Group 1: Multivariate analysis of australian climate data

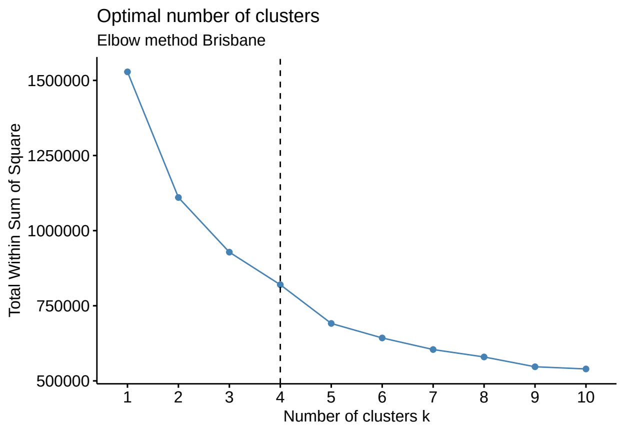
Data input

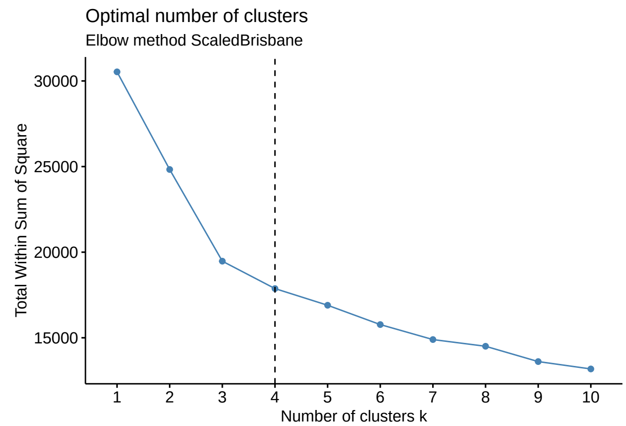
To perform the clustering analysis are used the original datasets (numeric variables) for Brisbane, Perth and Cairns.

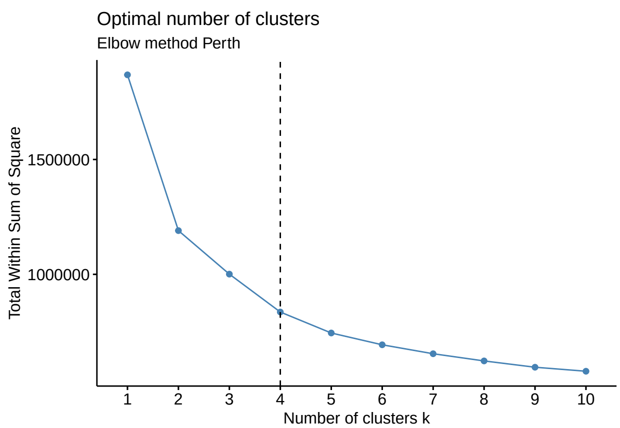
Clustering Analysis

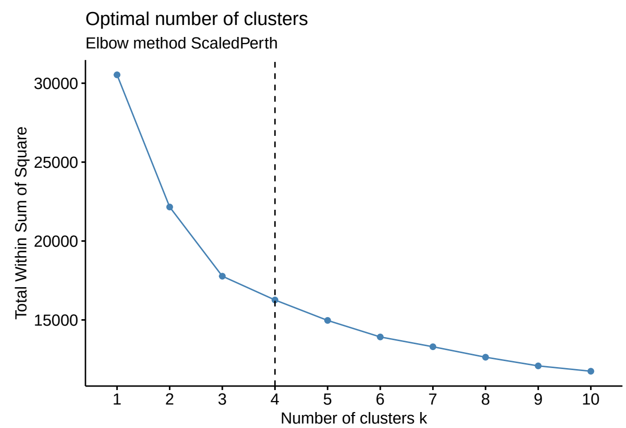
In order to analyze if data presents patterns of association are it is performed a clustering analysis. For this purpose, all incomplete cases remaining are removed and as a first step, the optimal number of clusters are estimated through direct methods: elbow, average silhouette and ASM to choose the most common value of optimal clusters.

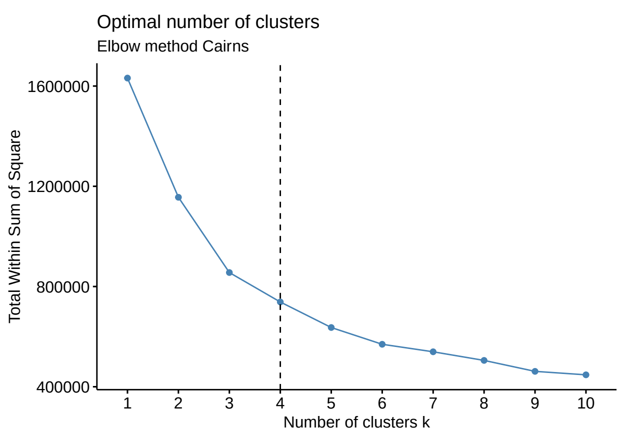
```
par(mar = c(4,4,.1,.1))
fun01<-function(x){ tmp_df = listall[[x]]
                    tmp_name = names(listall)[x]
                    fviz_nbclust(tmp_df, kmeans, method = "wss") +
                    geom_vline(xintercept = 4, linetype = 2) +
                    labs(subtitle = paste("Elbow method",tmp_name))}
fun02<-function(x){ tmp_df = listall[[x]]
                    tmp_name = names(listall)[x]
                    fviz_nbclust(tmp_df, kmeans, method = "silhouette") +
                    geom_vline(xintercept = 4, linetype = 2) +
                    labs(subtitle = paste("Elbow method",tmp_name))}
fun03<-function(x){ tmp_df = listall[[x]]
                    tmp_name = names(listall)[x]
                    fviz_nbclust(tmp_df, kmeans, method = "gap_stat") +
                    geom_vline(xintercept = 4, linetype = 2) +
                    labs(subtitle = paste("Elbow method",tmp_name))}

wss<-lapply(1:length(listall),fun01)
wss

silhouette<-lapply(1:length(listall),fun02)
silhouette

#Gaps<-lapply(1:length(listall),fun03)
#Gaps
```

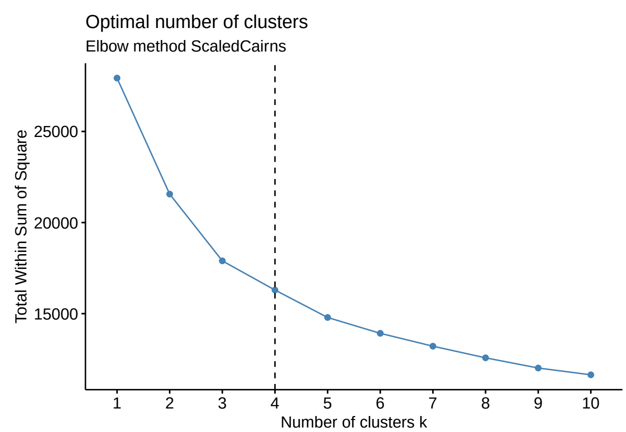

Optimal number of clusters
Elbow method Brisbane
Total Within Sum of Square
1500000
1250000
1000000
750000
500000
1 2 3 4 5 6 7 8 9 10
Number of clusters k

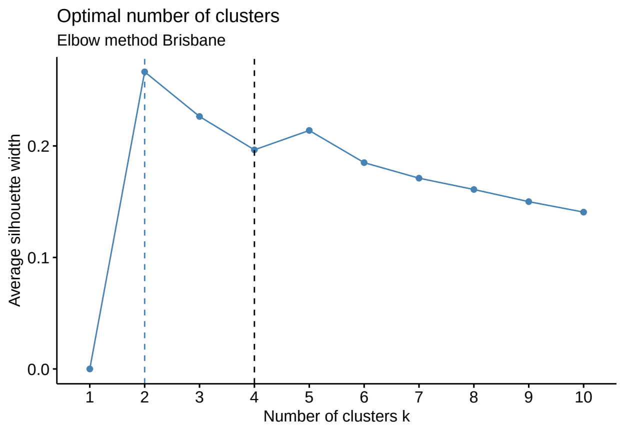

Optimal number of clusters
Elbow method ScaledBrisbane
Total Within Sum of Square
30000
25000
20000
15000
1 2 3 4 5 6 7 8 9 10
Number of clusters k

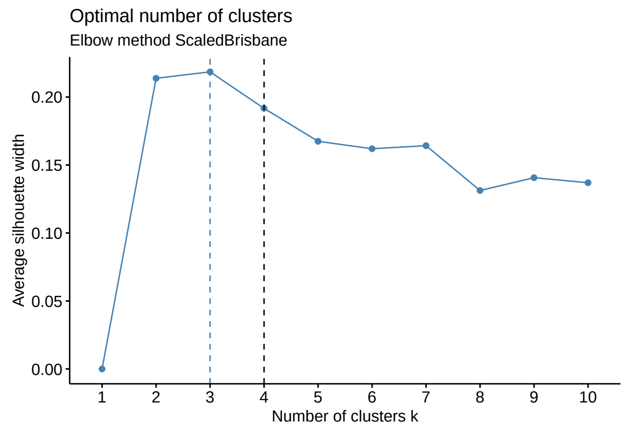

Optimal number of clusters
Elbow method Perth
Total Within Sum of Square
1500000
1000000
1 2 3 4 5 6 7 8 9 10
Number of clusters k

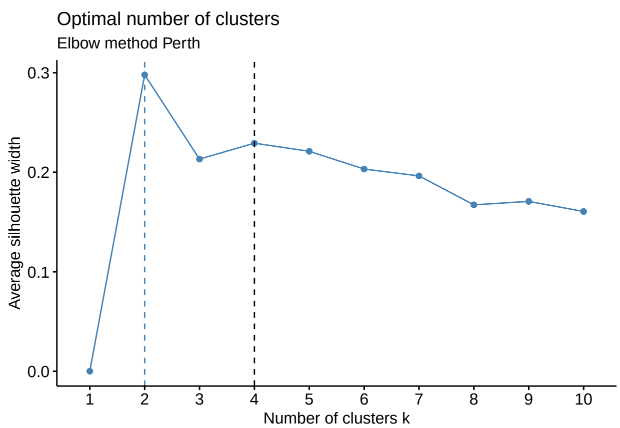

Optimal number of clusters
Elbow method ScaledPerth
Total Within Sum of Square
30000
25000
20000
15000
1 2 3 4 5 6 7 8 9 10
Number of clusters k

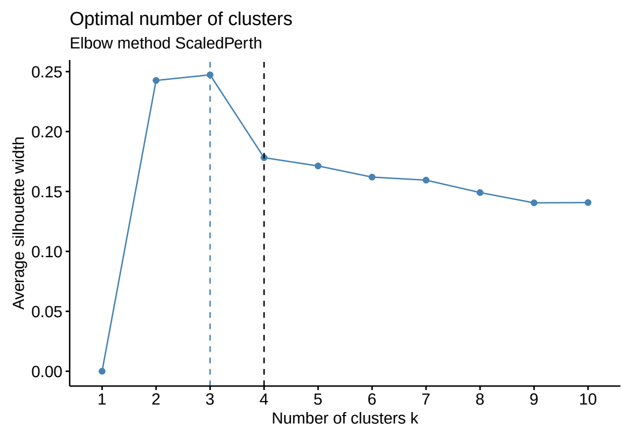

Optimal number of clusters
Elbow method Cairns
Total Within Sum of Square
1600000
1200000
800000
400000
1 2 3 4 5 6 7 8 9 10
Number of clusters k

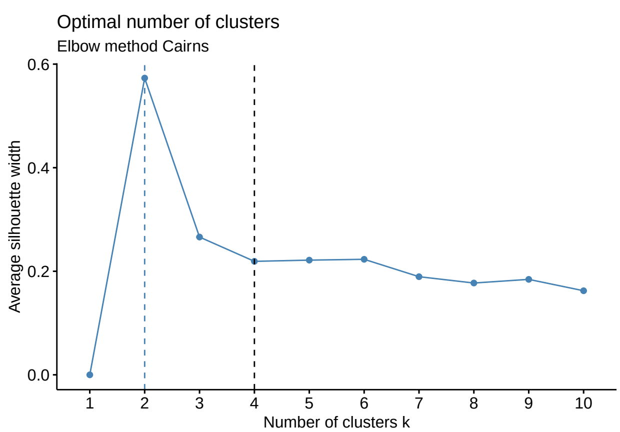

Optimal number of clusters
Elbow method ScaledCairns
Total Within Sum of Square
25000
20000
15000
1 2 3 4 5 6 7 8 9 10
Number of clusters k

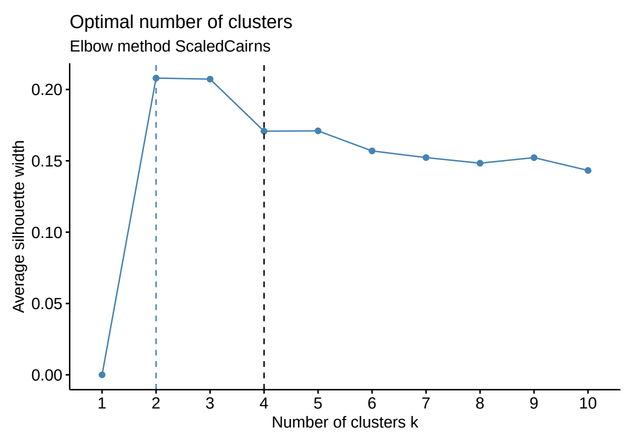












Given the results provided by the methods, it can be concluded the clustering can be performed with 4 cluster for all the dataset, the original numerical variables and the coordinates of the performed MCA.

```
funVizKm<- function(i){ tmp_df = listall[[i]];
                        tmp_kmeans = kmeans(x = listall[[i]], centers = 4)
                        tmp_name = names(listall)[i]
                        fviz_cluster(object = tmp_kmeans, data = listall[[i]],
                                     show.clust.cent = TRUE, ellipse.type = "euclid",
                                     star.plot = TRUE, repel = TRUE) +
                     theme_bw() + theme(legend.position = "none") +
                          labs(title = paste("Results clustering K-means (4 clusters)",
                                             tmp_name))}
```

```r
VizKmeans<-lapply(1:length(listall),funVizKm)
VizKmeans
```

```
## Warning: ggrepel: 1751 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps

## Warning: ggrepel: 1751 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps

## Warning: ggrepel: 1771 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps

## Warning: ggrepel: 1771 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps

## Warning: ggrepel: 1618 unlabeled data points (too many overlaps). Consider
## increasing max.overlaps

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## increasing max.overlaps
```
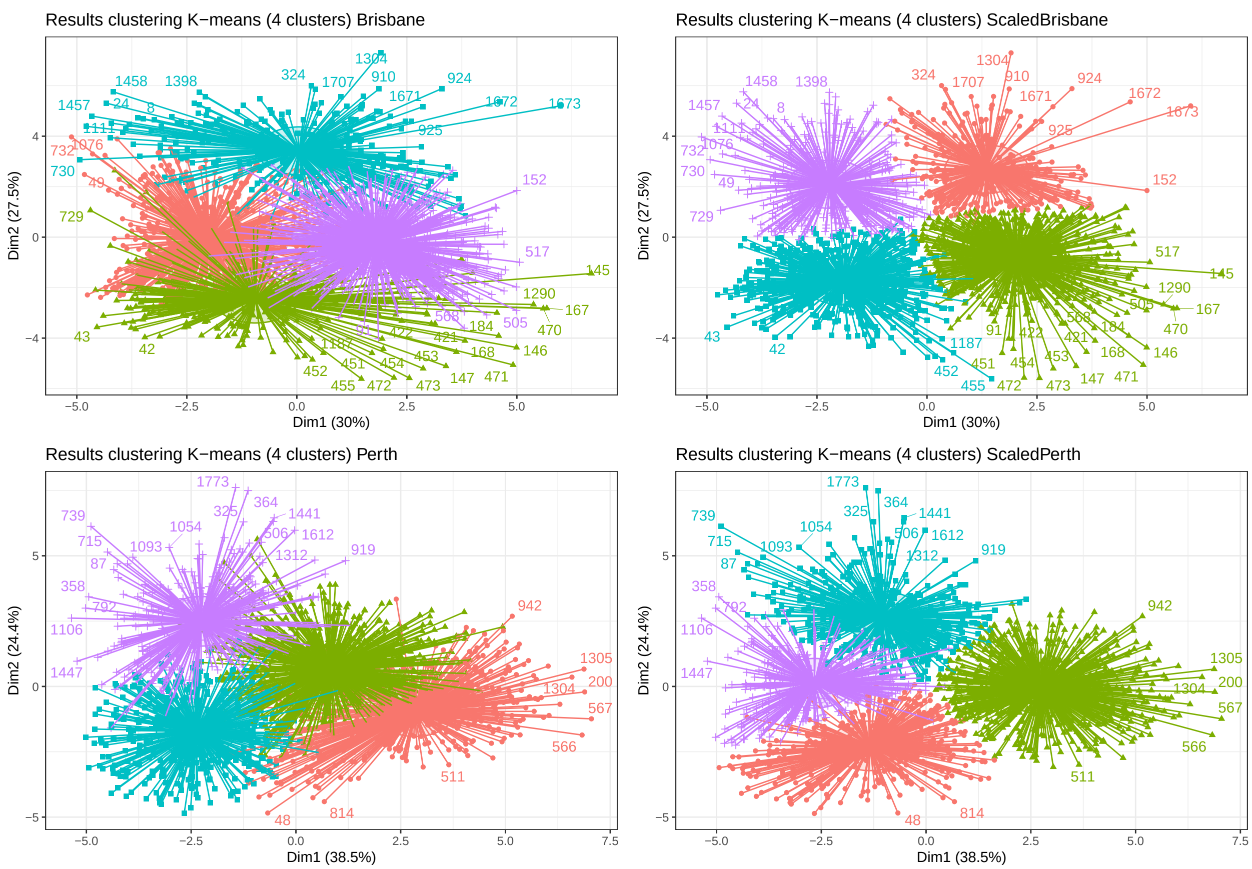
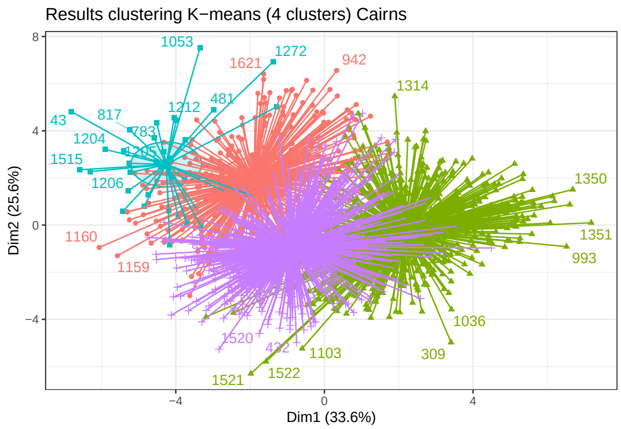
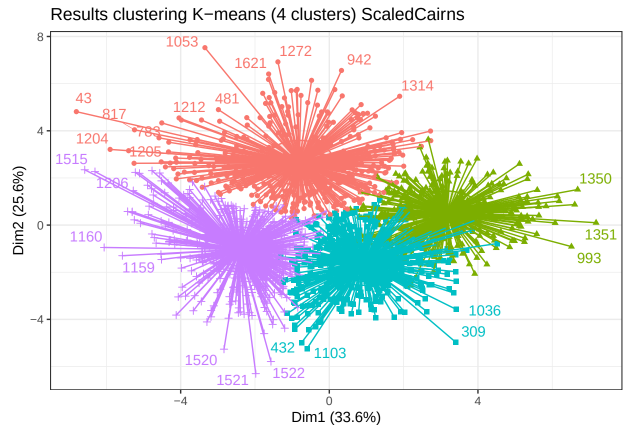



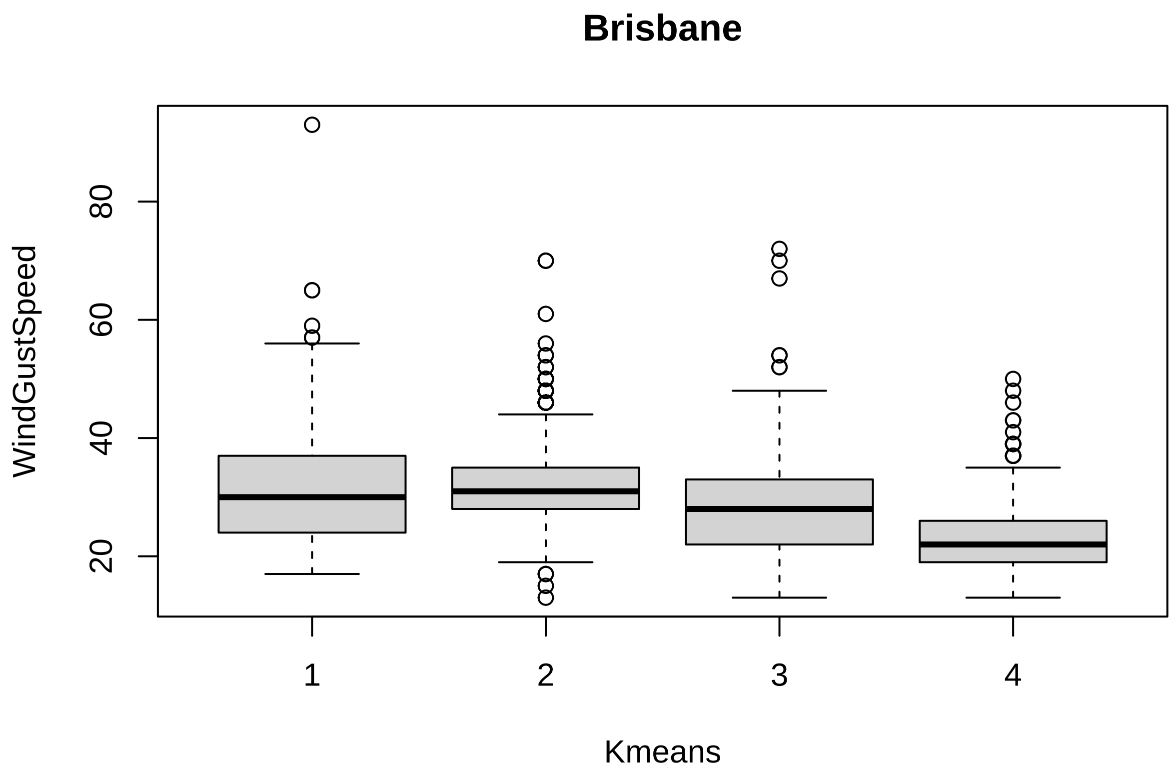


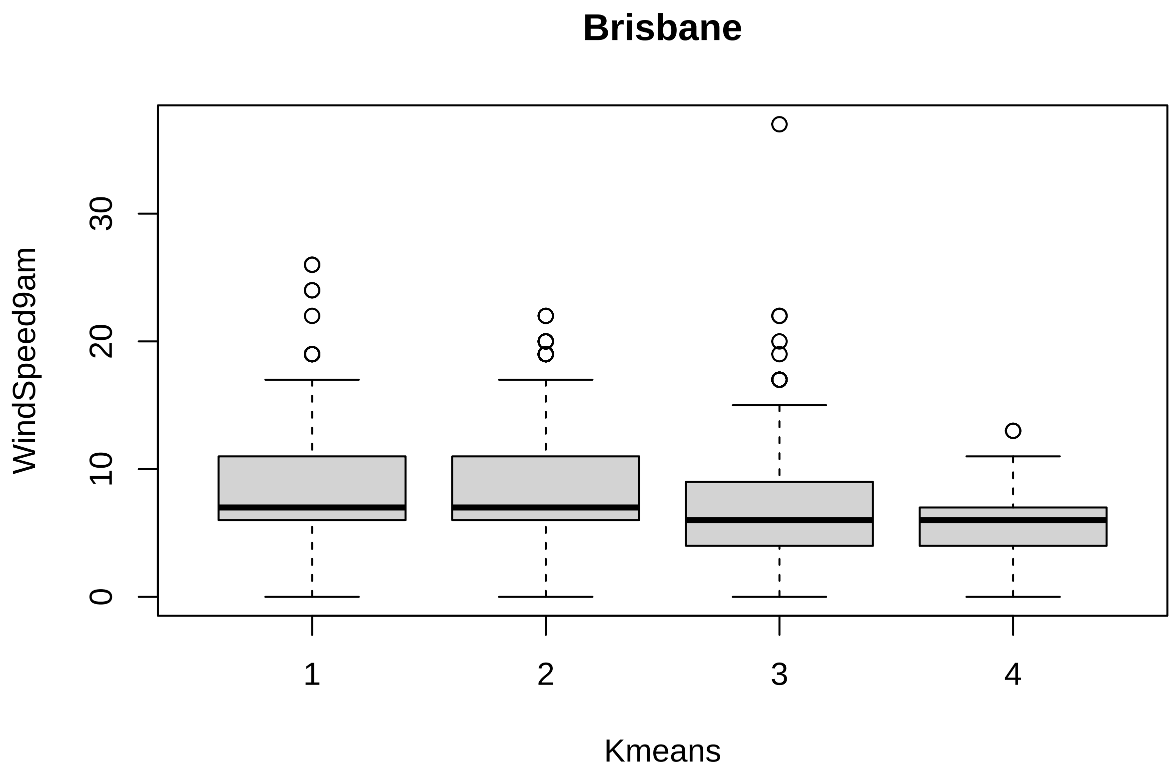


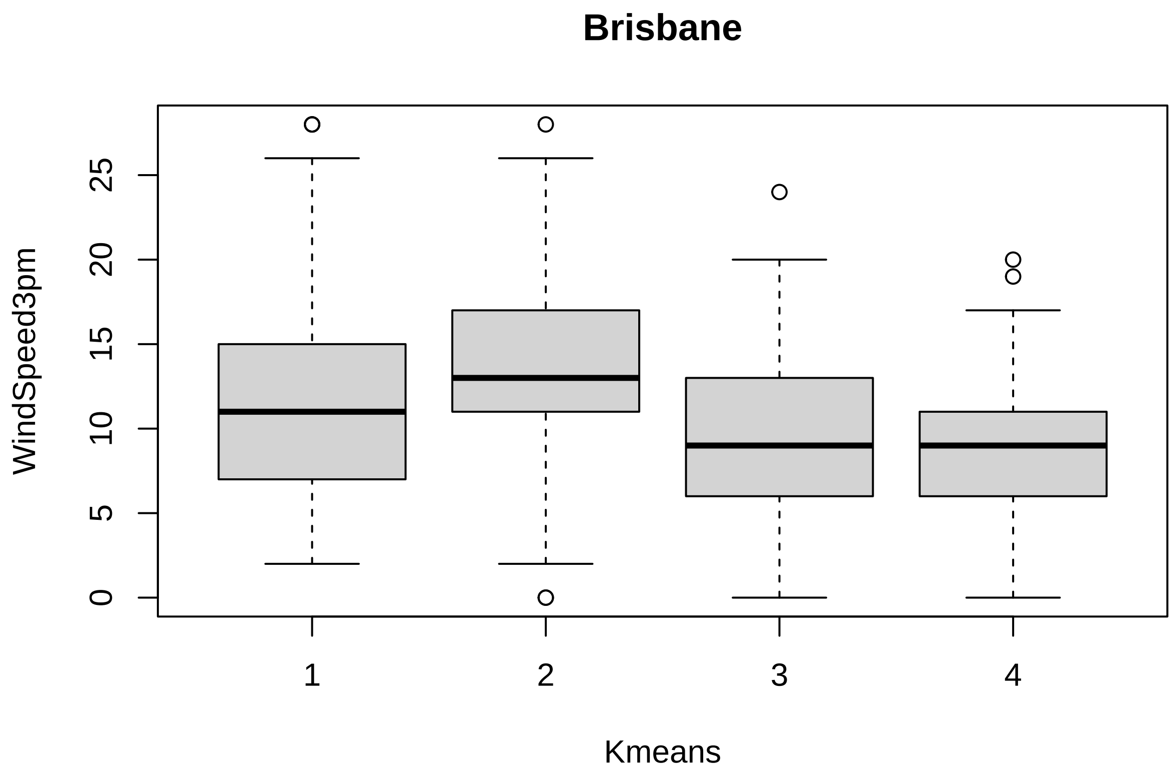

```
funKm<- function(i){ tmp_df = listall[[i]];
                     tmp_kmeans = kmeans(x = listall[[i]], centers = 4)
                     listall[[i]]<-add_column(listall[[i]], KmeansCluster =
                                              tmp_kmeans$cluster)}

Kmeans<-lapply(1:length(listall),funKm)
names(Kmeans)<-c("Brisbane","ScaledBrisbane","Perth","ScaledPerth",
                 "Cairns","ScaledCairns")

#a<-Kmeans[[1]]

#fun08<-function(a,i) {
#  for (i in 1:17) {boxplot(a[,i] ~ a[,18], xlab = 'Kmeans', ylab = names(a)[i])}}

#lapply(Kmeans,fun08)

#boxplot(a[,1] ~ a[,18])
#boxplot(a[,2] ~ a[,18])

#boxplot(a)

#plot(formula = KmeansCluster ~ ., data = a)


lapply(1:length(Kmeans), function(x){

  # Get the dataframe and the name
  tmp_df = Kmeans[[x]]
  tmp_name = names(Kmeans)[x]

  for (i in 1:17) {boxplot(tmp_df[,i] ~ tmp_df[,18], xlab = 'Kmeans',
                           ylab = names(tmp_df)[i], main = tmp_name)}
  })
```

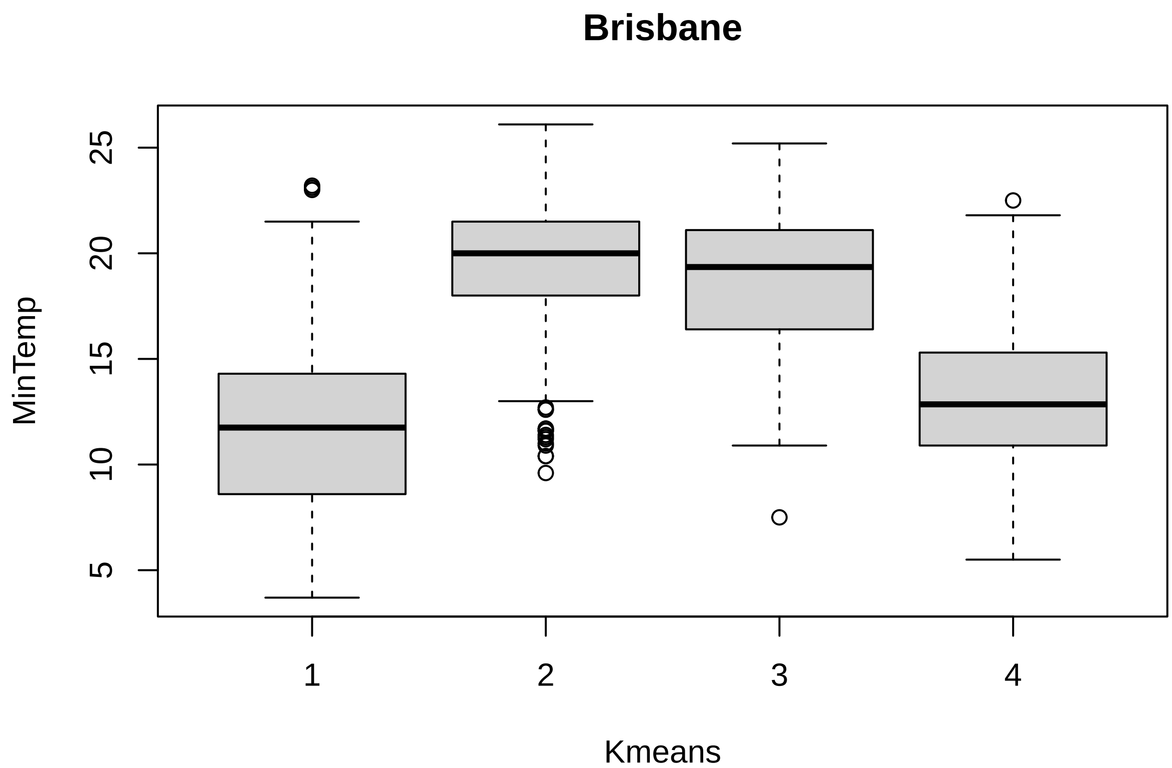
```
## [[1]]
## NULL
##
## [[2]]
## NULL
```

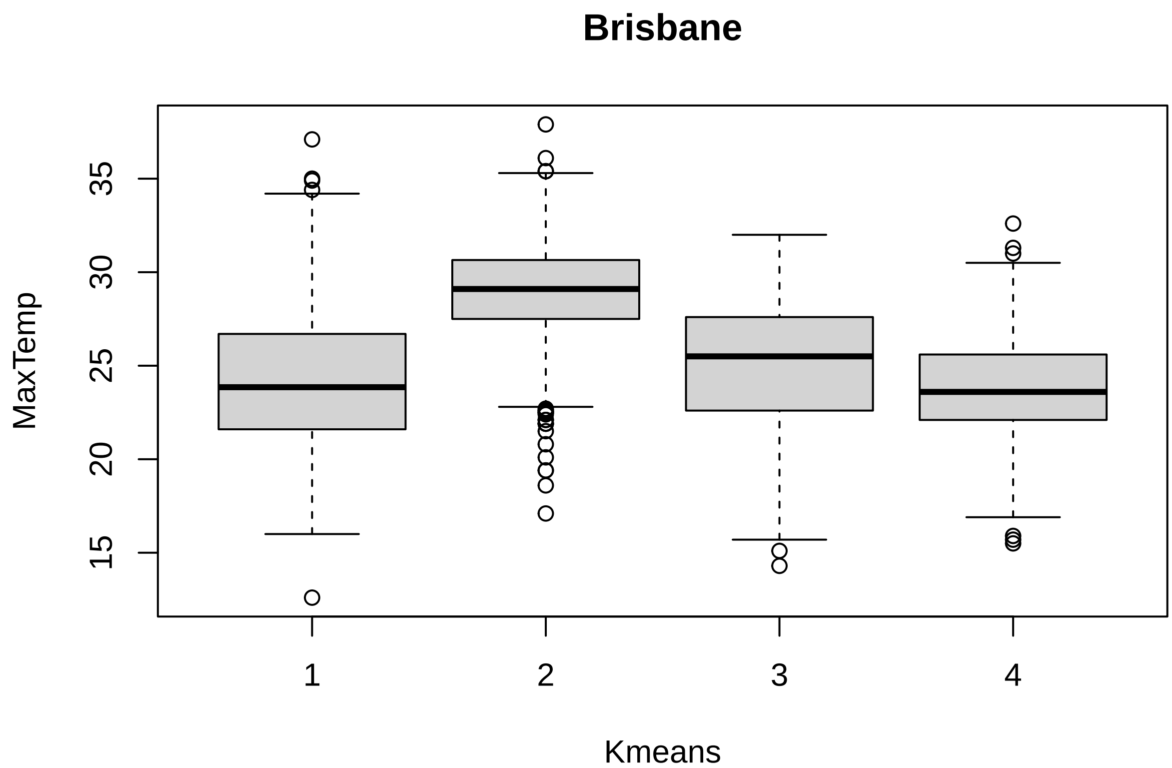
```
##
## [[3]]
## NULL
##
## [[4]]
## NULL
##
## [[5]]
## NULL
##
## [[6]]
## NULL
```

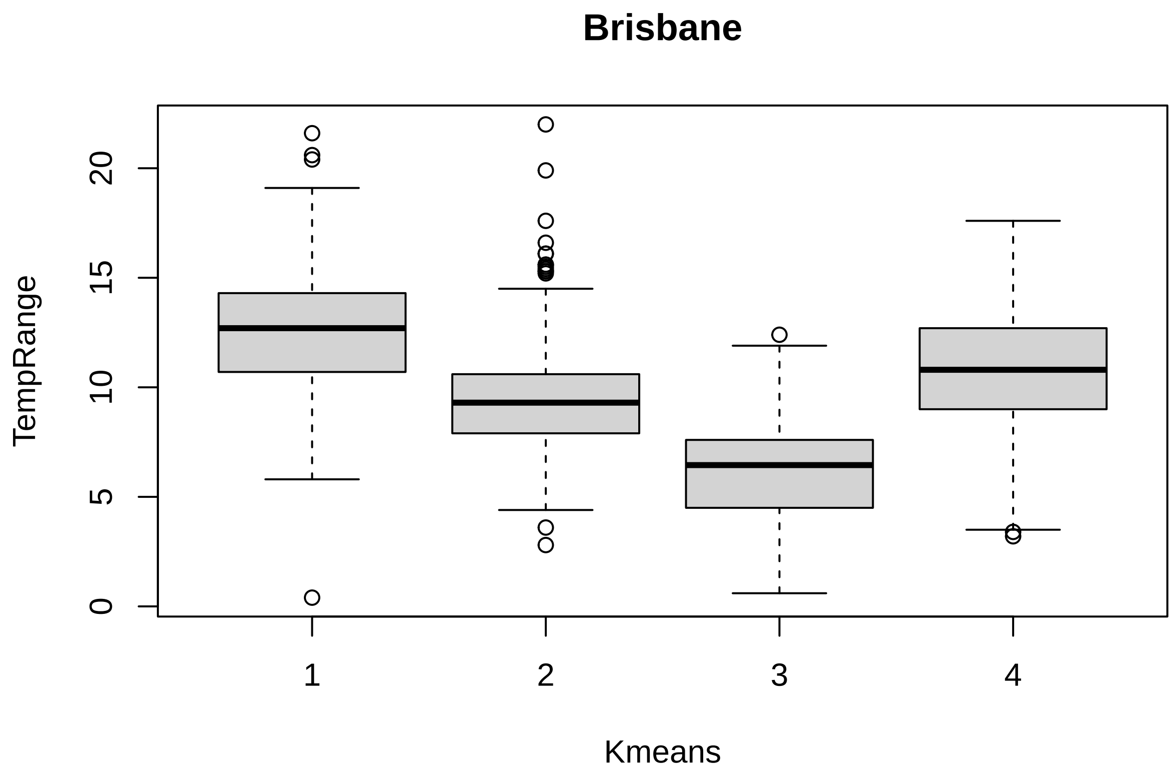


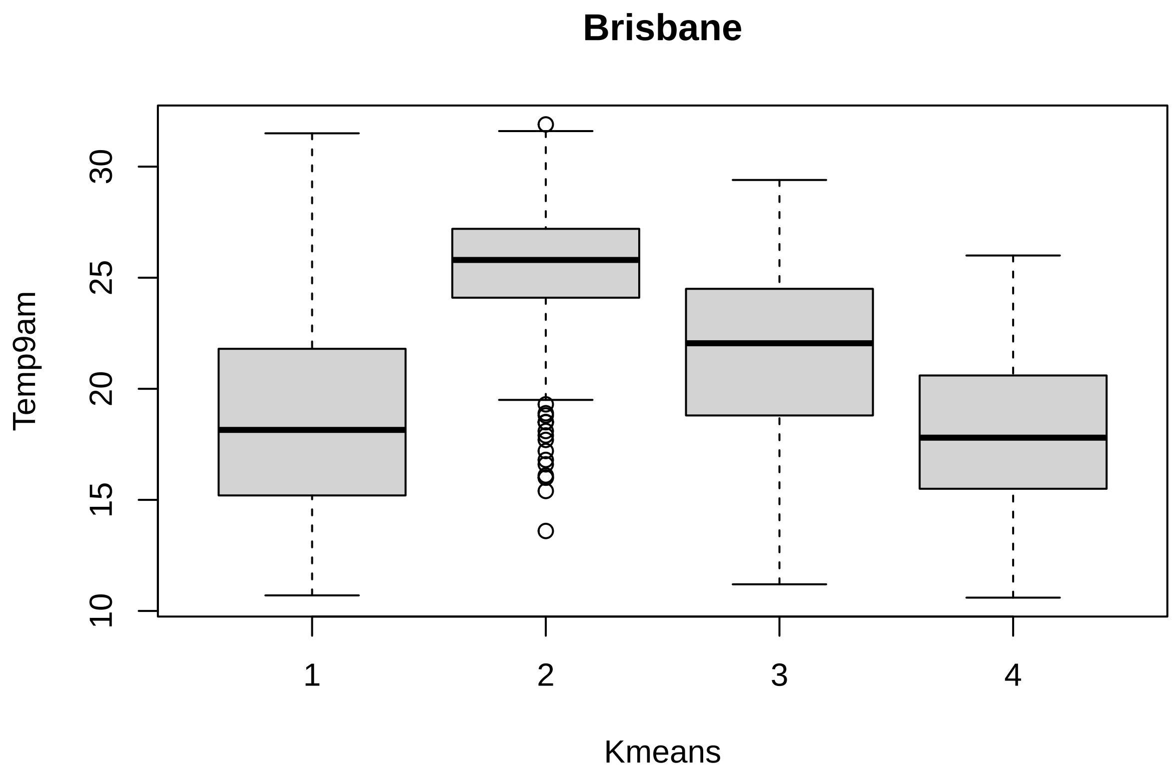

Brisbane
WindSpeed9am
0
10
20
30
1
2
3
4
Kmeans

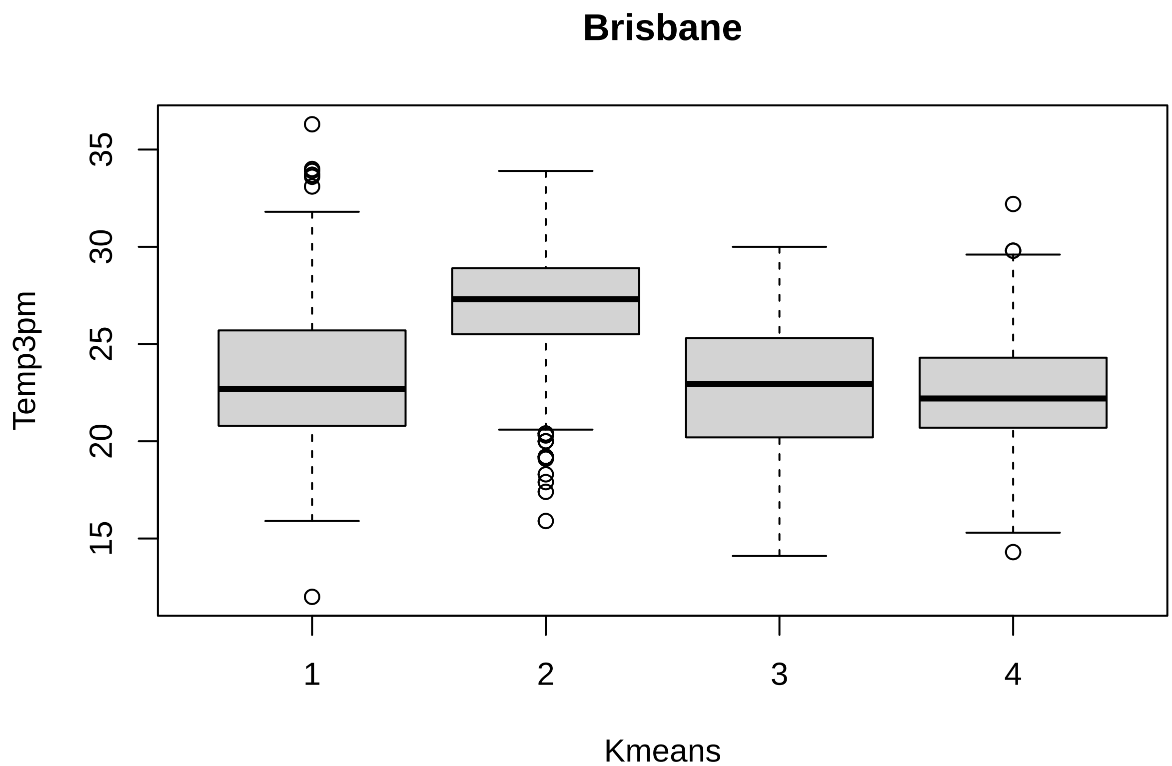

Brisbane
WindSpeed3pm
0
5
10
15
20
25
1
2
3
4
Kmeans

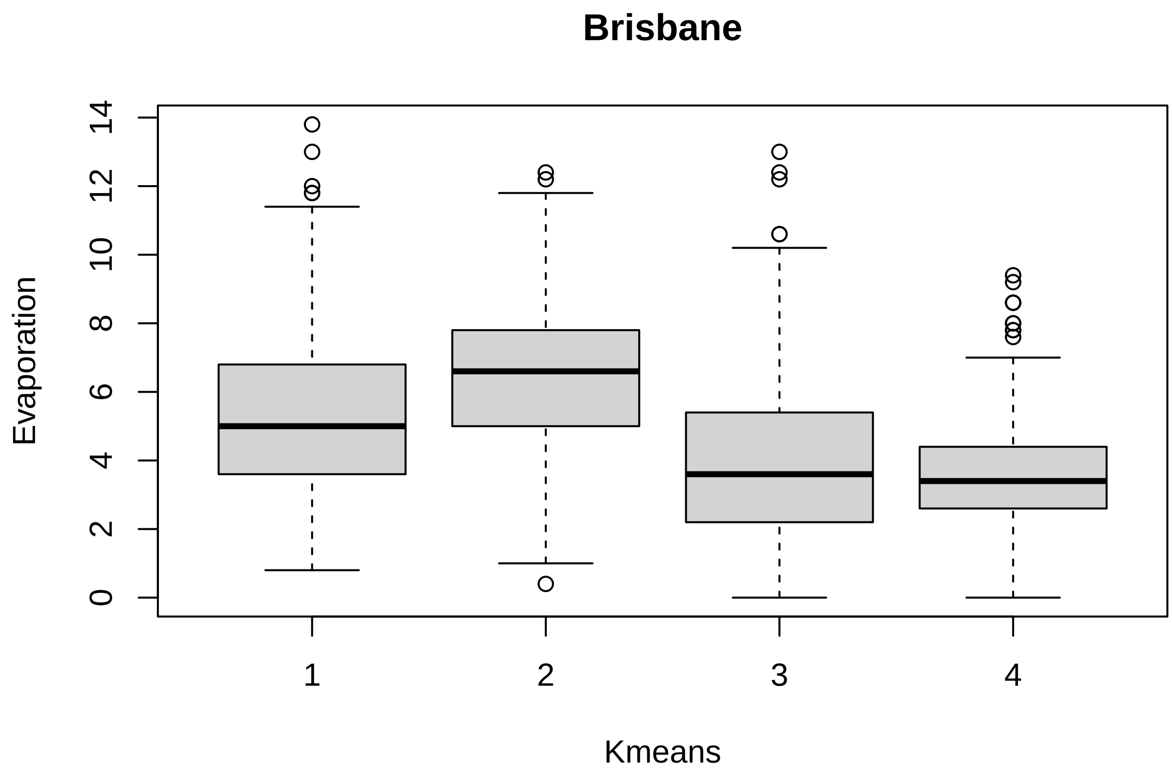

Brisbane
MinTemp
5
10
15
20
25
1
2
3
4
Kmeans

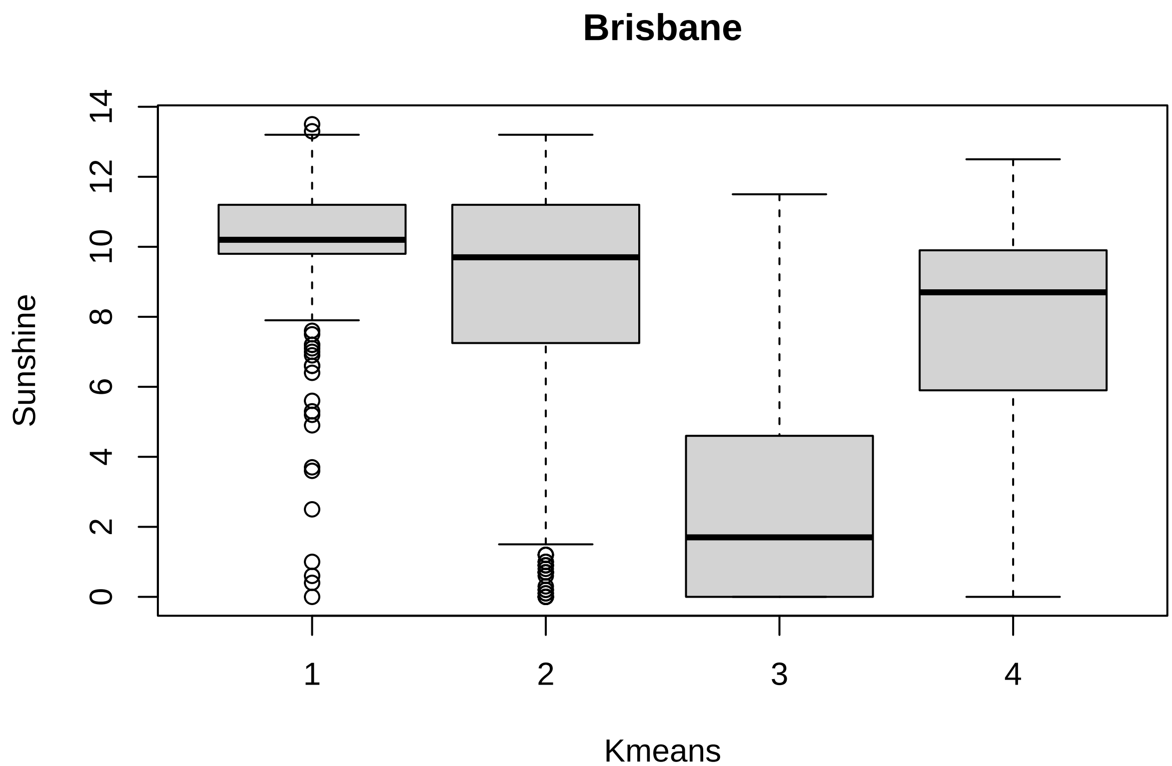

Brisbane
MaxTemp
15
20
25
30
35
1
2
3
4
Kmeans

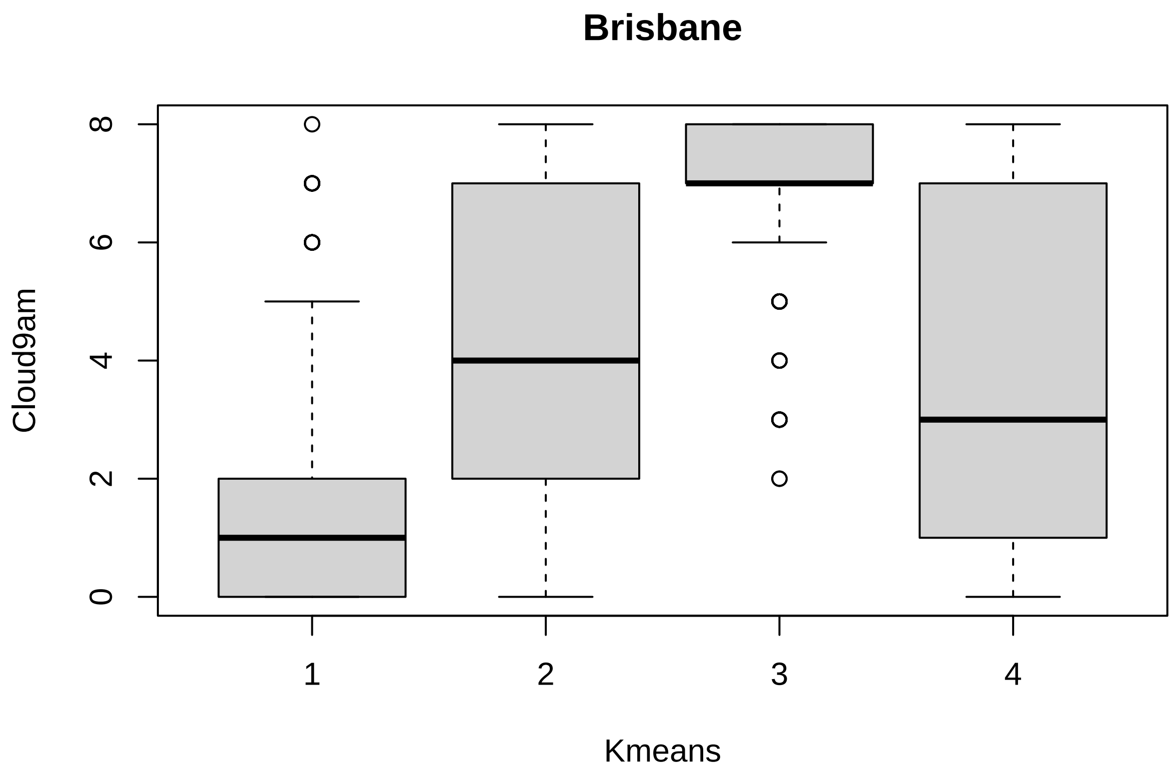

Brisbane
TempRange
0
5
10
15
20
1
2
3
4
Kmeans

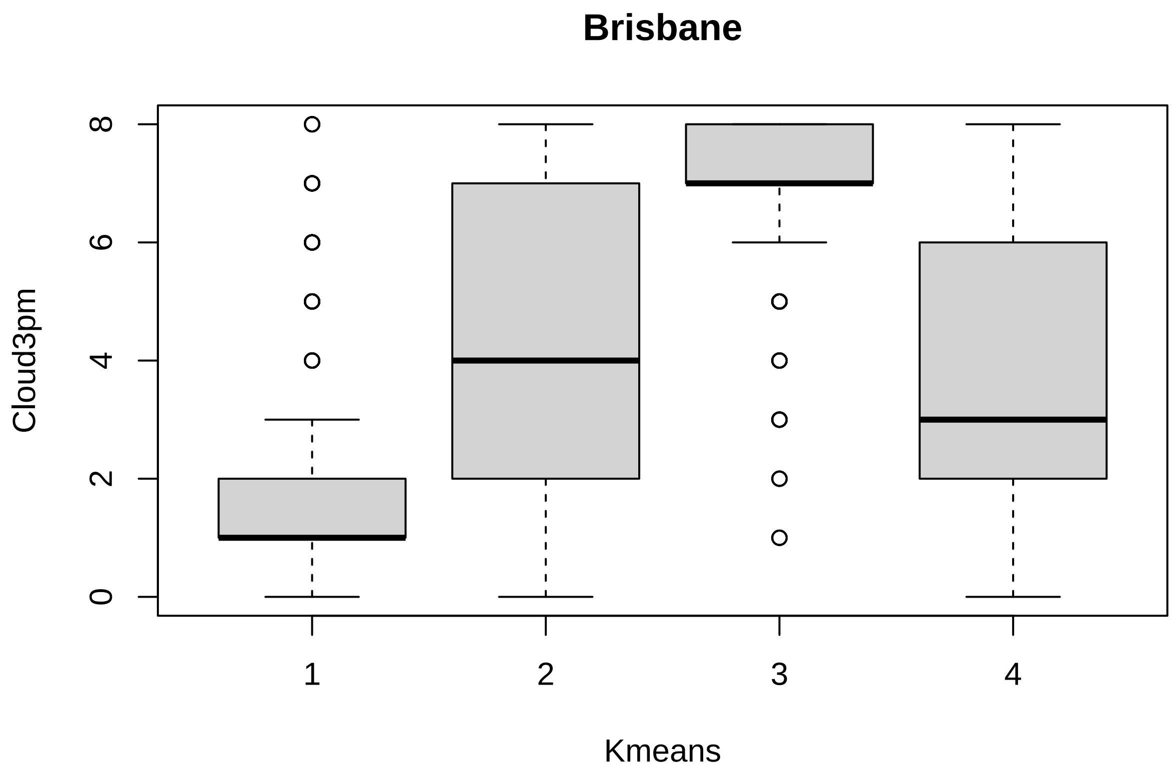

Brisbane
Temp9am
10
15
20
25
30
1
2
3
4
Kmeans

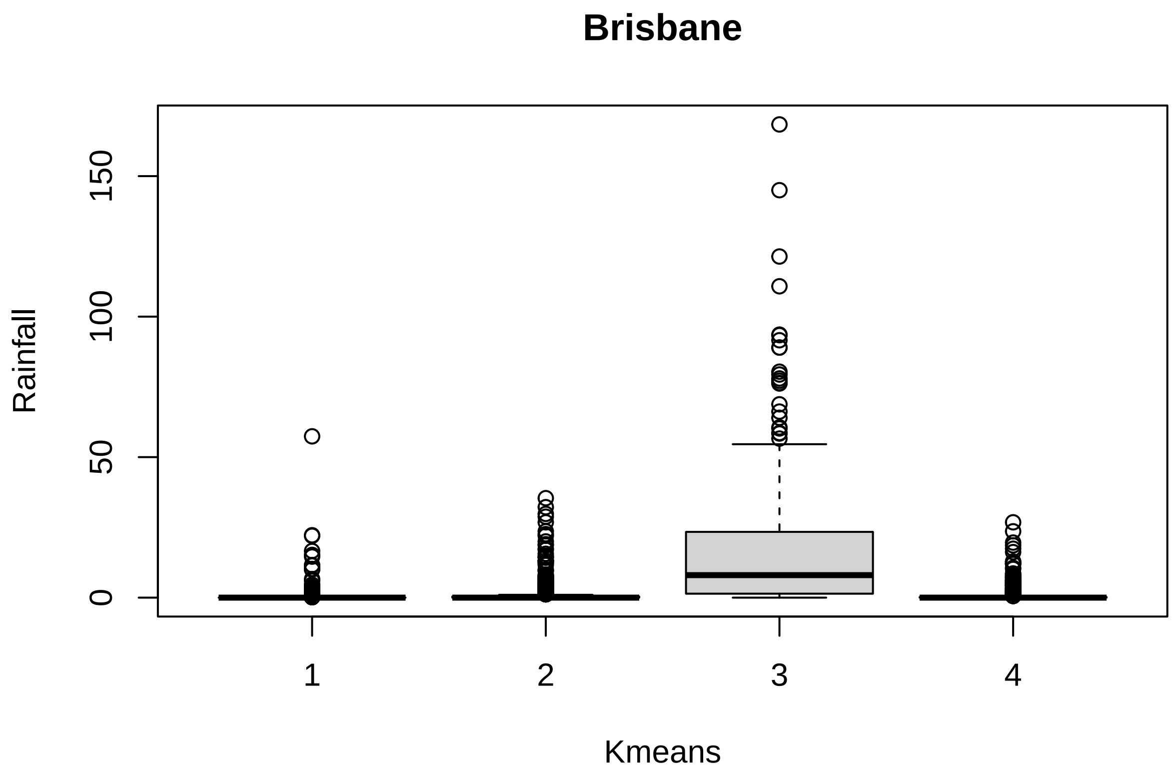

Brisbane
35
30
25
20
15
Temp3pm
1
2
3
4
Kmeans

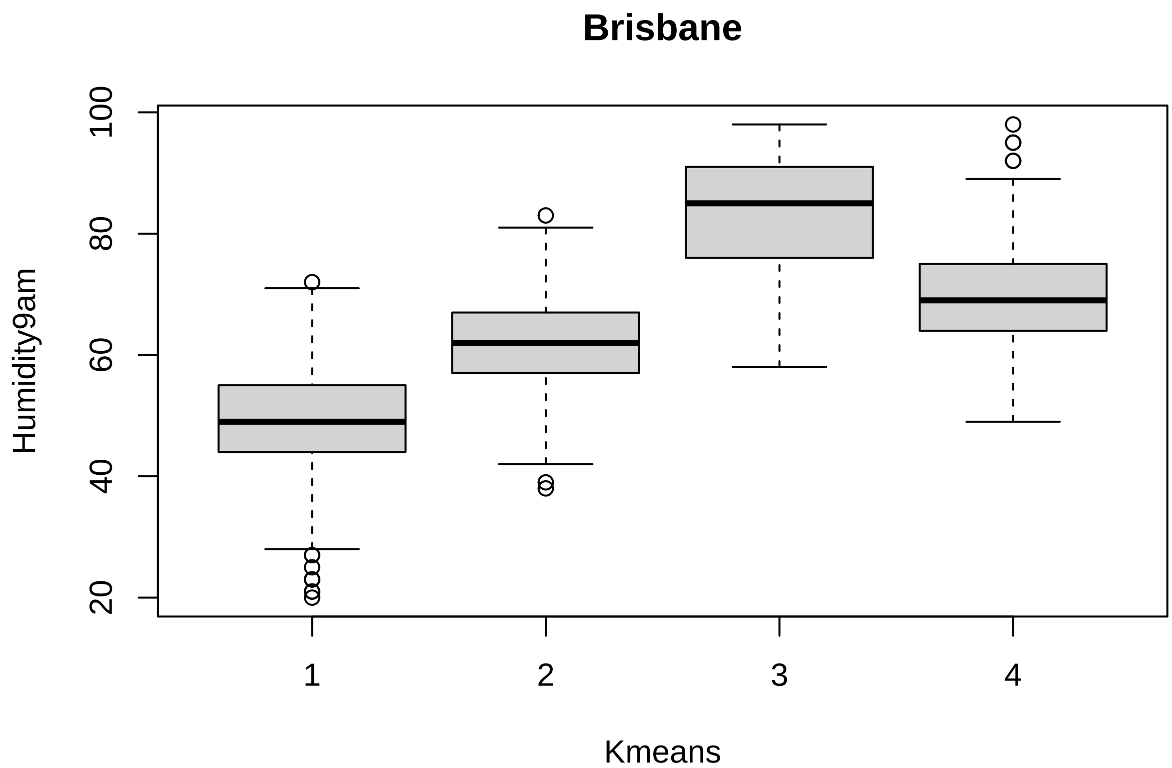

Brisbane
Evaporation
0
2
4
6
8
10
12
14
1
2
3
4
Kmeans

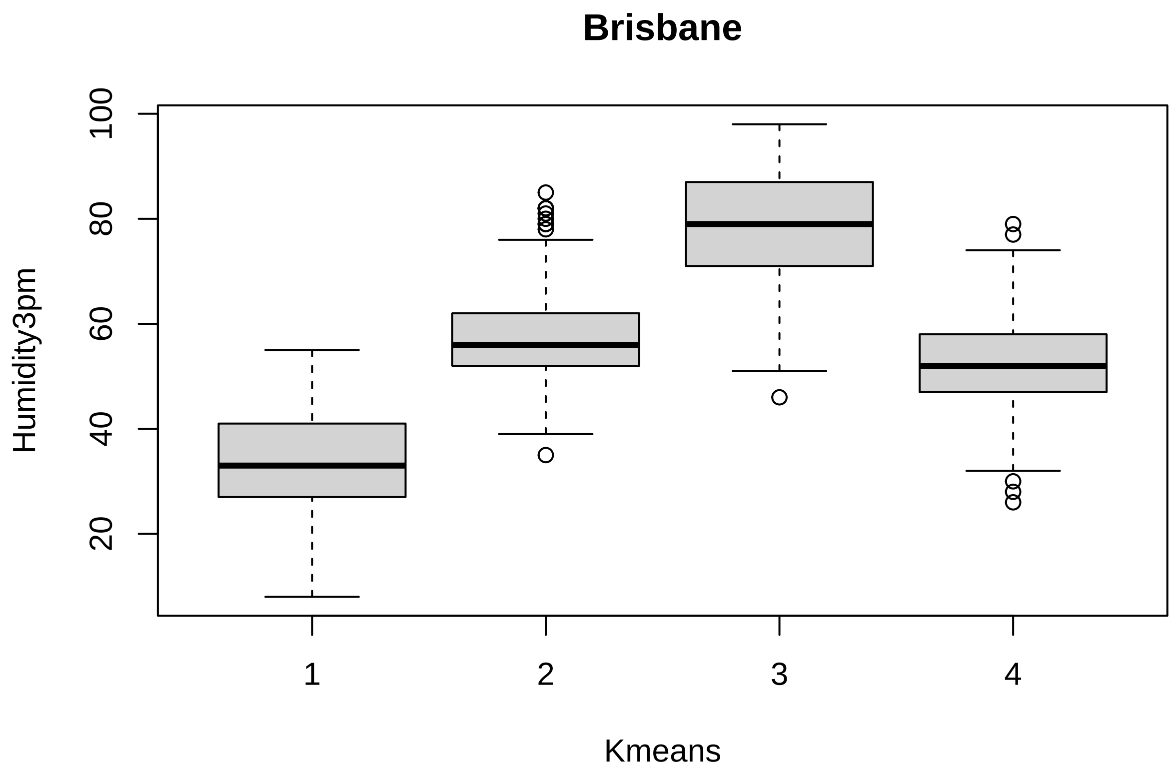

Brisbane
Sunshine
0
2
4
6
8
10
12
14
1
2
3
4
Kmeans

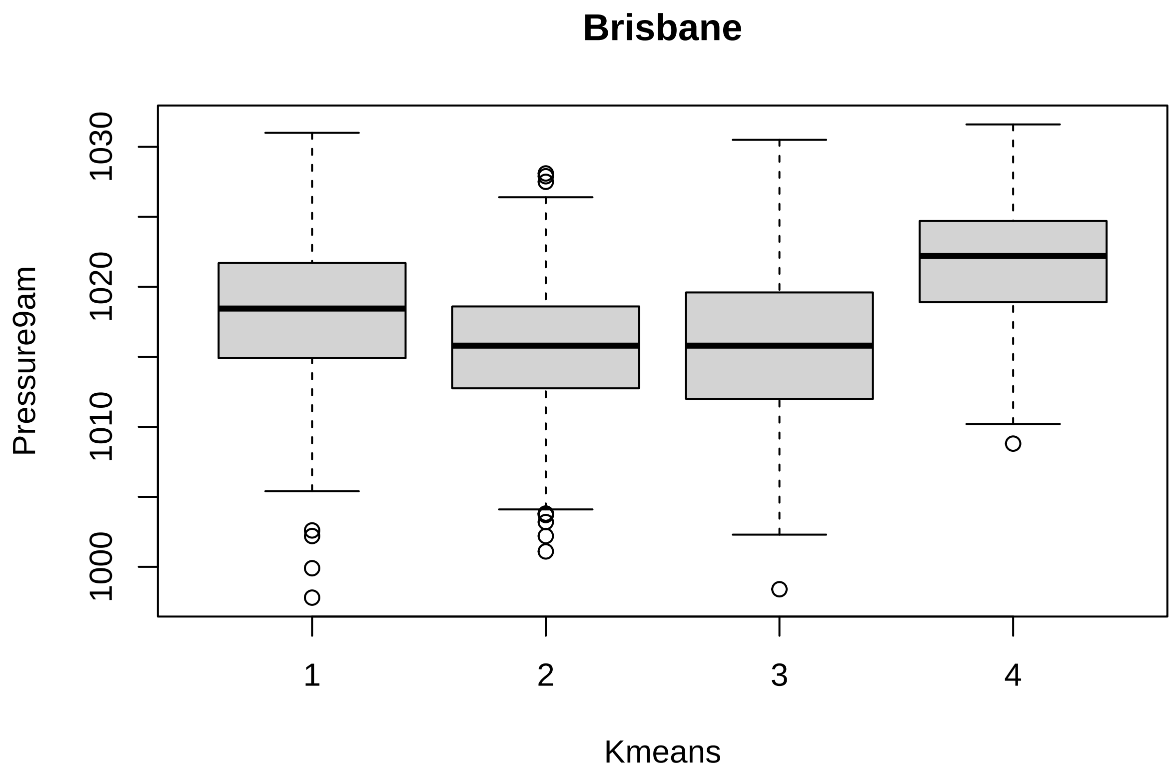

Brisbane
Cloud9am
0
2
4
6
8
1
2
3
4
Kmeans

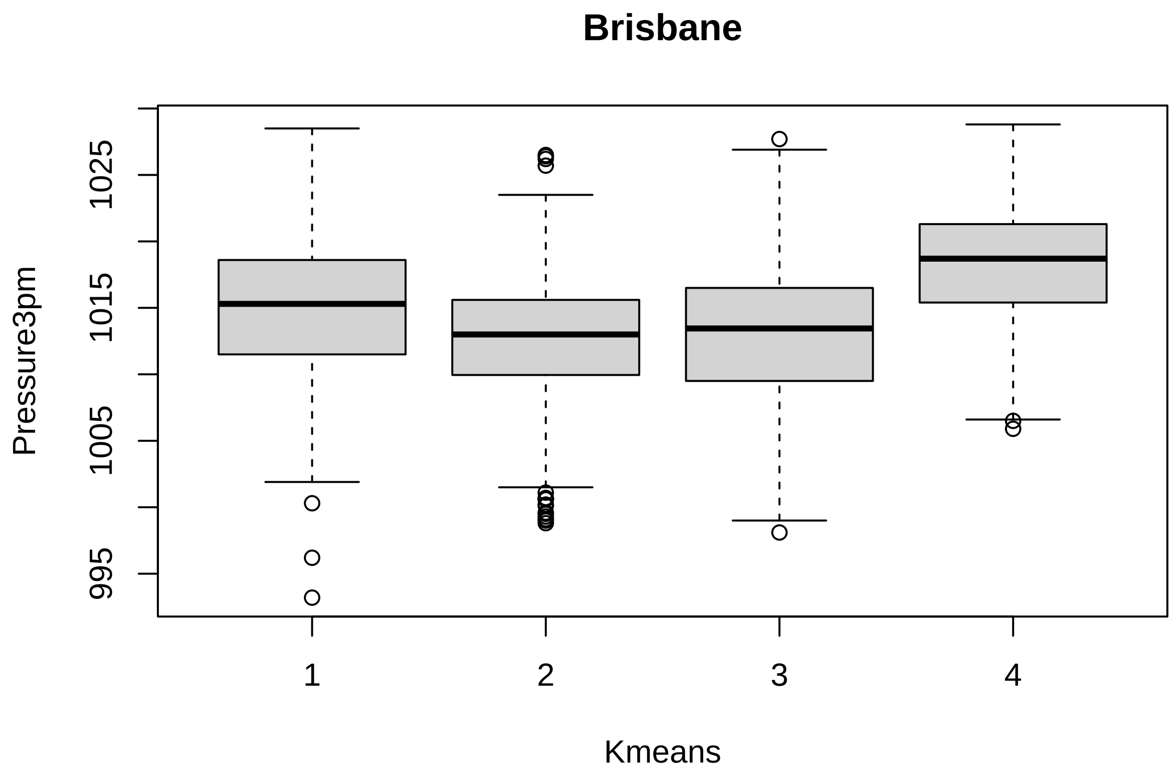

Brisbane
Cloud3pm
0
2
4
6
8
1
2
3
4
Kmeans

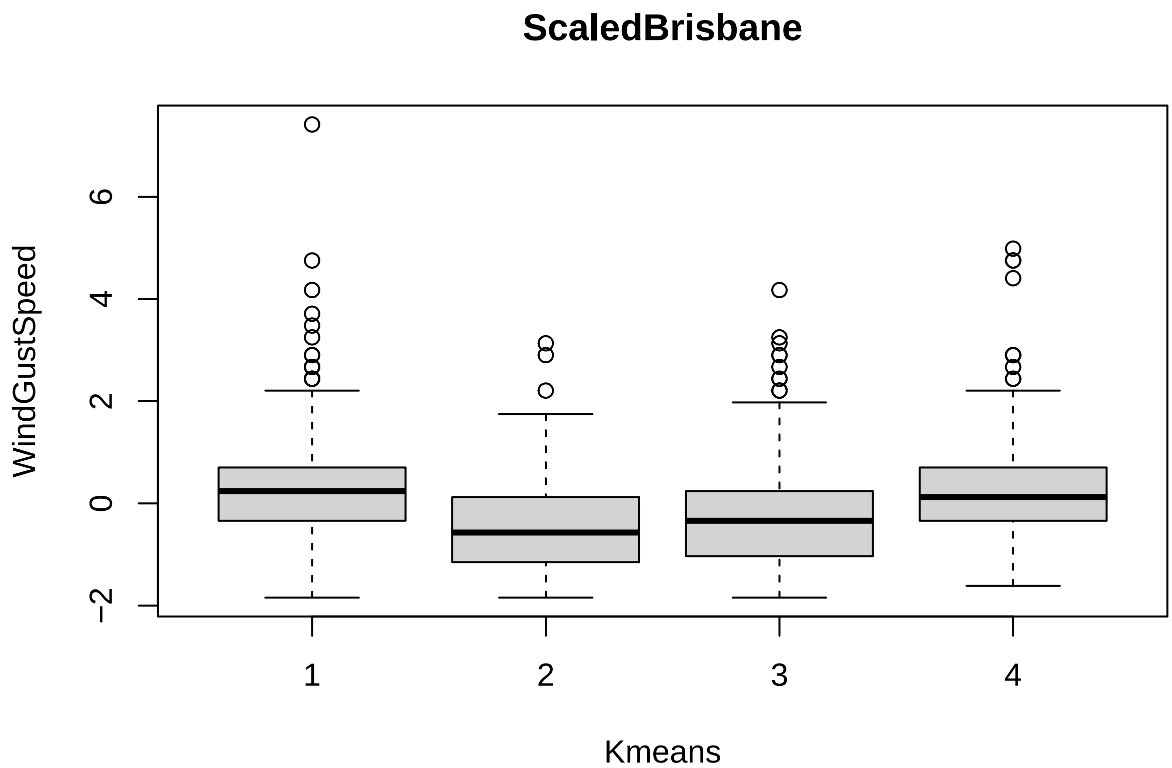

Brisbane
Rainfall
0
50
100
150
1
2
3
4
Kmeans

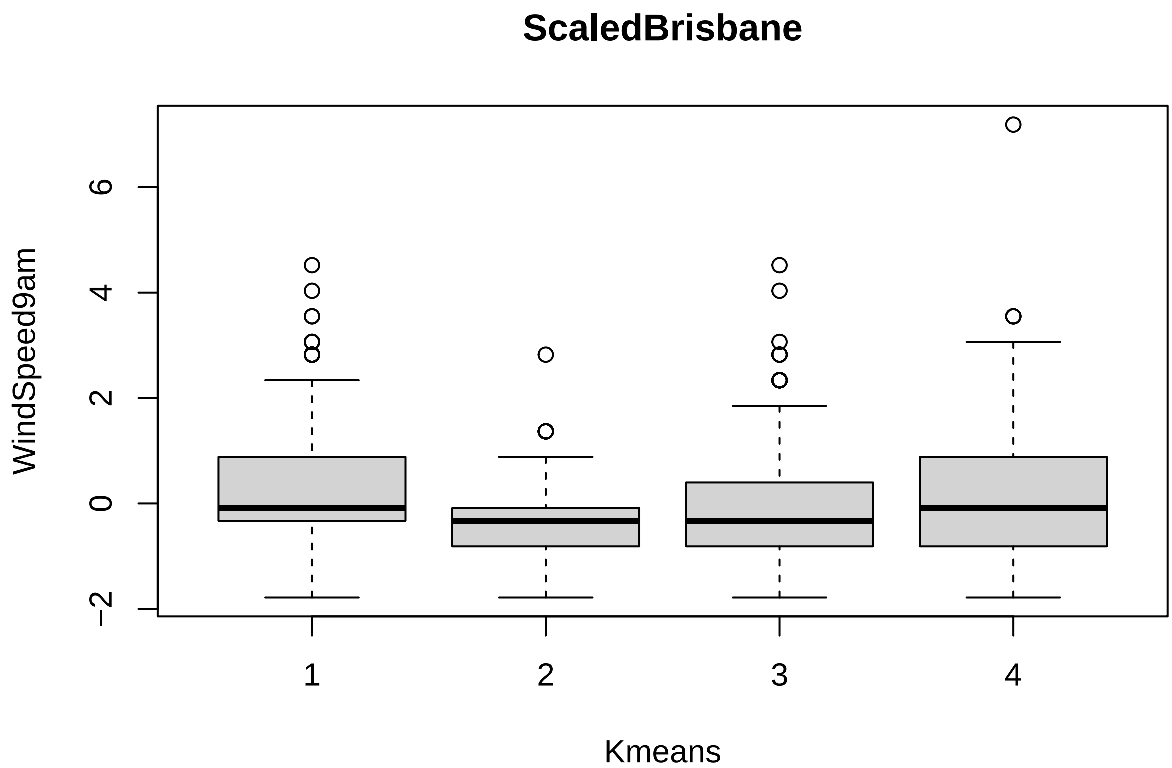

Brisbane
Humidity9am
100
80
60
40
20
1
2
3
4
Kmeans

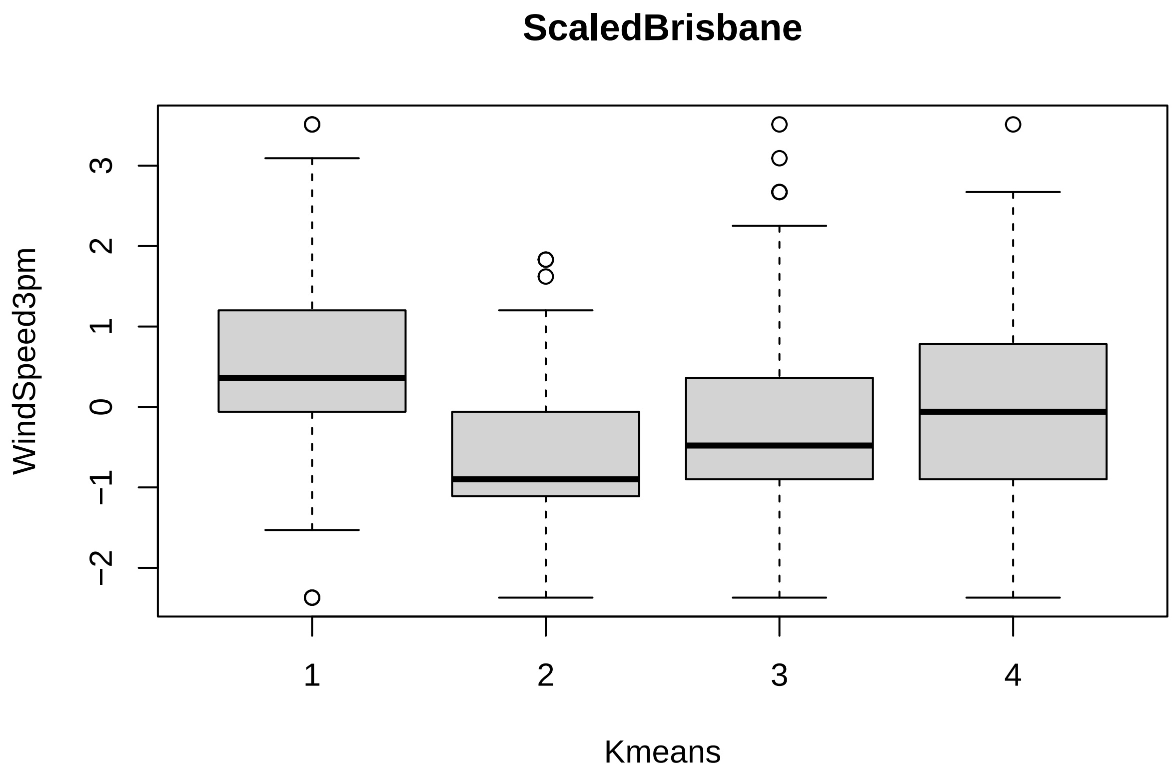

Brisbane
Humidity3pm
100
80
60
40
20
1
2
3
4
Kmeans


Brisbane
Pressure9am
1000
1010
1020
1030
1
2
3
4
Kmeans

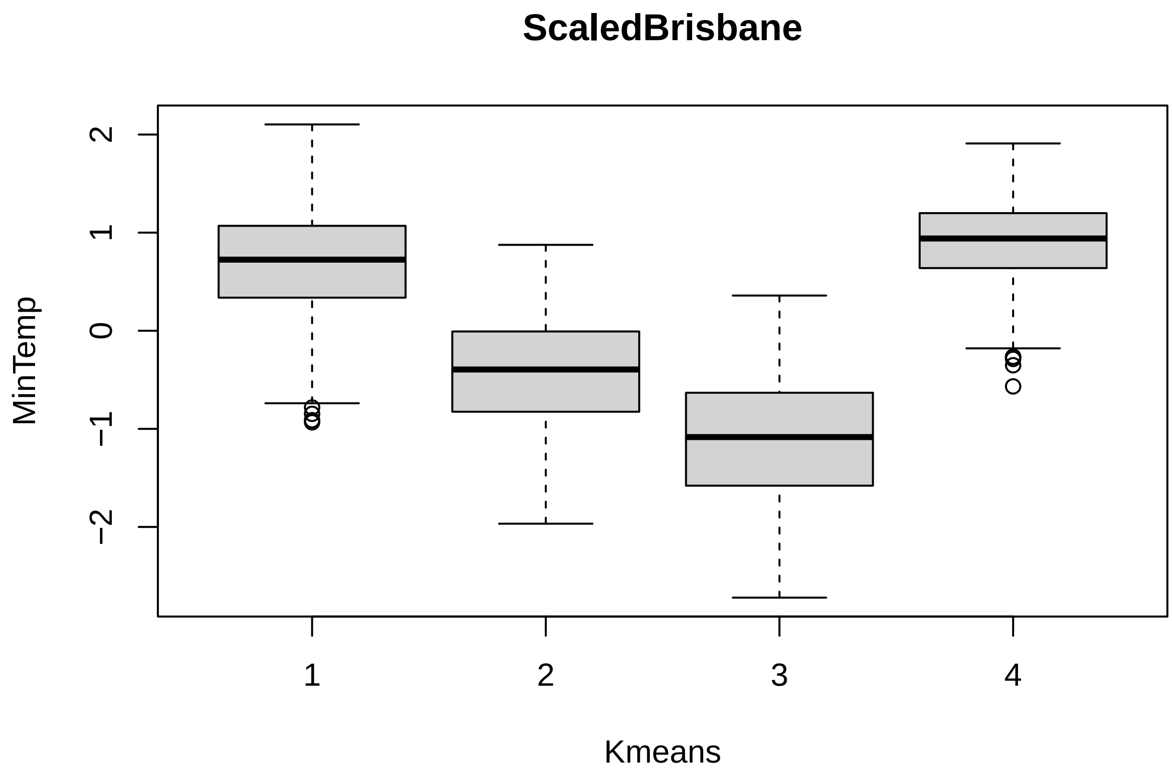

Brisbane
1025
1015
1005
995
Pressure3pm
1
2
3
4
Kmeans

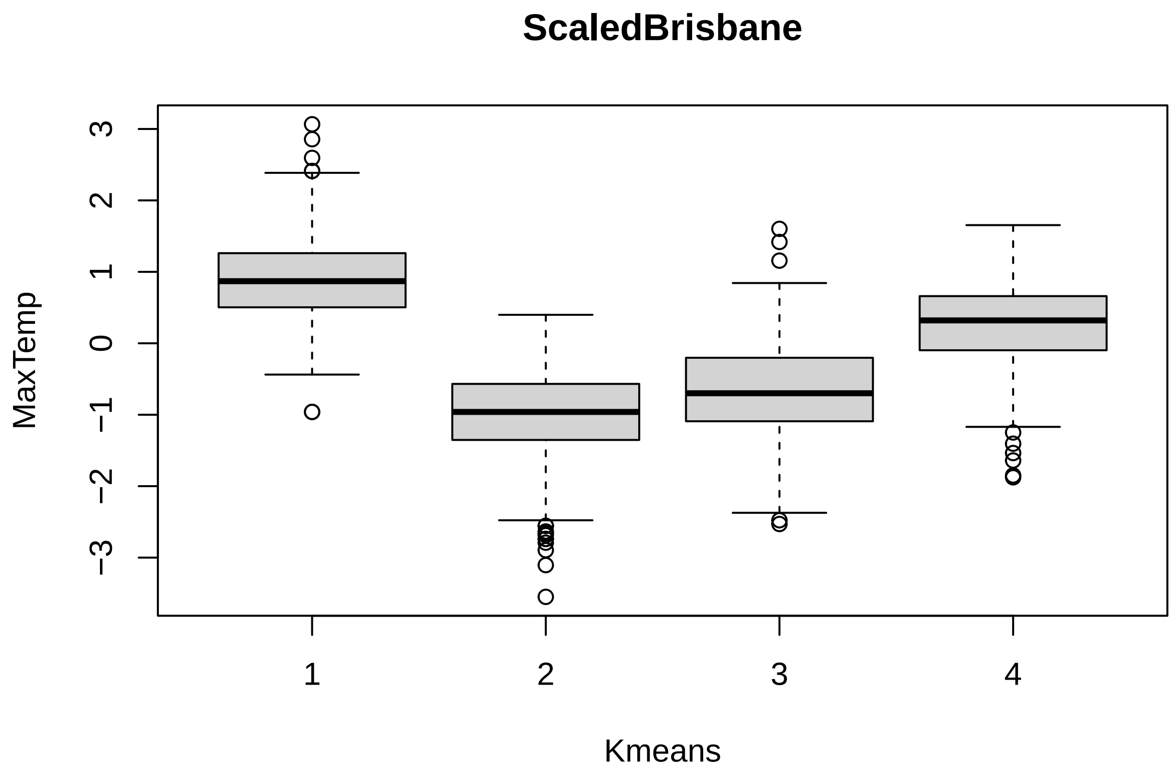

ScaledBrisbane
WindGustSpeed
6
4
2
0
−2
1
2
3
4
Kmeans

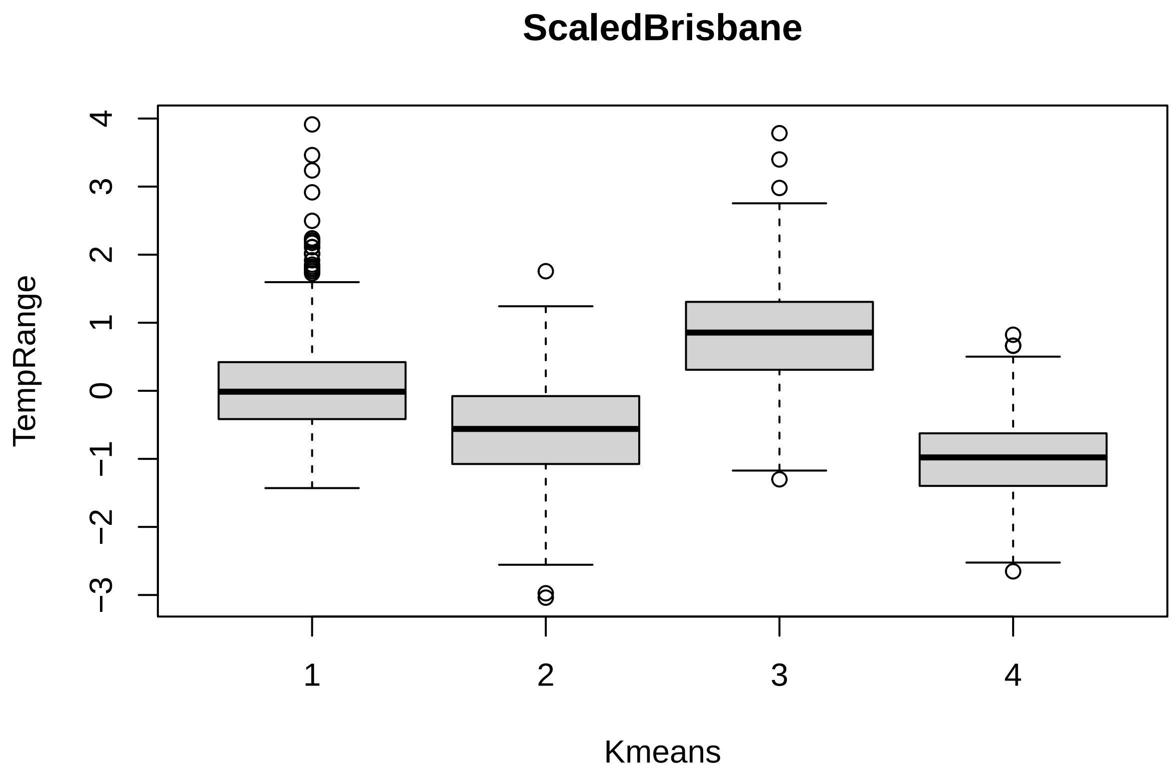

ScaledBrisbane
WindSpeed9am
6
4
2
0
−2
1
2
3
4
Kmeans

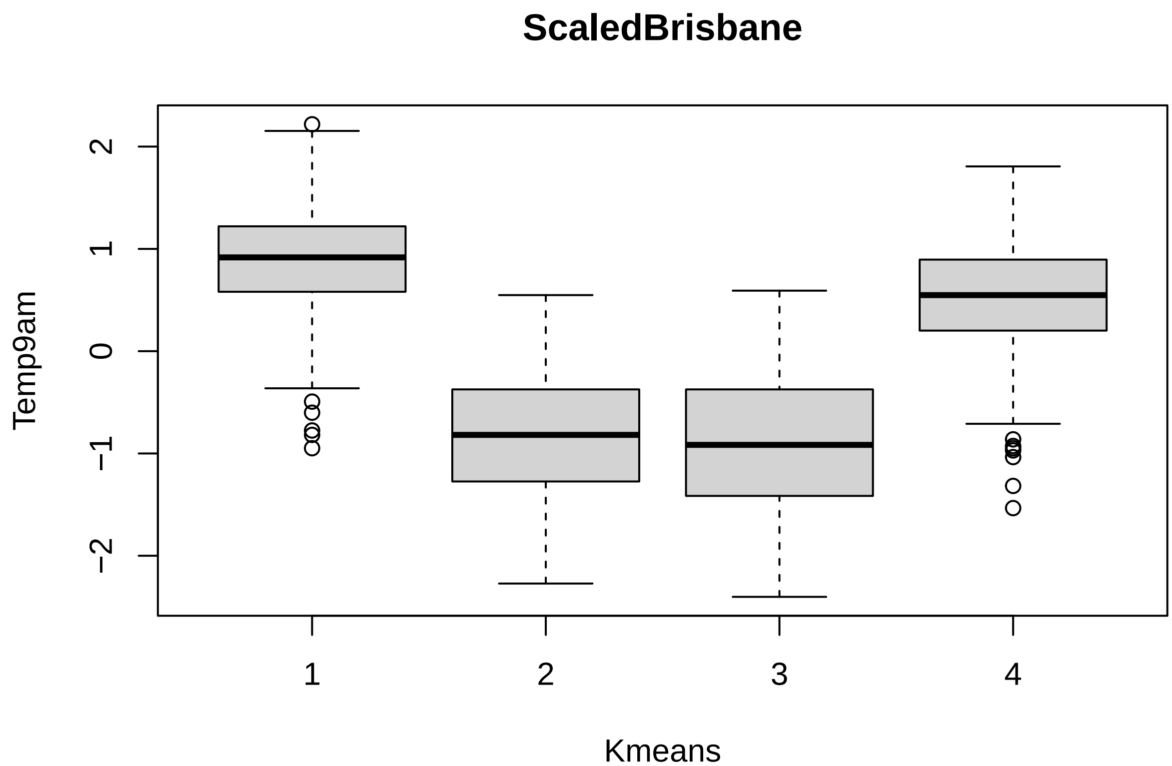


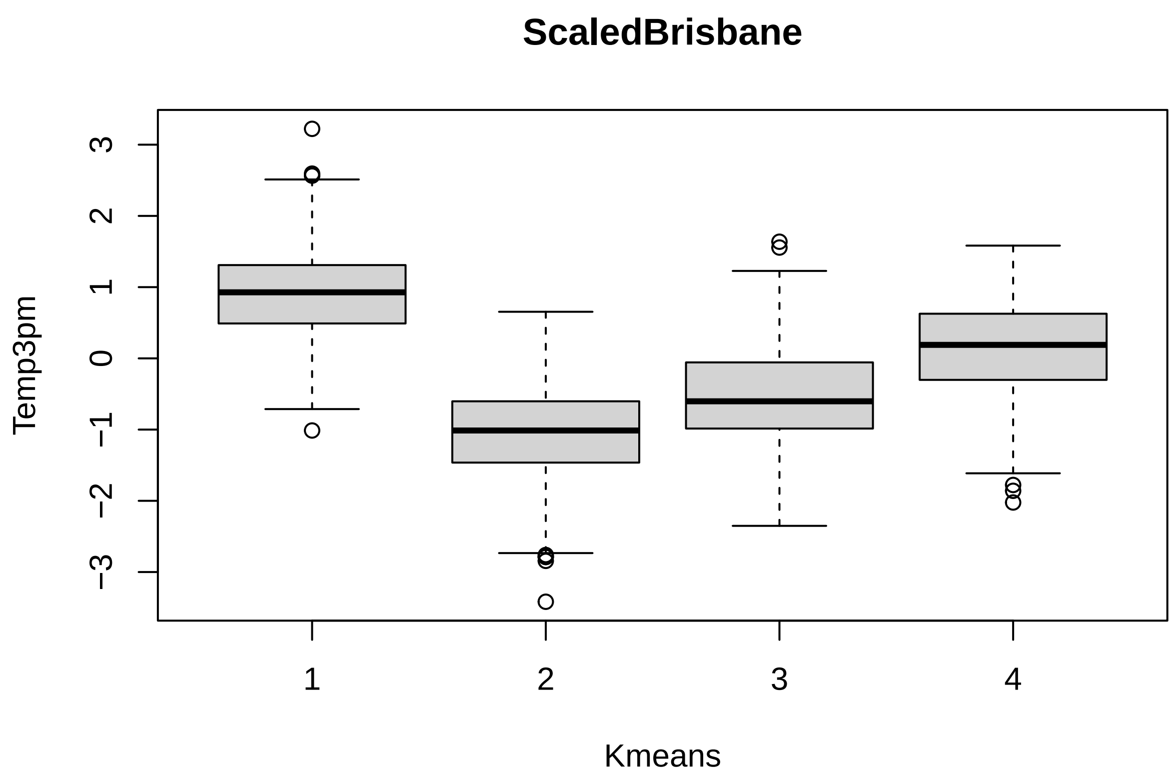
ScaledBrisbane
WindSpeed3pm
−2
−1
0
1
2
3
1
2
3
4
Kmeans

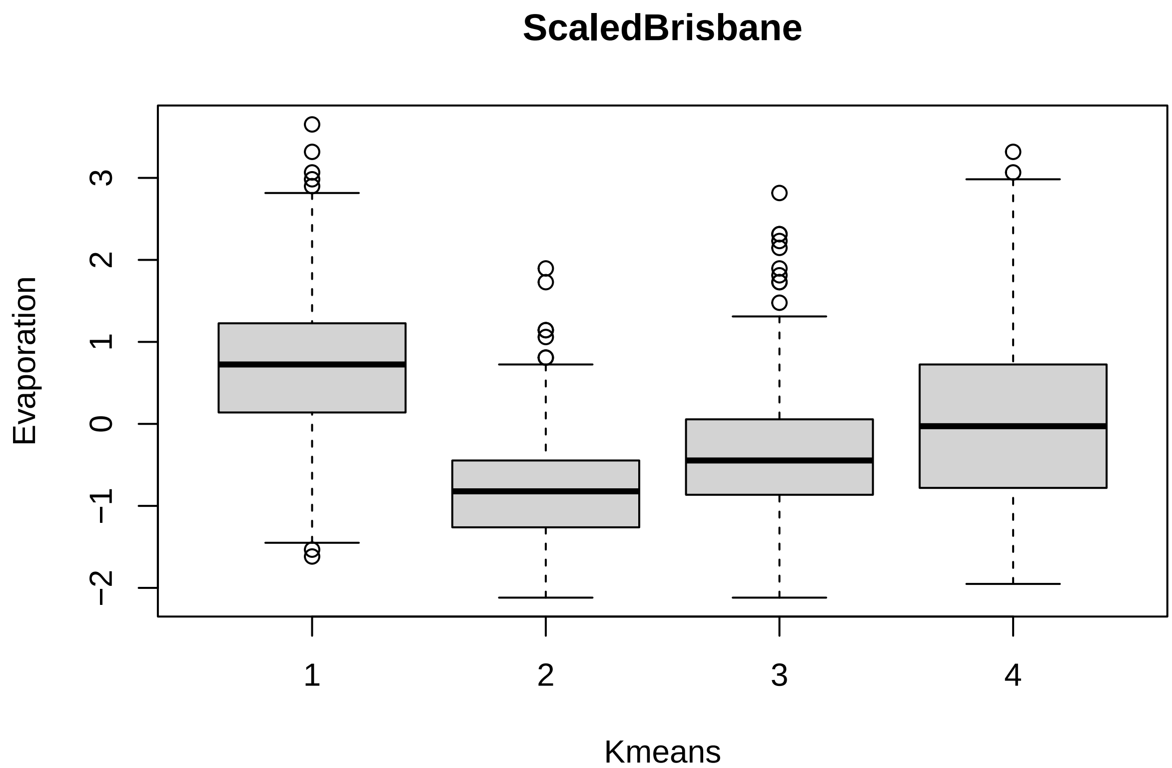

ScaledBrisbane
MinTemp
2
1
0
−1
−2
1
2
3
4
Kmeans


ScaledBrisbane
MaxTemp
3
2
1
0
−1
−2
−3
1
2
3
4
Kmeans

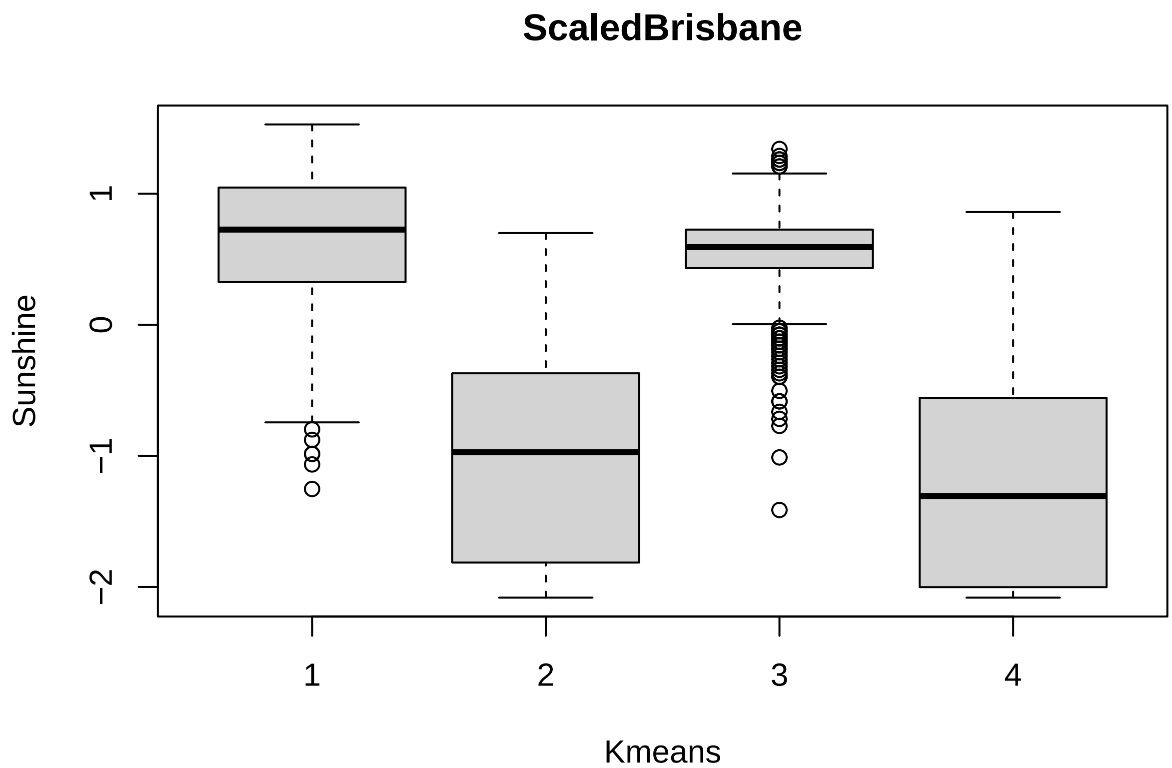

ScaledBrisbane
TempRange
Kmeans
4
3
2
1
0
−1
−2
−3
1
2
3
4

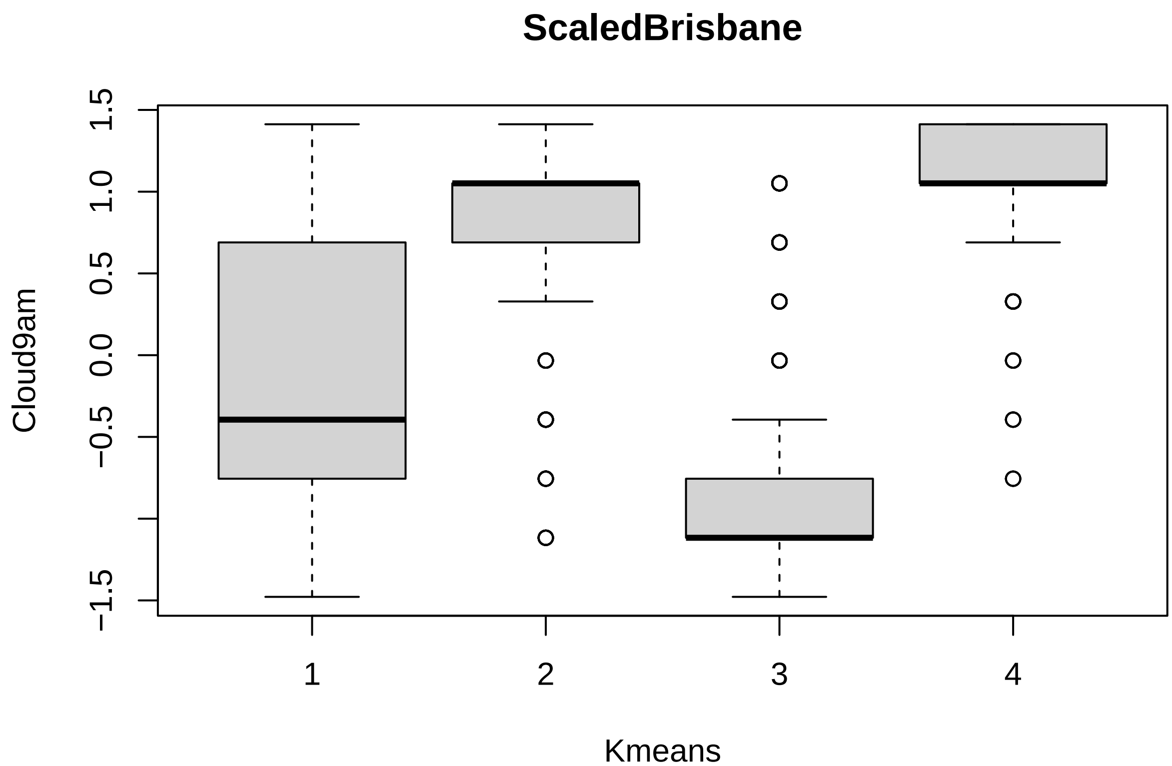

ScaledBrisbane
Temp9am
2
1
0
−1
−2
1
2
3
4
Kmeans


ScaledBrisbane
Temp3pm
3
2
1
0
−1
−2
−3
1
2
3
4
Kmeans

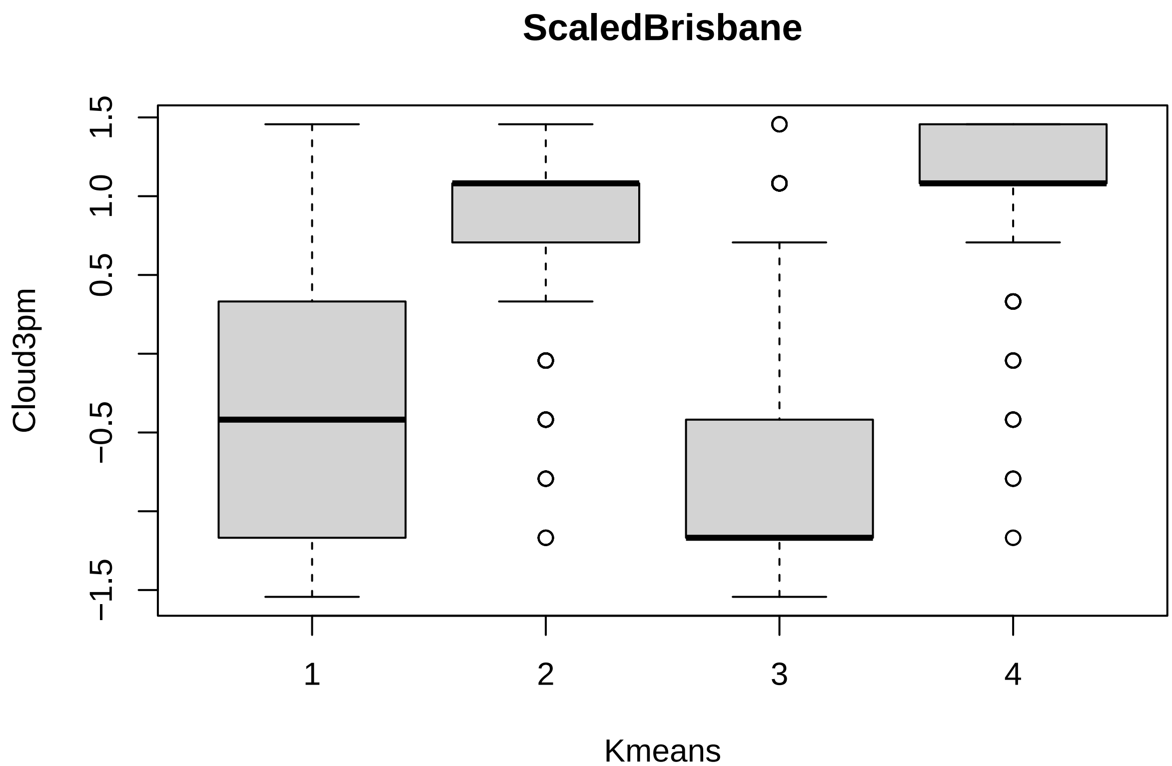


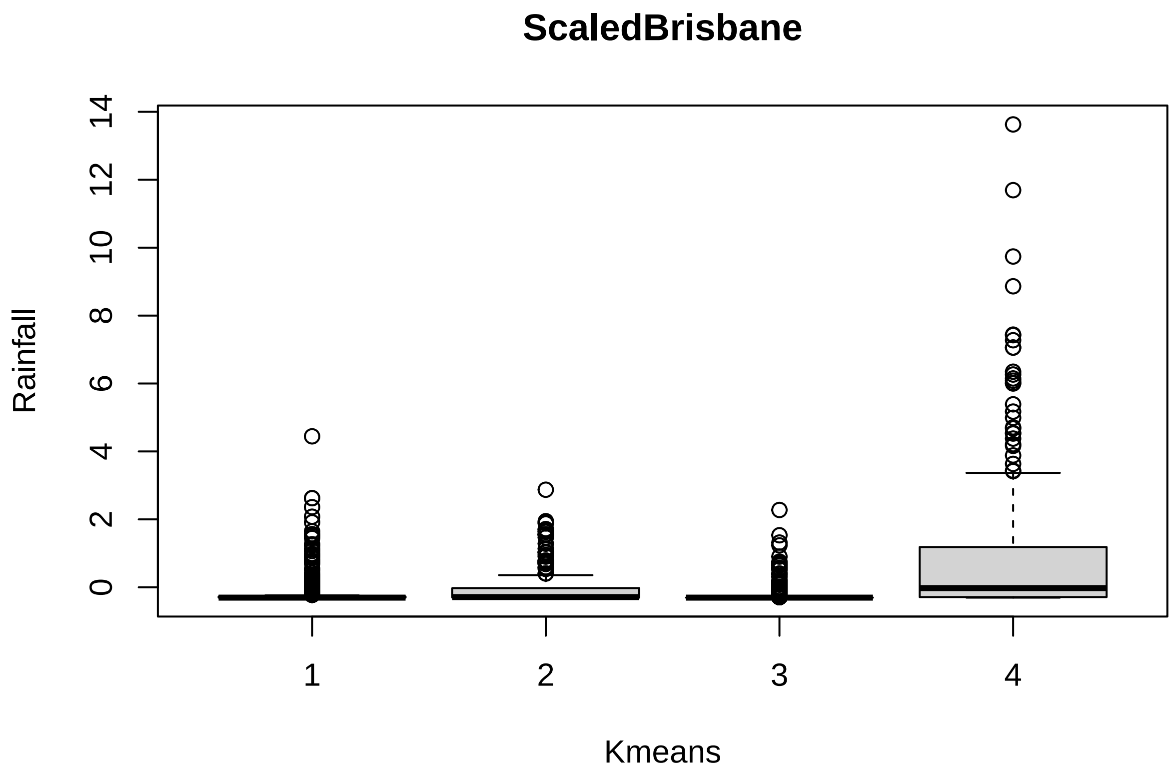
ScaledBrisbane
Evaporation
3
2
1
0
−1
−2
1
2
3
4
Kmeans

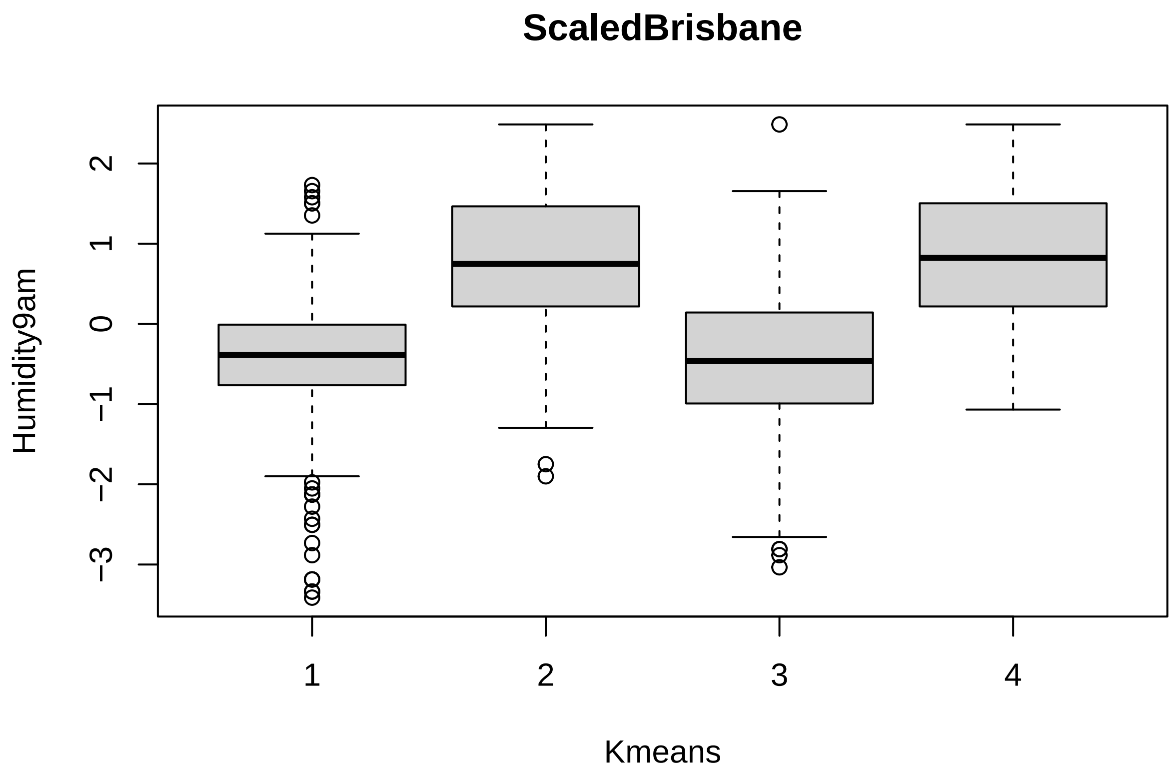

ScaledBrisbane
Sunshine
1
0
−1
−2
1
2
3
4
Kmeans

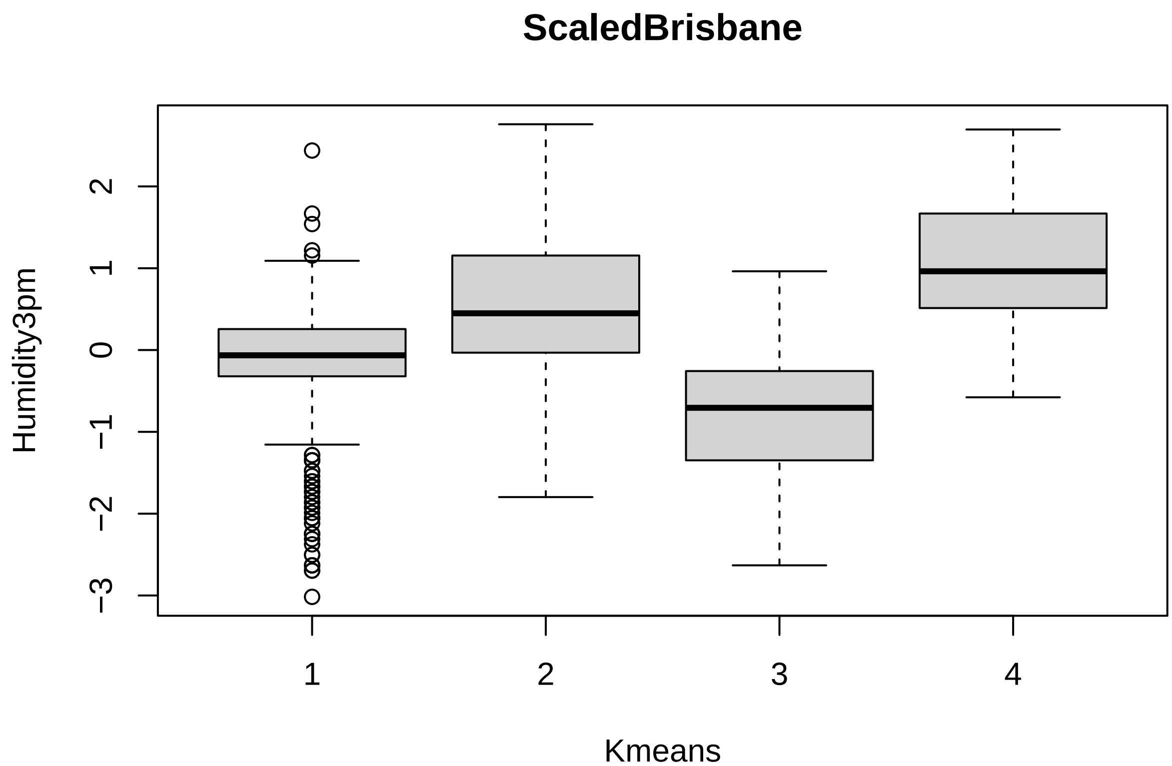


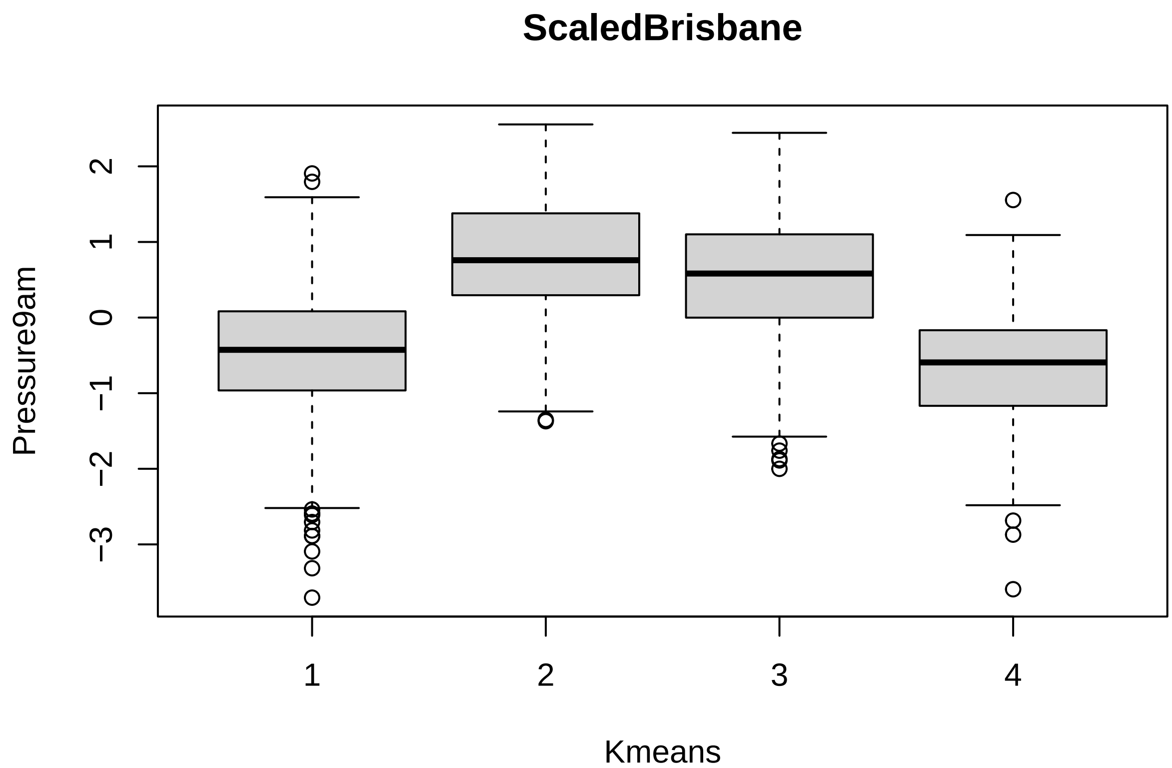
ScaledBrisbane
Cloud9am
1.5
1.0
0.5
0.0
−0.5
−1.5
1
2
3
4
Kmeans


ScaledBrisbane
Cloud3pm
1.5
1.0
0.5
−0.5
−1.5
1
2
3
4
Kmeans

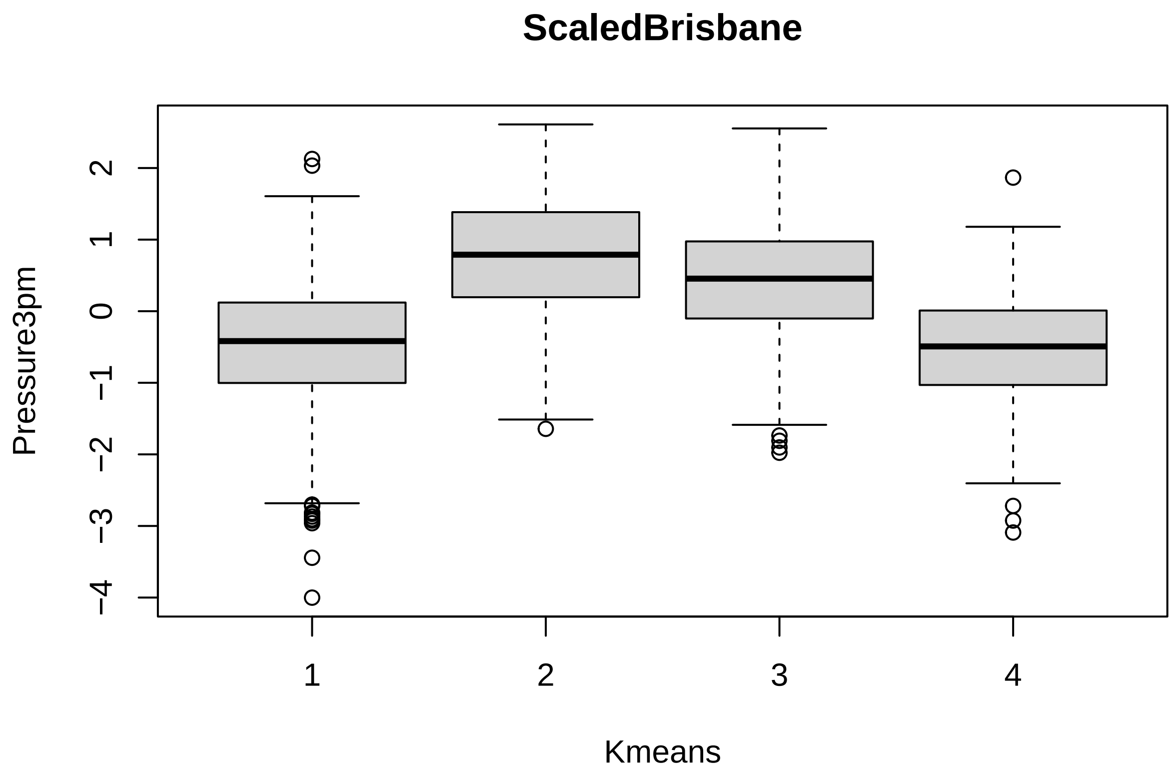

ScaledBrisbane
Rainfall
0
2
4
6
8
10
12
14
1
2
3
4
Kmeans


ScaledBrisbane
Humidity9am
2
1
0
−1
−2
−3
1
2
3
4
Kmeans


ScaledBrisbane
Humidity3pm
−3
−2
−1
0
1
2
1
2
3
4
Kmeans



ScaledBrisbane
Pressure9am
2
1
0
−1
−2
−3
1
2
3
4
Kmeans


ScaledBrisbane
Pressure3pm
2
1
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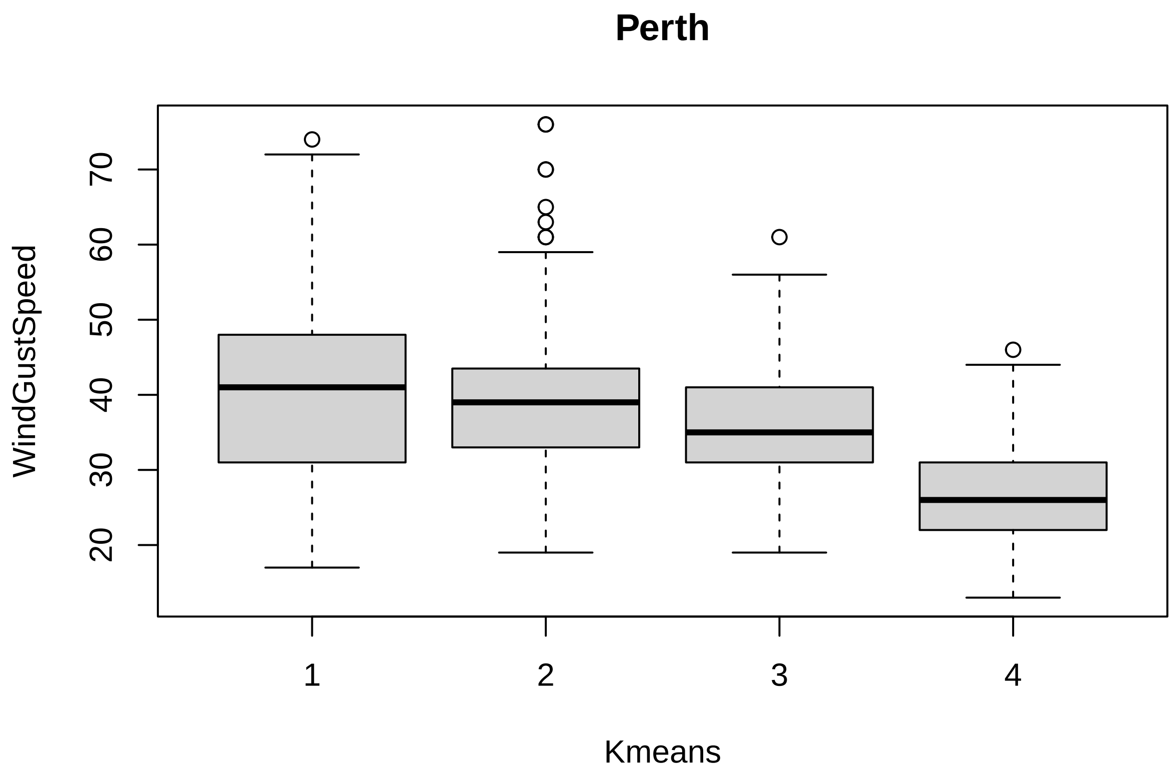
−1
−2
−3
−4
1
2
3
4
Kmeans



Perth
WindGustSpeed
20
30
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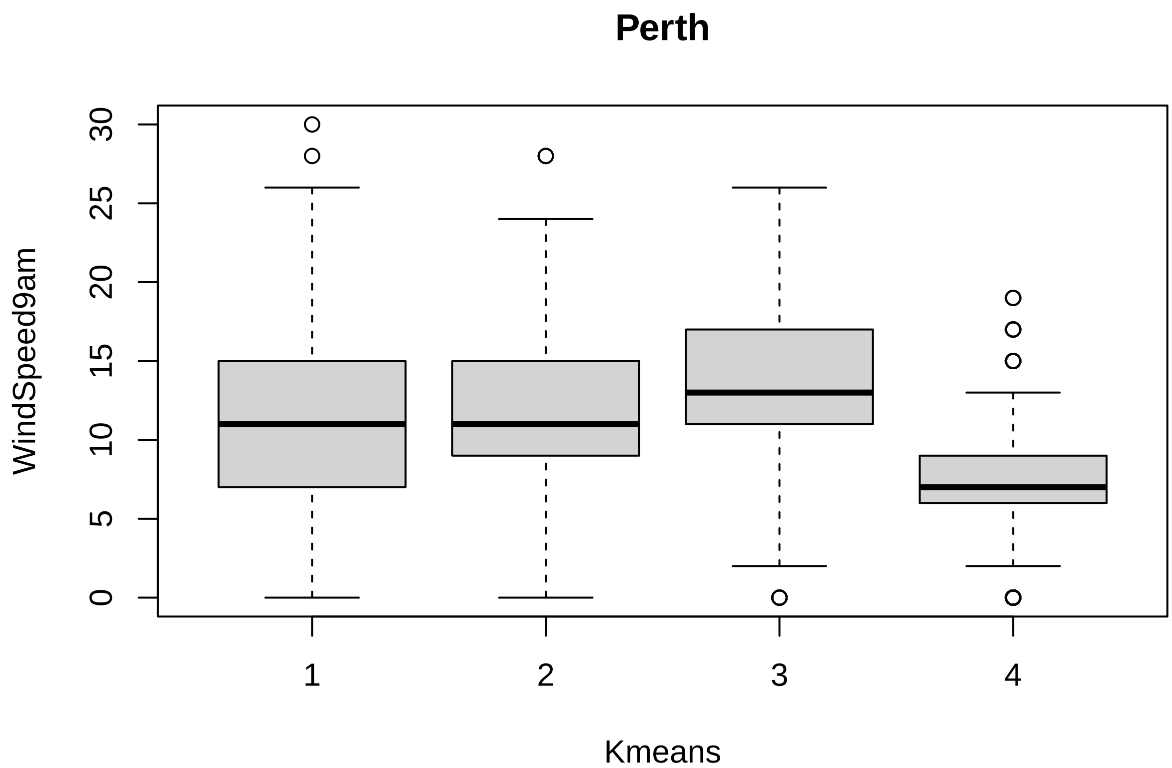
50
60
70
1
2
3
4
Kmeans



Perth
WindSpeed9am
0
5
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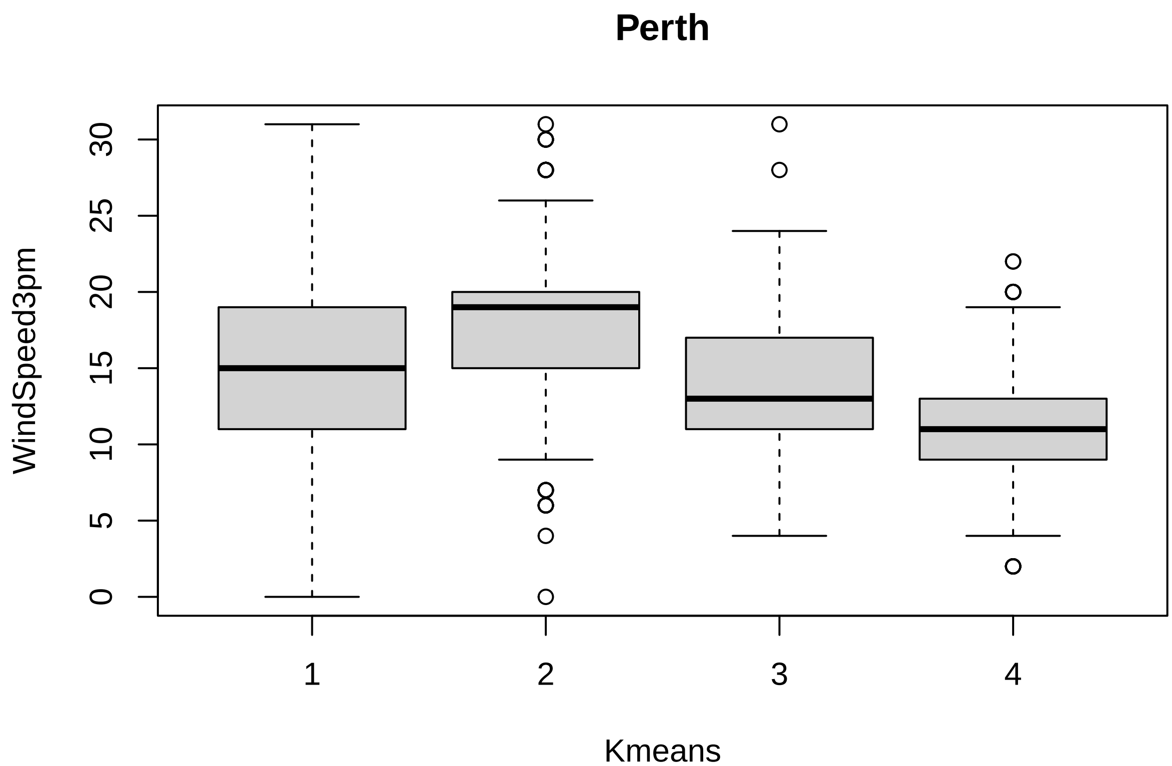
2
3
4
Kmeans


Perth
WindSpeed3pm
0
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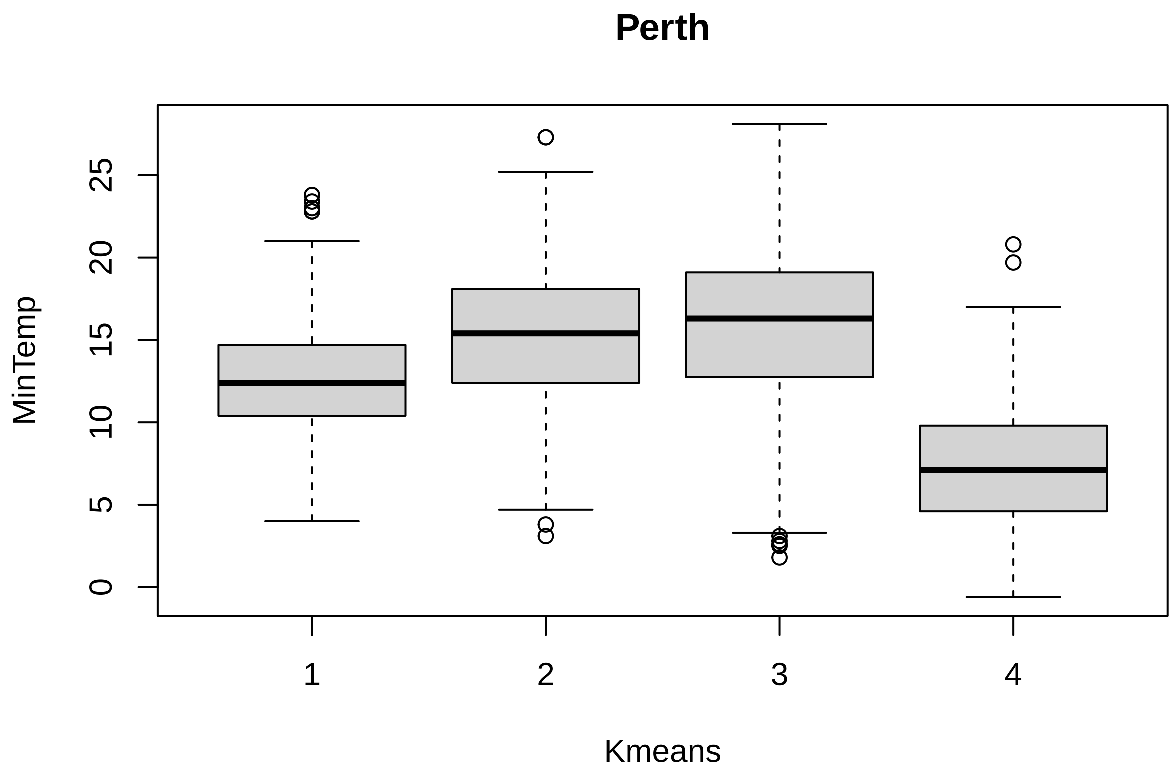
Kmeans


Perth
MinTemp
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2
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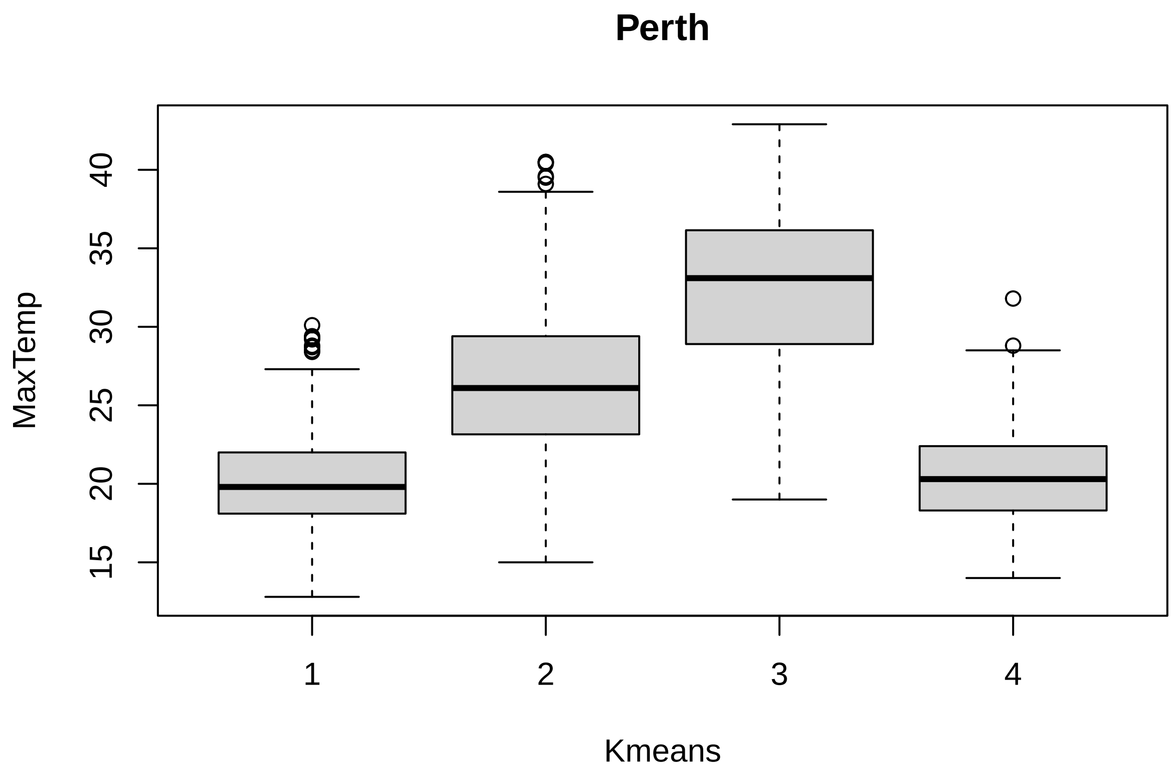
4
Kmeans


Perth
MaxTemp
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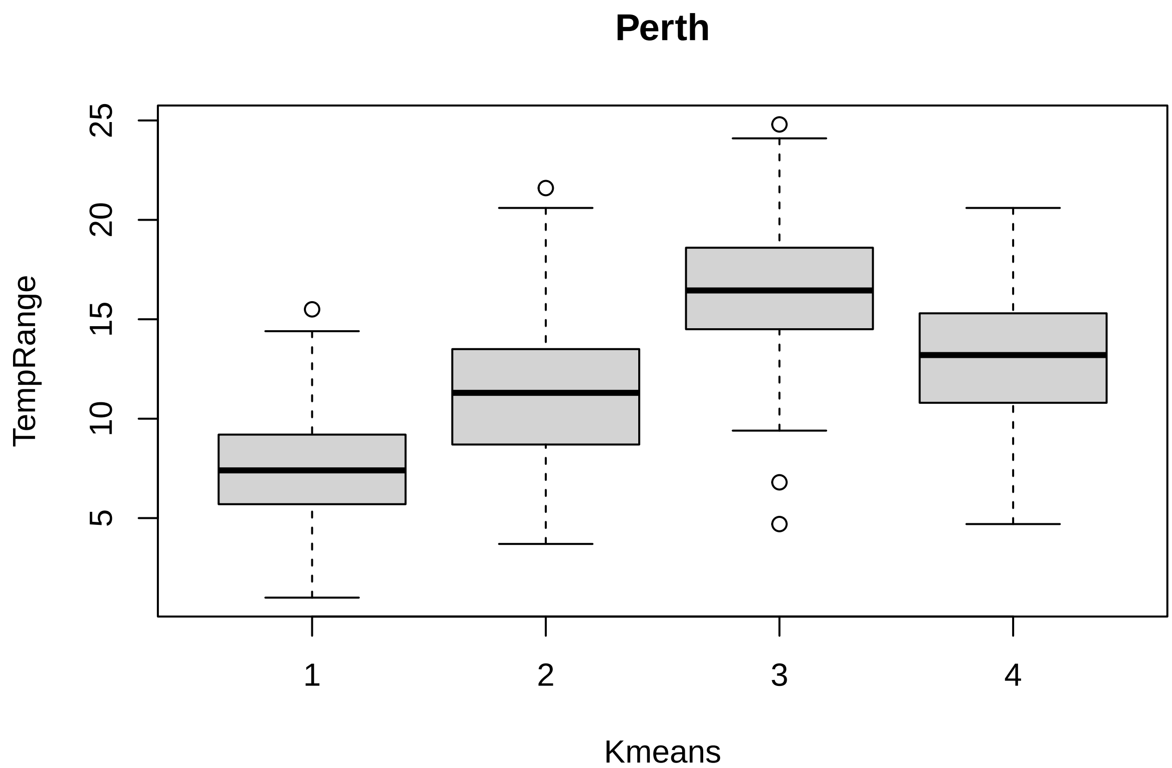
Kmeans


Perth
TempRange
25
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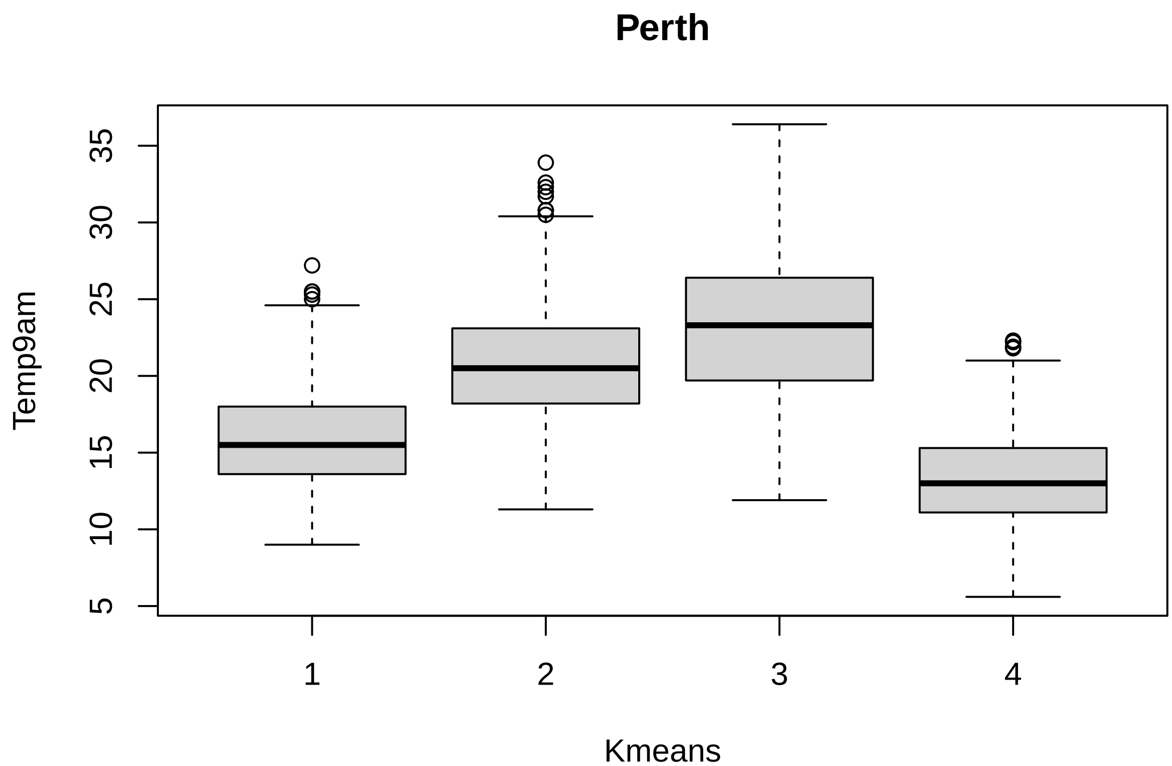
Kmeans


Perth
Temp9am
5
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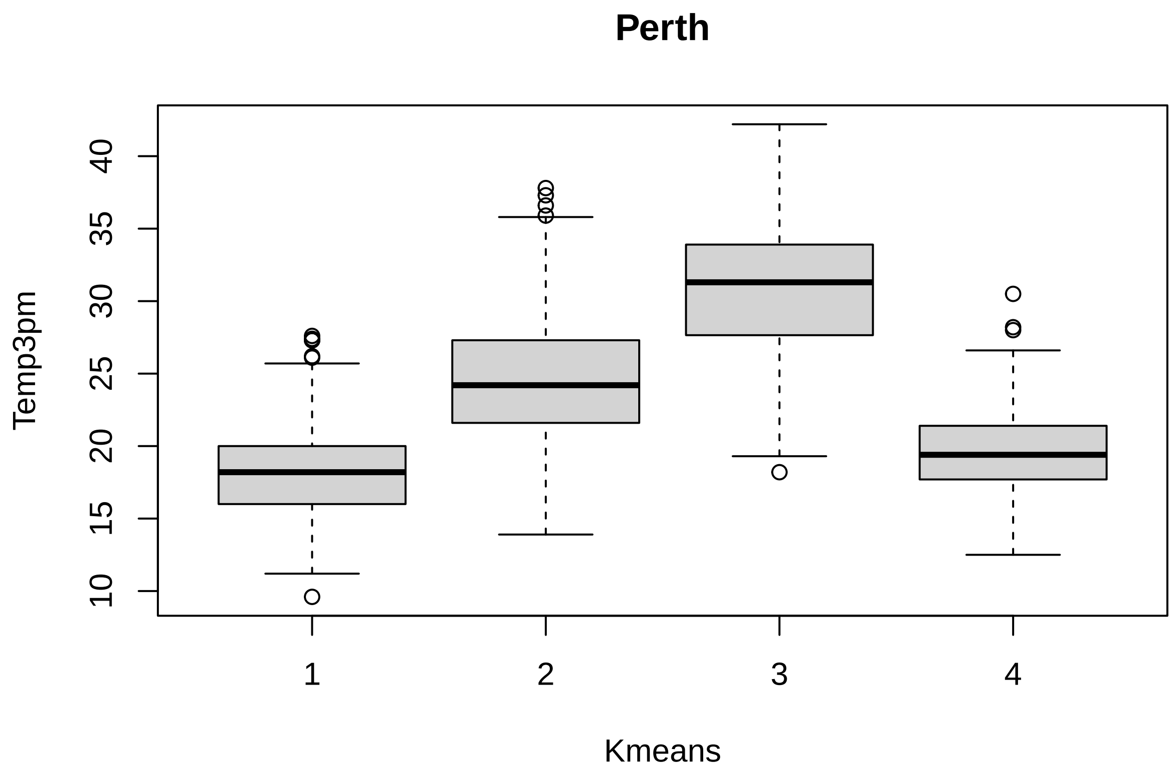
Kmeans


Perth
Temp3pm
10
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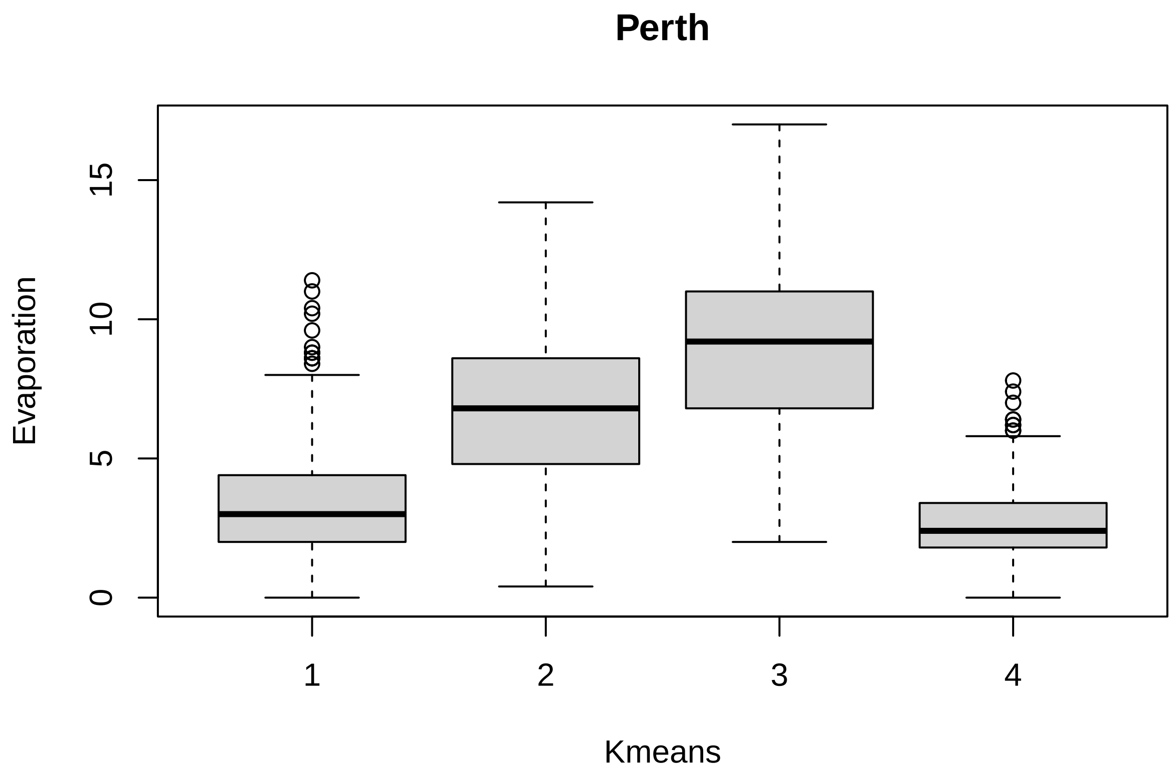
Kmeans


Perth
Evaporation
0
5
10
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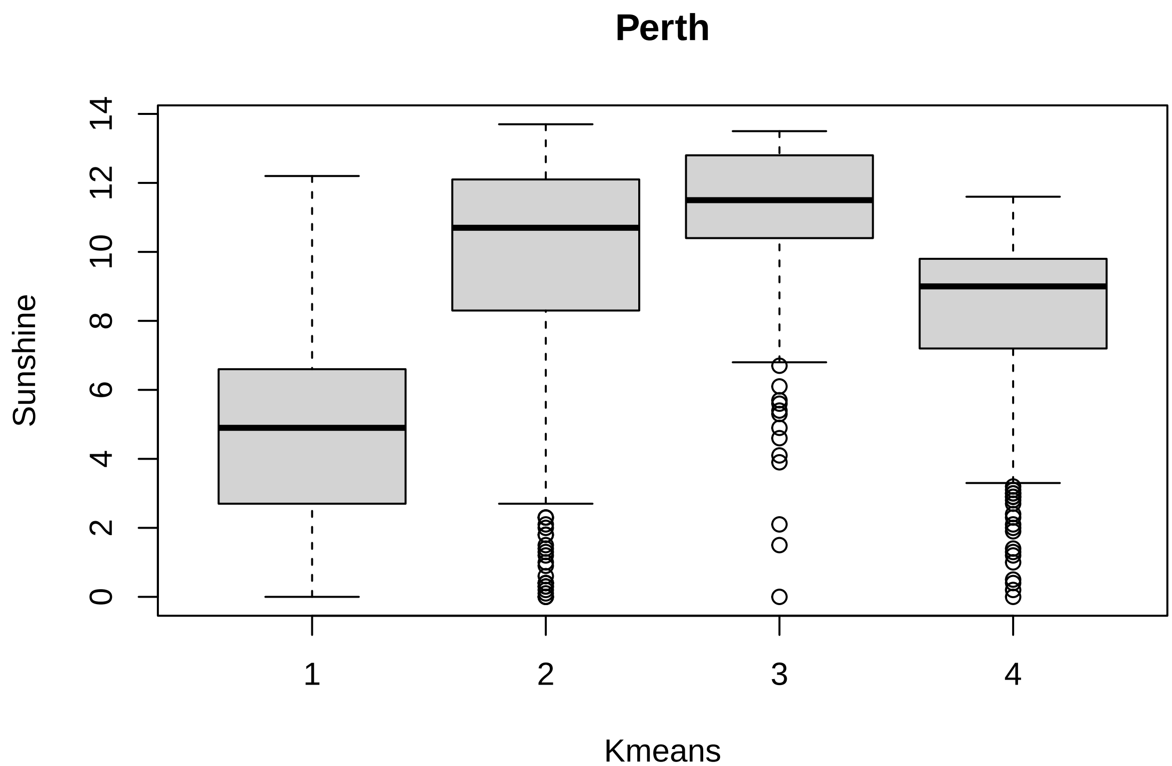
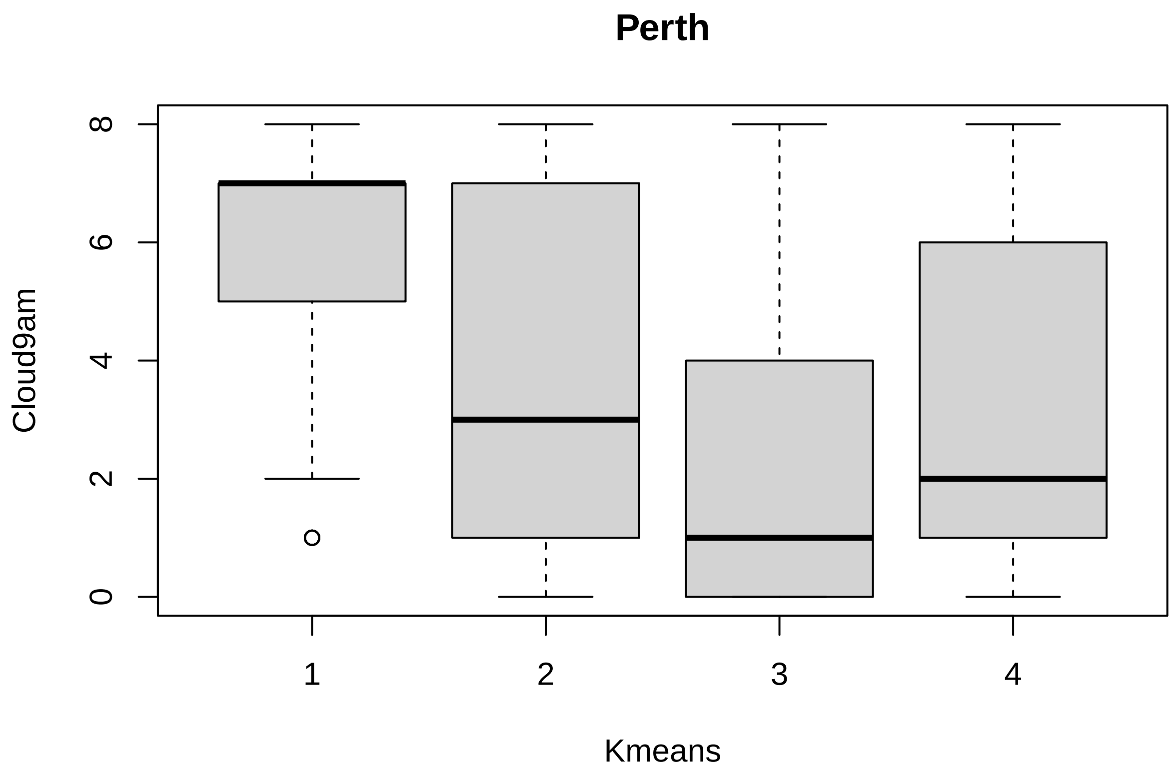
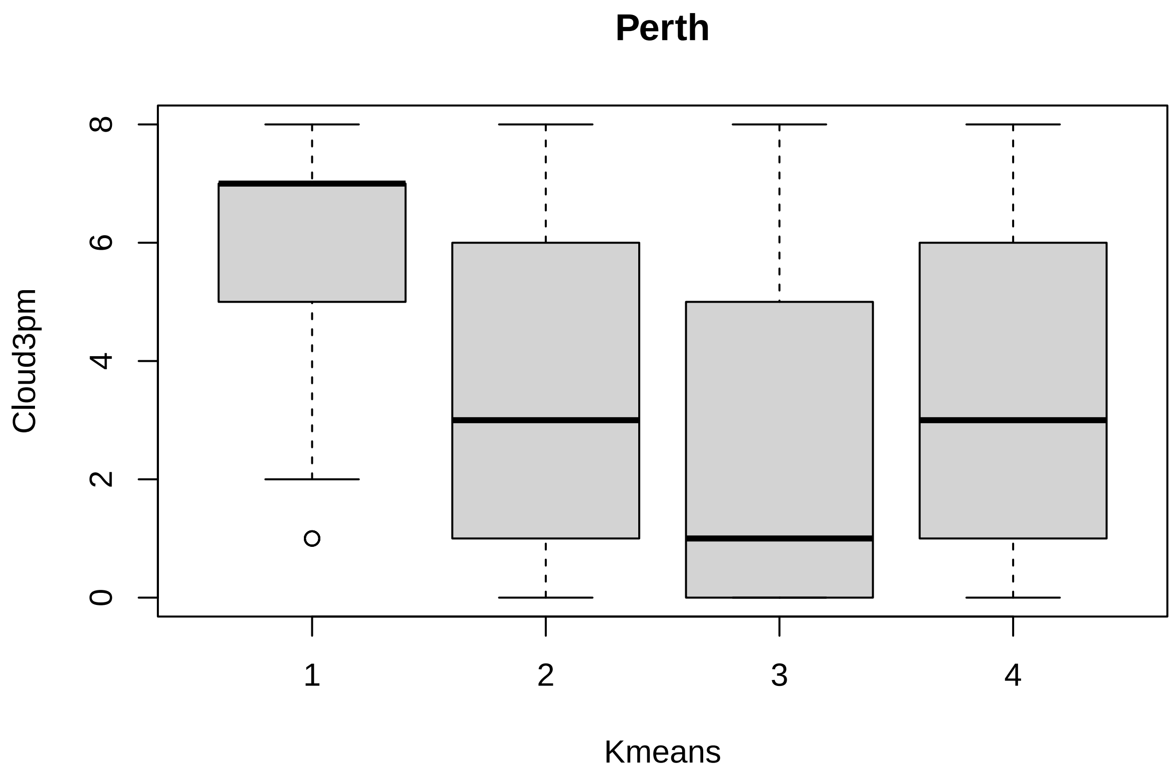
Kmeans


Perth
Sunshine
0
2
4
6
8
10
12
14
1
2
3
4
Kmeans


Perth
Cloud9am
0
2
4
6
8
1
2
3
4
Kmeans


Perth
Cloud3pm
0
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2
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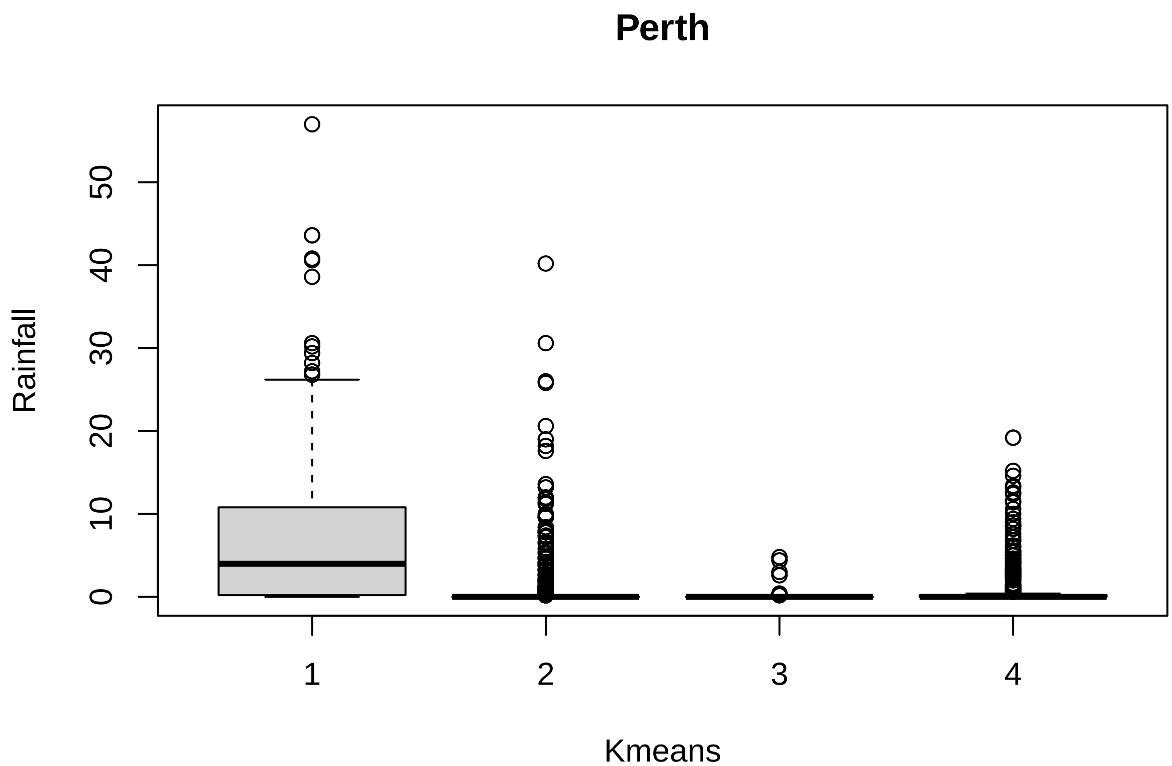
Kmeans


Perth
Rainfall
0
10
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30
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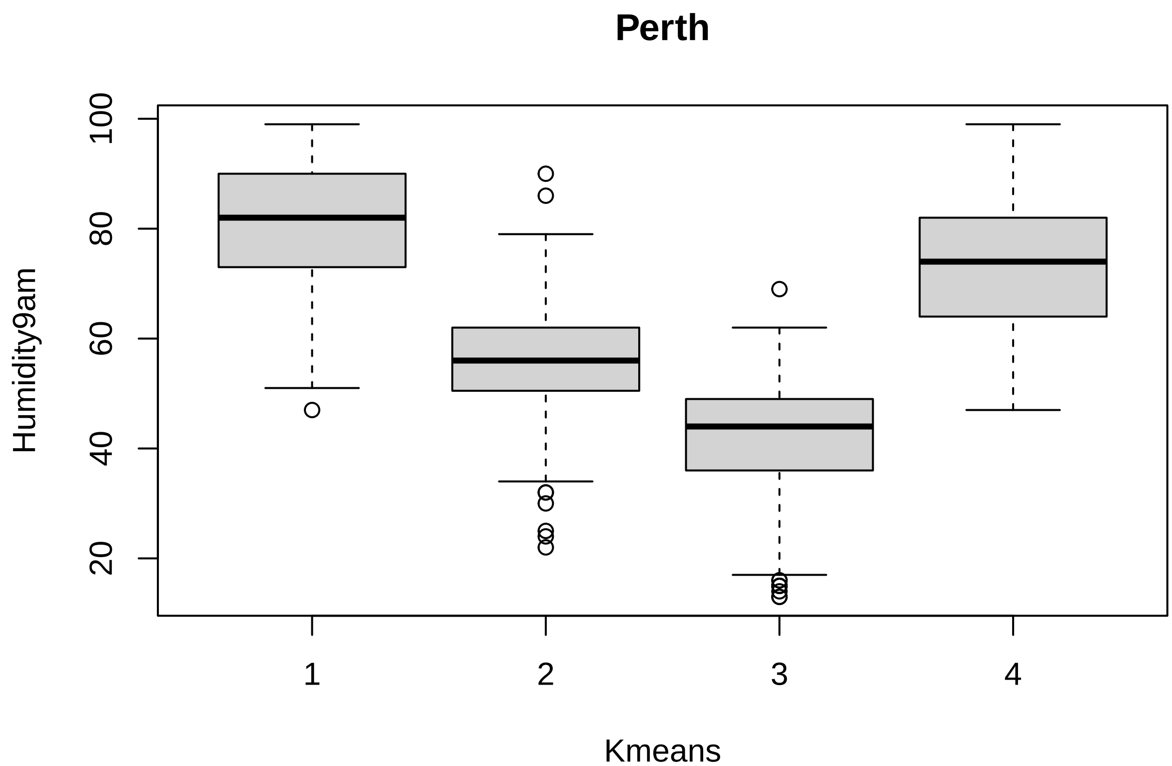
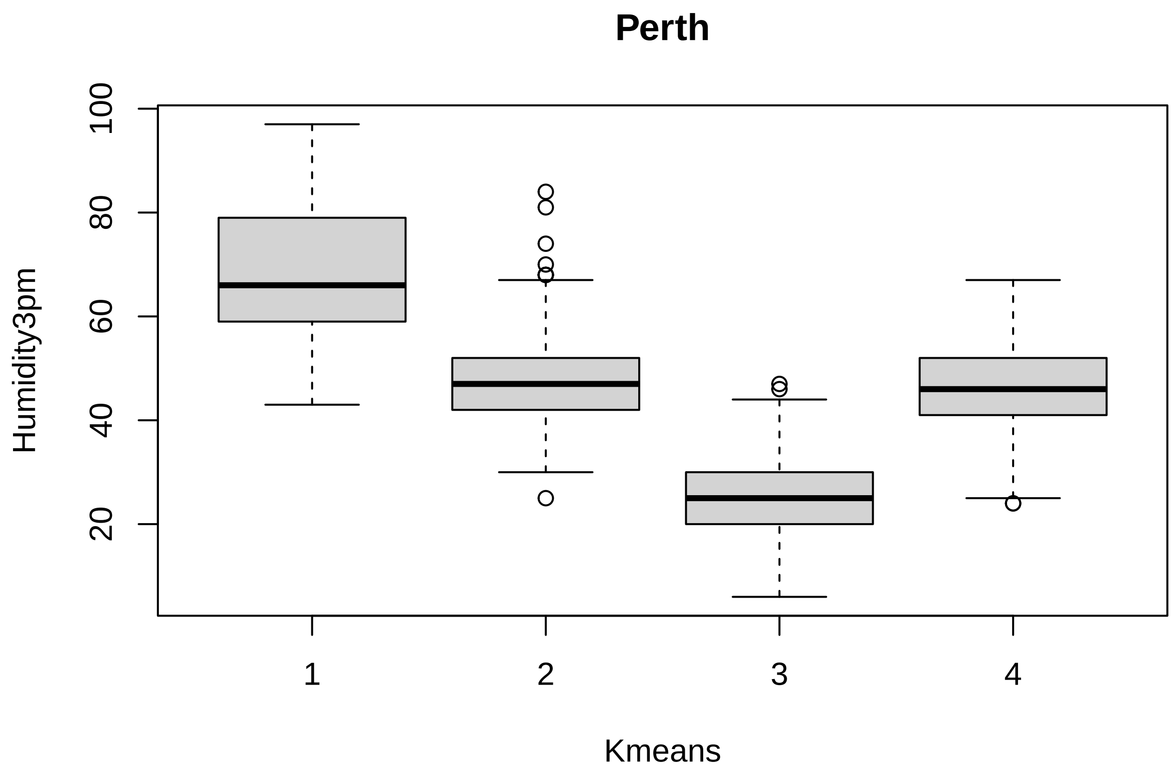
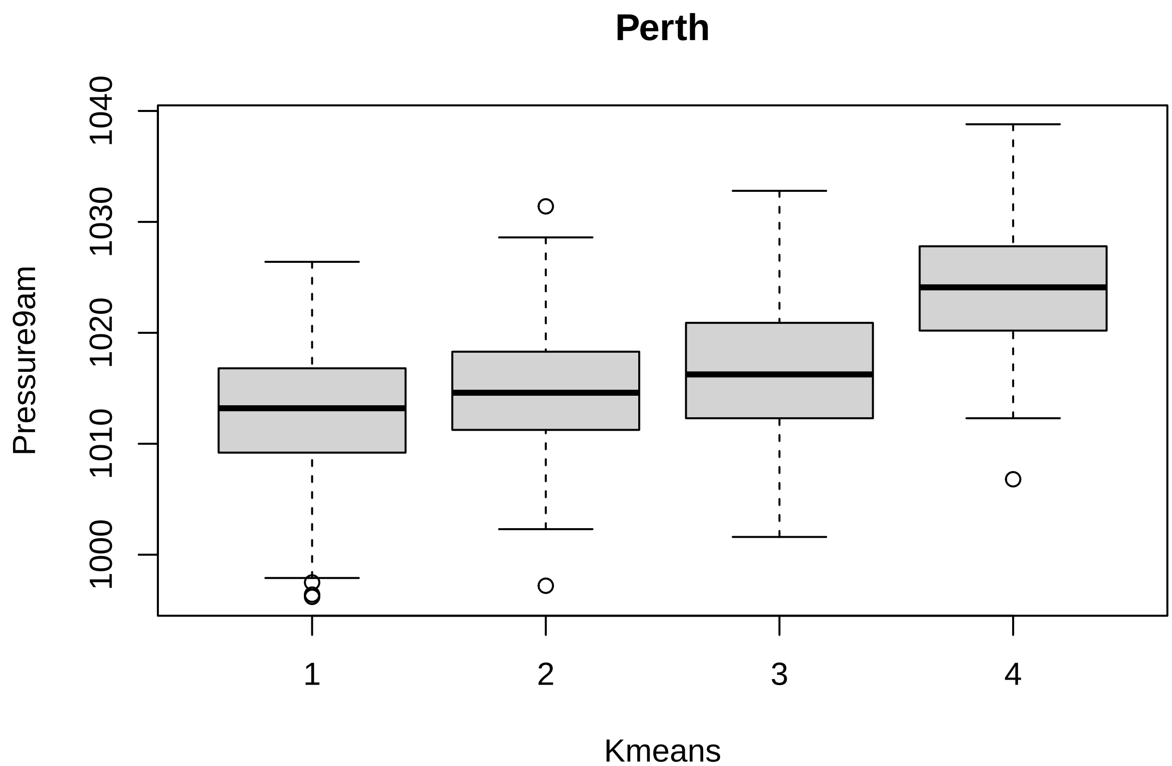
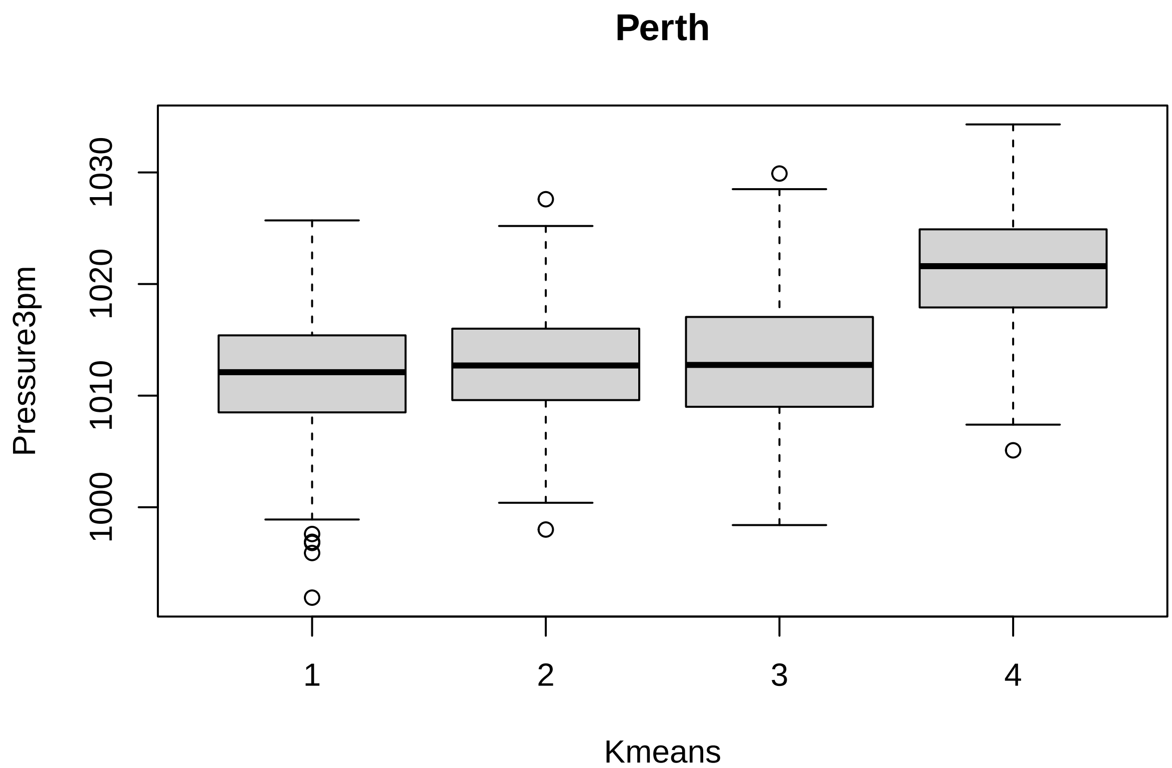
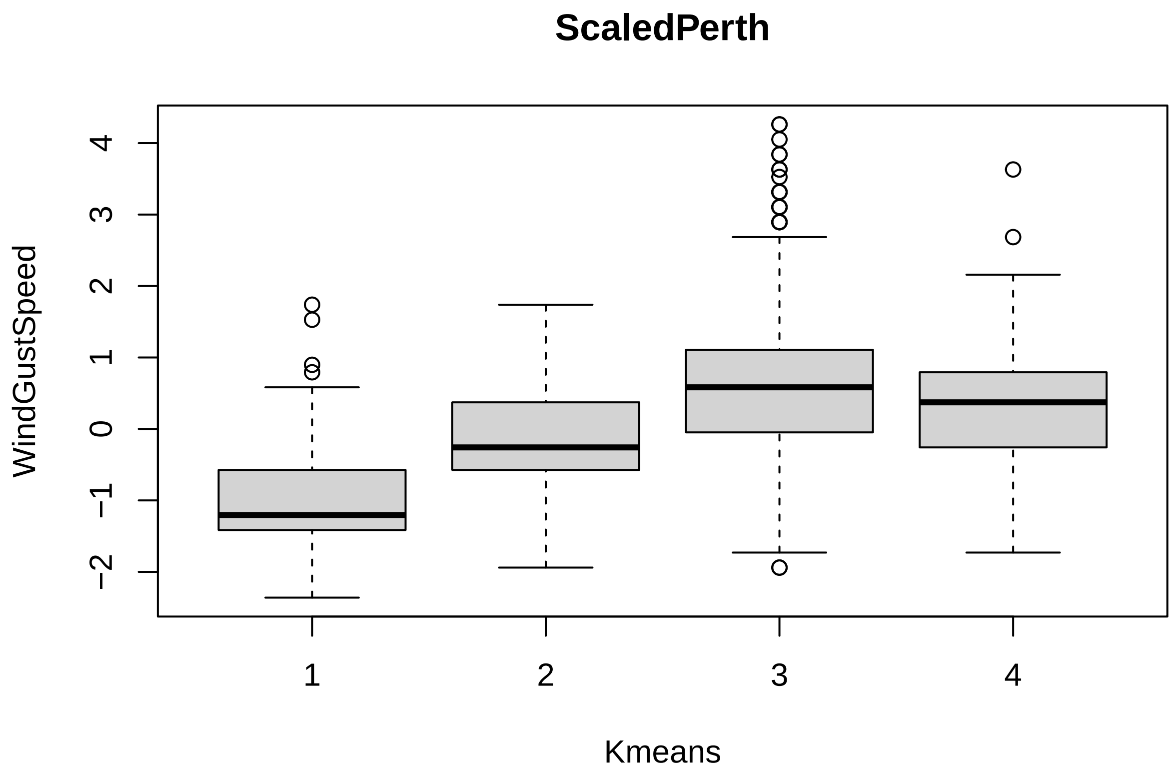
50
1
2
3
4
Kmeans


Perth
Humidity9am
100
80
60
40
20
1
2
3
4
Kmeans


Perth
Humidity3pm
100
80
60
40
20
1
2
3
4
Kmeans


Perth
Pressure9am
1000
1010
1020
1030
1040
1
2
3
4
Kmeans


Perth
Pressure3pm
1000
1010
1020
1030
1
2
3
4
Kmeans


ScaledPerth
WindGustSpeed
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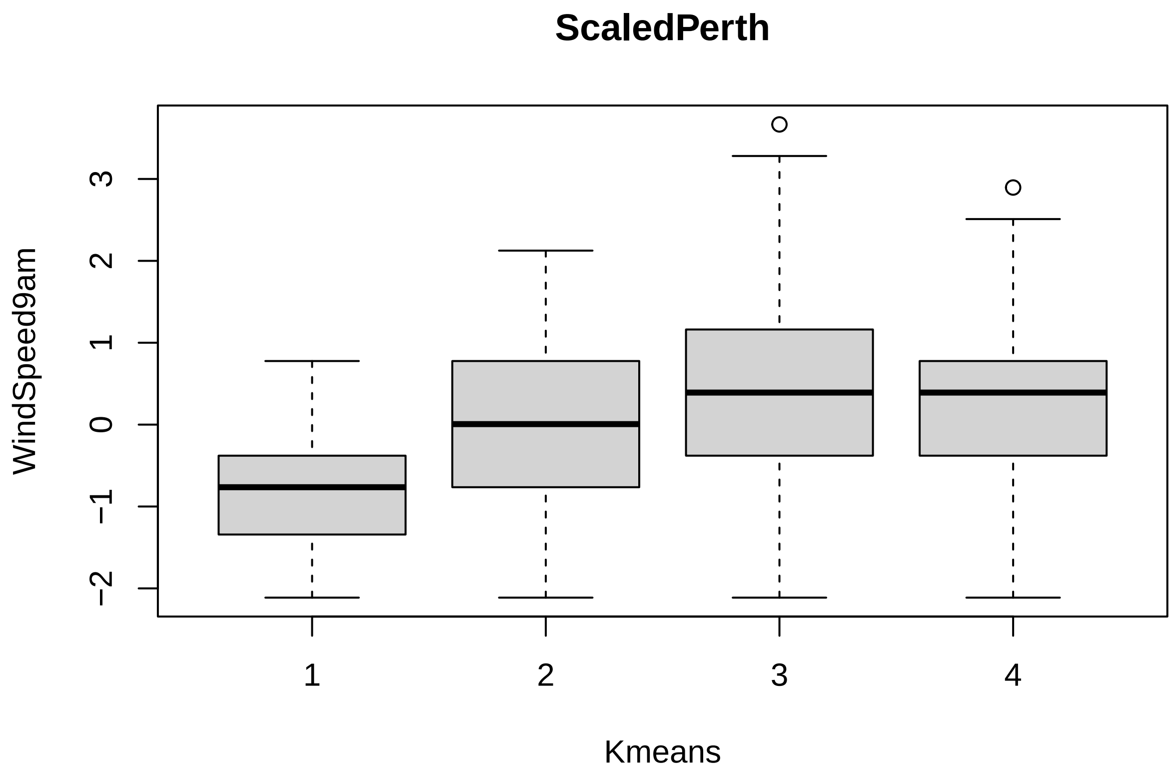
−1
0
1
2
3
4
1
2
3
4
Kmeans


ScaledPerth
WindSpeed9am
3
2
1
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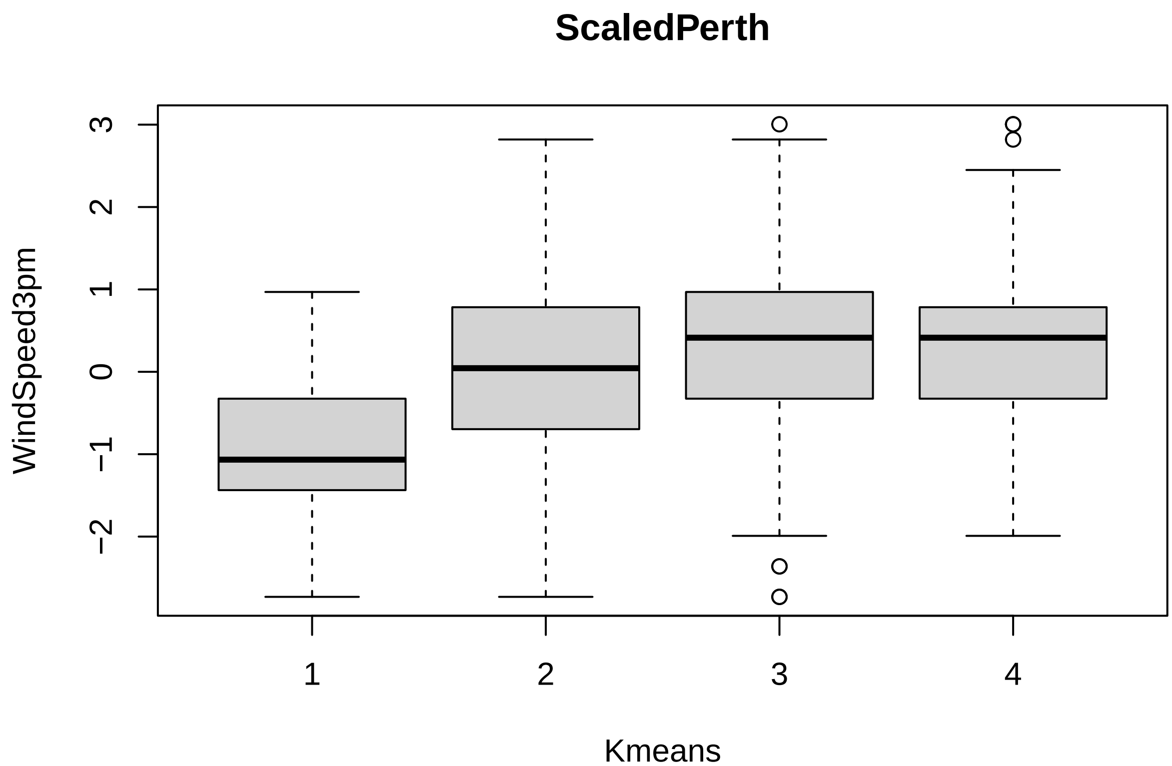
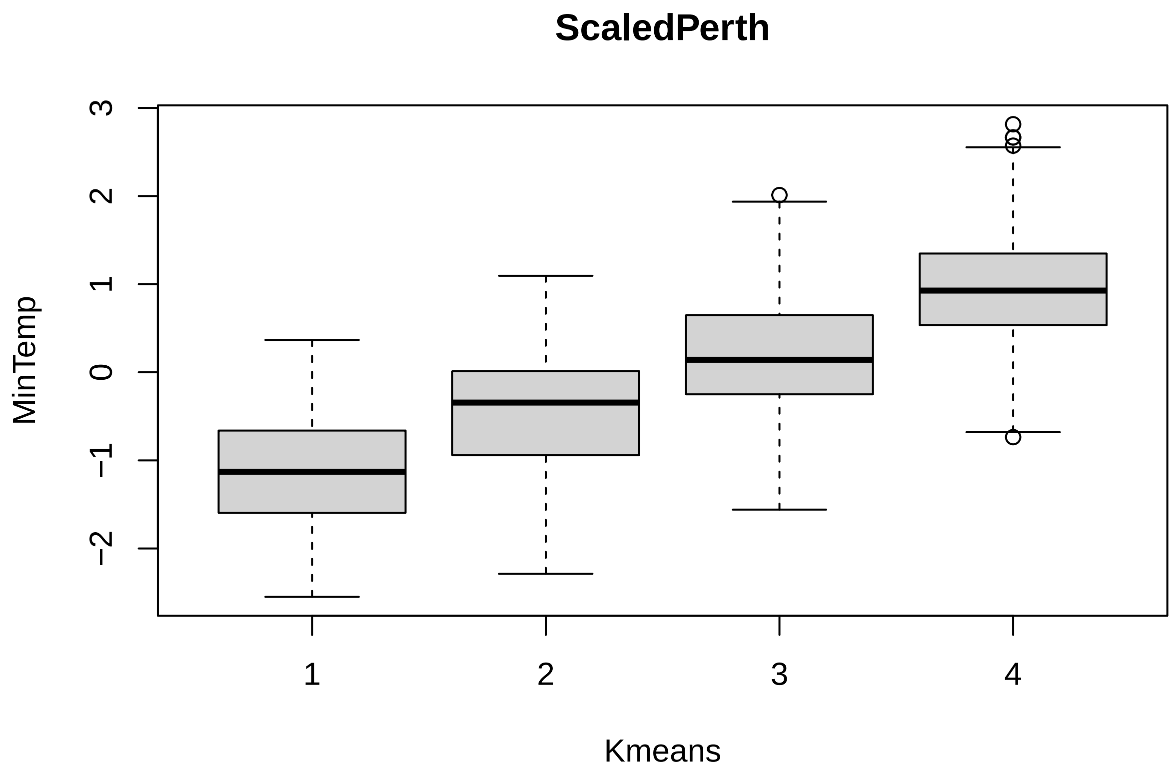
−1
−2
1
2
3
4
Kmeans


ScaledPerth
WindSpeed3pm
3
2
1
0
−1
−2
1
2
3
4
Kmeans


ScaledPerth
MinTemp
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2
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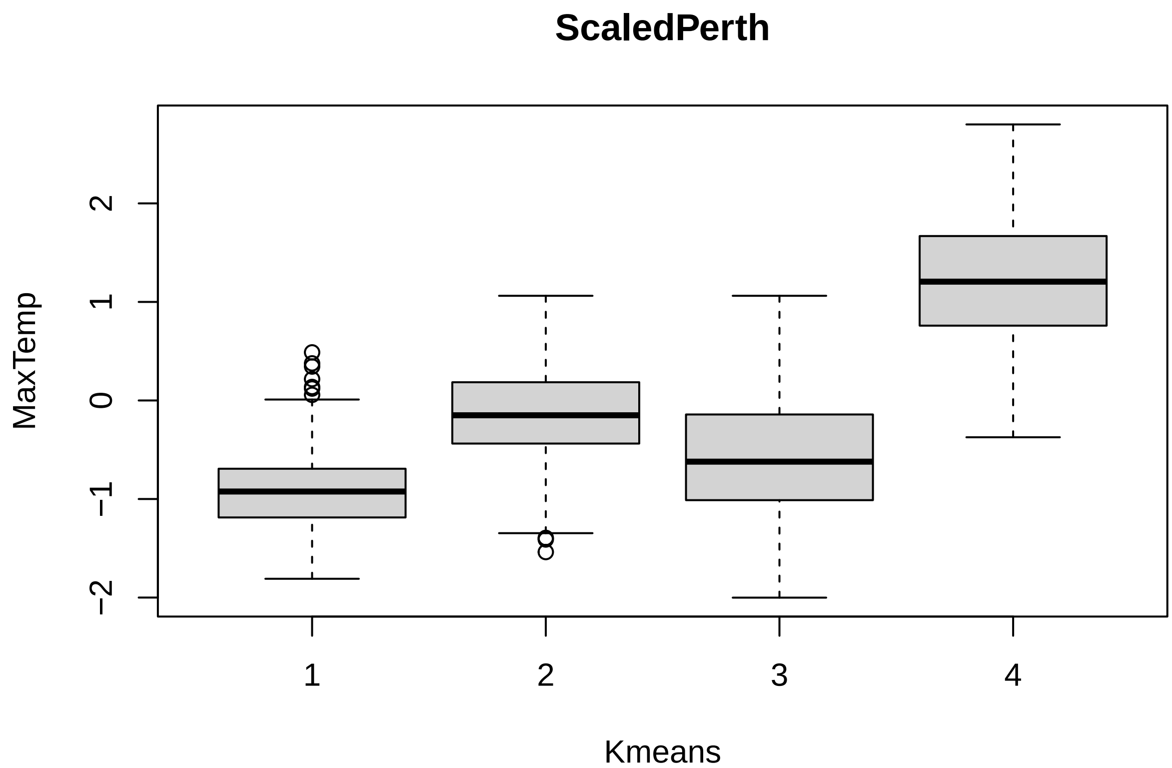
0
−1
−2
1
2
3
4
Kmeans


ScaledPerth
MaxTemp
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1
0
−1
−2
1
2
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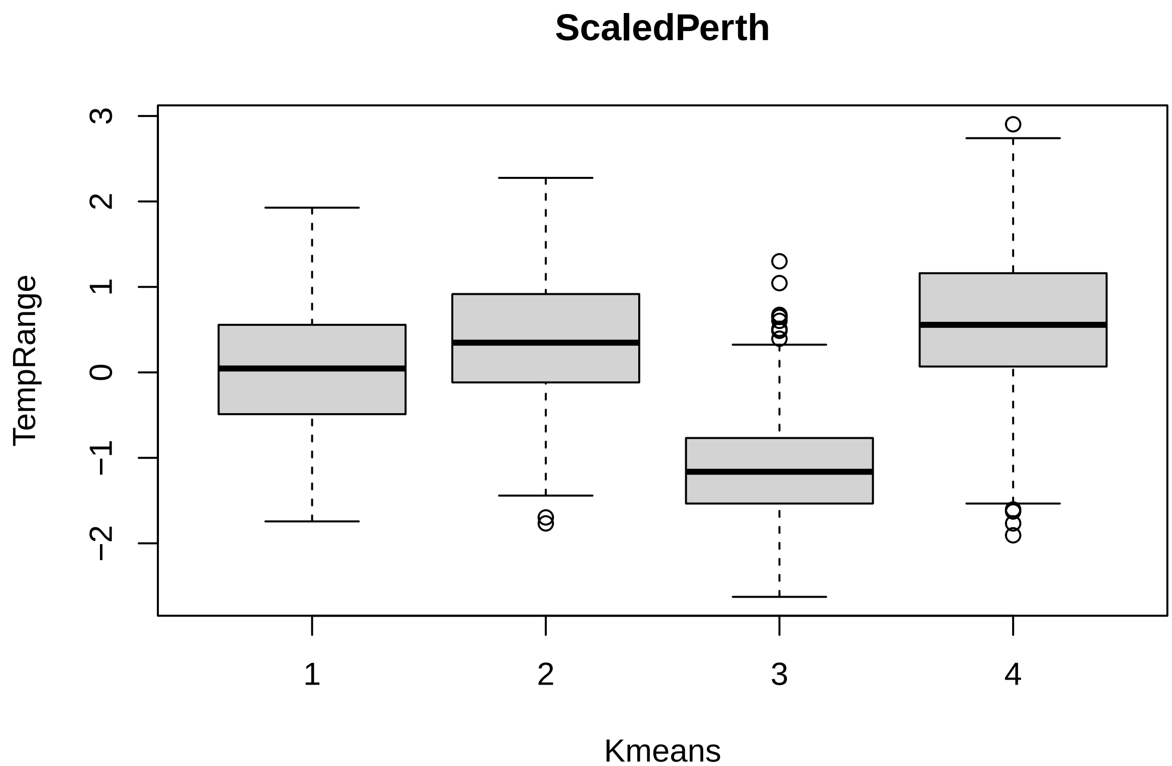
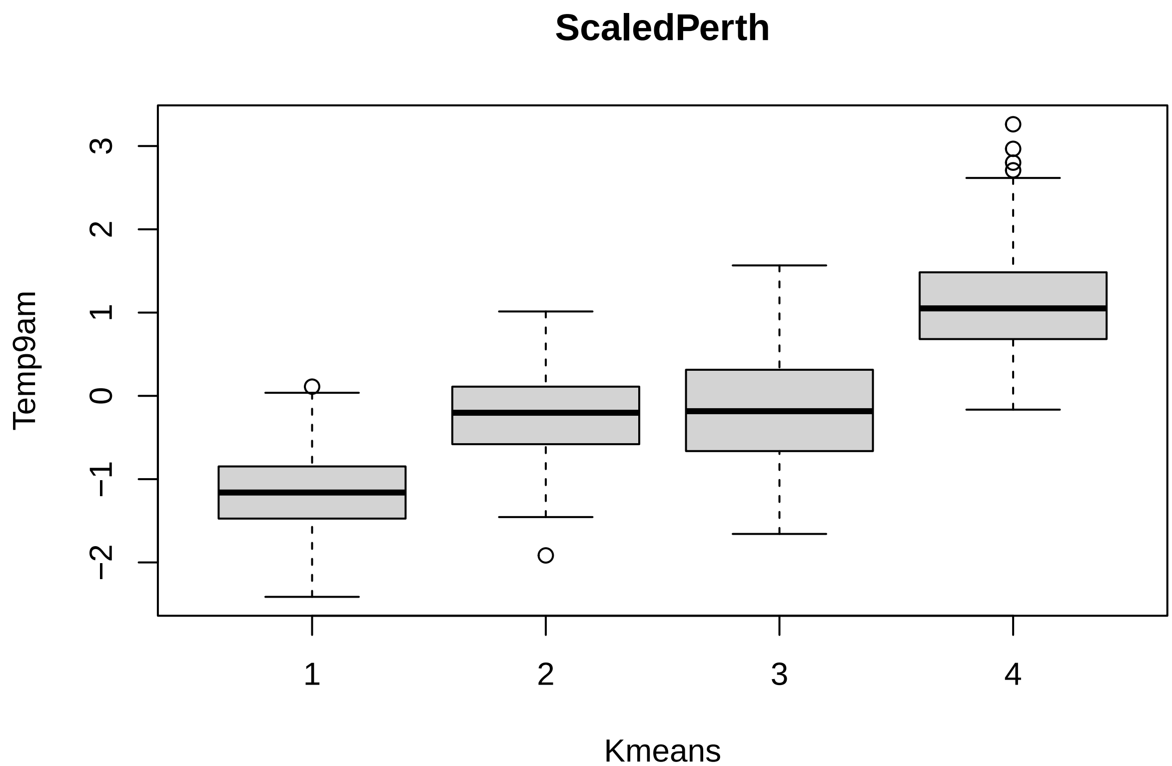
4
Kmeans


ScaledPerth
TempRange
3
2
1
0
−1
−2
1
2
3
4
Kmeans


ScaledPerth
Temp9am
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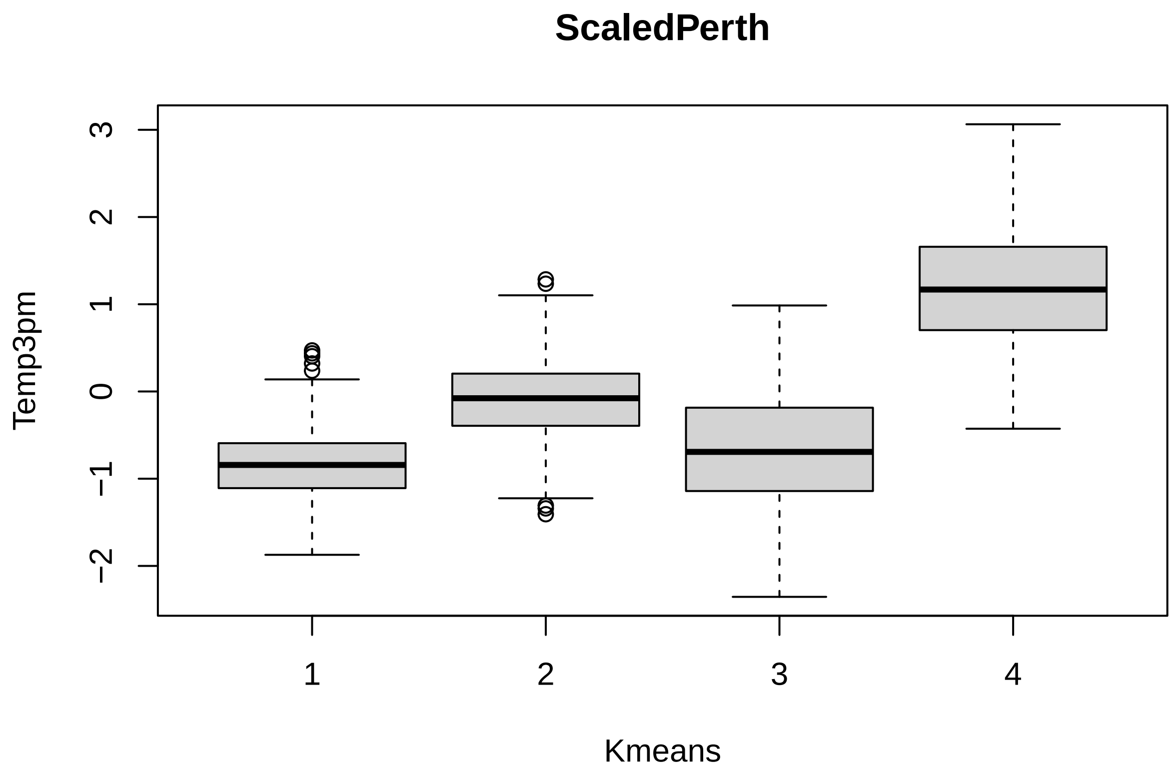
Kmeans


ScaledPerth
Temp3pm
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1
2
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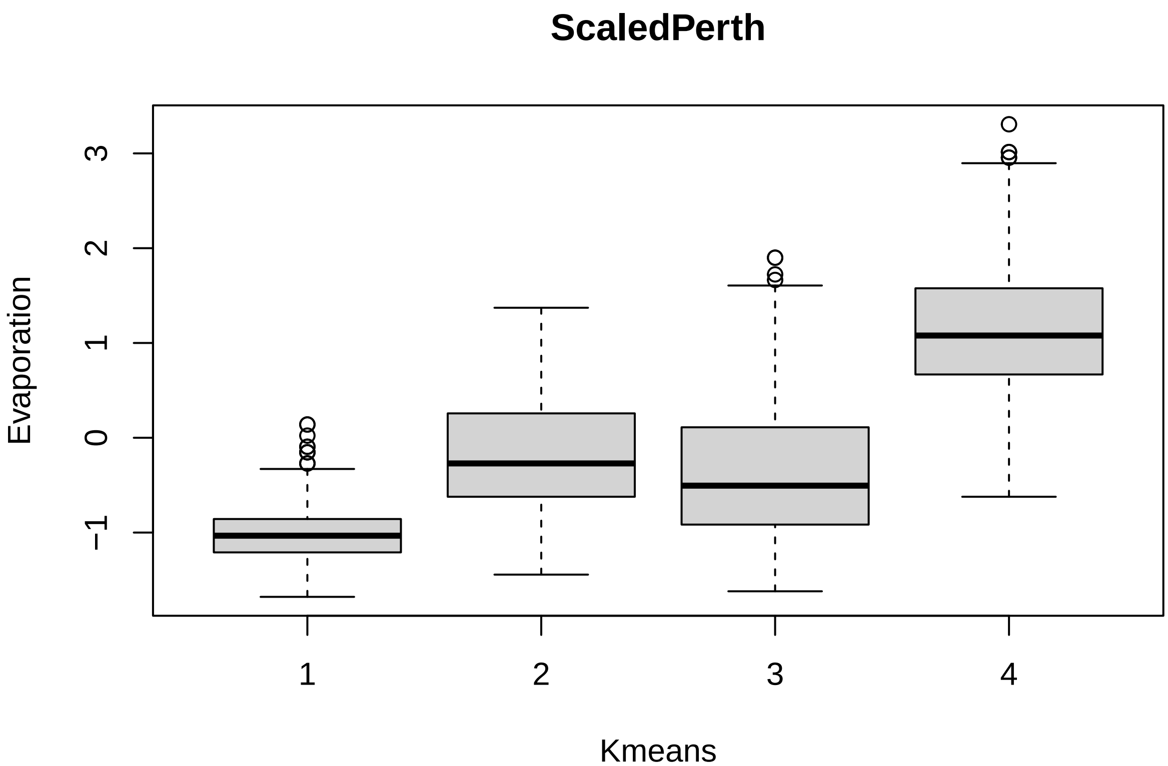
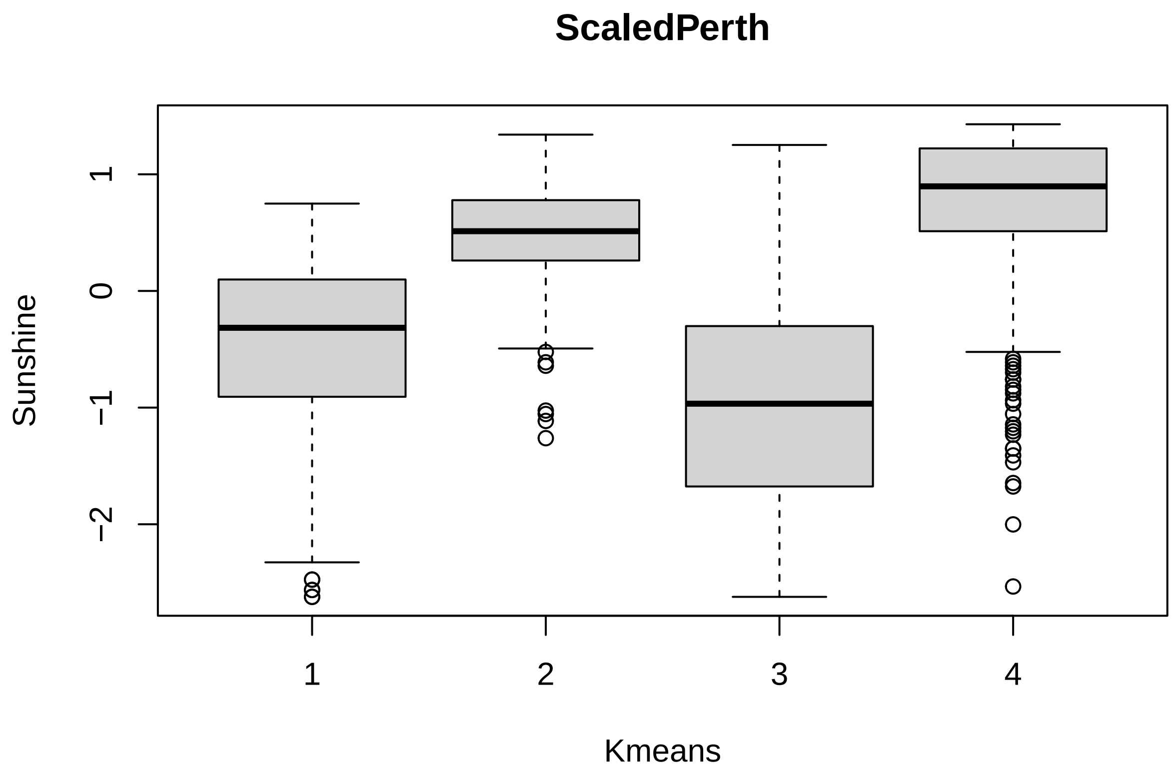
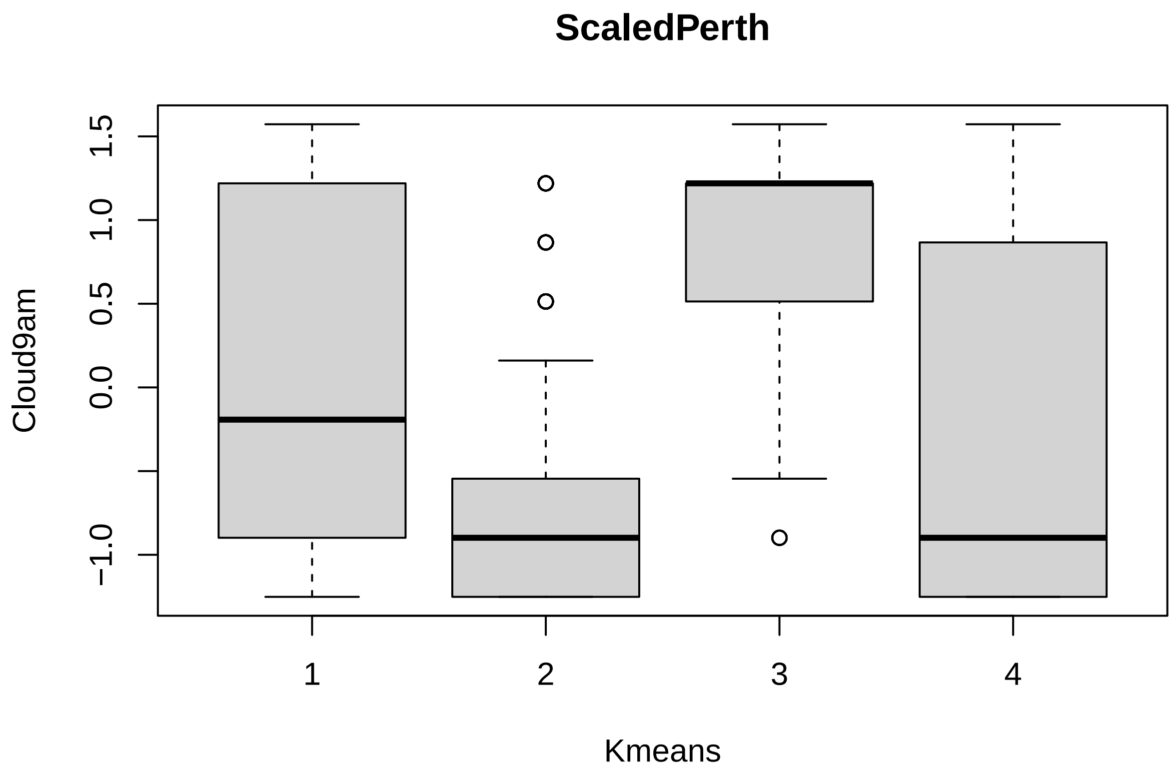
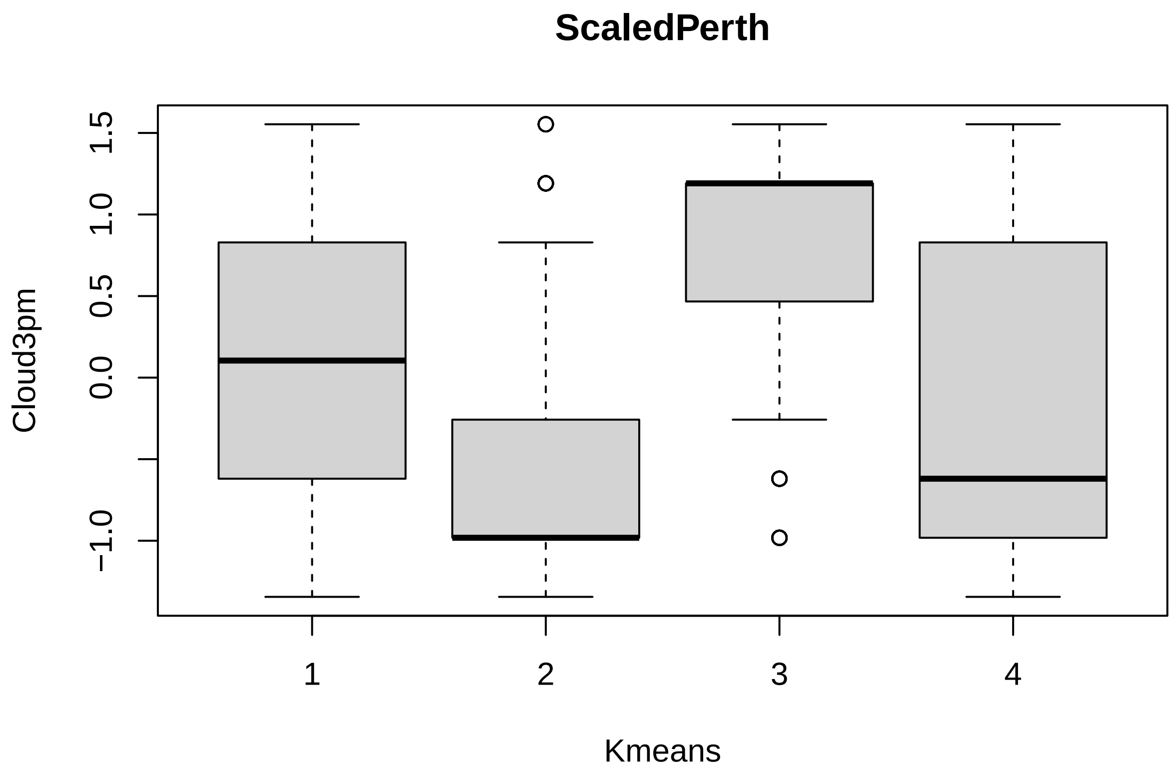
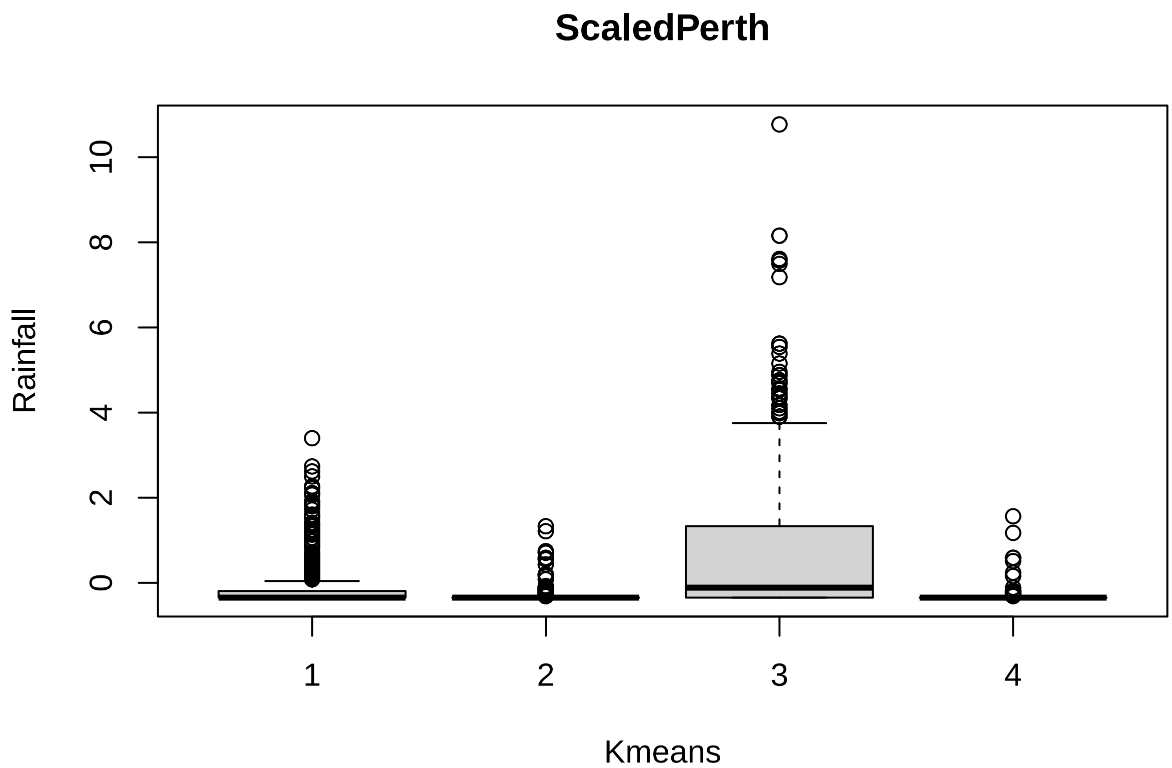
Kmeans

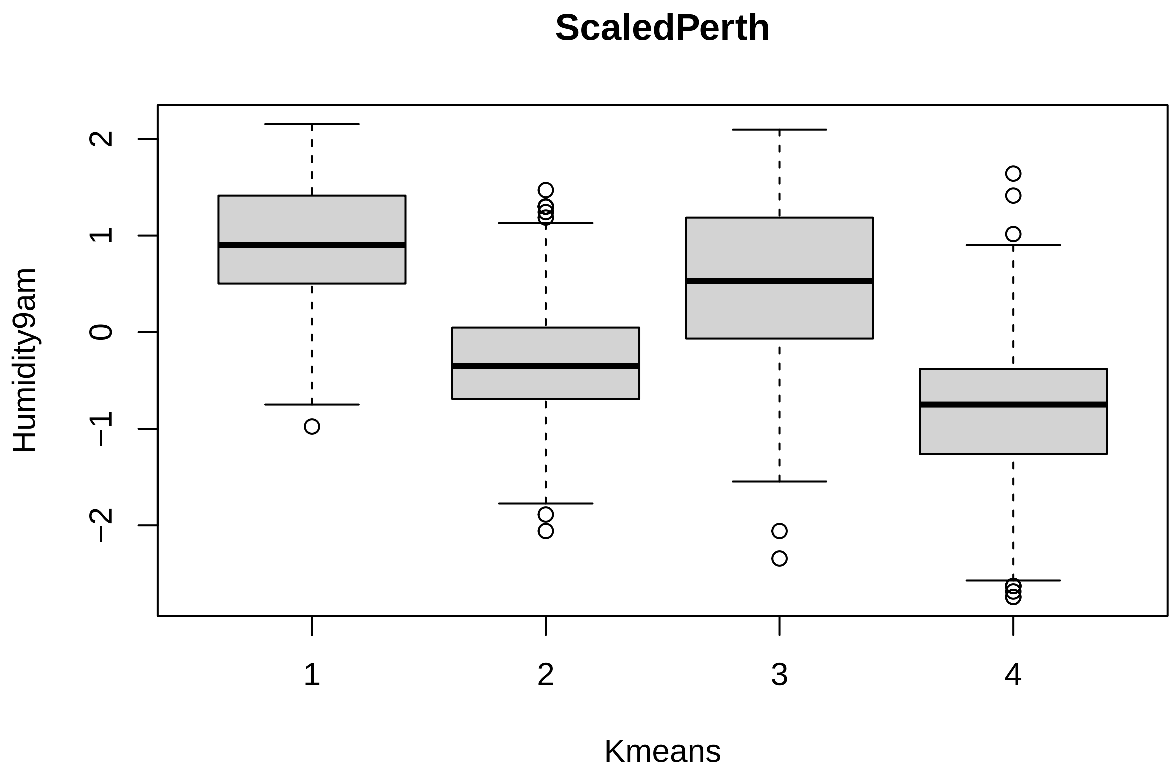

ScaledPerth
Evaporation
Kmeans
3
2
1
0
−1
1
2
3
4

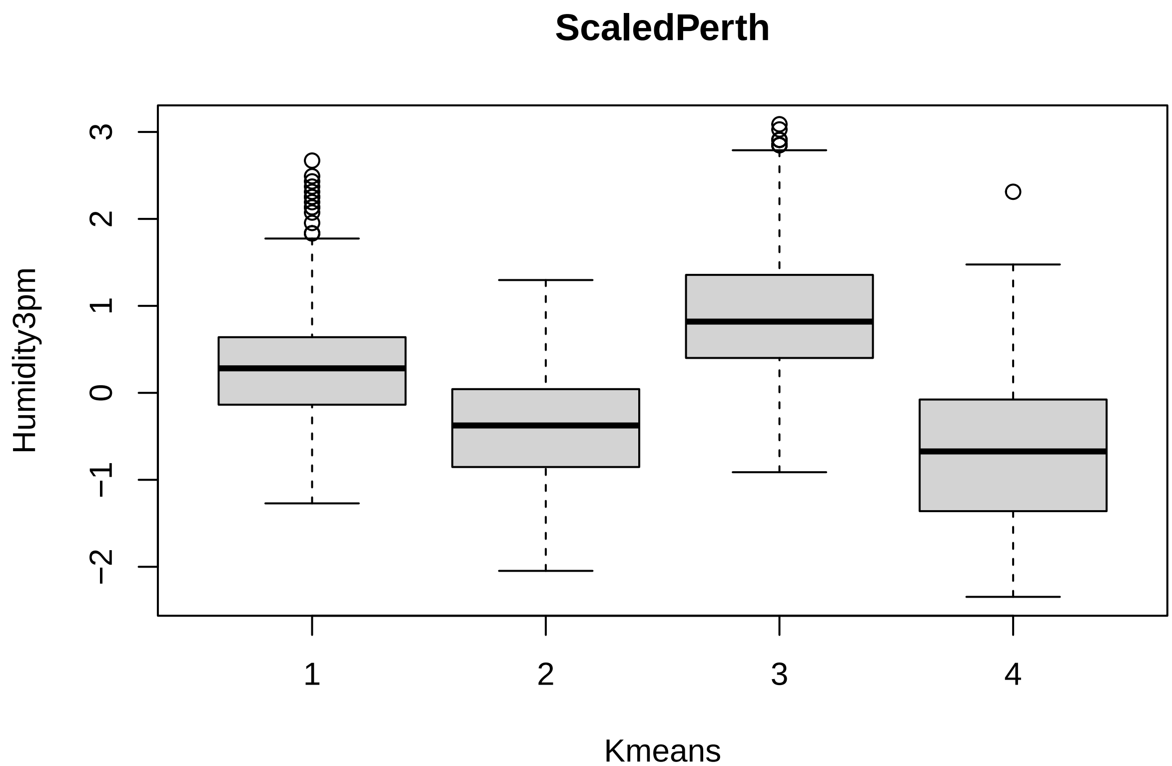

ScaledPerth
Sunshine
1
0
−1
−2
1
2
3
4
Kmeans


ScaledPerth
Cloud9am
1.5
1.0
0.5
0.0
−1.0
1
2
3
4
Kmeans


ScaledPerth
Cloud3pm
1.5
1.0
0.5
0.0
−1.0
1
2
3
4
Kmeans


ScaledPerth
Rainfall
0
2
4
6
8
10
1
2
3
4
Kmeans


ScaledPerth
Humidity9am
2
1
0
−1
−2
1
2
3
4
Kmeans


ScaledPerth
Humidity3pm
3
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1
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−1
−2
1
2
3
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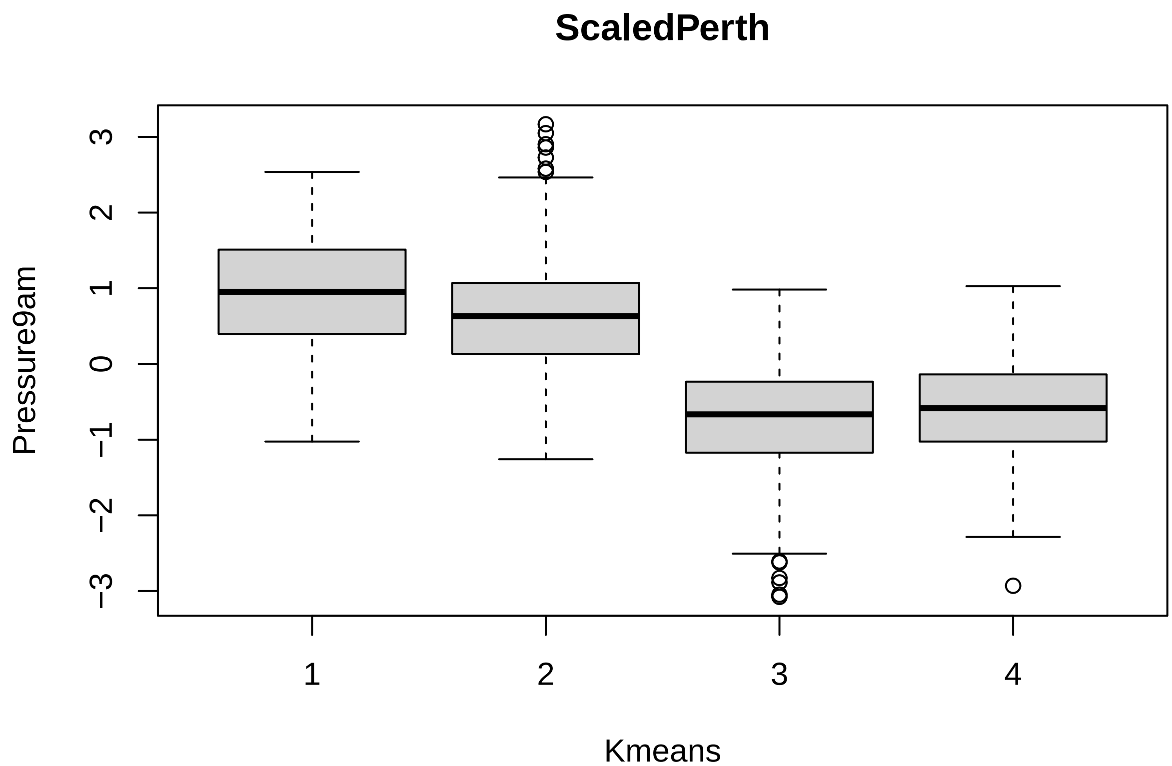
Kmeans


ScaledPerth
Pressure9am
3
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0
−1
−2
−3
1
2
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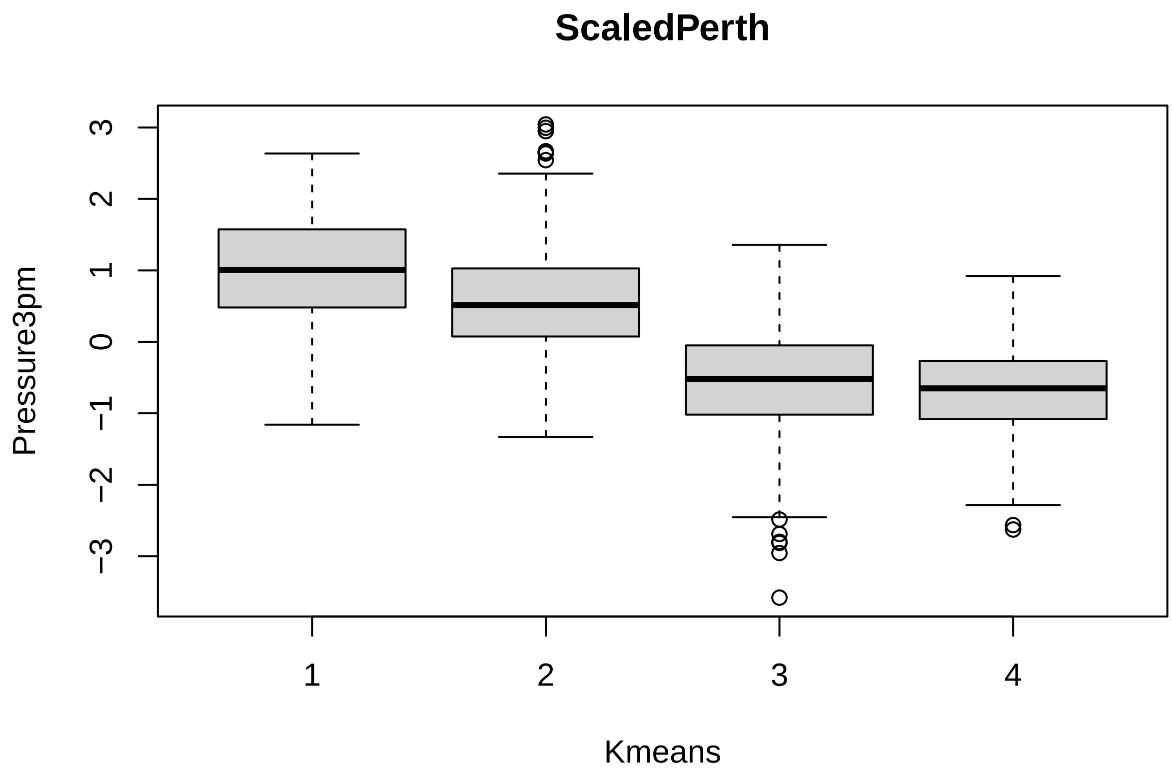
Kmeans


ScaledPerth
Pressure3pm
3
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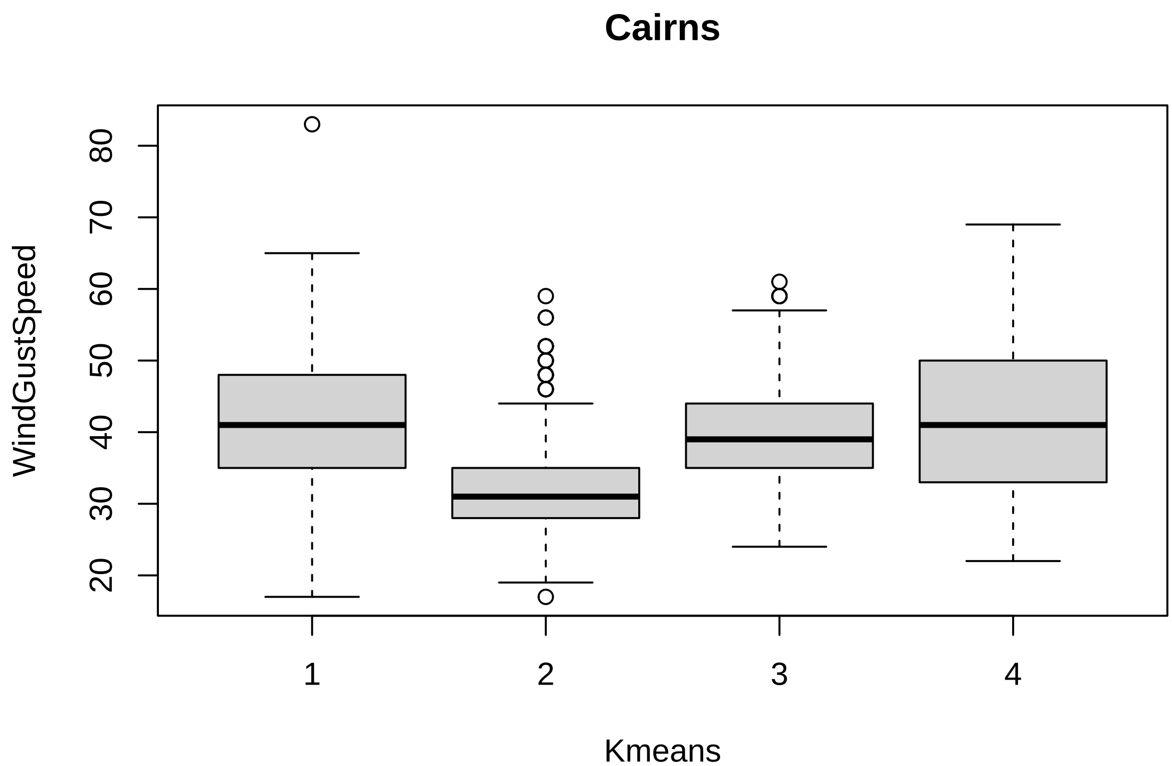
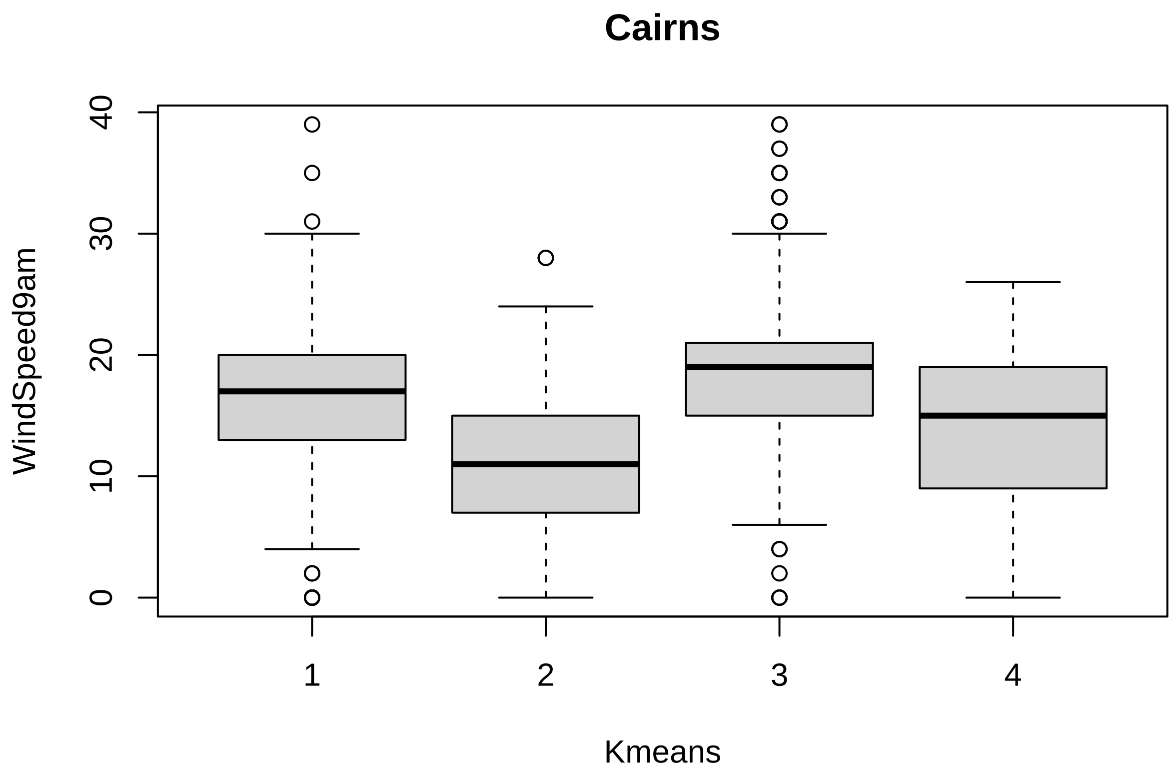
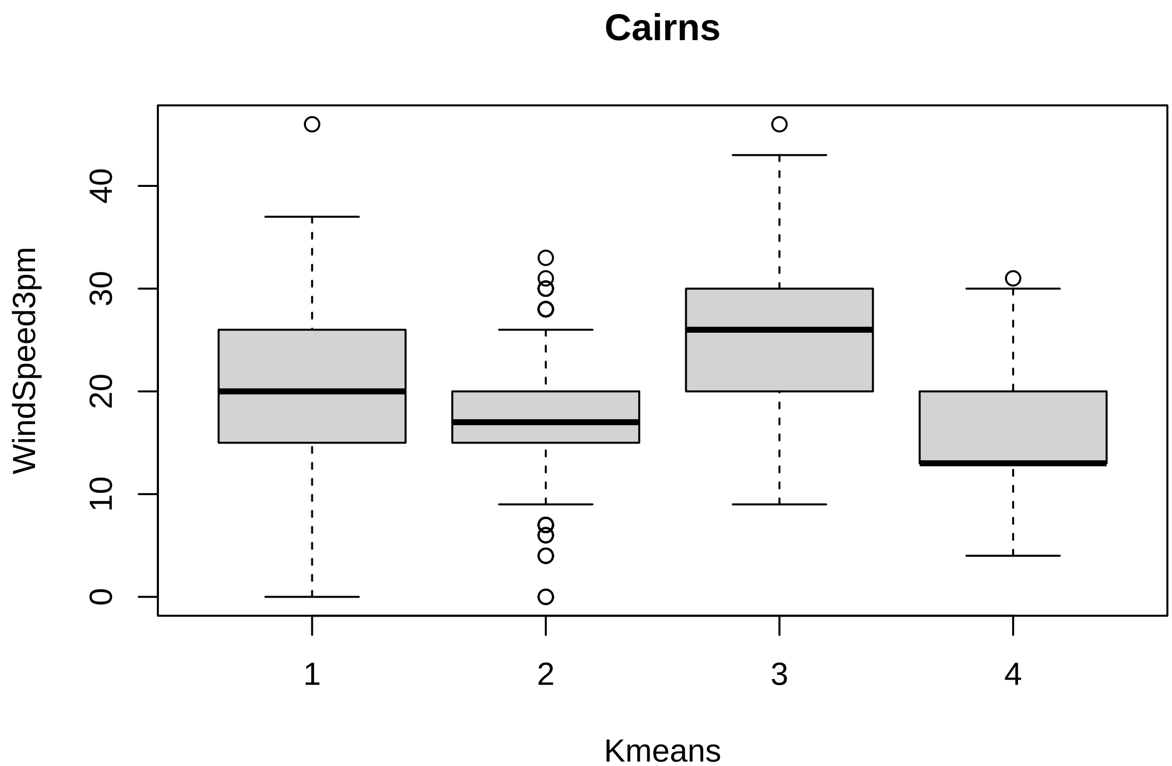
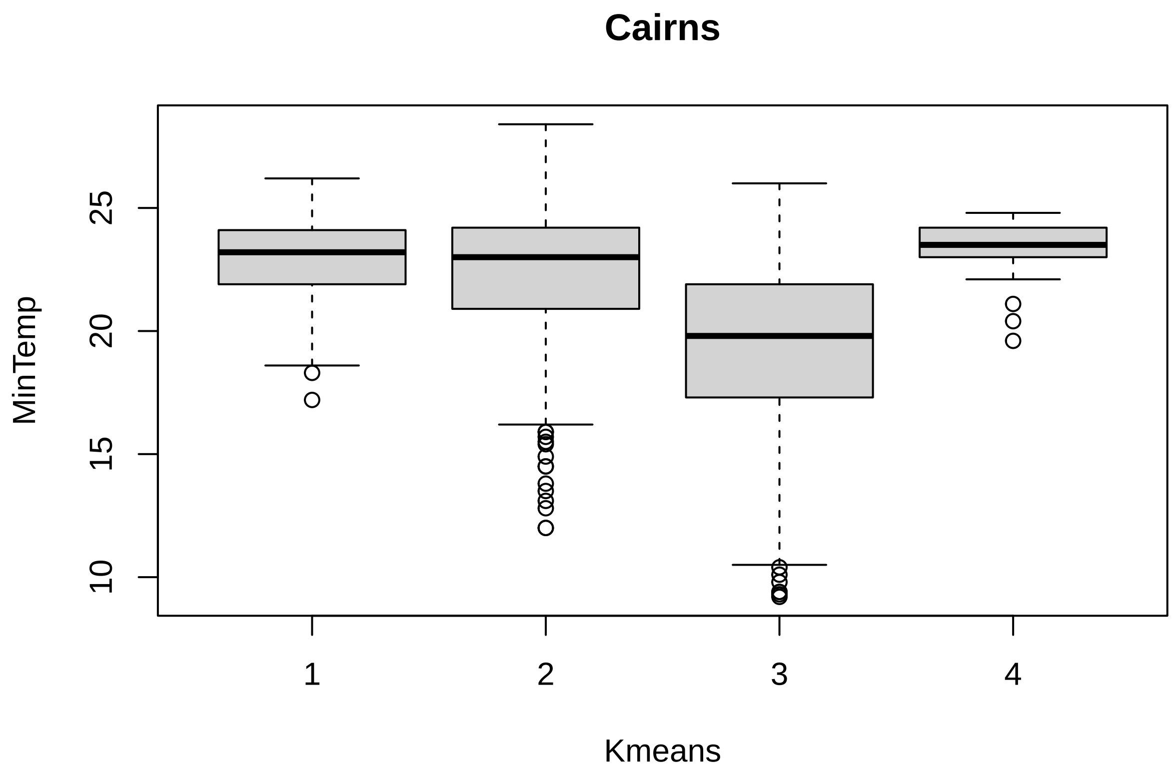
Kmeans

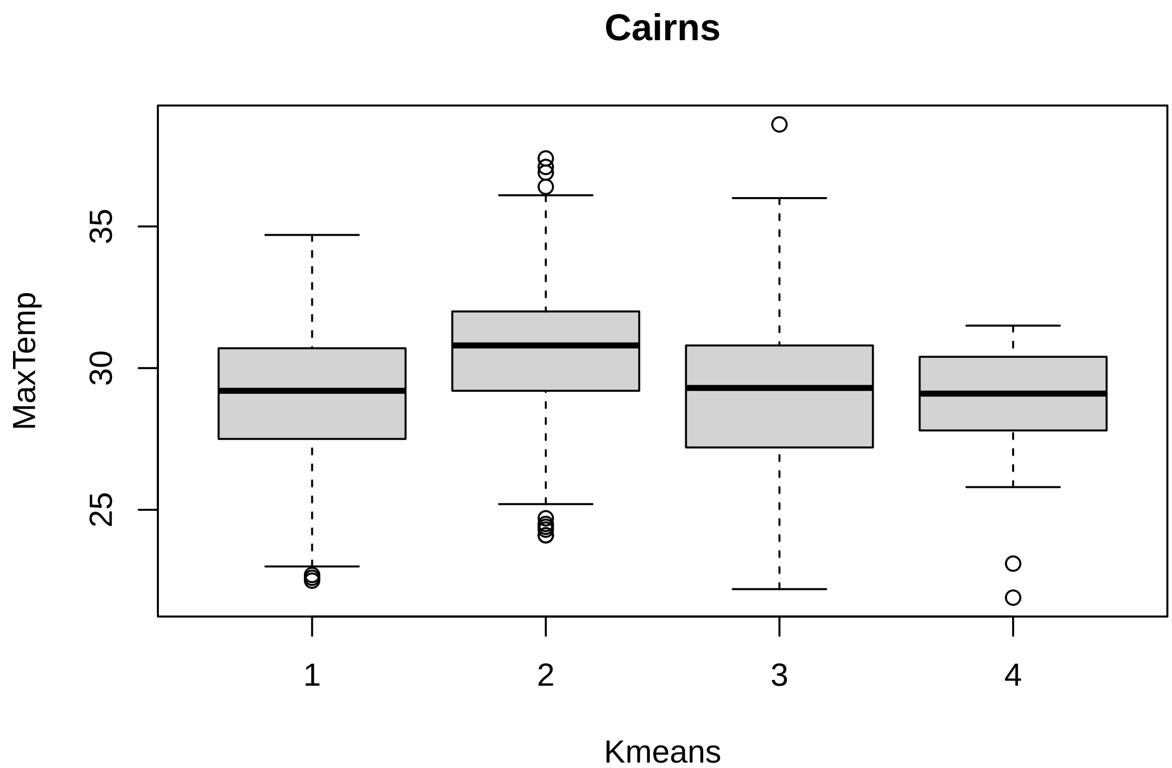

Cairns
WindGustSpeed
20
30
40
50
60
70
80
1
2
3
4
Kmeans


Cairns
WindSpeed9am
0
10
20
30
40
1
2
3
4
Kmeans



Cairns
WindSpeed3pm
0
10
20
30
40
1
2
3
4
Kmeans


Cairns
MinTemp
10
15
20
25
1
2
3
4
Kmeans


Cairns
MaxTemp
25
30
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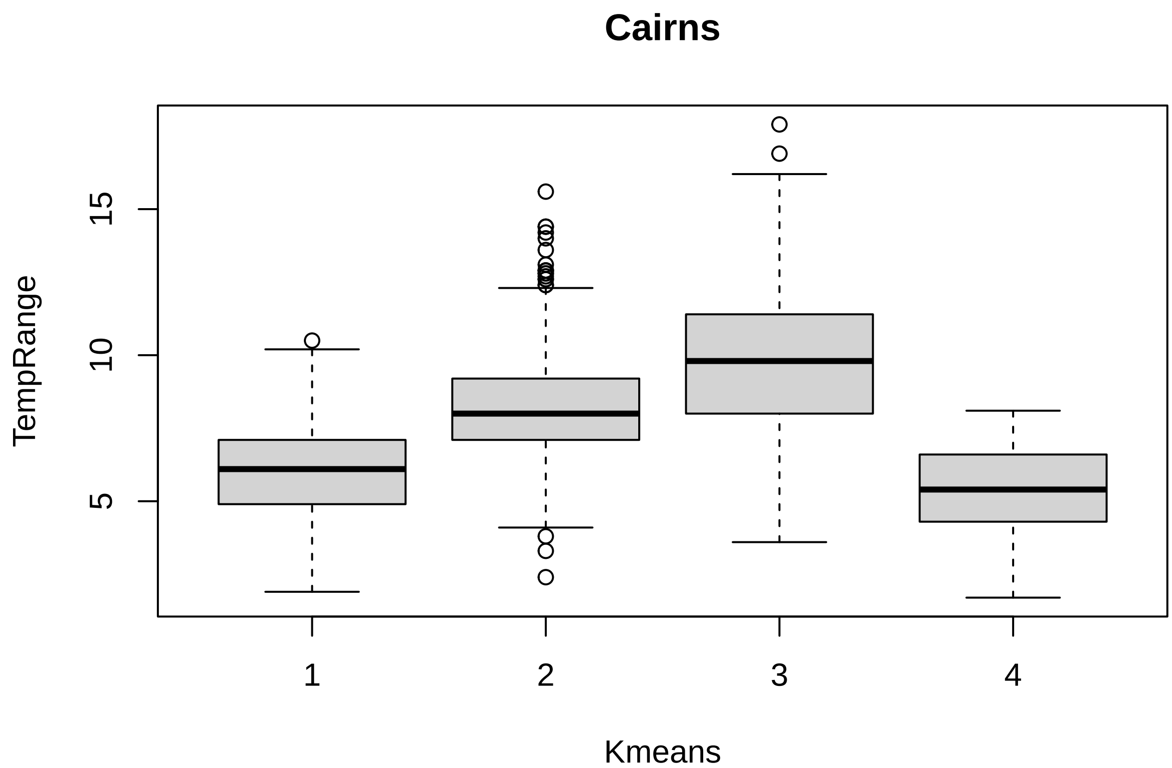
Kmeans


Cairns
TempRange
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10
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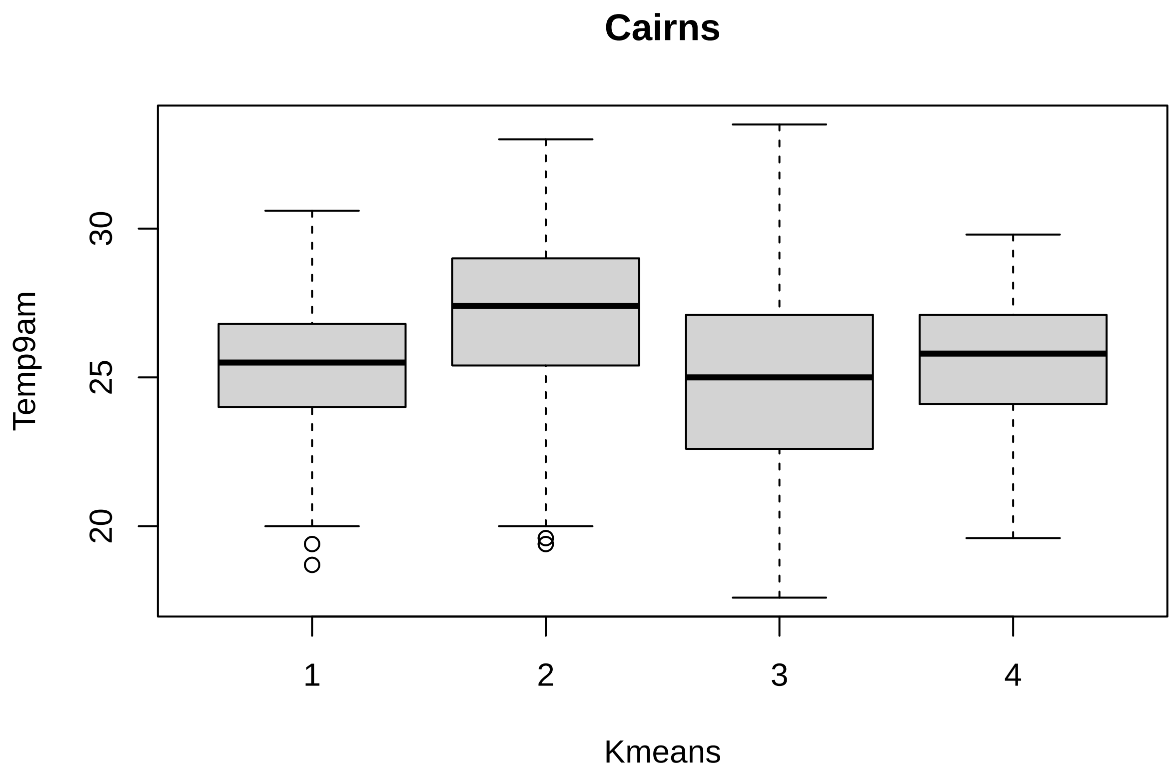
1
2
3
4
Kmeans


Cairns
Temp9am
20
25
30
1
2
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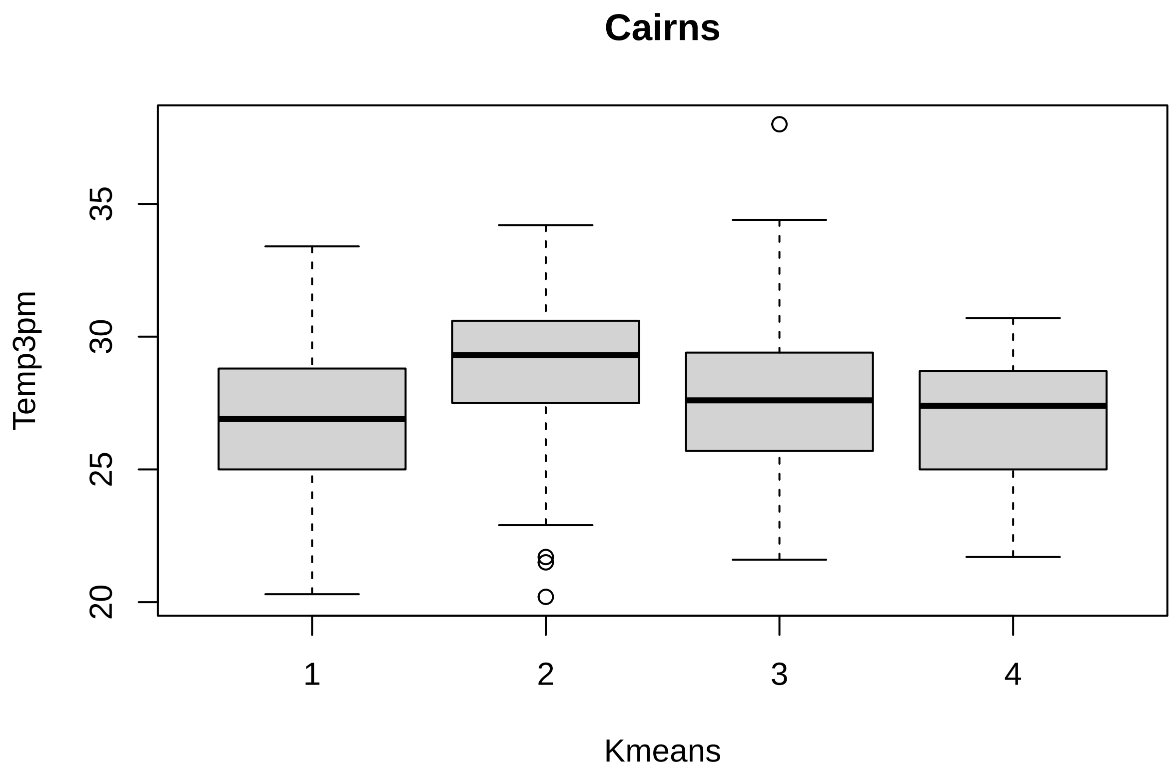
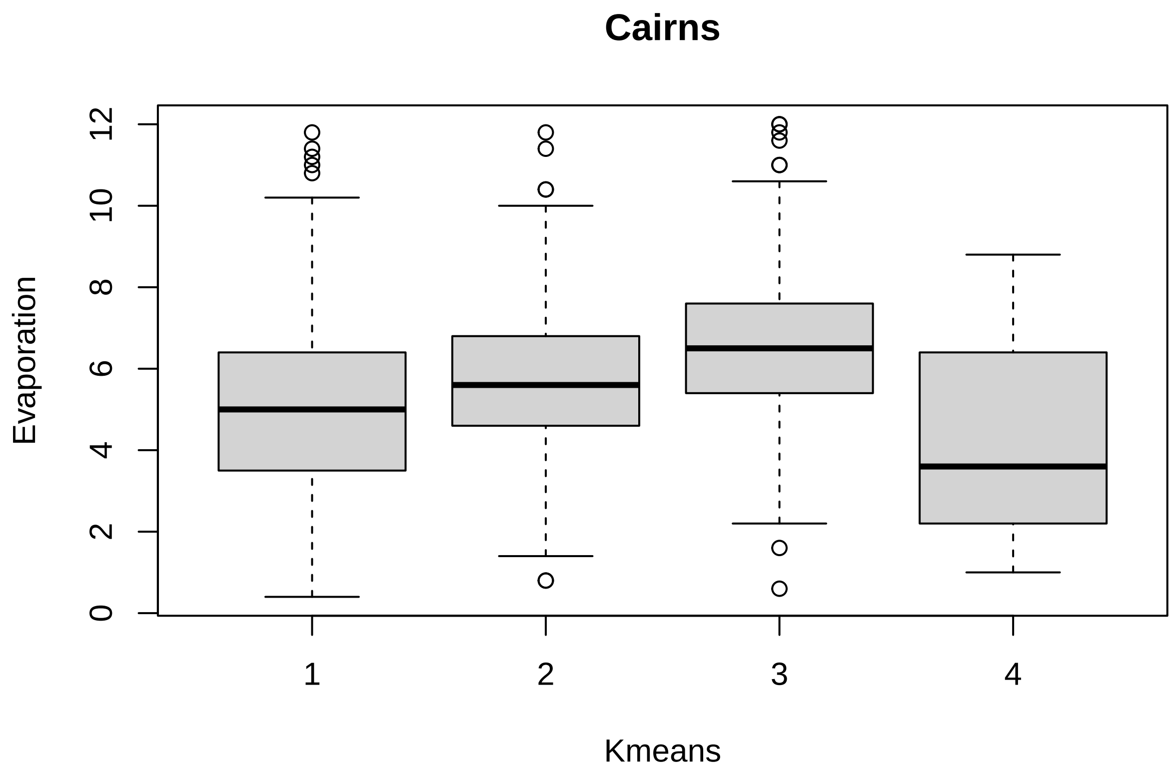
4
Kmeans


Cairns
Temp3pm
20
25
30
35
1
2
3
4
Kmeans


Cairns
Evaporation
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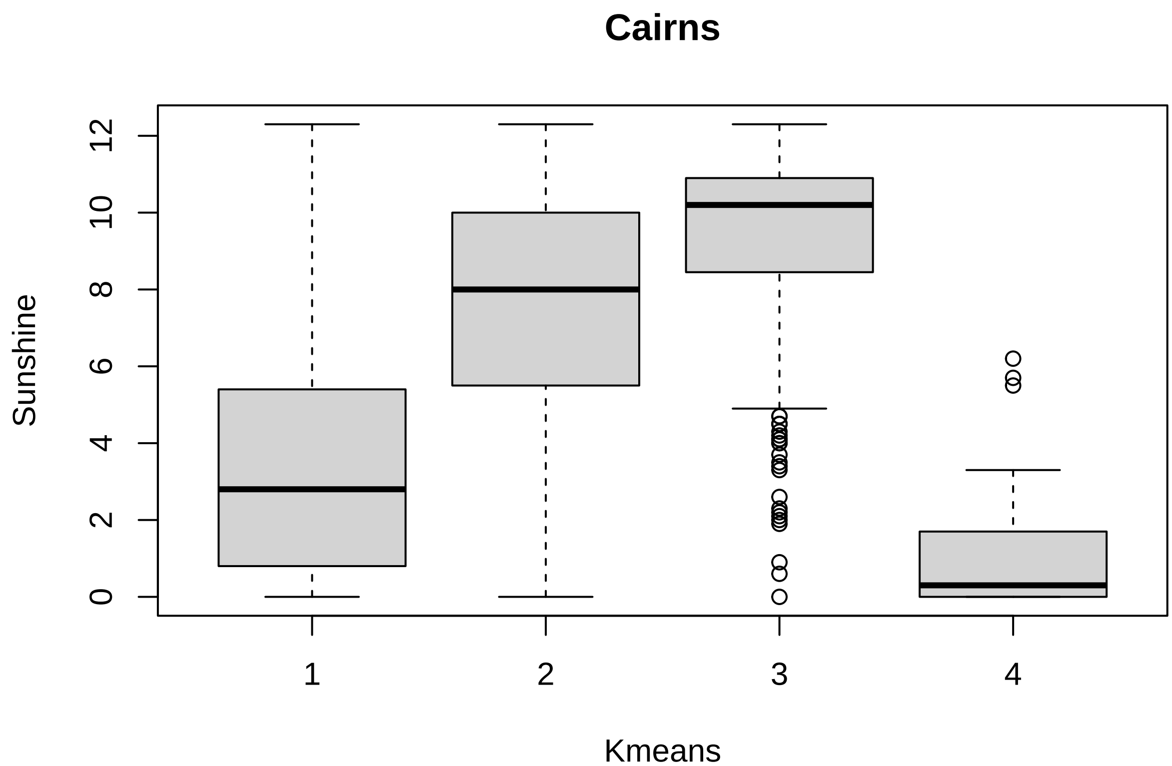
2
4
6
8
10
12
1
2
3
4
Kmeans


Cairns
Sunshine
0
2
4
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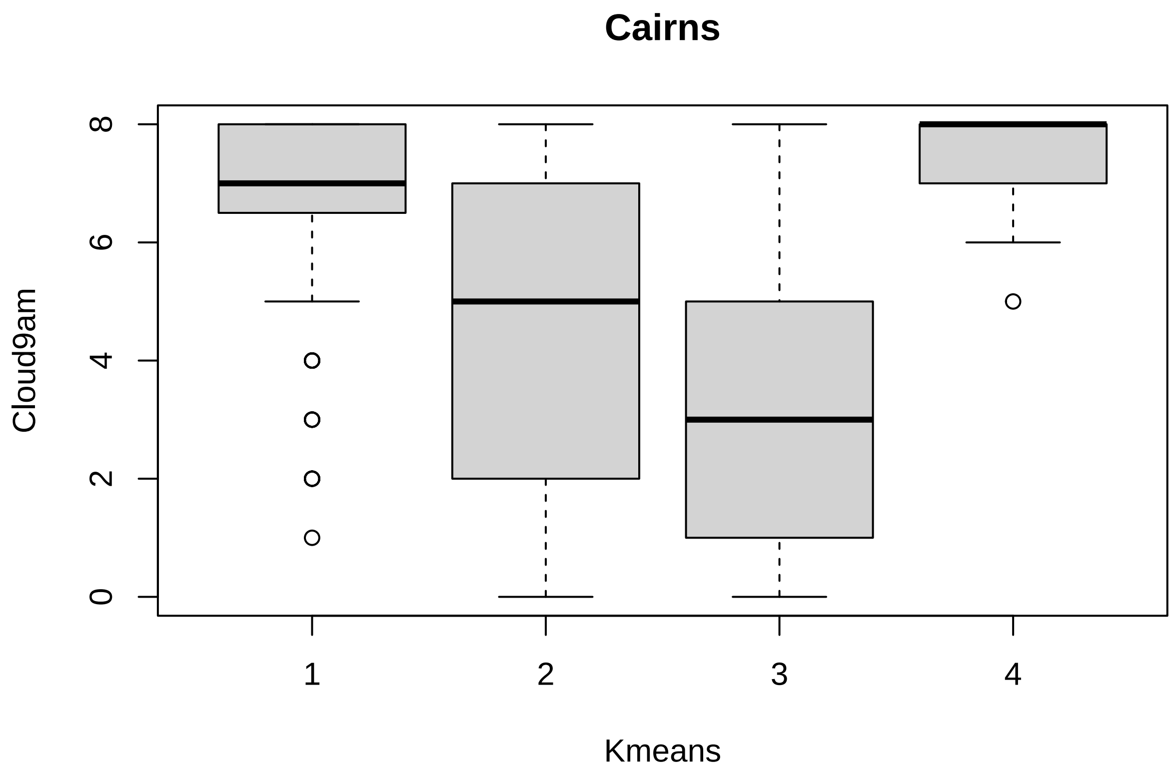
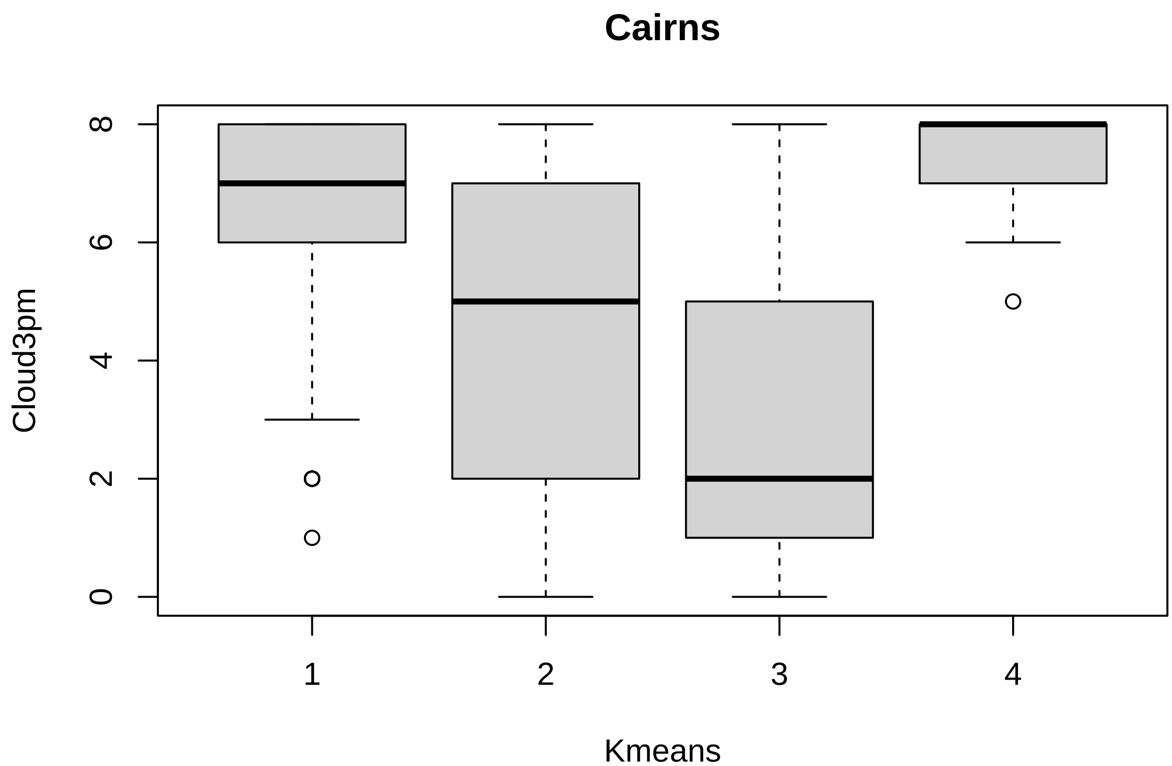
8
10
12
1
2
3
4
Kmeans


Cairns
Cloud9am
0
2
4
6
8
1
2
3
4
Kmeans


Cairns
Cloud3pm
0
2
4
6
8
1
2
3
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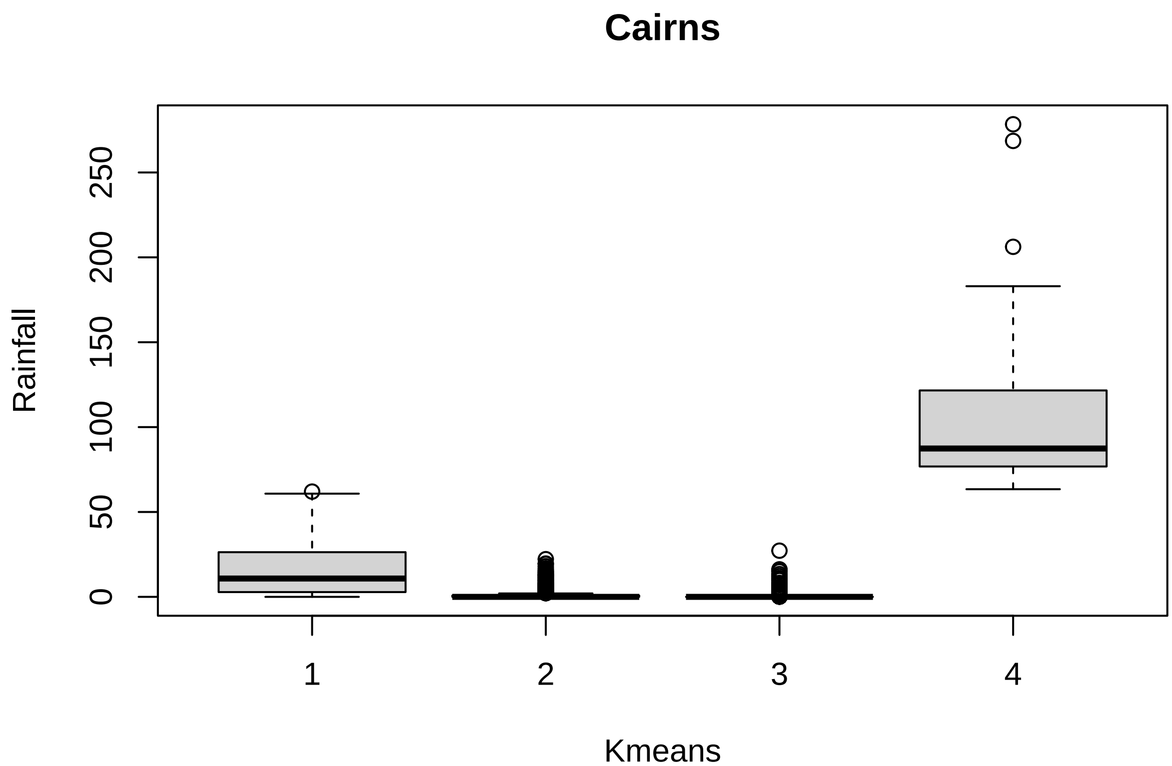
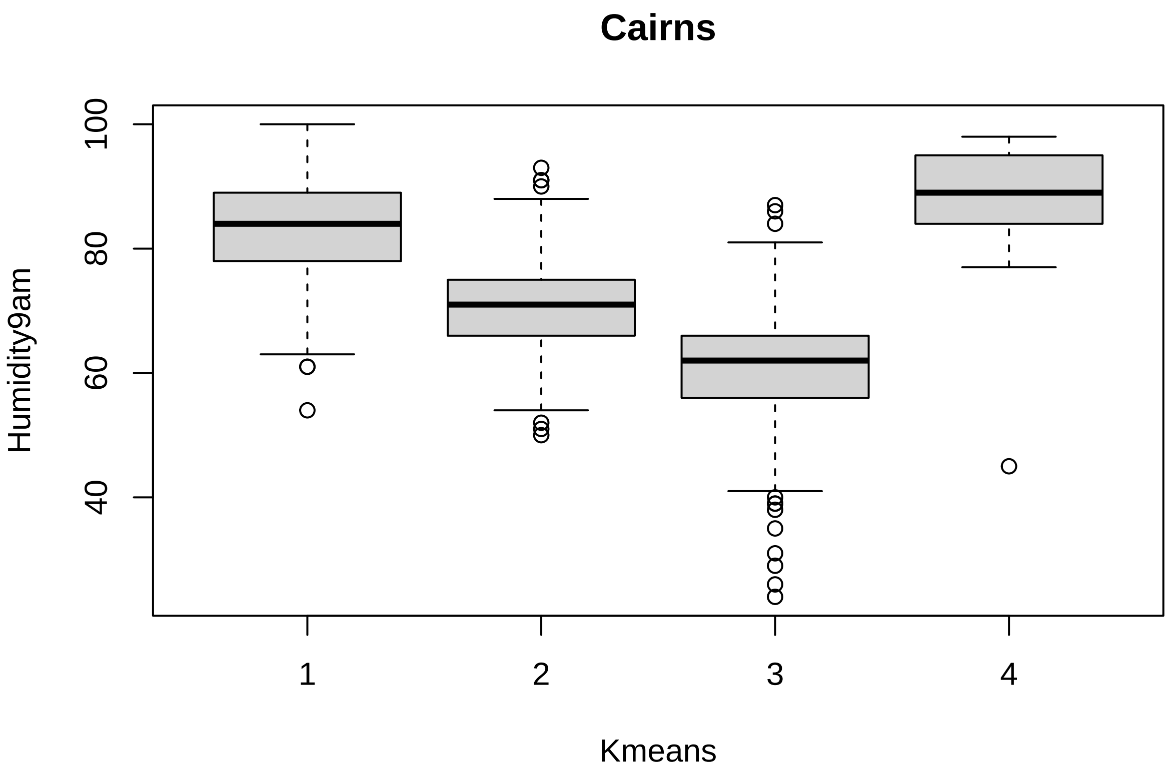
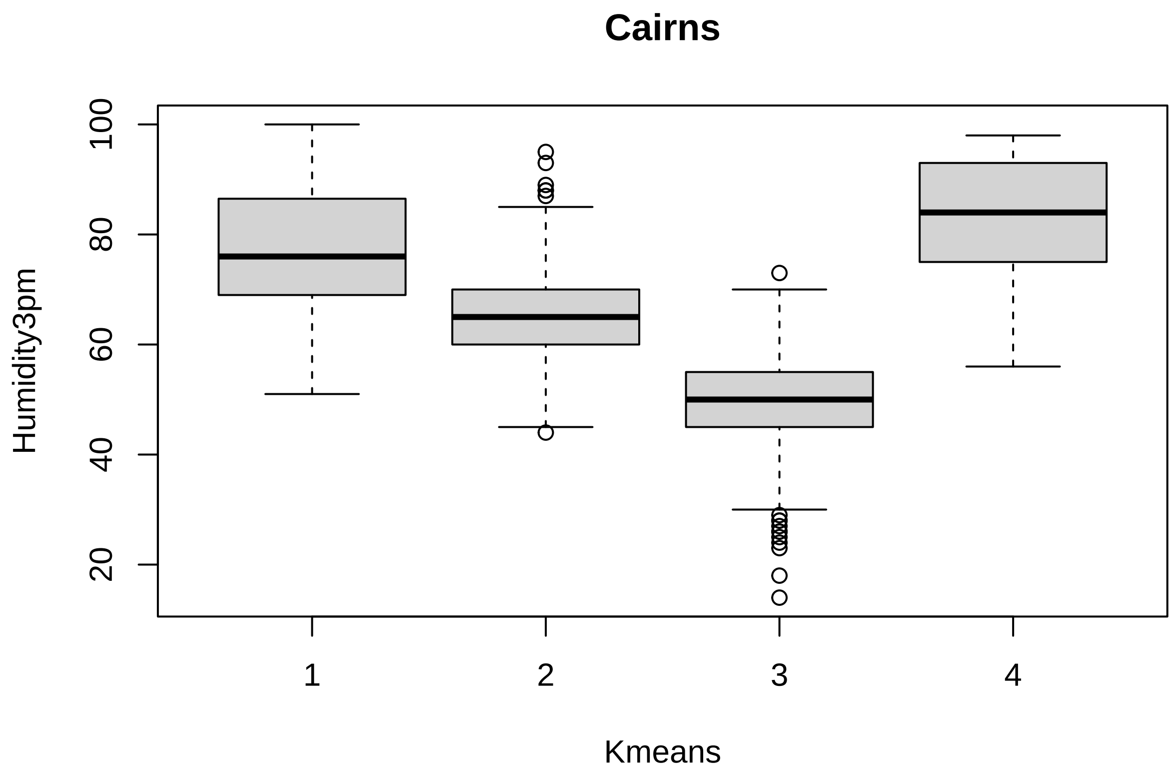
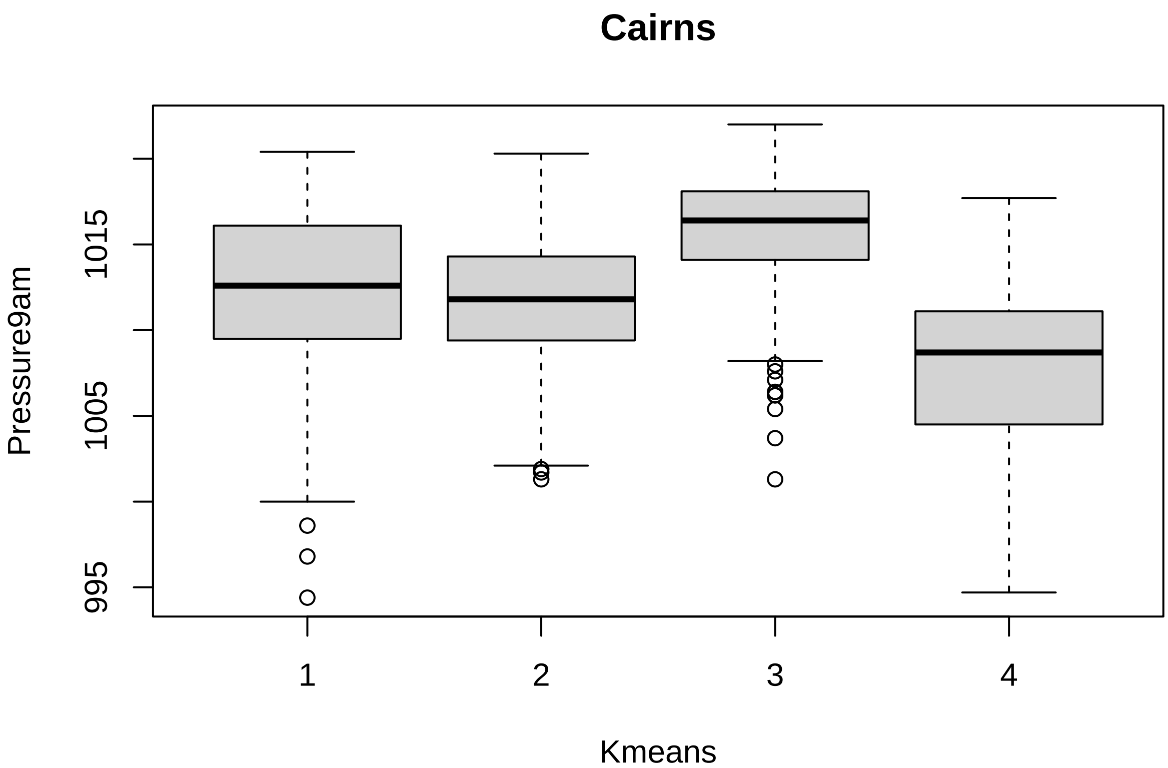
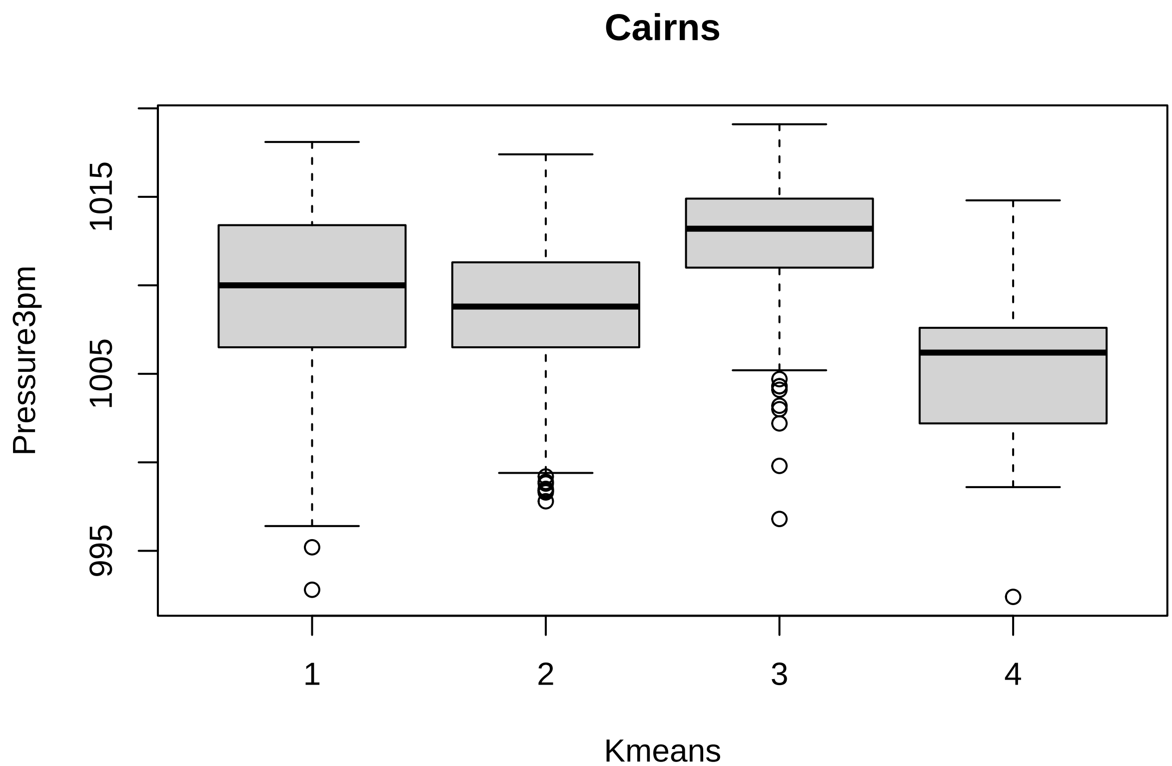
Kmeans


Cairns
Rainfall
0
50
100
150
200
250
1
2
3
4
Kmeans

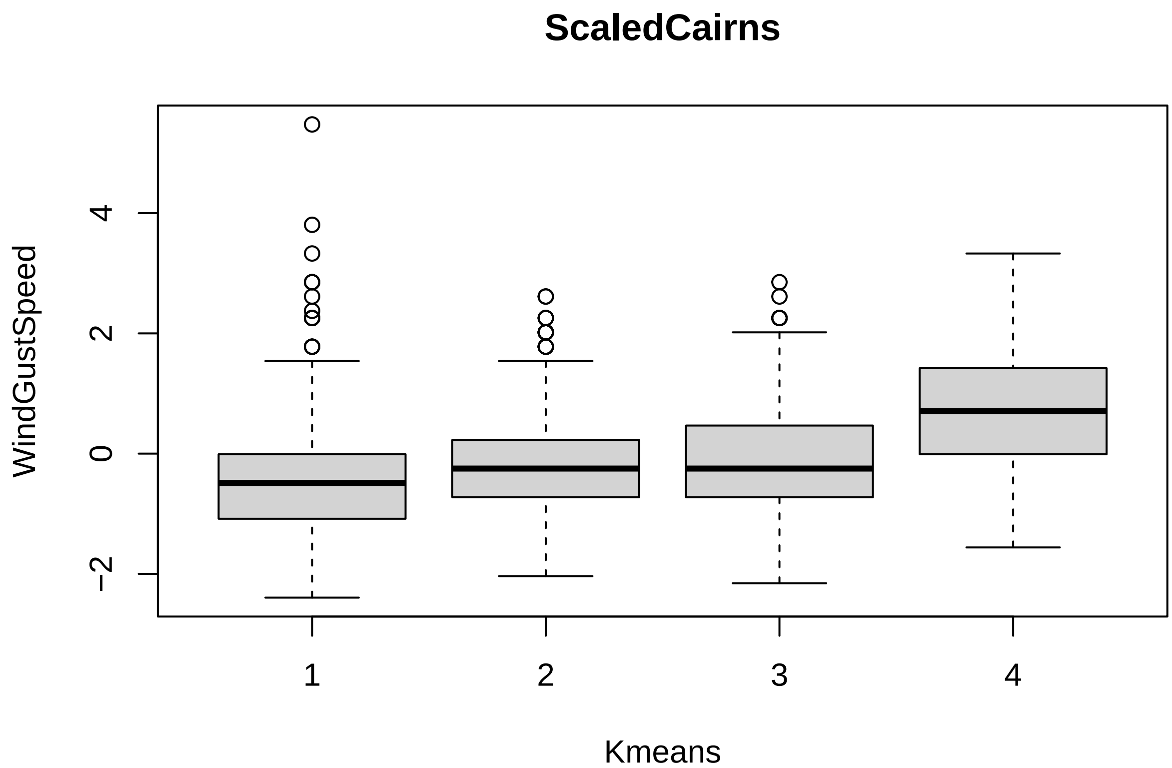

Cairns
100
80
60
40
Humidity9am
1
2
3
4
Kmeans

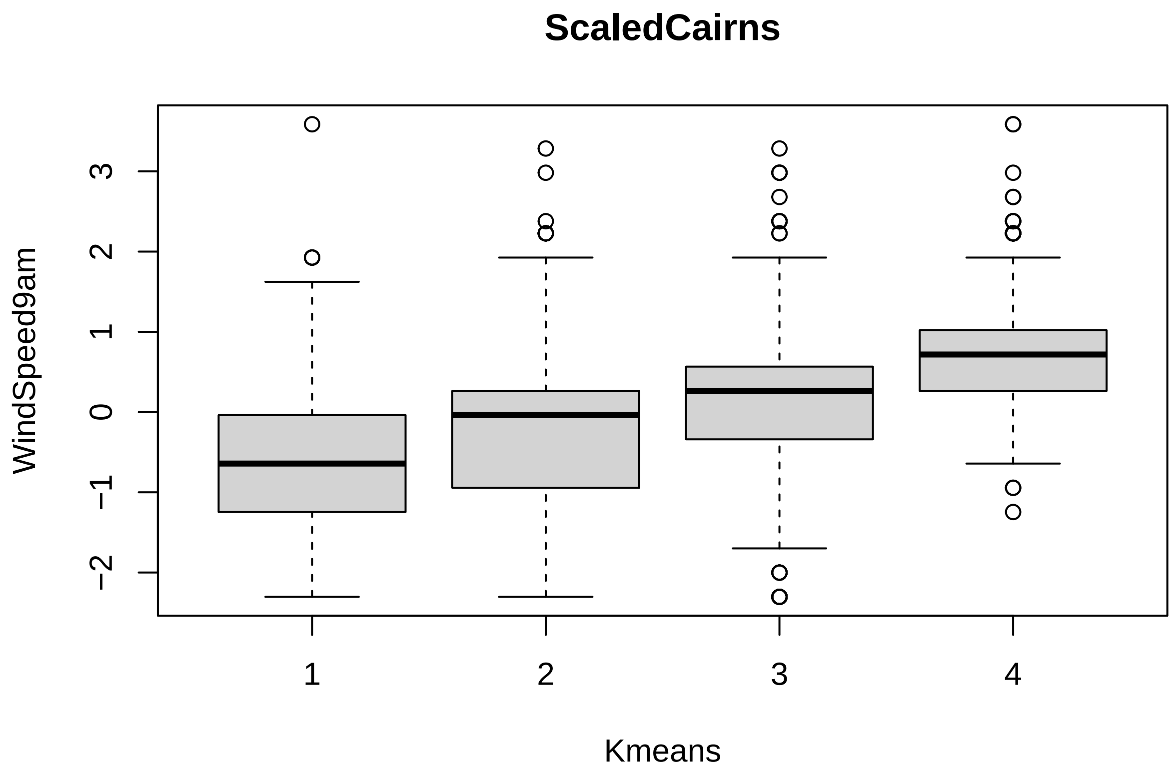

Cairns
Humidity3pm
100
80
60
40
20
1
2
3
4
Kmeans

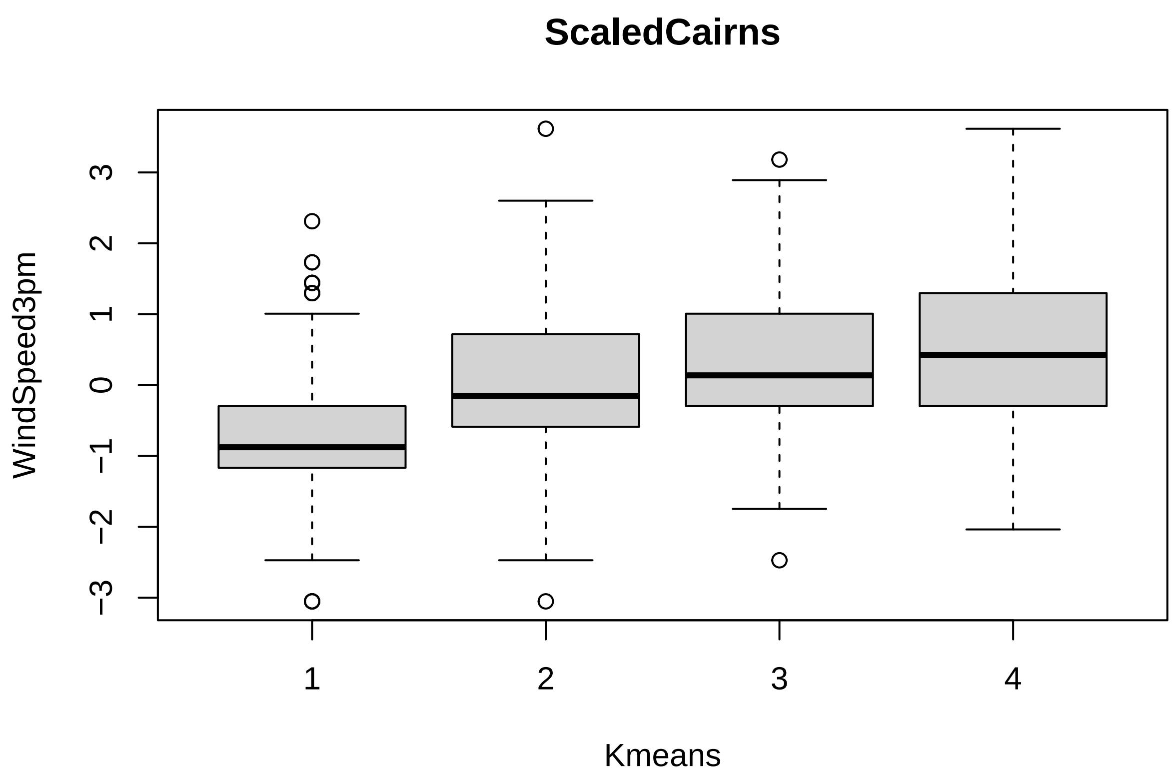

Cairns
Pressure9am
995
1005
1015
1
2
3
4
Kmeans

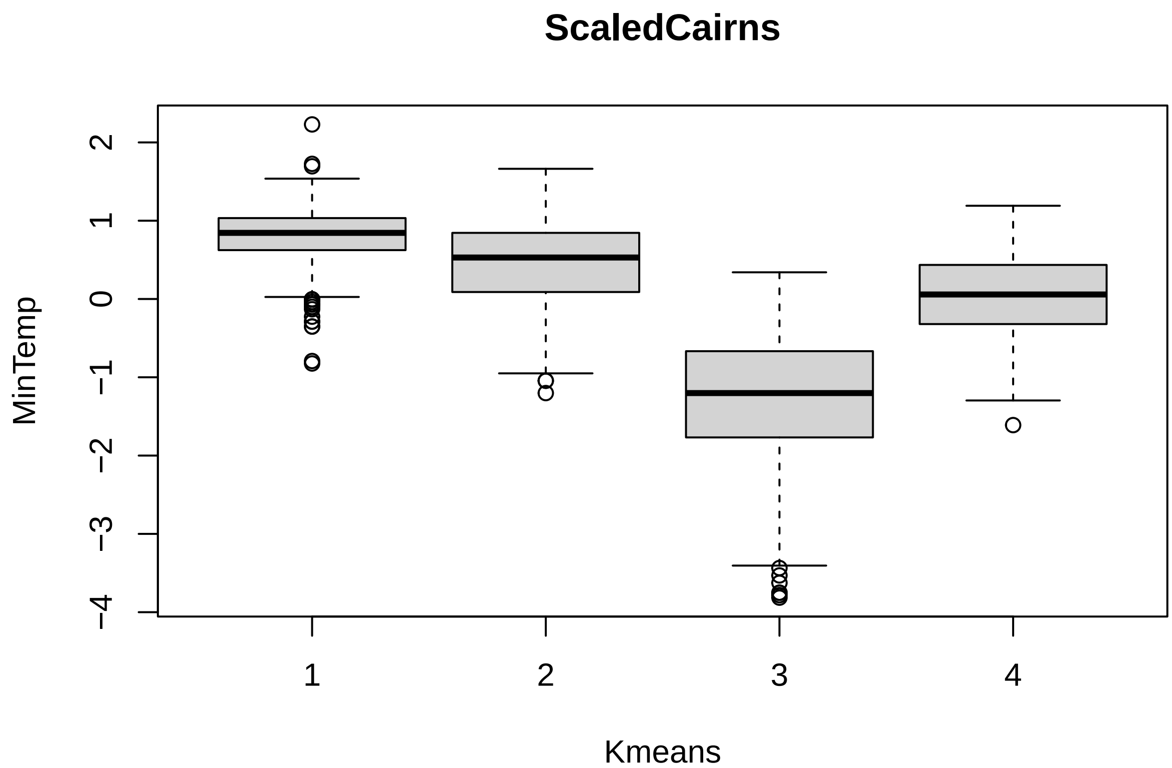


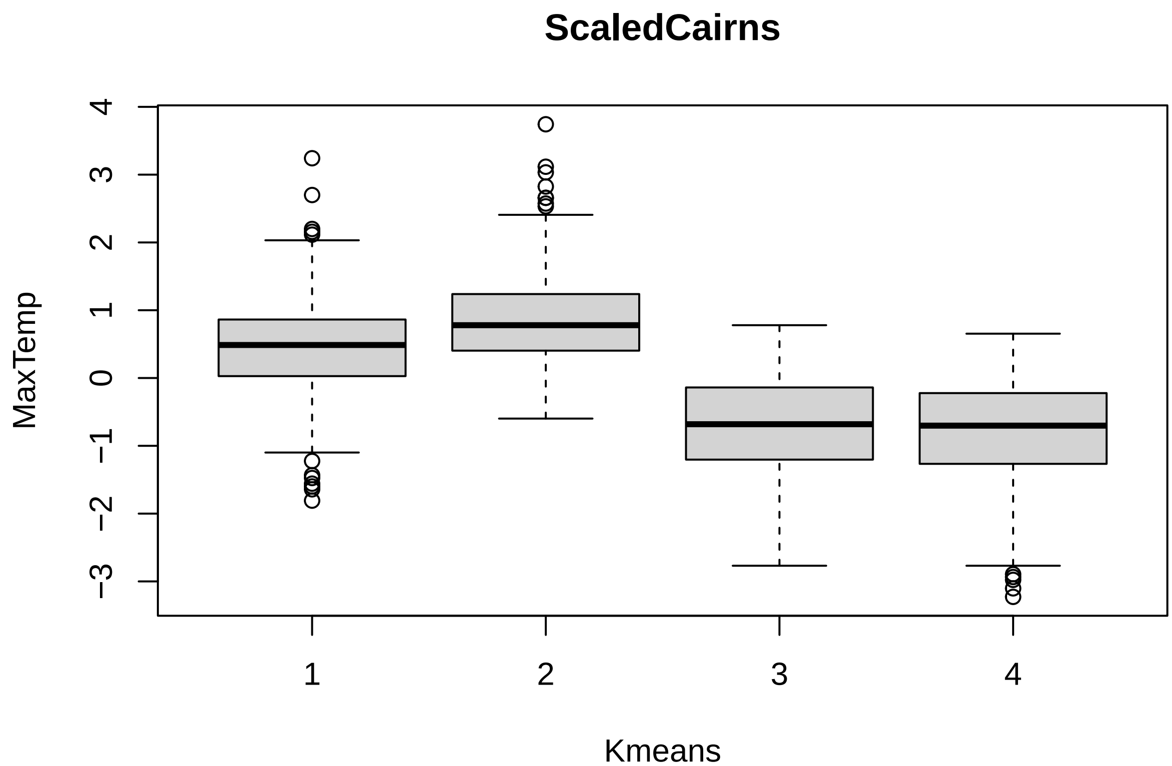
Cairns
Pressure3pm
1015
1005
995
1
2
3
4
Kmeans

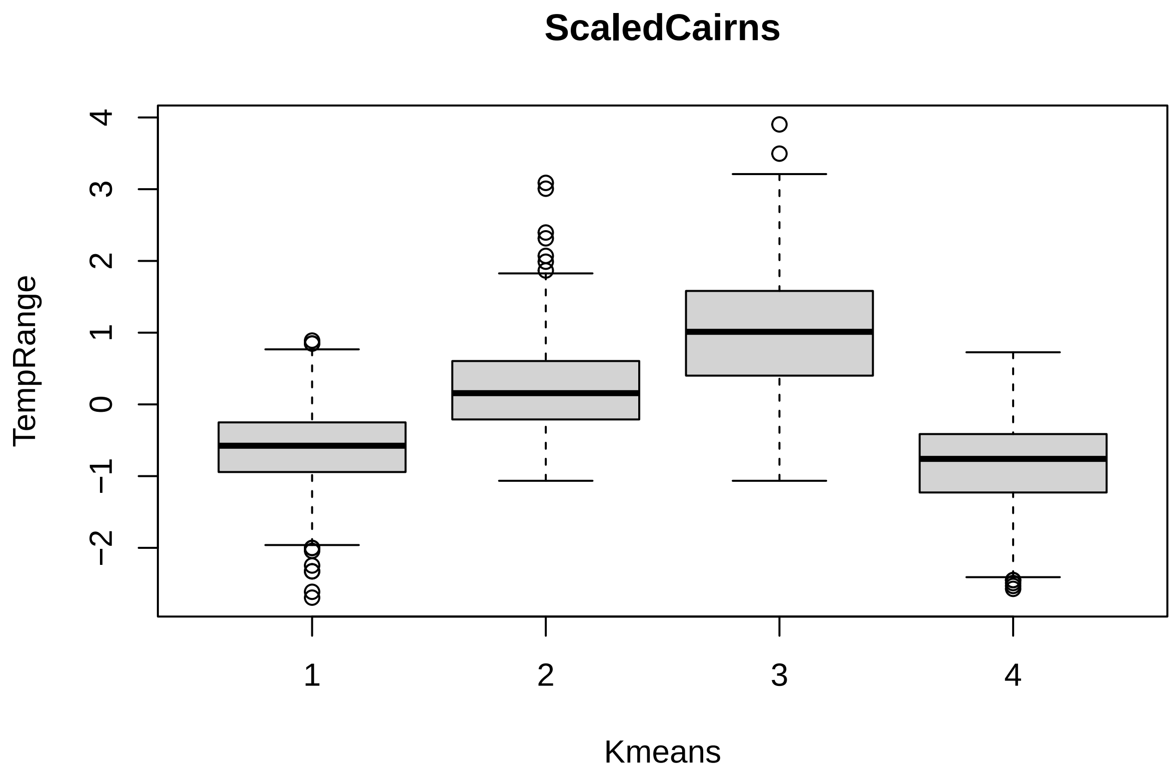

ScaledCairns
WindGustSpeed
4
2
0
−2
1
2
3
4
Kmeans

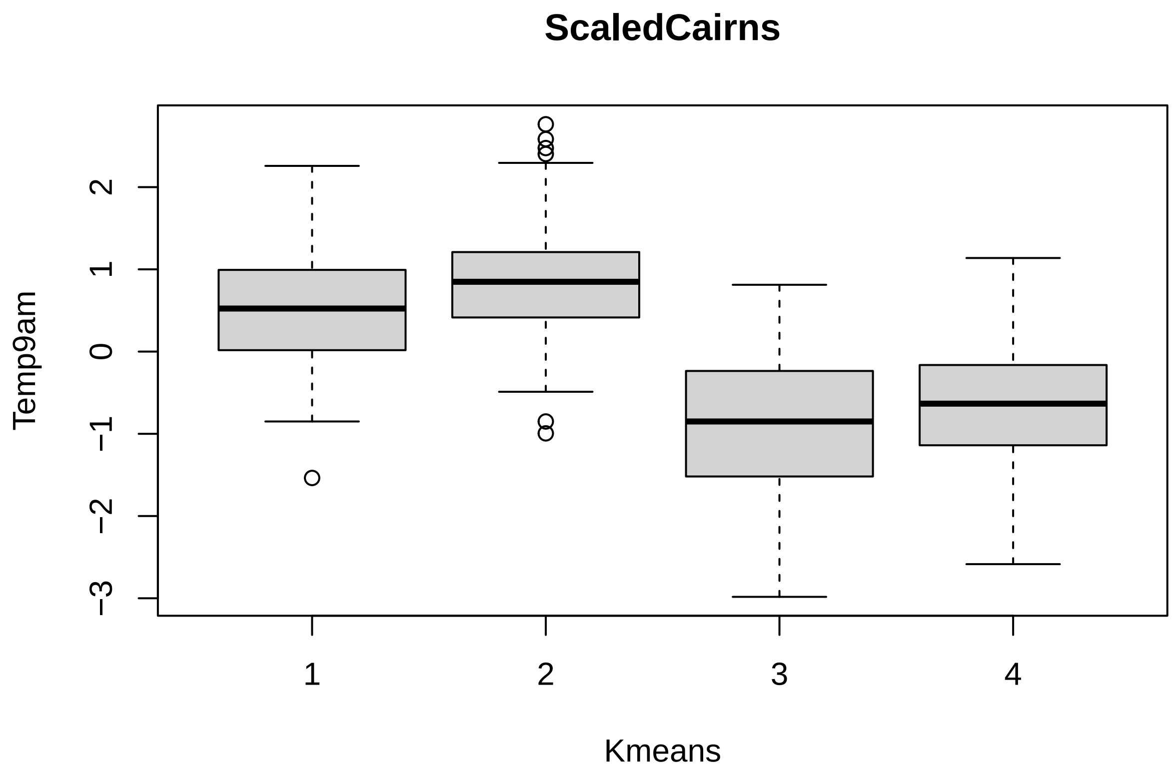

ScaledCairns
WindSpeed9am
3
2
1
0
−1
−2
1
2
3
4
Kmeans

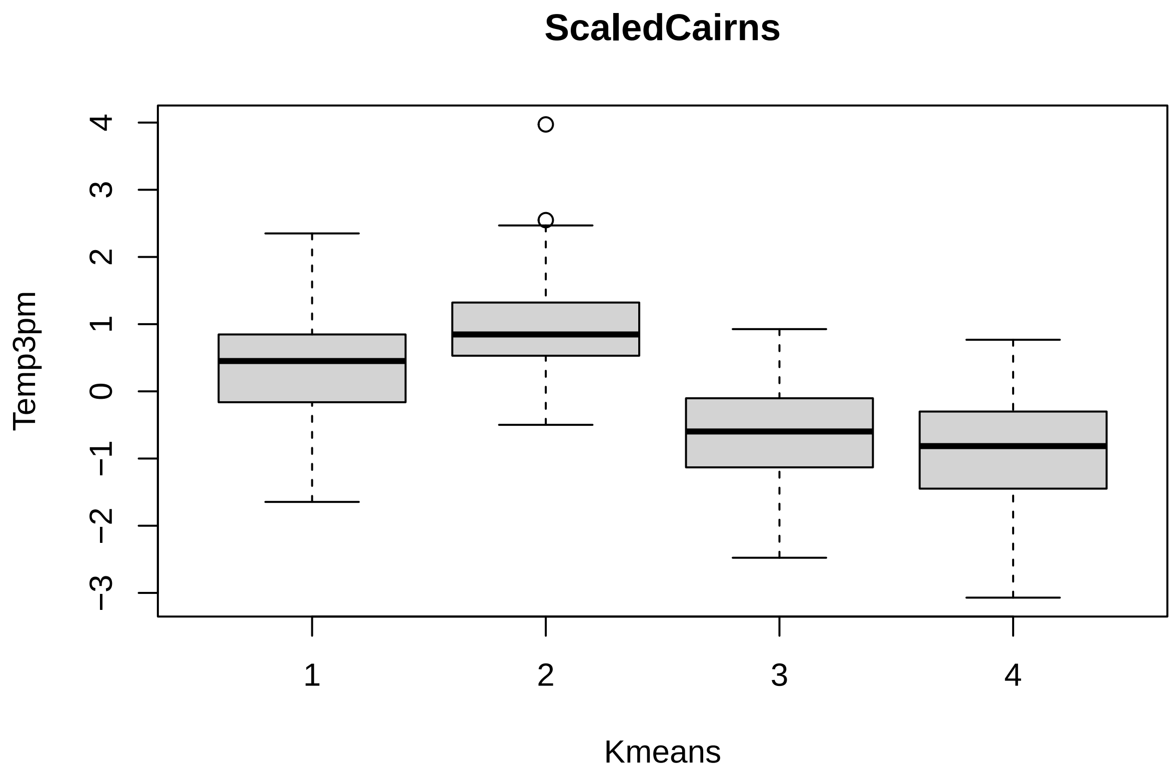

ScaledCairns
WindSpeed3pm
−3
−2
−1
0
1
2
3
1
2
3
4
Kmeans

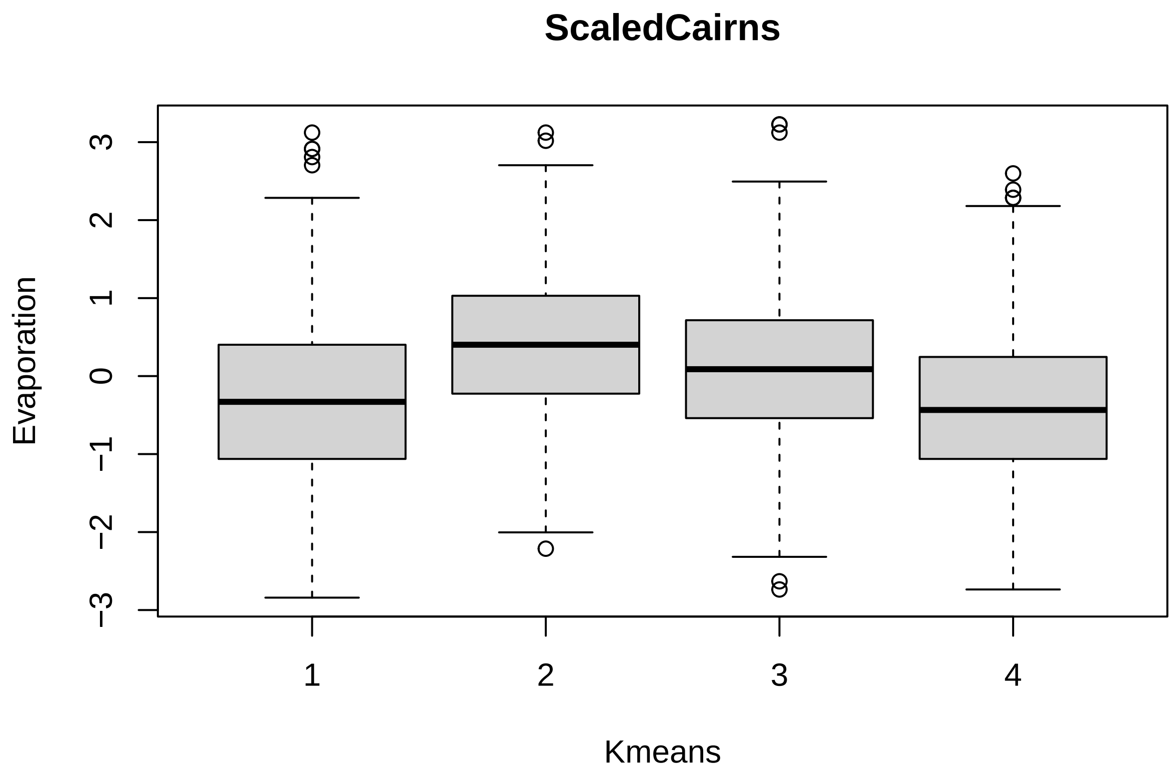

ScaledCairns
MinTemp
2
1
0
−1
−2
−3
−4
1
2
3
4
Kmeans

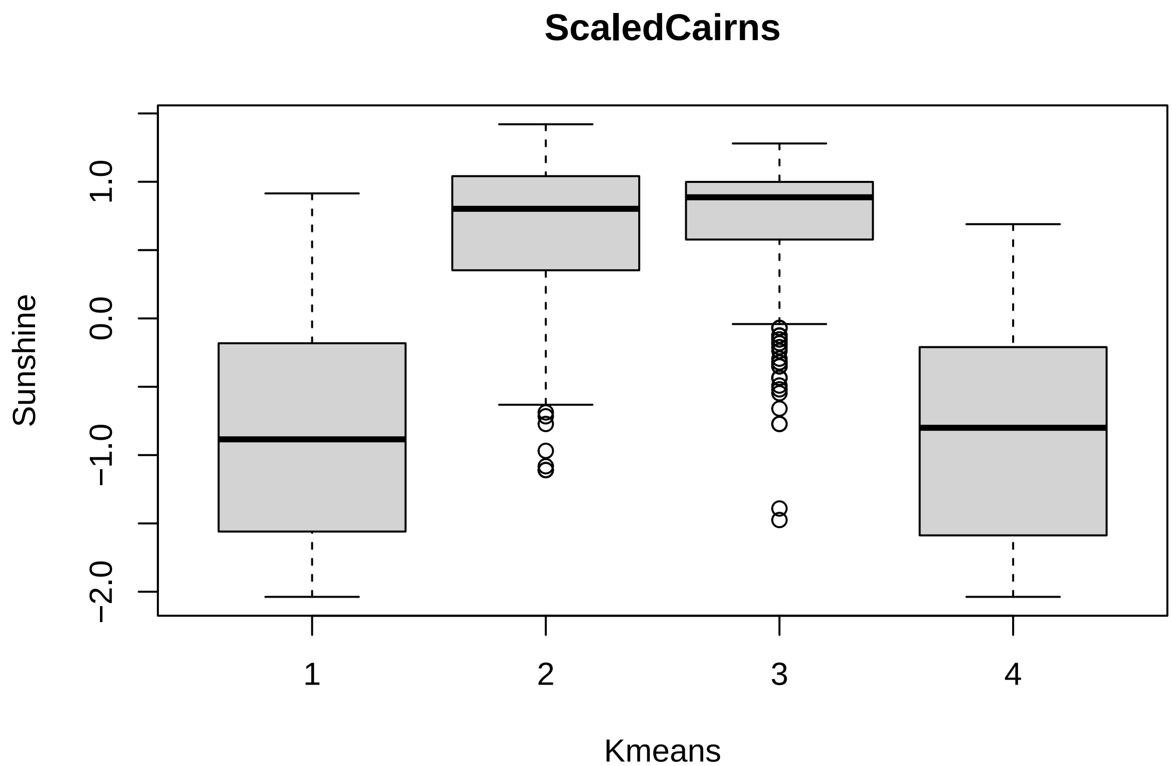

ScaledCairns
MaxTemp
4
3
2
1
0
−1
−2
−3
1
2
3
4
Kmeans

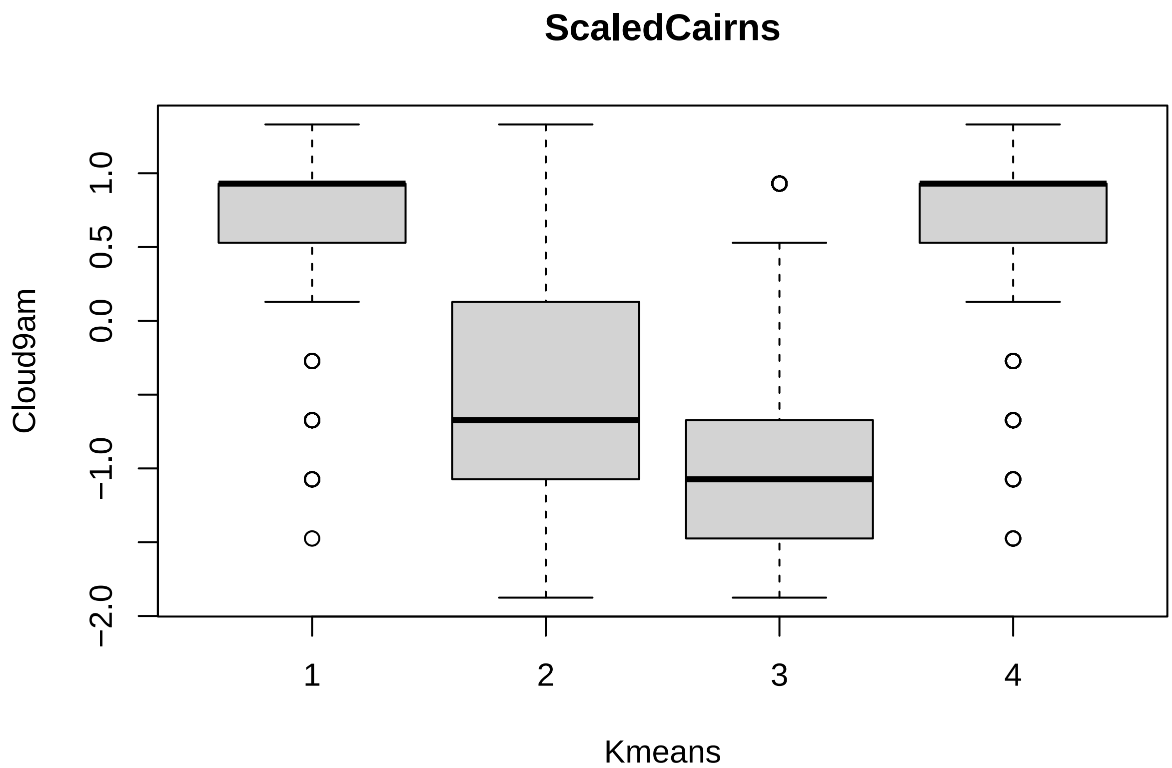

ScaledCairns
TempRange
4
3
2
1
0
−1
−2
1
2
3
4
Kmeans

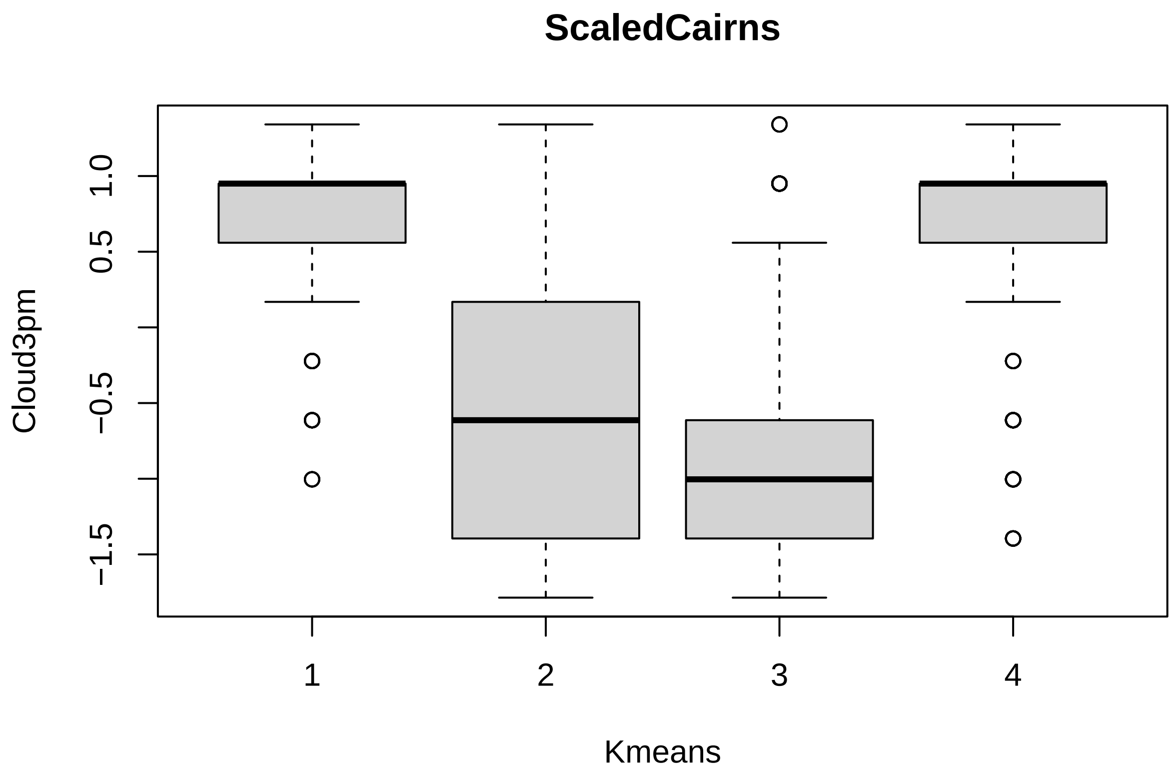

ScaledCairns
Temp9am
Kmeans
1
2
3
4
2
1
0
−1
−2
−3

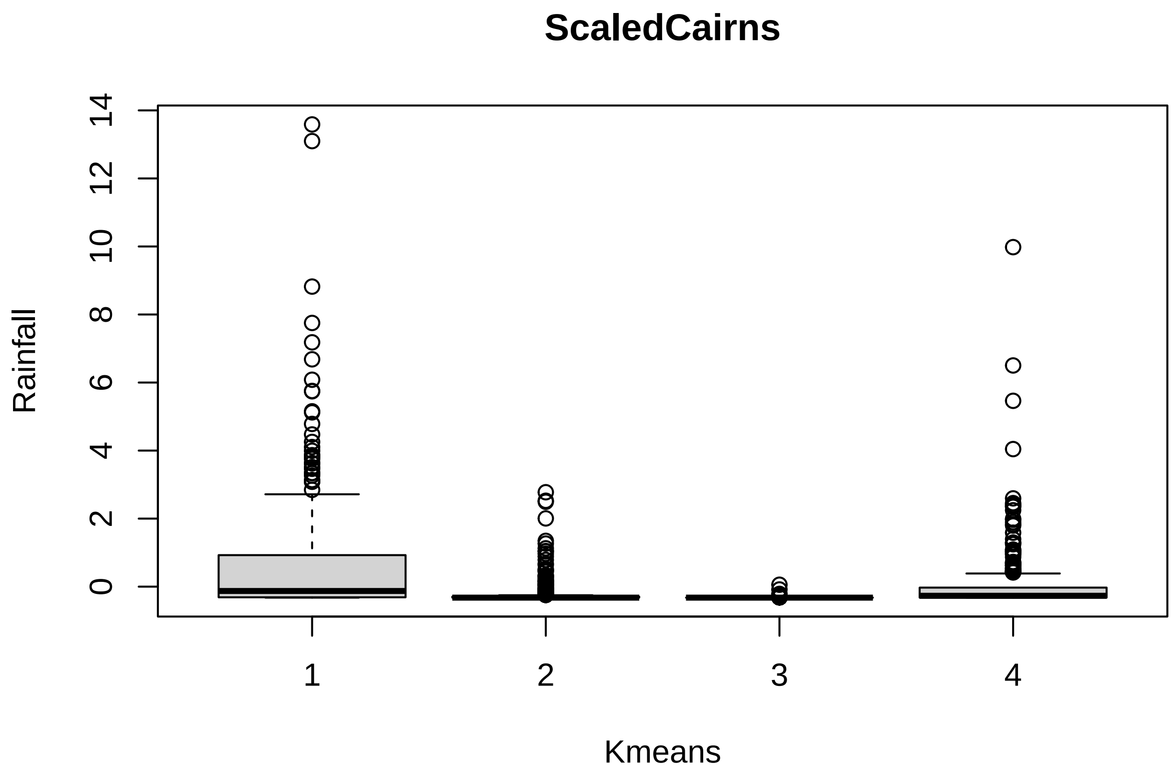

ScaledCairns
Temp3pm
Kmeans
4
3
2
1
0
−1
−2
−3
1
2
3
4

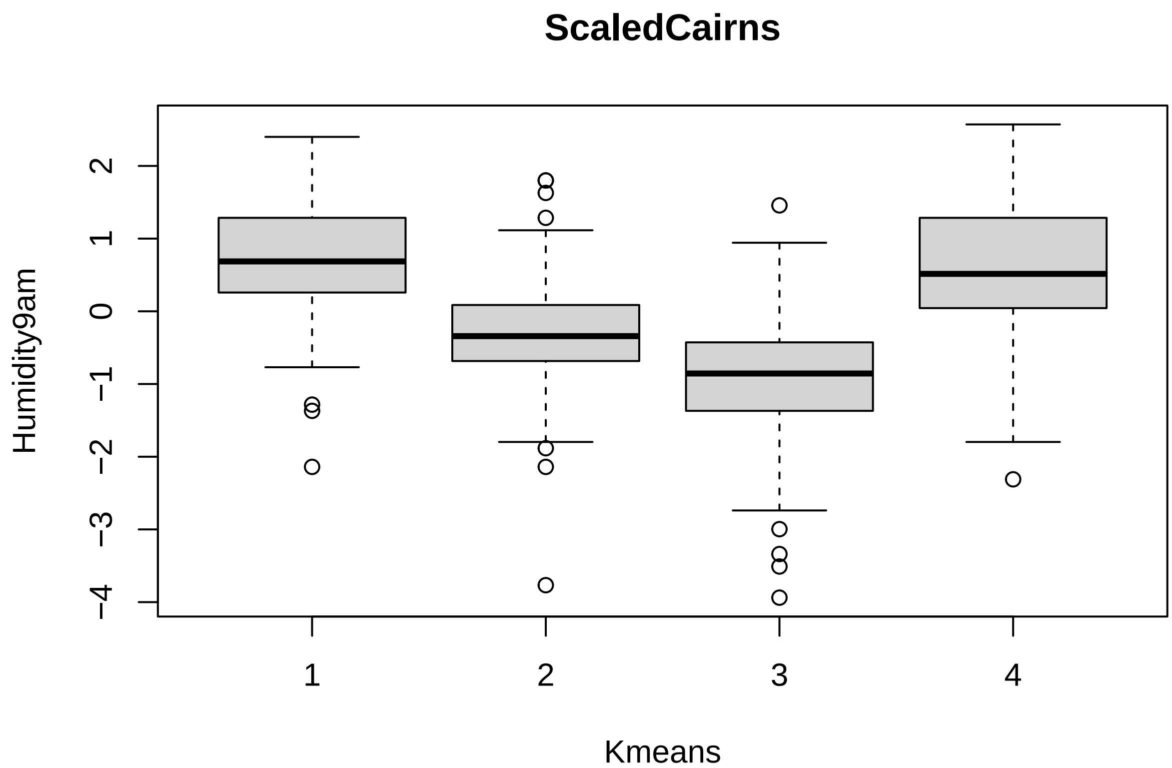

ScaledCairns
Evaporation
3
2
1
0
−1
−2
−3
1
2
3
4
Kmeans

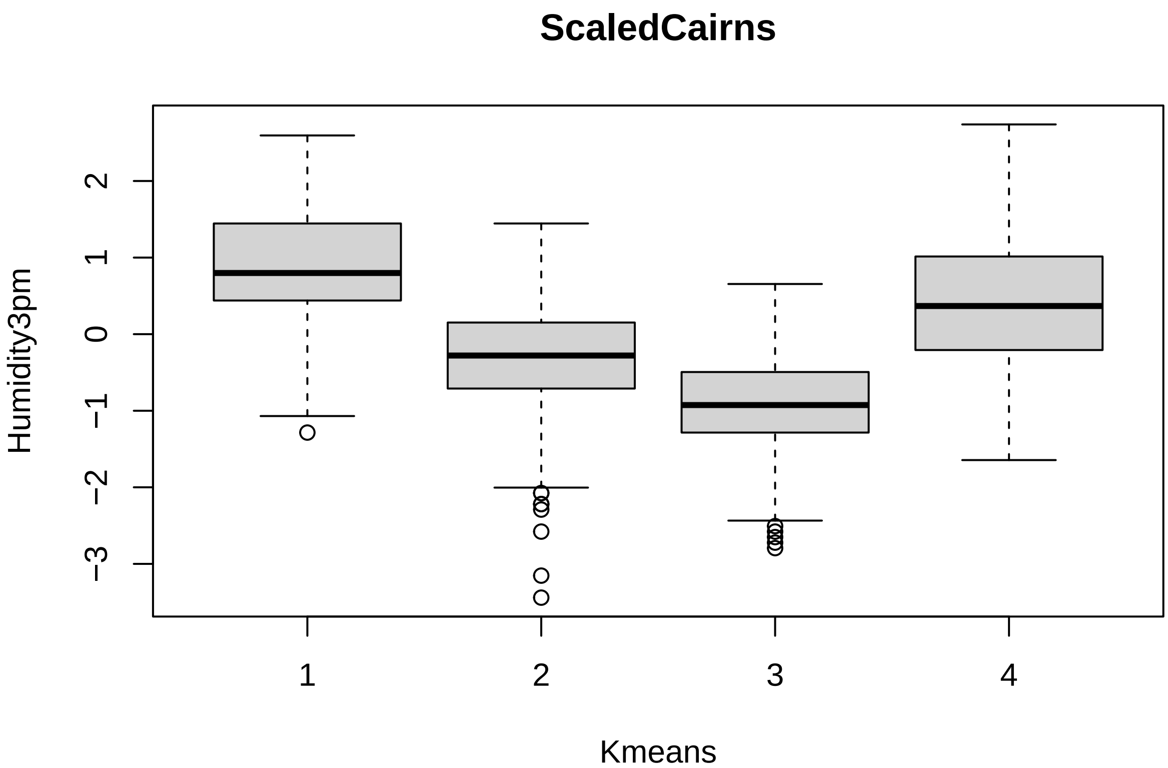

ScaledCairns
Sunshine
1.0
0.0
−1.0
−2.0
1
2
3
4
Kmeans

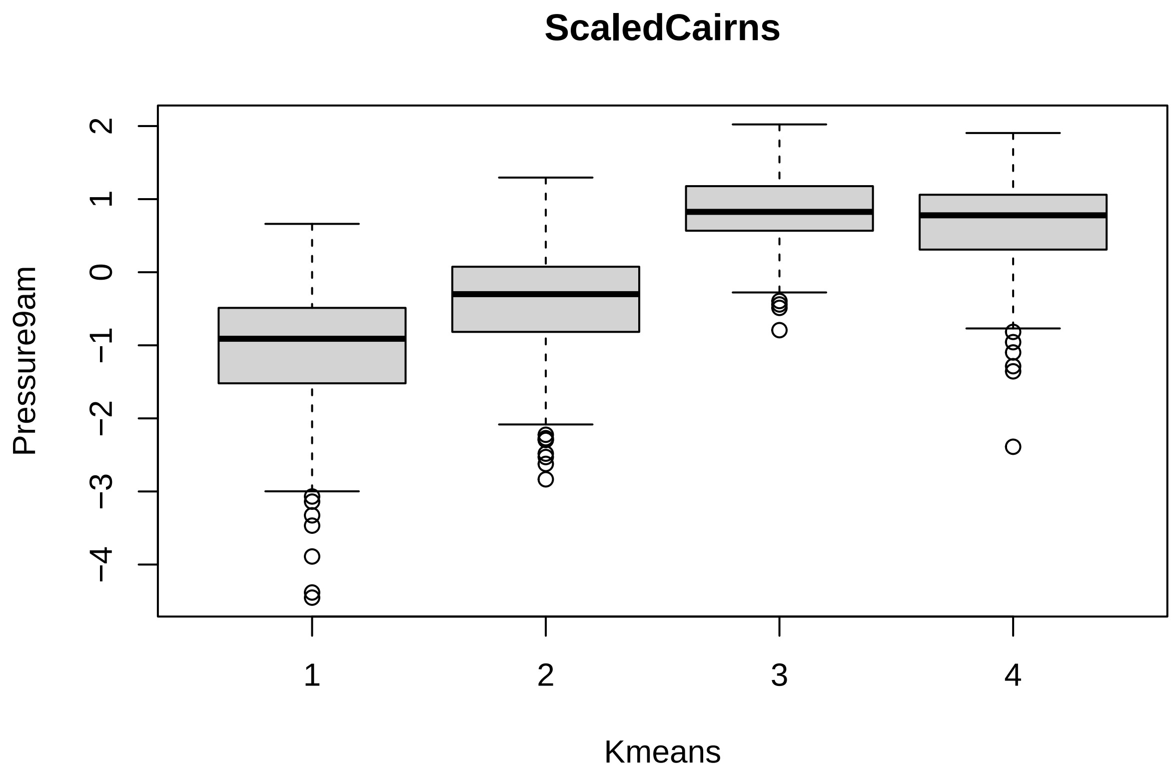

ScaledCairns
Cloud9am
1.0
0.5
0.0
−1.0
−2.0
1
2
3
4
Kmeans

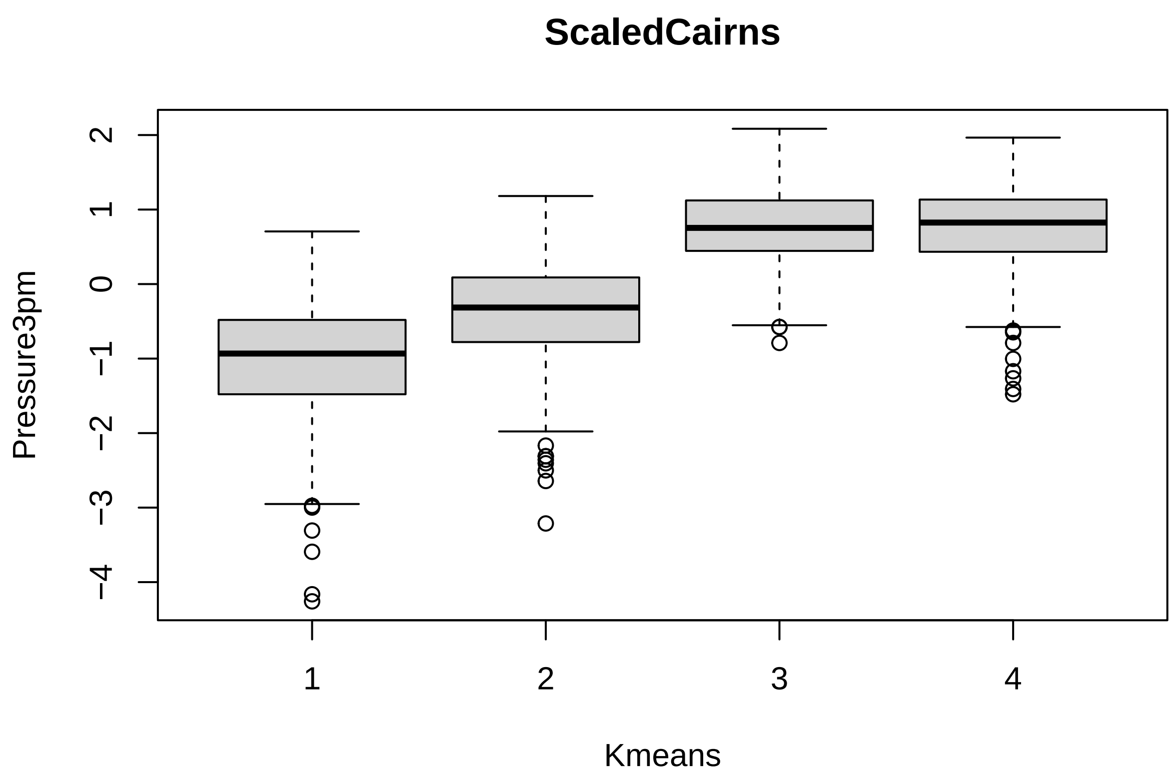

ScaledCairns
Cloud3pm
1.0
0.5
−0.5
−1.5
1
2
3
4
Kmeans


ScaledCairns
Rainfall
0
2
4
6
8
10
12
14
1
2
3
4
Kmeans


ScaledCairns
Humidity9am
2
1
0
−1
−2
−3
−4
1
2
3
4
Kmeans


ScaledCairns
Humidity3pm
2
1
0
−1
−2
−3
1
2
3
4
Kmeans


ScaledCairns
Pressure9am
2
1
0
−1
−2
−3
−4
1
2
3
4
Kmeans




```r
fun04<-function(x) print(names(x))
lapply(Kmeans, fun04)

fun05<-function(x){x[,ncol(x)]
                   x$KMCluster<-x[,ncol(x)]
                   return(x$KMCluster)}

clusters<-lapply(Kmeans,fun05)

BrisbaneClusters<-as.data.frame(cbind(originaldata[[1]],as.factor(clusters[[1]]),
                                      as.factor(clusters[[2]])))
names(BrisbaneClusters)<-c(names(originaldata[[1]]),"KmeansDF","KmeansScaled")

PerthClusters<-as.data.frame(cbind(originaldata[[2]],as.factor(clusters[[3]]),
                                   as.factor(clusters[[4]])))

names(PerthClusters)<-c(names(originaldata[[3]]),"KmeansDF","KmeansScaled")

CairnsClusters<-as.data.frame(cbind(originaldata[[3]],as.factor(clusters[[5]]),
                                    as.factor(clusters[[6]])))
names(CairnsClusters)<-c(names(originaldata[[3]]),"KmeansDF","KmeansScaled")



funMetrics<-function(i){ tmp_df = listall[[i]]
```

```
                      }
lapply(1:length(listall), funMetrics)
```

```
write.csv(BrisbaneClusters,"BrisbaneClusters.csv")
write.csv(PerthClusters,"PerthClusters.csv")
write.csv(CairnsClusters,"CairnsClusters.csv")

DFClusters<-list(BrisbaneClusters,PerthClusters,CairnsClusters)


fun06<-function(x){tmpdf=DFClusters[[x]]
                   levels(tmpdf[,24])<-list(C1="1",C2="2",C3="3",C4="4")
                   levels(tmpdf[,25])<-list(G1="1",G2="2",G3="3",G4="4")
                   return(tmpdf)}
data<-lapply(1:length(DFClusters),fun06)
```

```
funtableKmeans<-function(x){table(x$KmeansDF,x$KmeansScaled)}
funtabseason<-function(x){table(x$KmeansDF,x$Season) }
funtabseason2<-function(x){table(x$KmeansScaled,x$Season) }
funtabseason2<-function(x){table(x$KmeansScaled,x$RainTomorrow) }

lapply(data, funtableKmeans)
```

```
## [[1]]
##
##       G1  G2  G3  G4
##   C1  66   8 228   0
##   C2 534  20  44 113
##   C3   4  98   1 179
##   C4  36 190 263  13
##
## [[2]]
##
##       G1  G2  G3  G4
##   C1  54   0 259   0
##   C2   9 204 178 216
##   C3   2 109   2 327
##   C4 309 110  17   1
##
## [[3]]
##
##       G1  G2  G3  G4
##   C1 153  17   0 170
##   C2 186 280  70  99
##   C3   0 203 334  95
##   C4  33   0   0   4
```

```
lapply(data,funtabseason)
```

```
## [[1]]
##
##      autumn spring summer winter
```

```
##   C1     48    104     15    135
##   C2    149    204    339     19
##   C3     97     48     96     41
##   C4    166     99      1    236
##
## [[2]]
##
##      autumn spring summer winter
##   C1     57     84     21    151
##   C2    149    198    231     29
##   C3    127     97    198     18
##   C4    127     76      1    233
##
## [[3]]
##
##      dry wet
##   C1 155 185
##   C2 268 367
##   C3 492 140
##   C4   3  34
```

```r
lapply(data,funtabseason2)
```

```
## [[1]]
##
##       No Yes
##   G1 526 114
##   G2 182 134
##   G3 521  15
##   G4 117 188
##
## [[2]]
##
##       No Yes
##   G1 316  58
##   G2 397  26
##   G3 222 234
##   G4 520  24
##
## [[3]]
##
##       No Yes
##   G1 133 239
##   G2 381 119
##   G3 390  14
##   G4 200 168
```

```r
#boxplot(BrisbaneClusters$Pressure9am ~ BrisbaneClusters$KmeansDF)

funtableKmeans<-function(x){table(x$KmeansDF,x$KmeansScaled)}
funtabseason<-function(x){table(x$KmeansDF,x$Season) }
funtabseason2<-function(x){table(x$KmeansScaled,x$Season) }
funtabseason2<-function(x){table(x$KmeansScaled,x$Season) }
```

```r
lapply(data, funtableKmeans)
```

```
## [[1]]
##
##      G1  G2  G3  G4
##   C1  66   8 228   0
##   C2 534  20  44 113
##   C3   4  98   1 179
##   C4  36 190 263  13
##
## [[2]]
##
##      G1  G2  G3  G4
##   C1  54   0 259   0
##   C2   9 204 178 216
##   C3   2 109   2 327
##   C4 309 110  17   1
##
## [[3]]
##
##      G1  G2  G3  G4
##   C1 153  17   0 170
##   C2 186 280  70  99
##   C3   0 203 334  95
##   C4  33   0   0   4
```

```r
lapply(data,funtabseason)
```

```
## [[1]]
##
##     autumn spring summer winter
##   C1     48    104     15    135
##   C2    149    204    339     19
##   C3     97     48     96     41
##   C4    166     99      1    236
##
## [[2]]
##
##     autumn spring summer winter
##   C1     57     84     21    151
##   C2    149    198    231     29
##   C3    127     97    198     18
##   C4    127     76      1    233
##
## [[3]]
##
##     dry wet
##   C1 155 185
##   C2 268 367
##   C3 492 140
##   C4   3  34
```

```r
lapply(data,funtabseason2)
```

```
## [[1]]
##
##      autumn spring summer winter
##   G1    147    198    289      6
##   G2    105     66      0    145
##   G3    117    141      0    278
##   G4     91     50    162      2
##
## [[2]]
##
##      autumn spring summer winter
##   G1     77     42      1    254
##   G2    153    186     33     51
##   G3    108    158     64    126
##   G4    122     69    353      0
##
## [[3]]
##
##      dry wet
##   G1  56 316
##   G2 141 359
##   G3 400   4
##   G4 321  47
```

```r
kruskal.test(Kmeans$Brisbane$Rainfall ~ Kmeans$Brisbane$KmeansCluster, data = Kmeans$Brisbane)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  Kmeans$Brisbane$Rainfall by Kmeans$Brisbane$KmeansCluster
## Kruskal-Wallis chi-squared = 570.6, df = 3, p-value < 2.2e-16
```

```r
kruskal.test(Kmeans$Perth$Rainfall ~ Kmeans$Perth$KmeansCluster, data = Kmeans$Perth)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  Kmeans$Perth$Rainfall by Kmeans$Perth$KmeansCluster
## Kruskal-Wallis chi-squared = 647.99, df = 3, p-value < 2.2e-16
```

```r
kruskal.test(Kmeans$Cairns$Rainfall ~Kmeans$Cairns$KmeansCluster, data = Kmeans$Cairns)
```

```
##
##  Kruskal-Wallis rank sum test
##
## data:  Kmeans$Cairns$Rainfall by Kmeans$Cairns$KmeansCluster
## Kruskal-Wallis chi-squared = 813.73, df = 3, p-value < 2.2e-16
```

```r
# As the p-value is less than the significance level 0.05, we can conclude that there are significant d

#From the output of the Kruskal-Wallis test, we know that there is a significant difference between gro

pairwise.wilcox.test(Kmeans$Brisbane$Rainfall,Kmeans$Brisbane$KmeansCluster, p.adjust.method = "BH")
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  Kmeans$Brisbane$Rainfall and Kmeans$Brisbane$KmeansCluster
##
##   1       2       3
## 2 1.2e-08 -       -
## 3 < 2e-16 < 2e-16 -
## 4 0.00014 0.02033 < 2e-16
##
## P value adjustment method: BH
```

```r
pairwise.wilcox.test(Kmeans$Perth$Rainfall,Kmeans$Perth$KmeansCluster, p.adjust.method = "BH")
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  Kmeans$Perth$Rainfall and Kmeans$Perth$KmeansCluster
##
##   1      2      3
## 2 <2e-16 -      -
## 3 <2e-16 <2e-16 -
## 4 <2e-16 0.0072 <2e-16
##
## P value adjustment method: BH
```

```r
pairwise.wilcox.test(Kmeans$Cairns$Rainfall,Kmeans$Cairns$KmeansCluster, p.adjust.method = "BH")
```

```
##
##  Pairwise comparisons using Wilcoxon rank sum test with continuity correction
##
## data:  Kmeans$Cairns$Rainfall and Kmeans$Cairns$KmeansCluster
##
##   1      2      3
## 2 <2e-16 -      -
## 3 <2e-16 2e-15  -
## 4 <2e-16 <2e-16 <2e-16
##
## P value adjustment method: BH
```

```r
funProfile<-function(x){catdes(x, num.var=18, prob = 0.01)
                        catdes(x, num.var=19, prob = 0.01)}


#lapply(temp,funProfile)
```