

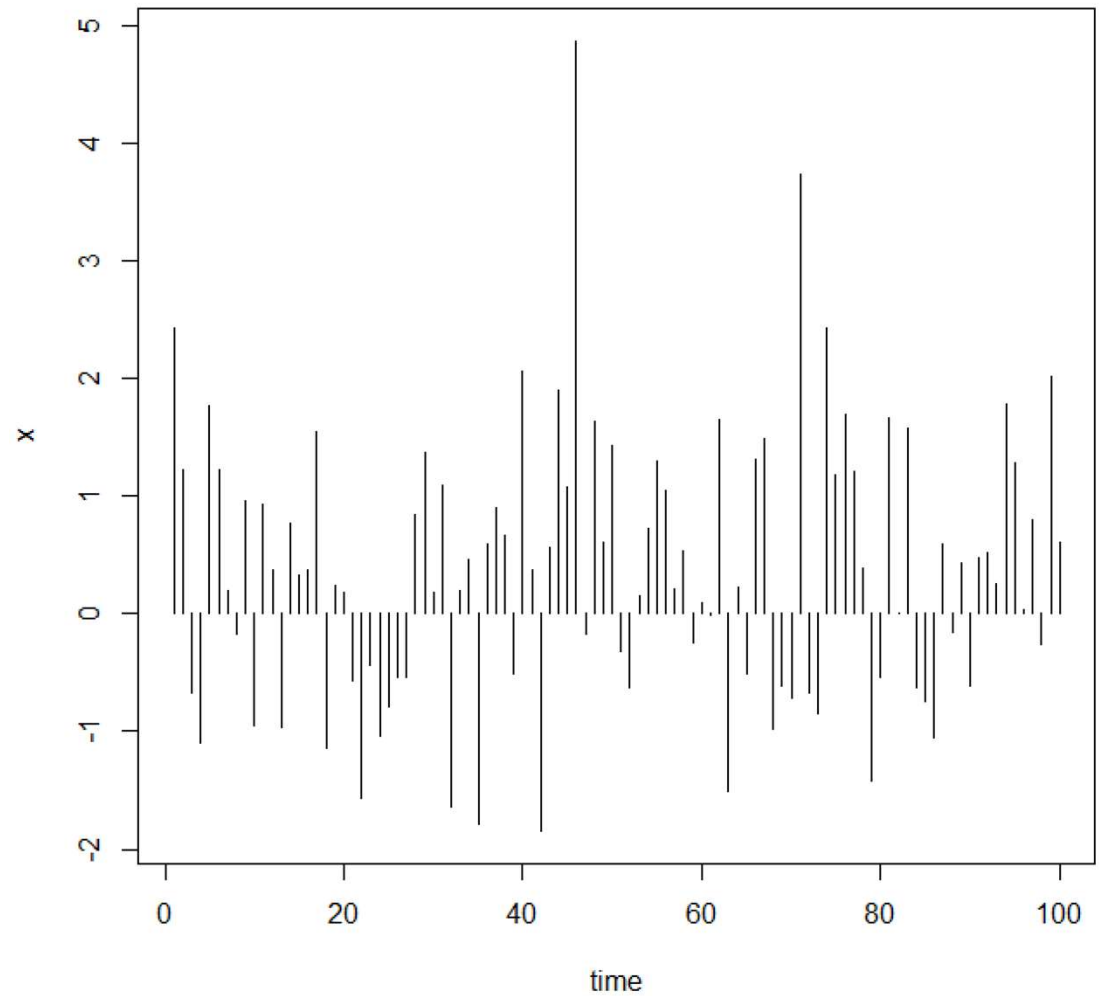
Earth System Extremes Affinity Group

extRemes: An R package for statistical extreme-value analysis (EVA)

Eric Gilleland

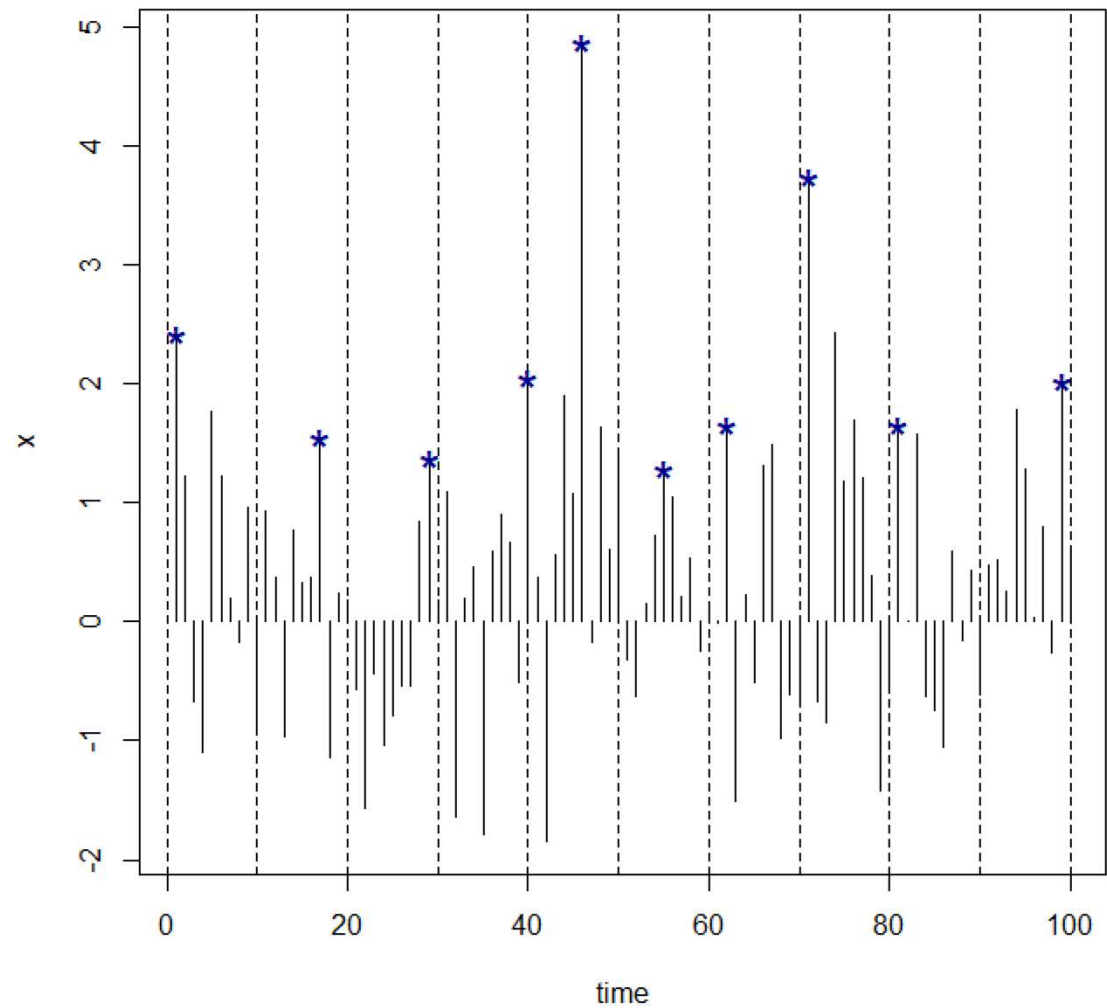
7 April 2022

What is
extreme?



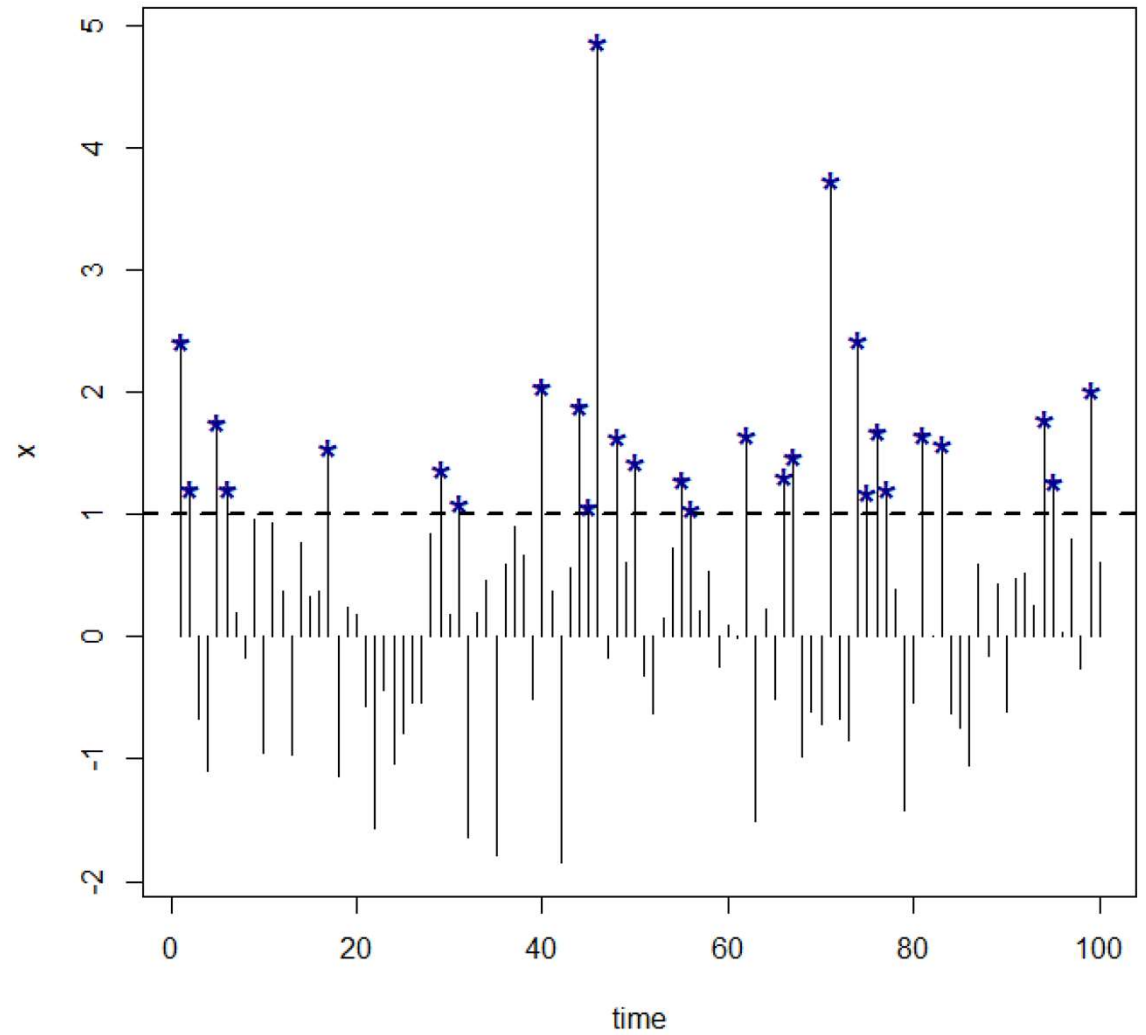
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What is
extreme?



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What is
extreme?

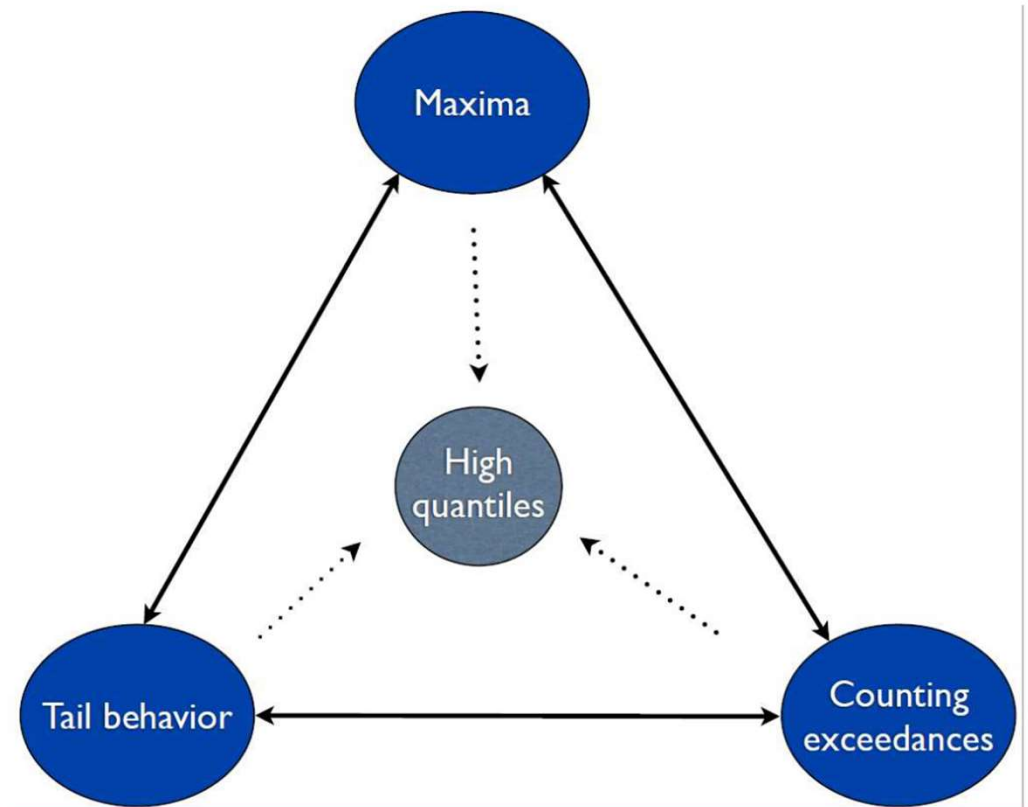


Figure from Philippe Naveau

Inference for the Maximum

- Only one maximum in a data set, but are we sure we've already recorded it? How much larger could it get?
- Let $X_1, \dots, X_n$ be iid with common (cumulative) distribution F , and let $M_n = \max\{X_1, \dots, X_n\}$.
- $\mathbb{P}[M_n \leq z] = \mathbb{P}[X_1 \leq z, \dots, X_n \leq z] = \prod_{i=1}^n \mathbb{P}[X_i \leq z] = F^n(z)$.



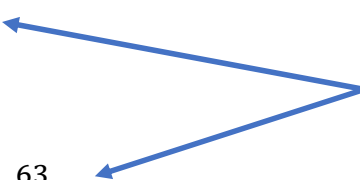
Problematic for large n !

Sum Stability

$$\frac{2 + 7 + 14 + 8 + 10 + 22}{6} = \frac{63}{6}$$

$$\frac{1}{2} \cdot \left(\frac{2+7+14}{3} + \frac{8+10+22}{3} \right) = \frac{1}{2} \cdot \left(\frac{23}{3} + \frac{40}{3} \right) = \frac{63}{6}$$

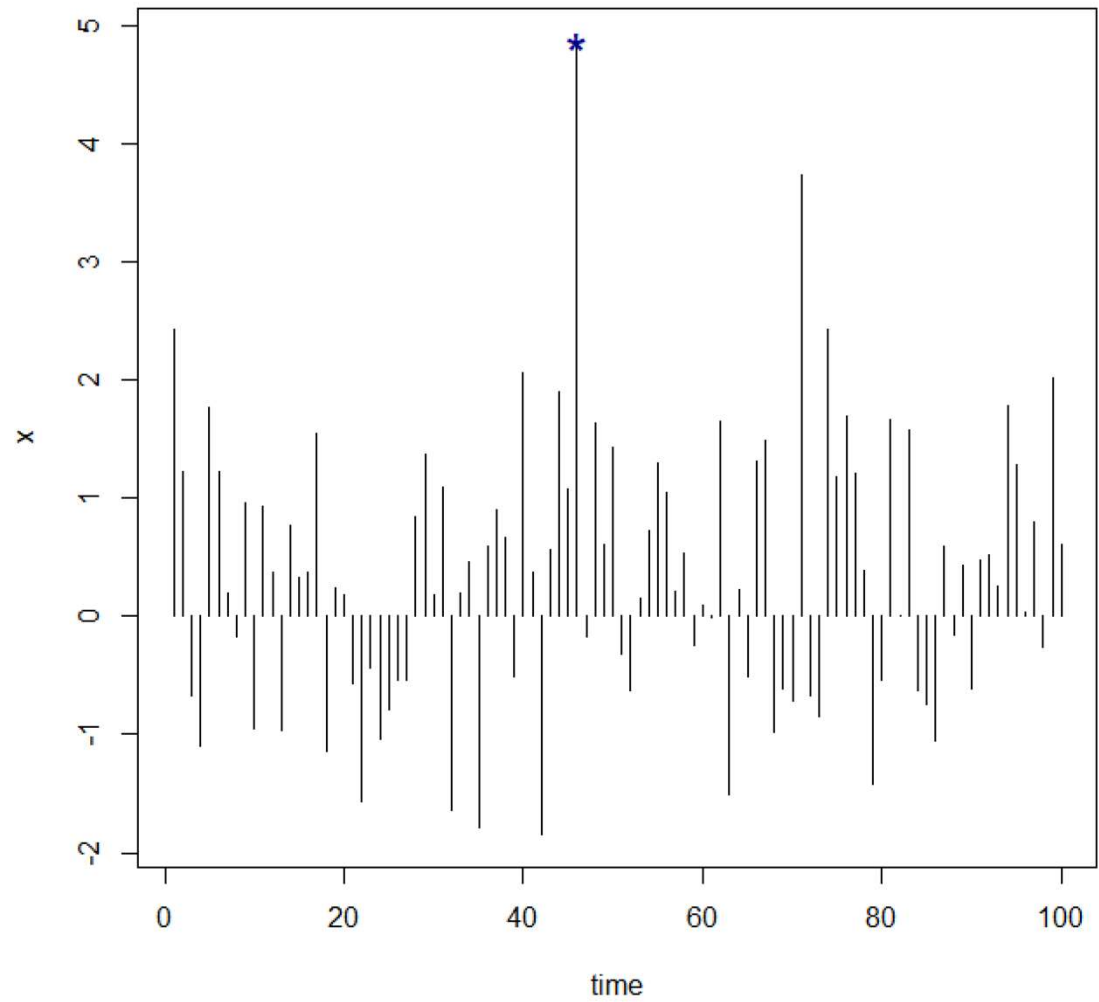
The two averages are the same. The first averages six numbers while the second averages only two.



Let $X_1, X_2, \dots, X_n$ be iid random variables. Let $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$ and let $\bar{Y}_m = \frac{1}{mk} \sum_{j=1}^m Y_j$, where $Y_1 = X_1 + X_2 + \dots + X_k, Y_2 = X_{k+1} + X_{k+2} + \dots + X_{2k}, \dots, Y_m = X_{n-k+1} + \dots + X_n$.

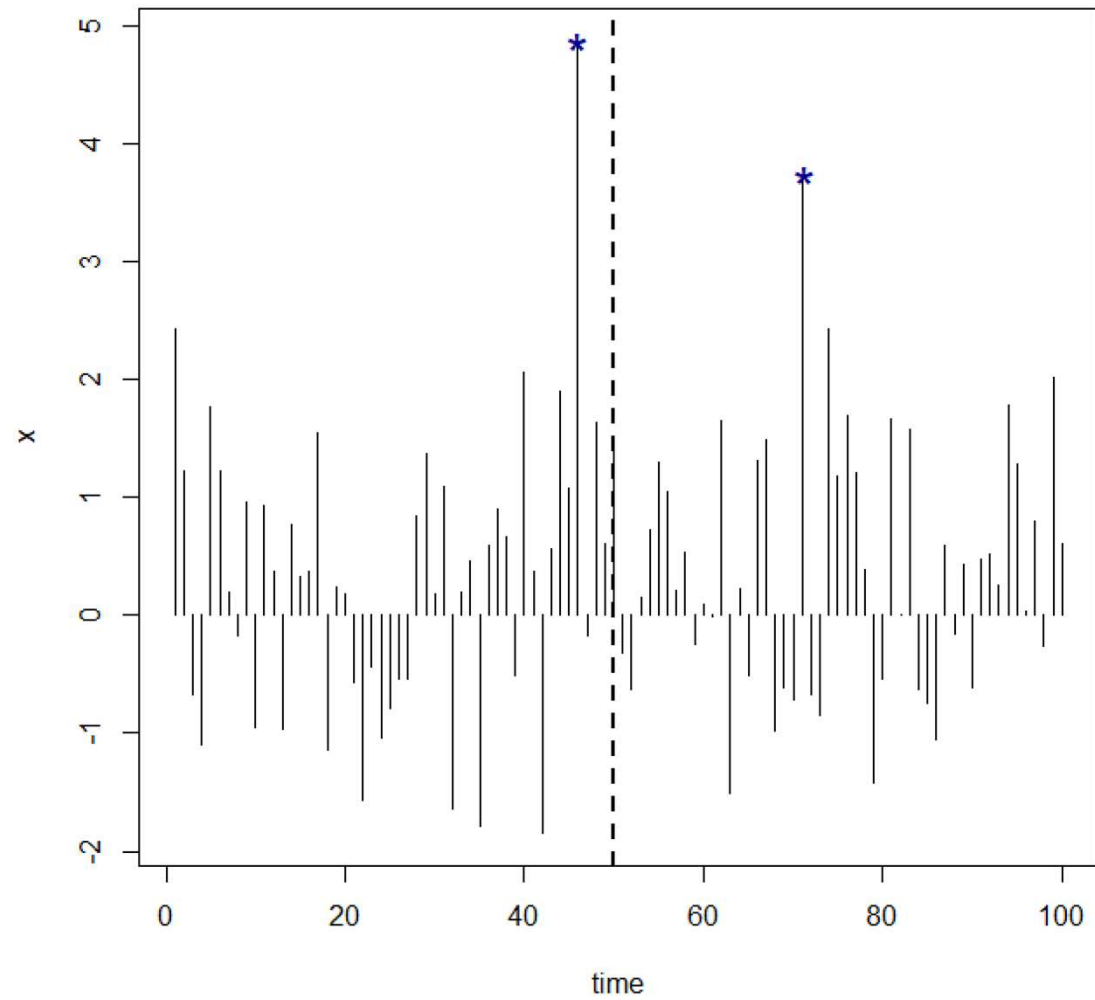
The distribution of $\bar{X}_n$ should be the same as that of $\bar{Y}_m$. And sum stability says that it is! In this case, the normal distribution is sum-stable (among others). For example, if $X_i \sim N(\mu, \sigma^2)$ for all $i = 1, \dots, n$, then $\sum_{i=1}^n X_i \sim N(n\mu, n\sigma^2)$. Note the distribution is the same but for some re-scaling.

Max Stability



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Max Stability



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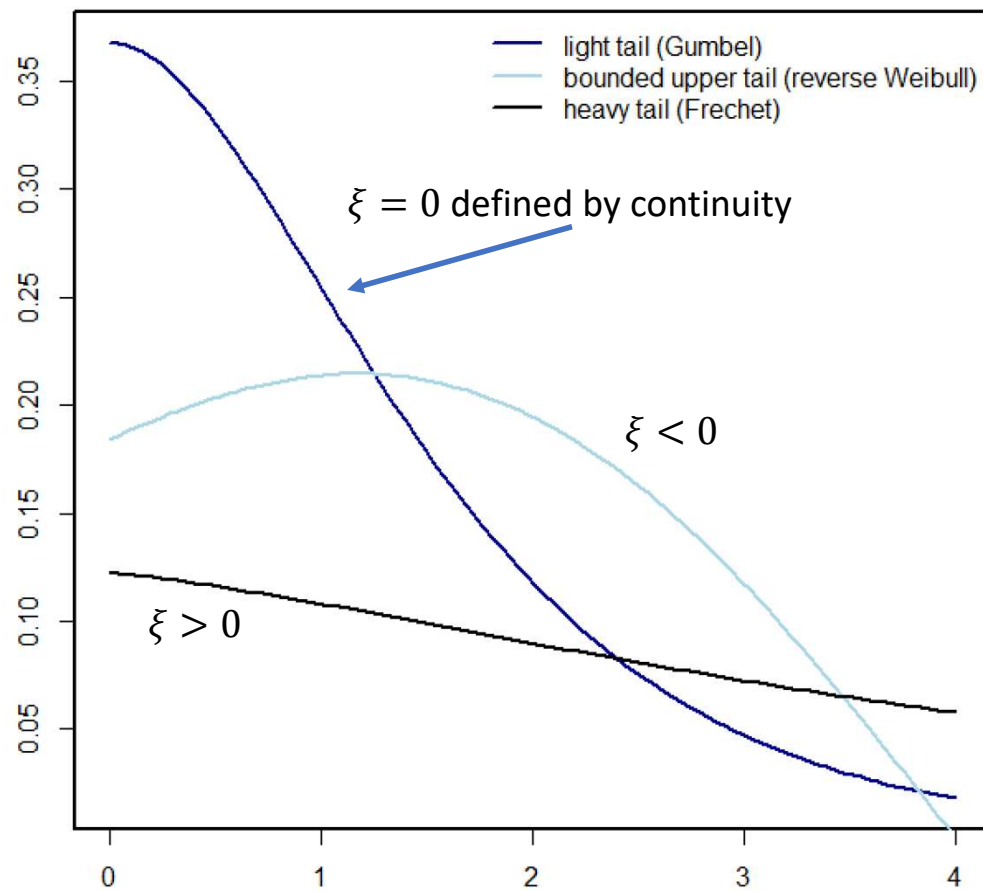
Similar to the sum-stable case,
 $\max\{X_1, \dots, X_n\} = \max\left\{\max\{X_1, \dots, X_{\lfloor \frac{n}{2} \rfloor}\}, \max\{X_{\lfloor \frac{n}{2} \rfloor + 1}, \dots, X_n\}\right\}$ and so on.

So, apart from some re-scaling, we seek a distribution G such that $G(a_n z + b_n) = G^n(z)$ for some sequences of constants $a_n > 0$ and b_n .

Such a distribution is said to be max-stable, and there is only one (family) that fits the bill! The generalized extreme-value distribution (GEV).

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

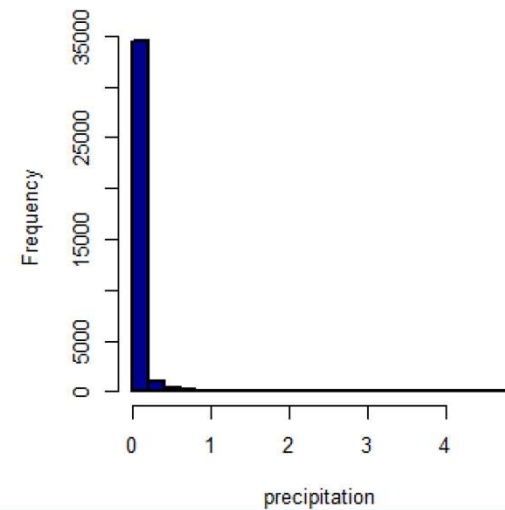
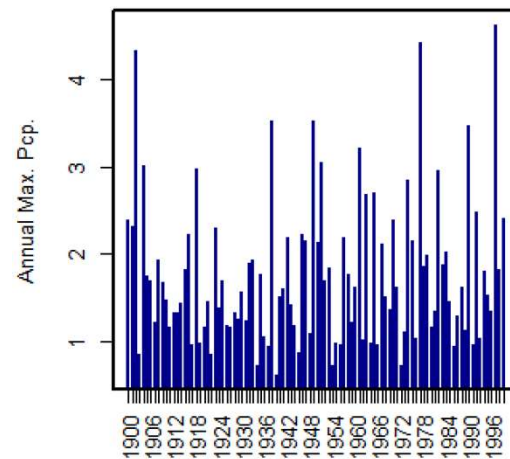
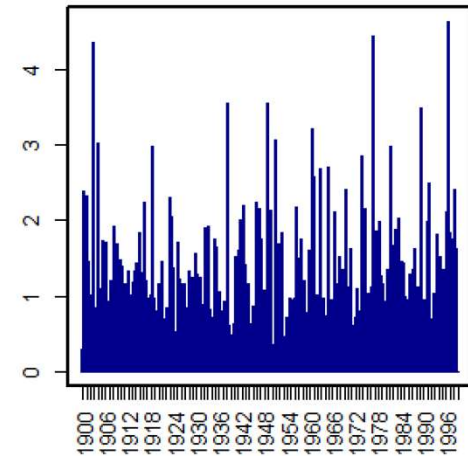
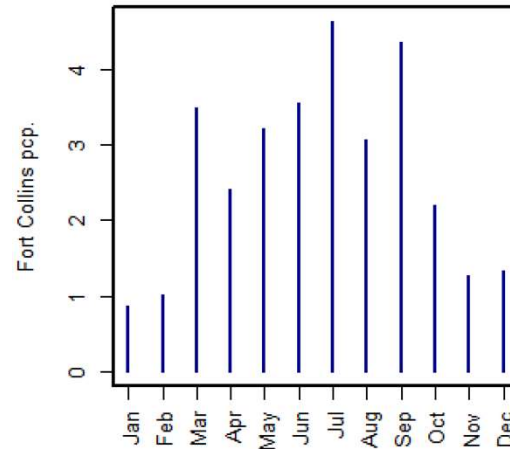
Max Stability



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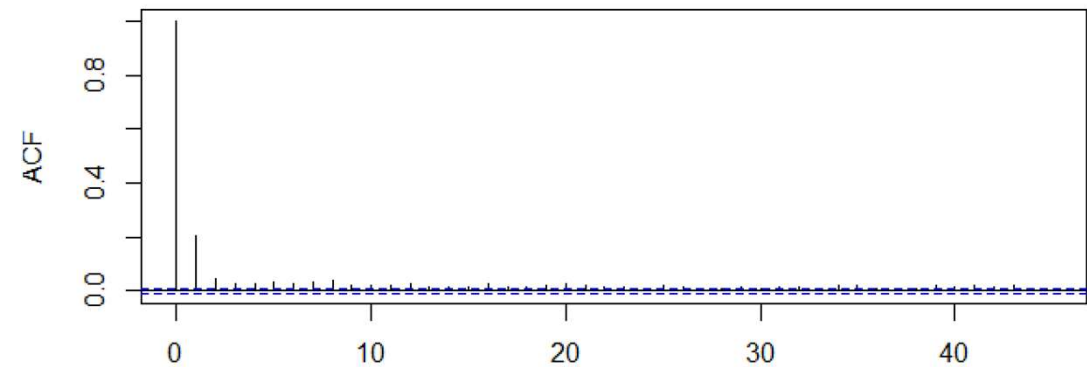
```
data( "Fort" )
```



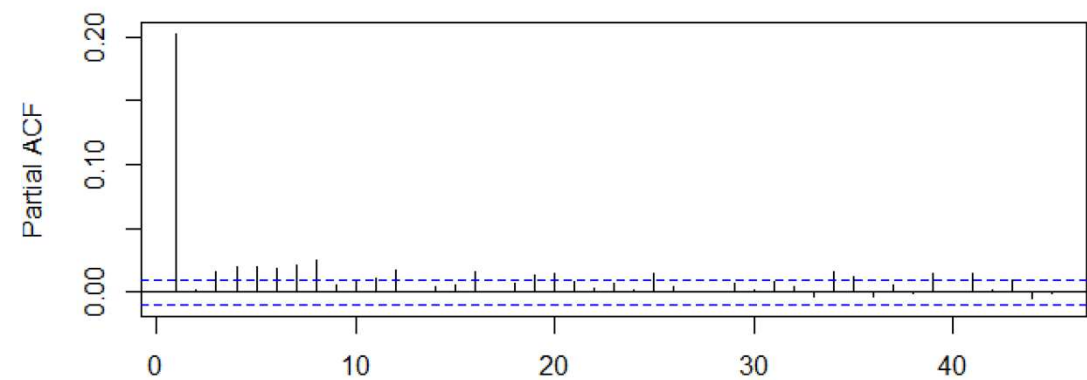
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extRemes:
An R
software
package

Fort Collins daily pcp.



Fort Collins daily pcp.

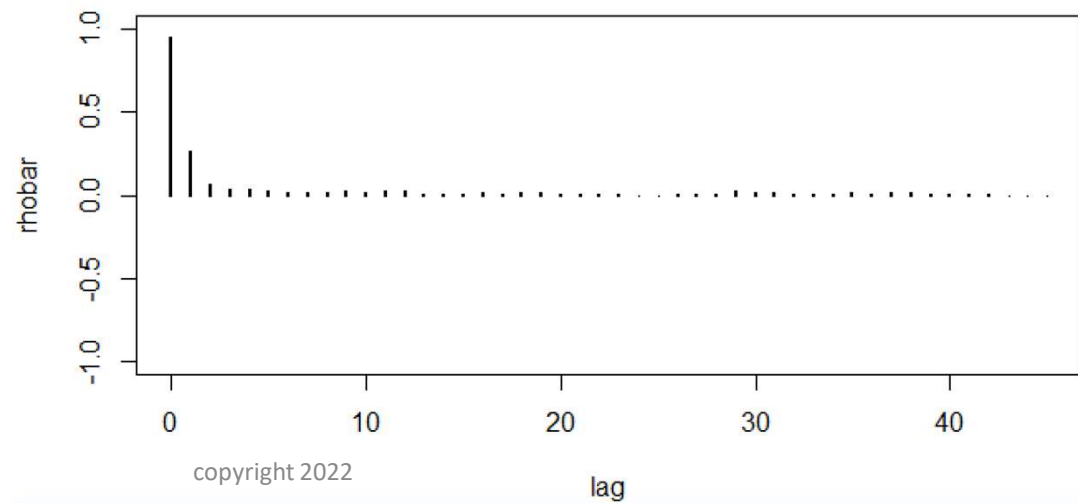
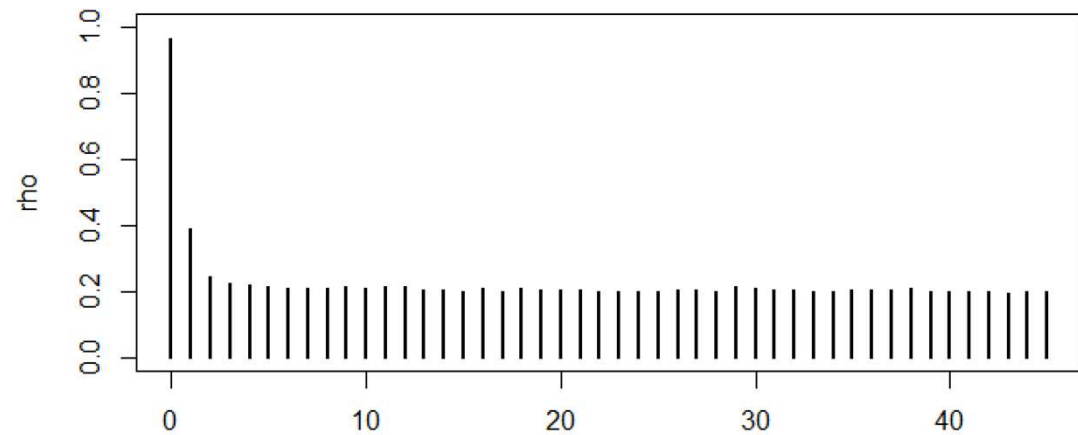


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```
atdf( Fort$Prec, u = 0.8 )
```

extRemes: An R software package

Auto tail-dependence function (Fort Collins pcp.)



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lag

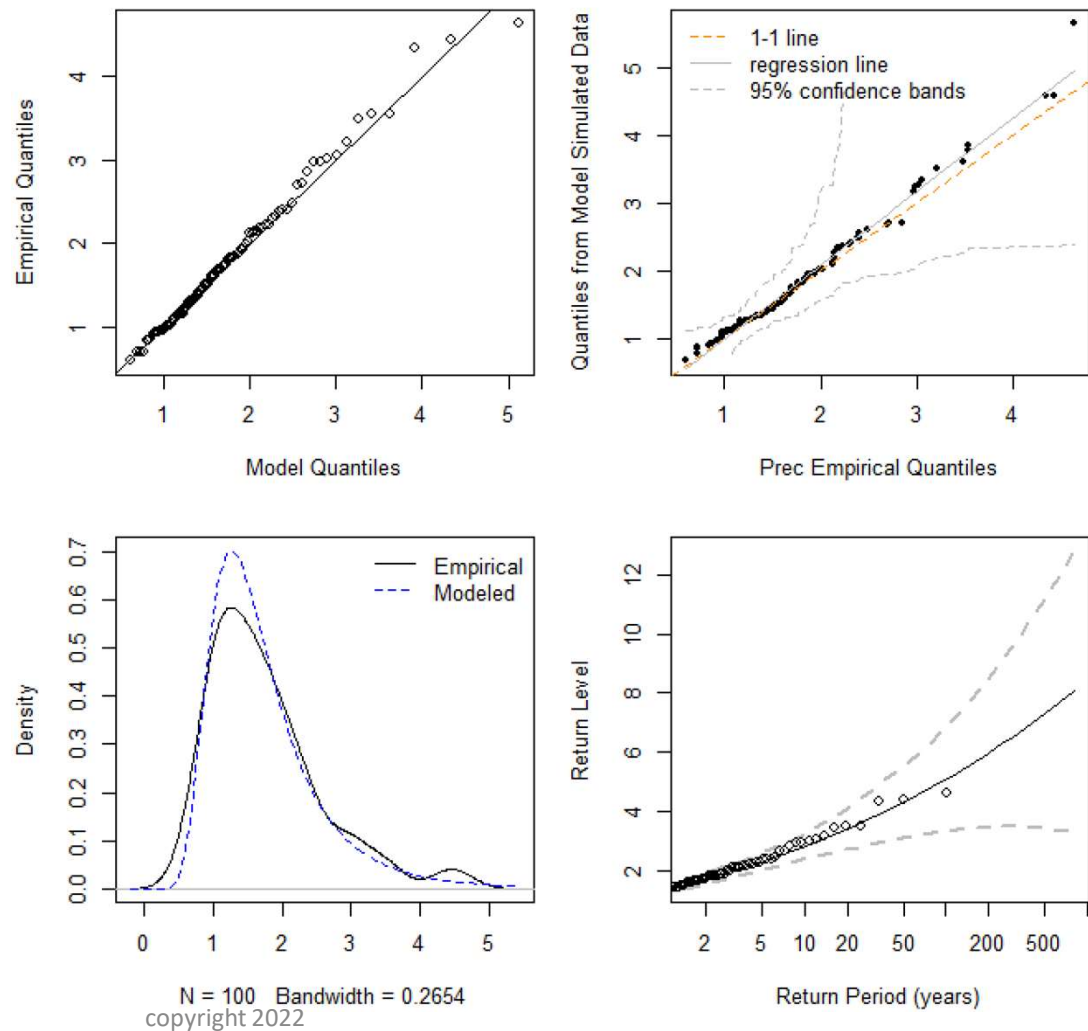
```
bmpcp <- blockmaxxer(
  Fort, which = "Prec",
  blocks = Fort$year )
```

```
fit0 <- fevd( Prec,
  data = bmpcp )
```

```
fit0
plot( fit0 )
```

extRemes: An R software package

fevd(x = Prec, data = bmpcp)



extRemes: An R software package

```
fevd(x = Prec, data = bmpcp)
```

```
[1] "Estimation Method used: MLE"
```

Negative Log-Likelihood Value: 104.9645

Estimated parameters:

location	scale	shape
1.3466597	0.5328046	0.1736264

Standard Error Estimates:

location	scale	shape
0.06168793	0.04878843	0.09195458

Estimated parameter covariance matrix.

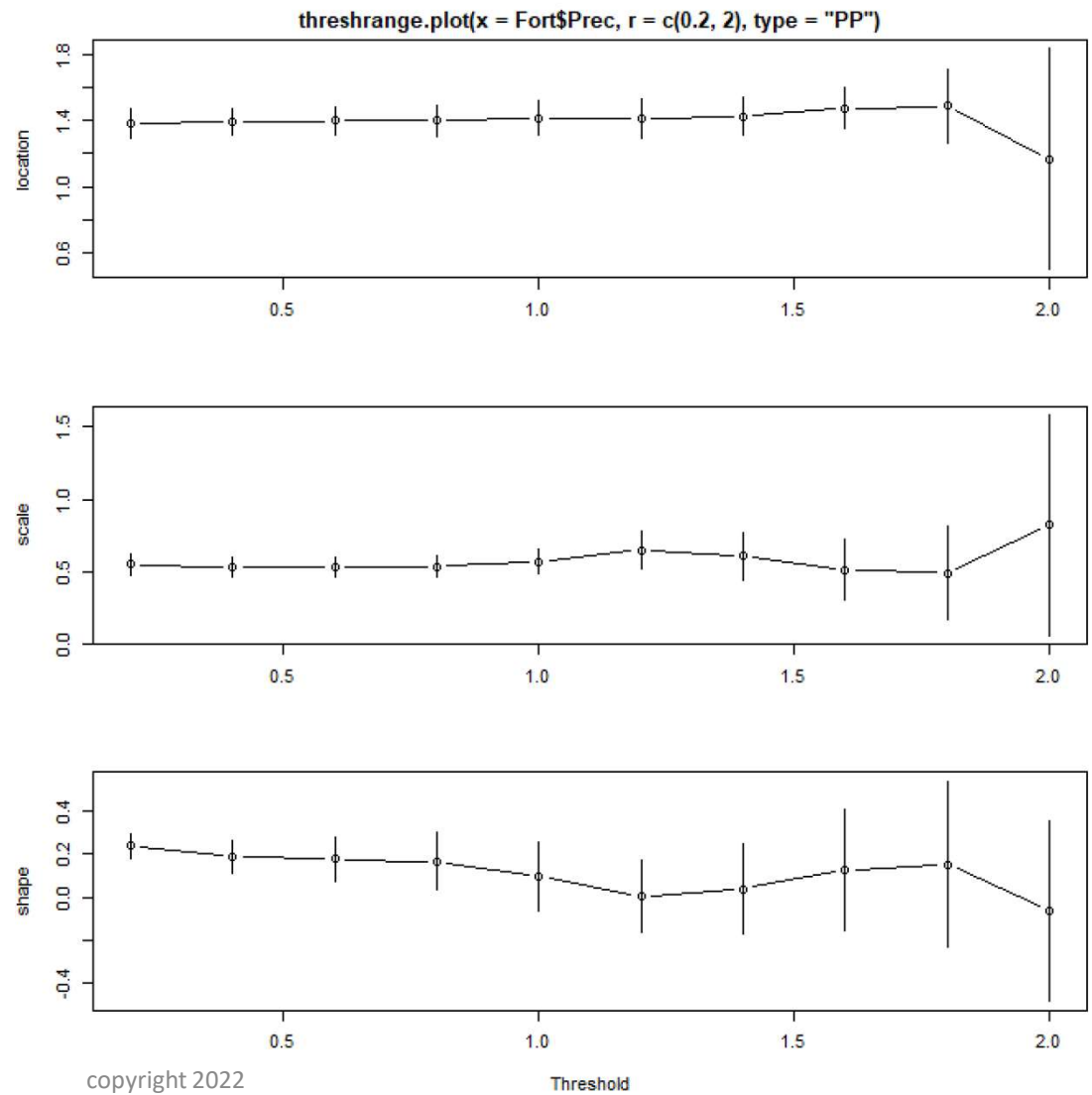
	location	scale	shape
location	0.003805401	0.0017067043	-0.0020838301
scale	0.001706704	0.0023803113	-0.0008692638
shape	-0.002083830	-0.0008692638	0.0084556445

AIC = 215.9291

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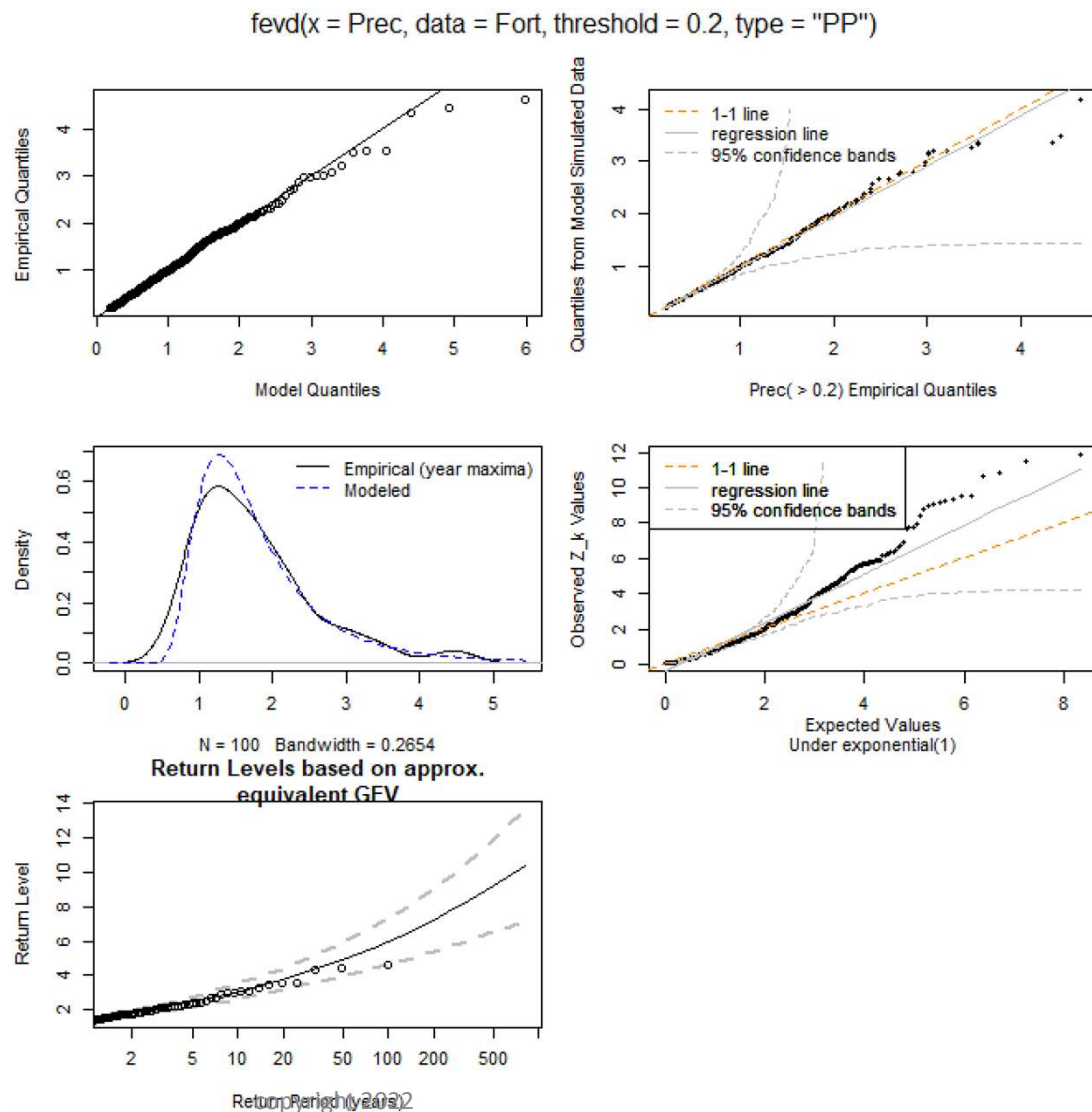
BIC = 223.7446

extRemes: An R software package



```
fit1 <- fevd( Prec,
  data = Fort,
  threshold = 0.2,
  type = "PP" )
fit1
plot( fit1 )
```

extRemes: An R software package



```
fit1 <- fevd( Prec,  
             data = Fort,  
             threshold = 0.2,  
             type = "PP" )  
fit1  
plot( fit1 )
```

extRemes: An R software package

```
fevd(x = Prec, data = Fort, threshold = 0.2, type = "PP")
```

```
[1] "Estimation Method used: MLE"
```

Negative Log-Likelihood Value: -4417.258

Estimated parameters:

location	scale	shape
1.3832749	0.5476977	0.2383581

Standard Error Estimates:

location	scale	shape
0.04456320	0.03705234	0.02796421

Estimated parameter covariance matrix.

	location	scale	shape
location	0.0019858784	0.0014822808	0.0008135954
scale	0.0014822808	0.0013728757	0.0009489163
shape	0.0008135954	0.0009489163	0.0007819970

AIC = -8828.515

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BIC = -8811.593

extRemes: An R software package

```
fit2 <- fevd(x = Prec, data = Fort, threshold = 0.2, location.fun = ~year,  
            type = "PP")
```

```
[1] "Estimation Method used: MLE"
```

Negative Log-Likelihood Value: -4417.386

Estimated parameters:

mu0	mu1	scale	shape
1.5793476649	-0.0001005235	0.5478486937	0.2384873599

Standard Error Estimates:

mu0	mu1	scale	shape
4.453367e-02	2.000003e-08	3.702638e-02	2.794186e-02

Estimated parameter covariance matrix.

	mu0	mu1	scale	shape
mu0	1.983248e-03	-1.935322e-12	1.480016e-03	8.118021e-04
mu1	-1.935322e-12	4.000013e-16	-1.557991e-12	-9.375119e-13
scale	1.480016e-03	-1.557991e-12	1.370953e-03	9.473656e-04
shape	8.118021e-04	-9.375119e-13	9.473656e-04	7.807476e-04

AIC = -8826.772

BIC = -8804.209

Higher values for both AIC and BIC,
suggest annual trend not important

extRemes: An R software package

```
lr.test( fit1, fit2 )
```

Likelihood-ratio Test

data: PrecPrec

Likelihood-ratio = 0.25649, chi-square critical value = 3.8415,

alpha =

0.0500, Degrees of Freedom = 1.0000, p-value = 0.6125

alternative hypothesis: greater

Propinquity Model

Example: Maximum
Updraft Velocity $\times$ 0-
6 km vertical wind
shear (WmSh, m^2s^{-2})

Mean of simulated WmSh at each grid point conditioned on high q_{75} . Using the propinquity model with HT2004.

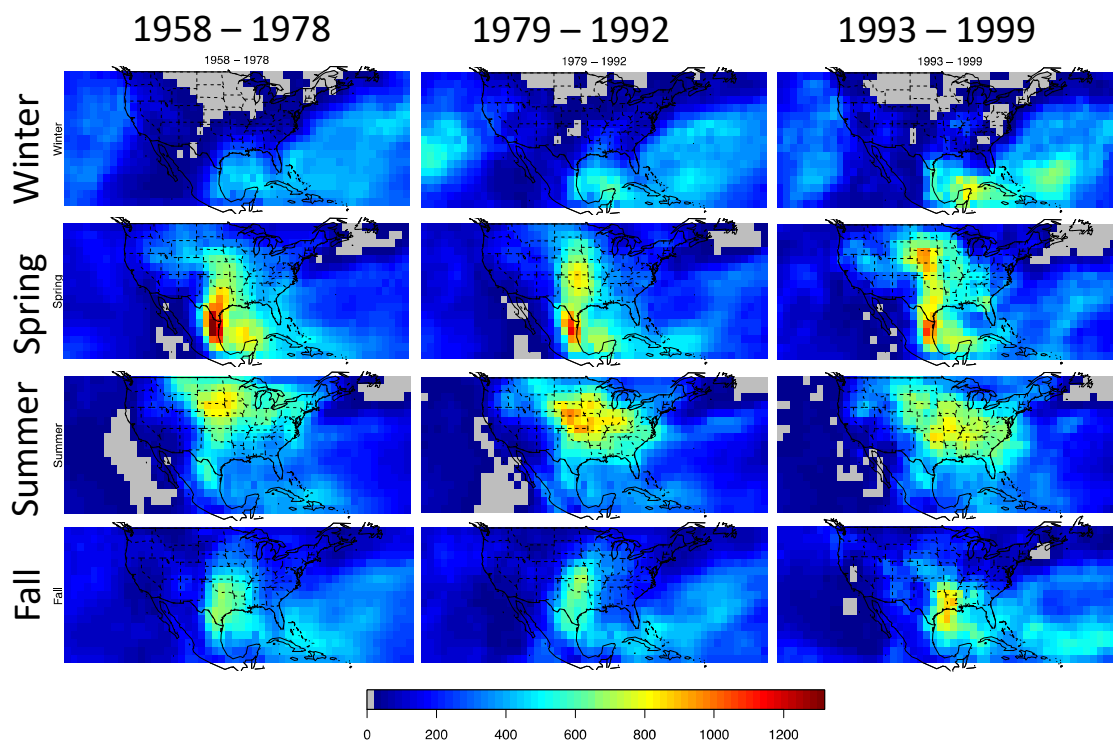
G. et al 2013. Spatial extreme value analysis to project extremes of large-scale indicators for severe weather.

Environmetrics, **24** (6), 418 - 432, DOI: 10.1002/env.2234

Note: The R package **texmex** was used for fitting the HT2004 model in these slides.

Harry Southworth, Janet E. Heffernan and Paul D. Metcalfe (2018). **texmex**: Statistical modelling of extreme values. R package version 2.4.2.

$$[WmSh_1, \dots, WmSh_n | q_{75} > u]$$



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Proximity Model
Example: Maximum
Updraft Velocity $\times$ 0-
6 km vertical wind
shear (WmSh, m^2s^{-2})

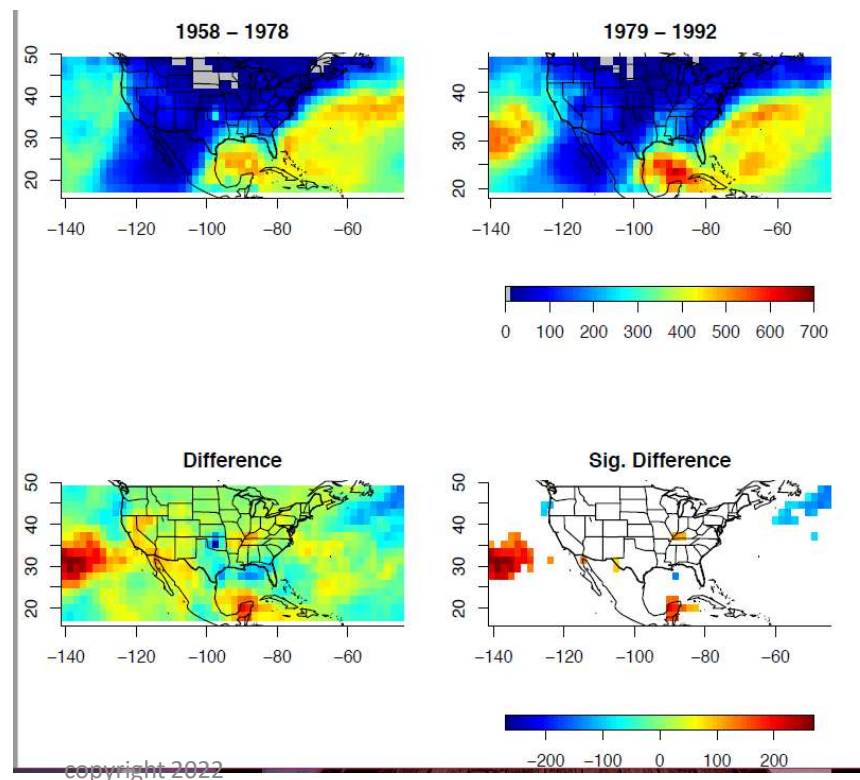
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$$[WmSh_1, \dots, WmSh_n | q75 > u]$$

Fall (SON)



Proximity Model
Example: Maximum
Updraft Velocity $\times$ 0-
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shear (WmSh, m^2s^{-2})

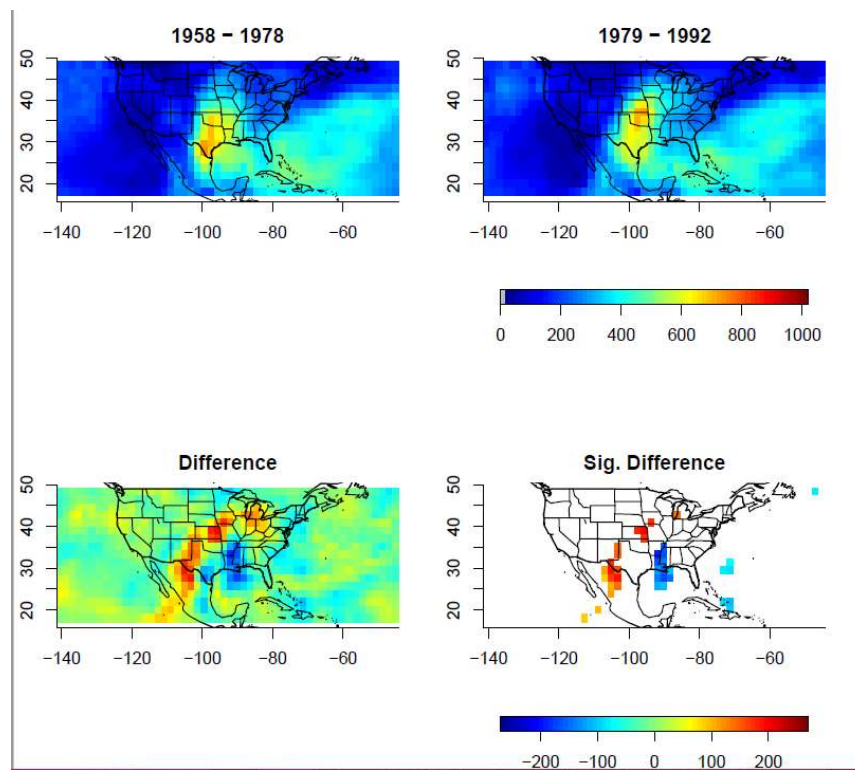
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$$[WmSh_1, \dots, WmSh_n | q75 > u]$$

Winter (DJF)

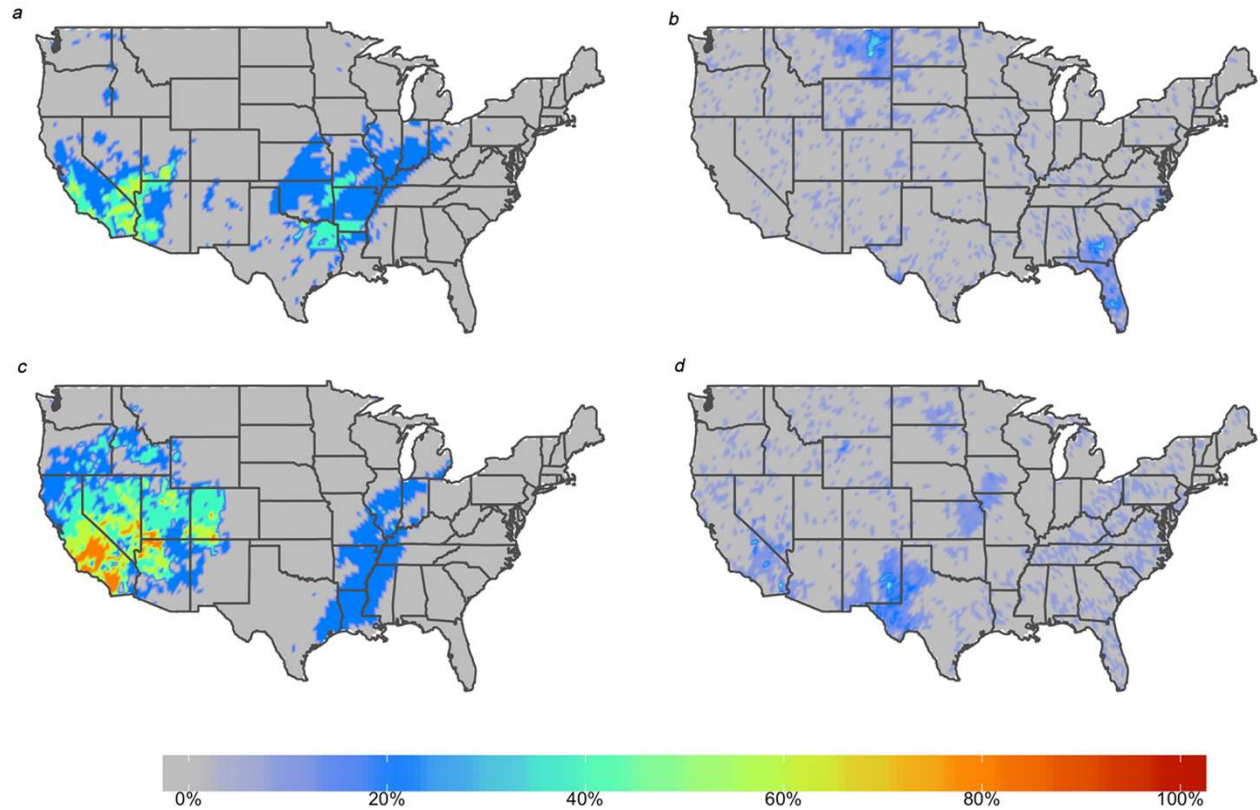


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Example: GHCN-Daily precipitation data

Propinquity Model

Traditional (individual grid points)



Kholodovsky, V. and X. Liang, 2021. A generalized spatio-temporal threshold clustering method for identification of extreme event patterns. *Adv. Stat. Clim. Meteorol. Oceanogr.*, 7, 35–52, doi: 10.5194/ascmo-7-35-2021.

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Other References for further information

de Oliveira, M. M. F., J. L. F. de Oliveira, P. J. F., Fernandes, P. J. F., E. Gilleland, and N. F. F. Ebecken, 2021. Extreme climate characteristics near the coastline of the southeast region of Brazil in the last 40 years. *Theoretical and Applied Climatology*, **146**, 657 - 674, doi: [10.1007/s00704-021-03711-z](https://doi.org/10.1007/s00704-021-03711-z).

Jha, S., M. Goyal, B. B. Gupta, C.-H. Hsu, E. Gilleland, and J. Das, 2021. A methodological framework for extreme climate risk assessment integrating satellite and location based datasets in Intelligent Systems. *International Journal of Intelligent Systems*, (in press), doi: [10.1002/int.22475](https://doi.org/10.1002/int.22475).

Towler, E., D. Llewellyn, A. Prein, and E. Gilleland, 2020. Extreme-value analysis for the characterization of extremes in water resources: A generalized workflow and case study on New Mexico monsoon precipitation. *Weather and Climate Extremes*, **29**, 100260, doi: [10.1016/j.wace.2020.100260](https://doi.org/10.1016/j.wace.2020.100260).

Gilleland, E., 2020. Bootstrap methods for statistical inference. Part II: Extreme-value analysis. *Journal of Atmospheric and Oceanic Technology*, **37** (11), 2135 - 2144, doi: [10.1175/JTECH-D-20-0070.1](https://doi.org/10.1175/JTECH-D-20-0070.1).

Gilleland, E., R. W. Katz, and P. Naveau, 2017. Quantifying the risk of extreme events under climate change. *Chance*, **30** (4), 30 - 36, doi: [10.1080/09332480.2017.1406757](https://doi.org/10.1080/09332480.2017.1406757).

Gilleland, E. and R. W. Katz, 2016. extRemes 2.0: An Extreme Value Analysis Package in R. *Journal of Statistical Software*, **72** (8), 1 - 39, doi: [10.18637/jss.v072.i08](https://doi.org/10.18637/jss.v072.i08).

Towler, E., B. Rajagopalan, E. Gilleland, R.S. Summers, D. Yates, and R.W. Katz, 2010. Modeling hydrologic and water quality extremes in a changing climate. *Water Resources Research*, **46**, W11504, doi: [10.1029/2009WR008876](https://doi.org/10.1029/2009WR008876).