SRFN project analysis

Marissa Dyck

2025-1-10

Contents

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

Marissa A. Dyck
Postdoctoral research fellow
University of Victoria
School of Environmental Studies
Email: marissadyck17@gmail.com

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('ggpubr')
install.packages('corrplot')
install.packages('Hmisc')
install.packages('glmmTMB')
install.packages('MuMIn')
install.packages('TMB', type = 'source')
install.packages('rphylopic')
install.packages('broom')
install.packages('lme4')
```

```
install.packages('car')
install.packages('ggeffects')
install.packages('flextable', type = 'binary')
install.packages('gfonts') # needed for flextable
install.packages('officer') # needed for flextable
```

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(ggpubr) # make modifications to plot for publication (arrange plots)
```

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

```
library(PerformanceAnalytics)    # Used to generate a correlation plot
library(Hmisc) # used to generate histograms for all variables in data frame
library(glmmTMB)      # Constructing GLMMs
library(MuMIn) # for model selection
library(rphylopic) # add animal silhouettes to graphs
library(broom) # extracting odds ratios in a tidy format
library(lme4) # constructing generalized linear mixed effects models
library(car) # used for calculating variance inflation factor (VIF) to assess model fit
library(ggeffects) # for extracting predicted probabilities from glms for plotting
```

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

```r
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 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 1 0 0 0 ...
##   ..$ red_squirrel     : num [1:63] 0 0 0 0 0 0 0 1 0 0 ...
##   ..$ other            : num [1:63] 0 0 0 0 0 0 0 0 14 0 ...
##   ..$ 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>
##  $ 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 1 0 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 1 1 1 0 0 ...
##    ..$ cougar           : num [1:63] 0 0 0 0 0 0 1 0 0 0 ...
##    ..$ red_squirrel     : num [1:63] 0 0 0 0 0 0 0 1 0 0 ...
##    ..$ other            : num [1:63] 0 0 0 0 0 0 0 0 1 0 ...
##    ..$ 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

```r
# 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

```r
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

```
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

```r
covariates <- read_csv('data/processed/srfn_covariates_grouped.csv',

                       # also specify how site is read in
                       col_types = cols(site = col_factor())
                       )
```

Data checks

```r
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 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 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>
```

```r
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.   :0.00000   Min.   :0.00000   Min.   :0.000000
##  1st Qu.:0.008954   1st Qu.:0.00000   1st Qu.:0.00000   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.   :0.00000
##  1st Qu.:0.001827   1st Qu.:0.003484   1st Qu.:0.0008336   1st Qu.:0.00000
##  Median :0.003612   Median :0.012634   Median :0.0089454   Median :0.00000
##  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.:0.00000
##  Max.   :0.030028   Max.   :0.099551   Max.   :0.0957837   Max.   :0.49000
##
##   lc_broadleaf     lc_coniferous      lc_developed      lc_grassland
##  Min.   :0.0000   Min.   :0.00000   Min.   :0.00000   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.   :0.00000
##  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 very with spatial scales

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

```r
buffer_frames <- list()
```

```r
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
```

```r
# 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

```r
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>, ...
```

```r
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

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

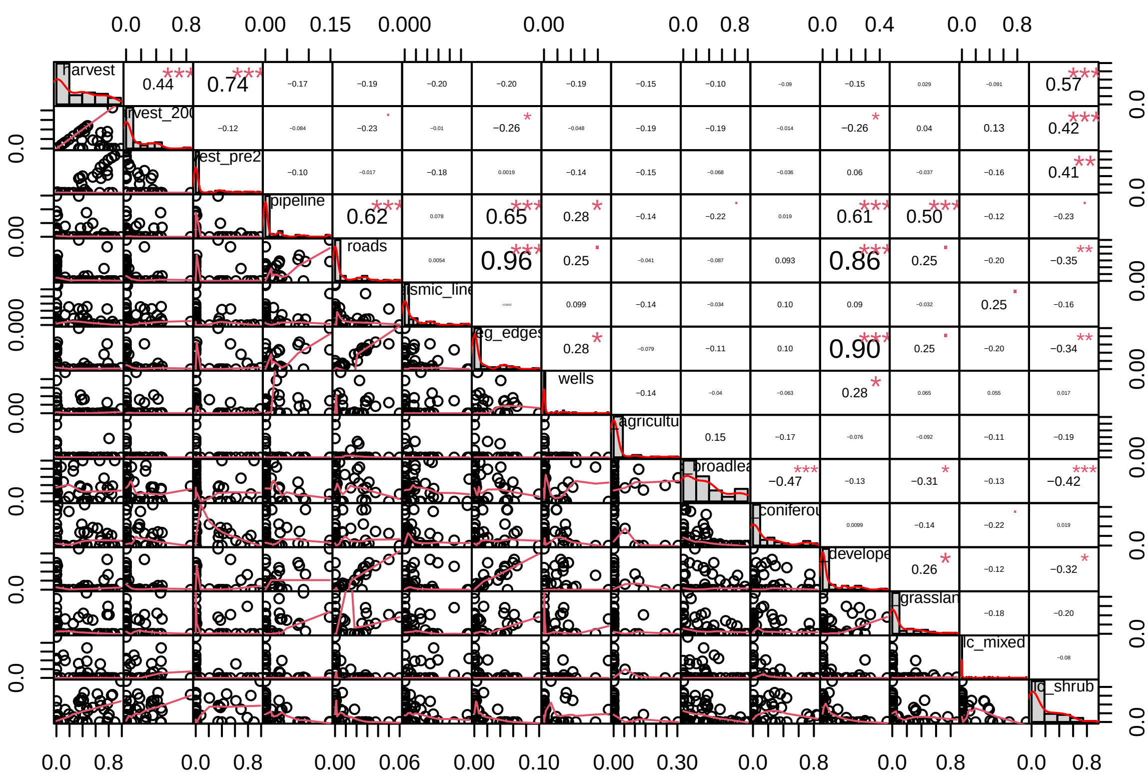
Let's also save this so we can use it in a later script to make figures

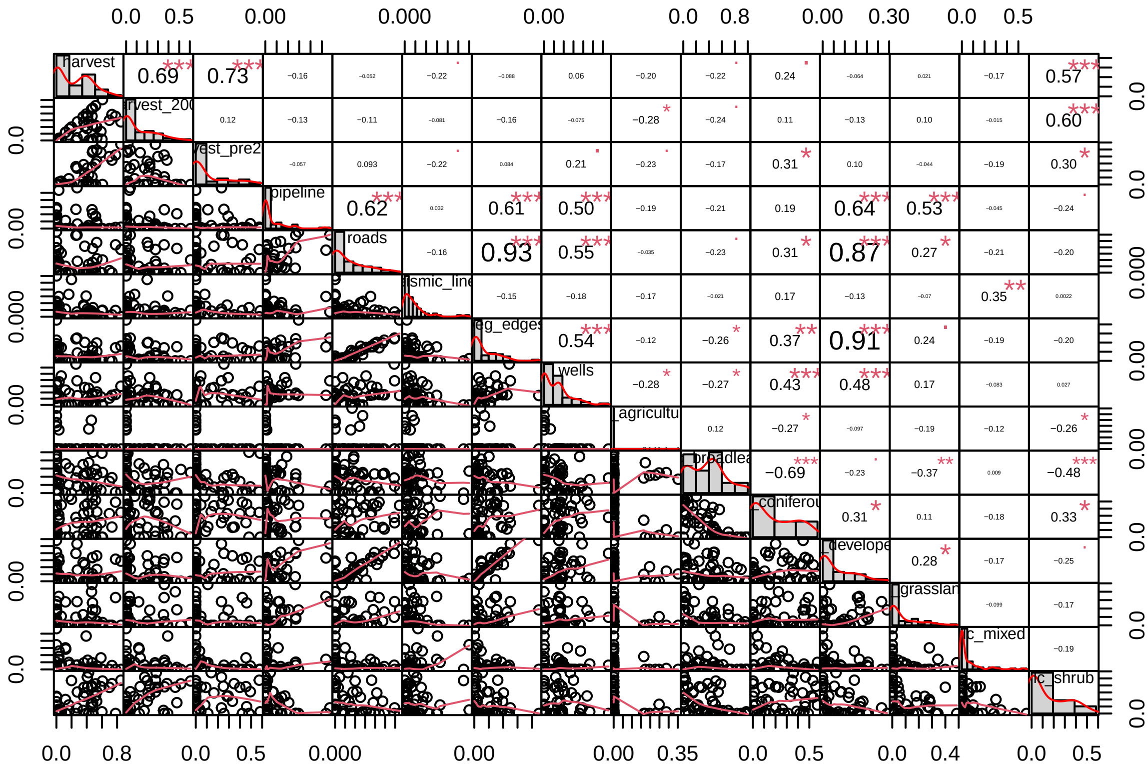
```
saveRDS(prop_det_data, 'data/processed/prop_det_data.rds')
```

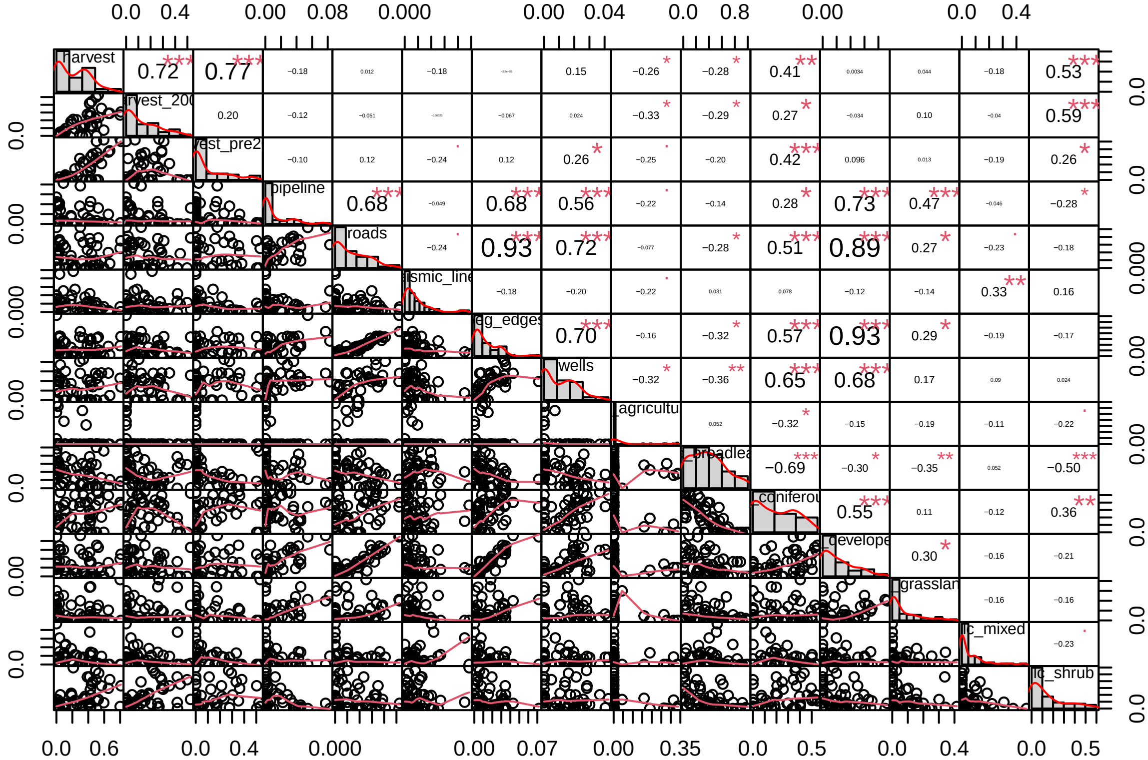
Correlation plots

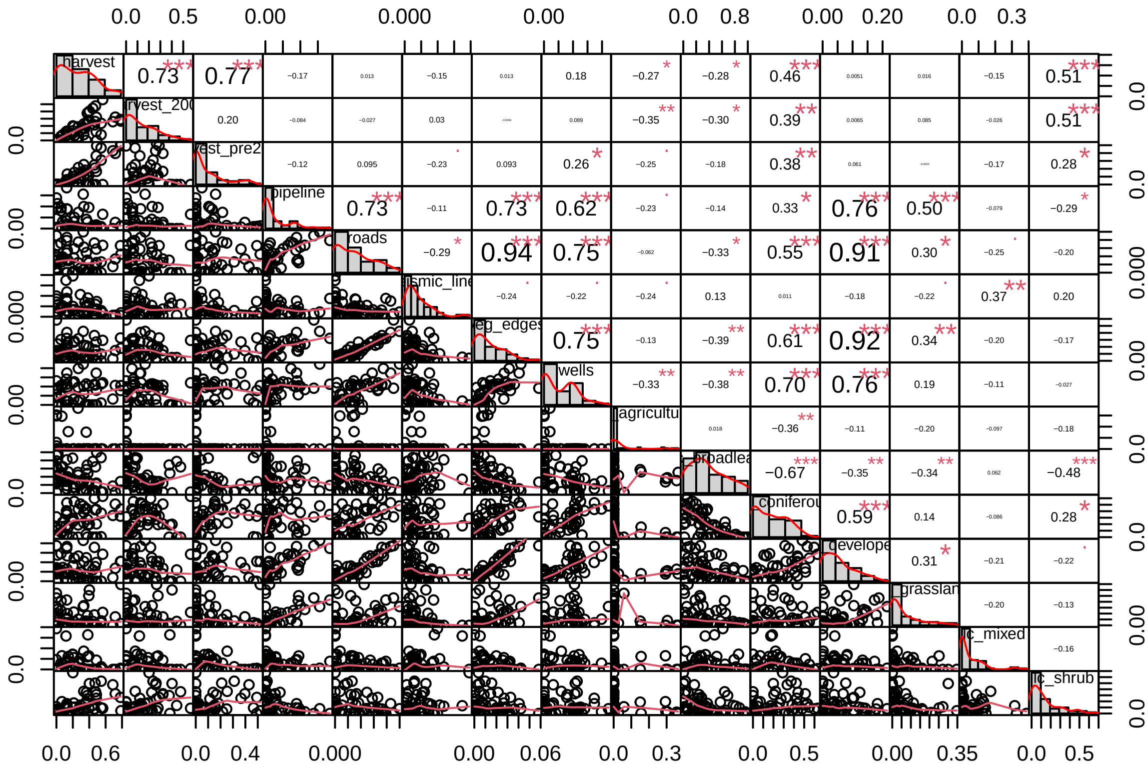
Before we can develop any models we need to look at your covariates and see if there are any major violations of the model assumptions of independence, e.g. variables that are highly correlated - in which case we need to choose which variable in each pair to include in a model

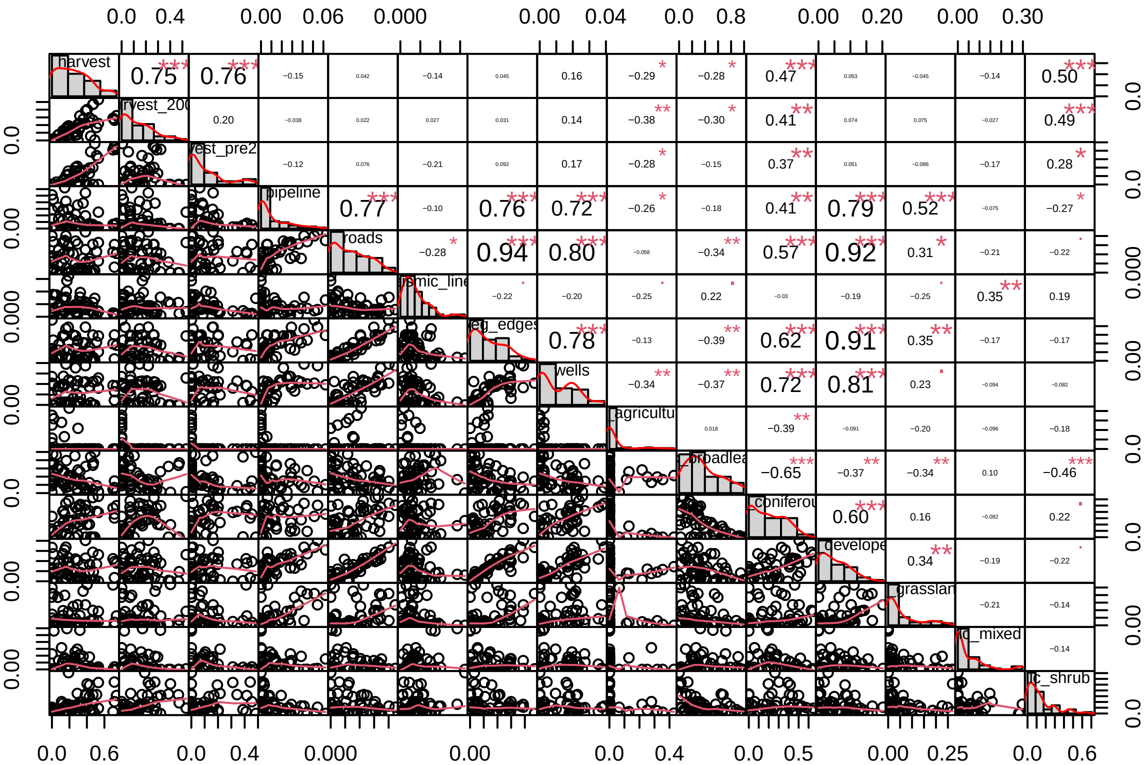
```
prop_det_data %>%

  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")
  )
```

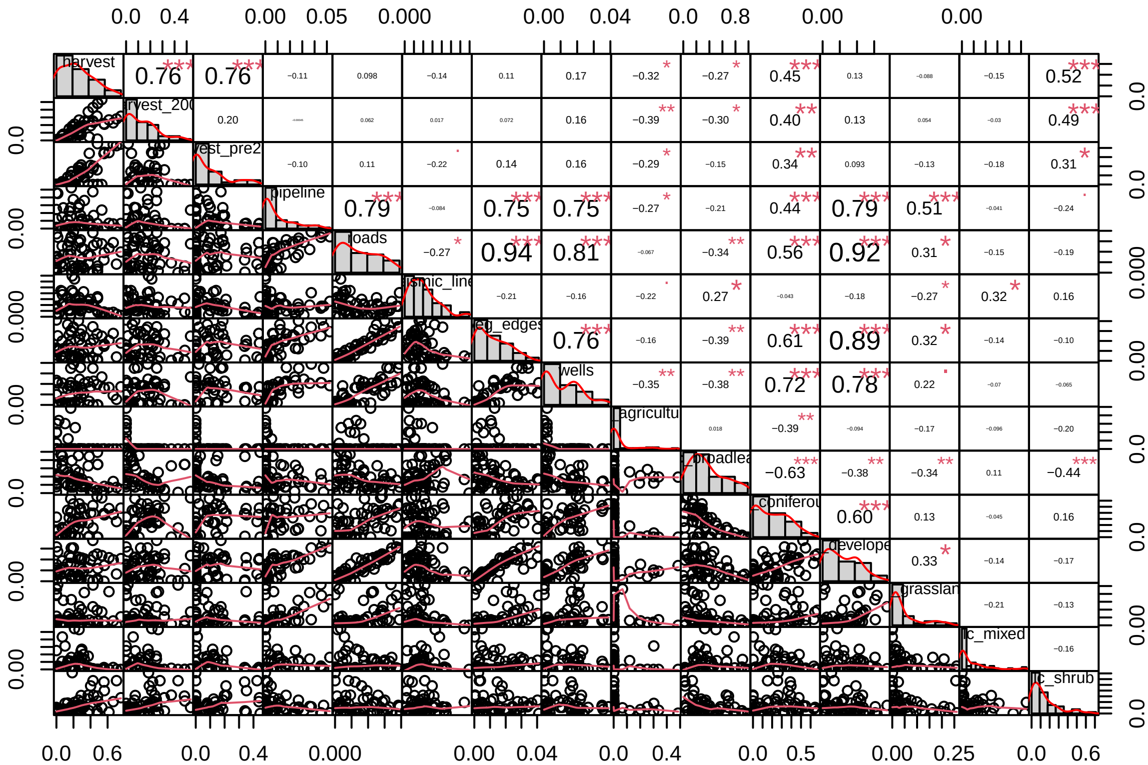


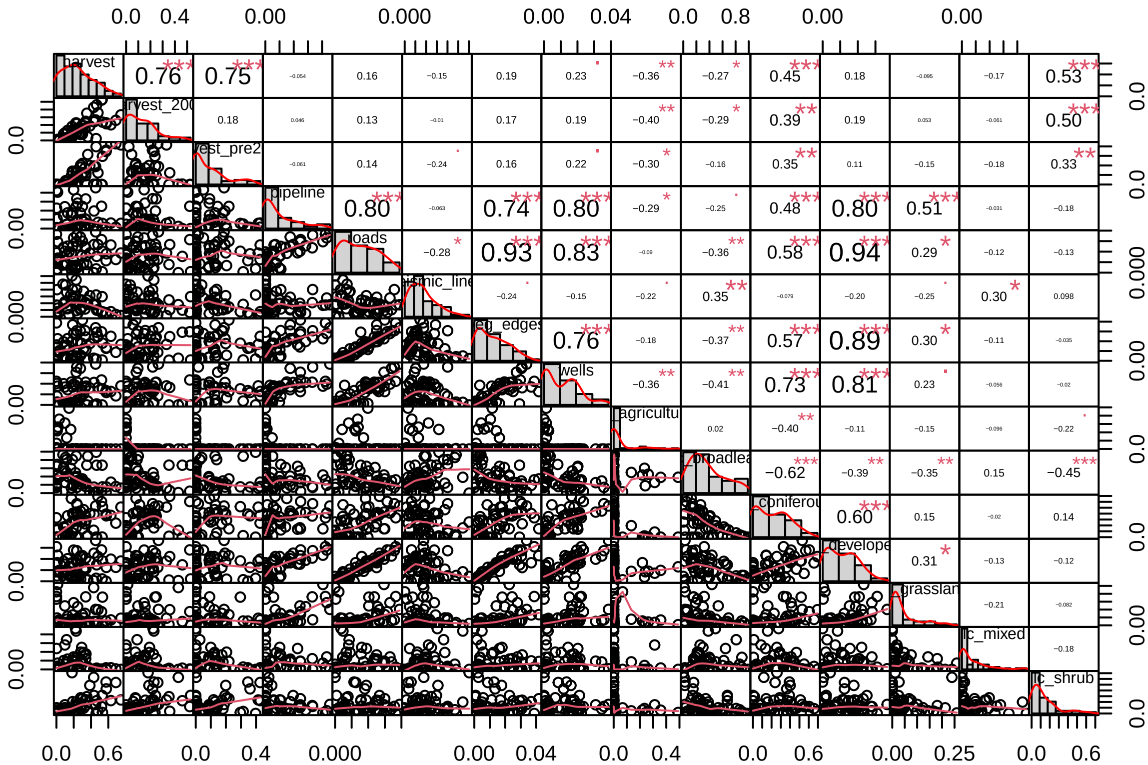


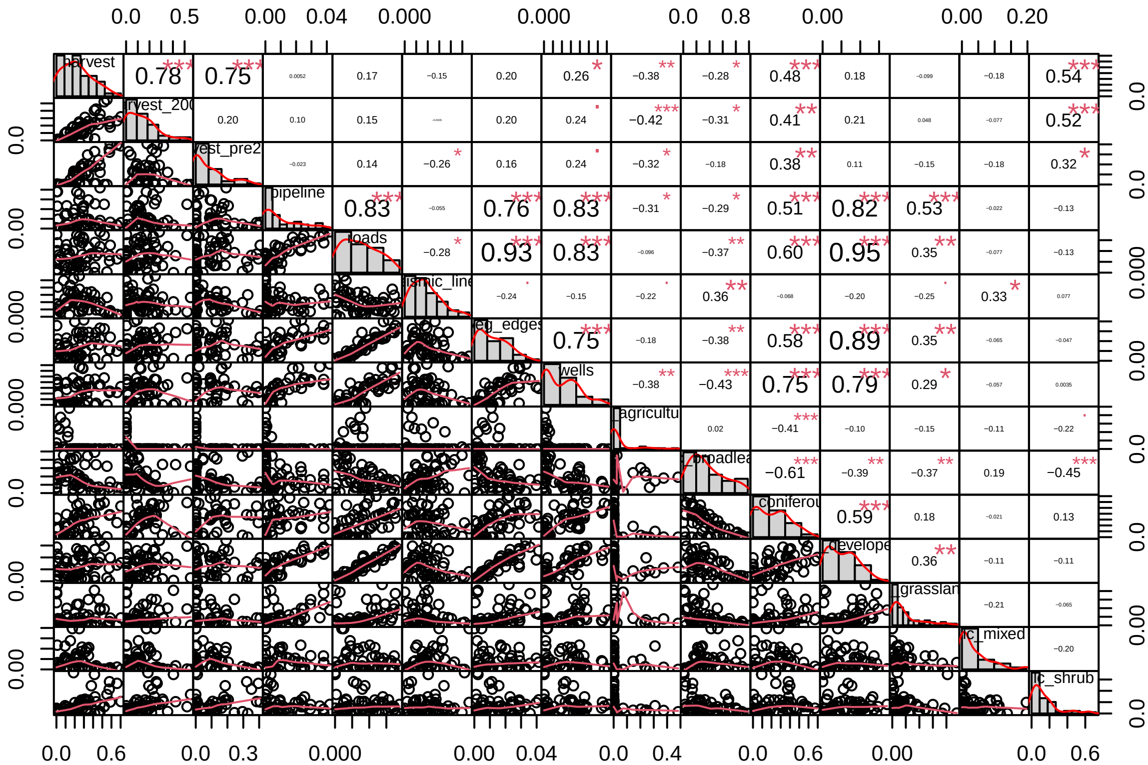


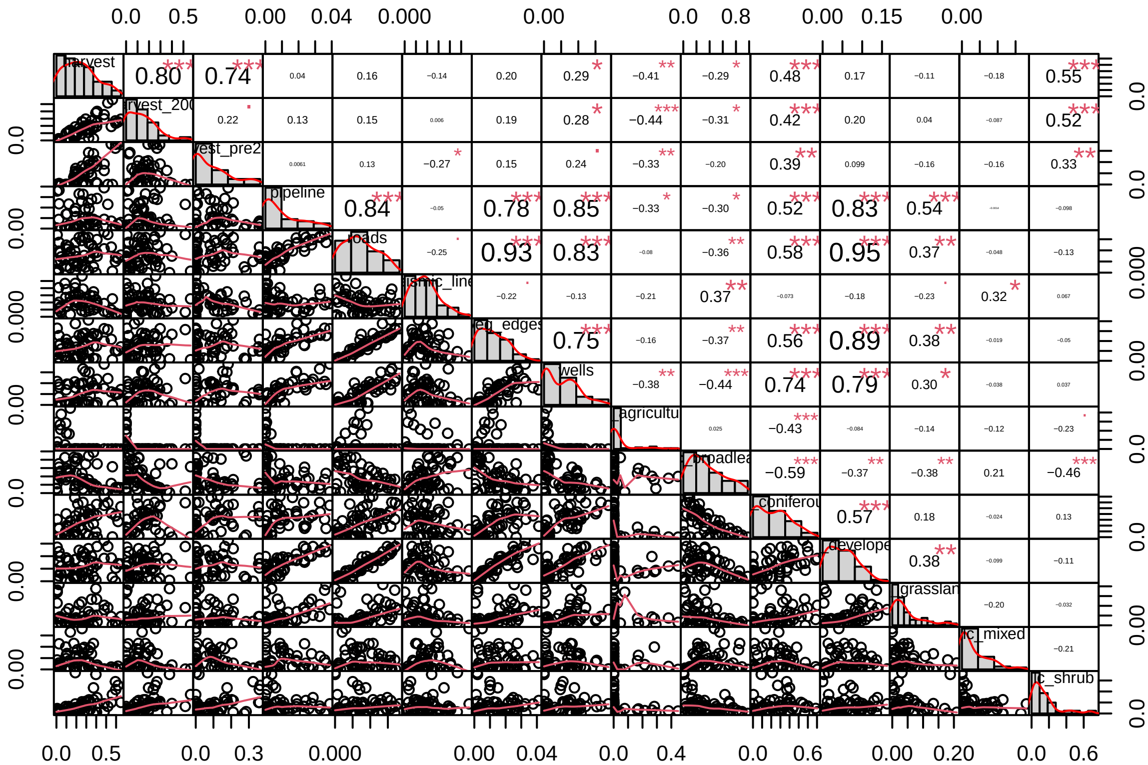

harvest
rvest_200
rest_pre2
pipeline
roads
ismic_line
eg_edges
wells
agricultu
broadlea
coniferou
develope
grasslan
c_mixed
c_shrub

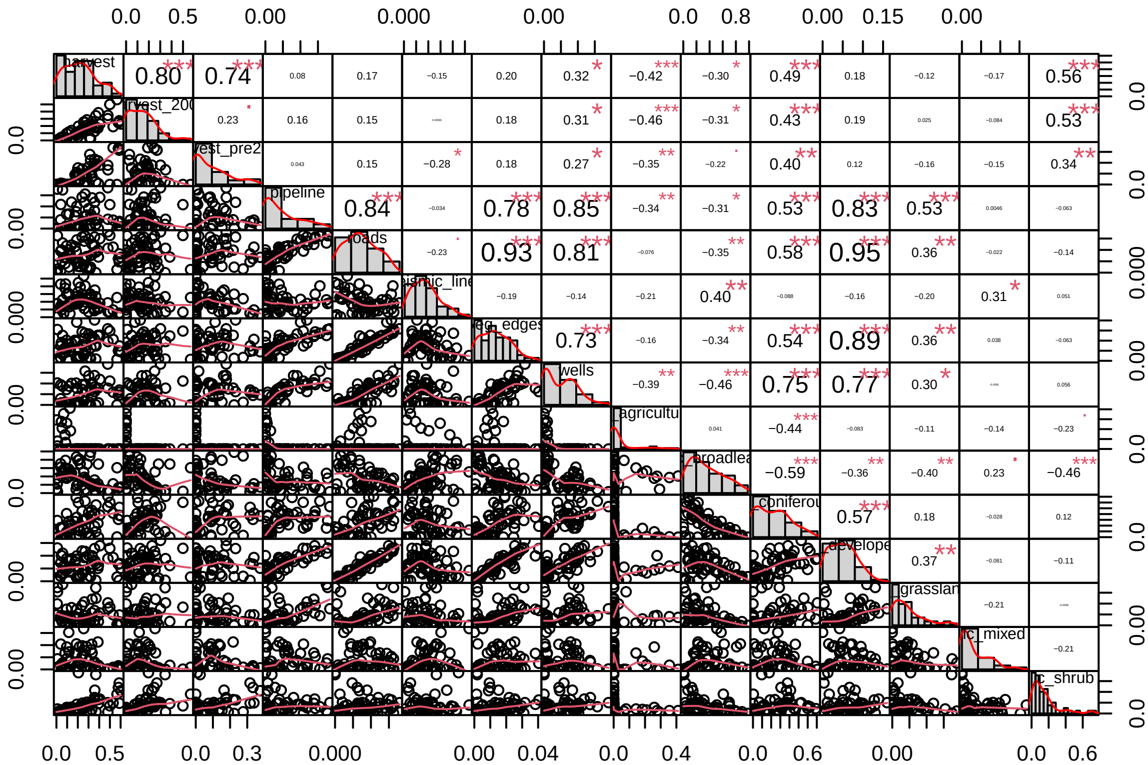

harvest
rvest_200
vest_pre2
pipeline
roads
smic_line
eg_edges
wells
agricultu
broadlea
coniferou
develope
grasslan
c_mixed
lc_shrub

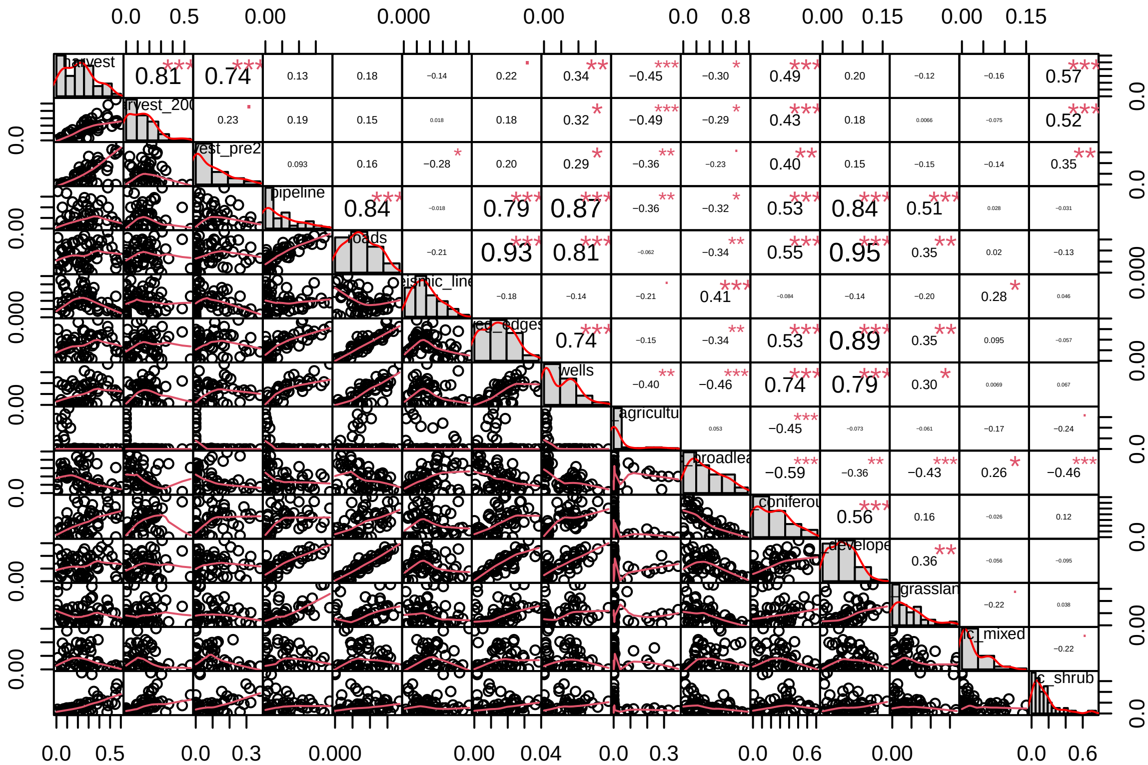

harvest
rvest_200
vest_pre2
pipeline
roads
ismic_line
g_edges
wells
agricultu
broadlea
coniferou
develope
grasslan
c_mixed
c_shrub

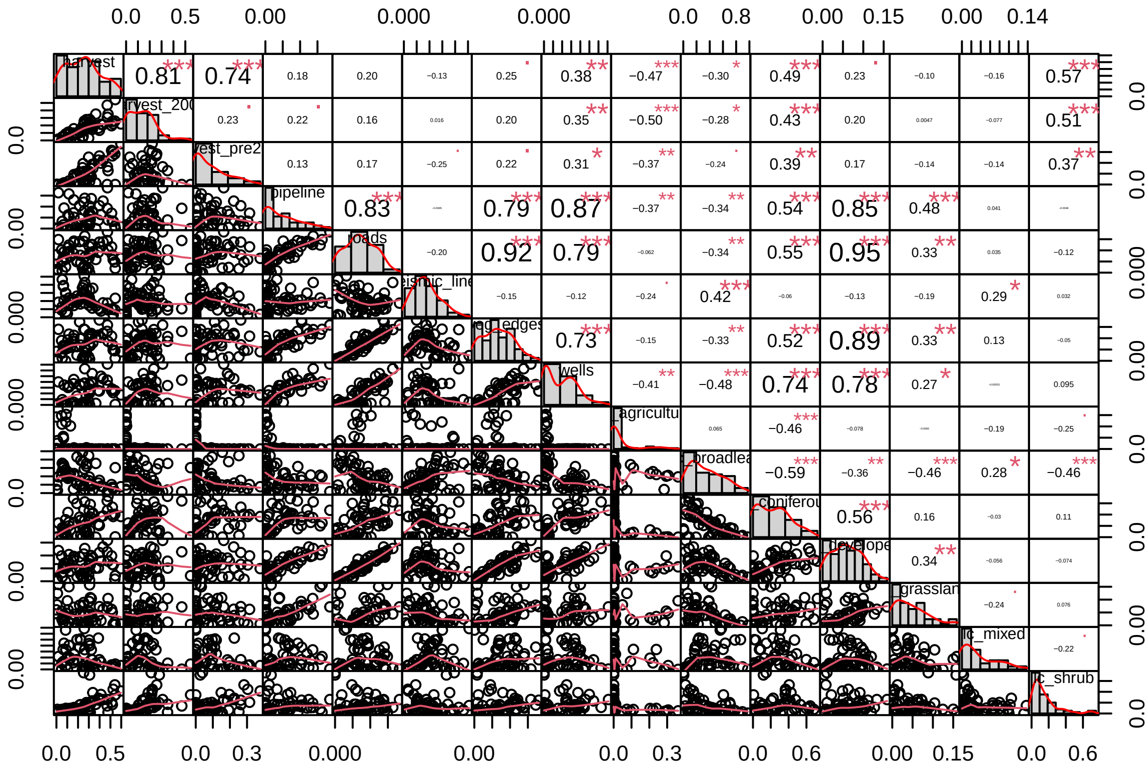

harvest
pipeline
roads
wells
agricultu
broadlea
coniferou
grasslan
lc_mixed
lc_shrub

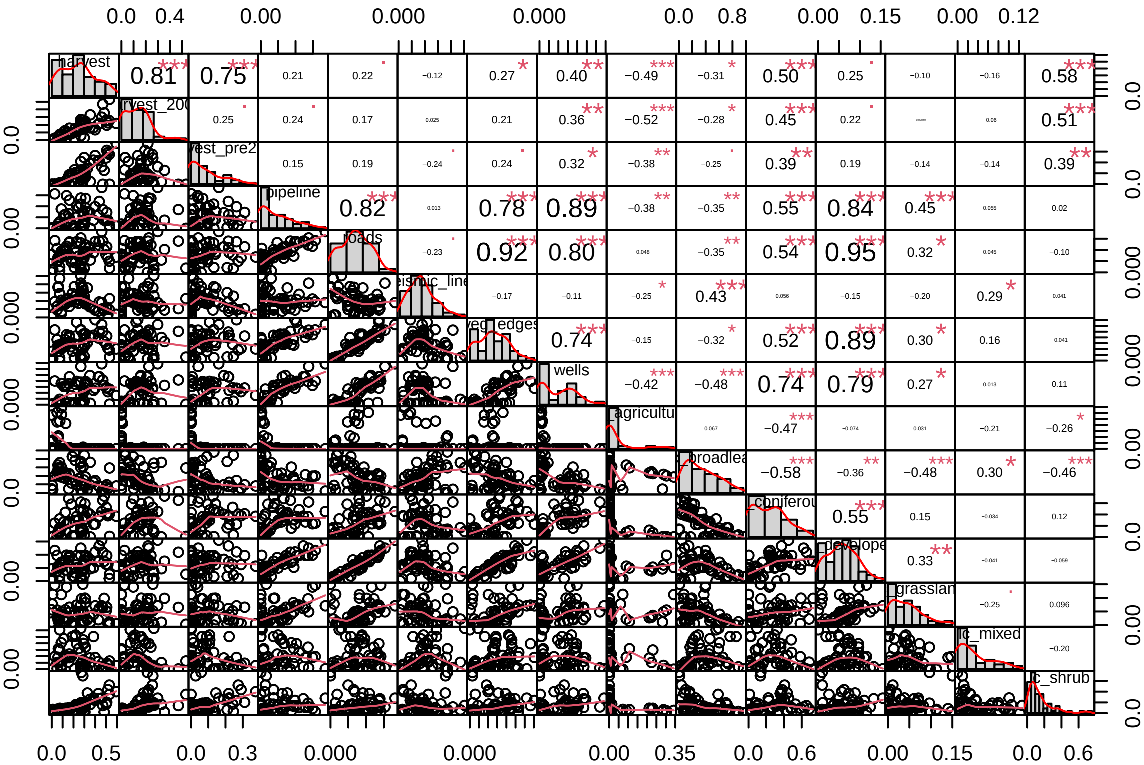


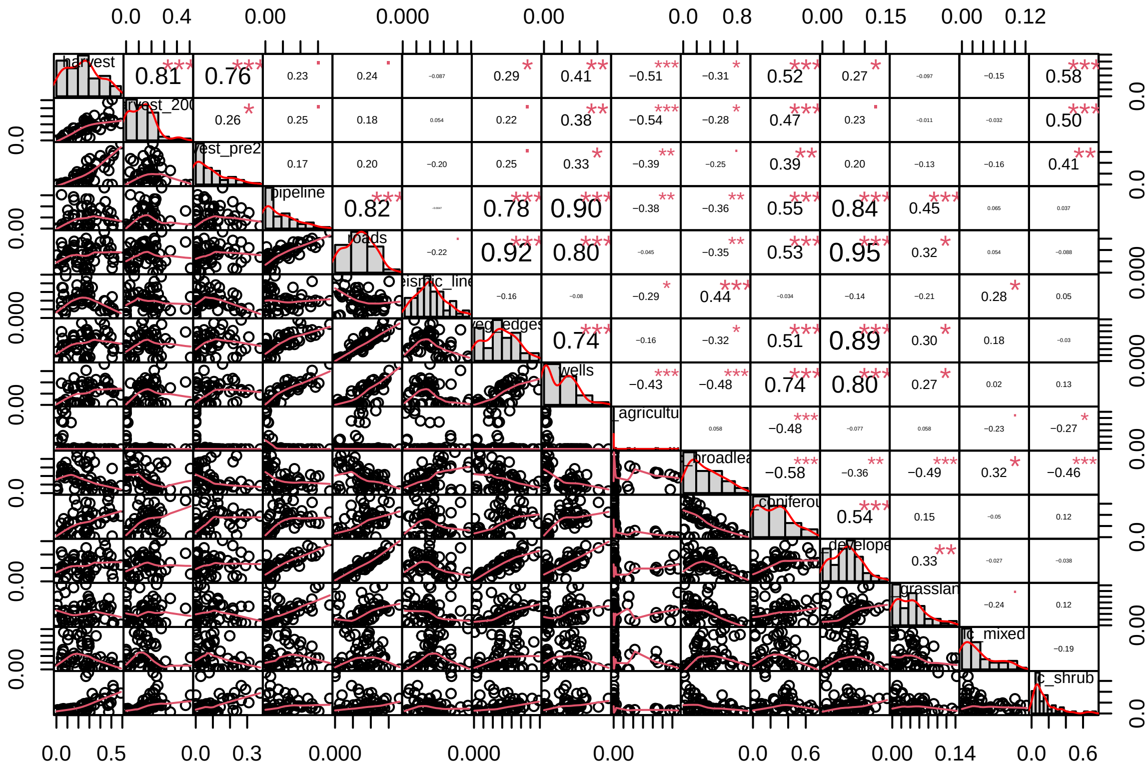


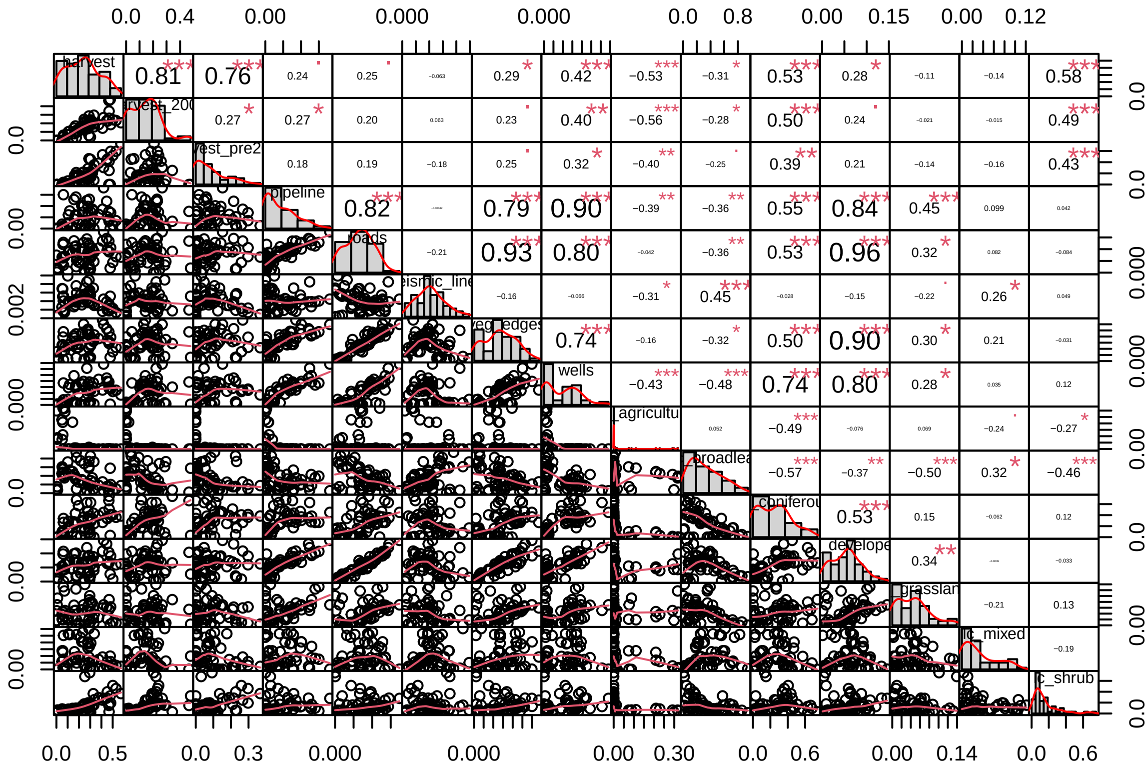


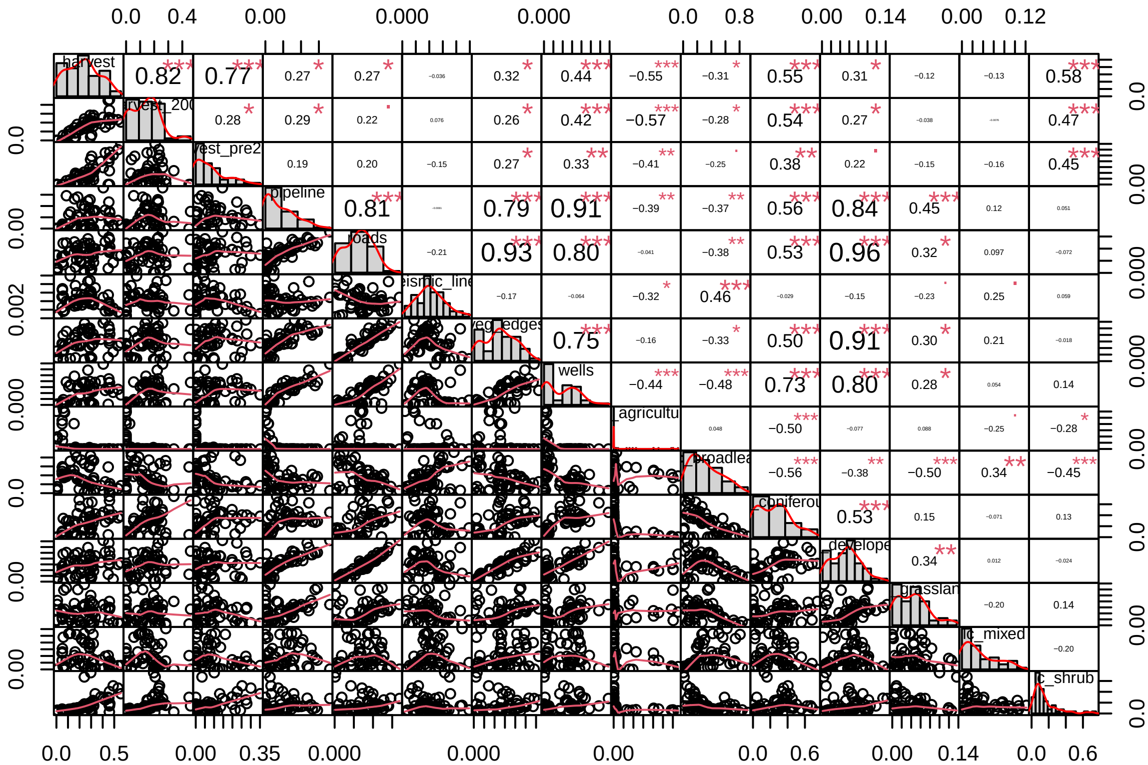


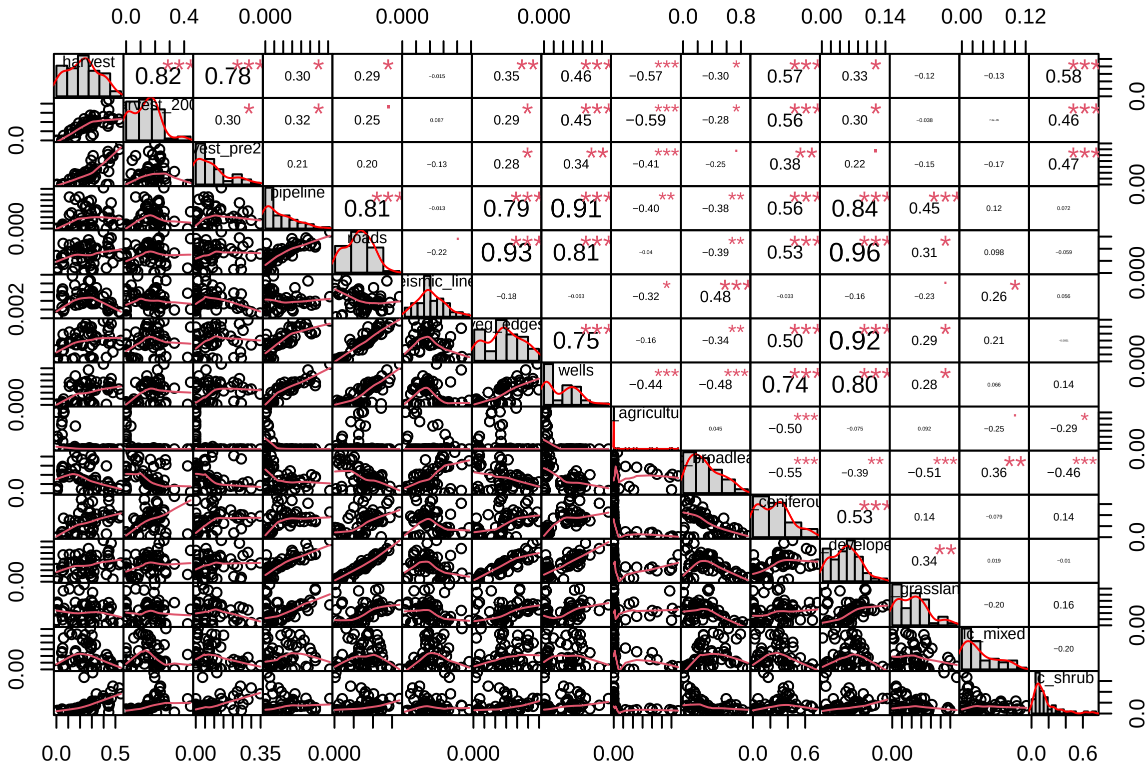


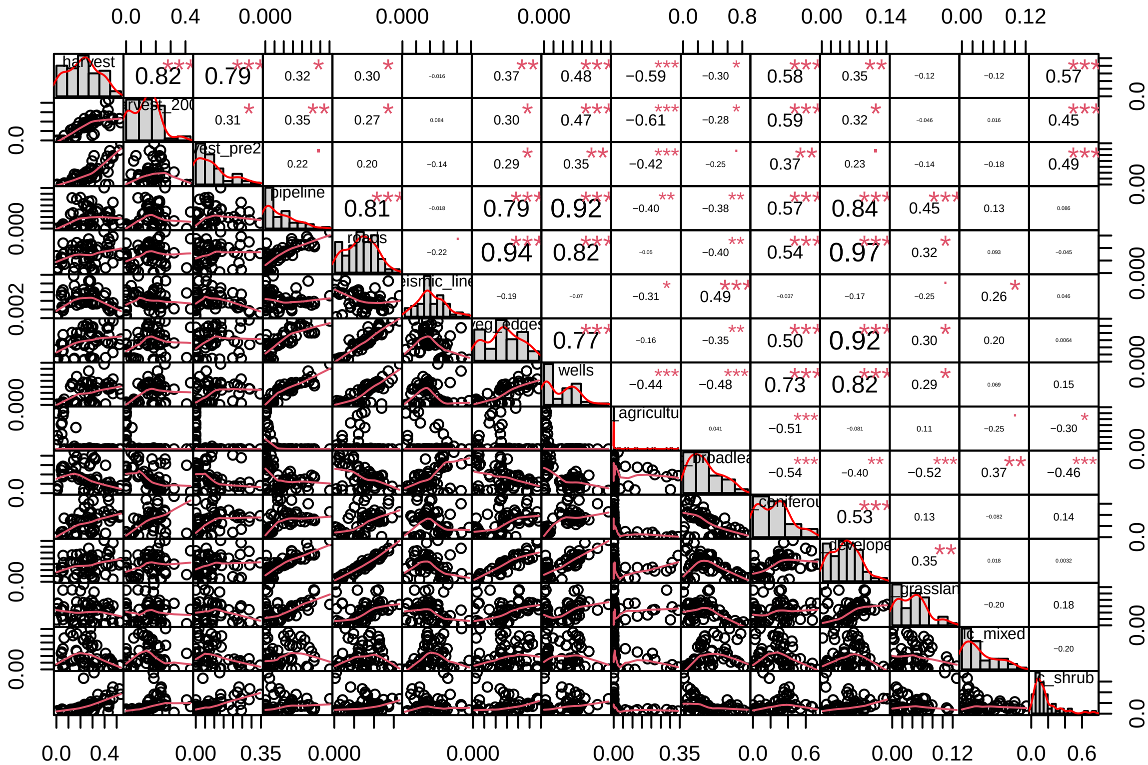

harvest
pipeline
roads
wells
agricultu
broadlea
coniferou
grasslan
ic_mixed
ic_shrub

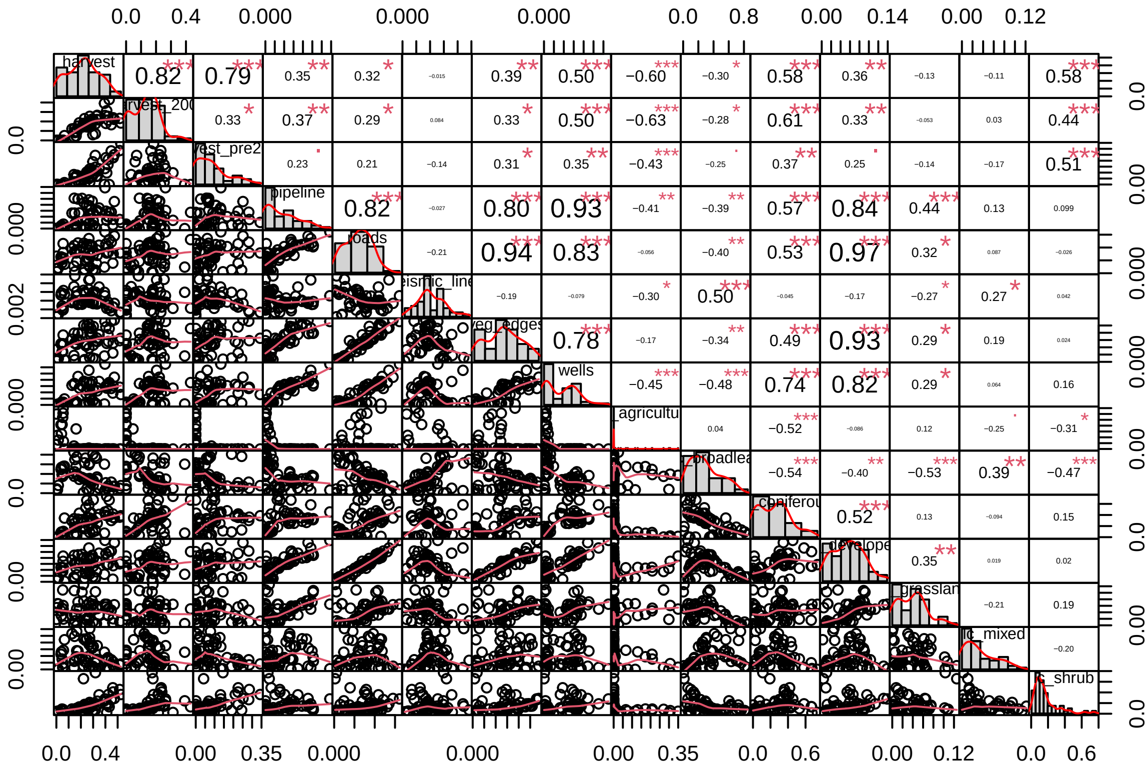


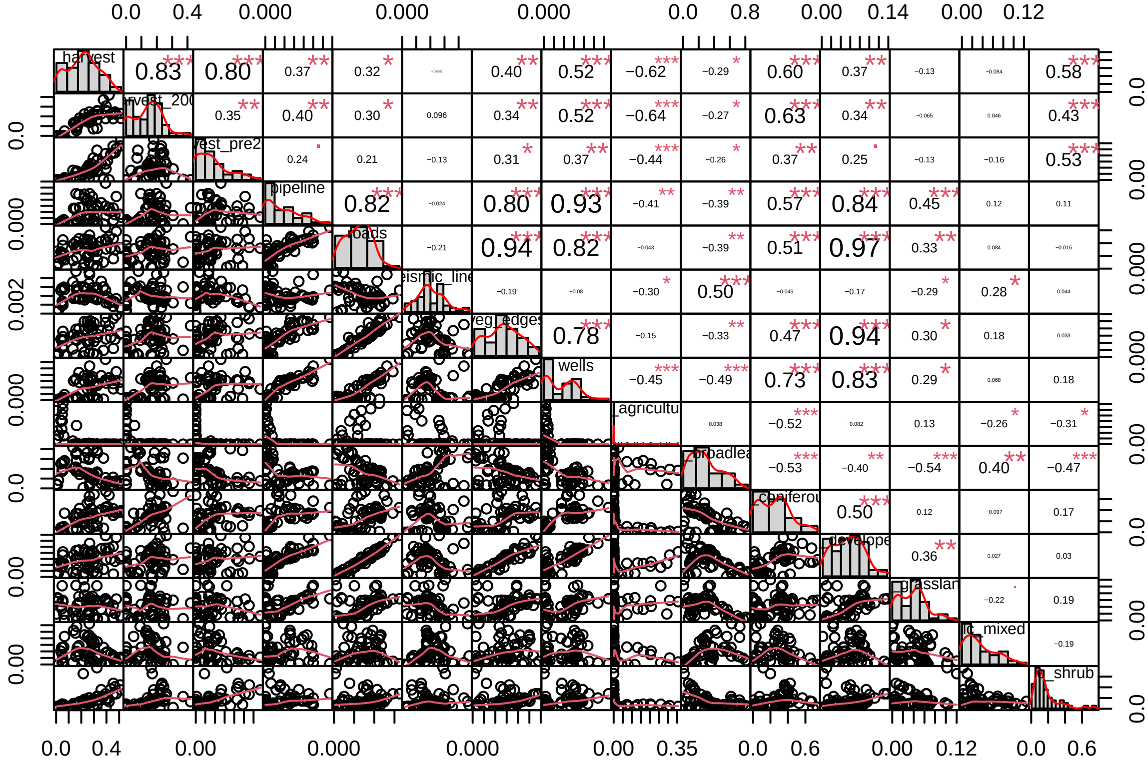

harvest
rvest_200
vest_pre2
pipeline
roads
eismic_line
veg_edges
wells
agricultu
broadlea
coniferou
develope
grasslan
lc_mixed
lc_shrub


harvest
pipeline
roads
wells
broadlea
coniferou
grasslan
lc_mixed
c_shrub


harvest
harvest_200
vest_pre2
pipeline
roads
eismic_line
veg_edges
wells
_agricultu
broadlea
coniferou
develope
grasslan
lc_mixed
c_shrub


harvest
rvest_200
vest_pre2
pipeline
roads
eismic_line
veg_edges
wells
agricultu
broadlea
coniferou
develope
grasslan
lc_mixed
c_shrub






```
## $`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 releveant 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 purr 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 + ',
```

```r
            '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
```

```
## 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
```

```
## 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
```

```
## 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
```

```r
# 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
```

```
##                   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
```

```
## 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
```

```
## 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
```

```
## 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
```

```
## 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
```

```
## 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
```

```
## 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
```

```
## 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
```

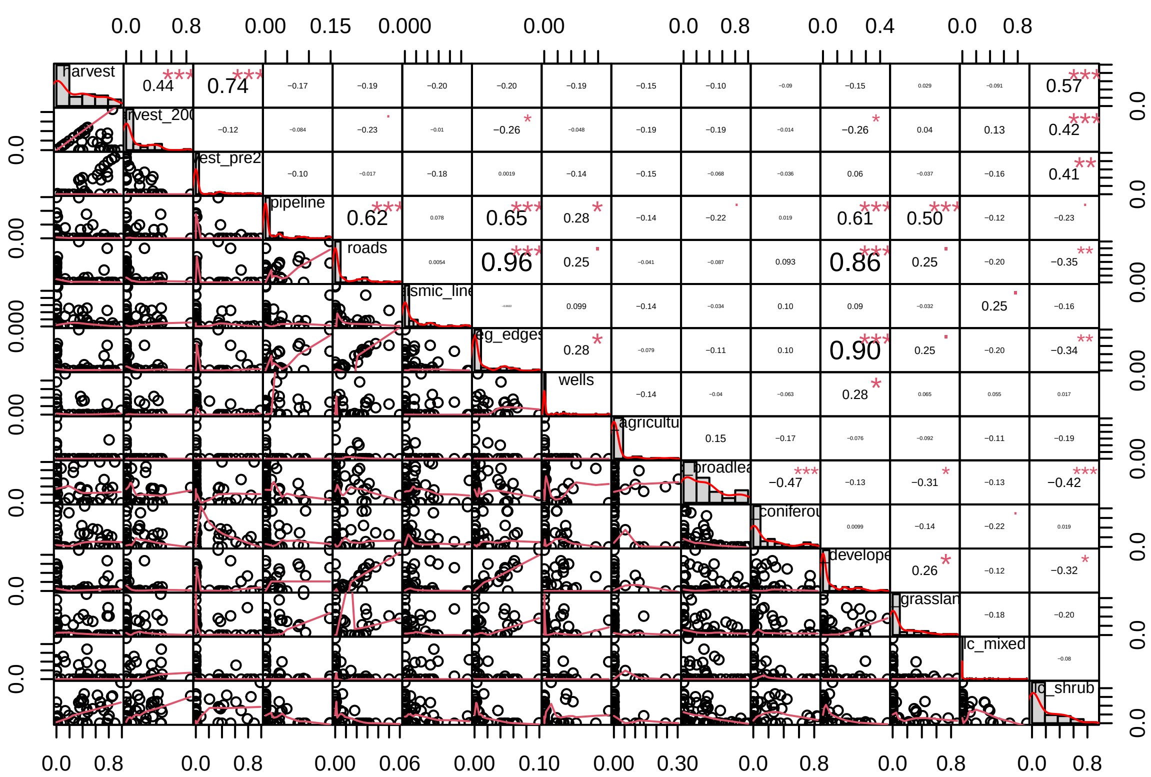
Black bear

Depending on which variables I include in the buffer seleciton 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.

```r
# 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 vaiables 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),
```

```r
                    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                             -0.04492
## 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                               0.13040
##                     scl(hrv_2000) scl(hrv_p20) scl(lc_agr) scl(rds) scl(ppl)
## 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 analsyis for black bears

Top model/s summary

```r
# 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
```

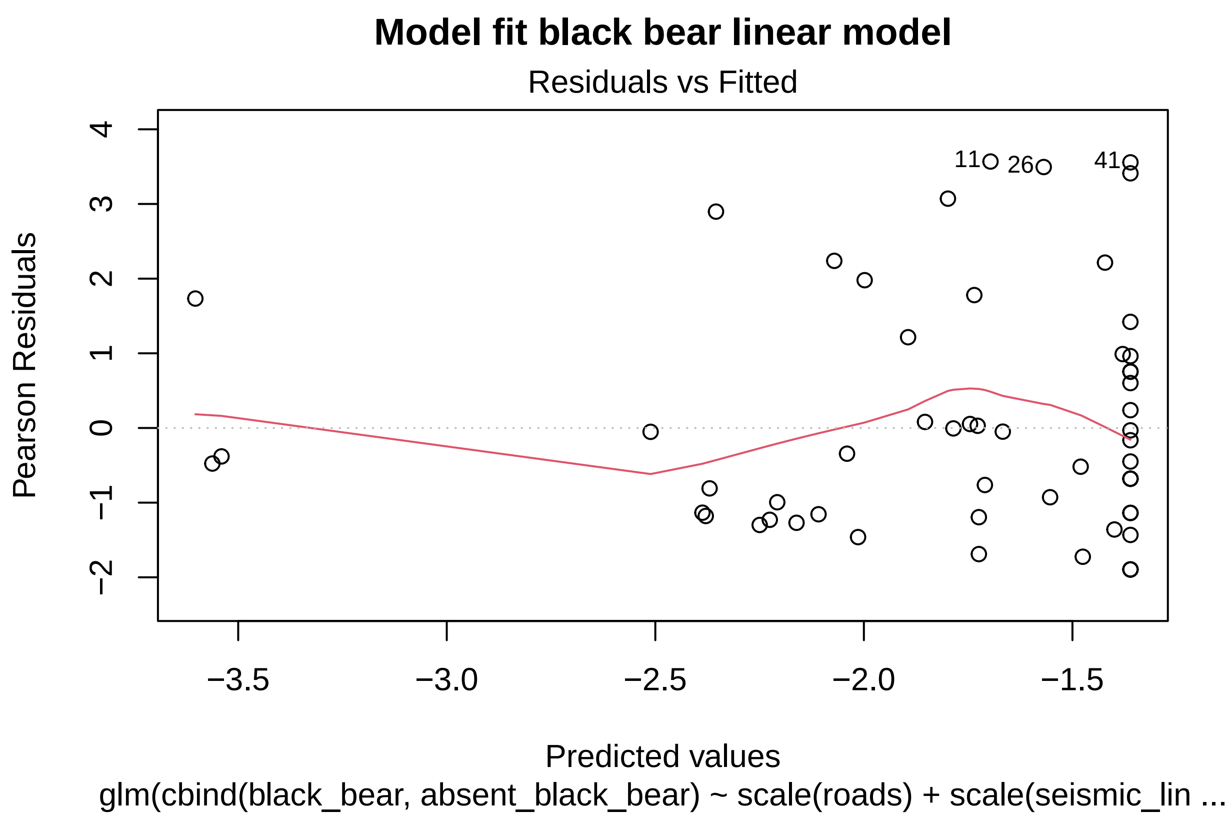
Model fit

We will start with VIF

```
vif(bbear_linear)
```

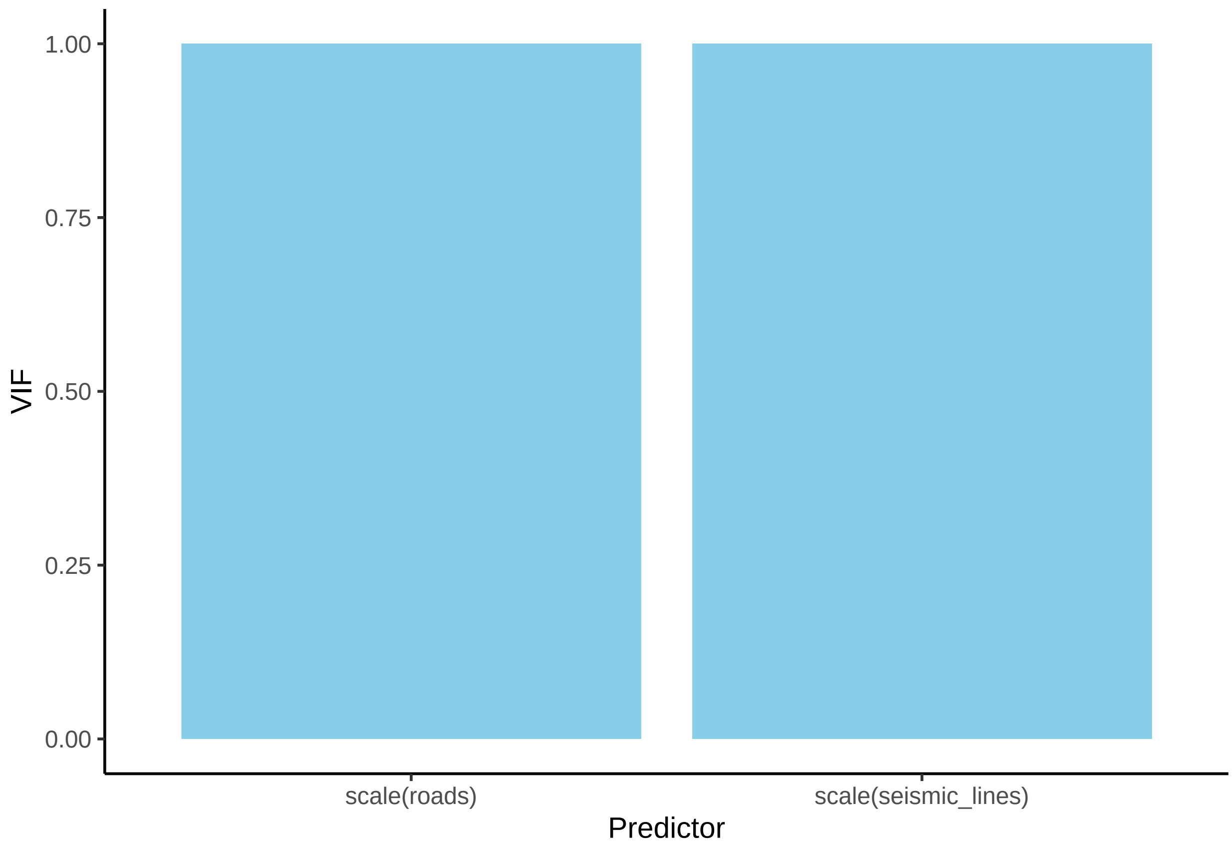
```
##          scale(roads) scale(seismic_lines)
##              1.000006             1.000006
```

```
  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()
```



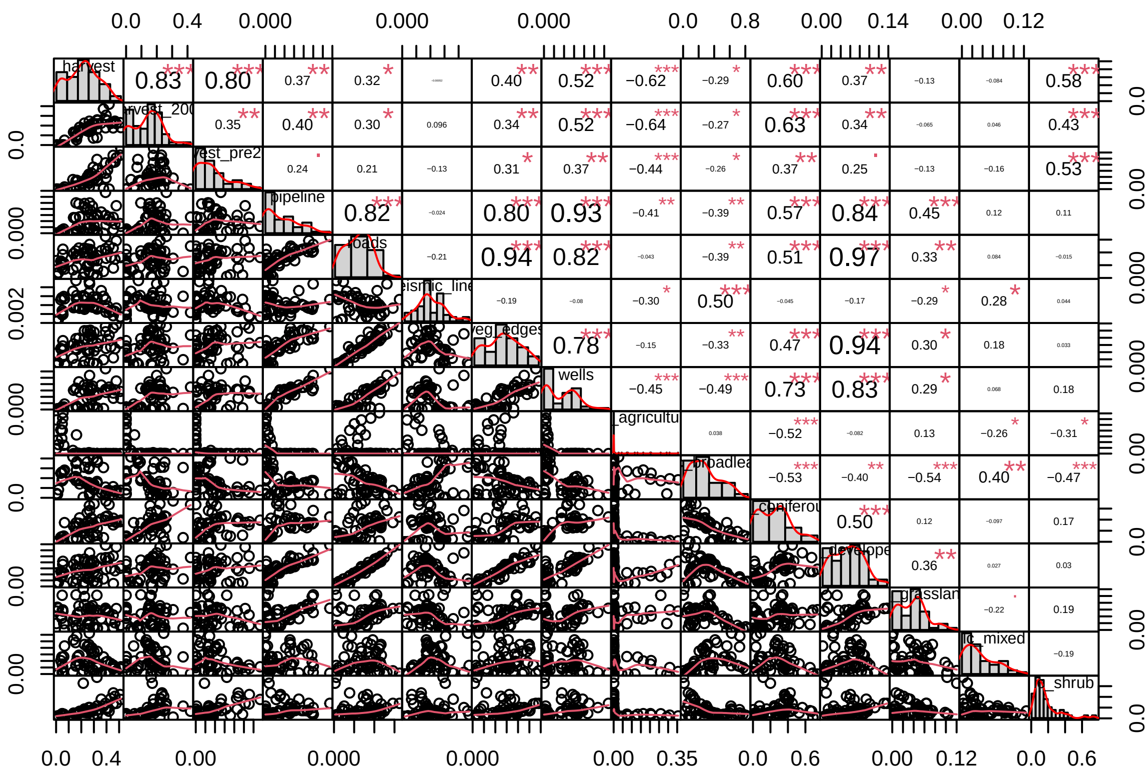
Coyote

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) %>%
```

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




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

Models

```r
# 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 wit
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 alrea
# 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) +
```

```r
                      # 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

```r
# 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(ppl)
## coyote_disturb             -0.5657      -0.4061               0.4584
## coyote_ag                                           0.5285
## coyote_poly                -0.5073      -0.4199
## coyote_harvest             -0.3749      -0.3868
## coyote_poly_nat            -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                                   2 -141.478 287.2  6.82  0.032
## coyote_poly                         0.2148  4 -140.927 290.6 10.24  0.006
## coyote_harvest                              3 -142.309 291.1 10.70  0.005
## coyote_poly_nat                     0.1872  6 -140.607 294.8 14.48  0.001
## coyote_nat                                  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                                 1 -162.221 326.5 46.16  0.000
## coyote_rds                                  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

```r
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
```

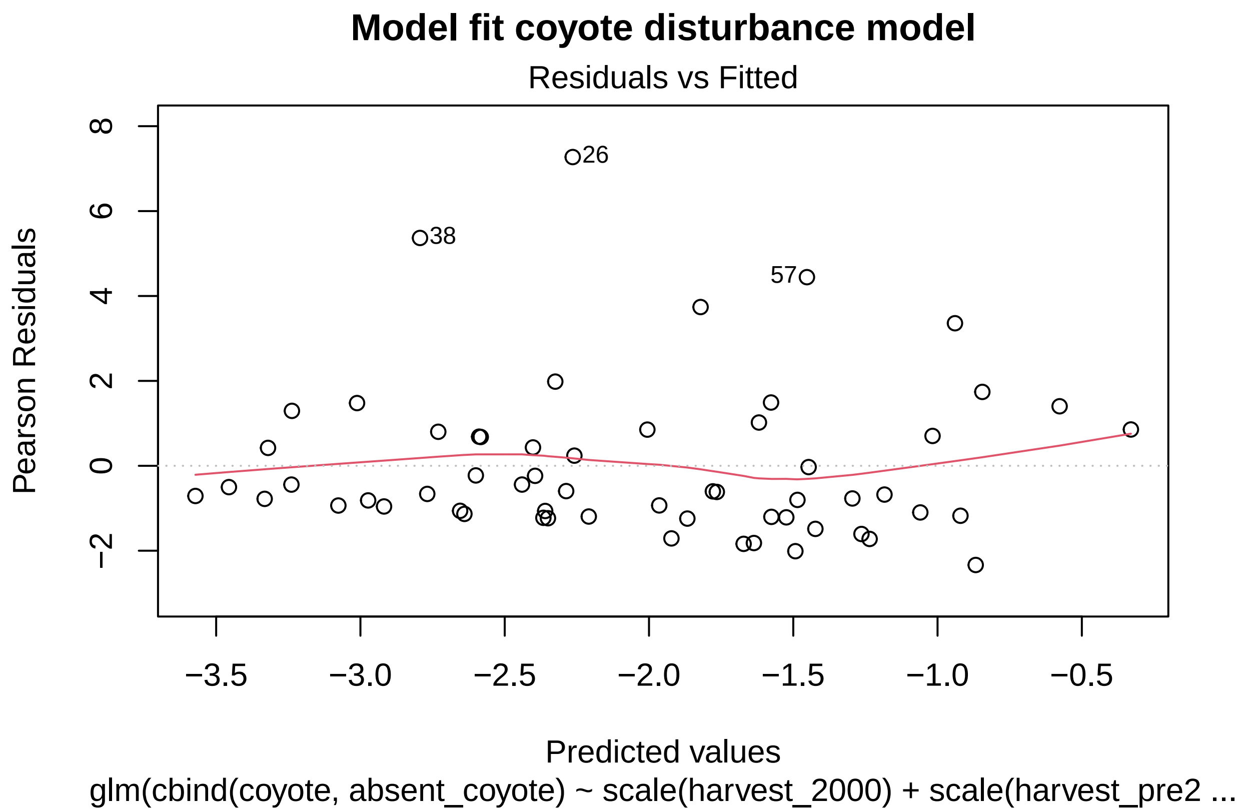
Model assumptions and fit

VIF

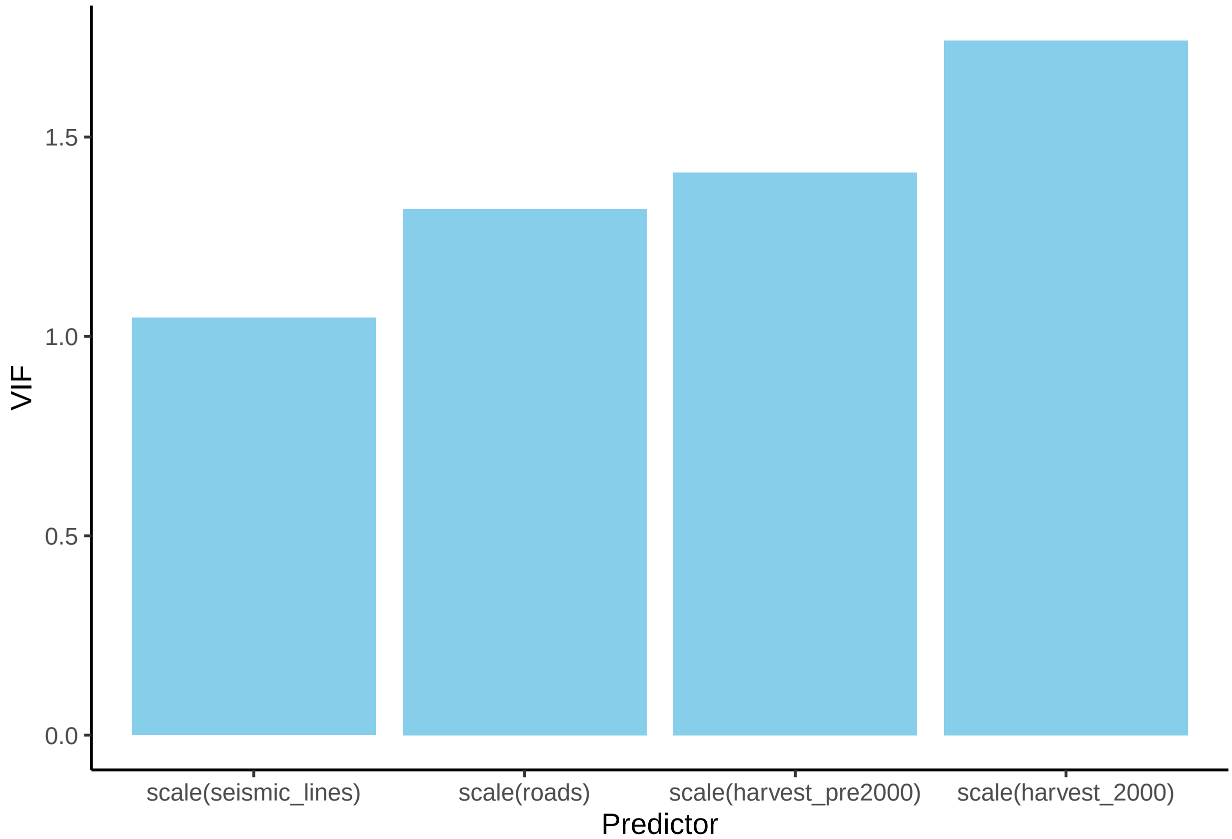
```
# report VIF
vif(coyote_disturb)
```

```
##    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')
```




```
# 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()
```

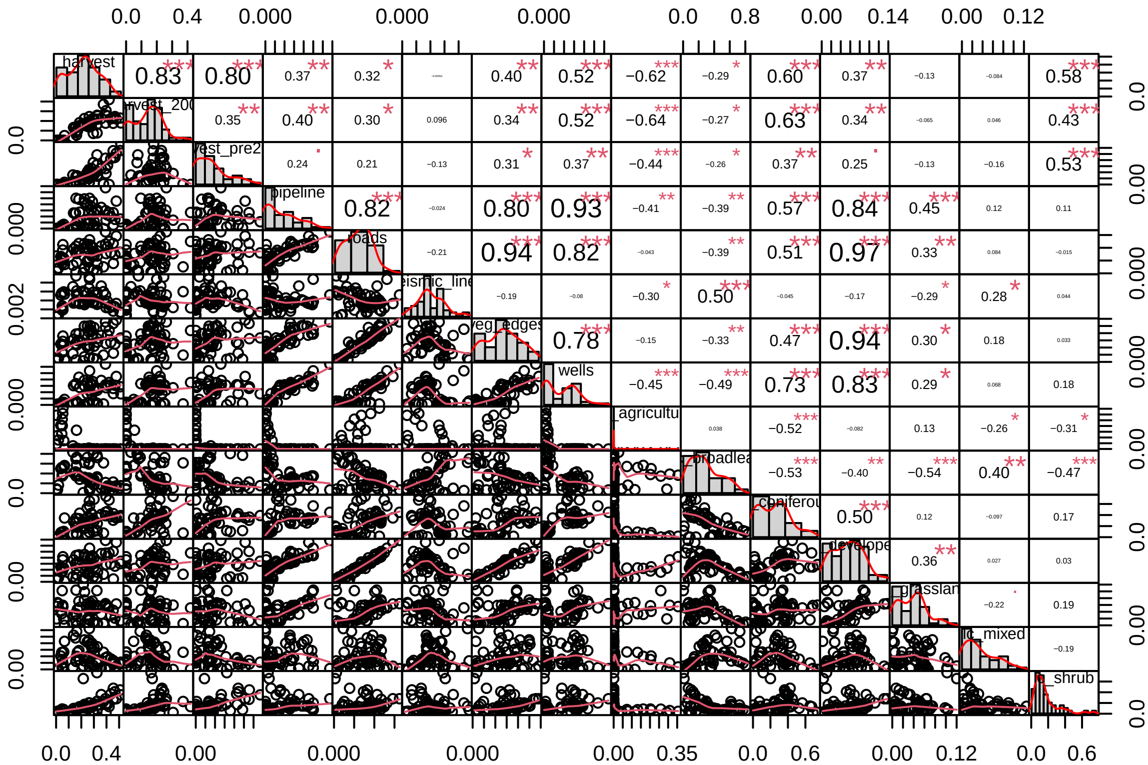


Grey wolf

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) ~
```

```r
                      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 wit
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')
```

```r
# linear + natural (have to pix 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

```r
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

```r
# 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
```

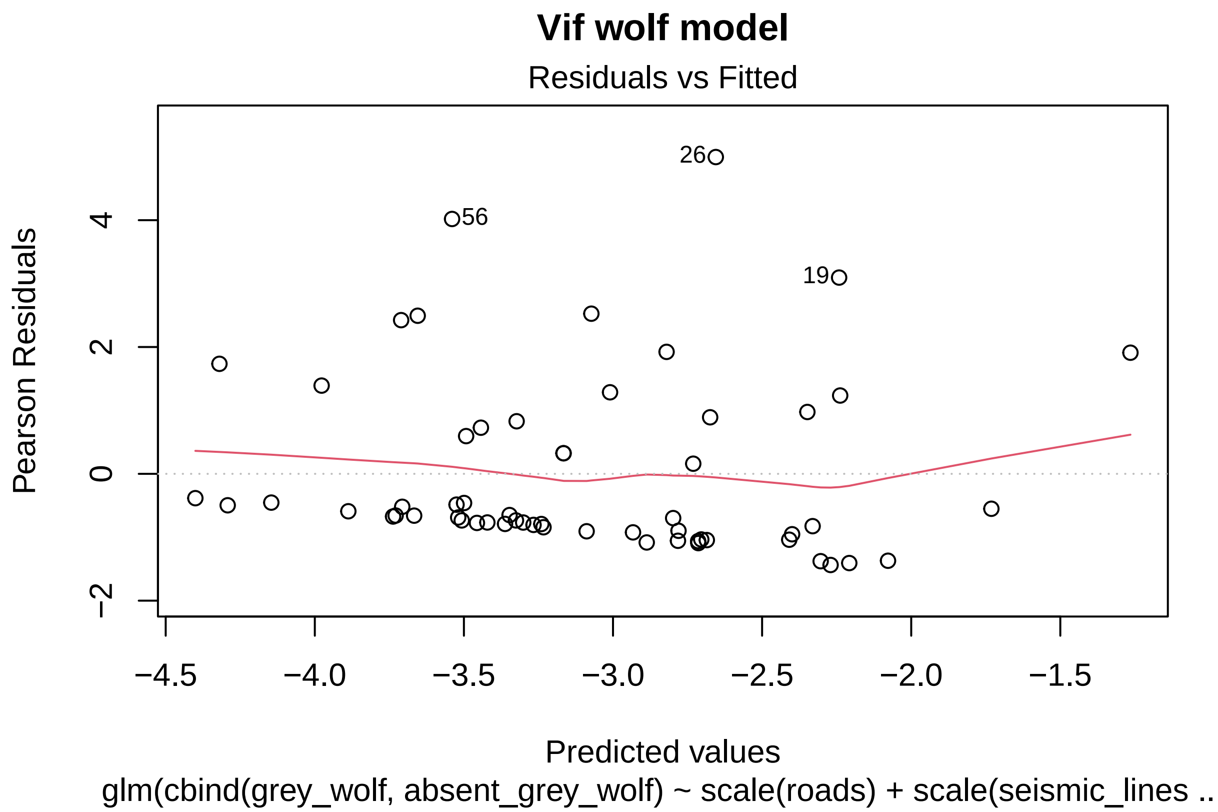
Model Aassumptions and fit

VIF

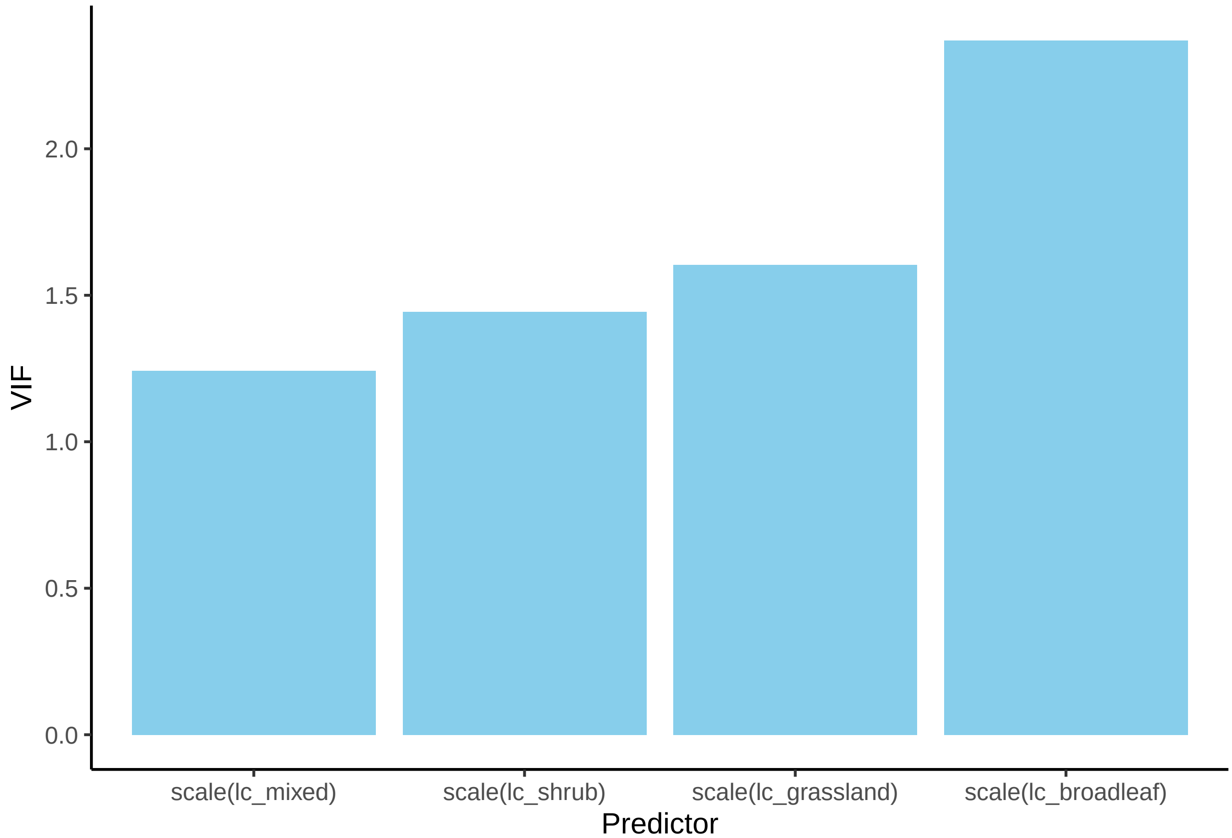
```r
# report VIF
vif(grey_wolf_linear_nat)
```

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

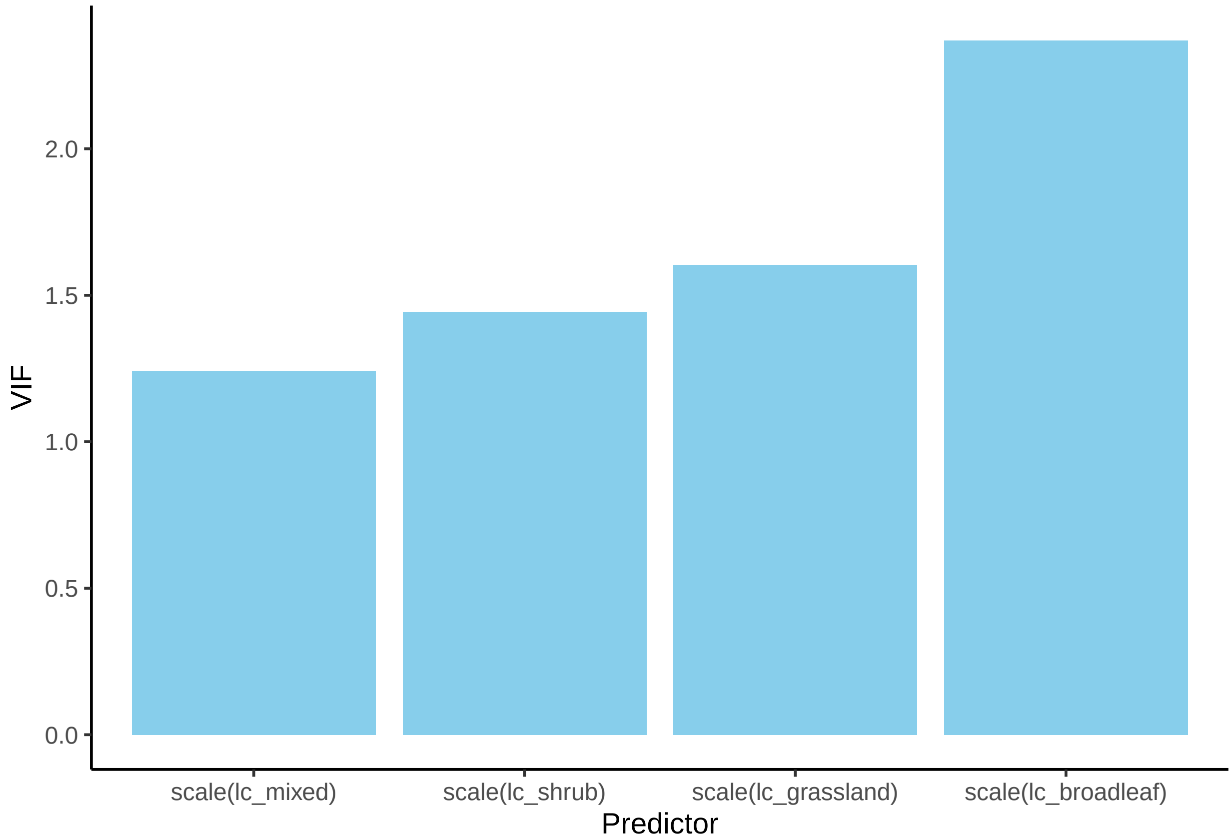
```r
# plot VIF
plot(grey_wolf_linear_nat,
       which = 1,
       main = 'Vif wolf model')
```




```
# 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()
```



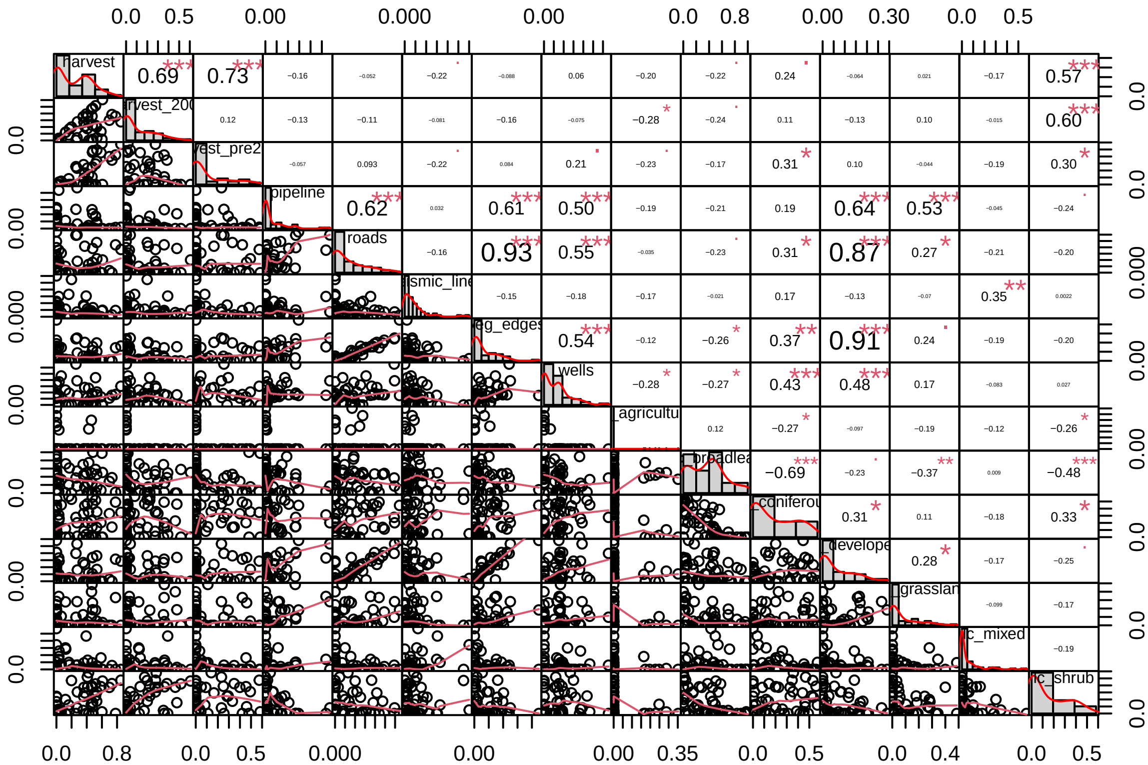
Lynx

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")
```



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

Models

```r
# 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 wit
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')
```

```r
# 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

```r
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

```r
#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 ***
```

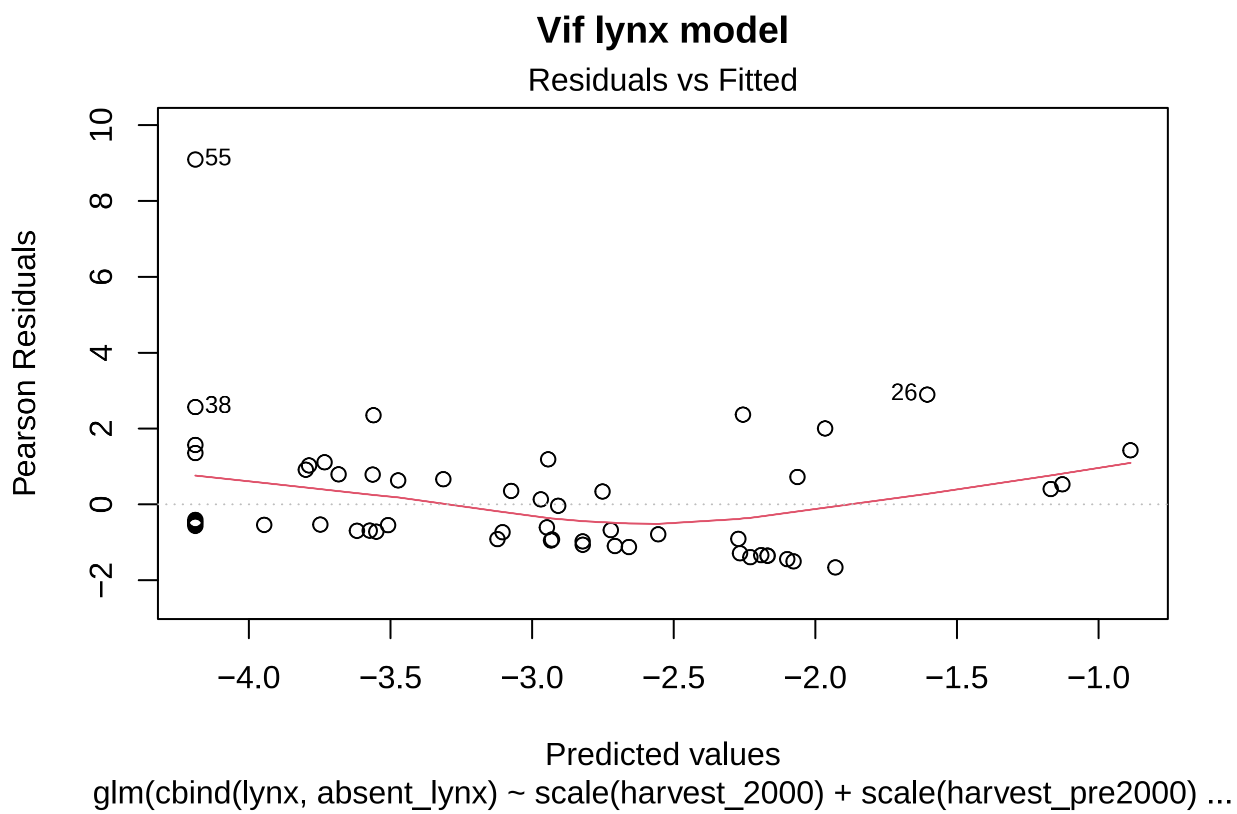
```
## scale(harvest_2000)      0.5261     0.1476   3.564 0.000366 ***
## scale(harvest_pre2000)   0.3975     0.1281   3.103 0.001919 **
## scale(wells)             0.5514     0.1292   4.268 1.97e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter 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

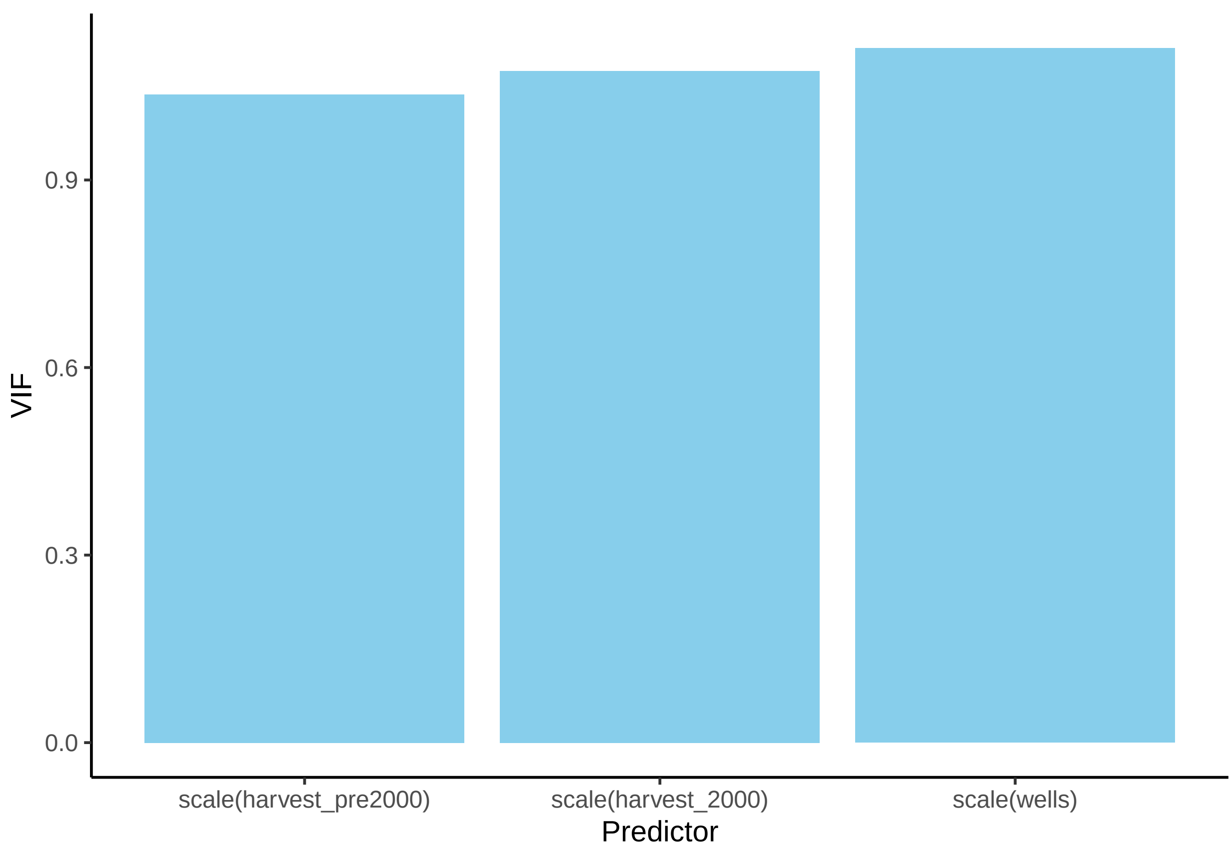
```r
# report VIF
vif(lynx_poly)
```

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

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



```r
# 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()
```



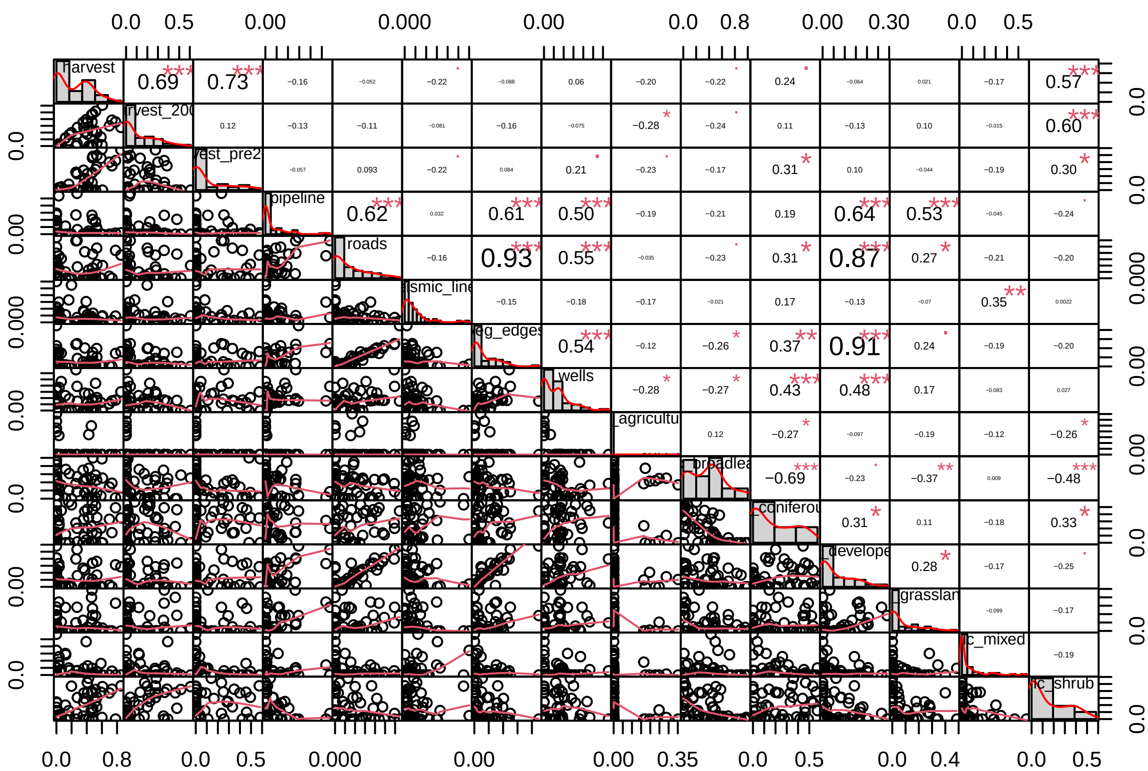
Moose

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

```r
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

```r
# 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)  +
```

```r
                      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 wit
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')
```

```r
# 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

```r
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(ppl)
## 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

```r
summary(moose_linear)
```

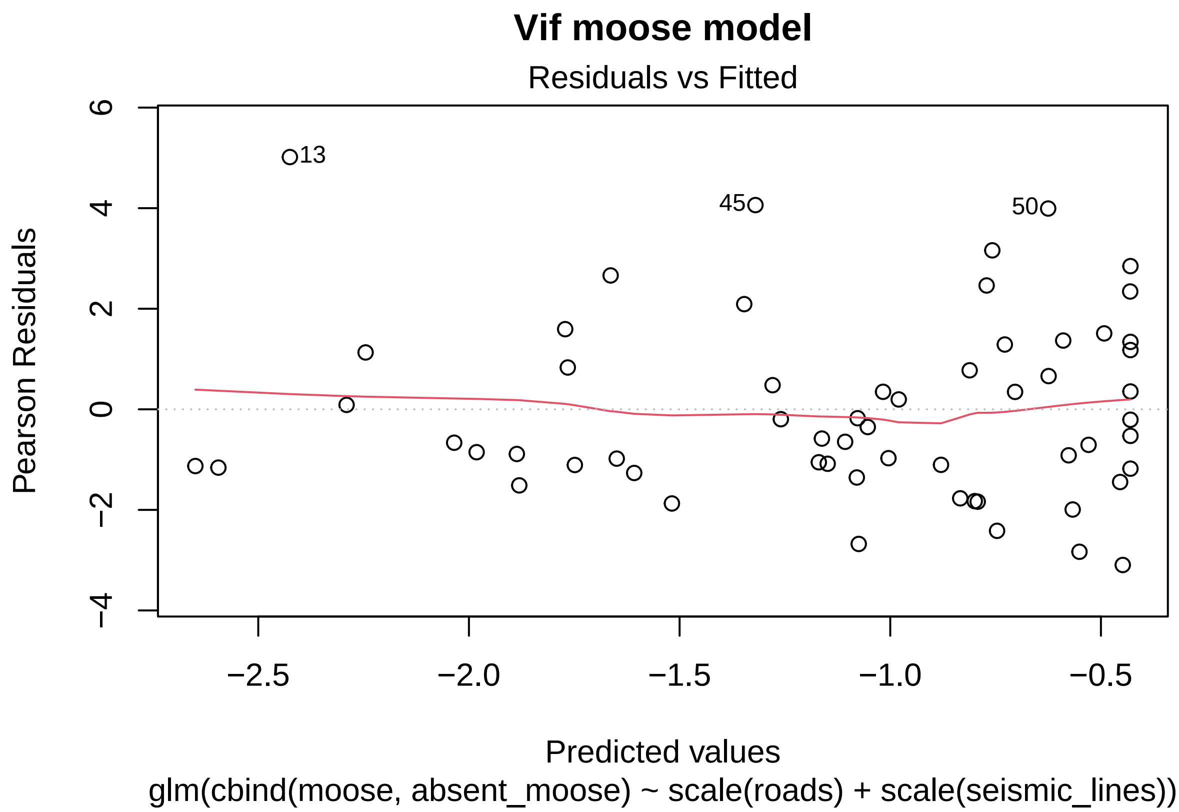
```
##
## Call:
## glm(formula = cbind(moose, absent_moose) ~ scale(roads) + scale(seismic_lines),
##     family = "binomial", data = prop_det_data$`500 meter buffer`)
##
## Coefficients:
##                      Estimate Std. Error z value Pr(>|z|)
## (Intercept)          -1.12721    0.08298 -13.584  < 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

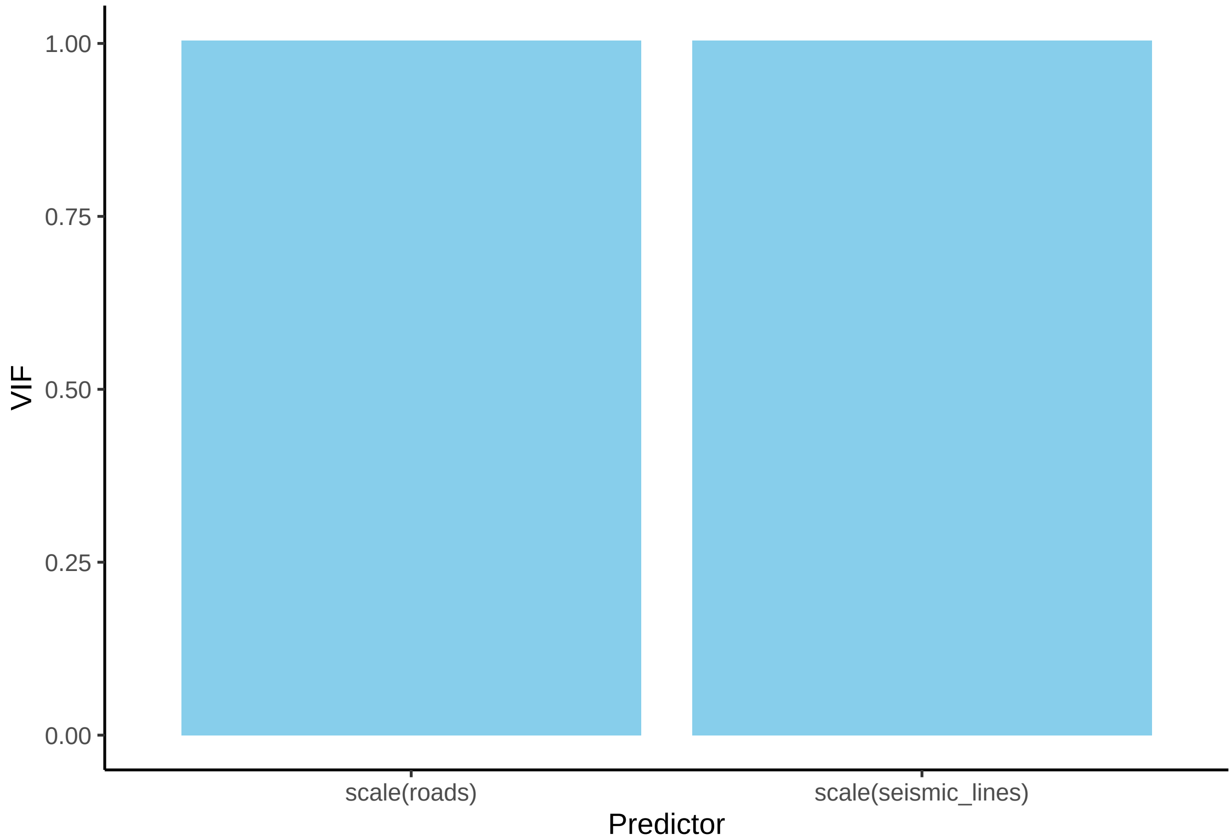
```r
# report VIF
vif(moose_linear)
```

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

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




```
# 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()
```

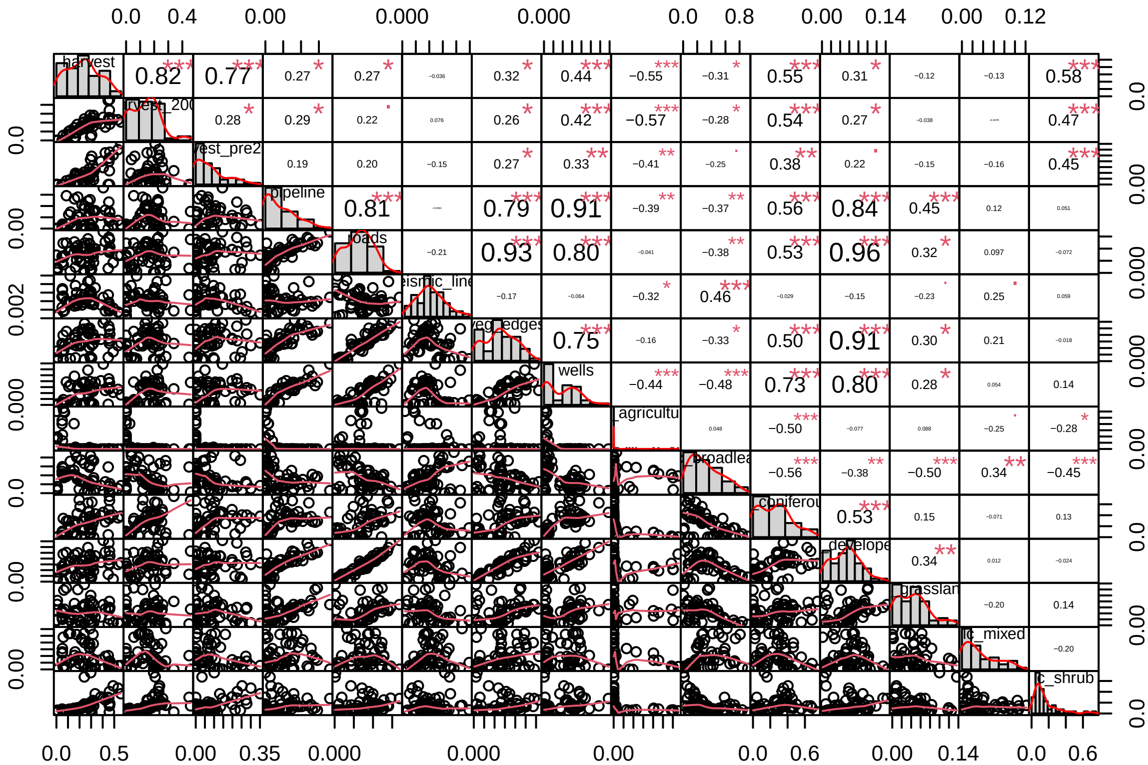


Snowshoe hare

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')
```

```r
# 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')
```

```r
# 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 pic 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

```r
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(ppl) scl(ssm_lns) scl(wll) 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)
```

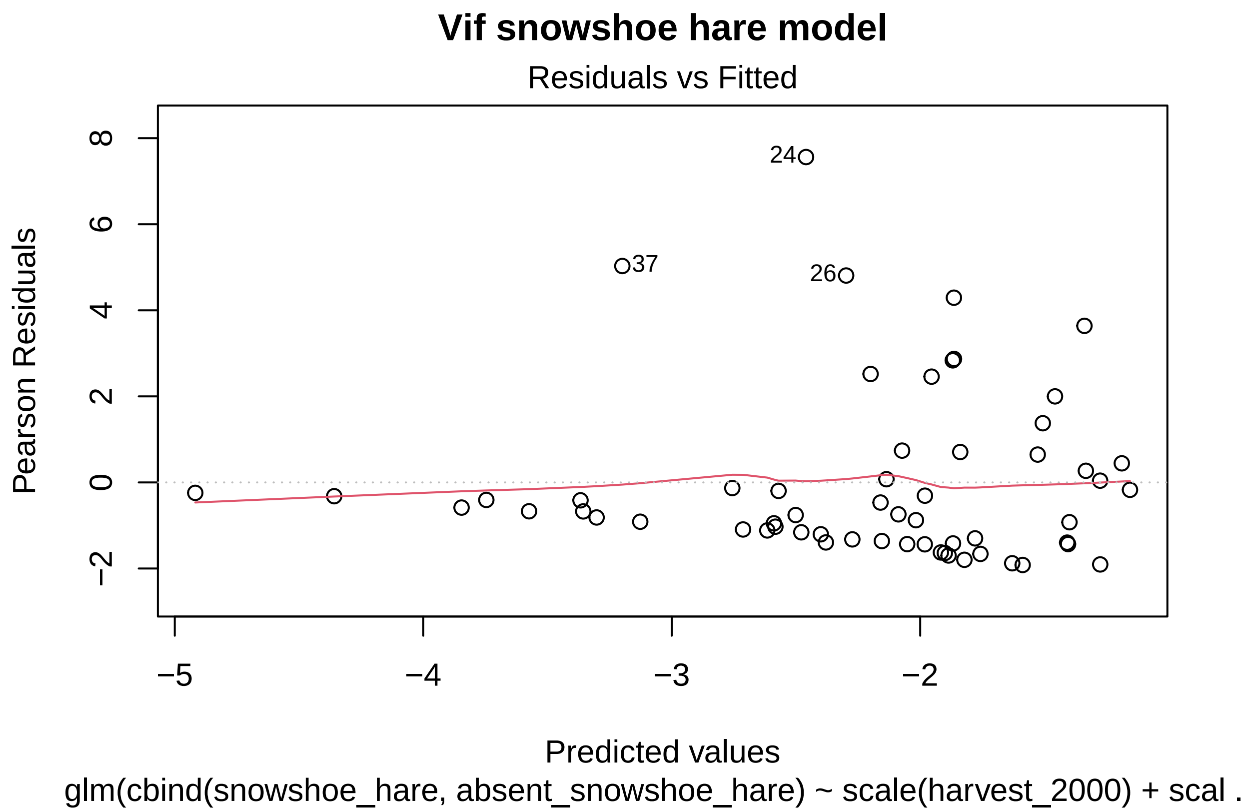
```
##
## Call:
## glm(formula = cbind(snowshoe_hare, absent_snowshoe_hare) ~ scale(harvest_2000) +
##     scale(harvest_pre2000) + scale(seismic_lines) + scale(wells),
##     family = "binomial", data = prop_det_data$`4000 meter buffer`)
##
## Coefficients:
##                        Estimate Std. Error 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

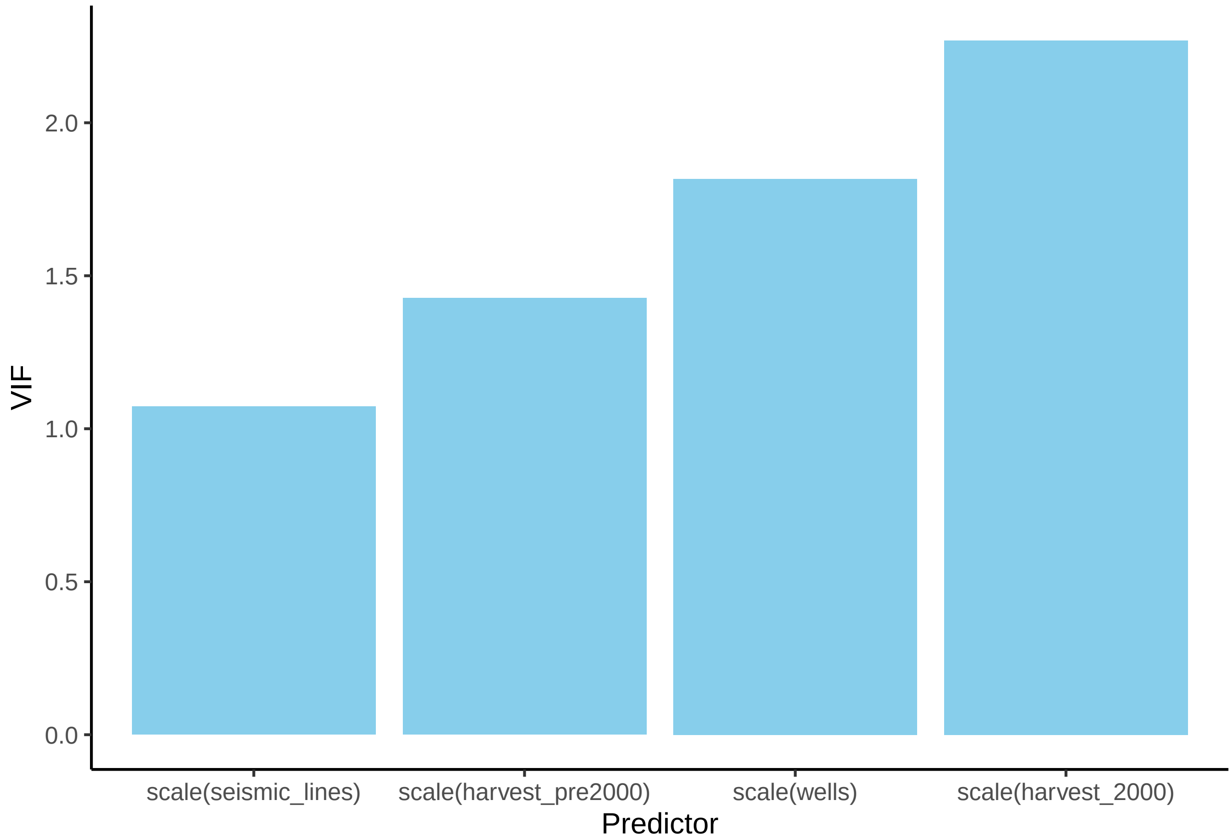
```r
# report VIF
vif(snowshoe_hare_disturb)
```

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

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




```
# 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()
```

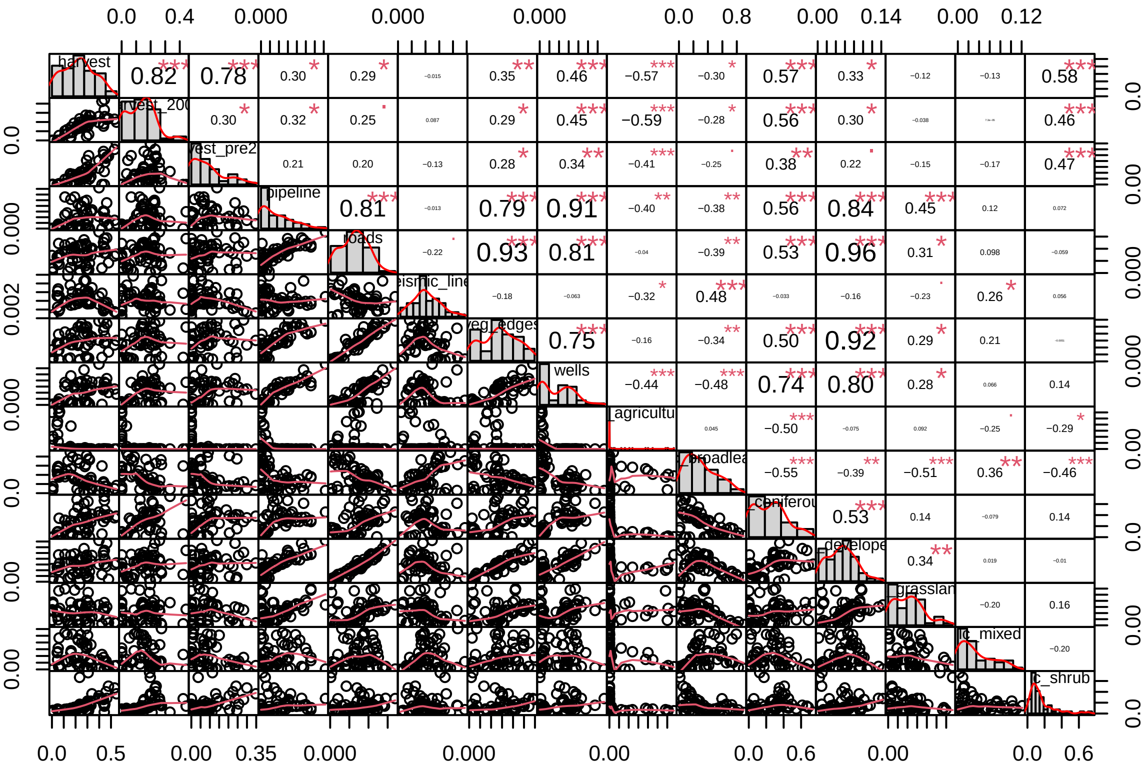


White-tailed deer

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")
```



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

Models

```r
# 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')
```

```r
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 42500m buffer can't combine with other industrial features (correlated wi
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' 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                             -0.1841
## 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

```r
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
```

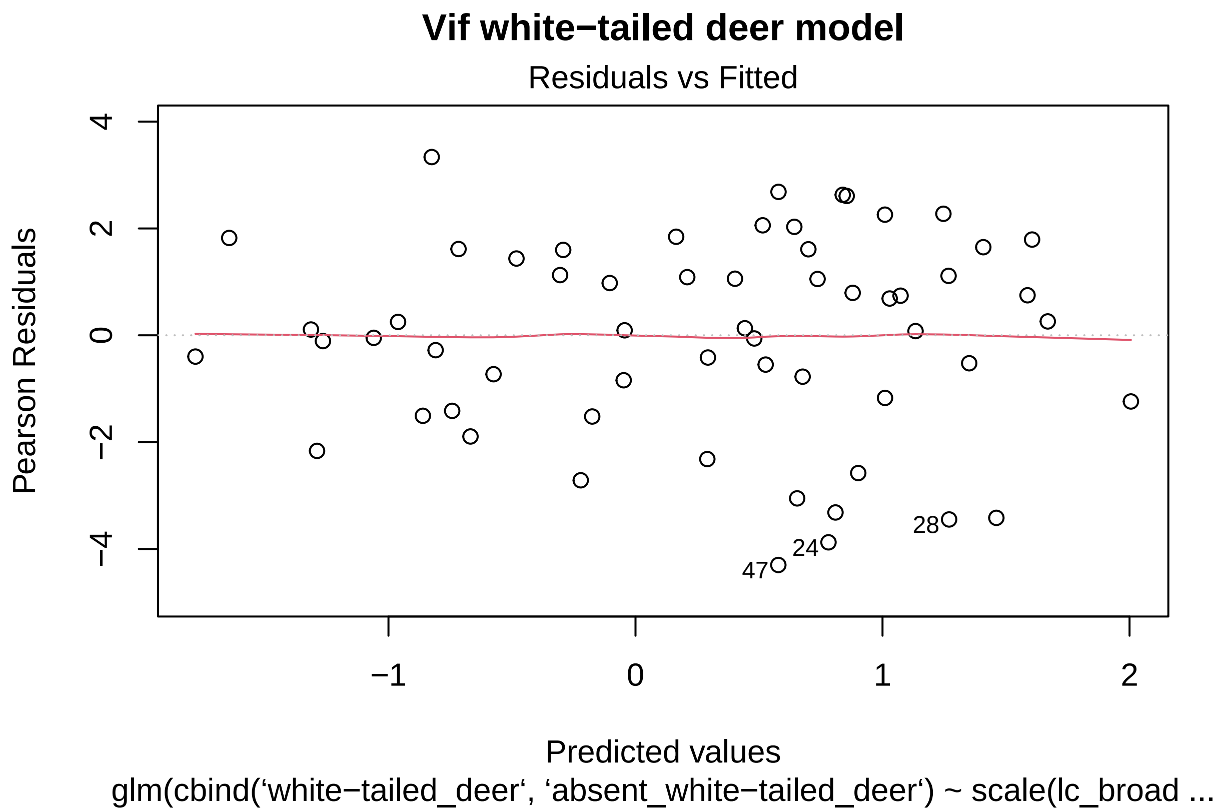
```r
#summary(w_deer_nat_broadleaf)

#summary(w_deer_nat_grass)
```

Model assumptions and fit

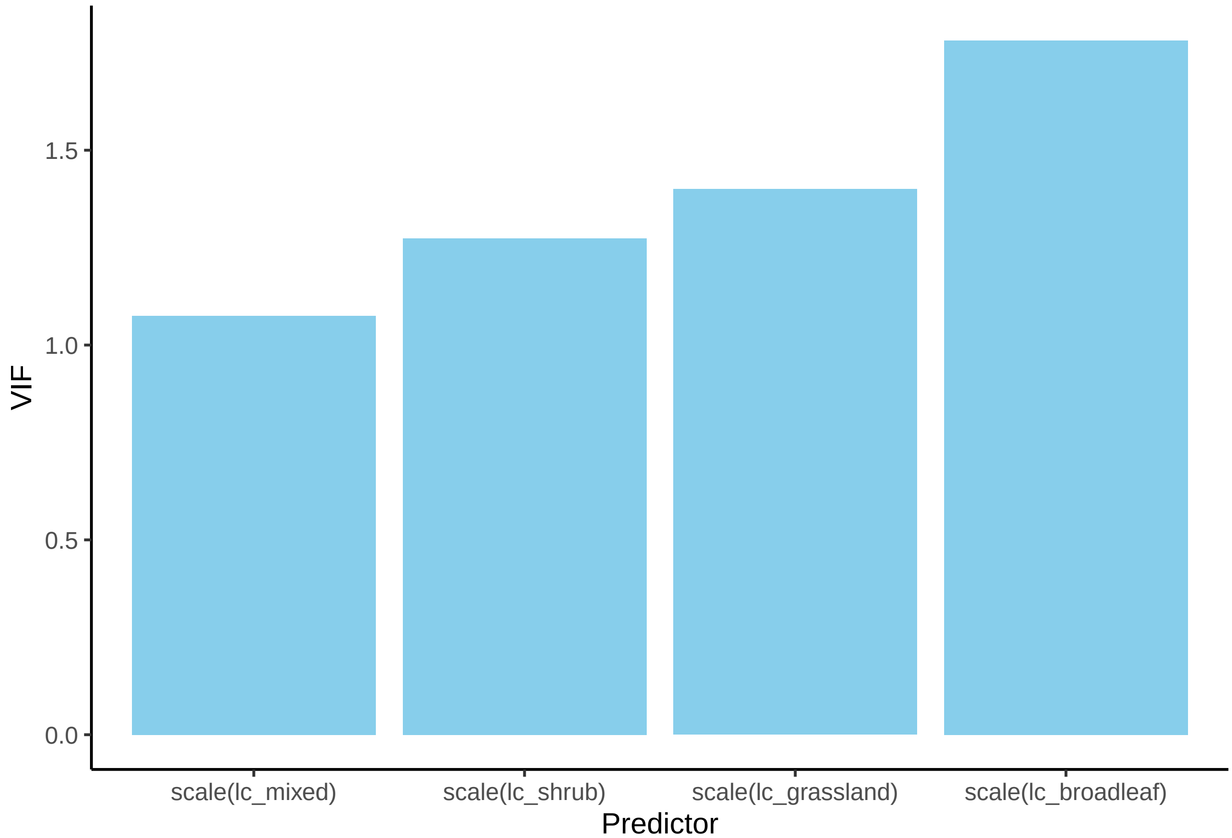
```r
# report VIF
vif(w_deer_nat)
```

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

```r
# 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) {
```

```r
  # 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 regeression model

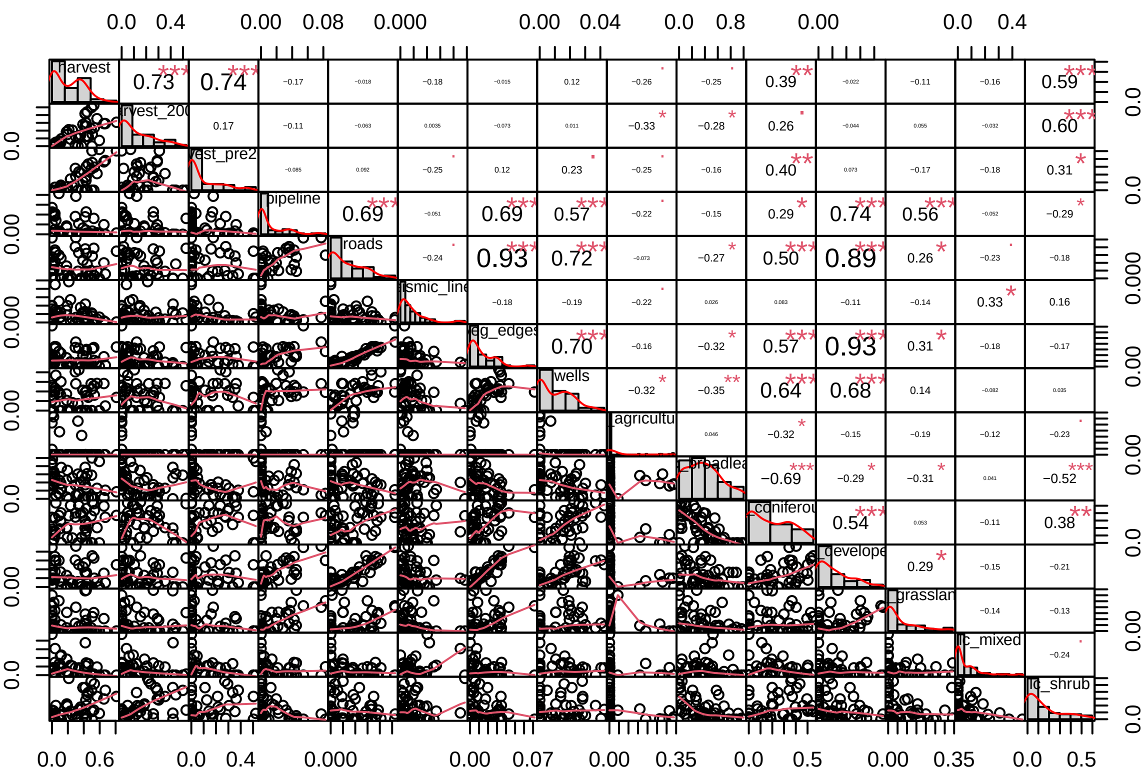
> 750m

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` %>%
```

```r
  # 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")
```




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

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

```r
# 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

```r
# 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')
```

```r
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

```r
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

```r
# 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

```r
# 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

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

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