

## Introduction

- There are two ways of classifying an extreme event.
- The first method is to split the time series into fixed blocks, and take the maximum of each block to be extreme:

- Let  $X_i$  denote the  $i^{\text{th}}$  observation of a random variable  $X$ .
- Let  $M_n = \max\{X_1, \dots, X_n\}$ .
- Let  $M_n^*$  be the normalised maxima, satisfying

$$P(M_n^* \leq z) \rightarrow G(z) \text{ as } n \rightarrow \infty,$$

where  $G$  is a non-degenerate distribution function.

- Then  $G$  is a Generalised Extreme Value (GEV) distribution, where

$$G(z) = \exp\left(-\left(1 + \xi \left(\frac{z-\mu}{\sigma}\right)\right)^{-1/\xi}\right)$$

- There are three parameters:
  - The location parameter  $\mu$ , where  $-\infty < \mu < \infty$
  - The scale parameter  $\sigma$ , where  $\sigma > 0$
  - The shape parameter  $\xi$ , where  $-\infty < \xi < \infty$

- This distribution is defined on the set

$$\{z : 1 + \xi(z-\mu)/\sigma > 0\}$$

- The second method of classifying extremes is to choose a threshold and take all values above this threshold to be extreme:

- Assume that the block maxima are GEV distributed.

- Then for large enough  $u$ , the distribution of  $(X - u)$  given  $X > u$  is approximately a Generalised Pareto Distribution (GPD), defined by

$$H(y) = P(X > u + y | X > u) = 1 - (1 + \xi y/\tilde{\sigma})^{-1/\xi}$$

where  $\tilde{\sigma} = \sigma + \xi(u - \mu)$

- The distribution is defined on the set

$$\{y : y > 0 \ \& \ (1 + \xi y/\tilde{\sigma}) > 0\}$$

- The  $\xi$  of both the GEV and GPD are identical given the same data set.

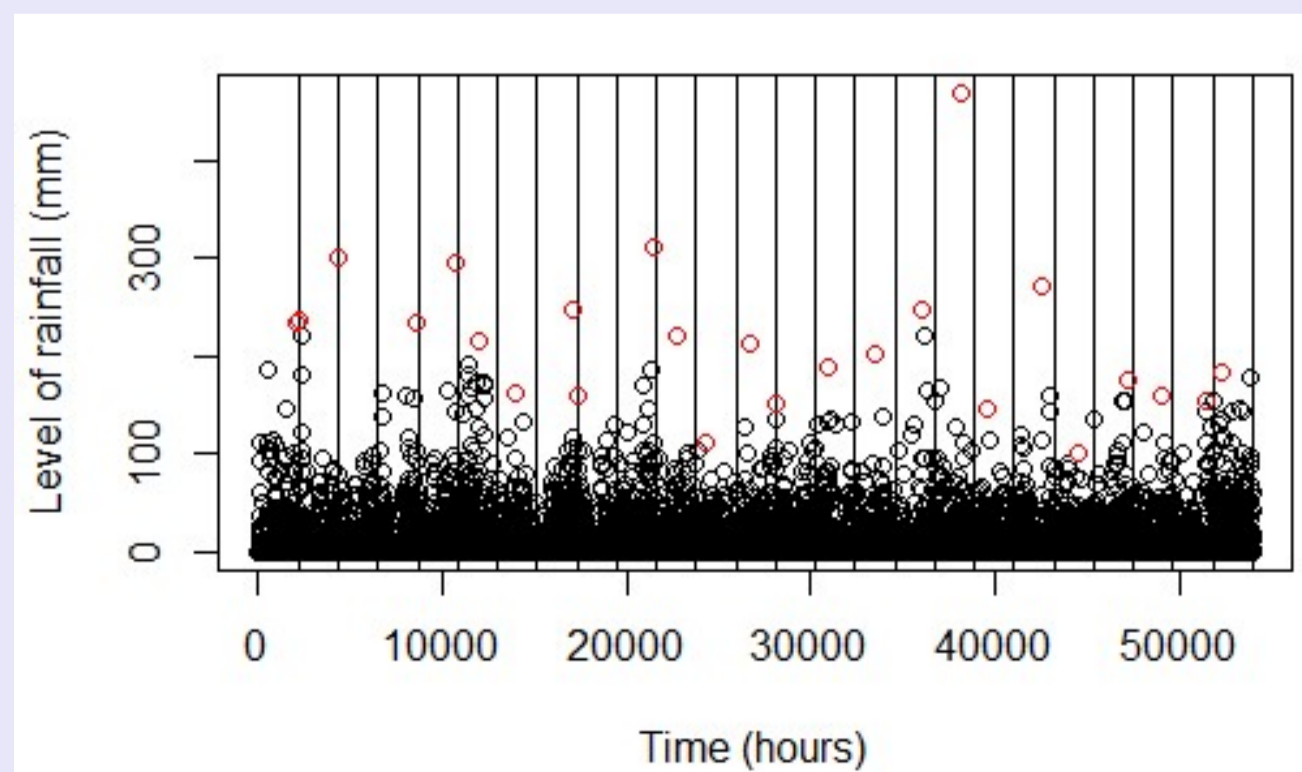


Figure 1: Local maxima of rainfall at fixed location over time

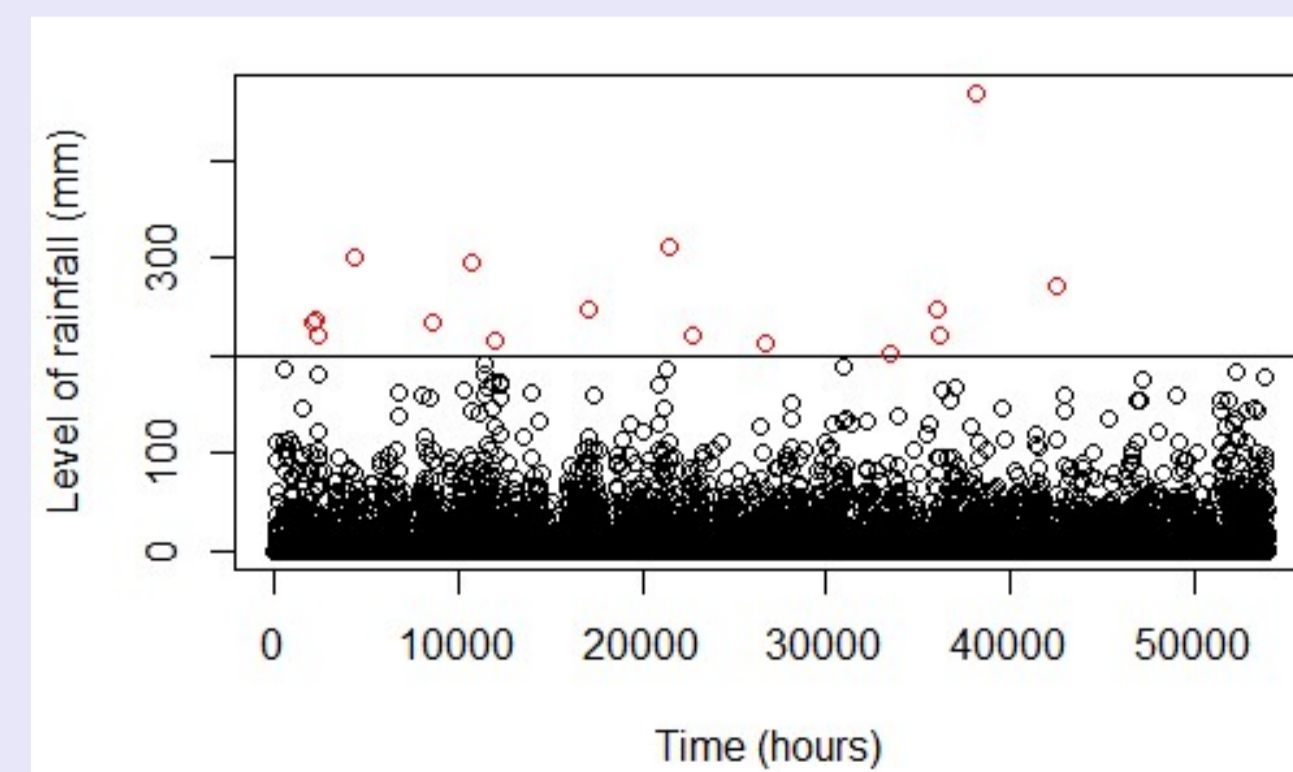


Figure 2: Rainfall observations above threshold at fixed location over time

## Return levels

- A series of independent observations  $X_i, i = 1, \dots, d$ , can be blocked into sequences of length  $n$  (the length is often 1 year), generating a series of block maxima  $M_{n,1}, \dots, M_{n,m}$ , where  $m$  is the number of maxima.
- A GEV distribution can be fitted to these maxima, and extreme quantiles can be estimated by inverting the distribution function:

$$z_p = \begin{cases} \mu - \frac{\sigma}{\xi} (1 - (-\log(1-p))^{-\xi}) & \text{for } \xi \neq 0 \\ \mu - \sigma \log(-\log(1-p)) & \text{for } \xi = 0 \end{cases}$$

where  $G(z_p) = 1 - p$ .

- $z_p$  is the return level associated with the return period  $1/p$ , i.e.  $z_p$  is expected to be exceeded every  $1/p$  years.

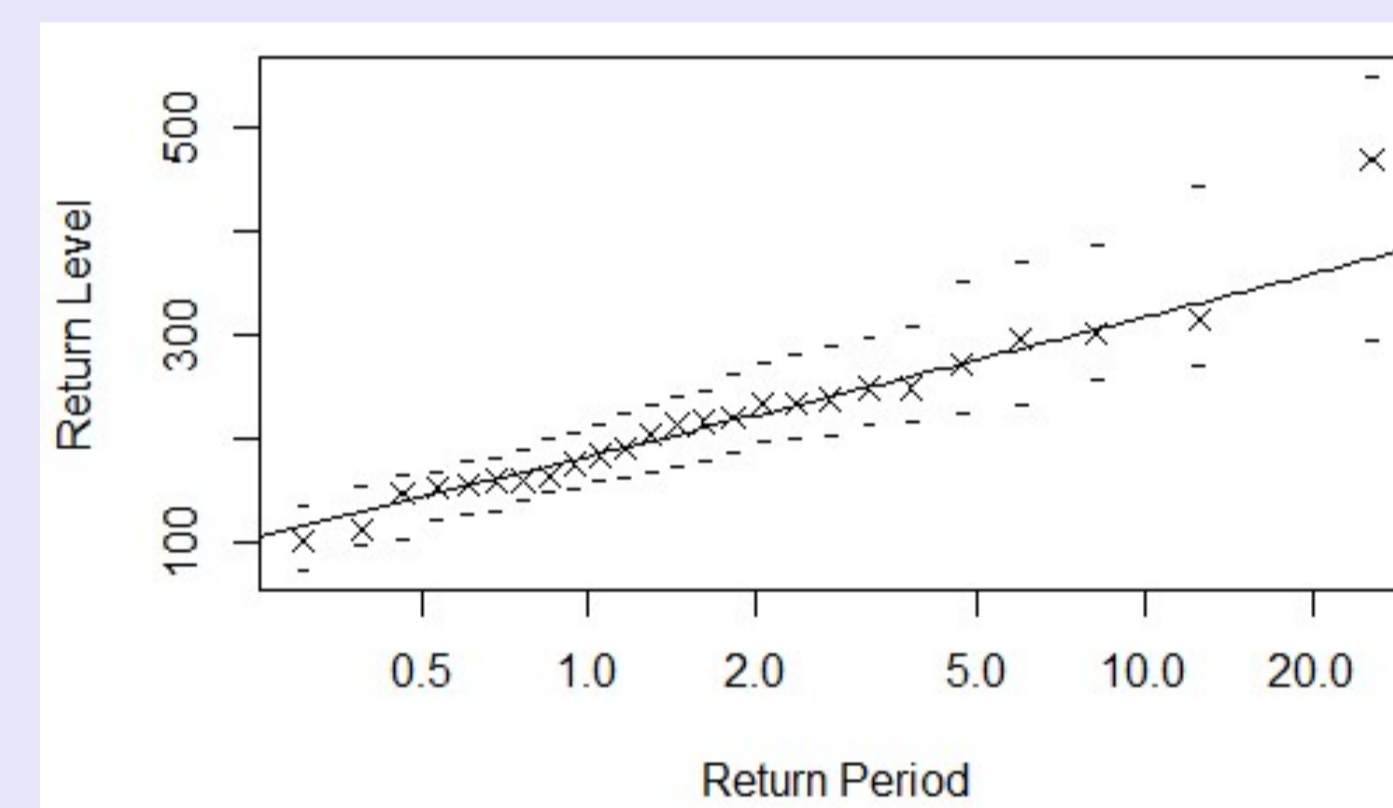


Figure 3: Expected return level after given period of years

## Extremal Dependence Measures

- Asymptotic dependence is a measure of extremes occurring together.
- One dependence measure is  $\chi$ , which is the upper tail index. Given two random variables  $X$  and  $Y$ , and their respective uniform transformations  $U$  and  $V$ ,

$$\chi = \lim_{u \rightarrow 1} P(V > u | U > u)$$

- This can be calculated empirically.
- $\chi$  takes values between 0 and 1, with 1 signifying perfect asymptotic dependence and 0 signifying asymptotic independence.
- The data below has high asymptotic dependence.

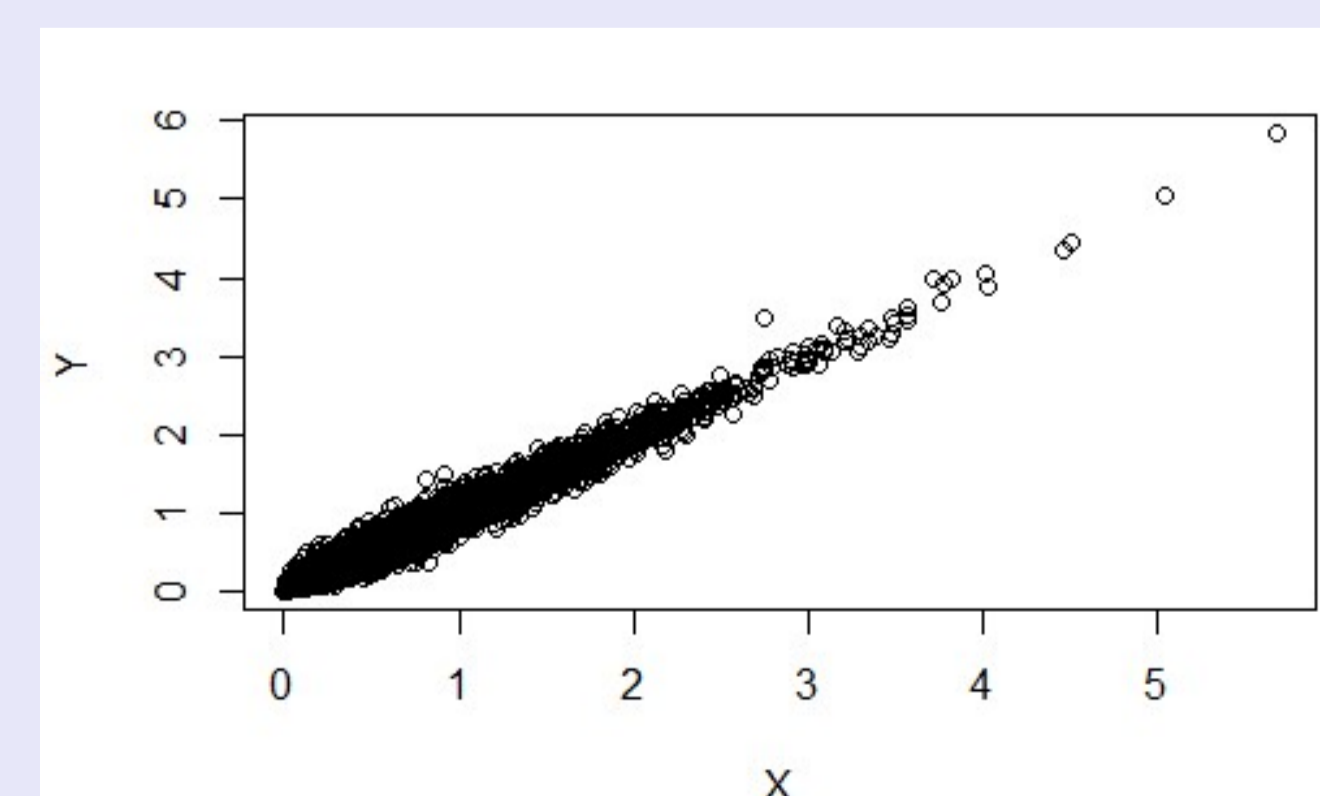


Figure 4: Simulation of random variables  $X$  and  $Y$  such that  $\chi = 0.9$

## Extremal Dependence Measures (cont.)

- Another dependence measure is  $\eta$ , which is the coefficient of tail dependence. Given two random variables  $X$  and  $Y$  on exponential margins,

$$P(X > x, Y > x) \sim L(x) \exp(-x/\eta)$$

where  $L(x)$  is a slowly varying function

- It can be estimated by Hill's estimator, and takes values between 0.5 and 1, with 1 signifying asymptotic dependence.
- The data below has low asymptotic dependence

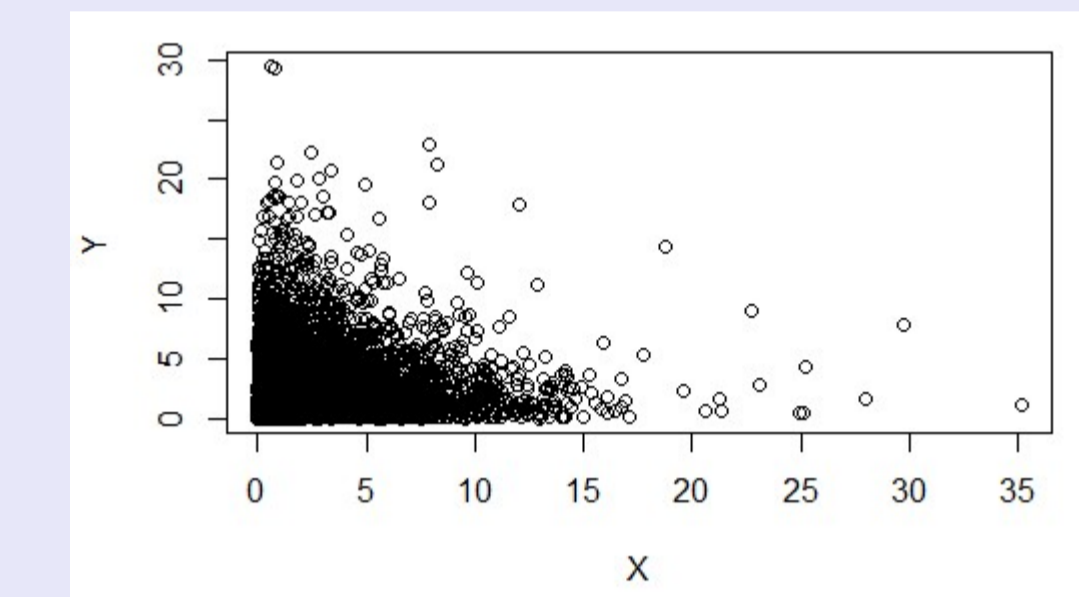


Figure 5: Simulation of random variables  $X$  and  $Y$  such that  $\eta = 0.51$

## Applications

- The data I am using consists of a 16x16 grid of locations across Lancashire, with rainfall levels recorded every hour from December to February for 25 years.
- I looked into two areas:
  - How distance between points affects the asymptotic dependence between rainfall
  - How asymptotic dependence changes as the aggregation level increases
- Here it can be seen that as distance increases, the values of chi decrease at the same rate for both levels.

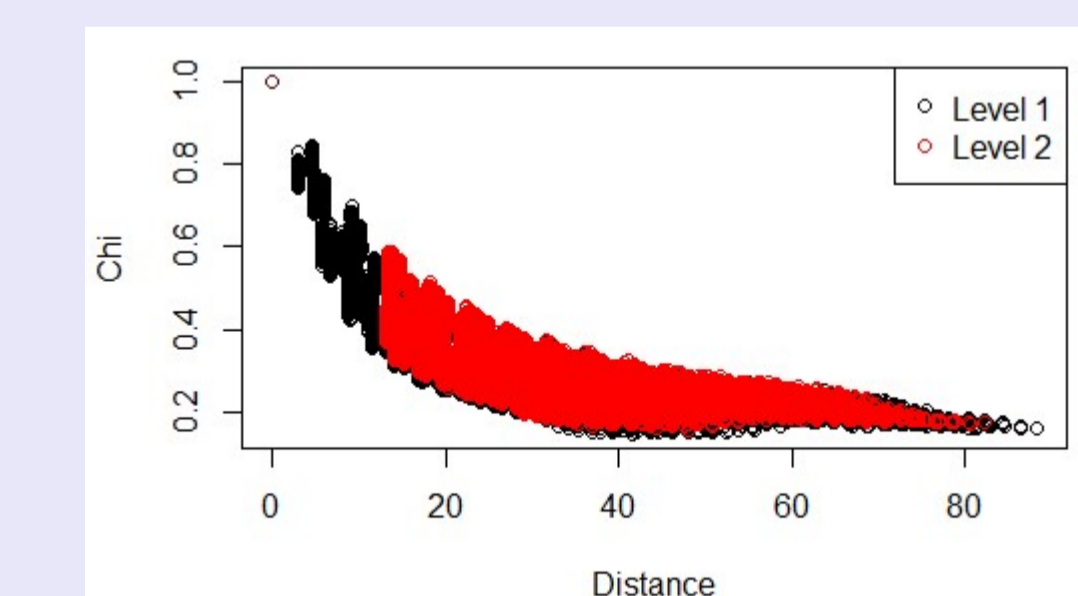


Figure 6: Values of  $\chi$  for aggregation levels 1 and 2 with respect to distance

## References

- Stuart Coles, Janet Heffernan, and Jonathan Tawn (2000) *Dependence Measure for Extreme Value Analyses*
- Stuart Coles (2001) *An Introduction to Statistical Modelling of Extreme Values*