Generalized Additive Modelling for Sample Extremes: An Environmental Example

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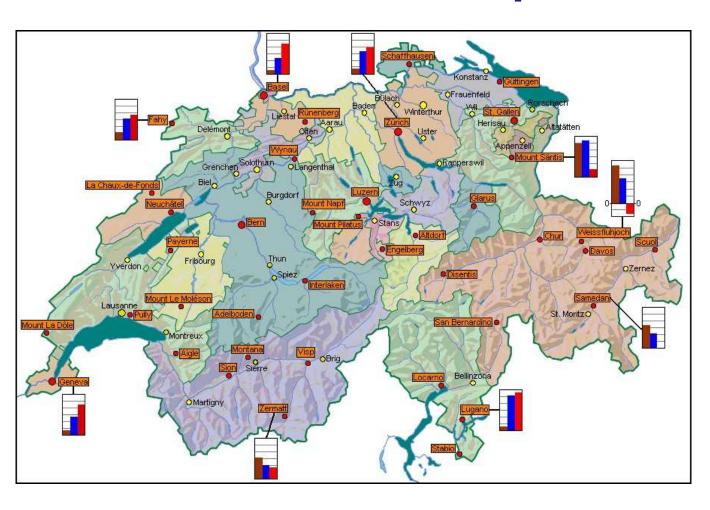
Changes in extremes?

Likely to be slow in environmental applications

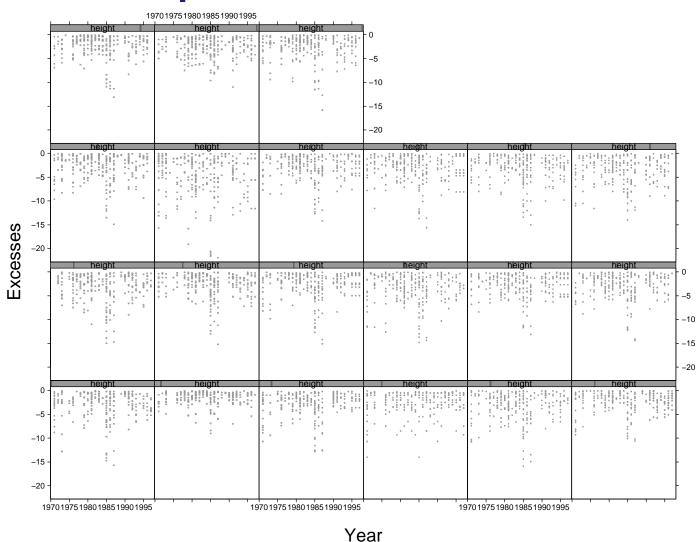
May be difficult to detect because of noise

Aim to combine the point process approach to exceedances with smoothing methods to give a flexible exploratory approach to modelling changes in extremes

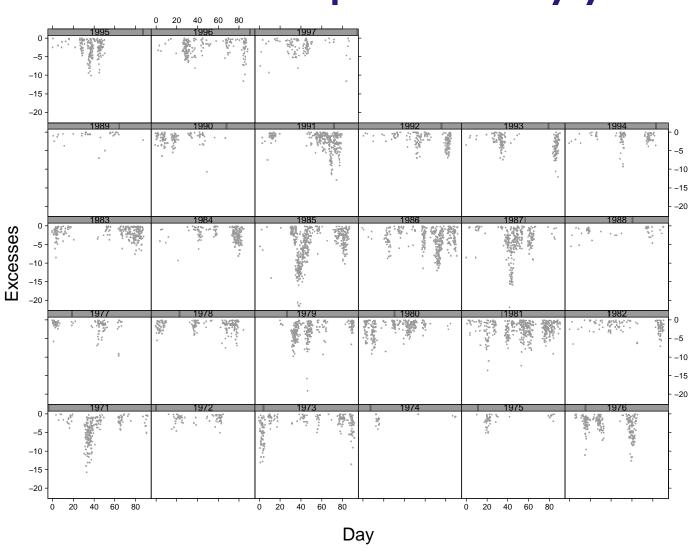
Stations in Swiss Alps



Winter temperatures at 21 Swiss stations



Swiss winter temperatures by year



Summary

- Climate change and extremes? Need flexible models
- Mix threshold approach to extremal modelling, semiparametric smoothing, and bootstrap
- Brief description of the threshold method
- Implementation of spline smoothers
- Application to the Swiss Alps data
- Discussion

Traditional Method

The mathematical foundation of EVT is the class of extreme value limit laws

 X_1, X_2, \ldots , are independent random variables with common distribution function F and $M_n = \max{\{X_1, \ldots, X_n\}}$

for suitable normalising constants $a_n>0$ and b_n , we seek a limit law satisfying

$$P\left\{\frac{M_n - b_n}{a_n} \le x\right\} = F^n(a_n x + b_n) \to G(x)$$

There are only 3 fundamental types of extreme value limit laws that can be combined into a simple GEV distribution

$$H(x) = \exp\left\{-\left(1 + \kappa \frac{x - \mu}{\psi}\right)_{+}^{-1/\kappa}\right\}$$

The parameters $-\infty < \mu < \infty$, $\psi > 0$ and $-\infty < \kappa < \infty$ are resp. the location, scale and shape parameters

r-largest Extremes

 $M_{-}^{n}, \ldots, M_{r}^{n}$: the r-largest observations among X_{1}, \ldots, X_{n} to get more information about the extremes than the max alone

The asymptotic joint distribution of M_1^n,\dots,M_r^n at m_1^n,\dots,m_r^n is

$$\exp\left\{-\left(1+\kappa\frac{m_n^r-\mu}{\psi}\right)^{-1/\kappa}\right\} \times \prod_{j=1}^r \frac{1}{\psi} \left(1+\kappa\frac{m_n^i-\mu}{\psi}\right)_+^{-1/\kappa-1}$$

which forms a likelihood for the parameters

In case m years of data are available, the likelihood is constructed from the r-largest values in each year, considering data for different years as independent, an overall likelihood is simply the product of such terms, for all years

ightharpoonup Choice of r; bias if r is too large

Threshold method

- Treat occurrences of events over (or under) threshold u as Poisson process
- Number of exceedances N over u follows homogeneous Poisson process, rate λ
- Exceedance sizes $W_j = Y_j u$ are random sample from GPD

$$G(w) = \begin{cases} 1 - (1 + \kappa w/\sigma)_{+}^{-1/\kappa} & \text{if } \kappa \neq 0 \\ 1 - \exp(-w/\sigma) & \text{if } \kappa = 0 \end{cases}$$

where σ and κ are scale and shape parameters

- Use orthogonal parametrization κ , $\nu=\sigma(1+\kappa)$ below
- Log likelihood for data splits into two parts

$$l(\lambda, \kappa, \sigma) = l_N(\lambda) + l_W(\kappa, \nu)$$

Semiparametric model

Generalize previous approach

▶ Take λ to be time-varying, where

$$\lambda = \exp\left\{x^T \alpha + f(t)\right\}$$

Take exceedances to be GPD with

$$\kappa = x^T \beta + g(t), \quad \nu = \exp\left\{x^T \eta + s(t)\right\}$$

lacktriangleright f, g and s are smooth functions of time t, and parameters can also depend on ordinary covariates

Penalize roughness of f, g and s through second derivatives

Other link functions possible

Penalized log likelihoods

For rate of exceedances λ , maximize

$$l_N(\lambda) - \frac{1}{2}\gamma_\lambda \int f''(t)^2 dt,$$

equivalent to fitting standard generalized additive model

For sizes of exceedances, maximize

$$l_W \{\kappa(\beta, g), \nu(\eta, s)\} - \frac{1}{2} \gamma_{\kappa} \int g''(t)^2 dt - \frac{1}{2} \gamma_{\nu} \int s''(t)^2 dt$$

If g, s are cubic splines, equivalent to maximizing

$$l_W \left\{ \kappa(\beta, g), \nu(\eta, s) \right\} - \frac{1}{2} \gamma_{\kappa} g^T K g - \frac{1}{2} \gamma_{\nu} s^T K s$$

over β , η , g, s and leads to generalized ridge regression

Parameters γ_{λ} , γ_{κ} and γ_{ν} control smoothness of f , g and s

Methodology

▶ Choose forms for λ , κ and ν and fit

- Choose smoothing parameters γ_{λ} etc using AIC

Use likelihood ratio statistics/AIC for model comparisons When model correct, residuals

$$R_{j} = -\hat{\kappa}_{j}^{-1} \log \{1 - \hat{\kappa}_{j} W_{j} (1 - \hat{\kappa}_{j}) \hat{\nu}_{j} \}$$

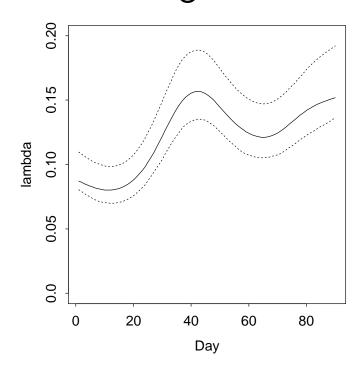
are approximately independent unit exponential variables

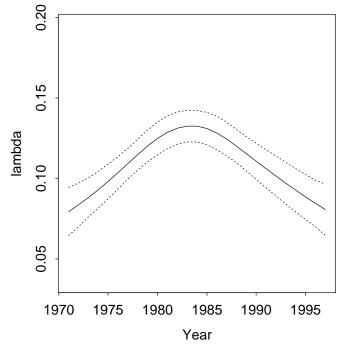
Bootstrap uncertainty assessment

- Need model-robust assessment of uncertainty
- Clustering across stations must be taken into account
- lacksquare Use bootstrap, either resampling the R_j
 - computed from undersmoothed curves
 - added to oversmoothed curves
- or resample seasons within blocks
- Either yields percentile confidence intervals/pointwise bands

Alpine winter temperatures

Fitted intensity $\log \hat{\lambda} = \hat{\alpha_0} + \hat{f}(d,4) + \hat{q}(t,2)$ at Vattis for 1984–5 (left) and for January 1 from 1971–95 (right)

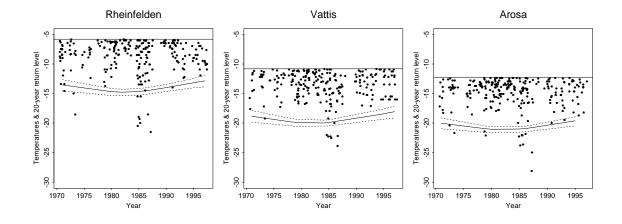




Fitted model and 20-year return level

$$\log \hat{\lambda} = \hat{\alpha}_0 + \hat{f}(d, 4) + \hat{q}(t, 2),$$

$$\hat{\kappa} = \hat{\beta}_0 + 10^{-2} (h - 1000) \hat{\beta}_1, \qquad \log \hat{\nu} = \hat{\eta}_0 + \hat{\eta}_2 t + \hat{s}(d, 4)$$



Discussion

- Inhomogeneous Poisson process λ depends on time but not location
- Shape parameter κ varies with altitude exceedances at higher stations have shorter tails
- ightharpoonup 'Scale' parameter u depends on time but not on altitude
- Increase since 1985 is consistent with the supposed effect of climate change but also with short-term fluctuations (decrease from 1970–85!)

Conclusion

- Exceedances over/under thresholds
 - widely-used approach with natural interpretation
 - exceedance times modelled using existing code (GAM)
- Smoothing extremes by penalized log likelihood
 - convenient and rapid exploration technique
 - highlights features of underlying distribution

References

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