Univariate Extreme Value Analysis of Daily Clemson Rainfall Data

Whitney Huang

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These data were taken from United States Historical Climatology Network (http://cdiac.ornl.gov/epubs/ndp/ushcn.html). These data were compiled by Will Kleiber from CU-Boulder, thanks Will!

Load the USHCN dataset

```
# Note: you should place the data in the same folder as the R code
load("USHCNprcpSetup.rdata")
ls()

## [1] "days" "elev" "lon.lat" "ns" "PRCP" "stn.name" "years"
```

Extract the time series from a station near Clemson

```
Clemson.lon.lat <- c(-82.8374, 34.6834)
library(fields)
dist2Clemson <- rdist.earth(matrix(Clemson.lon.lat, 1, 2), lon.lat, miles = F)
id <- which.min(dist2Clemson)
lon.lat[id,] # near Lamaster Dairy Center</pre>
```

```
## lon lat
## -82.8236 34.6603

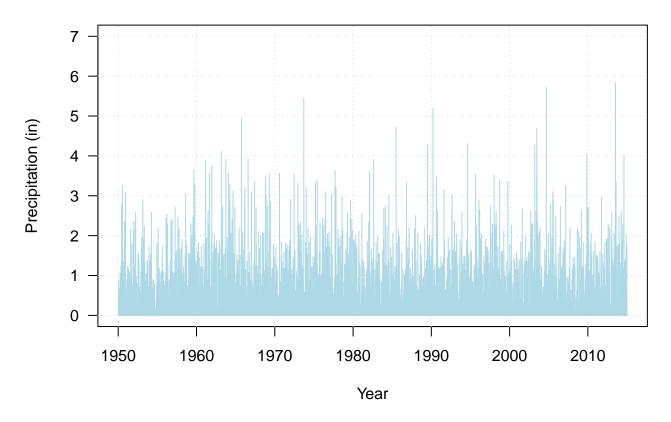
stn.name[id]

## [1] "CLEMSON UNIV, SC, 381770"

## Use data from 1950/1/1-2014/12/31
dat <- PRCP[(50 * 365 + 1):41975, id]</pre>
```

Extract Annual Maximum Values

Daily Precip in Clemson



Block-Maxima Method

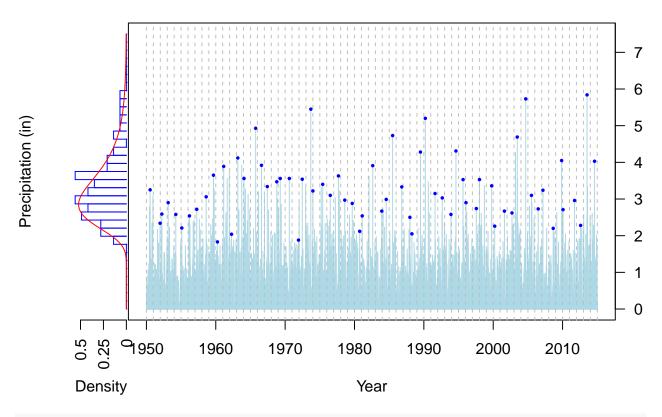
We are going to conduct an extreme value analysis using the extRemes package, developed and maintained by Eric Gilleland.

Step 1: Determine the block size and compute the maxima for the blocks

```
# Setting up the figure configuration
old.par <- par(no.readonly = TRUE)</pre>
mar.default <- par("mar")</pre>
mar.left <- mar.default</pre>
mar.right <- mar.default</pre>
mar.left[2] \leftarrow 0
mar.right[4] <- 0</pre>
# Time series plot
par(fig = c(0.2, 1, 0, 1), mar = mar.left)
plot(1950 + 1:23725/365, c(rain),
      xlab = "Year", ylab = "",
      main = "Daily Precip in Clemson",
      type = "h", pch = 19, cex = 0.5, col = "lightblue",
      ylim = c(0, 7.5), yaxt = "n")
par(las = 2)
axis(4, at = 0:8)
par(las = 0)
mtext("Precipitation (in)", side = 2, line = 5)
abline(v = 1950:2015, col = "gray", lty = 2)
points(1950:2014 + annmxT / 365, annmx,
       pch = 16, col = "blue", cex = 0.5)
# Histogram
hs <- hist(annmx,
           breaks = seq(0, 7.5, length.out = 35),
           plot = FALSE)
par(fig = c(0, 0.2, 0, 1.0), mar = mar.right, new = T)
plot (NA, type = 'n', axes = FALSE, yaxt = 'n',
      col = rgb(0, 0, 0.5, alpha = 0.5),
      xlab = "Density", ylab = NA, main = NA,
      xlim = c(-0.55, 0),
      ylim = c(0, 7.5))
axis(1, at = c(-0.5, -0.25, 0), c(0.5, 0.25, 0), las = 2)
arrows(rep(0, length(hs$breaks[-35])), hs$breaks[-35],
       -hs$density, hs$breaks[-35], col = "blue",
       length = 0, angle = 0, 1 \text{wd} = 1)
arrows(rep(0, length(hs$breaks[-1])), hs$breaks[-1],
       -hs$density, hs$breaks[-1], col = "blue",
       length = 0, angle = 0, lwd = 1)
arrows(-hs$density, hs$breaks[-35], -hs$density,
       hs$breaks[-1], col = "blue", angle = 0,
       length = 0)
library(extRemes)
mle <- fevd(annmx)$results$par</pre>
```

```
xg <- seq(0, 7.5, length.out = 100)
library(ismev)
lines(-gev.dens(mle, xg), xg, col = "red")</pre>
```

Daily Precip in Clemson



par(old.par)

Step 2: Fit a GEV to the maxima and assess the fit

We assume the annual maxima m_1, \dots, m_t follows a GEV distribution $GEV(\mu_n, \sigma_n, \xi)$ and we maximize the log-likelihood

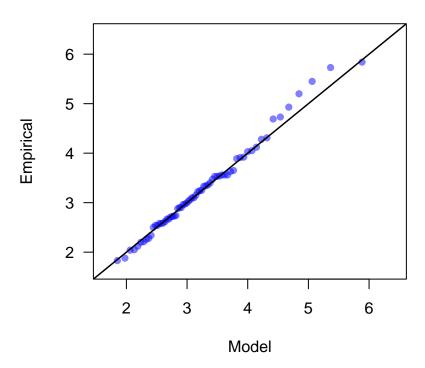
$$-\sum_{i=1}^{t} m_i^{-\frac{1}{\xi}} - t log(\sigma) - (\frac{1}{\xi} + 1) \sum_{i=1}^{t} log(m_i)$$

```
# Fit a GEV to annual maximum daily precip using MLE
library(scales)
gevfit <- fevd(annmx)
# Print the results
gevfit</pre>
```

```
##
## fevd(x = annmx)
##
## [1] "Estimation Method used: MLE"
```

```
##
##
##
   Negative Log-Likelihood Value: 80.60481
##
##
## Estimated parameters:
   location
                scale
                             shape
## 2.85348346 0.70628902 0.01229713
##
## Standard Error Estimates:
   location
                 scale
                             shape
## 0.09985002 0.07338167 0.10043952
## Estimated parameter covariance matrix.
##
               location
                              scale
## location 0.009970026 0.003021057 -0.003803483
## scale
            -0.003803483 -0.002348046 0.010088098
## shape
##
## AIC = 167.2096
##
## BIC = 173.7328
#QQ plot
nmax <- length(annmx)</pre>
p <- 1:nmax / (nmax + 1)
qm <- gevq(mle, 1 - p)
rg \leftarrow c(0.9 * min(annmx), 1.1 * max(annmx))
plot(qm, sort(annmx), xlim = rg, ylim = rg, pch = 16,
    cex = 1, col = alpha("blue", 0.5), xlab = "Model",
    ylab = "Empirical", main ="Quantile Plot", las = 1)
abline(0, 1, lwd = 1.5)
```

Quantile Plot



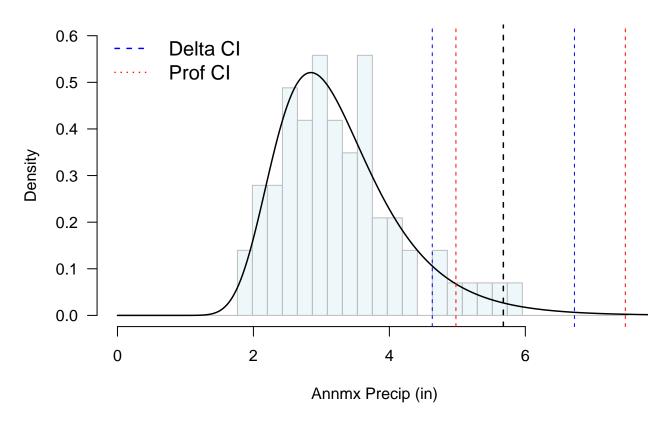
Step 3: Perform inference for return levels

Suppose we are interested in estimating the 50-year return level

```
RL50 <- return.level(gevfit, return.period = 50) # Estimate of the 100-year event
RL50
## fevd(x = annmx)
## get(paste("return.level.fevd.", newcl, sep = ""))(x = x, return.period = return.period)
  GEV model fitted to annmx
## Data are assumed to be stationary
## [1] "Return Levels for period units in years"
## 50-year level
##
        5.676568
# Quantify the estimate uncertainty
## Delta method
CI_delta <- ci(gevfit, return.period = 50, verbose = T)</pre>
##
    Preparing to calculate 95 % CI for 50-year return level
##
##
   Model is
               fixed
##
##
   Using Normal Approximation Method.
```

```
CI_delta
## fevd(x = annmx)
## [1] "Normal Approx."
## [1] "50-year return level: 5.677"
##
## [1] "95% Confidence Interval: (4.6309, 6.7223)"
## Profile likelihood method
CI_prof <- ci(gevfit, method = "proflik", xrange = c(4, 10),</pre>
  return.period = 50, verbose = F)
CI_prof
## fevd(x = annmx)
## [1] "Profile Likelihood"
## [1] "50-year return level: 5.677"
## [1] "95% Confidence Interval: (4.9791, 7.4705)"
hist(annmx, breaks = seq(0, 7.5, length.out = 35),
     col = alpha("lightblue", 0.2), border = "gray",
     xlim = c(0, 7.5), prob = T, ylim = c(0, 0.6),
     xlab = " Annmx Precip (in)",
     main = "95% CI for 50-yr RL",
     las = 1)
xg \leftarrow seq(0, 10, len = 1000)
mle <- gevfit$results$par</pre>
lines(xg, gev.dens(mle, xg), lwd = 1.5)
for (i in c(1, 3)) abline(v = CI_delta[i], lty = 2, col = "blue")
for (i in c(1, 3)) abline(v = CI_prof[i], lty = 2, col = "red")
abline(v = RL50, lwd = 1.5, lty = 2)
legend("topleft", legend = c("Delta CI", "Prof CI"), col = c("blue", "red"),
       lty = c(2, 3), bty = "n", cex = 1.25, lwd = 1.5)
```

95% CI for 50-yr RL



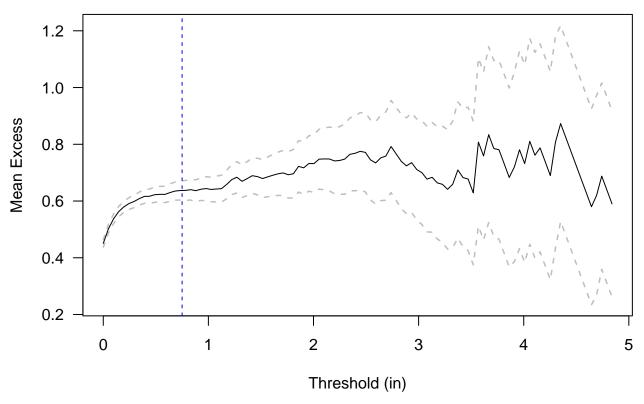
Peak-Over-Threshold Method

Step 1: Pick a threshold and extract the threshold exceedances

I choose 0.75 as the threshold, but note that the 'straightness' of the mean residual life plot is difficult to assess in general

```
mrlplot(dat[!is.na(dat)] / 100, main = "Mean Residual Life", xlab = "Threshold (in)", las = 1)
# I choose 0.75 as the threshold but note that the "straightness"
# is difficult to assess
abline(v = 0.75, col = "blue", lty = 2)
```

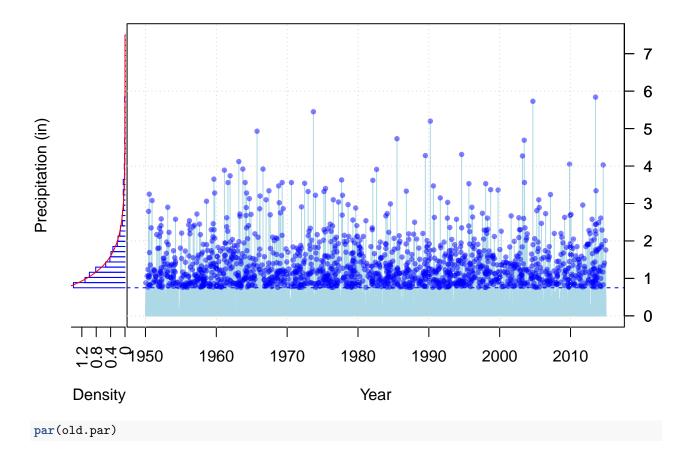
Mean Residual Life



```
old.par <- par(no.readonly = TRUE)</pre>
mar.default <- par('mar')</pre>
mar.left <- mar.default</pre>
mar.right <- mar.default</pre>
mar.left[2] <- 0
mar.right[4] <- 0
# Time series plot
par(fig = c(0.2, 1, 0, 1), mar = mar.left)
plot(1950 + 1:23725/365, c(rain),
      xlab = "Year", ylab = "",
      main = "Daily Precip in Clemson",
      type = "h", pch = 19, cex = 0.5, col = "lightblue",
      ylim = c(0, 7.5), yaxt = "n")
par(las = 2)
axis(4, at = 0:8)
par(las = 0)
mtext("Precipitation (in)", side = 2, line = 4)
#Threshold exceedances
thres <- 0.75
ex_id <- which(rain > thres)
ex <- rain[ex_id]</pre>
nex <- length(ex)</pre>
#Extract the timing of POT
abline(h = thres, col = "blue", lty = 2)
points(1950 + ex_id / 365, ex, col = alpha("blue", 0.5), pch = 16,
       cex = 0.75)
```

```
par(las = 2)
axis(4, at = 0:8)
par(las = 0)
grid()
hs <- hist(ex, seq(thres, 7.5, len = 50), plot = FALSE)
par(fig = c(0, 0.2, 0, 1.0), mar = mar.right, new = T)
plot (NA, type = 'n', axes = FALSE, yaxt = 'n',
      col = rgb(0,0,0.5, alpha = 0.5),
      xlab = "Density", ylab = NA, main = NA,
      xlim = c(-max(hs\$density), 0),
      ylim = c(0, 7.5)
axis(1, at = c(-1.6, -1.2, -0.8, -0.4, 0),
     c(1.6, 1.2, 0.8, 0.4, 0), las = 2)
\#abline(h = 21, col = "red", lty = 5)
arrows(rep(0, length(hs$breaks[-50])), hs$breaks[-50],
       -hs$density, hs$breaks[-50], col = "blue",
       length = 0, angle = 0, lwd = 1)
arrows(rep(0, length(hs$breaks[-1])), hs$breaks[-1],
       -hs$density, hs$breaks[-1], col = "blue",
       length = 0, angle = 0, lwd = 1)
arrows(-hs$density, hs$breaks[-50], -hs$density,
       hs$breaks[-1], col = "blue", angle = 0,
       length = 0)
mle <- fevd(c(rain[!is.na(rain)]), threshold = thres, type = "GP")$results$par</pre>
xg <- seq(thres, 7.5, length.out = 100)</pre>
lines(-gpd.dens(mle, thres, xg), xg, col = "red")
```

Daily Precip in Clemson

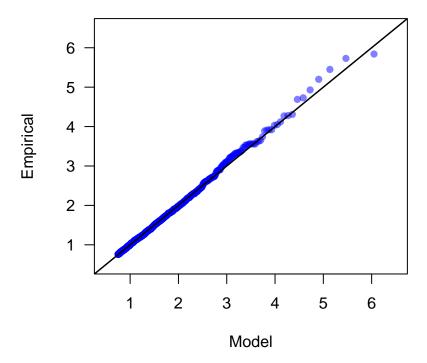


Step 2: Fit a GPD to threshold excesses and assess the fit

```
# Fit a GPD for threshold exceenances using MLE
gpdfit1 <- fevd(c(rain[!is.na(rain)]), threshold = thres, type = "GP")</pre>
# Print the results
gpdfit1
##
## fevd(x = c(rain[!is.na(rain)]), threshold = thres, type = "GP")
## [1] "Estimation Method used: MLE"
##
##
    Negative Log-Likelihood Value: 825.0139
##
##
##
    Estimated parameters:
##
##
        scale
                   shape
## 0.61188988 0.04527592
##
##
    Standard Error Estimates:
##
        scale
                   shape
```

```
## 0.02290870 0.02704591
##
    Estimated parameter covariance matrix.
##
##
                 scale
                                shape
## scale 0.0005248087 -0.0004281417
## shape -0.0004281417 0.0007314815
##
   AIC = 1654.028
##
##
##
  BIC = 1664.64
# QQ plot
p <- 1:nex / (nex + 1)
qm \leftarrow gpdq(mle, 0.75, 1 - p)
plot(qm, sort(ex), xlim = c(0.5, 6.5), ylim = c(0.5, 6.5),
     pch = 16, cex = 1, col = alpha("blue", 0.5),
     xlab = "Model", ylab = "Empirical", main = "Quantile Plot",
     las = 1)
abline(0, 1, lwd = 1.5)
```

Quantile Plot



Step 3: Perform inference for return levels

Again we are interested in estimating 50-year return level

```
RL50 <- return.level(gpdfit1, return.period = 50 * 365 / 365.25)
RL50</pre>
```

```
## fevd(x = c(rain[!is.na(rain)]), threshold = thres, type = "GP")
```

```
## get(paste("return.level.fevd.", newcl, sep = ""))(x = x, return.period = return.period)
##
## GP model fitted to c(rain[!is.na(rain)])
## Data are assumed to be stationary
## [1] "Return Levels for period units in years"
## 49.9657768651608-year level
                      5.829943
CI_delta <- ci(gpdfit1, return.period = 50 * 365 / 365.25,
               verbose = F)
CI_delta
## fevd(x = c(rain[!is.na(rain)]), threshold = thres, type = "GP")
## [1] "Normal Approx."
## [1] "49.9657768651608-year return level: 5.83"
## [1] "95% Confidence Interval: (5.0405, 6.6194)"
CI_prof <- ci(gpdfit1, method = "proflik", xrange = c(4, 10),</pre>
   return.period = 50 * 365 / 365.25, verbose = F)
CI_prof
## fevd(x = c(rain[!is.na(rain)]), threshold = thres, type = "GP")
## [1] "Profile Likelihood"
## [1] "49.9657768651608-year return level: 5.83"
##
## [1] "95% Confidence Interval: (5.2632, 6.7866)"
hist(ex, breaks = seq(thres, 6, 0.1), col = alpha("lightblue", 0.2), border = "gray",
     xlim = c(thres, 7.5), prob = T, ylim = c(0, 2),
     xlab = "Threshold excess (in)",
     main = "95% CI for 50-yr RL", las = 1)
xg \leftarrow seq(thres, 10, len = 1000)
mle <- gpdfit1$results$par</pre>
lines(xg, gpd.dens(mle, thres, xg), lwd = 1.5)
for (i in c(1, 3)) abline(v = CI_delta[i], lty = 2, col = "blue")
for (i in c(1,3)) abline(v = CI_prof[i], lty = 2, col = "red")
abline(v = RL50, lwd = 1.5, lty = 2)
legend("topleft", legend = c("Delta CI", "Prof CI"),
       col = c("blue", "red"), lty = c(2, 3), bty = "n", cex = 1.25,
       lwd = 1.5)
```

95% CI for 50-yr RL

