DATA410 Project

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Predicting core body temperature using infrared thermography (IRT)

Introduction

In recent years, the medical field has seen a significant increase in the use of non-invasive diagnostic techniques, which are techniques that do not require the introduction of instruments into the body, to get real-time estimates of a patient's core body temperature, with infrared thermography (IRT) becoming an important tool for physiological monitoring and disease detection. This is particularly useful for clinical settings and during infectious disease epidemics. For example, in the year 2020 during the COVID-19 pandemic, the Kuala Lumpur International Airport (KLIA) utilized thermal scanners to detect passenger's body temperatures to determine if they were potential carriers of the COVID-19 disease. Only passengers with a core body temperature of below 37 degrees Celsius were allowed to move into the airport's check-in area.

The non-invasive nature of IRT enables its extensive utilization in various medical applications, as abnormal body temperature serves as a natural indicator of illnesses. Biomedical research has showcased the efficiency of IRT in diverse diagnostic endeavors, including the detection of breast cancer, diabetes neuropathy, peripheral vascular disorders, gynecological issues, kidney transplantation, dermatological conditions, cardiac abnormalities, neonatal physiology, fever screening, and brain imaging (Kylili et al., 2014).

IRT's capability to visualize and quantify changes in surface temperatures has led to its application in monitoring a wide range of medical conditions, such as severe acute respiratory syndrome, Ebola virus disease, or even the coronavirus disease in 2019. A crucial aspect of using IRT lies in the accurate interpretation of thermal images, particularly in correlating external thermal readings with core body temperatures.

Our project aims to close this gap by developing a predictive model that can estimate oral temperature—a common measuring technique of core body temperature—using thermal imaging data from IRTs and environmental factors such as ambient temperature, relative humidity, and the distance between the subjects and the IRTs. This model could potentially enhance the clinical use of IRT by providing non-invasive measurement methods, offering a significant advantage in both routine health assessments and the early detection of health problems, as well as the detection of carriers of infectious diseases. We hypothesize that by using environmental factors and IRTs, we can predict oral temperature.

Data Preparation

```r
#load features and targets and then combine the two
X = read.csv("infrared_thermography_data_features.csv")
Y = read.csv("infrared_thermography_data_targets.csv")

attach(Y)
```

```r
#combine x and y
data = cbind(aveOralM,X)
attach(data)
```

```
## The following object is masked from Y:
##
##     aveOralM
```

```r
#factor categorical variables
data$Gender = factor(data$Gender, levels = c("Male", "Female"), labels = c(0, 1))
data$Age[data$Age %in% c("26-30", "21-25")]  = "21-30"
data$Age = factor(data$Age, levels = c("18-20", "21-30", "31-40", "41-50", "51-60", ">60"), labels = c(
data$Ethnicity <- factor(data$Ethnicity, levels = c("White", "Black or African-American", "Asian", "Mul

#check data for missing values and to check which column is missing data
sum(is.na(data))
```

```
## [1] 2
```

```r
colSums(is.na(data))
```

```
##    aveOralM      Gender         Age   Ethnicity       T_atm    Humidity
##           0           0           0           0           0           0
##    Distance    T_offset1   Max1R13_1   Max1L13_1 aveAllR13_1 aveAllL13_1
##           2           0           0           0           0           0
##       T_RC1   T_RC_Dry1   T_RC_Wet1   T_RC_Max1       T_LC1   T_LC_Dry1
##           0           0           0           0           0           0
##   T_LC_Wet1   T_LC_Max1        RCC1        LCC1  canthiMax1 canthi4Max1
##           0           0           0           0           0           0
##     T_FHCC1     T_FHRC1     T_FHLC1     T_FHBC1     T_FHTC1   T_FH_Max1
##           0           0           0           0           0           0
##  T_FHC_Max1      T_Max1       T_OR1   T_OR_Max1
##           0           0           0           0
```

```r
data = na.omit(data) #Removing the 2 observations we found in the distance column, easy to deal with as

summary(data)
```

```
##     aveOralM     Gender  Age     Ethnicity     T_atm          Humidity
##  Min.   :35.54   0:413   0:532   0:504     Min.   :20.20   Min.   : 9.90
##  1st Qu.:36.75   1:605   1:432   1:143     1st Qu.:23.40   1st Qu.:17.60
##  Median :36.94           2: 31   2:260     Median :24.00   Median :26.30
##  Mean   :37.03           3:  9   3: 50     Mean   :24.12   Mean   :28.75
##  3rd Qu.:37.14           4: 11   4: 57     3rd Qu.:24.70   3rd Qu.:36.20
##  Max.   :40.34           5:  3   5:  4     Max.   :29.10   Max.   :61.20
##     Distance          T_offset1          Max1R13_1       Max1L13_1
##  Min.   : 0.5400   Min.   :-0.5900   Min.   :33.90   Min.   :34.12
##  1st Qu.: 0.6000   1st Qu.: 0.7725   1st Qu.:35.25   1st Qu.:35.27
##  Median : 0.6200   Median : 0.9400   Median :35.55   Median :35.58
##  Mean   : 0.7298   Mean   : 0.9690   Mean   :35.60   Mean   :35.61
##  3rd Qu.: 0.7000   3rd Qu.: 1.1400   3rd Qu.:35.87   3rd Qu.:35.88
```

```
##  Max.   :79.0000   Max.   : 2.8750   Max.   :38.41   Max.   :38.04  
##   aveAllR13_1     aveAllL13_1        T_RC1          T_RC_Dry1    
##  Min.   :31.77   Min.   :32.90   Min.   :33.98   Min.   :33.83  
##  1st Qu.:34.46   1st Qu.:34.66   1st Qu.:35.33   1st Qu.:35.25  
##  Median :34.91   Median :35.00   Median :35.60   Median :35.53  
##  Mean   :34.89   Mean   :35.01   Mean   :35.66   Mean   :35.59  
##  3rd Qu.:35.30   3rd Qu.:35.36   3rd Qu.:35.91   3rd Qu.:35.86  
##  Max.   :37.58   Max.   :37.68   Max.   :38.38   Max.   :38.38  
##    T_RC_Wet1       T_RC_Max1         T_LC1         T_LC_Dry1    
##  Min.   :33.93   Min.   :34.00   Min.   :34.10   Min.   :34.10  
##  1st Qu.:35.21   1st Qu.:35.36   1st Qu.:35.31   1st Qu.:35.28  
##  Median :35.48   Median :35.63   Median :35.60   Median :35.57  
##  Mean   :35.55   Mean   :35.69   Mean   :35.64   Mean   :35.61  
##  3rd Qu.:35.81   3rd Qu.:35.94   3rd Qu.:35.90   3rd Qu.:35.86  
##  Max.   :38.33   Max.   :38.41   Max.   :38.04   Max.   :38.04  
##    T_LC_Wet1       T_LC_Max1          RCC1             LCC1      
##  Min.   :33.73   Min.   :34.12   Min.   :33.62   Min.   :33.38  
##  1st Qu.:35.13   1st Qu.:35.33   1st Qu.:34.88   1st Qu.:34.86  
##  Median :35.42   Median :35.63   Median :35.20   Median :35.17  
##  Mean   :35.47   Mean   :35.67   Mean   :35.25   Mean   :35.21  
##  3rd Qu.:35.76   3rd Qu.:35.92   3rd Qu.:35.56   3rd Qu.:35.50  
##  Max.   :37.96   Max.   :38.08   Max.   :38.16   Max.   :37.83  
##    canthiMax1     canthi4Max1       T_FHCC1         T_FHRC1     
##  Min.   :34.38   Min.   :34.35   Min.   :31.05   Min.   :31.45  
##  1st Qu.:35.45   1st Qu.:35.43   1st Qu.:34.22   1st Qu.:34.18  
##  Median :35.71   Median :35.68   Median :34.61   Median :34.60  
##  Mean   :35.79   Mean   :35.76   Mean   :34.57   Mean   :34.57  
##  3rd Qu.:36.03   3rd Qu.:36.00   3rd Qu.:34.97   3rd Qu.:34.97  
##  Max.   :38.41   Max.   :38.38   Max.   :37.12   Max.   :37.08  
##     T_FHLC1         T_FHBC1         T_FHTC1        T_FH_Max1    
##  Min.   :31.66   Min.   :31.28   Min.   :31.15   Min.   :33.41  
##  1st Qu.:34.18   1st Qu.:34.10   1st Qu.:34.23   1st Qu.:35.12  
##  Median :34.60   Median :34.51   Median :34.62   Median :35.39  
##  Mean   :34.57   Mean   :34.49   Mean   :34.58   Mean   :35.42  
##  3rd Qu.:34.97   3rd Qu.:34.88   3rd Qu.:35.01   3rd Qu.:35.67  
##  Max.   :37.16   Max.   :37.21   Max.   :37.37   Max.   :38.00  
##    T_FHC_Max1        T_Max1          T_OR1         T_OR_Max1    
##  Min.   :32.44   Min.   :34.89   Min.   :33.80   Min.   :33.84  
##  1st Qu.:34.76   1st Qu.:35.77   1st Qu.:35.47   1st Qu.:35.50  
##  Median :35.10   Median :36.03   Median :35.79   Median :35.83  
##  Mean   :35.09   Mean   :36.08   Mean   :35.81   Mean   :35.84  
##  3rd Qu.:35.41   3rd Qu.:36.28   3rd Qu.:36.09   3rd Qu.:36.12  
##  Max.   :37.63   Max.   :38.81   Max.   :38.42   Max.   :38.45
```

```
attach(data)
```

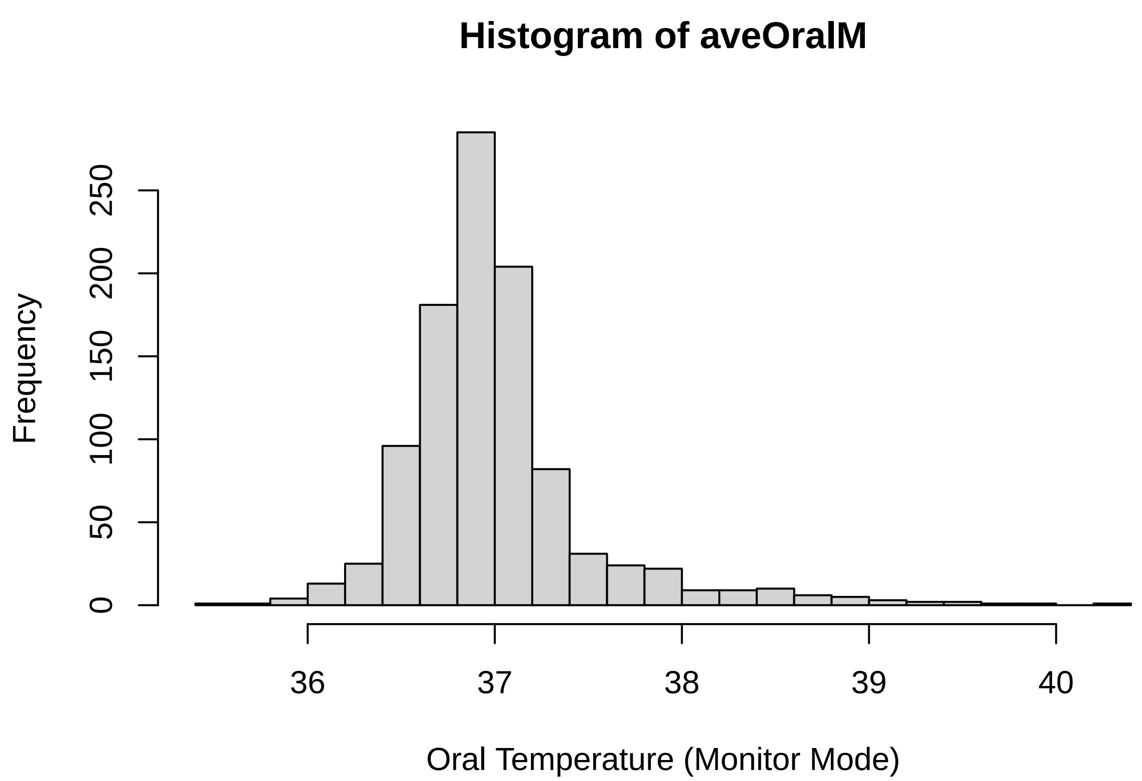
```
## The following objects are masked from data (pos = 3):
## 
##     Age, aveAllL13_1, aveAllR13_1, aveOralM, canthi4Max1, canthiMax1,
##     Distance, Ethnicity, Gender, Humidity, LCC1, Max1L13_1, Max1R13_1,
##     RCC1, T_atm, T_FH_Max1, T_FHBC1, T_FHC_Max1, T_FHCC1, T_FHLC1,
##     T_FHRC1, T_FHTC1, T_LC_Dry1, T_LC_Max1, T_LC_Wet1, T_LC1, T_Max1,
##     T_offset1, T_OR_Max1, T_OR1, T_RC_Dry1, T_RC_Max1, T_RC_Wet1, T_RC1
## 
```

```
## The following object is masked from Y:
##
##     aveOralM
```

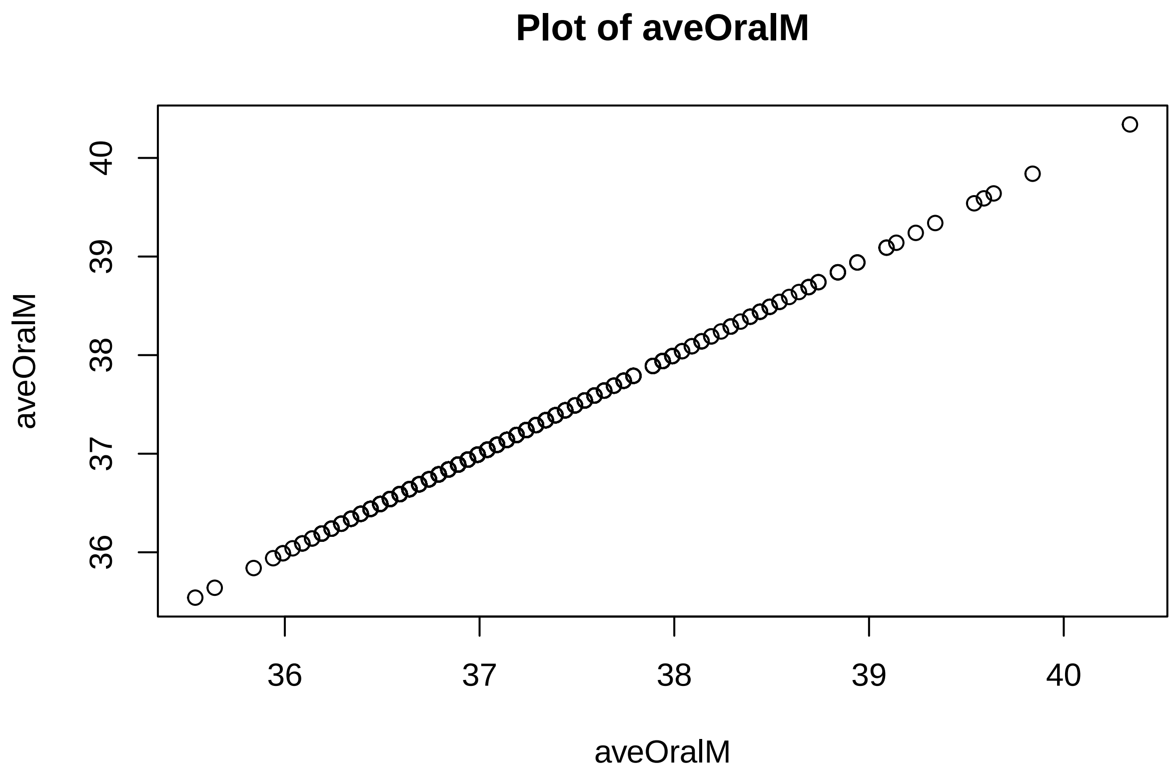
There are two missing values in the dataset, which we simply remove as the amount of missing data is minimal. The 2 missing values are in the Distance column.

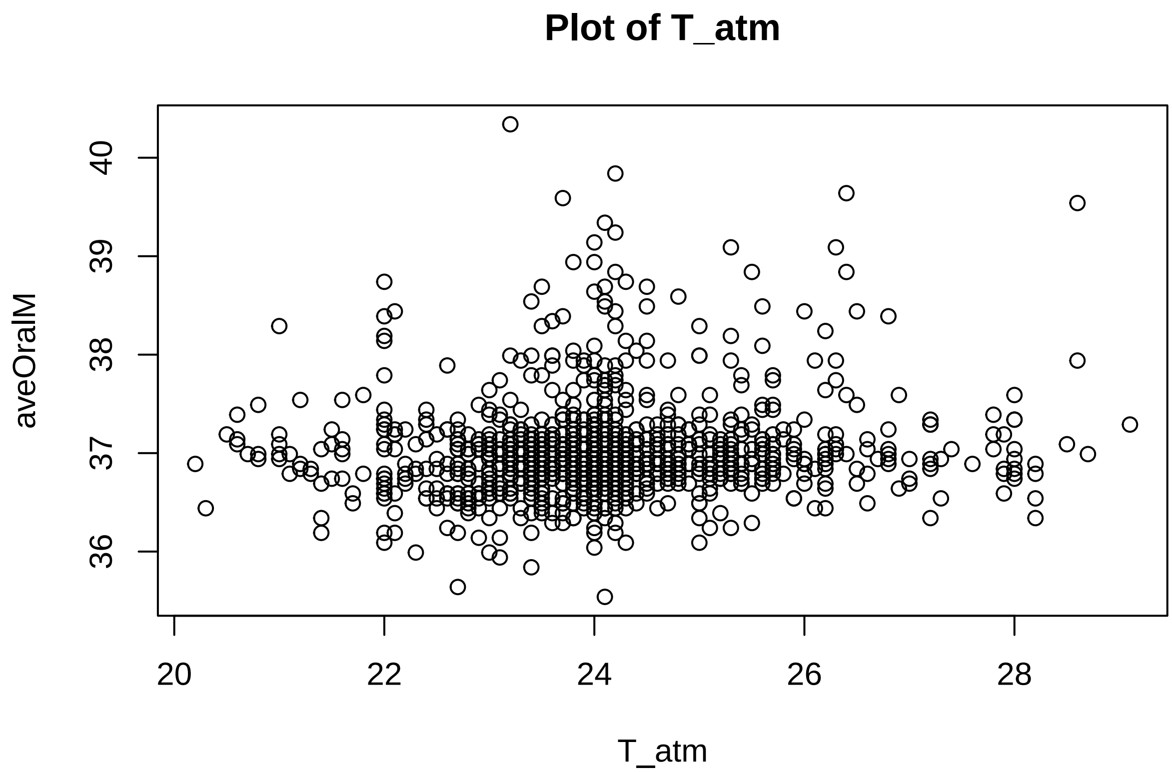
Exploratory Data Analysis (EDA)

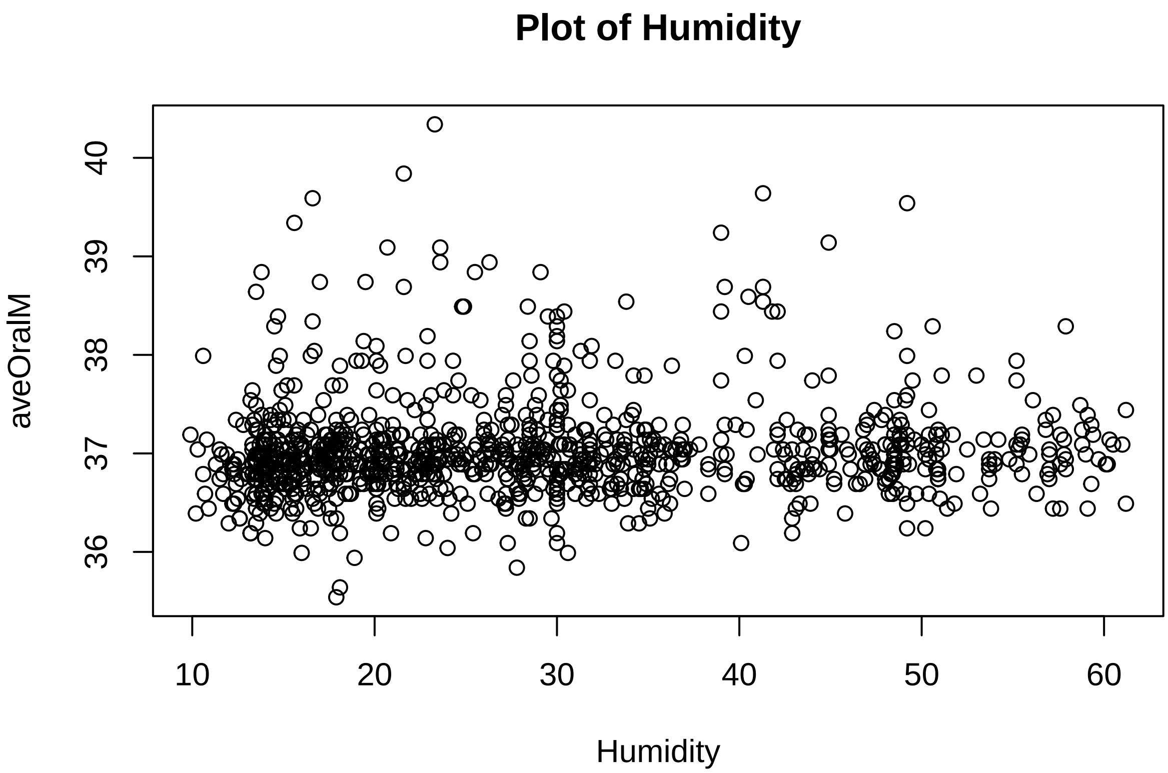
```
#Looking at our target variables first
# add the breaks so that we can see the data clearer, otherwise bins are too wide to be able to show an
# hist(data$aveOralF, main = "Histogram of aveOralF", xlab = "Oral Temperature (Fast Mode)", breaks = 2
hist(data$aveOralM, main = "Histogram of aveOralM", xlab = "Oral Temperature (Monitor Mode)", breaks = 
```



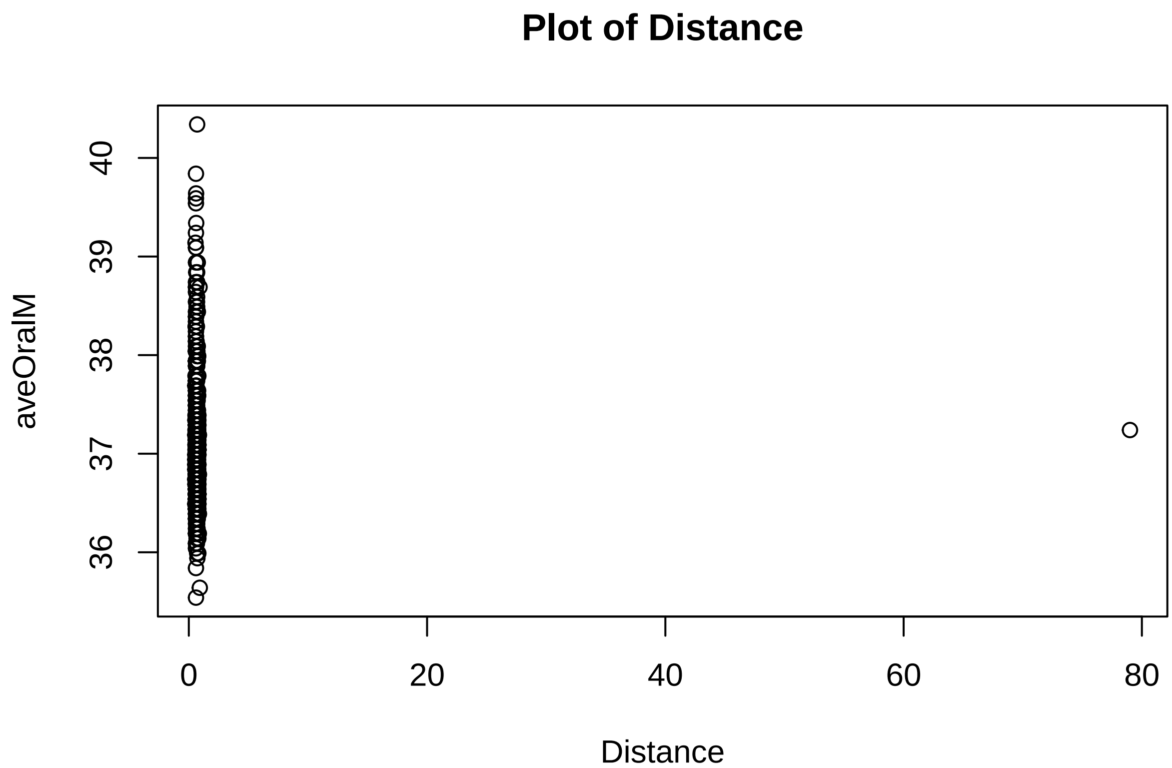

```
#Checking plot of each variable
# For numeric variables: histograms
for(i in 1:ncol(data)){
  if(is.numeric(data[[i]])){
    plot( data[[i]], aveOralM,main=paste("Plot of", names(data)[i]), xlab=names(data)[i])
  }
}
```

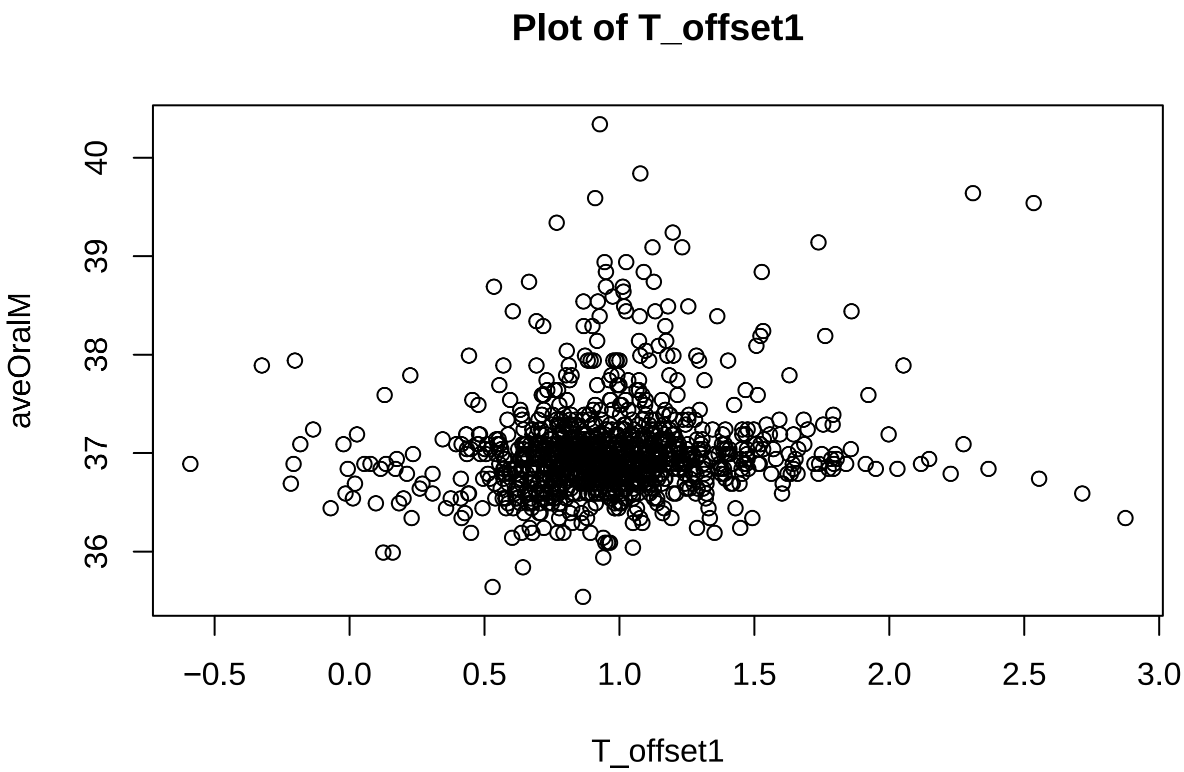

Plot of aveOralM
aveOralM
36
37
38
39
40
aveOralM
36
37
38
39
40

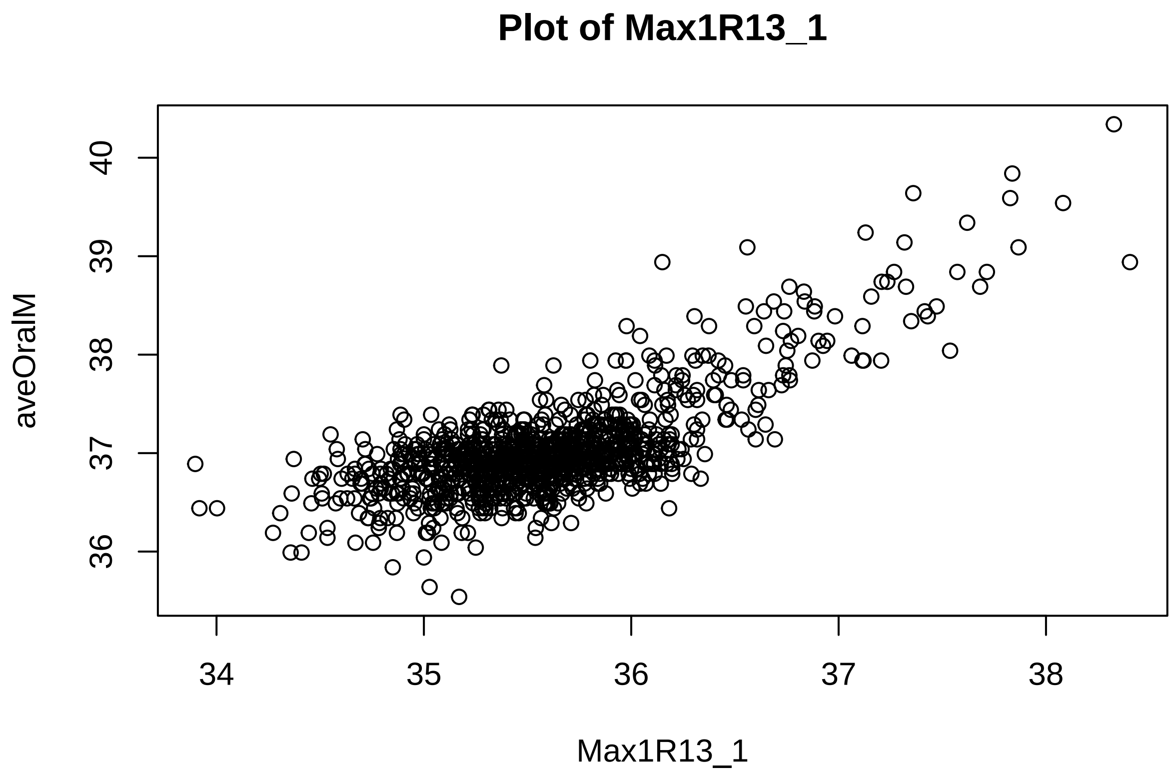

Plot of T_atm
aveOralM
36
37
38
39
40
20
22
24
26
28
T_atm

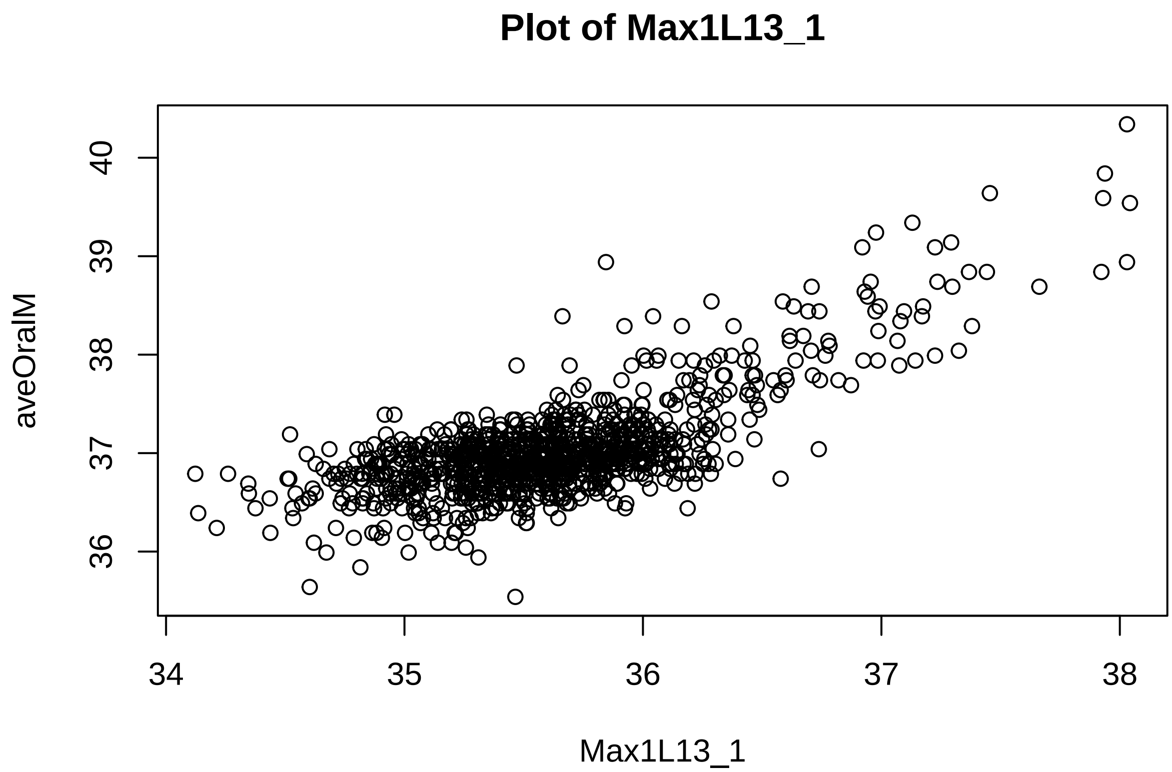


Plot of Humidity
aveOralM
36
37
38
39
40
10
20
30
40
50
60
Humidity


Plot of Distance
aveOralM
40
39
38
37
36
0
20
40
60
80
Distance


Plot of T_offset1
aveOralM
40
39
38
37
36
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
T_offset1


Plot of Max1R13_1
40
39
38
37
36
aveOralM
34
35
36
37
38
Max1R13_1


Plot of Max1L13_1
aveOralM
36
37
38
39
40
34
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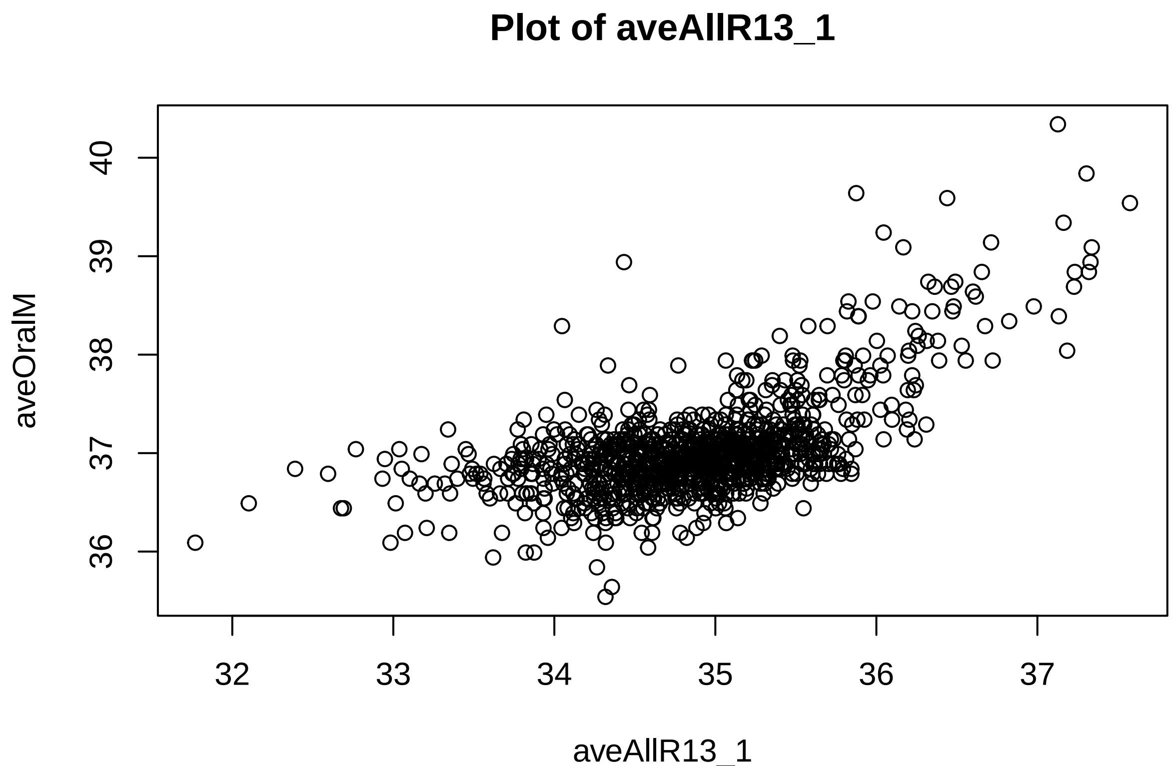
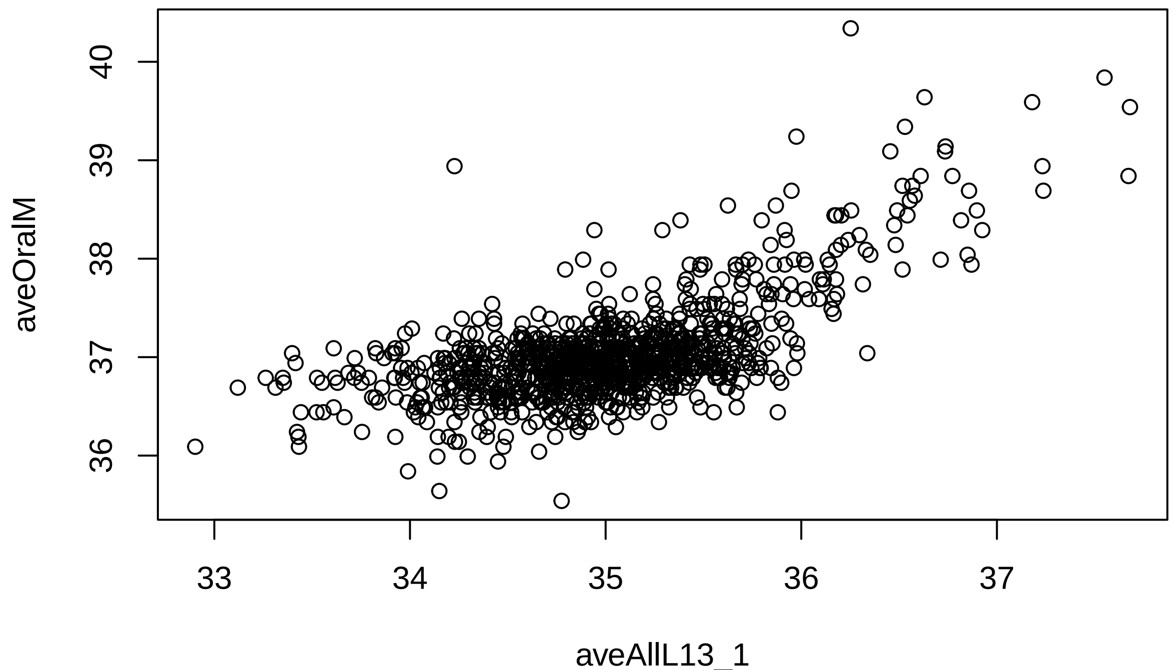
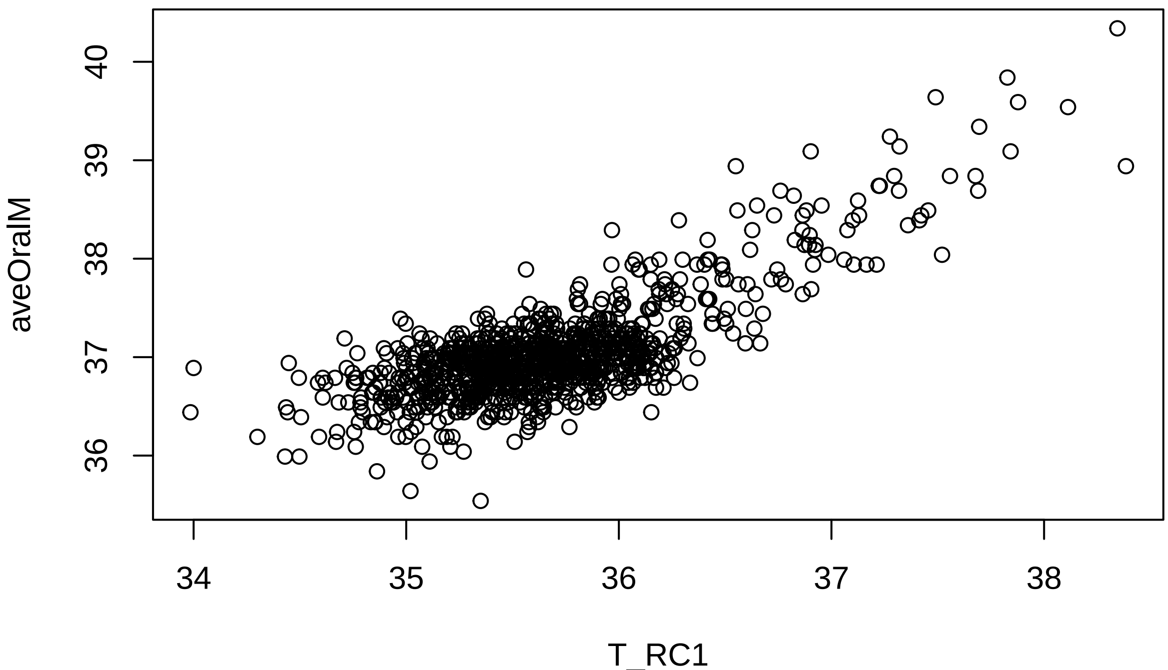
36
37
38
Max1L13_1

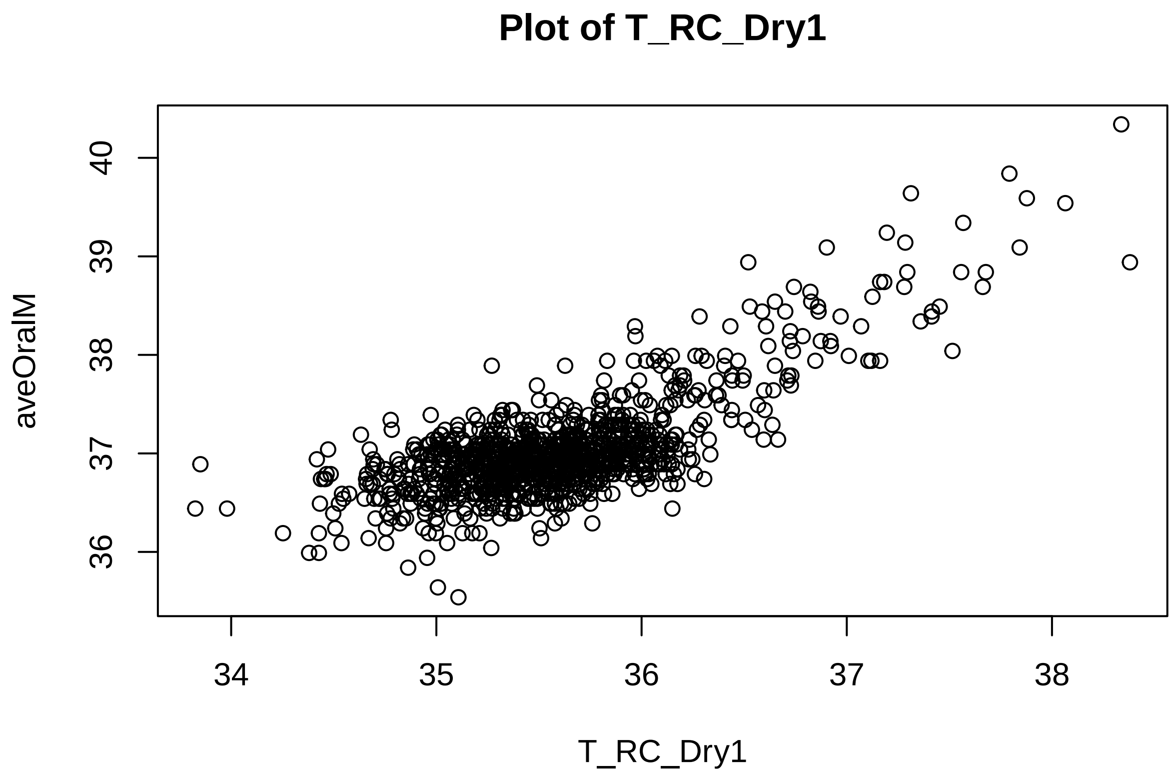

Plot of aveAllR13_1
aveOralM
36
37
38
39
40
32
33
34
35
36
37
aveAllR13_1

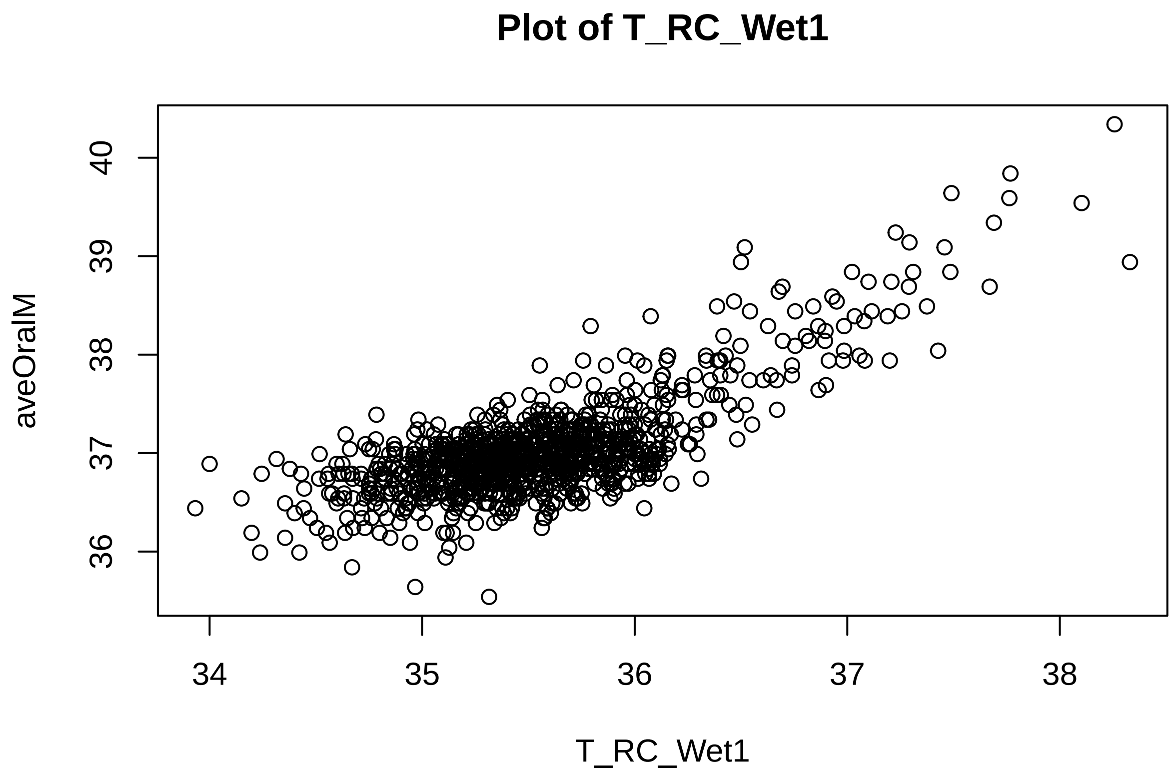
Plot of aveAllL13_1

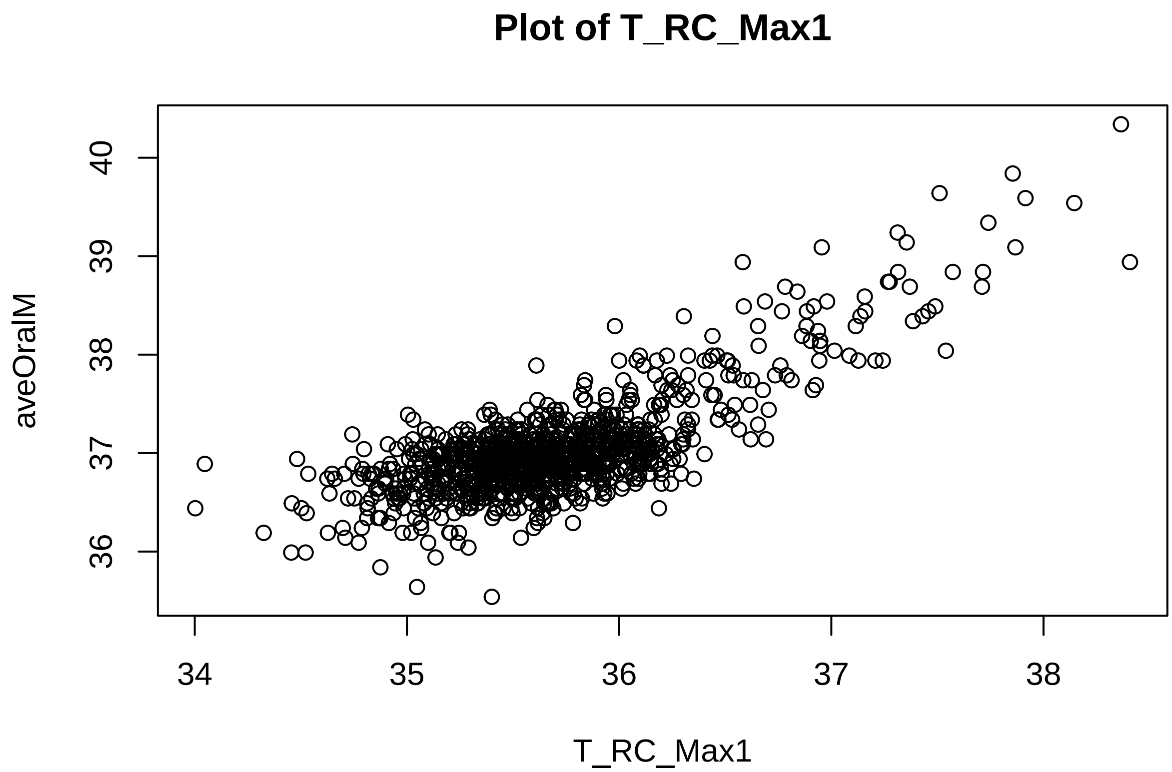


Plot of T_RC1




Plot of T_RC_Dry1
aveOralM
36
37
38
39
40
34
35
36
37
38
T_RC_Dry1


Plot of T_RC_Wet1
aveOralM
T_RC_Wet1
34
35
36
37
38
36
37
38
39
40



Plot of T_RC_Max1
aveOralM
T_RC_Max1
36
37
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39
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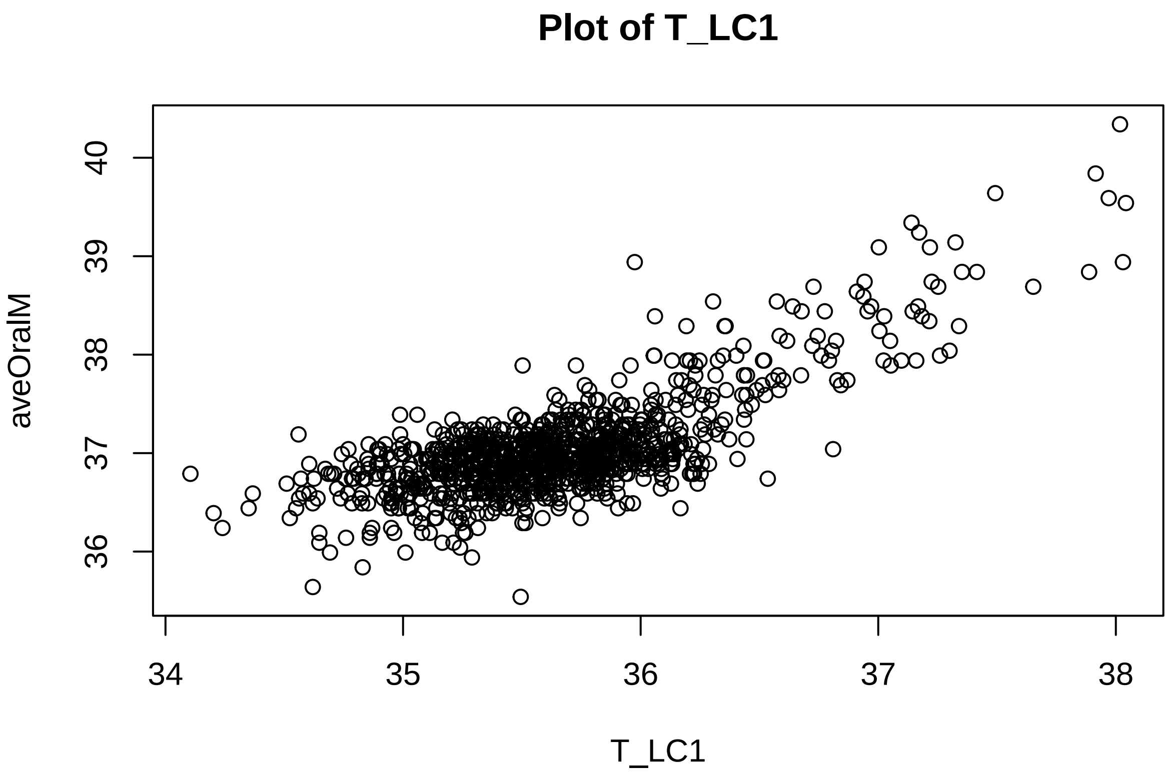
34
35
36
37
38


Plot of T_LC1
aveOralM
T_LC1
34
35
36
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36
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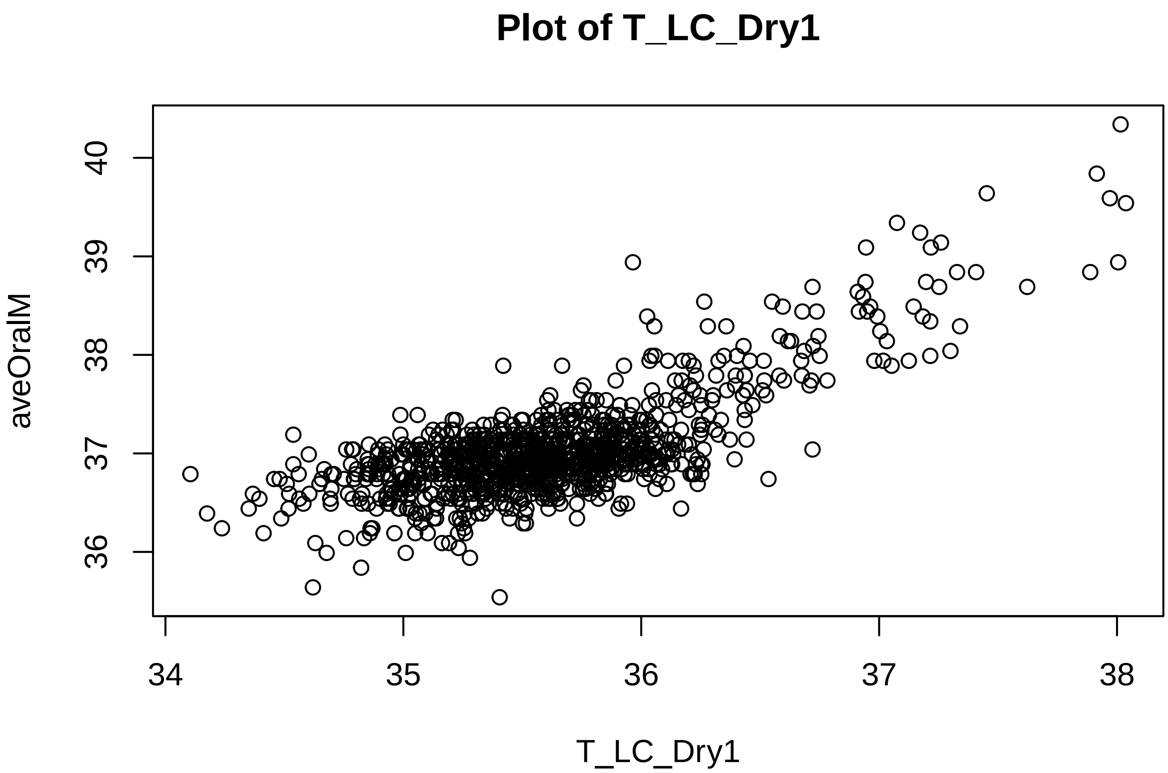
40


Plot of T_LC_Dry1
aveOralM
36
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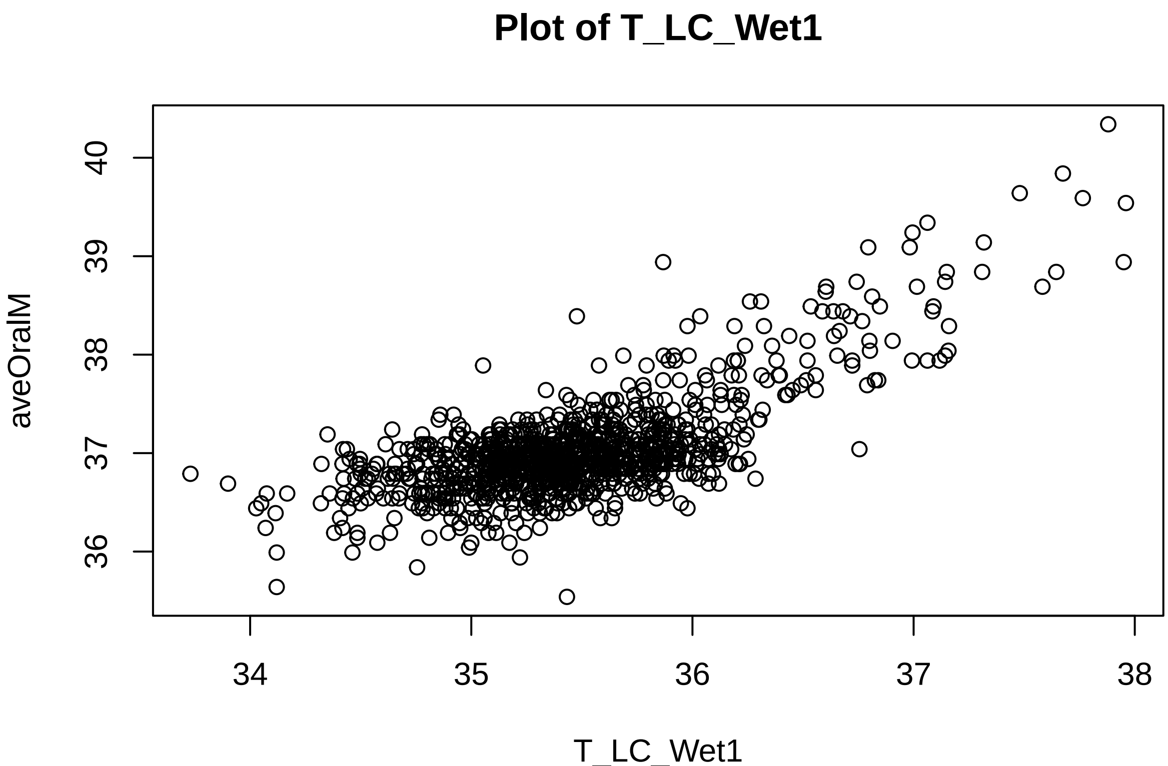
39
40
34
35
36
37
38
T_LC_Dry1


Plot of T_LC_Wet1
aveOralM
40
39
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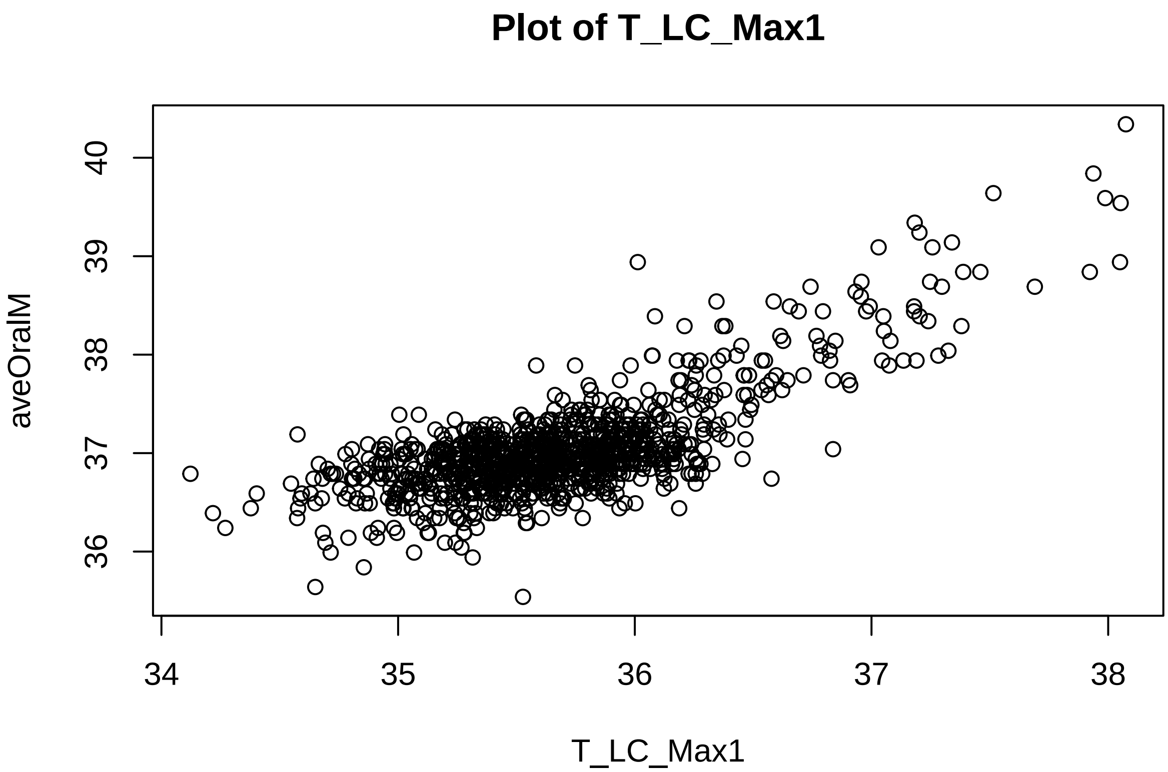
37
36
34
35
36
37
38
T_LC_Wet1


Plot of T_LC_Max1
aveOralM
36
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39
40
34
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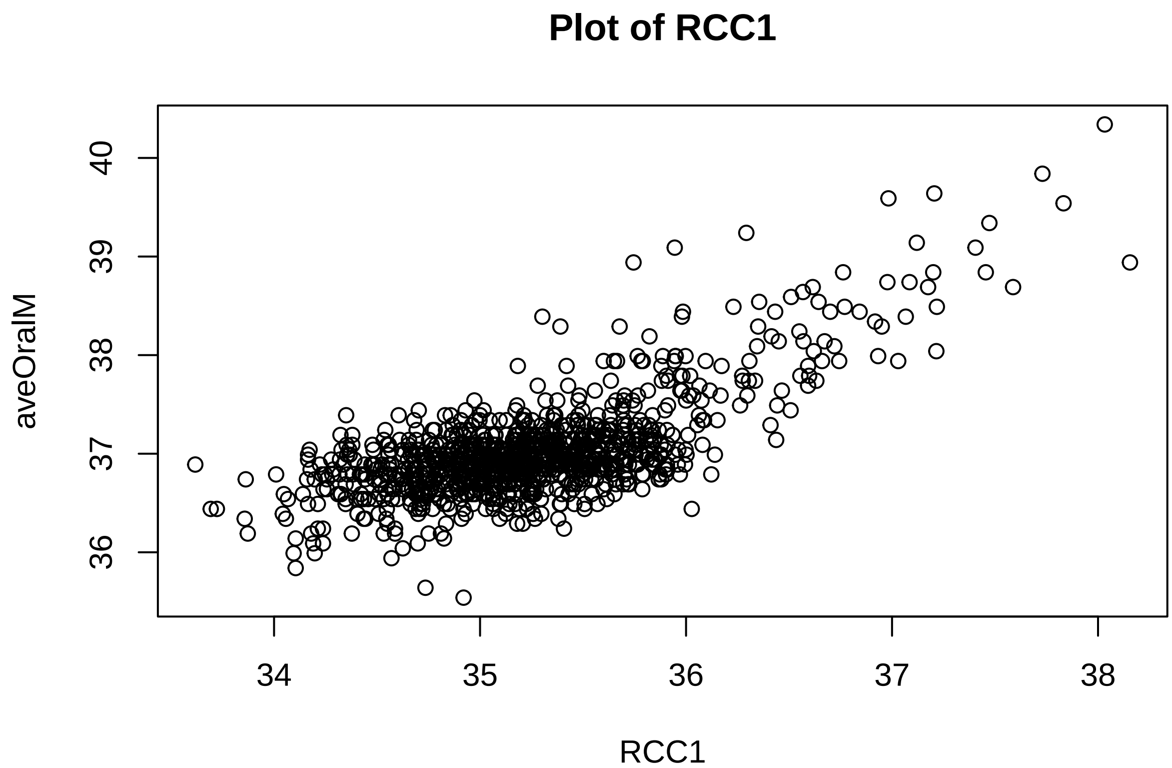
36
37
38
T_LC_Max1


Plot of RCC1
aveOralM
36
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34
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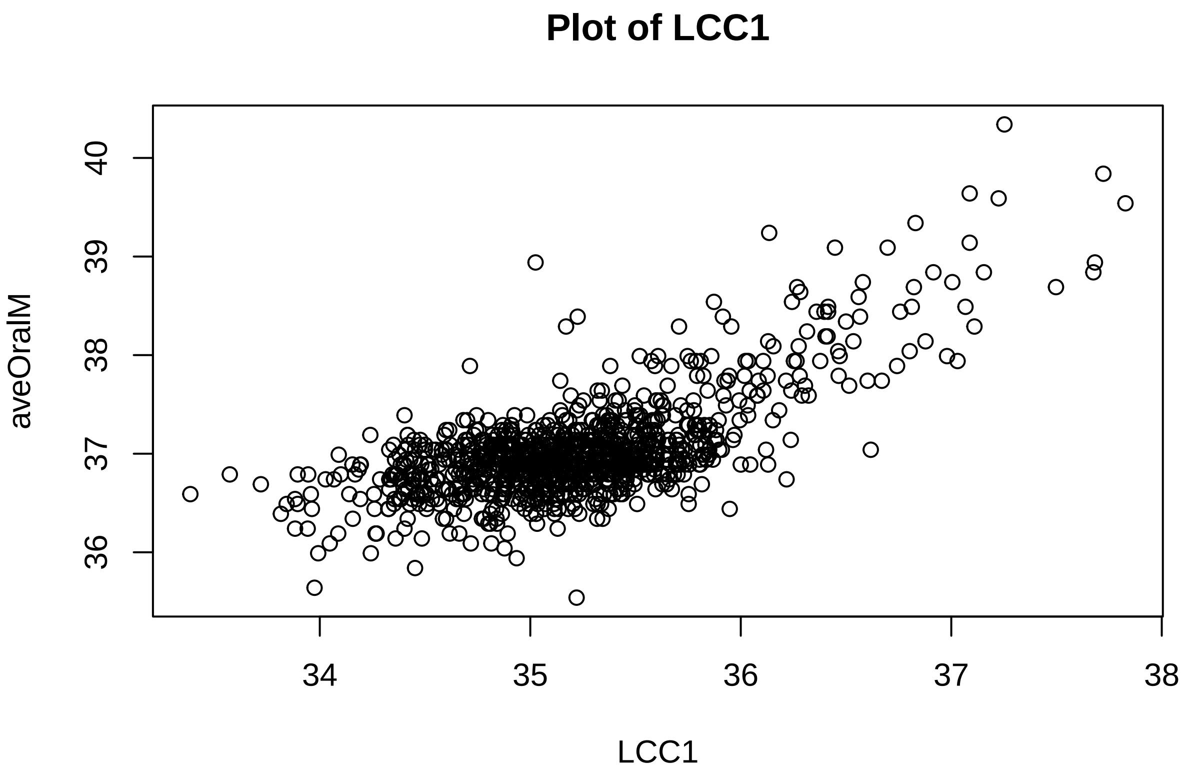
36
37
38
RCC1



Plot of LCC1
aveOralM
LCC1
36
37
38
39
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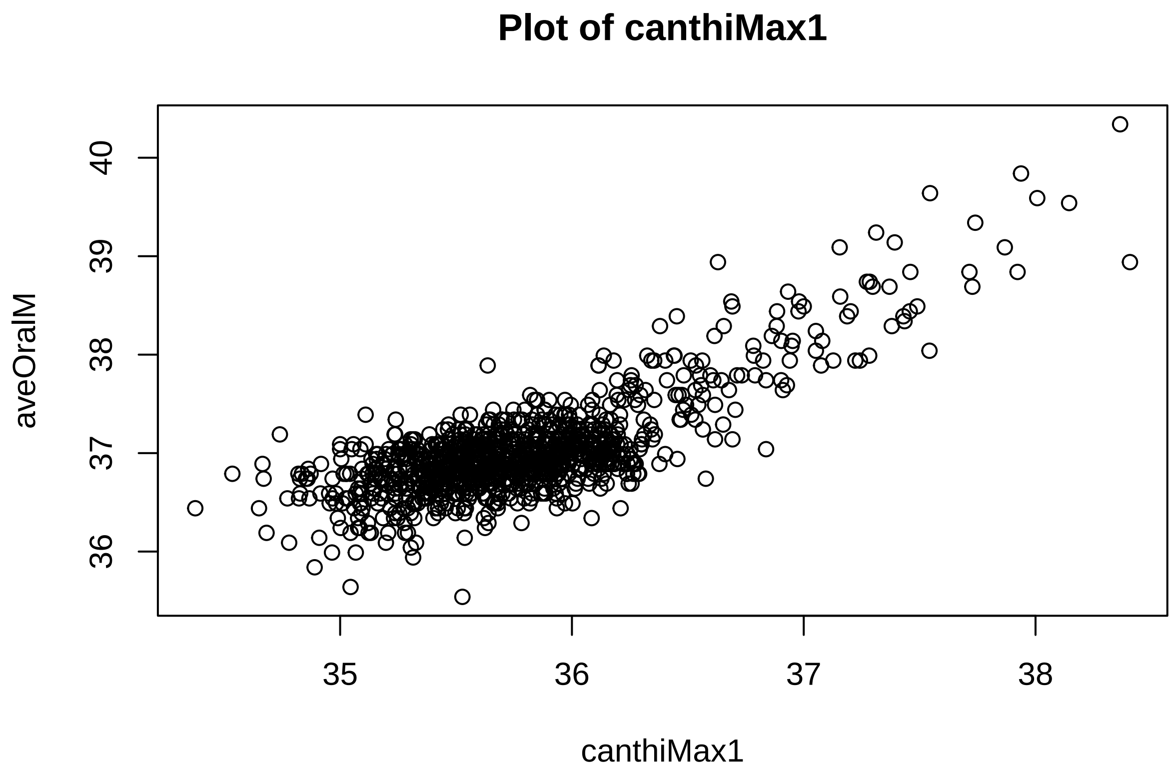
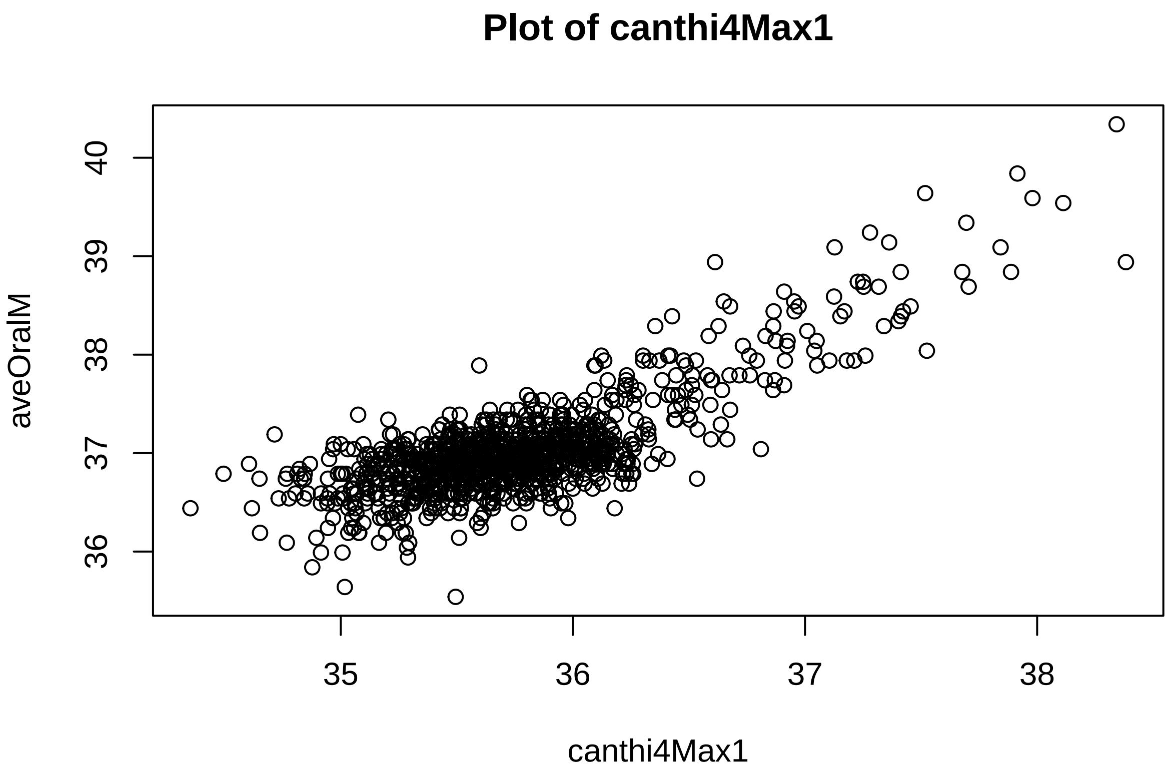
36
37
38


Plot of canthiMax1
aveOralM
40
39
38
37
36
35
36
37
38
canthiMax1



Plot of canthi4Max1
aveOralM
36
37
38
39
40
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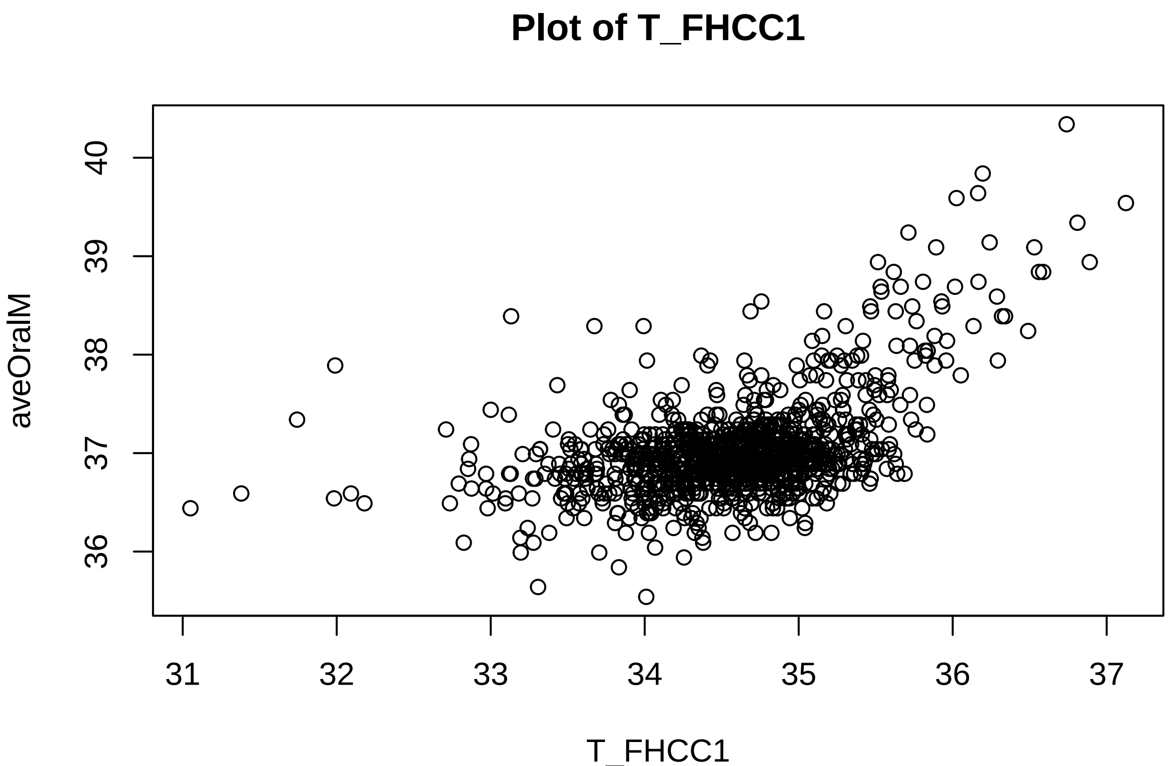
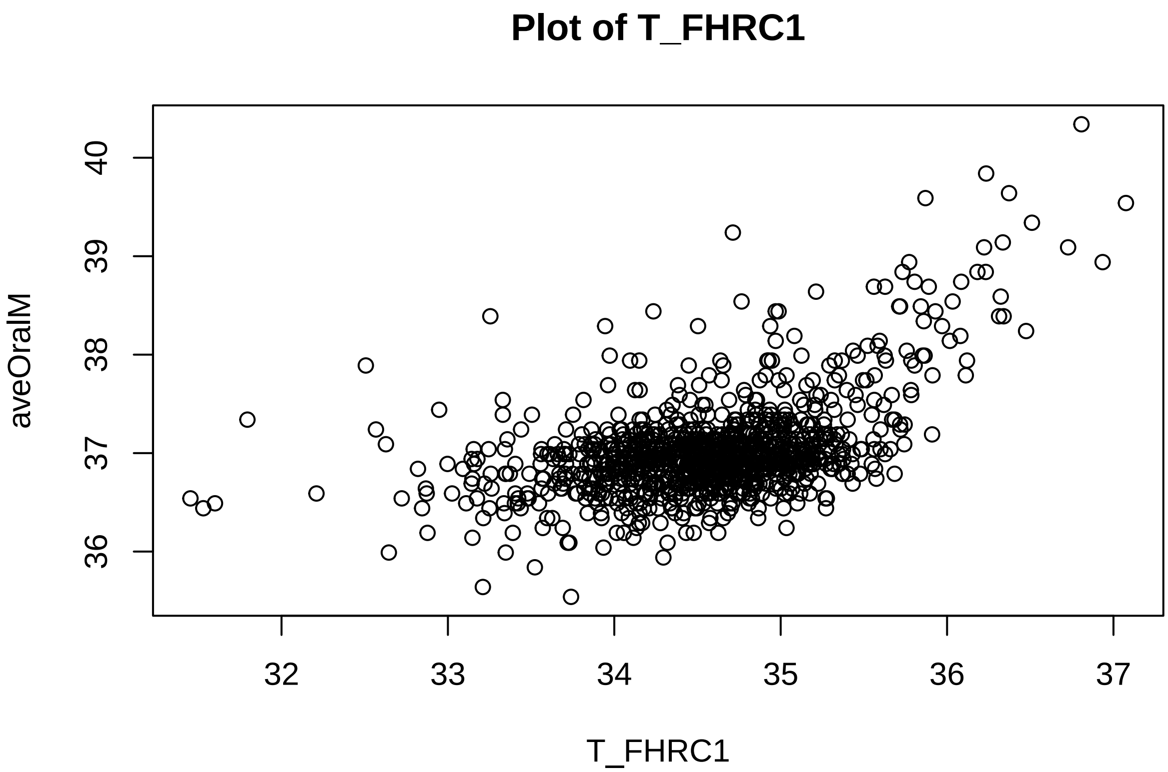
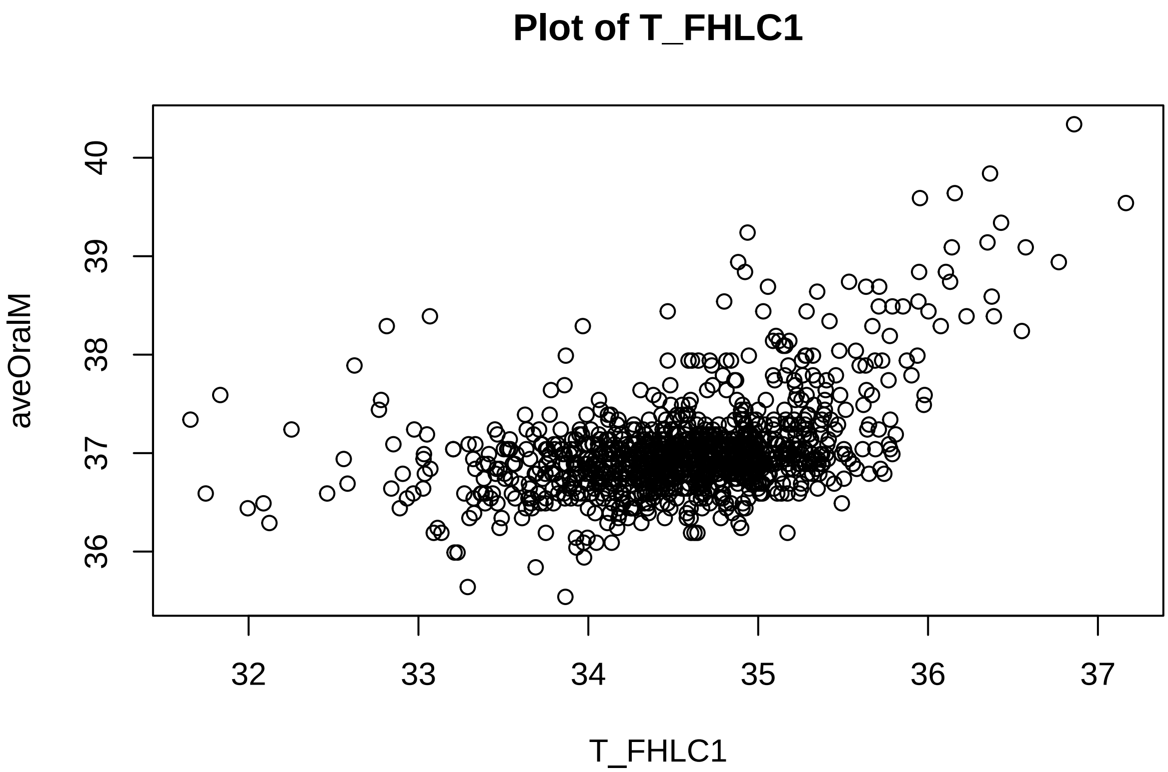
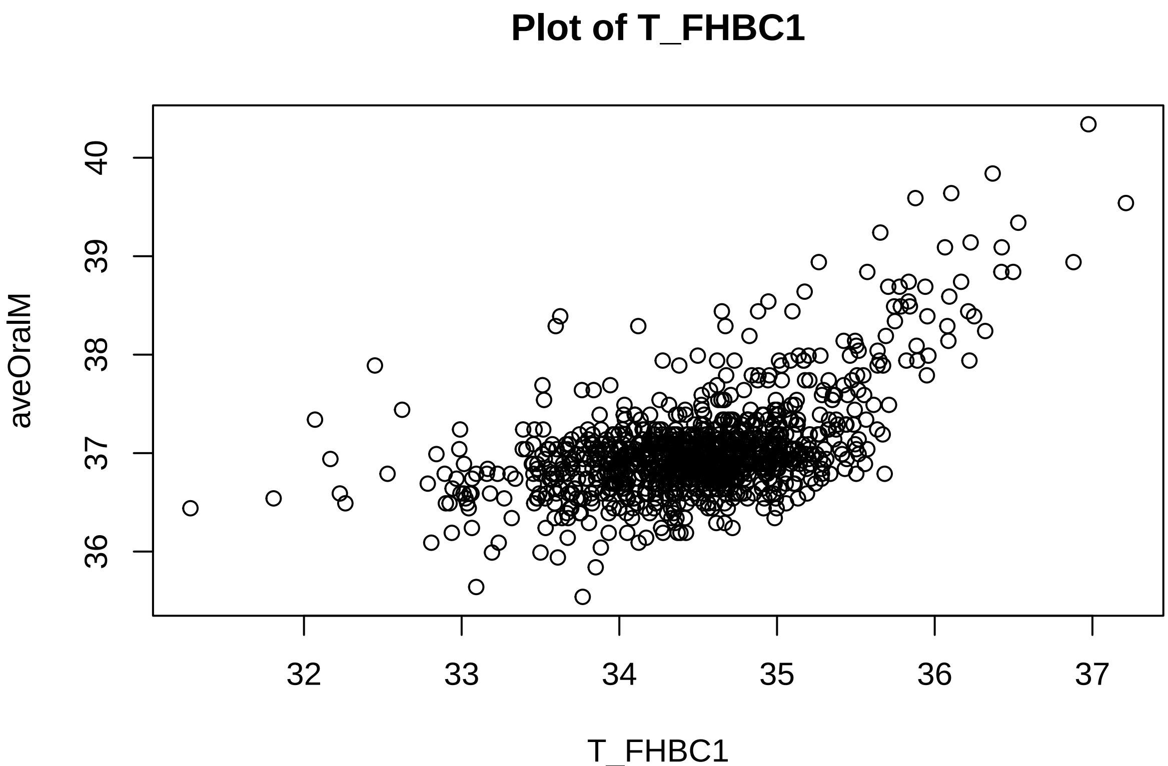
37
38
canthi4Max1


Plot of T_FHCC1
aveOralM
36
37
38
39
40
31
32
33
34
35
36
37
T_FHCC1


Plot of T_FHRC1
aveOralM
36
37
38
39
40
32
33
34
35
36
37
T_FHRC1



Plot of T_FHLC1
aveOralM
36
37
38
39
40
32
33
34
35
36
37
T_FHLC1


Plot of T_FHBC1
aveOralM
36
37
38
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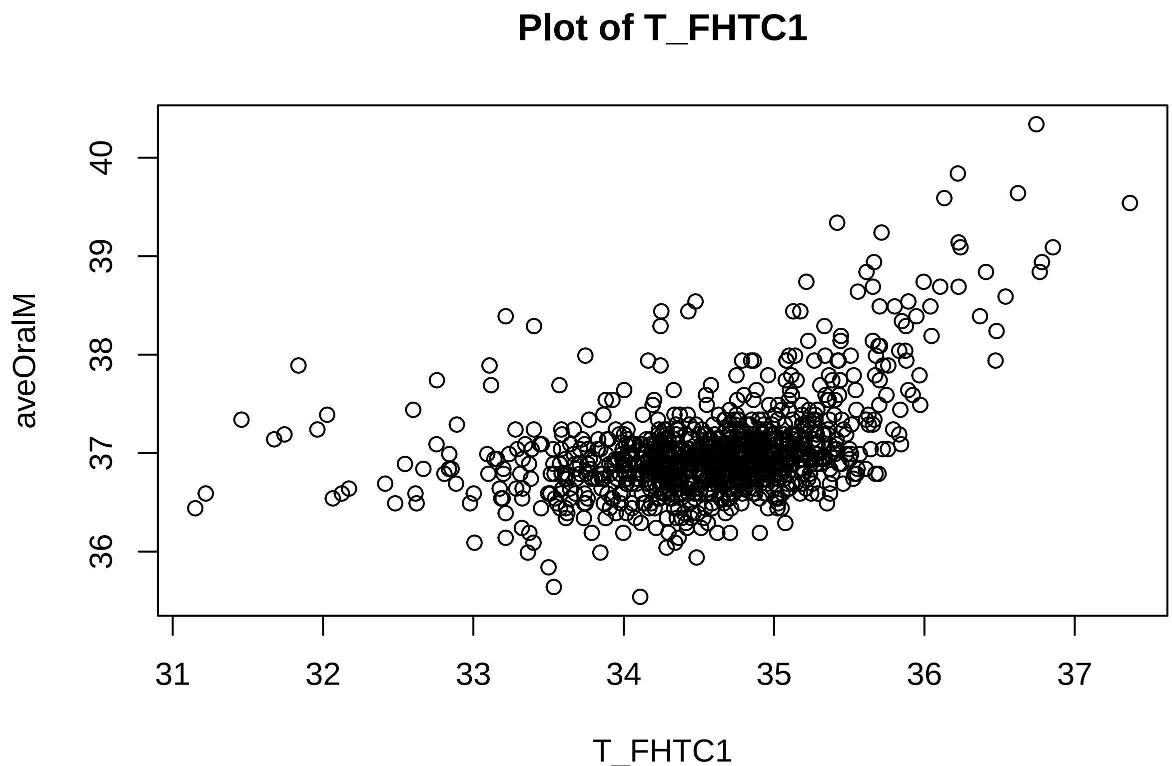
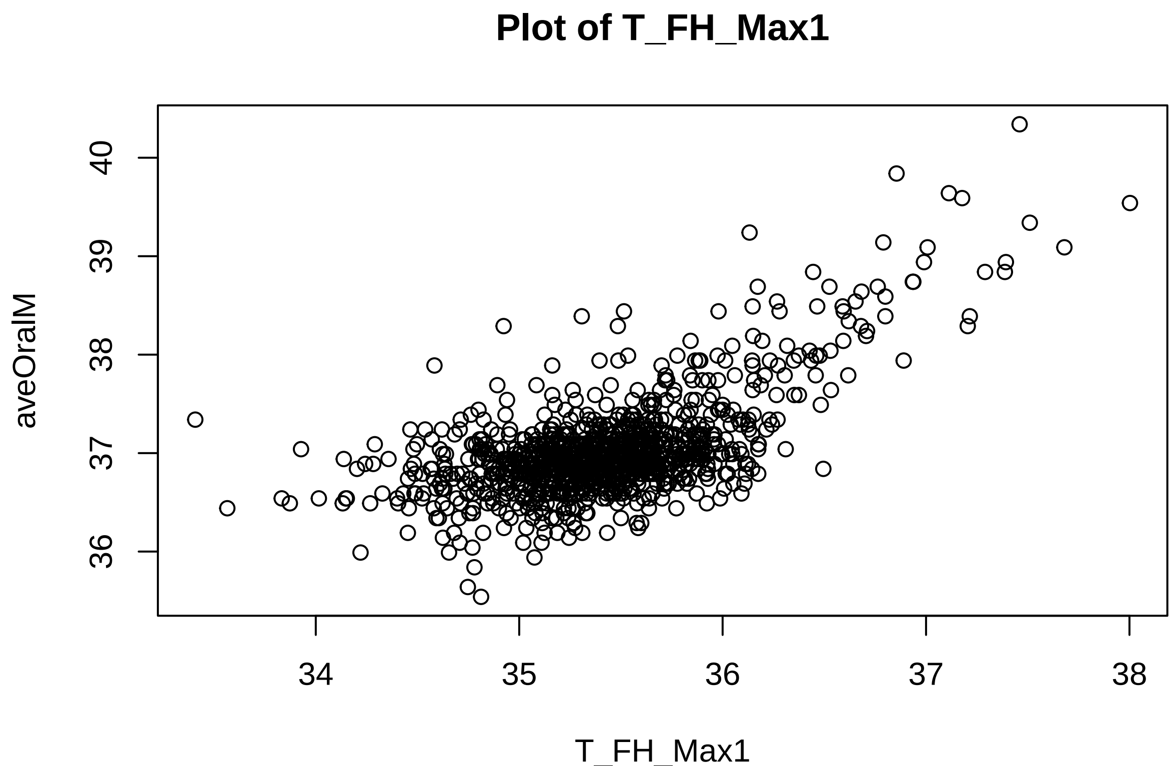
40
32
33
34
35
36
37
T_FHBC1



Plot of T_FHTC1
aveOralM
40
39
38
37
36
31
32
33
34
35
36
37
T_FHTC1


Plot of T_FH_Max1
aveOralM
T_FH_Max1
34
35
36
37
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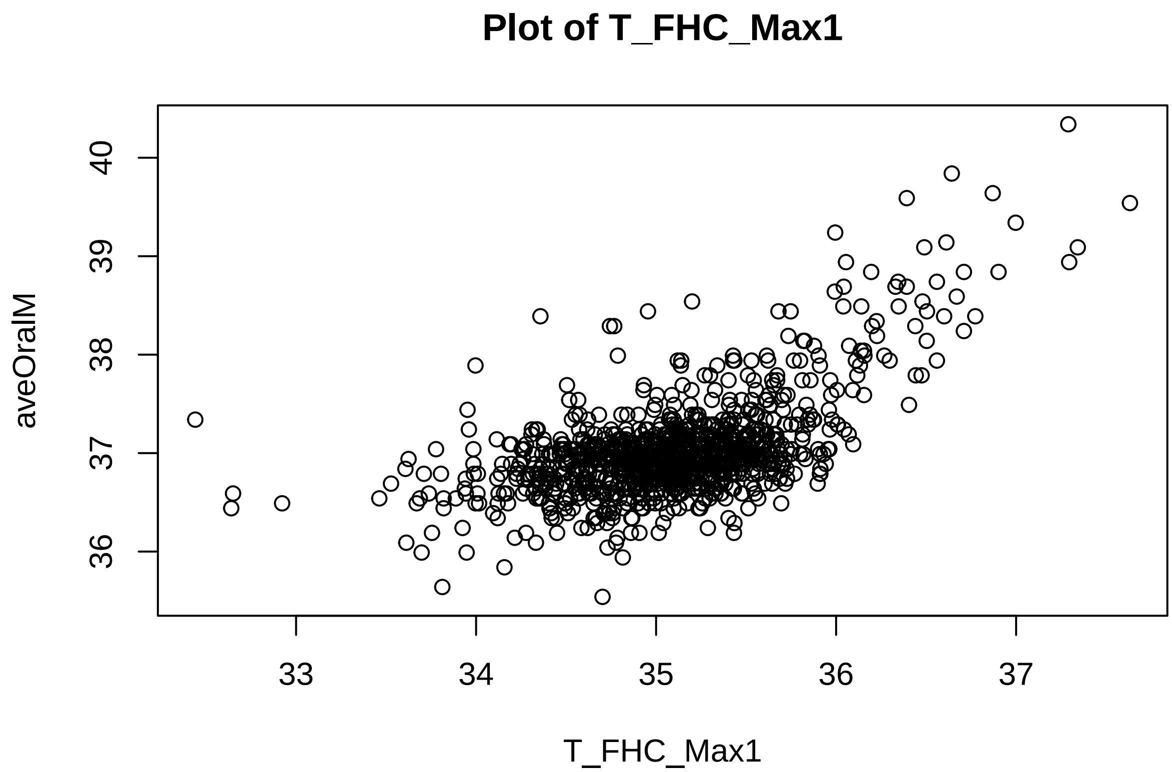
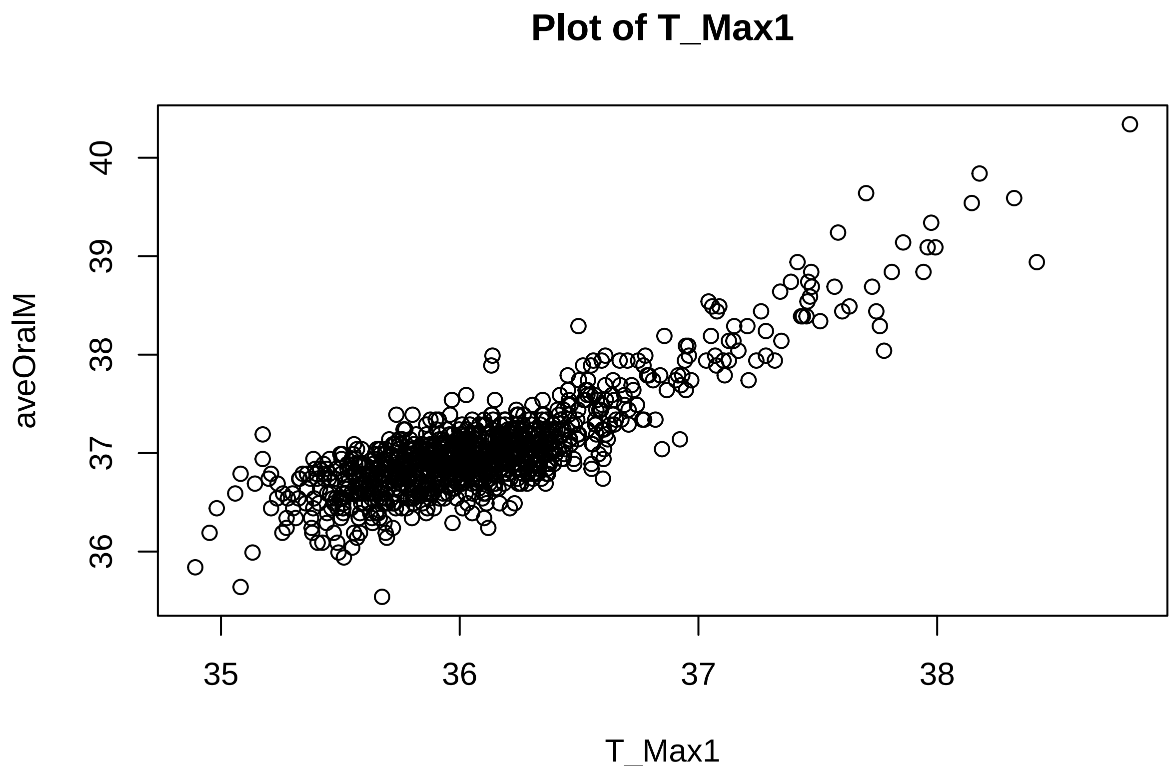
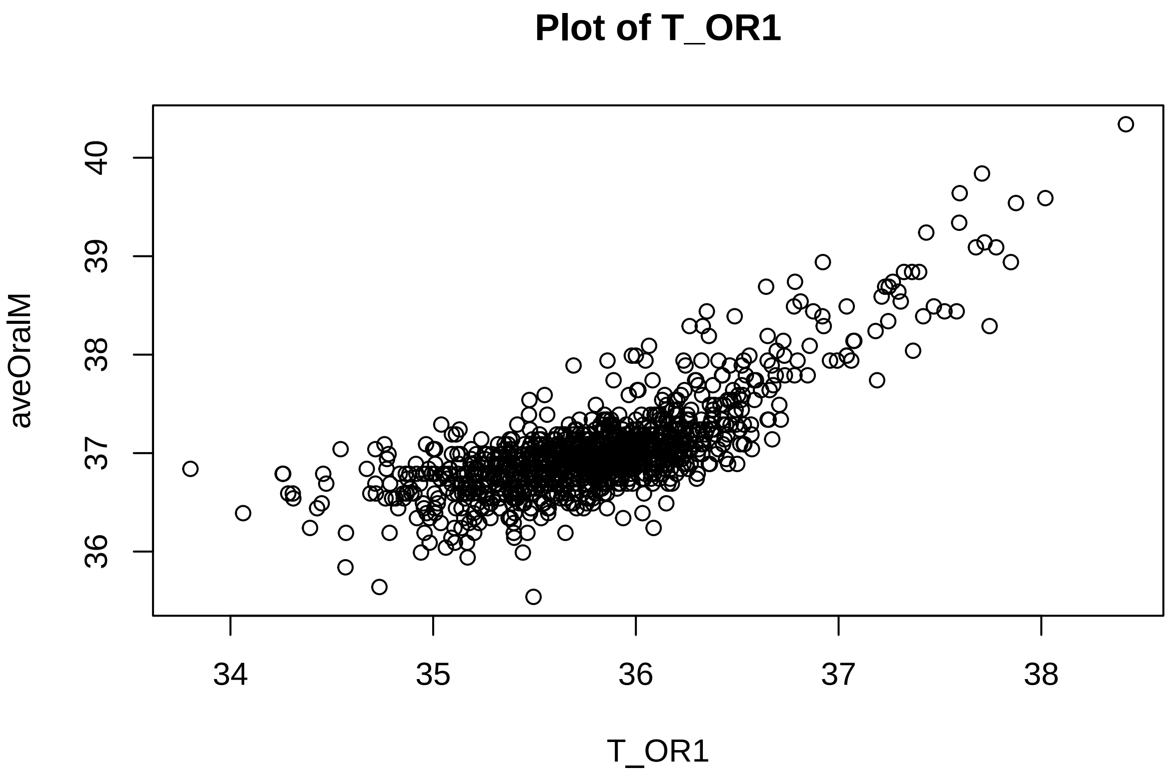
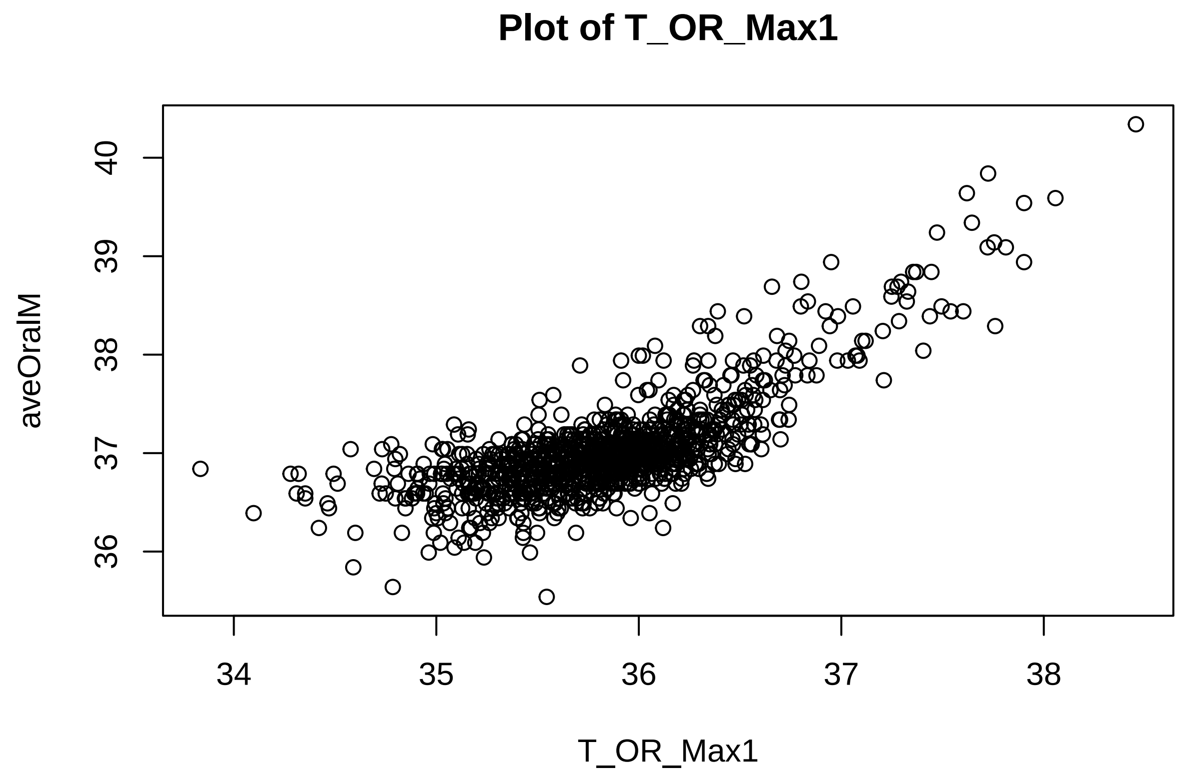
37
38
39
40


Plot of T_FHC_Max1
aveOralM
36
37
38
39
40
33
34
35
36
37
T_FHC_Max1

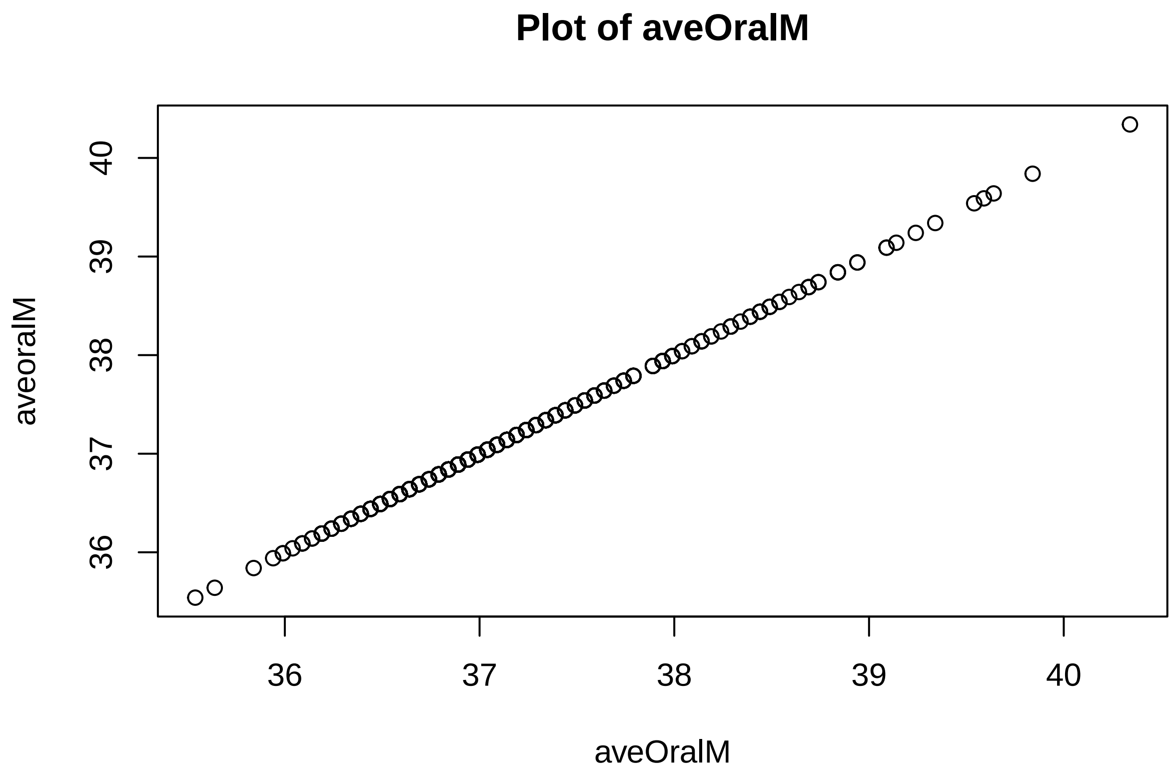


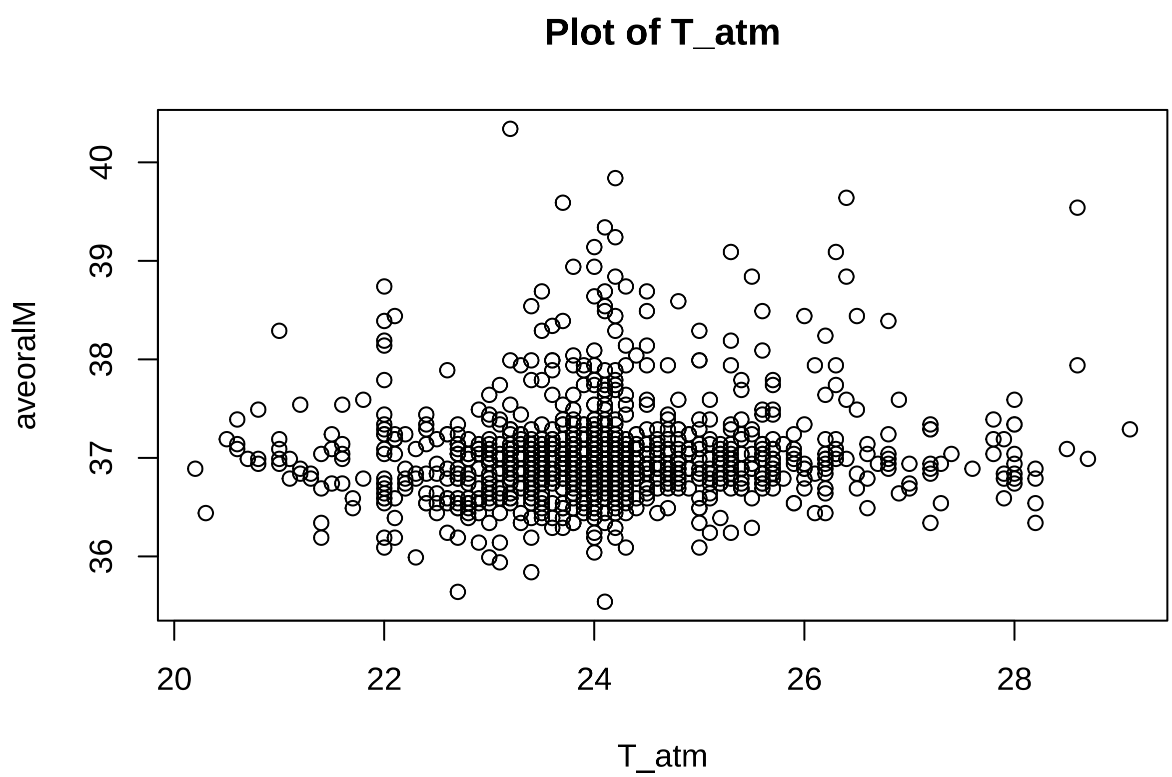
Plot of T_Max1
aveOralM
T_Max1
35
36
37
38
36
37
38
39
40


Plot of T_OR1
aveOralM
40
39
38
37
36
34
35
36
37
38
T_OR1

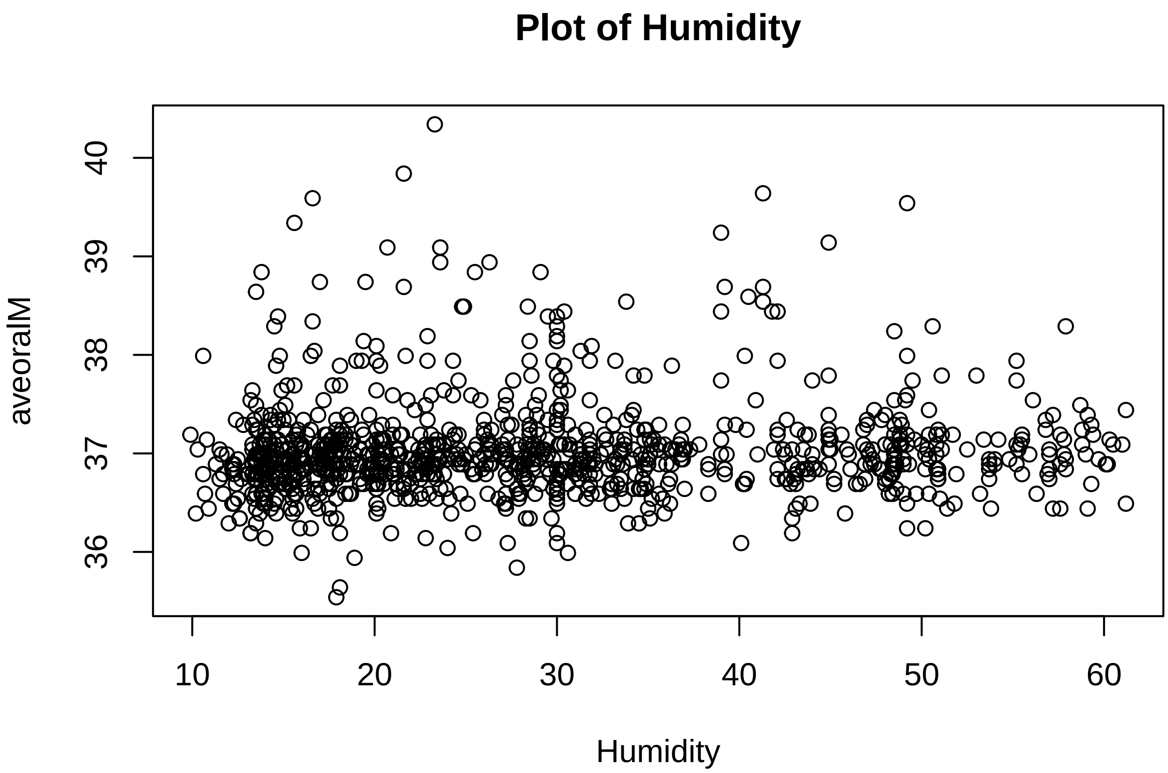


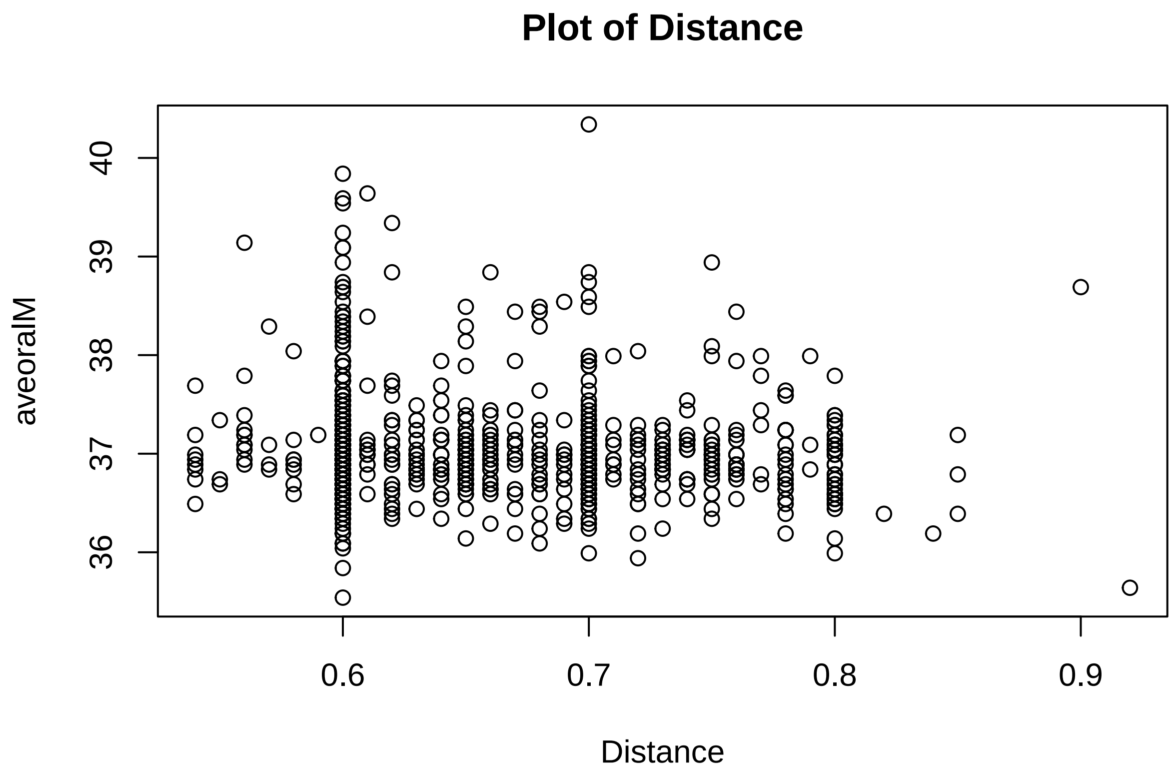

```
data <- subset(data, Distance <= 60)

# For numeric variables: histograms
i = 0
for(i in 1:ncol(data)){
  if(is.numeric(data[[i]])){
    plot( data[[i]], data$aveOralM,main=paste("Plot of", names(data)[i]), xlab=names(data)[i], ylab = "a
  }
}
```

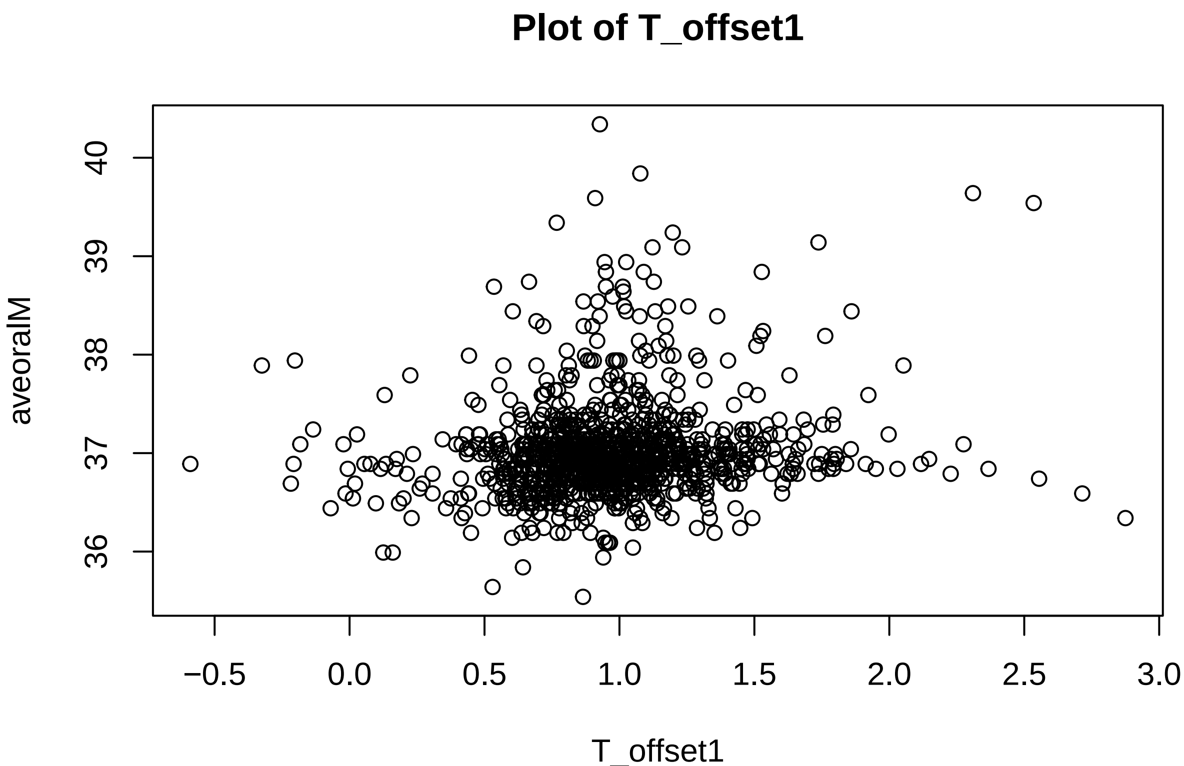

Plot of aveOralM
aveoralM
36
37
38
39
40
aveOralM

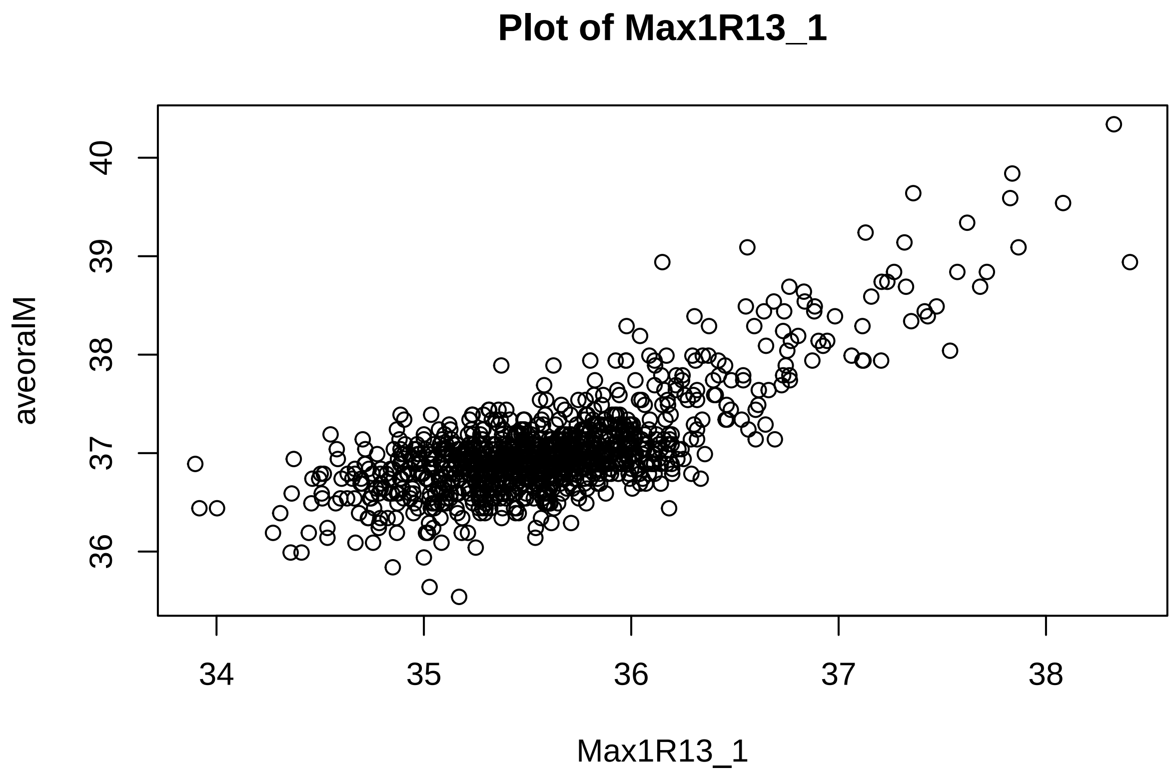


Plot of T_atm
aveoralM
T_atm
36
37
38
39
40
20
22
24
26
28

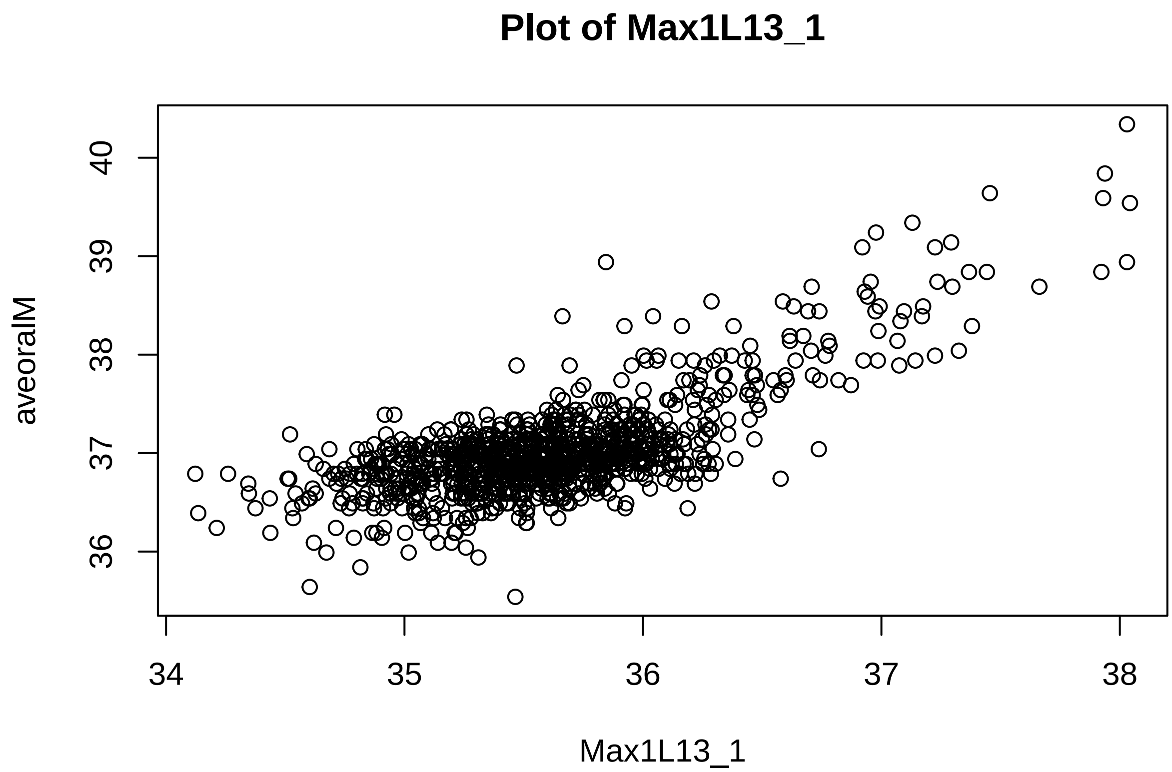

Plot of Humidity
aveoralM
40
39
38
37
36
10
20
30
40
50
60
Humidity

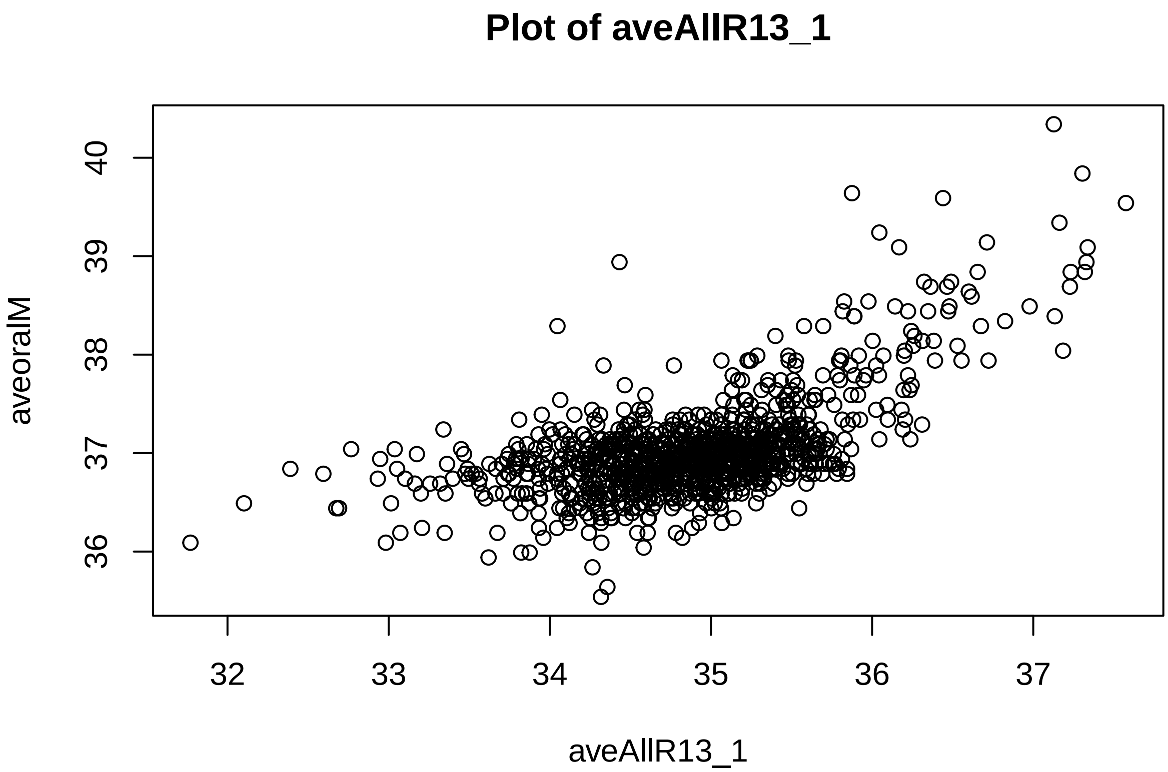

Plot of Distance
aveoralM
40
39
38
37
36
0.6
0.7
0.8
0.9
Distance

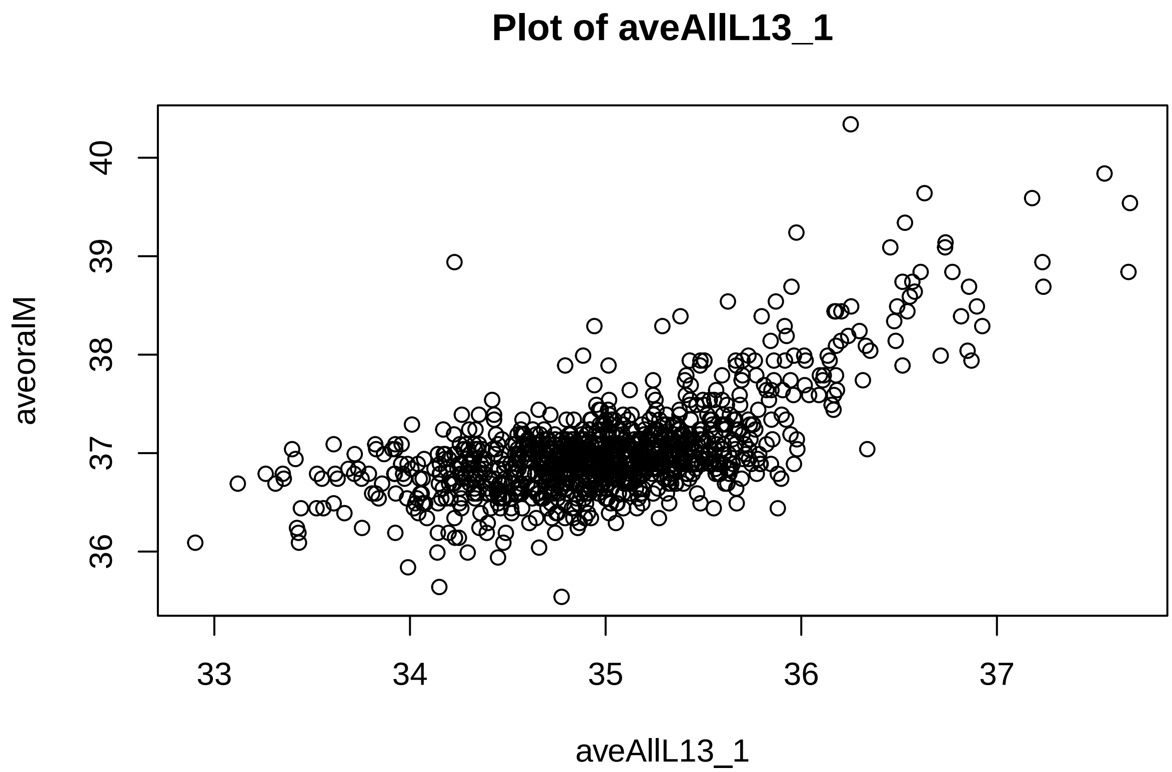

Plot of T_offset1
aveoralM
T_offset1
40
39
38
37
36
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0



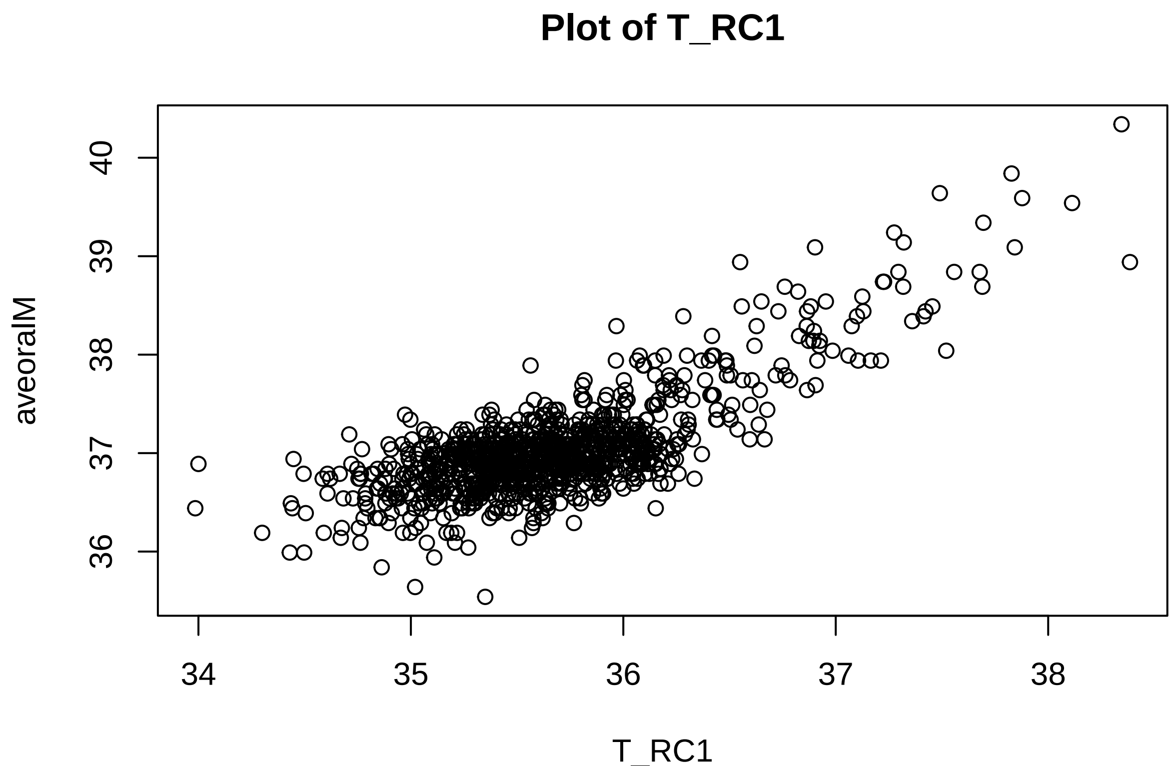
Plot of Max1R13_1
aveoralM
40
39
38
37
36
34
35
36
37
38
Max1R13_1


Plot of Max1L13_1
aveoralM
40
39
38
37
36
34
35
36
37
38
Max1L13_1

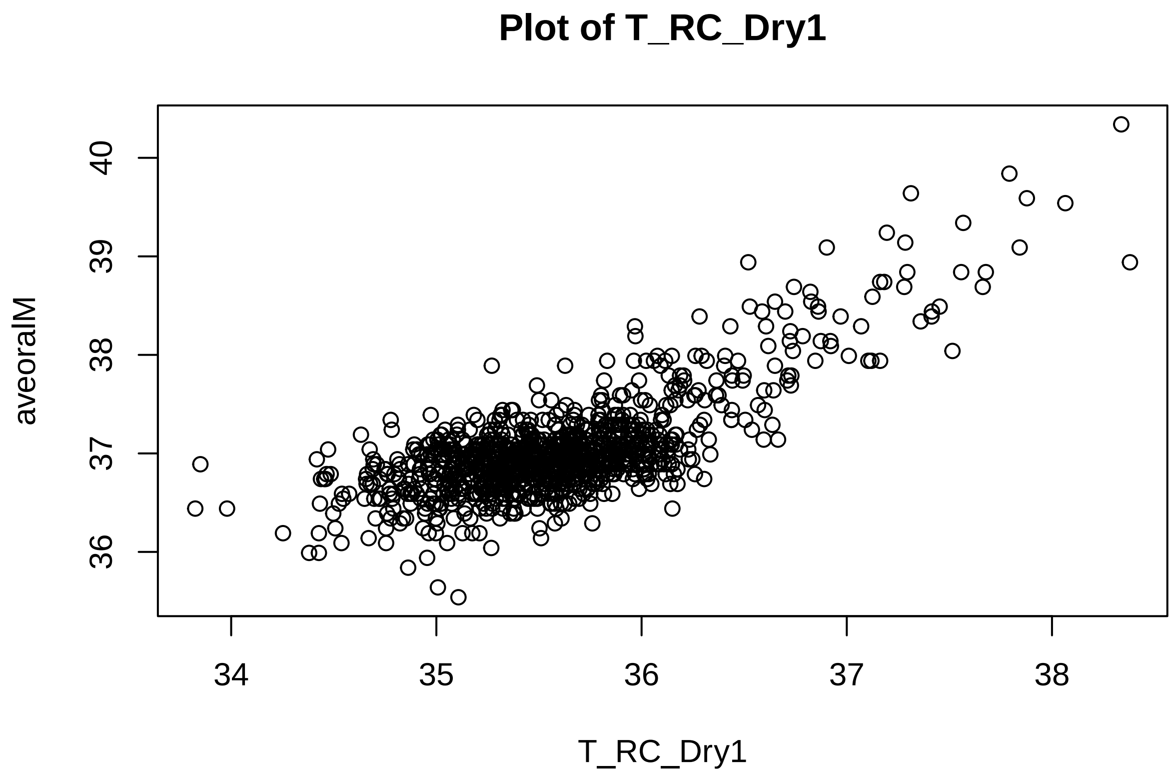

Plot of aveAllR13_1
aveoralM
40
39
38
37
36
32
33
34
35
36
37
aveAllR13_1

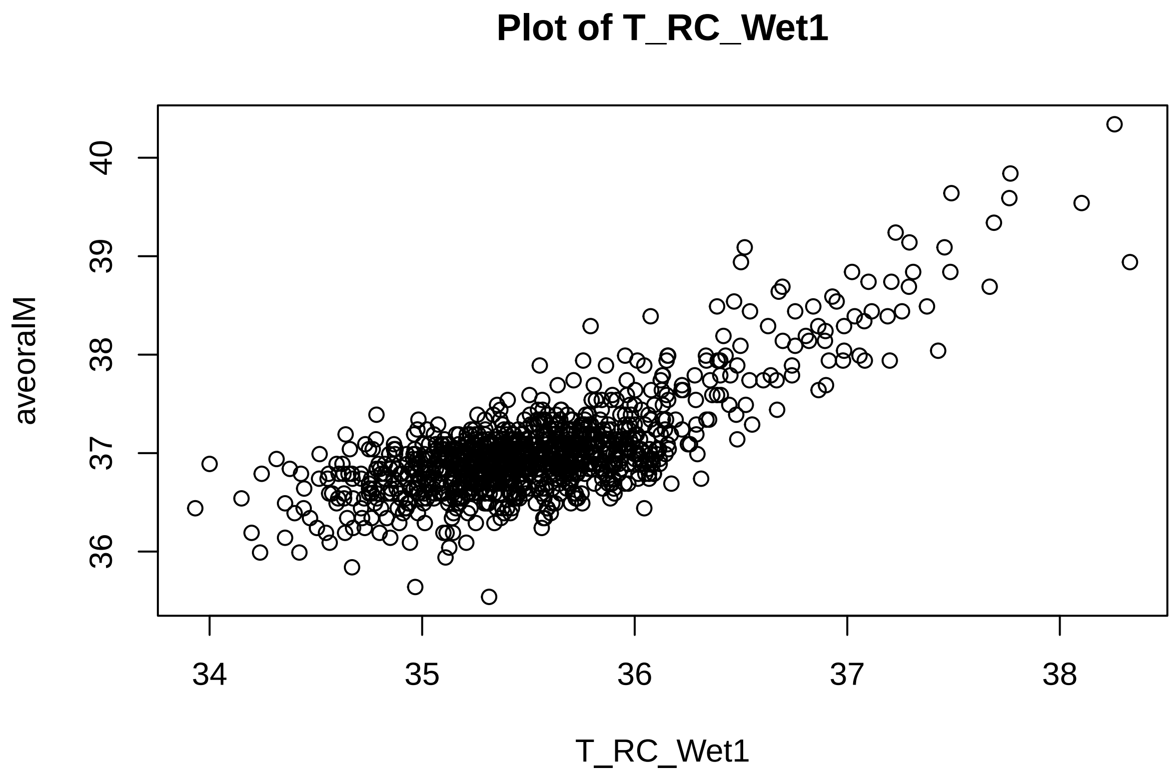


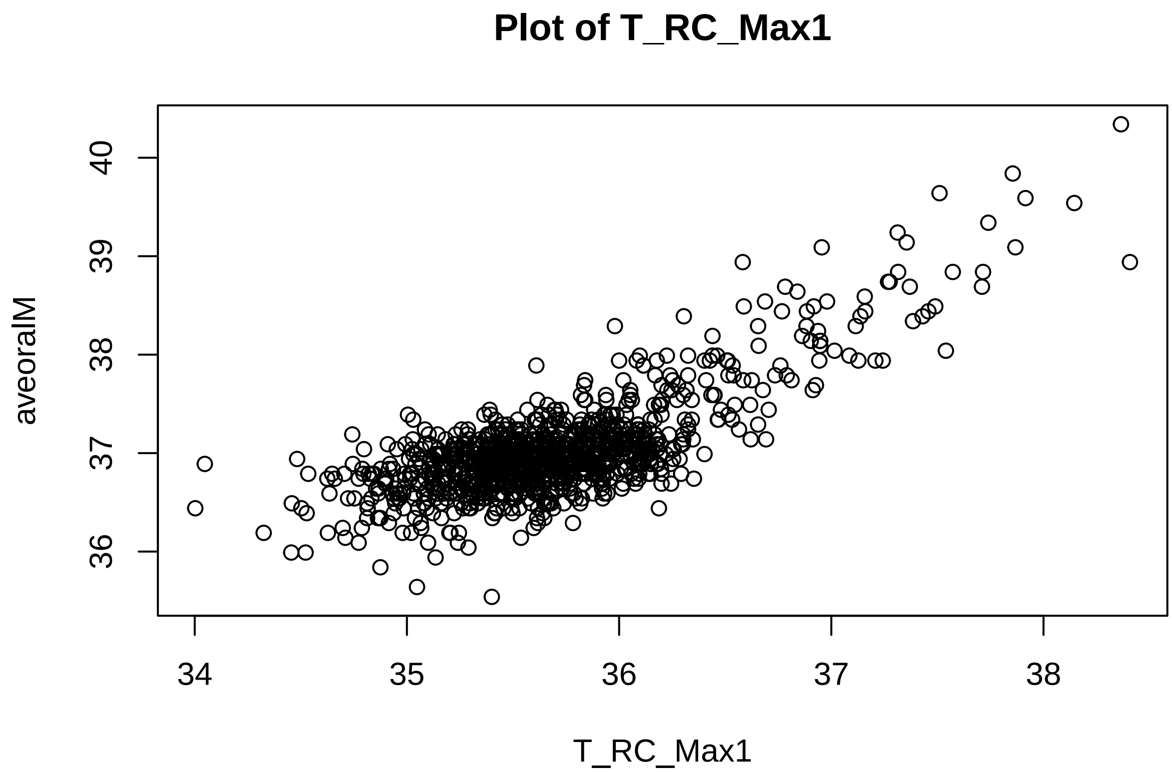
Plot of aveAllL13_1
aveoralM
aveAllL13_1
33
34
35
36
37
36
37
38
39
40



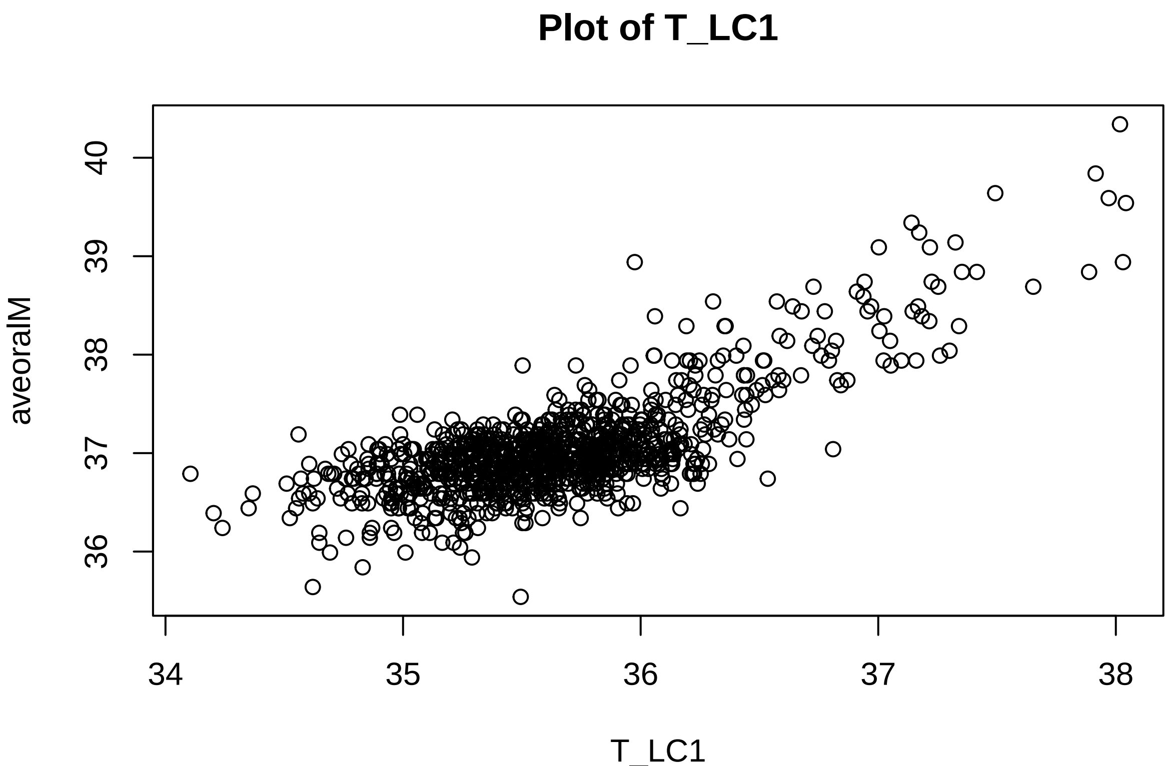
Plot of T_RC1
aveoralM
40
39
38
37
36
34
35
36
37
38
T_RC1


Plot of T_RC_Dry1
aveoralM
40
39
38
37
36
34
35
36
37
38
T_RC_Dry1

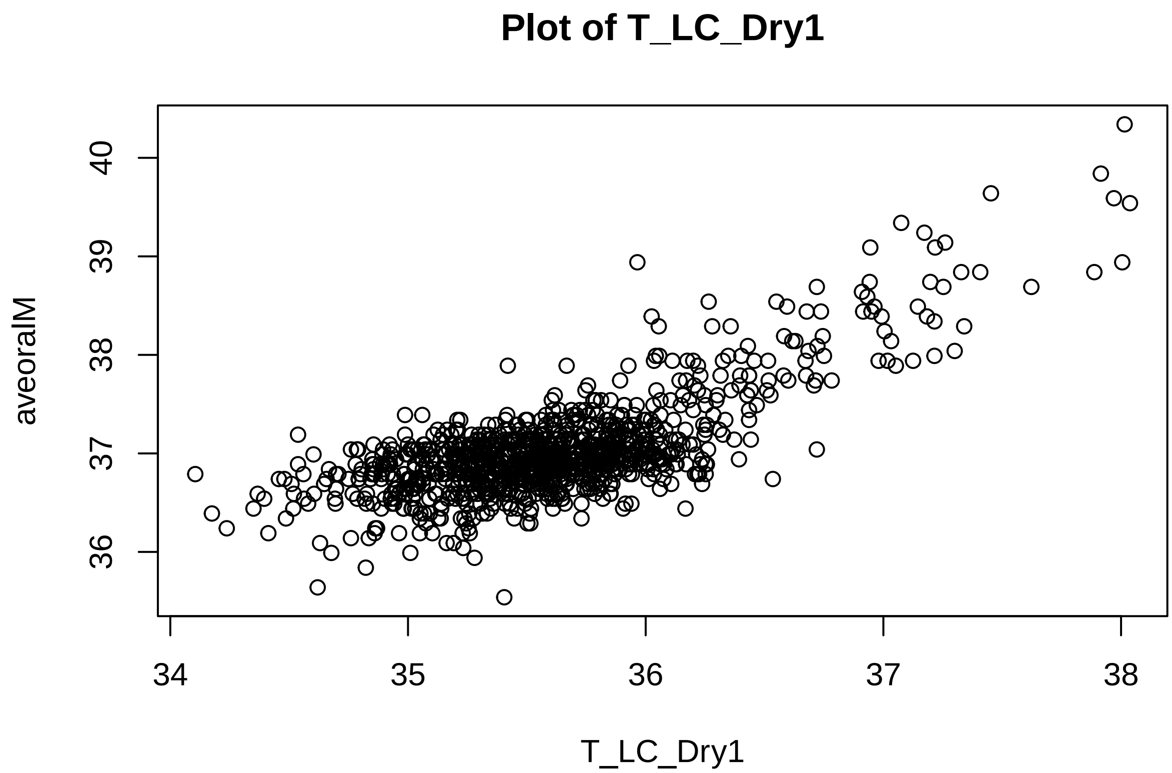

Plot of T_RC_Wet1
aveoralM
36
37
38
39
40
34
35
36
37
38
T_RC_Wet1

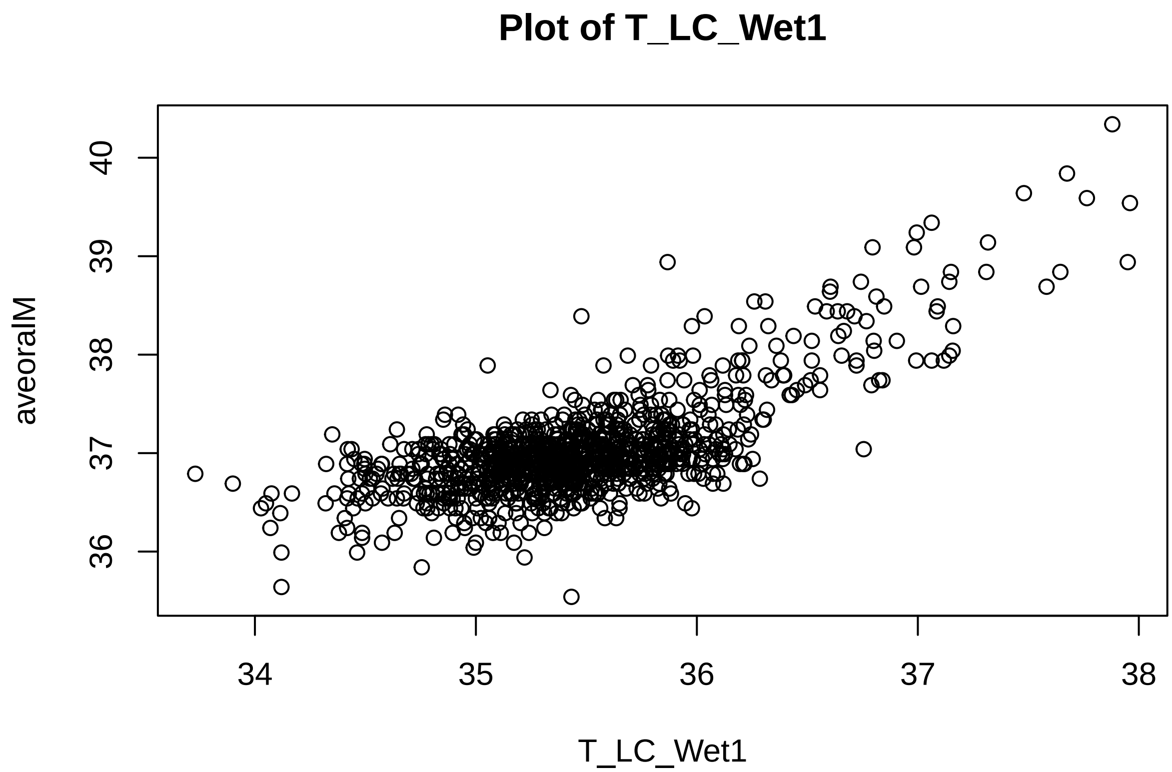


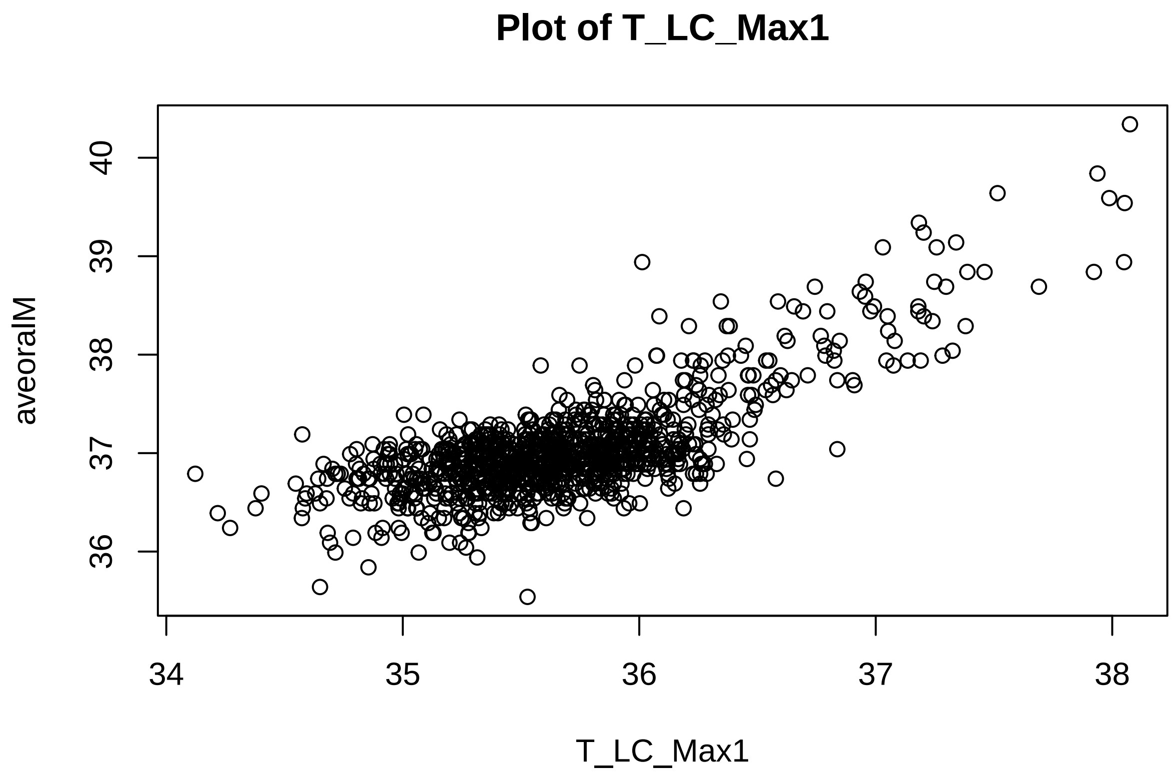
Plot of T_RC_Max1
aveoralM
36
37
38
39
40
34
35
36
37
38
T_RC_Max1

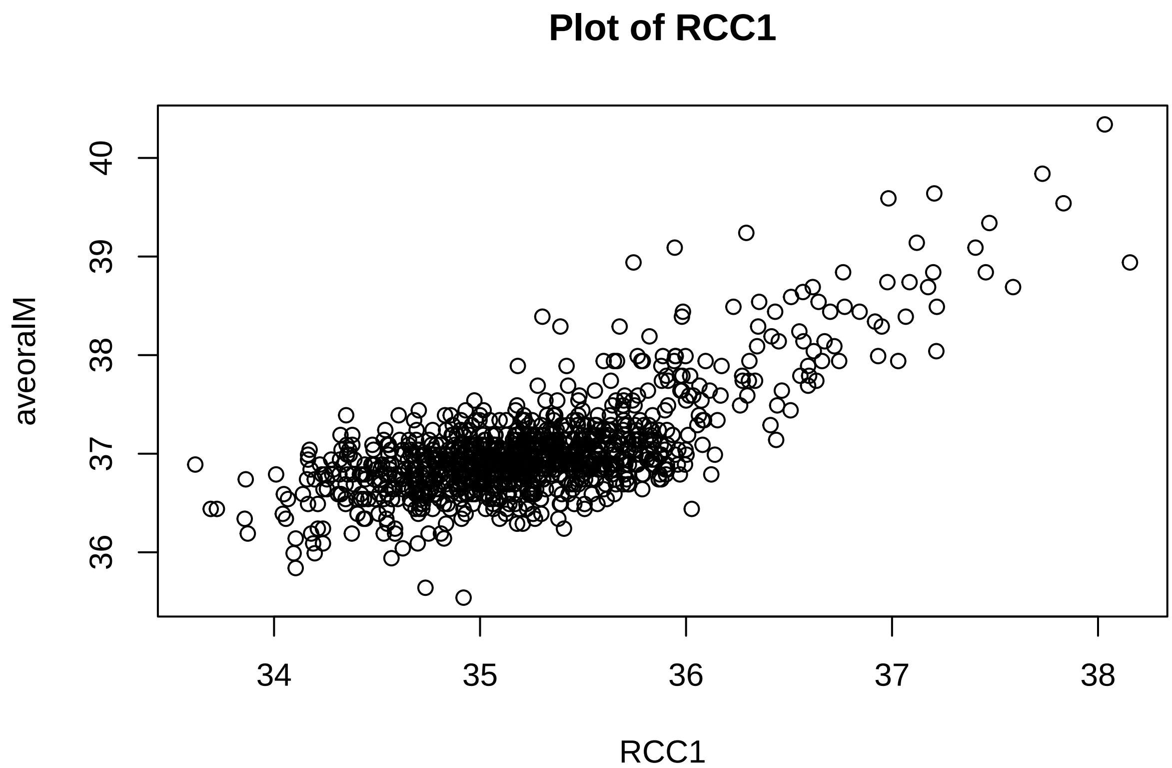


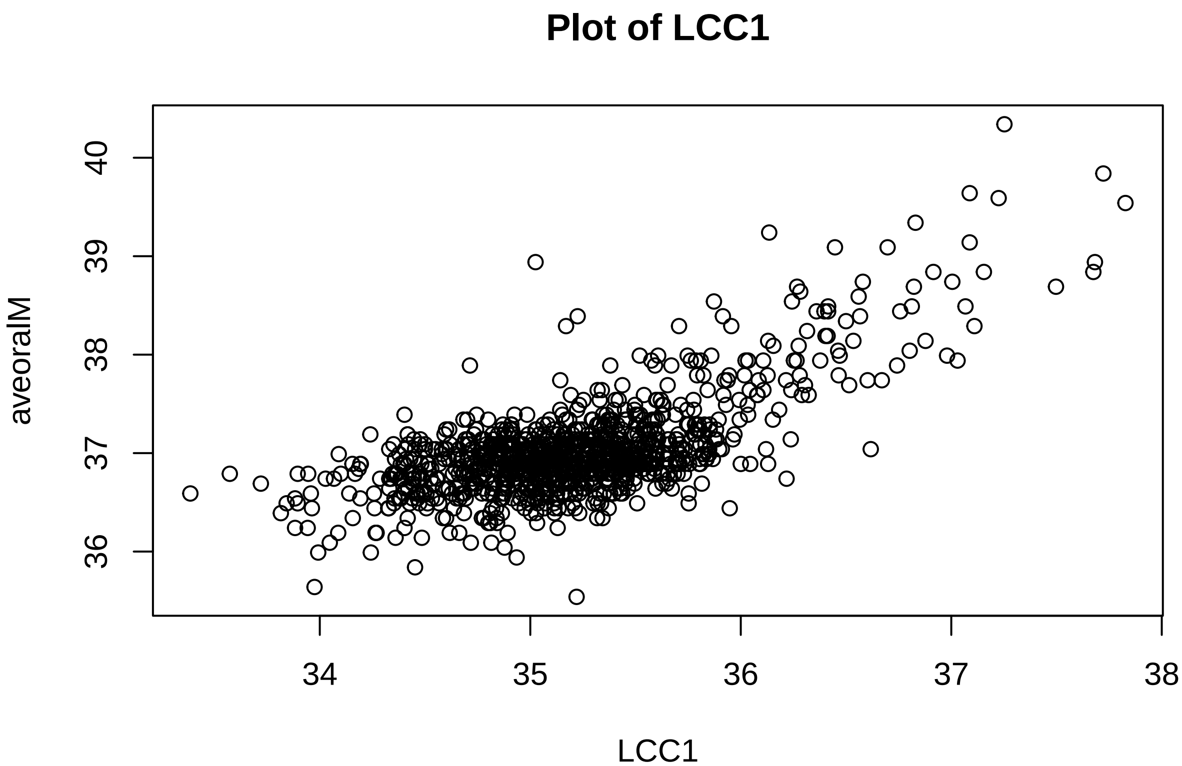
Plot of T_LC1
aveoralM
T_LC1
34
35
36
37
38
36
37
38
39
40


Plot of T_LC_Dry1
aveoralM
40
39
38
37
36
34
35
36
37
38
T_LC_Dry1

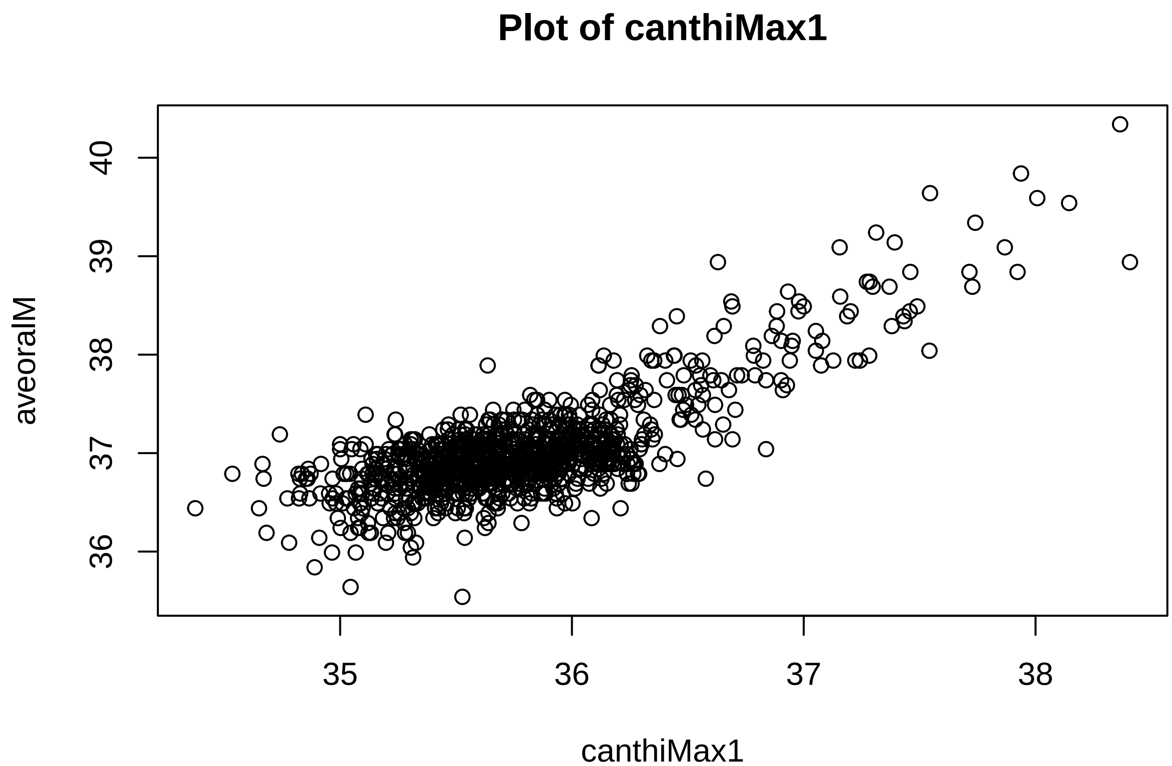

Plot of T_LC_Wet1
aveoralM
40
39
38
37
36
34
35
36
37
38
T_LC_Wet1


Plot of T_LC_Max1
aveoralM
T_LC_Max1
36
37
38
39
40
34
35
36
37
38

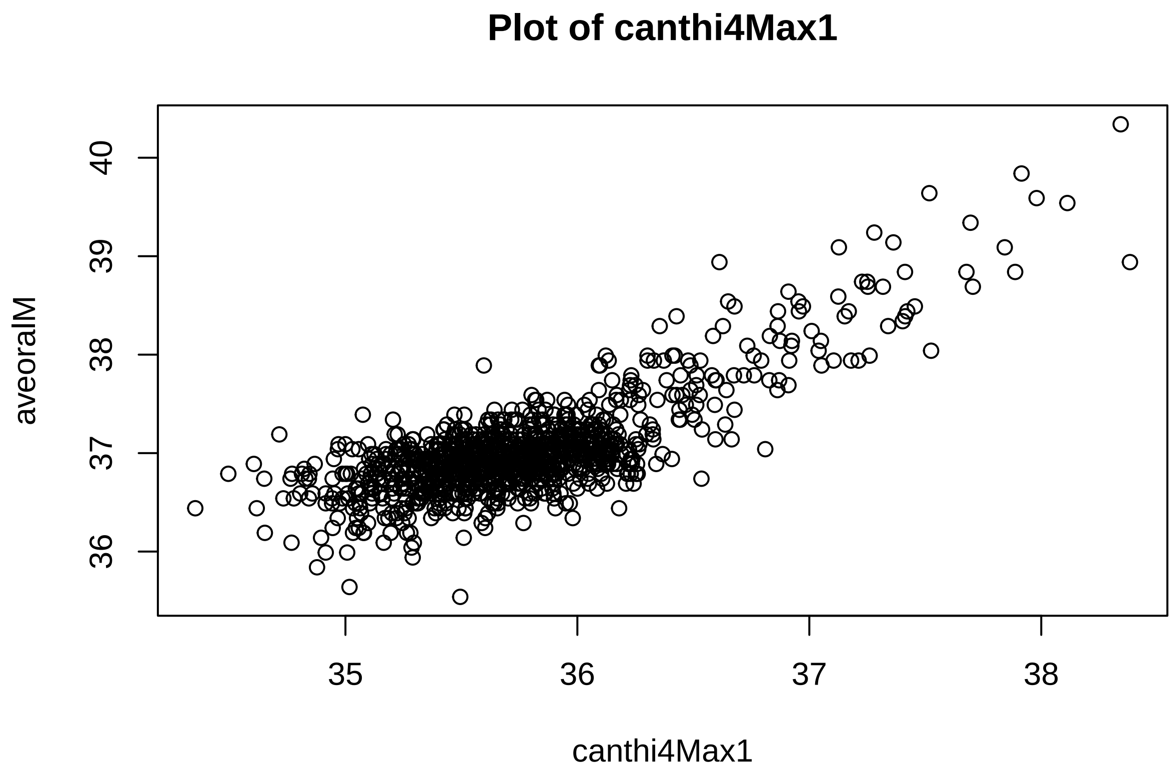

Plot of RCC1
aveoralM
RCC1
36
37
38
39
40
34
35
36
37
38

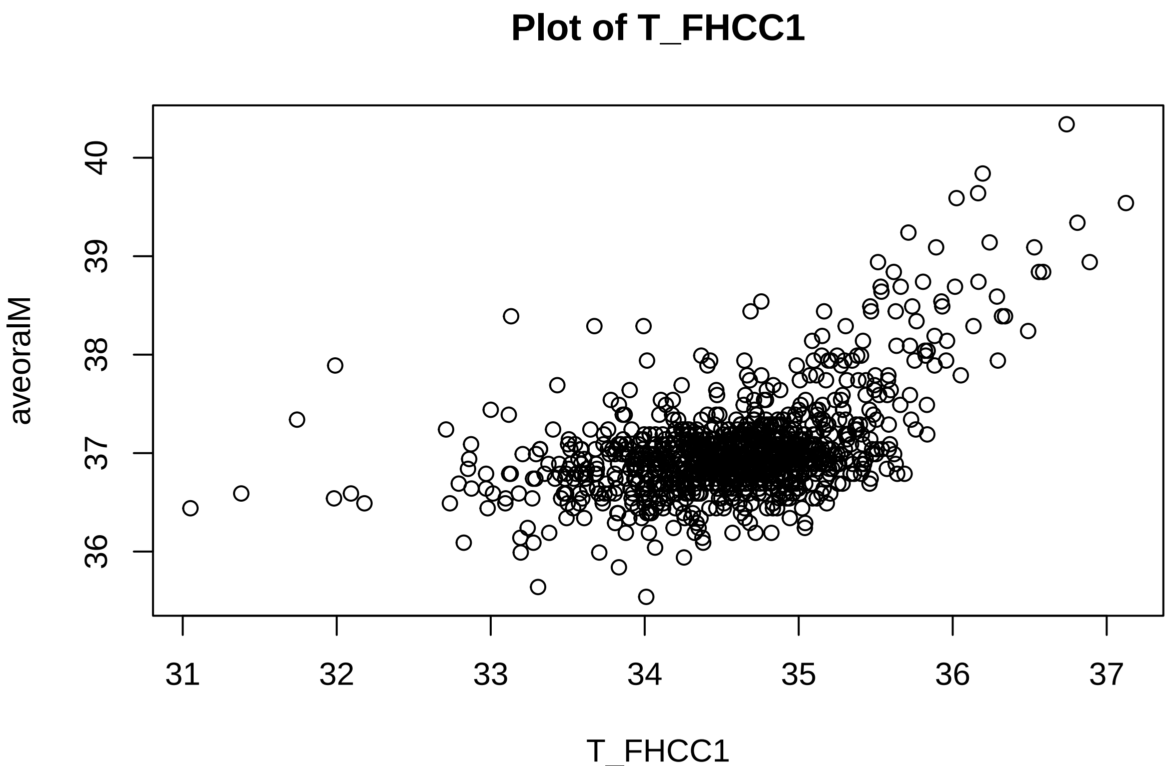


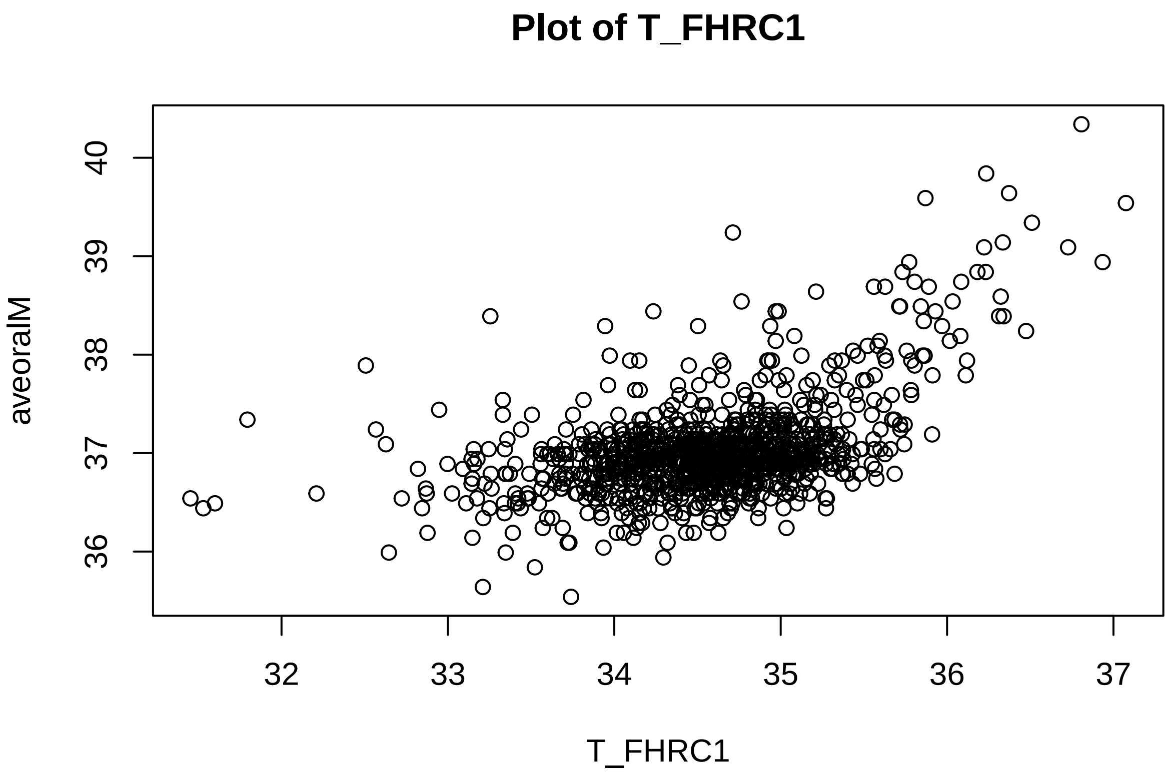
Plot of LCC1
40
39
38
37
36
aveoralM
34
35
36
37
38
LCC1

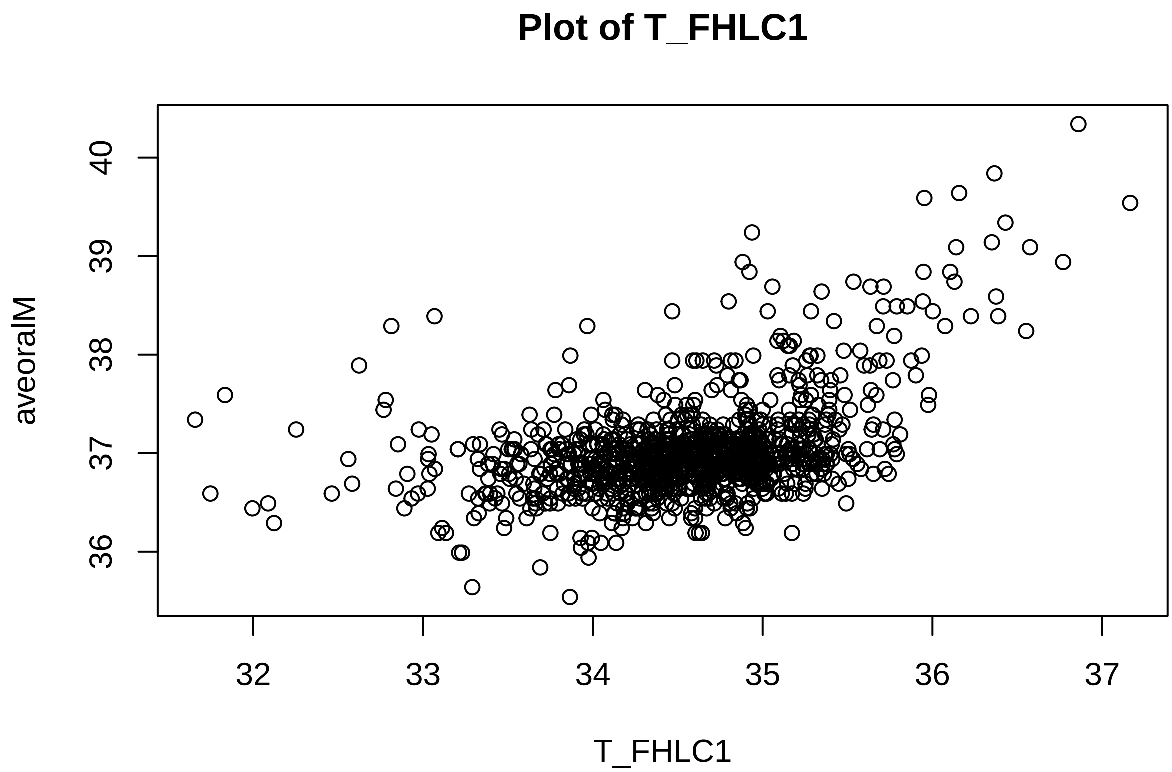


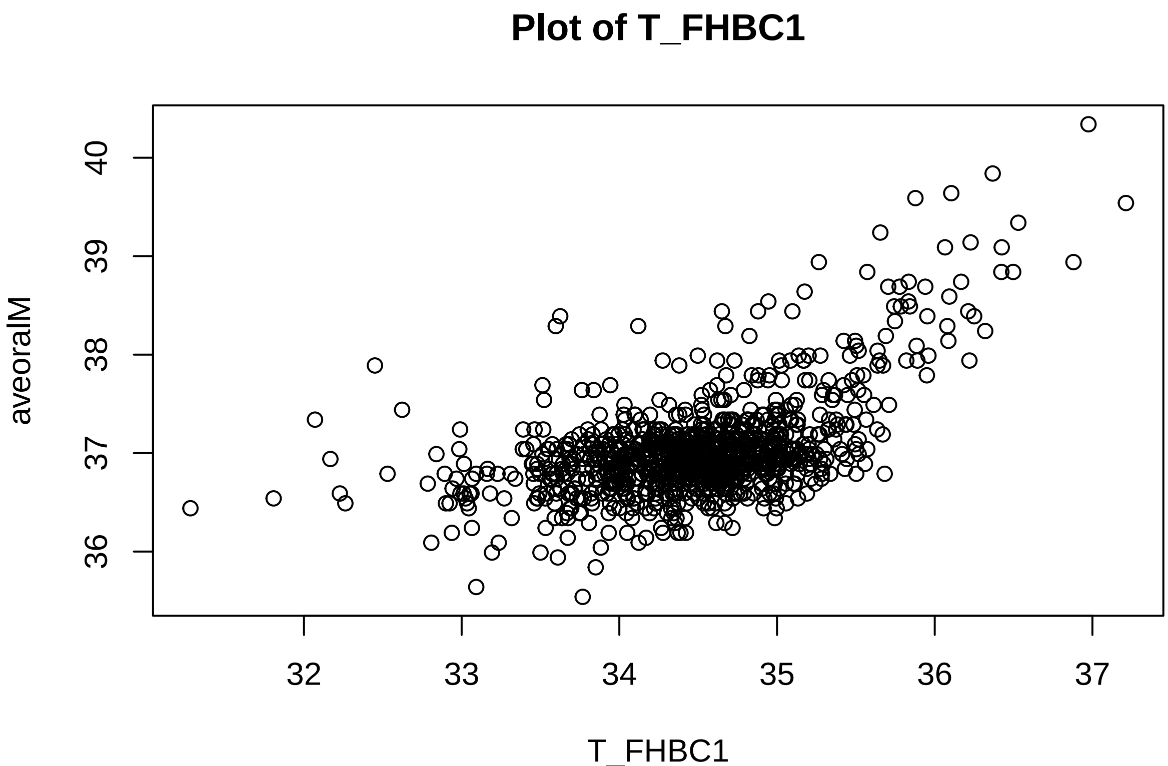
Plot of canthiMax1
aveoralM
36
37
38
39
40
35
36
37
38
canthiMax1

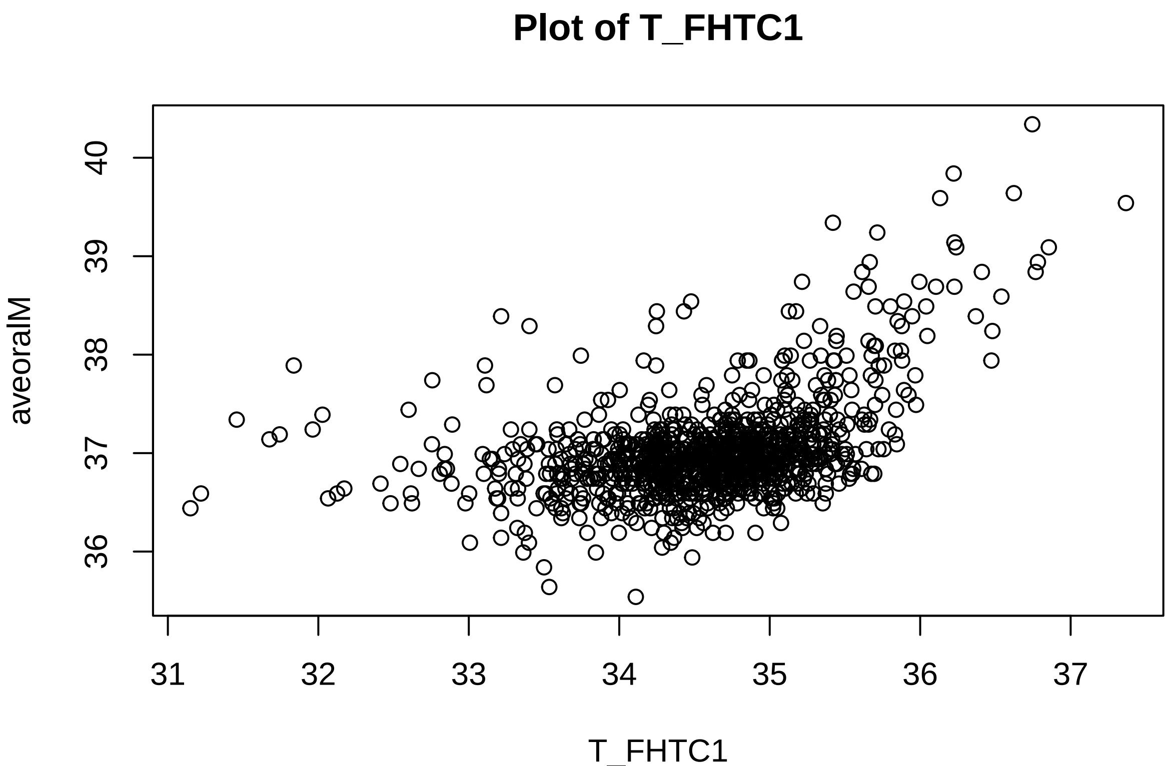

Plot of canthi4Max1
aveoralM
36
37
38
39
40
35
36
37
38
canthi4Max1

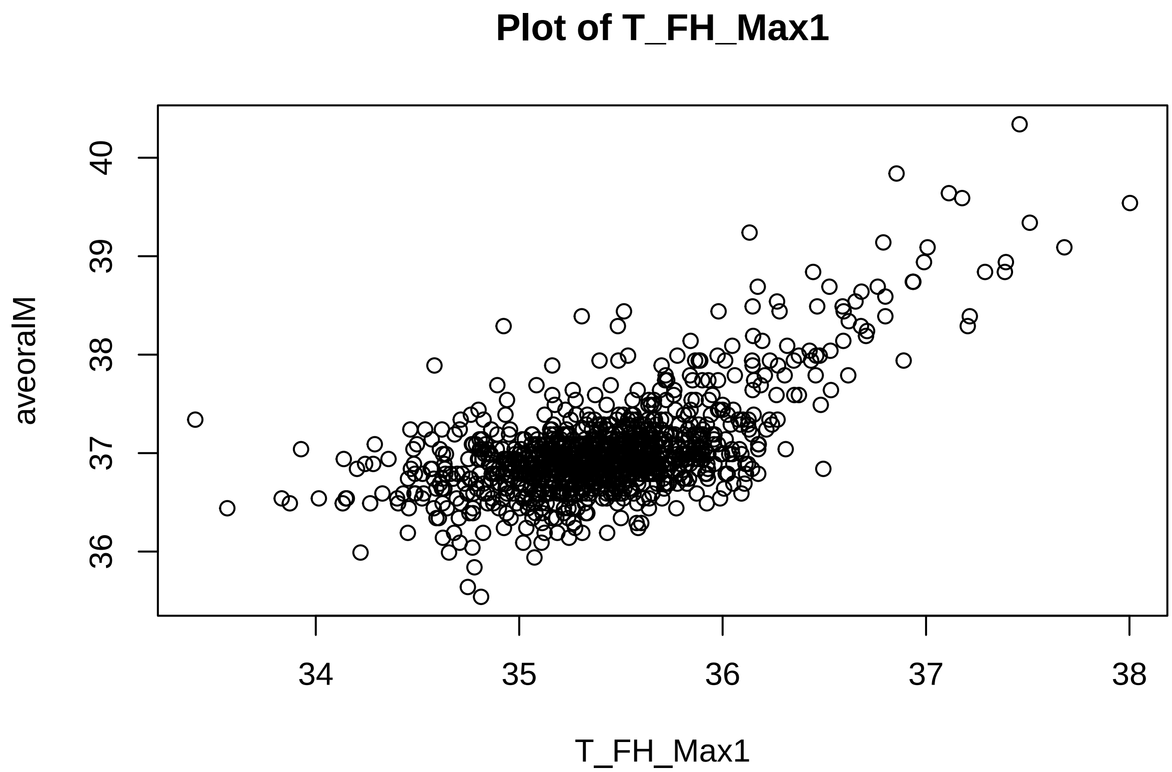

Plot of T_FHCC1
aveoralM
40
39
38
37
36
31
32
33
34
35
36
37
T_FHCC1

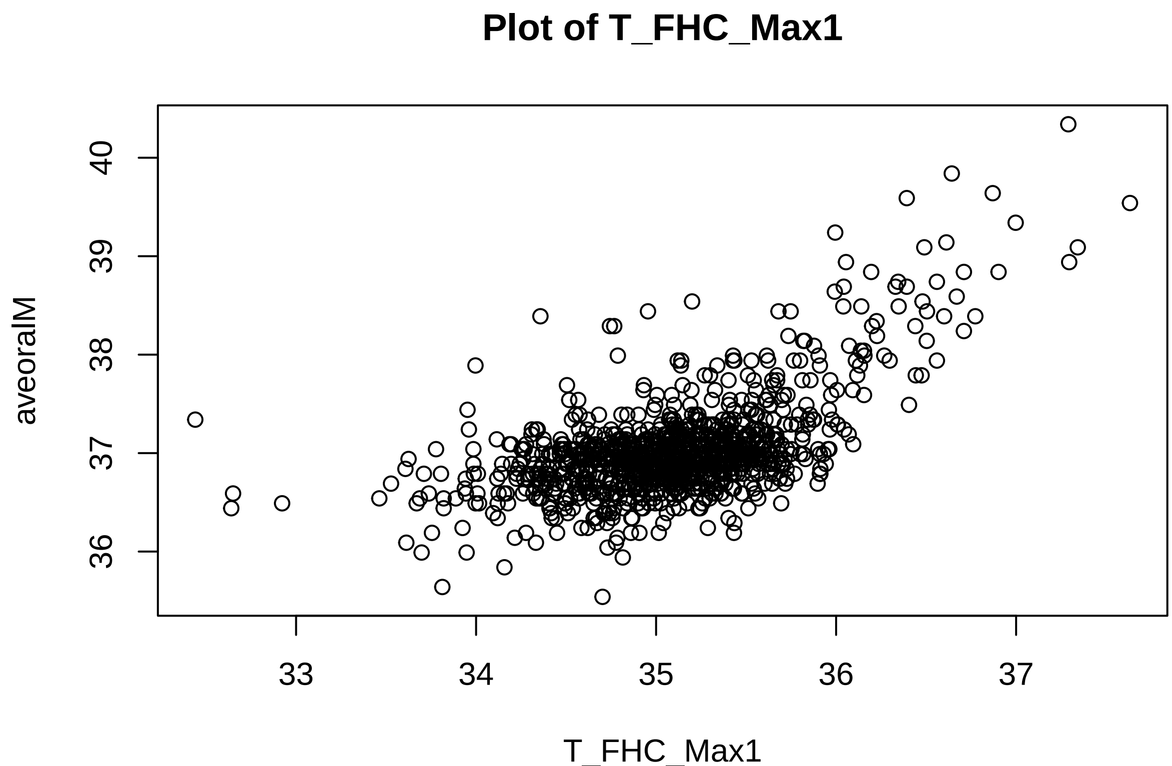

Plot of T_FHRC1
aveoralM
T_FHRC1
36
37
38
39
40
32
33
34
35
36
37

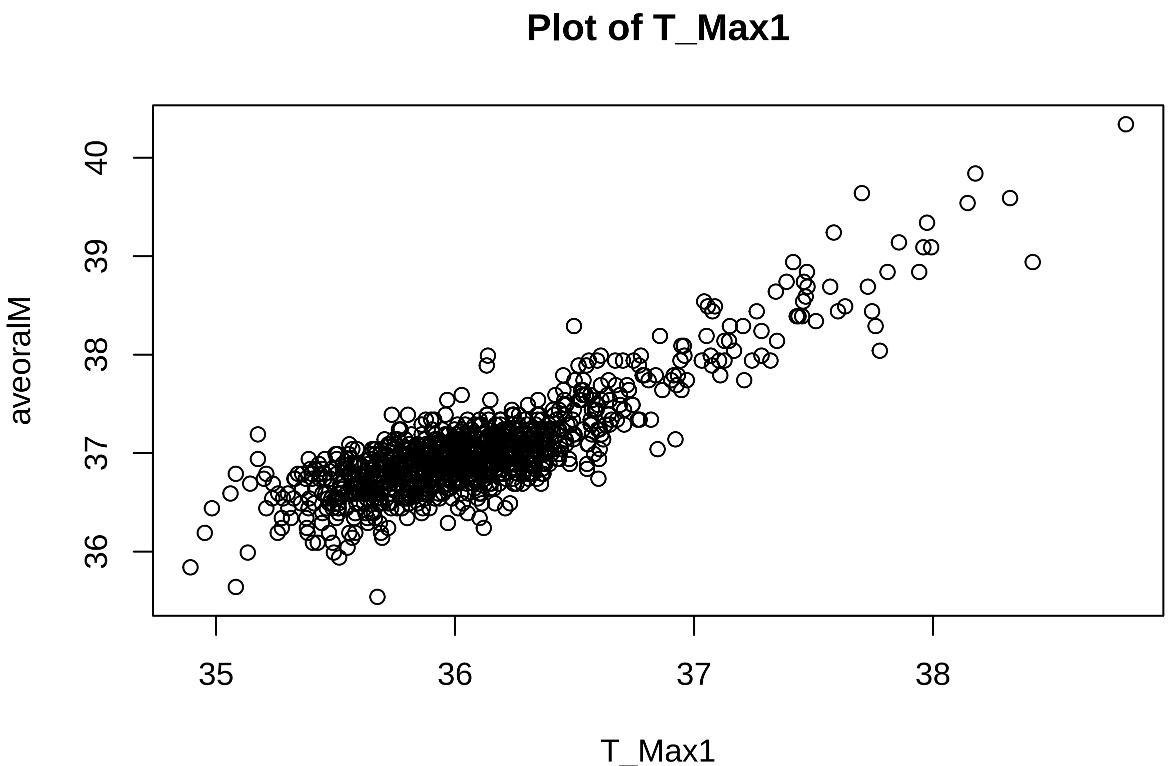

Plot of T_FHLC1
aveoralM
40
39
38
37
36
32
33
34
35
36
37
T_FHLC1

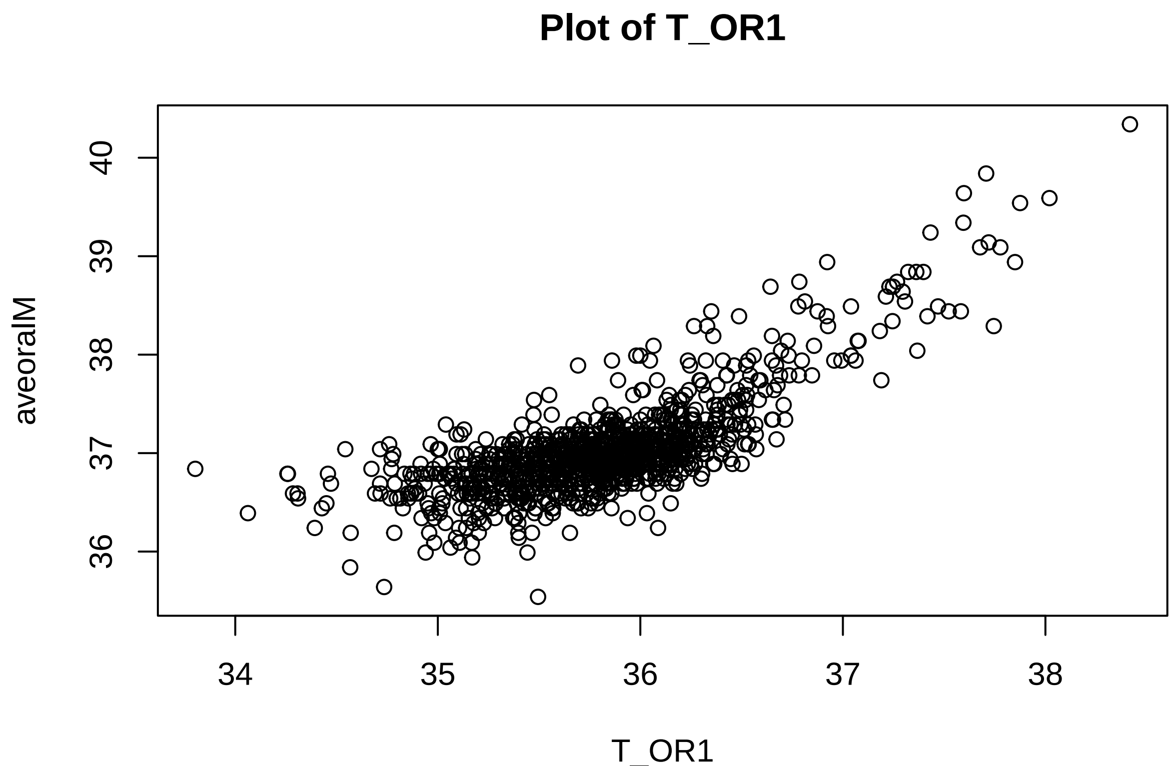

Plot of T_FHBC1
aveoralM
40
39
38
37
36
32
33
34
35
36
37
T_FHBC1


Plot of T_FHTC1
aveoralM
40
39
38
37
36
31
32
33
34
35
36
37
T_FHTC1

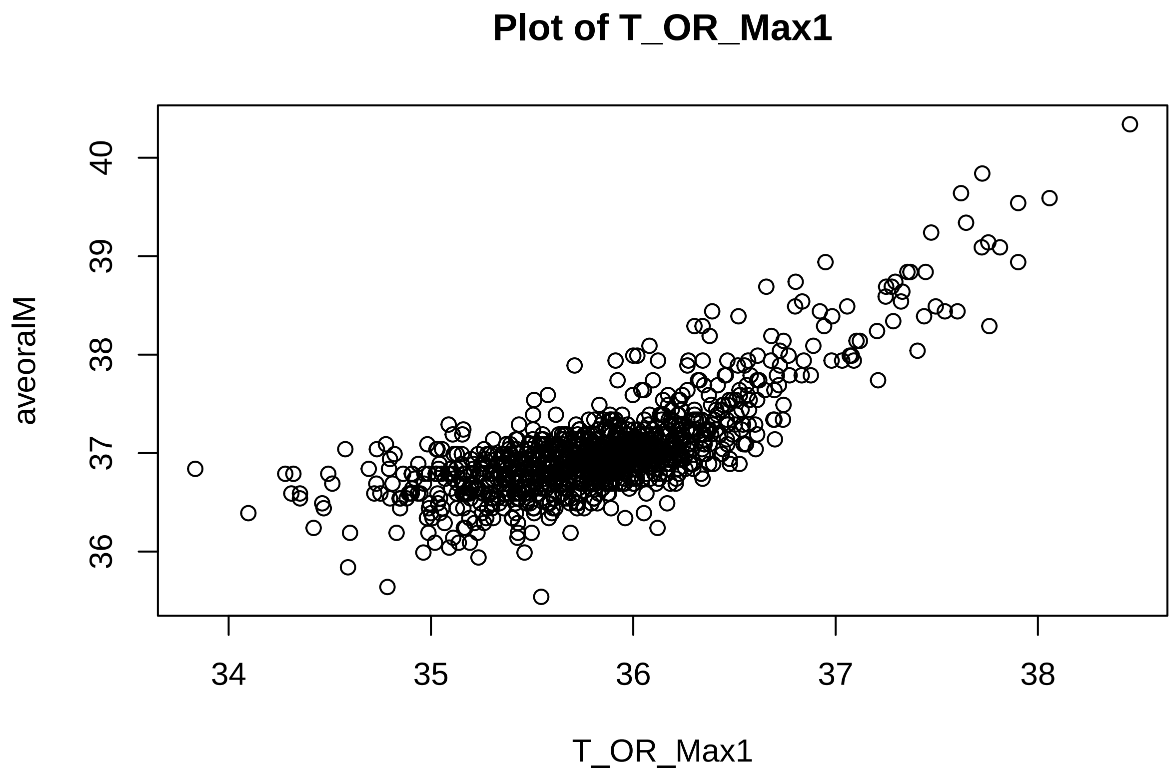

Plot of T_FH_Max1
aveoralM
36
37
38
39
40
34
35
36
37
38
T_FH_Max1


Plot of T_FHC_Max1
aveoralM
36
37
38
39
40
33
34
35
36
37
T_FHC_Max1


Plot of T_Max1
aveoralM
40
39
38
37
36
35
36
37
38
T_Max1

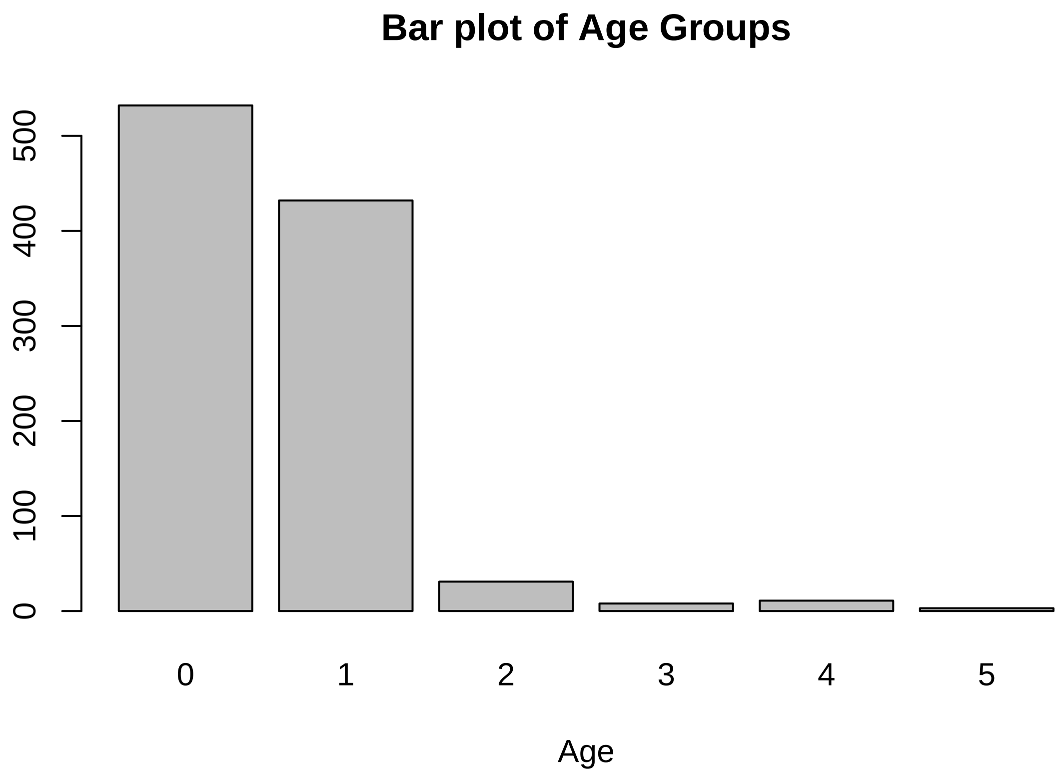


Plot of T_OR1
aveoralM
36
37
38
39
40
34
35
36
37
38
T_OR1

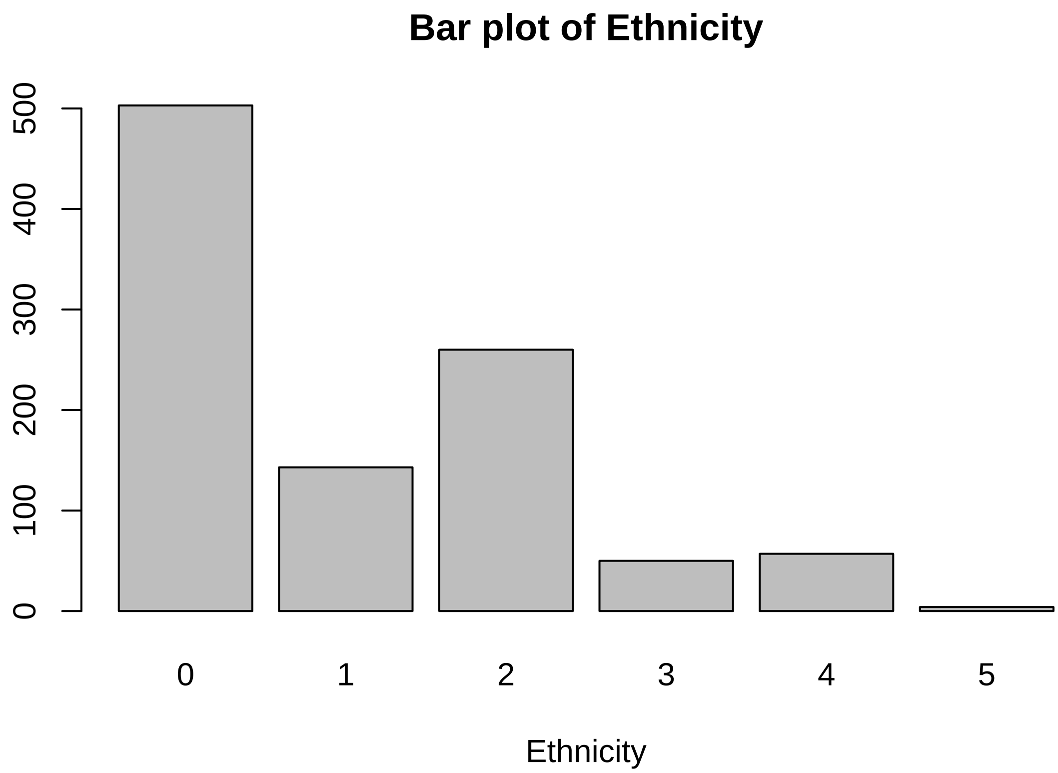



```
# data description/EDA
barplot(table(data[[2]]), main=paste("Bar plot of", names(data)[2]), xlab=names(data)[2])
```


```
barplot(table(data[[3]]), main=paste("Bar plot of Age Groups"), xlab=names(data)[3])
```




```
barplot(table(data[[4]]), main=paste("Bar plot of", names(data)[4]), xlab=names(data)[4])
```




```r
head(data)
```

```
##   aveOralM Gender Age Ethnicity T_atm Humidity Distance T_offset1 Max1R13_1
## 1    36.59      0   3         0    24       28      0.8    0.7025   35.0300
## 2    37.19      1   2         1    24       26      0.8    0.7800   34.5500
## 3    37.34      1   1         0    24       26      0.8    0.8625   35.6525
## 4    37.09      1   1         1    24       27      0.8    0.9300   35.2225
## 5    37.04      0   0         0    24       27      0.8    0.8950   35.5450
## 6    36.99      1   1         0    24       26      0.8    0.8275   35.1325
##   Max1L13_1 aveAllR13_1 aveAllL13_1   T_RC1 T_RC_Dry1 T_RC_Wet1 T_RC_Max1
## 1   35.3775     34.4000     34.9175 34.9850   34.9850   34.7625   35.0325
## 2   34.5200     33.9300     34.2250 34.7100   34.6325   34.6400   34.7425
## 3   35.5175     34.2775     34.8000 35.6850   35.6675   35.6150   35.7175
## 4   35.6125     34.3850     35.2475 35.2075   35.2000   35.1175   35.2250
## 5   35.6650     34.9100     35.3675 35.6025   35.4750   35.5700   35.6400
## 6   35.2025     34.5275     34.5825 35.1300   35.1225   35.0500   35.1475
##     T_LC1 T_LC_Dry1 T_LC_Wet1 T_LC_Max1    RCC1    LCC1 canthiMax1 canthi4Max1
## 1 35.3375   35.3375   34.4850   35.3775 34.7850 34.4650    35.3775     35.3375
## 2 34.5600   34.5375   34.3500   34.5750 34.3225 34.2400    34.7400     34.7150
## 3 35.5025   35.5025   35.2950   35.5300 35.3575 35.0925    35.7175     35.6825
## 4 35.5950   35.5950   35.3275   35.6125 34.9100 35.1700    35.6125     35.5950
## 5 35.6400   35.6400   35.0775   35.6675 35.3550 35.1200    35.6650     35.6475
## 6 35.2150   35.1875   35.0625   35.2375 34.9525 34.7775    35.2500     35.2275
##   T_FHCC1 T_FHRC1 T_FHLC1 T_FHBC1 T_FHTC1 T_FH_Max1 T_FHC_Max1  T_Max1   T_OR1
## 1 33.5775 33.4775 33.3725 33.4925 33.0025   34.5300    34.0075 35.6925 35.6350
## 2 34.0325 34.0550 33.6775 33.9700 34.0025   34.6825    34.6600 35.1750 35.0925
```

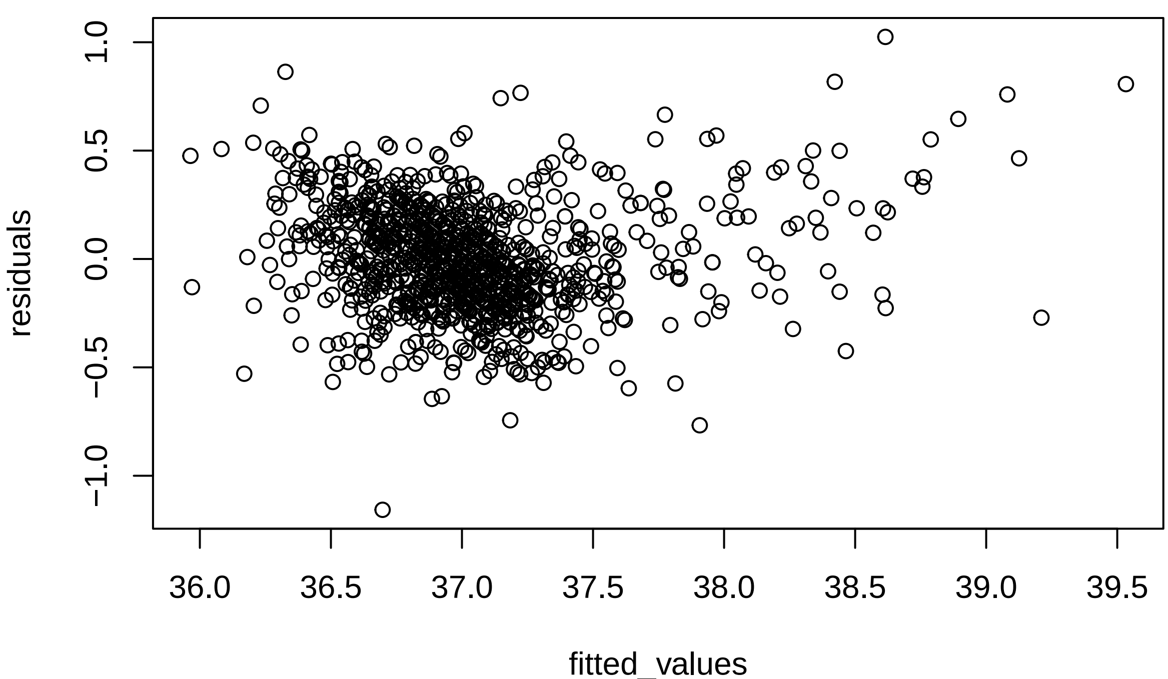
```
## 3 34.9000 34.8275 34.6475 34.8200 34.6700   35.3450    35.2225 35.9125 35.8600
## 4 34.4400 34.4225 34.6550 34.3025 34.9175   35.6025    35.3150 35.7200 34.9650
## 5 35.0900 35.1600 34.3975 34.6700 33.8275   35.4175    35.3725 35.8950 35.5875
## 6 34.1925 34.2825 34.4800 34.2850 34.2425   34.8600    34.6925 35.8500 35.8175
##   T_OR_Max1
## 1   35.6525
## 2   35.1075
## 3   35.8850
## 4   34.9825
## 5   35.6175
## 6   35.8500
```

```
model <- glm(aveOralM~., data = data)
residuals <- residuals(model)
fitted_values <- fitted(model)

summary(model)
```

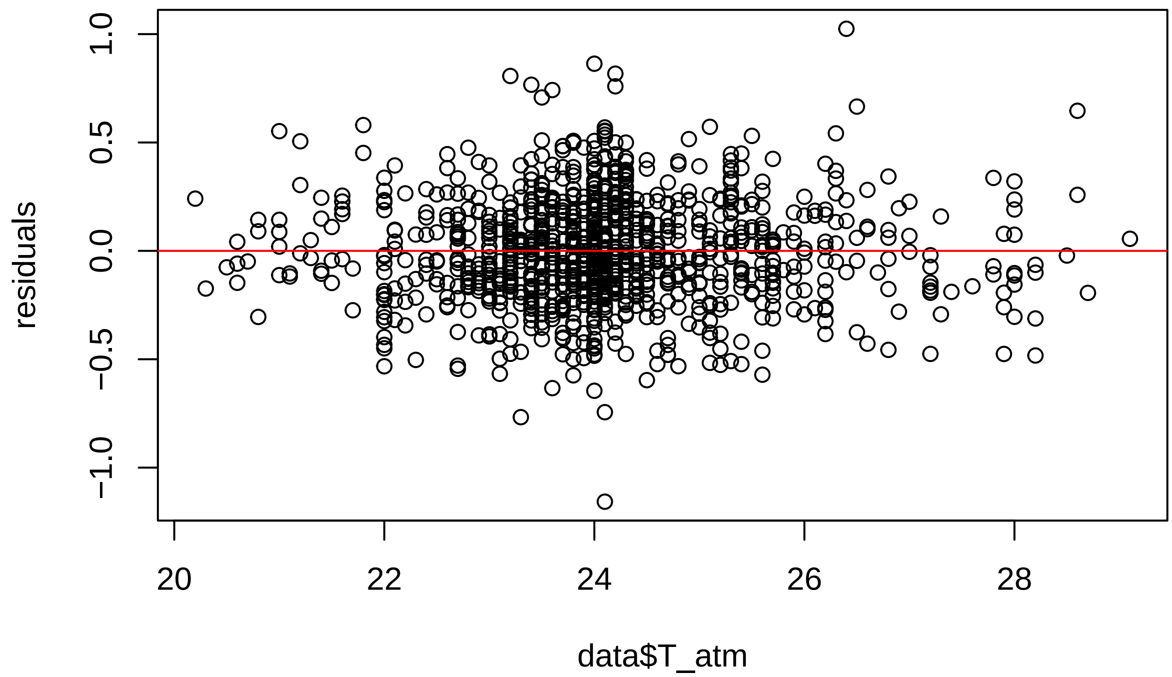
```
##
## Call:
## glm(formula = aveOralM ~ ., data = data)
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.4017527  0.6763427   6.508 1.21e-10 ***
## Gender1      0.0391609  0.0183415   2.135 0.033002 *
## Age1         0.0169253  0.0169780   0.997 0.319062
## Age2        -0.0239847  0.0480420  -0.499 0.617720
## Age3         0.1093256  0.0930292   1.175 0.240212
## Age4         0.0266481  0.0812828   0.328 0.743100
## Age5         0.0027217  0.1499499   0.018 0.985522
## Ethnicity1   0.0981851  0.0262896   3.735 0.000199 ***
## Ethnicity2   0.0562205  0.0226621   2.481 0.013276 *
## Ethnicity3   0.0012295  0.0387599   0.032 0.974701
## Ethnicity4   0.0131432  0.0359559   0.366 0.714791
## Ethnicity5   0.0495122  0.1289803   0.384 0.701155
## T_atm       -0.0682295  0.0080230  -8.504  < 2e-16 ***
## Humidity     0.0001682  0.0006607   0.255 0.799108
## Distance    -0.1119162  0.1313625  -0.852 0.394443
## T_offset1    0.0609974  0.0296530   2.057 0.039948 *
## Max1R13_1   -0.3621770  0.1816313  -1.994 0.046428 *
## Max1L13_1   -0.1197475  0.1539755  -0.778 0.436931
## aveAllR13_1 -0.0337971  0.0351362  -0.962 0.336345
## aveAllL13_1 -0.0608947  0.0437427  -1.392 0.164206
## T_RC1       -0.2451894  0.9196425  -0.267 0.789823
## T_RC_Dry1    0.2611177  0.1906322   1.370 0.171081
## T_RC_Wet1    0.0598349  0.1000170   0.598 0.549814
## T_RC_Max1    0.4307559  0.8760232   0.492 0.623030
## T_LC1        1.4137436  0.8782130   1.610 0.107766
## T_LC_Dry1   -0.1851850  0.2418481  -0.766 0.444036
## T_LC_Wet1   -0.1422439  0.0848801  -1.676 0.094094 .
## T_LC_Max1   -0.9742501  0.8127692  -1.199 0.230944
## RCC1         0.0641938  0.0654435   0.981 0.326883
## LCC1         0.1478274  0.0615859   2.400 0.016566 *
```

```
## canthiMax1  -0.3590968  0.9574371  -0.375 0.707697
## canthi4Max1  0.2807439  0.9813588   0.286 0.774880
## T_FHCC1     -0.0943043  0.0520964  -1.810 0.070574 .
## T_FHRC1     -0.0232803  0.0351938  -0.661 0.508455
## T_FHLC1     -0.1026527  0.0313957  -3.270 0.001115 **
## T_FHBC1      0.0933407  0.0478541   1.951 0.051399 .
## T_FHTC1      0.0054775  0.0237210   0.231 0.817431
## T_FH_Max1    0.1111360  0.0411540   2.700 0.007044 **
## T_FHC_Max1   0.0977564  0.0585131   1.671 0.095107 .
## T_Max1       0.5687421  0.0750738   7.576 8.28e-14 ***
## T_OR1        0.2046445  0.6772813   0.302 0.762598
## T_OR_Max1   -0.0843778  0.6752644  -0.125 0.900585
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.06447247)
##
##     Null deviance: 264.210  on 1016  degrees of freedom
## Residual deviance:  62.861  on  975  degrees of freedom
## AIC: 141.11
##
## Number of Fisher Scoring iterations: 2
```

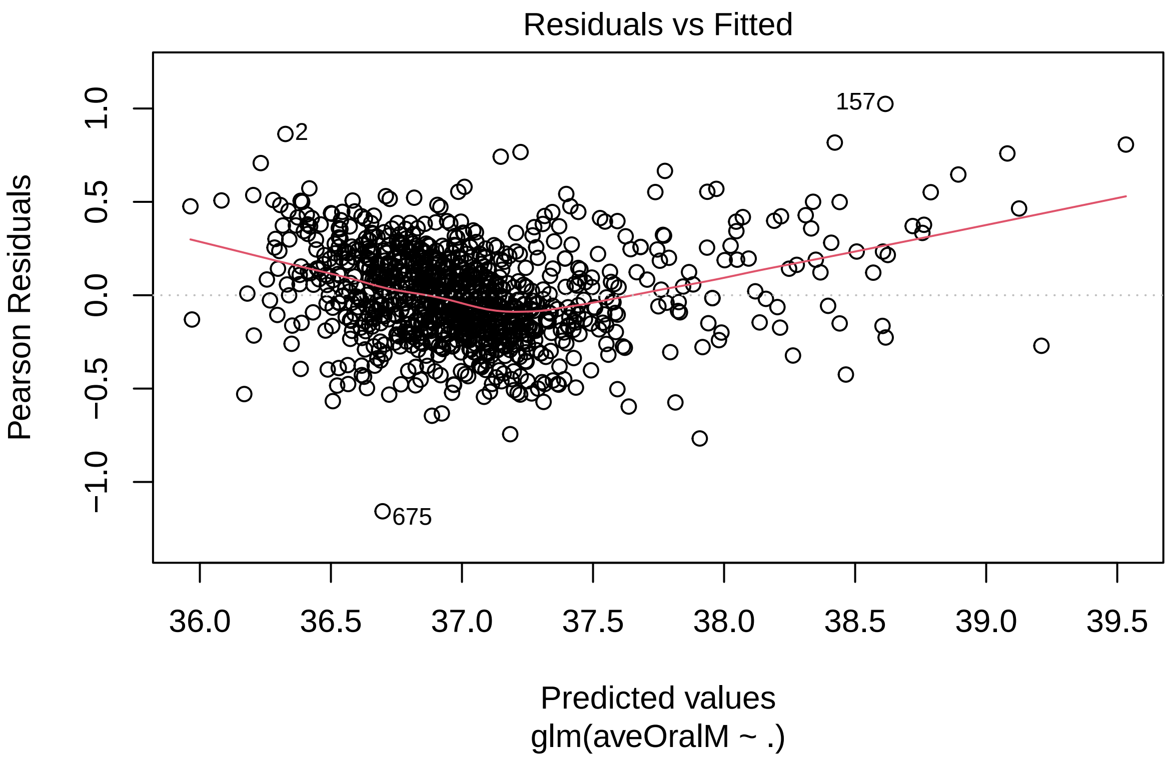
```r
plot(fitted_values,residuals)
```



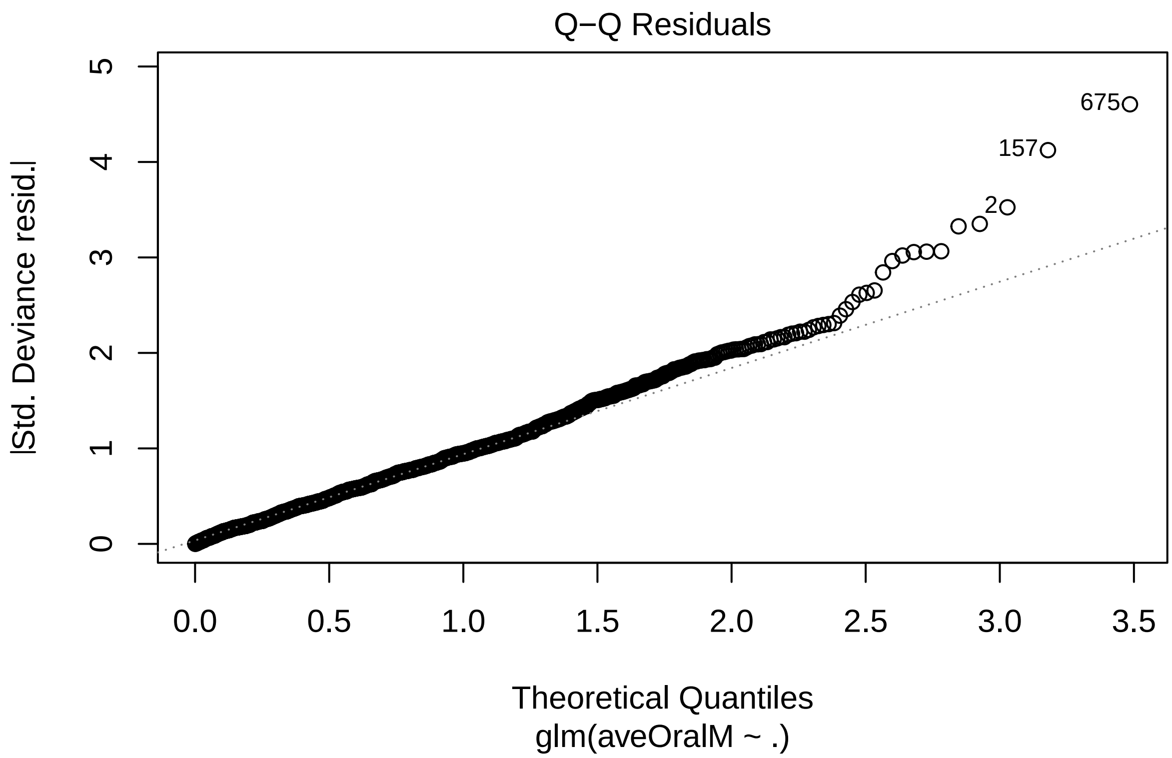
```r
plot(data$T_atm,residuals)
abline(h = 0, col = "red")
```

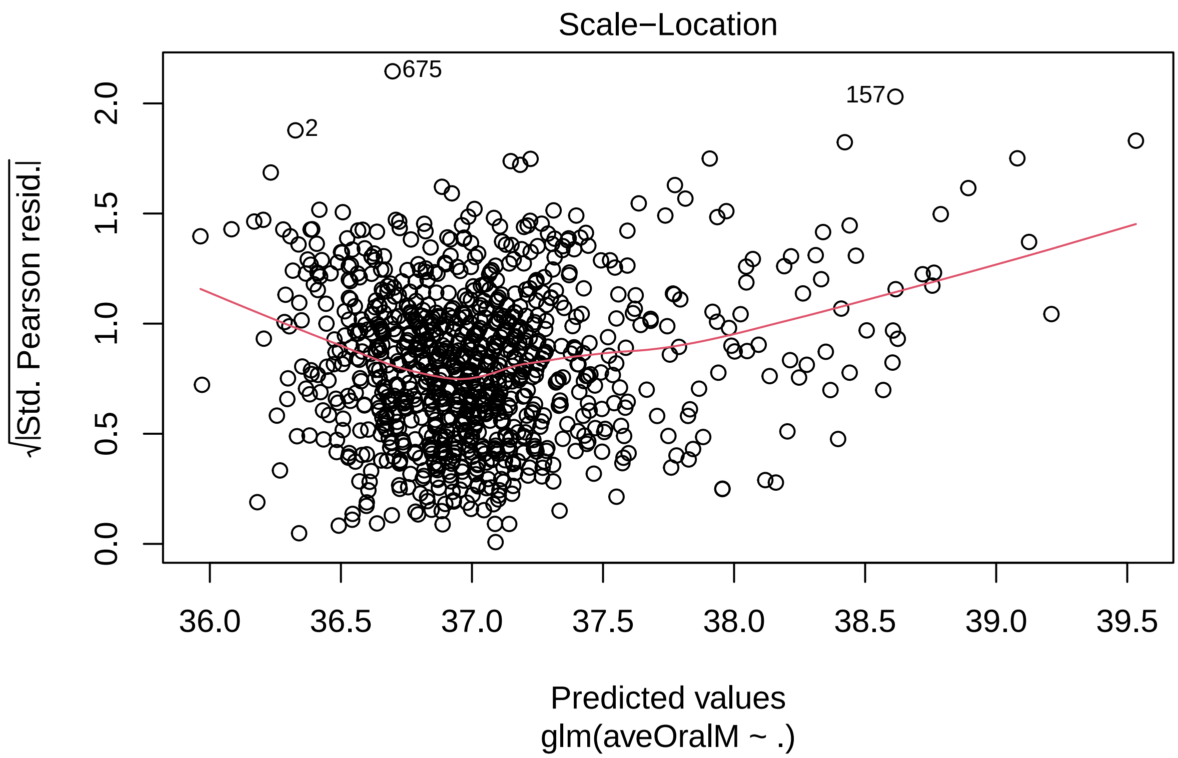



```r
plot(model)
```

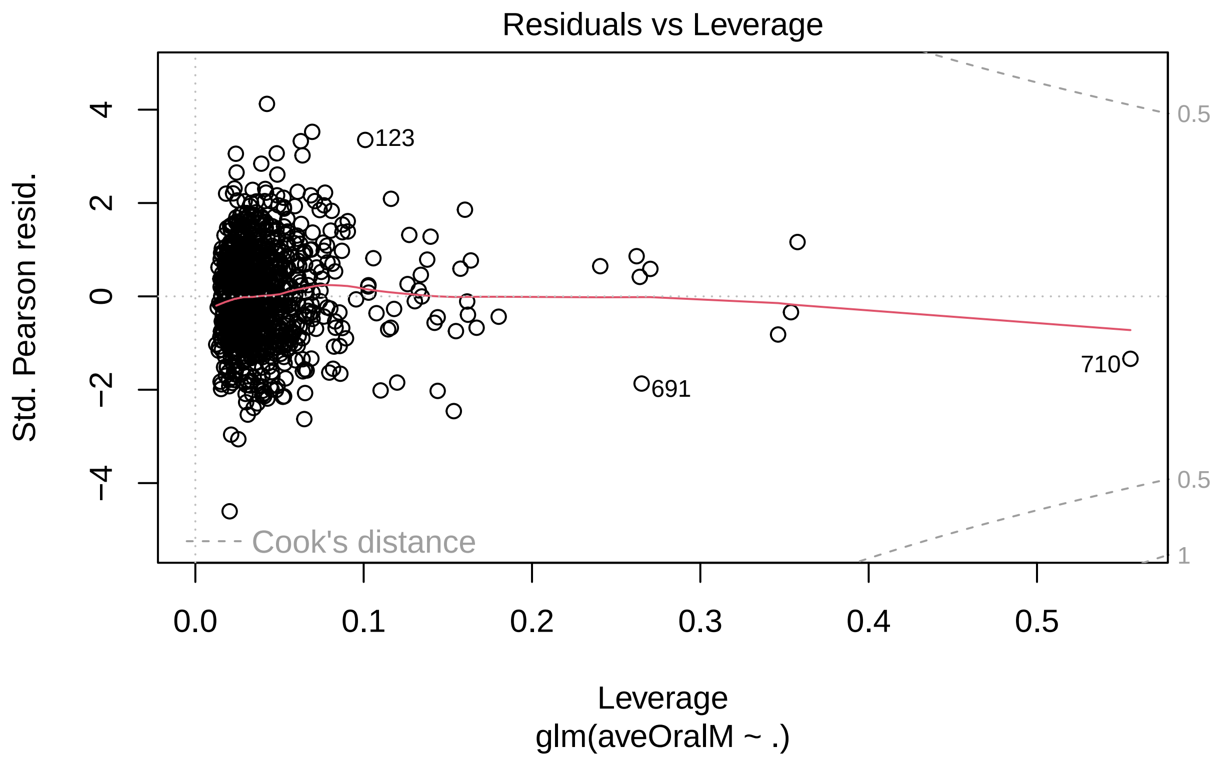


Residuals vs Fitted
Pearson Residuals
1.0
0.5
0.0
−0.5
−1.0
157
2
675
36.0
36.5
37.0
37.5
38.0
38.5
39.0
39.5
Predicted values
glm(aveOralM ~ .)


Q−Q Residuals
675
157
2
|Std. Deviance resid.|
0
1
2
3
4
5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Theoretical Quantiles
glm(aveOralM ~ .)



Scale−Location
√|Std. Pearson resid.|
0.0
0.5
1.0
1.5
2.0
675
157
2
36.0
36.5
37.0
37.5
38.0
38.5
39.0
39.5
Predicted values
glm(aveOralM ~ .)



By plotting the histogram of oral temperature fast mode and monitor mode, we can see that both histograms are right-skewed, which could indicate potential outliers. Let's see how the boxplot looks to determine if we need to transform the data