Exploratory analysis

Attach packages

```
library(tidyverse)
library(caret)
library(psych)
library(BioStatR)
library(car)
library(lattice)
```

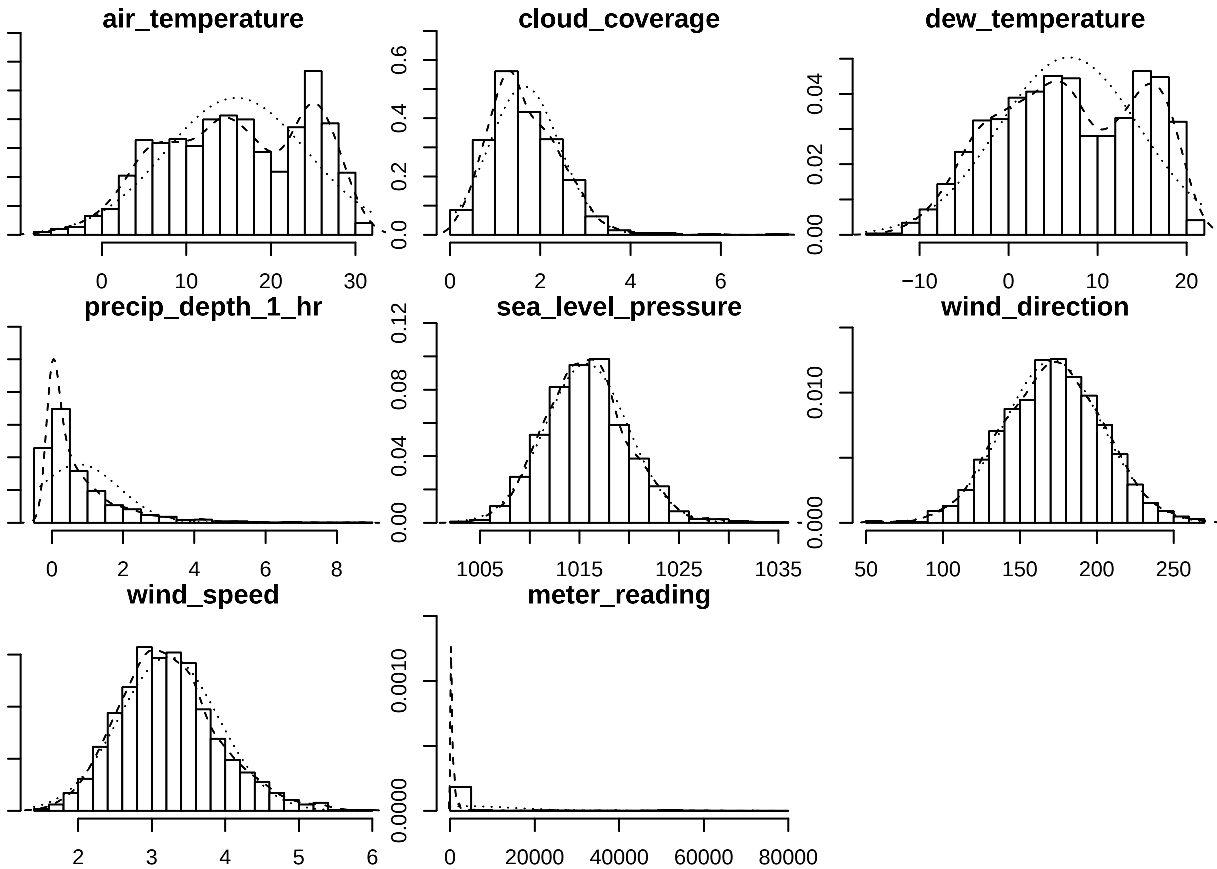
Load the datafile

```
daily_data <- readRDS("daily_data.rds")
summary(daily_data)
```

```
##       date                meter      air_temperature  cloud_coverage
##  Min.   :2016-01-01   Min.   :0.00   Min.   :-6.569   Min.   :0.000
##  1st Qu.:2016-04-01   1st Qu.:0.75   1st Qu.: 9.224   1st Qu.:1.108
##  Median :2016-07-01   Median :1.50   Median :15.902   Median :1.524
##  Mean   :2016-07-01   Mean   :1.50   Mean   :15.899   Mean   :1.646
##  3rd Qu.:2016-10-01   3rd Qu.:2.25   3rd Qu.:23.825   3rd Qu.:2.148
##  Max.   :2016-12-31   Max.   :3.00   Max.   :31.616   Max.   :7.292
##  dew_temperature   precip_depth_1_hr  sea_level_pressure wind_direction
##  Min.   :-14.147   Min.   :-0.46323   Min.   :1003       Min.   : 56.52
##  1st Qu.:  0.537   1st Qu.: 0.01168   1st Qu.:1013       1st Qu.:149.43
##  Median :  6.577   Median : 0.33109   Median :1016       Median :171.41
##  Mean   :  6.785   Mean   : 0.76072   Mean   :1016       Mean   :171.48
##  3rd Qu.: 14.060   3rd Qu.: 1.07500   3rd Qu.:1018       3rd Qu.:193.54
##  Max.   : 21.655   Max.   : 8.69171   Max.   :1035       Max.   :267.27
##    wind_speed    meter_reading
##  Min.   :1.453   Min.   :  110.5
##  1st Qu.:2.775   1st Qu.:  186.4
##  Median :3.185   Median :  411.5
##  Mean   :3.231   Mean   : 3859.2
##  3rd Qu.:3.616   3rd Qu.:  990.0
##  Max.   :5.953   Max.   :77117.7
```

Examine distributions

```
numeric <- daily_data[,3:10]
multi.hist(numeric)
```



The target variable (meter_reading) is heavily right-skewed. cloud_coverage and precip_depth_1_hr are also right-skewed.

Examine correlations

```r
round(cor(numeric), 2)
```

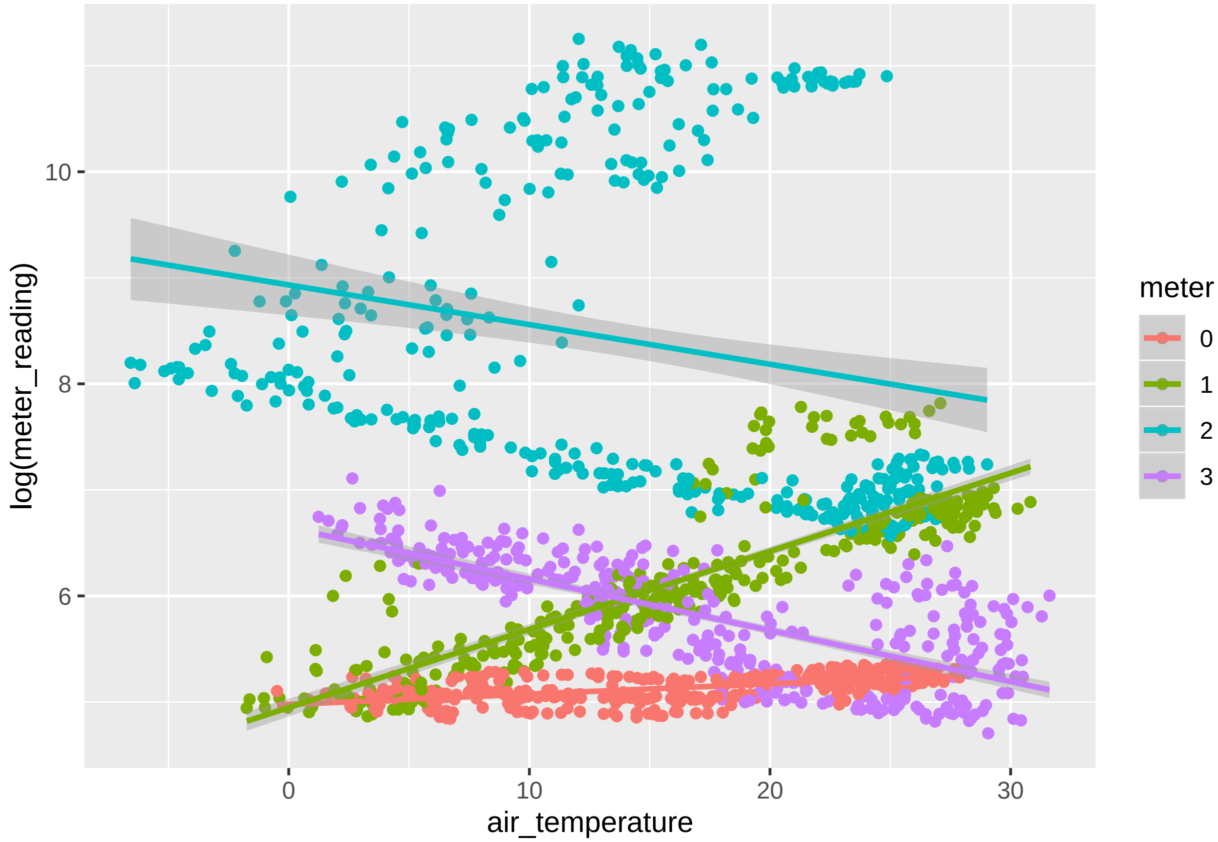
```
##                    air_temperature cloud_coverage dew_temperature
## air_temperature               1.00           0.03            0.92
## cloud_coverage                0.03           1.00            0.20
## dew_temperature               0.92           0.20            1.00
## precip_depth_1_hr             0.16           0.15            0.26
## sea_level_pressure           -0.44          -0.08           -0.34
## wind_direction               -0.12          -0.05           -0.20
## wind_speed                   -0.20           0.21           -0.23
## meter_reading                -0.04          -0.08            0.03
##                    precip_depth_1_hr sea_level_pressure wind_direction
## air_temperature                 0.16              -0.44          -0.12
## cloud_coverage                  0.15              -0.08          -0.05
## dew_temperature                 0.26              -0.34          -0.20
## precip_depth_1_hr               1.00              -0.15          -0.11
## sea_level_pressure             -0.15               1.00          -0.15
## wind_direction                 -0.11              -0.15           1.00
## wind_speed                      0.01              -0.18           0.45
## meter_reading                   0.10              -0.09          -0.08
##                    wind_speed meter_reading
```

```
## air_temperature         -0.20         -0.04
## cloud_coverage           0.21         -0.08
## dew_temperature         -0.23          0.03
## precip_depth_1_hr        0.01          0.10
## sea_level_pressure      -0.18         -0.09
## wind_direction           0.45         -0.08
## wind_speed               1.00          0.05
## meter_reading            0.05          1.00
```

None of the weather variables are strongly linearly correlated with meter-reading. A fact that we will see in the following plots.

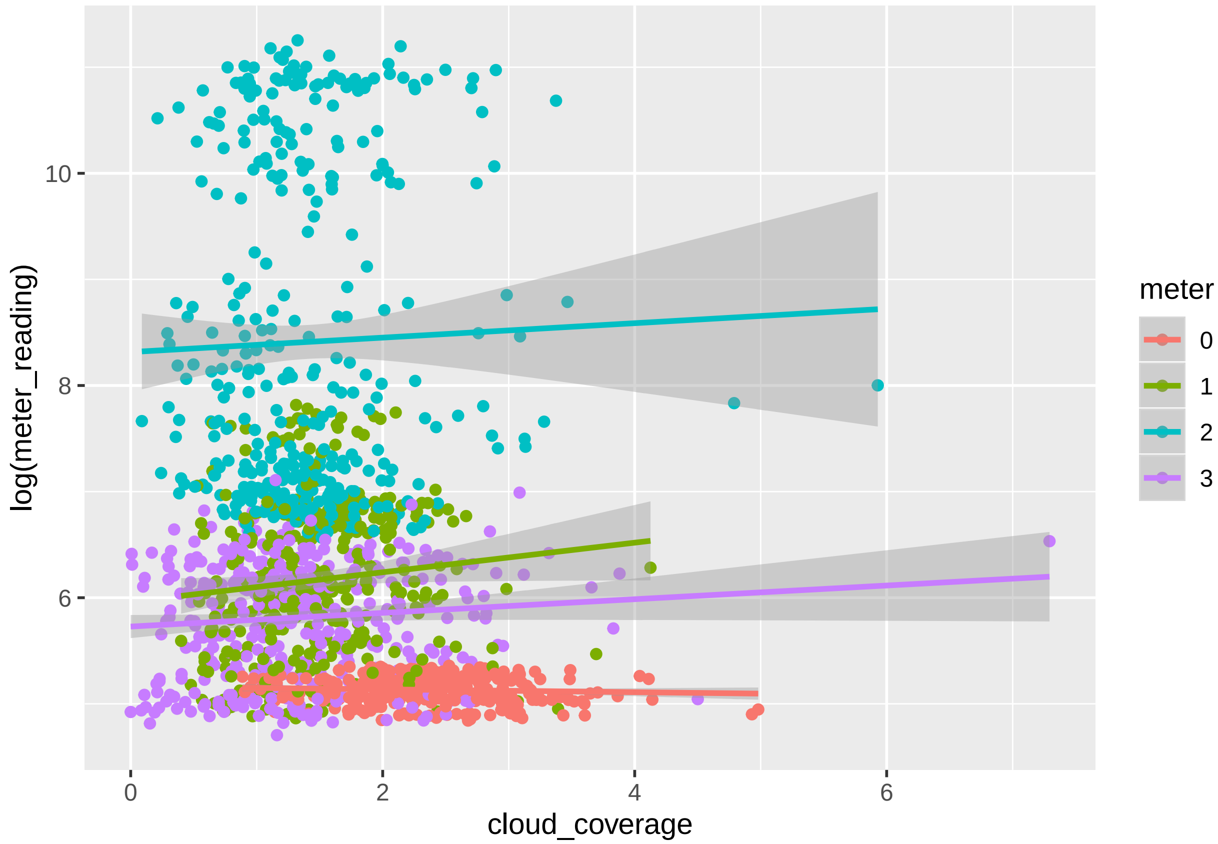
Examine scatterplots

```
daily_data$meter <- as.factor(daily_data$meter)
air_temp <- ggplot(daily_data, aes(x = air_temperature, y = log(meter_reading), colour = meter)) + geom_
air_temp
```



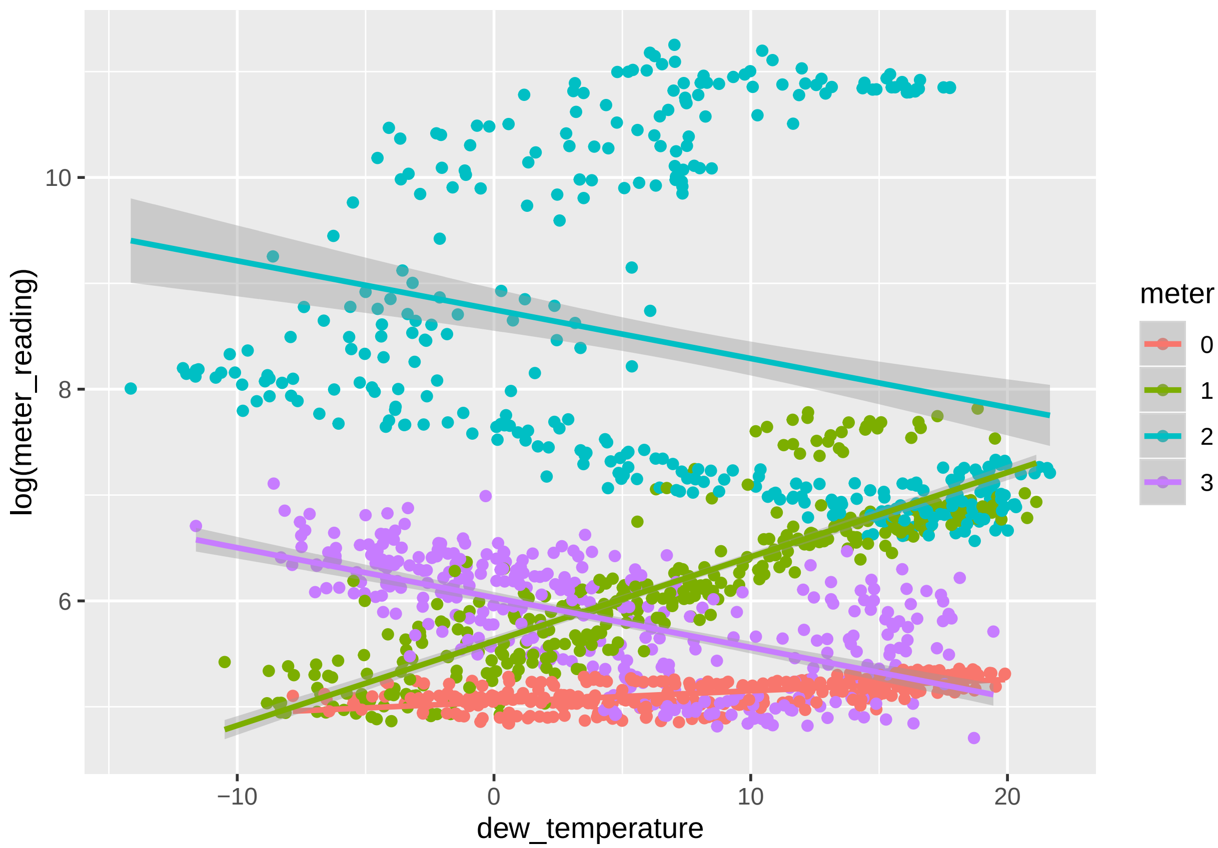
There are outliers but for the most part there is not much of a linear relationship between air_temperature and meter_reading. meter type 3 does show a stronger linear relationship than the other two meter types.

```
cloud_cover <- ggplot(daily_data, aes(x = cloud_coverage, y = log(meter_reading), colour = meter)) + geo
cloud_cover
```



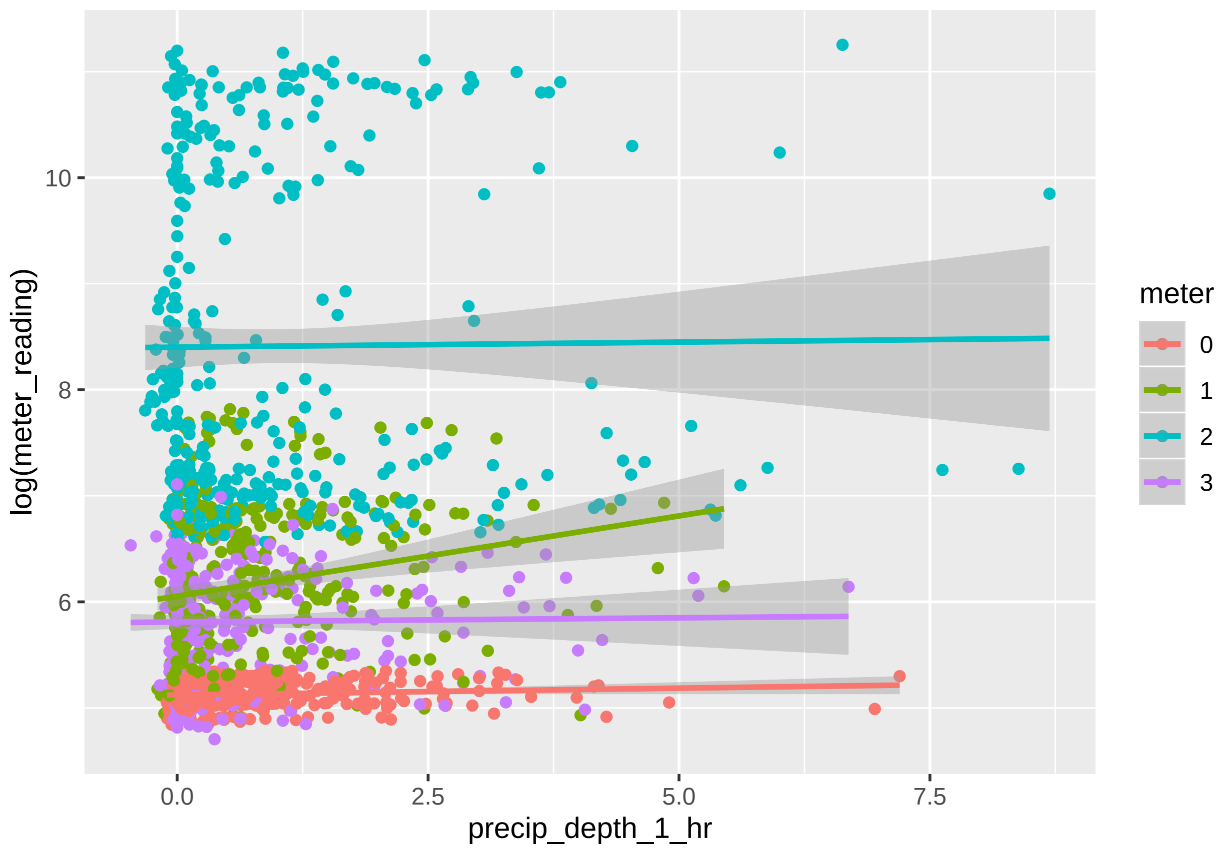
cloud_coverage does not have a clear linear relationship with meter reading except for meter 3.

```
dew_temp <- ggplot(daily_data, aes(x = dew_temperature, y = log(meter_reading), colour = meter)) + geom_
dew_temp
```



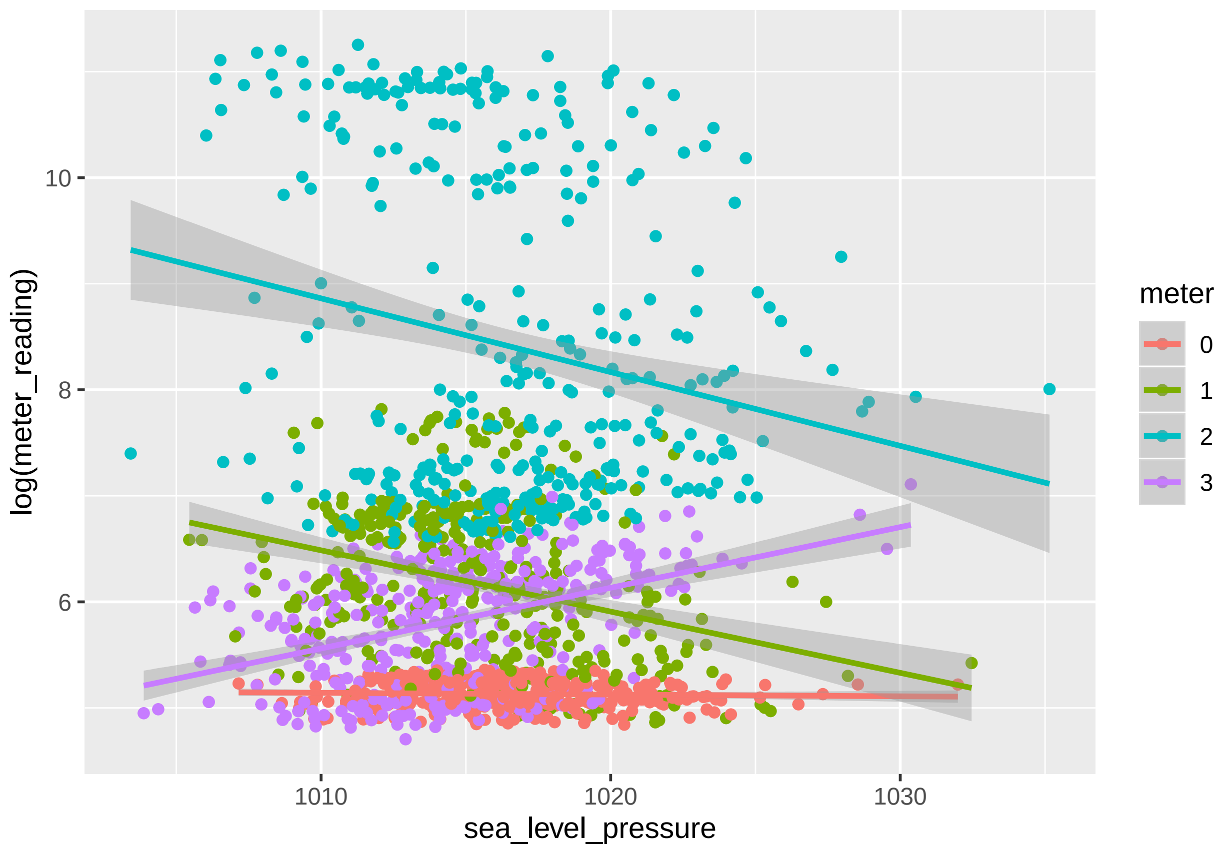
We see the same trend in dew temperature as the earlier two temperature variables. There is not much of a linear relationship, except for meter 3.

```
precip_depth <- ggplot(daily_data, aes(x = precip_depth_1_hr, y = log(meter_reading), colour = meter))
precip_depth
```



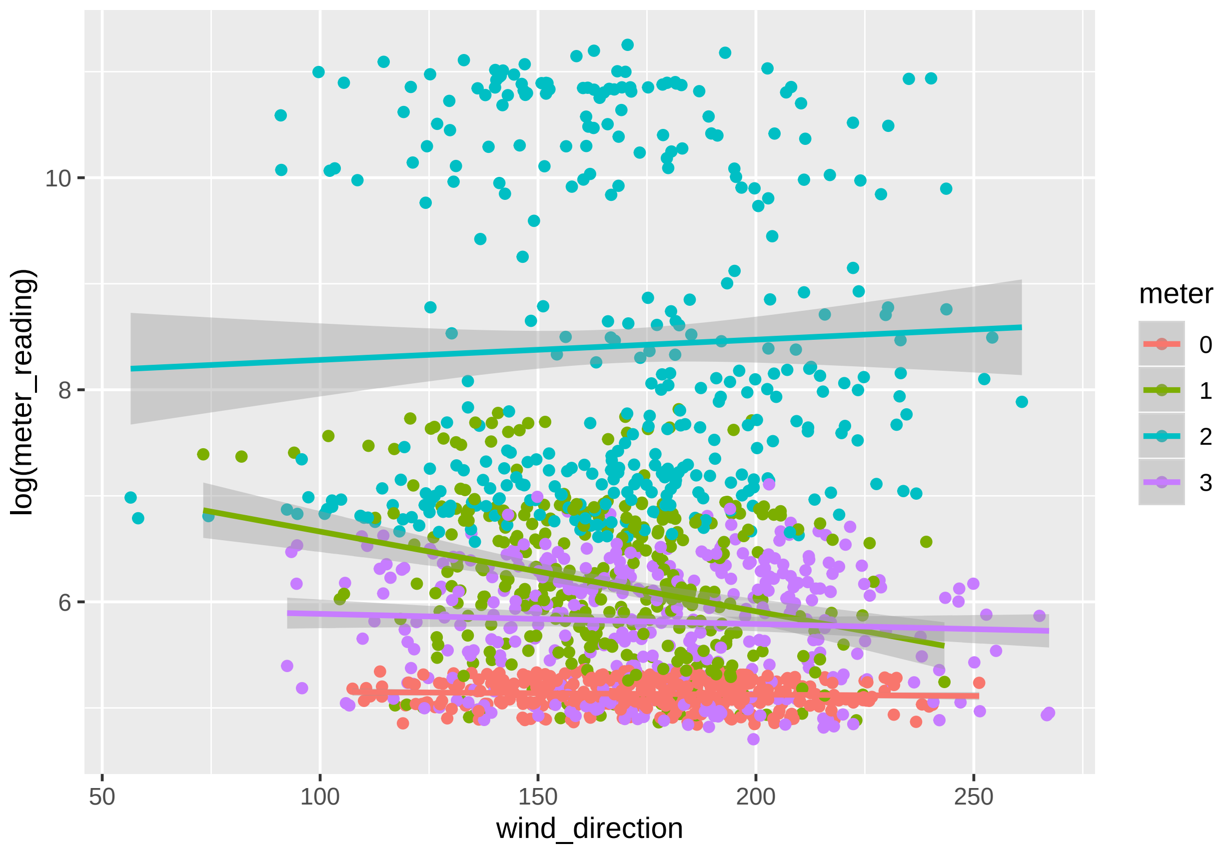
Precip_depth_1_hr does not have any relationship with meter reading. Even meter 3 is all over the place.

```
sea_pressure <- ggplot(daily_data, aes(x = sea_level_pressure, y = log(meter_reading), colour = meter))
sea_pressure
```



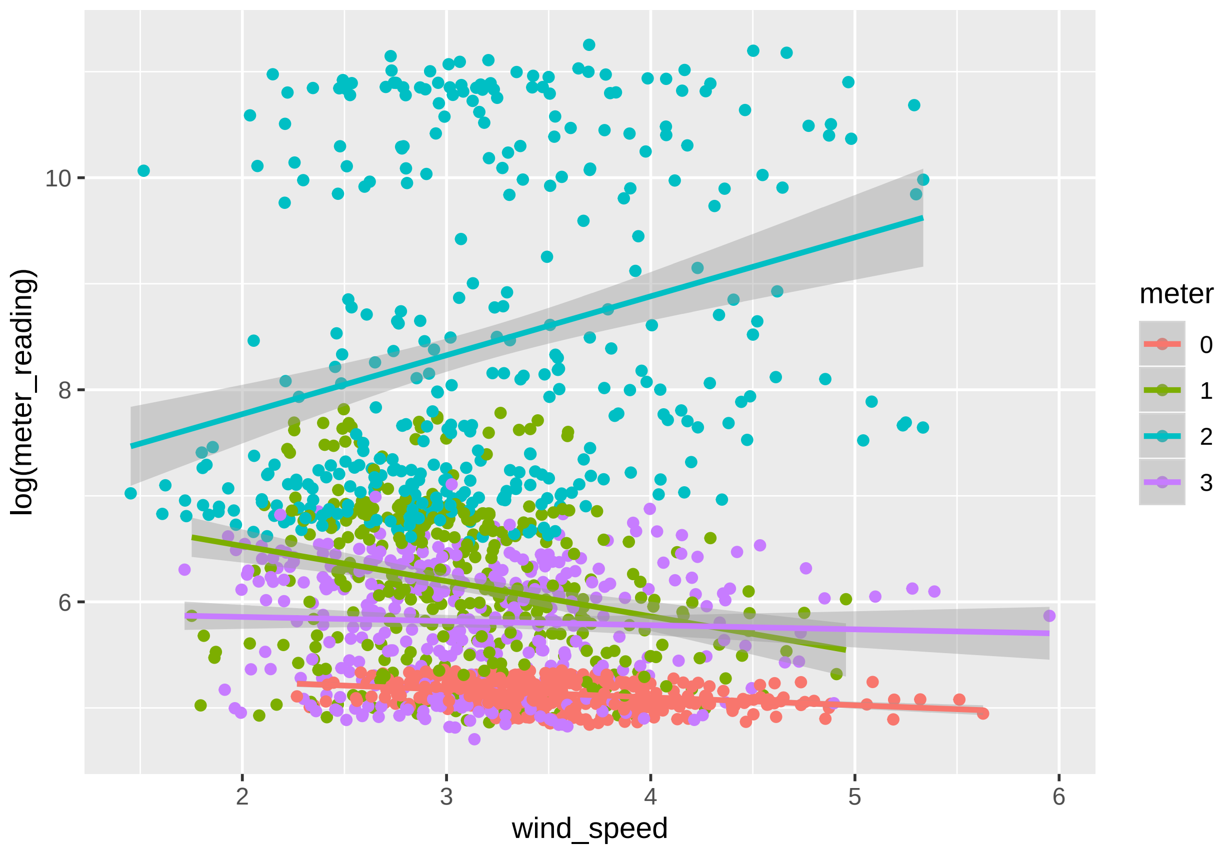
sea_level pressure has no relationship with meter reading for all meter types.

```
wind_direction <- ggplot(daily_data, aes(x = wind_direction, y = log(meter_reading), colour = meter)) +
wind_direction
```



No relationship between wind direction and meter reading. meter 3 is all over the place!

```
wind_speed <- ggplot(daily_data, aes(x = wind_speed, y = log(meter_reading), colour = meter)) + geom_po
wind_speed
```



No relationship between wind speed and meter reading.

Look at the Building related variables

```
building_vars <- readRDS("building_vars.rds")
summary(building_vars)
```

```
##  meter_reading        building_id     primary_use          square_feet
##  Min.   :      0.0   Min.   :   0   Length:1449        Min.   :   283
##  1st Qu.:     32.0   1st Qu.: 362   Class :character   1st Qu.: 23012
##  Median :     94.1   Median : 724   Mode  :character   Median : 57673
##  Mean   :   1652.3   Mean   : 724                      Mean   : 92112
##  3rd Qu.:    256.9   3rd Qu.:1086                      3rd Qu.:115676
##  Max.   :1907445.9   Max.   :1448                      Max.   :875000
##
##   year_built    floor_count
##  Min.   :1900   Min.   : 1.000
##  1st Qu.:1949   1st Qu.: 1.000
##  Median :1970   Median : 3.000
##  Mean   :1968   Mean   : 3.741
##  3rd Qu.:1995   3rd Qu.: 5.000
##  Max.   :2017   Max.   :26.000
##  NA's   :774    NA's   :1094
```

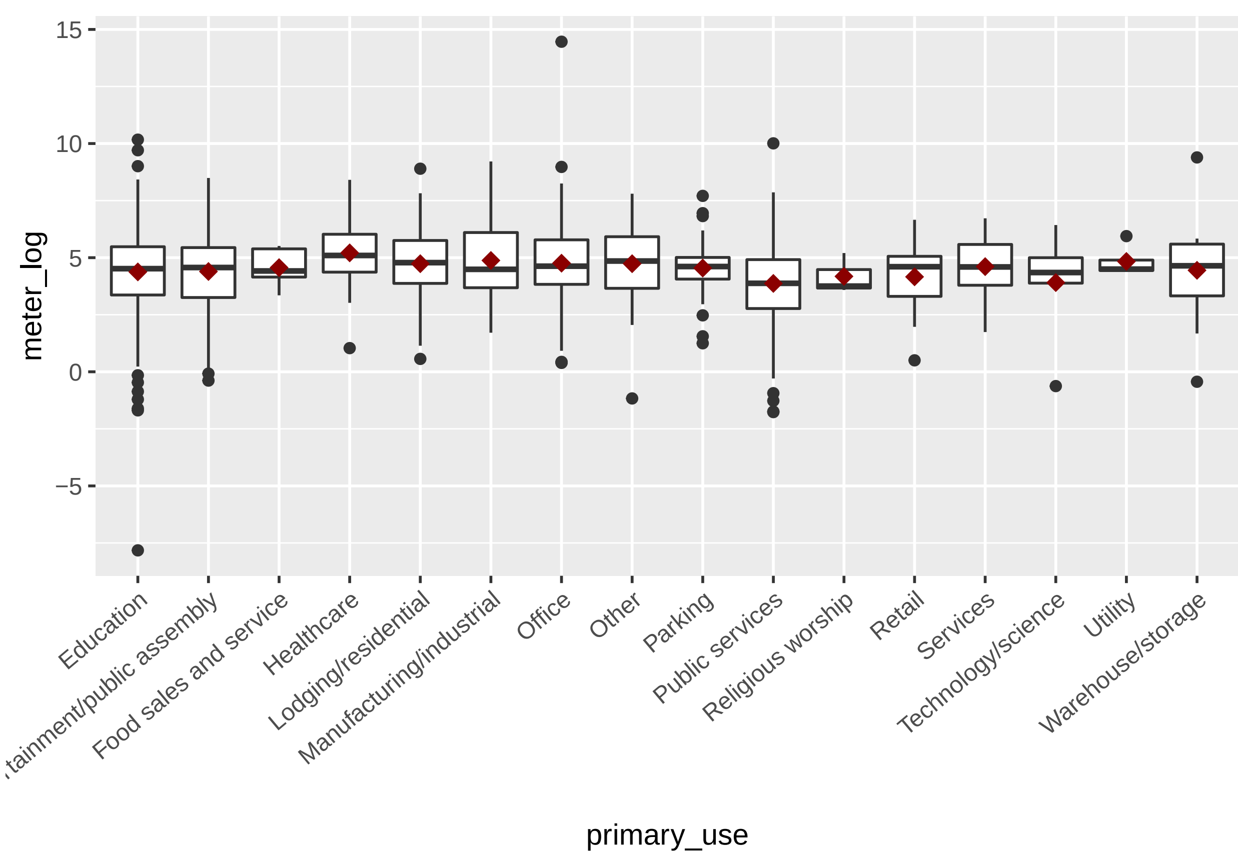
```
dim(building_vars)
```

```
## [1] 1449    6
```

```r
building_vars$primary_use <- as.factor(building_vars$primary_use)
summary(building_vars$primary_use)
```

```
##                     Education Entertainment/public assembly
##                           549                           184
##         Food sales and service                    Healthcare
##                             5                            23
##           Lodging/residential      Manufacturing/industrial
##                           147                            12
##                        Office                         Other
##                           279                            25
##                       Parking               Public services
##                            22                           156
##             Religious worship                        Retail
##                             3                            11
##                      Services           Technology/science
##                            10                             6
##                       Utility             Warehouse/storage
##                             4                            13
```

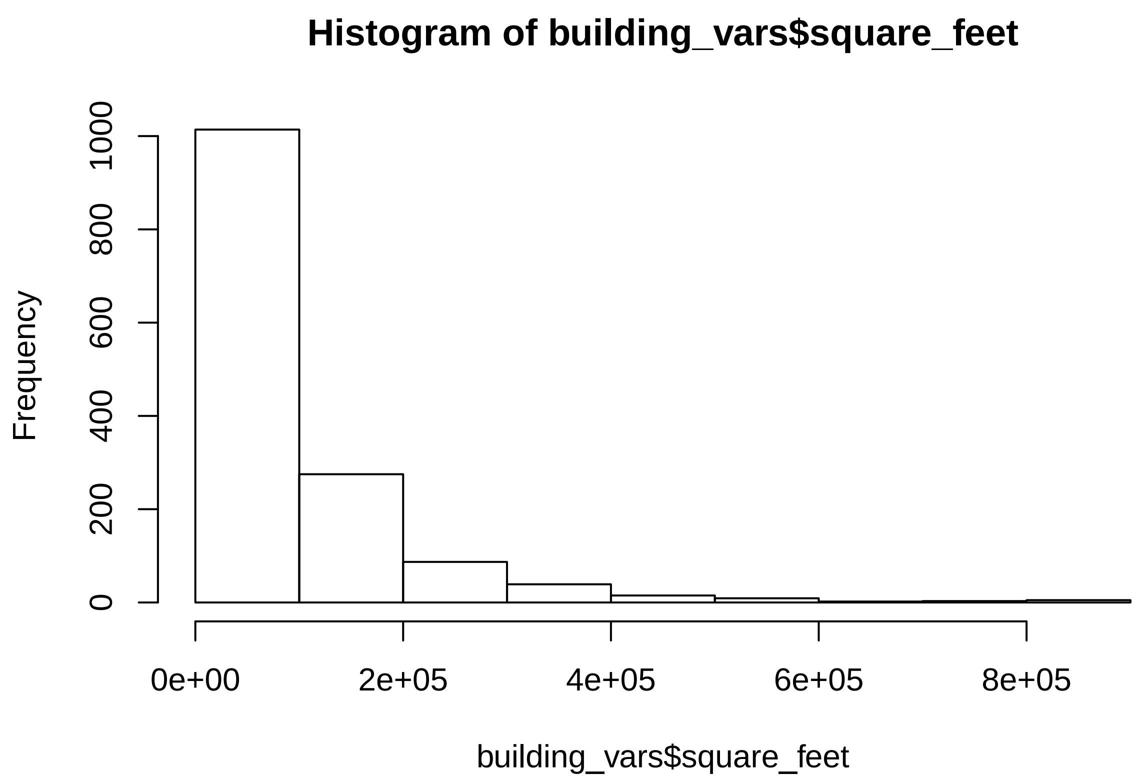
```r
meter_log <- log(building_vars$meter_reading)
use <- ggplot(building_vars, aes(x = primary_use, y = meter_log)) + geom_boxplot() +
   stat_summary(fun.y=mean, colour="darkred", geom="point",
            shape=18, size=3)
use + theme(axis.text.x = element_text(angle = 40, hjust = 1))
```



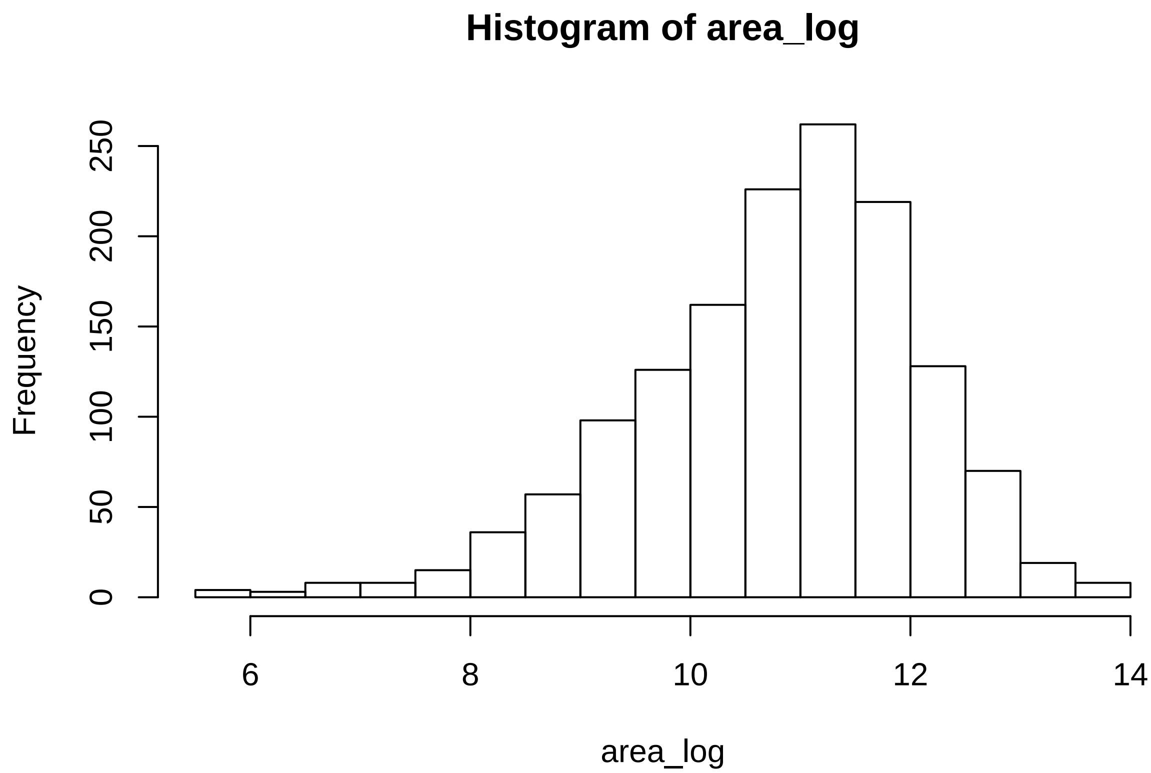
Not much of a difference in means. I logged meter readings because they are so strongly right skewed. I could not see a trend if I did not log them. No relationship between use of building and meter reading.

Now, lets look at the area of the buildings. Again this variable is highly right-skewed. I'm going to log it.

```
hist(building_vars$square_feet)
```

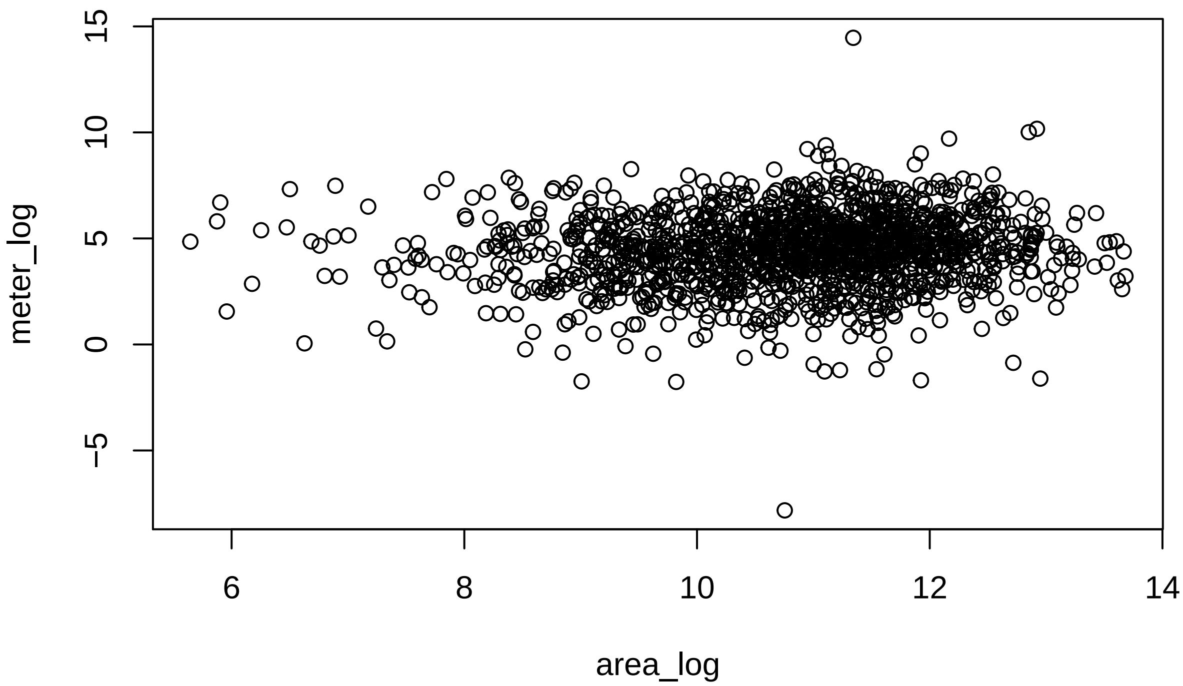



```
area_log <- log(building_vars$square_feet)
hist(area_log)
```



looks much better!

```r
plot(area_log, meter_log)
```



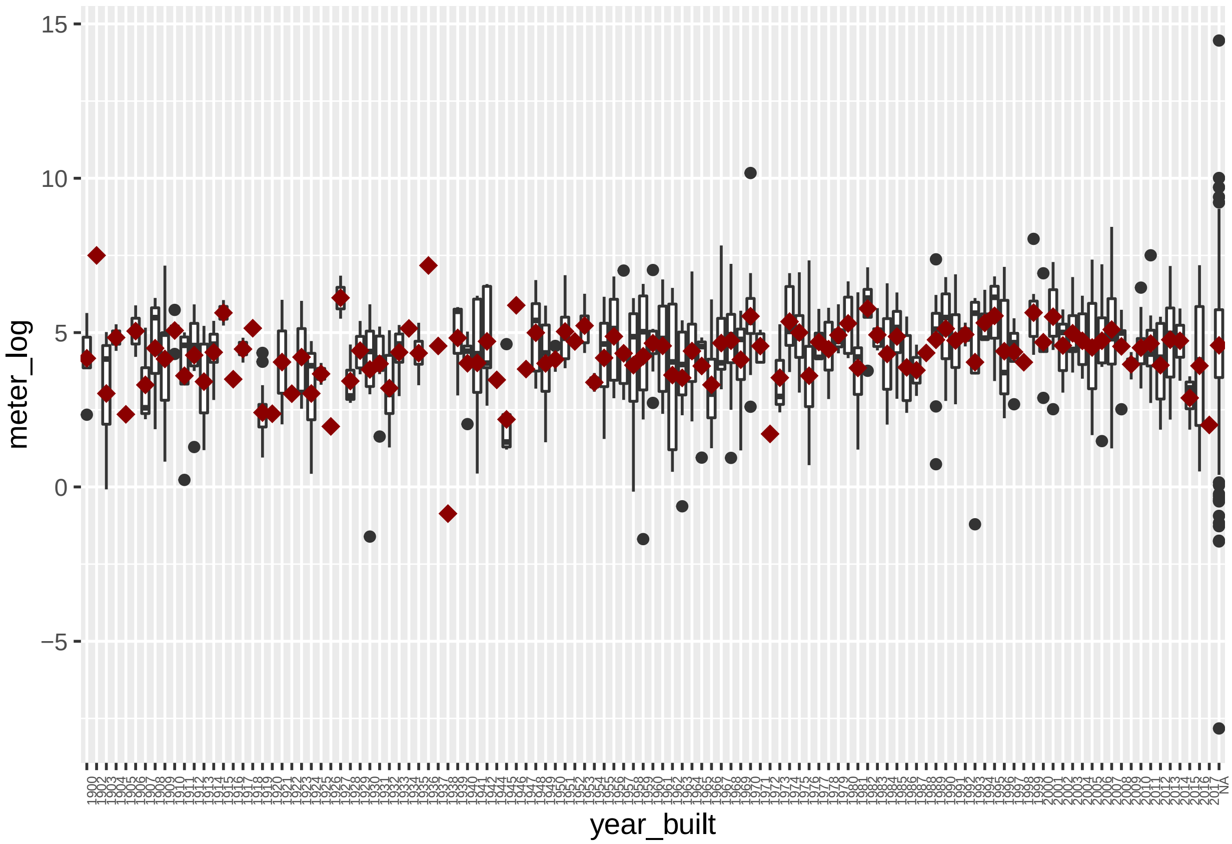
Nothing going on here! There is no relationship between area and meter readings.

```
building_vars$year_built <- as.factor(building_vars$year_built)
summary(building_vars$year_built)
```

```
##     1976    1966    1968    1919    1964    2004    1960    1975    2006
##       55      23      18      17      15      14      13      13      13
##     2007    1970    2001    2010    2014    2002    1930    1959    1967
##       13      12      12      12      12      11      10      10      10
##     2005    1989    2013    1923    1956    1999    1958    1963    1969
##       10       9       9       8       8       8       7       7       7
##     1990    2011    2016    1912    1913    1931    1932    1953    1965
##        7       7       7       6       6       6       6       6       6
##     1974    1981    1996    1900    1909    1910    1940    1941    1942
##        6       6       6       5       5       5       5       5       5
##     1948    1951    1955    1957    1961    1962    1971    1978    1986
##        5       5       5       5       5       5       5       5       5
##     1995    2000    2003    2008    1911    1914    1929    1933    1935
##        5       5       5       5       4       4       4       4       4
##     1945    1949    1950    1979    1980    1982    1983    1985    1991
##        4       4       4       4       4       4       4       4       4
##     1993    1997    2009    2012    1903    1907    1908    1917    1924
##        4       4       4       4       3       3       3       3       3
##     1927    1928    1939    1973    1977    1994    2015    1904    1906
##        3       3       3       3       3       3       3       2       2
##     1915    1920    1921    1925    1952    1954    1984    1987 (Other)
##        2       2       2       2       2       2       2       2      21
```

```
##    NA's
##     774
```

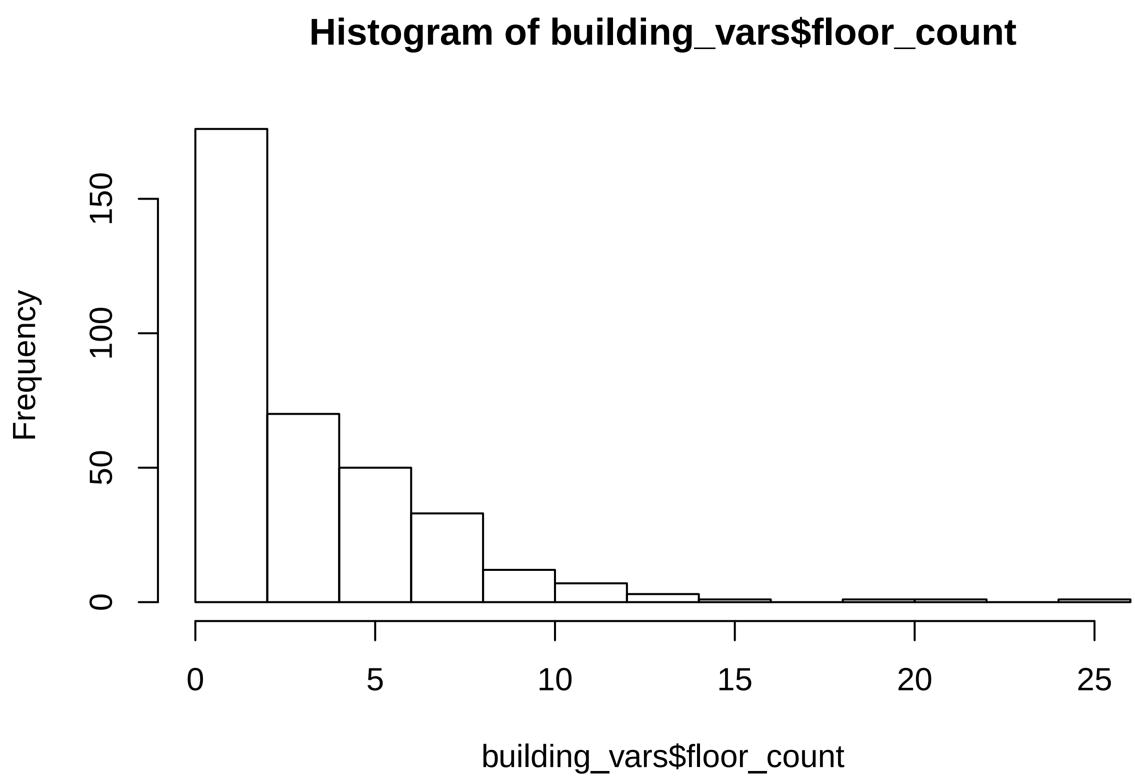
```
meter_log <- log(building_vars$meter_reading)
year <- ggplot(building_vars, aes(x = year_built, y = meter_log)) + geom_boxplot() + stat_summary(fun.y=
year + theme(axis.text.x = element_text(size = 5, angle = 90, hjust = 1))
```



There is some variation but not much of a trend. It almost seems random. Surprisingly, the newer buildings are not using less energy!!

Now lets look at floor count!

```
hist(building_vars$floor_count)
```




```r
table(building_vars$floor_count)
```

```
##
##   1   2   3   4   5   6   7   8   9  10  11  12  13  14  16  19  21  26
## 109  67  33  37  25  25  14  19   8   4   5   2   2   1   1   1   1   1
```

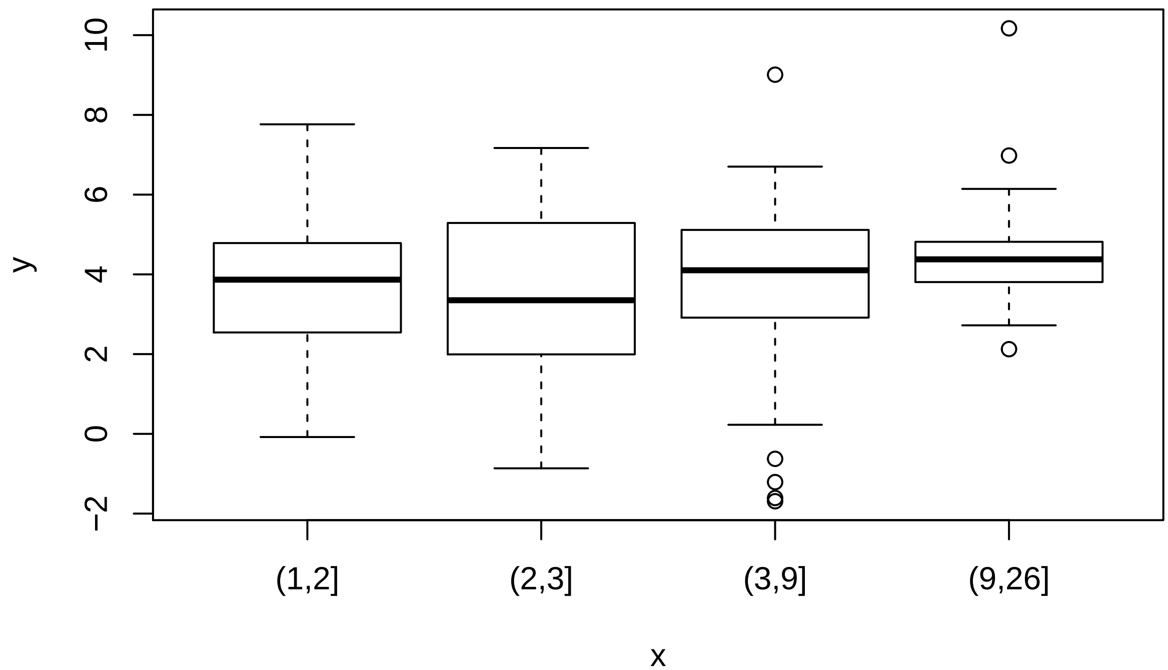
High number of 1 storey buildings. Lets cut this into a factor with 1 storey, 2 storey, 3 to 9 storey and more than 9 storey buildings. That looks like a natural grouping to me looking at the histogram.

```r
cut_storey <- cut(building_vars$floor_count, breaks = c(1, 2, 3, 9, 26))

summary(cut_storey)
```

```
##  (1,2]  (2,3]  (3,9] (9,26]   NA's
##     67     33    128     18   1203
```

```r
cut_storey <- as.factor(cut_storey)
plot(cut_storey, meter_log)
```



Not much of a difference in the medians!

Main conclusion: My EDA does not show any strong relationships between the predictors and the target in this dataset.