st542_project10

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```r
#load packages for analysis
library(tidyverse)
```

```
## -- Attaching core tidyverse packages ------------------------ tidyverse 2.0.0 --
## v dplyr     1.1.2     v readr     2.1.4
## v forcats   1.0.0     v stringr   1.5.0
## v ggplot2   3.4.2     v tibble    3.2.1
## v lubridate 1.9.2     v tidyr     1.3.0
## v purrr     1.0.1
## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```r
library(ggplot2)
library(haven)
library(tidyverse)
library(ggplot2)
library(haven)
library(psych)
```

```
## Warning: package 'psych' was built under R version 4.3.1
```

```
##
## Attaching package: 'psych'
##
## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
```

Exploring the merged data

```r
survey_merged <- read_dta("../data/merged_survey_panel96_19_noID.dta")
dim(survey_merged)
```

```
## [1] 55734   165
```

```r
survey_merged_clean <- survey_merged %>%
  filter(!is.na(lotid_qualtrics))
# Removing duplicates for modelling - forgot to ask Mariana which should be kept, so just keeping first
# Also open to just dropping all duplicated lotids - there's only 42
survey_final <- survey_merged_clean %>% distinct(lotid_qualtrics, .keep_all = TRUE)
```

Now to check for nulls in columns:

```r
missing_vals <- survey_final %>% summarise_all(~sum(is.na(.)))
t(missing_vals)
```

```
##                          [,1]
## technician_times         2284
## family                   1026
## north                    1026
## northeast                1026
## southeast                1026
## south                    1026
## lotid_qualtrics             0
## studycode                1026
## havecattle               1131
## havecattleother          1147
## cattleherd               1184
## cattlemilk               1152
## milkhardry               1651
## milkharwet               1651
## milkhardry_min_dairy     1167
## milkharwet_max_dairy     1166
## pmilkdrynominal          1825
## pmilkwetnominal          1771
## milkincwet               1226
## milkincdry               1226
## irrigation_pas           2251
## drought_year             2032
## risk                     1086
## annual_crops             1026
## perennial_crops          1026
## incbeef                  1577
## cattle_price             2150
## incpension               1058
## incbolsafam              1058
## incoff                   1182
## lotprice                 1098
## housecity                1026
## keep_veg                 1026
## soiltype_sand            1194
## soiltype_silt            1194
## soiltype_clay            1194
## soiltype_other           1194
## soiltype_dontknow        1194
## fishtanks_year           2062
## reservoir_year           2256
## trough_year              2099
```

```
## dam_year               1751
## milk_room_year         2236
## milktanks_lot_year     2180
## irrigation_year        2255
## well_year              1464
## caixa_seca_year        2227
## fishtanks_have         1372
## reservoir_have         1436
## trough_have            1392
## dam_have               1281
## milk_room_have         1438
## well_have              1148
## caixa_seca_have        1467
## vechval                1026
## loan                   1853
## loan_investment        1853
## unions                 1026
## documents              1026
## aveeduhh               1098
## fert_pasture           1026
## pest_pasture           1026
## cattleinputs_breed     1026
## semiconfine            1250
## fallow                 1132
## soil_analysis          1096
## pasture                1026
## annuals                1026
## perennials             1026
## forest                 1026
## yearmove               1034
## techvisit              1039
## sellcattle_droughtexp 1971
## waterstructure         1026
## feed_cattle            1026
## pasture_productivity  1026
## forest_rec             1026
## fish_bee               1026
## milktank_have          1026
## yearmig                2347
## inchf                  2347
## inccalf                2347
## incpigs                2347
## incchicken             2347
## incsheepgoat           2347
## inchorses              2347
## incmules               2347
## incdonkey              2347
## incotherlive           2347
## valcattle              2347
## plows                  2347
## central                2347
## pricebeef              2347
## incbolsaescola         2347
## mow                    2347
```

```
## landsold_year        2347
## landbuy_year         2347
## honey_har            2347
## honey_price          2347
## fish_har             2347
## workers              2347
## PIgrass_cattle          0
## PIbuilding_cattle       0
## PIsilage_cattle         0
## PImowing_cattle         0
## soil                 2347
## aveslope             2347
## distopo              2347
## opo_ttmin            2347
## jiparana_ttmin       2347
## closest_ttmin        2347
## pmilkdryreal         2347
## pmilkwetreal         2347
## rainfallmin_year     1026
## rainfallmax_year     1026
## rainfall_wet6        1026
## rainfall_dry6        1026
## rainfall_dry         1026
## rainfall_wet         1026
## rainfall_year        1026
## rainfall             1026
## rainfall_jan         1026
## rainfall_feb         1026
## rainfall_mar         1026
## rainfall_apr         1026
## rainfall_may         1026
## rainfall_june        1026
## rainfall_july        1026
## rainfall_aug         1026
## rainfall_sep         1026
## rainfall_oct         1026
## rainfall_nov         1026
## rainfall_dec         1026
## SPImin_year          1026
## SPImax_year          1026
## SPI_wet6             1026
## SPI_dry6             1026
## SPI_dry              1026
## SPI_wet              1026
## SPI_year             1026
## SPI_jan              1026
## SPI_feb              1026
## SPI_mar              1026
## SPI_apr              1026
## SPI_may              1026
## SPI_june             1027
## SPI_july             1113
## SPI_aug              1026
## SPI_sep              1026
```

```
## SPI_oct                1026
## SPI_nov                1026
## SPI_dec                1026
## off_farm               1182
## unions_part            1026
## cleared_area           1029
## cleared_area_fraction  1029
## Drainage_AreaKM_Ari    1970
## ARIQ_drainage          1017
## OPO_area_km            1869
## OPO_drainage            982
## RO_area_km             1858
## C                      2347
## Rolim_drainage          886
## lotsize_GIS_ponds         0
## ponds_2019                0
```

There seem to be a lot of columns missing 1026 values, which puts the numbers back to what we saw in the original data. Clearly there is a lot of missing data across all areas, so I don't think we should drop all rows missing data.

Feature Engineering

Creating One Drainage Area Column

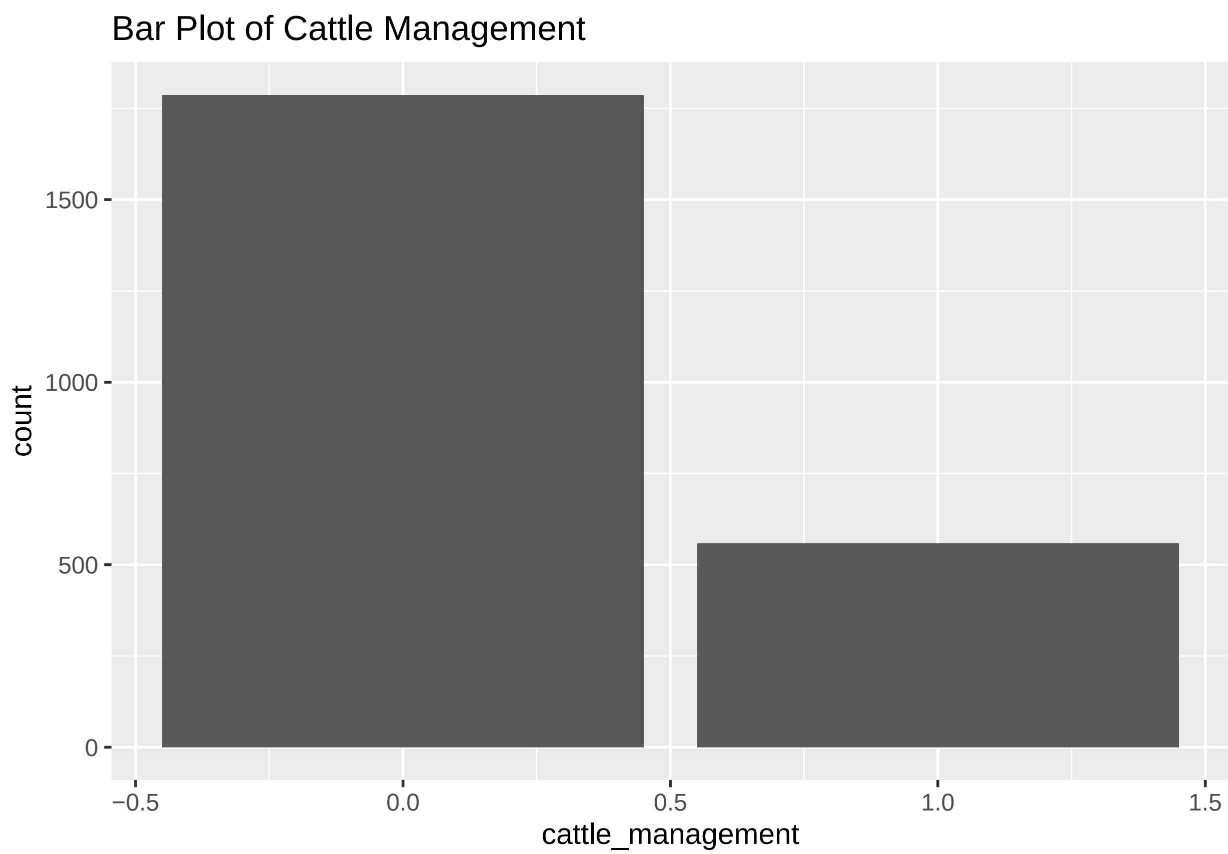
I will create one drainage area column, and then will drop all rows that don't have drainage area. Not sure if this is the best approach but this data is so messy!

```
# There are two lots that have areas in each region - will drop them
duplicate_regions <- survey_final %>% filter(!is.na(OPO_area_km) & !is.na(RO_area_km)) %>% select(lotid_
survey_final <- survey_final %>% filter(!(lotid_qualtrics %in% duplicate_regions$lotid_qualtrics))
survey_final <- survey_final %>% mutate(drainage_area_km = ifelse(!is.na(Drainage_AreaKM_Ari), Drainage_
                                        region = ifelse(studycode == 1, "Ariquemes",
                                                        ifelse(studycode == 2, "Ouro Preto do Oeste", i
  select(-c(Drainage_AreaKM_Ari, RO_area_km, OPO_area_km))
```

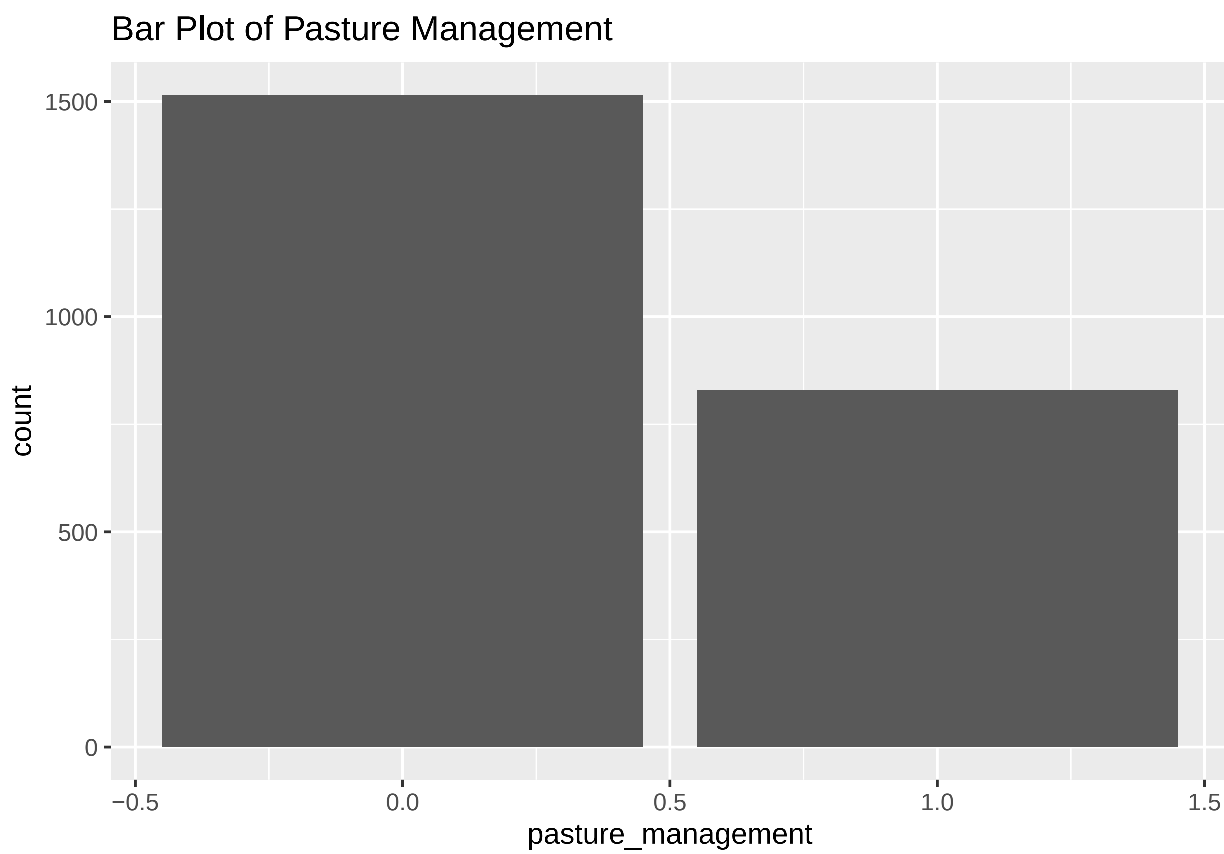
Creating Individual Adaptation Method Booleans

First, I need to create the indivdual adaptation method booleans i.e. `cattle_management` if the farmer employed any cattle management strategy. Then I can combine these to make a general adaptation method boolean.

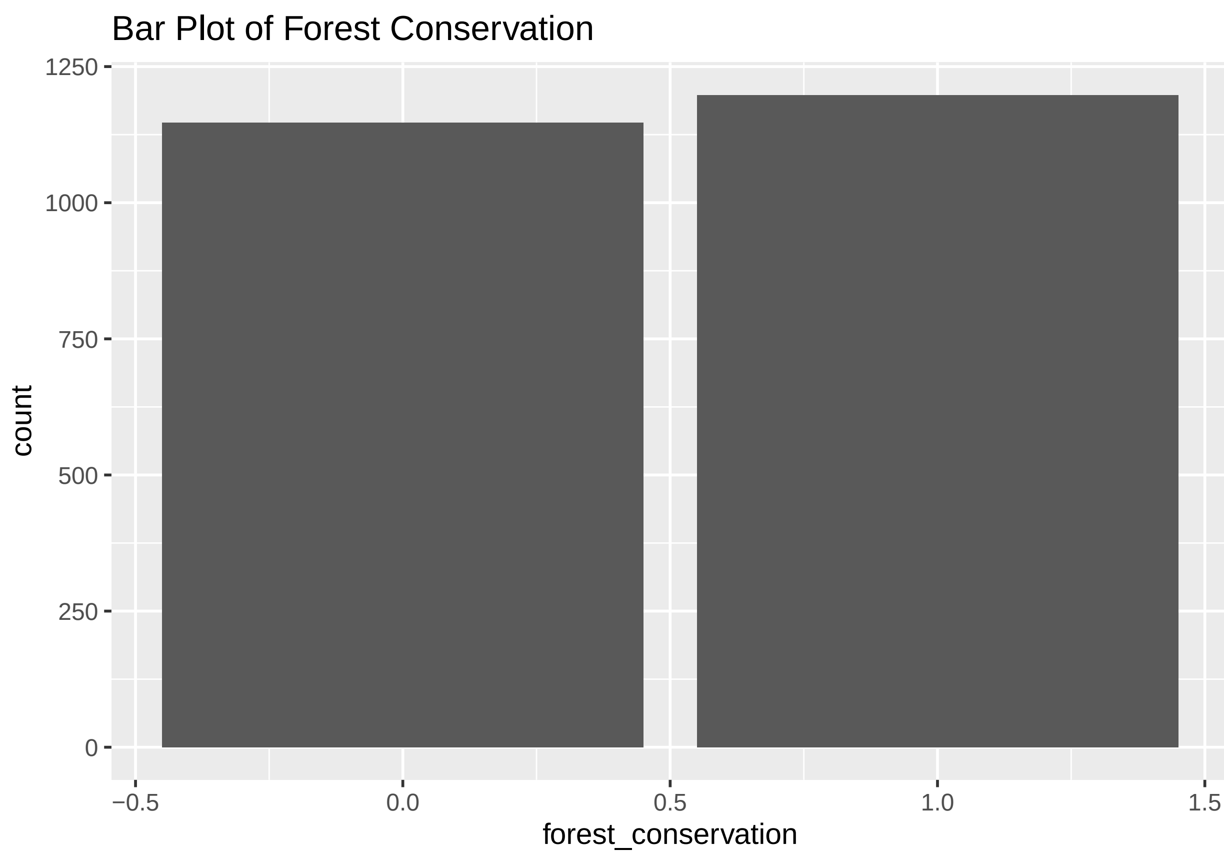
```
survey_final <- survey_final %>% mutate(cattle_management = case_when(feed_cattle == 1  | soil_analysis
                                        pasture_management = case_when(irrigation_pas == 1 | pasture_pr
                                        forest_conservation = case_when(forest_rec == 1 | keep_veg == 1
                                        water_management = case_when(waterstructure == 1 | well_have ==

# Looking at distributions
g <- ggplot(data = survey_final, aes(x = cattle_management))
g + geom_bar() + labs(title = "Bar Plot of Cattle Management")
```



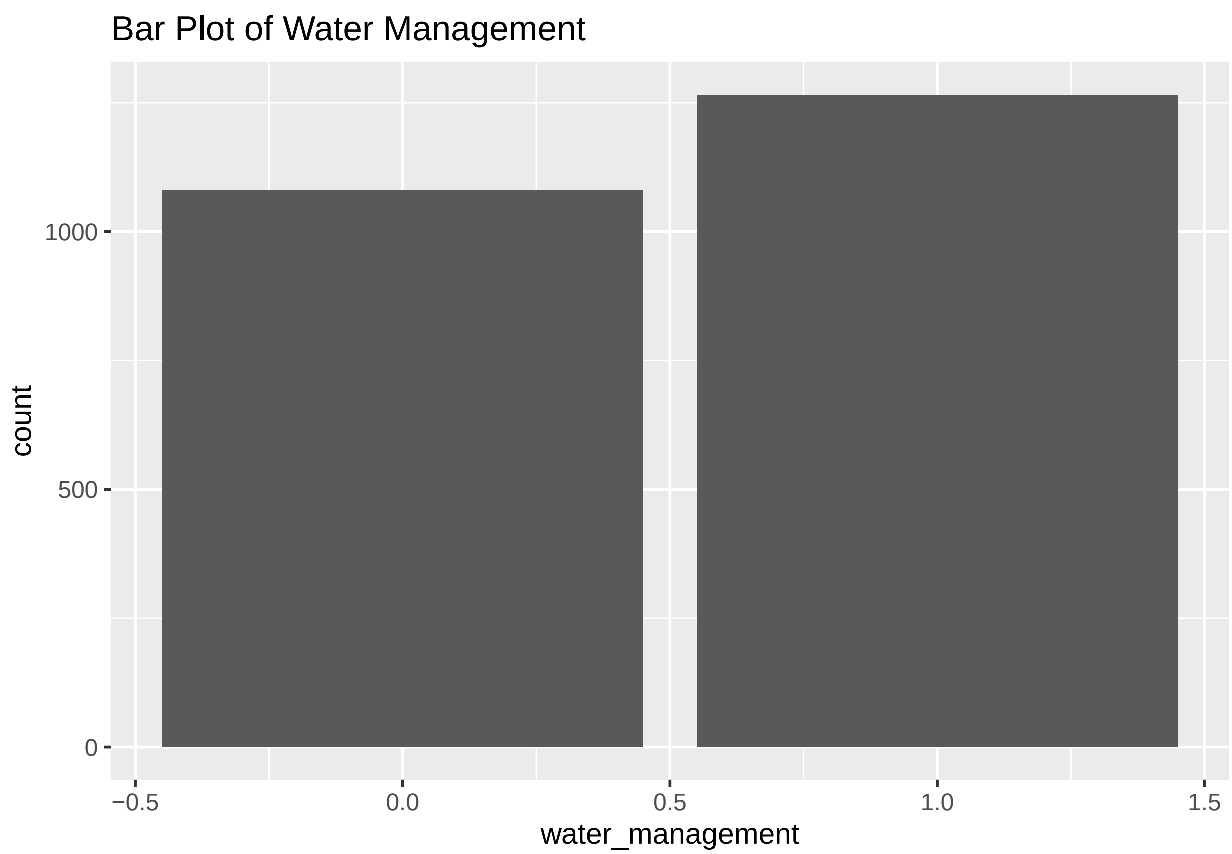

```r
g <- ggplot(data = survey_final, aes(x = pasture_management))
g + geom_bar() + labs(title = "Bar Plot of Pasture Management")
```




```
g <- ggplot(data = survey_final, aes(x = forest_conservation))
g + geom_bar() + labs(title = "Bar Plot of Forest Conservation")
```



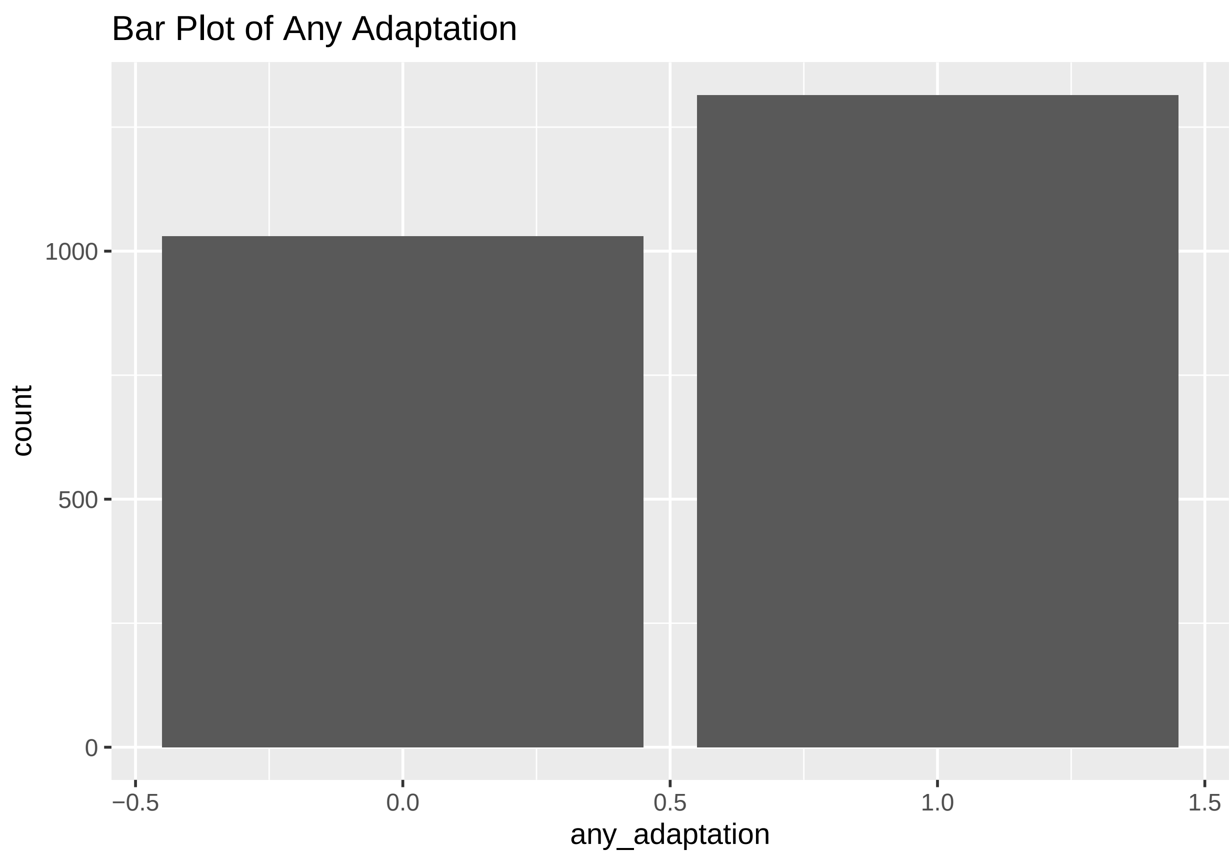

```
g <- ggplot(data = survey_final, aes(x = water_management))
g + geom_bar() + labs(title = "Bar Plot of Water Management")
```



Creating General Adaptation Method Boolean

Now that the indivdual adaptation measures have been created, I will create a general adaptation method boolean

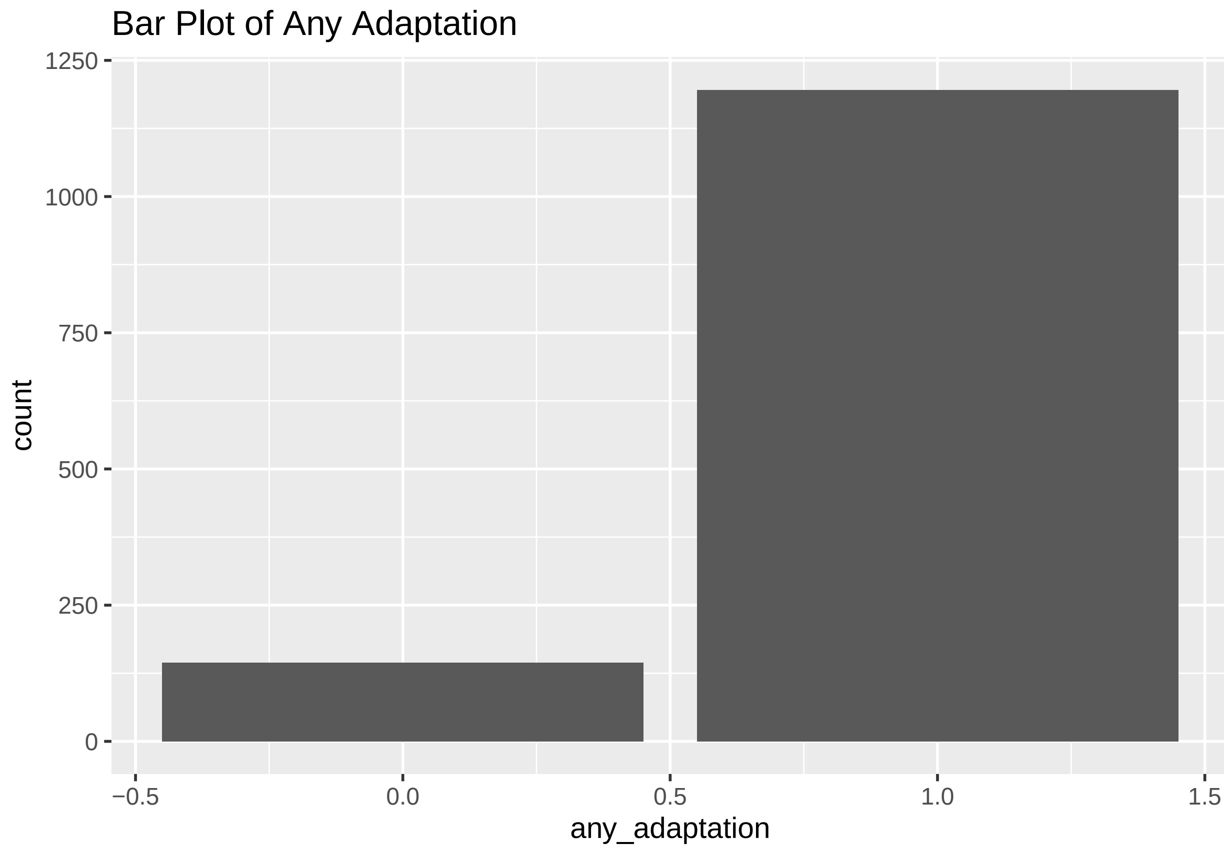
```
survey_final <- survey_final %>% mutate(any_adaptation = ifelse(cattle_management == 1 | pasture_manage

# Looking at the distribution
g <- ggplot(data = survey_final, aes(x = any_adaptation))
g + geom_bar() + labs(title = "Bar Plot of Any Adaptation")
```



Not a fully even data set, but better balanced than I predicted it would be. I don't think rebalancing is needed for the final analysis.

Now let's see if we remove farmers who don't have GIS information

```r
survey_final_gis <- survey_final %>% filter(!is.na(drainage_area_km))

# Looking at the distribution
g <- ggplot(data = survey_final_gis, aes(x = any_adaptation))
g + geom_bar() + labs(title = "Bar Plot of Any Adaptation")
```



Now it is very imbalanced. Not as horrible as it could be - but could affect the outputs of the model. Is SPI still missing for these?

```
missing_vals_gis <- survey_final_gis %>% summarise_all(~sum(is.na(.)))
t(missing_vals_gis)
```

```
##                       [,1]
## technician_times      1280
## family                 140
## north                  140
## northeast              140
## southeast              140
## south                  140
## lotid_qualtrics          0
## studycode              140
## havecattle             234
## havecattleother        247
## cattleherd             276
## cattlemilk             249
## milkhardry             725
## milkharwet             725
## milkhardry_min_dairy   262
## milkharwet_max_dairy   262
## pmilkdrynominal        858
## pmilkwetnominal        807
## milkincwet             320
```

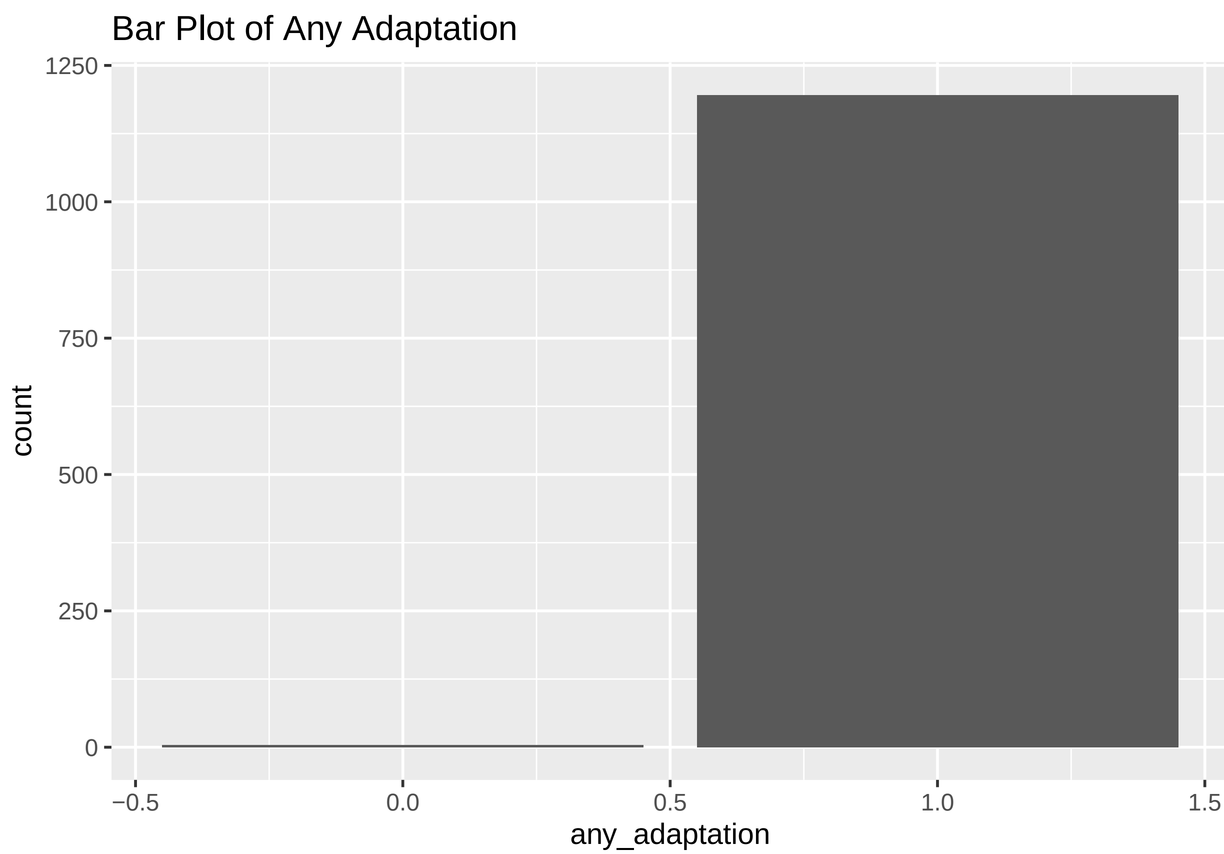
```
## milkincdry             320
## irrigation_pas        1262
## drought_year          1051
## risk                   194
## annual_crops           140
## perennial_crops        140
## incbeef                642
## cattle_price          1162
## incpension             168
## incbolsafam            168
## incoff                 284
## lotprice               203
## housecity              140
## keep_veg               140
## soiltype_sand          293
## soiltype_silt          293
## soiltype_clay          293
## soiltype_other         293
## soiltype_dontknow      293
## fishtanks_year        1093
## reservoir_year        1259
## trough_year           1114
## dam_year               802
## milk_room_year        1237
## milktanks_lot_year    1188
## irrigation_year       1264
## well_year              536
## caixa_seca_year       1229
## fishtanks_have         469
## reservoir_have         527
## trough_have            485
## dam_have               377
## milk_room_have         528
## well_have              256
## caixa_seca_have        559
## vechval                140
## loan                   889
## loan_investment        889
## unions                 140
## documents              140
## aveeduhh               208
## fert_pasture           140
## pest_pasture           140
## cattleinputs_breed     140
## semiconfine            345
## fallow                 235
## soil_analysis          202
## pasture                140
## annuals                140
## perennials             140
## forest                 140
## yearmove               146
## techvisit              153
## sellcattle_droughtexp  996
```

```
## waterstructure          140
## feed_cattle             140
## pasture_productivity    140
## forest_rec              140
## fish_bee                140
## milktank_have           140
## yearmig                1340
## inchf                  1340
## inccalf                1340
## incpigs                1340
## incchicken             1340
## incsheepgoat           1340
## inchorses              1340
## incmules               1340
## incdonkey              1340
## incotherlive           1340
## valcattle              1340
## plows                  1340
## central                1340
## pricebeef              1340
## incbolsaescola         1340
## mow                    1340
## landsold_year          1340
## landbuy_year           1340
## honey_har              1340
## honey_price            1340
## fish_har               1340
## workers                1340
## PIgrass_cattle            0
## PIbuilding_cattle         0
## PIsilage_cattle           0
## PImowing_cattle           0
## soil                   1340
## aveslope               1340
## distopo                1340
## opo_ttmin              1340
## jiparana_ttmin         1340
## closest_ttmin          1340
## pmilkdryreal           1340
## pmilkwetreal           1340
## rainfallmin_year        140
## rainfallmax_year        140
## rainfall_wet6           140
## rainfall_dry6           140
## rainfall_dry            140
## rainfall_wet            140
## rainfall_year           140
## rainfall                140
## rainfall_jan            140
## rainfall_feb            140
## rainfall_mar            140
## rainfall_apr            140
## rainfall_may            140
## rainfall_june           140
```

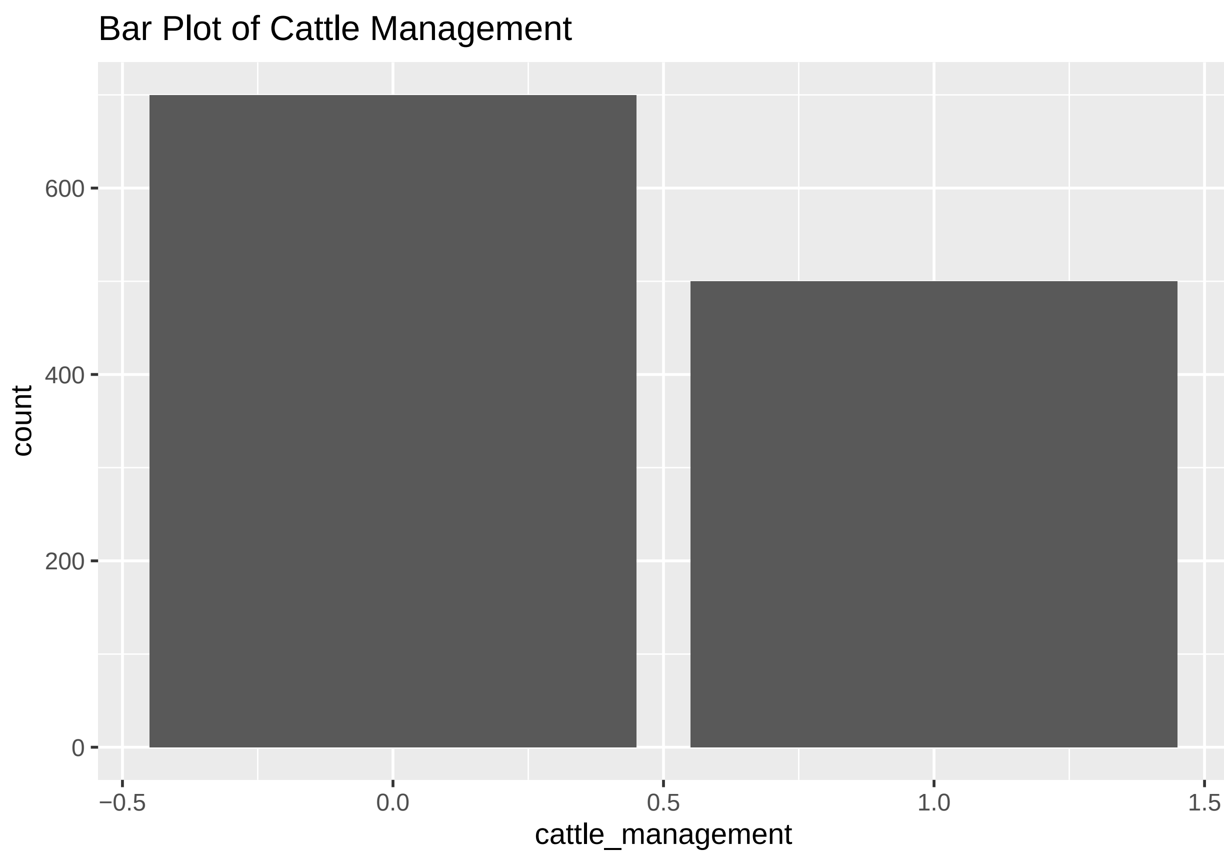
```
## rainfall_july          140
## rainfall_aug           140
## rainfall_sep           140
## rainfall_oct           140
## rainfall_nov           140
## rainfall_dec           140
## SPImin_year            140
## SPImax_year            140
## SPI_wet6               140
## SPI_dry6               140
## SPI_dry                140
## SPI_wet                140
## SPI_year               140
## SPI_jan                140
## SPI_feb                140
## SPI_mar                140
## SPI_apr                140
## SPI_may                140
## SPI_june               141
## SPI_july               209
## SPI_aug                140
## SPI_sep                140
## SPI_oct                140
## SPI_nov                140
## SPI_dec                140
## off_farm               284
## unions_part            140
## cleared_area           143
## cleared_area_fraction  143
## ARIQ_drainage          131
## OPO_drainage            96
## C                     1340
## Rolim_drainage           0
## lotsize_GIS_ponds        0
## ponds_2019               0
## drainage_area_km         0
## region                 140
## cattle_management        0
## pasture_management       0
## forest_conservation      0
## water_management         0
## any_adaptation           0
```

Now only for 140 of them, who are also missing region. Let's drop those and see:

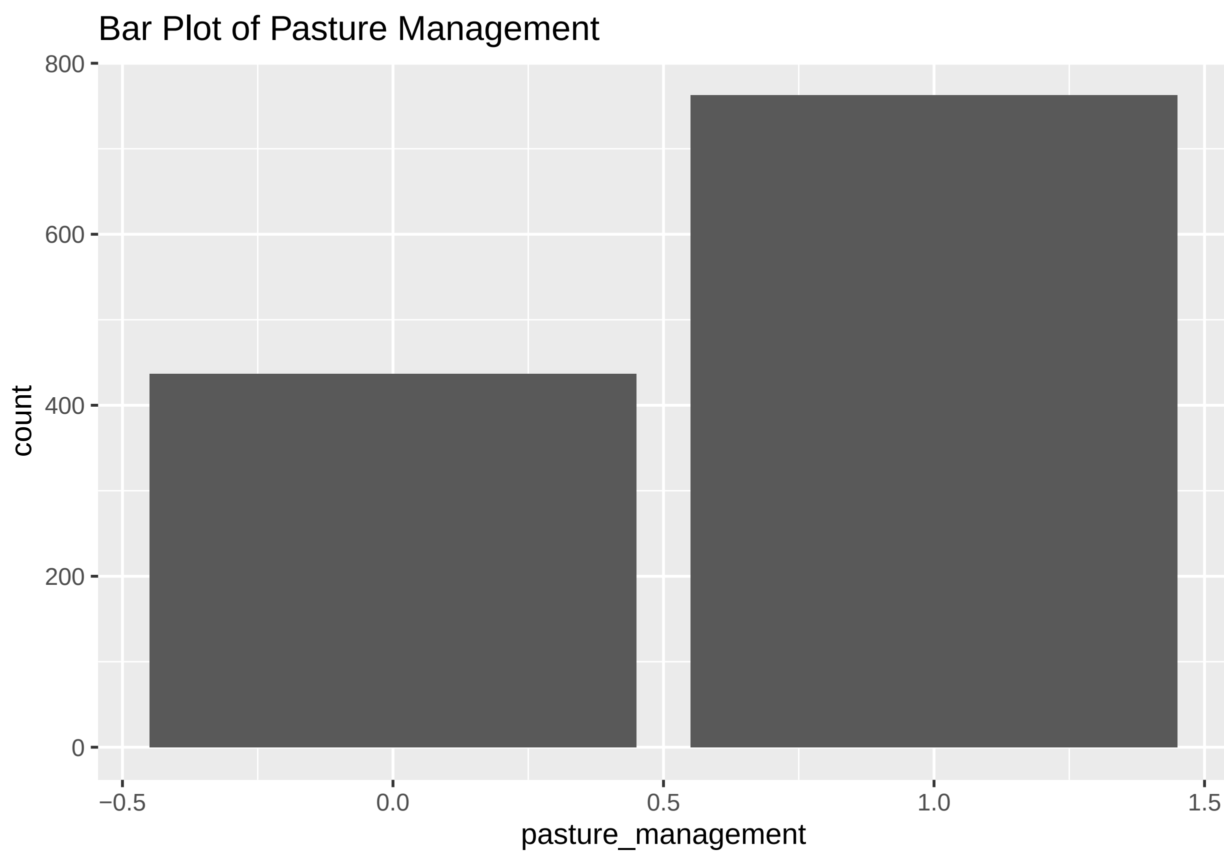
```
survey_final_gis_clean <- survey_final_gis %>% filter(!is.na(SPImin_year))

# Looking at the distribution
g <- ggplot(data = survey_final_gis_clean, aes(x = any_adaptation))
g + geom_bar() + labs(title = "Bar Plot of Any Adaptation")
```



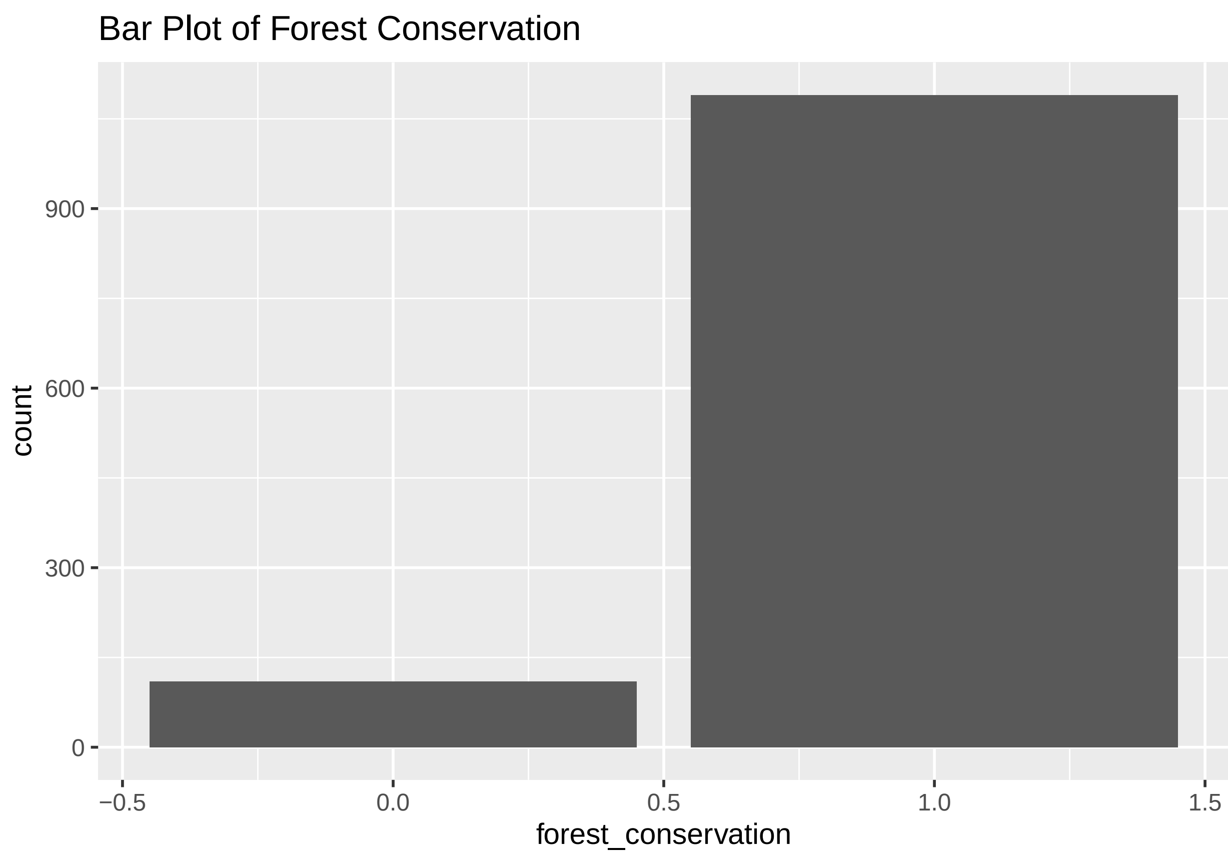

```r
# Looking at the distribution for the individual variables
g <- ggplot(data = survey_final_gis_clean, aes(x = cattle_management))
g + geom_bar() + labs(title = "Bar Plot of Cattle Management")
```



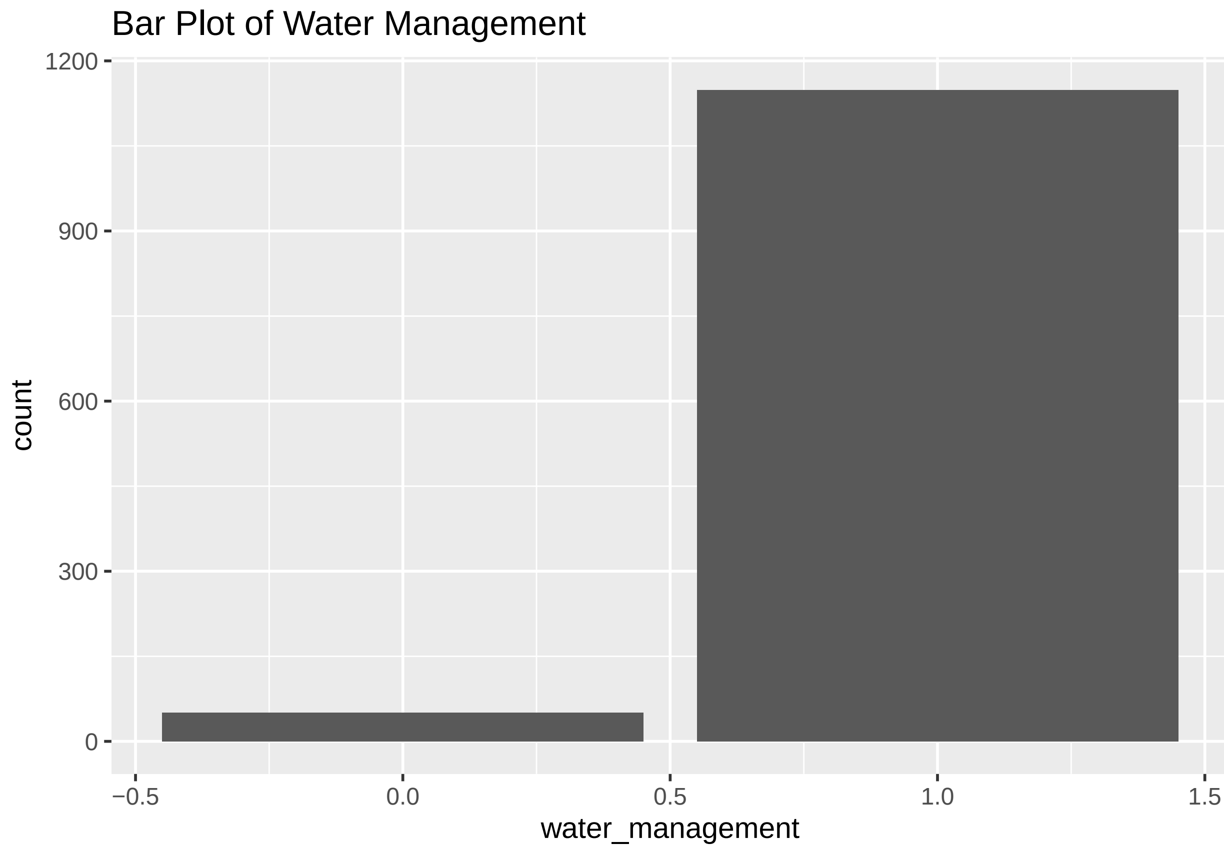

```
g <- ggplot(data = survey_final_gis_clean, aes(x = pasture_management))
g + geom_bar() + labs(title = "Bar Plot of Pasture Management")
```




```
g <- ggplot(data = survey_final_gis_clean, aes(x = forest_conservation))
g + geom_bar() + labs(title = "Bar Plot of Forest Conservation")
```




```
g <- ggplot(data = survey_final_gis_clean, aes(x = water_management))
g + geom_bar() + labs(title = "Bar Plot of Water Management")
```



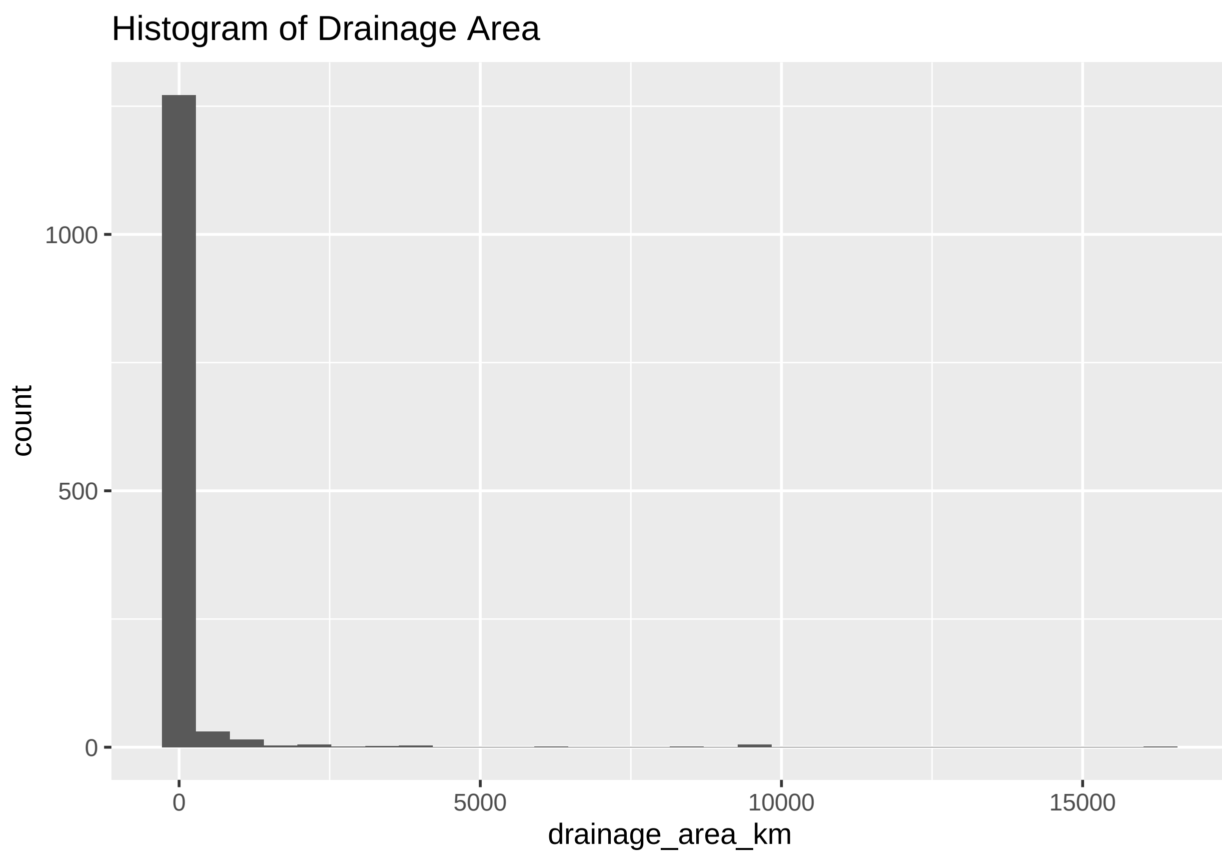
And everyone did some sort of adaptation method. Great - this means if we drop all missing water data, we can't look at a relationship between general adaptation and results. If we include rows that are missing SPI and just use drainage area, there is still a model that can be run.

Exploratory Data Analysis

Start EDA with some individual variable histograms.

```
g <- ggplot(data = survey_final_gis, aes(x = drainage_area_km))
g + geom_histogram() + labs(title = "Histogram of Drainage Area")
```

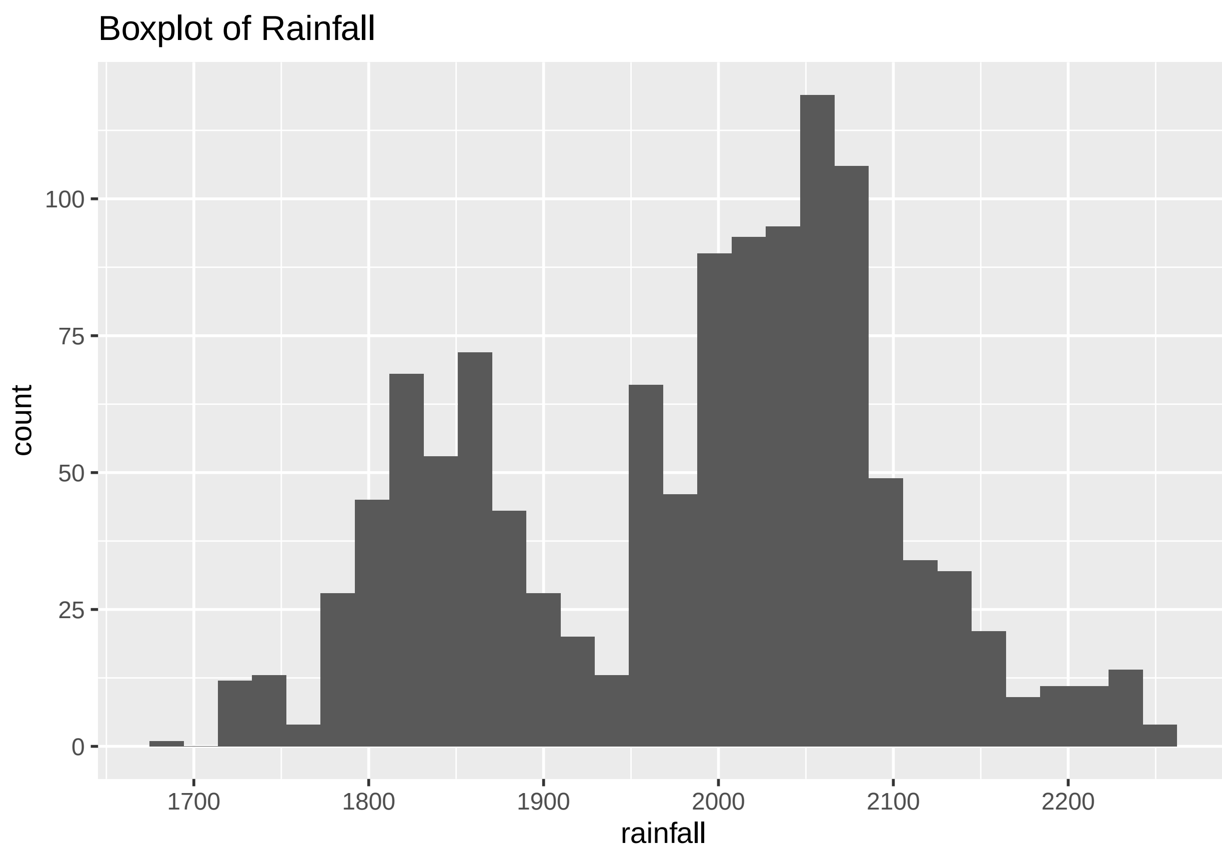
```
## ‘stat_bin()‘ using ‘bins = 30‘. Pick better value with ‘binwidth‘.
```




```
g <- ggplot(data = survey_final_gis, aes(x = rainfall))
g + geom_histogram() + labs(title = "Boxplot of Rainfall")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

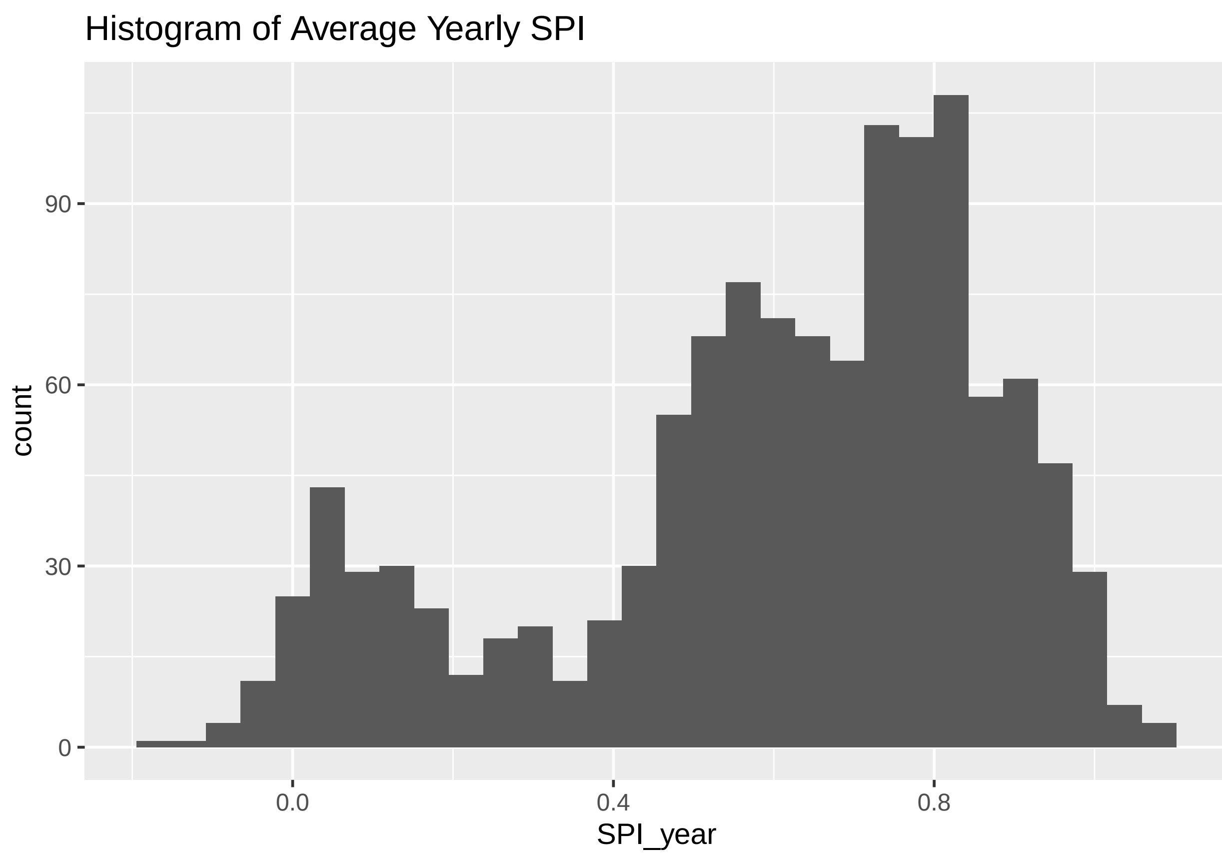
```
## Warning: Removed 140 rows containing non-finite values (`stat_bin()`).
```




```
g <- ggplot(data = survey_final_gis, aes(x = SPI_year))
g + geom_histogram() + labs(title = "Histogram of Average Yearly SPI")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

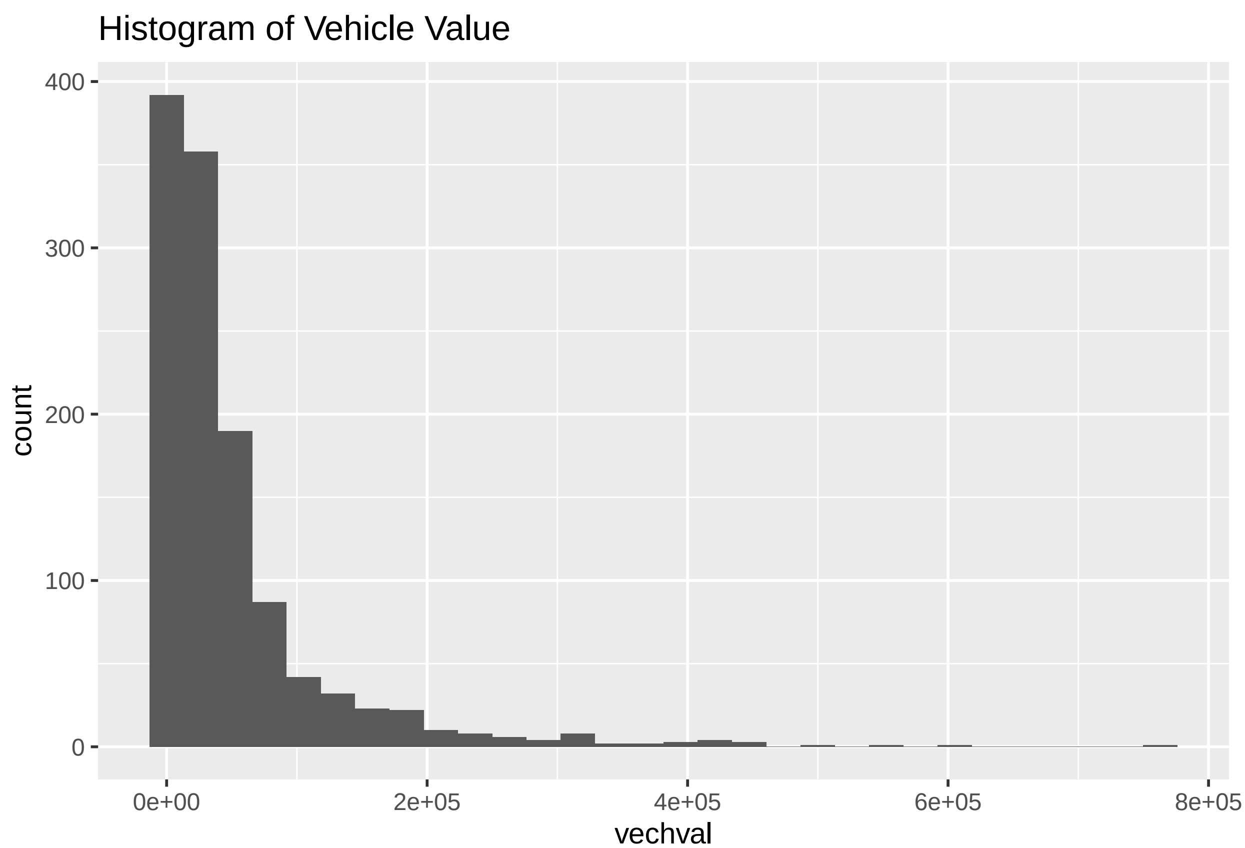
```
## Warning: Removed 140 rows containing non-finite values (`stat_bin()`).
```




```
g <- ggplot(data = survey_final_gis, aes(x = vechval))
g + geom_histogram() + labs(title = "Histogram of Vehicle Value")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

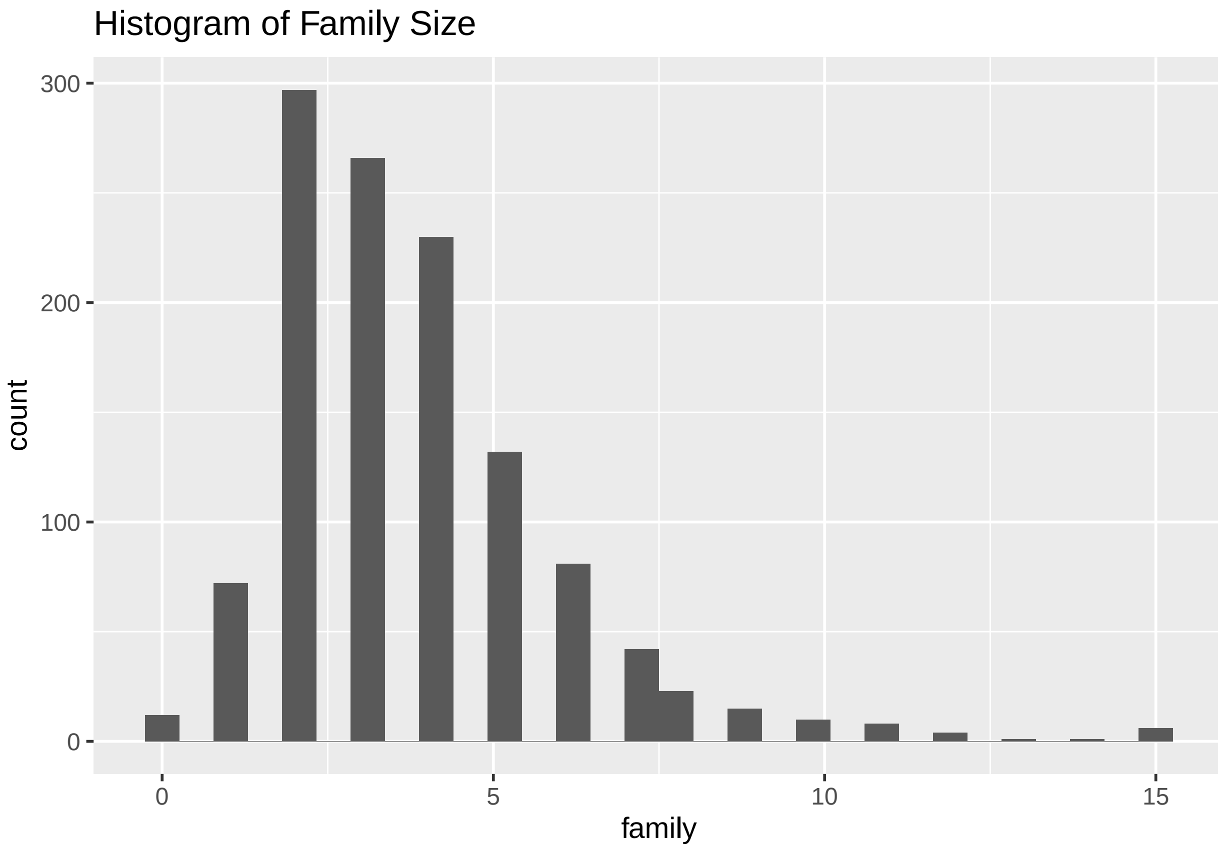
```
## Warning: Removed 140 rows containing non-finite values (`stat_bin()`).
```




```r
g <- ggplot(data = survey_final_gis, aes(x = family))
g + geom_histogram() + labs(title = "Histogram of Family Size")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

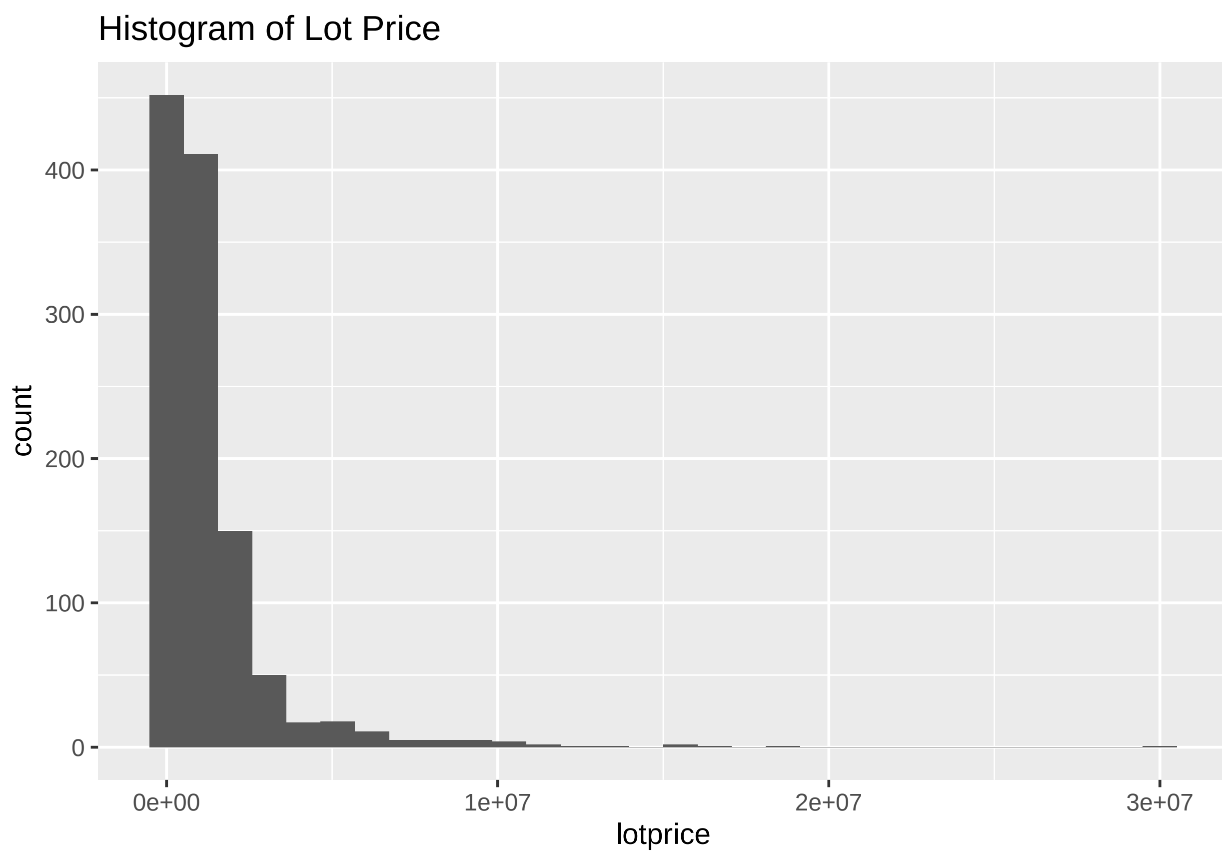
```
## Warning: Removed 140 rows containing non-finite values (`stat_bin()`).
```




```
g <- ggplot(data = survey_final_gis, aes(x = lotprice))
g + geom_histogram() + labs(title = "Histogram of Lot Price")
```

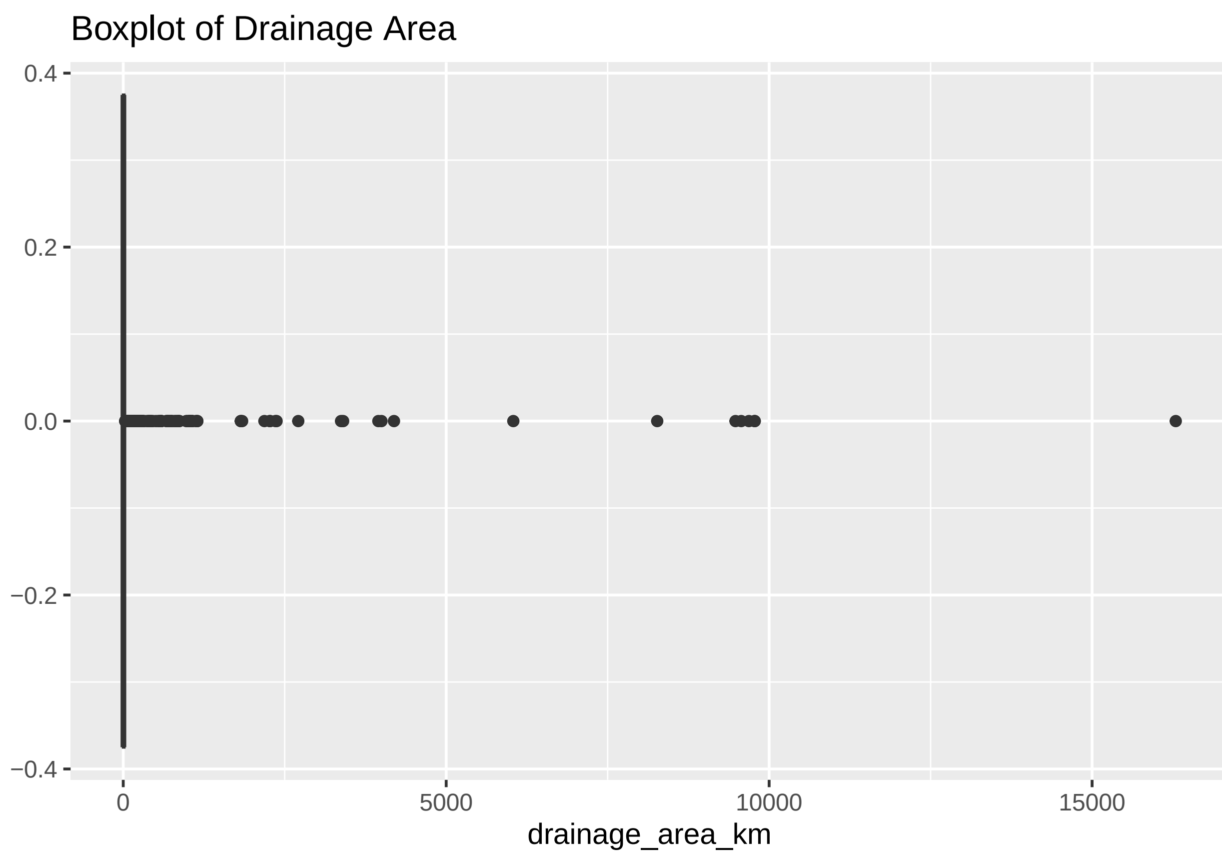
```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 203 rows containing non-finite values (`stat_bin()`).
```



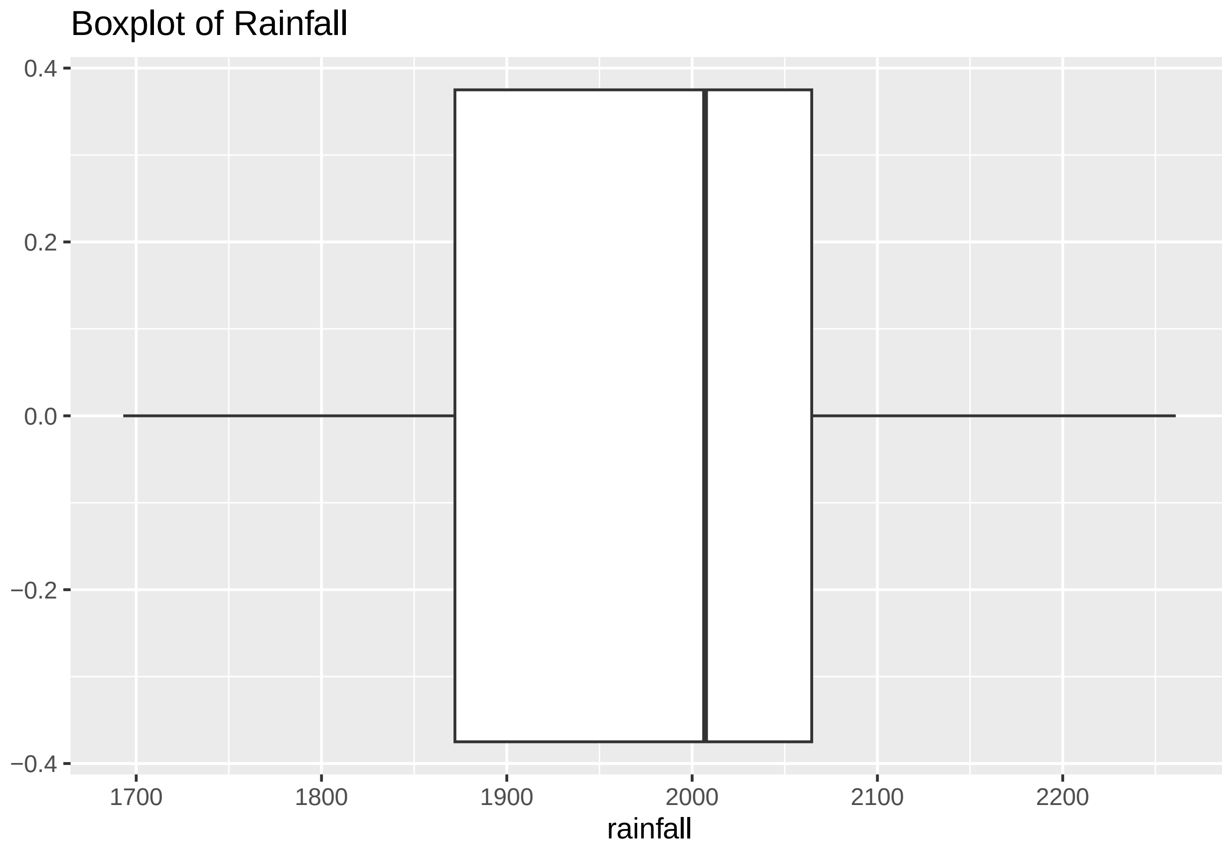
Next, we can look at some box plots

```
g <- ggplot(data = survey_final_gis, aes(x = drainage_area_km))
g + geom_boxplot() + labs(title = "Boxplot of Drainage Area")
```



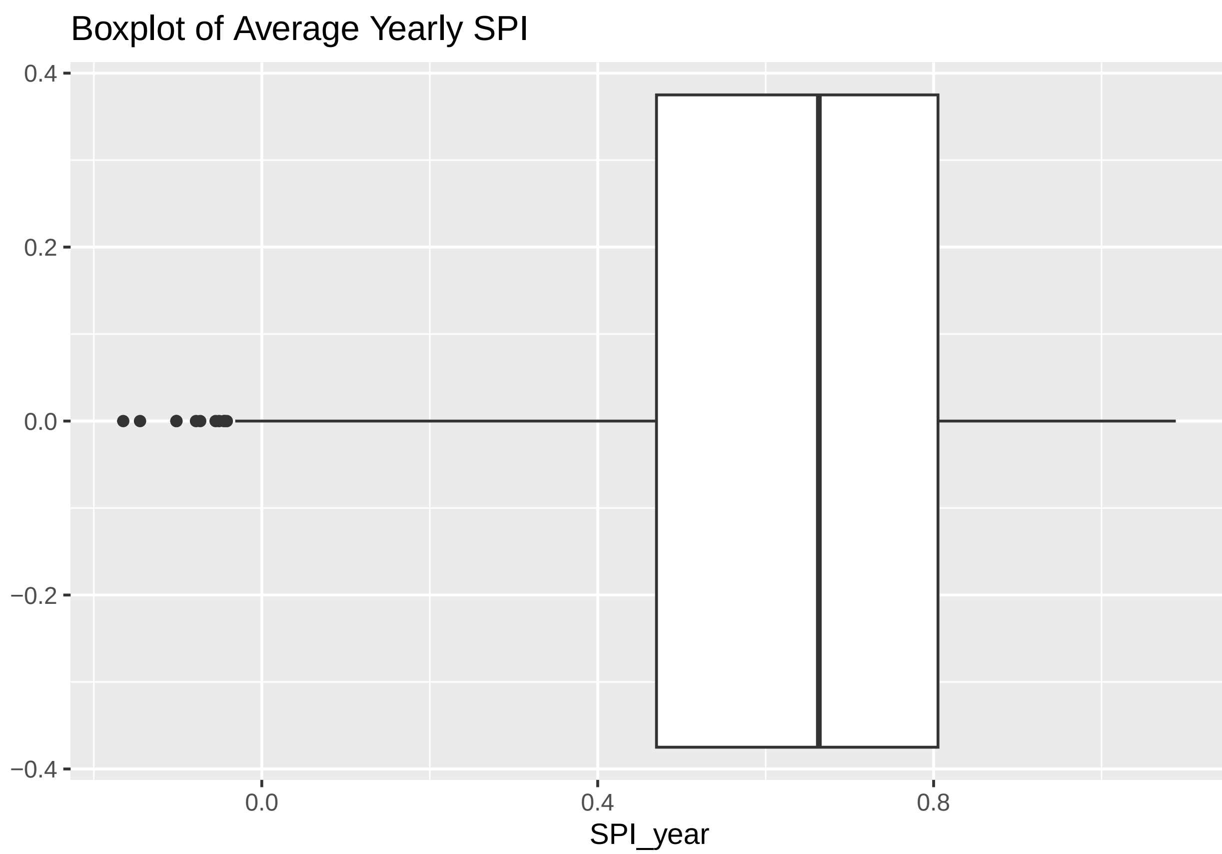

```
g <- ggplot(data = survey_final_gis, aes(x = rainfall))
g + geom_boxplot() + labs(title = "Boxplot of Rainfall")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```



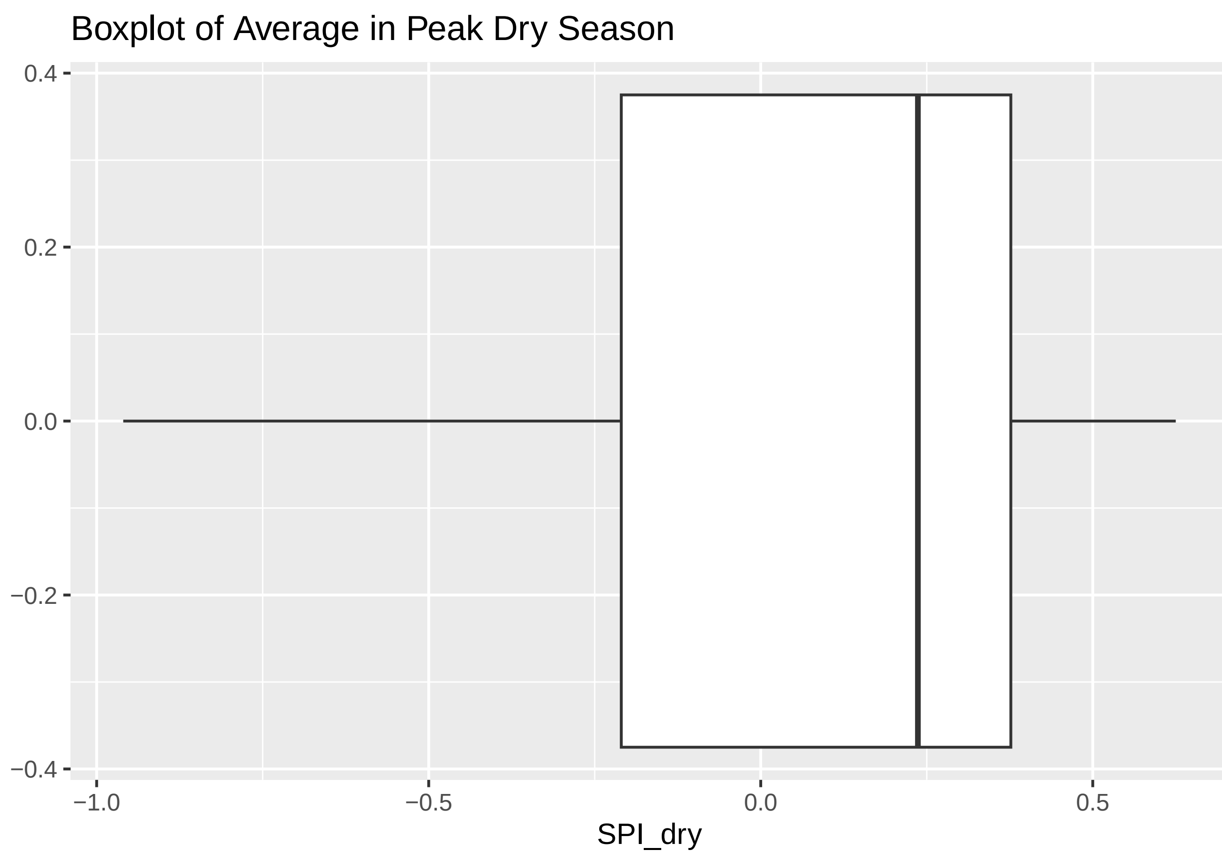

```r
g <- ggplot(data = survey_final_gis, aes(x = SPI_year))
g + geom_boxplot() + labs(title = "Boxplot of Average Yearly SPI")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```



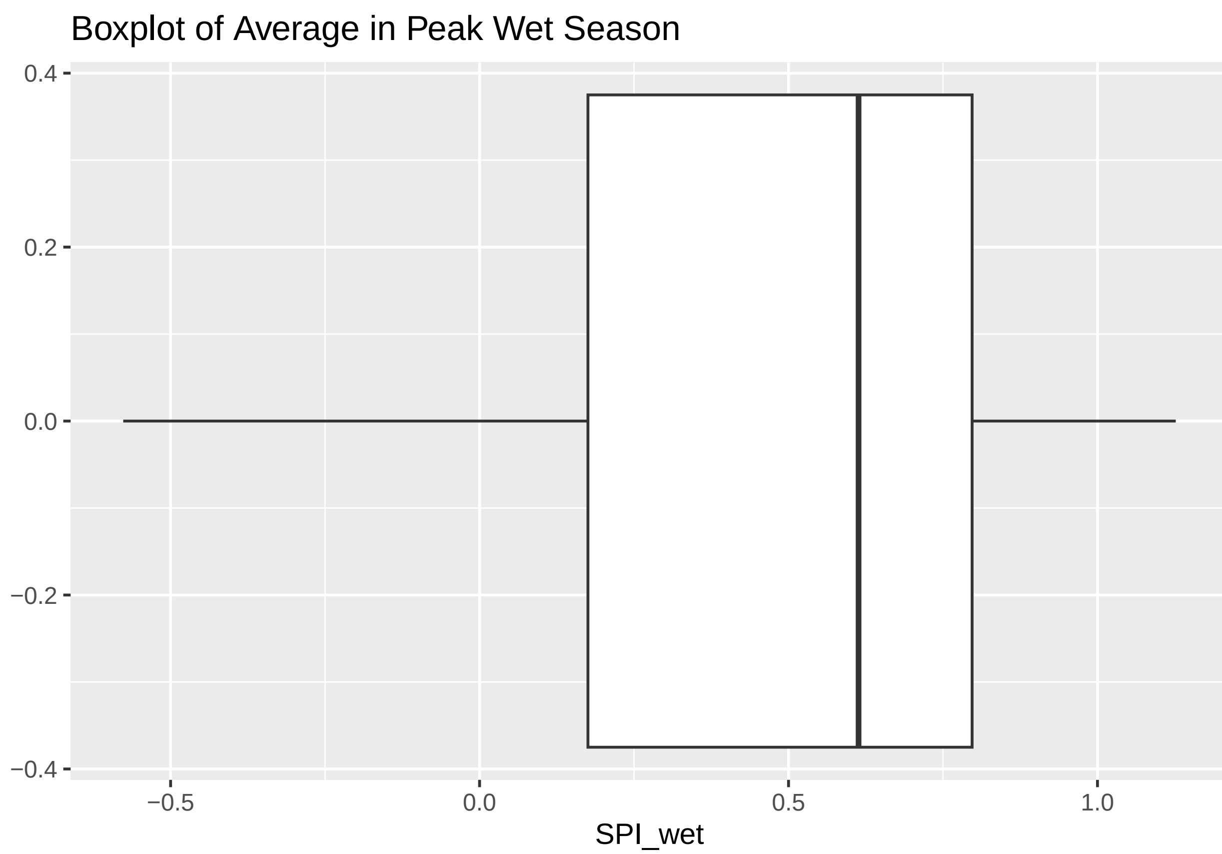

```r
g <- ggplot(data = survey_final_gis, aes(x = SPI_dry))
g + geom_boxplot() + labs(title = "Boxplot of Average in Peak Dry Season")
```

```
## Warning: Removed 140 rows containing non-finite values (‘stat_boxplot()‘).
```



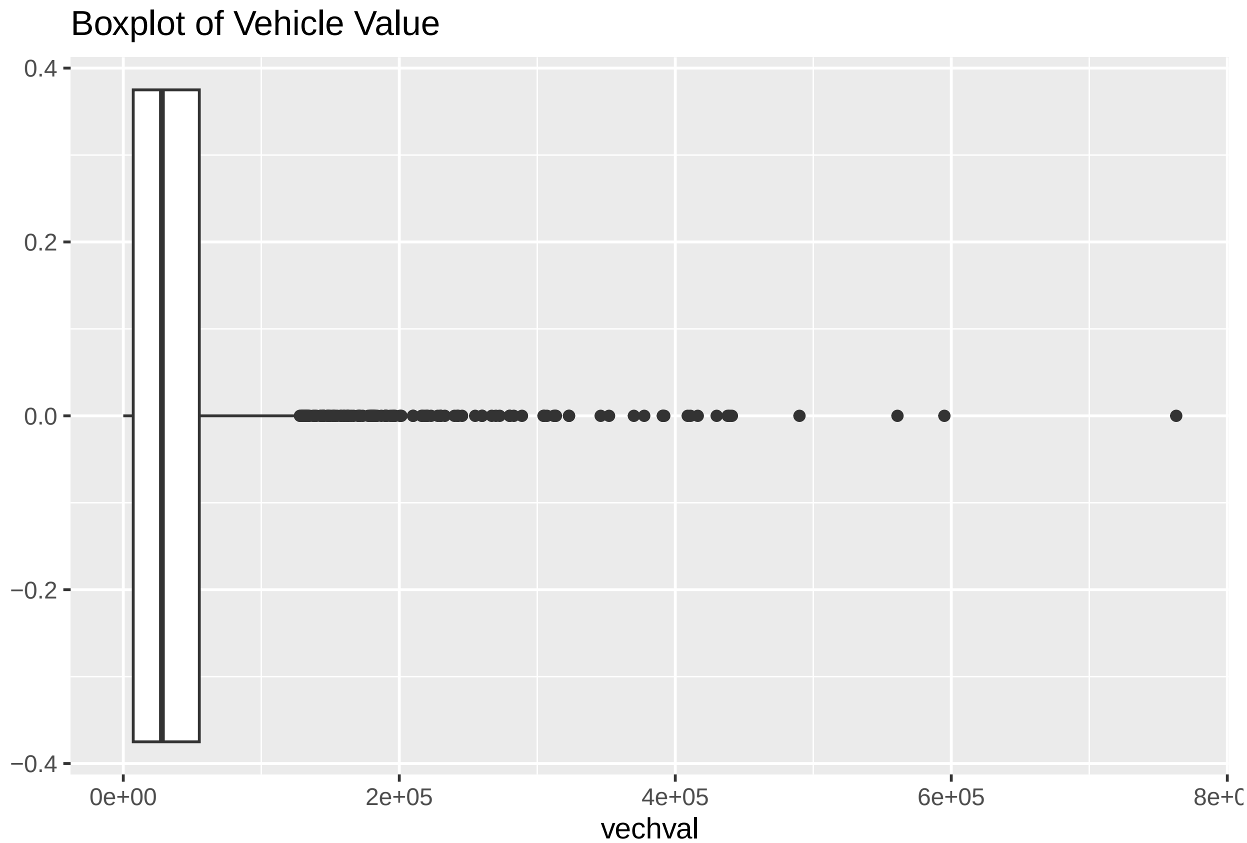

```
g <- ggplot(data = survey_final_gis, aes(x = SPI_wet))
g + geom_boxplot() + labs(title = "Boxplot of Average in Peak Wet Season")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```



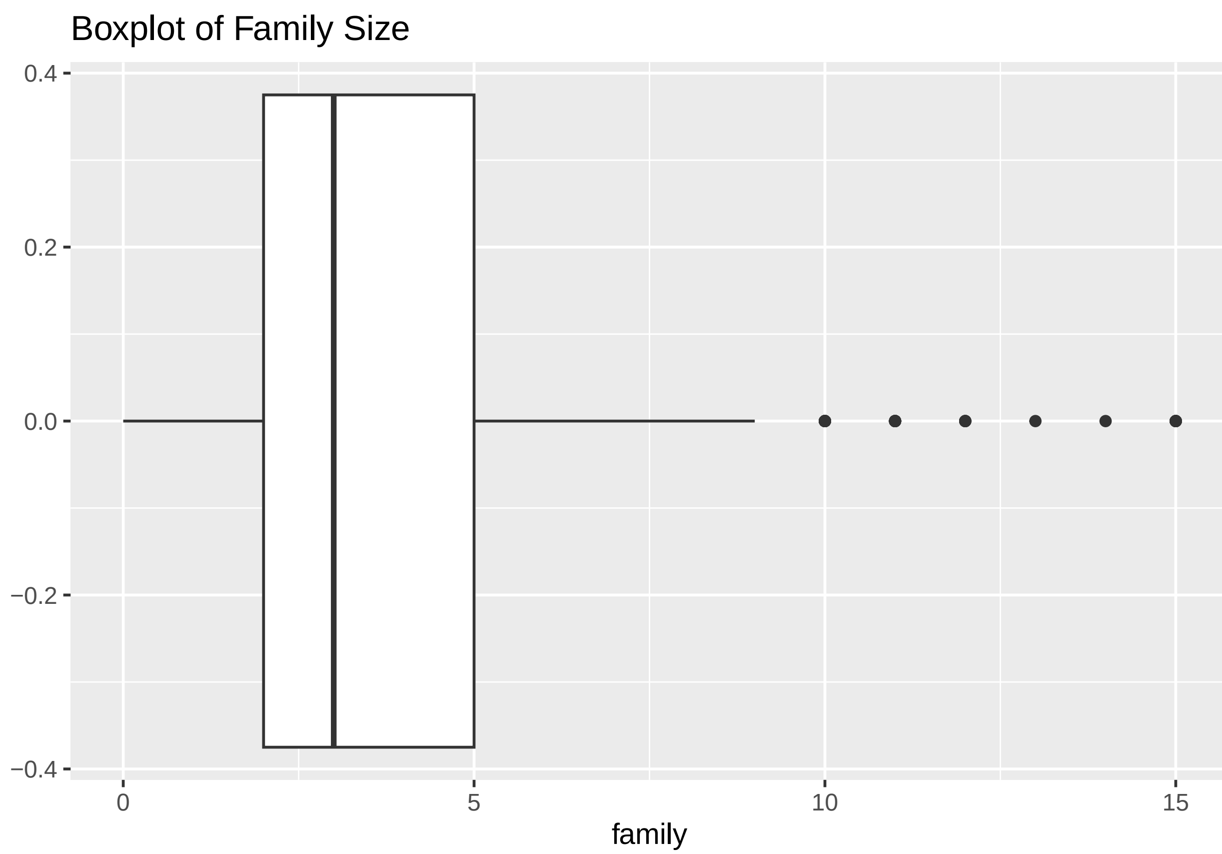

```r
g <- ggplot(data = survey_final_gis, aes(x = vechval))
g + geom_boxplot() + labs(title = "Boxplot of Vehicle Value")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```



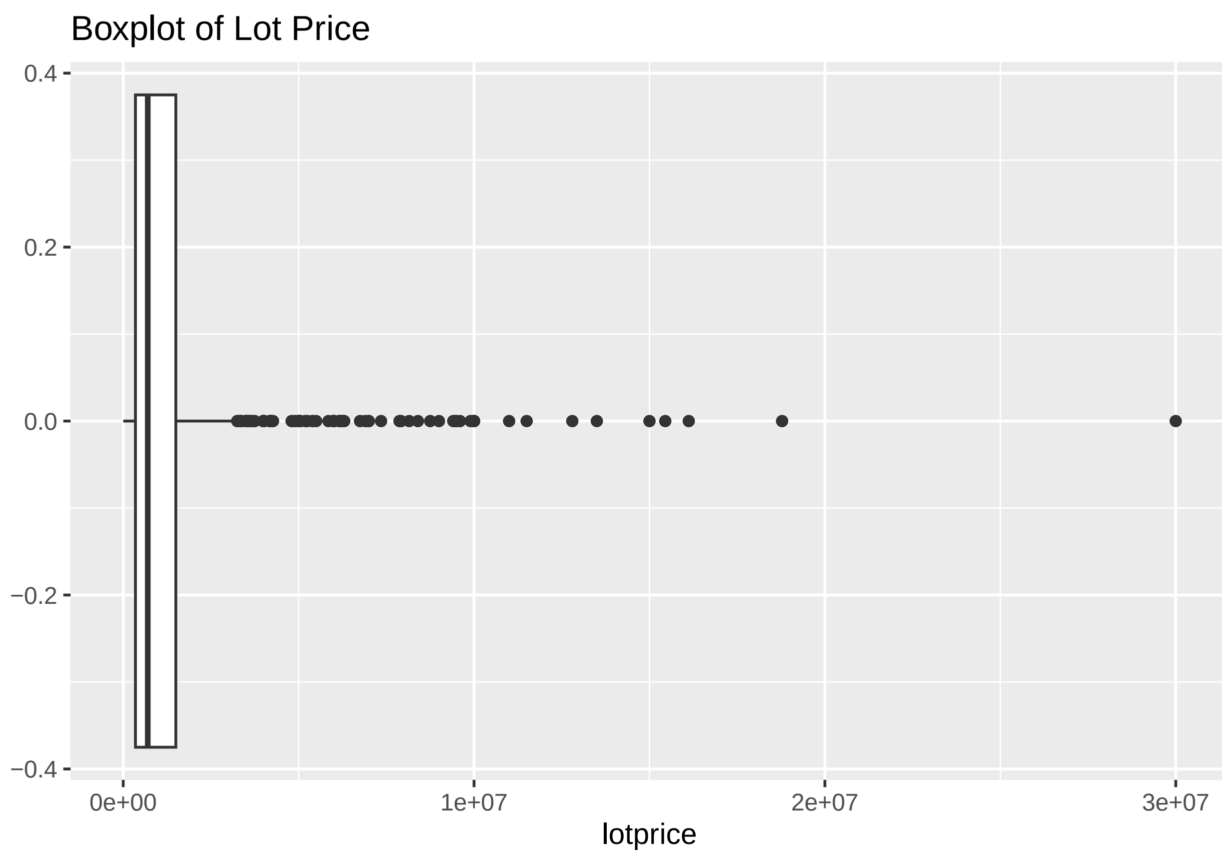

```
g <- ggplot(data = survey_final_gis, aes(x = family))
g + geom_boxplot() + labs(title = "Boxplot of Family Size")
```

```
## Warning: Removed 140 rows containing non-finite values (‘stat_boxplot()‘).
```



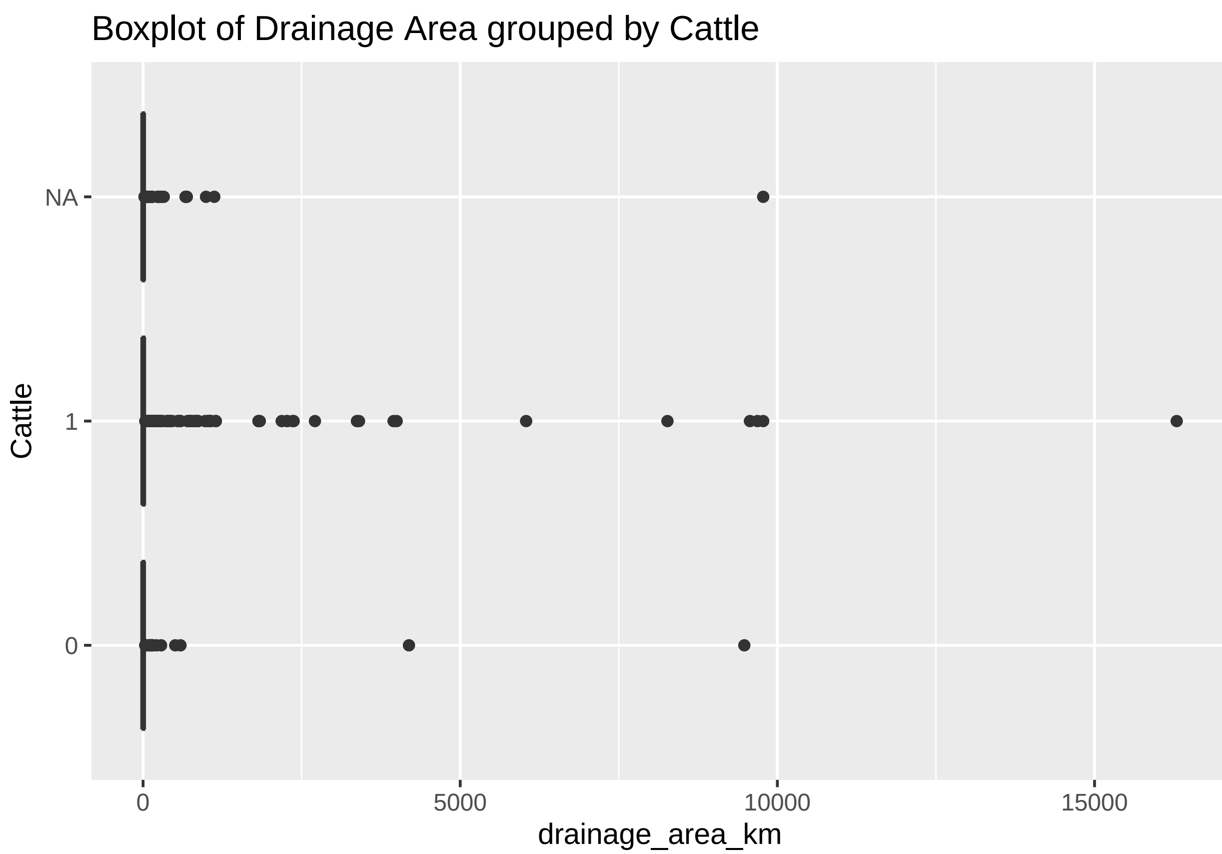

```
g <- ggplot(data = survey_final_gis, aes(x = lotprice))
g + geom_boxplot() + labs(title = "Boxplot of Lot Price")
```

```
## Warning: Removed 203 rows containing non-finite values (`stat_boxplot()`).
```



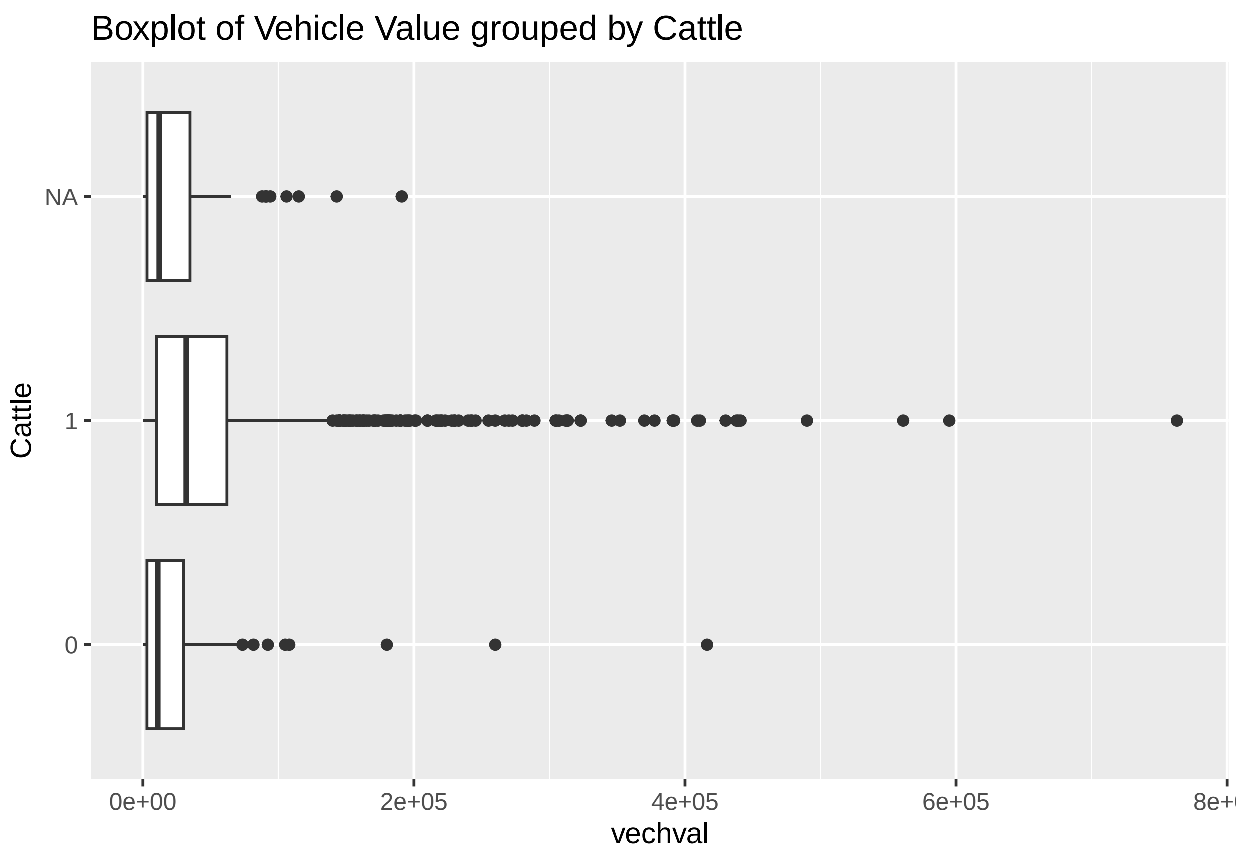
Let's look at boxplots of drainage area and vehicle value (wealth) grouped by cattle.

```
g <- ggplot(data = survey_final_gis, aes(x = drainage_area_km, y = as.factor(havecattle)))
g + geom_boxplot() + labs(title = "Boxplot of Drainage Area grouped by Cattle") +
  ylab("Cattle")
```



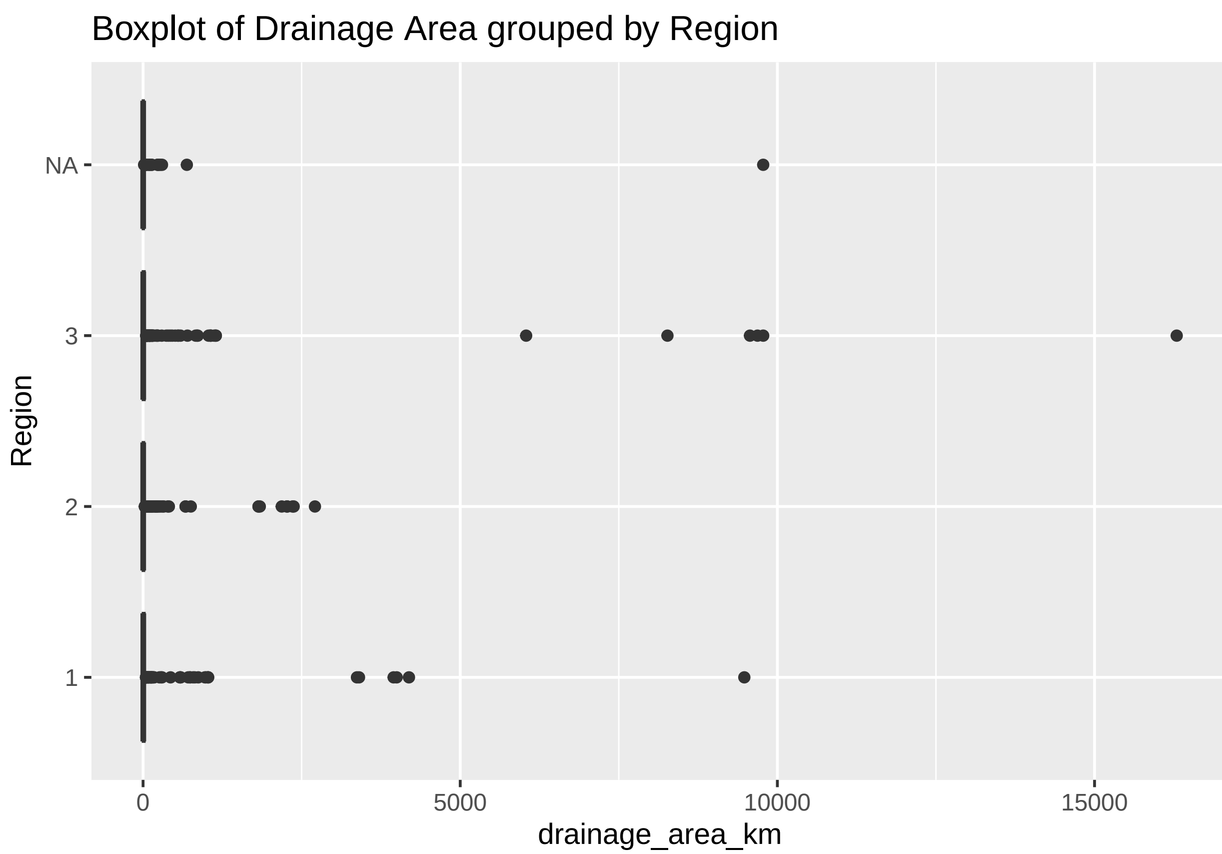

```
g <- ggplot(data = survey_final_gis, aes(x = vechval, y = as.factor(havecattle)))
g + geom_boxplot() + labs(title = "Boxplot of Vehicle Value grouped by Cattle") +
  ylab("Cattle")
```

```
## Warning: Removed 140 rows containing non-finite values (‘stat_boxplot()‘).
```



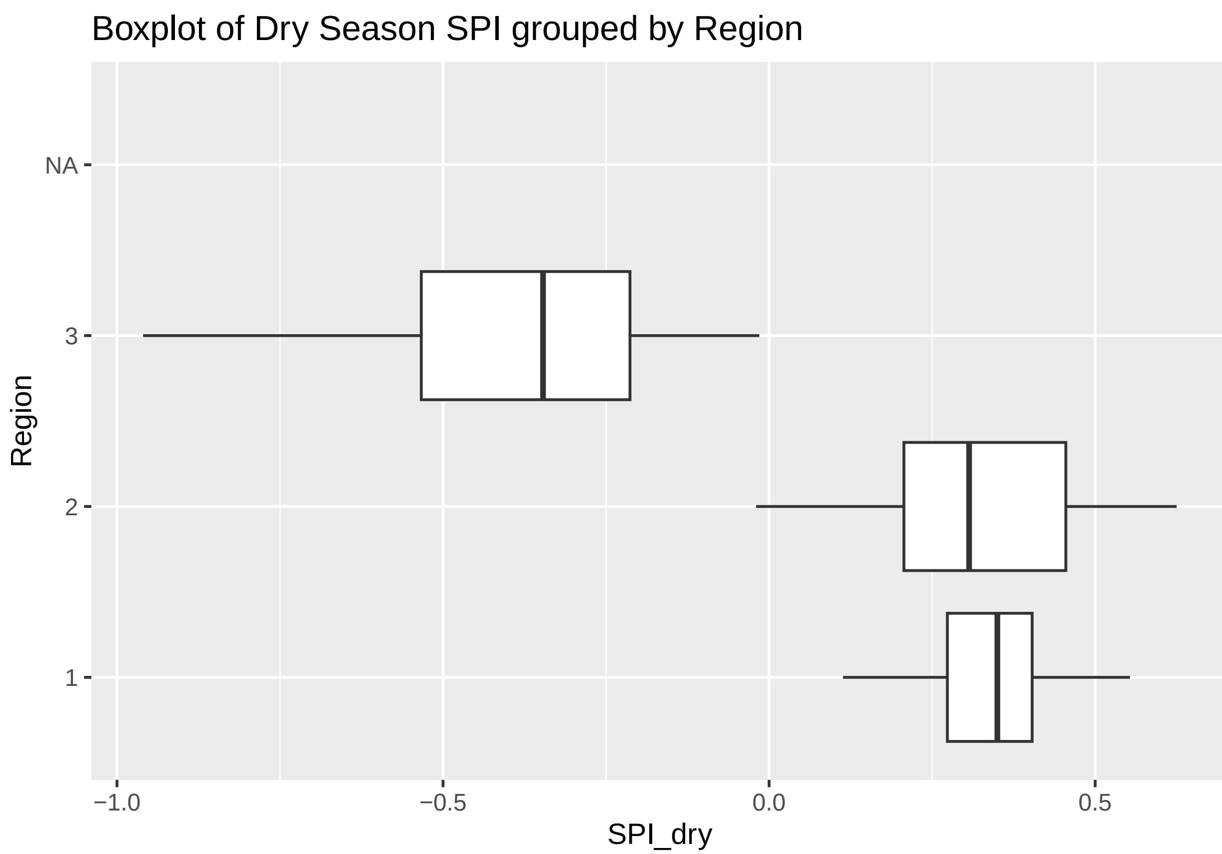
Let's look at a few box plots split by region

```
g <- ggplot(data = survey_final_gis, aes(x = drainage_area_km, y = as.factor(studycode)))
g + geom_boxplot() + labs(title = "Boxplot of Drainage Area grouped by Region") +
  ylab("Region")
```



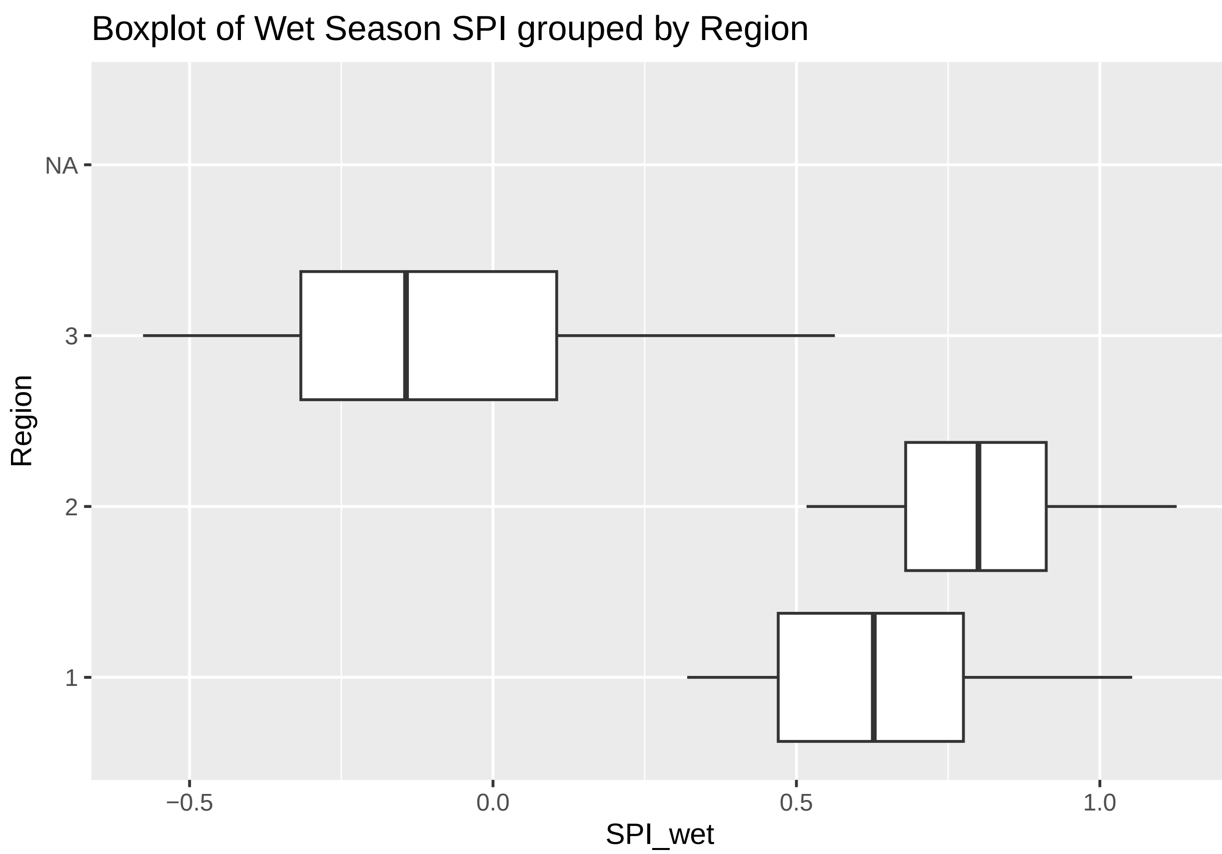

```r
g <- ggplot(data = survey_final_gis, aes(x = SPI_dry, y = as.factor(studycode)))
g + geom_boxplot() + labs(title = "Boxplot of Dry Season SPI grouped by Region") +
  ylab("Region")
```

```
## Warning: Removed 140 rows containing non-finite values (‘stat_boxplot()‘).
```



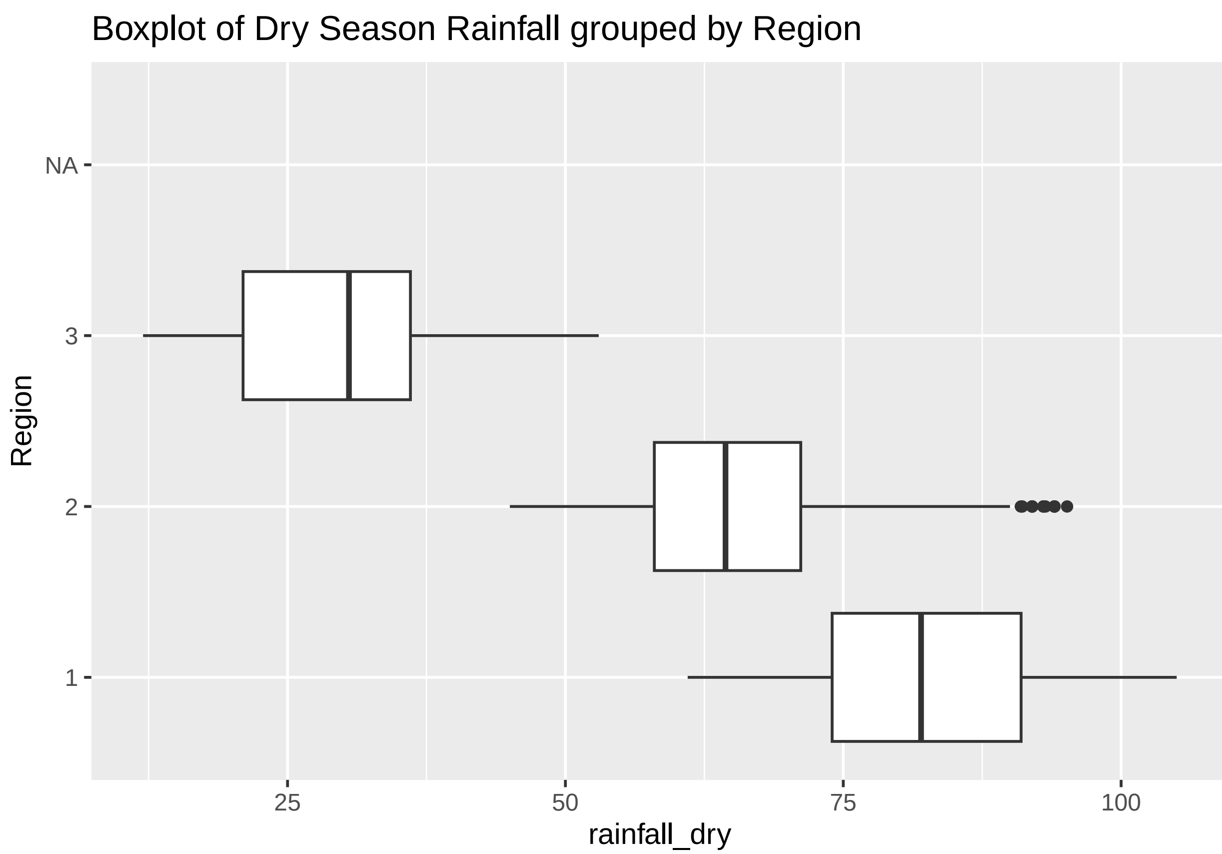

```r
g <- ggplot(data = survey_final_gis, aes(x = SPI_wet, y = as.factor(studycode)))
g + geom_boxplot() + labs(title = "Boxplot of Wet Season SPI grouped by Region") +
  ylab("Region")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```



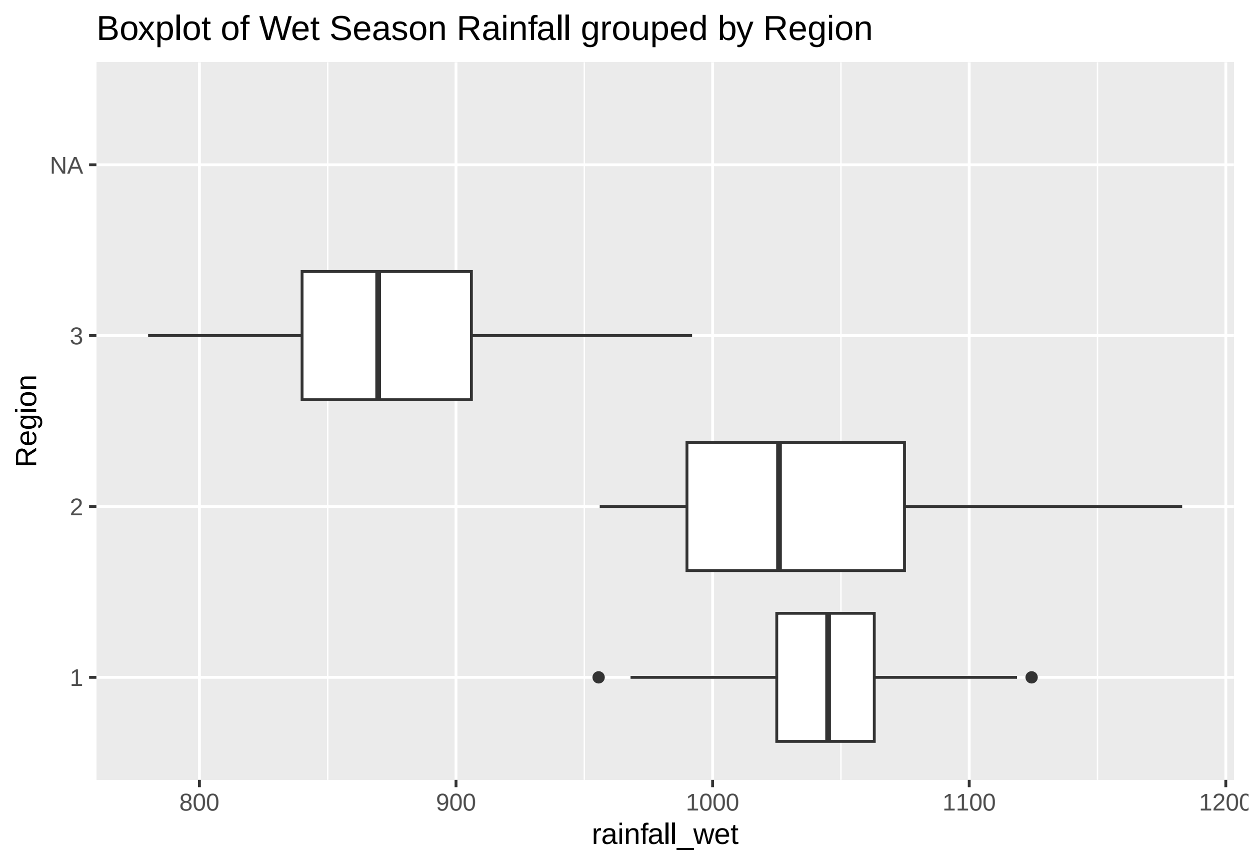

```r
g <- ggplot(data = survey_final_gis, aes(x = rainfall_dry, y = as.factor(studycode)))
g + geom_boxplot() + labs(title = "Boxplot of Dry Season Rainfall grouped by Region") +
  ylab("Region")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```



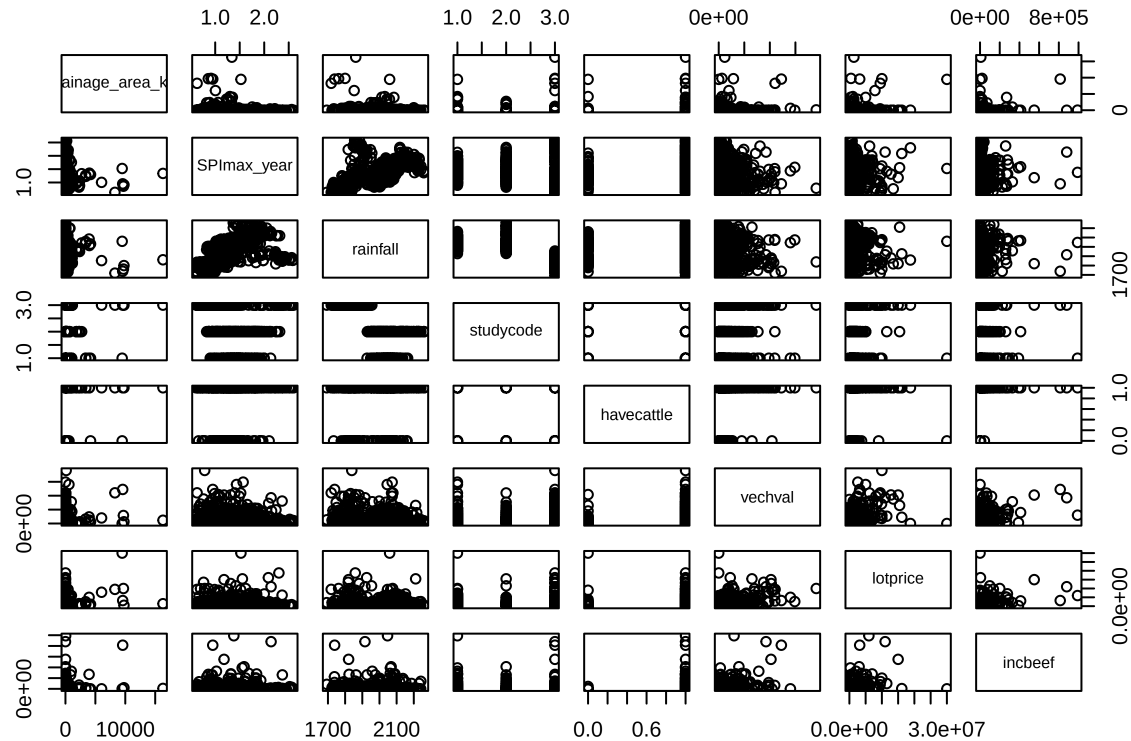

```
g <- ggplot(data = survey_final_gis, aes(x = rainfall_wet, y = as.factor(studycode)))
g + geom_boxplot() + labs(title = "Boxplot of Wet Season Rainfall grouped by Region") +
  ylab("Region")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```



Next lets look at pair plots

```
pairs_subset <- survey_final_gis %>% select(c(drainage_area_km, SPImax_year, rainfall, studycode, haveca
pairs(pairs_subset)
```



Let's look at how many households fall into each region

```r
table(survey_final_gis$studycode)
```

```
##
##   1   2   3
## 368 441 391
```

Let's also look at some basic summary statistics

```r
describe(survey_final_gis[c('drainage_area_km', 'rainfall', 'rainfall_wet', 'rainfall_dry', 'SPI_wet',
```

```
##                  vars    n       mean         sd     min         max
## drainage_area_km    1 1340     126.10     846.22    0.01    16295.36
## rainfall            2 1200    1982.59     116.73 1693.00     2261.00
## rainfall_wet        3 1200     984.51      89.15  780.00     1183.00
## rainfall_dry        4 1200      59.03      24.22   12.00      105.00
## SPI_wet             5 1200       0.46       0.44   -0.58        1.13
## SPI_dry             6 1200       0.10       0.37   -0.96        0.62
## incbeef             7  698   27979.62   78088.34    0.00   990000.00
## vechval             8 1200   50514.90   74844.85    0.00   763000.00
## lotprice            9 1137 1315067.21 2034041.25 1000.00 30000000.00
## family             10 1200       3.75       2.18    0.00       15.00
##                     range       se
## drainage_area_km 16295.35    23.12
```

```
## rainfall              568.00     3.37
## rainfall_wet          403.00     2.57
## rainfall_dry           93.00     0.70
## SPI_wet                 1.70     0.01
## SPI_dry                 1.58     0.01
## incbeef            990000.00  2955.69
## vechval            763000.00  2160.58
## lotprice         29999000.00 60322.53
## family                 15.00     0.06
```

I'm curious about how many farms made multiple adaptations

```r
table(survey_final_gis$cattle_management, survey_final_gis$pasture_management)
```

```
##
##       0   1
##   0 467 373
##   1 110 390
```

```r
table(survey_final_gis$cattle_management, survey_final_gis$forest_conservation)
```

```
##
##       0   1
##   0 216 624
##   1  34 466
```

```r
table(survey_final_gis$cattle_management, survey_final_gis$water_management)
```

```
##
##       0   1
##   0 169 671
##   1  22 478
```

```r
table(survey_final_gis$pasture_management, survey_final_gis$forest_conservation)
```

```
##
##       0   1
##   0 194 383
##   1  56 707
```

```r
table(survey_final_gis$pasture_management, survey_final_gis$water_management)
```

```
##
##       0   1
##   0 162 415
##   1  29 734
```

```r
table(survey_final_gis$forest_conservation, survey_final_gis$water_management)
```

```
##
##         0    1
##   0   149  101
##   1    42 1048
```

It looks like the majority of farmers who adapted did more than one thing.

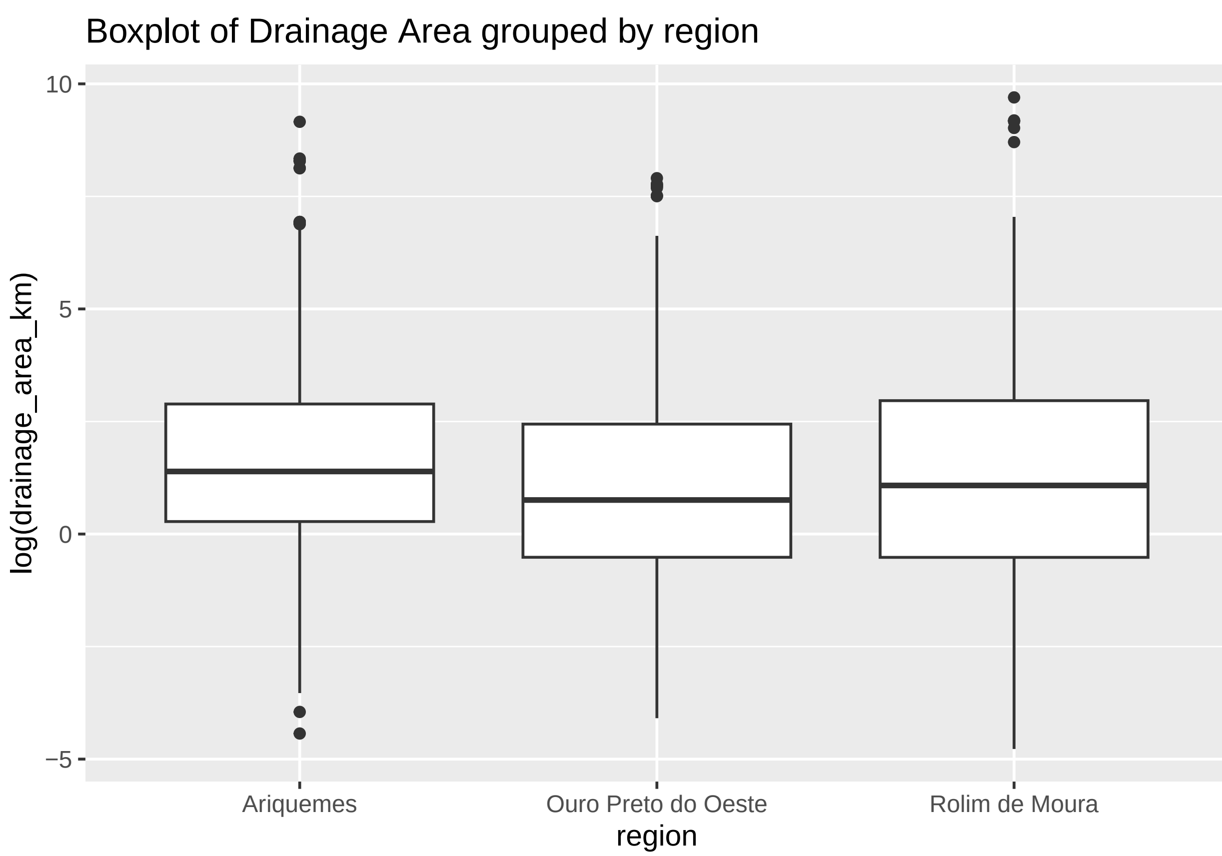
boxplots for checking the effect of categoricals on numeric variables

Boxplots can help us to overview the relationship of categorical variables such as regions and adaptations and numeric variables such as drainage area, rainfall and wealth.

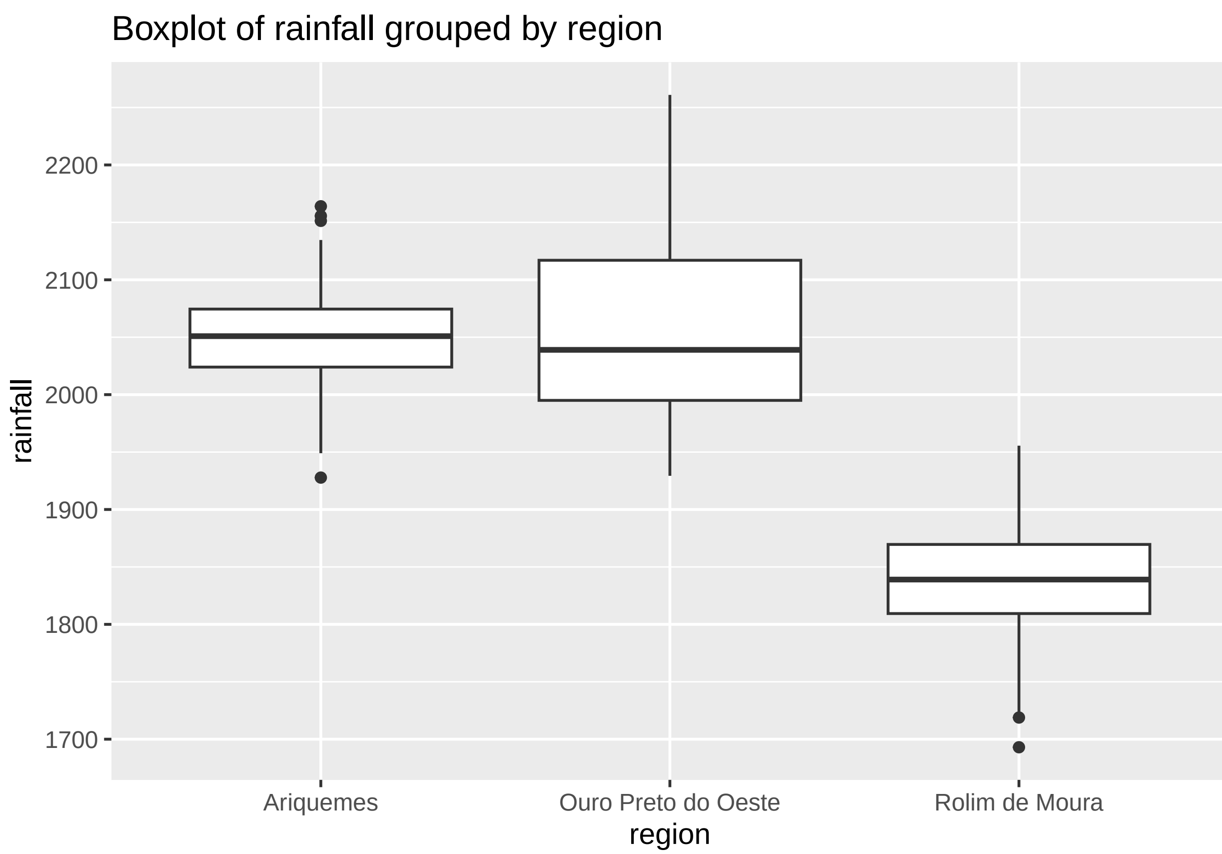
Effect of region on drainage area, rainfall and vechval

Considering our data are based on three regions, we first would like to see drainage area, rainfall and wealth differ in three regions. Note that we use the data without "NA" here.

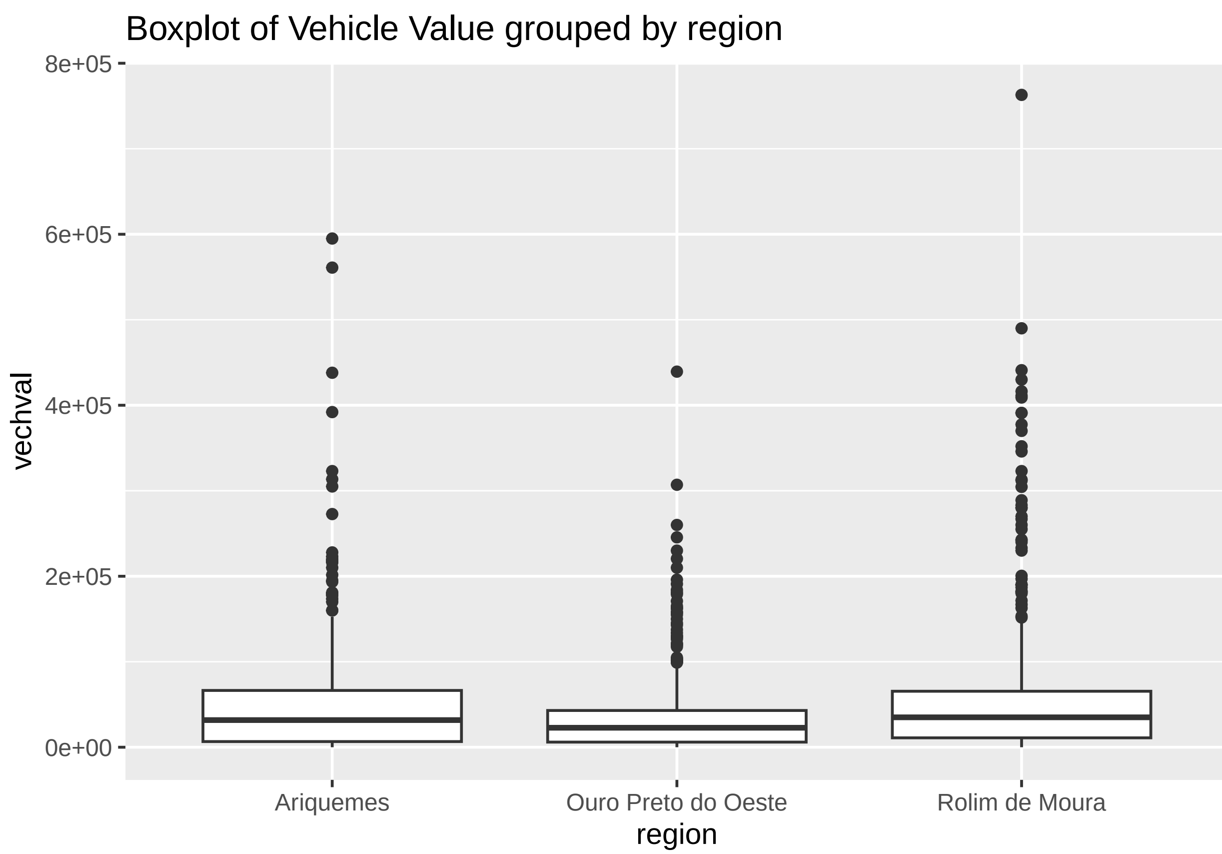
```r
g <- ggplot(data = survey_final_gis_clean, aes(x = as.factor(region),y = log(drainage_area_km)))
g + geom_boxplot() + labs(title = "Boxplot of Drainage Area grouped by region") +
  xlab("region")
```




```r
g <- ggplot(data = survey_final_gis_clean, aes(x= as.factor(region),y = rainfall))
g + geom_boxplot() + labs(title = "Boxplot of rainfall grouped by region") +
  xlab("region")
```




```r
g <- ggplot(data = survey_final_gis_clean, aes( x = as.factor(region),y = vechval))
g + geom_boxplot() + labs(title = "Boxplot of Vehicle Value grouped by region") +
  xlab("region")
```

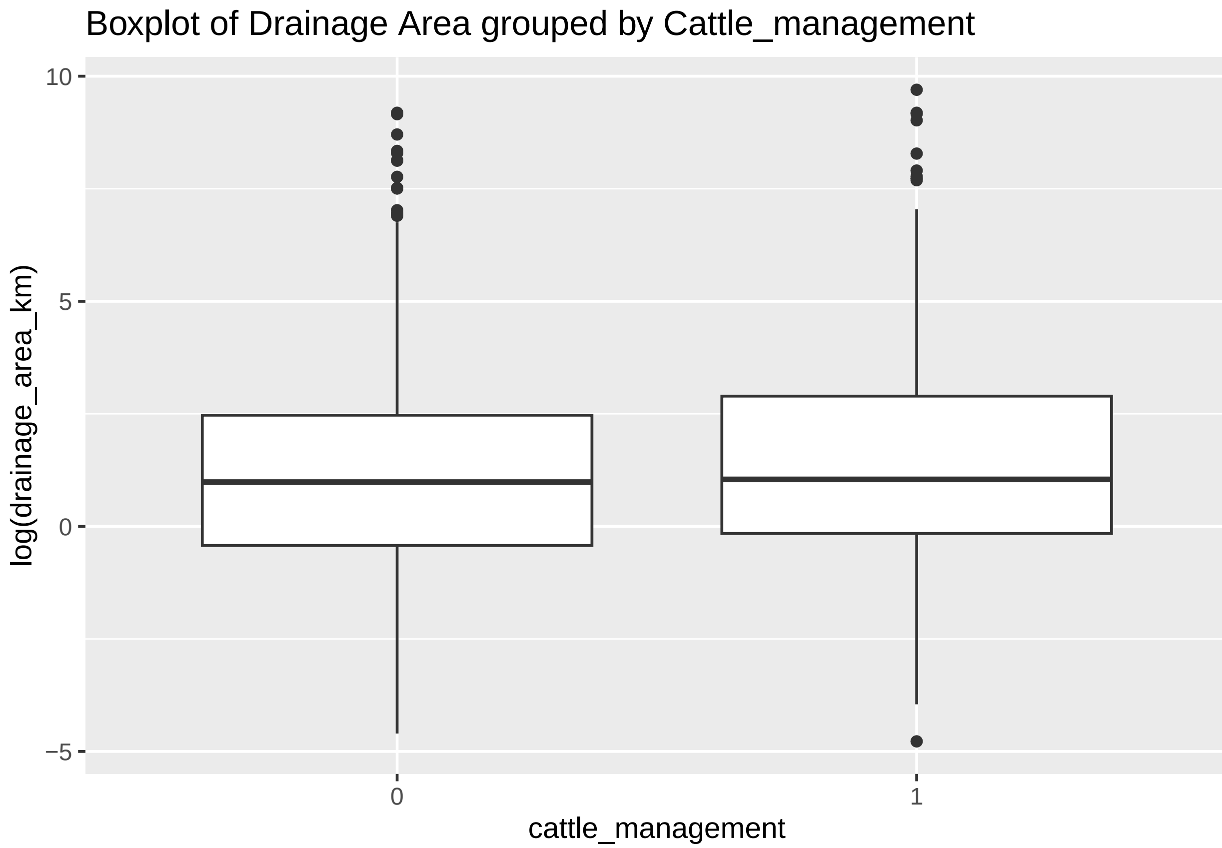


Above figure shows drainage area and vechval is marginly different in three regions, while the rainfall on region "Rolim" is much less than the other two. This indicates there is interaction between drainage area and rainfall and we need to be cautious during the modeling using these two variables. On the other hand, some outliers exist in the data. It is necessary to remove outliers during statistical analysis.

Next, We can designate binary adaptation measures as factors and compare numeric variables with and without adaptation measures and estimate the relationship between them. We are going to investigate all four adaptation measures at first and then the combined one, any_adaptation.

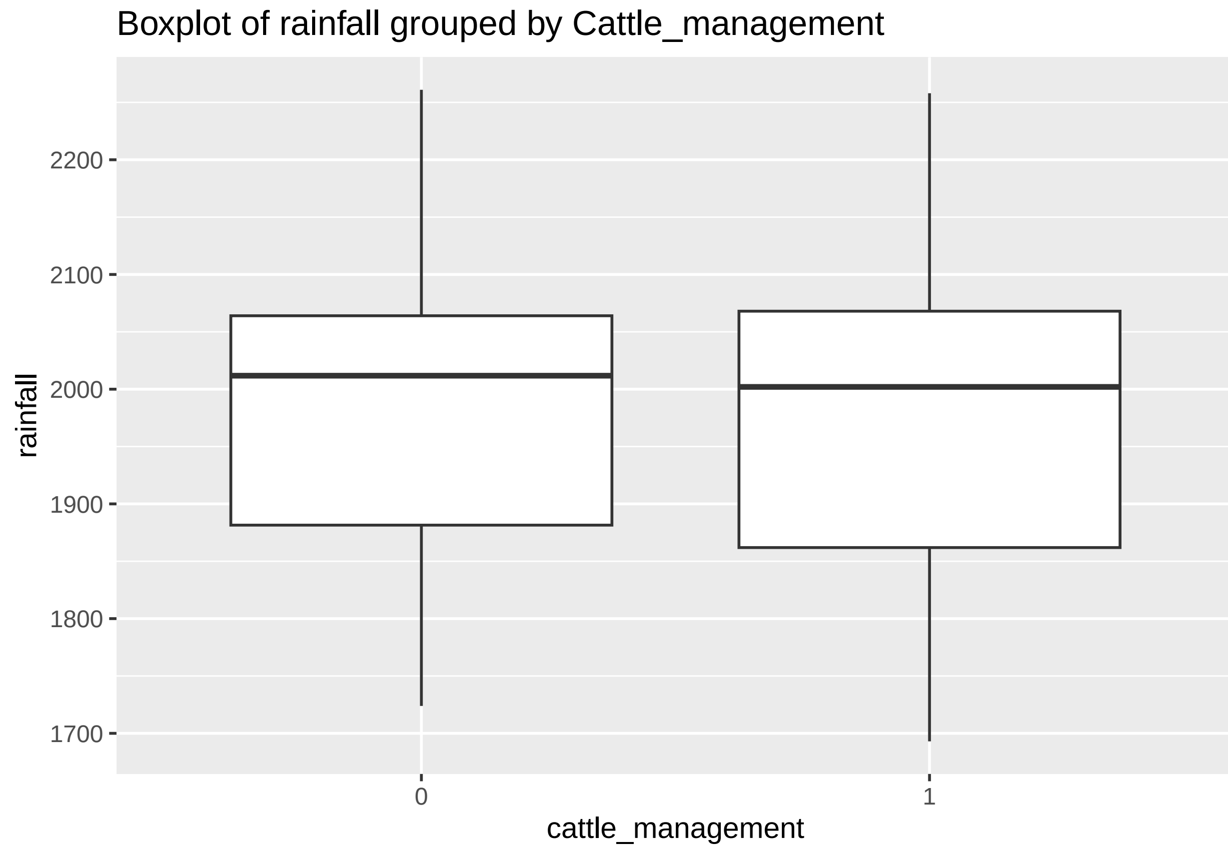
Effect of cattle_management on drainage area, rainfall and vechval

```
g <- ggplot(data = survey_final_gis, aes(x = as.factor(cattle_management), y = log(drainage_area_km)))
g + geom_boxplot() + labs(title = "Boxplot of Drainage Area grouped by Cattle_management") +
  xlab("cattle_management")
```



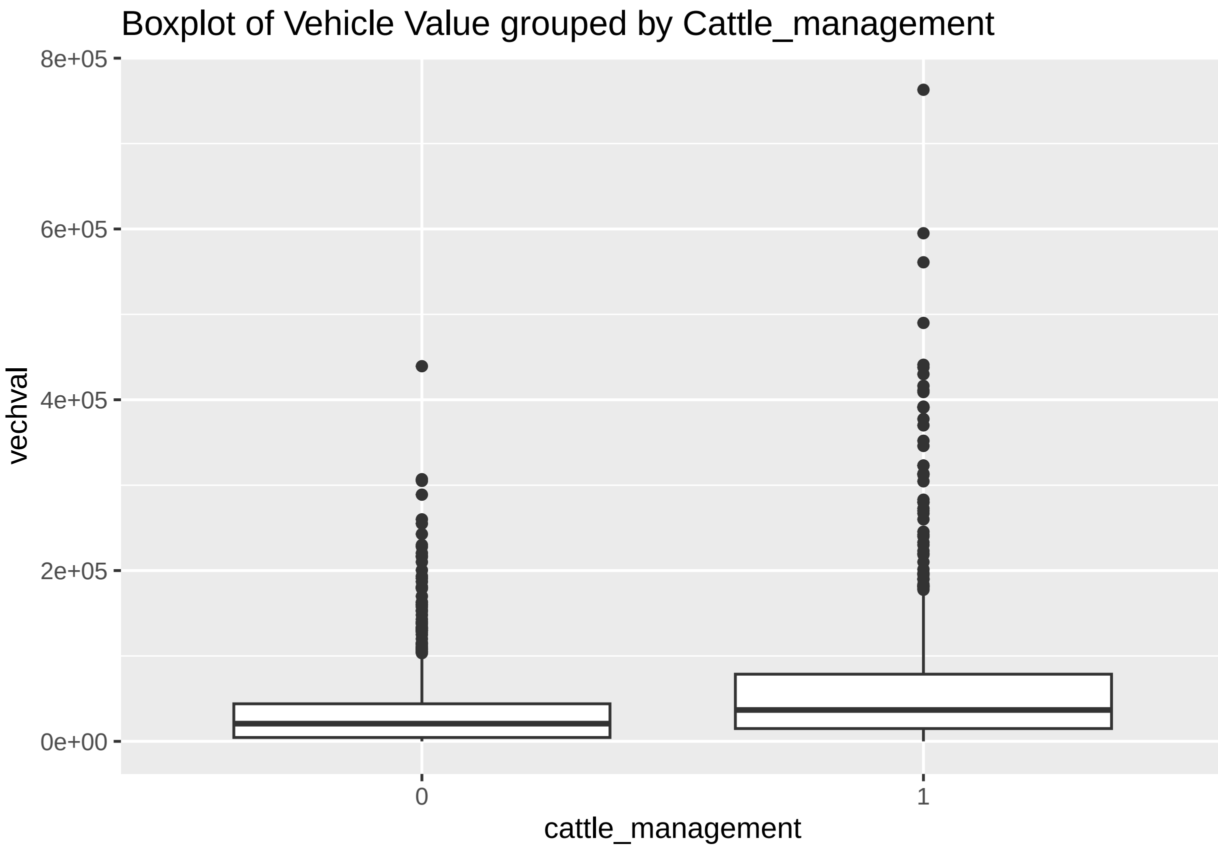

```
g <- ggplot(data = survey_final_gis, aes(x = as.factor(cattle_management), y = rainfall))
g + geom_boxplot() + labs(title = "Boxplot of rainfall grouped by Cattle_management") +
  xlab("cattle_management")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```




```
g <- ggplot(data = survey_final_gis, aes(x = as.factor(cattle_management),y = vechval))
g + geom_boxplot() + labs(title = "Boxplot of Vehicle Value grouped by Cattle_management") +
  xlab("cattle_management")
```

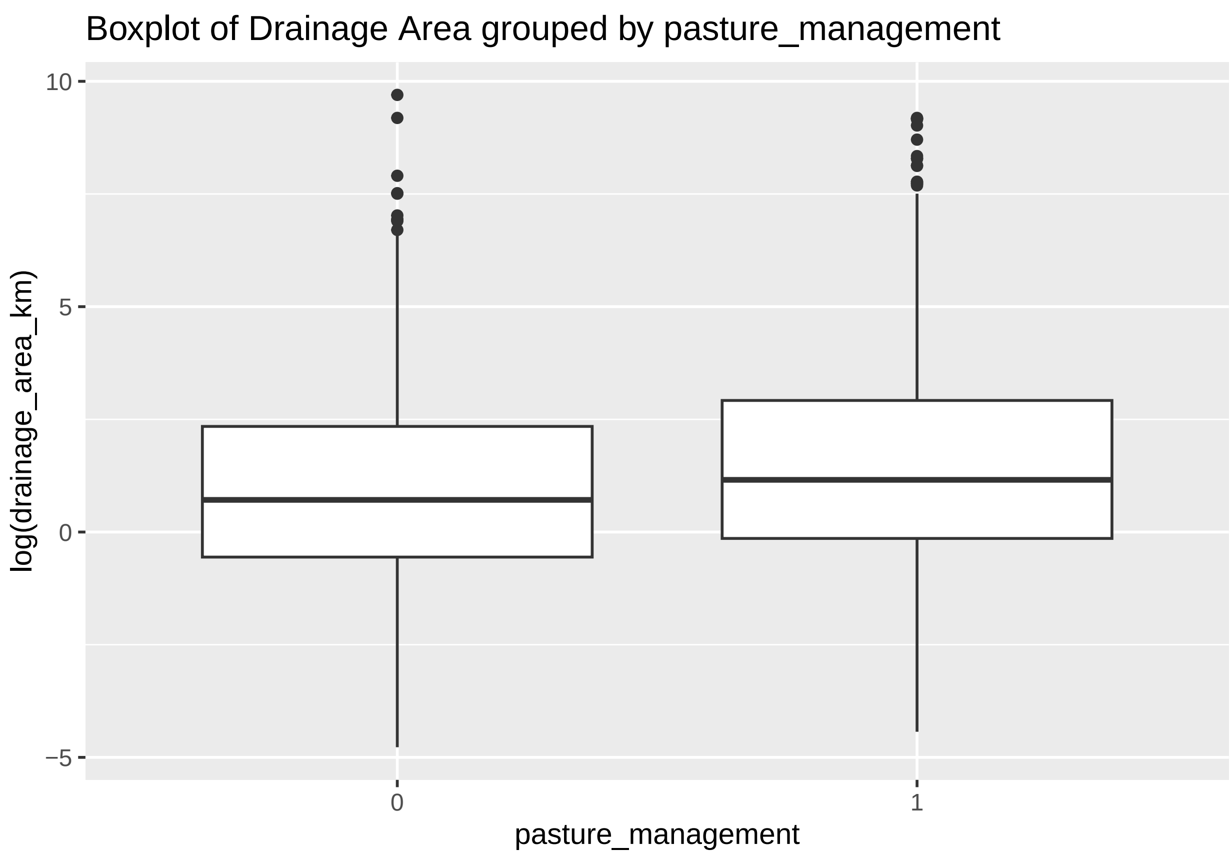
```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```



Cattle_management sounds exhibit slightly lower rainfall and higher wealth than the control without it. No visible log drainage area

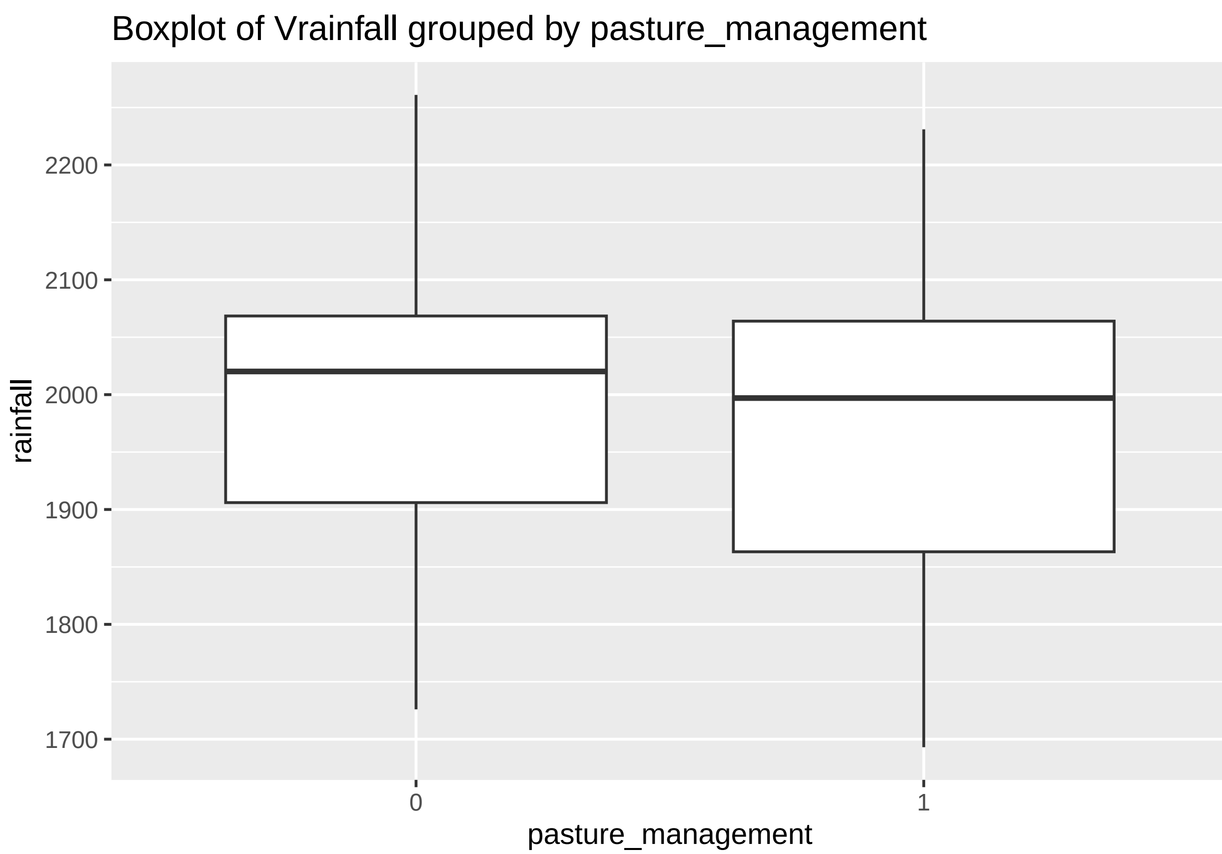
Effect of pasture_management on drainage area, rainfall and vechval

```
g <- ggplot(data = survey_final_gis, aes(x = as.factor(pasture_management), y = log(drainage_area_km)))
g + geom_boxplot() + labs(title = "Boxplot of Drainage Area grouped by pasture_management") +
  xlab("pasture_management")
```



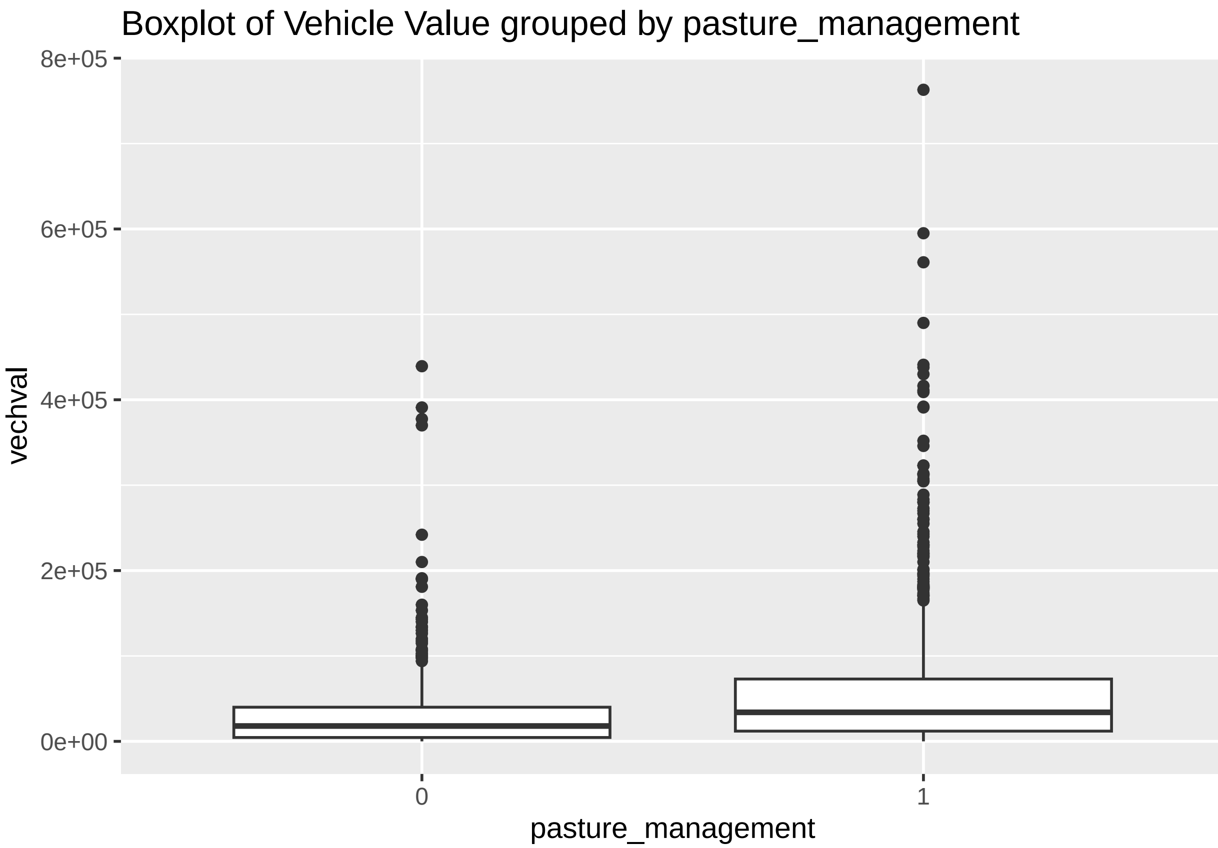

```r
g <- ggplot(data = survey_final_gis, aes(x = as.factor(pasture_management),y = rainfall))
g + geom_boxplot() + labs(title = "Boxplot of Vrainfall grouped by pasture_management") +
  xlab("pasture_management")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```




```
g <- ggplot(data = survey_final_gis, aes(x = as.factor(pasture_management),y = vechval))
g + geom_boxplot() + labs(title = "Boxplot of Vehicle Value grouped by pasture_management") +
  xlab("pasture_management")
```

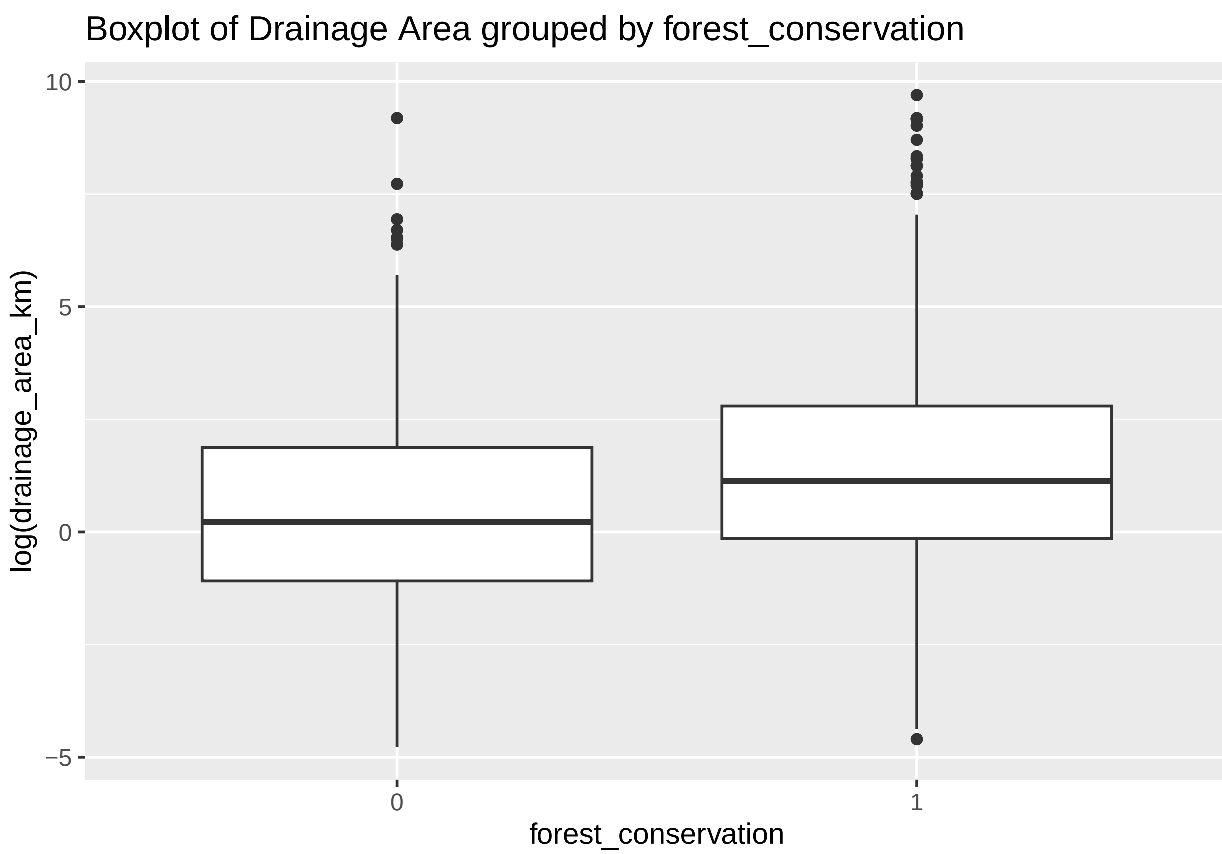
```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```



Pasture_management shows higher log drainage area, lower rainfall and higher wealth than the control.

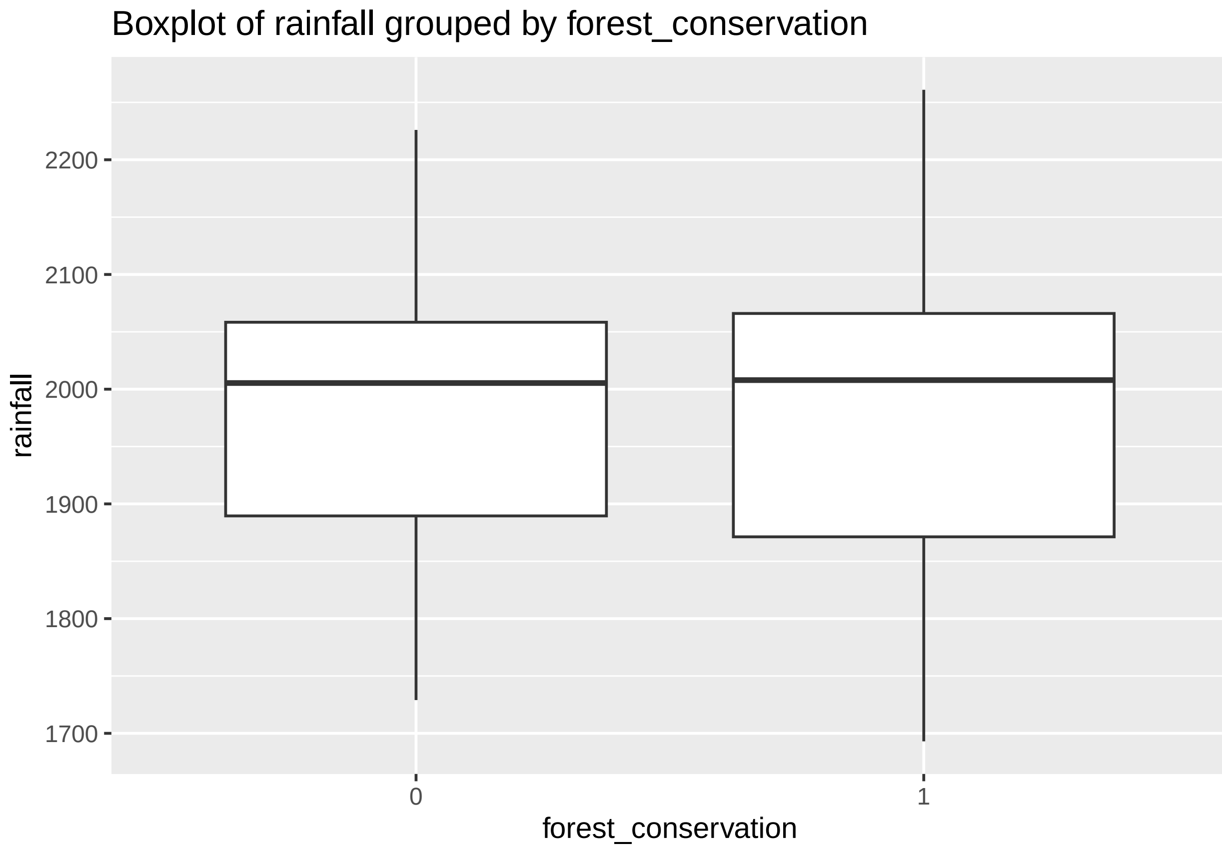
Effect of forest_conservation on drainage area, rainfall and vechval

```
g <- ggplot(data = survey_final_gis, aes(y = log(drainage_area_km), x = as.factor(forest_conservation)))
g + geom_boxplot() + labs(title = "Boxplot of Drainage Area grouped by forest_conservation") +
  xlab("forest_conservation")
```



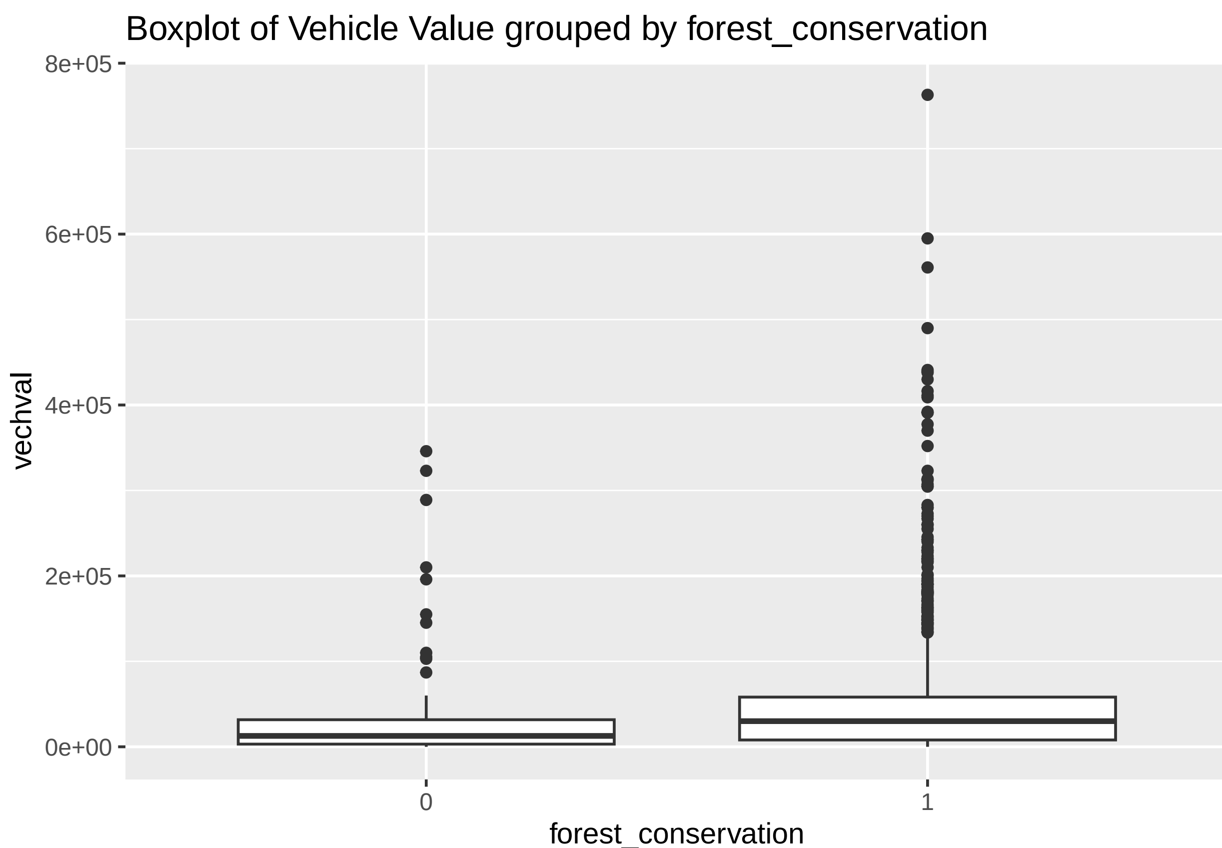

```r
g <- ggplot(data = survey_final_gis, aes(y = rainfall, x = as.factor(forest_conservation)))
g + geom_boxplot() + labs(title = "Boxplot of rainfall grouped by forest_conservation") +
  xlab("forest_conservation")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```




```r
g <- ggplot(data = survey_final_gis, aes(y = vechval, x = as.factor(forest_conservation)))
g + geom_boxplot() + labs(title = "Boxplot of Vehicle Value grouped by forest_conservation") +
  xlab("forest_conservation")
```

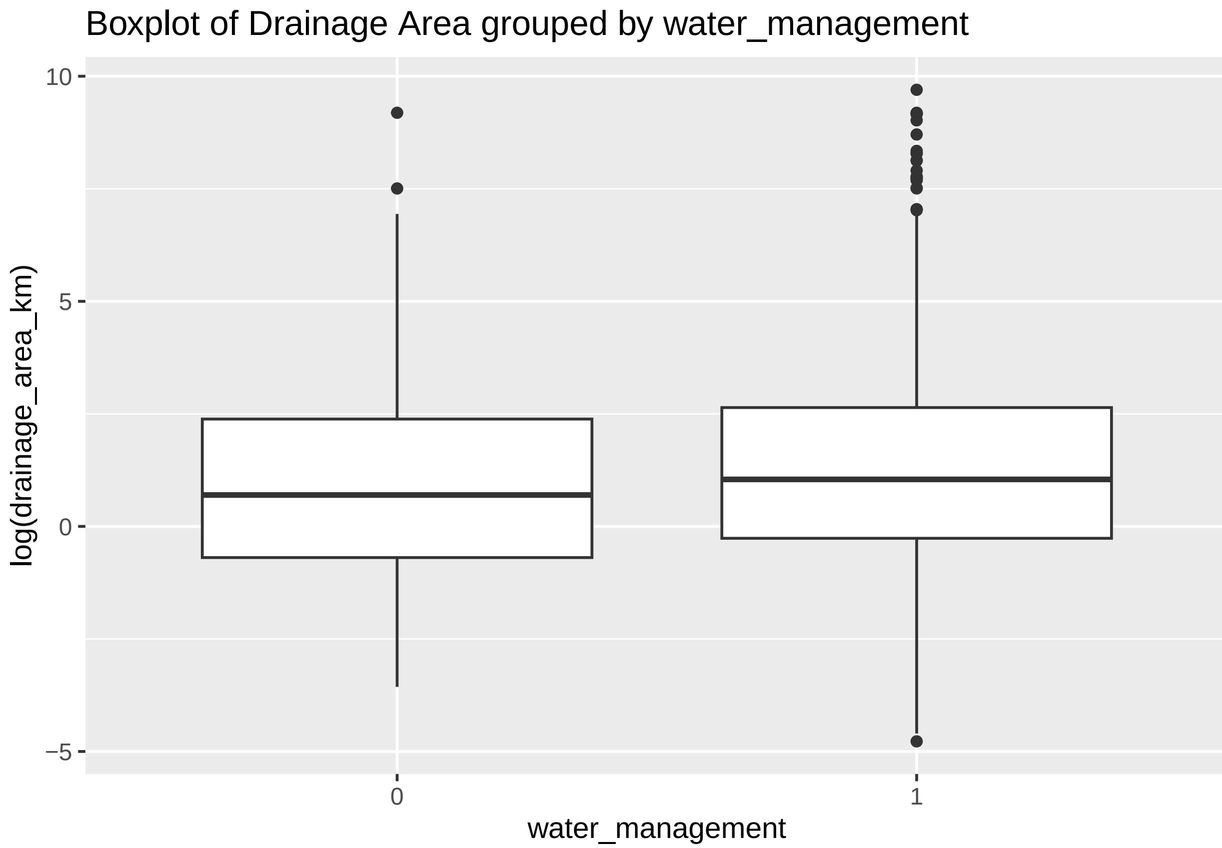
```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```



Forst_conservation has higher drainage area, similar rainfall and higher wealth.

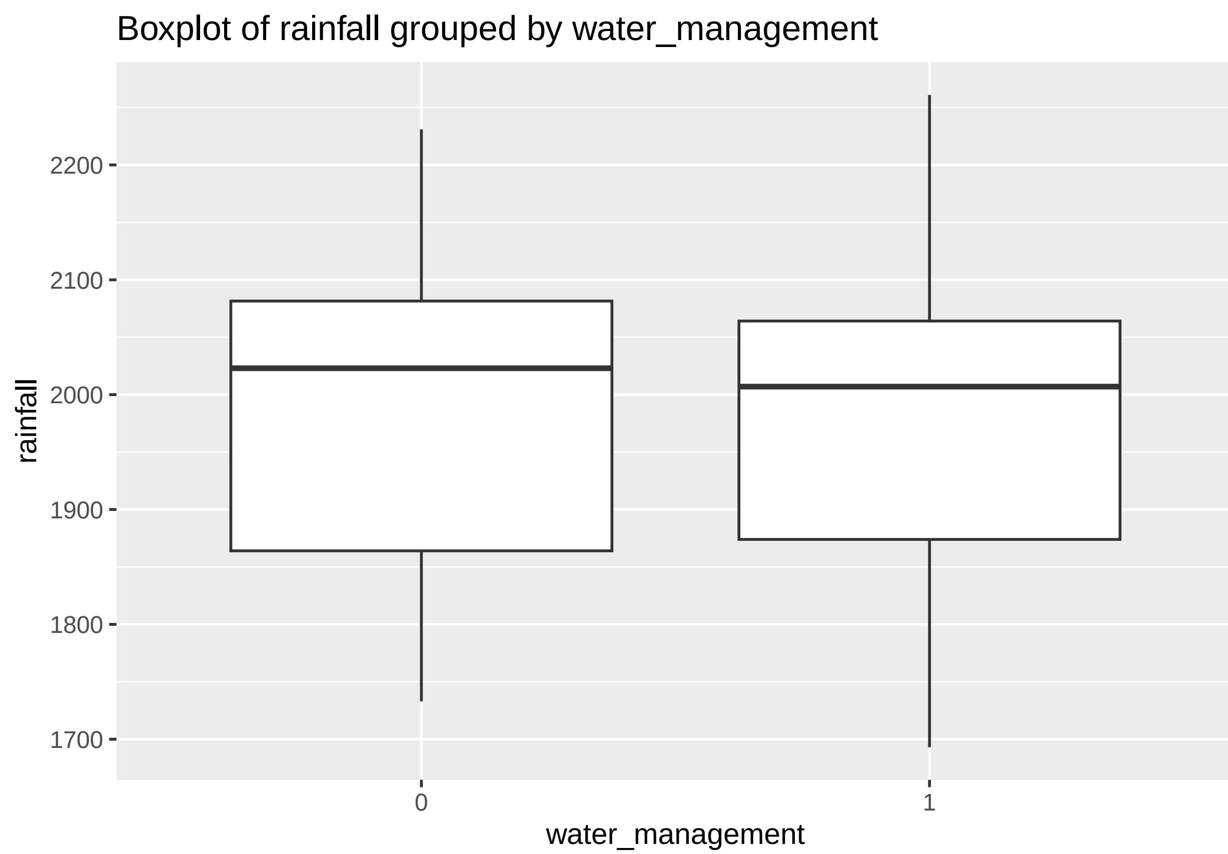
Effect of water_management on drainage area, rainfall and vechval

```
g <- ggplot(data = survey_final_gis, aes(y = log(drainage_area_km), x = as.factor(water_management)))
g + geom_boxplot() + labs(title = "Boxplot of Drainage Area grouped by water_management") +
  xlab("water_management")
```



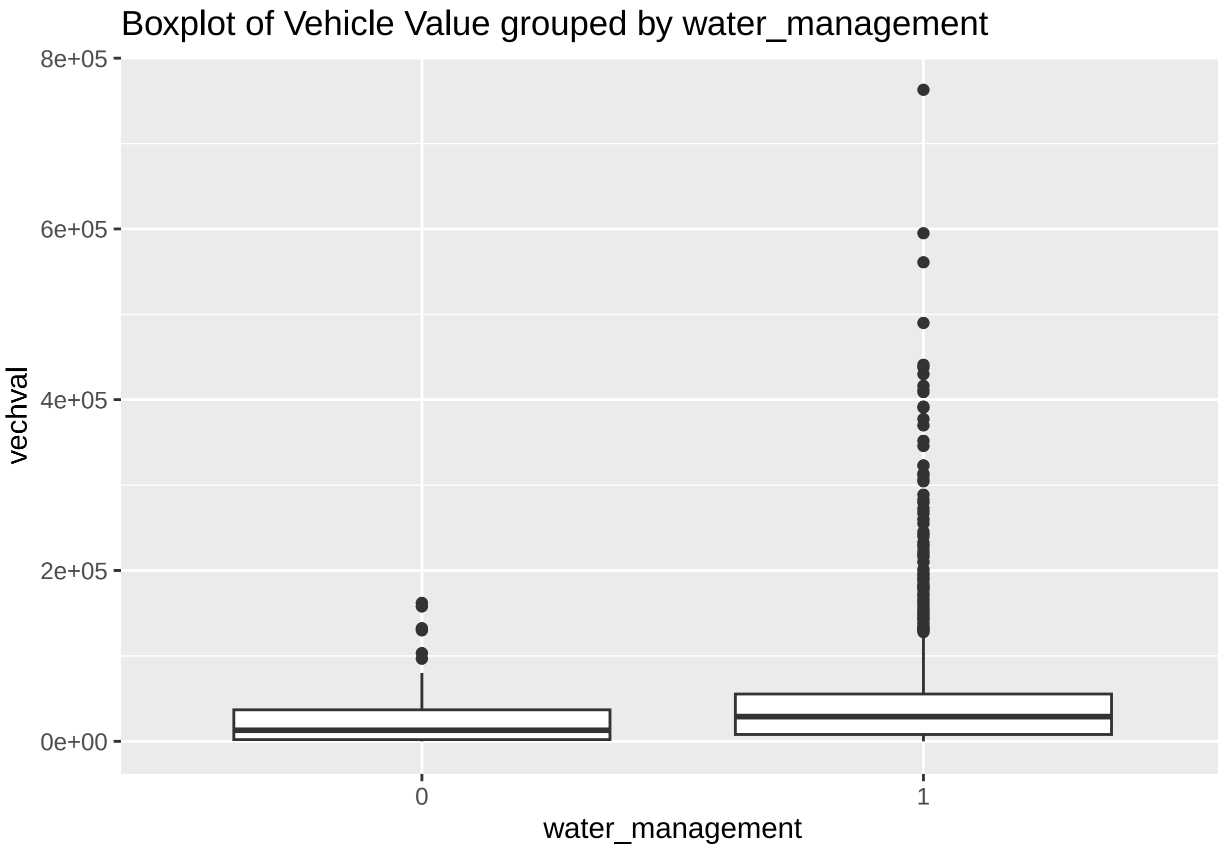

```
g <- ggplot(data = survey_final_gis, aes(y = rainfall, x = as.factor(water_management)))
g + geom_boxplot() + labs(title = "Boxplot of rainfall grouped by water_management") +
  xlab("water_management")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```




```
g <- ggplot(data = survey_final_gis, aes(y = vechval, x = as.factor(water_management)))
g + geom_boxplot() + labs(title = "Boxplot of Vehicle Value grouped by water_management") +
  xlab("water_management")
```

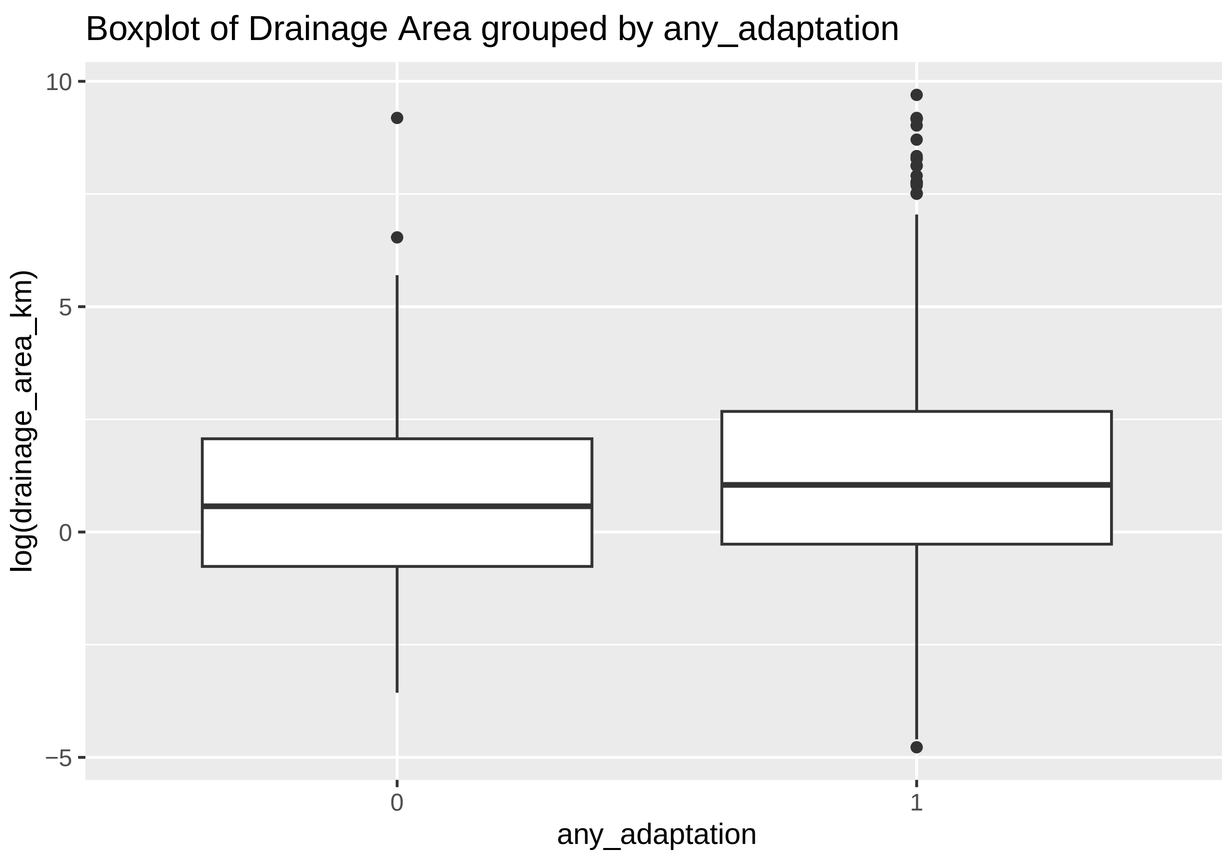
```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```



Water_management has slightly higher log drainage area, lower rainfall and higher wealth.

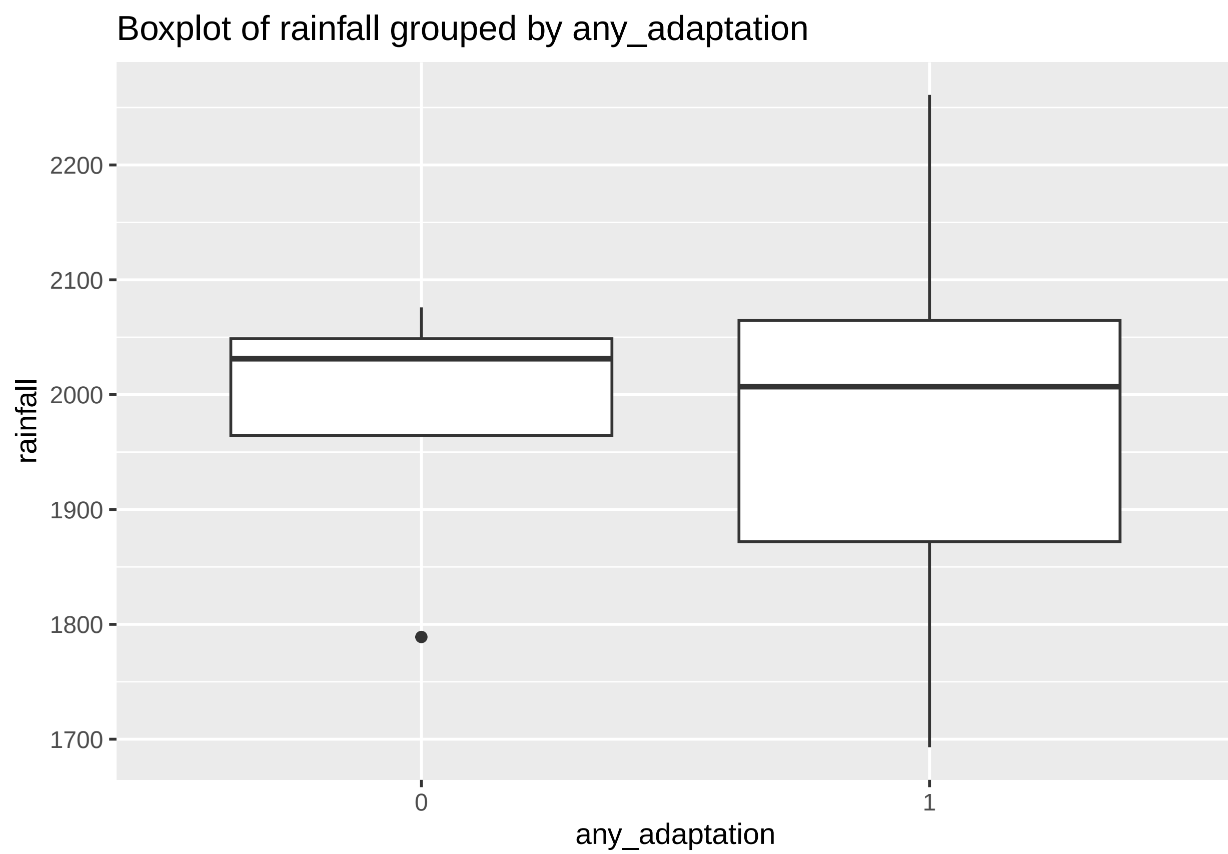
Effect of any_adaptation on drainage area, rainfall and vechval

```
g <- ggplot(data = survey_final_gis, aes(y = log(drainage_area_km), x = as.factor(any_adaptation)))
g + geom_boxplot() + labs(title = "Boxplot of Drainage Area grouped by any_adaptation") +
  xlab("any_adaptation")
```



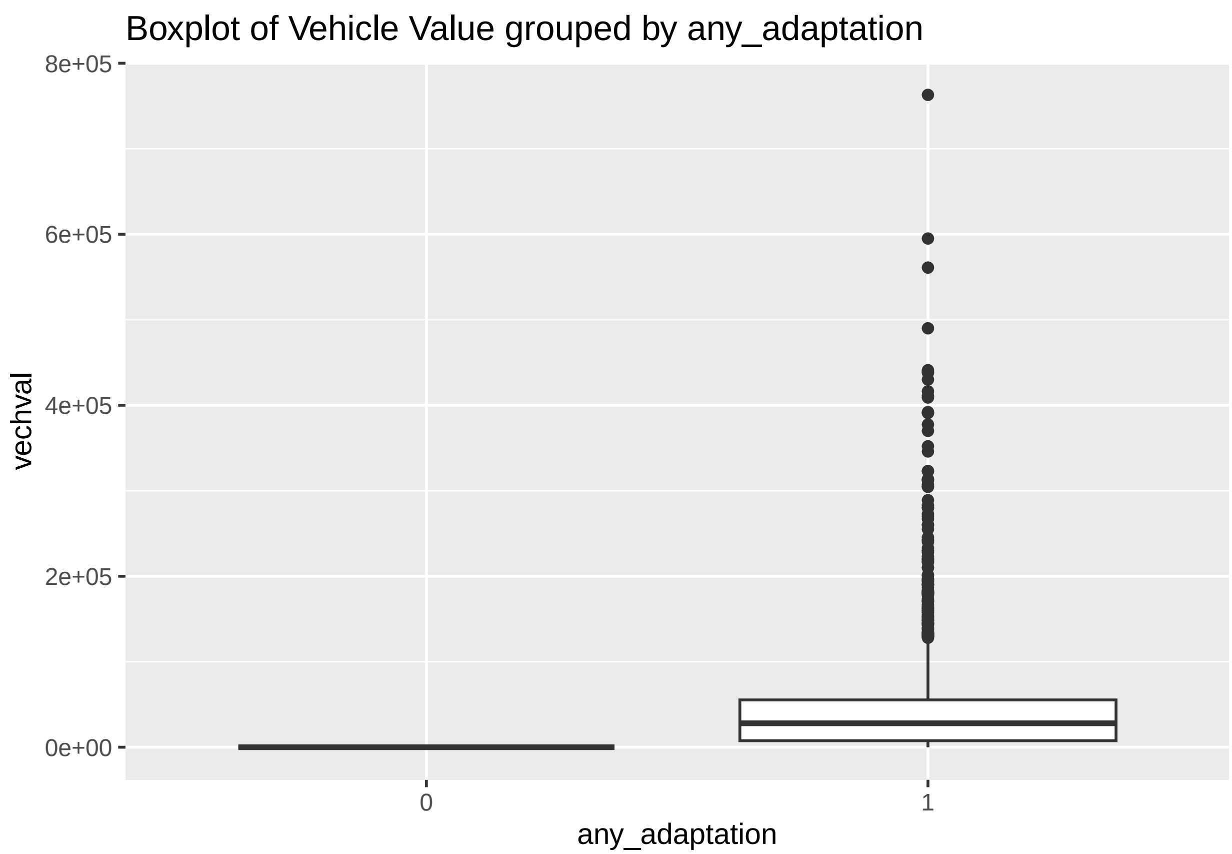

```r
g <- ggplot(data = survey_final_gis, aes(y = rainfall, x = as.factor(any_adaptation)))
g + geom_boxplot() + labs(title = "Boxplot of rainfall grouped by any_adaptation") +
  xlab("any_adaptation")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```




```
g <- ggplot(data = survey_final_gis, aes(y = vechval, x = as.factor(any_adaptation)))
g + geom_boxplot() + labs(title = "Boxplot of Vehicle Value grouped by any_adaptation") +
  xlab("any_adaptation")
```

```
## Warning: Removed 140 rows containing non-finite values (`stat_boxplot()`).
```

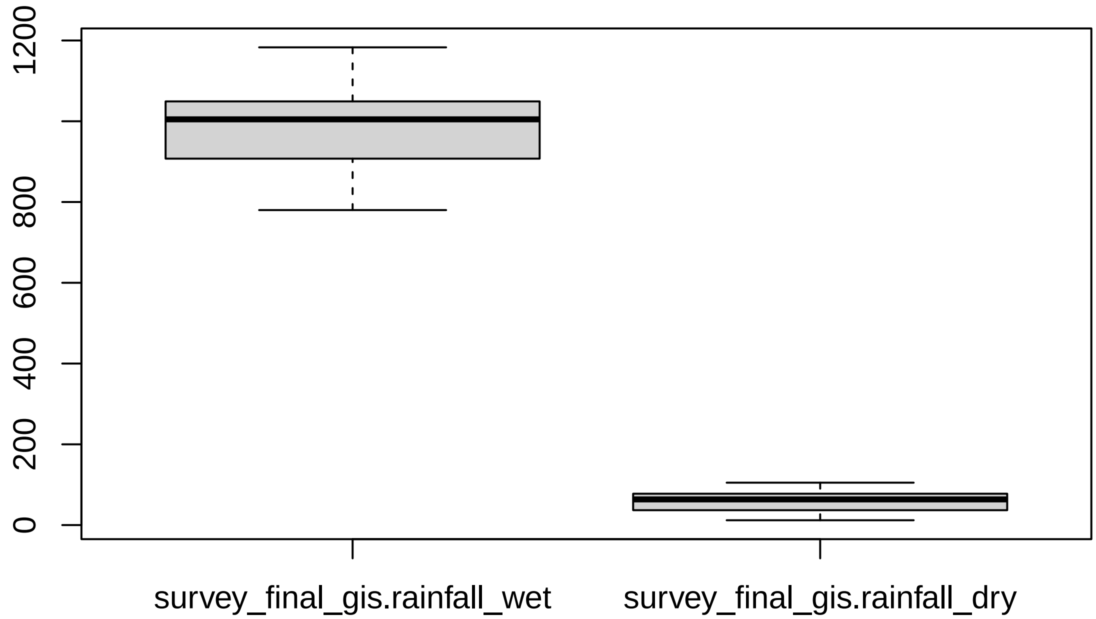


Any_Adaptation shows higher log drainage area, lower rainfall than the control. Wealth data for the control is unavailable.

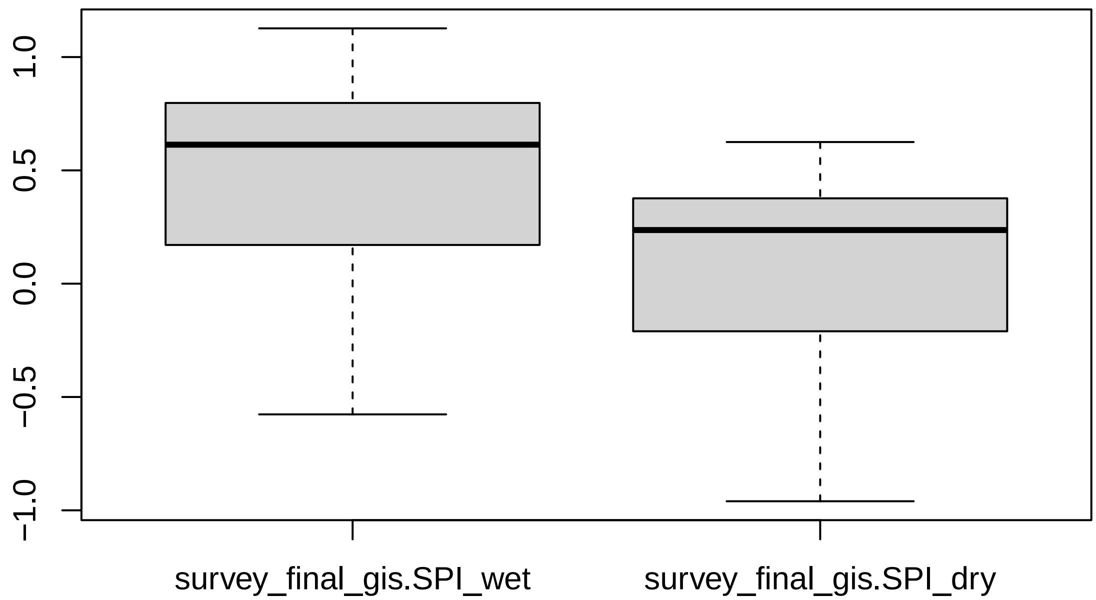
Boxplots of milkincome, SPI and rainfall

Data also contain three numeric variables based on wet and dry season, which is suitable to see their difference

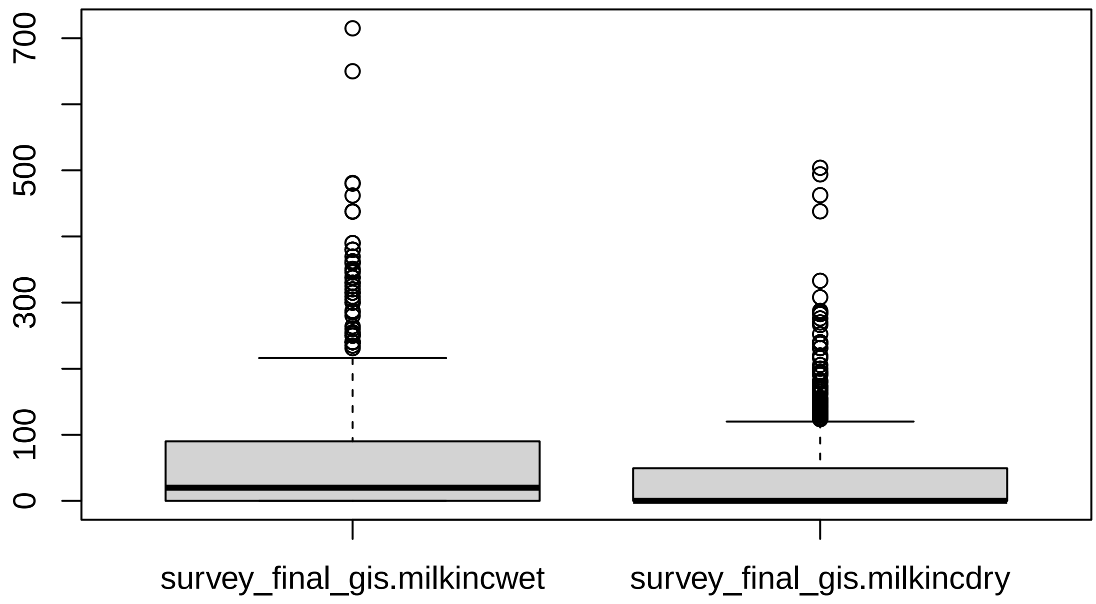
```
rainfall <- data.frame(survey_final_gis$rainfall_wet,survey_final_gis$rainfall_dry)
boxplot(rainfall)
```




```
SPI <- data.frame(survey_final_gis$SPI_wet,survey_final_gis$SPI_dry)
boxplot(SPI)
```




```
milkcinc <- data.frame(survey_final_gis$milkincwet,survey_final_gis$milkincdry)
boxplot(milkcinc)
```



It is apparent that wet season has much high rainfall (or SPI) than dry season. Wet season led to higher milkincome than dry season.

Statisitcal analysis

t test for drainage area

Mean value of log drainage area with and without adaptation measures will be subjected to t test to see if they are significant different. As we show in EDA, log drainage area is basically normal distributed, it is reasonable two sample t-test is applied here. We first need to get rid of outliers. We regarded the data more than 1.5 times IQR as the outliers. Null hypothesis $\mu_x = \mu_y$ vs Ha: $\mu_x \neq \mu_y$ where μ_x and μ_y denote log drainage area, rainfall and wealth with and wihout any adaptation measures respectively.

```
quartiles_1 <- quantile(log(survey_final_gis[survey_final_gis$any_adaptation==1,]$drainage_area_km), pro
IQR_1 <- IQR(log(survey_final_gis[survey_final_gis$any_adaptation==1,]$drainage_area_km),na.rm = TRUE)

Lower_1 <- quartiles_1[1] - 1.5*IQR_1
Upper_1 <- quartiles_1[2] + 1.5*IQR_1

data_no_outlier_1<- subset(log(survey_final_gis[survey_final_gis$any_adaptation==1,]$drainage_area_km),

quartiles_0 <- quantile(log(survey_final_gis[survey_final_gis$any_adaptation==0,]$drainage_area_km), pro
IQR_0 <- IQR(log(survey_final_gis[survey_final_gis$any_adaptation==0,]$drainage_area_km),na.rm = TRUE)
```

```
Lower_0 <- quartiles_0[1] - 1.5*IQR_0
Upper_0 <- quartiles_0[2] + 1.5*IQR_0

data_no_outlier_0 <- subset(log(survey_final_gis[survey_final_gis$any_adaptation==0,]$drainage_area_km)

t.test(data_no_outlier_1 , data_no_outlier_0 ,na.rm=TRUE,var.equal = FALSE)
```

```
##
##  Welch Two Sample t-test
##
## data:  data_no_outlier_1 and data_no_outlier_0
## t = 2.8995, df = 181.93, p-value = 0.004198
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.1717096 0.9031118
## sample estimates:
## mean of x mean of y
## 1.2086764 0.6712657
```

T-test demonstrated that any_adaptation has significant higher log drainage area than the control.

t test for rainfall

```
quartiles_1 <- quantile(survey_final_gis[survey_final_gis$any_adaptation==1,]$rainfall, probs=c(.25, .75
IQR_1 <- IQR(survey_final_gis[survey_final_gis$any_adaptation==1,]$rainfall,na.rm = TRUE)

Lower_1 <- quartiles_1[1] - 1.5*IQR_1
Upper_1 <- quartiles_1[2] + 1.5*IQR_1

data_no_outlier_1<- subset(survey_final_gis[survey_final_gis$any_adaptation==1,]$rainfall, survey_final_

quartiles_0 <- quantile(survey_final_gis[survey_final_gis$any_adaptation==0,]$rainfall, probs=c(.25, .75
IQR_0 <- IQR(survey_final_gis[survey_final_gis$any_adaptation==0,]$rainfall,na.rm = TRUE)

Lower_0 <- quartiles_0[1] - 1.5*IQR_0
Upper_0 <- quartiles_0[2] + 1.5*IQR_0

data_no_outlier_0 <- subset(survey_final_gis[survey_final_gis$any_adaptation==0,]$rainfall, survey_final

t.test(data_no_outlier_1 , data_no_outlier_0 ,na.rm=TRUE,var.equal = FALSE)
```

```
##
##  Welch Two Sample t-test
##
## data:  data_no_outlier_1 and data_no_outlier_0
## t = -3.9741, df = 2.1904, p-value = 0.04973
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -127.0720236   -0.1718252
## sample estimates:
```

```
## mean of x mean of y
##  1982.589  2046.211
```

T-test demonstrated that any_adaptation has significant lower rainfall than the control.

t test for vechval

Below is the code for wealth. Because the control has no available data, we don't run code here.

```
quartiles_1 <- quantile(survey_final_gis_clean[survey_final_gis_clean$any_adaptation==1,]$vechval, prob
IQR_1 <- IQR(survey_final_gis_clean[survey_final_gis_clean$any_adaptation==1,]$vechval,na.rm = FALSE)

Lower_1 <- quartiles_1[1] - 1.5*IQR_1
Upper_1 <- quartiles_1[2] + 1.5*IQR_1

data_no_outlier_1<- subset(survey_final_gis_clean[survey_final_gis_clean$any_adaptation==1,]$vechval, s

quartiles_0 <- quantile(survey_final_gis_clean[survey_final_gis_clean$any_adaptation==0,]$vechval, prob
IQR_0 <- IQR(survey_final_gis_clean[survey_final_gis_clean$any_adaptation==0,]$vechval,na.rm = FALSE)

Lower_0 <- quartiles_0[1] - 1.5*IQR_0
Upper_0 <- quartiles_0[2] + 1.5*IQR_0

data_no_outlier_0 <- subset(survey_final_gis_clean[survey_final_gis_clean$any_adaptation==0,]$vechval, 

t.test(data_no_outlier_1 , data_no_outlier_0 ,na.rm=TRUE,var.equal = FALSE)
```

t-test for rainfall at different seasons

```
t.test(survey_final_gis_clean$rainfall_wet,survey_final_gis_clean$rainfall_dry,na.rm=TRUE,var.equal = F
```

```
##
##  Welch Two Sample t-test
##
## data:  survey_final_gis_clean$rainfall_wet and survey_final_gis_clean$rainfall_dry
## t = 347.03, df = 1375.1, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  920.2497 930.7128
## sample estimates:
## mean of x mean of y
## 984.50655  59.02528
```

As we expected, wet season has much higher rainfall than dry season.

t-test for SPI at different seasons

We would like to see if there is any difference in SPI between dry and wet season. The null hypothesis is mean value of SPI is the same for dry and wet season. H0: $\mu_{SPI,dry} = \mu_{SPI,wet)}$ vs Ha: $\mu_{SPI,dry} \neq \mu_{SPI,wet)}$

```r
t.test(survey_final_gis_clean$SPI_wet,survey_final_gis_clean$SPI_dry,na.rm=TRUE,var.equal = FALSE)
```

```
##
##  Welch Two Sample t-test
##
## data:  survey_final_gis_clean$SPI_wet and survey_final_gis_clean$SPI_dry
## t = 22.235, df = 2328.1, p-value < 2.2e-16
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  0.3328086 0.3971907
## sample estimates:
## mean of x mean of y
## 0.4610647 0.0960650
```

Average SPI and average monthly SPI in the peak of wet season is significantly higher than those of dry season.

t test for milkincome at different seasons

We would like to see if there is any difference of milkincome between dry and wet season. milkincome is supposed to be related to adaptation measures. The null hypothesis is mean value of milkincome is the same for dry and wet season. H0: $\mu_{mlkinc,dry} = \mu_{mlkinc,wet}$ vs Ha: $\mu_{mlkinc,dry} \neq \mu_{mlkinc,wet}$

```r
t.test(survey_final_gis_clean$milkincwet,survey_final_gis_clean$milkincdry,na.rm=TRUE,var.equal = FALSE)
```

```
##
##  Welch Two Sample t-test
##
## data:  survey_final_gis_clean$milkincwet and survey_final_gis_clean$milkincdry
## t = 7.5306, df = 1816.9, p-value = 7.911e-14
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  18.16078 30.95159
## sample estimates:
## mean of x mean of y
##  57.62763  33.07144
```

As p is much less than 0.05, we are confident the mean value of milkincome of wetseason is significant higher than dry season.

Anova analysis

We hypothesize drainage area of three regions may be different. We propose null hypothesis is drainage area means of three regions are the same. The alternativae hypothesis is drainage area means of three regions are different.

effect of region on drainage_area_km

```r
survey_final_gis_clean$region<- factor(survey_final_gis_clean$region)
aov_drainage <- aov(log(drainage_area_km) ~ region, data=survey_final_gis)

summary(aov_drainage)
```

```
##               Df Sum Sq Mean Sq F value  Pr(>F)
## region         2     64   32.14   5.706 0.00342 **
## Residuals   1197   6742    5.63
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 140 observations deleted due to missingness
```

```r
TukeyHSD(aov_drainage, conf.level=.95)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = log(drainage_area_km) ~ region, data = survey_final_gis)
##
## $region
##                                          diff         lwr        upr     p adj
## Ouro Preto do Oeste-Ariquemes      -0.5630356 -0.95623345 -0.1698377 0.0023152
## Rolim de Moura-Ariquemes           -0.2559672 -0.66043949  0.1485050 0.2984517
## Rolim de Moura-Ouro Preto do Oeste  0.3070683 -0.07977413  0.6939108 0.1500875
```

As p-value of F test is extremely small, we are confident that the drainage means of three regions are different. We further compared drainage means of three regions and found region "Rolim de Moura" has the highest drainage area, OPO has the smallest.

effect of region on income from beef

We then wants to see if there is difference in income from beef at different regions.

```r
aov_incbeef <- aov(incbeef ~ region, data=survey_final_gis)
summary(aov_incbeef)
```

```
##              Df    Sum Sq   Mean Sq F value Pr(>F)
## region        2 1.371e+10 6.853e+09   1.124  0.325
## Residuals   695 4.236e+12 6.096e+09
## 642 observations deleted due to missingness
```

```r
TukeyHSD(aov_incbeef, conf.level=.95)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = incbeef ~ region, data = survey_final_gis)
##
## $region
```

```
##                                           diff       lwr       upr     p adj
## Ouro Preto do Oeste-Ariquemes      -11239.618 -29238.61  6759.375 0.3076587
## Rolim de Moura-Ariquemes            -6577.226 -22674.83  9520.381 0.6026638
## Rolim de Moura-Ouro Preto do Oeste   4662.393 -13029.43 22354.211 0.8097785
```

As p value is larger than 0.05, we can not reject our hypothesis that the means of income from beef at different regions are the same.

effect of region on rainfall

```r
aov_rainfall <- aov(rainfall~ region, data=survey_final_gis )
summary(aov_rainfall)
```

```
##                Df   Sum Sq Mean Sq F value Pr(>F)
## region          2 12088742 6044371    1703 <2e-16 ***
## Residuals    1197  4249056    3550
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 140 observations deleted due to missingness
```

```r
TukeyHSD(aov_rainfall, conf.level=.95)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = rainfall ~ region, data = survey_final_gis)
##
## $region
##                                          diff         lwr        upr     p adj
## Ouro Preto do Oeste-Ariquemes        7.163234   -2.708057   17.03452 0.2045033
## Rolim de Moura-Ariquemes           -210.154234 -220.308569 -199.99990 0.0000000
## Rolim de Moura-Ouro Preto do Oeste -217.317468 -227.029204 -207.60573 0.0000000
```

As p-value for F test of AONVA is very small, rainfall in three regions is not the same. It can be seen the rainfall in region "Rolim de Moura" is less than that in the other two.

effect of region on wealth

```r
aov_vechval <- aov(vechval~ region, data=survey_final_gis_clean)
summary(aov_vechval)
```

```
##                Df    Sum Sq   Mean Sq F value   Pr(>F)
## region          2 1.581e+11 7.907e+10   14.43 6.41e-07 ***
## Residuals    1197 6.558e+12 5.479e+09
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
TukeyHSD(aov_vechval, conf.level=.95)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = vechval ~ region, data = survey_final_gis_clean)
##
## $region
##                                         diff         lwr       upr     p adj
## Ouro Preto do Oeste-Ariquemes      -15301.14 -27564.9489 -3037.328 0.0097323
## Rolim de Moura-Ariquemes            12195.46   -420.0017 24810.912 0.0606958
## Rolim de Moura-Ouro Preto do Oeste  27496.59  15431.0086 39562.178 0.0000003
```

The family wealth is significant different in three regions. The wealth in region "3"Rolim de Moura" is the largest.

Effect of region on adapatation method

Will need to do this for each method, since methods can overlap

First - cattle management

```r
# Need to change studycode into a factor
survey_final_gis$studycode <- as.factor(survey_final_gis$studycode)
aov_cattle_management <- aov(cattle_management ~ studycode, data = survey_final_gis)
summary(aov_cattle_management)
```

```
##               Df Sum Sq Mean Sq F value Pr(>F)
## studycode      2   0.99  0.4958   2.042   0.13
## Residuals   1197 290.68  0.2428
## 140 observations deleted due to missingness
```

Cattle management appears to be the same across all three regions based on the p-value

Next - water management

```r
aov_water_management <- aov(water_management ~ studycode, data = survey_final_gis)
summary(aov_water_management)
```

```
##               Df Sum Sq Mean Sq F value  Pr(>F)
## studycode      2   0.55 0.27330   6.775 0.00119 **
## Residuals   1197  48.29 0.04034
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 140 observations deleted due to missingness
```

```r
TukeyHSD(aov_water_management, conf.level=.95)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
```

```
## Fit: aov(formula = water_management ~ studycode, data = survey_final_gis)
##
## $studycode
##            diff         lwr          upr     p adj
## 2-1 -0.05217268 -0.08544920 -0.018896162 0.0007144
## 3-1 -0.02989130 -0.06412198  0.004339368 0.1011412
## 3-2  0.02228138 -0.01045728  0.055020031 0.2472685
```

Based on the p-value, we know at least two regions are signficantly different Using the results of Tukey's HSD, we can see that regions 1 and 2 (Ariquemes and OPO) are significantly different when it comes to water management

Next - pasture management

```
aov_pasture_management <- aov(pasture_management ~ studycode, data = survey_final_gis)
summary(aov_pasture_management)
```

```
##               Df Sum Sq Mean Sq F value   Pr(>F)
## studycode      2   3.81  1.9064   8.327 0.000256 ***
## Residuals   1197 274.05  0.2289
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 140 observations deleted due to missingness
```

```
TukeyHSD(aov_pasture_management, conf.level=.95)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = pasture_management ~ studycode, data = survey_final_gis)
##
## $studycode
##            diff         lwr          upr     p adj
## 2-1 -0.08256310 -0.16183872 -0.003287472 0.0389323
## 3-1  0.05131074 -0.03023799  0.132859475 0.3025965
## 3-2  0.13387384  0.05587959  0.211868094 0.0001767
```

From the result of the ANOVA, we can see there is a difference between at least one region. Looking at the result of Tukey, we can see the difference is significant between regions 1 and 2, and regions 2 and 3

Next - forest conservation

```
aov_forest_conservation <- aov(forest_conservation ~ studycode, data = survey_final_gis)
summary(aov_forest_conservation)
```

```
##               Df Sum Sq Mean Sq F value Pr(>F)
## studycode      2   0.33  0.1644   1.976  0.139
## Residuals   1197  99.59  0.0832
## 140 observations deleted due to missingness
```

```r
TukeyHSD(aov_pasture_management, conf.level=.95)
```

```
##   Tukey multiple comparisons of means
##     95% family-wise confidence level
##
## Fit: aov(formula = pasture_management ~ studycode, data = survey_final_gis)
##
## $studycode
##            diff         lwr          upr     p adj
## 2-1 -0.08256310 -0.16183872 -0.003287472 0.0389323
## 3-1  0.05131074 -0.03023799  0.132859475 0.3025965
## 3-2  0.13387384  0.05587959  0.211868094 0.0001767
```

There is not a significant difference amongst regions due to forest conservation

Effect of wealth on number of adaptations

```r
survey_final_gis <- survey_final_gis %>% mutate(adaptation_count = cattle_management + pasture_manageme
aov_vechval_adaptation_count <- aov(vechval ~ adaptation_count, data = survey_final_gis)
summary(aov_vechval_adaptation_count)
```

```
##                    Df    Sum Sq   Mean Sq F value Pr(>F)
## adaptation_count    1 4.354e+11 4.354e+11   83.05 <2e-16 ***
## Residuals        1198 6.281e+12 5.243e+09
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 140 observations deleted due to missingness
```

```r
fit_lr <- lm(adaptation_count ~ vechval, data = survey_final_gis)
summary(fit_lr)
```

```
##
## Call:
## lm(formula = adaptation_count ~ vechval, data = survey_final_gis)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.7671 -0.7821  0.1191  0.8003  1.2329
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 2.767e+00  2.965e-02  93.340   <2e-16 ***
## vechval     2.993e-06  3.284e-07   9.113   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8511 on 1198 degrees of freedom
##   (140 observations deleted due to missingness)
## Multiple R-squared:  0.06483,    Adjusted R-squared:  0.06405
## F-statistic: 83.05 on 1 and 1198 DF,  p-value: < 2.2e-16
```

Modelling

Multiple Logistic Regression Model

First to create a few different MLRs to see what the relationship is between adaptation methods and water availability.

Model 1

In this model, I will select the largest amount of variables. The dependent variable will be the general adaptation variable. The independent variables will be: - Drainage area - Lot size (can't find in data - ask Mariana) - Soil type (100% missing - so maybe not) - Vehicle value - SPI - using the maximum in the year - Risk - Lot value

(This model did not converge)

Model 2

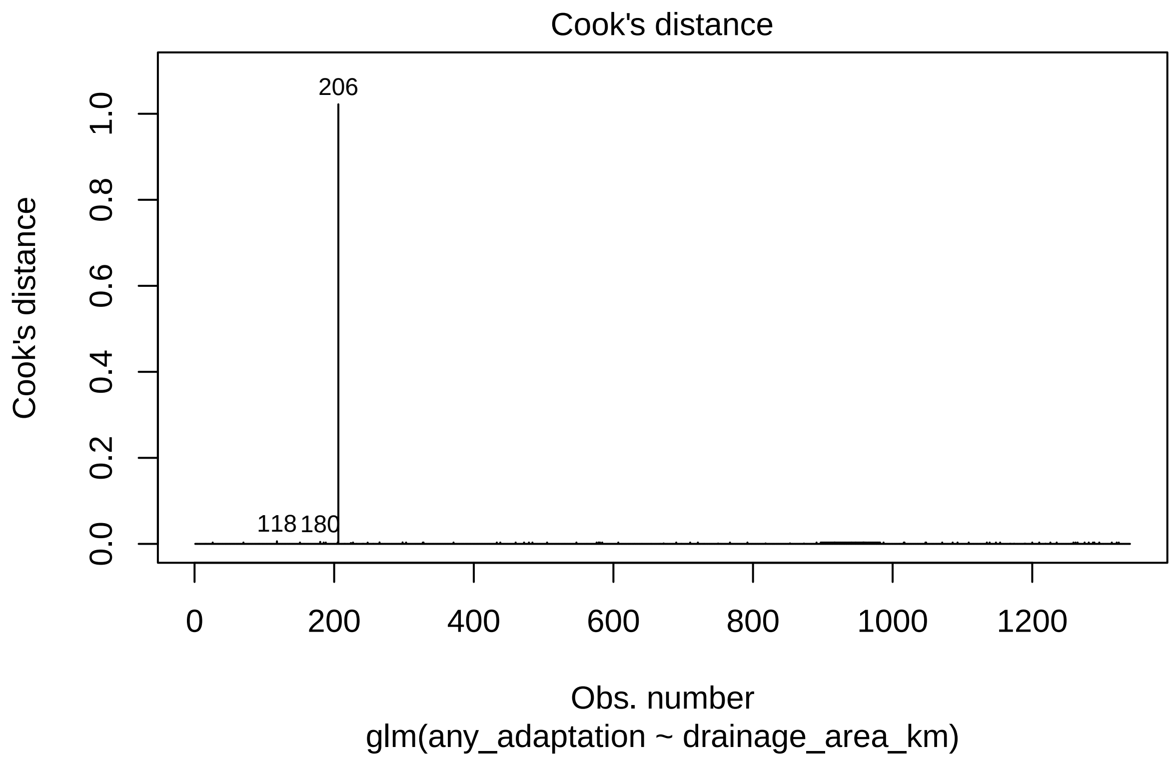
Trying with only drainage area to see if there's a relationship since previous model did not converge

```
fit_2 <- glm(any_adaptation ~ drainage_area_km, family = binomial,data = survey_final_gis)
summary(fit_2)
```

```
##
## Call:
## glm(formula = any_adaptation ~ drainage_area_km, family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)      2.1088684  0.0891751   23.65   <2e-16 ***
## drainage_area_km 0.0000746  0.0001408    0.53    0.596
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 914.36  on 1339  degrees of freedom
## Residual deviance: 914.01  on 1338  degrees of freedom
## AIC: 918.01
##
## Number of Fisher Scoring iterations: 5
```

The drainage area is not a statistically significant parameter in this case. However, there are outliers in the data that might be affecting this. Let's investigate.

```
plot(fit_2, which = 4)
```

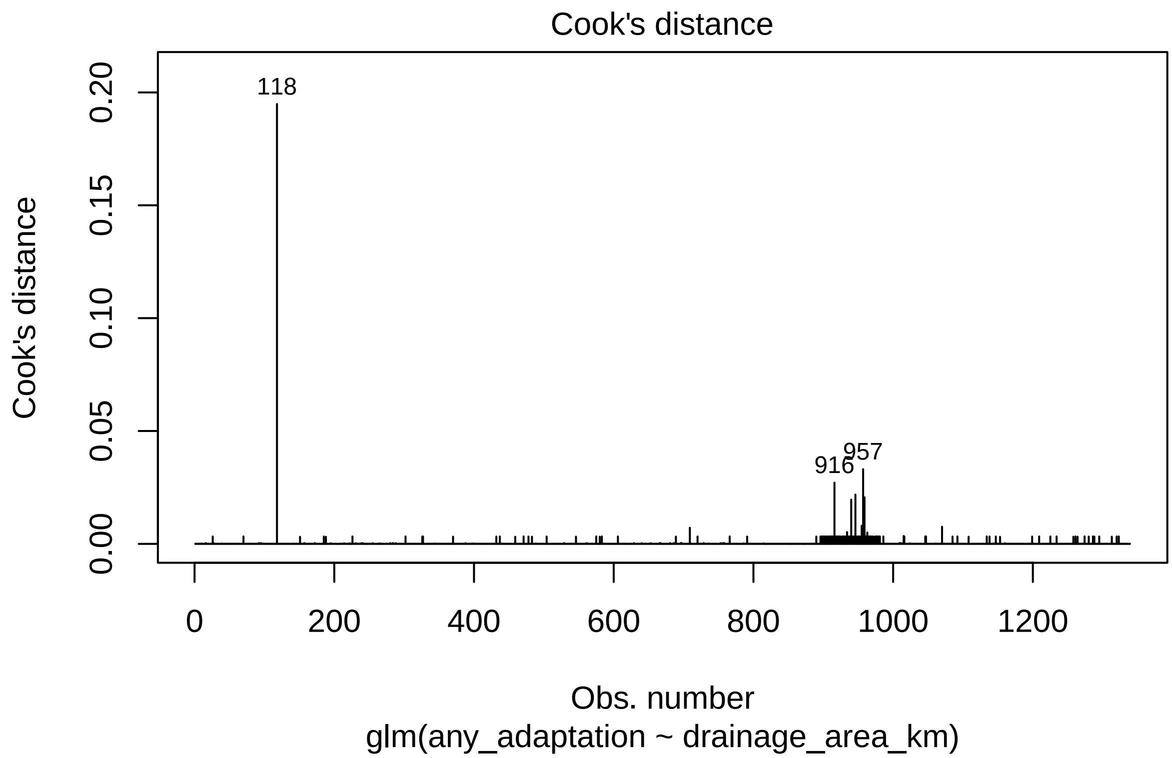


Fitting the model without observation 206

```
survey_final_gis_no <- survey_final_gis[-c(206),]
fit_3 <- glm(any_adaptation ~ drainage_area_km, family = binomial,data = survey_final_gis_no)
summary(fit_3)
```

```
##
## Call:
## glm(formula = any_adaptation ~ drainage_area_km, family = binomial,
##     data = survey_final_gis_no)
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)      2.0599143  0.0913975  22.538   <2e-16 ***
## drainage_area_km 0.0015679  0.0009512   1.648   0.0993 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 909.89  on 1338  degrees of freedom
## Residual deviance: 902.26  on 1337  degrees of freedom
## AIC: 906.26
##
## Number of Fisher Scoring iterations: 8
```

```r
plot(fit_3, which = 4)
```

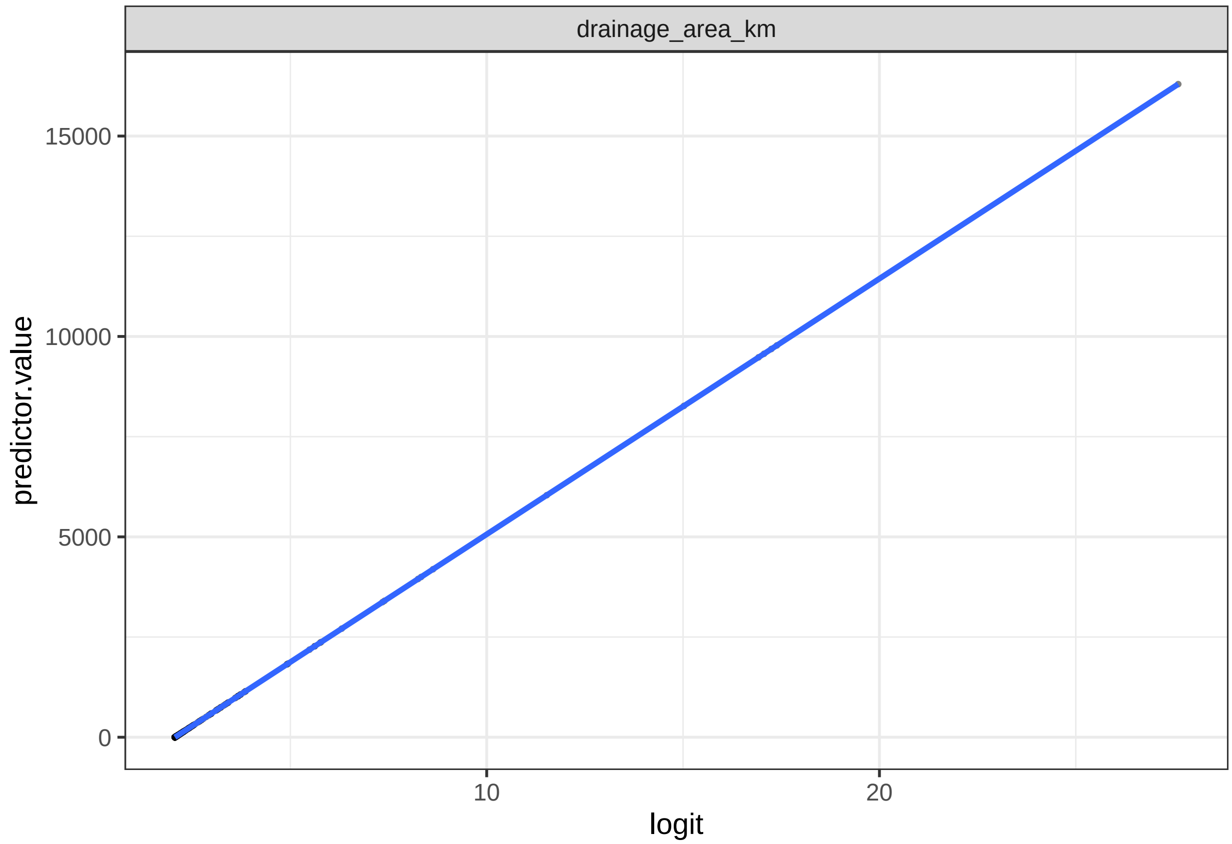


Now to check Log Reg assumptions

```r
probabilities <- predict(fit_3, type = "response")
# Select only numeric predictors
mydata <- survey_final_gis_no %>%
  dplyr::select_if(is.numeric) %>%
  select(drainage_area_km)
predictors <- colnames(mydata)
# Bind the logit and tidying the data for plot
mydata <- mydata %>%
  mutate(logit = log(probabilities/(1-probabilities))) %>%
  gather(key = "predictors", value = "predictor.value", -logit)
```

```r
ggplot(mydata, aes(logit, predictor.value))+
  geom_point(size = 0.5, alpha = 0.5) +
  geom_smooth(method = "loess") +
  theme_bw() +
  facet_wrap(~predictors, scales = "free_y")
```

```
## `geom_smooth()` using formula = 'y ~ x'
```

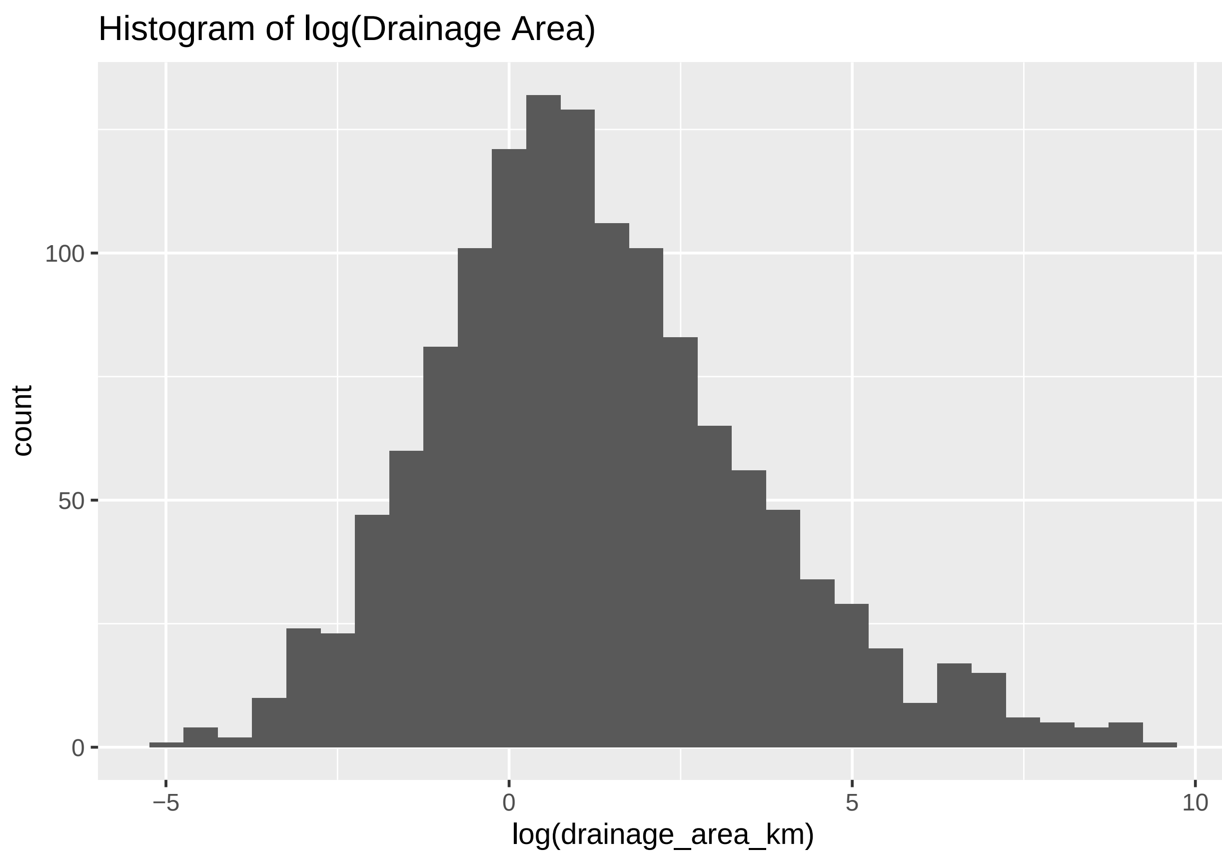


Model 3 - Transforming Drainage Area

Let's look at the distribution of drainage area to see if we should transform it

```
g <- ggplot(data = survey_final_gis_no, aes(x = log(drainage_area_km)))
g + geom_histogram() + labs(title = "Histogram of log(Drainage Area)")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



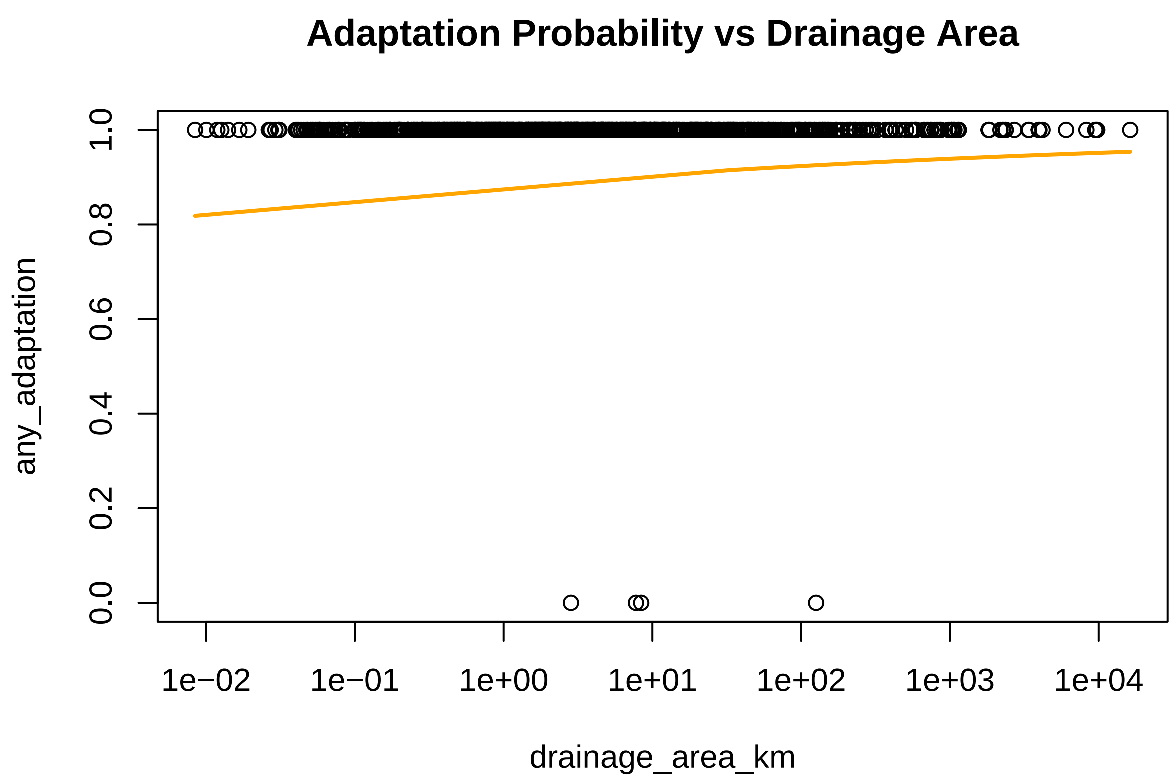
Now to create the model:

```
fit_transform <- glm(any_adaptation ~ log(drainage_area_km), family = binomial,data = survey_final_gis)
summary(fit_transform)
```

```
##
## Call:
## glm(formula = any_adaptation ~ log(drainage_area_km), family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##                        Estimate Std. Error z value Pr(>|z|)
## (Intercept)             2.00718    0.09431  21.282  < 2e-16 ***
## log(drainage_area_km)  0.10519    0.03962   2.655  0.00792 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 914.36  on 1339  degrees of freedom
## Residual deviance: 906.98  on 1338  degrees of freedom
## AIC: 910.98
##
## Number of Fisher Scoring iterations: 5
```

Let's plot it to get a visual to help wrap our heads around this model

```r
# remove data of vechval with "NA"
survey_final_gis_wealth <- survey_final_gis %>% filter(!is.na(survey_final_gis$vechval))
Predicted_data <- data.frame(drainage_area_km=seq(
  min(survey_final_gis$drainage_area_km), max(survey_final_gis_wealth$drainage_area_km),len=500))

# Fill predicted values using regression model
Predicted_data$any_adaptation = predict(
  fit_transform, Predicted_data, type="response")

# Plot Predicted data and original data points
plot(any_adaptation ~ drainage_area_km, data=survey_final_gis_wealth, log="x")
lines(any_adaptation ~ drainage_area_km, Predicted_data, lwd=2, col="orange")
title(main = "Adaptation Probability vs Drainage Area")
```



Model 4

For this model, we will take Dr. Harris's suggestion of an indicator variable for the large drainage area lots (I believe is what he meant)

First going to see the fit with outliers chopped off

```r
survey_final_gis_filtered <- survey_final_gis %>% filter(drainage_area_km < 500)
fit_4 <- glm(any_adaptation ~ drainage_area_km, data = survey_final_gis_filtered, family = binomial)
summary(fit_4)
```

```
##
## Call:
## glm(formula = any_adaptation ~ drainage_area_km, family = binomial,
##     data = survey_final_gis_filtered)
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)      2.0771756  0.0949895  21.867   <2e-16 ***
## drainage_area_km 0.0004578  0.0018537   0.247    0.805
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 893.26  on 1284  degrees of freedom
## Residual deviance: 893.20  on 1283  degrees of freedom
## AIC: 897.2
##
## Number of Fisher Scoring iterations: 4
```

model 5

```
 survey_final_gis2<- drop_na(survey_final_gis,SPI_year)
survey_final_gis2$rainfall2 <- scale(survey_final_gis2$rainfall,center=TRUE,scale=T)
survey_final_gis2$drainage_area_km2 <-  scale(survey_final_gis2$drainage_area_km,center=TRUE,scale=T)
fit_3 <- glm(any_adaptation ~ log (drainage_area_km) + log(rainfall), family = binomial,data = survey_fi
summary(fit_3)
```

```
##
## Call:
## glm(formula = any_adaptation ~ log(drainage_area_km) + log(rainfall),
##     family = binomial, data = survey_final_gis2)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)             9.5080    63.5680   0.150    0.881
## log(drainage_area_km)  -0.1858     0.1883  -0.987    0.324
## log(rainfall)          -0.4552     8.3677  -0.054    0.957
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 53.617  on 1199  degrees of freedom
## Residual deviance: 52.706  on 1197  degrees of freedom
## AIC: 58.706
##
## Number of Fisher Scoring iterations: 8
```

Now look at individual adaptation variables

```
fit_cattle <- glm(cattle_management ~ drainage_area_km, family = binomial,data = survey_final_gis)
summary(fit_cattle)
```

```
##
## Call:
## glm(formula = cattle_management ~ drainage_area_km, family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -5.298e-01  5.717e-02  -9.267   <2e-16 ***
## drainage_area_km  8.492e-05  6.657e-05   1.276    0.202
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1770.4  on 1339  degrees of freedom
## Residual deviance: 1768.7  on 1338  degrees of freedom
## AIC: 1772.7
##
## Number of Fisher Scoring iterations: 4
```

```
fit_cattle_log = glm(cattle_management ~ log(drainage_area_km), family = binomial,data = survey_final_gi
summary(fit_cattle_log)
```

```
##
## Call:
## glm(formula = cattle_management ~ log(drainage_area_km), family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -0.58609    0.06488  -9.033   <2e-16 ***
## log(drainage_area_km)  0.05162    0.02374   2.174   0.0297 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1770.4  on 1339  degrees of freedom
## Residual deviance: 1765.7  on 1338  degrees of freedom
## AIC: 1769.7
##
## Number of Fisher Scoring iterations: 4
```

Saw significance when using log(drainage area)

Next lets look at pasture management

```
fit_pasture <- glm(pasture_management ~ drainage_area_km, family = binomial,data = survey_final_gis)
summary(fit_pasture)
```

```
##
## Call:
## glm(formula = pasture_management ~ drainage_area_km, family = binomial,
```

```
##     data = survey_final_gis)
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)      2.674e-01  5.583e-02   4.790 1.66e-06 ***
## drainage_area_km 1.028e-04  7.926e-05   1.296    0.195
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1831.7  on 1339  degrees of freedom
## Residual deviance: 1829.7  on 1338  degrees of freedom
## AIC: 1833.7
##
## Number of Fisher Scoring iterations: 4
```

```r
fit_pasture_log <- glm(pasture_management ~ log(drainage_area_km), family = binomial,data = survey_final
summary(fit_pasture_log)
```

```
##
## Call:
## glm(formula = pasture_management ~ log(drainage_area_km), family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            0.16275    0.06229   2.613  0.00898 **
## log(drainage_area_km)  0.09512    0.02396   3.971 7.17e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1831.7  on 1339  degrees of freedom
## Residual deviance: 1815.5  on 1338  degrees of freedom
## AIC: 1819.5
##
## Number of Fisher Scoring iterations: 4
```

Similar results, but with a super low p for log(drainage area)

Next lets look at forest conservation

```r
fit_forest <- glm(forest_conservation ~ drainage_area_km, family = binomial,data = survey_final_gis)
summary(fit_forest)
```

```
##
## Call:
## glm(formula = forest_conservation ~ drainage_area_km, family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
```

```
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)      1.4593884  0.0709507  20.569   <2e-16 ***
## drainage_area_km 0.0001294  0.0001311   0.987    0.324
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1289.6  on 1339  degrees of freedom
## Residual deviance: 1288.3  on 1338  degrees of freedom
## AIC: 1292.3
##
## Number of Fisher Scoring iterations: 5
```

```
fit_forest_log <- glm(forest_conservation ~ log(drainage_area_km), family = binomial,data = survey_final
summary(fit_forest_log)
```

```
##
## Call:
## glm(formula = forest_conservation ~ log(drainage_area_km), family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            1.30277    0.07451  17.485  < 2e-16 ***
## log(drainage_area_km)  0.17455    0.03290   5.305 1.12e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1289.6  on 1339  degrees of freedom
## Residual deviance: 1259.1  on 1338  degrees of freedom
## AIC: 1263.1
##
## Number of Fisher Scoring iterations: 4
```

Log(drainage area) is highly significant again

Let's now look at water management

```
fit_water <- glm(water_management ~ drainage_area_km, family = binomial,data = survey_final_gis)
summary(fit_water)
```

```
##
## Call:
## glm(formula = water_management ~ drainage_area_km, family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##                  Estimate Std. Error z value Pr(>|z|)
## (Intercept)      1.785e+00  7.901e-02  22.598   <2e-16 ***
## drainage_area_km 8.384e-05  1.268e-04   0.661    0.509
```

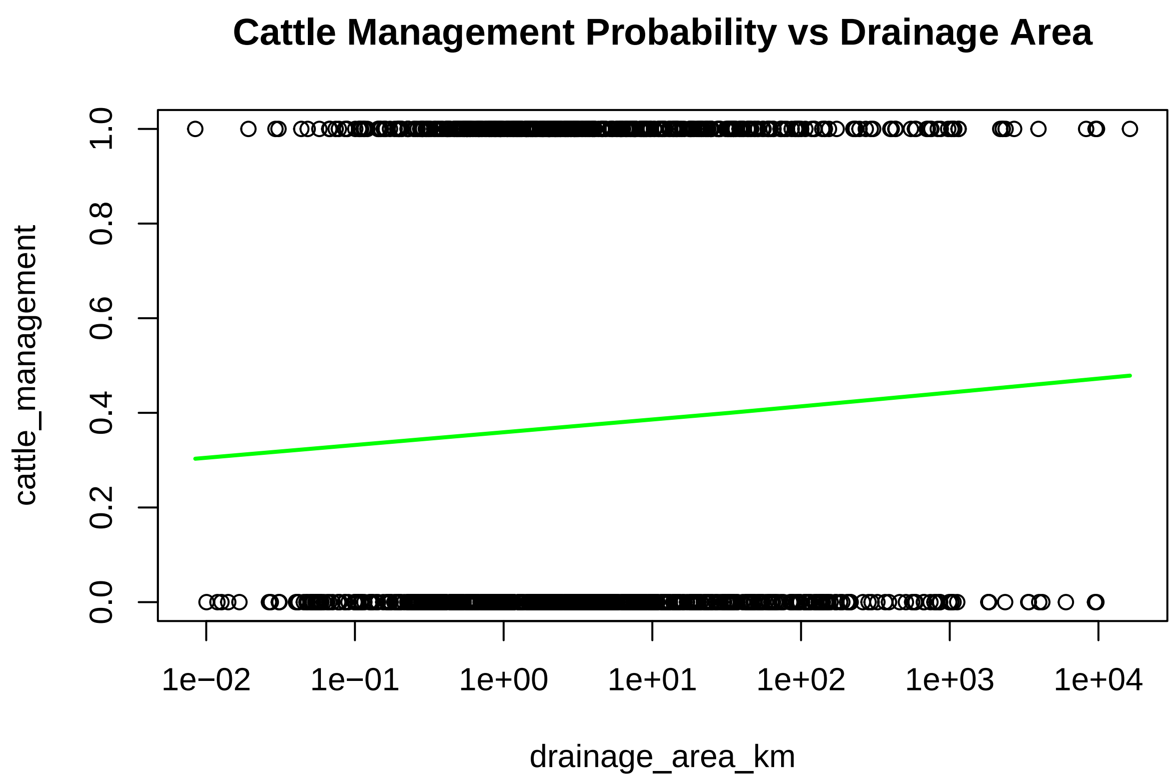
```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1097.6  on 1339  degrees of freedom
## Residual deviance: 1097.0  on 1338  degrees of freedom
## AIC: 1101
##
## Number of Fisher Scoring iterations: 4
```

```r
fit_water_log <- glm(water_management ~ log(drainage_area_km), family = binomial,data = survey_final_gi
summary(fit_water_log)
```

```
##
## Call:
## glm(formula = water_management ~ log(drainage_area_km), family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            1.71958    0.08552  20.108   <2e-16 ***
## log(drainage_area_km)  0.06572    0.03416   1.924   0.0543 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1097.6  on 1339  degrees of freedom
## Residual deviance: 1093.8  on 1338  degrees of freedom
## AIC: 1097.8
##
## Number of Fisher Scoring iterations: 4
```

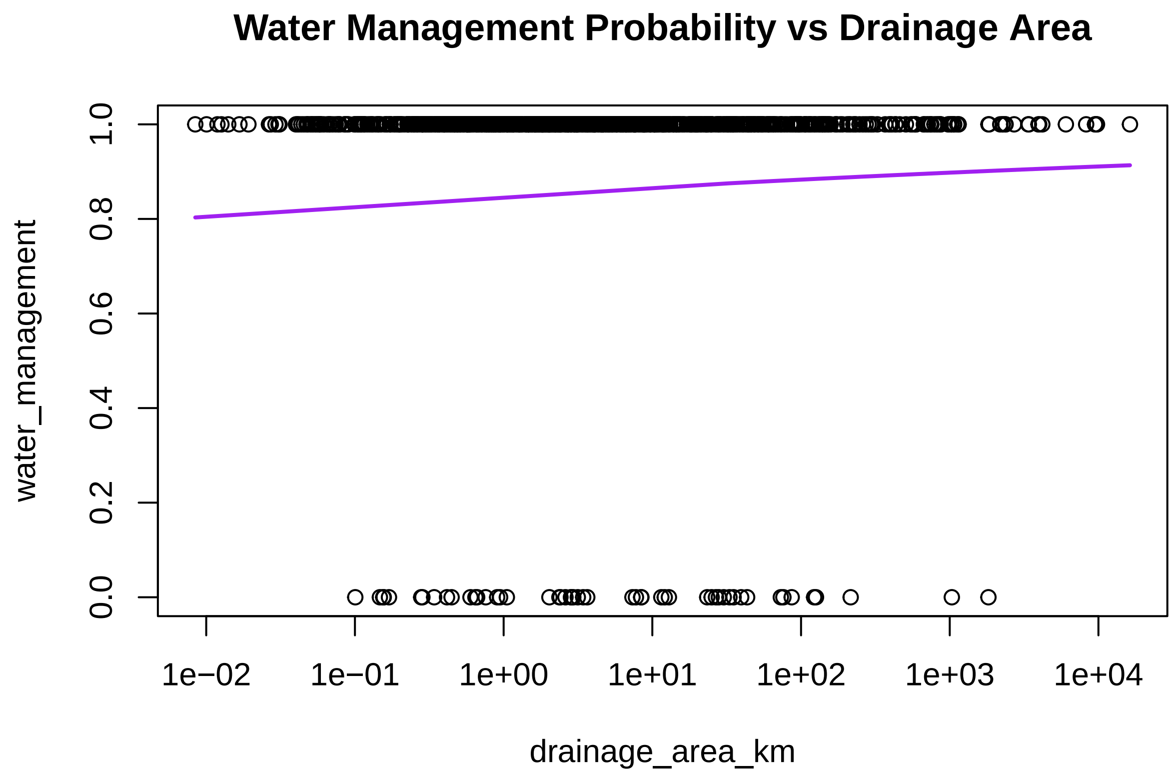
et's make some plots to visualize them, starting with cattle management

```r
Predicted_data <- data.frame(drainage_area_km=seq(
  min(survey_final_gis$drainage_area_km), max(survey_final_gis_wealth$drainage_area_km),len=500))

# Fill predicted values using regression model
Predicted_data$cattle_management = predict(
  fit_cattle_log, Predicted_data, type="response")

# Plot Predicted data and original data points
plot(cattle_management ~ drainage_area_km, data=survey_final_gis_wealth, log="x")
lines(cattle_management ~ drainage_area_km, Predicted_data, lwd=2, col="green")
title(main = "Cattle Management Probability vs Drainage Area")
```



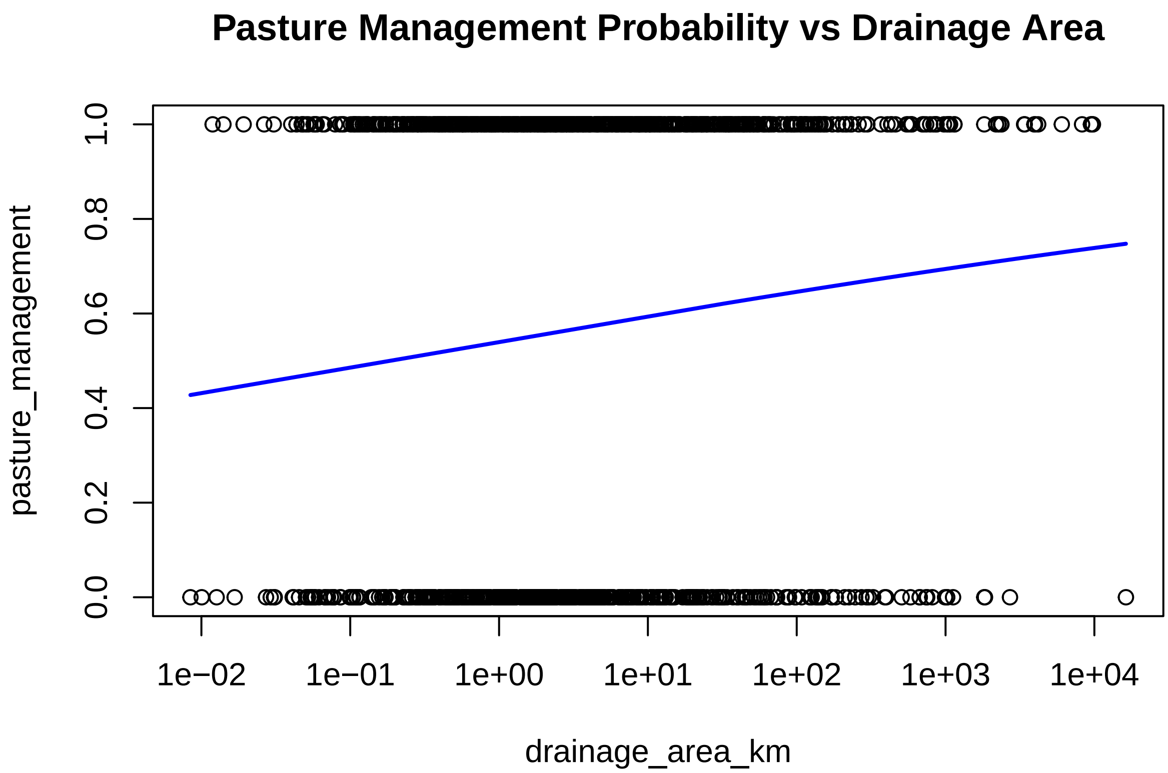
Now let's look at water management

```
Predicted_data <- data.frame(drainage_area_km=seq(
  min(survey_final_gis$drainage_area_km), max(survey_final_gis_wealth$drainage_area_km),len=500))

# Fill predicted values using regression model
Predicted_data$water_management = predict(
  fit_water_log, Predicted_data, type="response")

# Plot Predicted data and original data points
plot(water_management ~ drainage_area_km, data=survey_final_gis_wealth, log="x")
lines(water_management ~ drainage_area_km, Predicted_data, lwd=2, col="purple")
title(main = "Water Management Probability vs Drainage Area")
```



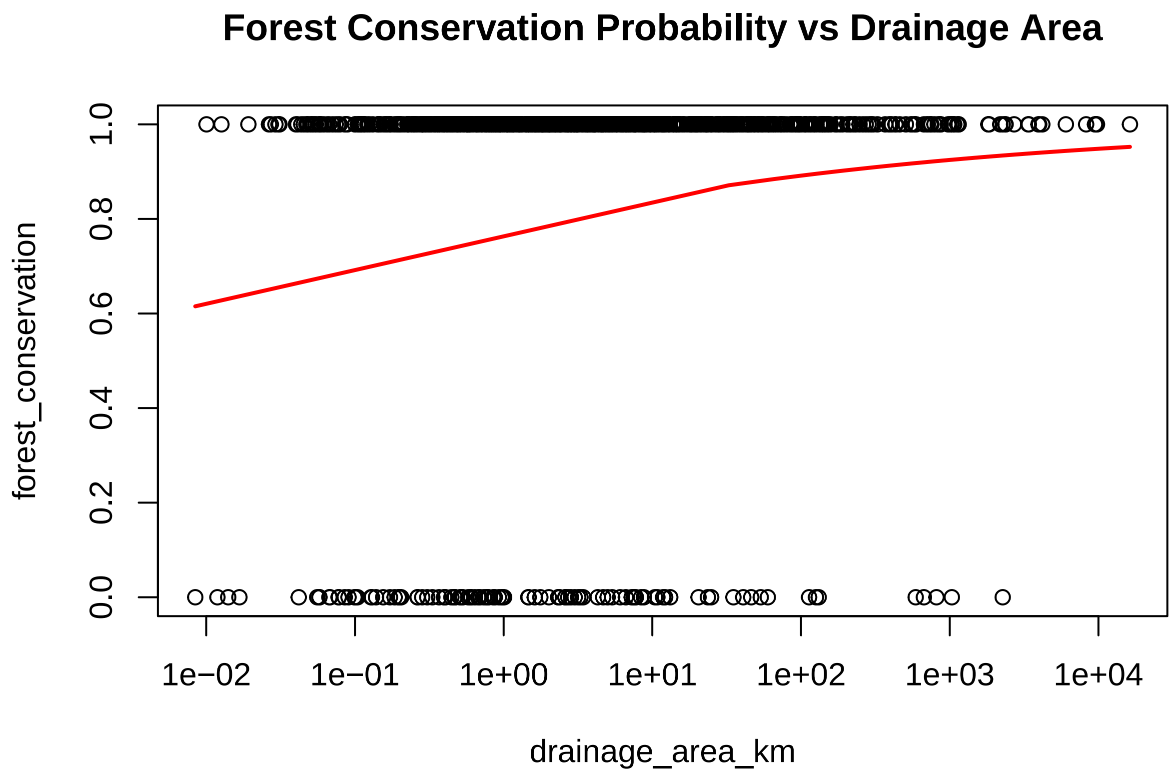
Next, let's look at pasture management

```
Predicted_data <- data.frame(drainage_area_km=seq(
  min(survey_final_gis$drainage_area_km), max(survey_final_gis_wealth$drainage_area_km),len=500))

# Fill predicted values using regression model
Predicted_data$pasture_management = predict(
  fit_pasture_log, Predicted_data, type="response")

# Plot Predicted data and original data points
plot(pasture_management ~ drainage_area_km, data=survey_final_gis_wealth, log="x")
lines(pasture_management ~ drainage_area_km, Predicted_data, lwd=2, col="blue")
title(main = "Pasture Management Probability vs Drainage Area")
```



And finally, forest conservation

```
Predicted_data <- data.frame(drainage_area_km=seq(
  min(survey_final_gis$drainage_area_km), max(survey_final_gis_wealth$drainage_area_km),len=500))

# Fill predicted values using regression model
Predicted_data$forest_conservation = predict(
  fit_forest_log, Predicted_data, type="response")

# Plot Predicted data and original data points
plot(forest_conservation~ drainage_area_km, data=survey_final_gis_wealth, log="x")
lines(forest_conservation ~ drainage_area_km, Predicted_data, lwd=2, col="red")
title(main = "Forest Conservation Probability vs Drainage Area")
```



Similar results again. Log(drainage area) is significant for each of the adaptation categories.

What happens if I filter by "have cattle" and look at cattle_management

```
survey_havecattle <-survey_final_gis %>% filter(havecattle ==1)
fit_cattle_have <- glm(cattle_management ~ drainage_area_km, family = binomial,data = survey_havecattle)
summary(fit_cattle_have)
```

```
##
## Call:
## glm(formula = cattle_management ~ drainage_area_km, family = binomial,
##     data = survey_havecattle)
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -1.137e-01  6.405e-02  -1.775   0.0759 .
## drainage_area_km  1.082e-04  8.377e-05   1.291   0.1966
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1389.3  on 1003  degrees of freedom
## Residual deviance: 1387.4  on 1002  degrees of freedom
## AIC: 1391.4
##
## Number of Fisher Scoring iterations: 3
```

```r
fit_cattle_have_log <- glm(cattle_management ~ log(drainage_area_km), family = binomial,data = survey_ha
summary(fit_cattle_have_log)
```

```
##
## Call:
## glm(formula = cattle_management ~ log(drainage_area_km), family = binomial,
##     data = survey_havecattle)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -0.13422    0.07437  -1.805   0.0711 .
## log(drainage_area_km)  0.02411    0.02729   0.883   0.3770
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1389.3  on 1003  degrees of freedom
## Residual deviance: 1388.6  on 1002  degrees of freedom
## AIC: 1392.6
##
## Number of Fisher Scoring iterations: 3
```

Interesting, if we only include those that have cattle, the significance of the log(drainage area) disappears.

Let's see if anything similar happens when filtered by havecattle for any of the other adaptations

```r
fit_pasture_have_log <- glm(pasture_management ~ log(drainage_area_km), family = binomial,data = survey_
summary(fit_pasture_have_log)
```

```
##
## Call:
## glm(formula = pasture_management ~ log(drainage_area_km), family = binomial,
##     data = survey_havecattle)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            0.76591    0.07953   9.630   <2e-16 ***
## log(drainage_area_km)  0.07154    0.03075   2.327     0.02 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1221.1  on 1003  degrees of freedom
## Residual deviance: 1215.6  on 1002  degrees of freedom
## AIC: 1219.6
##
## Number of Fisher Scoring iterations: 4
```

```r
fit_forest_have_log <- glm(forest_conservation ~ log(drainage_area_km), family = binomial,data = survey_
summary(fit_forest_have_log)
```

```
##
## Call:
## glm(formula = forest_conservation ~ log(drainage_area_km), family = binomial,
##     data = survey_havecattle)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            2.22569    0.12126  18.354  < 2e-16 ***
## log(drainage_area_km)  0.26151    0.06041   4.329  1.5e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 553.3  on 1003  degrees of freedom
## Residual deviance: 532.1  on 1002  degrees of freedom
## AIC: 536.1
##
## Number of Fisher Scoring iterations: 6
```

```
fit_water_have_log <- glm(water_management ~ log(drainage_area_km), family = binomial,data = survey_have
summary(fit_forest_have_log)
```

```
##
## Call:
## glm(formula = forest_conservation ~ log(drainage_area_km), family = binomial,
##     data = survey_havecattle)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)            2.22569    0.12126  18.354  < 2e-16 ***
## log(drainage_area_km)  0.26151    0.06041   4.329  1.5e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 553.3  on 1003  degrees of freedom
## Residual deviance: 532.1  on 1002  degrees of freedom
## AIC: 536.1
##
## Number of Fisher Scoring iterations: 6
```

We still have a significant log(drainage area) for all of the other adaptation categories.

Let's also look at deforestation as a linear model

```
fit_deforest <- lm(cleared_area ~ drainage_area_km, data = survey_final_gis)
summary(fit_deforest)
```

```
##
## Call:
## lm(formula = cleared_area ~ drainage_area_km, data = survey_final_gis)
```

```
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -375.73  -55.97  -34.22    6.90 2102.51
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      75.319662   4.286540  17.571  < 2e-16 ***
## drainage_area_km  0.033203   0.004989   6.655 4.29e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 146.6 on 1195 degrees of freedom
##   (143 observations deleted due to missingness)
## Multiple R-squared:  0.03574,    Adjusted R-squared:  0.03493
## F-statistic: 44.29 on 1 and 1195 DF,  p-value: 4.295e-11
```

```
fit_deforest_log <- lm(cleared_area ~ log(drainage_area_km), data = survey_final_gis)
summary(fit_deforest_log)
```

```
##
## Call:
## lm(formula = cleared_area ~ log(drainage_area_km), data = survey_final_gis)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -172.64  -52.52  -24.31    7.40 2093.49
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)             59.849      4.797  12.475   <2e-16 ***
## log(drainage_area_km)   14.910      1.759   8.477   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 145 on 1195 degrees of freedom
##   (143 observations deleted due to missingness)
## Multiple R-squared:  0.05672,    Adjusted R-squared:  0.05594
## F-statistic: 71.86 on 1 and 1195 DF,  p-value: < 2.2e-16
```

We see significance for both the drainage area and the log(drainage area). Both had positive coefficients, which is interesting, but we may not be able to do much with cleared area unless we looked at multiple years of data and compared.

Now let's look at logistic regression with wealth.

```
fit_wealth_water <- glm(water_management~  vechval , family = binomial, data = survey_final_gis_wealth )
fit_wealth_cattle  <- glm(cattle_management~  vechval , family = binomial, data = survey_final_gis_weal
fit_wealth_pasture  <- glm(pasture_management~  vechval , family = binomial, data = survey_final_gis_wea
fit_wealth_forest <- glm(forest_conservation~  vechval , family = binomial, data = survey_final_gis_weal
#fit_wealth_any_adaptation <- glm(any_adaptation~  vechval , family = binomial, data = survey_final_gis
summary(fit_wealth_water)
```

```
##
## Call:
## glm(formula = water_management ~ vechval, family = binomial,
##     data = survey_final_gis_wealth)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) 2.833e+00  1.817e-01  15.588   <2e-16 ***
## vechval     7.353e-06  3.675e-06   2.001   0.0454 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 421.94  on 1199  degrees of freedom
## Residual deviance: 415.92  on 1198  degrees of freedom
## AIC: 419.92
##
## Number of Fisher Scoring iterations: 7
```

```
summary(fit_wealth_cattle)
```

```
##
## Call:
## glm(formula = cattle_management ~ vechval, family = binomial,
##     data = survey_final_gis_wealth)
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -6.724e-01  7.585e-02  -8.866  < 2e-16 ***
## vechval      6.795e-06  1.005e-06   6.763 1.35e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1630.1  on 1199  degrees of freedom
## Residual deviance: 1571.4  on 1198  degrees of freedom
## AIC: 1575.4
##
## Number of Fisher Scoring iterations: 4
```

```
summary(fit_wealth_pasture)
```

```
##
## Call:
## glm(formula = pasture_management ~ vechval, family = binomial,
##     data = survey_final_gis_wealth)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) 2.314e-01  7.769e-02   2.978   0.0029 **
## vechval     7.489e-06  1.288e-06   5.813 6.12e-09 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1573.9  on 1199  degrees of freedom
## Residual deviance: 1525.9  on 1198  degrees of freedom
## AIC: 1529.9
##
## Number of Fisher Scoring iterations: 4
```

```
summary(fit_wealth_forest)
```

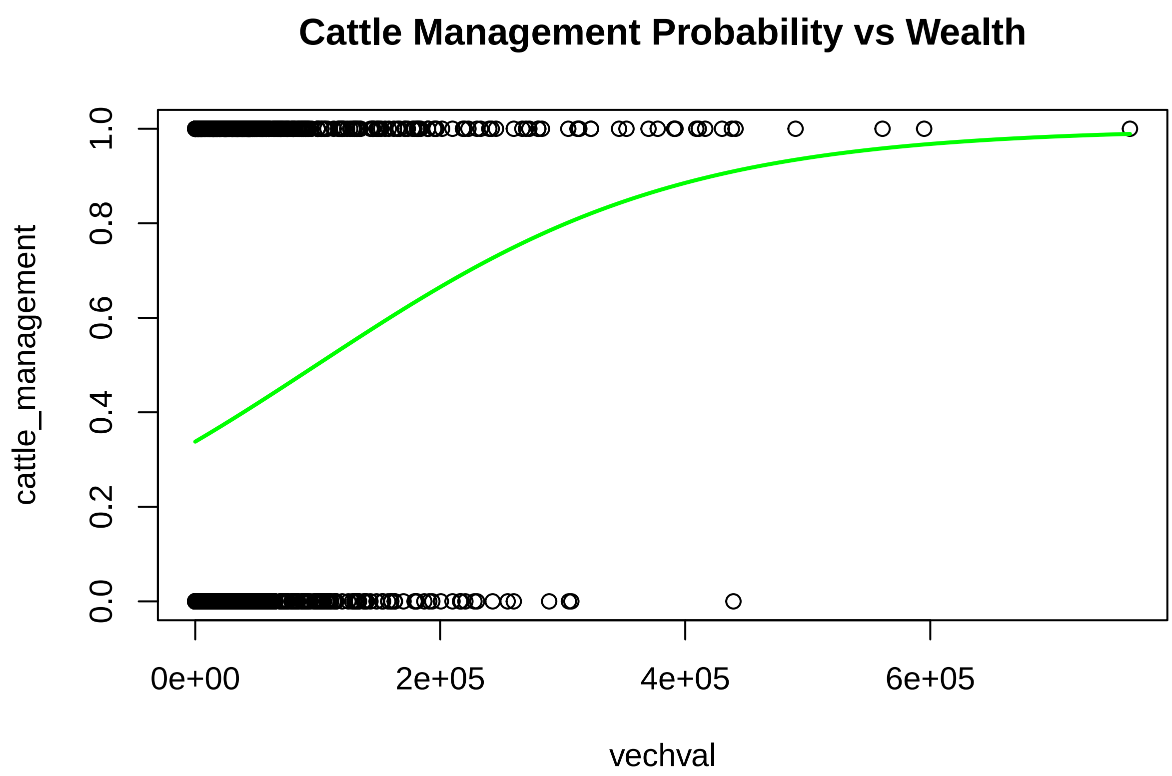
```
##
## Call:
## glm(formula = forest_conservation ~ vechval, family = binomial,
##     data = survey_final_gis_wealth)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) 2.059e+00  1.260e-01  16.340   <2e-16 ***
## vechval     5.742e-06  2.253e-06   2.549   0.0108 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 735.30  on 1199  degrees of freedom
## Residual deviance: 726.19  on 1198  degrees of freedom
## AIC: 730.19
##
## Number of Fisher Scoring iterations: 6
```

```
#summary(fit_wealth_any_adaptation )
```

Now, we'll plot these models to get a visual on what they mean

First with cattle management

```
Predicted_data <- data.frame(vechval=seq(
  min(survey_final_gis_wealth$vechval), max(survey_final_gis_wealth$vechval),len=500))

# Fill predicted values using regression model
Predicted_data$cattle_management = predict(
  fit_wealth_cattle, Predicted_data, type="response")

# Plot Predicted data and original data points
plot(cattle_management ~ vechval, data=survey_final_gis_wealth)
lines(cattle_management ~ vechval, Predicted_data, lwd=2, col="green")
title(main = "Cattle Management Probability vs Wealth")
```



Now water management

```
Predicted_data <- data.frame(vechval=seq(
  min(survey_final_gis_wealth$vechval), max(survey_final_gis_wealth$vechval),len=500))

# Fill predicted values using regression model
Predicted_data$water_management = predict(
  fit_wealth_water, Predicted_data, type="response")

# Plot Predicted data and original data points
plot(water_management ~ vechval, data=survey_final_gis_wealth)
lines(water_management ~ vechval, Predicted_data, lwd=2, col="purple")
title(main = "Water Management Probability vs Wealth")
```

Now pasture management

```
Predicted_data <- data.frame(vechval=seq(
  min(survey_final_gis_wealth$vechval), max(survey_final_gis_wealth$vechval),len=500))

# Fill predicted values using regression model
Predicted_data$pasture_management = predict(
  fit_wealth_pasture, Predicted_data, type="response")

# Plot Predicted data and original data points
plot(pasture_management ~ vechval, data=survey_final_gis_wealth)
```

```r
lines(pasture_management ~ vechval, Predicted_data, lwd=2, col="blue")
title(main = "Pasture Management Probability vs Wealth")
```

and finally forest conservation

```r
Predicted_data <- data.frame(vechval=seq(
  min(survey_final_gis_wealth$vechval), max(survey_final_gis_wealth$vechval),len=500))

# Fill predicted values using regression model
Predicted_data$forest_conservation = predict(
  fit_wealth_forest, Predicted_data, type="response")

# Plot Predicted data and original data points
plot(forest_conservation ~ vechval, data=survey_final_gis_wealth)
lines(forest_conservation ~ vechval, Predicted_data, lwd=2, col="red")
title(main = "Forest Conservation Probability vs Wealth")
```

Look at models with vehicle value and drainage area. Drainage area was not significant in any models, but log(drainage area) is for some.

```r
survey_final_gis_wealth <- survey_final_gis %>% filter(!is.na(survey_final_gis$vechval))
fit_wealth_ldrain_water <- glm(water_management~  vechval + log(drainage_area_km), family = binomial, da
fit_wealth_ldrain_cattle  <- glm(cattle_management~  vechval + log(drainage_area_km) , family = binomia
fit_wealth_ldrain_pasture  <- glm(pasture_management~  vechval + log(drainage_area_km), family = binomi
fit_wealth_ldrain_forest <- glm(forest_conservation~  vechval + log(drainage_area_km), family = binomial
#fit_wealth_drainn_any_adaptation <- glm(any_adaptation~  vechval + log(drainage_area_km), family = bin
summary(fit_wealth_ldrain_water)
summary(fit_wealth_ldrain_cattle)
summary(fit_wealth_ldrain_pasture)
summary(fit_wealth_ldrain_forest)
#summary(fit_wealth_drain_any_adaptation )
```

The model for any adaptation did not converge, but all of the others did. Vehicle value was still significant for all of the adaptation measures. Log(drainage area) was not significant for water or cattle management when vehicle value is included, but it is for pasture management and forest conservation. For forest conservation, drainage area has a much smaller p value than vehicle value.

Try using draianage area with the tail chopped off instead of log transform

```r
survey_final_gis_wealth_filtered <- survey_final_gis_wealth %>% filter(drainage_area_km < 500)
fit_wealth_drain_water <- glm(water_management~  vechval + drainage_area_km, family = binomial, data = s
fit_wealth_drain_cattle  <- glm(cattle_management~  vechval + drainage_area_km , family = binomial, data
fit_wealth_drain_pasture  <- glm(pasture_management~  vechval + drainage_area_km, family = binomial, dat
fit_wealth_drain_forest <- glm(forest_conservation~  vechval + drainage_area_km, family = binomial, data
#fit_wealth_drainn_any_adaptation <- glm(any_adaptation~  vechval + drainage_area_km, family = binomial
summary(fit_wealth_drain_water)
summary(fit_wealth_drain_cattle)
summary(fit_wealth_drain_pasture)
summary(fit_wealth_drain_forest)
#summary(fit_wealth_drain_any_adaptation )
```

With the drainage area outliers removed, drainage area is significant for forest conservation but none of the others.

```r
rainfall_group<- cut(survey_final_gis_wealth_filtered$rainfall , c(0,1950,2300), label=c("low","high"))
rainfall_group <-factor(rainfall_group)
survey_final_gis_wealth_filtered$studycode <-factor(survey_final_gis_wealth_filtered$studycode)
fit_wealth_drain_water <- glm(water_management~  vechval + drainage_area_km, family = binomial, data = s
fit_wealth_drain_cattle  <- glm(cattle_management~  vechval + drainage_area_km, family = binomial, data
fit_wealth_drain_pasture  <- glm(pasture_management~  vechval + drainage_area_km, family = binomial, da
fit_wealth_drain_forest <- glm(forest_conservation~  vechval + log(drainage_area_km) + log(rainfall_yea
#fit_wealth_drainn_any_adaptation <- glm(any_adaptation~  vechval + drainage_area_km, family = binomial
summary(fit_wealth_drain_water)
summary(fit_wealth_drain_cattle)
summary(fit_wealth_drain_pasture)
summary(fit_wealth_drain_forest)
#summary(fit_wealth_drain_any_adaptation )
```

Since we've seen that wealth is so important for adaptation, but drainage area importance decreases for wealth, let's see if other water availability proxies are signficant for the individual adaptations

```r
fit_cattle_full <- glm(cattle_management ~ SPImax_year + vechval, family = binomial,data = survey_final_
summary(fit_cattle)
```

```
##
## Call:
## glm(formula = cattle_management ~ drainage_area_km, family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -5.298e-01  5.717e-02  -9.267   <2e-16 ***
## drainage_area_km  8.492e-05  6.657e-05   1.276    0.202
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1770.4  on 1339  degrees of freedom
## Residual deviance: 1768.7  on 1338  degrees of freedom
## AIC: 1772.7
##
## Number of Fisher Scoring iterations: 4
```

```r
fit_water_full <- glm(water_management ~ SPImax_year + vechval, family = binomial,data = survey_final_gi
summary(fit_water_full)
```

```
##
## Call:
## glm(formula = water_management ~ SPImax_year + vechval, family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  4.223e+00  5.507e-01   7.669 1.73e-14 ***
## SPImax_year -9.839e-01  3.508e-01  -2.805  0.00503 **
```

```
## vechval      7.471e-06  3.777e-06   1.978  0.04792 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 421.94  on 1199  degrees of freedom
## Residual deviance: 408.44  on 1197  degrees of freedom
##   (140 observations deleted due to missingness)
## AIC: 414.44
##
## Number of Fisher Scoring iterations: 7
```

```r
fit_pasture_full <- glm(pasture_management ~ rainfall+ vechval, family = binomial,data = survey_final_gi
summary(fit_pasture_full)
```

```
##
## Call:
## glm(formula = pasture_management ~ rainfall + vechval, family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  2.909e+00  1.071e+00   2.715  0.00663 **
## rainfall    -1.345e-03  5.365e-04  -2.507  0.01217 *
## vechval      7.361e-06  1.299e-06   5.668 1.45e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1573.9  on 1199  degrees of freedom
## Residual deviance: 1519.6  on 1197  degrees of freedom
##   (140 observations deleted due to missingness)
## AIC: 1525.6
##
## Number of Fisher Scoring iterations: 4
```

```r
fit_forest_full <- glm(forest_conservation ~ SPImin_year + vechval, family = binomial,data = survey_fina
summary(fit_forest_full)
```

```
##
## Call:
## glm(formula = forest_conservation ~ SPImin_year + vechval, family = binomial,
##     data = survey_final_gis)
##
## Coefficients:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1.165e+00  4.268e-01   2.729  0.00634 **
## SPImin_year -8.688e-01  4.047e-01  -2.147  0.03183 *
## vechval      5.614e-06  2.248e-06   2.497  0.01252 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 735.30  on 1199  degrees of freedom
## Residual deviance: 721.45  on 1197  degrees of freedom
##   (140 observations deleted due to missingness)
## AIC: 727.45
##
## Number of Fisher Scoring iterations: 6
```