

An Introduction to Statistical Modelling of Extreme Values

```
library(ismev)

## Loading required package: mgcv
## Loading required package: nlme
## This is mgcv 1.8-23. For overview type 'help("mgcv-package")'.
library(extRemes)

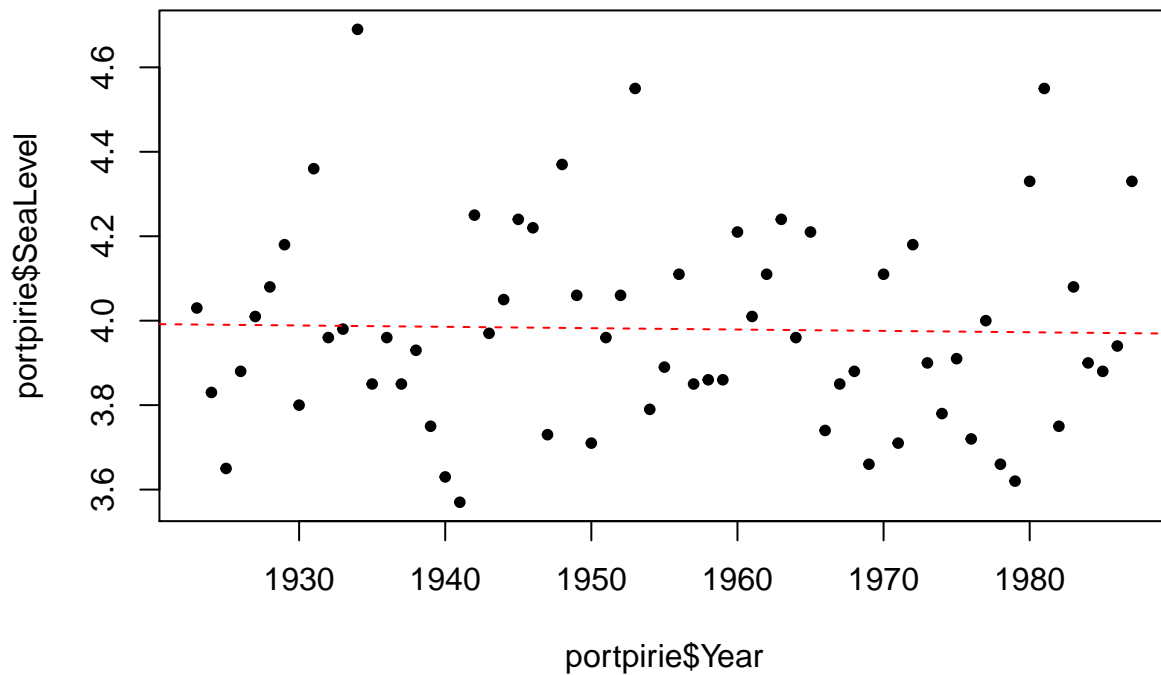
## Loading required package: Lmoments
## Loading required package: distillery
## Loading required package: car
##
## Attaching package: 'extRemes'
## The following objects are masked from 'package:stats':
##
##      qqnorm, qqplot
source("extreme_functions.r")
```

Chapter 6: Non-stationary sequence

Port Pirie

```
library(ismev)
data("portpirie")

plot(x=portpirie$Year, y=portpirie$SeaLevel, pch=20)
fit <- lm(SeaLevel ~ Year, data = portpirie)
abline(fit, col="red", lty=2)
```



```
summary(fit)
```

```
##
## Call:
## lm(formula = SeaLevel ~ Year, data = portpirie)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.4151 -0.1606 -0.0280  0.1316  0.7026
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  4.6086420   3.1322646   1.471   0.146
## Year        -0.0003212   0.0016021  -0.201   0.842
##
## Residual standard error: 0.2423 on 63 degrees of freedom
## Multiple R-squared:  0.0006378, Adjusted R-squared:  -0.01523
## F-statistic: 0.0402 on 1 and 63 DF, p-value: 0.8417
```

Fit with normal model

```
fitgev <- gev.fit(portpirie$SeaLevel)
```

```
## $conv
## [1] 0
```

```
##
## $nllh
## [1] -4.339058
##
## $mle
## [1] 3.87474692 0.19804120 -0.05008773
##
## $se
## [1] 0.02793211 0.02024610 0.09825633
```

Fit with linear time model for u

```
ti <- matrix(ncol=1,nrow=length(portpirie$SeaLevel))
ti[,1] <- seq(1,65,1)

fitgev.ut <- gev.fit(portpirie$SeaLevel, ydat = ti, mul = 1)
```

```
## $model
## $model[[1]]
## [1] 1
##
## $model[[2]]
## NULL
##
## $model[[3]]
## NULL
##
##
## $link
## [1] "c(identity, identity, identity)"
##
## $conv
## [1] 0
##
## $nllh
## [1] -4.375107
##
## $mle
## [1] 3.8865633240 -0.0003548552 0.1979732663 -0.0504552135
##
## $se
## [1] 0.051248878 0.001306864 0.020207615 0.097786572
```

Ratio test

```
2*(-fitgev.ut$nllh - -fitgev$nllh)
```

```
## [1] 0.07209759
```

No difference

Sea levels and Southern Oscillation Index

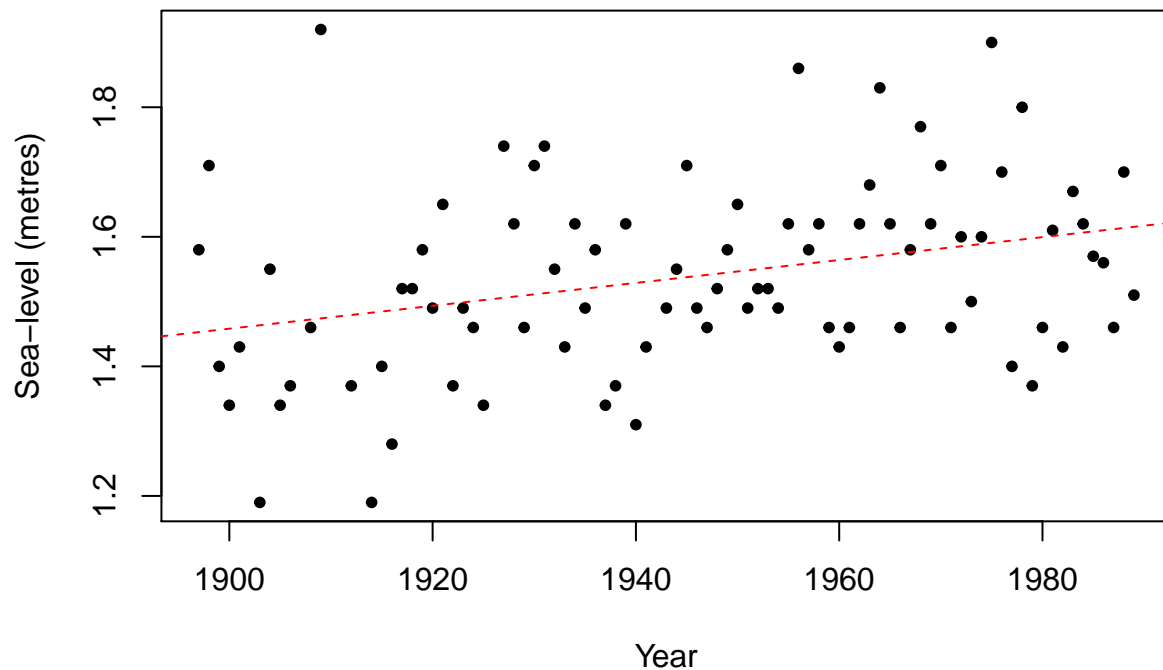
Data

The fremantle data frame has 86 rows and 3 columns. The second column gives 86 annual maximum sea levels recorded at Fremantle, Western Australia, within the period 1897 to 1989. The first column gives the corresponding years. The third column gives annual mean values of the Southern Oscillation Index (SOI), which is a proxy for meteorological volatility.

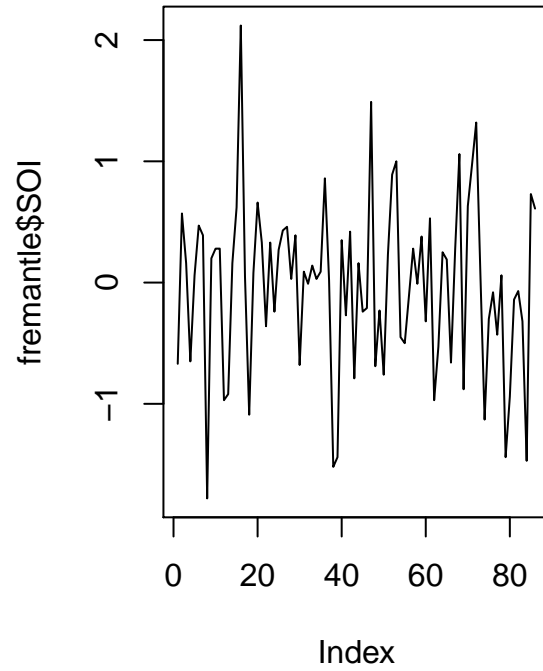
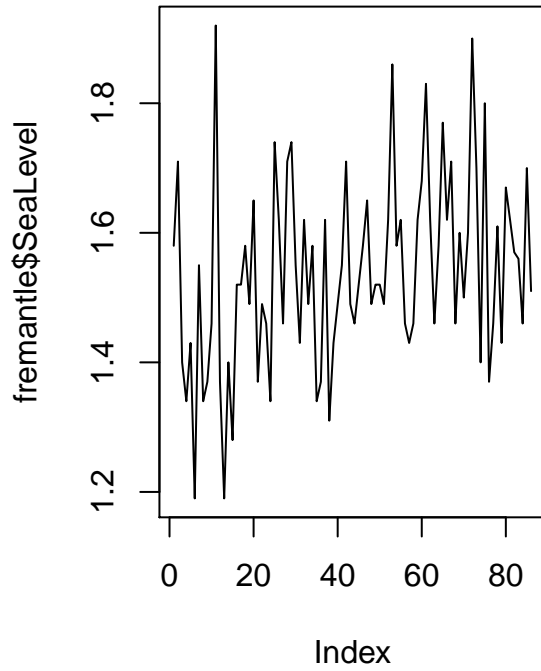
```
data("fremantle")
head(fremantle)
```

```
##   Year SeaLevel  SOI
## 1 1897    1.58 -0.67
## 2 1898    1.71  0.57
## 3 1899    1.40  0.16
## 4 1900    1.34 -0.65
## 5 1901    1.43  0.06
## 7 1903    1.19  0.47
```

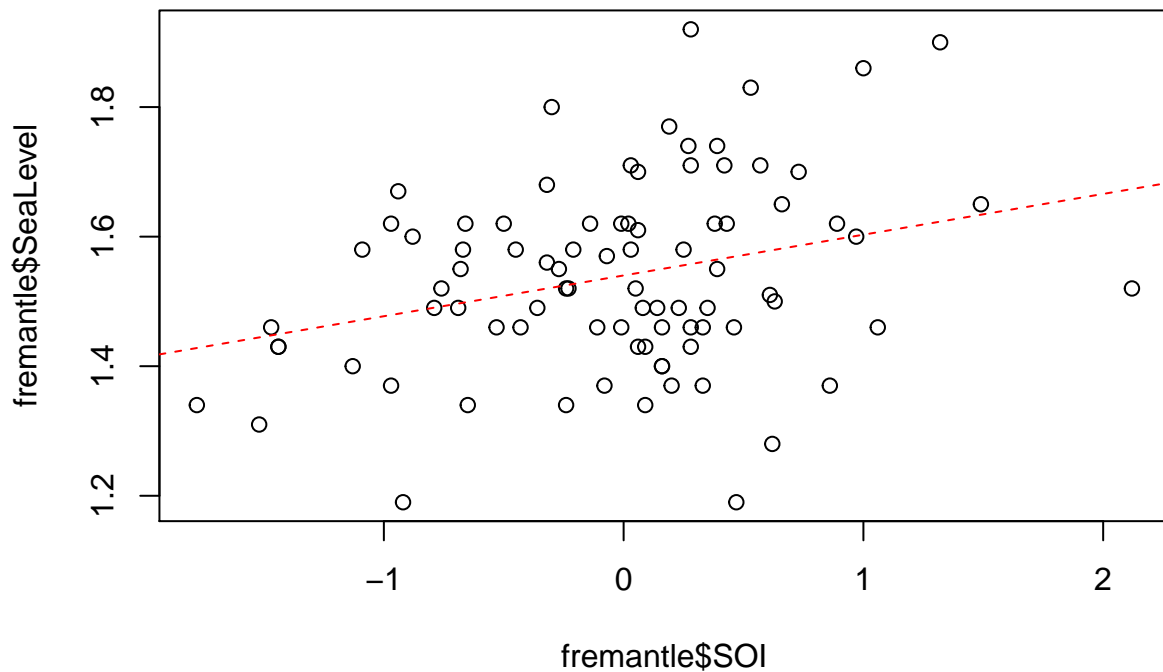
```
plot(x=fremantle$Year, fremantle$SeaLevel, pch=20,
     ylab="Sea-level (metres)", xlab="Year")
fit <- lm(SeaLevel ~ Year, data = fremantle)
abline(fit, col="red", lty=2)
```



```
par(mfrow=c(1,2))
plot(fremantle$SeaLevel, t="l")
plot(fremantle$SOI, t="l")
```



```
par(mfrow=c(1,1))
plot(fremantle$SOI, fremantle$SeaLevel)
abline(lm(SeaLevel ~ SOI, data = fremantle), col="red", lty=2)
```



Covariates

```
n <- dim(fremantle)[1]

#Covariates
covar <- matrix(ncol = 3, nrow = n)
covar[,1] <- fremantle$SOI
covar[,2] <- seq(1, n, 1) # Linear trend
covar[,3] <- covar[,2]^2 # Quadratic trend

head(covar)
```

```
##      [,1] [,2] [,3]
## [1,] -0.67  1    1
## [2,]  0.57  2    4
## [3,]  0.16  3    9
## [4,] -0.65  4   16
## [5,]  0.06  5   25
## [6,]  0.47  6   36
```

Model stationary

```
fitgev <- gev.fit(fremantle$SeaLevel, show = F)
fitgev$nullh
```

```
## [1] -43.56663
```

```
fitgev$mle
```

```
## [1] 1.4823409 0.1412671 -0.2174320
```

```
fitgev$se
```

```
## [1] 0.01672502 0.01149461 0.06377394
```

Model with SOI

```
fitgev.SOI <- gev.fit(fremantle$SeaLevel, ydat = covar, mul = 1, show = F)
fitgev.SOI$nullh
```

```
## [1] -47.21114
```

```
fitgev.SOI$mle
```

```
## [1] 1.48985338 0.06188902 0.13960518 -0.26848380
```

```
fitgev.SOI$se
```

```
## [1] 0.01655406 0.02315637 0.01150991 0.06399288
```

Model with Linear time

```
fitgev.ut <- gev.fit(fremantle$SeaLevel, ydat = covar, mul = 2, show = F)
fitgev.ut$nullh
```

```
## [1] -49.78972
```

```
fitgev.ut$mle
```

```
## [1] 1.387186155 0.002140832 0.124716473 -0.128545018
```

```
fitgev.ut$se
```

```
## [1] 0.0274796482 0.0005215259 0.0104146285 0.0679844086
```

Model with quadratic time

```
fitgev.ut2 <- gev.fit(fremantle$SeaLevel, ydat = covar, mul = c(2,3), show = F)
```

```
## Warning in sqrt(diag(z$cov)): NaNs produced
```

```
fitgev.ut2$nullh
```

```
## [1] -50.95252
```

```
fitgev.ut2$mle
```

```
## [1] 1.331932e+00 5.642570e-03 -3.921111e-05 1.208444e-01 -9.821101e-02
```

```
fitgev.ut2$se
```

```
## [1] 0.0265635286 0.0005200551 NaN 0.0090983484 0.0060969134
```

Model with SOI and Linear time

```
fitgev.SOIut <- gev.fit(fremantle$SeaLevel, ydat = covar, mul = c(1, 2), show = F)
fitgev.SOIut$nllh
```

```
## [1] -53.8257
```

```
fitgev.SOIut$mle
```

```
## [1] 1.389381297 0.055171074 0.002232467 0.121147089 -0.154480161
```

```
fitgev.SOIut$sse
```

```
## [1] 0.0272538644 0.0197789753 0.0005178779 0.0100390306 0.0636920071
```

Model with linear time for sigma

```
fitgev.st <- gev.fit(fremantle$SeaLevel, ydat = covar, sigl = 2, show = F)
fitgev.st$nllh
```

```
## [1] -44.67998
```

```
fitgev.st$mle
```

```
## [1] 1.4920666018 0.1666643314 -0.0007118848 -0.1609604077
```

```
fitgev.st$sse
```

```
## [1] 1.587629e-02 1.122782e-02 1.999940e-06 7.249364e-02
```

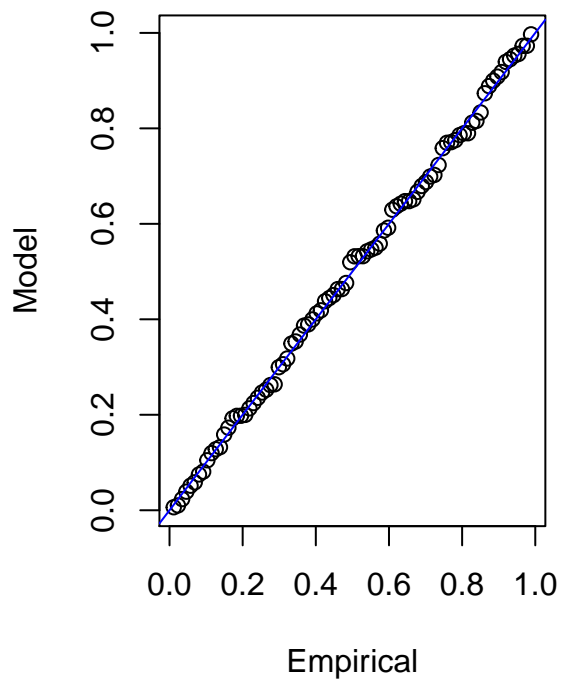
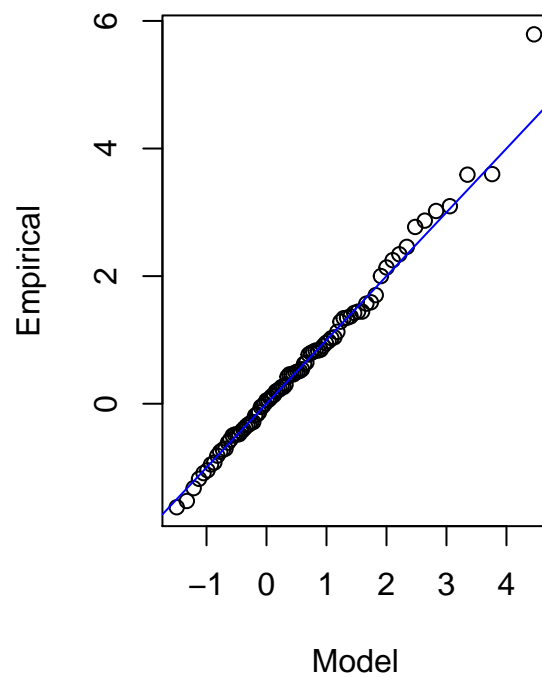
Ratio test between stationary and linear trend

```
2*(-fitgev.ut$nllh - -fitgev$nllh)
```

```
## [1] 12.44618
```

Diag

```
gev.diag(fitgev.ut)
```


Residual Probability Plot**Residual Quantile Plot (Gumbel Sc**

Sea level in Venice

Data

The venice data frame has 51 rows and 11 columns. The final ten columns contain the 10 largest sea levels observed within the year given by the first column. The ten largest sea levels are given for every year in the period 1931 to 1981, excluding 1935 in which only the six largest measurements are available. SeaLevel is measured in cm.

```
library(ismev)
data("venice")
head(venice)
```

```
##   Year  r1  r2  r3  r4  r5  r6  r7  r8  r9  r10
## 1 1931 103  99  98  96  94  89  86  85  84   79
## 2 1932  78  78  74  73  73  72  71  70  70   69
## 3 1933 121 113 106 105 102  89  89  88  86   85
## 4 1934 116 113  91  91  91  89  88  88  86   81
## 5 1935 115 107 105 101  93  91  NA  NA  NA   NA
## 6 1936 147 106  93  90  87  87  87  84  82   81
```

Covariates

```

n <- dim(venice)[1]

#Covariates
covar <- matrix(ncol = 1, nrow = n)
covar[,1] <- seq(1, n, 1) # Linear trend

head(covar)

##      [,1]
## [1,]    1
## [2,]    2
## [3,]    3
## [4,]    4
## [5,]    5
## [6,]    6

```

Fit

r=1 model

```

venice.r1 <- venice$r1
fitgev.r1 <- gev.fit(venice.r1, show = F)
fitgev.r1.ut <- gev.fit(venice.r1, ydat = covar, mul = 1, show = F)

```

r=5 model

```

venice.r5 <- venice[,c(2:6)]
fitgev.r5 <- rlarg.fit(venice.r5, show = F)
fitgev.r5.ut <- rlarg.fit(venice.r5, ydat = covar, mul = 1, show = F)

```

r=10 model

```

venice.r10 <- venice[, -1]
fitgev.r10 <- rlarg.fit(venice.r10, show = F)
fitgev.r10.ut <- rlarg.fit(venice.r10, ydat = covar, mul = 1, show = F)

```

Results for parameters

```

gev.result <- function(gevfit){
  loglik <- -gevfit$nullh
  par.mu0 <- gevfit$mle[1]
  par.mu1 <- NaN
  par.sigma <- gevfit$mle[2]
  par.xi <- gevfit$mle[3]
  se.mu0 <- gevfit$se[1]
  se.mu1 <- NaN
  se.sigma <- gevfit$se[2]
  se.xi <- gevfit$se[3]

  result <- data.frame(loglik=loglik, mu0=par.mu0, se.mu0=se.mu0,
                        mu1=par.mu1, se.mu1=se.mu1,

```

```

        sigma=par.sigma, se.sigma=se.sigma,
        xi=par.xi, se.xi=se.xi)
    return(round(result, 3))
}

gev.ut.result <- function(gevfit){
  loglik <- -gevfit$nullh
  par.mu0 <- gevfit$mle[1]
  par.mu1 <- gevfit$mle[2]
  par.sigma <- gevfit$mle[3]
  par.xi <- gevfit$mle[4]
  se.mu0 <- gevfit$se[1]
  se.mu1 <- gevfit$se[2]
  se.sigma <- gevfit$se[3]
  se.xi <- gevfit$se[4]

  result <- data.frame(loglik=loglik, mu0=par.mu0, se.mu0=se.mu0,
                        mu1=par.mu1, se.mu1=se.mu1,
                        sigma=par.sigma, se.sigma=se.sigma,
                        xi=par.xi, se.xi=se.xi)
  return(round(result, 3))
}

```

Stationary models

```

rbind(gev.result(fitgev.r1), gev.result(fitgev.r5), gev.result(fitgev.r10))

```

```

##      loglik      mu0 se.mu0 mu1 se.mu1  sigma se.sigma      xi se.xi
## 1  -222.715 111.099  2.628 NaN    NaN 17.175    1.803 -0.077 0.074
## 2  -731.967 118.569  1.567 NaN    NaN 13.662    0.776 -0.088 0.033
## 3 -1139.090 120.548  1.362 NaN    NaN 12.784    0.549 -0.113 0.020

```

Non-stationary models

```

rbind(gev.ut.result(fitgev.r1.ut),
      gev.ut.result(fitgev.r5.ut),
      gev.ut.result(fitgev.r10.ut))

```

```

##      loglik      mu0 se.mu0  mu1 se.mu1  sigma se.sigma      xi se.xi
## 1  -216.063  96.986  4.249 0.564  0.139 14.584    1.578 -0.027 0.083
## 2  -704.760 104.233  2.038 0.458  0.055 12.290    0.805 -0.037 0.042
## 3 -1084.059 104.513  1.667 0.482  0.041 11.737    0.641 -0.065 0.028

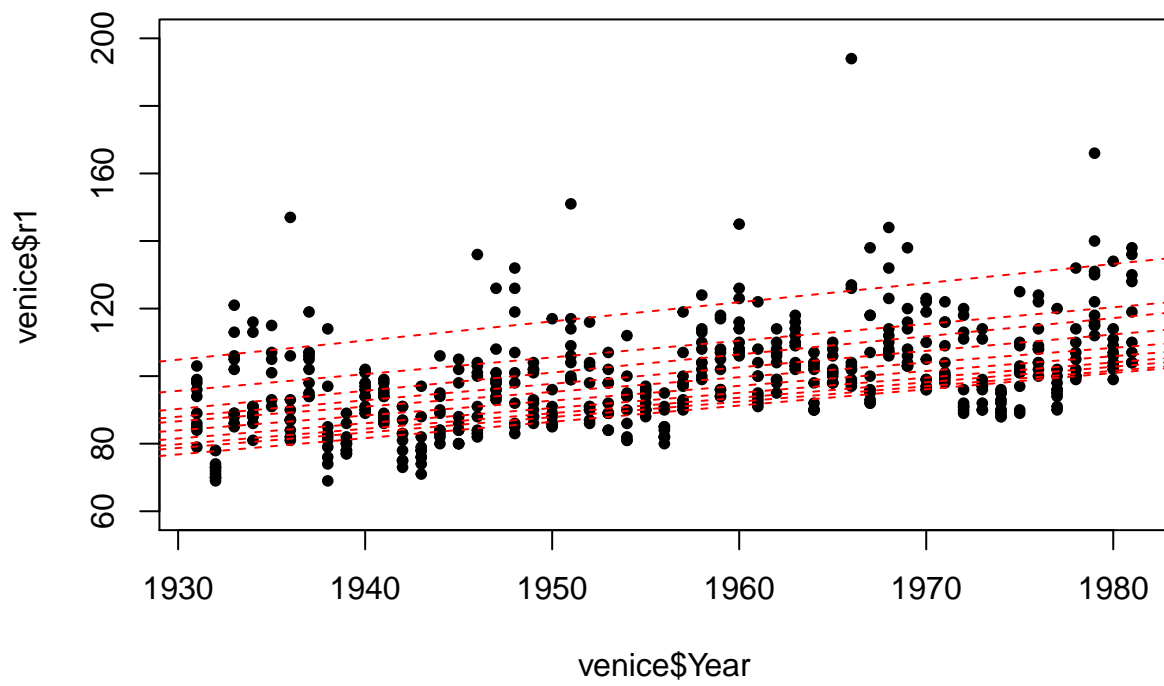
```

Plot with linear lines

```

plot(x=venice$Year, y=venice$r1, pch=20, ylim=c(60,200))
for(i in 3:11){
  points(x=venice$Year, y=venice[,i], pch=20)
}
for(i in 2:11){
  abline(lm(venice[,i] ~ venice$Year), col="red", lty=2)
}

```

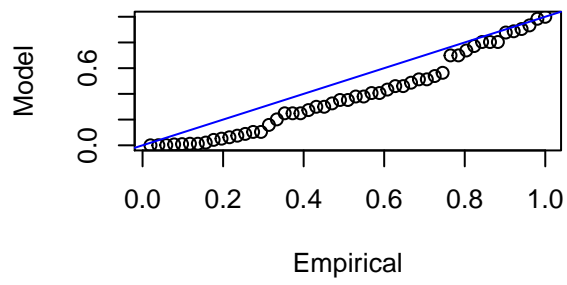


Models check

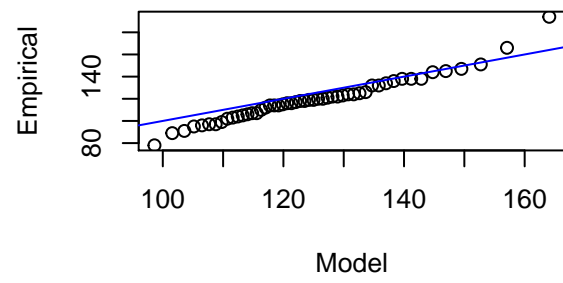
Stationary model

```
rlarg.diag(fitgev.r5)
```

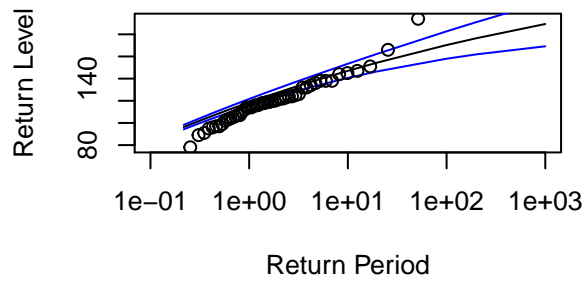
Probability Plot



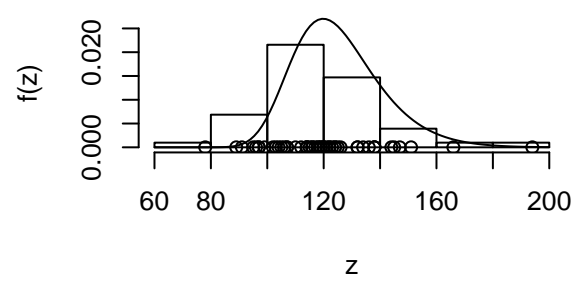
Quantile Plot



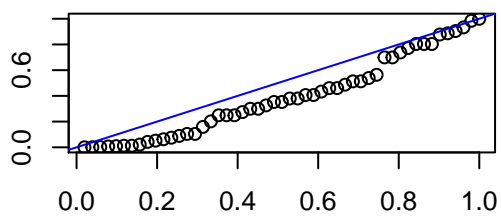
Return Level Plot



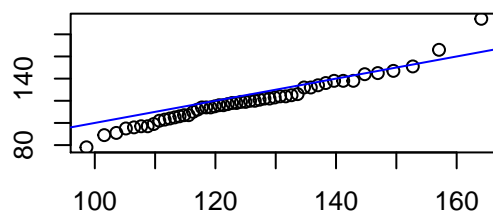
Density Plot



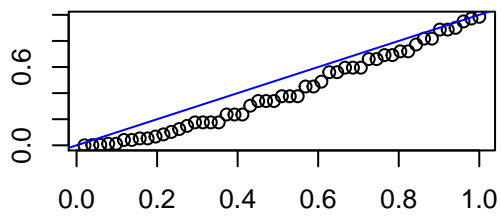
k=1



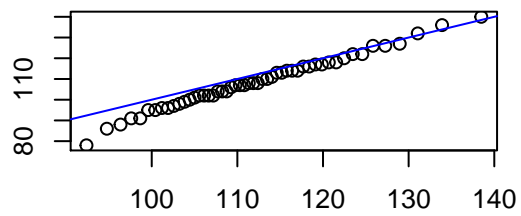
k=1



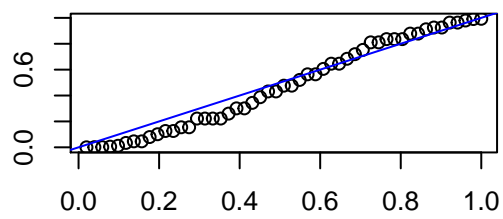
k=2



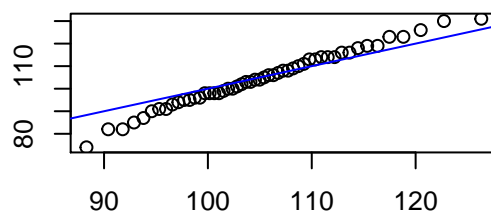
k=2



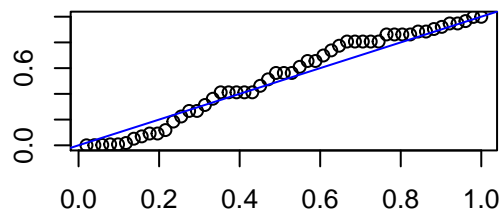
k=3



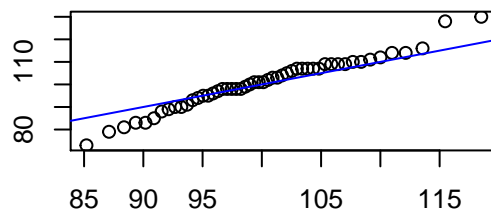
k=3

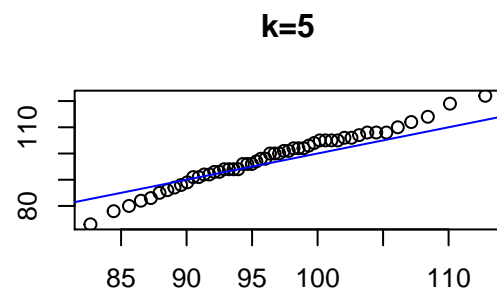
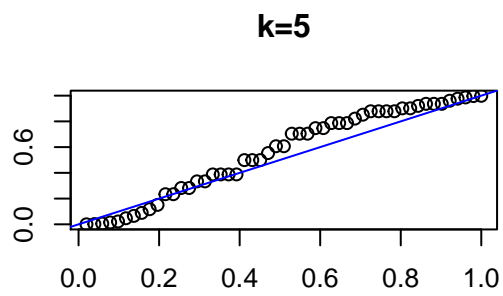


k=4



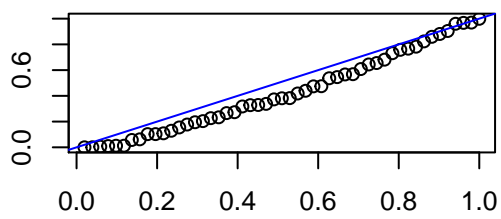
k=4



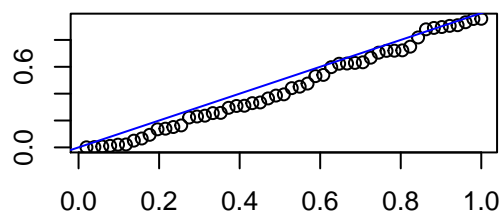


```
rlarg.diag(fitgev.r5.ut)
```

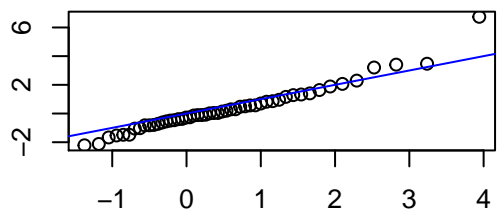

k=1



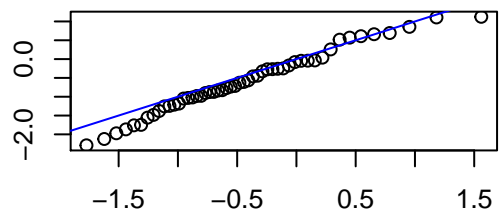
k=2



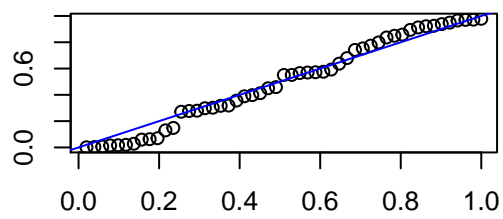
k=1



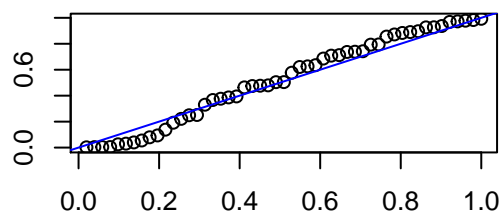
k=2



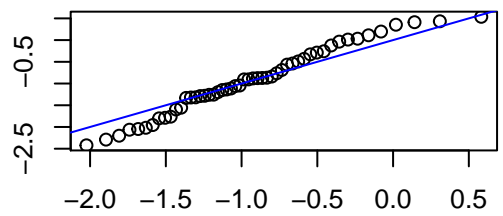
k=3



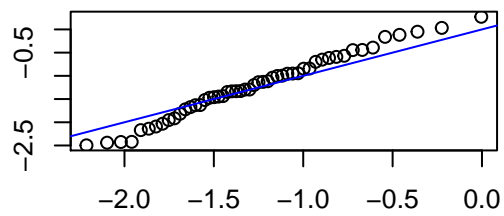
k=4

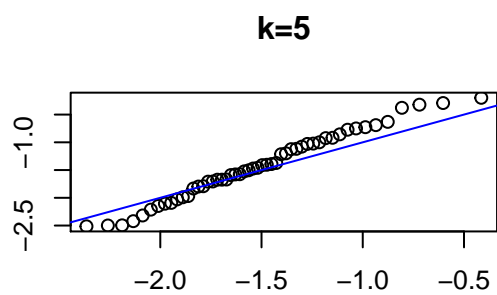
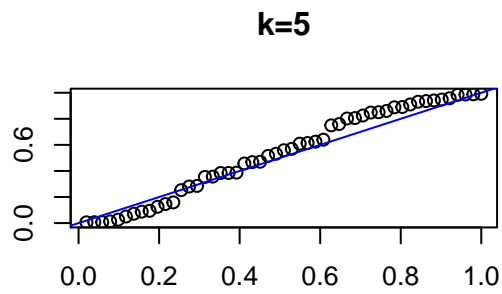


k=3



k=4





Daily rainfall

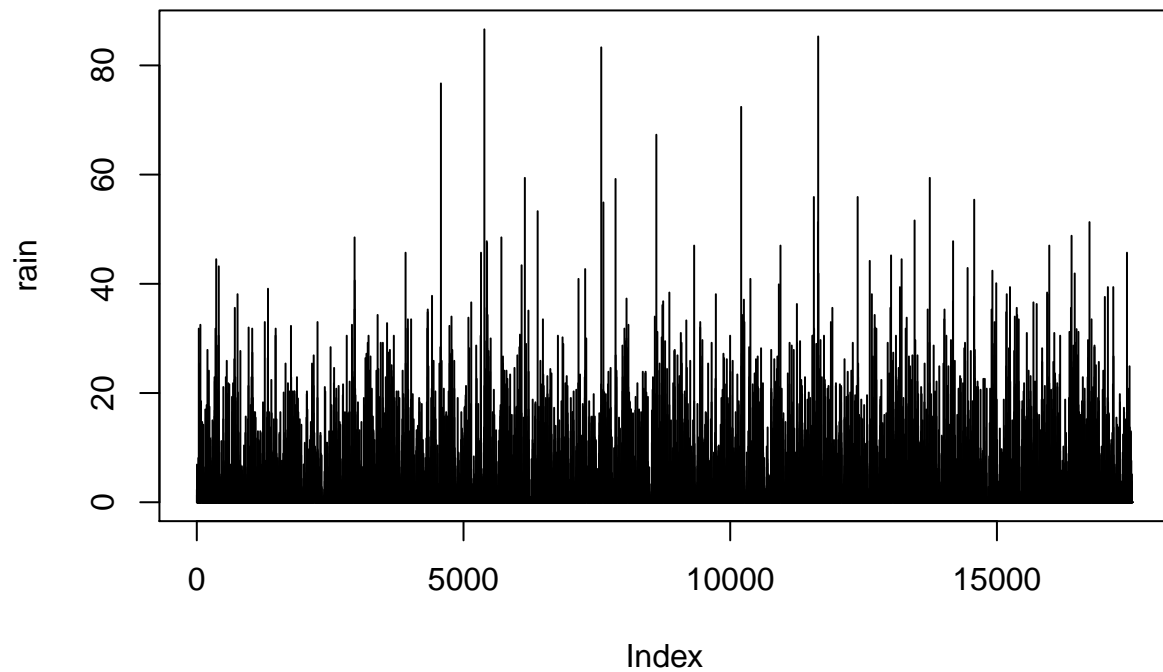
Data

A numeric vector containing daily rainfall accumulations at a location in south-west England over the period 1914 to 1962.

```
library(ismev)
data("rain")
head(rain)
```

```
## [1] 0.0 2.3 1.3 6.9 4.6 0.0
```

```
plot(rain, t="h")
```



Covariates

```
n <- length(rain)[1]

#Covariates
covar <- matrix(ncol = 1, nrow = n)
covar[,1] <- seq(1, n, 1) # Linear trend

head(covar,3)
```

```
##      [,1]
## [1,]    1
## [2,]    2
## [3,]    3
```

Fit with stationary model

```
fitgpd <- gpd.fit(rain, threshold = 30, show = F)
fitgpd$nullh
```

```
## [1] 485.0937
```

```
fitgpd$mle
```

```
## [1] 7.4422639 0.1843027
```

Fit with non-stationary model

```
fitgpd.st <- gpd.fit(rain, 30, ydat = covar, sigl = 1, siglink = exp, show = F)
```

```
## Warning in sqrt(diag(z$cov)): NaNs produced
```

```
fitgpd.st$nlh
```

```
## [1] 484.6016
```

```
fitgpd.st$mle
```

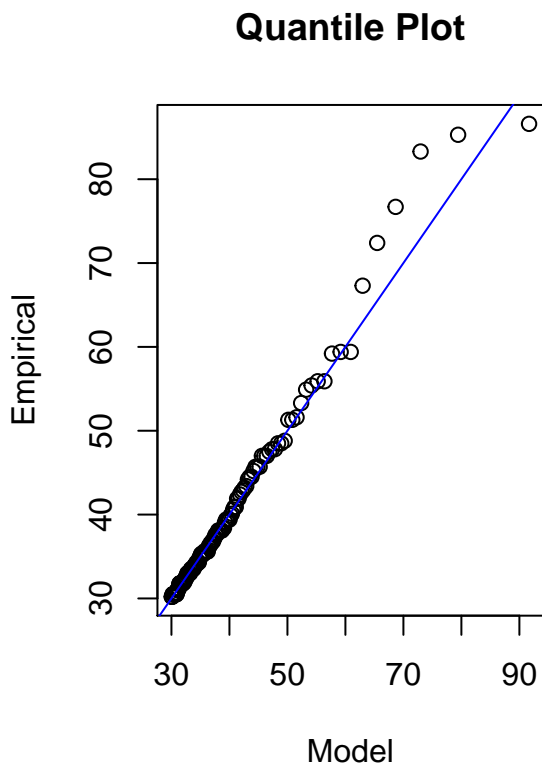
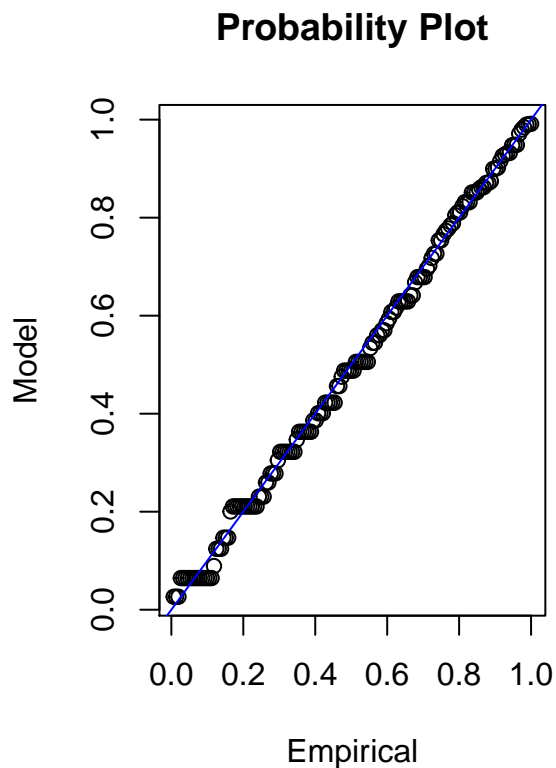
```
## [1] 1.8039221883 0.0000196265 0.1977440505
```

Model check

Stationary model

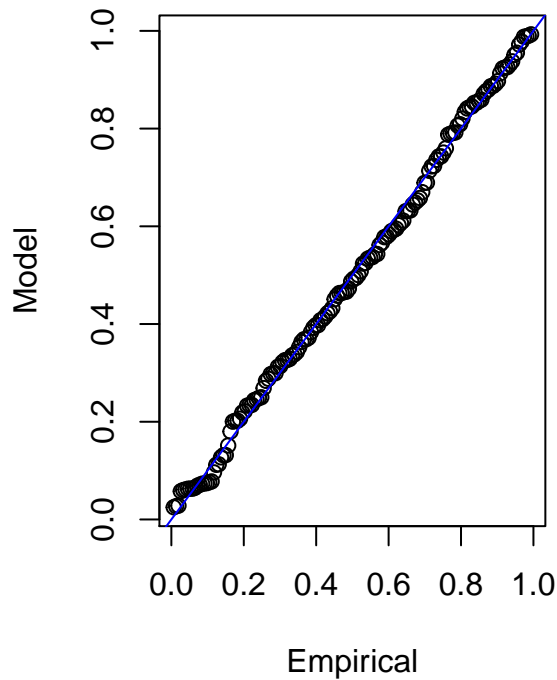
```
par(mfrow=c(1,2))
```

```
cgpd.pp(fitgpd); cgpd.qq(fitgpd)
```

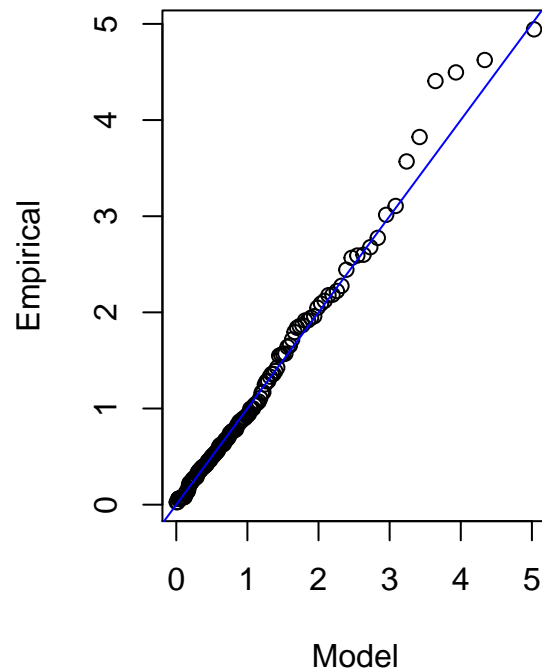


```
gpd.diag(fitgpd.st)
```

Residual Probability Plot



Residual Quantile Plot (Exptl. Sca



Wooster temperature

Data

```
data("wooster")
wooster.dat <- data.frame(temp=-wooster)

start.date <- as.Date("01-01-1983", format="%d-%m-%Y")
end.date <- as.Date("01-01-1988", format="%d-%m-%Y")
dates <- seq(start.date, end.date, by=1)
dates <- dates[-length(dates)]

wooster.dat <- cbind(wooster.dat, dates)
wooster.dat$year <- as.numeric(format(as.Date(wooster.dat$dates,
                                             format="%d/%m/%Y"), "%Y"))
wooster.dat$month <- as.numeric(format(as.Date(wooster.dat$dates,
                                              format="%d/%m/%Y"), "%m"))

wooster.dat$spring[wooster.dat$month==3 |
                    wooster.dat$month==4 |
                    wooster.dat$month==5 ] <- 1
wooster.dat$spring[is.na(wooster.dat$spring)] <- 0

wooster.dat$summer[wooster.dat$month==6 |
                    wooster.dat$month==7 |
```

```

        wooster.dat$month==8 ] <- 1
wooster.dat$summer[is.na(wooster.dat$summer)] <- 0

wooster.dat$fall[wooster.dat$month==9 |
                 wooster.dat$month==10 |
                 wooster.dat$month==11 ] <- 1
wooster.dat$fall[is.na(wooster.dat$fall)] <- 0

wooster.dat$winter[wooster.dat$month==12 |
                   wooster.dat$month==1 |
                   wooster.dat$month==2 ] <- 1
wooster.dat$winter[is.na(wooster.dat$winter)] <- 0

head(wooster.dat)

##    temp      dates year month spring summer fall winter
## 1  -23 1983-01-01 1983     1      0      0      0      1
## 2  -29 1983-01-02 1983     1      0      0      0      1
## 3  -19 1983-01-03 1983     1      0      0      0      1
## 4  -14 1983-01-04 1983     1      0      0      0      1
## 5  -27 1983-01-05 1983     1      0      0      0      1
## 6  -32 1983-01-06 1983     1      0      0      0      1

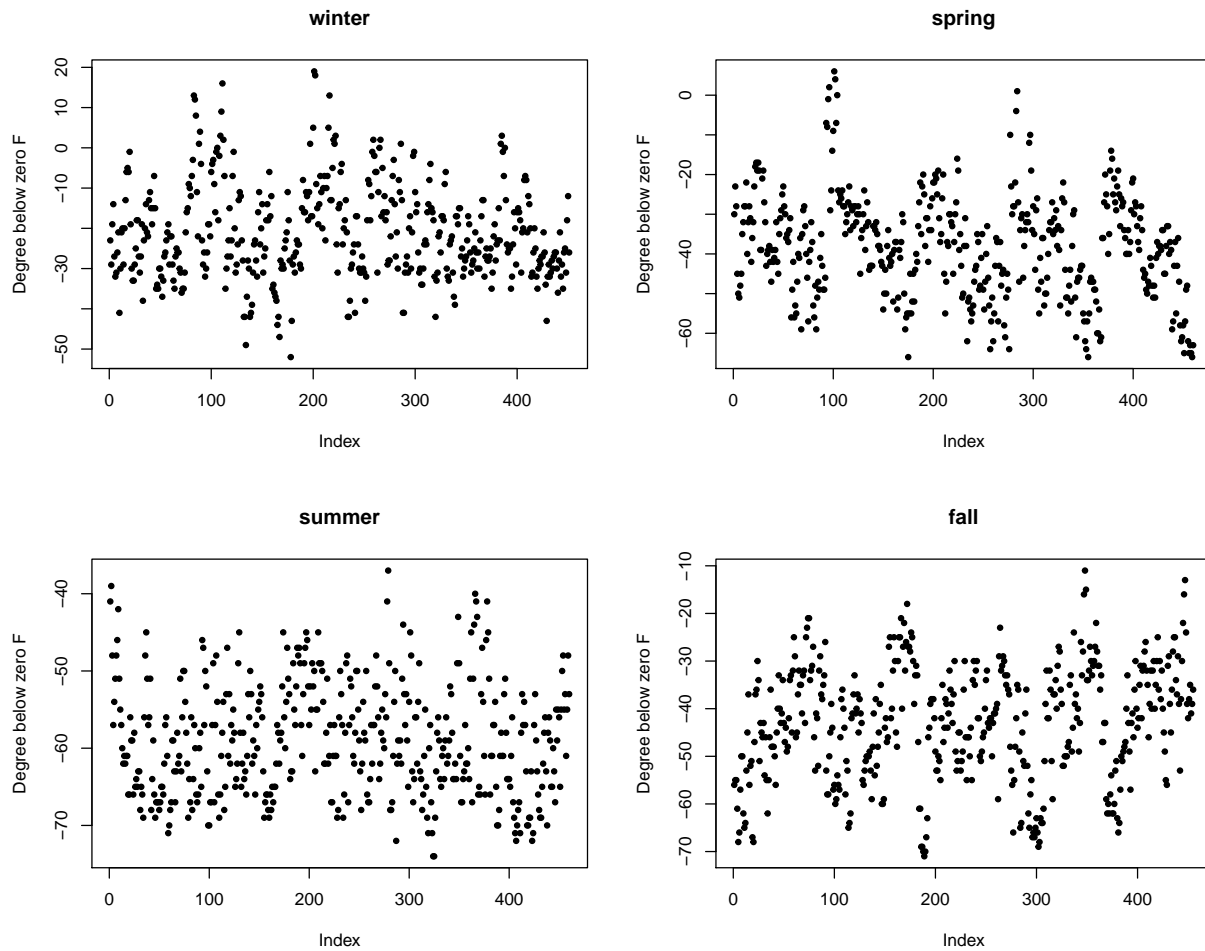
```

Plot by season

```

par(mfrow=c(2,2))
plot(wooster.dat$temp[wooster.dat$winter==1], pch=20,
     ylab="Degree below zero F", main="winter")
plot(wooster.dat$temp[wooster.dat$spring==1], pch=20,
     ylab="Degree below zero F", main="spring")
plot(wooster.dat$temp[wooster.dat$summer==1], pch=20,
     ylab="Degree below zero F", main="summer")
plot(wooster.dat$temp[wooster.dat$fall==1], pch=20,
     ylab="Degree below zero F", main="fall")

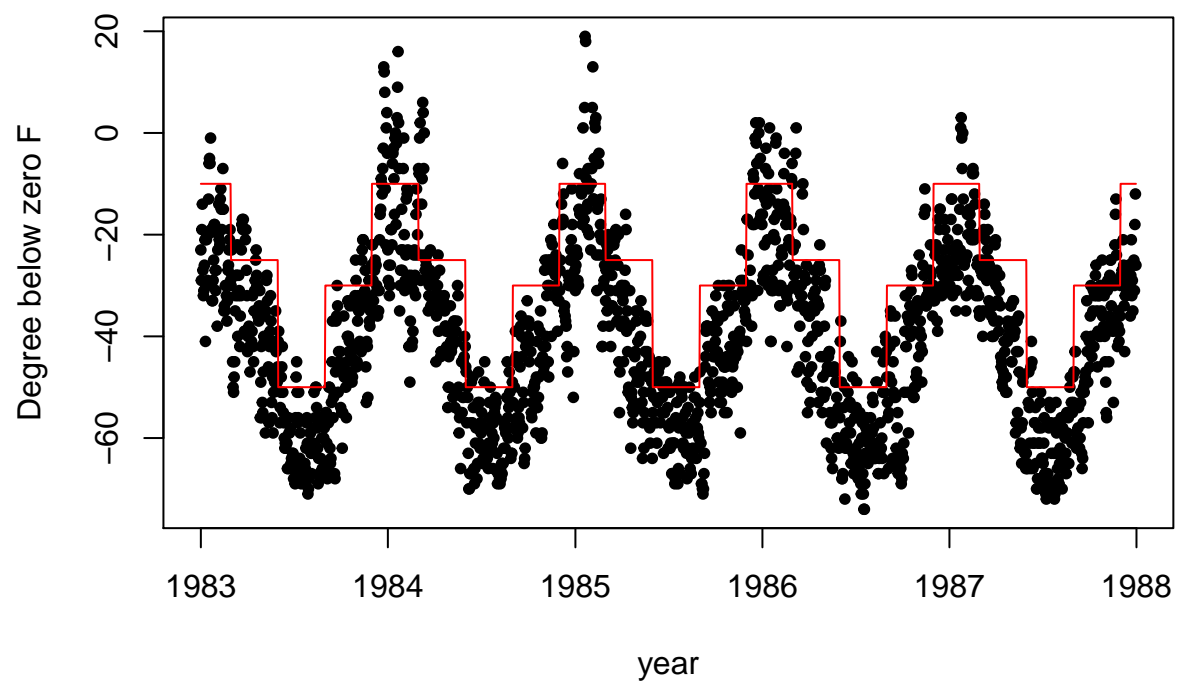
```



Seasonal threshold

```
wooster.dat$thres <- 0
wooster.dat$thres[wooster.dat$winter==1] <- -10
wooster.dat$thres[wooster.dat$spring==1] <- -25
wooster.dat$thres[wooster.dat$summer==1] <- -50
wooster.dat$thres[wooster.dat$fall==1] <- -30

plot(x=wooster.dat$dates, y=wooster.dat$temp, pch=20,
     ylab="Degree below zero F", xlab="year")
lines(x=wooster.dat$dates, y=wooster.dat$thres, col="red")
```

Fit with stationary model

```
fitgpd21 <- gpd.fit(wooster.dat$temp, threshold = -10)
```

```
## $threshold
## [1] -10
##
## $nexc
## [1] 85
##
## $conv
## [1] 0
##
## $nllh
## [1] 262.1725
##
## $mle
## [1] 10.6402671 -0.2802218
##
## $rate
## [1] 0.04654984
##
## $se
## [1] 1.48317853 0.09270039
```

Non-stationary model

```
fitgpd2 <- gpd.fit(wooster.dat$temp, threshold = wooster.dat$thres)
```

```
## $model
## $model[[1]]
## NULL
##
## $model[[2]]
## NULL
##
##
## $link
## [1] "c(identity, identity)"
##
## $nexc
## [1] 235
##
## $conv
## [1] 0
##
## $nllh
## [1] 684.7317
##
## $mle
## [1] 7.41154486 -0.08939142
##
## $rate
## [1] 0.1286966
##
## $se
## [1] 0.6664141 0.0621433
```

Sea level in Venice (UNC)

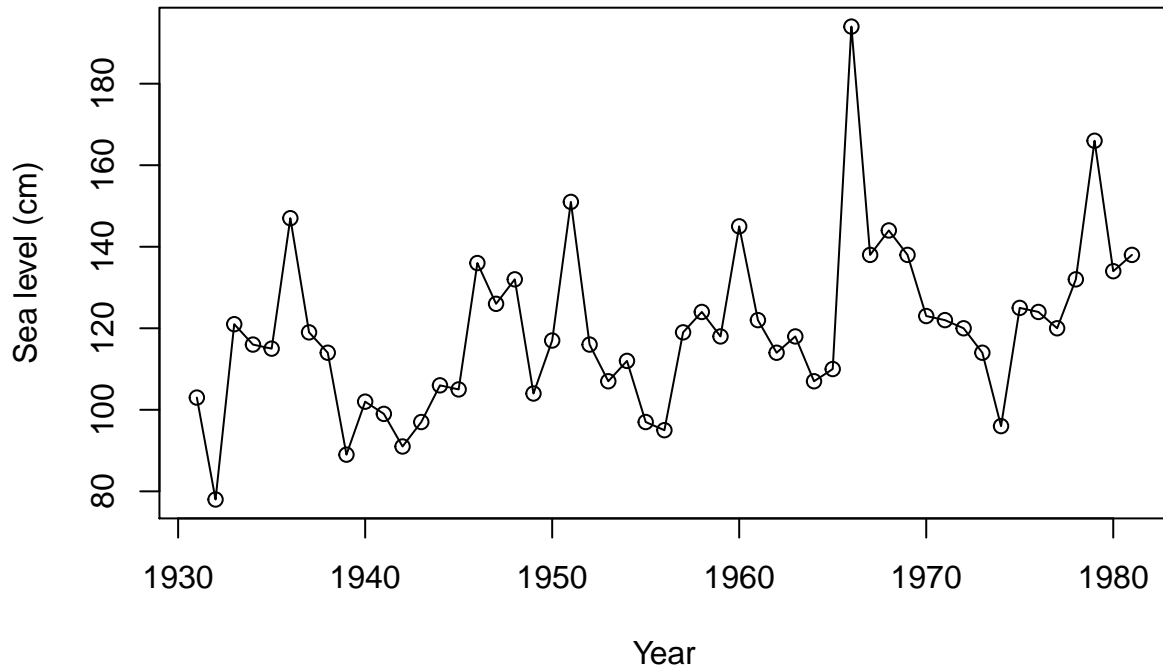
Data

```
library(ismev)
data("venice")
head(venice)
```

```
##   Year  r1  r2  r3  r4  r5  r6  r7  r8  r9  r10
## 1 1931 103  99  98  96  94  89  86  85  84  79
## 2 1932  78  78  74  73  73  72  71  70  70  69
## 3 1933 121 113 106 105 102  89  89  88  86  85
## 4 1934 116 113  91  91  91  89  88  88  86  81
## 5 1935 115 107 105 101  93  91  NA  NA  NA  NA
## 6 1936 147 106  93  90  87  87  87  84  82  81
```

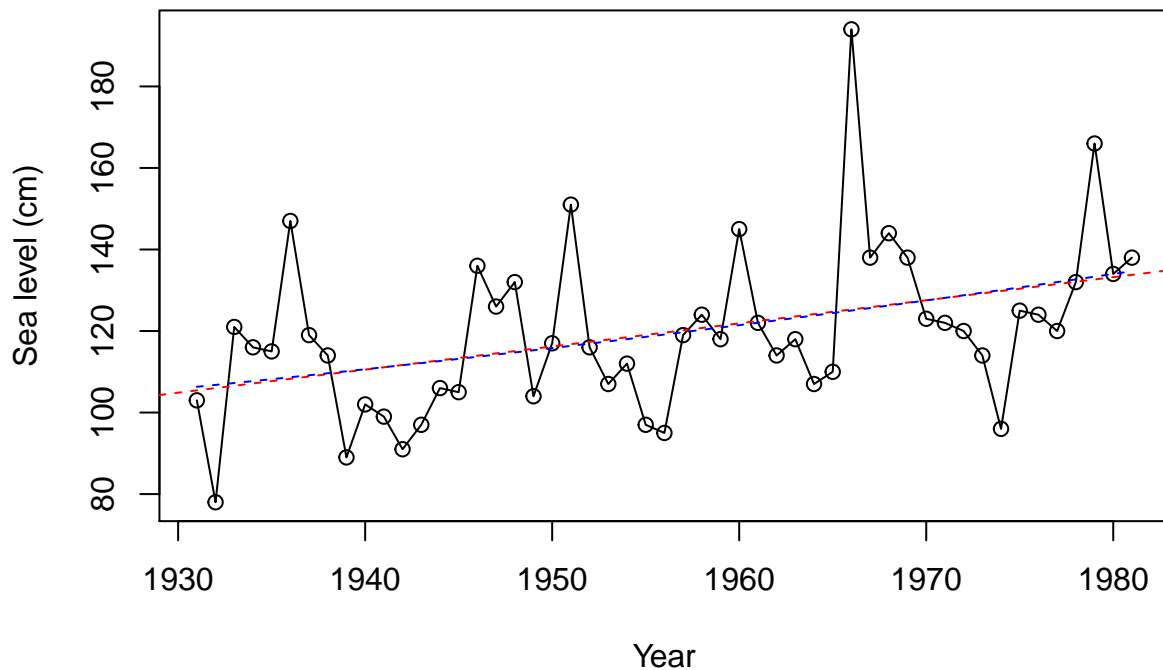
Maxima

```
venice.anmax <- venice[,c(1,2)]  
plot(x=venice.anmax$Year, y=venice.anmax$r1, t="o",  
      xlab="Year", ylab="Sea level (cm)")
```



Trend analysis

```
plot(x=venice.anmax$Year, y=venice.anmax$r1, t="o",  
      xlab="Year", ylab="Sea level (cm)")  
  
#Linear  
fit <- lm(r1 ~ Year, data = venice.anmax)  
abline(fit, col="red", lty=2)  
  
#Quadratic  
fit2 <- lm(r1 ~ poly(Year,2,raw=TRUE), data = venice.anmax)  
curve(predict(fit2, newdata=data.frame(Year=x)), add=T, col="blue", lty=2)
```



```
summary(fit)
```

```
##
## Call:
## lm(formula = r1 ~ Year, data = venice.anmax)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -33.813 -11.211  -3.309   9.515  68.722
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -989.3822   346.4770  -2.856  0.00628 **
## Year          0.5670     0.1771   3.201  0.00241 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 18.62 on 49 degrees of freedom
## Multiple R-squared:  0.1729, Adjusted R-squared:  0.1561
## F-statistic: 10.25 on 1 and 49 DF,  p-value: 0.002406
```

```
summary(fit2)
```

```
##
## Call:
## lm(formula = r1 ~ poly(Year, 2, raw = TRUE), data = venice.anmax)
##
```

```
## Residuals:
##      Min       1Q   Median       3Q      Max
## -34.047 -10.865  -3.322   9.067  68.976
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      7.334e+03  5.202e+04   0.141   0.888
## poly(Year, 2, raw = TRUE)1 -7.944e+00  5.319e+01  -0.149   0.882
## poly(Year, 2, raw = TRUE)2  2.176e-03  1.360e-02   0.160   0.874
##
## Residual standard error: 18.81 on 48 degrees of freedom
## Multiple R-squared:  0.1734, Adjusted R-squared:  0.1389
## F-statistic: 5.034 on 2 and 48 DF,  p-value: 0.01036
```

GEV

Stationary

```
fitgev <- gev.fit(venice.anmax$r1)
```

```
## $conv
## [1] 0
##
## $nllh
## [1] 222.7145
##
## $mle
## [1] 111.09925486 17.17548761 -0.07673265
##
## $se
## [1] 2.6280070 1.8033672 0.0735214
```

Linear trend for location

```
#Time index
ti <- matrix(ncol=1,nrow=length(venice.anmax$Year))
ti[,1] <- seq(1,length(venice.anmax$Year),1)

#Fit
fitgev.ut <- gev.fit(venice.anmax$r1, ydat = ti, mul = 1)

## $model
## $model[[1]]
## [1] 1
##
## $model[[2]]
## NULL
##
## $model[[3]]
## NULL
##
## $link
## [1] "c(identity, identity, identity)"
```

```
##
## $conv
## [1] 0
##
## $nllh
## [1] 216.0626
##
## $mle
## [1] 96.98579330 0.56414269 14.58435088 -0.02731421
##
## $se
## [1] 4.24930969 0.13948421 1.57840034 0.08270996
```

Quadratic trend for location

```
#Time index
ti2 <- matrix(ncol = 2, nrow = length(venice.anmax$Year))
ti2[,1] <- seq(1,length(venice.anmax$Year),1)
ti2[,2] <- (ti2[,1])^2

#Fit
fitgev.ut2 <- gev.fit(venice.anmax$r1, ydat = ti2, mul = c(1,2))
```

```
## $model
## $model[[1]]
## [1] 1 2
##
## $model[[2]]
## NULL
##
## $model[[3]]
## NULL
##
##
## $link
## [1] "c(identity, identity, identity)"
##
## $conv
## [1] 0
##
## $nllh
## [1] 216.0555
##
## $mle
## [1] 96.385006916 0.632499970 -0.001340599 14.564915436 -0.025471589
##
## $se
## [1] 6.64848069 0.59400203 0.01130770 1.59752694 0.08578017
```

Model selection

Linear and Stationary

```
2*(-fitgev.ut$nullh - -fitgev$nullh)
```

```
## [1] 13.30386
```

```
as.numeric(pchisq(-fitgev.ut$nullh - -fitgev$nullh, df=1, lower.tail=FALSE))
```

```
## [1] 0.009904848
```

fitgev.ut is better

Linear and Quadratic

```
2*(-fitgev.ut2$nullh - -fitgev.ut$nullh)
```

```
## [1] 0.01417277
```

```
as.numeric(pchisq(-fitgev.ut2$nullh - -fitgev.ut$nullh, df=1, lower.tail=FALSE))
```

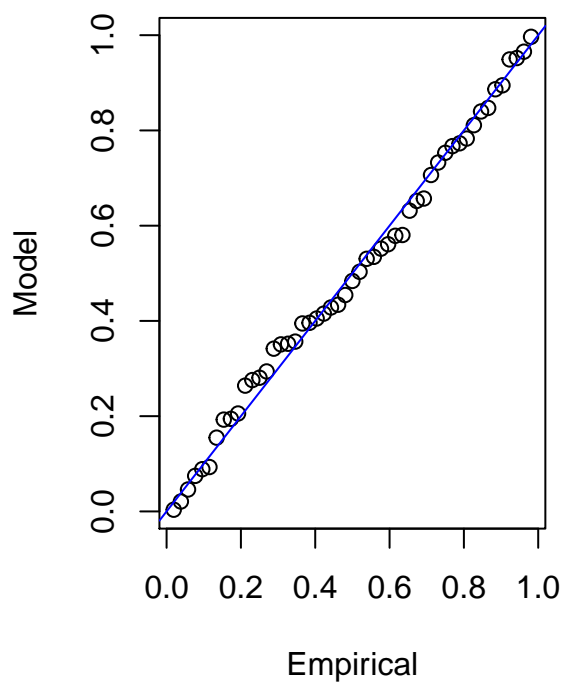
```
## [1] 0.9329128
```

No difference -> choose linear model

Model diagnostics

```
gev.diag(fitgev.ut)
```

Residual Probability Plot



Residual Quantile Plot (Gumbel Sc

