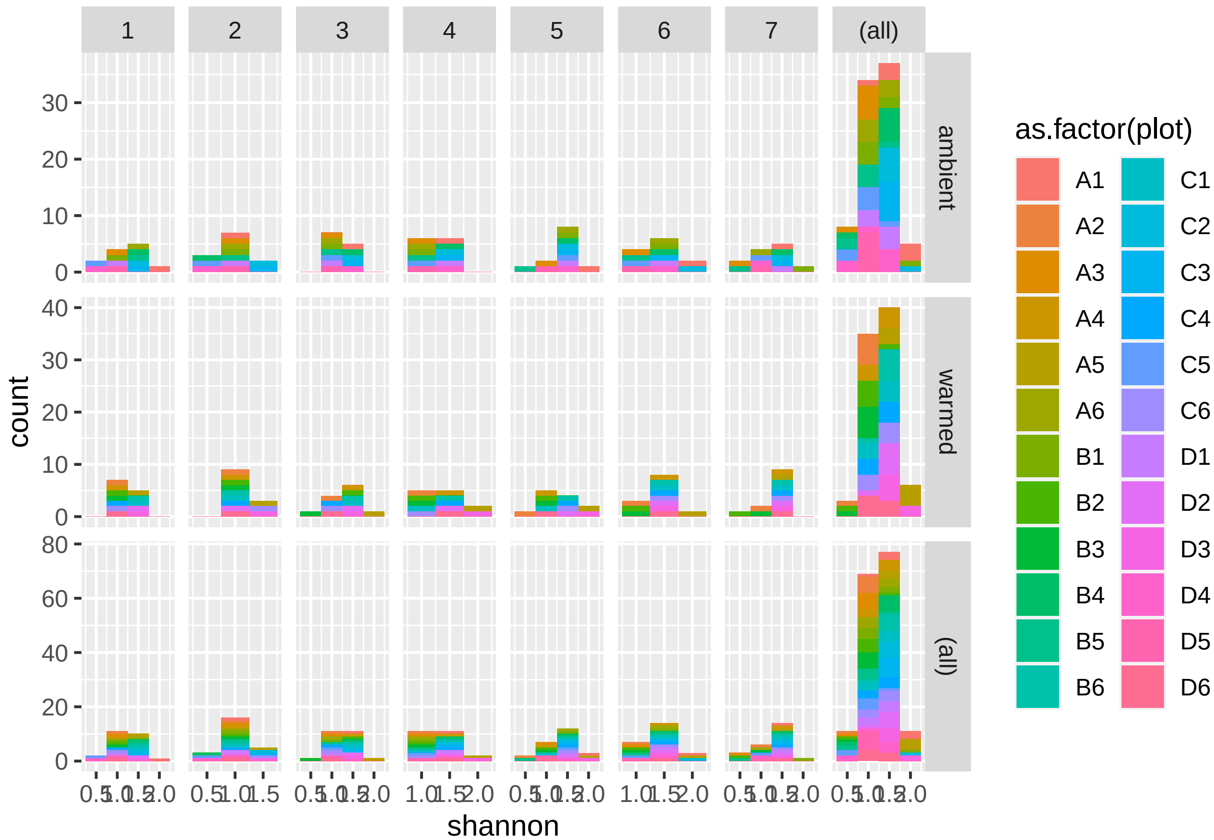
```r
shapiro.test(umbs_diversity$shannon)  # pvalue is > 0.05 so we do not reject the null hypothesis that t
```

```
##
##  Shapiro-Wilk normality test
##
## data:  umbs_diversity$shannon
## W = 0.98934, p-value = 0.2377
```

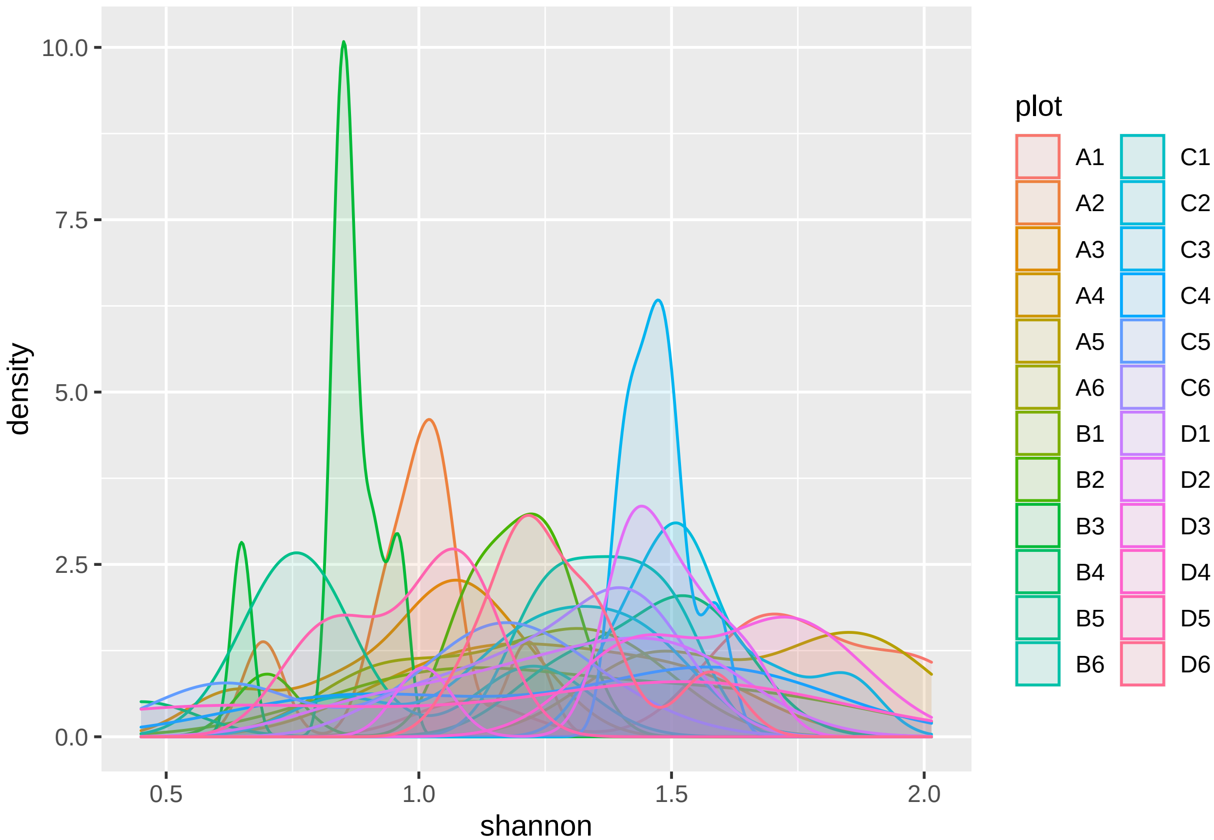
```r
# Visualizing plot average totals for umbs at the PLOT LEVEL
ggplot(umbs_diversity, aes(shannon, fill = plot)) + geom_histogram(binwidth = 0.5) +
    facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



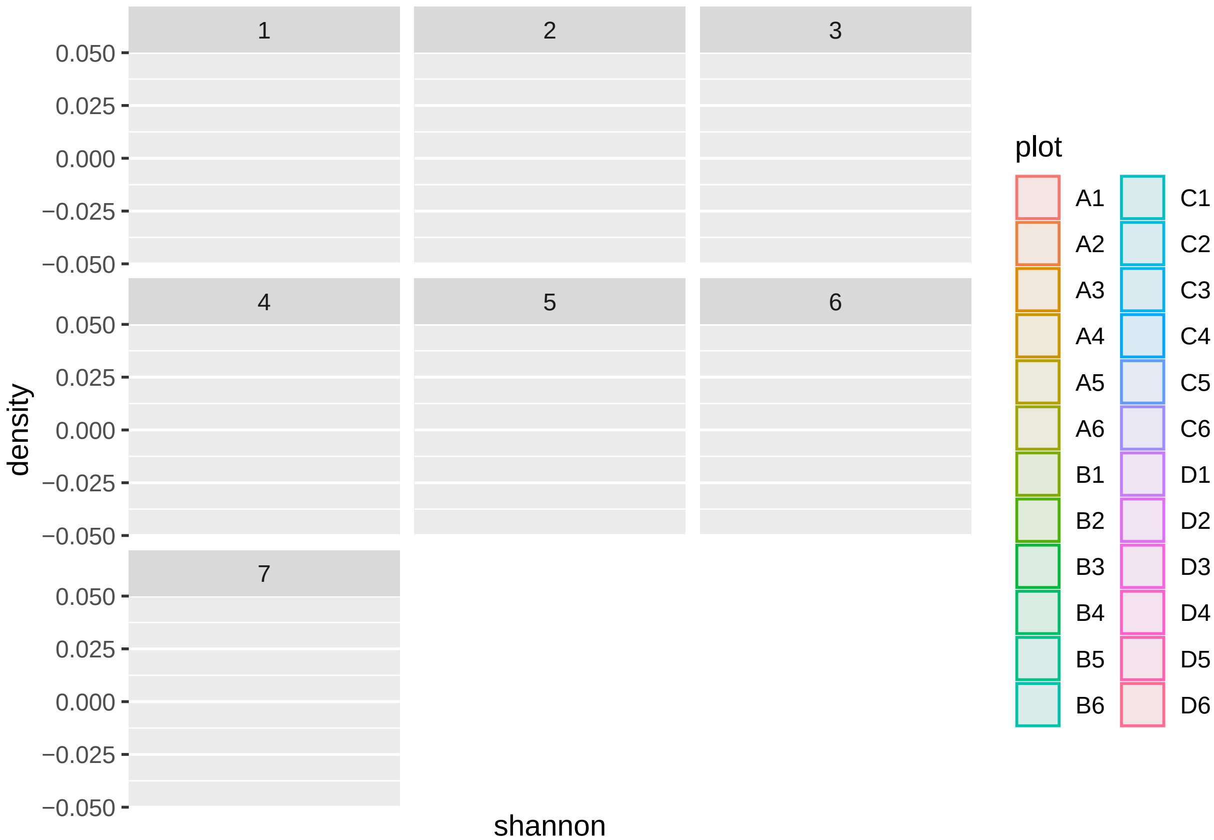

```r
ggplot(umbs_diversity, aes(shannon, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
    facet_grid(state ~ year_factor, margins = TRUE, scales = "free")
```



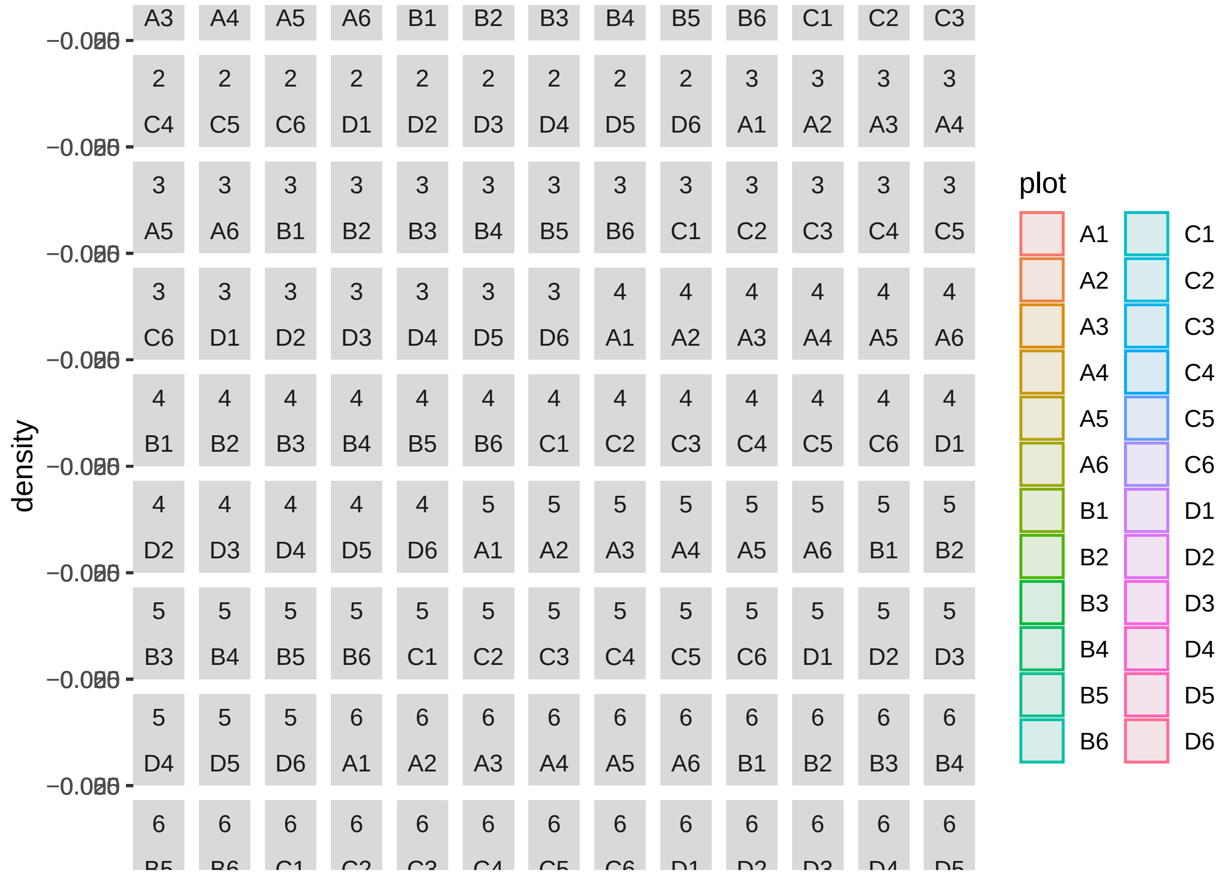

```r
ggplot(umbs_diversity, aes(shannon, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



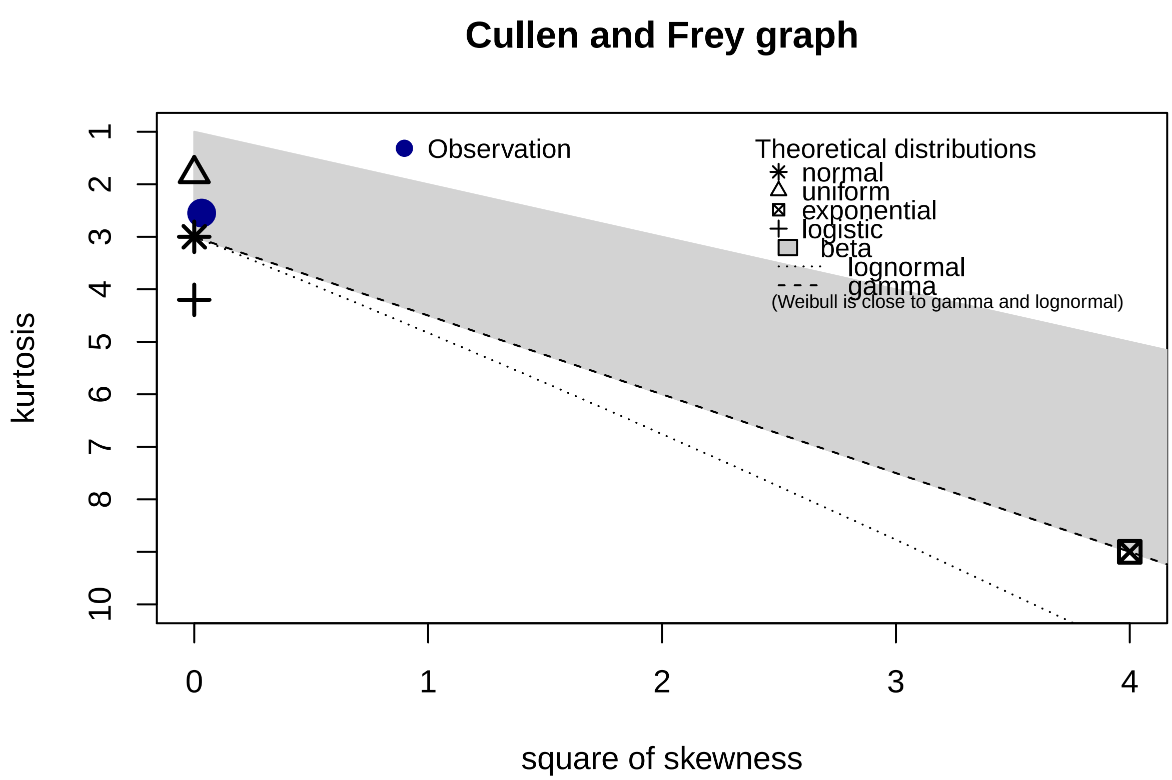

```r
ggplot(umbs_diversity, aes(shannon, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
    facet_wrap(~year_factor)
```




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

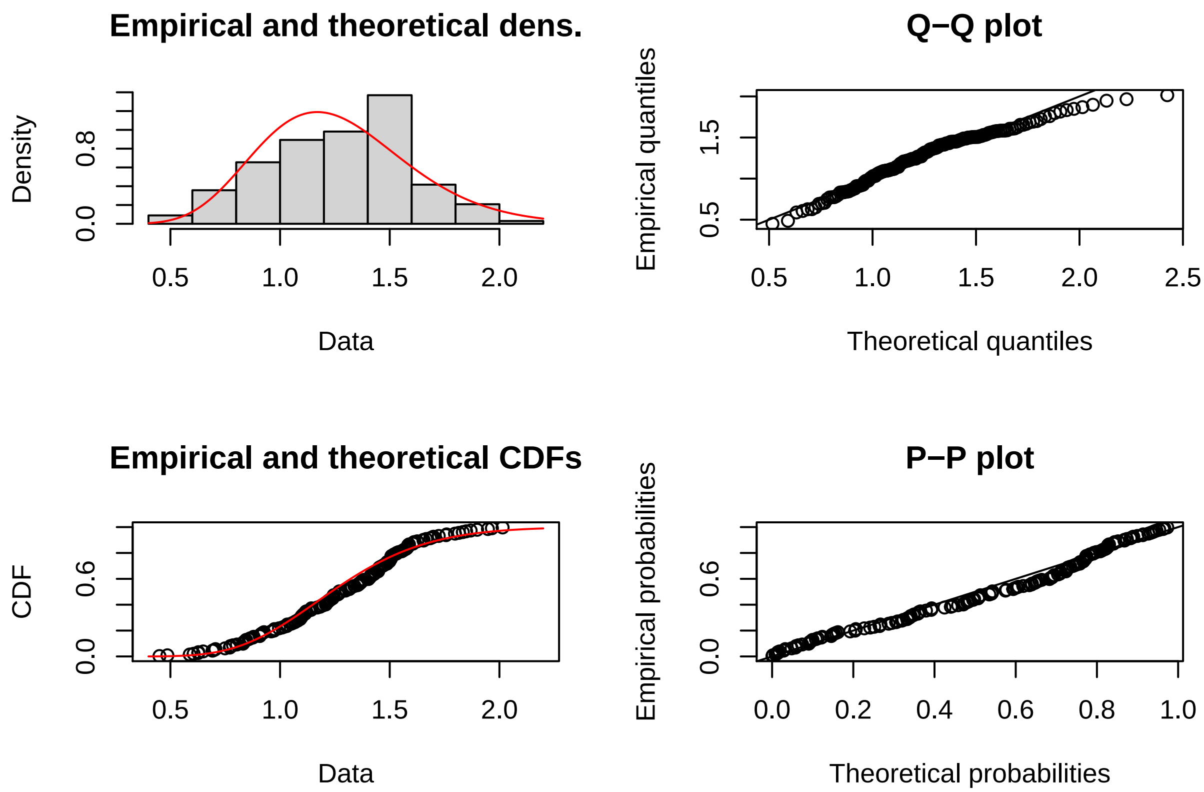



```r
# Exploring distributions for these right-skewed data:
descdist(umbs_diversity$shannon, discrete = FALSE)
```

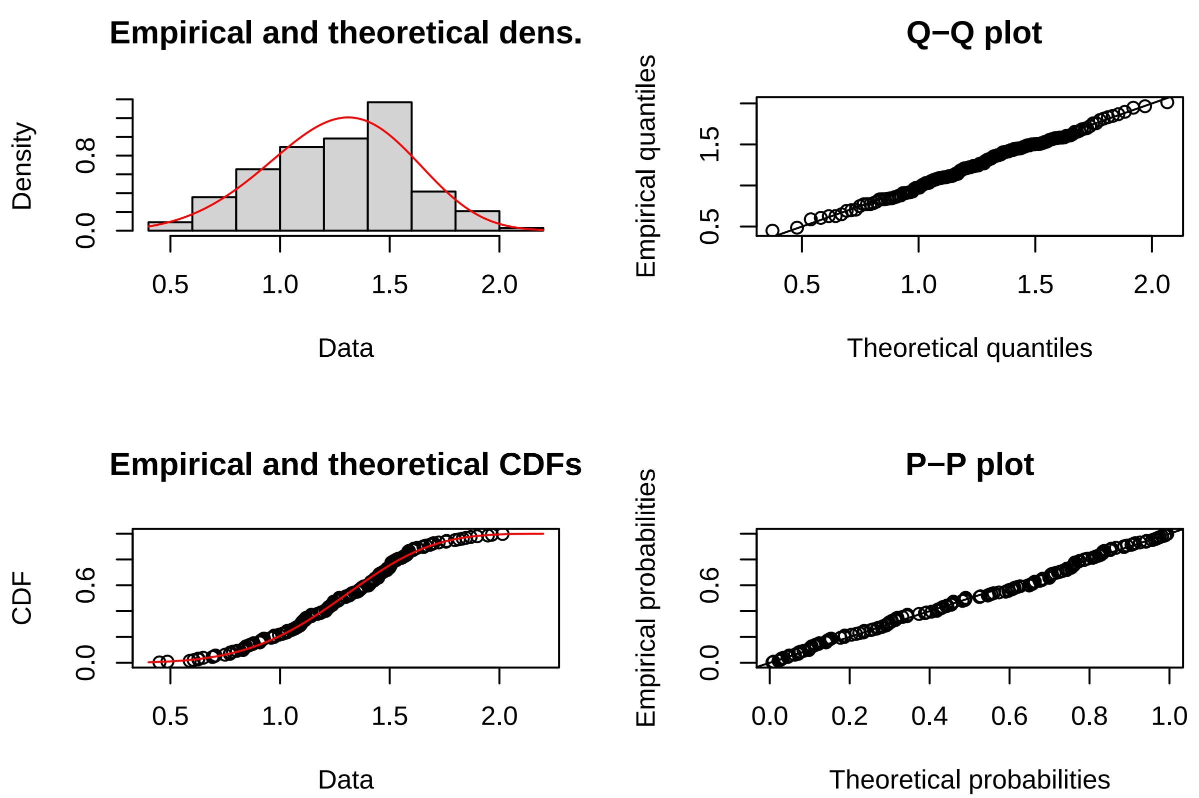



```
## summary statistics
## ------
## min:  0.4501077   max:  2.014592
## median:  1.269487
## mean:  1.264579
## estimated sd:  0.3273682
## estimated skewness:  -0.1779162
## estimated kurtosis:  2.548224
```

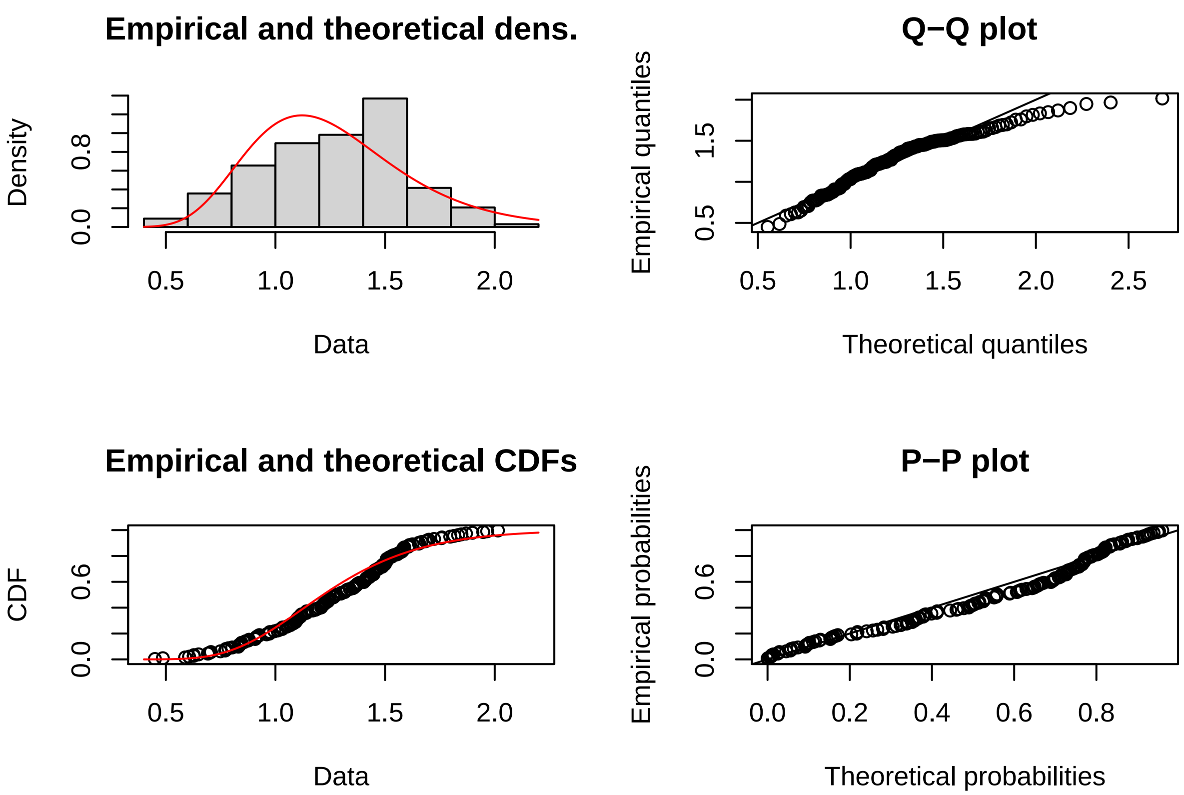
```
# Gamma distribution
fit.gamma <- fitdist(umbs_diversity$shannon, "gamma")
plot(fit.gamma)
```



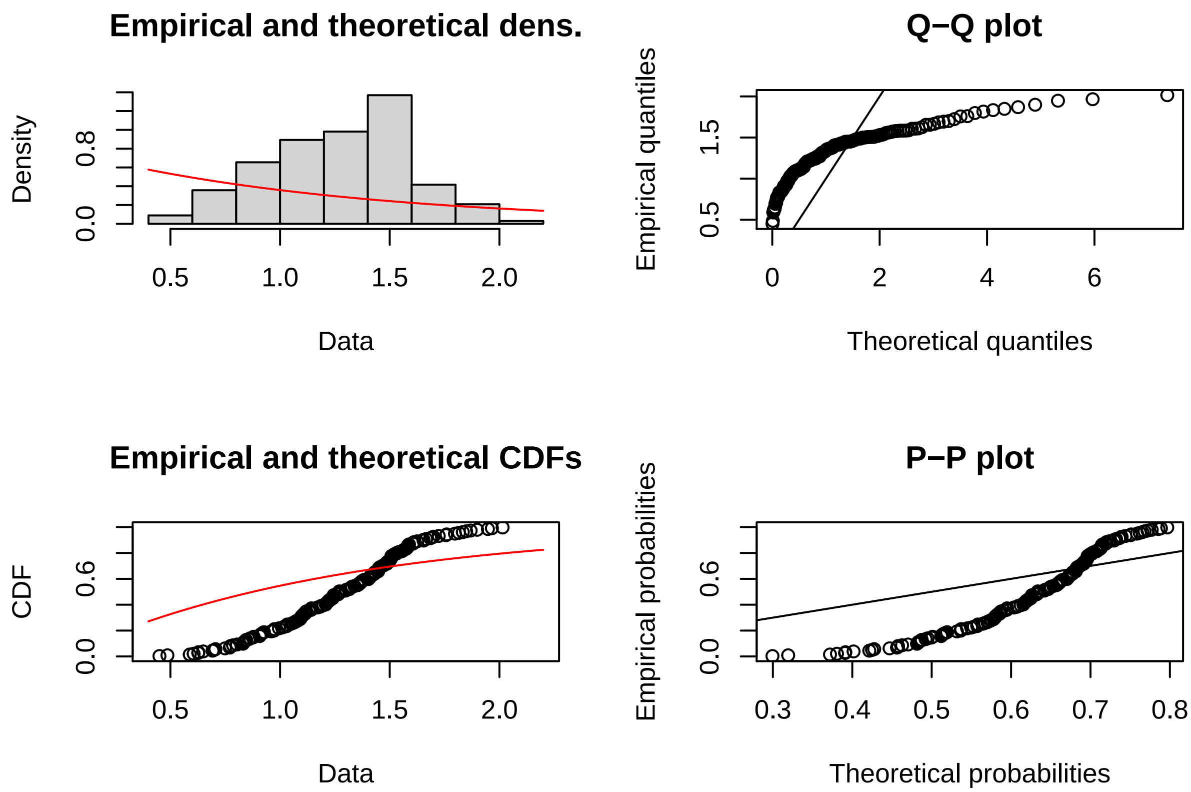

```r
# Weibull distribution
fit.weibull <- fitdist(umbs_diversity$shannon, "weibull")
plot(fit.weibull)
```



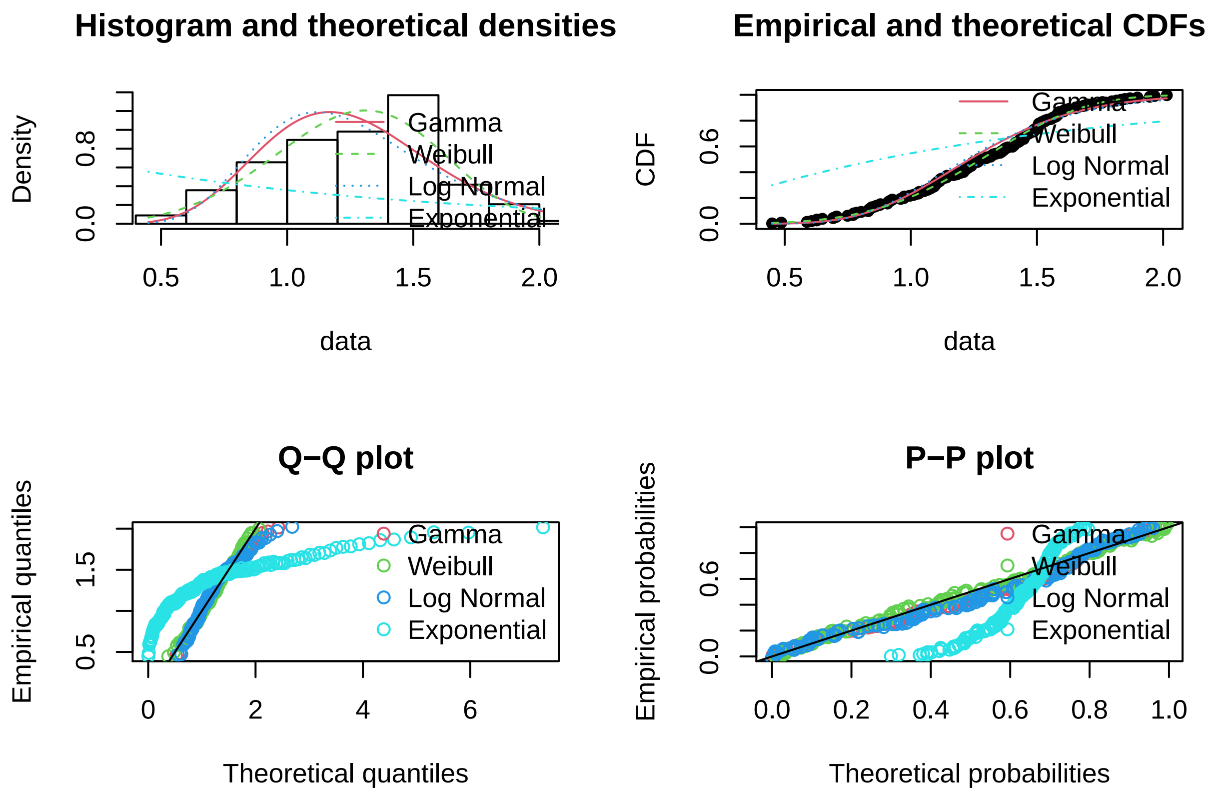
```r
# Lognormal distribution
fit.ln <- fitdist(umbs_diversity$shannon, "lnorm")
plot(fit.ln)
```




```r
# Exponential distribution is another option
fit.exp <- fitdist(umbs_diversity$shannon, "exp")
plot(fit.exp)
```




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



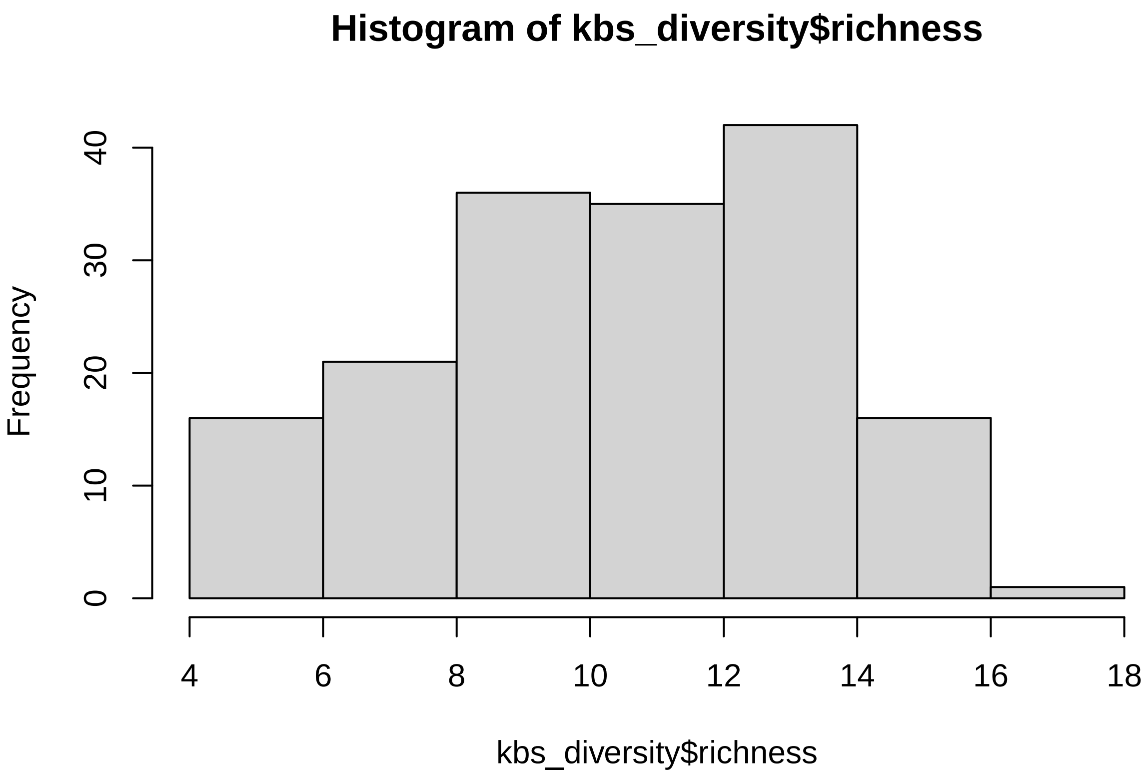

```
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull",
    "Log Normal", "Exp"))
```

```
## Goodness-of-fit statistics
##                                   Gamma    Weibull Log Normal        Exp
## Kolmogorov-Smirnov statistic 0.08782824 0.05392438 0.09595017  0.3908947
## Cramer-von Mises statistic   0.29026235 0.06430453 0.43311966  8.6819449
## Anderson-Darling statistic   1.65928687 0.36756815 2.52777169 42.1398264
##
## Goodness-of-fit criteria
##                                   Gamma  Weibull Log Normal      Exp
## Akaike's Information Criterion 115.9484 101.4268   127.6275 416.8723
## Bayesian Information Criterion 122.1963 107.6748   133.8755 419.9963
```

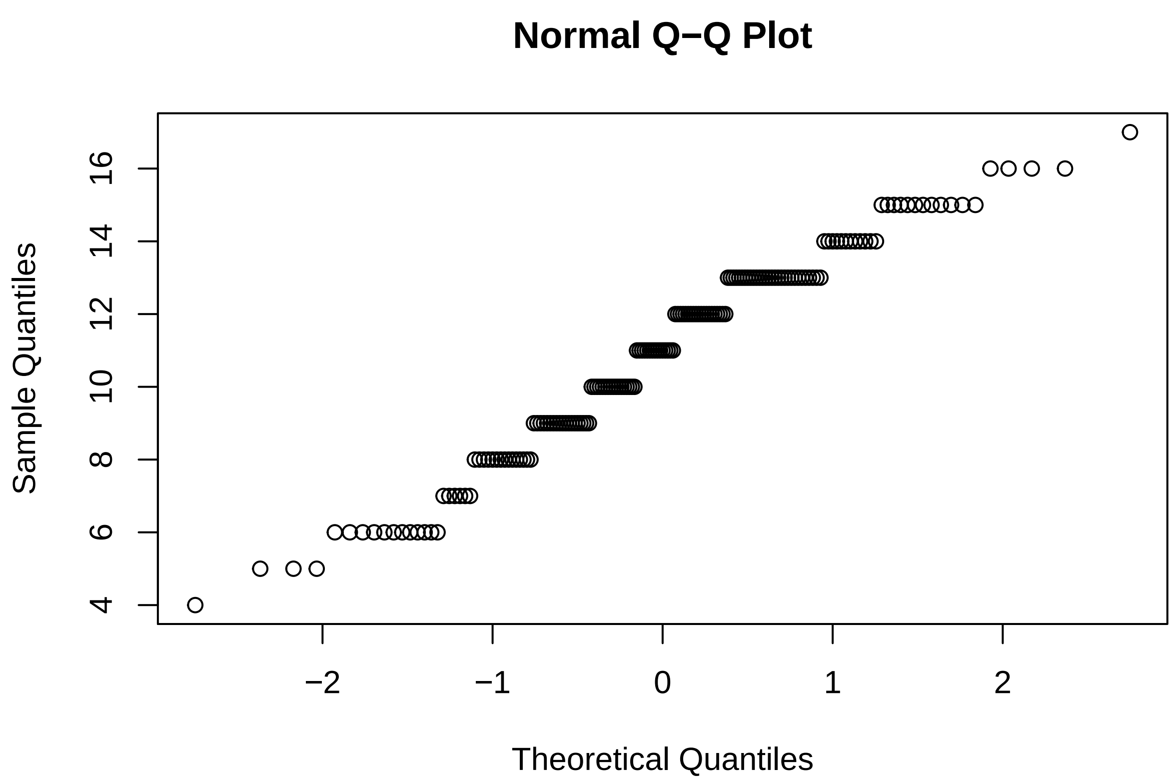
```
# weibull best distributions based on AIC and BIC values
```

Species Richness KBS

```
### KBS ###
hist(kbs_diversity$richness)  # looks pretty good
```



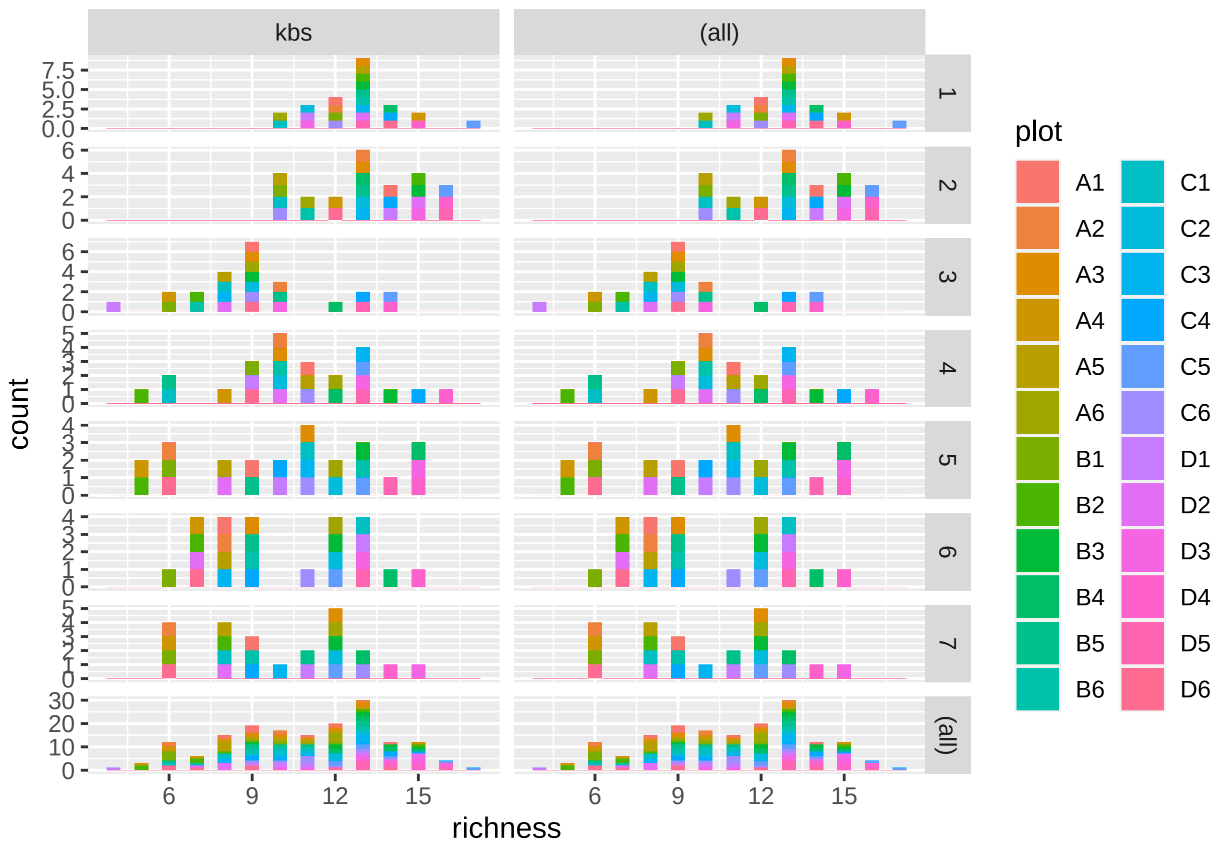

```
qqnorm(kbs_diversity$richness)
```



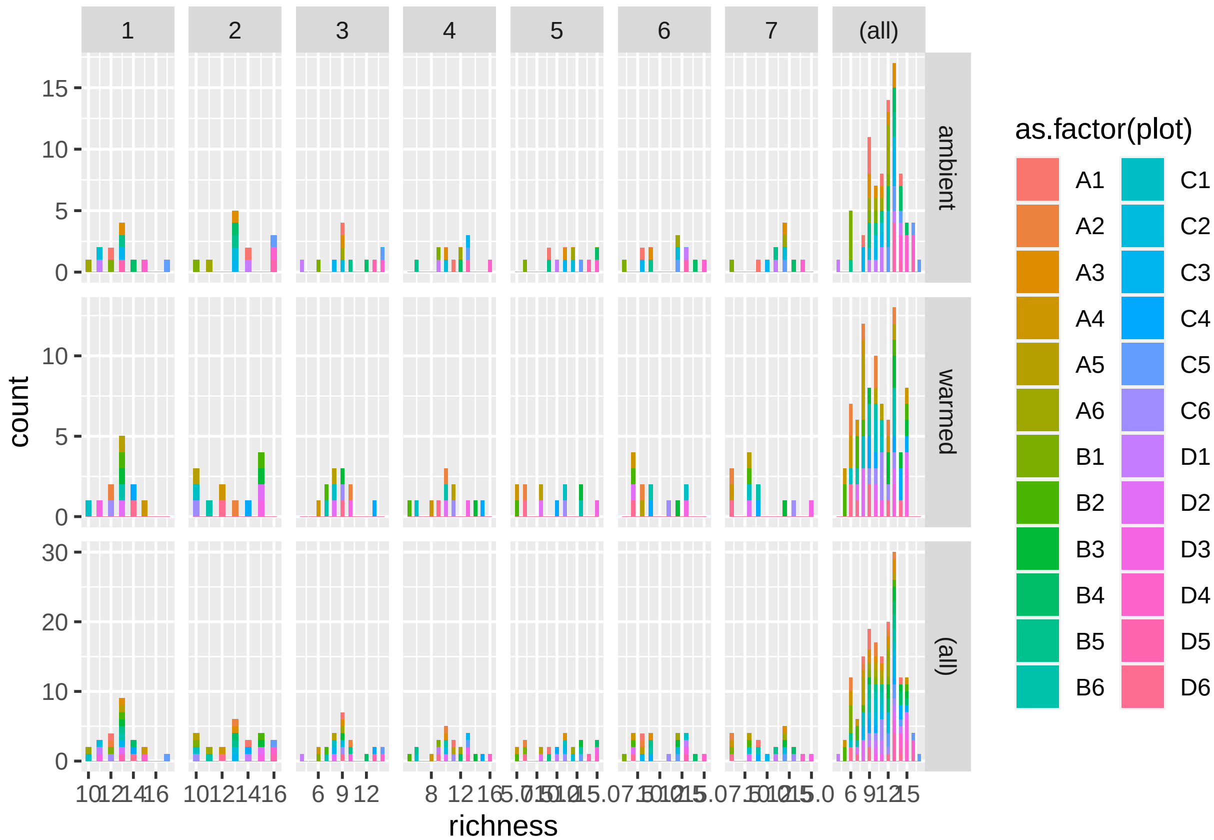
```r
shapiro.test(kbs_diversity$richness)  # pvalue is < 0.05 so we reject the null hypothesis that the data
```

```
##
##  Shapiro-Wilk normality test
##
## data:  kbs_diversity$richness
## W = 0.96791, p-value = 0.0006545
```

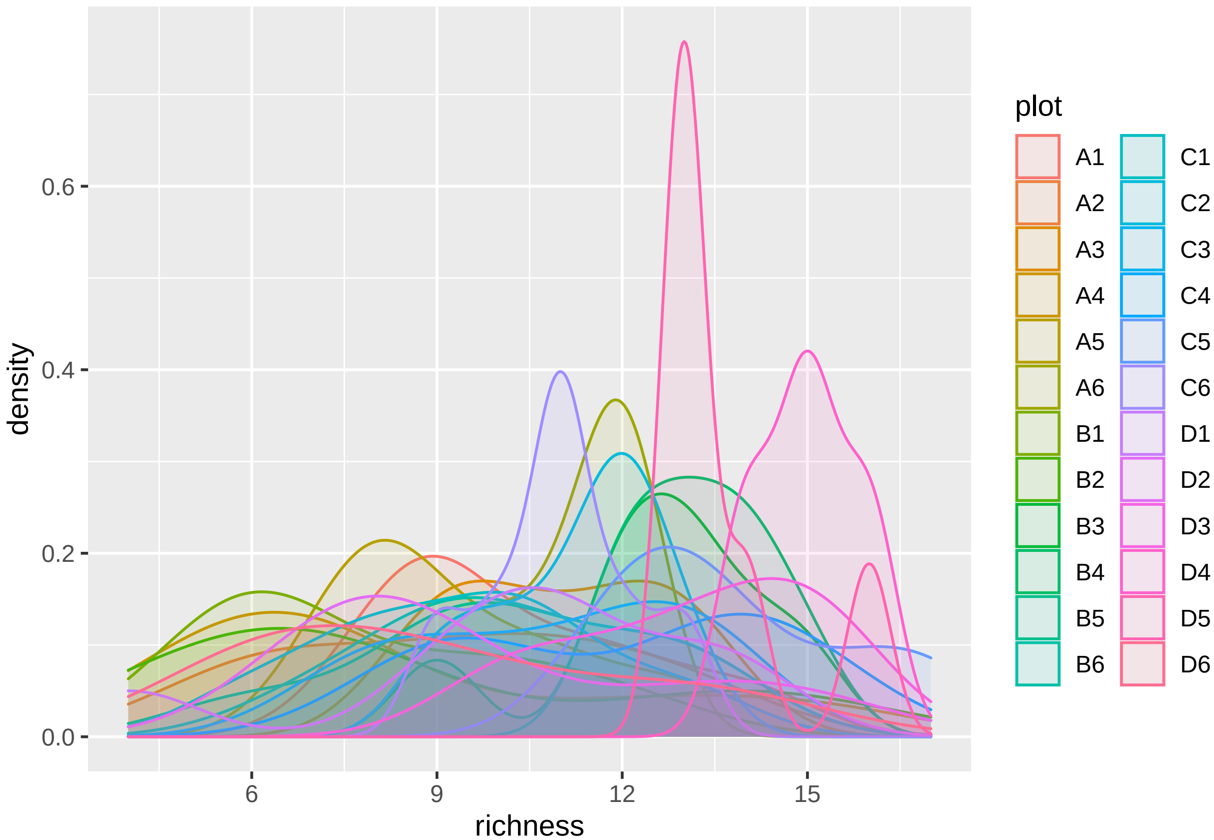
```r
# Visualizing plot average totals for kbs at the PLOT LEVEL
ggplot(kbs_diversity, aes(richness, fill = plot)) + geom_histogram(binwidth = 0.5) +
    facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



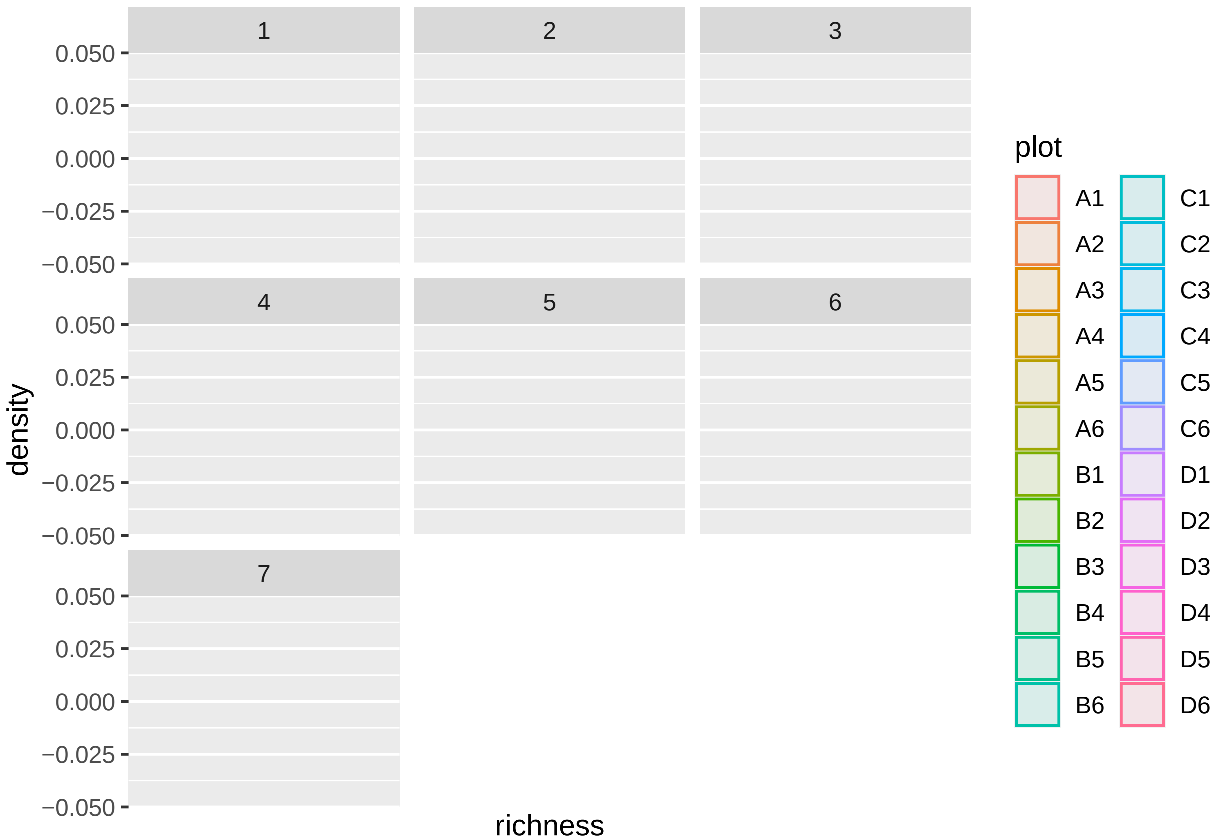

```r
ggplot(kbs_diversity, aes(richness, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
    facet_grid(state ~ year_factor, margins = TRUE, scales = "free")
```



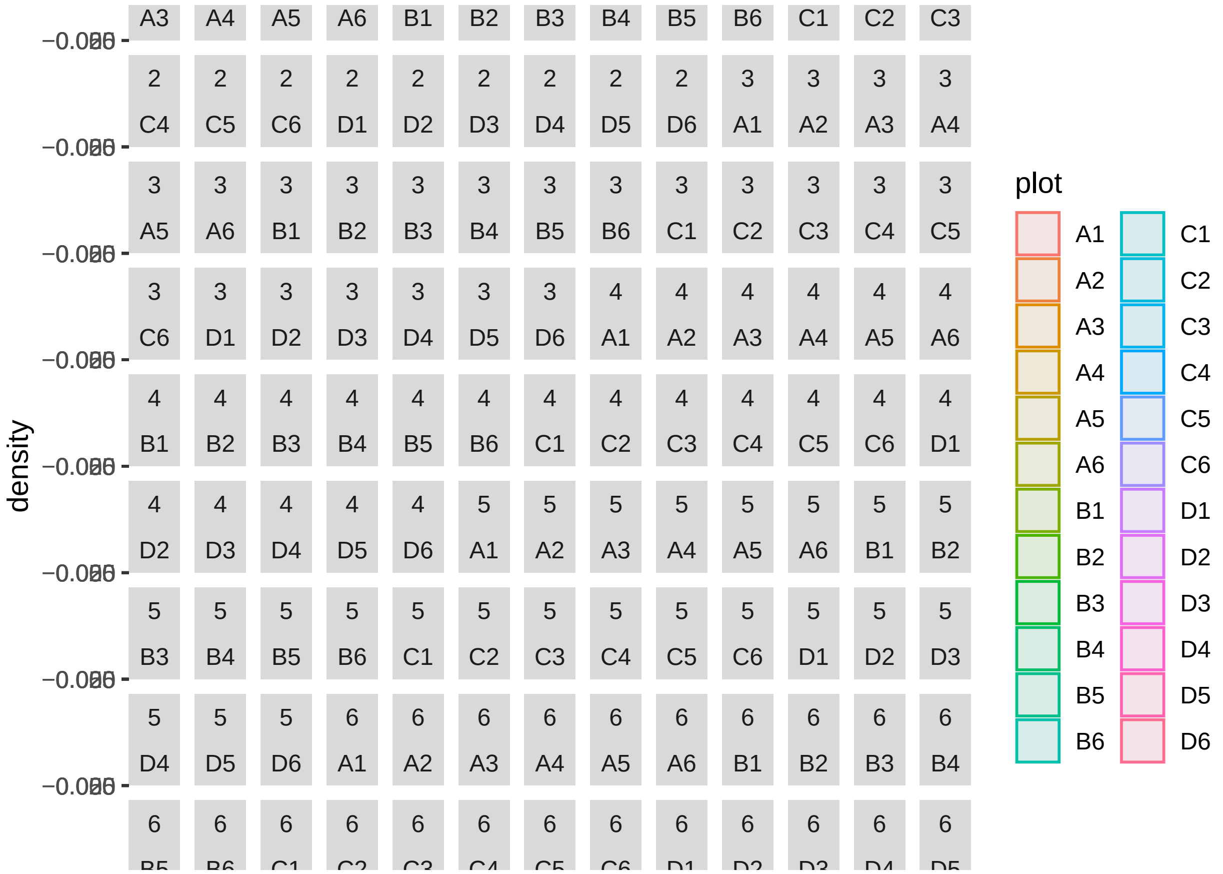

```r
ggplot(kbs_diversity, aes(richness, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



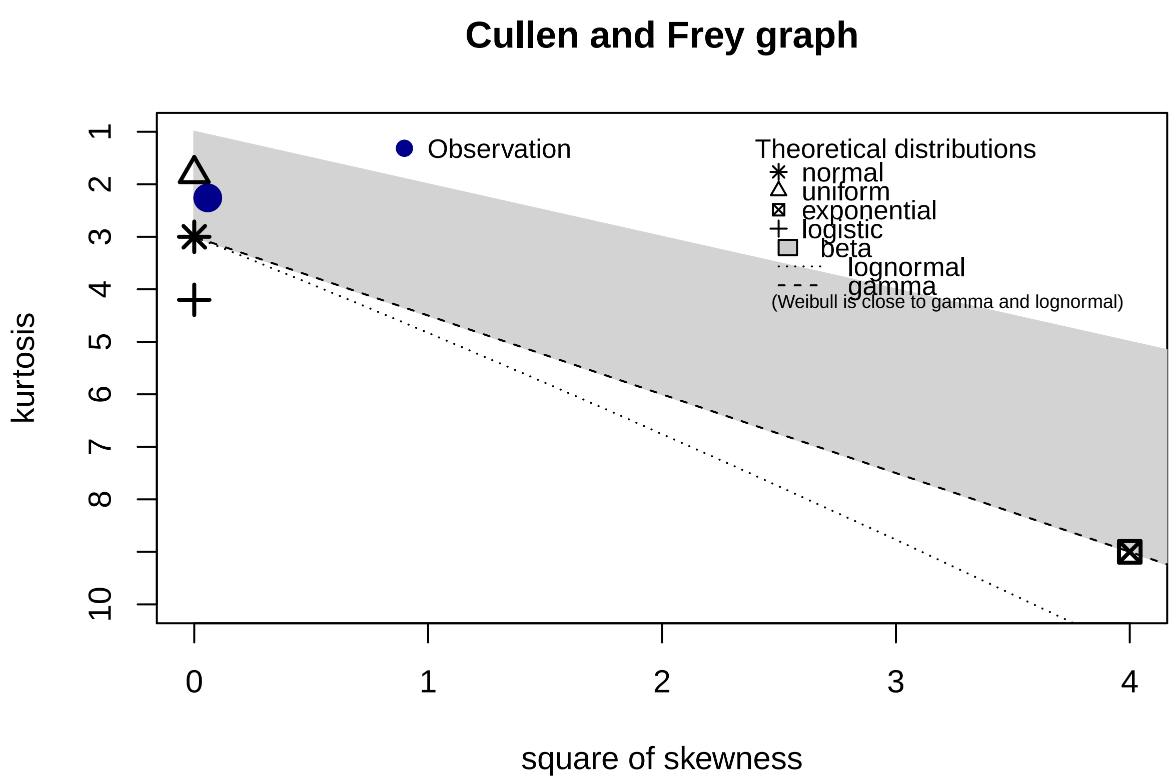

```
ggplot(kbs_diversity, aes(richness, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
    facet_wrap(~year_factor)
```




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

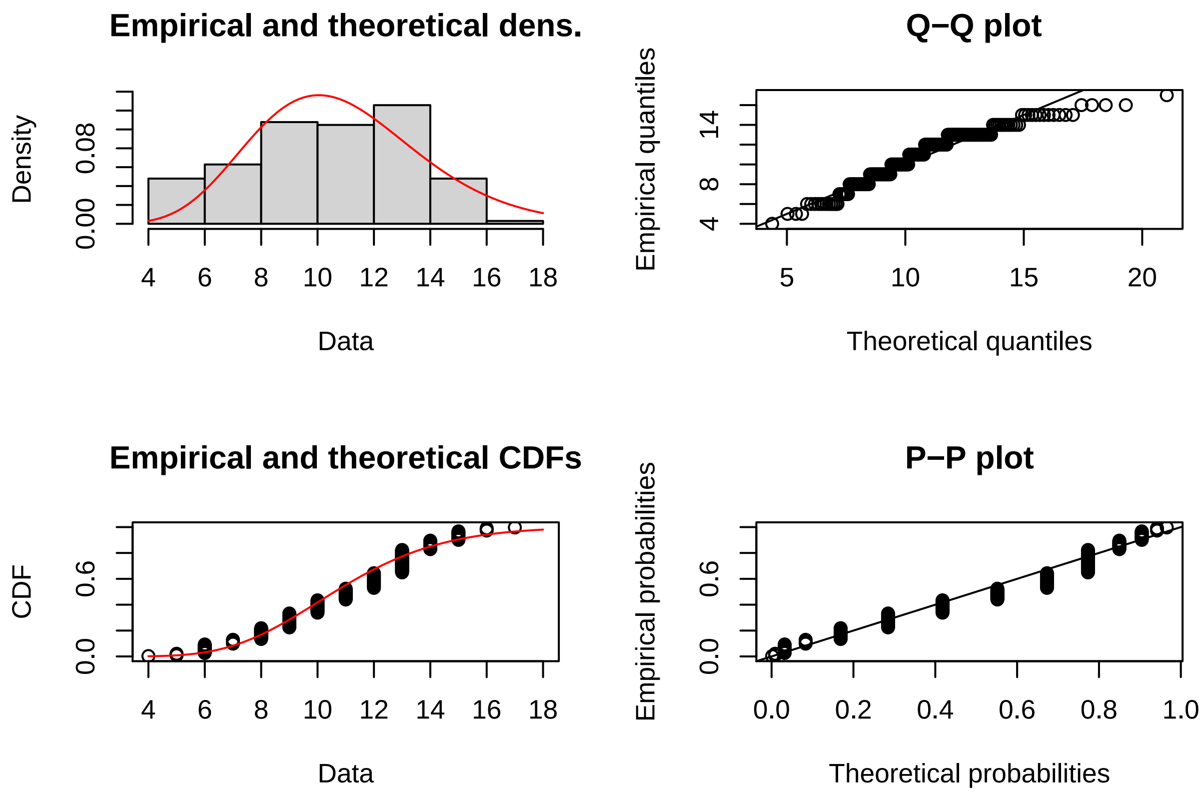



```r
# Exploring distributions for these right-skewed data:
descdist(kbs_diversity$richness, discrete = FALSE)
```

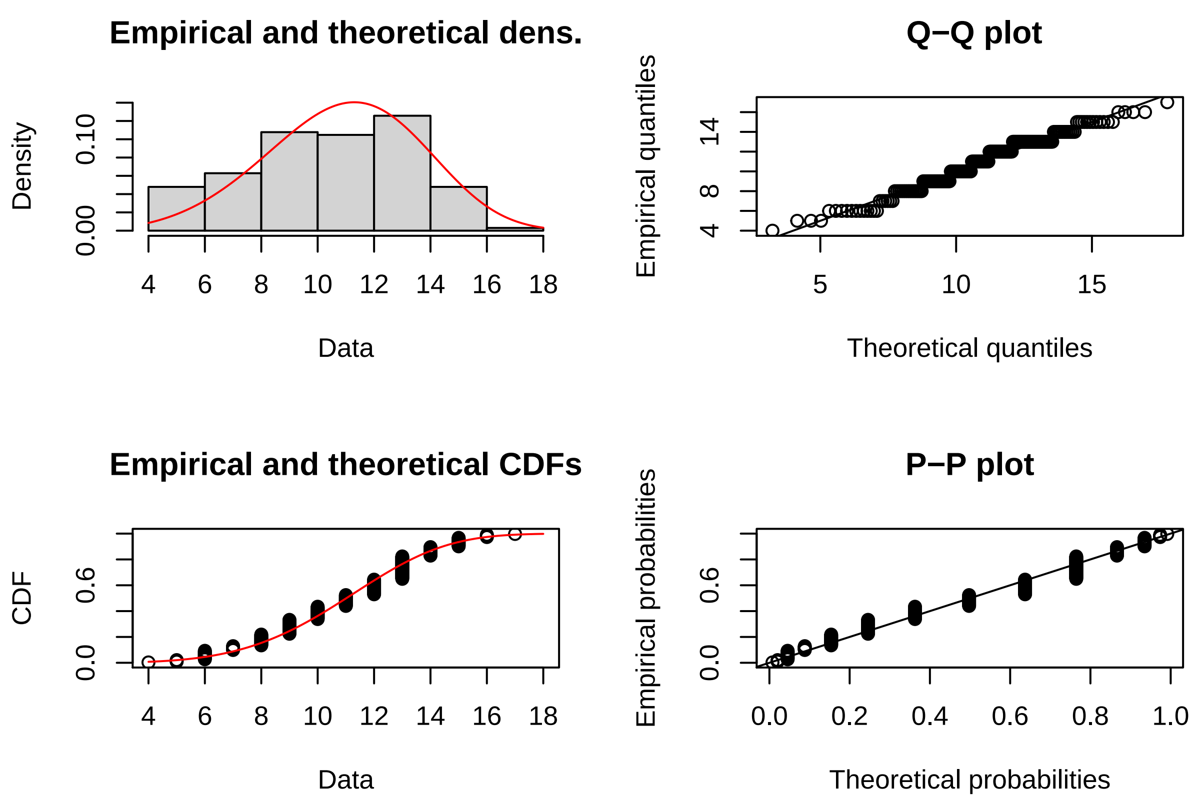



```
## summary statistics
## ------
## min:  4   max:  17
## median:  11
## mean:  10.88623
## estimated sd:  2.856865
## estimated skewness:  -0.2401328
## estimated kurtosis:  2.258876
```

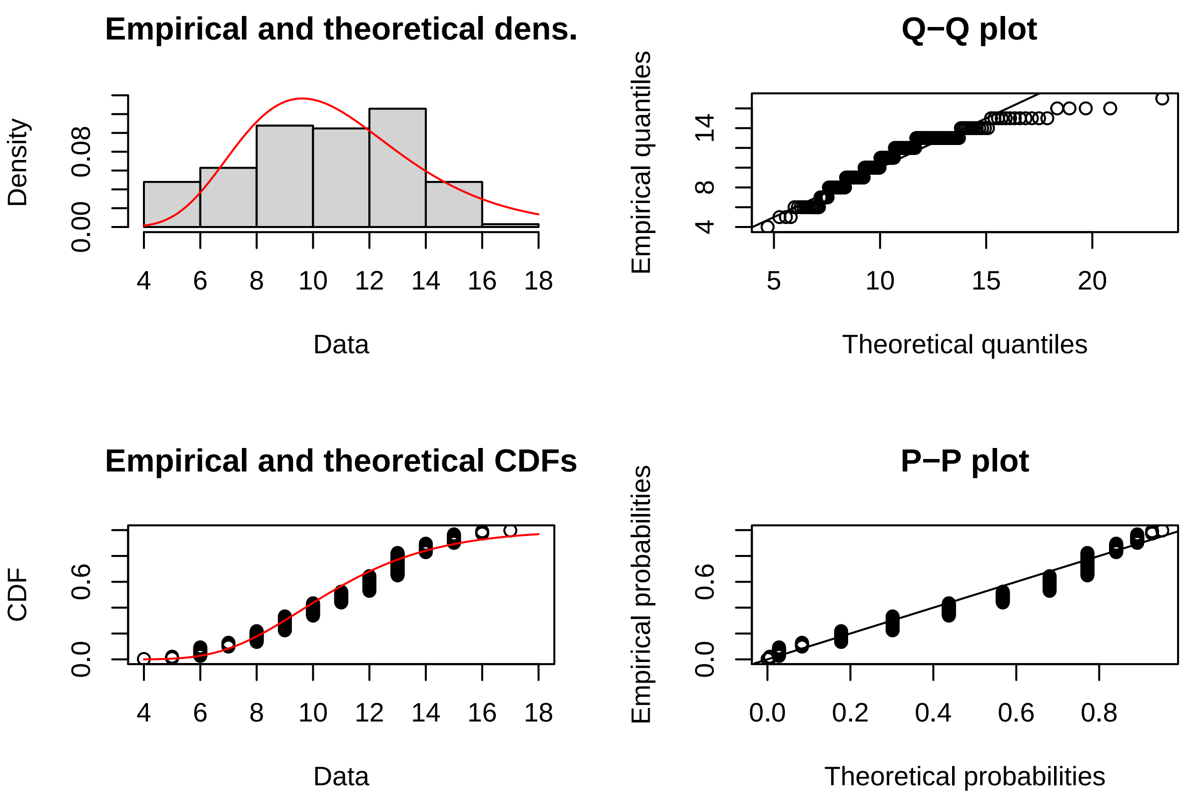
```
# Gamma distribution
fit.gamma <- fitdist(kbs_diversity$richness, "gamma")
plot(fit.gamma)
```



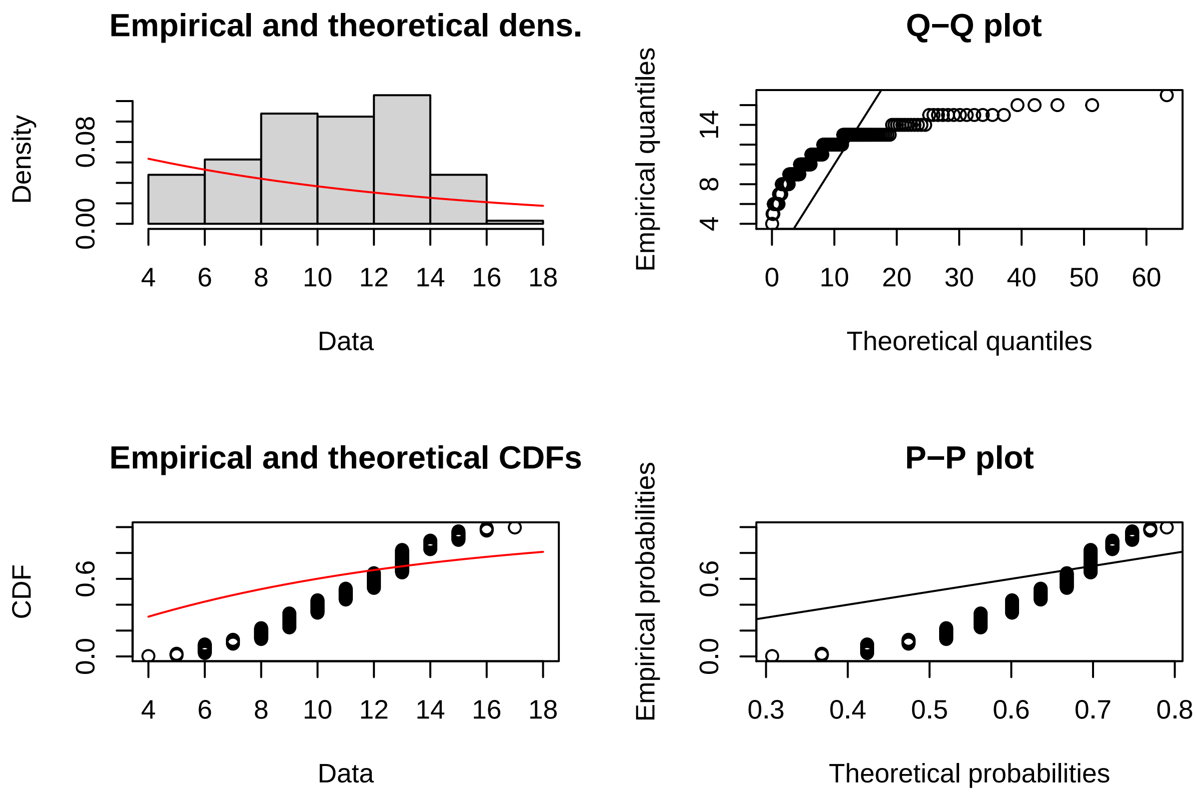

```r
# Weibull distribution
fit.weibull <- fitdist(kbs_diversity$richness, "weibull")
plot(fit.weibull)
```



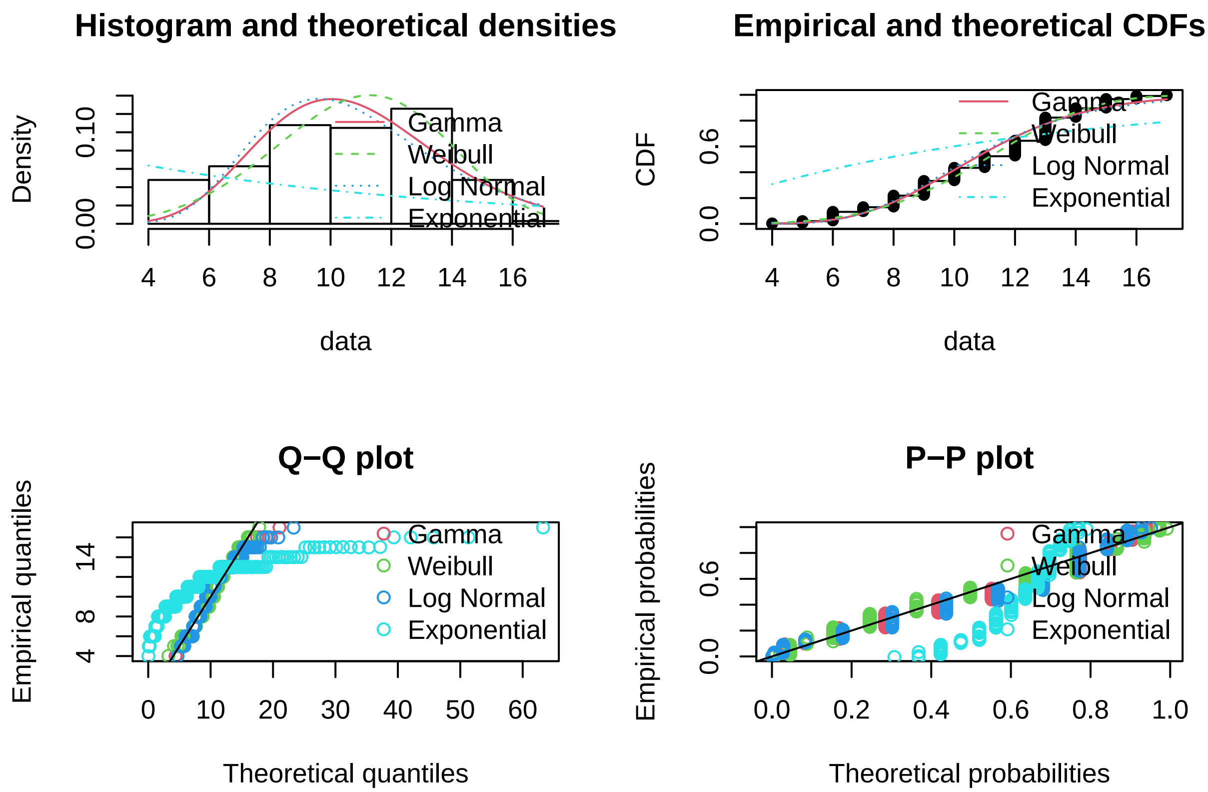
```
# Lognormal distribution
fit.ln <- fitdist(kbs_diversity$richness, "lnorm")
plot(fit.ln)
```




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




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



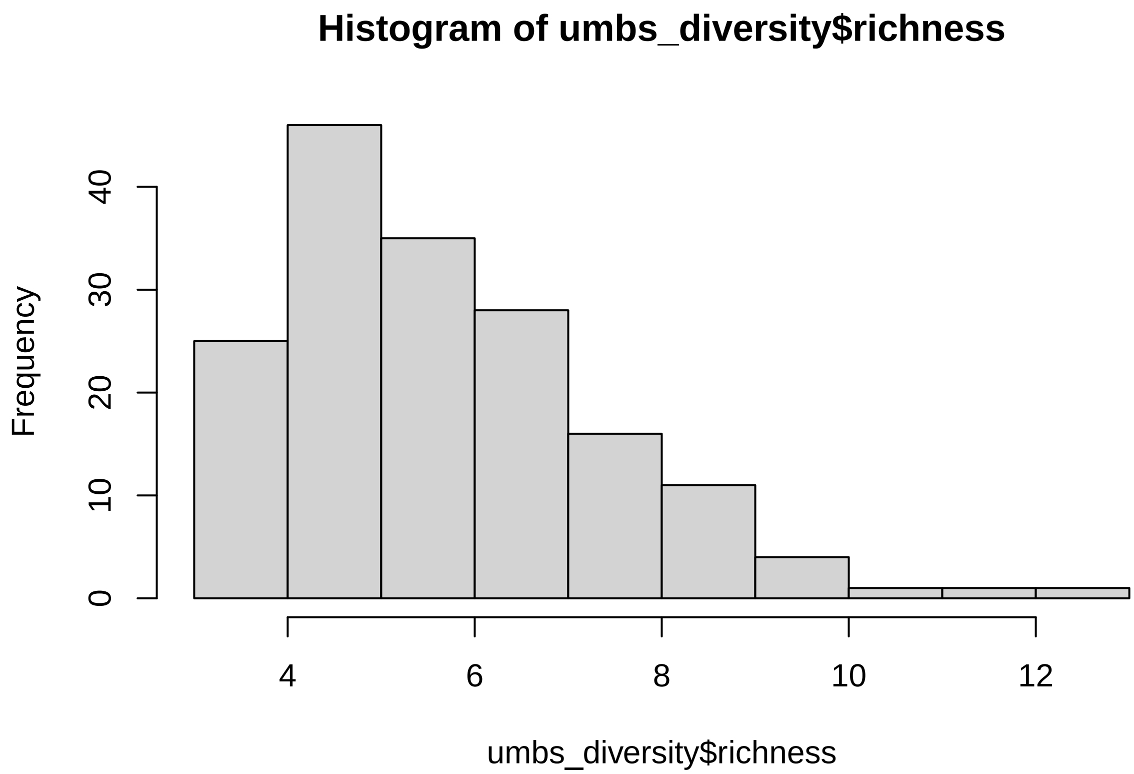

```r
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull",
    "Log Normal", "Exp"))
```

```
## Goodness-of-fit statistics
##                                  Gamma   Weibull Log Normal        Exp
## Kolmogorov-Smirnov statistic 0.1460555 0.1179610  0.1535637  0.3997642
## Cramer-von Mises statistic   0.4914279 0.2986025  0.6125018  8.5046594
## Anderson-Darling statistic   2.9681463 1.7301320  3.7637821 41.4413599
##
## Goodness-of-fit criteria
##                                   Gamma  Weibull Log Normal      Exp
## Akaike's Information Criterion 838.9661 822.2434   850.0313 1133.424
## Bayesian Information Criterion 845.2021 828.4794   856.2673 1136.542
```

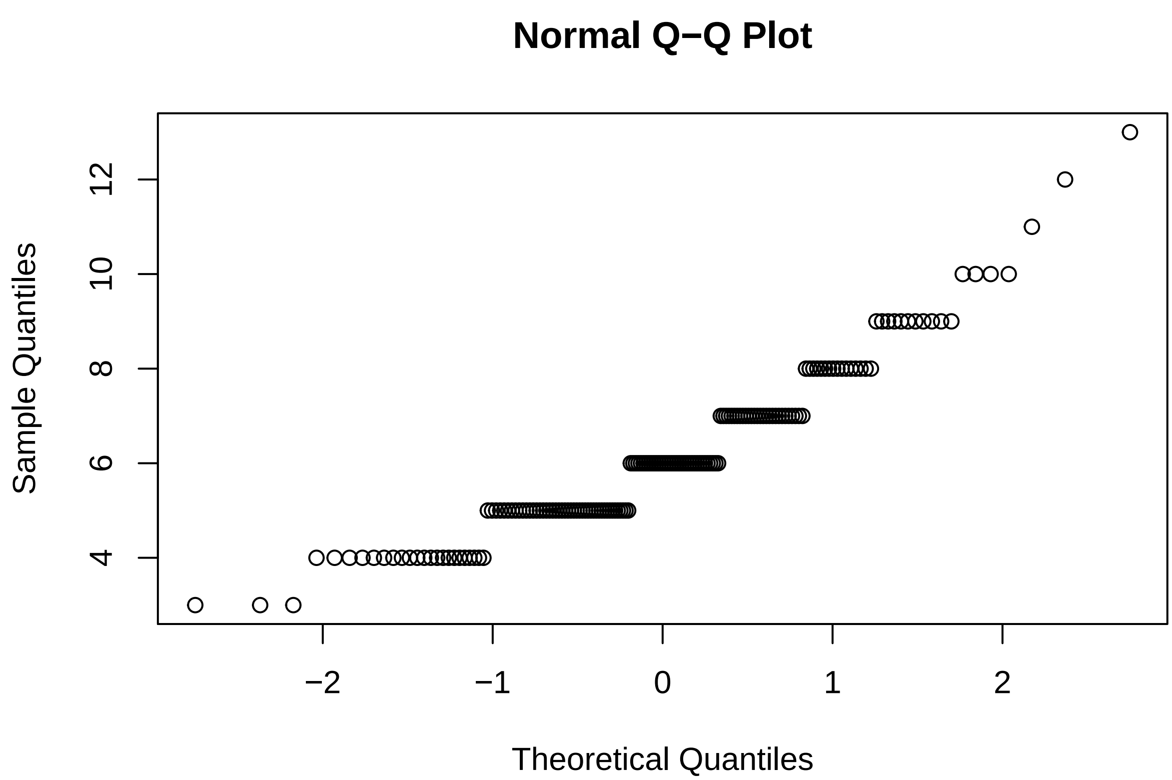
```r
# weibull distribution looks to be the best based on AIC and BIC values
```

UMBS

```r
### UMBS ###
hist(umbs_diversity$richness)  # skewed to the right
```



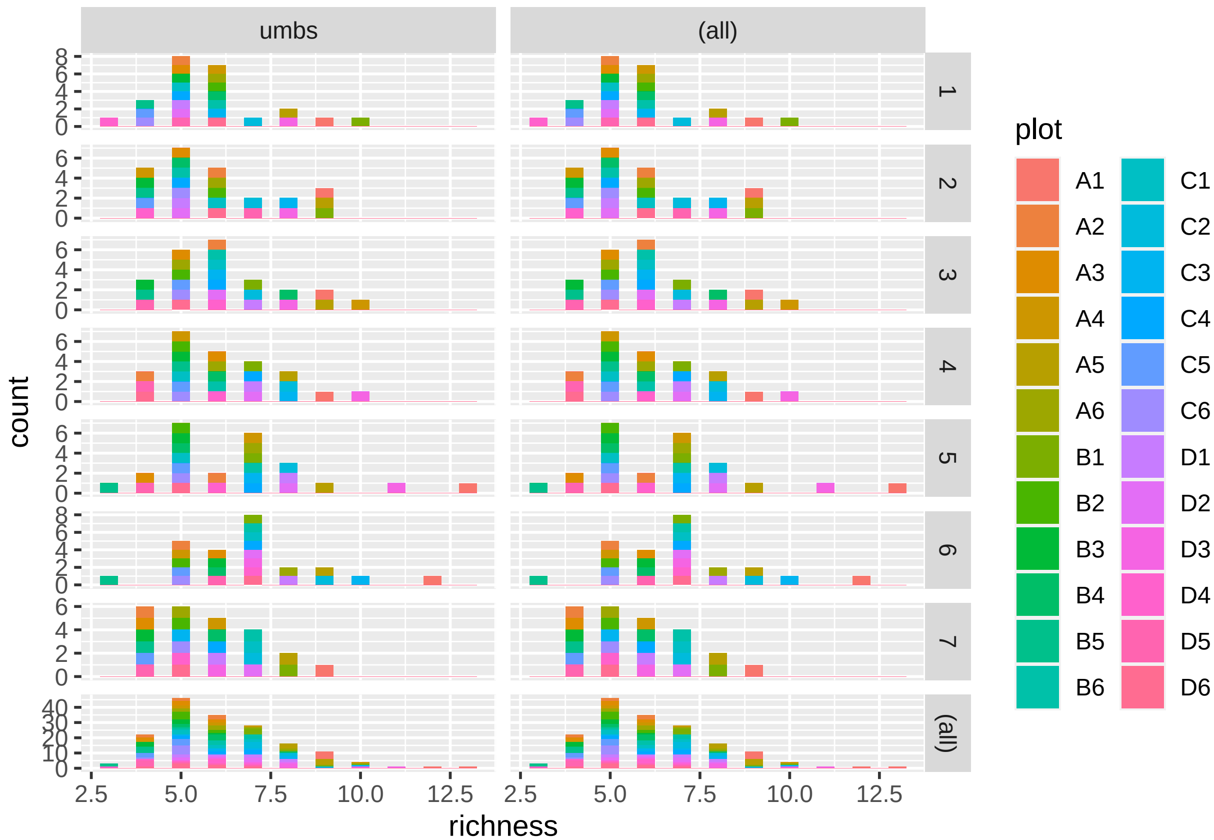

```r
qqnorm(umbs_diversity$richness)
```



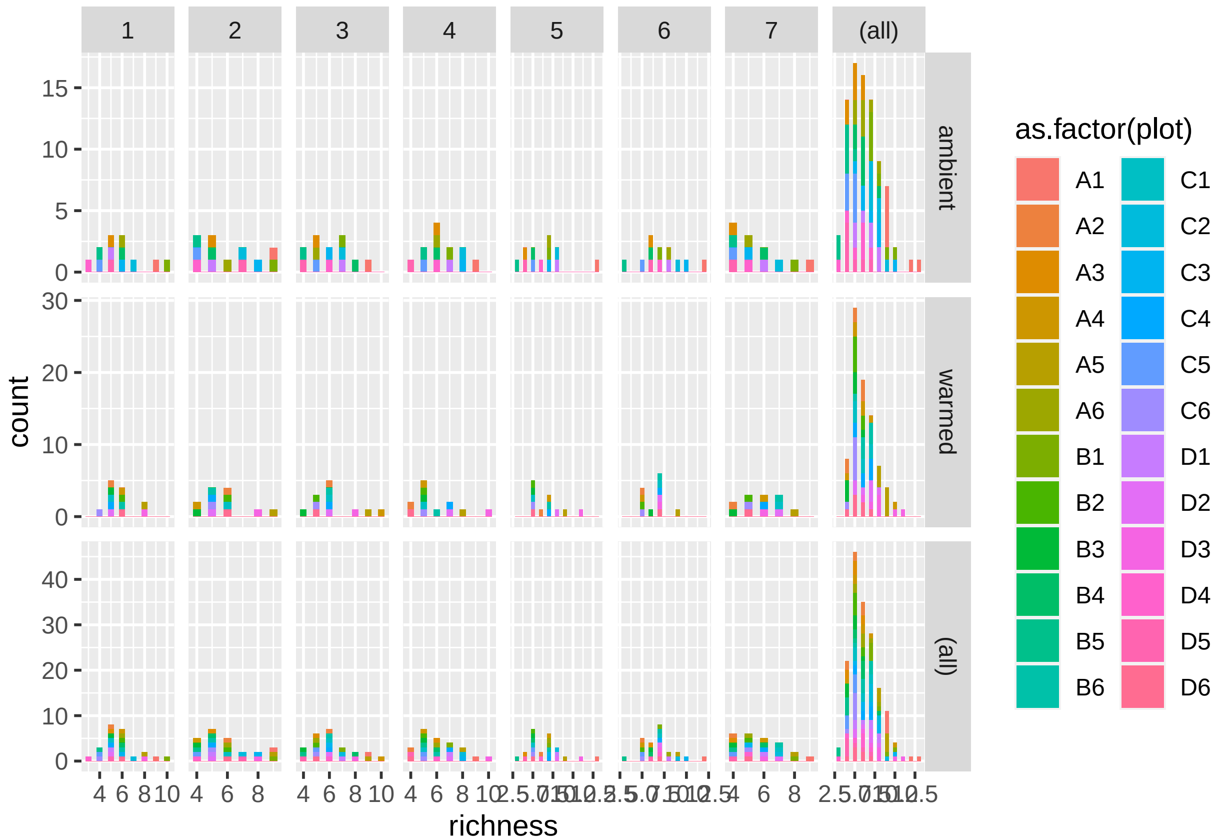
```r
shapiro.test(umbs_diversity$richness)  # pvalue is < 0.05 so we reject the null hypothesis that the dat
```

```
##
##  Shapiro-Wilk normality test
##
## data:  umbs_diversity$richness
## W = 0.92384, p-value = 1.009e-07
```

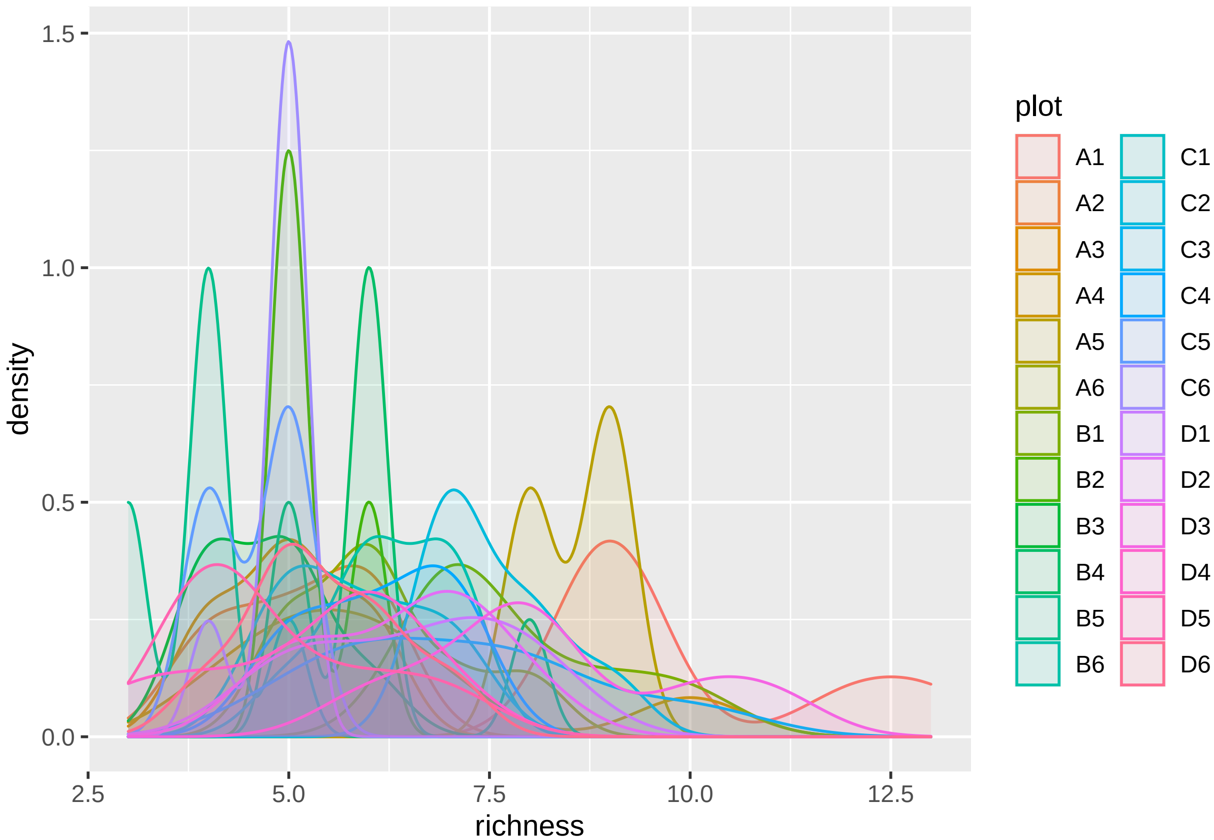
```r
# Visualizing plot average totals for umbs at the PLOT LEVEL
ggplot(umbs_diversity, aes(richness, fill = plot)) + geom_histogram(binwidth = 0.5) +
    facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



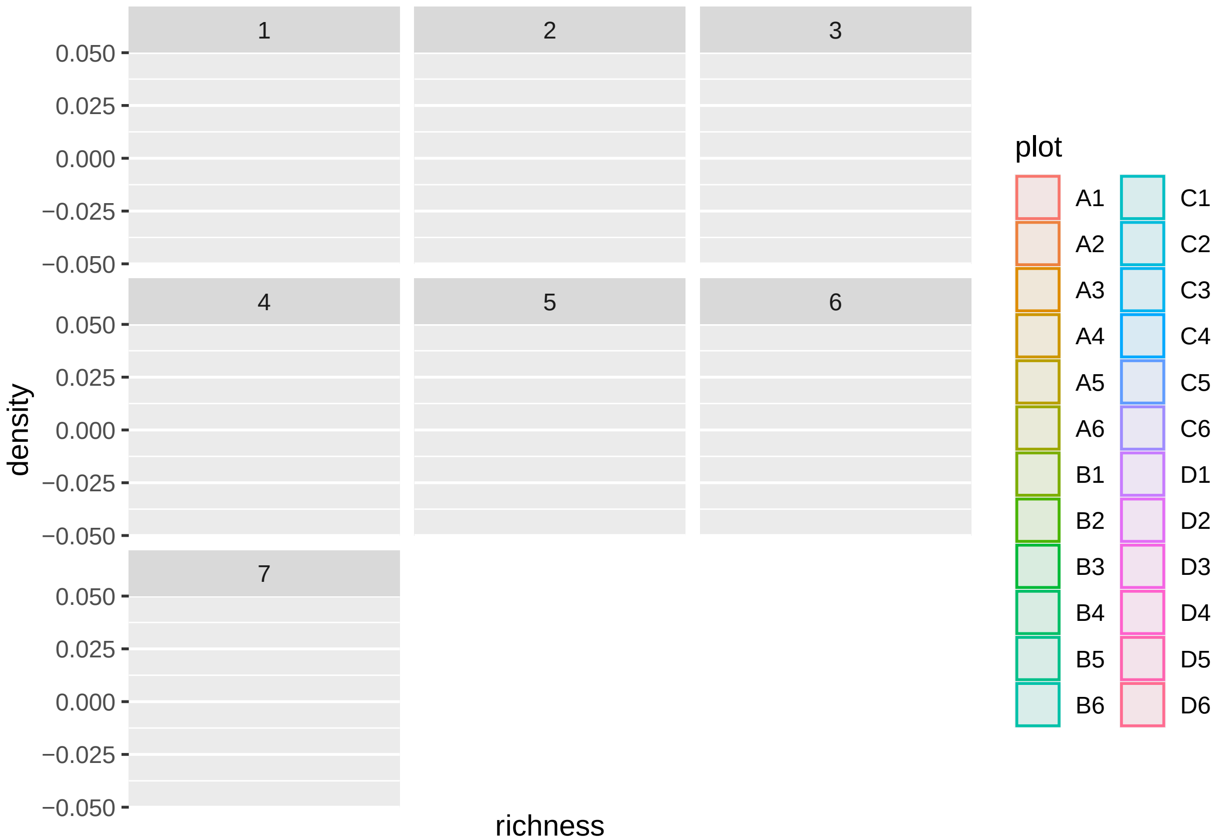

```r
ggplot(umbs_diversity, aes(richness, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
    facet_grid(state ~ year_factor, margins = TRUE, scales = "free")
```



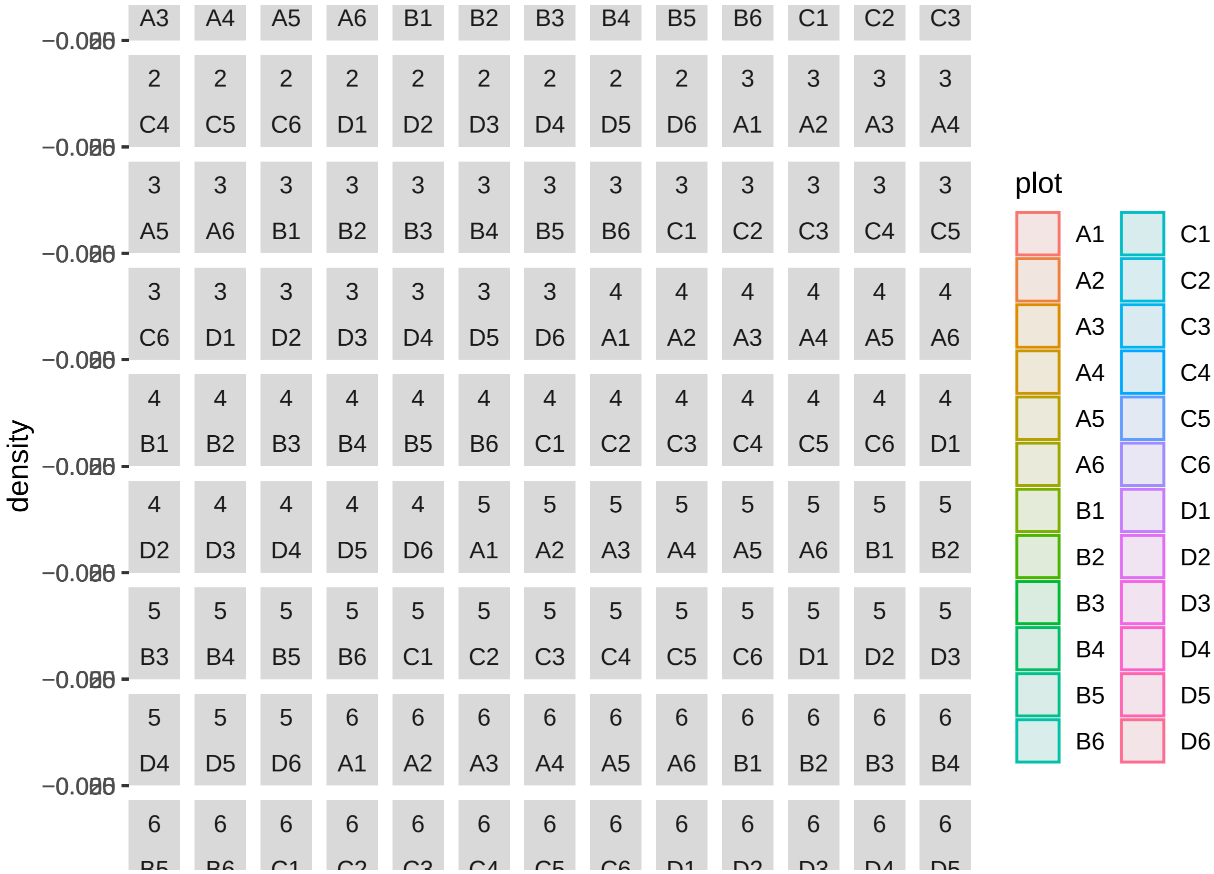

```
ggplot(umbs_diversity, aes(richness, fill = plot, color = plot)) + geom_density(alpha = 0.1)
```



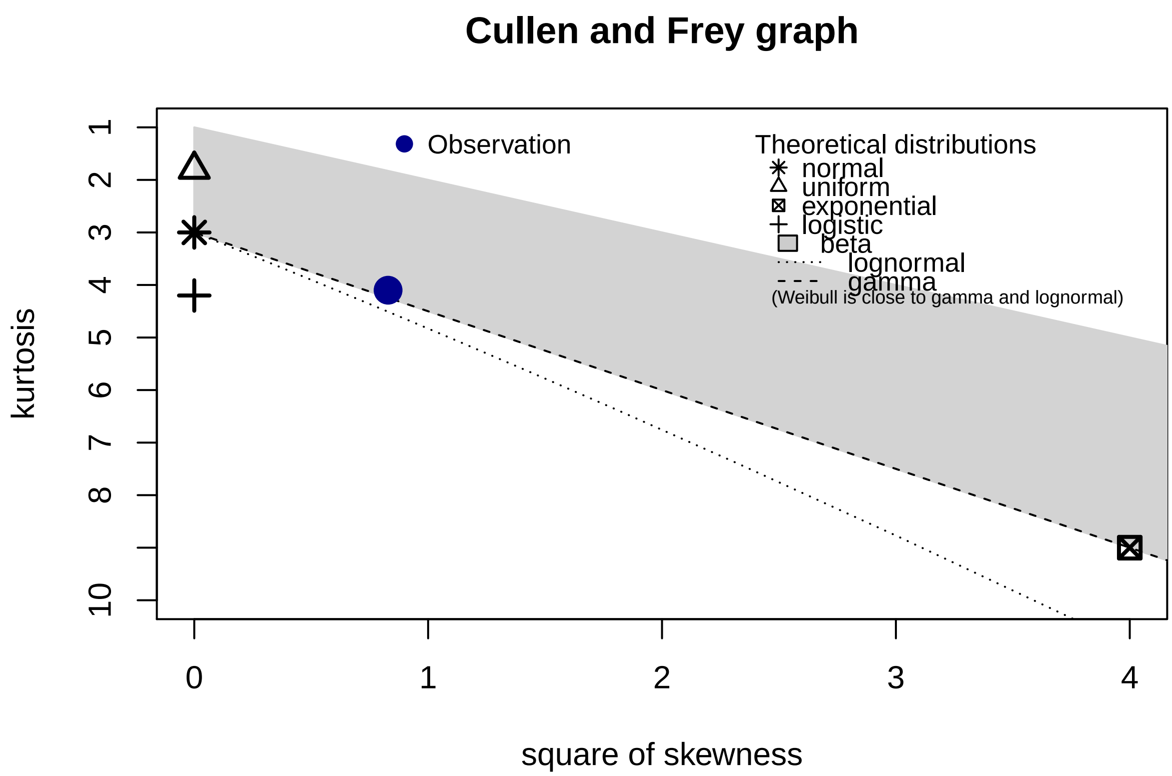

```
ggplot(umbs_diversity, aes(richness, fill = plot, color = plot)) + geom_density(alpha = 0.1) +
    facet_wrap(~year_factor)
```




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

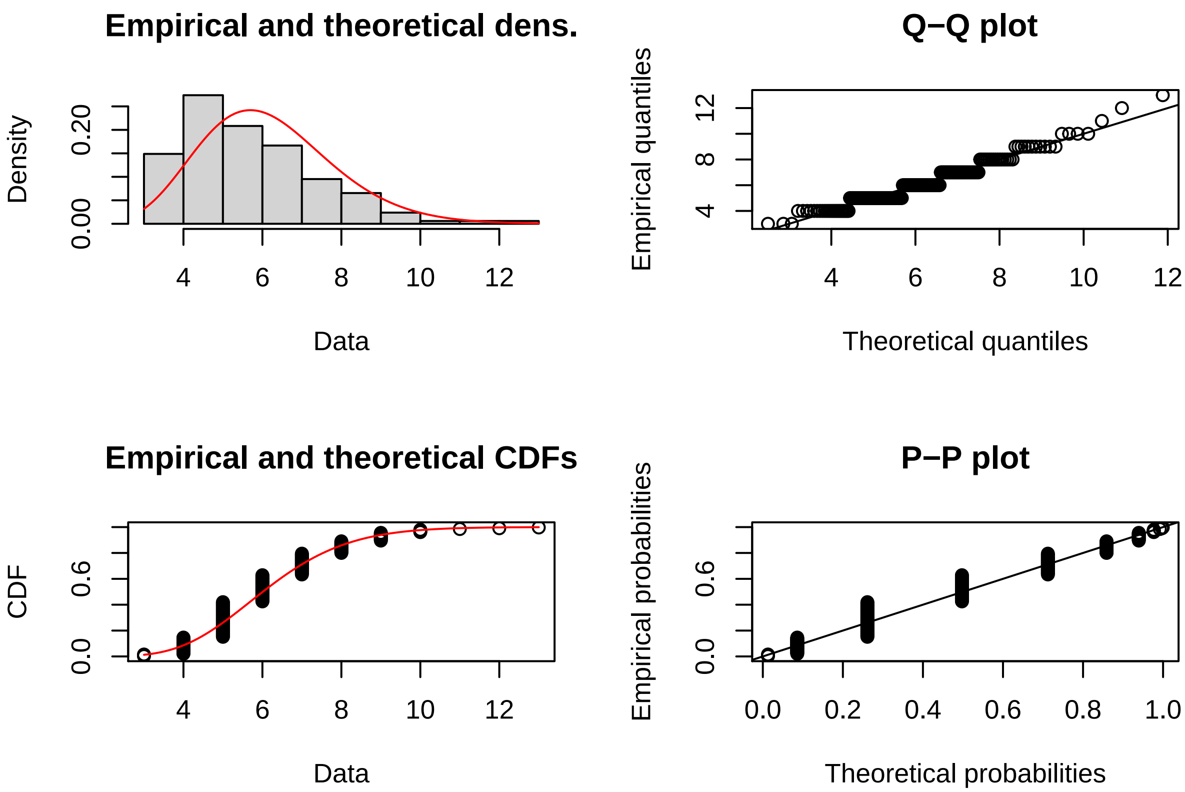



```r
# Exploring distributions for these right-skewed data:
descdist(umbs_diversity$richness, discrete = FALSE)
```

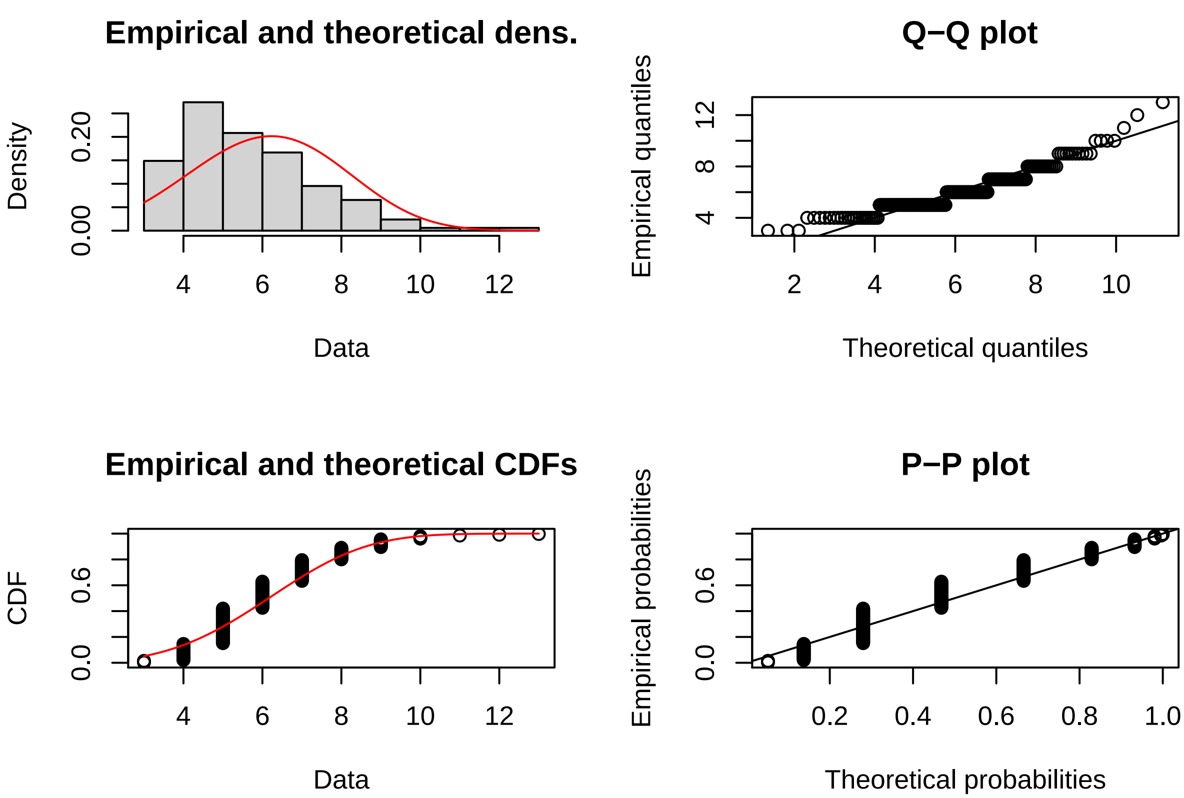



```
## summary statistics
## ------
## min:  3   max:  13
## median:  6
## mean:  6.166667
## estimated sd:  1.766849
## estimated skewness:  0.9103488
## estimated kurtosis:  4.09977
```

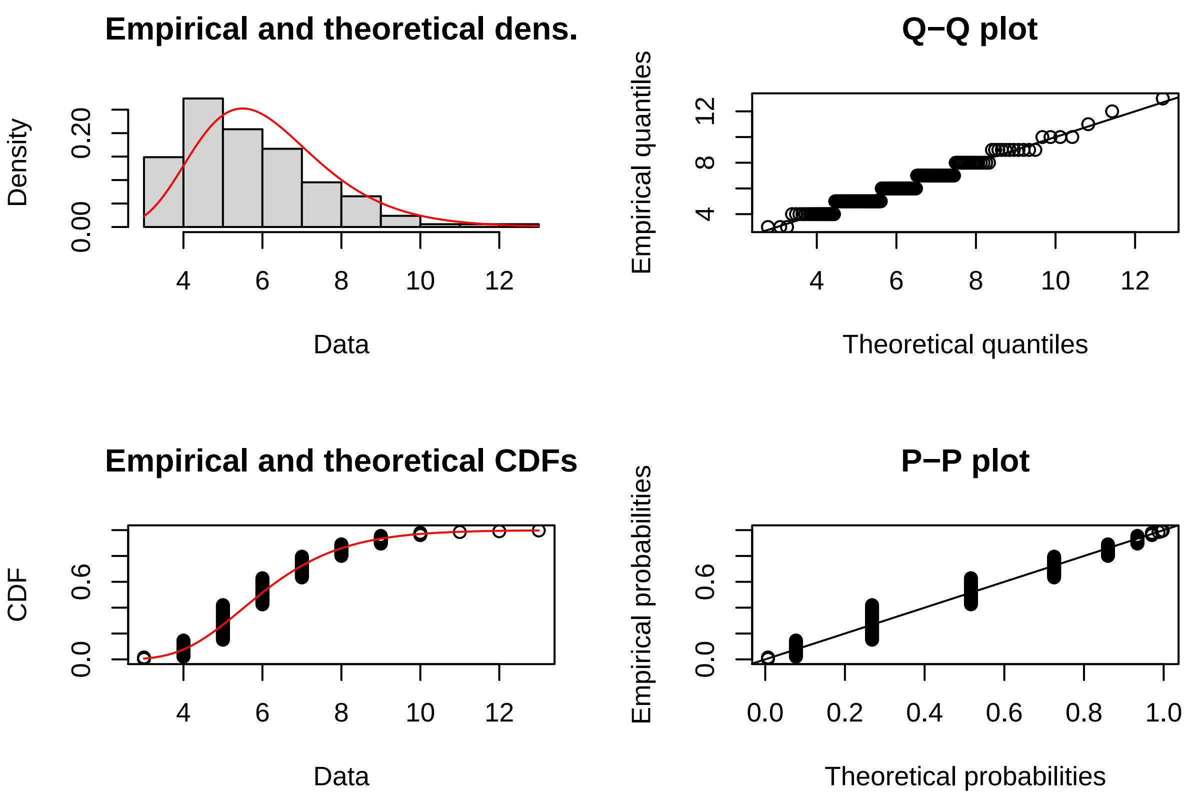
```
# Gamma distribution
fit.gamma <- fitdist(umbs_diversity$richness, "gamma")
plot(fit.gamma)
```



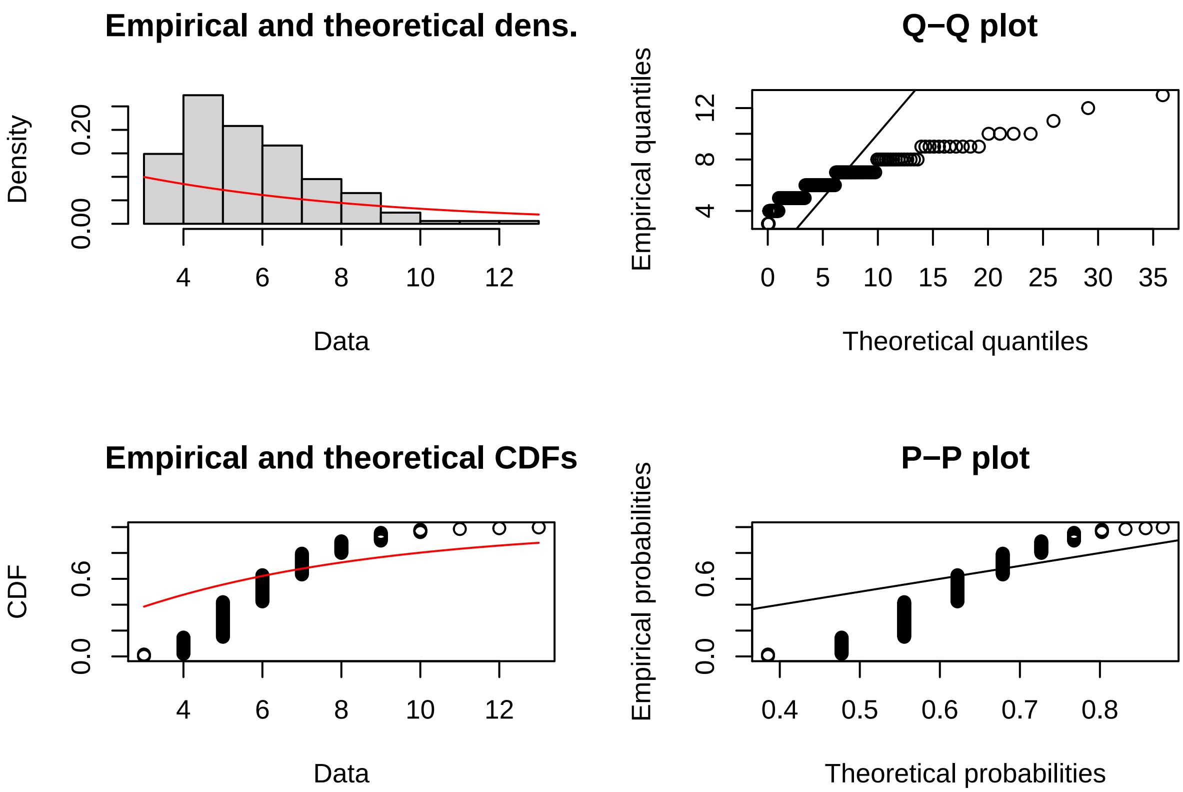

```r
# Weibull distribution
fit.weibull <- fitdist(umbs_diversity$richness, "weibull")
plot(fit.weibull)
```



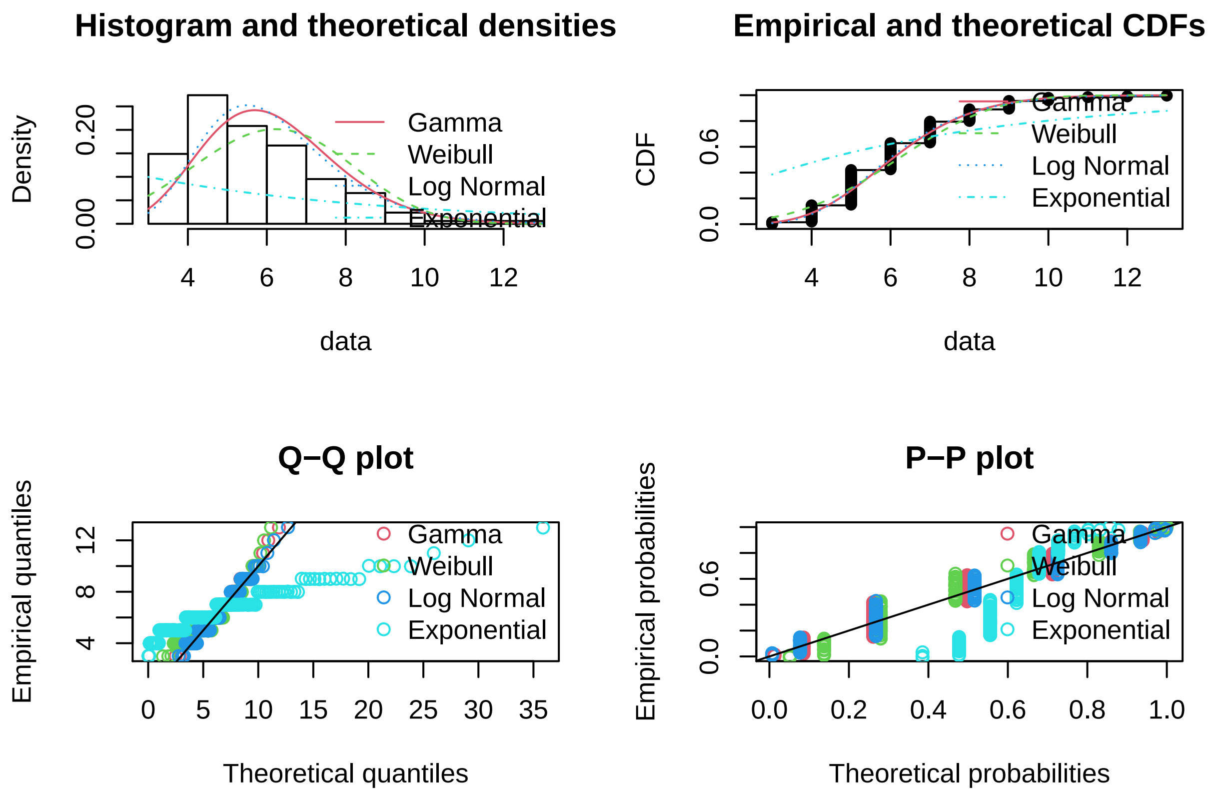
```r
# Lognormal distribution
fit.ln <- fitdist(umbs_diversity$richness, "lnorm")
plot(fit.ln)
```




```r
# Exponential distribution is another option
fit.exp <- fitdist(umbs_diversity$richness, "exp")
plot(fit.exp)
```




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




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

```
## Goodness-of-fit statistics
##                                  Gamma   Weibull Log Normal        Exp
## Kolmogorov-Smirnov statistic 0.1614184 0.1629549  0.1544784  0.4593911
## Cramer-von Mises statistic   0.5898290 0.7901708  0.5531209  8.7336038
## Anderson-Darling statistic   3.2245464 4.5846350  3.0351228 41.9122865
##
## Goodness-of-fit criteria
##                                   Gamma  Weibull Log Normal      Exp
## Akaike's Information Criterion 651.1049 678.0539   647.1918 949.2372
## Bayesian Information Criterion 657.3528 684.3019   653.4397 952.3612
```

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

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

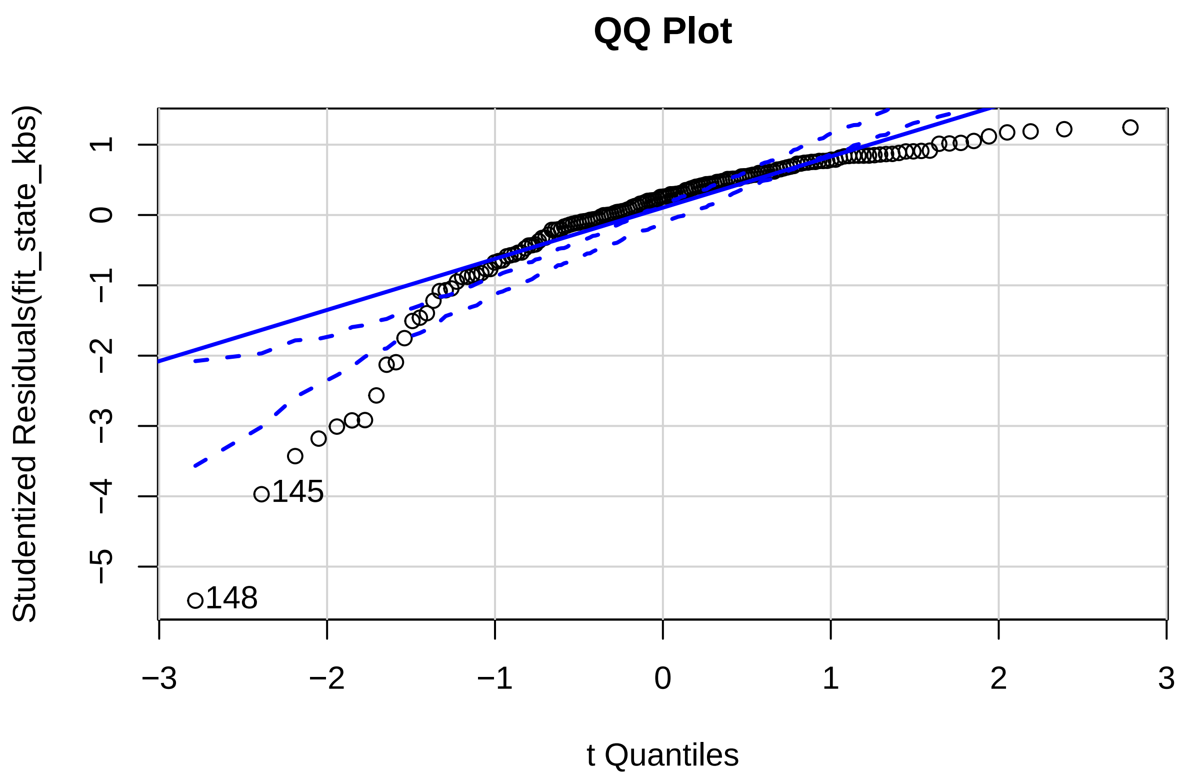
These illustrate whether certain data points have more leverage (more influence), and thus could be outliers. It's a way of detecting outliers. Leverage plots can help identify whether a point has high or low influence, based on its leverage and residual and determining model fit with and without the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

SIMPSON

```
# KBS State-only model
fit_state_kbs <- lm(log(simpson) ~ state, data = kbs_diversity)
outlierTest(fit_state_kbs)  # yes row 148, 145
```

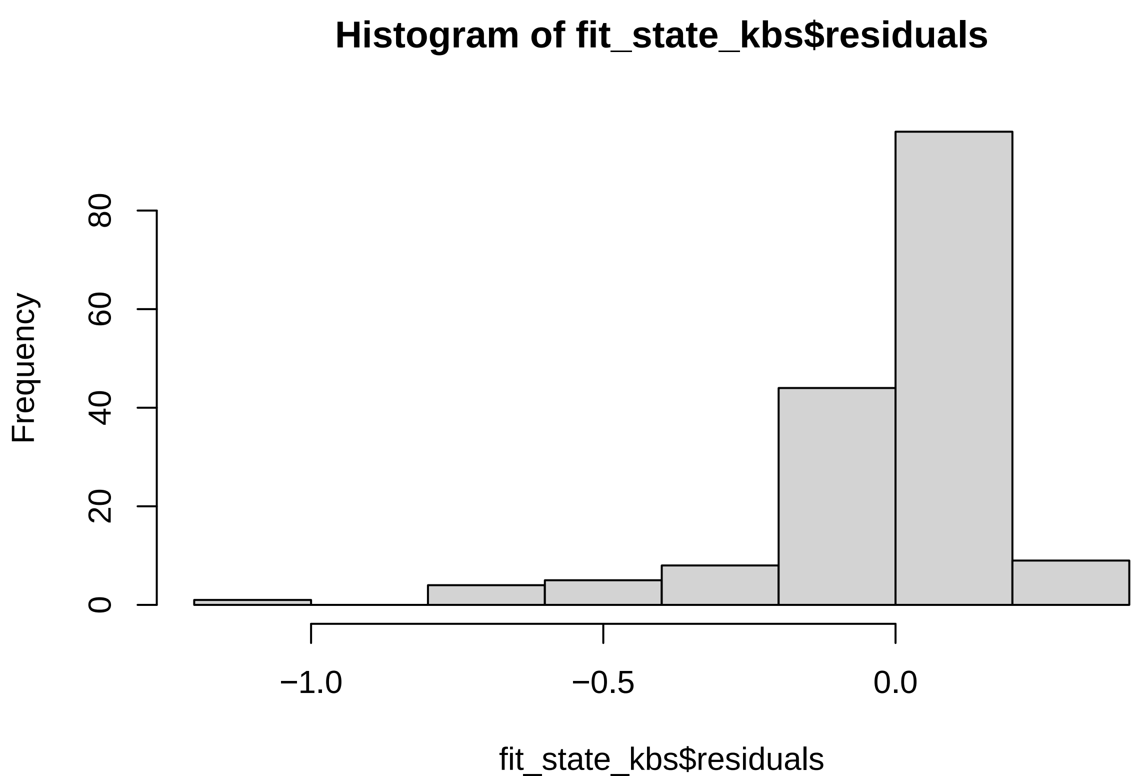
```
##      rstudent unadjusted p-value Bonferroni p
## 148 -5.483740         1.5483e-07   2.5856e-05
## 145 -3.970437         1.0714e-04   1.7892e-02
```

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

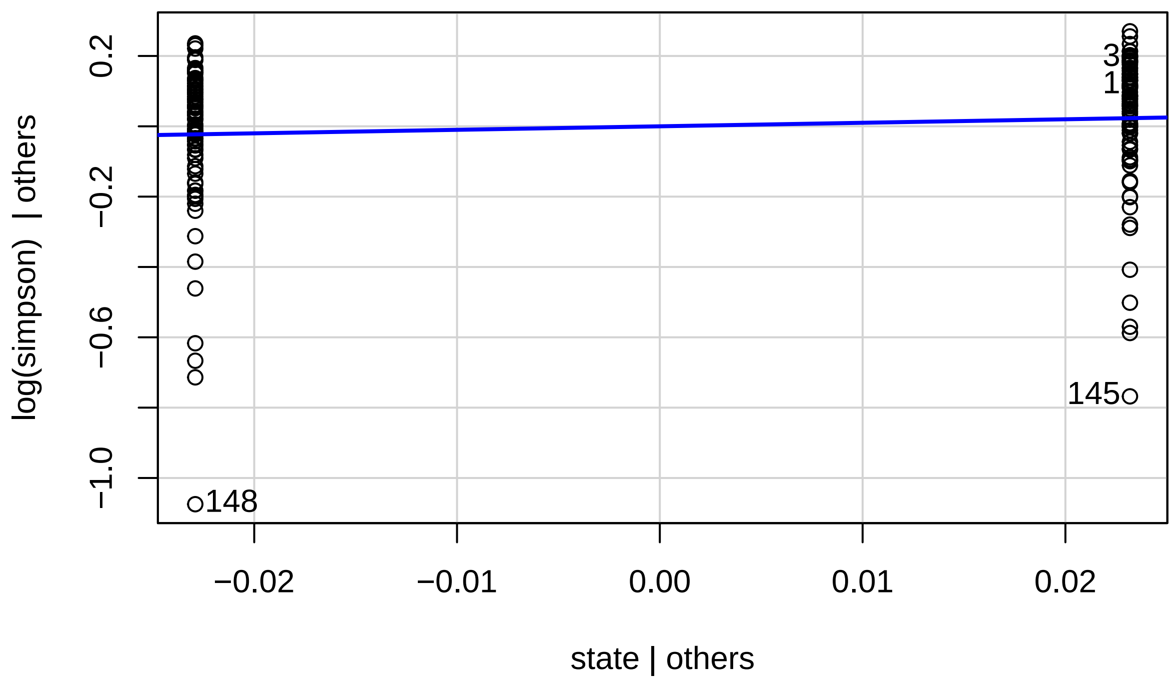



```
## [1] 145 148
```

```r
hist(fit_state_kbs$residuals)
```



```r
leveragePlots(fit_state_kbs)
```




```r
ols_test_normality(fit_state_kbs)
```

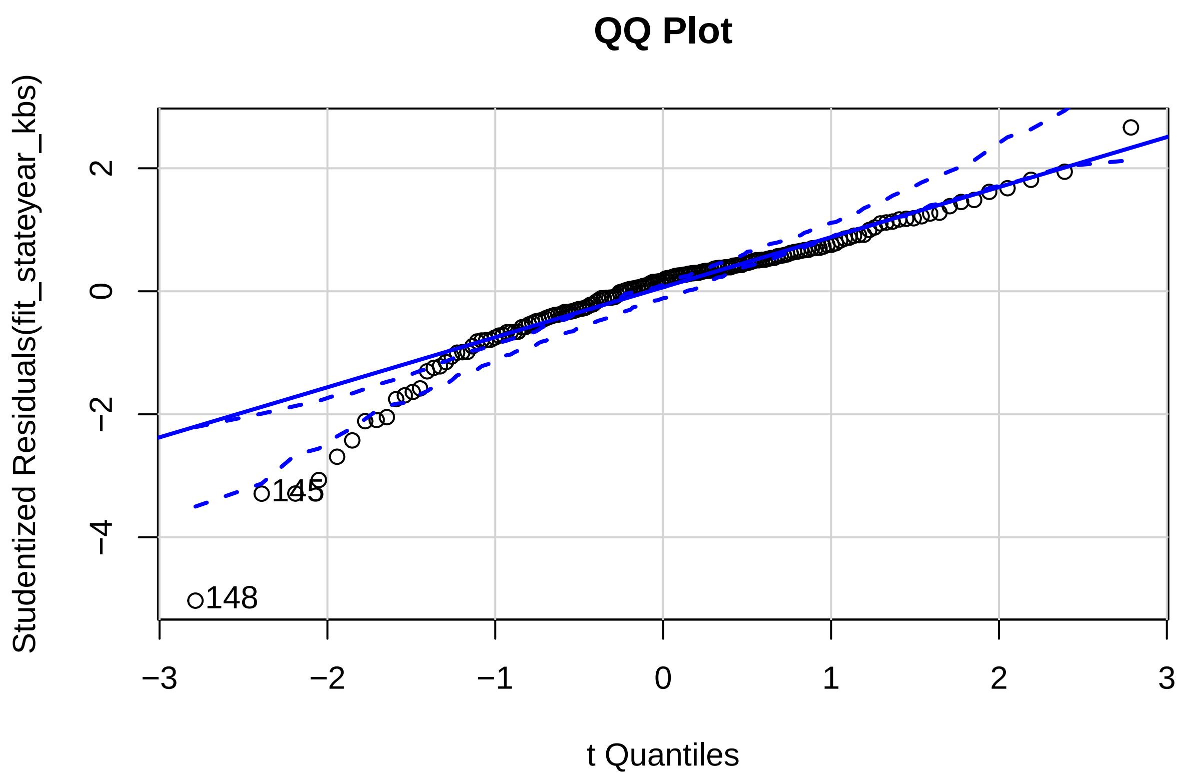
```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.8069         0.0000
## Kolmogorov-Smirnov        0.165           2e-04
## Cramer-von Mises         38.5386         0.0000
## Anderson-Darling          8.312          0.0000
## -----------------------------------------------
```

```r
# KBS State and year model
fit_stateyear_kbs <- lm(log(simpson) ~ state + year, data = kbs_diversity)
outlierTest(fit_stateyear_kbs)  # yes, row 148
```

```
##      rstudent unadjusted p-value Bonferroni p
## 148 -5.029821         1.3202e-06   0.00022047
```

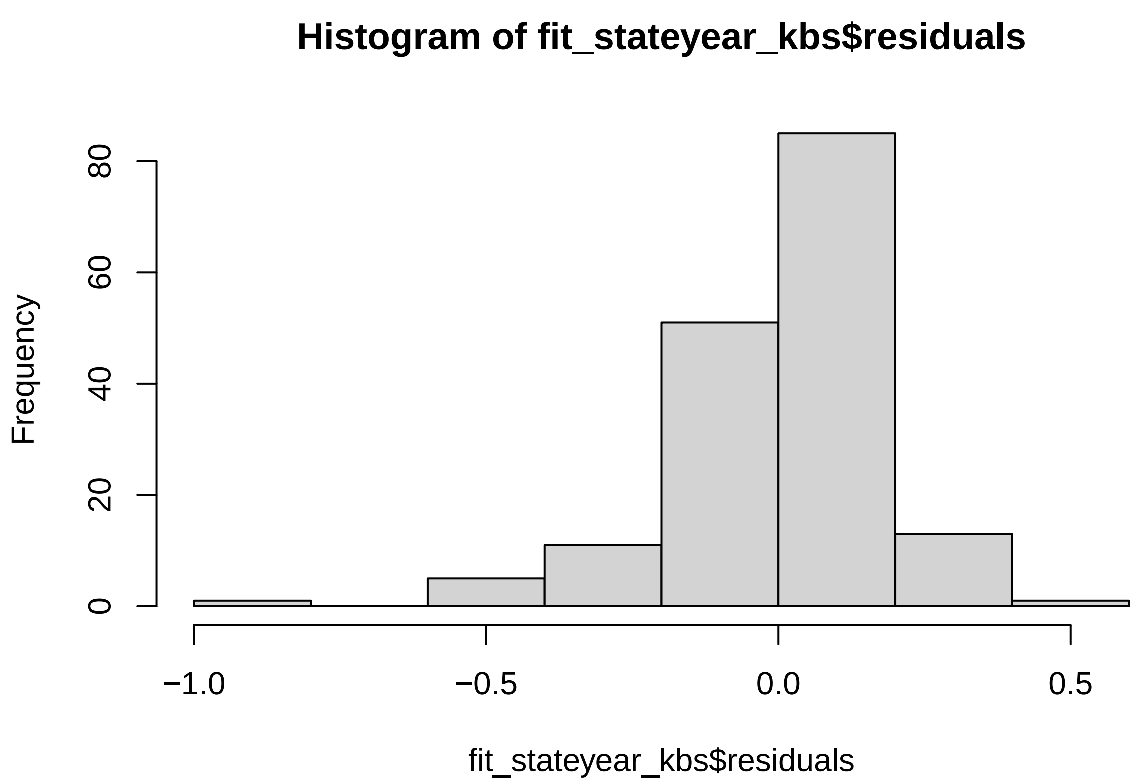
```r
qqPlot(fit_stateyear_kbs, main = "QQ Plot")
```

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

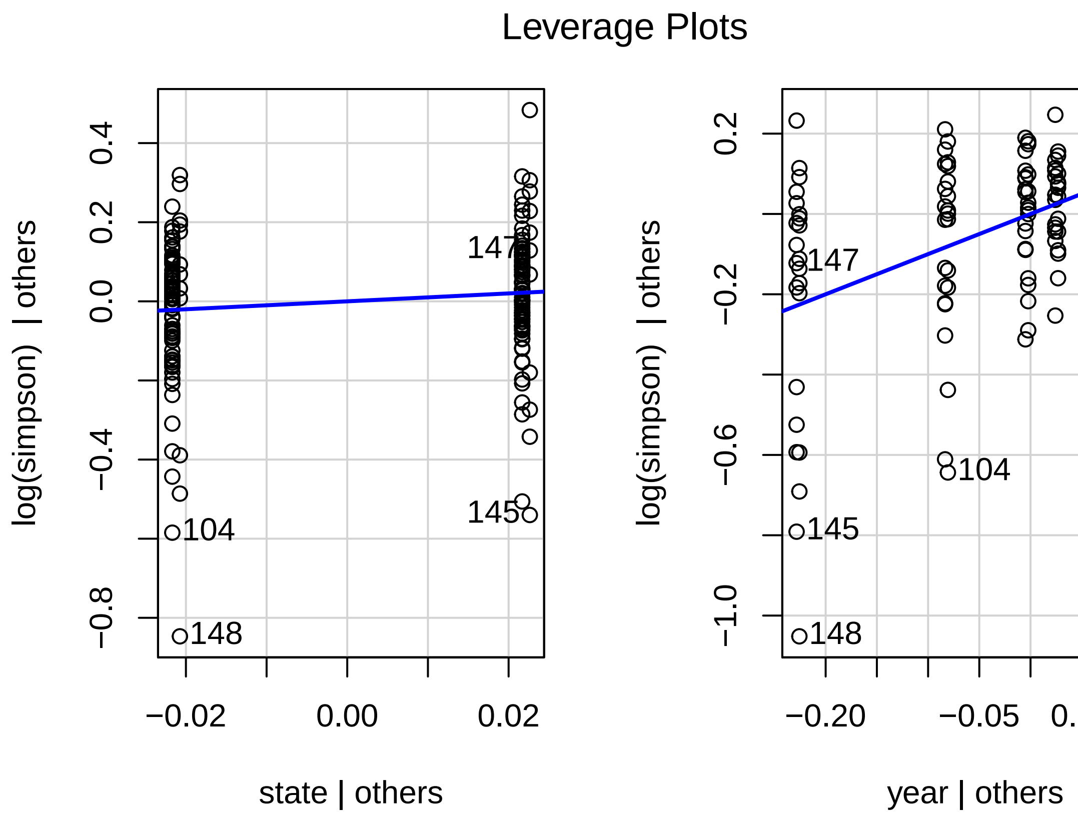



```
## [1] 145 148
```

```r
hist(fit_stateyear_kbs$residuals)
```



```r
leveragePlots(fit_stateyear_kbs)
```



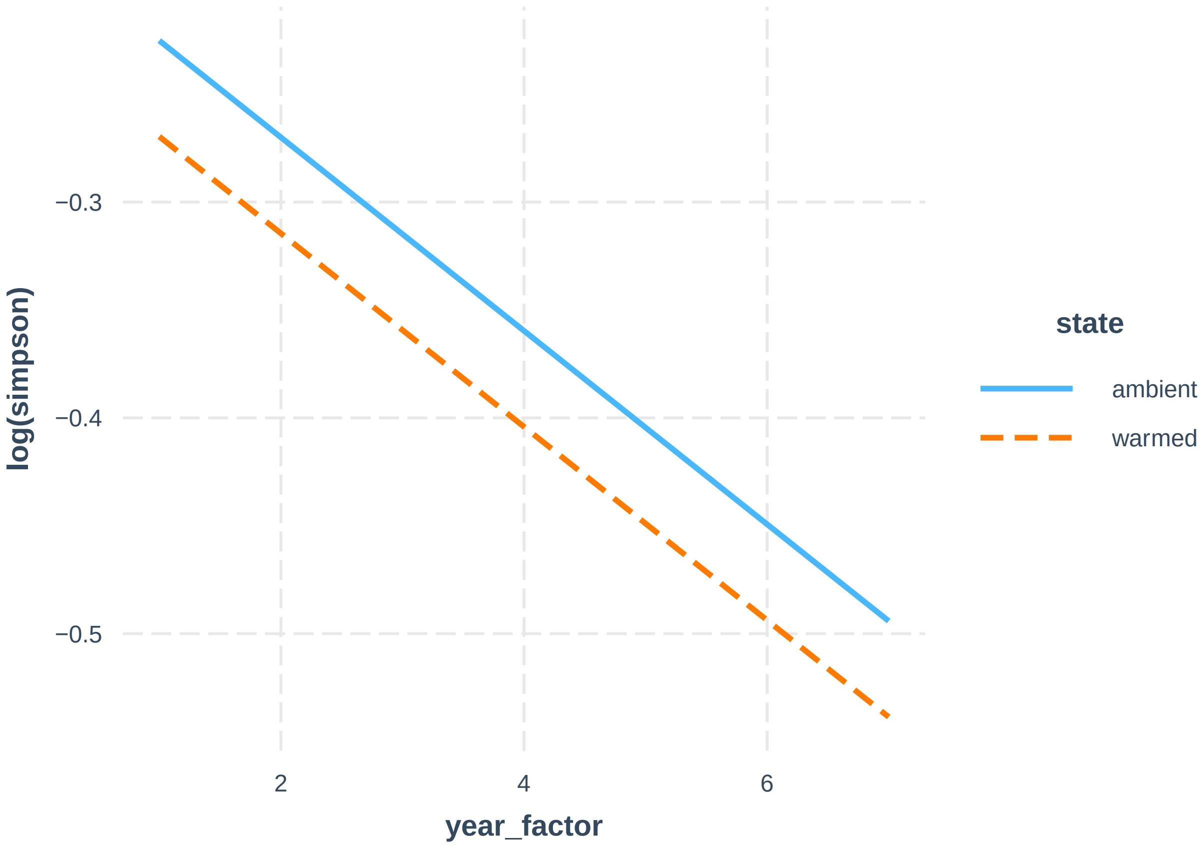

```r
ols_test_normality(fit_stateyear_kbs)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9195         0.0000
## Kolmogorov-Smirnov        0.1014         0.0644
## Cramer-von Mises         40.0065         0.0000
## Anderson-Darling          3.4358         0.0000
## -----------------------------------------------
```

```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/

fit3 <- lm(log(simpson) ~ state + year_factor, data = kbs_diversity)
interact_plot(fit3, pred = year_factor, modx = state)
```

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

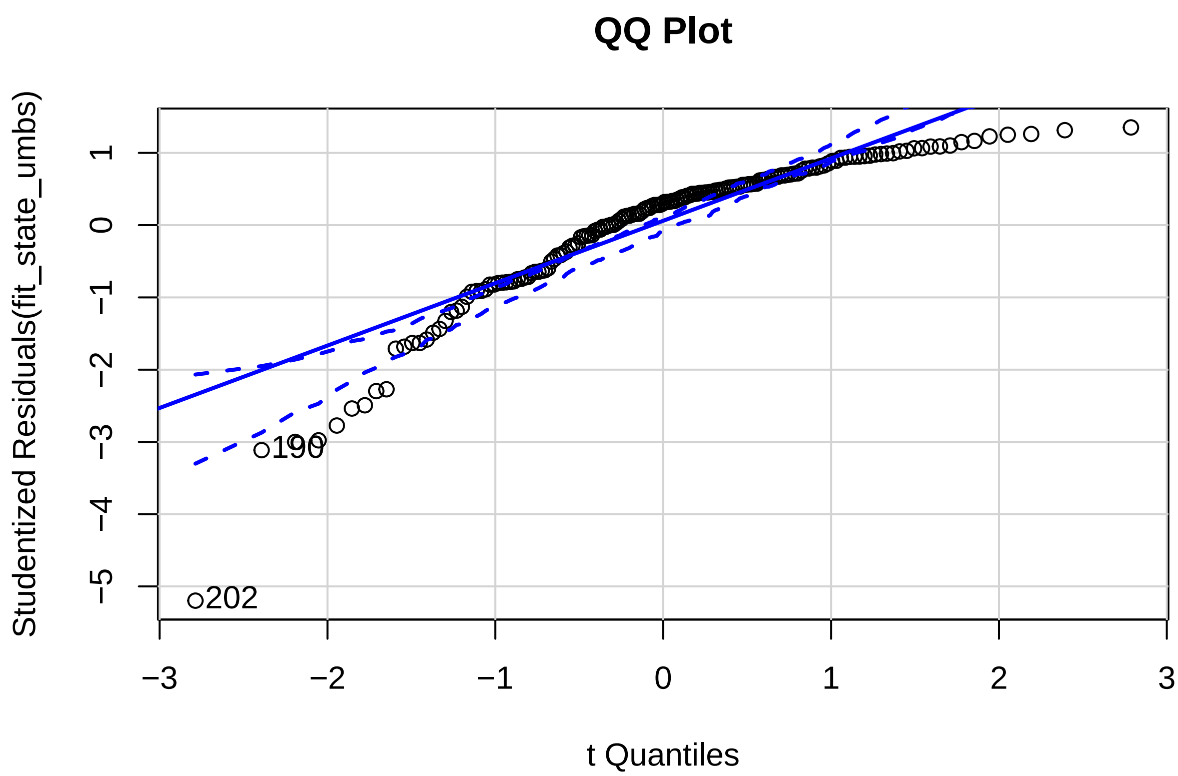
```
## Warning: year_factor and state are not included in an interaction with one another
## in the model.
```




```r
# UMBS State-only model
fit_state_umbs <- lm(log(simpson) ~ state, data = umbs_diversity)
outlierTest(fit_state_umbs)  # yes, row 202
```

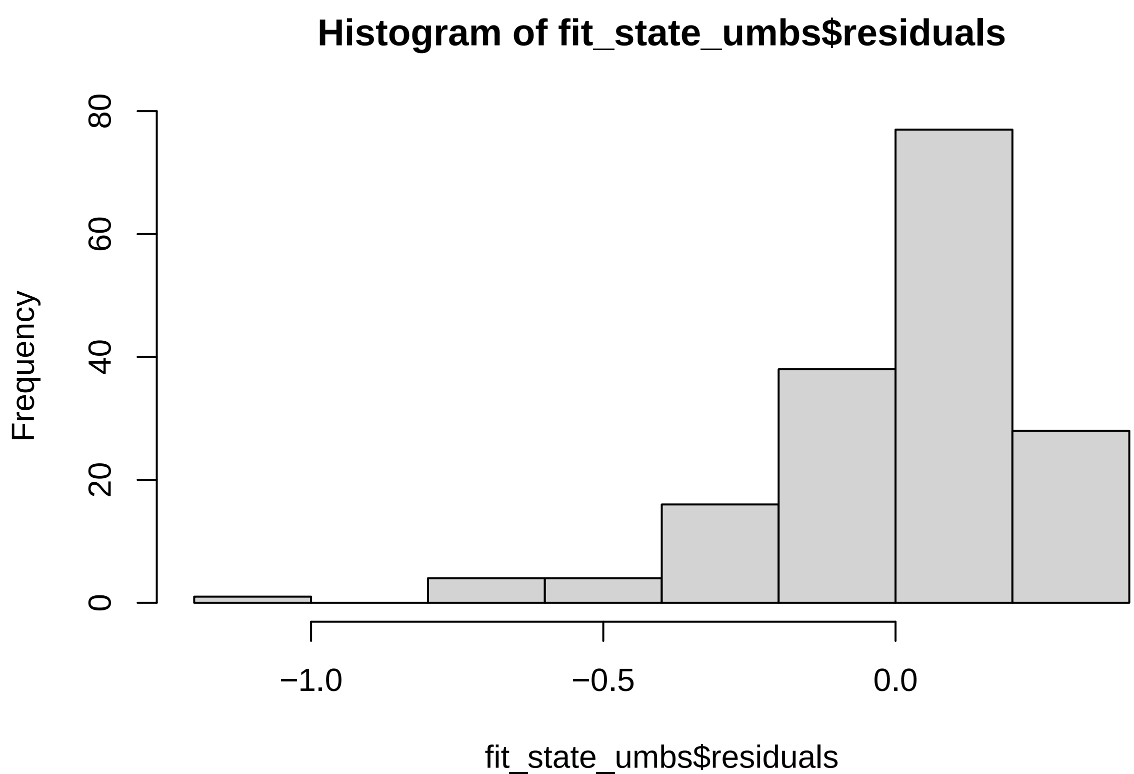
```
##      rstudent unadjusted p-value Bonferroni p
## 202 -5.196615         5.9291e-07    9.961e-05
```

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

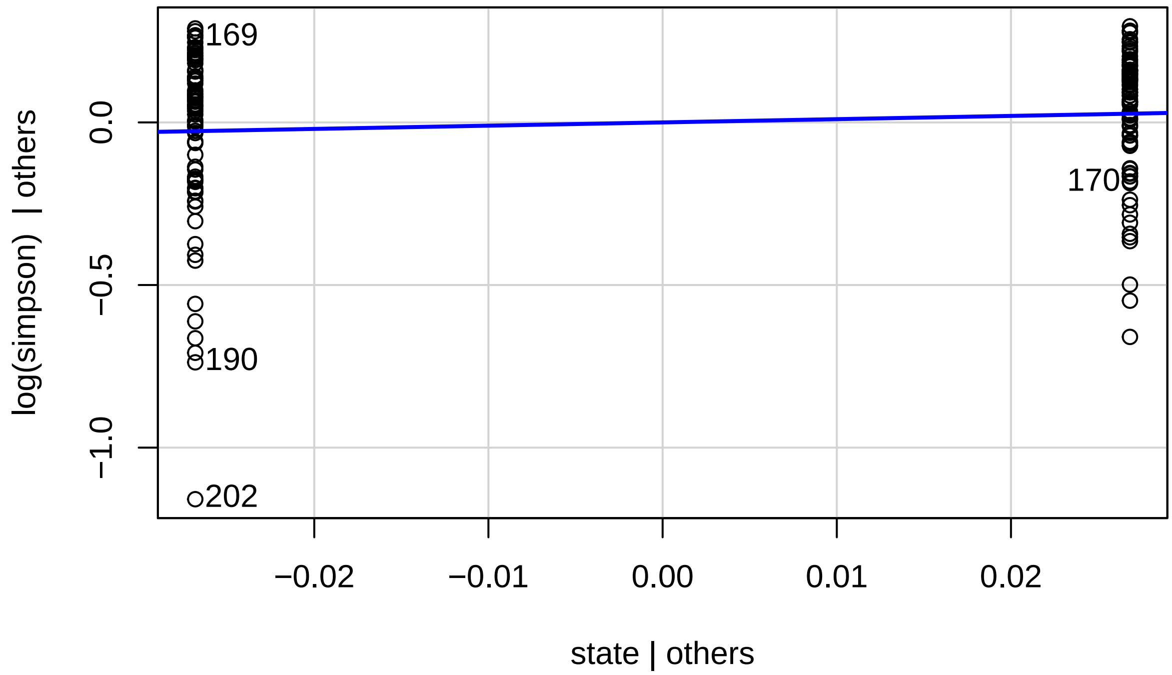



```
## 190 202
##  22  34
```

```r
hist(fit_state_umbs$residuals)
```



```r
leveragePlots(fit_state_umbs)
```



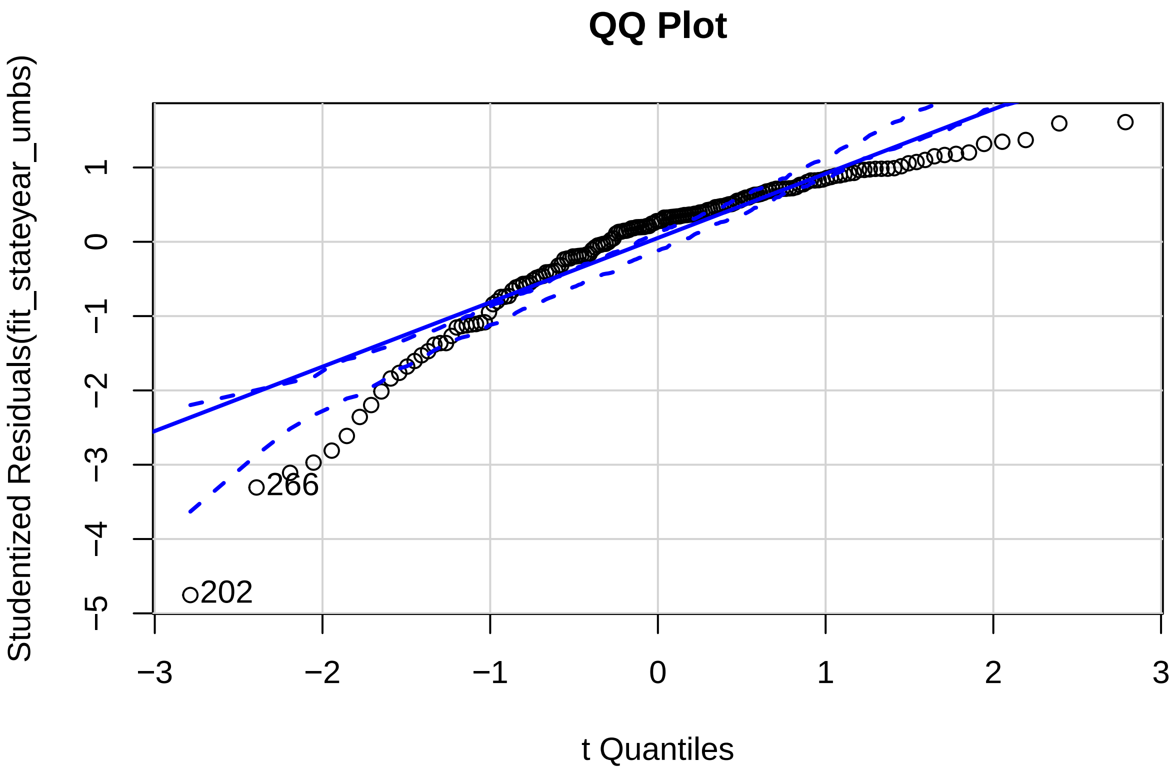

```r
ols_test_normality(fit_state_umbs)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.8718         0.0000
## Kolmogorov-Smirnov        0.1413         0.0024
## Cramer-von Mises         35.3584         0.0000
## Anderson-Darling          5.5761         0.0000
## -----------------------------------------------
```

```r
# UMBS State and year model
fit_stateyear_umbs <- lm(log(simpson) ~ state + year, data = umbs_diversity)
outlierTest(fit_stateyear_kbs)  # row 48
```

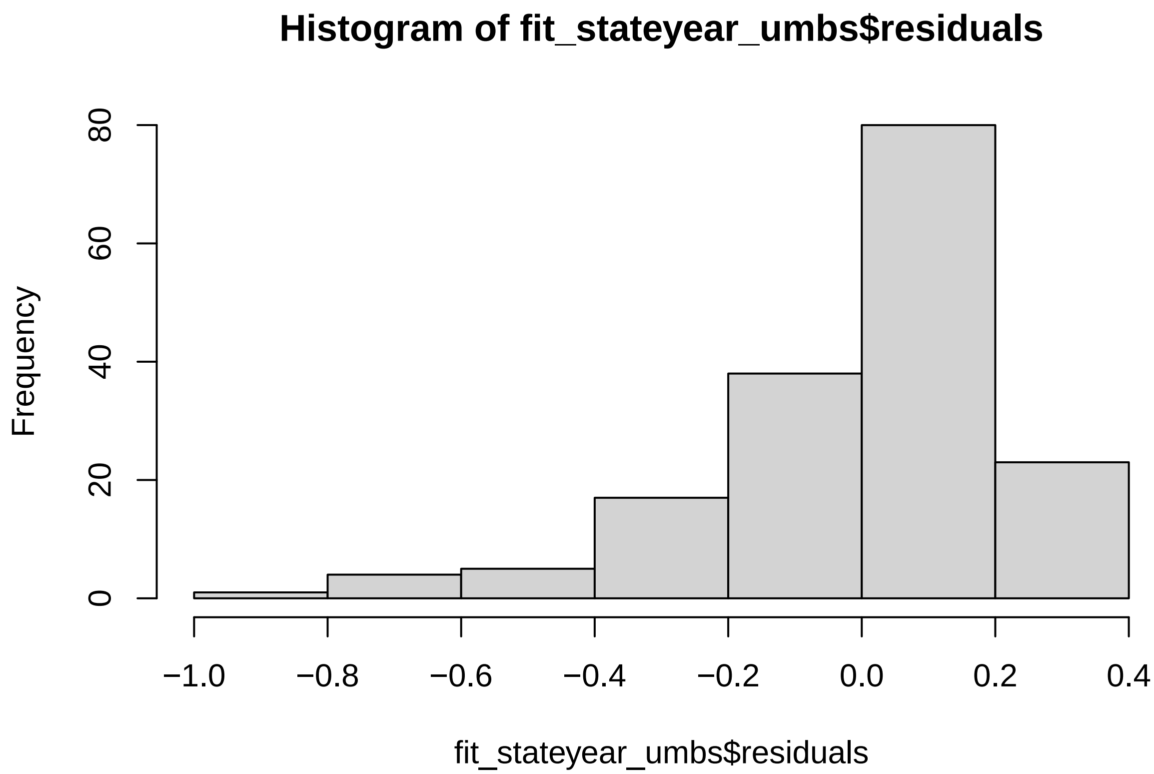
```
##      rstudent unadjusted p-value Bonferroni p
## 148 -5.029821         1.3202e-06   0.00022047
```

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

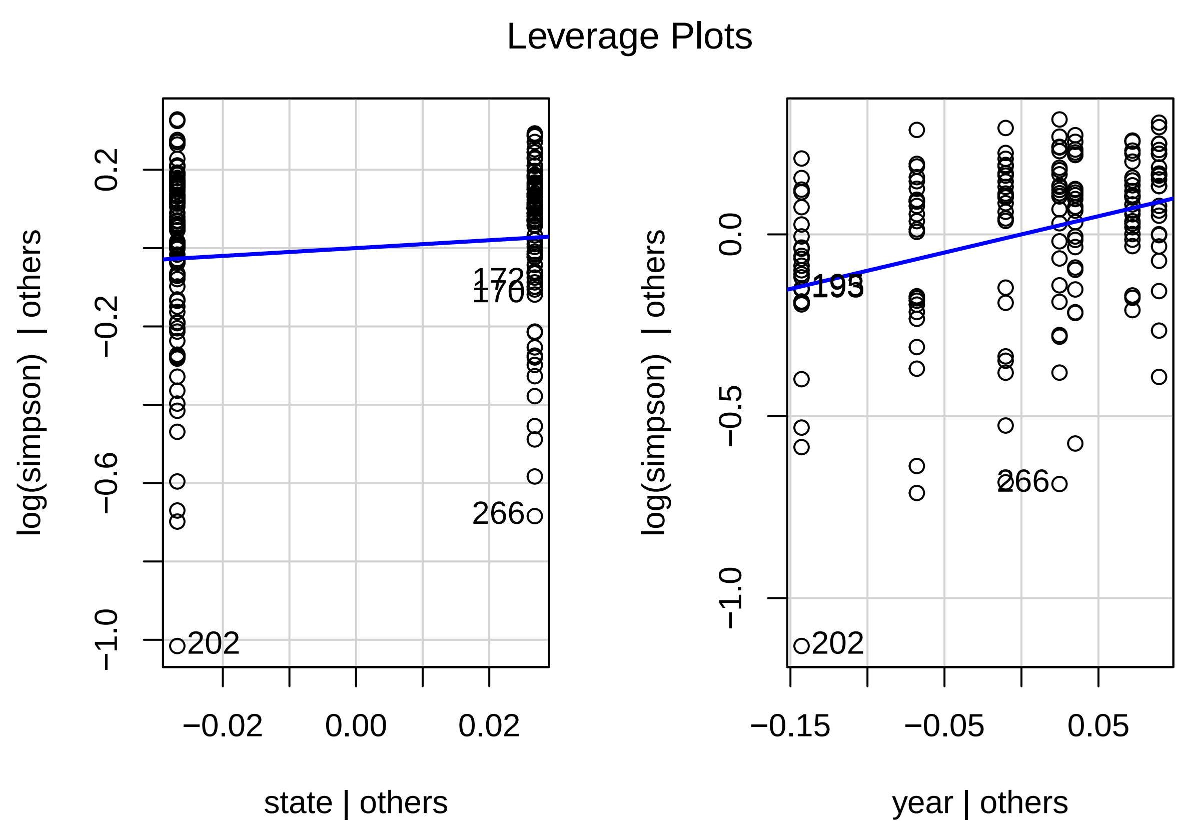



```
## 202 266
##  34  98
```

```r
hist(fit_stateyear_umbs$residuals)
```




```
leveragePlots(fit_stateyear_umbs)
```



```r
ols_test_normality(fit_stateyear_umbs)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.89          0.0000
## Kolmogorov-Smirnov        0.1479        0.0013
## Cramer-von Mises         36.3067        0.0000
## Anderson-Darling          5.0956        0.0000
## -----------------------------------------------
```

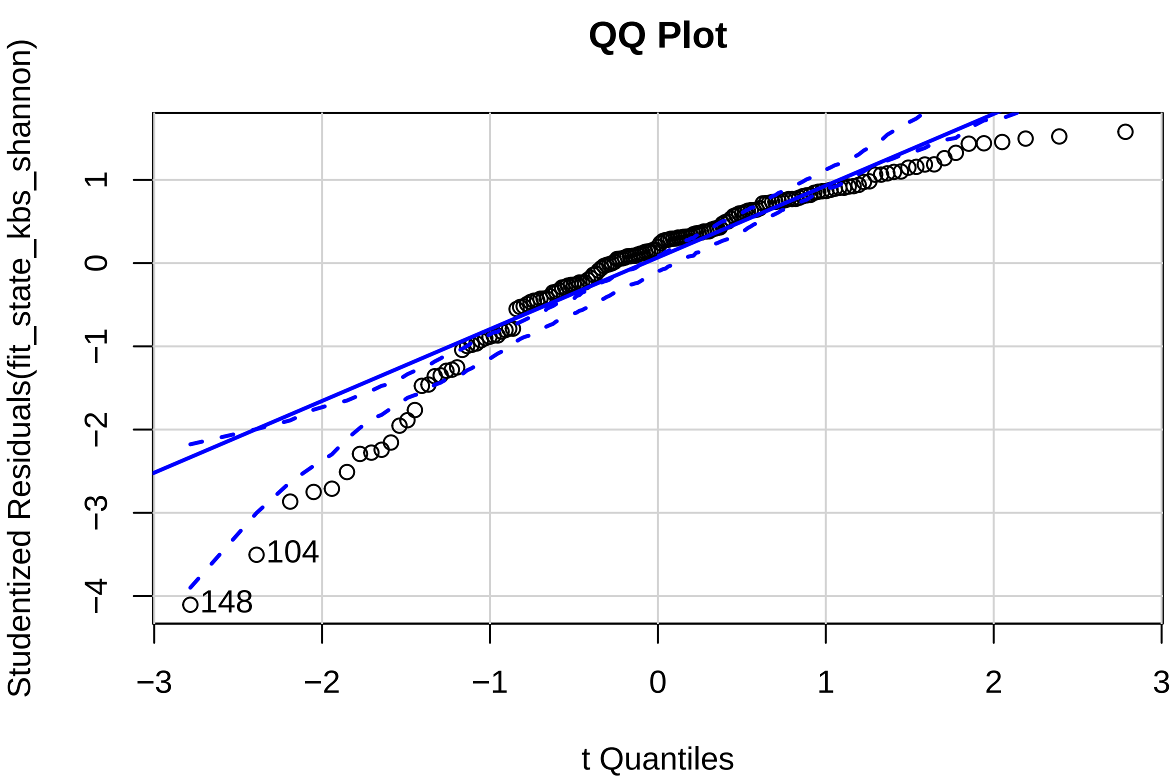
```r
# Interaction plot (ignore for now the repeated measures with species); see:
# https://cran.r-project.org/web/packages/interactions/vignettes/interactions.html
# and: https://interactions.jacob-long.com/

# I can't get these to work
fit3 <- lm(log(simpson) ~ state + year, data = umbs_diversity)
# interact_plot(fit3, pred = year_factor, modx = state)
```

SHANNON

```r
# KBS State-only model
fit_state_kbs_shannon <- lm(log(shannon) ~ state, data = kbs_diversity)
outlierTest(fit_state_kbs_shannon)  # yes row 148
```

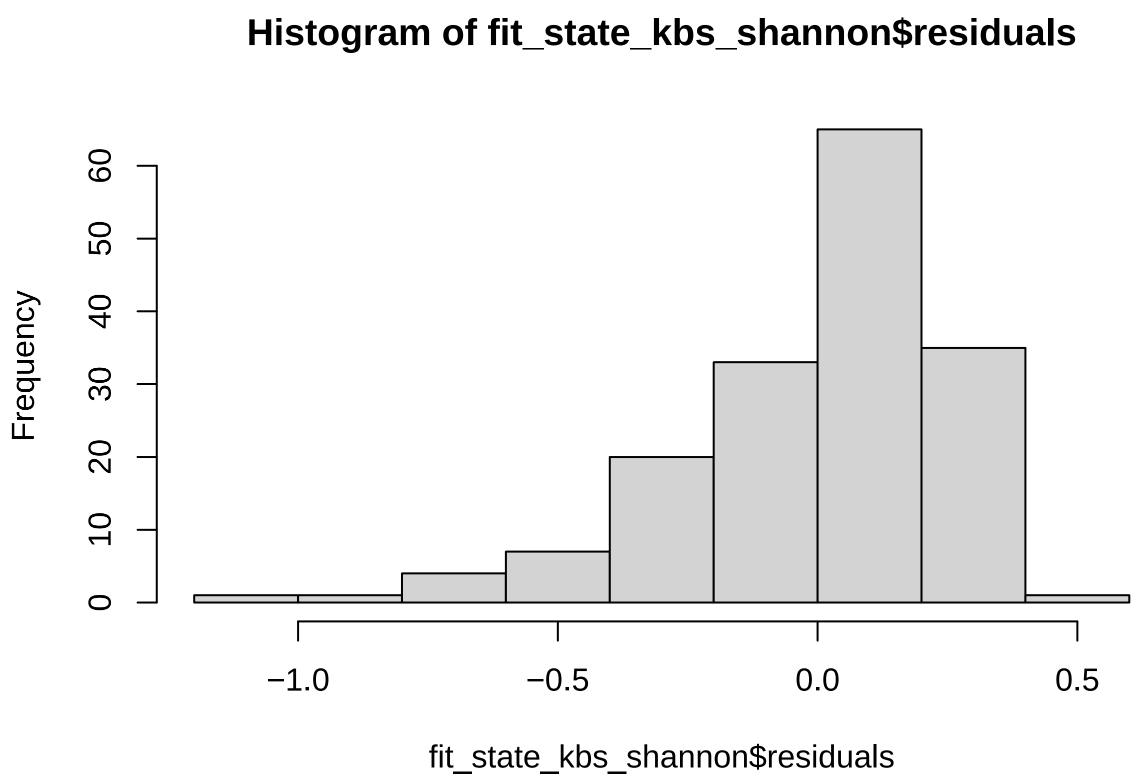
```
##      rstudent unadjusted p-value Bonferroni p
## 148 -4.104478         6.3743e-05     0.010645
```

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

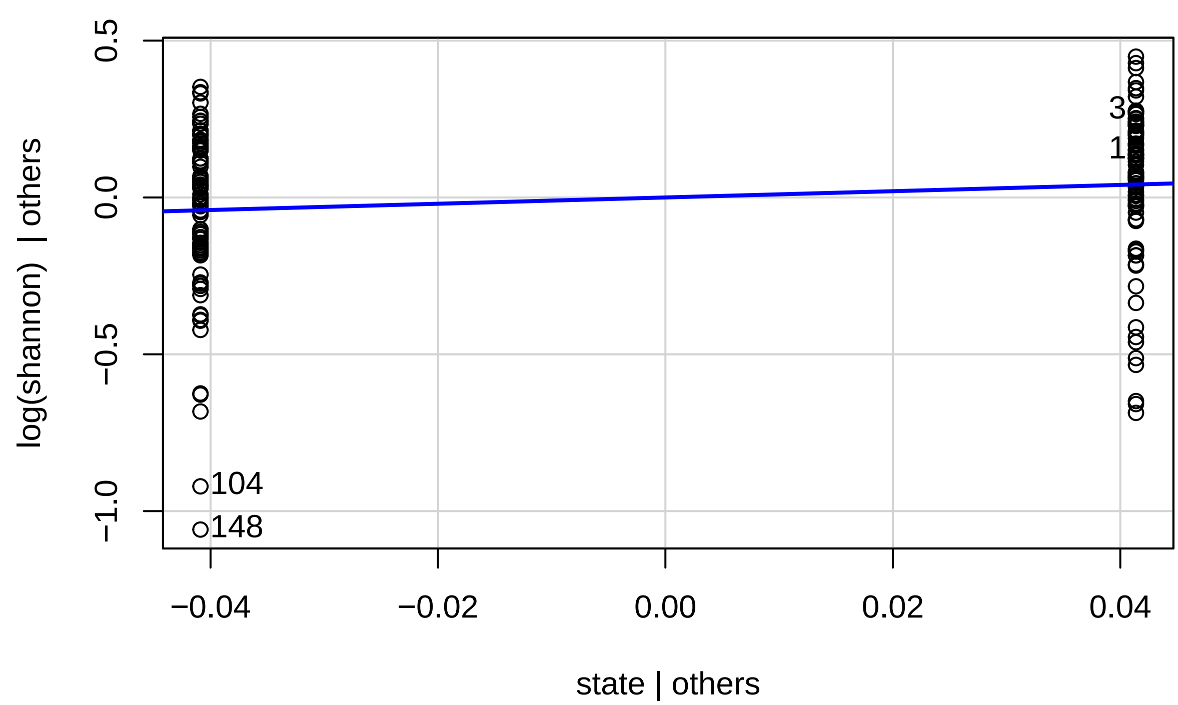


```
## [1] 104 148
```

```r
hist(fit_state_kbs_shannon$residuals)
```




```r
leveragePlots(fit_state_kbs_shannon)
```



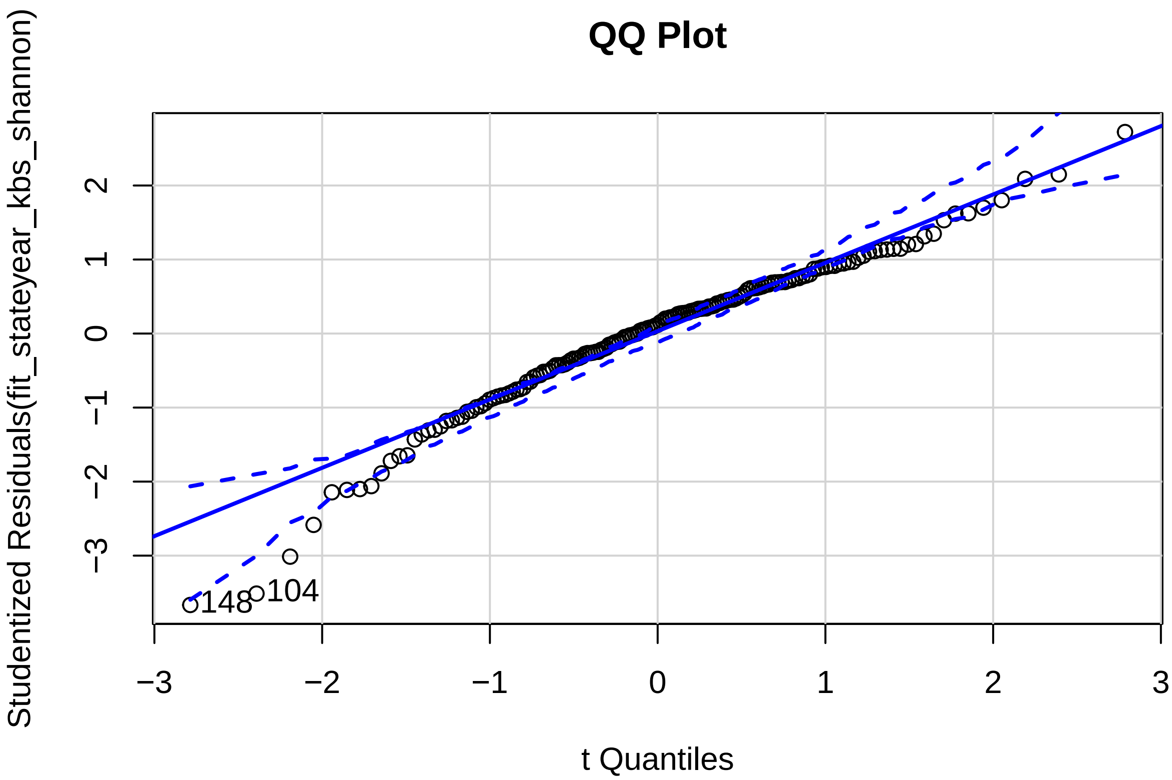
```r
ols_test_normality(fit_state_kbs_shannon)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.911          0.0000
## Kolmogorov-Smirnov        0.1184         0.0185
## Cramer-von Mises         33.0384         0.0000
## Anderson-Darling          3.9793         0.0000
## -----------------------------------------------
```

```r
# KBS State and year model
fit_stateyear_kbs_shannon <- lm(log(shannon) ~ state + year, data = kbs_diversity)
outlierTest(fit_stateyear_kbs_shannon)  # no outliers
```

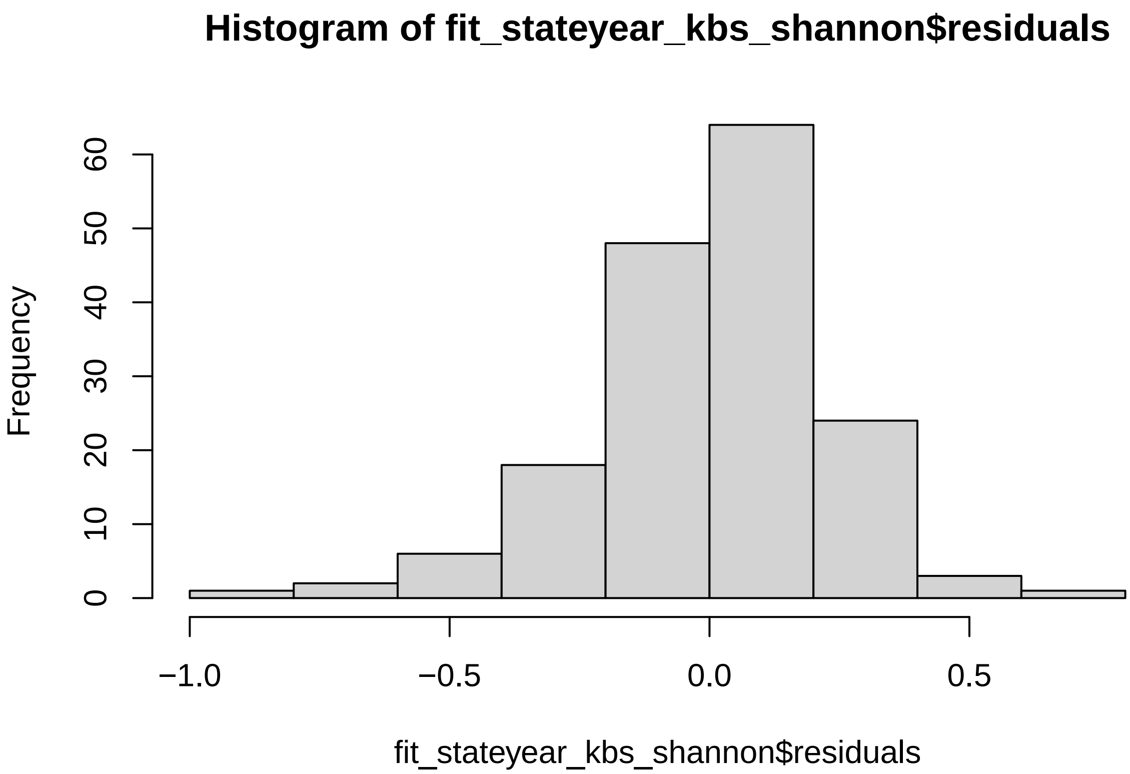
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 148 -3.666526         0.00033541     0.056013
```

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

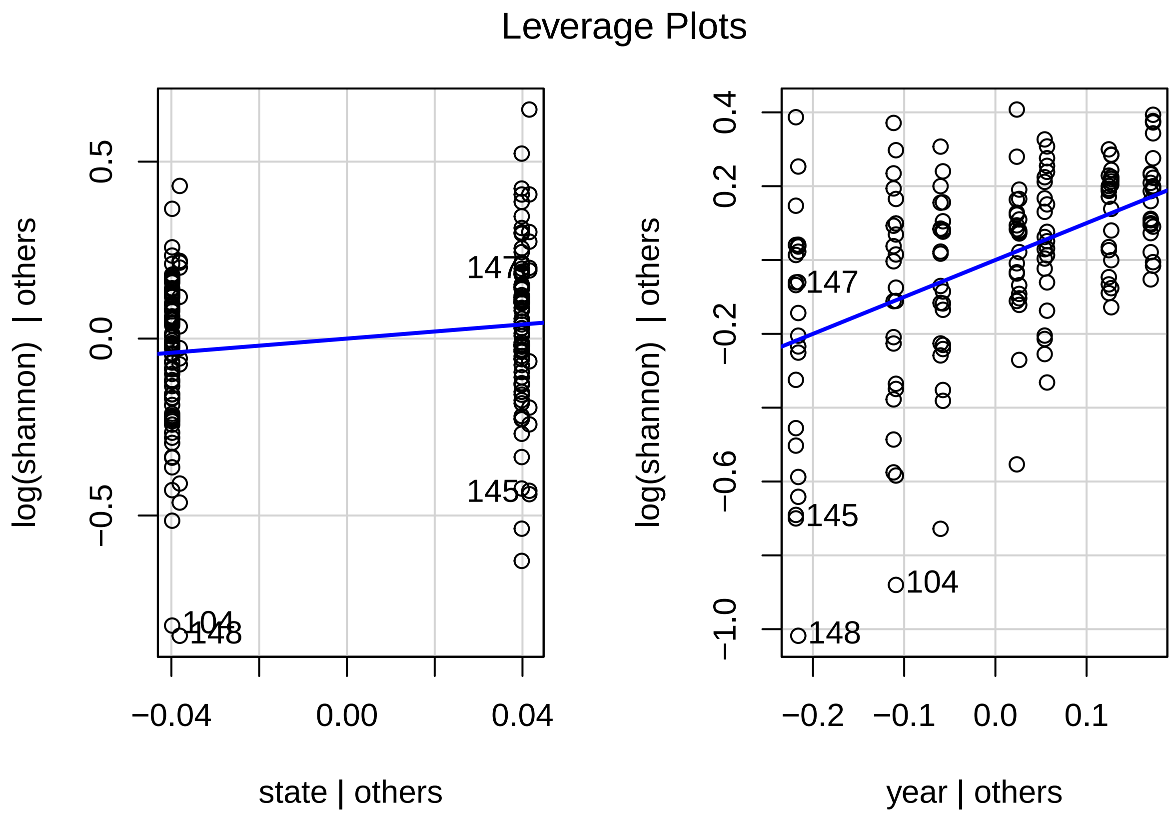



```
## [1] 104 148
```

```
hist(fit_stateyear_kbs_shannon$residuals)
```




```
leveragePlots(fit_stateyear_kbs_shannon)
```



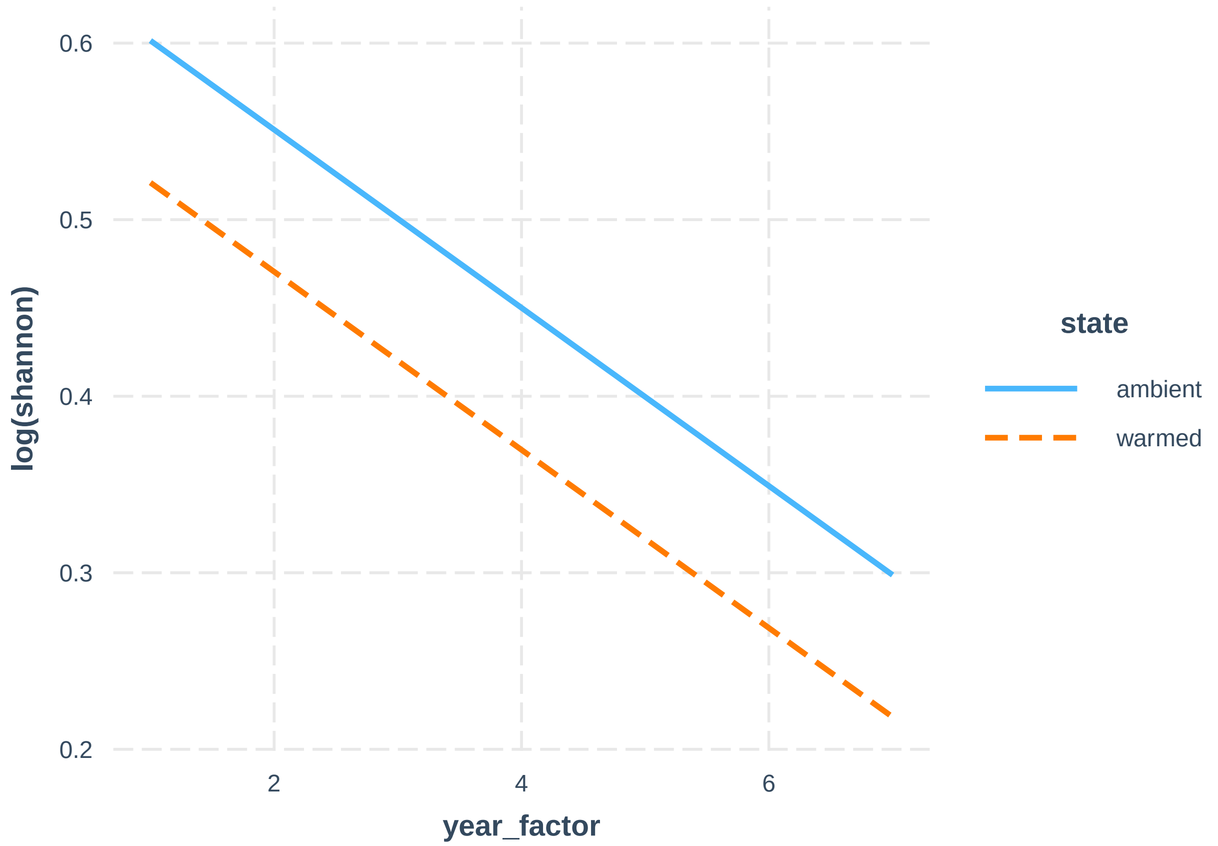

```r
ols_test_normality(fit_stateyear_kbs_shannon)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9685         8e-04
## Kolmogorov-Smirnov        0.0646        0.4880
## Cramer-von Mises         35.0287        0.0000
## Anderson-Darling          1.3398        0.0017
## -----------------------------------------------
```

```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/

# I can't get these to work
fit3 <- lm(log(shannon) ~ state + year_factor, data = kbs_diversity)
interact_plot(fit3, pred = year_factor, modx = state)
```

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

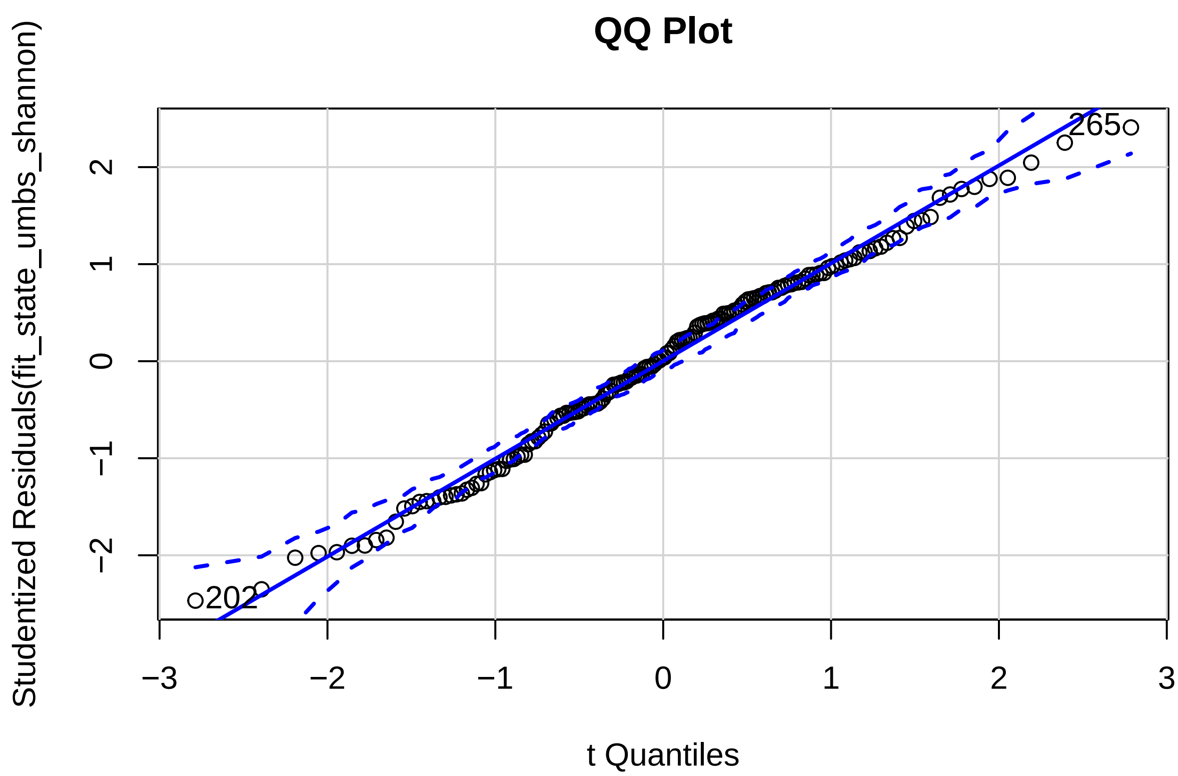
```
## Warning: year_factor and state are not included in an interaction with one another
## in the model.
```




```r
# UMBS State-only model
fit_state_umbs_shannon <- lm(shannon ~ state, data = umbs_diversity)
outlierTest(fit_state_umbs_shannon)  # no outliers
```

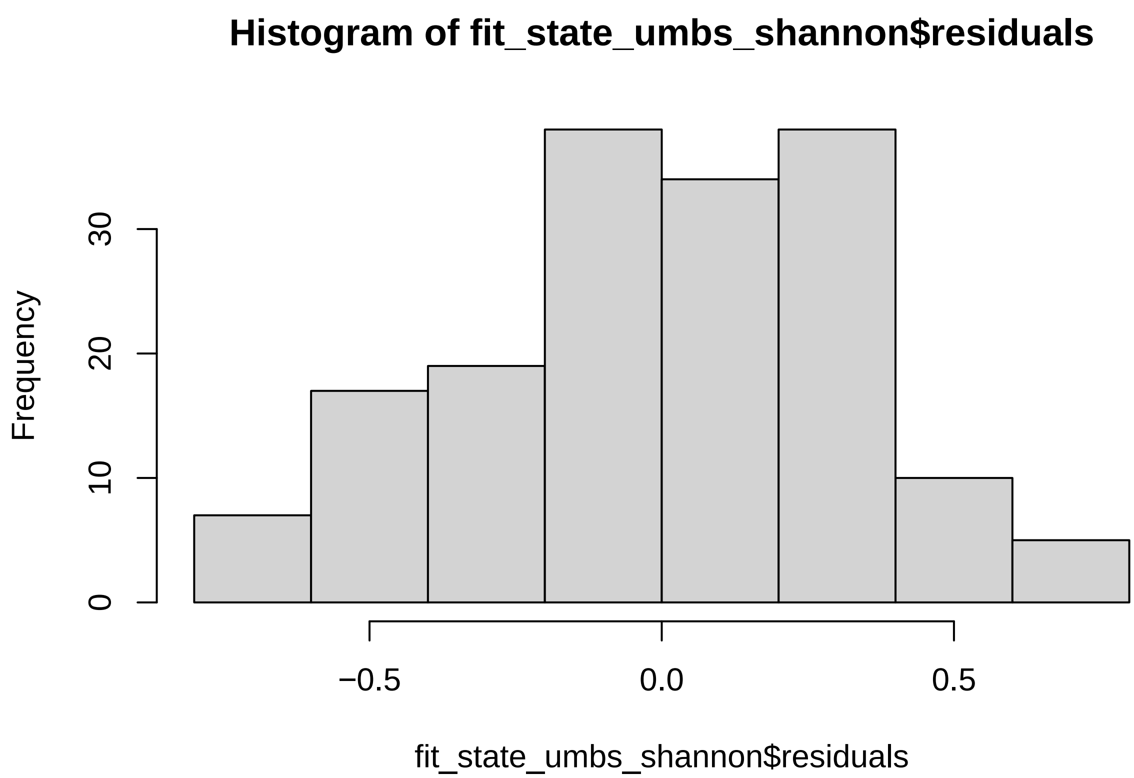
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 202 -2.467454           0.014629           NA
```

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

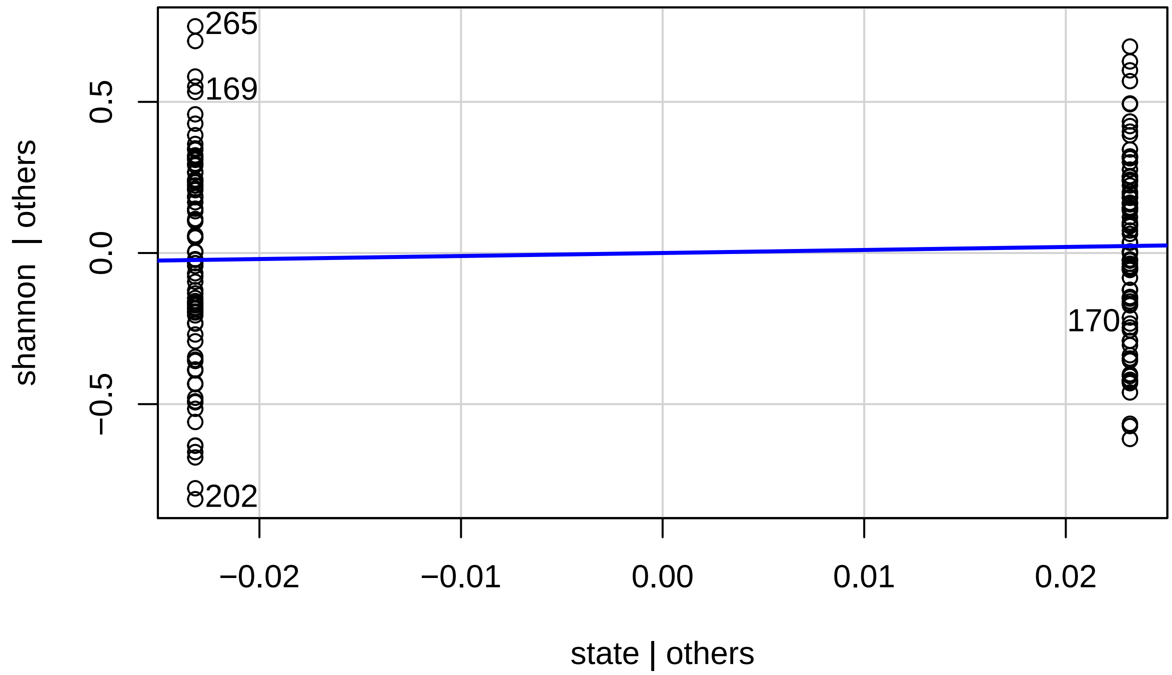



```
## 202 265
##  34  97
```

```r
hist(fit_state_umbs_shannon$residuals)
```



```r
leveragePlots(fit_state_umbs_shannon)
```



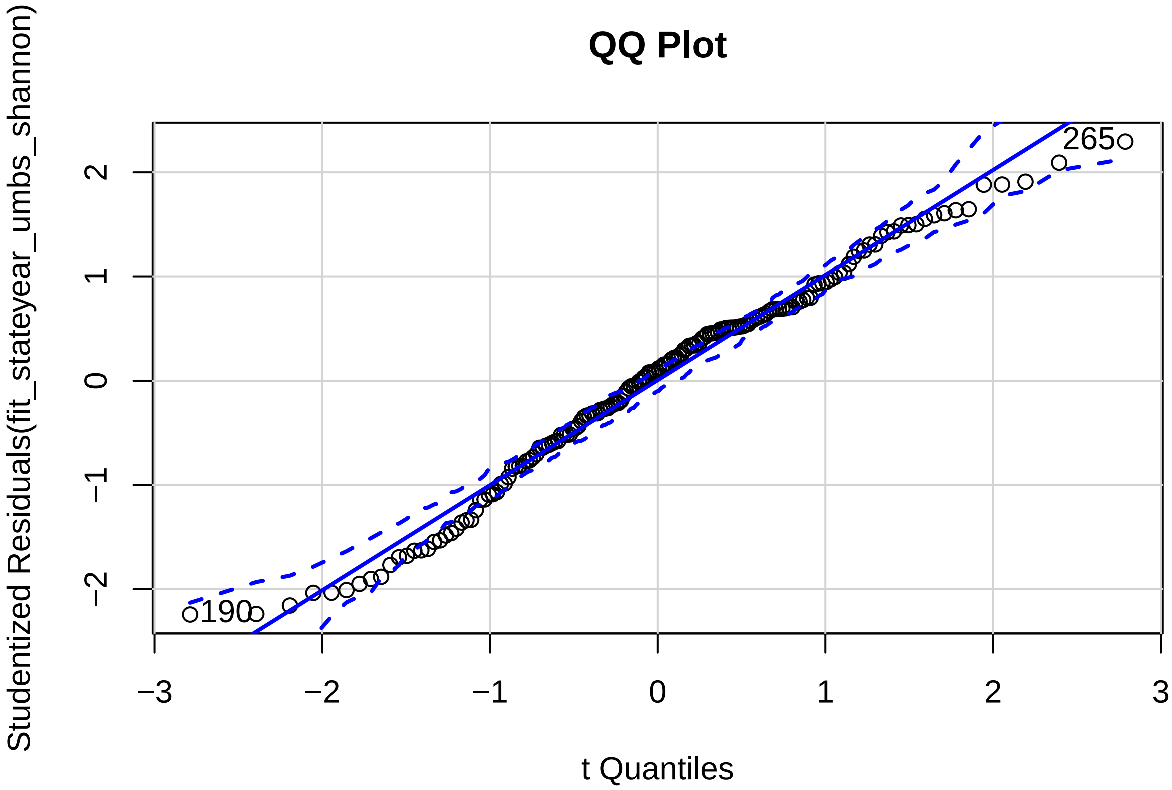

```r
ols_test_normality(fit_state_umbs_shannon)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.99          0.2854
## Kolmogorov-Smirnov        0.0622        0.5346
## Cramer-von Mises         26.7224        0.0000
## Anderson-Darling          0.5368        0.1668
## -----------------------------------------------
```

```r
# UMBS State and year model
fit_stateyear_umbs_shannon <- lm(shannon ~ state + year, data = umbs_diversity)
outlierTest(fit_stateyear_umbs_shannon)  # no outliers
```

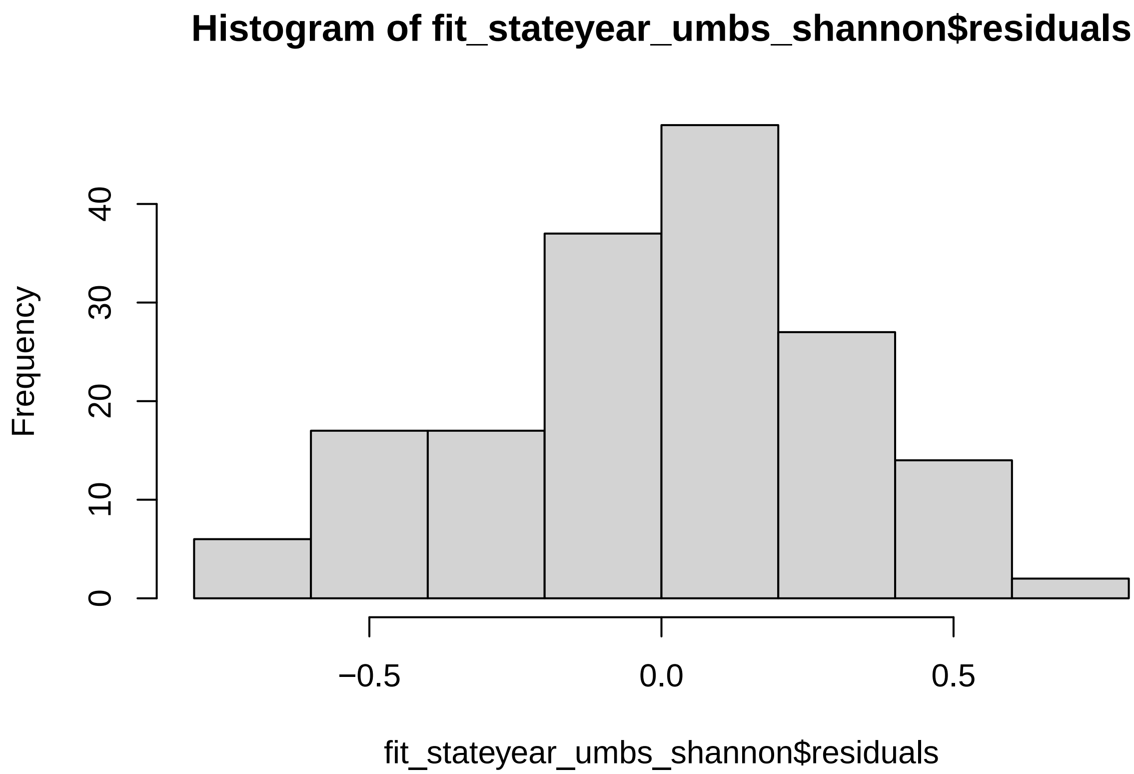
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##     rstudent unadjusted p-value Bonferroni p
## 265 2.294605           0.023064           NA
```

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

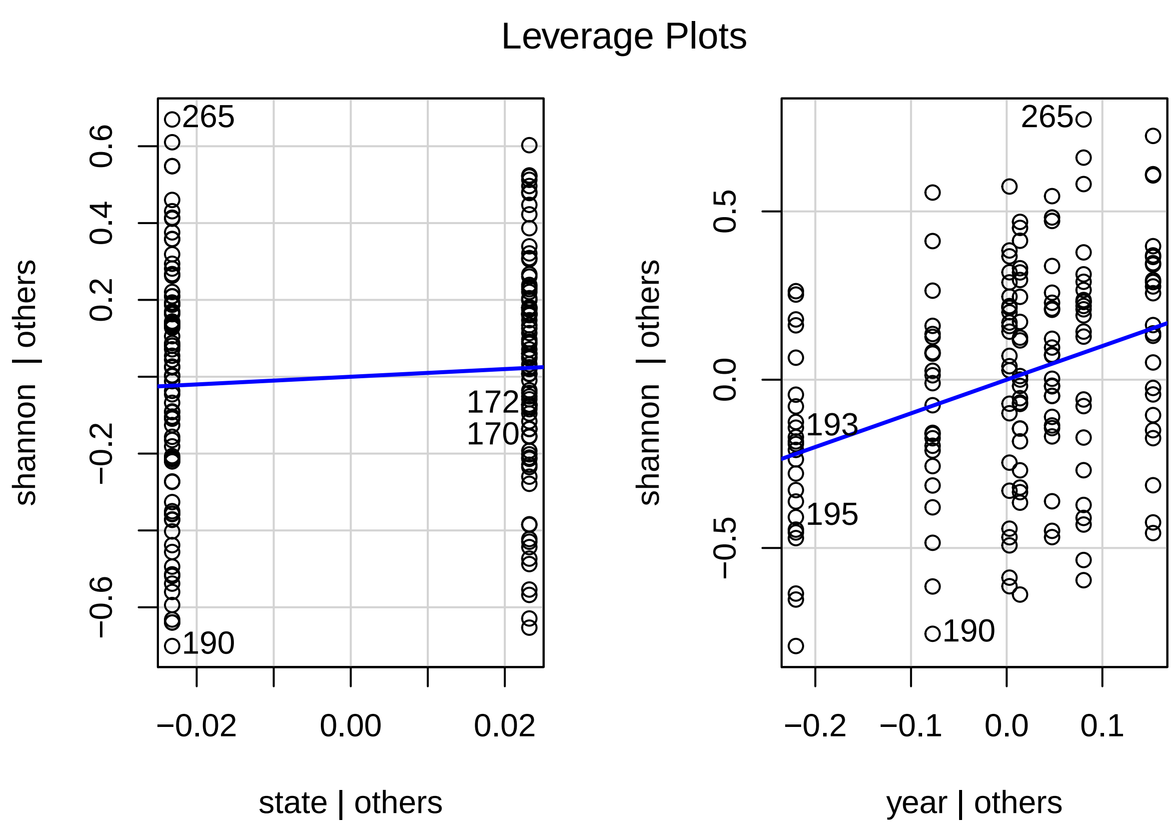



```
## 190 265
##  22  97
```

```
hist(fit_stateyear_umbs_shannon$residuals)
```




```r
leveragePlots(fit_stateyear_umbs_shannon)
```

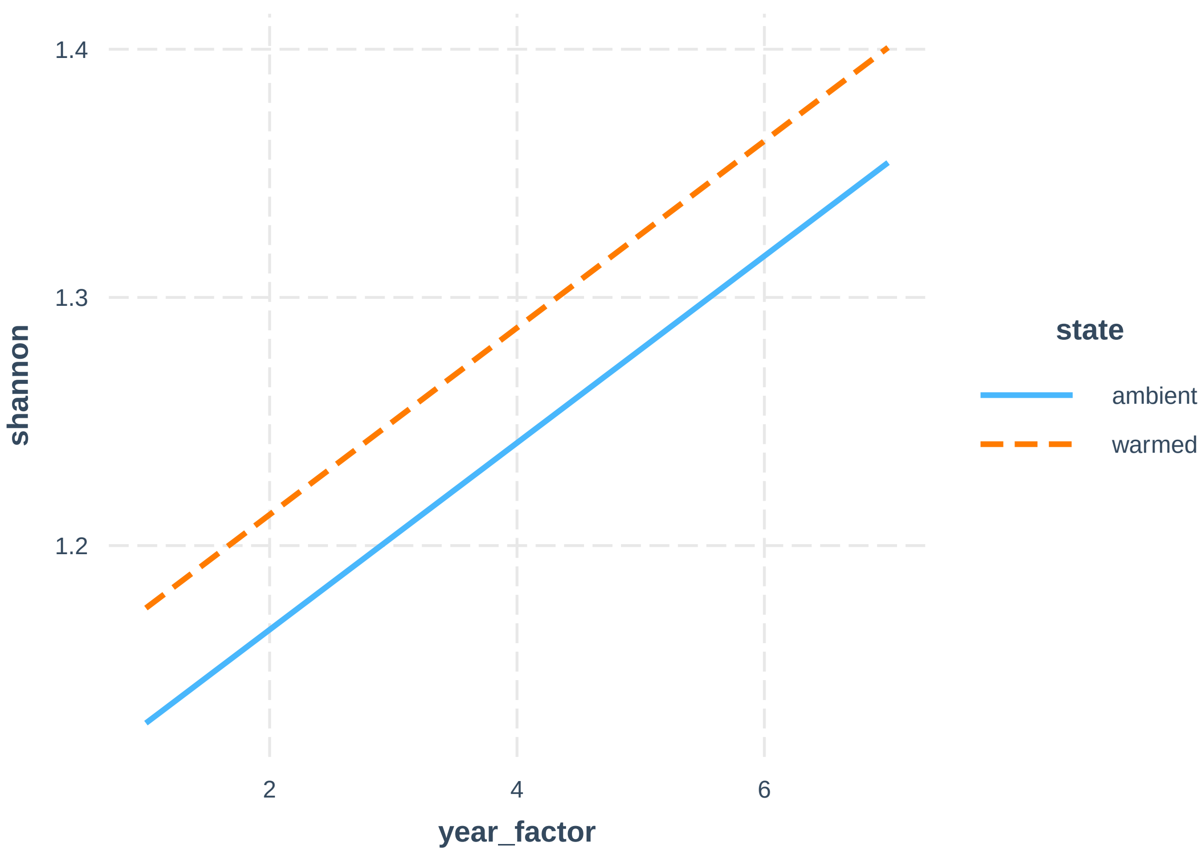


```r
ols_test_normality(fit_stateyear_umbs_shannon)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9836         0.0455
## Kolmogorov-Smirnov        0.0596         0.5884
## Cramer-von Mises         28.2896         0.0000
## Anderson-Darling          0.7546         0.0486
## -----------------------------------------------
```

```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/

# I can't get these to work
fit3 <- lm(shannon ~ state + year_factor, data = umbs_diversity)
interact_plot(fit3, pred = year_factor, modx = state)
```

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

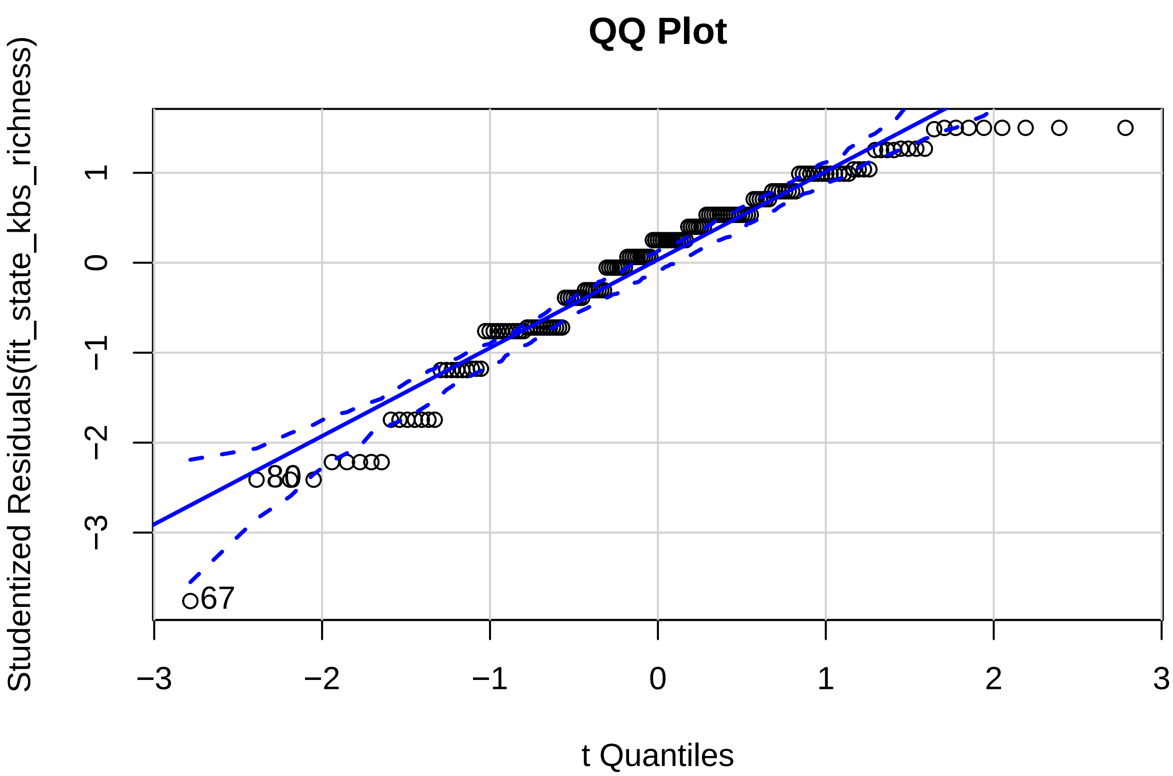


RICHNESS

```r
# KBS State-only model
fit_state_kbs_richness <- lm(log(richness) ~ state, data = kbs_diversity)
outlierTest(fit_state_kbs_richness)  # yes row 67
```

```
##     rstudent unadjusted p-value Bonferroni p
## 67 -3.761253         0.00023493     0.039234
```

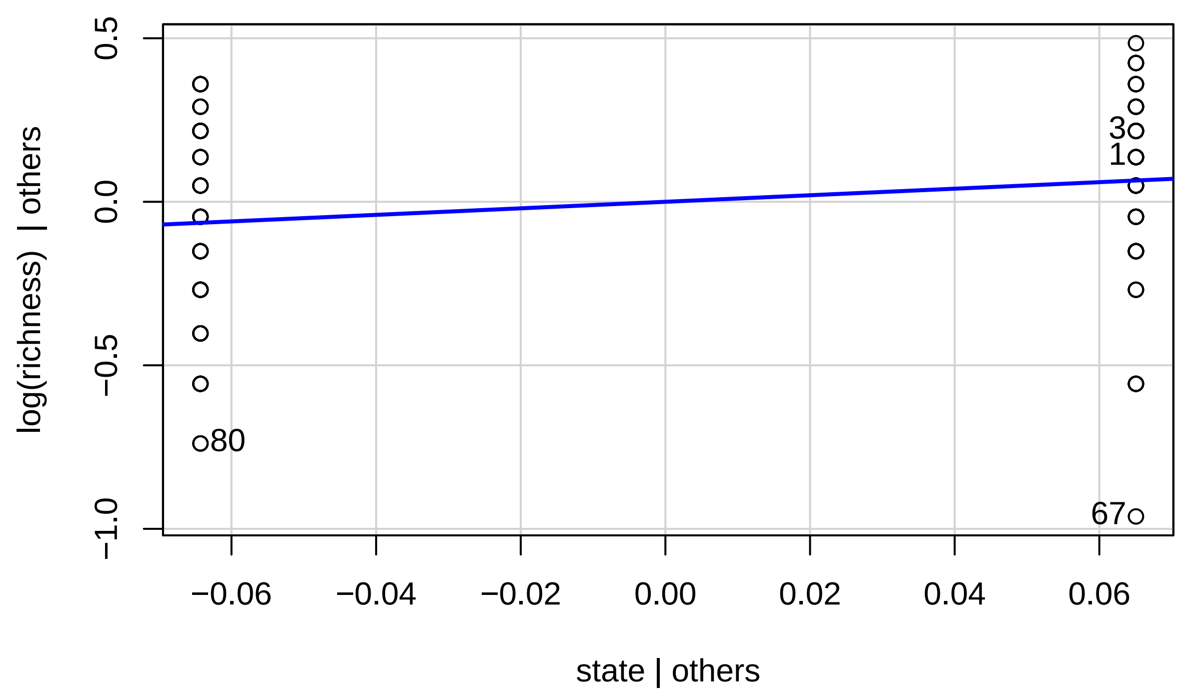
```r
qqPlot(fit_state_kbs_richness, main = "QQ Plot")
```




```
## [1] 67 80
```

```r
hist(fit_state_kbs_richness$residuals)
```


```
leveragePlots(fit_state_kbs_richness)
```




```
ols_test_normality(fit_state_kbs_richness)
```

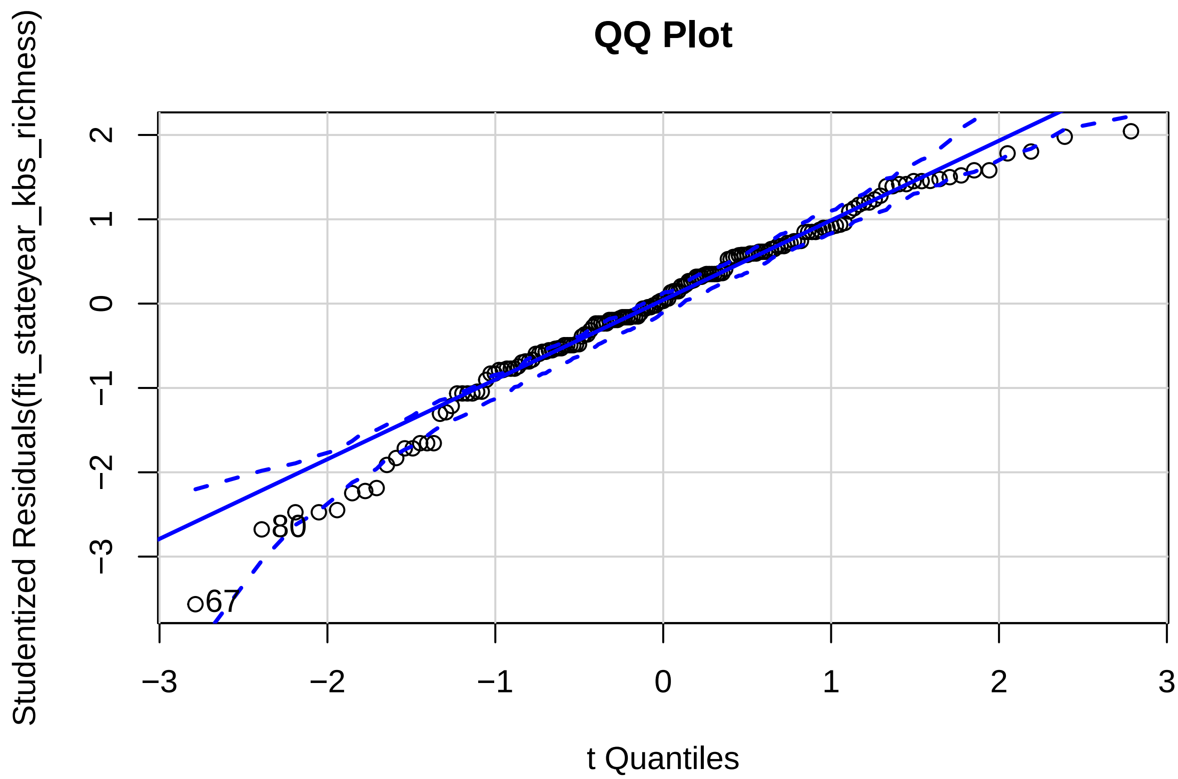
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9463         0.0000
## Kolmogorov-Smirnov        0.1141         0.0258
## Cramer-von Mises         29.8829         0.0000
## Anderson-Darling          2.353          0.0000
## -----------------------------------------------
```

```r
# KBS State and year model
fit_stateyear_kbs_richness <- lm(log(richness) ~ state + year, data = kbs_diversity)
outlierTest(fit_stateyear_kbs_richness)  # no outliers
```

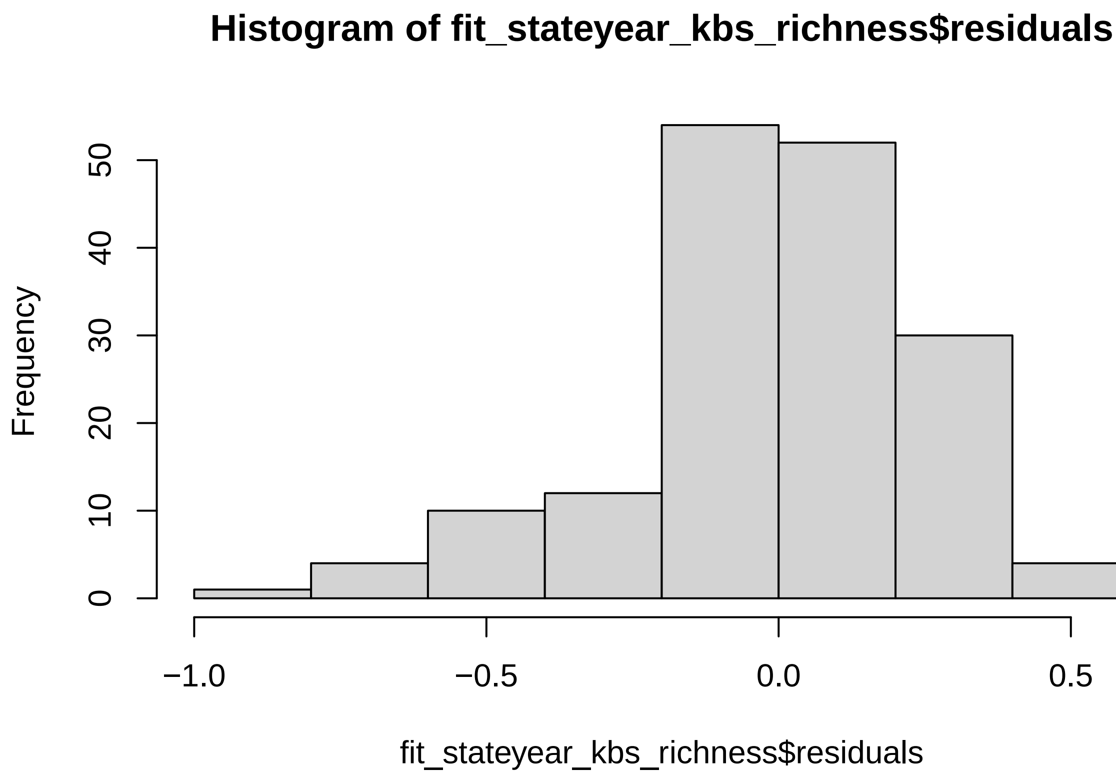
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##     rstudent unadjusted p-value Bonferroni p
## 67 -3.564283         0.00048283     0.080633
```

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

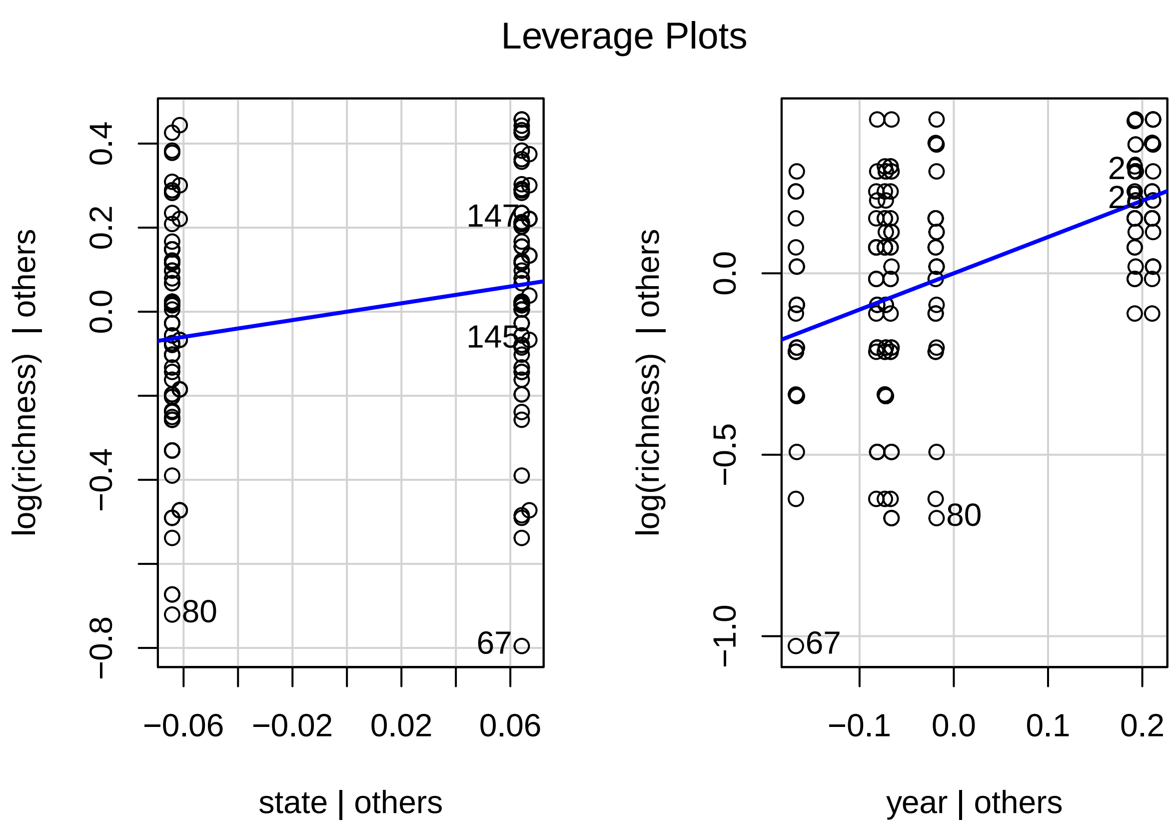



```
## [1] 67 80
```

```r
hist(fit_stateyear_kbs_richness$residuals)
```




```r
leveragePlots(fit_stateyear_kbs_richness)
```



```r
ols_test_normality(fit_stateyear_kbs_richness)
```

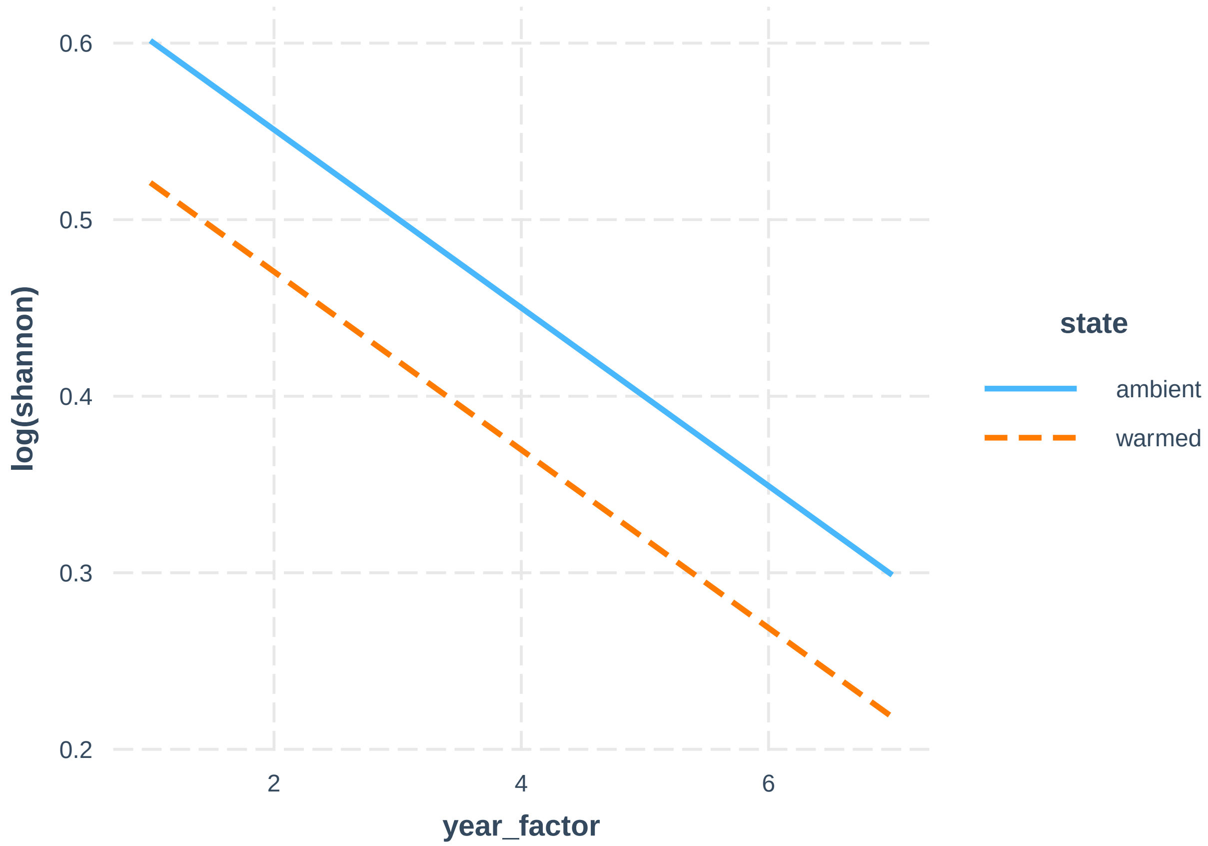
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.974          0.0032
## Kolmogorov-Smirnov        0.0657         0.4665
## Cramer-von Mises         32.7554         0.0000
## Anderson-Darling          0.9903         0.0127
## -----------------------------------------------
```

```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/

# I can't get these to work
fit3 <- lm(log(shannon) ~ state + year_factor, data = kbs_diversity)
interact_plot(fit3, pred = year_factor, modx = state)
```

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

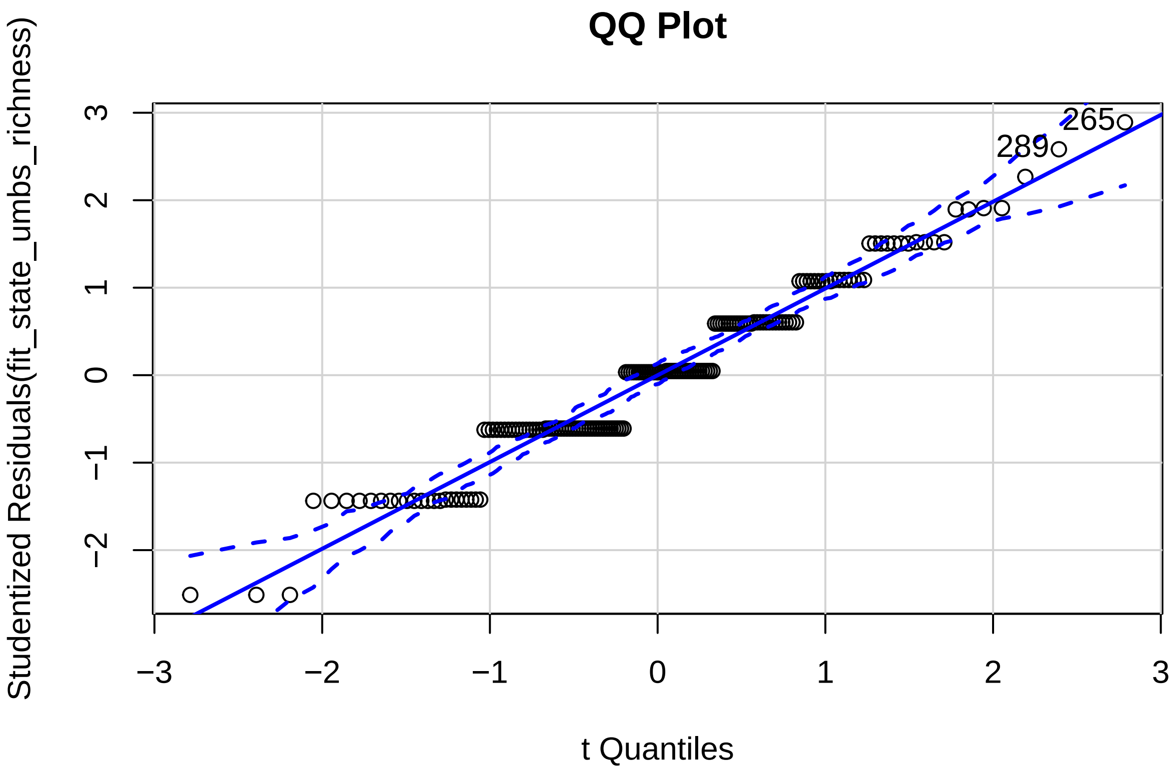
```
## Warning: year_factor and state are not included in an interaction with one another
## in the model.
```




```r
# UMBS State-only model
fit_state_umbs_richness <- lm(log(richness) ~ state, data = umbs_diversity)
outlierTest(fit_state_umbs_richness)  # no outliers
```

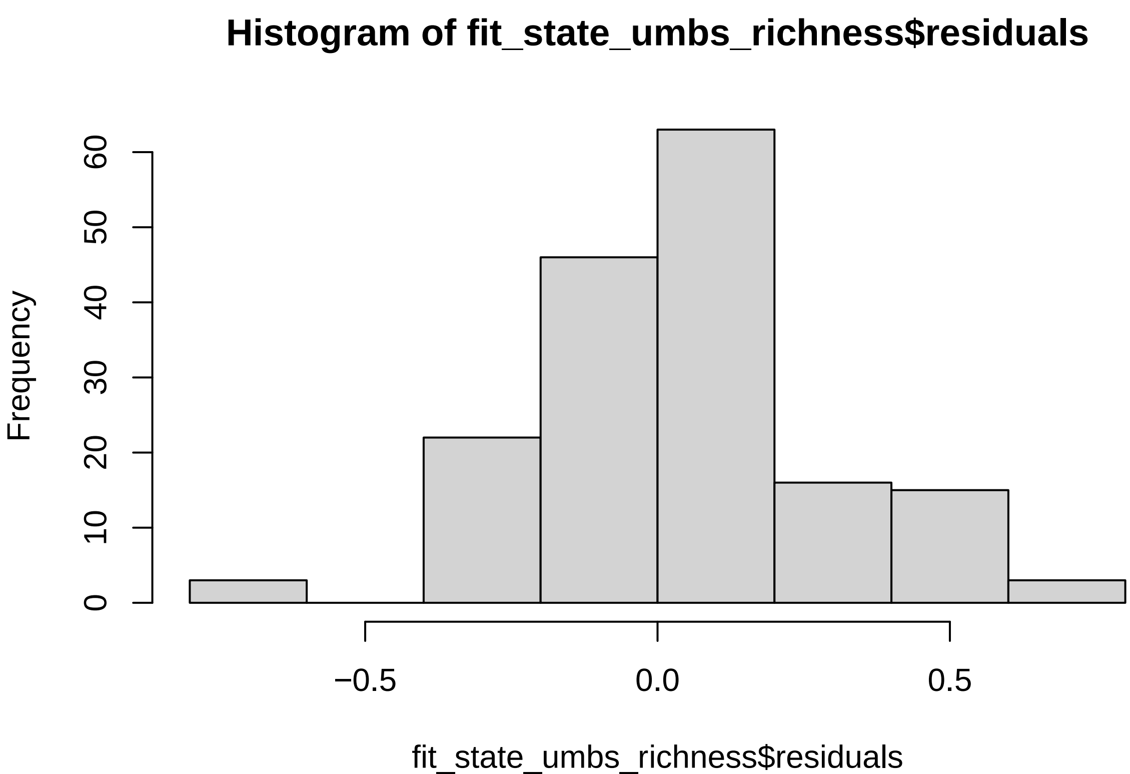
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##     rstudent unadjusted p-value Bonferroni p
## 265 2.891068          0.0043565       0.7319
```

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

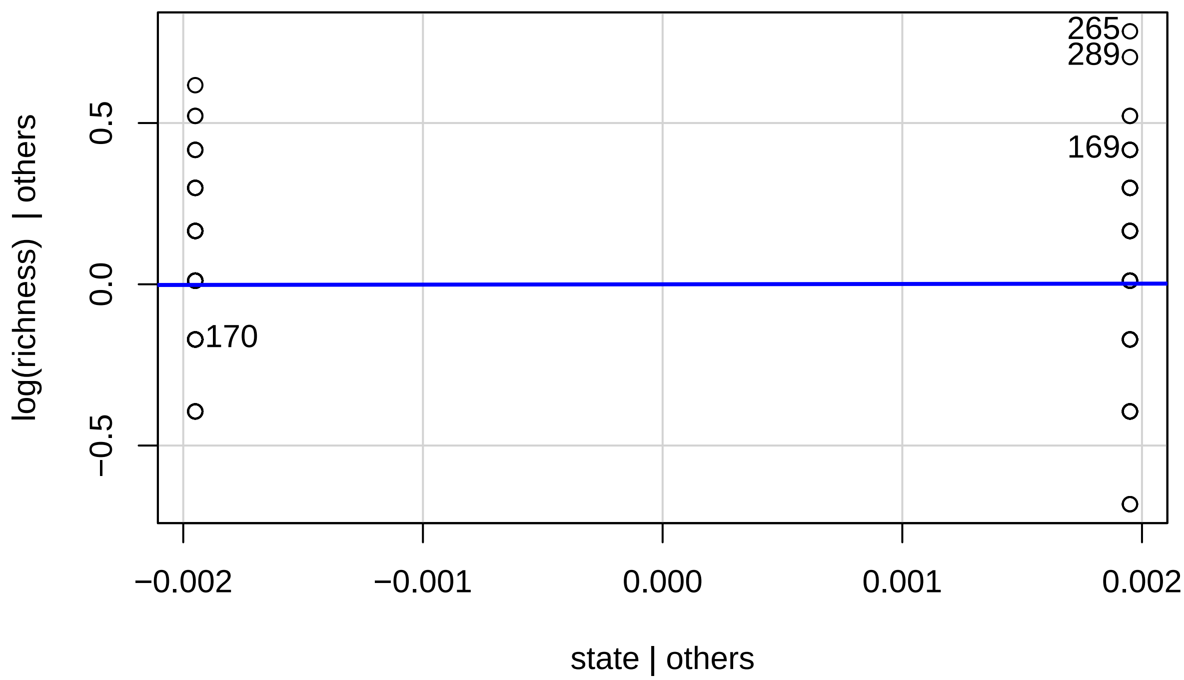



```
## 265 289
##  97 121
```

```
hist(fit_state_umbs_richness$residuals)
```



```r
leveragePlots(fit_state_umbs_richness)
```




```r
ols_test_normality(fit_state_umbs_richness)
```

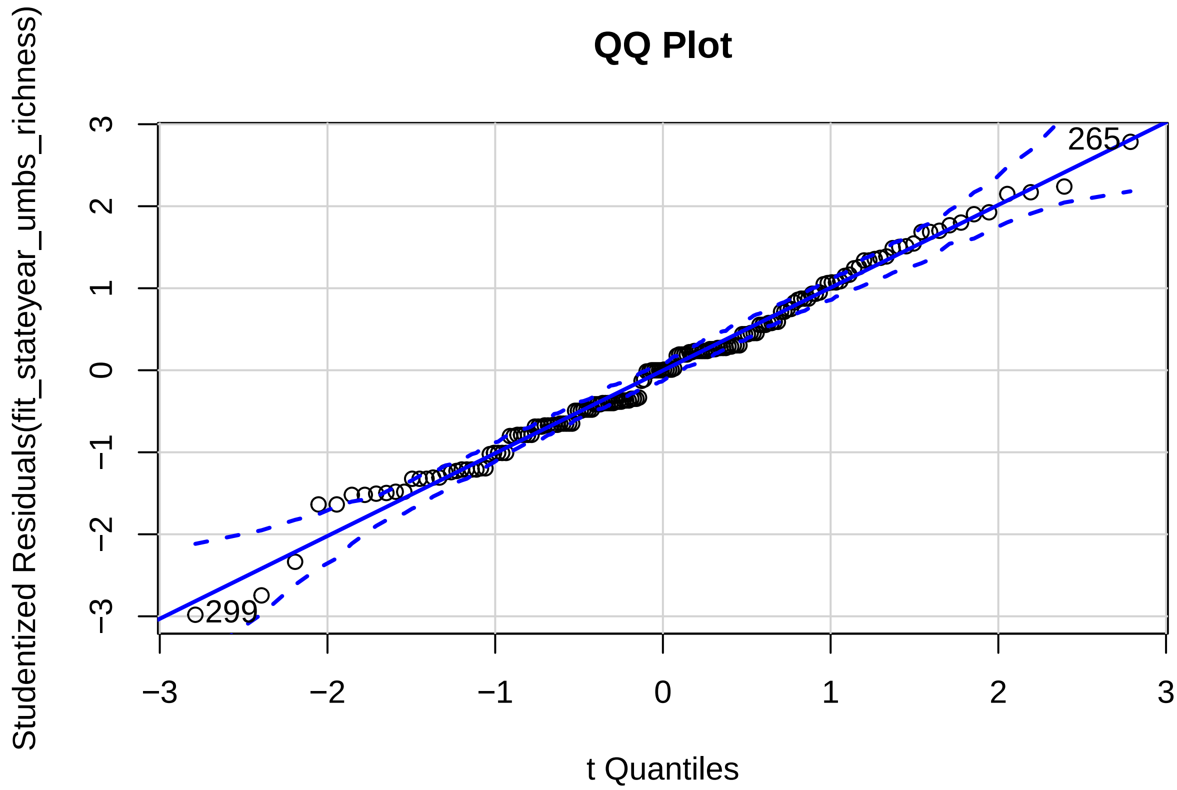
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9625         2e-04
## Kolmogorov-Smirnov        0.1516         9e-04
## Cramer-von Mises         30.8527        0.0000
## Anderson-Darling          2.848         0.0000
## -----------------------------------------------
```

```r
# UMBS State and year model
fit_stateyear_umbs_richness <- lm(log(richness) ~ state + year, data = umbs_diversity)
outlierTest(fit_stateyear_umbs_richness)  # no outliers
```

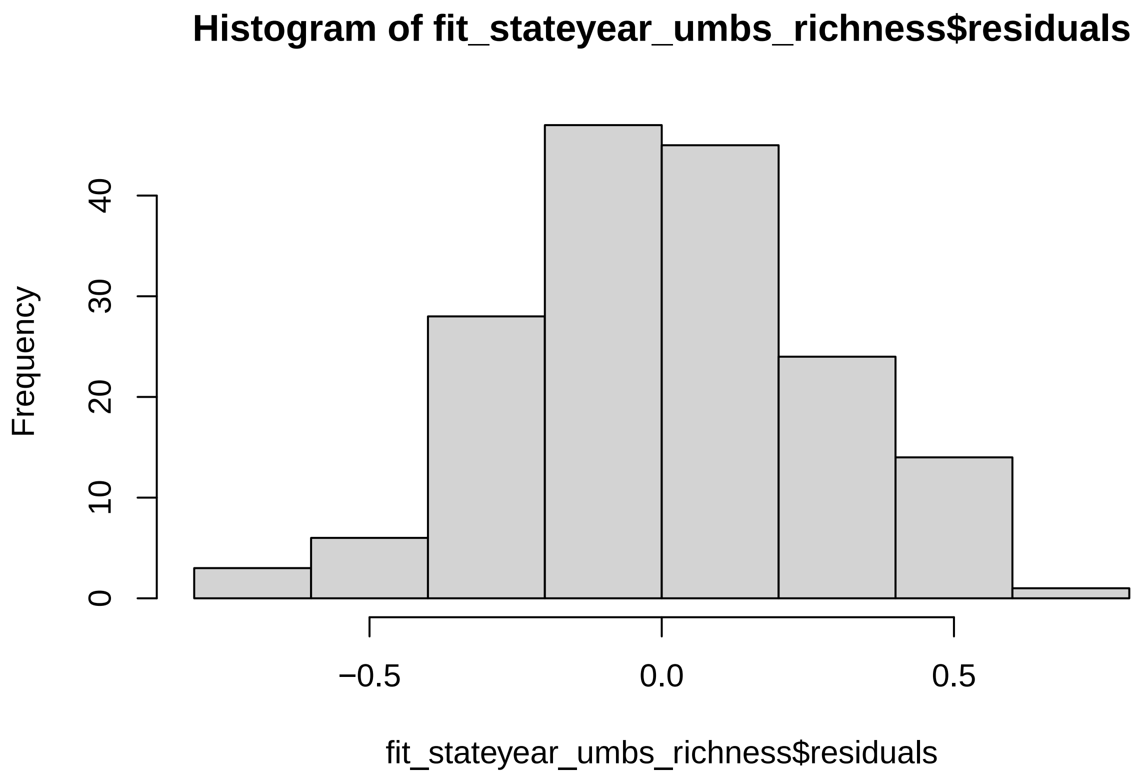
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 299 -2.981038          0.0033247      0.55855
```

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

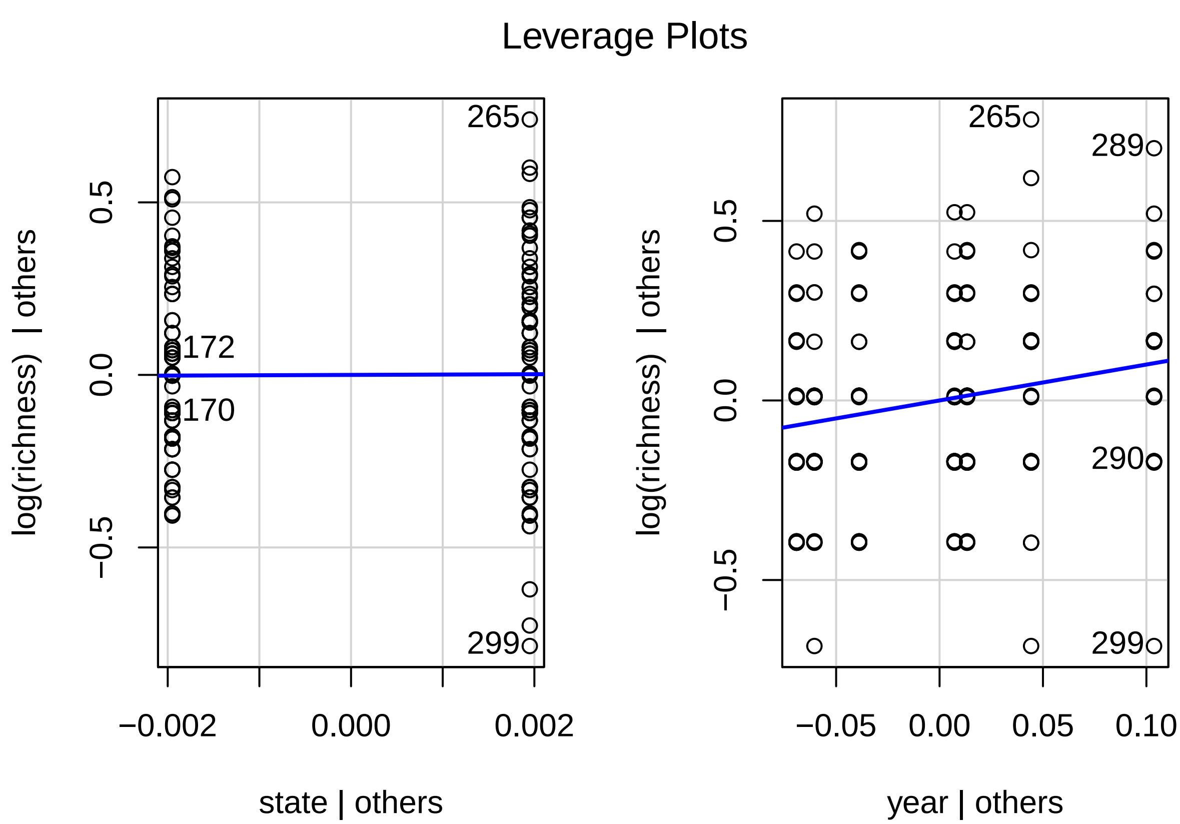



```
## 265 299
##  97 131
```

```
hist(fit_stateyear_umbs_richness$residuals)
```




```
leveragePlots(fit_stateyear_umbs_richness)
```



```r
ols_test_normality(fit_stateyear_umbs_richness)
```

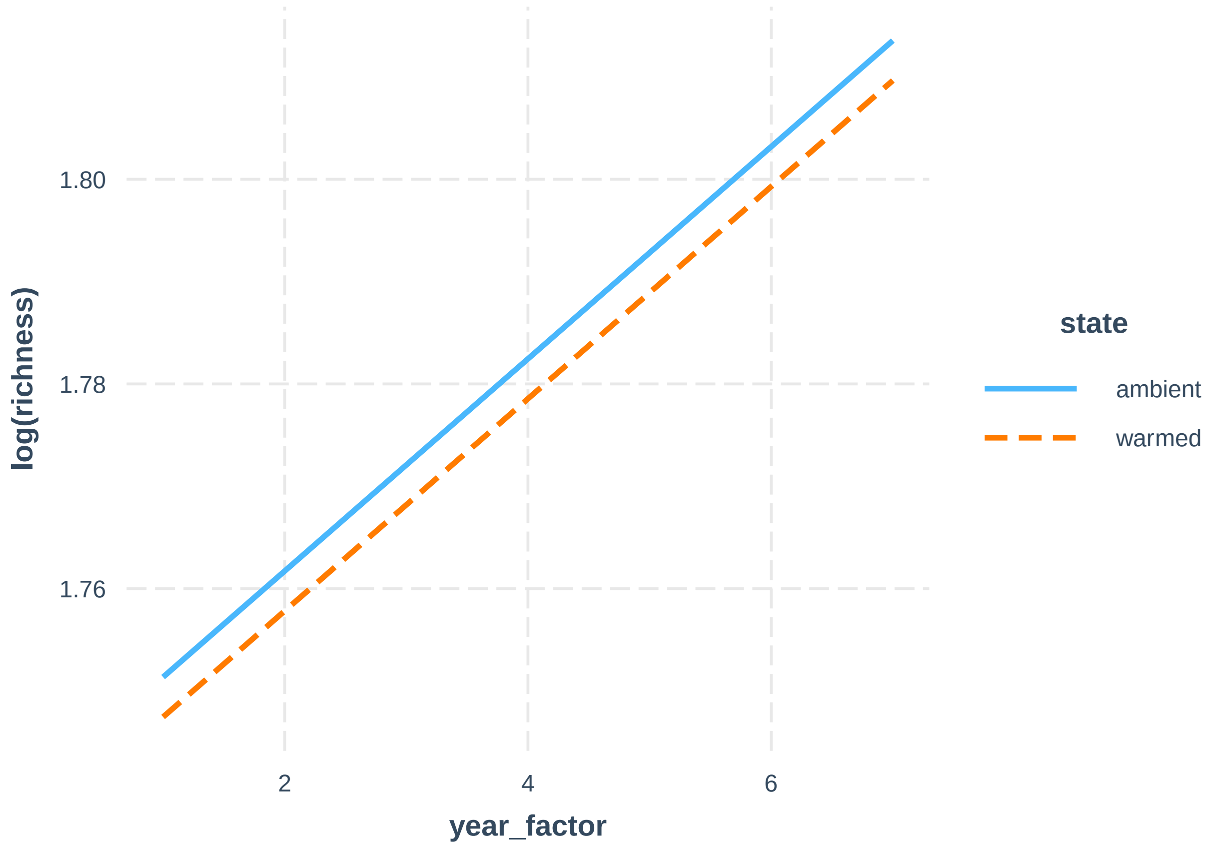
```
## Warning in ks.test(y, "pnorm", mean(y), sd(y)): ties should not be present for
## the Kolmogorov-Smirnov test
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9907         0.3459
## Kolmogorov-Smirnov        0.077          0.2719
## Cramer-von Mises         31.0512         0.0000
## Anderson-Darling          0.5649         0.1415
## -----------------------------------------------
```

```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/

# I can't get these to work
fit3 <- lm(log(richness) ~ state + year_factor, data = umbs_diversity)
interact_plot(fit3, pred = year_factor, modx = state)
```

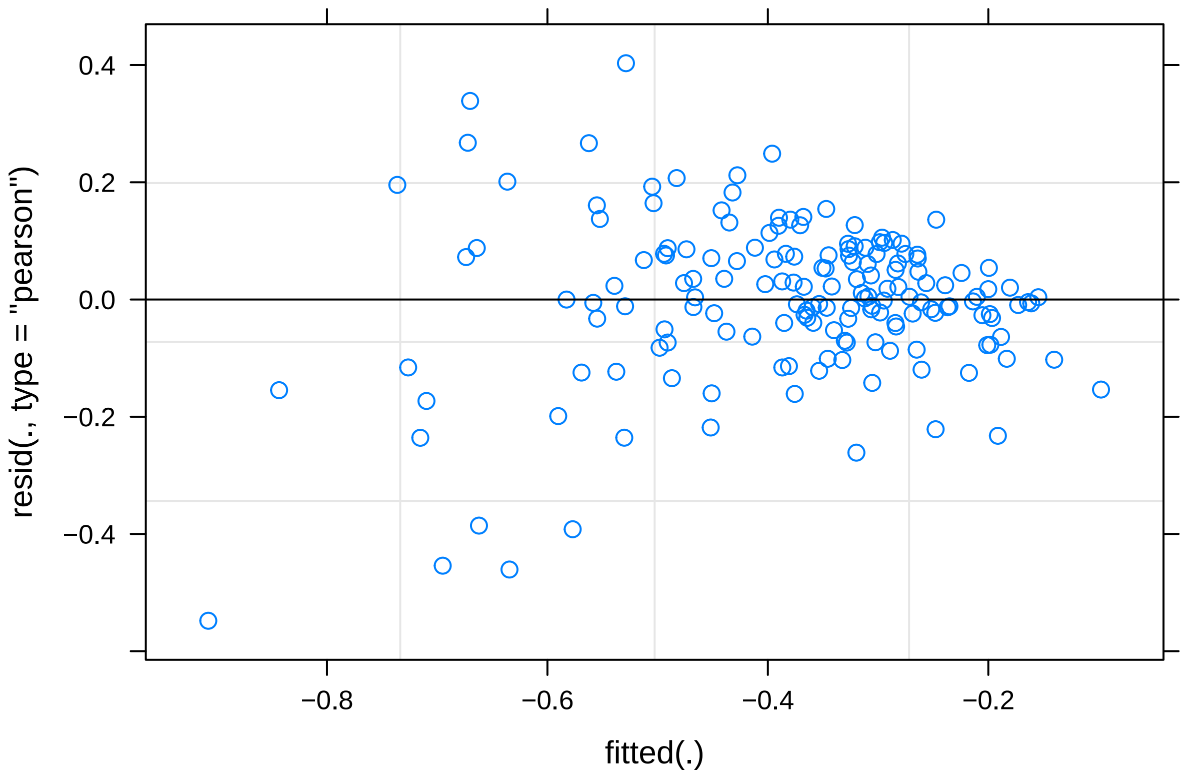
```
## Using data umbs_diversity from global environment. This could cause
## incorrect results if umbs_diversity has been altered since the model was
## fit. You can manually provide the data to the "data =" argument.
```

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



MIXED EFFECT MODELS SIMPSON KBS

```
mod1 <- lmer(log(simpson) ~ state * year + insecticide * year + (1 | plot), kbs_diversity,
    REML = FALSE)

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




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

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

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

```
## Levene's Test for Homogeneity of Variance (center = median)
##        Df F value Pr(>F)
## group   1  0.1398  0.709
##       165
```

```r
# Assumption not met
leveneTest(residuals(mod1) ~ kbs_diversity$insecticide)
```

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

```
## Levene's Test for Homogeneity of Variance (center = median)
```

```
##         Df F value   Pr(>F)
## group   1  10.776 0.001255 **
##        165
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# Assumption met
leveneTest(residuals(mod1) ~ kbs_diversity$plot)
```

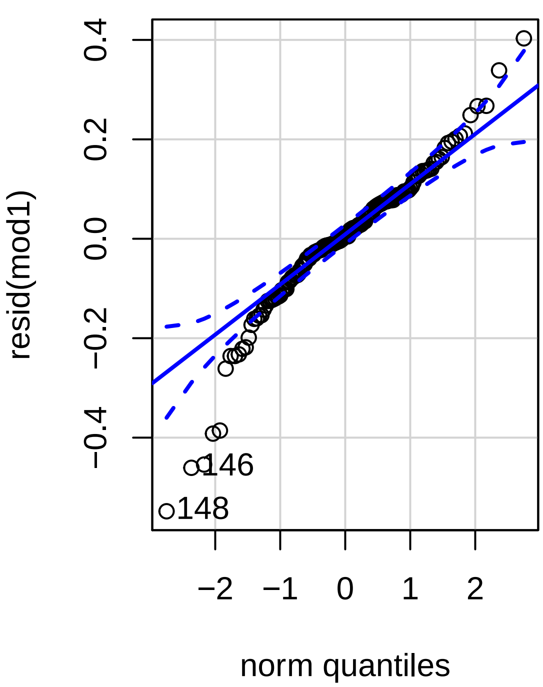
```
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.
```

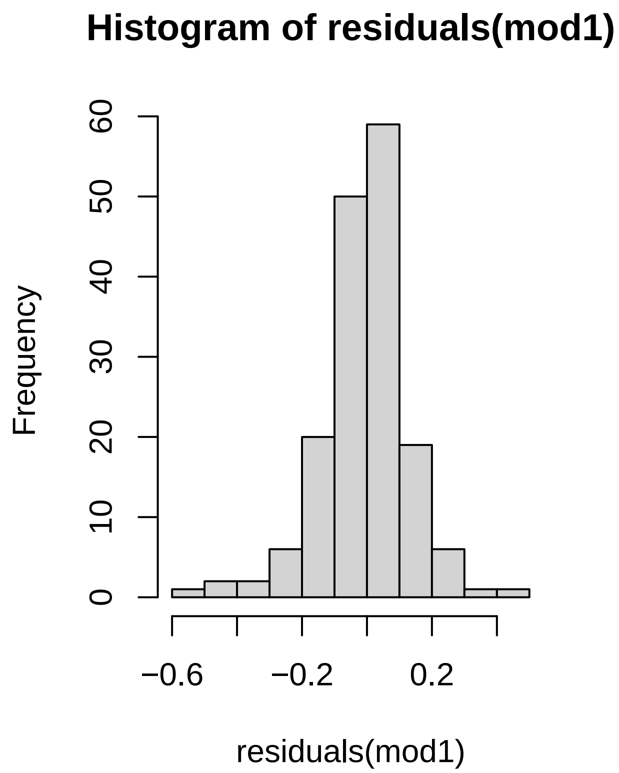
```
## Levene's Test for Homogeneity of Variance (center = median)
##         Df F value Pr(>F)
## group  23  1.1147 0.3367
##        143
```

```r
# Assumption not met

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

```
## [1] 148 146
```

```r
hist(residuals(mod1))
```





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

```
##
##  Shapiro-Wilk normality test
##
## data:  resid(mod1)
## W = 0.94058, p-value = 1.935e-06
```

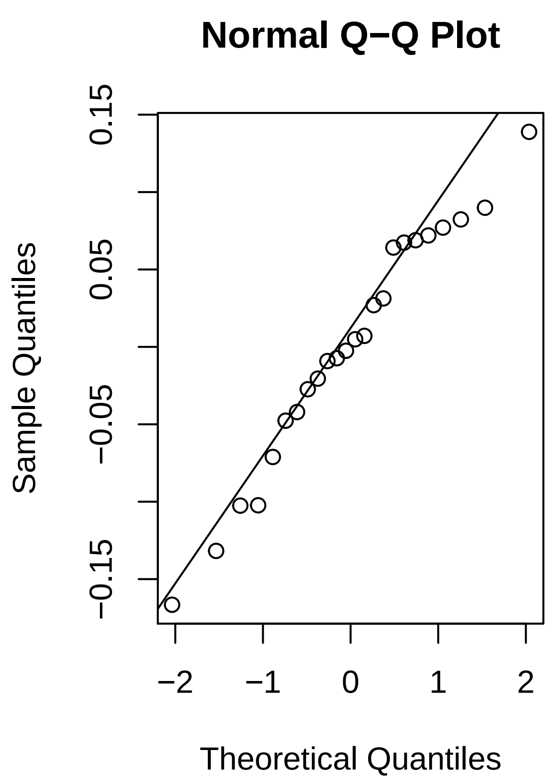
```r
outlierTest(mod1)  # row 148
```

```
##      rstudent unadjusted p-value Bonferroni p
## 148 -4.354042          2.5316e-05    0.0042278
```

```r
# (4) Normality of random effect: Get the estimate of random effect (e.g., random
# intercepts), and check them as you would check the residual.
require(lme4)
r_int <- ranef(mod1)$plot$`(Intercept)`
qqnorm(r_int)
qqline(r_int)
shapiro.test(r_int)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  r_int
## W = 0.96918, p-value = 0.6467
```

```r
# Normally distributed random effect pvalue > 0.05
```



```r
# Do we need to include plot as a random effect with the KBS models?
mod1 <- lmer(log(simpson) ~ state * year + insecticide * year + (1 | plot), kbs_diversity,
    REML = FALSE)
mod2 <- lmer(log(simpson) ~ state * year + insecticide + year + (1 | plot), kbs_diversity,
    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)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq Mean Sq F value
## state               1 0.02531 0.02531  1.2492
## year                6 1.98589 0.33098 16.3328
## insecticide         1 0.01949 0.01949  0.9615
## state:year          6 0.03755 0.00626  0.3088
## year:insecticide    6 0.41266 0.06878  3.3939
```

```r
anova(mod2)
```

```
## Analysis of Variance Table
##             npar  Sum Sq Mean Sq F value
## state          1 0.02917 0.02917  1.2581
## year           6 1.98842 0.33140 14.2935
## insecticide    1 0.02247 0.02247  0.9692
## state:year     6 0.03746 0.00624  0.2693
```

```r
anova(mod1, mod2)  # Go with model 1 since pvalue <0.05, aka more complex model does have something in
```

```
## Data: kbs_diversity
## Models:
## mod2: log(simpson) ~ state * year + insecticide + year + (1 | plot)
## mod1: log(simpson) ~ state * year + insecticide * year + (1 | plot)
##      npar     AIC     BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod2   17 -92.859 -39.853 63.430  -126.86
## mod1   23 -99.865 -28.151 72.932  -145.87 19.005  6   0.004155 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod1)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(simpson) ~ state * year + insecticide * year + (1 | plot)
##    Data: kbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##    -99.9    -28.2     72.9   -145.9      144
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.8502 -0.4153  0.0271  0.5410  2.8316
```

```
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.00783  0.08849
##  Residual             0.02026  0.14235
## Number of obs: 167, groups:  plot, 24
##
## Fixed effects:
##                                Estimate Std. Error t value
## (Intercept)                   -0.255226   0.059261  -4.307
## statewarmed                    0.010736   0.068429   0.157
## year2016                      -0.041051   0.071177  -0.577
## year2017                      -0.125531   0.071177  -1.764
## year2018                      -0.027139   0.071177  -0.381
## year2019                      -0.111216   0.071177  -1.563
## year2020                      -0.064007   0.071177  -0.899
## year2021                      -0.203187   0.073961  -2.747
## insecticideno_insects         -0.023876   0.068429  -0.349
## statewarmed:year2016          -0.039587   0.082188  -0.482
## statewarmed:year2017          -0.096517   0.082188  -1.174
## statewarmed:year2018          -0.074540   0.082188  -0.907
## statewarmed:year2019          -0.035519   0.082188  -0.432
## statewarmed:year2020          -0.065045   0.082188  -0.791
## statewarmed:year2021          -0.084216   0.083274  -1.011
## year2016:insecticideno_insects  0.083505   0.082188   1.016
## year2017:insecticideno_insects  0.101822   0.082188   1.239
## year2018:insecticideno_insects  0.006322   0.082188   0.077
## year2019:insecticideno_insects -0.144687   0.082188  -1.760
## year2020:insecticideno_insects  0.005591   0.082188   0.068
## year2021:insecticideno_insects -0.185358   0.083274  -2.226

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

```r
summary(mod2)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(simpson) ~ state * year + insecticide + year + (1 | plot)
##    Data: kbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##    -92.9    -39.9     63.4   -126.9      150
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2104 -0.3910  0.0519  0.6361  2.2046
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.00730  0.08544
##  Residual             0.02319  0.15227
```

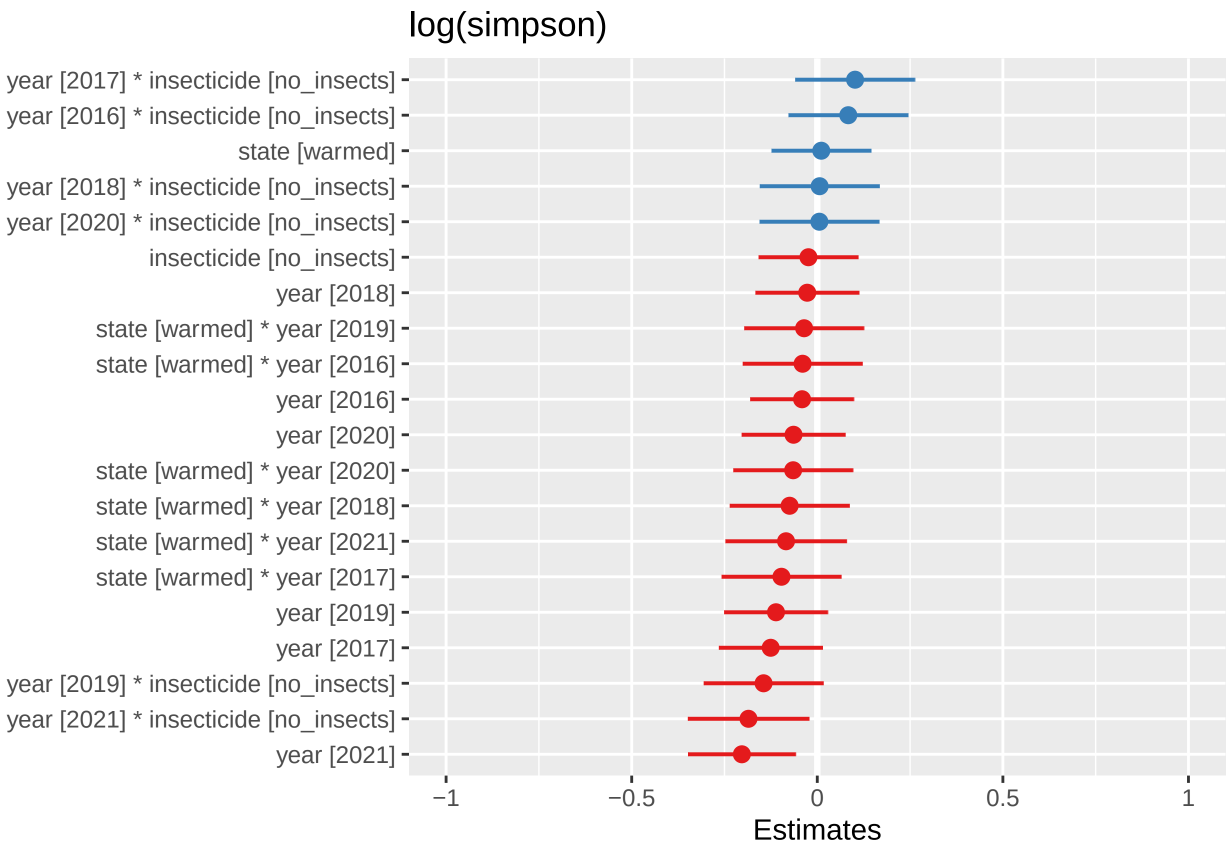
```
## Number of obs: 167, groups:  plot, 24
##
## Fixed effects:
##                          Estimate Std. Error t value
## (Intercept)           -0.2463705  0.0546223  -4.510
## statewarmed            0.0107357  0.0712802   0.151
## year2016               0.0007018  0.0621632   0.011
## year2017              -0.0746198  0.0621632  -1.200
## year2018              -0.0239776  0.0621632  -0.386
## year2019              -0.1835591  0.0621632  -2.953
## year2020              -0.0612118  0.0621632  -0.985
## year2021              -0.3046923  0.0637141  -4.782
## insecticideno_insects -0.0415872  0.0421026  -0.988
## statewarmed:year2016  -0.0395873  0.0879120  -0.450
## statewarmed:year2017  -0.0965165  0.0879120  -1.098
## statewarmed:year2018  -0.0745396  0.0879120  -0.848
## statewarmed:year2019  -0.0355190  0.0879120  -0.404
## statewarmed:year2020  -0.0650450  0.0879120  -0.740
## statewarmed:year2021  -0.0753895  0.0890154  -0.847
```

```
##
## Correlation matrix not shown by default, as p = 15 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```r
AICctab(mod1, mod2, weights = T)  # model 1
```

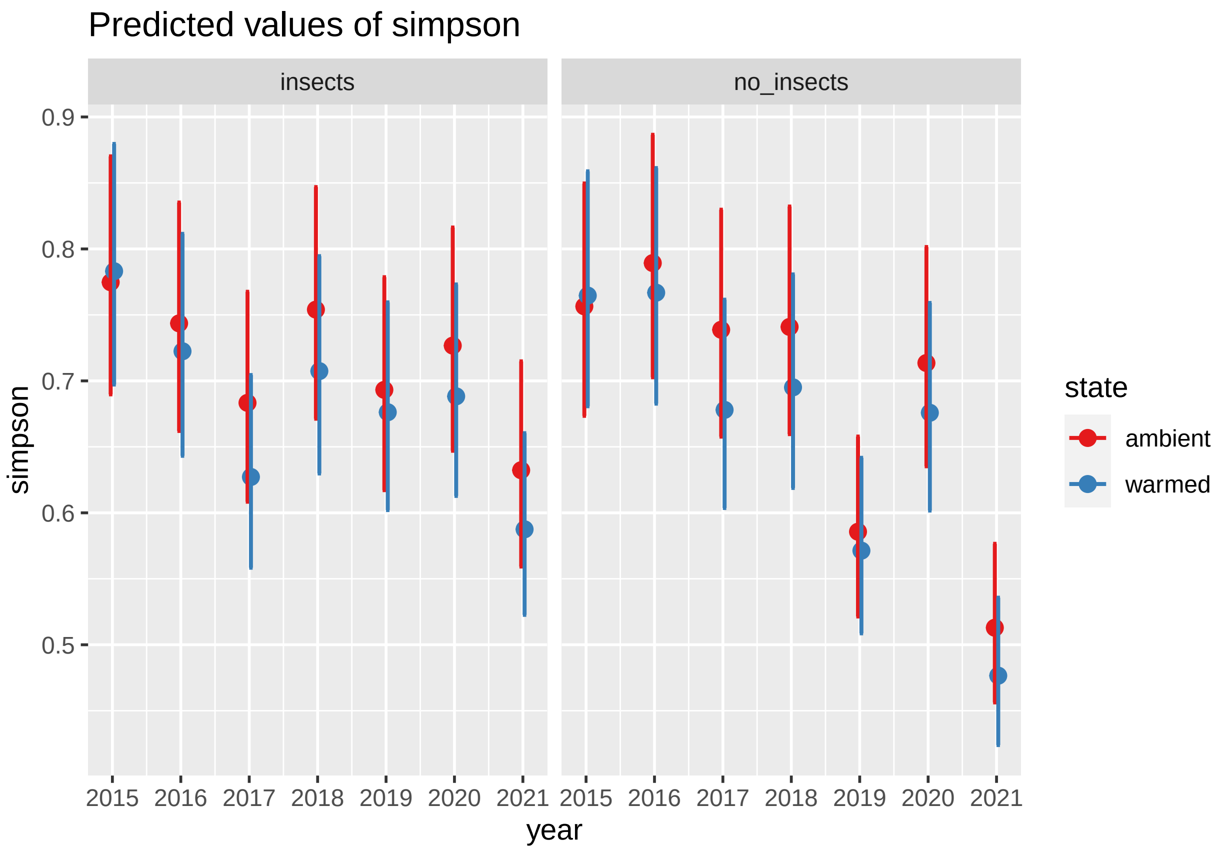
```
##      dAICc df weight
## mod1  0.0  23 0.85
## mod2  3.4  17 0.15
```

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

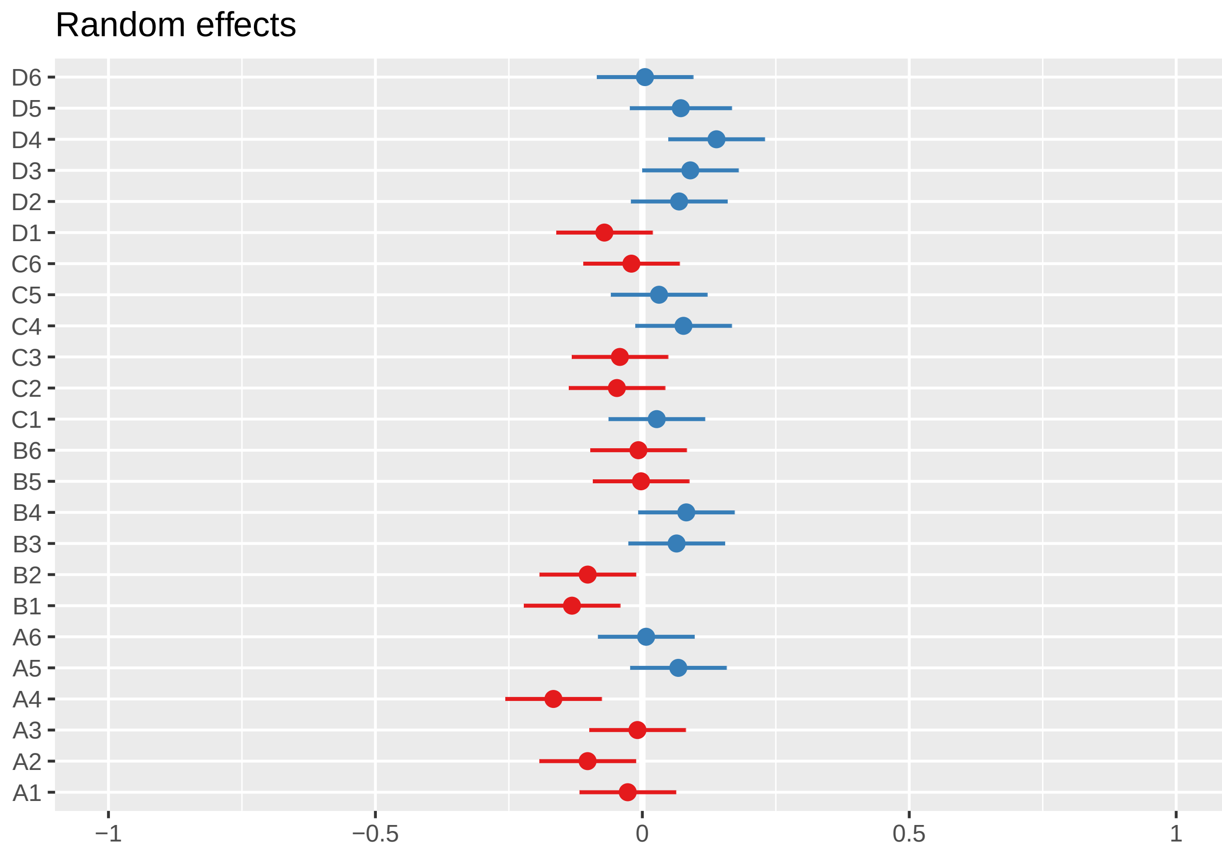



```r
# these are the fixed predicted values:
plot_model(mod1, type = "pred", terms = c("year", "state", "insecticide"))
```

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




```r
# these are the random effects estimates
plot_model(mod1, type = "re", terms = c("species"))
```




```r
# Does year need to be interactive with state?
mod3 <- lmer(log(simpson) ~ state + year + insecticide * year + (1 | plot), kbs_diversity,
    REML = FALSE)
anova(mod2, mod3)
```

```
## Data: kbs_diversity
## Models:
## mod2: log(simpson) ~ state * year + insecticide + year + (1 | plot)
## mod3: log(simpson) ~ state + year + insecticide * year + (1 | plot)
##      npar      AIC     BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod2   17  -92.859 -39.853 63.430  -126.86
## mod3   17 -109.911 -56.905 71.955  -143.91 17.051  0
```

```r
AICctab(mod1, mod3, weights = T)  # going with mod3
```

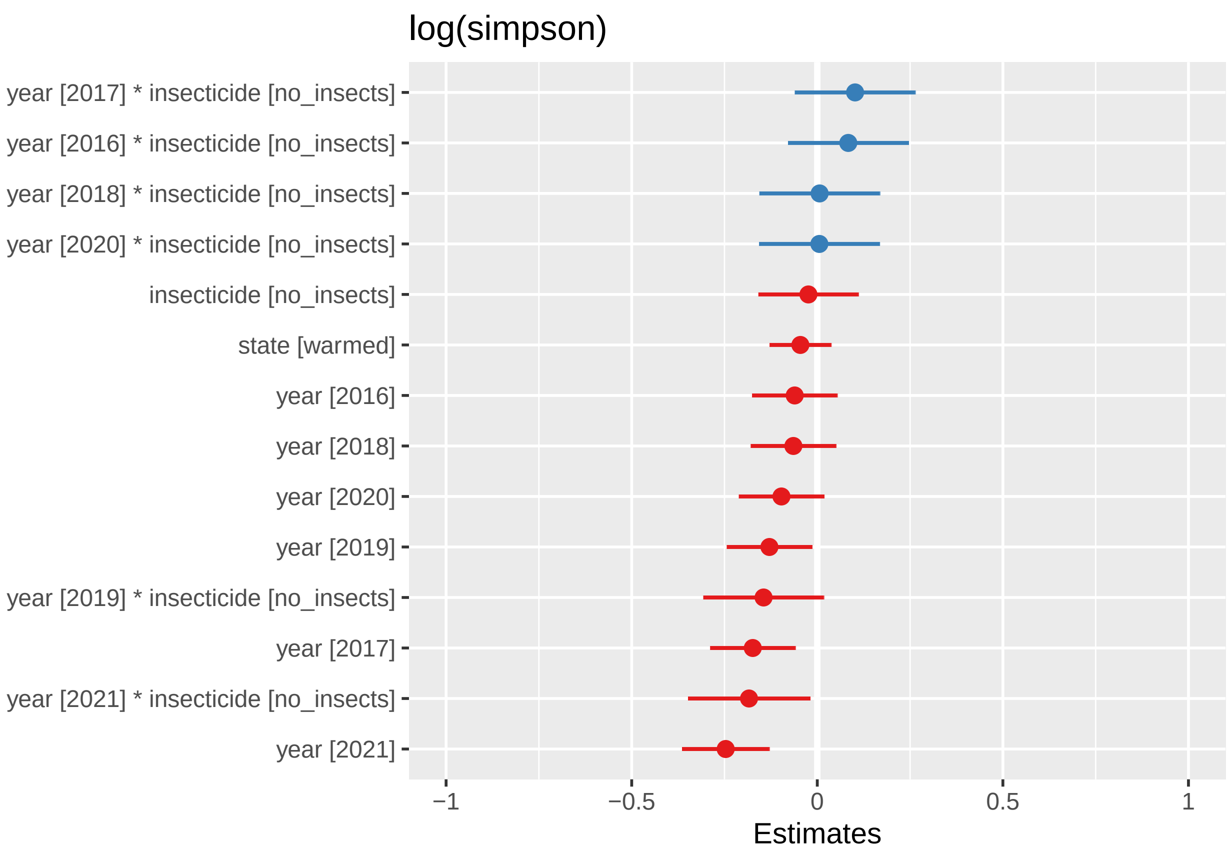
```
##      dAICc df weight
## mod3  0.0  17 0.9989
## mod1 13.7  23 0.0011
```

```r
# Do we need to include insecticide? (dropping insecticide from the model)
mod5 <- lmer(log(simpson) ~ state + year + (1 | plot), kbs_diversity, REML = FALSE)
anova(mod3, mod5)
```

```
## Data: kbs_diversity
## Models:
```

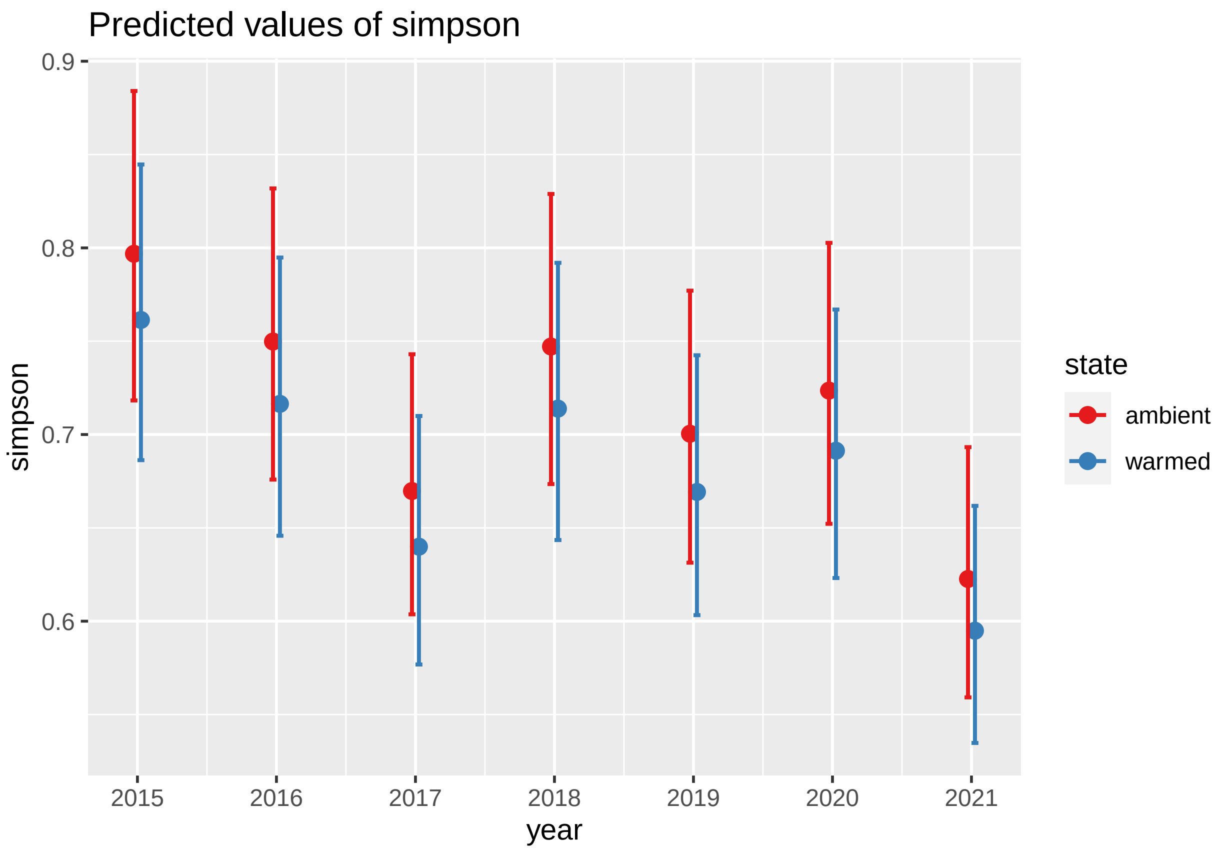
```
## mod5: log(simpson) ~ state + year + (1 | plot)
## mod3: log(simpson) ~ state + year + insecticide * year + (1 | plot)
##      npar     AIC     BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod5   10 -104.30 -73.121 62.151  -124.30
## mod3   17 -109.91 -56.905 71.955  -143.91 19.609  7   0.006478 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Yes, p<0.05 so insecticide*year does strongly improve model fit so we will
# stick with the more complex mod3

# Plot the fixed effects estimates for different models these are the fixed
# effects estimates from summary(mod5)
plot_model(mod3, sort.est = TRUE)
```

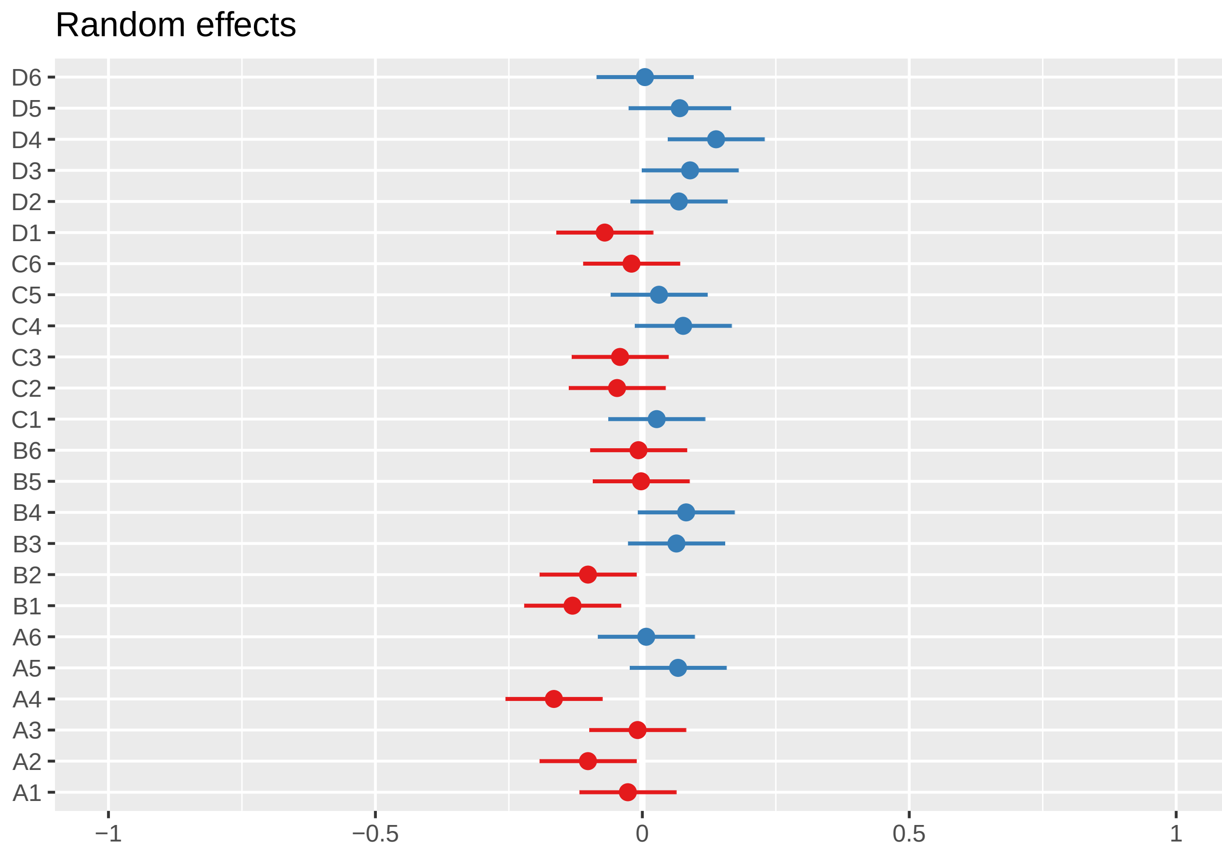



```
# these are the fixed predicted values:
plot_model(mod3, type = "pred", terms = c("year", "state"))
```

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




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




```r
# the best model fit appears to be = mod3 <- lmer(log(simpson) ~ state + year +
# insecticide*year + (1|plot), kbs_diversity, REML = FALSE)
summ(mod3)
```

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

AIC	-109.91
BIC	-56.90
Pseudo-R^2 (fixed effects)	0.35
Pseudo-R^2 (total)	0.53

```r
emmeans(mod3, list(pairwise ~ state + year + insecticide * year), adjust = "tukey")
```

```
## $`emmeans of state, year, insecticide`
##  state   year insecticide emmean     SE   df lower.CL upper.CL
##  ambient 2015 insects     -0.227 0.0560 99.3   -0.338   -0.116
##  warmed  2015 insects     -0.273 0.0560 99.4   -0.384   -0.162
##  ambient 2016 insects     -0.288 0.0560 99.3   -0.399   -0.177
##  warmed  2016 insects     -0.333 0.0560 99.4   -0.445   -0.222
##  ambient 2017 insects     -0.401 0.0560 99.3   -0.512   -0.290
##  warmed  2017 insects     -0.446 0.0560 99.4   -0.557   -0.335
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	-0.23	0.05	-4.29	87.62	0.00
statewarmed	-0.05	0.04	-1.08	24.01	0.29
year2016	-0.06	0.06	-1.04	143.00	0.30
year2017	-0.17	0.06	-2.97	143.00	0.00
year2018	-0.06	0.06	-1.10	143.00	0.27
year2019	-0.13	0.06	-2.20	143.00	0.03
year2020	-0.10	0.06	-1.65	143.00	0.10
year2021	-0.25	0.06	-4.11	143.58	0.00
insecticideno_insects	-0.02	0.07	-0.35	115.28	0.73
year2016:insecticideno_insects	0.08	0.08	1.01	143.00	0.31
year2017:insecticideno_insects	0.10	0.08	1.23	143.00	0.22
year2018:insecticideno_insects	0.01	0.08	0.08	143.00	0.94
year2019:insecticideno_insects	-0.14	0.08	-1.75	143.00	0.08
year2020:insecticideno_insects	0.01	0.08	0.07	143.00	0.95
year2021:insecticideno_insects	-0.18	0.08	-2.19	143.30	0.03

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.09
Residual		0.14

Grouping Variables		
Group	# groups	ICC
plot	24	0.27

```
##  ambient 2018 insects     -0.291 0.0560  99.3   -0.403   -0.180
##  warmed  2018 insects     -0.337 0.0560  99.4   -0.448   -0.226
##  ambient 2019 insects     -0.356 0.0560  99.3   -0.467   -0.245
##  warmed  2019 insects     -0.402 0.0560  99.4   -0.513   -0.291
##  ambient 2020 insects     -0.324 0.0560  99.3   -0.435   -0.213
##  warmed  2020 insects     -0.369 0.0560  99.4   -0.480   -0.258
##  ambient 2021 insects     -0.474 0.0579 107.6   -0.589   -0.359
##  warmed  2021 insects     -0.519 0.0574 105.7   -0.633   -0.406
##  ambient 2015 no_insects  -0.251 0.0560  99.4   -0.362   -0.140
##  warmed  2015 no_insects  -0.297 0.0560  99.4   -0.408   -0.185
##  ambient 2016 no_insects  -0.228 0.0560  99.4   -0.339   -0.117
##  warmed  2016 no_insects  -0.274 0.0560  99.4   -0.385   -0.163
##  ambient 2017 no_insects  -0.323 0.0560  99.4   -0.434   -0.212
##  warmed  2017 no_insects  -0.368 0.0560  99.4   -0.480   -0.257
##  ambient 2018 no_insects  -0.309 0.0560  99.4   -0.420   -0.198
##  warmed  2018 no_insects  -0.355 0.0560  99.4   -0.466   -0.244
##  ambient 2019 no_insects  -0.525 0.0560  99.4   -0.636   -0.414
##  warmed  2019 no_insects  -0.570 0.0560  99.4   -0.681   -0.459
##  ambient 2020 no_insects  -0.342 0.0560  99.4   -0.453   -0.231
##  warmed  2020 no_insects  -0.387 0.0560  99.4   -0.499   -0.276
```

```
##  ambient 2021 no_insects  -0.682 0.0560  99.4   -0.793   -0.571
##  warmed  2021 no_insects  -0.727 0.0560  99.4   -0.838   -0.616
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, year, insecticide`
##  1                                                 estimate     SE    df
##  ambient 2015 insects - warmed 2015 insects         0.045546 0.0452  27.4
##  ambient 2015 insects - ambient 2016 insects        0.060844 0.0611 156.1
##  ambient 2015 insects - warmed 2016 insects         0.106390 0.0760 141.8
##  ambient 2015 insects - ambient 2017 insects        0.173789 0.0611 156.1
##  ambient 2015 insects - warmed 2017 insects         0.219335 0.0760 141.8
##  ambient 2015 insects - ambient 2018 insects        0.064409 0.0611 156.1
##  ambient 2015 insects - warmed 2018 insects         0.109955 0.0760 141.8
##  ambient 2015 insects - ambient 2019 insects        0.128975 0.0611 156.1
##  ambient 2015 insects - warmed 2019 insects         0.174521 0.0760 141.8
##  ambient 2015 insects - ambient 2020 insects        0.096530 0.0611 156.1
##  ambient 2015 insects - warmed 2020 insects         0.142075 0.0760 141.8
##  ambient 2015 insects - ambient 2021 insects        0.246747 0.0627 156.7
##  ambient 2015 insects - warmed 2021 insects         0.292293 0.0769 144.1
##  ambient 2015 insects - ambient 2015 no_insects     0.023876 0.0724 129.8
##  ambient 2015 insects - warmed 2015 no_insects      0.069422 0.0854  81.3
##  ambient 2015 insects - ambient 2016 no_insects     0.001215 0.0724 129.8
##  ambient 2015 insects - warmed 2016 no_insects      0.046761 0.0854  81.3
##  ambient 2015 insects - ambient 2017 no_insects     0.095843 0.0724 129.8
##  ambient 2015 insects - warmed 2017 no_insects      0.141389 0.0854  81.3
##  ambient 2015 insects - ambient 2018 no_insects     0.081962 0.0724 129.8
##  ambient 2015 insects - warmed 2018 no_insects      0.127508 0.0854  81.3
##  ambient 2015 insects - ambient 2019 no_insects     0.297538 0.0724 129.8
##  ambient 2015 insects - warmed 2019 no_insects      0.343084 0.0854  81.3
##  ambient 2015 insects - ambient 2020 no_insects     0.114815 0.0724 129.8
##  ambient 2015 insects - warmed 2020 no_insects      0.160361 0.0854  81.3
##  ambient 2015 insects - ambient 2021 no_insects     0.454529 0.0724 129.8
##  ambient 2015 insects - warmed 2021 no_insects      0.500074 0.0854  81.3
##  warmed 2015 insects - ambient 2016 insects         0.015298 0.0760 141.8
##  warmed 2015 insects - warmed 2016 insects          0.060844 0.0611 156.1
##  warmed 2015 insects - ambient 2017 insects         0.128243 0.0760 141.8
##  warmed 2015 insects - warmed 2017 insects          0.173789 0.0611 156.1
##  warmed 2015 insects - ambient 2018 insects         0.018863 0.0760 141.8
##  warmed 2015 insects - warmed 2018 insects          0.064409 0.0611 156.1
##  warmed 2015 insects - ambient 2019 insects         0.083429 0.0760 141.8
##  warmed 2015 insects - warmed 2019 insects          0.128975 0.0611 156.1
##  warmed 2015 insects - ambient 2020 insects         0.050984 0.0760 141.8
##  warmed 2015 insects - warmed 2020 insects          0.096530 0.0611 156.1
##  warmed 2015 insects - ambient 2021 insects         0.201201 0.0776 145.9
##  warmed 2015 insects - warmed 2021 insects          0.246747 0.0627 156.7
##  warmed 2015 insects - ambient 2015 no_insects     -0.021670 0.0854  81.3
##  warmed 2015 insects - warmed 2015 no_insects       0.023876 0.0724 129.8
##  warmed 2015 insects - ambient 2016 no_insects     -0.044331 0.0854  81.3
##  warmed 2015 insects - warmed 2016 no_insects       0.001215 0.0724 129.8
##  warmed 2015 insects - ambient 2017 no_insects      0.050297 0.0854  81.3
##  warmed 2015 insects - warmed 2017 no_insects       0.095843 0.0724 129.8
```

```
##  warmed 2015 insects - ambient 2018 no_insects      0.036416 0.0854  81.3
##  warmed 2015 insects - warmed 2018 no_insects       0.081962 0.0724 129.8
##  warmed 2015 insects - ambient 2019 no_insects      0.251992 0.0854  81.3
##  warmed 2015 insects - warmed 2019 no_insects       0.297538 0.0724 129.8
##  warmed 2015 insects - ambient 2020 no_insects      0.069269 0.0854  81.3
##  warmed 2015 insects - warmed 2020 no_insects       0.114815 0.0724 129.8
##  warmed 2015 insects - ambient 2021 no_insects      0.408983 0.0854  81.3
##  warmed 2015 insects - warmed 2021 no_insects       0.454529 0.0724 129.8
##  ambient 2016 insects - warmed 2016 insects         0.045546 0.0452  27.4
##  ambient 2016 insects - ambient 2017 insects        0.112945 0.0611 156.1
##  ambient 2016 insects - warmed 2017 insects         0.158490 0.0760 141.8
##  ambient 2016 insects - ambient 2018 insects        0.003564 0.0611 156.1
##  ambient 2016 insects - warmed 2018 insects         0.049110 0.0760 141.8
##  ambient 2016 insects - ambient 2019 insects        0.068131 0.0611 156.1
##  ambient 2016 insects - warmed 2019 insects         0.113677 0.0760 141.8
##  ambient 2016 insects - ambient 2020 insects        0.035685 0.0611 156.1
##  ambient 2016 insects - warmed 2020 insects         0.081231 0.0760 141.8
##  ambient 2016 insects - ambient 2021 insects        0.185903 0.0627 156.7
##  ambient 2016 insects - warmed 2021 insects         0.231449 0.0769 144.1
##  ambient 2016 insects - ambient 2015 no_insects    -0.036968 0.0724 129.8
##  ambient 2016 insects - warmed 2015 no_insects      0.008578 0.0854  81.3
##  ambient 2016 insects - ambient 2016 no_insects    -0.059629 0.0724 129.8
##  ambient 2016 insects - warmed 2016 no_insects     -0.014083 0.0854  81.3
##  ambient 2016 insects - ambient 2017 no_insects     0.034999 0.0724 129.8
##  ambient 2016 insects - warmed 2017 no_insects      0.080545 0.0854  81.3
##  ambient 2016 insects - ambient 2018 no_insects     0.021118 0.0724 129.8
##  ambient 2016 insects - warmed 2018 no_insects      0.066664 0.0854  81.3
##  ambient 2016 insects - ambient 2019 no_insects     0.236694 0.0724 129.8
##  ambient 2016 insects - warmed 2019 no_insects      0.282239 0.0854  81.3
##  ambient 2016 insects - ambient 2020 no_insects     0.053971 0.0724 129.8
##  ambient 2016 insects - warmed 2020 no_insects      0.099517 0.0854  81.3
##  ambient 2016 insects - ambient 2021 no_insects     0.393684 0.0724 129.8
##  ambient 2016 insects - warmed 2021 no_insects      0.439230 0.0854  81.3
##  warmed 2016 insects - ambient 2017 insects         0.067399 0.0760 141.8
##  warmed 2016 insects - warmed 2017 insects          0.112945 0.0611 156.1
##  warmed 2016 insects - ambient 2018 insects        -0.041982 0.0760 141.8
##  warmed 2016 insects - warmed 2018 insects          0.003564 0.0611 156.1
##  warmed 2016 insects - ambient 2019 insects         0.022585 0.0760 141.8
##  warmed 2016 insects - warmed 2019 insects          0.068131 0.0611 156.1
##  warmed 2016 insects - ambient 2020 insects        -0.009861 0.0760 141.8
##  warmed 2016 insects - warmed 2020 insects          0.035685 0.0611 156.1
##  warmed 2016 insects - ambient 2021 insects         0.140357 0.0776 145.9
##  warmed 2016 insects - warmed 2021 insects          0.185903 0.0627 156.7
##  warmed 2016 insects - ambient 2015 no_insects     -0.082514 0.0854  81.3
##  warmed 2016 insects - warmed 2015 no_insects      -0.036968 0.0724 129.8
##  warmed 2016 insects - ambient 2016 no_insects     -0.105175 0.0854  81.3
##  warmed 2016 insects - warmed 2016 no_insects      -0.059629 0.0724 129.8
##  warmed 2016 insects - ambient 2017 no_insects     -0.010547 0.0854  81.3
##  warmed 2016 insects - warmed 2017 no_insects       0.034999 0.0724 129.8
##  warmed 2016 insects - ambient 2018 no_insects     -0.024428 0.0854  81.3
##  warmed 2016 insects - warmed 2018 no_insects       0.021118 0.0724 129.8
##  warmed 2016 insects - ambient 2019 no_insects      0.191148 0.0854  81.3
##  warmed 2016 insects - warmed 2019 no_insects       0.236694 0.0724 129.8
##  warmed 2016 insects - ambient 2020 no_insects      0.008425 0.0854  81.3
```

```
## warmed 2016 insects - warmed 2020 no_insects       0.053971 0.0724 129.8
## warmed 2016 insects - ambient 2021 no_insects      0.348138 0.0854  81.3
## warmed 2016 insects - warmed 2021 no_insects       0.393684 0.0724 129.8
## ambient 2017 insects - warmed 2017 insects         0.045546 0.0452  27.4
## ambient 2017 insects - ambient 2018 insects       -0.109380 0.0611 156.1
## ambient 2017 insects - warmed 2018 insects        -0.063834 0.0760 141.8
## ambient 2017 insects - ambient 2019 insects       -0.044814 0.0611 156.1
## ambient 2017 insects - warmed 2019 insects         0.000732 0.0760 141.8
## ambient 2017 insects - ambient 2020 insects       -0.077259 0.0611 156.1
## ambient 2017 insects - warmed 2020 insects        -0.031713 0.0760 141.8
## ambient 2017 insects - ambient 2021 insects        0.072958 0.0627 156.7
## ambient 2017 insects - warmed 2021 insects         0.118504 0.0769 144.1
## ambient 2017 insects - ambient 2015 no_insects    -0.149913 0.0724 129.8
## ambient 2017 insects - warmed 2015 no_insects     -0.104367 0.0854  81.3
## ambient 2017 insects - ambient 2016 no_insects    -0.172573 0.0724 129.8
## ambient 2017 insects - warmed 2016 no_insects     -0.127028 0.0854  81.3
## ambient 2017 insects - ambient 2017 no_insects    -0.077946 0.0724 129.8
## ambient 2017 insects - warmed 2017 no_insects     -0.032400 0.0854  81.3
## ambient 2017 insects - ambient 2018 no_insects    -0.091827 0.0724 129.8
## ambient 2017 insects - warmed 2018 no_insects     -0.046281 0.0854  81.3
## ambient 2017 insects - ambient 2019 no_insects     0.123749 0.0724 129.8
## ambient 2017 insects - warmed 2019 no_insects      0.169295 0.0854  81.3
## ambient 2017 insects - ambient 2020 no_insects    -0.058974 0.0724 129.8
## ambient 2017 insects - warmed 2020 no_insects     -0.013428 0.0854  81.3
## ambient 2017 insects - ambient 2021 no_insects     0.280740 0.0724 129.8
## ambient 2017 insects - warmed 2021 no_insects      0.326286 0.0854  81.3
## warmed 2017 insects - ambient 2018 insects        -0.154926 0.0760 141.8
## warmed 2017 insects - warmed 2018 insects         -0.109380 0.0611 156.1
## warmed 2017 insects - ambient 2019 insects        -0.090359 0.0760 141.8
## warmed 2017 insects - warmed 2019 insects         -0.044814 0.0611 156.1
## warmed 2017 insects - ambient 2020 insects        -0.122805 0.0760 141.8
## warmed 2017 insects - warmed 2020 insects         -0.077259 0.0611 156.1
## warmed 2017 insects - ambient 2021 insects         0.027412 0.0776 145.9
## warmed 2017 insects - warmed 2021 insects          0.072958 0.0627 156.7
## warmed 2017 insects - ambient 2015 no_insects     -0.195459 0.0854  81.3
## warmed 2017 insects - warmed 2015 no_insects      -0.149913 0.0724 129.8
## warmed 2017 insects - ambient 2016 no_insects     -0.218119 0.0854  81.3
## warmed 2017 insects - warmed 2016 no_insects      -0.172573 0.0724 129.8
## warmed 2017 insects - ambient 2017 no_insects     -0.123492 0.0854  81.3
## warmed 2017 insects - warmed 2017 no_insects      -0.077946 0.0724 129.8
## warmed 2017 insects - ambient 2018 no_insects     -0.137373 0.0854  81.3
## warmed 2017 insects - warmed 2018 no_insects      -0.091827 0.0724 129.8
## warmed 2017 insects - ambient 2019 no_insects      0.078203 0.0854  81.3
## warmed 2017 insects - warmed 2019 no_insects       0.123749 0.0724 129.8
## warmed 2017 insects - ambient 2020 no_insects     -0.104520 0.0854  81.3
## warmed 2017 insects - warmed 2020 no_insects      -0.058974 0.0724 129.8
## warmed 2017 insects - ambient 2021 no_insects      0.235194 0.0854  81.3
## warmed 2017 insects - warmed 2021 no_insects       0.280740 0.0724 129.8
## ambient 2018 insects - warmed 2018 insects         0.045546 0.0452  27.4
## ambient 2018 insects - ambient 2019 insects        0.064567 0.0611 156.1
## ambient 2018 insects - warmed 2019 insects         0.110113 0.0760 141.8
## ambient 2018 insects - ambient 2020 insects        0.032121 0.0611 156.1
## ambient 2018 insects - warmed 2020 insects         0.077667 0.0760 141.8
## ambient 2018 insects - ambient 2021 insects        0.182338 0.0627 156.7
```

```
##  ambient 2018 insects - warmed 2021 insects         0.227884 0.0769 144.1
##  ambient 2018 insects - ambient 2015 no_insects    -0.040533 0.0724 129.8
##  ambient 2018 insects - warmed 2015 no_insects      0.005013 0.0854  81.3
##  ambient 2018 insects - ambient 2016 no_insects    -0.063193 0.0724 129.8
##  ambient 2018 insects - warmed 2016 no_insects     -0.017647 0.0854  81.3
##  ambient 2018 insects - ambient 2017 no_insects     0.031435 0.0724 129.8
##  ambient 2018 insects - warmed 2017 no_insects      0.076981 0.0854  81.3
##  ambient 2018 insects - ambient 2018 no_insects     0.017554 0.0724 129.8
##  ambient 2018 insects - warmed 2018 no_insects      0.063100 0.0854  81.3
##  ambient 2018 insects - ambient 2019 no_insects     0.233129 0.0724 129.8
##  ambient 2018 insects - warmed 2019 no_insects      0.278675 0.0854  81.3
##  ambient 2018 insects - ambient 2020 no_insects     0.050406 0.0724 129.8
##  ambient 2018 insects - warmed 2020 no_insects      0.095952 0.0854  81.3
##  ambient 2018 insects - ambient 2021 no_insects     0.390120 0.0724 129.8
##  ambient 2018 insects - warmed 2021 no_insects      0.435666 0.0854  81.3
##  warmed 2018 insects - ambient 2019 insects         0.019021 0.0760 141.8
##  warmed 2018 insects - warmed 2019 insects          0.064567 0.0611 156.1
##  warmed 2018 insects - ambient 2020 insects        -0.013425 0.0760 141.8
##  warmed 2018 insects - warmed 2020 insects          0.032121 0.0611 156.1
##  warmed 2018 insects - ambient 2021 insects         0.136793 0.0776 145.9
##  warmed 2018 insects - warmed 2021 insects          0.182338 0.0627 156.7
##  warmed 2018 insects - ambient 2015 no_insects     -0.086079 0.0854  81.3
##  warmed 2018 insects - warmed 2015 no_insects      -0.040533 0.0724 129.8
##  warmed 2018 insects - ambient 2016 no_insects     -0.108739 0.0854  81.3
##  warmed 2018 insects - warmed 2016 no_insects      -0.063193 0.0724 129.8
##  warmed 2018 insects - ambient 2017 no_insects     -0.014111 0.0854  81.3
##  warmed 2018 insects - warmed 2017 no_insects       0.031435 0.0724 129.8
##  warmed 2018 insects - ambient 2018 no_insects     -0.027992 0.0854  81.3
##  warmed 2018 insects - warmed 2018 no_insects       0.017554 0.0724 129.8
##  warmed 2018 insects - ambient 2019 no_insects      0.187583 0.0854  81.3
##  warmed 2018 insects - warmed 2019 no_insects       0.233129 0.0724 129.8
##  warmed 2018 insects - ambient 2020 no_insects      0.004861 0.0854  81.3
##  warmed 2018 insects - warmed 2020 no_insects       0.050406 0.0724 129.8
##  warmed 2018 insects - ambient 2021 no_insects      0.344574 0.0854  81.3
##  warmed 2018 insects - warmed 2021 no_insects       0.390120 0.0724 129.8
##  ambient 2019 insects - warmed 2019 insects         0.045546 0.0452  27.4
##  ambient 2019 insects - ambient 2020 insects       -0.032446 0.0611 156.1
##  ambient 2019 insects - warmed 2020 insects         0.013100 0.0760 141.8
##  ambient 2019 insects - ambient 2021 insects        0.117772 0.0627 156.7
##  ambient 2019 insects - warmed 2021 insects         0.163318 0.0769 144.1
##  ambient 2019 insects - ambient 2015 no_insects    -0.105099 0.0724 129.8
##  ambient 2019 insects - warmed 2015 no_insects     -0.059553 0.0854  81.3
##  ambient 2019 insects - ambient 2016 no_insects    -0.127760 0.0724 129.8
##  ambient 2019 insects - warmed 2016 no_insects     -0.082214 0.0854  81.3
##  ambient 2019 insects - ambient 2017 no_insects    -0.033132 0.0724 129.8
##  ambient 2019 insects - warmed 2017 no_insects      0.012414 0.0854  81.3
##  ambient 2019 insects - ambient 2018 no_insects    -0.047013 0.0724 129.8
##  ambient 2019 insects - warmed 2018 no_insects     -0.001467 0.0854  81.3
##  ambient 2019 insects - ambient 2019 no_insects     0.168563 0.0724 129.8
##  ambient 2019 insects - warmed 2019 no_insects      0.214109 0.0854  81.3
##  ambient 2019 insects - ambient 2020 no_insects    -0.014160 0.0724 129.8
##  ambient 2019 insects - warmed 2020 no_insects      0.031386 0.0854  81.3
##  ambient 2019 insects - ambient 2021 no_insects     0.325553 0.0724 129.8
##  ambient 2019 insects - warmed 2021 no_insects      0.371099 0.0854  81.3
```

```
##  warmed 2019 insects - ambient 2020 insects        -0.077992 0.0760 141.8
##  warmed 2019 insects - warmed 2020 insects         -0.032446 0.0611 156.1
##  warmed 2019 insects - ambient 2021 insects         0.072226 0.0776 145.9
##  warmed 2019 insects - warmed 2021 insects          0.117772 0.0627 156.7
##  warmed 2019 insects - ambient 2015 no_insects     -0.150645 0.0854  81.3
##  warmed 2019 insects - warmed 2015 no_insects      -0.105099 0.0724 129.8
##  warmed 2019 insects - ambient 2016 no_insects     -0.173306 0.0854  81.3
##  warmed 2019 insects - warmed 2016 no_insects      -0.127760 0.0724 129.8
##  warmed 2019 insects - ambient 2017 no_insects     -0.078678 0.0854  81.3
##  warmed 2019 insects - warmed 2017 no_insects      -0.033132 0.0724 129.8
##  warmed 2019 insects - ambient 2018 no_insects     -0.092559 0.0854  81.3
##  warmed 2019 insects - warmed 2018 no_insects      -0.047013 0.0724 129.8
##  warmed 2019 insects - ambient 2019 no_insects      0.123017 0.0854  81.3
##  warmed 2019 insects - warmed 2019 no_insects       0.168563 0.0724 129.8
##  warmed 2019 insects - ambient 2020 no_insects     -0.059706 0.0854  81.3
##  warmed 2019 insects - warmed 2020 no_insects      -0.014160 0.0724 129.8
##  warmed 2019 insects - ambient 2021 no_insects      0.280007 0.0854  81.3
##  warmed 2019 insects - warmed 2021 no_insects       0.325553 0.0724 129.8
##  ambient 2020 insects - warmed 2020 insects         0.045546 0.0452  27.4
##  ambient 2020 insects - ambient 2021 insects        0.150218 0.0627 156.7
##  ambient 2020 insects - warmed 2021 insects         0.195764 0.0769 144.1
##  ambient 2020 insects - ambient 2015 no_insects    -0.072653 0.0724 129.8
##  ambient 2020 insects - warmed 2015 no_insects     -0.027108 0.0854  81.3
##  ambient 2020 insects - ambient 2016 no_insects    -0.095314 0.0724 129.8
##  ambient 2020 insects - warmed 2016 no_insects     -0.049768 0.0854  81.3
##  ambient 2020 insects - ambient 2017 no_insects    -0.000686 0.0724 129.8
##  ambient 2020 insects - warmed 2017 no_insects      0.044860 0.0854  81.3
##  ambient 2020 insects - ambient 2018 no_insects    -0.014567 0.0724 129.8
##  ambient 2020 insects - warmed 2018 no_insects      0.030979 0.0854  81.3
##  ambient 2020 insects - ambient 2019 no_insects     0.201008 0.0724 129.8
##  ambient 2020 insects - warmed 2019 no_insects      0.246554 0.0854  81.3
##  ambient 2020 insects - ambient 2020 no_insects     0.018285 0.0724 129.8
##  ambient 2020 insects - warmed 2020 no_insects      0.063831 0.0854  81.3
##  ambient 2020 insects - ambient 2021 no_insects     0.357999 0.0724 129.8
##  ambient 2020 insects - warmed 2021 no_insects      0.403545 0.0854  81.3
##  warmed 2020 insects - ambient 2021 insects         0.104672 0.0776 145.9
##  warmed 2020 insects - warmed 2021 insects          0.150218 0.0627 156.7
##  warmed 2020 insects - ambient 2015 no_insects     -0.118199 0.0854  81.3
##  warmed 2020 insects - warmed 2015 no_insects      -0.072653 0.0724 129.8
##  warmed 2020 insects - ambient 2016 no_insects     -0.140860 0.0854  81.3
##  warmed 2020 insects - warmed 2016 no_insects      -0.095314 0.0724 129.8
##  warmed 2020 insects - ambient 2017 no_insects     -0.046232 0.0854  81.3
##  warmed 2020 insects - warmed 2017 no_insects      -0.000686 0.0724 129.8
##  warmed 2020 insects - ambient 2018 no_insects     -0.060113 0.0854  81.3
##  warmed 2020 insects - warmed 2018 no_insects      -0.014567 0.0724 129.8
##  warmed 2020 insects - ambient 2019 no_insects      0.155463 0.0854  81.3
##  warmed 2020 insects - warmed 2019 no_insects       0.201008 0.0724 129.8
##  warmed 2020 insects - ambient 2020 no_insects     -0.027260 0.0854  81.3
##  warmed 2020 insects - warmed 2020 no_insects       0.018285 0.0724 129.8
##  warmed 2020 insects - ambient 2021 no_insects      0.312453 0.0854  81.3
##  warmed 2020 insects - warmed 2021 no_insects       0.357999 0.0724 129.8
##  ambient 2021 insects - warmed 2021 insects         0.045546 0.0452  27.4
##  ambient 2021 insects - ambient 2015 no_insects    -0.222871 0.0737 133.8
##  ambient 2021 insects - warmed 2015 no_insects     -0.177325 0.0868  85.2
```

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##  ambient 2021 insects - ambient 2016 no_insects    -0.245532 0.0737 133.8
##  ambient 2021 insects - warmed 2016 no_insects     -0.199986 0.0868  85.2
##  ambient 2021 insects - ambient 2017 no_insects    -0.150904 0.0737 133.8
##  ambient 2021 insects - warmed 2017 no_insects     -0.105358 0.0868  85.2
##  ambient 2021 insects - ambient 2018 no_insects    -0.164785 0.0737 133.8
##  ambient 2021 insects - warmed 2018 no_insects     -0.119239 0.0868  85.2
##  ambient 2021 insects - ambient 2019 no_insects     0.050791 0.0737 133.8
##  ambient 2021 insects - warmed 2019 no_insects      0.096337 0.0868  85.2
##  ambient 2021 insects - ambient 2020 no_insects    -0.131932 0.0737 133.8
##  ambient 2021 insects - warmed 2020 no_insects     -0.086386 0.0868  85.2
##  ambient 2021 insects - ambient 2021 no_insects     0.207782 0.0737 133.8
##  ambient 2021 insects - warmed 2021 no_insects      0.253327 0.0868  85.2
##  warmed 2021 insects - ambient 2015 no_insects     -0.268417 0.0862  83.5
##  warmed 2021 insects - warmed 2015 no_insects      -0.222871 0.0737 133.8
##  warmed 2021 insects - ambient 2016 no_insects     -0.291078 0.0862  83.5
##  warmed 2021 insects - warmed 2016 no_insects      -0.245532 0.0737 133.8
##  warmed 2021 insects - ambient 2017 no_insects     -0.196450 0.0862  83.5
##  warmed 2021 insects - warmed 2017 no_insects      -0.150904 0.0737 133.8
##  warmed 2021 insects - ambient 2018 no_insects     -0.210331 0.0862  83.5
##  warmed 2021 insects - warmed 2018 no_insects      -0.164785 0.0737 133.8
##  warmed 2021 insects - ambient 2019 no_insects      0.005245 0.0862  83.5
##  warmed 2021 insects - warmed 2019 no_insects       0.050791 0.0737 133.8
##  warmed 2021 insects - ambient 2020 no_insects     -0.177478 0.0862  83.5
##  warmed 2021 insects - warmed 2020 no_insects      -0.131932 0.0737 133.8
##  warmed 2021 insects - ambient 2021 no_insects      0.162236 0.0862  83.5
##  warmed 2021 insects - warmed 2021 no_insects       0.207782 0.0737 133.8
##  ambient 2015 no_insects - warmed 2015 no_insects   0.045546 0.0452  27.4
##  ambient 2015 no_insects - ambient 2016 no_insects -0.022661 0.0611 156.1
##  ambient 2015 no_insects - warmed 2016 no_insects   0.022885 0.0760 141.8
##  ambient 2015 no_insects - ambient 2017 no_insects  0.071967 0.0611 156.1
##  ambient 2015 no_insects - warmed 2017 no_insects   0.117513 0.0760 141.8
##  ambient 2015 no_insects - ambient 2018 no_insects  0.058086 0.0611 156.1
##  ambient 2015 no_insects - warmed 2018 no_insects   0.103632 0.0760 141.8
##  ambient 2015 no_insects - ambient 2019 no_insects  0.273662 0.0611 156.1
##  ambient 2015 no_insects - warmed 2019 no_insects   0.319208 0.0760 141.8
##  ambient 2015 no_insects - ambient 2020 no_insects  0.090939 0.0611 156.1
##  ambient 2015 no_insects - warmed 2020 no_insects   0.136485 0.0760 141.8
##  ambient 2015 no_insects - ambient 2021 no_insects  0.430653 0.0611 156.1
##  ambient 2015 no_insects - warmed 2021 no_insects   0.476199 0.0760 141.8
##  warmed 2015 no_insects - ambient 2016 no_insects  -0.068207 0.0760 141.8
##  warmed 2015 no_insects - warmed 2016 no_insects   -0.022661 0.0611 156.1
##  warmed 2015 no_insects - ambient 2017 no_insects   0.026421 0.0760 141.8
##  warmed 2015 no_insects - warmed 2017 no_insects    0.071967 0.0611 156.1
##  warmed 2015 no_insects - ambient 2018 no_insects   0.012540 0.0760 141.8
##  warmed 2015 no_insects - warmed 2018 no_insects    0.058086 0.0611 156.1
##  warmed 2015 no_insects - ambient 2019 no_insects   0.228116 0.0760 141.8
##  warmed 2015 no_insects - warmed 2019 no_insects    0.273662 0.0611 156.1
##  warmed 2015 no_insects - ambient 2020 no_insects   0.045393 0.0760 141.8
##  warmed 2015 no_insects - warmed 2020 no_insects    0.090939 0.0611 156.1
##  warmed 2015 no_insects - ambient 2021 no_insects   0.385107 0.0760 141.8
##  warmed 2015 no_insects - warmed 2021 no_insects    0.430653 0.0611 156.1
##  ambient 2016 no_insects - warmed 2016 no_insects   0.045546 0.0452  27.4
##  ambient 2016 no_insects - ambient 2017 no_insects  0.094628 0.0611 156.1
##  ambient 2016 no_insects - warmed 2017 no_insects   0.140174 0.0760 141.8
```

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##  ambient 2016 no_insects - ambient 2018 no_insects  0.080747 0.0611 156.1
##  ambient 2016 no_insects - warmed 2018 no_insects   0.126293 0.0760 141.8
##  ambient 2016 no_insects - ambient 2019 no_insects  0.296323 0.0611 156.1
##  ambient 2016 no_insects - warmed 2019 no_insects   0.341869 0.0760 141.8
##  ambient 2016 no_insects - ambient 2020 no_insects  0.113600 0.0611 156.1
##  ambient 2016 no_insects - warmed 2020 no_insects   0.159146 0.0760 141.8
##  ambient 2016 no_insects - ambient 2021 no_insects  0.453313 0.0611 156.1
##  ambient 2016 no_insects - warmed 2021 no_insects   0.498859 0.0760 141.8
##  warmed 2016 no_insects - ambient 2017 no_insects   0.049082 0.0760 141.8
##  warmed 2016 no_insects - warmed 2017 no_insects    0.094628 0.0611 156.1
##  warmed 2016 no_insects - ambient 2018 no_insects   0.035201 0.0760 141.8
##  warmed 2016 no_insects - warmed 2018 no_insects    0.080747 0.0611 156.1
##  warmed 2016 no_insects - ambient 2019 no_insects   0.250777 0.0760 141.8
##  warmed 2016 no_insects - warmed 2019 no_insects    0.296323 0.0611 156.1
##  warmed 2016 no_insects - ambient 2020 no_insects   0.068054 0.0760 141.8
##  warmed 2016 no_insects - warmed 2020 no_insects    0.113600 0.0611 156.1
##  warmed 2016 no_insects - ambient 2021 no_insects   0.407767 0.0760 141.8
##  warmed 2016 no_insects - warmed 2021 no_insects    0.453313 0.0611 156.1
##  ambient 2017 no_insects - warmed 2017 no_insects   0.045546 0.0452  27.4
##  ambient 2017 no_insects - ambient 2018 no_insects -0.013881 0.0611 156.1
##  ambient 2017 no_insects - warmed 2018 no_insects   0.031665 0.0760 141.8
##  ambient 2017 no_insects - ambient 2019 no_insects  0.201695 0.0611 156.1
##  ambient 2017 no_insects - warmed 2019 no_insects   0.247241 0.0760 141.8
##  ambient 2017 no_insects - ambient 2020 no_insects  0.018972 0.0611 156.1
##  ambient 2017 no_insects - warmed 2020 no_insects   0.064518 0.0760 141.8
##  ambient 2017 no_insects - ambient 2021 no_insects  0.358685 0.0611 156.1
##  ambient 2017 no_insects - warmed 2021 no_insects   0.404231 0.0760 141.8
##  warmed 2017 no_insects - ambient 2018 no_insects  -0.059427 0.0760 141.8
##  warmed 2017 no_insects - warmed 2018 no_insects   -0.013881 0.0611 156.1
##  warmed 2017 no_insects - ambient 2019 no_insects   0.156149 0.0760 141.8
##  warmed 2017 no_insects - warmed 2019 no_insects    0.201695 0.0611 156.1
##  warmed 2017 no_insects - ambient 2020 no_insects  -0.026574 0.0760 141.8
##  warmed 2017 no_insects - warmed 2020 no_insects    0.018972 0.0611 156.1
##  warmed 2017 no_insects - ambient 2021 no_insects   0.313139 0.0760 141.8
##  warmed 2017 no_insects - warmed 2021 no_insects    0.358685 0.0611 156.1
##  ambient 2018 no_insects - warmed 2018 no_insects   0.045546 0.0452  27.4
##  ambient 2018 no_insects - ambient 2019 no_insects  0.215576 0.0611 156.1
##  ambient 2018 no_insects - warmed 2019 no_insects   0.261122 0.0760 141.8
##  ambient 2018 no_insects - ambient 2020 no_insects  0.032853 0.0611 156.1
##  ambient 2018 no_insects - warmed 2020 no_insects   0.078399 0.0760 141.8
##  ambient 2018 no_insects - ambient 2021 no_insects  0.372566 0.0611 156.1
##  ambient 2018 no_insects - warmed 2021 no_insects   0.418112 0.0760 141.8
##  warmed 2018 no_insects - ambient 2019 no_insects   0.170030 0.0760 141.8
##  warmed 2018 no_insects - warmed 2019 no_insects    0.215576 0.0611 156.1
##  warmed 2018 no_insects - ambient 2020 no_insects  -0.012693 0.0760 141.8
##  warmed 2018 no_insects - warmed 2020 no_insects    0.032853 0.0611 156.1
##  warmed 2018 no_insects - ambient 2021 no_insects   0.327020 0.0760 141.8
##  warmed 2018 no_insects - warmed 2021 no_insects    0.372566 0.0611 156.1
##  ambient 2019 no_insects - warmed 2019 no_insects   0.045546 0.0452  27.4
##  ambient 2019 no_insects - ambient 2020 no_insects -0.182723 0.0611 156.1
##  ambient 2019 no_insects - warmed 2020 no_insects  -0.137177 0.0760 141.8
##  ambient 2019 no_insects - ambient 2021 no_insects  0.156991 0.0611 156.1
##  ambient 2019 no_insects - warmed 2021 no_insects   0.202537 0.0760 141.8
##  warmed 2019 no_insects - ambient 2020 no_insects  -0.228269 0.0760 141.8
```

```
##  warmed 2019 no_insects - warmed 2020 no_insects   -0.182723 0.0611 156.1
##  warmed 2019 no_insects - ambient 2021 no_insects   0.111445 0.0760 141.8
##  warmed 2019 no_insects - warmed 2021 no_insects    0.156991 0.0611 156.1
##  ambient 2020 no_insects - warmed 2020 no_insects   0.045546 0.0452  27.4
##  ambient 2020 no_insects - ambient 2021 no_insects  0.339714 0.0611 156.1
##  ambient 2020 no_insects - warmed 2021 no_insects   0.385259 0.0760 141.8
##  warmed 2020 no_insects - ambient 2021 no_insects   0.294168 0.0760 141.8
##  warmed 2020 no_insects - warmed 2021 no_insects    0.339714 0.0611 156.1
##  ambient 2021 no_insects - warmed 2021 no_insects   0.045546 0.0452  27.4
##  t.ratio p.value
##   1.008  1.0000
##   0.995  1.0000
##   1.399  0.9998
##   2.842  0.4841
##   2.884  0.4527
##   1.053  1.0000
##   1.446  0.9997
##   2.109  0.9405
##   2.295  0.8668
##   1.579  0.9987
##   1.868  0.9852
##   3.936  0.0307
##   3.799  0.0487
##   0.330  1.0000
##   0.813  1.0000
##   0.017  1.0000
##   0.548  1.0000
##   1.324  0.9999
##   1.656  0.9966
##   1.132  1.0000
##   1.494  0.9993
##   4.109  0.0183
##   4.019  0.0301
##   1.585  0.9985
##   1.878  0.9818
##   6.277  <.0001
##   5.858  <.0001
##   0.201  1.0000
##   0.995  1.0000
##   1.687  0.9964
##   2.842  0.4841
##   0.248  1.0000
##   1.053  1.0000
##   1.097  1.0000
##   2.109  0.9405
##   0.670  1.0000
##   1.579  0.9987
##   2.591  0.6786
##   3.936  0.0307
##  -0.254  1.0000
##   0.330  1.0000
##  -0.519  1.0000
##   0.017  1.0000
##   0.589  1.0000
```

```
##   1.324  0.9999
##   0.427  1.0000
##   1.132  1.0000
##   2.952  0.4113
##   4.109  0.0183
##   0.811  1.0000
##   1.585  0.9985
##   4.791  0.0022
##   6.277  <.0001
##   1.008  1.0000
##   1.847  0.9875
##   2.084  0.9469
##   0.058  1.0000
##   0.646  1.0000
##   1.114  1.0000
##   1.495  0.9995
##   0.584  1.0000
##   1.068  1.0000
##   2.965  0.3923
##   3.008  0.3631
##  -0.510  1.0000
##   0.100  1.0000
##  -0.823  1.0000
##  -0.165  1.0000
##   0.483  1.0000
##   0.944  1.0000
##   0.292  1.0000
##   0.781  1.0000
##   3.269  0.2109
##   3.306  0.2044
##   0.745  1.0000
##   1.166  1.0000
##   5.436  0.0001
##   5.145  0.0006
##   0.886  1.0000
##   1.847  0.9875
##  -0.552  1.0000
##   0.058  1.0000
##   0.297  1.0000
##   1.114  1.0000
##  -0.130  1.0000
##   0.584  1.0000
##   1.808  0.9905
##   2.965  0.3923
##  -0.967  1.0000
##  -0.510  1.0000
##  -1.232  1.0000
##  -0.823  1.0000
##  -0.124  1.0000
##   0.483  1.0000
##  -0.286  1.0000
##   0.292  1.0000
##   2.239  0.8870
##   3.269  0.2109
```

```
##    0.099  1.0000
##    0.745  1.0000
##    4.078  0.0251
##    5.436  0.0001
##    1.008  1.0000
##   -1.789  0.9918
##   -0.839  1.0000
##   -0.733  1.0000
##    0.010  1.0000
##   -1.264  1.0000
##   -0.417  1.0000
##    1.164  1.0000
##    1.540  0.9991
##   -2.070  0.9500
##   -1.223  1.0000
##   -2.383  0.8185
##   -1.488  0.9993
##   -1.076  1.0000
##   -0.380  1.0000
##   -1.268  1.0000
##   -0.542  1.0000
##    1.709  0.9955
##    1.983  0.9659
##   -0.814  1.0000
##   -0.157  1.0000
##    3.877  0.0392
##    3.822  0.0541
##   -2.037  0.9585
##   -1.789  0.9918
##   -1.188  1.0000
##   -0.733  1.0000
##   -1.615  0.9981
##   -1.264  1.0000
##    0.353  1.0000
##    1.164  1.0000
##   -2.290  0.8637
##   -2.070  0.9500
##   -2.555  0.7025
##   -2.383  0.8185
##   -1.447  0.9996
##   -1.076  1.0000
##   -1.609  0.9978
##   -1.268  1.0000
##    0.916  1.0000
##    1.709  0.9955
##   -1.224  1.0000
##   -0.814  1.0000
##    2.755  0.5551
##    3.877  0.0392
##    1.008  1.0000
##    1.056  1.0000
##    1.448  0.9997
##    0.525  1.0000
##    1.021  1.0000
```

```
##   2.908  0.4339
##   2.962  0.3956
##  -0.560  1.0000
##   0.059  1.0000
##  -0.873  1.0000
##  -0.207  1.0000
##   0.434  1.0000
##   0.902  1.0000
##   0.242  1.0000
##   0.739  1.0000
##   3.219  0.2360
##   3.264  0.2242
##   0.696  1.0000
##   1.124  1.0000
##   5.387  0.0001
##   5.103  0.0007
##   0.250  1.0000
##   1.056  1.0000
##  -0.177  1.0000
##   0.525  1.0000
##   1.762  0.9933
##   2.908  0.4339
##  -1.008  1.0000
##  -0.560  1.0000
##  -1.274  1.0000
##  -0.873  1.0000
##  -0.165  1.0000
##   0.434  1.0000
##  -0.328  1.0000
##   0.242  1.0000
##   2.197  0.9044
##   3.219  0.2360
##   0.057  1.0000
##   0.696  1.0000
##   4.036  0.0285
##   5.387  0.0001
##   1.008  1.0000
##  -0.531  1.0000
##   0.172  1.0000
##   1.879  0.9844
##   2.123  0.9359
##  -1.451  0.9997
##  -0.698  1.0000
##  -1.764  0.9930
##  -0.963  1.0000
##  -0.458  1.0000
##   0.145  1.0000
##  -0.649  1.0000
##  -0.017  1.0000
##   2.328  0.8494
##   2.508  0.7350
##  -0.196  1.0000
##   0.368  1.0000
##   4.496  0.0045
```

```
##   4.347  0.0105
##  -1.026  1.0000
##  -0.531  1.0000
##   0.930  1.0000
##   1.879  0.9844
##  -1.765  0.9918
##  -1.451  0.9997
##  -2.030  0.9560
##  -1.764  0.9930
##  -0.922  1.0000
##  -0.458  1.0000
##  -1.084  1.0000
##  -0.649  1.0000
##   1.441  0.9996
##   2.328  0.8494
##  -0.699  1.0000
##  -0.196  1.0000
##   3.280  0.2166
##   4.496  0.0045
##   1.008  1.0000
##   2.396  0.8122
##   2.544  0.7129
##  -1.003  1.0000
##  -0.318  1.0000
##  -1.316  0.9999
##  -0.583  1.0000
##  -0.009  1.0000
##   0.525  1.0000
##  -0.201  1.0000
##   0.363  1.0000
##   2.776  0.5367
##   2.888  0.4565
##   0.253  1.0000
##   0.748  1.0000
##   4.944  0.0008
##   4.727  0.0028
##   1.348  0.9999
##   2.396  0.8122
##  -1.385  0.9998
##  -1.003  1.0000
##  -1.650  0.9968
##  -1.316  0.9999
##  -0.542  1.0000
##  -0.009  1.0000
##  -0.704  1.0000
##  -0.201  1.0000
##   1.821  0.9876
##   2.776  0.5367
##  -0.319  1.0000
##   0.253  1.0000
##   3.660  0.0850
##   4.944  0.0008
##   1.008  1.0000
##  -3.023  0.3542
```

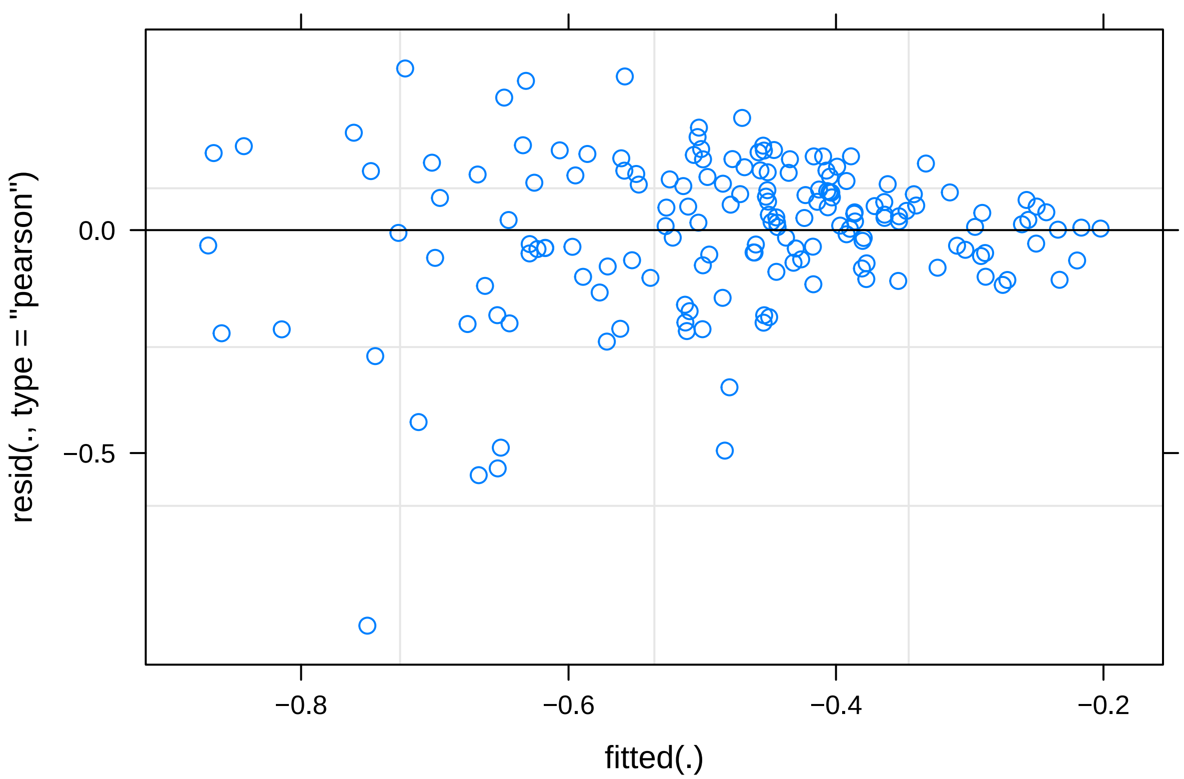
```
##  -2.043  0.9535
##  -3.330  0.1816
##  -2.304  0.8572
##  -2.047  0.9560
##  -1.214  1.0000
##  -2.235  0.8941
##  -1.374  0.9998
##   0.689  1.0000
##   1.110  1.0000
##  -1.789  0.9915
##  -0.995  1.0000
##   2.818  0.5037
##   2.918  0.4340
##  -3.115  0.3046
##  -3.023  0.3542
##  -3.378  0.1726
##  -3.330  0.1816
##  -2.280  0.8687
##  -2.047  0.9560
##  -2.441  0.7791
##  -2.235  0.8941
##   0.061  1.0000
##   0.689  1.0000
##  -2.060  0.9491
##  -1.789  0.9915
##   1.883  0.9814
##   2.818  0.5037
##   1.008  1.0000
##  -0.371  1.0000
##   0.301  1.0000
##   1.177  1.0000
##   1.545  0.9991
##   0.950  1.0000
##   1.363  0.9999
##   4.476  0.0044
##   4.198  0.0129
##   1.487  0.9995
##   1.795  0.9913
##   7.043  <.0001
##   6.262  <.0001
##  -0.897  1.0000
##  -0.371  1.0000
##   0.347  1.0000
##   1.177  1.0000
##   0.165  1.0000
##   0.950  1.0000
##   3.000  0.3691
##   4.476  0.0044
##   0.597  1.0000
##   1.487  0.9995
##   5.064  0.0004
##   7.043  <.0001
##   1.008  1.0000
##   1.548  0.9991
```

```
##    1.843  0.9876
##    1.321  0.9999
##    1.661  0.9971
##    4.846  0.0010
##    4.496  0.0043
##    1.858  0.9865
##    2.093  0.9446
##    7.414  <.0001
##    6.560  <.0001
##    0.645  1.0000
##    1.548  0.9991
##    0.463  1.0000
##    1.321  0.9999
##    3.298  0.1952
##    4.846  0.0010
##    0.895  1.0000
##    1.858  0.9865
##    5.363  0.0001
##    7.414  <.0001
##    1.008  1.0000
##   -0.227  1.0000
##    0.416  1.0000
##    3.299  0.1932
##    3.251  0.2177
##    0.310  1.0000
##    0.848  1.0000
##    5.866  <.0001
##    5.316  0.0001
##   -0.782  1.0000
##   -0.227  1.0000
##    2.053  0.9547
##    3.299  0.1932
##   -0.349  1.0000
##    0.310  1.0000
##    4.118  0.0171
##    5.866  <.0001
##    1.008  1.0000
##    3.526  0.1073
##    3.434  0.1390
##    0.537  1.0000
##    1.031  1.0000
##    6.093  <.0001
##    5.499  0.0001
##    2.236  0.8941
##    3.526  0.1073
##   -0.167  1.0000
##    0.537  1.0000
##    4.301  0.0089
##    6.093  <.0001
##    1.008  1.0000
##   -2.988  0.3759
##   -1.804  0.9907
##    2.568  0.6964
##    2.664  0.6236
```

```
##   -3.002  0.3677
##   -2.988  0.3759
##    1.466  0.9996
##    2.568  0.6964
##    1.008  1.0000
##    5.556  <.0001
##    5.067  0.0004
##    3.869  0.0393
##    5.556  <.0001
##    1.008  1.0000
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 28 estimates
```

UMBS

```
mod1u <- lmer(log(simpson) ~ state * year + insecticide * year + (1 | plot), umbs_diversity,
    REML = FALSE)

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




```
# Homogeneity of variance is ok here (increasing variance in resids is not
# increasing with fitted values) Check for homogeneity of variances (true if
```

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

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

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

## Levene's Test for Homogeneity of Variance (center = median)
##        Df F value   Pr(>F)
## group   1   8.534 0.003971 **
##       166
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Assumption met
leveneTest(residuals(mod1u) ~ umbs_diversity$insecticide)
```

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

## Levene's Test for Homogeneity of Variance (center = median)
##        Df F value Pr(>F)
## group   1  0.2813 0.5965
##       166
```

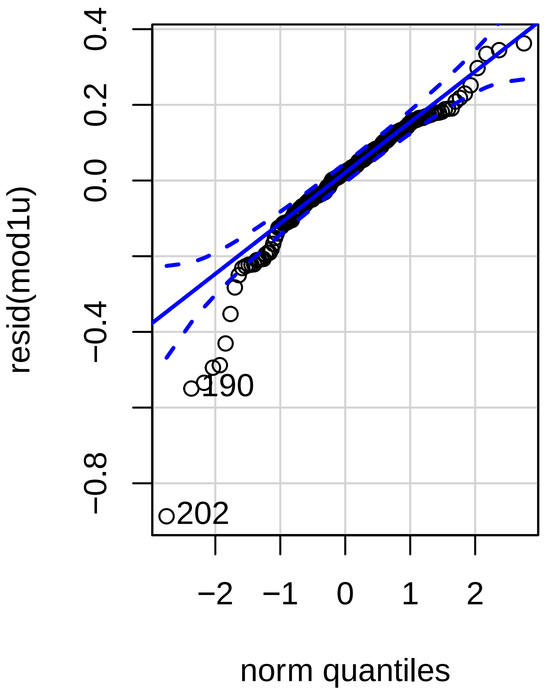
```
# Assumption not met
leveneTest(residuals(mod1u) ~ umbs_diversity$plot)
```

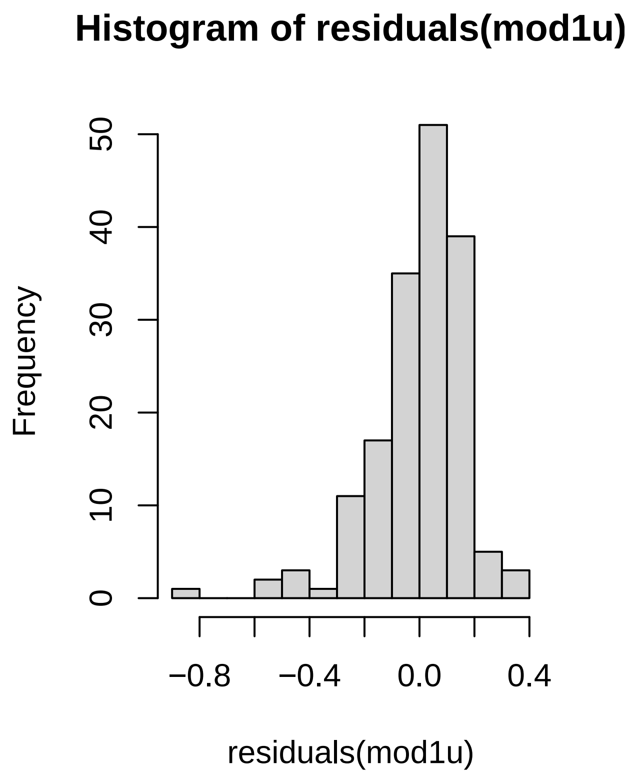
```
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.

## Levene's Test for Homogeneity of Variance (center = median)
##        Df F value Pr(>F)
## group  23  0.6955 0.8444
##       144
```

```
# Assumption not met

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

```
## 202 190
##  34  22
```

```r
hist(residuals(mod1u))
```






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

```
##
##  Shapiro-Wilk normality test
##
## data:  resid(mod1u)
## W = 0.907, p-value = 7.878e-09
```

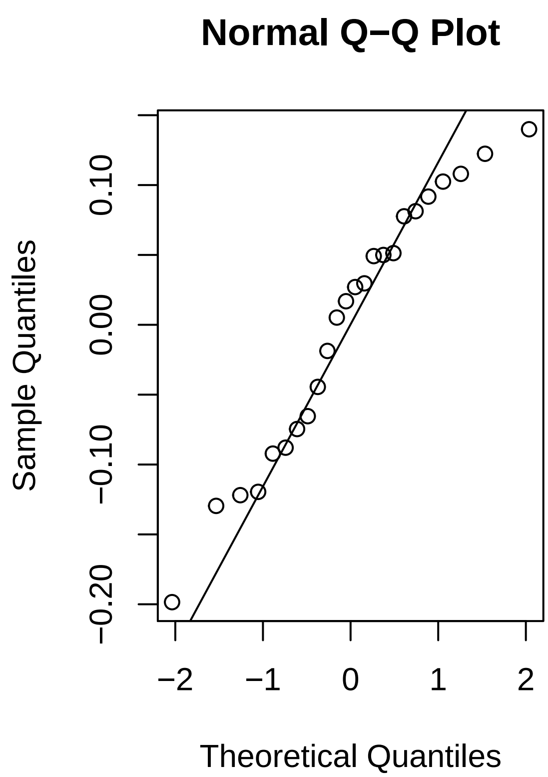
```r
outlierTest(mod1u)  # row 202
```

```
##      rstudent unadjusted p-value Bonferroni p
## 202 -5.580415         1.1545e-07   1.9395e-05
```

```r
# (4) Normality of random effect: Get the estimate of random effect (e.g., random
# intercepts), and check them as you would check the residual.
require(lme4)
r_int_u <- ranef(mod1u)$plot$`(Intercept)`
qqnorm(r_int_u)
qqline(r_int_u)
shapiro.test(r_int_u)
```

```
##
##  Shapiro-Wilk normality test
##
## data:  r_int_u
## W = 0.95313, p-value = 0.3163
```

```r
# Normally distributed random effect pvalue > 0.05
```



UMBS

```r
# Do we need to include plot as a random effect with the UMBS models?
mod1u <- lmer(log(simpson) ~ state * year + insecticide * year + (1 | plot), umbs_diversity,
    REML = FALSE)
mod2u <- lmer(log(simpson) ~ state * year + insecticide + year + (1 | plot), umbs_diversity,
    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(mod1u)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq  Mean Sq F value
## state               1 0.03418 0.034176  1.0619
## year                6 0.96253 0.160422  4.9846
## insecticide         1 0.06748 0.067485  2.0969
## state:year          6 0.45830 0.076384  2.3734
## year:insecticide    6 0.18939 0.031564  0.9808
```

```r
anova(mod2u)
```

```
## Analysis of Variance Table
##             npar  Sum Sq  Mean Sq F value
## state          1 0.03557 0.035573  1.0619
## year           6 0.96253 0.160422  4.7889
## insecticide    1 0.07024 0.070242  2.0969
## state:year     6 0.45830 0.076384  2.2802
```

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

```
## Data: umbs_diversity
## Models:
## mod2u: log(simpson) ~ state * year + insecticide + year + (1 | plot)
## mod1u: log(simpson) ~ state * year + insecticide * year + (1 | plot)
##       npar     AIC    BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod2u   17 -30.436 22.671 32.218  -64.436
## mod1u   23 -24.203 47.648 35.102  -70.203 5.7675  6     0.4497
```

```r
summary(mod1u)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(simpson) ~ state * year + insecticide * year + (1 | plot)
##    Data: umbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##    -24.2     47.6     35.1    -70.2      145
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.9453 -0.3867  0.1177  0.6189  2.0206
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.01167  0.1080
##  Residual             0.03218  0.1794
## Number of obs: 168, groups:  plot, 24
##
## Fixed effects:
##                                Estimate Std. Error t value
## (Intercept)                   -0.541204   0.074041  -7.310
## statewarmed                    0.039924   0.085495   0.467
## year2016                      -0.236235   0.089699  -2.634
## year2017                       0.011708   0.089699   0.131
## year2018                       0.079766   0.089699   0.889
## year2019                       0.067832   0.089699   0.756
## year2020                       0.107045   0.089699   1.193
## year2021                      -0.046374   0.089699  -0.517
## insecticideno_insects         -0.051378   0.085495  -0.601
## statewarmed:year2016           0.233853   0.103575   2.258
## statewarmed:year2017          -0.056493   0.103575  -0.545
## statewarmed:year2018          -0.009044   0.103575  -0.087
## statewarmed:year2019          -0.095269   0.103575  -0.920
## statewarmed:year2020          -0.060551   0.103575  -0.585
## statewarmed:year2021           0.083678   0.103575   0.808
## year2016:insecticideno_insects  0.088943   0.103575   0.859
## year2017:insecticideno_insects  0.238806   0.103575   2.306
## year2018:insecticideno_insects  0.129502   0.103575   1.250
## year2019:insecticideno_insects  0.144871   0.103575   1.399
## year2020:insecticideno_insects  0.160973   0.103575   1.554
## year2021:insecticideno_insects  0.124402   0.103575   1.201
```

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

```r
summary(mod2u)
```

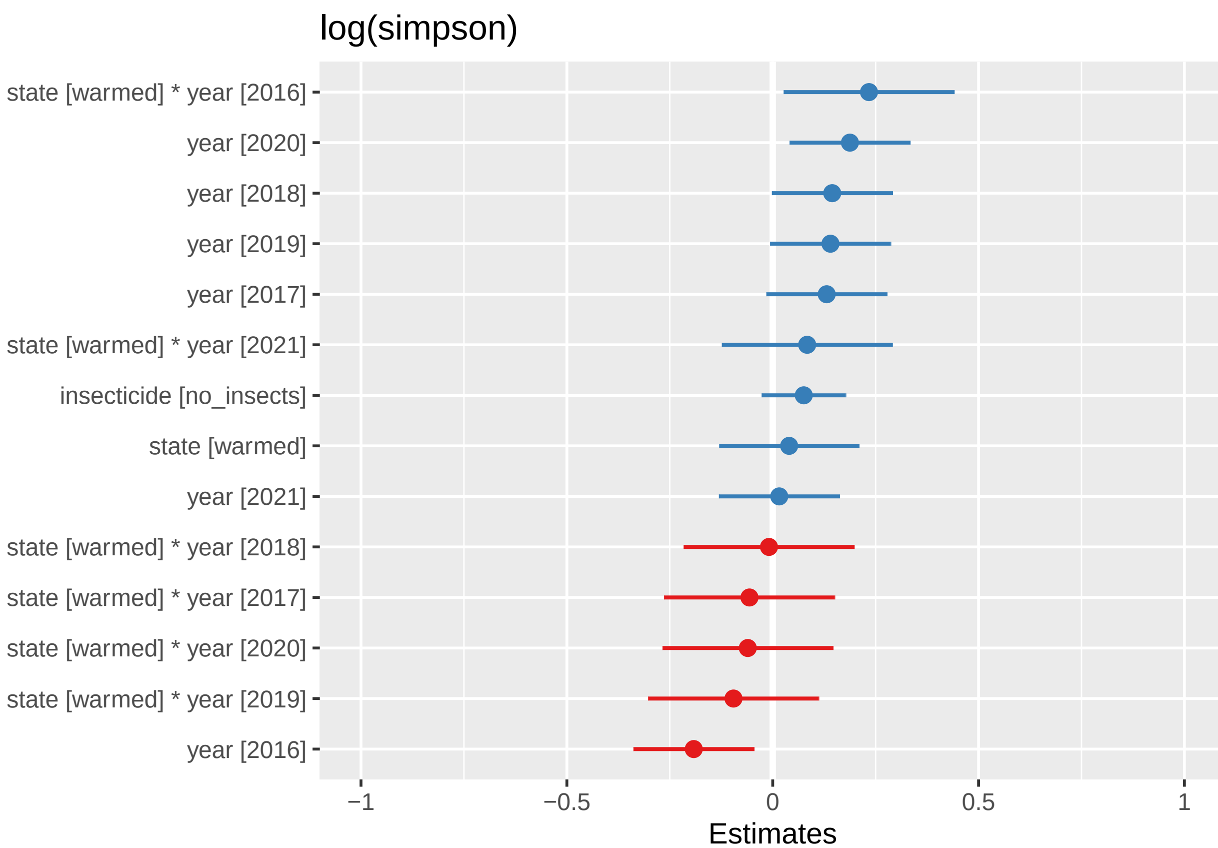
```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(simpson) ~ state * year + insecticide + year + (1 | plot)
##    Data: umbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##    -30.4     22.7     32.2    -64.4      151
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.7415 -0.4131  0.1352  0.6404  1.8919
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.01149  0.1072
##  Residual             0.03350  0.1830
## Number of obs: 168, groups:  plot, 24
##
## Fixed effects:
##                        Estimate Std. Error t value
## (Intercept)           -0.604596   0.066533  -9.087
## statewarmed            0.039924   0.086587   0.461
## year2016              -0.191764   0.074720  -2.566
## year2017               0.131111   0.074720   1.755
## year2018               0.144516   0.074720   1.934
## year2019               0.140267   0.074720   1.877
## year2020               0.187532   0.074720   2.510
## year2021               0.015828   0.074720   0.212
## insecticideno_insects  0.075407   0.052075   1.448
## statewarmed:year2016   0.233853   0.105670   2.213
## statewarmed:year2017  -0.056493   0.105670  -0.535
## statewarmed:year2018  -0.009044   0.105670  -0.086
## statewarmed:year2019  -0.095269   0.105670  -0.902
## statewarmed:year2020  -0.060551   0.105670  -0.573
## statewarmed:year2021   0.083678   0.105670   0.792
```

```
##
## Correlation matrix not shown by default, as p = 15 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```r
AICctab(mod1u, mod2u, weights = T)  # model 2u
```

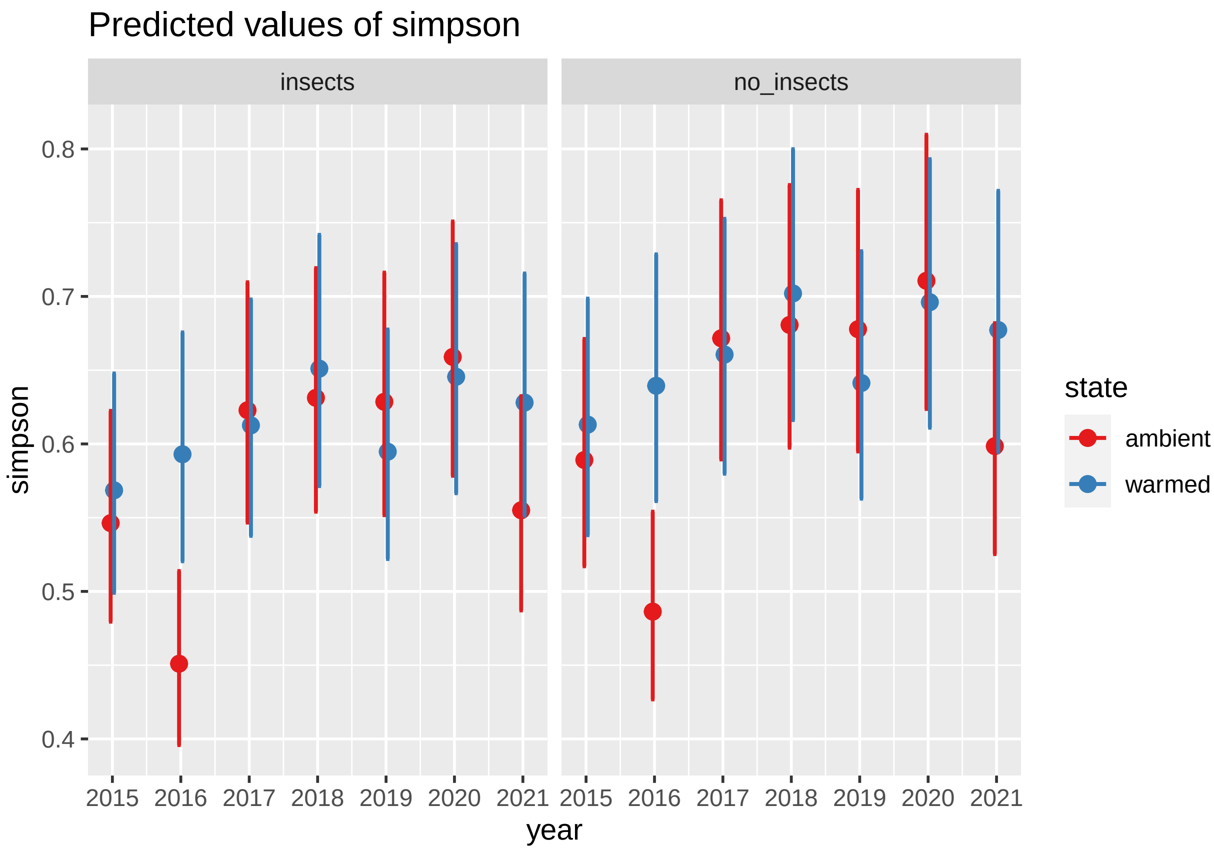
```
##       dAICc df weight
## mod2u  0.0  17 0.9927
## mod1u  9.8  23 0.0073
```

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

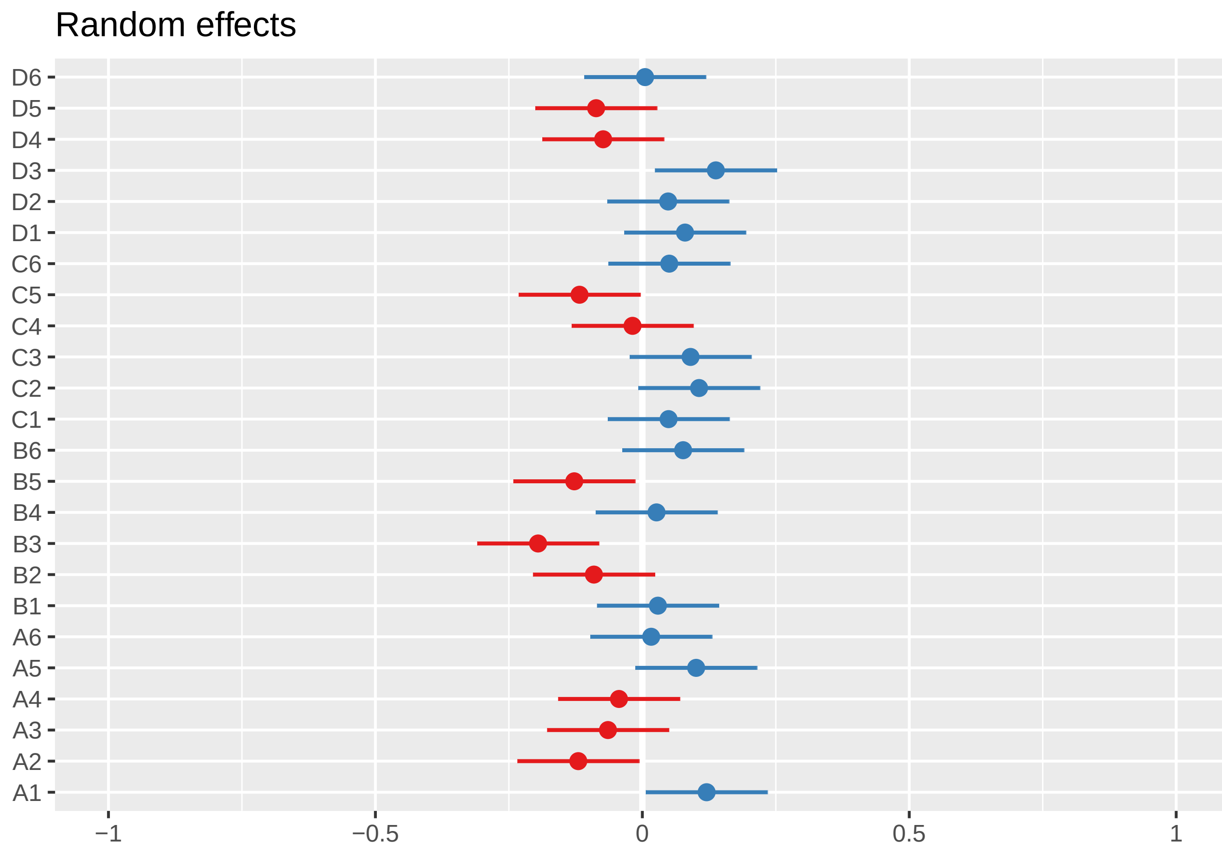



```r
# these are the fixed predicted values:
plot_model(mod2u, type = "pred", terms = c("year", "state", "insecticide"))
```

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




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




```r
# Does year need to be interactive with state?
mod3u <- lmer(log(simpson) ~ state + insecticide + year + (1 | plot), umbs_diversity,
    REML = FALSE)
anova(mod2u, mod3u)
```

```
## Data: umbs_diversity
## Models:
## mod3u: log(simpson) ~ state + insecticide + year + (1 | plot)
## mod2u: log(simpson) ~ state * year + insecticide + year + (1 | plot)
##       npar     AIC     BIC logLik deviance Chisq Df Pr(>Chisq)
## mod3u   11 -29.366  4.9974 25.683  -51.366
## mod2u   17 -30.436 22.6714 32.218  -64.436 13.07  6    0.04194 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

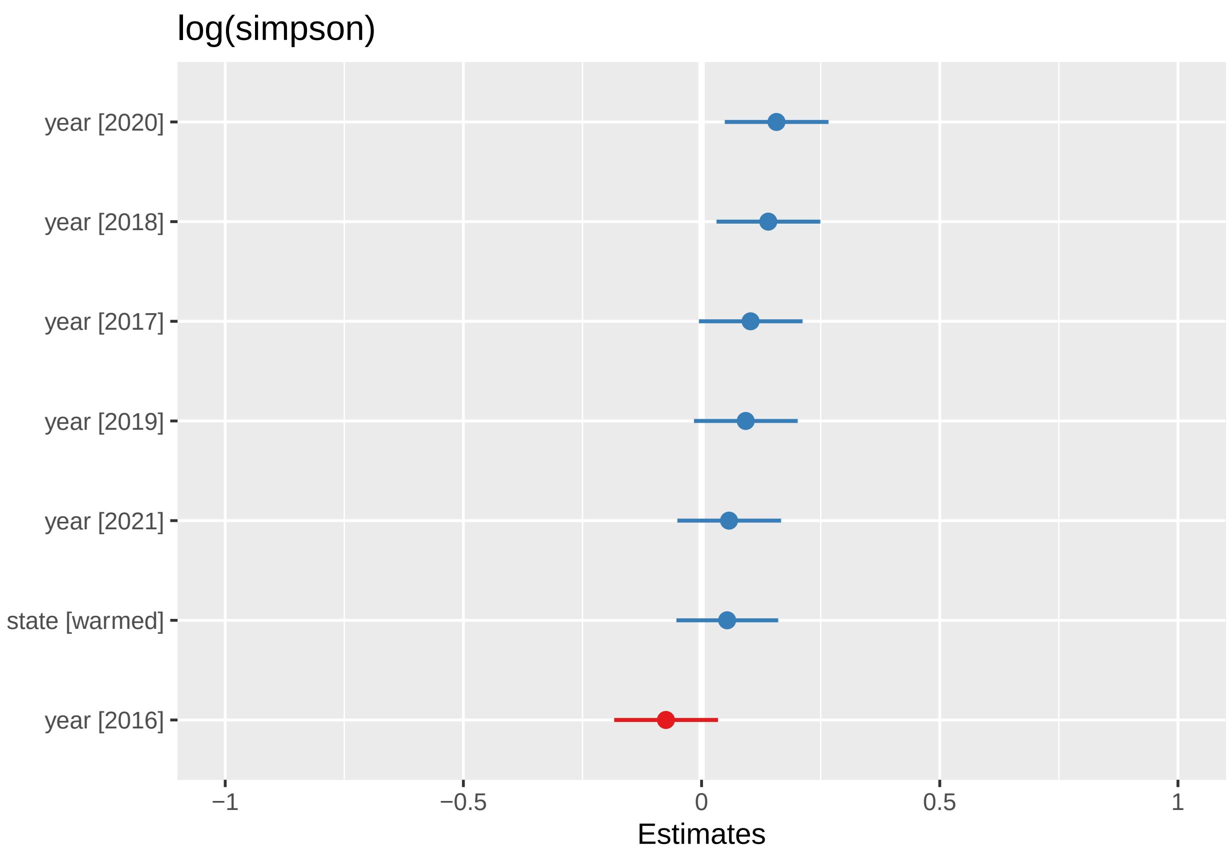
```r
AICctab(mod1u, mod3u, weights = T)  # going with mod3u
```

```
##       dAICc df weight
## mod3u  0.0  11 0.9962
## mod1u 11.1  23 0.0038
```

```r
# Do we need to include insecticide? (dropping insecticide from the model)
mod5u <- lmer(log(simpson) ~ state + year + (1 | plot), umbs_diversity, REML = FALSE)
anova(mod3u, mod5u)
```

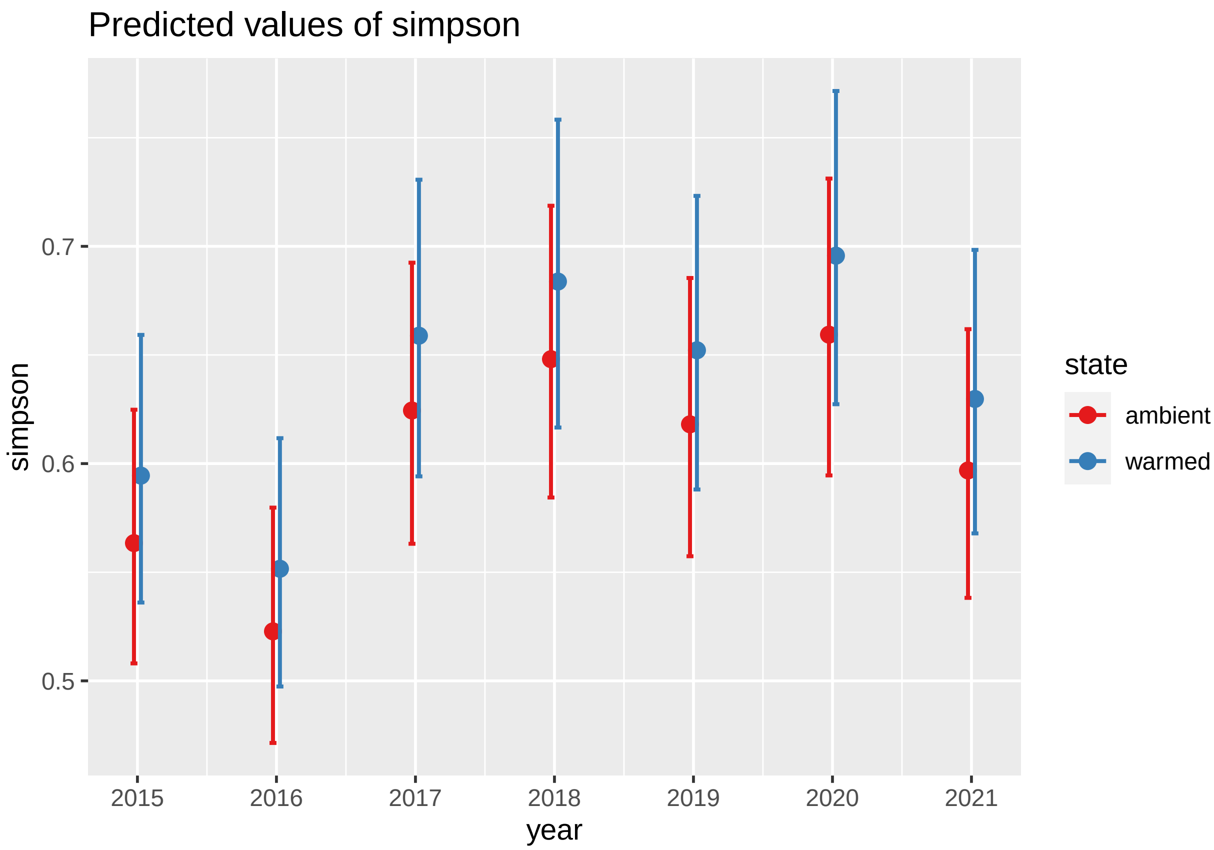
```
## Data: umbs_diversity
## Models:
## mod5u: log(simpson) ~ state + year + (1 | plot)
## mod3u: log(simpson) ~ state + insecticide + year + (1 | plot)
##       npar     AIC    BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod5u   10 -29.356 1.8837 24.678  -49.356
## mod3u   11 -29.366 4.9974 25.683  -51.366 2.0103  1     0.1562
```

```r
# No, p>0.05 so insecticide*year doesn't strongly improve model fit so we will go
# with the more simple model mod5u

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

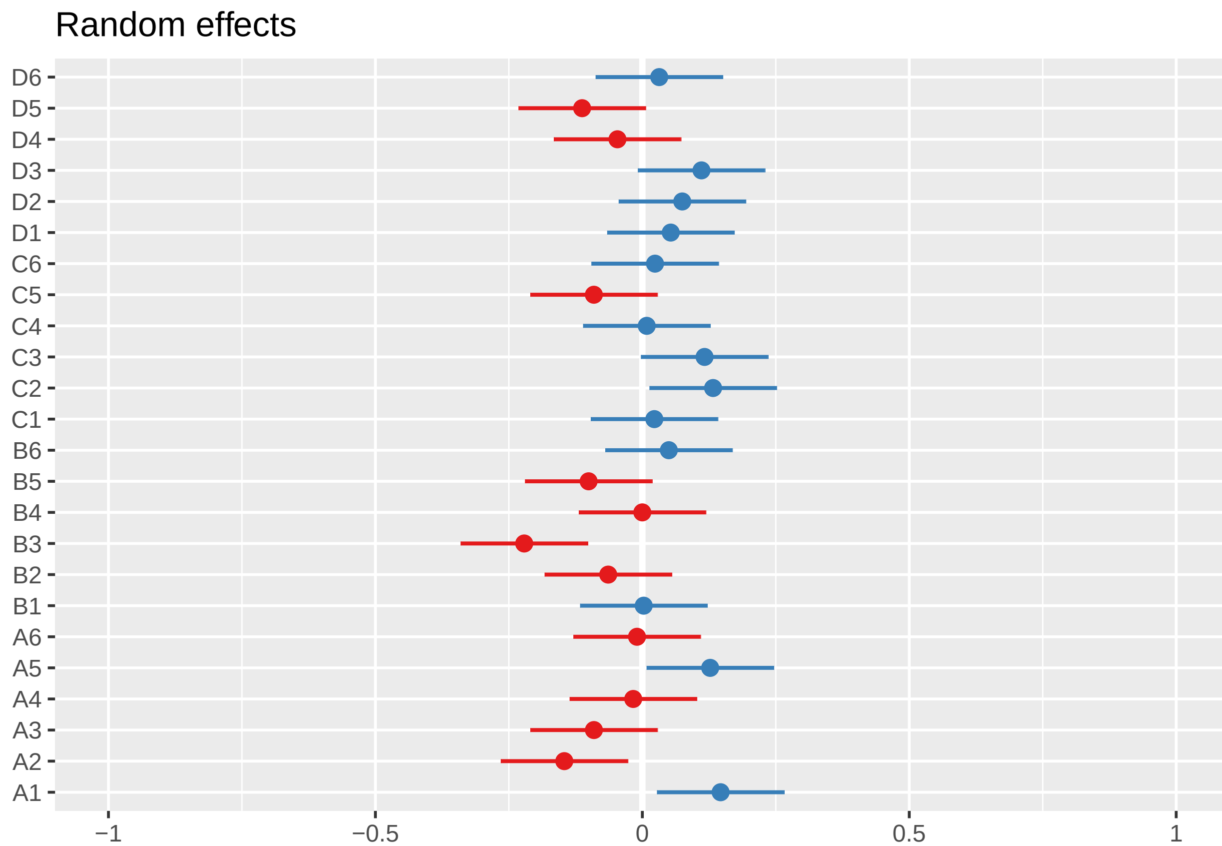



```r
# these are the fixed predicted values:
plot_model(mod5u, type = "pred", terms = c("year", "state"))
```

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




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




```r
# If we wanted to include plots nested within year it would look like this: mod6
# <- lmer(log(simpson) ~ state + year + insecticide*year + (1 + year|plot),
# kbs_diversity, REML=FALSE) anova(mod5, mod6) anova(mod5) cant get mod6 to work

# the best model fit appears to be = mod5u <- lmer(log(simpson) ~ state + year +
# (1|plot), umbs_diversity, REML = FALSE)
summ(mod5u)
```

Observations	168
Dependent variable	log(simpson)
Type	Mixed effects linear regression

AIC	-29.36
BIC	1.88
Pseudo-R^2 (fixed effects)	0.12
Pseudo-R^2 (total)	0.34

```r
emmeans(mod5u, list(pairwise ~ state + year), adjust = "tukey")
```

```
## $`emmeans of state, year`
##  state    year emmean     SE   df lower.CL upper.CL
##  ambient 2015 -0.574 0.0545 82.1   -0.682   -0.465
##  warmed  2015 -0.520 0.0545 82.1   -0.629   -0.412
##  ambient 2016 -0.649 0.0545 82.1   -0.757   -0.540
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	-0.57	0.05	-10.87	75.65	0.00
statewarmed	0.05	0.05	0.99	24.00	0.33
year2016	-0.07	0.06	-1.35	144.00	0.18
year2017	0.10	0.06	1.86	144.00	0.06
year2018	0.14	0.06	2.53	144.00	0.01
year2019	0.09	0.06	1.68	144.00	0.10
year2020	0.16	0.06	2.84	144.00	0.01
year2021	0.06	0.06	1.04	144.00	0.30

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.11
Residual		0.19

Grouping Variables		
Group	# groups	ICC
plot	24	0.25

```
##  warmed  2016 -0.595 0.0545 82.1   -0.703   -0.486
##  ambient 2017 -0.471 0.0545 82.1   -0.579   -0.362
##  warmed  2017 -0.417 0.0545 82.1   -0.526   -0.309
##  ambient 2018 -0.434 0.0545 82.1   -0.542   -0.325
##  warmed  2018 -0.380 0.0545 82.1   -0.489   -0.272
##  ambient 2019 -0.481 0.0545 82.1   -0.590   -0.373
##  warmed  2019 -0.427 0.0545 82.1   -0.536   -0.319
##  ambient 2020 -0.417 0.0545 82.1   -0.525   -0.308
##  warmed  2020 -0.363 0.0545 82.1   -0.471   -0.254
##  ambient 2021 -0.516 0.0545 82.1   -0.625   -0.408
##  warmed  2021 -0.462 0.0545 82.1   -0.571   -0.354
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, year`
##  1                              estimate     SE    df t.ratio p.value
##  ambient 2015 - warmed 2015  -0.053663 0.0567  26.2 -0.946  0.9992
##  ambient 2015 - ambient 2016  0.074838 0.0565 150.3  1.325  0.9880
##  ambient 2015 - warmed 2016   0.021175 0.0800  91.5  0.265  1.0000
##  ambient 2015 - ambient 2017 -0.102864 0.0565 150.3 -1.821  0.8630
##  ambient 2015 - warmed 2017  -0.156527 0.0800  91.5 -1.956  0.7900
##  ambient 2015 - ambient 2018 -0.139995 0.0565 150.3 -2.479  0.4298
##  ambient 2015 - warmed 2018  -0.193657 0.0800  91.5 -2.419  0.4747
##  ambient 2015 - ambient 2019 -0.092633 0.0565 150.3 -1.640  0.9324
##  ambient 2015 - warmed 2019  -0.146296 0.0800  91.5 -1.828  0.8576
##  ambient 2015 - ambient 2020 -0.157256 0.0565 150.3 -2.784  0.2439
```

```
##  ambient 2015 - warmed 2020  -0.210919 0.0800  91.5 -2.635  0.3337
##  ambient 2015 - ambient 2021 -0.057666 0.0565 150.3 -1.021  0.9991
##  ambient 2015 - warmed 2021  -0.111329 0.0800  91.5 -1.391  0.9807
##  warmed 2015 - ambient 2016   0.128500 0.0800  91.5  1.605  0.9403
##  warmed 2015 - warmed 2016    0.074838 0.0565 150.3  1.325  0.9880
##  warmed 2015 - ambient 2017  -0.049201 0.0800  91.5 -0.615  1.0000
##  warmed 2015 - warmed 2017   -0.102864 0.0565 150.3 -1.821  0.8630
##  warmed 2015 - ambient 2018  -0.086332 0.0800  91.5 -1.079  0.9982
##  warmed 2015 - warmed 2018   -0.139995 0.0565 150.3 -2.479  0.4298
##  warmed 2015 - ambient 2019  -0.038970 0.0800  91.5 -0.487  1.0000
##  warmed 2015 - warmed 2019   -0.092633 0.0565 150.3 -1.640  0.9324
##  warmed 2015 - ambient 2020  -0.103593 0.0800  91.5 -1.294  0.9897
##  warmed 2015 - warmed 2020   -0.157256 0.0565 150.3 -2.784  0.2439
##  warmed 2015 - ambient 2021  -0.004004 0.0800  91.5 -0.050  1.0000
##  warmed 2015 - warmed 2021   -0.057666 0.0565 150.3 -1.021  0.9991
##  ambient 2016 - warmed 2016  -0.053663 0.0567  26.2 -0.946  0.9992
##  ambient 2016 - ambient 2017 -0.177702 0.0565 150.3 -3.146  0.1039
##  ambient 2016 - warmed 2017  -0.231364 0.0800  91.5 -2.891  0.2011
##  ambient 2016 - ambient 2018 -0.214832 0.0565 150.3 -3.804  0.0144
##  ambient 2016 - warmed 2018  -0.268495 0.0800  91.5 -3.354  0.0644
##  ambient 2016 - ambient 2019 -0.167470 0.0565 150.3 -2.965  0.1630
##  ambient 2016 - warmed 2019  -0.221133 0.0800  91.5 -2.763  0.2621
##  ambient 2016 - ambient 2020 -0.232093 0.0565 150.3 -4.110  0.0049
##  ambient 2016 - warmed 2020  -0.285756 0.0800  91.5 -3.570  0.0349
##  ambient 2016 - ambient 2021 -0.132504 0.0565 150.3 -2.346  0.5241
##  ambient 2016 - warmed 2021  -0.186167 0.0800  91.5 -2.326  0.5408
##  warmed 2016 - ambient 2017  -0.124039 0.0800  91.5 -1.550  0.9541
##  warmed 2016 - warmed 2017   -0.177702 0.0565 150.3 -3.146  0.1039
##  warmed 2016 - ambient 2018  -0.161169 0.0800  91.5 -2.014  0.7551
##  warmed 2016 - warmed 2018   -0.214832 0.0565 150.3 -3.804  0.0144
##  warmed 2016 - ambient 2019  -0.113808 0.0800  91.5 -1.422  0.9768
##  warmed 2016 - warmed 2019   -0.167470 0.0565 150.3 -2.965  0.1630
##  warmed 2016 - ambient 2020  -0.178431 0.0800  91.5 -2.229  0.6097
##  warmed 2016 - warmed 2020   -0.232093 0.0565 150.3 -4.110  0.0049
##  warmed 2016 - ambient 2021  -0.078841 0.0800  91.5 -0.985  0.9993
##  warmed 2016 - warmed 2021   -0.132504 0.0565 150.3 -2.346  0.5241
##  ambient 2017 - warmed 2017  -0.053663 0.0567  26.2 -0.946  0.9992
##  ambient 2017 - ambient 2018 -0.037130 0.0565 150.3 -0.657  1.0000
##  ambient 2017 - warmed 2018  -0.090793 0.0800  91.5 -1.134  0.9970
##  ambient 2017 - ambient 2019  0.010231 0.0565 150.3  0.181  1.0000
##  ambient 2017 - warmed 2019  -0.043431 0.0800  91.5 -0.543  1.0000
##  ambient 2017 - ambient 2020 -0.054392 0.0565 150.3 -0.963  0.9995
##  ambient 2017 - warmed 2020  -0.108054 0.0800  91.5 -1.350  0.9851
##  ambient 2017 - ambient 2021  0.045198 0.0565 150.3  0.800  0.9999
##  ambient 2017 - warmed 2021  -0.008465 0.0800  91.5 -0.106  1.0000
##  warmed 2017 - ambient 2018   0.016532 0.0800  91.5  0.207  1.0000
##  warmed 2017 - warmed 2018   -0.037130 0.0565 150.3 -0.657  1.0000
##  warmed 2017 - ambient 2019   0.063894 0.0800  91.5  0.798  0.9999
##  warmed 2017 - warmed 2019    0.010231 0.0565 150.3  0.181  1.0000
##  warmed 2017 - ambient 2020  -0.000729 0.0800  91.5 -0.009  1.0000
##  warmed 2017 - warmed 2020   -0.054392 0.0565 150.3 -0.963  0.9995
##  warmed 2017 - ambient 2021   0.098861 0.0800  91.5  1.235  0.9933
##  warmed 2017 - warmed 2021    0.045198 0.0565 150.3  0.800  0.9999
##  ambient 2018 - warmed 2018  -0.053663 0.0567  26.2 -0.946  0.9992
```

```
##  ambient 2018 - ambient 2019  0.047362 0.0565 150.3  0.839  0.9999
##  ambient 2018 - warmed 2019  -0.006301 0.0800  91.5 -0.079  1.0000
##  ambient 2018 - ambient 2020 -0.017261 0.0565 150.3 -0.306  1.0000
##  ambient 2018 - warmed 2020  -0.070924 0.0800  91.5 -0.886  0.9998
##  ambient 2018 - ambient 2021  0.082328 0.0565 150.3  1.458  0.9728
##  ambient 2018 - warmed 2021   0.028665 0.0800  91.5  0.358  1.0000
##  warmed 2018 - ambient 2019   0.101025 0.0800  91.5  1.262  0.9918
##  warmed 2018 - warmed 2019    0.047362 0.0565 150.3  0.839  0.9999
##  warmed 2018 - ambient 2020   0.036401 0.0800  91.5  0.455  1.0000
##  warmed 2018 - warmed 2020   -0.017261 0.0565 150.3 -0.306  1.0000
##  warmed 2018 - ambient 2021   0.135991 0.0800  91.5  1.699  0.9110
##  warmed 2018 - warmed 2021    0.082328 0.0565 150.3  1.458  0.9728
##  ambient 2019 - warmed 2019  -0.053663 0.0567  26.2 -0.946  0.9992
##  ambient 2019 - ambient 2020 -0.064623 0.0565 150.3 -1.144  0.9970
##  ambient 2019 - warmed 2020  -0.118286 0.0800  91.5 -1.478  0.9683
##  ambient 2019 - ambient 2021  0.034966 0.0565 150.3  0.619  1.0000
##  ambient 2019 - warmed 2021  -0.018696 0.0800  91.5 -0.234  1.0000
##  warmed 2019 - ambient 2020  -0.010960 0.0800  91.5 -0.137  1.0000
##  warmed 2019 - warmed 2020   -0.064623 0.0565 150.3 -1.144  0.9970
##  warmed 2019 - ambient 2021   0.088629 0.0800  91.5  1.107  0.9977
##  warmed 2019 - warmed 2021    0.034966 0.0565 150.3  0.619  1.0000
##  ambient 2020 - warmed 2020  -0.053663 0.0567  26.2 -0.946  0.9992
##  ambient 2020 - ambient 2021  0.099590 0.0565 150.3  1.763  0.8886
##  ambient 2020 - warmed 2021   0.045927 0.0800  91.5  0.574  1.0000
##  warmed 2020 - ambient 2021   0.153252 0.0800  91.5  1.915  0.8131
##  warmed 2020 - warmed 2021    0.099590 0.0565 150.3  1.763  0.8886
##  ambient 2021 - warmed 2021  -0.053663 0.0567  26.2 -0.946  0.9992
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 14 estimates
```

SHANNON KBS

```r
# Do we need to include plot as a random effect with the KBS models?
mod1ks <- lmer(log(shannon) ~ state * year + insecticide * year + (1 | plot), kbs_diversity,
    REML = FALSE)
mod2ks <- lmer(log(shannon) ~ state * year + insecticide + year + (1 | plot), kbs_diversity,
    REML = FALSE)
# Run analysis of variance on each model (see this for more explanation on how
# anova on a linear mixed effects model is similar to an anova on a regular
# linear model: https://m-clark.github.io/docs/mixedModels/anovamixed.html)
anova(mod1ks)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq Mean Sq F value
## state               1 0.04923 0.04923  1.7925
## year                6 2.56579 0.42763 15.5716
## insecticide         1 0.00417 0.00417  0.1517
## state:year          6 0.10694 0.01782  0.6490
## year:insecticide    6 0.62226 0.10371  3.7764
```

```r
anova(mod2ks)
```

```
## Analysis of Variance Table
##             npar  Sum Sq Mean Sq F value
## state          1 0.05752 0.05752  1.8056
## year           6 2.56846 0.42808 13.4379
## insecticide    1 0.00485 0.00485  0.1522
## state:year     6 0.10668 0.01778  0.5581
```

```r
anova(mod1ks, mod2ks)  # Go with model 1 since pvalue <0.05, aka more complex model does have something
```

```
## Data: kbs_diversity
## Models:
## mod2ks: log(shannon) ~ state * year + insecticide + year + (1 | plot)
## mod1ks: log(shannon) ~ state * year + insecticide * year + (1 | plot)
##        npar     AIC    BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod2ks   17 -28.256 24.750 31.128  -62.256
## mod1ks   23 -37.258 34.456 41.629  -83.258 21.002  6   0.001833 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod1ks)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(shannon) ~ state * year + insecticide * year + (1 | plot)
##    Data: kbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##    -37.3     34.5     41.6    -83.3      144
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.93439 -0.46009  0.05937  0.58195  2.45210
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.01991  0.1411
##  Residual             0.02746  0.1657
## Number of obs: 167, groups:  plot, 24
##
## Fixed effects:
##                                Estimate Std. Error t value
## (Intercept)                     0.56061    0.07695   7.285
## statewarmed                     0.01463    0.08885   0.165
## year2016                       -0.05695    0.08286  -0.687
## year2017                       -0.21499    0.08286  -2.595
## year2018                       -0.06251    0.08286  -0.754
## year2019                       -0.09392    0.08286  -1.134
## year2020                       -0.04152    0.08286  -0.501
## year2021                       -0.19385    0.08615  -2.250
## insecticideno_insects           0.02893    0.08885   0.326
## statewarmed:year2016           -0.06684    0.09568  -0.699
```

```
## statewarmed:year2017           -0.12632    0.09568  -1.320
## statewarmed:year2018           -0.06268    0.09568  -0.655
## statewarmed:year2019           -0.14113    0.09568  -1.475
## statewarmed:year2020           -0.13665    0.09568  -1.428
## statewarmed:year2021           -0.15061    0.09696  -1.553
## year2016:insecticideno_insects  0.08898    0.09568   0.930
## year2017:insecticideno_insects  0.09540    0.09568   0.997
## year2018:insecticideno_insects -0.04480    0.09568  -0.468
## year2019:insecticideno_insects -0.23494    0.09568  -2.456
## year2020:insecticideno_insects -0.07393    0.09568  -0.773
## year2021:insecticideno_insects -0.21572    0.09696  -2.225
```

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

```r
summary(mod2ks)
```

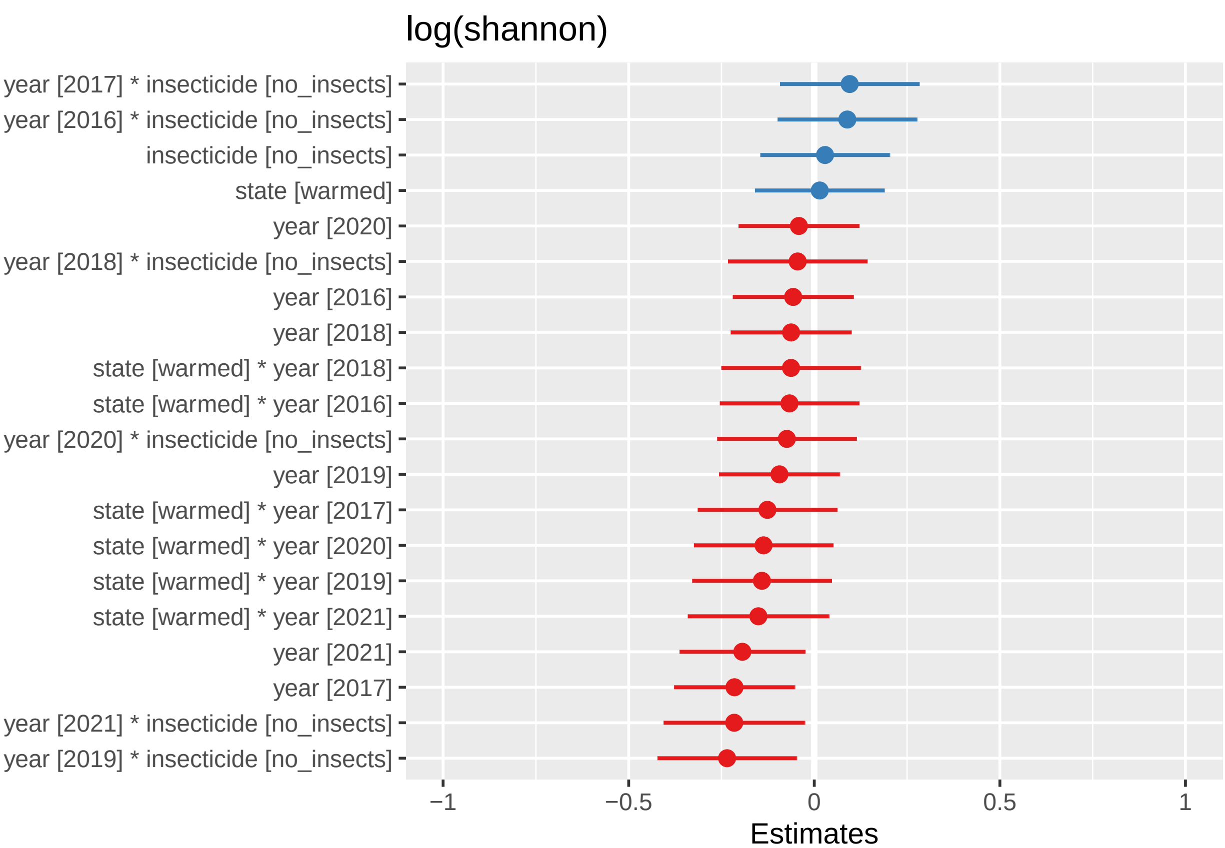
```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(shannon) ~ state * year + insecticide + year + (1 | plot)
##    Data: kbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##    -28.3     24.7     31.1    -62.3      150
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.2592 -0.4062  0.0534  0.6898  1.9171
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.01906  0.1381
##  Residual             0.03186  0.1785
## Number of obs: 167, groups:  plot, 24
##
## Fixed effects:
##                      Estimate Std. Error t value
## (Intercept)           0.58749    0.07230   8.125
## statewarmed           0.01463    0.09212   0.159
## year2016             -0.01246    0.07287  -0.171
## year2017             -0.16729    0.07287  -2.296
## year2018             -0.08492    0.07287  -1.165
## year2019             -0.21139    0.07287  -2.901
## year2020             -0.07849    0.07287  -1.077
## year2021             -0.31052    0.07472  -4.156
## insecticideno_insects -0.02481    0.06277  -0.395
## statewarmed:year2016  -0.06684    0.10305  -0.649
## statewarmed:year2017  -0.12632    0.10305  -1.226
## statewarmed:year2018  -0.06268    0.10305  -0.608
## statewarmed:year2019  -0.14113    0.10305  -1.370
## statewarmed:year2020  -0.13665    0.10305  -1.326
## statewarmed:year2021  -0.14180    0.10436  -1.359
```

```
##
## Correlation matrix not shown by default, as p = 15 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```r
AICctab(mod1ks, mod2ks, weights = T)  # model 1
```

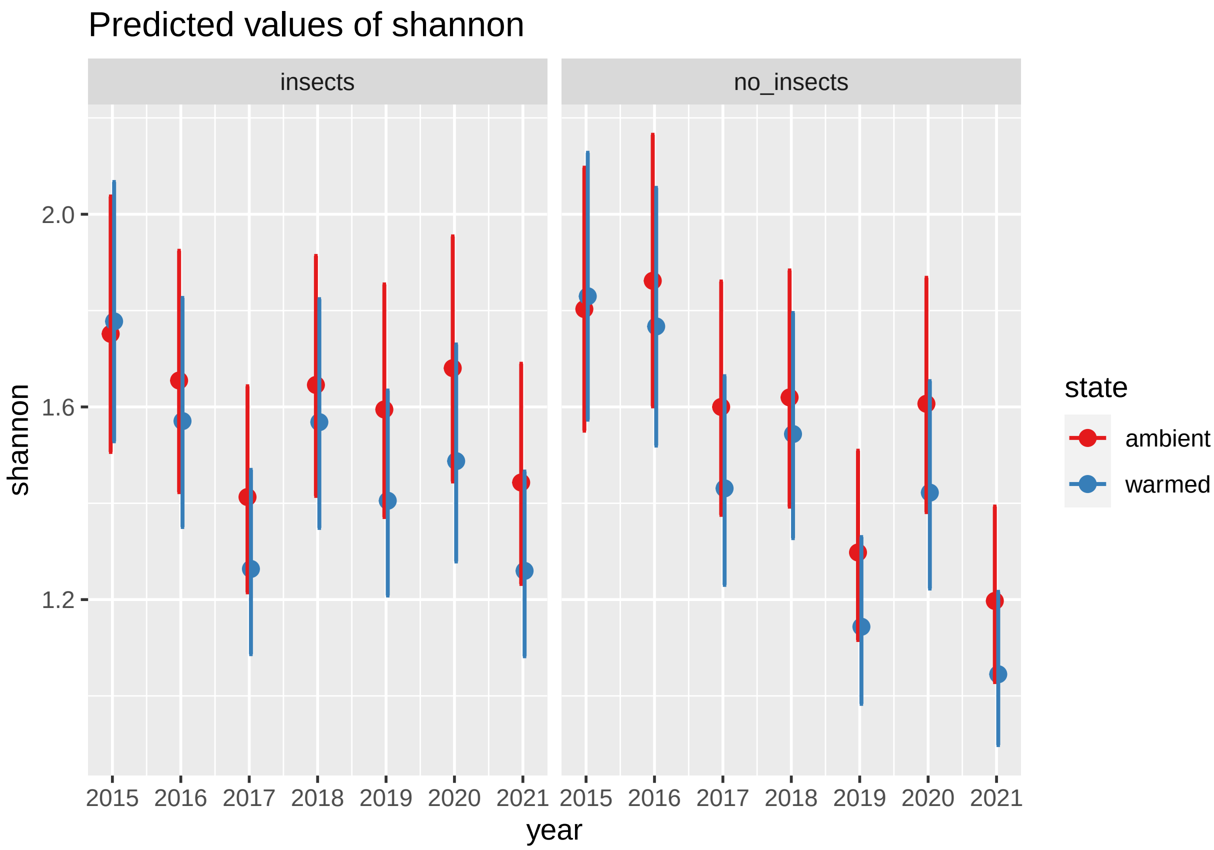
```
##        dAICc df weight
## mod1ks  0.0  23 0.937
## mod2ks  5.4  17 0.063
```

```r
# Plot the fixed effects estimates for different models these are the fixed
# effects estimates from summary(mod1)
plot_model(mod1ks, sort.est = TRUE)
```

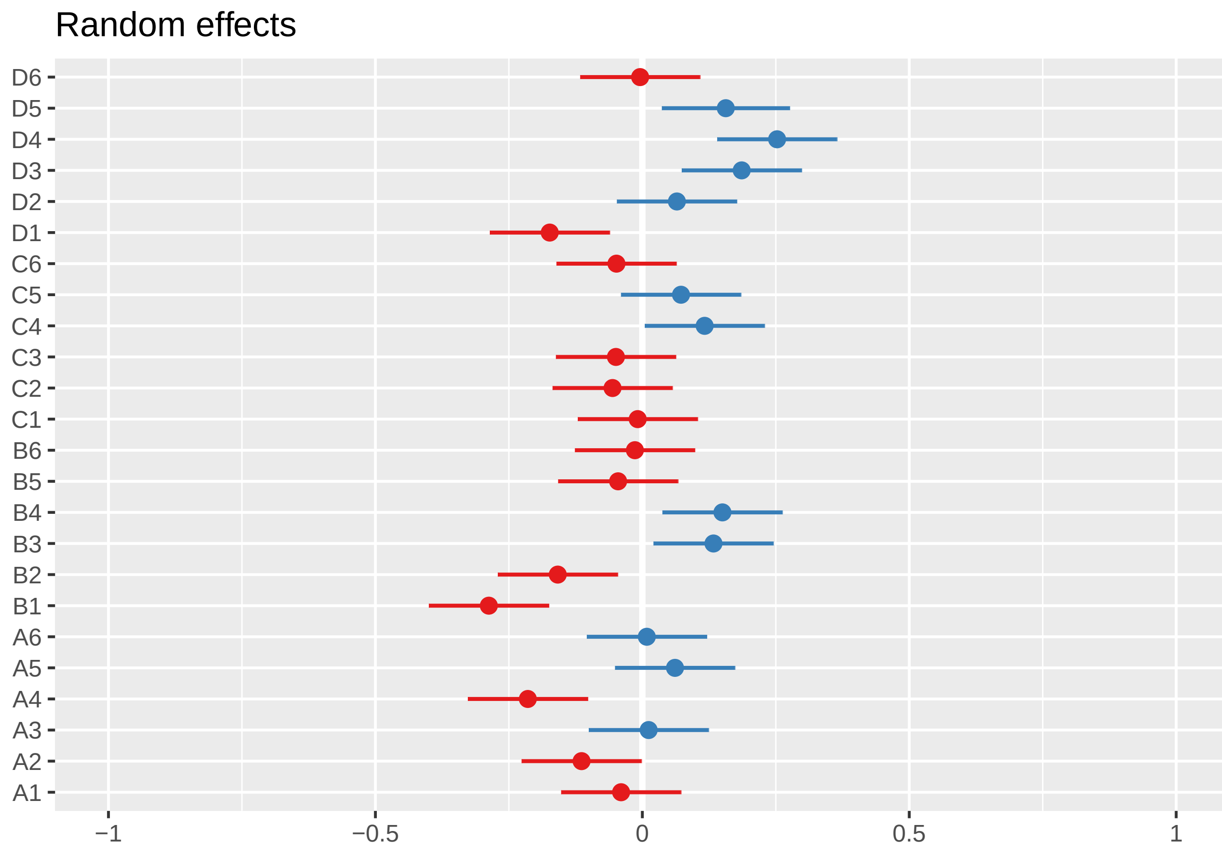



```r
# these are the fixed predicted values:
plot_model(mod1ks, type = "pred", terms = c("year", "state", "insecticide"))
```

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




```r
# these are the random effects estimates
plot_model(mod1ks, type = "re", terms = c("species"))
```




```r
# Does year need to be interactive with state?
mod3ks <- lmer(log(shannon) ~ state + year + insecticide * year + (1 | plot), kbs_diversity,
    REML = FALSE)
anova(mod2ks, mod3ks)
```

```
## Data: kbs_diversity
## Models:
## mod2ks: log(shannon) ~ state * year + insecticide + year + (1 | plot)
## mod3ks: log(shannon) ~ state + year + insecticide * year + (1 | plot)
##        npar     AIC     BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod2ks   17 -28.256 24.7497 31.128  -62.256
## mod3ks   17 -45.253  7.7528 39.627  -79.253 16.997  0
```

```r
AICctab(mod1ks, mod3ks, weights = T)  # going with mod3
```

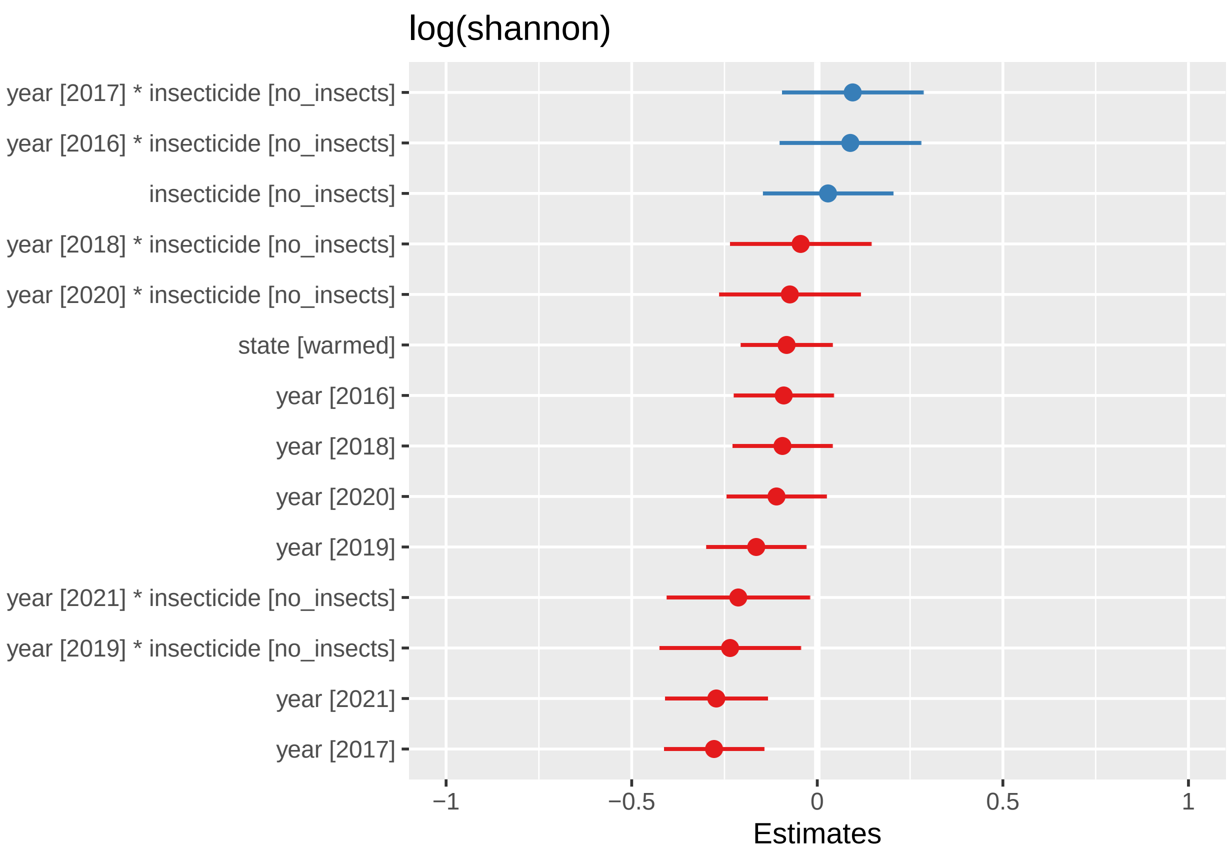
```
##        dAICc df weight
## mod3ks  0.0  17 0.997
## mod1ks 11.6  23 0.003
```

```r
# Do we need to include insecticide? (dropping insecticide from the model)
mod5ks <- lmer(log(shannon) ~ state + year + (1 | plot), kbs_diversity, REML = FALSE)
anova(mod3ks, mod5ks)
```

```
## Data: kbs_diversity
## Models:
```

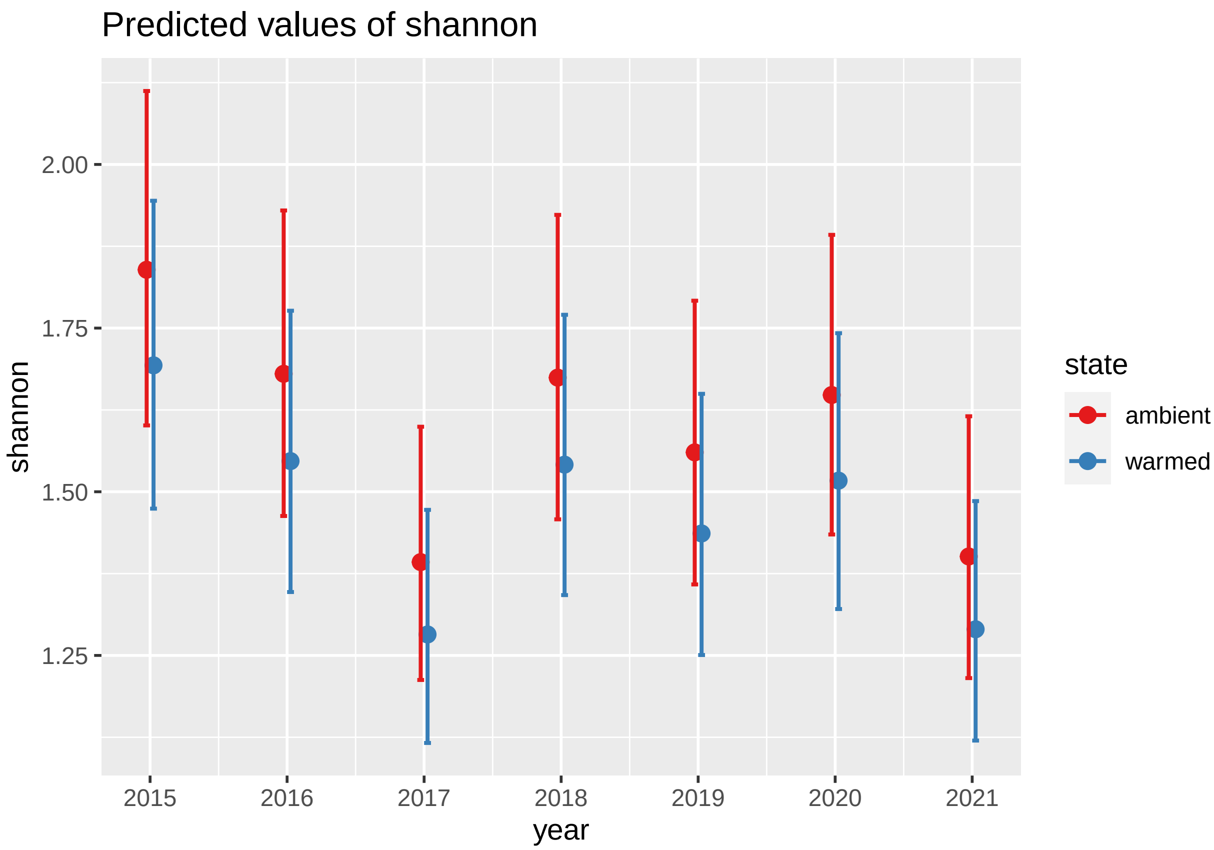
```
## mod5ks: log(shannon) ~ state + year + (1 | plot)
## mod3ks: log(shannon) ~ state + year + insecticide * year + (1 | plot)
##        npar     AIC     BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod5ks   10 -38.795 -7.6155 29.398  -58.795
## mod3ks   17 -45.253  7.7528 39.627  -79.253 20.458  7   0.004662 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Yes, p<0.05 so insecticide*year does strongly improve model fit so we will
# stick with the more complex mod3

# Plot the fixed effects estimates for different models these are the fixed
# effects estimates from summary(mod5)
plot_model(mod3ks, sort.est = TRUE)
```

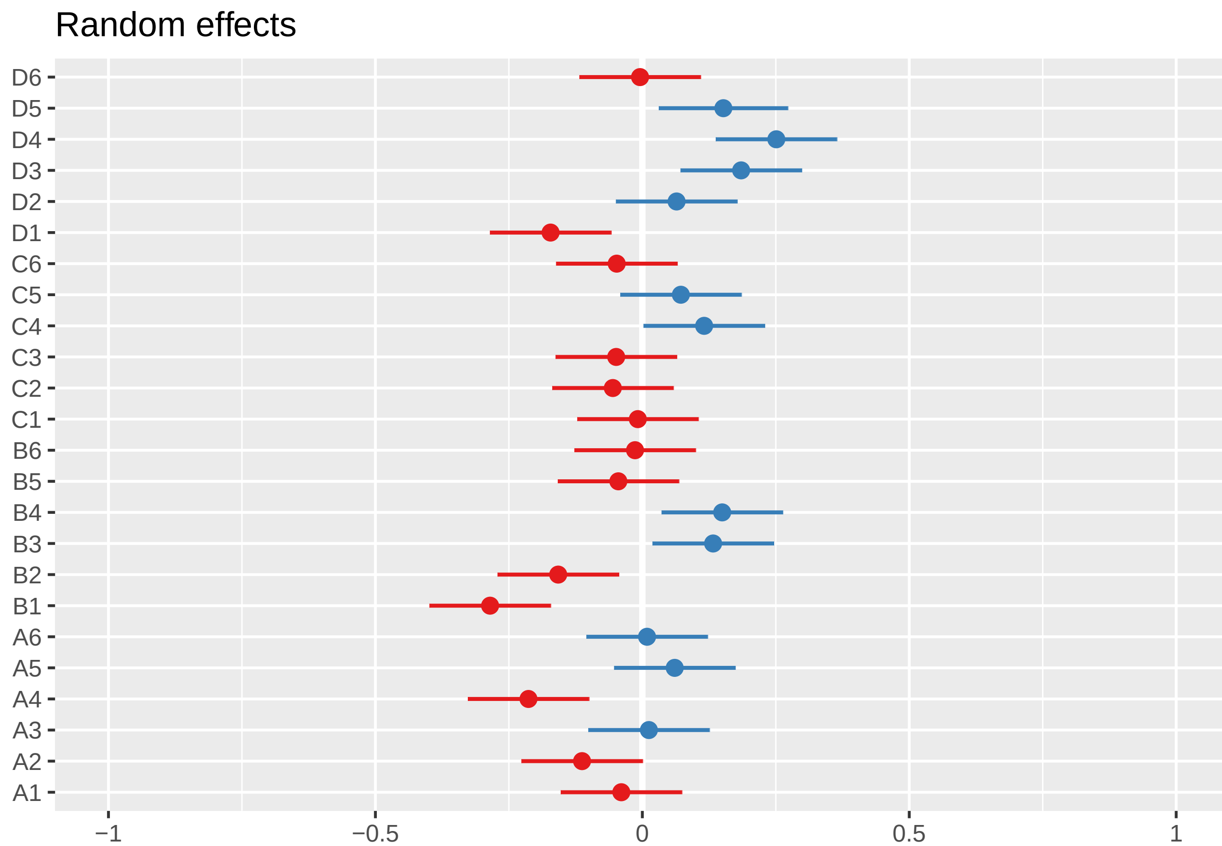



```
# these are the fixed predicted values:
plot_model(mod3ks, type = "pred", terms = c("year", "state"))
```

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




```r
# these are the random effects estimates
plot_model(mod3ks, type = "re", terms = c("species"))
```




```
# If we wanted to include plots nested within year it would look like this:
# mod6ks <- lmer(log(shannon) ~ state + year + insecticide*year + (1 +
# year|plot), kbs_diversity, REML=FALSE) anova(mod5ks, mod6ks) anova(mod5ks) cant
# get mod6 to work

# the best model fit appears to be = mod3ks <- lmer(log(shannon) ~ state + year +
# insecticide*year + (1|plot), kbs_diversity, REML = FALSE)
summ(mod3ks)
```

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

AIC	-45.25
BIC	7.75
Pseudo-R^2 (fixed effects)	0.31
Pseudo-R^2 (total)	0.59

```
emmeans(mod3ks, list(pairwise ~ state + year + insecticide * year), adjust = "tukey")
```

```
## $`emmeans of state, year, insecticide`
##  state   year insecticide emmean     SE   df lower.CL upper.CL
##  ambient 2015 insects     0.6093 0.0748 71.5  0.46010    0.758
##  warmed  2015 insects     0.5266 0.0748 71.5  0.37739    0.676
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	0.61	0.07	8.63	62.69	0.00
statewarmed	-0.08	0.06	-1.31	23.97	0.20
year2016	-0.09	0.07	-1.32	142.97	0.19
year2017	-0.28	0.07	-4.05	142.97	0.00
year2018	-0.09	0.07	-1.37	142.97	0.17
year2019	-0.16	0.07	-2.40	142.97	0.02
year2020	-0.11	0.07	-1.60	142.97	0.11
year2021	-0.27	0.07	-3.86	143.34	0.00
insecticideno_insects	0.03	0.09	0.32	83.14	0.75
year2016:insecticideno_insects	0.09	0.10	0.92	142.97	0.36
year2017:insecticideno_insects	0.10	0.10	0.98	142.97	0.33
year2018:insecticideno_insects	-0.04	0.10	-0.46	142.97	0.65
year2019:insecticideno_insects	-0.23	0.10	-2.42	142.97	0.02
year2020:insecticideno_insects	-0.07	0.10	-0.76	142.97	0.45
year2021:insecticideno_insects	-0.21	0.10	-2.17	143.16	0.03

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.14
Residual		0.17

Grouping Variables		
Group	# groups	ICC
plot	24	0.41

```
##  ambient 2016 insects     0.5189 0.0748 71.5  0.36973    0.668
##  warmed  2016 insects     0.4362 0.0748 71.5  0.28703    0.585
##  ambient 2017 insects     0.3311 0.0748 71.5  0.18196    0.480
##  warmed  2017 insects     0.2484 0.0748 71.5  0.09925    0.398
##  ambient 2018 insects     0.5154 0.0748 71.5  0.36624    0.665
##  warmed  2018 insects     0.4327 0.0748 71.5  0.28354    0.582
##  ambient 2019 insects     0.4448 0.0748 71.5  0.29561    0.594
##  warmed  2019 insects     0.3621 0.0748 71.5  0.21290    0.511
##  ambient 2020 insects     0.4994 0.0748 71.5  0.35025    0.649
##  warmed  2020 insects     0.4167 0.0748 71.5  0.26754    0.566
##  ambient 2021 insects     0.3373 0.0768 77.6  0.18431    0.490
##  warmed  2021 insects     0.2546 0.0763 76.1  0.10254    0.407
##  ambient 2015 no_insects  0.6382 0.0748 71.5  0.48903    0.787
##  warmed  2015 no_insects  0.5555 0.0748 71.5  0.40632    0.705
##  ambient 2016 no_insects  0.6368 0.0748 71.5  0.48764    0.786
##  warmed  2016 no_insects  0.5541 0.0748 71.5  0.40494    0.703
##  ambient 2017 no_insects  0.4555 0.0748 71.5  0.30629    0.605
##  warmed  2017 no_insects  0.3728 0.0748 71.5  0.22358    0.522
##  ambient 2018 no_insects  0.4996 0.0748 71.5  0.35037    0.649
##  warmed  2018 no_insects  0.4169 0.0748 71.5  0.26767    0.566
```

```
##  ambient 2019 no_insects  0.2388 0.0748 71.5  0.08961    0.388
##  warmed  2019 no_insects  0.1561 0.0748 71.5  0.00690    0.305
##  ambient 2020 no_insects  0.4544 0.0748 71.5  0.30525    0.604
##  warmed  2020 no_insects  0.3717 0.0748 71.5  0.22254    0.521
##  ambient 2021 no_insects  0.1533 0.0748 71.5  0.00416    0.303
##  warmed  2021 no_insects  0.0706 0.0748 71.5 -0.07855    0.220
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, year, insecticide`
##  1                                             estimate     SE    df
##  ambient 2015 insects - warmed 2015 insects         0.082709 0.0673  27.4
##  ambient 2015 insects - ambient 2016 insects        0.090367 0.0717 156.1
##  ambient 2015 insects - warmed 2016 insects         0.173076 0.0983 105.2
##  ambient 2015 insects - ambient 2017 insects        0.278145 0.0717 156.1
##  ambient 2015 insects - warmed 2017 insects         0.360853 0.0983 105.2
##  ambient 2015 insects - ambient 2018 insects        0.093855 0.0717 156.1
##  ambient 2015 insects - warmed 2018 insects         0.176564 0.0983 105.2
##  ambient 2015 insects - ambient 2019 insects        0.164491 0.0717 156.1
##  ambient 2015 insects - warmed 2019 insects         0.247200 0.0983 105.2
##  ambient 2015 insects - ambient 2020 insects        0.109848 0.0717 156.1
##  ambient 2015 insects - warmed 2020 insects         0.192557 0.0983 105.2
##  ambient 2015 insects - ambient 2021 insects        0.271989 0.0735 156.5
##  ambient 2015 insects - warmed 2021 insects         0.354698 0.0993 107.7
##  ambient 2015 insects - ambient 2015 no_insects    -0.028931 0.0945  94.5
##  ambient 2015 insects - warmed 2015 no_insects      0.053777 0.1160  59.7
##  ambient 2015 insects - ambient 2016 no_insects    -0.027543 0.0945  94.5
##  ambient 2015 insects - warmed 2016 no_insects      0.055165 0.1160  59.7
##  ambient 2015 insects - ambient 2017 no_insects     0.153815 0.0945  94.5
##  ambient 2015 insects - warmed 2017 no_insects      0.236524 0.1160  59.7
##  ambient 2015 insects - ambient 2018 no_insects     0.109727 0.0945  94.5
##  ambient 2015 insects - warmed 2018 no_insects      0.192436 0.1160  59.7
##  ambient 2015 insects - ambient 2019 no_insects     0.370496 0.0945  94.5
##  ambient 2015 insects - warmed 2019 no_insects      0.453205 0.1160  59.7
##  ambient 2015 insects - ambient 2020 no_insects     0.154847 0.0945  94.5
##  ambient 2015 insects - warmed 2020 no_insects      0.237556 0.1160  59.7
##  ambient 2015 insects - ambient 2021 no_insects     0.455944 0.0945  94.5
##  ambient 2015 insects - warmed 2021 no_insects      0.538652 0.1160  59.7
##  warmed 2015 insects - ambient 2016 insects         0.007658 0.0983 105.2
##  warmed 2015 insects - warmed 2016 insects          0.090367 0.0717 156.1
##  warmed 2015 insects - ambient 2017 insects         0.195436 0.0983 105.2
##  warmed 2015 insects - warmed 2017 insects          0.278145 0.0717 156.1
##  warmed 2015 insects - ambient 2018 insects         0.011146 0.0983 105.2
##  warmed 2015 insects - warmed 2018 insects          0.093855 0.0717 156.1
##  warmed 2015 insects - ambient 2019 insects         0.081783 0.0983 105.2
##  warmed 2015 insects - warmed 2019 insects          0.164491 0.0717 156.1
##  warmed 2015 insects - ambient 2020 insects         0.027140 0.0983 105.2
##  warmed 2015 insects - warmed 2020 insects          0.109848 0.0717 156.1
##  warmed 2015 insects - ambient 2021 insects         0.189280 0.1001 109.7
##  warmed 2015 insects - warmed 2021 insects          0.271989 0.0735 156.5
##  warmed 2015 insects - ambient 2015 no_insects     -0.111640 0.1160  59.7
##  warmed 2015 insects - warmed 2015 no_insects      -0.028931 0.0945  94.5
```

```
##  warmed 2015 insects - ambient 2016 no_insects     -0.110252 0.1160  59.7
##  warmed 2015 insects - warmed 2016 no_insects      -0.027543 0.0945  94.5
##  warmed 2015 insects - ambient 2017 no_insects      0.071107 0.1160  59.7
##  warmed 2015 insects - warmed 2017 no_insects       0.153815 0.0945  94.5
##  warmed 2015 insects - ambient 2018 no_insects      0.027018 0.1160  59.7
##  warmed 2015 insects - warmed 2018 no_insects       0.109727 0.0945  94.5
##  warmed 2015 insects - ambient 2019 no_insects      0.287787 0.1160  59.7
##  warmed 2015 insects - warmed 2019 no_insects       0.370496 0.0945  94.5
##  warmed 2015 insects - ambient 2020 no_insects      0.072139 0.1160  59.7
##  warmed 2015 insects - warmed 2020 no_insects       0.154847 0.0945  94.5
##  warmed 2015 insects - ambient 2021 no_insects      0.373235 0.1160  59.7
##  warmed 2015 insects - warmed 2021 no_insects       0.455944 0.0945  94.5
##  ambient 2016 insects - warmed 2016 insects         0.082709 0.0673  27.4
##  ambient 2016 insects - ambient 2017 insects        0.187778 0.0717 156.1
##  ambient 2016 insects - warmed 2017 insects         0.270486 0.0983 105.2
##  ambient 2016 insects - ambient 2018 insects        0.003488 0.0717 156.1
##  ambient 2016 insects - warmed 2018 insects         0.086197 0.0983 105.2
##  ambient 2016 insects - ambient 2019 insects        0.074124 0.0717 156.1
##  ambient 2016 insects - warmed 2019 insects         0.156833 0.0983 105.2
##  ambient 2016 insects - ambient 2020 insects        0.019481 0.0717 156.1
##  ambient 2016 insects - warmed 2020 insects         0.102190 0.0983 105.2
##  ambient 2016 insects - ambient 2021 insects        0.181622 0.0735 156.5
##  ambient 2016 insects - warmed 2021 insects         0.264331 0.0993 107.7
##  ambient 2016 insects - ambient 2015 no_insects    -0.119298 0.0945  94.5
##  ambient 2016 insects - warmed 2015 no_insects     -0.036590 0.1160  59.7
##  ambient 2016 insects - ambient 2016 no_insects    -0.117910 0.0945  94.5
##  ambient 2016 insects - warmed 2016 no_insects     -0.035202 0.1160  59.7
##  ambient 2016 insects - ambient 2017 no_insects     0.063448 0.0945  94.5
##  ambient 2016 insects - warmed 2017 no_insects      0.146157 0.1160  59.7
##  ambient 2016 insects - ambient 2018 no_insects     0.019360 0.0945  94.5
##  ambient 2016 insects - warmed 2018 no_insects      0.102069 0.1160  59.7
##  ambient 2016 insects - ambient 2019 no_insects     0.280129 0.0945  94.5
##  ambient 2016 insects - warmed 2019 no_insects      0.362837 0.1160  59.7
##  ambient 2016 insects - ambient 2020 no_insects     0.064480 0.0945  94.5
##  ambient 2016 insects - warmed 2020 no_insects      0.147189 0.1160  59.7
##  ambient 2016 insects - ambient 2021 no_insects     0.365577 0.0945  94.5
##  ambient 2016 insects - warmed 2021 no_insects      0.448286 0.1160  59.7
##  warmed 2016 insects - ambient 2017 insects         0.105069 0.0983 105.2
##  warmed 2016 insects - warmed 2017 insects          0.187778 0.0717 156.1
##  warmed 2016 insects - ambient 2018 insects        -0.079221 0.0983 105.2
##  warmed 2016 insects - warmed 2018 insects          0.003488 0.0717 156.1
##  warmed 2016 insects - ambient 2019 insects        -0.008585 0.0983 105.2
##  warmed 2016 insects - warmed 2019 insects          0.074124 0.0717 156.1
##  warmed 2016 insects - ambient 2020 insects        -0.063227 0.0983 105.2
##  warmed 2016 insects - warmed 2020 insects          0.019481 0.0717 156.1
##  warmed 2016 insects - ambient 2021 insects         0.098913 0.1001 109.7
##  warmed 2016 insects - warmed 2021 insects          0.181622 0.0735 156.5
##  warmed 2016 insects - ambient 2015 no_insects     -0.202007 0.1160  59.7
##  warmed 2016 insects - warmed 2015 no_insects      -0.119298 0.0945  94.5
##  warmed 2016 insects - ambient 2016 no_insects     -0.200619 0.1160  59.7
##  warmed 2016 insects - warmed 2016 no_insects      -0.117910 0.0945  94.5
##  warmed 2016 insects - ambient 2017 no_insects     -0.019260 0.1160  59.7
##  warmed 2016 insects - warmed 2017 no_insects       0.063448 0.0945  94.5
##  warmed 2016 insects - ambient 2018 no_insects     -0.063349 0.1160  59.7
```

```
##  warmed 2016 insects - warmed 2018 no_insects       0.019360 0.0945  94.5
##  warmed 2016 insects - ambient 2019 no_insects      0.197420 0.1160  59.7
##  warmed 2016 insects - warmed 2019 no_insects       0.280129 0.0945  94.5
##  warmed 2016 insects - ambient 2020 no_insects     -0.018228 0.1160  59.7
##  warmed 2016 insects - warmed 2020 no_insects       0.064480 0.0945  94.5
##  warmed 2016 insects - ambient 2021 no_insects      0.282868 0.1160  59.7
##  warmed 2016 insects - warmed 2021 no_insects       0.365577 0.0945  94.5
##  ambient 2017 insects - warmed 2017 insects         0.082709 0.0673  27.4
##  ambient 2017 insects - ambient 2018 insects       -0.184290 0.0717 156.1
##  ambient 2017 insects - warmed 2018 insects        -0.101581 0.0983 105.2
##  ambient 2017 insects - ambient 2019 insects       -0.113654 0.0717 156.1
##  ambient 2017 insects - warmed 2019 insects        -0.030945 0.0983 105.2
##  ambient 2017 insects - ambient 2020 insects       -0.168296 0.0717 156.1
##  ambient 2017 insects - warmed 2020 insects        -0.085588 0.0983 105.2
##  ambient 2017 insects - ambient 2021 insects       -0.006156 0.0735 156.5
##  ambient 2017 insects - warmed 2021 insects         0.076553 0.0993 107.7
##  ambient 2017 insects - ambient 2015 no_insects    -0.307076 0.0945  94.5
##  ambient 2017 insects - warmed 2015 no_insects     -0.224367 0.1160  59.7
##  ambient 2017 insects - ambient 2016 no_insects    -0.305688 0.0945  94.5
##  ambient 2017 insects - warmed 2016 no_insects     -0.222979 0.1160  59.7
##  ambient 2017 insects - ambient 2017 no_insects    -0.124329 0.0945  94.5
##  ambient 2017 insects - warmed 2017 no_insects     -0.041621 0.1160  59.7
##  ambient 2017 insects - ambient 2018 no_insects    -0.168418 0.0945  94.5
##  ambient 2017 insects - warmed 2018 no_insects     -0.085709 0.1160  59.7
##  ambient 2017 insects - ambient 2019 no_insects     0.092351 0.0945  94.5
##  ambient 2017 insects - warmed 2019 no_insects      0.175060 0.1160  59.7
##  ambient 2017 insects - ambient 2020 no_insects    -0.123297 0.0945  94.5
##  ambient 2017 insects - warmed 2020 no_insects     -0.040589 0.1160  59.7
##  ambient 2017 insects - ambient 2021 no_insects     0.177799 0.0945  94.5
##  ambient 2017 insects - warmed 2021 no_insects      0.260508 0.1160  59.7
##  warmed 2017 insects - ambient 2018 insects        -0.266998 0.0983 105.2
##  warmed 2017 insects - warmed 2018 insects         -0.184290 0.0717 156.1
##  warmed 2017 insects - ambient 2019 insects        -0.196362 0.0983 105.2
##  warmed 2017 insects - warmed 2019 insects         -0.113654 0.0717 156.1
##  warmed 2017 insects - ambient 2020 insects        -0.251005 0.0983 105.2
##  warmed 2017 insects - warmed 2020 insects         -0.168296 0.0717 156.1
##  warmed 2017 insects - ambient 2021 insects        -0.088864 0.1001 109.7
##  warmed 2017 insects - warmed 2021 insects         -0.006156 0.0735 156.5
##  warmed 2017 insects - ambient 2015 no_insects     -0.389784 0.1160  59.7
##  warmed 2017 insects - warmed 2015 no_insects      -0.307076 0.0945  94.5
##  warmed 2017 insects - ambient 2016 no_insects     -0.388397 0.1160  59.7
##  warmed 2017 insects - warmed 2016 no_insects      -0.305688 0.0945  94.5
##  warmed 2017 insects - ambient 2017 no_insects     -0.207038 0.1160  59.7
##  warmed 2017 insects - warmed 2017 no_insects      -0.124329 0.0945  94.5
##  warmed 2017 insects - ambient 2018 no_insects     -0.251126 0.1160  59.7
##  warmed 2017 insects - warmed 2018 no_insects      -0.168418 0.0945  94.5
##  warmed 2017 insects - ambient 2019 no_insects      0.009643 0.1160  59.7
##  warmed 2017 insects - warmed 2019 no_insects       0.092351 0.0945  94.5
##  warmed 2017 insects - ambient 2020 no_insects     -0.206006 0.1160  59.7
##  warmed 2017 insects - warmed 2020 no_insects      -0.123297 0.0945  94.5
##  warmed 2017 insects - ambient 2021 no_insects      0.095091 0.1160  59.7
##  warmed 2017 insects - warmed 2021 no_insects       0.177799 0.0945  94.5
##  ambient 2018 insects - warmed 2018 insects         0.082709 0.0673  27.4
##  ambient 2018 insects - ambient 2019 insects        0.070636 0.0717 156.1
```

```
##  ambient 2018 insects - warmed 2019 insects        0.153345 0.0983 105.2
##  ambient 2018 insects - ambient 2020 insects       0.015993 0.0717 156.1
##  ambient 2018 insects - warmed 2020 insects        0.098702 0.0983 105.2
##  ambient 2018 insects - ambient 2021 insects       0.178134 0.0735 156.5
##  ambient 2018 insects - warmed 2021 insects        0.260843 0.0993 107.7
##  ambient 2018 insects - ambient 2015 no_insects   -0.122786 0.0945  94.5
##  ambient 2018 insects - warmed 2015 no_insects    -0.040078 0.1160  59.7
##  ambient 2018 insects - ambient 2016 no_insects   -0.121398 0.0945  94.5
##  ambient 2018 insects - warmed 2016 no_insects    -0.038690 0.1160  59.7
##  ambient 2018 insects - ambient 2017 no_insects    0.059960 0.0945  94.5
##  ambient 2018 insects - warmed 2017 no_insects     0.142669 0.1160  59.7
##  ambient 2018 insects - ambient 2018 no_insects    0.015872 0.0945  94.5
##  ambient 2018 insects - warmed 2018 no_insects     0.098581 0.1160  59.7
##  ambient 2018 insects - ambient 2019 no_insects    0.276641 0.0945  94.5
##  ambient 2018 insects - warmed 2019 no_insects     0.359349 0.1160  59.7
##  ambient 2018 insects - ambient 2020 no_insects    0.060992 0.0945  94.5
##  ambient 2018 insects - warmed 2020 no_insects     0.143701 0.1160  59.7
##  ambient 2018 insects - ambient 2021 no_insects    0.362089 0.0945  94.5
##  ambient 2018 insects - warmed 2021 no_insects     0.444798 0.1160  59.7
##  warmed 2018 insects - ambient 2019 insects       -0.012072 0.0983 105.2
##  warmed 2018 insects - warmed 2019 insects         0.070636 0.0717 156.1
##  warmed 2018 insects - ambient 2020 insects       -0.066715 0.0983 105.2
##  warmed 2018 insects - warmed 2020 insects         0.015993 0.0717 156.1
##  warmed 2018 insects - ambient 2021 insects        0.095425 0.1001 109.7
##  warmed 2018 insects - warmed 2021 insects         0.178134 0.0735 156.5
##  warmed 2018 insects - ambient 2015 no_insects    -0.205495 0.1160  59.7
##  warmed 2018 insects - warmed 2015 no_insects     -0.122786 0.0945  94.5
##  warmed 2018 insects - ambient 2016 no_insects    -0.204107 0.1160  59.7
##  warmed 2018 insects - warmed 2016 no_insects     -0.121398 0.0945  94.5
##  warmed 2018 insects - ambient 2017 no_insects    -0.022748 0.1160  59.7
##  warmed 2018 insects - warmed 2017 no_insects      0.059960 0.0945  94.5
##  warmed 2018 insects - ambient 2018 no_insects    -0.066837 0.1160  59.7
##  warmed 2018 insects - warmed 2018 no_insects      0.015872 0.0945  94.5
##  warmed 2018 insects - ambient 2019 no_insects     0.193932 0.1160  59.7
##  warmed 2018 insects - warmed 2019 no_insects      0.276641 0.0945  94.5
##  warmed 2018 insects - ambient 2020 no_insects    -0.021716 0.1160  59.7
##  warmed 2018 insects - warmed 2020 no_insects      0.060992 0.0945  94.5
##  warmed 2018 insects - ambient 2021 no_insects     0.279380 0.1160  59.7
##  warmed 2018 insects - warmed 2021 no_insects      0.362089 0.0945  94.5
##  ambient 2019 insects - warmed 2019 insects        0.082709 0.0673  27.4
##  ambient 2019 insects - ambient 2020 insects      -0.054643 0.0717 156.1
##  ambient 2019 insects - warmed 2020 insects        0.028066 0.0983 105.2
##  ambient 2019 insects - ambient 2021 insects       0.107498 0.0735 156.5
##  ambient 2019 insects - warmed 2021 insects        0.190206 0.0993 107.7
##  ambient 2019 insects - ambient 2015 no_insects   -0.193422 0.0945  94.5
##  ambient 2019 insects - warmed 2015 no_insects    -0.110714 0.1160  59.7
##  ambient 2019 insects - ambient 2016 no_insects   -0.192034 0.0945  94.5
##  ambient 2019 insects - warmed 2016 no_insects    -0.109326 0.1160  59.7
##  ambient 2019 insects - ambient 2017 no_insects   -0.010676 0.0945  94.5
##  ambient 2019 insects - warmed 2017 no_insects     0.072033 0.1160  59.7
##  ambient 2019 insects - ambient 2018 no_insects   -0.054764 0.0945  94.5
##  ambient 2019 insects - warmed 2018 no_insects     0.027944 0.1160  59.7
##  ambient 2019 insects - ambient 2019 no_insects    0.206005 0.0945  94.5
##  ambient 2019 insects - warmed 2019 no_insects     0.288713 0.1160  59.7
```

```
##  ambient 2019 insects - ambient 2020 no_insects    -0.009644 0.0945  94.5
##  ambient 2019 insects - warmed 2020 no_insects      0.073065 0.1160  59.7
##  ambient 2019 insects - ambient 2021 no_insects     0.291453 0.0945  94.5
##  ambient 2019 insects - warmed 2021 no_insects      0.374161 0.1160  59.7
##  warmed 2019 insects - ambient 2020 insects        -0.137351 0.0983 105.2
##  warmed 2019 insects - warmed 2020 insects         -0.054643 0.0717 156.1
##  warmed 2019 insects - ambient 2021 insects         0.024789 0.1001 109.7
##  warmed 2019 insects - warmed 2021 insects          0.107498 0.0735 156.5
##  warmed 2019 insects - ambient 2015 no_insects     -0.276131 0.1160  59.7
##  warmed 2019 insects - warmed 2015 no_insects      -0.193422 0.0945  94.5
##  warmed 2019 insects - ambient 2016 no_insects     -0.274743 0.1160  59.7
##  warmed 2019 insects - warmed 2016 no_insects      -0.192034 0.0945  94.5
##  warmed 2019 insects - ambient 2017 no_insects     -0.093384 0.1160  59.7
##  warmed 2019 insects - warmed 2017 no_insects      -0.010676 0.0945  94.5
##  warmed 2019 insects - ambient 2018 no_insects     -0.137473 0.1160  59.7
##  warmed 2019 insects - warmed 2018 no_insects      -0.054764 0.0945  94.5
##  warmed 2019 insects - ambient 2019 no_insects      0.123296 0.1160  59.7
##  warmed 2019 insects - warmed 2019 no_insects       0.206005 0.0945  94.5
##  warmed 2019 insects - ambient 2020 no_insects     -0.092352 0.1160  59.7
##  warmed 2019 insects - warmed 2020 no_insects      -0.009644 0.0945  94.5
##  warmed 2019 insects - ambient 2021 no_insects      0.208744 0.1160  59.7
##  warmed 2019 insects - warmed 2021 no_insects       0.291453 0.0945  94.5
##  ambient 2020 insects - warmed 2020 insects         0.082709 0.0673  27.4
##  ambient 2020 insects - ambient 2021 insects        0.162141 0.0735 156.5
##  ambient 2020 insects - warmed 2021 insects         0.244849 0.0993 107.7
##  ambient 2020 insects - ambient 2015 no_insects    -0.138779 0.0945  94.5
##  ambient 2020 insects - warmed 2015 no_insects     -0.056071 0.1160  59.7
##  ambient 2020 insects - ambient 2016 no_insects    -0.137392 0.0945  94.5
##  ambient 2020 insects - warmed 2016 no_insects     -0.054683 0.1160  59.7
##  ambient 2020 insects - ambient 2017 no_insects     0.043967 0.0945  94.5
##  ambient 2020 insects - warmed 2017 no_insects      0.126676 0.1160  59.7
##  ambient 2020 insects - ambient 2018 no_insects    -0.000121 0.0945  94.5
##  ambient 2020 insects - warmed 2018 no_insects      0.082587 0.1160  59.7
##  ambient 2020 insects - ambient 2019 no_insects     0.260647 0.0945  94.5
##  ambient 2020 insects - warmed 2019 no_insects      0.343356 0.1160  59.7
##  ambient 2020 insects - ambient 2020 no_insects     0.044999 0.0945  94.5
##  ambient 2020 insects - warmed 2020 no_insects      0.127708 0.1160  59.7
##  ambient 2020 insects - ambient 2021 no_insects     0.346096 0.0945  94.5
##  ambient 2020 insects - warmed 2021 no_insects      0.428804 0.1160  59.7
##  warmed 2020 insects - ambient 2021 insects         0.079432 0.1001 109.7
##  warmed 2020 insects - warmed 2021 insects          0.162141 0.0735 156.5
##  warmed 2020 insects - ambient 2015 no_insects     -0.221488 0.1160  59.7
##  warmed 2020 insects - warmed 2015 no_insects      -0.138779 0.0945  94.5
##  warmed 2020 insects - ambient 2016 no_insects     -0.220100 0.1160  59.7
##  warmed 2020 insects - warmed 2016 no_insects      -0.137392 0.0945  94.5
##  warmed 2020 insects - ambient 2017 no_insects     -0.038741 0.1160  59.7
##  warmed 2020 insects - warmed 2017 no_insects       0.043967 0.0945  94.5
##  warmed 2020 insects - ambient 2018 no_insects     -0.082830 0.1160  59.7
##  warmed 2020 insects - warmed 2018 no_insects      -0.000121 0.0945  94.5
##  warmed 2020 insects - ambient 2019 no_insects      0.177939 0.1160  59.7
##  warmed 2020 insects - warmed 2019 no_insects       0.260647 0.0945  94.5
##  warmed 2020 insects - ambient 2020 no_insects     -0.037709 0.1160  59.7
##  warmed 2020 insects - warmed 2020 no_insects       0.044999 0.0945  94.5
##  warmed 2020 insects - ambient 2021 no_insects      0.263387 0.1160  59.7
```

```
##  warmed 2020 insects - warmed 2021 no_insects       0.346096 0.0945  94.5
##  ambient 2021 insects - warmed 2021 insects         0.082709 0.0673  27.4
##  ambient 2021 insects - ambient 2015 no_insects    -0.300920 0.0959  98.2
##  ambient 2021 insects - warmed 2015 no_insects     -0.218212 0.1175  62.3
##  ambient 2021 insects - ambient 2016 no_insects    -0.299532 0.0959  98.2
##  ambient 2021 insects - warmed 2016 no_insects     -0.216824 0.1175  62.3
##  ambient 2021 insects - ambient 2017 no_insects    -0.118174 0.0959  98.2
##  ambient 2021 insects - warmed 2017 no_insects     -0.035465 0.1175  62.3
##  ambient 2021 insects - ambient 2018 no_insects    -0.162262 0.0959  98.2
##  ambient 2021 insects - warmed 2018 no_insects     -0.079553 0.1175  62.3
##  ambient 2021 insects - ambient 2019 no_insects     0.098507 0.0959  98.2
##  ambient 2021 insects - warmed 2019 no_insects      0.181215 0.1175  62.3
##  ambient 2021 insects - ambient 2020 no_insects    -0.117141 0.0959  98.2
##  ambient 2021 insects - warmed 2020 no_insects     -0.034433 0.1175  62.3
##  ambient 2021 insects - ambient 2021 no_insects     0.183955 0.0959  98.2
##  ambient 2021 insects - warmed 2021 no_insects      0.266663 0.1175  62.3
##  warmed 2021 insects - ambient 2015 no_insects     -0.383629 0.1169  61.2
##  warmed 2021 insects - warmed 2015 no_insects      -0.300920 0.0959  98.2
##  warmed 2021 insects - ambient 2016 no_insects     -0.382241 0.1169  61.2
##  warmed 2021 insects - warmed 2016 no_insects      -0.299532 0.0959  98.2
##  warmed 2021 insects - ambient 2017 no_insects     -0.200882 0.1169  61.2
##  warmed 2021 insects - warmed 2017 no_insects      -0.118174 0.0959  98.2
##  warmed 2021 insects - ambient 2018 no_insects     -0.244971 0.1169  61.2
##  warmed 2021 insects - warmed 2018 no_insects      -0.162262 0.0959  98.2
##  warmed 2021 insects - ambient 2019 no_insects      0.015798 0.1169  61.2
##  warmed 2021 insects - warmed 2019 no_insects       0.098507 0.0959  98.2
##  warmed 2021 insects - ambient 2020 no_insects     -0.199850 0.1169  61.2
##  warmed 2021 insects - warmed 2020 no_insects      -0.117141 0.0959  98.2
##  warmed 2021 insects - ambient 2021 no_insects      0.101246 0.1169  61.2
##  warmed 2021 insects - warmed 2021 no_insects       0.183955 0.0959  98.2
##  ambient 2015 no_insects - warmed 2015 no_insects   0.082709 0.0673  27.4
##  ambient 2015 no_insects - ambient 2016 no_insects  0.001388 0.0717 156.1
##  ambient 2015 no_insects - warmed 2016 no_insects   0.084096 0.0983 105.2
##  ambient 2015 no_insects - ambient 2017 no_insects  0.182747 0.0717 156.1
##  ambient 2015 no_insects - warmed 2017 no_insects   0.265455 0.0983 105.2
##  ambient 2015 no_insects - ambient 2018 no_insects  0.138658 0.0717 156.1
##  ambient 2015 no_insects - warmed 2018 no_insects   0.221367 0.0983 105.2
##  ambient 2015 no_insects - ambient 2019 no_insects  0.399427 0.0717 156.1
##  ambient 2015 no_insects - warmed 2019 no_insects   0.482136 0.0983 105.2
##  ambient 2015 no_insects - ambient 2020 no_insects  0.183779 0.0717 156.1
##  ambient 2015 no_insects - warmed 2020 no_insects   0.266487 0.0983 105.2
##  ambient 2015 no_insects - ambient 2021 no_insects  0.484875 0.0717 156.1
##  ambient 2015 no_insects - warmed 2021 no_insects   0.567584 0.0983 105.2
##  warmed 2015 no_insects - ambient 2016 no_insects  -0.081321 0.0983 105.2
##  warmed 2015 no_insects - warmed 2016 no_insects    0.001388 0.0717 156.1
##  warmed 2015 no_insects - ambient 2017 no_insects   0.100038 0.0983 105.2
##  warmed 2015 no_insects - warmed 2017 no_insects    0.182747 0.0717 156.1
##  warmed 2015 no_insects - ambient 2018 no_insects   0.055949 0.0983 105.2
##  warmed 2015 no_insects - warmed 2018 no_insects    0.138658 0.0717 156.1
##  warmed 2015 no_insects - ambient 2019 no_insects   0.316718 0.0983 105.2
##  warmed 2015 no_insects - warmed 2019 no_insects    0.399427 0.0717 156.1
##  warmed 2015 no_insects - ambient 2020 no_insects   0.101070 0.0983 105.2
##  warmed 2015 no_insects - warmed 2020 no_insects    0.183779 0.0717 156.1
##  warmed 2015 no_insects - ambient 2021 no_insects   0.402166 0.0983 105.2
```

```
##  warmed 2015 no_insects - warmed 2021 no_insects    0.484875 0.0717 156.1
##  ambient 2016 no_insects - warmed 2016 no_insects   0.082709 0.0673  27.4
##  ambient 2016 no_insects - ambient 2017 no_insects  0.181359 0.0717 156.1
##  ambient 2016 no_insects - warmed 2017 no_insects   0.264068 0.0983 105.2
##  ambient 2016 no_insects - ambient 2018 no_insects  0.137270 0.0717 156.1
##  ambient 2016 no_insects - warmed 2018 no_insects   0.219979 0.0983 105.2
##  ambient 2016 no_insects - ambient 2019 no_insects  0.398039 0.0717 156.1
##  ambient 2016 no_insects - warmed 2019 no_insects   0.480748 0.0983 105.2
##  ambient 2016 no_insects - ambient 2020 no_insects  0.182391 0.0717 156.1
##  ambient 2016 no_insects - warmed 2020 no_insects   0.265099 0.0983 105.2
##  ambient 2016 no_insects - ambient 2021 no_insects  0.483487 0.0717 156.1
##  ambient 2016 no_insects - warmed 2021 no_insects   0.566196 0.0983 105.2
##  warmed 2016 no_insects - ambient 2017 no_insects   0.098650 0.0983 105.2
##  warmed 2016 no_insects - warmed 2017 no_insects    0.181359 0.0717 156.1
##  warmed 2016 no_insects - ambient 2018 no_insects   0.054562 0.0983 105.2
##  warmed 2016 no_insects - warmed 2018 no_insects    0.137270 0.0717 156.1
##  warmed 2016 no_insects - ambient 2019 no_insects   0.315331 0.0983 105.2
##  warmed 2016 no_insects - warmed 2019 no_insects    0.398039 0.0717 156.1
##  warmed 2016 no_insects - ambient 2020 no_insects   0.099682 0.0983 105.2
##  warmed 2016 no_insects - warmed 2020 no_insects    0.182391 0.0717 156.1
##  warmed 2016 no_insects - ambient 2021 no_insects   0.400779 0.0983 105.2
##  warmed 2016 no_insects - warmed 2021 no_insects    0.483487 0.0717 156.1
##  ambient 2017 no_insects - warmed 2017 no_insects   0.082709 0.0673  27.4
##  ambient 2017 no_insects - ambient 2018 no_insects -0.044089 0.0717 156.1
##  ambient 2017 no_insects - warmed 2018 no_insects   0.038620 0.0983 105.2
##  ambient 2017 no_insects - ambient 2019 no_insects  0.216680 0.0717 156.1
##  ambient 2017 no_insects - warmed 2019 no_insects   0.299389 0.0983 105.2
##  ambient 2017 no_insects - ambient 2020 no_insects  0.001032 0.0717 156.1
##  ambient 2017 no_insects - warmed 2020 no_insects   0.083741 0.0983 105.2
##  ambient 2017 no_insects - ambient 2021 no_insects  0.302128 0.0717 156.1
##  ambient 2017 no_insects - warmed 2021 no_insects   0.384837 0.0983 105.2
##  warmed 2017 no_insects - ambient 2018 no_insects  -0.126797 0.0983 105.2
##  warmed 2017 no_insects - warmed 2018 no_insects   -0.044089 0.0717 156.1
##  warmed 2017 no_insects - ambient 2019 no_insects   0.133972 0.0983 105.2
##  warmed 2017 no_insects - warmed 2019 no_insects    0.216680 0.0717 156.1
##  warmed 2017 no_insects - ambient 2020 no_insects  -0.081677 0.0983 105.2
##  warmed 2017 no_insects - warmed 2020 no_insects    0.001032 0.0717 156.1
##  warmed 2017 no_insects - ambient 2021 no_insects   0.219420 0.0983 105.2
##  warmed 2017 no_insects - warmed 2021 no_insects    0.302128 0.0717 156.1
##  ambient 2018 no_insects - warmed 2018 no_insects   0.082709 0.0673  27.4
##  ambient 2018 no_insects - ambient 2019 no_insects  0.260769 0.0717 156.1
##  ambient 2018 no_insects - warmed 2019 no_insects   0.343477 0.0983 105.2
##  ambient 2018 no_insects - ambient 2020 no_insects  0.045121 0.0717 156.1
##  ambient 2018 no_insects - warmed 2020 no_insects   0.127829 0.0983 105.2
##  ambient 2018 no_insects - ambient 2021 no_insects  0.346217 0.0717 156.1
##  ambient 2018 no_insects - warmed 2021 no_insects   0.428926 0.0983 105.2
##  warmed 2018 no_insects - ambient 2019 no_insects   0.178060 0.0983 105.2
##  warmed 2018 no_insects - warmed 2019 no_insects    0.260769 0.0717 156.1
##  warmed 2018 no_insects - ambient 2020 no_insects  -0.037588 0.0983 105.2
##  warmed 2018 no_insects - warmed 2020 no_insects    0.045121 0.0717 156.1
##  warmed 2018 no_insects - ambient 2021 no_insects   0.263508 0.0983 105.2
##  warmed 2018 no_insects - warmed 2021 no_insects    0.346217 0.0717 156.1
##  ambient 2019 no_insects - warmed 2019 no_insects   0.082709 0.0673  27.4
##  ambient 2019 no_insects - ambient 2020 no_insects -0.215648 0.0717 156.1
```

```
##  ambient 2019 no_insects - warmed 2020 no_insects  -0.132940 0.0983 105.2
##  ambient 2019 no_insects - ambient 2021 no_insects  0.085448 0.0717 156.1
##  ambient 2019 no_insects - warmed 2021 no_insects   0.168157 0.0983 105.2
##  warmed 2019 no_insects - ambient 2020 no_insects  -0.298357 0.0983 105.2
##  warmed 2019 no_insects - warmed 2020 no_insects   -0.215648 0.0717 156.1
##  warmed 2019 no_insects - ambient 2021 no_insects   0.002740 0.0983 105.2
##  warmed 2019 no_insects - warmed 2021 no_insects    0.085448 0.0717 156.1
##  ambient 2020 no_insects - warmed 2020 no_insects   0.082709 0.0673  27.4
##  ambient 2020 no_insects - ambient 2021 no_insects  0.301096 0.0717 156.1
##  ambient 2020 no_insects - warmed 2021 no_insects   0.383805 0.0983 105.2
##  warmed 2020 no_insects - ambient 2021 no_insects   0.218388 0.0983 105.2
##  warmed 2020 no_insects - warmed 2021 no_insects    0.301096 0.0717 156.1
##  ambient 2021 no_insects - warmed 2021 no_insects   0.082709 0.0673  27.4
##  t.ratio p.value
##   1.229  0.9999
##   1.260  1.0000
##   1.760  0.9928
##   3.879  0.0370
##   3.669  0.0774
##   1.309  1.0000
##   1.795  0.9905
##   2.294  0.8680
##   2.514  0.7331
##   1.532  0.9992
##   1.958  0.9721
##   3.699  0.0651
##   3.571  0.1008
##  -0.306  1.0000
##   0.463  1.0000
##  -0.291  1.0000
##   0.475  1.0000
##   1.627  0.9975
##   2.038  0.9507
##   1.161  1.0000
##   1.658  0.9959
##   3.920  0.0382
##   3.906  0.0490
##   1.638  0.9973
##   2.047  0.9485
##   4.824  0.0017
##   4.642  0.0052
##   0.078  1.0000
##   1.260  1.0000
##   1.987  0.9670
##   3.879  0.0370
##   0.113  1.0000
##   1.309  1.0000
##   0.832  1.0000
##   2.294  0.8680
##   0.276  1.0000
##   1.532  0.9992
##   1.891  0.9818
##   3.699  0.0651
##  -0.962  1.0000
```

```
## -0.306 1.0000
## -0.950 1.0000
## -0.291 1.0000
##  0.613 1.0000
##  1.627 0.9975
##  0.233 1.0000
##  1.161 1.0000
##  2.480 0.7504
##  3.920 0.0382
##  0.622 1.0000
##  1.638 0.9973
##  3.217 0.2583
##  4.824 0.0017
##  1.229 0.9999
##  2.619 0.6579
##  2.750 0.5573
##  0.049 1.0000
##  0.876 1.0000
##  1.034 1.0000
##  1.595 0.9983
##  0.272 1.0000
##  1.039 1.0000
##  2.470 0.7653
##  2.662 0.6252
## -1.262 1.0000
## -0.315 1.0000
## -1.248 1.0000
## -0.303 1.0000
##  0.671 1.0000
##  1.260 1.0000
##  0.205 1.0000
##  0.880 1.0000
##  2.964 0.4002
##  3.127 0.3073
##  0.682 1.0000
##  1.268 0.9999
##  3.868 0.0447
##  3.863 0.0551
##  1.068 1.0000
##  2.619 0.6579
## -0.806 1.0000
##  0.049 1.0000
## -0.087 1.0000
##  1.034 1.0000
## -0.643 1.0000
##  0.272 1.0000
##  0.988 1.0000
##  2.470 0.7653
## -1.741 0.9922
## -1.262 1.0000
## -1.729 0.9928
## -1.248 1.0000
## -0.166 1.0000
##  0.671 1.0000
```

```
## -0.546 1.0000
##  0.205 1.0000
##  1.701 0.9942
##  2.964 0.4002
## -0.157 1.0000
##  0.682 1.0000
##  2.438 0.7771
##  3.868 0.0447
##  1.229 0.9999
## -2.570 0.6944
## -1.033 1.0000
## -1.585 0.9986
## -0.315 1.0000
## -2.347 0.8403
## -0.870 1.0000
## -0.084 1.0000
##  0.771 1.0000
## -3.249 0.2277
## -1.934 0.9719
## -3.234 0.2351
## -1.922 0.9738
## -1.315 0.9999
## -0.359 1.0000
## -1.782 0.9911
## -0.739 1.0000
##  0.977 1.0000
##  1.509 0.9990
## -1.305 0.9999
## -0.350 1.0000
##  1.881 0.9823
##  2.245 0.8799
## -2.715 0.5845
## -2.570 0.6944
## -1.997 0.9652
## -1.585 0.9986
## -2.552 0.7060
## -2.347 0.8403
## -0.888 1.0000
## -0.084 1.0000
## -3.359 0.1915
## -3.249 0.2277
## -3.347 0.1966
## -3.234 0.2351
## -1.784 0.9892
## -1.315 0.9999
## -2.164 0.9125
## -1.782 0.9911
##  0.083 1.0000
##  0.977 1.0000
## -1.775 0.9899
## -1.305 0.9999
##  0.819 1.0000
##  1.881 0.9823
##  1.229 0.9999
```

```
##   0.985  1.0000
##   1.559  0.9988
##   0.223  1.0000
##   1.004  1.0000
##   2.422  0.7960
##   2.626  0.6516
##  -1.299  0.9999
##  -0.345  1.0000
##  -1.284  1.0000
##  -0.333  1.0000
##   0.634  1.0000
##   1.230  1.0000
##   0.168  1.0000
##   0.850  1.0000
##   2.927  0.4263
##   3.097  0.3250
##   0.645  1.0000
##   1.238  1.0000
##   3.831  0.0499
##   3.833  0.0597
##  -0.123  1.0000
##   0.985  1.0000
##  -0.678  1.0000
##   0.223  1.0000
##   0.953  1.0000
##   2.422  0.7960
##  -1.771  0.9902
##  -1.299  0.9999
##  -1.759  0.9910
##  -1.284  1.0000
##  -0.196  1.0000
##   0.634  1.0000
##  -0.576  1.0000
##   0.168  1.0000
##   1.671  0.9955
##   2.927  0.4263
##  -0.187  1.0000
##   0.645  1.0000
##   2.408  0.7952
##   3.831  0.0499
##   1.229  0.9999
##  -0.762  1.0000
##   0.285  1.0000
##   1.462  0.9996
##   1.915  0.9786
##  -2.047  0.9535
##  -0.954  1.0000
##  -2.032  0.9569
##  -0.942  1.0000
##  -0.113  1.0000
##   0.621  1.0000
##  -0.579  1.0000
##   0.241  1.0000
##   2.180  0.9129
```

```
##   2.488  0.7452
##  -0.102  1.0000
##   0.630  1.0000
##   3.084  0.3209
##   3.225  0.2542
##  -1.397  0.9998
##  -0.762  1.0000
##   0.248  1.0000
##   1.462  0.9996
##  -2.380  0.8115
##  -2.047  0.9535
##  -2.368  0.8182
##  -2.032  0.9569
##  -0.805  1.0000
##  -0.113  1.0000
##  -1.185  1.0000
##  -0.579  1.0000
##   1.063  1.0000
##   2.180  0.9129
##  -0.796  1.0000
##  -0.102  1.0000
##   1.799  0.9881
##   3.084  0.3209
##   1.229  0.9999
##   2.205  0.9078
##   2.465  0.7657
##  -1.468  0.9995
##  -0.483  1.0000
##  -1.454  0.9996
##  -0.471  1.0000
##   0.465  1.0000
##   1.092  1.0000
##  -0.001  1.0000
##   0.712  1.0000
##   2.758  0.5521
##   2.959  0.4127
##   0.476  1.0000
##   1.101  1.0000
##   3.662  0.0812
##   3.695  0.0859
##   0.794  1.0000
##   2.205  0.9078
##  -1.909  0.9757
##  -1.468  0.9995
##  -1.897  0.9774
##  -1.454  0.9996
##  -0.334  1.0000
##   0.465  1.0000
##  -0.714  1.0000
##  -0.001  1.0000
##   1.533  0.9987
##   2.758  0.5521
##  -0.325  1.0000
##   0.476  1.0000
```

```
##   2.270  0.8686
##   3.662  0.0812
##   1.229  0.9999
##  -3.137  0.2876
##  -1.857  0.9827
##  -3.123  0.2961
##  -1.845  0.9840
##  -1.232  1.0000
##  -0.302  1.0000
##  -1.692  0.9957
##  -0.677  1.0000
##   1.027  1.0000
##   1.542  0.9986
##  -1.221  1.0000
##  -0.293  1.0000
##   1.918  0.9778
##   2.269  0.8695
##  -3.283  0.2246
##  -3.137  0.2876
##  -3.271  0.2302
##  -3.123  0.2961
##  -1.719  0.9934
##  -1.232  1.0000
##  -2.096  0.9353
##  -1.692  0.9957
##   0.135  1.0000
##   1.027  1.0000
##  -1.710  0.9939
##  -1.221  1.0000
##   0.866  1.0000
##   1.918  0.9778
##   1.229  0.9999
##   0.019  1.0000
##   0.855  1.0000
##   2.549  0.7101
##   2.699  0.5966
##   1.934  0.9776
##   2.251  0.8849
##   5.571  <.0001
##   4.902  0.0011
##   2.563  0.6996
##   2.710  0.5885
##   6.763  <.0001
##   5.771  <.0001
##  -0.827  1.0000
##   0.019  1.0000
##   1.017  1.0000
##   2.549  0.7101
##   0.569  1.0000
##   1.934  0.9776
##   3.220  0.2398
##   5.571  <.0001
##   1.028  1.0000
##   2.563  0.6996
```

```
##    4.089  0.0213
##    6.763  <.0001
##    1.229  0.9999
##    2.529  0.7240
##    2.685  0.6073
##    1.915  0.9802
##    2.237  0.8911
##    5.552  <.0001
##    4.888  0.0012
##    2.544  0.7137
##    2.696  0.5993
##    6.743  <.0001
##    5.757  <.0001
##    1.003  1.0000
##    2.529  0.7240
##    0.555  1.0000
##    1.915  0.9802
##    3.206  0.2473
##    5.552  <.0001
##    1.014  1.0000
##    2.544  0.7137
##    4.075  0.0223
##    6.743  <.0001
##    1.229  0.9999
##   -0.615  1.0000
##    0.393  1.0000
##    3.022  0.3526
##    3.044  0.3440
##    0.014  1.0000
##    0.851  1.0000
##    4.214  0.0117
##    3.913  0.0375
##   -1.289  1.0000
##   -0.615  1.0000
##    1.362  0.9999
##    3.022  0.3526
##   -0.830  1.0000
##    0.014  1.0000
##    2.231  0.8935
##    4.214  0.0117
##    1.229  0.9999
##    3.637  0.0781
##    3.492  0.1249
##    0.629  1.0000
##    1.300  0.9999
##    4.829  0.0011
##    4.361  0.0084
##    1.811  0.9894
##    3.637  0.0781
##   -0.382  1.0000
##    0.629  1.0000
##    2.679  0.6117
##    4.829  0.0011
##    1.229  0.9999
```

```
##  -3.008  0.3625
##  -1.352  0.9999
##   1.192  1.0000
##   1.710  0.9952
##  -3.034  0.3509
##  -3.008  0.3625
##   0.028  1.0000
##   1.192  1.0000
##   1.229  0.9999
##   4.199  0.0124
##   3.902  0.0387
##   2.221  0.8980
##   4.199  0.0124
##   1.229  0.9999
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 28 estimates
```

UMBS

```
# Do we need to include plot as a random effect with the UMBS models?
mod1us <- lmer(shannon ~ state * year + insecticide * year + (1 | plot), umbs_diversity,
    REML = FALSE)
mod2us <- lmer(shannon ~ state * year + insecticide + year + (1 | plot), umbs_diversity,
    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(mod1us)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq Mean Sq F value
## state               1 0.01067 0.01067  0.2578
## year                6 2.08450 0.34742  8.3979
## insecticide         1 0.08050 0.08050  1.9458
## state:year          6 0.28620 0.04770  1.1530
## year:insecticide    6 0.39249 0.06541  1.5812
```

```
anova(mod2us)
```

```
## Analysis of Variance Table
##             npar  Sum Sq Mean Sq F value
## state          1 0.01137 0.01137  0.2578
## year           6 2.08450 0.34742  7.8788
## insecticide    1 0.08580 0.08580  1.9458
## state:year     6 0.28620 0.04770  1.0818
```

```
anova(mod1us, mod2us)  # Go with model 2 since pvalue >0.05, aka more complex model does not have somet
```

```
## Data: umbs_diversity
## Models:
```

```
## mod2us: shannon ~ state * year + insecticide + year + (1 | plot)
## mod1us: shannon ~ state * year + insecticide * year + (1 | plot)
##        npar    AIC     BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod2us   17 36.100  89.208 -1.0501   2.1002
## mod1us   23 38.912 110.763  3.5439  -7.0878 9.1879  6     0.1633
```

```r
summary(mod1us)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: shannon ~ state * year + insecticide * year + (1 | plot)
##    Data: umbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##     38.9    110.8      3.5     -7.1      145
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.91874 -0.55550  0.06359  0.67005  2.72307
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.04412  0.2101
##  Residual             0.04137  0.2034
## Number of obs: 168, groups:  plot, 24
##
## Fixed effects:
##                                Estimate Std. Error t value
## (Intercept)                    1.185864   0.103375  11.472
## statewarmed                    0.019446   0.119367   0.163
## year2016                      -0.262066   0.101698  -2.577
## year2017                      -0.060449   0.101698  -0.594
## year2018                       0.040282   0.101698   0.396
## year2019                       0.101685   0.101698   1.000
## year2020                       0.154443   0.101698   1.519
## year2021                      -0.030996   0.101698  -0.305
## insecticideno_insects         -0.016839   0.119367  -0.141
## statewarmed:year2016           0.176903   0.117430   1.506
## statewarmed:year2017          -0.016900   0.117430  -0.144
## statewarmed:year2018           0.005587   0.117430   0.048
## statewarmed:year2019          -0.049622   0.117430  -0.423
## statewarmed:year2020          -0.053412   0.117430  -0.455
## statewarmed:year2021           0.125883   0.117430   1.072
## year2016:insecticideno_insects  0.061432   0.117430   0.523
## year2017:insecticideno_insects  0.320550   0.117430   2.730
## year2018:insecticideno_insects  0.163524   0.117430   1.393
## year2019:insecticideno_insects  0.161884   0.117430   1.379
## year2020:insecticideno_insects  0.205338   0.117430   1.749
## year2021:insecticideno_insects  0.096794   0.117430   0.824

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

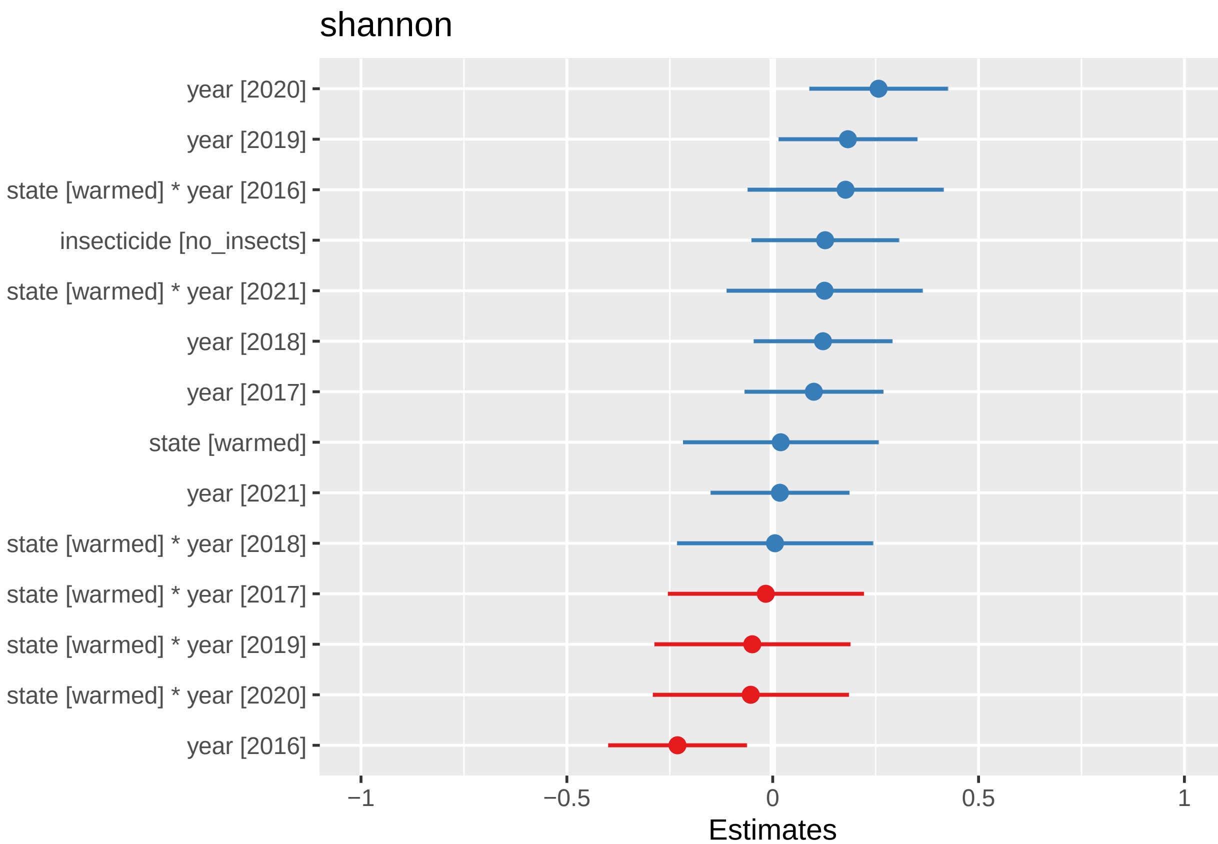
```r
summary(mod2us)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: shannon ~ state * year + insecticide + year + (1 | plot)
##    Data: umbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##     36.1     89.2     -1.1      2.1      151
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.08121 -0.60563  0.06519  0.62579  2.75496
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.04373  0.2091
##  Residual             0.04410  0.2100
## Number of obs: 168, groups:  plot, 24
##
## Fixed effects:
##                        Estimate Std. Error t value
## (Intercept)            1.113755   0.096972  11.485
## statewarmed            0.019446   0.120987   0.161
## year2016              -0.231350   0.085727  -2.699
## year2017               0.099826   0.085727   1.164
## year2018               0.122045   0.085727   1.424
## year2019               0.182627   0.085727   2.130
## year2020               0.257112   0.085727   2.999
## year2021               0.017401   0.085727   0.203
## insecticideno_insects  0.127379   0.091315   1.395
## statewarmed:year2016   0.176903   0.121237   1.459
## statewarmed:year2017  -0.016900   0.121237  -0.139
## statewarmed:year2018   0.005587   0.121237   0.046
## statewarmed:year2019  -0.049622   0.121237  -0.409
## statewarmed:year2020  -0.053412   0.121237  -0.441
## statewarmed:year2021   0.125883   0.121237   1.038

##
## Correlation matrix not shown by default, as p = 15 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

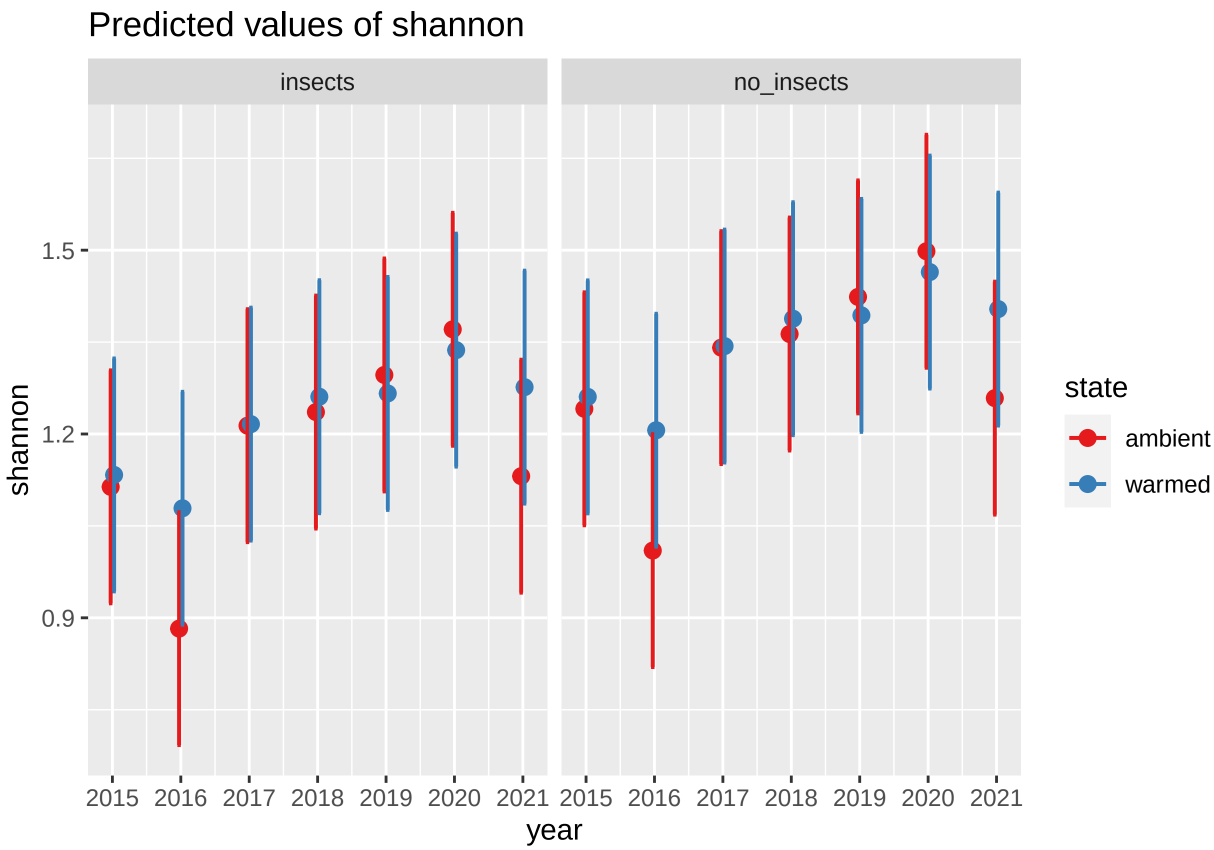
```r
AICctab(mod1us, mod2us, weights = T)  # model 1
```

```
##        dAICc df weight
## mod2us  0.0  17 0.961
## mod1us  6.4  23 0.039
```

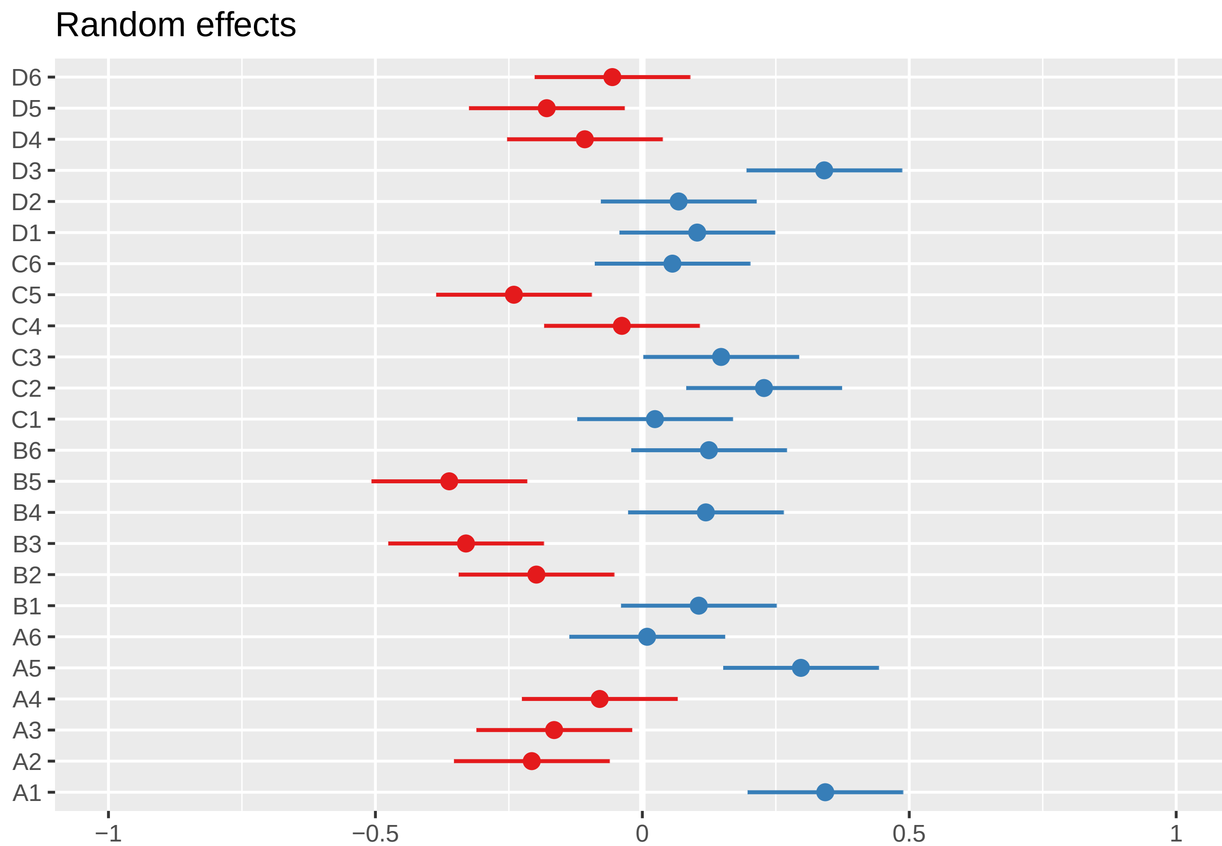
```r
# Plot the fixed effects estimates for different models these are the fixed
# effects estimates from summary(mod1)
plot_model(mod2us, sort.est = TRUE)
```




```r
# these are the fixed predicted values:
plot_model(mod2us, type = "pred", terms = c("year", "state", "insecticide"))
```




```r
# these are the random effects estimates
plot_model(mod2us, type = "re", terms = c("species"))
```




```r
# Does year need to be interactive with state?
mod3us <- lmer(shannon ~ state + year + insecticide + (1 | plot), umbs_diversity,
    REML = FALSE)
anova(mod2us, mod3us)
```

```
## Data: umbs_diversity
## Models:
## mod3us: shannon ~ state + year + insecticide + (1 | plot)
## mod2us: shannon ~ state * year + insecticide + year + (1 | plot)
##        npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod3us   11 30.449 64.812 -4.2244   8.4487
## mod2us   17 36.100 89.208 -1.0501   2.1002 6.3485  6     0.3853
```

```r
AICctab(mod1us, mod3us, weights = T)  # going with mod3
```

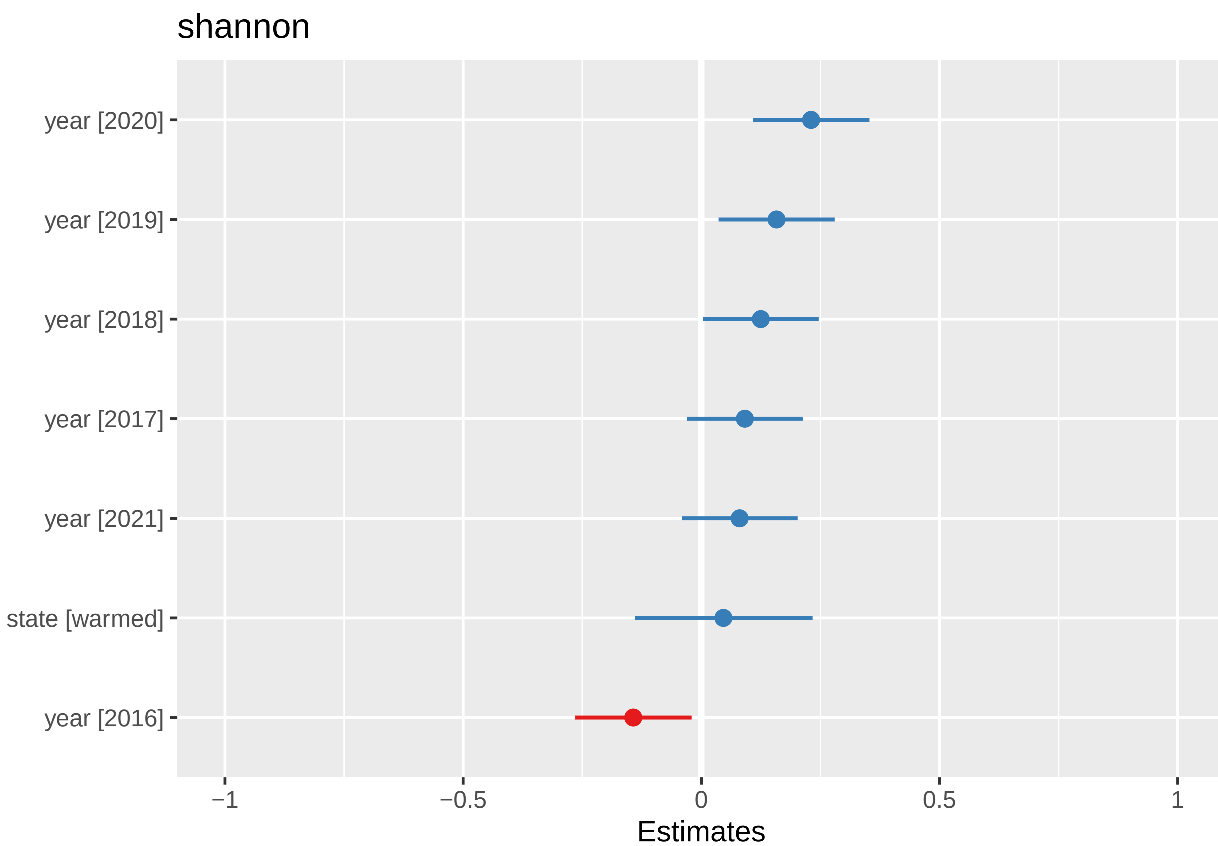
```
##        dAICc df weight
## mod3us  0.0  11 1
## mod1us 14.4  23 <0.001
```

```r
# Do we need to include insecticide? (dropping insecticide from the model)
mod5us <- lmer(shannon ~ state + year + (1 | plot), umbs_diversity, REML = FALSE)
anova(mod3us, mod5us)
```

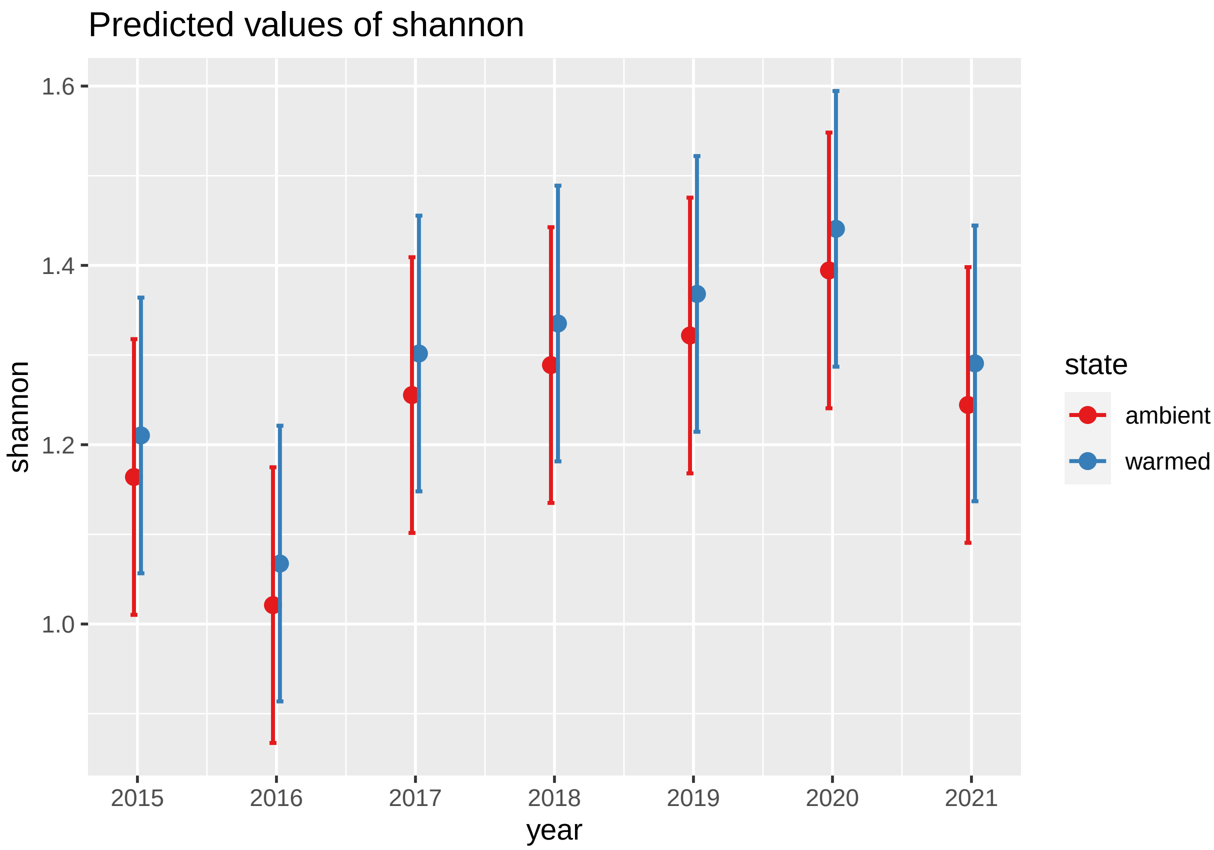
```
## Data: umbs_diversity
## Models:
```

```
## mod5us: shannon ~ state + year + (1 | plot)
## mod3us: shannon ~ state + year + insecticide + (1 | plot)
##        npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod5us   10 30.320 61.559 -5.1598  10.3197
## mod3us   11 30.449 64.812 -4.2244   8.4487 1.871  1     0.1714
```

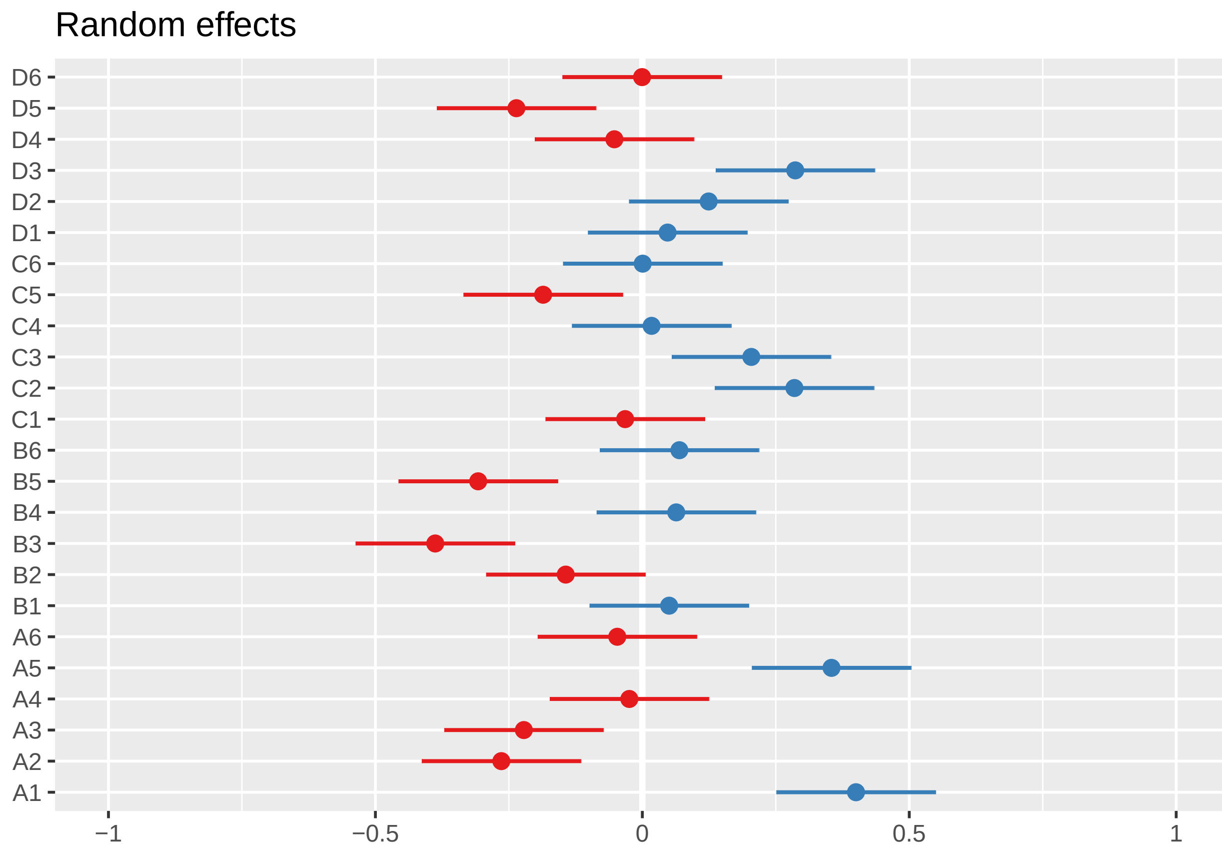
```r
# No p>0.05 so insecticide does not strongly improve model fit so we will go with
# model 5

# Plot the fixed effects estimates for different models these are the fixed
# effects estimates from summary(mod5)
plot_model(mod5us, sort.est = TRUE)
```




```r
# these are the fixed predicted values:
plot_model(mod5us, type = "pred", terms = c("year", "state"))
```




```
# these are the random effects estimates
plot_model(mod5us, type = "re", terms = c("species"))
```




```r
# If we wanted to include plots nested within year it would look like this:
# mod6us <- lmer(log(shannon) ~ state + year + insecticide*year + (1 +
# year|plot), umbs_diversity, REML=FALSE) anova(mod5us, mod6us) anova(mod5us)
# cant get mod6 to work

# the best model fit appears to be = mod5us <- lmer(shannon ~ state + year +
# (1|plot), umbs_diversity, REML = FALSE)
summ(mod5us)
```

Observations	168
Dependent variable	shannon
Type	Mixed effects linear regression

AIC	30.32
BIC	61.56
Pseudo-R^2 (fixed effects)	0.12
Pseudo-R^2 (total)	0.57

```r
emmeans(mod5us, list(pairwise ~ state + year), adjust = "tukey")
```

```
## $`emmeans of state, year`
##  state   year emmean     SE   df lower.CL upper.CL
##  ambient 2015   1.16 0.0815 47.7    1.000     1.33
##  warmed  2015   1.21 0.0815 47.7    1.047     1.37
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	1.16	0.08	14.84	43.75	0.00
statewarmed	0.05	0.09	0.49	24.00	0.63
year2016	-0.14	0.06	-2.31	144.00	0.02
year2017	0.09	0.06	1.47	144.00	0.14
year2018	0.12	0.06	2.01	144.00	0.05
year2019	0.16	0.06	2.55	144.00	0.01
year2020	0.23	0.06	3.72	144.00	0.00
year2021	0.08	0.06	1.30	144.00	0.20

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.22
Residual		0.21

Grouping Variables		
Group	# groups	ICC
plot	24	0.51

```
##  ambient 2016   1.02 0.0815 47.7    0.857     1.18
##  warmed  2016   1.07 0.0815 47.7    0.904     1.23
##  ambient 2017   1.26 0.0815 47.7    1.092     1.42
##  warmed  2017   1.30 0.0815 47.7    1.138     1.47
##  ambient 2018   1.29 0.0815 47.7    1.125     1.45
##  warmed  2018   1.34 0.0815 47.7    1.171     1.50
##  ambient 2019   1.32 0.0815 47.7    1.158     1.49
##  warmed  2019   1.37 0.0815 47.7    1.204     1.53
##  ambient 2020   1.39 0.0815 47.7    1.231     1.56
##  warmed  2020   1.44 0.0815 47.7    1.277     1.60
##  ambient 2021   1.24 0.0815 47.7    1.081     1.41
##  warmed  2021   1.29 0.0815 47.7    1.127     1.45
##
## Degrees-of-freedom method: kenward-roger
## Confidence level used: 0.95
##
## $`pairwise differences of state, year`
##  1                           estimate     SE    df t.ratio p.value
##  ambient 2015 - warmed 2015  -0.04637 0.0992  26.2 -0.468  1.0000
##  ambient 2015 - ambient 2016  0.14290 0.0633 150.3  2.257  0.5886
##  ambient 2015 - warmed 2016   0.09653 0.1176  51.6  0.821  0.9999
##  ambient 2015 - ambient 2017 -0.09138 0.0633 150.3 -1.443  0.9749
##  ambient 2015 - warmed 2017  -0.13774 0.1176  51.6 -1.171  0.9954
##  ambient 2015 - ambient 2018 -0.12484 0.0633 150.3 -1.972  0.7822
##  ambient 2015 - warmed 2018  -0.17120 0.1176  51.6 -1.455  0.9696
##  ambient 2015 - ambient 2019 -0.15782 0.0633 150.3 -2.493  0.4200
##  ambient 2015 - warmed 2019  -0.20418 0.1176  51.6 -1.736  0.8931
##  ambient 2015 - ambient 2020 -0.23041 0.0633 150.3 -3.640  0.0246
```

```
##  ambient 2015 - warmed 2020  -0.27677 0.1176  51.6 -2.353  0.5263
##  ambient 2015 - ambient 2021 -0.08034 0.0633 150.3 -1.269  0.9919
##  ambient 2015 - warmed 2021  -0.12671 0.1176  51.6 -1.077  0.9979
##  warmed 2015 - ambient 2016   0.18926 0.1176  51.6  1.609  0.9357
##  warmed 2015 - warmed 2016    0.14290 0.0633 150.3  2.257  0.5886
##  warmed 2015 - ambient 2017  -0.04501 0.1176  51.6 -0.383  1.0000
##  warmed 2015 - warmed 2017   -0.09138 0.0633 150.3 -1.443  0.9749
##  warmed 2015 - ambient 2018  -0.07847 0.1176  51.6 -0.667  1.0000
##  warmed 2015 - warmed 2018   -0.12484 0.0633 150.3 -1.972  0.7822
##  warmed 2015 - ambient 2019  -0.11145 0.1176  51.6 -0.947  0.9994
##  warmed 2015 - warmed 2019   -0.15782 0.0633 150.3 -2.493  0.4200
##  warmed 2015 - ambient 2020  -0.18404 0.1176  51.6 -1.564  0.9474
##  warmed 2015 - warmed 2020   -0.23041 0.0633 150.3 -3.640  0.0246
##  warmed 2015 - ambient 2021  -0.03398 0.1176  51.6 -0.289  1.0000
##  warmed 2015 - warmed 2021   -0.08034 0.0633 150.3 -1.269  0.9919
##  ambient 2016 - warmed 2016  -0.04637 0.0992  26.2 -0.468  1.0000
##  ambient 2016 - ambient 2017 -0.23427 0.0633 150.3 -3.701  0.0202
##  ambient 2016 - warmed 2017  -0.28064 0.1176  51.6 -2.385  0.5039
##  ambient 2016 - ambient 2018 -0.26774 0.0633 150.3 -4.229  0.0031
##  ambient 2016 - warmed 2018  -0.31410 0.1176  51.6 -2.670  0.3249
##  ambient 2016 - ambient 2019 -0.30071 0.0633 150.3 -4.750  0.0004
##  ambient 2016 - warmed 2019  -0.34708 0.1176  51.6 -2.950  0.1905
##  ambient 2016 - ambient 2020 -0.37330 0.0633 150.3 -5.897  <.0001
##  ambient 2016 - warmed 2020  -0.41967 0.1176  51.6 -3.567  0.0439
##  ambient 2016 - ambient 2021 -0.22324 0.0633 150.3 -3.527  0.0351
##  ambient 2016 - warmed 2021  -0.26961 0.1176  51.6 -2.292  0.5681
##  warmed 2016 - ambient 2017  -0.18791 0.1176  51.6 -1.597  0.9389
##  warmed 2016 - warmed 2017   -0.23427 0.0633 150.3 -3.701  0.0202
##  warmed 2016 - ambient 2018  -0.22137 0.1176  51.6 -1.882  0.8266
##  warmed 2016 - warmed 2018   -0.26774 0.0633 150.3 -4.229  0.0031
##  warmed 2016 - ambient 2019  -0.25435 0.1176  51.6 -2.162  0.6567
##  warmed 2016 - warmed 2019   -0.30071 0.0633 150.3 -4.750  0.0004
##  warmed 2016 - ambient 2020  -0.32694 0.1176  51.6 -2.779  0.2669
##  warmed 2016 - warmed 2020   -0.37330 0.0633 150.3 -5.897  <.0001
##  warmed 2016 - ambient 2021  -0.17688 0.1176  51.6 -1.503  0.9609
##  warmed 2016 - warmed 2021   -0.22324 0.0633 150.3 -3.527  0.0351
##  ambient 2017 - warmed 2017  -0.04637 0.0992  26.2 -0.468  1.0000
##  ambient 2017 - ambient 2018 -0.03346 0.0633 150.3 -0.529  1.0000
##  ambient 2017 - warmed 2018  -0.07983 0.1176  51.6 -0.679  1.0000
##  ambient 2017 - ambient 2019 -0.06644 0.0633 150.3 -1.050  0.9987
##  ambient 2017 - warmed 2019  -0.11281 0.1176  51.6 -0.959  0.9994
##  ambient 2017 - ambient 2020 -0.13903 0.0633 150.3 -2.196  0.6328
##  ambient 2017 - warmed 2020  -0.18540 0.1176  51.6 -1.576  0.9446
##  ambient 2017 - ambient 2021  0.01103 0.0633 150.3  0.174  1.0000
##  ambient 2017 - warmed 2021  -0.03533 0.1176  51.6 -0.300  1.0000
##  warmed 2017 - ambient 2018   0.01290 0.1176  51.6  0.110  1.0000
##  warmed 2017 - warmed 2018   -0.03346 0.0633 150.3 -0.529  1.0000
##  warmed 2017 - ambient 2019  -0.02007 0.1176  51.6 -0.171  1.0000
##  warmed 2017 - warmed 2019   -0.06644 0.0633 150.3 -1.050  0.9987
##  warmed 2017 - ambient 2020  -0.09266 0.1176  51.6 -0.788  0.9999
##  warmed 2017 - warmed 2020   -0.13903 0.0633 150.3 -2.196  0.6328
##  warmed 2017 - ambient 2021   0.05740 0.1176  51.6  0.488  1.0000
##  warmed 2017 - warmed 2021    0.01103 0.0633 150.3  0.174  1.0000
##  ambient 2018 - warmed 2018  -0.04637 0.0992  26.2 -0.468  1.0000
```

```
##  ambient 2018 - ambient 2019 -0.03298 0.0633 150.3 -0.521  1.0000
##  ambient 2018 - warmed 2019  -0.07934 0.1176  51.6 -0.674  1.0000
##  ambient 2018 - ambient 2020 -0.10557 0.0633 150.3 -1.668  0.9238
##  ambient 2018 - warmed 2020  -0.15193 0.1176  51.6 -1.291  0.9888
##  ambient 2018 - ambient 2021  0.04449 0.0633 150.3  0.703  1.0000
##  ambient 2018 - warmed 2021  -0.00187 0.1176  51.6 -0.016  1.0000
##  warmed 2018 - ambient 2019   0.01339 0.1176  51.6  0.114  1.0000
##  warmed 2018 - warmed 2019   -0.03298 0.0633 150.3 -0.521  1.0000
##  warmed 2018 - ambient 2020  -0.05920 0.1176  51.6 -0.503  1.0000
##  warmed 2018 - warmed 2020   -0.10557 0.0633 150.3 -1.668  0.9238
##  warmed 2018 - ambient 2021   0.09086 0.1176  51.6  0.772  0.9999
##  warmed 2018 - warmed 2021    0.04449 0.0633 150.3  0.703  1.0000
##  ambient 2019 - warmed 2019  -0.04637 0.0992  26.2 -0.468  1.0000
##  ambient 2019 - ambient 2020 -0.07259 0.0633 150.3 -1.147  0.9969
##  ambient 2019 - warmed 2020  -0.11896 0.1176  51.6 -1.011  0.9989
##  ambient 2019 - ambient 2021  0.07747 0.0633 150.3  1.224  0.9942
##  ambient 2019 - warmed 2021   0.03111 0.1176  51.6  0.264  1.0000
##  warmed 2019 - ambient 2020  -0.02622 0.1176  51.6 -0.223  1.0000
##  warmed 2019 - warmed 2020   -0.07259 0.0633 150.3 -1.147  0.9969
##  warmed 2019 - ambient 2021   0.12384 0.1176  51.6  1.053  0.9984
##  warmed 2019 - warmed 2021    0.07747 0.0633 150.3  1.224  0.9942
##  ambient 2020 - warmed 2020  -0.04637 0.0992  26.2 -0.468  1.0000
##  ambient 2020 - ambient 2021  0.15006 0.0633 150.3  2.371  0.5064
##  ambient 2020 - warmed 2021   0.10370 0.1176  51.6  0.881  0.9997
##  warmed 2020 - ambient 2021   0.19643 0.1176  51.6  1.670  0.9170
##  warmed 2020 - warmed 2021    0.15006 0.0633 150.3  2.371  0.5064
##  ambient 2021 - warmed 2021  -0.04637 0.0992  26.2 -0.468  1.0000
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 14 estimates
```

RICHNESS KBS

```r
# Do we need to include plot as a random effect with the UMBS models?
mod1kr <- lmer(log(richness) ~ state * year + insecticide * year + (1 | plot), kbs_diversity,
    REML = FALSE)
mod2kr <- lmer(log(richness) ~ state * year + insecticide + year + (1 | plot), kbs_diversity,
    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(mod1kr)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq Mean Sq F value
## state               1 0.10889 0.10889  3.5282
## year                6 2.99710 0.49952 16.1856
## insecticide         1 0.01226 0.01226  0.3971
## state:year          6 0.30270 0.05045  1.6347
## year:insecticide    6 0.77172 0.12862  4.1676
```

```r
anova(mod2kr)
```

```
## Analysis of Variance Table
##             npar  Sum Sq Mean Sq F value
## state          1 0.12838 0.12838  3.5387
## year           6 2.99797 0.49966 13.7726
## insecticide    1 0.01443 0.01443  0.3976
## state:year     6 0.30210 0.05035  1.3878
```

```
anova(mod1kr, mod2kr)  # Go with model 1 since pvalue <0.05, aka more complex model does have something
```

```
## Data: kbs_diversity
## Models:
## mod2kr: log(richness) ~ state * year + insecticide + year + (1 | plot)
## mod1kr: log(richness) ~ state * year + insecticide * year + (1 | plot)
##        npar     AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod2kr   17  -4.587 48.419 19.294  -38.587
## mod1kr   23 -15.617 56.096 30.809  -61.617 23.03  6  0.0007863 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(mod1kr)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(richness) ~ state * year + insecticide * year + (1 | plot)
##    Data: kbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##    -15.6     56.1     30.8    -61.6      144
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.6919 -0.4574  0.0857  0.5959  2.0406
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.02489  0.1578
##  Residual             0.03086  0.1757
## Number of obs: 167, groups:  plot, 24
##
## Fixed effects:
##                                   Estimate Std. Error t value
## (Intercept)                       2.480674   0.083478  29.716
## statewarmed                      -0.002258   0.096392  -0.023
## year2016                          0.071898   0.087838   0.819
## year2017                         -0.302011   0.087838  -3.438
## year2018                         -0.072577   0.087838  -0.826
## year2019                          0.039176   0.087838   0.446
## year2020                         -0.022692   0.087838  -0.258
## year2021                         -0.007724   0.091338  -0.085
## insecticideno_insects             0.123370   0.096392   1.280
## statewarmed:year2016             -0.065195   0.101426  -0.643
## statewarmed:year2017             -0.080512   0.101426  -0.794
## statewarmed:year2018             -0.108830   0.101426  -1.073
## statewarmed:year2019             -0.245817   0.101426  -2.424
```

```
## statewarmed:year2020           -0.158337   0.101426  -1.561
## statewarmed:year2021           -0.248311   0.102791  -2.416
## year2016:insecticideno_insects -0.041662   0.101426  -0.411
## year2017:insecticideno_insects -0.034538   0.101426  -0.341
## year2018:insecticideno_insects -0.168476   0.101426  -1.661
## year2019:insecticideno_insects -0.350653   0.101426  -3.457
## year2020:insecticideno_insects -0.326531   0.101426  -3.219
## year2021:insecticideno_insects -0.260565   0.102791  -2.535

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

```r
summary(mod2kr)
```

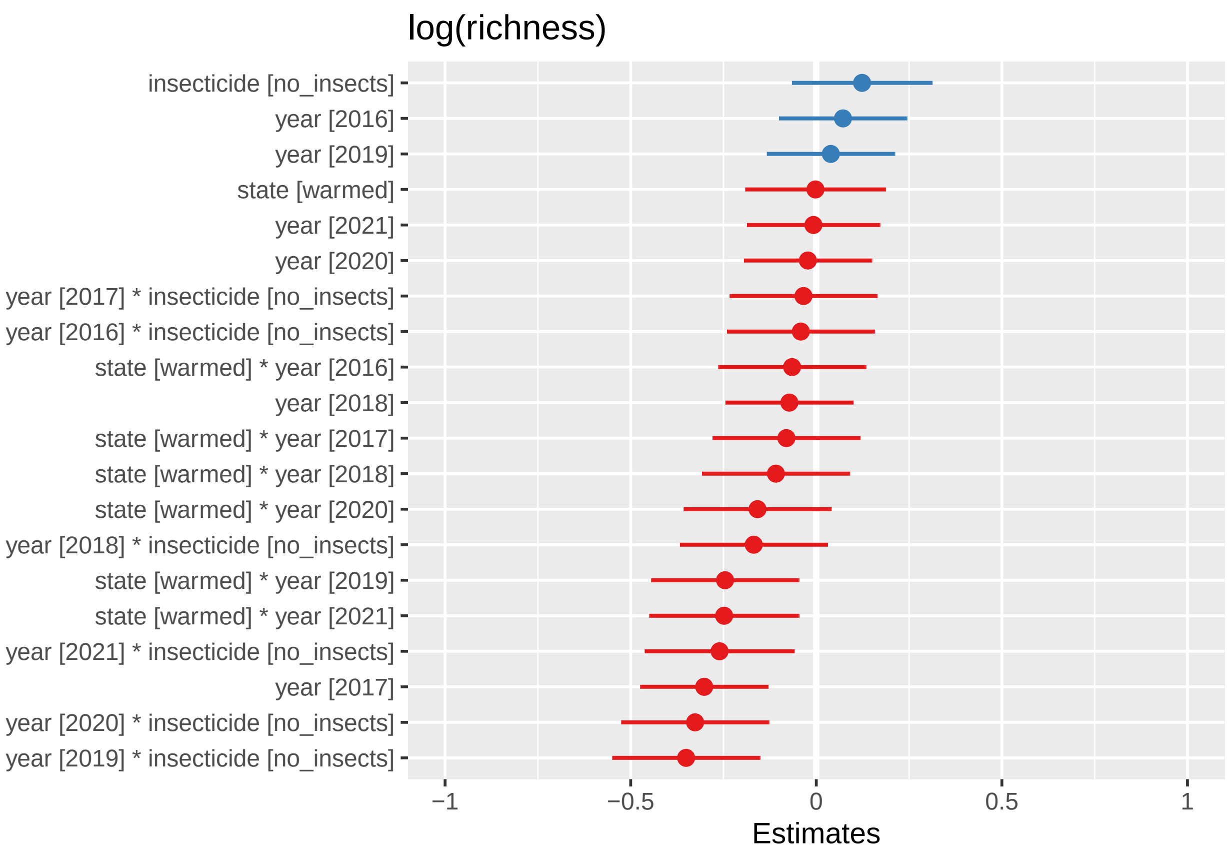
```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(richness) ~ state * year + insecticide + year + (1 | plot)
##    Data: kbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##     -4.6     48.4     19.3    -38.6      150
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.7849 -0.4689  0.0144  0.5996  2.2070
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.02399  0.1549
##  Residual             0.03628  0.1905
## Number of obs: 167, groups:  plot, 24
##
## Fixed effects:
##                        Estimate Std. Error t value
## (Intercept)            2.564760   0.078991  32.469
## statewarmed           -0.002258   0.100224  -0.023
## year2016               0.051067   0.077760   0.657
## year2017              -0.319280   0.077760  -4.106
## year2018              -0.156815   0.077760  -2.017
## year2019              -0.136150   0.077760  -1.751
## year2020              -0.185957   0.077760  -2.391
## year2021              -0.143222   0.079740  -1.796
## insecticideno_insects -0.044803   0.069774  -0.642
## statewarmed:year2016  -0.065195   0.109969  -0.593
## statewarmed:year2017  -0.080512   0.109969  -0.732
## statewarmed:year2018  -0.108830   0.109969  -0.990
## statewarmed:year2019  -0.245817   0.109969  -2.235
## statewarmed:year2020  -0.158337   0.109969  -1.440
## statewarmed:year2021  -0.243095   0.111378  -2.183

##
## Correlation matrix not shown by default, as p = 15 > 12.
```

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

```
AICctab(mod1kr, mod2kr, weights = T)  # model 1
```

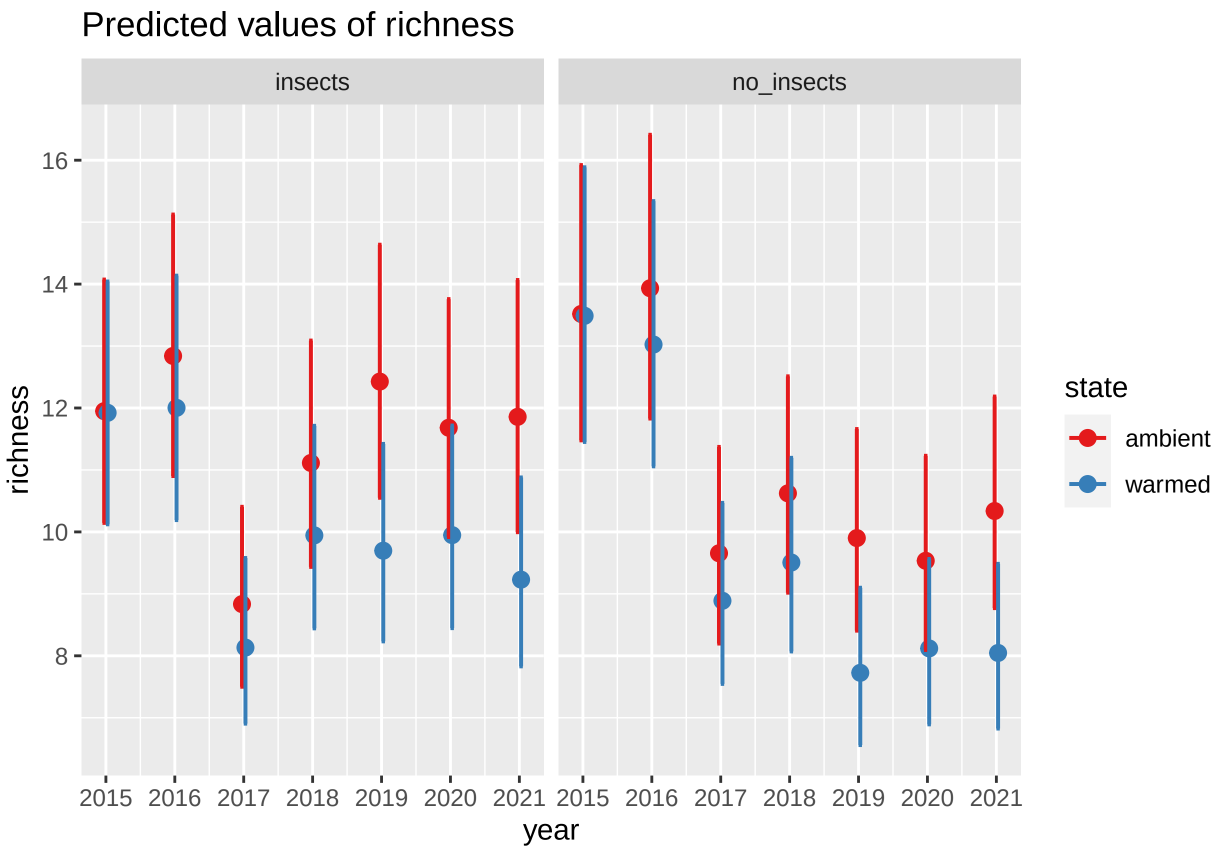
```
##        dAICc df weight
## mod1kr  0.0  23 0.976
## mod2kr  7.4  17 0.024
```

```
# Plot the fixed effects estimates for different models these are the fixed
# effects estimates from summary(mod1)
plot_model(mod1kr, sort.est = TRUE)
```

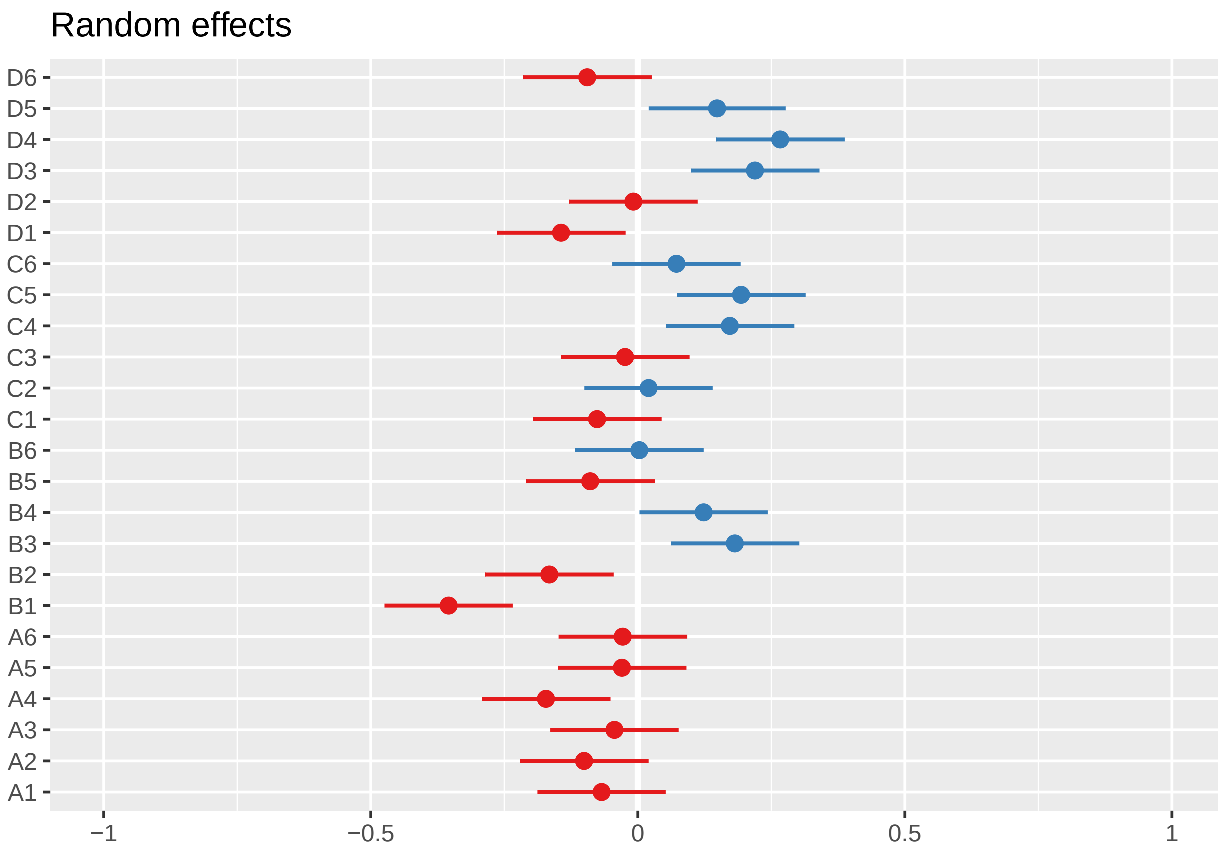



```
# these are the fixed predicted values:
plot_model(mod1kr, type = "pred", terms = c("year", "state", "insecticide"))
```

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




```r
# these are the random effects estimates
plot_model(mod1kr, type = "re", terms = c("species"))
```




```r
# Does year need to be interactive with state?
mod3kr <- lmer(log(richness) ~ state + year + insecticide * year + (1 | plot), kbs_diversity,
    REML = FALSE)
anova(mod1kr, mod3kr)  # go with less complex model
```

```
## Data: kbs_diversity
## Models:
## mod3kr: log(richness) ~ state + year + insecticide * year + (1 | plot)
## mod1kr: log(richness) ~ state * year + insecticide * year + (1 | plot)
##        npar     AIC    BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod3kr   17 -17.952 35.054 25.976  -51.952
## mod1kr   23 -15.617 56.096 30.809  -61.617 9.6653  6     0.1395
```

```r
AICctab(mod1kr, mod3kr, weights = T)  # going with mod3
```

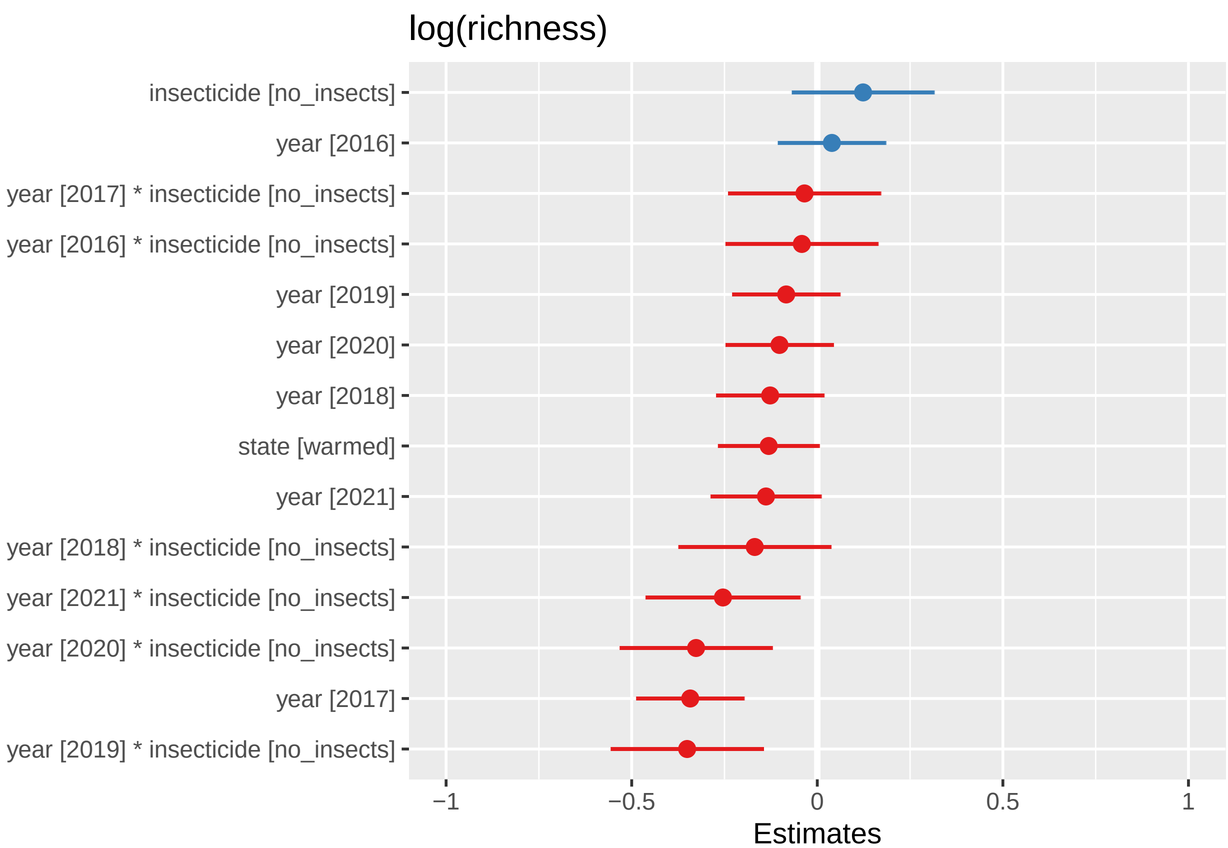
```
##        dAICc df weight
## mod3kr  0.0  17 0.951
## mod1kr  5.9  23 0.049
```

```r
# Do we need to include insecticide? (dropping insecticide from the model)
mod5kr <- lmer(log(richness) ~ state + year + (1 | plot), kbs_diversity, REML = FALSE)
anova(mod3kr, mod5kr)
```

```
## Data: kbs_diversity
## Models:
```

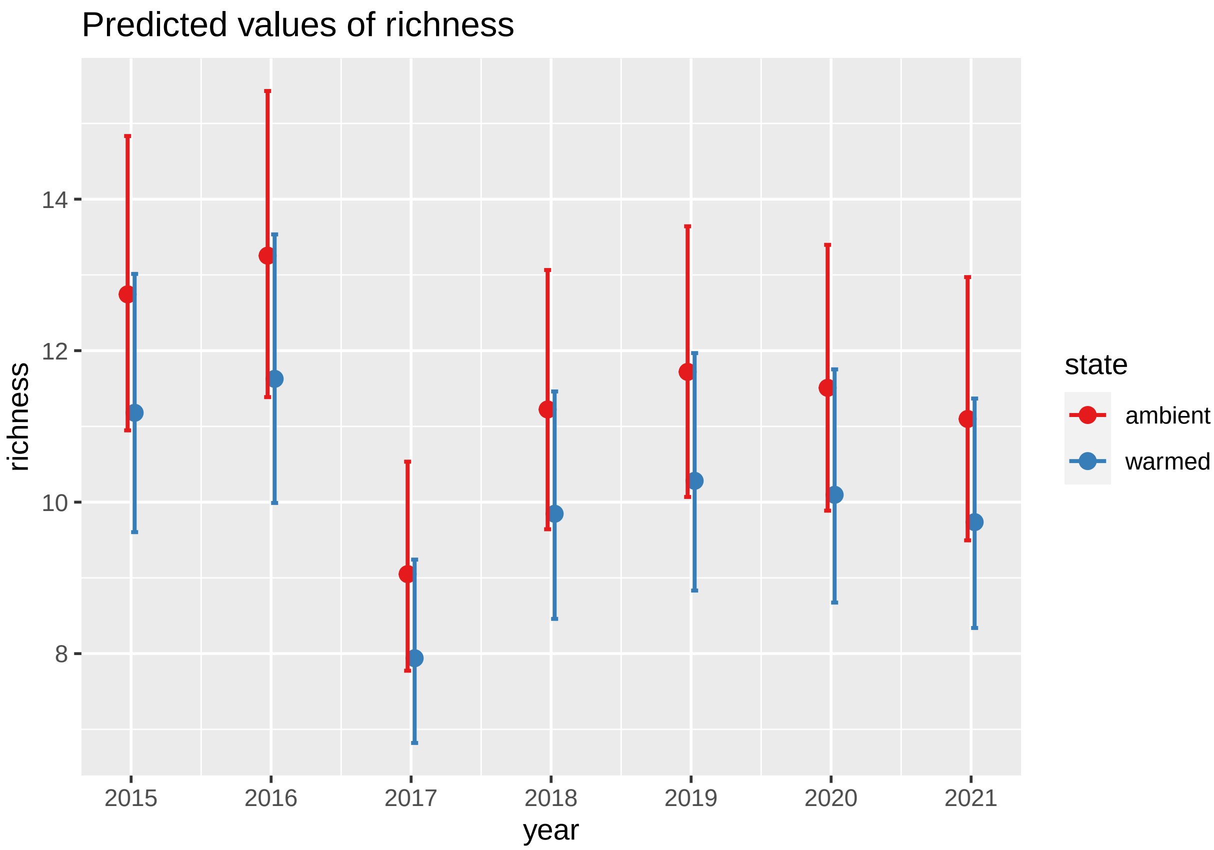
```
## mod5kr: log(richness) ~ state + year + (1 | plot)
## mod3kr: log(richness) ~ state + year + insecticide * year + (1 | plot)
##        npar     AIC    BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod5kr   10 -10.104 21.076 15.052  -30.104
## mod3kr   17 -17.952 35.054 25.976  -51.952 21.848  7   0.002698 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Yes, p<0.05 so insecticide*year does strongly improve model fit so we will
# stick with the more complex mod3

# Plot the fixed effects estimates for different models these are the fixed
# effects estimates from summary(mod5)
plot_model(mod3kr, sort.est = TRUE)
```

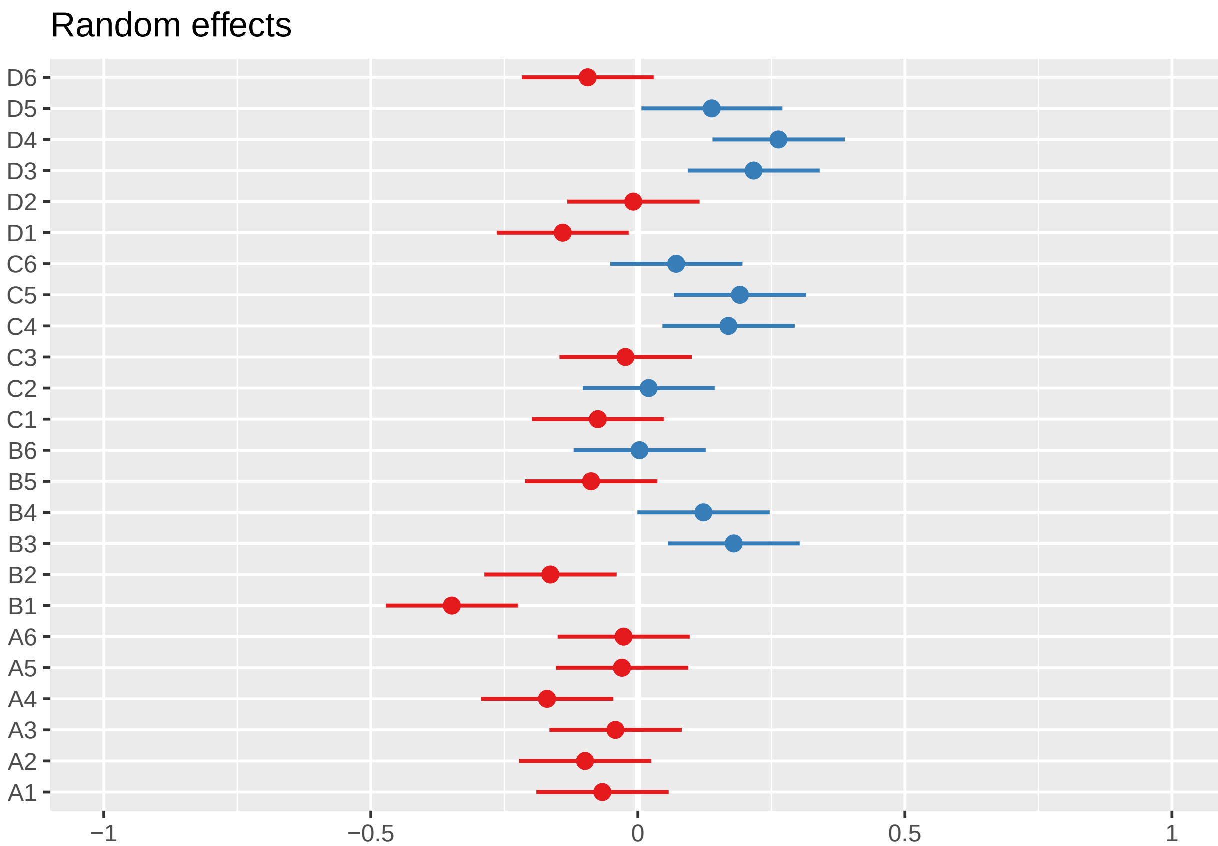



```
# these are the fixed predicted values:
plot_model(mod3kr, type = "pred", terms = c("year", "state"))
```

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




```r
# these are the random effects estimates
plot_model(mod3kr, type = "re", terms = c("species"))
```




```r
# If we wanted to include plots nested within year it would look like this:
# mod6ks <- lmer(log(richness) ~ state + year + insecticide*year + (1 +
# year|plot), kbs_diversity, REML=FALSE) anova(mod5kr, mod6kr) anova(mod5kr) cant
# get mod6 to work

# the best model fit appears to be = mod3kr <- lmer(log(richness) ~ state + year
# + insecticide*year + (1|plot), kbs_diversity, REML = FALSE)
summ(mod3kr)
```

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

AIC	-17.95
BIC	35.05
Pseudo-R^2 (fixed effects)	0.32
Pseudo-R^2 (total)	0.61

```r
emmeans(mod3kr, list(pairwise ~ state + year + insecticide * year), adjust = "tukey")
```

```
## $`emmeans of state, year, insecticide`
##  state   year insecticide emmean     SE   df lower.CL upper.CL
##  ambient 2015 insects       2.55 0.0821 69.3     2.38     2.71
##  warmed  2015 insects       2.41 0.0821 69.3     2.25     2.58
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	2.55	0.08	32.84	60.80	0.00
statewarmed	-0.13	0.07	-1.88	24.00	0.07
year2016	0.04	0.07	0.53	143.00	0.60
year2017	-0.34	0.07	-4.61	143.00	0.00
year2018	-0.13	0.07	-1.71	143.00	0.09
year2019	-0.08	0.07	-1.13	143.00	0.26
year2020	-0.10	0.07	-1.37	143.00	0.17
year2021	-0.14	0.08	-1.82	143.35	0.07
insecticideno_insects	0.12	0.10	1.26	80.42	0.21
year2016:insecticideno_insects	-0.04	0.10	-0.40	143.00	0.69
year2017:insecticideno_insects	-0.03	0.10	-0.33	143.00	0.74
year2018:insecticideno_insects	-0.17	0.10	-1.61	143.00	0.11
year2019:insecticideno_insects	-0.35	0.10	-3.34	143.00	0.00
year2020:insecticideno_insects	-0.33	0.10	-3.11	143.00	0.00
year2021:insecticideno_insects	-0.25	0.11	-2.39	143.18	0.02

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.16
Residual		0.18

Grouping Variables		
Group	# groups	ICC
plot	24	0.42

```
##  ambient 2016 insects       2.58 0.0821 69.3     2.42     2.75
##  warmed  2016 insects       2.45 0.0821 69.3     2.29     2.62
##  ambient 2017 insects       2.20 0.0821 69.3     2.04     2.37
##  warmed  2017 insects       2.07 0.0821 69.3     1.91     2.24
##  ambient 2018 insects       2.42 0.0821 69.3     2.25     2.58
##  warmed  2018 insects       2.29 0.0821 69.3     2.12     2.45
##  ambient 2019 insects       2.46 0.0821 69.3     2.30     2.63
##  warmed  2019 insects       2.33 0.0821 69.3     2.17     2.49
##  ambient 2020 insects       2.44 0.0821 69.3     2.28     2.61
##  warmed  2020 insects       2.31 0.0821 69.3     2.15     2.48
##  ambient 2021 insects       2.41 0.0843 75.2     2.24     2.57
##  warmed  2021 insects       2.28 0.0837 73.7     2.11     2.44
##  ambient 2015 no_insects    2.67 0.0821 69.3     2.50     2.83
##  warmed  2015 no_insects    2.54 0.0821 69.3     2.37     2.70
##  ambient 2016 no_insects    2.67 0.0821 69.3     2.50     2.83
##  warmed  2016 no_insects    2.54 0.0821 69.3     2.37     2.70
##  ambient 2017 no_insects    2.29 0.0821 69.3     2.13     2.46
##  warmed  2017 no_insects    2.16 0.0821 69.3     2.00     2.32
##  ambient 2018 no_insects    2.37 0.0821 69.3     2.21     2.54
##  warmed  2018 no_insects    2.24 0.0821 69.3     2.08     2.41
```

```
##  ambient 2019 no_insects    2.23 0.0821 69.3     2.07     2.40
##  warmed  2019 no_insects    2.10 0.0821 69.3     1.94     2.27
##  ambient 2020 no_insects    2.24 0.0821 69.3     2.08     2.40
##  warmed  2020 no_insects    2.11 0.0821 69.3     1.95     2.27
##  ambient 2021 no_insects    2.28 0.0821 69.3     2.11     2.44
##  warmed  2021 no_insects    2.15 0.0821 69.3     1.98     2.31
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, year, insecticide`
##  1                                                estimate     SE    df
##  ambient 2015 insects - warmed 2015 insects         1.31e-01 0.0746  27.4
##  ambient 2015 insects - ambient 2016 insects       -3.93e-02 0.0775 156.1
##  ambient 2015 insects - warmed 2016 insects         9.16e-02 0.1076 101.8
##  ambient 2015 insects - ambient 2017 insects        3.42e-01 0.0775 156.1
##  ambient 2015 insects - warmed 2017 insects         4.73e-01 0.1076 101.8
##  ambient 2015 insects - ambient 2018 insects        1.27e-01 0.0775 156.1
##  ambient 2015 insects - warmed 2018 insects         2.58e-01 0.1076 101.8
##  ambient 2015 insects - ambient 2019 insects        8.37e-02 0.0775 156.1
##  ambient 2015 insects - warmed 2019 insects         2.15e-01 0.1076 101.8
##  ambient 2015 insects - ambient 2020 insects        1.02e-01 0.0775 156.1
##  ambient 2015 insects - warmed 2020 insects         2.33e-01 0.1076 101.8
##  ambient 2015 insects - ambient 2021 insects        1.38e-01 0.0795 156.5
##  ambient 2015 insects - warmed 2021 insects         2.69e-01 0.1086 104.3
##  ambient 2015 insects - ambient 2015 no_insects    -1.23e-01 0.1035  91.3
##  ambient 2015 insects - warmed 2015 no_insects      7.55e-03 0.1275  58.1
##  ambient 2015 insects - ambient 2016 no_insects    -1.21e-01 0.1035  91.3
##  ambient 2015 insects - warmed 2016 no_insects      9.91e-03 0.1275  58.1
##  ambient 2015 insects - ambient 2017 no_insects     2.53e-01 0.1035  91.3
##  ambient 2015 insects - warmed 2017 no_insects      3.84e-01 0.1275  58.1
##  ambient 2015 insects - ambient 2018 no_insects     1.72e-01 0.1035  91.3
##  ambient 2015 insects - warmed 2018 no_insects      3.03e-01 0.1275  58.1
##  ambient 2015 insects - ambient 2019 no_insects     3.11e-01 0.1035  91.3
##  ambient 2015 insects - warmed 2019 no_insects      4.42e-01 0.1275  58.1
##  ambient 2015 insects - ambient 2020 no_insects     3.05e-01 0.1035  91.3
##  ambient 2015 insects - warmed 2020 no_insects      4.36e-01 0.1275  58.1
##  ambient 2015 insects - ambient 2021 no_insects     2.69e-01 0.1035  91.3
##  ambient 2015 insects - warmed 2021 no_insects      4.00e-01 0.1275  58.1
##  warmed 2015 insects - ambient 2016 insects        -1.70e-01 0.1076 101.8
##  warmed 2015 insects - warmed 2016 insects         -3.93e-02 0.0775 156.1
##  warmed 2015 insects - ambient 2017 insects         2.11e-01 0.1076 101.8
##  warmed 2015 insects - warmed 2017 insects          3.42e-01 0.0775 156.1
##  warmed 2015 insects - ambient 2018 insects        -3.93e-03 0.1076 101.8
##  warmed 2015 insects - warmed 2018 insects          1.27e-01 0.0775 156.1
##  warmed 2015 insects - ambient 2019 insects        -4.72e-02 0.1076 101.8
##  warmed 2015 insects - warmed 2019 insects          8.37e-02 0.0775 156.1
##  warmed 2015 insects - ambient 2020 insects        -2.91e-02 0.1076 101.8
##  warmed 2015 insects - warmed 2020 insects          1.02e-01 0.0775 156.1
##  warmed 2015 insects - ambient 2021 insects         7.30e-03 0.1094 106.2
##  warmed 2015 insects - warmed 2021 insects          1.38e-01 0.0795 156.5
##  warmed 2015 insects - ambient 2015 no_insects     -2.54e-01 0.1275  58.1
##  warmed 2015 insects - warmed 2015 no_insects      -1.23e-01 0.1035  91.3
```

```
## warmed 2015 insects - ambient 2016 no_insects     -2.52e-01 0.1275  58.1
## warmed 2015 insects - warmed 2016 no_insects      -1.21e-01 0.1035  91.3
## warmed 2015 insects - ambient 2017 no_insects      1.23e-01 0.1275  58.1
## warmed 2015 insects - warmed 2017 no_insects       2.53e-01 0.1035  91.3
## warmed 2015 insects - ambient 2018 no_insects      4.12e-02 0.1275  58.1
## warmed 2015 insects - warmed 2018 no_insects       1.72e-01 0.1035  91.3
## warmed 2015 insects - ambient 2019 no_insects      1.80e-01 0.1275  58.1
## warmed 2015 insects - warmed 2019 no_insects       3.11e-01 0.1035  91.3
## warmed 2015 insects - ambient 2020 no_insects      1.74e-01 0.1275  58.1
## warmed 2015 insects - warmed 2020 no_insects       3.05e-01 0.1035  91.3
## warmed 2015 insects - ambient 2021 no_insects      1.38e-01 0.1275  58.1
## warmed 2015 insects - warmed 2021 no_insects       2.69e-01 0.1035  91.3
## ambient 2016 insects - warmed 2016 insects         1.31e-01 0.0746  27.4
## ambient 2016 insects - ambient 2017 insects        3.82e-01 0.0775 156.1
## ambient 2016 insects - warmed 2017 insects         5.12e-01 0.1076 101.8
## ambient 2016 insects - ambient 2018 insects        1.66e-01 0.0775 156.1
## ambient 2016 insects - warmed 2018 insects         2.97e-01 0.1076 101.8
## ambient 2016 insects - ambient 2019 insects        1.23e-01 0.0775 156.1
## ambient 2016 insects - warmed 2019 insects         2.54e-01 0.1076 101.8
## ambient 2016 insects - ambient 2020 insects        1.41e-01 0.0775 156.1
## ambient 2016 insects - warmed 2020 insects         2.72e-01 0.1076 101.8
## ambient 2016 insects - ambient 2021 insects        1.78e-01 0.0795 156.5
## ambient 2016 insects - warmed 2021 insects         3.08e-01 0.1086 104.3
## ambient 2016 insects - ambient 2015 no_insects    -8.41e-02 0.1035  91.3
## ambient 2016 insects - warmed 2015 no_insects      4.69e-02 0.1275  58.1
## ambient 2016 insects - ambient 2016 no_insects    -8.17e-02 0.1035  91.3
## ambient 2016 insects - warmed 2016 no_insects      4.92e-02 0.1275  58.1
## ambient 2016 insects - ambient 2017 no_insects     2.93e-01 0.1035  91.3
## ambient 2016 insects - warmed 2017 no_insects      4.24e-01 0.1275  58.1
## ambient 2016 insects - ambient 2018 no_insects     2.11e-01 0.1035  91.3
## ambient 2016 insects - warmed 2018 no_insects      3.42e-01 0.1275  58.1
## ambient 2016 insects - ambient 2019 no_insects     3.50e-01 0.1035  91.3
## ambient 2016 insects - warmed 2019 no_insects      4.81e-01 0.1275  58.1
## ambient 2016 insects - ambient 2020 no_insects     3.44e-01 0.1035  91.3
## ambient 2016 insects - warmed 2020 no_insects      4.75e-01 0.1275  58.1
## ambient 2016 insects - ambient 2021 no_insects     3.08e-01 0.1035  91.3
## ambient 2016 insects - warmed 2021 no_insects      4.39e-01 0.1275  58.1
## warmed 2016 insects - ambient 2017 insects         2.51e-01 0.1076 101.8
## warmed 2016 insects - warmed 2017 insects          3.82e-01 0.0775 156.1
## warmed 2016 insects - ambient 2018 insects         3.54e-02 0.1076 101.8
## warmed 2016 insects - warmed 2018 insects          1.66e-01 0.0775 156.1
## warmed 2016 insects - ambient 2019 insects        -7.89e-03 0.1076 101.8
## warmed 2016 insects - warmed 2019 insects          1.23e-01 0.0775 156.1
## warmed 2016 insects - ambient 2020 insects         1.02e-02 0.1076 101.8
## warmed 2016 insects - warmed 2020 insects          1.41e-01 0.0775 156.1
## warmed 2016 insects - ambient 2021 insects         4.66e-02 0.1094 106.2
## warmed 2016 insects - warmed 2021 insects          1.78e-01 0.0795 156.5
## warmed 2016 insects - ambient 2015 no_insects     -2.15e-01 0.1275  58.1
## warmed 2016 insects - warmed 2015 no_insects      -8.41e-02 0.1035  91.3
## warmed 2016 insects - ambient 2016 no_insects     -2.13e-01 0.1275  58.1
## warmed 2016 insects - warmed 2016 no_insects      -8.17e-02 0.1035  91.3
## warmed 2016 insects - ambient 2017 no_insects      1.62e-01 0.1275  58.1
## warmed 2016 insects - warmed 2017 no_insects       2.93e-01 0.1035  91.3
## warmed 2016 insects - ambient 2018 no_insects      8.05e-02 0.1275  58.1
```

```
##  warmed 2016 insects - warmed 2018 no_insects       2.11e-01 0.1035  91.3
##  warmed 2016 insects - ambient 2019 no_insects      2.19e-01 0.1275  58.1
##  warmed 2016 insects - warmed 2019 no_insects       3.50e-01 0.1035  91.3
##  warmed 2016 insects - ambient 2020 no_insects      2.13e-01 0.1275  58.1
##  warmed 2016 insects - warmed 2020 no_insects       3.44e-01 0.1035  91.3
##  warmed 2016 insects - ambient 2021 no_insects      1.77e-01 0.1275  58.1
##  warmed 2016 insects - warmed 2021 no_insects       3.08e-01 0.1035  91.3
##  ambient 2017 insects - warmed 2017 insects         1.31e-01 0.0746  27.4
##  ambient 2017 insects - ambient 2018 insects       -2.15e-01 0.0775 156.1
##  ambient 2017 insects - warmed 2018 insects        -8.44e-02 0.1076 101.8
##  ambient 2017 insects - ambient 2019 insects       -2.59e-01 0.0775 156.1
##  ambient 2017 insects - warmed 2019 insects        -1.28e-01 0.1076 101.8
##  ambient 2017 insects - ambient 2020 insects       -2.40e-01 0.0775 156.1
##  ambient 2017 insects - warmed 2020 insects        -1.09e-01 0.1076 101.8
##  ambient 2017 insects - ambient 2021 insects       -2.04e-01 0.0795 156.5
##  ambient 2017 insects - warmed 2021 insects        -7.31e-02 0.1086 104.3
##  ambient 2017 insects - ambient 2015 no_insects    -4.66e-01 0.1035  91.3
##  ambient 2017 insects - warmed 2015 no_insects     -3.35e-01 0.1275  58.1
##  ambient 2017 insects - ambient 2016 no_insects    -4.63e-01 0.1035  91.3
##  ambient 2017 insects - warmed 2016 no_insects     -3.32e-01 0.1275  58.1
##  ambient 2017 insects - ambient 2017 no_insects    -8.88e-02 0.1035  91.3
##  ambient 2017 insects - warmed 2017 no_insects      4.21e-02 0.1275  58.1
##  ambient 2017 insects - ambient 2018 no_insects    -1.70e-01 0.1035  91.3
##  ambient 2017 insects - warmed 2018 no_insects     -3.92e-02 0.1275  58.1
##  ambient 2017 insects - ambient 2019 no_insects    -3.13e-02 0.1035  91.3
##  ambient 2017 insects - warmed 2019 no_insects      9.97e-02 0.1275  58.1
##  ambient 2017 insects - ambient 2020 no_insects    -3.72e-02 0.1035  91.3
##  ambient 2017 insects - warmed 2020 no_insects      9.37e-02 0.1275  58.1
##  ambient 2017 insects - ambient 2021 no_insects    -7.32e-02 0.1035  91.3
##  ambient 2017 insects - warmed 2021 no_insects      5.77e-02 0.1275  58.1
##  warmed 2017 insects - ambient 2018 insects        -3.46e-01 0.1076 101.8
##  warmed 2017 insects - warmed 2018 insects         -2.15e-01 0.0775 156.1
##  warmed 2017 insects - ambient 2019 insects        -3.89e-01 0.1076 101.8
##  warmed 2017 insects - warmed 2019 insects         -2.59e-01 0.0775 156.1
##  warmed 2017 insects - ambient 2020 insects        -3.71e-01 0.1076 101.8
##  warmed 2017 insects - warmed 2020 insects         -2.40e-01 0.0775 156.1
##  warmed 2017 insects - ambient 2021 insects        -3.35e-01 0.1094 106.2
##  warmed 2017 insects - warmed 2021 insects         -2.04e-01 0.0795 156.5
##  warmed 2017 insects - ambient 2015 no_insects     -5.97e-01 0.1275  58.1
##  warmed 2017 insects - warmed 2015 no_insects      -4.66e-01 0.1035  91.3
##  warmed 2017 insects - ambient 2016 no_insects     -5.94e-01 0.1275  58.1
##  warmed 2017 insects - warmed 2016 no_insects      -4.63e-01 0.1035  91.3
##  warmed 2017 insects - ambient 2017 no_insects     -2.20e-01 0.1275  58.1
##  warmed 2017 insects - warmed 2017 no_insects      -8.88e-02 0.1035  91.3
##  warmed 2017 insects - ambient 2018 no_insects     -3.01e-01 0.1275  58.1
##  warmed 2017 insects - warmed 2018 no_insects      -1.70e-01 0.1035  91.3
##  warmed 2017 insects - ambient 2019 no_insects     -1.62e-01 0.1275  58.1
##  warmed 2017 insects - warmed 2019 no_insects      -3.13e-02 0.1035  91.3
##  warmed 2017 insects - ambient 2020 no_insects     -1.68e-01 0.1275  58.1
##  warmed 2017 insects - warmed 2020 no_insects      -3.72e-02 0.1035  91.3
##  warmed 2017 insects - ambient 2021 no_insects     -2.04e-01 0.1275  58.1
##  warmed 2017 insects - warmed 2021 no_insects      -7.32e-02 0.1035  91.3
##  ambient 2018 insects - warmed 2018 insects         1.31e-01 0.0746  27.4
##  ambient 2018 insects - ambient 2019 insects       -4.33e-02 0.0775 156.1
```

```
##  ambient 2018 insects - warmed 2019 insects        8.77e-02 0.1076 101.8
##  ambient 2018 insects - ambient 2020 insects      -2.51e-02 0.0775 156.1
##  ambient 2018 insects - warmed 2020 insects        1.06e-01 0.1076 101.8
##  ambient 2018 insects - ambient 2021 insects       1.12e-02 0.0795 156.5
##  ambient 2018 insects - warmed 2021 insects        1.42e-01 0.1086 104.3
##  ambient 2018 insects - ambient 2015 no_insects   -2.50e-01 0.1035  91.3
##  ambient 2018 insects - warmed 2015 no_insects    -1.19e-01 0.1275  58.1
##  ambient 2018 insects - ambient 2016 no_insects   -2.48e-01 0.1035  91.3
##  ambient 2018 insects - warmed 2016 no_insects    -1.17e-01 0.1275  58.1
##  ambient 2018 insects - ambient 2017 no_insects    1.26e-01 0.1035  91.3
##  ambient 2018 insects - warmed 2017 no_insects     2.57e-01 0.1275  58.1
##  ambient 2018 insects - ambient 2018 no_insects    4.51e-02 0.1035  91.3
##  ambient 2018 insects - warmed 2018 no_insects     1.76e-01 0.1275  58.1
##  ambient 2018 insects - ambient 2019 no_insects    1.84e-01 0.1035  91.3
##  ambient 2018 insects - warmed 2019 no_insects     3.15e-01 0.1275  58.1
##  ambient 2018 insects - ambient 2020 no_insects    1.78e-01 0.1035  91.3
##  ambient 2018 insects - warmed 2020 no_insects     3.09e-01 0.1275  58.1
##  ambient 2018 insects - ambient 2021 no_insects    1.42e-01 0.1035  91.3
##  ambient 2018 insects - warmed 2021 no_insects     2.73e-01 0.1275  58.1
##  warmed 2018 insects - ambient 2019 insects       -1.74e-01 0.1076 101.8
##  warmed 2018 insects - warmed 2019 insects        -4.33e-02 0.0775 156.1
##  warmed 2018 insects - ambient 2020 insects       -1.56e-01 0.1076 101.8
##  warmed 2018 insects - warmed 2020 insects        -2.51e-02 0.0775 156.1
##  warmed 2018 insects - ambient 2021 insects       -1.20e-01 0.1094 106.2
##  warmed 2018 insects - warmed 2021 insects         1.12e-02 0.0795 156.5
##  warmed 2018 insects - ambient 2015 no_insects    -3.81e-01 0.1275  58.1
##  warmed 2018 insects - warmed 2015 no_insects     -2.50e-01 0.1035  91.3
##  warmed 2018 insects - ambient 2016 no_insects    -3.79e-01 0.1275  58.1
##  warmed 2018 insects - warmed 2016 no_insects     -2.48e-01 0.1035  91.3
##  warmed 2018 insects - ambient 2017 no_insects    -4.48e-03 0.1275  58.1
##  warmed 2018 insects - warmed 2017 no_insects      1.26e-01 0.1035  91.3
##  warmed 2018 insects - ambient 2018 no_insects    -8.58e-02 0.1275  58.1
##  warmed 2018 insects - warmed 2018 no_insects      4.51e-02 0.1035  91.3
##  warmed 2018 insects - ambient 2019 no_insects     5.31e-02 0.1275  58.1
##  warmed 2018 insects - warmed 2019 no_insects      1.84e-01 0.1035  91.3
##  warmed 2018 insects - ambient 2020 no_insects     4.71e-02 0.1275  58.1
##  warmed 2018 insects - warmed 2020 no_insects      1.78e-01 0.1035  91.3
##  warmed 2018 insects - ambient 2021 no_insects     1.12e-02 0.1275  58.1
##  warmed 2018 insects - warmed 2021 no_insects      1.42e-01 0.1035  91.3
##  ambient 2019 insects - warmed 2019 insects        1.31e-01 0.0746  27.4
##  ambient 2019 insects - ambient 2020 insects       1.81e-02 0.0775 156.1
##  ambient 2019 insects - warmed 2020 insects        1.49e-01 0.1076 101.8
##  ambient 2019 insects - ambient 2021 insects       5.45e-02 0.0795 156.5
##  ambient 2019 insects - warmed 2021 insects        1.85e-01 0.1086 104.3
##  ambient 2019 insects - ambient 2015 no_insects   -2.07e-01 0.1035  91.3
##  ambient 2019 insects - warmed 2015 no_insects    -7.62e-02 0.1275  58.1
##  ambient 2019 insects - ambient 2016 no_insects   -2.05e-01 0.1035  91.3
##  ambient 2019 insects - warmed 2016 no_insects    -7.38e-02 0.1275  58.1
##  ambient 2019 insects - ambient 2017 no_insects    1.70e-01 0.1035  91.3
##  ambient 2019 insects - warmed 2017 no_insects     3.01e-01 0.1275  58.1
##  ambient 2019 insects - ambient 2018 no_insects    8.84e-02 0.1035  91.3
##  ambient 2019 insects - warmed 2018 no_insects     2.19e-01 0.1275  58.1
##  ambient 2019 insects - ambient 2019 no_insects    2.27e-01 0.1035  91.3
##  ambient 2019 insects - warmed 2019 no_insects     3.58e-01 0.1275  58.1
```

```
##  ambient 2019 insects - ambient 2020 no_insects     2.21e-01 0.1035  91.3
##  ambient 2019 insects - warmed 2020 no_insects      3.52e-01 0.1275  58.1
##  ambient 2019 insects - ambient 2021 no_insects     1.85e-01 0.1035  91.3
##  ambient 2019 insects - warmed 2021 no_insects      3.16e-01 0.1275  58.1
##  warmed 2019 insects - ambient 2020 insects        -1.13e-01 0.1076 101.8
##  warmed 2019 insects - warmed 2020 insects          1.81e-02 0.0775 156.1
##  warmed 2019 insects - ambient 2021 insects        -7.64e-02 0.1094 106.2
##  warmed 2019 insects - warmed 2021 insects          5.45e-02 0.0795 156.5
##  warmed 2019 insects - ambient 2015 no_insects     -3.38e-01 0.1275  58.1
##  warmed 2019 insects - warmed 2015 no_insects      -2.07e-01 0.1035  91.3
##  warmed 2019 insects - ambient 2016 no_insects     -3.36e-01 0.1275  58.1
##  warmed 2019 insects - warmed 2016 no_insects      -2.05e-01 0.1035  91.3
##  warmed 2019 insects - ambient 2017 no_insects      3.88e-02 0.1275  58.1
##  warmed 2019 insects - warmed 2017 no_insects       1.70e-01 0.1035  91.3
##  warmed 2019 insects - ambient 2018 no_insects     -4.26e-02 0.1275  58.1
##  warmed 2019 insects - warmed 2018 no_insects       8.84e-02 0.1035  91.3
##  warmed 2019 insects - ambient 2019 no_insects      9.64e-02 0.1275  58.1
##  warmed 2019 insects - warmed 2019 no_insects       2.27e-01 0.1035  91.3
##  warmed 2019 insects - ambient 2020 no_insects      9.04e-02 0.1275  58.1
##  warmed 2019 insects - warmed 2020 no_insects       2.21e-01 0.1035  91.3
##  warmed 2019 insects - ambient 2021 no_insects      5.44e-02 0.1275  58.1
##  warmed 2019 insects - warmed 2021 no_insects       1.85e-01 0.1035  91.3
##  ambient 2020 insects - warmed 2020 insects         1.31e-01 0.0746  27.4
##  ambient 2020 insects - ambient 2021 insects        3.64e-02 0.0795 156.5
##  ambient 2020 insects - warmed 2021 insects         1.67e-01 0.1086 104.3
##  ambient 2020 insects - ambient 2015 no_insects    -2.25e-01 0.1035  91.3
##  ambient 2020 insects - warmed 2015 no_insects     -9.43e-02 0.1275  58.1
##  ambient 2020 insects - ambient 2016 no_insects    -2.23e-01 0.1035  91.3
##  ambient 2020 insects - warmed 2016 no_insects     -9.19e-02 0.1275  58.1
##  ambient 2020 insects - ambient 2017 no_insects     1.52e-01 0.1035  91.3
##  ambient 2020 insects - warmed 2017 no_insects      2.82e-01 0.1275  58.1
##  ambient 2020 insects - ambient 2018 no_insects     7.02e-02 0.1035  91.3
##  ambient 2020 insects - warmed 2018 no_insects      2.01e-01 0.1275  58.1
##  ambient 2020 insects - ambient 2019 no_insects     2.09e-01 0.1035  91.3
##  ambient 2020 insects - warmed 2019 no_insects      3.40e-01 0.1275  58.1
##  ambient 2020 insects - ambient 2020 no_insects     2.03e-01 0.1035  91.3
##  ambient 2020 insects - warmed 2020 no_insects      3.34e-01 0.1275  58.1
##  ambient 2020 insects - ambient 2021 no_insects     1.67e-01 0.1035  91.3
##  ambient 2020 insects - warmed 2021 no_insects      2.98e-01 0.1275  58.1
##  warmed 2020 insects - ambient 2021 insects        -9.46e-02 0.1094 106.2
##  warmed 2020 insects - warmed 2021 insects          3.64e-02 0.0795 156.5
##  warmed 2020 insects - ambient 2015 no_insects     -3.56e-01 0.1275  58.1
##  warmed 2020 insects - warmed 2015 no_insects      -2.25e-01 0.1035  91.3
##  warmed 2020 insects - ambient 2016 no_insects     -3.54e-01 0.1275  58.1
##  warmed 2020 insects - warmed 2016 no_insects      -2.23e-01 0.1035  91.3
##  warmed 2020 insects - ambient 2017 no_insects      2.07e-02 0.1275  58.1
##  warmed 2020 insects - warmed 2017 no_insects       1.52e-01 0.1035  91.3
##  warmed 2020 insects - ambient 2018 no_insects     -6.07e-02 0.1275  58.1
##  warmed 2020 insects - warmed 2018 no_insects       7.02e-02 0.1035  91.3
##  warmed 2020 insects - ambient 2019 no_insects      7.82e-02 0.1275  58.1
##  warmed 2020 insects - warmed 2019 no_insects       2.09e-01 0.1035  91.3
##  warmed 2020 insects - ambient 2020 no_insects      7.22e-02 0.1275  58.1
##  warmed 2020 insects - warmed 2020 no_insects       2.03e-01 0.1035  91.3
##  warmed 2020 insects - ambient 2021 no_insects      3.63e-02 0.1275  58.1
```

```
##  warmed 2020 insects - warmed 2021 no_insects       1.67e-01 0.1035  91.3
##  ambient 2021 insects - warmed 2021 insects         1.31e-01 0.0746  27.4
##  ambient 2021 insects - ambient 2015 no_insects    -2.62e-01 0.1050  95.0
##  ambient 2021 insects - warmed 2015 no_insects     -1.31e-01 0.1291  60.6
##  ambient 2021 insects - ambient 2016 no_insects    -2.59e-01 0.1050  95.0
##  ambient 2021 insects - warmed 2016 no_insects     -1.28e-01 0.1291  60.6
##  ambient 2021 insects - ambient 2017 no_insects     1.15e-01 0.1050  95.0
##  ambient 2021 insects - warmed 2017 no_insects      2.46e-01 0.1291  60.6
##  ambient 2021 insects - ambient 2018 no_insects     3.39e-02 0.1050  95.0
##  ambient 2021 insects - warmed 2018 no_insects      1.65e-01 0.1291  60.6
##  ambient 2021 insects - ambient 2019 no_insects     1.73e-01 0.1050  95.0
##  ambient 2021 insects - warmed 2019 no_insects      3.04e-01 0.1291  60.6
##  ambient 2021 insects - ambient 2020 no_insects     1.67e-01 0.1050  95.0
##  ambient 2021 insects - warmed 2020 no_insects      2.98e-01 0.1291  60.6
##  ambient 2021 insects - ambient 2021 no_insects     1.31e-01 0.1050  95.0
##  ambient 2021 insects - warmed 2021 no_insects      2.62e-01 0.1291  60.6
##  warmed 2021 insects - ambient 2015 no_insects     -3.93e-01 0.1284  59.5
##  warmed 2021 insects - warmed 2015 no_insects      -2.62e-01 0.1050  95.0
##  warmed 2021 insects - ambient 2016 no_insects     -3.90e-01 0.1284  59.5
##  warmed 2021 insects - warmed 2016 no_insects      -2.59e-01 0.1050  95.0
##  warmed 2021 insects - ambient 2017 no_insects     -1.57e-02 0.1284  59.5
##  warmed 2021 insects - warmed 2017 no_insects       1.15e-01 0.1050  95.0
##  warmed 2021 insects - ambient 2018 no_insects     -9.71e-02 0.1284  59.5
##  warmed 2021 insects - warmed 2018 no_insects       3.39e-02 0.1050  95.0
##  warmed 2021 insects - ambient 2019 no_insects      4.19e-02 0.1284  59.5
##  warmed 2021 insects - warmed 2019 no_insects       1.73e-01 0.1050  95.0
##  warmed 2021 insects - ambient 2020 no_insects      3.59e-02 0.1284  59.5
##  warmed 2021 insects - warmed 2020 no_insects       1.67e-01 0.1050  95.0
##  warmed 2021 insects - ambient 2021 no_insects     -7.44e-05 0.1284  59.5
##  warmed 2021 insects - warmed 2021 no_insects       1.31e-01 0.1050  95.0
##  ambient 2015 no_insects - warmed 2015 no_insects   1.31e-01 0.0746  27.4
##  ambient 2015 no_insects - ambient 2016 no_insects  2.36e-03 0.0775 156.1
##  ambient 2015 no_insects - warmed 2016 no_insects   1.33e-01 0.1076 101.8
##  ambient 2015 no_insects - ambient 2017 no_insects  3.77e-01 0.0775 156.1
##  ambient 2015 no_insects - warmed 2017 no_insects   5.08e-01 0.1076 101.8
##  ambient 2015 no_insects - ambient 2018 no_insects  2.95e-01 0.0775 156.1
##  ambient 2015 no_insects - warmed 2018 no_insects   4.26e-01 0.1076 101.8
##  ambient 2015 no_insects - ambient 2019 no_insects  4.34e-01 0.0775 156.1
##  ambient 2015 no_insects - warmed 2019 no_insects   5.65e-01 0.1076 101.8
##  ambient 2015 no_insects - ambient 2020 no_insects  4.28e-01 0.0775 156.1
##  ambient 2015 no_insects - warmed 2020 no_insects   5.59e-01 0.1076 101.8
##  ambient 2015 no_insects - ambient 2021 no_insects  3.92e-01 0.0775 156.1
##  ambient 2015 no_insects - warmed 2021 no_insects   5.23e-01 0.1076 101.8
##  warmed 2015 no_insects - ambient 2016 no_insects  -1.29e-01 0.1076 101.8
##  warmed 2015 no_insects - warmed 2016 no_insects    2.36e-03 0.0775 156.1
##  warmed 2015 no_insects - ambient 2017 no_insects   2.46e-01 0.1076 101.8
##  warmed 2015 no_insects - warmed 2017 no_insects    3.77e-01 0.0775 156.1
##  warmed 2015 no_insects - ambient 2018 no_insects   1.65e-01 0.1076 101.8
##  warmed 2015 no_insects - warmed 2018 no_insects    2.95e-01 0.0775 156.1
##  warmed 2015 no_insects - ambient 2019 no_insects   3.03e-01 0.1076 101.8
##  warmed 2015 no_insects - warmed 2019 no_insects    4.34e-01 0.0775 156.1
##  warmed 2015 no_insects - ambient 2020 no_insects   2.97e-01 0.1076 101.8
##  warmed 2015 no_insects - warmed 2020 no_insects    4.28e-01 0.0775 156.1
##  warmed 2015 no_insects - ambient 2021 no_insects   2.62e-01 0.1076 101.8
```

```
##  warmed 2015 no_insects - warmed 2021 no_insects    3.92e-01 0.0775 156.1
##  ambient 2016 no_insects - warmed 2016 no_insects   1.31e-01 0.0746  27.4
##  ambient 2016 no_insects - ambient 2017 no_insects  3.74e-01 0.0775 156.1
##  ambient 2016 no_insects - warmed 2017 no_insects   5.05e-01 0.1076 101.8
##  ambient 2016 no_insects - ambient 2018 no_insects  2.93e-01 0.0775 156.1
##  ambient 2016 no_insects - warmed 2018 no_insects   4.24e-01 0.1076 101.8
##  ambient 2016 no_insects - ambient 2019 no_insects  4.32e-01 0.0775 156.1
##  ambient 2016 no_insects - warmed 2019 no_insects   5.63e-01 0.1076 101.8
##  ambient 2016 no_insects - ambient 2020 no_insects  4.26e-01 0.0775 156.1
##  ambient 2016 no_insects - warmed 2020 no_insects   5.57e-01 0.1076 101.8
##  ambient 2016 no_insects - ambient 2021 no_insects  3.90e-01 0.0775 156.1
##  ambient 2016 no_insects - warmed 2021 no_insects   5.21e-01 0.1076 101.8
##  warmed 2016 no_insects - ambient 2017 no_insects   2.44e-01 0.1076 101.8
##  warmed 2016 no_insects - warmed 2017 no_insects    3.74e-01 0.0775 156.1
##  warmed 2016 no_insects - ambient 2018 no_insects   1.62e-01 0.1076 101.8
##  warmed 2016 no_insects - warmed 2018 no_insects    2.93e-01 0.0775 156.1
##  warmed 2016 no_insects - ambient 2019 no_insects   3.01e-01 0.1076 101.8
##  warmed 2016 no_insects - warmed 2019 no_insects    4.32e-01 0.0775 156.1
##  warmed 2016 no_insects - ambient 2020 no_insects   2.95e-01 0.1076 101.8
##  warmed 2016 no_insects - warmed 2020 no_insects    4.26e-01 0.0775 156.1
##  warmed 2016 no_insects - ambient 2021 no_insects   2.59e-01 0.1076 101.8
##  warmed 2016 no_insects - warmed 2021 no_insects    3.90e-01 0.0775 156.1
##  ambient 2017 no_insects - warmed 2017 no_insects   1.31e-01 0.0746  27.4
##  ambient 2017 no_insects - ambient 2018 no_insects -8.13e-02 0.0775 156.1
##  ambient 2017 no_insects - warmed 2018 no_insects   4.96e-02 0.1076 101.8
##  ambient 2017 no_insects - ambient 2019 no_insects  5.76e-02 0.0775 156.1
##  ambient 2017 no_insects - warmed 2019 no_insects   1.89e-01 0.1076 101.8
##  ambient 2017 no_insects - ambient 2020 no_insects  5.16e-02 0.0775 156.1
##  ambient 2017 no_insects - warmed 2020 no_insects   1.83e-01 0.1076 101.8
##  ambient 2017 no_insects - ambient 2021 no_insects  1.56e-02 0.0775 156.1
##  ambient 2017 no_insects - warmed 2021 no_insects   1.47e-01 0.1076 101.8
##  warmed 2017 no_insects - ambient 2018 no_insects  -2.12e-01 0.1076 101.8
##  warmed 2017 no_insects - warmed 2018 no_insects   -8.13e-02 0.0775 156.1
##  warmed 2017 no_insects - ambient 2019 no_insects  -7.33e-02 0.1076 101.8
##  warmed 2017 no_insects - warmed 2019 no_insects    5.76e-02 0.0775 156.1
##  warmed 2017 no_insects - ambient 2020 no_insects  -7.93e-02 0.1076 101.8
##  warmed 2017 no_insects - warmed 2020 no_insects    5.16e-02 0.0775 156.1
##  warmed 2017 no_insects - ambient 2021 no_insects  -1.15e-01 0.1076 101.8
##  warmed 2017 no_insects - warmed 2021 no_insects    1.56e-02 0.0775 156.1
##  ambient 2018 no_insects - warmed 2018 no_insects   1.31e-01 0.0746  27.4
##  ambient 2018 no_insects - ambient 2019 no_insects  1.39e-01 0.0775 156.1
##  ambient 2018 no_insects - warmed 2019 no_insects   2.70e-01 0.1076 101.8
##  ambient 2018 no_insects - ambient 2020 no_insects  1.33e-01 0.0775 156.1
##  ambient 2018 no_insects - warmed 2020 no_insects   2.64e-01 0.1076 101.8
##  ambient 2018 no_insects - ambient 2021 no_insects  9.70e-02 0.0775 156.1
##  ambient 2018 no_insects - warmed 2021 no_insects   2.28e-01 0.1076 101.8
##  warmed 2018 no_insects - ambient 2019 no_insects   7.99e-03 0.1076 101.8
##  warmed 2018 no_insects - warmed 2019 no_insects    1.39e-01 0.0775 156.1
##  warmed 2018 no_insects - ambient 2020 no_insects   2.00e-03 0.1076 101.8
##  warmed 2018 no_insects - warmed 2020 no_insects    1.33e-01 0.0775 156.1
##  warmed 2018 no_insects - ambient 2021 no_insects  -3.39e-02 0.1076 101.8
##  warmed 2018 no_insects - warmed 2021 no_insects    9.70e-02 0.0775 156.1
##  ambient 2019 no_insects - warmed 2019 no_insects   1.31e-01 0.0746  27.4
##  ambient 2019 no_insects - ambient 2020 no_insects -5.99e-03 0.0775 156.1
```

```
##  ambient 2019 no_insects - warmed 2020 no_insects   1.25e-01 0.1076 101.8
##  ambient 2019 no_insects - ambient 2021 no_insects -4.19e-02 0.0775 156.1
##  ambient 2019 no_insects - warmed 2021 no_insects   8.90e-02 0.1076 101.8
##  warmed 2019 no_insects - ambient 2020 no_insects  -1.37e-01 0.1076 101.8
##  warmed 2019 no_insects - warmed 2020 no_insects   -5.99e-03 0.0775 156.1
##  warmed 2019 no_insects - ambient 2021 no_insects  -1.73e-01 0.1076 101.8
##  warmed 2019 no_insects - warmed 2021 no_insects   -4.19e-02 0.0775 156.1
##  ambient 2020 no_insects - warmed 2020 no_insects   1.31e-01 0.0746  27.4
##  ambient 2020 no_insects - ambient 2021 no_insects -3.59e-02 0.0775 156.1
##  ambient 2020 no_insects - warmed 2021 no_insects   9.50e-02 0.1076 101.8
##  warmed 2020 no_insects - ambient 2021 no_insects  -1.67e-01 0.1076 101.8
##  warmed 2020 no_insects - warmed 2021 no_insects   -3.59e-02 0.0775 156.1
##  ambient 2021 no_insects - warmed 2021 no_insects   1.31e-01 0.0746  27.4
##  t.ratio p.value
##   1.756  0.9861
##  -0.507  1.0000
##   0.852  1.0000
##   4.414  0.0056
##   4.399  0.0075
##   1.638  0.9977
##   2.398  0.8076
##   1.080  1.0000
##   1.996  0.9652
##   1.314  0.9999
##   2.164  0.9194
##   1.738  0.9945
##   2.478  0.7569
##  -1.192  1.0000
##   0.059  1.0000
##  -1.170  1.0000
##   0.078  1.0000
##   2.449  0.7746
##   3.014  0.3773
##   1.663  0.9966
##   2.376  0.8131
##   3.006  0.3721
##   3.465  0.1518
##   2.948  0.4119
##   3.418  0.1690
##   2.601  0.6704
##   3.136  0.3028
##  -1.582  0.9984
##  -0.507  1.0000
##   1.965  0.9708
##   4.414  0.0056
##  -0.037  1.0000
##   1.638  0.9977
##  -0.439  1.0000
##   1.080  1.0000
##  -0.270  1.0000
##   1.314  0.9999
##   0.067  1.0000
##   1.738  0.9945
##  -1.994  0.9605
```

```
##  -1.192  1.0000
##  -1.975  0.9642
##  -1.170  1.0000
##   0.961  1.0000
##   2.449  0.7746
##   0.323  1.0000
##   1.663  0.9966
##   1.412  0.9996
##   3.006  0.3721
##   1.365  0.9998
##   2.948  0.4119
##   1.083  1.0000
##   2.601  0.6704
##   1.756  0.9861
##   4.921  0.0007
##   4.764  0.0019
##   2.145  0.9295
##   2.763  0.5477
##   1.587  0.9986
##   2.361  0.8289
##   1.820  0.9897
##   2.529  0.7219
##   2.232  0.8966
##   2.840  0.4889
##  -0.813  1.0000
##   0.367  1.0000
##  -0.790  1.0000
##   0.386  1.0000
##   2.829  0.4984
##   3.322  0.2086
##   2.043  0.9540
##   2.684  0.6088
##   3.386  0.1670
##   3.774  0.0709
##   3.328  0.1914
##   3.727  0.0802
##   2.980  0.3894
##   3.445  0.1592
##   2.330  0.8458
##   4.921  0.0007
##   0.329  1.0000
##   2.145  0.9295
##  -0.073  1.0000
##   1.587  0.9986
##   0.095  1.0000
##   1.820  0.9897
##   0.426  1.0000
##   2.232  0.8966
##  -1.686  0.9948
##  -0.813  1.0000
##  -1.667  0.9956
##  -0.790  1.0000
##   1.269  0.9999
##   2.829  0.4984
```

```
##    0.631  1.0000
##    2.043  0.9540
##    1.720  0.9932
##    3.386  0.1670
##    1.673  0.9953
##    3.328  0.1914
##    1.391  0.9997
##    2.980  0.3894
##    1.756  0.9861
##   -2.776  0.5354
##   -0.784  1.0000
##   -3.334  0.1771
##   -1.186  1.0000
##   -3.100  0.3014
##   -1.018  1.0000
##   -2.566  0.6979
##   -0.673  1.0000
##   -4.500  0.0056
##   -2.625  0.6516
##   -4.477  0.0061
##   -2.606  0.6648
##   -0.859  1.0000
##    0.330  1.0000
##   -1.645  0.9971
##   -0.308  1.0000
##   -0.302  1.0000
##    0.782  1.0000
##   -0.360  1.0000
##    0.735  1.0000
##   -0.707  1.0000
##    0.453  1.0000
##   -3.218  0.2416
##   -2.776  0.5354
##   -3.621  0.0893
##   -3.334  0.1771
##   -3.452  0.1393
##   -3.100  0.3014
##   -3.061  0.3328
##   -2.566  0.6979
##   -4.678  0.0048
##   -4.500  0.0056
##   -4.659  0.0051
##   -4.477  0.0061
##   -1.723  0.9931
##   -0.859  1.0000
##   -2.361  0.8216
##   -1.645  0.9971
##   -1.272  0.9999
##   -0.302  1.0000
##   -1.319  0.9999
##   -0.360  1.0000
##   -1.601  0.9975
##   -0.707  1.0000
##    1.756  0.9861
```

```
## -0.558 1.0000
##  0.815 1.0000
## -0.324 1.0000
##  0.983 1.0000
##  0.141 1.0000
##  1.309 0.9999
## -2.420 0.7932
## -0.937 1.0000
## -2.397 0.8070
## -0.918 1.0000
##  1.222 1.0000
##  2.018 0.9552
##  0.436 1.0000
##  1.380 0.9998
##  1.779 0.9913
##  2.470 0.7568
##  1.721 0.9944
##  2.423 0.7860
##  1.373 0.9998
##  2.141 0.9204
## -1.619 0.9978
## -0.558 1.0000
## -1.451 0.9996
## -0.324 1.0000
## -1.094 1.0000
##  0.141 1.0000
## -2.990 0.3930
## -2.420 0.7932
## -2.971 0.4052
## -2.397 0.8070
## -0.035 1.0000
##  1.222 1.0000
## -0.673 1.0000
##  0.436 1.0000
##  0.416 1.0000
##  1.779 0.9913
##  0.369 1.0000
##  1.721 0.9944
##  0.087 1.0000
##  1.373 0.9998
##  1.756 0.9861
##  0.234 1.0000
##  1.386 0.9998
##  0.685 1.0000
##  1.707 0.9952
## -2.002 0.9632
## -0.597 1.0000
## -1.979 0.9676
## -0.579 1.0000
##  1.640 0.9972
##  2.357 0.8236
##  0.854 1.0000
##  1.720 0.9932
##  2.197 0.9060
```

```
##    2.809  0.5185
##    2.139  0.9269
##    2.762  0.5525
##    1.791  0.9904
##    2.480  0.7502
##   -1.049  1.0000
##    0.234  1.0000
##   -0.698  1.0000
##    0.685  1.0000
##   -2.651  0.6331
##   -2.002  0.9632
##   -2.632  0.6463
##   -1.979  0.9676
##    0.304  1.0000
##    1.640  0.9972
##   -0.334  1.0000
##    0.854  1.0000
##    0.756  1.0000
##    2.197  0.9060
##    0.709  1.0000
##    2.139  0.9269
##    0.427  1.0000
##    1.791  0.9904
##    1.756  0.9861
##    0.457  1.0000
##    1.540  0.9990
##   -2.177  0.9136
##   -0.739  1.0000
##   -2.154  0.9218
##   -0.721  1.0000
##    1.465  0.9995
##    2.215  0.8922
##    0.679  1.0000
##    1.577  0.9980
##    2.021  0.9590
##    2.667  0.6215
##    1.964  0.9703
##    2.620  0.6551
##    1.616  0.9978
##    2.338  0.8341
##   -0.864  1.0000
##    0.457  1.0000
##   -2.793  0.5301
##   -2.177  0.9136
##   -2.774  0.5435
##   -2.154  0.9218
##    0.162  1.0000
##    1.465  0.9995
##   -0.476  1.0000
##    0.679  1.0000
##    0.613  1.0000
##    2.021  0.9590
##    0.566  1.0000
##    1.964  0.9703
```

```
##    0.285  1.0000
##    1.616  0.9978
##    1.756  0.9861
##   -2.492  0.7470
##   -1.012  1.0000
##   -2.470  0.7619
##   -0.994  1.0000
##    1.098  1.0000
##    1.907  0.9762
##    0.323  1.0000
##    1.277  0.9999
##    1.646  0.9971
##    2.353  0.8268
##    1.589  0.9983
##    2.306  0.8512
##    1.247  1.0000
##    2.028  0.9535
##   -3.057  0.3494
##   -2.492  0.7470
##   -3.039  0.3609
##   -2.470  0.7619
##   -0.122  1.0000
##    1.098  1.0000
##   -0.756  1.0000
##    0.323  1.0000
##    0.326  1.0000
##    1.646  0.9971
##    0.279  1.0000
##    1.589  0.9983
##   -0.001  1.0000
##    1.247  1.0000
##    1.756  0.9861
##    0.030  1.0000
##    1.239  1.0000
##    4.859  0.0009
##    4.720  0.0023
##    3.811  0.0461
##    3.964  0.0323
##    5.602  <.0001
##    5.255  0.0003
##    5.525  <.0001
##    5.200  0.0003
##    5.061  0.0004
##    4.865  0.0013
##   -1.195  1.0000
##    0.030  1.0000
##    2.286  0.8682
##    4.859  0.0009
##    1.530  0.9991
##    3.811  0.0461
##    2.821  0.5035
##    5.602  <.0001
##    2.765  0.5459
##    5.525  <.0001
```

```
##   2.431  0.7871
##   5.061  0.0004
##   1.756  0.9861
##   4.829  0.0011
##   4.698  0.0025
##   3.780  0.0507
##   3.942  0.0347
##   5.572  <.0001
##   5.233  0.0003
##   5.494  0.0001
##   5.178  0.0004
##   5.031  0.0004
##   4.843  0.0014
##   2.264  0.8786
##   4.829  0.0011
##   1.508  0.9993
##   3.780  0.0507
##   2.799  0.5202
##   5.572  <.0001
##   2.743  0.5627
##   5.494  0.0001
##   2.409  0.8007
##   5.031  0.0004
##   1.756  0.9861
##  -1.049  1.0000
##   0.461  1.0000
##   0.743  1.0000
##   1.752  0.9931
##   0.665  1.0000
##   1.697  0.9956
##   0.202  1.0000
##   1.363  0.9999
##  -1.973  0.9693
##  -1.049  1.0000
##  -0.682  1.0000
##   0.743  1.0000
##  -0.738  1.0000
##   0.665  1.0000
##  -1.072  1.0000
##   0.202  1.0000
##   1.756  0.9861
##   1.792  0.9917
##   2.509  0.7363
##   1.714  0.9955
##   2.453  0.7734
##   1.251  1.0000
##   2.119  0.9344
##   0.074  1.0000
##   1.792  0.9917
##   0.019  1.0000
##   1.714  0.9955
##  -0.316  1.0000
##   1.251  1.0000
##   1.756  0.9861
```

```
##  -0.077  1.0000
##   1.161  1.0000
##  -0.541  1.0000
##   0.827  1.0000
##  -1.273  1.0000
##  -0.077  1.0000
##  -1.607  0.9980
##  -0.541  1.0000
##   1.756  0.9861
##  -0.464  1.0000
##   0.883  1.0000
##  -1.551  0.9989
##  -0.464  1.0000
##   1.756  0.9861
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 28 estimates
```

UMBS

```
# Do we need to include plot as a random effect with the UMBS models?
mod1ur <- lmer(log(richness) ~ state * year + insecticide * year + (1 | plot), umbs_diversity,
    REML = FALSE)
mod2ur <- lmer(log(richness) ~ state * year + insecticide + year + (1 | plot), umbs_diversity,
    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(mod1ur)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq  Mean Sq F value
## state               1 0.00005 0.000048  0.0019
## year                6 0.54951 0.091585  3.5657
## insecticide         1 0.00702 0.007016  0.2732
## state:year          6 0.17263 0.028772  1.1202
## year:insecticide    6 0.09450 0.015751  0.6132
```

```
anova(mod2ur)
```

```
## Analysis of Variance Table
##             npar  Sum Sq  Mean Sq F value
## state          1 0.00005 0.000049  0.0019
## year           6 0.54951 0.091585  3.4768
## insecticide    1 0.00720 0.007195  0.2732
## state:year     6 0.17263 0.028772  1.0922
```

```
anova(mod1ur, mod2ur)  # Go with model 2 since pvalue >0.05, aka more complex model does not have somet
```

```
## Data: umbs_diversity
## Models:
```

```
## mod2ur: log(richness) ~ state * year + insecticide + year + (1 | plot)
## mod1ur: log(richness) ~ state * year + insecticide * year + (1 | plot)
##        npar     AIC    BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod2ur   17 -38.555 14.553 36.277  -72.555
## mod1ur   23 -30.188 41.663 38.094  -76.188 3.6331  6     0.7262
```

```r
summary(mod1ur)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(richness) ~ state * year + insecticide * year + (1 | plot)
##    Data: umbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##    -30.2     41.7     38.1    -76.2      145
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.71979 -0.68974  0.07783  0.55792  2.94405
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.04540  0.2131
##  Residual             0.02569  0.1603
## Number of obs: 168, groups:  plot, 24
##
## Fixed effects:
##                                  Estimate Std. Error t value
## (Intercept)                      1.723398   0.094264  18.283
## statewarmed                      0.019908   0.108846   0.183
## year2016                         0.049656   0.080133   0.620
## year2017                         0.009932   0.080133   0.124
## year2018                         0.070745   0.080133   0.883
## year2019                         0.015205   0.080133   0.190
## year2020                         0.179661   0.080133   2.242
## year2021                        -0.077256   0.080133  -0.964
## insecticideno_insects           -0.026711   0.108846  -0.245
## statewarmed:year2016            -0.060793   0.092530  -0.657
## statewarmed:year2017             0.017912   0.092530   0.194
## statewarmed:year2018            -0.114470   0.092530  -1.237
## statewarmed:year2019             0.055746   0.092530   0.602
## statewarmed:year2020            -0.104620   0.092530  -1.131
## statewarmed:year2021             0.039573   0.092530   0.428
## year2016:insecticideno_insects  0.004714   0.092530   0.051
## year2017:insecticideno_insects  0.109854   0.092530   1.187
## year2018:insecticideno_insects  0.108447   0.092530   1.172
## year2019:insecticideno_insects  0.123403   0.092530   1.334
## year2020:insecticideno_insects  0.073717   0.092530   0.797
## year2021:insecticideno_insects  0.097691   0.092530   1.056

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

```r
summary(mod2ur)
```

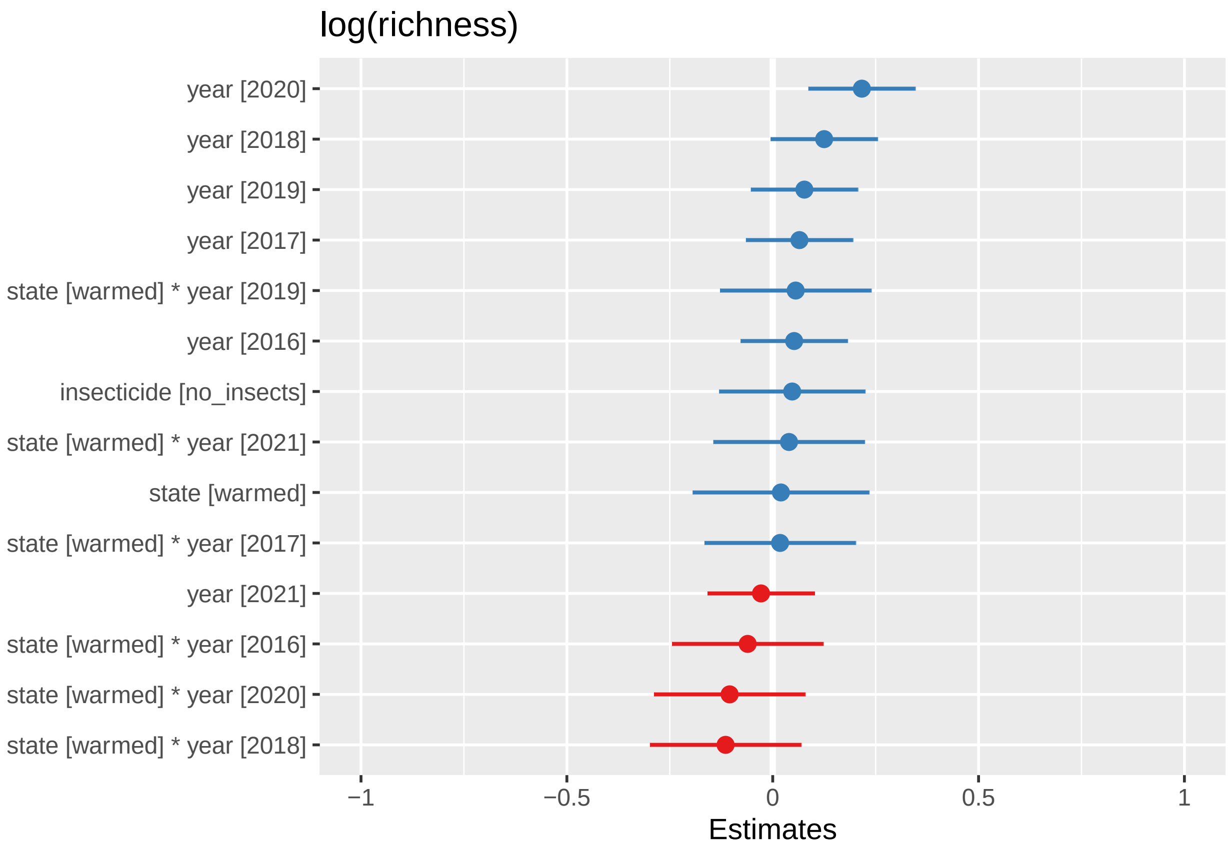
```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(richness) ~ state * year + insecticide + year + (1 | plot)
##    Data: umbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##    -38.6     14.6     36.3    -72.6      151
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.91565 -0.68043  0.09461  0.56920  3.01737
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.04531  0.2129
##  Residual             0.02634  0.1623
## Number of obs: 168, groups:  plot, 24
##
## Fixed effects:
##                       Estimate Std. Error t value
## (Intercept)            1.68641    0.08953  18.837
## statewarmed            0.01991    0.10928   0.182
## year2016               0.05201    0.06626   0.785
## year2017               0.06486    0.06626   0.979
## year2018               0.12497    0.06626   1.886
## year2019               0.07691    0.06626   1.161
## year2020               0.21652    0.06626   3.268
## year2021              -0.02841    0.06626  -0.429
## insecticideno_insects  0.04726    0.09043   0.523
## statewarmed:year2016  -0.06079    0.09370  -0.649
## statewarmed:year2017   0.01791    0.09370   0.191
## statewarmed:year2018  -0.11447    0.09370  -1.222
## statewarmed:year2019   0.05575    0.09370   0.595
## statewarmed:year2020  -0.10462    0.09370  -1.116
## statewarmed:year2021   0.03957    0.09370   0.422
```

```
##
## Correlation matrix not shown by default, as p = 15 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```r
AICctab(mod1ur, mod2ur, weights = T)  # model 2
```

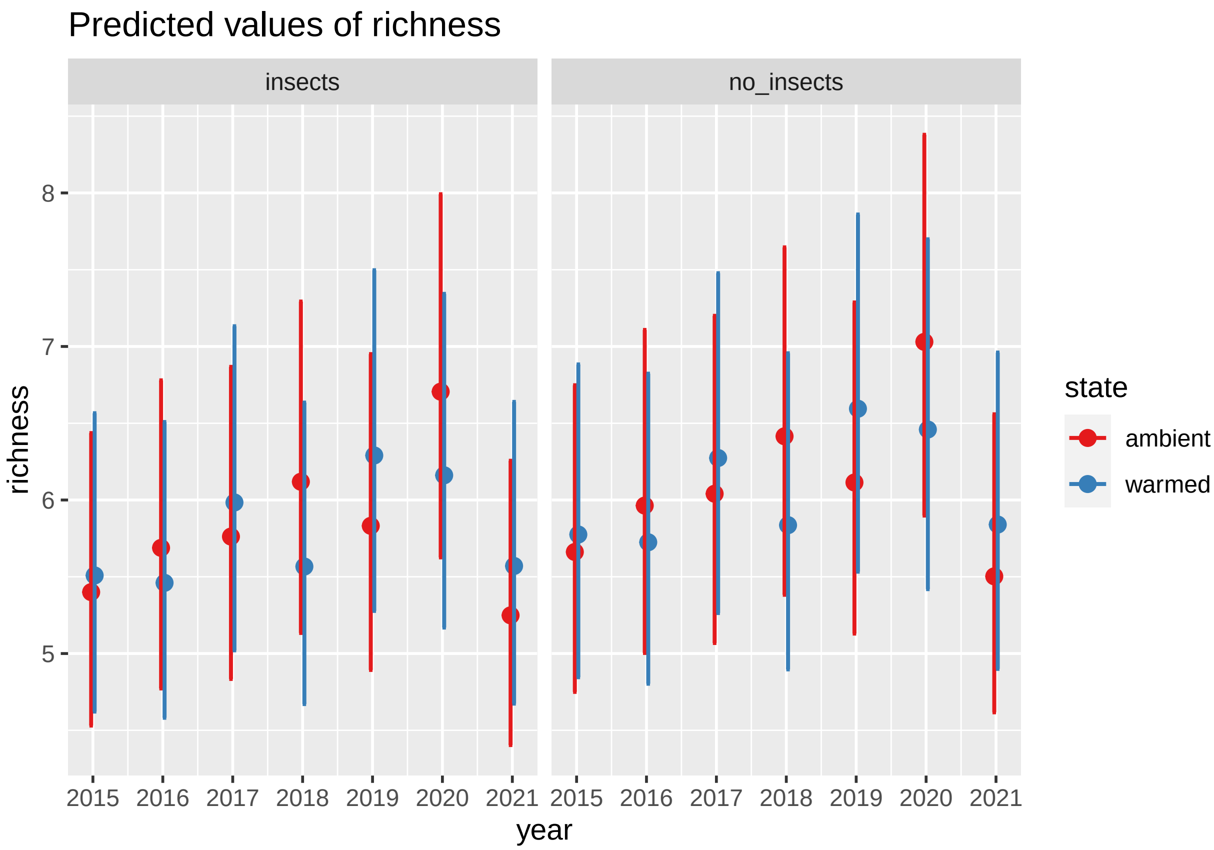
```
##        dAICc df weight
## mod2ur  0    17 0.9975
## mod1ur 12    23 0.0025
```

```r
# Plot the fixed effects estimates for different models these are the fixed
# effects estimates from summary(mod1)
plot_model(mod2ur, sort.est = TRUE)
```

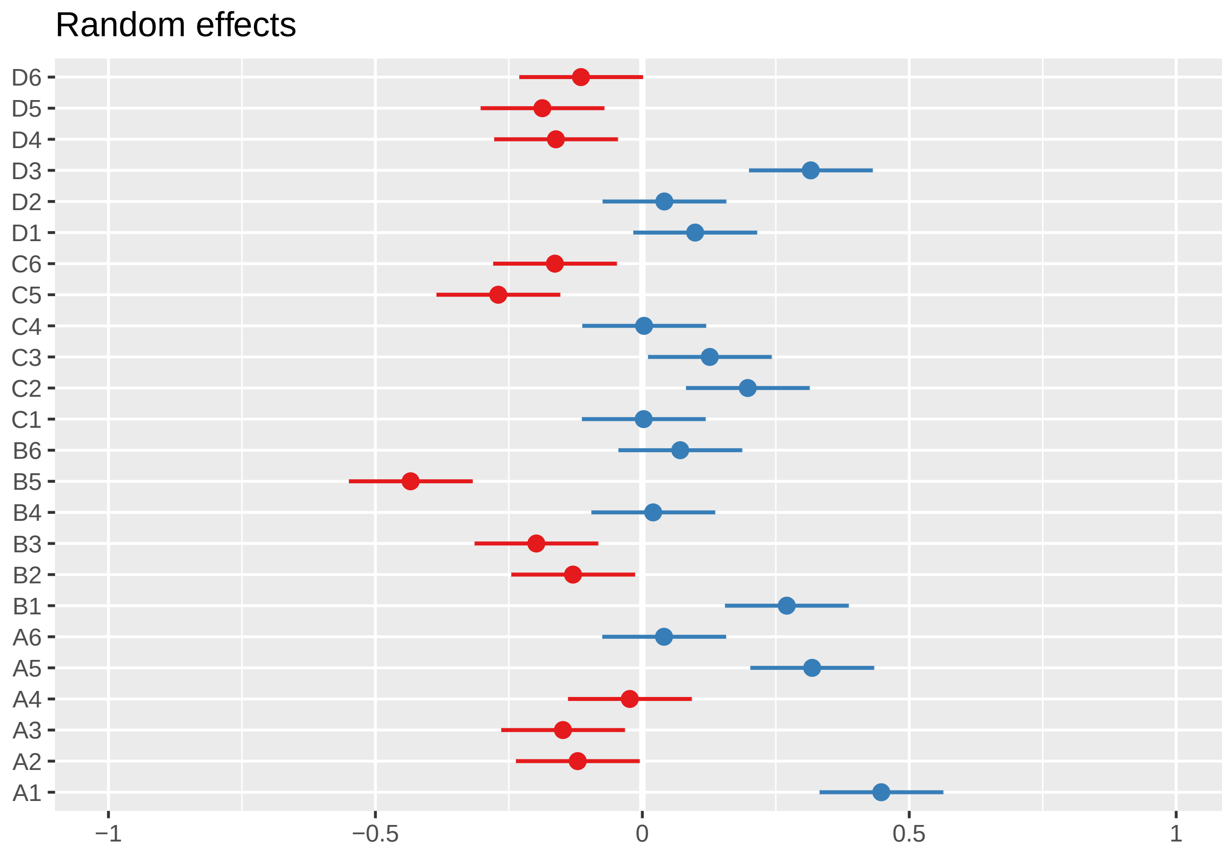



```r
# these are the fixed predicted values:
plot_model(mod2ur, type = "pred", terms = c("year", "state", "insecticide"))
```

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




```
# these are the random effects estimates
plot_model(mod2ur, type = "re", terms = c("species"))
```




```r
# Does year need to be interactive with state?
mod3ur <- lmer(log(richness) ~ state + year + insecticide * year + (1 | plot), umbs_diversity,
    REML = FALSE)
anova(mod2ur, mod3ur)
```

```
## Data: umbs_diversity
## Models:
## mod2ur: log(richness) ~ state * year + insecticide + year + (1 | plot)
## mod3ur: log(richness) ~ state + year + insecticide * year + (1 | plot)
##        npar     AIC    BIC logLik deviance Chisq Df Pr(>Chisq)
## mod2ur   17 -38.555 14.553 36.277  -72.555
## mod3ur   17 -35.619 17.488 34.809  -69.619     0  0
```

```r
AICctab(mod1ur, mod3ur, weights = T)  # going with mod3
```

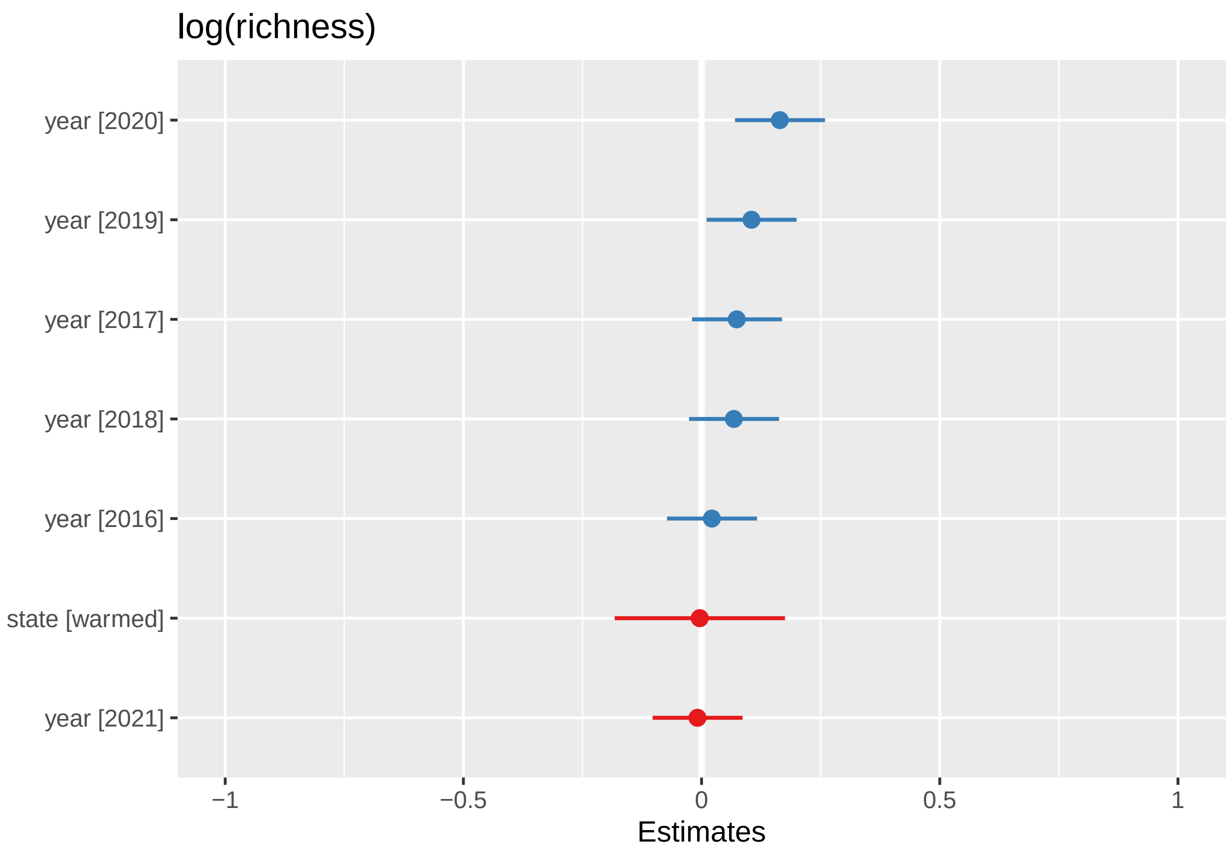
```
##        dAICc df weight
## mod3ur  0    17 0.989
## mod1ur  9    23 0.011
```

```r
# Do we need to include insecticide? (dropping insecticide from the model)
mod5ur <- lmer(log(richness) ~ state + year + (1 | plot), umbs_diversity, REML = FALSE)
anova(mod3ur, mod5ur)
```

```
## Data: umbs_diversity
## Models:
```

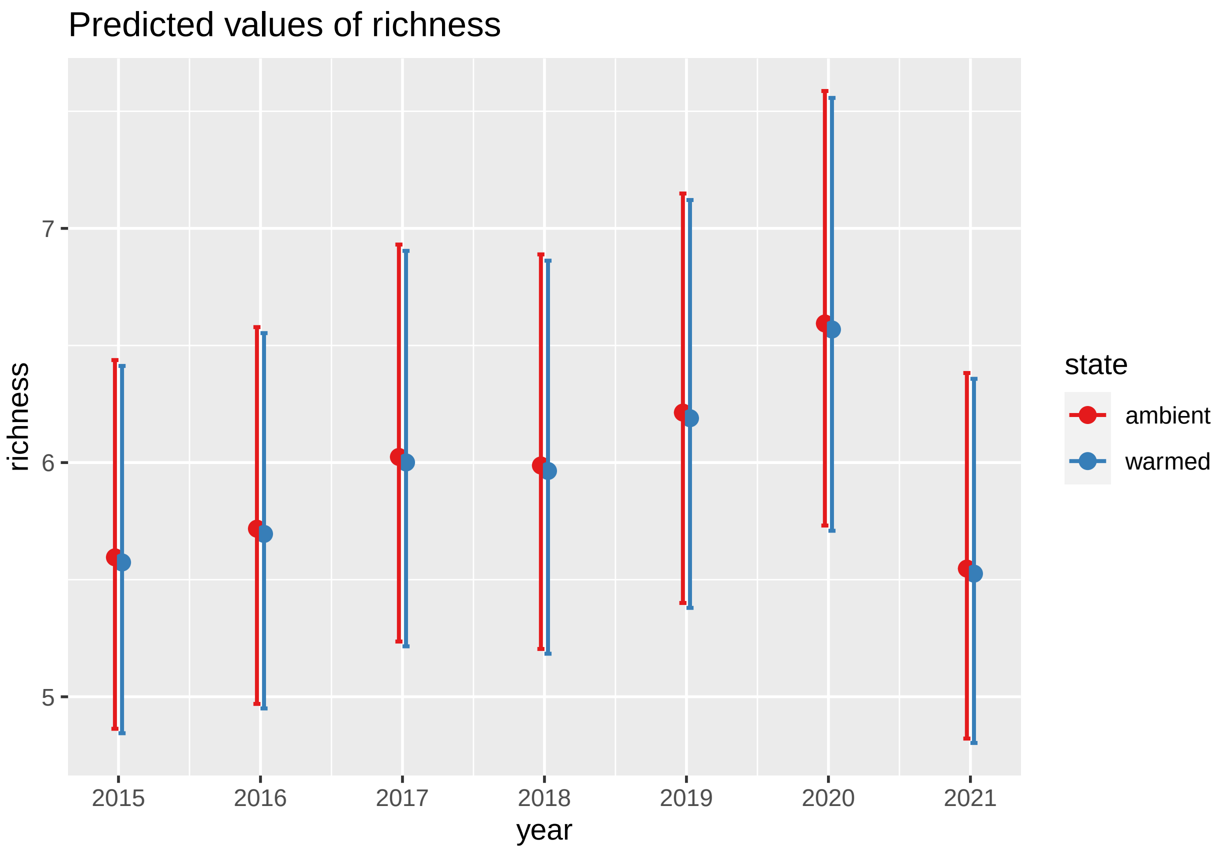
```
## mod5ur: log(richness) ~ state + year + (1 | plot)
## mod3ur: log(richness) ~ state + year + insecticide * year + (1 | plot)
##        npar     AIC     BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod5ur   10 -45.874 -14.635 32.937  -65.874
## mod3ur   17 -35.619  17.488 34.809  -69.619 3.7446  7     0.8087
```

```
# p>0.05 so insecticide*year does not strongly improve model fit so we will go
# with mod5

# Plot the fixed effects estimates for different models these are the fixed
# effects estimates from summary(mod5)
plot_model(mod5ur, sort.est = TRUE)
```

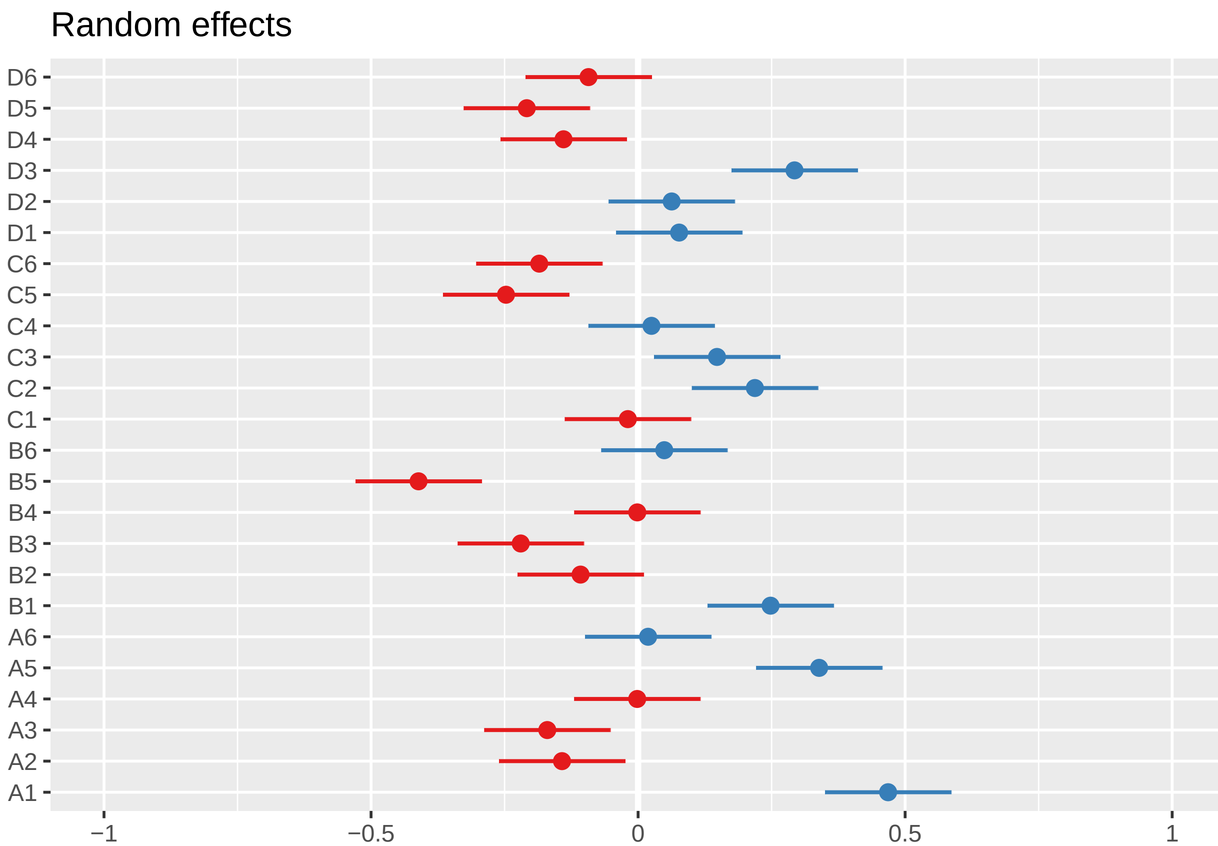



```
# these are the fixed predicted values:
plot_model(mod5ur, type = "pred", terms = c("year", "state"))
```

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




```r
# these are the random effects estimates
plot_model(mod5ur, type = "re", terms = c("species"))
```




```r
# If we wanted to include plots nested within year it would look like this:
# mod6us <- lmer(log(richness) ~ state + year + insecticide*year + (1 +
# year|plot), umbs_diversity, REML=FALSE) anova(mod5ur, mod6ur) anova(mod5ur)
# cant get mod6 to work

# the best model fit appears to be = mod5ur <- lmer(log(richness) ~ state + year
# + (1|plot), umbs_diversity, REML = FALSE)
summ(mod5ur)
```

Observations	168
Dependent variable	log(richness)
Type	Mixed effects linear regression

AIC	-45.87
BIC	-14.63
Pseudo-R² (fixed effects)	0.04
Pseudo-R² (total)	0.64

```r
emmeans(mod5ur, list(pairwise ~ state + year), adjust = "tukey")
```

```
## $`emmeans of state, year`
##  state    year emmean     SE   df lower.CL upper.CL
##  ambient 2015    1.72 0.0744 39.7     1.57     1.87
##  warmed  2015    1.72 0.0744 39.7     1.57     1.87
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	1.72	0.07	24.07	36.43	0.00
statewarmed	-0.00	0.09	-0.04	24.00	0.97
year2016	0.02	0.05	0.45	144.00	0.65
year2017	0.07	0.05	1.54	144.00	0.13
year2018	0.07	0.05	1.41	144.00	0.16
year2019	0.10	0.05	2.19	144.00	0.03
year2020	0.16	0.05	3.43	144.00	0.00
year2021	-0.01	0.05	-0.18	144.00	0.86

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.21
Residual		0.17

Grouping Variables		
Group	# groups	ICC
plot	24	0.62

```
##  ambient 2016   1.74 0.0744 39.7     1.59     1.89
##  warmed  2016   1.74 0.0744 39.7     1.59     1.89
##  ambient 2017   1.80 0.0744 39.7     1.65     1.95
##  warmed  2017   1.79 0.0744 39.7     1.64     1.94
##  ambient 2018   1.79 0.0744 39.7     1.64     1.94
##  warmed  2018   1.79 0.0744 39.7     1.64     1.94
##  ambient 2019   1.83 0.0744 39.7     1.68     1.98
##  warmed  2019   1.82 0.0744 39.7     1.67     1.97
##  ambient 2020   1.89 0.0744 39.7     1.74     2.04
##  warmed  2020   1.88 0.0744 39.7     1.73     2.03
##  ambient 2021   1.71 0.0744 39.7     1.56     1.86
##  warmed  2021   1.71 0.0744 39.7     1.56     1.86
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, year`
##  1                           estimate     SE    df t.ratio p.value
##  ambient 2015 - warmed 2015   0.00390 0.0950  26.2  0.041  1.0000
##  ambient 2015 - ambient 2016 -0.02162 0.0489 150.3 -0.442  1.0000
##  ambient 2015 - warmed 2016  -0.01772 0.1069  42.2 -0.166  1.0000
##  ambient 2015 - ambient 2017 -0.07381 0.0489 150.3 -1.508  0.9642
##  ambient 2015 - warmed 2017  -0.06992 0.1069  42.2 -0.654  1.0000
##  ambient 2015 - ambient 2018 -0.06773 0.0489 150.3 -1.384  0.9824
##  ambient 2015 - warmed 2018  -0.06383 0.1069  42.2 -0.597  1.0000
##  ambient 2015 - ambient 2019 -0.10478 0.0489 150.3 -2.141  0.6718
##  ambient 2015 - warmed 2019  -0.10088 0.1069  42.2 -0.944  0.9994
```

```
##  ambient 2015 - ambient 2020 -0.16421 0.0489 150.3 -3.356  0.0585
##  ambient 2015 - warmed 2020  -0.16031 0.1069  42.2 -1.500  0.9601
##  ambient 2015 - ambient 2021  0.00862 0.0489 150.3  0.176  1.0000
##  ambient 2015 - warmed 2021   0.01252 0.1069  42.2  0.117  1.0000
##  warmed 2015 - ambient 2016  -0.02552 0.1069  42.2 -0.239  1.0000
##  warmed 2015 - warmed 2016   -0.02162 0.0489 150.3 -0.442  1.0000
##  warmed 2015 - ambient 2017  -0.07771 0.1069  42.2 -0.727  1.0000
##  warmed 2015 - warmed 2017   -0.07381 0.0489 150.3 -1.508  0.9642
##  warmed 2015 - ambient 2018  -0.07163 0.1069  42.2 -0.670  1.0000
##  warmed 2015 - warmed 2018   -0.06773 0.0489 150.3 -1.384  0.9824
##  warmed 2015 - ambient 2019  -0.10868 0.1069  42.2 -1.017  0.9988
##  warmed 2015 - warmed 2019   -0.10478 0.0489 150.3 -2.141  0.6718
##  warmed 2015 - ambient 2020  -0.16811 0.1069  42.2 -1.573  0.9435
##  warmed 2015 - warmed 2020   -0.16421 0.0489 150.3 -3.356  0.0585
##  warmed 2015 - ambient 2021   0.00472 0.1069  42.2  0.044  1.0000
##  warmed 2015 - warmed 2021    0.00862 0.0489 150.3  0.176  1.0000
##  ambient 2016 - warmed 2016   0.00390 0.0950  26.2  0.041  1.0000
##  ambient 2016 - ambient 2017 -0.05220 0.0489 150.3 -1.067  0.9985
##  ambient 2016 - warmed 2017  -0.04830 0.1069  42.2 -0.452  1.0000
##  ambient 2016 - ambient 2018 -0.04612 0.0489 150.3 -0.942  0.9996
##  ambient 2016 - warmed 2018  -0.04222 0.1069  42.2 -0.395  1.0000
##  ambient 2016 - ambient 2019 -0.08316 0.0489 150.3 -1.699  0.9131
##  ambient 2016 - warmed 2019  -0.07926 0.1069  42.2 -0.742  1.0000
##  ambient 2016 - ambient 2020 -0.14259 0.0489 150.3 -2.914  0.1837
##  ambient 2016 - warmed 2020  -0.13869 0.1069  42.2 -1.298  0.9876
##  ambient 2016 - ambient 2021  0.03024 0.0489 150.3  0.618  1.0000
##  ambient 2016 - warmed 2021   0.03414 0.1069  42.2  0.320  1.0000
##  warmed 2016 - ambient 2017  -0.05610 0.1069  42.2 -0.525  1.0000
##  warmed 2016 - warmed 2017   -0.05220 0.0489 150.3 -1.067  0.9985
##  warmed 2016 - ambient 2018  -0.05002 0.1069  42.2 -0.468  1.0000
##  warmed 2016 - warmed 2018   -0.04612 0.0489 150.3 -0.942  0.9996
##  warmed 2016 - ambient 2019  -0.08706 0.1069  42.2 -0.815  0.9999
##  warmed 2016 - warmed 2019   -0.08316 0.0489 150.3 -1.699  0.9131
##  warmed 2016 - ambient 2020  -0.14649 0.1069  42.2 -1.371  0.9804
##  warmed 2016 - warmed 2020   -0.14259 0.0489 150.3 -2.914  0.1837
##  warmed 2016 - ambient 2021   0.02634 0.1069  42.2  0.247  1.0000
##  warmed 2016 - warmed 2021    0.03024 0.0489 150.3  0.618  1.0000
##  ambient 2017 - warmed 2017   0.00390 0.0950  26.2  0.041  1.0000
##  ambient 2017 - ambient 2018  0.00608 0.0489 150.3  0.124  1.0000
##  ambient 2017 - warmed 2018   0.00998 0.1069  42.2  0.093  1.0000
##  ambient 2017 - ambient 2019 -0.03097 0.0489 150.3 -0.633  1.0000
##  ambient 2017 - warmed 2019  -0.02707 0.1069  42.2 -0.253  1.0000
##  ambient 2017 - ambient 2020 -0.09039 0.0489 150.3 -1.847  0.8506
##  ambient 2017 - warmed 2020  -0.08649 0.1069  42.2 -0.809  0.9999
##  ambient 2017 - ambient 2021  0.08244 0.0489 150.3  1.685  0.9182
##  ambient 2017 - warmed 2021   0.08634 0.1069  42.2  0.808  0.9999
##  warmed 2017 - ambient 2018   0.00218 0.1069  42.2  0.020  1.0000
##  warmed 2017 - warmed 2018    0.00608 0.0489 150.3  0.124  1.0000
##  warmed 2017 - ambient 2019  -0.03487 0.1069  42.2 -0.326  1.0000
##  warmed 2017 - warmed 2019   -0.03097 0.0489 150.3 -0.633  1.0000
##  warmed 2017 - ambient 2020  -0.09429 0.1069  42.2 -0.882  0.9997
##  warmed 2017 - warmed 2020   -0.09039 0.0489 150.3 -1.847  0.8506
##  warmed 2017 - ambient 2021   0.07854 0.1069  42.2  0.735  1.0000
##  warmed 2017 - warmed 2021    0.08244 0.0489 150.3  1.685  0.9182
```

```
##  ambient 2018 - warmed 2018   0.00390 0.0950  26.2  0.041  1.0000
##  ambient 2018 - ambient 2019 -0.03705 0.0489 150.3 -0.757  1.0000
##  ambient 2018 - warmed 2019  -0.03315 0.1069  42.2 -0.310  1.0000
##  ambient 2018 - ambient 2020 -0.09648 0.0489 150.3 -1.971  0.7826
##  ambient 2018 - warmed 2020  -0.09258 0.1069  42.2 -0.866  0.9998
##  ambient 2018 - ambient 2021  0.07636 0.0489 150.3  1.560  0.9533
##  ambient 2018 - warmed 2021   0.08026 0.1069  42.2  0.751  1.0000
##  warmed 2018 - ambient 2019  -0.04095 0.1069  42.2 -0.383  1.0000
##  warmed 2018 - warmed 2019   -0.03705 0.0489 150.3 -0.757  1.0000
##  warmed 2018 - ambient 2020  -0.10038 0.1069  42.2 -0.939  0.9994
##  warmed 2018 - warmed 2020   -0.09648 0.0489 150.3 -1.971  0.7826
##  warmed 2018 - ambient 2021   0.07246 0.1069  42.2  0.678  1.0000
##  warmed 2018 - warmed 2021    0.07636 0.0489 150.3  1.560  0.9533
##  ambient 2019 - warmed 2019   0.00390 0.0950  26.2  0.041  1.0000
##  ambient 2019 - ambient 2020 -0.05943 0.0489 150.3 -1.214  0.9946
##  ambient 2019 - warmed 2020  -0.05553 0.1069  42.2 -0.520  1.0000
##  ambient 2019 - ambient 2021  0.11340 0.0489 150.3  2.317  0.5450
##  ambient 2019 - warmed 2021   0.11730 0.1069  42.2  1.098  0.9973
##  warmed 2019 - ambient 2020  -0.06333 0.1069  42.2 -0.593  1.0000
##  warmed 2019 - warmed 2020   -0.05943 0.0489 150.3 -1.214  0.9946
##  warmed 2019 - ambient 2021   0.10950 0.1069  42.2  1.025  0.9987
##  warmed 2019 - warmed 2021    0.11340 0.0489 150.3  2.317  0.5450
##  ambient 2020 - warmed 2020   0.00390 0.0950  26.2  0.041  1.0000
##  ambient 2020 - ambient 2021  0.17283 0.0489 150.3  3.532  0.0346
##  ambient 2020 - warmed 2021   0.17673 0.1069  42.2  1.654  0.9202
##  warmed 2020 - ambient 2021   0.16893 0.1069  42.2  1.581  0.9415
##  warmed 2020 - warmed 2021    0.17283 0.0489 150.3  3.532  0.0346
##  ambient 2021 - warmed 2021   0.00390 0.0950  26.2  0.041  1.0000
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 14 estimates
```

Code below is a function written by Pat but unsuccessfully subsets sites so you get the same values for both kbs and umbs - above is a clumsy fix by Moriah (no function)

```r
#' function to calculate annual diversity index for a specific site
#'
#' after reading a comp file, this function should do all that's needed to prep it and
#' run the diversity function on for each year.  diversity indexes are for the year only,
#' the diversity indexes use total abundances for a year,  do not sum/count/pool abundances in other ye
#'
#' @param comp plant composition data as read from project folder
#' @param site one of kbs or umbs as coded in the comp data
#' @param div_index is the same as 'index' for vegan::diversity function 'shannon', 'simpson' or 'invsi
#'
#' @returns a matrix (data frame) of diversity indices for one site with years in the columns, and plot
#'
diversity_by_year <- function(comp, site, div_index = "shannon") {
    comp_site <- subset(comp, site == site) %>% dplyr::select(plot, species, cover,
        year)

    # remove non-species using 'not in' obs_to_exclude = c('Bare_Ground',
    # 'Unknown','Brown','Litter', 'Vert_Litter', 'Animal_Disturbance') comp_site
```

```r
    # <-dplyr::filter(comp_site, !(species %in% obs_to_exclude))

    # convert the abundance data to abundance for each species in columns for the
    # vegan package
    comp_wide <- matrify2(comp_site)

    # comp_wide_data is assumes to have columns Year, Plot, and columns for each
    # species found, e.g. for Vegan

    # first, split up the wide data into a list of years.  Each list item is a year
    # of data
    comp_wide_by_year <- dplyr::group_by(comp_wide, Year) %>% dplyr::group_split()

    # we need to add plot names.  Get those Plot names by taking a column from any
    # one of the years since we are assuming the Plot column is the exact same across
    # years and IN THE SAME ORDER
    plot_names <- comp_wide_by_year[[1]]$Plot

    # remove the plot and year columns from each item in the list so that Vegan will
    # work.  This assumes row order is the exact same for all years (each row a plot)
    comp_wide_by_year <- lapply(comp_wide_by_year, dplyr::select, c(-Year, -Plot))

    # apply the diversity function to each year - in this case the main index is
    # plot, each year considered separately
    diversity_by_year_list <- lapply(comp_wide_by_year, vegan::diversity, index = div_index)

    # each item in the list is a year of diversity, so name those with the years we
    # know we have
    names(diversity_by_year_list) <- as.character(2015:2021)

    # 'unlist' and create a new data frame, each year a column, each row a plot, and
    # add a new row with the plot names
    x <- do.call(cbind, diversity_by_year_list) %>% cbind(Plot = plot_names) %>%
        as.data.frame()
    # an alternative tidyverse way x<- diversity_by_year(diversity_by_year_list)

    ## optional step!
    return(x)
}

comp$cover <- as.numeric(comp$cover)

# use the one function above to both matrify and calculate Shannon diversity
# index per year
diversity_by_year_kbs <- diversity_by_year(comp, site = "kbs", div_index = "shannon")
diversity_by_year_umbs <- diversity_by_year(comp, site = "umbs", div_index = "shannon")

# this output has a column for each year 2015, 2016, and Plot, but if you need it
# narrow use 'melt' from reshape2:
library(reshape2)
diversity_by_plot_year_kbs <- reshape2::melt(diversity_by_year_kbs, id = "Plot",
    variable.name = c("Year"), value.name = "shannon")
diversity_by_plot_year_umbs <- reshape2::melt(diversity_by_year_umbs, id = "Plot",
```

```r
    variable.name = c("Year"), value.name = "shannon")

# To do just August (peak_comp):

peak_comp <- dplyr::filter(comp, month == 8)

peak_shannon_by_year_kbs <- diversity_by_year(peak_comp, site = "kbs", div_index = "shannon")
peak_shannon_by_year_umbs <- diversity_by_year(peak_comp, site = "umbs", div_index = "shannon")

peak_simpson_by_year_kbs <- diversity_by_year(peak_comp, site = "kbs", div_index = "simpson")
peak_simpson_by_year_umbs <- diversity_by_year(peak_comp, site = "umbs", div_index = "simpson")

# this output has a column for each year 2015, 2016, and Plot, but if you need it
# narrow use 'melt' from reshape2:
peak_shannon_by_plot_year_kbs <- reshape2::melt(peak_shannon_by_year_kbs, id = "Plot",
    variable.name = c("Year"), value.name = "shannon")
peak_shannon_by_plot_year_umbs <- reshape2::melt(peak_shannon_by_year_umbs, id = "Plot",
    variable.name = c("Year"), value.name = "shannon")

# this output has a column for each year 2015, 2016, and Plot, but if you need it
# narrow use 'melt' from reshape2:
peak_simpson_by_plot_year_kbs <- reshape2::melt(peak_simpson_by_year_kbs, id = "Plot",
    variable.name = c("Year"), value.name = "simpson")
peak_simpson_by_plot_year_umbs <- reshape2::melt(peak_simpson_by_year_umbs, id = "Plot",
    variable.name = c("Year"), value.name = "simpson")

diversity_kbs <- left_join(peak_shannon_by_plot_year_kbs, peak_simpson_by_plot_year_kbs)
diversity_kbs$site <- "kbs"  #add site column

diversity_umbs <- left_join(peak_shannon_by_plot_year_umbs, peak_simpson_by_plot_year_umbs)
diversity_umbs$site <- "umbs"  #add site column
```