

SRFN project analysis

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The first two chunks of this r markdown file after the r setup allow for plot zooming, but it also means that the html file must be opened in a browser to view the document properly. When it knits in RStudio the preview will appear empty but the html when opened in a browser will have all the info and you can click on each plot to Zoom in on it.

Before you begin

Notes

A few notes about this script.

If you are running this make sure you download the whole SRFN (GitHub repository)[https://github.com/marissadyck/SRFN_ACME_Camera_Project] from my GitHub. This will ensure you have all the files, data, and proper folder structure you will need to run this code and associated analyses.

Also make sure you open RStudio through the R project (ARFN_ACME_Camera_Project.Rproj) this will automatically set your working directory to the correct place (wherever you saved the repository and it's files) and ensure you don't have to change the file paths for some of the data.

Lastly, if you are looking to adapt this code for a future year of data, you will want to ensure you have run all the code through 2_ACME_SRFN_landscape_covariate_exploration_script.Rmd with your data as there is much data formatting, cleaning, and restructuring that has to be done before this code will work. *Helpful note: The files are numbered in the order they are used to prep for this analysis.*

If you have question please email the most recent author, currently

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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).

```
install.packages('tidyverse')
install.packages('corrplot')
install.packages('Hmisc')
install.packages('glmmTMB')
install.packages('MuMIn')
install.packages('TMB', type = 'source')
install.packages('lme4')
install.packages('car')
```

Load libraries

Then load the packages to your library so they are usable for this session.

```
library(tidyverse) # data tidying, visualization, and much more; this will load all tidyverse packages,
library(PerformanceAnalytics) # Used to generate a correlation plot
library(Hmisc) # used to generate histograms for all variables in data frame
library(glmmTMB) # Constructing GLMMs
```

```
## Warning: package 'glmmTMB' was built under R version 4.5.1
```

```
library(MuMIn) # for model selection
library(lme4) # constructing generalized linear mixed effects models
library(car) # used for calculating variance inflation factor (VIF) to assess model fit
```

Summary info

I've added this short section, while not directly related to the analysis, will provide some summary statistics in one convenient location to report in results etc.

Images of wildlife

First let's read in the cleaned raw data with all the timelapse images and drop any with no species id

```
timelapse <- read_csv('data/raw/srfn_timelapse_data.csv',
                      col_types = cols(species = col_factor())) %>%
  drop_na(species)
```

```
## New names:
```

```
## * '' -> '...1'
```

```
## Warning: One or more parsing issues, call 'problems()' on your data frame for details,
```

```
## e.g.:
```

```
##   dat <- vroom(...)
```

```
##   problems(dat)
```

The number of observations of this timelapse object gives us the total non-blank images from the study

```
levels(timelapse$species)
```

```
## [1] "White-tailed deer" "Other"          "Moose"
## [4] "Black bear"        "Unknown bear"   "Unknown"
## [7] "Unknown ungulate"  "Human"          "Mule deer"
## [10] "Elk"               "Owl"            "Coyote"
## [13] "Red fox"           "Grey wolf"       "Lynx"
## [16] "ATVer"             "Unknown deer"    "Grizzly bear"
## [19] "Snowshoe hare"     "Fisher"          "Ruffed grouse"
## [22] "Red squirrel"      "Raven"           "Cougar"
## [25] "Spruce grouse"     "Marten"          "Domestic dog"
## [28] "Staff"
```

Then we can filter to how many of those were identified to species as mammals

```
mammals <- c('White-tailed deer',
             'Moose',
             'Black bear',
```

```

      'Mule deer',
      'Elk',
      'Snowshoe hare',
      'Grizzly bear',
      'Caribou',
      'Coyote',
      'Fisher',
      'Grey wolf',
      'Lynx',
      'Red fox',
      'White-tailed deer',
      'Red squirrel',
      'Cougar')

timelapse_mammals <- timelapse %>%

  filter(species %in% mammals) %>%

  droplevels()

# check the levels
levels(timelapse_mammals$species)

## [1] "White-tailed deer" "Moose"           "Black bear"
## [4] "Mule deer"         "Elk"             "Coyote"
## [7] "Red fox"           "Grey wolf"       "Lynx"
## [10] "Grizzly bear"      "Snowshoe hare"   "Fisher"
## [13] "Red squirrel"      "Cougar"

# Now get summaries of each mammal
timelapse_mammals %>%
  group_by(species) %>%

  summarise(count = n()) %>%

  arrange(desc(count))

## # A tibble: 14 x 2
##   species      count
##   <fct>      <int>
## 1 White-tailed deer 31478
## 2 Moose            6842
## 3 Elk              1875
## 4 Black bear        885
## 5 Coyote            709
## 6 Mule deer         666
## 7 Snowshoe hare     268
## 8 Grey wolf         114
## 9 Grizzly bear      102
## 10 Lynx              63
## 11 Red fox           60
## 12 Red squirrel      27
## 13 Cougar            24
## 14 Fisher            16

```

Independent detections

Analysis prep

Now we can start the analysis prep.

First we need to read in the proportional detection (response metrics) and covariate (explanatory metrics) data files for all 6 LUs (fiscal years 2021-2022 and 2022-2023)

Response metrics

We have multiple response metric files that were generated in script #1, since there were a few very rare species we want to look at, let's load in both files for now and make sure they are formatted properly for the analysis

Import response metric data

I'm going to load them all at once using purrr and we can separate them later depending on what we want to use them for

```
response_metrics <- file.path('data/processed',  
  
                               # provide file names  
                               c('srfn_proportional_detections.csv',  
                                 'srfn_total_detections.csv',  
                                 'srfn_presence_absence.csv')) %>%  
  
# use purrr map to read in all files  
map(~.x %>%  
  
     # use tidyverse read_csv  
     read_csv(.,  
  
              # specify how some columns are read in  
              col_types = cols(site = col_factor())) %>%  
  
# set column names to lowercase for coding ease  
set_names(  
  names(.) %>%  
  tolower()) %>%  
  
# set names for list items  
purrr::set_names('prop_detections',  
                  'total_detections',  
                  'presence_absence')
```

Data checks

```
str(response_metrics)
```

```
## List of 3  
## $ prop_detections : spc_tbl_ [63 x 29] (S3: spec_tbl_df/tbl_df/tbl/data.frame)  
##   ..$ site          : Factor w/ 63 levels "LUAG_119","LUAG_124",...: 1 2 3 4 5 6 7 8 9 10 .  
##   ..$ black_bear    : num [1:63] 4 1 3 1 0 0 6 3 0 4 ...  
##   ..$ coyote        : num [1:63] 8 2 6 2 0 1 11 7 1 8 ...
```

```

## ..$ red_fox : num [1:63] 1 1 1 1 0 0 1 2 0 0 ...
## ..$ white-tailed_deer : num [1:63] 13 12 9 16 11 7 14 8 5 11 ...
## ..$ fisher : num [1:63] 0 1 0 0 0 0 0 1 0 0 ...
## ..$ grey_wolf : num [1:63] 0 1 0 1 0 0 2 3 0 3 ...
## ..$ grizzly_bear : num [1:63] 0 1 0 0 0 0 0 0 0 0 ...
## ..$ marten : num [1:63] 0 1 2 0 0 0 0 0 0 0 ...
## ..$ snowshoe_hare : num [1:63] 0 5 1 0 1 5 1 3 0 0 ...
## ..$ elk : num [1:63] 0 0 7 2 0 0 0 0 0 8 ...
## ..$ moose : num [1:63] 0 0 4 8 11 1 7 7 13 3 ...
## ..$ mule_deer : num [1:63] 0 0 1 3 0 1 0 0 0 0 ...
## ..$ lynx : num [1:63] 0 0 0 0 0 1 1 2 0 0 ...
## ..$ cougar : num [1:63] 0 0 0 0 0 0 1 0 0 0 ...
## ..$ absent_black_bear : num [1:63] 9 12 6 15 16 14 8 10 14 8 ...
## ..$ absent_coyote : num [1:63] 8 13 5 17 19 17 6 9 17 7 ...
## ..$ absent_red_fox : num [1:63] 15 14 10 18 19 18 16 14 18 15 ...
## ..$ absent_white-tailed_deer : num [1:63] 3 3 2 3 8 11 3 8 13 4 ...
## ..$ absent_fisher : num [1:63] 16 14 11 19 19 18 17 15 18 15 ...
## ..$ absent_grey_wolf : num [1:63] 16 14 11 18 19 18 15 13 18 12 ...
## ..$ absent_grizzly_bear : num [1:63] 13 12 9 16 16 14 14 13 14 12 ...
## ..$ absent_marten : num [1:63] 16 14 9 19 19 18 17 16 18 15 ...
## ..$ absent_snowshoe_hare : num [1:63] 16 10 10 19 18 13 16 13 18 15 ...
## ..$ absent_elk : num [1:63] 16 15 4 17 19 18 17 16 18 7 ...
## ..$ absent_moose : num [1:63] 16 15 7 11 8 17 10 9 5 12 ...
## ..$ absent_mule_deer : num [1:63] 16 15 10 16 19 17 17 16 18 15 ...
## ..$ absent_lynx : num [1:63] 16 15 11 19 19 17 16 14 18 15 ...
## ..$ absent_cougar : num [1:63] 16 15 11 19 19 18 16 16 18 15 ...
## ..- attr(*, "spec")=
## .. .. cols(
## .. .. site = col_factor(levels = NULL, ordered = FALSE, include_na = FALSE),
## .. .. black_bear = col_double(),
## .. .. coyote = col_double(),
## .. .. red_fox = col_double(),
## .. .. 'white-tailed_deer' = col_double(),
## .. .. fisher = col_double(),
## .. .. grey_wolf = col_double(),
## .. .. grizzly_bear = col_double(),
## .. .. marten = col_double(),
## .. .. snowshoe_hare = col_double(),
## .. .. elk = col_double(),
## .. .. moose = col_double(),
## .. .. mule_deer = col_double(),
## .. .. lynx = col_double(),
## .. .. cougar = col_double(),
## .. .. absent_black_bear = col_double(),
## .. .. absent_coyote = col_double(),
## .. .. absent_red_fox = col_double(),
## .. .. 'absent_white-tailed_deer' = col_double(),
## .. .. absent_fisher = col_double(),
## .. .. absent_grey_wolf = col_double(),
## .. .. absent_grizzly_bear = col_double(),
## .. .. absent_marten = col_double(),
## .. .. absent_snowshoe_hare = col_double(),
## .. .. absent_elk = col_double(),
## .. .. absent_moose = col_double(),

```

```

## .. .. absent_mule_deer = col_double(),
## .. .. absent_lynx = col_double(),
## .. .. absent_cougar = col_double()
## .. .. )
## ..- attr(*, "problems")=<externalptr>
## $ total_detections: spc_tbl_ [63 x 33] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
## ..$ array          : chr [1:63] "LUAG" "LUAG" "LUAG" "LUBF" ...
## ..$ site_number    : num [1:63] 119 124 137 104 105 12 121 126 130 132 ...
## ..$ site           : Factor w/ 63 levels "LUAG_119","LUAG_124",...: 1 2 3 4 5 6 7 8 9 10 ...
## ..$ black_bear     : num [1:63] 4 2 17 1 0 0 18 5 0 12 ...
## ..$ coyote         : num [1:63] 21 3 23 2 0 1 28 21 2 27 ...
## ..$ red_fox        : num [1:63] 4 1 2 1 0 0 1 2 0 0 ...
## ..$ white-tailed_deer: num [1:63] 62 141 153 48 22 32 187 187 10 666 ...
## ..$ domestic_dog   : num [1:63] 0 1 1 0 0 0 0 0 0 0 ...
## ..$ fisher         : num [1:63] 0 1 0 0 0 0 0 0 1 0 0 ...
## ..$ grey_wolf      : num [1:63] 0 2 0 1 0 0 4 6 0 26 ...
## ..$ grizzly_bear   : num [1:63] 0 1 0 0 0 0 0 0 0 0 ...
## ..$ marten         : num [1:63] 0 1 3 0 0 0 0 0 0 0 ...
## ..$ snowshoe_hare  : num [1:63] 0 20 1 0 1 21 2 19 0 0 ...
## ..$ elk            : num [1:63] 0 0 43 2 0 0 0 0 0 66 ...
## ..$ moose          : num [1:63] 0 0 4 9 20 1 16 22 148 3 ...
## ..$ mule_deer      : num [1:63] 0 0 4 8 0 1 0 0 0 0 ...
## ..$ unknown        : num [1:63] 0 0 2 3 0 9 1 0 12 1 ...
## ..$ unknown_ungulate : num [1:63] 0 0 41 4 0 0 0 0 7 0 ...
## ..$ lynx           : num [1:63] 0 0 0 0 0 1 1 3 0 0 ...
## ..$ cougar         : num [1:63] 0 0 0 0 0 0 0 1 0 0 0 ...
## ..$ red_squirrel   : num [1:63] 0 0 0 0 0 0 0 0 1 0 0 ...
## ..$ other          : num [1:63] 0 0 0 0 0 0 0 0 0 14 0 ...
## ..$ atver          : num [1:63] 0 0 0 0 0 0 0 0 0 0 0 ...
## ..$ unknown_deer   : num [1:63] 0 0 0 0 0 0 0 0 0 0 0 ...
## ..$ unknown_bear   : num [1:63] 0 0 0 0 0 0 0 0 0 0 0 ...
## ..$ other_birds    : num [1:63] 0 0 0 0 0 0 0 0 0 0 0 ...
## ..$ human          : num [1:63] 0 0 0 0 0 0 0 0 0 0 0 ...
## ..$ staff          : num [1:63] 0 0 0 0 0 0 0 0 0 0 0 ...
## ..$ spruce_grouse  : num [1:63] 0 0 0 0 0 0 0 0 0 0 0 ...
## ..$ hunter         : num [1:63] 0 0 0 0 0 0 0 0 0 0 0 ...
## ..$ ruffed_grouse  : num [1:63] 0 0 0 0 0 0 0 0 0 0 0 ...
## ..$ raven          : num [1:63] 0 0 0 0 0 0 0 0 0 0 0 ...
## ..$ owl          : num [1:63] 0 0 0 0 0 0 0 0 0 0 0 ...
## ..- attr(*, "spec")=
## .. .. cols(
## .. ..   array = col_character(),
## .. ..   site_number = col_double(),
## .. ..   site = col_factor(levels = NULL, ordered = FALSE, include_na = FALSE),
## .. ..   black_bear = col_double(),
## .. ..   coyote = col_double(),
## .. ..   red_fox = col_double(),
## .. ..   'white-tailed_deer' = col_double(),
## .. ..   domestic_dog = col_double(),
## .. ..   fisher = col_double(),
## .. ..   grey_wolf = col_double(),
## .. ..   grizzly_bear = col_double(),
## .. ..   marten = col_double(),
## .. ..   snowshoe_hare = col_double(),

```

```

## .. .. elk = col_double(),
## .. .. moose = col_double(),
## .. .. mule_deer = col_double(),
## .. .. unknown = col_double(),
## .. .. unknown_ungulate = col_double(),
## .. .. lynx = col_double(),
## .. .. cougar = col_double(),
## .. .. red_squirrel = col_double(),
## .. .. other = col_double(),
## .. .. atver = col_double(),
## .. .. unknown_deer = col_double(),
## .. .. unknown_bear = col_double(),
## .. .. other_birds = col_double(),
## .. .. human = col_double(),
## .. .. staff = col_double(),
## .. .. spruce_grouse = col_double(),
## .. .. hunter = col_double(),
## .. .. ruffed_grouse = col_double(),
## .. .. raven = col_double(),
## .. .. owl = col_double()
## .. .. )
## ..- attr(*, "problems")=<externalptr>
## $ presence_absence: spc_tbl_ [63 x 33] (S3: spec_tbl_df/tbl_df/tbl/data.frame)
## ..$ array : chr [1:63] "LUAG" "LUAG" "LUAG" "LUBF" ...
## ..$ site_number : num [1:63] 119 124 137 104 105 12 121 126 130 132 ...
## ..$ site : Factor w/ 63 levels "LUAG_119","LUAG_124",...: 1 2 3 4 5 6 7 8 9 10 ...
## ..$ black_bear : num [1:63] 1 1 1 1 0 0 1 1 0 1 ...
## ..$ coyote : num [1:63] 1 1 1 1 0 1 1 1 1 1 ...
## ..$ red_fox : num [1:63] 1 1 1 1 0 0 1 1 0 0 ...
## ..$ white-tailed_deer: num [1:63] 1 1 1 1 1 1 1 1 1 1 ...
## ..$ domestic_dog : num [1:63] 0 1 1 0 0 0 0 0 0 0 ...
## ..$ fisher : num [1:63] 0 1 0 0 0 0 0 0 1 0 ...
## ..$ grey_wolf : num [1:63] 0 1 0 1 0 0 1 1 0 1 ...
## ..$ grizzly_bear : num [1:63] 0 1 0 0 0 0 0 0 0 0 ...
## ..$ marten : num [1:63] 0 1 1 0 0 0 0 0 0 0 ...
## ..$ snowshoe_hare : num [1:63] 0 1 1 0 1 1 1 1 0 0 ...
## ..$ elk : num [1:63] 0 0 1 1 0 0 0 0 0 1 ...
## ..$ moose : num [1:63] 0 0 1 1 1 1 1 1 1 1 ...
## ..$ mule_deer : num [1:63] 0 0 1 1 0 1 0 0 0 0 ...
## ..$ unknown : num [1:63] 0 0 1 1 0 1 1 0 1 1 ...
## ..$ unknown_ungulate : num [1:63] 0 0 1 1 0 0 0 0 1 0 ...
## ..$ lynx : num [1:63] 0 0 0 0 0 0 1 1 1 0 ...
## ..$ cougar : num [1:63] 0 0 0 0 0 0 0 1 0 0 ...
## ..$ red_squirrel : num [1:63] 0 0 0 0 0 0 0 0 1 0 ...
## ..$ other : num [1:63] 0 0 0 0 0 0 0 0 0 1 ...
## ..$ atver : num [1:63] 0 0 0 0 0 0 0 0 0 0 ...
## ..$ unknown_deer : num [1:63] 0 0 0 0 0 0 0 0 0 0 ...
## ..$ unknown_bear : num [1:63] 0 0 0 0 0 0 0 0 0 0 ...
## ..$ other_birds : num [1:63] 0 0 0 0 0 0 0 0 0 0 ...
## ..$ human : num [1:63] 0 0 0 0 0 0 0 0 0 0 ...
## ..$ staff : num [1:63] 0 0 0 0 0 0 0 0 0 0 ...
## ..$ spruce_grouse : num [1:63] 0 0 0 0 0 0 0 0 0 0 ...
## ..$ hunter : num [1:63] 0 0 0 0 0 0 0 0 0 0 ...
## ..$ ruffed_grouse : num [1:63] 0 0 0 0 0 0 0 0 0 0 ...

```

```
## ..$ raven          : num [1:63] 0 0 0 0 0 0 0 0 0 0 ...
## ..$ owl          : num [1:63] 0 0 0 0 0 0 0 0 0 0 ...
## ..- attr(*, "spec")=
## .. .. cols(
## .. ..   array = col_character(),
## .. ..   site_number = col_double(),
## .. ..   site = col_factor(levels = NULL, ordered = FALSE, include_na = FALSE),
## .. ..   black_bear = col_double(),
## .. ..   coyote = col_double(),
## .. ..   red_fox = col_double(),
## .. ..   'white-tailed_deer' = col_double(),
## .. ..   domestic_dog = col_double(),
## .. ..   fisher = col_double(),
## .. ..   grey_wolf = col_double(),
## .. ..   grizzly_bear = col_double(),
## .. ..   marten = col_double(),
## .. ..   snowshoe_hare = col_double(),
## .. ..   elk = col_double(),
## .. ..   moose = col_double(),
## .. ..   mule_deer = col_double(),
## .. ..   unknown = col_double(),
## .. ..   unknown_ungulate = col_double(),
## .. ..   lynx = col_double(),
## .. ..   cougar = col_double(),
## .. ..   red_squirrel = col_double(),
## .. ..   other = col_double(),
## .. ..   atver = col_double(),
## .. ..   unknown_deer = col_double(),
## .. ..   unknown_bear = col_double(),
## .. ..   other_birds = col_double(),
## .. ..   human = col_double(),
## .. ..   staff = col_double(),
## .. ..   spruce_grouse = col_double(),
## .. ..   hunter = col_double(),
## .. ..   ruffed_grouse = col_double(),
## .. ..   raven = col_double(),
## .. ..   owl = col_double()
## .. .. )
## ..- attr(*, "problems")=<externalptr>
```

First checks look good, but let's remove a few species we aren't interested in modeling for this analysis from all three data sets

```
# first create focal species object with only species we have enough data to model in one response metr
glm_focal_vars <- c('site',
                    'white-tailed_deer',
                    'black_bear',
                    'coyote',
                    'elk',
                    'grey_wolf',
                    'grizzly_bear',
                    'lynx',
                    'moose',
                    'mule_deer',
                    'red_fox',
```

```

      'snowshoe_hare')

response_metrics_subset <- response_metrics %>%

  map(~.x %>%

    # use purrr map to select only columns that match the focal species in all data sets
    select(matches(paste(glm_focal_vars,
                        collapse = '|'))))
  )

```

Subset response metrics

Now we should subset each data frame individually even further

We prioritize the proportional monthly detection data as it gives us the most information, so for any species we have enough (we think) data for we will keep them in this data frame, otherwise we will remove

```

response_metrics_subset$prop_detections <- response_metrics_subset$prop_detections %>%

  # remove mule deer, red fox, and grizzly bear
  select(-contains(c('red_fox',
                    'mule_deer',
                    'grizzly_bear'))))

head(response_metrics_subset$prop_detections)

```

```

## # A tibble: 6 x 17
##   site      black_bear coyote 'white-tailed_deer' grey_wolf snowshoe_hare  elk
##   <fct>      <dbl>  <dbl>          <dbl>      <dbl>      <dbl> <dbl>
## 1 LUAG_119      4      8             13         0          0      0
## 2 LUAG_124      1      2             12         1          5      0
## 3 LUAG_137      3      6              9         0          1      7
## 4 LUBF_104      1      2             16         1          0      2
## 5 LUBF_105      0      0             11         0          1      0
## 6 LUBF_12       0      1              7         0          5      0
## # i 10 more variables: moose <dbl>, lynx <dbl>, absent_black_bear <dbl>,
## #   absent_coyote <dbl>, 'absent_white-tailed_deer' <dbl>,
## #   absent_grey_wolf <dbl>, absent_snowshoe_hare <dbl>, absent_elk <dbl>,
## #   absent_moose <dbl>, absent_lynx <dbl>

```

Now moving onto our alternative response metrics, I'm not sure which we will use yet for the remaining three species so we will keep all three in both

Basically this code will be the inverse of the code above to simply keep only those species instead of remove them

```

# presence absence
response_metrics_subset$presence_absence <- response_metrics_subset$presence_absence %>%

  # remove mule deer, red fox, and grizzly bear
  select(contains(c('site',
                  'elk',
                  'red_fox',

```

```

      'mule_deer',
      'grizzly_bear'))))

head(response_metrics_subset$presence_absence)

## # A tibble: 6 x 6
##   site_number site      elk red_fox mule_deer grizzly_bear
##       <dbl> <fct>    <dbl>   <dbl>   <dbl>      <dbl>
## 1         119 LUAG_119      0       1       0          0
## 2         124 LUAG_124      0       1       0          1
## 3         137 LUAG_137      1       1       1          0
## 4         104 LUBF_104      1       1       1          0
## 5         105 LUBF_105      0       0       0          0
## 6          12 LUBF_12       0       0       1          0

# total detections
response_metrics_subset$total_detections <- response_metrics_subset$total_detections %>%

  # remove mule deer, red fox, and grizzly bear
  select(contains(c('site',
                    'red_fox',
                    'mule_deer',
                    'grizzly_bear'))))

head(response_metrics_subset$total_detections)

## # A tibble: 6 x 5
##   site_number site      red_fox mule_deer grizzly_bear
##       <dbl> <fct>    <dbl>   <dbl>      <dbl>
## 1         119 LUAG_119      4       0          0
## 2         124 LUAG_124      1       0          1
## 3         137 LUAG_137      2       4          0
## 4         104 LUBF_104      1       8          0
## 5         105 LUBF_105      0       0          0
## 6          12 LUBF_12       0       1          0

```

Okay now that these are cleaned up we can remove the full response metrics list from our environment so we don't use it

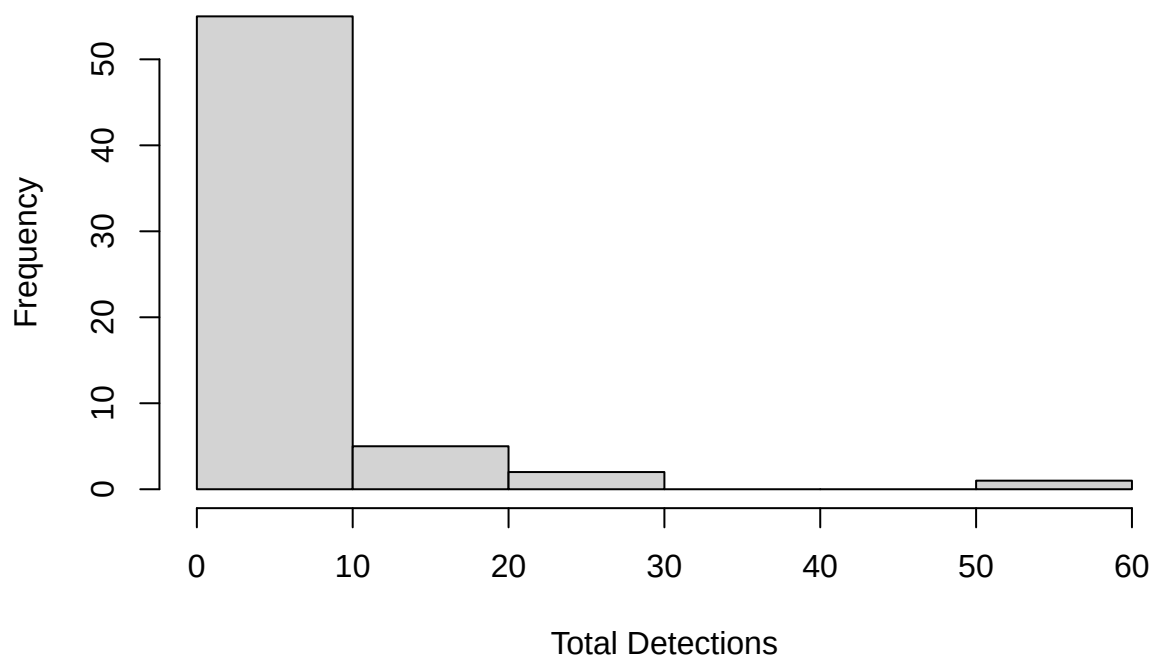
Histograms

```

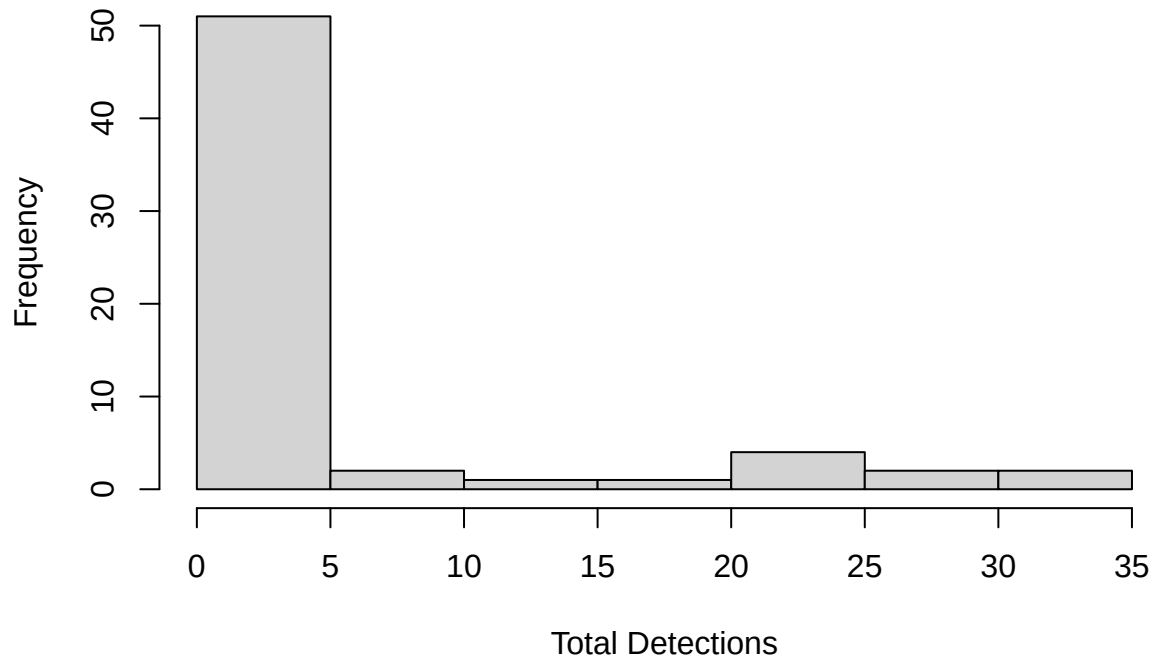
#Loop over columns from black_bear to owl and make histograms of raw data to determined species for mo
response_metrics$total_detections %>%
  select(black_bear:owl) %>% # select species columns directly
  imap(~ {
    hist(.x,
        main = paste("Histogram of", .y),
        xlab = "Total Detections")
  })

```

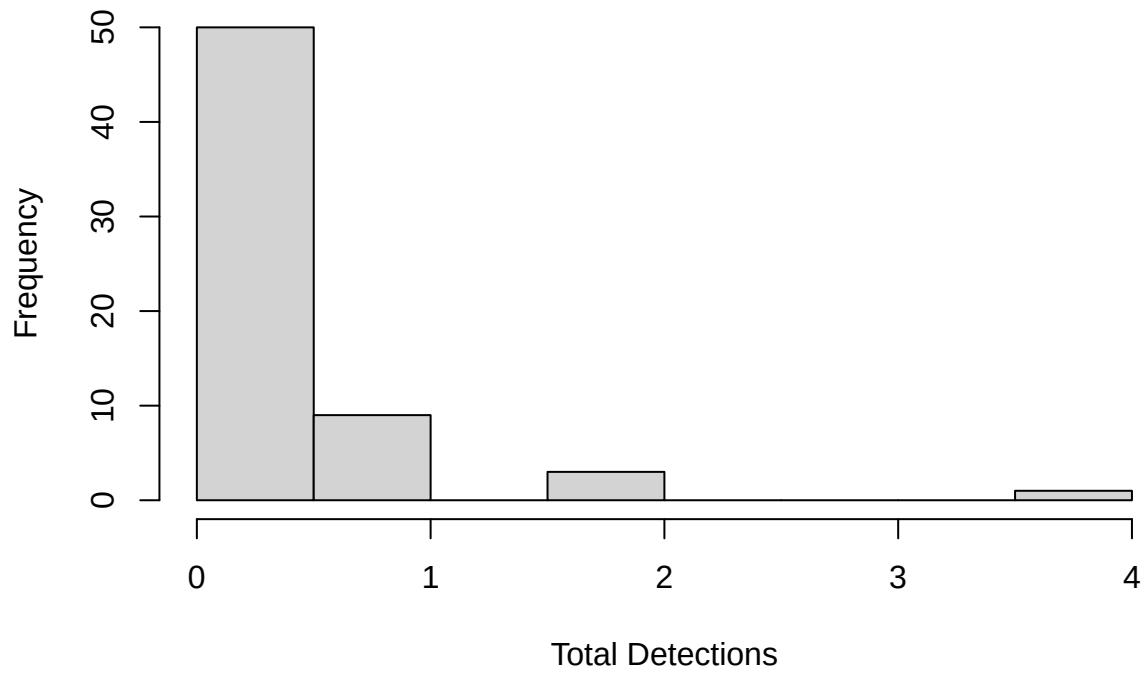
Histogram of black_bear



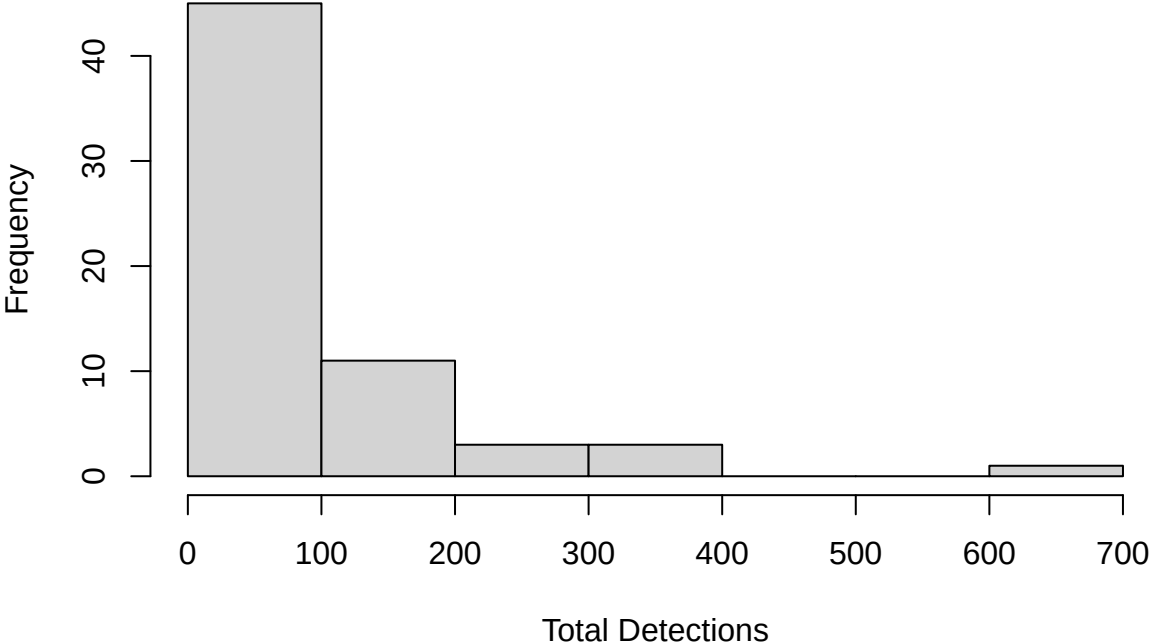
Histogram of coyote



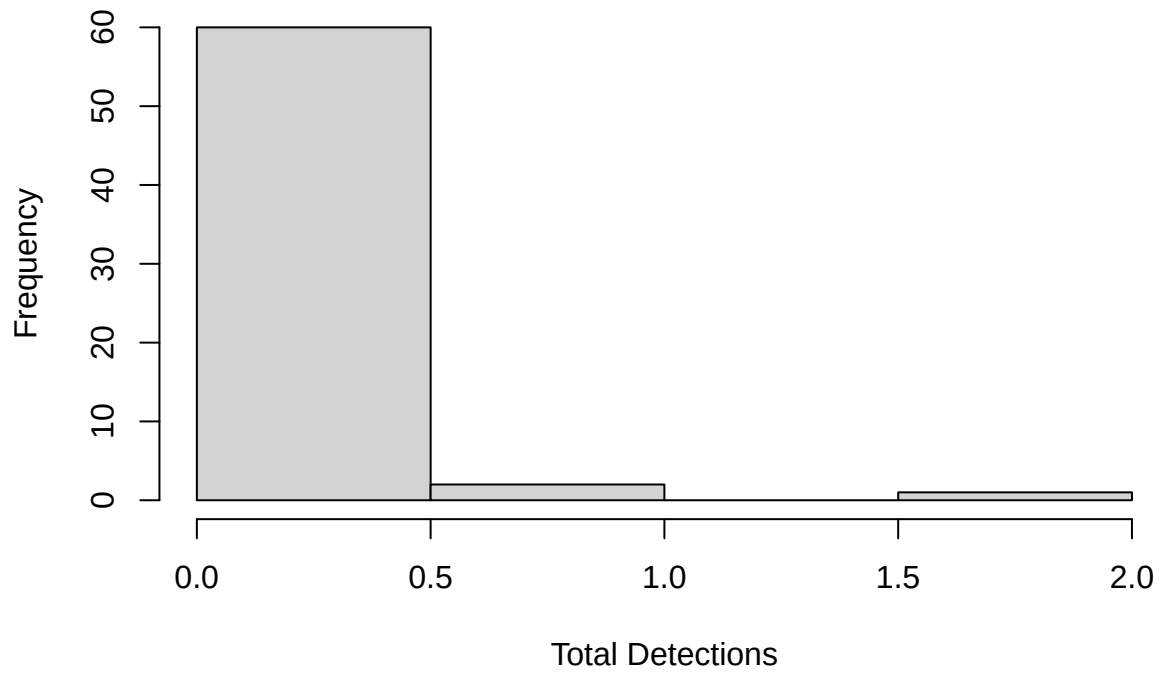
Histogram of red_fox



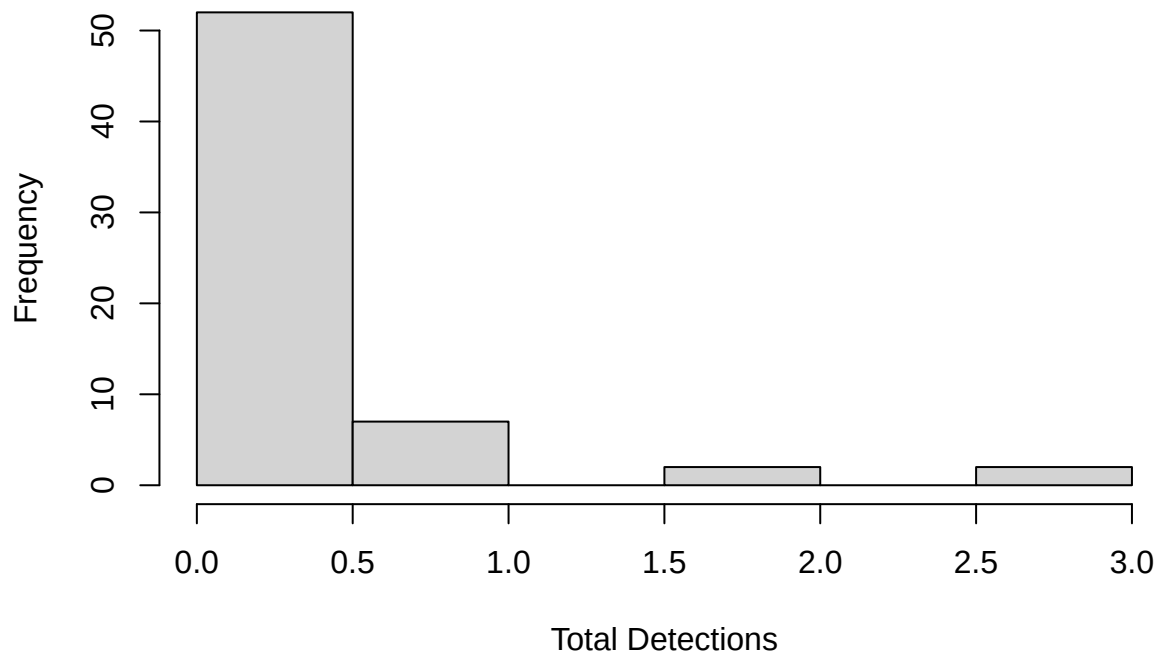
Histogram of white-tailed_deer



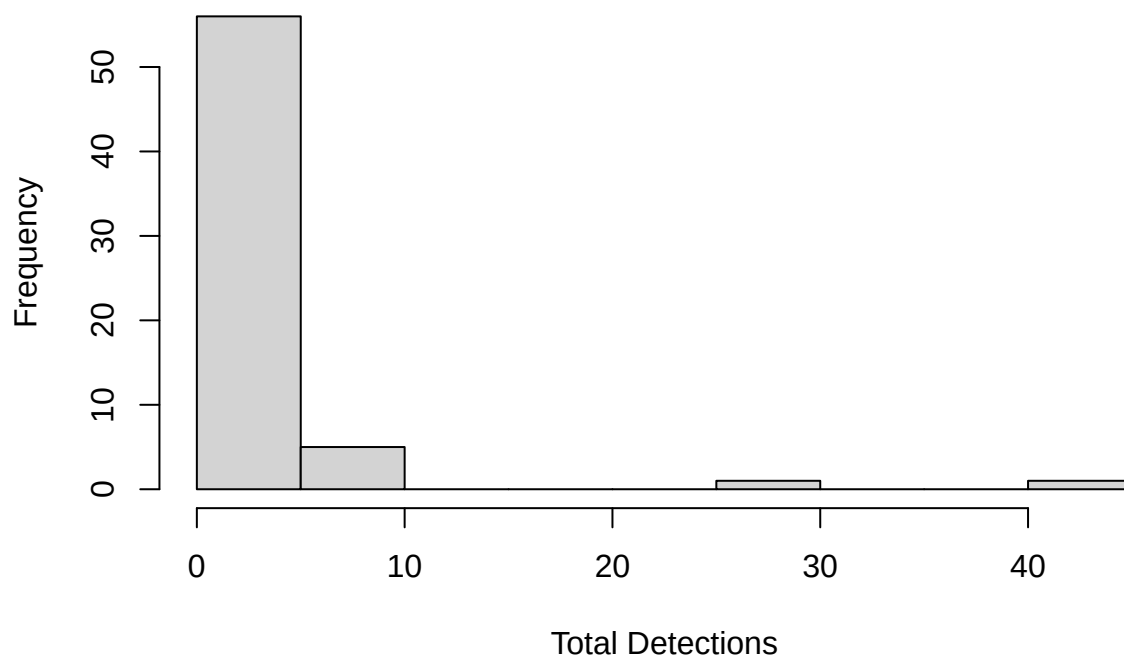
Histogram of domestic_dog



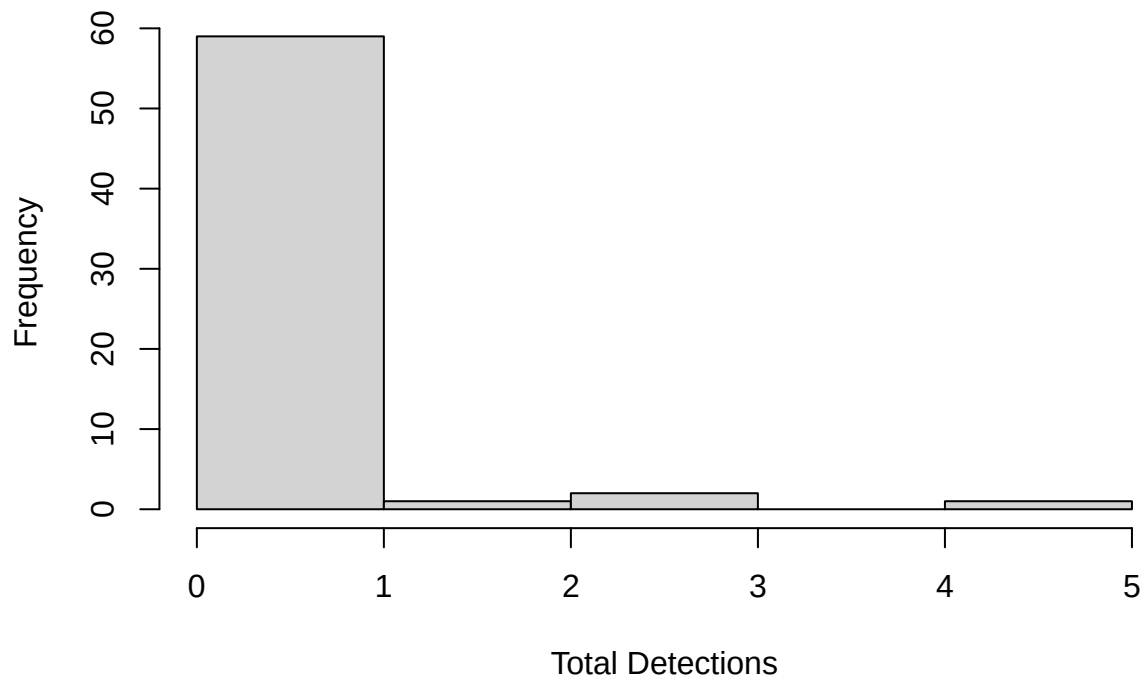
Histogram of fisher



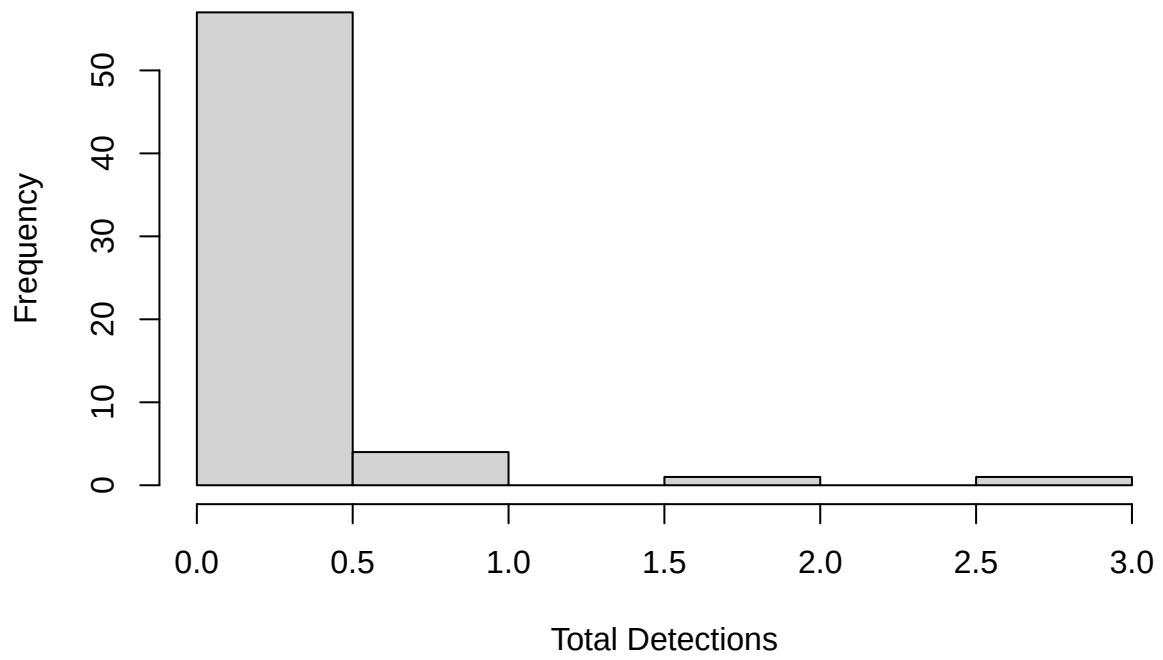
Histogram of grey_wolf



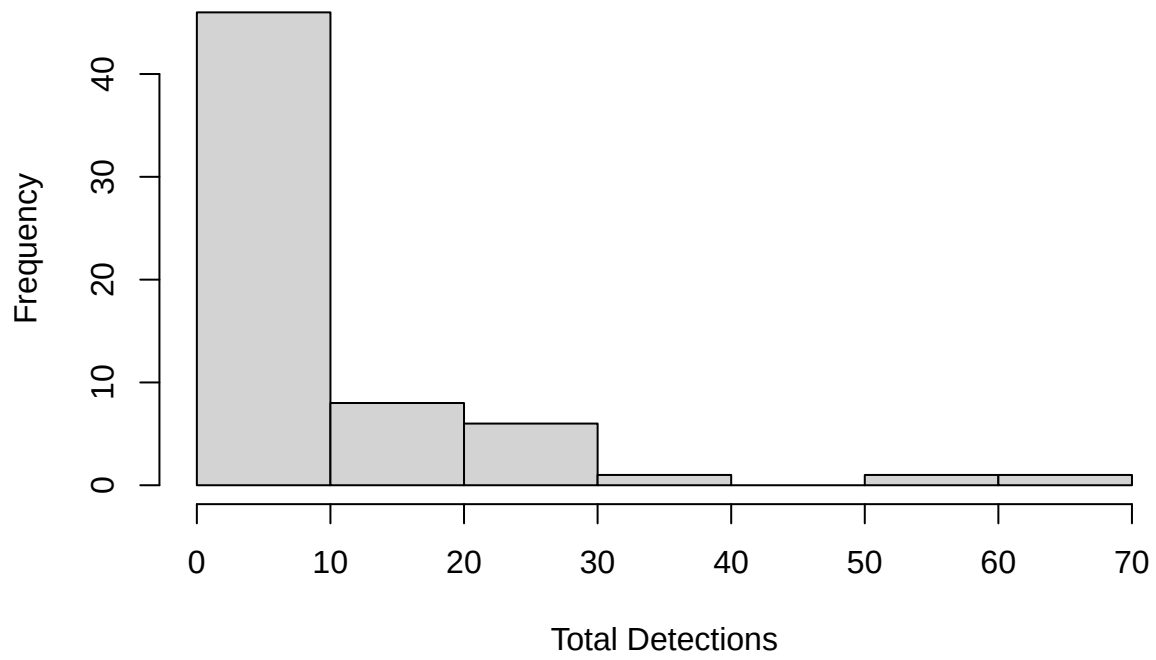
Histogram of grizzly_bear



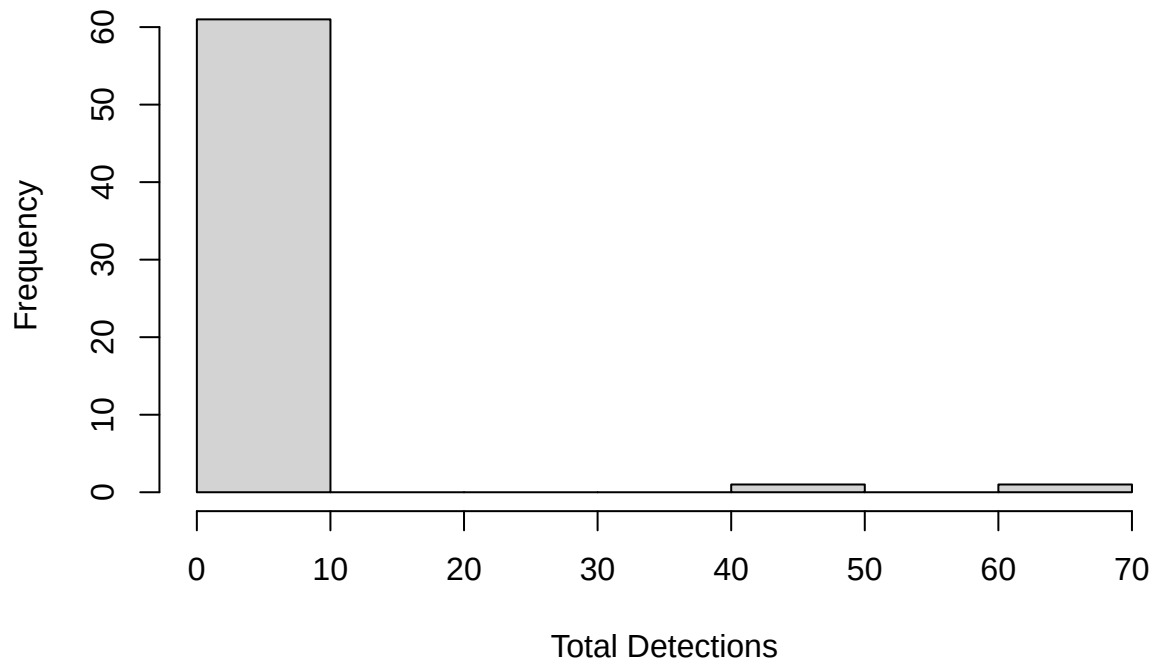
Histogram of marten



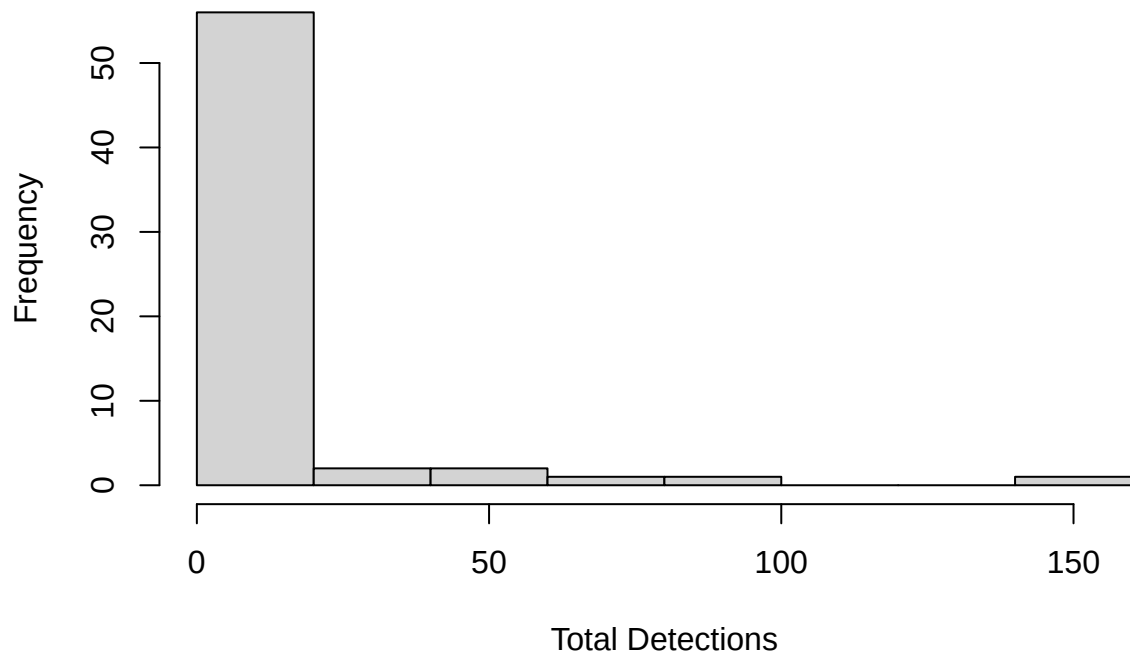
Histogram of snowshoe_hare



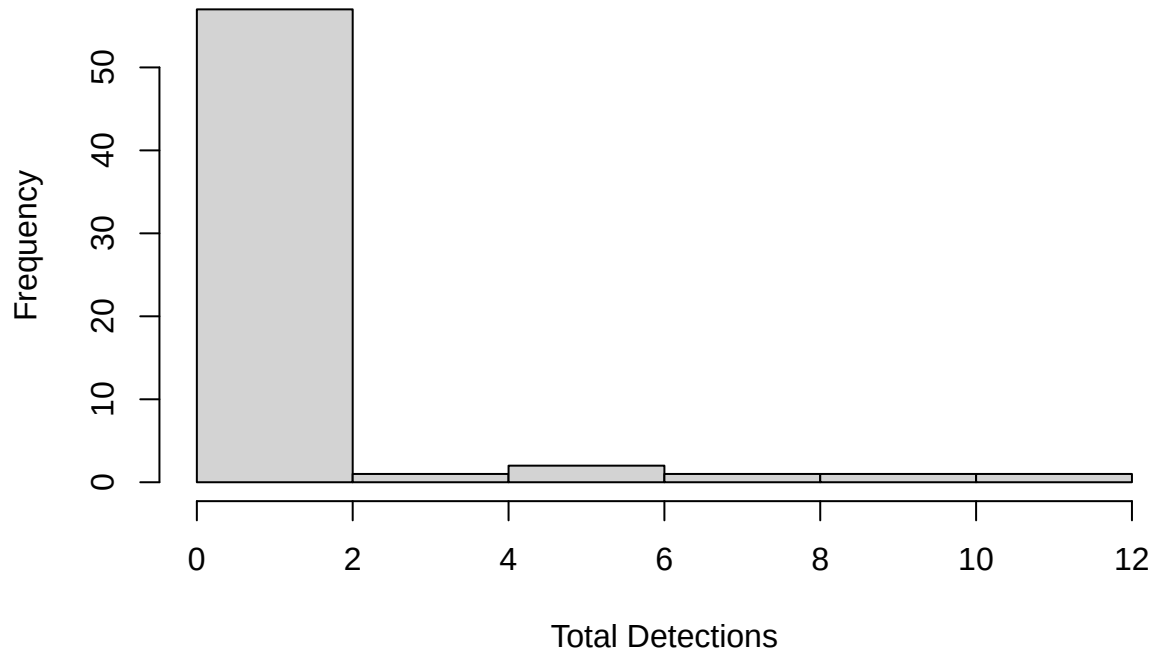
Histogram of elk



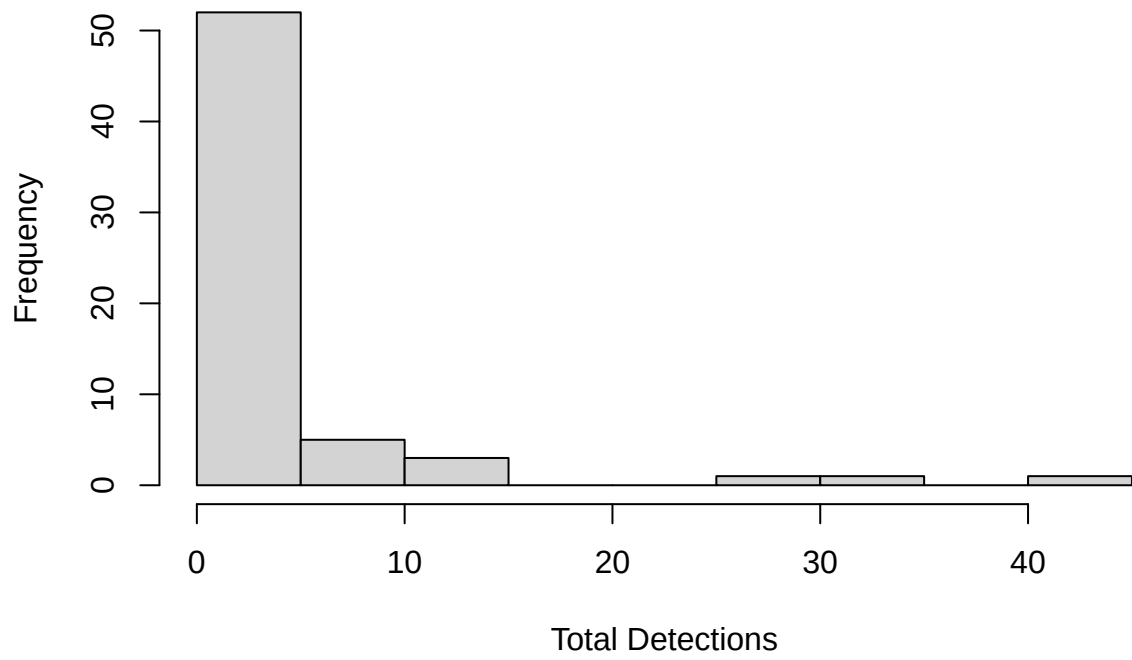
Histogram of moose



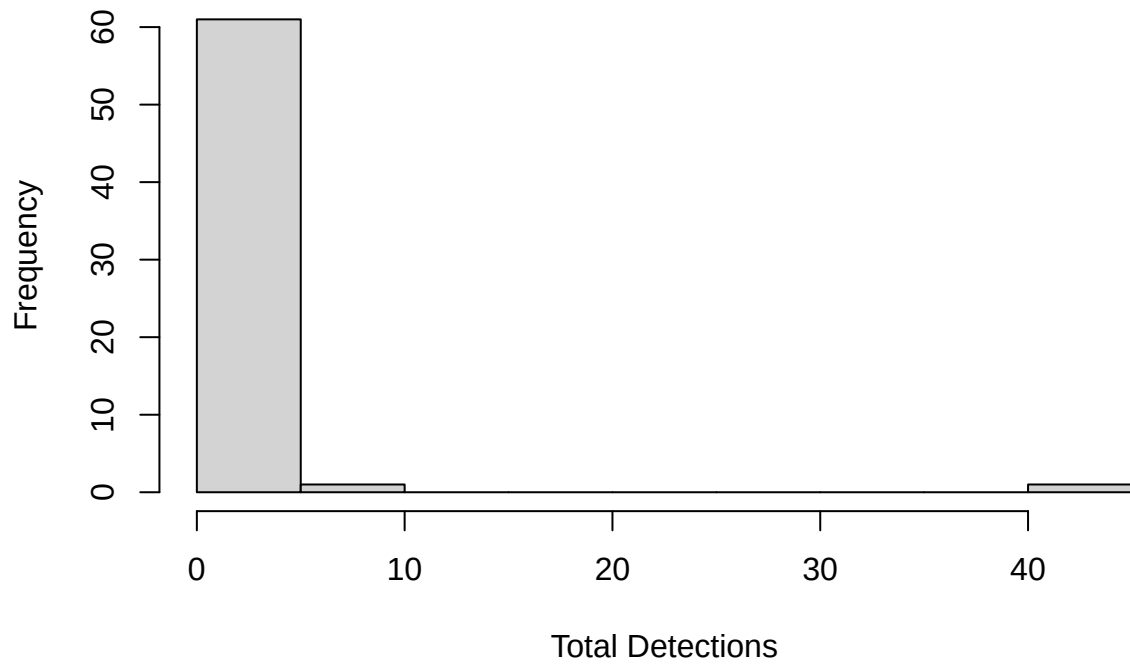
Histogram of mule_deer



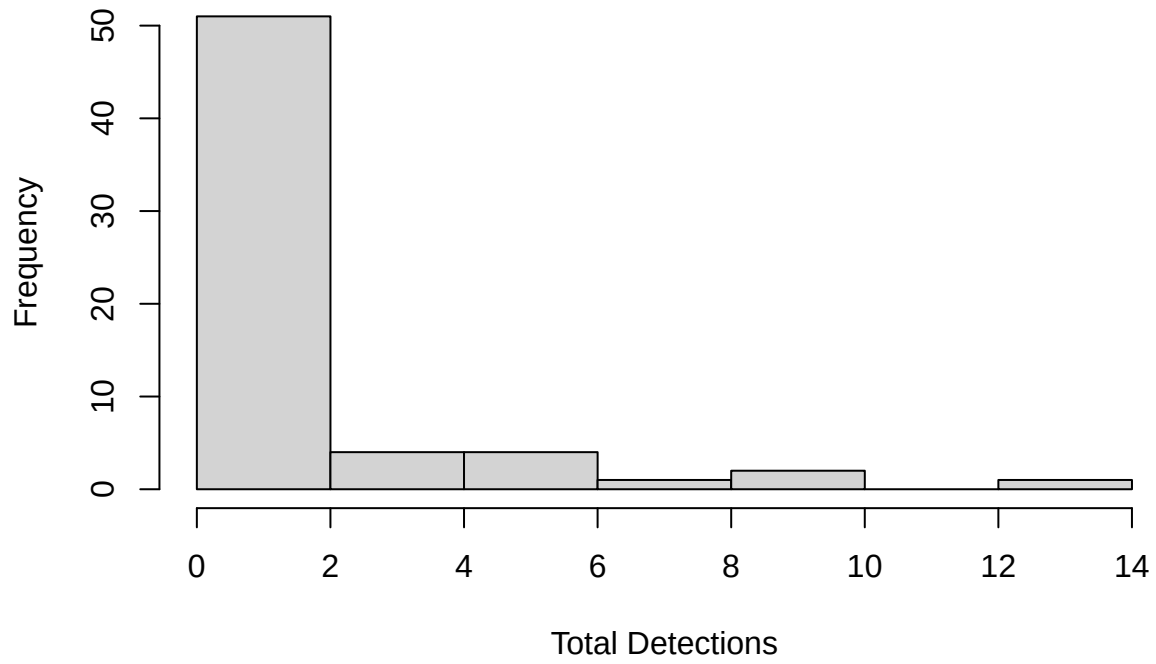
Histogram of unknown



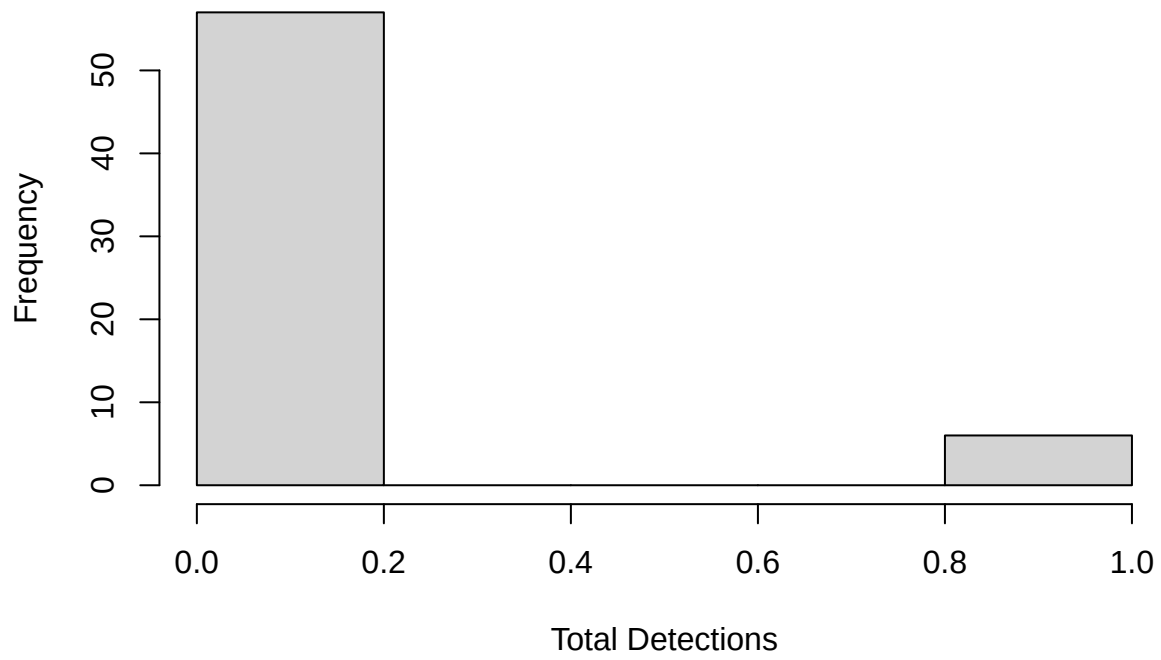
Histogram of unknown_ungulate



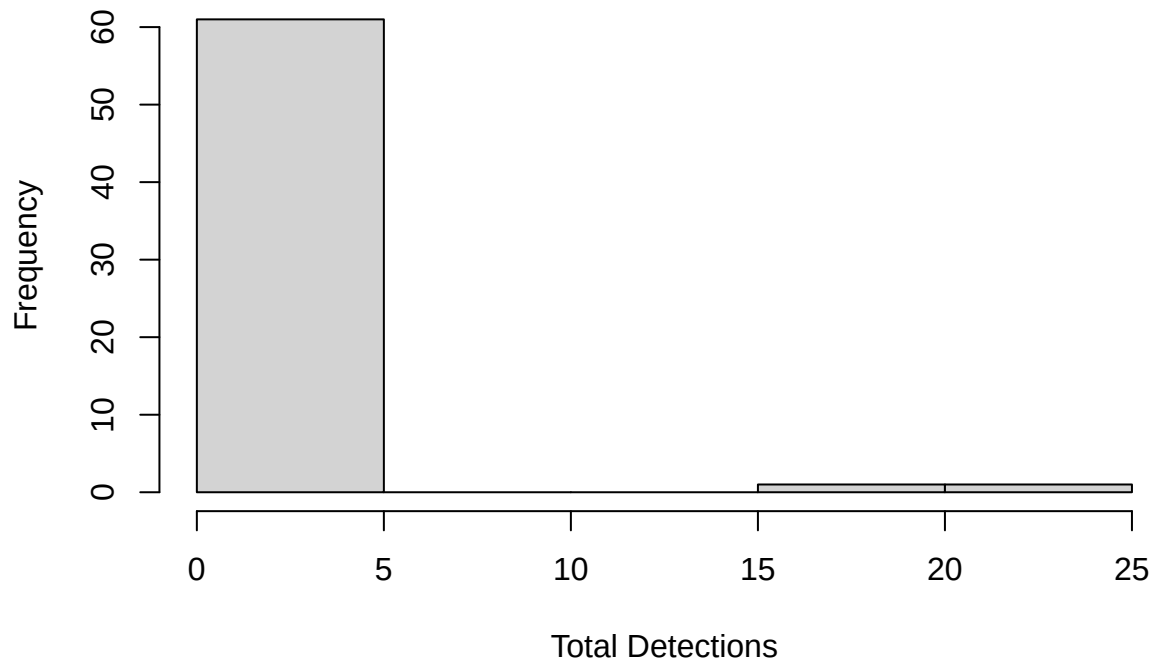
Histogram of lynx



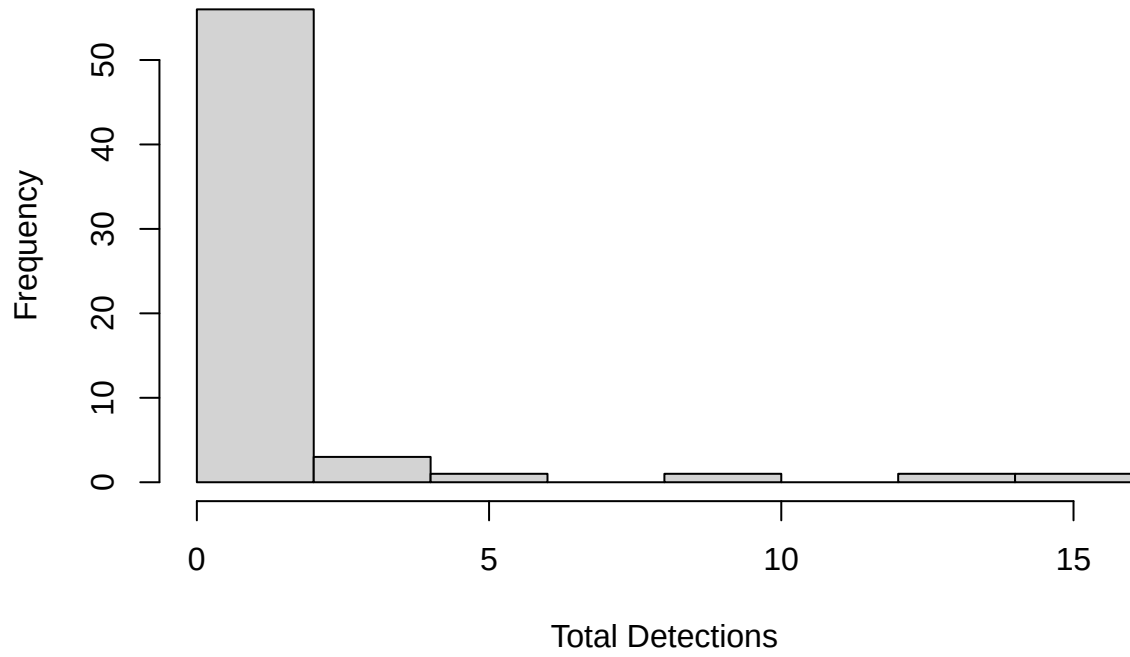
Histogram of cougar



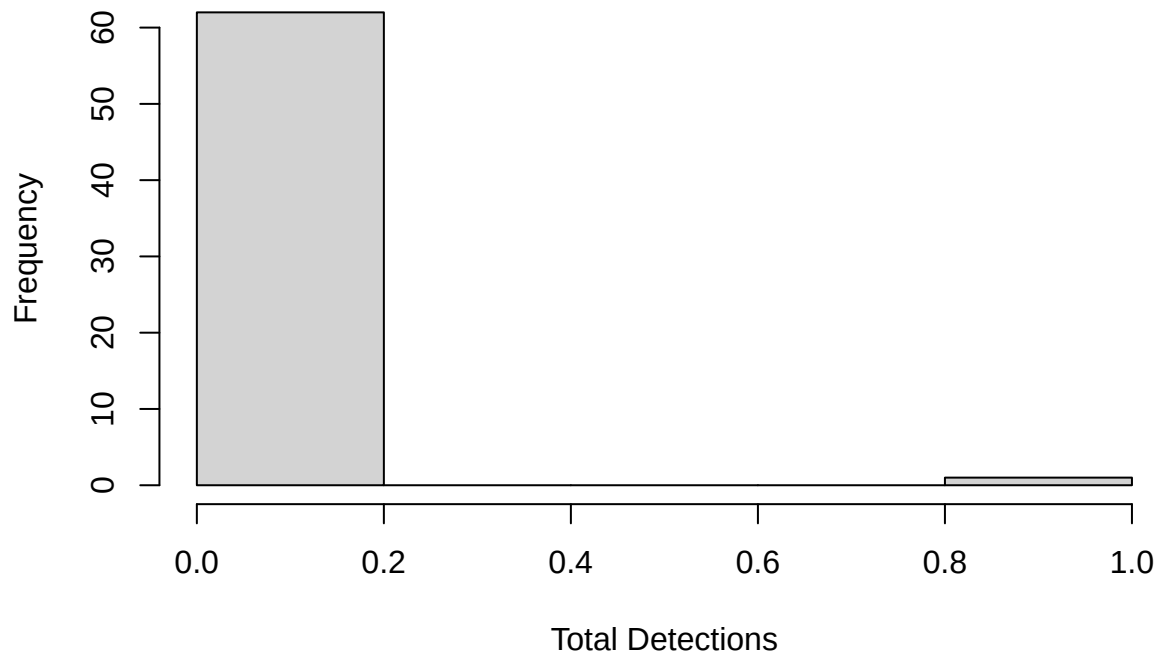
Histogram of red_squirrel



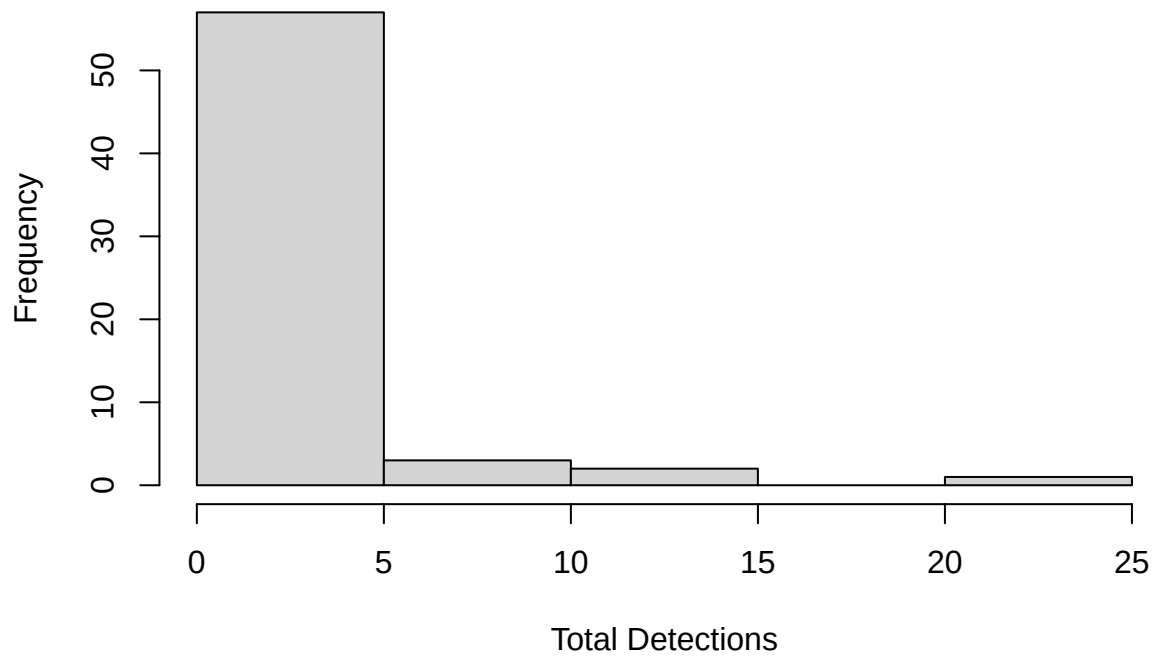
Histogram of other



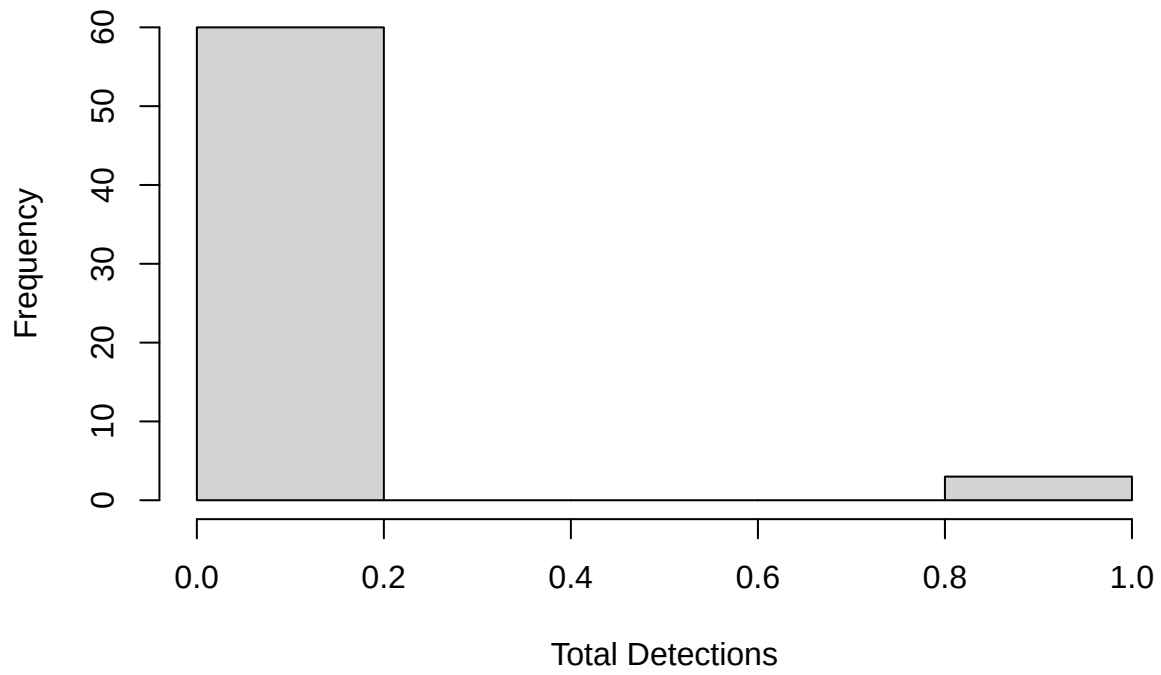
Histogram of atver



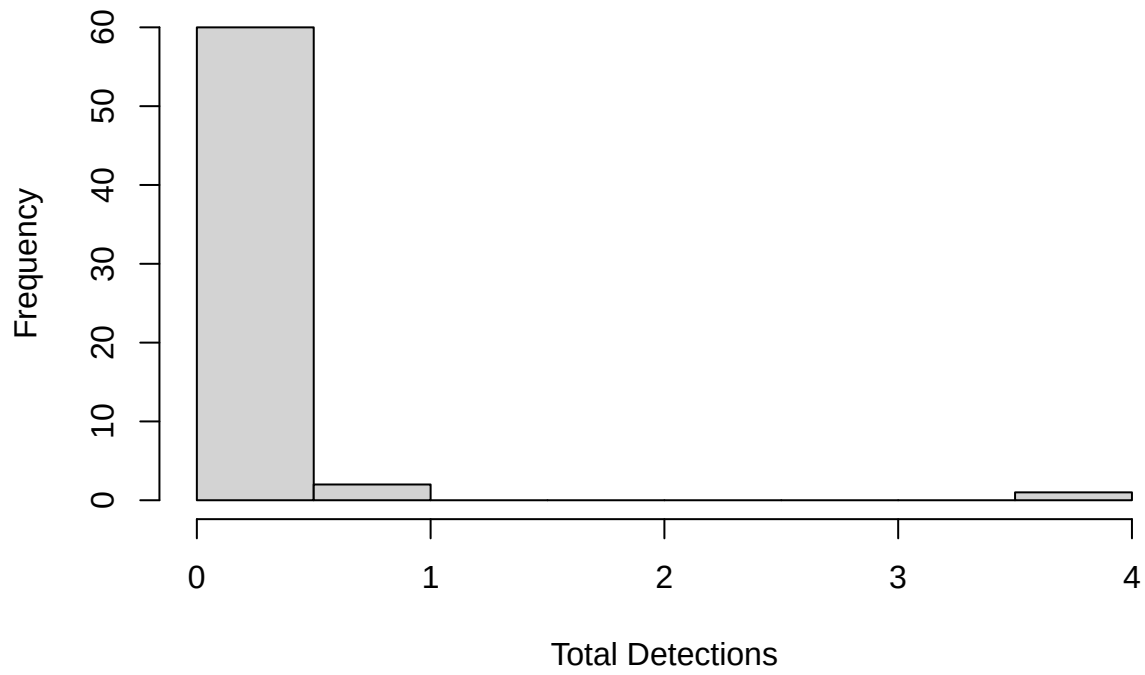
Histogram of unknown_deer



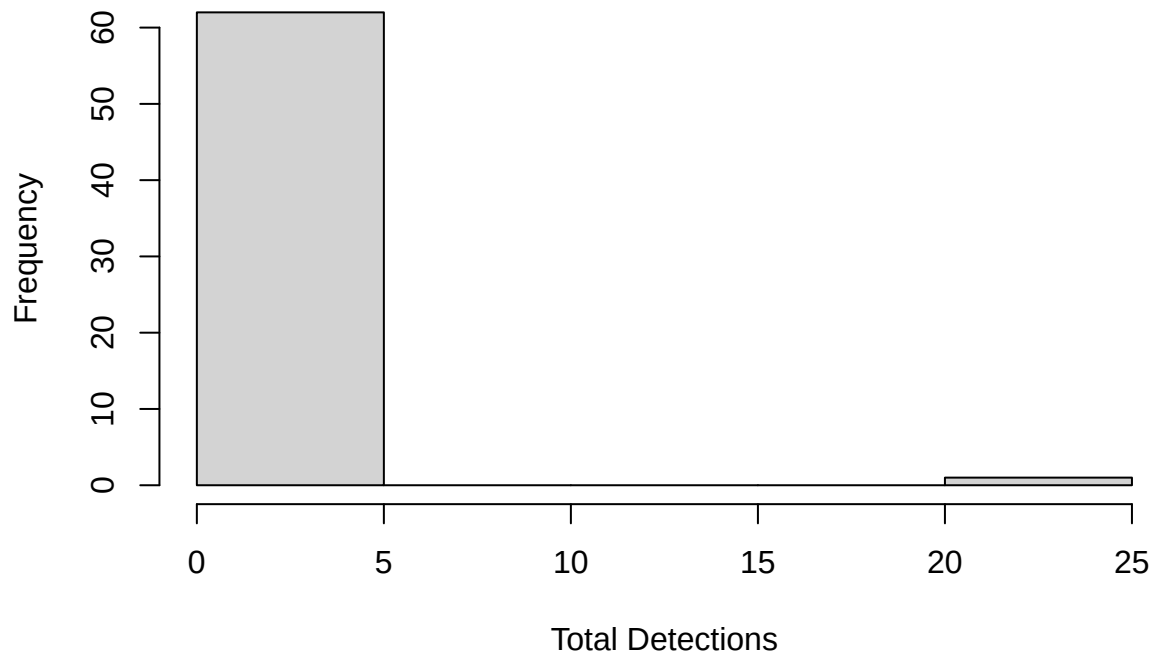
Histogram of unknown_bear



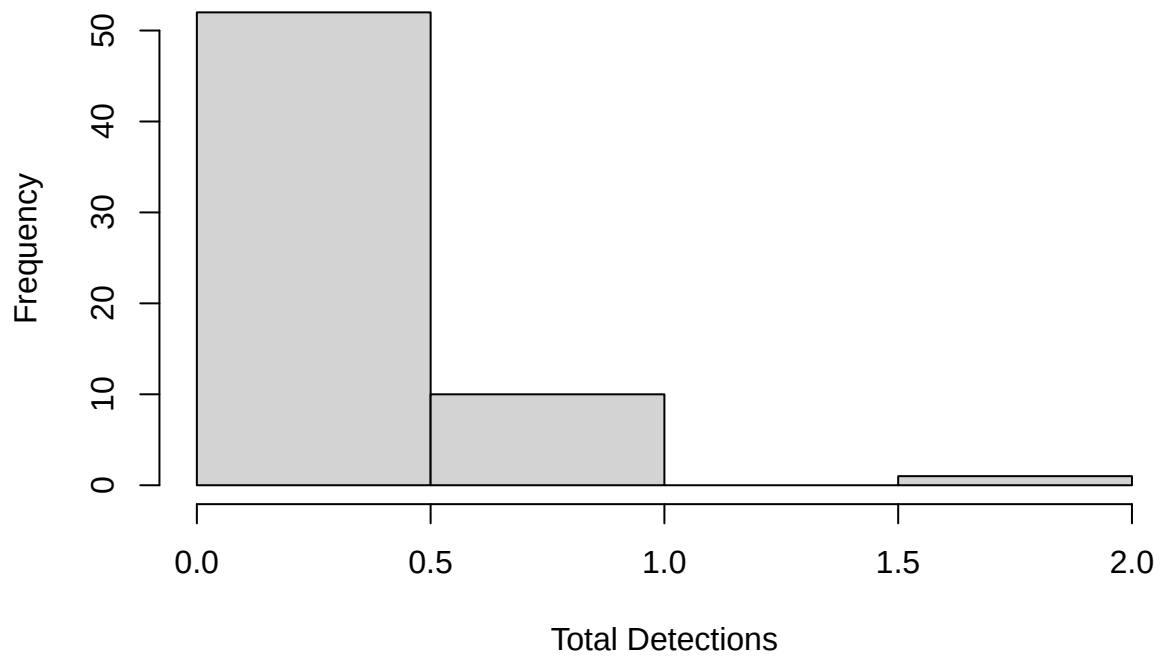
Histogram of other_birds



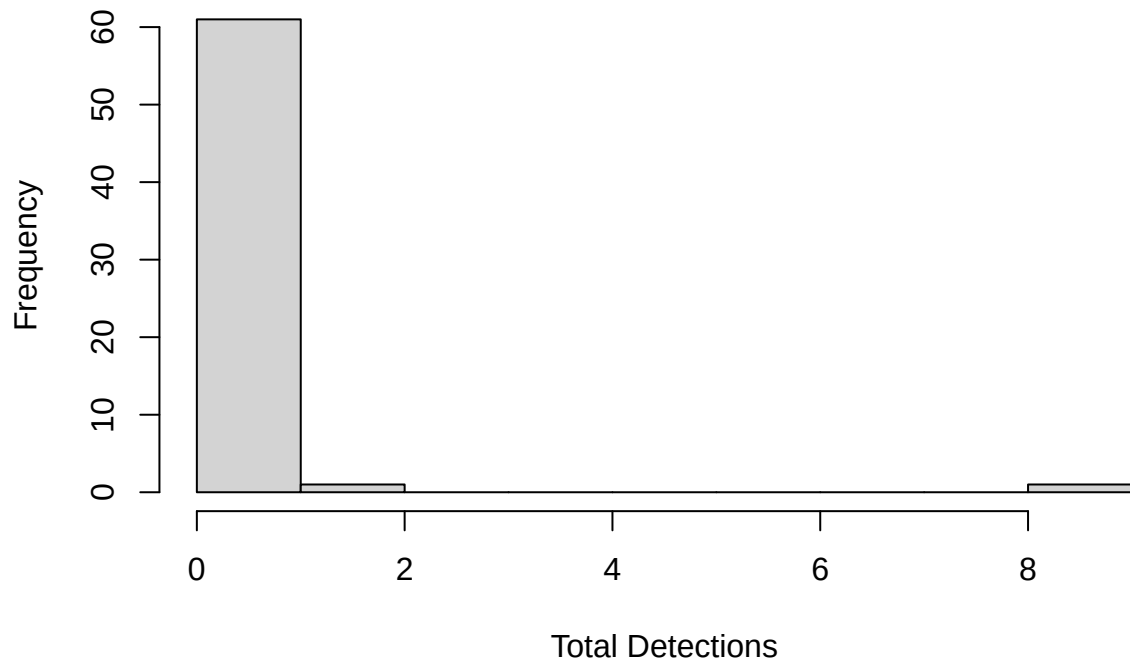
Histogram of human



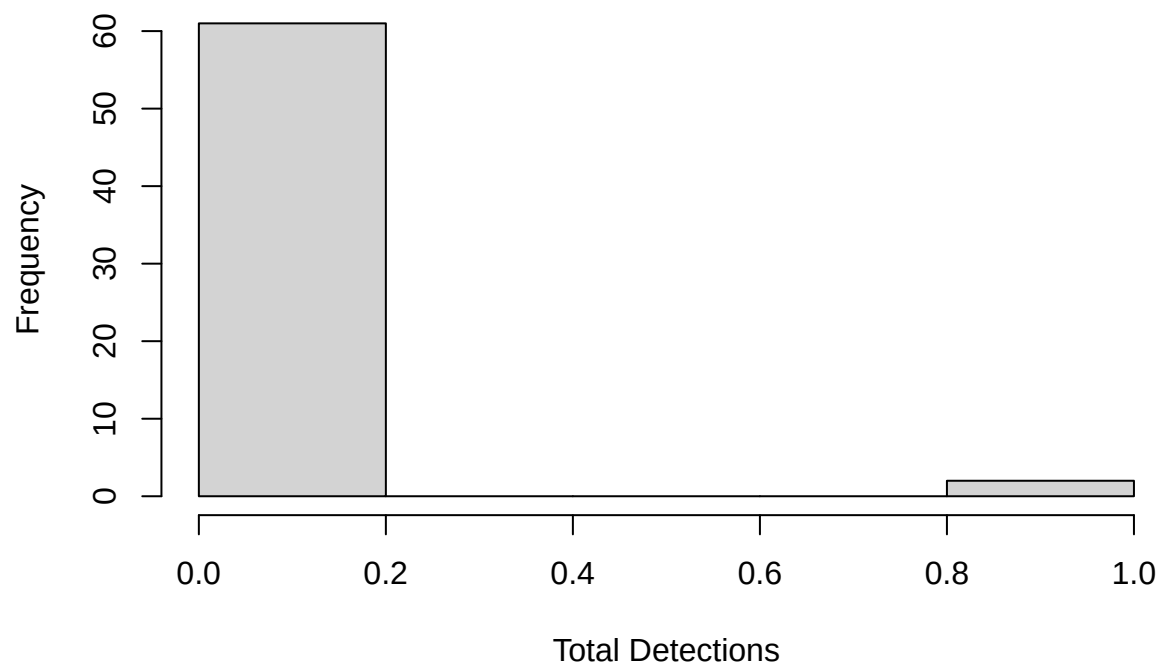
Histogram of staff



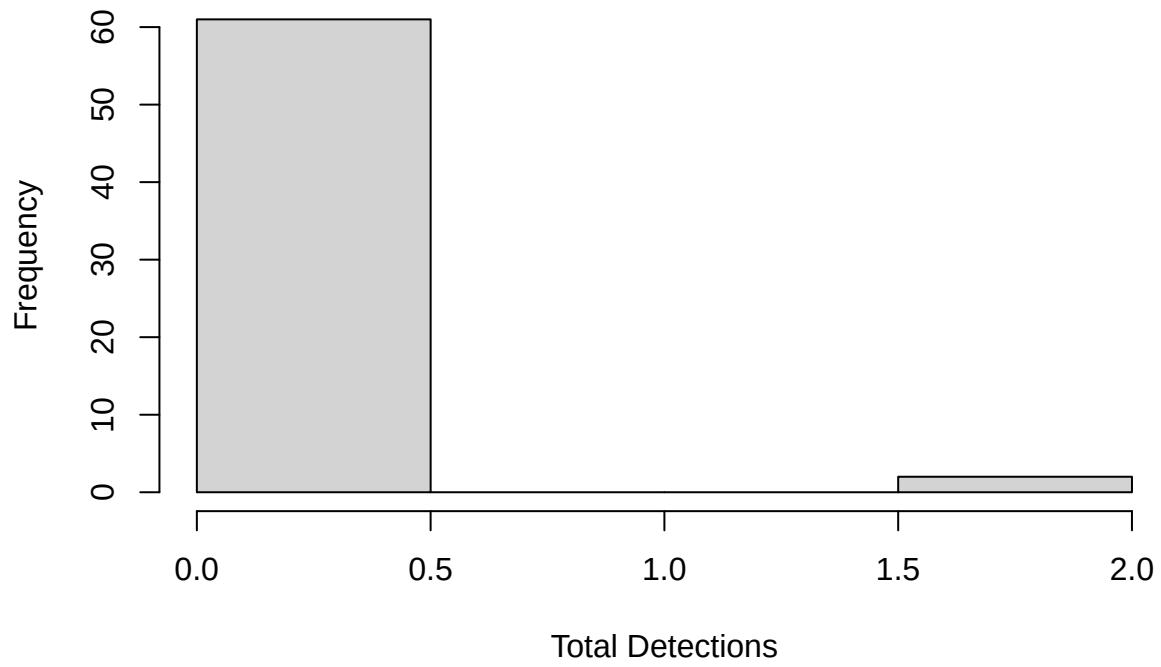
Histogram of spruce_grouse



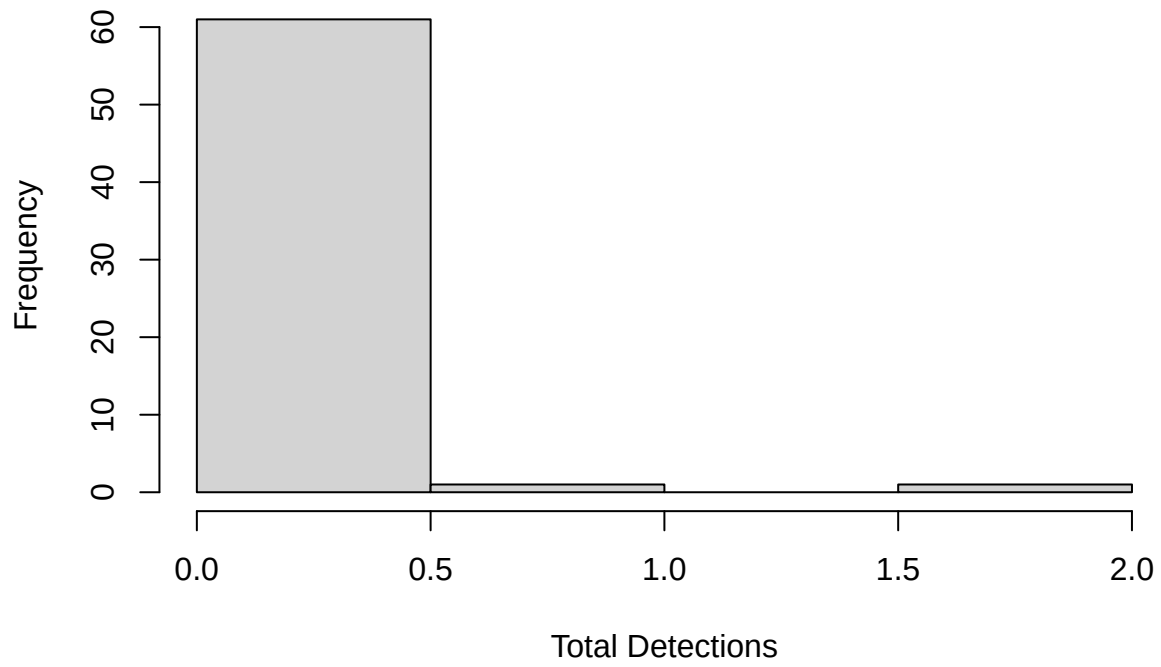
Histogram of hunter



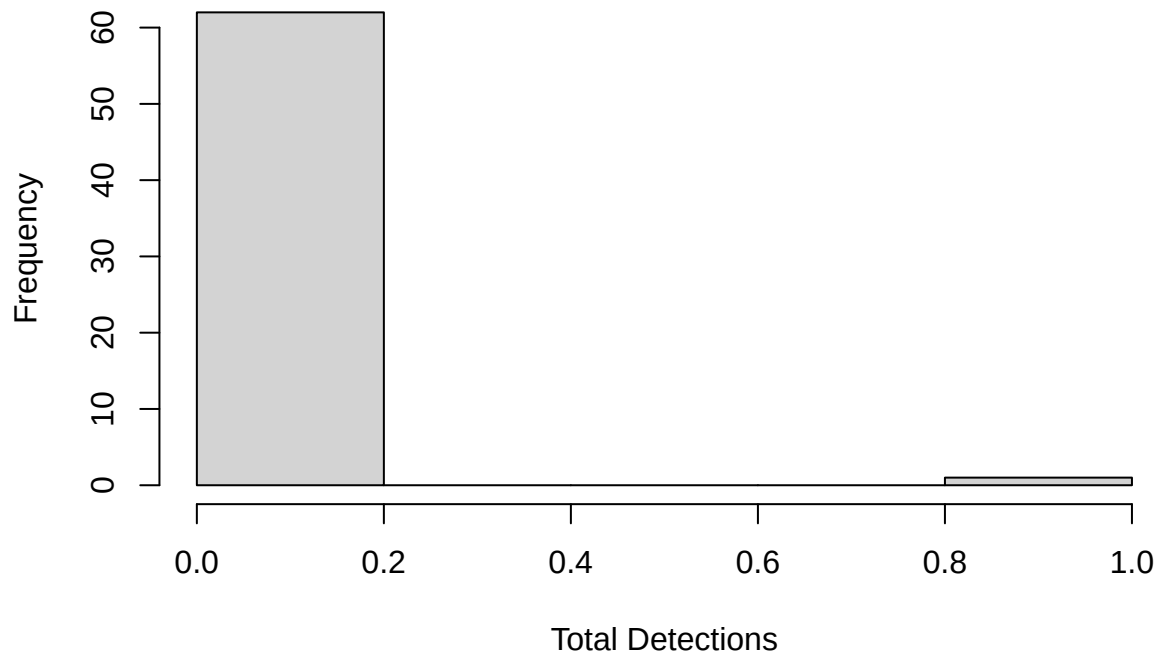
Histogram of ruffed_grouse



Histogram of raven



Histogram of owl



```
## $black_bear
## $breaks
## [1] 0 10 20 30 40 50 60
##
## $counts
## [1] 55 5 2 0 0 1
##
## $density
## [1] 0.087301587 0.007936508 0.003174603 0.000000000 0.000000000 0.001587302
##
## $mids
## [1] 5 15 25 35 45 55
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr(,"class")
## [1] "histogram"
##
## $coyote
## $breaks
## [1] 0 5 10 15 20 25 30 35
##
```

```

## $counts
## [1] 51  2  1  1  4  2  2
##
## $density
## [1] 0.161904762 0.006349206 0.003174603 0.003174603 0.012698413 0.006349206
## [7] 0.006349206
##
## $mids
## [1]  2.5  7.5 12.5 17.5 22.5 27.5 32.5
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $red_fox
## $breaks
## [1] 0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0
##
## $counts
## [1] 50  9  0  3  0  0  0  1
##
## $density
## [1] 1.58730159 0.28571429 0.00000000 0.09523810 0.00000000 0.00000000 0.00000000
## [8] 0.03174603
##
## $mids
## [1] 0.25 0.75 1.25 1.75 2.25 2.75 3.25 3.75
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $'white-tailed_deer'
## $breaks
## [1]  0 100 200 300 400 500 600 700
##
## $counts
## [1] 45 11  3  3  0  0  1
##
## $density
## [1] 0.0071428571 0.0017460317 0.0004761905 0.0004761905 0.0000000000
## [6] 0.0000000000 0.0001587302
##
## $mids

```

```

## [1] 50 150 250 350 450 550 650
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $domestic_dog
## $breaks
## [1] 0.0 0.5 1.0 1.5 2.0
##
## $counts
## [1] 60 2 0 1
##
## $density
## [1] 1.90476190 0.06349206 0.00000000 0.03174603
##
## $mids
## [1] 0.25 0.75 1.25 1.75
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $fisher
## $breaks
## [1] 0.0 0.5 1.0 1.5 2.0 2.5 3.0
##
## $counts
## [1] 52 7 0 2 0 2
##
## $density
## [1] 1.65079365 0.22222222 0.00000000 0.06349206 0.00000000 0.06349206
##
## $mids
## [1] 0.25 0.75 1.25 1.75 2.25 2.75
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"

```

```

##
## $grey_wolf
## $breaks
## [1] 0 5 10 15 20 25 30 35 40 45
##
## $counts
## [1] 56 5 0 0 0 1 0 0 1
##
## $density
## [1] 0.177777778 0.015873016 0.000000000 0.000000000 0.000000000 0.003174603
## [7] 0.000000000 0.000000000 0.003174603
##
## $mids
## [1] 2.5 7.5 12.5 17.5 22.5 27.5 32.5 37.5 42.5
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $grizzly_bear
## $breaks
## [1] 0 1 2 3 4 5
##
## $counts
## [1] 59 1 2 0 1
##
## $density
## [1] 0.93650794 0.01587302 0.03174603 0.00000000 0.01587302
##
## $mids
## [1] 0.5 1.5 2.5 3.5 4.5
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $marten
## $breaks
## [1] 0.0 0.5 1.0 1.5 2.0 2.5 3.0
##
## $counts
## [1] 57 4 0 1 0 1
##
## $density

```

```

## [1] 1.80952381 0.12698413 0.00000000 0.03174603 0.00000000 0.03174603
##
## $mids
## [1] 0.25 0.75 1.25 1.75 2.25 2.75
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $snowshoe_hare
## $breaks
## [1] 0 10 20 30 40 50 60 70
##
## $counts
## [1] 46 8 6 1 0 1 1
##
## $density
## [1] 0.073015873 0.012698413 0.009523810 0.001587302 0.000000000 0.001587302
## [7] 0.001587302
##
## $mids
## [1] 5 15 25 35 45 55 65
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $elk
## $breaks
## [1] 0 10 20 30 40 50 60 70
##
## $counts
## [1] 61 0 0 0 1 0 1
##
## $density
## [1] 0.096825397 0.000000000 0.000000000 0.000000000 0.001587302 0.000000000
## [7] 0.001587302
##
## $mids
## [1] 5 15 25 35 45 55 65
##
## $xname
## [1] ".x"
##

```

```

## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $moose
## $breaks
## [1] 0 20 40 60 80 100 120 140 160
##
## $counts
## [1] 56 2 2 1 1 0 0 1
##
## $density
## [1] 0.04444444444 0.0015873016 0.0015873016 0.0007936508 0.0007936508
## [6] 0.0000000000 0.0000000000 0.0007936508
##
## $mids
## [1] 10 30 50 70 90 110 130 150
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $mule_deer
## $breaks
## [1] 0 2 4 6 8 10 12
##
## $counts
## [1] 57 1 2 1 1 1
##
## $density
## [1] 0.452380952 0.007936508 0.015873016 0.007936508 0.007936508 0.007936508
##
## $mids
## [1] 1 3 5 7 9 11
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $unknown
## $breaks
## [1] 0 5 10 15 20 25 30 35 40 45

```

```

##
## $counts
## [1] 52  5  3  0  0  1  1  0  1
##
## $density
## [1] 0.165079365 0.015873016 0.009523810 0.000000000 0.000000000 0.003174603
## [7] 0.003174603 0.000000000 0.003174603
##
## $mids
## [1]  2.5  7.5 12.5 17.5 22.5 27.5 32.5 37.5 42.5
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $unknown_ungulate
## $breaks
## [1]  0  5 10 15 20 25 30 35 40 45
##
## $counts
## [1] 61  1  0  0  0  0  0  0  1
##
## $density
## [1] 0.193650794 0.003174603 0.000000000 0.000000000 0.000000000 0.000000000
## [7] 0.000000000 0.000000000 0.003174603
##
## $mids
## [1]  2.5  7.5 12.5 17.5 22.5 27.5 32.5 37.5 42.5
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $lynx
## $breaks
## [1]  0  2  4  6  8 10 12 14
##
## $counts
## [1] 51  4  4  1  2  0  1
##
## $density
## [1] 0.404761905 0.031746032 0.031746032 0.007936508 0.015873016 0.000000000
## [7] 0.007936508
##

```

```

## $mids
## [1] 1 3 5 7 9 11 13
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $cougar
## $breaks
## [1] 0.0 0.2 0.4 0.6 0.8 1.0
##
## $counts
## [1] 57 0 0 0 6
##
## $density
## [1] 4.5238095 0.0000000 0.0000000 0.0000000 0.4761905
##
## $mids
## [1] 0.1 0.3 0.5 0.7 0.9
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $red_squirrel
## $breaks
## [1] 0 5 10 15 20 25
##
## $counts
## [1] 61 0 0 1 1
##
## $density
## [1] 0.193650794 0.000000000 0.000000000 0.003174603 0.003174603
##
## $mids
## [1] 2.5 7.5 12.5 17.5 22.5
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")

```

```

## [1] "histogram"
##
## $other
## $breaks
## [1] 0 2 4 6 8 10 12 14 16
##
## $counts
## [1] 56 3 1 0 1 0 1 1
##
## $density
## [1] 0.444444444 0.023809524 0.007936508 0.000000000 0.007936508 0.000000000
## [7] 0.007936508 0.007936508
##
## $mids
## [1] 1 3 5 7 9 11 13 15
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $atver
## $breaks
## [1] 0.0 0.2 0.4 0.6 0.8 1.0
##
## $counts
## [1] 62 0 0 0 1
##
## $density
## [1] 4.92063492 0.00000000 0.00000000 0.00000000 0.07936508
##
## $mids
## [1] 0.1 0.3 0.5 0.7 0.9
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $unknown_deer
## $breaks
## [1] 0 5 10 15 20 25
##
## $counts
## [1] 57 3 2 0 1
##

```

```

## $density
## [1] 0.180952381 0.009523810 0.006349206 0.000000000 0.003174603
##
## $mids
## [1] 2.5 7.5 12.5 17.5 22.5
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $unknown_bear
## $breaks
## [1] 0.0 0.2 0.4 0.6 0.8 1.0
##
## $counts
## [1] 60 0 0 0 3
##
## $density
## [1] 4.7619048 0.0000000 0.0000000 0.0000000 0.2380952
##
## $mids
## [1] 0.1 0.3 0.5 0.7 0.9
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $other_birds
## $breaks
## [1] 0.0 0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0
##
## $counts
## [1] 60 2 0 0 0 0 0 1
##
## $density
## [1] 1.90476190 0.06349206 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000
## [8] 0.03174603
##
## $mids
## [1] 0.25 0.75 1.25 1.75 2.25 2.75 3.25 3.75
##
## $xname
## [1] ".x"
##

```

```

## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $human
## $breaks
## [1] 0 5 10 15 20 25
##
## $counts
## [1] 62 0 0 0 1
##
## $density
## [1] 0.196825397 0.000000000 0.000000000 0.000000000 0.003174603
##
## $mids
## [1] 2.5 7.5 12.5 17.5 22.5
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $staff
## $breaks
## [1] 0.0 0.5 1.0 1.5 2.0
##
## $counts
## [1] 52 10 0 1
##
## $density
## [1] 1.65079365 0.31746032 0.00000000 0.03174603
##
## $mids
## [1] 0.25 0.75 1.25 1.75
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $spruce_grouse
## $breaks
## [1] 0 1 2 3 4 5 6 7 8 9
##

```

```

## $counts
## [1] 61  1  0  0  0  0  0  0  1
##
## $density
## [1] 0.96825397 0.01587302 0.00000000 0.00000000 0.00000000 0.00000000 0.00000000
## [8] 0.00000000 0.01587302
##
## $mids
## [1] 0.5 1.5 2.5 3.5 4.5 5.5 6.5 7.5 8.5
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $hunter
## $breaks
## [1] 0.0 0.2 0.4 0.6 0.8 1.0
##
## $counts
## [1] 61  0  0  0  2
##
## $density
## [1] 4.8412698 0.0000000 0.0000000 0.0000000 0.1587302
##
## $mids
## [1] 0.1 0.3 0.5 0.7 0.9
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $ruffed_grouse
## $breaks
## [1] 0.0 0.5 1.0 1.5 2.0
##
## $counts
## [1] 61  0  0  2
##
## $density
## [1] 1.93650794 0.00000000 0.00000000 0.06349206
##
## $mids
## [1] 0.25 0.75 1.25 1.75
##

```

```

## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $raven
## $breaks
## [1] 0.0 0.5 1.0 1.5 2.0
##
## $counts
## [1] 61 1 0 1
##
## $density
## [1] 1.93650794 0.03174603 0.00000000 0.03174603
##
## $mids
## [1] 0.25 0.75 1.25 1.75
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"
##
## $owl
## $breaks
## [1] 0.0 0.2 0.4 0.6 0.8 1.0
##
## $counts
## [1] 62 0 0 0 1
##
## $density
## [1] 4.92063492 0.00000000 0.00000000 0.00000000 0.07936508
##
## $mids
## [1] 0.1 0.3 0.5 0.7 0.9
##
## $xname
## [1] ".x"
##
## $equidist
## [1] TRUE
##
## attr("class")
## [1] "histogram"

```

```
rm(response_metrics)
```

Covariates

We also need our potential explanatory variables

Read in data

In the previous script, 2_ACME_SRFN_landscape_covariate_exploration_script.Rmd we cleaned up the covariates data let's also read that in as we will need to join it with the response metric data to run the models

```
covariates <- read_csv('data/processed/srfn_covariates_grouped.csv',  
                      # also specify how site is read in  
                      col_types = cols(site = col_factor())  
                      )
```

Data checks

```
str(covariates)  
  
## spc_tbl_ [1,200 x 18] (S3: spec_tbl_df/tbl_df/tbl/data.frame)  
## $ site_number : num [1:1200] 1 2 4 6 10 12 13 17 18 21 ...  
## $ site : Factor w/ 60 levels "LUD_1","LUC_2",...: 1 2 3 4 5 6 7 8 9 10 ...  
## $ buff_dist : num [1:1200] 250 250 250 250 250 250 250 250 250 250 ...  
## $ harvest : num [1:1200] 0.432 0.342 0 0.388 0.424 ...  
## $ harvest_2000 : num [1:1200] 0.355 0 0 0.179 0.424 ...  
## $ harvest_pre2000: num [1:1200] 0.0763 0.3418 0 0.209 0 ...  
## $ pipeline : num [1:1200] 0 0.148 0.0148 0 0 ...  
## $ roads : num [1:1200] 0.00 5.99e-02 7.05e-03 7.11e-06 6.75e-03 ...  
## $ seismic_lines : num [1:1200] 0.00 5.41e-05 0.00 0.00 0.00 ...  
## $ veg_edges : num [1:1200] 0 0.09955 0.0129 0.00112 0.01425 ...  
## $ wells : num [1:1200] 0 0 0.0183 0.0318 0.0332 ...  
## $ lc_agriculture : num [1:1200] 0 0 0 0 0 0 0 0 0 ...  
## $ lc_broadleaf : num [1:1200] 0 0.18 0 0 0 ...  
## $ lc_coniferous : num [1:1200] 0.847 0 0.743 0.442 0.284 ...  
## $ lc_developed : num [1:1200] 0 0.4514 0.0716 0.00837 0.04522 ...  
## $ lc_grassland : num [1:1200] 0 0.3608 0.0618 0 0 ...  
## $ lc_mixed : num [1:1200] 0 0 0 0 0 0 0 0 0 ...  
## $ lc_shrub : num [1:1200] 0.15301 0.00776 0.12401 0.54941 0.6703 ...  
## - attr(*, "spec")=  
## .. cols(  
## .. site_number = col_double(),  
## .. site = col_factor(levels = NULL, ordered = FALSE, include_na = FALSE),  
## .. buff_dist = col_double(),  
## .. harvest = col_double(),  
## .. harvest_2000 = col_double(),  
## .. harvest_pre2000 = col_double(),  
## .. pipeline = col_double(),  
## .. roads = col_double(),  
## .. seismic_lines = col_double(),  
## .. veg_edges = col_double(),  
## .. wells = col_double(),
```

```
## .. lc_agriculture = col_double(),
## .. lc_broadleaf = col_double(),
## .. lc_coniferous = col_double(),
## .. lc_developed = col_double(),
## .. lc_grassland = col_double(),
## .. lc_mixed = col_double(),
## .. lc_shrub = col_double()
## .. )
## - attr(*, "problems")=<externalptr>
```

```
summary(covariates)
```

```
##   site_number      site      buff_dist      harvest
##   Min.   : 1.00   LUD_1   : 20   Min.   : 250   Min.   :0.0000
##   1st Qu.: 34.00  LUC_2   : 20   1st Qu.:1438   1st Qu.:0.0879
##   Median : 65.00  LUC_4   : 20   Median :2625   Median :0.2466
##   Mean   : 69.82  LUS_6   : 20   Mean   :2625   Mean   :0.2517
##   3rd Qu.:107.75  LUS_10  : 20   3rd Qu.:3812   3rd Qu.:0.3814
##   Max.   :141.00  LUBF_12: 20   Max.   :5000   Max.   :0.9863
##               (Other):1080
##   harvest_2000   harvest_pre2000   pipeline   roads
##   Min.   :0.000000   Min.   :0.000000   Min.   :0.000000   Min.   :0.000000
##   1st Qu.:0.008954   1st Qu.:0.000000   1st Qu.:0.000000   1st Qu.:0.002420
##   Median :0.133834   Median :0.05305    Median :0.00450    Median :0.007065
##   Mean   :0.142348   Mean   :0.09638    Mean   :0.01031    Mean   :0.007511
##   3rd Qu.:0.221274   3rd Qu.:0.14270    3rd Qu.:0.01523    3rd Qu.:0.011097
##   Max.   :0.856826   Max.   :0.98631    Max.   :0.14867    Max.   :0.059875
##
##   seismic_lines   veg_edges       wells       lc_agriculture
##   Min.   :0.000000   Min.   :0.000000   Min.   :0.0000000   Min.   :0.000000
##   1st Qu.:0.001827   1st Qu.:0.003484   1st Qu.:0.0008336   1st Qu.:0.000000
##   Median :0.003612   Median :0.012634   Median :0.0089454   Median :0.000000
##   Mean   :0.004028   Mean   :0.013908   Mean   :0.0103535   Mean   :0.03587
##   3rd Qu.:0.005451   3rd Qu.:0.021155   3rd Qu.:0.0175866   3rd Qu.:0.000000
##   Max.   :0.030028   Max.   :0.099551   Max.   :0.0957837   Max.   :0.49000
##
##   lc_broadleaf   lc_coniferous   lc_developed   lc_grassland
##   Min.   :0.0000   Min.   :0.000000   Min.   :0.000000   Min.   :0.000000
##   1st Qu.:0.1463   1st Qu.:0.03179    1st Qu.:0.01782    1st Qu.:0.006635
##   Median :0.3010   Median :0.23137    Median :0.05463    Median :0.034291
##   Mean   :0.3502   Mean   :0.23902    Mean   :0.05948    Mean   :0.055123
##   3rd Qu.:0.5250   3rd Qu.:0.38303    3rd Qu.:0.08856    3rd Qu.:0.068804
##   Max.   :1.0000   Max.   :0.84699    Max.   :0.45140    Max.   :0.883334
##
##   lc_mixed       lc_shrub
##   Min.   :0.00000   Min.   :0.000000
##   1st Qu.:0.00000   1st Qu.:0.04624
##   Median :0.01965   Median :0.10172
##   Mean   :0.04277   Mean   :0.15602
##   3rd Qu.:0.06350   3rd Qu.:0.20080
##   Max.   :0.93137   Max.   :0.93212
##
```

Subset data by buffer

We do need to subset the data so we have separate data frames for each buffer width to work with in the analysis **AND** to explore correlations between variables at each buffer width, as these may vary with spatial scales

Let's use a for loop to subset the data, thanks Andrew!

```
buffer_frames <- list()

for (i in unique(covariates$buff_dist)){

  print(i)

  # Subset data based on radius
  df <- covariates %>%
    filter(buff_dist == i)

  # list of dataframes
  buffer_frames <-c (buffer_frames, list(df))
}

## [1] 250
## [1] 500
## [1] 750
## [1] 1000
## [1] 1250
## [1] 1500
## [1] 1750
## [1] 2000
## [1] 2250
## [1] 2500
## [1] 2750
## [1] 3000
## [1] 3250
## [1] 3500
## [1] 3750
## [1] 4000
## [1] 4250
## [1] 4500
## [1] 4750
## [1] 5000

# name list objects so we can extract names for plotting

buffer_frames <- buffer_frames %>%

  # absurdly long way to do this but for sake of time fuck it
  purrr::set_names('250 meter buffer',
                    '500 meter buffer',
                    '750 meter buffer',
                    '1000 meter buffer',
                    '1250 meter buffer',
                    '1500 meter buffer',
                    '1750 meter buffer',
                    '2000 meter buffer',
```

```

'2250 meter buffer',
'2500 meter buffer',
'2750 meter buffer',
'3000 meter buffer',
'3250 meter buffer',
'3500 meter buffer',
'3750 meter buffer',
'4000 meter buffer',
'4250 meter buffer',
'4500 meter buffer',
'4750 meter buffer',
'5000 meter buffer')

```

Now we have a list with data frames for each buffer width which we can work with later.

Add response metrics

Now that we have the covariate data formatted we need to the response metric data frames that we will use for each species and tidy up the resulting data

We will want separate data frames for each type of response metric - we will use the proportional detection data for all the species we have enough detections for, otherwise we will use either the total detections or presence absence data depending how the models fit.

```

# proportional detections
prop_det_data <- buffer_frames %>%

  # use purrr to join data to all individual buffer frames data sets
  purrr::map(
    ~.x %>%

      # use left join so only sites with covariate data are kept
      left_join(response_metrics_subset$prop_detections,
                by = 'site'))

# total detections
total_det_data <- buffer_frames %>%

  # use purrr to join data to all individual buffer frames data sets
  purrr::map(
    ~.x %>%

      # use left join so only sites with covariate data are kept
      left_join(response_metrics_subset$total_detections,
                by = 'site'))

# presence absence
pres_absen_dat <- buffer_frames %>%

  # use purrr to join data to all individual buffer frames data sets
  purrr::map(
    ~.x %>%

      # use inner join so only sites with both data

```

```
inner_join(response_metrics_subset$presence_absence,
           by = 'site') %>%

mutate(across(c(elk:grizzly_bear), as.factor)))
```

I'm going to view each of these through the RStudio environemnt to look at them in depth and will print a subset of each ehre

```
head(prop_det_data$`250 meter buffer`)
```

```
## # A tibble: 6 x 34
##   site_number site      buff_dist harvest harvest_2000 harvest_pre2000 pipeline
##   <dbl> <fct>      <dbl>    <dbl>      <dbl>      <dbl>      <dbl>
## 1         1 LUD_1        250    0.432      0.355      0.0763      0
## 2         2 LUC_2        250    0.342      0         0.342      0.148
## 3         4 LUC_4        250    0         0         0         0.0148
## 4         6 LUS_6        250    0.388      0.179      0.209      0
## 5        10 LUS_10       250    0.424      0.424      0         0
## 6        12 LUBF_12     250    0         0         0         0.0752
## # i 27 more variables: roads <dbl>, seismic_lines <dbl>, veg_edges <dbl>,
## # wells <dbl>, lc_agriculture <dbl>, lc_broadleaf <dbl>, lc_coniferous <dbl>,
## # lc_developed <dbl>, lc_grassland <dbl>, lc_mixed <dbl>, lc_shrub <dbl>,
## # black_bear <dbl>, coyote <dbl>, 'white-tailed_deer' <dbl>, grey_wolf <dbl>,
## # snowshoe_hare <dbl>, elk <dbl>, moose <dbl>, lynx <dbl>,
## # absent_black_bear <dbl>, absent_coyote <dbl>,
## # 'absent_white-tailed_deer' <dbl>, absent_grey_wolf <dbl>, ...
```

```
str(pres_absen_dat$`2000 meter buffer`)
```

```
## tibble [59 x 23] (S3: tbl_df/tbl/data.frame)
## $ site_number.x : num [1:59] 1 2 4 6 10 12 13 17 18 21 ...
## $ site          : Factor w/ 64 levels "LUD_1","LUC_2",...: 1 2 3 4 5 6 7 8 9 10 ...
## $ buff_dist     : num [1:59] 2000 2000 2000 2000 2000 2000 2000 2000 2000 2000 ...
## $ harvest       : num [1:59] 0.381 0.476 0.252 0.421 0.576 ...
## $ harvest_2000  : num [1:59] 0.195 0.284 0.232 0.243 0.224 ...
## $ harvest_pre2000: num [1:59] 0.186 0.1917 0.0194 0.1777 0.3515 ...
## $ pipeline      : num [1:59] 0.00509 0.042 0.03546 0.02548 0.00134 ...
## $ roads         : num [1:59] 0.00872 0.01885 0.01674 0.01398 0.00797 ...
## $ seismic_lines : num [1:59] 0.006809 0.003832 0.007541 0.004027 0.000759 ...
## $ veg_edges     : num [1:59] 0.0157 0.0332 0.0289 0.0229 0.0115 ...
## $ wells         : num [1:59] 0.0164 0.0359 0.0337 0.0226 0.011 ...
## $ lc_agriculture : num [1:59] 0 0 0 0 0 0 0 0 0 0 ...
## $ lc_broadleaf  : num [1:59] 0.035 0.0264 0.1201 0.1349 0.1353 ...
## $ lc_coniferous : num [1:59] 0.398 0.55 0.576 0.386 0.375 ...
## $ lc_developed  : num [1:59] 0.0772 0.1714 0.1277 0.133 0.0555 ...
## $ lc_grassland  : num [1:59] 0 0.08906 0.0449 0.04254 0.00478 ...
## $ lc_mixed      : num [1:59] 0 0.00275 0 0.00869 0 ...
## $ lc_shrub      : num [1:59] 0.49 0.16 0.132 0.294 0.429 ...
## $ site_number.y : num [1:59] 1 2 4 6 10 12 13 17 18 21 ...
## $ elk           : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 2 1 1 1 ...
## $ red_fox       : Factor w/ 2 levels "0","1": 1 2 1 1 1 1 2 1 1 1 ...
## $ mule_deer     : Factor w/ 2 levels "0","1": 1 1 1 1 1 2 1 1 1 1 ...
## $ grizzly_bear  : Factor w/ 2 levels "0","1": 1 1 1 2 1 1 1 1 1 1 ...
```

Finish with data formatting

Let's remove the objects we no longer need from the environment to keep our work space clean

```
rm(buffer_frames,
    covariates,
    df,
    response_metrics_subset)
```

Let's also save this so we can use it in a later script to make figures

```
saveRDS(prop_det_data, 'data/processed/prop_det_data.rds')
```

Correlation plots

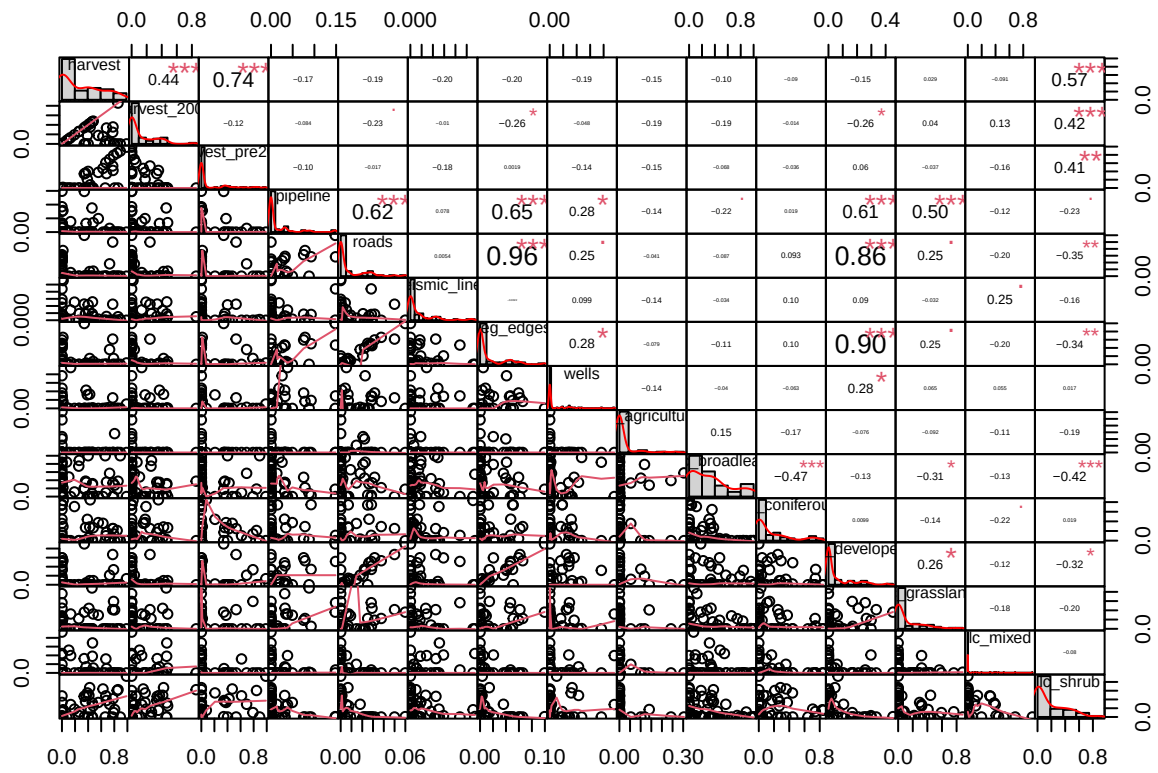
Before we can develop any models we need to look at your covariates and see if there are any major violations of the model assumptions of independence, e.g. variables that are highly correlated - in which case we need to choose which variable in each pair to include in a model

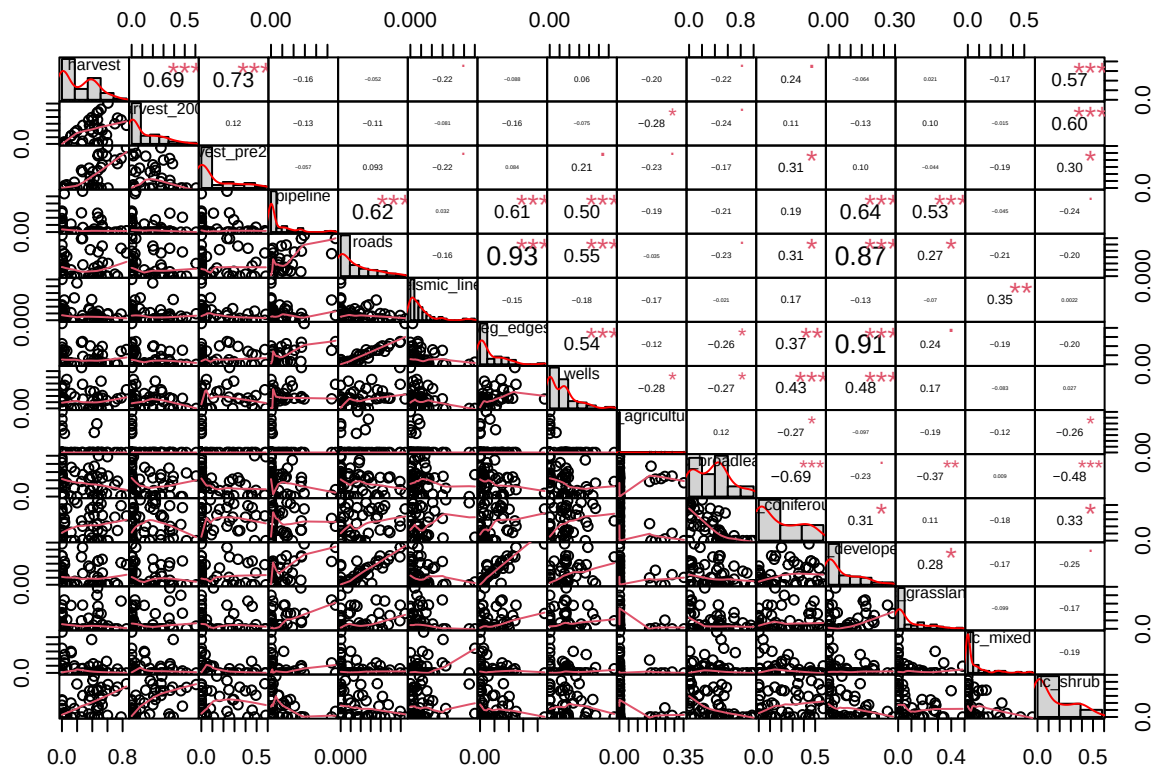
```
prop_det_data %>%

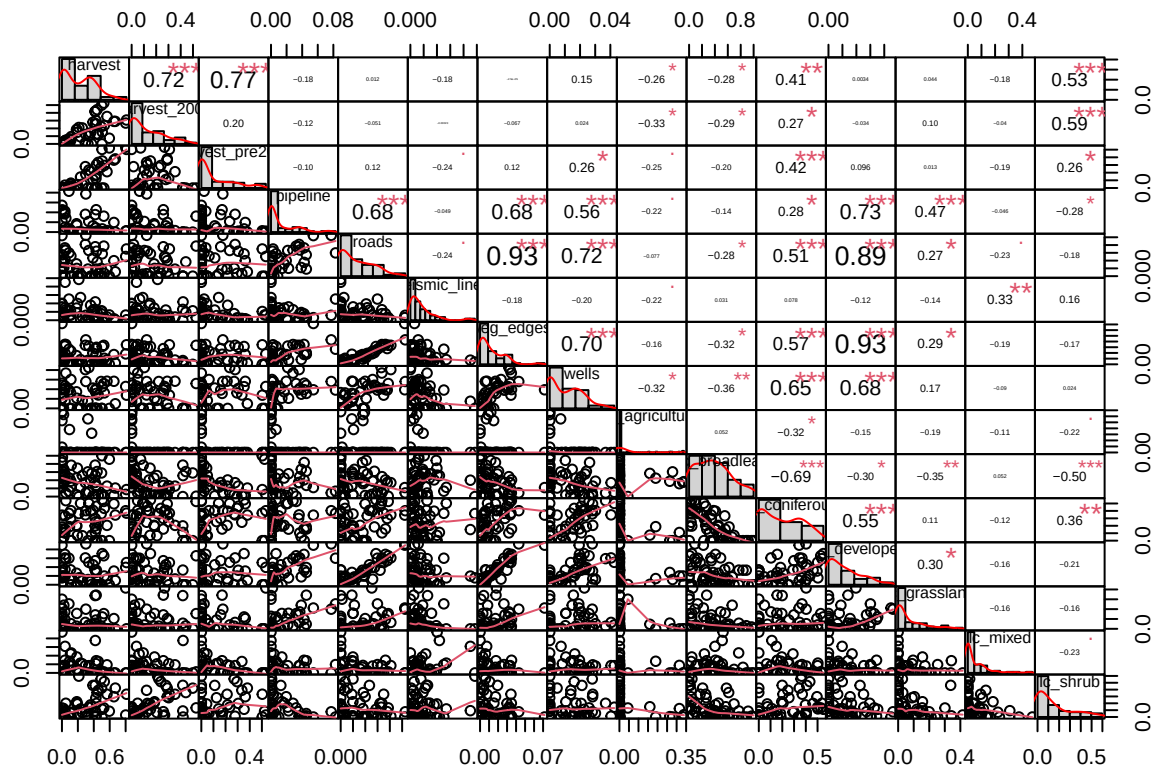
  purrr::map(
    ~.x %>%

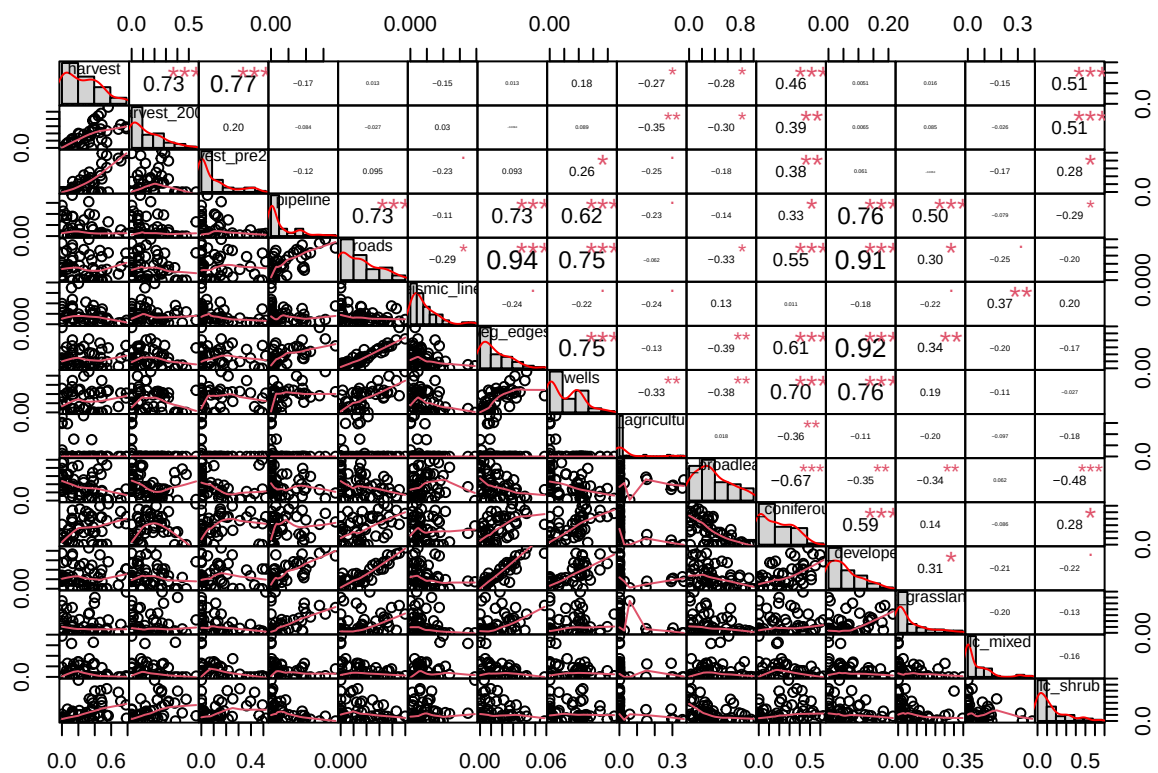
      # select only columns with covariates not other info to simplify the plot a bit
      select(harvest:lc_shrub) %>%

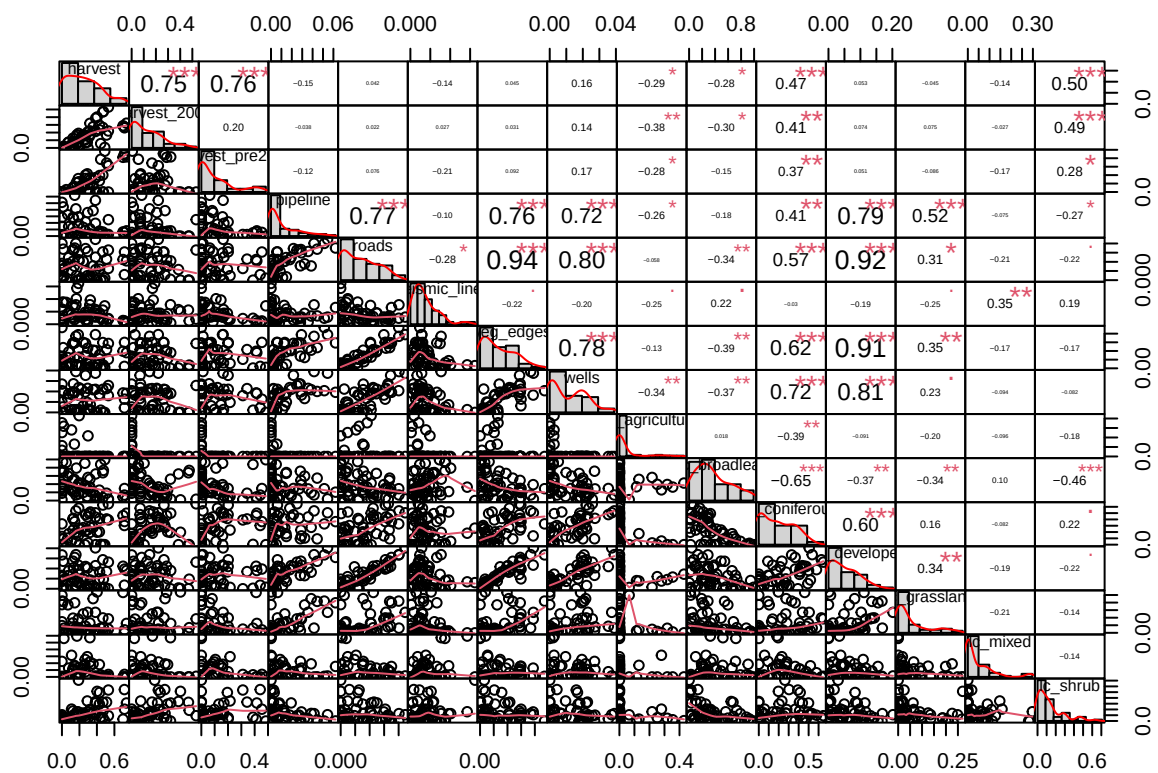
      # use chart.correlation to produce plots for each buffer size
      chart.Correlation(.,
        histogram = TRUE,
        method = "pearson")
  )
```

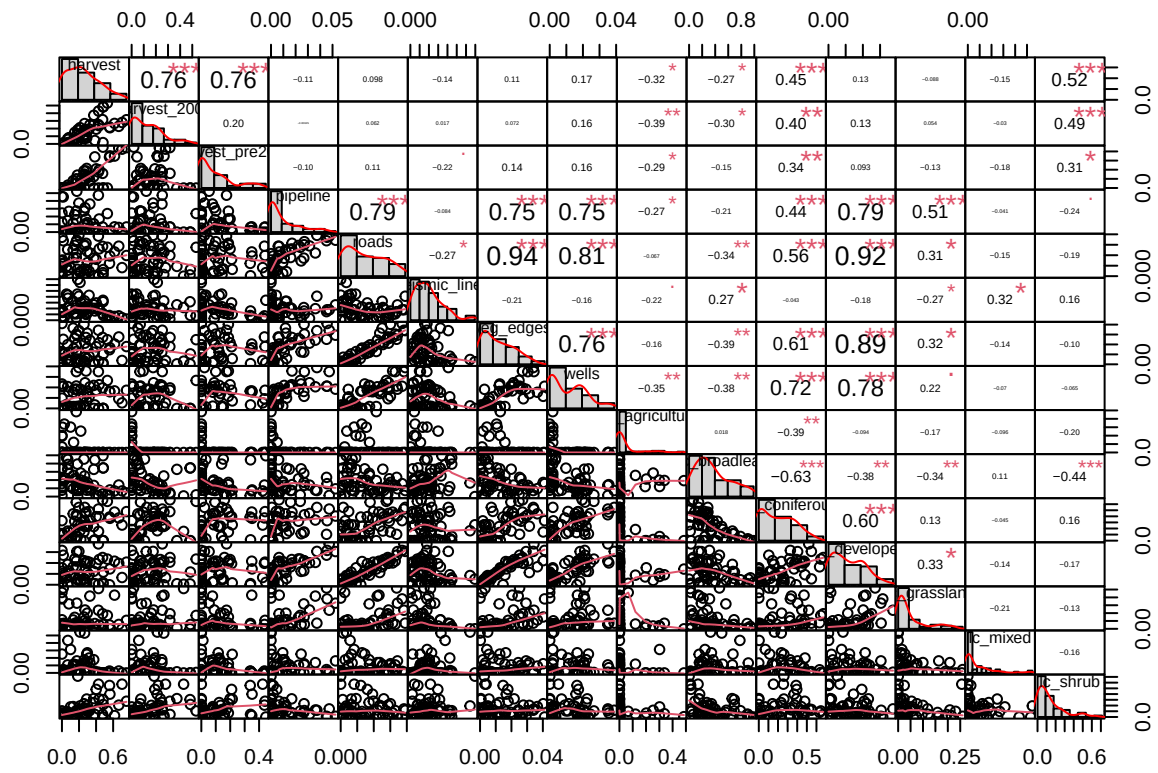


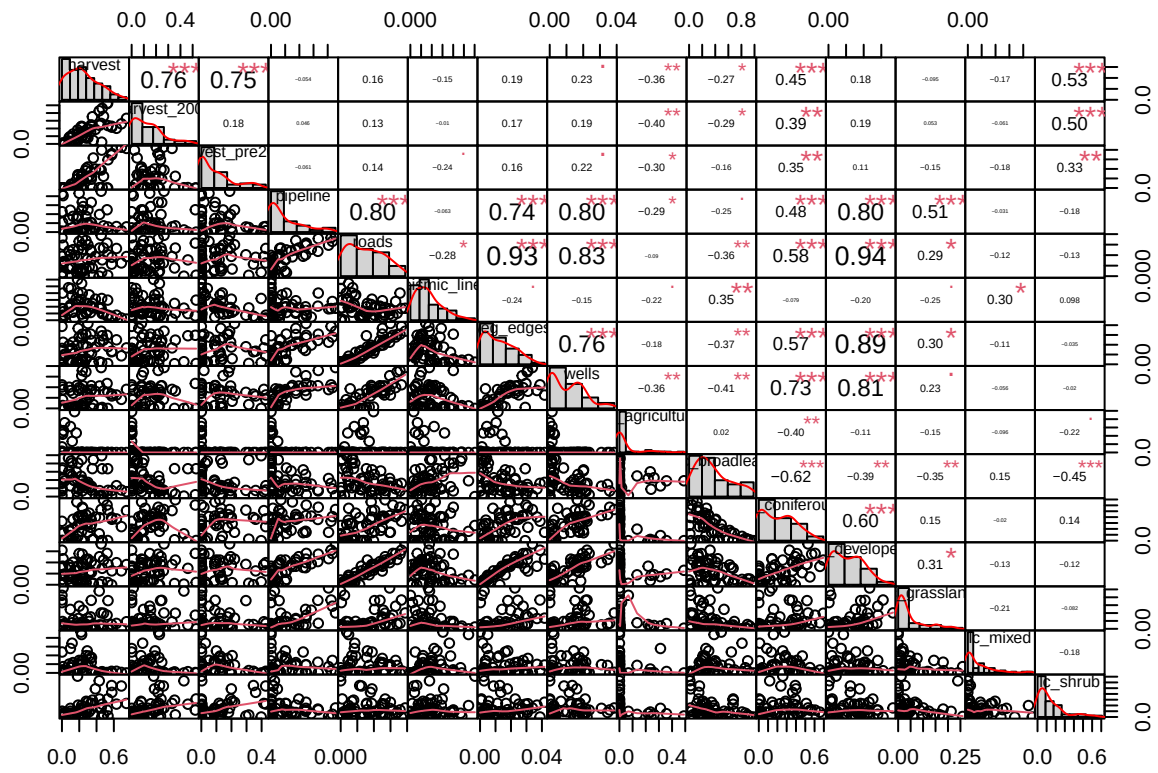


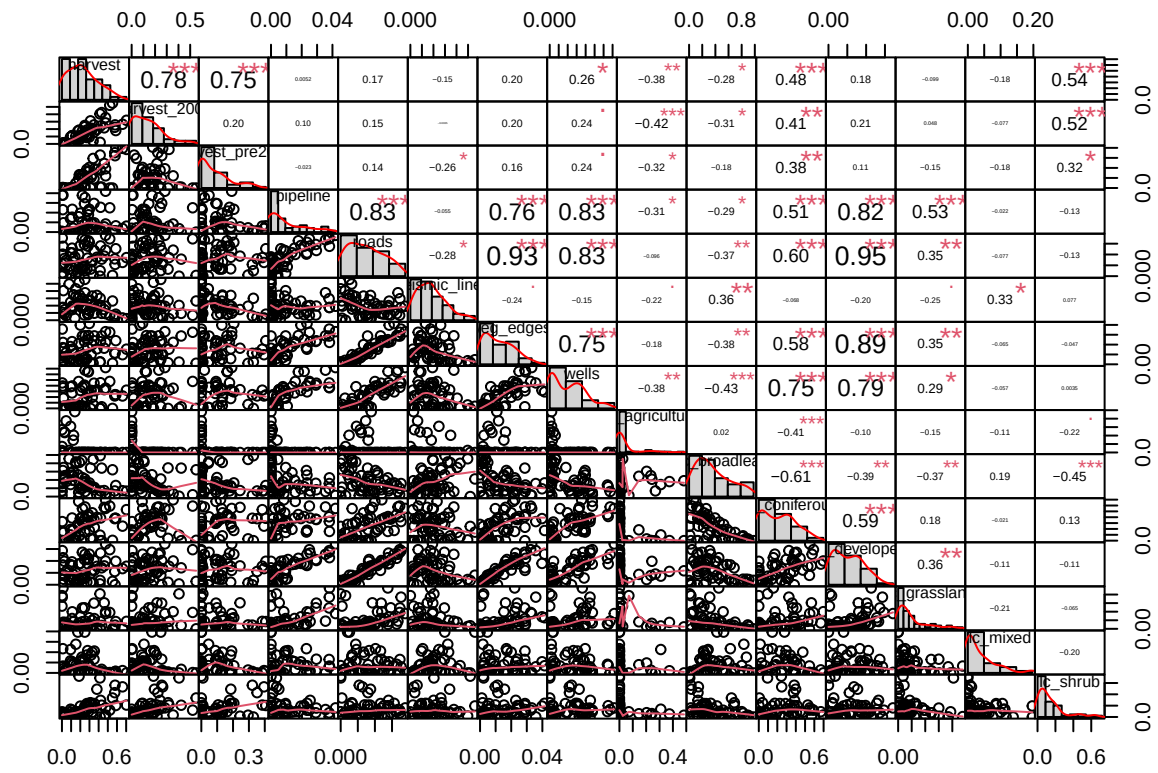


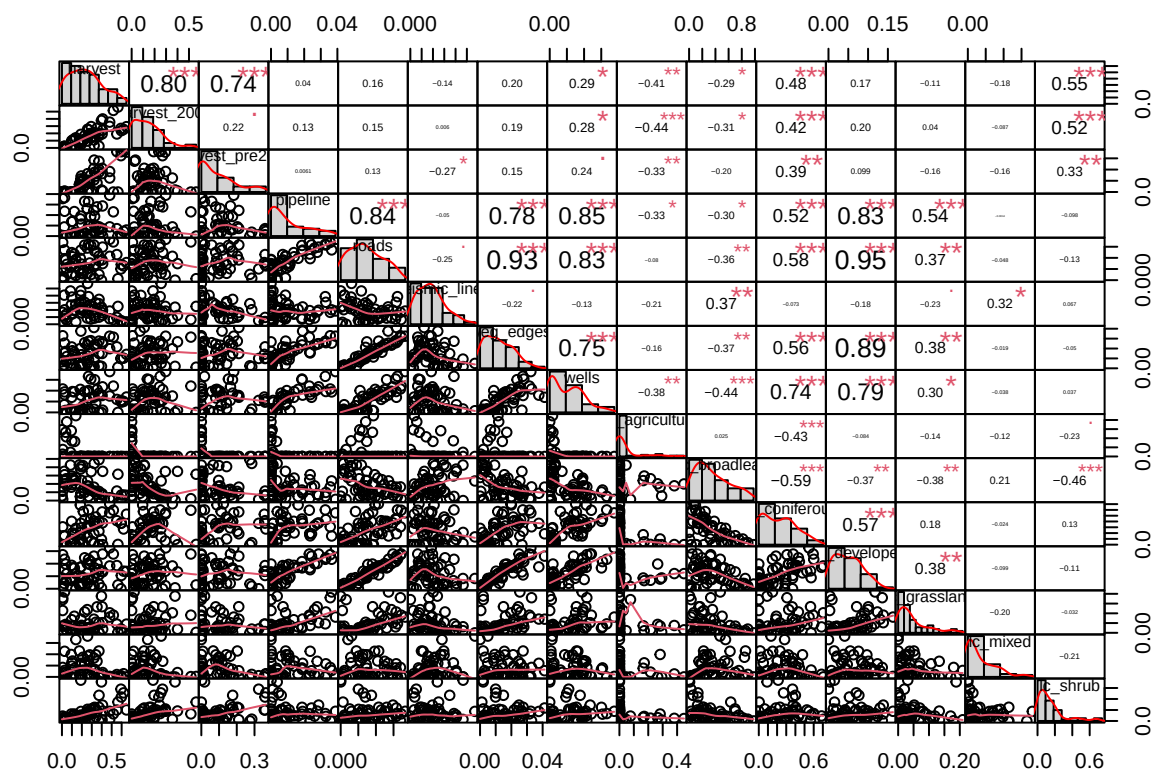


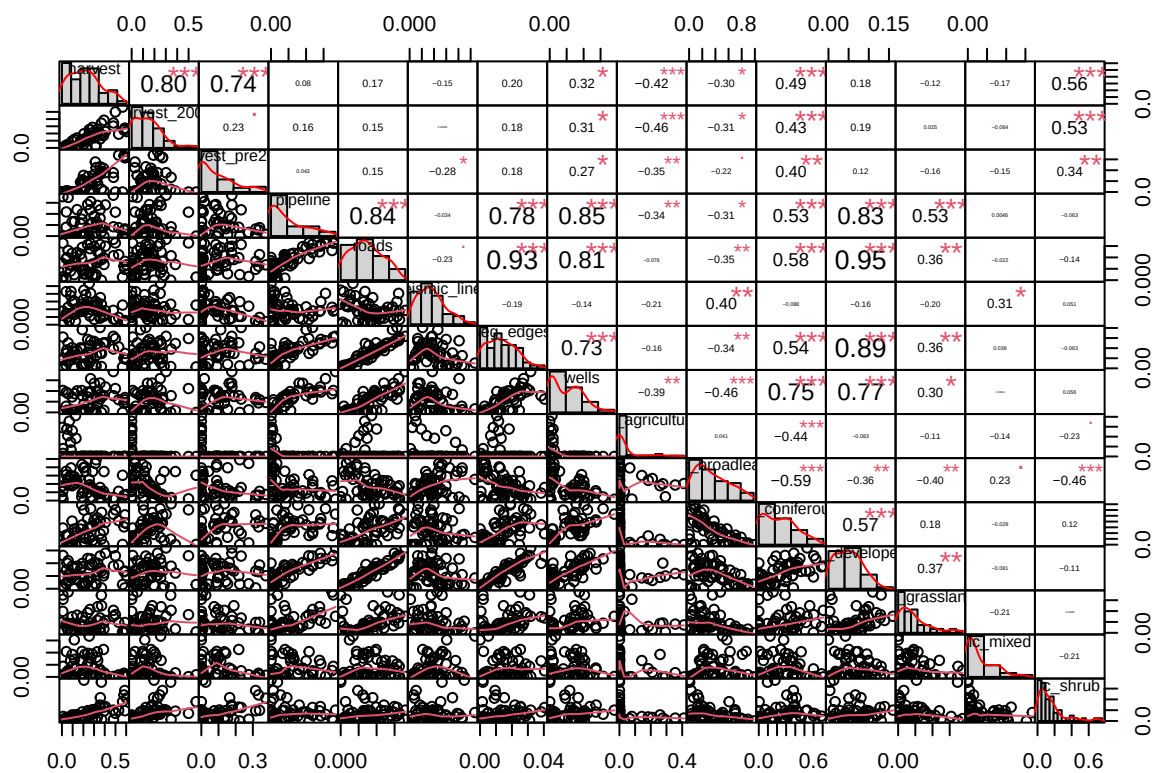


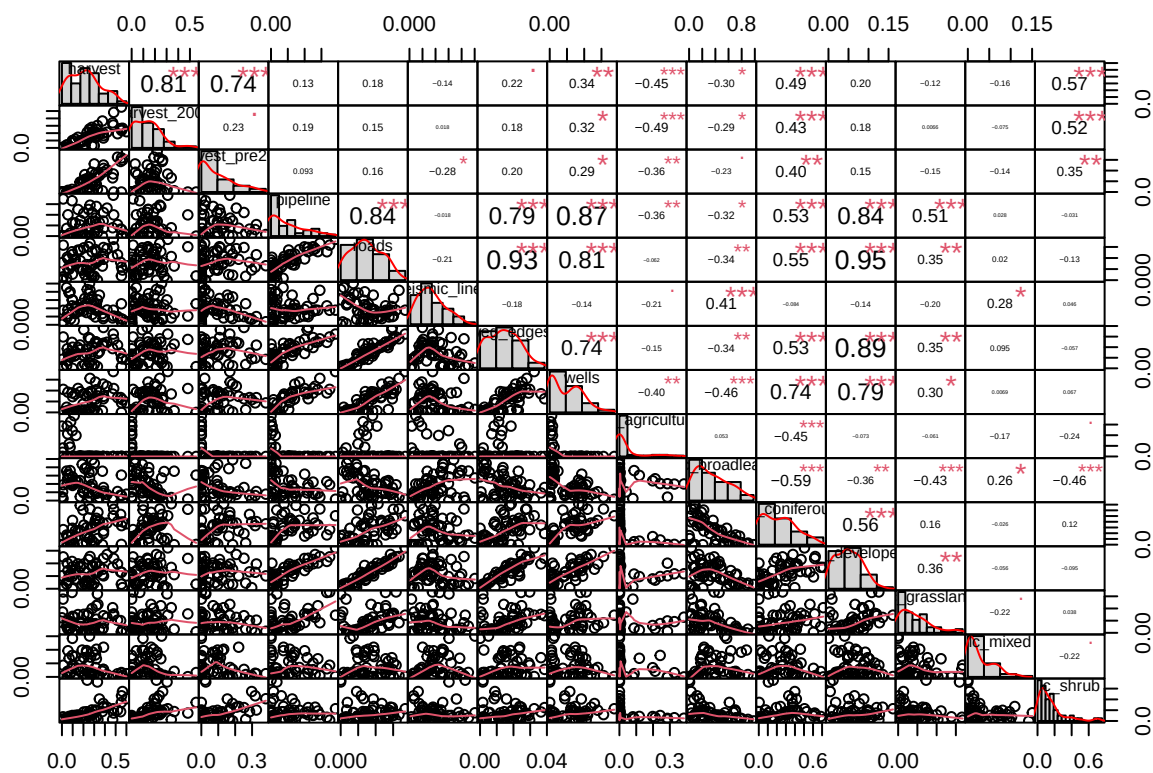


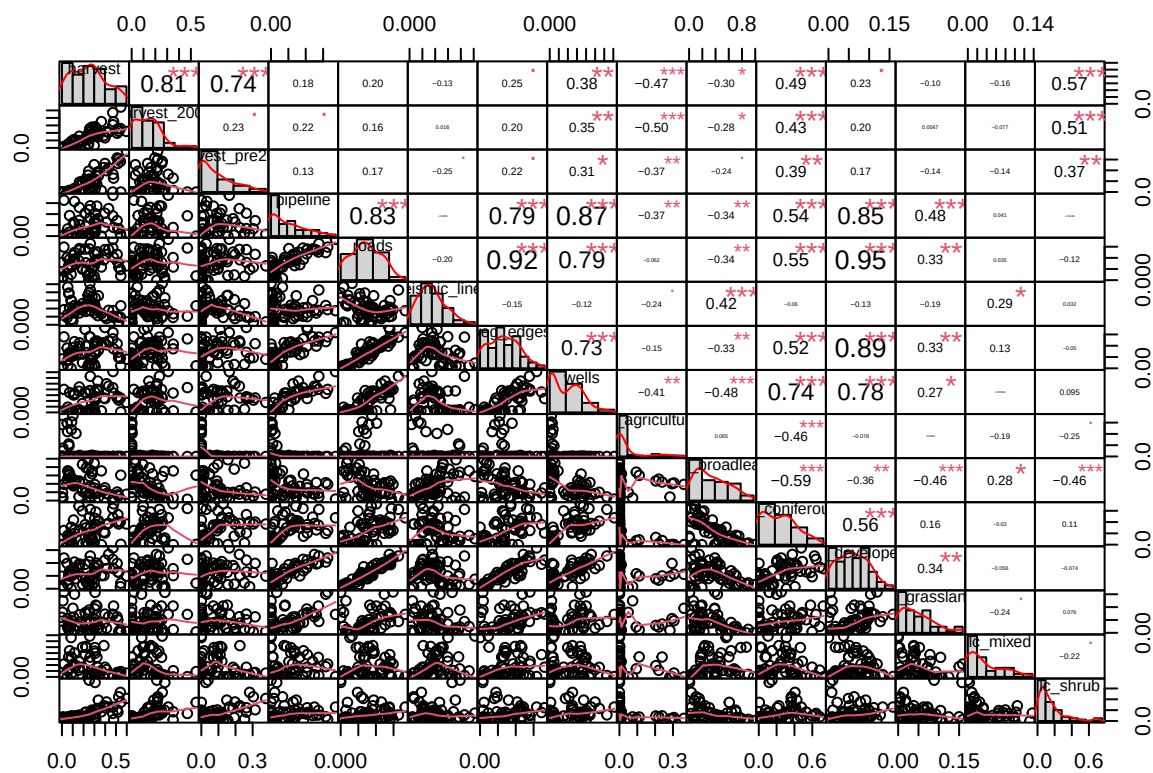


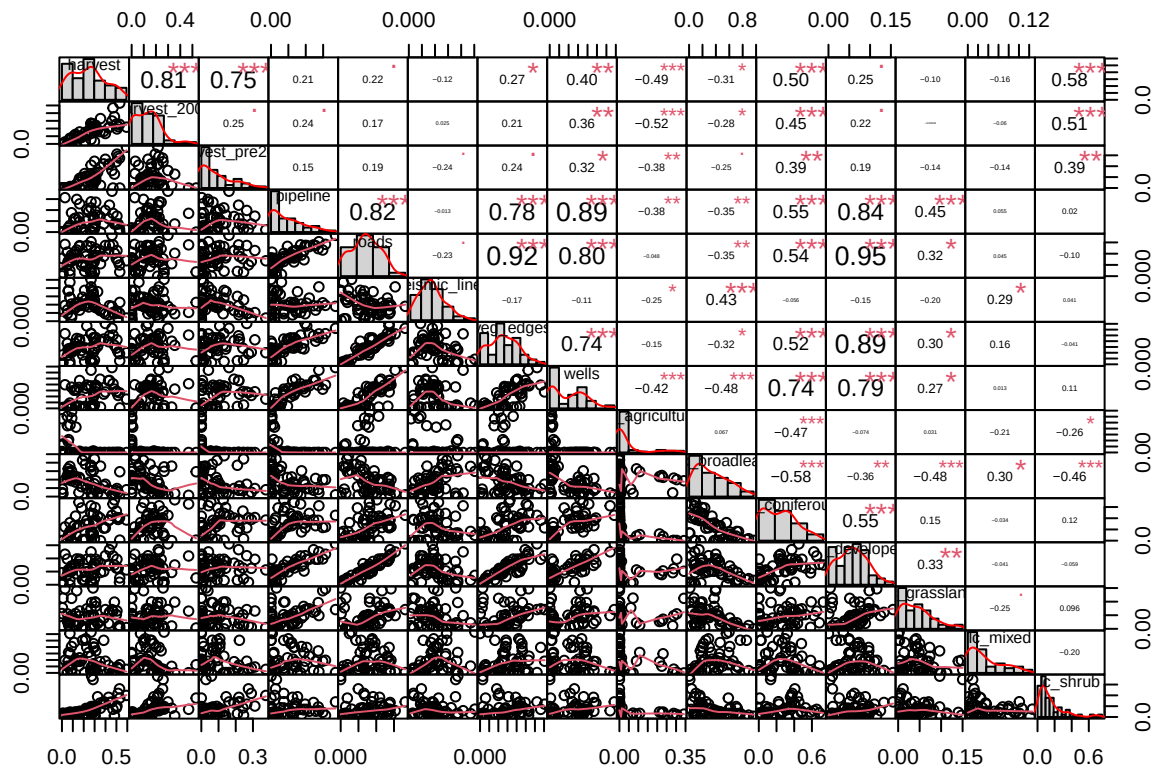


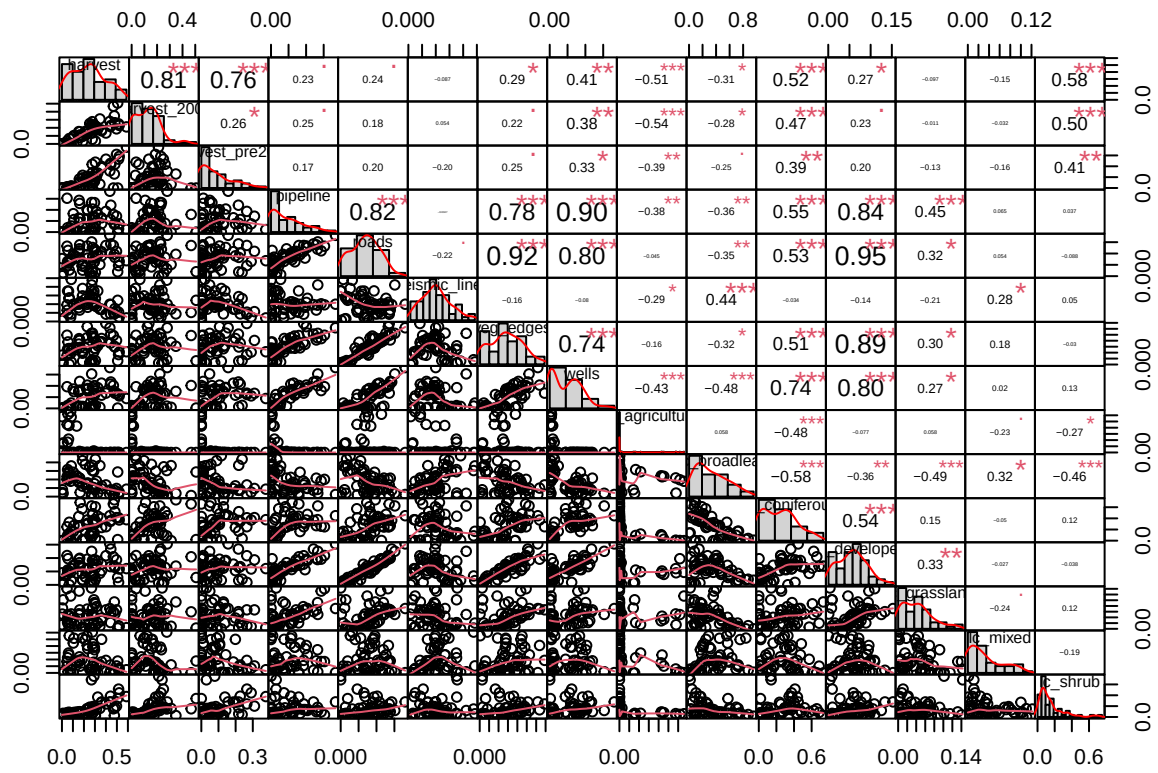


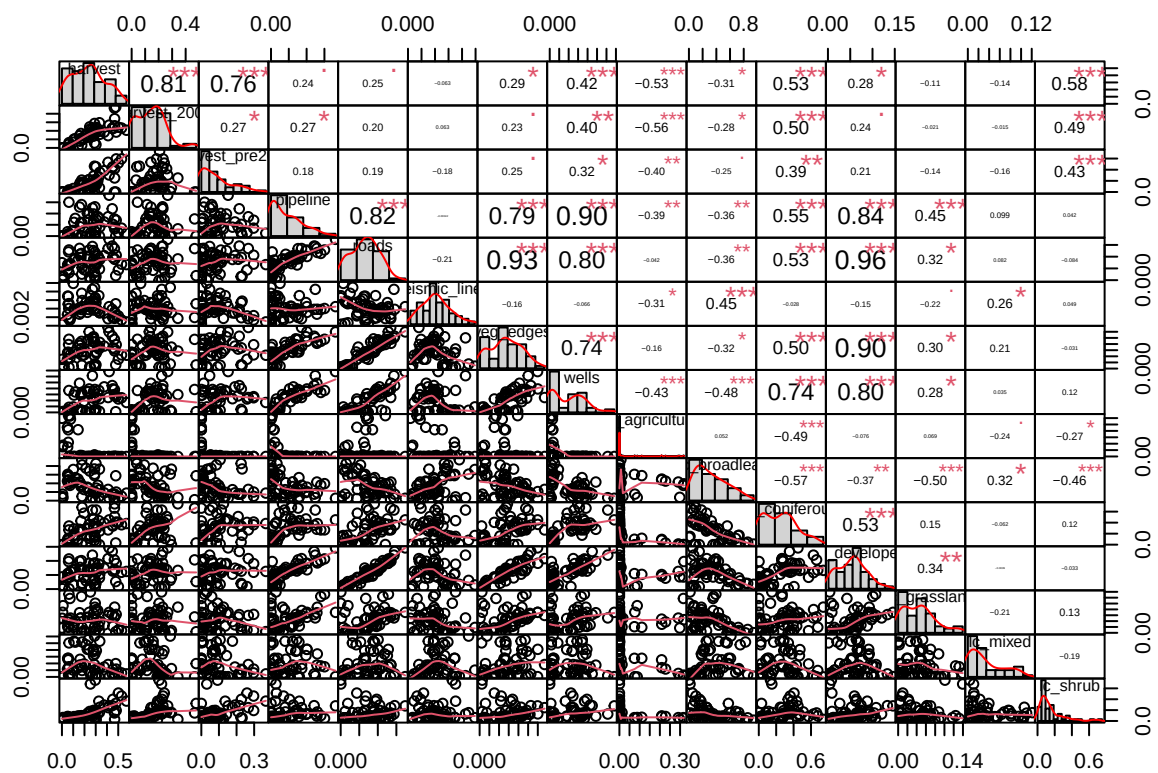


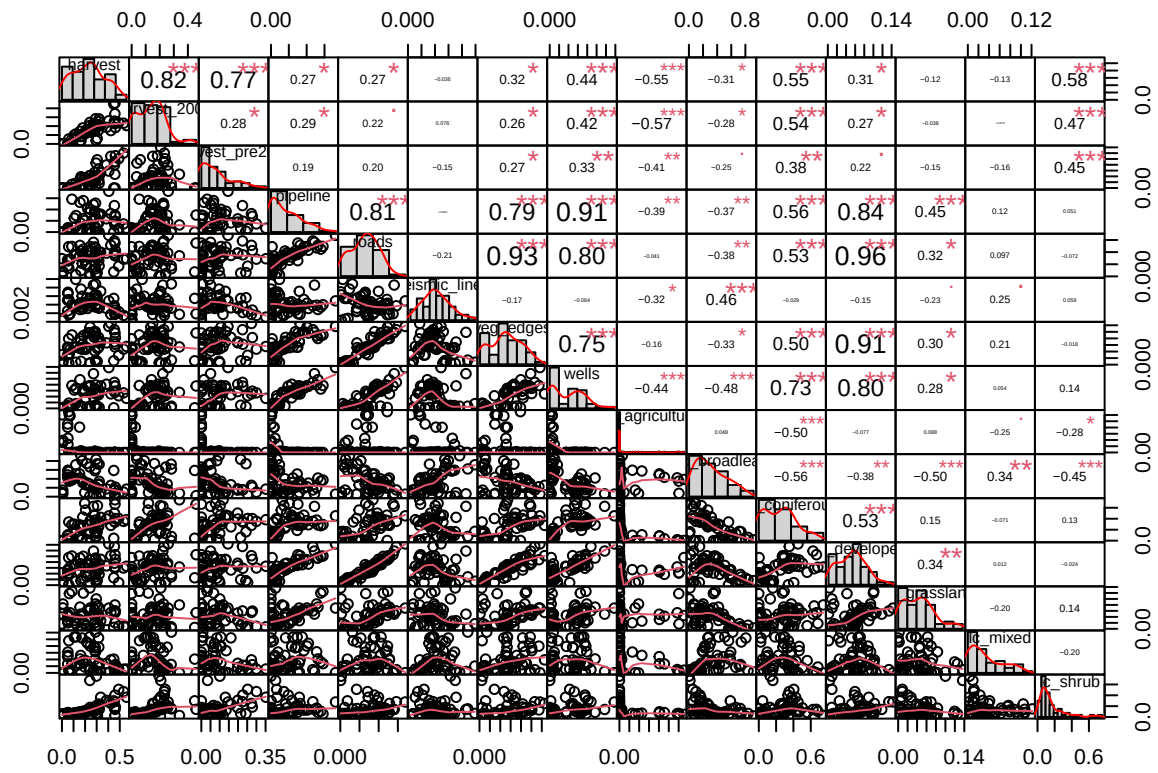


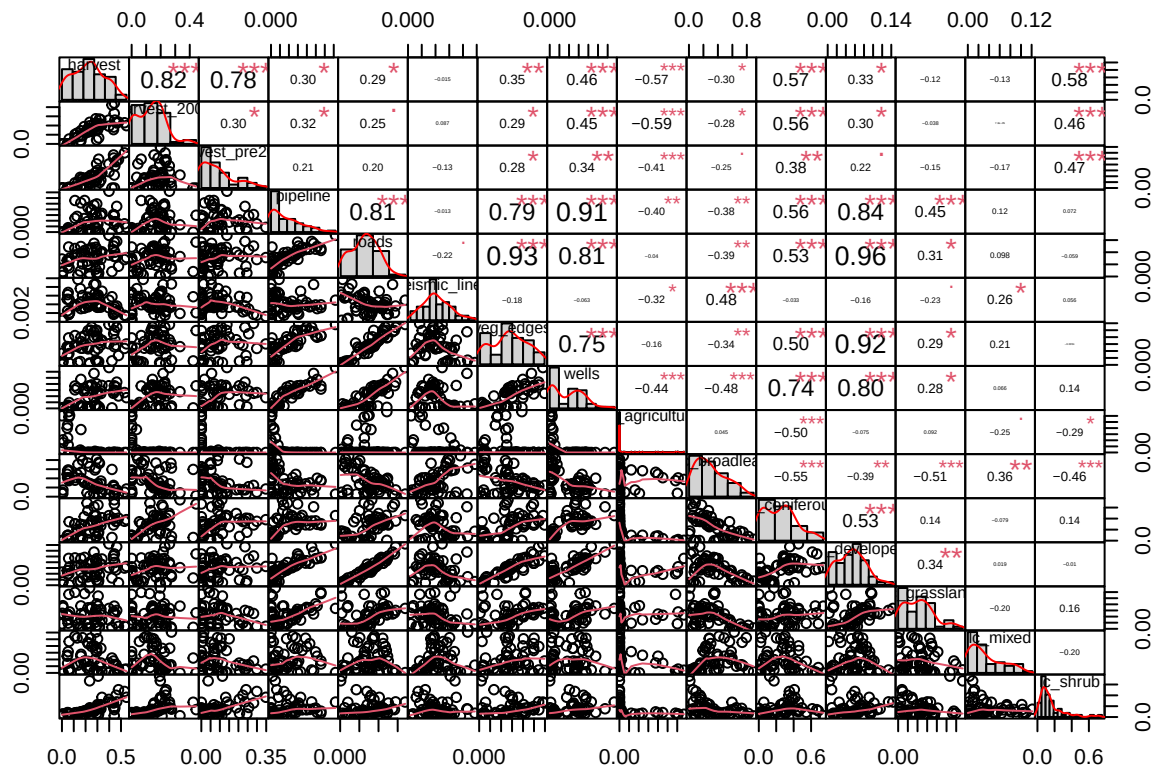


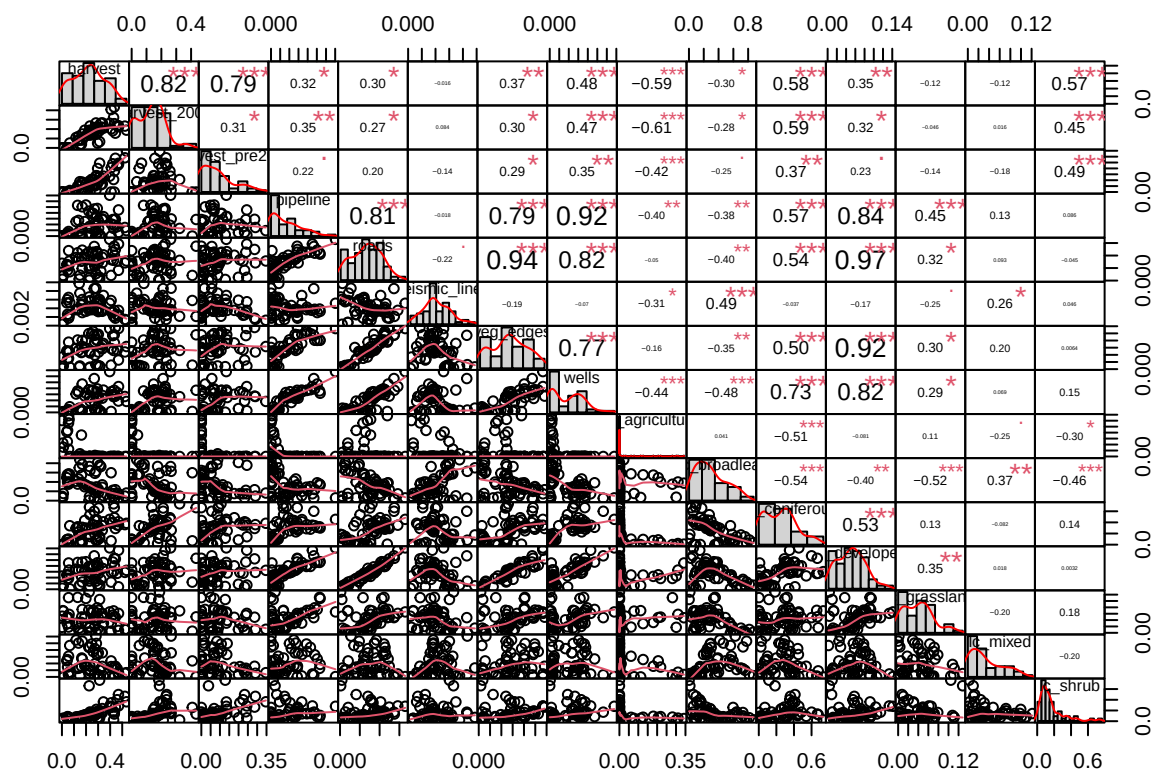


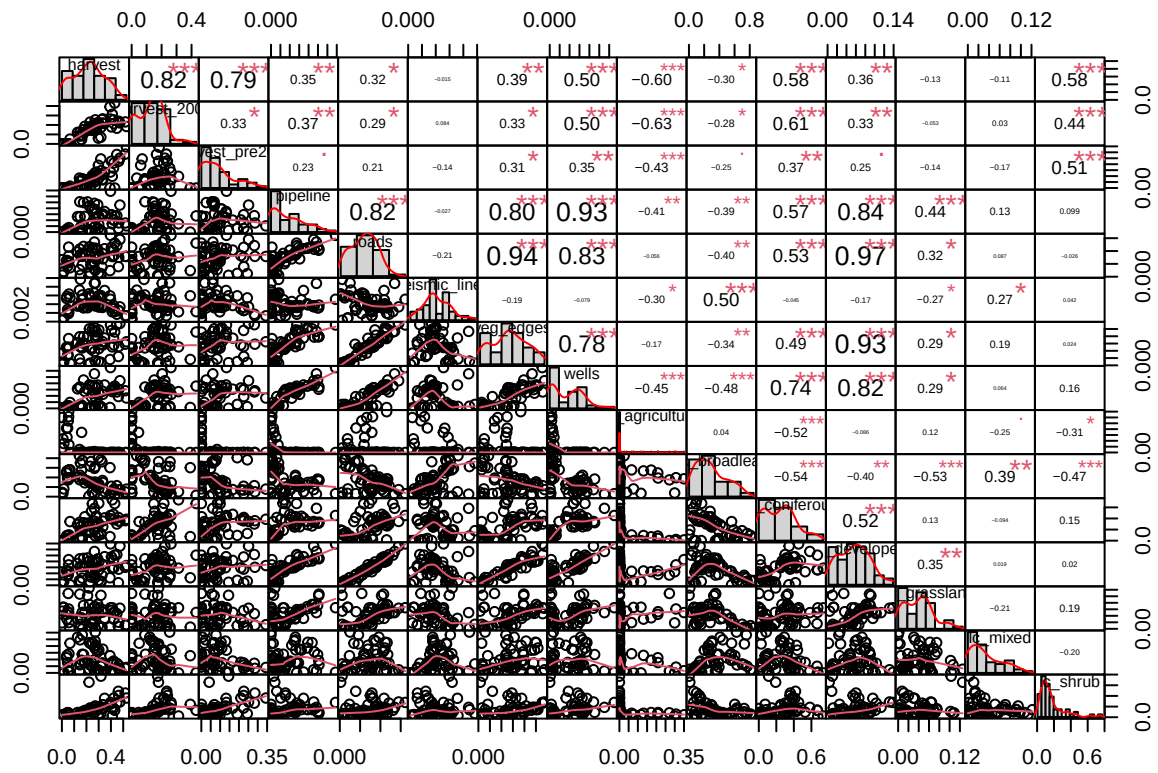


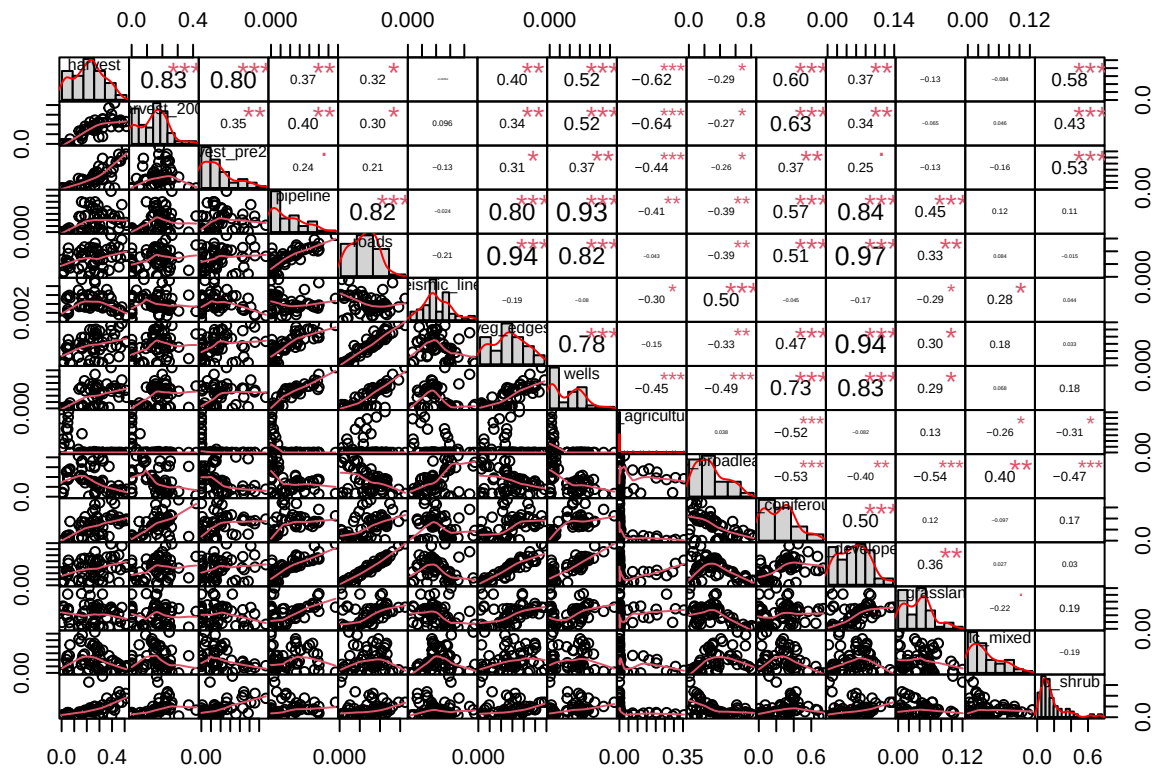












```
## $'250 meter buffer'
## NULL
##
## $'500 meter buffer'
## NULL
##
## $'750 meter buffer'
## NULL
##
## $'1000 meter buffer'
## NULL
##
## $'1250 meter buffer'
## NULL
##
## $'1500 meter buffer'
## NULL
##
## $'1750 meter buffer'
## NULL
##
## $'2000 meter buffer'
## NULL
##
## $'2250 meter buffer'
## NULL
```

```

##
## $'2500 meter buffer'
## NULL
##
## $'2750 meter buffer'
## NULL
##
## $'3000 meter buffer'
## NULL
##
## $'3250 meter buffer'
## NULL
##
## $'3500 meter buffer'
## NULL
##
## $'3750 meter buffer'
## NULL
##
## $'4000 meter buffer'
## NULL
##
## $'4250 meter buffer'
## NULL
##
## $'4500 meter buffer'
## NULL
##
## $'4750 meter buffer'
## NULL
##
## $'5000 meter buffer'
## NULL

```

Summary of correlation plots per buffer

Here I summarize any pairs of highly correlated variables

Overall

- harvest is correlated with the two new harvest groups (rightfully so) so we use the two groups or the overall harvest variable in a model
- several things correlated with veg edges which we expected so will drop veg edges
- several HFI features and lc_developed, also expected will use the features when possible as they are more specific/informative
- roads correlated with wells and pipelines - also expected you need roads to access/build these features
- lc_broadleaf and lc_coniferous also expected as they are the main landcover types and tend to be very inversely related, for each species will choose based on ecology

Buffer specific deviations from overall

750 m buffer * roads and wells (continues as buffer size increases)

1000m buffer

* wells and lc_coniferous are positively correlated starting around 750m buffer - kind of a weird one maybe?

1250m buffer

* pipeline and wells (starts here 0.72 and continues with increasing buffer size)

So based on this the global model for buffer size selection should generally include the following set of variables
harvest_2000 + harvest_pre2000 + roads OR wells OR pipelines (depending on which is of greatest interest to the nation and ecologically relevant for each species) seismic_lines + lc_broadleaf + lc_grassland + lc_mixed + lc_shrub,

Proportional binomial models

Buffer selection

An attempt to run glms for each species with every buffer and compare models all in one section combining purrr with a custom function

```
# create a vector with the species in the proportional detection data (prop_det_data) this one is unnec
```

```
# pb = proportional binomial  
pb_species_list <- c('black_bear',  
                    'coyote',  
                    'elk',  
                    'grey_wolf',  
                    'lynx',  
                    'moose',  
                    'snowshoe_hare',  
                    'white-tailed_deer')
```

```
# create custom function to run models for a given species  
run_pb_models_for_species <- function(species) {
```

```
  # provide pb data  
  prop_det_data %>%
```

```
    # use purrr to apply following function to all species  
    purrr::map(  
      ~.x %>%
```

```
        # run glm by pasting the species name in for the cbind function  
        glm(  
          formula = as.formula(paste0(  
            'cbind(`', species, '`', `absent_', species, '`') ~ ',
```

```
            # use non-correlated variables  
            'harvest_2000 + ',  
            'harvest_pre2000 + ',  
            # 'roads + ',  
            'seismic_lines + ',  
            'wells + ',  
            # 'lc_agriculture + ',  
            'lc_broadleaf + ',  
            'lc_grassland + ',  
            'lc_mixed + ',
```

```

        'lc_shrub'
      )),
      data = .,
      family = 'binomial'
    )
  }
}

# Iterate this function over each species in the list and run the models
pb_models_by_species <- purrr::map(pb_species_list, run_pb_models_for_species)

# Custom function to compare models for a single species and print species name
compare_pb_models <- function(models, species_name) {
  cat("\nModel Selection for Species:", species_name, "\n")
  pb_model_sel_results <- model.sel(models)
  print(as.data.frame(pb_model_sel_results))
  return(as.data.frame(pb_model_sel_results))
}

# Use map2 to iterate over each species' models and names, and compare models
pb_model_comparisons <- purrr::map2(pb_models_by_species,
  pb_species_list,
  compare_pb_models)

##
## Model Selection for Species: black_bear
##
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 250 meter buffer -2.059146 -0.3378064 -0.88233771 0.83729012
## 4500 meter buffer -2.372325 2.2975305 0.46107409 -1.52052797
## 4250 meter buffer -2.288064 2.0867732 0.18119315 -1.43470120
## 4750 meter buffer -2.495759 2.4083728 0.67605384 -1.41926797
## 3750 meter buffer -2.081110 1.7729986 -0.28456597 -1.33193564
## 3500 meter buffer -2.048327 1.6306169 -0.25427193 -1.27557220
## 500 meter buffer -2.443361 1.3809175 -0.60560101 0.92861788
## 4000 meter buffer -2.213247 1.8261586 -0.20066281 -1.22202149
## 5000 meter buffer -2.557951 2.4342661 0.64967147 -1.25074494
## 3250 meter buffer -2.039680 1.3600784 -0.21263624 -1.02686970
## 3000 meter buffer -1.995805 1.1710648 -0.07068775 -0.86206822
## 1250 meter buffer -1.932589 1.2581442 -0.89834498 0.29817876
## 2750 meter buffer -1.943458 1.1160056 0.10140965 -0.84918198
## 750 meter buffer -2.021735 2.0656310 -0.65777849 0.26566571
## 2250 meter buffer -1.940194 1.0257062 0.06023561 -0.48215407
## 1500 meter buffer -1.979067 0.7815287 -0.83634888 0.39187000
## 2000 meter buffer -1.989611 0.9486441 -0.03364114 -0.21431747
## 2500 meter buffer -1.855031 1.1158819 -0.14030644 -0.68981830
## 1750 meter buffer -1.993815 0.7102694 -0.52575637 0.09852972
## 1000 meter buffer -1.767241 1.8241159 -0.58354146 -0.02131919
##
## lc_grassland lc_mixed lc_shrub seismic_lines wells
## 250 meter buffer 1.6976984 0.3056115 1.68850868 -71.059104 -14.0414740
## 4500 meter buffer 5.3952849 7.2050063 -2.10437097 205.006347 -20.6939912
## 4250 meter buffer 4.1592840 6.4196267 -1.98248067 199.139132 -16.8149671
## 4750 meter buffer 6.8824661 7.5203591 -2.17060010 199.580951 -20.5415422
## 3750 meter buffer 1.5175986 5.0625727 -1.73748757 182.734060 -10.6341560
## 3500 meter buffer 1.1852300 4.4706547 -1.70254487 179.056785 -8.1553038

```

## 500 meter buffer	0.4620187	-0.5761446	0.73363236	-23.384577	21.6170376
## 4000 meter buffer	2.7176619	5.7025731	-1.69906265	177.476515	-9.8889509
## 5000 meter buffer	7.8856353	7.4732731	-2.07821875	186.225227	-19.5291253
## 3250 meter buffer	0.2174492	3.5205036	-1.48751335	159.682382	-0.4217571
## 3000 meter buffer	-0.4108316	2.8512335	-1.31341370	141.139077	2.0059244
## 1250 meter buffer	-4.1224997	-0.4974476	0.07851946	3.868440	23.8809814
## 2750 meter buffer	-0.7997133	2.3257965	-1.31451190	137.700205	1.7373687
## 750 meter buffer	-1.7002969	-0.4021954	-0.41501249	-1.189560	19.3466478
## 2250 meter buffer	-2.4591490	1.1327165	-1.21852313	105.959747	12.8024514
## 1500 meter buffer	-3.9657032	-0.4775480	0.21185283	7.290423	26.0982630
## 2000 meter buffer	-3.1967359	0.4414975	-0.94487894	85.948591	18.5481405
## 2500 meter buffer	-2.0323822	1.7008046	-1.23714345	112.161804	6.7981196
## 1750 meter buffer	-3.5978359	0.1406642	-0.21491342	49.293051	22.8116862
## 1000 meter buffer	-3.0226900	-0.6680647	-0.55283606	13.233820	12.2014057
##	df	logLik	AICc	delta	weight
## 250 meter buffer	9	-118.2727	258.2190	0.000000	0.8902069689
## 4500 meter buffer	9	-122.0750	265.8235	7.604501	0.0198698465
## 4250 meter buffer	9	-122.2763	266.2262	8.007210	0.0162460357
## 4750 meter buffer	9	-122.2959	266.2654	8.046413	0.0159306913
## 3750 meter buffer	9	-122.6263	266.9260	8.707026	0.0114494403
## 3500 meter buffer	9	-122.6885	267.0504	8.831453	0.0107588362
## 500 meter buffer	9	-122.9427	267.5588	9.339858	0.0083438511
## 4000 meter buffer	9	-122.9562	267.5859	9.366976	0.0082314795
## 5000 meter buffer	9	-122.9779	267.6293	9.410393	0.0080547144
## 3250 meter buffer	9	-123.6472	268.9678	10.748824	0.0041249003
## 3000 meter buffer	9	-124.7995	271.2725	13.053517	0.0013030341
## 1250 meter buffer	9	-124.8505	271.3744	13.155491	0.0012382616
## 2750 meter buffer	9	-125.2570	272.1874	13.968480	0.0008246583
## 750 meter buffer	9	-125.5395	272.7526	14.533610	0.0006216667
## 2250 meter buffer	9	-125.5598	272.7931	14.574142	0.0006091949
## 1500 meter buffer	9	-125.5921	272.8576	14.638635	0.0005898638
## 2000 meter buffer	9	-125.7810	273.2356	15.016602	0.0004882893
## 2500 meter buffer	9	-125.8267	273.3269	15.107942	0.0004664907
## 1750 meter buffer	9	-126.1628	273.9991	15.780150	0.0003333304
## 1000 meter buffer	9	-126.2404	274.1543	15.935325	0.0003084460
##					
## Model Selection for Species: coyote					
##	(Intercept)	harvest_2000	harvest_pre2000	lc_broadleaf	
## 5000 meter buffer	-0.8790642	-5.487940	-5.08650049	-0.6168698	
## 4750 meter buffer	-0.8648903	-5.373024	-4.78964820	-0.6075930	
## 4500 meter buffer	-0.8266783	-5.163728	-4.71171392	-0.7046345	
## 4250 meter buffer	-0.8021582	-4.967429	-4.65030374	-0.8358988	
## 250 meter buffer	-1.4786851	-1.833862	-0.92718095	0.4866877	
## 4000 meter buffer	-0.8218994	-4.785163	-4.31836108	-0.8410067	
## 3750 meter buffer	-0.7969870	-4.260655	-3.88368194	-0.9727922	
## 3500 meter buffer	-0.8241528	-4.044774	-3.61853425	-0.9874046	
## 3250 meter buffer	-0.7710165	-3.522892	-3.32423362	-1.1125345	
## 3000 meter buffer	-0.7077937	-2.935783	-2.95875900	-1.3005898	
## 2750 meter buffer	-0.6290841	-2.660089	-2.49237779	-1.4947145	
## 2250 meter buffer	-0.5016087	-2.228074	-1.15521911	-1.9369423	
## 2500 meter buffer	-0.5222681	-2.600031	-2.01097666	-1.7237813	
## 1250 meter buffer	-0.4808645	-1.299509	-1.77315574	-1.1625187	
## 2000 meter buffer	-0.4770337	-2.095074	-0.66403219	-1.9037212	
## 1500 meter buffer	-0.5477439	-1.809453	-1.69954545	-1.1767928	

```

## 1750 meter buffer -0.5506511 -2.209611 -1.33079401 -1.3971082
## 1000 meter buffer -0.5088300 -1.394205 -0.80700040 -1.2481981
## 750 meter buffer -0.4380426 -1.055380 -0.07292074 -1.3984229
## 500 meter buffer -1.1548213 -1.219980 -0.06162276 -0.1975097
## lc_grassland lc_mixed lc_shrub seismic_lines wells
## 5000 meter buffer -0.6834831 1.38638762 0.46582840 19.13493917 20.212048
## 4750 meter buffer -0.7226074 1.37845244 0.56508226 8.61401418 17.517470
## 4500 meter buffer -1.1274983 1.84466433 0.69529179 4.59655363 12.730836
## 4250 meter buffer -1.3146989 2.38676410 0.78522172 6.66951467 7.879403
## 250 meter buffer -0.1342708 -0.41394694 0.72452448 -13.31017608 -43.790703
## 4000 meter buffer -0.8459502 2.59249778 0.83899613 0.02908335 3.886720
## 3750 meter buffer -0.2682300 3.02518021 0.71790004 0.01695982 -6.515643
## 3500 meter buffer 0.0904137 2.80373954 0.65360801 1.80707997 -7.943298
## 3250 meter buffer -0.1900806 2.65426536 0.47088278 5.76144389 -13.949645
## 3000 meter buffer -0.3191547 2.38686312 0.09032889 16.30774028 -20.003976
## 2750 meter buffer -0.6941826 2.02273644 -0.31176889 28.23356408 -23.234497
## 2250 meter buffer -1.6236103 0.29240831 -1.30977758 80.72141282 -30.431442
## 2500 meter buffer -1.9337727 1.11085606 -0.68499659 49.60400306 -23.657617
## 1250 meter buffer -2.1202624 2.27779213 -0.11518959 -75.17954561 -27.566347
## 2000 meter buffer -1.4466674 -0.09410975 -1.44185324 76.45536517 -35.049764
## 1500 meter buffer -1.8752643 1.76520504 -0.17399766 -37.67398665 -26.346594
## 1750 meter buffer -1.8688520 1.06277928 -0.53542813 6.23756997 -26.173227
## 1000 meter buffer -1.4818571 0.88374379 -0.46604929 -57.76938737 -26.557698
## 750 meter buffer -0.7893212 -1.39232853 -1.38766552 -23.08032969 -30.700657
## 500 meter buffer 0.2873841 -1.14384601 -0.14483827 -39.31930225 -21.635928
## df logLik AICc delta weight
## 5000 meter buffer 9 -140.3957 302.4648 0.000000 3.985102e-01
## 4750 meter buffer 9 -141.0062 303.6859 1.221080 2.164139e-01
## 4500 meter buffer 9 -141.5589 304.7912 2.326413 1.245275e-01
## 4250 meter buffer 9 -141.8100 305.2934 2.828654 9.687350e-02
## 250 meter buffer 9 -142.1156 305.9046 3.439803 7.136671e-02
## 4000 meter buffer 9 -142.5260 306.7255 4.260689 4.734156e-02
## 3750 meter buffer 9 -143.1454 307.9643 5.499547 2.548167e-02
## 3500 meter buffer 9 -144.0604 309.7942 7.329462 1.020627e-02
## 3250 meter buffer 9 -145.0700 311.8134 9.348638 3.718849e-03
## 3000 meter buffer 9 -145.9445 313.5624 11.097660 1.551005e-03
## 2750 meter buffer 9 -146.3991 314.4717 12.006887 9.844123e-04
## 2250 meter buffer 9 -146.6496 314.9726 12.507816 7.663050e-04
## 2500 meter buffer 9 -146.7293 315.1321 12.667297 7.075724e-04
## 1250 meter buffer 9 -146.8516 315.3767 12.911954 6.261008e-04
## 2000 meter buffer 9 -146.9013 315.4761 13.011351 5.957451e-04
## 1500 meter buffer 9 -148.0363 317.7460 15.281190 1.915011e-04
## 1750 meter buffer 9 -148.7680 319.2094 16.744663 9.212598e-05
## 1000 meter buffer 9 -149.7695 321.2125 18.747668 3.384037e-05
## 750 meter buffer 9 -150.9219 323.5174 21.052584 1.068880e-05
## 500 meter buffer 9 -153.9147 329.5028 27.038043 5.360470e-07
##
## Model Selection for Species: elk
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 1250 meter buffer -2.681814 -6.690159 -1.6699857 3.5718819
## 1500 meter buffer -3.101126 -9.592601 -2.9183619 4.7455791
## 4000 meter buffer -2.635330 -11.657665 -8.3005243 5.0848358
## 4250 meter buffer -2.690113 -11.733136 -8.5545981 5.3415636
## 4750 meter buffer -2.994387 -11.303001 -8.3896156 5.7198467

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##	5000 meter buffer	-3.162106	-10.818276	-7.1732459	5.6931888
##	3750 meter buffer	-2.634251	-11.265812	-7.4204650	4.5782132
##	4500 meter buffer	-2.788975	-11.410341	-8.4648807	5.2949466
##	3500 meter buffer	-2.822389	-10.154766	-6.6265786	4.2726631
##	1000 meter buffer	-1.679121	-3.343239	0.8341307	0.5149961
##	3250 meter buffer	-2.906651	-10.057601	-6.5674045	4.2557482
##	1750 meter buffer	-2.876549	-10.185915	-2.6734567	3.6280596
##	750 meter buffer	-1.563526	-2.076186	1.1528370	-0.2085301
##	3000 meter buffer	-2.902798	-9.449895	-5.6906605	3.9419752
##	2000 meter buffer	-2.473212	-9.897122	-2.3294108	2.5844112
##	500 meter buffer	-2.266520	-1.548477	0.4742107	0.6191934
##	2750 meter buffer	-2.670307	-8.580322	-3.7952685	2.9160786
##	2250 meter buffer	-2.325418	-8.269284	-2.2471226	1.9751308
##	2500 meter buffer	-2.391372	-8.002479	-2.6948669	2.2735395
##	250 meter buffer	-2.513696	-2.220813	-0.1691255	0.3134186
##		lc_grassland	lc_mixed	lc_shrub	seismic_lines wells
##	1250 meter buffer	-5.7706352	-17.797425	3.7615833	-388.5302 -19.280282
##	1500 meter buffer	-5.2258682	-25.703391	5.9094570	-437.5971 15.452301
##	4000 meter buffer	-11.1329089	-24.258285	3.3851726	-288.9717 92.851825
##	4250 meter buffer	-9.7100812	-25.053986	2.8784649	-292.0079 104.167849
##	4750 meter buffer	-3.6267003	-22.510768	0.9867135	-276.9219 107.731440
##	5000 meter buffer	0.8688698	-18.424500	-1.7835655	-262.1779 103.800251
##	3750 meter buffer	-10.9120944	-22.417730	3.3719676	-259.3296 78.555302
##	4500 meter buffer	-6.8695248	-23.703003	1.9183575	-266.2052 103.097616
##	3500 meter buffer	-7.2582799	-21.211793	3.1617701	-225.0083 58.026235
##	1000 meter buffer	-4.9898574	-10.862308	-1.5255762	-180.6189 -54.076417
##	3250 meter buffer	-6.5238807	-21.361828	4.0047567	-231.1099 51.319283
##	1750 meter buffer	-5.8627180	-19.789867	4.9058447	-285.4235 13.859106
##	750 meter buffer	-2.0348887	-9.570460	-3.5392895	-132.7332 -58.058604
##	3000 meter buffer	-5.3713296	-19.582493	3.7581835	-222.2752 37.661402
##	2000 meter buffer	-6.4279742	-15.251557	3.3872545	-220.6538 8.389893
##	500 meter buffer	-0.5554444	-10.497405	-1.9390325	-113.8900 -51.028563
##	2750 meter buffer	-4.4217654	-13.462399	2.6925587	-190.6732 8.493926
##	2250 meter buffer	-5.4713983	-11.592642	2.0542577	-178.0923 -5.294808
##	2500 meter buffer	-5.5419505	-10.370334	1.7972448	-194.4078 -1.675048
##	250 meter buffer	-0.1625115	-6.184284	-2.1005680	-59.2219 -48.359779
##		df	logLik	AICc	delta weight
##	1250 meter buffer	9	-56.36117	134.3958	0.00000000 2.315873e-01
##	1500 meter buffer	9	-56.37898	134.4314	0.03563585 2.274975e-01
##	4000 meter buffer	9	-56.88156	135.4366	1.04078875 1.376291e-01
##	4250 meter buffer	9	-57.14313	135.9597	1.56392675 1.059528e-01
##	4750 meter buffer	9	-57.41864	136.5108	2.11495444 8.043745e-02
##	5000 meter buffer	9	-57.57606	136.8256	2.42979721 6.872125e-02
##	3750 meter buffer	9	-57.72127	137.1160	2.72020867 5.943319e-02
##	4500 meter buffer	9	-57.81386	137.3012	2.90538355 5.417748e-02
##	3500 meter buffer	9	-59.43063	140.5347	6.13892912 1.075631e-02
##	1000 meter buffer	9	-59.59908	140.8716	6.47582055 9.088836e-03
##	3250 meter buffer	9	-59.95189	141.5773	7.18145658 6.386771e-03
##	1750 meter buffer	9	-60.83295	143.3394	8.94355783 2.646342e-03
##	750 meter buffer	9	-60.87349	143.4204	9.02464317 2.541198e-03
##	3000 meter buffer	9	-61.17107	144.0156	9.61980458 1.887126e-03
##	2000 meter buffer	9	-62.50465	146.6828	12.28696766 4.973175e-04
##	500 meter buffer	9	-62.81031	147.2941	12.89827774 3.663443e-04
##	2750 meter buffer	9	-63.46848	148.6104	14.21463633 1.896906e-04

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## 2250 meter buffer 9 -64.12005 149.9136 15.51777629 9.887182e-05
## 2500 meter buffer 9 -64.18834 150.0501 15.65433897 9.234605e-05
## 250 meter buffer 9 -66.17391 154.0213 19.62547949 1.267932e-05
##
## Model Selection for Species: grey_wolf
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 5000 meter buffer -4.267763 1.6555134 2.8022407 -2.69019203
## 500 meter buffer -5.762530 -1.6774160 1.7779177 2.43302245
## 3500 meter buffer -4.159795 0.9220134 1.2832261 -1.51689396
## 4250 meter buffer -4.275641 1.8002409 1.7110811 -1.82961288
## 3750 meter buffer -4.205701 1.3575019 1.2155974 -1.53510477
## 4750 meter buffer -4.234019 1.6677947 2.3559456 -2.27027649
## 4000 meter buffer -4.333802 1.6119414 1.3935156 -1.49637795
## 4500 meter buffer -4.211303 1.8060651 2.0504595 -2.02085914
## 750 meter buffer -4.929309 -0.2810575 1.7051863 1.05979292
## 3250 meter buffer -4.116175 0.2615882 0.9954575 -1.15396057
## 1250 meter buffer -3.567545 -1.0884599 0.1389096 -0.22277993
## 1500 meter buffer -3.411943 -1.8496180 0.4488252 -0.35062506
## 250 meter buffer -4.373220 -1.8398068 0.3949764 1.40566435
## 1750 meter buffer -3.341609 -1.9677748 0.8406549 -0.58153304
## 3000 meter buffer -3.836095 -0.1226713 0.5879639 -0.99559914
## 2250 meter buffer -3.109082 -1.1701281 1.7203356 -1.31536983
## 2000 meter buffer -3.280202 -1.7481448 1.9125078 -1.07461065
## 1000 meter buffer -3.714102 -0.7841404 0.6761526 -0.08258719
## 2750 meter buffer -3.493111 -0.3896048 0.4940127 -0.96022726
## 2500 meter buffer -3.244753 -0.9031487 0.6803183 -0.97381858
## lc_grassland lc_mixed lc_shrub seismic_lines wells
## 5000 meter buffer 14.12367738 21.315689 -3.2829858 279.67821 -51.2629282
## 500 meter buffer 1.41101104 3.797738 4.9646889 51.87586 27.1031304
## 3500 meter buffer 7.00382555 16.555700 -1.6080870 224.45338 -23.6117412
## 4250 meter buffer 10.07454957 18.323180 -2.4407659 235.03331 -34.8847852
## 3750 meter buffer 7.86173736 17.034863 -1.7720076 220.35778 -27.8883051
## 4750 meter buffer 11.37290598 19.792536 -2.8585587 250.76739 -40.7385090
## 4000 meter buffer 9.52974950 17.730029 -2.0114955 217.36814 -28.6578351
## 4500 meter buffer 10.30915615 18.914575 -2.5737160 234.94126 -38.9732939
## 750 meter buffer -1.01184944 3.496699 2.1542023 75.89291 41.5291172
## 3250 meter buffer 4.67600110 15.451310 -0.9567911 194.06970 -8.7446097
## 1250 meter buffer -3.19473208 7.109202 1.7565921 15.43382 21.7576902
## 1500 meter buffer -3.37322645 8.121376 1.3764186 25.32328 19.3277033
## 250 meter buffer 1.78354289 2.430543 2.7754999 34.70254 -8.0095751
## 1750 meter buffer -3.48731179 9.368741 0.8818826 53.60763 13.4591661
## 3000 meter buffer 2.54667215 14.234646 -0.4899263 150.30708 -5.4386417
## 2250 meter buffer -3.37433411 10.280217 -1.0714633 124.87656 -0.6351178
## 2000 meter buffer -2.76483197 9.780781 -0.4411610 115.97247 4.5511334
## 1000 meter buffer -1.82066702 4.877123 1.7963308 34.89441 15.8663831
## 2750 meter buffer 0.02791245 12.677881 -0.4045565 115.60673 -3.4105729
## 2500 meter buffer -3.15029162 10.956116 -0.4878997 100.20504 5.2179790
## df logLik AICc delta weight
## 5000 meter buffer 9 -74.99450 171.6625 0.0000000 0.250776715
## 500 meter buffer 9 -75.22719 172.1279 0.4653877 0.198714494
## 3500 meter buffer 9 -76.26121 174.1959 2.5334113 0.070658422
## 4250 meter buffer 9 -76.28321 174.2399 2.5774232 0.069120502
## 3750 meter buffer 9 -76.31711 174.3077 2.6452187 0.066816738
## 4750 meter buffer 9 -76.33905 174.3516 2.6890960 0.065366832

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## 4000 meter buffer 9 -76.36532 174.4041 2.7416339 0.063672070
## 4500 meter buffer 9 -76.60844 174.8904 3.2278878 0.049929853
## 750 meter buffer 9 -76.77219 175.2178 3.5553694 0.042388550
## 3250 meter buffer 9 -77.23095 176.1354 4.4729091 0.026792136
## 1250 meter buffer 9 -77.25268 176.1788 4.5163517 0.026216451
## 1500 meter buffer 9 -77.59307 176.8596 5.1971300 0.018652832
## 250 meter buffer 9 -78.18788 178.0492 6.3867495 0.010290161
## 1750 meter buffer 9 -78.29433 178.2621 6.5996661 0.009250984
## 3000 meter buffer 9 -78.41607 178.5056 6.8431372 0.008190659
## 2250 meter buffer 9 -78.57896 178.8314 7.1689096 0.006959504
## 2000 meter buffer 9 -78.60447 178.8824 7.2199322 0.006784203
## 1000 meter buffer 9 -79.04131 179.7561 8.0936113 0.004383105
## 2750 meter buffer 9 -79.55611 180.7857 9.1232107 0.002619432
## 2500 meter buffer 9 -79.63680 180.9471 9.2846029 0.002416358
##
## Model Selection for Species: lynx
##
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 500 meter buffer -4.638798 2.188900 1.7925432 0.1910742
## 750 meter buffer -3.363738 3.316632 2.1511847 -1.2662431
## 1500 meter buffer -2.014705 2.156057 3.1970223 -2.1224406
## 1750 meter buffer -1.911235 2.025076 3.1905282 -2.1740819
## 5000 meter buffer -3.445486 3.854474 7.8096569 -4.2867685
## 1250 meter buffer -2.122074 2.606918 2.8187974 -2.3130125
## 1000 meter buffer -2.463963 2.839992 2.5963825 -2.1205547
## 4750 meter buffer -3.228794 3.427634 7.1840843 -3.9564187
## 4500 meter buffer -3.048877 3.425353 6.7310356 -3.7006338
## 2000 meter buffer -1.833974 2.058312 3.8285921 -2.4075812
## 4250 meter buffer -2.975361 3.092680 6.4661854 -3.6042517
## 2250 meter buffer -1.806369 2.115197 3.8118564 -2.6025584
## 4000 meter buffer -2.836414 2.585671 5.8358009 -3.2606681
## 3500 meter buffer -2.637542 2.436327 5.3612957 -3.4600274
## 3750 meter buffer -2.716822 2.662083 5.4168895 -3.3310330
## 3250 meter buffer -2.544037 1.796901 5.2079978 -3.0540838
## 2500 meter buffer -1.816007 1.973550 3.8062152 -2.5542238
## 3000 meter buffer -2.308146 1.762154 4.8355802 -2.7613587
## 2750 meter buffer -2.100276 1.837350 4.2652158 -2.5736326
## 250 meter buffer -3.035887 -0.649130 0.6592757 -0.6453718
##
## lc_grassland lc_mixed lc_shrub seismic_lines wells
## 500 meter buffer -0.33833666 2.0603815 1.9860741 7.7418410 42.0726557
## 750 meter buffer -4.26216070 1.6666314 -0.6897007 14.8009193 27.6118854
## 1500 meter buffer -12.15271363 3.3152505 -2.7817060 -49.6910985 17.2418942
## 1750 meter buffer -14.27717468 3.8342442 -2.9886307 -60.9107141 20.6903781
## 5000 meter buffer 13.15514501 19.8739446 -4.0878674 66.8915095 -39.5827092
## 1250 meter buffer -8.90053358 3.6388111 -2.4424652 -32.4122637 9.2795419
## 1000 meter buffer -5.79899889 2.3594124 -1.5528189 -3.6435035 3.6468649
## 4750 meter buffer 9.74701145 18.0291414 -3.8070291 35.4188872 -28.9470505
## 4500 meter buffer 7.14759949 16.4744346 -3.6445517 16.9267394 -26.9069998
## 2000 meter buffer -13.04828431 4.6973390 -3.6934003 -46.7609149 15.0537007
## 4250 meter buffer 5.33549754 15.2952417 -3.6818718 30.5937604 -21.4433876
## 2250 meter buffer -12.44895274 6.1457926 -3.8834363 -50.6324236 15.4924741
## 4000 meter buffer 2.51352340 13.7933172 -3.5209046 7.9171481 -7.6926952
## 3500 meter buffer 0.88760036 12.8526403 -3.3906093 39.3497087 -13.7010964
## 3750 meter buffer 1.62635917 12.9499435 -3.3546784 23.1638784 -13.3296181
## 3250 meter buffer -0.91301148 11.6532278 -3.5528727 0.9716624 3.3452942

```

```

## 2500 meter buffer -9.77267053 6.6594612 -3.7541280 -73.2581881 12.7841480
## 3000 meter buffer -2.53286185 9.5965548 -3.5541090 -36.5317170 4.6944040
## 2750 meter buffer -5.20369551 7.9021737 -3.5698783 -57.8557842 8.7067708
## 250 meter buffer 0.07101097 0.4347604 1.7039200 -9.2477270 0.8116645
##
## df logLik AICc delta weight
## 500 meter buffer 9 -78.62374 178.9210 0.000000 9.648048e-01
## 750 meter buffer 9 -82.61504 186.9035 7.982586 1.782555e-02
## 1500 meter buffer 9 -84.33310 190.3397 11.418715 3.198136e-03
## 1750 meter buffer 9 -84.35443 190.3823 11.461361 3.130665e-03
## 5000 meter buffer 9 -84.53782 190.7491 11.828157 2.606080e-03
## 1250 meter buffer 9 -84.54318 190.7598 11.838877 2.592149e-03
## 1000 meter buffer 9 -84.91909 191.5117 12.590695 1.779938e-03
## 4750 meter buffer 9 -85.42391 192.5213 13.600339 1.074393e-03
## 4500 meter buffer 9 -85.92674 193.5269 14.605984 6.498160e-04
## 2000 meter buffer 9 -86.08610 193.8457 14.924717 5.540874e-04
## 4250 meter buffer 9 -86.23031 194.1341 15.213131 4.796782e-04
## 2250 meter buffer 9 -86.66011 194.9937 16.072735 3.120968e-04
## 4000 meter buffer 9 -86.84315 195.3598 16.438820 2.598933e-04
## 3500 meter buffer 9 -87.04317 195.7598 16.838853 2.127792e-04
## 3750 meter buffer 9 -87.24150 196.1565 17.235517 1.744996e-04
## 3250 meter buffer 9 -87.46720 196.6079 17.686913 1.392436e-04
## 2500 meter buffer 9 -87.89951 197.4725 18.551529 9.037039e-05
## 3000 meter buffer 9 -88.27422 198.2219 19.300956 6.212840e-05
## 2750 meter buffer 9 -88.58266 198.8388 19.917829 4.563919e-05
## 250 meter buffer 9 -90.31836 202.3102 23.389229 8.045127e-06
##
## Model Selection for Species: moose
##
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 500 meter buffer -2.2301609 -0.7875774 0.7698777 2.00379740
## 750 meter buffer -1.9179235 -0.5592863 1.0960012 1.66542760
## 250 meter buffer -2.3241198 -0.5110314 -0.6715524 1.75141880
## 1000 meter buffer -1.3660374 0.4848453 1.1504745 0.93213457
## 3750 meter buffer -0.2287966 1.5613611 1.4406725 -0.75649073
## 1750 meter buffer -0.9155644 1.1536271 1.5944787 0.11715174
## 3500 meter buffer -0.3227275 1.5447327 1.4097746 -0.69325634
## 4000 meter buffer -0.3119877 1.4429672 1.4382023 -0.46744021
## 2000 meter buffer -0.9152462 1.3164230 1.6713940 0.12256165
## 1500 meter buffer -1.0427061 1.0166686 1.2935874 0.33197950
## 4500 meter buffer -0.3440631 1.4886848 1.4718373 -0.17752514
## 4250 meter buffer -0.3836815 1.5297145 1.5769807 -0.36047832
## 1250 meter buffer -1.1941955 0.7979169 1.0875110 0.62792960
## 4750 meter buffer -0.2889701 1.3419989 1.2374821 0.01430409
## 5000 meter buffer -0.3095362 1.3434390 1.2945983 0.08528960
## 2250 meter buffer -0.8266371 1.4241393 1.4774349 0.03461669
## 3250 meter buffer -0.4630858 1.5006025 1.4487979 -0.47463117
## 2500 meter buffer -0.6883477 1.4784096 1.2476576 -0.03811787
## 2750 meter buffer -0.6214425 1.5134475 1.1718354 -0.11339635
## 3000 meter buffer -0.5319969 1.5143633 1.2352276 -0.24036218
##
## lc_grassland lc_mixed lc_shrub seismic_lines wells
## 500 meter buffer 3.9226120 2.69373315 3.4263290 -64.64828 -28.05807
## 750 meter buffer 3.6695298 2.58759907 2.6793639 -56.16744 -32.58800
## 250 meter buffer 2.4114288 2.26748550 2.9020550 -23.20201 -15.46067
## 1000 meter buffer 2.5884135 1.32238164 0.5622808 -15.38316 -39.73788
## 3750 meter buffer -4.7011072 4.05169405 -3.7503459 40.44538 -47.43275

```

```

## 1750 meter buffer      1.6812222 -1.12360632 -1.9765218      68.80572 -47.59561
## 3500 meter buffer     -3.9045537  3.87394318 -3.4746360      44.37860 -46.68728
## 4000 meter buffer     -4.1201866  3.86176789 -3.7304451      20.53772 -41.54811
## 2000 meter buffer      1.4268416 -0.77678587 -2.2796937      69.37404 -46.25686
## 1500 meter buffer      2.1368082 -1.13657723 -1.4439454      58.29034 -43.54578
## 4500 meter buffer     -3.5495752  3.57075801 -3.7595552      -8.39386 -39.27685
## 4250 meter buffer     -2.9072933  3.78139814 -3.8593298      15.71576 -42.01169
## 1250 meter buffer      2.3410305  0.08681804 -0.4868094      21.73740 -40.91531
## 4750 meter buffer     -4.5813973  2.76000516 -3.7956725     -25.97033 -32.24342
## 5000 meter buffer     -4.2265366  2.58627206 -3.9576331     -28.77138 -30.45687
## 2250 meter buffer      0.5750740  0.11148007 -2.4552013      58.63542 -44.49240
## 3250 meter buffer     -2.7204273  3.13540402 -3.1621727      41.86992 -44.77615
## 2500 meter buffer     -0.8134624  1.00735284 -2.6230306      37.93657 -41.90972
## 2750 meter buffer     -1.2435174  1.41803809 -2.7482263      33.43772 -41.63385
## 3000 meter buffer     -2.2179314  1.83847871 -2.8541132      31.59953 -41.98404
##
##              df      logLik      AICc      delta      weight
## 500 meter buffer      9 -158.7347 339.1429  0.000000 9.883570e-01
## 750 meter buffer      9 -163.6239 348.9213  9.778343 7.440012e-03
## 250 meter buffer      9 -164.2312 350.1360 10.993049 4.053252e-03
## 1000 meter buffer     9 -168.0911 357.8557 18.712815 8.540391e-05
## 3750 meter buffer     9 -169.6350 360.9434 21.800493 1.823883e-05
## 1750 meter buffer     9 -170.4613 362.5961 23.453187 7.982133e-06
## 3500 meter buffer     9 -170.6361 362.9456 23.802712 6.702249e-06
## 4000 meter buffer     9 -170.8873 363.4481 24.305193 5.213247e-06
## 2000 meter buffer     9 -170.9417 363.5569 24.413988 4.937233e-06
## 1500 meter buffer     9 -171.0275 363.7284 24.585514 4.531451e-06
## 4500 meter buffer     9 -171.3676 364.4087 25.265766 3.224946e-06
## 4250 meter buffer     9 -171.4531 364.5796 25.436658 2.960831e-06
## 1250 meter buffer     9 -171.6322 364.9378 25.794853 2.475327e-06
## 4750 meter buffer     9 -171.6445 364.9624 25.819472 2.445044e-06
## 5000 meter buffer     9 -171.7176 365.1086 25.965705 2.272651e-06
## 2250 meter buffer     9 -172.2814 366.2363 27.093378 1.293188e-06
## 3250 meter buffer     9 -172.4848 366.6430 27.500083 1.055229e-06
## 2500 meter buffer     9 -173.3166 368.3066 29.163696 4.593014e-07
## 2750 meter buffer     9 -173.6910 369.0555 29.912590 3.158475e-07
## 3000 meter buffer     9 -173.8592 369.3918 30.248922 2.669586e-07
##
## Model Selection for Species: snowshoe_hare
##              (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 4000 meter buffer     -0.8635970    -7.0383983          7.087796    -4.733352
## 3500 meter buffer     -0.8333932    -6.0722844          5.908161    -4.454474
## 3750 meter buffer     -0.8822427    -6.6679669          6.475600    -4.460603
## 4250 meter buffer     -0.8092547    -6.6721939          7.233734    -4.929891
## 3250 meter buffer     -0.8496310    -5.6672635          5.513688    -4.256570
## 4500 meter buffer     -0.7617888    -5.9427552          6.970662    -4.856169
## 4750 meter buffer     -0.7759291    -5.7173012          7.011581    -4.808025
## 2000 meter buffer     -0.7105139    -6.2466944          6.137331    -3.946574
## 250 meter buffer      -1.3164060    -0.5092921          1.006582    -1.245722
## 5000 meter buffer     -0.8925434    -5.0474197          7.458819    -5.077472
## 3000 meter buffer     -0.8843952    -4.8928575          5.290588    -3.959757
## 2250 meter buffer     -0.6833235    -5.9829256          6.228984    -3.996968
## 1750 meter buffer     -0.6108544    -5.3528186          5.453430    -3.888911
## 2500 meter buffer     -0.7252853    -5.3213424          5.812407    -3.922944
## 2750 meter buffer     -0.8397297    -4.8059990          5.400768    -3.776883

```

```

## 1500 meter buffer -0.5492953 -4.3791511 4.736385 -3.735853
## 1250 meter buffer -0.4735189 -3.4726757 4.128543 -3.522310
## 1000 meter buffer -0.5906434 -2.8563772 3.490384 -3.048234
## 500 meter buffer -1.4746455 -1.9725971 1.696574 -1.224776
## 750 meter buffer -1.0135047 -1.9582852 1.881091 -2.044391
## lc_grassland lc_mixed lc_shrub seismic_lines
## 4000 meter buffer 2.02051756 9.20437113 -3.434223413 90.475010
## 3500 meter buffer 2.39228077 10.29217178 -3.083065745 44.854106
## 3750 meter buffer 2.49462686 8.87942589 -3.109586726 67.615331
## 4250 meter buffer 1.70632777 10.02437232 -3.592812489 96.396861
## 3250 meter buffer 1.97439273 10.18732646 -3.014340098 26.524675
## 4500 meter buffer 1.13322980 10.58070379 -3.745895642 71.440962
## 4750 meter buffer 1.02186669 11.01639168 -3.938605921 63.074744
## 2000 meter buffer -2.78247604 0.06920634 -2.465937623 133.601692
## 250 meter buffer -4.13441378 -1.29557314 -0.005035104 -7.872473
## 5000 meter buffer 2.72840467 12.26517125 -4.201314560 97.252420
## 3000 meter buffer 1.46046552 8.48959435 -2.780990055 30.631418
## 2250 meter buffer -3.04798507 1.64445318 -2.709271464 118.464512
## 1750 meter buffer -3.01438096 -1.10214536 -2.601045294 133.675570
## 2500 meter buffer -1.92479648 3.29518790 -2.671741163 91.282696
## 2750 meter buffer -0.05034923 5.83898049 -2.599260731 47.917897
## 1500 meter buffer -3.15095804 -0.85356512 -2.463322087 114.406212
## 1250 meter buffer -3.09010615 -0.78464199 -2.197572964 70.643291
## 1000 meter buffer -2.42065208 -1.01832227 -1.538858761 35.333186
## 500 meter buffer -2.41430452 -0.44469555 1.159795198 -26.169242
## 750 meter buffer -2.66022306 -0.07981444 -0.205713578 -29.244289
## wells df logLik AICc delta weight
## 4000 meter buffer 21.6282311 9 -123.6466 268.9666 0.0000000 2.766139e-01
## 3500 meter buffer 15.3326894 9 -123.8853 269.4440 0.4773261 2.178833e-01
## 3750 meter buffer 19.5051908 9 -124.2061 270.0857 1.1190995 1.580755e-01
## 4250 meter buffer 16.4464590 9 -124.3371 270.3477 1.3811018 1.386665e-01
## 3250 meter buffer 17.1324643 9 -124.5278 270.7290 1.7623740 1.145986e-01
## 4500 meter buffer 16.5752711 9 -125.8147 273.3030 4.3363062 3.164150e-02
## 4750 meter buffer 19.8078487 9 -126.5962 274.8659 5.8992933 1.448301e-02
## 2000 meter buffer 5.3199660 9 -126.7540 275.1814 6.2147653 1.236958e-02
## 250 meter buffer -0.7544795 9 -126.8176 275.3087 6.3420873 1.160666e-02
## 5000 meter buffer 7.6154507 9 -127.1412 275.9559 6.9892796 8.397910e-03
## 3000 meter buffer 9.8736898 9 -127.4494 276.5722 7.6055869 6.170805e-03
## 2250 meter buffer 8.4406742 9 -127.6556 276.9847 8.0180938 5.020732e-03
## 1750 meter buffer -2.7496297 9 -128.4566 278.5867 9.6200036 2.253807e-03
## 2500 meter buffer 6.4445539 9 -129.3853 280.4440 11.4773952 8.904085e-04
## 2750 meter buffer 7.3371218 9 -129.6434 280.9602 11.9935538 6.878708e-04
## 1500 meter buffer -9.5311600 9 -130.1423 281.9581 12.9914777 4.176480e-04
## 1250 meter buffer -13.9295104 9 -131.0609 283.7953 14.8286874 1.666731e-04
## 1000 meter buffer -15.2974449 9 -132.4248 286.5231 17.5565016 4.261163e-05
## 500 meter buffer -5.3032805 9 -133.6967 289.0670 20.1003043 1.194396e-05
## 750 meter buffer -1.4744239 9 -136.1483 293.9701 25.0034528 1.029066e-06
##
## Model Selection for Species: white-tailed_deer
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 4250 meter buffer -1.1822056 1.14343043 -1.8834843 2.802128
## 4500 meter buffer -1.2038471 1.21415878 -1.9982928 2.932885
## 4000 meter buffer -1.1289590 1.04233940 -1.9146238 2.685332
## 5000 meter buffer -1.2598819 1.62499973 -2.1683633 3.022530

```

##	4750 meter buffer	-1.2263757	1.33988705	-2.0945529	3.004885		
##	3750 meter buffer	-1.0202517	0.98989688	-1.9877274	2.531560		
##	3500 meter buffer	-0.9879060	0.87157660	-2.0010532	2.466731		
##	3250 meter buffer	-0.9625354	0.85494359	-1.8809632	2.480554		
##	3000 meter buffer	-0.8609327	0.72568260	-1.9435536	2.455735		
##	2750 meter buffer	-0.7531394	0.46589217	-2.1471248	2.424378		
##	2500 meter buffer	-0.6365687	0.19400560	-2.0400752	2.293254		
##	2250 meter buffer	-0.5603410	0.02568109	-1.6805481	2.193318		
##	250 meter buffer	-0.8283441	-0.32007758	-0.8484051	2.669069		
##	2000 meter buffer	-0.5690241	-0.07473877	-1.4270125	2.272065		
##	1750 meter buffer	-0.5672793	-0.16619208	-1.5205997	2.386394		
##	1000 meter buffer	-0.6073692	1.01263407	-1.7999201	2.605424		
##	1500 meter buffer	-0.5179250	-0.01768650	-1.6083860	2.433740		
##	1250 meter buffer	-0.6387061	0.47234607	-1.9229082	2.601845		
##	500 meter buffer	-1.0782608	0.60665680	-0.9689404	3.011916		
##	750 meter buffer	-0.7888550	0.60091446	-1.3461206	2.699542		
##		lc_grassland	lc_mixed	lc_shrub	seismic_lines		
##	4250 meter buffer	11.607434	14.220662	-1.115235082	-80.55536		
##	4500 meter buffer	12.255756	13.973197	-1.086811061	-92.80220		
##	4000 meter buffer	10.595938	14.348802	-1.115987071	-70.87871		
##	5000 meter buffer	13.912499	13.559719	-1.314789347	-93.22439		
##	4750 meter buffer	12.839041	13.585375	-1.202844022	-94.10298		
##	3750 meter buffer	9.137674	14.471510	-1.116846791	-64.57006		
##	3500 meter buffer	8.404464	14.547320	-1.037855043	-58.28079		
##	3250 meter buffer	7.467349	14.137400	-1.001448459	-55.50837		
##	3000 meter buffer	5.801788	13.382764	-0.881081349	-57.94611		
##	2750 meter buffer	4.293622	13.155888	-0.655709373	-63.21303		
##	2500 meter buffer	2.877479	12.992145	-0.568562928	-61.88847		
##	2250 meter buffer	2.176251	12.734835	-0.553861307	-62.69667		
##	250 meter buffer	1.535771	3.906366	0.838543727	-45.31721		
##	2000 meter buffer	2.231763	12.280033	-0.410576556	-72.65662		
##	1750 meter buffer	1.931654	11.351970	0.009169897	-87.29078		
##	1000 meter buffer	1.500682	7.050765	1.110916576	-121.40003		
##	1500 meter buffer	1.820417	9.171592	0.303250874	-98.86607		
##	1250 meter buffer	1.460169	8.229826	0.862744213	-110.77848		
##	500 meter buffer	1.371856	3.599306	0.996997687	-52.83966		
##	750 meter buffer	1.546146	5.146763	1.310522934	-88.05679		
##		wells	df	logLik	AICc	delta	weight
##	4250 meter buffer	-1.18409781	9	-180.7871	383.2477	0.0000000	2.604575e-01
##	4500 meter buffer	-0.04458674	9	-180.9312	383.5359	0.2881926	2.255052e-01
##	4000 meter buffer	-1.82040186	9	-181.1819	384.0373	0.7896184	1.754985e-01
##	5000 meter buffer	-3.82891881	9	-181.2818	384.2371	0.9894219	1.588132e-01
##	4750 meter buffer	0.25235450	9	-181.4040	384.4815	1.2338516	1.405430e-01
##	3750 meter buffer	-3.00710711	9	-182.8823	387.4380	4.1903378	3.204915e-02
##	3500 meter buffer	-3.11237315	9	-184.6046	390.8827	7.6350076	5.725534e-03
##	3250 meter buffer	-3.68285995	9	-186.2825	394.2386	10.9908669	1.069302e-03
##	3000 meter buffer	-1.99354774	9	-188.0639	397.8012	14.5534884	1.800889e-04
##	2750 meter buffer	-0.02466137	9	-188.4675	398.6084	15.3607220	1.202814e-04
##	2500 meter buffer	0.54562503	9	-189.7066	401.0867	17.8390218	3.483714e-05
##	2250 meter buffer	-0.65948101	9	-192.2718	406.2171	22.9693942	2.679145e-06
##	250 meter buffer	-8.56110993	9	-194.3452	410.3639	27.1161694	3.369267e-07
##	2000 meter buffer	-1.00919284	9	-194.3647	410.4028	27.1551050	3.304309e-07
##	1750 meter buffer	0.23507559	9	-196.5420	414.7575	31.5097558	3.745246e-08
##	1000 meter buffer	-11.07039650	9	-198.7540	419.1815	35.9337720	4.100317e-09

```
## 1500 meter buffer -1.72211704 9 -200.6176 422.9087 39.6610075 6.360020e-10
## 1250 meter buffer -1.39095318 9 -201.5449 424.7633 41.5156356 2.516118e-10
## 500 meter buffer 5.02340281 9 -202.0697 425.8129 42.5651836 1.488760e-10
## 750 meter buffer -6.34253628 9 -205.4496 432.5726 49.3248939 5.069583e-12
```

```
# Name the list elements by species for clarity
names(pb_model_comparisons) <- pb_species_list
```

```
# View comparisons for each species
pb_model_comparisons
```

```
## $black_bear
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 250 meter buffer -2.059146 -0.3378064 -0.88233771 0.83729012
## 4500 meter buffer -2.372325 2.2975305 0.46107409 -1.52052797
## 4250 meter buffer -2.288064 2.0867732 0.18119315 -1.43470120
## 4750 meter buffer -2.495759 2.4083728 0.67605384 -1.41926797
## 3750 meter buffer -2.081110 1.7729986 -0.28456597 -1.33193564
## 3500 meter buffer -2.048327 1.6306169 -0.25427193 -1.27557220
## 500 meter buffer -2.443361 1.3809175 -0.60560101 0.92861788
## 4000 meter buffer -2.213247 1.8261586 -0.20066281 -1.22202149
## 5000 meter buffer -2.557951 2.4342661 0.64967147 -1.25074494
## 3250 meter buffer -2.039680 1.3600784 -0.21263624 -1.02686970
## 3000 meter buffer -1.995805 1.1710648 -0.07068775 -0.86206822
## 1250 meter buffer -1.932589 1.2581442 -0.89834498 0.29817876
## 2750 meter buffer -1.943458 1.1160056 0.10140965 -0.84918198
## 750 meter buffer -2.021735 2.0656310 -0.65777849 0.26566571
## 2250 meter buffer -1.940194 1.0257062 0.06023561 -0.48215407
## 1500 meter buffer -1.979067 0.7815287 -0.83634888 0.39187000
## 2000 meter buffer -1.989611 0.9486441 -0.03364114 -0.21431747
## 2500 meter buffer -1.855031 1.1158819 -0.14030644 -0.68981830
## 1750 meter buffer -1.993815 0.7102694 -0.52575637 0.09852972
## 1000 meter buffer -1.767241 1.8241159 -0.58354146 -0.02131919
## lc_grassland lc_mixed lc_shrub seismic_lines wells
## 250 meter buffer 1.6976984 0.3056115 1.68850868 -71.059104 -14.0414740
## 4500 meter buffer 5.3952849 7.2050063 -2.10437097 205.006347 -20.6939912
## 4250 meter buffer 4.1592840 6.4196267 -1.98248067 199.139132 -16.8149671
## 4750 meter buffer 6.8824661 7.5203591 -2.17060010 199.580951 -20.5415422
## 3750 meter buffer 1.5175986 5.0625727 -1.73748757 182.734060 -10.6341560
## 3500 meter buffer 1.1852300 4.4706547 -1.70254487 179.056785 -8.1553038
## 500 meter buffer 0.4620187 -0.5761446 0.73363236 -23.384577 21.6170376
## 4000 meter buffer 2.7176619 5.7025731 -1.69906265 177.476515 -9.8889509
## 5000 meter buffer 7.8856353 7.4732731 -2.07821875 186.225227 -19.5291253
## 3250 meter buffer 0.2174492 3.5205036 -1.48751335 159.682382 -0.4217571
## 3000 meter buffer -0.4108316 2.8512335 -1.31341370 141.139077 2.0059244
## 1250 meter buffer -4.1224997 -0.4974476 0.07851946 3.868440 23.8809814
## 2750 meter buffer -0.7997133 2.3257965 -1.31451190 137.700205 1.7373687
## 750 meter buffer -1.7002969 -0.4021954 -0.41501249 -1.189560 19.3466478
## 2250 meter buffer -2.4591490 1.1327165 -1.21852313 105.959747 12.8024514
## 1500 meter buffer -3.9657032 -0.4775480 0.21185283 7.290423 26.0982630
## 2000 meter buffer -3.1967359 0.4414975 -0.94487894 85.948591 18.5481405
## 2500 meter buffer -2.0323822 1.7008046 -1.23714345 112.161804 6.7981196
## 1750 meter buffer -3.5978359 0.1406642 -0.21491342 49.293051 22.8116862
## 1000 meter buffer -3.0226900 -0.6680647 -0.55283606 13.233820 12.2014057
```

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##          df    logLik      AICc      delta      weight
## 250 meter buffer    9 -118.2727 258.2190 0.000000 0.8902069689
## 4500 meter buffer    9 -122.0750 265.8235 7.604501 0.0198698465
## 4250 meter buffer    9 -122.2763 266.2262 8.007210 0.0162460357
## 4750 meter buffer    9 -122.2959 266.2654 8.046413 0.0159306913
## 3750 meter buffer    9 -122.6263 266.9260 8.707026 0.0114494403
## 3500 meter buffer    9 -122.6885 267.0504 8.831453 0.0107588362
## 500 meter buffer     9 -122.9427 267.5588 9.339858 0.0083438511
## 4000 meter buffer    9 -122.9562 267.5859 9.366976 0.0082314795
## 5000 meter buffer    9 -122.9779 267.6293 9.410393 0.0080547144
## 3250 meter buffer    9 -123.6472 268.9678 10.748824 0.0041249003
## 3000 meter buffer    9 -124.7995 271.2725 13.053517 0.0013030341
## 1250 meter buffer    9 -124.8505 271.3744 13.155491 0.0012382616
## 2750 meter buffer    9 -125.2570 272.1874 13.968480 0.0008246583
## 750 meter buffer     9 -125.5395 272.7526 14.533610 0.0006216667
## 2250 meter buffer    9 -125.5598 272.7931 14.574142 0.0006091949
## 1500 meter buffer    9 -125.5921 272.8576 14.638635 0.0005898638
## 2000 meter buffer    9 -125.7810 273.2356 15.016602 0.0004882893
## 2500 meter buffer    9 -125.8267 273.3269 15.107942 0.0004664907
## 1750 meter buffer    9 -126.1628 273.9991 15.780150 0.0003333304
## 1000 meter buffer    9 -126.2404 274.1543 15.935325 0.0003084460
##
## $coyote
##          (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 5000 meter buffer -0.8790642      -5.487940      -5.08650049    -0.6168698
## 4750 meter buffer -0.8648903      -5.373024      -4.78964820    -0.6075930
## 4500 meter buffer -0.8266783      -5.163728      -4.71171392    -0.7046345
## 4250 meter buffer -0.8021582      -4.967429      -4.65030374    -0.8358988
## 250 meter buffer  -1.4786851      -1.833862      -0.92718095     0.4866877
## 4000 meter buffer -0.8218994      -4.785163      -4.31836108    -0.8410067
## 3750 meter buffer -0.7969870      -4.260655      -3.88368194    -0.9727922
## 3500 meter buffer -0.8241528      -4.044774      -3.61853425    -0.9874046
## 3250 meter buffer -0.7710165      -3.522892      -3.32423362    -1.1125345
## 3000 meter buffer -0.7077937      -2.935783      -2.95875900    -1.3005898
## 2750 meter buffer -0.6290841      -2.660089      -2.49237779    -1.4947145
## 2250 meter buffer -0.5016087      -2.228074      -1.15521911    -1.9369423
## 2500 meter buffer -0.5222681      -2.600031      -2.01097666    -1.7237813
## 1250 meter buffer -0.4808645      -1.299509      -1.77315574    -1.1625187
## 2000 meter buffer -0.4770337      -2.095074      -0.66403219    -1.9037212
## 1500 meter buffer -0.5477439      -1.809453      -1.69954545    -1.1767928
## 1750 meter buffer -0.5506511      -2.209611      -1.33079401    -1.3971082
## 1000 meter buffer -0.5088300      -1.394205      -0.80700040    -1.2481981
## 750 meter buffer  -0.4380426      -1.055380      -0.07292074    -1.3984229
## 500 meter buffer  -1.1548213      -1.219980      -0.06162276    -0.1975097
##
##          lc_grassland    lc_mixed    lc_shrub seismic_lines    wells
## 5000 meter buffer -0.6834831  1.38638762 0.46582840 19.13493917 20.212048
## 4750 meter buffer -0.7226074  1.37845244 0.56508226  8.61401418 17.517470
## 4500 meter buffer -1.1274983  1.84466433 0.69529179  4.59655363 12.730836
## 4250 meter buffer -1.3146989  2.38676410 0.78522172  6.66951467  7.879403
## 250 meter buffer  -0.1342708 -0.41394694 0.72452448 -13.31017608 -43.790703
## 4000 meter buffer -0.8459502  2.59249778 0.83899613  0.02908335  3.886720
## 3750 meter buffer -0.2682300  3.02518021 0.71790004  0.01695982 -6.515643
## 3500 meter buffer  0.0904137  2.80373954 0.65360801  1.80707997 -7.943298
## 3250 meter buffer -0.1900806  2.65426536 0.47088278  5.76144389 -13.949645

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## 3000 meter buffer -0.3191547 2.38686312 0.09032889 16.30774028 -20.003976
## 2750 meter buffer -0.6941826 2.02273644 -0.31176889 28.23356408 -23.234497
## 2250 meter buffer -1.6236103 0.29240831 -1.30977758 80.72141282 -30.431442
## 2500 meter buffer -1.9337727 1.11085606 -0.68499659 49.60400306 -23.657617
## 1250 meter buffer -2.1202624 2.27779213 -0.11518959 -75.17954561 -27.566347
## 2000 meter buffer -1.4466674 -0.09410975 -1.44185324 76.45536517 -35.049764
## 1500 meter buffer -1.8752643 1.76520504 -0.17399766 -37.67398665 -26.346594
## 1750 meter buffer -1.8688520 1.06277928 -0.53542813 6.23756997 -26.173227
## 1000 meter buffer -1.4818571 0.88374379 -0.46604929 -57.76938737 -26.557698
## 750 meter buffer -0.7893212 -1.39232853 -1.38766552 -23.08032969 -30.700657
## 500 meter buffer 0.2873841 -1.14384601 -0.14483827 -39.31930225 -21.635928
##
## df logLik AICc delta weight
## 5000 meter buffer 9 -140.3957 302.4648 0.000000 3.985102e-01
## 4750 meter buffer 9 -141.0062 303.6859 1.221080 2.164139e-01
## 4500 meter buffer 9 -141.5589 304.7912 2.326413 1.245275e-01
## 4250 meter buffer 9 -141.8100 305.2934 2.828654 9.687350e-02
## 250 meter buffer 9 -142.1156 305.9046 3.439803 7.136671e-02
## 4000 meter buffer 9 -142.5260 306.7255 4.260689 4.734156e-02
## 3750 meter buffer 9 -143.1454 307.9643 5.499547 2.548167e-02
## 3500 meter buffer 9 -144.0604 309.7942 7.329462 1.020627e-02
## 3250 meter buffer 9 -145.0700 311.8134 9.348638 3.718849e-03
## 3000 meter buffer 9 -145.9445 313.5624 11.097660 1.551005e-03
## 2750 meter buffer 9 -146.3991 314.4717 12.006887 9.844123e-04
## 2250 meter buffer 9 -146.6496 314.9726 12.507816 7.663050e-04
## 2500 meter buffer 9 -146.7293 315.1321 12.667297 7.075724e-04
## 1250 meter buffer 9 -146.8516 315.3767 12.911954 6.261008e-04
## 2000 meter buffer 9 -146.9013 315.4761 13.011351 5.957451e-04
## 1500 meter buffer 9 -148.0363 317.7460 15.281190 1.915011e-04
## 1750 meter buffer 9 -148.7680 319.2094 16.744663 9.212598e-05
## 1000 meter buffer 9 -149.7695 321.2125 18.747668 3.384037e-05
## 750 meter buffer 9 -150.9219 323.5174 21.052584 1.068880e-05
## 500 meter buffer 9 -153.9147 329.5028 27.038043 5.360470e-07
##
## $elk
##
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 1250 meter buffer -2.681814 -6.690159 -1.6699857 3.5718819
## 1500 meter buffer -3.101126 -9.592601 -2.9183619 4.7455791
## 4000 meter buffer -2.635330 -11.657665 -8.3005243 5.0848358
## 4250 meter buffer -2.690113 -11.733136 -8.5545981 5.3415636
## 4750 meter buffer -2.994387 -11.303001 -8.3896156 5.7198467
## 5000 meter buffer -3.162106 -10.818276 -7.1732459 5.6931888
## 3750 meter buffer -2.634251 -11.265812 -7.4204650 4.5782132
## 4500 meter buffer -2.788975 -11.410341 -8.4648807 5.2949466
## 3500 meter buffer -2.822389 -10.154766 -6.6265786 4.2726631
## 1000 meter buffer -1.679121 -3.343239 0.8341307 0.5149961
## 3250 meter buffer -2.906651 -10.057601 -6.5674045 4.2557482
## 1750 meter buffer -2.876549 -10.185915 -2.6734567 3.6280596
## 750 meter buffer -1.563526 -2.076186 1.1528370 -0.2085301
## 3000 meter buffer -2.902798 -9.449895 -5.6906605 3.9419752
## 2000 meter buffer -2.473212 -9.897122 -2.3294108 2.5844112
## 500 meter buffer -2.266520 -1.548477 0.4742107 0.6191934
## 2750 meter buffer -2.670307 -8.580322 -3.7952685 2.9160786
## 2250 meter buffer -2.325418 -8.269284 -2.2471226 1.9751308
## 2500 meter buffer -2.391372 -8.002479 -2.6948669 2.2735395

```

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## 250 meter buffer      -2.513696      -2.220813      -0.1691255      0.3134186
##          lc_grassland      lc_mixed      lc_shrub seismic_lines      wells
## 1250 meter buffer     -5.7706352    -17.797425     3.7615833      -388.5302    -19.280282
## 1500 meter buffer     -5.2258682    -25.703391     5.9094570      -437.5971     15.452301
## 4000 meter buffer     -11.1329089   -24.258285     3.3851726      -288.9717     92.851825
## 4250 meter buffer     -9.7100812    -25.053986     2.8784649      -292.0079    104.167849
## 4750 meter buffer     -3.6267003    -22.510768     0.9867135      -276.9219    107.731440
## 5000 meter buffer      0.8688698    -18.424500    -1.7835655      -262.1779    103.800251
## 3750 meter buffer    -10.9120944   -22.417730     3.3719676      -259.3296     78.555302
## 4500 meter buffer     -6.8695248    -23.703003     1.9183575      -266.2052    103.097616
## 3500 meter buffer     -7.2582799   -21.211793     3.1617701      -225.0083     58.026235
## 1000 meter buffer     -4.9898574    -10.862308    -1.5255762      -180.6189    -54.076417
## 3250 meter buffer     -6.5238807   -21.361828     4.0047567      -231.1099     51.319283
## 1750 meter buffer     -5.8627180   -19.789867     4.9058447      -285.4235    13.859106
## 750 meter buffer      -2.0348887    -9.570460     -3.5392895      -132.7332   -58.058604
## 3000 meter buffer     -5.3713296   -19.582493     3.7581835      -222.2752     37.661402
## 2000 meter buffer     -6.4279742   -15.251557     3.3872545      -220.6538     8.389893
## 500 meter buffer      -0.5554444   -10.497405    -1.9390325      -113.8900   -51.028563
## 2750 meter buffer     -4.4217654   -13.462399     2.6925587      -190.6732     8.493926
## 2250 meter buffer     -5.4713983   -11.592642     2.0542577      -178.0923    -5.294808
## 2500 meter buffer     -5.5419505   -10.370334     1.7972448      -194.4078    -1.675048
## 250 meter buffer     -0.1625115    -6.184284     -2.1005680      -59.2219   -48.359779
##          df      logLik      AICc      delta      weight
## 1250 meter buffer     9 -56.36117    134.3958    0.00000000    2.315873e-01
## 1500 meter buffer     9 -56.37898    134.4314    0.03563585    2.274975e-01
## 4000 meter buffer     9 -56.88156    135.4366    1.04078875    1.376291e-01
## 4250 meter buffer     9 -57.14313    135.9597    1.56392675    1.059528e-01
## 4750 meter buffer     9 -57.41864    136.5108    2.11495444    8.043745e-02
## 5000 meter buffer     9 -57.57606    136.8256    2.42979721    6.872125e-02
## 3750 meter buffer     9 -57.72127    137.1160    2.72020867    5.943319e-02
## 4500 meter buffer     9 -57.81386    137.3012    2.90538355    5.417748e-02
## 3500 meter buffer     9 -59.43063    140.5347    6.13892912    1.075631e-02
## 1000 meter buffer     9 -59.59908    140.8716    6.47582055    9.088836e-03
## 3250 meter buffer     9 -59.95189    141.5773    7.18145658    6.386771e-03
## 1750 meter buffer     9 -60.83295    143.3394    8.94355783    2.646342e-03
## 750 meter buffer      9 -60.87349    143.4204    9.02464317    2.541198e-03
## 3000 meter buffer     9 -61.17107    144.0156    9.61980458    1.887126e-03
## 2000 meter buffer     9 -62.50465    146.6828    12.28696766    4.973175e-04
## 500 meter buffer      9 -62.81031    147.2941    12.89827774    3.663443e-04
## 2750 meter buffer     9 -63.46848    148.6104    14.21463633    1.896906e-04
## 2250 meter buffer     9 -64.12005    149.9136    15.51777629    9.887182e-05
## 2500 meter buffer     9 -64.18834    150.0501    15.65433897    9.234605e-05
## 250 meter buffer     9 -66.17391    154.0213    19.62547949    1.267932e-05
##
## $grey_wolf
##          (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 5000 meter buffer    -4.267763      1.6555134      2.8022407    -2.69019203
## 500 meter buffer     -5.762530     -1.6774160      1.7779177     2.43302245
## 3500 meter buffer    -4.159795      0.9220134      1.2832261    -1.51689396
## 4250 meter buffer    -4.275641      1.8002409      1.7110811    -1.82961288
## 3750 meter buffer    -4.205701      1.3575019      1.2155974    -1.53510477
## 4750 meter buffer    -4.234019      1.6677947      2.3559456    -2.27027649
## 4000 meter buffer    -4.333802      1.6119414      1.3935156    -1.49637795
## 4500 meter buffer    -4.211303      1.8060651      2.0504595    -2.02085914

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## 750 meter buffer	-4.929309	-0.2810575	1.7051863	1.05979292
## 3250 meter buffer	-4.116175	0.2615882	0.9954575	-1.15396057
## 1250 meter buffer	-3.567545	-1.0884599	0.1389096	-0.22277993
## 1500 meter buffer	-3.411943	-1.8496180	0.4488252	-0.35062506
## 250 meter buffer	-4.373220	-1.8398068	0.3949764	1.40566435
## 1750 meter buffer	-3.341609	-1.9677748	0.8406549	-0.58153304
## 3000 meter buffer	-3.836095	-0.1226713	0.5879639	-0.99559914
## 2250 meter buffer	-3.109082	-1.1701281	1.7203356	-1.31536983
## 2000 meter buffer	-3.280202	-1.7481448	1.9125078	-1.07461065
## 1000 meter buffer	-3.714102	-0.7841404	0.6761526	-0.08258719
## 2750 meter buffer	-3.493111	-0.3896048	0.4940127	-0.96022726
## 2500 meter buffer	-3.244753	-0.9031487	0.6803183	-0.97381858
##	lc_grassland	lc_mixed	lc_shrub	seismic_lines wells
## 5000 meter buffer	14.12367738	21.315689	-3.2829858	279.67821 -51.2629282
## 500 meter buffer	1.41101104	3.797738	4.9646889	51.87586 27.1031304
## 3500 meter buffer	7.00382555	16.555700	-1.6080870	224.45338 -23.6117412
## 4250 meter buffer	10.07454957	18.323180	-2.4407659	235.03331 -34.8847852
## 3750 meter buffer	7.86173736	17.034863	-1.7720076	220.35778 -27.8883051
## 4750 meter buffer	11.37290598	19.792536	-2.8585587	250.76739 -40.7385090
## 4000 meter buffer	9.52974950	17.730029	-2.0114955	217.36814 -28.6578351
## 4500 meter buffer	10.30915615	18.914575	-2.5737160	234.94126 -38.9732939
## 750 meter buffer	-1.01184944	3.496699	2.1542023	75.89291 41.5291172
## 3250 meter buffer	4.67600110	15.451310	-0.9567911	194.06970 -8.7446097
## 1250 meter buffer	-3.19473208	7.109202	1.7565921	15.43382 21.7576902
## 1500 meter buffer	-3.37322645	8.121376	1.3764186	25.32328 19.3277033
## 250 meter buffer	1.78354289	2.430543	2.7754999	34.70254 -8.0095751
## 1750 meter buffer	-3.48731179	9.368741	0.8818826	53.60763 13.4591661
## 3000 meter buffer	2.54667215	14.234646	-0.4899263	150.30708 -5.4386417
## 2250 meter buffer	-3.37433411	10.280217	-1.0714633	124.87656 -0.6351178
## 2000 meter buffer	-2.76483197	9.780781	-0.4411610	115.97247 4.5511334
## 1000 meter buffer	-1.82066702	4.877123	1.7963308	34.89441 15.8663831
## 2750 meter buffer	0.02791245	12.677881	-0.4045565	115.60673 -3.4105729
## 2500 meter buffer	-3.15029162	10.956116	-0.4878997	100.20504 5.2179790
##	df	logLik	AICc	delta weight
## 5000 meter buffer	9	-74.99450	171.6625	0.0000000 0.250776715
## 500 meter buffer	9	-75.22719	172.1279	0.4653877 0.198714494
## 3500 meter buffer	9	-76.26121	174.1959	2.5334113 0.070658422
## 4250 meter buffer	9	-76.28321	174.2399	2.5774232 0.069120502
## 3750 meter buffer	9	-76.31711	174.3077	2.6452187 0.066816738
## 4750 meter buffer	9	-76.33905	174.3516	2.6890960 0.065366832
## 4000 meter buffer	9	-76.36532	174.4041	2.7416339 0.063672070
## 4500 meter buffer	9	-76.60844	174.8904	3.2278878 0.049929853
## 750 meter buffer	9	-76.77219	175.2178	3.5553694 0.042388550
## 3250 meter buffer	9	-77.23095	176.1354	4.4729091 0.026792136
## 1250 meter buffer	9	-77.25268	176.1788	4.5163517 0.026216451
## 1500 meter buffer	9	-77.59307	176.8596	5.1971300 0.018652832
## 250 meter buffer	9	-78.18788	178.0492	6.3867495 0.010290161
## 1750 meter buffer	9	-78.29433	178.2621	6.5996661 0.009250984
## 3000 meter buffer	9	-78.41607	178.5056	6.8431372 0.008190659
## 2250 meter buffer	9	-78.57896	178.8314	7.1689096 0.006959504
## 2000 meter buffer	9	-78.60447	178.8824	7.2199322 0.006784203
## 1000 meter buffer	9	-79.04131	179.7561	8.0936113 0.004383105
## 2750 meter buffer	9	-79.55611	180.7857	9.1232107 0.002619432
## 2500 meter buffer	9	-79.63680	180.9471	9.2846029 0.002416358

```

##
## $lynx
##               (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 500 meter buffer -4.638798      2.188900      1.7925432      0.1910742
## 750 meter buffer -3.363738      3.316632      2.1511847     -1.2662431
## 1500 meter buffer -2.014705      2.156057      3.1970223     -2.1224406
## 1750 meter buffer -1.911235      2.025076      3.1905282     -2.1740819
## 5000 meter buffer -3.445486      3.854474      7.8096569     -4.2867685
## 1250 meter buffer -2.122074      2.606918      2.8187974     -2.3130125
## 1000 meter buffer -2.463963      2.839992      2.5963825     -2.1205547
## 4750 meter buffer -3.228794      3.427634      7.1840843     -3.9564187
## 4500 meter buffer -3.048877      3.425353      6.7310356     -3.7006338
## 2000 meter buffer -1.833974      2.058312      3.8285921     -2.4075812
## 4250 meter buffer -2.975361      3.092680      6.4661854     -3.6042517
## 2250 meter buffer -1.806369      2.115197      3.8118564     -2.6025584
## 4000 meter buffer -2.836414      2.585671      5.8358009     -3.2606681
## 3500 meter buffer -2.637542      2.436327      5.3612957     -3.4600274
## 3750 meter buffer -2.716822      2.662083      5.4168895     -3.3310330
## 3250 meter buffer -2.544037      1.796901      5.2079978     -3.0540838
## 2500 meter buffer -1.816007      1.973550      3.8062152     -2.5542238
## 3000 meter buffer -2.308146      1.762154      4.8355802     -2.7613587
## 2750 meter buffer -2.100276      1.837350      4.2652158     -2.5736326
## 250 meter buffer -3.035887     -0.649130      0.6592757     -0.6453718
##               lc_grassland lc_mixed lc_shrub seismic_lines wells
## 500 meter buffer -0.33833666  2.0603815  1.9860741    7.7418410  42.0726557
## 750 meter buffer -4.26216070  1.6666314 -0.6897007   14.8009193  27.6118854
## 1500 meter buffer -12.15271363  3.3152505 -2.7817060  -49.6910985  17.2418942
## 1750 meter buffer -14.27717468  3.8342442 -2.9886307  -60.9107141  20.6903781
## 5000 meter buffer 13.15514501 19.8739446 -4.0878674   66.8915095 -39.5827092
## 1250 meter buffer -8.90053358  3.6388111 -2.4424652  -32.4122637   9.2795419
## 1000 meter buffer -5.79899889  2.3594124 -1.5528189   -3.6435035   3.6468649
## 4750 meter buffer  9.74701145 18.0291414 -3.8070291   35.4188872 -28.9470505
## 4500 meter buffer  7.14759949 16.4744346 -3.6445517   16.9267394 -26.9069998
## 2000 meter buffer -13.04828431  4.6973390 -3.6934003  -46.7609149  15.0537007
## 4250 meter buffer  5.33549754 15.2952417 -3.6818718   30.5937604 -21.4433876
## 2250 meter buffer -12.44895274  6.1457926 -3.8834363  -50.6324236  15.4924741
## 4000 meter buffer  2.51352340 13.7933172 -3.5209046    7.9171481  -7.6926952
## 3500 meter buffer  0.88760036 12.8526403 -3.3906093   39.3497087 -13.7010964
## 3750 meter buffer  1.62635917 12.9499435 -3.3546784   23.1638784 -13.3296181
## 3250 meter buffer -0.91301148 11.6532278 -3.5528727    0.9716624   3.3452942
## 2500 meter buffer -9.77267053  6.6594612 -3.7541280  -73.2581881  12.7841480
## 3000 meter buffer -2.53286185  9.5965548 -3.5541090  -36.5317170   4.6944040
## 2750 meter buffer -5.20369551  7.9021737 -3.5698783  -57.8557842   8.7067708
## 250 meter buffer  0.07101097  0.4347604  1.7039200   -9.2477270   0.8116645
##               df logLik      AICc      delta      weight
## 500 meter buffer  9 -78.62374 178.9210  0.000000  9.648048e-01
## 750 meter buffer  9 -82.61504 186.9035  7.982586  1.782555e-02
## 1500 meter buffer  9 -84.33310 190.3397 11.418715  3.198136e-03
## 1750 meter buffer  9 -84.35443 190.3823 11.461361  3.130665e-03
## 5000 meter buffer  9 -84.53782 190.7491 11.828157  2.606080e-03
## 1250 meter buffer  9 -84.54318 190.7598 11.838877  2.592149e-03
## 1000 meter buffer  9 -84.91909 191.5117 12.590695  1.779938e-03
## 4750 meter buffer  9 -85.42391 192.5213 13.600339  1.074393e-03
## 4500 meter buffer  9 -85.92674 193.5269 14.605984  6.498160e-04

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## 2000 meter buffer 9 -86.08610 193.8457 14.924717 5.540874e-04
## 4250 meter buffer 9 -86.23031 194.1341 15.213131 4.796782e-04
## 2250 meter buffer 9 -86.66011 194.9937 16.072735 3.120968e-04
## 4000 meter buffer 9 -86.84315 195.3598 16.438820 2.598933e-04
## 3500 meter buffer 9 -87.04317 195.7598 16.838853 2.127792e-04
## 3750 meter buffer 9 -87.24150 196.1565 17.235517 1.744996e-04
## 3250 meter buffer 9 -87.46720 196.6079 17.686913 1.392436e-04
## 2500 meter buffer 9 -87.89951 197.4725 18.551529 9.037039e-05
## 3000 meter buffer 9 -88.27422 198.2219 19.300956 6.212840e-05
## 2750 meter buffer 9 -88.58266 198.8388 19.917829 4.563919e-05
## 250 meter buffer 9 -90.31836 202.3102 23.389229 8.045127e-06
##
## $moose
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 500 meter buffer -2.2301609 -0.7875774 0.7698777 2.00379740
## 750 meter buffer -1.9179235 -0.5592863 1.0960012 1.66542760
## 250 meter buffer -2.3241198 -0.5110314 -0.6715524 1.75141880
## 1000 meter buffer -1.3660374 0.4848453 1.1504745 0.93213457
## 3750 meter buffer -0.2287966 1.5613611 1.4406725 -0.75649073
## 1750 meter buffer -0.9155644 1.1536271 1.5944787 0.11715174
## 3500 meter buffer -0.3227275 1.5447327 1.4097746 -0.69325634
## 4000 meter buffer -0.3119877 1.4429672 1.4382023 -0.46744021
## 2000 meter buffer -0.9152462 1.3164230 1.6713940 0.12256165
## 1500 meter buffer -1.0427061 1.0166686 1.2935874 0.33197950
## 4500 meter buffer -0.3440631 1.4886848 1.4718373 -0.17752514
## 4250 meter buffer -0.3836815 1.5297145 1.5769807 -0.36047832
## 1250 meter buffer -1.1941955 0.7979169 1.0875110 0.62792960
## 4750 meter buffer -0.2889701 1.3419989 1.2374821 0.01430409
## 5000 meter buffer -0.3095362 1.3434390 1.2945983 0.08528960
## 2250 meter buffer -0.8266371 1.4241393 1.4774349 0.03461669
## 3250 meter buffer -0.4630858 1.5006025 1.4487979 -0.47463117
## 2500 meter buffer -0.6883477 1.4784096 1.2476576 -0.03811787
## 2750 meter buffer -0.6214425 1.5134475 1.1718354 -0.11339635
## 3000 meter buffer -0.5319969 1.5143633 1.2352276 -0.24036218
## lc_grassland lc_mixed lc_shrub seismic_lines wells
## 500 meter buffer 3.9226120 2.69373315 3.4263290 -64.64828 -28.05807
## 750 meter buffer 3.6695298 2.58759907 2.6793639 -56.16744 -32.58800
## 250 meter buffer 2.4114288 2.26748550 2.9020550 -23.20201 -15.46067
## 1000 meter buffer 2.5884135 1.32238164 0.5622808 -15.38316 -39.73788
## 3750 meter buffer -4.7011072 4.05169405 -3.7503459 40.44538 -47.43275
## 1750 meter buffer 1.6812222 -1.12360632 -1.9765218 68.80572 -47.59561
## 3500 meter buffer -3.9045537 3.87394318 -3.4746360 44.37860 -46.68728
## 4000 meter buffer -4.1201866 3.86176789 -3.7304451 20.53772 -41.54811
## 2000 meter buffer 1.4268416 -0.77678587 -2.2796937 69.37404 -46.25686
## 1500 meter buffer 2.1368082 -1.13657723 -1.4439454 58.29034 -43.54578
## 4500 meter buffer -3.5495752 3.57075801 -3.7595552 -8.39386 -39.27685
## 4250 meter buffer -2.9072933 3.78139814 -3.8593298 15.71576 -42.01169
## 1250 meter buffer 2.3410305 0.08681804 -0.4868094 21.73740 -40.91531
## 4750 meter buffer -4.5813973 2.76000516 -3.7956725 -25.97033 -32.24342
## 5000 meter buffer -4.2265366 2.58627206 -3.9576331 -28.77138 -30.45687
## 2250 meter buffer 0.5750740 0.11148007 -2.4552013 58.63542 -44.49240
## 3250 meter buffer -2.7204273 3.13540402 -3.1621727 41.86992 -44.77615
## 2500 meter buffer -0.8134624 1.00735284 -2.6230306 37.93657 -41.90972
## 2750 meter buffer -1.2435174 1.41803809 -2.7482263 33.43772 -41.63385

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## 3000 meter buffer    -2.2179314  1.83847871 -2.8541132      31.59953 -41.98404
##                      df      logLik      AICc      delta      weight
## 500 meter buffer     9 -158.7347  339.1429   0.000000  9.883570e-01
## 750 meter buffer     9 -163.6239  348.9213   9.778343  7.440012e-03
## 250 meter buffer     9 -164.2312  350.1360  10.993049  4.053252e-03
## 1000 meter buffer    9 -168.0911  357.8557  18.712815  8.540391e-05
## 3750 meter buffer    9 -169.6350  360.9434  21.800493  1.823883e-05
## 1750 meter buffer    9 -170.4613  362.5961  23.453187  7.982133e-06
## 3500 meter buffer    9 -170.6361  362.9456  23.802712  6.702249e-06
## 4000 meter buffer    9 -170.8873  363.4481  24.305193  5.213247e-06
## 2000 meter buffer    9 -170.9417  363.5569  24.413988  4.937233e-06
## 1500 meter buffer    9 -171.0275  363.7284  24.585514  4.531451e-06
## 4500 meter buffer    9 -171.3676  364.4087  25.265766  3.224946e-06
## 4250 meter buffer    9 -171.4531  364.5796  25.436658  2.960831e-06
## 1250 meter buffer    9 -171.6322  364.9378  25.794853  2.475327e-06
## 4750 meter buffer    9 -171.6445  364.9624  25.819472  2.445044e-06
## 5000 meter buffer    9 -171.7176  365.1086  25.965705  2.272651e-06
## 2250 meter buffer    9 -172.2814  366.2363  27.093378  1.293188e-06
## 3250 meter buffer    9 -172.4848  366.6430  27.500083  1.055229e-06
## 2500 meter buffer    9 -173.3166  368.3066  29.163696  4.593014e-07
## 2750 meter buffer    9 -173.6910  369.0555  29.912590  3.158475e-07
## 3000 meter buffer    9 -173.8592  369.3918  30.248922  2.669586e-07
##
## $snowshoe_hare
##              (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 4000 meter buffer -0.8635970   -7.0383983           7.087796   -4.733352
## 3500 meter buffer -0.8333932   -6.0722844           5.908161   -4.454474
## 3750 meter buffer -0.8822427   -6.6679669           6.475600   -4.460603
## 4250 meter buffer -0.8092547   -6.6721939           7.233734   -4.929891
## 3250 meter buffer -0.8496310   -5.6672635           5.513688   -4.256570
## 4500 meter buffer -0.7617888   -5.9427552           6.970662   -4.856169
## 4750 meter buffer -0.7759291   -5.7173012           7.011581   -4.808025
## 2000 meter buffer -0.7105139   -6.2466944           6.137331   -3.946574
## 250 meter buffer  -1.3164060   -0.5092921           1.006582   -1.245722
## 5000 meter buffer -0.8925434   -5.0474197           7.458819   -5.077472
## 3000 meter buffer -0.8843952   -4.8928575           5.290588   -3.959757
## 2250 meter buffer -0.6833235   -5.9829256           6.228984   -3.996968
## 1750 meter buffer -0.6108544   -5.3528186           5.453430   -3.888911
## 2500 meter buffer -0.7252853   -5.3213424           5.812407   -3.922944
## 2750 meter buffer -0.8397297   -4.8059990           5.400768   -3.776883
## 1500 meter buffer -0.5492953   -4.3791511           4.736385   -3.735853
## 1250 meter buffer -0.4735189   -3.4726757           4.128543   -3.522310
## 1000 meter buffer -0.5906434   -2.8563772           3.490384   -3.048234
## 500 meter buffer  -1.4746455   -1.9725971           1.696574   -1.224776
## 750 meter buffer  -1.0135047   -1.9582852           1.881091   -2.044391
##
##              lc_grassland   lc_mixed   lc_shrub seismic_lines
## 4000 meter buffer  2.02051756  9.20437113 -3.434223413   90.475010
## 3500 meter buffer  2.39228077 10.29217178 -3.083065745   44.854106
## 3750 meter buffer  2.49462686  8.87942589 -3.109586726   67.615331
## 4250 meter buffer  1.70632777 10.02437232 -3.592812489   96.396861
## 3250 meter buffer  1.97439273 10.18732646 -3.014340098   26.524675
## 4500 meter buffer  1.13322980 10.58070379 -3.745895642   71.440962
## 4750 meter buffer  1.02186669 11.01639168 -3.938605921   63.074744
## 2000 meter buffer -2.78247604  0.06920634 -2.465937623  133.601692

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## 250 meter buffer -4.13441378 -1.29557314 -0.005035104 -7.872473
## 5000 meter buffer 2.72840467 12.26517125 -4.201314560 97.252420
## 3000 meter buffer 1.46046552 8.48959435 -2.780990055 30.631418
## 2250 meter buffer -3.04798507 1.64445318 -2.709271464 118.464512
## 1750 meter buffer -3.01438096 -1.10214536 -2.601045294 133.675570
## 2500 meter buffer -1.92479648 3.29518790 -2.671741163 91.282696
## 2750 meter buffer -0.05034923 5.83898049 -2.599260731 47.917897
## 1500 meter buffer -3.15095804 -0.85356512 -2.463322087 114.406212
## 1250 meter buffer -3.09010615 -0.78464199 -2.197572964 70.643291
## 1000 meter buffer -2.42065208 -1.01832227 -1.538858761 35.333186
## 500 meter buffer -2.41430452 -0.44469555 1.159795198 -26.169242
## 750 meter buffer -2.66022306 -0.07981444 -0.205713578 -29.244289
##
## wells df logLik AICc delta weight
## 4000 meter buffer 21.6282311 9 -123.6466 268.9666 0.0000000 2.766139e-01
## 3500 meter buffer 15.3326894 9 -123.8853 269.4440 0.4773261 2.178833e-01
## 3750 meter buffer 19.5051908 9 -124.2061 270.0857 1.1190995 1.580755e-01
## 4250 meter buffer 16.4464590 9 -124.3371 270.3477 1.3811018 1.386665e-01
## 3250 meter buffer 17.1324643 9 -124.5278 270.7290 1.7623740 1.145986e-01
## 4500 meter buffer 16.5752711 9 -125.8147 273.3030 4.3363062 3.164150e-02
## 4750 meter buffer 19.8078487 9 -126.5962 274.8659 5.8992933 1.448301e-02
## 2000 meter buffer 5.3199660 9 -126.7540 275.1814 6.2147653 1.236958e-02
## 250 meter buffer -0.7544795 9 -126.8176 275.3087 6.3420873 1.160666e-02
## 5000 meter buffer 7.6154507 9 -127.1412 275.9559 6.9892796 8.397910e-03
## 3000 meter buffer 9.8736898 9 -127.4494 276.5722 7.6055869 6.170805e-03
## 2250 meter buffer 8.4406742 9 -127.6556 276.9847 8.0180938 5.020732e-03
## 1750 meter buffer -2.7496297 9 -128.4566 278.5867 9.6200036 2.253807e-03
## 2500 meter buffer 6.4445539 9 -129.3853 280.4440 11.4773952 8.904085e-04
## 2750 meter buffer 7.3371218 9 -129.6434 280.9602 11.9935538 6.878708e-04
## 1500 meter buffer -9.5311600 9 -130.1423 281.9581 12.9914777 4.176480e-04
## 1250 meter buffer -13.9295104 9 -131.0609 283.7953 14.8286874 1.666731e-04
## 1000 meter buffer -15.2974449 9 -132.4248 286.5231 17.5565016 4.261163e-05
## 500 meter buffer -5.3032805 9 -133.6967 289.0670 20.1003043 1.194396e-05
## 750 meter buffer -1.4744239 9 -136.1483 293.9701 25.0034528 1.029066e-06
##
## $'white-tailed_deer'
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 4250 meter buffer -1.1822056 1.14343043 -1.8834843 2.802128
## 4500 meter buffer -1.2038471 1.21415878 -1.9982928 2.932885
## 4000 meter buffer -1.1289590 1.04233940 -1.9146238 2.685332
## 5000 meter buffer -1.2598819 1.62499973 -2.1683633 3.022530
## 4750 meter buffer -1.2263757 1.33988705 -2.0945529 3.004885
## 3750 meter buffer -1.0202517 0.98989688 -1.9877274 2.531560
## 3500 meter buffer -0.9879060 0.87157660 -2.0010532 2.466731
## 3250 meter buffer -0.9625354 0.85494359 -1.8809632 2.480554
## 3000 meter buffer -0.8609327 0.72568260 -1.9435536 2.455735
## 2750 meter buffer -0.7531394 0.46589217 -2.1471248 2.424378
## 2500 meter buffer -0.6365687 0.19400560 -2.0400752 2.293254
## 2250 meter buffer -0.5603410 0.02568109 -1.6805481 2.193318
## 250 meter buffer -0.8283441 -0.32007758 -0.8484051 2.669069
## 2000 meter buffer -0.5690241 -0.07473877 -1.4270125 2.272065
## 1750 meter buffer -0.5672793 -0.16619208 -1.5205997 2.386394
## 1000 meter buffer -0.6073692 1.01263407 -1.7999201 2.605424
## 1500 meter buffer -0.5179250 -0.01768650 -1.6083860 2.433740
## 1250 meter buffer -0.6387061 0.47234607 -1.9229082 2.601845

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## 500 meter buffer	-1.0782608	0.60665680	-0.9689404	3.011916
## 750 meter buffer	-0.7888550	0.60091446	-1.3461206	2.699542
##	lc_grassland	lc_mixed	lc_shrub	seismic_lines
## 4250 meter buffer	11.607434	14.220662	-1.115235082	-80.55536
## 4500 meter buffer	12.255756	13.973197	-1.086811061	-92.80220
## 4000 meter buffer	10.595938	14.348802	-1.115987071	-70.87871
## 5000 meter buffer	13.912499	13.559719	-1.314789347	-93.22439
## 4750 meter buffer	12.839041	13.585375	-1.202844022	-94.10298
## 3750 meter buffer	9.137674	14.471510	-1.116846791	-64.57006
## 3500 meter buffer	8.404464	14.547320	-1.037855043	-58.28079
## 3250 meter buffer	7.467349	14.137400	-1.001448459	-55.50837
## 3000 meter buffer	5.801788	13.382764	-0.881081349	-57.94611
## 2750 meter buffer	4.293622	13.155888	-0.655709373	-63.21303
## 2500 meter buffer	2.877479	12.992145	-0.568562928	-61.88847
## 2250 meter buffer	2.176251	12.734835	-0.553861307	-62.69667
## 250 meter buffer	1.535771	3.906366	0.838543727	-45.31721
## 2000 meter buffer	2.231763	12.280033	-0.410576556	-72.65662
## 1750 meter buffer	1.931654	11.351970	0.009169897	-87.29078
## 1000 meter buffer	1.500682	7.050765	1.110916576	-121.40003
## 1500 meter buffer	1.820417	9.171592	0.303250874	-98.86607
## 1250 meter buffer	1.460169	8.229826	0.862744213	-110.77848
## 500 meter buffer	1.371856	3.599306	0.996997687	-52.83966
## 750 meter buffer	1.546146	5.146763	1.310522934	-88.05679
##	wells	df	logLik	AICc
## 4250 meter buffer	-1.18409781	9	-180.7871	383.2477
## 4500 meter buffer	-0.04458674	9	-180.9312	383.5359
## 4000 meter buffer	-1.82040186	9	-181.1819	384.0373
## 5000 meter buffer	-3.82891881	9	-181.2818	384.2371
## 4750 meter buffer	0.25235450	9	-181.4040	384.4815
## 3750 meter buffer	-3.00710711	9	-182.8823	387.4380
## 3500 meter buffer	-3.11237315	9	-184.6046	390.8827
## 3250 meter buffer	-3.68285995	9	-186.2825	394.2386
## 3000 meter buffer	-1.99354774	9	-188.0639	397.8012
## 2750 meter buffer	-0.02466137	9	-188.4675	398.6084
## 2500 meter buffer	0.54562503	9	-189.7066	401.0867
## 2250 meter buffer	-0.65948101	9	-192.2718	406.2171
## 250 meter buffer	-8.56110993	9	-194.3452	410.3639
## 2000 meter buffer	-1.00919284	9	-194.3647	410.4028
## 1750 meter buffer	0.23507559	9	-196.5420	414.7575
## 1000 meter buffer	-11.07039650	9	-198.7540	419.1815
## 1500 meter buffer	-1.72211704	9	-200.6176	422.9087
## 1250 meter buffer	-1.39095318	9	-201.5449	424.7633
## 500 meter buffer	5.02340281	9	-202.0697	425.8129
## 750 meter buffer	-6.34253628	9	-205.4496	432.5726
			delta	weight
			0.0000000	2.604575e-01
			0.2881926	2.255052e-01
			0.7896184	1.754985e-01
			0.9894219	1.588132e-01
			1.2338516	1.405430e-01
			4.1903378	3.204915e-02
			7.6350076	5.725534e-03
			10.9908669	1.069302e-03
			14.5534884	1.800889e-04
			15.3607220	1.202814e-04
			17.8390218	3.483714e-05
			22.9693942	2.679145e-06
			27.1161694	3.369267e-07
			27.1551050	3.304309e-07
			31.5097558	3.745246e-08
			35.9337720	4.100317e-09
			39.6610075	6.360020e-10
			41.5156356	2.516118e-10
			42.5651836	1.488760e-10
			49.3248939	5.069583e-12

Black bear

Depending on which variables I include in the buffer selection model the 250m or one of the 4250-4750m buffers comes out on top - similar to OSM scale results. Interesting that it is so sensitive to changes in single variables

Correlation plot

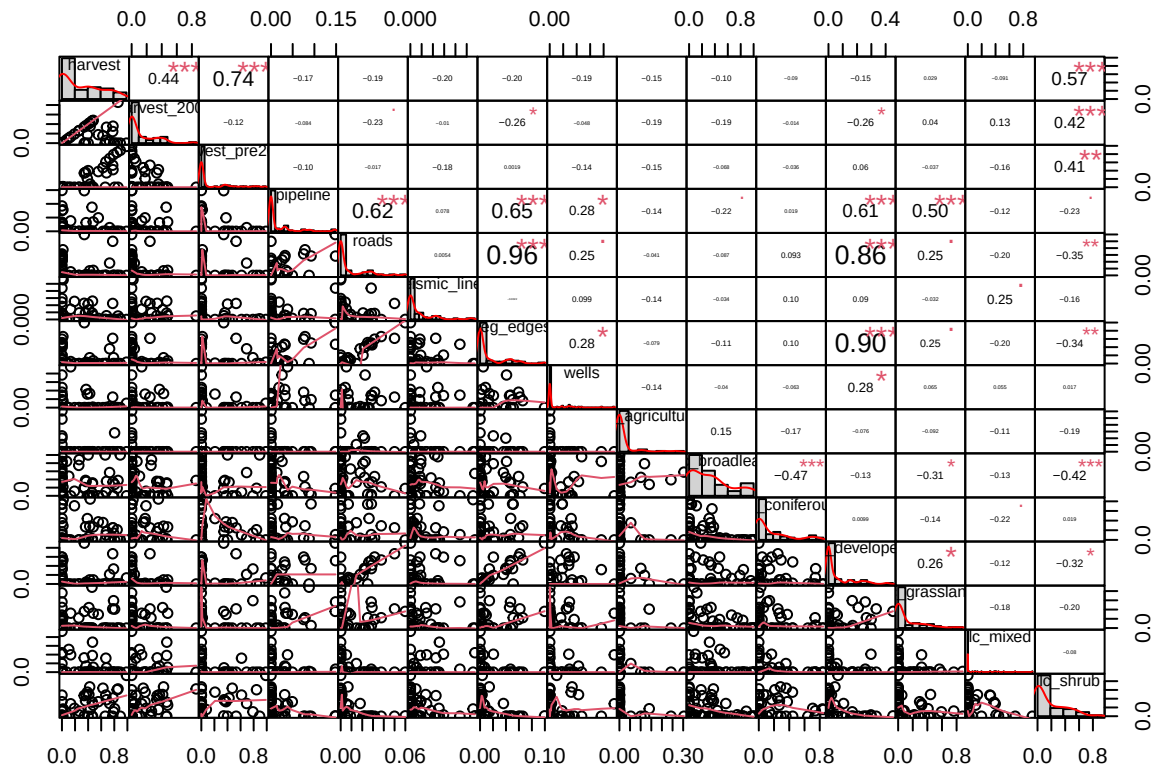
Let's reprint the correlation plot for this specific buffer so we have to reference when constructing models. I've commented out the code to save the plot but can uncomment to use

```
# open file to save plot
# png("figures/corr_plot_250.png",
#     width = 1000,
#     height = 800)

prop_det_data$`250 meter buffer` %>%

# select only columns with covariates not other info to simplify the plot a bit
select(harvest:lc_shrub) %>%

# use chart.correlation to produce plots for each buffer size
chart.Correlation(.,
  histogram = TRUE,
  method = "pearson")
```



```
## close file
# dev.off()
```

Models

Now that we have best fit buffer size (250m) we can run several candidate models based on a priori hypotheses for what covariates might influence monthly presence/absence of black bears in our study area.

```

# Null model
bbear_null <- glm(cbind(black_bear, absent_black_bear) ~ 1,
  data = prop_det_data$`250 meter buffer`,
  family = 'binomial')

# # global model - removed because too many variables for sample size
# bbear_global <- glm(cbind(black_bear, absent_black_bear) ~
#   scale(harvest_2000) +
#   scale(harvest_pre2000) +
#   roads +
#   # scale(pipeline) + can't include with roads
#   scale(seismic_lines) +
#   scale(wells) +
#   scale(lc_agriculture) +
#   scale(lc_broadleaf) +
#   scale(lc_grassland) +
#   scale(lc_mixed) +
#   scale(lc_shrub),
#   data = prop_det_data$`250 meter buffer`,
#   family = 'binomial')

# Natural heterogeneity
bbear_nat <- glm(cbind(black_bear, absent_black_bear) ~
  scale(lc_broadleaf) +
  scale(lc_grassland) +
  scale(lc_mixed) +
  scale(lc_shrub),
  data = prop_det_data$`250 meter buffer`,
  family = 'binomial')

# forest harvest (TBD how this will look with yearly harvest data)
bbear_harvest <- glm(cbind(black_bear, absent_black_bear) ~
  scale(harvest_2000) +
  scale(harvest_pre2000),
  data = prop_det_data$`250 meter buffer`,
  family = 'binomial')

# agriculture - put on it's own because it doesn't fit with some of other variables but I am interested
bbear_ag <- glm(cbind(black_bear, absent_black_bear) ~
  scale(lc_agriculture),
  data = prop_det_data$`250 meter buffer`,
  family = 'binomial')

# transportation (roads) * at 250m buffer can't combine with other industrial features (correlated with
bbear_rds <- glm(cbind(black_bear, absent_black_bear) ~
  scale(roads),
  data = prop_det_data$`250 meter buffer`,
  family = 'binomial')

# linear energy development
bbear_linear_energy <- glm(cbind(black_bear, absent_black_bear) ~
  scale(pipeline) +
  scale(seismic_lines),

```

```

data = prop_det_data$`250 meter buffer`,
family = 'binomial')

# polygonal energy development
bbear_poly_energy <- glm(cbind(black_bear, absent_black_bear) ~
  scale(wells),
  data = prop_det_data$`250 meter buffer`,
  family = 'binomial')

# energy development
bbear_energy <- glm(cbind(black_bear, absent_black_bear) ~
  scale(pipeline) +
  scale(seismic_lines) +
  scale(wells),
  data = prop_det_data$`250 meter buffer`,
  family = 'binomial')

# polygonal disturbance (harvest + polygonal energy development + agriculture)
bbear_poly <- glm(cbind(black_bear, absent_black_bear) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  scale(wells),
  data = prop_det_data$`250 meter buffer`,
  family = 'binomial')

# linear disturbance (transportation + linear energy development)
bbear_linear <- glm(cbind(black_bear, absent_black_bear) ~
  scale(roads) +
  # pipeline + can't include correlated w/ roads 0.62
  scale(seismic_lines),
  data = prop_det_data$`250 meter buffer`,
  family = 'binomial')

# overall human disturbance from energy and harvest
bbear_disturb <- glm(cbind(black_bear, absent_black_bear) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  scale(roads) +
  # pipeline + can't include correlated w/ roads 0.62
  scale(seismic_lines) +
  scale(wells),
  data = prop_det_data$`250 meter buffer`,
  family = 'binomial')

# linear + natural
bbear_linear_nat <- glm(cbind(black_bear, absent_black_bear) ~
  scale(roads) +
  scale(seismic_lines) +
  scale(lc_broadleaf) +

```

```

        scale(lc_shrub),
data = prop_det_data$`250 meter buffer`,
family = 'binomial')

# polygonal + natural
bbear_poly_nat <- glm(cbind(black_bear, absent_black_bear) ~
        scale(harvest_2000) +
        scale(harvest_pre2000) +
        scale(wells) +
        scale(lc_broadleaf) +
        scale(lc_shrub),
data = prop_det_data$`250 meter buffer`,
family = 'binomial')

```

Model selection

```
# compare black bear models
```

```
model.sel(bbear_null,
          bbear_nat,
          bbear_harvest,
          bbear_ag,
          bbear_rds,
          bbear_linear_energy,
          bbear_poly_energy,
          bbear_energy,
          bbear_poly,
          bbear_linear,
          bbear_disturb,
          bbear_linear_nat,
          bbear_poly_nat)

```

```
## Model selection table
```

```
##          (Int) scl(lc_brd) scl(lc_grs) scl(lc_mxd) scl(lc_shr)
## bbear_linear      -1.792
## bbear_energy      -1.771
## bbear_linear_energy -1.767
## bbear_disturb     -1.798
## bbear_linear_nat  -1.791      -0.02568
## bbear_poly_energy -1.668
## bbear_nat         -1.685      0.19290      0.3349      -0.04131      0.23840
## bbear_rds         -1.673
## bbear_null        -1.647
## bbear_poly        -1.668
## bbear_ag          -1.647
## bbear_harvest     -1.649
## bbear_poly_nat    -1.676      0.02292
##          scl(hrv_2000) scl(hrv_p20) scl(lc_agr) scl(rds) scl(pp1)
## bbear_linear              -0.2317
## bbear_energy              -0.04520
## bbear_linear_energy       -0.09015
## bbear_disturb      0.05118      -0.119000      -0.1842
## bbear_linear_nat              -0.2489

```

```
## bbear_poly_energy
## bbear_nat
## bbear_rds -0.2261
## bbear_null
## bbear_poly 0.07682 -0.044020
## bbear_ag 0.0319
## bbear_harvest 0.10080 0.000408
## bbear_poly_nat 0.01609 -0.111600
## scl(ssm_lns) scl(wll) df logLik AICc delta weight
## bbear_linear -0.5193 3 -124.146 254.7 0.00 0.540
## bbear_energy -0.4650 -0.2065 4 -124.275 257.3 2.56 0.150
## bbear_linear_energy -0.5114 3 -125.708 257.9 3.12 0.113
## bbear_disturb -0.5222 -0.1865 6 -122.227 258.1 3.34 0.102
## bbear_linear_nat -0.5225 5 -124.072 259.3 4.55 0.056
## bbear_poly_energy -0.2715 2 -128.686 261.6 6.86 0.018
## bbear_nat 5 -126.031 263.2 8.47 0.008
## bbear_rds 2 -129.719 263.7 8.92 0.006
## bbear_null 1 -131.465 265.0 10.27 0.003
## bbear_poly -0.2731 4 -128.218 265.2 10.45 0.003
## bbear_ag 2 -131.414 267.0 12.31 0.001
## bbear_harvest 3 -130.932 268.3 13.57 0.001
## bbear_poly_nat -0.2943 6 -127.818 269.3 14.52 0.000
## Models ranked by AICc(x)
```

The model with linear features (roads and seismic lines) was best fit, similar to unofficial OSM results I got in the scale analysis for black bears

Top model/s summary

```
# linear
summary(bbear_linear)

##
## Call:
## glm(formula = cbind(black_bear, absent_black_bear) ~ scale(roads) +
##     scale(seismic_lines), family = "binomial", data = prop_det_data$'250 meter buffer')
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -1.7919    0.1175 -15.251  < 2e-16 ***
## scale(roads)   -0.2317    0.1270  -1.825  0.06807 .
## scale(seismic_lines) -0.5193    0.1803  -2.880  0.00398 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 162.60 on 58 degrees of freedom
## Residual deviance: 147.96 on 56 degrees of freedom
## (1 observation deleted due to missingness)
## AIC: 254.29
##
## Number of Fisher Scoring iterations: 5
```

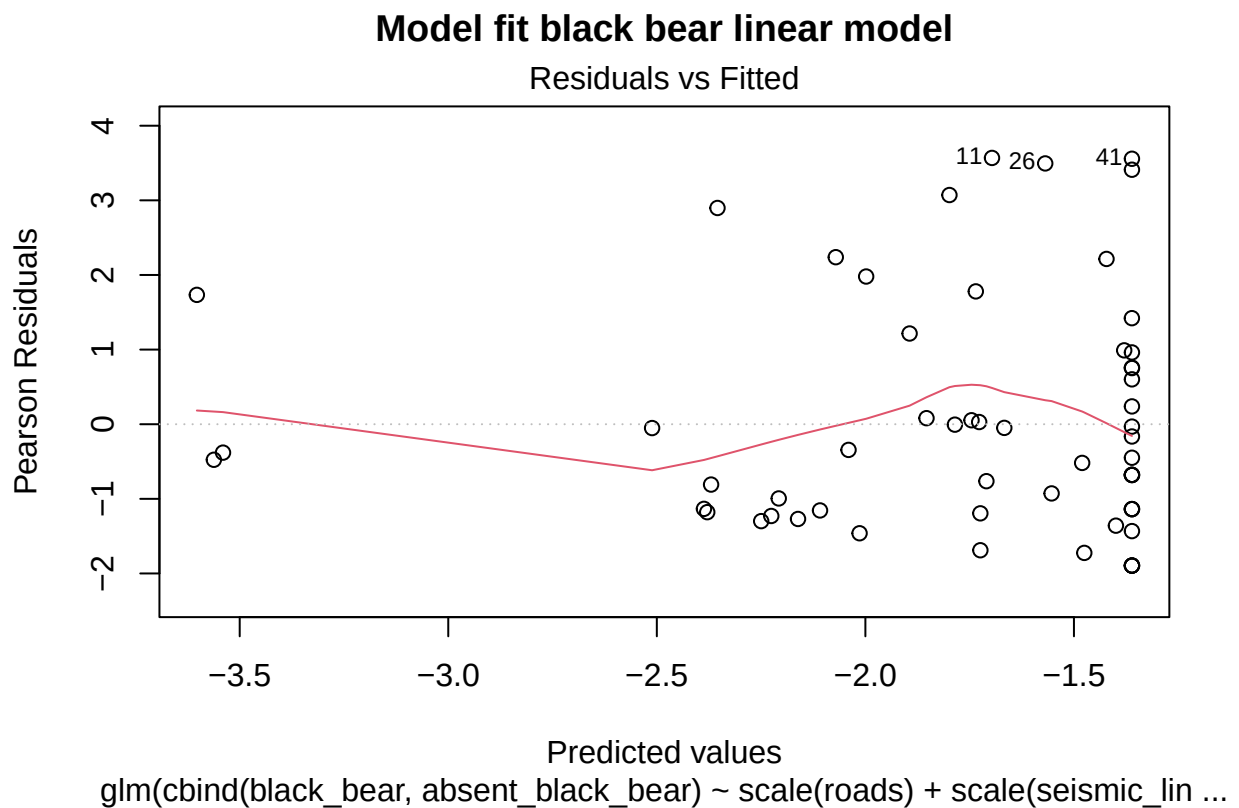
Model fit

We will start with VIF

```
vif(bbear_linear)
```

```
##          scale(roads) scale(seismic_lines)
##          1.000006      1.000006
```

```
plot(bbear_linear,
      which = 1,
      main = 'Model fit black bear linear model')
```



```
# calculate vif
vif(bbear_linear) %>%
```

```
  # 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 (not sure I want like
                        y = VIF)) +
```

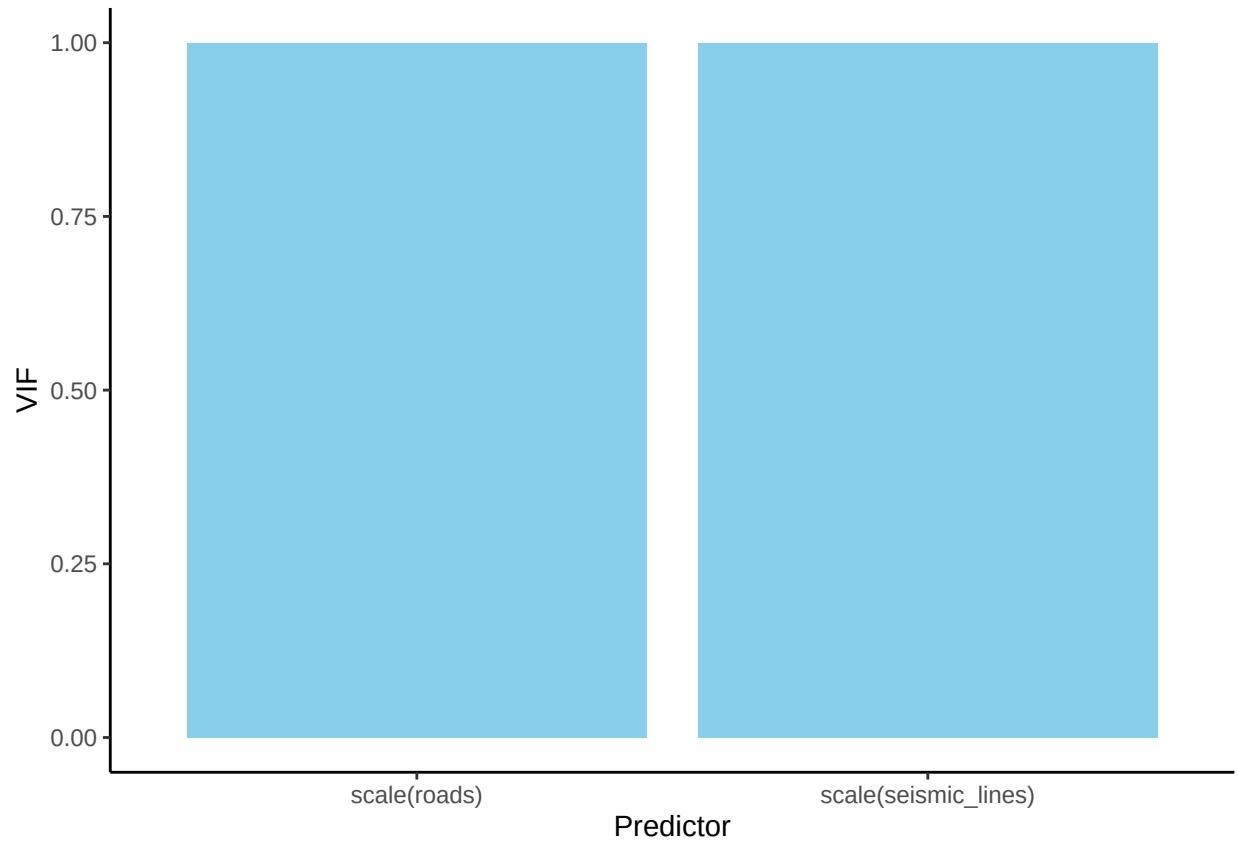
```
  # plot as bars
```

```
  geom_bar(stat = 'identity', fill = 'skyblue') +
```

```
  # add labels
```

```
labs(x = 'Predictor',
     y = 'VIF') +
```

```
# set theme
theme_classic()
```



Coyote

The top buffer for coyote was 5000m, other similarly performing buffers were around same size 4750, 4500

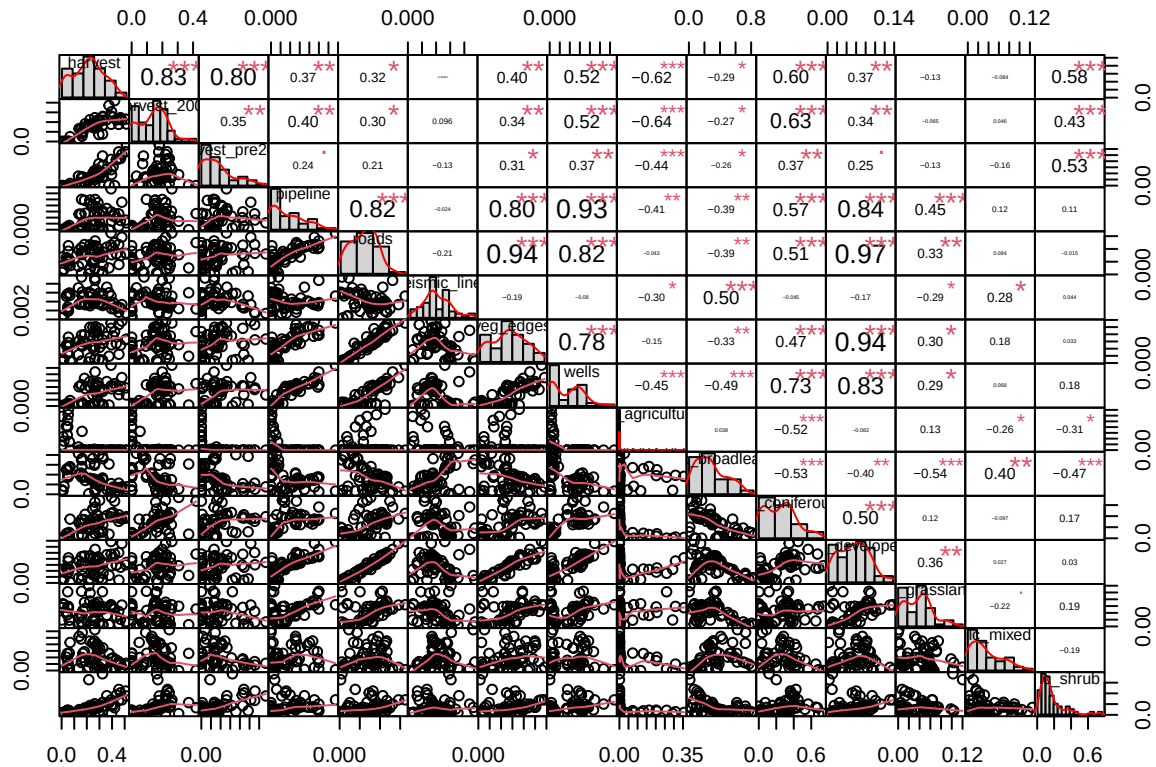
Correlation plot

```
# # open file to save plot
# png("figures/corr_plot_5000.png",
#     width = 1000,
#     height = 800)
```

```
prop_det_data$`5000 meter buffer` %>%
```

```
# select only columns with covariates not other info to simplify the plot a bit
select(harvest:lc_shrub) %>%
```

```
# use chart.correlation to produce plots for each buffer size
chart.Correlation(.,
  histogram = TRUE,
  method = "pearson")
```



```
# # close file
# dev.off()
```

Models

```
# Null model
coyote_null <- glm(cbind(coyote, absent_coyote) ~ 1,
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# Natural heterogeneity
coyote_nat <- glm(cbind(coyote, absent_coyote) ~
  scale(lc_broadleaf) +
  scale(lc_grassland) +
  scale(lc_mixed) +
  scale(lc_shrub),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# forest harvest
```

```

coyote_harvest <- glm(cbind(coyote, absent_coyote) ~
  scale(harvest_2000) +
  scale(harvest_pre2000),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# agriculture
coyote_ag <- glm(cbind(coyote, absent_coyote) ~
  scale(lc_agriculture),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# transportation (roads) * at 5000m buffer can't combine with other industrial features (correlated with
coyote_rds <- glm(cbind(coyote, absent_coyote) ~
  scale(roads),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# linear energy development
coyote_linear_energy <- glm(cbind(coyote, absent_coyote) ~
  scale(pipeline) +
  scale(seismic_lines),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# polygonal energy development
coyote_poly_energy <- glm(cbind(coyote, absent_coyote) ~
  scale(wells),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# energy development - can't do at 5000 pipeline and wells correlated and other two variables are already
# coyote_energy <- glm(cbind(coyote, absent_coyote) ~
#   scale(pipeline) +
#   scale(seismic_lines) +
#   scale(wells),
#   data = prop_det_data$`5000 meter buffer`,
#   family = 'binomial')

# polygonal disturbance (harvest + polygonal energy development)
coyote_poly <- glm(cbind(coyote, absent_coyote) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  scale(wells),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# linear disturbance (transportation + linear energy development)
coyote_linear <- glm(cbind(coyote, absent_coyote) ~
  scale(roads) +

```

```

      # pipeline + can't include correlated w/ roads
      scale(seismic_lines),
      data = prop_det_data$`5000 meter buffer`,
      family = 'binomial')

# overall human disturbance (can't include pipeline or wells which are correlated with roads)
coyote_disturb <- glm(cbind(coyote, absent_coyote) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  scale(roads) +
  scale(seismic_lines),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# linear + habitat
coyote_linear_nat <- glm(cbind(coyote, absent_coyote) ~
  scale(roads) +
  scale(seismic_lines) +
  scale(lc_broadleaf) +
  scale(lc_grassland),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# polygonal + habitat
coyote_poly_nat <- glm(cbind(coyote, absent_coyote) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  scale(wells) +
  scale(lc_broadleaf) +
  scale(lc_grassland),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

```

Conifer model performed better - will use conifer instead of broadleaf for now

Model selection

```

# compare coyote models
model.sel(coyote_null,
  coyote_nat,
  coyote_harvest,
  coyote_ag,
  coyote_rds,
  coyote_linear_energy,
  coyote_poly_energy,
  coyote_poly,
  coyote_linear,
  coyote_disturb,
  coyote_linear_nat,
  coyote_poly_nat)

## Model selection table
##               (Int) scl(lc_brd) scl(lc_grs) scl(lc_mxd) scl(lc_shr)

```

```

## coyote_disturb      -2.053
## coyote_ag           -1.919
## coyote_poly         -1.984
## coyote_harvest      -1.954
## coyote_poly_nat     -1.977   -0.10280   -0.02923
## coyote_nat          -1.926   -0.06812    0.15490    0.01279    -0.582
## coyote_poly_energy  -1.831
## coyote_null         -1.825
## coyote_rds          -1.839
## coyote_linear_energy -1.826
## coyote_linear_nat   -1.867    0.26790    0.21630
## coyote_linear       -1.841
##                    scl(hrv_2000) scl(hrv_p20) scl(lc_agr) scl(rds) scl(pp1)
## coyote_disturb      -0.5657    -0.4061                0.4584
## coyote_ag           -0.5073    -0.4199                0.5285
## coyote_poly         -0.3749    -0.3868
## coyote_harvest      -0.5106    -0.4223
## coyote_nat
## coyote_poly_energy
## coyote_null
## coyote_rds                0.1109
## coyote_linear_energy                -0.165
## coyote_linear_nat                0.1276
## coyote_linear                0.1040
##                    scl(ssm_lns) scl(wll) df    logLik  AICc  delta  weight
## coyote_disturb      0.02096                5 -134.611  280.4  0.00  0.957
## coyote_ag           0.2148                2 -141.478  287.2  6.82  0.032
## coyote_poly         0.1872                4 -140.927  290.6 10.24  0.006
## coyote_harvest      -0.2463                3 -142.309  291.1 10.70  0.005
## coyote_poly_nat     -0.2463                6 -140.607  294.8 14.48  0.001
## coyote_nat          -0.2463                5 -153.055  317.2 36.89  0.000
## coyote_poly_energy  -0.2463                2 -159.055  322.3 41.97  0.000
## coyote_null         -0.2463                1 -162.221  326.5 46.16  0.000
## coyote_rds          -0.2463                2 -161.565  327.3 46.99  0.000
## coyote_linear_energy -0.06554                3 -160.536  327.5 47.15  0.000
## coyote_linear_nat   -0.11490                5 -158.589  328.3 47.96  0.000
## coyote_linear       -0.05422                3 -161.421  329.3 48.92  0.000
## Models ranked by AICc(x)

```

Top model summary

```
summary(coyote_disturb)
```

```

##
## Call:
## glm(formula = cbind(coyote, absent_coyote) ~ scale(harvest_2000) +
##     scale(harvest_pre2000) + scale(roads) + scale(seismic_lines),
##     family = "binomial", data = prop_det_data$'5000 meter buffer')
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -2.05325    0.11548  -17.781  < 2e-16 ***
## scale(harvest_2000) -0.56572    0.13603   -4.159  3.2e-05 ***

```

```
## scale(harvest_pre2000) -0.40614    0.14141  -2.872 0.004078 **
## scale(roads)           0.45843    0.12048   3.805 0.000142 ***
## scale(seismic_lines)   0.02096    0.10330   0.203 0.839211
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 228.68  on 58  degrees of freedom
## Residual deviance: 173.46  on 54  degrees of freedom
## (1 observation deleted due to missingness)
## AIC: 279.22
##
## Number of Fisher Scoring iterations: 5
```

Model assumptions and fit

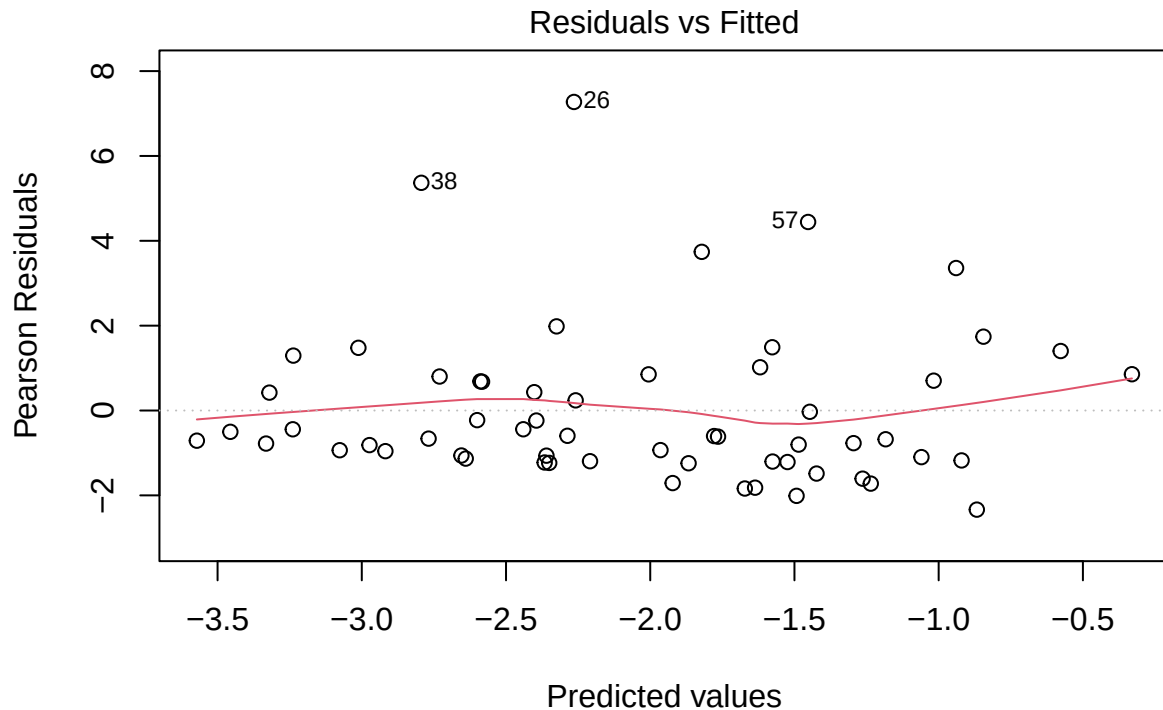
VIF

```
# report VIF
vif(coyote_disturb)
```

```
##      scale(harvest_2000) scale(harvest_pre2000)      scale(roads)
##              1.742479              1.411446              1.319502
##      scale(seismic_lines)
##              1.046699
```

```
# plot VIF
plot(coyote_disturb,
      which = 1,
      main = 'Model fit coyote disturbance model')
```

Model fit coyote disturbance model



`glm(cbind(coyote, absent_coyote) ~ scale(harvest_2000) + scale(harvest_pre2 ...`

```
# additional plot of each variable
# calculate vif
vif(coyote_disturb) %>%

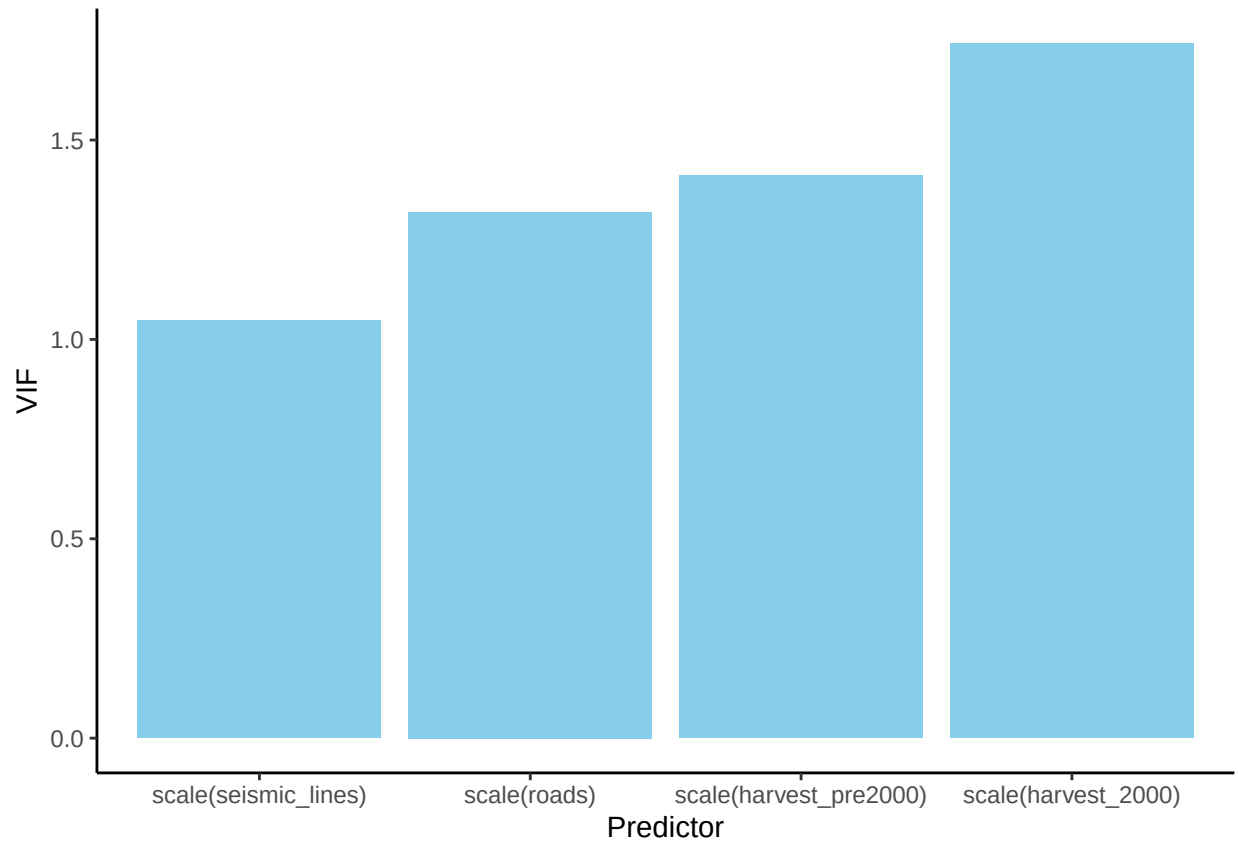
  # Converts the named vector returned by vif() into a tidy tibble
  enframe(name = 'Predictor',
           value = 'VIF') %>%

  # plot with ggplot
  ggplot(aes(x = reorder(Predictor, VIF), # reorders from smallest VIF to largest (not sure I want like
                        y = VIF)) +

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

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

  # set theme
  theme_classic()
```

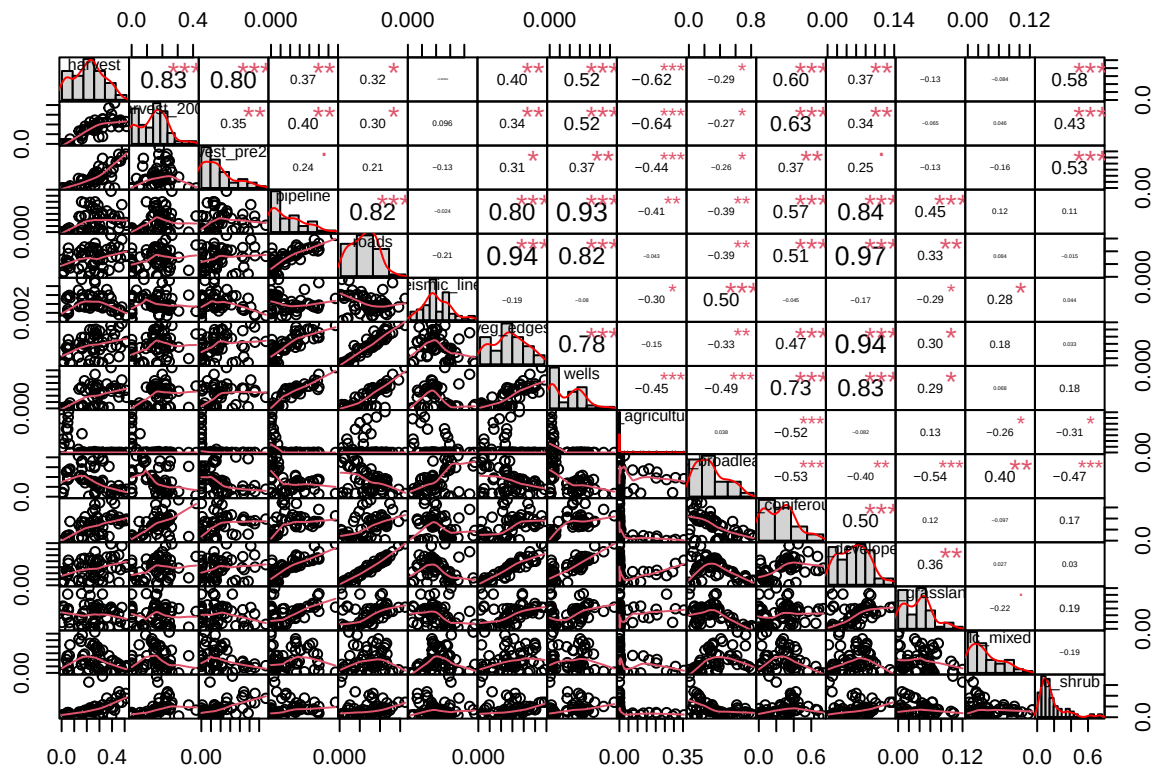


Grey wolf

Correlation plot

The 5000m buffer was also the best fit for grey wolf

```
prop_det_data$`5000 meter buffer` %>%  
  
  # select only columns with covariates not other info to simplify the plot a bit  
  select(harvest:lc_shrub) %>%  
  
  # use chart.correlation to produce plots for each buffer size  
  chart.Correlation(.,  
    histogram = TRUE,  
    method = "pearson")
```



Models

```
# Null model
grey_wolf_null <- glm(cbind(grey_wolf, absent_grey_wolf) ~ 1,
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# Natural heterogeneity
grey_wolf_nat <- glm(cbind(grey_wolf, absent_grey_wolf) ~
  scale(lc_broadleaf) +
  scale(lc_grassland) +
  scale(lc_mixed) +
  scale(lc_shrub),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# forest harvest (TBD how this will look with yearly harvest data)
grey_wolf_harvest <- glm(cbind(grey_wolf, absent_grey_wolf) ~
  scale(harvest_2000) +
  scale(harvest_pre2000),
  data = prop_det_data$`5000 meter buffer`,
  family = 'binomial')

# agriculture
grey_wolf_ag <- glm(cbind(grey_wolf, absent_grey_wolf) ~
```

```

        scale(lc_agriculture),
        data = prop_det_data$`5000 meter buffer`,
        family = 'binomial')

# transportation (roads) * at 5000m buffer can't combine with other industrial features (correlated with
grey_wolf_rds <- glm(cbind(grey_wolf, absent_grey_wolf) ~
        scale(roads),
        data = prop_det_data$`5000 meter buffer`,
        family = 'binomial')

# linear energy development
grey_wolf_linear_energy <- glm(cbind(grey_wolf, absent_grey_wolf) ~
        scale(pipeline) +
        scale(seismic_lines),
        data = prop_det_data$`5000 meter buffer`,
        family = 'binomial')

# polygonal energy development
grey_wolf_poly_energy <- glm(cbind(grey_wolf, absent_grey_wolf) ~
        scale(wells),
        data = prop_det_data$`5000 meter buffer`,
        family = 'binomial')

# polygonal disturbance (harvest + polygonal energy development)
grey_wolf_poly <- glm(cbind(grey_wolf, absent_grey_wolf) ~
        scale(harvest_2000) +
        scale(harvest_pre2000) +
        scale(wells),
        data = prop_det_data$`5000 meter buffer`,
        family = 'binomial')

# linear disturbance (transportation + linear energy development)
grey_wolf_linear <- glm(cbind(grey_wolf, absent_grey_wolf) ~
        scale(roads) +
        # pipeline + can't include correlated w/ roads 0.82
        scale(seismic_lines),
        data = prop_det_data$`5000 meter buffer`,
        family = 'binomial')

# overall human disturbance
grey_wolf_disturb <- glm(cbind(grey_wolf, absent_grey_wolf) ~
        scale(harvest_2000) +
        scale(harvest_pre2000) +
        scale(roads) +
        # pipeline + can't include correlated w/ roads 0.82
        scale(seismic_lines),
        # wells can't include correlated w/ roads 0.82
        data = prop_det_data$`5000 meter buffer`,
        family = 'binomial')

```

```

# linear + natural (have to pick max of 5 variables) based on the detections per habitat type I chose sh
grey_wolf_linear_nat <- glm(cbind(grey_wolf, absent_grey_wolf) ~
                           scale(roads) +
                           scale(seismic_lines) +
                           scale(lc_mixed) +
                           scale(lc_shrub),
                           data = prop_det_data$`5000 meter buffer`,
                           family = 'binomial')

# polygonal and natural
grey_wolf_poly_nat <- glm(cbind(grey_wolf, absent_grey_wolf) ~
                          scale(harvest_2000) +
                          scale(harvest_pre2000) +
                          scale(wells) +
                          scale(lc_mixed) +
                          scale(lc_shrub),
                          data = prop_det_data$`5000 meter buffer`,
                          family = 'binomial')

```

Model selection

```

grey_wolf_model_sel <- model.sel(grey_wolf_null,
                                grey_wolf_nat,
                                grey_wolf_harvest,
                                grey_wolf_ag,
                                grey_wolf_rds,
                                grey_wolf_linear_energy,
                                grey_wolf_poly_energy,
                                grey_wolf_poly,
                                grey_wolf_linear,
                                grey_wolf_disturb,
                                grey_wolf_linear_nat,
                                grey_wolf_poly_nat)

grey_wolf_model_sel

## Model selection table
##              (Int) scl(lc_brd) scl(lc_grs) scl(lc_mxd) scl(lc_shr)
## grey_wolf_linear_nat -3.099          0.5112    0.004006
## grey_wolf_nat        -3.081    -0.1118    0.1436    0.6176    -0.068240
## grey_wolf_poly_nat   -3.067          0.5435    -0.015630
## grey_wolf_linear     -2.963
## grey_wolf_null       -2.916
## grey_wolf_linear_energy -2.955
## grey_wolf_rds        -2.923
## grey_wolf_poly_energy -2.922
## grey_wolf_ag         -2.917
## grey_wolf_harvest    -2.922
## grey_wolf_disturb    -2.967
## grey_wolf_poly       -2.929
##              scl(hrv_2000) scl(hrv_p20) scl(lc_agr) scl(rds)
## grey_wolf_linear_nat          0.14130
## grey_wolf_nat

```

```
## grey_wolf_poly_nat          0.08115      -0.06951
## grey_wolf_linear                                0.12330
## grey_wolf_null
## grey_wolf_linear_energy
## grey_wolf_rds                                0.06416
## grey_wolf_poly_energy
## grey_wolf_ag                                -0.0497
## grey_wolf_harvest          0.11420      -0.18080
## grey_wolf_disturb          0.05663      -0.15660          0.12720
## grey_wolf_poly          0.07452      -0.19860
##          scl(ppl) scl(ssm_lns) scl(wll) df  logLik  AICc delta
## grey_wolf_linear_nat          0.2647          5 -78.579 168.3  0.00
## grey_wolf_nat          5 -78.914 169.0  0.67
## grey_wolf_poly_nat          0.03287          6 -79.515 172.6  4.35
## grey_wolf_linear          0.3224          3 -84.990 176.4  8.13
## grey_wolf_null          1 -87.377 176.8  8.53
## grey_wolf_linear_energy  0.06974          0.2980          3 -85.211 176.9  8.57
## grey_wolf_rds          2 -87.287 178.8 10.50
## grey_wolf_poly_energy          0.05922          2 -87.296 178.8 10.52
## grey_wolf_ag          2 -87.329 178.9 10.58
## grey_wolf_harvest          3 -86.690 179.8 11.53
## grey_wolf_disturb          0.3038          5 -84.596 180.3 12.03
## grey_wolf_poly          0.08209          4 -86.583 181.9 13.62
##          weight
## grey_wolf_linear_nat    0.527
## grey_wolf_nat          0.377
## grey_wolf_poly_nat      0.060
## grey_wolf_linear        0.009
## grey_wolf_null          0.007
## grey_wolf_linear_energy  0.007
## grey_wolf_rds           0.003
## grey_wolf_poly_energy    0.003
## grey_wolf_ag            0.003
## grey_wolf_harvest        0.002
## grey_wolf_disturb        0.001
## grey_wolf_poly          0.001
## Models ranked by AICc(x)
```

Whether linear natural or just natural comes up as the ‘top model’ is very dependent on which landcover variables you include for linear natural. I’d say the driving force is mostly from mixed forest

Format to word doc

Top model summary

```
# summary(grey_wolf_nat)

summary(grey_wolf_linear_nat)
```

```
##
## Call:
## glm(formula = cbind(grey_wolf, absent_grey_wolf) ~ scale(roads) +
##       scale(seismic_lines) + scale(lc_mixed) + scale(lc_shrub),
```

```
##      family = "binomial", data = prop_det_data$'5000 meter buffer')
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -3.098974   0.176665 -17.542 < 2e-16 ***
## scale(roads)     0.141322   0.179285   0.788 0.430550
## scale(seismic_lines) 0.264687   0.176907   1.496 0.134603
## scale(lc_mixed)   0.511205   0.146789   3.483 0.000497 ***
## scale(lc_shrub)   0.004006   0.240727   0.017 0.986722
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 124.78  on 58  degrees of freedom
## Residual deviance: 107.18  on 54  degrees of freedom
##      (1 observation deleted due to missingness)
## AIC: 167.16
##
## Number of Fisher Scoring iterations: 5
```

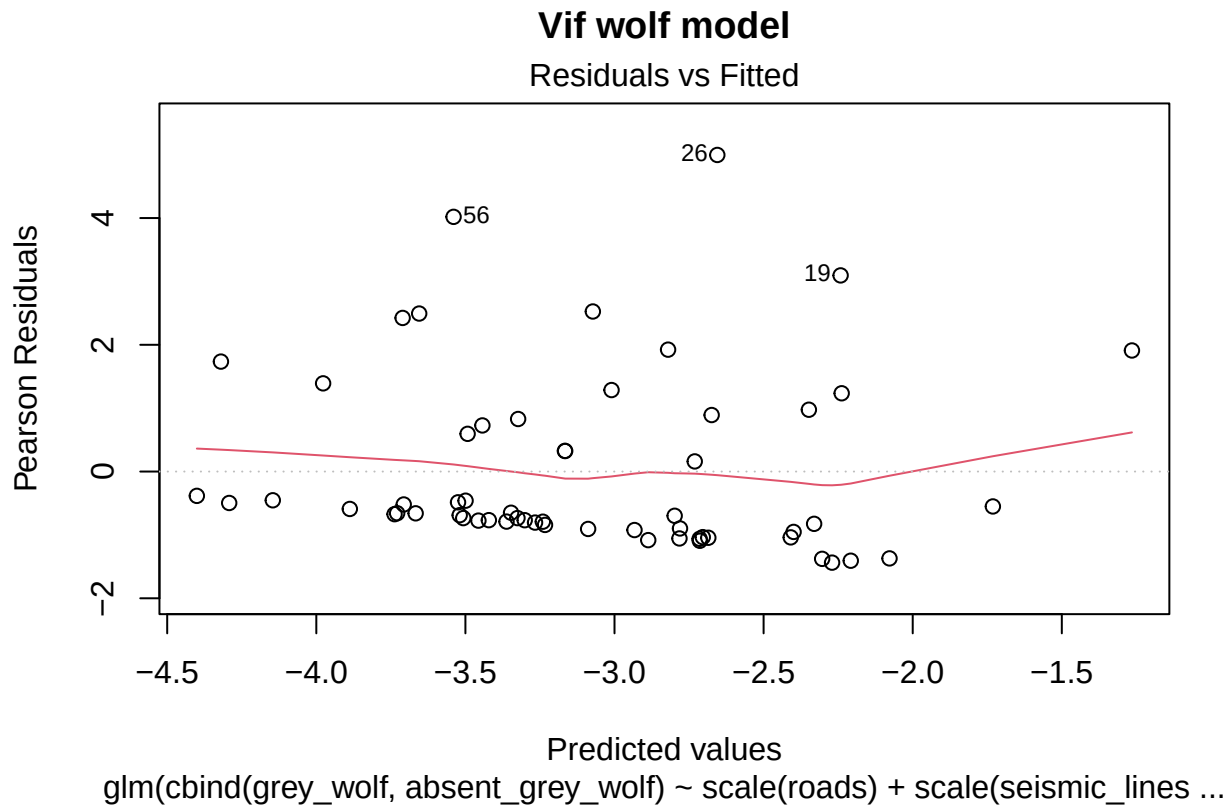
Model Assumptions and fit

VIF

```
# report VIF
vif(grey_wolf_linear_nat)
```

```
##          scale(roads) scale(seismic_lines)      scale(lc_mixed)
##          1.217899      1.207234          1.106791
##          scale(lc_shrub)
##          1.132095
```

```
# plot VIF
plot(grey_wolf_linear_nat,
     which = 1,
     main = 'Vif wolf model')
```



```
# additional plot of each variable
# calculate vif
vif(grey_wolf_nat) %>%

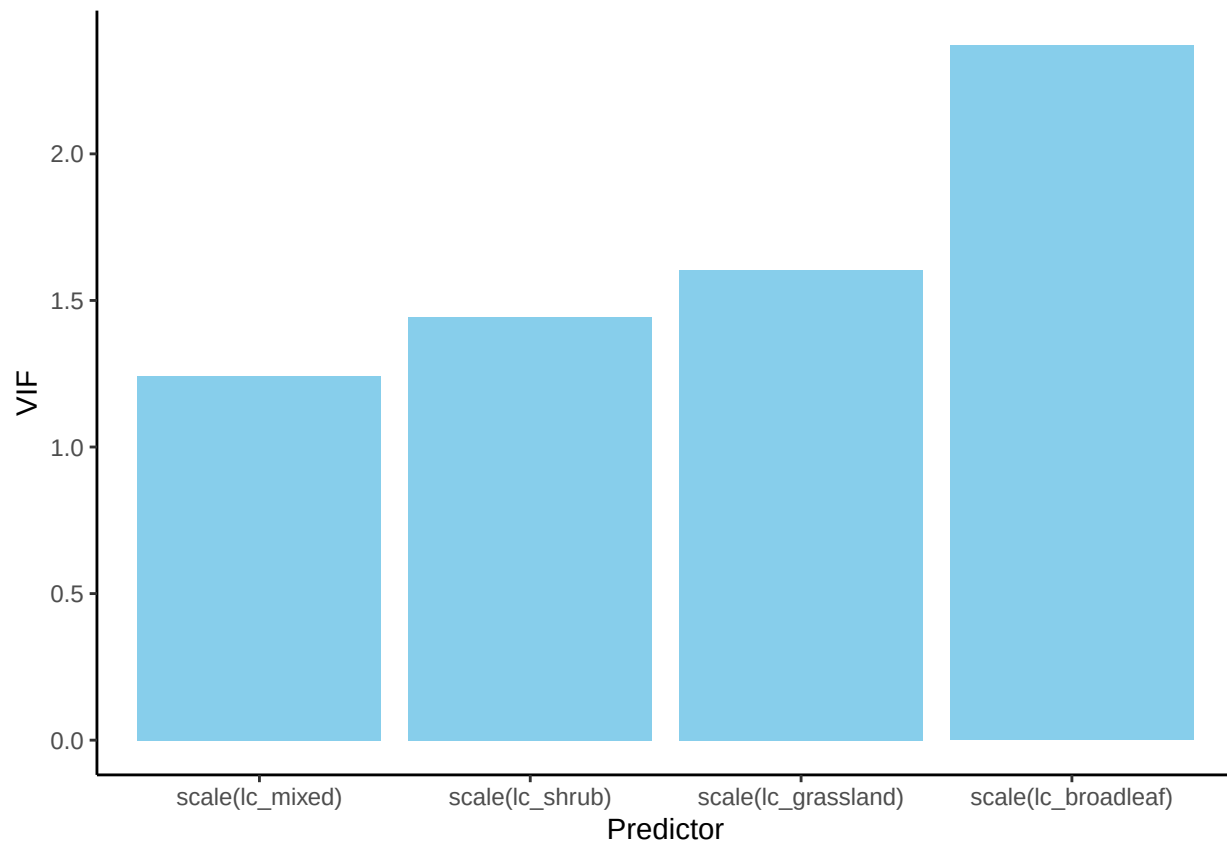
  # Converts the named vector returned by vif() into a tidy tibble
  enframe(name = 'Predictor',
           value = 'VIF') %>%

  # plot with ggplot
  ggplot(aes(x = reorder(Predictor, VIF), # reorders from smallest VIF to largest (not sure I want like
                        y = VIF)) +

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

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

  # set theme
  theme_classic()
```



```
# additional plot of each variable from the just nat model
# calculate vif
vif(grey_wolf_nat) %>%

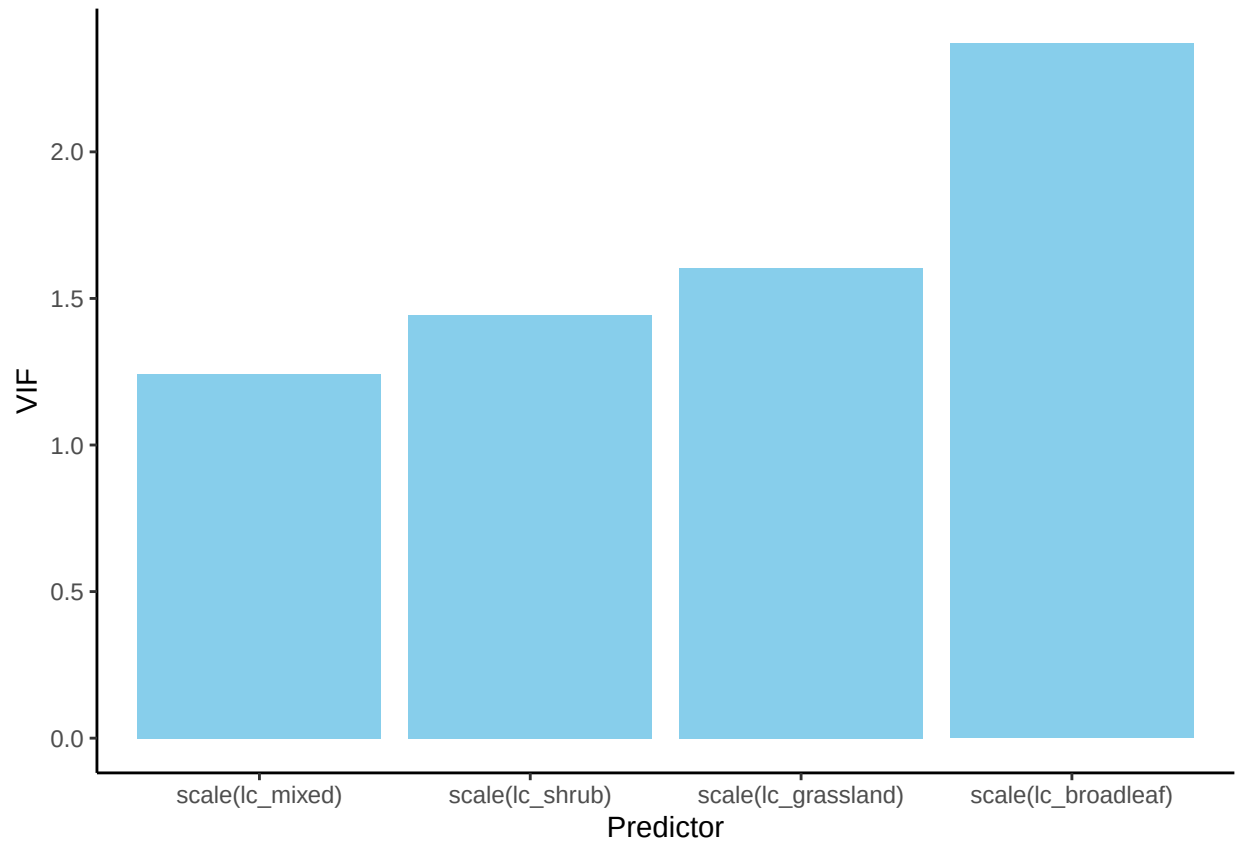
  # Converts the named vector returned by vif() into a tidy tibble
  enframe(name = 'Predictor',
           value = 'VIF') %>%

  # plot with ggplot
  ggplot(aes(x = reorder(Predictor, VIF), # reorders from smallest VIF to largest (not sure I want like
                        y = VIF)) +

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

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

  # set theme
  theme_classic()
```



Lynx

The best lynx buffer size was the 500m buffer

Correlation plot

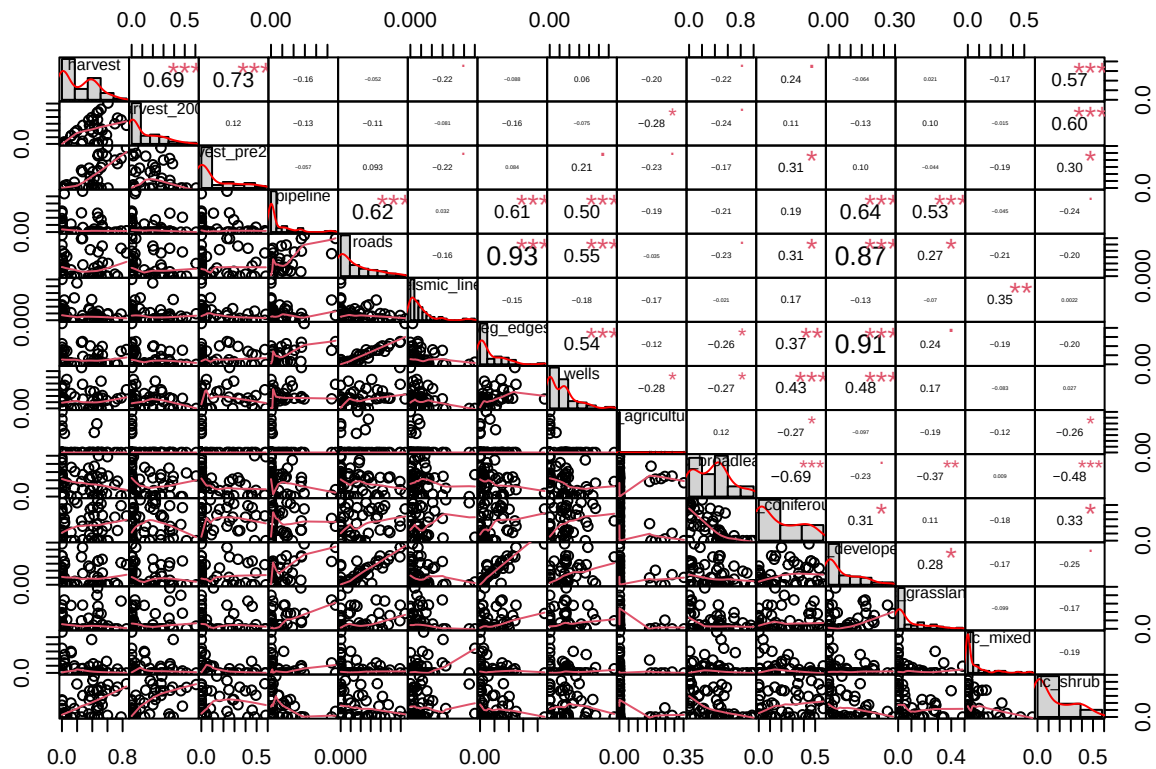
Let's print the correlation plot for the 500m buffer again here for reference when developing the lynx specific models

```
# # open file to save plot
# png("figures/corr_plot_500.png",
#     width = 1000,
#     height = 800)

prop_det_data$`500 meter buffer` %>%

  # select only columns with covariates not other info to simplify the plot a bit
  select(harvest:lc_shrub) %>%

  # use chart.correlation to produce plots for each buffer size
  chart.Correlation(.,
    histogram = TRUE,
    method = "pearson")
```



```
## close file
# dev.off()
```

Models

```
# Null model
lynx_null <- glm(cbind(lynx, absent_lynx) ~ 1,
  data = prop_det_data$`500 meter buffer`,
  family = 'binomial')

# Natural heterogeneity
lynx_nat <- glm(cbind(lynx, absent_lynx) ~
  scale(lc_broadleaf) +
  scale(lc_grassland) +
  scale(lc_mixed) +
  scale(lc_shrub),
  data = prop_det_data$`500 meter buffer`,
  family = 'binomial')

# forest harvest (TBD how this will look with yearly harvest data)
lynx_harvest <- glm(cbind(lynx, absent_lynx) ~
  scale(harvest_2000) +
  scale(harvest_pre2000),
  data = prop_det_data$`500 meter buffer`,
  family = 'binomial')
```

```

# agriculture
lynx_ag <- glm(cbind(lynx, absent_lynx) ~
               scale(lc_agriculture),
               data = prop_det_data$`500 meter buffer`,
               family = 'binomial')

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

# transportation (roads) * at 5000m buffer can't combine with other industrial features (correlated with
lynx_rds <- glm(cbind(lynx, absent_lynx) ~
               scale(roads),
               data = prop_det_data$`500 meter buffer`,
               family = 'binomial')

# linear energy development
lynx_linear_energy <- glm(cbind(lynx, absent_lynx) ~
                          scale(pipeline) +
                          scale(seismic_lines),
                          data = prop_det_data$`500 meter buffer`,
                          family = 'binomial')

# polygonal energy development
lynx_poly_energy <- glm(cbind(lynx, absent_lynx) ~
                       scale(wells),
                       data = prop_det_data$`500 meter buffer`,
                       family = 'binomial')

# energy development - can do at this scale pipeline and well corr = 0.50
lynx_energy <- glm(cbind(lynx, absent_lynx) ~
                  scale(pipeline) +
                  scale(seismic_lines) +
                  scale(wells),
                  data = prop_det_data$`500 meter buffer`,
                  family = 'binomial')

# polygonal disturbance (harvest + polygonal energy development + agriculture)
lynx_poly <- glm(cbind(lynx, absent_lynx) ~
                scale(harvest_2000) +
                scale(harvest_pre2000) +
                scale(wells),
                data = prop_det_data$`500 meter buffer`,
                family = 'binomial')

# linear disturbance (transportation + linear energy development)
lynx_linear <- glm(cbind(lynx, absent_lynx) ~
                  scale(roads) +
                  # pipeline + can't include correlated w/ roads 0.62
                  scale(seismic_lines),
                  data = prop_det_data$`500 meter buffer`,
                  family = 'binomial')

```

```

# overall human disturbance (limit to 5 vars)
lynx_disturb <- glm(cbind(lynx, absent_lynx) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  scale(roads) +
  # pipeline + can't include correlated w/ roads 0.62
  scale(seismic_lines) +
  scale(wells),
  data = prop_det_data$`500 meter buffer`,
  family = 'binomial')

# linear + natural (have to pic max of 5) based on detections chose grassland had most detections and b
lynx_linear_nat <- glm(cbind(lynx, absent_lynx) ~
  scale(roads) +
  scale(seismic_lines) +
  scale(lc_grassland) +
  scale(lc_broadleaf),
  data = prop_det_data$`500 meter buffer`,
  family = 'binomial')

# polygonal features and nat (limit 5 vars)
lynx_poly_nat <- glm(cbind(lynx, absent_lynx) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  scale(wells) +
  scale(lc_grassland) +
  scale(lc_broadleaf),
  data = prop_det_data$`500 meter buffer`,
  family = 'binomial')

```

Model selection

```

model.sel(lynx_null,
  lynx_nat,
  lynx_harvest,
  lynx_ag,
  lynx_rds,
  lynx_energy,
  lynx_linear_energy,
  lynx_poly_energy,
  lynx_poly,
  lynx_linear,
  lynx_disturb,
  lynx_linear_nat,
  lynx_poly_nat)

## Model selection table
##               (Int) scl(lc_brd) scl(lc_grs) scl(lc_mxd) scl(lc_shr)
## lynx_poly      -3.054
## lynx_disturb    -3.088
## lynx_poly_nat   -3.077      -0.1784      -0.22260
## lynx_harvest    -2.895

```

```

## lynx_energy -2.936
## lynx_poly_energy -2.847
## lynx_nat -2.897 -0.2371 -0.03393 0.08888 0.5084
## lynx_ag -10.930
## lynx_linear_nat -2.900 -0.6166 -0.31440
## lynx_null -2.693
## lynx_linear -2.756
## lynx_linear_energy -2.756
## lynx_rds -2.694
## scl(hrv_2000) scl(hrv_p20) scl(lc_agr) scl(rds) scl(ppl)
## lynx_poly 0.5261 0.3975
## lynx_disturb 0.5356 0.4273 -0.2921000
## lynx_poly_nat 0.4882 0.3233
## lynx_harvest 0.4406 0.4906
## lynx_energy -0.528000
## lynx_poly_energy
## lynx_nat
## lynx_ag -24.13
## lynx_linear_nat 0.0005603
## lynx_null
## lynx_linear 0.0271300
## lynx_linear_energy -0.009947
## lynx_rds 0.0499000
## scl(ssm_lns) scl(wll) df logLik AICc delta weight
## lynx_poly 0.5514 4 -81.072 170.9 0.00 0.533
## lynx_disturb 0.1513 0.7173 6 -79.150 171.9 1.03 0.319
## lynx_poly_nat 0.5458 6 -79.918 173.5 2.57 0.148
## lynx_harvest 3 -89.701 185.8 14.95 0.000
## lynx_energy -0.1876 0.7485 4 -88.684 186.1 15.22 0.000
## lynx_poly_energy 0.5396 2 -93.474 191.2 20.28 0.000
## lynx_nat 5 -91.222 193.6 22.69 0.000
## lynx_ag 2 -95.695 195.6 24.72 0.000
## lynx_linear_nat -0.2650 5 -94.139 199.4 28.53 0.000
## lynx_null 1 -103.399 208.9 37.98 0.000
## lynx_linear -0.3255 3 -102.082 210.6 39.72 0.000
## lynx_linear_energy -0.3275 3 -102.100 210.6 39.75 0.000
## lynx_rds 2 -103.331 210.9 39.99 0.000
## Models ranked by AICc(x)

```

Top model/s summary

```
#summary(lynx_disturb)
```

```
summary(lynx_poly)
```

```

##
## Call:
## glm(formula = cbind(lynx, absent_lynx) ~ scale(harvest_2000) +
##     scale(harvest_pre2000) + scale(wells), family = "binomial",
##     data = prop_det_data$'500 meter buffer')
##
## Coefficients:
## Estimate Std. Error z value Pr(>|z|)
## (Intercept) -3.0538 0.1781 -17.147 < 2e-16 ***

```

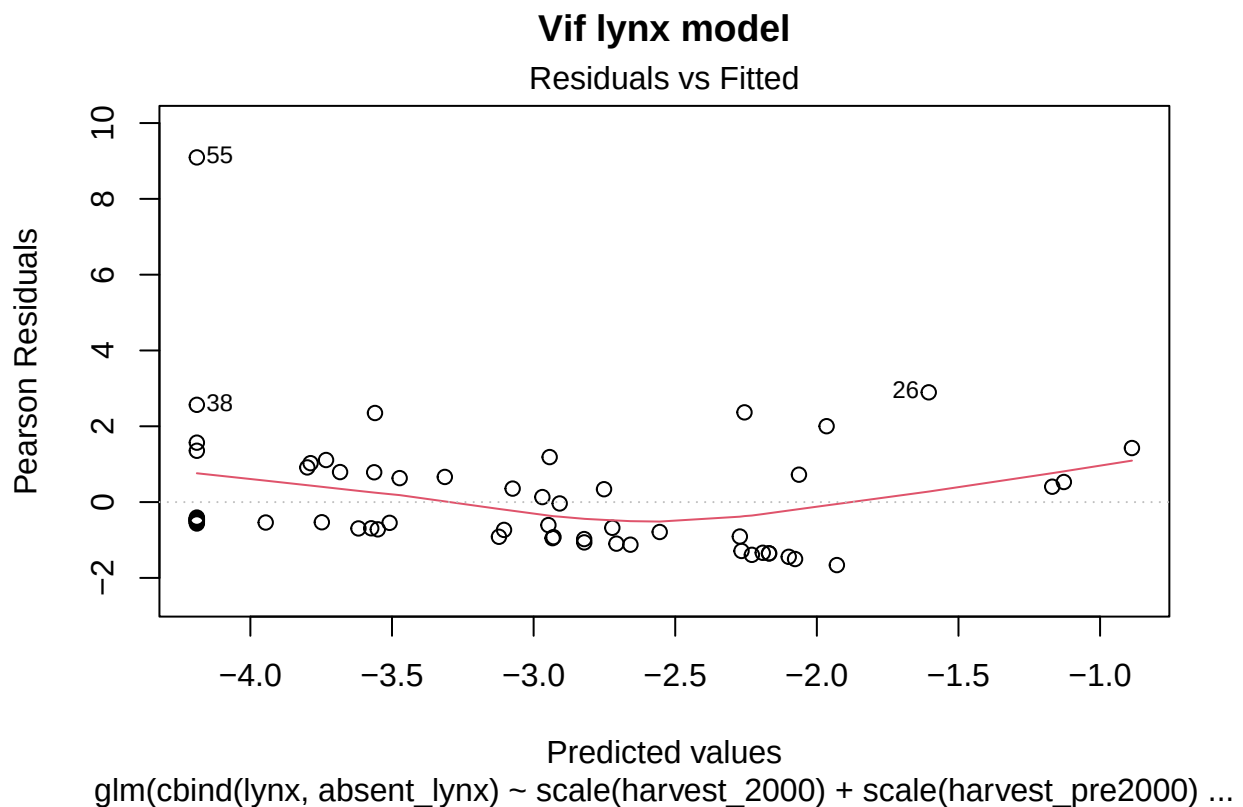
```
## scale(harvest_2000)      0.5261      0.1476      3.564 0.000366 ***
## scale(harvest_pre2000)  0.3975      0.1281      3.103 0.001919 **
## scale(wells)            0.5514      0.1292      4.268 1.97e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 150.75  on 58  degrees of freedom
## Residual deviance: 106.09  on 55  degrees of freedom
## (1 observation deleted due to missingness)
## AIC: 170.14
##
## Number of Fisher Scoring iterations: 5
```

Model assumptions and fit

```
# report VIF
vif(lynx_poly)
```

```
##      scale(harvest_2000) scale(harvest_pre2000)      scale(wells)
##                1.074548                1.036778                1.110789
```

```
# plot VIF
plot(lynx_poly,
     which = 1,
     main = 'Vif lynx model')
```



```

# additional plot of each variable
# calculate vif
vif(lynx_poly) %>%

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

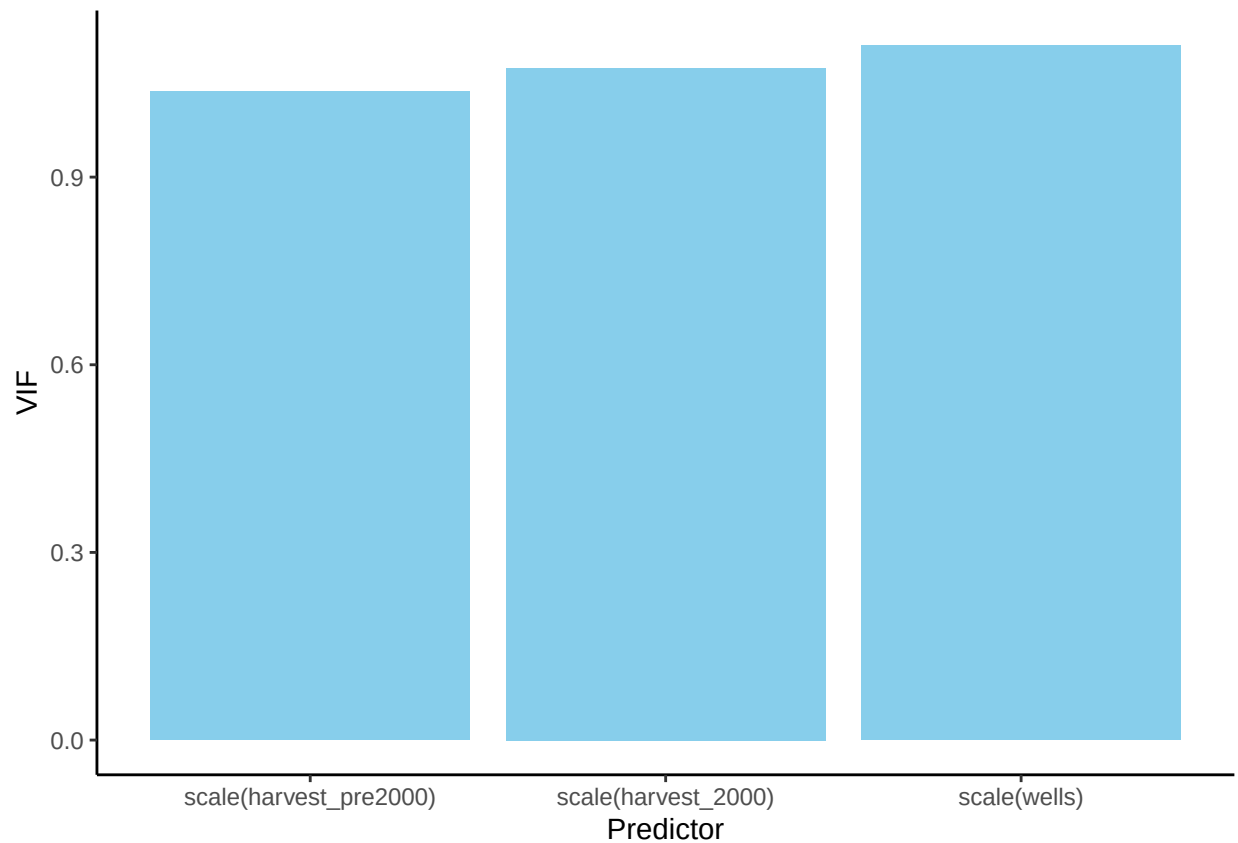
  # plot with ggplot
  ggplot(aes(x = reorder(Predictor, VIF), # reorders from smallest VIF to largest (not sure I want like
                        y = VIF)) +

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

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

  # set theme
  theme_classic()

```



Moose

500m was best fit buffer for moose

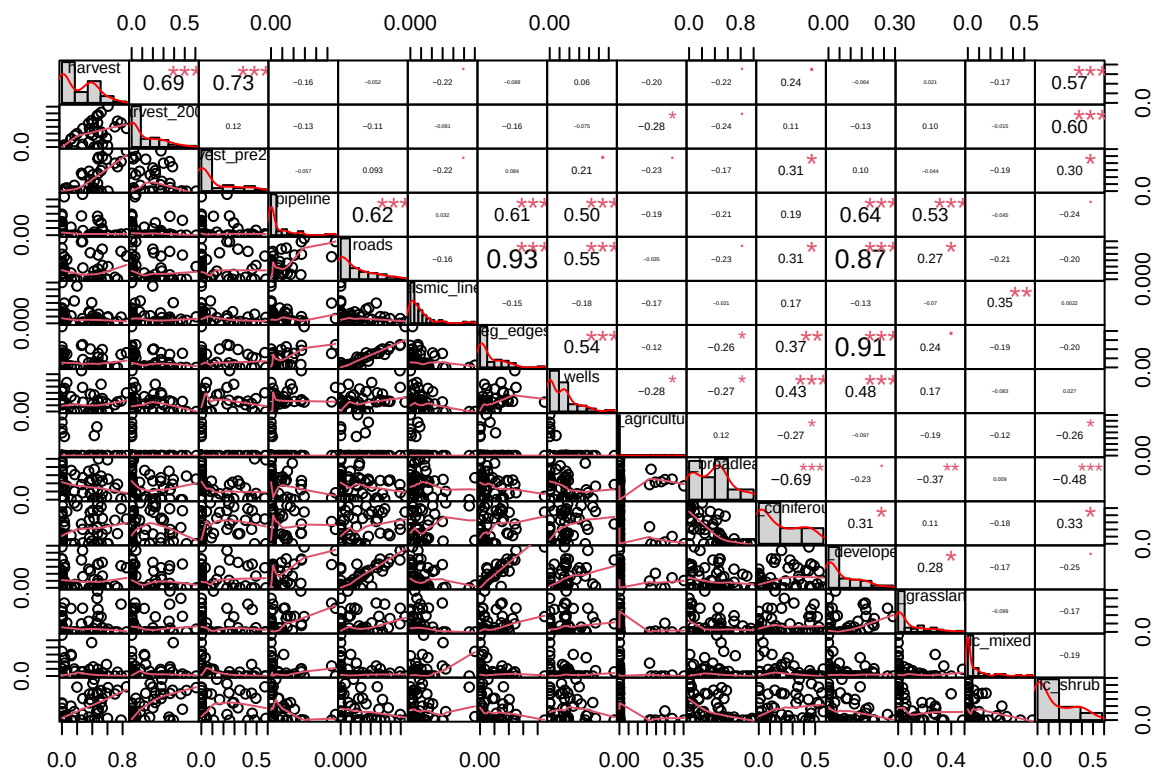
Correlation plot

Let's print the correlation plot for the 500m buffer again here for reference when developing the lynx specific models

```
prop_det_data$`500 meter buffer` %>%

# select only columns with covariates not other info to simplify the plot a bit
select(harvest:lc_shrub) %>%

# use chart.correlation to produce plots for each buffer size
chart.Correlation(.,
  histogram = TRUE,
  method = "pearson")
```



Models

```
# Null model
moose_null <- glm(cbind(moose, absent_moose) ~ 1,
  data = prop_det_data$`500 meter buffer`,
  family = 'binomial')

# Natural heterogeneity
moose_nat <- glm(cbind(moose, absent_moose) ~
  scale(lc_broadleaf) +
  scale(lc_grassland) +
  scale(lc_mixed) +
```

```

        scale(lc_shrub),
        data = prop_det_data$`500 meter buffer`,
        family = 'binomial')

# forest harvest (TBD how this will look with yearly harvest data)
moose_harvest <- glm(cbind(moose, absent_moose) ~
    scale(harvest_2000) +
    scale(harvest_pre2000),
    data = prop_det_data$`500 meter buffer`,
    family = 'binomial')

# agriculture
moose_ag <- glm(cbind(moose, absent_moose) ~
    scale(lc_agriculture),
    data = prop_det_data$`500 meter buffer`,
    family = 'binomial')

# transportation (roads) * at 5000m buffer can't combine with other industrial features (correlated with
moose_rds <- glm(cbind(moose, absent_moose) ~
    scale(roads),
    data = prop_det_data$`500 meter buffer`,
    family = 'binomial')

# linear energy development
moose_linear_energy <- glm(cbind(moose, absent_moose) ~
    scale(pipeline) +
    scale(seismic_lines),
    data = prop_det_data$`500 meter buffer`,
    family = 'binomial')

# polygonal energy development
moose_poly_energy <- glm(cbind(moose, absent_moose) ~
    scale(wells),
    data = prop_det_data$`500 meter buffer`,
    family = 'binomial')

# energy development - can do at this scale pipeline and well corr = 0.50
moose_energy <- glm(cbind(moose, absent_moose) ~
    scale(pipeline) +
    scale(seismic_lines) +
    scale(wells),
    data = prop_det_data$`500 meter buffer`,
    family = 'binomial')

# polygonal disturbance (harvest + polygonal energy development + agriculture)
moose_poly <- glm(cbind(moose, absent_moose) ~
    scale(harvest_2000) +
    scale(harvest_pre2000) +
    scale(wells),
    data = prop_det_data$`500 meter buffer`,
    family = 'binomial')

```

```

# linear disturbance (transportation + linear energy development)
moose_linear <- glm(cbind(moose, absent_moose) ~
  scale(roads) +
  # pipeline + can't include correlated w/ roads 0.62
  scale(seismic_lines),
  data = prop_det_data$`500 meter buffer`,
  family = 'binomial')

# overall human disturbance (limit to 5 vars)
moose_disturb <- glm(cbind(moose, absent_moose) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  scale(roads) +
  # pipeline + can't include correlated w/ roads 0.62
  scale(seismic_lines) +
  scale(wells),
  data = prop_det_data$`500 meter buffer`,
  family = 'binomial')

# linear + natural (have to pic max of 5) based on detections (most and least)
moose_linear_nat <- glm(cbind(moose, absent_moose) ~
  scale(roads) +
  # pipeline + can't include correlated w/ roads 0.62
  scale(seismic_lines) +
  scale(lc_broadleaf) +
  scale(lc_shrub),
  data = prop_det_data$`500 meter buffer`,
  family = 'binomial')

# polygonal features and nat (limit 5 vars)
moose_poly_nat <- glm(cbind(moose, absent_moose) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  scale(wells) +
  scale(lc_broadleaf) +
  scale(lc_shrub),
  data = prop_det_data$`500 meter buffer`,
  family = 'binomial')

```

Model selection

```

model.sel(moose_null,
  moose_nat,
  moose_harvest,
  moose_ag,
  moose_rds,
  moose_energy,
  moose_linear_energy,
  moose_poly_energy,

```

```

    moose_poly,
    moose_linear,
    moose_disturb,
    moose_linear_nat,
    moose_poly_nat)

## Model selection table
##              (Int) scl(lc_brd) scl(lc_grs) scl(lc_mxd) scl(lc_shr)
## moose_disturb    -1.125
## moose_linear      -1.127
## moose_linear_nat  -1.138      0.1878                0.14330
## moose_rds         -1.088
## moose_nat         -1.057      0.5851      0.36      0.2408      0.52700
## moose_poly        -1.042
## moose_poly_nat    -1.049      0.1905                0.09757
## moose_energy      -1.071
## moose_poly_energy -1.031
## moose_linear_energy -1.064
## moose_harvest     -1.014
## moose_null        -1.012
## moose_ag          -1.013
##              scl(hrv_2000) scl(hrv_p20) scl(lc_agr) scl(rds) scl(pp1)
## moose_disturb          0.1131      0.1206                -0.4982
## moose_linear                -0.6126
## moose_linear_nat          -0.5550
## moose_rds                  -0.5935
## moose_nat
## moose_poly          0.1611      0.1882
## moose_poly_nat      0.1409      0.1679
## moose_energy                -0.2275
## moose_poly_energy
## moose_linear_energy          -0.4117
## moose_harvest          0.1691      0.1107
## moose_null
## moose_ag                -0.1023
##              scl(ssm_lns) scl(wll) df   logLik  AICc delta weight
## moose_disturb      -0.2332  -0.2167  6 -162.613 338.8  0.00  0.445
## moose_linear        -0.2690                3 -166.573 339.6  0.74  0.307
## moose_linear_nat    -0.2745                5 -164.552 340.2  1.39  0.222
## moose_rds                2 -170.156 344.5  5.68  0.026
## moose_nat                5 -174.004 359.1 20.30  0.000
## moose_poly          -0.4444  4 -175.820 360.4 21.54  0.000
## moose_poly_nat      -0.3790  6 -173.847 361.3 22.47  0.000
## moose_energy        -0.2150  -0.2938  4 -176.567 361.9 23.03  0.000
## moose_poly_energy    -0.3949  2 -181.639 367.5 28.65  0.000
## moose_linear_energy  -0.1765  3 -180.684 367.8 28.96  0.000
## moose_harvest                3 -188.594 383.6 44.78  0.000
## moose_null                1 -192.490 387.1 48.21  0.000
## moose_ag                2 -191.625 387.5 48.62  0.000
## Models ranked by AICc(x)

```

Top model/s summary

```
summary(moose_linear)

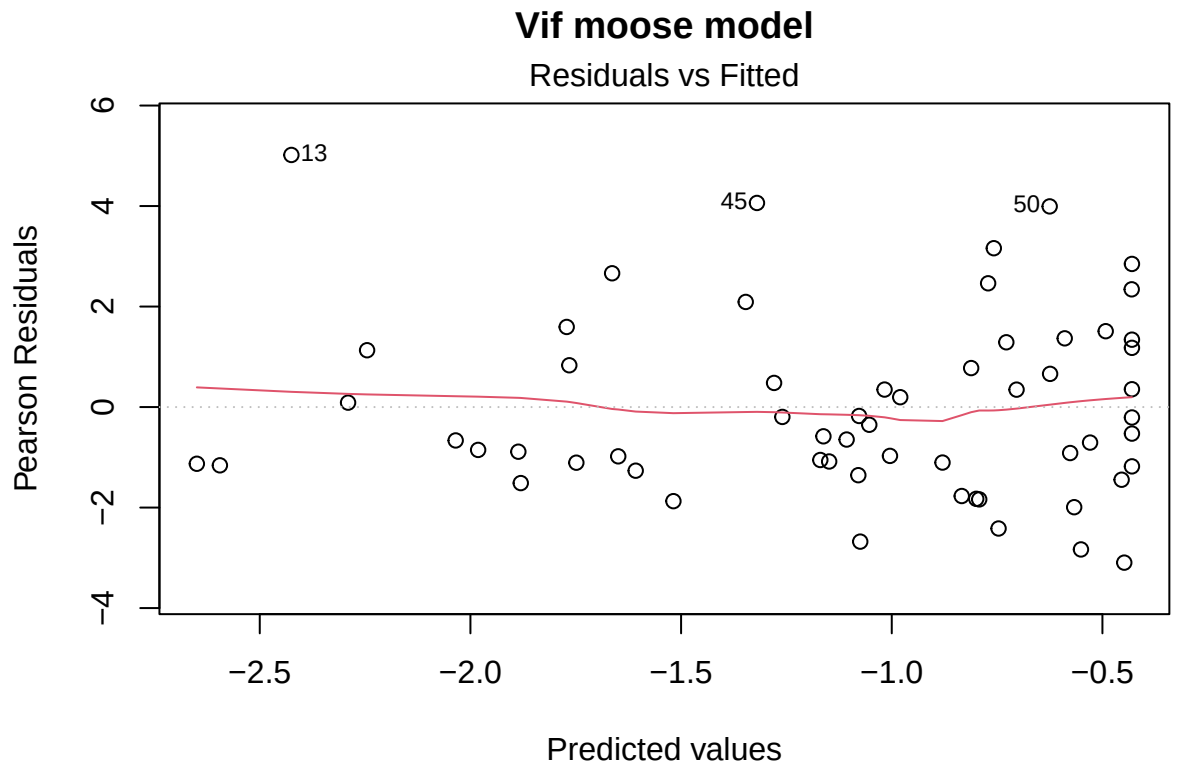
##
## Call:
## glm(formula = cbind(moose, absent_moose) ~ scale(roads) + scale(seismic_lines),
##      family = "binomial", data = prop_det_data$'500 meter buffer')
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -1.12721    0.08298 -13.584  < 2e-16 ***
## scale(roads)   -0.61257    0.09856  -6.215 5.12e-10 ***
## scale(seismic_lines) -0.26902    0.10605  -2.537  0.0112 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 246.28  on 58  degrees of freedom
## Residual deviance: 194.45  on 56  degrees of freedom
## (1 observation deleted due to missingness)
## AIC: 339.15
##
## Number of Fisher Scoring iterations: 5
```

Model assumptions and fit

```
# report VIF
vif(moose_linear)

##          scale(roads) scale(seismic_lines)
##          1.004489          1.004489

# plot VIF
plot(moose_linear,
     which = 1,
     main = 'Vif moose model')
```



`glm(cbind(moose, absent_moose) ~ scale(roads) + scale(seismic_lines))`

```
# additional plot of each variable
# calculate vif
vif(moose_linear) %>%

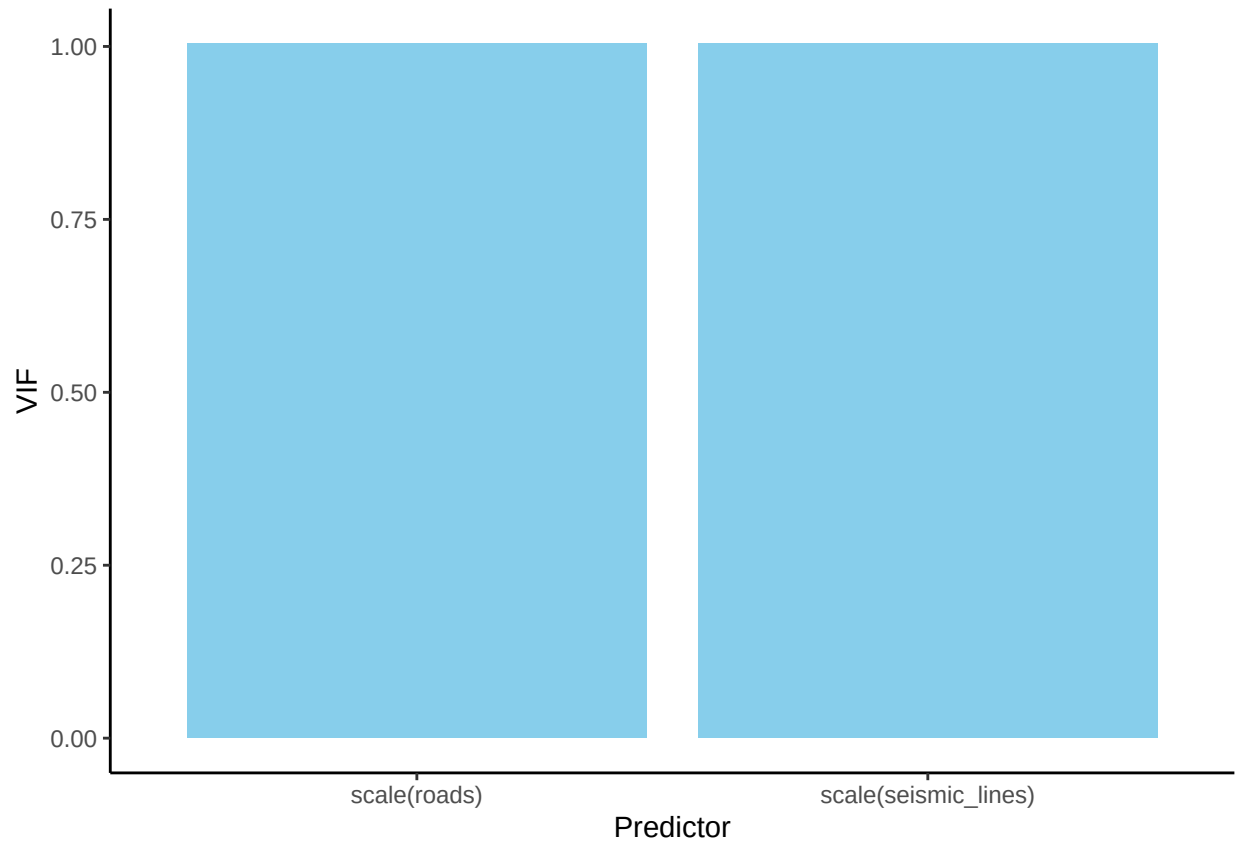
  # Converts the named vector returned by vif() into a tidy tibble
  enframe(name = 'Predictor',
           value = 'VIF') %>%

  # plot with ggplot
  ggplot(aes(x = reorder(Predictor, VIF), # reorders from smallest VIF to largest (not sure I want like
                        y = VIF)) +

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

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

  # set theme
  theme_classic()
```



Snowshoe hare

4000m was top buffer for hares

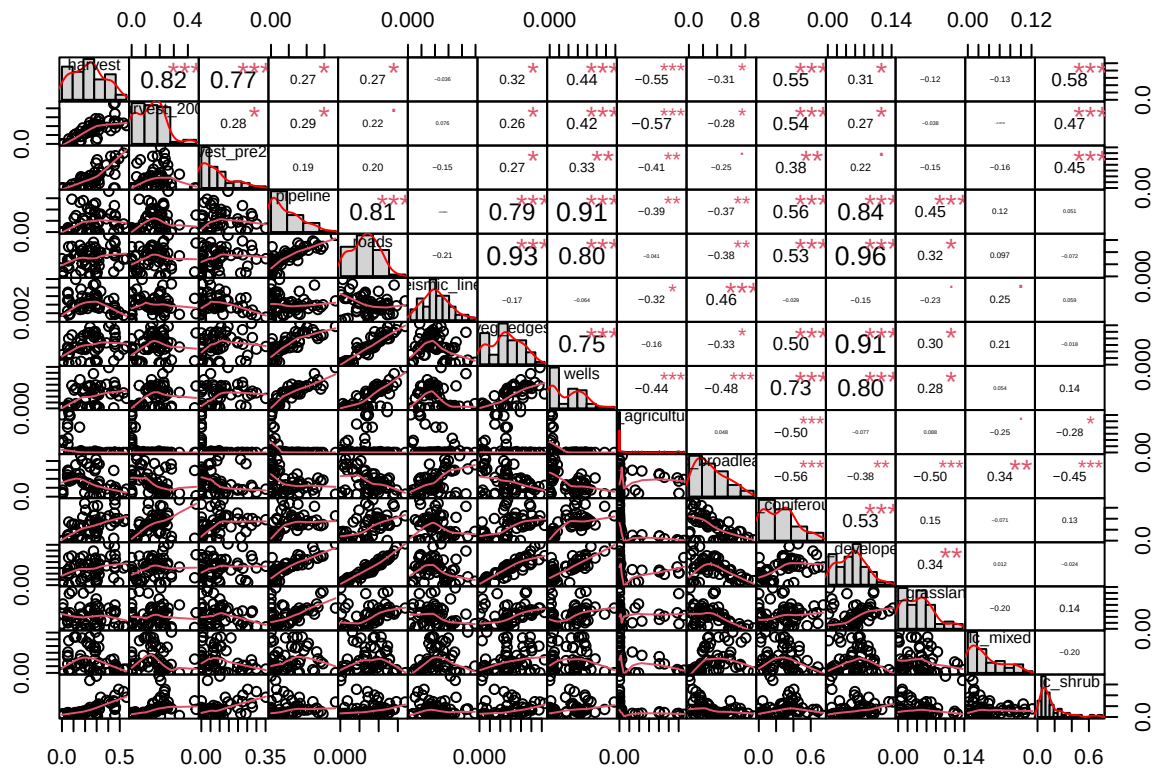
Correlation plot

```
# open file to save plot
# png("figures/corr_plot_4000.png",
#     width = 1000,
#     height = 800)

prop_det_data$`4000 meter buffer` %>%

  # select only columns with covariates not other info to simplify the plot a bit
  select(harvest:lc_shrub) %>%

  # use chart.correlation to produce plots for each buffer size
  chart.Correlation(.,
    histogram = TRUE,
    method = "pearson")
```



```
# # close file
# dev.off()
```

Models

```
# Null model
snowshoe_hare_null <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~ 1,
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')

# Natural heterogeneity (I've taken broadleaf out of this model because the sign and significance were
snowshoe_hare_nat <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
  # scale(lc_broadleaf) +
  scale(lc_grassland) +
  scale(lc_mixed) +
  scale(lc_shrub),
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')

# forest harvest
snowshoe_hare_harvest <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
  scale(harvest_2000) +
  scale(harvest_pre2000),
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')
```

```

# agriculture
snowshoe_hare_ag <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
  scale(lc_agriculture),
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')

# transportation (roads) * at 40000m buffer can't combine with other industrial features (correlated wi
snowshoe_hare_rds <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
  scale(roads),
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')

# linear energy development
snowshoe_hare_linear_energy <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
  scale(pipeline) +
  scale(seismic_lines),
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')

# polygonal energy development
snowshoe_hare_poly_energy <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
  scale(wells),
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')

# # energy development - can't do due to correlations between wells and pipeline 0.91
# snowshoe_hare_energy <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
#   scale(pipeline) +
#   scale(seismic_lines) +
#   scale(wells),
#   data = prop_det_data$`4000 meter buffer`,
#   family = 'binomial')

# polygonal disturbance (harvest + polygonal energy development + agriculture)
snowshoe_hare_poly <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  scale(wells),
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')

# linear disturbance (transportation + linear energy development)
snowshoe_hare_linear <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
  scale(roads) +
  # scale(pipeline) + can't include correlated with pipeline 0.81
  scale(seismic_lines),
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')

```

```

# overall human disturbance (limit to 5 vars)
snowshoe_hare_disturb <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  # scale(roads) + correlated w/ wells 0.80
  # pipeline + can't include correlated w/ wells 0.91
  scale(seismic_lines) +
  scale(wells),
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')

# linear + natural (have to pick max of 5) based on detections
snowshoe_hare_linear_nat <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
  scale(pipeline) +
  scale(seismic_lines) +
  scale(lc_grassland) +
  scale(lc_shrub),
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')

# polygonal features and nat (limit 5 vars)
snowshoe_hare_poly_nat <- glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~
  scale(harvest_2000) +
  scale(harvest_pre2000) +
  scale(wells) +
  scale(lc_grassland) +
  scale(lc_shrub),
  data = prop_det_data$`4000 meter buffer`,
  family = 'binomial')

```

Model selection

```

model.sel(snowshoe_hare_null,
  snowshoe_hare_nat,
  snowshoe_hare_harvest,
  snowshoe_hare_ag,
  snowshoe_hare_rds,
  snowshoe_hare_linear_energy,
  snowshoe_hare_poly_energy,
  snowshoe_hare_poly,
  snowshoe_hare_linear,
  snowshoe_hare_disturb,
  snowshoe_hare_linear_nat,
  snowshoe_hare_poly_nat)

## Model selection table
##               (Int) scl(lc_grs) scl(lc_mxd) scl(lc_shr)
## snowshoe_hare_disturb    -2.239
## snowshoe_hare_poly       -2.195
## snowshoe_hare_poly_nat   -2.195    0.17570          -0.068540
## snowshoe_hare_linear_energy -2.104
## snowshoe_hare_poly_energy -2.055

```

```

## snowshoe_hare_linear_nat      -2.106      -0.02587              0.008613
## snowshoe_hare_linear          -2.079
## snowshoe_hare_harvest         -2.060
## snowshoe_hare_rds             -2.044
## snowshoe_hare_null            -2.001
## snowshoe_hare_ag              -2.009
## snowshoe_hare_nat             -2.012      0.24110      0.05564      0.084590
##                               scl(hrv_2000) scl(hrv_p20) scl(lc_agr) scl(rds)
## snowshoe_hare_disturb         -0.5864      0.2927
## snowshoe_hare_poly            -0.5872      0.3385
## snowshoe_hare_poly_nat        -0.5062      0.4055
## snowshoe_hare_linear_energy
## snowshoe_hare_poly_energy
## snowshoe_hare_linear_nat
## snowshoe_hare_linear          0.2465
## snowshoe_hare_harvest         -0.1994      0.3116
## snowshoe_hare_rds             0.2637
## snowshoe_hare_null
## snowshoe_hare_ag              -0.1501
## snowshoe_hare_nat
##                               scl(pp1) scl(ssm_lns) scl(w11) df    logLik  AICc
## snowshoe_hare_disturb         -0.2804      0.5655      5 -138.199 287.5
## snowshoe_hare_poly            0.5232      4 -140.944 290.6
## snowshoe_hare_poly_nat        0.4278      6 -139.949 293.5
## snowshoe_hare_linear_energy   0.3068      -0.3211      3 -146.222 298.9
## snowshoe_hare_poly_energy     0.3108      2 -149.304 302.8
## snowshoe_hare_linear_nat      0.3199      -0.3289      5 -146.199 303.5
## snowshoe_hare_linear          -0.2593      3 -148.570 303.6
## snowshoe_hare_harvest         3 -149.249 304.9
## snowshoe_hare_rds             2 -151.119 306.5
## snowshoe_hare_null            1 -154.247 310.6
## snowshoe_hare_ag              2 -153.390 311.0
## snowshoe_hare_nat             4 -151.400 311.5
##                               delta weight
## snowshoe_hare_disturb         0.00 0.789
## snowshoe_hare_poly            3.10 0.168
## snowshoe_hare_poly_nat        5.98 0.040
## snowshoe_hare_linear_energy  11.35 0.003
## snowshoe_hare_poly_energy     15.29 0.000
## snowshoe_hare_linear_nat      16.00 0.000
## snowshoe_hare_linear          16.05 0.000
## snowshoe_hare_harvest         17.40 0.000
## snowshoe_hare_rds             18.92 0.000
## snowshoe_hare_null            23.03 0.000
## snowshoe_hare_ag              23.46 0.000
## snowshoe_hare_nat             24.01 0.000
## Models ranked by AICc(x)

```

Top model/s summary

```

#summary(snowshoe_hare_nat)

summary(snowshoe_hare_disturb)

```

```
##
## Call:
## glm(formula = cbind(snowshoe_hare, absent_snowshoe_hare) ~ scale(harvest_2000) +
##      scale(harvest_pre2000) + scale(seismic_lines) + scale(wells),
##      family = "binomial", data = prop_det_data$'4000 meter buffer')
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -2.2388     0.1284 -17.441 < 2e-16 ***
## scale(harvest_2000) -0.5864     0.1852  -3.166  0.00154 **
## scale(harvest_pre2000) 0.2927     0.1102   2.656  0.00790 **
## scale(seismic_lines) -0.2804     0.1234  -2.271  0.02313 *
## scale(wells)         0.5655     0.1364   4.145  3.4e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 234.52 on 58 degrees of freedom
## Residual deviance: 202.42 on 54 degrees of freedom
## (1 observation deleted due to missingness)
## AIC: 286.4
##
## Number of Fisher Scoring iterations: 5
```

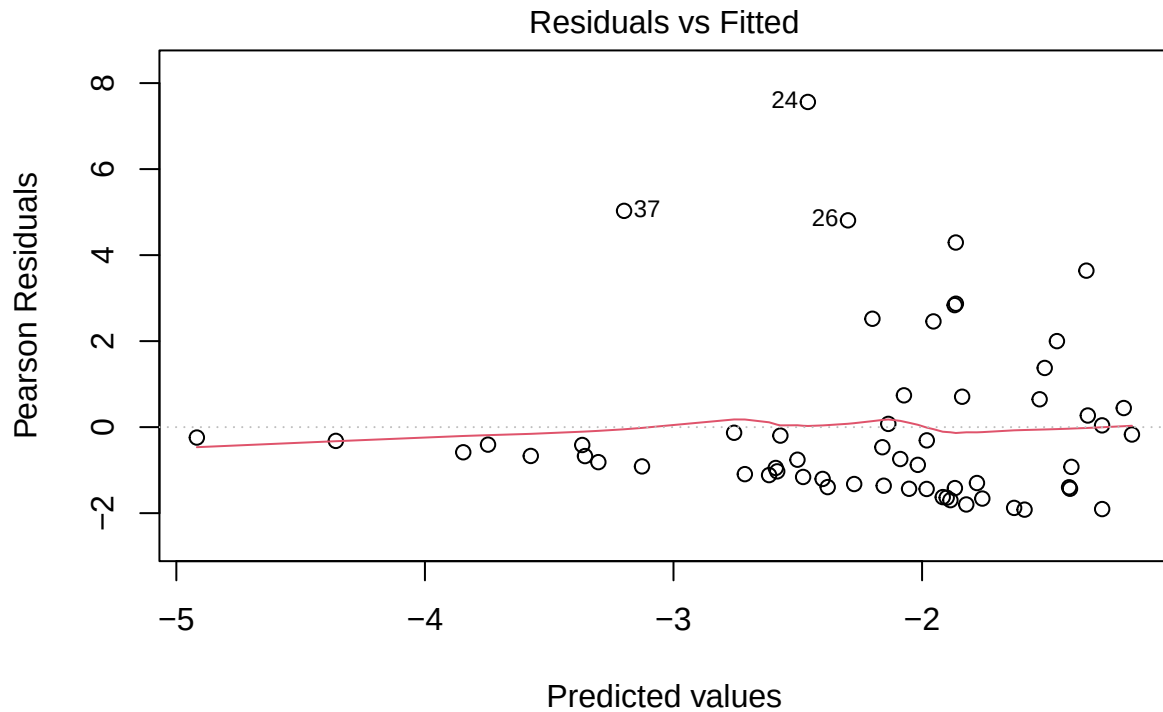
Model assumptions and fit

```
# report VIF
vif(snowshoe_hare_disturb)

##      scale(harvest_2000) scale(harvest_pre2000)   scale(seismic_lines)
##              2.269465              1.427346              1.072494
##      scale(wells)
##              1.816374

# plot VIF
plot(snowshoe_hare_disturb,
     which = 1,
     main = 'Vif snowshoe hare model')
```

Vif snowshoe hare model



`glm(cbind(snowshoe_hare, absent_snowshoe_hare) ~ scale(harvest_2000) + scal ..`

```
# additional plot of each variable
# calculate vif
vif(snowshoe_hare_disturb) %>%

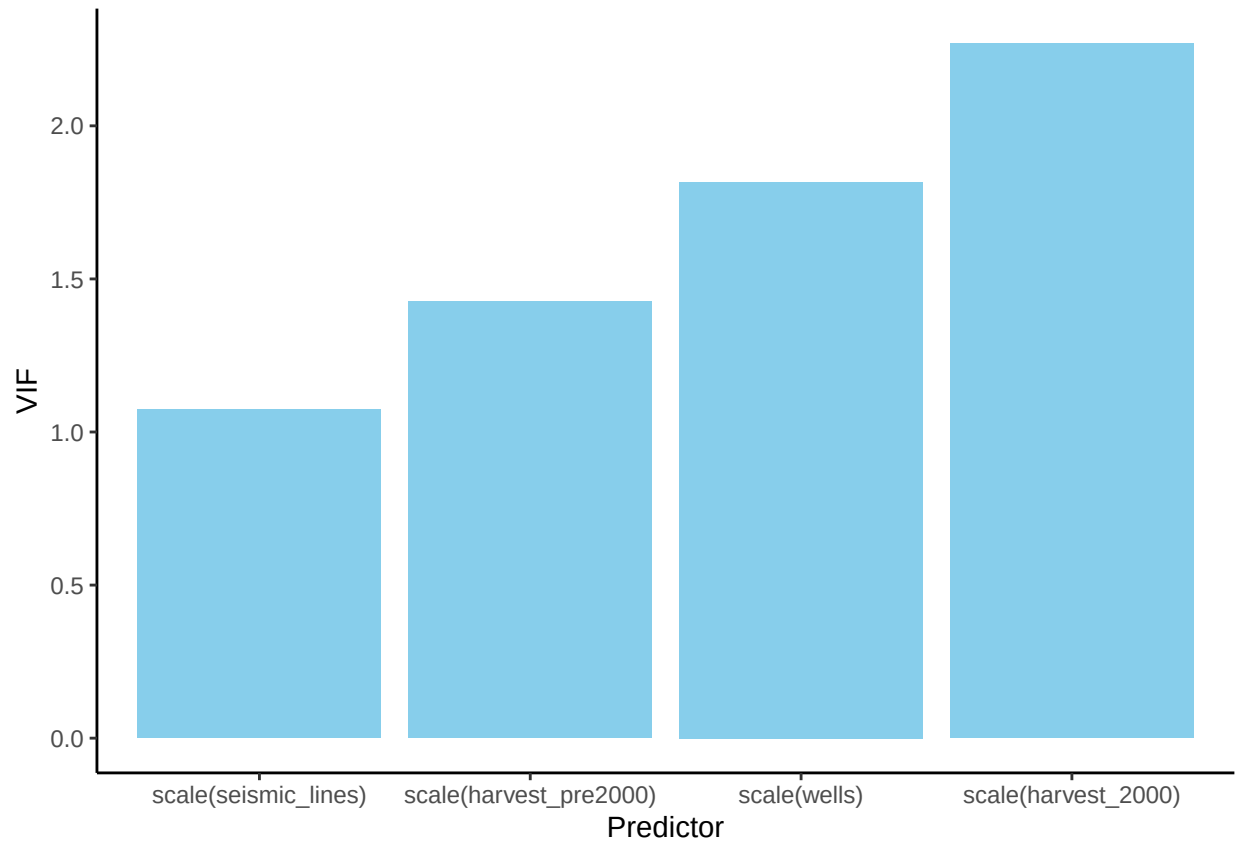
  # Converts the named vector returned by vif() into a tidy tibble
  enframe(name = 'Predictor',
           value = 'VIF') %>%

  # plot with ggplot
  ggplot(aes(x = reorder(Predictor, VIF), # reorders from smallest VIF to largest (not sure I want like
                        y = VIF)) +

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

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

  # set theme
  theme_classic()
```



White-tailed deer

4250m was best buffer

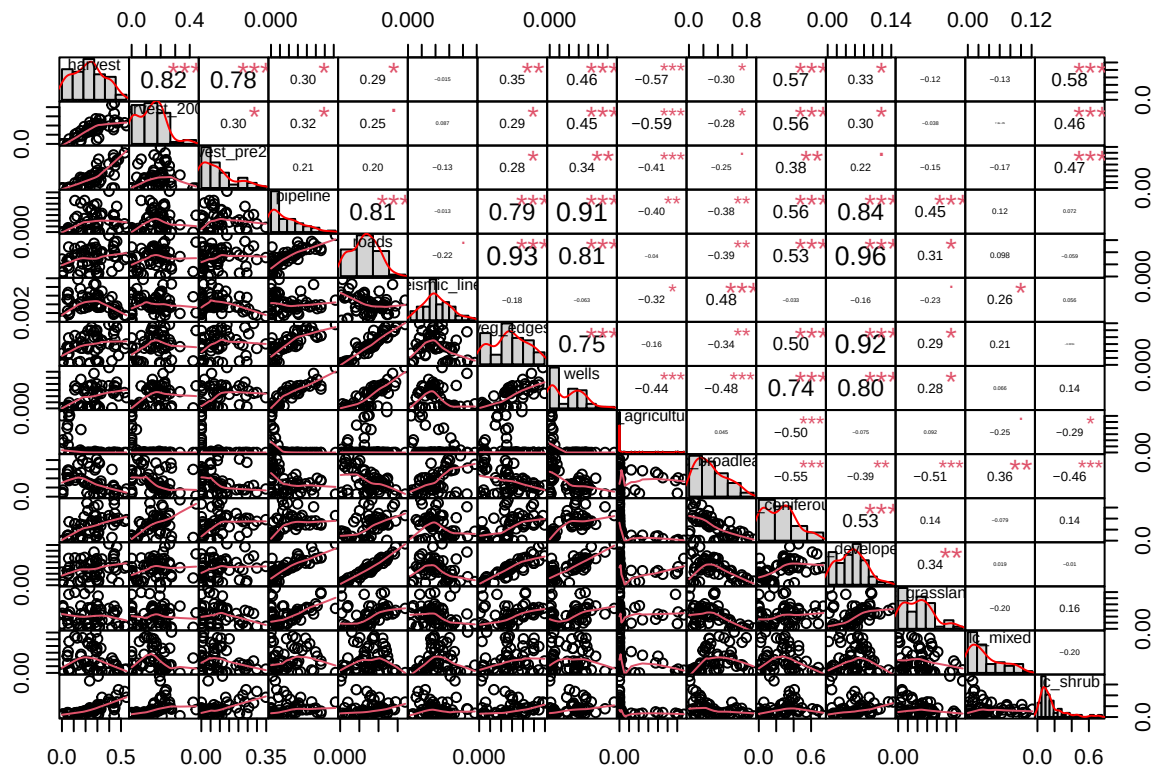
Correlation plot

```
# # open file to save plot
# png("figures/corr_plot_4250.png",
#     width = 1000,
#     height = 800)

prop_det_data$`4250 meter buffer` %>%

  # select only columns with covariates not other info to simplify the plot a bit
  select(harvest:lc_shrub) %>%

  # use chart.correlation to produce plots for each buffer size
  chart.Correlation(.,
    histogram = TRUE,
    method = "pearson")
```



```
## close file
# dev.off()
```

Models

```
# Null model
w_deer_null <- glm(cbind(`white-tailed_deer`, `absent_white-tailed_deer`) ~ 1,
  data = prop_det_data$`4250 meter buffer`,
  family = 'binomial')

# Natural heterogeneity (checked how taking out broadleaf or grassland affected model results since thi
w_deer_nat <- glm(cbind(`white-tailed_deer`, `absent_white-tailed_deer`) ~
  scale(lc_broadleaf) +
  scale(lc_grassland) +
  scale(lc_mixed) +
  scale(lc_shrub),
  data = prop_det_data$`4250 meter buffer`,
  family = 'binomial')

w_deer_nat_grass <- glm(cbind(`white-tailed_deer`, `absent_white-tailed_deer`) ~
  # scale(lc_broadleaf) +
  scale(lc_grassland) +
  scale(lc_mixed) +
  scale(lc_shrub),
  data = prop_det_data$`4250 meter buffer`,
  family = 'binomial')
```

```

w_deer_nat_broadleaf <- glm(cbind(`white-tailed_deer`, `absent_white-tailed_deer`) ~
  scale(lc_broadleaf) +
  # scale(lc_grassland) +
  scale(lc_mixed) +
  scale(lc_shrub),
  data = prop_det_data$`4250 meter buffer`,
  family = 'binomial')

# forest harvest
w_deer_harvest <- glm(cbind(`white-tailed_deer`, `absent_white-tailed_deer`) ~
  scale(harvest_2000) +
  scale(harvest_pre2000),
  data = prop_det_data$`4250 meter buffer`,
  family = 'binomial')

# agriculture
w_deer_ag <- glm(cbind(`white-tailed_deer`, `absent_white-tailed_deer`) ~
  scale(lc_agriculture),
  data = prop_det_data$`4250 meter buffer`,
  family = 'binomial')

# transportation (roads) * at 4250m buffer can't combine with other industrial features (correlated with roads)
w_deer_rds <- glm(cbind(`white-tailed_deer`, `absent_white-tailed_deer`) ~
  scale(roads),
  data = prop_det_data$`4250 meter buffer`,
  family = 'binomial')

# linear energy development
w_deer_linear_energy <- glm(cbind(`white-tailed_deer`, `absent_white-tailed_deer`) ~
  scale(pipeline) +
  scale(seismic_lines),
  data = prop_det_data$`4250 meter buffer`,
  family = 'binomial')

# polygonal energy development
w_deer_poly_energy <- glm(cbind(`white-tailed_deer`, `absent_white-tailed_deer`) ~
  scale(wells),
  data = prop_det_data$`4250 meter buffer`,
  family = 'binomial')

# # energy development - can't do at this scale pipeline and well corr = 0.50't do due to correlations
# w_deer_energy <- glm(cbind(`white-tailed_deer`, `absent_white-tailed_deer`) ~
#   scale(pipeline) +
#   scale(seismic_lines) +
#   scale(wells),
#   data = prop_det_data$`4250 meter buffer`,
#   family = 'binomial')

# polygonal disturbance (harvest + polygonal energy development + agriculture)
w_deer_poly <- glm(cbind(`white-tailed_deer`, `absent_white-tailed_deer`) ~
  scale(harvest_2000) +

```

```

        scale(harvest_pre2000) +
        scale(wells),
data = prop_det_data$`4250 meter buffer`,
family = 'binomial')

# linear disturbance (transportation + linear energy development)
w_deer_linear <- glm(cbind(`white-tailed-deer`, `absent-white-tailed-deer`) ~
        scale(roads) +
        # pipeline + can't include correlated w/ roads 0.81
        scale(seismic_lines),
data = prop_det_data$`4250 meter buffer`,
family = 'binomial')

# overall human disturbance (limit to 5 vars)
w_deer_disturb <- glm(cbind(`white-tailed-deer`, `absent-white-tailed-deer`) ~
        scale(harvest_2000) +
        scale(harvest_pre2000) +
        # scale(roads) +
        # pipeline + can't include correlated w/ roads 0.81 and wells 0.91
        scale(seismic_lines) +
        scale(wells),
data = prop_det_data$`4250 meter buffer`,
family = 'binomial')

# linear + natural (have to pic max of 5) based on detections
w_deer_linear_nat <- glm(cbind(`white-tailed-deer`, `absent-white-tailed-deer`) ~
        scale(roads) +
        # pipeline + can't include correlated w/ roads 0.81
        scale(seismic_lines) +
        scale(lc_broadleaf) +
        scale(lc_shrub),
data = prop_det_data$`4250 meter buffer`,
family = 'binomial')

# polygonal features and nat (limit 5 vars)
w_deer_poly_nat <- glm(cbind(`white-tailed-deer`, `absent-white-tailed-deer`) ~
        scale(harvest_2000) +
        scale(harvest_pre2000) +
        scale(wells) +
        scale(lc_broadleaf) +
        scale(lc_shrub),
data = prop_det_data$`4250 meter buffer`,
family = 'binomial')

```

Model selection

```

model.sel(w_deer_null,
        w_deer_nat,
        #w_deer_nat_broadleaf,
        #w_deer_nat_grass,

```

```

w_deer_harvest,
w_deer_ag,
w_deer_rds,
w_deer_linear_energy,
w_deer_poly_energy,
w_deer_poly,
w_deer_linear,
w_deer_disturb,
w_deer_linear_nat,
w_deer_poly_nat)

## Model selection table
##
##          (Int) scl(lc_brd) scl(lc_grs) scl(lc_mxd) scl(lc_shr)
## w_deer_nat      0.2826      0.5422      0.4071      0.5062      -0.2718
## w_deer_poly_nat  0.2729      0.6053
## w_deer_linear_nat 0.2251      0.6985      -0.3588
## w_deer_harvest   0.3001
## w_deer_disturb    0.3074
## w_deer_poly       0.3043
## w_deer_poly_energy 0.2901
## w_deer_linear     0.2883
## w_deer_linear_energy 0.2847
## w_deer_null       0.2749
## w_deer_ag         0.2761
## w_deer_rds        0.2810
##
##          scl(hrv_2000) scl(hrv_p20) scl(lc_agr) scl(rds)    scl(ppl)
## w_deer_nat
## w_deer_poly_nat      0.006951      -0.3136
## w_deer_linear_nat                    0.27180
## w_deer_harvest       -0.131800      -0.4057
## w_deer_disturb       -0.110200      -0.3805
## w_deer_poly          -0.104600      -0.3974
## w_deer_poly_energy
## w_deer_linear                    -0.05016
## w_deer_linear_energy                    -0.0008187
## w_deer_null
## w_deer_ag                                0.09962
## w_deer_rds                                -0.07812
##
##          scl(ssm_lns) scl(wll) df    logLik  AICc  delta weight
## w_deer_nat                                5 -184.491 380.1    0.00    1
## w_deer_poly_nat                        0.22020 6 -207.628 428.9  48.76    0
## w_deer_linear_nat                    -0.1409    5 -210.150 431.4  51.32    0
## w_deer_harvest                        3 -238.537 483.5 103.40    0
## w_deer_disturb                    0.1393 -0.05577 5 -236.398 483.9 103.81    0
## w_deer_poly                      -0.05697 4 -238.281 485.3 105.19    0
## w_deer_poly_energy                -0.22040 2 -257.078 518.4 138.26    0
## w_deer_linear                    0.1777    3 -258.658 523.8 143.64    0
## w_deer_linear_energy                0.1855    3 -258.919 524.3 144.16    0
## w_deer_null                        1 -262.559 527.2 147.07    0
## w_deer_ag                          2 -261.542 527.3 147.18    0
## w_deer_rds                        2 -261.899 528.0 147.90    0
## Models ranked by AICc(x)

```

White-tailed deer top model/s

I ran three natural models because it was coming out suspiciously on top (70+ AIC better than other models) and I wanted to ensure no issues were arising with changing sign etc for beta coefficients with grassland and broadleaf since $r = 0.51$, and the snowshoe hare model had issues but it seems the full natural model still performs best and none of the beta coefficient signs are changing if the variables included in the model don't change, so will stick with the full natural model

```
summary(w_deer_nat)

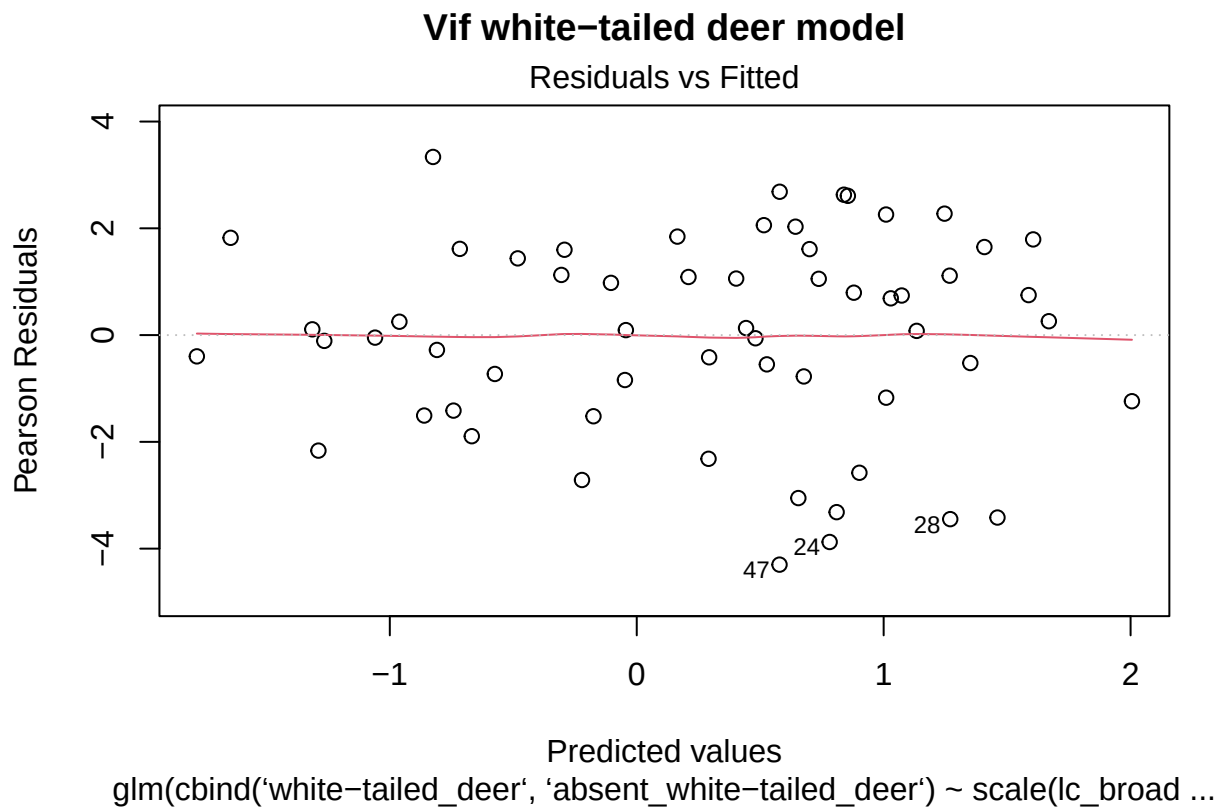
##
## Call:
## glm(formula = cbind('white-tailed_deer', 'absent_white-tailed_deer') ~
##       scale(lc_broadleaf) + scale(lc_grassland) + scale(lc_mixed) +
##       scale(lc_shrub), family = "binomial", data = prop_det_data$'4250 meter buffer')
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    0.28257    0.07367   3.836 0.000125 ***
## scale(lc_broadleaf) 0.54215    0.09979   5.433 5.55e-08 ***
## scale(lc_grassland) 0.40707    0.09496   4.287 1.81e-05 ***
## scale(lc_mixed)    0.50619    0.08272   6.119 9.41e-10 ***
## scale(lc_shrub)   -0.27179    0.10421  -2.608 0.009104 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 377.77  on 58  degrees of freedom
## Residual deviance: 221.63  on 54  degrees of freedom
## (1 observation deleted due to missingness)
## AIC: 378.98
##
## Number of Fisher Scoring iterations: 4
#summary(w_deer_nat_broadleaf)
#summary(w_deer_nat_grass)
```

Model assumptions and fit

```
# report VIF
vif(w_deer_nat)

## scale(lc_broadleaf) scale(lc_grassland)    scale(lc_mixed)    scale(lc_shrub)
##           1.782017           1.400047           1.074848           1.274127

# plot VIF
plot(w_deer_nat,
      which = 1,
      main = 'Vif white-tailed deer model')
```



```
# additional plot of each variable
# calculate vif
vif(w_deer_nat) %>%

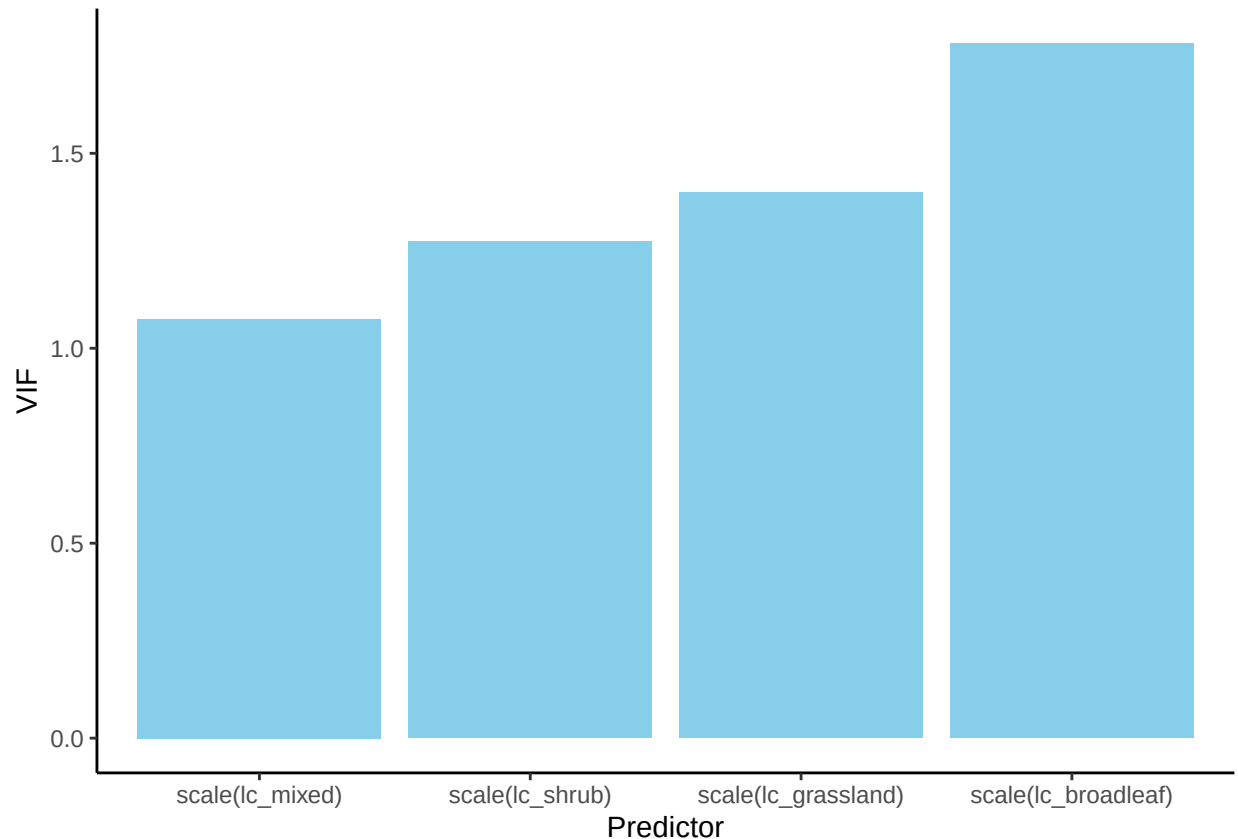
  # Converts the named vector returned by vif() into a tidy tibble
  enframe(name = 'Predictor',
           value = 'VIF') %>%

  # plot with ggplot
  ggplot(aes(x = reorder(Predictor, VIF), # reorders from smallest VIF to largest (not sure I want like
                        y = VIF)) +

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

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

  # set theme
  theme_classic()
```



Logistic regression

For the species we have less data for we will run a logistic regression with overall presence absence data instead of proportional monthly presence absence data. This data is much more coarse which is why we'd prefer the proportional binomial, but for these elusive/rare species we can use it to get some insights into responses to landscape disturbance etc.

Note this was purely exploratory for SRFN info and report, we did not use this analysis for publication

Buffer selection

We will repeat the buffer selection process for each species in our logistic regression, like we did for the proportional binomial models

```
# create a vector with the species in the proportional detection data (prop_det_data) this one is unnec

# pb = proportional binomial
log_species_list <- c('elk',
                     'red_fox',
                     'grizzly_bear',
                     'mule_deer')

# create custom function to run models for a given species
run_log_models_for_species <- function(species) {
```

```

# provide pb data
pres_absen_dat %>%

# use purrr to apply following function to all species
purrr::map(
  ~.x %>%

  # run glm by pasting the species name in for the cbind function
  glm(
    formula = as.formula(paste0(
      '\', species, '\', ~',

      # use non-correlated variables
      'harvest_2000 + ',
      'harvest_pre2000 + ',
      # 'roads + ',
      'seismic_lines + ',
      'wells + ',
      # 'lc_agriculture + ',
      'lc_broadleaf + ',
      'lc_grassland + ',
      'lc_mixed + ',
      'lc_shrub'
    )),
    data = .,
    family = 'binomial'
  )
)
}

# Iterate this function over each species in the list and run the models
log_models_by_species <- purrr::map(log_species_list, run_log_models_for_species)

# Custom function to compare models for a single species and print species name
compare_log_models <- function(models, species_name) {
  cat("\nModel Selection for Species:", species_name, "\n")
  log_model_sel_results <- model.sel(models)
  print(as.data.frame(log_model_sel_results))
  return(as.data.frame(log_model_sel_results))
}

# Use map2 to iterate over each species' models and names, and compare models
log_model_comparisons <- purrr::map2(log_models_by_species,
  log_species_list,
  compare_log_models)

```

```

##
## Model Selection for Species: elk
##
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 750 meter buffer -2.984556 -1.1847804 6.8438514 3.377765
## 5000 meter buffer -3.869485 -8.2085193 0.9390016 6.399096
## 500 meter buffer -3.699477 -0.5344409 4.2024218 3.918399
## 250 meter buffer -3.944921 -1.2637958 1.2416182 3.868219
## 4750 meter buffer -3.601657 -7.2334969 0.5160077 6.089971

```

##	4500 meter buffer	-3.265856	-6.6882020	0.4293326	5.561618
##	1000 meter buffer	-2.473577	-0.2742373	6.2442696	2.643027
##	4250 meter buffer	-3.038668	-6.5246570	0.5858783	5.331202
##	4000 meter buffer	-2.728440	-6.5438656	1.0138478	5.024380
##	3750 meter buffer	-2.544838	-6.2241463	1.6065982	4.352093
##	1250 meter buffer	-2.603551	-1.7328852	3.8945277	3.460962
##	1500 meter buffer	-2.464689	-2.9825744	3.5988760	3.023027
##	3500 meter buffer	-2.657565	-5.3842407	1.9073805	3.861357
##	1750 meter buffer	-2.394250	-3.5555478	3.5222124	2.681559
##	3250 meter buffer	-2.739237	-4.6606051	1.8315329	3.669955
##	2000 meter buffer	-2.249801	-3.8848902	4.0009541	2.208290
##	3000 meter buffer	-2.650114	-3.8537193	2.1574270	3.228236
##	2750 meter buffer	-2.408576	-3.8566084	3.1730430	2.419082
##	2250 meter buffer	-2.165379	-3.5492701	4.1652221	1.776832
##	2500 meter buffer	-2.204187	-3.5591083	3.7155130	2.068868
##		lc_grassland	lc_mixed	lc_shrub	seismic_lines wells
##	750 meter buffer	7.5176304	-2.064569	-0.8752784	-106.17191427 -45.331971
##	5000 meter buffer	15.3323068	-8.782072	-4.6846132	-44.51253157 146.836650
##	500 meter buffer	6.4974412	-4.305941	0.8451838	-61.24629775 -16.521856
##	250 meter buffer	4.4722239	-3.359274	2.3639918	-3.85363474 -11.018721
##	4750 meter buffer	12.4009303	-10.358547	-3.3287502	-62.81252602 132.766061
##	4500 meter buffer	8.9230945	-10.829839	-2.6043598	-65.72019615 119.256618
##	1000 meter buffer	6.2353847	-2.768505	-2.1899571	-93.09845745 -38.661007
##	4250 meter buffer	6.1333504	-11.861745	-2.1336444	-76.85098945 113.977863
##	4000 meter buffer	2.3815256	-11.444242	-2.0026893	-98.52585952 108.672204
##	3750 meter buffer	1.2248224	-9.599093	-1.7911292	-77.32424720 91.281970
##	1250 meter buffer	4.6223961	-4.591243	0.3317447	-172.69007875 -5.851660
##	1500 meter buffer	3.6999742	-8.826869	0.1958494	-83.26312938 6.848499
##	3500 meter buffer	3.1959024	-8.396753	-1.4627892	-32.31899826 69.472866
##	1750 meter buffer	2.4359324	-8.612482	-0.2707444	-27.10912088 16.982073
##	3250 meter buffer	3.4608238	-8.462050	-0.7640113	-17.96656402 58.388582
##	2000 meter buffer	1.1283210	-7.226841	-1.0864604	16.40038339 21.197511
##	3000 meter buffer	3.2027819	-7.637719	-0.6486410	0.05988636 41.896024
##	2750 meter buffer	1.8148418	-5.773519	-1.1819112	38.89002874 29.771298
##	2250 meter buffer	1.0766063	-5.116110	-1.5171569	50.16596625 16.453486
##	2500 meter buffer	0.6707906	-4.959452	-1.5023843	32.03186480 23.364920
##		df	logLik	AICc	delta weight
##	750 meter buffer	9	-21.74340	65.16026	0.0000000 0.181818462
##	5000 meter buffer	9	-21.89391	65.46129	0.3010248 0.156412432
##	500 meter buffer	9	-22.08711	65.84769	0.6874302 0.128933093
##	250 meter buffer	9	-22.23336	66.14019	0.9799245 0.111390991
##	4750 meter buffer	9	-22.38939	66.45225	1.2919924 0.095298351
##	4500 meter buffer	9	-22.87604	67.42556	2.2652929 0.058578181
##	1000 meter buffer	9	-22.93500	67.54348	2.3832155 0.055224185
##	4250 meter buffer	9	-23.07705	67.82756	2.6673013 0.047911621
##	4000 meter buffer	9	-23.26059	68.19465	3.0343841 0.039877676
##	3750 meter buffer	9	-23.85020	69.37388	4.2136163 0.022113772
##	1250 meter buffer	9	-23.86941	69.41229	4.2520311 0.021693077
##	1500 meter buffer	9	-24.06996	69.81338	4.6531221 0.017751103
##	3500 meter buffer	9	-24.34850	70.37048	5.2102135 0.013435520
##	1750 meter buffer	9	-24.48939	70.65226	5.4919965 0.011669872
##	3250 meter buffer	9	-24.71155	71.09656	5.9363002 0.009345161
##	2000 meter buffer	9	-24.77881	71.23108	6.0708213 0.008737273
##	3000 meter buffer	9	-25.14873	71.97094	6.8106741 0.006035578

```

## 2750 meter buffer 9 -25.37258 72.41863 7.2583667 0.004825071
## 2250 meter buffer 9 -25.40865 72.49076 7.3304987 0.004654150
## 2500 meter buffer 9 -25.48909 72.65164 7.4913796 0.004294430
##
## Model Selection for Species: red_fox
##
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 4750 meter buffer -1.67421192 -9.462017 5.8739222 -1.0474395
## 5000 meter buffer -1.75161828 -9.062945 5.3539256 -0.6927321
## 4500 meter buffer -1.43415288 -9.802087 5.2138997 -0.9940044
## 4000 meter buffer -1.24527417 -11.009671 5.8859194 -0.8359904
## 3750 meter buffer -1.20230078 -10.162246 6.2707291 -0.7888612
## 3500 meter buffer -1.13660218 -9.588080 6.3272370 -0.8194820
## 4250 meter buffer -1.22314508 -10.191180 4.9513524 -0.8663478
## 250 meter buffer -2.35959325 -3.661237 -0.5327085 2.7657475
## 3250 meter buffer -0.98747230 -7.945267 6.0575060 -0.8895046
## 3000 meter buffer -0.74245894 -7.004071 5.6784377 -1.2134070
## 2750 meter buffer -0.43544139 -7.410979 5.2754014 -1.4077034
## 2500 meter buffer -0.20569071 -7.566560 5.1930833 -1.7175311
## 2250 meter buffer -0.07776786 -6.923804 4.4688210 -1.5175109
## 2000 meter buffer -0.03232413 -5.967370 3.8446830 -1.3354461
## 500 meter buffer -2.28908738 -5.941814 0.7361307 2.5793769
## 1250 meter buffer -0.45763908 -2.887739 1.1354691 0.7343673
## 750 meter buffer -0.37280006 -2.787769 2.0834140 -0.1902017
## 1750 meter buffer -0.25695368 -4.961400 2.0138520 -0.3376095
## 1500 meter buffer -0.37674990 -3.940810 1.0483061 0.4832832
## 1000 meter buffer -0.44743570 -2.687067 1.9308469 0.2158028
##
## lc_grassland lc_mixed lc_shrub seismic_lines wells
## 4750 meter buffer 21.959955766 -11.62308384 -5.67336926 414.19353 -26.29736
## 5000 meter buffer 21.957043560 -12.67497266 -5.75450759 411.34785 -20.57623
## 4500 meter buffer 18.287130872 -11.35273471 -4.60969468 368.35682 -22.04678
## 4000 meter buffer 15.481427276 -10.18530408 -3.16159159 289.22692 -20.49281
## 3750 meter buffer 16.079699271 -10.03708844 -3.13120233 259.16909 -34.25327
## 3500 meter buffer 15.217095257 -11.37868173 -3.18814472 250.67931 -36.34426
## 4250 meter buffer 15.273648428 -10.58510484 -3.62320697 312.01261 -20.84173
## 250 meter buffer 2.059767918 1.09938288 3.68620619 -104.89423 -96.37473
## 3250 meter buffer 13.429870588 -11.35882726 -3.29313250 228.66690 -46.78166
## 3000 meter buffer 10.786236049 -11.38242911 -3.46843764 233.31944 -54.51880
## 2750 meter buffer 6.445704331 -11.11161792 -3.21553965 212.84022 -42.44627
## 2500 meter buffer 3.298851576 -10.25229903 -3.32927411 216.21725 -38.01881
## 2250 meter buffer 1.301694918 -9.19181632 -3.21649965 168.12111 -33.99653
## 2000 meter buffer 0.673606384 -6.45610847 -3.11303605 117.51691 -39.27699
## 500 meter buffer 4.022937917 -0.58285720 6.05242429 -132.09829 -24.09794
## 1250 meter buffer -0.125715991 1.81380563 0.09216825 -193.83348 -35.96894
## 750 meter buffer 0.773021053 -2.48628914 0.02483707 -77.76918 -43.70306
## 1750 meter buffer 0.041406009 -2.40835384 -1.57237664 -11.51499 -29.02200
## 1500 meter buffer -0.044172167 -0.04154692 -0.25092001 -128.07258 -32.60843
## 1000 meter buffer 0.004585398 0.11584798 -0.15919406 -136.63575 -35.09561
##
## df logLik AICc delta weight
## 4750 meter buffer 9 -23.47287 68.61922 0.0000000 0.143249353
## 5000 meter buffer 9 -23.57064 68.81474 0.1955216 0.129907940
## 4500 meter buffer 9 -23.79046 69.25439 0.6351723 0.104271773
## 4000 meter buffer 9 -23.90812 69.48971 0.8704931 0.092697388
## 3750 meter buffer 9 -23.91786 69.50919 0.8899704 0.091799020
## 3500 meter buffer 9 -23.99070 69.65486 1.0356449 0.085350338

```

```

## 4250 meter buffer 9 -24.07394 69.82135 1.2021329 0.078533116
## 250 meter buffer 9 -24.14223 69.95793 1.3387073 0.073349317
## 3250 meter buffer 9 -24.42025 70.51397 1.8947491 0.055546043
## 3000 meter buffer 9 -24.70097 71.07542 2.4562005 0.041950342
## 2750 meter buffer 9 -25.07898 71.83144 3.2122194 0.028745382
## 2500 meter buffer 9 -25.29220 72.25787 3.6386529 0.023225722
## 2250 meter buffer 9 -25.71198 73.09743 4.4782096 0.015263770
## 2000 meter buffer 9 -26.11002 73.89352 5.2742997 0.010251633
## 500 meter buffer 9 -26.39609 74.46564 5.8464231 0.007701193
## 1250 meter buffer 9 -27.02959 75.73266 7.1134382 0.004087231
## 750 meter buffer 9 -27.09660 75.86666 7.2474414 0.003822353
## 1750 meter buffer 9 -27.14163 75.95673 7.3375095 0.003654035
## 1500 meter buffer 9 -27.16871 76.01088 7.3916623 0.003556425
## 1000 meter buffer 9 -27.32639 76.32624 7.7070218 0.003037625
##
## Model Selection for Species: grizzly_bear
##
## (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 500 meter buffer -3.2190637 1.96276237 -10.7970414 -1.09321381
## 1500 meter buffer -0.8179933 0.26758897 -8.3351078 -1.75317863
## 1750 meter buffer -0.8628394 -0.18279150 -8.2955521 -1.60118814
## 2250 meter buffer -1.0741304 -1.22942630 -10.2178731 -0.44707497
## 1000 meter buffer -1.2344741 1.22831022 -7.6575574 -1.83642838
## 1250 meter buffer -0.8645059 0.69440477 -7.0823279 -2.03046134
## 2000 meter buffer -0.9908101 -0.35301367 -9.0095702 -1.12566083
## 5000 meter buffer -3.8951105 7.05292074 4.8113246 0.59778663
## 4750 meter buffer -3.8732596 6.37013650 4.3002633 0.45643624
## 750 meter buffer -1.0965108 1.71220500 -5.6098538 -2.44844721
## 4500 meter buffer -3.5265494 4.99637976 2.4996811 0.51123077
## 2500 meter buffer -1.2192509 -1.40573520 -8.9010552 -0.30345774
## 250 meter buffer -0.7704370 -0.45314157 -4.1512397 -2.33707372
## 4250 meter buffer -3.2168473 3.79565335 0.8800248 0.65687361
## 4000 meter buffer -3.0413082 2.73722575 -0.3557537 0.79075131
## 3750 meter buffer -2.8575209 1.67143898 -1.5365930 0.94528556
## 2750 meter buffer -1.6055359 -1.25338738 -6.4430367 0.01344852
## 3500 meter buffer -2.5613938 0.71111237 -2.2634500 0.78665539
## 3250 meter buffer -2.2863844 -0.06805864 -2.7954171 0.55771128
## 3000 meter buffer -2.0042030 -0.81920581 -4.0346013 0.27626265
##
## lc_grassland lc_mixed lc_shrub seismic_lines wells
## 500 meter buffer -2.0792603 -1.1226536 3.3022369 60.840634 101.720498
## 1500 meter buffer -16.0395555 -2.5848846 2.4122741 -56.405679 74.591183
## 1750 meter buffer -16.6932282 -2.1554289 2.9296052 -62.751389 75.808908
## 2250 meter buffer -16.4993466 -3.7665389 4.7292531 -151.987395 92.089819
## 1000 meter buffer -8.1682537 -2.6656681 0.8566460 32.257597 63.341371
## 1250 meter buffer -11.5652601 -3.2252639 0.9130060 16.486032 61.330369
## 2000 meter buffer -15.9761080 -3.2355262 3.4030382 -95.743744 83.361159
## 5000 meter buffer 20.4025827 -15.2803526 0.8468933 55.455045 -49.623930
## 4750 meter buffer 19.3949270 -12.9615088 0.9209398 73.537035 -43.152532
## 750 meter buffer -5.3479766 -1.9217648 -0.5869029 53.872079 51.310160
## 4500 meter buffer 14.9426439 -11.9688972 1.6079028 46.680261 -22.208726
## 2500 meter buffer -12.6173740 -4.3965413 4.6432870 -126.029368 79.819445
## 250 meter buffer 0.3514854 -0.2358895 -0.1082480 20.979424 -9.157483
## 4250 meter buffer 10.8405383 -12.1745082 2.2569781 14.212517 -1.921045
## 4000 meter buffer 8.1765526 -12.8025063 2.7539529 2.156558 14.514723
## 3750 meter buffer 6.1016974 -12.3526015 3.3085848 -31.946626 29.893195

```

```

## 2750 meter buffer    -8.0573235   -7.5184102   4.0794287    -69.026061   68.687380
## 3500 meter buffer     3.4722506  -13.3919641   3.3483987    -25.524572   38.322697
## 3250 meter buffer     1.3519411  -12.5286868   3.3226162    -31.251309   44.552860
## 3000 meter buffer    -2.4585444  -10.0695966   3.4821198    -34.001414   55.594007
##
##          df      logLik      AICc      delta      weight
## 500 meter buffer      9 -17.75783  57.18912   0.000000  0.739388293
## 1500 meter buffer      9 -20.64682  62.96712   5.777991  0.041133692
## 1750 meter buffer      9 -21.09201  63.85750   6.668371  0.026354463
## 2250 meter buffer      9 -21.21584  64.10515   6.916031  0.023284962
## 1000 meter buffer      9 -21.26162  64.19671   7.007588  0.022243040
## 1250 meter buffer      9 -21.32245  64.31837   7.129251  0.020930300
## 2000 meter buffer      9 -21.33723  64.34794   7.158814  0.020623188
## 5000 meter buffer      9 -21.46832  64.61011   7.420984  0.018089492
## 4750 meter buffer      9 -21.64738  64.96823   7.779110  0.015123778
## 750 meter buffer       9 -21.69783  65.06913   7.880009  0.014379721
## 4500 meter buffer      9 -22.09045  65.85437   8.665251  0.009710403
## 2500 meter buffer      9 -22.23293  66.13932   8.950199  0.008420957
## 250 meter buffer       9 -22.29749  66.26845   9.079326  0.007894452
## 4250 meter buffer      9 -22.40860  66.49067   9.301541  0.007064290
## 4000 meter buffer      9 -22.58924  66.85194   9.662819  0.005896823
## 3750 meter buffer      9 -22.76745  67.20836  10.019239  0.004934264
## 2750 meter buffer      9 -22.91246  67.49839  10.309263  0.004268198
## 3500 meter buffer      9 -22.94147  67.55642  10.367294  0.004146135
## 3250 meter buffer      9 -23.20371  68.08089  10.891769  0.003189737
## 3000 meter buffer      9 -23.29076  68.25499  11.065868  0.002923815
##
## Model Selection for Species: mule_deer
##
##          (Intercept) harvest_2000 harvest_pre2000 lc_broadleaf
## 750 meter buffer    -3.1292299    -6.3576372         1.8610623         2.930140
## 1000 meter buffer   -3.7131449    -5.2245405         1.4017844         3.780531
## 1250 meter buffer   -3.7885810    -3.6427315         1.0409759         3.882477
## 1500 meter buffer   -3.8855367    -2.7014616         1.4868726         3.809702
## 1750 meter buffer   -3.8365747    -2.1733092         1.4344405         4.099388
## 2000 meter buffer   -3.6974280    -1.9615883         1.1071738         3.900098
## 2250 meter buffer   -3.5592365    -1.4567441         1.0949685         3.728742
## 2500 meter buffer   -3.5727703    -1.1122621         0.8166103         4.266187
## 500 meter buffer    -1.9222060    -2.0738875         0.4360065         1.657459
## 2750 meter buffer   -3.5148213    -0.6908063         0.7201640         4.421626
## 3000 meter buffer   -3.4257902    -0.5846699         0.6033678         4.340469
## 3250 meter buffer   -3.3621775    -0.5635506         0.7805070         4.193213
## 3500 meter buffer   -3.1213205    -0.7476825         0.2409047         4.195602
## 3750 meter buffer   -2.8544068    -0.4891239        -0.2956295         4.395500
## 4250 meter buffer   -2.4422943    -0.8353376        -1.5949223         4.825207
## 4500 meter buffer   -2.2216632    -1.2787595        -2.4959773         4.949997
## 4000 meter buffer   -2.6235878    -0.5506916        -0.8554360         4.479570
## 5000 meter buffer   -1.9701593    -0.9041669        -4.2099555         5.075073
## 4750 meter buffer   -1.9846569    -1.1782371        -3.3117422         4.854453
## 250 meter buffer    -0.6425509    -0.3562470        -0.1974735        -0.170585
##
##          lc_grassland lc_mixed lc_shrub seismic_lines wells df
## 750 meter buffer      6.7925293  7.988791  2.2257006    10.996978   1.806159  9
## 1000 meter buffer     9.1068795 10.014914  3.0027515   -35.610818  11.710408  9
## 1250 meter buffer    10.2137456 10.618885  2.7241663   -48.775130  11.667112  9
## 1500 meter buffer    11.1565159 11.381501  1.7935036   -33.759720  15.117430  9
## 1750 meter buffer    11.8955782 12.716375  1.6931460   -75.781785  10.853072  9

```

```
## 2000 meter buffer 12.0158711 12.083161 1.4474379 -57.827061 11.451082 9
## 2250 meter buffer 11.9940602 10.630171 1.0159702 -41.767225 9.129137 9
## 2500 meter buffer 12.9418396 10.305415 1.2896287 -99.938608 5.048277 9
## 500 meter buffer 2.2791037 2.534968 -1.9518491 44.388329 -1.329792 9
## 2750 meter buffer 12.9515972 9.852599 1.0976579 -117.210017 2.103905 9
## 3000 meter buffer 11.3935669 8.755112 0.8215858 -101.129377 7.982603 9
## 3250 meter buffer 11.1261518 8.644488 0.5058774 -84.109410 7.854180 9
## 3500 meter buffer 8.6090250 7.327412 0.7978514 -102.742487 13.970564 9
## 3750 meter buffer 6.9126922 5.796932 1.1375897 -156.837849 13.565027 9
## 4250 meter buffer 1.5881787 3.879579 2.0466899 -241.086467 28.475725 9
## 4500 meter buffer -0.9987698 3.224561 2.4848706 -269.982985 36.633221 9
## 4000 meter buffer 4.2907029 4.476669 1.4782517 -184.721622 18.318944 9
## 5000 meter buffer -2.7232666 3.496807 3.1100175 -322.684924 35.235272 9
## 4750 meter buffer -2.6944964 3.159181 2.7288727 -288.057345 34.531749 9
## 250 meter buffer 0.5880810 1.048010 -2.8554404 2.831985 -12.631979 9
## logLik AICc delta weight
## 750 meter buffer -27.20696 76.08740 0.0000000 0.212964495
## 1000 meter buffer -27.26101 76.19549 0.1080946 0.201759860
## 1250 meter buffer -27.83688 77.34722 1.2598203 0.113433334
## 1500 meter buffer -27.85157 77.37662 1.2892180 0.111778189
## 1750 meter buffer -28.09456 77.86258 1.7751802 0.087666106
## 2000 meter buffer -28.62135 78.91617 2.8287753 0.051766221
## 2250 meter buffer -29.12514 79.92374 3.8363434 0.031279212
## 2500 meter buffer -29.14732 79.96811 3.8807068 0.030593026
## 500 meter buffer -29.16526 80.00398 3.9165821 0.030049151
## 2750 meter buffer -29.30665 80.28677 4.1993719 0.026087062
## 3000 meter buffer -29.62085 80.91517 4.8277668 0.019053334
## 3250 meter buffer -29.80465 81.28278 5.1953767 0.015854242
## 3500 meter buffer -30.11478 81.90303 5.8156276 0.011626787
## 3750 meter buffer -30.30637 82.28620 6.1988020 0.009599629
## 4250 meter buffer -30.41215 82.49777 6.4103674 0.008636019
## 4500 meter buffer -30.42430 82.52207 6.4346673 0.008531727
## 4000 meter buffer -30.44635 82.56617 6.4787712 0.008345645
## 5000 meter buffer -30.45066 82.57480 6.4873977 0.008309726
## 4750 meter buffer -30.52570 82.72488 6.6374785 0.007708982
## 250 meter buffer -30.96724 83.60795 7.5205477 0.004957252
```

Now that we have a best-fit buffer size for each species we can proceed with a logistic regression

Elk

I didn't like how elk was performing as a proportional binomial and based on the detection data I don't think there is enough to run it in that model framework, we will see how it looks as a logistic regression model

750m

Correlation plot

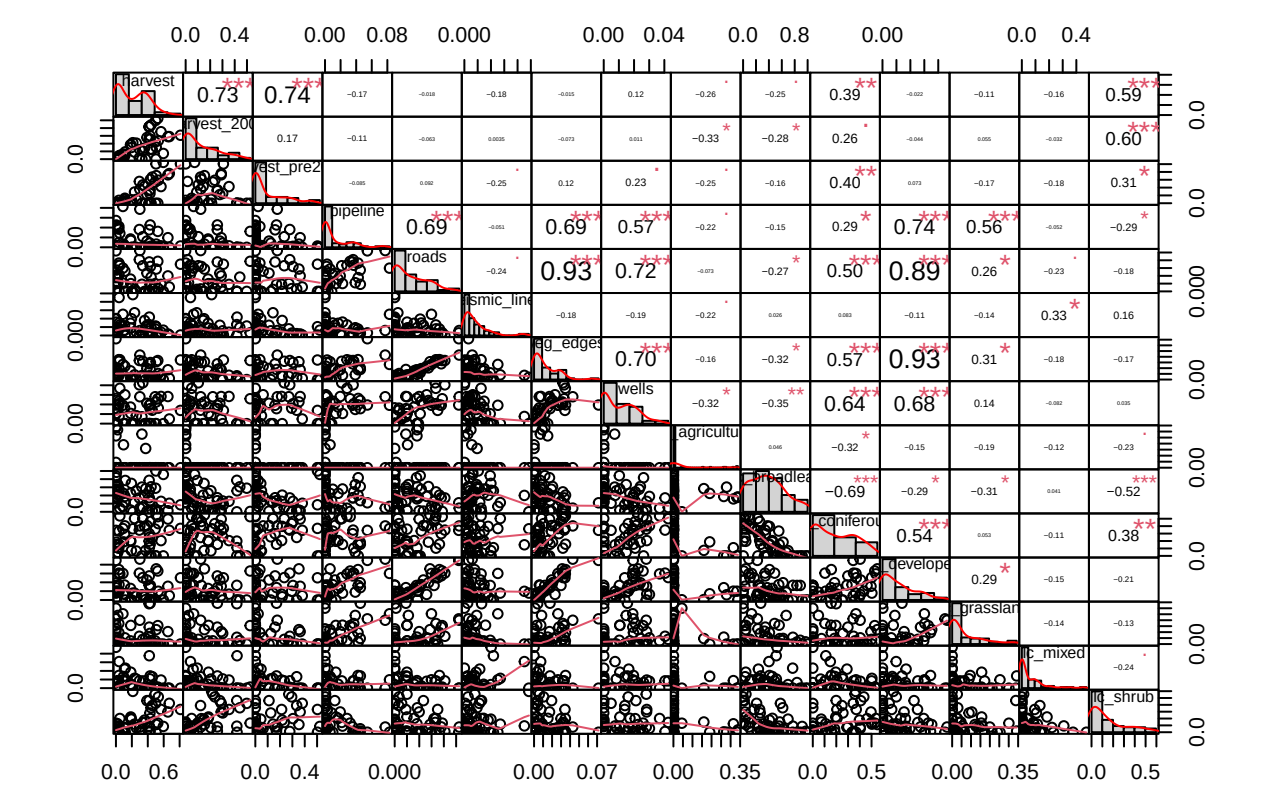
Let's reprint the correlation plot for the best fit buffer size to reference when defining our models

```
## open file to save plot
## png("figures/logistic_regression/corr_plot_750.png",
## width = 1000,
## height = 800)

pres_absen_dat$`750 meter buffer` %>%
```

```
# select only columns with covariates not other info to simplify the plot a bit
select(harvest:lc_shrub) %>%

# use chart.correlation to produce plots for each buffer size
chart.Correlation(.,
  histogram = TRUE,
  method = "pearson")
```



```
# # close file
# dev.off()
```

Minority class

Overparameterization is much easier with logistic regression models because the rule is $n = 10$ for the observations in your minority class (presence) for each parameter. So we need to calculate how many 1's we have with each species so we know how many parameters we can have in our models. We have 59 observations total

```
# get number of presence and absences
summary(pres_absen_dat$`750 meter buffer`$elk)
```

```
## 0 1
## 48 11
```

With only 11 in our minority class we can run single model variables only, not sure if this will actually be useful for report or publication but will do an example model set with elk to take a look

Models

```
# null
elk_null <- glm(elk ~ 1,
               data = pres_absen_dat$`750 meter buffer`,
               family = 'binomial')

# each landcover type
elk_ag <- glm(elk ~ scale(lc_agriculture),
             data = pres_absen_dat$`750 meter buffer`,
             family = 'binomial')

elk_broadleaf <- glm(elk ~ scale(lc_broadleaf),
                   data = pres_absen_dat$`750 meter buffer`,
                   family = 'binomial')

elk_coniferous <- glm(elk ~ scale(lc_coniferous),
                    data = pres_absen_dat$`750 meter buffer`,
                    family = 'binomial')

elk_grassland <- glm(elk ~ scale(lc_grassland),
                   data = pres_absen_dat$`750 meter buffer`,
                   family = 'binomial')

elk_mixed <- glm(elk ~ scale(lc_mixed),
                data = pres_absen_dat$`750 meter buffer`,
                family = 'binomial')

elk_shrub <- glm(elk ~ scale(lc_shrub),
               data = pres_absen_dat$`750 meter buffer`,
               family = 'binomial')

# HFI variables

elk_road <- glm(elk ~ scale(roads),
               data = pres_absen_dat$`750 meter buffer`,
               family = 'binomial')

elk_harvest <- glm(elk ~ scale(harvest),
                  data = pres_absen_dat$`750 meter buffer`,
                  family = 'binomial')

elk_harvest2000 <- glm(elk ~ scale(harvest_2000),
                      data = pres_absen_dat$`750 meter buffer`,
                      family = 'binomial')

elk_harvest_pre2000 <- glm(elk ~ scale(harvest_pre2000),
                          data = pres_absen_dat$`750 meter buffer`,
                          family = 'binomial')

elk_seismic <- glm(elk ~ scale(seismic_lines),
                  data = pres_absen_dat$`750 meter buffer`,
                  family = 'binomial')
```

```

elk_pipe <- glm(elk ~ scale(pipeline),
               data = pres_absen_dat$`750 meter buffer`,
               family = 'binomial')

elk_well <- glm(elk ~ scale(wells),
               data = pres_absen_dat$`750 meter buffer`,
               family = 'binomial')

```

Model selection

```

model.sel(elk_null,
          elk_ag,
          elk_broadleaf,
          elk_coniferous,
          elk_grassland,
          elk_mixed,
          elk_road,
          elk_harvest,
          elk_harvest2000,
          elk_harvest_pre2000,
          elk_seismic,
          elk_pipe,
          elk_well)

```

```

## Model selection table
##               (Int) scl(lc_agr) scl(lc_brd) scl(lc_cnf) scl(lc_grs)
## elk_coniferous   -1.695                               -0.8751
## elk_broadleaf    -1.595                               0.6394
## elk_harvest_pre2000 -1.565
## elk_road         -1.572
## elk_null         -1.473
## elk_ag           -1.521           0.3997
## elk_seismic      -1.551
## elk_harvest      -1.525
## elk_mixed        -1.548
## elk_well         -1.518
## elk_harvest2000  -1.485
## elk_pipe         -1.482
## elk_grassland    -1.479                               0.1404
##               scl(lc_mxd) scl(rds) scl(hrv) scl(hrv_2000) scl(hrv_p20)
## elk_coniferous
## elk_broadleaf
## elk_harvest_pre2000                               0.5537
## elk_road              -0.5825
## elk_null
## elk_ag
## elk_seismic
## elk_harvest              0.41
## elk_mixed              -0.5303
## elk_well
## elk_harvest2000              -0.1973
## elk_pipe
## elk_grassland

```

	scl(ssm_lns)	scl(ppl)	scl(wll)	df	logLik	AICc	delta	weight
## elk_coniferous				2	-25.873	56.0	0.00	0.282
## elk_broadleaf				2	-26.574	57.4	1.40	0.140
## elk_harvest_pre2000				2	-26.760	57.7	1.77	0.116
## elk_road				2	-27.238	58.7	2.73	0.072
## elk_null				1	-28.380	58.8	2.87	0.067
## elk_ag				2	-27.432	59.1	3.12	0.059
## elk_seismic	-0.5378			2	-27.617	59.4	3.49	0.049
## elk_harvest				2	-27.624	59.5	3.50	0.049
## elk_mixed				2	-27.669	59.6	3.59	0.047
## elk_well			-0.3835	2	-27.815	59.8	3.88	0.040
## elk_harvest2000				2	-28.224	60.7	4.70	0.027
## elk_pipe			-0.1707	2	-28.268	60.8	4.79	0.026
## elk_grassland				2	-28.286	60.8	4.83	0.025

Models ranked by AICc(x)

Grizzly bear

Minority class

Overparameterization is much easier with logistic regression models because the rule is $n = 10$ fr the observations in your minority class (presence) for each parameter. So we need to calculate how many 1's we have with each species so we know how many parameters we can have in our models. We have 59 observations total

```
# get number of presence and absences
summary(pres_absen_dat$`750 meter buffer`$grizzly_bear)
```

```
## 0 1
## 50 9
```

Mule deer

Minority class

Overparameterization is much easier with logistic regression models because the rule is $n = 10$ fr the observations in your minority class (presence) for each parameter. So we need to calculate how many 1's we have with each species so we know how many parameters we can have in our models. We have 59 observations total

```
# get number of presence and absences
summary(pres_absen_dat$`750 meter buffer`$mule_deer)
```

```
## 0 1
## 44 15
```

Red fox

Minority class

Overparameterization is much easier with logistic regression models because the rule is $n = 10$ fr the observations in your minority class (presence) for each parameter. So we need to calculate how many 1's we have with each species so we know how many parameters we can have in our models. We have 59 observations total

```
# get number of presence and absences
summary(pres_absen_dat$`750 meter buffer`$red_fox)
```

```
## 0 1
## 47 12
```