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
library(knitr)

# 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"
```

```
# 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"), ]

# select peak biomass dates - for this I'm choosing August % cover date
peak_comp <- dplyr::filter(comp, month %in% c(8))

# 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

```
# 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 emp
    plt.list <- rep(plt.codes,length(yrs.codes))##Create a list of all the plot numbers (in order of in
    yrs.list <- rep(yrs.codes,each=length(plt.codes))##Create a list of all the Year numbers (in order 
    col <- match(spc, spc.codes)##object that determines the alphabetical order ranking of each SPEC in
    row.plt <- match(plt, plt.codes)##object that determines the rank order ranking of each plot of the
    row.yrs <- match(yrs,yrs.codes)##object that determines the rank order ranking of each Year of the 
    for (i in 1:length(abu)) {
        row <- (row.plt[i])+length(plt.codes)*(row.yrs[i]-1)##Determine row number by assuming each row
        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 the 
        }
    }
    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 represe
    names(taxa) <- c('Year','Plot',spc.codes)
    taxa
}
```

Calculating Shannon and Simpsons Diversity and Species Richness

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

```
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 ye
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 consider
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(2016:2021)
names(simpson_by_year_list_kbs) <- as.character(2015:2021)
names(simpson_by_year_list_umbs) <- as.character(2016:2021)
names(richness_by_year_list_kbs) <- as.character(2015:2021)
names(richness_by_year_list_umbs) <- as.character(2016:2021)
```

```r
# "unlist" and create a new data frame, each year a column, each row a plot, and add a new row with the
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.fra
#  an alternative tidyverse way x<- diversity_by_year(diversity_by_year_list)

## optional step!
shannon_kbs
```

```
##                2015               2016              2017              2018
## 1  1.48714183816761   1.7886786650152  1.12695924834029  1.51985273633153
## 2  1.62182756494049  1.50022327674727  1.06400562502073  1.13577314513968
## 3  1.76874791073199  1.70797734396608 0.950971964086859  1.58152809040125
## 4  1.69062544074028  1.50634538868553 0.304636097349238 0.793857408010338
## 5  1.77274703306201  1.41264180804036  1.05234498645549  1.32942443928456
## 6  1.54206911993697  1.38808083951554 0.800045853053124  1.55455566912716
## 7  1.46447128705238  1.54227874866632 0.607860991840969  1.27602463227692
## 8  1.84948214267822  1.65918772823104   1.0726224355616  1.22669116245919
## 9  1.42262306389973  1.24641848286103 0.206192050633232  1.15515598671275
## 10 2.02656889401158  1.56775845004331 0.952167873059245  1.38248694547404
## 11 1.75480354234564  1.74795274193417 0.430300567447988 0.894854203046441
## 12 1.79910692554111 0.946661962609671 0.100436761357287 0.832490671379545
## 13 1.39883948378428  1.49646612341831 0.515704277154341   1.0748707547276
## 14 1.63519303281335   1.5378762155815 0.931882032436429  1.03919694706126
## 15 1.77184459818404  1.63748776596684 0.809571798876039  1.45818288178431
## 16  1.4246539472321  1.69283426320638 0.821876372750341  1.78572933422875
## 17 1.71253918106815  1.60736721856577 0.412554393097084  1.44146386314261
## 18  1.5487242779819  1.39174136582823 0.604534659804783  1.14176293008829
## 19 1.37818405037086  1.52809035680194 0.324424802499284   1.0845967382199
## 20 1.89294182977601  1.86594238102726  1.01356870859232  1.07406343274787
## 21 1.80253981827949  1.49989607439621 0.594024165582471  1.41982338164528
## 22 1.80825074404026  1.60255388457745 0.928404949504928  2.20155955534954
## 23 1.89935453773088  1.80587055819209 0.988927362608731  1.46133705387313
## 24 1.76732960701149  1.56020444814242 0.566776071301863  1.31646516088989
##                 2019              2020              2021 Plot
## 1   1.02356300027237 0.989932627439946 0.256860519098639   A1
## 2  0.730390006264756  1.19724362802389 0.485547208584167   A2
## 3  0.781637339243882 0.679822218984042 0.900050593172552   A3
## 4  0.691091135906884 0.878169227311687 0.223050952919035   A4
## 5   1.30096938419748  1.29073760005139 0.604422930915346   A5
## 6  0.995937393312417  1.00075277275958  1.10638333149865   A6
## 7  0.696582351540805 0.725524442492238 0.737509237392413   B1
## 8   0.70898665256545  1.07381199627739 0.176326264540061   B2
## 9   1.08160005555793  1.24315819349427 0.954189840760023   B3
## 10 0.927953957431102  1.41620088675748  1.40830029442056   B4
## 11 0.582271355243469  1.08737246700595   1.3740106195784   B5
## 12  1.13768990660815  1.36560878837414 0.781328812196672   B6
## 13  1.29273477358903  1.04206501262644  1.31951525670318   C1
## 14 0.560731574405335 0.958245976163955 0.390855872952205   C2
## 15 0.562446535914892                 0 0.599947621050843   C3
```

```
## 16  1.20405607981985  1.30246623684602 0.471660467695779   C4
## 17 0.686668594502021 0.934848740257604  1.18936237845111   C5
## 18  1.30293296480444  0.95357542653233  1.00541143412021   C6
## 19 0.876920063268514  1.73318400299949 0.966732695086683   D1
## 20  1.55810348426901                 0  1.04642966080439   D2
## 21  1.74492323277034  1.19701972017342  1.32016230500596   D3
## 22  1.98803994329177                 0  1.61987196387195   D4
## 23  1.84573662452729  2.32562534691052                 0   D5
## 24 0.931419451204098  1.55693710653775 0.780152332523009   D6
```

```
shannon_umbs
```

```
##                 2016              2017              2018              2019
## 1   1.31289084499164  1.59547116722798   1.8214877170674   1.8969082447089
## 2  0.910233729544386 0.791896801242128 0.870305827001272 0.650752381427209
## 3    0.8922918741233 0.918770779365289  1.04577984530793 0.786269404299992
## 4   1.29339809612243  1.42515145673387  1.17765236547455  0.93159649582878
## 5   1.65791868918507  1.48741465877146  1.81060716953942  1.32226079324541
## 6   1.03726220340722 0.831984237192845  1.02629074608417  1.38944635130092
## 7    0.82047026557996 0.804101127664309 0.741994928571576  1.26360563092826
## 8   1.32251010692748  1.33225256302437 0.973596578235699 0.808276130338727
## 9  0.993944679814011 0.663284935489549 0.978433998332865 0.733946818591263
## 10  0.35902424176608  1.05649414532508  1.35482879262509   1.4562746143372
## 11  1.16482137672446 0.673011667009257 0.685782896004546 0.691416077617118
## 12  1.33799778544805  1.31963894497645  1.26083573130951  1.52535561476622
## 13 0.756324320548944 0.898137003187868  1.14588668027251 0.980848953832705
## 14 0.983443005028768  1.13438367819395  1.64329102988064  1.59874430102613
## 15  1.21477987655929  1.52749562513349  1.39838534592216  1.41009265147966
## 16 0.950456078545709 0.905524100080506  1.62522450341299  1.55662716428163
## 17 0.464276819309739 0.846365829626287  1.14489612453776  1.32187465985747
## 18  1.10185115636325 0.934769897858279  1.16520530372479  1.33635625113969
## 19 0.800868199307521  1.31104628216132  1.33269027319047  1.45316055049158
## 20  1.17165524062191  1.27589387825919  1.47215709931272  1.52399346126881
## 21  1.16903780876511  1.77780642228417  1.82884461242772  1.60806677045541
## 22 0.400537930802524  0.86415020319497  1.64632664826071  1.51522098517663
## 23 0.849854787640237 0.940691180657543  1.00211377698415  0.57758250887089
## 24 0.798172242701068 0.876604302054336  1.17458112610055  1.28001209599995
##                 2020              2021 Plot
## 1    1.8214182047633   1.5707810728711   A1
## 2   1.17425489194578  1.29390776797201   A2
## 3    1.0434765968831 0.630927130539433   A3
## 4    1.3388789657916  1.56706506446278   A4
## 5   1.56717272314092  1.32093159510695   A5
## 6   1.16722263278353 0.959948949395338   A6
## 7   1.68500416373244  1.80432288067321   B1
## 8  0.883978293733624 0.567468518062428   B2
## 9  0.888159881581725 0.881011381917933   B3
## 10  1.13350897189075   1.2038172622238   B4
## 11 0.831208340348334 0.870359382954959   B5
## 12  1.44425210521721  1.46666216458813   B6
## 13  1.55102676152733  1.50848730662435   C1
## 14   1.7047877033749  1.40218812312872   C2
## 15  1.57149220070316  1.41430760573461   C3
## 16  1.37907689527751  1.52977663157557   C4
```

```
## 17 0.910511041237768  1.11251215188366   C5
## 18  1.56538163494307  1.38941023272311   C6
## 19  1.72714274030891  1.55177657956432   D1
## 20  1.65673456354735  1.74877541829721   D2
## 21  1.39411430485255  1.33213079368626   D3
## 22  1.66952029631328  1.17838146868797   D4
## 23 0.960546628300725 0.890584046199421   D5
## 24  1.23049375213249  1.32891572908175   D6
```

```
simpson_kbs
```

```
##                 2015              2016               2017              2018
## 1  0.683204994797086 0.793058984910837  0.529407157960686 0.729467455621302
## 2   0.73805660717505 0.731524348422496  0.594954648526077 0.610855431368252
## 3  0.751873648206831 0.757786153540964            0.42375 0.730728838479311
## 4  0.761022927689594  0.71571963739312  0.165289256198347   0.4336273780423
## 5  0.797659194604245 0.698595935461355  0.494461327320851 0.688780722312361
## 6  0.705714285714286 0.706945889698231  0.399092970521542 0.727861606462429
## 7  0.697819911264324 0.741418488206077  0.354191263282172 0.652882797731569
## 8   0.81998338673312 0.740352166794748  0.603448275862069 0.685544539176729
## 9  0.628808364881918 0.587531887755102 0.0997229916897509           0.54848
## 10 0.841797476146507 0.742859835988312  0.528946272386506 0.622610949141561
## 11 0.775848765432099  0.76125845496618  0.192239231043076 0.529298036882808
## 12 0.808561236623068 0.553011908891201 0.0403868636411946 0.399743604685042
## 13 0.695652173913043 0.734492046124064  0.260261748958953   0.6313714951178
## 14 0.746446280991736    0.710842988924  0.452107988165681 0.547681660899654
## 15 0.792997421146598 0.729861495844875  0.377240972982072 0.689616428950407
## 16       0.697265625  0.76530612244898  0.379490639230899 0.789710677501165
## 17 0.731676627870399 0.727955939508924  0.177959183673469 0.678518518518519
## 18 0.743313609467456 0.678873934376799  0.293156478277586 0.544485275089281
## 19 0.668337379591197 0.709873858199217  0.146102365915732           0.56655
## 20  0.81979631344163 0.778785588309398  0.541605029585799 0.584539986633994
## 21  0.79983584692726 0.731252264219297  0.321995464852608 0.687928669410151
## 22  0.78140943877551  0.73692767950052  0.414818820984316 0.868977777777778
## 23 0.817262713143202 0.787171856732915  0.519239474875509 0.674066034102447
## 24 0.781835339872458 0.718836565096953  0.263236168947055 0.645328719723183
##                 2019              2020               2021 Plot
## 1  0.481512287334594 0.405664306538942 0.0931952662721894   A1
## 2  0.421412721893491 0.598714416896235  0.209902259253325   A2
## 3  0.344962620149519            0.2732  0.365416666666667   A3
## 4  0.384450566268748   0.4830322265625 0.0751150558842867   A4
## 5  0.688914868742693  0.68834302440568  0.366018905432269   A5
## 6  0.407210571674806 0.419188323246707  0.480971329456178   A6
## 7  0.465640623468287 0.455096184504198  0.456870910172516   B1
## 8  0.442329873125721 0.564172408267906 0.0683287165281625   B2
## 9  0.579940822365065  0.64416406345085  0.537708512804448   B3
## 10 0.385925925925926 0.599958350687214  0.587463017751479   B4
## 11 0.243023740108288 0.463950617283951  0.655104636374147   B5
## 12 0.605672923154617            0.6914  0.476743391844819   B6
## 13 0.598936899862826 0.455666372091066  0.662843649856637   C1
## 14 0.232255632010557          0.367104  0.176507936507937   C2
## 15 0.258258258258258                 1        0.255859375   C3
## 16 0.646115702479339           0.61888  0.227899550007258   C4
## 17 0.317492603550296 0.426610204221023        0.607734375   C5
```

```
## 18 0.674333113394288 0.533624280896647  0.560171658144631   C6
## 19   0.4669189453125 0.768404185125837  0.551783264746228   D1
## 20 0.757564969740121                 1  0.582325335448477   D2
## 21 0.747849705749208 0.517092789428325  0.568888888888889   D3
## 22 0.830680964414999                 1  0.763241285649615   D4
## 23 0.799286265432099 0.891090262805198                  1   D5
## 24 0.541992647751909 0.755463059313215  0.413365776369398   D6
```

```
simpson_umbs
```

```
##                 2016              2017              2018              2019
## 1           0.627072  0.71806500377929 0.816782668365846 0.797979797979798
## 2  0.566369900910417 0.457856399583767 0.509548611111111 0.296932205529605
## 3  0.544064307420841 0.520663243834694 0.589473684210526 0.413706223230033
## 4   0.70216049382716 0.701538461538461 0.628988850442137 0.419982698961938
## 5  0.779897876914808 0.671396683673469            0.8224 0.596836419753086
## 6    0.5535888671875 0.455986457371499 0.500192233756248 0.717231833910035
## 7  0.438456632653061 0.439899358818278 0.368333333333333 0.597079502433748
## 8  0.72147106544077 9 0.72562358276644 0.591715976331361 0.427427685950413
## 9  0.604419599965062 0.404521118381916 0.575680272108844 0.406064209274673
## 10 0.168662506324844  0.50734188923575 0.676515851031086 0.748021657642649
## 11             0.645              0.48 0.492653810835629 0.498269896193772
## 12 0.670553935860058 0.695064740101332 0.690058479532164 0.708333333333333
## 13 0.499807766243752 0.556213017751479 0.621913580246914 0.538781163434903
## 14 0.558842866535174 0.641771439294427  0.76701988677602 0.727110582639715
## 15            0.6316 0.734615793389308 0.664514785506039 0.683137029589199
## 16 0.561564281528051 0.547035382200217 0.771468144044321 0.737034331628926
## 17 0.214532871972318 0.525951557093426 0.607166337935569          0.718125
## 18  0.58083713548899 0.578512396694215 0.659582176065693 0.690541781450872
## 19 0.501821019771072 0.632777777777778 0.673008323424495              0.68
## 20 0.624933574237432 0.661625708884688 0.748711677875797 0.718933333333333
## 21 0.606938775510204 0.810650887573965 0.791578947368421 0.731190650109569
## 22 0.170578512396694 0.498866213151927 0.783631820074969 0.755918367346939
## 23 0.401228733459357 0.553571428571429  0.61095806550352 0.286482128460091
## 24           0.41125  0.52930056710775 0.633955555555556 0.686577777777778
##                 2020              2021 Plot
## 1  0.787232540074853 0.723856948845631   A1
## 2  0.619973433160246 0.699791883454735   A2
## 3  0.584812623274162 0.296006944444444   A3
## 4  0.680851063829787 0.752580989676041   A4
## 5  0.722321110715557 0.682630385487528   A5
## 6  0.604450544064307 0.563052672049212   A6
## 7  0.776119402985075 0.806189248165047   B1
## 8    0.5441435667361 0.273136094674556   B2
## 9          0.4609375               0.5   B3
## 10 0.625918924595673 0.683287165281625   B4
## 11 0.536716647443291 0.505540166204986   B5
## 12 0.722840236686391  0.71907281431091   B6
## 13 0.758333333333333            0.6942   C1
## 14 0.782283737024221 0.658934911242604   C2
## 15 0.715041572184429 0.725874663590927   C3
## 16  0.67168714493328         0.7490625   C4
## 17 0.523550295857988 0.627269490922036   C5
## 18            0.7816 0.714737144498707   C6
```

```
## 19 0.783737024221453 0.740591783970123   D1
## 20 0.791701804688818 0.802768166089965   D2
## 21 0.671077504725898 0.637571910335251   D3
## 22 0.780661284121492 0.587344510546241   D4
## 23 0.563327032136106 0.501890359168242   D5
## 24 0.678250266727633  0.70444736348283   D6
```

```
richness_kbs
```

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

```
richness_umbs
```

```
##    2016 2017 2018 2019 2020 2021 Plot
## 1     8    8    8   11   11    9   A1
## 2     3    3    4    6    5    4   A2
## 3     4    4    4    4    5    4   A3
## 4     4    6    4    7    5    6   A4
## 5     7    7    7    7    8    6   A5
## 6     4    4    5    6    7    5   A6
## 7     6    4    4    6    7    8   B1
## 8     4    4    3    5    3    4   B2
## 9     3    3    4    4    5    4   B3
## 10    3    6    5    5    4    4   B4
## 11    4    2    2    2    3    3   B5
## 12    5    5    4    7    6    6   B6
## 13    3    3    5    4    6    7   C1
## 14    4    4    7    8    8    7   C2
## 15    6    6    7    7    8    5   C3
```

```
## 16    4    4    6    7    6    6   C4
## 17    4    3    4    4    4    4   C5
## 18    4    3    4    5    5    5   C6
## 19    4    7    5    8    8    6   D1
## 20    5    5    5    8    7    7   D2
## 21    5    7    9    8    6    6   D3
## 22    4    3    6    6    7    5   D4
## 23    6    3    3    4    4    4   D5
## 24    4    3    4    5    4    5   D6
```

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

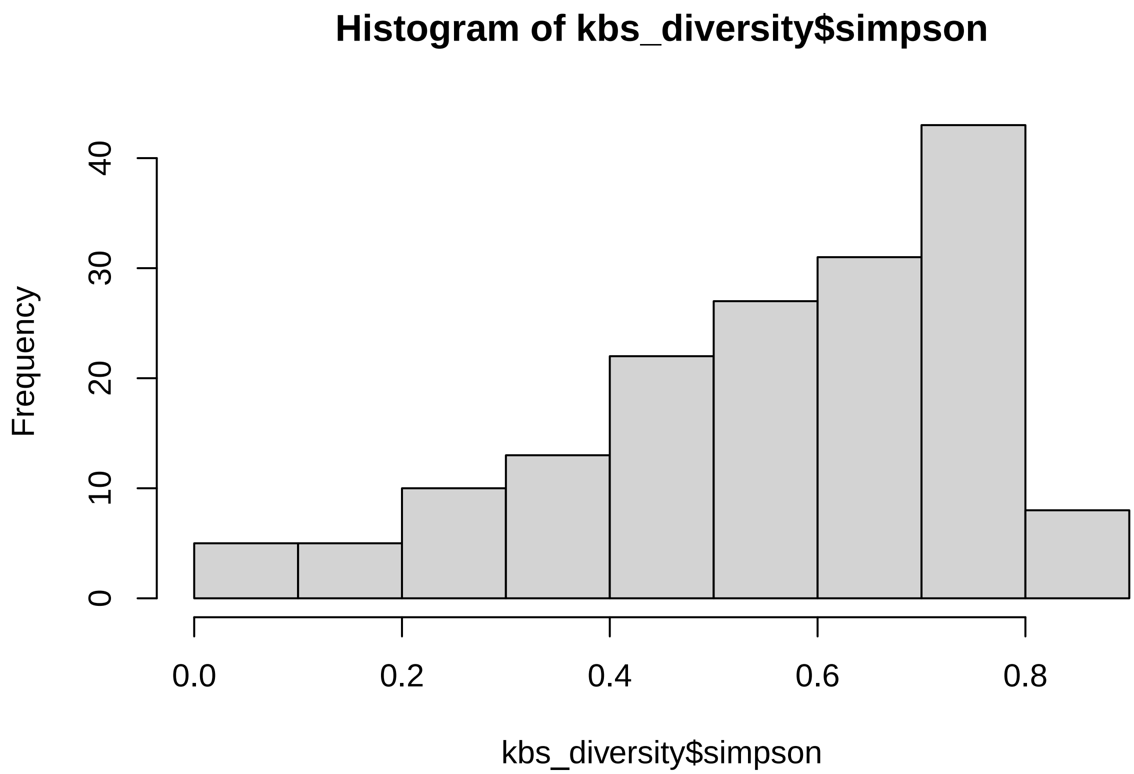
```
##
## Attaching package: 'reshape2'

## 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.n
shannon_by_plot_year_kbs$site <- "kbs" # adding site column
shannon_by_plot_year_umbs <- reshape2::melt(shannon_umbs, id =  "Plot", variable.name = c("Year"), valu
shannon_by_plot_year_umbs$site <- "umbs" # adding site column

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

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

#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", "Yea

#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", "ri

# 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 t
```

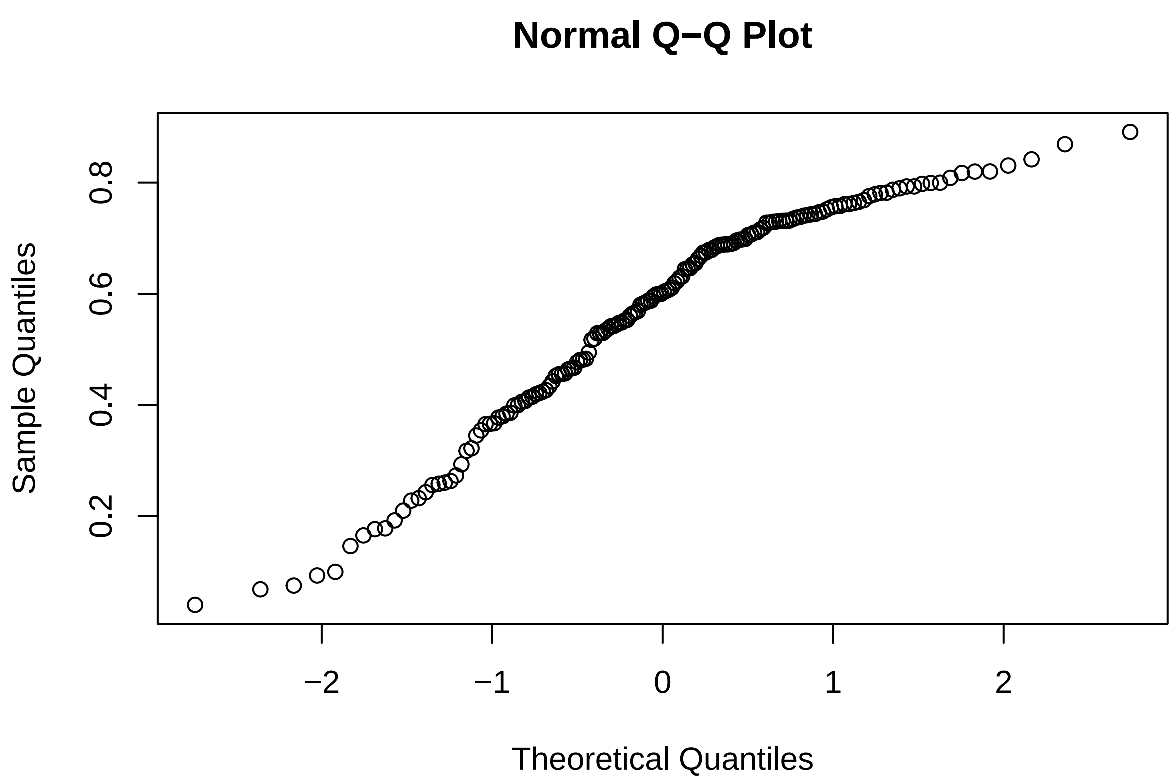
```r
# merge meta data with comp_diversity
comp_diversity <- full_join(comp_diversity, meta, by = "plot")

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 l
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", "i

comp_diversity <- comp_diversity[-c(135, 140, 142, 167),] # remove this row with zero values for shanno

# 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")
umbs_diversity <- subset(comp_diversity, site == "umbs")
```

Simpson's Index KBS

```r
### KBS ###
hist(kbs_diversity$simpson)
```



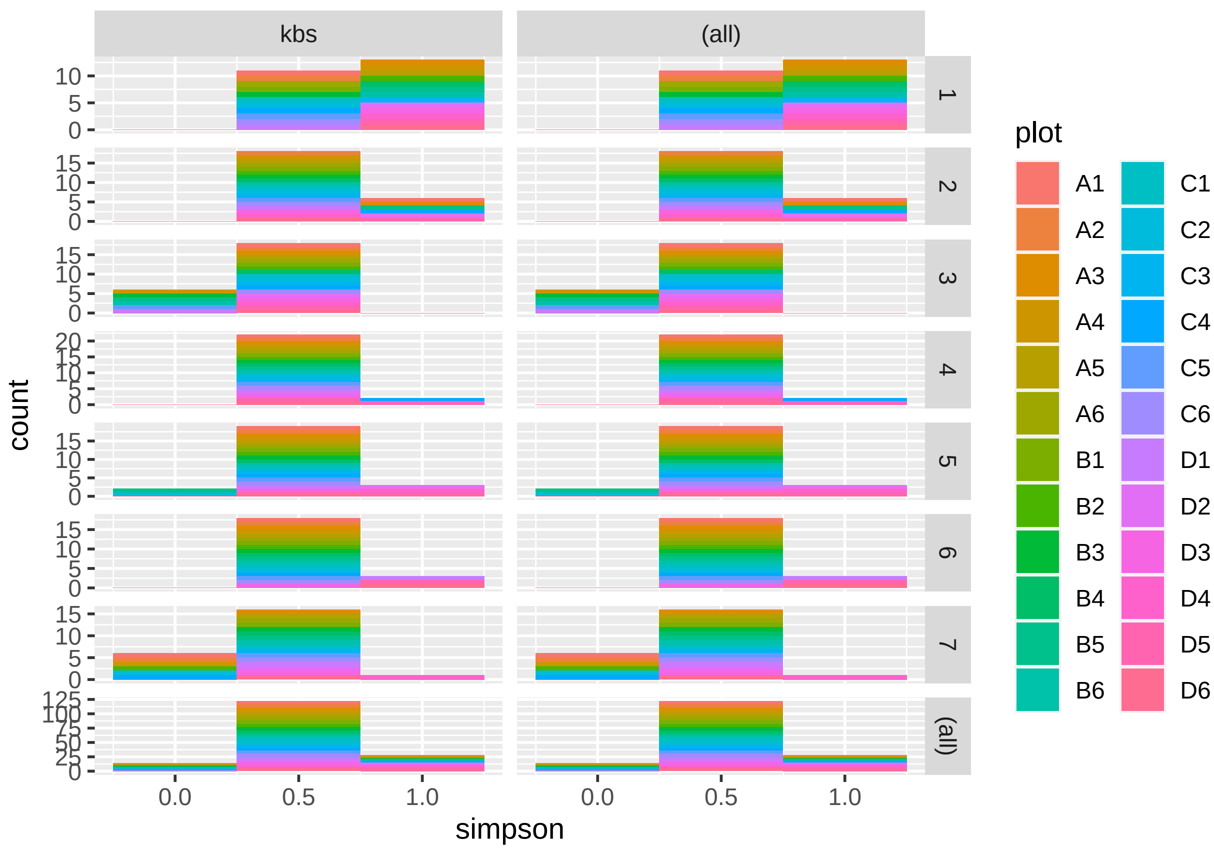

```
qqnorm(kbs_diversity$simpson)
```



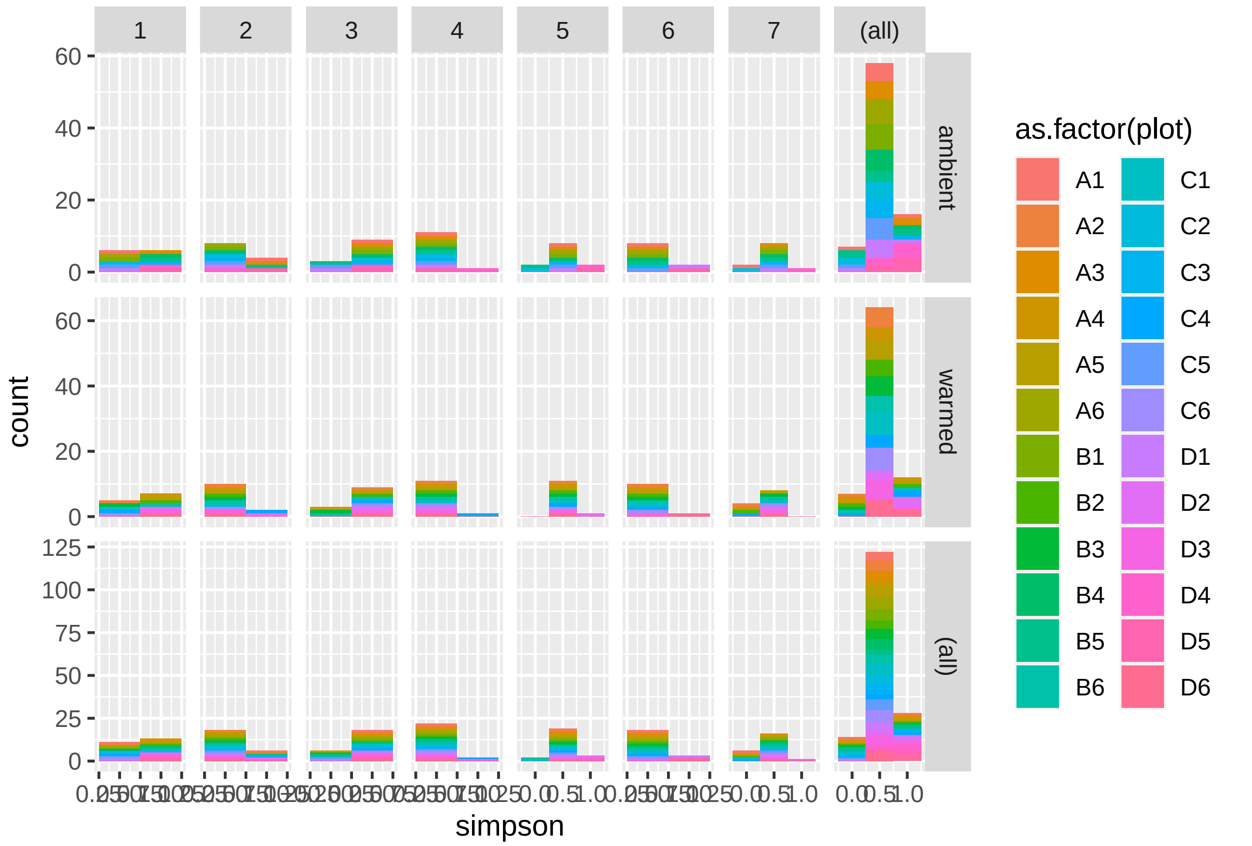
```
shapiro.test(kbs_diversity$simpson) # pvalue is < 0.05 so we reject the null hypothesis that the data i
```

```
##
##  Shapiro-Wilk normality test
##
## data:  kbs_diversity$simpson
## W = 0.93811, p-value = 1.496e-06
```

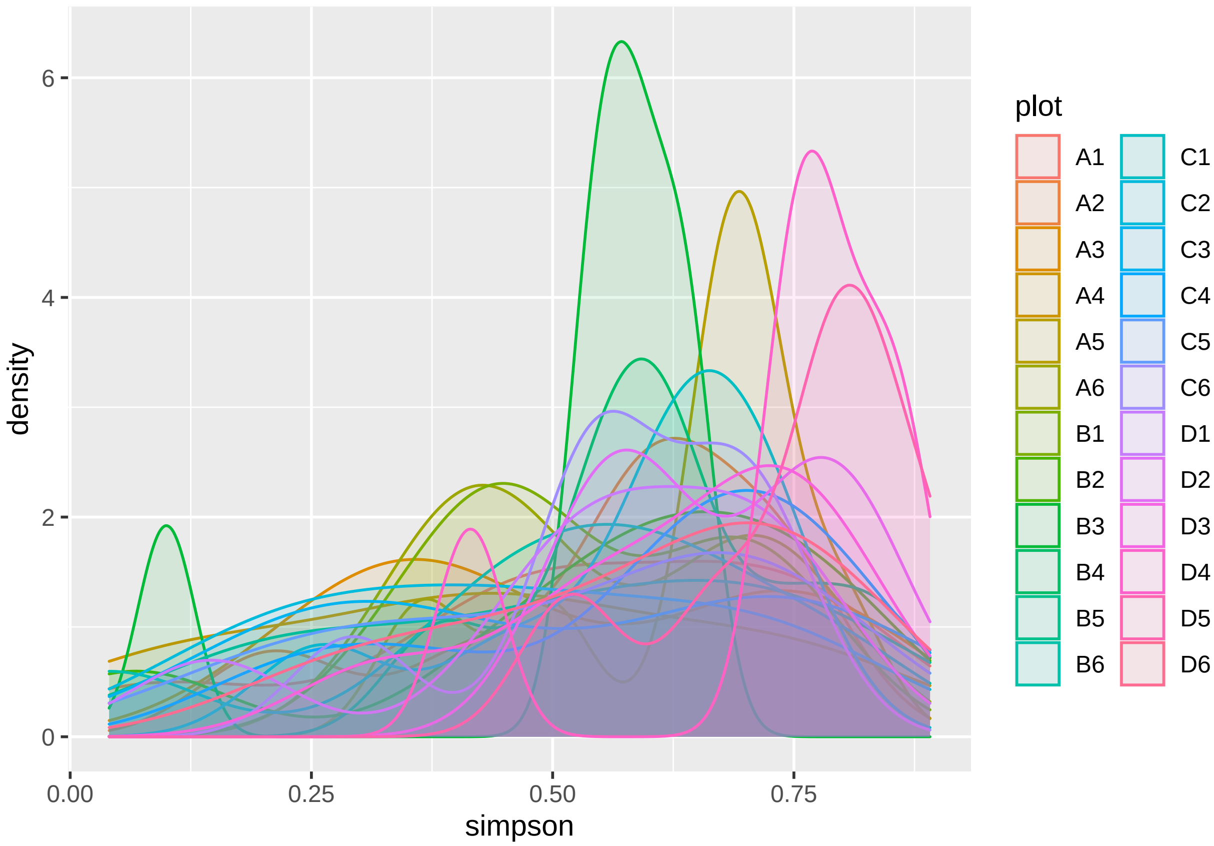
```
# Visualizing plot average totals for kbs at the PLOT LEVEL
ggplot(kbs_diversity, aes(simpson, fill = plot)) +
        geom_histogram(binwidth = 0.5) +
        facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



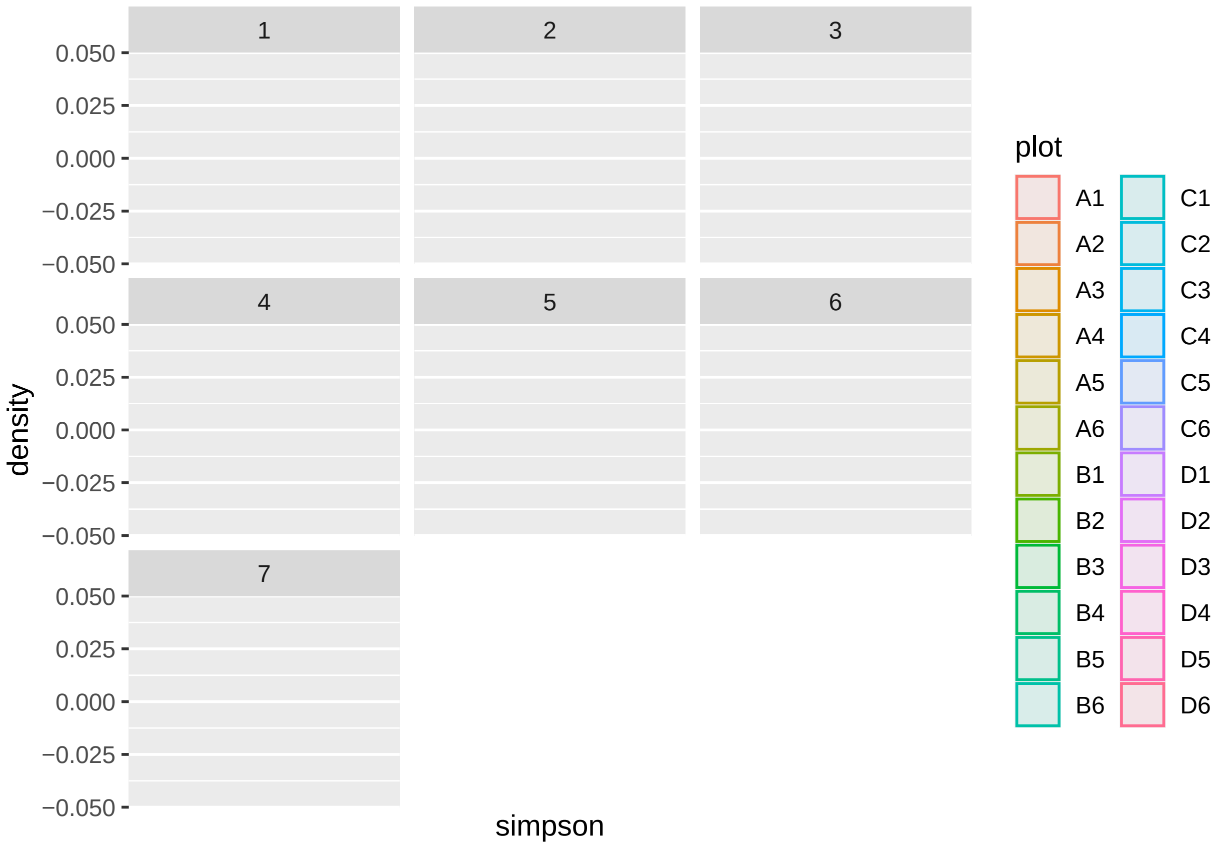

```
ggplot(kbs_diversity, aes(simpson, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
        facet_grid(state~year_factor, margins = TRUE, scales = "free")
```



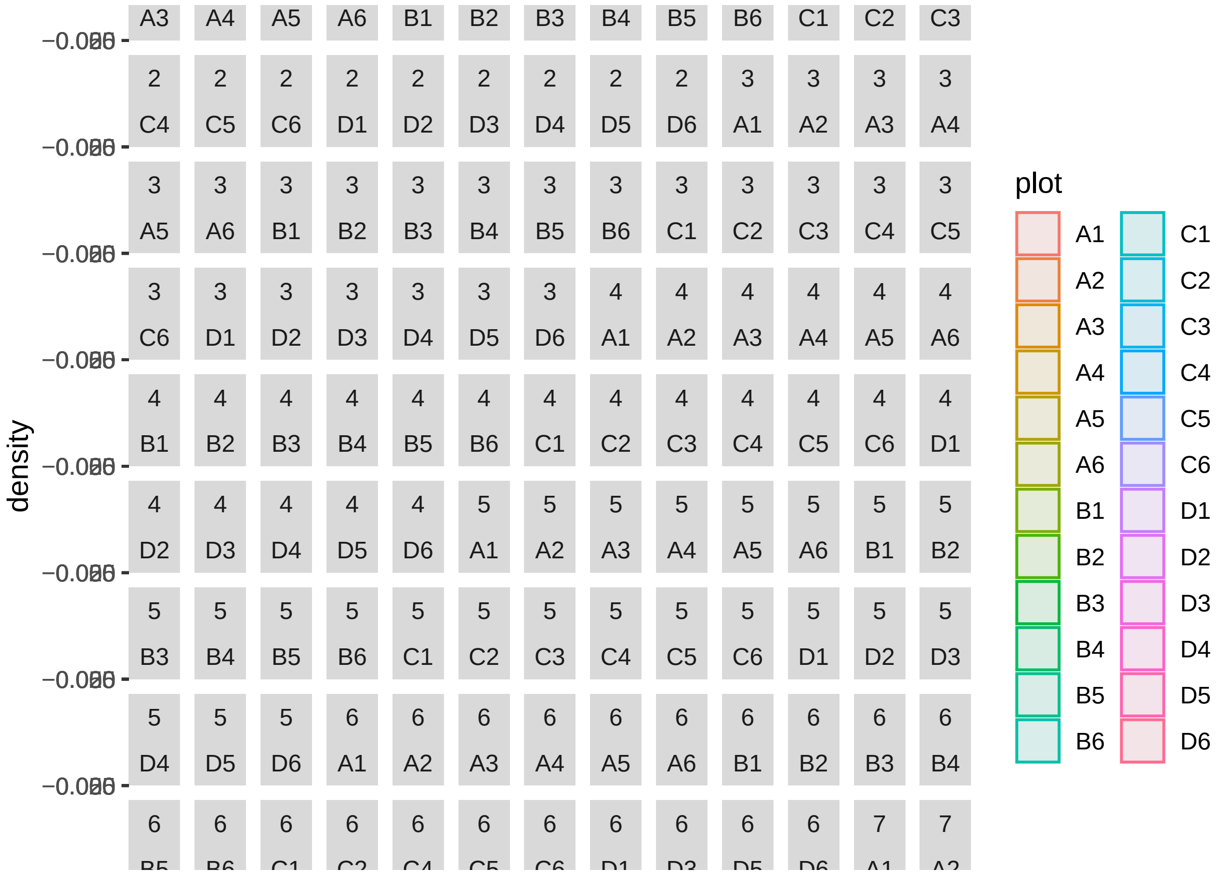

```
ggplot(kbs_diversity, aes(simpson, fill = plot, color=plot)) +
        geom_density(alpha = 0.1)
```



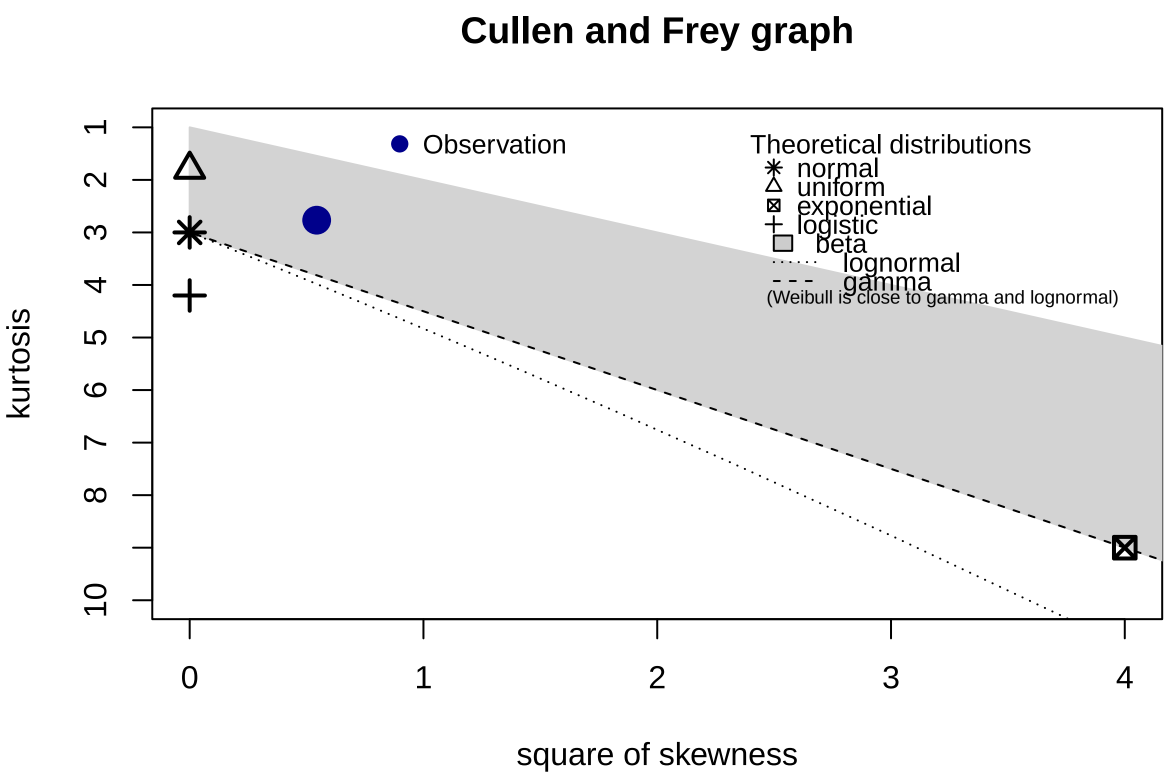

```
ggplot(kbs_diversity, aes(simpson, fill = plot, color=plot)) +
        geom_density(alpha = 0.1) +
        facet_wrap(~year_factor)
```




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

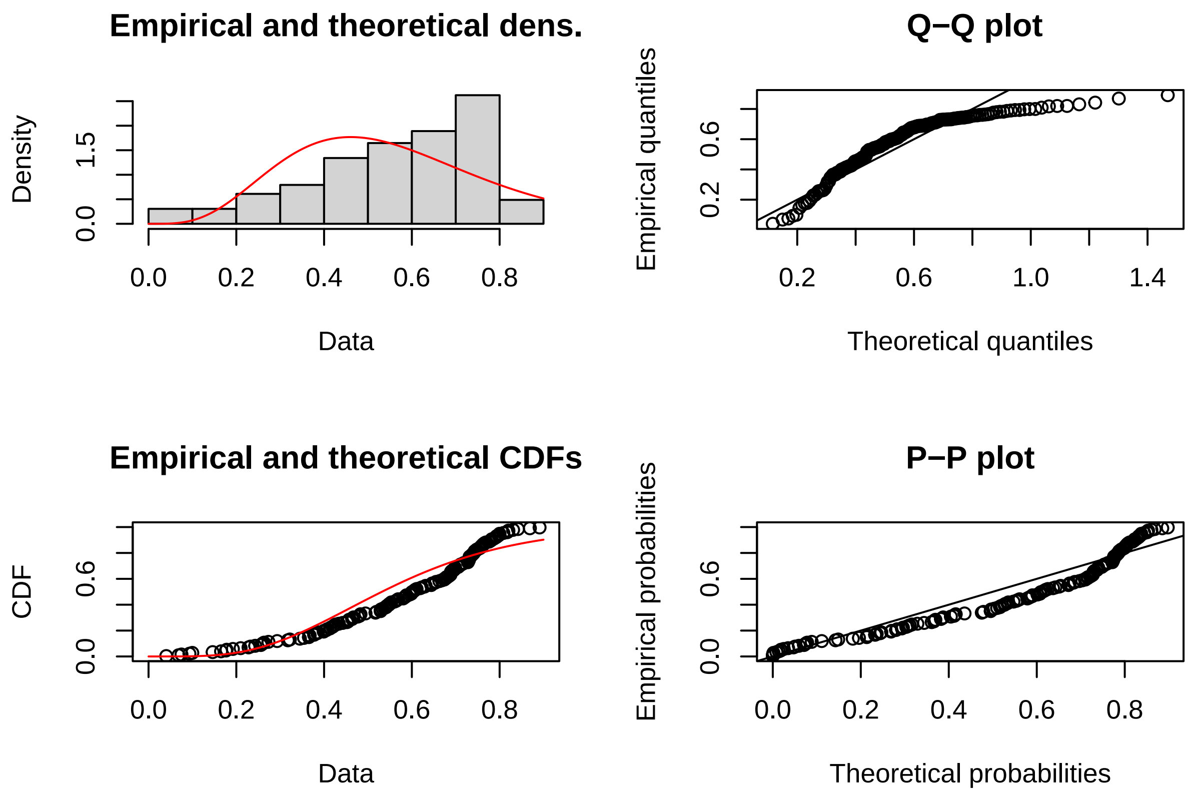



```
# Exploring distributions for these data:
descdist(kbs_diversity$simpson, discrete = FALSE)
```

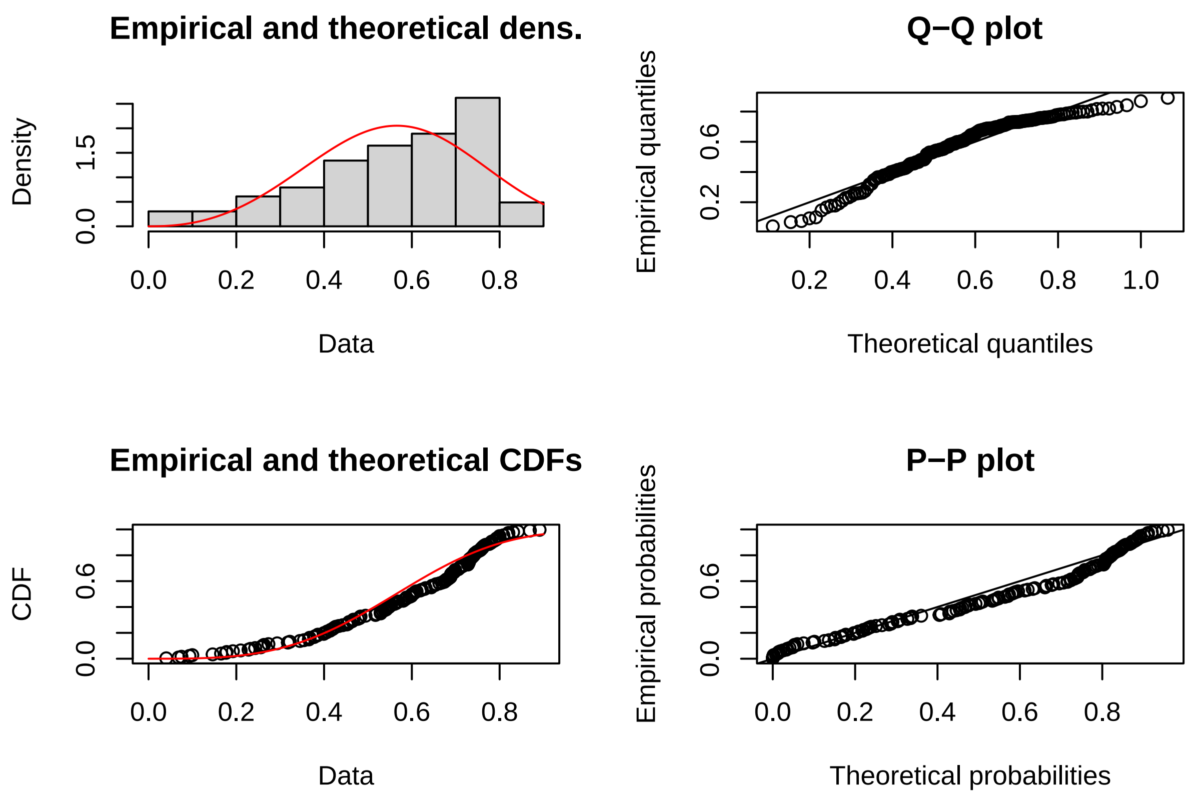



```
## summary statistics
## ------
## min:  0.04038686   max:  0.8910903
## median:  0.6017033
## mean:  0.5667997
## estimated sd:  0.1959864
## estimated skewness:  -0.7370631
## estimated kurtosis:  2.767029
```

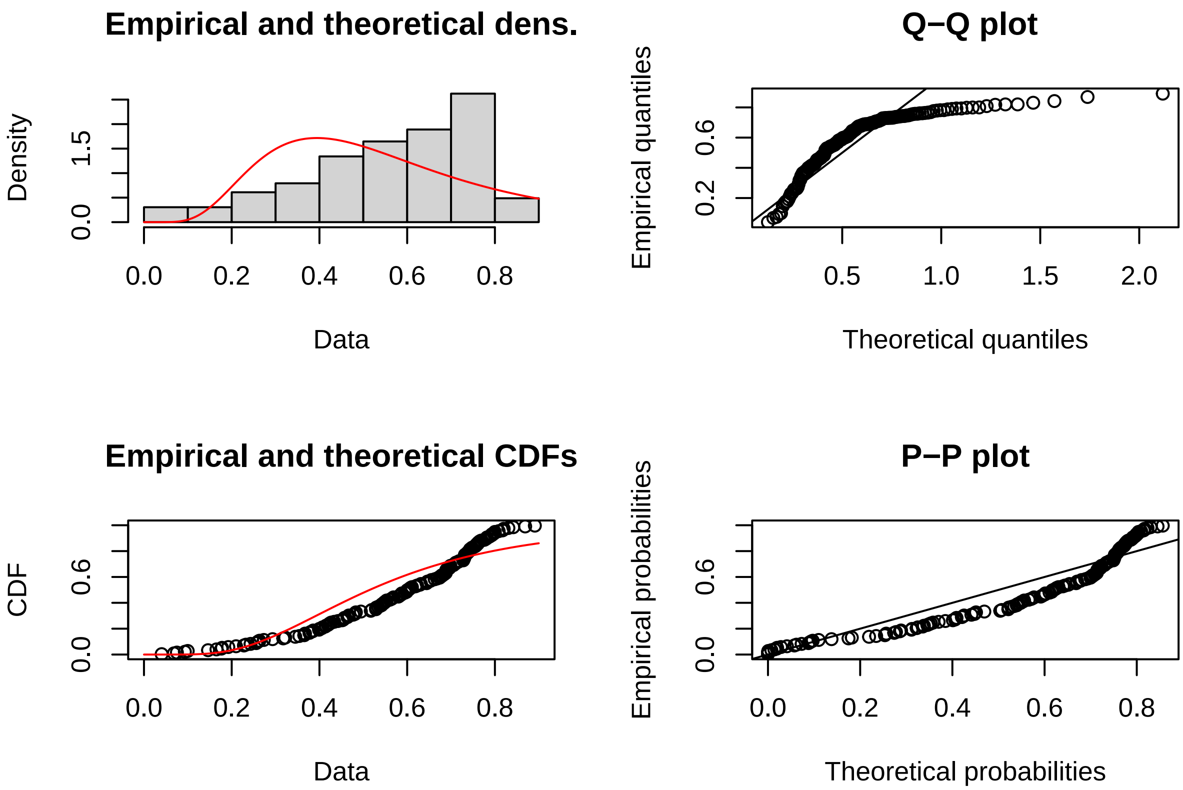
```
# Gamma distribution
fit.gamma <- fitdist(kbs_diversity$simpson, "gamma")
plot(fit.gamma)
```



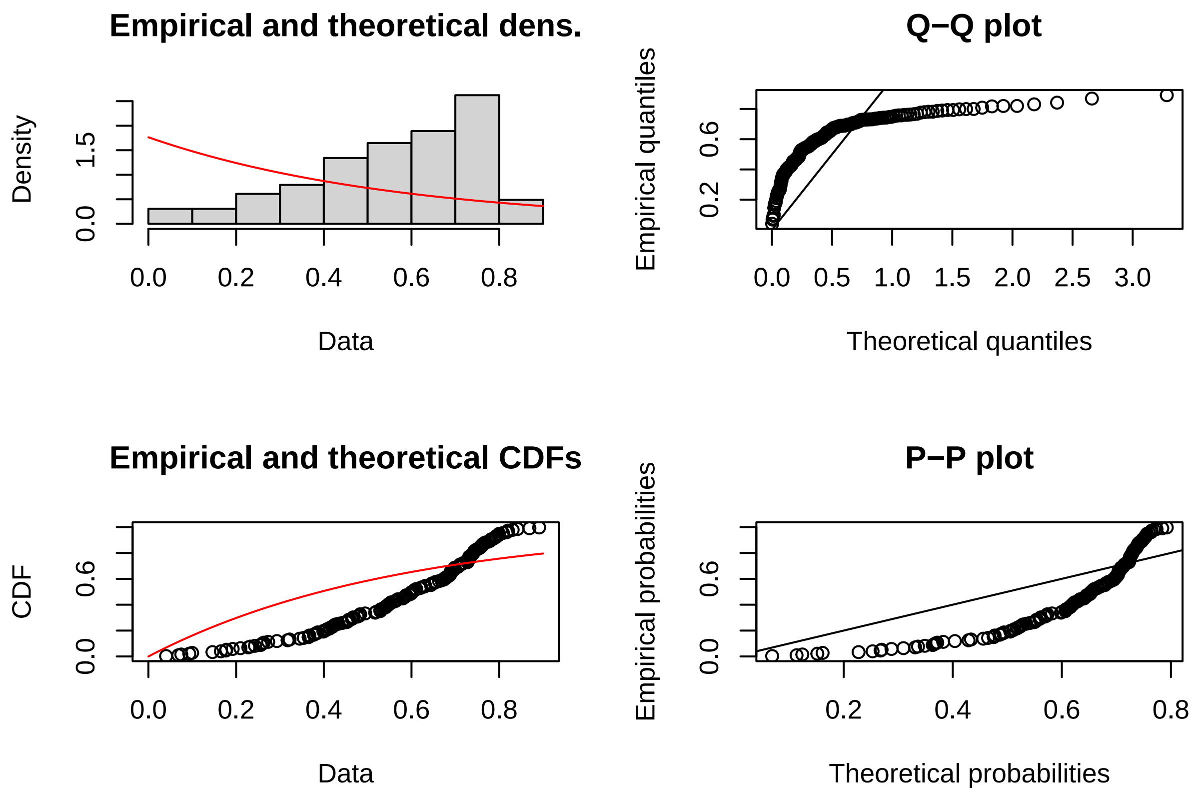

```
# Weibull distribution
fit.weibull  <- fitdist(kbs_diversity$simpson, "weibull")
plot(fit.weibull)
```



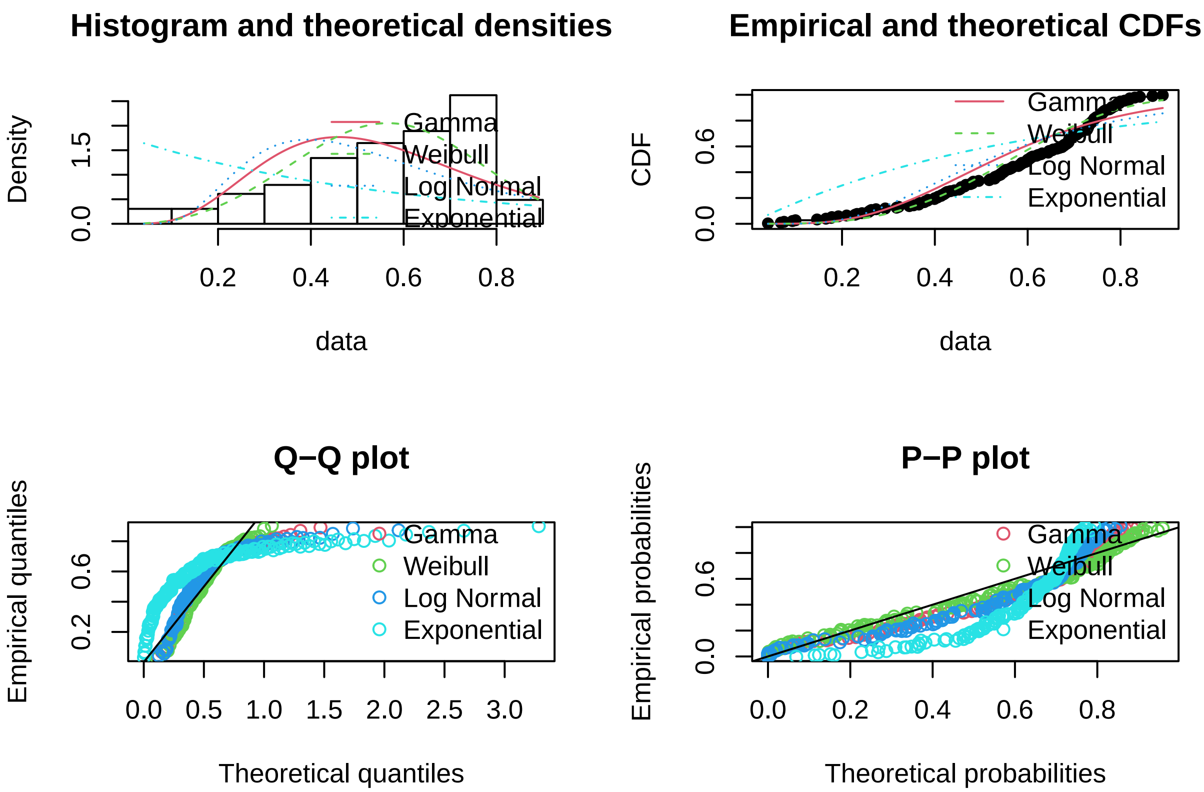
```r
# Lognormal distribution
fit.ln <- fitdist(kbs_diversity$simpson, "lnorm")
plot(fit.ln)
```




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




```
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)
```



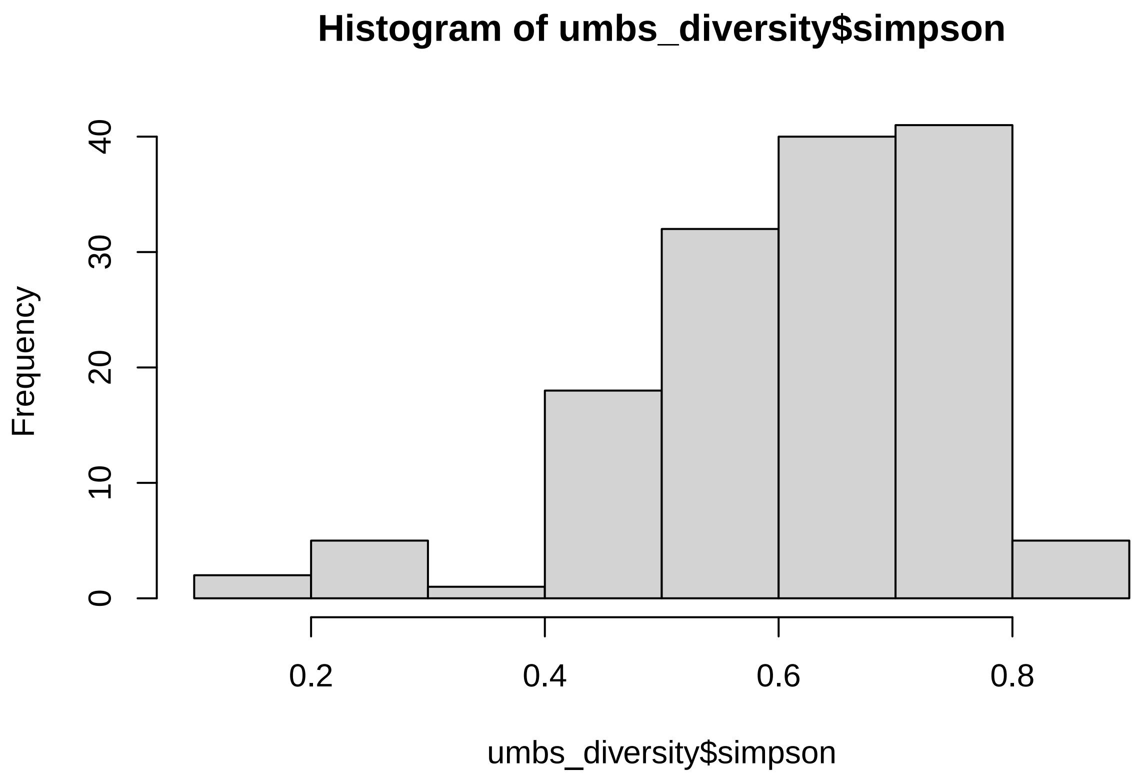

```r
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull", "Log Normal", "
```

```
## Goodness-of-fit statistics
##                                  Gamma   Weibull Log Normal        Exp
## Kolmogorov-Smirnov statistic 0.1476911 0.1242521  0.1738101  0.3288394
## Cramer-von Mises statistic   1.1995960 0.5733871  1.7445630  6.3304771
## Anderson-Darling statistic   7.1190544 3.8421868 10.1125013 31.3778151
##
## Goodness-of-fit criteria
##                                    Gamma   Weibull Log Normal      Exp
## Akaike's Information Criterion -12.667377 -60.83559   34.48901 143.7782
## Bayesian Information Criterion  -6.467644 -54.63586   40.68874 146.8781
```

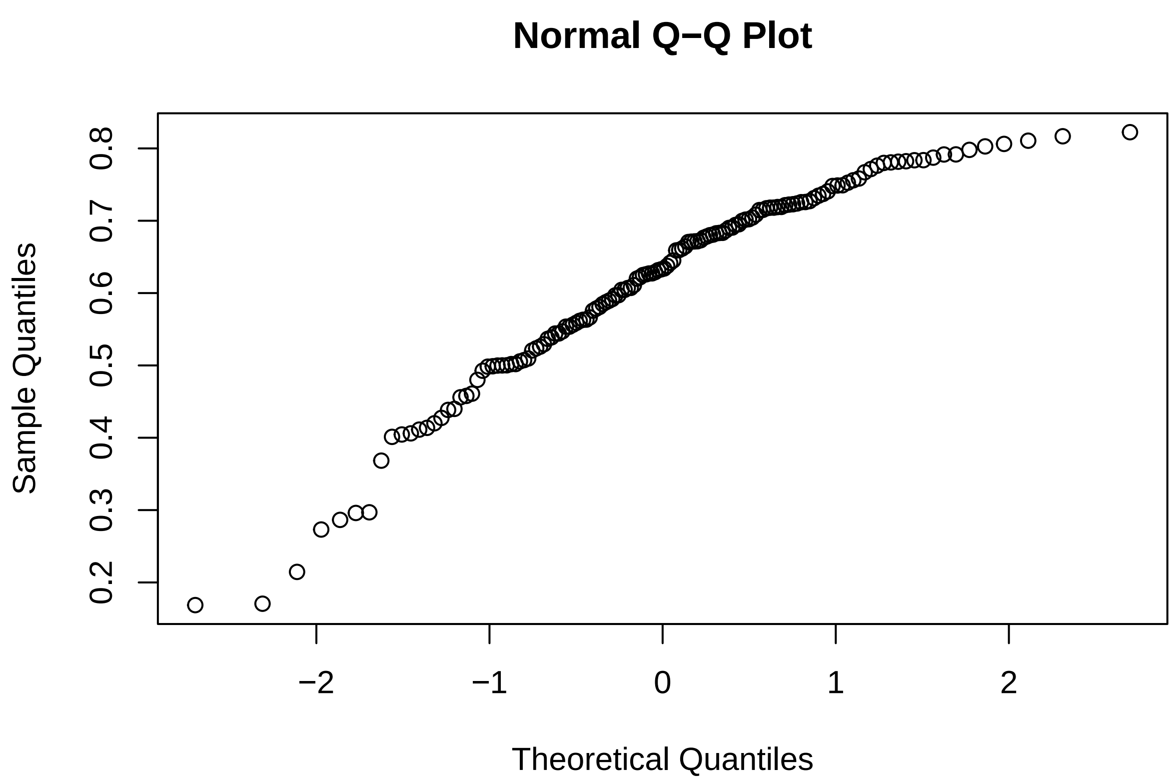
```r
# log normal distribution looks to be the best based on AIC and BIC values or would it be gamma? (close
```

UMBS

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



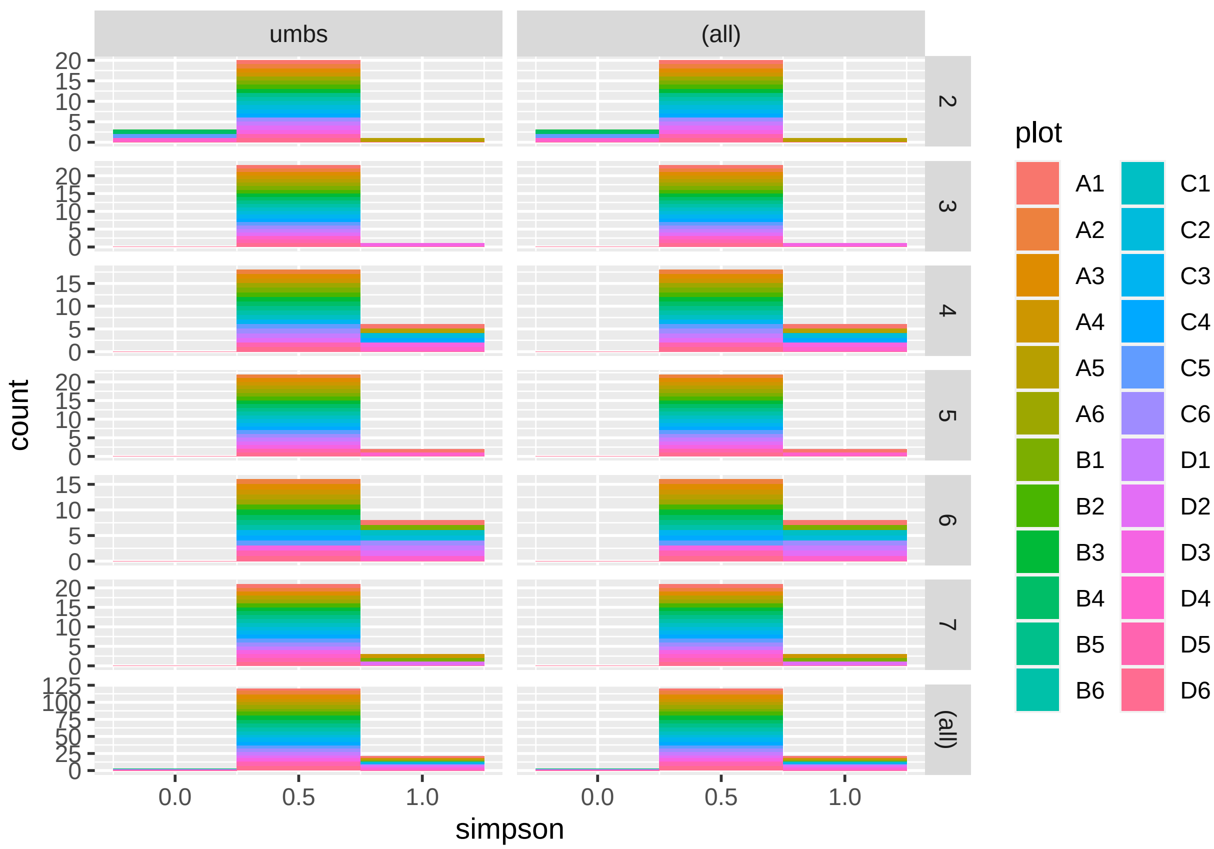

```
qqnorm(umbs_diversity$simpson)
```



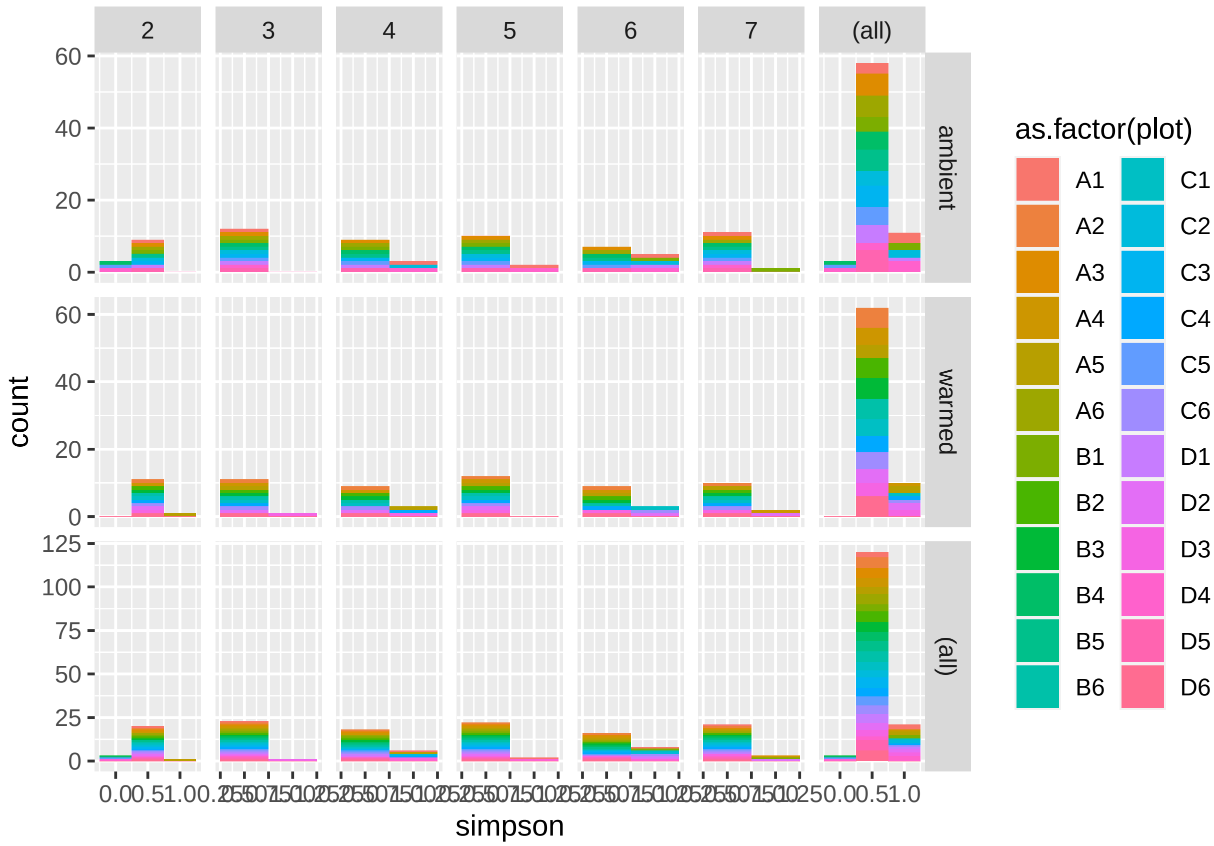
```r
shapiro.test(umbs_diversity$simpson) # pvalue is < 0.05 so we reject the null hypothesis that the data
```

```
##
##  Shapiro-Wilk normality test
##
## data:  umbs_diversity$simpson
## W = 0.93733, p-value = 5.042e-06
```

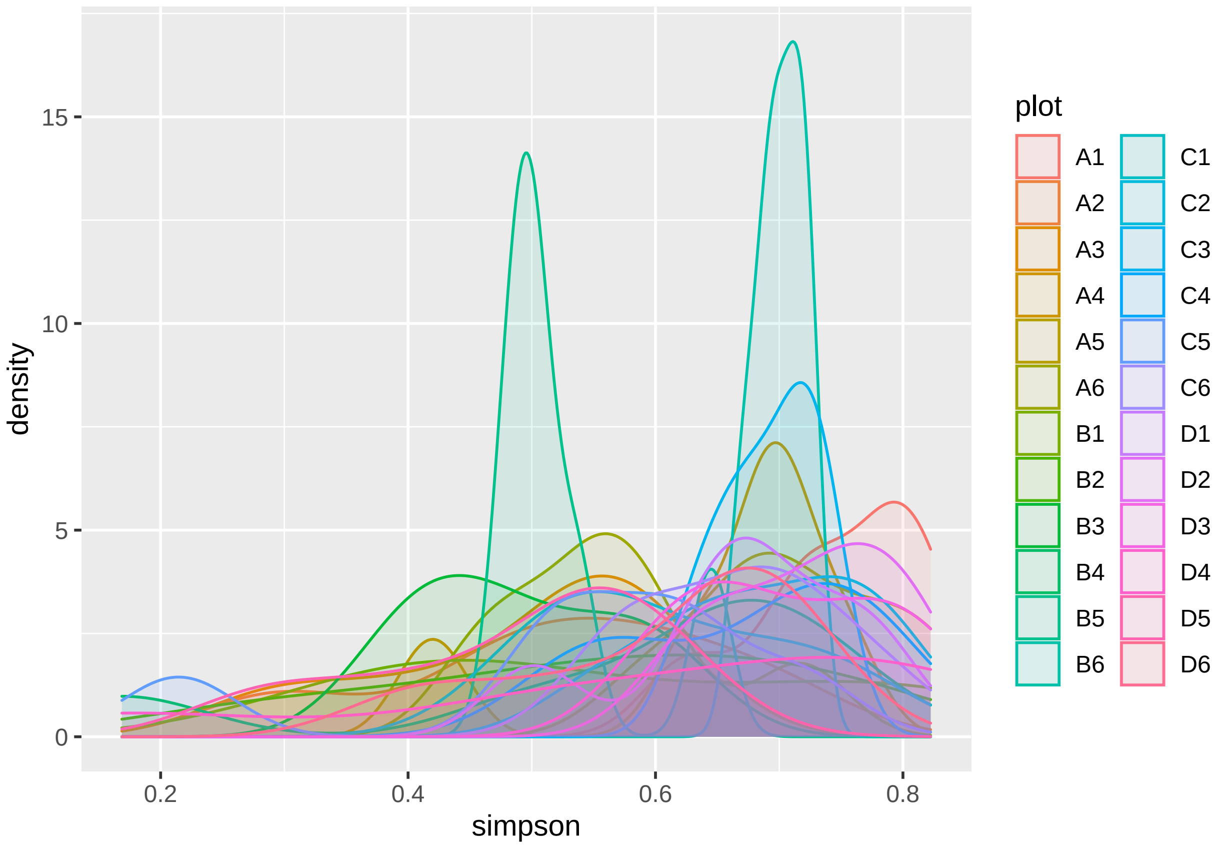
```r
# Visualizing plot average totals for umbs at the PLOT LEVEL
ggplot(umbs_diversity, aes(simpson, fill = plot)) +
        geom_histogram(binwidth = 0.5) +
        facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



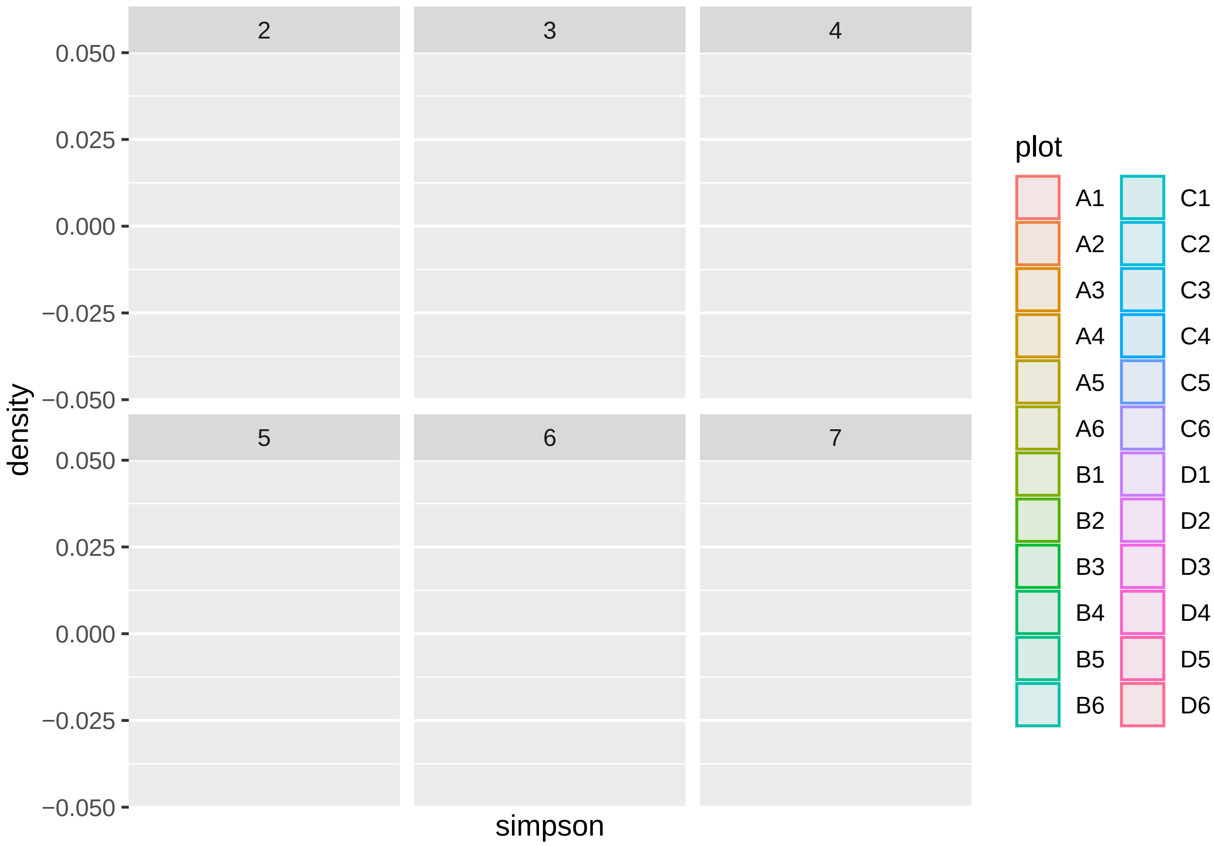

```r
ggplot(umbs_diversity, aes(simpson, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
       facet_grid(state~year_factor, margins = TRUE, scales = "free")
```



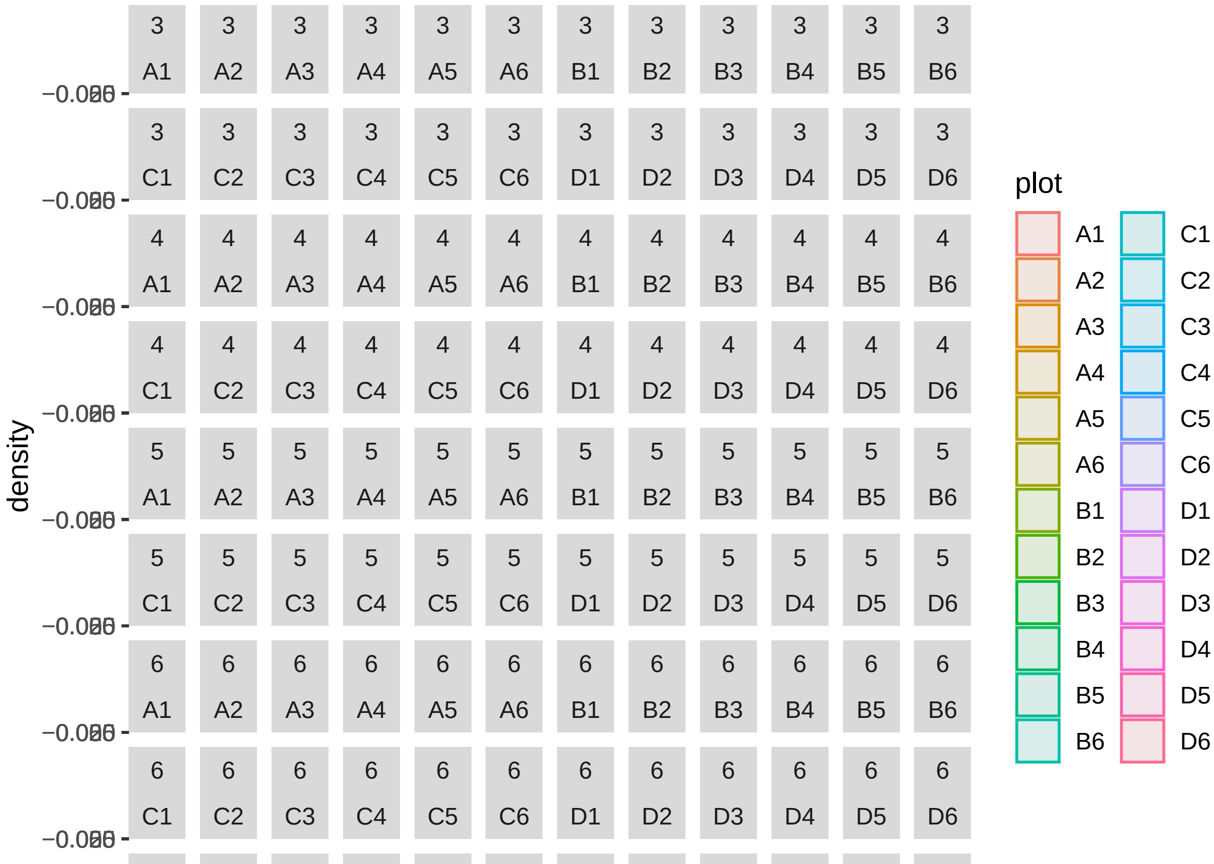

```
ggplot(umbs_diversity, aes(simpson, fill = plot, color=plot)) +
        geom_density(alpha = 0.1)
```



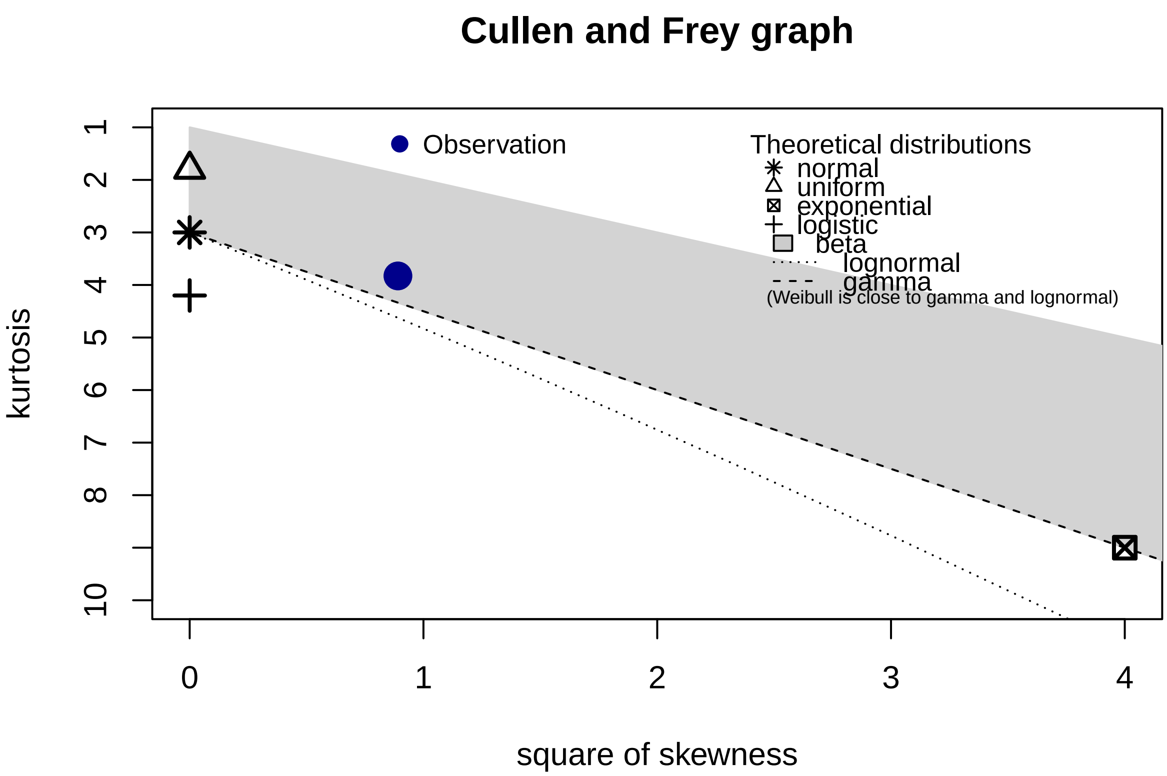

```
ggplot(umbs_diversity, aes(simpson, fill = plot, color=plot)) +
        geom_density(alpha = 0.1) +
        facet_wrap(~year_factor)
```




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

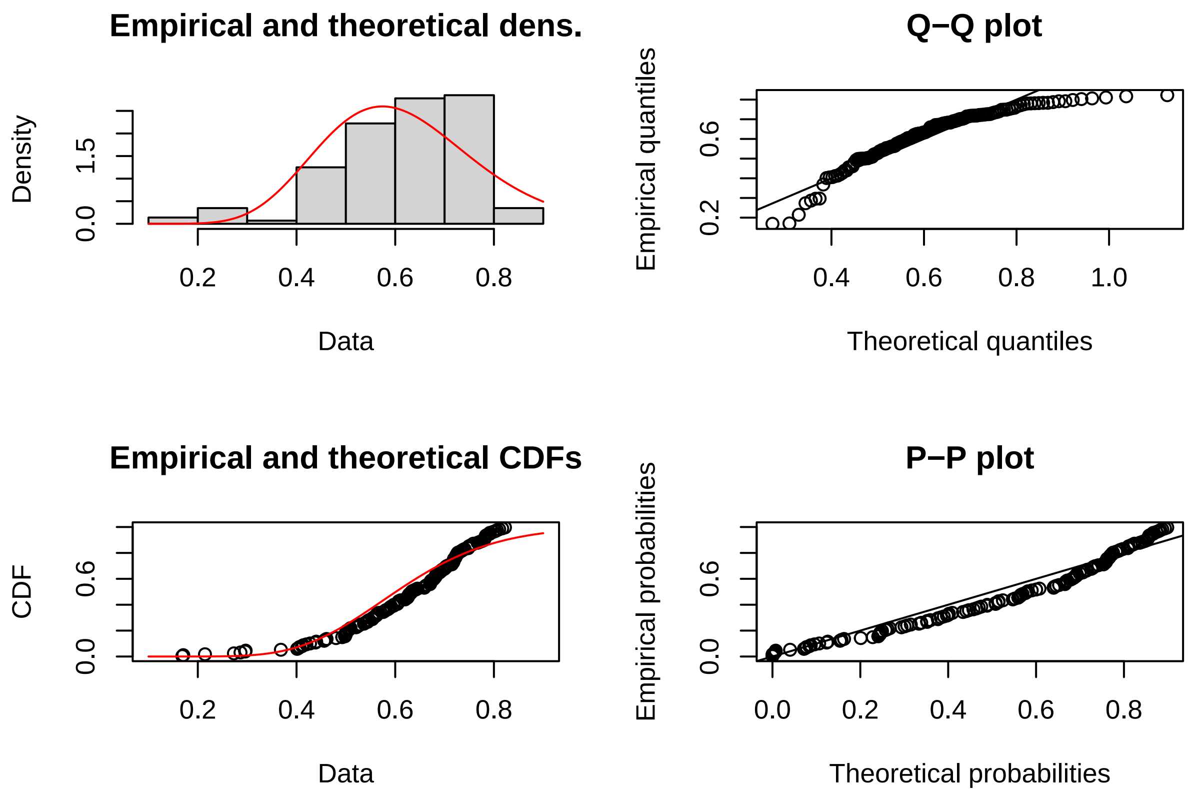



```
# Exploring distributions for these data:
descdist(umbs_diversity$simpson, discrete = FALSE)
```

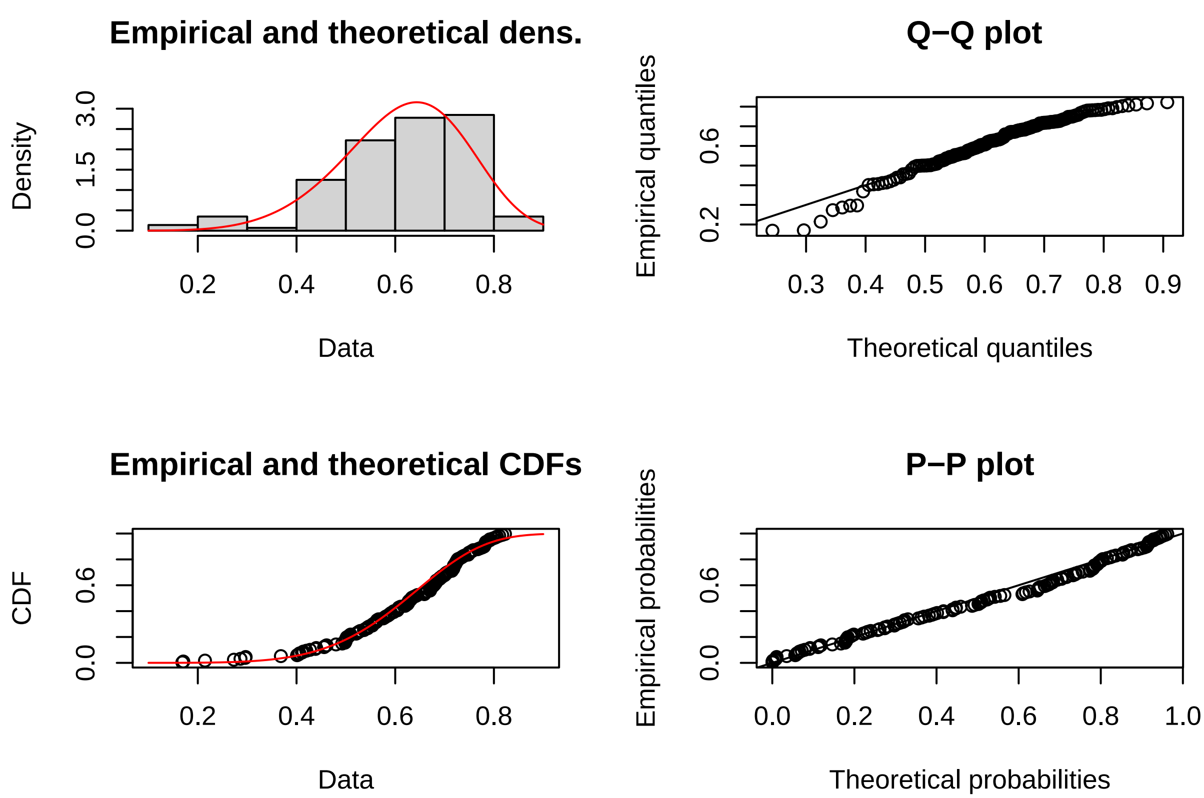



```
## summary statistics
## ------
## min:  0.1686625   max:  0.8224
## median:  0.6333667
## mean:  0.6147879
## estimated sd:  0.1383529
## estimated skewness:  -0.9438167
## estimated kurtosis:  3.827659
```

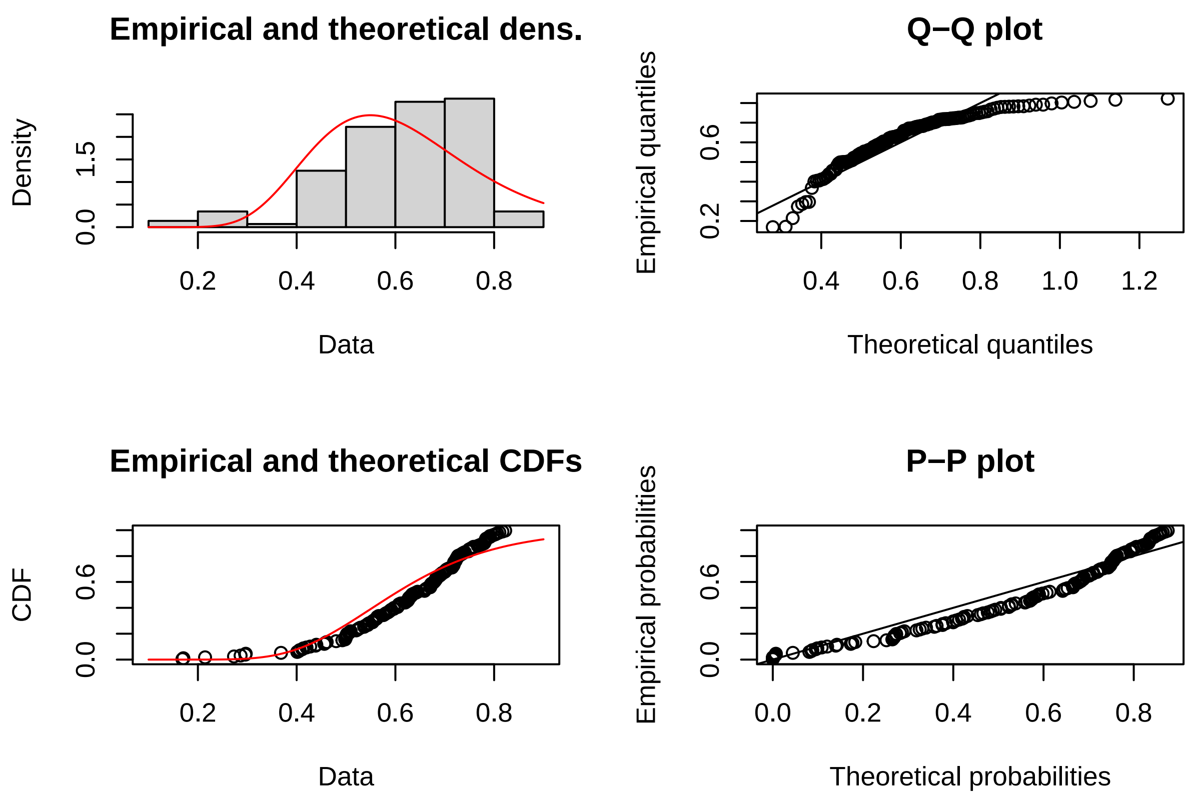
```
# Gamma distribution
fit.gamma <- fitdist(umbs_diversity$simpson, "gamma")
plot(fit.gamma)
```



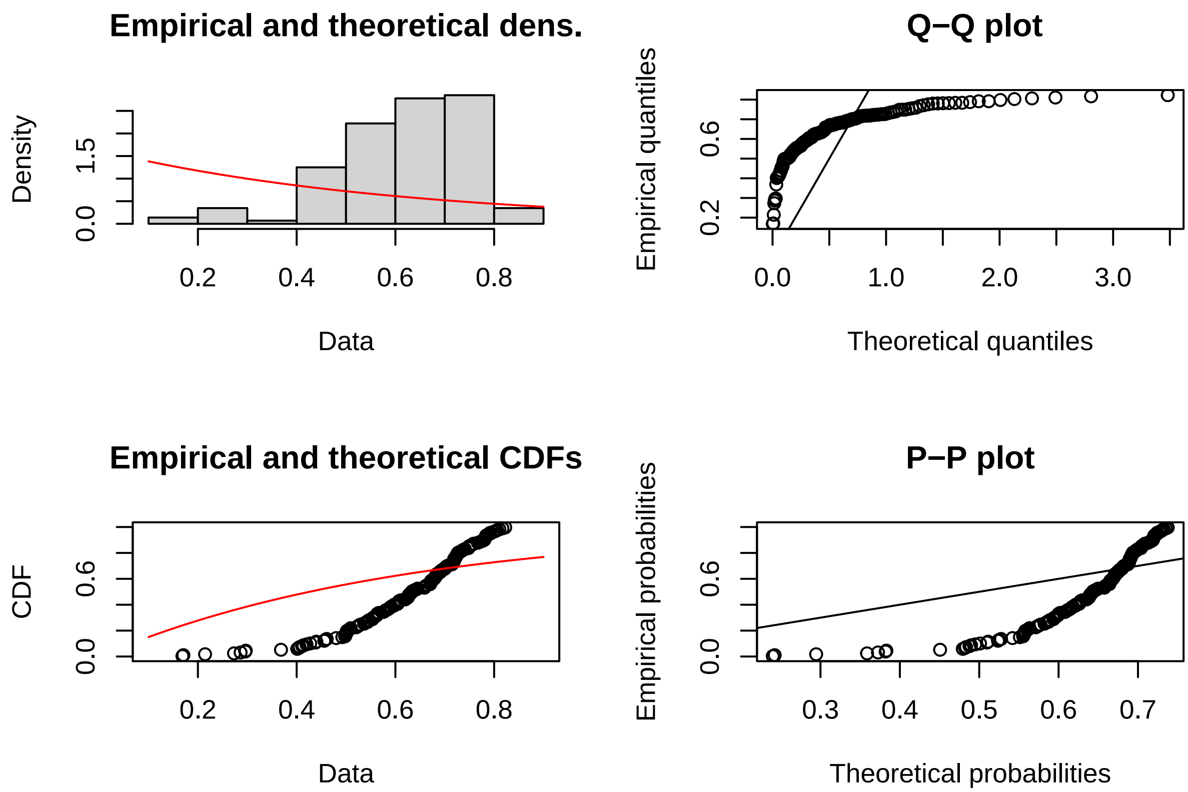

```r
# Weibull distribution
fit.weibull  <- fitdist(umbs_diversity$simpson, "weibull")
plot(fit.weibull)
```



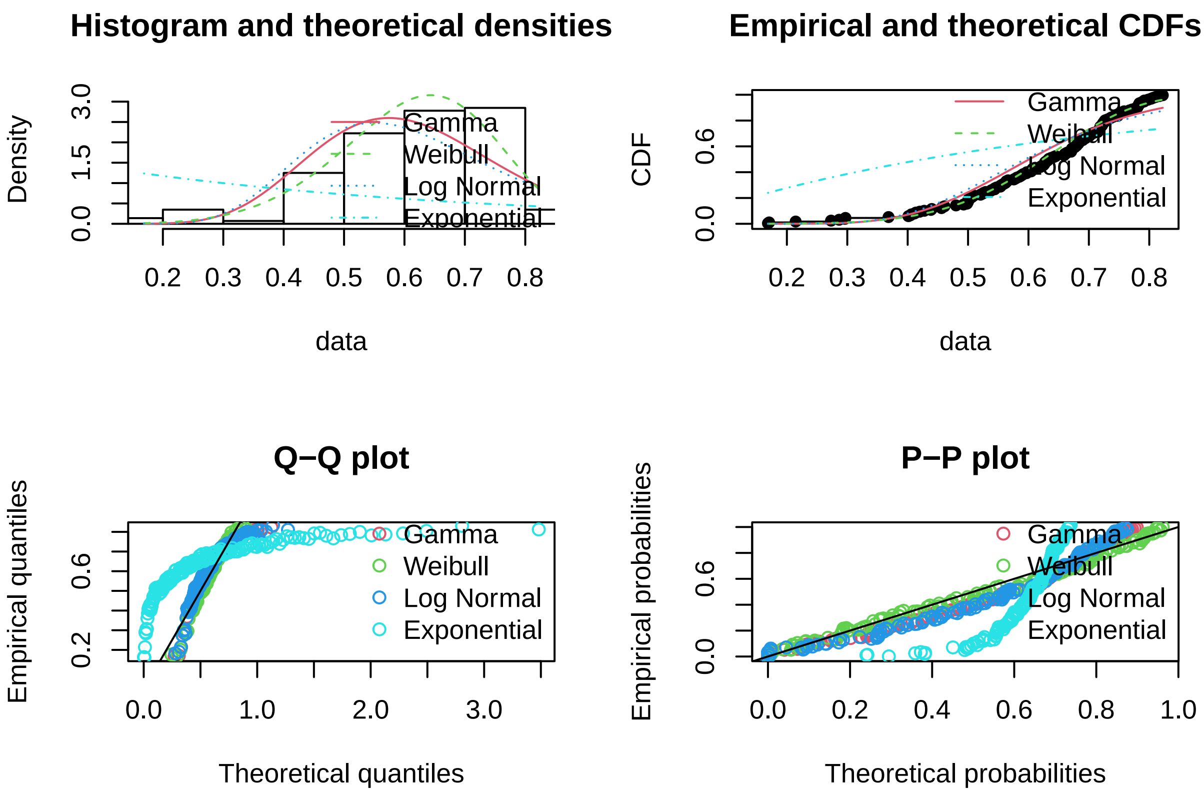
```r
# Lognormal distribution
fit.ln <- fitdist(umbs_diversity$simpson, "lnorm")
plot(fit.ln)
```




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



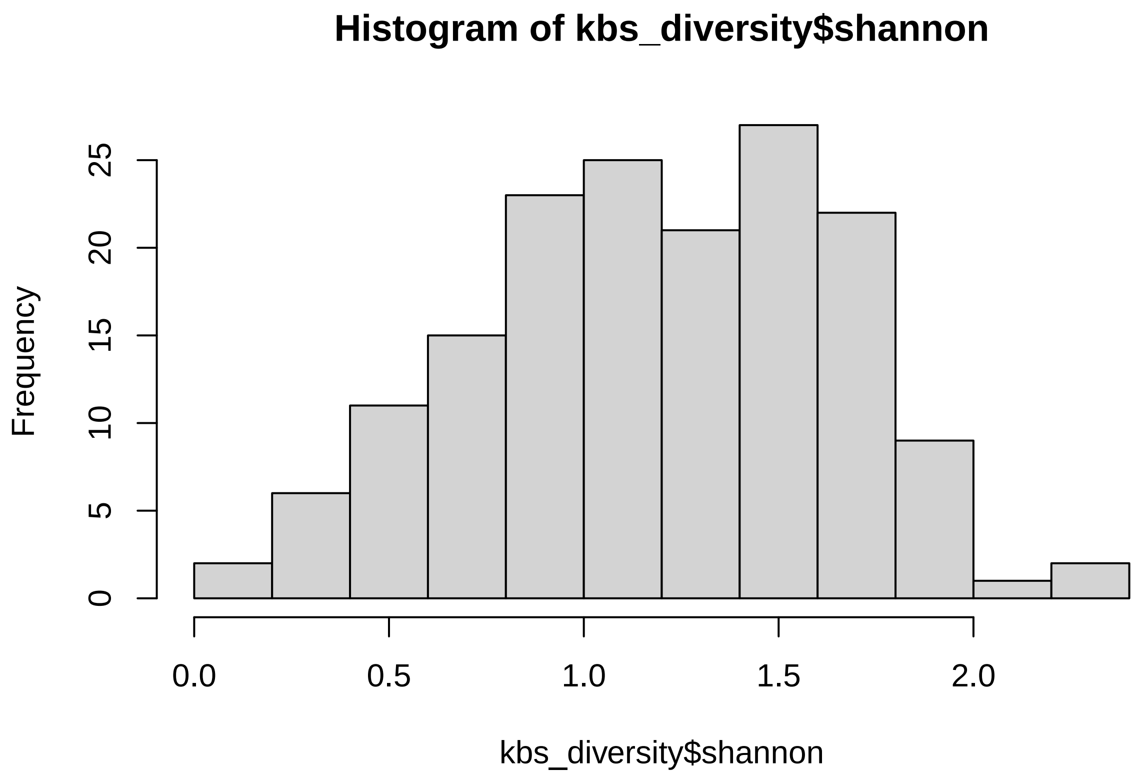

```
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull", "Log Normal", "E
```

```
## Goodness-of-fit statistics
##                                  Gamma    Weibull Log Normal         Exp
## Kolmogorov-Smirnov statistic 0.1121609 0.08985245  0.1246401  0.4237696
## Cramer-von Mises statistic   0.6571710 0.16674884  0.9227639  8.3923702
## Anderson-Darling statistic   4.2771961 1.22653612  5.8658306 40.1742545
##
## Goodness-of-fit criteria
##                                    Gamma   Weibull Log Normal      Exp
## Akaike's Information Criterion -125.3367 -170.8740 -102.14396 149.8944
## Bayesian Information Criterion -119.3971 -164.9343  -96.20434 152.8642
```

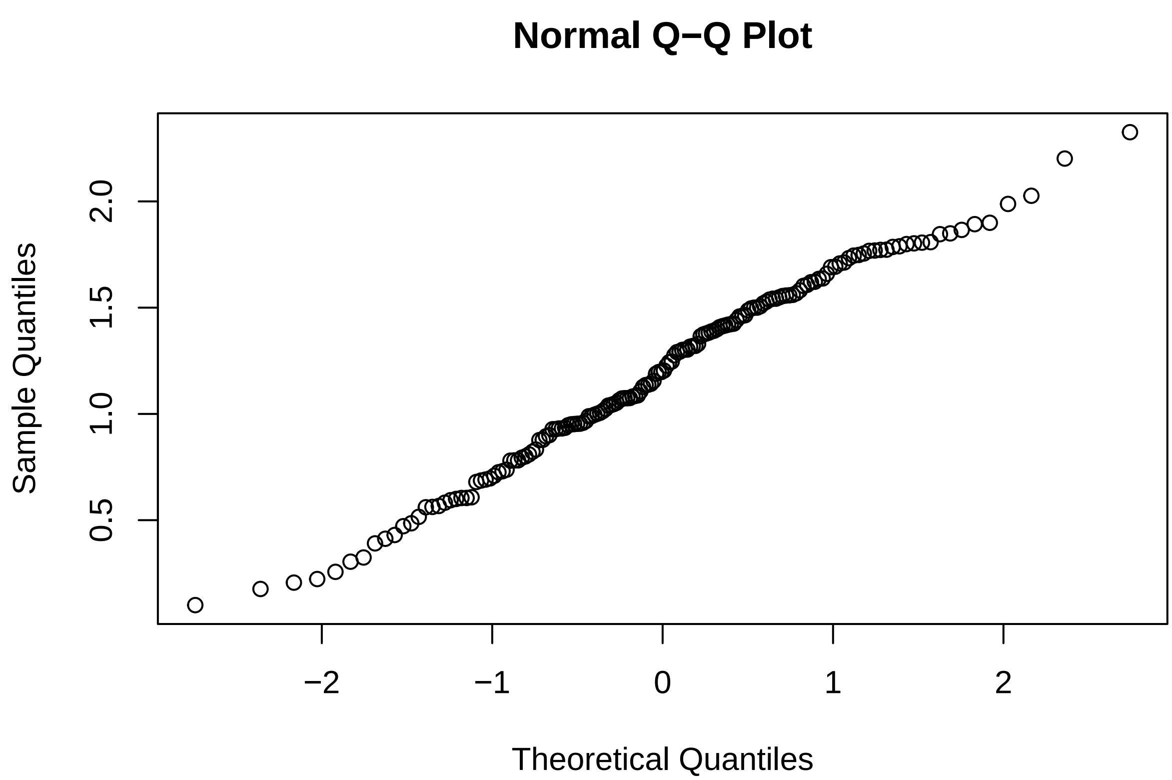
```
# log normal distribution looks to be the best based on AIC and BIC values
```

Shannon Index KBS

```
### KBS ###
hist(kbs_diversity$shannon)
```



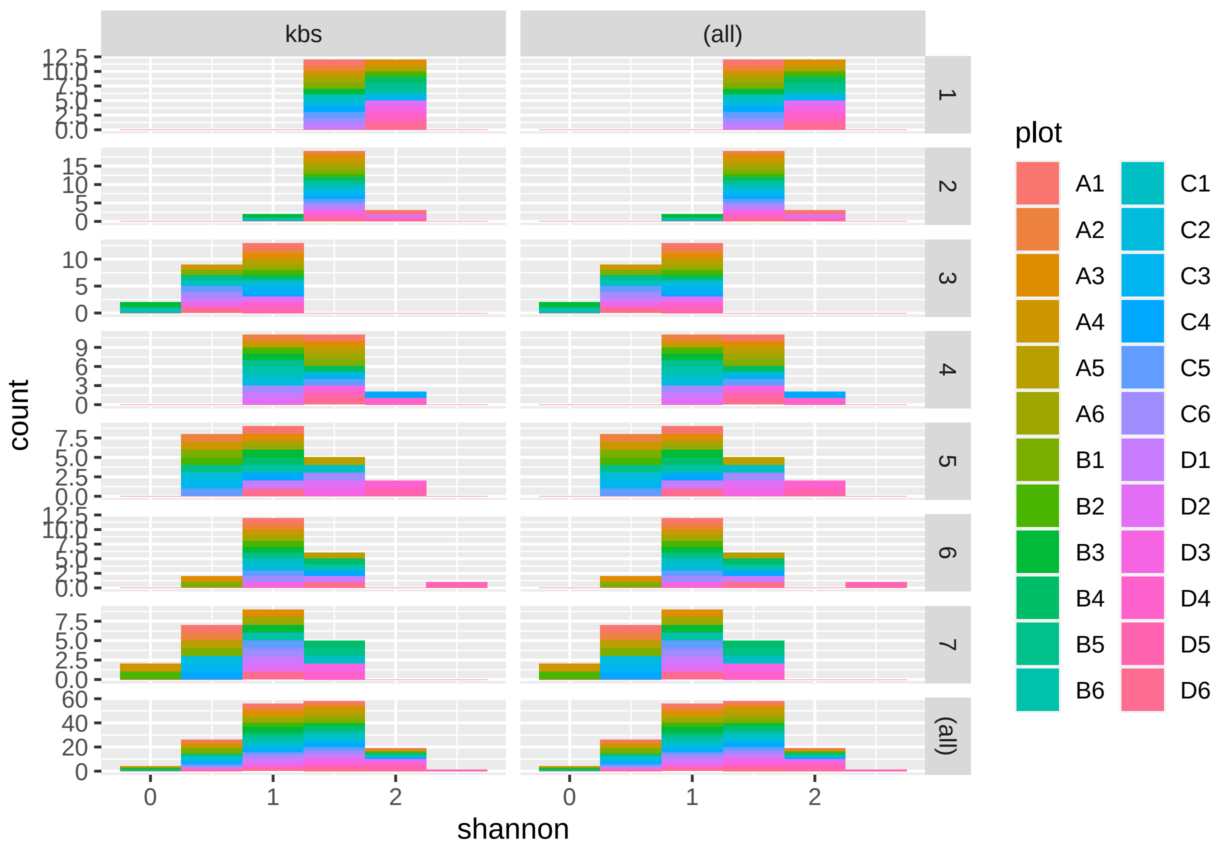

```
qqnorm(kbs_diversity$shannon)
```



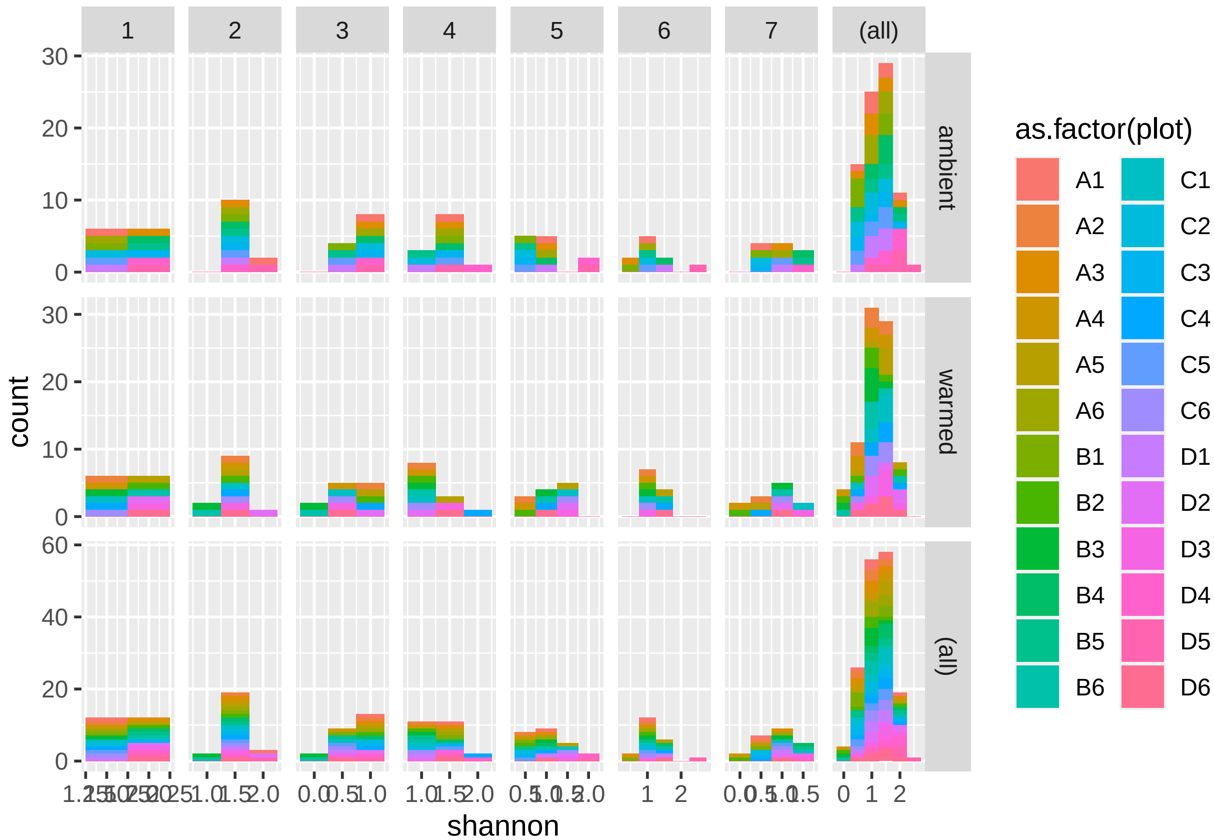
```r
shapiro.test(kbs_diversity$shannon) # pvalue is > 0.05 - normally distributed
```

```
##
##  Shapiro-Wilk normality test
##
## data:  kbs_diversity$shannon
## W = 0.98693, p-value = 0.1292
```

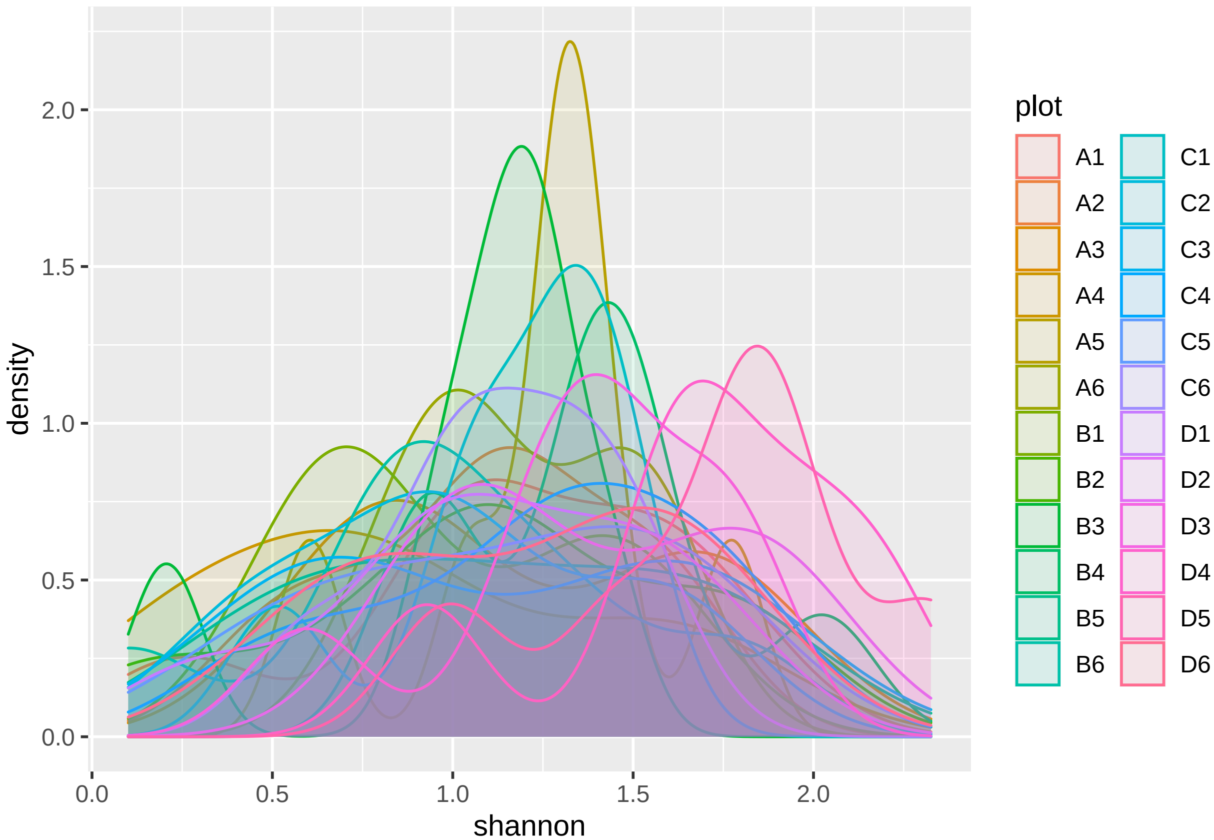
```r
# Visualizing plot average totals for kbs at the PLOT LEVEL
ggplot(kbs_diversity, aes(shannon, fill = plot)) +
        geom_histogram(binwidth = 0.5) +
        facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



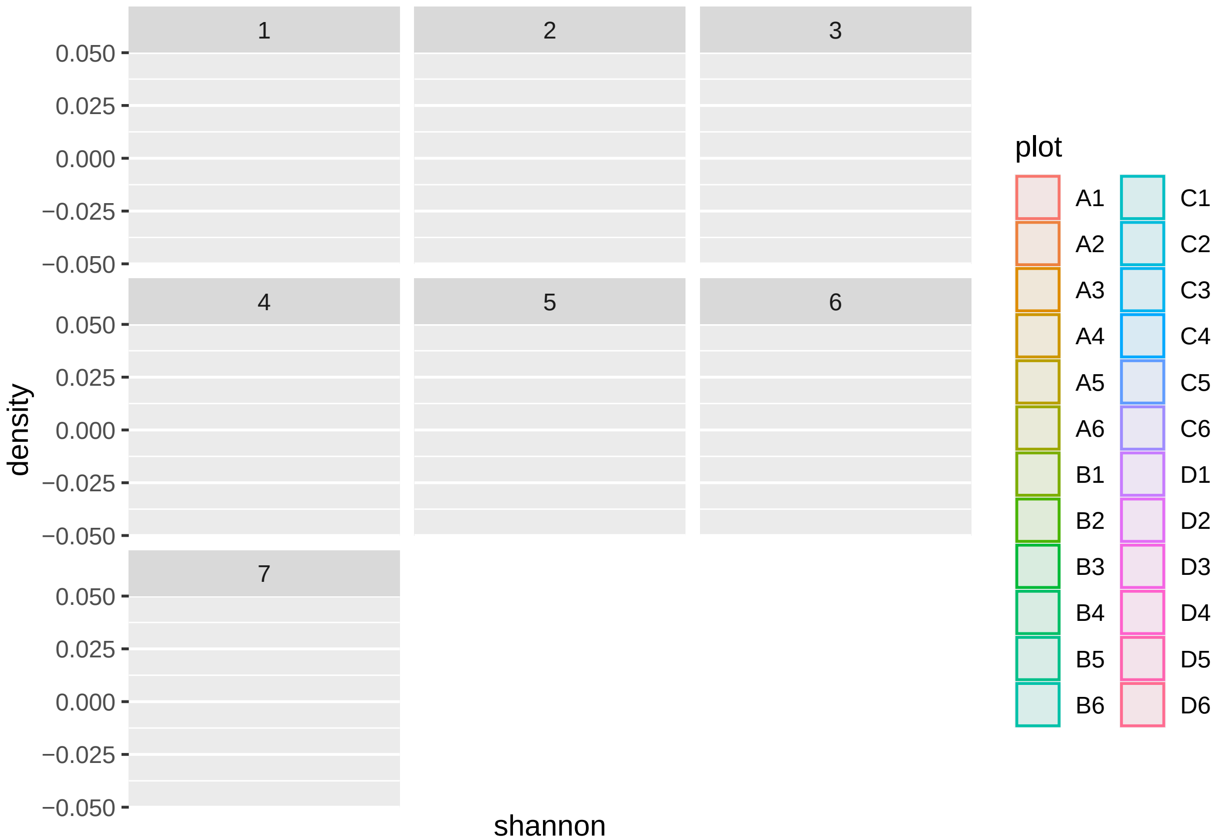

```r
ggplot(kbs_diversity, aes(shannon, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
        facet_grid(state~year_factor, margins = TRUE, scales = "free")
```



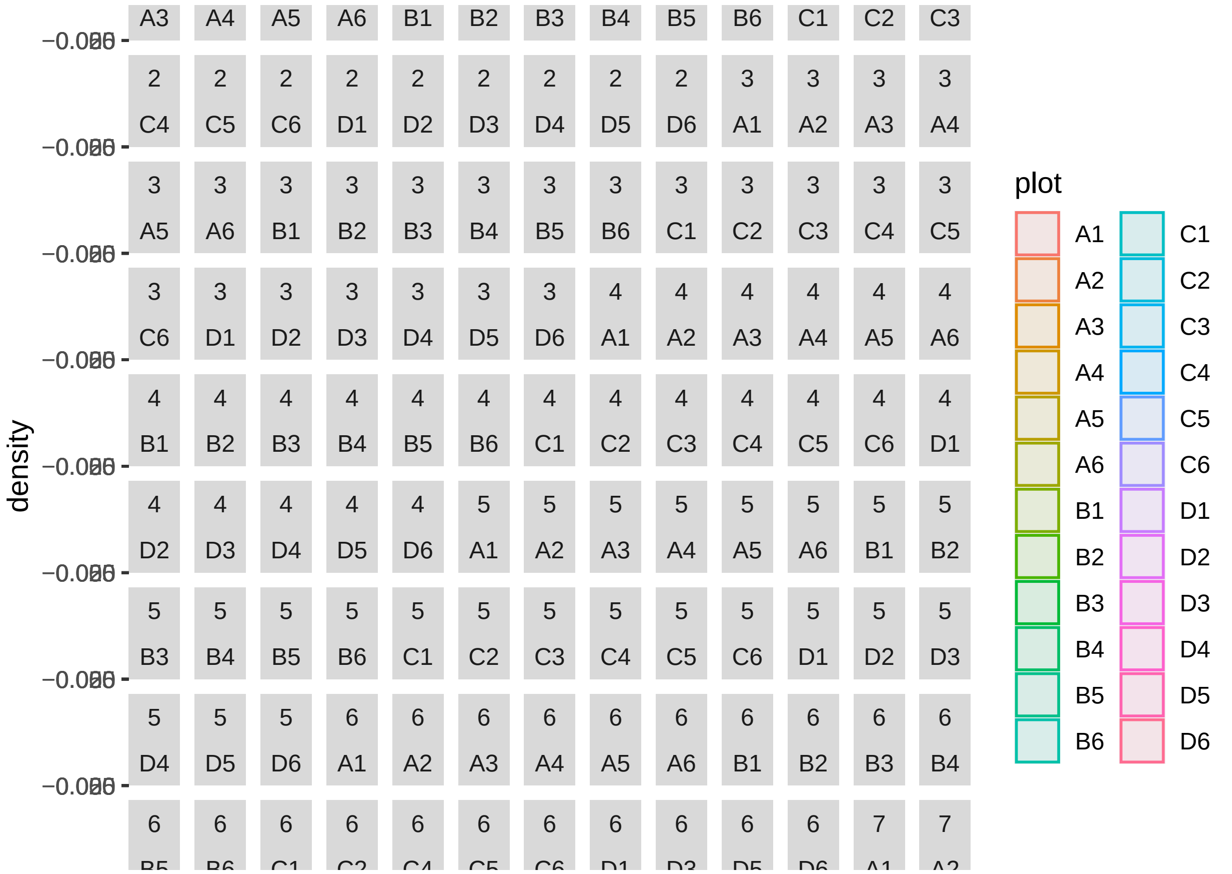

```
ggplot(kbs_diversity, aes(shannon, fill = plot, color=plot)) +
        geom_density(alpha = 0.1)
```



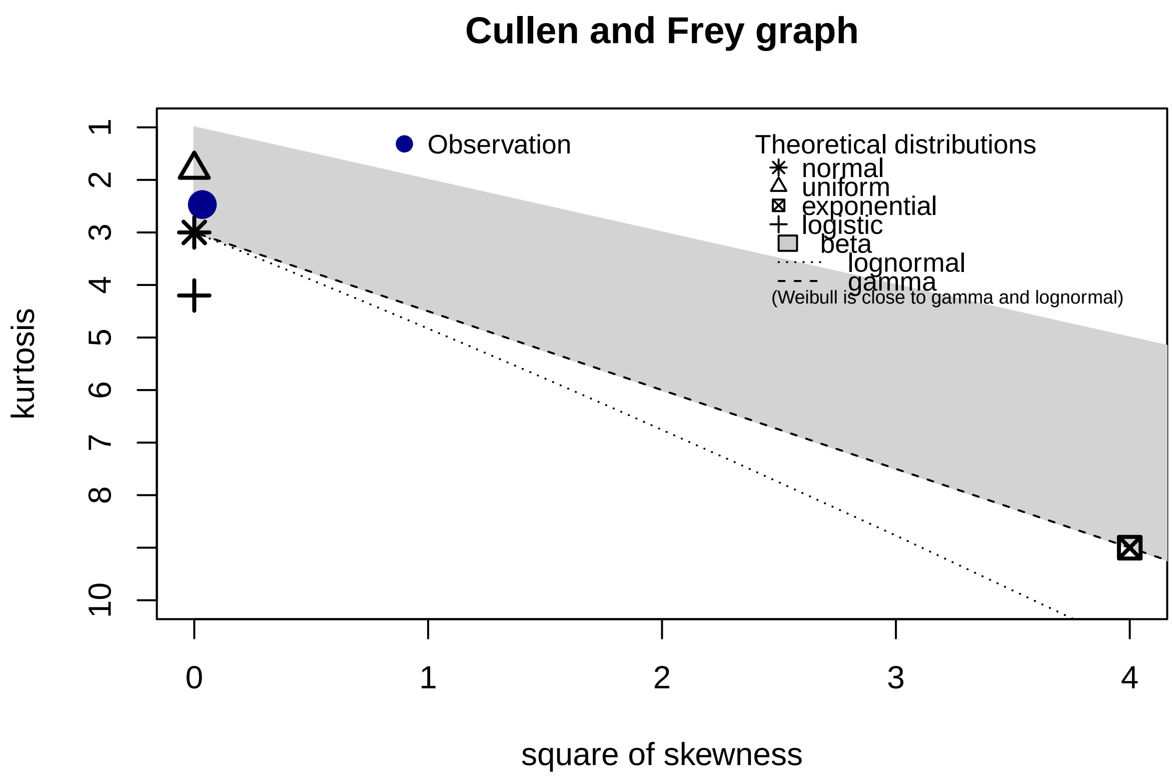

```
ggplot(kbs_diversity, aes(shannon, fill = plot, color=plot)) +
        geom_density(alpha = 0.1) +
        facet_wrap(~year_factor)
```




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

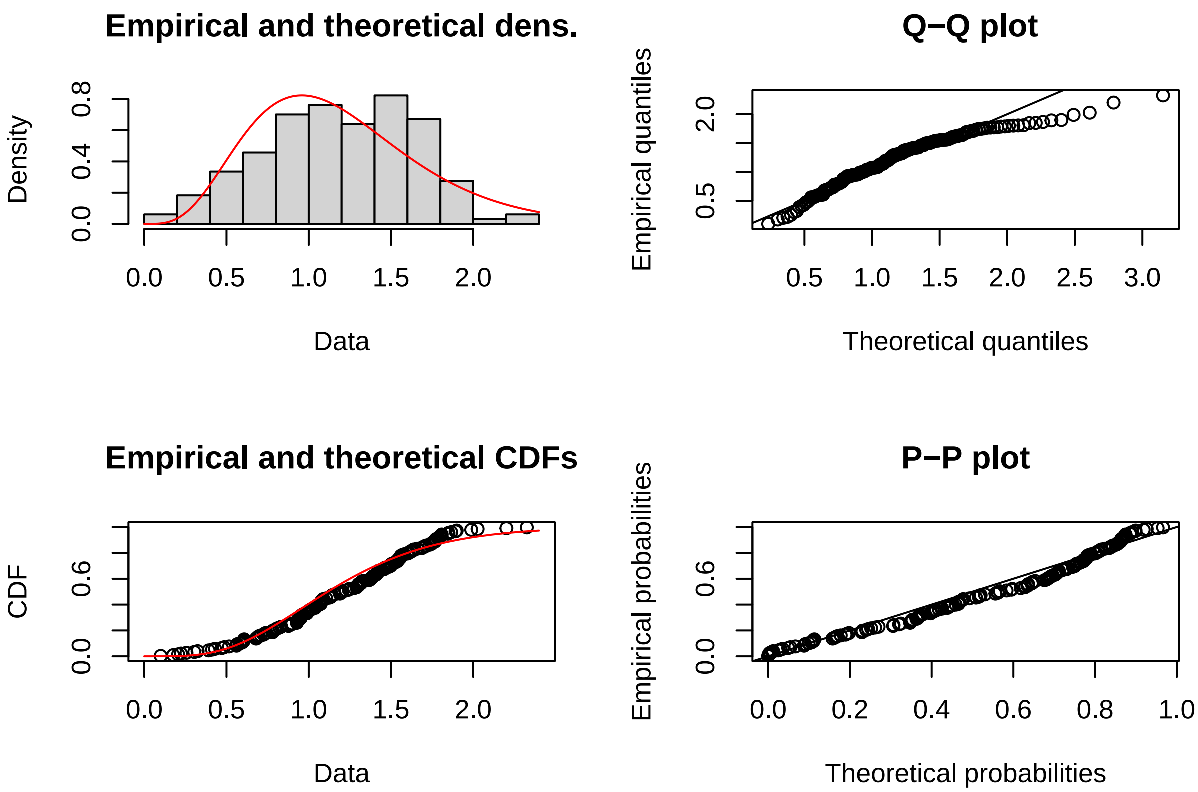



```
# Exploring distributions for these data:
descdist(kbs_diversity$shannon, discrete = FALSE)
```

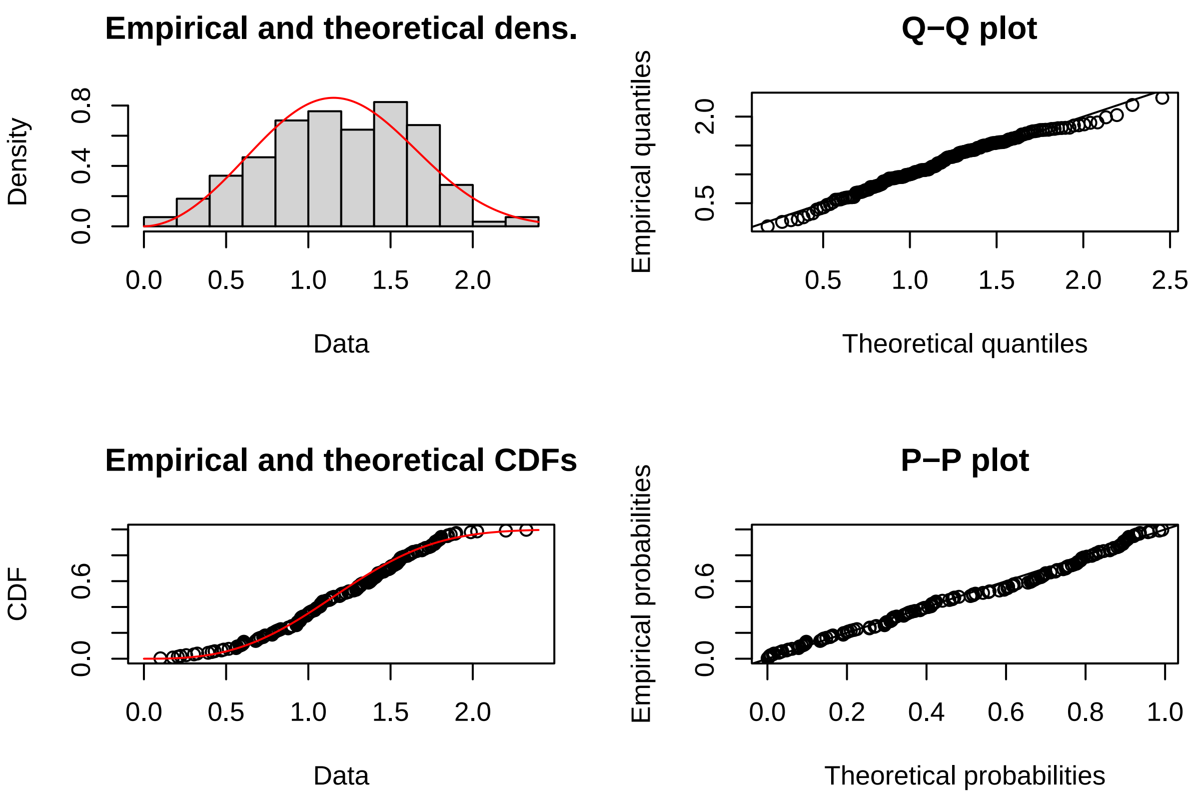



```
## summary statistics
## ------
## min:  0.1004368   max:  2.325625
## median:  1.20065
## mean:  1.19346
## estimated sd:  0.4559918
## estimated skewness:  -0.1855955
## estimated kurtosis:  2.4695
```

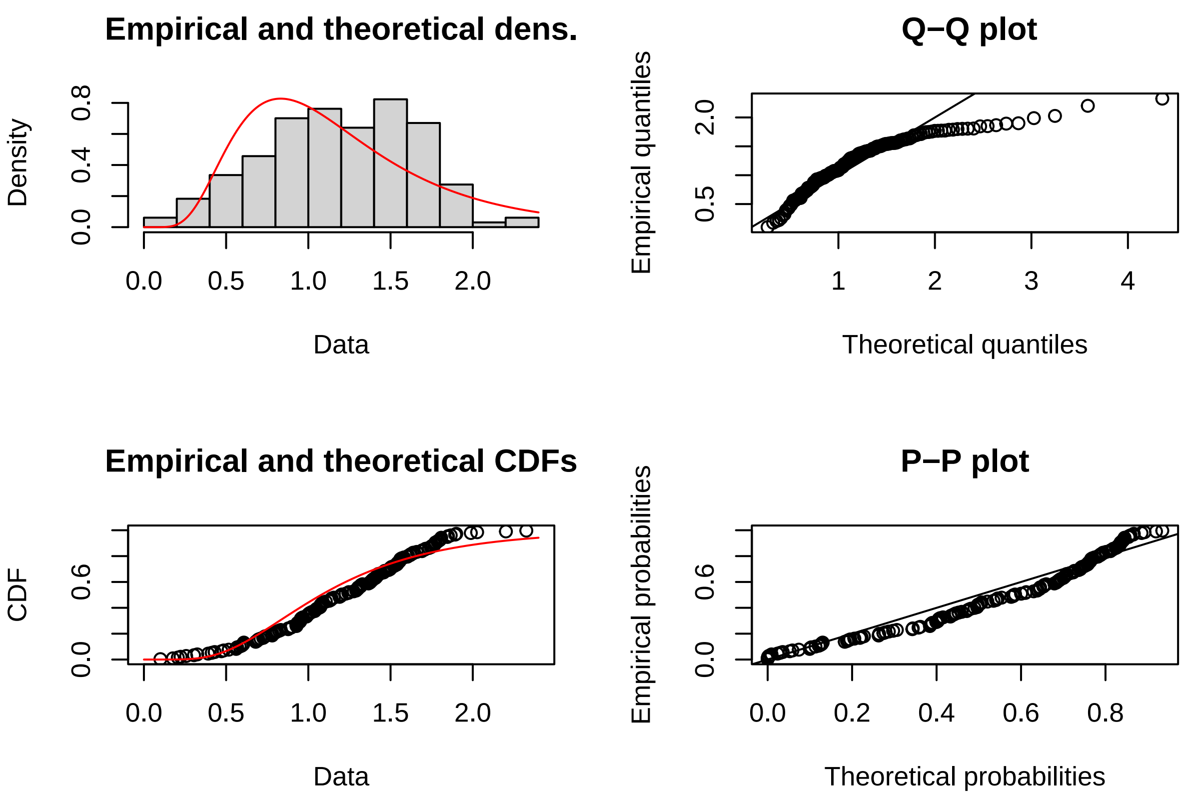
```
# Gamma distribution
fit.gamma <- fitdist(kbs_diversity$shannon, "gamma")
plot(fit.gamma)
```



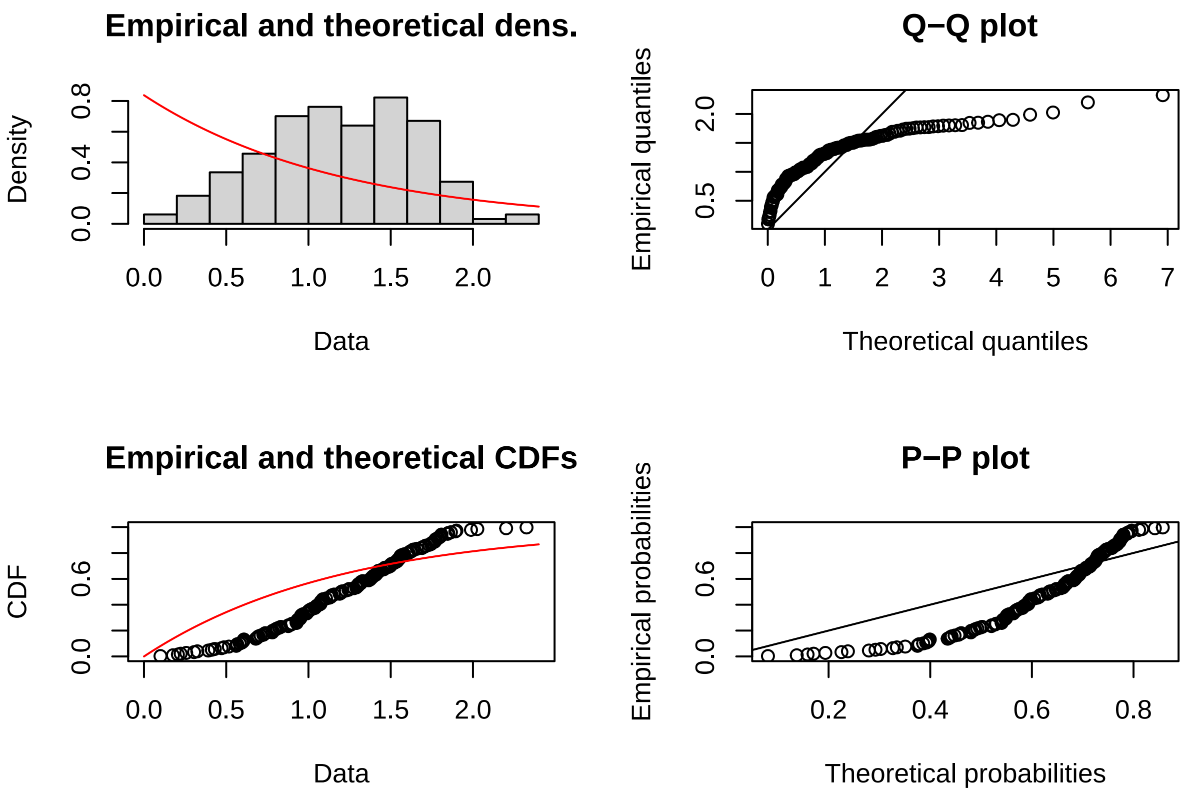

```r
# Weibull distribution
fit.weibull  <- fitdist(kbs_diversity$shannon, "weibull")
plot(fit.weibull)
```



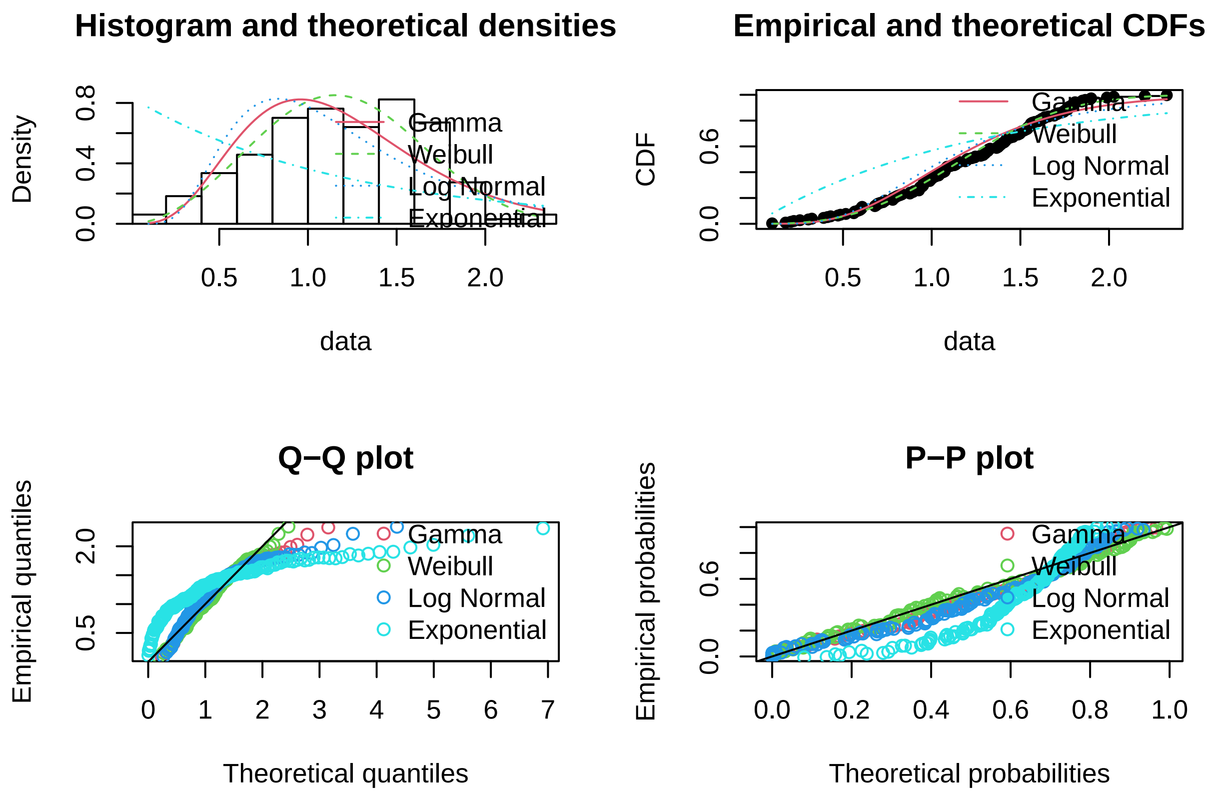
```r
# Lognormal distribution
fit.ln <- fitdist(kbs_diversity$shannon, "lnorm")
plot(fit.ln)
```




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




```
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)
```



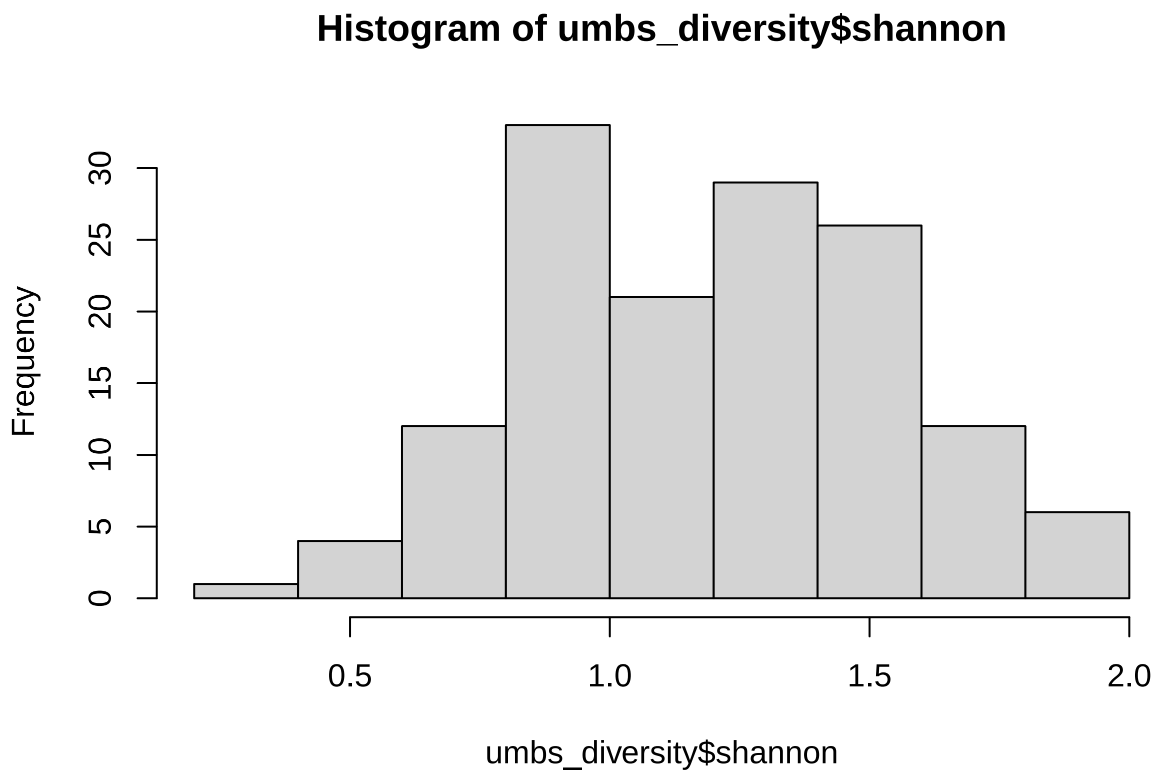

```
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull", "Log Normal", "E
```

```
## Goodness-of-fit statistics
##                                  Gamma    Weibull Log Normal        Exp
## Kolmogorov-Smirnov statistic 0.0975017 0.07020449  0.1281871  0.3001149
## Cramer-von Mises statistic   0.4293426 0.13410465  0.7999633  5.4032000
## Anderson-Darling statistic   2.7611544 0.93763683  5.0294349 27.2396378
##
## Goodness-of-fit criteria
##                                   Gamma  Weibull Log Normal      Exp
## Akaike's Information Criterion 238.4708 212.2707   272.6674 388.0090
## Bayesian Information Criterion 244.6705 218.4704   278.8671 391.1089
```

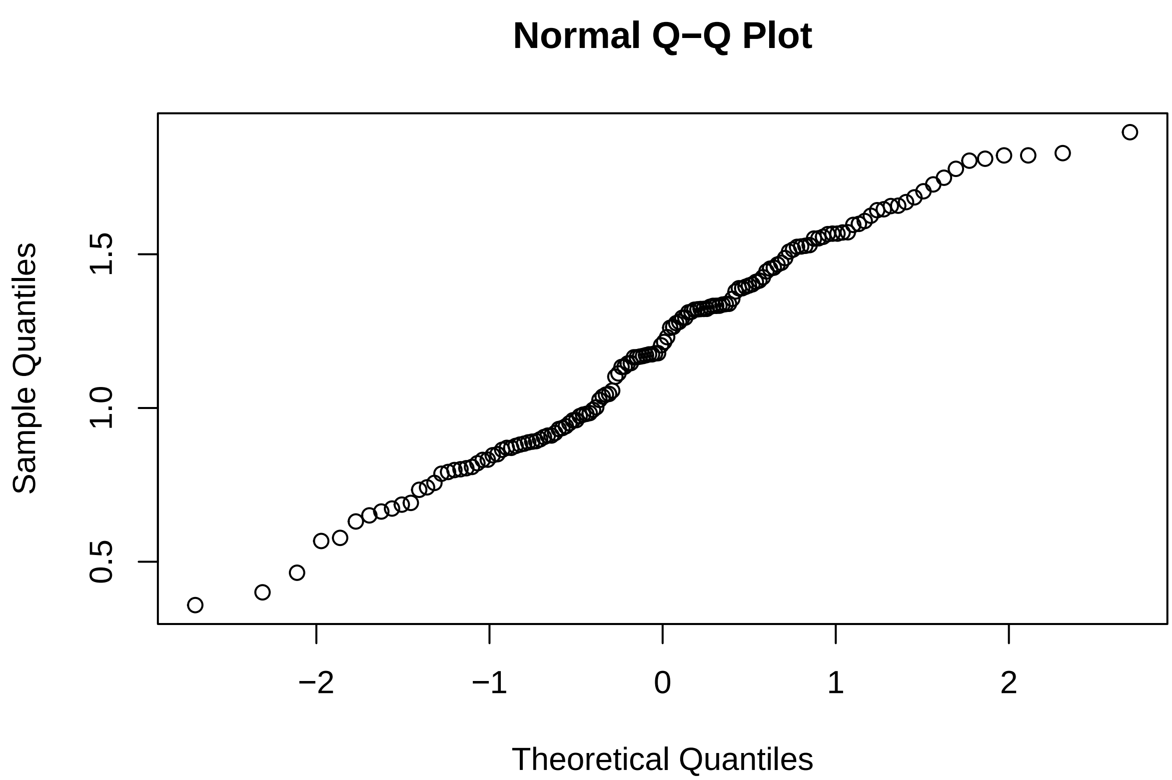
```
# weibull distribution looks to be the best based on AIC and BIC values
```

UMBS

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



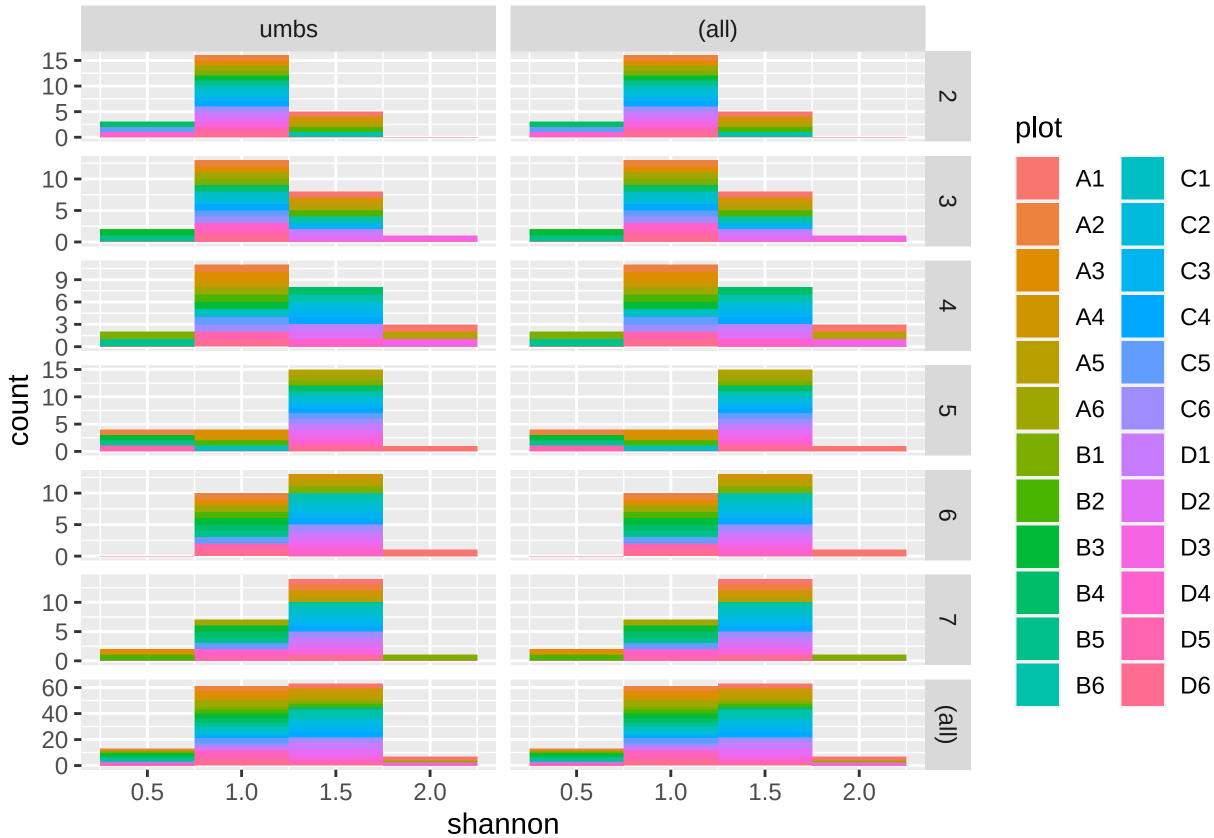

```
qqnorm(umbs_diversity$shannon)
```



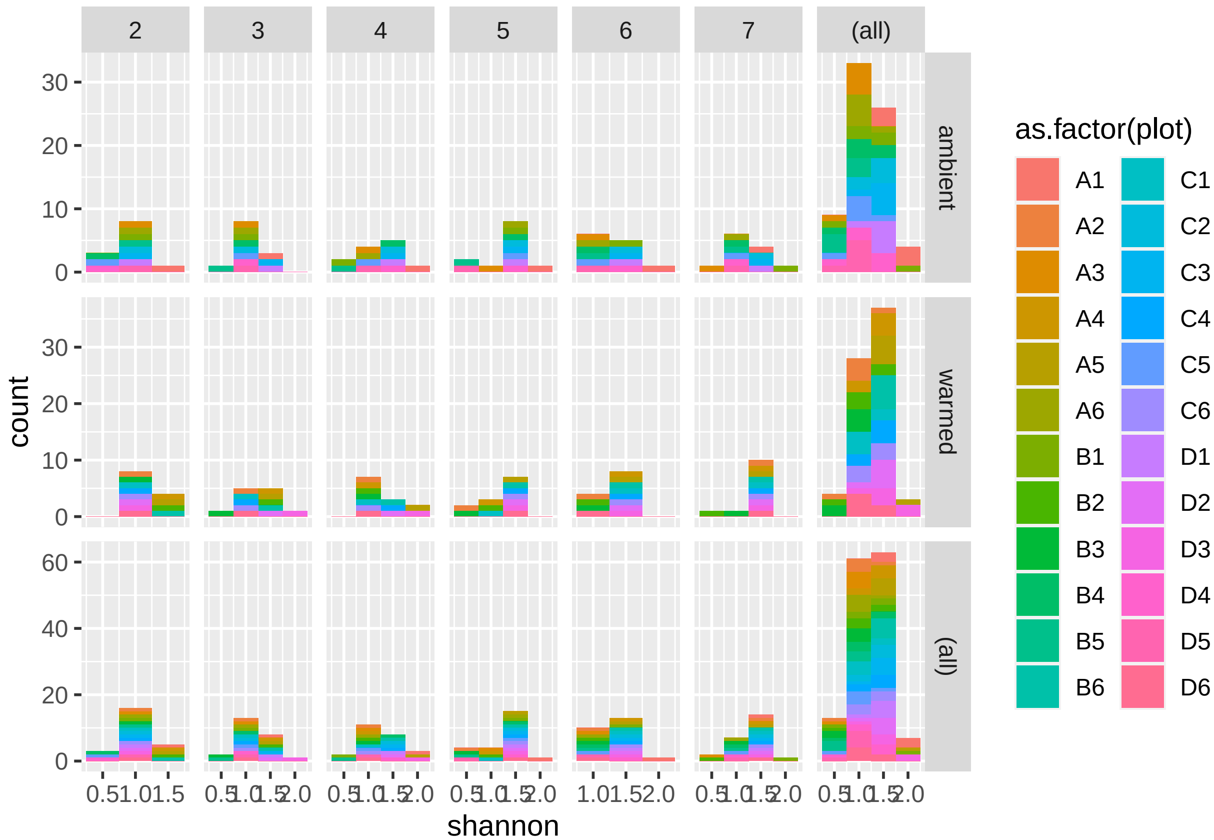
```r
shapiro.test(umbs_diversity$shannon) # pvalue is close to > 0.05 so we do not reject the null hypothesi
```

```
##
##  Shapiro-Wilk normality test
##
## data:  umbs_diversity$shannon
## W = 0.98094, p-value = 0.04248
```

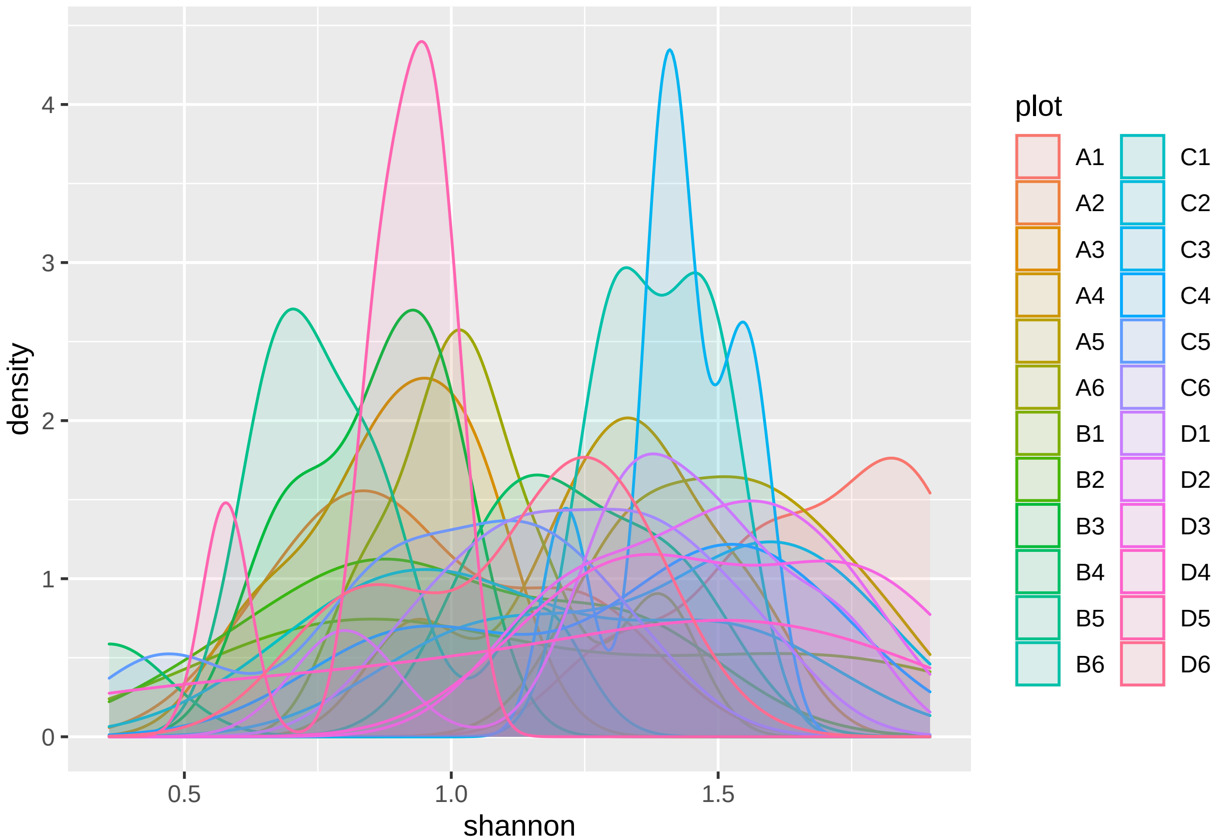
```r
# Visualizing plot average totals for umbs at the PLOT LEVEL
ggplot(umbs_diversity, aes(shannon, fill = plot)) +
        geom_histogram(binwidth = 0.5) +
        facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



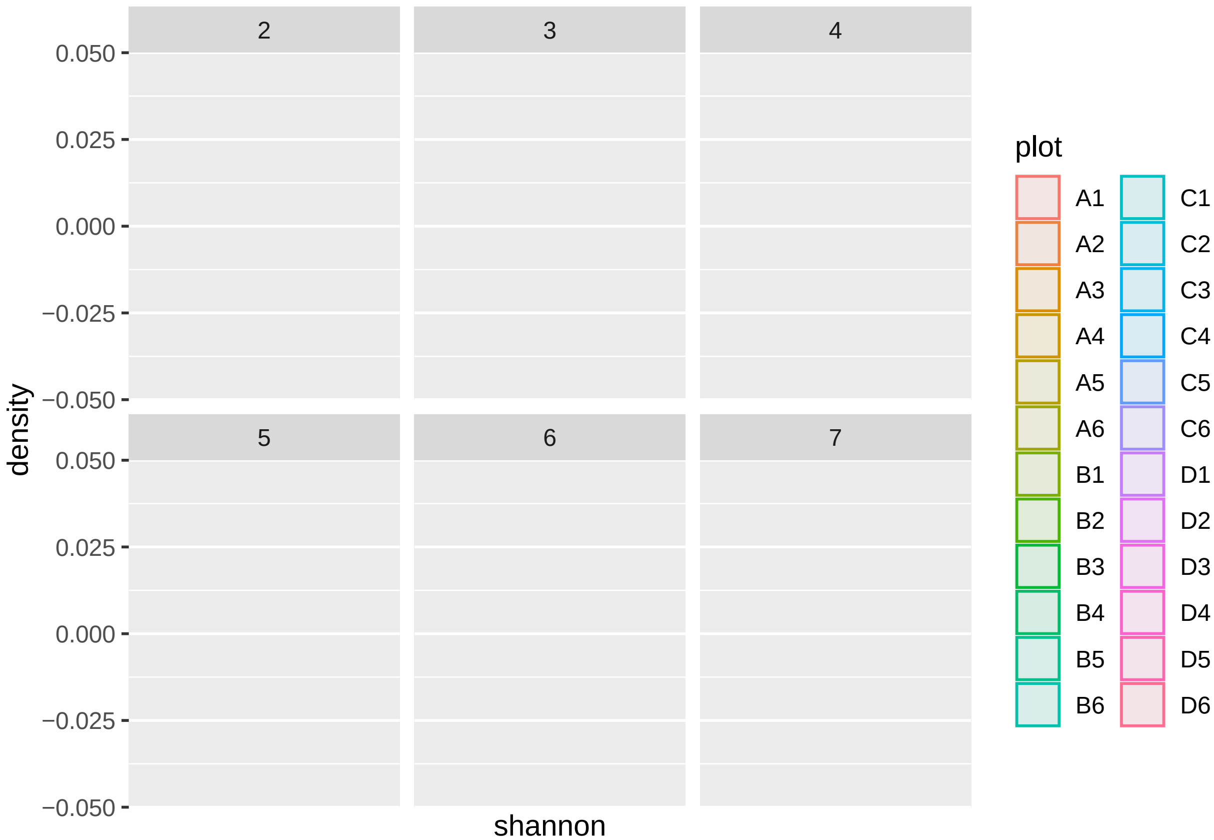

```r
ggplot(umbs_diversity, aes(shannon, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
       facet_grid(state~year_factor, margins = TRUE, scales = "free")
```



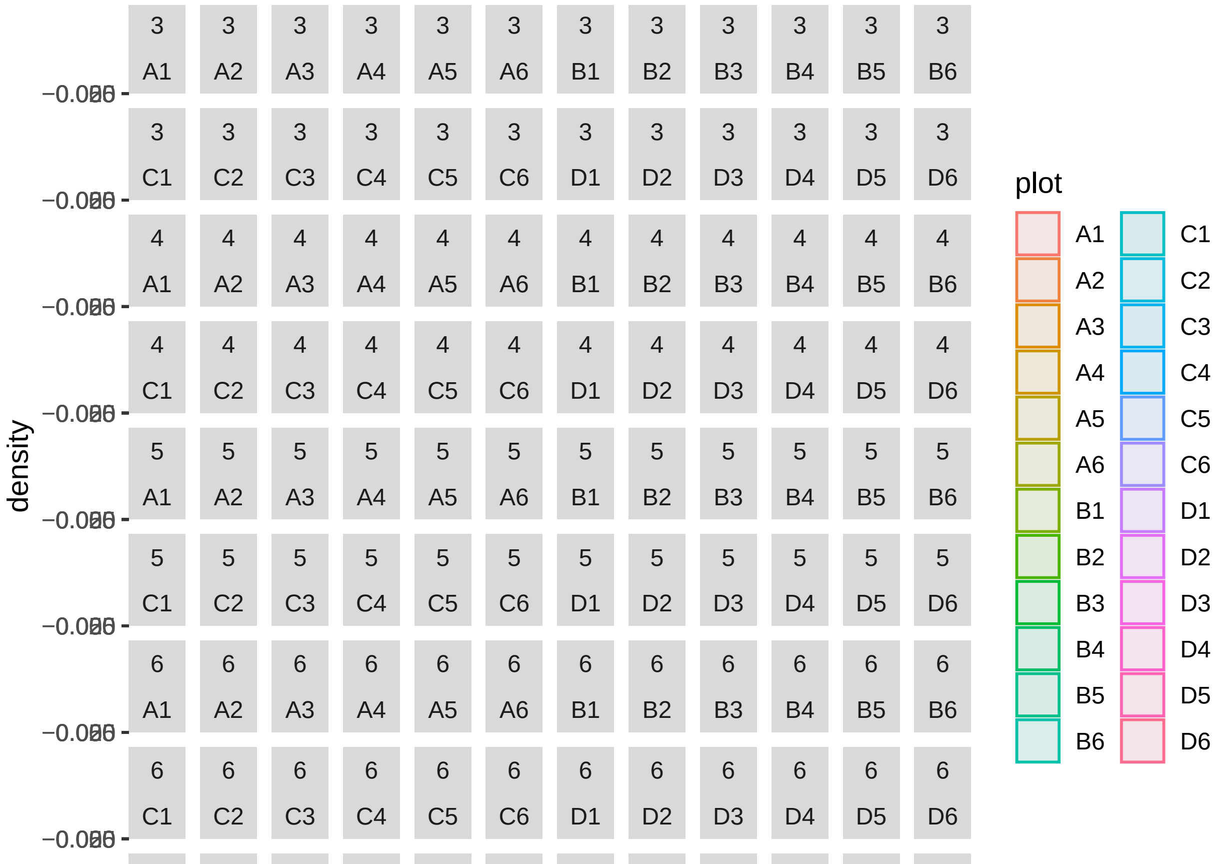

```
ggplot(umbs_diversity, aes(shannon, fill = plot, color=plot)) +
        geom_density(alpha = 0.1)
```



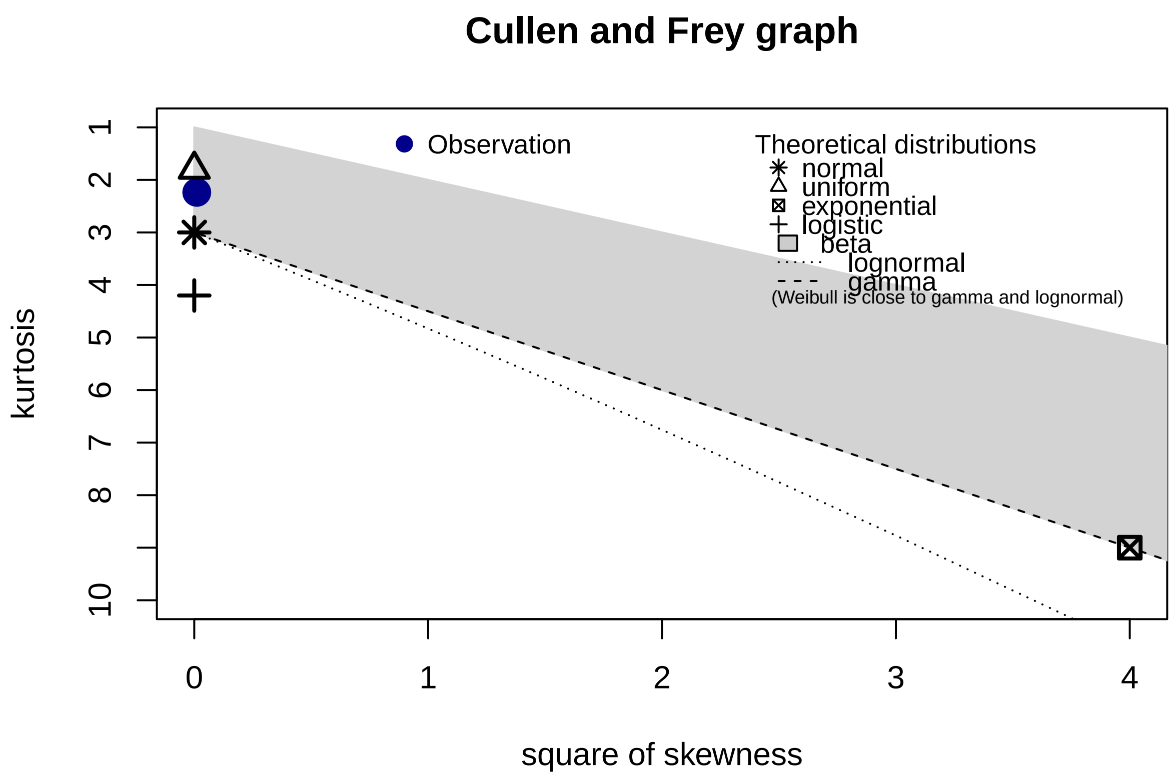

```r
ggplot(umbs_diversity, aes(shannon, fill = plot, color=plot)) +
        geom_density(alpha = 0.1) +
        facet_wrap(~year_factor)
```




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

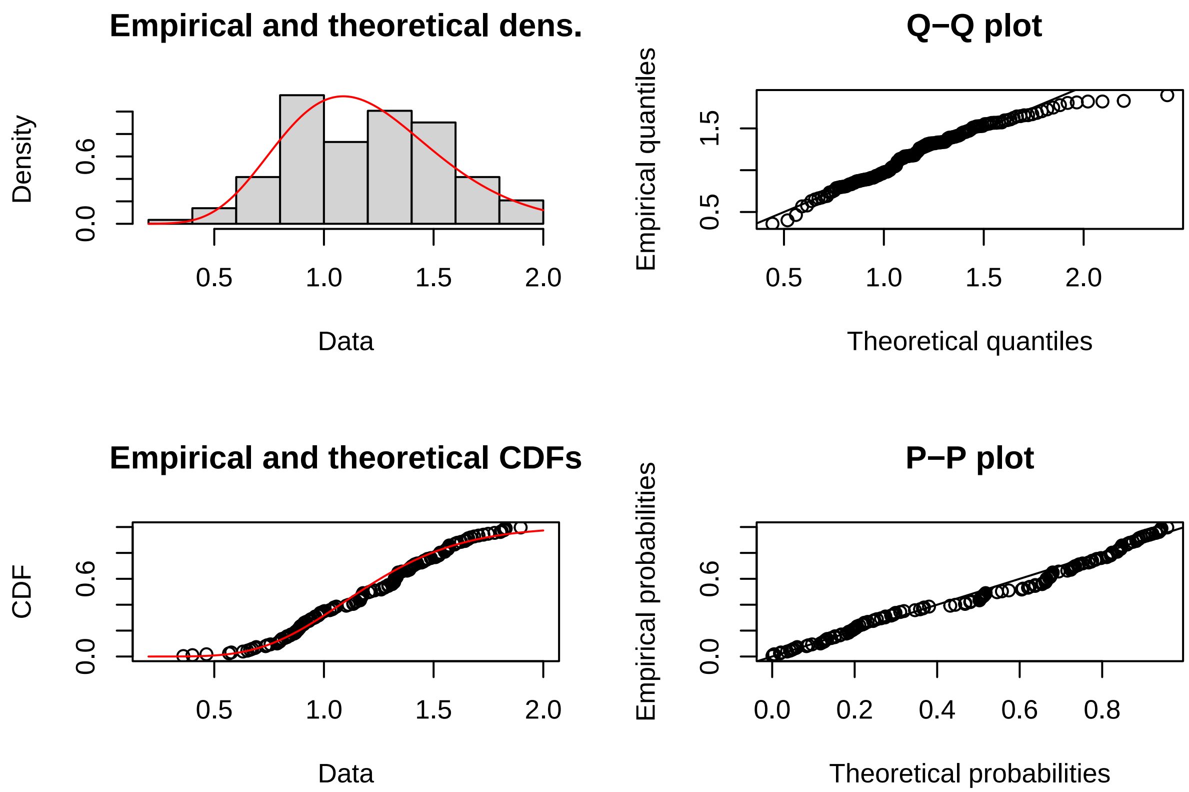



```
# Exploring distributions for these data:
descdist(umbs_diversity$shannon, discrete = FALSE)
```

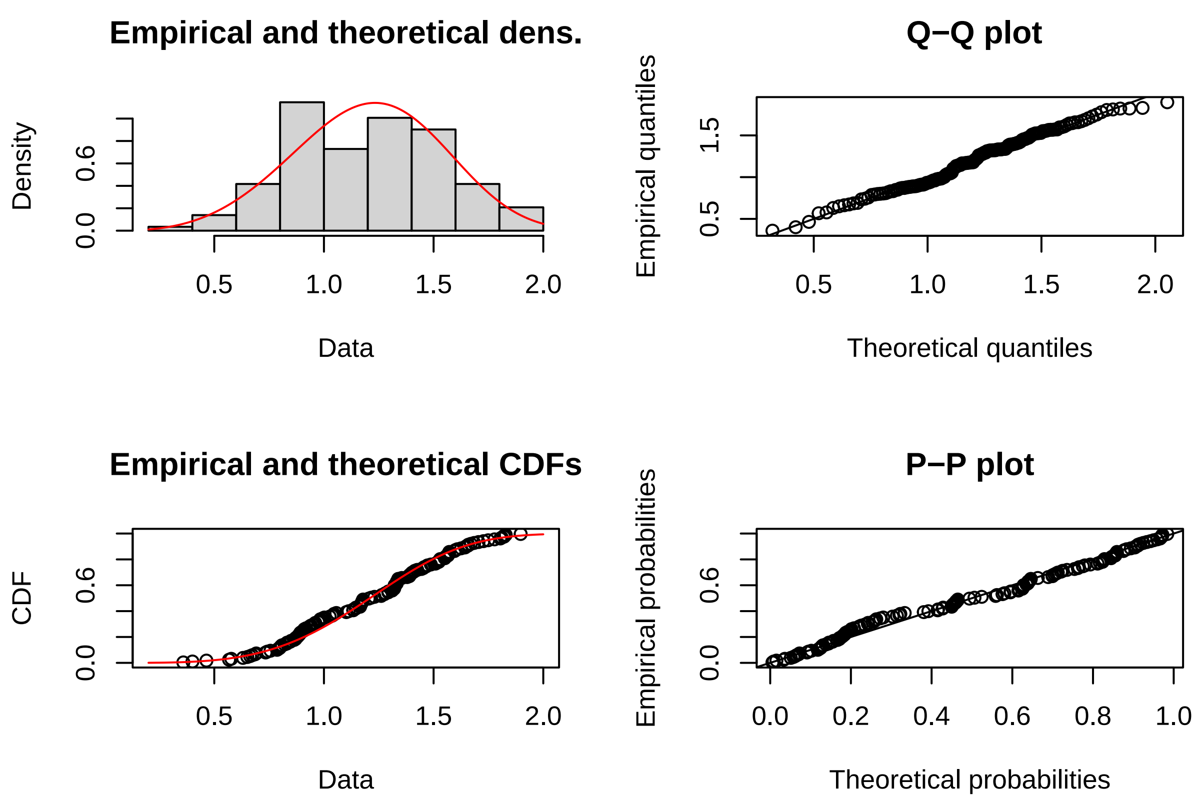



```
## summary statistics
## ------
## min:  0.3590242   max:  1.896908
## median:  1.209299
## mean:  1.199487
## estimated sd:  0.3453557
## estimated skewness:  -0.1036792
## estimated kurtosis:  2.237862
```

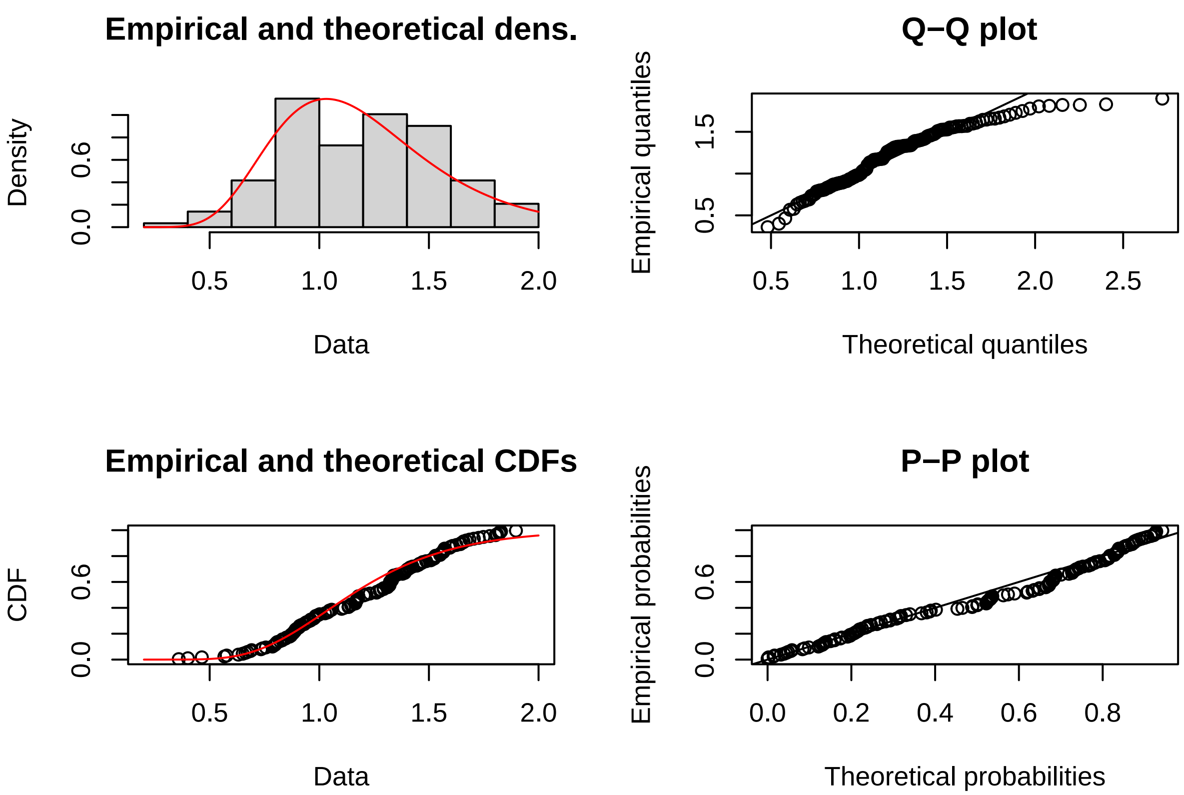
```
# Gamma distribution
fit.gamma <- fitdist(umbs_diversity$shannon, "gamma")
plot(fit.gamma)
```



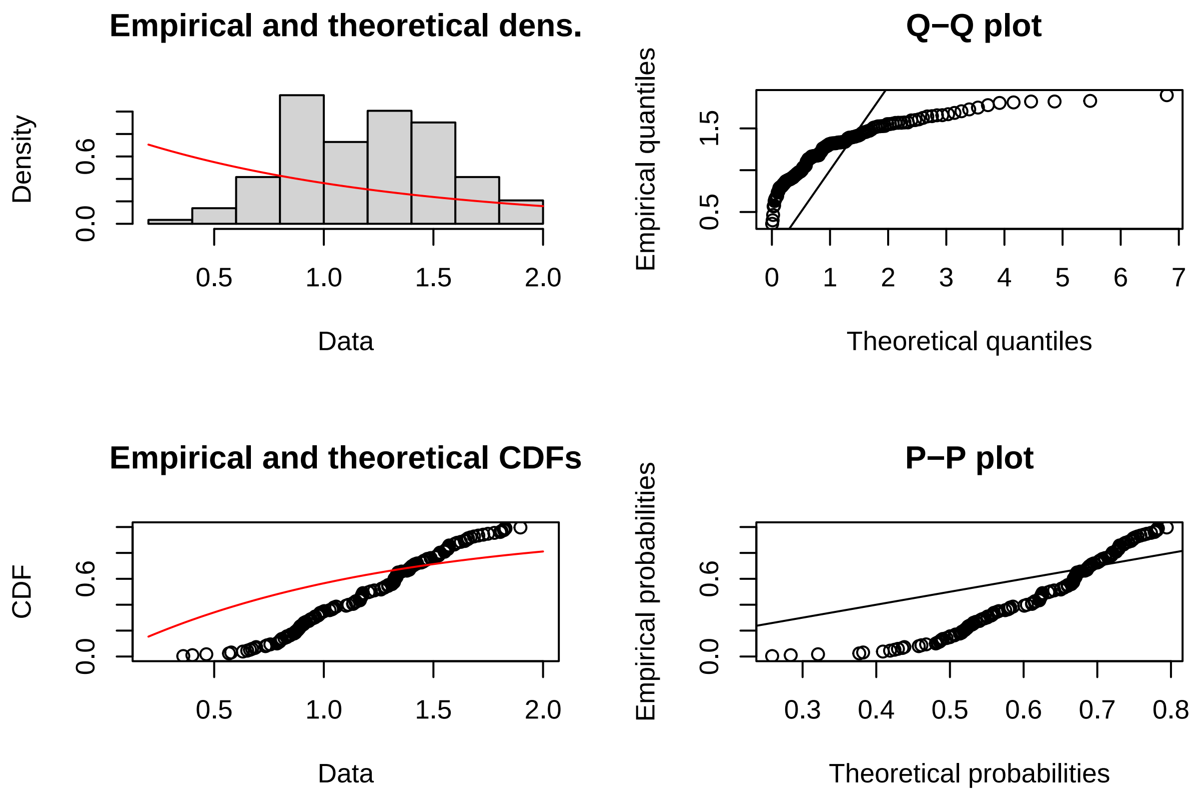

```r
# Weibull distribution
fit.weibull  <- fitdist(umbs_diversity$shannon, "weibull")
plot(fit.weibull)
```



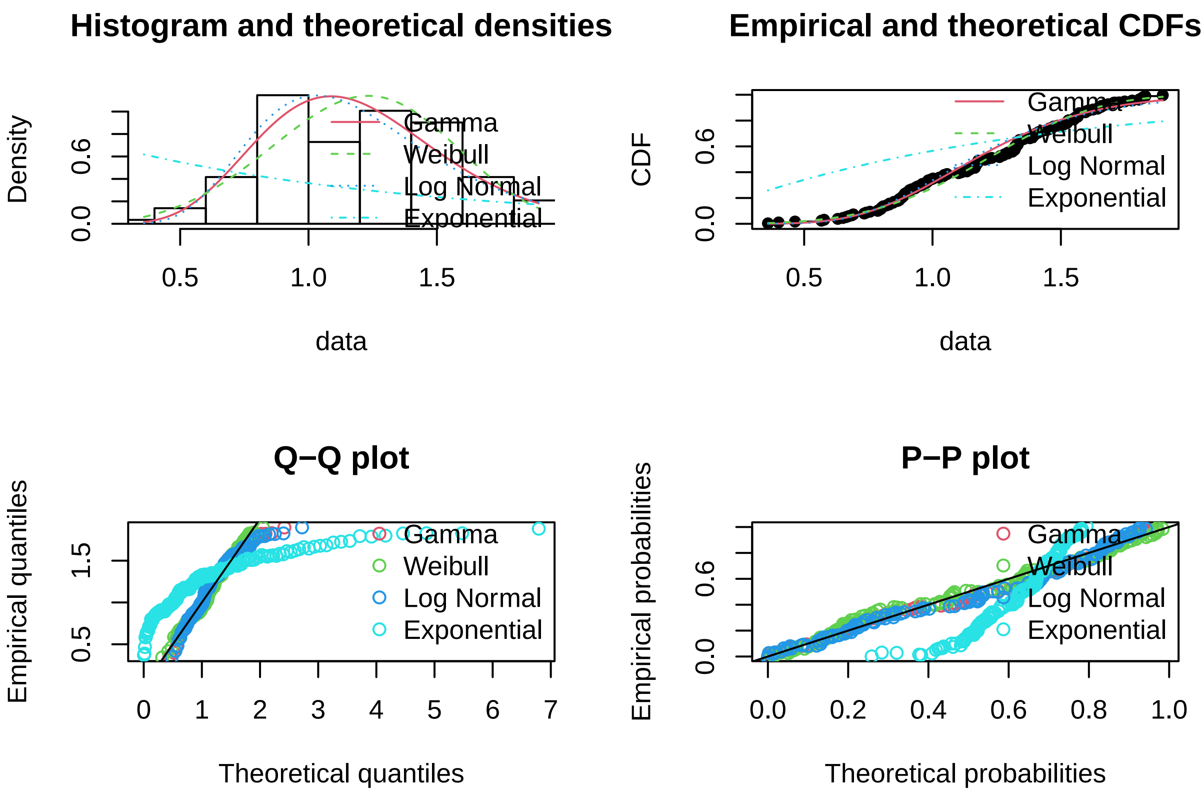
```
# Lognormal distribution
fit.ln <- fitdist(umbs_diversity$shannon, "lnorm")
plot(fit.ln)
```




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



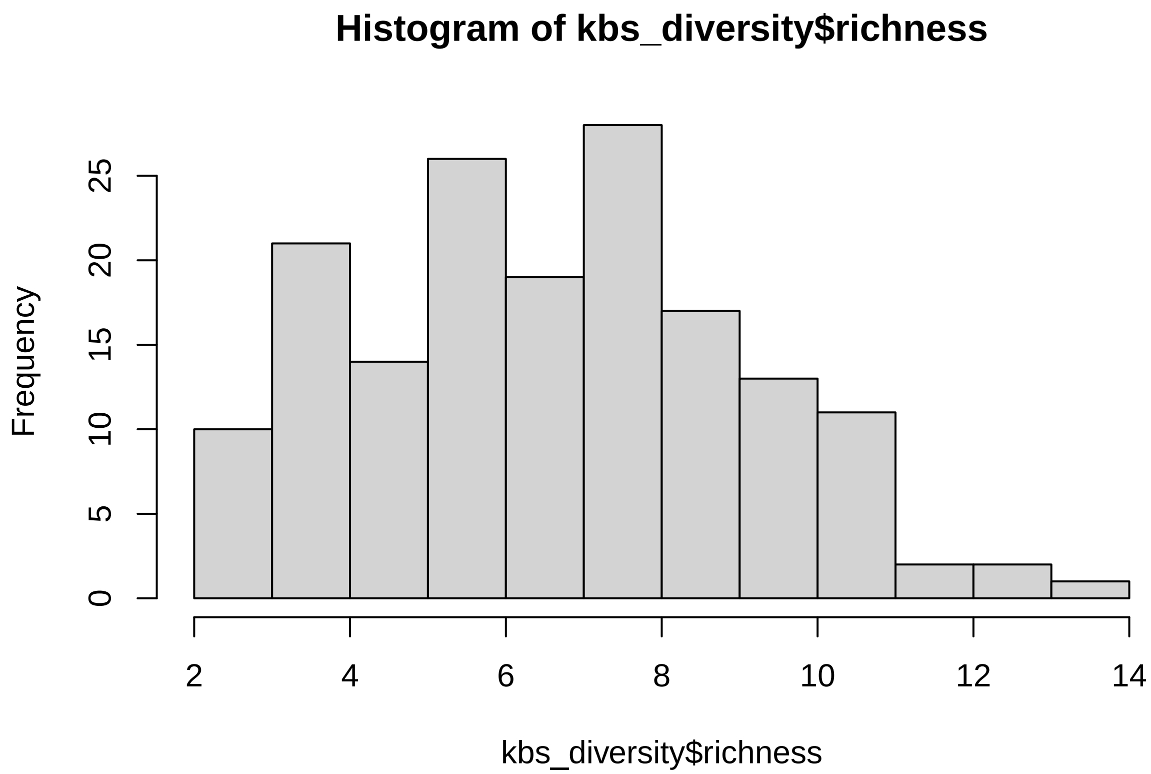

```r
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull", "Log Normal", "E
```

```
## Goodness-of-fit statistics
##                                   Gamma    Weibull Log Normal       Exp
## Kolmogorov-Smirnov statistic 0.09883347 0.07738115  0.1086246  0.383598
## Cramer-von Mises statistic   0.22906356 0.14136759  0.3053123  6.737411
## Anderson-Darling statistic   1.32366964 0.78557156  1.8540960 33.067741
##
## Goodness-of-fit criteria
##                                   Gamma  Weibull Log Normal      Exp
## Akaike's Information Criterion 113.7296 102.5119   124.2549 342.3854
## Bayesian Information Criterion 119.6692 108.4515   130.1945 345.3552
```

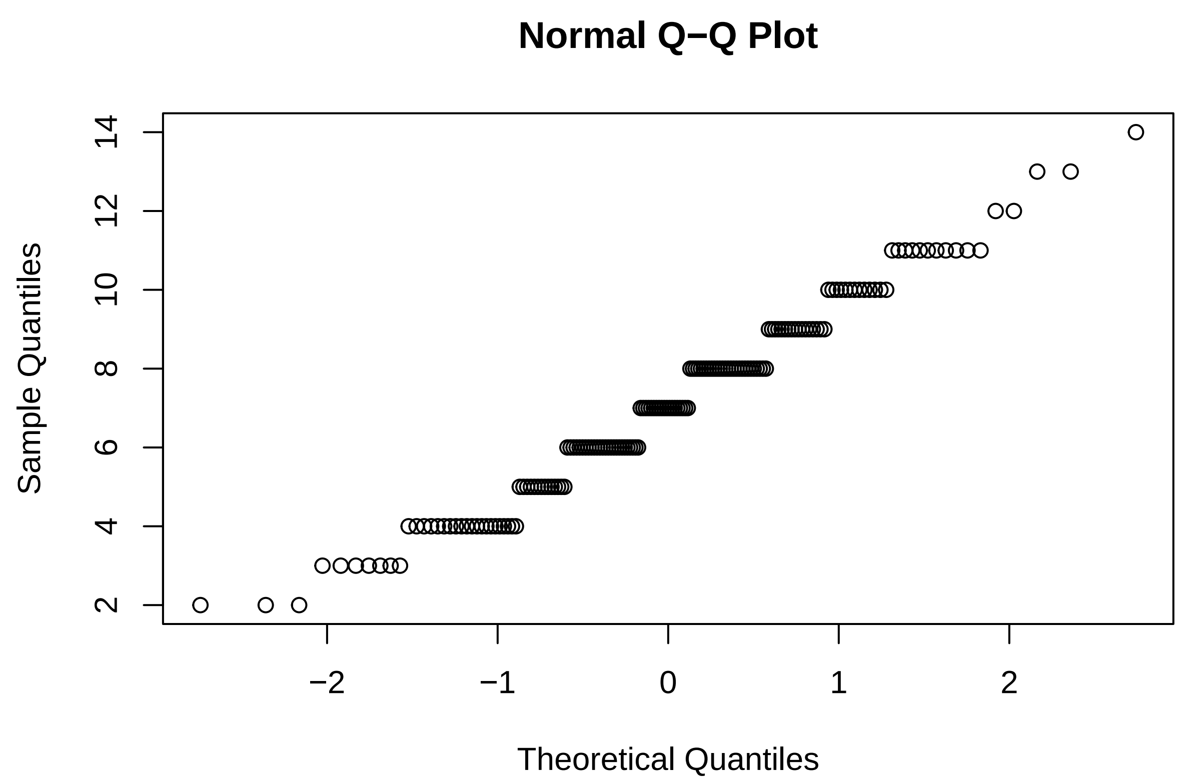
```r
# weibull best distributions based on AIC and BIC values
```

Species Richness KBS

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



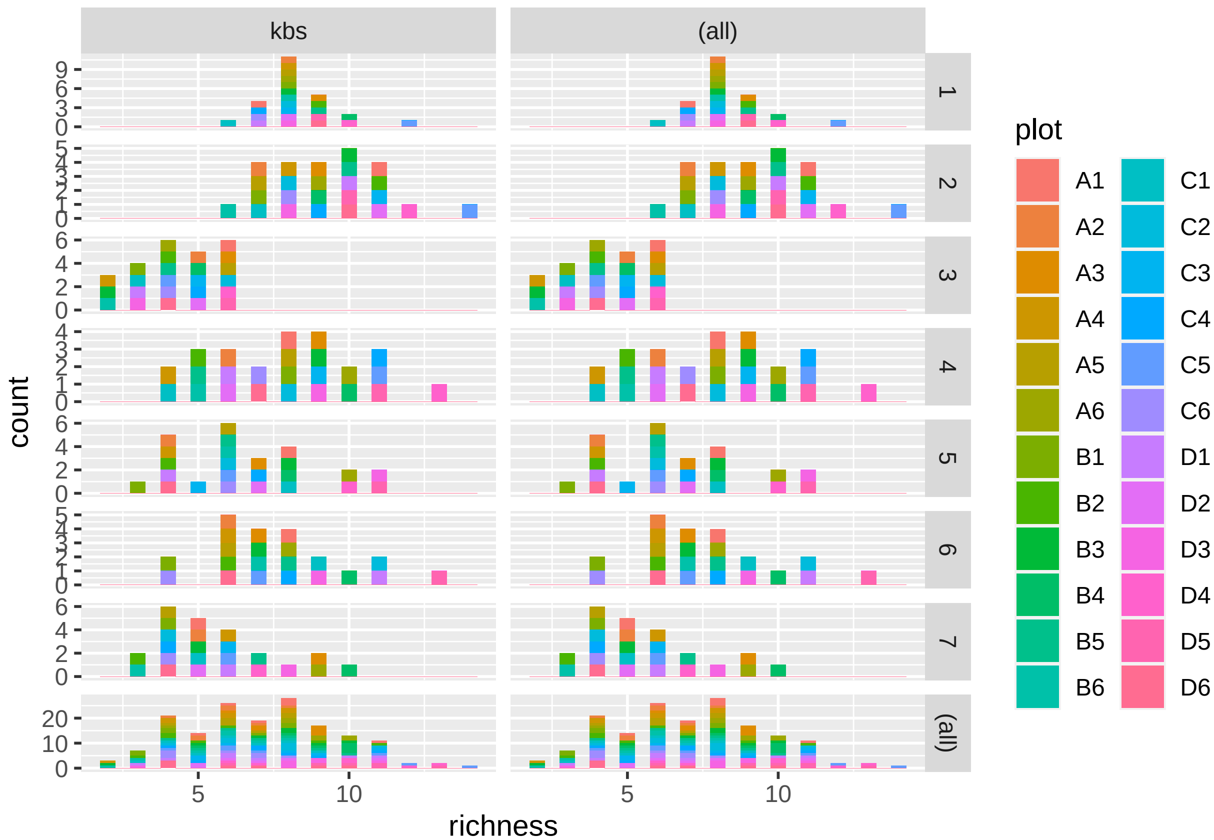

```
qqnorm(kbs_diversity$richness)
```



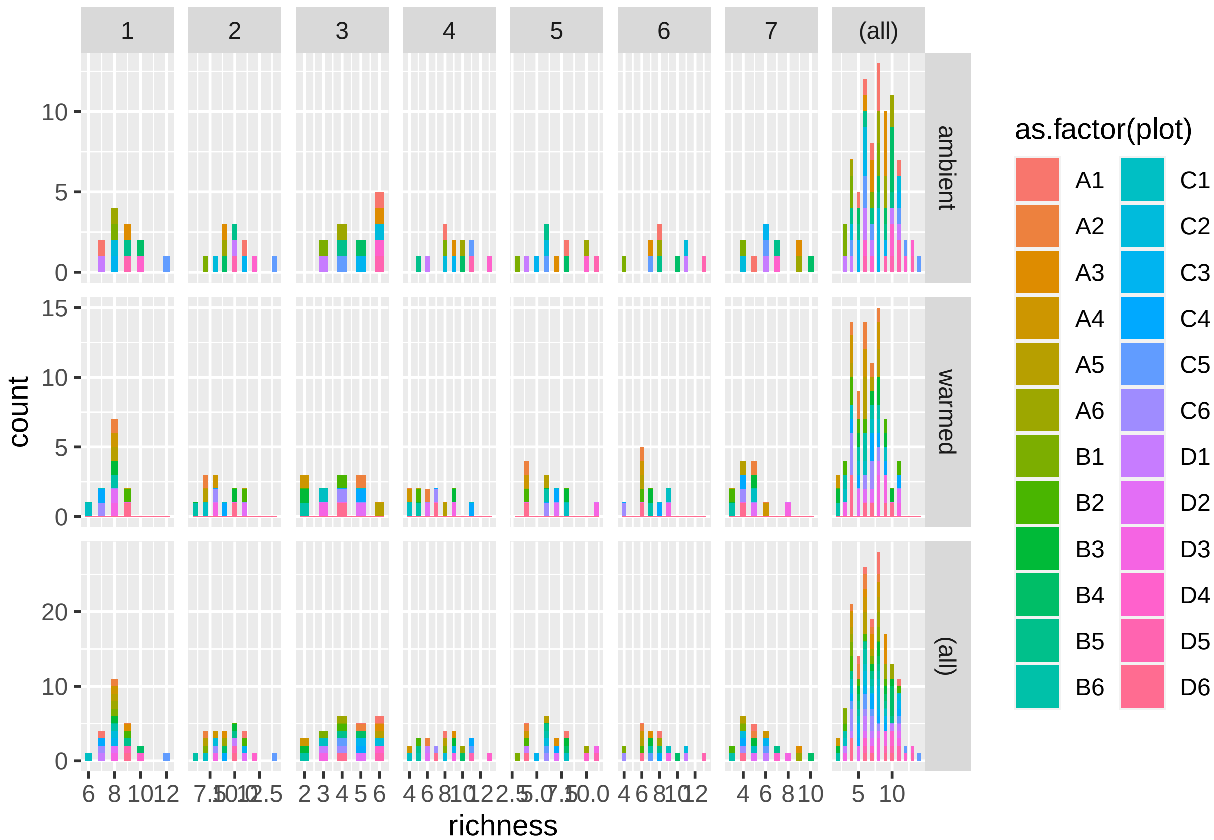
```
shapiro.test(kbs_diversity$richness) # pvalue is < 0.05 so we reject the null hypothesis that the data
```

```
##
##  Shapiro-Wilk normality test
##
## data:  kbs_diversity$richness
## W = 0.97542, p-value = 0.005117
```

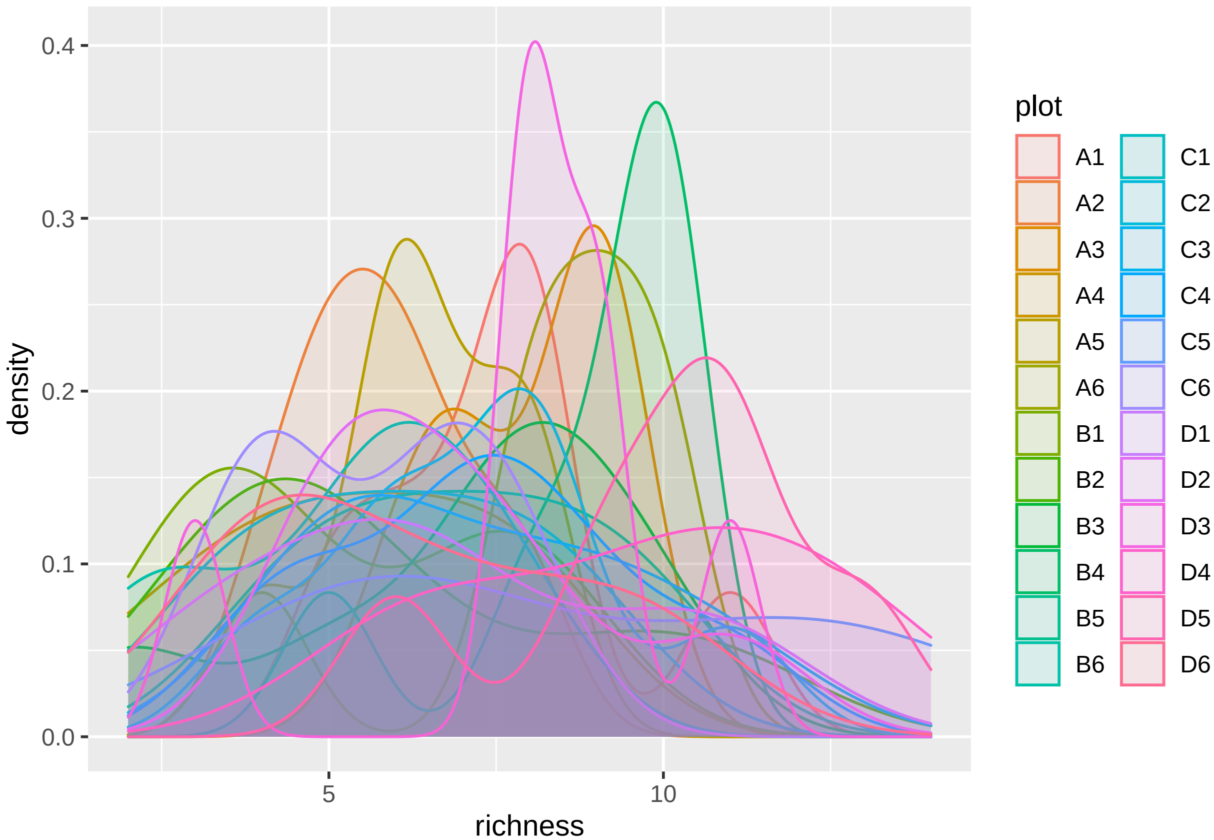
```
# Visualizing plot average totals for kbs at the PLOT LEVEL
ggplot(kbs_diversity, aes(richness, fill = plot)) +
        geom_histogram(binwidth = 0.5) +
        facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



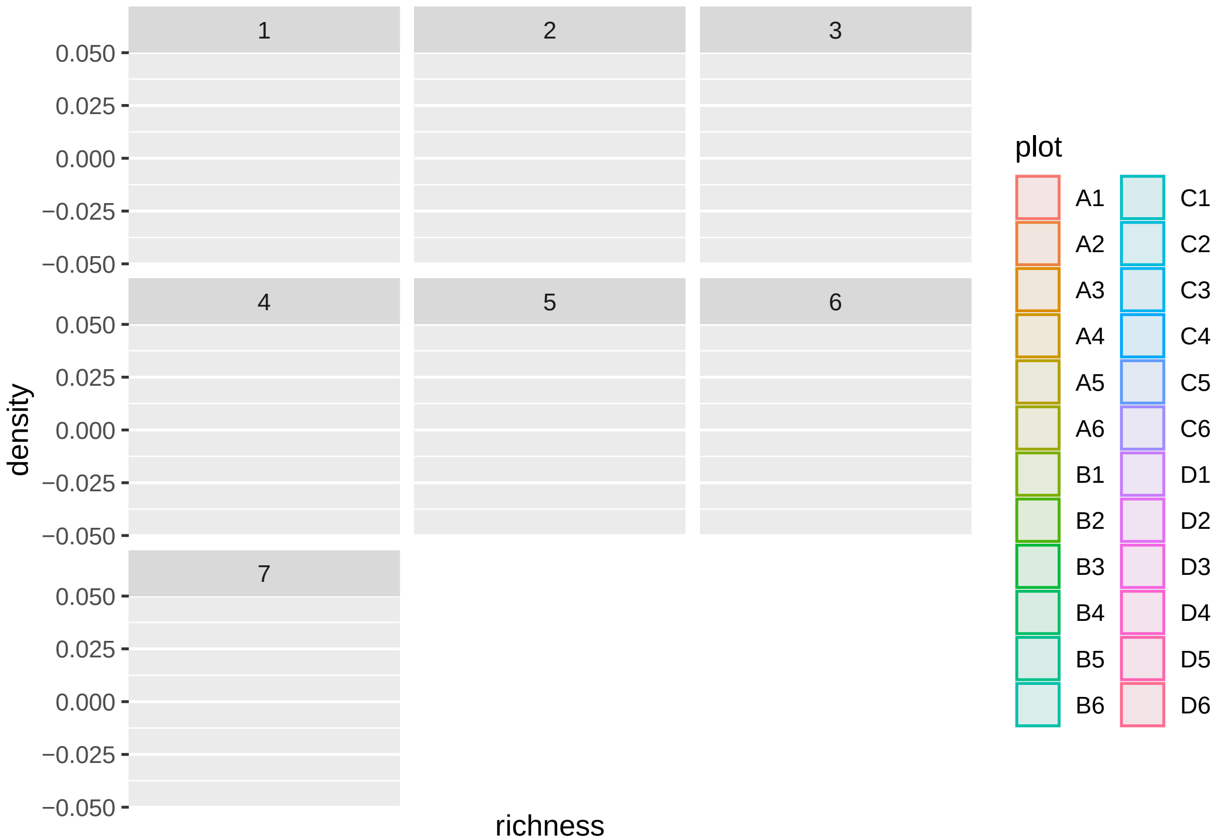

```
ggplot(kbs_diversity, aes(richness, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
        facet_grid(state~year_factor, margins = TRUE, scales = "free")
```



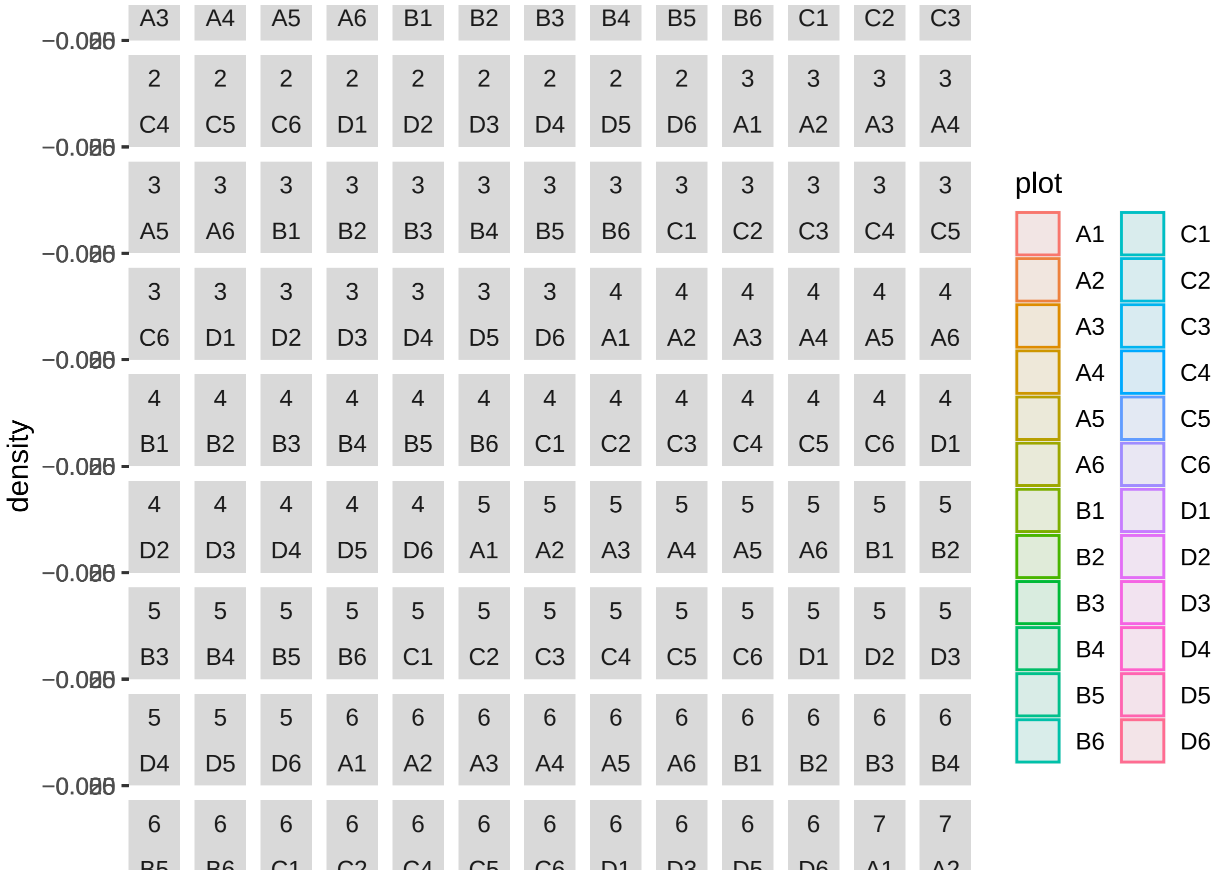

```r
ggplot(kbs_diversity, aes(richness, fill = plot, color=plot)) +
        geom_density(alpha = 0.1)
```



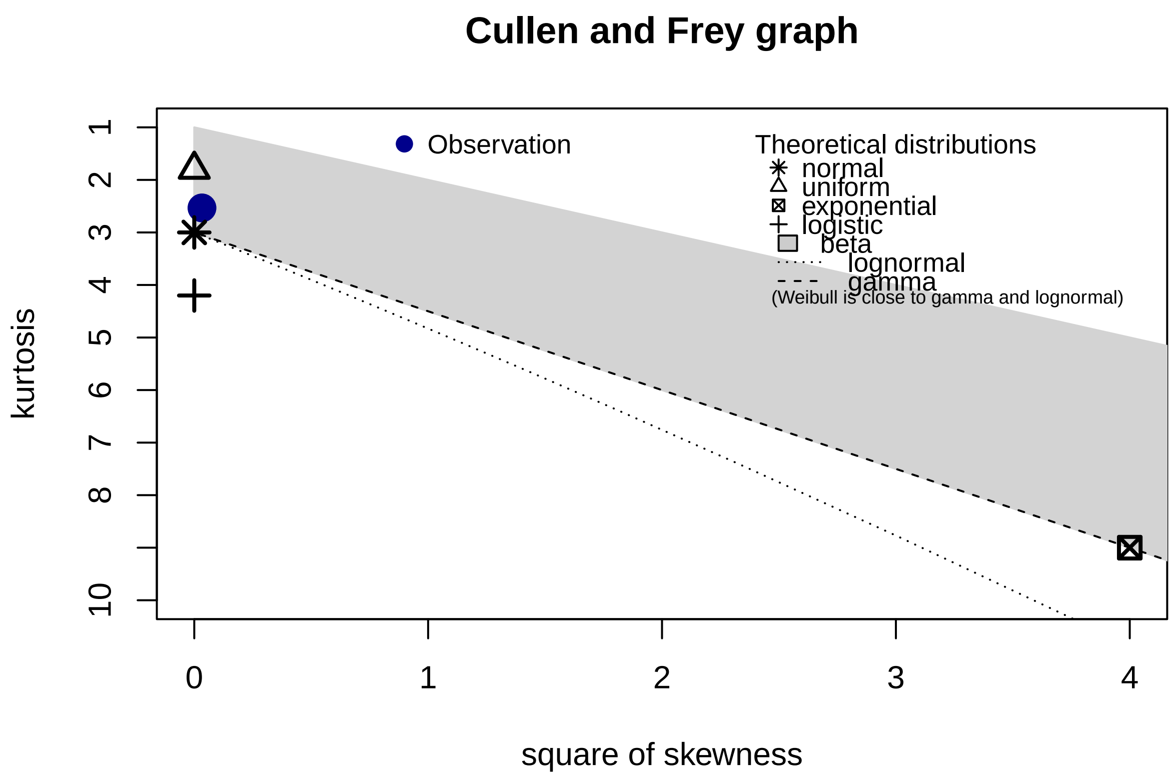

```
ggplot(kbs_diversity, aes(richness, fill = plot, color=plot)) +
        geom_density(alpha = 0.1) +
        facet_wrap(~year_factor)
```




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

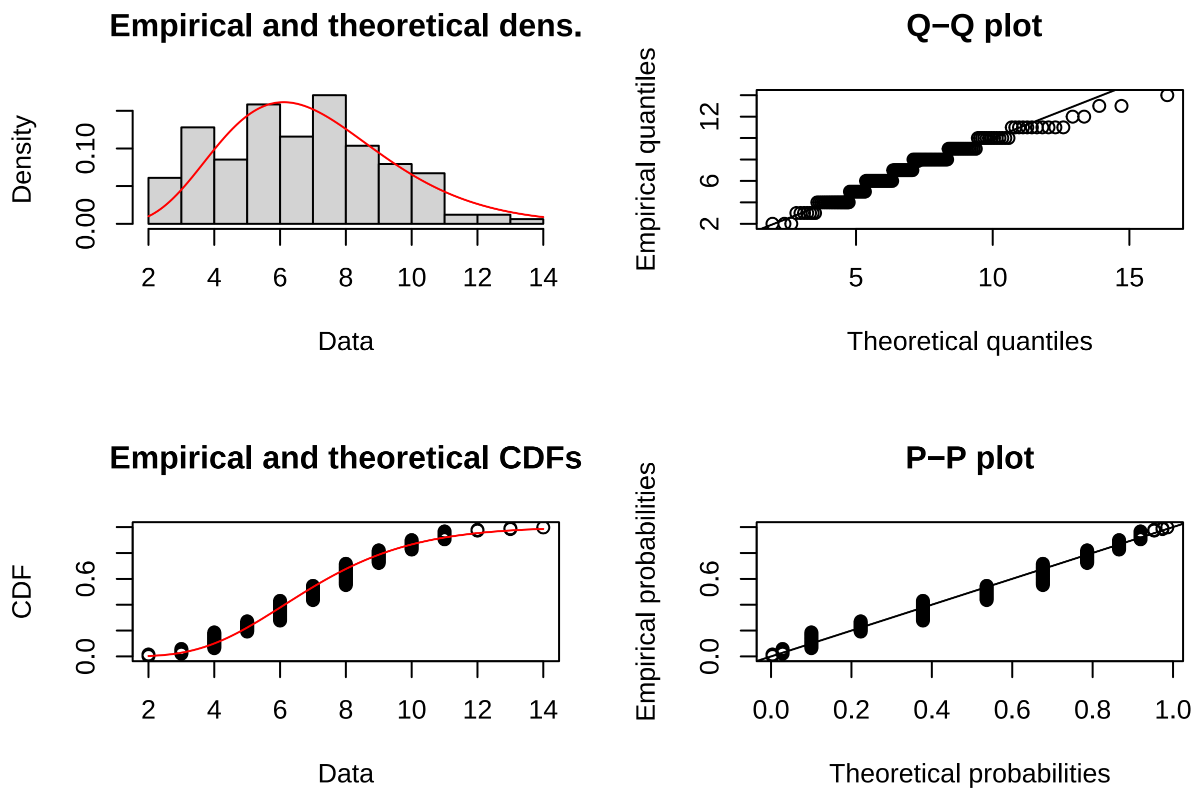



```
# Exploring distributions for these data:
descdist(kbs_diversity$richness, discrete = FALSE) # close to normal
```

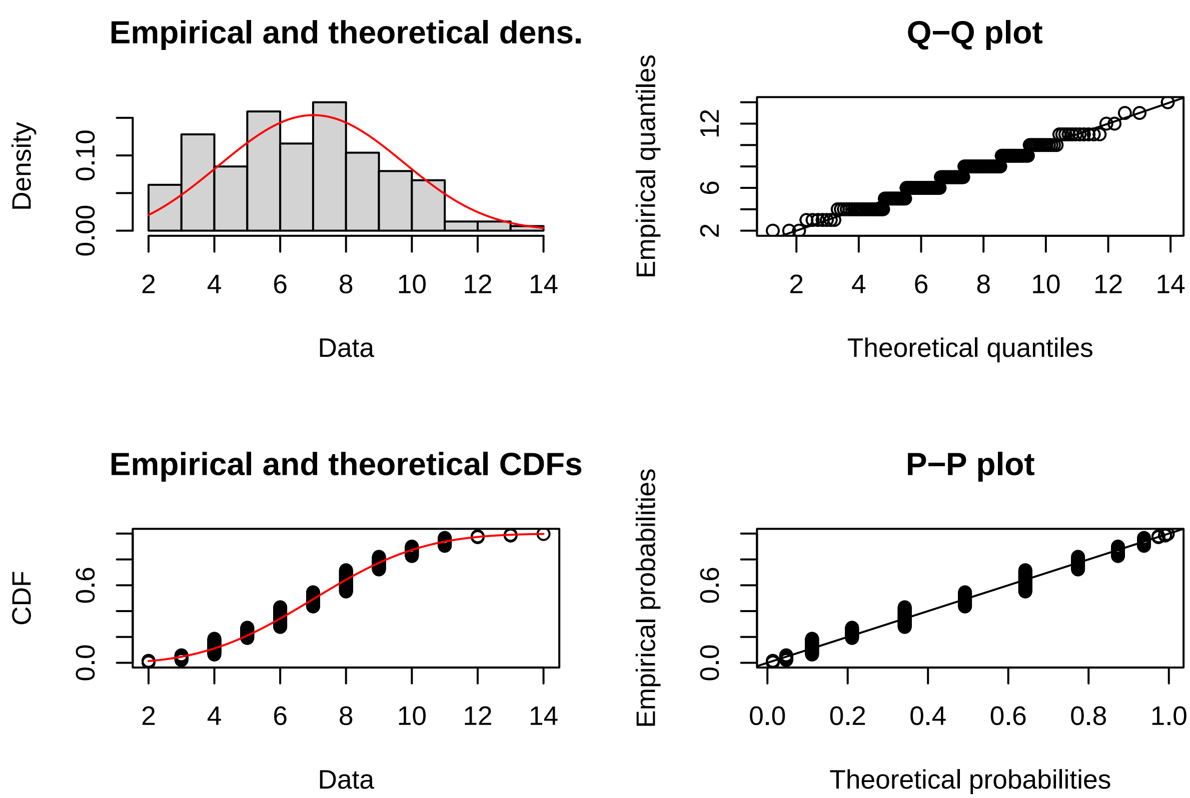



```
## summary statistics
## ------
## min:  2   max:  14
## median:  7
## mean:  7.085366
## estimated sd:  2.497612
## estimated skewness:  0.1815731
## estimated kurtosis:  2.533271
```

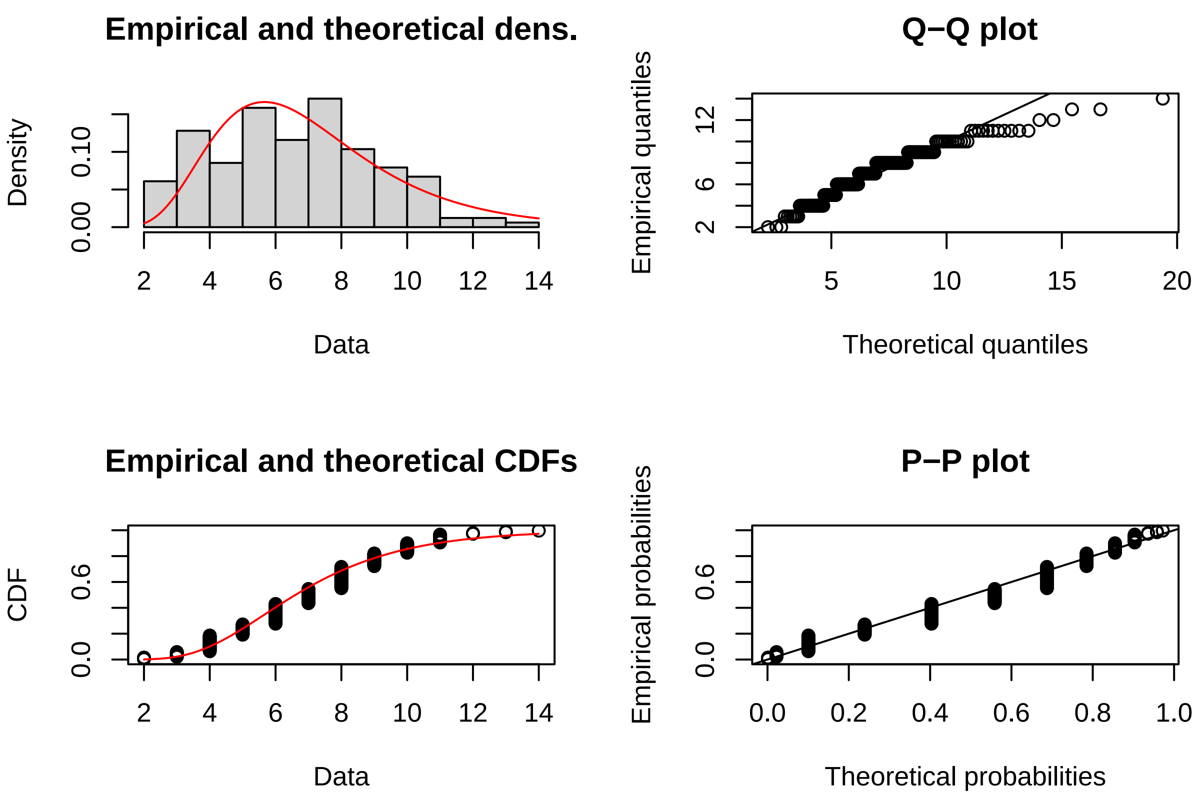
```
# Gamma distribution
fit.gamma <- fitdist(kbs_diversity$richness, "gamma")
plot(fit.gamma)
```



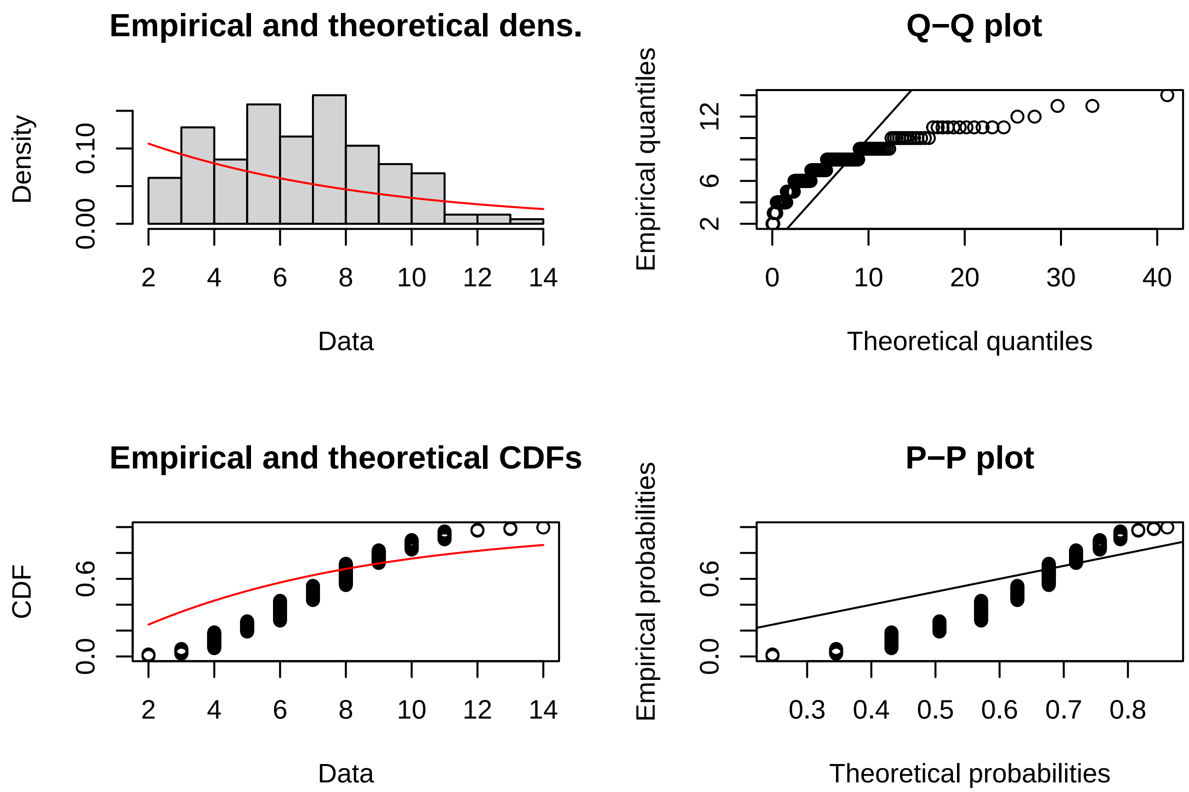

```r
# Weibull distribution
fit.weibull  <- fitdist(kbs_diversity$richness, "weibull")
plot(fit.weibull)
```



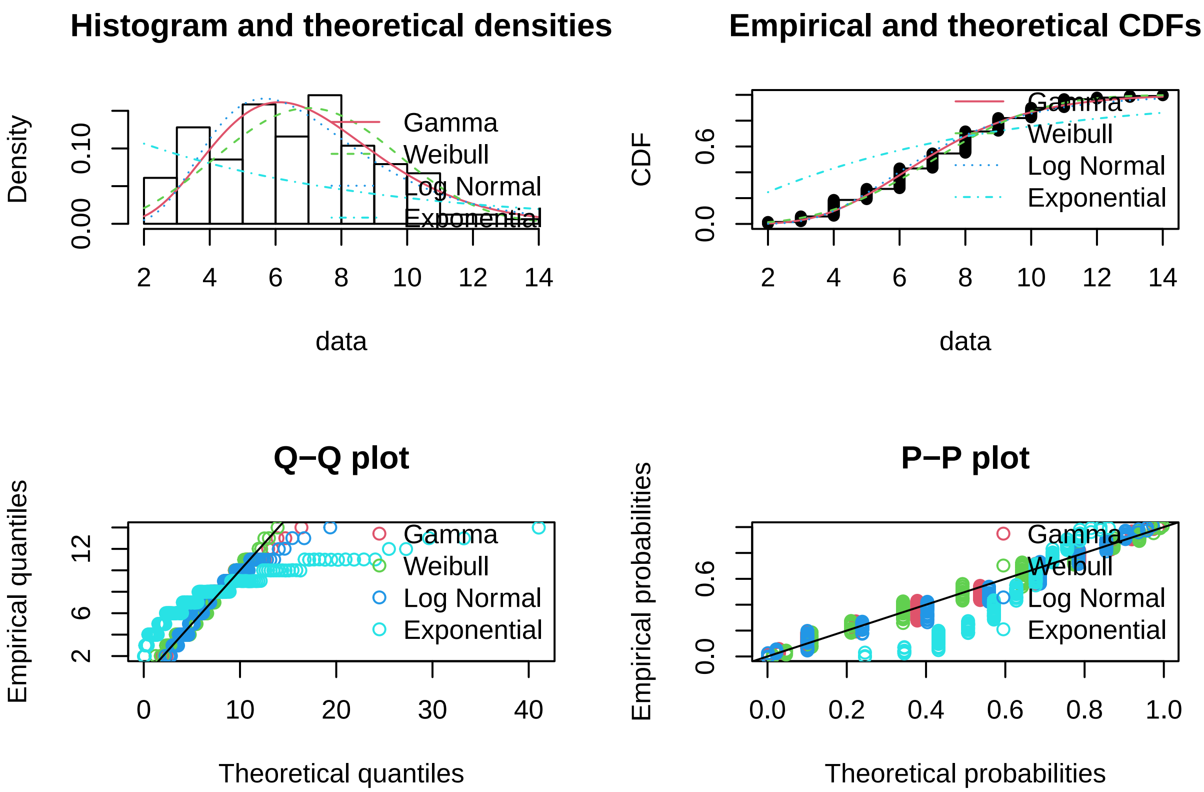
```r
# Lognormal distribution
fit.ln <- fitdist(kbs_diversity$richness, "lnorm")
plot(fit.ln)
```




```r
# Exponential distribution is another option
fit.exp <- fitdist(kbs_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)
```



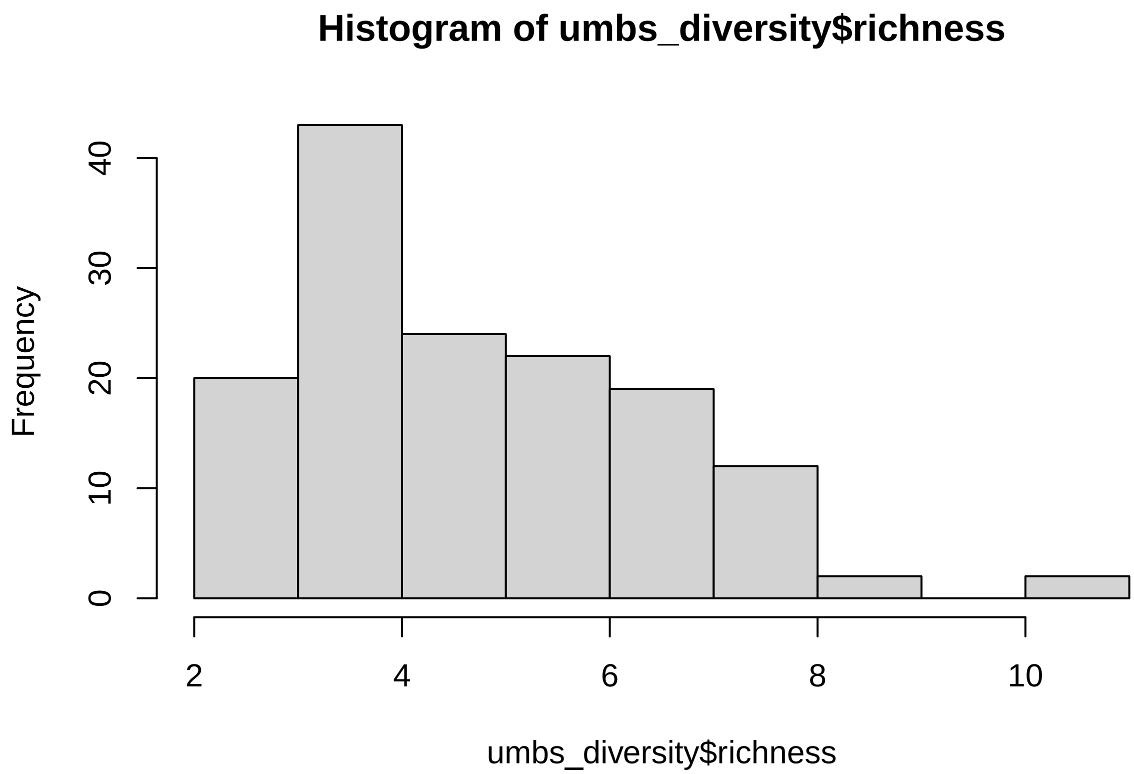

```
# Goodness of fit comparisons across fits
gofstat(list(fit.gamma, fit.weibull, fit.ln, fit.exp), fitnames = c("Gamma", "Weibull", "Log Normal", "E
```

```
## Goodness-of-fit statistics
##                                  Gamma   Weibull Log Normal       Exp
## Kolmogorov-Smirnov statistic 0.1274482 0.0936834  0.1385545  0.370405
## Cramer-von Mises statistic   0.3359487 0.2258529  0.4764064  6.239862
## Anderson-Darling statistic   1.9507448 1.3226919  2.7986159 31.312288
##
## Goodness-of-fit criteria
##                                  Gamma   Weibull Log Normal      Exp
## Akaike's Information Criterion 770.5116 764.7587   781.8298 972.2343
## Bayesian Information Criterion 776.7113 770.9585   788.0295 975.3342
```

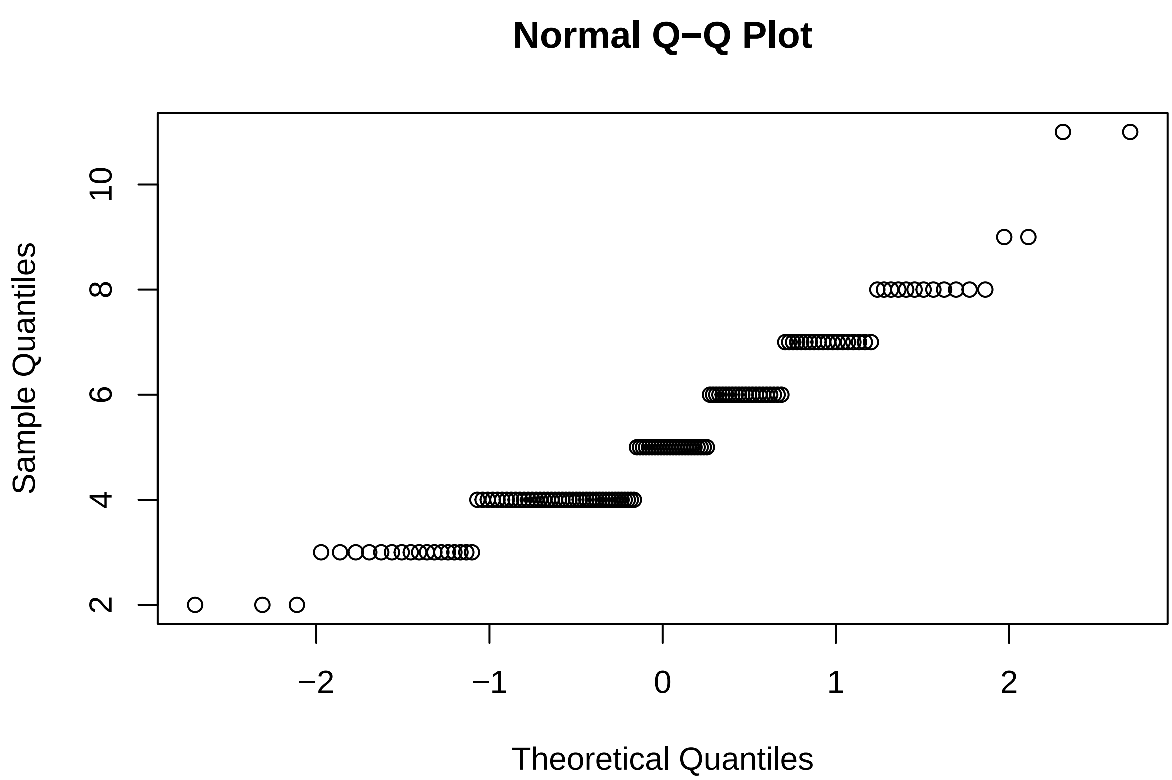
```
# weibull distribution looks to be the best based on AIC and BIC values
```

UMBS

```
### UMBS ###
hist(umbs_diversity$richness)
```



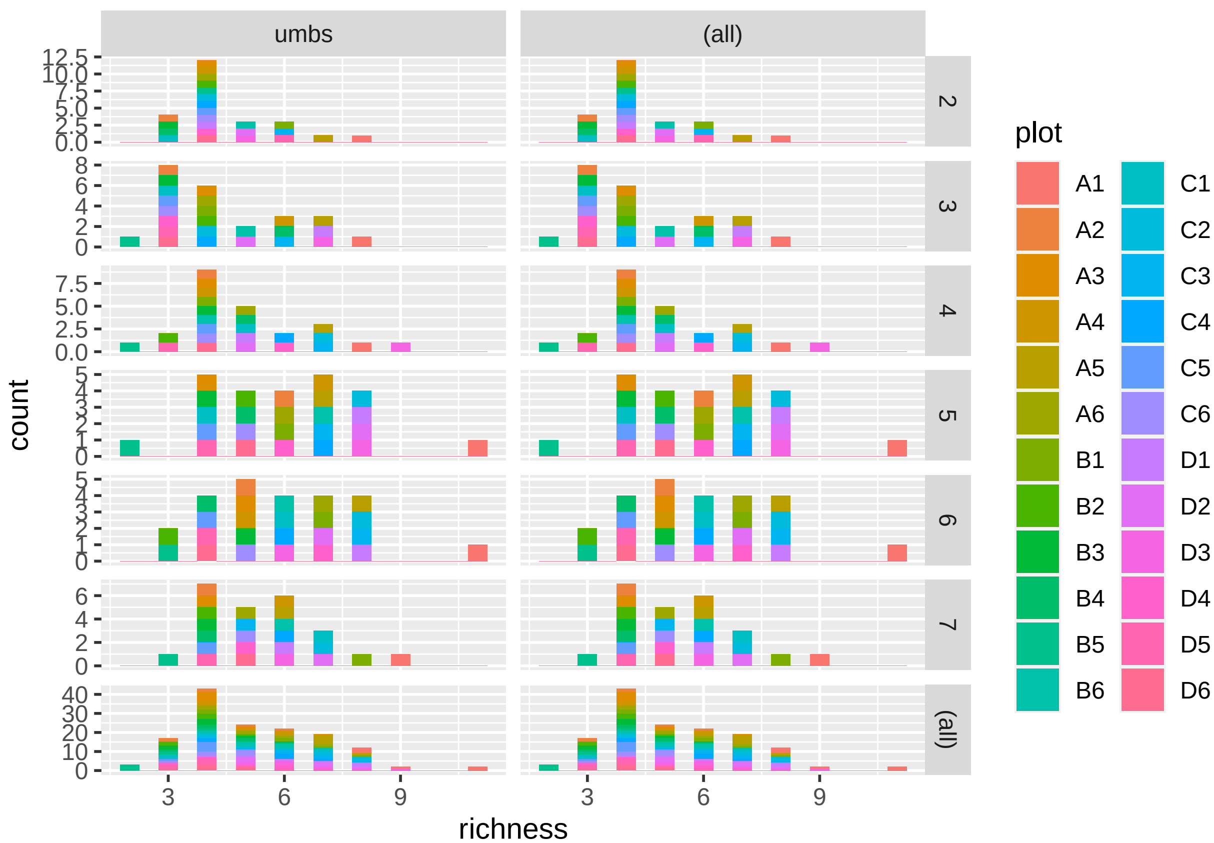

```
qqnorm(umbs_diversity$richness)
```



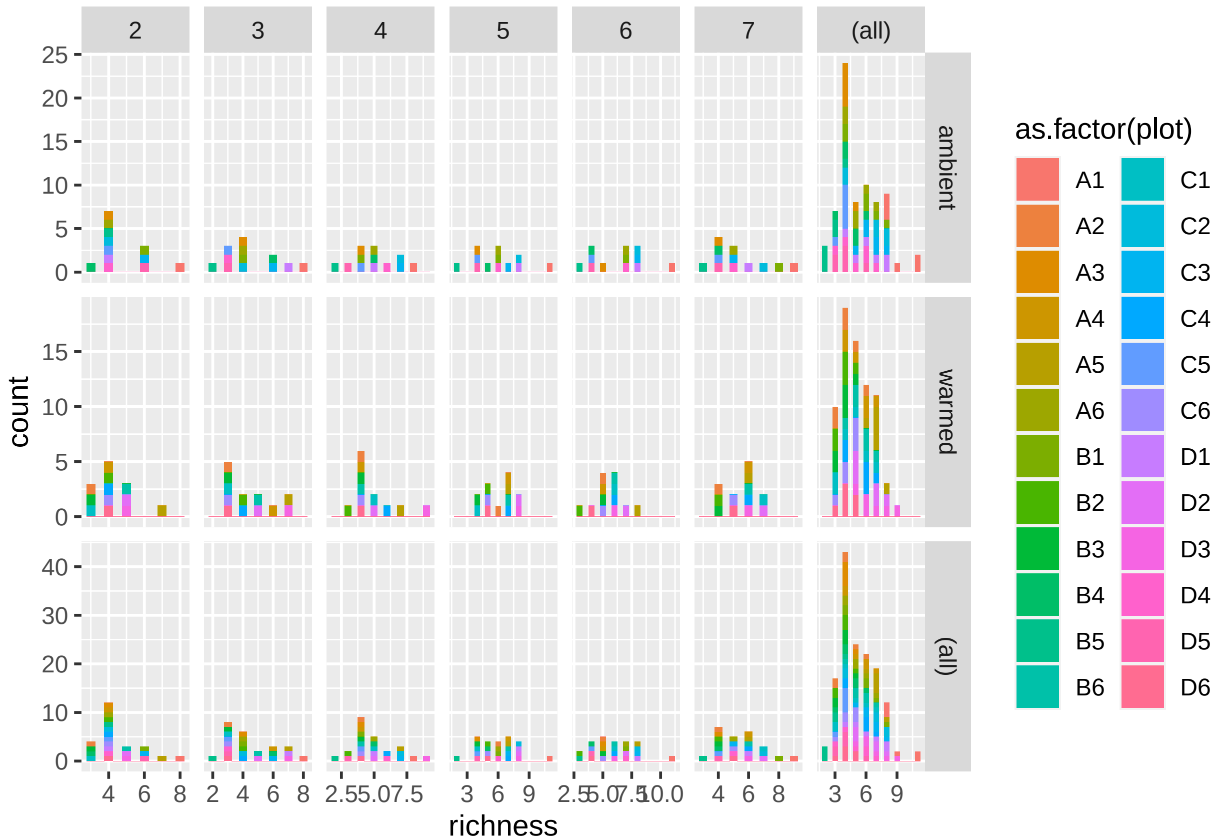
```r
shapiro.test(umbs_diversity$richness) # pvalue is < 0.05 so we reject the null hypothesis that the data
```

```
##
##  Shapiro-Wilk normality test
##
## data:  umbs_diversity$richness
## W = 0.93006, p-value = 1.553e-06
```

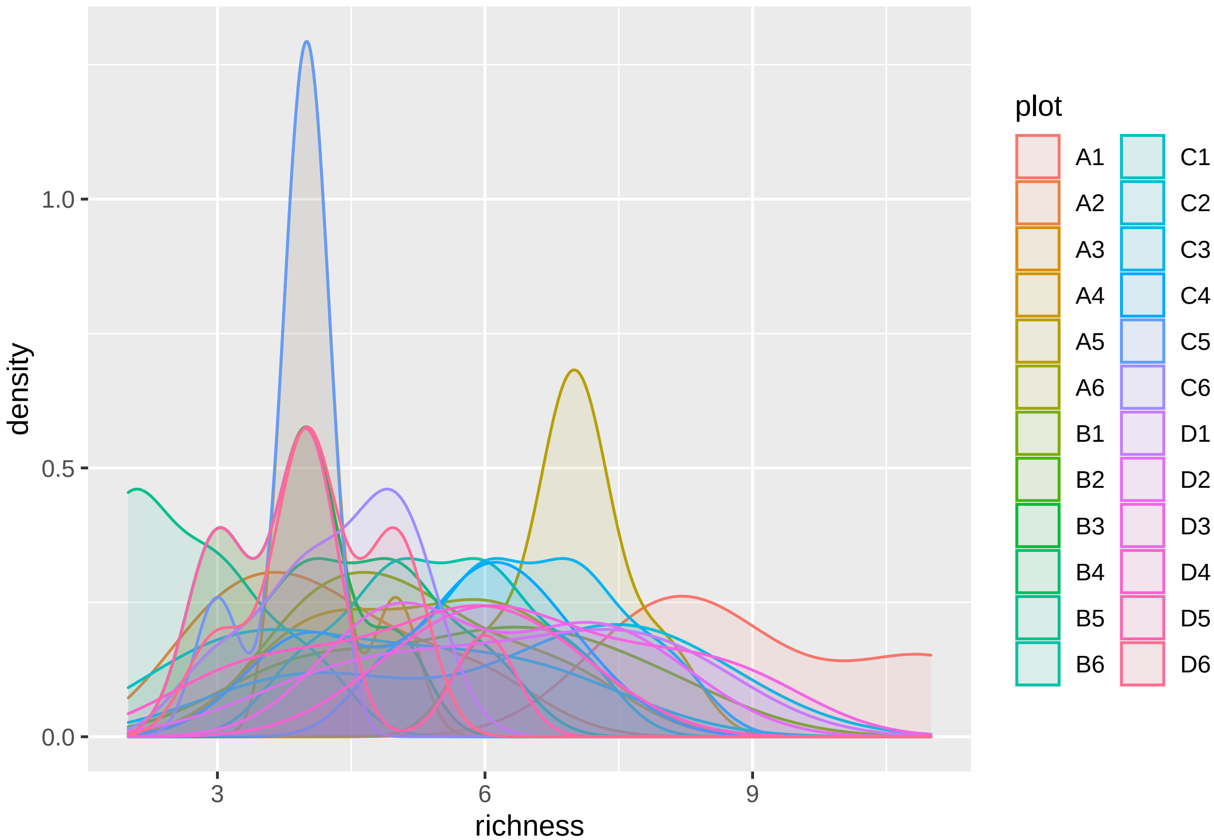
```r
# Visualizing plot average totals for umbs at the PLOT LEVEL
ggplot(umbs_diversity, aes(richness, fill = plot)) +
        geom_histogram(binwidth = 0.5) +
        facet_grid(year_factor ~ site, margins = TRUE, scales = "free")
```



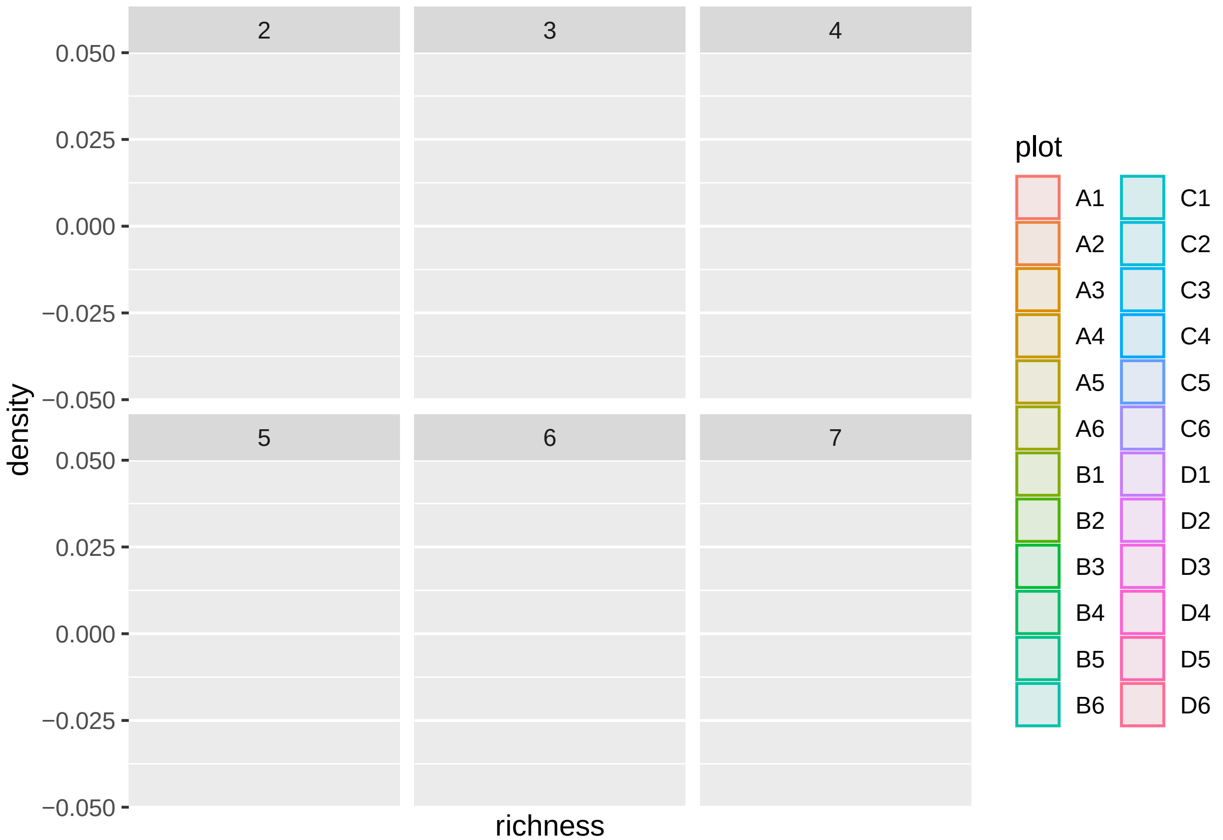

```r
ggplot(umbs_diversity, aes(richness, fill = as.factor(plot))) + geom_histogram(binwidth = 0.5) +
       facet_grid(state~year_factor, margins = TRUE, scales = "free")
```



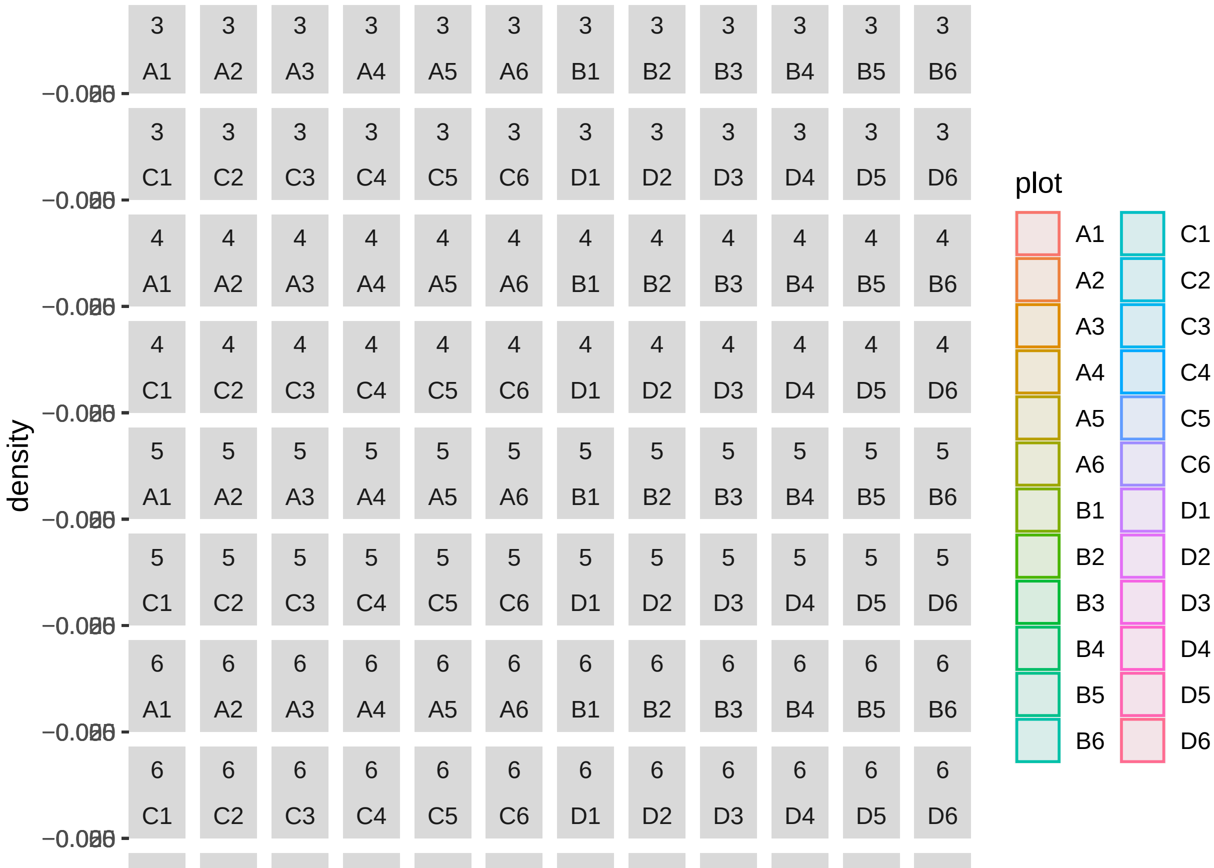

```
ggplot(umbs_diversity, aes(richness, fill = plot, color=plot)) +
        geom_density(alpha = 0.1)
```



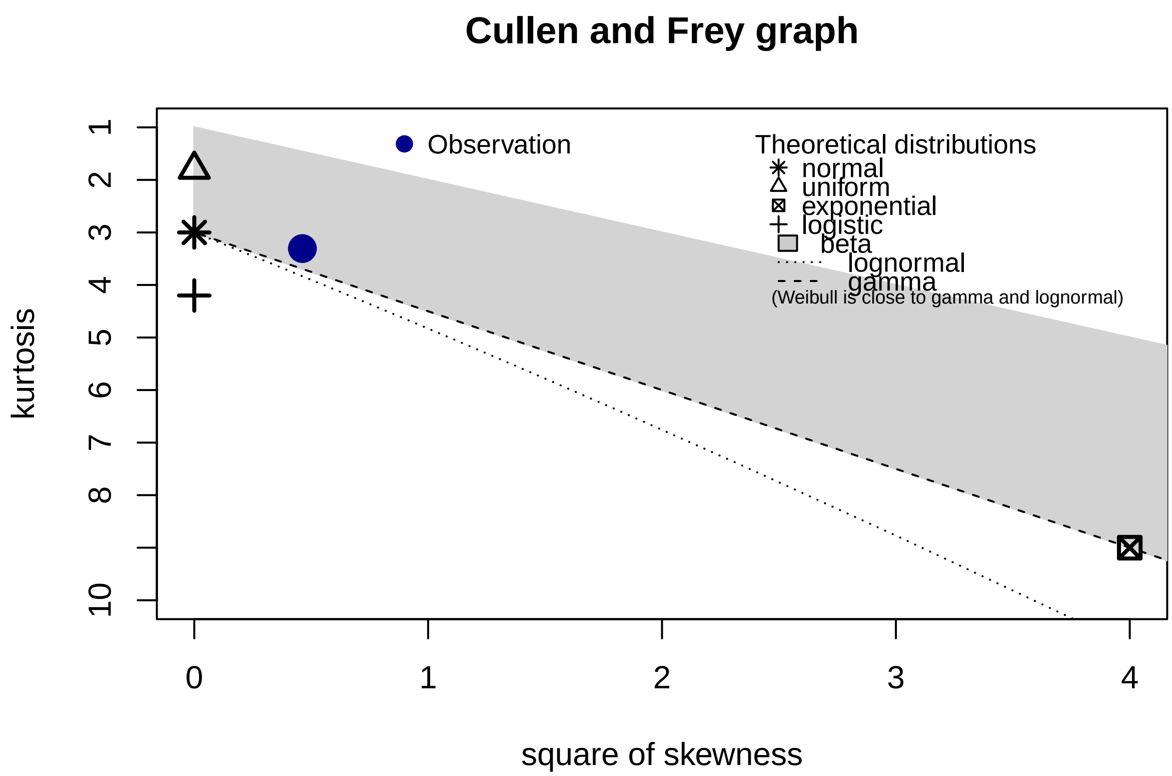

```
ggplot(umbs_diversity, aes(richness, fill = plot, color=plot)) +
        geom_density(alpha = 0.1) +
        facet_wrap(~year_factor)
```




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

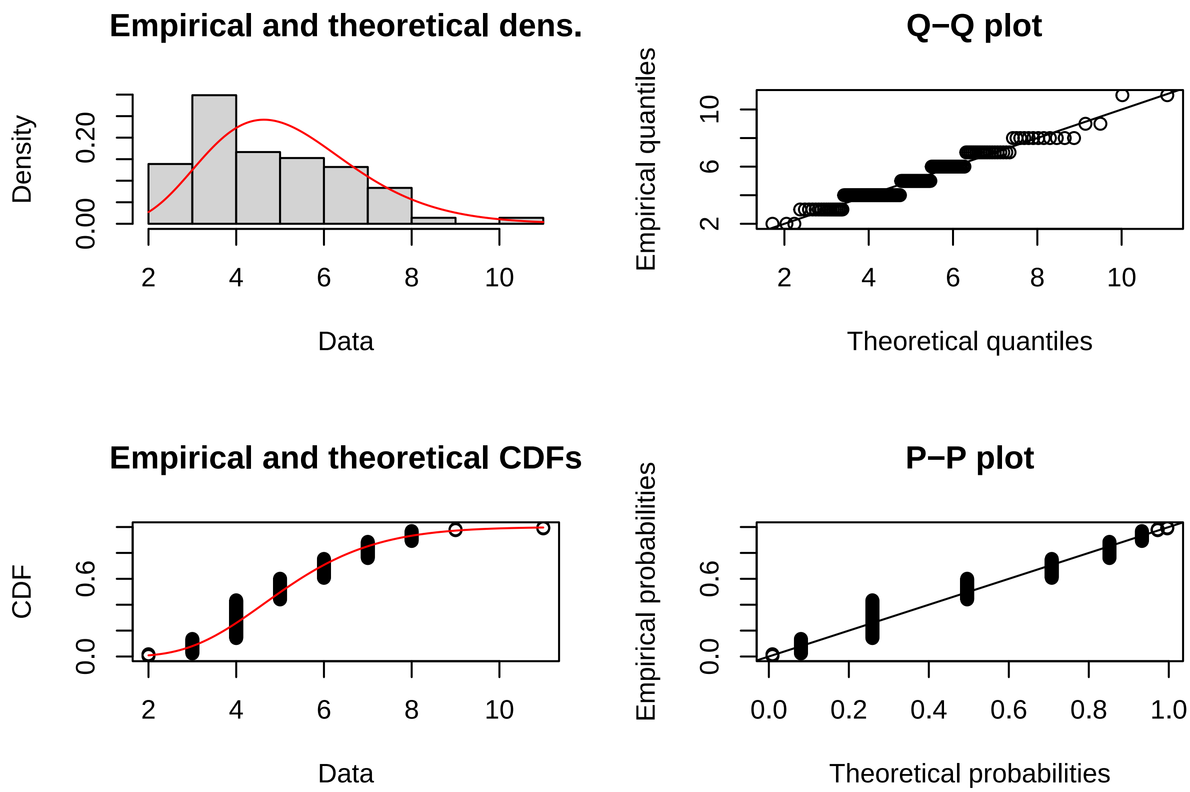


```
# Exploring distributions for these data:
descdist(umbs_diversity$richness, discrete = FALSE)
```

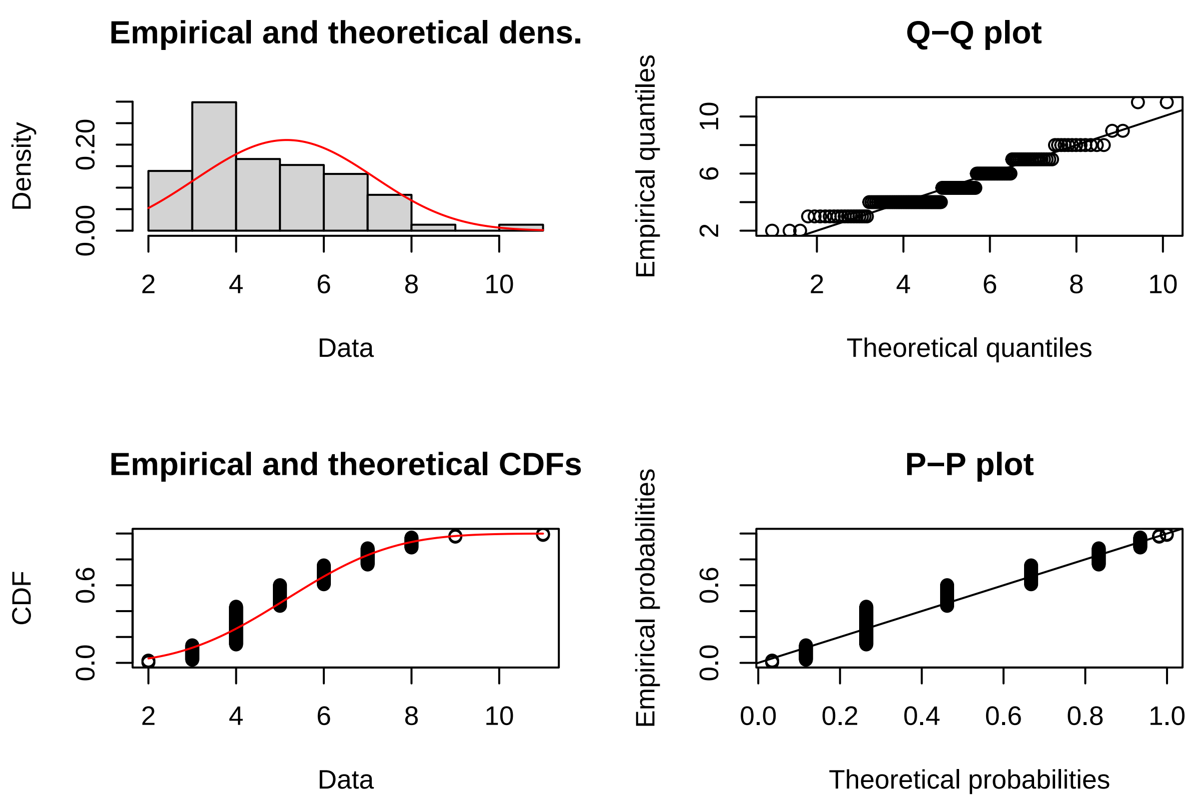



```
## summary statistics
## ------
## min:  2   max:  11
## median:  5
## mean:  5.208333
## estimated sd:  1.757601
## estimated skewness:  0.6799625
## estimated kurtosis:  3.306786
```

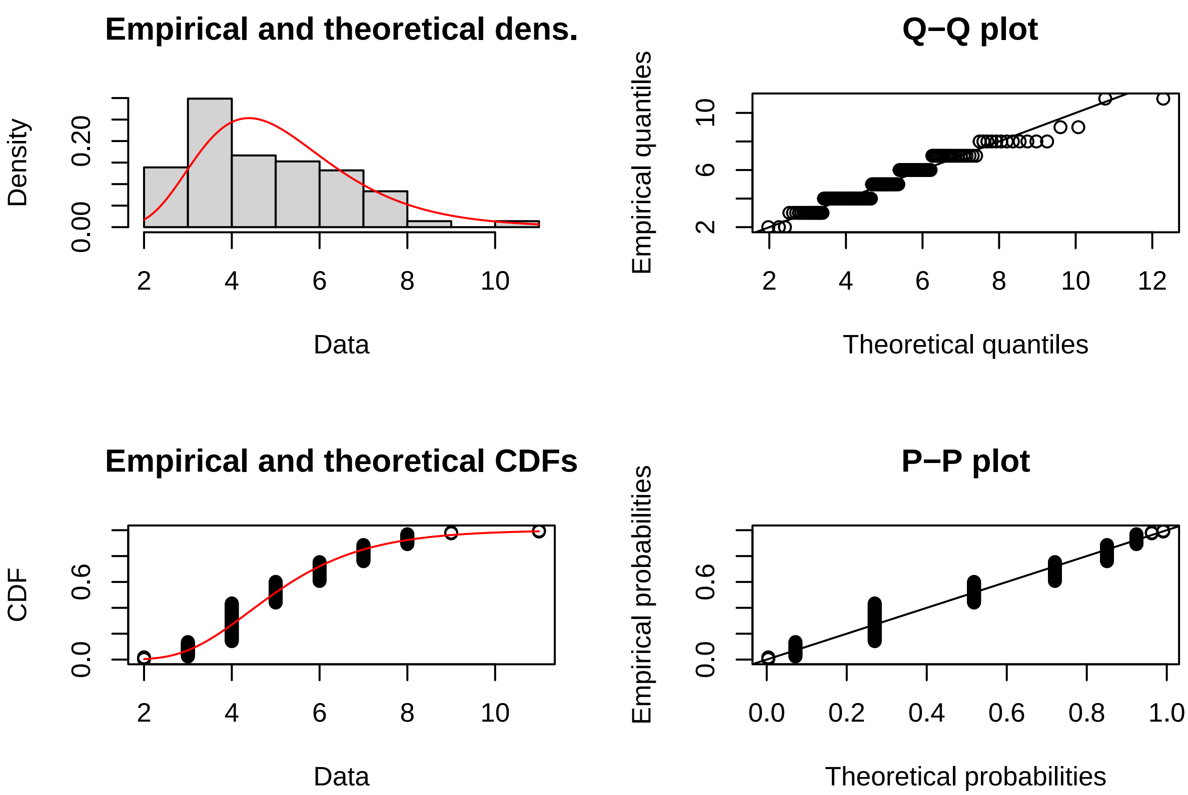
```
# Gamma distribution
fit.gamma <- fitdist(umbs_diversity$richness, "gamma")
plot(fit.gamma)
```



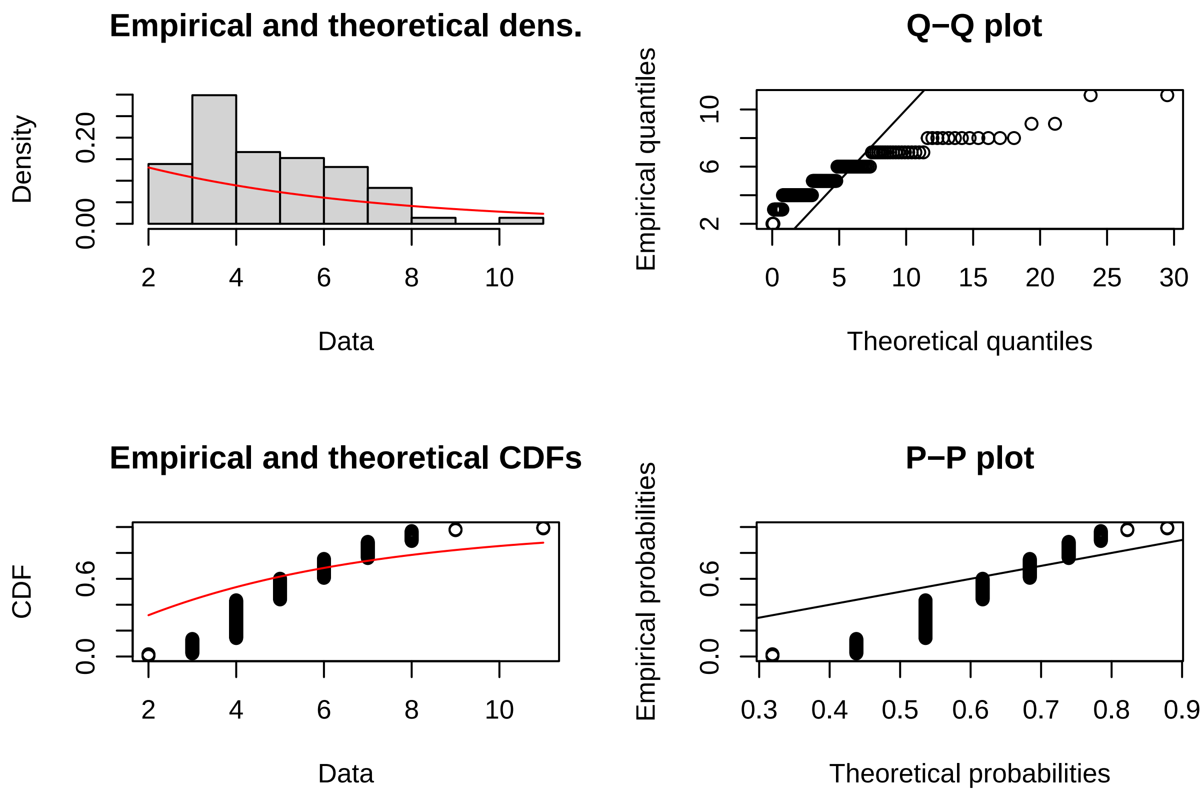

```
# Weibull distribution
fit.weibull  <- fitdist(umbs_diversity$richness, "weibull")
plot(fit.weibull)
```



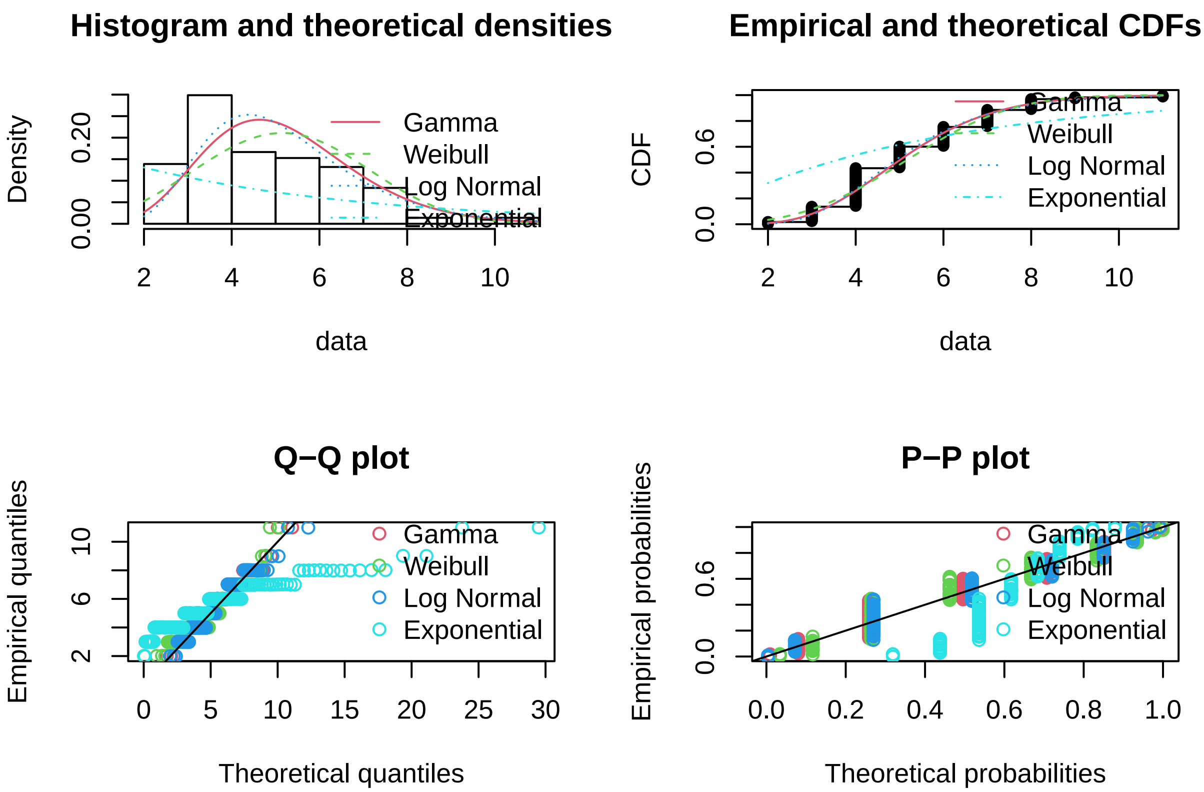
```r
# Lognormal distribution
fit.ln <- fitdist(umbs_diversity$richness, "lnorm")
plot(fit.ln)
```




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




```
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", "
```

```
## Goodness-of-fit statistics
##                                  Gamma   Weibull Log Normal        Exp
## Kolmogorov-Smirnov statistic 0.1786124 0.1731823  0.1675270  0.4170242
## Cramer-von Mises statistic   0.5557841 0.6102608  0.5383802  6.2644112
## Anderson-Darling statistic   3.0702644 3.4695190  3.0338536 30.7412398
##
## Goodness-of-fit criteria
##                                  Gamma  Weibull Log Normal      Exp
## Akaike's Information Criterion 559.9507 572.2835   559.9916 765.2749
## Bayesian Information Criterion 565.8903 578.2231   565.9312 768.2447
```

```
# log normal and gamma are essentially tied
```

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

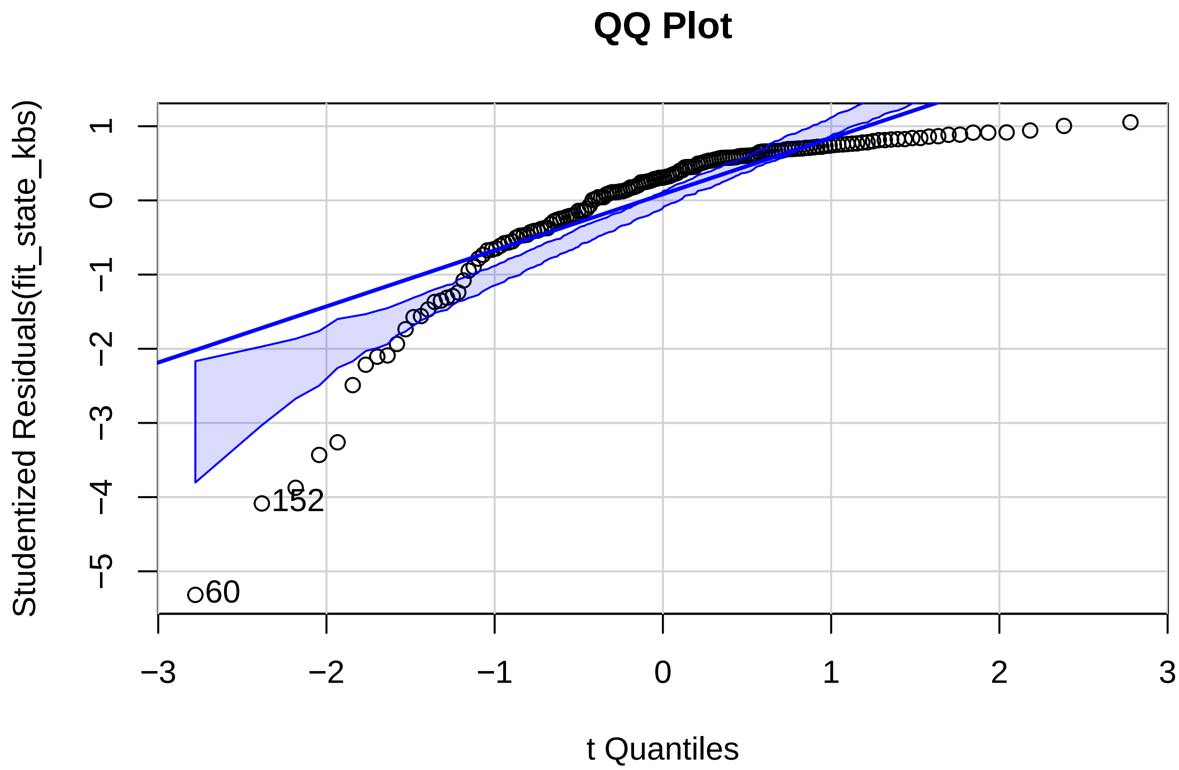
These illustrate whether certain data points have more leverage (more influence), and thus could be outliers. It's a way of detecting outliers. Leverage plots can help identify whether a point has high or low influence, based on its leverage and residual and determining model fit with and without the 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 60, 152, 148
```

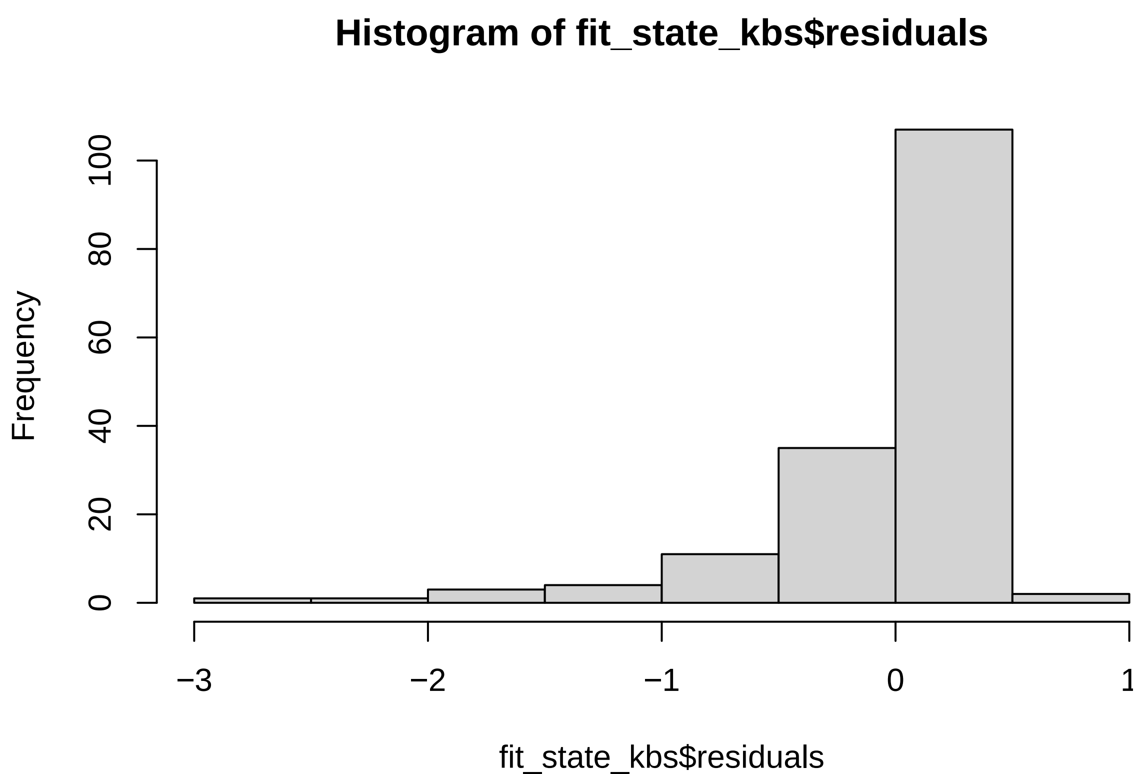
```
##      rstudent unadjusted p-value Bonferroni p
## 60  -5.317501         3.4672e-07   5.6862e-05
## 152 -4.085134         6.9293e-05   1.1364e-02
## 148 -3.874580         1.5512e-04   2.5440e-02
```

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

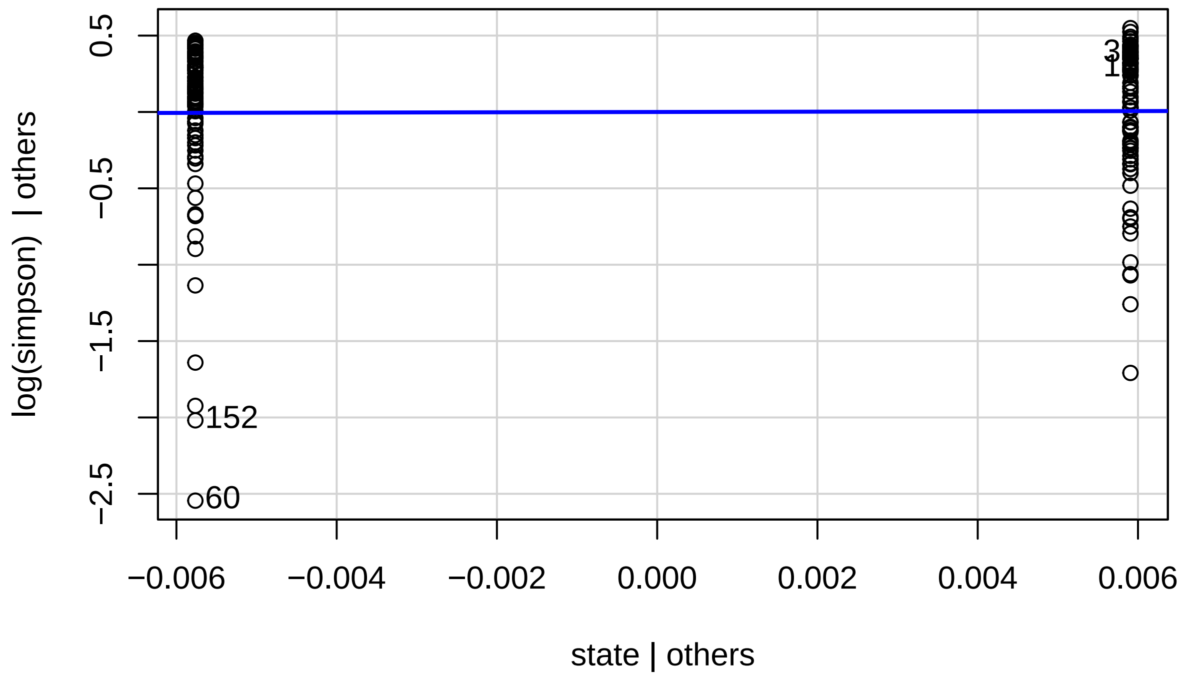



```
##   60 152
##   60 149
```

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



```r
leveragePlots(fit_state_kbs)
```



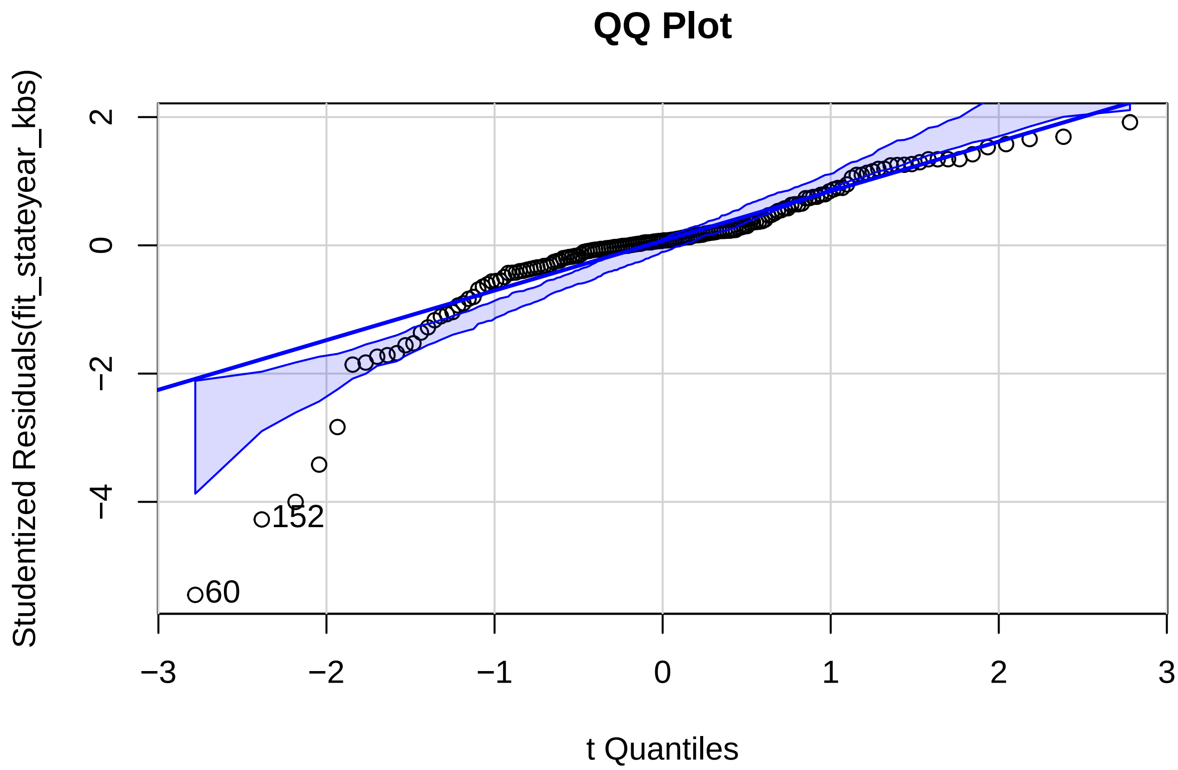

```r
ols_test_normality(fit_state_kbs)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.7755         0.0000
## Kolmogorov-Smirnov        0.1692          2e-04
## Cramer-von Mises         19.1592         0.0000
## Anderson-Darling         10.1782         0.0000
## -----------------------------------------------
```

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

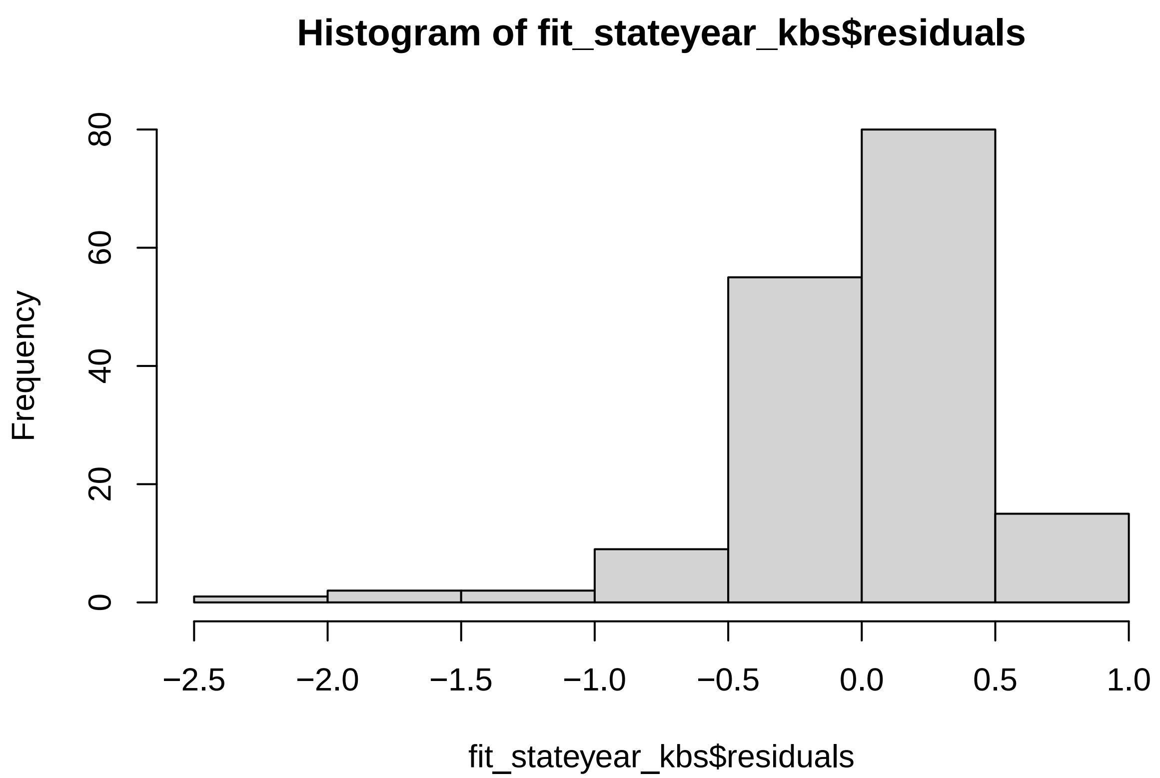
```
##      rstudent unadjusted p-value Bonferroni p
## 60  -5.450001         1.9434e-07   3.1872e-05
## 152 -4.274329         3.3365e-05   5.4718e-03
## 148 -4.000809         9.7518e-05   1.5993e-02
```

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

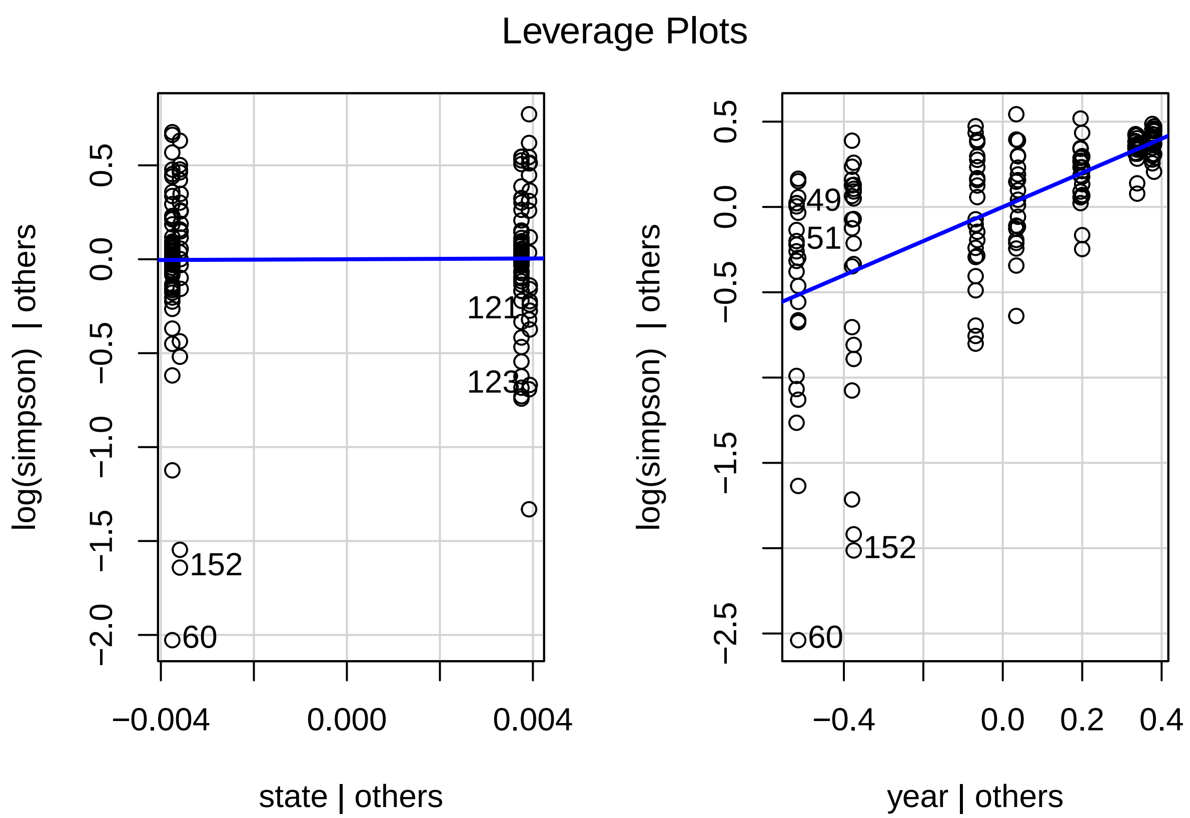



```
##   60 152
##   60 149
```

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



```
leveragePlots(fit_stateyear_kbs)
```



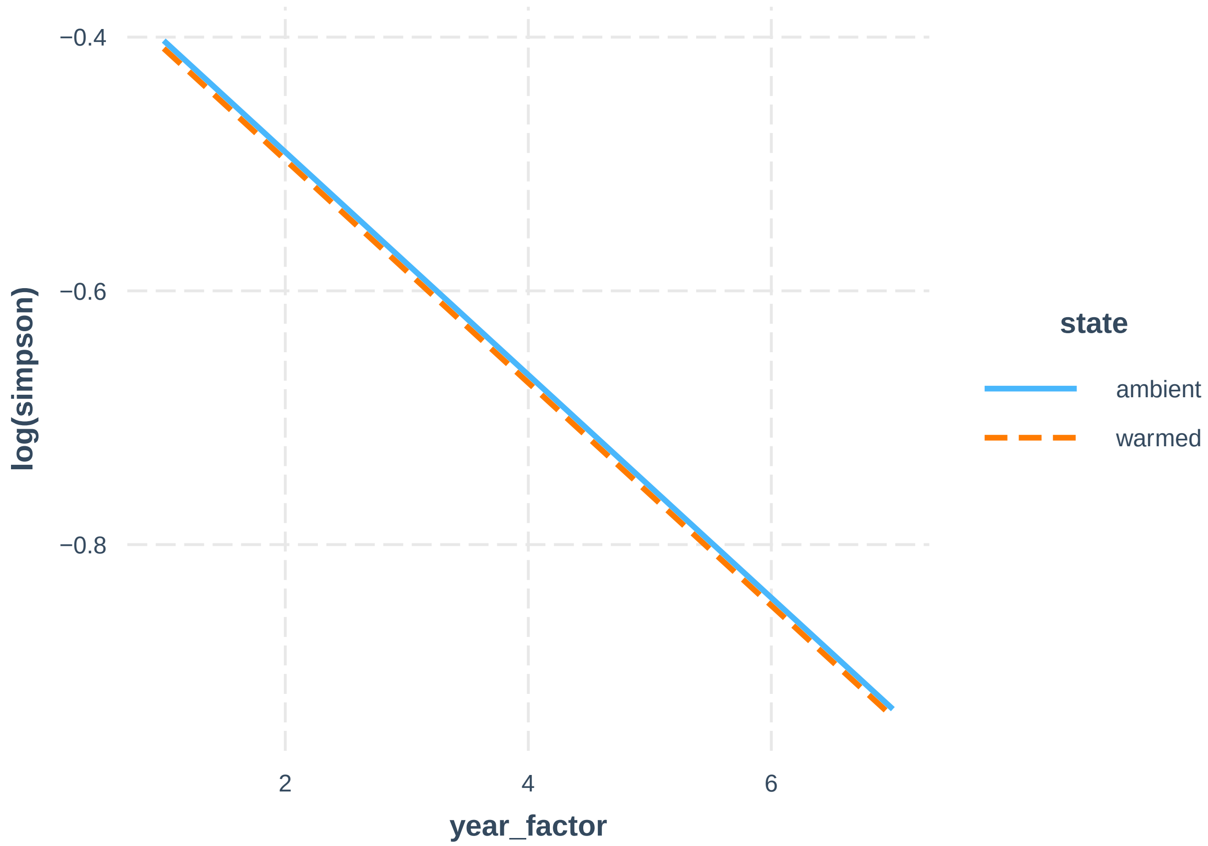

```
ols_test_normality(fit_stateyear_kbs)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.861          0.0000
## Kolmogorov-Smirnov        0.1564         7e-04
## Cramer-von Mises         26.8333         0.0000
## Anderson-Darling          5.3717         0.0000
## -----------------------------------------------
```

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

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.
```

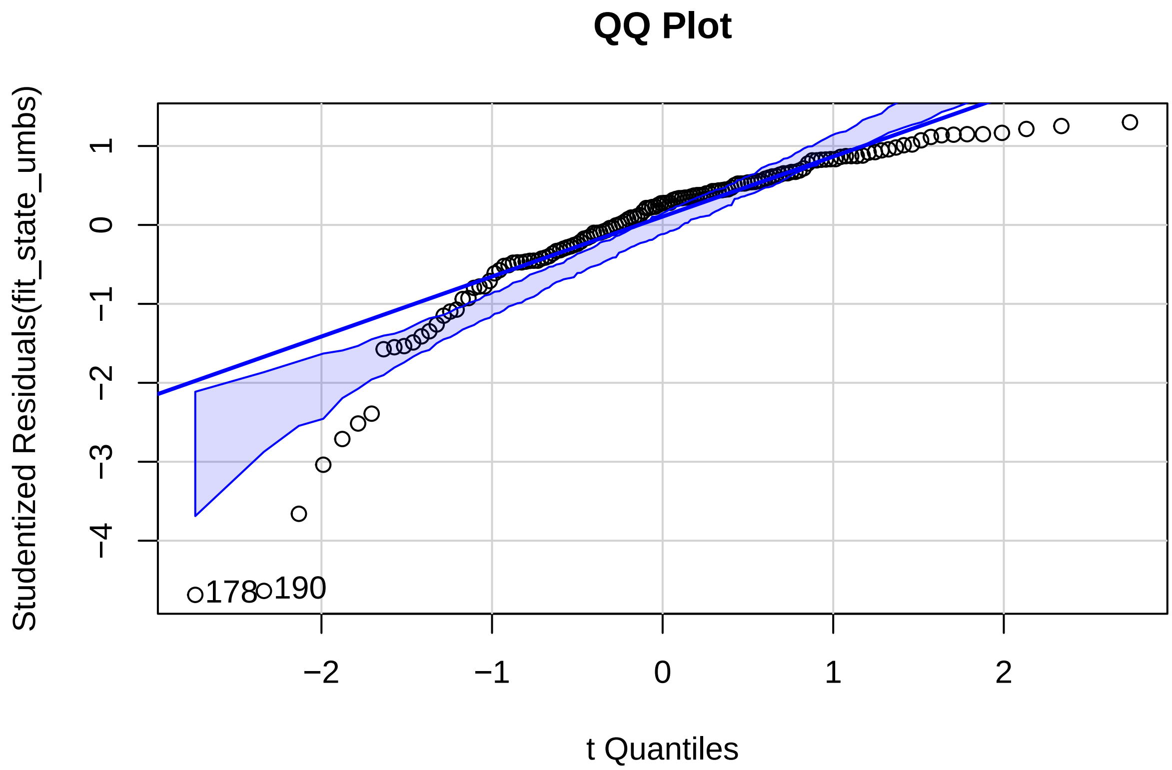
```
## Warning: year_factor and state are not included in an interaction with one another
## in the model.
```




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

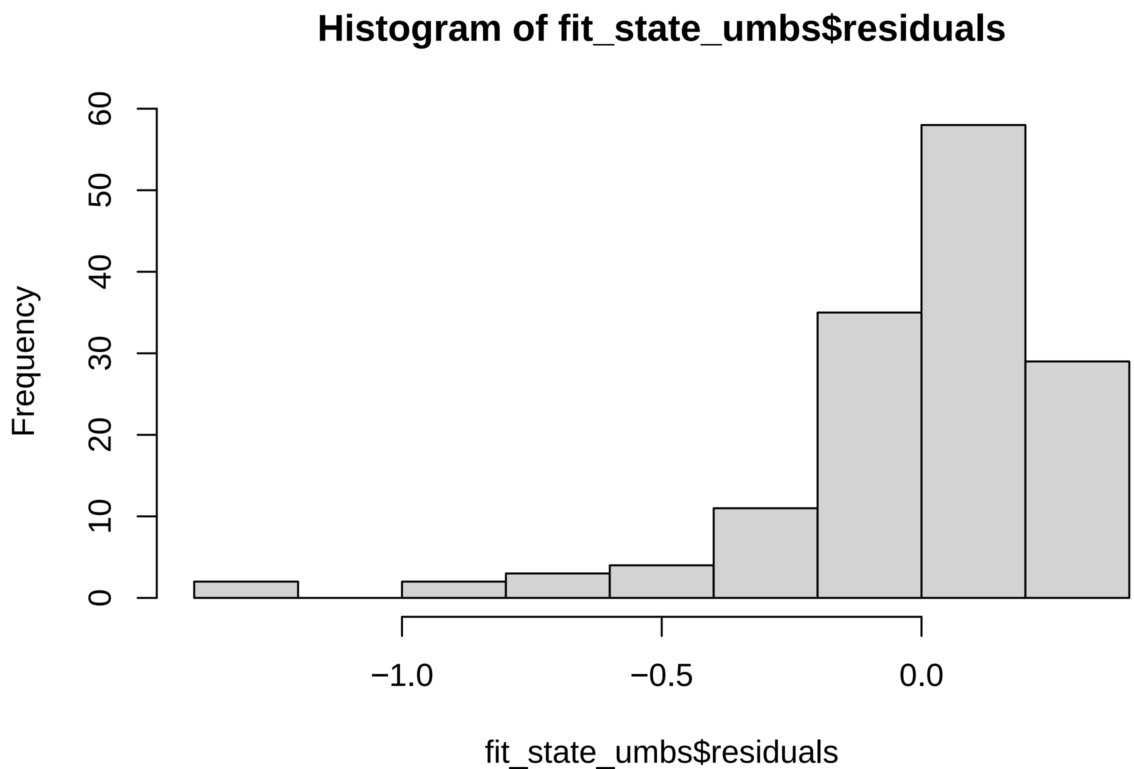
```
##      rstudent unadjusted p-value Bonferroni p
## 178 -4.686093         6.4926e-06   0.00093494
## 190 -4.635915         8.0192e-06   0.00115480
```

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

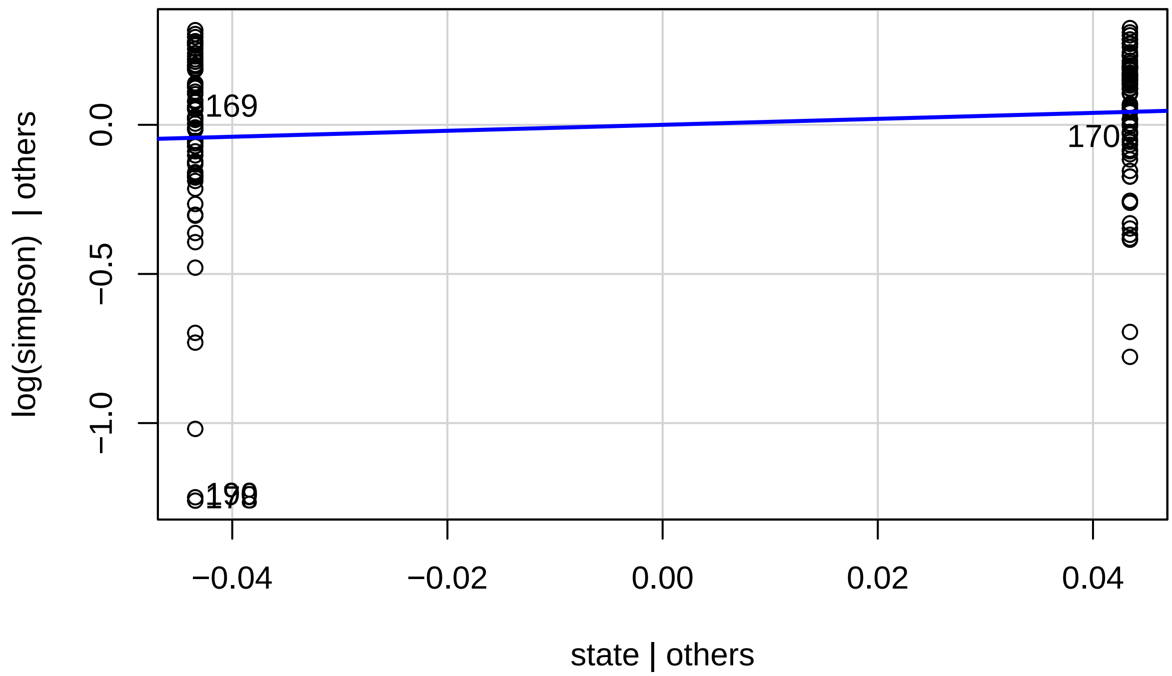



```
## 178 190
##  10  22
```

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



```r
leveragePlots(fit_state_umbs)
```



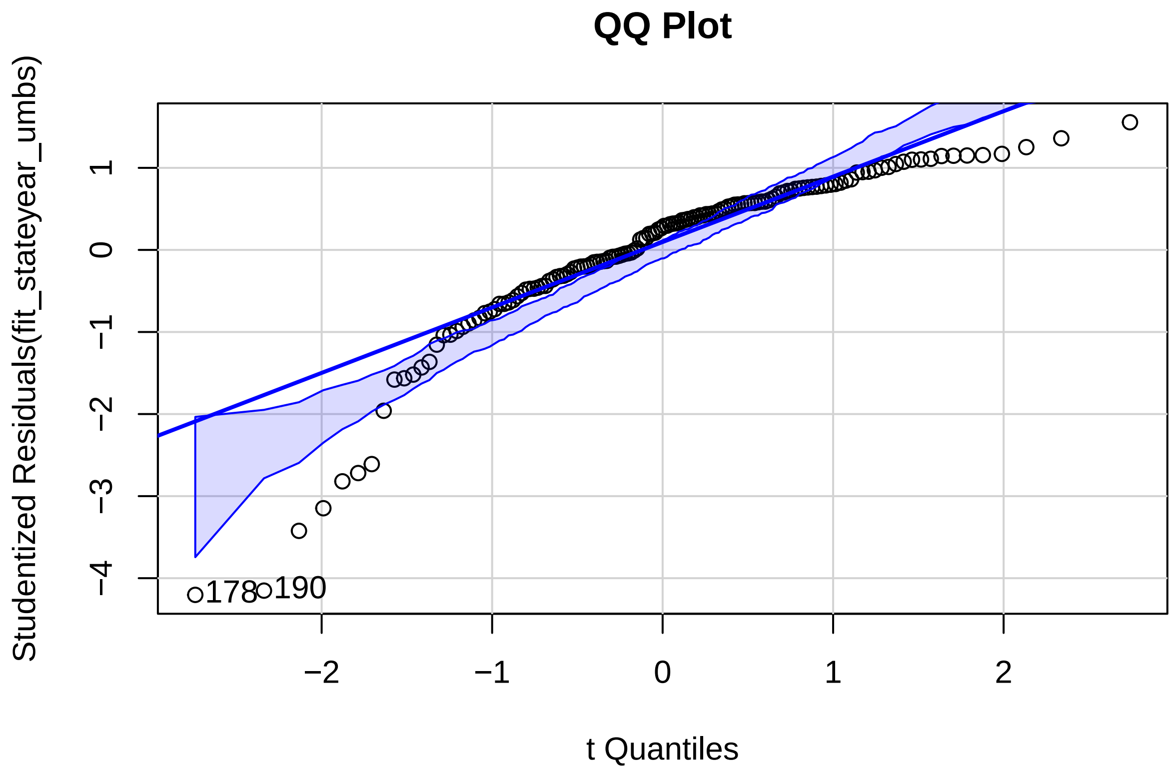

```r
ols_test_normality(fit_state_umbs)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.8367         0.0000
## Kolmogorov-Smirnov        0.1289         0.0167
## Cramer-von Mises         28.3918         0.0000
## Anderson-Darling          5.3404         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
```

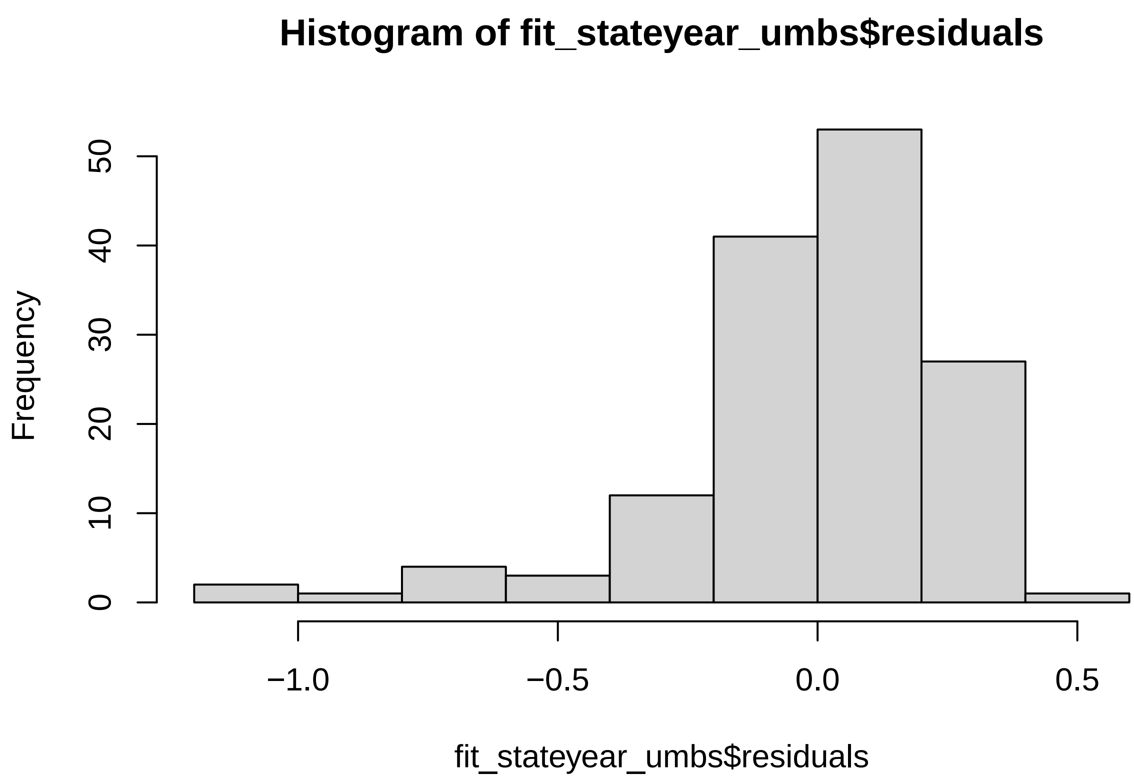
```
##      rstudent unadjusted p-value Bonferroni p
## 60  -5.450001         1.9434e-07   3.1872e-05
## 152 -4.274329         3.3365e-05   5.4718e-03
## 148 -4.000809         9.7518e-05   1.5993e-02
```

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

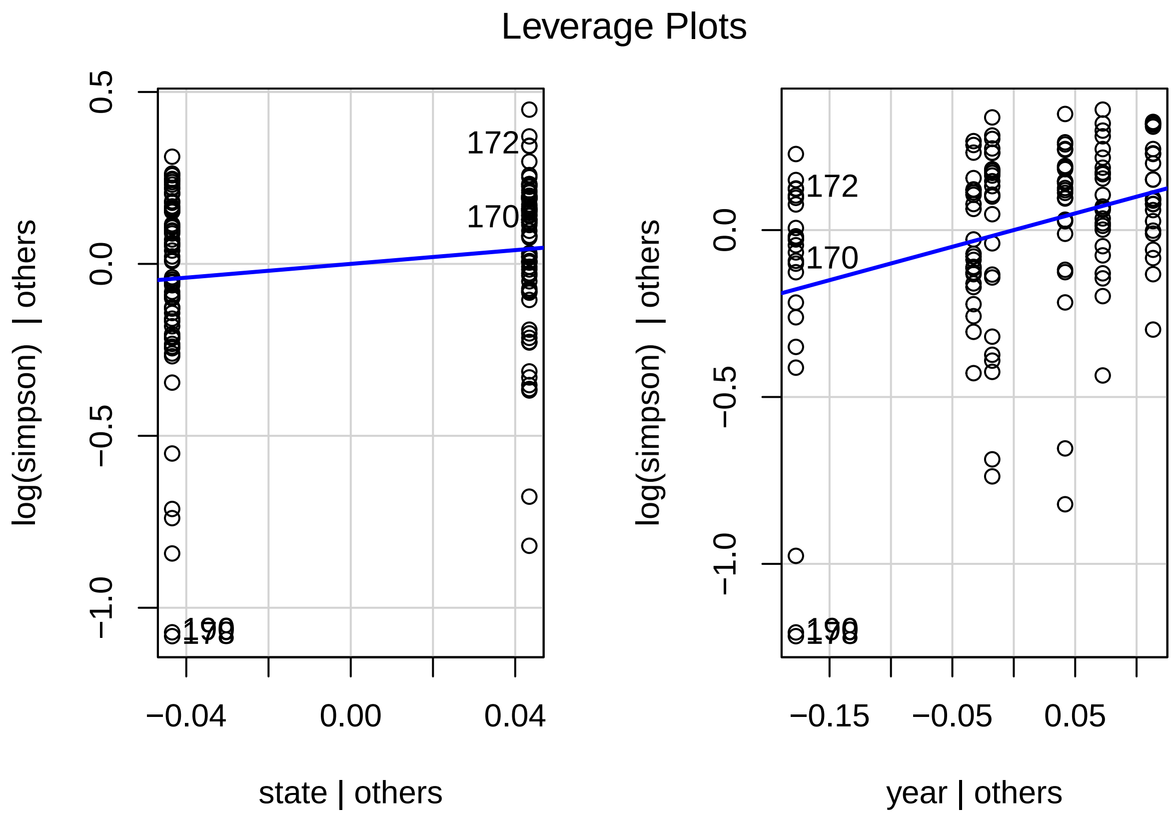



```
## 178 190
##  10  22
```

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



```
leveragePlots(fit_stateyear_umbs)
```




```
ols_test_normality(fit_stateyear_umbs)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.8637         0.0000
## Kolmogorov-Smirnov        0.1149         0.0446
## Cramer-von Mises          28.903         0.0000
## Anderson-Darling          4.6403         0.0000
## -----------------------------------------------
```

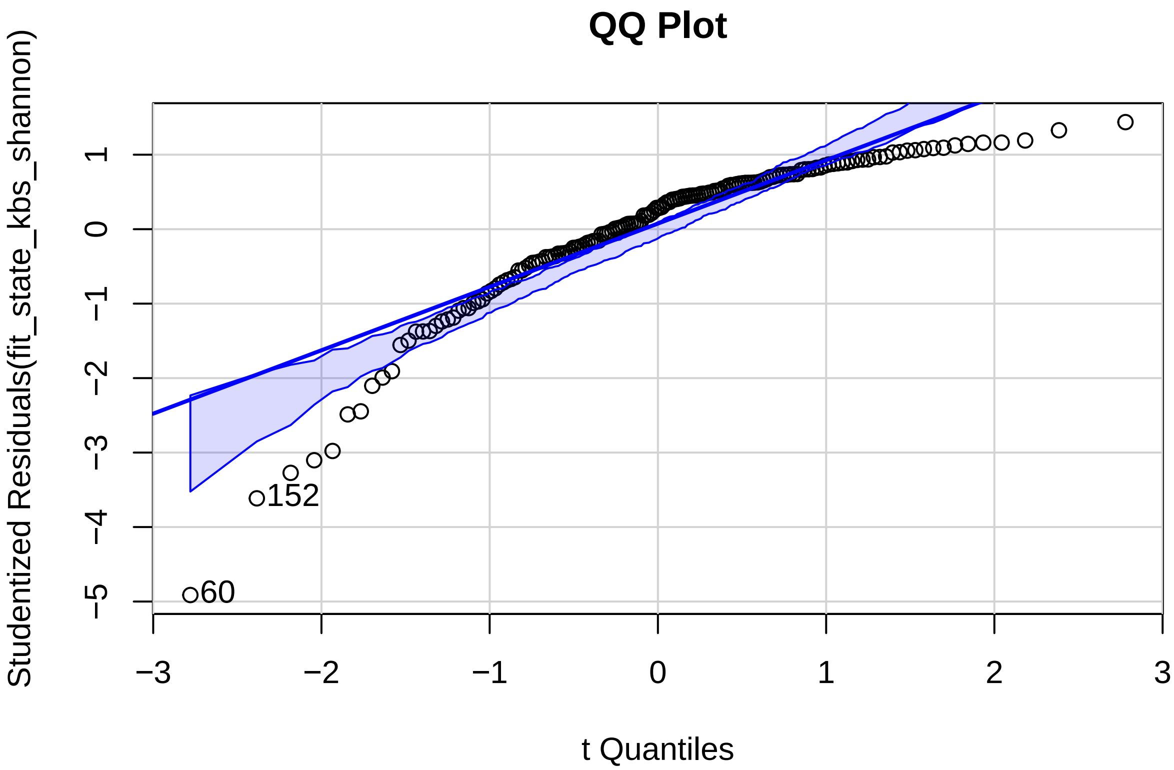
```
# Interaction plot (ignore for now the repeated measures with species); see: https://cran.r-project.org/

# 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

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

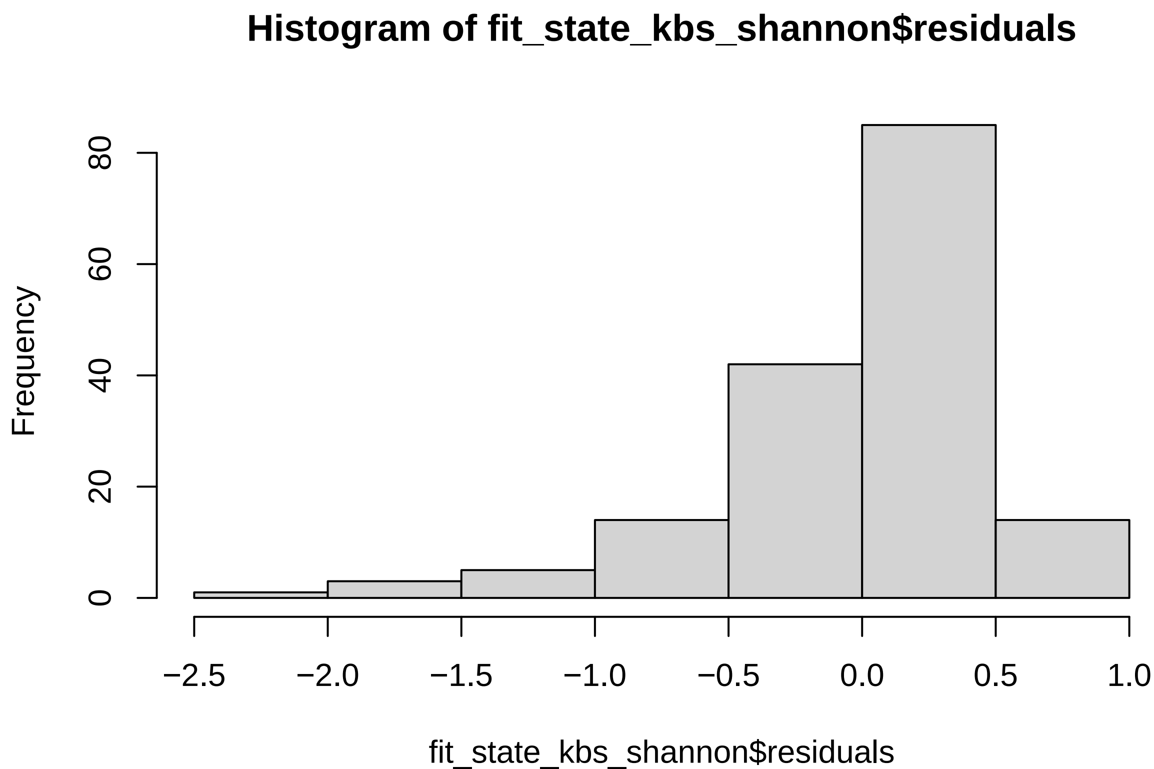
```
##     rstudent unadjusted p-value Bonferroni p
## 60 -4.912675         2.1918e-06   0.00035945
```

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

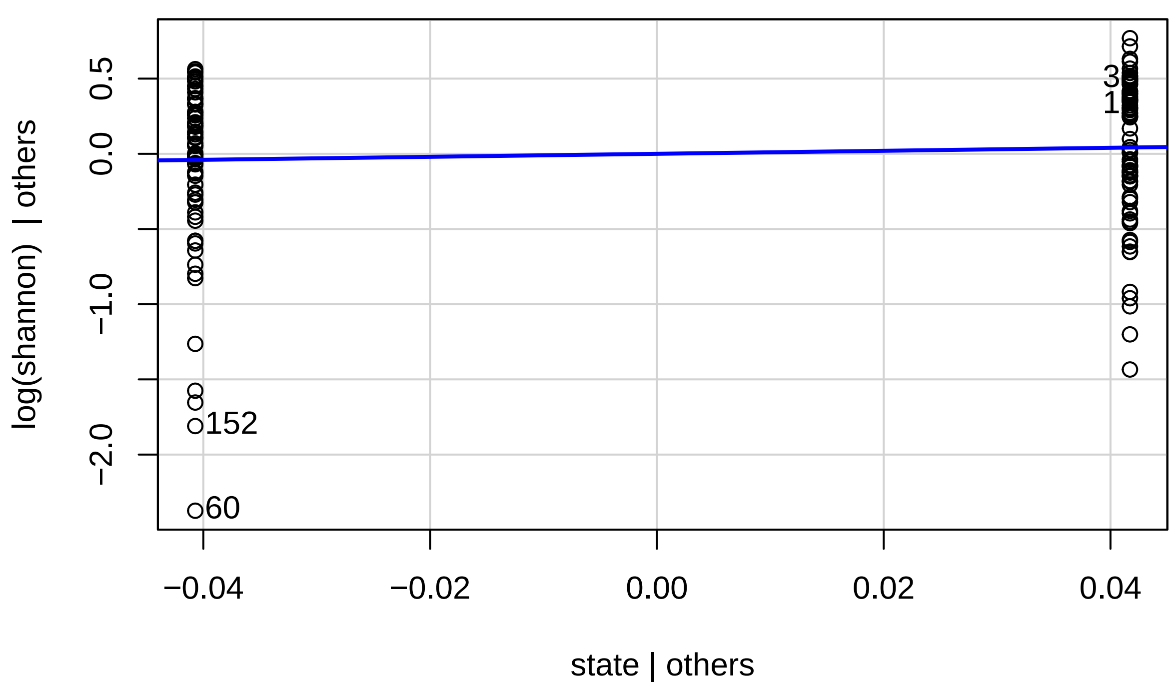



```
##  60 152
##  60 149
```

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




```
leveragePlots(fit_state_kbs_shannon)
```



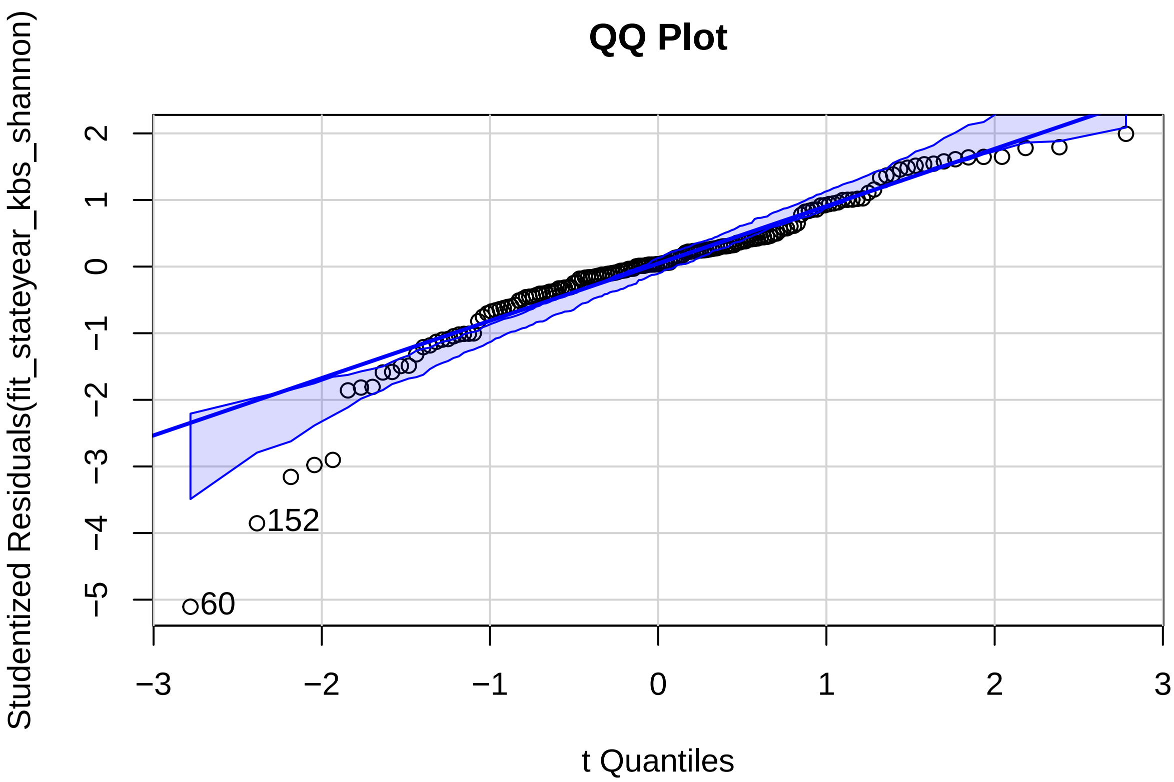
```r
ols_test_normality(fit_state_kbs_shannon)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.8692         0.0000
## Kolmogorov-Smirnov        0.123          0.0140
## Cramer-von Mises         18.0307         0.0000
## Anderson-Darling          5.2328         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
```

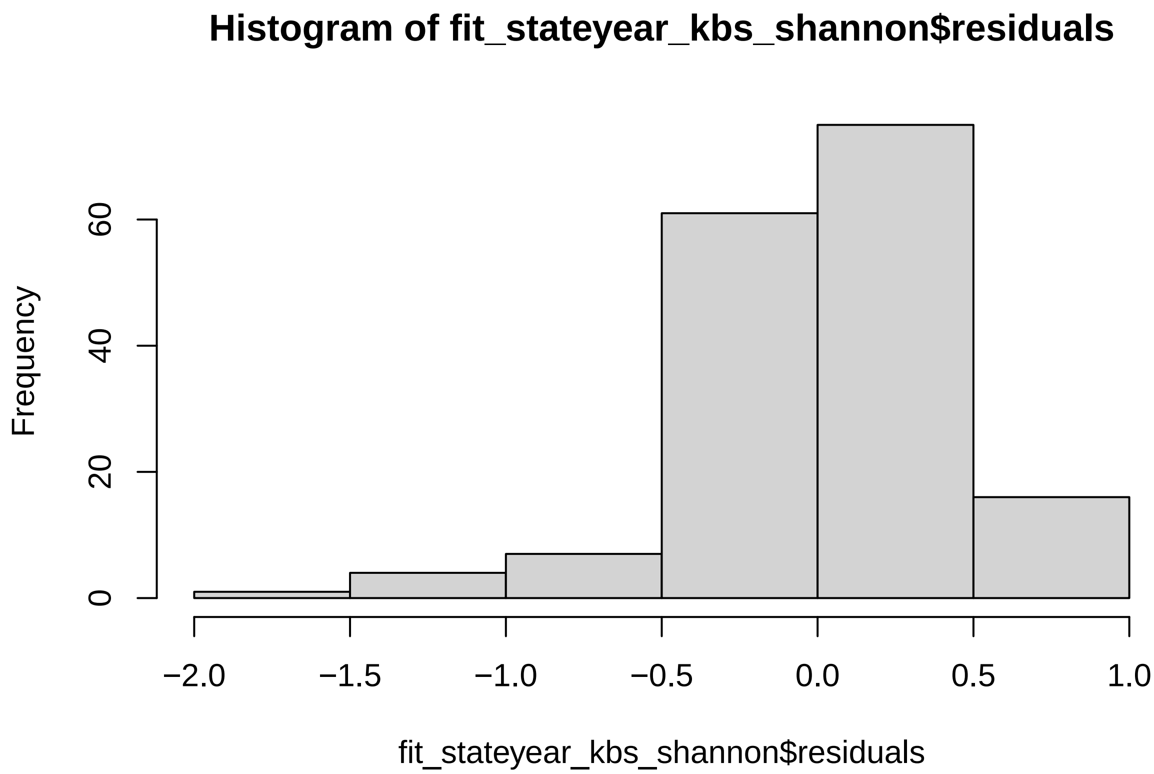
```
##      rstudent unadjusted p-value Bonferroni p
## 60  -5.105926         9.5345e-07   0.00015637
## 152 -3.852926         1.7049e-04   0.02796100
```

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

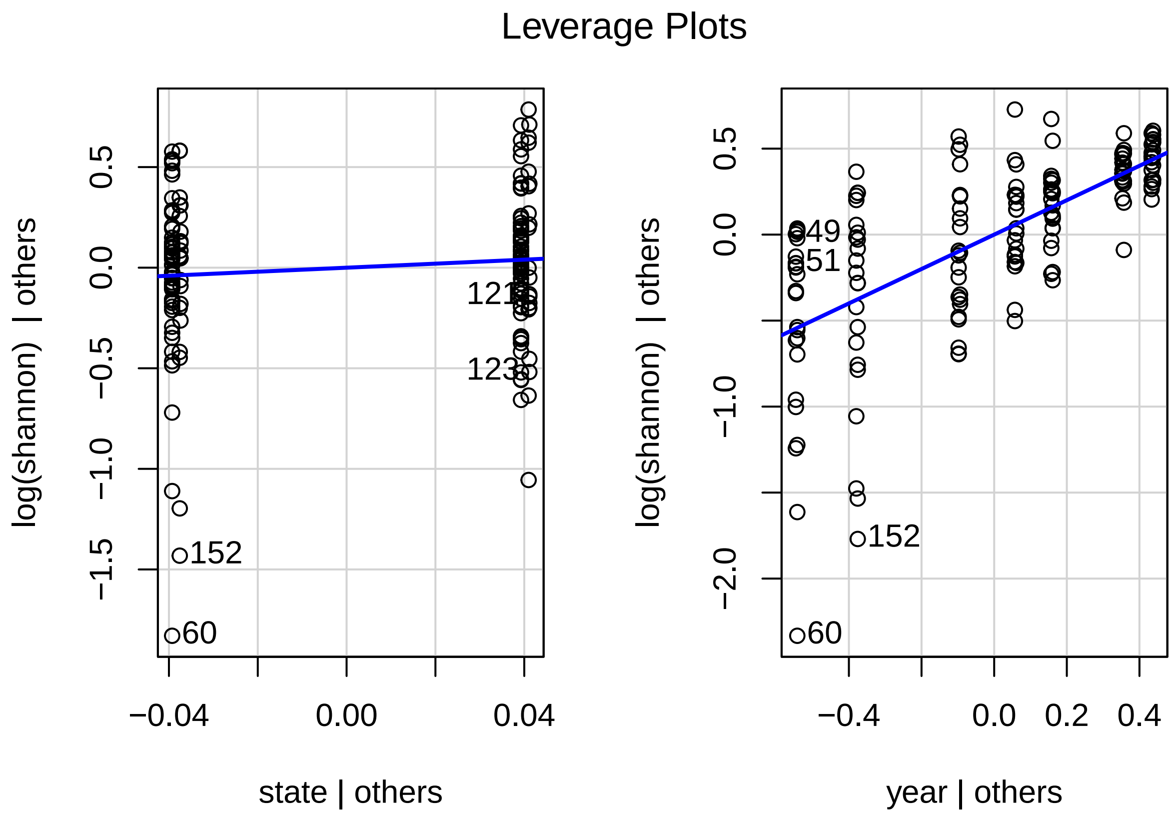



```
##  60 152
##  60 149
```

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




```
leveragePlots(fit_stateyear_kbs_shannon)
```

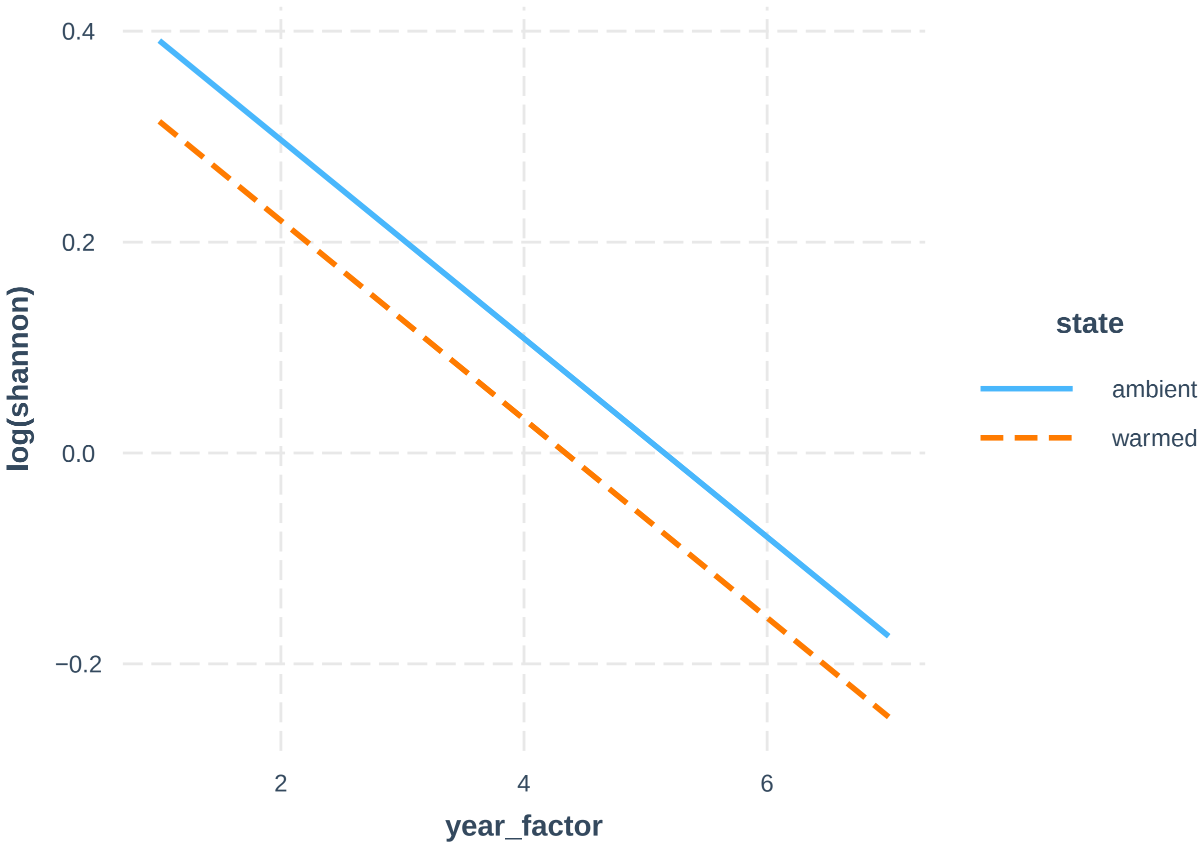



```r
ols_test_normality(fit_stateyear_kbs_shannon)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9188         0.0000
## Kolmogorov-Smirnov        0.111          0.0352
## Cramer-von Mises         26.7361         0.0000
## Anderson-Darling          2.7739         0.0000
## -----------------------------------------------
```

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

# 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)
```

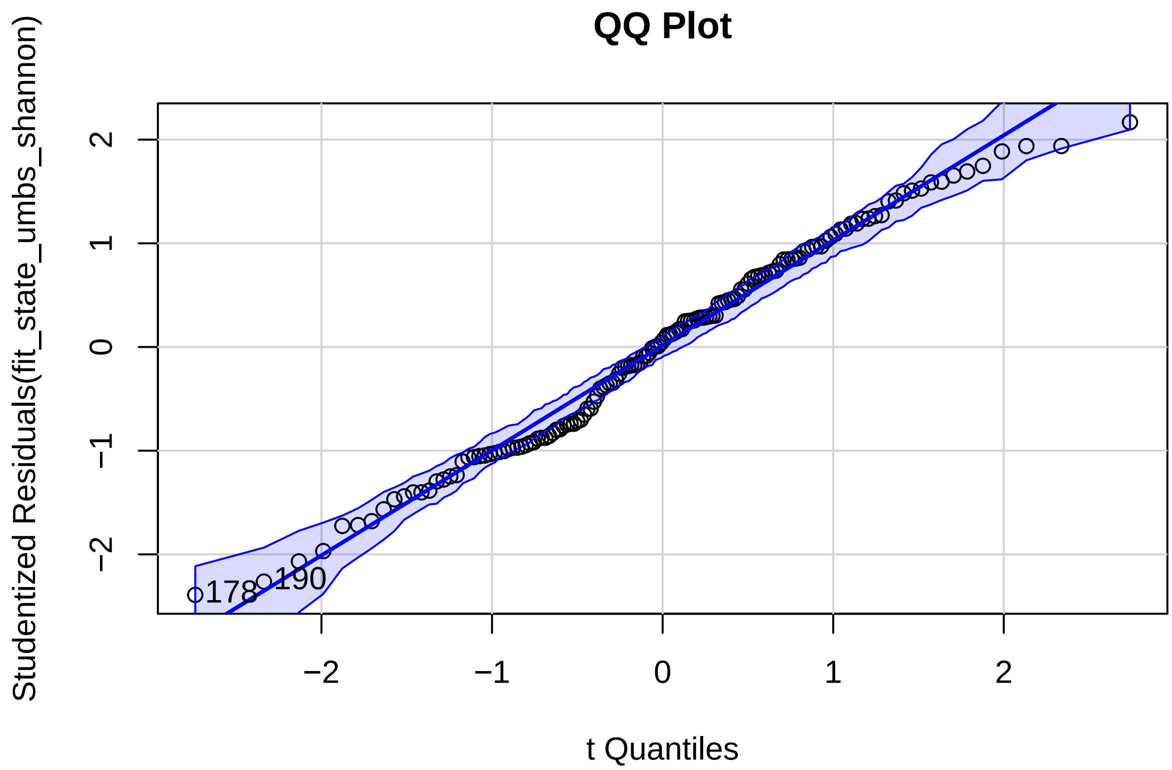
```
## Using data kbs_diversity from global environment. This could cause
## incorrect results if kbs_diversity has been altered since the model was
## fit. You can manually provide the data to the "data =" argument.

## 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
```

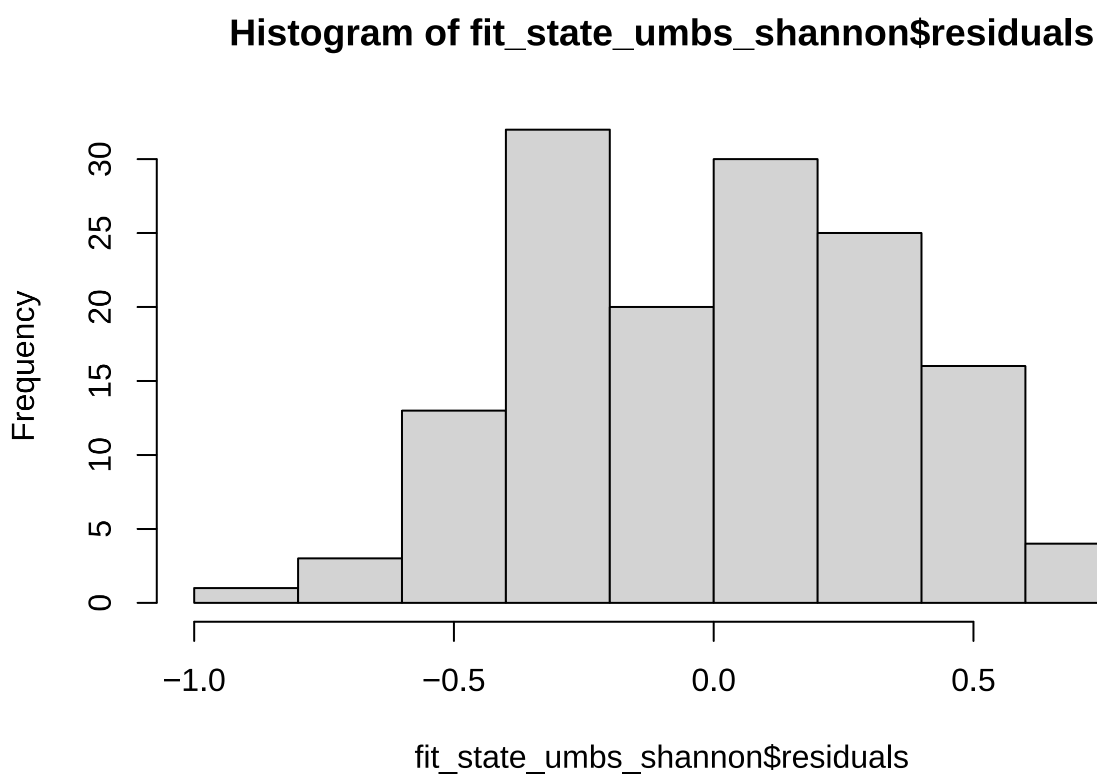
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 178 -2.390779           0.018133           NA
```

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

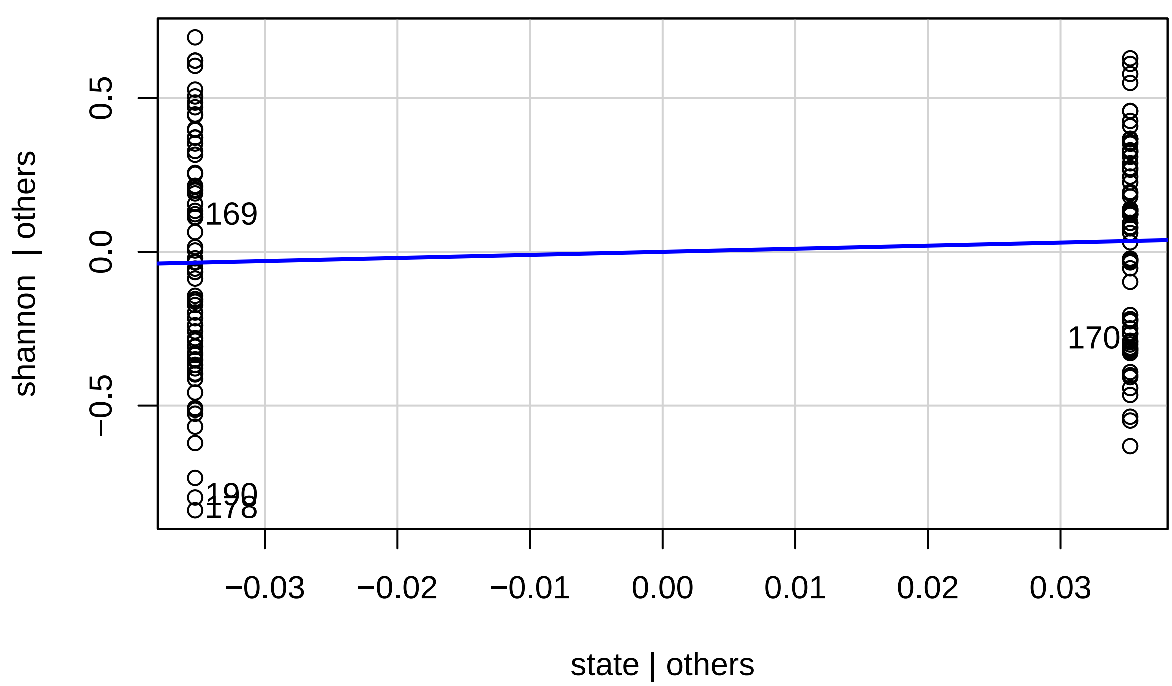



```
## 178 190
##  10  22
```

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



```r
leveragePlots(fit_state_umbs_shannon)
```



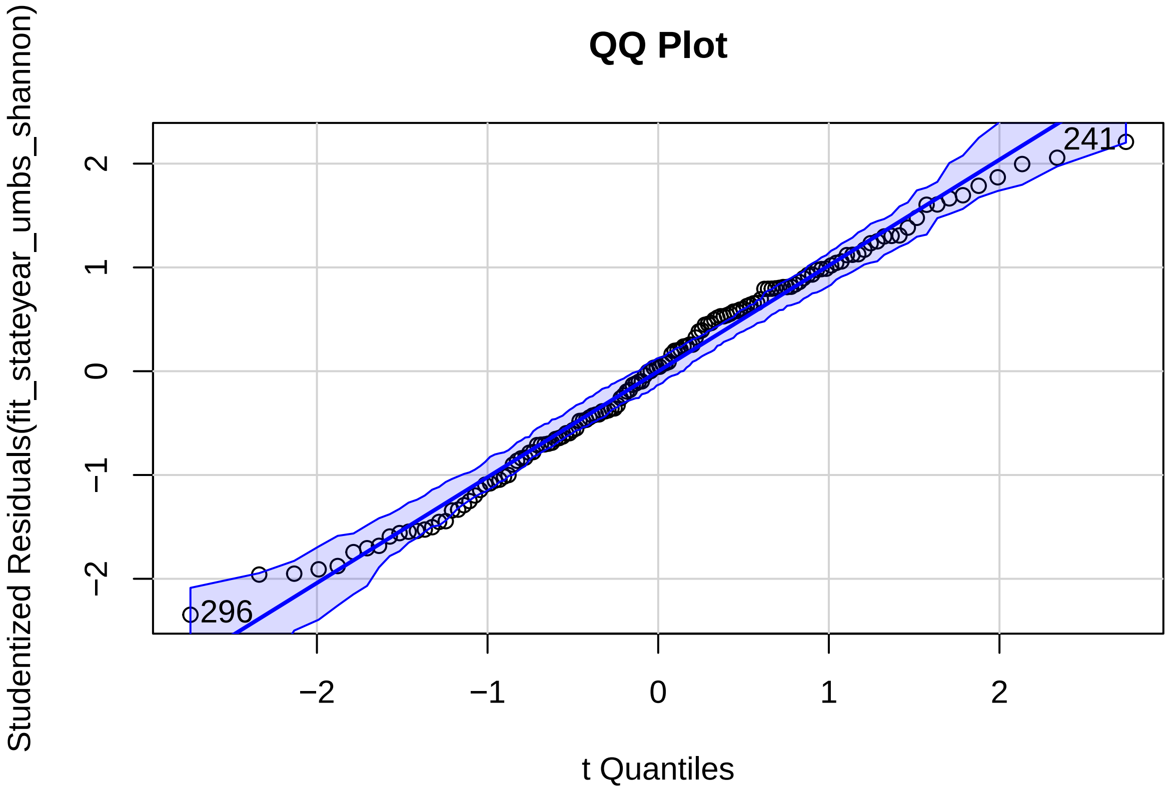

```r
ols_test_normality(fit_state_umbs_shannon)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9846         0.1073
## Kolmogorov-Smirnov        0.0778         0.3485
## Cramer-von Mises         21.5354         0.0000
## Anderson-Darling          0.6917         0.0694
## -----------------------------------------------
```

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

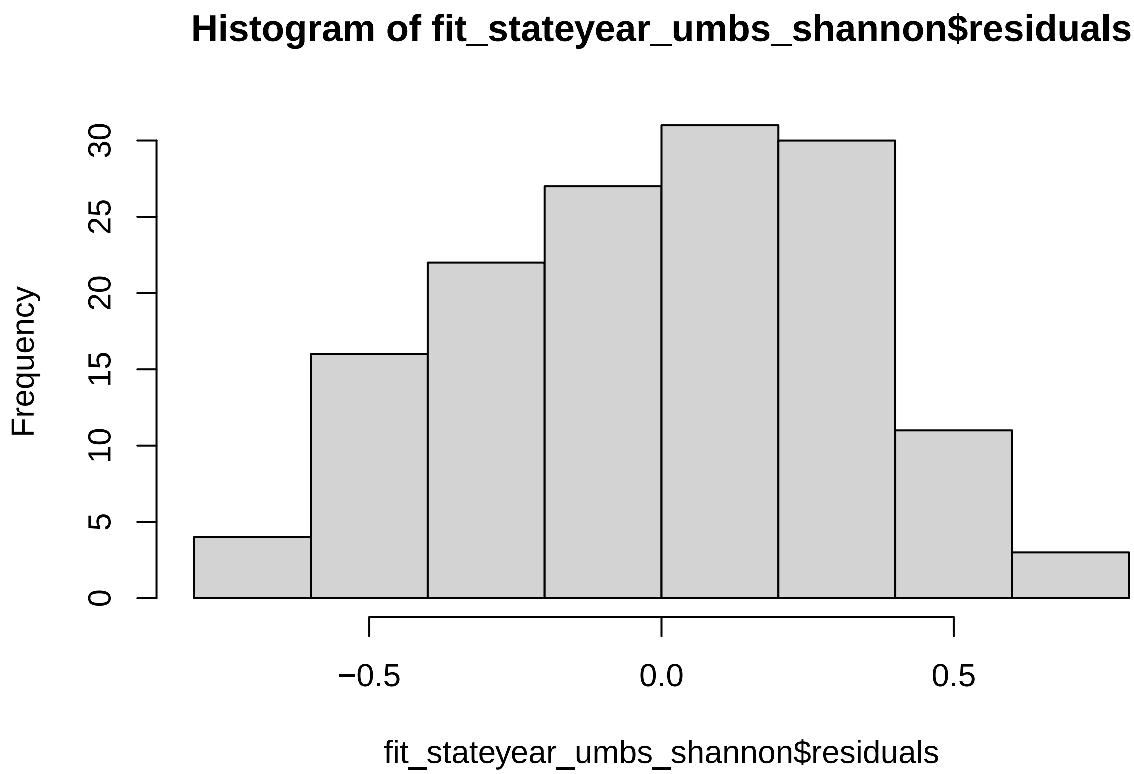
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 296 -2.346541           0.020393           NA
```

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

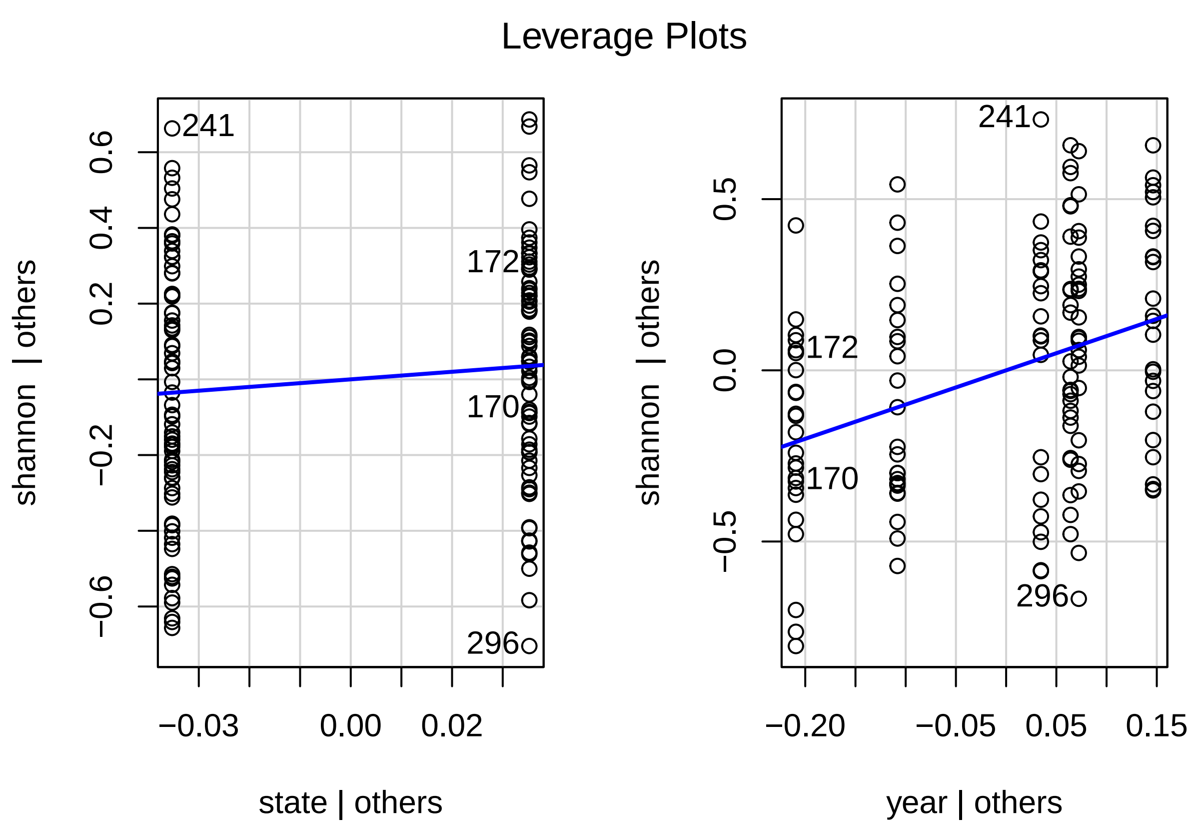



```
## 241 296
##  73 128
```

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




```
leveragePlots(fit_stateyear_umbs_shannon)
```

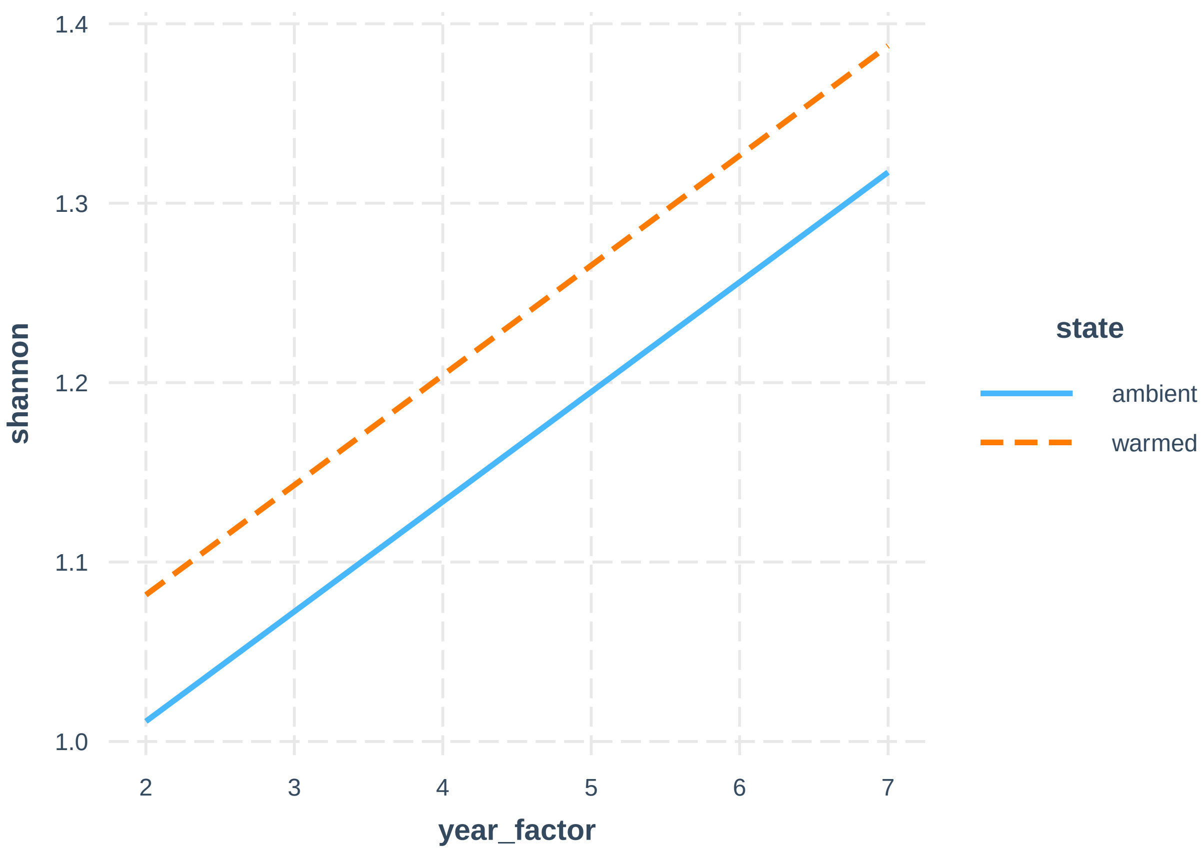


```
ols_test_normality(fit_stateyear_umbs_shannon)
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9854         0.1310
## Kolmogorov-Smirnov        0.0683         0.5125
## Cramer-von Mises         22.7869         0.0000
## Anderson-Darling          0.5826         0.1272
## -----------------------------------------------
```

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

# 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.
```

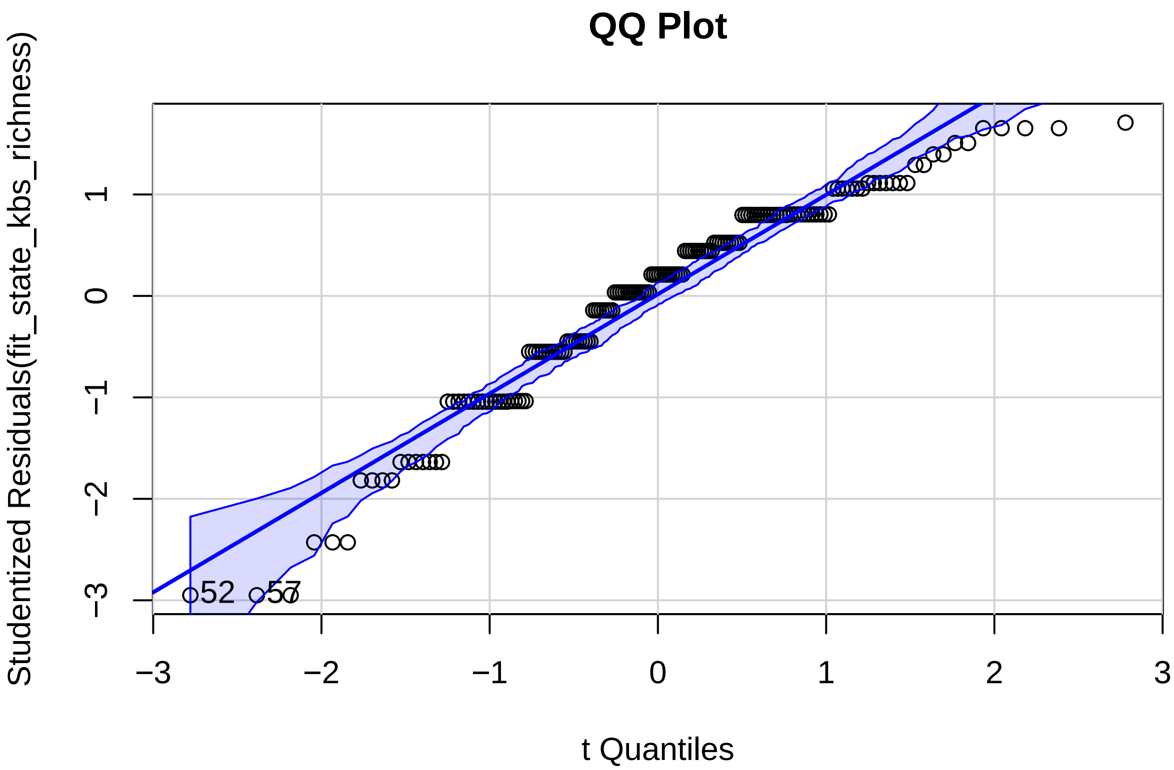


RICHNESS

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

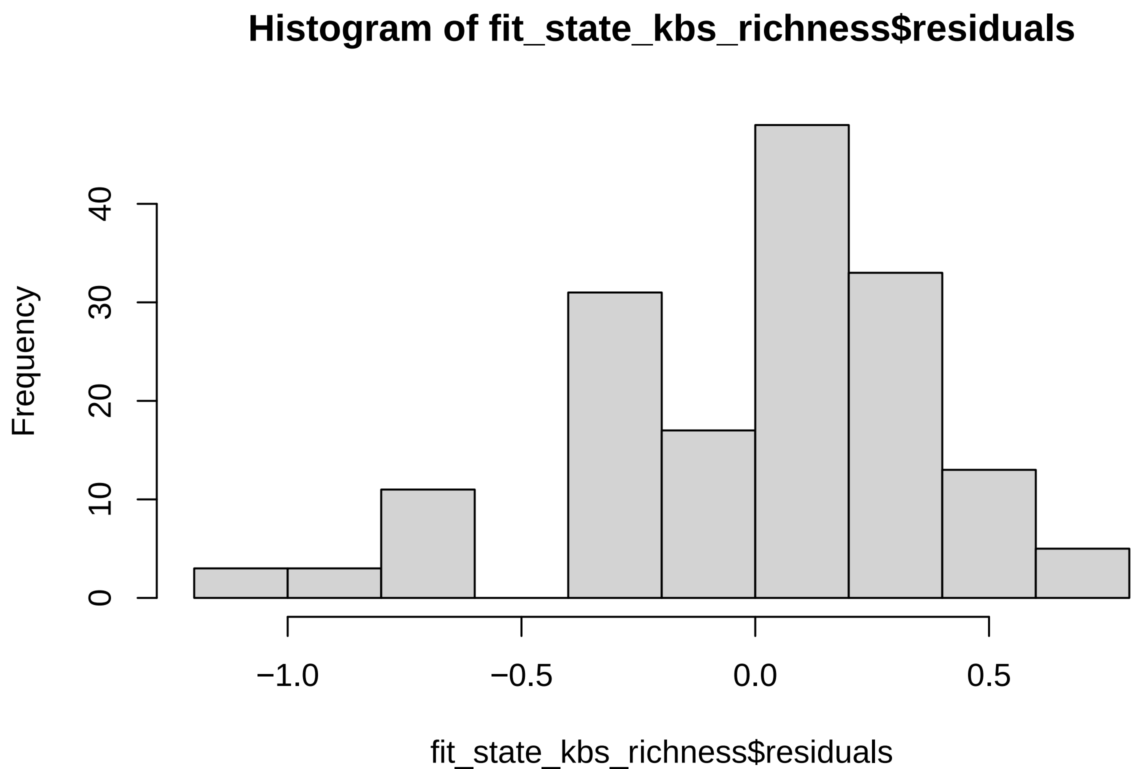
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##     rstudent unadjusted p-value Bonferroni p
## 52 -2.949908          0.0036529      0.59908
```

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

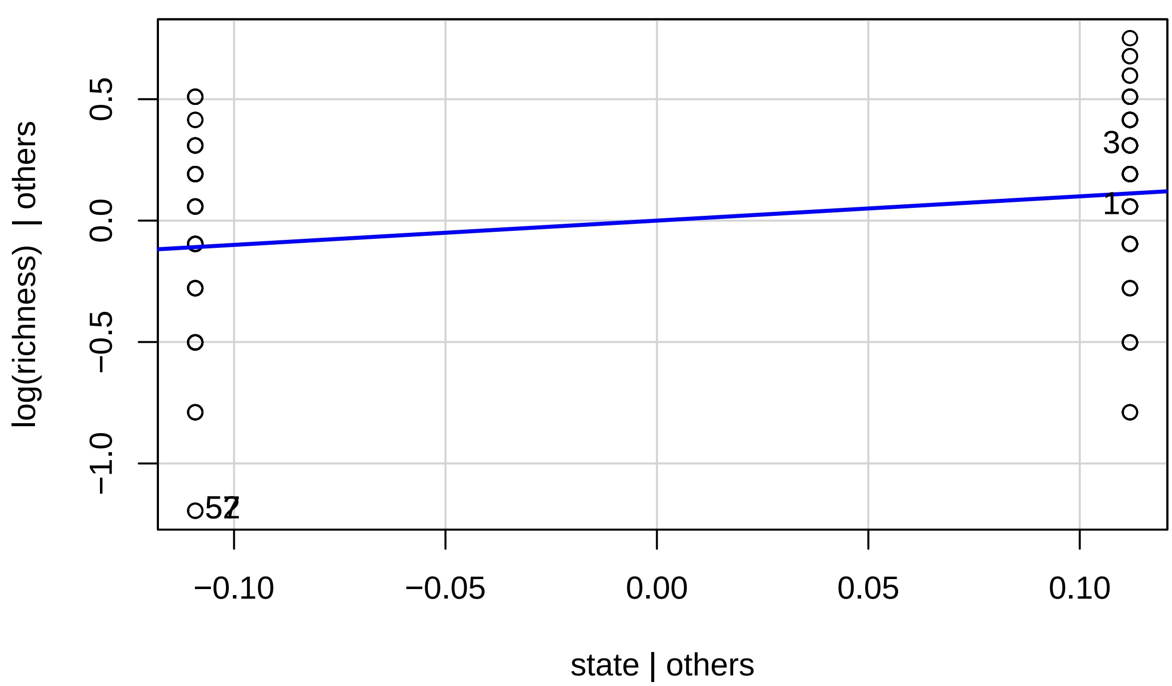



```
## [1] 52 57
```

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




```
leveragePlots(fit_state_kbs_richness)
```



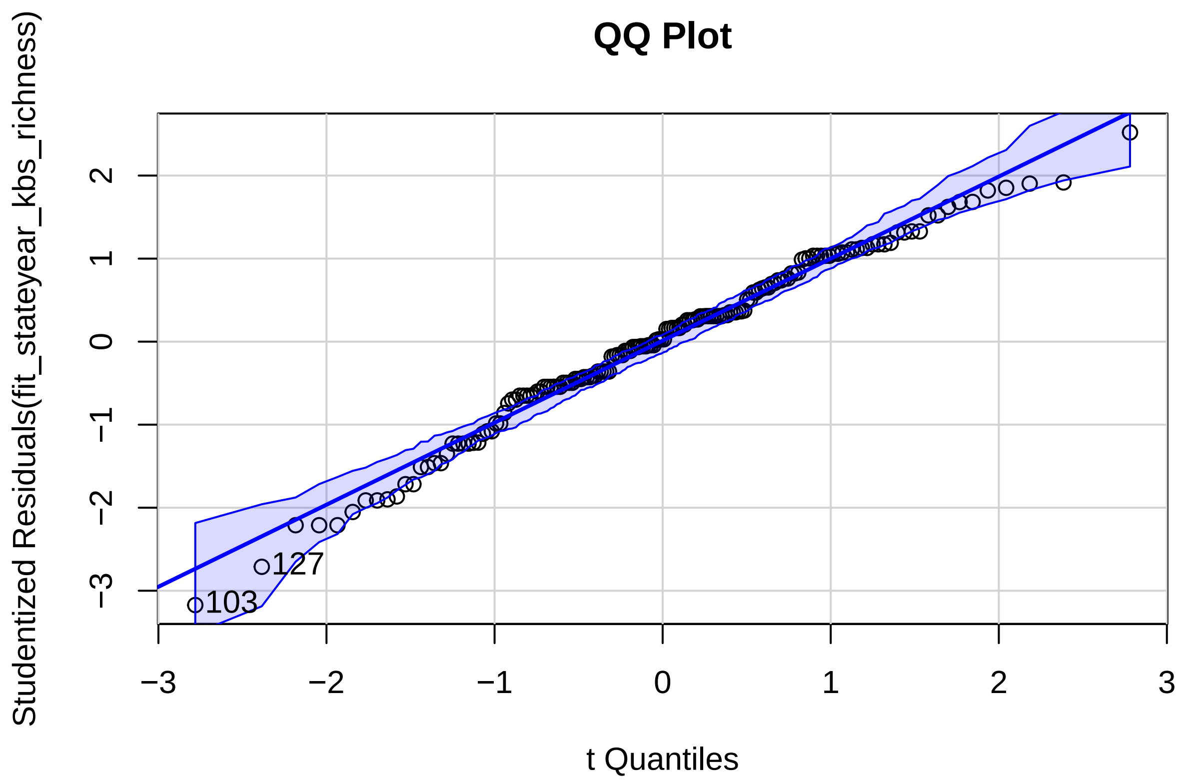
```
ols_test_normality(fit_state_kbs_richness)
```

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

## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9487         0.0000
## Kolmogorov-Smirnov        0.1175         0.0215
## Cramer-von Mises          23.347         0.0000
## Anderson-Darling          2.553          0.0000
## -----------------------------------------------
```

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

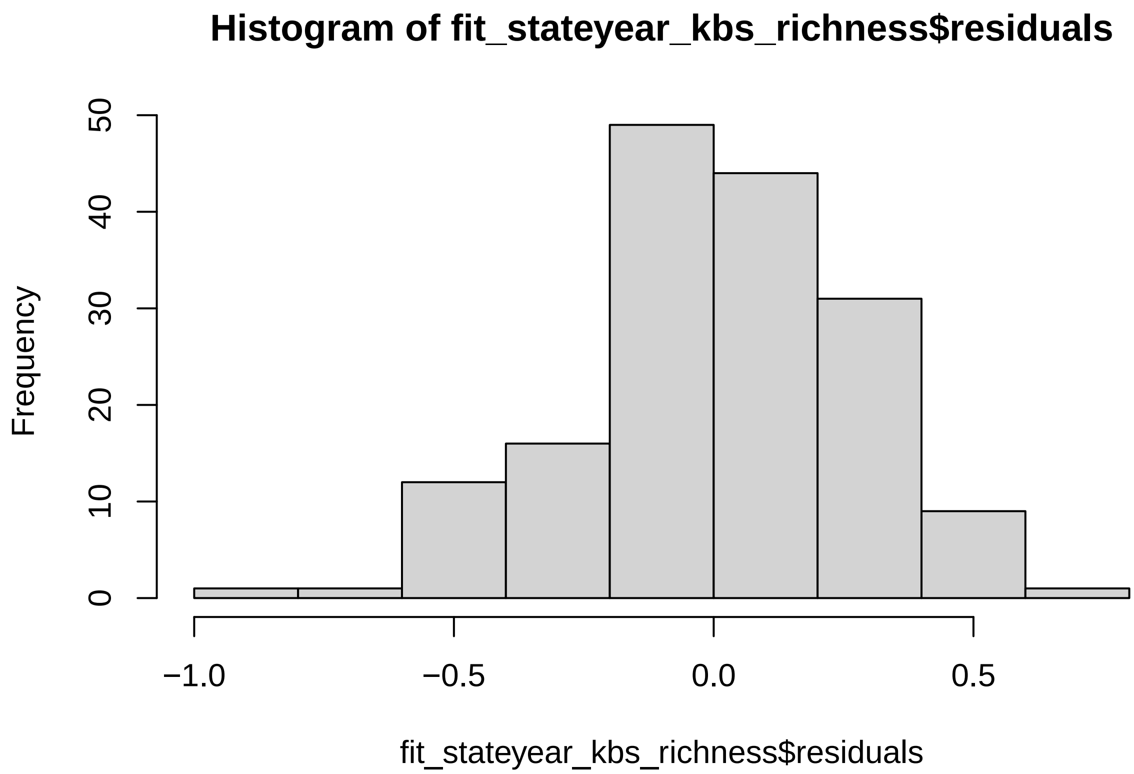
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 103 -3.172657          0.0018216      0.29874
```

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

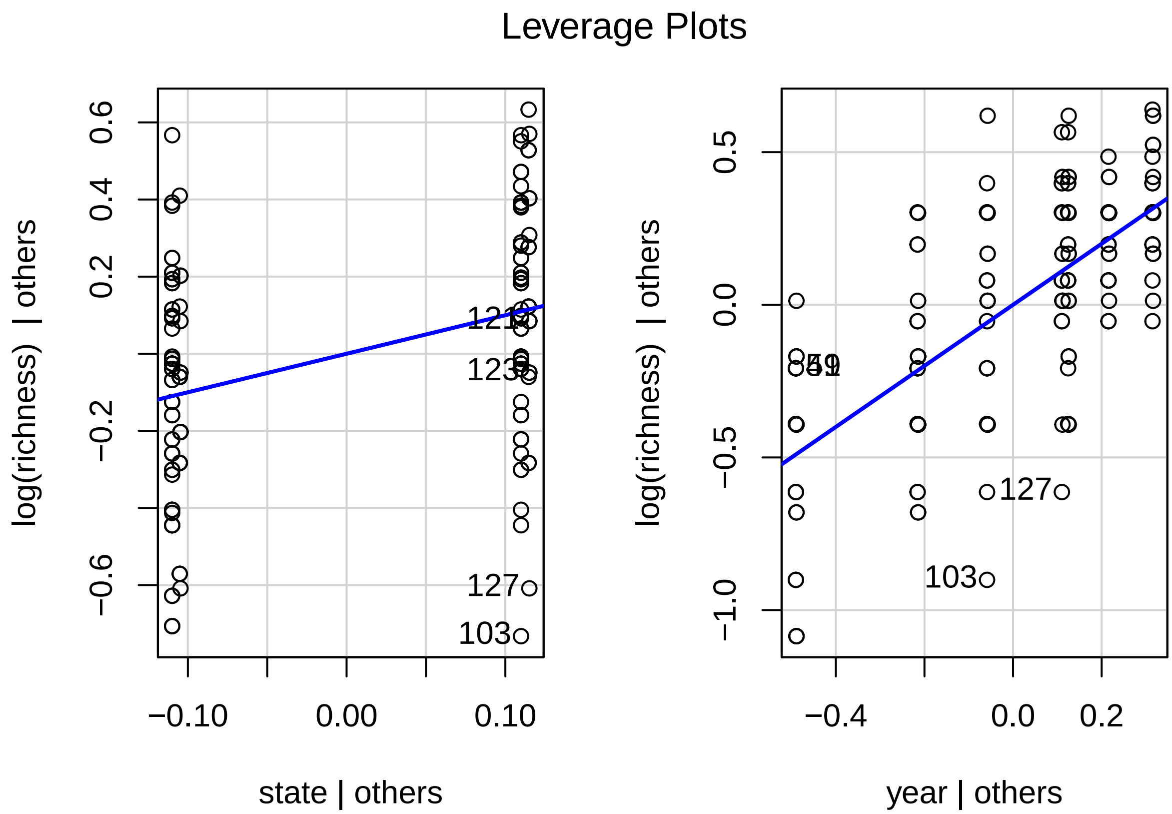



```
## [1] 103 127
```

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




```
leveragePlots(fit_stateyear_kbs_richness)
```




```
ols_test_normality(fit_stateyear_kbs_richness)
```

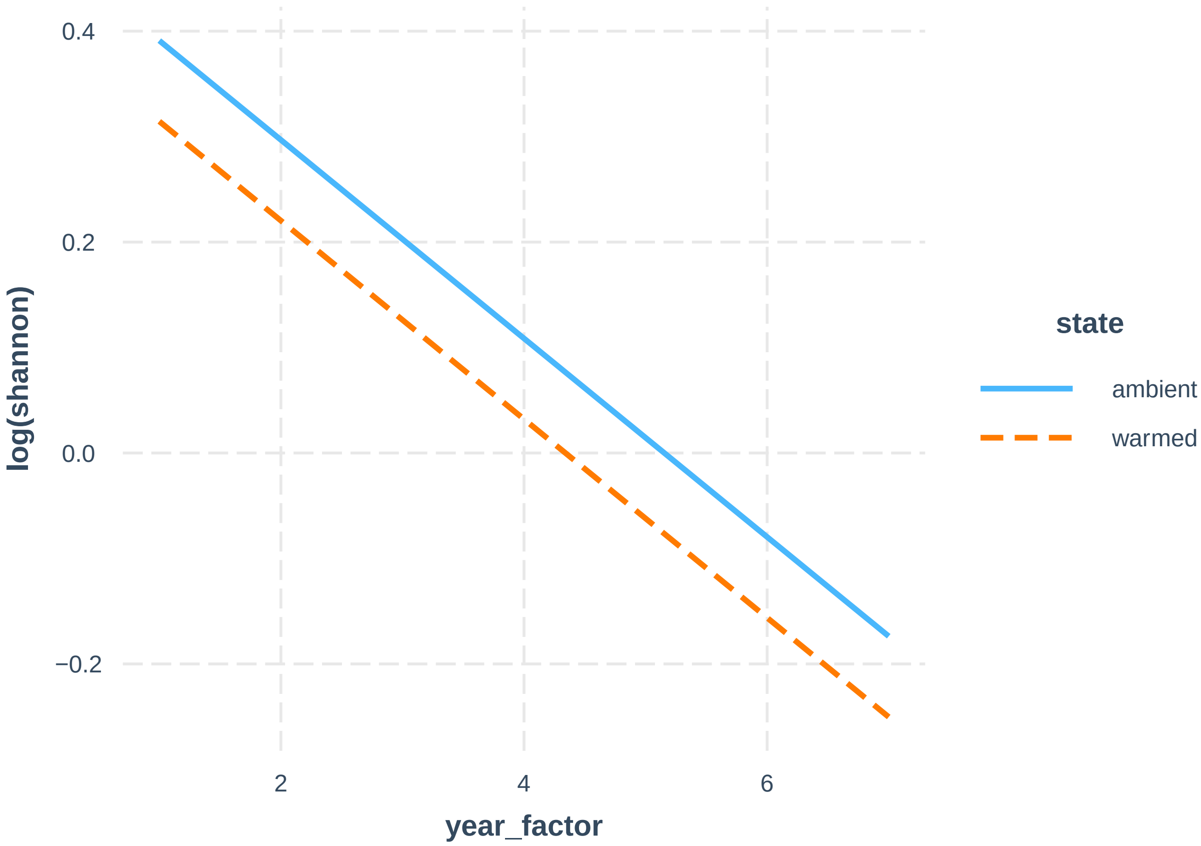
```
## Warning in ks.test.default(y, "pnorm", mean(y), sd(y)): ties should not be
## present for the Kolmogorov-Smirnov test
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9866         0.1184
## Kolmogorov-Smirnov        0.0626         0.5407
## Cramer-von Mises         30.3812         0.0000
## Anderson-Darling          0.6882         0.0710
## -----------------------------------------------
```

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

# 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.
```

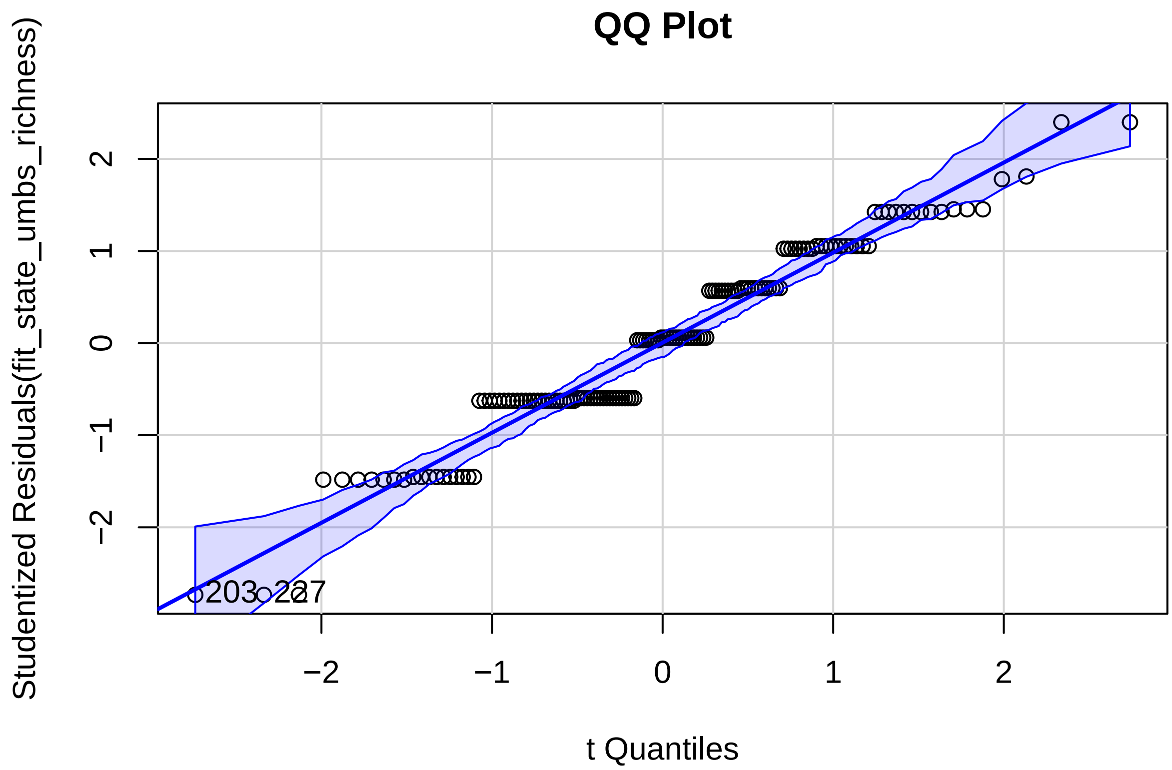
```
## Warning: year_factor and state are not included in an interaction with one another
## in the model.
```




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

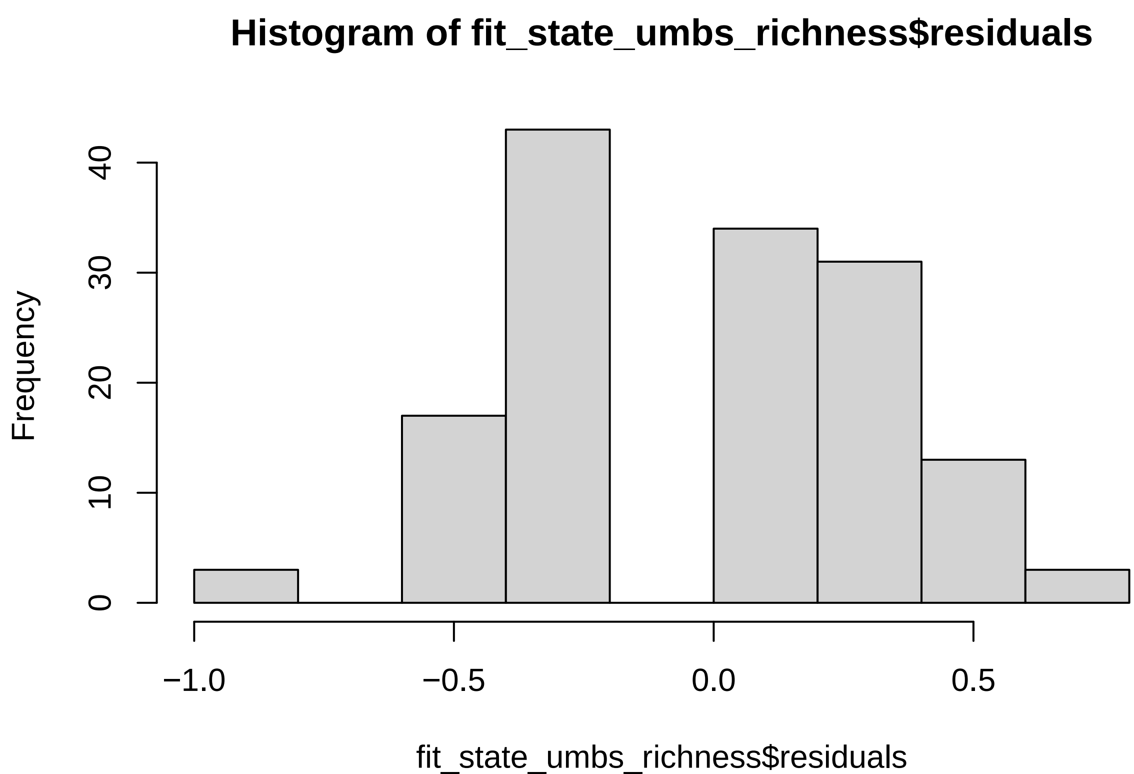
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 203 -2.733466          0.0070707           NA
```

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

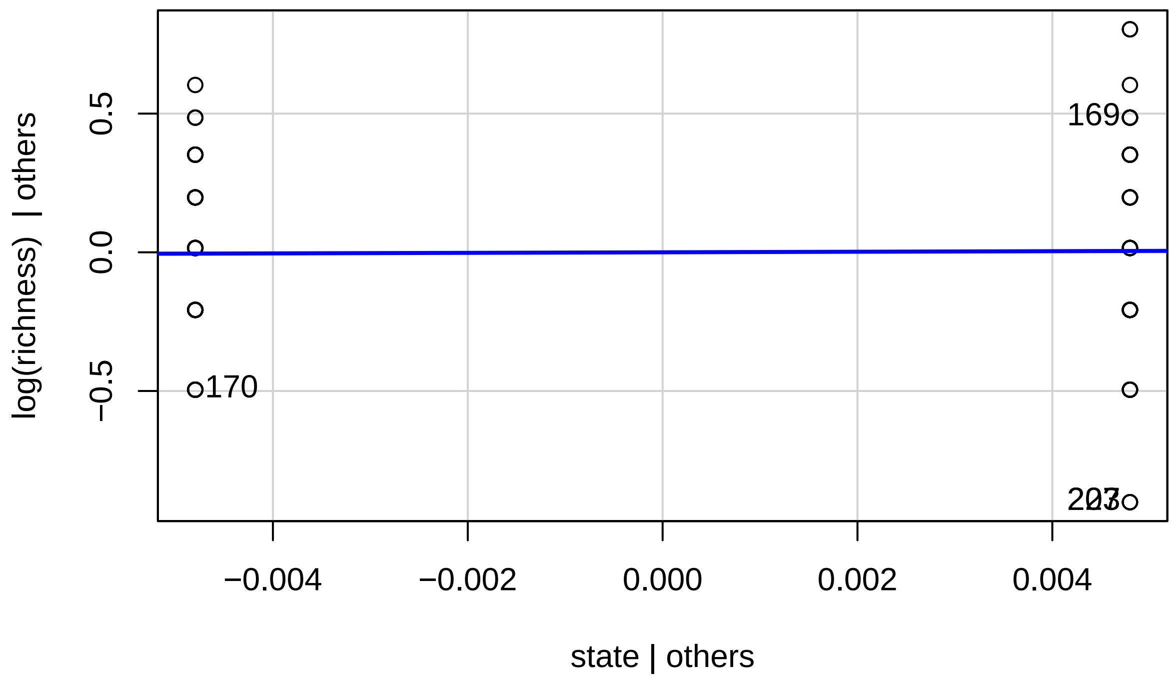



```
## 203 227
##  35  59
```

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



```r
leveragePlots(fit_state_umbs_richness)
```




```r
ols_test_normality(fit_state_umbs_richness)
```

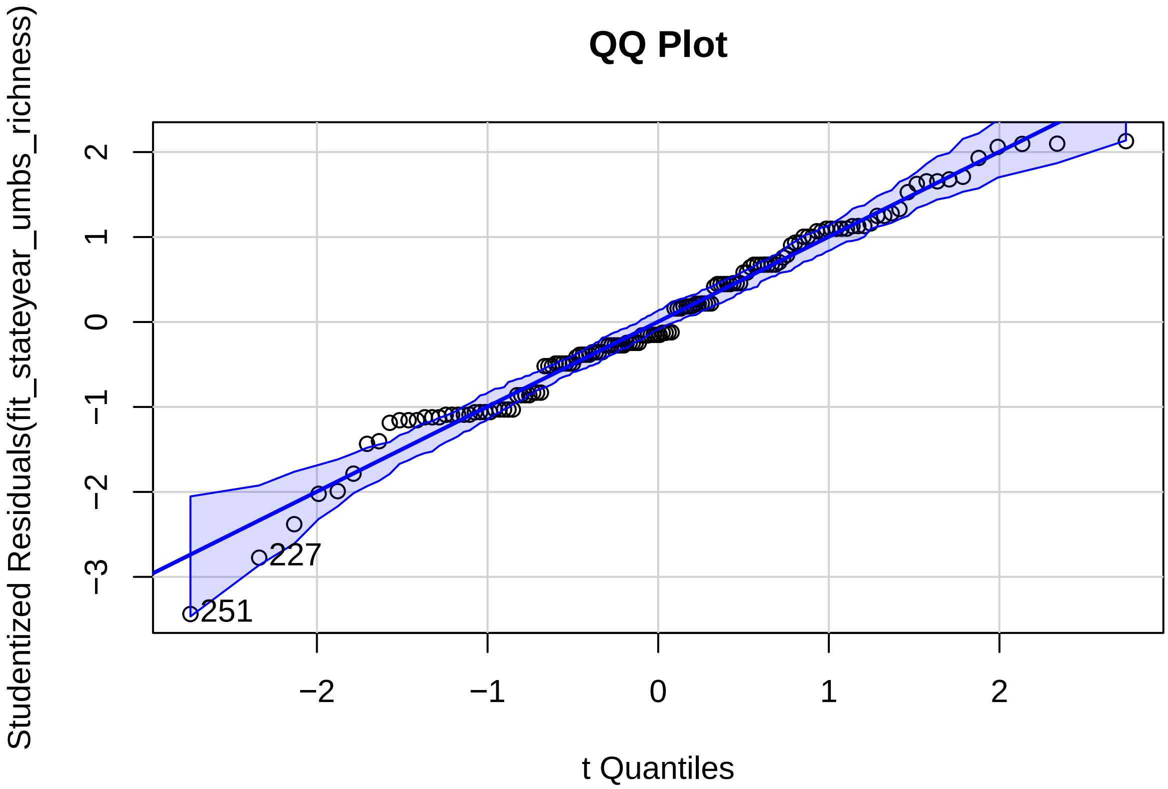
```
## Warning in ks.test.default(y, "pnorm", mean(y), sd(y)): ties should not be
## present for the Kolmogorov-Smirnov test
```

```
## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9555         1e-04
## Kolmogorov-Smirnov        0.1622        0.0010
## Cramer-von Mises         22.2983        0.0000
## Anderson-Darling          2.7431        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
```

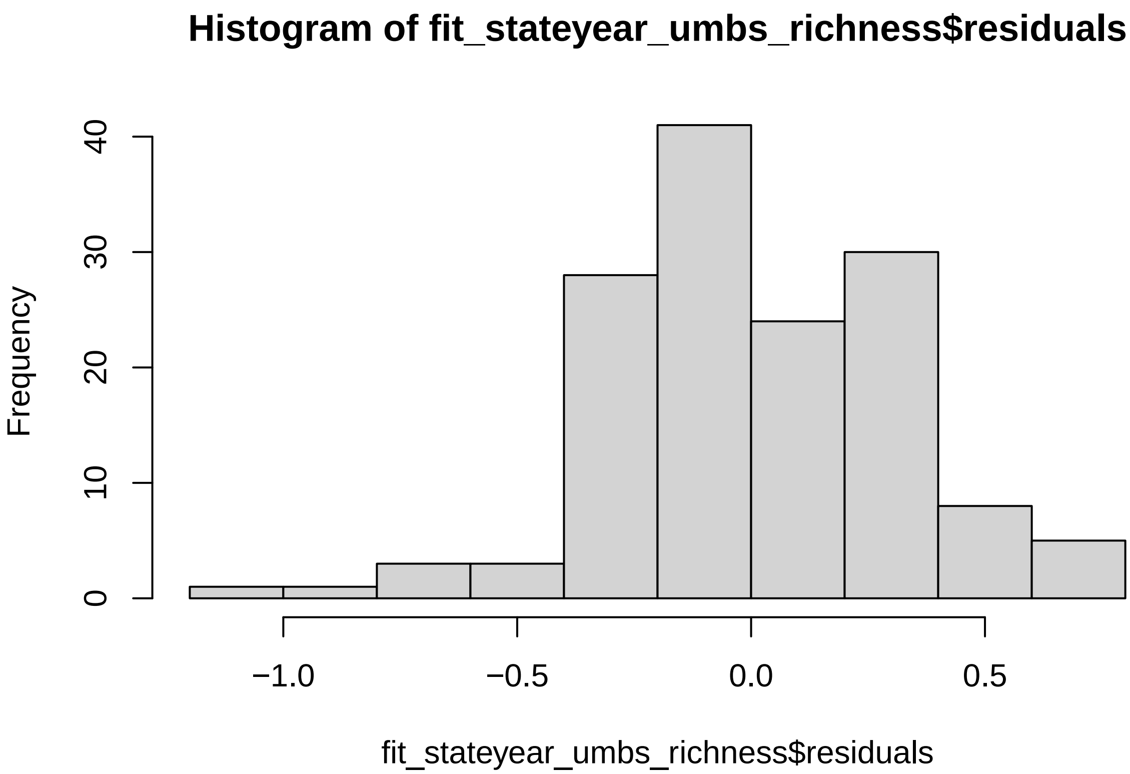
```
## No Studentized residuals with Bonferroni p < 0.05
## Largest |rstudent|:
##      rstudent unadjusted p-value Bonferroni p
## 251 -3.437196         0.00078019      0.11235
```

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

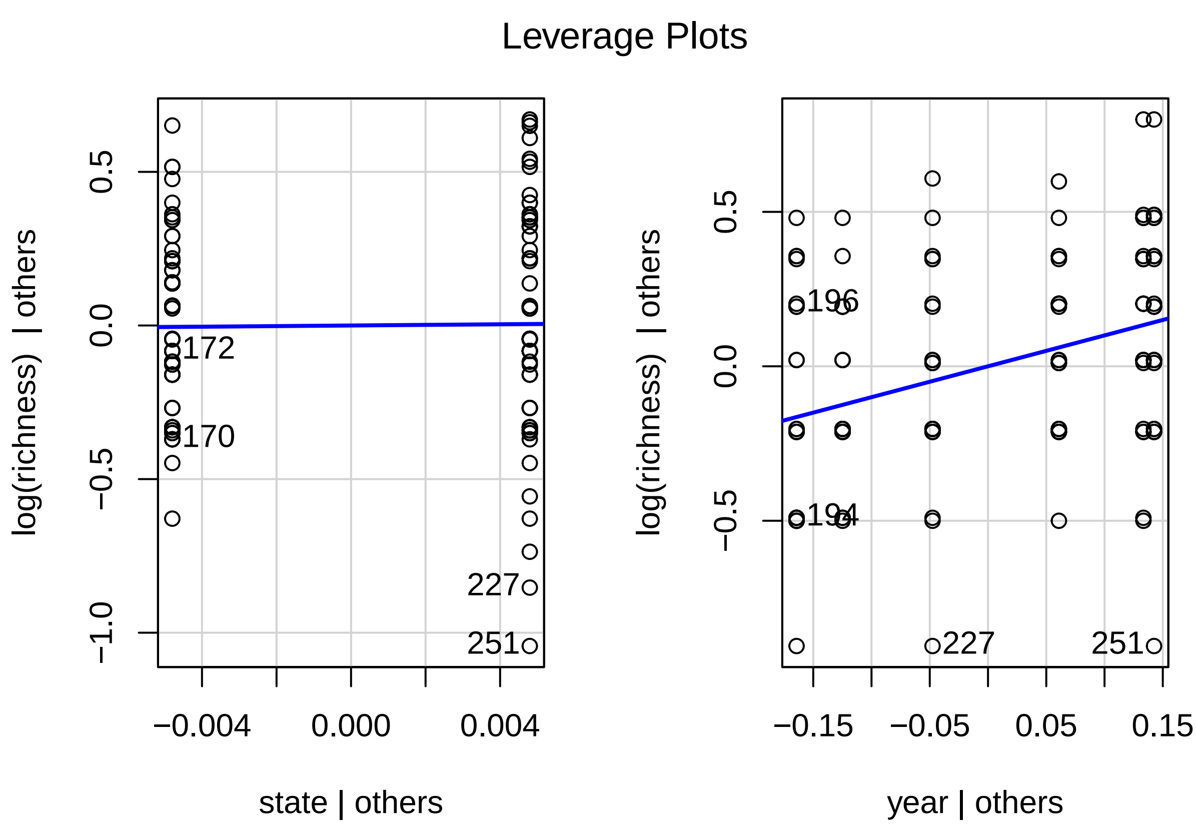



```
## 227 251
##  59  83
```

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




```
leveragePlots(fit_stateyear_umbs_richness)
```

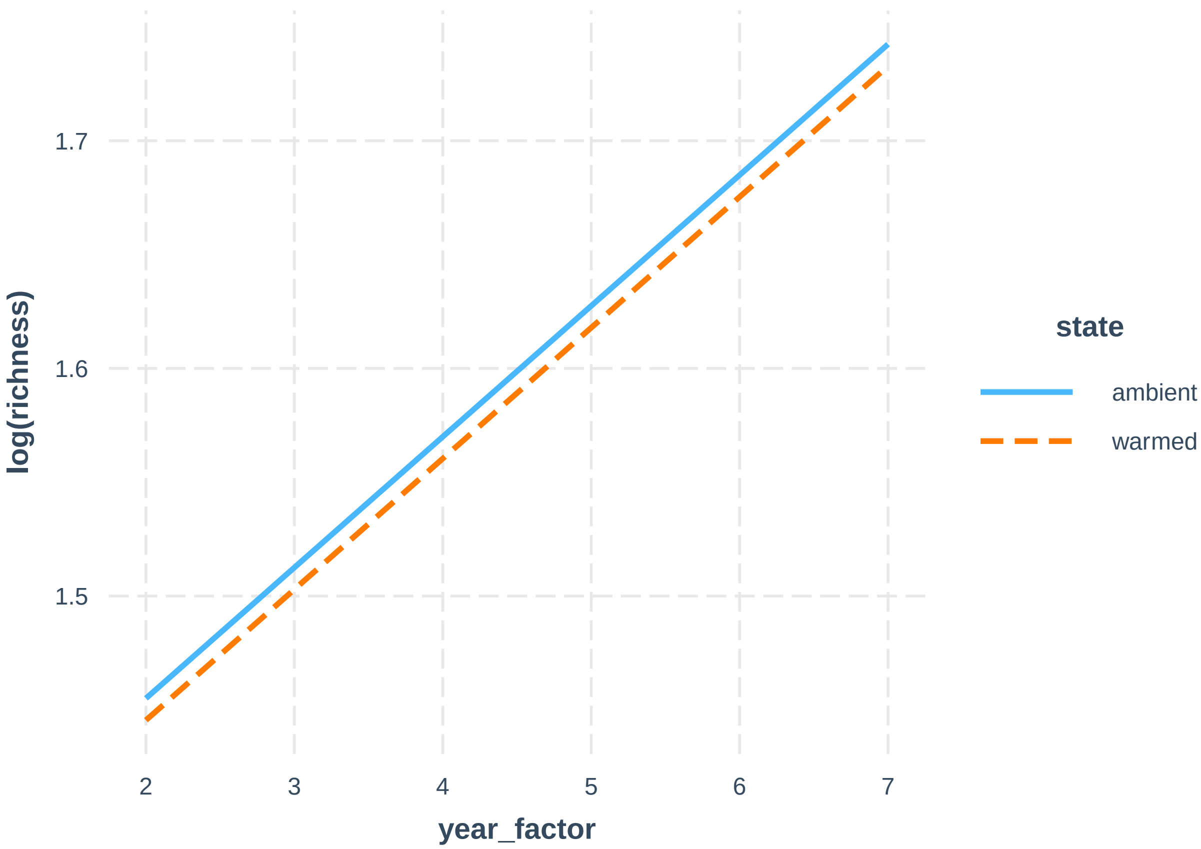


```
ols_test_normality(fit_stateyear_umbs_richness)
```

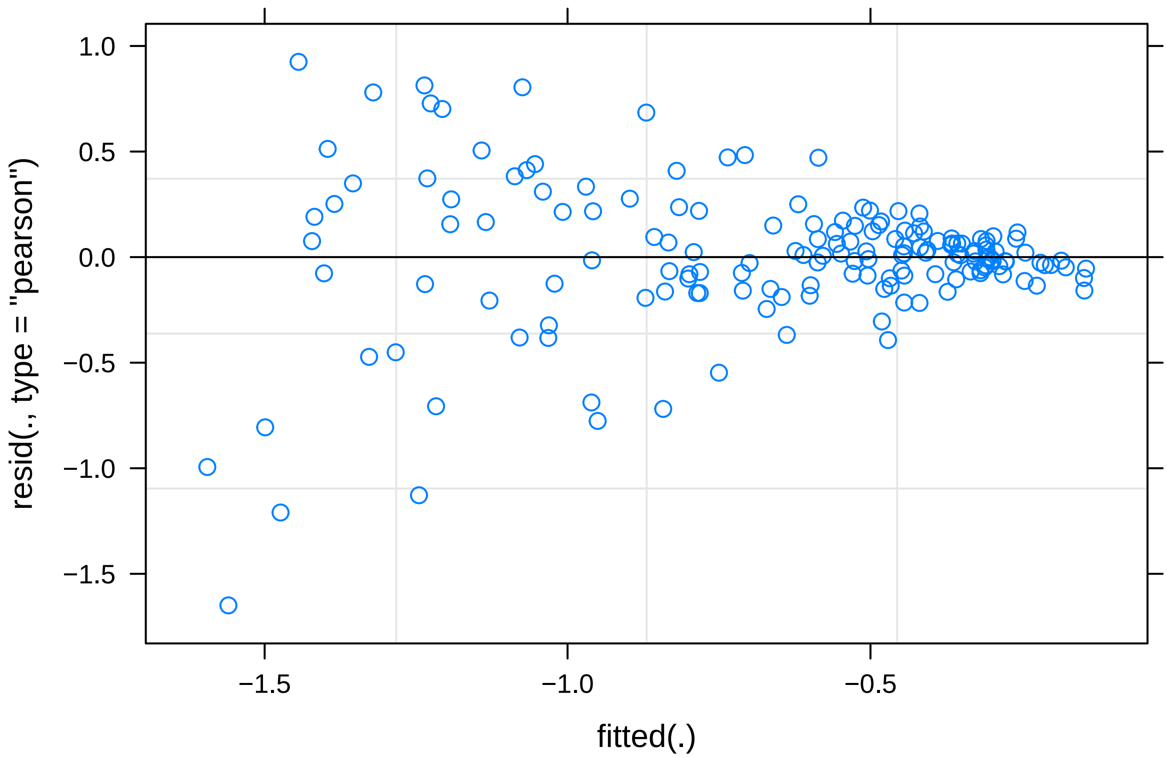
```
## Warning in ks.test.default(y, "pnorm", mean(y), sd(y)): ties should not be
## present for the Kolmogorov-Smirnov test

## -----------------------------------------------
##        Test             Statistic       pvalue
## -----------------------------------------------
## Shapiro-Wilk              0.9818         0.0522
## Kolmogorov-Smirnov        0.083          0.2746
## Cramer-von Mises         23.7014         0.0000
## Anderson-Darling          0.7381         0.0533
## -----------------------------------------------
```

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

# 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.
```



```
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)
```




```
# Homogeneity of variance is ok here (increasing variance in resids is not increasing with fitted value
# Check for homogeneity of variances (true if p>0.05). If the result is not significant, the assumption
# *****Levene's Test - tests whether or not the variance among two or more groups is equal - If the p-v

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  0.0335 0.8549
##       162
```

```
# 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  1.0529 0.3064
##       162
```

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

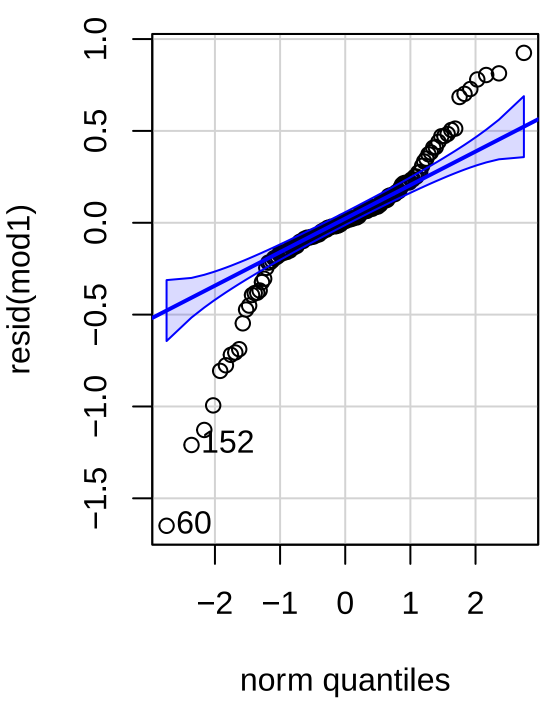
```
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.
```

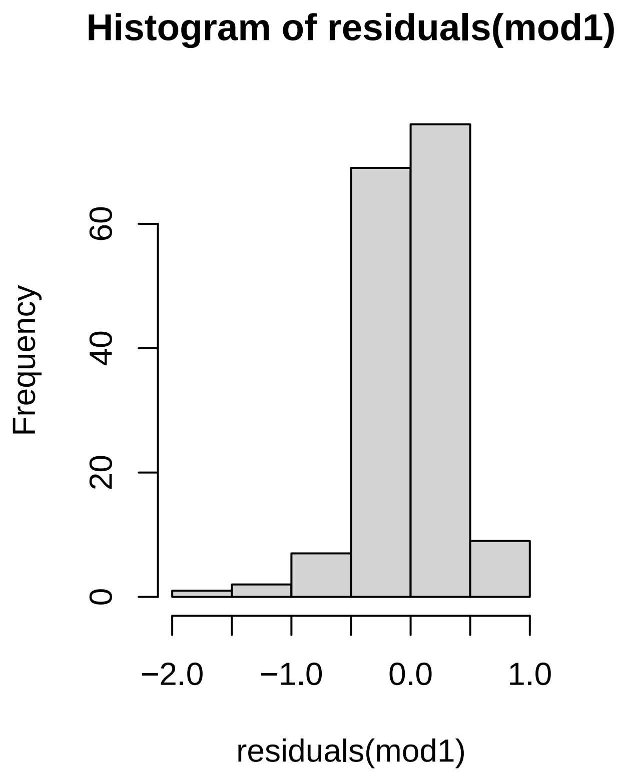
```
## Levene's Test for Homogeneity of Variance (center = median)
##        Df F value Pr(>F)
## group  23  0.7612 0.7733
##       140
```

```
# Assumption not met

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

```
##  60 152
##  60 149
```

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





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

```
##
##  Shapiro-Wilk normality test
##
## data:  resid(mod1)
## W = 0.88642, p-value = 7.067e-10
```

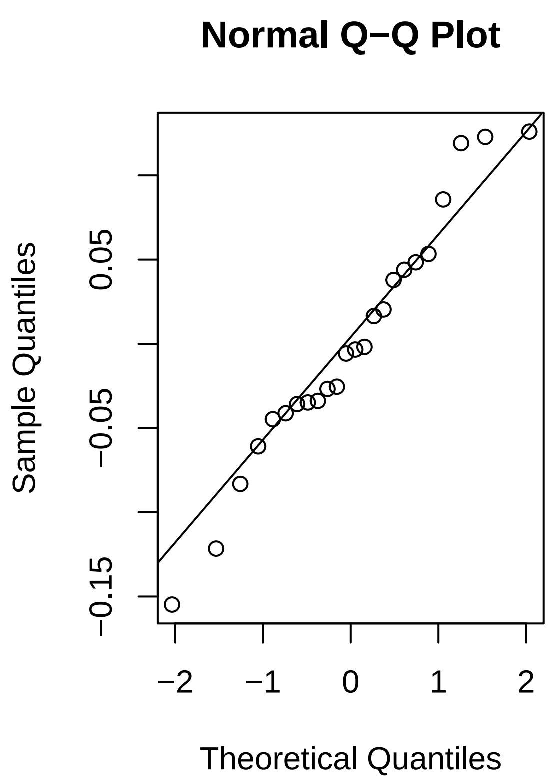
```r
outlierTest(mod1) # row 60 and 152
```

```
##      rstudent unadjusted p-value Bonferroni p
## 60  -5.155000         8.4776e-07   0.00013903
## 152 -3.784997         2.2722e-04   0.03726400
```

```r
# (4) Normality of random effect: Get the estimate of random effect (e.g., random intercepts), and chec
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 = 0.96934, p-value = 0.6506
```

```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
anova(mod1)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq Mean Sq F value
## state               1  0.0041 0.00415  0.0334
## year                6 16.8502 2.80836 22.5942
## insecticide         1  0.0646 0.06455  0.5193
## state:year          6  1.7474 0.29123  2.3431
## year:insecticide    6  2.6015 0.43358  3.4883
```

```r
anova(mod2)
```

```
## Analysis of Variance Table
##             npar  Sum Sq Mean Sq F value
## state          1  0.0047 0.00470  0.0327
## year           6 16.8744 2.81239 19.5501
## insecticide    1  0.0799 0.07993  0.5557
## state:year     6  1.7400 0.29000  2.0159
```

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

```
## 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   17 189.25 241.94 -77.623   155.25
## mod1   23 181.89 253.19 -67.945   135.89 19.355  6   0.003604 **
## ---
## 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
##    181.9    253.2    -67.9    135.9      141
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.6785 -0.2850  0.0282  0.4135  2.6230
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.01235  0.1111
```

```
##  Residual             0.12430  0.3526
## Number of obs: 164, groups:  plot, 24
##
## Fixed effects:
##                                 Estimate Std. Error t value
## (Intercept)                     -0.30790    0.13070  -2.356
## statewarmed                      0.01022    0.15091   0.068
## year2016                        -0.01691    0.17628  -0.096
## year2017                        -0.88235    0.17628  -5.005
## year2018                        -0.13340    0.17628  -0.757
## year2019                        -0.52221    0.17628  -2.962
## year2020                        -0.40095    0.17859  -2.245
## year2021                        -0.28904    0.18284  -1.581
## insecticideno_insects            0.03436    0.15091   0.228
## statewarmed:year2016            -0.06863    0.20355  -0.337
## statewarmed:year2017            -0.25821    0.20355  -1.269
## statewarmed:year2018            -0.11867    0.20355  -0.583
## statewarmed:year2019             0.35462    0.20355   1.742
## statewarmed:year2020             0.20095    0.21145   0.950
## statewarmed:year2021            -0.24963    0.20611  -1.211
## year2016:insecticideno_insects  0.01758    0.20355   0.086
## year2017:insecticideno_insects  0.23105    0.20355   1.135
## year2018:insecticideno_insects  0.02363    0.20355   0.116
## year2019:insecticideno_insects -0.20026    0.20355  -0.984
## year2020:insecticideno_insects -0.08146    0.21255  -0.383
## year2021:insecticideno_insects -0.63787    0.20611  -3.095

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

```
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
##    189.2    241.9    -77.6    155.2      147
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.8722 -0.2568  0.0555  0.3561  2.2453
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.008113 0.09007
##  Residual             0.143856 0.37928
## Number of obs: 164, groups:  plot, 24
##
## Fixed effects:
##                         Estimate Std. Error t value
```

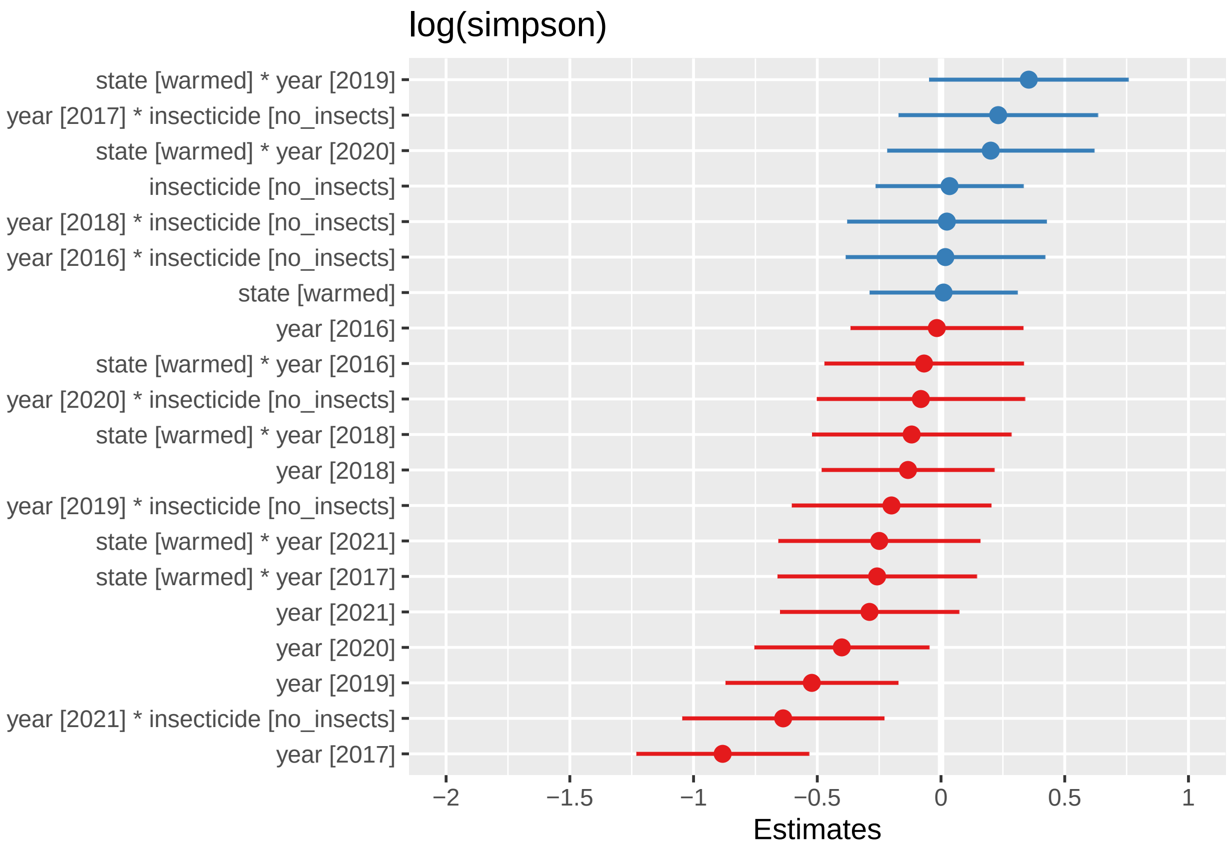
```
## (Intercept)           -0.263239   0.117828  -2.234
## statewarmed            0.010217   0.159148   0.064
## year2016              -0.008125   0.154842  -0.052
## year2017              -0.766828   0.154842  -4.952
## year2018              -0.121590   0.154842  -0.785
## year2019              -0.622340   0.154842  -4.019
## year2020              -0.445289   0.162795  -2.735
## year2021              -0.637513   0.158485  -4.023
## insecticideno_insects -0.054971   0.069836  -0.787
## statewarmed:year2016  -0.068627   0.218979  -0.313
## statewarmed:year2017  -0.258206   0.218979  -1.179
## statewarmed:year2018  -0.118672   0.218979  -0.542
## statewarmed:year2019   0.354616   0.218979   1.619
## statewarmed:year2020   0.200641   0.227144   0.883
## statewarmed:year2021  -0.220093   0.221570  -0.993
```

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

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

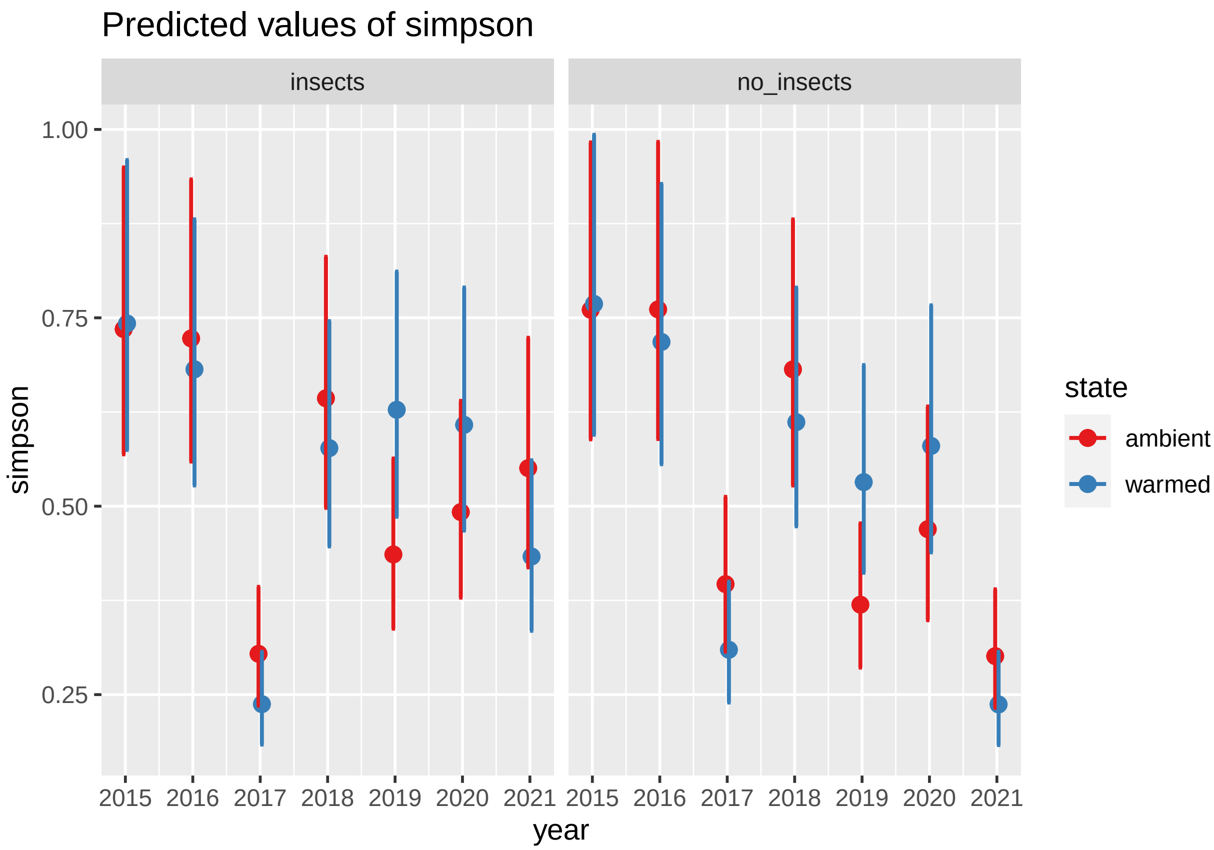
```
##      dAICc df weight
## mod1  0.0  23 0.86
## mod2  3.7  17 0.14
```

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

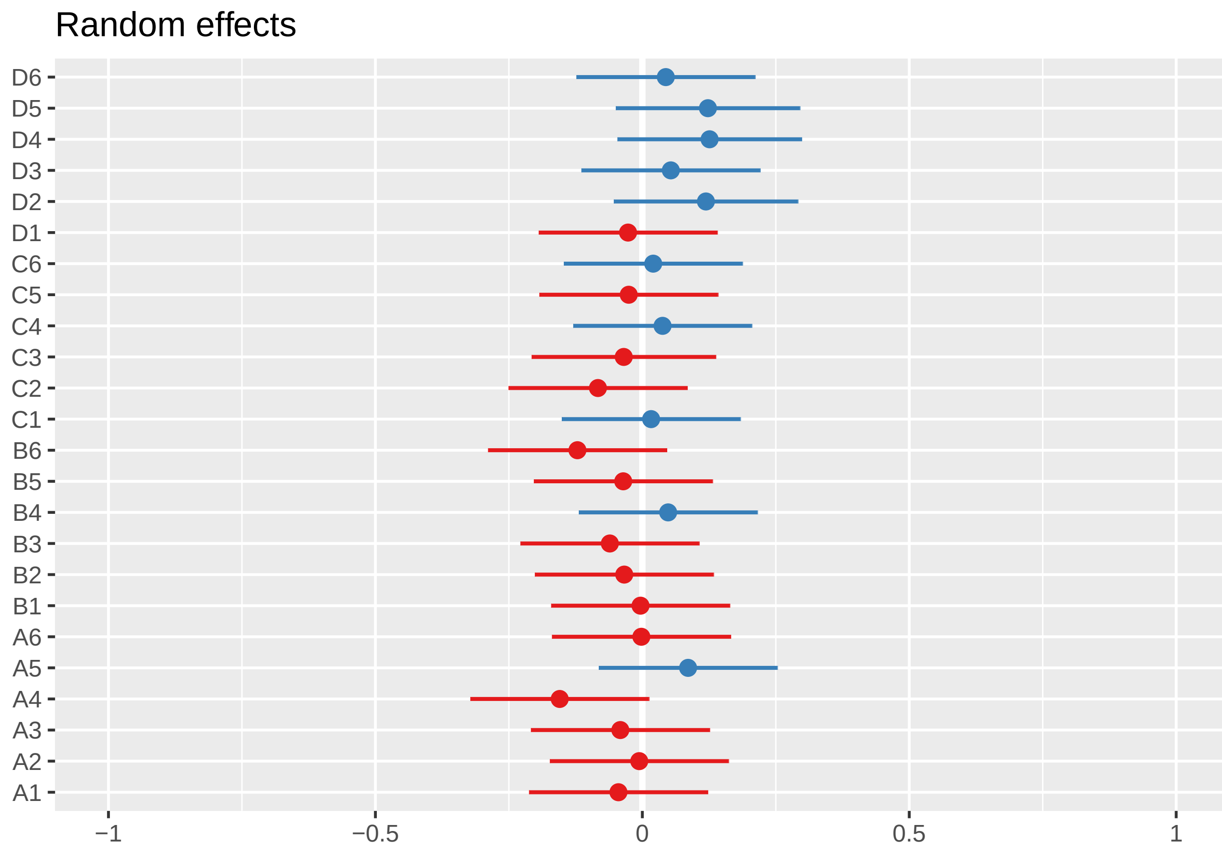



```
# these are the fixed predicted values:
plot_model(mod1, type = "pred", terms = c("year", "state", "insecticide"))
```

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




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




```
# 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   17 189.25 241.94 -77.623   155.25
## mod3   17 183.71 236.40 -74.853   149.71 5.5397  0
```

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

```
##      dAICc df weight
## mod3  0.0  17 0.72
## mod1  1.9  23 0.28
```

```
# Does year need to be interactive with insecticide?
mod4 <- lmer(log(simpson) ~ state + year + insecticide + (1|plot), kbs_diversity, REML=FALSE)
anova(mod3, mod4) # stick with mod3
```

```
## Data: kbs_diversity
## Models:
## mod4: log(simpson) ~ state + year + insecticide + (1 | plot)
```

```
## mod3: log(simpson) ~ state + year + insecticide * year + (1 | plot)
##      npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## mod4   11 188.82 222.91 -83.408   166.82
## mod3   17 183.71 236.40 -74.853   149.71 17.11  6   0.008886 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

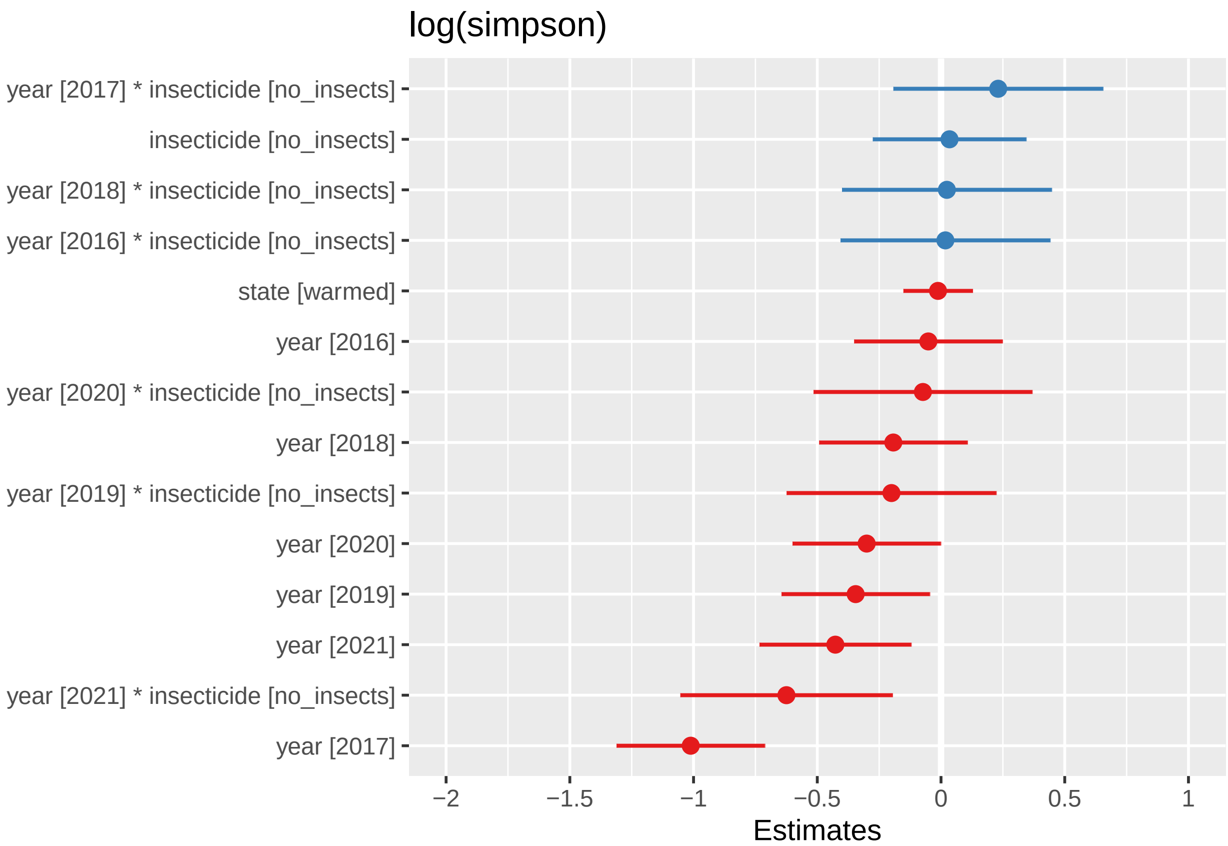
```
AICctab(mod3, mod4, weights=T) # mod3
```

```
##      dAICc df weight
## mod3  0.0  17 0.79
## mod4  2.7  11 0.21
```

```
# 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)
```

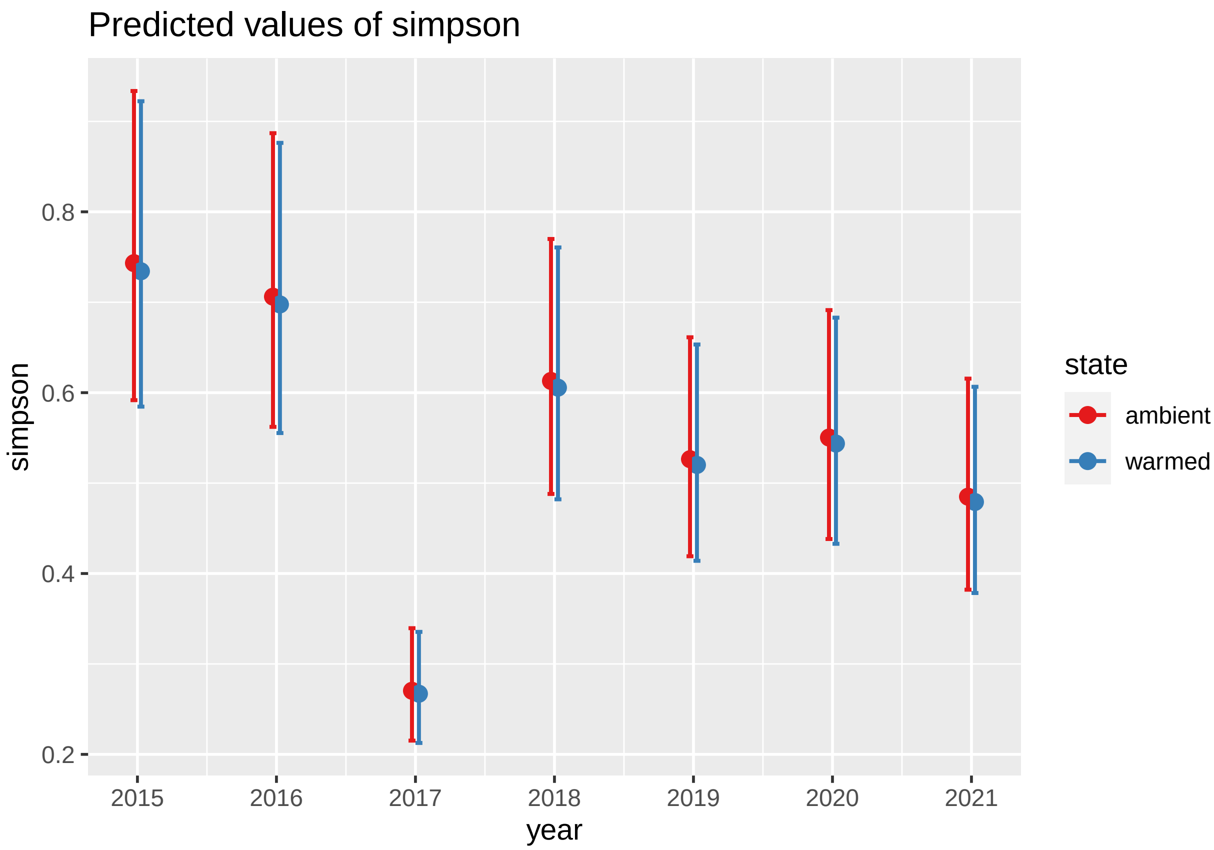
```
## Data: kbs_diversity
## Models:
## mod5: log(simpson) ~ state + year + (1 | plot)
## mod3: log(simpson) ~ state + year + insecticide * year + (1 | plot)
##      npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod5   10 187.38 218.38 -83.690   167.38
## mod3   17 183.71 236.40 -74.853   149.71 17.674  7    0.01353 *
## ---
## 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 comple

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



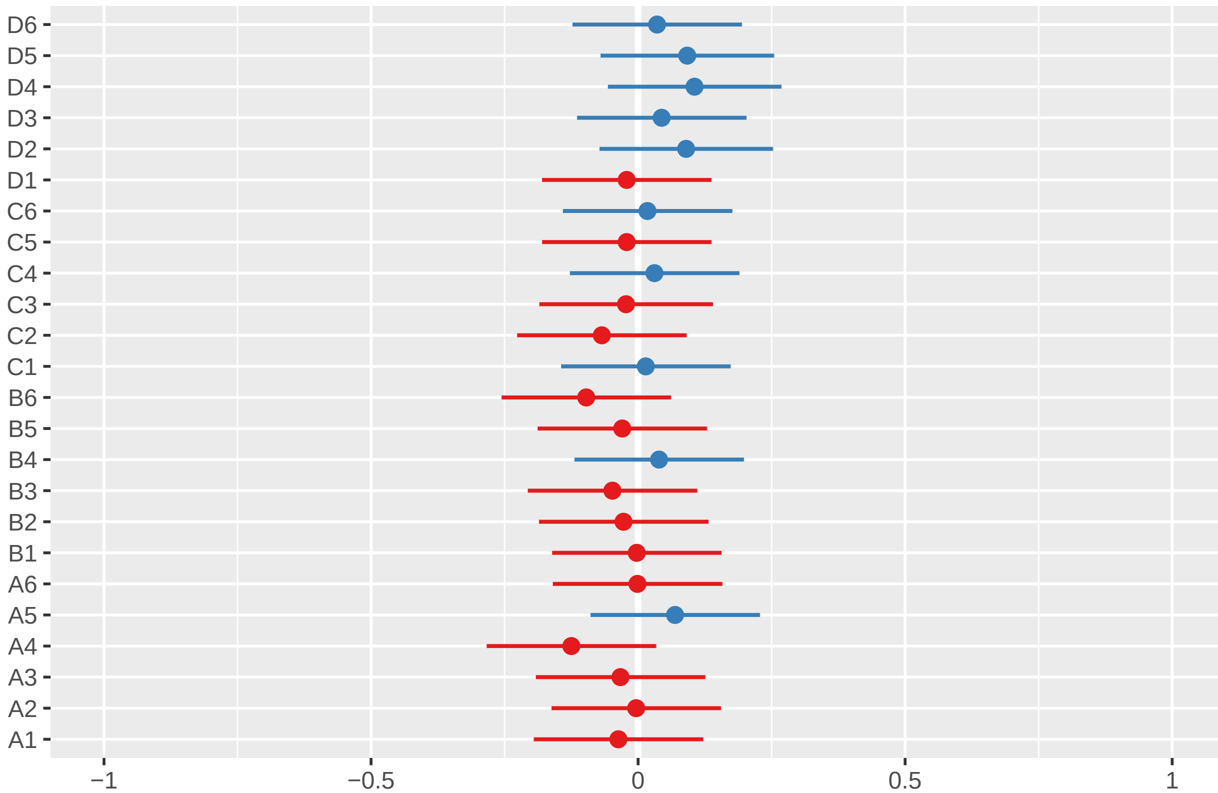

```r
# these are the fixed predicted values:
plot_model(mod3, type = "pred", terms = c("year", "state"))
```

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




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

Random effects




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

Observations	164
Dependent variable	log(simpson)
Type	Mixed effects linear regression

AIC	183.71
BIC	236.40
Pseudo-R^2 (fixed effects)	0.45
Pseudo-R^2 (total)	0.48

```
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     -0.297 0.122 162   -0.539  -0.0549
##  warmed  2015 insects     -0.309 0.122 162   -0.551  -0.0671
##  ambient 2016 insects     -0.348 0.122 162   -0.590  -0.1061
##  warmed  2016 insects     -0.360 0.122 162   -0.602  -0.1183
##  ambient 2017 insects     -1.308 0.122 162   -1.550  -1.0663
##  warmed  2017 insects     -1.320 0.122 162   -1.562  -1.0785
##  ambient 2018 insects     -0.489 0.122 162   -0.731  -0.2476
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	-0.30	0.12	-2.55	143.27	0.01
statewarmed	-0.01	0.07	-0.17	22.66	0.86
year2016	-0.05	0.15	-0.34	138.63	0.74
year2017	-1.01	0.15	-6.68	138.63	0.00
year2018	-0.19	0.15	-1.27	138.63	0.21
year2019	-0.34	0.15	-2.28	138.63	0.02
year2020	-0.30	0.15	-1.98	138.63	0.05
year2021	-0.43	0.16	-2.75	139.93	0.01
insecticideno_insects	0.03	0.16	0.22	159.63	0.83
year2016:insecticideno_insects	0.02	0.21	0.08	138.63	0.93
year2017:insecticideno_insects	0.23	0.21	1.08	138.63	0.28
year2018:insecticideno_insects	0.02	0.21	0.11	138.63	0.91
year2019:insecticideno_insects	-0.20	0.21	-0.93	138.63	0.35
year2020:insecticideno_insects	-0.07	0.22	-0.33	140.97	0.74
year2021:insecticideno_insects	-0.62	0.22	-2.88	139.30	0.00

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.10
Residual		0.37

Grouping Variables		
Group	# groups	ICC
plot	24	0.07

```
##  warmed  2018 insects     -0.502 0.122 162   -0.743  -0.2598
##  ambient 2019 insects     -0.642 0.122 162   -0.883  -0.3998
##  warmed  2019 insects     -0.654 0.122 162   -0.896  -0.4120
##  ambient 2020 insects     -0.597 0.122 162   -0.839  -0.3553
##  warmed  2020 insects     -0.609 0.122 162   -0.851  -0.3675
##  ambient 2021 insects     -0.724 0.128 166   -0.977  -0.4708
##  warmed  2021 insects     -0.736 0.127 165   -0.986  -0.4857
##  ambient 2015 no_insects  -0.262 0.122 161   -0.504  -0.0205
##  warmed  2015 no_insects  -0.275 0.122 162   -0.516  -0.0327
##  ambient 2016 no_insects  -0.296 0.122 161   -0.538  -0.0542
##  warmed  2016 no_insects  -0.308 0.122 162   -0.550  -0.0663
##  ambient 2017 no_insects  -1.043 0.122 161   -1.285  -0.8009
##  warmed  2017 no_insects  -1.055 0.122 162   -1.297  -0.8131
##  ambient 2018 no_insects  -0.431 0.122 161   -0.673  -0.1896
##  warmed  2018 no_insects  -0.444 0.122 162   -0.685  -0.2018
##  ambient 2019 no_insects  -0.808 0.122 161   -1.049  -0.5657
##  warmed  2019 no_insects  -0.820 0.122 162   -1.062  -0.5778
##  ambient 2020 no_insects  -0.636 0.140 172   -0.913  -0.3588
##  warmed  2020 no_insects  -0.648 0.139 171   -0.922  -0.3741
##  ambient 2021 no_insects  -1.314 0.122 161   -1.556  -1.0722
```

```
##  warmed  2021 no_insects  -1.326 0.122 162   -1.568  -1.0844
##
## 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
##  ambient year2015 insects - warmed year2015 insects         0.012183 0.0757
##  ambient year2015 insects - ambient year2016 insects        0.051228 0.1584
##  ambient year2015 insects - warmed year2016 insects         0.063410 0.1755
##  ambient year2015 insects - ambient year2017 insects        1.011455 0.1584
##  ambient year2015 insects - warmed year2017 insects         1.023637 0.1755
##  ambient year2015 insects - ambient year2018 insects        0.192741 0.1584
##  ambient year2015 insects - warmed year2018 insects         0.204923 0.1755
##  ambient year2015 insects - ambient year2019 insects        0.344904 0.1584
##  ambient year2015 insects - warmed year2019 insects         0.357086 0.1755
##  ambient year2015 insects - ambient year2020 insects        0.300477 0.1584
##  ambient year2015 insects - warmed year2020 insects         0.312659 0.1755
##  ambient year2015 insects - ambient year2021 insects        0.426988 0.1622
##  ambient year2015 insects - warmed year2021 insects         0.439170 0.1780
##  ambient year2015 insects - ambient year2015 no_insects    -0.034360 0.1647
##  ambient year2015 insects - warmed year2015 no_insects     -0.022177 0.1813
##  ambient year2015 insects - ambient year2016 no_insects    -0.000711 0.1647
##  ambient year2015 insects - warmed year2016 no_insects      0.011472 0.1813
##  ambient year2015 insects - ambient year2017 no_insects     0.746047 0.1647
##  ambient year2015 insects - warmed year2017 no_insects      0.758230 0.1813
##  ambient year2015 insects - ambient year2018 no_insects     0.134751 0.1647
##  ambient year2015 insects - warmed year2018 no_insects      0.146933 0.1813
##  ambient year2015 insects - ambient year2019 no_insects     0.510799 0.1647
##  ambient year2015 insects - warmed year2019 no_insects      0.522982 0.1813
##  ambient year2015 insects - ambient year2020 no_insects     0.339312 0.1779
##  ambient year2015 insects - warmed year2020 no_insects      0.351495 0.1922
##  ambient year2015 insects - ambient year2021 no_insects     1.017367 0.1647
##  ambient year2015 insects - warmed year2021 no_insects      1.029550 0.1813
##  warmed year2015 insects - ambient year2016 insects         0.039045 0.1755
##  warmed year2015 insects - warmed year2016 insects          0.051228 0.1584
##  warmed year2015 insects - ambient year2017 insects         0.999272 0.1755
##  warmed year2015 insects - warmed year2017 insects          1.011455 0.1584
##  warmed year2015 insects - ambient year2018 insects         0.180558 0.1755
##  warmed year2015 insects - warmed year2018 insects          0.192741 0.1584
##  warmed year2015 insects - ambient year2019 insects         0.332722 0.1755
##  warmed year2015 insects - warmed year2019 insects          0.344904 0.1584
##  warmed year2015 insects - ambient year2020 insects         0.288295 0.1755
##  warmed year2015 insects - warmed year2020 insects          0.300477 0.1584
##  warmed year2015 insects - ambient year2021 insects         0.414805 0.1800
##  warmed year2015 insects - warmed year2021 insects          0.426988 0.1622
##  warmed year2015 insects - ambient year2015 no_insects     -0.046542 0.1813
##  warmed year2015 insects - warmed year2015 no_insects      -0.034360 0.1647
##  warmed year2015 insects - ambient year2016 no_insects     -0.012893 0.1813
##  warmed year2015 insects - warmed year2016 no_insects      -0.000711 0.1647
##  warmed year2015 insects - ambient year2017 no_insects      0.733865 0.1813
##  warmed year2015 insects - warmed year2017 no_insects       0.746047 0.1647
##  warmed year2015 insects - ambient year2018 no_insects      0.122568 0.1813
```

```
## warmed year2015 insects - warmed year2018 no_insects       0.134751 0.1647
## warmed year2015 insects - ambient year2019 no_insects      0.498617 0.1813
## warmed year2015 insects - warmed year2019 no_insects       0.510799 0.1647
## warmed year2015 insects - ambient year2020 no_insects      0.327130 0.1944
## warmed year2015 insects - warmed year2020 no_insects       0.339312 0.1779
## warmed year2015 insects - ambient year2021 no_insects      1.005185 0.1813
## warmed year2015 insects - warmed year2021 no_insects       1.017367 0.1647
## ambient year2016 insects - warmed year2016 insects         0.012183 0.0757
## ambient year2016 insects - ambient year2017 insects        0.960227 0.1584
## ambient year2016 insects - warmed year2017 insects         0.972409 0.1755
## ambient year2016 insects - ambient year2018 insects        0.141513 0.1584
## ambient year2016 insects - warmed year2018 insects         0.153695 0.1755
## ambient year2016 insects - ambient year2019 insects        0.293676 0.1584
## ambient year2016 insects - warmed year2019 insects         0.305859 0.1755
## ambient year2016 insects - ambient year2020 insects        0.249249 0.1584
## ambient year2016 insects - warmed year2020 insects         0.261431 0.1755
## ambient year2016 insects - ambient year2021 insects        0.375760 0.1622
## ambient year2016 insects - warmed year2021 insects         0.387942 0.1780
## ambient year2016 insects - ambient year2015 no_insects    -0.085588 0.1647
## ambient year2016 insects - warmed year2015 no_insects     -0.073405 0.1813
## ambient year2016 insects - ambient year2016 no_insects    -0.051939 0.1647
## ambient year2016 insects - warmed year2016 no_insects     -0.039756 0.1813
## ambient year2016 insects - ambient year2017 no_insects     0.694819 0.1647
## ambient year2016 insects - warmed year2017 no_insects      0.707002 0.1813
## ambient year2016 insects - ambient year2018 no_insects     0.083523 0.1647
## ambient year2016 insects - warmed year2018 no_insects      0.095705 0.1813
## ambient year2016 insects - ambient year2019 no_insects     0.459571 0.1647
## ambient year2016 insects - warmed year2019 no_insects      0.471754 0.1813
## ambient year2016 insects - ambient year2020 no_insects     0.288084 0.1779
## ambient year2016 insects - warmed year2020 no_insects      0.300267 0.1922
## ambient year2016 insects - ambient year2021 no_insects     0.966140 0.1647
## ambient year2016 insects - warmed year2021 no_insects      0.978322 0.1813
## warmed year2016 insects - ambient year2017 insects         0.948044 0.1755
## warmed year2016 insects - warmed year2017 insects          0.960227 0.1584
## warmed year2016 insects - ambient year2018 insects         0.129330 0.1755
## warmed year2016 insects - warmed year2018 insects          0.141513 0.1584
## warmed year2016 insects - ambient year2019 insects         0.281494 0.1755
## warmed year2016 insects - warmed year2019 insects          0.293676 0.1584
## warmed year2016 insects - ambient year2020 insects         0.237067 0.1755
## warmed year2016 insects - warmed year2020 insects          0.249249 0.1584
## warmed year2016 insects - ambient year2021 insects         0.363577 0.1800
## warmed year2016 insects - warmed year2021 insects          0.375760 0.1622
## warmed year2016 insects - ambient year2015 no_insects     -0.097770 0.1813
## warmed year2016 insects - warmed year2015 no_insects      -0.085588 0.1647
## warmed year2016 insects - ambient year2016 no_insects     -0.064121 0.1813
## warmed year2016 insects - warmed year2016 no_insects      -0.051939 0.1647
## warmed year2016 insects - ambient year2017 no_insects      0.682637 0.1813
## warmed year2016 insects - warmed year2017 no_insects       0.694819 0.1647
## warmed year2016 insects - ambient year2018 no_insects      0.071341 0.1813
## warmed year2016 insects - warmed year2018 no_insects       0.083523 0.1647
## warmed year2016 insects - ambient year2019 no_insects      0.447389 0.1813
## warmed year2016 insects - warmed year2019 no_insects       0.459571 0.1647
## warmed year2016 insects - ambient year2020 no_insects      0.275902 0.1944
## warmed year2016 insects - warmed year2020 no_insects       0.288084 0.1779
```

```
##  warmed year2016 insects - ambient year2021 no_insects      0.953957 0.1813
##  warmed year2016 insects - warmed year2021 no_insects       0.966140 0.1647
##  ambient year2017 insects - warmed year2017 insects         0.012183 0.0757
##  ambient year2017 insects - ambient year2018 insects       -0.818714 0.1584
##  ambient year2017 insects - warmed year2018 insects        -0.806532 0.1755
##  ambient year2017 insects - ambient year2019 insects       -0.666551 0.1584
##  ambient year2017 insects - warmed year2019 insects        -0.654368 0.1755
##  ambient year2017 insects - ambient year2020 insects       -0.710978 0.1584
##  ambient year2017 insects - warmed year2020 insects        -0.698795 0.1755
##  ambient year2017 insects - ambient year2021 insects       -0.584467 0.1622
##  ambient year2017 insects - warmed year2021 insects        -0.572284 0.1780
##  ambient year2017 insects - ambient year2015 no_insects    -1.045815 0.1647
##  ambient year2017 insects - warmed year2015 no_insects     -1.033632 0.1813
##  ambient year2017 insects - ambient year2016 no_insects    -1.012166 0.1647
##  ambient year2017 insects - warmed year2016 no_insects     -0.999983 0.1813
##  ambient year2017 insects - ambient year2017 no_insects    -0.265408 0.1647
##  ambient year2017 insects - warmed year2017 no_insects     -0.253225 0.1813
##  ambient year2017 insects - ambient year2018 no_insects    -0.876704 0.1647
##  ambient year2017 insects - warmed year2018 no_insects     -0.864521 0.1813
##  ambient year2017 insects - ambient year2019 no_insects    -0.500656 0.1647
##  ambient year2017 insects - warmed year2019 no_insects     -0.488473 0.1813
##  ambient year2017 insects - ambient year2020 no_insects    -0.672143 0.1779
##  ambient year2017 insects - warmed year2020 no_insects     -0.659960 0.1922
##  ambient year2017 insects - ambient year2021 no_insects     0.005913 0.1647
##  ambient year2017 insects - warmed year2021 no_insects      0.018095 0.1813
##  warmed year2017 insects - ambient year2018 insects        -0.830897 0.1755
##  warmed year2017 insects - warmed year2018 insects         -0.818714 0.1584
##  warmed year2017 insects - ambient year2019 insects        -0.678733 0.1755
##  warmed year2017 insects - warmed year2019 insects         -0.666551 0.1584
##  warmed year2017 insects - ambient year2020 insects        -0.723160 0.1755
##  warmed year2017 insects - warmed year2020 insects         -0.710978 0.1584
##  warmed year2017 insects - ambient year2021 insects        -0.596650 0.1800
##  warmed year2017 insects - warmed year2021 insects         -0.584467 0.1622
##  warmed year2017 insects - ambient year2015 no_insects     -1.057997 0.1813
##  warmed year2017 insects - warmed year2015 no_insects      -1.045815 0.1647
##  warmed year2017 insects - ambient year2016 no_insects     -1.024348 0.1813
##  warmed year2017 insects - warmed year2016 no_insects      -1.012166 0.1647
##  warmed year2017 insects - ambient year2017 no_insects     -0.277590 0.1813
##  warmed year2017 insects - warmed year2017 no_insects      -0.265408 0.1647
##  warmed year2017 insects - ambient year2018 no_insects     -0.888886 0.1813
##  warmed year2017 insects - warmed year2018 no_insects      -0.876704 0.1647
##  warmed year2017 insects - ambient year2019 no_insects     -0.512838 0.1813
##  warmed year2017 insects - warmed year2019 no_insects      -0.500656 0.1647
##  warmed year2017 insects - ambient year2020 no_insects     -0.684325 0.1944
##  warmed year2017 insects - warmed year2020 no_insects      -0.672143 0.1779
##  warmed year2017 insects - ambient year2021 no_insects     -0.006270 0.1813
##  warmed year2017 insects - warmed year2021 no_insects       0.005913 0.1647
##  ambient year2018 insects - warmed year2018 insects         0.012183 0.0757
##  ambient year2018 insects - ambient year2019 insects        0.152163 0.1584
##  ambient year2018 insects - warmed year2019 insects         0.164346 0.1755
##  ambient year2018 insects - ambient year2020 insects        0.107736 0.1584
##  ambient year2018 insects - warmed year2020 insects         0.119919 0.1755
##  ambient year2018 insects - ambient year2021 insects        0.234247 0.1622
##  ambient year2018 insects - warmed year2021 insects         0.246430 0.1780
```

```
##  ambient year2018 insects - ambient year2015 no_insects    -0.227101 0.1647
##  ambient year2018 insects - warmed year2015 no_insects     -0.214918 0.1813
##  ambient year2018 insects - ambient year2016 no_insects    -0.193452 0.1647
##  ambient year2018 insects - warmed year2016 no_insects     -0.181269 0.1813
##  ambient year2018 insects - ambient year2017 no_insects     0.553306 0.1647
##  ambient year2018 insects - warmed year2017 no_insects      0.565489 0.1813
##  ambient year2018 insects - ambient year2018 no_insects    -0.057990 0.1647
##  ambient year2018 insects - warmed year2018 no_insects     -0.045807 0.1813
##  ambient year2018 insects - ambient year2019 no_insects     0.318059 0.1647
##  ambient year2018 insects - warmed year2019 no_insects      0.330241 0.1813
##  ambient year2018 insects - ambient year2020 no_insects     0.146571 0.1779
##  ambient year2018 insects - warmed year2020 no_insects      0.158754 0.1922
##  ambient year2018 insects - ambient year2021 no_insects     0.824627 0.1647
##  ambient year2018 insects - warmed year2021 no_insects      0.836809 0.1813
##  warmed year2018 insects - ambient year2019 insects         0.139981 0.1755
##  warmed year2018 insects - warmed year2019 insects          0.152163 0.1584
##  warmed year2018 insects - ambient year2020 insects         0.095554 0.1755
##  warmed year2018 insects - warmed year2020 insects          0.107736 0.1584
##  warmed year2018 insects - ambient year2021 insects         0.222064 0.1800
##  warmed year2018 insects - warmed year2021 insects          0.234247 0.1622
##  warmed year2018 insects - ambient year2015 no_insects     -0.239283 0.1813
##  warmed year2018 insects - warmed year2015 no_insects      -0.227101 0.1647
##  warmed year2018 insects - ambient year2016 no_insects     -0.205634 0.1813
##  warmed year2018 insects - warmed year2016 no_insects      -0.193452 0.1647
##  warmed year2018 insects - ambient year2017 no_insects      0.541124 0.1813
##  warmed year2018 insects - warmed year2017 no_insects       0.553306 0.1647
##  warmed year2018 insects - ambient year2018 no_insects     -0.070172 0.1813
##  warmed year2018 insects - warmed year2018 no_insects      -0.057990 0.1647
##  warmed year2018 insects - ambient year2019 no_insects      0.305876 0.1813
##  warmed year2018 insects - warmed year2019 no_insects       0.318059 0.1647
##  warmed year2018 insects - ambient year2020 no_insects      0.134389 0.1944
##  warmed year2018 insects - warmed year2020 no_insects       0.146571 0.1779
##  warmed year2018 insects - ambient year2021 no_insects      0.812444 0.1813
##  warmed year2018 insects - warmed year2021 no_insects       0.824627 0.1647
##  ambient year2019 insects - warmed year2019 insects         0.012183 0.0757
##  ambient year2019 insects - ambient year2020 insects       -0.044427 0.1584
##  ambient year2019 insects - warmed year2020 insects        -0.032245 0.1755
##  ambient year2019 insects - ambient year2021 insects        0.082084 0.1622
##  ambient year2019 insects - warmed year2021 insects         0.094266 0.1780
##  ambient year2019 insects - ambient year2015 no_insects    -0.379264 0.1647
##  ambient year2019 insects - warmed year2015 no_insects     -0.367081 0.1813
##  ambient year2019 insects - ambient year2016 no_insects    -0.345615 0.1647
##  ambient year2019 insects - warmed year2016 no_insects     -0.333432 0.1813
##  ambient year2019 insects - ambient year2017 no_insects     0.401143 0.1647
##  ambient year2019 insects - warmed year2017 no_insects      0.413326 0.1813
##  ambient year2019 insects - ambient year2018 no_insects    -0.210153 0.1647
##  ambient year2019 insects - warmed year2018 no_insects     -0.197971 0.1813
##  ambient year2019 insects - ambient year2019 no_insects     0.165895 0.1647
##  ambient year2019 insects - warmed year2019 no_insects      0.178078 0.1813
##  ambient year2019 insects - ambient year2020 no_insects    -0.005592 0.1779
##  ambient year2019 insects - warmed year2020 no_insects      0.006591 0.1922
##  ambient year2019 insects - ambient year2021 no_insects     0.672463 0.1647
##  ambient year2019 insects - warmed year2021 no_insects      0.684646 0.1813
##  warmed year2019 insects - ambient year2020 insects        -0.056610 0.1755
```

```
## warmed year2019 insects - warmed year2020 insects        -0.044427 0.1584
## warmed year2019 insects - ambient year2021 insects         0.069901 0.1800
## warmed year2019 insects - warmed year2021 insects          0.082084 0.1622
## warmed year2019 insects - ambient year2015 no_insects     -0.391446 0.1813
## warmed year2019 insects - warmed year2015 no_insects      -0.379264 0.1647
## warmed year2019 insects - ambient year2016 no_insects     -0.357797 0.1813
## warmed year2019 insects - warmed year2016 no_insects      -0.345615 0.1647
## warmed year2019 insects - ambient year2017 no_insects      0.388961 0.1813
## warmed year2019 insects - warmed year2017 no_insects       0.401143 0.1647
## warmed year2019 insects - ambient year2018 no_insects     -0.222336 0.1813
## warmed year2019 insects - warmed year2018 no_insects      -0.210153 0.1647
## warmed year2019 insects - ambient year2019 no_insects      0.153713 0.1813
## warmed year2019 insects - warmed year2019 no_insects       0.165895 0.1647
## warmed year2019 insects - ambient year2020 no_insects     -0.017774 0.1944
## warmed year2019 insects - warmed year2020 no_insects      -0.005592 0.1779
## warmed year2019 insects - ambient year2021 no_insects      0.660281 0.1813
## warmed year2019 insects - warmed year2021 no_insects       0.672463 0.1647
## ambient year2020 insects - warmed year2020 insects         0.012183 0.0757
## ambient year2020 insects - ambient year2021 insects        0.126511 0.1622
## ambient year2020 insects - warmed year2021 insects         0.138693 0.1780
## ambient year2020 insects - ambient year2015 no_insects    -0.334837 0.1647
## ambient year2020 insects - warmed year2015 no_insects     -0.322654 0.1813
## ambient year2020 insects - ambient year2016 no_insects    -0.301188 0.1647
## ambient year2020 insects - warmed year2016 no_insects     -0.289005 0.1813
## ambient year2020 insects - ambient year2017 no_insects     0.445570 0.1647
## ambient year2020 insects - warmed year2017 no_insects      0.457753 0.1813
## ambient year2020 insects - ambient year2018 no_insects    -0.165726 0.1647
## ambient year2020 insects - warmed year2018 no_insects     -0.153543 0.1813
## ambient year2020 insects - ambient year2019 no_insects     0.210322 0.1647
## ambient year2020 insects - warmed year2019 no_insects      0.222505 0.1813
## ambient year2020 insects - ambient year2020 no_insects     0.038835 0.1779
## ambient year2020 insects - warmed year2020 no_insects      0.051018 0.1922
## ambient year2020 insects - ambient year2021 no_insects     0.716890 0.1647
## ambient year2020 insects - warmed year2021 no_insects      0.729073 0.1813
## warmed year2020 insects - ambient year2021 insects         0.114328 0.1800
## warmed year2020 insects - warmed year2021 insects          0.126511 0.1622
## warmed year2020 insects - ambient year2015 no_insects     -0.347019 0.1813
## warmed year2020 insects - warmed year2015 no_insects      -0.334837 0.1647
## warmed year2020 insects - ambient year2016 no_insects     -0.313370 0.1813
## warmed year2020 insects - warmed year2016 no_insects      -0.301188 0.1647
## warmed year2020 insects - ambient year2017 no_insects      0.433388 0.1813
## warmed year2020 insects - warmed year2017 no_insects       0.445570 0.1647
## warmed year2020 insects - ambient year2018 no_insects     -0.177908 0.1813
## warmed year2020 insects - warmed year2018 no_insects      -0.165726 0.1647
## warmed year2020 insects - ambient year2019 no_insects      0.198140 0.1813
## warmed year2020 insects - warmed year2019 no_insects       0.210322 0.1647
## warmed year2020 insects - ambient year2020 no_insects      0.026653 0.1944
## warmed year2020 insects - warmed year2020 no_insects       0.038835 0.1779
## warmed year2020 insects - ambient year2021 no_insects      0.704708 0.1813
## warmed year2020 insects - warmed year2021 no_insects       0.716890 0.1647
## ambient year2021 insects - warmed year2021 insects         0.012183 0.0757
## ambient year2021 insects - ambient year2015 no_insects    -0.461348 0.1684
## ambient year2021 insects - warmed year2015 no_insects     -0.449165 0.1856
## ambient year2021 insects - ambient year2016 no_insects    -0.427699 0.1684
```

```
##  ambient year2021 insects - warmed year2016 no_insects     -0.415516 0.1856
##  ambient year2021 insects - ambient year2017 no_insects     0.319059 0.1684
##  ambient year2021 insects - warmed year2017 no_insects      0.331242 0.1856
##  ambient year2021 insects - ambient year2018 no_insects    -0.292237 0.1684
##  ambient year2021 insects - warmed year2018 no_insects     -0.280054 0.1856
##  ambient year2021 insects - ambient year2019 no_insects     0.083811 0.1684
##  ambient year2021 insects - warmed year2019 no_insects      0.095994 0.1856
##  ambient year2021 insects - ambient year2020 no_insects    -0.087676 0.1813
##  ambient year2021 insects - warmed year2020 no_insects     -0.075493 0.1962
##  ambient year2021 insects - ambient year2021 no_insects     0.590380 0.1684
##  ambient year2021 insects - warmed year2021 no_insects      0.602562 0.1856
##  warmed year2021 insects - ambient year2015 no_insects     -0.473530 0.1837
##  warmed year2021 insects - warmed year2015 no_insects      -0.461348 0.1684
##  warmed year2021 insects - ambient year2016 no_insects     -0.439881 0.1837
##  warmed year2021 insects - warmed year2016 no_insects      -0.427699 0.1684
##  warmed year2021 insects - ambient year2017 no_insects      0.306877 0.1837
##  warmed year2021 insects - warmed year2017 no_insects       0.319059 0.1684
##  warmed year2021 insects - ambient year2018 no_insects     -0.304419 0.1837
##  warmed year2021 insects - warmed year2018 no_insects      -0.292237 0.1684
##  warmed year2021 insects - ambient year2019 no_insects      0.071629 0.1837
##  warmed year2021 insects - warmed year2019 no_insects       0.083811 0.1684
##  warmed year2021 insects - ambient year2020 no_insects     -0.099858 0.1966
##  warmed year2021 insects - warmed year2020 no_insects      -0.087676 0.1813
##  warmed year2021 insects - ambient year2021 no_insects      0.578197 0.1837
##  warmed year2021 insects - warmed year2021 no_insects       0.590380 0.1684
##  ambient year2015 no_insects - warmed year2015 no_insects   0.012183 0.0757
##  ambient year2015 no_insects - ambient year2016 no_insects  0.033649 0.1584
##  ambient year2015 no_insects - warmed year2016 no_insects   0.045832 0.1755
##  ambient year2015 no_insects - ambient year2017 no_insects  0.780407 0.1584
##  ambient year2015 no_insects - warmed year2017 no_insects   0.792590 0.1755
##  ambient year2015 no_insects - ambient year2018 no_insects  0.169111 0.1584
##  ambient year2015 no_insects - warmed year2018 no_insects   0.181293 0.1755
##  ambient year2015 no_insects - ambient year2019 no_insects  0.545159 0.1584
##  ambient year2015 no_insects - warmed year2019 no_insects   0.557342 0.1755
##  ambient year2015 no_insects - ambient year2020 no_insects  0.373672 0.1720
##  ambient year2015 no_insects - warmed year2020 no_insects   0.385855 0.1868
##  ambient year2015 no_insects - ambient year2021 no_insects  1.051727 0.1584
##  ambient year2015 no_insects - warmed year2021 no_insects   1.063910 0.1755
##  warmed year2015 no_insects - ambient year2016 no_insects   0.021467 0.1755
##  warmed year2015 no_insects - warmed year2016 no_insects    0.033649 0.1584
##  warmed year2015 no_insects - ambient year2017 no_insects   0.768225 0.1755
##  warmed year2015 no_insects - warmed year2017 no_insects    0.780407 0.1584
##  warmed year2015 no_insects - ambient year2018 no_insects   0.156928 0.1755
##  warmed year2015 no_insects - warmed year2018 no_insects    0.169111 0.1584
##  warmed year2015 no_insects - ambient year2019 no_insects   0.532977 0.1755
##  warmed year2015 no_insects - warmed year2019 no_insects    0.545159 0.1584
##  warmed year2015 no_insects - ambient year2020 no_insects   0.361490 0.1891
##  warmed year2015 no_insects - warmed year2020 no_insects    0.373672 0.1720
##  warmed year2015 no_insects - ambient year2021 no_insects   1.039545 0.1755
##  warmed year2015 no_insects - warmed year2021 no_insects    1.051727 0.1584
##  ambient year2016 no_insects - warmed year2016 no_insects   0.012183 0.0757
##  ambient year2016 no_insects - ambient year2017 no_insects  0.746758 0.1584
##  ambient year2016 no_insects - warmed year2017 no_insects   0.758940 0.1755
##  ambient year2016 no_insects - ambient year2018 no_insects  0.135462 0.1584
```

```
##  ambient year2016 no_insects - warmed year2018 no_insects   0.147644 0.1755
##  ambient year2016 no_insects - ambient year2019 no_insects  0.511510 0.1584
##  ambient year2016 no_insects - warmed year2019 no_insects   0.523693 0.1755
##  ambient year2016 no_insects - ambient year2020 no_insects  0.340023 0.1720
##  ambient year2016 no_insects - warmed year2020 no_insects   0.352205 0.1868
##  ambient year2016 no_insects - ambient year2021 no_insects  1.018078 0.1584
##  ambient year2016 no_insects - warmed year2021 no_insects   1.030261 0.1755
##  warmed year2016 no_insects - ambient year2017 no_insects   0.734575 0.1755
##  warmed year2016 no_insects - warmed year2017 no_insects    0.746758 0.1584
##  warmed year2016 no_insects - ambient year2018 no_insects   0.123279 0.1755
##  warmed year2016 no_insects - warmed year2018 no_insects    0.135462 0.1584
##  warmed year2016 no_insects - ambient year2019 no_insects   0.499328 0.1755
##  warmed year2016 no_insects - warmed year2019 no_insects    0.511510 0.1584
##  warmed year2016 no_insects - ambient year2020 no_insects   0.327840 0.1891
##  warmed year2016 no_insects - warmed year2020 no_insects    0.340023 0.1720
##  warmed year2016 no_insects - ambient year2021 no_insects   1.005896 0.1755
##  warmed year2016 no_insects - warmed year2021 no_insects    1.018078 0.1584
##  ambient year2017 no_insects - warmed year2017 no_insects   0.012183 0.0757
##  ambient year2017 no_insects - ambient year2018 no_insects -0.611296 0.1584
##  ambient year2017 no_insects - warmed year2018 no_insects  -0.599114 0.1755
##  ambient year2017 no_insects - ambient year2019 no_insects -0.235248 0.1584
##  ambient year2017 no_insects - warmed year2019 no_insects  -0.223065 0.1755
##  ambient year2017 no_insects - ambient year2020 no_insects -0.406735 0.1720
##  ambient year2017 no_insects - warmed year2020 no_insects  -0.394552 0.1868
##  ambient year2017 no_insects - ambient year2021 no_insects  0.271320 0.1584
##  ambient year2017 no_insects - warmed year2021 no_insects   0.283503 0.1755
##  warmed year2017 no_insects - ambient year2018 no_insects  -0.623479 0.1755
##  warmed year2017 no_insects - warmed year2018 no_insects   -0.611296 0.1584
##  warmed year2017 no_insects - ambient year2019 no_insects  -0.247430 0.1755
##  warmed year2017 no_insects - warmed year2019 no_insects   -0.235248 0.1584
##  warmed year2017 no_insects - ambient year2020 no_insects  -0.418917 0.1891
##  warmed year2017 no_insects - warmed year2020 no_insects   -0.406735 0.1720
##  warmed year2017 no_insects - ambient year2021 no_insects   0.259138 0.1755
##  warmed year2017 no_insects - warmed year2021 no_insects    0.271320 0.1584
##  ambient year2018 no_insects - warmed year2018 no_insects   0.012183 0.0757
##  ambient year2018 no_insects - ambient year2019 no_insects  0.376048 0.1584
##  ambient year2018 no_insects - warmed year2019 no_insects   0.388231 0.1755
##  ambient year2018 no_insects - ambient year2020 no_insects  0.204561 0.1720
##  ambient year2018 no_insects - warmed year2020 no_insects   0.216744 0.1868
##  ambient year2018 no_insects - ambient year2021 no_insects  0.882617 0.1584
##  ambient year2018 no_insects - warmed year2021 no_insects   0.894799 0.1755
##  warmed year2018 no_insects - ambient year2019 no_insects   0.363866 0.1755
##  warmed year2018 no_insects - warmed year2019 no_insects    0.376048 0.1584
##  warmed year2018 no_insects - ambient year2020 no_insects   0.192379 0.1891
##  warmed year2018 no_insects - warmed year2020 no_insects    0.204561 0.1720
##  warmed year2018 no_insects - ambient year2021 no_insects   0.870434 0.1755
##  warmed year2018 no_insects - warmed year2021 no_insects    0.882617 0.1584
##  ambient year2019 no_insects - warmed year2019 no_insects   0.012183 0.0757
##  ambient year2019 no_insects - ambient year2020 no_insects -0.171487 0.1720
##  ambient year2019 no_insects - warmed year2020 no_insects  -0.159305 0.1868
##  ambient year2019 no_insects - ambient year2021 no_insects  0.506568 0.1584
##  ambient year2019 no_insects - warmed year2021 no_insects   0.518751 0.1755
##  warmed year2019 no_insects - ambient year2020 no_insects  -0.183670 0.1891
##  warmed year2019 no_insects - warmed year2020 no_insects   -0.171487 0.1720
```

```
##  warmed year2019 no_insects - ambient year2021 no_insects   0.494386 0.1755
##  warmed year2019 no_insects - warmed year2021 no_insects    0.506568 0.1584
##  ambient year2020 no_insects - warmed year2020 no_insects   0.012183 0.0757
##  ambient year2020 no_insects - ambient year2021 no_insects  0.678055 0.1720
##  ambient year2020 no_insects - warmed year2021 no_insects   0.690238 0.1891
##  warmed year2020 no_insects - ambient year2021 no_insects   0.665873 0.1868
##  warmed year2020 no_insects - warmed year2021 no_insects    0.678055 0.1720
##  ambient year2021 no_insects - warmed year2021 no_insects   0.012183 0.0757
##     df t.ratio p.value
##   27.6   0.161  1.0000
##  152.9   0.323  1.0000
##  179.7   0.361  1.0000
##  152.9   6.387  <.0001
##  179.7   5.832  <.0001
##  152.9   1.217  1.0000
##  179.7   1.167  1.0000
##  152.9   2.178  0.9179
##  179.7   2.034  0.9603
##  152.9   1.897  0.9823
##  179.7   1.781  0.9925
##  154.3   2.632  0.6477
##  179.8   2.467  0.7678
##  177.2  -0.209  1.0000
##  142.9  -0.122  1.0000
##  177.2  -0.004  1.0000
##  142.9   0.063  1.0000
##  177.2   4.529  0.0033
##  142.9   4.183  0.0136
##  177.2   0.818  1.0000
##  142.9   0.811  1.0000
##  177.2   3.101  0.2992
##  142.9   2.885  0.4522
##  178.8   1.908  0.9815
##  151.2   1.829  0.9889
##  177.2   6.177  <.0001
##  142.9   5.680  <.0001
##  179.7   0.222  1.0000
##  152.9   0.323  1.0000
##  179.7   5.693  <.0001
##  152.9   6.387  <.0001
##  179.7   1.029  1.0000
##  152.9   1.217  1.0000
##  179.7   1.896  0.9829
##  152.9   2.178  0.9179
##  179.7   1.642  0.9977
##  152.9   1.897  0.9823
##  179.9   2.305  0.8638
##  154.3   2.632  0.6477
##  142.9  -0.257  1.0000
##  177.2  -0.209  1.0000
##  142.9  -0.071  1.0000
##  177.2  -0.004  1.0000
##  142.9   4.048  0.0216
##  177.2   4.529  0.0033
```

```
##   142.9   0.676  1.0000
##   177.2   0.818  1.0000
##   142.9   2.751  0.5558
##   177.2   3.101  0.2992
##   152.8   1.683  0.9966
##   178.8   1.908  0.9815
##   142.9   5.545  <.0001
##   177.2   6.177  <.0001
##    27.6   0.161  1.0000
##   152.9   6.063  <.0001
##   179.7   5.540  <.0001
##   152.9   0.894  1.0000
##   179.7   0.876  1.0000
##   152.9   1.854  0.9868
##   179.7   1.742  0.9945
##   152.9   1.574  0.9988
##   179.7   1.489  0.9995
##   154.3   2.316  0.8567
##   179.8   2.179  0.9184
##   177.2  -0.520  1.0000
##   142.9  -0.405  1.0000
##   177.2  -0.315  1.0000
##   142.9  -0.219  1.0000
##   177.2   4.218  0.0110
##   142.9   3.900  0.0354
##   177.2   0.507  1.0000
##   142.9   0.528  1.0000
##   177.2   2.790  0.5240
##   142.9   2.602  0.6702
##   178.8   1.620  0.9982
##   151.2   1.563  0.9989
##   177.2   5.866  <.0001
##   142.9   5.397  0.0001
##   179.7   5.401  0.0001
##   152.9   6.063  <.0001
##   179.7   0.737  1.0000
##   152.9   0.894  1.0000
##   179.7   1.604  0.9984
##   152.9   1.854  0.9868
##   179.7   1.351  0.9999
##   152.9   1.574  0.9988
##   179.9   2.020  0.9634
##   154.3   2.316  0.8567
##   142.9  -0.539  1.0000
##   177.2  -0.520  1.0000
##   142.9  -0.354  1.0000
##   177.2  -0.315  1.0000
##   142.9   3.766  0.0541
##   177.2   4.218  0.0110
##   142.9   0.394  1.0000
##   177.2   0.507  1.0000
##   142.9   2.468  0.7659
##   177.2   2.790  0.5240
##   152.8   1.419  0.9998
```

```
##  178.8   1.620  0.9982
##  142.9   5.263  0.0002
##  177.2   5.866  <.0001
##   27.6   0.161  1.0000
##  152.9  -5.170  0.0002
##  179.7  -4.595  0.0025
##  152.9  -4.209  0.0120
##  179.7  -3.728  0.0580
##  152.9  -4.489  0.0042
##  179.7  -3.981  0.0254
##  154.3  -3.603  0.0864
##  179.8  -3.215  0.2329
##  177.2  -6.349  <.0001
##  142.9  -5.702  <.0001
##  177.2  -6.145  <.0001
##  142.9  -5.516  0.0001
##  177.2  -1.611  0.9983
##  142.9  -1.397  0.9998
##  177.2  -5.323  0.0001
##  142.9  -4.769  0.0014
##  177.2  -3.040  0.3392
##  142.9  -2.695  0.5995
##  178.8  -3.779  0.0495
##  151.2  -3.434  0.1378
##  177.2   0.036  1.0000
##  142.9   0.100  1.0000
##  179.7  -4.734  0.0014
##  152.9  -5.170  0.0002
##  179.7  -3.867  0.0373
##  152.9  -4.209  0.0120
##  179.7  -4.120  0.0157
##  152.9  -4.489  0.0042
##  179.9  -3.315  0.1835
##  154.3  -3.603  0.0864
##  142.9  -5.837  <.0001
##  177.2  -6.349  <.0001
##  142.9  -5.651  <.0001
##  177.2  -6.145  <.0001
##  142.9  -1.531  0.9992
##  177.2  -1.611  0.9983
##  142.9  -4.904  0.0008
##  177.2  -5.323  0.0001
##  142.9  -2.829  0.4948
##  177.2  -3.040  0.3392
##  152.8  -3.520  0.1093
##  178.8  -3.779  0.0495
##  142.9  -0.035  1.0000
##  177.2   0.036  1.0000
##   27.6   0.161  1.0000
##  152.9   0.961  1.0000
##  179.7   0.936  1.0000
##  152.9   0.680  1.0000
##  179.7   0.683  1.0000
##  154.3   1.444  0.9997
```

```
##   179.8   1.384  0.9999
##   177.2  -1.379  0.9999
##   142.9  -1.186  1.0000
##   177.2  -1.174  1.0000
##   142.9  -1.000  1.0000
##   177.2   3.359  0.1645
##   142.9   3.120  0.2910
##   177.2  -0.352  1.0000
##   142.9  -0.253  1.0000
##   177.2   1.931  0.9785
##   142.9   1.822  0.9894
##   178.8   0.824  1.0000
##   151.2   0.826  1.0000
##   177.2   5.006  0.0004
##   142.9   4.616  0.0027
##   179.7   0.797  1.0000
##   152.9   0.961  1.0000
##   179.7   0.544  1.0000
##   152.9   0.680  1.0000
##   179.9   1.234  1.0000
##   154.3   1.444  0.9997
##   142.9  -1.320  0.9999
##   177.2  -1.379  0.9999
##   142.9  -1.134  1.0000
##   177.2  -1.174  1.0000
##   142.9   2.985  0.3793
##   177.2   3.359  0.1645
##   142.9  -0.387  1.0000
##   177.2  -0.352  1.0000
##   142.9   1.687  0.9964
##   177.2   1.931  0.9785
##   152.8   0.691  1.0000
##   178.8   0.824  1.0000
##   142.9   4.482  0.0045
##   177.2   5.006  0.0004
##    27.6   0.161  1.0000
##   152.9  -0.281  1.0000
##   179.7  -0.184  1.0000
##   154.3   0.506  1.0000
##   179.8   0.530  1.0000
##   177.2  -2.303  0.8647
##   142.9  -2.025  0.9612
##   177.2  -2.098  0.9444
##   142.9  -1.839  0.9879
##   177.2   2.435  0.7885
##   142.9   2.280  0.8742
##   177.2  -1.276  1.0000
##   142.9  -1.092  1.0000
##   177.2   1.007  1.0000
##   142.9   0.982  1.0000
##   178.8  -0.031  1.0000
##   151.2   0.034  1.0000
##   177.2   4.083  0.0180
##   142.9   3.777  0.0523
```

```
##  179.7  -0.323  1.0000
##  152.9  -0.281  1.0000
##  179.9   0.388  1.0000
##  154.3   0.506  1.0000
##  142.9  -2.159  0.9239
##  177.2  -2.303  0.8647
##  142.9  -1.974  0.9711
##  177.2  -2.098  0.9444
##  142.9   2.146  0.9285
##  177.2   2.435  0.7885
##  142.9  -1.227  1.0000
##  177.2  -1.276  1.0000
##  142.9   0.848  1.0000
##  177.2   1.007  1.0000
##  152.8  -0.091  1.0000
##  178.8  -0.031  1.0000
##  142.9   3.642  0.0781
##  177.2   4.083  0.0180
##   27.6   0.161  1.0000
##  154.3   0.780  1.0000
##  179.8   0.779  1.0000
##  177.2  -2.033  0.9606
##  142.9  -1.780  0.9922
##  177.2  -1.829  0.9893
##  142.9  -1.594  0.9985
##  177.2   2.705  0.5910
##  142.9   2.525  0.7266
##  177.2  -1.006  1.0000
##  142.9  -0.847  1.0000
##  177.2   1.277  1.0000
##  142.9   1.227  1.0000
##  178.8   0.218  1.0000
##  151.2   0.265  1.0000
##  177.2   4.352  0.0067
##  142.9   4.022  0.0237
##  179.9   0.635  1.0000
##  154.3   0.780  1.0000
##  142.9  -1.914  0.9799
##  177.2  -2.033  0.9606
##  142.9  -1.729  0.9948
##  177.2  -1.829  0.9893
##  142.9   2.391  0.8147
##  177.2   2.705  0.5910
##  142.9  -0.981  1.0000
##  177.2  -1.006  1.0000
##  142.9   1.093  1.0000
##  177.2   1.277  1.0000
##  152.8   0.137  1.0000
##  178.8   0.218  1.0000
##  142.9   3.888  0.0369
##  177.2   4.352  0.0067
##   27.6   0.161  1.0000
##  177.7  -2.739  0.5639
##  146.6  -2.420  0.7970
```

```
##   177.7  -2.540  0.7172
##   146.6  -2.239  0.8932
##   177.7   1.895  0.9830
##   146.6   1.785  0.9920
##   177.7  -1.735  0.9948
##   146.6  -1.509  0.9994
##   177.7   0.498  1.0000
##   146.6   0.517  1.0000
##   179.1  -0.484  1.0000
##   153.8  -0.385  1.0000
##   177.7   3.506  0.1115
##   146.6   3.247  0.2196
##   144.9  -2.578  0.6884
##   177.7  -2.739  0.5639
##   144.9  -2.395  0.8123
##   177.7  -2.540  0.7172
##   144.9   1.671  0.9969
##   177.7   1.895  0.9830
##   144.9  -1.657  0.9972
##   177.7  -1.735  0.9948
##   144.9   0.390  1.0000
##   177.7   0.498  1.0000
##   154.1  -0.508  1.0000
##   179.1  -0.484  1.0000
##   144.9   3.148  0.2738
##   177.7   3.506  0.1115
##    27.6   0.161  1.0000
##   152.9   0.212  1.0000
##   179.7   0.261  1.0000
##   152.9   4.928  0.0007
##   179.7   4.515  0.0035
##   152.9   1.068  1.0000
##   179.7   1.033  1.0000
##   152.9   3.442  0.1347
##   179.7   3.175  0.2548
##   157.4   2.172  0.9200
##   180.2   2.066  0.9530
##   152.9   6.641  <.0001
##   179.7   6.061  <.0001
##   179.7   0.122  1.0000
##   152.9   0.212  1.0000
##   179.7   4.377  0.0060
##   152.9   4.928  0.0007
##   179.7   0.894  1.0000
##   152.9   1.068  1.0000
##   179.7   3.036  0.3412
##   152.9   3.442  0.1347
##   180.3   1.912  0.9810
##   157.4   2.172  0.9200
##   179.7   5.922  <.0001
##   152.9   6.641  <.0001
##    27.6   0.161  1.0000
##   152.9   4.715  0.0017
##   179.7   4.324  0.0074
```

```
## 152.9 0.855 1.0000
## 179.7 0.841 1.0000
## 152.9 3.230 0.2275
## 179.7 2.983 0.3778
## 157.4 1.977 0.9710
## 180.2 1.886 0.9840
## 152.9 6.428 <.0001
## 179.7 5.869 <.0001
## 179.7 4.185 0.0124
## 152.9 4.715 0.0017
## 179.7 0.702 1.0000
## 152.9 0.855 1.0000
## 179.7 2.845 0.4813
## 152.9 3.230 0.2275
## 180.3 1.734 0.9949
## 157.4 1.977 0.9710
## 179.7 5.731 <.0001
## 152.9 6.428 <.0001
##  27.6 0.161 1.0000
## 152.9 -3.860 0.0396
## 179.7 -3.413 0.1429
## 152.9 -1.485 0.9995
## 179.7 -1.271 1.0000
## 157.4 -2.365 0.8306
## 180.2 -2.113 0.9404
## 152.9 1.713 0.9955
## 179.7 1.615 0.9982
## 179.7 -3.552 0.0978
## 152.9 -3.860 0.0396
## 179.7 -1.410 0.9998
## 152.9 -1.485 0.9995
## 180.3 -2.216 0.9044
## 157.4 -2.365 0.8306
## 179.7 1.476 0.9996
## 152.9 1.713 0.9955
##  27.6 0.161 1.0000
## 152.9 2.374 0.8248
## 179.7 2.212 0.9059
## 157.4 1.189 1.0000
## 180.2 1.161 1.0000
## 152.9 5.573 <.0001
## 179.7 5.098 0.0003
## 179.7 2.073 0.9512
## 152.9 2.374 0.8248
## 180.3 1.017 1.0000
## 157.4 1.189 1.0000
## 179.7 4.959 0.0005
## 152.9 5.573 <.0001
##  27.6 0.161 1.0000
## 157.4 -0.997 1.0000
## 180.2 -0.853 1.0000
## 152.9 3.199 0.2442
## 179.7 2.955 0.3980
## 180.3 -0.971 1.0000
```

```
##  157.4  -0.997  1.0000
##  179.7   2.817  0.5032
##  152.9   3.199  0.2442
##   27.6   0.161  1.0000
##  157.4   3.942  0.0301
##  180.3   3.651  0.0733
##  180.2   3.565  0.0941
##  157.4   3.942  0.0301
##   27.6   0.161  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
```

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

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

```
mod2 <- lmer(log(simpson) ~ insecticide + (1|plot), kbs_diversity, REML=FALSE)
```

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

```
mod3 <- lmer(log(simpson) ~ insecticide + state + (1|plot), kbs_diversity, REML=FALSE)
```

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

```
mod4 <- lmer(log(simpson) ~ insecticide * state + (1|plot), kbs_diversity, REML=FALSE)
```

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

```
mod5 <- lmer(log(simpson) ~ state + year_factor + (1|plot), kbs_diversity, REML=FALSE)
```

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

```
mod6 <- lmer(log(simpson) ~ state + year_factor + insecticide + (1|plot), kbs_diversity, REML=FALSE)
```

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

```
mod7 <- lmer(log(simpson) ~ state * year_factor + (1|plot), kbs_diversity, REML=FALSE)
```

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

```
mod8 <- lmer(log(simpson) ~ state * year_factor + insecticide + (1|plot), kbs_diversity, REML=FALSE)
```

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

```r
mod9 <- lmer(log(simpson) ~ state * insecticide + year_factor + (1|plot), kbs_diversity, REML=FALSE)
```

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

```r
mod10 <- lmer(log(simpson) ~ state + insecticide * year_factor + (1|plot), kbs_diversity, REML=FALSE)
```

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

```r
mod11 <- lmer(log(simpson) ~ state * year_factor * insecticide + (1|plot), kbs_diversity, REML=FALSE)
```

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

```r
AICctab(mod1, mod2, mod3, mod4, mod5, mod6, mod7, mod8, mod9, mod10, mod11, weights=T)
```

```
##       dAICc df weight
## mod10  0.0  7  0.590
## mod5   2.7  5  0.155
## mod6   4.2  6  0.074
## mod7   4.6  6  0.059
## mod11  4.8  10 0.053
## mod9   5.4  7  0.041
## mod8   6.1  7  0.028
## mod2  20.0  4  <0.001
## mod1  20.6  4  <0.001
## mod3  22.1  5  <0.001
## mod4  23.4  6  <0.001
```

```r
anova(mod10, mod5)
```

```
## Data: kbs_diversity
## Models:
## mod5: log(simpson) ~ state + year_factor + (1 | plot)
## mod10: log(simpson) ~ state + insecticide * year_factor + (1 | plot)
##       npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod5     5 238.43 253.93 -114.21   228.43
## mod10    7 235.41 257.11 -110.71   221.41 7.0115  2    0.03002 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
AICctab(mod10, mod5, weights=T) #10p
```

```
##       dAICc df weight
## mod10 0.0   7  0.79
## mod5  2.7   5  0.21
```

```r
summary(mod10)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(simpson) ~ state + insecticide * year_factor + (1 | plot)
##    Data: kbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##    235.4    257.1   -110.7    221.4      157
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -5.4916 -0.1826  0.2256  0.5194  1.7623
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.0000   0.0000
##  Residual             0.2259   0.4753
## Number of obs: 164, groups:  plot, 24
##
## Fixed effects:
##                                  Estimate Std. Error t value
## (Intercept)                     -0.470032   0.122018  -3.852
## statewarmed                     -0.006718   0.074238  -0.090
## insecticideno_insects            0.311276   0.164701   1.890
## year_factor                     -0.040857   0.026289  -1.554
## insecticideno_insects:year_factor -0.094714   0.037270  -2.541
##
## Correlation of Fixed Effects:
##             (Intr) sttwrm insct_ yr_fct
## statewarmed -0.297
## insctcdn_ns -0.675 -0.003
## year_factor -0.850 -0.013  0.633
## insctcdn_:_  0.601  0.003 -0.893 -0.705
## optimizer (nloptwrap) convergence code: 0 (OK)
## boundary (singular) fit: see help('isSingular')
```

```
summ(mod10)
```

Observations	164
Dependent variable	log(simpson)
Type	Mixed effects linear regression

AIC	235.42
BIC	257.11
Pseudo-R^2 (fixed effects)	0.15
Pseudo-R^2 (total)	0.15

```
anova(mod10)
```

```
## Analysis of Variance Table
##                         npar Sum Sq Mean Sq F value
## state                      1 0.0056  0.0056  0.0247
## insecticide                1 0.1428  0.1428  0.6320
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	-0.47	0.12	-3.85	164.00	0.00
statewarmed	-0.01	0.07	-0.09	164.00	0.93
insecticideno_insects	0.31	0.16	1.89	164.00	0.06
year_factor	-0.04	0.03	-1.55	164.00	0.12
insecticideno_insects:year_factor	-0.09	0.04	-2.54	164.00	0.01

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.00
Residual		0.48

Grouping Variables		
Group	# groups	ICC
plot	24	0.00

```
## year_factor                 1 5.0327  5.0327 22.2813
## insecticide:year_factor     1 1.4587  1.4587  6.4580
```

```
emmeans(mod10, list(pairwise ~ state + year_factor), adjust = "tukey")
```

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

```
## $`emmeans of state, year_factor`
##  state   year_factor emmean     SE   df lower.CL upper.CL
##  ambient        3.95 -0.662 0.0537 22.7   -0.773   -0.551
##  warmed         3.95 -0.669 0.0530 21.8   -0.779   -0.559
##
## Results are averaged over the levels of: insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, year_factor`
##  1
##  ambient year_factor3.94512195121951 - warmed year_factor3.94512195121951
##  estimate     SE   df t.ratio p.value
##   0.00672 0.0754 22.3   0.089  0.9298
##
## Results are averaged over the levels of: insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
```

```
emmeans(mod10, list(pairwise ~ insecticide*year_factor), adjust = "tukey")
```

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

```
## $`emmeans of insecticide, year_factor`
##  insecticide year_factor emmean     SE   df lower.CL upper.CL
##  insects            3.95 -0.635 0.0530 21.8   -0.745   -0.525
##  no_insects         3.95 -0.697 0.0537 22.7   -0.808   -0.586
##
## Results are averaged over the levels of: state
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of insecticide, year_factor`
##  1
##  insects year_factor3.94512195121951 - no_insects year_factor3.94512195121951
##  estimate     SE   df t.ratio p.value
##    0.0624 0.0754 22.2   0.827  0.4169
##
## Results are averaged over the levels of: state
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
```

```
emmeans(mod10, list(pairwise ~ year_factor), adjust = "tukey")
```

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

## NOTE: Results may be misleading due to involvement in interactions

## Note: Use 'contrast(regrid(object), ...)' to obtain contrasts of back-transformed estimates

## $`emmeans of year_factor`
##  year_factor emmean     SE   df lower.CL upper.CL
##         3.95 -0.666 0.0377 22.3   -0.744   -0.588
##
## Results are averaged over the levels of: state, insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $` of year_factor`
##  1         estimate SE df z.ratio p.value
##  (nothing)   nonEst NA NA      NA      NA
##
## Results are averaged over the levels of: state, insecticide
## Note: contrasts are still on the log scale
## Degrees-of-freedom method: kenward-roger
```

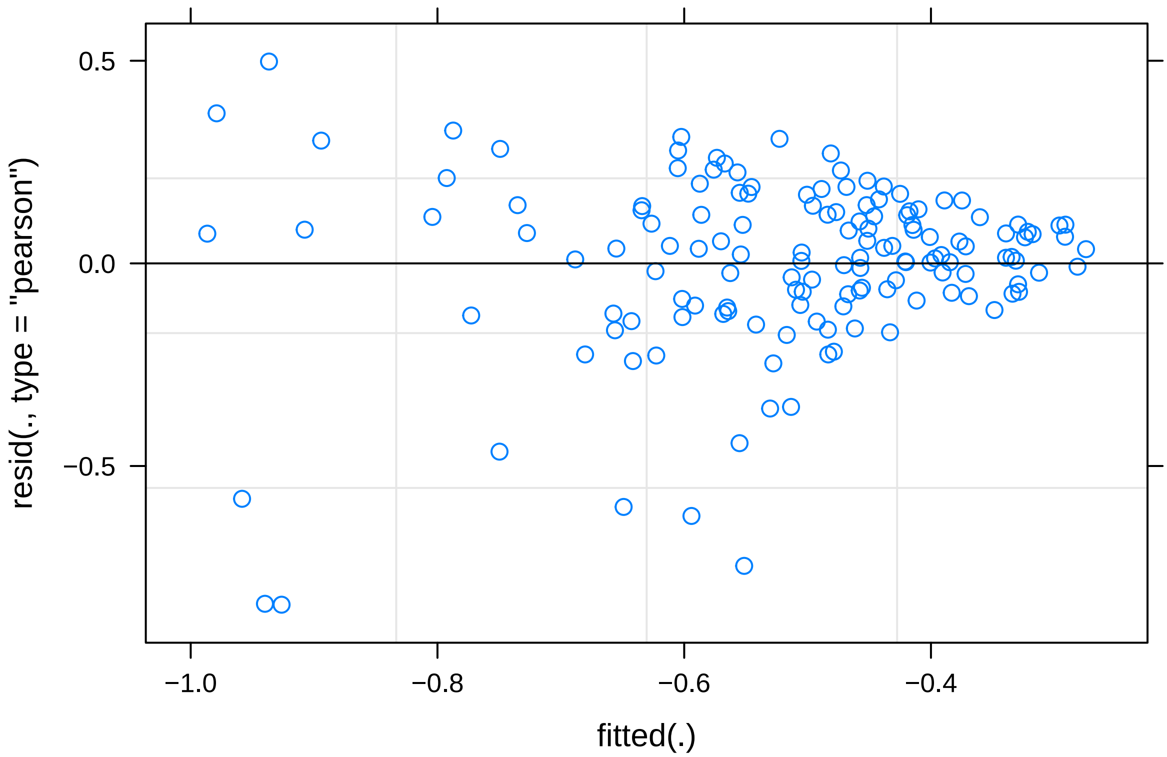
```
# with herb reduction as interactive term
anova(mod9)
```

```
## Analysis of Variance Table
##                   npar Sum Sq Mean Sq F value
## state                1 0.0056  0.0056  0.0239
## insecticide          1 0.1428  0.1428  0.6117
## year_factor          1 5.0327  5.0327 21.5657
## state:insecticide    1 0.2295  0.2295  0.9836
```

```
# code to get table information for manuscript
# table <- anova(mod10, mod9)
# kable(table) %>% kableExtra::kable_styling()
# AICctab(mod10pu, mod9pu, weights=T)
```

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 value
# Check for homogeneity of variances (true if p>0.05). If the result is not significant, the assumption
# *****Levene's Test - tests whether or not the variance among two or more groups is equal - If the p-v

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  2.4936 0.1165
##       142
```

```r
# Assumption not 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  0.0119 0.9134
##       142
```

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

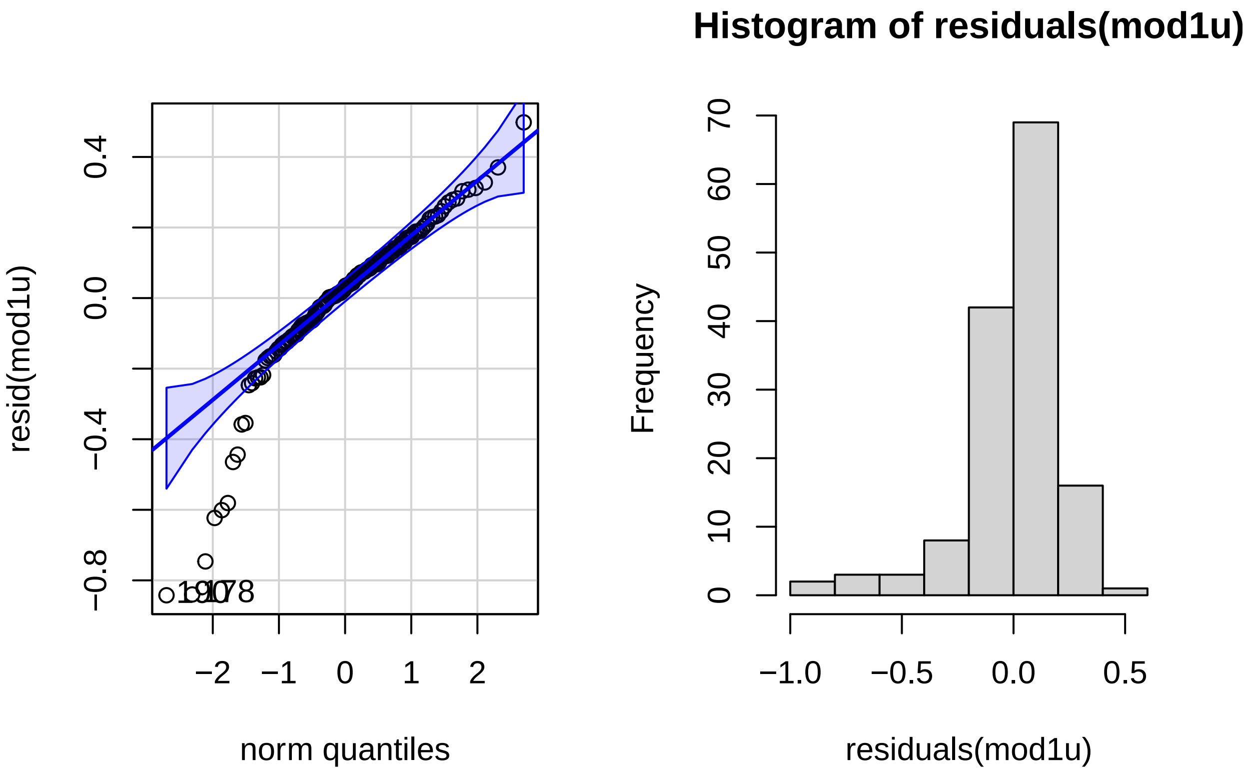
```
## Warning in leveneTest.default(y = y, group = group, ...): group coerced to
## factor.
```

```
## Levene's Test for Homogeneity of Variance (center = median)
##        Df F value Pr(>F)
## group  23  1.0856  0.371
##       120
```

```r
# Assumption not met

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

```
## 190 178
##  22  10
```

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




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

```
##
##  Shapiro-Wilk normality test
##
## data:  resid(mod1u)
## W = 0.89154, p-value = 7.739e-09
```

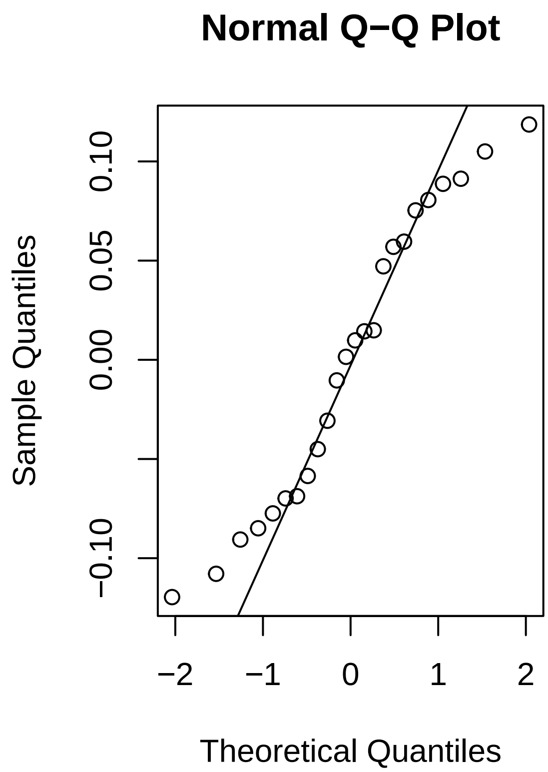
```
outlierTest(mod1u) # yes outliers
```

```
##      rstudent unadjusted p-value Bonferroni p
## 190 -4.189318         5.2931e-05    0.0076221
## 178 -4.178336         5.5217e-05    0.0079513
## 296 -3.712670         3.0945e-04    0.0445610
```

```
# (4) Normality of random effect: Get the estimate of random effect (e.g., random intercepts), and chec
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 = 0.94213, p-value = 0.1819
```

```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
anova(mod1u)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq  Mean Sq F value
## state               1 0.12577 0.125769  2.4791
## year                5 1.26509 0.253018  4.9873
## insecticide         1 0.13129 0.131286  2.5878
## state:year          5 0.76106 0.152212  3.0003
## year:insecticide    5 0.11034 0.022068  0.4350
```

```r
anova(mod2u)
```

```
## Analysis of Variance Table
##             npar  Sum Sq Mean Sq F value
## state          1 0.12805 0.12805  2.4791
## year           5 1.26509 0.25302  4.8985
## insecticide    1 0.13367 0.13367  2.5878
## state:year     5 0.76106 0.15221  2.9469
```

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

```
## 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   15 30.004 74.551 -0.00208  0.00416
## mod1u   20 37.849 97.245  1.07567 -2.15134 2.1555  5     0.8272
```

```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
##     37.8     97.2      1.1     -2.2      124
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.7392 -0.3666  0.1372  0.5638  2.2112
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.00981  0.09905
##  Residual             0.05073  0.22524
## Number of obs: 144, groups:  plot, 24
##
## Fixed effects:
##                                Estimate Std. Error t value
## (Intercept)                   -0.909133   0.086993 -10.451
## statewarmed                    0.382451   0.100451   3.807
## year2017                       0.251510   0.112619   2.233
## year2018                       0.352488   0.112619   3.130
## year2019                       0.337446   0.112619   2.996
## year2020                       0.482607   0.112619   4.285
## year2021                       0.384863   0.112619   3.417
## insecticideno_insects          0.041343   0.100451   0.412
## statewarmed:year2017          -0.297295   0.130042  -2.286
## statewarmed:year2018          -0.306131   0.130042  -2.354
## statewarmed:year2019          -0.475553   0.130042  -3.657
## statewarmed:year2020          -0.375818   0.130042  -2.890
## statewarmed:year2021          -0.318668   0.130042  -2.451
## year2017:insecticideno_insects  0.083606   0.130042   0.643
## year2018:insecticideno_insects  0.100844   0.130042   0.775
## year2019:insecticideno_insects  0.120419   0.130042   0.926
## year2020:insecticideno_insects -0.007735   0.130042  -0.059
## year2021:insecticideno_insects -0.012641   0.130042  -0.097

##
## Correlation matrix not shown by default, as p = 18 > 12.
```

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

```
summary(mod2u)
```

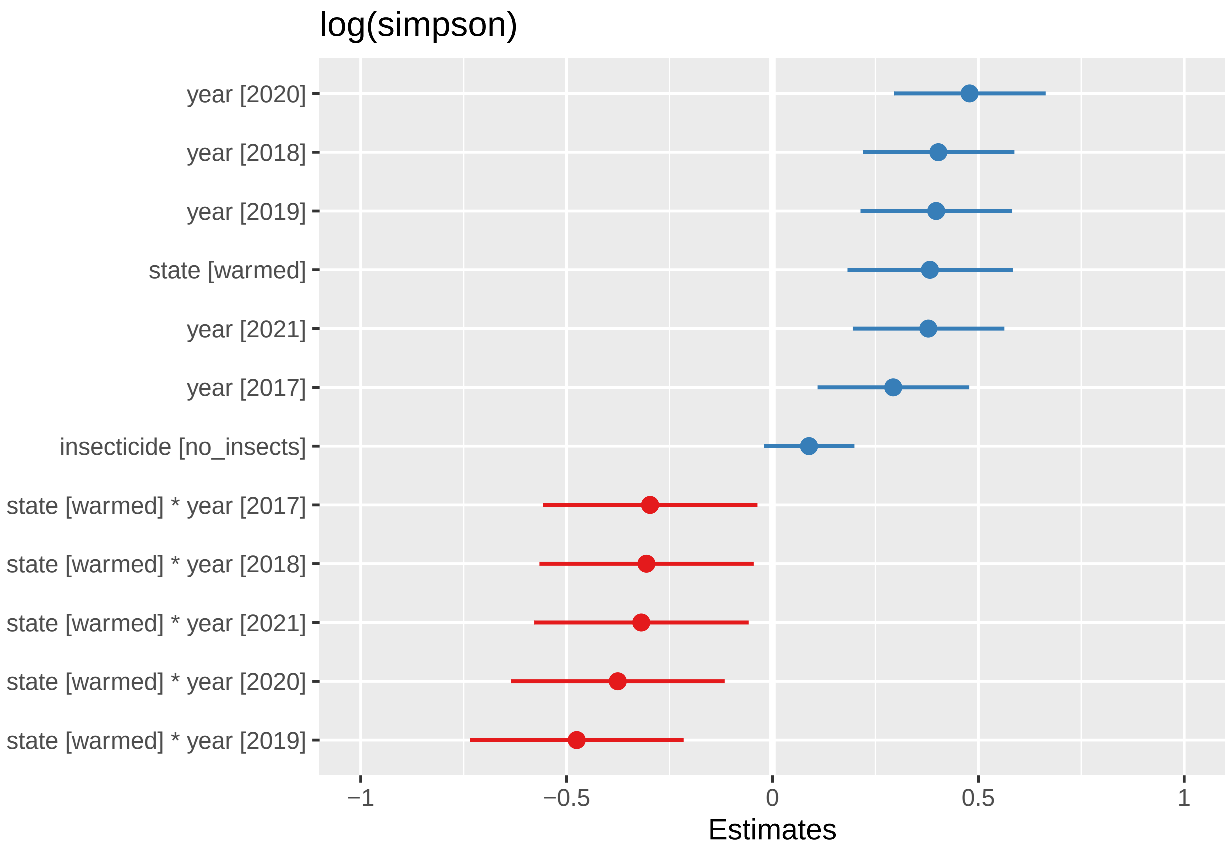
```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(simpson) ~ state * year + insecticide + year + (1 | plot)
##    Data: umbs_diversity
##
##      AIC      BIC   logLik deviance df.resid
##     30.0     74.6      0.0      0.0      129
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.8141 -0.2647  0.1022  0.5490  2.0824
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.009657 0.09827
##  Residual             0.051652 0.22727
## Number of obs: 144, groups:  plot, 24
##
## Fixed effects:
##                       Estimate Std. Error t value
## (Intercept)           -0.93284    0.07662 -12.175
## statewarmed            0.38245    0.10109   3.783
## year2017               0.29331    0.09278   3.161
## year2018               0.40291    0.09278   4.343
## year2019               0.39766    0.09278   4.286
## year2020               0.47874    0.09278   5.160
## year2021               0.37854    0.09278   4.080
## insecticideno_insects  0.08876    0.05518   1.609
## statewarmed:year2017  -0.29730    0.13121  -2.266
## statewarmed:year2018  -0.30613    0.13121  -2.333
## statewarmed:year2019  -0.47555    0.13121  -3.624
## statewarmed:year2020  -0.37582    0.13121  -2.864
## statewarmed:year2021  -0.31867    0.13121  -2.429
```

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

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

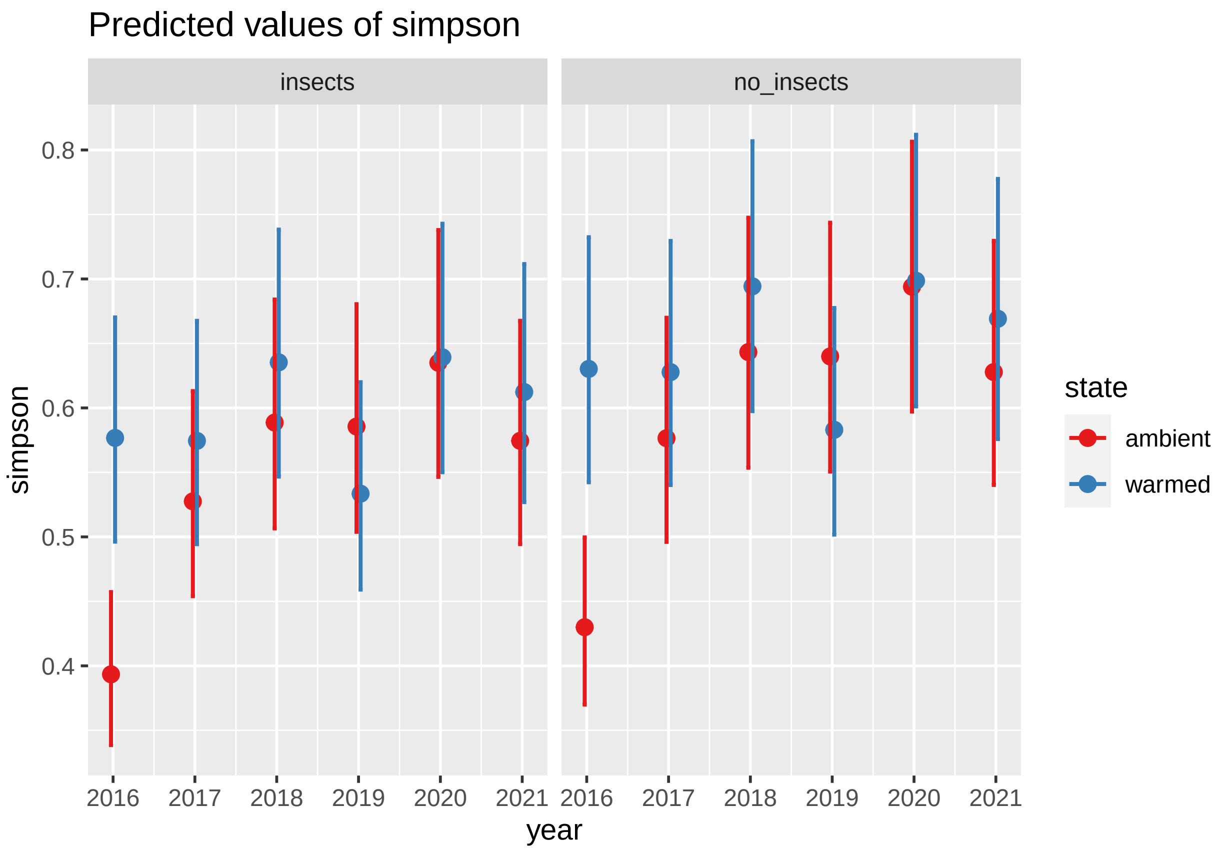
```
##       dAICc df weight
## mod2u  0.0  15 0.9958
## mod1u 10.9  20 0.0042
```

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

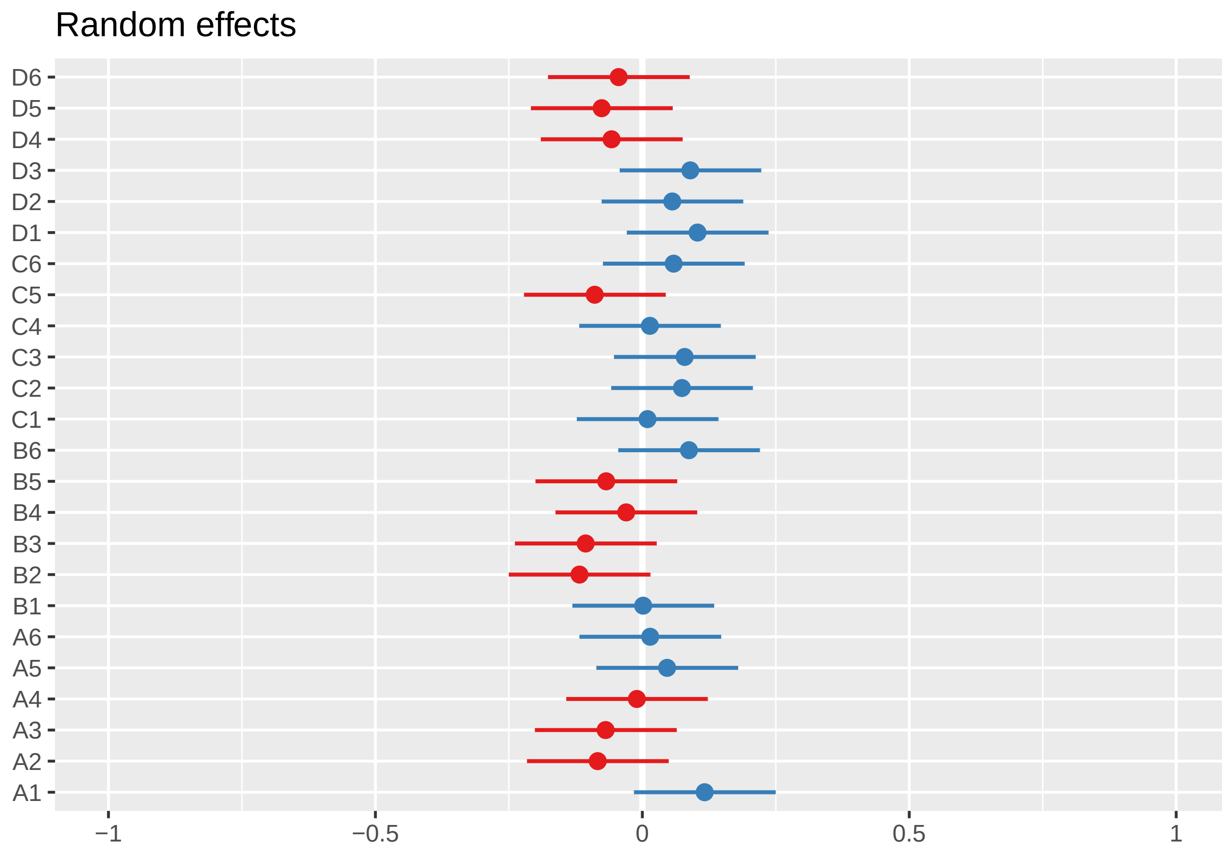



```
# these are the fixed predicted values:
plot_model(mod2u, type = "pred", terms = c("year", "state", "insecticide"))
```

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




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




```
# 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   10 33.902 63.600 -6.9509  13.9018
## mod2u   15 30.004 74.551 -0.0021   0.0042 13.898  5    0.01627 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
AICctab(mod2u, mod3u, weights=T) # going with mod2u
```

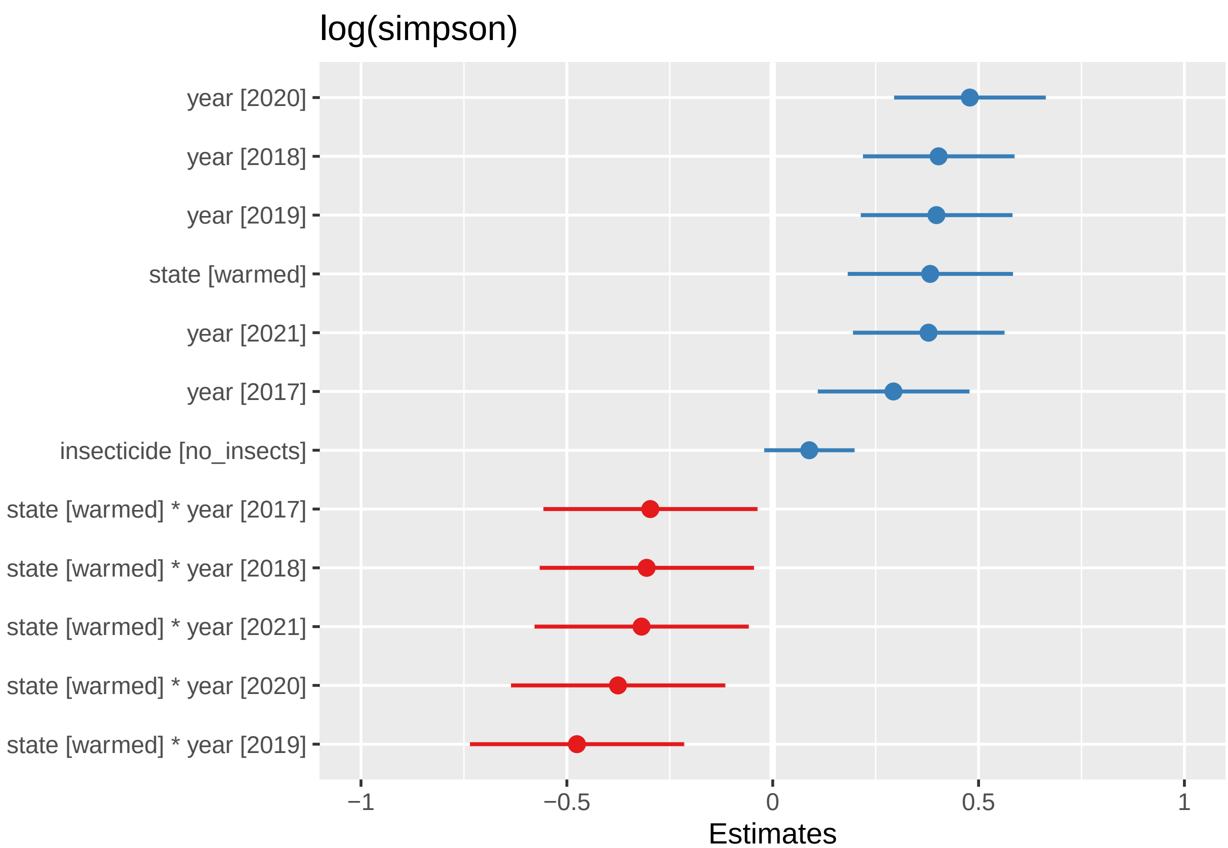
```
##       dAICc df weight
## mod2u  0.0  15 0.71
## mod3u  1.8  10 0.29
```

```
# Do we need to include insecticide? (dropping insecticide from the model)
mod5u <- lmer(log(simpson) ~ state + year + (1|plot), umbs_diversity, REML = FALSE)
anova(mod2u, mod5u)
```

```
## Data: umbs_diversity
```

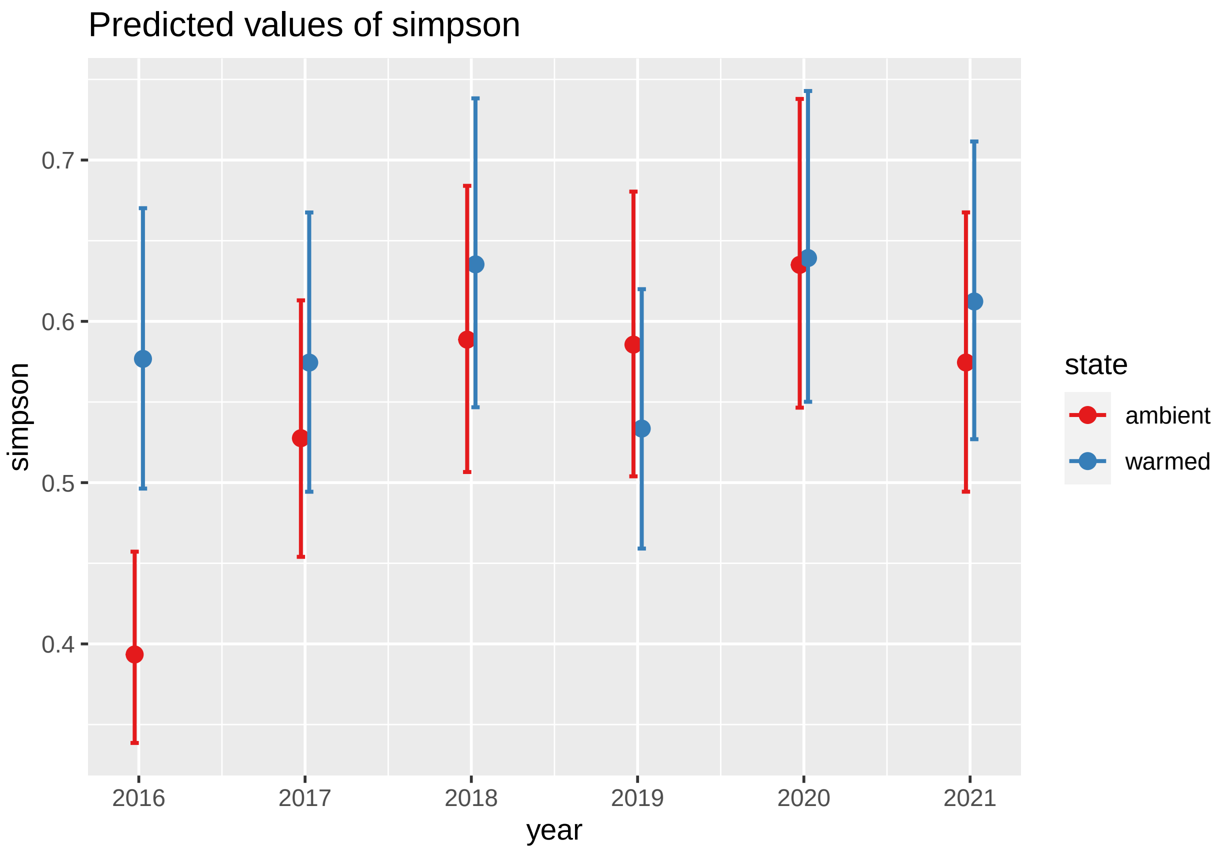
```
## Models:
## mod5u: log(simpson) ~ state + year + (1 | plot)
## mod2u: log(simpson) ~ state * year + insecticide + year + (1 | plot)
##       npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod5u    9 34.359 61.088 -8.1797  16.3593
## mod2u   15 30.004 74.551 -0.0021   0.0042 16.355  6    0.01197 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Yes, p<0.05 so stick with mod2u

# Plot the fixed effects estimates for different models
# these are the fixed effects estimates from summary(mod5u)
plot_model(mod2u, sort.est = TRUE)
```

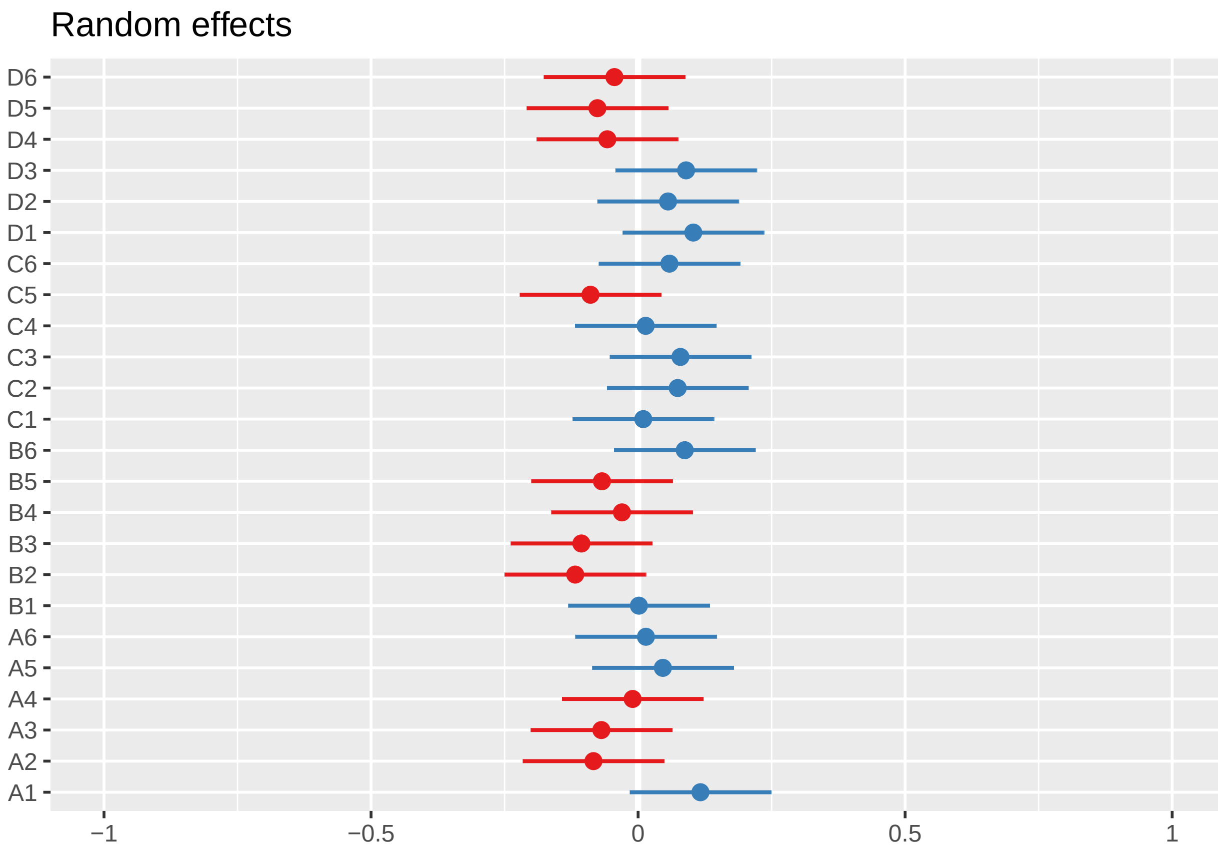



```
# these are the fixed predicted values:
plot_model(mod2u, type = "pred", terms = c("year", "state"))
```

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




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




```
# 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=FA
# anova(mod5, mod6)
# anova(mod5)
# cant get mod6 to work

# the best model fit appears to be =
# mod2u <- lmer(log(simpson) ~ state*year + insecticide + year + (1|plot), umbs_diversity, REML=FALSE)
summ(mod2u)
```

Observations	144
Dependent variable	log(simpson)
Type	Mixed effects linear regression

AIC	30.00
BIC	74.55
Pseudo-R^2 (fixed effects)	0.23
Pseudo-R^2 (total)	0.35

```
summary(mod2u)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(simpson) ~ state * year + insecticide + year + (1 | plot)
##    Data: umbs_diversity
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	-0.93	0.08	-12.18	106.21	0.00
statewarmed	0.38	0.10	3.78	128.11	0.00
year2017	0.29	0.09	3.16	120.00	0.00
year2018	0.40	0.09	4.34	120.00	0.00
year2019	0.40	0.09	4.29	120.00	0.00
year2020	0.48	0.09	5.16	120.00	0.00
year2021	0.38	0.09	4.08	120.00	0.00
insecticideno_insects	0.09	0.06	1.61	24.00	0.12
statewarmed:year2017	-0.30	0.13	-2.27	120.00	0.03
statewarmed:year2018	-0.31	0.13	-2.33	120.00	0.02
statewarmed:year2019	-0.48	0.13	-3.62	120.00	0.00
statewarmed:year2020	-0.38	0.13	-2.86	120.00	0.00
statewarmed:year2021	-0.32	0.13	-2.43	120.00	0.02

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.10
Residual		0.23

Grouping Variables		
Group	# groups	ICC
plot	24	0.16

```
##
##      AIC      BIC   logLik deviance df.resid
##     30.0     74.6      0.0      0.0      129
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.8141 -0.2647  0.1022  0.5490  2.0824
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.009657 0.09827
##  Residual             0.051652 0.22727
## Number of obs: 144, groups:  plot, 24
##
## Fixed effects:
##                       Estimate Std. Error t value
## (Intercept)           -0.93284    0.07662 -12.175
## statewarmed            0.38245    0.10109   3.783
## year2017               0.29331    0.09278   3.161
## year2018               0.40291    0.09278   4.343
## year2019               0.39766    0.09278   4.286
## year2020               0.47874    0.09278   5.160
```

```
## year2021               0.37854    0.09278   4.080
## insecticideno_insects  0.08876    0.05518   1.609
## statewarmed:year2017  -0.29730    0.13121  -2.266
## statewarmed:year2018  -0.30613    0.13121  -2.333
## statewarmed:year2019  -0.47555    0.13121  -3.624
## statewarmed:year2020  -0.37582    0.13121  -2.864
## statewarmed:year2021  -0.31867    0.13121  -2.429
```

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

```
emmeans(mod2u, list(pairwise ~ state*year), adjust = "tukey")
```

```
## $`emmeans of state, year`
##  state   year emmean     SE  df lower.CL upper.CL
##  ambient 2016 -0.888 0.0752 143   -1.037   -0.740
##  warmed  2016 -0.506 0.0752 143   -0.655   -0.357
##  ambient 2017 -0.595 0.0752 143   -0.744   -0.447
##  warmed  2017 -0.510 0.0752 143   -0.659   -0.361
##  ambient 2018 -0.486 0.0752 143   -0.634   -0.337
##  warmed  2018 -0.409 0.0752 143   -0.558   -0.261
##  ambient 2019 -0.491 0.0752 143   -0.639   -0.342
##  warmed  2019 -0.584 0.0752 143   -0.733   -0.435
##  ambient 2020 -0.410 0.0752 143   -0.558   -0.261
##  warmed  2020 -0.403 0.0752 143   -0.552   -0.254
##  ambient 2021 -0.510 0.0752 143   -0.659   -0.361
##  warmed  2021 -0.446 0.0752 143   -0.595   -0.298
##
## Results are averaged over the levels of: insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## Confidence level used: 0.95
##
## $`pairwise differences of state, year`
##  1                                      estimate     SE  df t.ratio p.value
##  ambient year2016 - warmed year2016   -3.82e-01 0.1063 143  -3.597  0.0217
##  ambient year2016 - ambient year2017 -2.93e-01 0.0969 131  -3.027  0.1127
##  ambient year2016 - warmed year2017   -3.78e-01 0.1063 143  -3.560  0.0245
##  ambient year2016 - ambient year2018 -4.03e-01 0.0969 131  -4.158  0.0032
##  ambient year2016 - warmed year2018   -4.79e-01 0.1063 143  -4.507  0.0008
##  ambient year2016 - ambient year2019 -3.98e-01 0.0969 131  -4.103  0.0040
##  ambient year2016 - warmed year2019   -3.05e-01 0.1063 143  -2.864  0.1654
##  ambient year2016 - ambient year2020 -4.79e-01 0.0969 131  -4.940  0.0001
##  ambient year2016 - warmed year2020   -4.85e-01 0.1063 143  -4.565  0.0006
##  ambient year2016 - ambient year2021 -3.79e-01 0.0969 131  -3.906  0.0080
##  ambient year2016 - warmed year2021   -4.42e-01 0.1063 143  -4.160  0.0031
##  warmed year2016 - ambient year2017    8.91e-02 0.1063 143   0.838  0.9995
##  warmed year2016 - warmed year2017     3.98e-03 0.0969 131   0.041  1.0000
##  warmed year2016 - ambient year2018   -2.05e-02 0.1063 143  -0.192  1.0000
##  warmed year2016 - warmed year2018    -9.68e-02 0.0969 131  -0.999  0.9975
##  warmed year2016 - ambient year2019   -1.52e-02 0.1063 143  -0.143  1.0000
```

```
##  warmed year2016 - warmed year2019    7.79e-02 0.0969 131   0.804  0.9997
##  warmed year2016 - ambient year2020  -9.63e-02 0.1063 143  -0.906  0.9990
##  warmed year2016 - warmed year2020   -1.03e-01 0.0969 131  -1.062  0.9957
##  warmed year2016 - ambient year2021   3.91e-03 0.1063 143   0.037  1.0000
##  warmed year2016 - warmed year2021   -5.99e-02 0.0969 131  -0.618  1.0000
##  ambient year2017 - warmed year2017  -8.52e-02 0.1063 143  -0.801  0.9997
##  ambient year2017 - ambient year2018 -1.10e-01 0.0969 131  -1.131  0.9927
##  ambient year2017 - warmed year2018  -1.86e-01 0.1063 143  -1.749  0.8422
##  ambient year2017 - ambient year2019 -1.04e-01 0.0969 131  -1.077  0.9952
##  ambient year2017 - warmed year2019  -1.12e-02 0.1063 143  -0.106  1.0000
##  ambient year2017 - ambient year2020 -1.85e-01 0.0969 131  -1.913  0.7488
##  ambient year2017 - warmed year2020  -1.92e-01 0.1063 143  -1.806  0.8119
##  ambient year2017 - ambient year2021 -8.52e-02 0.0969 131  -0.879  0.9992
##  ambient year2017 - warmed year2021  -1.49e-01 0.1063 143  -1.401  0.9615
##  warmed year2017 - ambient year2018  -2.44e-02 0.1063 143  -0.230  1.0000
##  warmed year2017 - warmed year2018   -1.01e-01 0.0969 131  -1.040  0.9964
##  warmed year2017 - ambient year2019  -1.92e-02 0.1063 143  -0.180  1.0000
##  warmed year2017 - warmed year2019    7.39e-02 0.0969 131   0.763  0.9998
##  warmed year2017 - ambient year2020  -1.00e-01 0.1063 143  -0.943  0.9985
##  warmed year2017 - warmed year2020   -1.07e-01 0.0969 131  -1.103  0.9941
##  warmed year2017 - ambient year2021  -7.35e-05 0.1063 143  -0.001  1.0000
##  warmed year2017 - warmed year2021   -6.39e-02 0.0969 131  -0.659  1.0000
##  ambient year2018 - warmed year2018  -7.63e-02 0.1063 143  -0.718  0.9999
##  ambient year2018 - ambient year2019  5.26e-03 0.0969 131   0.054  1.0000
##  ambient year2018 - warmed year2019   9.84e-02 0.1063 143   0.925  0.9988
##  ambient year2018 - ambient year2020 -7.58e-02 0.0969 131  -0.782  0.9997
##  ambient year2018 - warmed year2020  -8.25e-02 0.1063 143  -0.776  0.9998
##  ambient year2018 - ambient year2021  2.44e-02 0.0969 131   0.251  1.0000
##  ambient year2018 - warmed year2021  -3.94e-02 0.1063 143  -0.371  1.0000
##  warmed year2018 - ambient year2019   8.16e-02 0.1063 143   0.767  0.9998
##  warmed year2018 - warmed year2019    1.75e-01 0.0969 131   1.802  0.8138
##  warmed year2018 - ambient year2020   4.91e-04 0.1063 143   0.005  1.0000
##  warmed year2018 - warmed year2020   -6.14e-03 0.0969 131  -0.063  1.0000
##  warmed year2018 - ambient year2021   1.01e-01 0.1063 143   0.947  0.9985
##  warmed year2018 - warmed year2021    3.69e-02 0.0969 131   0.381  1.0000
##  ambient year2019 - warmed year2019   9.31e-02 0.1063 143   0.876  0.9993
##  ambient year2019 - ambient year2020 -8.11e-02 0.0969 131  -0.837  0.9995
##  ambient year2019 - warmed year2020  -8.77e-02 0.1063 143  -0.825  0.9996
##  ambient year2019 - ambient year2021  1.91e-02 0.0969 131   0.197  1.0000
##  ambient year2019 - warmed year2021  -4.47e-02 0.1063 143  -0.420  1.0000
##  warmed year2019 - ambient year2020  -1.74e-01 0.1063 143  -1.638  0.8918
##  warmed year2019 - warmed year2020   -1.81e-01 0.0969 131  -1.866  0.7777
##  warmed year2019 - ambient year2021  -7.40e-02 0.1063 143  -0.696  0.9999
##  warmed year2019 - warmed year2021   -1.38e-01 0.0969 131  -1.422  0.9572
##  ambient year2020 - warmed year2020  -6.63e-03 0.1063 143  -0.062  1.0000
##  ambient year2020 - ambient year2021  1.00e-01 0.0969 131   1.034  0.9966
##  ambient year2020 - warmed year2021   3.64e-02 0.1063 143   0.342  1.0000
##  warmed year2020 - ambient year2021   1.07e-01 0.1063 143   1.005  0.9974
##  warmed year2020 - warmed year2021    4.30e-02 0.0969 131   0.444  1.0000
##  ambient year2021 - warmed year2021  -6.38e-02 0.1063 143  -0.600  1.0000
##
## Results are averaged over the levels of: insecticide
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
```

```
## P value adjustment: tukey method for comparing a family of 12 estimates
```

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
anova(mod1ks)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq Mean Sq F value
## state               1  0.1210 0.12097  1.2074
## year                6 18.7509 3.12514 31.1936
## insecticide         1  0.0107 0.01072  0.1071
## state:year          6  1.1962 0.19937  1.9900
## year:insecticide    6  2.4472 0.40786  4.0710
```

```r
anova(mod2ks)
```

```
## Analysis of Variance Table
##             npar  Sum Sq Mean Sq F value
## state          1  0.1474 0.14741  1.2453
## year           6 18.7688 3.12813 26.4252
## insecticide    1  0.0137 0.01366  0.1154
## state:year     6  1.1905 0.19842  1.6762
```

```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   17 166.02 218.72 -66.012   132.02
## mod1ks   23 155.66 226.96 -54.830   109.66 22.364  6    0.00104 **
## ---
## 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
##    155.7    227.0    -54.8    109.7      141
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.2740 -0.4064  0.0273  0.4124  2.6485
```

```
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.02137  0.1462
##  Residual             0.10019  0.3165
## Number of obs: 164, groups:  plot, 24
##
## Fixed effects:
##                                Estimate Std. Error t value
## (Intercept)                     0.492726   0.123267   3.997
## statewarmed                    -0.012264   0.142336  -0.086
## year2016                       -0.069936   0.158260  -0.442
## year2017                       -0.972717   0.158260  -6.146
## year2018                       -0.196044   0.158260  -1.239
## year2019                       -0.539078   0.158260  -3.406
## year2020                       -0.364189   0.160394  -2.271
## year2021                       -0.348387   0.164326  -2.120
## insecticideno_insects           0.049022   0.142336   0.344
## statewarmed:year2016           -0.088094   0.182743  -0.482
## statewarmed:year2017           -0.270839   0.182743  -1.482
## statewarmed:year2018           -0.152552   0.182743  -0.835
## statewarmed:year2019            0.232653   0.182743   1.273
## statewarmed:year2020            0.074968   0.190039   0.394
## statewarmed:year2021           -0.293352   0.185107  -1.585
## year2016:insecticideno_insects  0.067212   0.182743   0.368
## year2017:insecticideno_insects  0.257252   0.182743   1.408
## year2018:insecticideno_insects -0.008095   0.182743  -0.044
## year2019:insecticideno_insects -0.217234   0.182743  -1.189
## year2020:insecticideno_insects -0.078017   0.191058  -0.408
## year2021:insecticideno_insects -0.584694   0.185107  -3.159

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

```
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
##    166.0    218.7    -66.0    132.0      147
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5042 -0.3702  0.0854  0.4301  2.1804
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.01724  0.1313
##  Residual             0.11838  0.3441
```

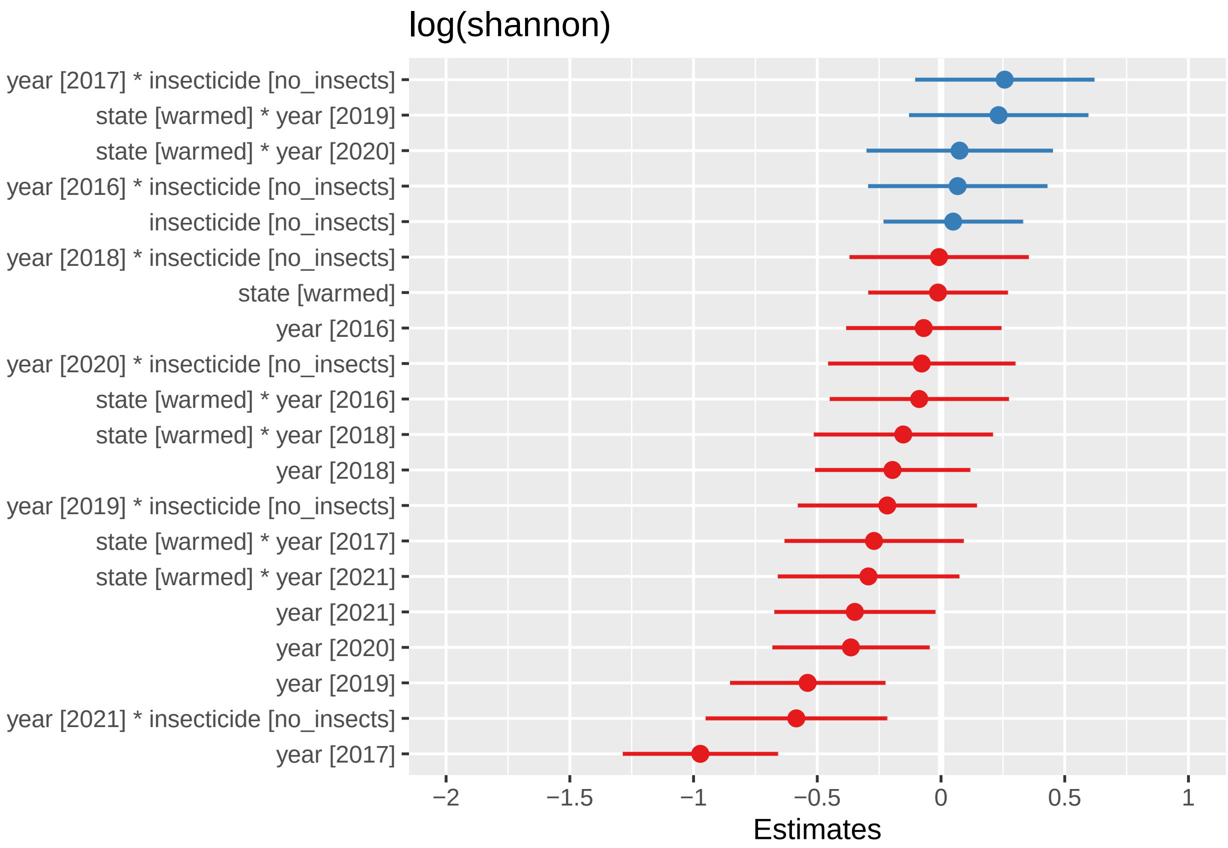
```
## Number of obs: 164, groups:  plot, 24
##
## Fixed effects:
##                          Estimate Std. Error t value
## (Intercept)               0.53136    0.11290   4.707
## statewarmed              -0.01226    0.15034  -0.082
## year2016                 -0.03633    0.14046  -0.259
## year2017                 -0.84409    0.14046  -6.009
## year2018                 -0.20009    0.14046  -1.425
## year2019                 -0.64770    0.14046  -4.611
## year2020                 -0.40573    0.14789  -2.743
## year2021                 -0.66872    0.14387  -4.648
## insecticideno_insects -0.02824    0.07600  -0.372
## statewarmed:year2016  -0.08809    0.19864  -0.443
## statewarmed:year2017  -0.27084    0.19864  -1.363
## statewarmed:year2018  -0.15255    0.19864  -0.768
## statewarmed:year2019   0.23265    0.19864   1.171
## statewarmed:year2020   0.07481    0.20629   0.363
## statewarmed:year2021  -0.26536    0.20107  -1.320
```

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

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

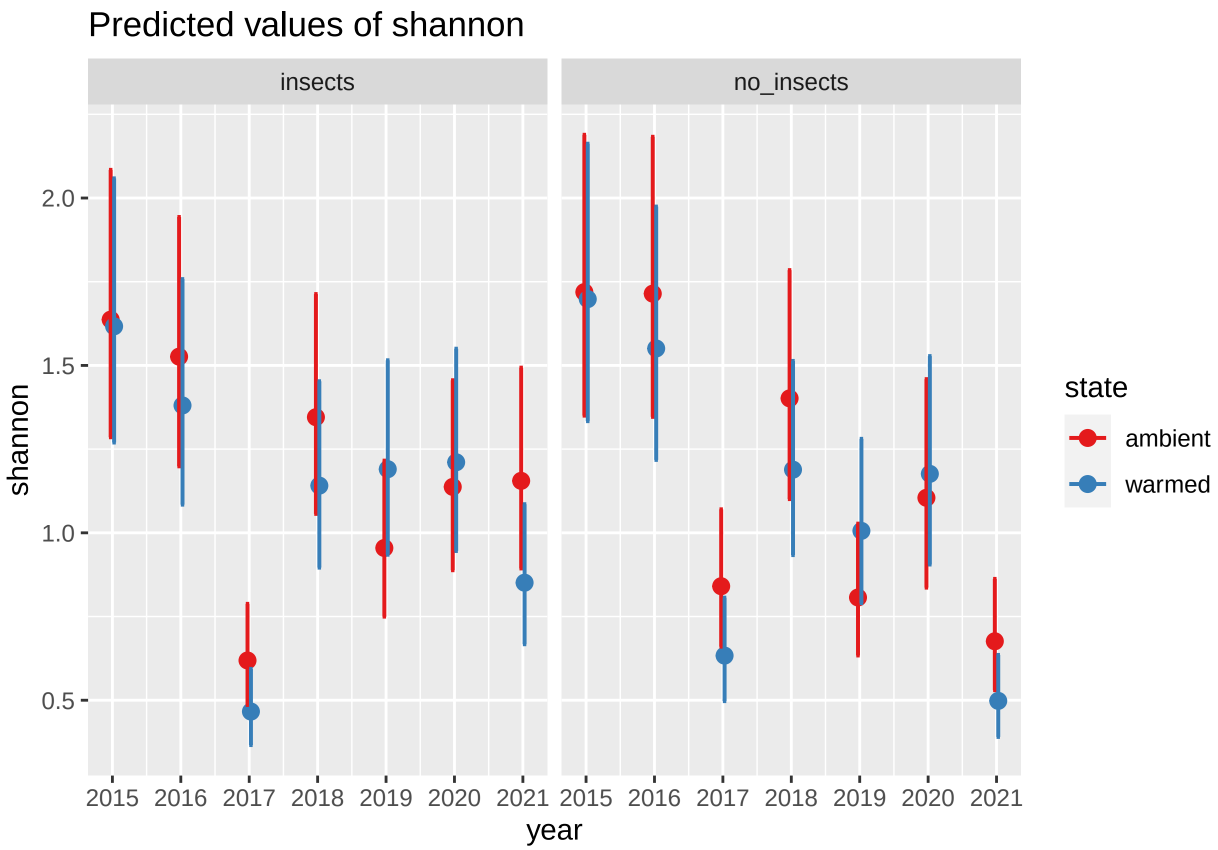
```
##        dAICc df weight
## mod1ks  0.0  23 0.966
## mod2ks  6.7  17 0.034
```

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

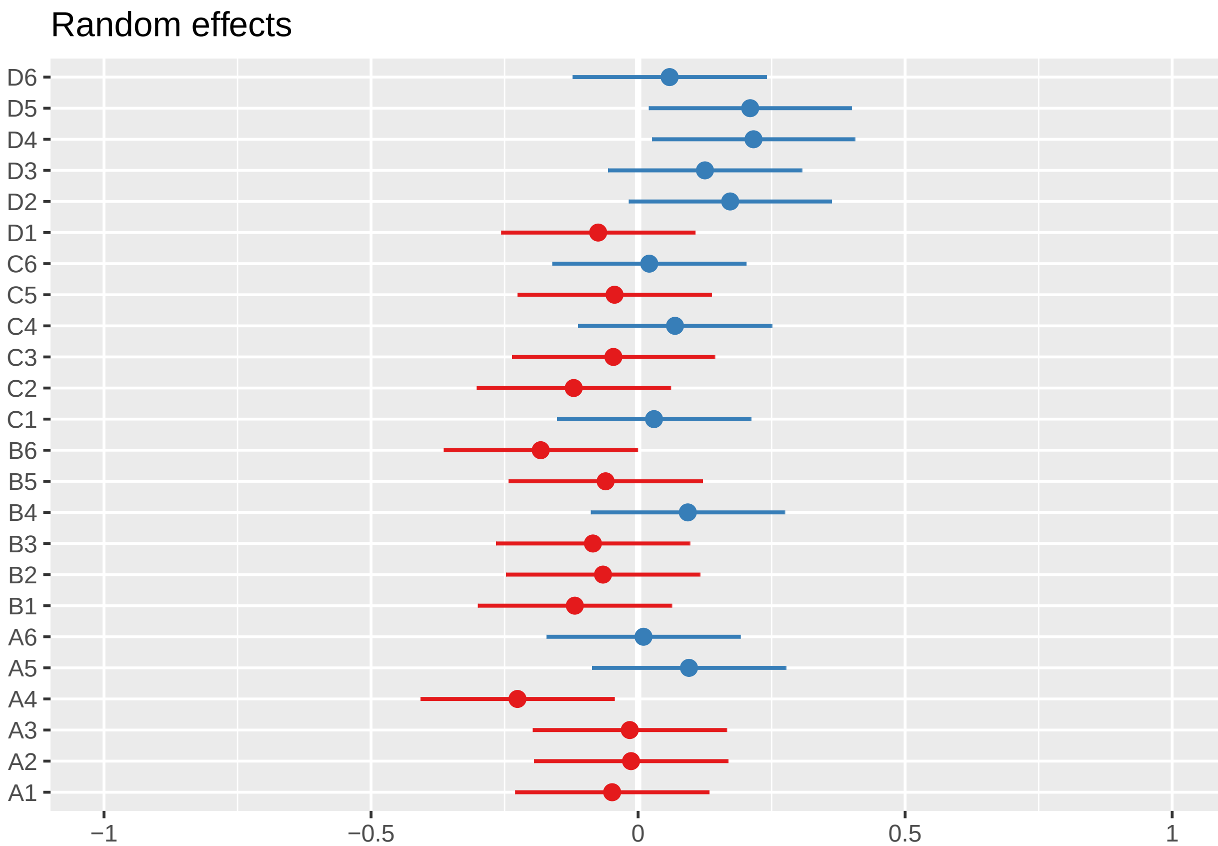



```r
# these are the fixed predicted values:
plot_model(mod1ks, type = "pred", terms = c("year", "state", "insecticide"))
```

```
## 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"))
```




```
# Does year need to be interactive with state?
mod3ks <- lmer(log(shannon) ~ state + year + insecticide*year + (1|plot), kbs_diversity, REML = FALSE)
anova(mod1ks, mod3ks)
```

```
## Data: kbs_diversity
## Models:
## mod3ks: 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)
## mod3ks   17 155.64 208.34 -60.818   121.64
## mod1ks   23 155.66 226.96 -54.830   109.66 11.977  6    0.06249 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

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

```
##        dAICc df weight
## mod3ks  0.0  17 0.87
## mod1ks  3.7  23 0.13
```

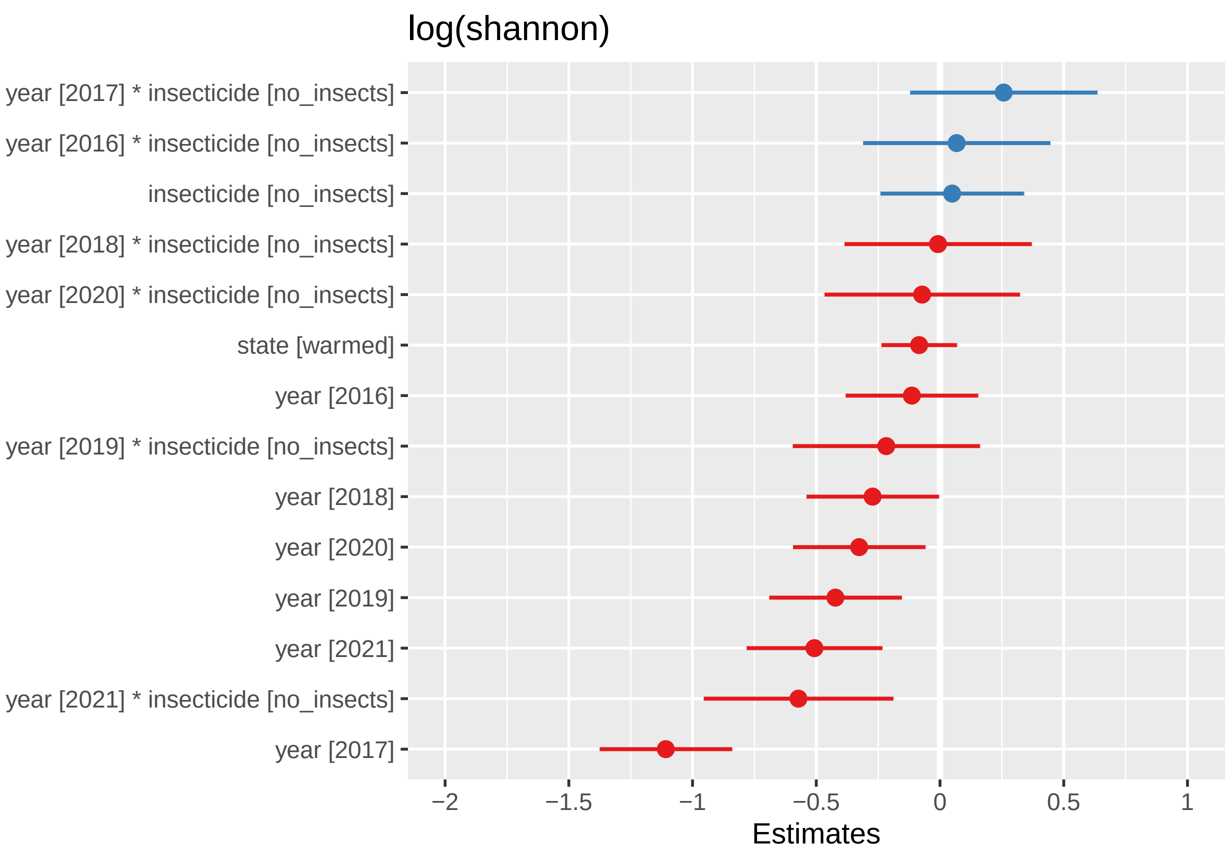
```
# Do we need to include insecticide? (dropping insecticide from the model)
mod5ks <- lmer(log(shannon) ~ state + year + (1|plot), kbs_diversity, REML = FALSE)
anova(mod3ks, mod5ks)
```

```
## 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    10 161.83 192.83 -70.917   141.83
## mod3ks    17 155.64 208.34 -60.818   121.64 20.196  7   0.005161 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

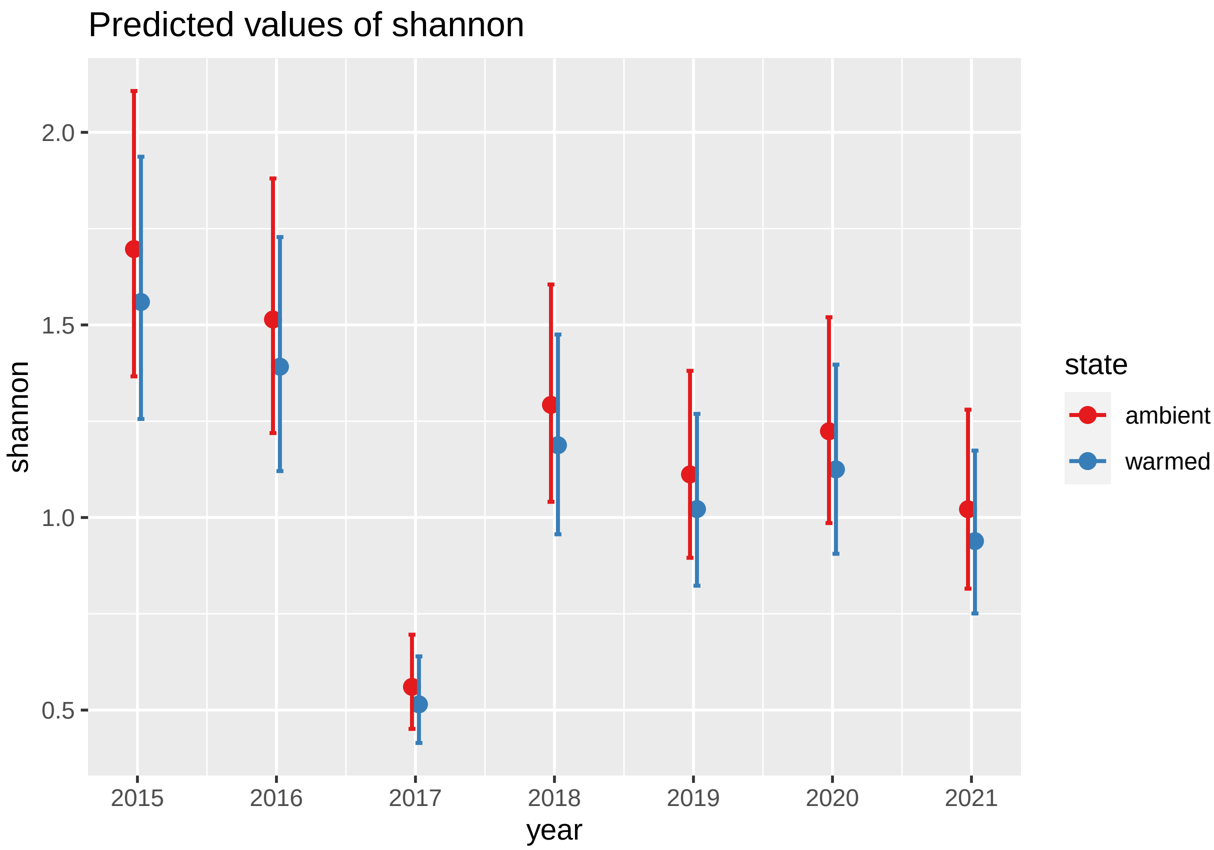
```
# Yes, p<0.05 so insecticide*year does strongly improve model fit so we will stick with the more comple

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

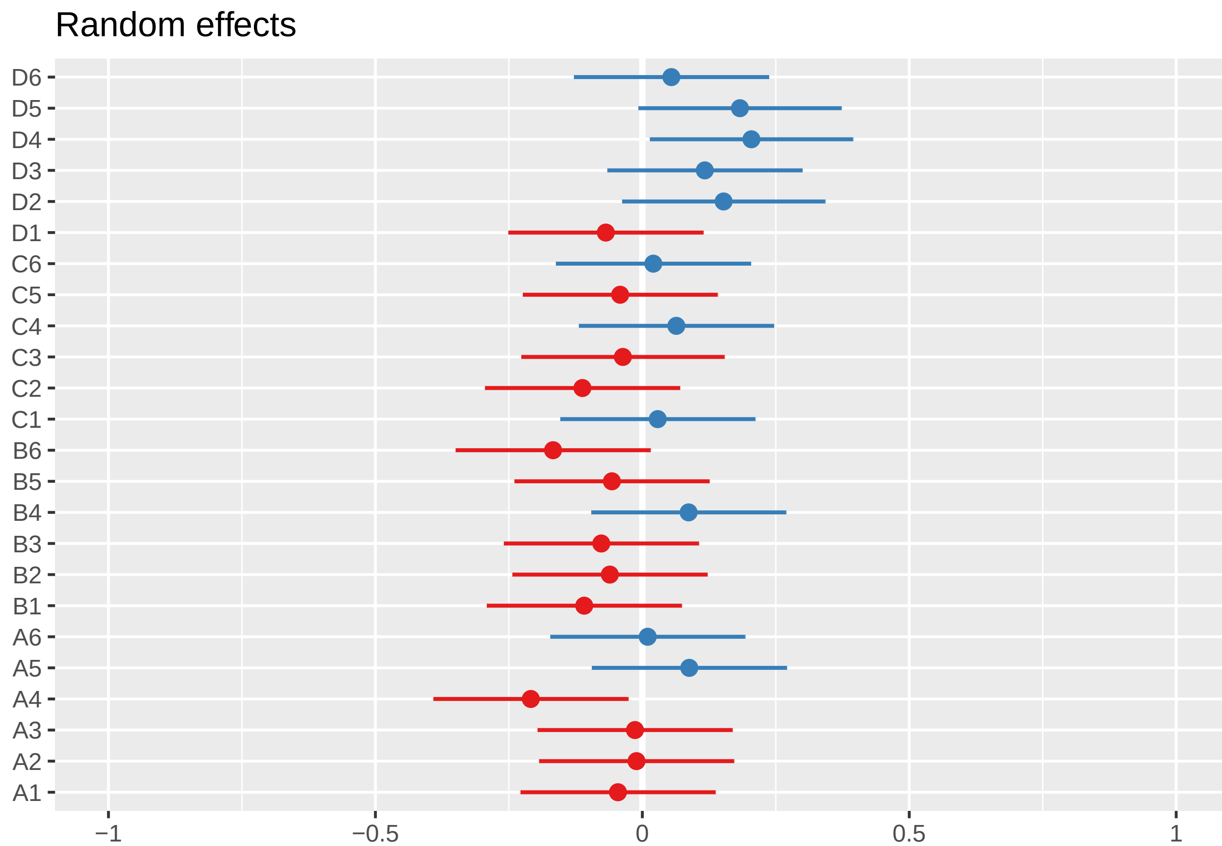



```
# these are the fixed predicted values:
plot_model(mod3ks, type = "pred", terms = c("year", "state"))
```

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




```
# 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=
# 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	164
Dependent variable	log(shannon)
Type	Mixed effects linear regression

AIC	155.64
BIC	208.33
Pseudo-R^2 (fixed effects)	0.51
Pseudo-R^2 (total)	0.58

```
summary(mod3ks)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(shannon) ~ state + year + insecticide * year + (1 | plot)
##    Data: kbs_diversity
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	0.53	0.11	4.78	117.70	0.00
statewarmed	-0.08	0.08	-1.10	23.02	0.28
year2016	-0.11	0.14	-0.84	138.99	0.40
year2017	-1.11	0.14	-8.20	138.99	0.00
year2018	-0.27	0.14	-2.02	138.99	0.05
year2019	-0.42	0.14	-3.13	138.99	0.00
year2020	-0.33	0.14	-2.42	138.99	0.02
year2021	-0.51	0.14	-3.67	139.91	0.00
insecticideno_insects	0.05	0.15	0.33	143.97	0.74
year2016:insecticideno_insects	0.07	0.19	0.35	138.99	0.73
year2017:insecticideno_insects	0.26	0.19	1.35	138.99	0.18
year2018:insecticideno_insects	-0.01	0.19	-0.04	138.99	0.97
year2019:insecticideno_insects	-0.22	0.19	-1.14	138.99	0.26
year2020:insecticideno_insects	-0.07	0.20	-0.36	140.64	0.72
year2021:insecticideno_insects	-0.57	0.19	-2.96	139.46	0.00

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.14
Residual		0.33

Grouping Variables		
Group	# groups	ICC
plot	24	0.15

```
##
##      AIC      BIC   logLik deviance df.resid
##    155.6    208.3    -60.8    121.6      147
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.4349 -0.4134  0.0445  0.5082  2.6498
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.01939  0.1393
##  Residual             0.10946  0.3308
## Number of obs: 164, groups:  plot, 24
##
## Fixed effects:
##                                 Estimate Std. Error t value
## (Intercept)                     0.528803   0.110522   4.785
## statewarmed                    -0.084418   0.076876  -1.098
## year2016                       -0.113983   0.135067  -0.844
## year2017                       -1.108136   0.135067  -8.204
```

```
## year2018                          -0.272320   0.135067  -2.016
## year2019                          -0.422752   0.135067  -3.130
## year2020                          -0.326705   0.135067  -2.419
## year2021                          -0.507579   0.138370  -3.668
## insecticideno_insects              0.049022   0.146544   0.335
## year2016:insecticideno_insects     0.067212   0.191013   0.352
## year2017:insecticideno_insects     0.257252   0.191013   1.347
## year2018:insecticideno_insects    -0.008095   0.191013  -0.042
## year2019:insecticideno_insects    -0.217234   0.191013  -1.137
## year2020:insecticideno_insects    -0.072304   0.199479  -0.362
## year2021:insecticideno_insects    -0.572178   0.193363  -2.959

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

```
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      0.5288 0.117 135   0.2983   0.7594
##  warmed  2015 insects      0.4444 0.117 135   0.2138   0.6749
##  ambient 2016 insects      0.4148 0.117 135   0.1843   0.6454
##  warmed  2016 insects      0.3304 0.117 135   0.0999   0.5609
##  ambient 2017 insects     -0.5793 0.117 135  -0.8099  -0.3488
##  warmed  2017 insects     -0.6638 0.117 135  -0.8943  -0.4332
##  ambient 2018 insects      0.2565 0.117 135   0.0259   0.4870
##  warmed  2018 insects      0.1721 0.117 135  -0.0585   0.4026
##  ambient 2019 insects      0.1061 0.117 135  -0.1245   0.3366
##  warmed  2019 insects      0.0216 0.117 135  -0.2089   0.2522
##  ambient 2020 insects      0.2021 0.117 135  -0.0284   0.4326
##  warmed  2020 insects      0.1177 0.117 135  -0.1129   0.3482
##  ambient 2021 insects      0.0212 0.121 142  -0.2188   0.2612
##  warmed  2021 insects     -0.0632 0.120 140  -0.3008   0.1744
##  ambient 2015 no_insects   0.5778 0.117 135   0.3473   0.8084
##  warmed  2015 no_insects   0.4934 0.117 135   0.2629   0.7240
##  ambient 2016 no_insects   0.5311 0.117 135   0.3005   0.7616
##  warmed  2016 no_insects   0.4466 0.117 135   0.2161   0.6772
##  ambient 2017 no_insects  -0.2731 0.117 135  -0.5036  -0.0425
##  warmed  2017 no_insects  -0.3575 0.117 135  -0.5880  -0.1269
##  ambient 2018 no_insects   0.2974 0.117 135   0.0669   0.5280
##  warmed  2018 no_insects   0.2130 0.117 135  -0.0176   0.4435
##  ambient 2019 no_insects  -0.0622 0.117 135  -0.2927   0.1684
##  warmed  2019 no_insects  -0.1466 0.117 135  -0.3771   0.0840
##  ambient 2020 no_insects   0.1788 0.132 155  -0.0821   0.4397
##  warmed  2020 no_insects   0.0944 0.131 154  -0.1638   0.3526
##  ambient 2021 no_insects  -0.5019 0.117 135  -0.7325  -0.2714
##  warmed  2021 no_insects  -0.5863 0.117 135  -0.8169  -0.3558
##
## 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
##  ambient year2015 insects - warmed year2015 insects         0.084418 0.0823
##  ambient year2015 insects - ambient year2016 insects        0.113983 0.1412
##  ambient year2015 insects - warmed year2016 insects         0.198401 0.1635
##  ambient year2015 insects - ambient year2017 insects        1.108136 0.1412
##  ambient year2015 insects - warmed year2017 insects         1.192554 0.1635
##  ambient year2015 insects - ambient year2018 insects        0.272320 0.1412
##  ambient year2015 insects - warmed year2018 insects         0.356738 0.1635
##  ambient year2015 insects - ambient year2019 insects        0.422752 0.1412
##  ambient year2015 insects - warmed year2019 insects         0.507170 0.1635
##  ambient year2015 insects - ambient year2020 insects        0.326705 0.1412
##  ambient year2015 insects - warmed year2020 insects         0.411123 0.1635
##  ambient year2015 insects - ambient year2021 insects        0.507579 0.1447
##  ambient year2015 insects - warmed year2021 insects         0.591997 0.1656
##  ambient year2015 insects - ambient year2015 no_insects    -0.049022 0.1542
##  ambient year2015 insects - warmed year2015 no_insects      0.035396 0.1748
##  ambient year2015 insects - ambient year2016 no_insects    -0.002251 0.1542
##  ambient year2015 insects - warmed year2016 no_insects      0.082167 0.1748
##  ambient year2015 insects - ambient year2017 no_insects     0.801862 0.1542
##  ambient year2015 insects - warmed year2017 no_insects      0.886280 0.1748
##  ambient year2015 insects - ambient year2018 no_insects     0.231392 0.1542
##  ambient year2015 insects - warmed year2018 no_insects      0.315810 0.1748
##  ambient year2015 insects - ambient year2019 no_insects     0.590963 0.1542
##  ambient year2015 insects - warmed year2019 no_insects      0.675381 0.1748
##  ambient year2015 insects - ambient year2020 no_insects     0.349986 0.1657
##  ambient year2015 insects - warmed year2020 no_insects      0.434404 0.1841
##  ambient year2015 insects - ambient year2021 no_insects     1.030735 0.1542
##  ambient year2015 insects - warmed year2021 no_insects      1.115153 0.1748
##  warmed year2015 insects - ambient year2016 insects         0.029565 0.1635
##  warmed year2015 insects - warmed year2016 insects          0.113983 0.1412
##  warmed year2015 insects - ambient year2017 insects         1.023718 0.1635
##  warmed year2015 insects - warmed year2017 insects          1.108136 0.1412
##  warmed year2015 insects - ambient year2018 insects         0.187902 0.1635
##  warmed year2015 insects - warmed year2018 insects          0.272320 0.1412
##  warmed year2015 insects - ambient year2019 insects         0.338334 0.1635
##  warmed year2015 insects - warmed year2019 insects          0.422752 0.1412
##  warmed year2015 insects - ambient year2020 insects         0.242287 0.1635
##  warmed year2015 insects - warmed year2020 insects          0.326705 0.1412
##  warmed year2015 insects - ambient year2021 insects         0.423161 0.1674
##  warmed year2015 insects - warmed year2021 insects          0.507579 0.1447
##  warmed year2015 insects - ambient year2015 no_insects     -0.133440 0.1748
##  warmed year2015 insects - warmed year2015 no_insects      -0.049022 0.1542
##  warmed year2015 insects - ambient year2016 no_insects     -0.086669 0.1748
##  warmed year2015 insects - warmed year2016 no_insects      -0.002251 0.1542
##  warmed year2015 insects - ambient year2017 no_insects      0.717444 0.1748
##  warmed year2015 insects - warmed year2017 no_insects       0.801862 0.1542
##  warmed year2015 insects - ambient year2018 no_insects      0.146975 0.1748
##  warmed year2015 insects - warmed year2018 no_insects       0.231392 0.1542
##  warmed year2015 insects - ambient year2019 no_insects      0.506546 0.1748
##  warmed year2015 insects - warmed year2019 no_insects       0.590963 0.1542
##  warmed year2015 insects - ambient year2020 no_insects      0.265569 0.1860
##  warmed year2015 insects - warmed year2020 no_insects       0.349986 0.1657
```

```
## warmed year2015 insects - ambient year2021 no_insects      0.946317 0.1748
## warmed year2015 insects - warmed year2021 no_insects       1.030735 0.1542
## ambient year2016 insects - warmed year2016 insects         0.084418 0.0823
## ambient year2016 insects - ambient year2017 insects        0.994153 0.1412
## ambient year2016 insects - warmed year2017 insects         1.078571 0.1635
## ambient year2016 insects - ambient year2018 insects        0.158336 0.1412
## ambient year2016 insects - warmed year2018 insects         0.242754 0.1635
## ambient year2016 insects - ambient year2019 insects        0.308768 0.1412
## ambient year2016 insects - warmed year2019 insects         0.393186 0.1635
## ambient year2016 insects - ambient year2020 insects        0.212722 0.1412
## ambient year2016 insects - warmed year2020 insects         0.297140 0.1635
## ambient year2016 insects - ambient year2021 insects        0.393595 0.1447
## ambient year2016 insects - warmed year2021 insects         0.478013 0.1656
## ambient year2016 insects - ambient year2015 no_insects    -0.163005 0.1542
## ambient year2016 insects - warmed year2015 no_insects     -0.078587 0.1748
## ambient year2016 insects - ambient year2016 no_insects    -0.116234 0.1542
## ambient year2016 insects - warmed year2016 no_insects     -0.031816 0.1748
## ambient year2016 insects - ambient year2017 no_insects     0.687879 0.1542
## ambient year2016 insects - warmed year2017 no_insects      0.772297 0.1748
## ambient year2016 insects - ambient year2018 no_insects     0.117409 0.1542
## ambient year2016 insects - warmed year2018 no_insects      0.201827 0.1748
## ambient year2016 insects - ambient year2019 no_insects     0.476980 0.1542
## ambient year2016 insects - warmed year2019 no_insects      0.561398 0.1748
## ambient year2016 insects - ambient year2020 no_insects     0.236003 0.1657
## ambient year2016 insects - warmed year2020 no_insects      0.320421 0.1841
## ambient year2016 insects - ambient year2021 no_insects     0.916752 0.1542
## ambient year2016 insects - warmed year2021 no_insects      1.001170 0.1748
## warmed year2016 insects - ambient year2017 insects         0.909735 0.1635
## warmed year2016 insects - warmed year2017 insects          0.994153 0.1412
## warmed year2016 insects - ambient year2018 insects         0.073919 0.1635
## warmed year2016 insects - warmed year2018 insects          0.158336 0.1412
## warmed year2016 insects - ambient year2019 insects         0.224350 0.1635
## warmed year2016 insects - warmed year2019 insects          0.308768 0.1412
## warmed year2016 insects - ambient year2020 insects         0.128304 0.1635
## warmed year2016 insects - warmed year2020 insects          0.212722 0.1412
## warmed year2016 insects - ambient year2021 insects         0.309178 0.1674
## warmed year2016 insects - warmed year2021 insects          0.393595 0.1447
## warmed year2016 insects - ambient year2015 no_insects     -0.247423 0.1748
## warmed year2016 insects - warmed year2015 no_insects      -0.163005 0.1542
## warmed year2016 insects - ambient year2016 no_insects     -0.200652 0.1748
## warmed year2016 insects - warmed year2016 no_insects      -0.116234 0.1542
## warmed year2016 insects - ambient year2017 no_insects      0.603461 0.1748
## warmed year2016 insects - warmed year2017 no_insects       0.687879 0.1542
## warmed year2016 insects - ambient year2018 no_insects      0.032991 0.1748
## warmed year2016 insects - warmed year2018 no_insects       0.117409 0.1542
## warmed year2016 insects - ambient year2019 no_insects      0.392562 0.1748
## warmed year2016 insects - warmed year2019 no_insects       0.476980 0.1542
## warmed year2016 insects - ambient year2020 no_insects      0.151585 0.1860
## warmed year2016 insects - warmed year2020 no_insects       0.236003 0.1657
## warmed year2016 insects - ambient year2021 no_insects      0.832334 0.1748
## warmed year2016 insects - warmed year2021 no_insects       0.916752 0.1542
## ambient year2017 insects - warmed year2017 insects         0.084418 0.0823
## ambient year2017 insects - ambient year2018 insects       -0.835817 0.1412
## ambient year2017 insects - warmed year2018 insects        -0.751399 0.1635
```

```
## ambient year2017 insects - ambient year2019 insects      -0.685385 0.1412
## ambient year2017 insects - warmed year2019 insects       -0.600967 0.1635
## ambient year2017 insects - ambient year2020 insects      -0.781431 0.1412
## ambient year2017 insects - warmed year2020 insects       -0.697014 0.1635
## ambient year2017 insects - ambient year2021 insects      -0.600558 0.1447
## ambient year2017 insects - warmed year2021 insects       -0.516140 0.1656
## ambient year2017 insects - ambient year2015 no_insects   -1.157158 0.1542
## ambient year2017 insects - warmed year2015 no_insects    -1.072741 0.1748
## ambient year2017 insects - ambient year2016 no_insects   -1.110388 0.1542
## ambient year2017 insects - warmed year2016 no_insects    -1.025970 0.1748
## ambient year2017 insects - ambient year2017 no_insects   -0.306274 0.1542
## ambient year2017 insects - warmed year2017 no_insects    -0.221857 0.1748
## ambient year2017 insects - ambient year2018 no_insects   -0.876744 0.1542
## ambient year2017 insects - warmed year2018 no_insects    -0.792326 0.1748
## ambient year2017 insects - ambient year2019 no_insects   -0.517173 0.1542
## ambient year2017 insects - warmed year2019 no_insects    -0.432755 0.1748
## ambient year2017 insects - ambient year2020 no_insects   -0.758150 0.1657
## ambient year2017 insects - warmed year2020 no_insects    -0.673732 0.1841
## ambient year2017 insects - ambient year2021 no_insects   -0.077401 0.1542
## ambient year2017 insects - warmed year2021 no_insects     0.007017 0.1748
## warmed year2017 insects - ambient year2018 insects       -0.920234 0.1635
## warmed year2017 insects - warmed year2018 insects        -0.835817 0.1412
## warmed year2017 insects - ambient year2019 insects       -0.769803 0.1635
## warmed year2017 insects - warmed year2019 insects        -0.685385 0.1412
## warmed year2017 insects - ambient year2020 insects       -0.865849 0.1635
## warmed year2017 insects - warmed year2020 insects        -0.781431 0.1412
## warmed year2017 insects - ambient year2021 insects       -0.684975 0.1674
## warmed year2017 insects - warmed year2021 insects        -0.600558 0.1447
## warmed year2017 insects - ambient year2015 no_insects    -1.241576 0.1748
## warmed year2017 insects - warmed year2015 no_insects     -1.157158 0.1542
## warmed year2017 insects - ambient year2016 no_insects    -1.194805 0.1748
## warmed year2017 insects - warmed year2016 no_insects     -1.110388 0.1542
## warmed year2017 insects - ambient year2017 no_insects    -0.390692 0.1748
## warmed year2017 insects - warmed year2017 no_insects     -0.306274 0.1542
## warmed year2017 insects - ambient year2018 no_insects    -0.961162 0.1748
## warmed year2017 insects - warmed year2018 no_insects     -0.876744 0.1542
## warmed year2017 insects - ambient year2019 no_insects    -0.601591 0.1748
## warmed year2017 insects - warmed year2019 no_insects     -0.517173 0.1542
## warmed year2017 insects - ambient year2020 no_insects    -0.842568 0.1860
## warmed year2017 insects - warmed year2020 no_insects     -0.758150 0.1657
## warmed year2017 insects - ambient year2021 no_insects    -0.161819 0.1748
## warmed year2017 insects - warmed year2021 no_insects     -0.077401 0.1542
## ambient year2018 insects - warmed year2018 insects        0.084418 0.0823
## ambient year2018 insects - ambient year2019 insects       0.150432 0.1412
## ambient year2018 insects - warmed year2019 insects        0.234850 0.1635
## ambient year2018 insects - ambient year2020 insects       0.054385 0.1412
## ambient year2018 insects - warmed year2020 insects        0.138803 0.1635
## ambient year2018 insects - ambient year2021 insects       0.235259 0.1447
## ambient year2018 insects - warmed year2021 insects        0.319677 0.1656
## ambient year2018 insects - ambient year2015 no_insects   -0.321342 0.1542
## ambient year2018 insects - warmed year2015 no_insects    -0.236924 0.1748
## ambient year2018 insects - ambient year2016 no_insects   -0.274571 0.1542
## ambient year2018 insects - warmed year2016 no_insects    -0.190153 0.1748
## ambient year2018 insects - ambient year2017 no_insects    0.529542 0.1542
```

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## ambient year2018 insects - warmed year2017 no_insects      0.613960 0.1748
## ambient year2018 insects - ambient year2018 no_insects    -0.040927 0.1542
## ambient year2018 insects - warmed year2018 no_insects      0.043491 0.1748
## ambient year2018 insects - ambient year2019 no_insects     0.318644 0.1542
## ambient year2018 insects - warmed year2019 no_insects      0.403062 0.1748
## ambient year2018 insects - ambient year2020 no_insects     0.077667 0.1657
## ambient year2018 insects - warmed year2020 no_insects      0.162085 0.1841
## ambient year2018 insects - ambient year2021 no_insects     0.758415 0.1542
## ambient year2018 insects - warmed year2021 no_insects      0.842833 0.1748
## warmed year2018 insects - ambient year2019 insects         0.066014 0.1635
## warmed year2018 insects - warmed year2019 insects          0.150432 0.1412
## warmed year2018 insects - ambient year2020 insects        -0.030033 0.1635
## warmed year2018 insects - warmed year2020 insects          0.054385 0.1412
## warmed year2018 insects - ambient year2021 insects         0.150841 0.1674
## warmed year2018 insects - warmed year2021 insects          0.235259 0.1447
## warmed year2018 insects - ambient year2015 no_insects     -0.405760 0.1748
## warmed year2018 insects - warmed year2015 no_insects      -0.321342 0.1542
## warmed year2018 insects - ambient year2016 no_insects     -0.358989 0.1748
## warmed year2018 insects - warmed year2016 no_insects      -0.274571 0.1542
## warmed year2018 insects - ambient year2017 no_insects      0.445124 0.1748
## warmed year2018 insects - warmed year2017 no_insects       0.529542 0.1542
## warmed year2018 insects - ambient year2018 no_insects     -0.125345 0.1748
## warmed year2018 insects - warmed year2018 no_insects      -0.040927 0.1542
## warmed year2018 insects - ambient year2019 no_insects      0.234226 0.1748
## warmed year2018 insects - warmed year2019 no_insects       0.318644 0.1542
## warmed year2018 insects - ambient year2020 no_insects     -0.006751 0.1860
## warmed year2018 insects - warmed year2020 no_insects       0.077667 0.1657
## warmed year2018 insects - ambient year2021 no_insects      0.673997 0.1748
## warmed year2018 insects - warmed year2021 no_insects       0.758415 0.1542
## ambient year2019 insects - warmed year2019 insects         0.084418 0.0823
## ambient year2019 insects - ambient year2020 insects       -0.096047 0.1412
## ambient year2019 insects - warmed year2020 insects        -0.011629 0.1635
## ambient year2019 insects - ambient year2021 insects        0.084827 0.1447
## ambient year2019 insects - warmed year2021 insects         0.169245 0.1656
## ambient year2019 insects - ambient year2015 no_insects    -0.471774 0.1542
## ambient year2019 insects - warmed year2015 no_insects     -0.387356 0.1748
## ambient year2019 insects - ambient year2016 no_insects    -0.425003 0.1542
## ambient year2019 insects - warmed year2016 no_insects     -0.340585 0.1748
## ambient year2019 insects - ambient year2017 no_insects     0.379110 0.1542
## ambient year2019 insects - warmed year2017 no_insects      0.463528 0.1748
## ambient year2019 insects - ambient year2018 no_insects    -0.191359 0.1542
## ambient year2019 insects - warmed year2018 no_insects     -0.106941 0.1748
## ambient year2019 insects - ambient year2019 no_insects     0.168212 0.1542
## ambient year2019 insects - warmed year2019 no_insects      0.252630 0.1748
## ambient year2019 insects - ambient year2020 no_insects    -0.072765 0.1657
## ambient year2019 insects - warmed year2020 no_insects      0.011653 0.1841
## ambient year2019 insects - ambient year2021 no_insects     0.607983 0.1542
## ambient year2019 insects - warmed year2021 no_insects      0.692401 0.1748
## warmed year2019 insects - ambient year2020 insects        -0.180465 0.1635
## warmed year2019 insects - warmed year2020 insects         -0.096047 0.1412
## warmed year2019 insects - ambient year2021 insects         0.000409 0.1674
## warmed year2019 insects - warmed year2021 insects          0.084827 0.1447
## warmed year2019 insects - ambient year2015 no_insects     -0.556191 0.1748
## warmed year2019 insects - warmed year2015 no_insects      -0.471774 0.1542
```

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## warmed year2019 insects - ambient year2016 no_insects     -0.509421 0.1748
## warmed year2019 insects - warmed year2016 no_insects      -0.425003 0.1542
## warmed year2019 insects - ambient year2017 no_insects      0.294693 0.1748
## warmed year2019 insects - warmed year2017 no_insects       0.379110 0.1542
## warmed year2019 insects - ambient year2018 no_insects     -0.275777 0.1748
## warmed year2019 insects - warmed year2018 no_insects      -0.191359 0.1542
## warmed year2019 insects - ambient year2019 no_insects      0.083794 0.1748
## warmed year2019 insects - warmed year2019 no_insects       0.168212 0.1542
## warmed year2019 insects - ambient year2020 no_insects     -0.157183 0.1860
## warmed year2019 insects - warmed year2020 no_insects      -0.072765 0.1657
## warmed year2019 insects - ambient year2021 no_insects      0.523566 0.1748
## warmed year2019 insects - warmed year2021 no_insects       0.607983 0.1542
## ambient year2020 insects - warmed year2020 insects         0.084418 0.0823
## ambient year2020 insects - ambient year2021 insects        0.180874 0.1447
## ambient year2020 insects - warmed year2021 insects         0.265292 0.1656
## ambient year2020 insects - ambient year2015 no_insects    -0.375727 0.1542
## ambient year2020 insects - warmed year2015 no_insects     -0.291309 0.1748
## ambient year2020 insects - ambient year2016 no_insects    -0.328956 0.1542
## ambient year2020 insects - warmed year2016 no_insects     -0.244538 0.1748
## ambient year2020 insects - ambient year2017 no_insects     0.475157 0.1542
## ambient year2020 insects - warmed year2017 no_insects      0.559575 0.1748
## ambient year2020 insects - ambient year2018 no_insects    -0.095312 0.1542
## ambient year2020 insects - warmed year2018 no_insects     -0.010895 0.1748
## ambient year2020 insects - ambient year2019 no_insects     0.264259 0.1542
## ambient year2020 insects - warmed year2019 no_insects      0.348677 0.1748
## ambient year2020 insects - ambient year2020 no_insects     0.023282 0.1657
## ambient year2020 insects - warmed year2020 no_insects      0.107699 0.1841
## ambient year2020 insects - ambient year2021 no_insects     0.704030 0.1542
## ambient year2020 insects - warmed year2021 no_insects      0.788448 0.1748
## warmed year2020 insects - ambient year2021 insects         0.096456 0.1674
## warmed year2020 insects - warmed year2021 insects          0.180874 0.1447
## warmed year2020 insects - ambient year2015 no_insects     -0.460145 0.1748
## warmed year2020 insects - warmed year2015 no_insects      -0.375727 0.1542
## warmed year2020 insects - ambient year2016 no_insects     -0.413374 0.1748
## warmed year2020 insects - warmed year2016 no_insects      -0.328956 0.1542
## warmed year2020 insects - ambient year2017 no_insects      0.390739 0.1748
## warmed year2020 insects - warmed year2017 no_insects       0.475157 0.1542
## warmed year2020 insects - ambient year2018 no_insects     -0.179730 0.1748
## warmed year2020 insects - warmed year2018 no_insects      -0.095312 0.1542
## warmed year2020 insects - ambient year2019 no_insects      0.179841 0.1748
## warmed year2020 insects - warmed year2019 no_insects       0.264259 0.1542
## warmed year2020 insects - ambient year2020 no_insects     -0.061136 0.1860
## warmed year2020 insects - warmed year2020 no_insects       0.023282 0.1657
## warmed year2020 insects - ambient year2021 no_insects      0.619612 0.1748
## warmed year2020 insects - warmed year2021 no_insects       0.704030 0.1542
## ambient year2021 insects - warmed year2021 insects         0.084418 0.0823
## ambient year2021 insects - ambient year2015 no_insects    -0.556601 0.1575
## ambient year2021 insects - warmed year2015 no_insects     -0.472183 0.1785
## ambient year2021 insects - ambient year2016 no_insects    -0.509830 0.1575
## ambient year2021 insects - warmed year2016 no_insects     -0.425412 0.1785
## ambient year2021 insects - ambient year2017 no_insects     0.294283 0.1575
## ambient year2021 insects - warmed year2017 no_insects      0.378701 0.1785
## ambient year2021 insects - ambient year2018 no_insects    -0.276186 0.1575
## ambient year2021 insects - warmed year2018 no_insects     -0.191768 0.1785
```

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##  ambient year2021 insects - ambient year2019 no_insects     0.083385 0.1575
##  ambient year2021 insects - warmed year2019 no_insects      0.167803 0.1785
##  ambient year2021 insects - ambient year2020 no_insects    -0.157592 0.1687
##  ambient year2021 insects - warmed year2020 no_insects     -0.073174 0.1875
##  ambient year2021 insects - ambient year2021 no_insects     0.523156 0.1575
##  ambient year2021 insects - warmed year2021 no_insects      0.607574 0.1785
##  warmed year2021 insects - ambient year2015 no_insects     -0.641019 0.1769
##  warmed year2021 insects - warmed year2015 no_insects      -0.556601 0.1575
##  warmed year2021 insects - ambient year2016 no_insects     -0.594248 0.1769
##  warmed year2021 insects - warmed year2016 no_insects      -0.509830 0.1575
##  warmed year2021 insects - ambient year2017 no_insects      0.209865 0.1769
##  warmed year2021 insects - warmed year2017 no_insects       0.294283 0.1575
##  warmed year2021 insects - ambient year2018 no_insects     -0.360604 0.1769
##  warmed year2021 insects - warmed year2018 no_insects      -0.276186 0.1575
##  warmed year2021 insects - ambient year2019 no_insects     -0.001033 0.1769
##  warmed year2021 insects - warmed year2019 no_insects       0.083385 0.1575
##  warmed year2021 insects - ambient year2020 no_insects     -0.242010 0.1879
##  warmed year2021 insects - warmed year2020 no_insects      -0.157592 0.1687
##  warmed year2021 insects - ambient year2021 no_insects      0.438738 0.1769
##  warmed year2021 insects - warmed year2021 no_insects       0.523156 0.1575
##  ambient year2015 no_insects - warmed year2015 no_insects   0.084418 0.0823
##  ambient year2015 no_insects - ambient year2016 no_insects  0.046771 0.1412
##  ambient year2015 no_insects - warmed year2016 no_insects   0.131189 0.1635
##  ambient year2015 no_insects - ambient year2017 no_insects  0.850884 0.1412
##  ambient year2015 no_insects - warmed year2017 no_insects   0.935302 0.1635
##  ambient year2015 no_insects - ambient year2018 no_insects  0.280414 0.1412
##  ambient year2015 no_insects - warmed year2018 no_insects   0.364832 0.1635
##  ambient year2015 no_insects - ambient year2019 no_insects  0.639985 0.1412
##  ambient year2015 no_insects - warmed year2019 no_insects   0.724403 0.1635
##  ambient year2015 no_insects - ambient year2020 no_insects  0.399008 0.1537
##  ambient year2015 no_insects - warmed year2020 no_insects   0.483426 0.1733
##  ambient year2015 no_insects - ambient year2021 no_insects  1.079757 0.1412
##  ambient year2015 no_insects - warmed year2021 no_insects   1.164175 0.1635
##  warmed year2015 no_insects - ambient year2016 no_insects  -0.037647 0.1635
##  warmed year2015 no_insects - warmed year2016 no_insects    0.046771 0.1412
##  warmed year2015 no_insects - ambient year2017 no_insects   0.766466 0.1635
##  warmed year2015 no_insects - warmed year2017 no_insects    0.850884 0.1412
##  warmed year2015 no_insects - ambient year2018 no_insects   0.195996 0.1635
##  warmed year2015 no_insects - warmed year2018 no_insects    0.280414 0.1412
##  warmed year2015 no_insects - ambient year2019 no_insects   0.555568 0.1635
##  warmed year2015 no_insects - warmed year2019 no_insects    0.639985 0.1412
##  warmed year2015 no_insects - ambient year2020 no_insects   0.314590 0.1753
##  warmed year2015 no_insects - warmed year2020 no_insects    0.399008 0.1537
##  warmed year2015 no_insects - ambient year2021 no_insects   0.995339 0.1635
##  warmed year2015 no_insects - warmed year2021 no_insects    1.079757 0.1412
##  ambient year2016 no_insects - warmed year2016 no_insects   0.084418 0.0823
##  ambient year2016 no_insects - ambient year2017 no_insects  0.804113 0.1412
##  ambient year2016 no_insects - warmed year2017 no_insects   0.888531 0.1635
##  ambient year2016 no_insects - ambient year2018 no_insects  0.233644 0.1412
##  ambient year2016 no_insects - warmed year2018 no_insects   0.318061 0.1635
##  ambient year2016 no_insects - ambient year2019 no_insects  0.593215 0.1412
##  ambient year2016 no_insects - warmed year2019 no_insects   0.677632 0.1635
##  ambient year2016 no_insects - ambient year2020 no_insects  0.352238 0.1537
##  ambient year2016 no_insects - warmed year2020 no_insects   0.436655 0.1733
```

```
##  ambient year2016 no_insects - ambient year2021 no_insects  1.032986 0.1412
##  ambient year2016 no_insects - warmed year2021 no_insects   1.117404 0.1635
##  warmed year2016 no_insects - ambient year2017 no_insects   0.719695 0.1635
##  warmed year2016 no_insects - warmed year2017 no_insects    0.804113 0.1412
##  warmed year2016 no_insects - ambient year2018 no_insects   0.149226 0.1635
##  warmed year2016 no_insects - warmed year2018 no_insects    0.233644 0.1412
##  warmed year2016 no_insects - ambient year2019 no_insects   0.508797 0.1635
##  warmed year2016 no_insects - warmed year2019 no_insects    0.593215 0.1412
##  warmed year2016 no_insects - ambient year2020 no_insects   0.267820 0.1753
##  warmed year2016 no_insects - warmed year2020 no_insects    0.352238 0.1537
##  warmed year2016 no_insects - ambient year2021 no_insects   0.948568 0.1635
##  warmed year2016 no_insects - warmed year2021 no_insects    1.032986 0.1412
##  ambient year2017 no_insects - warmed year2017 no_insects   0.084418 0.0823
##  ambient year2017 no_insects - ambient year2018 no_insects -0.570470 0.1412
##  ambient year2017 no_insects - warmed year2018 no_insects  -0.486052 0.1635
##  ambient year2017 no_insects - ambient year2019 no_insects -0.210898 0.1412
##  ambient year2017 no_insects - warmed year2019 no_insects  -0.126481 0.1635
##  ambient year2017 no_insects - ambient year2020 no_insects -0.451875 0.1537
##  ambient year2017 no_insects - warmed year2020 no_insects  -0.367458 0.1733
##  ambient year2017 no_insects - ambient year2021 no_insects  0.228873 0.1412
##  ambient year2017 no_insects - warmed year2021 no_insects   0.313291 0.1635
##  warmed year2017 no_insects - ambient year2018 no_insects  -0.654887 0.1635
##  warmed year2017 no_insects - warmed year2018 no_insects   -0.570470 0.1412
##  warmed year2017 no_insects - ambient year2019 no_insects  -0.295316 0.1635
##  warmed year2017 no_insects - warmed year2019 no_insects   -0.210898 0.1412
##  warmed year2017 no_insects - ambient year2020 no_insects  -0.536293 0.1753
##  warmed year2017 no_insects - warmed year2020 no_insects   -0.451875 0.1537
##  warmed year2017 no_insects - ambient year2021 no_insects   0.144455 0.1635
##  warmed year2017 no_insects - warmed year2021 no_insects    0.228873 0.1412
##  ambient year2018 no_insects - warmed year2018 no_insects   0.084418 0.0823
##  ambient year2018 no_insects - ambient year2019 no_insects  0.359571 0.1412
##  ambient year2018 no_insects - warmed year2019 no_insects   0.443989 0.1635
##  ambient year2018 no_insects - ambient year2020 no_insects  0.118594 0.1537
##  ambient year2018 no_insects - warmed year2020 no_insects   0.203012 0.1733
##  ambient year2018 no_insects - ambient year2021 no_insects  0.799343 0.1412
##  ambient year2018 no_insects - warmed year2021 no_insects   0.883760 0.1635
##  warmed year2018 no_insects - ambient year2019 no_insects   0.275153 0.1635
##  warmed year2018 no_insects - warmed year2019 no_insects    0.359571 0.1412
##  warmed year2018 no_insects - ambient year2020 no_insects   0.034176 0.1753
##  warmed year2018 no_insects - warmed year2020 no_insects    0.118594 0.1537
##  warmed year2018 no_insects - ambient year2021 no_insects   0.714925 0.1635
##  warmed year2018 no_insects - warmed year2021 no_insects    0.799343 0.1412
##  ambient year2019 no_insects - warmed year2019 no_insects   0.084418 0.0823
##  ambient year2019 no_insects - ambient year2020 no_insects -0.240977 0.1537
##  ambient year2019 no_insects - warmed year2020 no_insects  -0.156559 0.1733
##  ambient year2019 no_insects - ambient year2021 no_insects  0.439771 0.1412
##  ambient year2019 no_insects - warmed year2021 no_insects   0.524189 0.1635
##  warmed year2019 no_insects - ambient year2020 no_insects  -0.325395 0.1753
##  warmed year2019 no_insects - warmed year2020 no_insects   -0.240977 0.1537
##  warmed year2019 no_insects - ambient year2021 no_insects   0.355354 0.1635
##  warmed year2019 no_insects - warmed year2021 no_insects    0.439771 0.1412
##  ambient year2020 no_insects - warmed year2020 no_insects   0.084418 0.0823
##  ambient year2020 no_insects - ambient year2021 no_insects  0.680748 0.1537
##  ambient year2020 no_insects - warmed year2021 no_insects   0.765166 0.1753
```

```
##  warmed year2020 no_insects - ambient year2021 no_insects   0.596331 0.1733
##  warmed year2020 no_insects - warmed year2021 no_insects    0.680748 0.1537
##  ambient year2021 no_insects - warmed year2021 no_insects   0.084418 0.0823
##     df t.ratio p.value
##   27.6   1.026  1.0000
##  153.0   0.807  1.0000
##  169.4   1.214  1.0000
##  153.0   7.847  <.0001
##  169.4   7.296  <.0001
##  153.0   1.928  0.9783
##  169.4   2.182  0.9169
##  153.0   2.994  0.3726
##  169.4   3.103  0.2988
##  153.0   2.313  0.8582
##  169.4   2.515  0.7345
##  154.0   3.507  0.1131
##  170.4   3.574  0.0924
##  161.8  -0.318  1.0000
##  112.7   0.202  1.0000
##  161.8  -0.015  1.0000
##  112.7   0.470  1.0000
##  161.8   5.199  0.0002
##  112.7   5.069  0.0005
##  161.8   1.500  0.9995
##  112.7   1.806  0.9899
##  161.8   3.831  0.0428
##  112.7   3.863  0.0427
##  168.8   2.112  0.9402
##  123.9   2.360  0.8314
##  161.8   6.683  <.0001
##  112.7   6.379  <.0001
##  169.4   0.181  1.0000
##  153.0   0.807  1.0000
##  169.4   6.263  <.0001
##  153.0   7.847  <.0001
##  169.4   1.150  1.0000
##  153.0   1.928  0.9783
##  169.4   2.070  0.9517
##  153.0   2.994  0.3726
##  169.4   1.482  0.9996
##  153.0   2.313  0.8582
##  171.3   2.528  0.7252
##  154.0   3.507  0.1131
##  112.7  -0.763  1.0000
##  161.8  -0.318  1.0000
##  112.7  -0.496  1.0000
##  161.8  -0.015  1.0000
##  112.7   4.104  0.0197
##  161.8   5.199  0.0002
##  112.7   0.841  1.0000
##  161.8   1.500  0.9995
##  112.7   2.897  0.4455
##  161.8   3.831  0.0428
##  126.1   1.428  0.9997
```

```
##  168.8   2.112  0.9402
##  112.7   5.413  0.0001
##  161.8   6.683  <.0001
##   27.6   1.026  1.0000
##  153.0   7.040  <.0001
##  169.4   6.598  <.0001
##  153.0   1.121  1.0000
##  169.4   1.485  0.9995
##  153.0   2.186  0.9147
##  169.4   2.405  0.8070
##  153.0   1.506  0.9994
##  169.4   1.818  0.9900
##  154.0   2.719  0.5800
##  170.4   2.886  0.4500
##  161.8  -1.057  1.0000
##  112.7  -0.450  1.0000
##  161.8  -0.754  1.0000
##  112.7  -0.182  1.0000
##  161.8   4.460  0.0046
##  112.7   4.417  0.0066
##  161.8   0.761  1.0000
##  112.7   1.154  1.0000
##  161.8   3.092  0.3059
##  112.7   3.211  0.2431
##  168.8   1.424  0.9998
##  123.9   1.741  0.9941
##  161.8   5.944  <.0001
##  112.7   5.727  <.0001
##  169.4   5.566  <.0001
##  153.0   7.040  <.0001
##  169.4   0.452  1.0000
##  153.0   1.121  1.0000
##  169.4   1.373  0.9999
##  153.0   2.186  0.9147
##  169.4   0.785  1.0000
##  153.0   1.506  0.9994
##  171.3   1.847  0.9877
##  154.0   2.719  0.5800
##  112.7  -1.415  0.9998
##  161.8  -1.057  1.0000
##  112.7  -1.148  1.0000
##  161.8  -0.754  1.0000
##  112.7   3.452  0.1371
##  161.8   4.460  0.0046
##  112.7   0.189  1.0000
##  161.8   0.761  1.0000
##  112.7   2.245  0.8880
##  161.8   3.092  0.3059
##  126.1   0.815  1.0000
##  168.8   1.424  0.9998
##  112.7   4.761  0.0018
##  161.8   5.944  <.0001
##   27.6   1.026  1.0000
##  153.0  -5.918  <.0001
```

```
##   169.4  -4.597  0.0026
##   153.0  -4.853  0.0010
##   169.4  -3.677  0.0685
##   153.0  -5.533  <.0001
##   169.4  -4.264  0.0094
##   154.0  -4.149  0.0148
##   170.4  -3.116  0.2904
##   161.8  -7.502  <.0001
##   112.7  -6.136  <.0001
##   161.8  -7.199  <.0001
##   112.7  -5.868  <.0001
##   161.8  -1.986  0.9695
##   112.7  -1.269  1.0000
##   161.8  -5.684  <.0001
##   112.7  -4.532  0.0043
##   161.8  -3.353  0.1684
##   112.7  -2.475  0.7595
##   168.8  -4.575  0.0029
##   123.9  -3.660  0.0765
##   161.8  -0.502  1.0000
##   112.7   0.040  1.0000
##   169.4  -5.630  <.0001
##   153.0  -5.918  <.0001
##   169.4  -4.709  0.0016
##   153.0  -4.853  0.0010
##   169.4  -5.297  0.0001
##   153.0  -5.533  <.0001
##   171.3  -4.093  0.0175
##   154.0  -4.149  0.0148
##   112.7  -7.102  <.0001
##   161.8  -7.502  <.0001
##   112.7  -6.834  <.0001
##   161.8  -7.199  <.0001
##   112.7  -2.235  0.8927
##   161.8  -1.986  0.9695
##   112.7  -5.498  0.0001
##   161.8  -5.684  <.0001
##   112.7  -3.441  0.1409
##   161.8  -3.353  0.1684
##   126.1  -4.530  0.0040
##   168.8  -4.575  0.0029
##   112.7  -0.926  1.0000
##   161.8  -0.502  1.0000
##    27.6   1.026  1.0000
##   153.0   1.065  1.0000
##   169.4   1.437  0.9997
##   153.0   0.385  1.0000
##   169.4   0.849  1.0000
##   154.0   1.625  0.9980
##   170.4   1.930  0.9785
##   161.8  -2.083  0.9479
##   112.7  -1.355  0.9999
##   161.8  -1.780  0.9924
##   112.7  -1.088  1.0000
```

```
##   161.8   3.433  0.1370
##   112.7   3.512  0.1173
##   161.8  -0.265  1.0000
##   112.7   0.249  1.0000
##   161.8   2.066  0.9524
##   112.7   2.305  0.8596
##   168.8   0.469  1.0000
##   123.9   0.880  1.0000
##   161.8   4.917  0.0007
##   112.7   4.821  0.0014
##   169.4   0.404  1.0000
##   153.0   1.065  1.0000
##   169.4  -0.184  1.0000
##   153.0   0.385  1.0000
##   171.3   0.901  1.0000
##   154.0   1.625  0.9980
##   112.7  -2.321  0.8516
##   161.8  -2.083  0.9479
##   112.7  -2.053  0.9532
##   161.8  -1.780  0.9924
##   112.7   2.546  0.7107
##   161.8   3.433  0.1370
##   112.7  -0.717  1.0000
##   161.8  -0.265  1.0000
##   112.7   1.340  0.9999
##   161.8   2.066  0.9524
##   126.1  -0.036  1.0000
##   168.8   0.469  1.0000
##   112.7   3.855  0.0438
##   161.8   4.917  0.0007
##    27.6   1.026  1.0000
##   153.0  -0.680  1.0000
##   169.4  -0.071  1.0000
##   154.0   0.586  1.0000
##   170.4   1.022  1.0000
##   161.8  -3.059  0.3277
##   112.7  -2.216  0.9007
##   161.8  -2.755  0.5516
##   112.7  -1.948  0.9741
##   161.8   2.458  0.7734
##   112.7   2.651  0.6329
##   161.8  -1.241  1.0000
##   112.7  -0.612  1.0000
##   161.8   1.091  1.0000
##   112.7   1.445  0.9997
##   168.8  -0.439  1.0000
##   123.9   0.063  1.0000
##   161.8   3.942  0.0299
##   112.7   3.960  0.0315
##   169.4  -1.104  1.0000
##   153.0  -0.680  1.0000
##   171.3   0.002  1.0000
##   154.0   0.586  1.0000
##   112.7  -3.181  0.2594
```

```
## 161.8 -3.059 0.3277
## 112.7 -2.914 0.4334
## 161.8 -2.755 0.5516
## 112.7  1.686 0.9961
## 161.8  2.458 0.7734
## 112.7 -1.577 0.9986
## 161.8 -1.241 1.0000
## 112.7  0.479 1.0000
## 161.8  1.091 1.0000
## 126.1 -0.845 1.0000
## 168.8 -0.439 1.0000
## 112.7  2.995 0.3760
## 161.8  3.942 0.0299
##  27.6  1.026 1.0000
## 154.0  1.250 1.0000
## 170.4  1.602 0.9984
## 161.8 -2.436 0.7876
## 112.7 -1.666 0.9967
## 161.8 -2.133 0.9336
## 112.7 -1.399 0.9998
## 161.8  3.081 0.3134
## 112.7  3.201 0.2488
## 161.8 -0.618 1.0000
## 112.7 -0.062 1.0000
## 161.8  1.713 0.9956
## 112.7  1.994 0.9661
## 168.8  0.140 1.0000
## 123.9  0.585 1.0000
## 161.8  4.565 0.0030
## 112.7  4.510 0.0047
## 171.3  0.576 1.0000
## 154.0  1.250 1.0000
## 112.7 -2.632 0.6476
## 161.8 -2.436 0.7876
## 112.7 -2.364 0.8279
## 161.8 -2.133 0.9336
## 112.7  2.235 0.8926
## 161.8  3.081 0.3134
## 112.7 -1.028 1.0000
## 161.8 -0.618 1.0000
## 112.7  1.029 1.0000
## 161.8  1.713 0.9956
## 126.1 -0.329 1.0000
## 168.8  0.140 1.0000
## 112.7  3.544 0.1076
## 161.8  4.565 0.0030
##  27.6  1.026 1.0000
## 164.1 -3.535 0.1038
## 117.4 -2.645 0.6374
## 164.1 -3.238 0.2222
## 117.4 -2.383 0.8174
## 164.1  1.869 0.9855
## 117.4  2.122 0.9347
## 164.1 -1.754 0.9939
```

```
## 117.4 -1.074 1.0000
## 164.1  0.530 1.0000
## 117.4  0.940 1.0000
## 170.2 -0.934 1.0000
## 127.7 -0.390 1.0000
## 164.1  3.322 0.1815
## 117.4  3.404 0.1538
## 115.3 -3.624 0.0859
## 164.1 -3.535 0.1038
## 115.3 -3.360 0.1719
## 164.1 -3.238 0.2222
## 115.3  1.187 1.0000
## 164.1  1.869 0.9855
## 115.3 -2.039 0.9568
## 164.1 -1.754 0.9939
## 115.3 -0.006 1.0000
## 164.1  0.530 1.0000
## 128.1 -1.288 1.0000
## 170.2 -0.934 1.0000
## 115.3  2.481 0.7561
## 164.1  3.322 0.1815
##  27.6  1.026 1.0000
## 153.0  0.331 1.0000
## 169.4  0.803 1.0000
## 153.0  6.025 <.0001
## 169.4  5.722 <.0001
## 153.0  1.986 0.9693
## 169.4  2.232 0.8972
## 153.0  4.532 0.0036
## 169.4  4.432 0.0050
## 156.2  2.596 0.6751
## 173.4  2.789 0.5248
## 153.0  7.646 <.0001
## 169.4  7.122 <.0001
## 169.4 -0.230 1.0000
## 153.0  0.331 1.0000
## 169.4  4.689 0.0018
## 153.0  6.025 <.0001
## 169.4  1.199 1.0000
## 153.0  1.986 0.9693
## 169.4  3.399 0.1492
## 153.0  4.532 0.0036
## 174.2  1.794 0.9917
## 156.2  2.596 0.6751
## 169.4  6.089 <.0001
## 153.0  7.646 <.0001
##  27.6  1.026 1.0000
## 153.0  5.694 <.0001
## 169.4  5.436 0.0001
## 153.0  1.654 0.9973
## 169.4  1.946 0.9762
## 153.0  4.201 0.0124
## 169.4  4.146 0.0146
## 156.2  2.292 0.8691
```

```
##   173.4   2.519  0.7317
##   153.0   7.315  <.0001
##   169.4   6.836  <.0001
##   169.4   4.403  0.0056
##   153.0   5.694  <.0001
##   169.4   0.913  1.0000
##   153.0   1.654  0.9973
##   169.4   3.113  0.2927
##   153.0   4.201  0.0124
##   174.2   1.527  0.9993
##   156.2   2.292  0.8691
##   169.4   5.803  <.0001
##   153.0   7.315  <.0001
##    27.6   1.026  1.0000
##   153.0  -4.040  0.0218
##   169.4  -2.974  0.3855
##   153.0  -1.493  0.9995
##   169.4  -0.774  1.0000
##   156.2  -2.940  0.4104
##   173.4  -2.120  0.9379
##   153.0   1.621  0.9981
##   169.4   1.917  0.9802
##   169.4  -4.006  0.0237
##   153.0  -4.040  0.0218
##   169.4  -1.807  0.9908
##   153.0  -1.493  0.9995
##   174.2  -3.058  0.3269
##   156.2  -2.940  0.4104
##   169.4   0.884  1.0000
##   153.0   1.621  0.9981
##    27.6   1.026  1.0000
##   153.0   2.546  0.7120
##   169.4   2.716  0.5824
##   156.2   0.772  1.0000
##   173.4   1.171  1.0000
##   153.0   5.660  <.0001
##   169.4   5.407  0.0001
##   169.4   1.683  0.9966
##   153.0   2.546  0.7120
##   174.2   0.195  1.0000
##   156.2   0.772  1.0000
##   169.4   4.374  0.0063
##   153.0   5.660  <.0001
##    27.6   1.026  1.0000
##   156.2  -1.568  0.9989
##   173.4  -0.903  1.0000
##   153.0   3.114  0.2933
##   169.4   3.207  0.2381
##   174.2  -1.856  0.9870
##   156.2  -1.568  0.9989
##   169.4   2.174  0.9199
##   153.0   3.114  0.2933
##    27.6   1.026  1.0000
##   156.2   4.429  0.0052
```

```
##  174.2   4.364  0.0064
##  173.4   3.441  0.1334
##  156.2   4.429  0.0052
##   27.6   1.026  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

```
# 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
anova(mod1us)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq Mean Sq F value
## state               1 0.03029 0.03029  0.5860
## year                5 2.09925 0.41985  8.1224
## insecticide         1 0.11396 0.11396  2.2046
## state:year          5 0.44031 0.08806  1.7037
## year:insecticide    5 0.13123 0.02625  0.5078
```

```
anova(mod2us)
```

```
## Analysis of Variance Table
##             npar  Sum Sq Mean Sq F value
## state          1 0.03093 0.03093  0.5860
## year           5 2.09925 0.41985  7.9541
## insecticide    1 0.11637 0.11637  2.2046
## state:year     5 0.44031 0.08806  1.6684
```

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

```
## 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   15 57.202 101.75 -13.601   27.202
## mod1us   20 64.690 124.09 -12.345   24.690 2.5123  5     0.7746
```

```
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
```

```
##     64.7    124.1    -12.3     24.7      124
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.29685 -0.70152  0.00436  0.71214  2.54501
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.04229  0.2056
##  Residual             0.05169  0.2274
## Number of obs: 144, groups:  plot, 24
##
## Fixed effects:
##                                Estimate Std. Error t value
## (Intercept)                   0.7873060  0.1083839   7.264
## statewarmed                   0.2635815  0.1251509   2.106
## year2017                      0.1840621  0.1136776   1.619
## year2018                      0.3321506  0.1136776   2.922
## year2019                      0.4054371  0.1136776   3.567
## year2020                      0.5302147  0.1136776   4.664
## year2021                      0.3994164  0.1136776   3.514
## insecticideno_insects         0.1421416  0.1251509   1.136
## statewarmed:year2017         -0.1648808  0.1312635  -1.256
## statewarmed:year2018         -0.2102930  0.1312635  -1.602
## statewarmed:year2019         -0.3554568  0.1312635  -2.708
## statewarmed:year2020         -0.2762744  0.1312635  -2.105
## statewarmed:year2021         -0.1515285  0.1312635  -1.154
## year2017:insecticideno_insects -0.0008835  0.1312635  -0.007
## year2018:insecticideno_insects  0.0929232  0.1312635   0.708
## year2019:insecticideno_insects  0.0324715  0.1312635   0.247
## year2020:insecticideno_insects -0.0728765  0.1312635  -0.555
## year2021:insecticideno_insects -0.0839352  0.1312635  -0.639

##
## Correlation matrix not shown by default, as p = 18 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
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
##     57.2    101.7    -13.6     27.2      129
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.44890 -0.64524 -0.09725  0.78371  2.53246
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
```

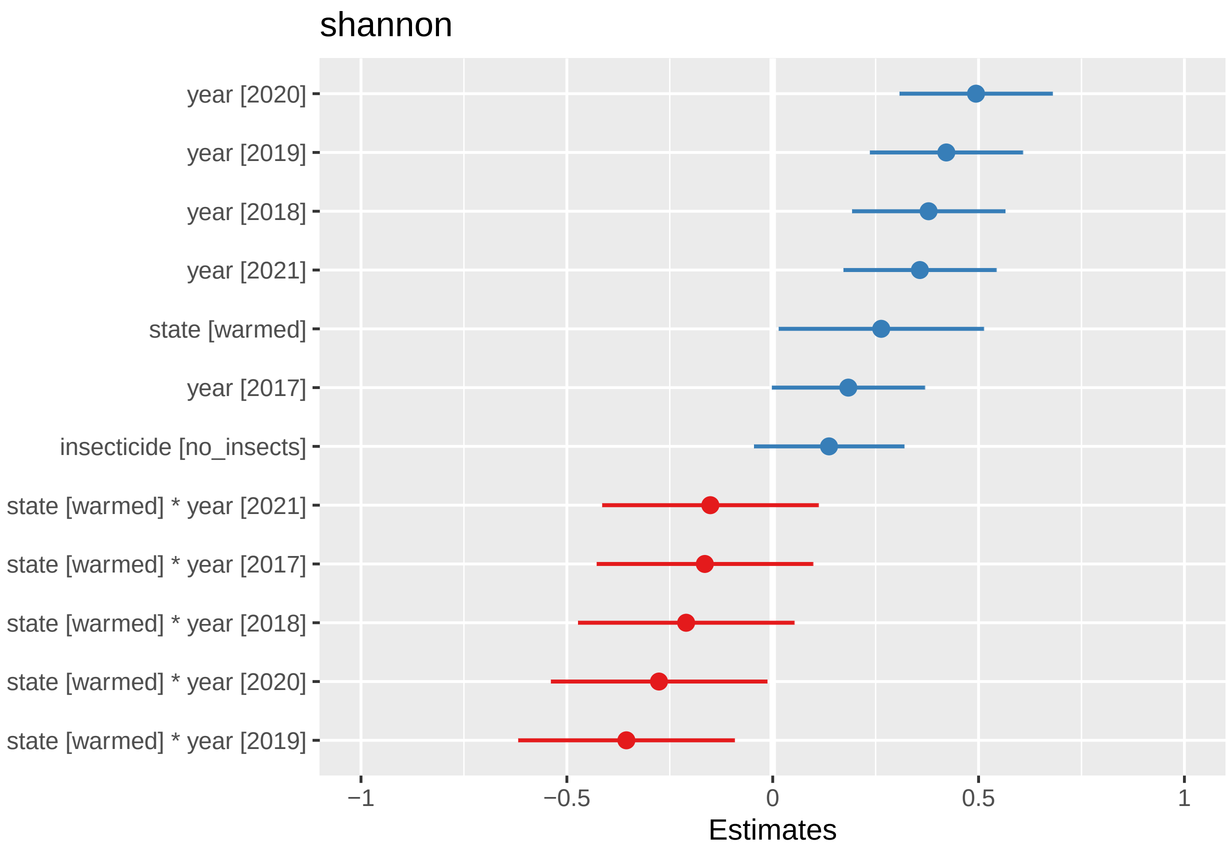
```
##  plot     (Intercept) 0.04210  0.2052
##  Residual             0.05278  0.2297
## Number of obs: 144, groups:  plot, 24
##
## Fixed effects:
##                         Estimate Std. Error t value
## (Intercept)              0.79000    0.10014   7.889
## statewarmed              0.26358    0.12576   2.096
## year2017                 0.18362    0.09379   1.958
## year2018                 0.37861    0.09379   4.037
## year2019                 0.42167    0.09379   4.496
## year2020                 0.49378    0.09379   5.264
## year2021                 0.35745    0.09379   3.811
## insecticideno_insects    0.13676    0.09211   1.485
## statewarmed:year2017    -0.16488    0.13264  -1.243
## statewarmed:year2018    -0.21029    0.13264  -1.585
## statewarmed:year2019    -0.35546    0.13264  -2.680
## statewarmed:year2020    -0.27627    0.13264  -2.083
## statewarmed:year2021    -0.15153    0.13264  -1.142
```

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

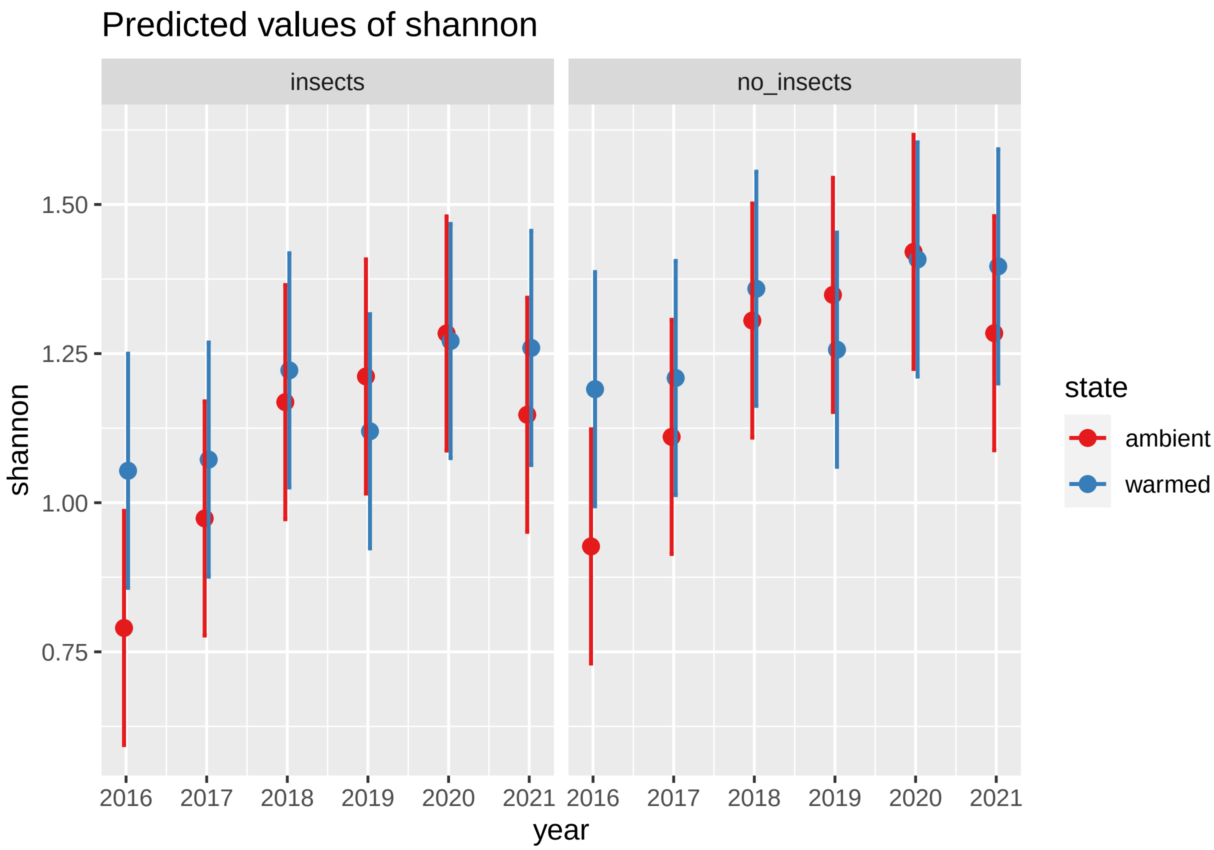
```
AICctab(mod1us, mod2us, weights=T) # model 2
```

```
##        dAICc df weight
## mod2us  0.0  15 0.995
## mod1us 10.6  20 0.005
```

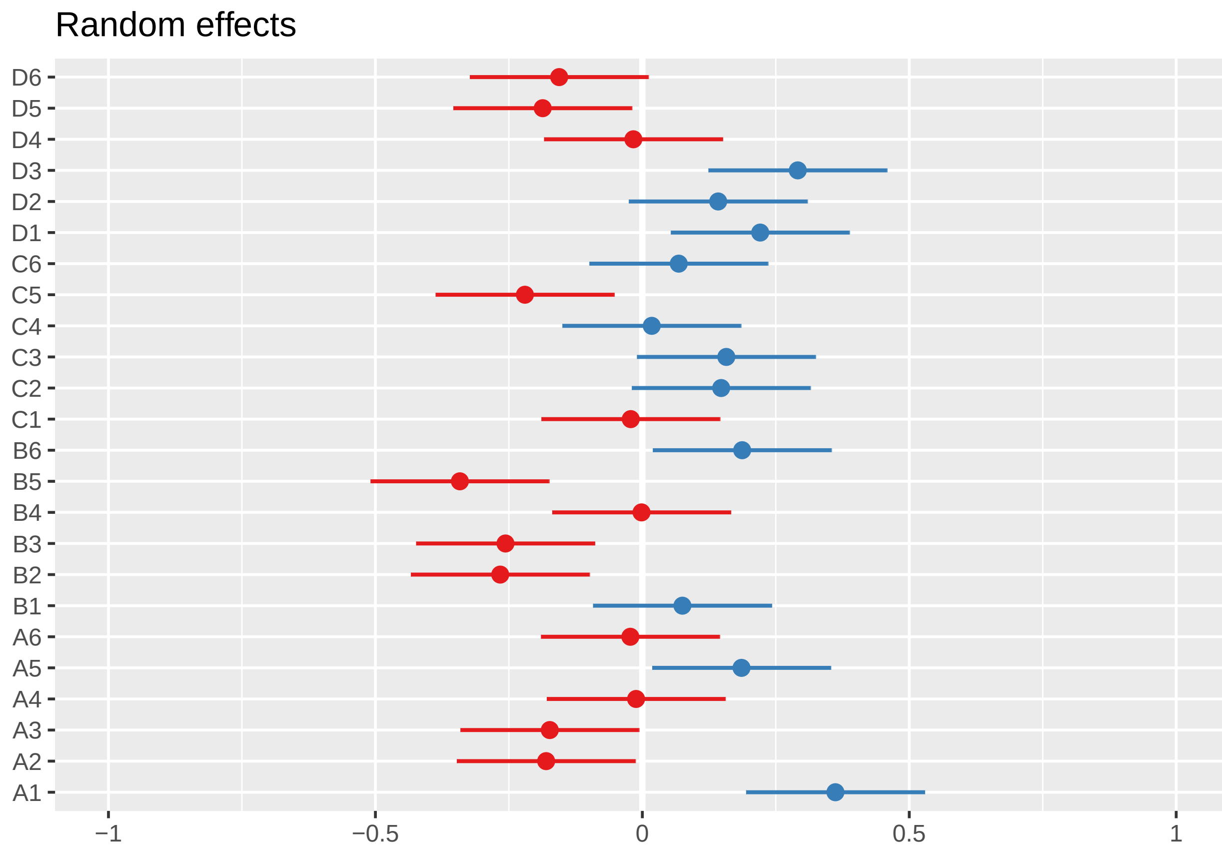
```
# Plot the fixed effects estimates for different models
# these are the fixed effects estimates from summary(mod1)
plot_model(mod2us, sort.est = TRUE)
```




```
# 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"))
```




```
# 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   10 55.267  84.965 -17.633   35.267
## mod2us   15 57.202 101.749 -13.601   27.202 8.0646  5     0.1527
```

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

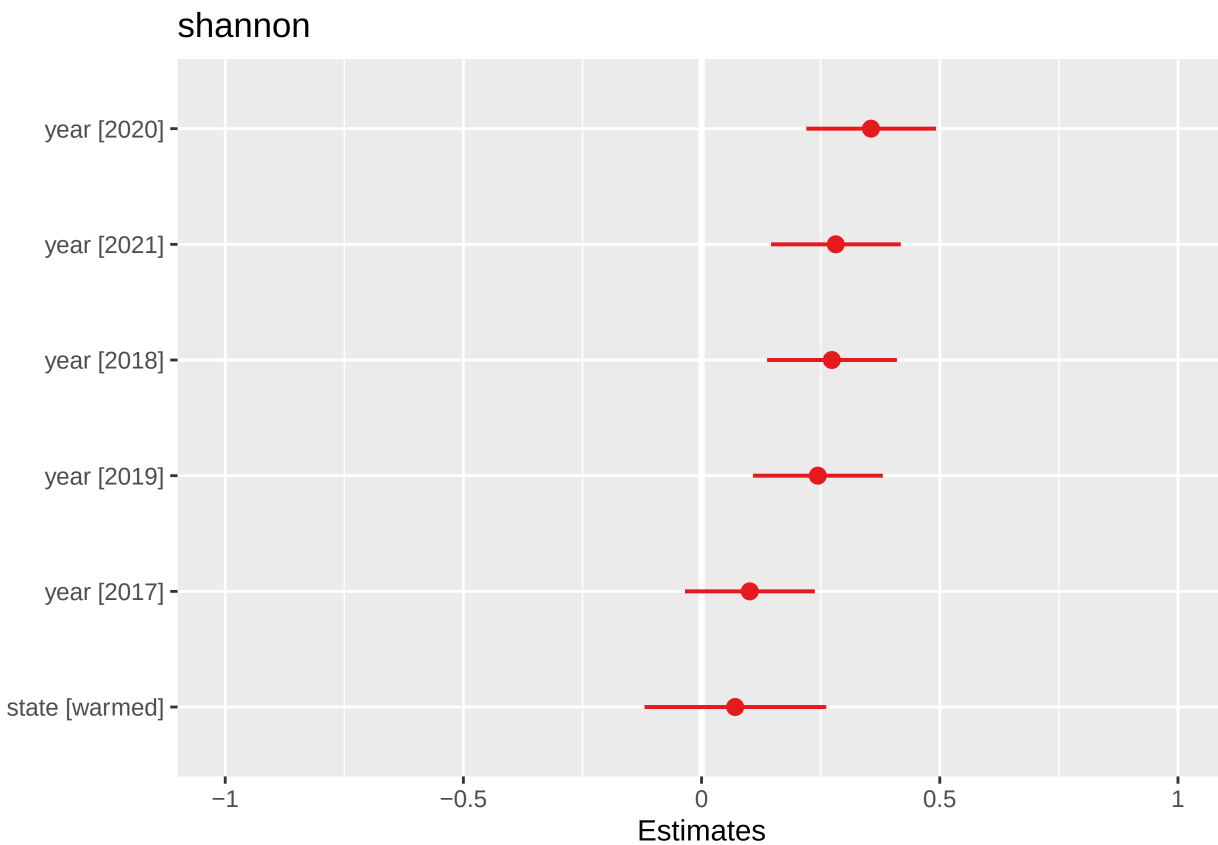
```
##        dAICc df weight
## mod3us  0.0  10 1
## mod1us 14.6  20 <0.001
```

```
# 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)
```

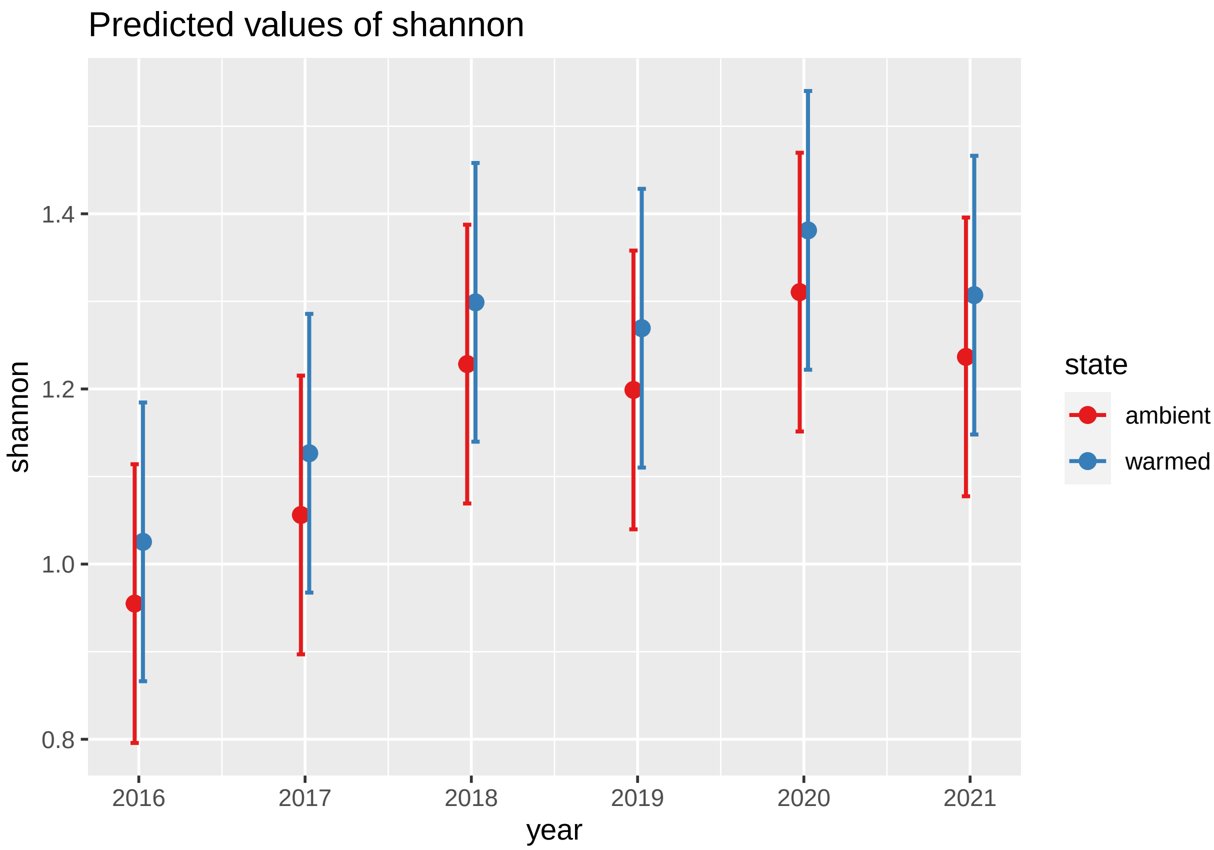
```
## Data: umbs_diversity
## Models:
## mod5us: shannon ~ state + year + (1 | plot)
```

```
## mod3us: shannon ~ state + year + insecticide + (1 | plot)
##        npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod5us    9 55.376 82.104 -18.688   37.376
## mod3us   10 55.267 84.965 -17.633   35.267 2.1091  1     0.1464
```

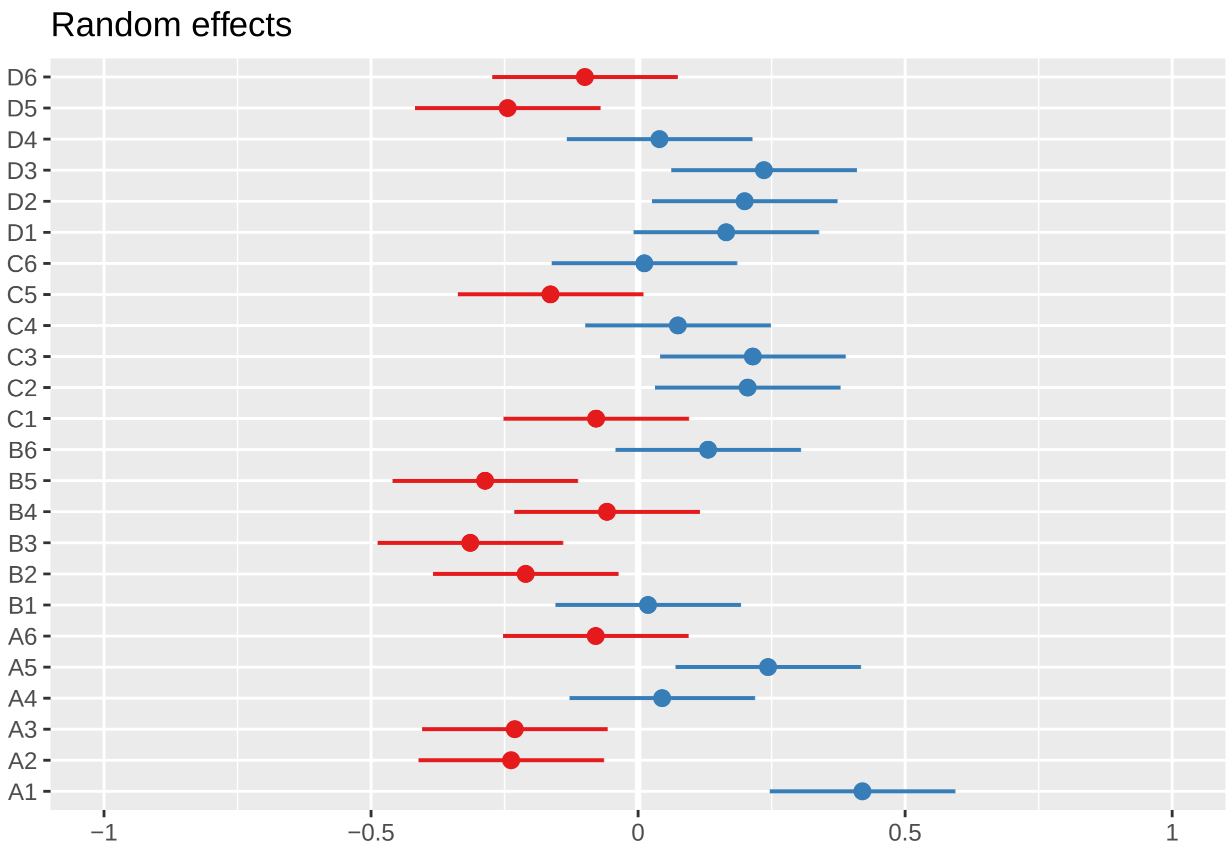
```
# No p>0.05 so insecticide does not strongly improve model fit so we will go with model 5

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




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




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




```
# 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
# 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	144
Dependent variable	shannon
Type	Mixed effects linear regression

AIC	55.38
BIC	82.10
Pseudo-R^2 (fixed effects)	0.13
Pseudo-R^2 (total)	0.52

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

```
## $`emmeans of state, year`
##  state   year emmean     SE   df lower.CL upper.CL
##  ambient 2016  0.955 0.0842 51.1    0.786     1.12
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	0.95	0.08	11.76	46.93	0.00
statewarmed	0.07	0.10	0.73	24.00	0.47
year2017	0.10	0.07	1.48	120.00	0.14
year2018	0.27	0.07	3.99	120.00	0.00
year2019	0.24	0.07	3.56	120.00	0.00
year2020	0.36	0.07	5.19	120.00	0.00
year2021	0.28	0.07	4.11	120.00	0.00

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.21
Residual		0.24

Grouping Variables		
Group	# groups	ICC
plot	24	0.45

```
##  warmed  2016  1.025 0.0842 51.1    0.856     1.19
##  ambient 2017  1.056 0.0842 51.1    0.887     1.23
##  warmed  2017  1.127 0.0842 51.1    0.957     1.30
##  ambient 2018  1.228 0.0842 51.1    1.059     1.40
##  warmed  2018  1.299 0.0842 51.1    1.130     1.47
##  ambient 2019  1.199 0.0842 51.1    1.030     1.37
##  warmed  2019  1.269 0.0842 51.1    1.100     1.44
##  ambient 2020  1.311 0.0842 51.1    1.141     1.48
##  warmed  2020  1.381 0.0842 51.1    1.212     1.55
##  ambient 2021  1.237 0.0842 51.1    1.067     1.41
##  warmed  2021  1.307 0.0842 51.1    1.138     1.48
##
## 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 year2016 - warmed year2016  -0.07051 0.1005  26.2  -0.701  0.9999
##  ambient year2016 - ambient year2017 -0.10118 0.0701 125.2  -1.444  0.9521
##  ambient year2016 - warmed year2017  -0.17169 0.1225  56.5  -1.401  0.9585
##  ambient year2016 - ambient year2018 -0.27347 0.0701 125.2  -3.903  0.0082
##  ambient year2016 - warmed year2018  -0.34397 0.1225  56.5  -2.807  0.2049
##  ambient year2016 - ambient year2019 -0.24394 0.0701 125.2  -3.482  0.0320
##  ambient year2016 - warmed year2019  -0.31445 0.1225  56.5  -2.566  0.3228
##  ambient year2016 - ambient year2020 -0.35564 0.0701 125.2  -5.076  0.0001
##  ambient year2016 - warmed year2020  -0.42615 0.1225  56.5  -3.478  0.0416
##  ambient year2016 - ambient year2021 -0.28168 0.0701 125.2  -4.020  0.0054
##  ambient year2016 - warmed year2021  -0.35219 0.1225  56.5  -2.874  0.1784
##  warmed year2016 - ambient year2017  -0.03067 0.1225  56.5  -0.250  1.0000
```

```
##  warmed year2016 - warmed year2017   -0.10118 0.0701 125.2  -1.444  0.9521
##  warmed year2016 - ambient year2018  -0.20296 0.1225  56.5  -1.656  0.8797
##  warmed year2016 - warmed year2018   -0.27347 0.0701 125.2  -3.903  0.0082
##  warmed year2016 - ambient year2019  -0.17344 0.1225  56.5  -1.415  0.9555
##  warmed year2016 - warmed year2019   -0.24394 0.0701 125.2  -3.482  0.0320
##  warmed year2016 - ambient year2020  -0.28513 0.1225  56.5  -2.327  0.4706
##  warmed year2016 - warmed year2020   -0.35564 0.0701 125.2  -5.076  0.0001
##  warmed year2016 - ambient year2021  -0.21118 0.1225  56.5  -1.723  0.8498
##  warmed year2016 - warmed year2021   -0.28168 0.0701 125.2  -4.020  0.0054
##  ambient year2017 - warmed year2017  -0.07051 0.1005  26.2  -0.701  0.9999
##  ambient year2017 - ambient year2018 -0.17229 0.0701 125.2  -2.459  0.3755
##  ambient year2017 - warmed year2018  -0.24280 0.1225  56.5  -1.981  0.7034
##  ambient year2017 - ambient year2019 -0.14276 0.0701 125.2  -2.038  0.6670
##  ambient year2017 - warmed year2019  -0.21327 0.1225  56.5  -1.741  0.8415
##  ambient year2017 - ambient year2020 -0.25446 0.0701 125.2  -3.632  0.0201
##  ambient year2017 - warmed year2020  -0.32497 0.1225  56.5  -2.652  0.2768
##  ambient year2017 - ambient year2021 -0.18050 0.0701 125.2  -2.576  0.3045
##  ambient year2017 - warmed year2021  -0.25101 0.1225  56.5  -2.049  0.6594
##  warmed year2017 - ambient year2018  -0.10178 0.1225  56.5  -0.831  0.9995
##  warmed year2017 - warmed year2018   -0.17229 0.0701 125.2  -2.459  0.3755
##  warmed year2017 - ambient year2019  -0.07226 0.1225  56.5  -0.590  1.0000
##  warmed year2017 - warmed year2019   -0.14276 0.0701 125.2  -2.038  0.6670
##  warmed year2017 - ambient year2020  -0.18395 0.1225  56.5  -1.501  0.9341
##  warmed year2017 - warmed year2020   -0.25446 0.0701 125.2  -3.632  0.0201
##  warmed year2017 - ambient year2021  -0.11000 0.1225  56.5  -0.898  0.9989
##  warmed year2017 - warmed year2021   -0.18050 0.0701 125.2  -2.576  0.3045
##  ambient year2018 - warmed year2018  -0.07051 0.1005  26.2  -0.701  0.9999
##  ambient year2018 - ambient year2019  0.02952 0.0701 125.2   0.421  1.0000
##  ambient year2018 - warmed year2019  -0.04099 0.1225  56.5  -0.335  1.0000
##  ambient year2018 - ambient year2020 -0.08217 0.0701 125.2  -1.173  0.9901
##  ambient year2018 - warmed year2020  -0.15268 0.1225  56.5  -1.246  0.9824
##  ambient year2018 - ambient year2021 -0.00822 0.0701 125.2  -0.117  1.0000
##  ambient year2018 - warmed year2021  -0.07873 0.1225  56.5  -0.643  1.0000
##  warmed year2018 - ambient year2019   0.10003 0.1225  56.5   0.816  0.9995
##  warmed year2018 - warmed year2019    0.02952 0.0701 125.2   0.421  1.0000
##  warmed year2018 - ambient year2020  -0.01166 0.1225  56.5  -0.095  1.0000
##  warmed year2018 - warmed year2020   -0.08217 0.0701 125.2  -1.173  0.9901
##  warmed year2018 - ambient year2021   0.06229 0.1225  56.5   0.508  1.0000
##  warmed year2018 - warmed year2021   -0.00822 0.0701 125.2  -0.117  1.0000
##  ambient year2019 - warmed year2019  -0.07051 0.1005  26.2  -0.701  0.9999
##  ambient year2019 - ambient year2020 -0.11169 0.0701 125.2  -1.594  0.9081
##  ambient year2019 - warmed year2020  -0.18220 0.1225  56.5  -1.487  0.9381
##  ambient year2019 - ambient year2021 -0.03774 0.0701 125.2  -0.539  1.0000
##  ambient year2019 - warmed year2021  -0.10825 0.1225  56.5  -0.883  0.9990
##  warmed year2019 - ambient year2020  -0.04119 0.1225  56.5  -0.336  1.0000
##  warmed year2019 - warmed year2020   -0.11169 0.0701 125.2  -1.594  0.9081
##  warmed year2019 - ambient year2021   0.03277 0.1225  56.5   0.267  1.0000
##  warmed year2019 - warmed year2021   -0.03774 0.0701 125.2  -0.539  1.0000
##  ambient year2020 - warmed year2020  -0.07051 0.1005  26.2  -0.701  0.9999
##  ambient year2020 - ambient year2021  0.07395 0.0701 125.2   1.056  0.9959
##  ambient year2020 - warmed year2021   0.00345 0.1225  56.5   0.028  1.0000
##  warmed year2020 - ambient year2021   0.14446 0.1225  56.5   1.179  0.9886
##  warmed year2020 - warmed year2021    0.07395 0.0701 125.2   1.056  0.9959
##  ambient year2021 - warmed year2021  -0.07051 0.1005  26.2  -0.701  0.9999
```

```
##
## Degrees-of-freedom method: kenward-roger
## P value adjustment: tukey method for comparing a family of 12 estimates
```

RICHNESS KBS

```
# 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
anova(mod1kr)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq Mean Sq F value
## state               1  0.6114 0.61141 12.2210
## year                6 11.0153 1.83589 36.6960
## insecticide         1  0.0096 0.00963  0.1925
## state:year          6  0.3702 0.06170  1.2333
## year:insecticide    6  0.8756 0.14593  2.9169
```

```
anova(mod2kr)
```

```
## Analysis of Variance Table
##             npar  Sum Sq Mean Sq F value
## state          1  0.6988 0.69877 12.3869
## year           6 11.0167 1.83611 32.5482
## insecticide    1  0.0110 0.01098  0.1947
## state:year     6  0.3685 0.06142  1.0888
```

```
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 53.685 106.38 -9.8423  19.6847
## mod1kr   23 49.235 120.53 -1.6175   3.2351 16.45  6    0.01153 *
## ---
## 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
##     49.2    120.5     -1.6      3.2      141
##
## Scaled residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -2.48424 -0.51231  0.00266  0.63593  2.32076
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.01724  0.1313
##  Residual             0.05003  0.2237
## Number of obs: 164, groups:  plot, 24
##
## Fixed effects:
##                                Estimate Std. Error t value
## (Intercept)                    2.123823   0.091696  23.162
## statewarmed                   -0.104768   0.105881  -0.989
## year2016                       0.065933   0.111837   0.590
## year2017                      -0.699255   0.111837  -6.252
## year2018                       0.045343   0.111837   0.405
## year2019                      -0.178694   0.111837  -1.598
## year2020                       0.007567   0.113370   0.067
## year2021                      -0.152749   0.116195  -1.315
## insecticideno_insects          0.067578   0.105881   0.638
## statewarmed:year2016          -0.060110   0.129138  -0.465
## statewarmed:year2017          -0.185078   0.129138  -1.433
## statewarmed:year2018          -0.200340   0.129138  -1.551
## statewarmed:year2019           0.004066   0.129138   0.031
## statewarmed:year2020          -0.134445   0.134380  -1.000
## statewarmed:year2021          -0.266339   0.130837  -2.036
## year2016:insecticideno_insects  0.127000   0.129138   0.983
## year2017:insecticideno_insects  0.172252   0.129138   1.334
## year2018:insecticideno_insects -0.072595   0.129138  -0.562
## year2019:insecticideno_insects -0.194921   0.129138  -1.509
## year2020:insecticideno_insects -0.070941   0.135112  -0.525
## year2021:insecticideno_insects -0.258950   0.130837  -1.979

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

```
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
##     53.7    106.4     -9.8     19.7      147
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.52036 -0.60400  0.02673  0.66422  2.08295
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
```

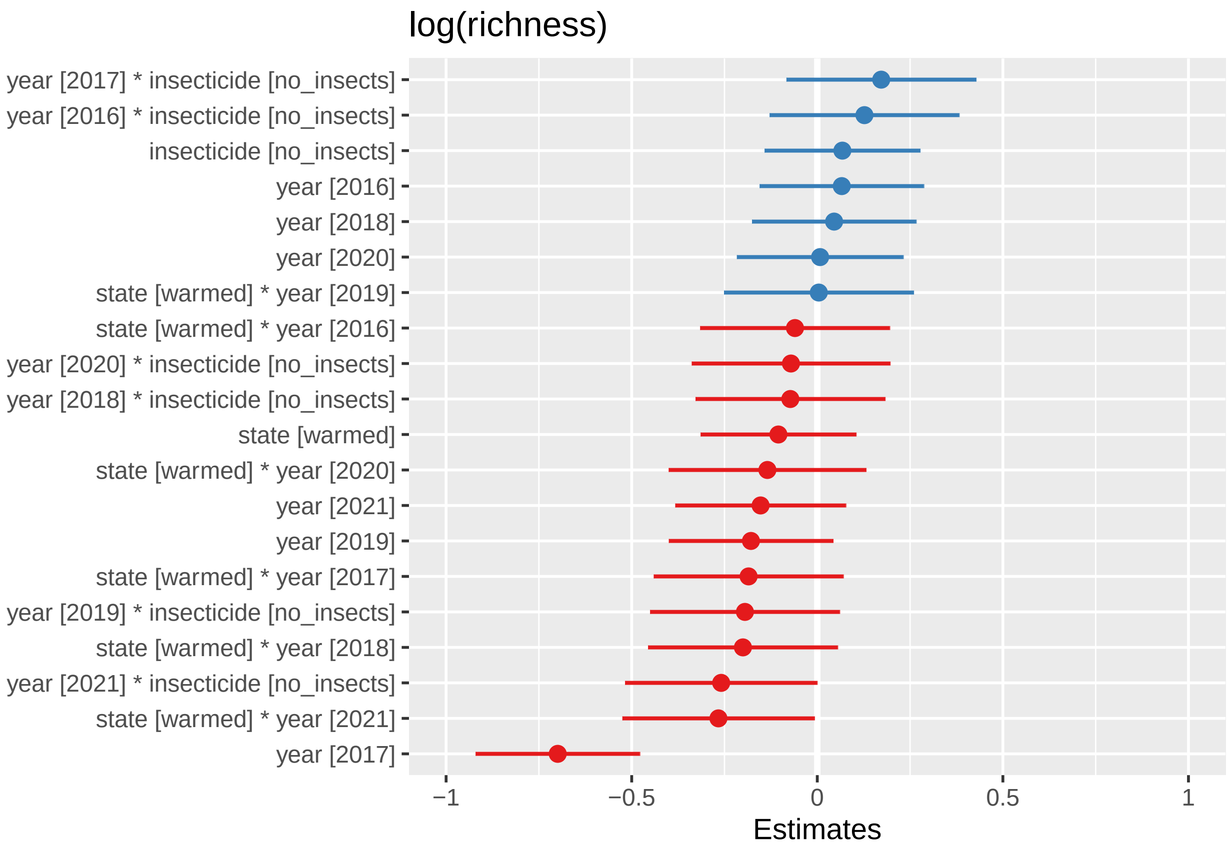
```
##  plot     (Intercept) 0.01593  0.1262
##  Residual             0.05641  0.2375
## Number of obs: 164, groups:  plot, 24
##
## Fixed effects:
##                         Estimate Std. Error t value
## (Intercept)             2.144001   0.083898  25.555
## statewarmed            -0.104768   0.109807  -0.954
## year2016                0.129433   0.096964   1.335
## year2017               -0.613130   0.096964  -6.323
## year2018                0.009045   0.096964   0.093
## year2019               -0.276155   0.096964  -2.848
## year2020               -0.025242   0.102209  -0.247
## year2021               -0.294291   0.099375  -2.961
## insecticideno_insects   0.027222   0.063561   0.428
## statewarmed:year2016   -0.060110   0.137128  -0.438
## statewarmed:year2017   -0.185078   0.137128  -1.350
## statewarmed:year2018   -0.200340   0.137128  -1.461
## statewarmed:year2019    0.004066   0.137128   0.030
## statewarmed:year2020   -0.136169   0.142537  -0.955
## statewarmed:year2021   -0.254272   0.138843  -1.831
```

```
##
## 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
```

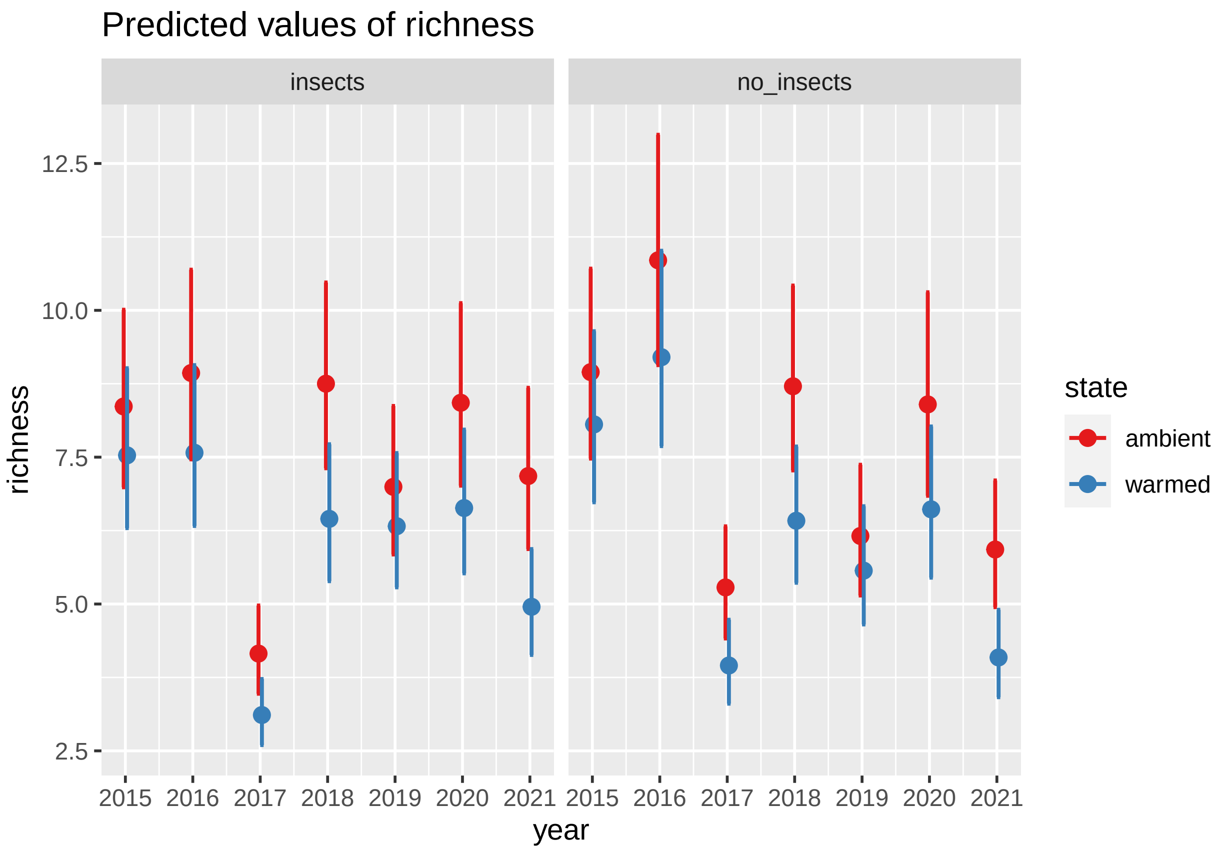
```
##        dAICc df weight
## mod1kr  0.0  23 0.59
## mod2kr  0.8  17 0.41
```

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

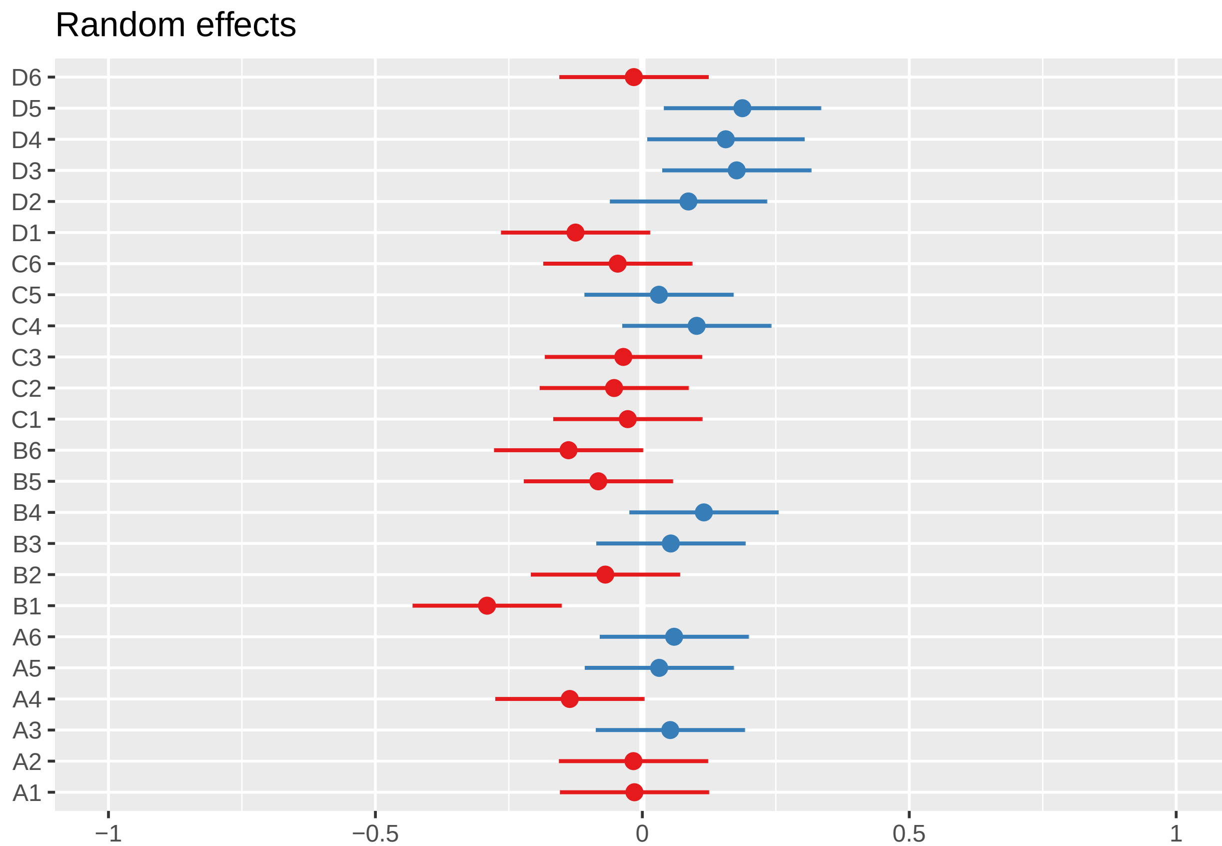



```r
# these are the fixed predicted values:
plot_model(mod1kr, type = "pred", terms = c("year", "state", "insecticide"))
```

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




```
# 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 44.757  97.454 -5.3783  10.7565
## mod1kr   23 49.235 120.532 -1.6175   3.2351 7.5215  6     0.2753
```

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

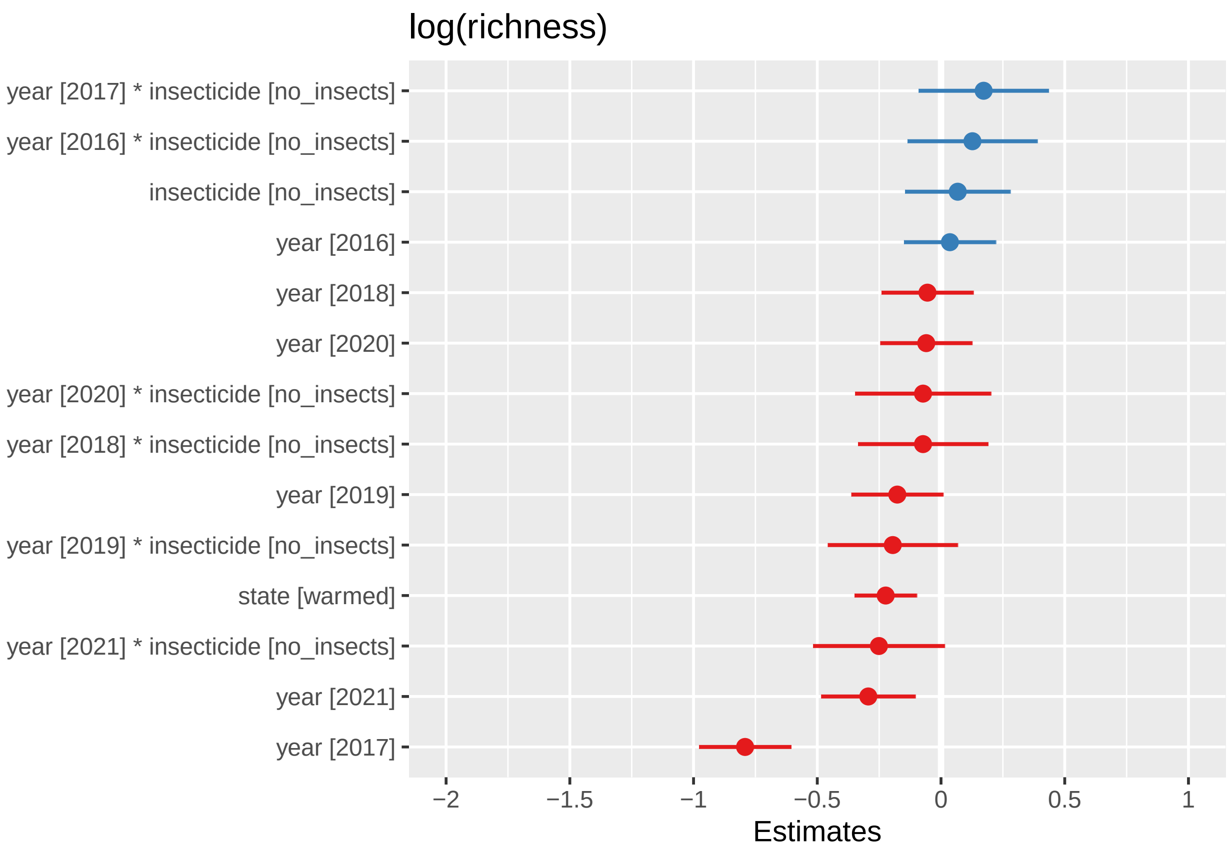
```
##        dAICc df weight
## mod3kr  0.0  17 0.983
## mod1kr  8.2  23 0.017
```

```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)
```

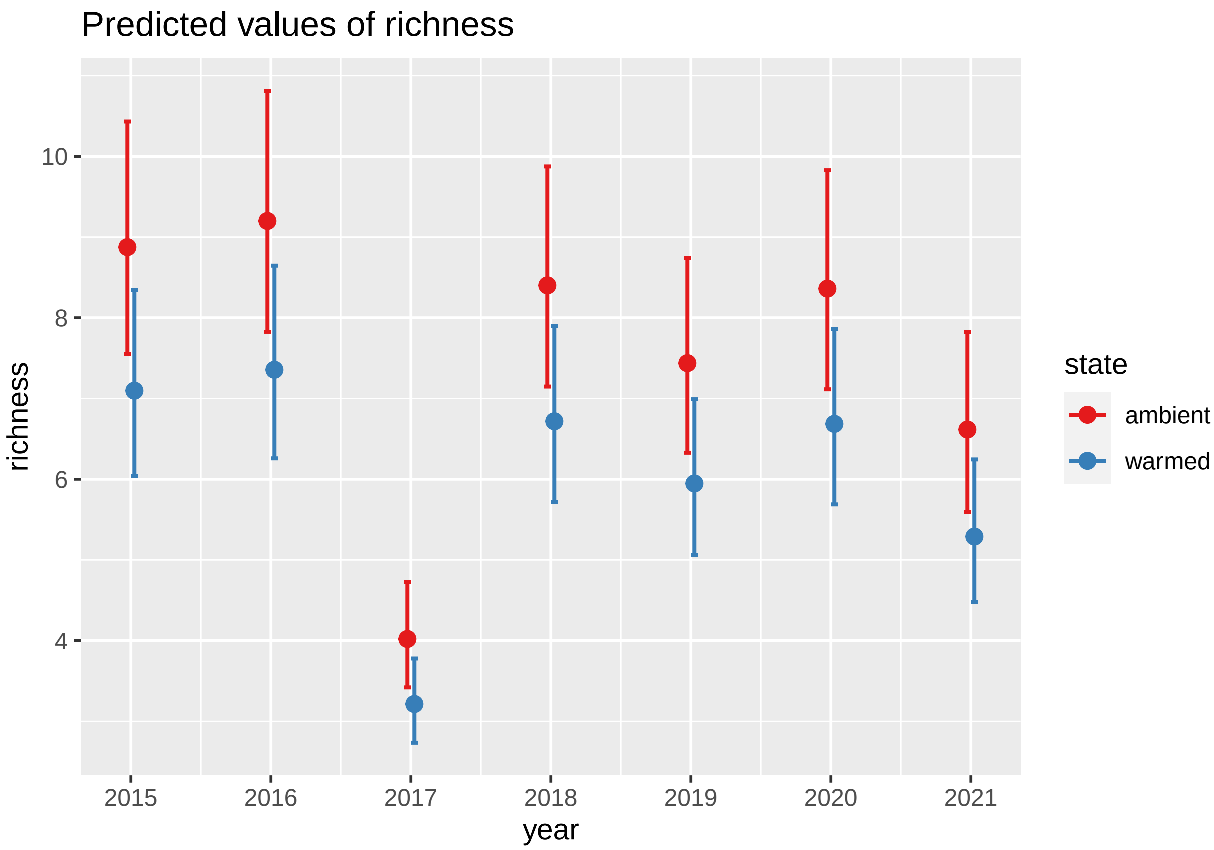
```
## mod3kr: log(richness) ~ state + year + insecticide * year + (1 | plot)
##        npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## mod5kr   10 46.253 77.252 -13.1266   26.253
## mod3kr   17 44.757 97.454  -5.3783   10.757 15.497  7    0.03013 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 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 comple

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

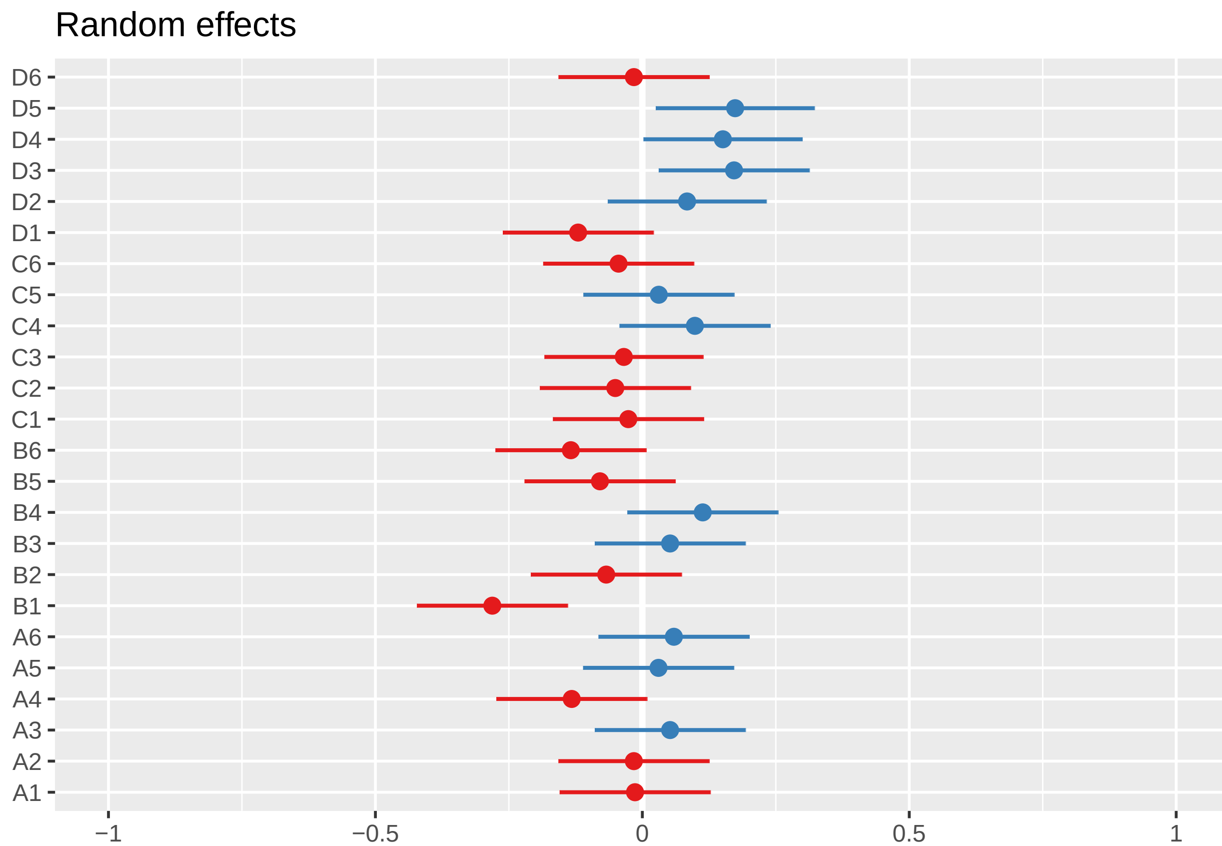



```
# these are the fixed predicted values:
plot_model(mod3kr, type = "pred", terms = c("year", "state"))
```

```
## 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"))
```




```
# 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
# 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 = FALS
summ(mod3kr)
```

Observations	164
Dependent variable	log(richness)
Type	Mixed effects linear regression

AIC	44.76
BIC	97.45
Pseudo-R^2 (fixed effects)	0.55
Pseudo-R^2 (total)	0.66

```
summary(mod3kr)
```

```
## Linear mixed model fit by maximum likelihood  ['lmerMod']
## Formula: log(richness) ~ state + year + insecticide * year + (1 | plot)
##    Data: kbs_diversity
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	2.18	0.08	26.48	94.87	0.00
statewarmed	-0.22	0.06	-3.52	23.78	0.00
year2016	0.04	0.09	0.38	139.78	0.70
year2017	-0.79	0.09	-8.43	139.78	0.00
year2018	-0.05	0.09	-0.58	139.78	0.56
year2019	-0.18	0.09	-1.88	139.78	0.06
year2020	-0.06	0.09	-0.64	139.78	0.53
year2021	-0.29	0.10	-3.05	140.43	0.00
insecticideno__insects	0.07	0.11	0.63	122.90	0.53
year2016:insecticideno__insects	0.13	0.13	0.96	139.78	0.34
year2017:insecticideno__insects	0.17	0.13	1.30	139.78	0.20
year2018:insecticideno__insects	-0.07	0.13	-0.55	139.78	0.59
year2019:insecticideno__insects	-0.19	0.13	-1.47	139.78	0.14
year2020:insecticideno__insects	-0.07	0.14	-0.52	140.95	0.60
year2021:insecticideno__insects	-0.25	0.13	-1.87	140.11	0.06

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.13
Residual		0.23

Grouping Variables		
Group	# groups	ICC
plot	24	0.24

```
##
##      AIC      BIC   logLik deviance df.resid
##     44.8     97.5     -5.4     10.8      147
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.72594 -0.55687  0.02799  0.76049  1.98919
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.01651  0.1285
##  Residual             0.05290  0.2300
## Number of obs: 164, groups:  plot, 24
##
## Fixed effects:
##                               Estimate Std. Error t value
## (Intercept)                    2.18326    0.08244  26.483
## statewarmed                   -0.22363    0.06362  -3.515
## year2016                       0.03588    0.09390   0.382
## year2017                      -0.79179    0.09390  -8.432
```

```
## year2018                          -0.05483    0.09390  -0.584
## year2019                          -0.17666    0.09390  -1.881
## year2020                          -0.05966    0.09390  -0.635
## year2021                          -0.29386    0.09624  -3.053
## insecticideno_insects              0.06758    0.10756   0.628
## year2016:insecticideno_insects  0.12700    0.13279   0.956
## year2017:insecticideno_insects  0.17225    0.13279   1.297
## year2018:insecticideno_insects -0.07260    0.13279  -0.547
## year2019:insecticideno_insects -0.19492    0.13279  -1.468
## year2020:insecticideno_insects -0.07259    0.13880  -0.523
## year2021:insecticideno_insects -0.25101    0.13446  -1.867
```

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

```
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       2.18 0.0871 108    2.011     2.36
##  warmed  2015 insects       1.96 0.0871 108    1.787     2.13
##  ambient 2016 insects       2.22 0.0871 108    2.046     2.39
##  warmed  2016 insects       2.00 0.0871 108    1.823     2.17
##  ambient 2017 insects       1.39 0.0871 108    1.219     1.56
##  warmed  2017 insects       1.17 0.0871 108    0.995     1.34
##  ambient 2018 insects       2.13 0.0871 108    1.956     2.30
##  warmed  2018 insects       1.90 0.0871 108    1.732     2.08
##  ambient 2019 insects       2.01 0.0871 108    1.834     2.18
##  warmed  2019 insects       1.78 0.0871 108    1.610     1.96
##  ambient 2020 insects       2.12 0.0871 108    1.951     2.30
##  warmed  2020 insects       1.90 0.0871 108    1.727     2.07
##  ambient 2021 insects       1.89 0.0903 116    1.711     2.07
##  warmed  2021 insects       1.67 0.0895 114    1.488     1.84
##  ambient 2015 no_insects    2.25 0.0871 108    2.078     2.42
##  warmed  2015 no_insects    2.03 0.0871 108    1.855     2.20
##  ambient 2016 no_insects    2.41 0.0871 108    2.241     2.59
##  warmed  2016 no_insects    2.19 0.0871 108    2.017     2.36
##  ambient 2017 no_insects    1.63 0.0871 108    1.459     1.80
##  warmed  2017 no_insects    1.41 0.0871 108    1.235     1.58
##  ambient 2018 no_insects    2.12 0.0871 108    1.951     2.30
##  warmed  2018 no_insects    1.90 0.0871 108    1.727     2.07
##  ambient 2019 no_insects    1.88 0.0871 108    1.707     2.05
##  warmed  2019 no_insects    1.66 0.0871 108    1.483     1.83
##  ambient 2020 no_insects    2.12 0.0974 133    1.926     2.31
##  warmed  2020 no_insects    1.89 0.0965 131    1.704     2.09
##  ambient 2021 no_insects    1.71 0.0871 108    1.533     1.88
##  warmed  2021 no_insects    1.48 0.0871 108    1.310     1.65
##
## 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
##  ambient year2015 insects - warmed year2015 insects        0.223633 0.0680
##  ambient year2015 insects - ambient year2016 insects      -0.035878 0.0982
##  ambient year2015 insects - warmed year2016 insects        0.187755 0.1195
##  ambient year2015 insects - ambient year2017 insects       0.791795 0.0982
##  ambient year2015 insects - warmed year2017 insects        1.015428 0.1195
##  ambient year2015 insects - ambient year2018 insects       0.054827 0.0982
##  ambient year2015 insects - warmed year2018 insects        0.278460 0.1195
##  ambient year2015 insects - ambient year2019 insects       0.176661 0.0982
##  ambient year2015 insects - warmed year2019 insects        0.400294 0.1195
##  ambient year2015 insects - ambient year2020 insects       0.059655 0.0982
##  ambient year2015 insects - warmed year2020 insects        0.283288 0.1195
##  ambient year2015 insects - ambient year2021 insects       0.293858 0.1007
##  ambient year2015 insects - warmed year2021 insects        0.517491 0.1209
##  ambient year2015 insects - ambient year2015 no_insects   -0.067577 0.1134
##  ambient year2015 insects - warmed year2015 no_insects     0.156056 0.1322
##  ambient year2015 insects - ambient year2016 no_insects   -0.230456 0.1134
##  ambient year2015 insects - warmed year2016 no_insects    -0.006823 0.1322
##  ambient year2015 insects - ambient year2017 no_insects    0.551966 0.1134
##  ambient year2015 insects - warmed year2017 no_insects     0.775599 0.1322
##  ambient year2015 insects - ambient year2018 no_insects    0.059845 0.1134
##  ambient year2015 insects - warmed year2018 no_insects     0.283478 0.1322
##  ambient year2015 insects - ambient year2019 no_insects    0.304005 0.1134
##  ambient year2015 insects - warmed year2019 no_insects     0.527638 0.1322
##  ambient year2015 insects - ambient year2020 no_insects    0.064669 0.1211
##  ambient year2015 insects - warmed year2020 no_insects     0.288303 0.1383
##  ambient year2015 insects - ambient year2021 no_insects    0.477292 0.1134
##  ambient year2015 insects - warmed year2021 no_insects     0.700925 0.1322
##  warmed year2015 insects - ambient year2016 insects       -0.259511 0.1195
##  warmed year2015 insects - warmed year2016 insects        -0.035878 0.0982
##  warmed year2015 insects - ambient year2017 insects        0.568161 0.1195
##  warmed year2015 insects - warmed year2017 insects         0.791795 0.0982
##  warmed year2015 insects - ambient year2018 insects       -0.168806 0.1195
##  warmed year2015 insects - warmed year2018 insects         0.054827 0.0982
##  warmed year2015 insects - ambient year2019 insects       -0.046972 0.1195
##  warmed year2015 insects - warmed year2019 insects         0.176661 0.0982
##  warmed year2015 insects - ambient year2020 insects       -0.163978 0.1195
##  warmed year2015 insects - warmed year2020 insects         0.059655 0.0982
##  warmed year2015 insects - ambient year2021 insects        0.070224 0.1221
##  warmed year2015 insects - warmed year2021 insects         0.293858 0.1007
##  warmed year2015 insects - ambient year2015 no_insects    -0.291211 0.1322
##  warmed year2015 insects - warmed year2015 no_insects     -0.067577 0.1134
##  warmed year2015 insects - ambient year2016 no_insects    -0.454089 0.1322
##  warmed year2015 insects - warmed year2016 no_insects     -0.230456 0.1134
##  warmed year2015 insects - ambient year2017 no_insects     0.328332 0.1322
##  warmed year2015 insects - warmed year2017 no_insects      0.551966 0.1134
##  warmed year2015 insects - ambient year2018 no_insects    -0.163789 0.1322
##  warmed year2015 insects - warmed year2018 no_insects      0.059845 0.1134
##  warmed year2015 insects - ambient year2019 no_insects     0.080372 0.1322
##  warmed year2015 insects - warmed year2019 no_insects      0.304005 0.1134
##  warmed year2015 insects - ambient year2020 no_insects    -0.158964 0.1395
##  warmed year2015 insects - warmed year2020 no_insects      0.064669 0.1211
```

```
##  warmed year2015 insects - ambient year2021 no_insects      0.253658 0.1322
##  warmed year2015 insects - warmed year2021 no_insects       0.477292 0.1134
##  ambient year2016 insects - warmed year2016 insects         0.223633 0.0680
##  ambient year2016 insects - ambient year2017 insects        0.827673 0.0982
##  ambient year2016 insects - warmed year2017 insects         1.051306 0.1195
##  ambient year2016 insects - ambient year2018 insects        0.090705 0.0982
##  ambient year2016 insects - warmed year2018 insects         0.314338 0.1195
##  ambient year2016 insects - ambient year2019 insects        0.212539 0.0982
##  ambient year2016 insects - warmed year2019 insects         0.436173 0.1195
##  ambient year2016 insects - ambient year2020 insects        0.095534 0.0982
##  ambient year2016 insects - warmed year2020 insects         0.319167 0.1195
##  ambient year2016 insects - ambient year2021 insects        0.329736 0.1007
##  ambient year2016 insects - warmed year2021 insects         0.553369 0.1209
##  ambient year2016 insects - ambient year2015 no_insects    -0.031699 0.1134
##  ambient year2016 insects - warmed year2015 no_insects      0.191934 0.1322
##  ambient year2016 insects - ambient year2016 no_insects    -0.194578 0.1134
##  ambient year2016 insects - warmed year2016 no_insects      0.029056 0.1322
##  ambient year2016 insects - ambient year2017 no_insects     0.587844 0.1134
##  ambient year2016 insects - warmed year2017 no_insects      0.811477 0.1322
##  ambient year2016 insects - ambient year2018 no_insects     0.095723 0.1134
##  ambient year2016 insects - warmed year2018 no_insects      0.319356 0.1322
##  ambient year2016 insects - ambient year2019 no_insects     0.339883 0.1134
##  ambient year2016 insects - warmed year2019 no_insects      0.563516 0.1322
##  ambient year2016 insects - ambient year2020 no_insects     0.100547 0.1211
##  ambient year2016 insects - warmed year2020 no_insects      0.324181 0.1383
##  ambient year2016 insects - ambient year2021 no_insects     0.513170 0.1134
##  ambient year2016 insects - warmed year2021 no_insects      0.736803 0.1322
##  warmed year2016 insects - ambient year2017 insects         0.604040 0.1195
##  warmed year2016 insects - warmed year2017 insects          0.827673 0.0982
##  warmed year2016 insects - ambient year2018 insects        -0.132928 0.1195
##  warmed year2016 insects - warmed year2018 insects          0.090705 0.0982
##  warmed year2016 insects - ambient year2019 insects        -0.011094 0.1195
##  warmed year2016 insects - warmed year2019 insects          0.212539 0.0982
##  warmed year2016 insects - ambient year2020 insects        -0.128100 0.1195
##  warmed year2016 insects - warmed year2020 insects          0.095534 0.0982
##  warmed year2016 insects - ambient year2021 insects         0.106103 0.1221
##  warmed year2016 insects - warmed year2021 insects          0.329736 0.1007
##  warmed year2016 insects - ambient year2015 no_insects     -0.255333 0.1322
##  warmed year2016 insects - warmed year2015 no_insects      -0.031699 0.1134
##  warmed year2016 insects - ambient year2016 no_insects     -0.418211 0.1322
##  warmed year2016 insects - warmed year2016 no_insects      -0.194578 0.1134
##  warmed year2016 insects - ambient year2017 no_insects      0.364211 0.1322
##  warmed year2016 insects - warmed year2017 no_insects       0.587844 0.1134
##  warmed year2016 insects - ambient year2018 no_insects     -0.127910 0.1322
##  warmed year2016 insects - warmed year2018 no_insects       0.095723 0.1134
##  warmed year2016 insects - ambient year2019 no_insects      0.116250 0.1322
##  warmed year2016 insects - warmed year2019 no_insects       0.339883 0.1134
##  warmed year2016 insects - ambient year2020 no_insects     -0.123086 0.1395
##  warmed year2016 insects - warmed year2020 no_insects       0.100547 0.1211
##  warmed year2016 insects - ambient year2021 no_insects      0.289537 0.1322
##  warmed year2016 insects - warmed year2021 no_insects       0.513170 0.1134
##  ambient year2017 insects - warmed year2017 insects         0.223633 0.0680
##  ambient year2017 insects - ambient year2018 insects       -0.736968 0.0982
##  ambient year2017 insects - warmed year2018 insects        -0.513335 0.1195
```

```
##  ambient year2017 insects - ambient year2019 insects      -0.615134 0.0982
##  ambient year2017 insects - warmed year2019 insects       -0.391500 0.1195
##  ambient year2017 insects - ambient year2020 insects      -0.732139 0.0982
##  ambient year2017 insects - warmed year2020 insects       -0.508506 0.1195
##  ambient year2017 insects - ambient year2021 insects      -0.497937 0.1007
##  ambient year2017 insects - warmed year2021 insects       -0.274304 0.1209
##  ambient year2017 insects - ambient year2015 no_insects   -0.859372 0.1134
##  ambient year2017 insects - warmed year2015 no_insects    -0.635739 0.1322
##  ambient year2017 insects - ambient year2016 no_insects   -1.022250 0.1134
##  ambient year2017 insects - warmed year2016 no_insects    -0.798617 0.1322
##  ambient year2017 insects - ambient year2017 no_insects   -0.239829 0.1134
##  ambient year2017 insects - warmed year2017 no_insects    -0.016196 0.1322
##  ambient year2017 insects - ambient year2018 no_insects   -0.731950 0.1134
##  ambient year2017 insects - warmed year2018 no_insects    -0.508317 0.1322
##  ambient year2017 insects - ambient year2019 no_insects   -0.487790 0.1134
##  ambient year2017 insects - warmed year2019 no_insects    -0.264157 0.1322
##  ambient year2017 insects - ambient year2020 no_insects   -0.727125 0.1211
##  ambient year2017 insects - warmed year2020 no_insects    -0.503492 0.1383
##  ambient year2017 insects - ambient year2021 no_insects   -0.314503 0.1134
##  ambient year2017 insects - warmed year2021 no_insects    -0.090870 0.1322
##  warmed year2017 insects - ambient year2018 insects       -0.960601 0.1195
##  warmed year2017 insects - warmed year2018 insects        -0.736968 0.0982
##  warmed year2017 insects - ambient year2019 insects       -0.838767 0.1195
##  warmed year2017 insects - warmed year2019 insects        -0.615134 0.0982
##  warmed year2017 insects - ambient year2020 insects       -0.955773 0.1195
##  warmed year2017 insects - warmed year2020 insects        -0.732139 0.0982
##  warmed year2017 insects - ambient year2021 insects       -0.721570 0.1221
##  warmed year2017 insects - warmed year2021 insects        -0.497937 0.1007
##  warmed year2017 insects - ambient year2015 no_insects    -1.083005 0.1322
##  warmed year2017 insects - warmed year2015 no_insects     -0.859372 0.1134
##  warmed year2017 insects - ambient year2016 no_insects    -1.245884 0.1322
##  warmed year2017 insects - warmed year2016 no_insects     -1.022250 0.1134
##  warmed year2017 insects - ambient year2017 no_insects    -0.463462 0.1322
##  warmed year2017 insects - warmed year2017 no_insects     -0.239829 0.1134
##  warmed year2017 insects - ambient year2018 no_insects    -0.955583 0.1322
##  warmed year2017 insects - warmed year2018 no_insects     -0.731950 0.1134
##  warmed year2017 insects - ambient year2019 no_insects    -0.711423 0.1322
##  warmed year2017 insects - warmed year2019 no_insects     -0.487790 0.1134
##  warmed year2017 insects - ambient year2020 no_insects    -0.950759 0.1395
##  warmed year2017 insects - warmed year2020 no_insects     -0.727125 0.1211
##  warmed year2017 insects - ambient year2021 no_insects    -0.538136 0.1322
##  warmed year2017 insects - warmed year2021 no_insects     -0.314503 0.1134
##  ambient year2018 insects - warmed year2018 insects        0.223633 0.0680
##  ambient year2018 insects - ambient year2019 insects       0.121834 0.0982
##  ambient year2018 insects - warmed year2019 insects        0.345467 0.1195
##  ambient year2018 insects - ambient year2020 insects       0.004829 0.0982
##  ambient year2018 insects - warmed year2020 insects        0.228462 0.1195
##  ambient year2018 insects - ambient year2021 insects       0.239031 0.1007
##  ambient year2018 insects - warmed year2021 insects        0.462664 0.1209
##  ambient year2018 insects - ambient year2015 no_insects   -0.122404 0.1134
##  ambient year2018 insects - warmed year2015 no_insects     0.101229 0.1322
##  ambient year2018 insects - ambient year2016 no_insects   -0.285283 0.1134
##  ambient year2018 insects - warmed year2016 no_insects    -0.061649 0.1322
##  ambient year2018 insects - ambient year2017 no_insects    0.497139 0.1134
```

```
##  ambient year2018 insects - warmed year2017 no_insects      0.720772 0.1322
##  ambient year2018 insects - ambient year2018 no_insects     0.005018 0.1134
##  ambient year2018 insects - warmed year2018 no_insects      0.228651 0.1322
##  ambient year2018 insects - ambient year2019 no_insects     0.249178 0.1134
##  ambient year2018 insects - warmed year2019 no_insects      0.472811 0.1322
##  ambient year2018 insects - ambient year2020 no_insects     0.009843 0.1211
##  ambient year2018 insects - warmed year2020 no_insects      0.233476 0.1383
##  ambient year2018 insects - ambient year2021 no_insects     0.422465 0.1134
##  ambient year2018 insects - warmed year2021 no_insects      0.646098 0.1322
##  warmed year2018 insects - ambient year2019 insects        -0.101799 0.1195
##  warmed year2018 insects - warmed year2019 insects          0.121834 0.0982
##  warmed year2018 insects - ambient year2020 insects        -0.218805 0.1195
##  warmed year2018 insects - warmed year2020 insects          0.004829 0.0982
##  warmed year2018 insects - ambient year2021 insects         0.015398 0.1221
##  warmed year2018 insects - warmed year2021 insects          0.239031 0.1007
##  warmed year2018 insects - ambient year2015 no_insects     -0.346037 0.1322
##  warmed year2018 insects - warmed year2015 no_insects      -0.122404 0.1134
##  warmed year2018 insects - ambient year2016 no_insects     -0.508916 0.1322
##  warmed year2018 insects - warmed year2016 no_insects      -0.285283 0.1134
##  warmed year2018 insects - ambient year2017 no_insects      0.273506 0.1322
##  warmed year2018 insects - warmed year2017 no_insects       0.497139 0.1134
##  warmed year2018 insects - ambient year2018 no_insects     -0.218615 0.1322
##  warmed year2018 insects - warmed year2018 no_insects       0.005018 0.1134
##  warmed year2018 insects - ambient year2019 no_insects      0.025545 0.1322
##  warmed year2018 insects - warmed year2019 no_insects       0.249178 0.1134
##  warmed year2018 insects - ambient year2020 no_insects     -0.213791 0.1395
##  warmed year2018 insects - warmed year2020 no_insects       0.009843 0.1211
##  warmed year2018 insects - ambient year2021 no_insects      0.198832 0.1322
##  warmed year2018 insects - warmed year2021 no_insects       0.422465 0.1134
##  ambient year2019 insects - warmed year2019 insects         0.223633 0.0680
##  ambient year2019 insects - ambient year2020 insects       -0.117006 0.0982
##  ambient year2019 insects - warmed year2020 insects         0.106628 0.1195
##  ambient year2019 insects - ambient year2021 insects        0.117197 0.1007
##  ambient year2019 insects - warmed year2021 insects         0.340830 0.1209
##  ambient year2019 insects - ambient year2015 no_insects    -0.244239 0.1134
##  ambient year2019 insects - warmed year2015 no_insects     -0.020605 0.1322
##  ambient year2019 insects - ambient year2016 no_insects    -0.407117 0.1134
##  ambient year2019 insects - warmed year2016 no_insects     -0.183484 0.1322
##  ambient year2019 insects - ambient year2017 no_insects     0.375304 0.1134
##  ambient year2019 insects - warmed year2017 no_insects      0.598938 0.1322
##  ambient year2019 insects - ambient year2018 no_insects    -0.116817 0.1134
##  ambient year2019 insects - warmed year2018 no_insects      0.106817 0.1322
##  ambient year2019 insects - ambient year2019 no_insects     0.127344 0.1134
##  ambient year2019 insects - warmed year2019 no_insects      0.350977 0.1322
##  ambient year2019 insects - ambient year2020 no_insects    -0.111992 0.1211
##  ambient year2019 insects - warmed year2020 no_insects      0.111641 0.1383
##  ambient year2019 insects - ambient year2021 no_insects     0.300631 0.1134
##  ambient year2019 insects - warmed year2021 no_insects      0.524264 0.1322
##  warmed year2019 insects - ambient year2020 insects        -0.340639 0.1195
##  warmed year2019 insects - warmed year2020 insects         -0.117006 0.0982
##  warmed year2019 insects - ambient year2021 insects        -0.106437 0.1221
##  warmed year2019 insects - warmed year2021 insects          0.117197 0.1007
##  warmed year2019 insects - ambient year2015 no_insects     -0.467872 0.1322
##  warmed year2019 insects - warmed year2015 no_insects      -0.244239 0.1134
```

```
## warmed year2019 insects - ambient year2016 no_insects     -0.630750 0.1322
## warmed year2019 insects - warmed year2016 no_insects      -0.407117 0.1134
## warmed year2019 insects - ambient year2017 no_insects      0.151671 0.1322
## warmed year2019 insects - warmed year2017 no_insects       0.375304 0.1134
## warmed year2019 insects - ambient year2018 no_insects     -0.340450 0.1322
## warmed year2019 insects - warmed year2018 no_insects      -0.116817 0.1134
## warmed year2019 insects - ambient year2019 no_insects     -0.096290 0.1322
## warmed year2019 insects - warmed year2019 no_insects       0.127344 0.1134
## warmed year2019 insects - ambient year2020 no_insects     -0.335625 0.1395
## warmed year2019 insects - warmed year2020 no_insects      -0.111992 0.1211
## warmed year2019 insects - ambient year2021 no_insects      0.076997 0.1322
## warmed year2019 insects - warmed year2021 no_insects       0.300631 0.1134
## ambient year2020 insects - warmed year2020 insects         0.223633 0.0680
## ambient year2020 insects - ambient year2021 insects        0.234202 0.1007
## ambient year2020 insects - warmed year2021 insects         0.457836 0.1209
## ambient year2020 insects - ambient year2015 no_insects    -0.127233 0.1134
## ambient year2020 insects - warmed year2015 no_insects      0.096400 0.1322
## ambient year2020 insects - ambient year2016 no_insects    -0.290111 0.1134
## ambient year2020 insects - warmed year2016 no_insects     -0.066478 0.1322
## ambient year2020 insects - ambient year2017 no_insects     0.492310 0.1134
## ambient year2020 insects - warmed year2017 no_insects      0.715943 0.1322
## ambient year2020 insects - ambient year2018 no_insects     0.000189 0.1134
## ambient year2020 insects - warmed year2018 no_insects      0.223822 0.1322
## ambient year2020 insects - ambient year2019 no_insects     0.244349 0.1134
## ambient year2020 insects - warmed year2019 no_insects      0.467983 0.1322
## ambient year2020 insects - ambient year2020 no_insects     0.005014 0.1211
## ambient year2020 insects - warmed year2020 no_insects      0.228647 0.1383
## ambient year2020 insects - ambient year2021 no_insects     0.417636 0.1134
## ambient year2020 insects - warmed year2021 no_insects      0.641269 0.1322
## warmed year2020 insects - ambient year2021 insects         0.010569 0.1221
## warmed year2020 insects - warmed year2021 insects          0.234202 0.1007
## warmed year2020 insects - ambient year2015 no_insects     -0.350866 0.1322
## warmed year2020 insects - warmed year2015 no_insects      -0.127233 0.1134
## warmed year2020 insects - ambient year2016 no_insects     -0.513744 0.1322
## warmed year2020 insects - warmed year2016 no_insects      -0.290111 0.1134
## warmed year2020 insects - ambient year2017 no_insects      0.268677 0.1322
## warmed year2020 insects - warmed year2017 no_insects       0.492310 0.1134
## warmed year2020 insects - ambient year2018 no_insects     -0.223444 0.1322
## warmed year2020 insects - warmed year2018 no_insects       0.000189 0.1134
## warmed year2020 insects - ambient year2019 no_insects      0.020716 0.1322
## warmed year2020 insects - warmed year2019 no_insects       0.244349 0.1134
## warmed year2020 insects - ambient year2020 no_insects     -0.218619 0.1395
## warmed year2020 insects - warmed year2020 no_insects       0.005014 0.1211
## warmed year2020 insects - ambient year2021 no_insects      0.194003 0.1322
## warmed year2020 insects - warmed year2021 no_insects       0.417636 0.1134
## ambient year2021 insects - warmed year2021 insects         0.223633 0.0680
## ambient year2021 insects - ambient year2015 no_insects    -0.361435 0.1155
## ambient year2021 insects - warmed year2015 no_insects     -0.137802 0.1346
## ambient year2021 insects - ambient year2016 no_insects    -0.524313 0.1155
## ambient year2021 insects - warmed year2016 no_insects     -0.300680 0.1346
## ambient year2021 insects - ambient year2017 no_insects     0.258108 0.1155
## ambient year2021 insects - warmed year2017 no_insects      0.481741 0.1346
## ambient year2021 insects - ambient year2018 no_insects    -0.234013 0.1155
## ambient year2021 insects - warmed year2018 no_insects     -0.010380 0.1346
```

```
## ambient year2021 insects - ambient year2019 no_insects     0.010147 0.1155
## ambient year2021 insects - warmed year2019 no_insects      0.233780 0.1346
## ambient year2021 insects - ambient year2020 no_insects    -0.229188 0.1231
## ambient year2021 insects - warmed year2020 no_insects     -0.005555 0.1405
## ambient year2021 insects - ambient year2021 no_insects     0.183434 0.1155
## ambient year2021 insects - warmed year2021 no_insects      0.407067 0.1346
## warmed year2021 insects - ambient year2015 no_insects     -0.585068 0.1336
## warmed year2021 insects - warmed year2015 no_insects      -0.361435 0.1155
## warmed year2021 insects - ambient year2016 no_insects     -0.747947 0.1336
## warmed year2021 insects - warmed year2016 no_insects      -0.524313 0.1155
## warmed year2021 insects - ambient year2017 no_insects      0.034475 0.1336
## warmed year2021 insects - warmed year2017 no_insects       0.258108 0.1155
## warmed year2021 insects - ambient year2018 no_insects     -0.457646 0.1336
## warmed year2021 insects - warmed year2018 no_insects      -0.234013 0.1155
## warmed year2021 insects - ambient year2019 no_insects     -0.213486 0.1336
## warmed year2021 insects - warmed year2019 no_insects       0.010147 0.1155
## warmed year2021 insects - ambient year2020 no_insects     -0.452822 0.1408
## warmed year2021 insects - warmed year2020 no_insects      -0.229188 0.1231
## warmed year2021 insects - ambient year2021 no_insects     -0.040199 0.1336
## warmed year2021 insects - warmed year2021 no_insects       0.183434 0.1155
## ambient year2015 no_insects - warmed year2015 no_insects   0.223633 0.0680
## ambient year2015 no_insects - ambient year2016 no_insects -0.162878 0.0982
## ambient year2015 no_insects - warmed year2016 no_insects   0.060755 0.1195
## ambient year2015 no_insects - ambient year2017 no_insects  0.619543 0.0982
## ambient year2015 no_insects - warmed year2017 no_insects   0.843176 0.1195
## ambient year2015 no_insects - ambient year2018 no_insects  0.127422 0.0982
## ambient year2015 no_insects - warmed year2018 no_insects   0.351055 0.1195
## ambient year2015 no_insects - ambient year2019 no_insects  0.371582 0.0982
## ambient year2015 no_insects - warmed year2019 no_insects   0.595216 0.1195
## ambient year2015 no_insects - ambient year2020 no_insects  0.132247 0.1070
## ambient year2015 no_insects - warmed year2020 no_insects   0.355880 0.1261
## ambient year2015 no_insects - ambient year2021 no_insects  0.544869 0.0982
## ambient year2015 no_insects - warmed year2021 no_insects   0.768502 0.1195
## warmed year2015 no_insects - ambient year2016 no_insects  -0.386512 0.1195
## warmed year2015 no_insects - warmed year2016 no_insects   -0.162878 0.0982
## warmed year2015 no_insects - ambient year2017 no_insects   0.395910 0.1195
## warmed year2015 no_insects - warmed year2017 no_insects    0.619543 0.0982
## warmed year2015 no_insects - ambient year2018 no_insects  -0.096211 0.1195
## warmed year2015 no_insects - warmed year2018 no_insects    0.127422 0.0982
## warmed year2015 no_insects - ambient year2019 no_insects   0.147949 0.1195
## warmed year2015 no_insects - warmed year2019 no_insects    0.371582 0.0982
## warmed year2015 no_insects - ambient year2020 no_insects  -0.091386 0.1275
## warmed year2015 no_insects - warmed year2020 no_insects    0.132247 0.1070
## warmed year2015 no_insects - ambient year2021 no_insects   0.321236 0.1195
## warmed year2015 no_insects - warmed year2021 no_insects    0.544869 0.0982
## ambient year2016 no_insects - warmed year2016 no_insects   0.223633 0.0680
## ambient year2016 no_insects - ambient year2017 no_insects  0.782421 0.0982
## ambient year2016 no_insects - warmed year2017 no_insects   1.006055 0.1195
## ambient year2016 no_insects - ambient year2018 no_insects  0.290300 0.0982
## ambient year2016 no_insects - warmed year2018 no_insects   0.513934 0.1195
## ambient year2016 no_insects - ambient year2019 no_insects  0.534461 0.0982
## ambient year2016 no_insects - warmed year2019 no_insects   0.758094 0.1195
## ambient year2016 no_insects - ambient year2020 no_insects  0.295125 0.1070
## ambient year2016 no_insects - warmed year2020 no_insects   0.518758 0.1261
```

```
## ambient year2016 no_insects - ambient year2021 no_insects  0.707747 0.0982
## ambient year2016 no_insects - warmed year2021 no_insects   0.931381 0.1195
## warmed year2016 no_insects - ambient year2017 no_insects   0.558788 0.1195
## warmed year2016 no_insects - warmed year2017 no_insects    0.782421 0.0982
## warmed year2016 no_insects - ambient year2018 no_insects   0.066667 0.1195
## warmed year2016 no_insects - warmed year2018 no_insects    0.290300 0.0982
## warmed year2016 no_insects - ambient year2019 no_insects   0.310827 0.1195
## warmed year2016 no_insects - warmed year2019 no_insects    0.534461 0.0982
## warmed year2016 no_insects - ambient year2020 no_insects   0.071492 0.1275
## warmed year2016 no_insects - warmed year2020 no_insects    0.295125 0.1070
## warmed year2016 no_insects - ambient year2021 no_insects   0.484114 0.1195
## warmed year2016 no_insects - warmed year2021 no_insects    0.707747 0.0982
## ambient year2017 no_insects - warmed year2017 no_insects   0.223633 0.0680
## ambient year2017 no_insects - ambient year2018 no_insects -0.492121 0.0982
## ambient year2017 no_insects - warmed year2018 no_insects  -0.268488 0.1195
## ambient year2017 no_insects - ambient year2019 no_insects -0.247961 0.0982
## ambient year2017 no_insects - warmed year2019 no_insects  -0.024328 0.1195
## ambient year2017 no_insects - ambient year2020 no_insects -0.487296 0.1070
## ambient year2017 no_insects - warmed year2020 no_insects  -0.263663 0.1261
## ambient year2017 no_insects - ambient year2021 no_insects -0.074674 0.0982
## ambient year2017 no_insects - warmed year2021 no_insects   0.148959 0.1195
## warmed year2017 no_insects - ambient year2018 no_insects  -0.715754 0.1195
## warmed year2017 no_insects - warmed year2018 no_insects   -0.492121 0.0982
## warmed year2017 no_insects - ambient year2019 no_insects  -0.471594 0.1195
## warmed year2017 no_insects - warmed year2019 no_insects   -0.247961 0.0982
## warmed year2017 no_insects - ambient year2020 no_insects  -0.710929 0.1275
## warmed year2017 no_insects - warmed year2020 no_insects   -0.487296 0.1070
## warmed year2017 no_insects - ambient year2021 no_insects  -0.298307 0.1195
## warmed year2017 no_insects - warmed year2021 no_insects   -0.074674 0.0982
## ambient year2018 no_insects - warmed year2018 no_insects   0.223633 0.0680
## ambient year2018 no_insects - ambient year2019 no_insects  0.244160 0.0982
## ambient year2018 no_insects - warmed year2019 no_insects   0.467793 0.1195
## ambient year2018 no_insects - ambient year2020 no_insects  0.004825 0.1070
## ambient year2018 no_insects - warmed year2020 no_insects   0.228458 0.1261
## ambient year2018 no_insects - ambient year2021 no_insects  0.417447 0.0982
## ambient year2018 no_insects - warmed year2021 no_insects   0.641080 0.1195
## warmed year2018 no_insects - ambient year2019 no_insects   0.020527 0.1195
## warmed year2018 no_insects - warmed year2019 no_insects    0.244160 0.0982
## warmed year2018 no_insects - ambient year2020 no_insects  -0.218808 0.1275
## warmed year2018 no_insects - warmed year2020 no_insects    0.004825 0.1070
## warmed year2018 no_insects - ambient year2021 no_insects   0.193814 0.1195
## warmed year2018 no_insects - warmed year2021 no_insects    0.417447 0.0982
## ambient year2019 no_insects - warmed year2019 no_insects   0.223633 0.0680
## ambient year2019 no_insects - ambient year2020 no_insects -0.239336 0.1070
## ambient year2019 no_insects - warmed year2020 no_insects  -0.015702 0.1261
## ambient year2019 no_insects - ambient year2021 no_insects  0.173287 0.0982
## ambient year2019 no_insects - warmed year2021 no_insects   0.396920 0.1195
## warmed year2019 no_insects - ambient year2020 no_insects  -0.462969 0.1275
## warmed year2019 no_insects - warmed year2020 no_insects   -0.239336 0.1070
## warmed year2019 no_insects - ambient year2021 no_insects  -0.050346 0.1195
## warmed year2019 no_insects - warmed year2021 no_insects    0.173287 0.0982
## ambient year2020 no_insects - warmed year2020 no_insects   0.223633 0.0680
## ambient year2020 no_insects - ambient year2021 no_insects  0.412622 0.1070
## ambient year2020 no_insects - warmed year2021 no_insects   0.636255 0.1275
```

```
##  warmed year2020 no_insects - ambient year2021 no_insects   0.188989 0.1261
##  warmed year2020 no_insects - warmed year2021 no_insects    0.412622 0.1070
##  ambient year2021 no_insects - warmed year2021 no_insects   0.223633 0.0680
##     df t.ratio p.value
##   27.5   3.286  0.2628
##  153.1  -0.365  1.0000
##  149.9   1.572  0.9988
##  153.1   8.064  <.0001
##  149.9   8.500  <.0001
##  153.1   0.558  1.0000
##  149.9   2.331  0.8489
##  153.1   1.799  0.9911
##  149.9   3.351  0.1707
##  153.1   0.608  1.0000
##  149.9   2.371  0.8265
##  153.8   2.919  0.4262
##  151.9   4.279  0.0093
##  138.6  -0.596  1.0000
##   88.5   1.180  1.0000
##  138.6  -2.032  0.9594
##   88.5  -0.052  1.0000
##  138.6   4.868  0.0010
##   88.5   5.865  <.0001
##  138.6   0.528  1.0000
##   88.5   2.144  0.9249
##  138.6   2.681  0.6100
##   88.5   3.990  0.0316
##  150.6   0.534  1.0000
##   99.1   2.085  0.9440
##  138.6   4.209  0.0125
##   88.5   5.300  0.0003
##  149.9  -2.172  0.9197
##  153.1  -0.365  1.0000
##  149.9   4.756  0.0015
##  153.1   8.064  <.0001
##  149.9  -1.413  0.9998
##  153.1   0.558  1.0000
##  149.9  -0.393  1.0000
##  153.1   1.799  0.9911
##  149.9  -1.373  0.9999
##  153.1   0.608  1.0000
##  153.4   0.575  1.0000
##  153.8   2.919  0.4262
##   88.5  -2.202  0.9035
##  138.6  -0.596  1.0000
##   88.5  -3.434  0.1494
##  138.6  -2.032  0.9594
##   88.5   2.483  0.7526
##  138.6   4.868  0.0010
##   88.5  -1.239  1.0000
##  138.6   0.528  1.0000
##   88.5   0.608  1.0000
##  138.6   2.681  0.6100
##  101.3  -1.139  1.0000
```

```
##   150.6   0.534  1.0000
##    88.5   1.918  0.9772
##   138.6   4.209  0.0125
##    27.5   3.286  0.2628
##   153.1   8.429  <.0001
##   149.9   8.800  <.0001
##   153.1   0.924  1.0000
##   149.9   2.631  0.6486
##   153.1   2.165  0.9226
##   149.9   3.651  0.0756
##   153.1   0.973  1.0000
##   149.9   2.672  0.6174
##   153.8   3.275  0.2045
##   151.9   4.576  0.0030
##   138.6  -0.280  1.0000
##    88.5   1.451  0.9996
##   138.6  -1.716  0.9953
##    88.5   0.220  1.0000
##   138.6   5.184  0.0003
##    88.5   6.136  <.0001
##   138.6   0.844  1.0000
##    88.5   2.415  0.7958
##   138.6   2.998  0.3710
##    88.5   4.261  0.0132
##   150.6   0.830  1.0000
##    99.1   2.345  0.8377
##   138.6   4.526  0.0039
##    88.5   5.572  0.0001
##   149.9   5.056  0.0004
##   153.1   8.429  <.0001
##   149.9  -1.113  1.0000
##   153.1   0.924  1.0000
##   149.9  -0.093  1.0000
##   153.1   2.165  0.9226
##   149.9  -1.072  1.0000
##   153.1   0.973  1.0000
##   153.4   0.869  1.0000
##   153.8   3.275  0.2045
##    88.5  -1.931  0.9754
##   138.6  -0.280  1.0000
##    88.5  -3.163  0.2755
##   138.6  -1.716  0.9953
##    88.5   2.754  0.5552
##   138.6   5.184  0.0003
##    88.5  -0.967  1.0000
##   138.6   0.844  1.0000
##    88.5   0.879  1.0000
##   138.6   2.998  0.3710
##   101.3  -0.882  1.0000
##   150.6   0.830  1.0000
##    88.5   2.190  0.9084
##   138.6   4.526  0.0039
##    27.5   3.286  0.2628
##   153.1  -7.505  <.0001
```

```
##   149.9  -4.297  0.0088
##   153.1  -6.265  <.0001
##   149.9  -3.277  0.2041
##   153.1  -7.456  <.0001
##   149.9  -4.256  0.0102
##   153.8  -4.946  0.0006
##   151.9  -2.268  0.8802
##   138.6  -7.579  <.0001
##    88.5  -4.808  0.0019
##   138.6  -9.016  <.0001
##    88.5  -6.039  <.0001
##   138.6  -2.115  0.9380
##    88.5  -0.122  1.0000
##   138.6  -6.455  <.0001
##    88.5  -3.844  0.0492
##   138.6  -4.302  0.0089
##    88.5  -1.998  0.9638
##   150.6  -6.005  <.0001
##    99.1  -3.641  0.0849
##   138.6  -2.774  0.5379
##    88.5  -0.687  1.0000
##   149.9  -8.041  <.0001
##   153.1  -7.505  <.0001
##   149.9  -7.021  <.0001
##   153.1  -6.265  <.0001
##   149.9  -8.000  <.0001
##   153.1  -7.456  <.0001
##   153.4  -5.910  <.0001
##   153.8  -4.946  0.0006
##    88.5  -8.190  <.0001
##   138.6  -7.579  <.0001
##    88.5  -9.421  <.0001
##   138.6  -9.016  <.0001
##    88.5  -3.505  0.1251
##   138.6  -2.115  0.9380
##    88.5  -7.226  <.0001
##   138.6  -6.455  <.0001
##    88.5  -5.380  0.0002
##   138.6  -4.302  0.0089
##   101.3  -6.815  <.0001
##   150.6  -6.005  <.0001
##    88.5  -4.069  0.0246
##   138.6  -2.774  0.5379
##    27.5   3.286  0.2628
##   153.1   1.241  1.0000
##   149.9   2.892  0.4468
##   153.1   0.049  1.0000
##   149.9   1.912  0.9804
##   153.8   2.374  0.8248
##   151.9   3.826  0.0442
##   138.6  -1.080  1.0000
##    88.5   0.766  1.0000
##   138.6  -2.516  0.7330
##    88.5  -0.466  1.0000
```

```
##   138.6   4.384  0.0066
##    88.5   5.451  0.0002
##   138.6   0.044  1.0000
##    88.5   1.729  0.9940
##   138.6   2.198  0.9097
##    88.5   3.575  0.1042
##   150.6   0.081  1.0000
##    99.1   1.689  0.9959
##   138.6   3.726  0.0614
##    88.5   4.886  0.0014
##   149.9  -0.852  1.0000
##   153.1   1.241  1.0000
##   149.9  -1.831  0.9887
##   153.1   0.049  1.0000
##   153.4   0.126  1.0000
##   153.8   2.374  0.8248
##    88.5  -2.617  0.6584
##   138.6  -1.080  1.0000
##    88.5  -3.848  0.0485
##   138.6  -2.516  0.7330
##    88.5   2.068  0.9475
##   138.6   4.384  0.0066
##    88.5  -1.653  0.9968
##   138.6   0.044  1.0000
##    88.5   0.193  1.0000
##   138.6   2.198  0.9097
##   101.3  -1.532  0.9991
##   150.6   0.081  1.0000
##    88.5   1.504  0.9993
##   138.6   3.726  0.0614
##    27.5   3.286  0.2628
##   153.1  -1.192  1.0000
##   149.9   0.893  1.0000
##   153.8   1.164  1.0000
##   151.9   2.818  0.5027
##   138.6  -2.154  0.9255
##    88.5  -0.156  1.0000
##   138.6  -3.591  0.0912
##    88.5  -1.388  0.9998
##   138.6   3.310  0.1900
##    88.5   4.529  0.0052
##   138.6  -1.030  1.0000
##    88.5   0.808  1.0000
##   138.6   1.123  1.0000
##    88.5   2.654  0.6307
##   150.6  -0.925  1.0000
##    99.1   0.807  1.0000
##   138.6   2.651  0.6330
##    88.5   3.965  0.0342
##   149.9  -2.851  0.4774
##   153.1  -1.192  1.0000
##   153.4  -0.872  1.0000
##   153.8   1.164  1.0000
##    88.5  -3.538  0.1149
```

```
## 138.6 -2.154 0.9255
##  88.5 -4.770 0.0022
## 138.6 -3.591 0.0912
##  88.5  1.147 1.0000
## 138.6  3.310 0.1900
##  88.5 -2.575 0.6891
## 138.6 -1.030 1.0000
##  88.5 -0.728 1.0000
## 138.6  1.123 1.0000
## 101.3 -2.406 0.8028
## 150.6 -0.925 1.0000
##  88.5  0.582 1.0000
## 138.6  2.651 0.6330
##  27.5  3.286 0.2628
## 153.8  2.326 0.8514
## 151.9  3.786 0.0501
## 138.6 -1.122 1.0000
##  88.5  0.729 1.0000
## 138.6 -2.559 0.7025
##  88.5 -0.503 1.0000
## 138.6  4.342 0.0077
##  88.5  5.414 0.0002
## 138.6  0.002 1.0000
##  88.5  1.693 0.9955
## 138.6  2.155 0.9252
##  88.5  3.539 0.1146
## 150.6  0.041 1.0000
##  99.1  1.654 0.9969
## 138.6  3.683 0.0698
##  88.5  4.849 0.0016
## 153.4  0.087 1.0000
## 153.8  2.326 0.8514
##  88.5 -2.653 0.6313
## 138.6 -1.122 1.0000
##  88.5 -3.885 0.0435
## 138.6 -2.559 0.7025
##  88.5  2.032 0.9564
## 138.6  4.342 0.0077
##  88.5 -1.690 0.9956
## 138.6  0.002 1.0000
##  88.5  0.157 1.0000
## 138.6  2.155 0.9252
## 101.3 -1.567 0.9987
## 150.6  0.041 1.0000
##  88.5  1.467 0.9995
## 138.6  3.683 0.0698
##  27.5  3.286 0.2628
## 142.3 -3.128 0.2858
##  92.8 -1.024 1.0000
## 142.3 -4.538 0.0036
##  92.8 -2.234 0.8910
## 142.3  2.234 0.8951
##  92.8  3.579 0.1022
## 142.3 -2.025 0.9611
```

```
##   92.8  -0.077  1.0000
##  142.3   0.088  1.0000
##   92.8   1.737  0.9937
##  153.2  -1.862  0.9861
##  103.0  -0.040  1.0000
##  142.3   1.588  0.9986
##   92.8   3.024  0.3597
##   90.9  -4.381  0.0086
##  142.3  -3.128  0.2858
##   90.9  -5.600  0.0001
##  142.3  -4.538  0.0036
##   90.9   0.258  1.0000
##  142.3   2.234  0.8951
##   90.9  -3.427  0.1514
##  142.3  -2.025  0.9611
##   90.9  -1.598  0.9981
##  142.3   0.088  1.0000
##  103.3  -3.217  0.2420
##  153.2  -1.862  0.9861
##   90.9  -0.301  1.0000
##  142.3   1.588  0.9986
##   27.5   3.286  0.2628
##  153.1  -1.659  0.9972
##  149.9   0.509  1.0000
##  153.1   6.309  <.0001
##  149.9   7.058  <.0001
##  153.1   1.298  1.0000
##  149.9   2.938  0.4121
##  153.1   3.784  0.0503
##  149.9   4.982  0.0006
##  155.4   1.236  1.0000
##  158.1   2.822  0.4998
##  153.1   5.549  <.0001
##  149.9   6.433  <.0001
##  149.9  -3.235  0.2250
##  153.1  -1.659  0.9972
##  149.9   3.314  0.1868
##  153.1   6.309  <.0001
##  149.9  -0.805  1.0000
##  153.1   1.298  1.0000
##  149.9   1.238  1.0000
##  153.1   3.784  0.0503
##  159.7  -0.717  1.0000
##  155.4   1.236  1.0000
##  149.9   2.689  0.6040
##  153.1   5.549  <.0001
##   27.5   3.286  0.2628
##  153.1   7.968  <.0001
##  149.9   8.421  <.0001
##  153.1   2.956  0.3989
##  149.9   4.302  0.0086
##  153.1   5.443  0.0001
##  149.9   6.346  <.0001
##  155.4   2.758  0.5494
```

```
##   158.1   4.113  0.0167
##   153.1   7.208  <.0001
##   149.9   7.796  <.0001
##   149.9   4.677  0.0020
##   153.1   7.968  <.0001
##   149.9   0.558  1.0000
##   153.1   2.956  0.3989
##   149.9   2.602  0.6708
##   153.1   5.443  0.0001
##   159.7   0.561  1.0000
##   155.4   2.758  0.5494
##   149.9   4.052  0.0210
##   153.1   7.208  <.0001
##    27.5   3.286  0.2628
##   153.1  -5.012  0.0005
##   149.9  -2.247  0.8896
##   153.1  -2.525  0.7269
##   149.9  -0.204  1.0000
##   155.4  -4.555  0.0032
##   158.1  -2.091  0.9458
##   153.1  -0.760  1.0000
##   149.9   1.247  1.0000
##   149.9  -5.991  <.0001
##   153.1  -5.012  0.0005
##   149.9  -3.947  0.0299
##   153.1  -2.525  0.7269
##   159.7  -5.577  <.0001
##   155.4  -4.555  0.0032
##   149.9  -2.497  0.7466
##   153.1  -0.760  1.0000
##    27.5   3.286  0.2628
##   153.1   2.487  0.7539
##   149.9   3.916  0.0332
##   155.4   0.045  1.0000
##   158.1   1.812  0.9903
##   153.1   4.251  0.0103
##   149.9   5.366  0.0001
##   149.9   0.172  1.0000
##   153.1   2.487  0.7539
##   159.7  -1.716  0.9955
##   155.4   0.045  1.0000
##   149.9   1.622  0.9980
##   153.1   4.251  0.0103
##    27.5   3.286  0.2628
##   155.4  -2.237  0.8944
##   158.1  -0.125  1.0000
##   153.1   1.765  0.9932
##   149.9   3.322  0.1830
##   159.7  -3.632  0.0790
##   155.4  -2.237  0.8944
##   149.9  -0.421  1.0000
##   153.1   1.765  0.9932
##    27.5   3.286  0.2628
##   155.4   3.857  0.0399
```

```
##  159.7   4.991  0.0005
##  158.1   1.499  0.9995
##  155.4   3.857  0.0399
##   27.5   3.286  0.2628
##
## 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
anova(mod1ur)
```

```
## Analysis of Variance Table
##                  npar  Sum Sq Mean Sq F value
## state               1 0.00028 0.00028  0.0081
## year                5 2.07948 0.41590 11.9188
## insecticide         1 0.01695 0.01695  0.4858
## state:year          5 0.18932 0.03786  1.0851
## year:insecticide    5 0.06174 0.01235  0.3539
```

```
anova(mod2ur)
```

```
## Analysis of Variance Table
##             npar  Sum Sq Mean Sq F value
## state          1 0.00029 0.00029  0.0081
## year           5 2.07948 0.41590 11.7456
## insecticide    1 0.01720 0.01720  0.4858
## state:year     5 0.18932 0.03786  1.0694
```

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

```
## 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   15 16.285 60.832 6.8577  -13.716
## mod1ur   20 24.528 83.924 7.7360  -15.472 1.7565  5     0.8817
```

```
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
```

```
##     24.5     83.9      7.7    -15.5      124
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.23918 -0.67778  0.02836  0.52120  2.83998
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  plot     (Intercept) 0.06230  0.2496
##  Residual             0.03489  0.1868
## Number of obs: 144, groups:  plot, 24
##
## Fixed effects:
##                                Estimate Std. Error t value
## (Intercept)                    1.447496   0.110226  13.132
## statewarmed                   -0.104655   0.127278  -0.822
## year2017                      -0.036461   0.093400  -0.390
## year2018                       0.055610   0.093400   0.595
## year2019                       0.198025   0.093400   2.120
## year2020                       0.316654   0.093400   3.390
## year2021                       0.150838   0.093400   1.615
## insecticideno_insects          0.147907   0.127278   1.162
## statewarmed:year2017           0.106744   0.107849   0.990
## statewarmed:year2018           0.107003   0.107849   0.992
## statewarmed:year2019           0.187634   0.107849   1.740
## statewarmed:year2020           0.002502   0.107849   0.023
## statewarmed:year2021           0.166483   0.107849   1.544
## year2017:insecticideno_insects -0.112806   0.107849  -1.046
## year2018:insecticideno_insects -0.063789   0.107849  -0.591
## year2019:insecticideno_insects -0.049043   0.107849  -0.455
## year2020:insecticideno_insects -0.119393   0.107849  -1.107
## year2021:insecticideno_insects -0.096835   0.107849  -0.898

##
## Correlation matrix not shown by default, as p = 18 > 12.
## Use print(x, correlation=TRUE)  or
##     vcov(x)        if you need it
```

```
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
##     16.3     60.8      6.9    -13.7      129
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.16211 -0.70257  0.06554  0.56290  2.62223
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
```

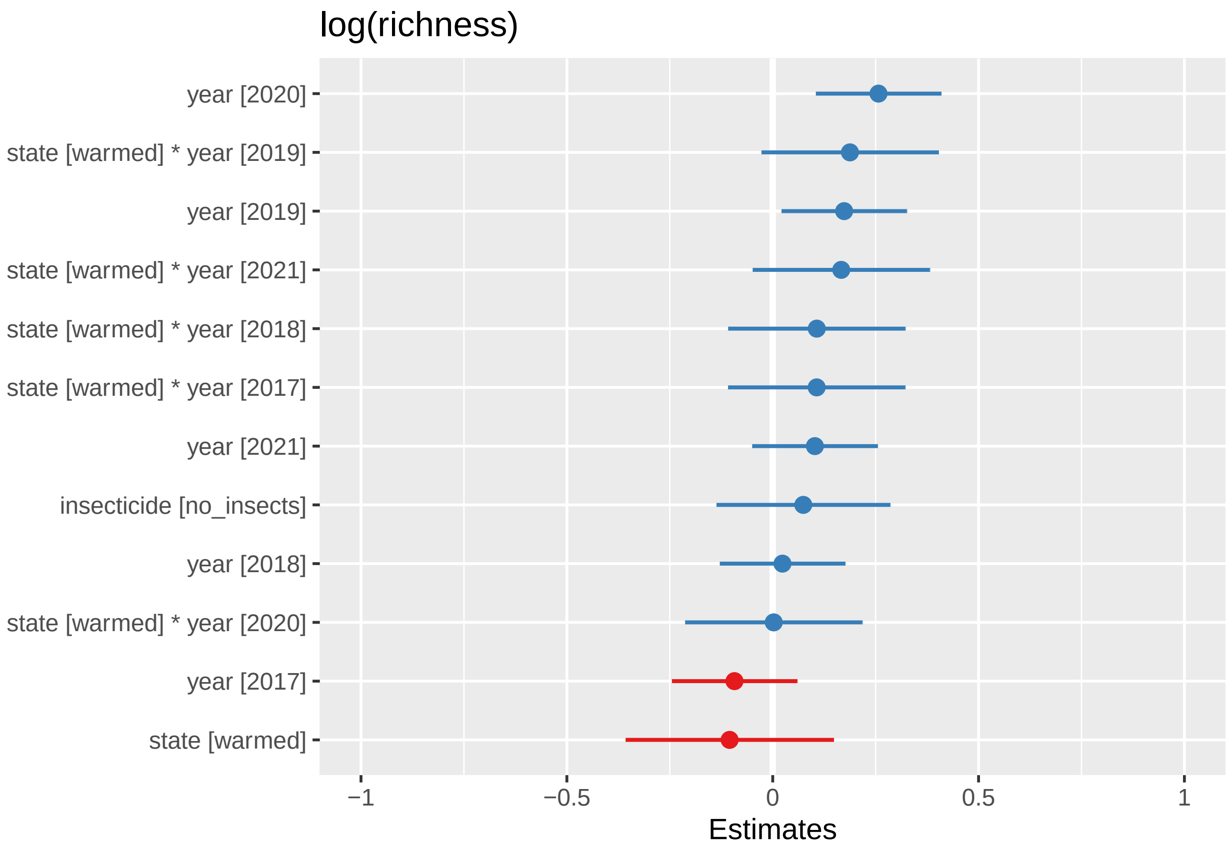
```
##  plot     (Intercept) 0.06222  0.2494
##  Residual             0.03541  0.1882
## Number of obs: 144, groups:  plot, 24
##
## Fixed effects:
##                         Estimate Std. Error t value
## (Intercept)             1.484318   0.104756  14.169
## statewarmed            -0.104655   0.127558  -0.820
## year2017               -0.092863   0.076821  -1.209
## year2018                0.023715   0.076821   0.309
## year2019                0.173504   0.076821   2.259
## year2020                0.256958   0.076821   3.345
## year2021                0.102421   0.076821   1.333
## insecticideno_insects   0.074263   0.106551   0.697
## statewarmed:year2017    0.106744   0.108641   0.983
## statewarmed:year2018    0.107003   0.108641   0.985
## statewarmed:year2019    0.187634   0.108641   1.727
## statewarmed:year2020    0.002502   0.108641   0.023
## statewarmed:year2021    0.166483   0.108641   1.532
```

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

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

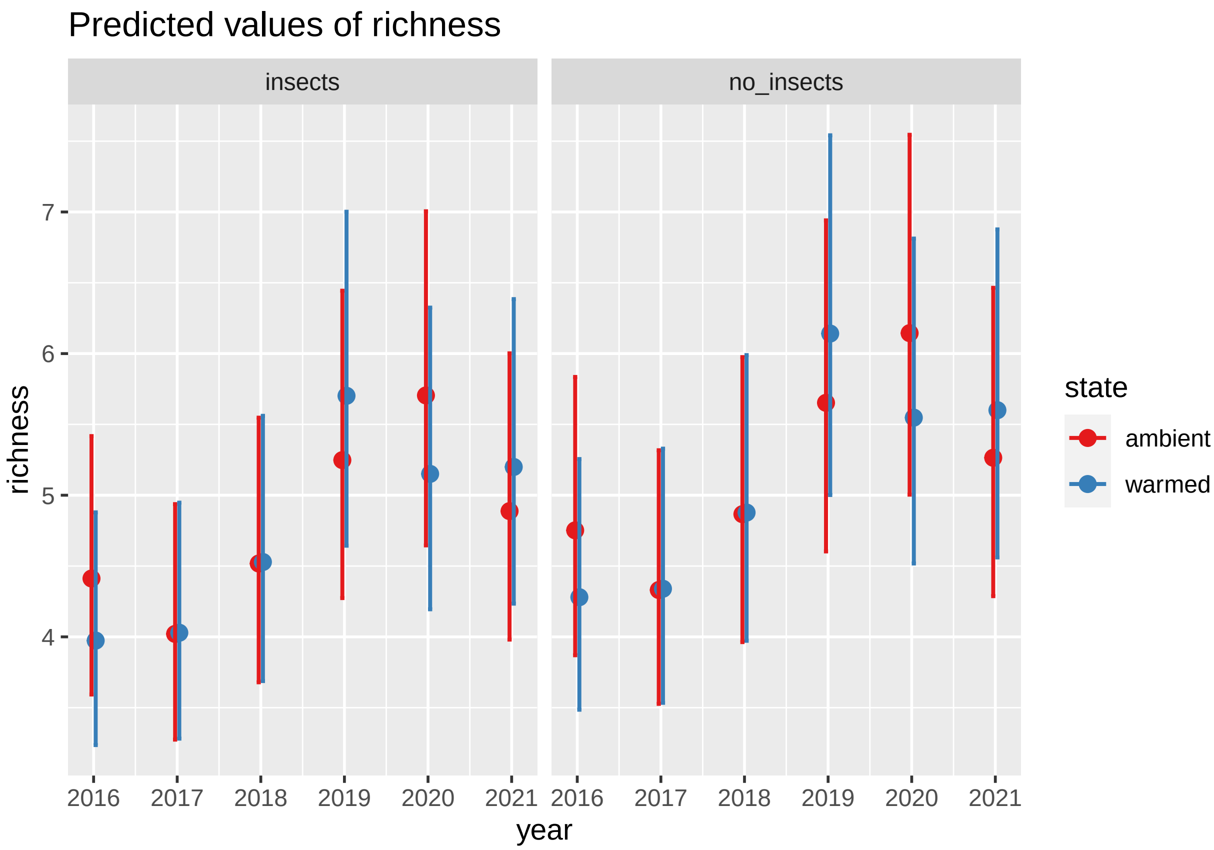
```
##        dAICc df weight
## mod2ur  0.0  15 0.9965
## mod1ur 11.3  20 0.0035
```

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

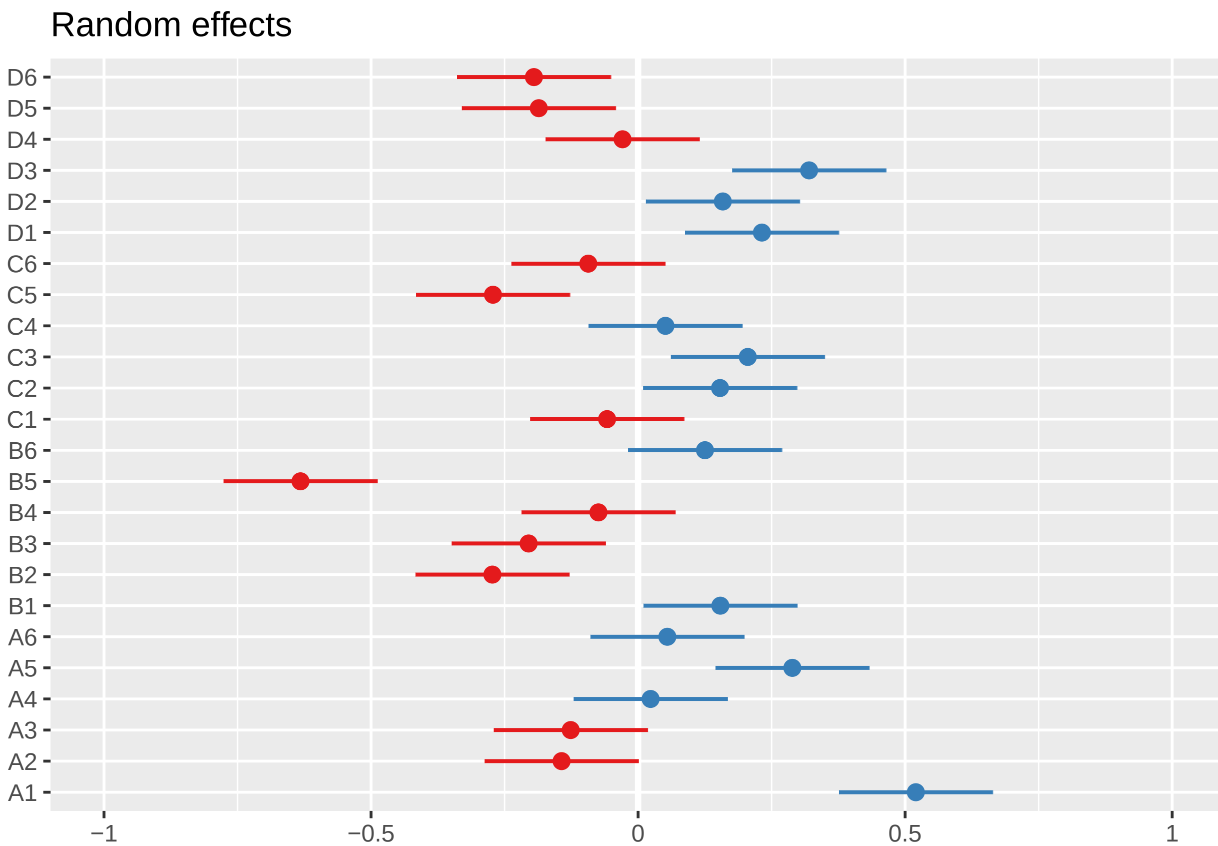



```
# these are the fixed predicted values:
plot_model(mod2ur, type = "pred", terms = c("year", "state", "insecticide"))
```

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




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




```
# 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   15 16.285 60.832 6.8577  -13.716
## mod3ur   15 19.835 64.382 5.0827  -10.165     0  0
```

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

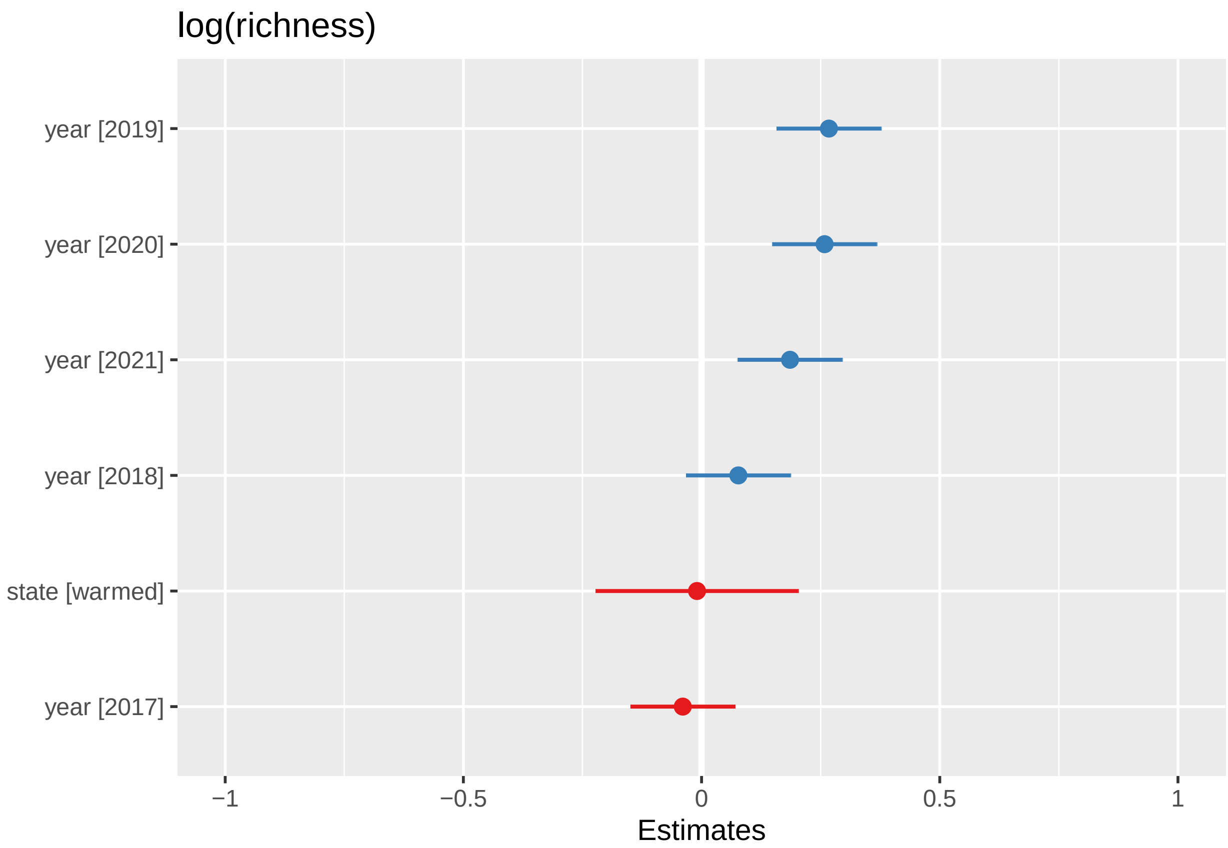
```
##        dAICc df weight
## mod3ur  0.0  15 0.98
## mod1ur  7.8  20 0.02
```

```
# 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)
```

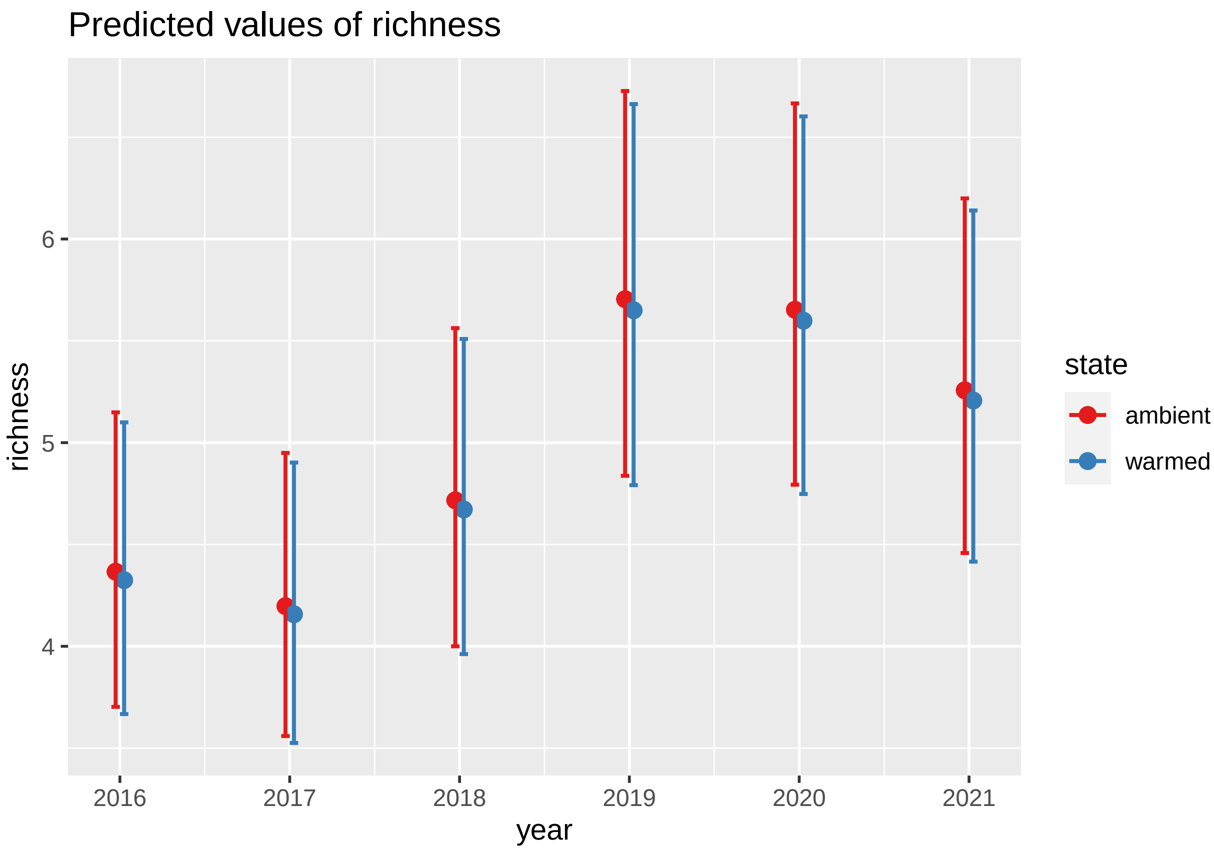
```
## mod3ur: log(richness) ~ state + year + insecticide * year + (1 | plot)
##        npar     AIC    BIC logLik deviance  Chisq Df Pr(>Chisq)
## mod5ur    9  9.9965 36.725 4.0017  -8.0035
## mod3ur   15 19.8346 64.382 5.0827 -10.1654 2.1619  6     0.9042
```

```
# 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)
```

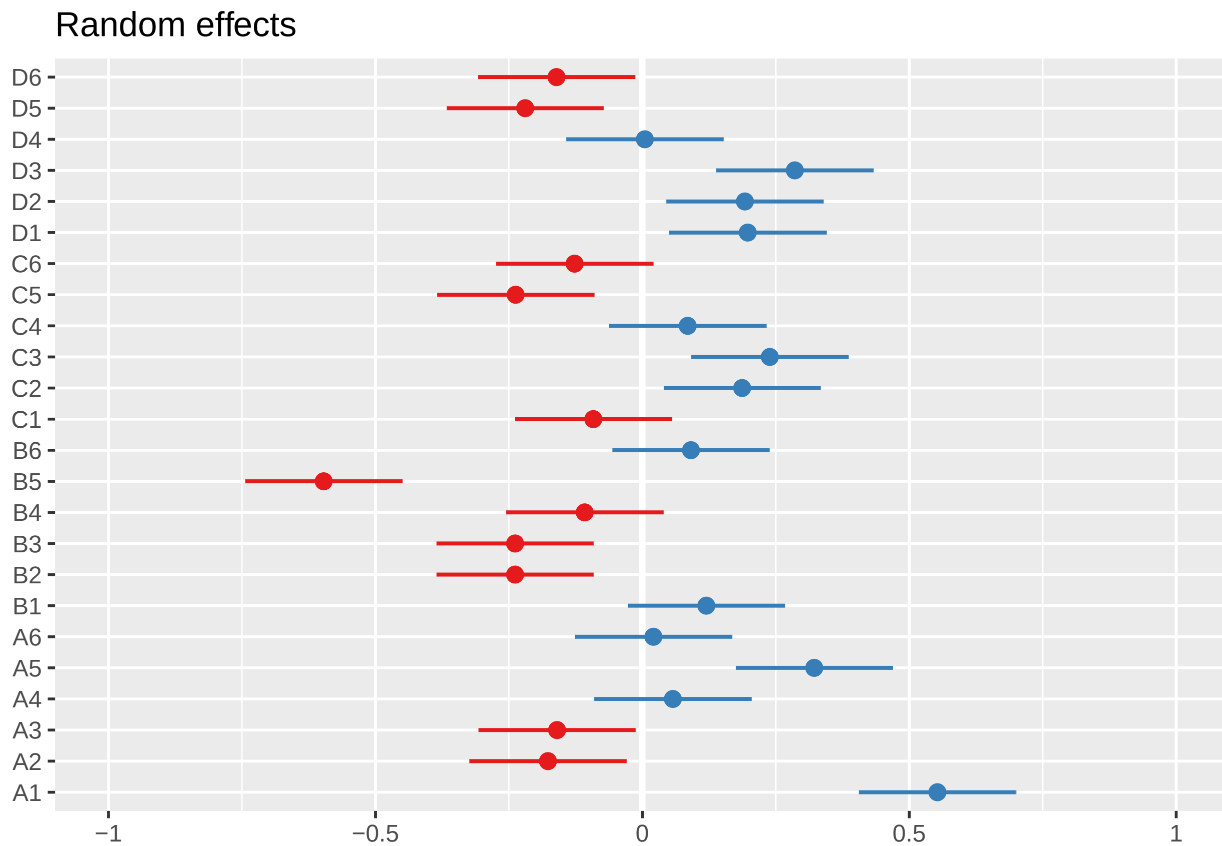



```
# these are the fixed predicted values:
plot_model(mod5ur, type = "pred", terms = c("year", "state"))
```

```
## 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"))
```




```
# 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, REM
# 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	144
Dependent variable	log(richness)
Type	Mixed effects linear regression

AIC	10.00
BIC	36.72
Pseudo-R^2 (fixed effects)	0.13
Pseudo-R^2 (total)	0.68

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

```
## $`emmeans of state, year`
##  state    year emmean     SE   df lower.CL upper.CL
##  ambient 2016   1.47 0.0875 38.7     1.30     1.65
```

Fixed Effects					
	Est.	S.E.	t val.	d.f.	p
(Intercept)	1.47	0.08	17.52	35.48	0.00
statewarmed	-0.01	0.11	-0.09	24.00	0.93
year2017	-0.04	0.06	-0.71	120.00	0.48
year2018	0.08	0.06	1.39	120.00	0.17
year2019	0.27	0.06	4.82	120.00	0.00
year2020	0.26	0.06	4.65	120.00	0.00
year2021	0.19	0.06	3.34	120.00	0.00

p values calculated using Satterthwaite d.f.

Random Effects		
Group	Parameter	Std. Dev.
plot	(Intercept)	0.25
Residual		0.19

Grouping Variables		
Group	# groups	ICC
plot	24	0.63

```
##  warmed  2016   1.46 0.0875 38.7     1.29     1.64
##  ambient 2017   1.43 0.0875 38.7     1.26     1.61
##  warmed  2017   1.42 0.0875 38.7     1.25     1.60
##  ambient 2018   1.55 0.0875 38.7     1.37     1.73
##  warmed  2018   1.54 0.0875 38.7     1.36     1.72
##  ambient 2019   1.74 0.0875 38.7     1.56     1.92
##  warmed  2019   1.73 0.0875 38.7     1.55     1.91
##  ambient 2020   1.73 0.0875 38.7     1.56     1.91
##  warmed  2020   1.72 0.0875 38.7     1.55     1.90
##  ambient 2021   1.66 0.0875 38.7     1.48     1.84
##  warmed  2021   1.65 0.0875 38.7     1.47     1.83
##
## 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 year2016 - warmed year2016   0.009594 0.1124  26.2   0.085  1.0000
##  ambient year2016 - ambient year2017  0.039491 0.0567 125.2   0.696  0.9999
##  ambient year2016 - warmed year2017   0.049085 0.1259  41.4   0.390  1.0000
##  ambient year2016 - ambient year2018 -0.077217 0.0567 125.2  -1.362  0.9685
##  ambient year2016 - warmed year2018  -0.067623 0.1259  41.4  -0.537  1.0000
##  ambient year2016 - ambient year2019 -0.267321 0.0567 125.2  -4.714  0.0004
##  ambient year2016 - warmed year2019  -0.257727 0.1259  41.4  -2.047  0.6604
##  ambient year2016 - ambient year2020 -0.258209 0.0567 125.2  -4.553  0.0007
##  ambient year2016 - warmed year2020  -0.248615 0.1259  41.4  -1.975  0.7068
##  ambient year2016 - ambient year2021 -0.185662 0.0567 125.2  -3.274  0.0588
##  ambient year2016 - warmed year2021  -0.176068 0.1259  41.4  -1.398  0.9573
```

```
##  warmed year2016 - ambient year2017   0.029897 0.1259  41.4   0.237  1.0000
##  warmed year2016 - warmed year2017    0.039491 0.0567 125.2   0.696  0.9999
##  warmed year2016 - ambient year2018  -0.086811 0.1259  41.4  -0.689  0.9999
##  warmed year2016 - warmed year2018   -0.077217 0.0567 125.2  -1.362  0.9685
##  warmed year2016 - ambient year2019  -0.276915 0.1259  41.4  -2.199  0.5592
##  warmed year2016 - warmed year2019   -0.267321 0.0567 125.2  -4.714  0.0004
##  warmed year2016 - ambient year2020  -0.267802 0.1259  41.4  -2.127  0.6075
##  warmed year2016 - warmed year2020   -0.258209 0.0567 125.2  -4.553  0.0007
##  warmed year2016 - ambient year2021  -0.195256 0.1259  41.4  -1.551  0.9165
##  warmed year2016 - warmed year2021   -0.185662 0.0567 125.2  -3.274  0.0588
##  ambient year2017 - warmed year2017   0.009594 0.1124  26.2   0.085  1.0000
##  ambient year2017 - ambient year2018 -0.116708 0.0567 125.2  -2.058  0.6531
##  ambient year2017 - warmed year2018  -0.107114 0.1259  41.4  -0.851  0.9993
##  ambient year2017 - ambient year2019 -0.306812 0.0567 125.2  -5.410  <.0001
##  ambient year2017 - warmed year2019  -0.297218 0.1259  41.4  -2.361  0.4533
##  ambient year2017 - ambient year2020 -0.297700 0.0567 125.2  -5.249  <.0001
##  ambient year2017 - warmed year2020  -0.288106 0.1259  41.4  -2.288  0.5002
##  ambient year2017 - ambient year2021 -0.225153 0.0567 125.2  -3.970  0.0065
##  ambient year2017 - warmed year2021  -0.215559 0.1259  41.4  -1.712  0.8525
##  warmed year2017 - ambient year2018  -0.126302 0.1259  41.4  -1.003  0.9968
##  warmed year2017 - warmed year2018   -0.116708 0.0567 125.2  -2.058  0.6531
##  warmed year2017 - ambient year2019  -0.316406 0.1259  41.4  -2.513  0.3605
##  warmed year2017 - warmed year2019   -0.306812 0.0567 125.2  -5.410  <.0001
##  warmed year2017 - ambient year2020  -0.307294 0.1259  41.4  -2.441  0.4034
##  warmed year2017 - warmed year2020   -0.297700 0.0567 125.2  -5.249  <.0001
##  warmed year2017 - ambient year2021  -0.234747 0.1259  41.4  -1.864  0.7731
##  warmed year2017 - warmed year2021   -0.225153 0.0567 125.2  -3.970  0.0065
##  ambient year2018 - warmed year2018   0.009594 0.1124  26.2   0.085  1.0000
##  ambient year2018 - ambient year2019 -0.190104 0.0567 125.2  -3.352  0.0470
##  ambient year2018 - warmed year2019  -0.180510 0.1259  41.4  -1.434  0.9495
##  ambient year2018 - ambient year2020 -0.180992 0.0567 125.2  -3.191  0.0737
##  ambient year2018 - warmed year2020  -0.171398 0.1259  41.4  -1.361  0.9646
##  ambient year2018 - ambient year2021 -0.108445 0.0567 125.2  -1.912  0.7494
##  ambient year2018 - warmed year2021  -0.098851 0.1259  41.4  -0.785  0.9997
##  warmed year2018 - ambient year2019  -0.199698 0.1259  41.4  -1.586  0.9044
##  warmed year2018 - warmed year2019   -0.190104 0.0567 125.2  -3.352  0.0470
##  warmed year2018 - ambient year2020  -0.190586 0.1259  41.4  -1.514  0.9282
##  warmed year2018 - warmed year2020   -0.180992 0.0567 125.2  -3.191  0.0737
##  warmed year2018 - ambient year2021  -0.118039 0.1259  41.4  -0.938  0.9982
##  warmed year2018 - warmed year2021   -0.108445 0.0567 125.2  -1.912  0.7494
##  ambient year2019 - warmed year2019   0.009594 0.1124  26.2   0.085  1.0000
##  ambient year2019 - ambient year2020  0.009112 0.0567 125.2   0.161  1.0000
##  ambient year2019 - warmed year2020   0.018706 0.1259  41.4   0.149  1.0000
##  ambient year2019 - ambient year2021  0.081658 0.0567 125.2   1.440  0.9531
##  ambient year2019 - warmed year2021   0.091253 0.1259  41.4   0.725  0.9998
##  warmed year2019 - ambient year2020  -0.000482 0.1259  41.4  -0.004  1.0000
##  warmed year2019 - warmed year2020    0.009112 0.0567 125.2   0.161  1.0000
##  warmed year2019 - ambient year2021   0.072065 0.1259  41.4   0.572  1.0000
##  warmed year2019 - warmed year2021    0.081658 0.0567 125.2   1.440  0.9531
##  ambient year2020 - warmed year2020   0.009594 0.1124  26.2   0.085  1.0000
##  ambient year2020 - ambient year2021  0.072546 0.0567 125.2   1.279  0.9803
##  ambient year2020 - warmed year2021   0.082140 0.1259  41.4   0.652  0.9999
##  warmed year2020 - ambient year2021   0.062953 0.1259  41.4   0.500  1.0000
##  warmed year2020 - warmed year2021    0.072546 0.0567 125.2   1.279  0.9803
```

```
##  ambient year2021 - warmed year2021   0.009594 0.1124  26.2   0.085  1.0000
##
## Degrees-of-freedom method: kenward-roger
## Results are given on the log (not the response) scale.
## P value adjustment: tukey method for comparing a family of 12 estimates
```