Assignment 6 STAT 315-463: Multivariable Statistical Methods and Applications

Lisa Lu 31088272

QUESTION 1 Generalised additive models

a) Import the data to R and fit a series of GAMs to the Value using a smoother on Date.

```
# Read in the datasets and convert the string "Date" into Date datatype variables
CCC05 <- read.table("CCC05.csv", header = TRUE, sep = ',', na.strings = "na")
CCC05$Date <- as.Date(CCC05$Date, "%d/%m/%Y")
```

```
library(gam)
library(ggplot2)

# Kept showing Error in names(dat) <- object$term :
# 'names' attribute [1] must be the same length as the vector [0]
CCC05 <- transform(CCC05, ndate = as.numeric(Date),
                   nyear  = as.numeric(format(Date, '%Y')),
                   nmonth = as.numeric(format(Date, '%m')),
                   nday = as.numeric(format(Date, '%j')))

# Start with the default model and 4 more with different spar parameters

CCC05.gam <- gam(Value ~ s(nyear) + s(nmonth) +s(nday), data = CCC05 )
pred_default <- predict(CCC05.gam)
summary(CCC05.gam)
```

```
##
## Call: gam(formula = Value ~ s(nyear) + s(nmonth) + s(nday), data = CCC05)
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.03005 -0.19084  0.08084  0.30188  0.86313
##
## (Dispersion Parameter for gaussian family taken to be 0.2553)
##
##     Null Deviance: 49.5862 on 122 degrees of freedom
## Residual Deviance: 28.0784 on 110.0003 degrees of freedom
## AIC: 195.3644
##
## Number of Local Scoring Iterations: NA
##
## Anova for Parametric Effects
##            Df  Sum Sq Mean Sq F value    Pr(>F)
```

```
## s(nyear)    1 12.0657 12.0657 47.2689 3.926e-10 ***
## s(nmonth)   1  0.2207  0.2207  0.8646    0.3545
## s(nday)     1  1.3653  1.3653  5.3487    0.0226 *
## Residuals 110 28.0784  0.2553
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Anova for Nonparametric Effects
##             Npar Df Npar F     Pr(F)
## (Intercept)
## s(nyear)          3 7.8969 8.091e-05 ***
## s(nmonth)         3 1.7100    0.1691
## s(nday)           3 1.8543    0.1416
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
CCC05.gam1 <- gam(Value ~ s(nyear, sp=1.0) + s(nmonth, sp = 1.0) +
                    s(nday, sp = 1.0), data = CCC05)
pred1 <- predict(CCC05.gam1)
summary(CCC05.gam1)
```

```
##
## Call: gam(formula = Value ~ s(nyear, sp = 1) + s(nmonth, sp = 1) +
##     s(nday, sp = 1), data = CCC05)
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.11710 -0.28785 -0.01818  0.38619  1.04720
##
## (Dispersion Parameter for gaussian family taken to be 0.2981)
##
##     Null Deviance: 49.5862 on 122 degrees of freedom
## Residual Deviance: 35.0015 on 117.3956 degrees of freedom
## AIC: 207.6818
##
## Number of Local Scoring Iterations: NA
##
## Anova for Parametric Effects
##                      Df Sum Sq Mean Sq F value    Pr(>F)
## s(nyear, sp = 1)    1.0 11.932 11.9322 40.0210 4.736e-09 ***
## s(nmonth, sp = 1)   1.0  0.111  0.1113  0.3732   0.54243
## s(nday, sp = 1)     1.0  1.666  1.6661  5.5882   0.01972 *
## Residuals         117.4 35.001  0.2981
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Anova for Nonparametric Effects
##                   Npar Df  Npar F    Pr(F)
## (Intercept)
## s(nyear, sp = 1)      0.0 17.4747 0.003987 **
## s(nmonth, sp = 1)     0.0  0.2069 0.015504 *
## s(nday, sp = 1)       1.6  1.7826 0.179368
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
CCC05.gam2 <- gam(Value ~ s(nyear, sp=0.01) + s(nmonth, sp = 0.01) +
                    s(nday, sp = 0.01), data = CCC05)
pred2 <- predict(CCC05.gam2)
summary(CCC05.gam2)
```

```
##
## Call: gam(formula = Value ~ s(nyear, sp = 0.01) + s(nmonth, sp = 0.01) +
##     s(nday, sp = 0.01), data = CCC05)
## Deviance Residuals:
##     Min      1Q  Median      3Q     Max
## -1.1183 -0.1609  0.0117  0.1688  0.6473
##
## (Dispersion Parameter for gaussian family taken to be 0.2468)
##
##     Null Deviance: 49.5862 on 122 degrees of freedom
## Residual Deviance: 9.5027 on 38.4959 degrees of freedom
## AIC: 205.1122
##
## Number of Local Scoring Iterations: NA
##
## Anova for Parametric Effects
##                         Df Sum Sq Mean Sq F value    Pr(>F)
## s(nyear, sp = 0.01)   1.000 9.5682  9.5682 38.7614 2.649e-07 ***
## s(nmonth, sp = 0.01)  1.000 0.1811  0.1811  0.7337   0.39699
## s(nday, sp = 0.01)    1.000 0.7149  0.7149  2.8960   0.09686 .
## Residuals            38.496 9.5027  0.2468
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Anova for Nonparametric Effects
##                      Npar Df Npar F     Pr(F)
## (Intercept)
## s(nyear, sp = 0.01)      8.9  3.585  0.002615 **
## s(nmonth, sp = 0.01)     9.9 87.522 < 2.2e-16 ***
## s(nday, sp = 0.01)      61.7 15.955 2.887e-15 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
CCC05.gam3 <- gam(Value ~ s(nyear, sp=0.25) + s(nmonth, sp = 0.25) +
                    s(nday, sp = 0.25), data = CCC05)
pred3 <- predict(CCC05.gam3)
summary(CCC05.gam3)
```

```
##
## Call: gam(formula = Value ~ s(nyear, sp = 0.25) + s(nmonth, sp = 0.25) +
##     s(nday, sp = 0.25), data = CCC05)
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.36086 -0.20307  0.04743  0.20540  0.81026
##
## (Dispersion Parameter for gaussian family taken to be 0.2527)
##
```

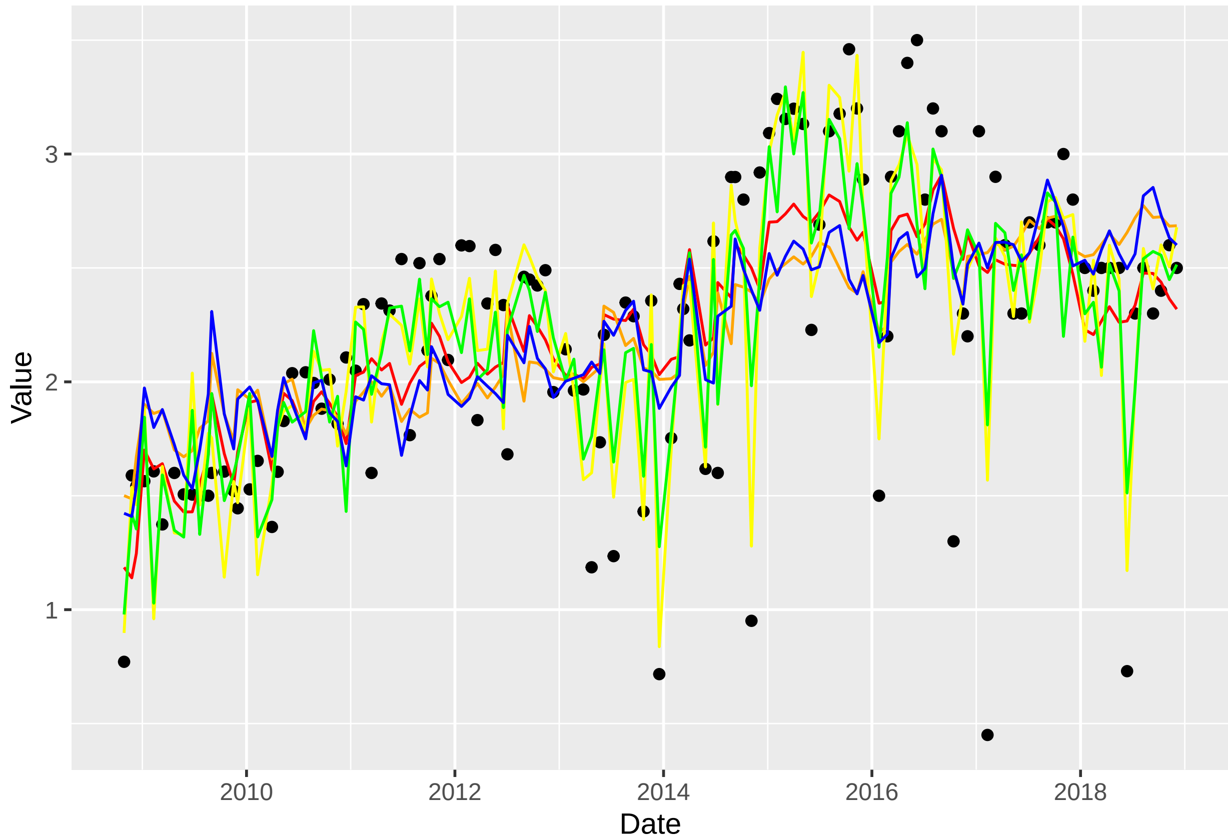
```
##     Null Deviance: 49.5862 on 122 degrees of freedom
## Residual Deviance: 15.182 on 60.0689 degrees of freedom
## AIC: 219.5961
##
## Number of Local Scoring Iterations: NA
##
## Anova for Parametric Effects
##                           Df  Sum Sq Mean Sq F value    Pr(>F)
## s(nyear, sp = 0.25)    1.000 11.2607 11.2607 44.5538 8.904e-09 ***
## s(nmonth, sp = 0.25)   1.000  0.2210  0.2210  0.8743   0.35351
## s(nday, sp = 0.25)     1.000  1.3014  1.3014  5.1492   0.02686 *
## Residuals             60.069 15.1820  0.2527
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Anova for Nonparametric Effects
##                       Npar Df  Npar F     Pr(F)
## (Intercept)
## s(nyear, sp = 0.25)       6.5  3.7308  0.002579 **
## s(nmonth, sp = 0.25)      7.3 18.7427 3.233e-13 ***
## s(nday, sp = 0.25)       45.2  3.9190 5.668e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
CCC05.gam4 <- gam(Value ~ s(nyear, sp=0.75) + s(nmonth, sp = 0.75) +
                    s(nday, sp = 0.75), data = CCC05)
pred4 <- predict(CCC05.gam4)
summary(CCC05.gam4)
```

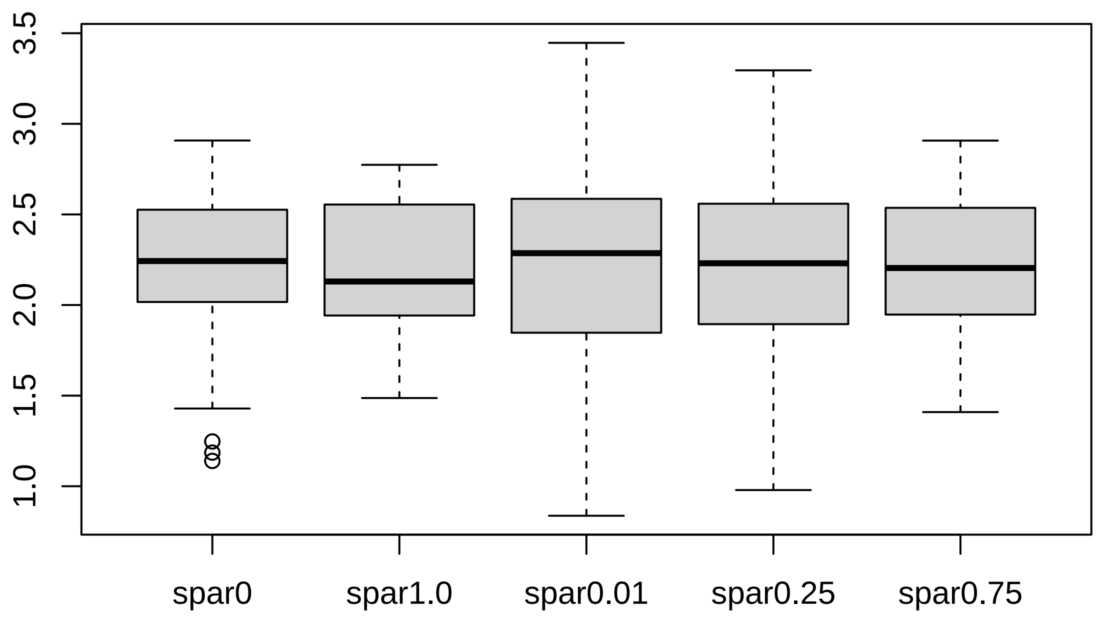
```
##
## Call: gam(formula = Value ~ s(nyear, sp = 0.75) + s(nmonth, sp = 0.75) +
##     s(nday, sp = 0.75), data = CCC05)
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.04990 -0.26239 -0.01294  0.35989  1.03976
##
## (Dispersion Parameter for gaussian family taken to be 0.2899)
##
##     Null Deviance: 49.5862 on 122 degrees of freedom
## Residual Deviance: 32.5685 on 112.3503 degrees of freedom
## AIC: 208.9111
##
## Number of Local Scoring Iterations: NA
##
## Anova for Parametric Effects
##                           Df Sum Sq Mean Sq F value    Pr(>F)
## s(nyear, sp = 0.75)     1.00 11.876 11.8764 40.9694 3.693e-09 ***
## s(nmonth, sp = 0.75)    1.00  0.126  0.1258  0.4339  0.511429
## s(nday, sp = 0.75)      1.00  2.015  2.0148  6.9502  0.009566 **
## Residuals             112.35 32.568  0.2899
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Anova for Nonparametric Effects
```

```
##                          Npar Df  Npar F   Pr(F)
## (Intercept)
## s(nyear, sp = 0.75)      0.1 16.8892 0.01278 *
## s(nmonth, sp = 0.75)     0.2  0.0438 0.43071
## s(nday, sp = 0.75)       6.3  1.4286 0.20731
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

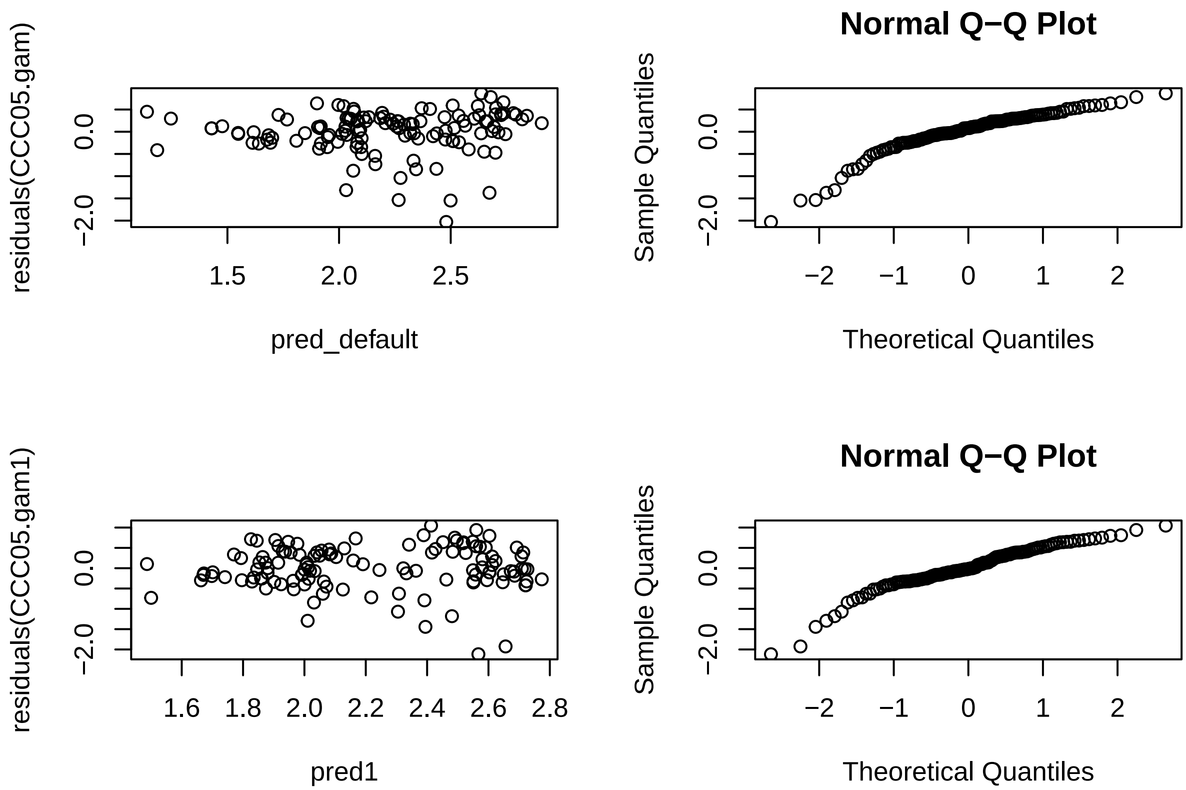
```
ggplot(data = CCC05, aes(x = Date, y = Value)) +
  geom_point() +
  geom_line(aes(x=Date, y=pred_default), colour = "red") +
  geom_line(aes(x=Date, y=pred1), colour = "orange") +
  geom_line(aes(x=Date, y=pred2), colour = "yellow") +
  geom_line(aes(x=Date, y=pred3), colour = "green") +
  geom_line(aes(x=Date, y=pred4), colour = "blue")
```



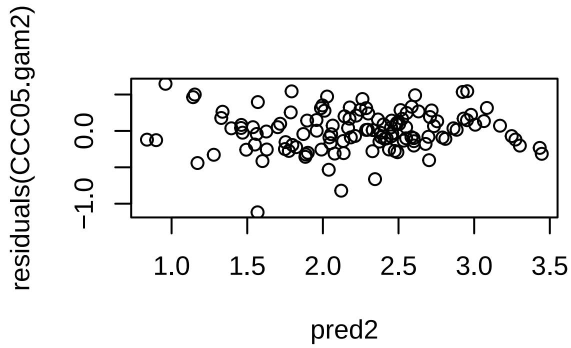

```
data <- data.frame(spar0 = fitted.values(CCC05.gam),
                   spar1.0 = fitted.values(CCC05.gam1),
                   spar0.01 = fitted.values(CCC05.gam2),
                   spar0.25 = fitted.values(CCC05.gam3),
                   spar0.75 = fitted.values(CCC05.gam4)
                   )

boxplot(data)
```

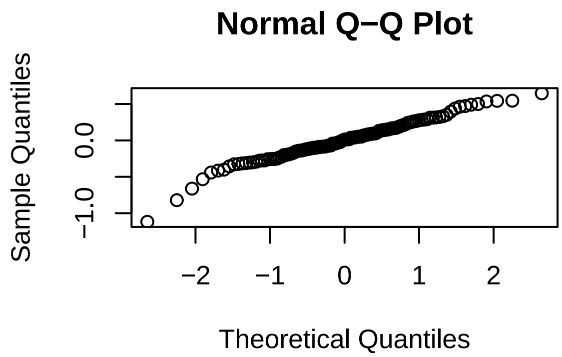


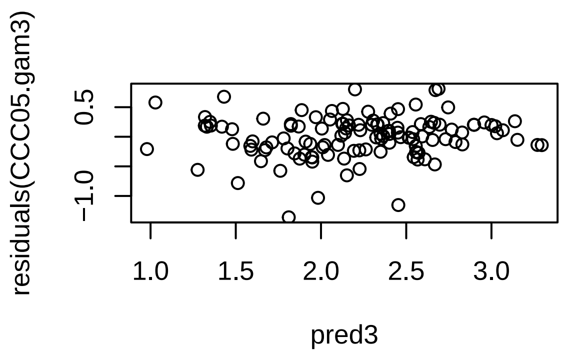

```
par(mfrow=c(2,2))
plot(pred_default, residuals(CCC05.gam),)
qqnorm(residuals(CCC05.gam))
plot(pred1, residuals(CCC05.gam1))
qqnorm(residuals(CCC05.gam1))
```

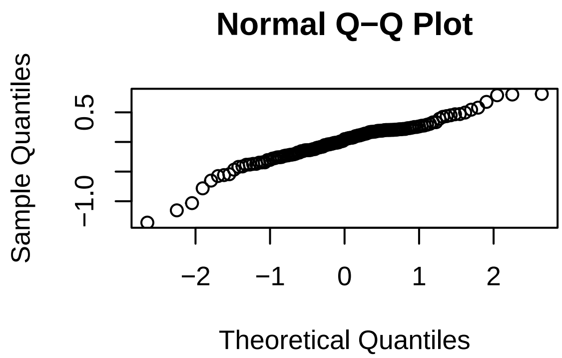



```
plot(pred2, residuals(CCC05.gam2))
qqnorm(residuals(CCC05.gam2))
plot(pred3, residuals(CCC05.gam3))
qqnorm(residuals(CCC05.gam3))
```

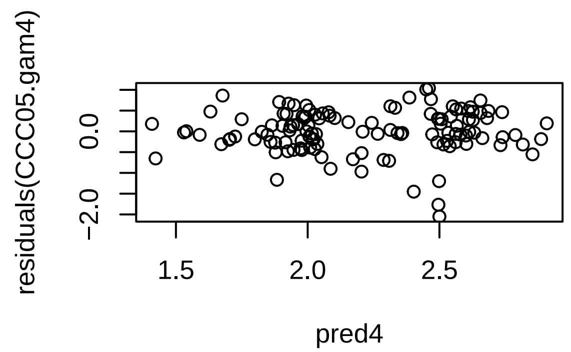


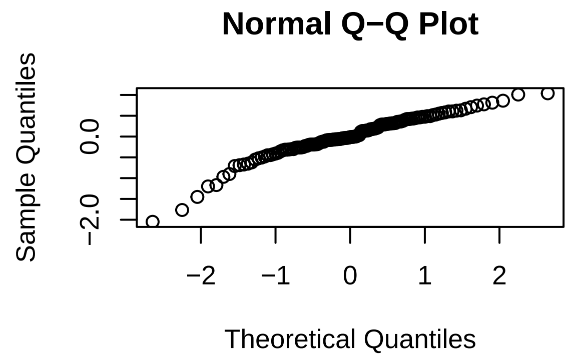







```
plot(pred4, residuals(CCC05.gam4))
qqnorm(residuals(CCC05.gam4))
```





From the summaries above, we can see that when spar had the value of 0.01, it provided the highest variance explained value, 54%. This can also be seen from the plot above, the yellow line has the best fitting. From the residual plots, we can see that all these models had similar residual distributions. The Q-Q plots suggested there is a slight skewness in the residuals.

```
ECAN93 <- read.table("ECAN93.csv", header = TRUE, sep = ',', na.strings = "na")
ECAN93$Date <- as.Date(ECAN93$Date, "%d/%m/%Y")

ECAN93 <- transform(ECAN93, ndate = as.numeric(Date),
                    nyear  = as.numeric(format(Date, '%Y')),
                    nmonth = as.numeric(format(Date, '%m')),
                    nday = as.numeric(format(Date, '%j')))


# Start with the default model and 4 more with different spar parameters
ECAN93.gam <- gam(Value ~ s(nyear) + s(nmonth) +s(nday), data = ECAN93 )
pred_default <- predict(ECAN93.gam)
summary(ECAN93.gam)
```

```
##
## Call: gam(formula = Value ~ s(nyear) + s(nmonth) + s(nday), data = ECAN93)
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -4.61712 -0.24791  0.05168  0.30614  1.31908
##
## (Dispersion Parameter for gaussian family taken to be 0.4072)
```

```
##
##     Null Deviance: 271.865 on 178 degrees of freedom
## Residual Deviance: 67.6002 on 165.9998 degrees of freedom
## AIC: 361.6745
##
## Number of Local Scoring Iterations: NA
##
## Anova for Parametric Effects
##             Df  Sum Sq Mean Sq  F value    Pr(>F)
## s(nyear)     1 187.412 187.412 460.2108 < 2.2e-16 ***
## s(nmonth)    1  12.344  12.344  30.3131 1.374e-07 ***
## s(nday)      1   0.135   0.135   0.3325     0.565
## Residuals 166  67.600   0.407
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Anova for Nonparametric Effects
##              Npar Df Npar F     Pr(F)
## (Intercept)
## s(nyear)           3 1.6923   0.17064
## s(nmonth)          3 9.1194 1.274e-05 ***
## s(nday)            3 3.5343   0.01612 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
ECAN93.gam1 <- gam(Value ~ s(nyear, sp=1.0) + s(nmonth, sp = 1.0) +
                    s(nday, sp = 1.0), data = ECAN93)
pred1 <- predict(CCC05.gam1)
summary(ECAN93.gam1)
```

```
##
## Call: gam(formula = Value ~ s(nyear, sp = 1) + s(nmonth, sp = 1) +
##     s(nday, sp = 1), data = ECAN93)
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -4.67518 -0.28111  0.03948  0.29924  1.38015
##
## (Dispersion Parameter for gaussian family taken to be 0.4135)
##
##     Null Deviance: 271.865 on 178 degrees of freedom
## Residual Deviance: 71.5782 on 173.1225 degrees of freedom
## AIC: 357.6645
##
## Number of Local Scoring Iterations: NA
##
## Anova for Parametric Effects
##                       Df  Sum Sq Mean Sq  F value    Pr(>F)
## s(nyear, sp = 1)    1.00 185.391 185.391 448.3950 < 2.2e-16 ***
## s(nmonth, sp = 1)   1.00  12.375  12.375  29.9317 1.547e-07 ***
## s(nday, sp = 1)     1.00   0.129   0.129   0.3126    0.5768
## Residuals         173.12  71.578   0.413
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Anova for Nonparametric Effects
##                     Npar Df  Npar F   Pr(F)
## (Intercept)
## s(nyear, sp = 1)        0.0 0.27713 0.03056 *
## s(nmonth, sp = 1)       0.0 0.50310 0.01365 *
## s(nday, sp = 1)         1.9 3.01404 0.05536 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
ECAN93.gam2 <- gam(Value ~ s(nyear, sp=0.01) + s(nmonth, sp = 0.01) +
                    s(nday, sp = 0.01), data = ECAN93)
pred2 <- predict(ECAN93.gam2)
summary(ECAN93.gam2)
```

```
##
## Call: gam(formula = Value ~ s(nyear, sp = 0.01) + s(nmonth, sp = 0.01) +
##     s(nday, sp = 0.01), data = ECAN93)
## Deviance Residuals:
##       Min        1Q    Median        3Q       Max
## -1.735764 -0.241031 -0.003287  0.187134  1.588007
##
## (Dispersion Parameter for gaussian family taken to be 0.3015)
##
##     Null Deviance: 271.865 on 178 degrees of freedom
## Residual Deviance: 25.3447 on 84.0508 degrees of freedom
## AIC: 349.9663
##
## Number of Local Scoring Iterations: NA
##
## Anova for Parametric Effects
##                          Df  Sum Sq Mean Sq  F value    Pr(>F)
## s(nyear, sp = 0.01)   1.000 169.259 169.259 561.3163 < 2.2e-16 ***
## s(nmonth, sp = 0.01)  1.000  12.600  12.600  41.7869 6.344e-09 ***
## s(nday, sp = 0.01)    1.000   0.029   0.029   0.0976    0.7555
## Residuals            84.051  25.345   0.302
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Anova for Nonparametric Effects
##                        Npar Df Npar F     Pr(F)
## (Intercept)
## s(nyear, sp = 0.01)      12.9  2.775  0.002577 **
## s(nmonth, sp = 0.01)      9.9 74.760 < 2.2e-16 ***
## s(nday, sp = 0.01)       68.2 12.293 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
ECAN93.gam3 <- gam(Value ~ s(nyear, sp=0.25) + s(nmonth, sp = 0.25) +
                    s(nday, sp = 0.25), data = ECAN93)
pred3 <- predict(ECAN93.gam3)
summary(ECAN93.gam3)
```

```
##
```

```
## Call: gam(formula = Value ~ s(nyear, sp = 0.25) + s(nmonth, sp = 0.25) +
##     s(nday, sp = 0.25), data = ECAN93)
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.85861 -0.22425 -0.01348  0.24210  1.14952
##
## (Dispersion Parameter for gaussian family taken to be 0.3098)
##
##     Null Deviance: 271.865 on 178 degrees of freedom
## Residual Deviance: 34.067 on 109.9649 degrees of freedom
## AIC: 351.0789
##
## Number of Local Scoring Iterations: NA
##
## Anova for Parametric Effects
##                          Df  Sum Sq Mean Sq F value    Pr(>F)
## s(nyear, sp = 0.25)    1.00 137.235 137.235 442.981 < 2.2e-16 ***
## s(nmonth, sp = 0.25)   1.00  13.659  13.659  44.089 1.237e-09 ***
## s(nday, sp = 0.25)     1.00   7.043   7.043  22.735 5.738e-06 ***
## Residuals            109.96  34.067   0.310
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Anova for Nonparametric Effects
##                      Npar Df  Npar F     Pr(F)
## (Intercept)
## s(nyear, sp = 0.25)      9.4  2.9618  0.002989 **
## s(nmonth, sp = 0.25)     7.3 17.1267 1.776e-15 ***
## s(nday, sp = 0.25)      48.3  3.4062 5.741e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
ECAN93.gam4 <- gam(Value ~ s(nyear, sp=0.75) + s(nmonth, sp = 0.75) +
                    s(nday, sp = 0.75), data = ECAN93)
pred4 <- predict(ECAN93.gam4)
summary(ECAN93.gam4)
```

```
##
## Call: gam(formula = Value ~ s(nyear, sp = 0.75) + s(nmonth, sp = 0.75) +
##     s(nday, sp = 0.75), data = ECAN93)
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -4.60281 -0.27861  0.03792  0.29949  1.26901
##
## (Dispersion Parameter for gaussian family taken to be 0.4149)
##
##     Null Deviance: 271.865 on 178 degrees of freedom
## Residual Deviance: 69.4372 on 167.3419 degrees of freedom
## AIC: 363.7898
##
## Number of Local Scoring Iterations: NA
##
## Anova for Parametric Effects
##                          Df  Sum Sq Mean Sq F value    Pr(>F)
```

```
## s(nyear, sp = 0.75)    1.00 186.155 186.155 448.630 < 2.2e-16 ***
## s(nmonth, sp = 0.75)   1.00  12.372  12.372  29.816 1.691e-07 ***
## s(nday, sp = 0.75)     1.00   0.126   0.126   0.304    0.5821
## Residuals            167.34  69.437   0.415
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Anova for Nonparametric Effects
##                      Npar Df  Npar F  Pr(F)
## (Intercept)
## s(nyear, sp = 0.75)      0.5 0.36689 0.3889
## s(nmonth, sp = 0.75)     0.2 0.29010 0.2919
## s(nday, sp = 0.75)       7.0 1.47183 0.1808
```

```
# ggplot(data = ECAN93, aes(x = Date, y = Value))
  # geom_point()
  # geom_line(aes(x=Date, y=pred_default), colour = "pink") +
  # geom_line(aes(x=Date, y=pred1), colour = "lightblue") +
  # geom_line(aes(x=Date, y=pred2), colour = "lightgreen") +
  # geom_line(aes(x=Date, y=pred3), colour = "purple") +
  # geom_line(aes(x=Date, y=pred4), colour = "black")
```

QUESTION 2 Multiple Comparisons

```
# Read in dataset
library(xlsx)
herbicides <- read.xlsx("herbicides.xlsx", sheetIndex = 1)
```

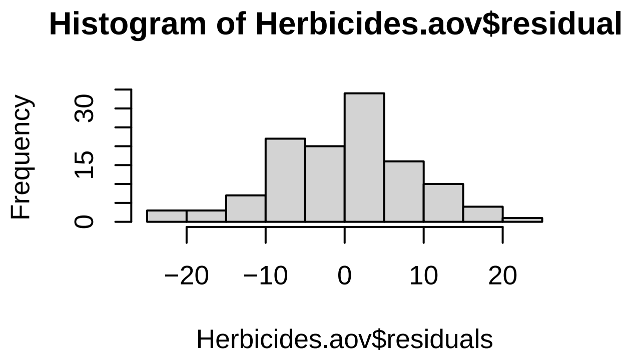
(a) Carry out an analysis of variance on the data with Herbicide as the explanatory variable and Grass_percent" as the response.

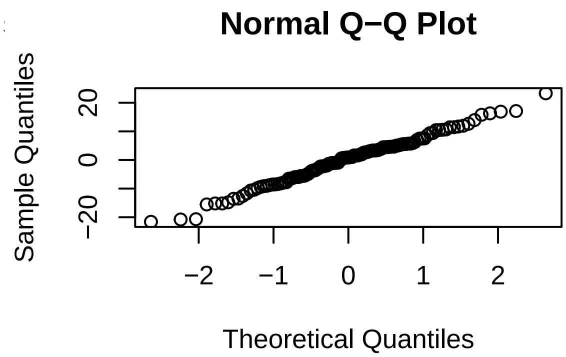
```
library(multcomp)

Herbicides.aov <- aov(Grass_percent ~ Herbicide, herbicides)
summary(Herbicides.aov)
```

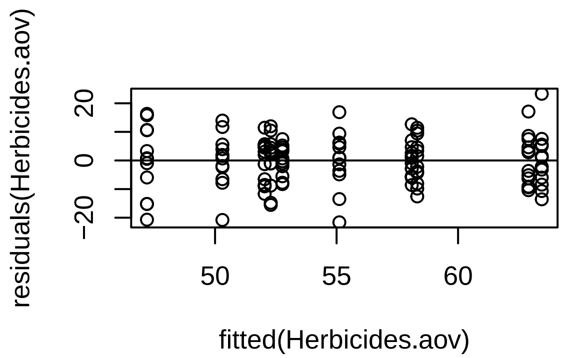
```
##              Df Sum Sq Mean Sq F value   Pr(>F)
## Herbicide     9   3092   343.5   4.412 6.09e-05 ***
## Residuals   110   8564    77.9
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

(b) Discuss the residuals

```
# Residual distribution
par(mfrow = c(2, 2))
hist(Herbicides.aov$residuals)
qqnorm(Herbicides.aov$residuals)
plot(fitted(Herbicides.aov), residuals(Herbicides.aov))
abline(0,0)
```







From the histogram of residuals, we can see that it is pretty close to be normally distributed. The Q-Q plot also suggests that as there is no obvious skewness or tailed part. The points in the residual-fitted plot also are evenly distributed around 0 without any patterns.

(c) Carry out an LSD type analysis comparing all possible pairs of treatments. Note which pairs have a significant difference.

```
library(agricolae)
pairwise.t.test(herbicides$Grass_percent, herbicides$Herbicide, p.adj = "none")
```

```
##
##  Pairwise comparisons using t tests with pooled SD
##
## data:  herbicides$Grass_percent and herbicides$Herbicide
##
##                          Aminopyralid Aminopyralid+triclopyr Chlorsulfuron
## Aminopyralid+triclopyr 0.87938      -                      -
## Chlorsulfuron          0.00374      0.00585                -
## Flumetsulam            0.14035      0.18525                0.14235
## MCPA                   0.15764      0.20653                0.12639
## MCPB                   0.02262      0.03293                0.51663
## MCPB+bentazone         0.00249      0.00396                0.89442
## Nil                    0.00200      0.00321                0.83996
## Sclerotinia            1.6e-05      3.0e-05                0.12471
## Thifensulfuron-methyl  0.00041      0.00068                0.49456
##                          Flumetsulam MCPA    MCPB    MCPB+bentazone Nil
```

```
## Aminopyralid+triclopyr -           -       -       -             -
## Chlorsulfuron         -           -       -       -             -
## Flumetsulam           -           -       -       -             -
## MCPA                  0.95031     -       -       -             -
## MCPB                  0.41000     0.37567 -       -             -
## MCPB+bentazone        0.11011     0.09713 0.43492 -             -
## Nil                   0.09577     0.08420 0.39547 0.94480       -
## Sclerotinia           0.00310     0.00256 0.03006 0.16016       0.18150
## Thifensulfuron-methyl  0.03270     0.02809 0.18431 0.58184       0.63011
##                       Sclerotinia
## Aminopyralid+triclopyr -
## Chlorsulfuron         -
## Flumetsulam           -
## MCPA                  -
## MCPB                  -
## MCPB+bentazone        -
## Nil                   -
## Sclerotinia           -
## Thifensulfuron-methyl  0.39070
##
## P value adjustment method: none
```

```
mse <- sum(Herbicides.aov$residuals * Herbicides.aov$residuals)/Herbicides.aov$df.residual
LSD.test(herbicides$Grass_percent, herbicides$Herbicide, Herbicides.aov$df.residual,
         mse, console = TRUE)
```

```
##
## Study: herbicides$Grass_percent ~ herbicides$Herbicide
##
## LSD t Test for herbicides$Grass_percent
##
## Mean Square Error:  77.8534
##
## herbicides$Herbicide,  means and individual ( 95 %) CI
##
##                       herbicides.Grass_percent       std  r      LCL      UCL
## Aminopyralid                          63.44375  9.913055 12 58.39597 68.49153
## Aminopyralid+triclopyr                62.89583  8.645617 12 57.84805 67.94361
## Chlorsulfuron                         52.77083  5.158244 12 47.72305 57.81861
## Flumetsulam                           58.09375  6.201202 12 53.04597 63.14153
## MCPA                                  58.31875  8.093657 12 53.27097 63.36653
## MCPB                                  55.11458 10.260590 12 50.06680 60.16236
## MCPB+bentazone                        52.29167  8.893201 12 47.24389 57.33945
## Nil                                   52.04167  7.303551 12 46.99389 57.08945
## Sclerotinia                           47.19792 12.355696 12 42.15014 52.24570
## Thifensulfuron-methyl                 50.30208  9.196476 12 45.25430 55.34986
##                          Min   Max
## Aminopyralid          49.875 86.75
## Aminopyralid+triclopyr 52.500 80.00
## Chlorsulfuron         44.500 60.25
## Flumetsulam           49.500 70.75
## MCPA                  45.750 69.75
## MCPB                  33.500 72.00
## MCPB+bentazone        36.750 64.25
```

```
## Nil                     40.375 63.50
## Sclerotinia             26.500 63.50
## Thifensulfuron-methyl  29.500 64.25
##
## Alpha: 0.05 ; DF Error: 110
## Critical Value of t: 1.981765
##
## least Significant Difference: 7.138638
##
## Treatments with the same letter are not significantly different.
##
##                          herbicides$Grass_percent groups
## Aminopyralid                             63.44375      a
## Aminopyralid+triclopyr                   62.89583      a
## MCPA                                     58.31875     ab
## Flumetsulam                              58.09375     ab
## MCPB                                     55.11458     bc
## Chlorsulfuron                            52.77083    bcd
## MCPB+bentazone                           52.29167    bcd
## Nil                                      52.04167    bcd
## Thifensulfuron-methyl                    50.30208     cd
## Sclerotinia                              47.19792      d
```

The LSD value obtained here is 7.14. From the result above, we can see that there is no significant difference between Aminopyralid and Aminopyralid + triclopyr, MCPA and Flumetsulam, Chlorsulfuron, MCPB+bentazone and Nil.

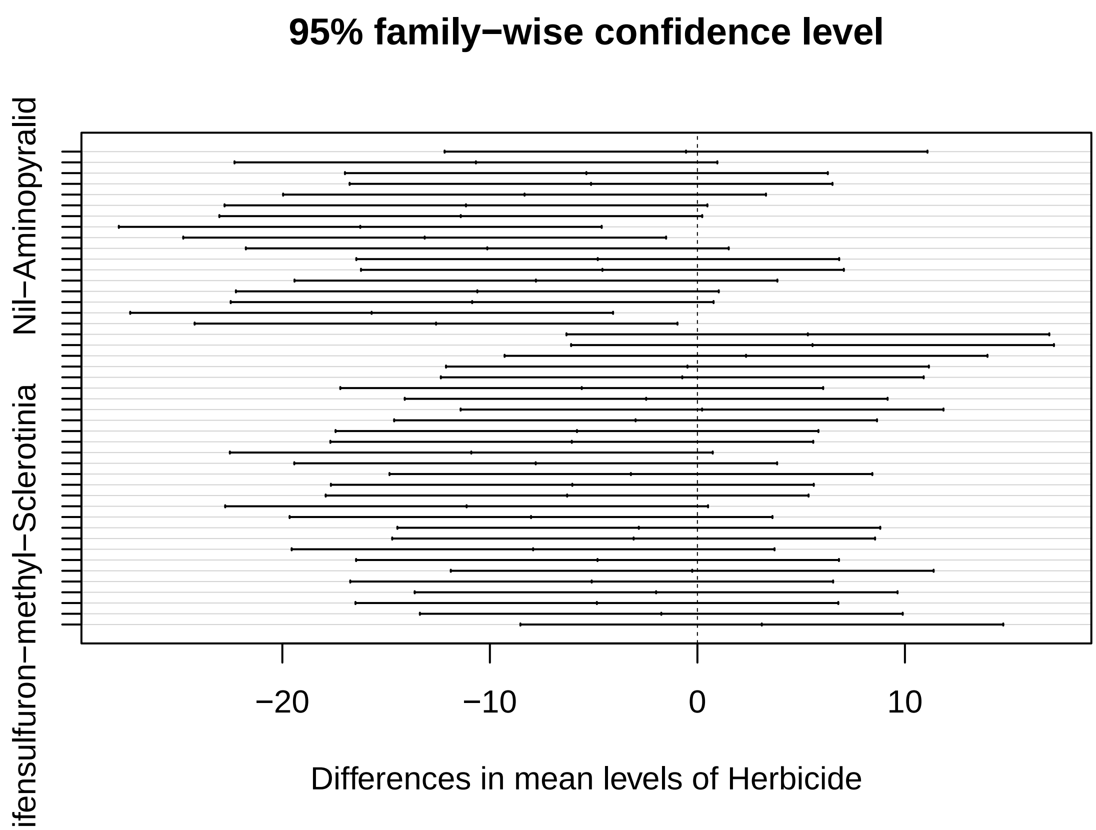
(d) Carry out pairwise comparisons using Bonferroni, Tukey and Dunnett adjustments and in each case show the pairs with significant differences.

```
# Bonferroni adjustment
pairwise.t.test(herbicides$Grass_percent, herbicides$Herbicide, p.adj = "bonferroni",
                console = TRUE)
```

```
##
##  Pairwise comparisons using t tests with pooled SD
##
## data:  herbicides$Grass_percent and herbicides$Herbicide
##
##                          Aminopyralid Aminopyralid+triclopyr Chlorsulfuron
## Aminopyralid+triclopyr 1.00000      -                      -
## Chlorsulfuron          0.16810      0.26332                -
## Flumetsulam            1.00000      1.00000                1.00000
## MCPA                   1.00000      1.00000                1.00000
## MCPB                   1.00000      1.00000                1.00000
## MCPB+bentazone         0.11201      0.17800                1.00000
## Nil                    0.09018      0.14438                1.00000
## Sclerotinia            0.00073      0.00133                1.00000
## Thifensulfuron-methyl  0.01824      0.03068                1.00000
##                        Flumetsulam MCPA    MCPB    MCPB+bentazone Nil
## Aminopyralid+triclopyr -           -       -       -              -
## Chlorsulfuron          -           -       -       -              -
## Flumetsulam            -           -       -       -              -
```

```
## MCPA                  1.00000     -       -       -            -      
## MCPB                  1.00000     1.00000 -       -            -      
## MCPB+bentazone        1.00000     1.00000 1.00000 -            -      
## Nil                   1.00000     1.00000 1.00000 1.00000      -      
## Sclerotinia           0.13938     0.11505 1.00000 1.00000      1.00000
## Thifensulfuron-methyl 1.00000     1.00000 1.00000 1.00000      1.00000
##                       Sclerotinia
## Aminopyralid+triclopyr -          
## Chlorsulfuron         -          
## Flumetsulam           -          
## MCPA                  -          
## MCPB                  -          
## MCPB+bentazone        -          
## Nil                   -          
## Sclerotinia           -          
## Thifensulfuron-methyl 1.00000    
## 
## P value adjustment method: bonferroni
```

```r
# Tukey adjustment
HerbicidesHSD <- TukeyHSD(aov(Grass_percent ~ Herbicide, herbicides))
plot(HerbicidesHSD)
```




```r
summary(HerbicidesHSD)
```

```
##           Length Class  Mode
```

```
## Herbicide 180    -none- numeric
```

```r
# Dunnett adjustment
herbicides$HerbicideA <- as.factor(herbicides$Herbicide)
tdaov <- aov(Grass_percent~HerbicideA, data = herbicides)
test.dunnett = glht(tdaov, linfct = mcp(HerbicideA="Dunnett"))
confint(test.dunnett)
```

```
##
##   Simultaneous Confidence Intervals
##
## Multiple Comparisons of Means: Dunnett Contrasts
##
##
## Fit: aov(formula = Grass_percent ~ HerbicideA, data = herbicides)
##
## Quantile = 2.7311
## 95% family-wise confidence level
##
##
## Linear Hypotheses:
##                                            Estimate lwr      upr
## Aminopyralid+triclopyr - Aminopyralid == 0  -0.5479 -10.3856   9.2898
## Chlorsulfuron - Aminopyralid == 0          -10.6729 -20.5106  -0.8352
## Flumetsulam - Aminopyralid == 0             -5.3500 -15.1877   4.4877
## MCPA - Aminopyralid == 0                    -5.1250 -14.9627   4.7127
## MCPB - Aminopyralid == 0                    -8.3292 -18.1669   1.5085
## MCPB+bentazone - Aminopyralid == 0         -11.1521 -20.9898  -1.3144
## Nil - Aminopyralid == 0                    -11.4021 -21.2398  -1.5644
## Sclerotinia - Aminopyralid == 0            -16.2458 -26.0835  -6.4081
## Thifensulfuron-methyl - Aminopyralid == 0  -13.1417 -22.9794  -3.3040
```