1. The Bootstrap in Climate Risk Analysis

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Climate risk is the probability of adverse effects from extreme values of variables in the climate system. Because climate changes, so can the various types of climate risk (floods, storms, etc.) change. This field is of strong socioeconomic relevance. Estimates of climate risk variations come from instrumental, proxy and documentary records of past climate extremes and projections of future extremes. Kernel estimation is a powerful statistical technique for quantifying trends in climate risk. It is not parametrically restricted and allows realistic, non-monotonic trends. The bootstrap is a computing-intensive statistical resampling method used here to provide a confidence band around the estimated risk curve. Confidence bands, like error bars, are essential for a reliable assessment whether changes and trends are significant or came by chance into the data. This methodology is presented using reconstructed flood records of the central European rivers Elbe, Oder and Werra over the past five centuries. Trends in flood risk differ among rivers and also between hydrological seasons. The scientific conclusion is that flood risk analysis has to take into account the high spatial variability from orographic rainfall, as well as different hydrological regimes in winter and summer. In an ideal co-operation between experts, quantitative knowledge with uncertainty ranges (like the estimated trends in climate risk) should form the deliverable from scientists to policy makers and decision takers.

◀ **Fig. 1.0.** Karl Friedrich Hieronymus Baron von Münchhausen, born 11 May 1720 at Bodenwerder (Germany), died 22 February 1797 at same place. In one of his stories, he claims to have escaped once from sinking into a swamp by pulling himself up by his own bootstraps... In applied sciences, the bootstrap resampling approach helps the statistician to obtain meaningful results when the data distribution is unknown, namely by using the data as realizations of their own distribution. (Painting by G. Bruckner, Rinteln (Germany), 1752. Reproduced with permission by Bibliographisches Institut & F. A. Brockhaus AG, Mannheim (Germany).)

1.1 Introduction

Climate in its original definition refers to the mean state and variability of the atmosphere. Today a wider definition, including the hydrosphere, cryosphere and biosphere, is viewed as more appropriate to recognize the interdependences within that complex system. Climate changes affect many variables and many timescales; an upper limit is set by the age of the Earth ($\sim$4.6 Ga). Humans play a significant role in the climate system by their ability to infer with the carbon cycle (CO_2 and CH_4 emissions). This may have been the case since the industrial revolution (via CO_2, see [1.21]) at around, say, AD 1800, or even earlier, since what might be termed the agricultural revolution (via CH_4, see [1.32]) at around the beginning of the Holocene climate stage ($\sim$10 ka ago).

Risk is in statistical science defined as "adverse probability" [1.15]. Climate risk may therefore be defined from an anthropocentric viewpoint as the probability that a climate variable takes values that lead to loss of human lives or damages to economies. Normally, such values are in the tails of the probability density function (PDF) of a variable, that means, climate risk comes from extreme values. Examples are storms (extremely high wind speed), droughts (extremely low precipitation and available water resources) or river floods (extremely large runoff values).

Because climate changes [1.21], so can the various types of climate risk change (Fig. 1.1). It is of immediate socioeconomic value to analyse changes in climate risk. As regards past changes, these can be analysed from documented records of climate extremes. Such records come from more or less direct observations within the instrumental period (back to, say, AD 1850). Going further back in time, indirect measurements can be used, yielding so-called proxy records [1.1]. Examples are width of tree-rings as indicator of summer temperature during the past centuries [1.4] and measured oxygen isotopic composition in a stalagmite from the Arabian peninsula as indicator of the strength of Indian Ocean monsoon rainfall during the Holocene [1.12]. Also written documents can be used to extend the time span from the beginning of the instrumental period back several centuries [1.2, 1.3, 1.26, 1.31]. Inevitably, records of past climate changes may contain measurement errors, proxy errors, textual interpretation errors or dating errors. As regards future changes, these can be inferred from mathematical models of the climate system. Although some of the most powerful computers are currently employed to do this task, owing to the limited computing power and the imperfect knowledge of the relevant processes acting in the climate system, also climate model projections are susceptible to uncertainties. One can try to improve the data situation by using better climate archives, measurement devices, model formulations and computers. In principle, however, our knowledge shall always be incomplete.

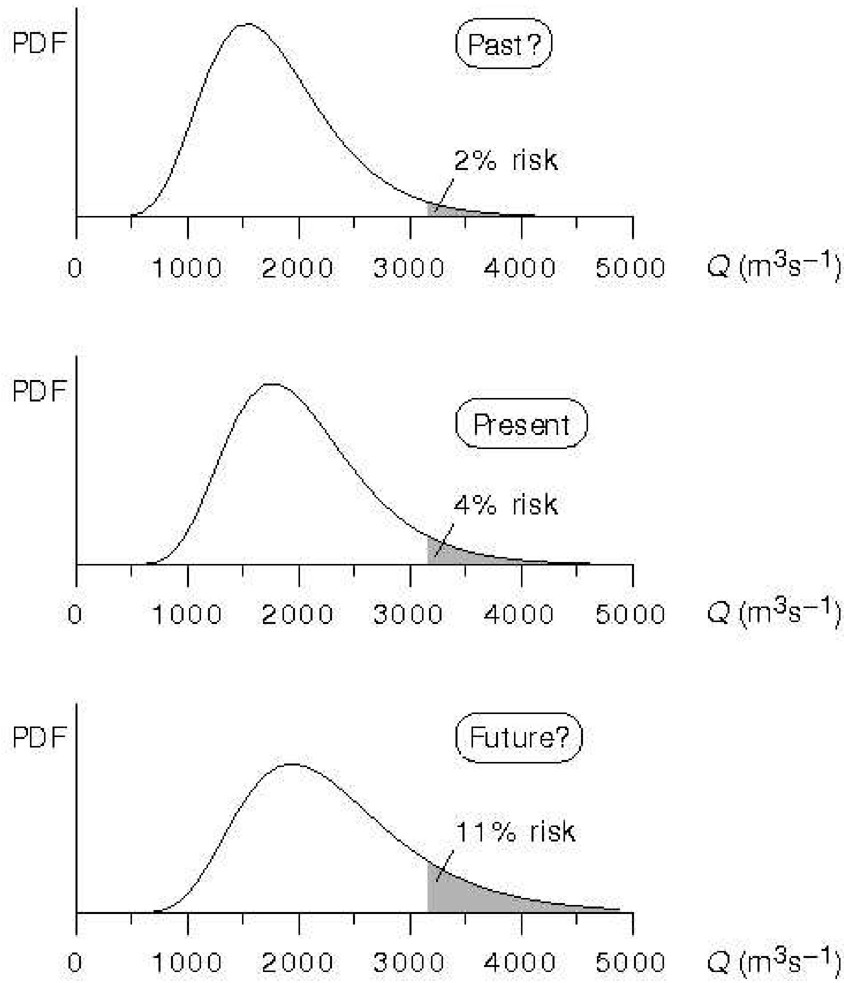

Fig. 1.1. Climate risk changes. This hypothetical example shows changes in the (right-skewed, non-Gaussian) PDF of maximum annual runoff, Q, at the station Dresden of the river Elbe. Climate risk is given by the integrated PDF. For example, in the hypothetical past the risk that within a year Q exceeds 3110 $m^3 s^{-1}$ (the peak value of the March 1940 flood [1.26]) was 2%, it rose to 4% (present) and might rise to 11% (future). The question marks emphasize that knowing the past as well as the future situation is not certain but relies on imperfect data, coarse climate models and the validity of made assumptions (e.g., regarding the statistical method). In principle, one could assign a question mark also to the present situation.

This means that estimated past or future climate risk changes have also errors. This is precisely the task of statistical analysis in climate risk research: to quantify the uncertainties, to give error bars or confidence intervals of our estimates and projections.

This paper illustrates the bootstrap approach to quantify uncertainties in estimated climate risk changes. The bootstrap is a relatively new, computing-intensive, statistical resampling technique [1.10, 1.11]. Its advantage is that it is less restricted by parametric assumptions than more traditional approaches. For example, the assumption that proxy or measurement errors in climatology follow nicely a Gaussian distribution has been used for decades although it is generally appreciated that this assumption is often wrong (Fig. 1.1). The reason for making this simplistic assumption was to obtain analytically tractable statistical problems. With today's computing power, however, one needs not rely on unrealistic assumptions and can instead use the bootstrap. The bootstrap approach is applied in this work to records of floods of European rivers from the past five centuries.

The major result is that changes in flood risk differ among the rivers Elbe, Oder and Werra. This reflects the spatial variability of rainfall [1.24], which in turn is partly owing to variations in orographic properties. The conclusion is that flood risk analysis has to take into account the high spatial variability, and also the different hydrological regimes in winter and summer. It is useless when applied on a too large spatial scale. Rivers have to be analysed separately to obtain reliable results.

1.2 Method

Regression methods fail to detect changes in climate risk because they model the mean value and not the extremes. We [1.27] gave an example where the prescribed trend in climate risk is upward and a weak downward trend is superimposed as background, plus some noise. The regression line is downward, reflecting the tendency of the majority of data points and not the extremes. Taking the regression line as indicative for risk changes would thus give the wrong, opposite result.

The situation may be less severe when instead of the original data (background plus noise), some upper quantile data are available; this method is then called quantile regression [1.23]. Related is the case when, for example, the monthly runoff maxima instead of their means are taken. However, this still bears the possibility of two large events within a single month, of which one would not find entry into the flood risk analysis.

The alternative approach to regression, namely peak-over threshold (POT) is preferred by us. For example, in runoff records one can find the POT data (flood dates) by applying a threshold (e.g., 50-year runoff level) and taking the data above that threshold. In documentary flood records as analysed here, the reported dates of floods are themselves already the POT data (time domain).

The simplest POT analysis technique compares two time intervals with respect to properties of the statistical distribution that describe the extreme values found inside. Typically chosen is the return period, which is the expected time for an extreme event to occur. That means, the return period estimated from data of the first time interval is compared with the return period for the second interval. The problem with the interval comparison technique is that the time information is seriously degraded. For example, comparing Elbe floods between 1500 and 1750 with those between 1750 and 2000 would merely provide two estimates and miss the variability within each interval.

Frei and Schär [1.14] introduced the logistic model as a parametric description of the risk curve into climatology. (The term "risk curve" refers to the time-dependent occurrence rate defined in the following subsection. The logistic model is a parametric formulation of that time dependence.) This has the advantage of not degrading the time information. On the other hand, the logistic model is strictly monotonically increasing or decreasing. This means that it is not suited for analysing longer records (above a span of, say, 100 a) because on such timescales one cannot assume monotonic trends in climate risk but rather highs and lows, which might be related to the general climatic situation.

A powerful method to quantify time-dependent climate risk could be fitting a Generalized Extreme Value (GEV) distribution to climate records, whereby the GEV parameters are allowed to vary with time [1.6, 1.22, 1.29]. Additional parameters are required for describing the time dependence. A challenge for this approach is adjusting the total number of parameters: allowing "enough" time variability while keeping the number of fit parameters low (Occam's razor). Because this nonstationary approach requires flood data measured with a reasonable accuracy and a sufficient size, it is hardly applicable to analysing flood risk in the pre-instrumental period.

The nonparametric kernel technique is therefore our method of choice. It analyses the extremes (POT advantage), does not degrade the time information and allows non-monotonic trends in climate risk. The kernel technique can be further combined with the bootstrap approach to yield confidence bands around the estimated risk curves. This helps the climate risk analyst to assess whether or not a high in flood risk is statistically significant, or whether we can expect a significant increase in flood risk coming with global climate changes. We explain the kernel technique with bootstrap confidence band construction in the following subsection. A detailed description of the kernel technique with bootstrap confidence band construction is given elsewhere [1.27].

1.2.1 Kernel Risk Estimation

As indicated above and said previously [1.28], the simplest method to quantify flood risk over time is to form intervals (say, decades) and count the number of floods that occurred within each interval. The problem hereby is that only few estimation points would be produced. An improvement is to use quasi-continuously shifted intervals (as in running mean smoothing). The method is then called kernel smoothing, and the kernel function used is a uniform function [1.34], because all floods within an interval have same weight. Uniform kernel functions for flood risk estimation have been used in previous papers (e.g., [1.18]). The method can be further enhanced by adopting a smooth kernel function (that means, weighting) and using a mathematical method to solve the smoothing problem (choice of interval width). Finally, a confidence band around the estimated flood risk curve can be constructed using bootstrap simulations. See our previous paper [1.27] and the original work [1.8] for a detailed explanation of the method.

The kernel technique [1.9] estimates the occurrence rate as

$$\widehat{\lambda}(t) = h^{-1} \sum_{i=1}^{n} K\left([t - T(i)]/h\right), \tag{1.1}$$

where $\lambda(t)$ is the time-dependent occurrence rate (probability of an extreme event per time unit), t is time, $T(i)$ are the flood dates, n is the total number of floods, K is the kernel function and h is the bandwidth. The "hat" denotes the estimate, reflecting that the true function $\lambda(t)$ is not known but has to be estimated from the data. A high time-resolution is obtained by letting t run quasi-continuously within the observation interval of the data, $[t_1, t_2]$. Using a smooth kernel function yields a more realistic smooth estimate of the occurrence rate. A Gaussian kernel, $K(y) = \exp\left(-y^2/2\right)/(2\pi)^{1/2}$, is a convenient choice because it yields a smooth estimated occurrence rate and allows to calculate $\widehat{\lambda}(t)$ efficiently in Fourier space [1.33], leading to considerable computational acceleration.

Boundary effects (underestimation of $\widehat{\lambda}(t)$ near (i.e., within $\sim 3h$ distance) t_1 and t_2) can be reduced by generating pseudodata outside of $[t_1, t_2]$ before occurrence rate estimation [1.7]. Since pseudodata generation is equivalent to an extrapolation of the empirical distribution function, results at the boundaries should be judged cautiously. It is also advisable to slightly undersmooth, that is, to take a slightly smaller bandwidth than indicated by cross-validation (see next paragraph) to keep boundary effects small. Regarding boundary effects and confidence interval accuracy, see the original papers on the kernel occurrence rate estimation method [1.7, 1.8].

Bandwidth (h) selection determines bias and variance properties of the occurrence rate estimation and is therefore a crucial step. Small h leads to only few data points effectively contributing to the kernel estimation (1.1) and therefore a large variance of the estimate. But small h keeps bias low because data far away from the time point, t, have less influence on the estimate (1.1). On the other hand, large h leads to smaller estimation variance and higher estimation bias. The optimum bandwidth choice lies therefore somewhere in the middle, as the best compromise between statistical and systematic estimation uncertainties. One mathematical method for finding the solution to this smoothing problem is cross-validation [1.5]. Thereby, a cost function, determined by two terms describing variance and bias, is minimized. Cross-validated h depends, amongst other factors, also on the data size, n. See [1.27] for more details. In addition to cross-validation, bandwidth selection may be guided by the objective to reduce boundary effects. Another guide is to look on the confidence bands (next subsection) around the estimated occurrence rates and evaluate whether changes in risk are significant. A user-interactive analysis process is therefore most suited. Select a bandwidth; look at the risk curves and the significance of the highs and lows; if many, insignificant changes are found, then increase h; if one or no significant changes are found, then reduce h; etc.

1.2.2 Bootstrap Confidence Band Construction

A confidence band around $\widehat{\lambda}(t)$ is essential for interpreting results. For example, it might be asked if a low in $\widehat{\lambda}(t)$ is real or came instead by chance into the data. A confidence band can be obtained using bootstrap simulations [1.8] as follows:

1. From the set of data (augmented by pseudodata) draw one by one, with replacement, a simulated set of flood dates of same data size. This is the bootstrap resampling step.
2. Calculate $\widehat{\lambda}^*(t)$ after (1.1) using simulated data and same h.
3. Repeat the procedure simulation–estimation until 2000 versions of $\widehat{\lambda}^*(t)$ are available.
4. A simple, percentile-based confidence interval (of level α) at time t is given by the central α values of ordered $\widehat{\lambda}^*(t)$. For example, for $\alpha = 90\%$, it is given by the interval between the 100th and 1900th largest values.
5. The confidence band is given by the confidence intervals over time $t \in [t_1, t_2]$.
6. Cowling and co-workers [1.8] describe construction of a percentile-t type confidence band (denoted as "Type 1" and used by us), which has higher accuracy than the percentile-based band.

Note that the confidence band is "pointwise", it reflects the variability of the point estimate, $\widehat{\lambda}(t)$. The cited work [1.8] gives further bootstrap schemes and confidence band types, which have similar properties as the method shown here. This pioneering work also analyses the performance of kernel risk estimation by employing Monte Carlo simulations, that is, numerical experiments where the artificial data are generated from prescribed $\lambda(t)$ curves.

The methods of kernel occurrence rate estimation with bootstrap confidence bands has been applied by us in following studies: floods of the rivers Elbe and Oder [1.26, 1.27] and Werra [1.28] over the past 500 to 1000 years, occurrence of wildfire events in the Canadian boreal shield since the end of the 18th century [1.16] and in climate model projections for the same region and the 21st century [1.17], North Sea storms since AD 1500 [1.30] and soil erosion events in Kenya over the past 300 years [1.13]. The methodology is currently being implemented into a user-friendly Windows version of the software.

1.3 Data

Table 1.1 shows the database of analysed river floods. The Elbe, Oder and Werra are rivers in central Europe. Their catchment areas (middle Elbe, 95000 km^2; middle Oder, 54000 km^2; middle and upper Werra, 5505 km^2) are under low-mountainous climate. Floods in hydrological summer (May to October) are caused by heavy and/or prolonged rainfall, and in the winter (November to April) also by thawing snow. Breaking river ice may function as water barrier and enhance a flood severely [1.19].

Table 1.1. Database.

River	Interval	Number of floods				Reference
		Total	Winter	Summer	Unknown	
Elbe	1021–2002	328	208	117	3	[1.26]
Oder	1269–2002	218	108	106	4	[1.26]
Werra	1500–2003	143	111	32	0	[1.28]

Documentary records of floods (Fig. 1.2) were consulted and analysed to construct the old parts of the flood database (Elbe, before 1850; Oder, before 1920; Werra, before 1900). Measured records of water stage and inferred runoff were used to complete the database to the present (Elbe, 1850 to 2002; Oder, 1854 to 2002; Werra, 1880 to 2003). Occasionally, the documentary entries contained information on the maximum flood water stage. Owing to overlapping documentary and instrumental periods, it was possible to quantify the size of a flood for number of events and to ensure data homogeneity across the boundary between documentary and instrumental periods [1.26]. The size of most of the flood events in the documentary periods could only roughly be quantified by means of information such as the duration of an event, the number of casualties, the economic damages caused, etc. Following standard practice in documentary climatology [1.2, 1.26], the flood records were allowed to take only three values: 1 (minor flood event), 2 (strong flood event) and 3 (exceptionally strong flood event). In the present paper, we focus on heavy floods (classes 2 to 3).

The most severe problem when dealing with documentary data of climate extremes is to reduce the effects of data inhomogeneities in form of document loss. In the earlier half of the last millennium, before the invention of printing in Europe, likely fewer documents (handwritings) survived, compared with the latter half, until they found entrance into permanent, secondary sources. Ignoring this type of data deficit could then lead to unjustified claims of increased flood risk in the second compared with the first half. In the case of Elbe and Oder floods (Table 1.1), the start of the observation intervals (1031 and

Unrealistische Darstellung der „Thüringischen Sintflut" auf dem Titelblatt einer im Jahr 1613 in Schmalkalden gedruckten Schrift (Quelle: Hellmann 1913 [55])

Fig. 1.2. Pamphlet on the "Thuringian Flood". This catastrophe happened on 29 May 1613 (Julian calendar). This rendering (printed 1613 in Schmalkalden) is likely not realistic; Hellmann's work [1.20] contains a reproduction (p. 40) and further bibliographic details.

1269, respectively) likely is not the start of the interval in which homogenous data can be assumed, which we set [1.26] to AD 1500. In the case of Werra floods (1500–2003), we tried by employing critical source interpretation and consultation of many documentary archives to achieve more or less complete information about floods within the relatively small area of the middle and upper Werra [1.28]. Despite this, the results (Section 1.4) suggest that minor document loss could have occurred for data before the beginning of the 18th century.

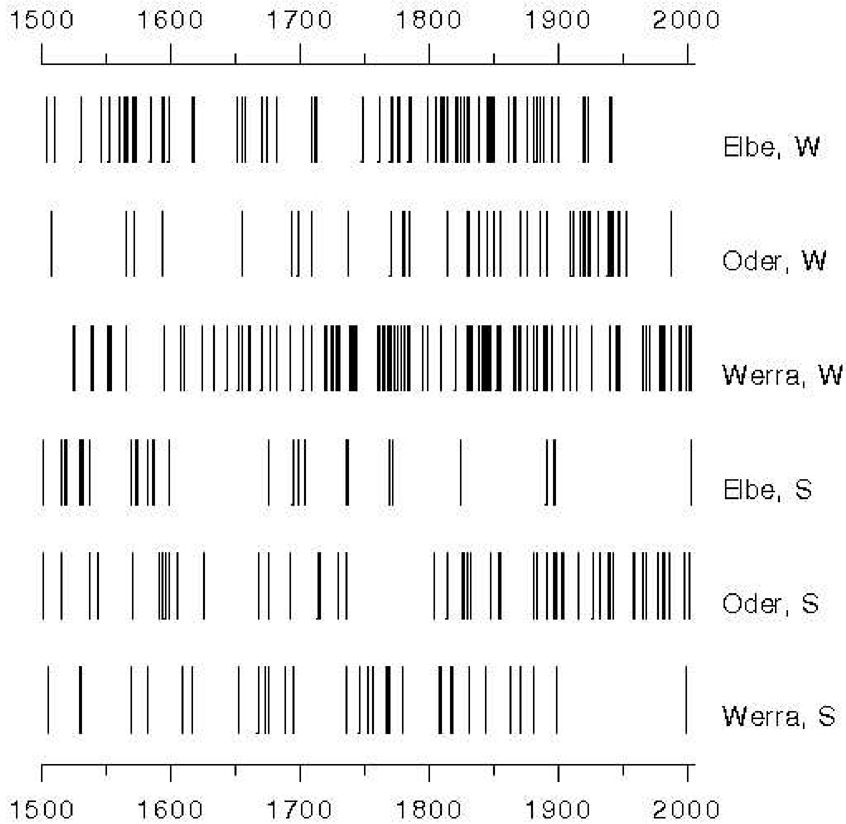

Fig. 1.3. Winter (W) and summer (S) floods of rivers Elbe, Oder and Werra since AD 1500. Floods with unknown season are few (Table 1.1); they are plotted here together with the winter floods. In case of Elbe and Oder floods, only the heavy events (class 2 and 3, see [1.26]) are shown.

See the data references [1.26–1.28] for more details on the rivers, river engineering work, orography, runoff–stage relations, critical source interpretation and comparisons of different sources.

1.4 Results

The results (Fig. 1.4) show that flood risk over the past five centuries varied significantly. There is further variation between winter and summer trends, and also among the various rivers. These trends have been discussed in detail in the original publications [1.26–1.28]. Here we make some general comments and investigate selected points.

Werra flood risk (winter and summer) shows small, long-term increases in the early part (∼1500–1700). It may be asked whether this reflects what really occurred in nature, or instead results from a trend towards reduced document loss. Arguing from a historical–critical perspective, we believe that document

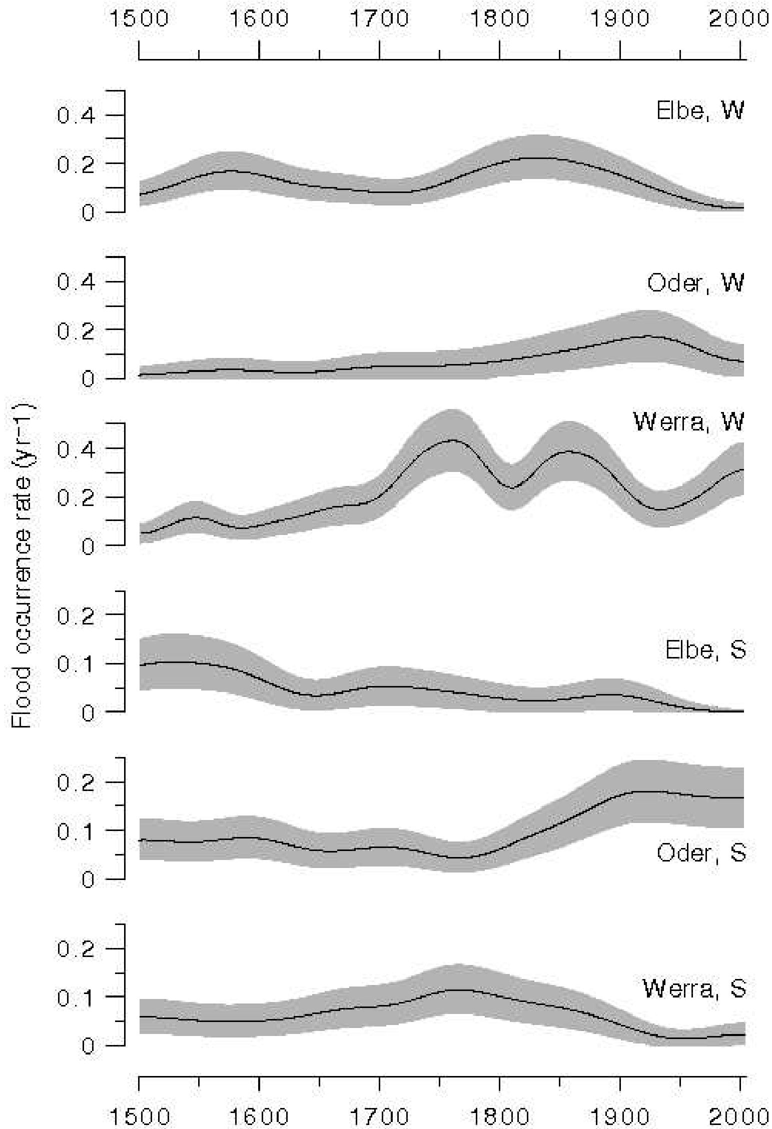

Fig. 1.4. Results: flood occurrence rates (heavy lines) for rivers Elbe, Oder and Werra in winter (W) and summer (S) with 90% confidence bands (shaded). In case of Elbe and Oder floods, only the heavy events (class 2 and 3, see [1.26]) are analysed. Floods with unknown season are assumed to have occured in winter. Owing to the small number of such events (Table 1.1), this has negligible effect on the estimated flood occurrence rates. Note that y-axes scaling differs between winter and summer flood risk. Statistical parameters used: Gaussian kernel function, K; pseudodata generation rule "reflection" (see [1.27]); bandwidth $h = 35$ a (Elbe, W; Oder, W; Elbe, S; Oder, S; Werra, S) and 20 a (Werra, W). Using $h = 20$ a for summer floods of the Werra produced additional, insignificant "wiggles" [1.28].

loss played only a minor role in case of the Werra because historical information from that region is quite abundant and well preserved.

The high in Elbe winter flood risk in the latter half of the 16th century (Fig. 1.4) corresponds to increased risk levels in rivers in central and southwest

Europe during that time, which were related to higher precipitation [1.2]. A low in Elbe flood risk at around 1700 could have been the effect of the cold and dry climate in Late Maunder Minimum [1.25], a period of nearly absent sunspots and reduced solar activity. However, the Oder does not exhibit such significant changes in the early period.

Length reductions of the middle Elbe (1740–1870) and middle Oder (1745–1850) did not leave a consistent imprint on winter and summer flood risk (Fig. 1.4) and were therefore only of minor influence.

The 18th and 19th centuries experienced strong, significant changes in flood occurrence rates (Fig. 1.4). The Elbe had a high in winter flood risk in 1800–1850, followed by a long-term decrease. Oder flood risk (winter and summer) increased, but this should be interpreted cautiously because the Oder flood record in the interval 1850–1920 is of reduced quality [1.26]. Werra winter flood risk peaked high at $\sim$1760, then low at $\sim$1810, then high again at $\sim$1860 [1.28]. This pseudo-periodicity of 100 a is not the result of bandwidth selection because $h = 20$ a is clearly smaller. These Werra winter flood changes contrast markedly with the findings for the Elbe. Werra summer flood risk decreased gradually since $\sim$1760 to the present.

In general, winter floods seem to have been more likely than summer floods over the past centuries, as is expressed most clearly by the Werra [1.28], the Elbe and, to a lesser degree, the Oder (Fig. 1.4).

The flood records for the past decades can be completely determined from instrumental observations. They have therefore an excellent degree of data homogeneity. Within the instrumental period, Elbe and Oder winter flood risk decreased significantly [1.26]. This is likely a climate signal from regional warming, which had reduced the probability of strong river freezing and, hence, the risk of “ice floods” [1.26, 1.27]. In this regard, the significant upward trend of Werra winter flood risk (Fig. 1.4) is interesting. We speculate that “ice flood” risk was reduced earlier (mid-19th century) for the Werra than for the other two rivers (mid-20th century [1.26, 1.27]). Contrary, summer flood risk shows no trends (Elbe, Oder and Werra) over the past decades.

1.5 Conclusions

Producing large amounts of rainfall in the affected catchment areas requires a combination of several factors [1.27, 1.28]:

1. northwesterly to southerly, cyclonic airflow;
2. high atmospheric water vapour content;
3. low convective lability, preventing cell formation;
4. prolonged (at least half a day) flow against the orography (Fig. 1.5).

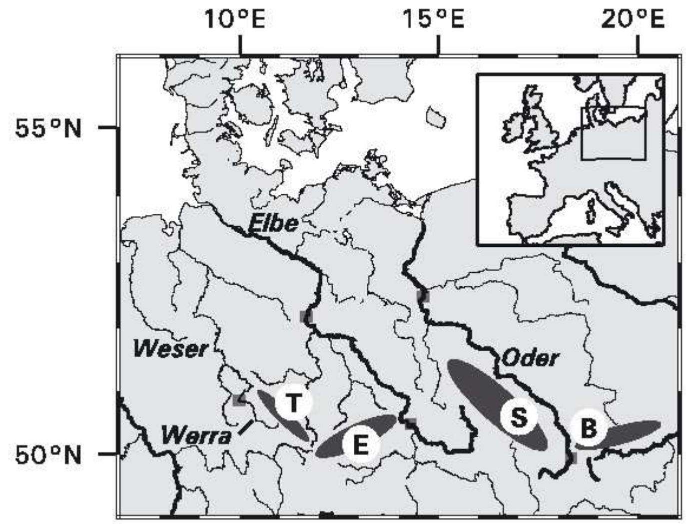

Fig. 1.5. Rivers Elbe, Oder and Werra in central Europe. Grey squares denote the places used [1.26, 1.28] to define the analysed river sections (middle Elbe, middle Oder and middle to upper Werra). Also shown are the mountain ranges relevant for orographically infuced rainfall in the catchment areas of the river sections. T, Thüringer Wald; E, Erzgebirge; S, Sudeten; B, Beskids.

It would be na-ive to assume that with climate changes only factor 2 would change (via the Clausius–Clapeyron equation). In particular, the role of factor 4, flow against orography, should be analysed in the case of flood risk changes in central European regions under low-mountainous climate. This is because of the differences among Werra, Elbe and Oder flood risk curves (Fig. 1.4), which indicate that the orographic differences among the catchment areas introduce a strong nonlinear component into the complex climate–hydrosphere system.

It is in our view required to carry out a large body of detailed scientific work to learn about flood risk and climate changes: (1) Produce records of past floods in a hydrologically more or less homogenous area, at monthly or at least seasonal resolution over the past centuries. (2) Combine documentary with instrumental evidence to achieve data homogeneity. (3) Use quantitative flood risk estimation methods with error band. (4) Use the results obtained from the analysis of past floods to train coupled climate models (global–regional–hydrological) that are used to make projections of future flood risk. Trends from observed, past floods serve as targets for successful models.

As said in the introduction, estimated past or future climate risk changes have errors. It is the task of climate scientists to give error bars or confidence intervals of the estimates and projections. It is then the duty of policy makers to make, in this uncertain situation, decisions of sometimes strong impact. Luckily, politicians are trained to doing exactly that: making decisions in uncertain situations. This is a plea for a rational approach in this challenging socioeconomic situation: let the scientists do the science and the politicians make the decisions.

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