



## **Weather extremes and global change: estimating time-dependent climate risk**

**M. Mudelsee** (1,2)

(1) Climate Risk Analysis – Manfred Mudelsee, Wasserweg 2, 06114 Halle (S), Germany ([www.climate-risk-analysis.com](http://www.climate-risk-analysis.com)), (2) Institute of Meteorology, University of Leipzig, Stephanstrasse 3, 04103 Leipzig, Germany ([mudelsee@uni-leipzig.de](mailto:mudelsee@uni-leipzig.de))

Extreme values of weather and climate variables sit per definition at the tails of the probability density function (PDF). The tail probability is for most variables rather small: extreme weather events are rare. It is clear that the ongoing greenhouse gas emissions will alter the global climate over the 21st century, unclear is the size of this change and its spatial pattern. The focus of climate research has over the past few years shifted from the effects of global change on the mean value of the PDF towards the tails of the PDF. One current task is therefore to estimate the time-dependent tail probability, that is, the time-dependent risk of weather extremes. This is not only scientifically challenging but also of high socio-economic relevance.

Climate risk analysis consists of data selection and statistical estimation. Data are time series, either obtained as model output from climate predictions or instead as observations (measurements, proxy techniques, documentary) of past climates. It makes therefore sense to define, closely related to risk, the time-dependent occurrence rate,  $\lambda(t)$ , of an extreme event as its probability per time interval. The time-dependent return period is then  $1/\lambda(t)$ . The estimation of  $\lambda(t)$  might be easier for climate model output than for observation data because climate model experiments can be repeated such that a large ensemble of runs yields a high precision. The caveat left then is how much the climate model physics deviates from nature.

This paper reviews methods to estimate  $\lambda(t)$  using uni-variate observations. It shows why regression-based approaches fail and peak-over-threshold (POT) approaches are to be preferred. It shows further that interval-comparison POT techniques degrade the time information and continuous-time POT techniques are to be preferred. Two imple-

mentations of the continuous-time POT technique are presented: parametric and non-parametric. The parametric implementation (logistic model) describes the occurrence of extremes over continuous time by a function. The non-parametric implementation (kernel smoothing) uses continuously shifted time intervals to explore the time dependence. Kernel smoothing allows to construct confidence bands for  $\lambda(t)$  by means of bootstrap resampling. The kernel estimation has no parametric restrictions, it allows also non-linear and non-monotonic  $\lambda(t)$ .

This paper illustrates kernel occurrence rate estimation with two examples: (1) the risk of extreme floods of the Elbe river over the past 1000 years and (2) the risk of major windstorms in the North Sea region over the past 50 years.