Reproducible Research in R Workshop

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Script last updated: ENTER DATE by ENTER NAME

Before you begin

Notes

A few notes about this script.

This is a mock script that walks through the steps of analyzing mammal data using generalized linear models. It uses slightly modified data from a real study on brown bear livestock predation in Romania that was published in Conservation Science and Practice.

Mihai I. Pop, Marissa A. Dyck, Silviu Chiriac, Berde Lajos, Szilárd Szabó, Cristian I. Iojă, Viorel D. Popescu. (2023). Predictors of brown bear predation events on livestock in the Romanian Carpathians

This code is derived from course materials developed by Dr. Marissa A. Dyck for undergraduate & graduate coursework at the University of Victoria, as well as international R workshops. The course is free and available online through Dr. Dyck's GitHub. You may find this a helpful resource for further developing your coding knowledge and skills beyond what we can cover in this workshop.

If you have question please email the author,

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R and RStudio

Before starting you should ensure you have the latest version of R and RStudio downloaded. This code was generated under R version 4.2.3 and with RStudio version 2024.04.2+764.

You can download R and RStudio HERE

R markdown

This script is written in R markdown and thus uses a mix of coding markup languages and R. If you are planning to run this script with new data or make any modifications you will want to be familiar with some basics of R markdown.

Below is an R markdown cheatsheet to help you get started,
R markdown cheatsheet

Install packages

If you don't already have the following packages installed, use the code below to install them. *NOTE this will not run automatically as eval=FALSE is included in the chunk setup (i.e. I don't want it to run every time I run this code since I have the packages installed)

```r
install.packages('tidyverse')
install.packages('MuMIn')
install.packages('car')
install.packages('lme4')
install.packages('PerformanceAnalytics')
install.packages('broom')
```

Load libraries

Then load the packages to your library so they are available for use during this current R session. I have this chode chunk set to message=FALSE so that my knitted doc doesn't print all the info about each library that is normally printed in the console.

```r
library(tidyverse) # for data formatting, cleaning, and much more!
library(PerformanceAnalytics) # for generating correlation matrix plots
library(lme4) # for fitting glms
library(car) # companion package for glm analysis with additional functions
library(MuMIn) # for model selection
library(broom) # extracting odds ratios in a tidy format
```

Data

README

As previously mentioned, this data is a slightly modified version of data associated with Pop et al., 2023. There is a published GitHub repository on Dr. Dyck's GitHub with the final data and analysis scripts from the publication if you are interested.

Brown Bear Predation GitHub repository

Although the data is slightly different, the README that was published with the final analysis should serve as a good enough reference for the data we are using if you want more information about the data collected.

Brown Bear README

Import data

This code will read in the data as a tibble and save it to the environment with a descriptive and tidy name - this is essential for well organized reproducible research to avoid errors with coding. Avoid naming your data files as 'data' or 'dat' for example, because as your workflow gets more complex you may be importing several datasets for a single project or you may be working on several projects at a time in one R session - if all your data are named very similarly or the exact same thing you can easily reference the wrong data set.

In the same code chunk we will also do a bit of data tidying that I consider the standard now for all of my analyses to ease coding, reduce errors, and increase reproduce-ability.

- First, we will set all the column names to lowercase - this reduces keystrokes and possible case sensitive errors while coding
- Then we will specify how each of the variables should be read in (e.g. factor, numeric, etc.). This will also reduce potential errors later in the process as R often misinterprets how to read in data. You should always be familiar enough with your data before beginning any analysis to complete this

section (i.e. you should know what each column is, how it was measured, and ideally what format you need it to be in for your analysis - some variables can be coded in several ways which are all correct depending on what you are doing with the data). **This is wear README files come in: You have to familiarize yourself with the data before beginning any analysis, and to have truly reproducible research when you publish or share your analysis you will need to have a thorough explanation of your data for someone else. This is all included in a README file and I recommend starting one at this phase in your process if not sooner!**

- Lastly, we will check the structure of the data and make sure things read in properly, and make any changes to this code if necessary

```r
# read in the bear data and do some data tidying
bear_damage <- read_csv('data/raw/pagube_2008_2016_spatial.csv',

                        # specify how the columns are read in
                        col_types = cols(Damage = col_factor(),
                                         Year = col_factor(),
                                         Month = col_factor(),
                                         Targetspp = col_factor(),
                                         Landcover_code = col_factor(),
                                         .default = col_number())) %>%

  # set all column names to lowercase
  rename_with(tolower)

# check the internal structure of the data
str(bear_damage)
```

```
## spc_tbl_ [3,024 x 24] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
##  $ damage          : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 2 1 1 2 ...
##  $ year            : Factor w/ 9 levels "2016","2009",..: 1 2 2 3 4 2 3 4 2 5 ...
##  $ month           : Factor w/ 12 levels "0","7","9","8",..: 1 1 1 1 1 1 2 1 1 3 ...
##  $ targetspp       : Factor w/ 3 levels "alte","ovine",..: NA NA NA NA NA NA 1 NA NA 2 ...
##  $ point_x         : num [1:3024] 489008 491321 491398 491758 492628 ...
##  $ point_y         : num [1:3024] 532778 542207 538028 536946 533069 ...
##  $ bear_abund      : num [1:3024] 0 0 26 26 0 26 26 26 26 26 ...
##  $ landcover_code  : Factor w/ 15 levels "311","112","231",..: 1 1 1 1 1 1 2 3 4 5 ...
##  $ altitude        : num [1:3024] 549 596 506 485 530 551 437 527 467 561 ...
##  $ human_population: num [1:3024] 0 0 54 32 0 0 229 0 0 0 ...
##  $ dist_to_forest  : num [1:3024] 0 0 0 0 0 ...
##  $ dist_to_town    : num [1:3024] 1558 2281.6 387.8 60.6 2076.3 ...
##  $ livestock_killed: num [1:3024] 0 0 0 0 0 1 1 0 1 1 ...
##  $ shannondivindex : num [1:3024] 1.083 0.692 0.908 1.555 0.81 ...
##  $ prop_arable     : num [1:3024] 0 0 0 14.1 4.7 ...
##  $ prop_orchards   : num [1:3024] 0 0 0 0 0 0 0 0 0 0 ...
##  $ prop_pasture    : num [1:3024] 25.2 20.2 42.7 25.4 70.1 ...
##  $ prop_ag_mosaic  : num [1:3024] 0 0 0 0 0 ...
##  $ prop_seminatural: num [1:3024] 9.427 1.668 0.166 22.149 2.001 ...
##  $ prop_deciduous  : num [1:3024] 59.4 75.7 50.6 27.4 23.2 ...
##  $ prop_coniferous : num [1:3024] 0 0 0 0 0 0 0 0 0 0 ...
##  $ prop_mixedforest: num [1:3024] 0 0 0 0 0 0 0 0 0 0 ...
##  $ prop_grassland  : num [1:3024] 0 2.4 0.26 0 0 ...
##  $ prop_for_regen  : num [1:3024] 4.17 0 0 0 0 ...
##  - attr(*, "spec")=
##   .. cols(
##   ..   .default = col_number(),
##   ..   Damage = col_factor(levels = NULL, ordered = FALSE, include_na = FALSE),
##   ..   Year = col_factor(levels = NULL, ordered = FALSE, include_na = FALSE),
##   ..   Month = col_factor(levels = NULL, ordered = FALSE, include_na = FALSE),
##   ..   Targetspp = col_factor(levels = NULL, ordered = FALSE, include_na = FALSE),
##   ..   POINT_X = col_number(),
##   ..   POINT_Y = col_number(),
##   ..   Bear_abund = col_number(),
##   ..   Landcover_code = col_factor(levels = NULL, ordered = FALSE, include_na = FALSE),
##   ..   Altitude = col_number(),
##   ..   Human_population = col_number(),
##   ..   Dist_to_forest = col_number(),
##   ..   Dist_to_town = col_number(),
##   ..   Livestock_killed = col_number(),
##   ..   ShannonDivIndex = col_number(),
##   ..   prop_arable = col_number(),
##   ..   prop_orchards = col_number(),
##   ..   prop_pasture = col_number(),
##   ..   prop_ag_mosaic = col_number(),
##   ..   prop_seminatural = col_number(),
##   ..   prop_deciduous = col_number(),
##   ..   prop_coniferous = col_number(),
##   ..   prop_mixedforest = col_number(),
##   ..   prop_grassland = col_number(),
##   ..   prop_for_regen = col_number()
##   .. )
##  - attr(*, "problems")=<externalptr>
```

Data checks and cleaning

Now we will do some mock data checks and data cleaning. This doesn't necessarily reflect what you would need to do with this exact data but provides some examples of things to check and gives you practice with different code.

Years

First we will check that the data represents all the years for the study and no years are missing and there isn't data from any years outside the study timeframe.

From the README file we know that we should have data for years 2008-2016

```
# check that year is correct
summary(bear_damage$year)
```

```
## 2016 2009 2014 2012 2013 2011 2010 2015 2008
##  348  408  396  620  392  160  140  324  236
```

You'll notice it isn't ordered because we read it in as a factor not a numeric variable there are ways to fix this but I will leave that to you to explore

Months

We will also check that all the for months looks correct and is entered properly. We should have 1-12 with 1 being January and 12 December, we will also have zeros from the pseudoabsence data generated for this dataset (see README)

```r
# check that month is correct
summary(bear_damage$month)
```

```
##    0    7    9    8    5   10    6    4    3   11   12    2
## 2268  139  160  155   84   50  105   27    8   20    7    1
```

> You'll notice after checking that there aren't any 1's, that is because brown bears are hibernating during this period and thus there were no records of damage for January. These are important details to know, check, and make note of in your code and README for reproducible science!

Filter data

Much of the spatial data for this dataset are represented as proportion (e.g., proportion of different types of habitat on the landscape). If we expect that our proportional data should all sum to 100 we can check that for each site and remove any sites (rows) that don't as a data cleaning step. The code below will do this.

We also may be interested in filtering out observations where a lot of animals were involved (likely these are smaller livestock such as chickens etc.), if we only want to use data where a certain number of livestock were killed we can do that data cleaning step here as well.

We will assign a new data set to the environment for this step so we can compare with the old data

```r
# create new data with prop_check column and filter out observations that don't sum to 100
bear_damage_tidy <- bear_damage %>%

  # create a column that sums across rows of spatial data
  mutate(prop_check = rowSums(across(contains('prop')))) %>%

  # filter to 100 and only livestock events with 10 or fewer animals
  filter(prop_check == 100 &
           livestock_killed <= 10)

# check new data
summary(bear_damage_tidy)
```

```
##  damage       year          month       targetspp       point_x
##  0:922   2012   :245   0      :922   alte  : 16   Min.   :491321
##  1:198   2013   :160   9      : 42   ovine : 39   1st Qu.:547710
##          2014   :142   6      : 38   bovine:143   Median :569859
##          2015   :136   8      : 34   NA's  :922   Mean   :575292
##          2009   :132   7      : 31                3rd Qu.:603439
##          2016   :122   5      : 21                Max.   :658416
##          (Other):183   (Other): 32
##     point_y          bear_abund    landcover_code    altitude
##  Min.   :447121   Min.   : 0.00   311    :261    Min.   : 255.0
##  1st Qu.:489899   1st Qu.:19.00   312    :254    1st Qu.: 697.0
##  Median :519150   Median :31.00   313    :159    Median : 915.0
##  Mean   :524433   Mean   :30.24   321    :135    Mean   : 917.8
##  3rd Qu.:552545   3rd Qu.:42.00   231    :129    3rd Qu.:1124.0
##  Max.   :628579   Max.   :77.00   211    : 80    Max.   :1707.0
##                                   (Other):102
##  human_population  dist_to_forest     dist_to_town   livestock_killed
##  Min.   :  0.000   Min.   :   0.00   Min.   :    0   Min.   :0.0000
##  1st Qu.:  0.000   1st Qu.:   0.00   1st Qu.: 1790   1st Qu.:0.0000
##  Median :  0.000   Median :   0.00   Median : 2941   Median :0.0000
##  Mean   :  2.546   Mean   : 253.24   Mean   : 3561   Mean   :0.5634
##  3rd Qu.:  0.000   3rd Qu.:  87.58   3rd Qu.: 4770   3rd Qu.:1.0000
##  Max.   :369.000   Max.   :7073.95   Max.   :13140   Max.   :7.0000
##
##  shannondivindex   prop_arable      prop_orchards  prop_pasture
##  Min.   :0.0000   Min.   :  0.000   Min.   :0     Min.   : 0.00
##  1st Qu.:0.5107   1st Qu.:  0.000   1st Qu.:0     1st Qu.: 0.00
##  Median :0.7850   Median :  0.000   Median :0     Median : 0.00
##  Mean   :0.7633   Mean   :  7.002   Mean   :0     Mean   : 8.88
##  3rd Qu.:1.0451   3rd Qu.:  0.000   3rd Qu.:0     3rd Qu.:11.23
##  Max.   :1.8951   Max.   :100.000   Max.   :0     Max.   :96.11
##
##  prop_ag_mosaic    prop_seminatural prop_deciduous   prop_coniferous
##  Min.   : 0.0000   Min.   : 0.000   Min.   :  0.00   Min.   :  0.000
##  1st Qu.: 0.0000   1st Qu.: 0.000   1st Qu.:  0.00   1st Qu.:  0.000
##  Median : 0.0000   Median : 0.000   Median :  3.13   Median :  6.774
##  Mean   : 0.8042   Mean   : 1.753   Mean   : 27.40   Mean   : 24.417
##  3rd Qu.: 0.0000   3rd Qu.: 0.000   3rd Qu.: 56.59   3rd Qu.: 45.989
##  Max.   :42.9740   Max.   :44.391   Max.   :100.00   Max.   :100.000
##
##  prop_mixedforest prop_grassland   prop_for_regen     prop_check
##  Min.   :  0.00   Min.   : 0.000   Min.   : 0.000   Min.   :100
##  1st Qu.:  0.00   1st Qu.: 0.000   1st Qu.: 0.000   1st Qu.:100
##  Median :  0.00   Median : 0.000   Median : 0.000   Median :100
##  Mean   : 15.26   Mean   : 8.732   Mean   : 5.758   Mean   :100
##  3rd Qu.: 22.11   3rd Qu.:13.614   3rd Qu.: 8.162   3rd Qu.:100
##  Max.   :100.00   Max.   :86.540   Max.   :61.234   Max.   :100
##
```

Remove old data

Now, if we aren't going to use the old version of the data any further, we should remove it from our environment. Keeping our environment clean helps ensure we don't accidentally use the wrong data and also makes it organized and easier to inspect objects if we need.

```r
# remove old data
rm(bear_damage)
```

Summary statistics

Often times for publications, reports, or other deliverables we need to provide some summary information about the raw data we collected. Besides that, this is a great way to begin to explore your data prior to conducting any formal analyses.

Total events

First we will calculate the total number of predation *events*, for this dataset, that is anything in the damage column that is coded as a one where zeros represent pseudoabsence events. We will also calculate the total number of livestock killed across all events.

Remember we are using the 'tidy' dataset which doesn't include all of the raw data. Depending on your needs you may want to use the messier raw data to report your summary stats

```r
# total number of events & total number of livestock killed
# with summary we can look at the number of events (1s in the damage column)
summary(bear_damage_tidy$damage)
```

```
##   0   1
## 922 198
```

```
# or with summarise we can calculate both
bear_damage_tidy %>%

  # ensure to only count events of damage
  filter(damage == '1') %>%

  summarise(n_events = n(),
            total_killed = sum(livestock_killed))
```

```
## # A tibble: 1 x 2
##   n_events total_killed
##      <int>        <dbl>
## 1      198          470
```

Events per livestock type

In this data there are several types of livestock that are affected, we may want to report specifics about each type of livestock. For that we can group our data before calculating some summary info.

```
# damage per livestock type (target species)
bear_damage_tidy %>%

  # ensure to only count events of damage not pseudoabsences
  filter(damage == '1') %>%

  # group by targetspp to get summaries for each species and year
  group_by(targetspp) %>%

  # calculate total number of events (n)
  summarise(n = n())
```

```
## # A tibble: 3 x 2
##   targetspp     n
##   <fct>     <int>
## 1 alte         16
## 2 ovine        39
## 3 bovine      143
```

```
# bovine highest, alte lowest
```

Events per year

This data was also collected over several years, so we may want to report some summary statistics for each year

```
# damage per year
bear_damage_tidy %>%

  # ensure to only count events of damage
  filter(damage == '1') %>%
  # group by targetspp to get summaries for each species and year
  group_by(year) %>%

   # calculate total number of events (n)
  summarise(n = n()) %>%

  # sort by largest to smallest number of events
  arrange(desc(n))
```

```
## # A tibble: 9 x 2
##   year      n
##   <fct> <int>
## 1 2012     42
## 2 2013     34
## 3 2014     28
## 4 2016     26
## 5 2015     25
## 6 2009     12
## 7 2011     11
## 8 2010     11
## 9 2008      9
```

```
# 2012 had highest number of events and 2008 had lowest number of events
```

Events per month

We may also be interested in the monthly number of events

```
# damage per month
bear_damage_tidy %>%

  # ensure to only count events of damage
  filter(damage == '1') %>%

  # group by targetspp to get summaries for each species and year
  group_by(month) %>%

  # calculate total number of events (n)
  summarise(n = n()) %>%

  # sort by largest to smallest number of events
  arrange(desc(n))
```

```
## # A tibble: 10 x 2
##    month     n
##    <fct> <int>
##  1 9        42
##  2 6        38
##  3 8        34
##  4 7        31
##  5 5        21
##  6 10       14
##  7 4        12
##  8 11        4
##  9 3         1
## 10 2         1
```

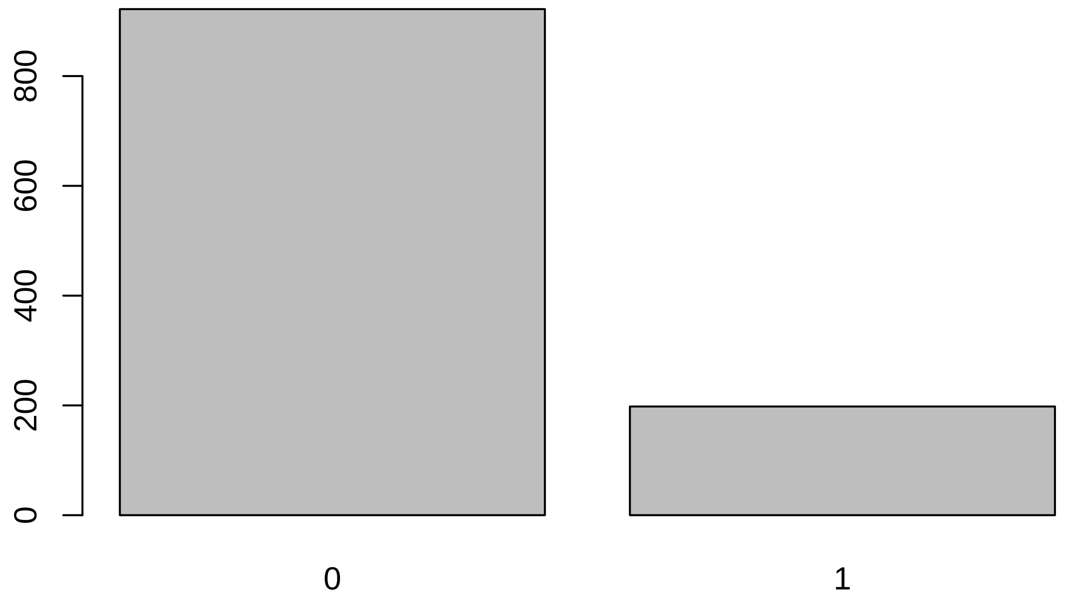
```
# september had the highest number of events and Dec/Jan had lowest with 0
```

Analysis prep

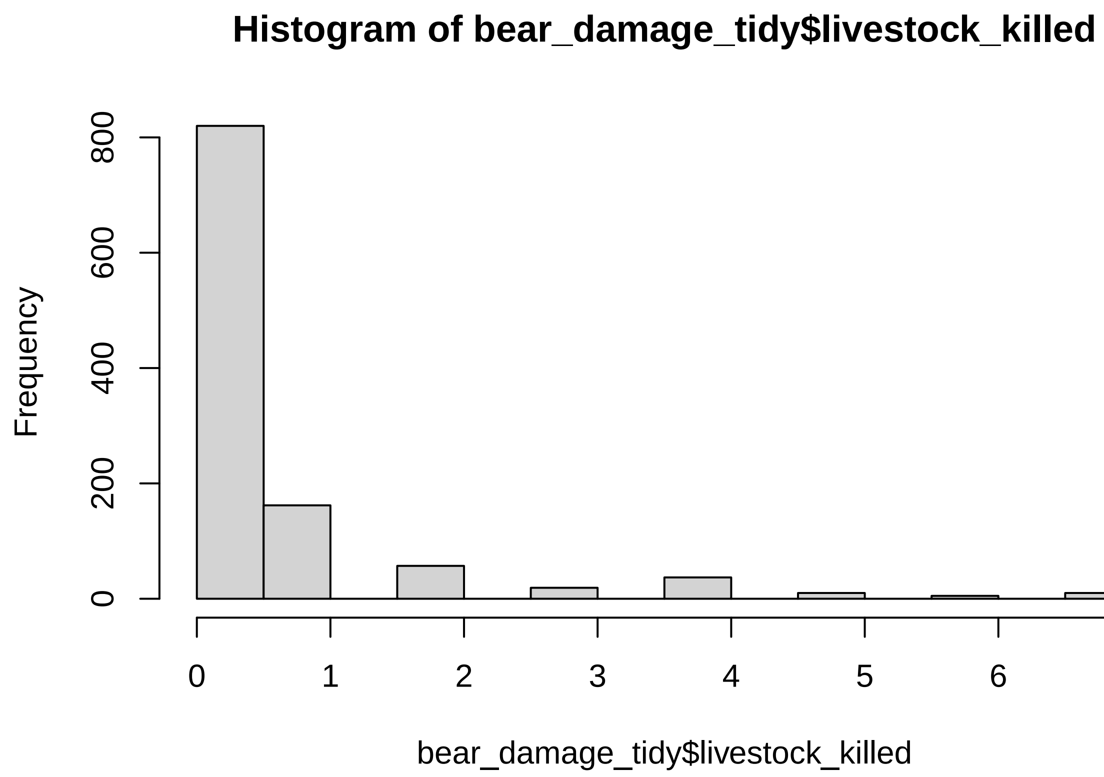
Determine distribution

We are going to analyze this data in a generalized linear model framework, first we will take a look at our potential response variable/s and determine which to use if there are more than one option and which distribution is appropriate for our model based on the response variable

```
# damage is on epossible response variable and the appropriate distribution is binomial as it is 0/1 da
plot(bear_damage_tidy$damage)
```



```
# or livestock killed is response variable which is count data so could be poisson or if highly zero-in
hist(bear_damage_tidy$livestock_killed)
```



```r
# lots of zeros lets do a quick test for dispersion with a simple glm
test_glm <-
glm(livestock_killed ~ bear_abund,
    data = bear_damage_tidy,
    family = 'poisson')

summary(test_glm)
```

```
##
## Call:
## glm(formula = livestock_killed ~ bear_abund, family = "poisson",
##     data = bear_damage_tidy)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.047516   0.087835 -11.926  < 2e-16 ***
## bear_abund   0.014560   0.002248   6.477 9.34e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for poisson family taken to be 1)
##
##     Null deviance: 1958.6  on 1119  degrees of freedom
## Residual deviance: 1916.5  on 1118  degrees of freedom
## AIC: 2662.3
##
```

```
## Number of Fisher Scoring iterations: 6
```

```
# calculate dispersion which is residual deviance / degrees of freedom
1916.5/1118
```

```
## [1] 1.714222
```

```
# 1.74 is high so over-dispersed - use negative binomial
```

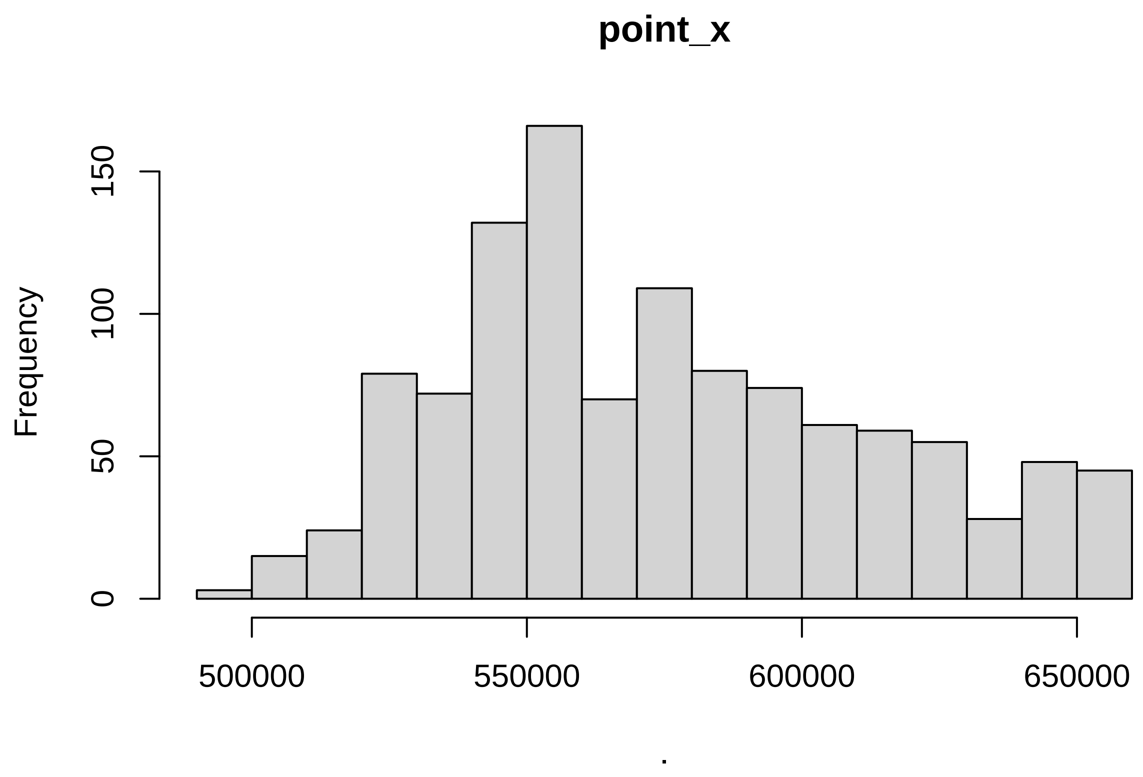
Explanatory variable data exploration

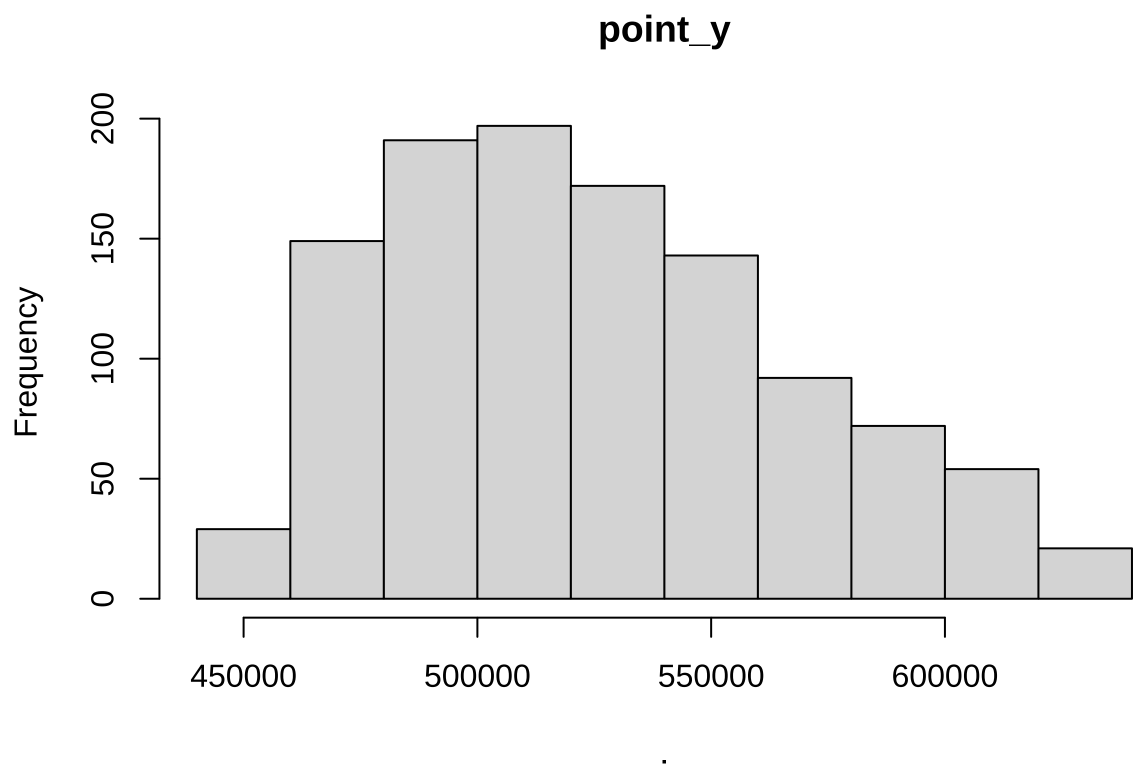
Before we can run an analysis we need to do some exploration of our explanatory variables as well.

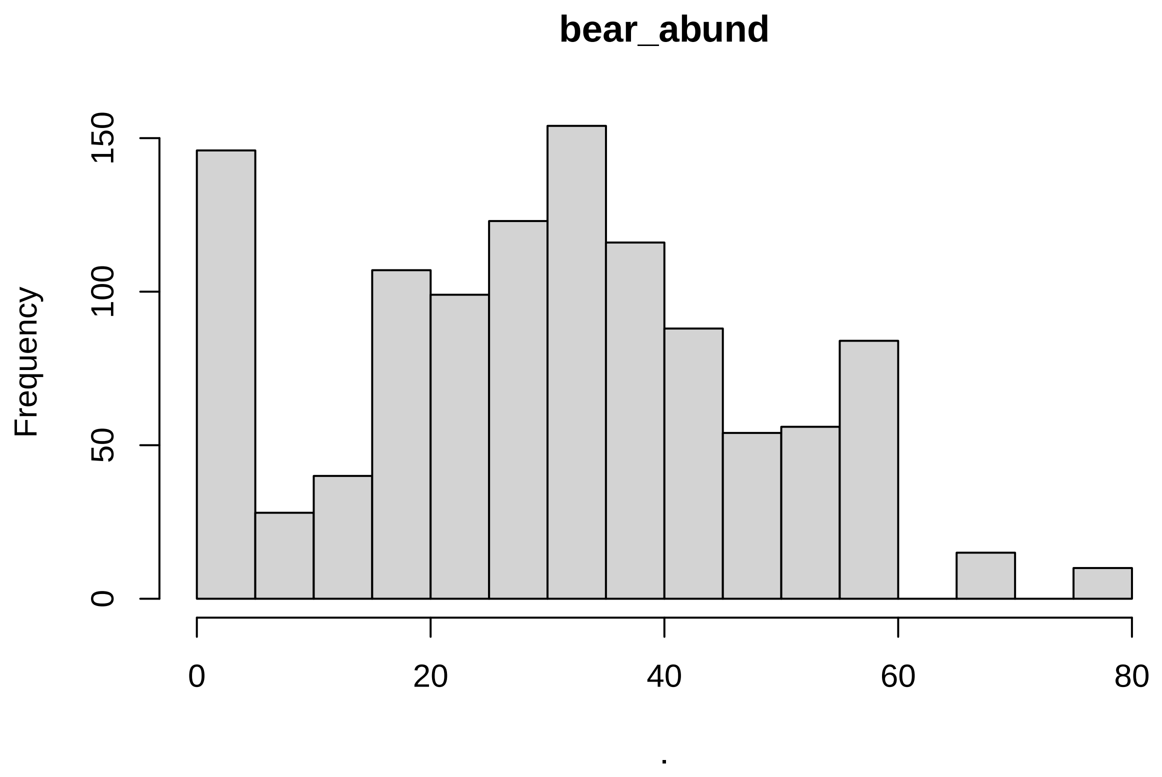
First we will plot histograms of each of our potential variables to insepct the data for issues and ensure there is enough variability to use each of our variables if we want

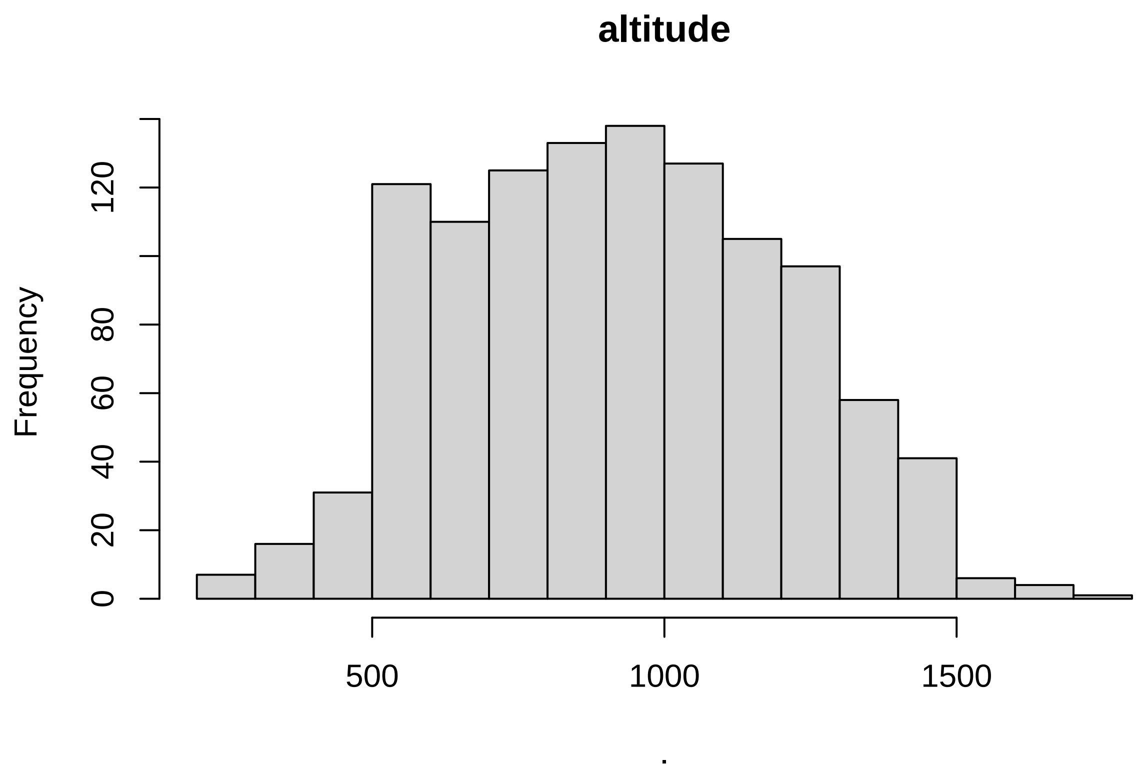
We could plot each with its own line of code or we could run an iteration using a handy tidyverse package called purrr; which is what the code below will do

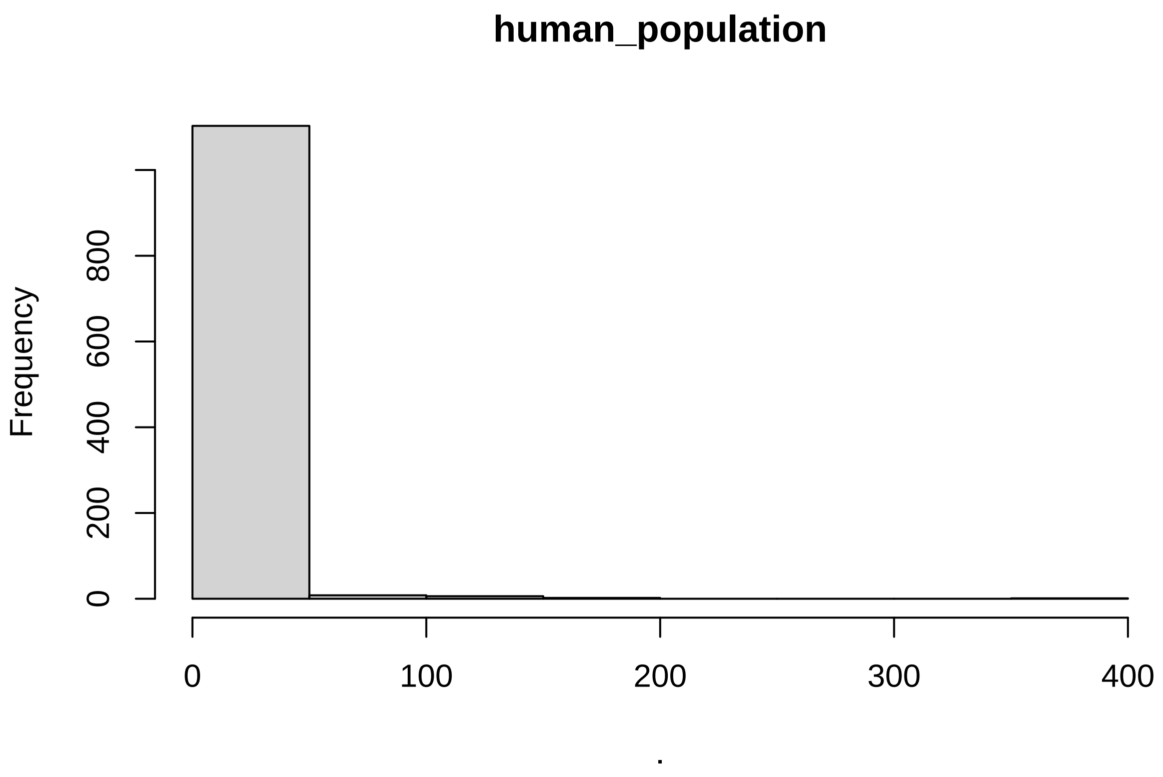
```
# using purr to generate histograms of each expl. variable
bear_damage_tidy %>%

  # select only numeric variables
  select_if(is.numeric) %>%

  # use imap which will retain both the data (x) and the variable names (y)
  imap(~.x %>%

         # use the hist function on the data from previous pipe
        hist(.,

             # set the main title to y (each variable)
             main = .y))
```

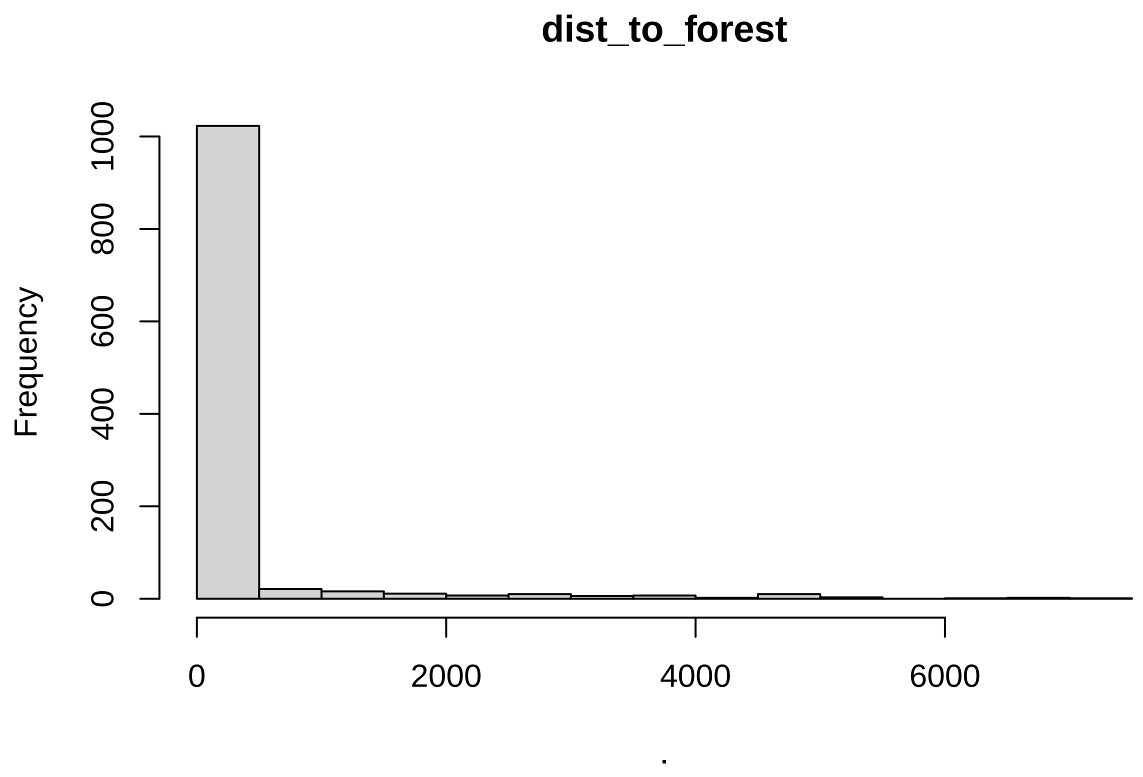

point_x
Frequency
0
50
100
150
500000
550000
600000
650000
.

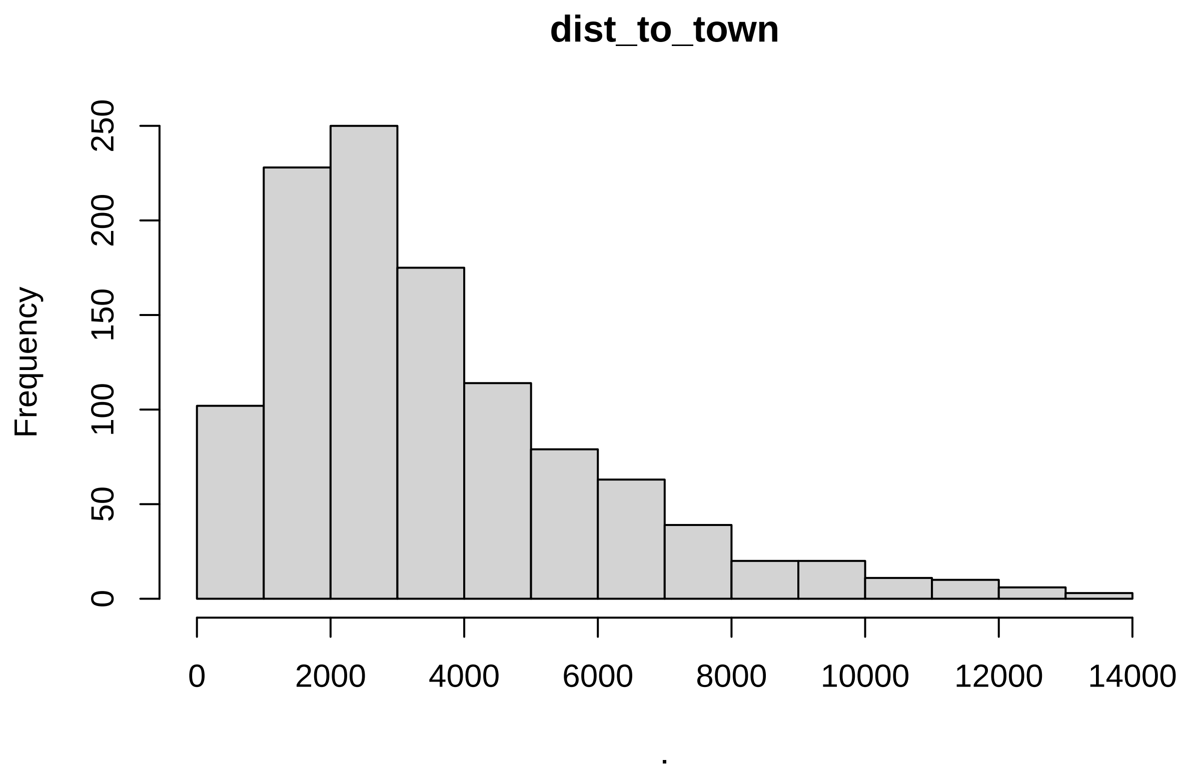

point_y
Frequency
0
50
100
150
200
450000
500000
550000
600000
.

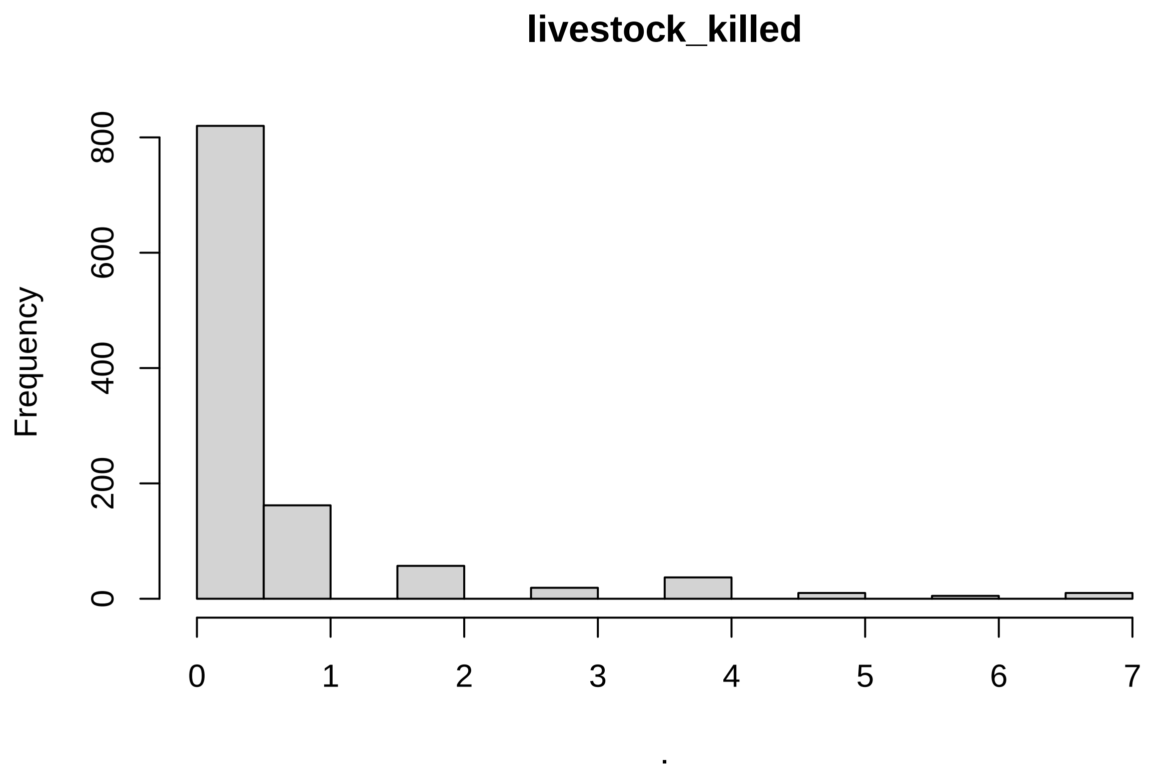

bear_abund
Frequency
0
50
100
150
0
20
40
60
80
.

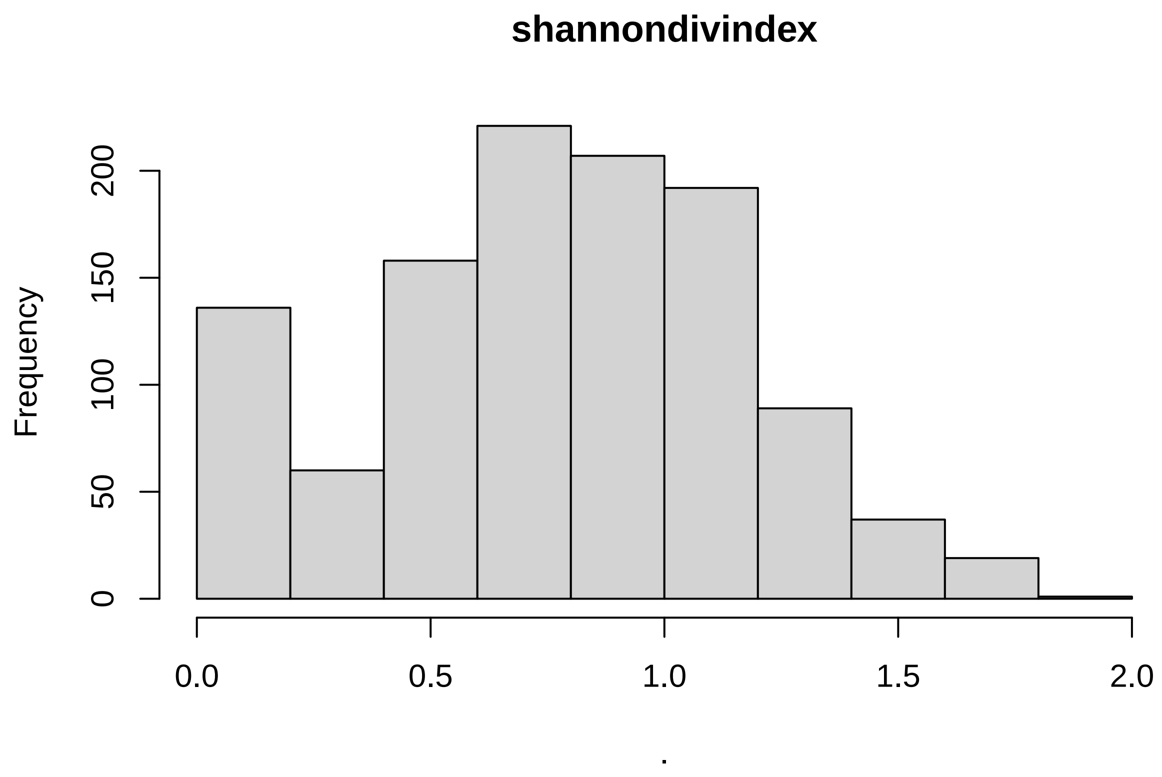

altitude
Frequency
0
20
40
60
80
120
500
1000
1500
.

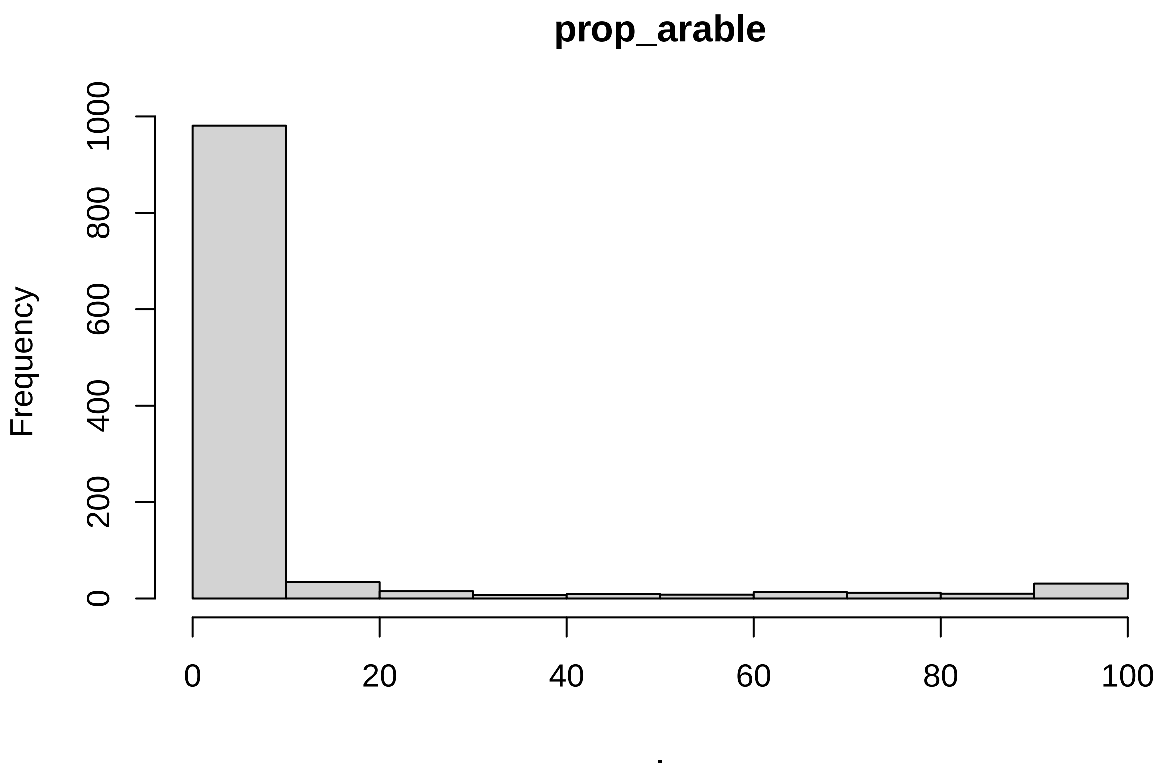

human_population
Frequency
0
200
400
600
800
0
100
200
300
400
.

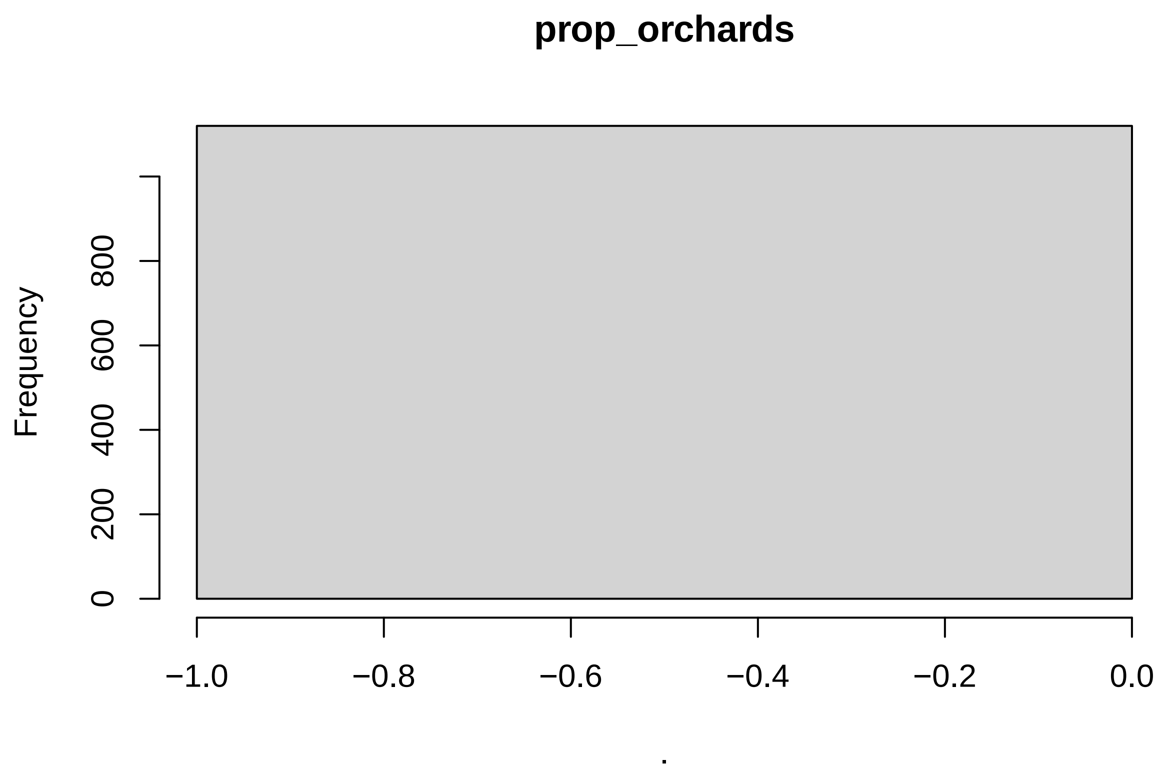

dist_to_forest
Frequency
0
200
400
600
800
1000
0
2000
4000
6000
.

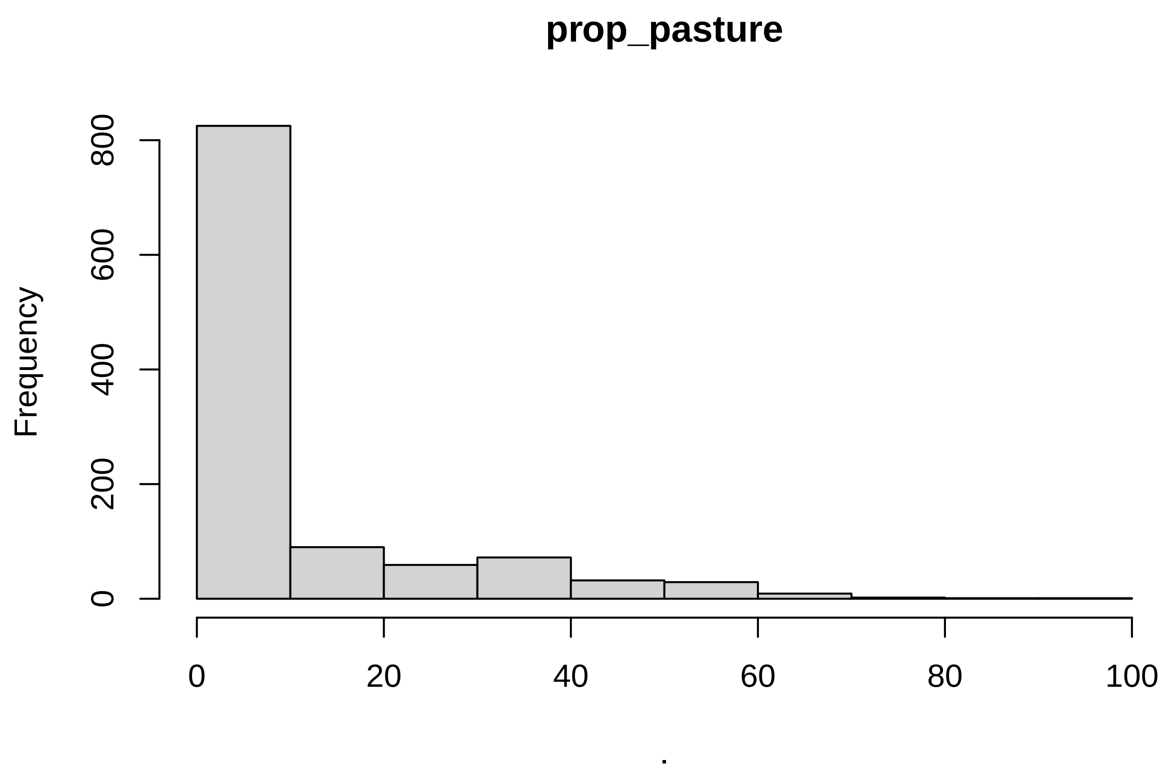

dist_to_town
Frequency
0
50
100
150
200
250
0
2000
4000
6000
8000
10000
12000
14000
.

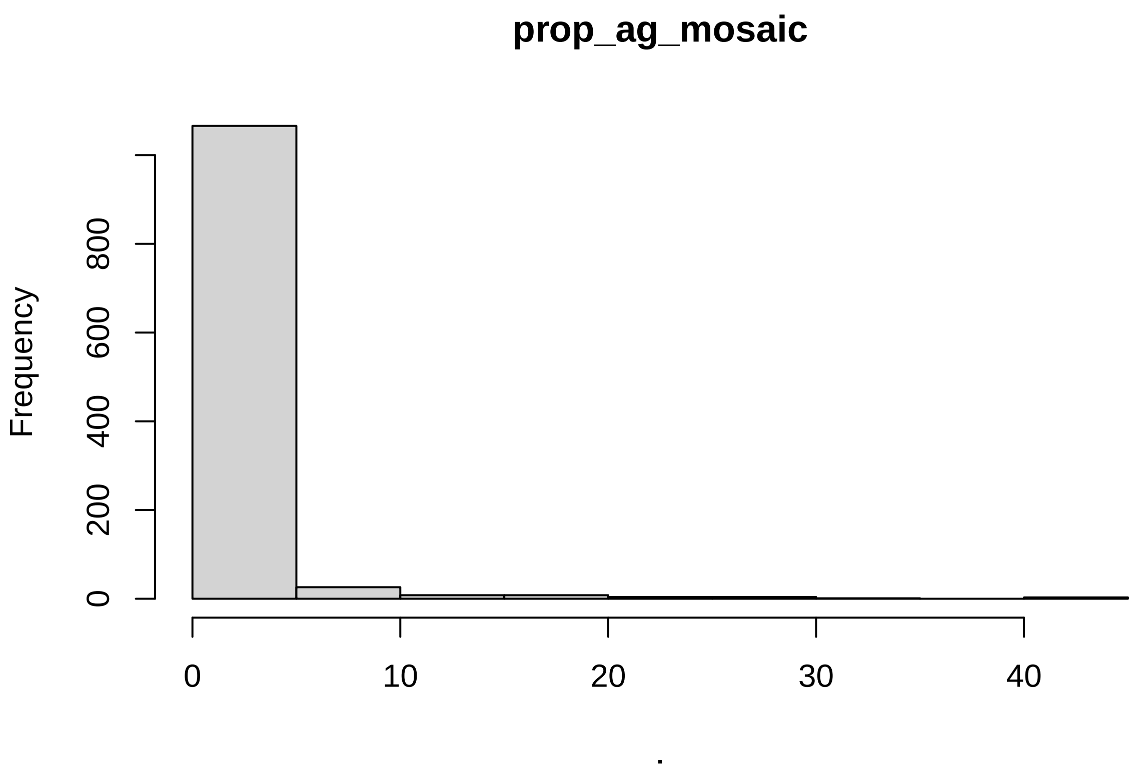

livestock_killed
Frequency
0
200
400
600
800
0
1
2
3
4
5
6
7
.


shannondivindex
Frequency
0
50
100
150
200
0.0
0.5
1.0
1.5
2.0
.

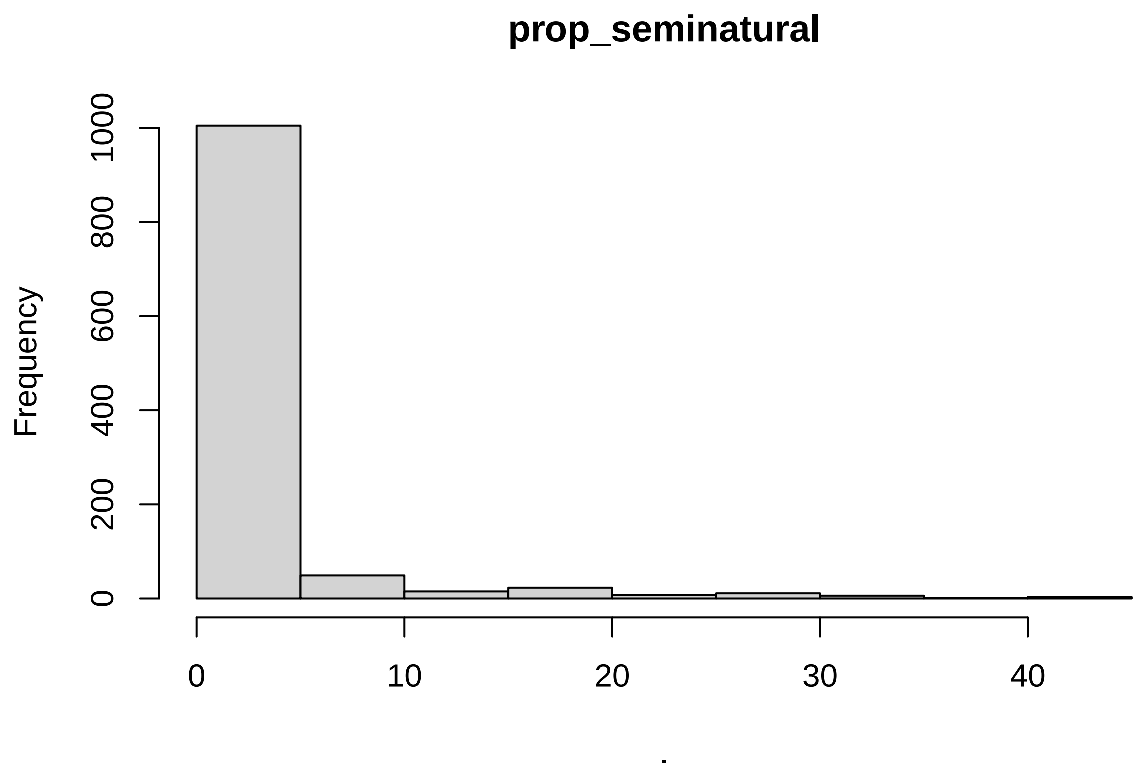

prop_arable
Frequency
0
200
400
600
800
1000
0
20
40
60
80
100
.

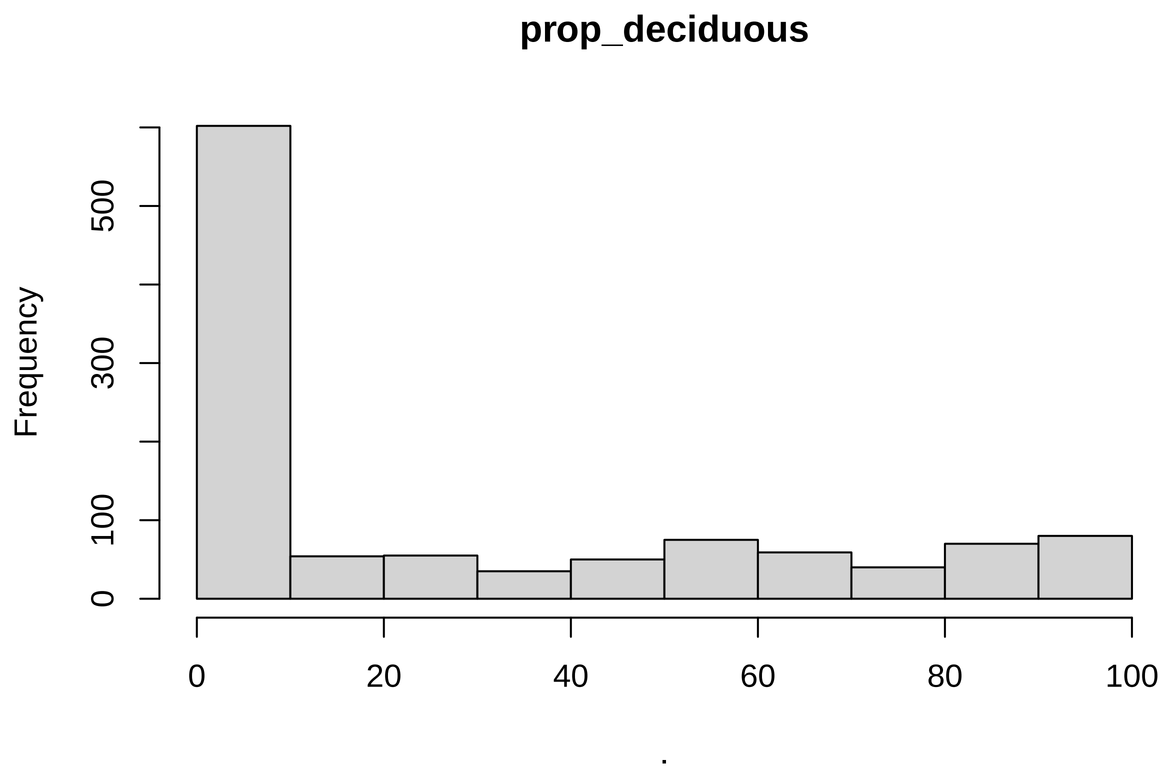

prop_orchards
Frequency
0
200
400
600
800
−1.0
−0.8
−0.6
−0.4
−0.2
0.0
.

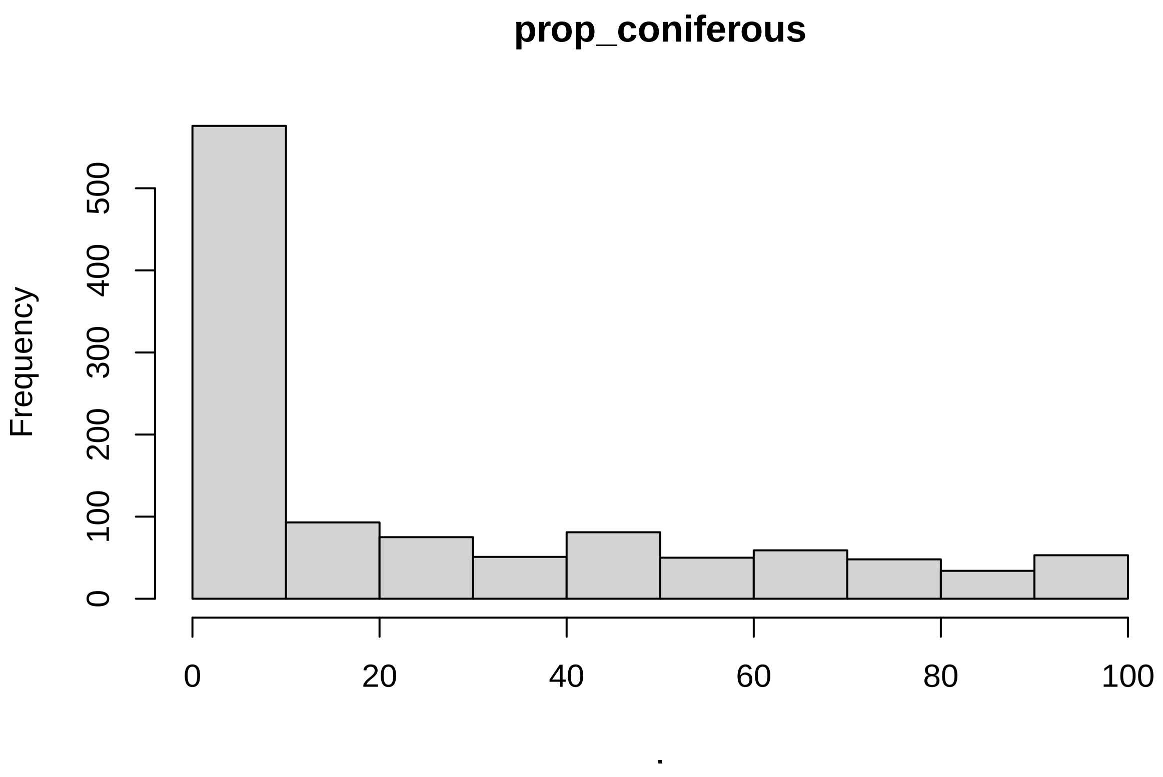

prop_pasture
Frequency
0
200
400
600
800
0
20
40
60
80
100
.



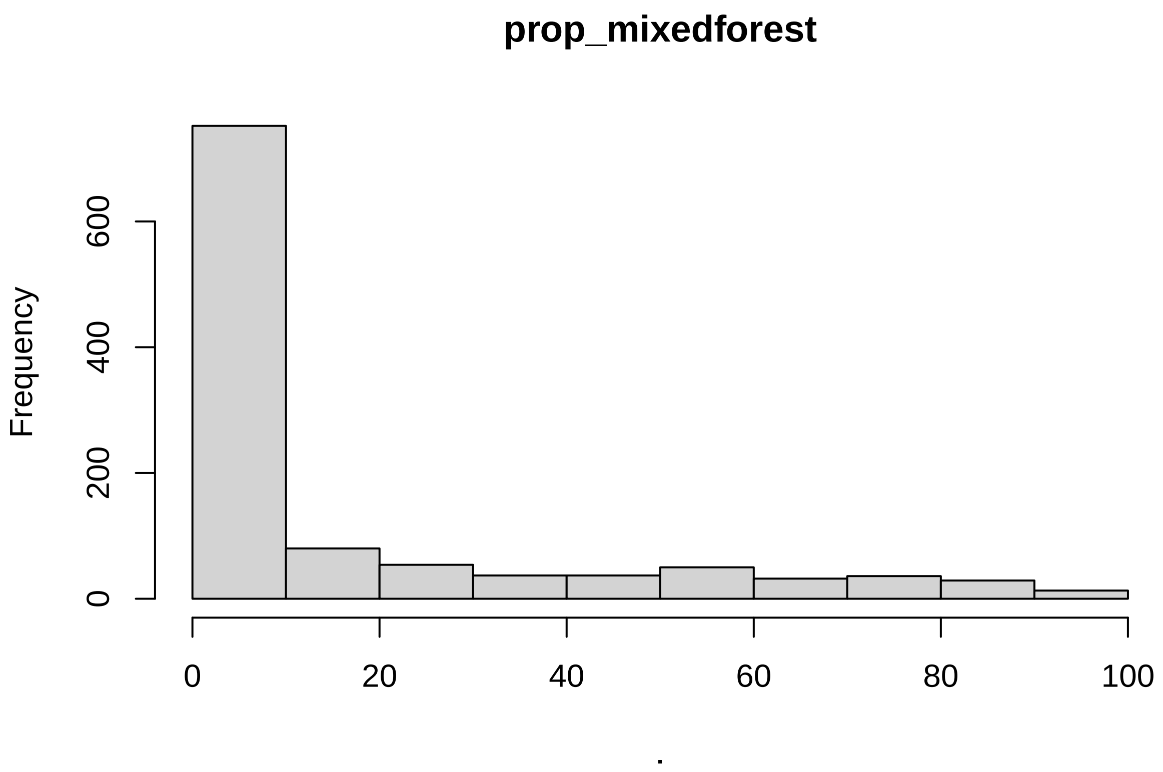
prop_ag_mosaic
Frequency
0
200
400
600
800
0
10
20
30
40
.

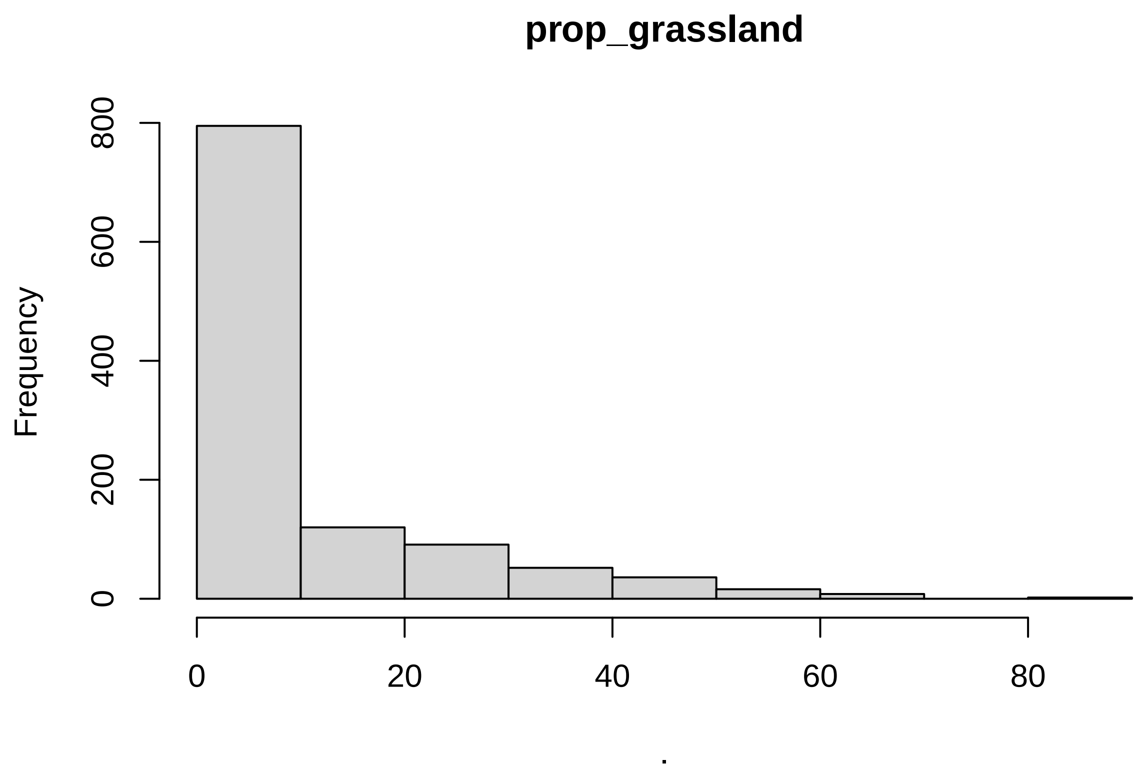

prop_seminatural
Frequency
0
200
400
600
800
1000
0
10
20
30
40
.

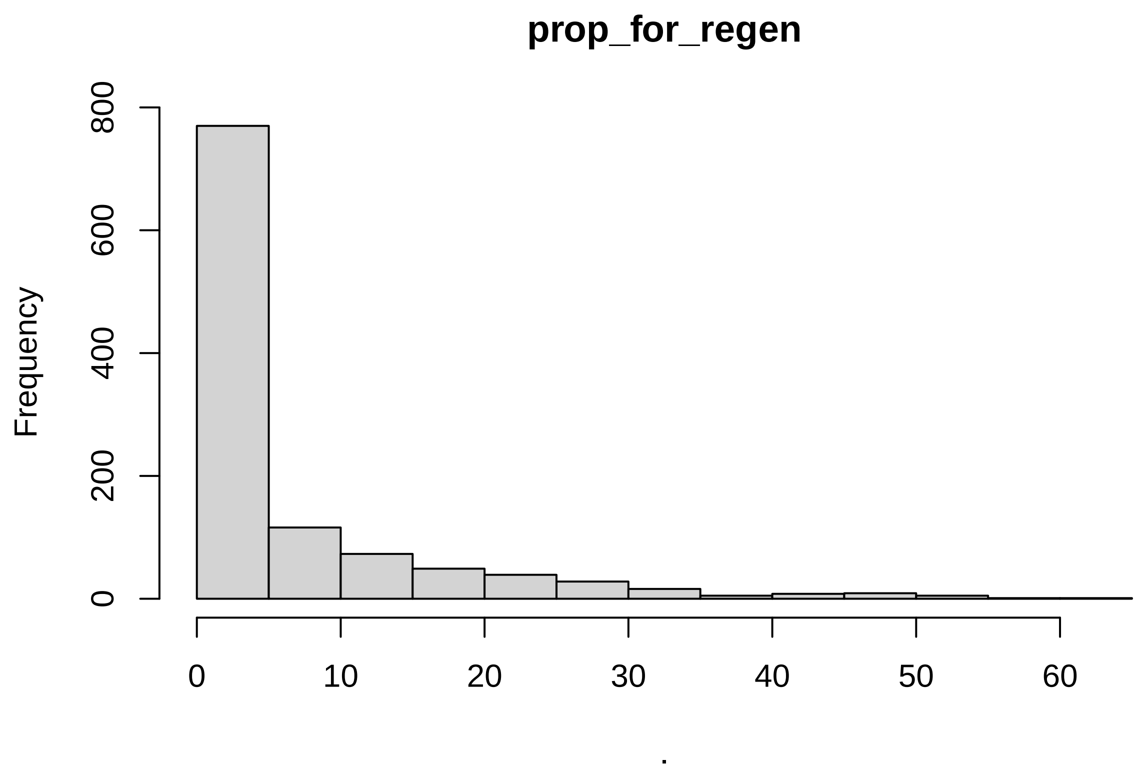

prop_deciduous
Frequency
0
100
300
500
0
20
40
60
80
100
.

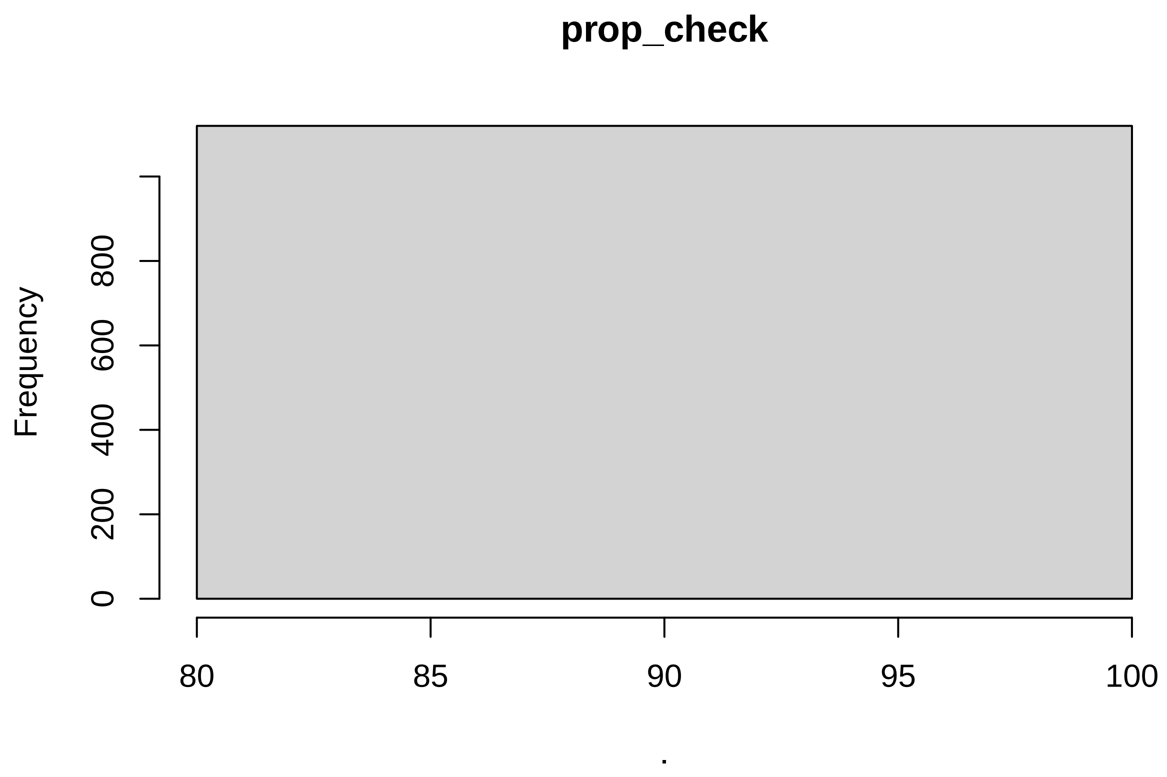


prop_coniferous
Frequency
0
100
200
300
400
500
0
20
40
60
80
100
.


prop_mixedforest
Frequency
0
200
400
600
0
20
40
60
80
100
.


prop_grassland
Frequency
0
200
400
600
800
0
20
40
60
80
.


prop_for_regen
Frequency
0
200
400
600
800
0
10
20
30
40
50
60
.



```
## $point_x
## $breaks
##  [1] 490000 500000 510000 520000 530000 540000 550000 560000 570000 580000
## [11] 590000 600000 610000 620000 630000 640000 650000 660000
##
## $counts
##  [1]   3  15  24  79  72 132 166  70 109  80  74  61  59  55  28  48  45
##
## $density
##  [1] 2.678571e-07 1.339286e-06 2.142857e-06 7.053571e-06 6.428571e-06
##  [6] 1.178571e-05 1.482143e-05 6.250000e-06 9.732143e-06 7.142857e-06
## [11] 6.607143e-06 5.446429e-06 5.267857e-06 4.910714e-06 2.500000e-06
## [16] 4.285714e-06 4.017857e-06
##
## $mids
##  [1] 495000 505000 515000 525000 535000 545000 555000 565000 575000 585000
## [11] 595000 605000 615000 625000 635000 645000 655000
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
```

```
##
## $point_y
## $breaks
##  [1] 440000 460000 480000 500000 520000 540000 560000 580000 600000 620000
## [11] 640000
##
## $counts
##  [1]  29 149 191 197 172 143  92  72  54  21
##
## $density
##  [1] 1.294643e-06 6.651786e-06 8.526786e-06 8.794643e-06 7.678571e-06
##  [6] 6.383929e-06 4.107143e-06 3.214286e-06 2.410714e-06 9.375000e-07
##
## $mids
##  [1] 450000 470000 490000 510000 530000 550000 570000 590000 610000 630000
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $bear_abund
## $breaks
##  [1]  0  5 10 15 20 25 30 35 40 45 50 55 60 65 70 75 80
##
## $counts
##  [1] 146  28  40 107  99 123 154 116  88  54  56  84   0  15   0  10
##
## $density
##  [1] 0.026071429 0.005000000 0.007142857 0.019107143 0.017678571 0.021964286
##  [7] 0.027500000 0.020714286 0.015714286 0.009642857 0.010000000 0.015000000
## [13] 0.000000000 0.002678571 0.000000000 0.001785714
##
## $mids
##  [1]  2.5  7.5 12.5 17.5 22.5 27.5 32.5 37.5 42.5 47.5 52.5 57.5 62.5 67.5 72.5
## [16] 77.5
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $altitude
## $breaks
##  [1]  200  300  400  500  600  700  800  900 1000 1100 1200 1300 1400 1500 1600
## [16] 1700 1800
```

```
##
## $counts
##  [1]   7  16  31 121 110 125 133 138 127 105  97  58  41   6   4   1
##
## $density
##  [1] 6.250000e-05 1.428571e-04 2.767857e-04 1.080357e-03 9.821429e-04
##  [6] 1.116071e-03 1.187500e-03 1.232143e-03 1.133929e-03 9.375000e-04
## [11] 8.660714e-04 5.178571e-04 3.660714e-04 5.357143e-05 3.571429e-05
## [16] 8.928571e-06
##
## $mids
##  [1]  250  350  450  550  650  750  850  950 1050 1150 1250 1350 1450 1550 1650
## [16] 1750
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $human_population
## $breaks
## [1]   0  50 100 150 200 250 300 350 400
##
## $counts
## [1] 1103    8    6    2    0    0    0    1
##
## $density
## [1] 1.969643e-02 1.428571e-04 1.071429e-04 3.571429e-05 0.000000e+00
## [6] 0.000000e+00 0.000000e+00 1.785714e-05
##
## $mids
## [1]  25  75 125 175 225 275 325 375
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $dist_to_forest
## $breaks
##  [1]    0  500 1000 1500 2000 2500 3000 3500 4000 4500 5000 5500 6000 6500 7000
## [16] 7500
##
## $counts
##  [1] 1023   21   16   11    7   10    6    7    2   10    3    0    1    2    1
##
```

```
## $density
##  [1] 1.826786e-03 3.750000e-05 2.857143e-05 1.964286e-05 1.250000e-05
##  [6] 1.785714e-05 1.071429e-05 1.250000e-05 3.571429e-06 1.785714e-05
## [11] 5.357143e-06 0.000000e+00 1.785714e-06 3.571429e-06 1.785714e-06
##
## $mids
##  [1]  250  750 1250 1750 2250 2750 3250 3750 4250 4750 5250 5750 6250 6750 7250
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $dist_to_town
## $breaks
##  [1]     0  1000  2000  3000  4000  5000  6000  7000  8000  9000 10000 11000
## [13] 12000 13000 14000
##
## $counts
##  [1] 102 228 250 175 114  79  63  39  20  20  11  10   6   3
##
## $density
##  [1] 9.107143e-05 2.035714e-04 2.232143e-04 1.562500e-04 1.017857e-04
##  [6] 7.053571e-05 5.625000e-05 3.482143e-05 1.785714e-05 1.785714e-05
## [11] 9.821429e-06 8.928571e-06 5.357143e-06 2.678571e-06
##
## $mids
##  [1]   500  1500  2500  3500  4500  5500  6500  7500  8500  9500 10500 11500
## [13] 12500 13500
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $livestock_killed
## $breaks
##  [1] 0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0 5.5 6.0 6.5 7.0
##
## $counts
##  [1] 820 162   0  57   0  19   0  37   0  10   0   5   0  10
##
## $density
##  [1] 1.464285714 0.289285714 0.000000000 0.101785714 0.000000000 0.033928571
##  [7] 0.000000000 0.066071429 0.000000000 0.017857143 0.000000000 0.008928571
## [13] 0.000000000 0.017857143
```

```
##
## $mids
##  [1] 0.25 0.75 1.25 1.75 2.25 2.75 3.25 3.75 4.25 4.75 5.25 5.75 6.25 6.75
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $shannondivindex
## $breaks
##  [1] 0.0 0.2 0.4 0.6 0.8 1.0 1.2 1.4 1.6 1.8 2.0
##
## $counts
##  [1] 136  60 158 221 207 192  89  37  19   1
##
## $density
##  [1] 0.607142857 0.267857143 0.705357143 0.986607143 0.924107143 0.857142857
##  [7] 0.397321429 0.165178571 0.084821429 0.004464286
##
## $mids
##  [1] 0.1 0.3 0.5 0.7 0.9 1.1 1.3 1.5 1.7 1.9
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $prop_arable
## $breaks
##  [1]   0  10  20  30  40  50  60  70  80  90 100
##
## $counts
##  [1] 981  34  15   7   9   8  13  12  10  31
##
## $density
##  [1] 0.0875892857 0.0030357143 0.0013392857 0.0006250000 0.0008035714
##  [6] 0.0007142857 0.0011607143 0.0010714286 0.0008928571 0.0027678571
##
## $mids
##  [1]  5 15 25 35 45 55 65 75 85 95
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $prop_orchards
## $breaks
## [1] -1  0
##
## $counts
## [1] 1120
##
## $density
## [1] 1
##
## $mids
## [1] -0.5
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $prop_pasture
## $breaks
##  [1]   0  10  20  30  40  50  60  70  80  90 100
##
## $counts
##  [1] 825  90  59  72  32  29   9   2   1   1
##
## $density
##  [1] 7.366071e-02 8.035714e-03 5.267857e-03 6.428571e-03 2.857143e-03
##  [6] 2.589286e-03 8.035714e-04 1.785714e-04 8.928571e-05 8.928571e-05
##
## $mids
##  [1]  5 15 25 35 45 55 65 75 85 95
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $prop_ag_mosaic
## $breaks
##  [1]  0  5 10 15 20 25 30 35 40 45
##
```

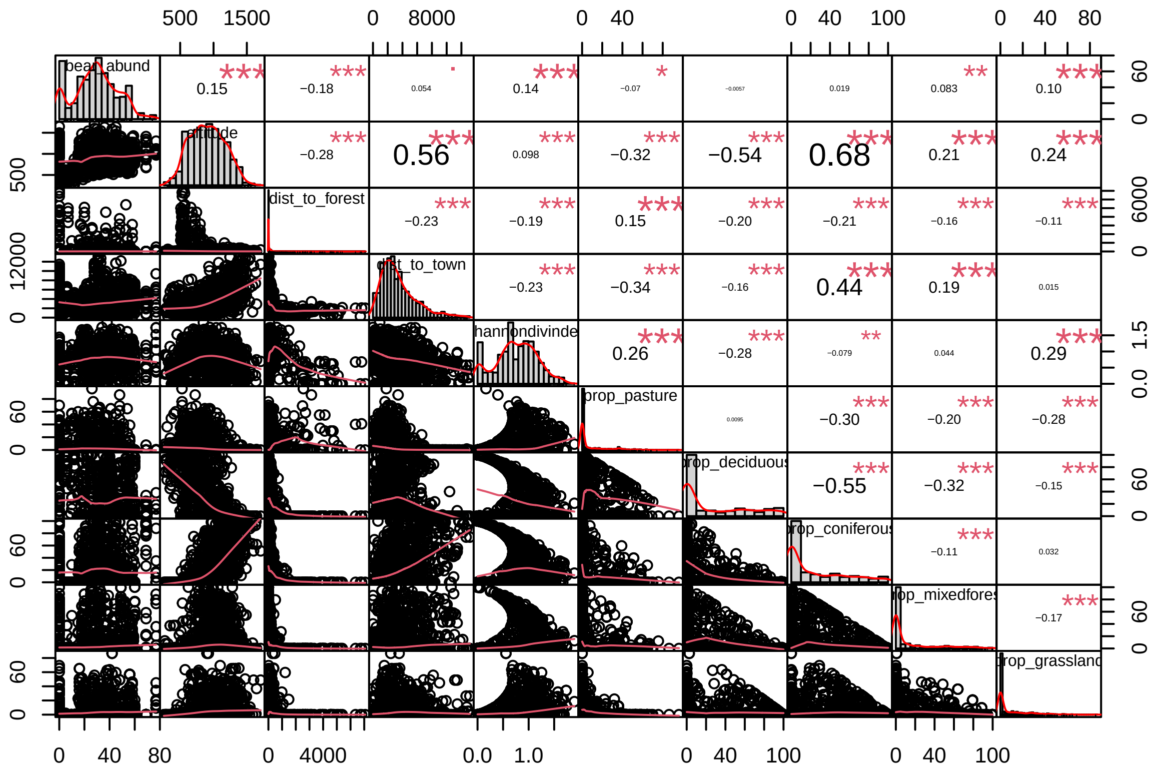
```
## $counts
## [1] 1066   26    8    8    4    4    1    0    3
##
## $density
## [1] 0.1903571429 0.0046428571 0.0014285714 0.0014285714 0.0007142857
## [6] 0.0007142857 0.0001785714 0.0000000000 0.0005357143
##
## $mids
## [1]  2.5  7.5 12.5 17.5 22.5 27.5 32.5 37.5 42.5
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $prop_seminatural
## $breaks
##  [1]  0  5 10 15 20 25 30 35 40 45
##
## $counts
## [1] 1005   49   15   23    7   11    6    1    3
##
## $density
## [1] 0.1794642857 0.0087500000 0.0026785714 0.0041071429 0.0012500000
## [6] 0.0019642857 0.0010714286 0.0001785714 0.0005357143
##
## $mids
## [1]  2.5  7.5 12.5 17.5 22.5 27.5 32.5 37.5 42.5
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $prop_deciduous
## $breaks
##  [1]   0  10  20  30  40  50  60  70  80  90 100
##
## $counts
##  [1] 602  54  55  35  50  75  59  40  70  80
##
## $density
##  [1] 0.053750000 0.004821429 0.004910714 0.003125000 0.004464286 0.006696429
##  [7] 0.005267857 0.003571429 0.006250000 0.007142857
##
## $mids
##  [1]  5 15 25 35 45 55 65 75 85 95
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $prop_coniferous
## $breaks
##  [1]   0  10  20  30  40  50  60  70  80  90 100
##
## $counts
##  [1] 576  93  75  51  81  50  59  48  34  53
##
## $density
##  [1] 0.051428571 0.008303571 0.006696429 0.004553571 0.007232143 0.004464286
##  [7] 0.005267857 0.004285714 0.003035714 0.004732143
##
## $mids
##  [1]  5 15 25 35 45 55 65 75 85 95
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $prop_mixedforest
## $breaks
##  [1]   0  10  20  30  40  50  60  70  80  90 100
##
## $counts
##  [1] 752  80  54  37  37  50  32  36  29  13
##
## $density
##  [1] 0.067142857 0.007142857 0.004821429 0.003303571 0.003303571 0.004464286
##  [7] 0.002857143 0.003214286 0.002589286 0.001160714
##
## $mids
##  [1]  5 15 25 35 45 55 65 75 85 95
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
```

```
## attr(,"class")
## [1] "histogram"
##
## $prop_grassland
## $breaks
##  [1]  0 10 20 30 40 50 60 70 80 90
##
## $counts
## [1] 795 120  91  52  36  16   8   0   2
##
## $density
## [1] 0.0709821429 0.0107142857 0.0081250000 0.0046428571 0.0032142857
## [6] 0.0014285714 0.0007142857 0.0000000000 0.0001785714
##
## $mids
## [1]  5 15 25 35 45 55 65 75 85
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $prop_for_regen
## $breaks
##  [1]  0  5 10 15 20 25 30 35 40 45 50 55 60 65
##
## $counts
##  [1] 770 116  73  49  39  28  16   5   8   9   5   1   1
##
## $density
##  [1] 0.1375000000 0.0207142857 0.0130357143 0.0087500000 0.0069642857
##  [6] 0.0050000000 0.0028571429 0.0008928571 0.0014285714 0.0016071429
## [11] 0.0008928571 0.0001785714 0.0001785714
##
## $mids
##  [1]  2.5  7.5 12.5 17.5 22.5 27.5 32.5 37.5 42.5 47.5 52.5 57.5 62.5
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $prop_check
## $breaks
## [1]  80 100
##
```

```
## $counts
## [1] 1120
##
## $density
## [1] 0.05
##
## $mids
## [1] 90
##
## $xname
## [1] "."
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
```

Once we have looked at this we can drop any columns of data that aren't usable or try to merge them with other variables if appropriate and check for multicolinearity between variables which is an assumption we need to meet for GLMs

```
bear_damage_tidy %>%

  # choose specific variables of interest
  select(bear_abund,
         altitude,
         dist_to_forest,
         dist_to_town,
         shannondivindex,
         prop_pasture,
         prop_deciduous,
         prop_coniferous,
         prop_mixedforest,
         prop_grassland) %>%

  chart.Correlation()
```



Above the diagonal of this matrix shows us Pearson's R correlation coefficient for each pairwise combination of our chosen explanatory variables, the diagonal has the name of each variable with a histogram of the raw data, and below the diagonal is a correlation plot of each pairwise combination of variables.

We don't want to include any variables that are highly correlated (absolute value r > 0.6) in the same model, so we will write some notes here about any that violate this or are close

altitude, prop_coniferous = 0.68
altitude, dist_to_town = 0.56 prop_deciduous, prop_coniferous = -0.55 (these are often inversely correlated in forested areas as they are the main two tree types so if there is a lot of one there's less of the other, it's not too high but if we know this ecological relationship exists we may want to be cautious about including them in the same model)

Data formatting

Once we've explored both our explanatory and response variables, we may want to do some reformatting to our data. This can be for several reasons, if variables are correlated or lacking enough data to use one individually we may combine them if ecologically justified, etc.

Here we will create a new variable that combines all the forest cover data because we are interested in overall forest cover not the effect of specific forest types.

```r
# formatting data to combine variables
bear_damage_tidy <-  bear_damage_tidy %>%

  # add new column that groups all forest types
  mutate(prop_forest = rowSums(across(c(prop_coniferous,
                                        prop_deciduous,
                                        prop_mixedforest))))
```

```
# check new data
summary(bear_damage_tidy$prop_forest)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00   48.67   73.72   67.07   93.29  100.00
```

Analysis

Fit GLMs

Here we will create a candidate set of models that represent hypotheses about what variables may explain our chosen response and fit these to a glm with the appropriate distribution. As this is a mock analysis and not a course on human-wildlife conflict with bears in eastern Europe we won't spend a ton of time justifying these models we will just use a few as examples.

> Note these are fit to a simple binomial distribution not a negative binomial distribution which is what we determined earlier would truly be the best-fit distribution

```
# going to scale data first for ease of coding
bear_damage_tidy <- bear_damage_tidy %>%

  # use mutate to change all numeric variables to scaled
  mutate_if(is.numeric,
            scale)


#I've done 3 models for demonstration

# null model
bear_null <- glm(damage ~ 1,
                 data = bear_damage_tidy,
                 family = 'binomial')

# interaction between distance to forest and distance to town (close to both town and forest would have
bear_distance_i <- glm(damage ~ dist_to_forest * dist_to_town,
                       data = bear_damage_tidy,
                 family = 'binomial')

# quick check that this model fit
summary(bear_distance_i)
```

```
##
## Call:
## glm(formula = damage ~ dist_to_forest * dist_to_town, family = "binomial",
##     data = bear_damage_tidy)
##
## Coefficients:
##                             Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  -1.1042     0.1433  -7.705 1.31e-14 ***
## dist_to_forest                1.6345     0.4750   3.441  0.00058 ***
## dist_to_town                  0.2209     0.2179   1.014  0.31070
## dist_to_forest:dist_to_town   3.5312     0.7857   4.494 6.99e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1044.92  on 1119  degrees of freedom
## Residual deviance:  960.37  on 1116  degrees of freedom
## AIC: 968.37
##
## Number of Fisher Scoring iterations: 7
```

```
# analog distance model w/o interaction
bear_distance <- glm(damage ~ dist_to_forest +
                       dist_to_town,
                       data = bear_damage_tidy,
                 family = 'binomial')

# quick check that this model fit
summary(bear_distance)
```

```
##
## Call:
## glm(formula = damage ~ dist_to_forest + dist_to_town, family = "binomial",
##     data = bear_damage_tidy)
##
## Coefficients:
##                Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -1.69548    0.09292 -18.247  < 2e-16 ***
## dist_to_forest -0.62093    0.18654  -3.329 0.000872 ***
## dist_to_town   -0.62435    0.10685  -5.843 5.12e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1044.92  on 1119  degrees of freedom
## Residual deviance:  991.73  on 1117  degrees of freedom
## AIC: 997.73
##
## Number of Fisher Scoring iterations: 6
```

Model selection

A common approach with GLMs is to use model selection and compare metrics like AIC to determine which set of explanatory variables best explains the observed data we collected.

We will do this using a function from the MuMIn package

```
# model selection on candidate set of models
model.sel(bear_null,
          bear_distance,
          bear_distance_i)
```

```
## Model selection table
##                   (Int) dst_to_frs dst_to_twn dst_to_frs:dst_to_twn df   logLik
## bear_distance_i -1.104     1.6340     0.2209                 3.531  4 -480.183
## bear_distance   -1.695    -0.6209    -0.6243                        3 -495.865
## bear_null       -1.538                                             1 -522.462
##                   AICc delta weight
## bear_distance_i  968.4  0.00      1
## bear_distance    997.8 29.35      0
## bear_null       1046.9 78.53      0
## Models ranked by AICc(x)
```

Lowest AIC and highest model weight generally indicates the best fitting model. The MuMIn function will automatically sort your models in decreasing order of weight

Based on this our best-fit model is the one with our interaction term

Check model assumptions

This section will vary depending on the response variable and other aspects of the data, models, etc.

For the best-fit model identified above we want to re-check assumption of independence with variance inflation factor (VIF), we also want to check for overdispersion, and any outliers

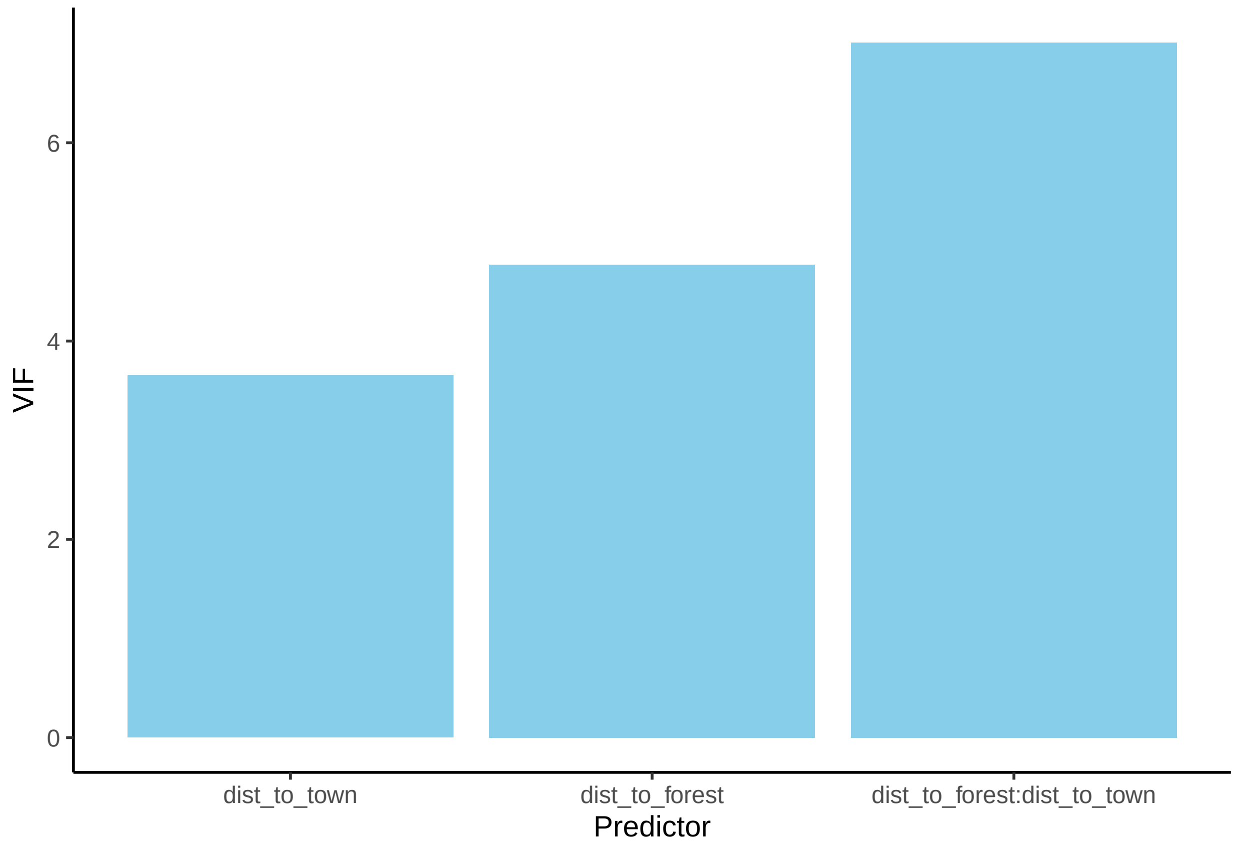
```
# check assumptions for top model

vif(bear_distance_i)
```

```
## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
```

```
##              dist_to_forest                dist_to_town
##                    4.770770                    3.652366
## dist_to_forest:dist_to_town
##                    7.012544
```

```
# plot VIF
vif(bear_distance_i) %>%

  # Converts the named vector returned by vif() into a tidy tibble
  enframe(name = 'Predictor',
          value = 'VIF') %>%

  # plot with ggplot
  ggplot(aes(x = reorder(Predictor, VIF), # reorders from smallest VIF to largest
             y = VIF)) +

  # plot as bars
  geom_bar(stat = 'identity', fill = 'skyblue') +

  # add labels
  labs(x = 'Predictor',
       y = 'VIF') +

  # set theme
  theme_classic()
```

```
## there are higher-order terms (interactions) in this model
## consider setting type = 'predictor'; see ?vif
```



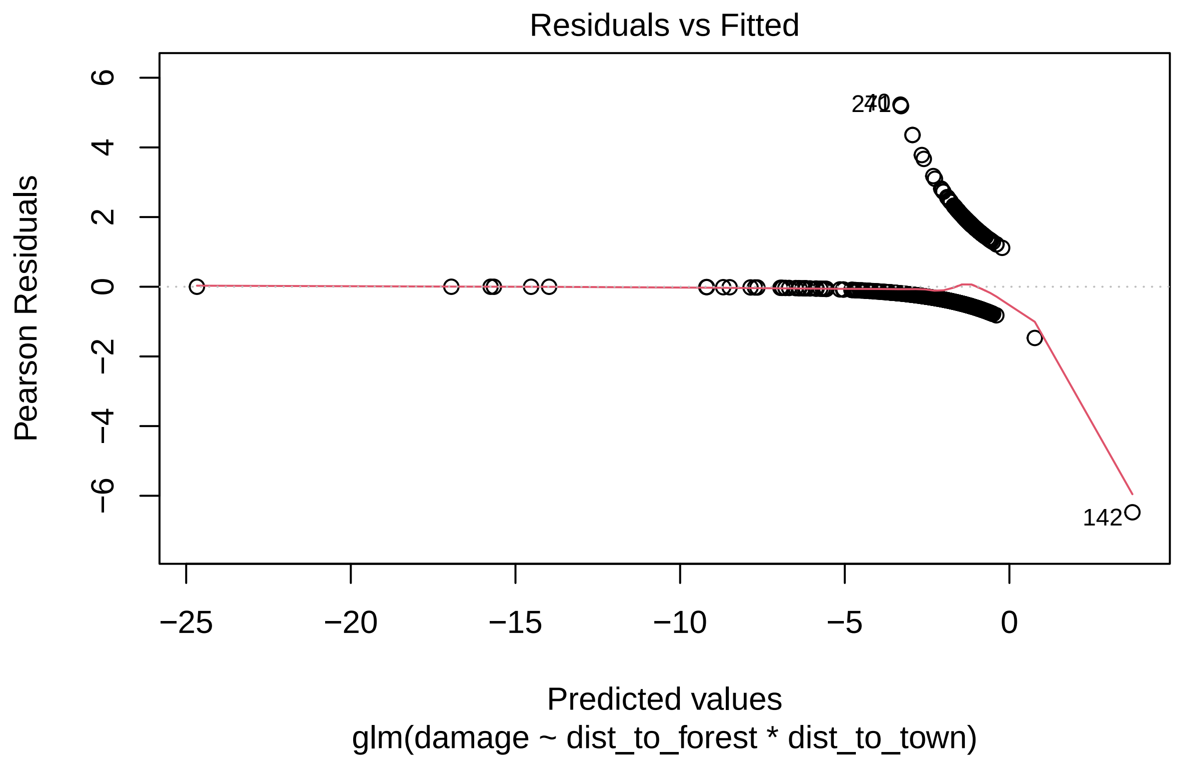
```r
# dispersion
summary(bear_distance_i)
```

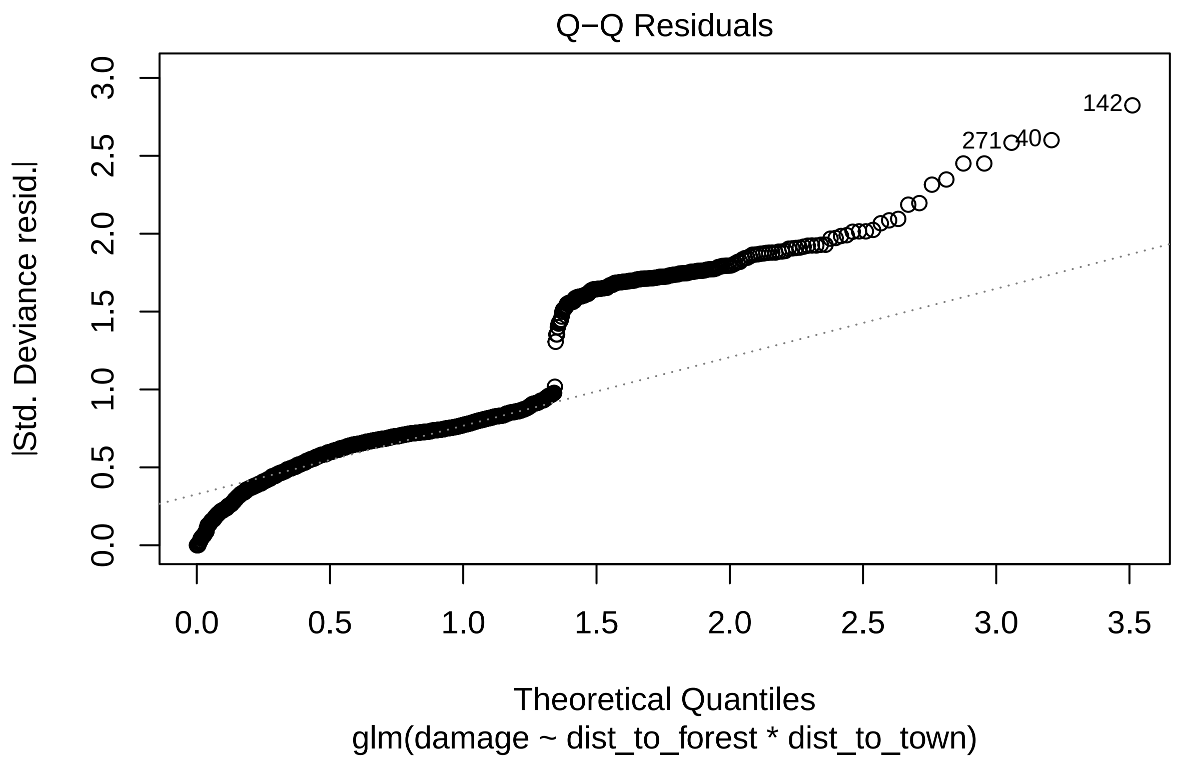
```
##
## Call:
## glm(formula = damage ~ dist_to_forest * dist_to_town, family = "binomial",
##     data = bear_damage_tidy)
##
## Coefficients:
##                             Estimate Std. Error z value Pr(>|z|)
## (Intercept)                  -1.1042     0.1433  -7.705 1.31e-14 ***
## dist_to_forest                1.6345     0.4750   3.441  0.00058 ***
## dist_to_town                  0.2209     0.2179   1.014  0.31070
## dist_to_forest:dist_to_town   3.5312     0.7857   4.494 6.99e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1044.92  on 1119  degrees of freedom
## Residual deviance:  960.37  on 1116  degrees of freedom
## AIC: 968.37
##
## Number of Fisher Scoring iterations: 7
```

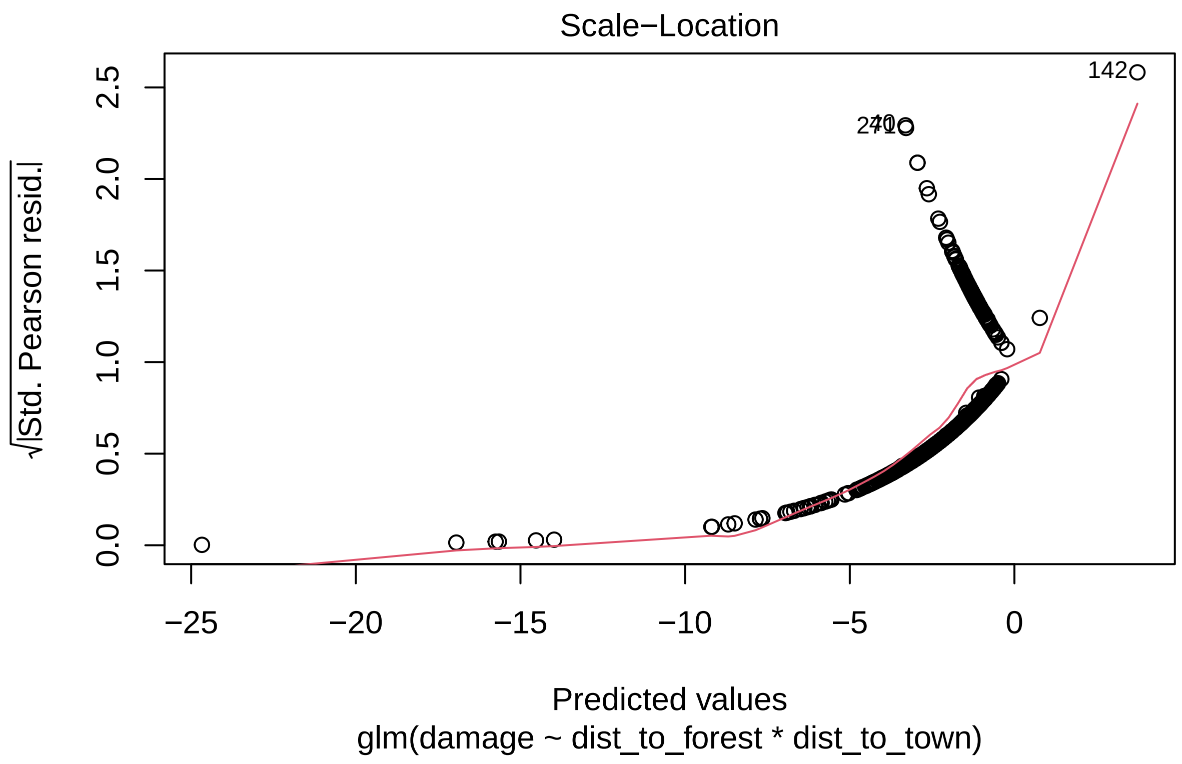
```
960.37/1116 # 0.86 slightly under dispersed but not a major issue for glm
```

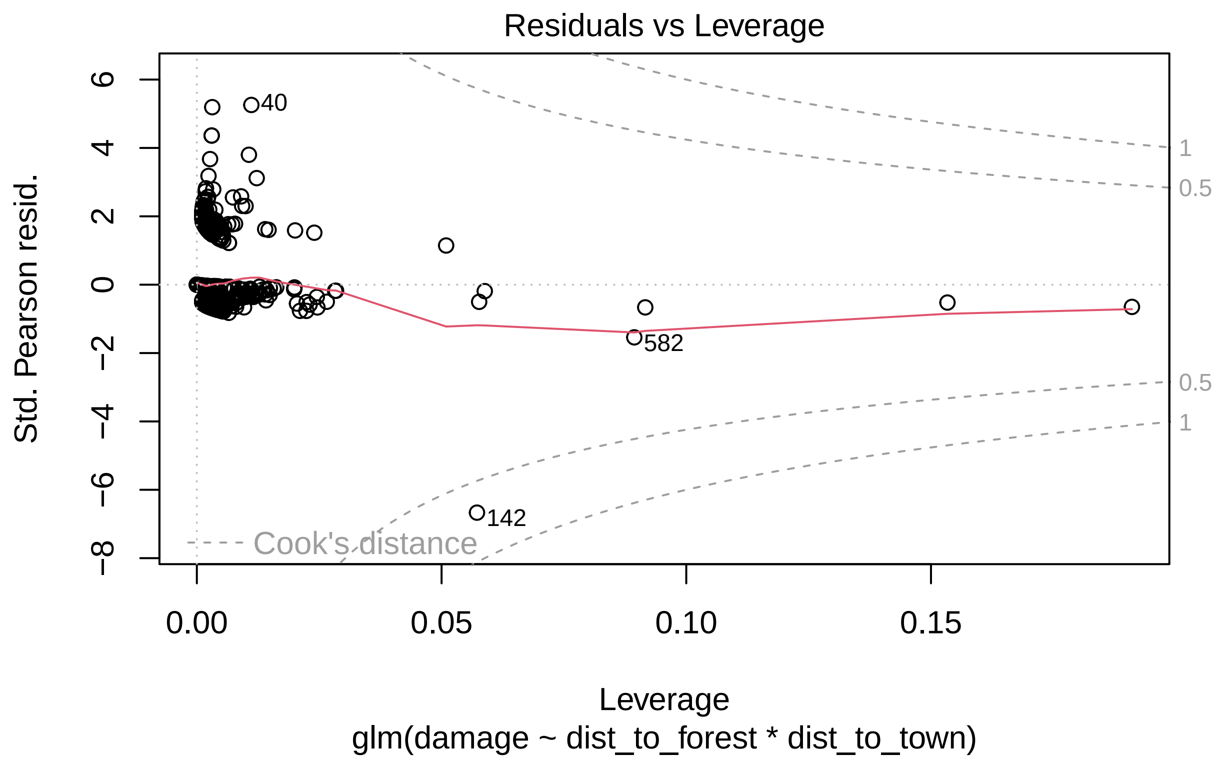
```
## [1] 0.8605466
```

```
# check for observations with high leverage
plot(bear_distance_i) # ignore first three
```




Q−Q Residuals
|Std. Deviance resid.|
Theoretical Quantiles
glm(damage ~ dist_to_forest * dist_to_town)
142
271
40
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5


Scale−Location
√|Std. Pearson resid.|
0.0
0.5
1.0
1.5
2.0
2.5
−25
−20
−15
−10
−5
0
Predicted values
glm(damage ~ dist_to_forest * dist_to_town)
142
271
40



Plot Results

There are several ways to plot results, for the purposes of this mock walk through we will plot odds ratios for the explanatory variables in our best-fit model. An odds ratio plot is a great way to show magnitude, confidence, and effect sizes for all your explanatory variables in one figure.

First we need to extract the odds ratios in a tidy format

```
# create a new data frame with the odds ratios
model_odds <-

  # use the broom package to extract odds ratios into a tidy format
broom::tidy(bear_distance_i,
     exponentiate = TRUE,
     conf.int = TRUE)  %>%

  # remove intercept and interaction term as we don't need to plot
  filter(term  %in% c('dist_to_forest',
                      'dist_to_town'))
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
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## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```
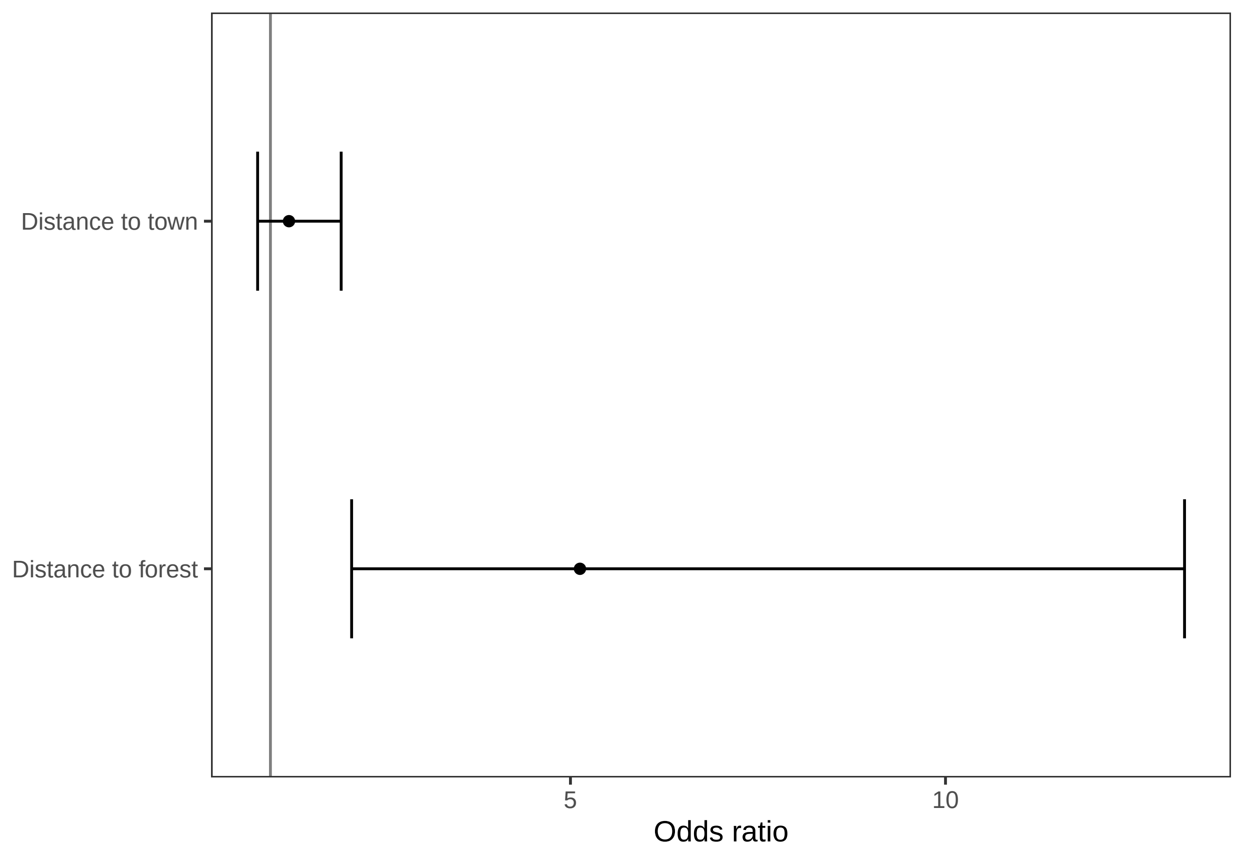

```
# check data
model_odds
```

```
## # A tibble: 2 x 7
##   term           estimate std.error statistic  p.value conf.low conf.high
##   <chr>             <dbl>     <dbl>     <dbl>    <dbl>    <dbl>     <dbl>
## 1 dist_to_forest     5.13     0.475      3.44 0.000580    2.08      13.2
## 2 dist_to_town       1.25     0.218      1.01 0.311       0.829      1.94
```

Ignore warning for now as this is a mock analysis

Now we need to plot them in a visually pleasing and easily interpretable manner

```
# plot
# specify data and mapping asesthetics
ggplot(data = model_odds,
       aes(x = term,
           y = estimate)) +

  # add points for the odss
  geom_point() +

  # add errorbars for the confidence intervals
  geom_errorbar(aes(ymin = conf.low,
                    ymax = conf.high),
                linewidth = 0.5,
                width = 0.4) +

  geom_hline(yintercept = 1,
             alpha = 0.5) +

  # rename the x axis labels
  scale_x_discrete(labels = c('Distance to forest',
                              'Distance to town')) +

  # rename y axis title
  ylab('Odds ratio') +

  # flip x and y axis
      coord_flip() +

  # specify theme
  theme_bw() +

  # specify theme elements
  theme(panel.grid = element_blank(),
        axis.title.y = element_blank())
```


Distance to town
Distance to forest
5
10
Odds ratio