

# Bush-Fire-Analysis.R

2025-04-16

```
setwd("C:/H/W/Data science/New folder")
#Loading the data set
BFdata = read.csv("BushFireData.csv")
attach(BFdata)
#Data overview
head(BFdata)
```

	ClaimID	Fire_Intensity	Distance_from_Fire	Building_Age	Property_Value
## 1	DQTA26862	5738.5	5.57	19	9.76
## 2	RDAQ32534	12247.9	5.49	27	5.89
## 3	WTLA41817	7316.6	5.12	16	3.98
## 4	YHZL16317	13479.2	4.89	30	4.91
## 5	LUKH77472	14226.0	6.13	21	9.31
## 6	YBOA62820	2592.2	7.66	27	6.41

	Population_Density	Emergency_Response_Time	Mitigation_Measures
## 1	520	16	3
## 2	433	18	3
## 3	634	17	4
## 4	576	14	2
## 5	644	12	2
## 6	476	10	1

	Construction_Quality	Insurance_Coverage	Wind_Speed	Humidity
## 1	Good	Fully	24.9	35.32
## 2	Good	None	21.0	28.24
## 3	Good	Partially	25.3	44.51
## 4	Good	Partially	22.3	53.77
## 5	Good	None	37.2	73.79
## 6	Good	Fully	31.8	50.89

```
Damage_Claims
## 1
7.02
## 2
7.45
## 3
4.30
## 4
7.78
## 5
9.46
## 6
4.54

dim(BFdata)

## [1] 600 13

sum(is.na(BFdata))

## [1] 0
```

### #Explore data structure

str(BFdata)

```
## 'data.frame':    600 obs. of  13 variables:
## $ ClaimID          : chr  "DQTA26862" "RDAQ32534" "WTLA41817"
## "YHZL16317" ...
## $ Fire_Intensity    : num  5738 12248 7317 13479 14226 ...
## $ Distance_from_Fire : num  5.57 5.49 5.12 4.89 6.13 ...
## $ Building_Age      : int   19 27 16 30 21 27 24 24 36 30 ...
## $ Property_Value    : num   9.76 5.89 3.98 4.91 9.31 ...
## $ Population_Density : int   520 433 634 576 644 476 500 591 487 441
## ...
## $ Emergency_Response_Time: int   16 18 17 14 12 10 16 19 15 18 ...
## $ Mitigation_Measures  : int    3 3 4 2 2 1 5 7 2 3 ...
## $ Construction_Quality : chr   "Good" "Good" "Good" "Good" ...
## $ Insurance_Coverage   : chr   "Fully" "None" "Partially" "Partially"
## ...
## $ Wind_Speed          : num   24.9 21 25.3 22.3 37.2 31.8 27.8 22.5
## 32.2 20.6 ...
## $ Humidity            : num   35.3 28.2 44.5 53.8 73.8 ...
## $ Damage_Claims       : num    7.02 7.45 4.3 7.78 9.46 4.54 7.14 7.73
## 6.03 5.37 ...
```

summary(BFdata)

```
##      ClaimID      Fire_Intensity Distance_from_Fire Building_Age
## Length:600      Min.   : 2006      Min.   : 1.380      Min.   :12.00
## Class :character 1st Qu.: 5379      1st Qu.: 5.710      1st Qu.:21.00
## Mode  :character Median : 8272      Median : 7.090      Median :25.00
##                Mean  : 8490      Mean  : 7.026      Mean  :24.88
##                3rd Qu.:11708      3rd Qu.: 8.410      3rd Qu.:28.00
##                Max.   :14992      Max.   :12.380      Max.   :42.00
## Property_Value Population_Density Emergency_Response_Time
## Min.   : 2.800      Min.   :372.0      Min.   : 2.00
## 1st Qu.: 5.737      1st Qu.:546.0      1st Qu.:13.00
## Median : 6.920      Median :597.5      Median :15.00
## Mean   : 7.278      Mean   :598.3      Mean   :14.97
## 3rd Qu.: 8.590      3rd Qu.:652.2      3rd Qu.:18.00
## Max.   :16.290      Max.   :842.0      Max.   :29.00
## Mitigation_Measures Construction_Quality Insurance_Coverage Wind_Speed
## Min.   :0.000      Length:600      Length:600      Min.   :10.00
## 1st Qu.:2.000      Class :character Class :character 1st Qu.:21.40
## Median :3.000      Mode  :character Mode  :character Median :24.95
## Mean   :2.978                                     Mean   :24.99
## 3rd Qu.:4.000                                     3rd Qu.:28.52
## Max.   :9.000                                     Max.   :39.50
## Humidity Damage_Claims
## Min.   : 5.46      Min.   : 0.100
## 1st Qu.:35.54      1st Qu.: 4.978
## Median :49.20      Median : 6.180
```

```

## Mean :49.77 Mean : 6.250
## 3rd Qu.:63.83 3rd Qu.: 7.362
## Max. :98.63 Max. :12.370

#Encoding construction quality Good and Bad to 1 and 0
BFdata$Construction_Quality = ifelse(BFdata$Construction_Quality ==
"Good",1,0)

#Encoding insurance coverage: 0 for none, 1 for partially and 2 for fully
IC_factor = factor(BFdata$Insurance_Coverage, levels = c("None", "Partially",
"Fully"))
BFdata$Insurance_Coverage = as.integer(IC_factor) - 1

#Divide 50% of the dataset into training and 50% for testing and remove
excess variable
set.seed(2)
tr.id = sample(1:nrow(BFdata),nrow(BFdata)/2)
training = BFdata[tr.id,]
training = training[,-1]
test = BFdata[-tr.id,]
test = test[,-1]
str(training)

## 'data.frame': 300 obs. of 12 variables:
## $ Fire_Intensity : num 4496 5852 2937 4980 8695 ...
## $ Distance_from_Fire : num 9.25 9.37 5.44 8.48 8.5 7.76 6.75 4.92
5.68 3.62 ...
## $ Building_Age : int 24 17 21 24 20 18 28 26 23 35 ...
## $ Property_Value : num 7.51 7.27 7.46 7.53 5.22 ...
## $ Population_Density : int 611 732 623 773 564 640 410 414 544 560
...
## $ Emergency_Response_Time: int 14 11 12 16 16 15 9 21 17 16 ...
## $ Mitigation_Measures : int 5 2 1 4 1 2 3 2 4 1 ...
## $ Construction_Quality : num 1 1 1 1 1 1 1 1 1 0 ...
## $ Insurance_Coverage : num 2 2 2 2 2 2 2 1 1 0 ...
## $ Wind_Speed : num 32 31.7 25.8 21.3 21.4 25.6 30.4 24.3
27.4 29.1 ...
## $ Humidity : num 60.9 32.9 44.1 49.4 64.8 ...
## $ Damage_Claims : num 4.57 4.53 6.8 6.65 2.39 5.5 7.63 7.89
5.14 9.18 ...

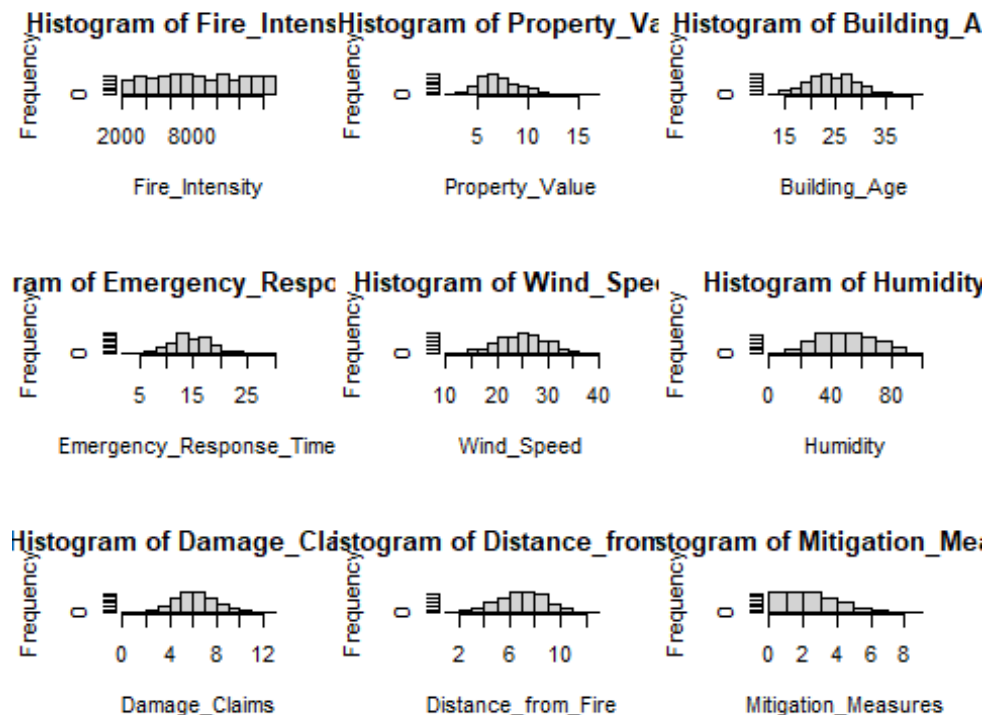
str(test)

## 'data.frame': 300 obs. of 12 variables:
## $ Fire_Intensity : num 12248 7317 14226 7936 14439 ...
## $ Distance_from_Fire : num 5.49 5.12 6.13 11.08 9.6 ...
## $ Building_Age : int 27 16 21 30 32 22 28 31 24 25 ...
## $ Property_Value : num 5.89 3.98 9.31 8.49 5.47 5.46 9.13 3.91
7.01 8.3 ...
## $ Population_Density : int 433 634 644 441 663 518 509 625 530 538
...
```

```
## $ Emergency_Response_Time: int 18 17 12 18 24 13 12 18 16 12 ...
## $ Mitigation_Measures      : int 3 4 2 3 2 5 5 3 0 3 ...
## $ Construction_Quality    : num 1 1 1 1 0 1 0 1 1 1 ...
## $ Insurance_Coverage       : num 0 1 0 1 1 1 1 1 1 0 ...
## $ Wind_Speed               : num 21 25.3 37.2 20.6 36.5 10 37.7 24.6 26.4
25.5 ...
## $ Humidity                 : num 28.2 44.5 73.8 76 61.1 ...
## $ Damage_Claims           : num 7.45 4.3 9.46 5.37 5.42 6.55 5.86 4.02
5.43 7.34 ...
```

*#Build histogram to explore the distribution of property value as well as building age*

```
par(mfrow = c(3,3))
hist(Fire_Intensity)
hist(Property_Value)
hist(Building_Age)
hist(Emergency_Response_Time)
hist(Wind_Speed)
hist(Humidity)
hist(Damage_Claims)
hist(Distance_from_Fire)
hist(Mitigation_Measures)
```



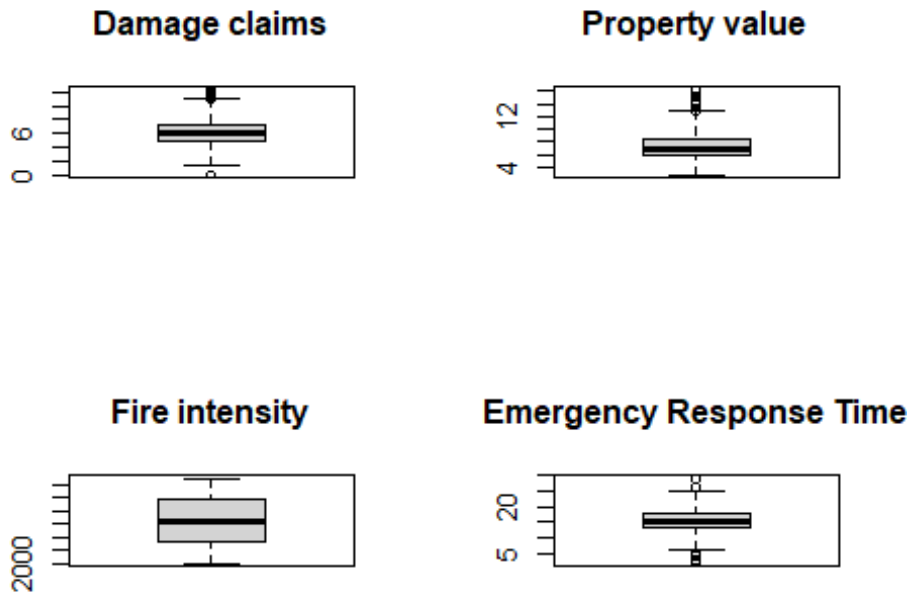
*#Build box-plot to detect outliers and summarising the distribution of the data set*

```
par(mfrow = c(2,2))
boxplot(Damage_Claims, main = "Damage claims")
```

```

boxplot(Property_Value, main = "Property value")
boxplot(Fire_Intensity, main = "Fire intensity")
boxplot(Emergency_Response_Time, main = "Emergency Response Time")

```



*#Correlation matrix for key numerical variables to explore the relationship between them*

```

cor_matrix =
BFdata[,c("Fire_Intensity", "Distance_from_Fire", "Building_Age", "Property_Valu
e", "Population_Density", "Emergency_Response_Time", "Wind_Speed", "Humidity", "Da
mage_Claims")]
cor(cor_matrix)

```

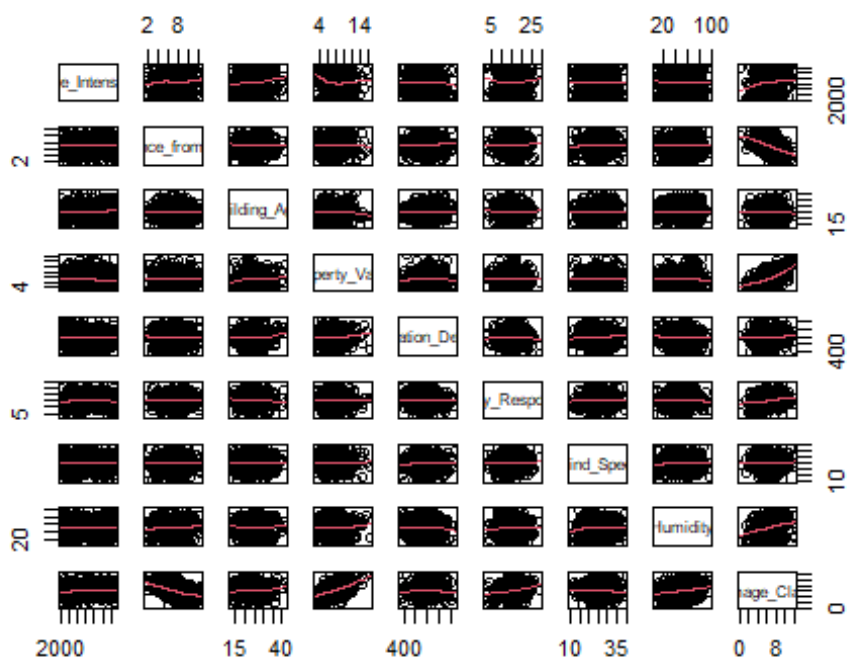
```

##           Fire_Intensity Distance_from_Fire Building_Age
## Fire_Intensity      1.000000000      0.00430711  0.07932316
## Distance_from_Fire  0.004307110      1.00000000 -0.01747107
## Building_Age        0.079323163     -0.01747107  1.00000000
## Property_Value     -0.092373683      0.01046487  0.01011021
## Population_Density  0.005966024      0.03368348 -0.01500278
## Emergency_Response_Time 0.006990306      0.01909041 -0.02546560
## Wind_Speed         -0.026135802      0.04742770 -0.05554963
## Humidity            0.002108686      0.03929606 -0.02762756
## Damage_Claims       0.094694540     -0.51972220  0.03508000
##
##           Property_Value Population_Density
## Fire_Intensity     -0.092373683      0.005966024
## Distance_from_Fire  0.010464875      0.033683480
## Building_Age        0.010110213     -0.015002777
## Property_Value      1.000000000      0.013515053

```

```
## Population_Density      0.013515053      1.000000000
## Emergency_Response_Time -0.007032240     -0.026580657
## Wind_Speed              0.035542394      0.061671042
## Humidity                -0.008731118     -0.016382216
## Damage_Claims           0.535456227     -0.005300330
##
##           Emergency_Response_Time  Wind_Speed  Humidity
## Fire_Intensity      0.006990306  -0.026135802  0.002108686
## Distance_from_Fire   0.019090406   0.047427705  0.039296064
## Building_Age         -0.025465605  -0.055549633 -0.027627558
## Property_Value       -0.007032240   0.035542394 -0.008731118
## Population_Density   -0.026580657   0.061671042 -0.016382216
## Emergency_Response_Time 1.000000000  -0.000547797  0.019014280
## Wind_Speed           -0.000547797   1.000000000  0.042964276
## Humidity              0.019014280   0.042964276  1.000000000
## Damage_Claims         0.204320762  -0.029321620  0.264199332
##
##           Damage_Claims
## Fire_Intensity      0.09469454
## Distance_from_Fire  -0.51972220
## Building_Age        0.03508000
## Property_Value       0.53545623
## Population_Density  -0.00530033
## Emergency_Response_Time 0.20432076
## Wind_Speed          -0.02932162
## Humidity             0.26419933
## Damage_Claims       1.00000000
```

```
pairs(cor_matrix, panel = panel.smooth)
```



```
#Build multiple linear regression
```

```
m1 = lm(Damage_Claims~.,data = training)
```

```
summary(m1)
```

```
##
```

```
## Call:
```

```
## lm(formula = Damage_Claims ~ ., data = training)
```

```
##
```

```
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max  
## -2.95324 -0.72569  0.01252  0.72947  2.73626
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)  
## (Intercept)    2.270e+00  8.074e-01   2.811  0.00527 **  
## Fire_Intensity  9.220e-05  1.657e-05   5.564 6.04e-08 ***  
## Distance_from_Fire -5.117e-01  3.155e-02 -16.221 < 2e-16 ***  
## Building_Age    -7.918e-03  1.221e-02  -0.648  0.51721  
## Property_Value   5.032e-01  2.856e-02  17.617 < 2e-16 ***  
## Population_Density 5.097e-04  7.512e-04   0.679  0.49800  
## Emergency_Response_Time 1.019e-01  1.499e-02   6.800 6.05e-11 ***  
## Mitigation_Measures 1.062e-01  3.705e-02   2.865  0.00448 **  
## Construction_Quality -2.450e-01  1.600e-01  -1.532  0.12672  
## Insurance_Coverage  1.417e-02  8.610e-02   0.165  0.86940  
## Wind_Speed      -9.135e-03  1.211e-02  -0.754  0.45128  
## Humidity         3.124e-02  3.333e-03   9.374 < 2e-16 ***
```

```
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
```

```
## Residual standard error: 1.027 on 288 degrees of freedom
```

```
## Multiple R-squared:  0.7214, Adjusted R-squared:  0.7108
```

```
## F-statistic: 67.8 on 11 and 288 DF, p-value: < 2.2e-16
```

```
#New model with only significant variables
```

```
m2 = lm(Damage_Claims~Fire_Intensity + Distance_from_Fire + Property_Value +  
Emergency_Response_Time + Mitigation_Measures + Humidity, data = training)
```

```
summary(m2)
```

```
##
```

```
## Call:
```

```
## lm(formula = Damage_Claims ~ Fire_Intensity + Distance_from_Fire +  
##      Property_Value + Emergency_Response_Time + Mitigation_Measures +  
##      Humidity, data = training)
```

```
##
```

```
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max  
## -2.64443 -0.66589  0.00145  0.68283  2.68320
```

```
##
```

```
## Coefficients:
```

```
##              Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)          1.940e+00  4.560e-01  4.256 2.81e-05 ***
## Fire_Intensity       9.092e-05  1.632e-05  5.569 5.78e-08 ***
## Distance_from_Fire   -5.074e-01  3.095e-02 -16.394 < 2e-16 ***
## Property_Value       5.038e-01  2.846e-02  17.701 < 2e-16 ***
## Emergency_Response_Time 9.911e-02  1.478e-02  6.707 1.02e-10 ***
## Mitigation_Measures  1.138e-01  3.659e-02  3.109 0.00206 **
## Humidity             3.159e-02  3.310e-03  9.542 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.026 on 293 degrees of freedom
## Multiple R-squared:  0.7172, Adjusted R-squared:  0.7114
## F-statistic: 123.8 on 6 and 293 DF,  p-value: < 2.2e-16
```

**anova(m2)**

```
## Analysis of Variance Table
##
## Response: Damage_Claims
##              Df Sum Sq Mean Sq F value    Pr(>F)
## Fire_Intensity    1  14.579   14.579   13.846 0.0002379 ***
## Distance_from_Fire  1 296.739  296.739  281.802 < 2.2e-16 ***
## Property_Value     1 308.056  308.056  292.550 < 2.2e-16 ***
## Emergency_Response_Time 1  52.895   52.895   50.233 1.022e-11 ***
## Mitigation_Measures  1  14.143   14.143   13.431 0.0002938 ***
## Humidity           1  95.881   95.881   91.055 < 2.2e-16 ***
## Residuals         293 308.530    1.053
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

*#Checking correlation between pairs of variable*

```
newdata = BFdata[, -1]
cor(training)
```

```
##              Fire_Intensity Distance_from_Fire Building_Age
## Fire_Intensity      1.00000000      -0.035130436  0.1485138507
## Distance_from_Fire  -0.03513044       1.000000000 -0.0161134463
## Building_Age         0.14851385      -0.016113446  1.0000000000
## Property_Value      -0.17214426      -0.023820894 -0.0171452193
## Population_Density  -0.02538997       0.086787272 -0.0692060492
## Emergency_Response_Time 0.05863044       0.044657527 -0.0009148271
## Mitigation_Measures  0.01526527      -0.026643380 -0.0479332316
## Construction_Quality -0.03832640      -0.046775779 -0.0463700387
## Insurance_Coverage  -0.06565339       0.137742116 -0.0555359597
## Wind_Speed          0.03641542       0.055297007 -0.0792001844
## Humidity            0.01384675      -0.006683554 -0.0584046267
## Damage_Claims       0.11560952      -0.525306240 -0.0147362895
##
##              Property_Value Population_Density
## Fire_Intensity      -0.17214426      -0.025389972
## Distance_from_Fire  -0.02382089       0.086787272
## Building_Age        -0.01714522      -0.069206049
```



## Property_Value	1.00000000	0.025901702
## Population_Density	0.02590170	1.000000000
## Emergency_Response_Time	-0.04334720	-0.087718406
## Mitigation_Measures	0.02048197	0.063686144
## Construction_Quality	0.01549979	-0.102322819
## Insurance_Coverage	0.07181407	0.038976909
## Wind_Speed	-0.02831214	0.003703872
## Humidity	-0.05192790	-0.018956106
## Damage_Claims	0.51893206	-0.025465268
##	Emergency_Response_Time	Mitigation_Measures
## Fire_Intensity	0.0586304446	0.01526527
## Distance_from_Fire	0.0446575271	-0.02664338
## Building_Age	-0.0009148271	-0.04793323
## Property_Value	-0.0433472014	0.02048197
## Population_Density	-0.0877184057	0.06368614
## Emergency_Response_Time	1.0000000000	-0.06621487
## Mitigation_Measures	-0.0662148722	1.00000000
## Construction_Quality	0.0943203397	-0.05027369
## Insurance_Coverage	-0.0702711129	-0.05920259
## Wind_Speed	-0.0281850915	-0.09958924
## Humidity	0.0601163065	0.05264768
## Damage_Claims	0.1846742970	0.12658484
##	Construction_Quality	Insurance_Coverage
Wind_Speed		
## Fire_Intensity	-0.03832640	-0.065653389
0.036415422		
## Distance_from_Fire	-0.04677578	0.137742116
0.055297007		
## Building_Age	-0.04637004	-0.055535960 -
0.079200184		
## Property_Value	0.01549979	0.071814067 -
0.028312138		
## Population_Density	-0.10232282	0.038976909
0.003703872		
## Emergency_Response_Time	0.09432034	-0.070271113 -
0.028185092		
## Mitigation_Measures	-0.05027369	-0.059202594 -
0.099589243		
## Construction_Quality	1.00000000	0.023503225
0.144957276		
## Insurance_Coverage	0.02350322	1.000000000 -
0.056819283		
## Wind_Speed	0.14495728	-0.056819283
1.000000000		
## Humidity	-0.06439629	0.002911288
0.034991268		
## Damage_Claims	-0.03088254	-0.054728683 -
0.072401102		
##	Humidity	Damage_Claims
## Fire_Intensity	0.013846751	0.11560952

```
## Distance_from_Fire      -0.006683554   -0.52530624
## Building_Age            -0.058404627   -0.01473629
## Property_Value          -0.051927902    0.51893206
## Population_Density      -0.018956106   -0.02546527
## Emergency_Response_Time  0.060116306    0.18467430
## Mitigation_Measures      0.052647684    0.12658484
## Construction_Quality    -0.064396286   -0.03088254
## Insurance_Coverage       0.002911288   -0.05472868
## Wind_Speed              0.034991268   -0.07240110
## Humidity                 1.000000000    0.29240552
## Damage_Claims           0.292405519    1.00000000
```

### *#Evaluation using MSE*

```
actual = test$Damage_Claims
predict1 = predict(m2,data = test)
MSE1 = mean((predict1-actual)^2)
MSE1
```

```
## [1] 6.479355
```

```
plot(predict1, actual, xlim = c(2,13),ylim = c(2,13))
abline(0,1)
```

### *#Interaction model*

```
m3<-lm(Damage_Claims~(Fire_Intensity+ Distance_from_Fire+ Property_Value+
Emergency_Response_Time+ Mitigation_Measures+ Humidity)^2, data=training)
anova(m3)
```

### *## Analysis of Variance Table*

```
##
## Response: Damage_Claims
##
```

	Df	Sum Sq	Mean Sq	F value
## Fire_Intensity	1	14.579	14.579	13.7251
## Distance_from_Fire	1	296.739	296.739	279.3490
## Property_Value	1	308.056	308.056	290.0031
## Emergency_Response_Time	1	52.895	52.895	49.7954
## Mitigation_Measures	1	14.143	14.143	13.3138
## Humidity	1	95.881	95.881	90.2620
## Fire_Intensity:Distance_from_Fire	1	0.452	0.452	0.4254
## Fire_Intensity:Property_Value	1	0.241	0.241	0.2269
## Fire_Intensity:Emergency_Response_Time	1	0.848	0.848	0.7985
## Fire_Intensity:Mitigation_Measures	1	0.336	0.336	0.3167
## Fire_Intensity:Humidity	1	1.096	1.096	1.0315
## Distance_from_Fire:Property_Value	1	3.600	3.600	3.3888
## Distance_from_Fire:Emergency_Response_Time	1	0.010	0.010	0.0093
## Distance_from_Fire:Mitigation_Measures	1	1.392	1.392	1.3108
## Distance_from_Fire:Humidity	1	0.022	0.022	0.0211
## Property_Value:Emergency_Response_Time	1	0.993	0.993	0.9352
## Property_Value:Mitigation_Measures	1	0.096	0.096	0.0905
## Property_Value:Humidity	1	0.099	0.099	0.0933
## Emergency_Response_Time:Mitigation_Measures	1	1.815	1.815	1.7082



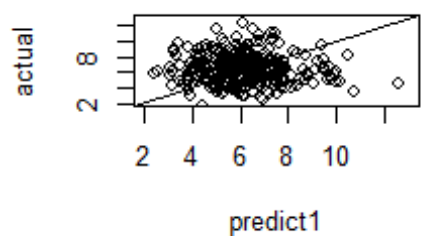
```

***
## poly(Fire_Intensity, 3)1      5.58858      1.07321      5.207 3.71e-07
***
## poly(Fire_Intensity, 3)2      -0.96902      1.06177     -0.913 0.36221
## poly(Fire_Intensity, 3)3      -0.36473      1.05548     -0.346 0.72993
## poly(Distance_from_Fire, 3)1  -16.64112     1.03161    -16.131 < 2e-16
***
## poly(Distance_from_Fire, 3)2      1.99287      1.03862      1.919 0.05603 .
## poly(Distance_from_Fire, 3)3      1.57936      1.04451      1.512 0.13165
## poly(Property_Value, 3)1      18.65842      1.05140     17.746 < 2e-16
***
## poly(Property_Value, 3)2      1.15974      1.04877      1.106 0.26976
## poly(Property_Value, 3)3      1.04355      1.05320      0.991 0.32262
## poly(Emergency_Response_Time, 3)1  6.57656      1.06310      6.186 2.17e-09
***
## poly(Emergency_Response_Time, 3)2  0.67633      1.04246      0.649 0.51701
## poly(Emergency_Response_Time, 3)3  1.93567      1.04969      1.844 0.06623 .
## poly(Mitigation_Measures, 3)1     2.94396      1.03879      2.834 0.00493 **
## poly(Mitigation_Measures, 3)2     -0.97380      1.05124     -0.926 0.35506
## poly(Mitigation_Measures, 3)3     1.02174      1.04661      0.976 0.32979
## poly(Humidity, 3)1              9.85806      1.04517      9.432 < 2e-16
***
## poly(Humidity, 3)2             -0.09953      1.05815     -0.094 0.92513
## poly(Humidity, 3)3              0.75487      1.05334      0.717 0.47419
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.02 on 281 degrees of freedom
## Multiple R-squared:  0.7318, Adjusted R-squared:  0.7147
## F-statistic: 42.61 on 18 and 281 DF,  p-value: < 2.2e-16

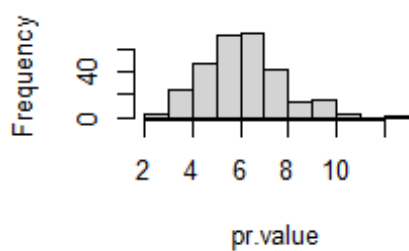
#Evaluation using Multivariate model
pr.value = predict(m2)
hist(pr.value)

par(mfrow = c(2,2))

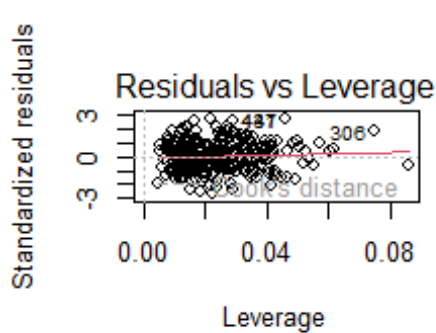
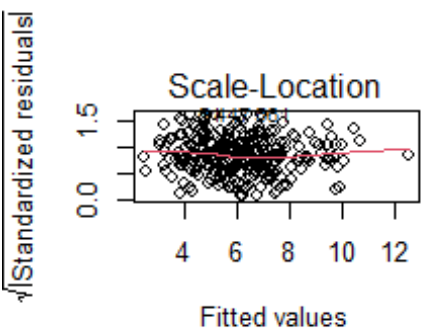
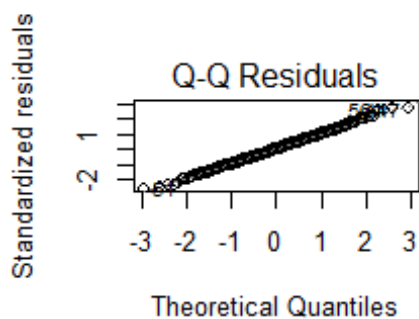
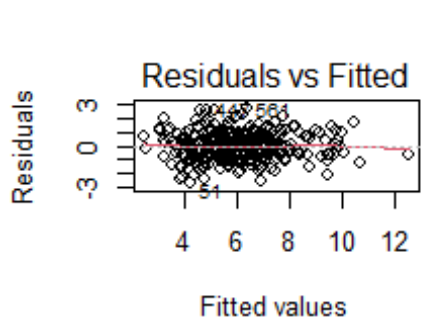
```



**Histogram of pr.value**



```
plot(m2)
```



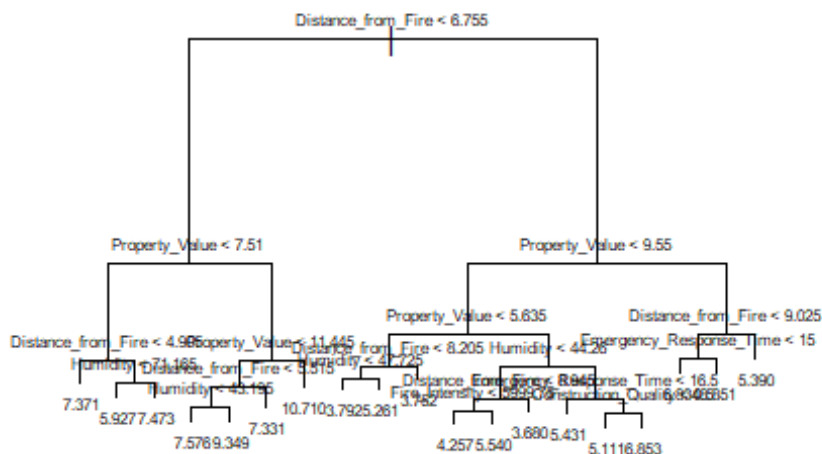
```
library(tree)
```

```
## Warning: package 'tree' was built under R version 4.4.1

#Build the regression tree model
tree = tree(Damage_Claims~.,newdata,subset = tr.id)
summary(tree)

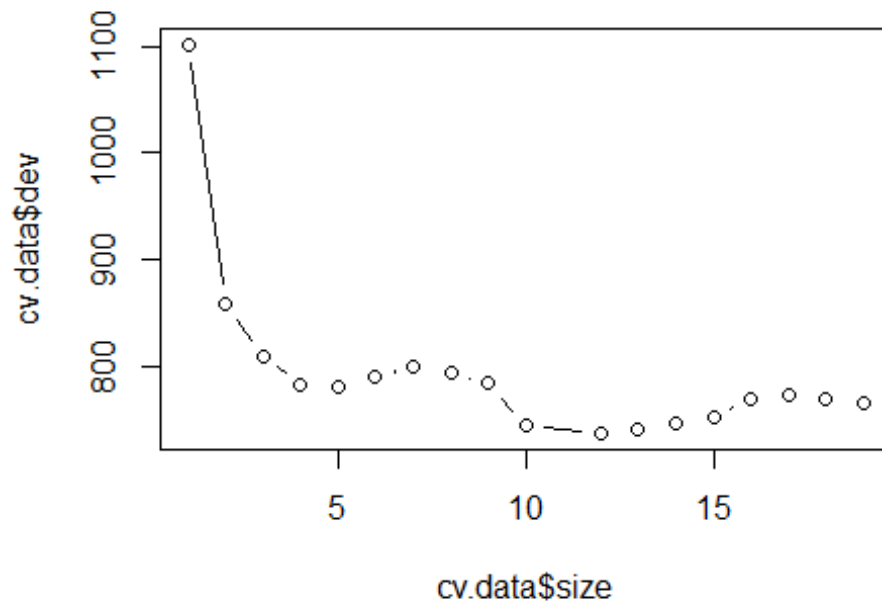
##
## Regression tree:
## tree(formula = Damage_Claims ~ ., data = newdata, subset = tr.id)
## Variables actually used in tree construction:
## [1] "Distance_from_Fire"      "Property_Value"
## [3] "Humidity"                "Fire_Intensity"
## [5] "Emergency_Response_Time" "Construction_Quality"
## Number of terminal nodes: 19
## Residual mean deviance: 1.221 = 343 / 281
## Distribution of residuals:
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -4.42700 -0.72700  0.08313  0.00000  0.71290  2.82900

#Visualise the tree
par(mfrow = c(1,1))
plot(tree)
text(tree,pretty = 0,cex =0.5)
```

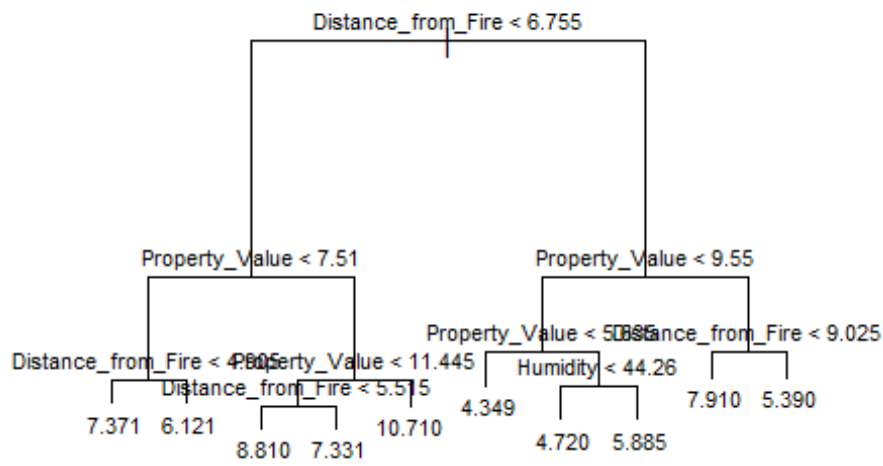


```
#Improve the model
set.seed(1)
cv.data = cv.tree(tree)
```

```
#Plot to choose the best tree size  
plot(cv.data$size,cv.data$dev, type = "b")
```



```
#Prune the tree  
pruned.model = prune.tree(tree, best = 10)  
plot(pruned.model)  
text(pruned.model,pretty = 0, cex = 0.7)
```



*#Calculate MSE and RMSE*

```
predict2 = predict(tree, data = test)
```

```
MSE2 = mean((predict2-actual)^2)
```

```
RMSE2 = sqrt(MSE2)
```

```
MSE2
```

```
## [1] 6.413686
```

```
RMSE2
```

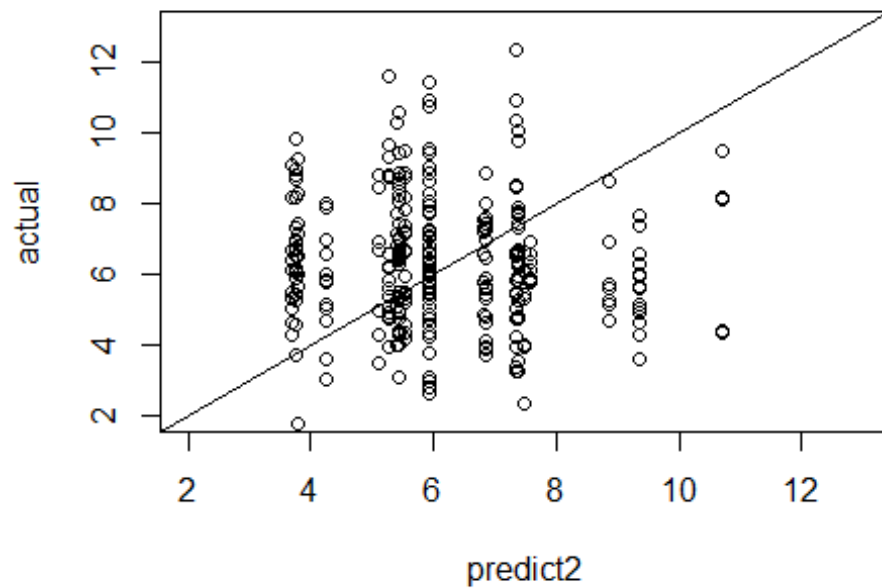
```
## [1] 2.532526
```

*#Plot the predict and actual value for testing data set*

```
plot(predict2,actual, xlim =c(2,13),ylim = c(2,13))
```

```
abline(0,1)
```





*#Compare two model using MSE*

MSE1

## [1] 6.479355

MSE2

## [1] 6.413686

*#Compare two model using residual plot*

`par(mfrow = c(1,2))`

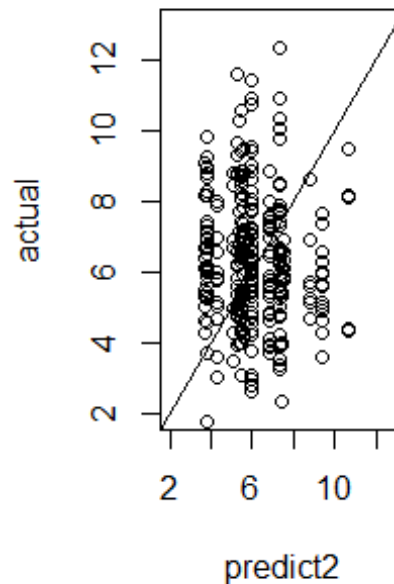
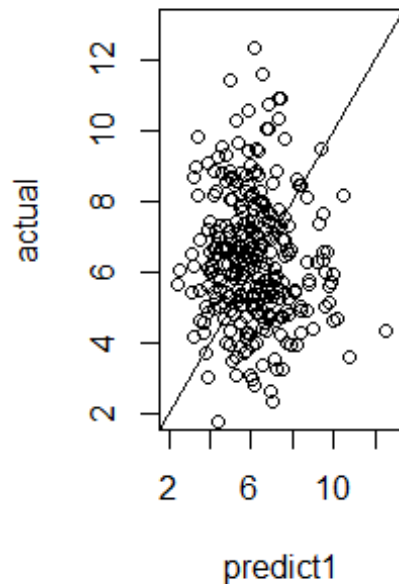
`plot(predict1, actual, xlim = c(2,13), ylim = c(2,13), main = "Multiple linear regression model")`

`abline(0,1)`

`plot(predict2, actual, xlim = c(2,13), ylim = c(2,13), main = "Regression tree model")`

`abline(0,1)`

## Multiple linear regression n      Regression tree model



*#Modify the target variable*

```
Highdamage = ifelse(newdata$Damage_Claims>7.5,"Yes","No")
```

```
Highdamage = as.factor(Highdamage)
```

```
newdata2 = data.frame(newdata,Highdamage)
```

```
newdata2 = newdata2[,-12]
```

```
str(newdata2)
```

```
## 'data.frame': 600 obs. of 12 variables:
```

```
## $ Fire_Intensity : num 5738 12248 7317 13479 14226 ...
```

```
## $ Distance_from_Fire : num 5.57 5.49 5.12 4.89 6.13 ...
```

```
## $ Building_Age : int 19 27 16 30 21 27 24 24 36 30 ...
```

```
## $ Property_Value : num 9.76 5.89 3.98 4.91 9.31 ...
```

```
## $ Population_Density : int 520 433 634 576 644 476 500 591 487 441
```

```
...
```

```
## $ Emergency_Response_Time: int 16 18 17 14 12 10 16 19 15 18 ...
```

```
## $ Mitigation_Measures : int 3 3 4 2 2 1 5 7 2 3 ...
```

```
## $ Construction_Quality : num 1 1 1 1 1 1 1 1 1 1 ...
```

```
## $ Insurance_Coverage : num 2 0 1 1 0 2 1 2 2 1 ...
```

```
## $ Wind_Speed : num 24.9 21 25.3 22.3 37.2 31.8 27.8 22.5
```

```
32.2 20.6 ...
```

```
## $ Humidity : num 35.3 28.2 44.5 53.8 73.8 ...
```

```
## $ Highdamage : Factor w/ 2 levels "No","Yes": 1 1 1 2 2 1 1 2
```

```
1 1 ...
```

*#Build classification tree*

```
training2 = newdata2[tr.id,]
```

```
testing2 = newdata2[-tr.id,]
```

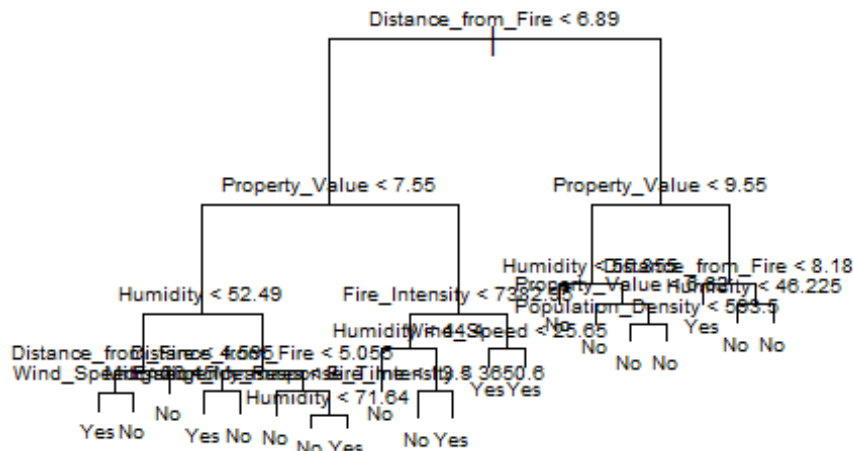
```
tree_new = tree(Highdamage~.,training2)
```

```
#visualise the tree
```

```
par(mfrow = c(1,1))
```

```
plot(tree_new)
```

```
text(tree_new,pretty=0,cex = 0.6)
```



```
summary(tree_new)
```

```
##
```

```
## Classification tree:
```

```
## tree(formula = Highdamage ~ ., data = training2)
```

```
## Variables actually used in tree construction:
```

```
## [1] "Distance_from_Fire"      "Property_Value"
```

```
## [3] "Humidity"                "Wind_Speed"
```

```
## [5] "Mitigation_Measures"     "Emergency_Response_Time"
```

```
## [7] "Fire_Intensity"          "Population_Density"
```

```
## Number of terminal nodes: 20
```

```
## Residual mean deviance: 0.3108 = 87.02 / 280
```

```
## Misclassification error rate: 0.07 = 21 / 300
```

```
#Calculate misclassification rate
```

```
tree_pred1=predict(tree_new,testing2,type="class")
```

```
table = table(tree_pred1,testing2$Highdamage)
```

```
misrate1 <- (table[1,2]+table[2,1])/sum(table)
```

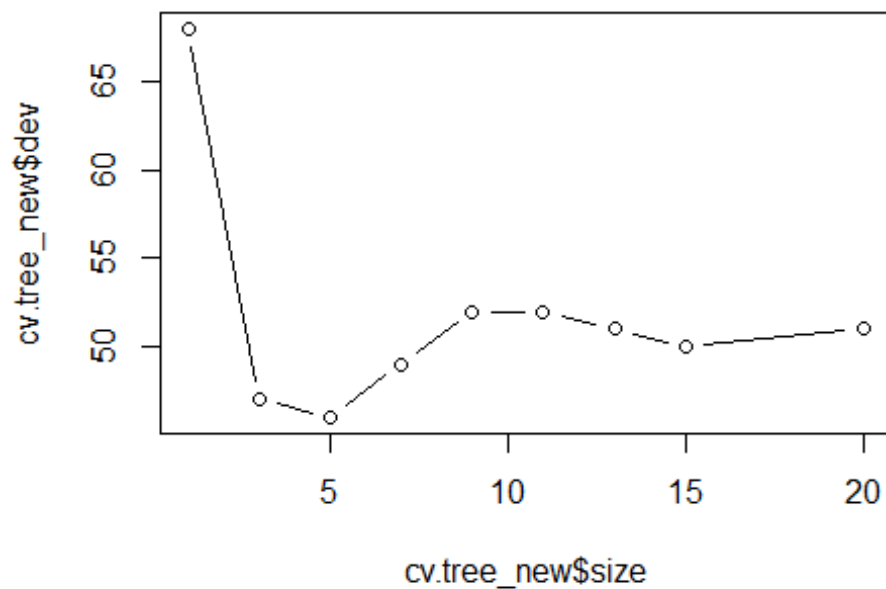
```
misrate1
```

```
## [1] 0.21

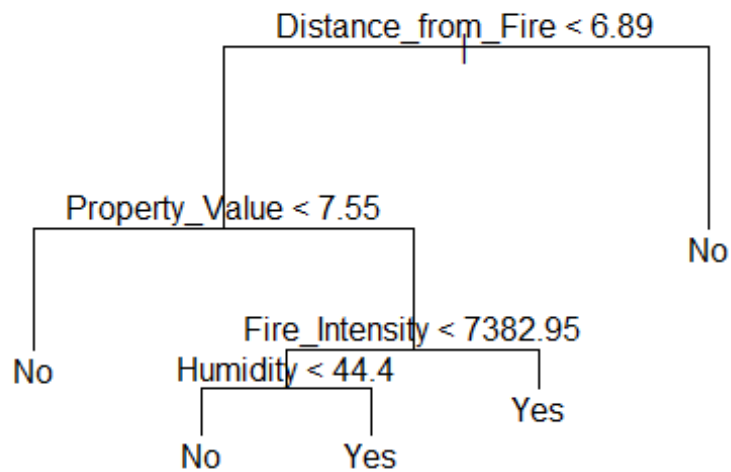
#Prunning tree
set.seed(12)
cv.tree_new=cv.tree(tree_new,FUN=prune.misclass)
names(cv.tree_new)

## [1] "size" "dev" "k" "method"

plot(cv.tree_new$size, cv.tree_new$dev, type = "b")
```



```
prune.tree_new=prune.misclass(tree_new,best=5)
plot(prune.tree_new)
text(prune.tree_new,pretty=0)
```



```

#Calculate misclassification rate
tree.pred2=predict(prune.tree_new,testing2,type='class')
table(tree.pred2,testing2$Highdamage)

##
## tree.pred2  No Yes
##           No  217 35
##           Yes  11 37

tab3 <- table(tree.pred2,testing2$Highdamage)
mis_rate2 <- (tab3[1,2]+tab3[2,1])/sum(tab3)
mis_rate2

## [1] 0.1533333

BFD = read.csv("BushFireData.csv")
#Encoding variables
Highdamage = ifelse(Damage_Claims>7.5, "1","0")
new_BFD = data.frame(BFD,Highdamage)
new_BFD$Highdamage = as.factor(new_BFD$Highdamage)
new_BFD$Construction_Quality = ifelse(new_BFD$Construction_Quality ==
"Good",1,0)
IC_factor = factor(new_BFD$Insurance_Coverage, levels = c("None",
"Partially", "Fully"))
new_BFD$Insurance_Coverage = as.integer(IC_factor)-1
#Remove excess variables
new_BFD = new_BFD[, -13]

```

```

new_BFD = new_BFD[, -1]

#Divide data set into training and testing set, 70% training, 30% testing
set.seed(1)
tr.id = sample(1:nrow(BFD), nrow(BFD)*0.7)
training = new_BFD[tr.id,]
testing = new_BFD[-tr.id,]

#Build support vector machines
library(e1071)

## Warning: package 'e1071' was built under R version 4.4.2

#Linear kernel model
set.seed(1)
linear_svm = tune(svm, Highdamage ~ ., data = training, kernel = "linear",
                  scale = TRUE, ranges = list(cost =
c(0.001, 0.01, 0.1, 1, 10, 100)))
summary(linear_svm)

##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost
##   0.1
##
## - best performance: 0.08809524
##
## - Detailed performance results:
##   cost      error dispersion
## 1 1e-03 0.21904762 0.05810478
## 2 1e-02 0.17142857 0.05475615
## 3 1e-01 0.08809524 0.05728598
## 4 1e+00 0.09047619 0.04994328
## 5 1e+01 0.09523810 0.04761905
## 6 1e+02 0.09285714 0.04821061

linear_bm = linear_svm$best.model
summary(linear_bm)

##
## Call:
## best.tune(METHOD = svm, train.x = Highdamage ~ ., data = training,
##   ranges = list(cost = c(0.001, 0.01, 0.1, 1, 10, 100)), kernel =
"linear",
##   scale = TRUE)
##
##

```

```

## Parameters:
##   SVM-Type:  C-classification
##   SVM-Kernel: linear
##           cost: 0.1
##
## Number of Support Vectors: 128
##
## ( 62 66 )
##
##
## Number of Classes: 2
##
## Levels:
##  0 1

#prediction for linear model
actual = testing$Highdamage
actual

##   [1] 1 0 0 0 0 0 0 0 1 0 1 0 0 0 0 1 0 0 0 1 1 0 0 0 0 1 0 1 0 0 0 1 1 1
##   [38] 0 0 1 0 1 0 0 0 1 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 1 0
##   [75] 0 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 1 0 1 0 1 1 0 1 0 0 1 0 0 0 0 1 0 0
##  [112] 0 0 0 1 0 0 0 0 1 1 0 0 0 0 0 0 1 0 1 1 0 1 0 0 0 0 0 0 1 0 0 0 0 0
##  [149] 0 0 0 0 0 1 1 0 0 1 0 0 0 1 0 0 0 0 1 1 0 0 0 0 0 0 1 0 0 1 0 0
## Levels: 0 1

pred1 = predict(linear_bm, newdata = testing)
pred1

##    4    6    9   10   11   12   13   17   23   24   52   54   55   57   59   61   63   66
## 67 68
##    0    0    0    0    0    0    0    0    1    1    1    0    0    0    0    1    0    0
##    0    1
## 70 76 80 82 85 87 88 90 94 95 96 100 101 107 118 120 125 128
## 142 144
##    1    1    0    0    0    1    0    0    0    0    0    1    0    0    0    1    0    0
##    0    1
## 146 149 151 154 155 158 165 166 170 171 172 175 178 182 184 186 188 191
## 196 200
##    0    1    0    0    0    0    1    0    0    0    0    0    1    0    0    0    0    0
##    0    0
## 206 210 211 213 215 216 225 226 227 228 232 240 243 244 245 250 251 257
## 258 259
##    0    0    1    0    0    0    0    0    0    0    1    0    0    0    0    0    0    1
##    0    0
## 261 262 263 267 272 278 281 283 289 301 302 303 308 312 318 319 320 322
## 332 340

```

```

## 1 0 1 1 1 1 0 0 0 0 1 0 0 0 1 0 0 0
0 0
## 341 342 347 348 350 351 353 354 357 360 366 367 370 374 376 384 387 389
392 394
## 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 1 0 0 0
0 0
## 395 398 401 407 417 420 424 431 432 433 444 445 447 449 450 452 455 456
457 458
## 1 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0
0 1
## 462 469 473 476 479 481 486 489 493 496 497 503 505 507 510 512 517 520
523 524
## 0 0 0 0 0 0 1 1 0 0 0 0 0 0 1 0 0 0
0 0
## 529 535 539 543 544 547 552 557 560 562 565 568 569 571 573 580 581 583
593 595
## 0 1 0 0 0 0 0 1 0 0 0 0 0 1 1 0 0 1
0 0
## Levels: 0 1

tab1 = table(pred1,actual)
tab1

##      actual
## pred1  0  1
##      0 124 18
##      1   8 30

misrate_linear = (tab1[1,2]+tab1[2,1])/sum(tab1)

#Polynomial kernel model
set.seed(1)
poly_svm = tune(svm,Highdamage~., data = training, kernel = "polynomial",
                scale = TRUE, ranges = list(cost =
c(0.001,0.01,0.1,1,10,100), d =c(2:5)))
summary(poly_svm)

##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost d
##     1 3
##
## - best performance: 0.1261905
##
## - Detailed performance results:
##   cost d      error dispersion
## 1 1e-03 2 0.2190476 0.05810478

```



```
## 2 1e-02 2 0.2190476 0.05810478
## 3 1e-01 2 0.2190476 0.05810478
## 4 1e+00 2 0.2071429 0.04768514
## 5 1e+01 2 0.2428571 0.08078102
## 6 1e+02 2 0.2547619 0.07780207
## 7 1e-03 3 0.2190476 0.05810478
## 8 1e-02 3 0.2190476 0.05810478
## 9 1e-01 3 0.2023810 0.05639949
## 10 1e+00 3 0.1261905 0.05270463
## 11 1e+01 3 0.1595238 0.06644900
## 12 1e+02 3 0.2214286 0.03731003
## 13 1e-03 4 0.2190476 0.05810478
## 14 1e-02 4 0.2190476 0.05810478
## 15 1e-01 4 0.2047619 0.05634362
## 16 1e+00 4 0.2095238 0.05810478
## 17 1e+01 4 0.2214286 0.07103064
## 18 1e+02 4 0.2666667 0.04994328
## 19 1e-03 5 0.2190476 0.05810478
## 20 1e-02 5 0.2190476 0.05810478
## 21 1e-01 5 0.1928571 0.05549884
## 22 1e+00 5 0.1809524 0.05745067
## 23 1e+01 5 0.1547619 0.07876759
## 24 1e+02 5 0.1952381 0.07342878
```

```
poly_bm = poly_svm$best.model
summary(poly_bm)
```

```
##
## Call:
## best.tune(METHOD = svm, train.x = Highdamage ~ ., data = training,
##   ranges = list(cost = c(0.001, 0.01, 0.1, 1, 10, 100), d = c(2:5)),
##   kernel = "polynomial", scale = TRUE)
##
##
## Parameters:
##   SVM-Type:  C-classification
##   SVM-Kernel: polynomial
##     cost:  1
##   degree:  3
##   coef.0:  0
##
## Number of Support Vectors:  179
##
## ( 75 104 )
##
## Number of Classes:  2
##
## Levels:
##  0 1
```

```
#Prediction for polynomial kernel model
pred2 = predict(poly_bm, newdata = testing)
pred2
```

```
##      4      6      9     10     11     12     13     17     23     24     52     54     55     57     59     61     63     66
67     68
##      0      0      0      0      0      0      0      0      1      1      0      0      0      0      1      0      0      0
0      1
##     70     76     80     82     85     87     88     90     94     95     96    100    101    107    118    120    125    128
142    144
##      0      0      0      0      0      0      0      0      0      0      0      1      0      0      0      1      0      0
0      0
##    146    149    151    154    155    158    165    166    170    171    172    175    178    182    184    186    188    191
196    200
##      0      1      0      0      0      0      0      0      0      0      0      0      1      0      0      0      0      0
0      0
##    206    210    211    213    215    216    225    226    227    228    232    240    243    244    245    250    251    257
258    259
##      0      0      0      0      0      0      0      0      0      0      1      0      0      0      0      0      0      1
0      0
##    261    262    263    267    272    278    281    283    289    301    302    303    308    312    318    319    320    322
332    340
##      1      0      1      1      0      1      0      0      0      0      1      0      0      0      0      0      0      0
0      0
##    341    342    347    348    350    351    353    354    357    360    366    367    370    374    376    384    387    389
392    394
##      0      0      0      0      0      0      0      0      0      1      0      0      0      0      1      0      0      0
0      1
##    395    398    401    407    417    420    424    431    432    433    444    445    447    449    450    452    455    456
457    458
##      1      0      0      0      0      0      0      0      0      1      0      0      0      0      0      0      0      0
0      0
##    462    469    473    476    479    481    486    489    493    496    497    503    505    507    510    512    517    520
523    524
##      0      0      0      0      0      0      0      1      0      0      0      0      0      0      1      0      0      0
0      0
##    529    535    539    543    544    547    552    557    560    562    565    568    569    571    573    580    581    583
593    595
##      0      0      0      0      0      0      0      1      0      0      0      0      0      0      0      0      0      0
0      0
## Levels: 0 1
```

```
tab2 = table(pred2,actual)
tab2
```

```
##      actual
## pred2    0    1
##      0 127   30
##      1   5   18
```

```

misrate_poly = (tab2[1,2]+tab2[2,1])/sum(tab2)

#Radial kernel model
set.seed(1)
ra_svm = tune(svm,Highdamage~., data = training, kernel = "radial",
              scale = TRUE, ranges = list(cost = c(0.001,0.01,0.1,1,10,100),
gamma = c(0.5, 1, 2, 3,4)))
summary(ra_svm)

##
## Parameter tuning of 'svm':
##
## - sampling method: 10-fold cross validation
##
## - best parameters:
##   cost gamma
##   10    0.5
##
## - best performance: 0.197619
##
## - Detailed performance results:
##   cost gamma      error dispersion
## 1  1e-03   0.5 0.2190476 0.05810478
## 2  1e-02   0.5 0.2190476 0.05810478
## 3  1e-01   0.5 0.2190476 0.05810478
## 4  1e+00   0.5 0.2119048 0.05772412
## 5  1e+01   0.5 0.1976190 0.05388649
## 6  1e+02   0.5 0.1976190 0.05388649
## 7  1e-03   1.0 0.2190476 0.05810478
## 8  1e-02   1.0 0.2190476 0.05810478
## 9  1e-01   1.0 0.2190476 0.05810478
## 10 1e+00   1.0 0.2190476 0.05810478
## 11 1e+01   1.0 0.2190476 0.06023386
## 12 1e+02   1.0 0.2190476 0.06023386
## 13 1e-03   2.0 0.2190476 0.05810478
## 14 1e-02   2.0 0.2190476 0.05810478
## 15 1e-01   2.0 0.2190476 0.05810478
## 16 1e+00   2.0 0.2190476 0.05810478
## 17 1e+01   2.0 0.2190476 0.05810478
## 18 1e+02   2.0 0.2190476 0.05810478
## 19 1e-03   3.0 0.2190476 0.05810478
## 20 1e-02   3.0 0.2190476 0.05810478
## 21 1e-01   3.0 0.2190476 0.05810478
## 22 1e+00   3.0 0.2190476 0.05810478
## 23 1e+01   3.0 0.2190476 0.05810478
## 24 1e+02   3.0 0.2190476 0.05810478
## 25 1e-03   4.0 0.2190476 0.05810478
## 26 1e-02   4.0 0.2190476 0.05810478
## 27 1e-01   4.0 0.2190476 0.05810478
## 28 1e+00   4.0 0.2190476 0.05810478

```

```

## 29 1e+01    4.0 0.2190476 0.05810478
## 30 1e+02    4.0 0.2190476 0.05810478

ra_bm = ra_svm$best.model
summary(ra_bm)

##
## Call:
## best.tune(METHOD = svm, train.x = Highdamage ~ ., data = training,
##   ranges = list(cost = c(0.001, 0.01, 0.1, 1, 10, 100), gamma = c(0.5,
##   1, 2, 3, 4)), kernel = "radial", scale = TRUE)
##
##
## Parameters:
##   SVM-Type:  C-classification
##   SVM-Kernel: radial
##     cost:  10
##
## Number of Support Vectors:  406
##
## ( 92 314 )
##
##
## Number of Classes:  2
##
## Levels:
##  0 1

#Prediction for radial kernel model
pred3 = predict(ra_bm, newdata = testing)
pred3

##   4   6   9  10  11  12  13  17  23  24  52  54  55  57  59  61  63  66
## 67 68
##   0   0   0   0   0   0   0   0   1   0   0   0   0   0   0   0   0   0
##  0   0
## 70 76 80 82 85 87 88 90 94 95 96 100 101 107 118 120 125 128
## 142 144
##   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
##  0   1
## 146 149 151 154 155 158 165 166 170 171 172 175 178 182 184 186 188 191
## 196 200
##   0   1   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
##  0   0
## 206 210 211 213 215 216 225 226 227 228 232 240 243 244 245 250 251 257
## 258 259
##   0   0   0   0   0   0   0   1   0   0   1   0   0   0   0   0   0   0
##  0   0
## 261 262 263 267 272 278 281 283 289 301 302 303 308 312 318 319 320 322
## 332 340
##   0   0   0   0   1   0   0   0   0   0   0   0   0   0   0   0   0   0

```

```

0 0
## 341 342 347 348 350 351 353 354 357 360 366 367 370 374 376 384 387 389
392 394
## 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0
## 395 398 401 407 417 420 424 431 432 433 444 445 447 449 450 452 455 456
457 458
## 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0
## 462 469 473 476 479 481 486 489 493 496 497 503 505 507 510 512 517 520
523 524
## 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0
0 0
## 529 535 539 543 544 547 552 557 560 562 565 568 569 571 573 580 581 583
593 595
## 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0
## Levels: 0 1

tab3 = table(pred3,actual)
tab3

##      actual
## pred3 0 1
##      0 130 42
##      1 2 6

misrate_ra = (tab3[1,2]+tab3[2,1])/sum(tab3)

#compare misclassification rate between the three kernels
misrate_linear

## [1] 0.1444444

misrate_poly

## [1] 0.1944444

misrate_ra

## [1] 0.2444444

#PCA
PCA_BFD = BFD[, -c(1,9,10,13)]
PCA_BFD

##      Fire_Intensity Distance_from_Fire Building_Age Property_Value
## 1          5738.5          5.57          19          9.76
## 2         12247.9          5.49          27          5.89
## 3          7316.6          5.12          16          3.98
## 4         13479.2          4.89          30          4.91

```

## 5	14226.0	6.13	21	9.31
## 6	2592.2	7.66	27	6.41
## 7	8865.3	2.97	24	3.65
## 8	13601.4	7.42	24	6.63
## 9	9168.6	9.47	36	10.68
## 10	7935.9	11.08	30	8.49
## 11	14438.8	9.60	32	5.47
## 12	7893.3	8.51	15	4.40
## 13	10808.4	3.55	22	5.46
## 14	9444.2	5.80	22	7.07
## 15	3338.0	6.30	28	9.13
## 16	13697.7	8.41	31	3.91
## 17	5199.1	6.79	31	9.51
## 18	2546.7	4.48	24	7.01
## 19	6262.9	10.37	25	8.30
## 20	14408.5	8.82	37	4.26
## 21	13564.0	7.47	27	5.73
## 22	11006.4	9.44	25	6.11
## 23	10326.5	4.32	18	9.57
## 24	14925.5	8.32	21	9.52
## 25	10524.1	5.95	24	7.97
## 26	11210.8	8.37	22	11.32
## 27	9072.8	6.88	23	5.99
## 28	9723.8	8.27	32	9.48
## 29	5759.0	9.67	19	6.92
## 30	3912.4	7.01	30	5.72
## 31	14519.3	9.04	23	9.23
## 32	13729.8	4.62	16	10.59
## 33	10979.1	5.56	23	9.11
## 34	12341.0	10.04	26	6.00
## 35	2319.9	7.75	36	6.07
## 36	8211.3	2.90	28	10.58
## 37	11859.9	4.27	25	7.78
## 38	4813.3	6.60	29	8.97
## 39	6136.3	8.73	25	6.32
## 40	5011.1	6.80	21	10.21
## 41	3856.4	8.25	25	5.49
## 42	7389.1	8.92	26	8.44
## 43	7378.4	10.34	26	5.47
## 44	6794.9	7.11	16	3.34
## 45	3981.7	6.90	26	4.67
## 46	3804.4	3.49	18	7.29
## 47	5029.4	7.20	29	9.12
## 48	8057.5	5.86	28	4.13
## 49	5457.6	5.05	36	4.80
## 50	13151.7	6.64	25	11.88
## 51	2595.8	9.03	25	6.14
## 52	7748.6	3.01	25	8.14
## 53	12386.0	6.15	25	5.97
## 54	3584.6	7.23	25	6.40

## 55	9292.3	5.21	29	7.18
## 56	4684.9	7.67	28	7.02
## 57	3657.9	7.82	22	6.60
## 58	11793.0	6.93	17	6.07
## 59	13635.5	2.07	27	2.80
## 60	6868.0	12.14	21	12.26
## 61	10646.4	6.59	21	11.97
## 62	3232.9	8.30	24	5.03
## 63	6991.6	7.55	28	6.65
## 64	5566.9	9.05	19	10.57
## 65	12590.3	8.64	19	9.44
## 66	7830.7	6.58	23	10.26
## 67	12530.8	7.76	16	5.07
## 68	12561.0	5.11	21	15.16
## 69	12326.4	8.71	25	4.98
## 70	7717.8	6.08	26	8.77
## 71	11808.1	11.83	22	7.30
## 72	10179.8	3.70	28	6.20
## 73	11232.3	6.07	19	6.24
## 74	2008.1	8.65	19	5.19
## 75	8179.1	8.02	26	11.38
## 76	4861.5	5.82	24	7.19
## 77	6937.6	5.01	30	7.56
## 78	9966.0	7.29	18	7.45
## 79	6573.3	6.97	28	6.25
## 80	3444.7	3.42	24	4.98
## 81	5167.0	7.07	19	7.55
## 82	10684.7	7.38	24	3.73
## 83	7429.4	7.35	24	4.57
## 84	12246.5	4.89	12	5.06
## 85	3337.2	7.95	21	5.06
## 86	7653.6	9.76	37	7.22
## 87	14804.4	7.91	28	11.30
## 88	13609.6	4.73	22	4.44
## 89	13524.0	6.13	24	7.97
## 90	4275.6	7.69	20	9.16
## 91	3699.0	5.71	27	5.20
## 92	10490.3	2.68	23	6.88
## 93	6465.7	8.77	25	8.96
## 94	10537.8	5.34	26	6.48
## 95	6164.8	5.85	18	6.55
## 96	4439.9	10.01	33	7.67
## 97	12169.8	5.45	28	6.87
## 98	3216.7	8.69	20	5.92
## 99	8068.1	4.48	31	6.71
## 100	8649.5	6.29	29	12.31
## 101	9799.8	6.85	16	9.09
## 102	6326.7	4.66	18	5.32
## 103	8351.9	5.73	32	4.81
## 104	14408.1	6.94	27	6.28

## 105	8277.7	8.34	28	10.42
## 106	13574.5	3.70	19	7.64
## 107	13887.6	6.30	29	5.67
## 108	9913.5	8.51	32	9.12
## 109	7338.9	5.92	27	6.72
## 110	3912.2	7.45	25	5.00
## 111	14158.8	7.98	34	8.03
## 112	5915.9	7.54	19	11.05
## 113	2789.3	8.31	18	7.97
## 114	14320.4	6.75	23	7.41
## 115	11367.7	6.17	27	5.74
## 116	3849.8	1.71	19	8.30
## 117	9140.7	6.81	15	5.07
## 118	14403.1	7.86	33	4.26
## 119	9611.2	8.07	25	6.90
## 120	7258.6	5.89	26	6.92
## 121	10422.6	10.56	24	14.23
## 122	6157.6	7.57	27	4.85
## 123	6000.3	7.25	20	7.36
## 124	4856.9	9.54	29	8.91
## 125	6803.3	5.56	22	9.59
## 126	14794.8	6.10	25	6.97
## 127	4004.6	11.79	28	5.60
## 128	3183.5	7.02	27	6.86
## 129	3844.7	10.27	32	12.52
## 130	10970.0	4.12	21	8.09
## 131	10050.3	6.62	15	3.79
## 132	13588.1	7.76	24	10.72
## 133	10748.9	7.60	20	8.23
## 134	11582.0	4.99	19	6.92
## 135	8774.7	7.04	24	6.96
## 136	10577.8	4.85	33	6.69
## 137	12683.4	8.43	27	7.56
## 138	12221.6	9.17	23	6.01
## 139	14737.6	2.55	19	7.60
## 140	7712.6	9.47	23	5.29
## 141	6052.1	4.52	27	7.43
## 142	7323.1	7.91	34	9.75
## 143	2136.0	8.32	20	8.15
## 144	4390.0	6.60	24	9.54
## 145	12955.4	5.71	21	5.04
## 146	5005.1	7.33	19	7.11
## 147	5108.2	7.88	26	8.42
## 148	2996.9	8.77	16	5.08
## 149	5194.4	2.90	24	11.19
## 150	11517.7	3.73	24	5.13
## 151	13016.8	9.86	24	7.35
## 152	8467.8	9.09	16	7.32
## 153	7042.8	7.87	16	7.26
## 154	5203.8	8.43	27	6.57



## 155	3444.2	8.83	24	8.01
## 156	7069.9	1.68	15	5.13
## 157	9435.1	9.22	21	4.75
## 158	4819.6	6.03	20	5.75
## 159	7781.9	7.46	30	6.88
## 160	4833.8	6.41	27	10.20
## 161	8529.8	8.74	23	11.27
## 162	6600.7	6.30	29	7.70
## 163	10449.8	8.04	29	7.84
## 164	6871.2	6.22	20	6.50
## 165	6620.7	4.81	27	7.10
## 166	8937.9	9.42	22	4.59
## 167	11624.3	8.48	20	7.63
## 168	4874.3	10.45	18	5.96
## 169	7365.6	7.13	25	7.73
## 170	5453.9	9.25	21	6.30
## 171	10189.6	10.95	24	5.73
## 172	4389.7	6.44	30	6.55
## 173	13227.3	4.35	29	6.27
## 174	11705.3	6.52	24	9.72
## 175	10687.7	6.57	22	7.45
## 176	10034.2	7.30	21	7.96
## 177	6839.0	10.42	21	4.82
## 178	8887.8	6.35	34	10.96
## 179	13370.8	7.75	30	7.34
## 180	9562.7	6.54	28	5.41
## 181	12916.9	7.04	22	7.68
## 182	6061.8	7.63	24	9.08
## 183	11207.7	9.66	22	4.62
## 184	5445.2	7.24	22	11.62
## 185	9726.4	8.43	27	6.67
## 186	8256.7	8.56	24	9.79
## 187	5445.4	8.83	27	7.15
## 188	9339.6	5.85	20	6.33
## 189	13871.4	10.25	21	4.03
## 190	13724.3	6.24	21	5.03
## 191	5564.1	6.79	33	6.91
## 192	6179.2	9.81	24	8.97
## 193	14813.3	9.59	16	3.98
## 194	10059.9	4.82	23	10.57
## 195	14185.0	5.25	25	10.65
## 196	8064.9	4.28	25	4.96
## 197	7288.8	7.36	26	8.06
## 198	10569.9	7.33	21	5.13
## 199	3980.5	7.73	24	6.74
## 200	9447.2	8.10	21	9.24
## 201	5103.4	5.80	26	9.08
## 202	14510.6	5.01	24	5.42
## 203	9817.7	9.05	20	6.23
## 204	8695.3	8.50	20	5.22

## 205	7233.4	3.98	31	7.75
## 206	13443.2	6.81	25	4.38
## 207	6733.1	5.21	23	3.18
## 208	5747.1	2.86	26	10.87
## 209	4218.3	7.30	19	13.84
## 210	4238.2	6.84	26	6.10
## 211	8266.5	6.81	25	8.79
## 212	5288.5	7.43	27	6.98
## 213	4811.3	8.76	21	10.89
## 214	10766.8	7.41	21	8.26
## 215	2619.6	5.77	20	7.44
## 216	11111.0	5.53	28	4.08
## 217	6574.5	6.74	18	9.68
## 218	7316.2	7.62	32	6.30
## 219	12672.3	4.92	19	4.59
## 220	13945.1	6.63	20	6.58
## 221	5672.8	8.93	23	6.73
## 222	14494.3	6.78	24	9.61
## 223	11469.1	5.60	29	4.93
## 224	10922.8	6.45	28	5.92
## 225	2686.9	9.23	17	10.93
## 226	7137.8	8.10	21	10.52
## 227	8211.9	9.47	27	9.92
## 228	9283.2	7.28	31	11.52
## 229	11077.4	7.82	21	7.44
## 230	13903.8	5.88	28	5.87
## 231	10038.5	8.21	30	8.26
## 232	7569.4	5.99	20	9.61
## 233	9047.0	4.16	21	14.43
## 234	2760.2	7.26	14	3.88
## 235	5391.1	10.89	33	7.59
## 236	7162.9	8.60	27	8.51
## 237	4570.6	9.33	13	6.88
## 238	12815.0	7.72	32	4.38
## 239	3987.5	5.78	20	8.74
## 240	12444.4	6.60	31	5.54
## 241	9108.7	6.45	26	8.14
## 242	10610.1	6.06	31	9.19
## 243	4232.0	8.41	22	10.28
## 244	10229.7	4.61	28	4.38
## 245	6054.3	8.73	30	9.68
## 246	11419.2	8.73	20	5.57
## 247	7186.2	4.60	18	4.75
## 248	14601.6	8.28	26	10.38
## 249	14576.1	11.86	26	9.87
## 250	11447.1	5.89	22	6.50
## 251	5343.8	8.69	24	8.79
## 252	4883.2	5.44	30	5.40
## 253	9709.5	9.22	28	6.68
## 254	5477.7	7.50	23	6.80

## 255	8903.9	10.30	28	6.43
## 256	12208.7	4.08	25	8.72
## 257	4184.7	6.90	27	11.10
## 258	7257.1	5.95	29	6.10
## 259	8130.4	6.61	21	6.93
## 260	13285.3	5.74	36	11.43
## 261	14034.2	5.33	36	6.34
## 262	13465.7	8.16	21	3.20
## 263	10764.4	4.82	20	8.16
## 264	14352.1	9.97	20	5.36
## 265	8713.7	4.63	15	5.18
## 266	9494.7	7.20	40	10.72
## 267	6372.3	8.07	22	14.58
## 268	6515.2	8.17	20	5.12
## 269	2260.3	6.40	21	9.53
## 270	8536.5	7.16	21	6.80
## 271	13323.5	8.92	21	7.30
## 272	2081.9	4.09	27	10.10
## 273	2936.7	5.44	21	7.46
## 274	4134.7	7.64	27	5.42
## 275	12014.3	6.11	32	6.07
## 276	11557.3	9.74	26	8.59
## 277	14634.3	8.35	30	3.47
## 278	8064.1	7.14	28	9.72
## 279	2966.9	3.98	27	4.37
## 280	10434.6	7.05	26	7.04
## 281	11861.7	6.37	31	6.61
## 282	3782.3	6.80	19	10.31
## 283	7155.5	4.64	21	7.40
## 284	4924.8	8.00	24	7.21
## 285	2753.4	4.92	25	8.63
## 286	7146.6	6.55	28	5.46
## 287	2844.0	7.76	28	6.60
## 288	4936.5	5.43	23	9.96
## 289	2710.1	8.17	23	8.59
## 290	10713.6	4.37	25	4.77
## 291	5870.6	1.38	30	8.47
## 292	3309.3	7.93	27	4.63
## 293	2934.7	8.68	32	5.84
## 294	13445.7	6.43	24	10.06
## 295	11805.2	8.01	30	3.56
## 296	12615.8	4.69	29	4.10
## 297	14767.8	6.75	28	10.34
## 298	3346.7	3.12	27	5.48
## 299	3287.5	9.36	23	10.16
## 300	12384.8	10.72	24	6.65
## 301	12199.4	9.15	26	7.95
## 302	2122.5	6.95	25	8.93
## 303	12127.8	6.93	29	5.75
## 304	11482.0	3.97	24	6.38

## 305	10191.7	8.58	24	6.18
## 306	8251.8	6.58	22	16.29
## 307	4036.2	5.69	24	7.26
## 308	2106.8	4.18	29	8.06
## 309	7881.9	6.40	22	6.31
## 310	8399.8	5.30	24	6.51
## 311	7064.6	6.21	23	10.58
## 312	8040.6	4.56	36	6.32
## 313	11272.6	10.38	18	7.04
## 314	2718.9	6.97	24	7.83
## 315	6612.1	9.15	32	6.14
## 316	12436.5	1.80	25	12.59
## 317	12864.2	6.09	25	4.56
## 318	5090.7	5.65	26	12.79
## 319	6601.8	4.55	20	6.29
## 320	13139.5	10.09	28	10.51
## 321	13098.9	4.17	22	3.84
## 322	5846.6	7.64	23	9.32
## 323	3911.6	8.69	19	9.10
## 324	11151.8	7.36	20	4.78
## 325	3349.4	5.25	28	5.55
## 326	2438.4	8.88	18	7.41
## 327	14992.2	7.34	28	9.86
## 328	2453.3	4.87	26	5.56
## 329	6399.0	4.22	32	6.54
## 330	13895.8	11.17	19	11.21
## 331	10024.0	5.64	28	4.99
## 332	5721.7	3.29	21	9.30
## 333	11591.3	8.07	16	8.00
## 334	12842.7	7.62	21	5.02
## 335	6085.5	4.29	18	5.72
## 336	8403.3	3.11	26	8.85
## 337	11065.8	6.77	22	7.54
## 338	10339.0	9.28	20	10.73
## 339	10370.9	8.27	41	5.84
## 340	14712.0	6.01	26	4.18
## 341	7391.5	5.33	29	9.58
## 342	3552.2	7.54	31	5.83
## 343	8838.3	7.31	21	7.25
## 344	4925.9	8.26	27	11.72
## 345	8323.3	6.21	27	6.49
## 346	6812.7	8.80	21	11.14
## 347	14783.5	5.34	23	5.03
## 348	7048.1	6.34	23	9.24
## 349	4980.1	8.48	24	7.53
## 350	10102.8	8.98	15	5.61
## 351	3775.0	3.12	28	4.76
## 352	14577.1	7.21	23	7.16
## 353	8695.9	8.22	32	7.55
## 354	4119.9	4.10	22	7.60

## 355	10084.7	7.96	32	8.22
## 356	14817.4	5.34	36	6.09
## 357	10694.0	9.04	22	6.00
## 358	7445.9	8.08	27	7.51
## 359	6203.4	8.54	20	5.95
## 360	12858.3	7.24	35	10.09
## 361	3869.6	8.73	27	7.37
## 362	4506.6	9.76	26	5.82
## 363	13657.6	10.93	31	4.07
## 364	6005.5	6.94	30	5.77
## 365	6722.9	2.50	23	12.93
## 366	12191.3	7.06	24	5.91
## 367	4513.9	7.41	22	5.44
## 368	2230.9	6.69	21	8.51
## 369	7285.9	8.14	25	7.99
## 370	8281.1	9.02	18	8.77
## 371	7483.9	5.96	30	6.43
## 372	6456.5	6.41	28	9.80
## 373	13264.2	7.80	19	4.92
## 374	7916.4	5.90	28	6.89
## 375	8938.9	7.18	24	5.66
## 376	14529.9	3.08	24	8.58
## 377	12069.6	4.76	28	7.27
## 378	4715.3	4.34	30	9.76
## 379	6014.2	5.29	42	12.98
## 380	14627.4	5.61	28	7.30
## 381	9603.7	7.76	18	5.96
## 382	11890.7	8.96	24	5.46
## 383	6845.2	5.55	32	6.46
## 384	11999.5	5.01	24	6.85
## 385	8989.8	4.92	22	12.72
## 386	13881.9	6.17	27	4.98
## 387	4408.8	6.52	27	5.04
## 388	5668.8	7.97	28	6.19
## 389	3234.5	6.36	15	8.34
## 390	4736.3	2.84	23	8.95
## 391	14702.2	6.82	30	5.33
## 392	5851.9	9.37	17	7.27
## 393	11437.7	9.38	22	6.91
## 394	12213.9	5.42	35	10.01
## 395	3370.4	3.90	26	9.70
## 396	5114.7	11.92	13	6.37
## 397	5517.0	6.68	18	7.09
## 398	3313.7	6.81	24	8.51
## 399	3532.8	7.84	23	4.26
## 400	14886.0	3.77	26	6.37
## 401	14818.7	5.54	31	8.31
## 402	3781.8	3.92	25	5.98
## 403	13769.0	5.61	17	6.87
## 404	9491.9	7.24	22	6.95

## 405	7140.8	4.27	33	5.63
## 406	7847.4	8.18	23	5.19
## 407	11184.5	7.58	29	6.59
## 408	3072.5	5.19	19	6.30
## 409	6411.0	7.45	23	8.99
## 410	10850.2	8.50	25	11.07
## 411	6120.3	9.12	27	6.97
## 412	12810.3	6.57	19	7.88
## 413	4797.2	6.81	21	6.85
## 414	8473.3	6.83	26	8.38
## 415	5588.6	9.88	27	7.47
## 416	4496.3	9.25	24	7.51
## 417	14358.0	8.67	29	9.77
## 418	6182.4	6.43	28	5.20
## 419	8219.9	7.75	24	10.80
## 420	2363.9	7.81	30	7.77
## 421	9116.9	4.92	26	7.39
## 422	10375.1	3.54	28	5.91
## 423	9751.4	8.28	22	6.66
## 424	6185.1	3.94	21	7.83
## 425	13584.4	7.00	29	3.76
## 426	10141.3	7.50	24	5.84
## 427	5937.7	8.13	23	8.34
## 428	7046.6	7.38	28	6.40
## 429	4086.1	5.53	17	5.50
## 430	13213.1	8.97	28	5.78
## 431	14390.3	10.48	32	7.51
## 432	9327.3	8.76	23	4.28
## 433	6284.1	3.11	18	9.09
## 434	14956.0	9.80	28	3.65
## 435	5052.6	6.89	22	6.01
## 436	9964.7	8.05	33	5.52
## 437	3406.3	8.24	27	4.81
## 438	8331.4	6.81	26	5.06
## 439	3292.7	6.85	31	7.54
## 440	4095.1	9.04	16	6.75
## 441	5678.9	8.42	40	6.39
## 442	9590.3	8.98	27	3.48
## 443	11512.1	11.77	17	4.70
## 444	4151.7	8.33	27	6.72
## 445	13264.0	7.41	29	5.37
## 446	11211.4	2.58	31	5.51
## 447	11885.1	12.38	22	9.59
## 448	3912.0	6.03	24	7.37
## 449	6654.7	11.75	22	5.11
## 450	10753.3	7.75	28	6.08
## 451	8809.6	10.08	27	6.42
## 452	6547.4	6.78	20	5.70
## 453	5126.8	8.02	21	5.24
## 454	2756.4	7.43	28	6.89

## 455	5076.0	6.63	27	8.74
## 456	13571.0	6.76	23	7.49
## 457	12553.7	9.03	24	6.59
## 458	11717.7	6.60	28	7.86
## 459	4013.8	2.92	25	8.88
## 460	3621.6	6.61	20	6.71
## 461	14671.4	8.08	30	8.02
## 462	7669.6	8.23	17	4.96
## 463	8032.2	8.23	24	6.49
## 464	4148.8	3.62	35	6.17
## 465	9604.1	7.74	20	7.42
## 466	5520.1	8.94	15	7.79
## 467	4991.2	9.55	17	6.74
## 468	10985.7	6.55	28	5.56
## 469	5677.0	6.36	27	5.29
## 470	12535.1	9.98	30	7.61
## 471	3220.9	3.66	21	10.51
## 472	12686.3	6.13	23	5.52
## 473	7556.5	7.91	17	6.23
## 474	11826.5	3.76	36	7.73
## 475	10611.0	7.56	29	5.92
## 476	7778.8	10.76	28	7.26
## 477	10152.9	6.99	19	6.90
## 478	2006.0	6.44	32	5.54
## 479	4824.1	7.95	22	8.98
## 480	11163.3	6.44	26	9.02
## 481	4797.1	8.63	29	9.51
## 482	12581.1	8.81	30	10.24
## 483	6000.9	7.01	30	6.01
## 484	10940.6	4.65	24	6.08
## 485	14124.8	4.36	20	7.57
## 486	3505.1	5.81	26	8.45
## 487	3660.1	8.59	27	6.32
## 488	10816.9	3.08	24	6.16
## 489	7576.3	3.23	29	5.81
## 490	12847.2	5.69	27	10.91
## 491	14628.6	7.79	32	3.29
## 492	2916.3	5.17	23	6.65
## 493	7977.2	8.77	17	7.08
## 494	11120.6	7.67	29	5.09
## 495	3130.2	6.66	33	7.85
## 496	14908.2	8.64	33	3.87
## 497	5290.2	7.78	24	9.32
## 498	2643.9	6.11	20	4.24
## 499	10922.2	7.46	24	3.61
## 500	12230.0	8.30	23	5.56
## 501	6596.8	7.71	25	7.34
## 502	6763.7	5.68	23	5.75
## 503	5732.3	8.71	22	5.91
## 504	3039.6	9.31	26	7.73

## 505	6750.9	7.55	29	5.09
## 506	4314.1	7.29	20	6.82
## 507	8968.6	6.85	18	8.12
## 508	8551.3	11.32	27	11.42
## 509	14285.4	7.55	36	8.08
## 510	6437.1	6.68	38	11.70
## 511	8041.2	1.98	24	8.01
## 512	3072.9	3.87	29	6.99
## 513	13181.3	6.84	22	3.55
## 514	7143.5	7.41	26	4.84
## 515	11566.6	7.55	28	6.36
## 516	4232.6	8.64	30	8.66
## 517	7911.9	6.61	26	6.35
## 518	12012.6	9.43	24	8.24
## 519	2814.4	5.16	31	5.08
## 520	12596.0	4.58	25	6.44
## 521	5914.8	4.54	32	7.47
## 522	6740.7	8.48	24	6.28
## 523	6057.4	6.83	28	7.24
## 524	2485.8	8.58	17	5.72
## 525	8744.4	6.46	20	7.83
## 526	10827.1	5.82	21	6.83
## 527	13742.0	6.26	25	6.90
## 528	2331.8	3.29	19	3.90
## 529	14858.0	4.66	18	5.71
## 530	5937.5	4.12	27	4.47
## 531	14208.7	9.11	35	4.32
## 532	10938.8	5.81	32	6.03
## 533	7811.4	8.58	25	6.67
## 534	12614.2	10.03	22	7.62
## 535	2513.4	6.62	25	9.71
## 536	11607.4	7.57	27	7.99
## 537	6533.3	3.50	22	9.48
## 538	12780.2	5.36	27	5.97
## 539	8962.0	7.11	21	6.38
## 540	5569.0	7.60	23	9.69
## 541	12412.3	5.48	25	7.00
## 542	3191.3	12.37	31	4.22
## 543	12817.4	6.08	21	5.43
## 544	5599.1	7.13	19	9.47
## 545	11790.4	8.30	17	5.82
## 546	14533.9	6.95	29	7.73
## 547	3059.0	5.71	21	7.02
## 548	13106.7	9.09	24	6.03
## 549	12429.0	10.23	22	6.30
## 550	7007.2	6.94	23	7.87
## 551	6258.7	8.12	21	7.45
## 552	4664.2	6.81	27	10.13
## 553	9401.9	9.03	21	6.59
## 554	13544.7	4.69	16	5.30



## 555	8886.2	11.64	22	7.35
## 556	9630.4	5.79	18	8.64
## 557	10654.5	4.08	14	13.88
## 558	8888.6	6.30	22	6.09
## 559	8627.9	7.29	19	6.34
## 560	2210.0	10.25	28	9.12
## 561	2620.2	8.82	27	10.28
## 562	14081.5	7.28	31	5.74
## 563	12000.7	4.22	28	8.54
## 564	4614.0	5.27	25	5.90
## 565	10453.3	6.67	20	5.24
## 566	10498.9	12.11	28	8.43
## 567	7138.2	3.28	22	7.22
## 568	12559.9	9.26	26	7.86
## 569	9111.3	5.95	26	5.88
## 570	13506.7	10.33	16	11.99
## 571	9193.0	4.72	29	8.54
## 572	13778.6	7.29	33	6.25
## 573	9636.9	4.80	29	8.64
## 574	7505.0	8.81	30	4.86
## 575	14344.6	9.97	29	6.71
## 576	11217.4	10.90	27	10.66
## 577	7372.9	8.60	22	6.61
## 578	2238.7	10.69	25	9.19
## 579	9367.5	9.49	23	6.54
## 580	8370.8	6.74	25	3.51
## 581	13422.7	7.95	25	5.37
## 582	12567.0	5.06	26	7.48
## 583	13103.2	6.63	26	10.80
## 584	6782.6	9.44	25	5.85
## 585	13361.3	8.08	32	7.60
## 586	3967.3	7.91	30	5.24
## 587	5663.5	4.92	26	5.16
## 588	10667.1	5.79	28	5.54
## 589	14705.9	5.47	37	10.55
## 590	9575.6	7.79	32	9.28
## 591	8845.6	5.02	34	8.36
## 592	2790.1	8.12	22	9.78
## 593	14597.5	4.77	23	6.16
## 594	3563.0	10.66	31	8.79
## 595	3148.7	7.92	30	7.45
## 596	13449.9	5.60	20	5.10
## 597	8608.8	7.48	24	5.45
## 598	6387.4	6.30	19	7.10
## 599	13626.3	7.74	33	7.44
## 600	2415.6	7.49	32	6.35
##	Population_Density	Emergency_Response_Time	Mitigation_Measures	
Wind_Speed				
## 1	520		16	3
24.9				

## 2	433	18	3
21.0			
## 3	634	17	4
25.3			
## 4	576	14	2
22.3			
## 5	644	12	2
37.2			
## 6	476	10	1
31.8			
## 7	500	16	5
27.8			
## 8	591	19	7
22.5			
## 9	487	15	2
32.2			
## 10	441	18	3
20.6			
## 11	663	24	2
36.5			
## 12	672	23	1
30.1			
## 13	518	13	5
10.0			
## 14	578	17	2
26.1			
## 15	509	12	5
37.7			
## 16	625	18	3
24.6			
## 17	598	15	4
22.9			
## 18	530	16	0
26.4			
## 19	538	12	3
25.5			
## 20	515	20	0
33.4			
## 21	635	15	6
19.2			
## 22	646	13	3
32.0			
## 23	630	15	1
25.6			
## 24	533	15	3
30.9			
## 25	457	22	5
18.3			
## 26	642	11	1
18.1			

## 27	586	25	6
23.4			
## 28	597	12	5
20.1			
## 29	683	16	3
26.1			
## 30	529	7	5
26.0			
## 31	692	12	4
24.0			
## 32	567	18	9
24.9			
## 33	543	17	4
25.0			
## 34	584	17	3
24.2			
## 35	631	13	5
16.9			
## 36	583	8	1
24.3			
## 37	528	11	1
25.7			
## 38	577	14	1
27.0			
## 39	397	17	4
25.7			
## 40	559	18	4
29.0			
## 41	636	14	0
23.1			
## 42	586	14	6
20.3			
## 43	655	14	7
32.4			
## 44	639	15	5
22.4			
## 45	652	21	2
31.3			
## 46	652	12	3
28.3			
## 47	461	14	2
32.7			
## 48	600	15	1
17.0			
## 49	730	10	3
20.5			
## 50	562	11	2
26.0			
## 51	636	16	1
29.3			

## 52	611	17	0
21.0			
## 53	645	20	2
21.5			
## 54	578	13	2
25.3			
## 55	548	21	3
26.7			
## 56	606	12	2
24.5			
## 57	617	9	2
33.8			
## 58	585	7	0
20.5			
## 59	603	19	7
16.8			
## 60	633	16	3
24.5			
## 61	538	14	0
29.1			
## 62	691	14	3
30.4			
## 63	776	21	3
19.3			
## 64	718	20	3
19.3			
## 65	564	11	5
21.1			
## 66	454	9	0
22.8			
## 67	604	19	2
24.4			
## 68	670	17	1
25.3			
## 69	662	13	3
28.3			
## 70	502	17	1
17.1			
## 71	511	7	7
24.1			
## 72	611	12	1
29.4			
## 73	650	17	0
22.9			
## 74	670	15	3
21.7			
## 75	665	10	2
25.2			
## 76	523	19	3
19.0			

## 77	495	20	1
21.4			
## 78	439	11	2
31.2			
## 79	640	14	4
22.8			
## 80	666	18	2
20.5			
## 81	627	18	1
22.8			
## 82	515	13	1
29.0			
## 83	725	11	4
21.1			
## 84	570	16	2
32.0			
## 85	742	7	2
29.3			
## 86	644	11	1
27.8			
## 87	695	18	3
14.7			
## 88	626	8	4
25.5			
## 89	595	10	4
14.3			
## 90	519	14	6
24.3			
## 91	555	14	3
25.3			
## 92	596	8	4
26.5			
## 93	623	17	0
24.3			
## 94	597	11	5
19.4			
## 95	586	14	2
27.3			
## 96	615	14	2
24.0			
## 97	558	18	4
25.3			
## 98	557	15	1
27.7			
## 99	484	14	7
26.5			
## 100	668	22	5
29.5			
## 101	604	16	1
34.1			

## 102	593	17	1
28.7			
## 103	541	17	2
25.7			
## 104	580	17	1
28.0			
## 105	513	20	3
26.1			
## 106	516	15	4
20.0			
## 107	446	16	2
26.1			
## 108	679	23	2
29.0			
## 109	610	13	1
15.0			
## 110	511	20	1
20.4			
## 111	693	13	7
20.2			
## 112	650	22	4
31.8			
## 113	659	12	6
25.6			
## 114	582	12	3
24.9			
## 115	566	19	1
28.1			
## 116	592	19	5
27.7			
## 117	632	17	0
17.4			
## 118	664	16	4
20.3			
## 119	727	16	2
27.8			
## 120	559	23	1
14.7			
## 121	519	9	4
13.4			
## 122	608	11	3
19.8			
## 123	842	10	3
36.2			
## 124	566	19	4
15.2			
## 125	692	14	5
24.1			
## 126	581	14	7
23.1			

## 127	562	22	2
22.4			
## 128	543	13	2
26.7			
## 129	583	23	1
23.9			
## 130	731	9	8
22.9			
## 131	624	20	6
35.3			
## 132	639	16	6
17.0			
## 133	667	13	2
32.1			
## 134	766	14	4
19.0			
## 135	662	20	2
26.0			
## 136	486	22	0
23.2			
## 137	517	8	2
27.8			
## 138	473	29	6
30.4			
## 139	372	25	3
20.2			
## 140	703	13	4
30.6			
## 141	561	15	0
25.0			
## 142	632	12	3
25.9			
## 143	695	15	4
28.8			
## 144	559	18	3
24.3			
## 145	589	15	4
19.5			
## 146	628	16	3
34.5			
## 147	618	21	4
23.0			
## 148	538	6	4
24.5			
## 149	658	13	2
22.9			
## 150	644	16	4
14.8			
## 151	577	12	3
33.7			

## 152	502	19	5
23.0			
## 153	651	13	1
29.1			
## 154	714	13	2
19.4			
## 155	710	20	3
29.0			
## 156	670	18	0
27.3			
## 157	561	14	2
26.0			
## 158	557	14	3
13.6			
## 159	553	9	5
16.3			
## 160	567	12	3
28.9			
## 161	657	25	1
25.2			
## 162	621	15	4
23.9			
## 163	451	19	0
33.7			
## 164	451	14	3
28.1			
## 165	598	17	3
20.2			
## 166	612	15	1
19.5			
## 167	415	20	1
23.9			
## 168	535	13	0
21.2			
## 169	602	8	1
27.9			
## 170	717	19	2
26.8			
## 171	439	14	4
23.3			
## 172	500	21	1
15.1			
## 173	514	15	7
23.7			
## 174	614	21	3
29.0			
## 175	626	16	2
26.0			
## 176	574	14	3
26.7			



## 177	471	18	5
24.3			
## 178	550	13	1
17.3			
## 179	555	22	1
33.4			
## 180	584	16	6
24.9			
## 181	730	7	6
14.1			
## 182	546	13	2
18.5			
## 183	606	8	3
27.4			
## 184	544	6	2
29.5			
## 185	501	15	2
30.5			
## 186	651	18	4
27.6			
## 187	516	12	4
18.4			
## 188	819	10	3
26.3			
## 189	607	13	2
23.0			
## 190	605	9	4
19.7			
## 191	595	18	3
24.2			
## 192	747	17	1
30.2			
## 193	653	9	3
32.9			
## 194	580	13	2
23.6			
## 195	507	19	5
19.9			
## 196	517	14	5
25.3			
## 197	537	15	2
20.7			
## 198	697	17	2
22.2			
## 199	585	18	2
27.8			
## 200	539	20	3
27.0			
## 201	663	18	3
16.7			

## 202	708	9	3
19.7			
## 203	544	14	4
22.7			
## 204	564	16	1
21.4			
## 205	628	15	7
25.8			
## 206	600	6	3
29.0			
## 207	633	12	6
21.7			
## 208	737	19	3
20.8			
## 209	595	16	5
34.5			
## 210	578	9	7
19.2			
## 211	639	16	0
28.3			
## 212	596	14	1
25.7			
## 213	650	18	5
31.3			
## 214	582	23	3
25.1			
## 215	635	9	4
19.2			
## 216	475	13	4
27.1			
## 217	601	14	2
27.4			
## 218	559	6	2
21.9			
## 219	505	15	2
17.3			
## 220	567	13	1
18.9			
## 221	630	24	1
26.0			
## 222	607	3	3
23.5			
## 223	655	21	3
24.1			
## 224	675	19	2
29.1			
## 225	666	18	3
21.0			
## 226	574	16	3
26.3			

## 227	494	12	0
22.2			
## 228	578	19	3
20.0			
## 229	694	11	1
30.4			
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21.8			
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19.2			
## 232	639	19	1
24.9			
## 233	623	13	1
29.7			
## 234	568	13	2
23.8			
## 235	614	16	2
20.3			
## 236	710	16	2
21.1			
## 237	704	20	5
20.7			
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27.1			
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28.7			
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18.6			
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34.4			
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23.7			
## 248	609	14	6
28.7			
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21.2			
## 250	686	12	3
31.5			
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28.1			

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21.7			
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18.9			
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26.9			
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21.5			
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33.4			
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19.6			
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14.6			
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24.6			
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25.8			
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24.9			
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30.2			
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18.4			

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26.9			
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19.1			
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26.1			
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24.5			
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26.4			

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39.2			
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31.5			
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32.9			
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20.9			
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22.7			
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27.5			
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27.7			
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22.7			
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30.5			
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36.5			
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28.4			
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27.5			
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38.1			
## 373	738	22	5
25.4			
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15.1			
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27.4			
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30.0			



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27.8			
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24.0			
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25.6			
## 382	624	12	1
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## 384	582	13	5
32.6			
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33.0			
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33.5			
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31.9			
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31.7			
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28.4			
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25.7			
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22.8			
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29.4			
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29.7			
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29.2			
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19.6			
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## 401	658	3	6
31.3			

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22.8			
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33.5			
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15.6			
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27.2			
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25.6			
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25.7			
## 412	613	23	2
32.0			
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19.1			
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29.9			
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35.1			
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## 447	723	11	4
16.3			
## 448	731	11	7
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16.2			
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20.2			

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21.6			
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23.9			
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21.7			
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21.8			
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33.8			
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21.7			
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22.2			
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22.6			
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18.5			
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22.5			
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15.2			
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26.2			
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19.3			



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27.8			
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16.1			
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27.9			
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23.3			
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23.6			
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17.6			
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23.6			
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21.4			
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24.3			
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25.0			
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20.3			
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25.6			
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21.0			
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35.8			
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24.9			
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17.9			
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22.0			
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23.3			
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15.4			
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21.7			
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28.6			
## Humidity			
## 1 35.32			

## 2	28.24
## 3	44.51
## 4	53.77
## 5	73.79
## 6	50.89
## 7	47.07
## 8	74.57
## 9	48.03
## 10	76.02
## 11	61.13
## 12	48.25
## 13	11.29
## 14	28.31
## 15	37.28
## 16	25.35
## 17	24.32
## 18	40.53
## 19	71.36
## 20	29.31
## 21	52.72
## 22	45.33
## 23	67.95
## 24	50.89
## 25	46.13
## 26	36.67
## 27	70.09
## 28	75.24
## 29	50.45
## 30	49.93
## 31	46.92
## 32	19.26
## 33	81.71
## 34	85.49
## 35	59.12
## 36	57.09
## 37	37.73
## 38	34.61
## 39	33.69
## 40	30.37
## 41	37.66
## 42	35.81
## 43	62.08
## 44	67.47
## 45	61.33
## 46	42.68
## 47	43.88
## 48	15.50
## 49	49.24
## 50	32.42
## 51	58.17

## 52	25.30
## 53	32.29
## 54	43.51
## 55	22.98
## 56	42.53
## 57	41.12
## 58	63.92
## 59	28.89
## 60	82.76
## 61	60.73
## 62	33.72
## 63	55.30
## 64	41.12
## 65	61.64
## 66	31.69
## 67	60.61
## 68	83.53
## 69	77.69
## 70	57.01
## 71	57.66
## 72	59.66
## 73	70.23
## 74	58.85
## 75	63.82
## 76	64.53
## 77	55.24
## 78	51.33
## 79	72.61
## 80	40.18
## 81	54.46
## 82	50.75
## 83	26.09
## 84	76.43
## 85	24.29
## 86	78.50
## 87	26.20
## 88	69.42
## 89	48.12
## 90	82.15
## 91	34.25
## 92	17.55
## 93	37.03
## 94	52.04
## 95	42.34
## 96	36.79
## 97	46.23
## 98	56.19
## 99	30.69
## 100	29.19
## 101	64.48

## 102	24.64
## 103	30.05
## 104	30.26
## 105	67.85
## 106	50.72
## 107	61.19
## 108	67.48
## 109	55.70
## 110	60.26
## 111	24.29
## 112	48.58
## 113	35.95
## 114	21.50
## 115	24.16
## 116	21.59
## 117	40.73
## 118	72.01
## 119	57.56
## 120	64.85
## 121	57.61
## 122	46.57
## 123	7.87
## 124	36.11
## 125	41.32
## 126	90.44
## 127	53.18
## 128	33.67
## 129	70.02
## 130	61.25
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## 132	44.76
## 133	46.65
## 134	48.36
## 135	64.12
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## 137	35.70
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## 139	34.12
## 140	78.58
## 141	28.04
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## 143	77.59
## 144	76.89
## 145	47.42
## 146	65.74
## 147	8.56
## 148	60.18
## 149	47.48
## 150	63.68
## 151	52.50

## 152	78.30
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## 154	66.65
## 155	47.56
## 156	64.93
## 157	22.93
## 158	63.83
## 159	41.06
## 160	59.06
## 161	30.27
## 162	62.38
## 163	82.80
## 164	71.96
## 165	35.89
## 166	57.46
## 167	46.36
## 168	44.48
## 169	42.73
## 170	47.94
## 171	37.84
## 172	64.84
## 173	88.68
## 174	65.03
## 175	51.27
## 176	51.74
## 177	75.61
## 178	78.05
## 179	36.49
## 180	71.32
## 181	23.88
## 182	23.69
## 183	83.74
## 184	50.85
## 185	50.78
## 186	45.47
## 187	30.89
## 188	53.19
## 189	14.42
## 190	39.18
## 191	46.39
## 192	18.94
## 193	54.25
## 194	33.37
## 195	74.73
## 196	43.54
## 197	25.74
## 198	55.50
## 199	48.77
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## 201	54.96

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## 203	42.50
## 204	64.76
## 205	84.26
## 206	46.88
## 207	71.95
## 208	23.96
## 209	75.79
## 210	41.30
## 211	66.08
## 212	81.62
## 213	70.23
## 214	7.78
## 215	22.11
## 216	63.27
## 217	29.51
## 218	37.39
## 219	79.99
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## 221	51.04
## 222	44.35
## 223	16.23
## 224	11.85
## 225	44.99
## 226	58.14
## 227	21.23
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## 230	61.60
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## 232	70.63
## 233	62.67
## 234	26.47
## 235	77.44
## 236	22.03
## 237	39.04
## 238	57.66
## 239	56.46
## 240	63.45
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## 242	31.69
## 243	21.84
## 244	24.19
## 245	63.12
## 246	39.40
## 247	59.47
## 248	76.12
## 249	34.72
## 250	70.79
## 251	35.31

## 252	64.06
## 253	50.78
## 254	30.80
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## 257	30.41
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## 260	46.16
## 261	80.34
## 262	25.28
## 263	93.92
## 264	34.81
## 265	38.08
## 266	49.11
## 267	73.92
## 268	98.63
## 269	61.06
## 270	64.13
## 271	20.21
## 272	53.25
## 273	44.06
## 274	81.40
## 275	45.44
## 276	48.67
## 277	50.90
## 278	47.15
## 279	52.30
## 280	17.71
## 281	38.99
## 282	42.16
## 283	63.01
## 284	54.77
## 285	32.80
## 286	69.17
## 287	76.98
## 288	21.99
## 289	54.23
## 290	33.01
## 291	36.13
## 292	59.63
## 293	58.72
## 294	37.77
## 295	75.05
## 296	73.04
## 297	27.85
## 298	57.20
## 299	24.35
## 300	81.50
## 301	56.21

## 302	73.77
## 303	58.91
## 304	47.51
## 305	67.02
## 306	25.49
## 307	35.62
## 308	56.06
## 309	40.51
## 310	39.35
## 311	70.70
## 312	38.51
## 313	71.84
## 314	32.49
## 315	44.10
## 316	31.33
## 317	40.23
## 318	24.31
## 319	60.24
## 320	76.10
## 321	56.51
## 322	85.64
## 323	15.52
## 324	32.96
## 325	62.00
## 326	64.43
## 327	57.51
## 328	86.16
## 329	85.05
## 330	18.64
## 331	40.43
## 332	19.09
## 333	26.98
## 334	55.71
## 335	58.07
## 336	32.32
## 337	56.93
## 338	33.48
## 339	55.74
## 340	52.61
## 341	43.47
## 342	28.46
## 343	39.34
## 344	61.24
## 345	38.69
## 346	42.52
## 347	26.18
## 348	40.05
## 349	49.43
## 350	33.45
## 351	41.22



## 352	25.54
## 353	66.99
## 354	40.25
## 355	60.69
## 356	83.51
## 357	41.18
## 358	41.07
## 359	64.74
## 360	28.63
## 361	46.02
## 362	37.36
## 363	59.65
## 364	46.80
## 365	64.70
## 366	31.43
## 367	43.42
## 368	25.79
## 369	63.20
## 370	61.20
## 371	29.49
## 372	46.23
## 373	54.11
## 374	48.87
## 375	45.04
## 376	51.86
## 377	26.99
## 378	75.52
## 379	64.72
## 380	51.82
## 381	71.23
## 382	23.11
## 383	74.14
## 384	54.88
## 385	61.51
## 386	39.56
## 387	32.28
## 388	37.52
## 389	73.13
## 390	74.25
## 391	48.57
## 392	32.86
## 393	81.60
## 394	17.01
## 395	46.34
## 396	63.76
## 397	24.30
## 398	61.20
## 399	84.16
## 400	33.76
## 401	34.38

## 402	28.85
## 403	81.82
## 404	33.91
## 405	31.08
## 406	36.58
## 407	36.36
## 408	63.83
## 409	56.93
## 410	60.87
## 411	35.64
## 412	66.45
## 413	75.01
## 414	54.60
## 415	40.71
## 416	60.89
## 417	23.09
## 418	35.58
## 419	52.51
## 420	16.82
## 421	49.07
## 422	49.16
## 423	43.59
## 424	21.73
## 425	75.79
## 426	18.17
## 427	18.32
## 428	36.70
## 429	82.95
## 430	52.46
## 431	55.97
## 432	45.03
## 433	56.23
## 434	64.43
## 435	66.08
## 436	79.74
## 437	32.38
## 438	46.36
## 439	59.48
## 440	68.65
## 441	42.35
## 442	64.82
## 443	37.47
## 444	42.16
## 445	72.63
## 446	11.82
## 447	55.10
## 448	70.81
## 449	42.08
## 450	64.24
## 451	33.95

## 452	53.94
## 453	50.23
## 454	49.34
## 455	22.06
## 456	46.26
## 457	31.59
## 458	41.74
## 459	72.88
## 460	37.06
## 461	49.25
## 462	52.37
## 463	45.64
## 464	68.24
## 465	49.02
## 466	53.57
## 467	29.95
## 468	41.23
## 469	35.26
## 470	60.86
## 471	75.49
## 472	39.45
## 473	7.70
## 474	30.91
## 475	29.01
## 476	53.29
## 477	83.21
## 478	59.20
## 479	17.08
## 480	61.33
## 481	33.04
## 482	50.01
## 483	47.66
## 484	46.68
## 485	42.39
## 486	88.71
## 487	29.97
## 488	54.57
## 489	75.48
## 490	74.49
## 491	29.84
## 492	80.46
## 493	33.99
## 494	52.92
## 495	53.88
## 496	11.30
## 497	46.93
## 498	10.68
## 499	57.36
## 500	57.84
## 501	71.84

## 502	58.71
## 503	34.67
## 504	31.88
## 505	68.20
## 506	81.22
## 507	68.08
## 508	54.99
## 509	48.41
## 510	72.23
## 511	46.14
## 512	25.01
## 513	68.90
## 514	28.04
## 515	57.90
## 516	54.27
## 517	53.25
## 518	53.74
## 519	38.71
## 520	34.01
## 521	23.87
## 522	24.77
## 523	30.91
## 524	77.38
## 525	65.80
## 526	56.32
## 527	85.70
## 528	84.01
## 529	70.32
## 530	23.87
## 531	80.89
## 532	45.35
## 533	44.42
## 534	55.46
## 535	51.45
## 536	38.70
## 537	65.58
## 538	38.96
## 539	37.10
## 540	44.15
## 541	32.78
## 542	53.54
## 543	47.76
## 544	43.20
## 545	60.62
## 546	12.65
## 547	55.81
## 548	70.29
## 549	69.84
## 550	35.42
## 551	28.04

## 552	57.49
## 553	76.67
## 554	26.64
## 555	60.05
## 556	42.24
## 557	55.96
## 558	25.50
## 559	70.74
## 560	5.46
## 561	46.98
## 562	26.51
## 563	33.48
## 564	71.01
## 565	39.28
## 566	52.99
## 567	81.42
## 568	34.48
## 569	72.09
## 570	78.11
## 571	46.12
## 572	18.50
## 573	67.21
## 574	76.90
## 575	35.92
## 576	38.29
## 577	67.91
## 578	81.40
## 579	12.83
## 580	75.34
## 581	79.33
## 582	58.53
## 583	55.57
## 584	35.84
## 585	57.79
## 586	39.64
## 587	90.31
## 588	39.70
## 589	61.44
## 590	68.60
## 591	17.11
## 592	44.05
## 593	58.96
## 594	45.46
## 595	19.21
## 596	30.80
## 597	84.22
## 598	47.08
## 599	77.93
## 600	54.13

### #Perform PCA

```
obj = prcomp(PCA_BFD,center = TRUE, scale = TRUE)
summary(obj)
```

## Importance of components:

```
##              PC1      PC2      PC3      PC4      PC5      PC6      PC7
PC8
## Standard deviation      1.1032 1.0420 1.0295 1.0070 0.9978 0.9800 0.9696
0.94216
## Proportion of Variance 0.1352 0.1206 0.1178 0.1127 0.1106 0.1067 0.1045
0.09863
## Cumulative Proportion 0.1352 0.2559 0.3736 0.4863 0.5969 0.7036 0.8081
0.90672
##              PC9
## Standard deviation      0.91624
## Proportion of Variance 0.09328
## Cumulative Proportion 1.00000
```

### #Loadings

```
obj$rotation
```

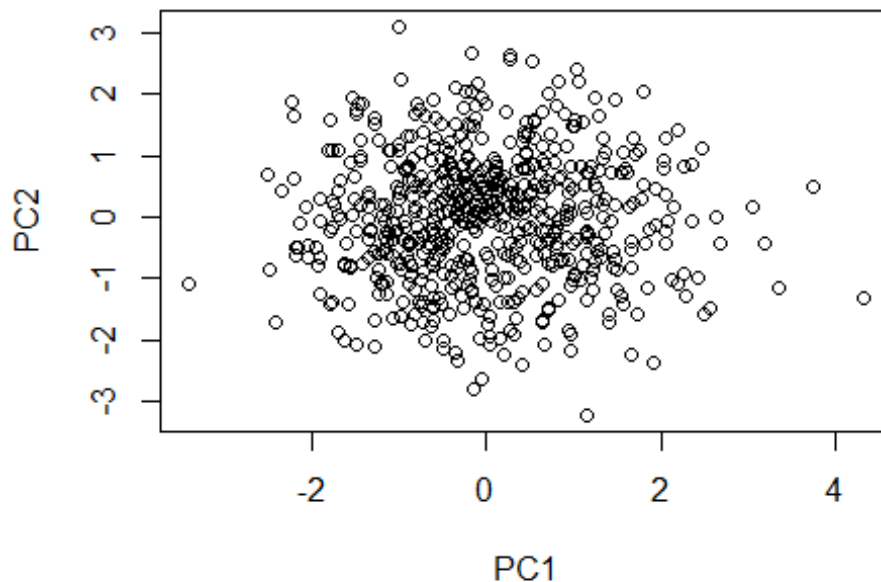
```
##              PC1      PC2      PC3      PC4
## Fire_Intensity      0.3879646 0.53114764 0.277551664 -0.1241035
## Distance_from_Fire -0.2886636 0.31299597 0.283544133 0.1461189
## Building_Age      0.3992121 0.01092616 0.188956016 -0.2397889
## Property_Value     -0.2343575 -0.56694049 0.046357169 0.1135330
## Population_Density -0.1844550 -0.03471533 0.665073999 -0.2027555
## Emergency_Response_Time -0.1559268 0.36447621 -0.481160270 -0.1691881
## Mitigation_Measures 0.4326790 -0.18691331 0.233395512 0.5172214
## Wind_Speed        -0.5238593 0.11616106 0.276349250 -0.1083837
## Humidity          -0.1785676 0.34043615 -0.005782125 0.7374684
##              PC5      PC6      PC7      PC8
## Fire_Intensity      0.06774495 0.05978999 0.17105479 -0.46566106
## Distance_from_Fire 0.39809326 -0.39041991 -0.63245462 -0.04322718
## Building_Age      0.63950630 0.32255633 0.06747088 0.33870550
## Property_Value     0.55375337 -0.06649410 0.24063293 -0.27686720
## Population_Density -0.19223228 -0.34593910 0.37214303 0.42027466
## Emergency_Response_Time 0.26021220 -0.48561646 0.48327720 -0.01756541
## Mitigation_Measures -0.06798850 -0.34429795 0.17163800 -0.30500609
## Wind_Speed        -0.03133774 0.41519685 0.19695159 -0.45038549
## Humidity          0.10513399 0.29850745 0.26074521 0.34219758
##              PC9
## Fire_Intensity     -0.46974977
## Distance_from_Fire 0.06469508
## Building_Age      0.33914973
## Property_Value     -0.40372316
## Population_Density -0.09792678
## Emergency_Response_Time 0.21284964
## Mitigation_Measures 0.45848552
```

```
## Wind_Speed          0.45711549
## Humidity            -0.15190984

#Principal components
head(obj$x)

##           PC1          PC2          PC3          PC4          PC5          PC6
## [1,] -0.5245971 -1.4173303 -1.3564853 -0.004936077 -0.28599453 -0.2470297
## [2,]  1.8103159  0.5301982 -1.8342258 -0.875235087  0.18356445  0.2213466
## [3,] -0.0967987  0.3485307 -0.5527159  0.069854381 -2.40385667 -0.7887507
## [4,]  1.5715451  1.0495303 -0.1293591 -0.669977650 -0.20716960  1.1520080
## [5,] -1.4997559  0.6674983  1.4491181  0.446020777 -0.25751187  1.6647432
## [6,] -1.1547775 -0.5263678 -0.6187590 -0.068258525  0.08416854  2.0334067
##           PC7          PC8          PC9
## [1,]  0.07927102 -1.0187599 -0.29485698
## [2,] -0.32898494 -1.0543512  0.07111559
## [3,]  0.50830477 -0.1184211  0.49628723
## [4,]  0.34139370  0.4354578 -0.46122443
## [5,]  1.27443050 -1.4171480 -0.98520328
## [6,] -1.62895108  0.1303434  1.02821475

#First two principal components
plot(obj$x[,1:2])
```



```
#biplot
biplot(obj,scale = 0)
```

