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Climate Change and Modelling of Extreme Temperatures in Switzerland*

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Abstract

This study models maximum temperatures in Switzerland monitored in twelve locations using the Generalised Extreme Value (GEV) distribution. The parameters of the GEV distribution are determined within a Bayesian framework. We find that the parameters of the underlying distribution underwent a substantial change in the beginning of the 1980s. This change is characterised by an increase both in the level and the variability. We assess the likelihood of a heat wave of the Summer of 2003 using the fitted GEV distribution by accounting for the presence of a structural break. The estimation results do suggest that the heat wave of 2003 appears not that statistically improbable event as it is generally accepted in the relevant literature.

Keywords: climate change, GEV, Bayesian modelling, Great Alpine Heat Wave
JEL code: Q54, C11

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1 Introduction

The heat wave of 2003 observed in continental Europe, including Switzerland, has attracted much attention in the literature on climate change as the unusually high temperatures led to a number of undesirable consequences including increased population mortality [World Health Organization (WHO), 2003] – especially among the elderly –, appearance and prolonged endurance of droughts accompanied by a shortfall in crop, an increased probability and severity of forest fires, change of vegetation cycles, and strongly reduced discharge in many rivers [De Bono et al., 2004; Fink et al., 2004]. In Switzerland, the heat wave of 2003 sped up the melting of glaciers in the Alps and it resulted in avalanches and flash floods.

Several papers are dedicated to the probability of this extraordinary hot summer both at the European level and more specifically for Switzerland, see Beniston [2004]; Schär et al. [2004]; Trigo et al. [2005]; Stott et al. [2004], among others. A common conclusion of these articles is that the heat wave of summer 2003 was a very unusual event given the pattern of temperatures observed over Europe in the past. In particular, Schär et al. [2004] concluded that such record-breaking extreme temperatures observed in Switzerland were very unlikely from a statistical point of stationarity and a shift in the distribution location alone is not sufficient for explaining the heat wave of 2003.

In this paper, we model the annual maxima of monthly mean temperatures in Switzerland with the main purpose of assessing the likelihood of occurrence of the heat wave of 2003. There is no unique definition of a heat wave but it is generally understood as a prolonged period of unusually high temperatures observed in a given region. Short-termed definitions are useful when looking at increased mortality by hot temperatures. Common definitions assume thresholds that have to be exceeded on subsequent days (see Robinson [2001] for a discussion). Other effects like melting of glaciers require more time to show an appreciable abnormal increase and therefore provide another definition of a heat wave. Since impacts of climate change are more visible by observing longer time spans, we choose an event of longer endurance than the usual few days and consider the annual maximum of the monthly mean temperatures observed at each measurement station. We believe that by working with the annual maxima of monthly mean temperatures the notion of heatwave could be better captured in comparison to focusing on the annual maxima of daily mean temperatures, for example.

We apply a Bayesian approach which is better suited for predictive purposes than the classical methodology since parameter uncertainty is directly incorporated into the forecast process, see Coles [2001]. Furthermore, investigation of model parameter instability and assessment of its severity is also straightforward within the Bayesian framework. Building on the Bayesian analysis of Jaeger et al. [2008], who assessed the feasibility of different trend models under the assumption of normally distributed error term, we employ the Generalised Extreme Value (GEV) distribution as possibly more appropriate.

Our main finding is that a proper accounting for features of the time series considerably increases the likelihood of occurrence of the heat wave of 2003. On the basis of our estimation results, we conclude that the heat wave of summer 2003 does not appear to be such an improbable event but it rather constitutes a future pattern of things to come.

In Section 2 we describe the data set used in our exercise. In Section 3 the methodology is presented. Section 4 contains the estimation results. The last section concludes.

2 Data

We analyse the temperature measured by the Swiss Federal Office of Meteorology and Climatology Begert et al. [2005] [1]. The mean monthly data are provided for the period from 1864 until present (2007) (with exception of Chateau d'Oex (since 1901) and Davos-Dorf (since 1876)) and are collected in 12 locations in Switzerland (Bern-Zollikofen, Geneve-Cointrin, Lugano, Segl-Maria, Basel-Binningen, Chateau d'Oex, Chaumont, Davos-Dorf, Engelberg, Saentis, Sion, and Zurich). The series are homogenous until 2003 (inclusive) for the first four locations, while for the remaining locations inhomogeneities have been provisionally corrected. Since 2004 several stations have been reconstructed. Those time series might contain minor inhomogeneities, where the reconstruction site has not changed (Davos-Dorf, Engelberg, Lugano, Saentis, Zurich) or was moved a bit (Sion). The temperature record is likely to be less homogeneous for the Bern station due to the fact that this station has been rebuild at a completely different place. Thus the most reliable data is provided by Geneve-Cointrin and Segl-Maria[2].

In our exercise, in contrast to Schär et al. [2004] where the data from four independent stations (Basel-Binningen, Geneve-Cointrin, Bern-Zollikofen, and Zürich) were amalgamated, we model each time series of temperature observations individually. In doing so, we avoid a possible aggregation bias. By using disaggregated data, we are also able to draw a comparison between the parameter estimates obtained for each station and, therefore, to establish a degree of generalisation of our results depending on the measurement location.

The descriptive statistics of the corresponding time series are given in Table 1. First, observe that the time series are quite heterogenous. Our sample includes Saentis where the average annual maximum temperature is around 5.6 degrees Celsius on the one hand, and Lugano with 21.5 on the other hand. Second, the summer of 2003 was indeed the hottest summer by the historical standard for all locations where the measurement took place. This record was broken in 2006 for three stations (Bern-Zollikofen, Davos-Dorf, and Sion).

Since our analysis is based on the assumption of independent observations, we check for the magnitude of autocorrelation in our data. The first autocorrelation coefficient is displayed in Table 1. It takes values in the range between 0.103 and 0.305, indicating presence of low to mild positive temporal dependence in our data. However, according to Perron [1989] the detected mild positive dependence may well be spuriously induced by the presence of an unmodelled structural break in the time series in question. Therefore, after conducting the initial analysis using the whole sample period, we investigate the structural stability of the fitted model by splitting the sample into two parts. We also calculate the first order autocorrelation for each of these subsamples. We find that the evidence of temporal dependence is substantially weakened when one allows for a structural break in the temperature time record.

3 Methodology

Since we model a maximum temperature, it is naturally to employ the generalised extreme value (GEV) distribution. Essentially, there are two main reasons for choosing this type of

[1] http://www.meteoschweiz.ch/web/en/climate/climate_*since*_1864/*homogeneous_data.html*.

[2] The deviations are assessed as 0.2 - 0.3 C for provisionally inhomogenisation, reconstruction at the same place or nearby (Sion) and as -0.5 C for the reconstruction in Bern, as reported by personal communication with MeteoSwiss.

distribution. First, as argued in Leadbetter et al. [1983], the distribution of the maximum of identically distributed random variables is well approximated by the GEV distribution. Second, the GEV distribution is very flexible in the sense that it incorporates a wide range of tail behaviours.

The GEV distribution has the distribution function

$$F(z;\mu,\sigma,\xi) = \exp\left\{-\left(1+\xi\frac{(z-\mu)}{\sigma}\right)_+^{-\frac{1}{\xi}}\right\} \tag{1}$$

where $y_+ = max(y,0)$ and μ is a location parameter, σ is a scale parameter, and ξ is a shape parameter. The shape parameter ξ determines the tail behaviour which can be sub-divided into three classes: the limit $\xi \to 0$ corresponds to the Gumbel distribution, $\xi > 0$ and $\xi < 0$ to the Fréchet and Weibull distributions, respectively. The Fréchet distribution is a "long-tailed" distribution, the Gumbel distribution is a "medium-tailed" distribution, whereas the Weibull distribution is a "short-tailed" distribution which has a finite endpoint.

The parameters of the GEV(μ,σ,ξ) distribution can be estimated in various manners, for example, by using the maximum likelihood procedure or by the Bayesian approach, see Coles [2001] for an accessible introduction to the modelling of extremes. In our paper, we have chosen the Bayesian approach for at least two reasons. First, as argued in Smith [1997] for the purpose of assessing the likelihood of more extreme events than observed in the past, Bayesian methods are more appropriate than classical estimation techniques. In particular, a Bayesian approach allows to account for uncertainty in model parameters which is not that straightforward in the classical approach. Second, the Bayesian approach offers a more elegant solution to model a structural break and to assess the uncertainty of its occurrence by the associated dispersion of the posterior distribution.

In order to assess the likelihood of observing the record-breaking temperature in the summer of 2003, z_{2003}, we compute the posterior predictive density of z_{2003}, given observed data $\mathbf{x}$,

$$f(z_{2003}|\mathbf{x}) = \int_\Theta f(z_{2003}|\theta)\pi(\theta|\mathbf{x})\mathrm{d}\theta \tag{2}$$

where $f(z_{2003}|\theta)$ is the density function of z_{2003} under conditional independence assumption for x_i given $\theta = (\mu,\sigma,\xi) \in \Theta$. $\pi(...|\mathbf{x})$ denotes the posterior density given past data $\mathbf{x}$, which can be evaluated using Markov Chain Monte Carlo (MCMC) methods. Then the posterior predictive distribution of z_{2003} is given by

$$Pr\{Z \leq z_{2003}|\mathbf{x}\} = \int_\Theta Pr\{Z \leq z_{2003}|\theta\}\pi(\theta|\mathbf{x})\mathrm{d}\theta \tag{3}$$

where Z is a GEV(μ,σ,ξ) distributed random variable and $Pr\{Z \leq z_{2003}|\theta\}$ is the distribution function given in (1) evaluated at z_{2003}. Then the probability of observing a more extreme observation than z_{2003}, given the past data, can be written as

$$Pr\{Z > z_{2003}|\mathbf{x}\} = 1 - Pr\{Z \leq z_{2003}|\mathbf{x}\} = 1 - p \tag{4}$$

Very low exceedance probabilities would indicate that the heat wave of summer 2003 was indeed an unusual and largely unanticipated event.

A common tool in extreme value statistics are return level plots. The return level z_p is defined as the $(1-p)$-quantile of the GEV-distribution derived from (1) with the associated return period $1/p$. The plot of z_p against a logarithmic scale for $-ln(1-p) \approx 1/p$ is called return level plot. Using $-ln(1-p)$ ensures that the relationship is linear for the Gumbel distribution. This procedure can be extended to what is called a "predictive return level plot". This is the plot of the quantiles z_{1-p} of the predictive distribution against $1/p$ displayed on a logarithmic scale and has a similar interpretation as conventional return level plots.

Our analysis of the data at hand reveals that the statistical behaviour of annual maxima drastically changes in the beginning of the 1980s. Since then we observe on average for all measurement locations a sharp increase in the level of the measurements. In the next section, we will introduce the timing of a breakpoint as an additional parameter in the model. This effectively splits our sample into two sub-samples; for both sub-samples a GEV distribution is separately fitted.

4 Results

4.1 Initial predictive inference results

First, we report the results of fitting the GEV distribution to the data available before 2003. The posterior distributions of the model parameters were obtained using a Metropolis-Hastings random walk algorithm [Gamerman, 1997]. We employ proper but diffuse priors that are also independent: the prior distribution is $N(0, 10000)$ for the location parameter μ and the logarithmic transformation of the scale parameter σ, and $N(0, 100)$ for the shape parameter ξ. We generated Markov chains of 100000 observations with an initial burn-in period equal to 20000 observations. Furthermore, in order to reduce autocorrelation in the generated Markov chains we have applied thinning by storing every 100th generated value. The convergence of the Markov chains was assessed using the convergence criterion suggested in Geweke [1992].

Table 2 presents estimation results derived from the posterior distribution based on all observations before 2003. All chains exhibit fast convergence and very good mixing properties. It is worth noting that in all cases the shape parameter of the fitted GEV distribution is negative with a very high probability which suggests that the Weibull distribution gives an appropriate characterisation of the tail behaviour in our data.

Using the generated values of the Markov chains, we can assess how likely the hot summer of 2003 was, given historical data. We calculate the predictive probability of exceeding the temperature observed in 2003, see Table 2. The associated predictive probabilities are very low suggesting that the heatwave of 2003 was indeed a rather unusual event. Thus, at this point, our conclusions conform with those of Schär et al. [2004]. The next column of Table 2 contains the corresponding predictive return periods. Such periods indicate that one should expect to observe such extreme temperature values on average once within a corresponding period [Coles, 2001]. For all measurement stations, the return periods are much larger than our observation period of 144 years.

4.2 Modelling a structural break

A casual examination of the time series reveals that, in the last 25 years of our sample, the average annual maximum is much higher than observed for the period up to the early 1980s. Table 3 presents the descriptive statistics for two subsamples: before 1982 and afterwards. The characteristics of these two sub-samples are quite different. We observe an increase in both the average values as well as in the range (minimum and maximum values) in the second sub-period compared to the first one. We also find that in the second sub-period the standard deviation is larger for all but three locations. This suggests that the whole distribution underwent a structural change such that extreme temperatures became more likely than they used to be. This also implies that the much discussed heat wave in 2003 may not have been a separate, undesirable incident, but rather the consequence of an increase in the level of temperatures as well as in their variability that take place since the early 1980s.

Given our earlier results indicating at most mild positive temporal dependence in the underlying time series, we also how accounting for a structural break influence our conclusions drawn for the whole sample period. The estimated first autocorrelation coefficient for two subsamples is presented in Table 3. As expected, splitting the sample into two parts resulted in much lower values of the first autocorrelation coefficient reported for the first subsample. It takes values in the range between -0.008 and 0.179. At the same time, it is interesting to observe that the magnitude of the first order autocorrelation observed in the second subsample largerly remained in the similar range reported for the whole sample but with the opposite sign taking values in the interval between -0.293 and 0.070. At the same time they appear to be somewhat larger than those observed for the first subsample. We attribute this difference to fact that the estimate of autocorrelation for the second subsample is based on a rather small number of observations (27 years). This naturally increases the variability of the autocorrelation estimator and therefore makes it less reliable in comparison to that based on the first subsample that is much larger.

In order to investigate the possibility of the presence and severity of a structural break, we extend our model by allowing for a breakpoint that splits the whole sample into two sub-samples. We allow the parameters of the fitted GEV distribution to differ across two sub-samples and the timing of the breakpoint appears as a new parameter in the model. As a matter of fact, such a modification of the model is easily implemented in the Bayesian framework as opposed to the maximum likelihood approach which becomes rather cumbersome when dealing with variable changepoints. We impose an uniform prior on our breakpoint timing parameter and allow for a minimum length of the sub-sample equal to six observations. The breakpoint timing parameter is easily included into our Metropolis-Hastings algorithm with a simple discrete random walk chain.

Table 4 presents the resulting parameter estimates. The posterior expected value of the location parameters and the observed temperature values appear in Figure 1. There is substantial evidence in favour of the two regimes such that in the second part of our sample the average annual maximum temperature is 1 to 1.6 degrees higher – depending on the station – than it used to be in the first part of our sample.

The posterior distributions of the parameters in each regime are displayed in Figure 2. Observe that the posterior distributions of the second sub-sample are more disperse than those of the first sub-sample due to the four times smaller sample size of the later sub-sample.

Figure 2 highlights the differences between the two different regimes. The posterior distributions of the location parameters μ_0 and μ_1 do not overlap at all, suggesting that the difference is statistically significant. At the same time, the posterior distributions of the scale parameters largely do overlap, suggesting that this parameter did not undergo much of a change. We however restrain from imposing the same value of the scale parameter in both regimes, following the advice of Coles and Pericchi [2003] who argue that when dealing with extreme events the parameter uncertainty always has to be accounted for.

The most interesting contrast we find in our model is provided by the substantially different distributions of the the shape parameter. For the first sub-sample, the value of the shape parameter ξ_0 is almost certainly negative. This implies that the tail behaviour of the GEV distribution fitted to the first sample is well approximated by a Weibull distribution. The posterior expectations of the shape parameter ξ_1 for the second sub-sample in all measurement locations but one exceeds zero and in three locations lies even above 0.2. This suggests that the tail behaviour in the second sub-sample has changed and now is rather consistent with the Fréchet distribution. However, a word of caution must be uttered as the dispersion in the posterior distribution of ξ_1 is up to three times as large as that of the shape parameter ξ_0, measured by the standard deviation, see Table 4. In addition, the probability mass on negative values of ξ_1 is still considerable, so the Weibull distribution still deserves an attention.

Figure 3 displays the return level plots associated with every regime along with the corresponding 95% credibility intervals. Not only the whole return level curve has shifted upwards, but also the uncertainty has substantially increased for large temperatures. One should not forget that the return level plot for the second sub-sample is based on less than thirty observations and therefore the parameters of the GEV distribution have been estimated with a rather large degree of uncertainty which is translated also into the return level plot.

Last but not least, Figure 4 contains the posterior distribution of the breakpoint timing denoted as the first year of the second sub-sample. The corresponding median along with the 10th and 90th percentiles are reported in Table 4. It is either 1981 (three times), 1982 (eight times), or 1983 (once). This similarity is a remarkable finding for the different and quite heterogeneous measurement locations. This observation is further strengthened by the fact that the corresponding posterior distribution is very tight. This finding, in our opinion, strongly favours our hypothesis that the distribution of maximum temperatures in Switzerland underwent a significant structural change in the beginning of the 1980s. It also is consistent with the descriptive statistics results presented in Table 3 indicating that there was an increase in average annual maximal since the beginning of the 1980s.

4.3 Model comparison and evidence of the heat event 2003

In a thought experiment we want to check whether already in 2002 enough information was available for infering a much higher probability for events like the 2003 heatwave. For this purpose, we first replicate our analysis relying only on observations before 2003 and calculate the predictive probabilities for the extreme values exceeding the 2003 numbers under assumption of a structural break. In Table 5 we compare the predictive probability and predictive return period with the ones infered without assuming a structural break. The introduction of the break point leads to a remarkable increase in probability for extreme temperatures and decrease of return period as compared to a stationary climate regime. The two decades of the new regime had been long enough to produce sufficient information for detecting this probability shift in the order of a magnitude already before the 2003 heatwave actually happened.

We further analyse how recent temperature records have altered the assessment of future extremes. We redo our analysis now based on all observations up to 2007, still under assumption of a structural break. These observations lead to a further increase in exceedance probability, roughly speaking doubling them (see Table 5).

Additional information on implications of a two-regime model can be drawn from the predictive return level plots, see Figure 5. These plots were constructed using the full sample information available at every location. The main message of the return level plots is that extreme observations are to occur within a shorter time span (note the difference to the return level plots in Figure 3 that are not derived from a sample of the posterior predictive distribution).

5 Conclusions

In this paper, we model the annual maxima of monthly mean temperatures in Switzerland measured in twelve locations over the period that in most cases cover 1864 till 2007. We apply the generalised extreme value distribution whose parameters are assessed using Bayesian methods.

Our main findings are the following: First, a mechanic application of fitting a GEV distribution on data prior to 2002 suggests that the heat wave 2003 was a very unusual phenomenon. Second, a more careful examination of the time series reveals that the pattern of occurrence of an enduring heat wave may have drastically changed already in the beginning of the 1980s. In order to investigate this formally we have introduced a breakpoint parameter in our model which endogenously splits the sample into two sub-samples. We find very clear statistical evidence in favour of a structural break, convincingly supported by the fact that the posterior distribution of the breakpoint timing is very tight and centered at 1982 plus/minus one year at every measurement location.

Third, we show that after accounting for a shift in the parameters of the fitted GEV distribution, the event observed in 2003 appears not that improbable after all. More generally, the huge discrepancy in implications of parameter estimates of different subperiods is well illustrated with predictive return level plots which suggest that for a given return period the likelihood of observing extreme events has increased substantially, or, equally, a certain threshold is expected to be surpassed within much shorter time periods.

Fourth, the implications of our research is that the first heat wave – now largely omitted from public discussion – occurred in 1983 which by historical standards was a year characterised by unusually high temperatures such that a new record has been established in all measurement stations but one. The conclusion of our analysis of extreme temperatures in Switzerland is that a careful examination of developments in the past combined with an appropriate statistical framework may have provided signals that could have mitigated some consequences of the heat wave observed in 2003. Moreover, such a procedure can serve as a useful tool for assessing the likelihood of more extreme things to come.

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Table 1: Descriptive statistics for the whole sample

Station	Sample	Obs.	Mean	Std.dev.	Min	Max	1st AC[a]	2003
Basel-Binningen	1864–2007	144	18.801	1.4495	16.0	23.8	0.128	23.8
Bern-Zollikofen	1864–2007	144	17.917	1.3919	15.2	22.1	0.156	21.9
Geneve-Cointrin	1864–2007	144	19.586	1.4516	16.8	24.1	0.230	24.1
Zurich	1864–2007	144	18.109	1.3983	15.4	22.7	0.136	22.7
Chateau d'Oex	1901–2007	107	15.327	1.3988	12.8	19.5	0.291	19.5
Chaumont	1864–2007	144	14.597	1.5495	11.1	19.5	0.103	19.5
Davos-Dorf	1876–2007	132	11.694	1.3039	8.8	16.1	0.280	15.7
Engelberg	1864–2007	144	14.586	1.2476	12.1	18.7	0.183	18.7
Lugano	1864–2007	144	21.476	1.1682	18.8	25.1	0.305	25.1
Saentis	1864–2007	144	5.6465	1.4258	2.9	10.1	0.247	10.1
Segl-Maria	1864–2007	144	11.015	1.0726	8.6	14.7	0.220	14.7
Sion	1864–2007	144	19.131	1.3549	16.4	23.3	0.271	23.1

[a] The first autocorrelation coefficient.

Table 2: GEV parameter estimates (posterior mean and standard deviation) and predictions on exceeding the temperature of 2003, sample 1864 – 2002

	$\hat{\mu}$	Std.dev.	$\hat{\sigma}$	Std.dev.	$\hat{\xi}$	Std.dev.	2003	Predictive probability	Predictive return period
Basel-Binningen	18.175	0.118	1.256	0.085	-0.156	0.060	23.8	0.0013	774.51
Bern-Zollikofen	17.333	0.123	1.269	0.087	-0.191	0.059	21.9	0.0033	299.62
Geneve-Cointrin	18.980	0.124	1.323	0.090	-0.200	0.063	24.1	0.0018	558.53
Zurich	17.503	0.115	1.232	0.083	-0.158	0.056	22.7	0.0017	572.27
Chateau d'Oex	14.676	0.132	1.212	0.099	-0.119	0.071	19.5	0.0058	172.50
Chaumont	13.956	0.135	1.445	0.095	-0.216	0.052	19.5	0.0011	919.12
Davos-Dorf	11.131	0.113	1.160	0.084	-0.172	0.061	15.7	0.0025	406.45
Engelberg	14.042	0.098	1.098	0.070	-0.144	0.050	18.7	0.0021	471.44
Lugano	20.958	0.103	1.053	0.070	-0.161	0.051	25.1	0.0028	359.94
Saentis	5.029	0.118	1.271	0.086	-0.156	0.054	10.1	0.0028	356.30
Segl-Maria	10.569	0.093	0.999	0.068	-0.214	0.056	14.7	0.0008	1310.46
Sion	18.588	0.120	1.282	0.086	-0.254	0.055	23.1	0.0011	912.24

Table 3: Descriptive statistics for two subsamples

	Subsample	Mean	Std.dev.	Min	Max	1st AC[a]	Subsample	Mean	Std.dev.	Min	Max	1st AC
Basel-Binningen	1864–1981	18.503	1.247	16.0	21.3	-0.008	1982–2007	20.154	1.532	18.2	23.8	-0.278
Bern-Zollikofen	1864–1981	17.676	1.276	15.2	20.6	0.101	1982–2007	19.012	1.370	17	22.1	-0.293
Geneve-Cointrin	1864–1981	19.298	1.318	16.8	22.6	0.133	1982–2007	20.892	1.305	18.8	24.1	-0.276
Zurich	1864–1981	17.870	1.245	15.4	20.6	0.078	1982–2007	19.192	1.539	17.2	22.7	-0.210
Chateau d'Oex	1901–1981	14.898	1.149	12.8	17.4	0.096	1982–2007	16.665	1.254	14.9	19.5	-0.261
Chaumont	1864–1981	14.347	1.442	11.1	17.9	0.041	1982–2007	15.731	1.513	13.9	19.5	-0.271
Davos-Dorf	1876–1981	11.359	1.067	8.8	13.8	0.105	1982–2007	13.058	1.295	11.1	16.1	-0.211
Engelberg	1864–1981	14.336	1.072	12.1	16.9	0.085	1982–2007	15.723	1.353	13.7	18.7	-0.229
Lugano	1864–1981	21.243	1.072	18.8	25	0.179	1982–2007	22.531	0.993	20.9	25.1	0.070
Saentis	1864–1981	5.335	1.204	2.9	8.7	0.143	1982–2007	7.062	1.497	4.8	10.1	-0.249
Segl-Maria	1864–1981	10.811	0.952	8.6	12.8	0.138	1982–2007	11.938	1.104	10.1	14.7	-0.146
Sion	1864–1981	18.836	1.211	16.4	21.8	0.126	1982–2007	20.469	1.150	18.9	23.3	-0.160

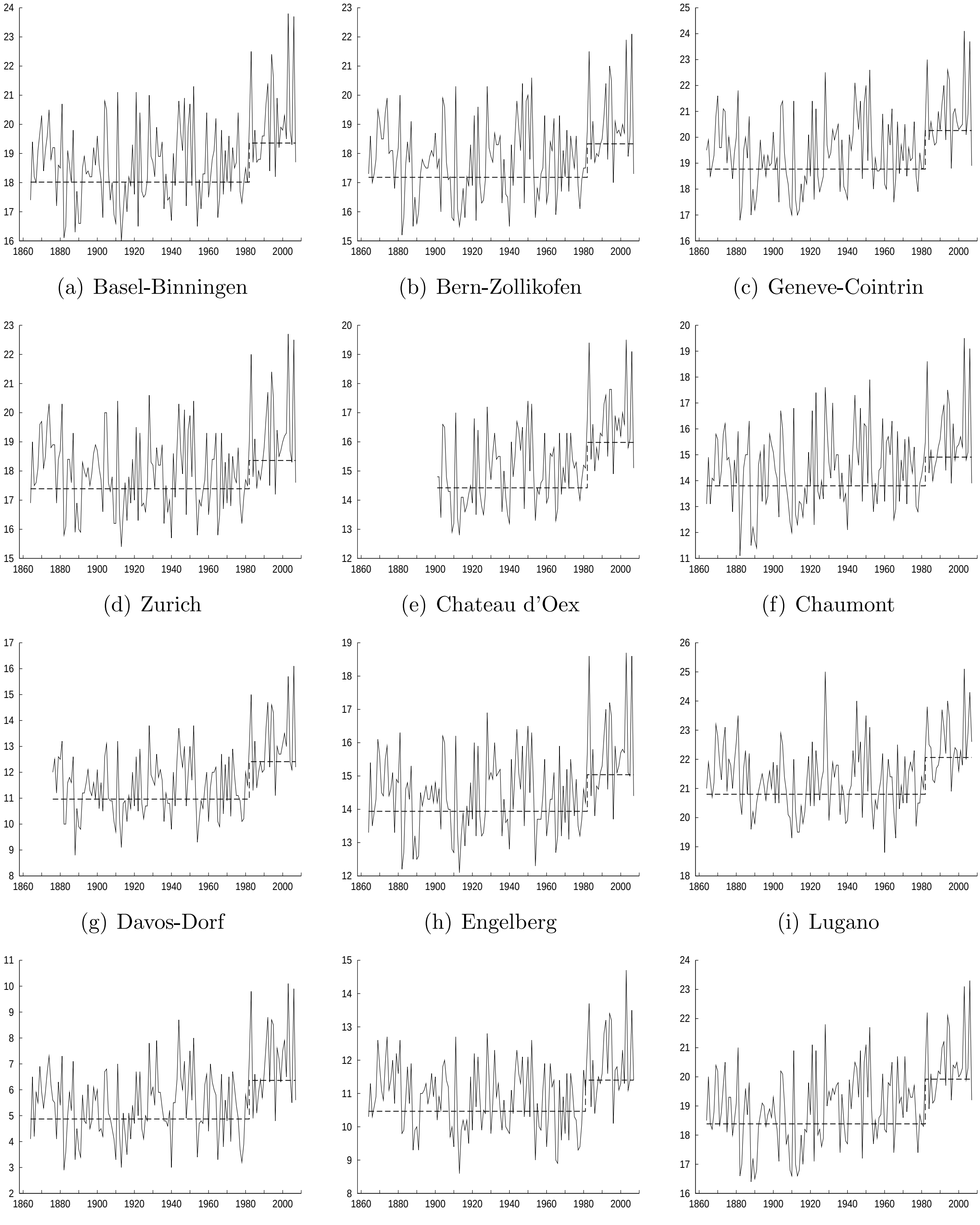
[a] The first autocorrelation coefficient.

Table 4: Parameter estimates for the model with a structural break

	First subsample						Second subsample						Breakpoint timing		
	$\hat{\mu}_0$	Std.dev.	$\hat{\sigma}_0$	Std.dev.	$\hat{\xi}_0$	Std.dev.	$\hat{\mu}_1$	Std.dev.	$\hat{\sigma}_1$	Std.dev.	$\hat{\xi}_1$	Std.dev.	10th quantile	Median	90th quantile
Basel-Binningen	18.018	0.123	1.194	0.092	-0.193	0.074	19.353	0.280	1.125	0.240	0.234	0.216	1980	1982	1984
Bern-Zollikofen	17.179	0.131	1.233	0.098	-0.200	0.079	18.296	0.263	1.075	0.214	0.128	0.182	1980	1981	1984
Geneve-Cointrin	18.771	0.126	1.243	0.100	-0.162	0.075	20.277	0.283	1.169	0.220	0.023	0.167	1981	1982	1985
Zurich	17.389	0.126	1.208	0.097	-0.204	0.084	18.383	0.323	1.161	0.270	0.226	0.231	1980	1982	1989
Chateau d'Oex	14.414	0.138	1.077	0.107	-0.142	0.110	16.006	0.248	1.039	0.197	0.106	0.205	1980	1982	1983
Chaumont	13.804	0.148	1.422	0.103	-0.222	0.062	14.919	0.258	1.067	0.235	0.256	0.214	1979	1981	1983
Davos-Dorf	10.957	0.112	1.066	0.082	-0.236	0.071	12.426	0.260	1.117	0.212	0.059	0.186	1980	1982	1983
Engelberg	13.934	0.107	1.056	0.078	-0.227	0.072	15.051	0.260	1.132	0.267	0.076	0.186	1980	1982	1983
Lugano	20.805	0.104	1.004	0.074	-0.126	0.055	22.057	0.208	0.897	0.167	0.028	0.172	1980	1982	1986
Saentis	4.867	0.119	1.179	0.085	-0.196	0.060	6.352	0.336	1.357	0.277	-0.009	0.203	1980	1982	1987
Segl-Maria	10.469	0.099	0.965	0.072	-0.281	0.073	11.401	0.219	0.968	0.165	0.002	0.161	1980	1981	1983
Sion	18.396	0.126	1.202	0.085	-0.231	0.062	19.938	0.221	0.905	0.196	0.150	0.203	1982	1983	1988

Table 5: Predictive probability and predictive return period for exceeding the temperature of 2003

	no breakpoint analysis time series till 2002		with breakpoint analysis time series till 2002		with breakpoint analysis time series till 2007	
	Predictive probability	Predictive return period	Predictive probability	Predictive return period	Predictive probability	Predictive return period
Basel-Binningen	0.0013	774.51	0.0354	27.72	0.0605	16.02
Bern-Zollikofen	0.0033	299.62	0.0346	28.41	0.0612	15.83
Geneve-Cointrin	0.0018	558.53	0.0171	58.15	0.0448	21.84
Zurich	0.0017	572.27	0.0413	23.72	0.0660	14.64
Chateau d'Oex	0.0058	172.50	0.0342	28.72	0.0561	17.33
Chaumont	0.0011	919.12	0.0276	35.76	0.0553	17.57
Davos-Dorf	0.0025	406.45	0.0333	29.49	0.0661	14.63
Engelberg	0.0021	471.44	0.0325	30.31	0.0557	17.45
Lugano	0.0028	359.94	0.0224	44.15	0.0413	23.69
Saentis	0.0028	356.30	0.0360	27.27	0.0605	16.03
Segl-Maria	0.0008	1310.46	0.0232	42.52	0.0360	27.29
Sion	0.0011	912.24	0.0274	36.00	0.0599	16.19



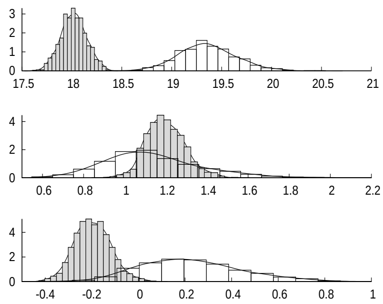
(a) Basel-Binningen (b) Bern-Zollikofen (c) Geneve-Cointrin

(d) Zurich (e) Chateau d'Oex (f) Chaumont

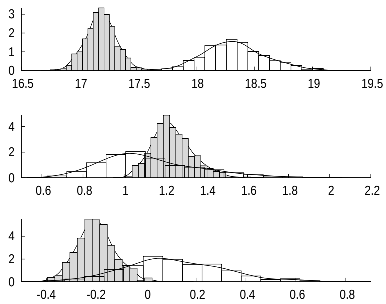
(g) Davos-Dorf (h) Engelberg (i) Lugano

(j) Saentis (k) Segl-Maria (l) Sion

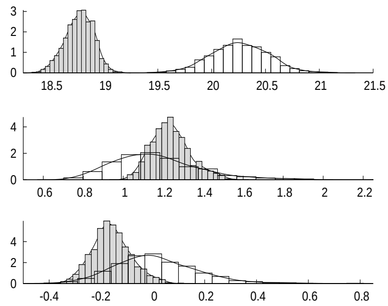
Figure 1: Observed annual maximum temperature (solid line) and the estimated location parameter of the fitted GEV distribution (dashed line)



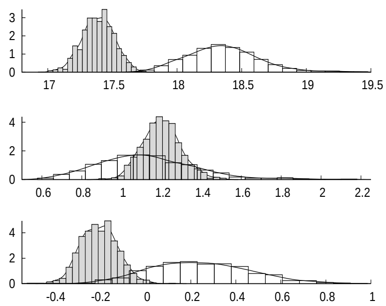
(a) Basel-Binningen



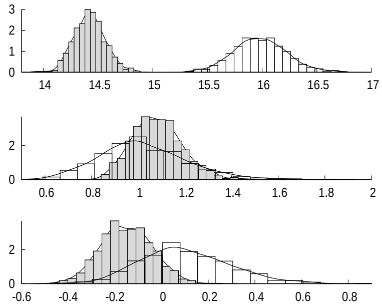
(b) Bern-Zollikofen



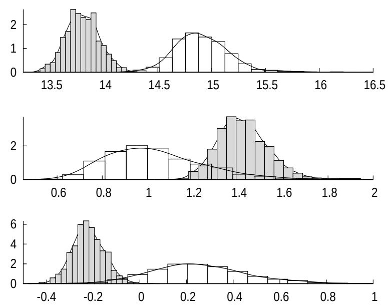
(c) Geneve-Cointrin



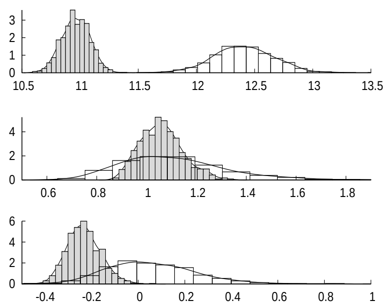
(d) Zurich



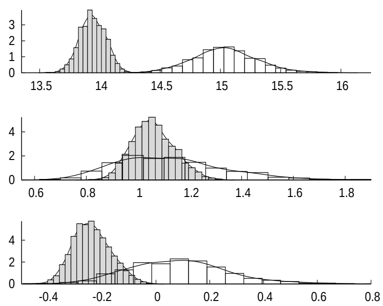
(e) Chateau d'Oex



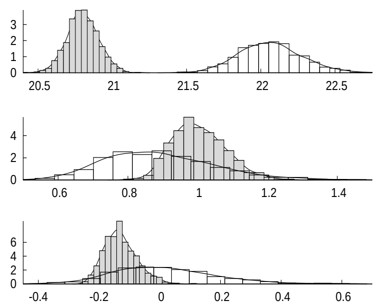
(f) Chaumont



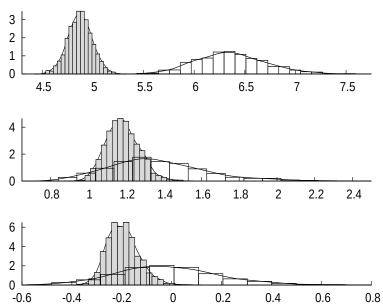
(g) Davos-Dorf



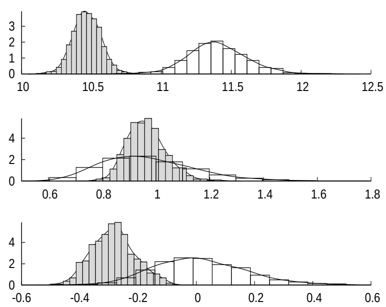
(h) Engelberg



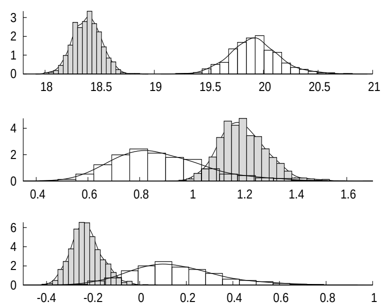
(i) Lugano



(j) Saentis

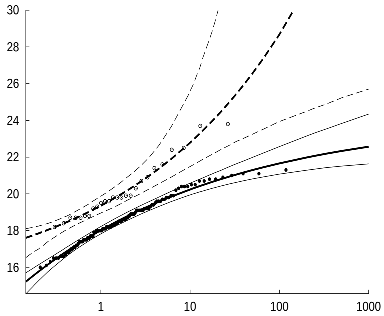


(k) Segl-Maria

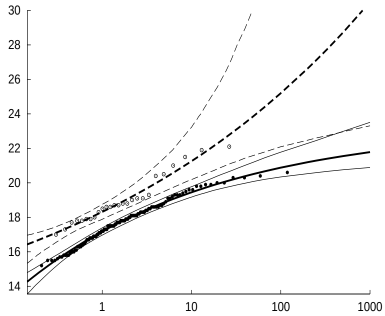


(l) Sion

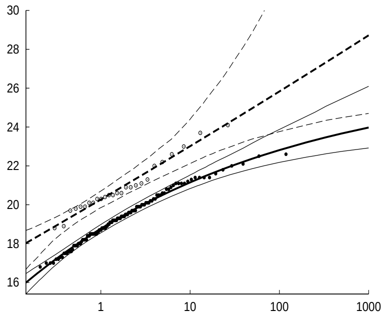
Figure 2: Posterior distributions of the parameters of the GEV distribution fitted for the first (shaded) and the second (transparent) subsamples: μ_0 and μ_1 – upper panel, σ_0 and σ_1 – middle panel, ξ_0 and ξ_1 – lower panel



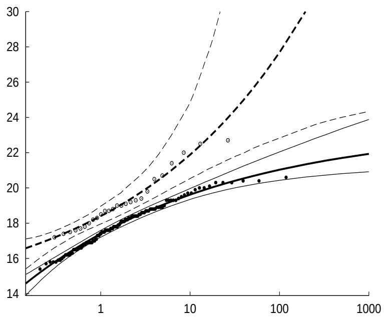
(a) Basel-Binningen



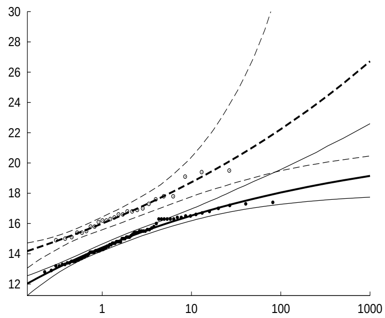
(b) Bern-Zollikofen



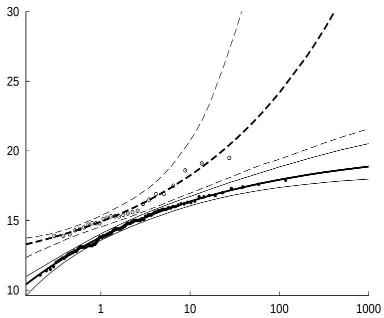
(c) Geneve-Cointrin



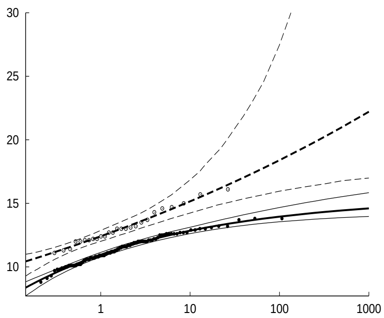
(d) Zurich



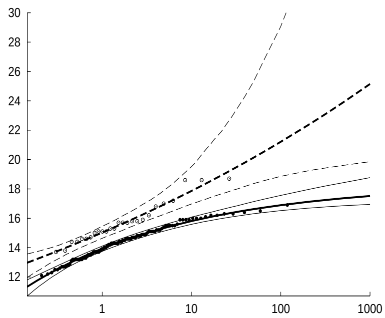
(e) Chateau d'Oex



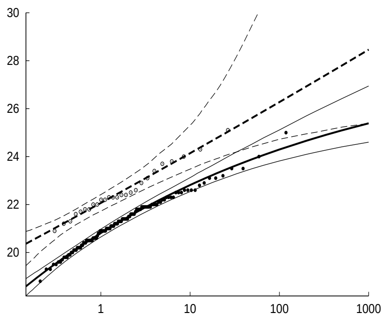
(f) Chaumont



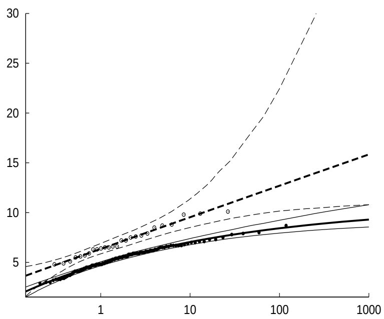
(g) Davos-Dorf



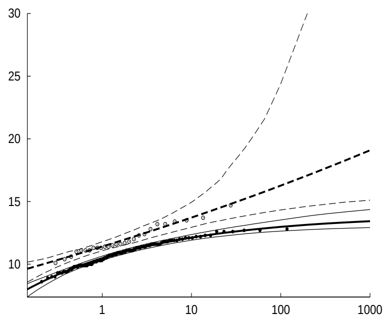
(h) Engelberg



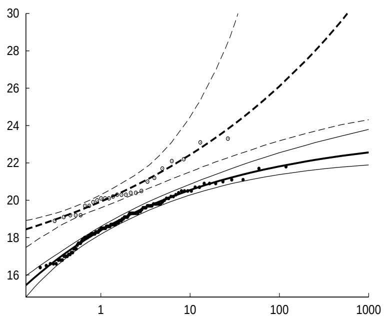
(i) Lugano



(j) Saentis

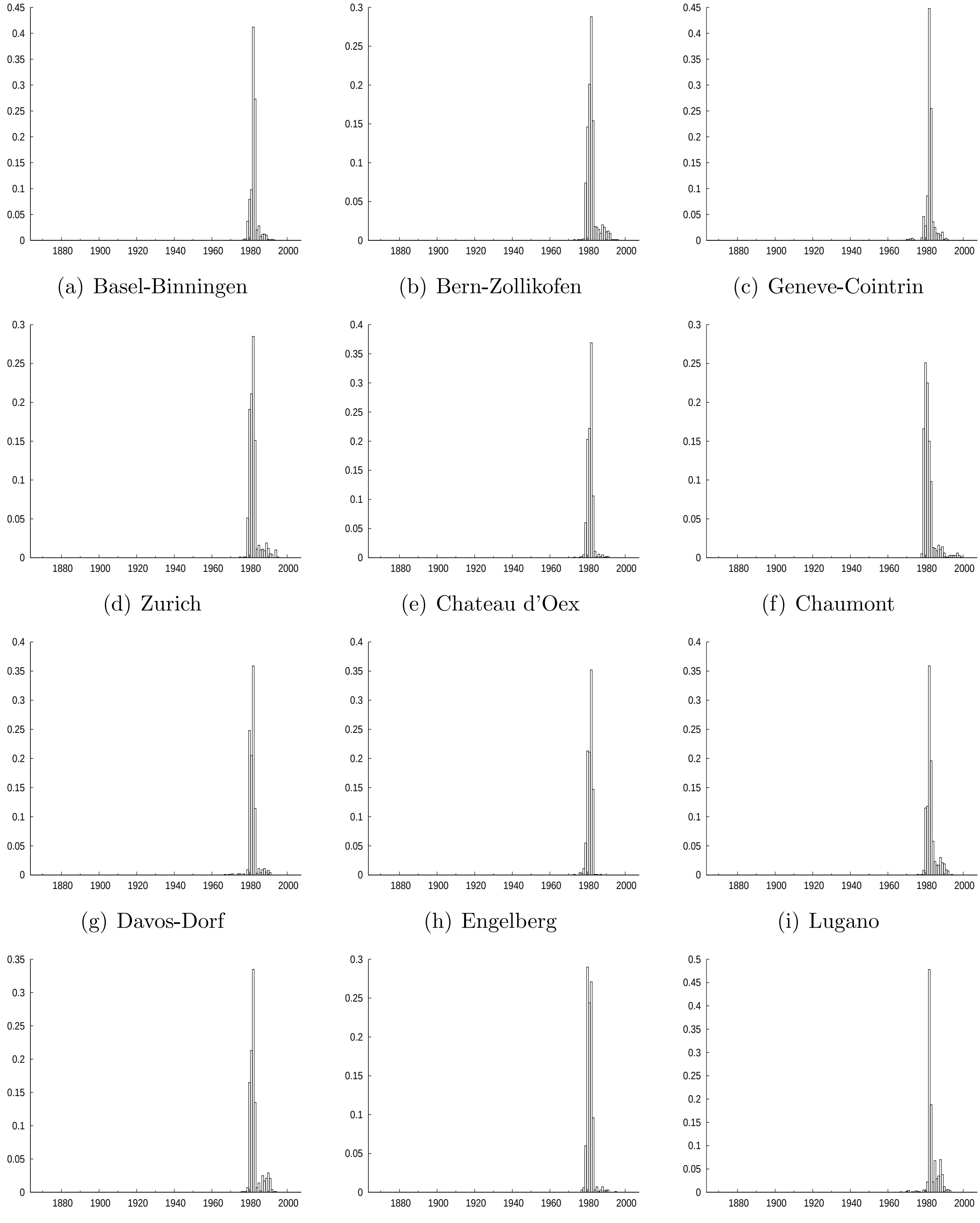


(k) Segl-Maria



(l) Sion

Figure 3: Return level plot with the corresponding 95% credibility interval for the first (solid line) and the second (dashed line) superiods: filled and empty circles correspond to the empirical estimates for the first and the second subperiods, respectively; the x-axis shows the return period (years), the y-axis shows the temperature in $^{\circ}C$



(a) Basel-Binningen (b) Bern-Zollikofen (c) Geneve-Cointrin

(d) Zurich (e) Chateau d'Oex (f) Chaumont

(g) Davos-Dorf (h) Engelberg (i) Lugano

(j) Saentis (k) Segl-Maria (l) Sion

Figure 4: Posterior distribution of the breakpoint timing parameter

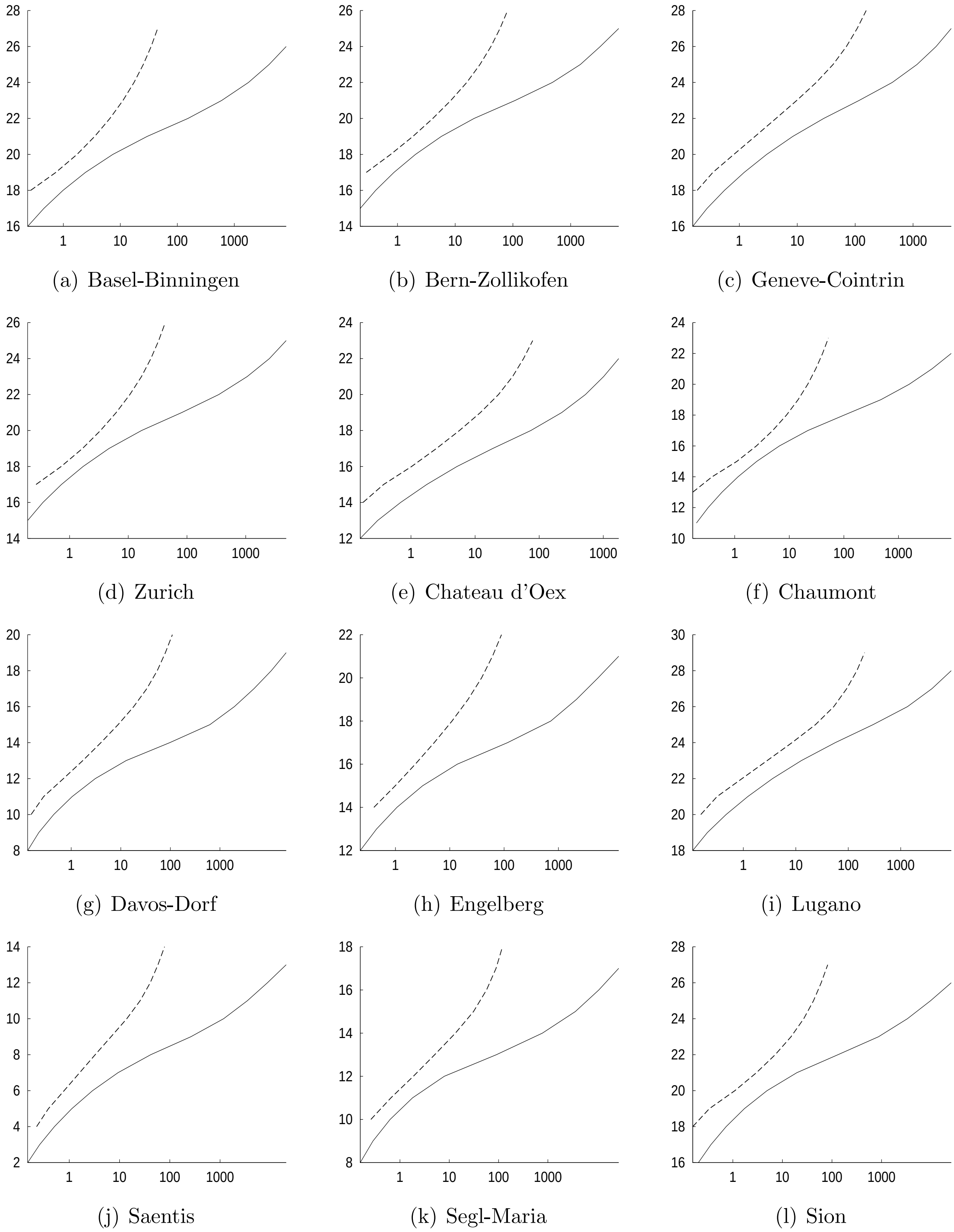


Figure 5: Predictive return level plot: solid line – first subperiod, dashed line – second subperiod; the x-axis shows the return period (years), the y-axis shows the temperature in $^{\circ}C$