# Lab 2: Exploratory Data Analysis and Causal Model Bulding

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```
library(tidyverse)
library(dplyr)
library(lmtest)
library(sandwich)
library(stargazer)
library(magrittr)
library(sandwich)
library(gridExtra)
library(funModeling)
library(cowplot)
library(MASS)
library(ggplot2)
```

## Data

```
fire_raw <- read_csv(file = '../src/data/forestfires.csv')


# add BUI variable
BUI_less <- 0.8*((fire_raw$DMC*fire_raw$DC)/(fire_raw$DMC+(0.4*fire_raw$DC)))
BUI_great <- fire_raw$DMC-(1-((0.8*fire_raw$DC)/(fire_raw$DMC+0.4*fire_raw$DC)))*(0.92+(0.0114*fire_raw$

fire_data <- fire_raw %>%
  mutate(
    BUI = case_when(
      DMC <= 0.4*DC ~ BUI_less,
      DMC > 0.4*DC ~ BUI_great,
    )
  )

# by adding BUI variable, we will remove DMC and DC variables that were used in
# the BUI calculation
fire_data <- fire_data %>%
  dplyr::select(wind, rain, temp, RH, FFMC, BUI, area)
```

```
summary(fire_raw)
```

```
##         X               Y           month                day
```

```
##  Min.   :1.000   Min.   :2.0   Length:517         Length:517
##  1st Qu.:3.000   1st Qu.:4.0   Class :character   Class :character
##  Median :4.000   Median :4.0   Mode  :character   Mode  :character
##  Mean   :4.669   Mean   :4.3
##  3rd Qu.:7.000   3rd Qu.:5.0
##  Max.   :9.000   Max.   :9.0
##       FFMC            DMC              DC             ISI
##  Min.   :18.70   Min.   :  1.1   Min.   :  7.9   Min.   : 0.000
##  1st Qu.:90.20   1st Qu.: 68.6   1st Qu.:437.7   1st Qu.: 6.500
##  Median :91.60   Median :108.3   Median :664.2   Median : 8.400
##  Mean   :90.64   Mean   :110.9   Mean   :547.9   Mean   : 9.022
##  3rd Qu.:92.90   3rd Qu.:142.4   3rd Qu.:713.9   3rd Qu.:10.800
##  Max.   :96.20   Max.   :291.3   Max.   :860.6   Max.   :56.100
##       temp             RH              wind            rain
##  Min.   : 2.20   Min.   : 15.00   Min.   :0.400   Min.   :0.00000
##  1st Qu.:15.50   1st Qu.: 33.00   1st Qu.:2.700   1st Qu.:0.00000
##  Median :19.30   Median : 42.00   Median :4.000   Median :0.00000
##  Mean   :18.89   Mean   : 44.29   Mean   :4.018   Mean   :0.02166
##  3rd Qu.:22.80   3rd Qu.: 53.00   3rd Qu.:4.900   3rd Qu.:0.00000
##  Max.   :33.30   Max.   :100.00   Max.   :9.400   Max.   :6.40000
##       area
##  Min.   :   0.00
##  1st Qu.:   0.00
##  Median :   0.52
##  Mean   :  12.85
##  3rd Qu.:   6.57
##  Max.   :1090.84
```

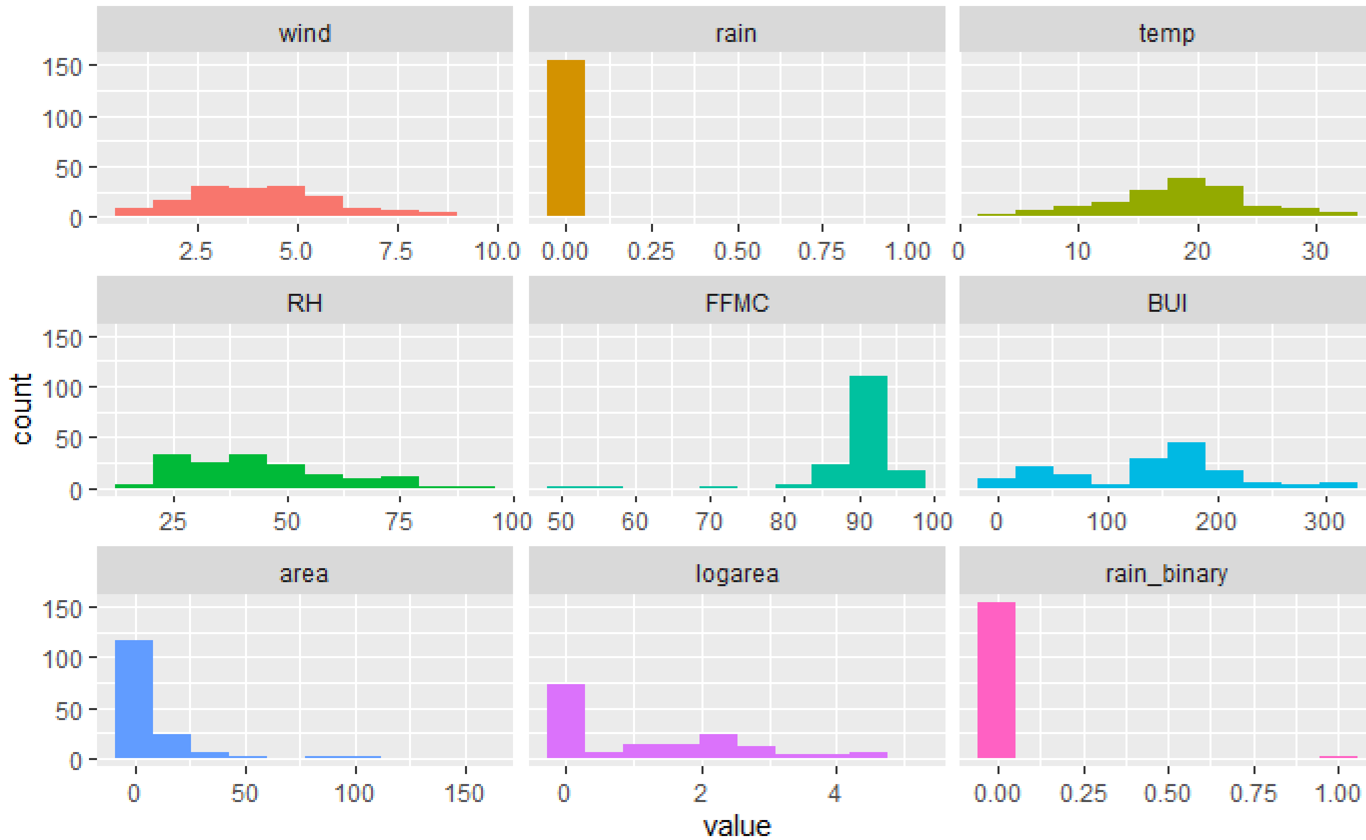
```r
# Split the data into training and testing sets
# We split the data into an EDA and a Prod dataset because we had a large enough dataset.
# We kept 30% data for EDA set and 70% for the Prod dataset.

sample_size = floor(0.7*nrow(fire_data))
set.seed(777)

# randomly split data in r
picked = sample(seq_len(nrow(fire_data)),size = sample_size)
Prod = fire_data[picked,]
EDA = fire_data[-picked,]
```

```r
describe(EDA)
```

```
## EDA
##
##  7  Variables      156  Observations
## --------------------------------------------------------------------------------
## wind
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      156        0       19    0.992    4.153    1.994      1.3      2.2
##      .25      .50      .75      .90      .95
##      2.7      4.0      5.4      6.3      7.6
##
## lowest : 0.9 1.3 1.8 2.2 2.7, highest: 7.2 7.6 8.0 8.5 9.4
```

```
##
## Value        0.9   1.3   1.8   2.2   2.7   3.1   3.6   4.0   4.5   4.9   5.4
## Frequency      6     3     4    12    20    11    12    16    15    15    16
## Proportion 0.038 0.019 0.026 0.077 0.128 0.071 0.077 0.103 0.096 0.096 0.103
##
## Value        5.8   6.3   6.7   7.2   7.6   8.0   8.5   9.4
## Frequency      5     8     1     2     4     1     4     1
## Proportion 0.032 0.051 0.006 0.013 0.026 0.006 0.026 0.006
## ---------------------------------------------------------------------------
## rain
##        n  missing distinct     Info     Mean      Gmd
##      156        0        3    0.038  0.01154  0.02294
##
## Value        0.0   0.8   1.0
## Frequency    154     1     1
## Proportion 0.987 0.006 0.006
## ---------------------------------------------------------------------------
## temp
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      156        0      106        1    18.55     6.96     6.40    10.40
##      .25      .50      .75      .90      .95
##    14.70    19.10    21.95    26.30    29.07
##
## lowest :  4.6  4.8  5.1  5.3  5.5, highest: 30.8 31.0 32.3 33.1 33.3
## ---------------------------------------------------------------------------
## RH
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      156        0       54    0.999    43.62    18.25    23.50    25.00
##      .25      .50      .75      .90      .95
##    30.75    41.50    53.25    66.00    75.00
##
## lowest : 15 19 21 22 24, highest: 77 78 79 82 90
## ---------------------------------------------------------------------------
## FFMC
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      156        0       67    0.999    90.52    4.331    84.18    86.05
##      .25      .50      .75      .90      .95
##    90.20    91.60    93.03    94.55    95.12
##
## lowest : 50.4 53.4 69.0 79.5 81.9, highest: 95.1 95.2 95.9 96.0 96.1
## ---------------------------------------------------------------------------
## BUI
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      156        0      112        1    139.4    85.33    15.02    27.23
##      .25      .50      .75      .90      .95
##    75.41   152.71   184.21   216.30   264.95
##
## lowest :   3.077922   3.460465   3.709973   4.533333   8.297248
## highest: 272.394414 294.624433 300.788508 311.260078 313.911283
## ---------------------------------------------------------------------------
## area
##        n  missing distinct     Info     Mean      Gmd      .05      .10
##      156        0       83    0.906    9.624    15.54    0.000    0.000
##      .25      .50      .75      .90      .95
```

```
##    0.000    1.225    8.613   25.180   47.368
##
## lowest :   0.00   0.21   0.24   0.47   1.01, highest:  86.45  88.49  95.18 103.39 154.88
## ---------------------------------------------------------------------------------
```




## Analysis of Outcome Variable : area

Area is very important for our study because it is our outcome variable. We want to find out what factors cause area to burn in forest fires. From the graph above, area seems to have a heavy left tail. We should use log transformation on area field to see if it helps improve a linear relationship with our predictor variables.

```
## Total observations in the dataset:  156
```

```
##
## Number of Observations where area is zero: 71
```

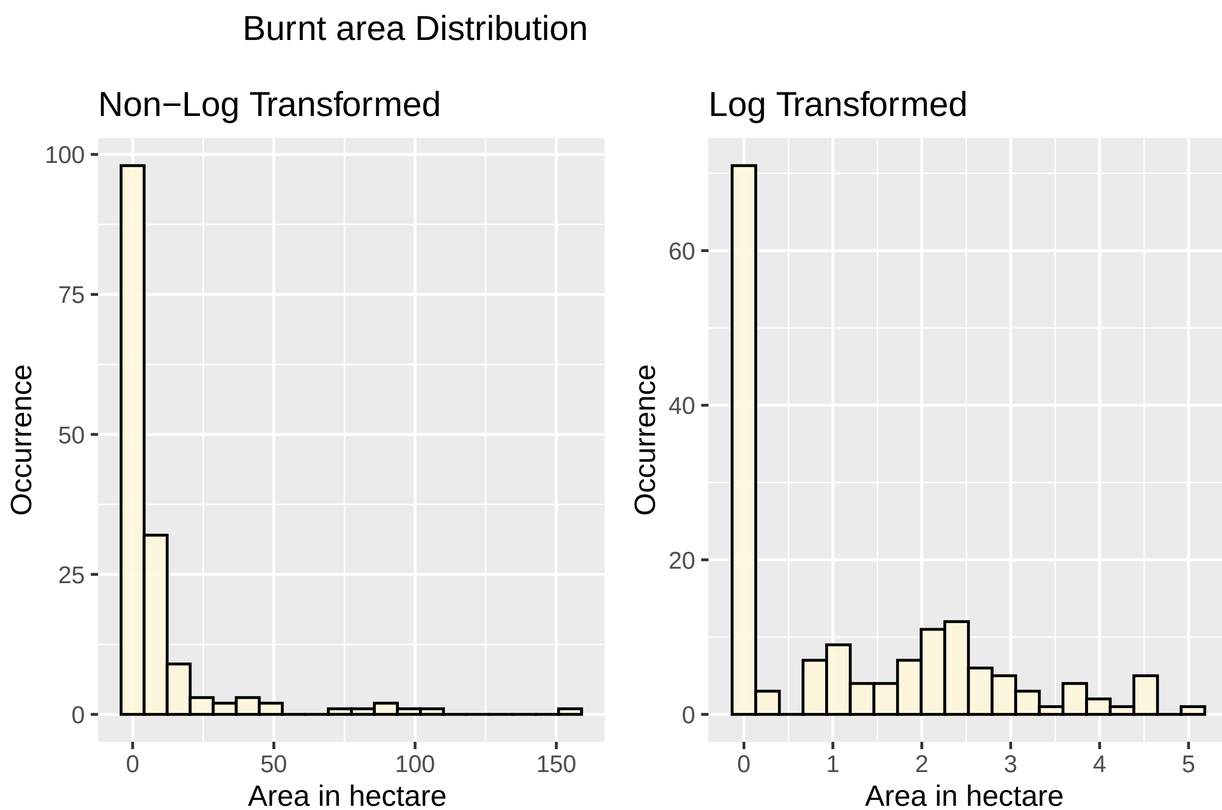



Figure 1

Figure 2

## Observation:

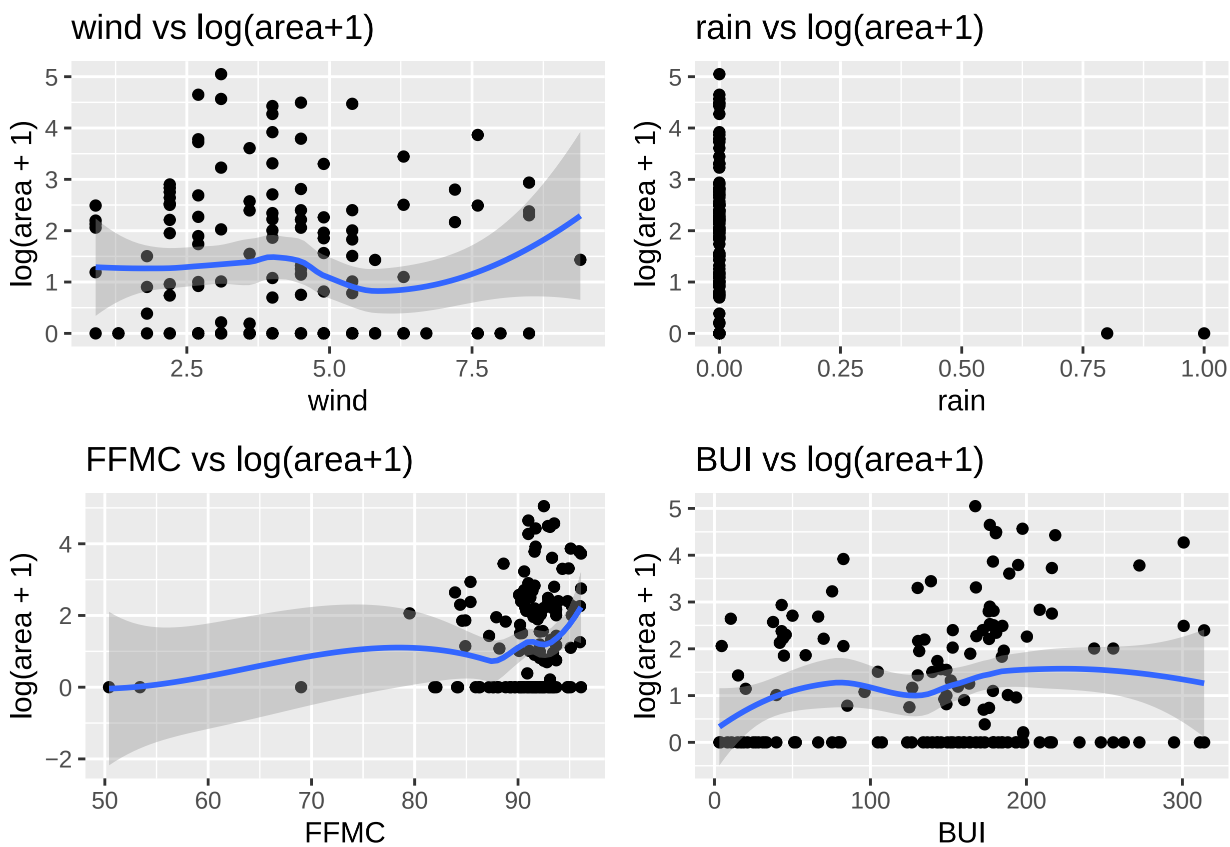
The graphs above has a very heavy right tail and log transformation helped improve the distribution to look more normal. However, it is still skewed right.

## Analyzing of Linear Relationship of Predictors Variables with Outcome

In our causal diagram we have identified four predictor variables 1. rain - outside rain in mm/m2 : 0.0 to 6.4 2. wind - wind speed in km/h: 0.40 to 9.40 3. FFMC - FFMC index from the FWI system: 18.7 to 96.20 4. BUI - potential heat release in heavier fuels (total amount of fuel available for combustion): 0.0 to infinity

```
a <- ggplot(EDA, aes(x = wind, y = log(area+1))) +
  geom_point() +
  geom_smooth() +
  ggtitle("wind vs log(area+1)")

b <- ggplot(EDA, aes(x = rain, y = log(area+1))) +
  geom_point() +
  geom_smooth() +
  ggtitle("rain vs log(area+1)")
```

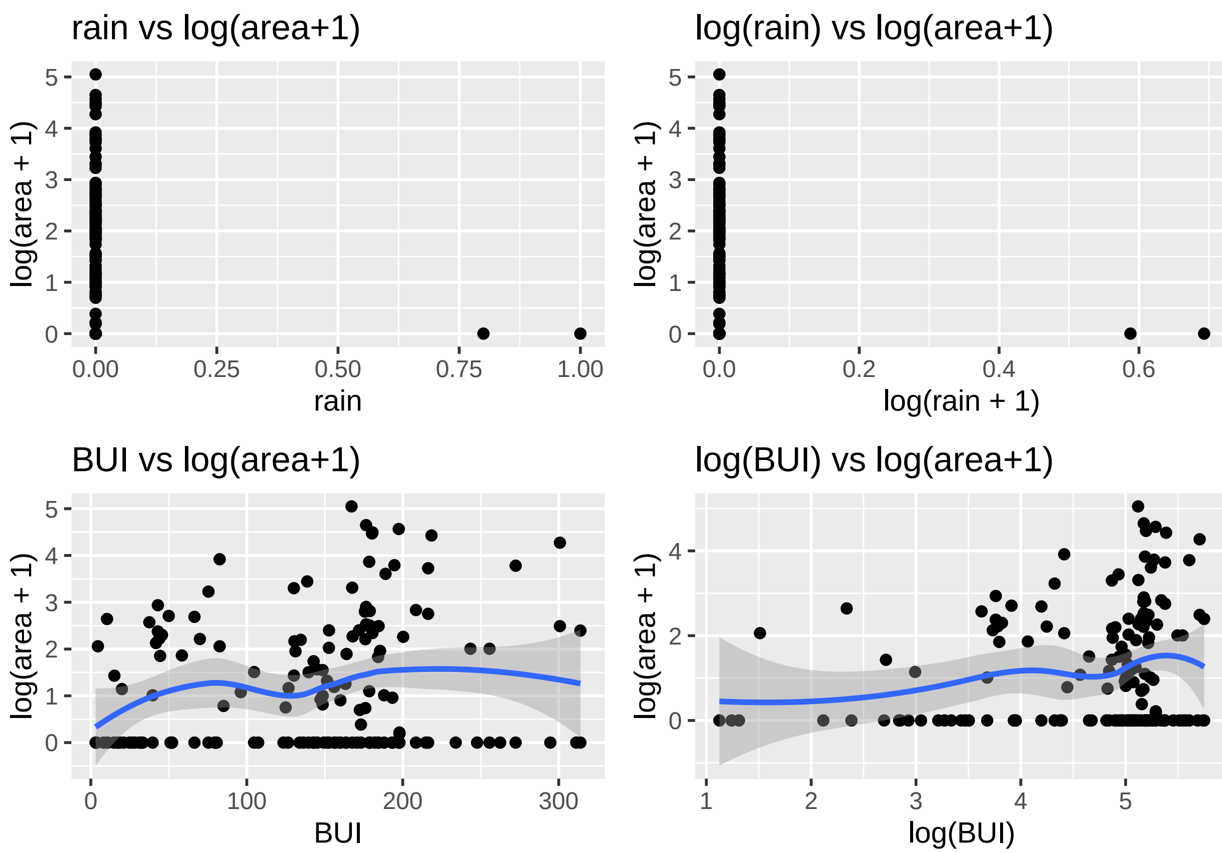
```r
c <- ggplot(EDA, aes(x = FFMC, y = log(area+1))) +
  geom_point() +
  geom_smooth() +
  ggtitle("FFMC vs log(area+1)")

d <- ggplot(EDA, aes(x = BUI, y = log(area+1))) +
  geom_point() +
  geom_smooth() +
  ggtitle("BUI vs log(area+1)")

grid.arrange(a, b, c, d, nrow = 2)
```




# Observation: Rain and BUI variables have room for improvement. Will try log transforms to see if it helps improve linearity.

```r
a <- ggplot(EDA, aes(x = rain, y = log(area+1))) +
  geom_point() +
  geom_smooth() +
  ggtitle("rain vs log(area+1)")

b <- ggplot(EDA, aes(x = log(rain+1), y = log(area+1))) +
  geom_point() +
  geom_smooth() +
  ggtitle("log(rain) vs log(area+1)")

c <- ggplot(EDA, aes(x = BUI, y = log(area+1))) +
```

```
  geom_point() +
  geom_smooth() +
  ggtitle("BUI vs log(area+1)")

d <- ggplot(EDA, aes(x = log(BUI), y = log(area+1))) +
  geom_point() +
  geom_smooth() +
  ggtitle("log(BUI) vs log(area+1)")

grid.arrange(a, b, c, d, nrow = 2)
```




## Conclusion rain predictor did not benefit from a log transform. However, log(BUI) seems to have slightly improved linear relationship with log(area+1).

## Analysis of rain

```
# all transformations failed to improve the plot of rain and log(area+1)/
# so, we will convert our rain variable to binary, is not raining (0) or is raining (1).

Prod <- Prod %>%
  mutate(
    rain_binary = case_when(
      rain > 0 ~ 1,
```

```
      rain == 0 ~ 0,
      )
  )

EDA <- EDA %>%
  mutate(
    rain_binary = case_when(
      rain > 0 ~ 1,
      rain == 0 ~ 0,
      )
  )
```

## Observation: wind and FFMC

```
hist_of_wind_dist <- EDA %>%
ggplot() + aes(x = wind ) +
geom_histogram( bins=20, fill="#C8E6C9", color="black", alpha=0.9) +
labs(
x = "wind speed in km/h", y="Occurrence",
subtitle = 'Wind occurrence',
caption = "Figure 5"
)


hist_of_BUI_dist <- EDA %>%
ggplot() + aes(x = log(BUI) ) +
geom_histogram( bins=20, fill="#D1C4E9", color="black", alpha=0.9) +
labs(
x = "log(BUI)", y="Occurrence",
subtitle = 'log of Build Up Index',
caption = "Figure 6"
)
hist_of_FFMC_dist <- EDA %>%
ggplot() + aes(x = FFMC ) +
geom_histogram( bins=20, fill="#FFCCBC", color="black", alpha=0.9) +
labs(
x = "FFMC code", y="Occurrence",
subtitle = 'Fine Fuel Moisture Code',
caption = "Figure 3"
)
hist_of_logFFMC_dist <- EDA %>%
ggplot() + aes(x = log(FFMC) ) +
geom_histogram( bins=20, fill="#FFCCBC", color="black", alpha=0.9) +
labs(
x = "log(FFMC code)", y="Occurrence",
subtitle = 'log of Fine Fuel Moisture Code',
caption = "Figure 4"
)
par(mfrow=c(2, 2))

plot_grid(hist_of_FFMC_dist, hist_of_logFFMC_dist, hist_of_wind_dist, hist_of_BUI_dist)
```

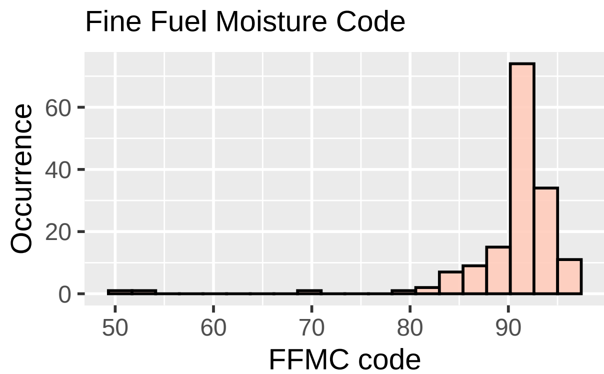



Figure 3

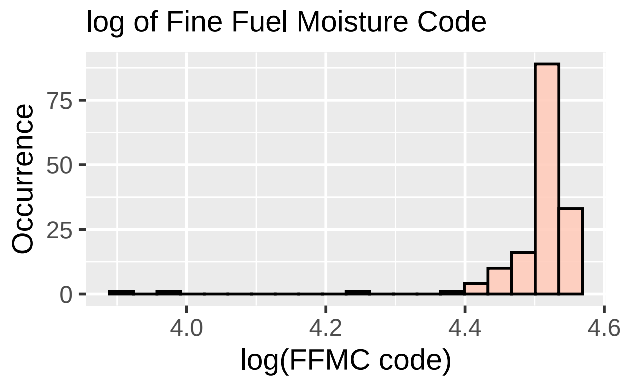



Figure 4

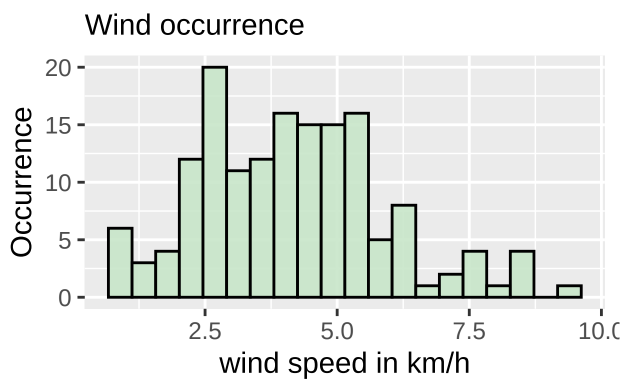



Figure 5

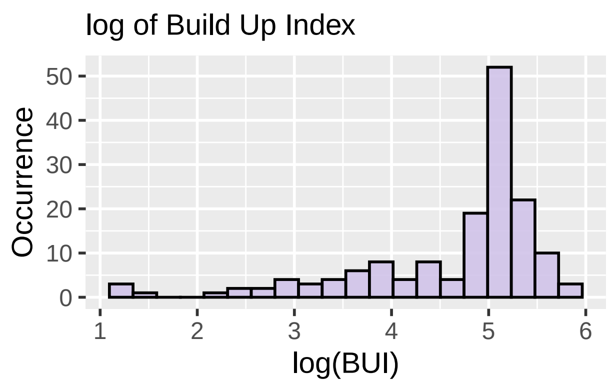



Figure 6

## Building Our Linear Models

```
# our primary model used to answer our Research Question
model1 <- lm(log(area+1) ~ log(BUI) , data = Prod)
coeftest(model1, vcov=vcovHAC)
```

```
##
## t test of coefficients:
##
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 0.946883   0.394191  2.4021  0.01681 *
## log(BUI)    0.024429   0.082624  0.2957  0.76766
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# a model that uses all available variables
model2 <- lm(log(area+1) ~ log(BUI) + wind + rain_binary + FFMC, data = Prod)
coeftest(model2, vcov=vcovHAC)
```

```
##
## t test of coefficients:
##
```

```
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.9629663  1.0575243  0.9106   0.3631
## log(BUI)     0.0954846  0.1002442  0.9525   0.3415
## wind         0.0961630  0.0402457  2.3894   0.0174 *
## rain_binary -0.6367068  0.4003307 -1.5905   0.1126
## FFMC        -0.0079667  0.0139260 -0.5721   0.5676
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# a model that uses only the direct atmospheric metrics
model3 <- lm(log(area+1) ~ wind , data = Prod)
coeftest(model3, vcov=vcovHAC)
```

```
##
## t test of coefficients:
##
##              Estimate Std. Error t value  Pr(>|t|)
## (Intercept) 0.735300   0.174045  4.2248 3.036e-05 ***
## wind        0.082652   0.039619  2.0862   0.03767 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# while you are writing you code, you can use `type = 'text'` to print to the console
stargazer(
  model1,
  model2,
  model3,
  type = 'text', header = FALSE,
  star.cutoffs = c(0.05, 0.01, 0.001) # the default isn't in line with w203
)
```

```
##
## ================================================================================
##                                         Dependent variable:
##                     ------------------------------------------------------------
##                                            log(area + 1)
##                             (1)                 (2)                 (3)
## --------------------------------------------------------------------------------
## log(BUI)                   0.024               0.095
##                           (0.087)             (0.105)
##
## wind                                          0.096*              0.083*
##                                               (0.042)             (0.041)
##
## rain_binary                                   -0.637
##                                               (0.581)
##
## FFMC                                          -0.008
##                                               (0.016)
##
## Constant                  0.947*               0.963             0.735***
##                           (0.416)             (1.267)             (0.178)
##
```

```
## ------------------------------------------------------------------------------
## Observations                   361                 361                 361
## R2                            0.0002              0.017               0.011
## Adjusted R2                   -0.003              0.006               0.008
## Residual Std. Error  1.402 (df = 359)    1.396 (df = 356)     1.394 (df = 359)
## F Statistic         0.080 (df = 1; 359) 1.509 (df = 4; 356) 4.083* (df = 1; 359)
## ==============================================================================
## Note:                                              *p<0.05; **p<0.01; ***p<0.001
```

```
anova(model1, model2, model3, test="F")
```

```
## Analysis of Variance Table
##
## Model 1: log(area + 1) ~ log(BUI)
## Model 2: log(area + 1) ~ log(BUI) + wind + rain_binary + FFMC
## Model 3: log(area + 1) ~ wind
##   Res.Df    RSS Df Sum of Sq      F Pr(>F)
## 1    359 705.79
## 2    356 694.18  3   11.6138 1.9853 0.1158
## 3    359 698.01 -3   -3.8326 0.6552 0.5802
```