Author's Response to NHESS-2016-373

Extreme weather exposure identification for road networks – a comparative assessment of statistical methods

Matthias Schlögl and Gregor Laaha

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1 Response to Reviewer 1

We would like to thank the referee for the very positive evaluation of our manuscript and the provided feedback. Please find our responses below, with referee comments in italics, and authors' responses in standard format.

1.1 Specific Comments

1. *page 2, line 30: Regarding works on extreme temperatures modelling, the authors may wish to consult (...).*

   Comparative studies on extreme temperature modelling are rare. Grotjahn et al. (2016) argue in favor of the POT approach for the application on large scale meteorological patterns, but the comparison is based on literature review rather than data-based analyses. We have added this information to the manuscript. Hasan et al. (2012), Caroni et al. (2016) and Kharin et al. (2007) appear less relevant, as they only apply a single approach (AMS) and did not compare the results to the alternative approach.

2. *page 7, line 14: The authors might wish to discuss why they haven't considered using distribution fitting statistical tests such as the Kolmogorov-Smirnov and/or the Anderson-Darling, for the assessment of the performance of the parameter estimation methods.*

   Distribution-fitting tests are primarily useful for gaining an appreciation whether a lack of fit is statistically significant, or rather an effect of sampling uncertainty, but they have little discriminative power to identify the "true" or "best" distribution to use (e.g. Stedinger, 1993). Hence, they do not provide a straightforward measure for comparing goodness-of-fit across AMS and PDS approaches. We have added a note to the text.

3. *page 7, line 21: adding a reference to Makkonen I., 2006, Plotting Positions in Extreme Value Analysis, J Applied Meteorolgy and Climatology, 45, 334–340 might*

be helpful to the less informed reader.

We have added this reference.

4. *page 8, line 2: The selection of the base value for the conditional performance measures, namely T, to be 10 years should be better justified and supported by relevant references (i.e. international or national technical ordinances or standards, best practice documentation etc).*

   Although different return periods, ranging from 2 – 100 years (and more) have been used in engineering and storm water management and no common standard about recommended return periods seems to exist, return periods of at least 5 – 10 years are often considered as a lower threshold in storm infrastructure design (e.g. Ganaraska Region Conservation Authority, 2014; EPA, 2014). Hence, such a level appears well suited to separate expected occurrence (i.e., non-extremes) from extreme events. We have added this information to section 2.5.

5. *page 8, line 13: Since "synoptic" has a reserved meaning in meteorology you might wish to replace it with "combined plotting" or any other suitable term throughout the manuscript.*

   We have followed this suggestion and replaced "synoptic" by "combined plotting".

6. *page 8, lines 16–17: Please rephrase/simplify the first sentence of section 3.1.*

   We have rephrased this sentence.

7. *page 13, line 7: From this point on the reader has to remember that GP refers to PDS and GEV refers to AMS. For the sake of clarity, it might be advisable to replace "GP" with "GP/PDS" and "GEV" with "GEV/AMS" in the remainder of the text.*

   We have replaced "AMS" and "GP" with "AMS/GEV" and "PDS/GP" in sections 4 and 5 as proposed.

8. *page 13, lines 8–9: "(indicated by negative deviations)" only 2 out of 4 diagrams in Fig 5 show negative values at low return periods.*

   Thanks for pointing this out; we have modified the text accordingly.

9. *page 13, line 9: "this behaviour changes in the opposite for higher returns periods" – If I am reading fig. 5 correctly, this is actually true only for precipitation. This would also have an effect on the text of the Discussion (p15, l13) and Conclusions (p20, l23) sections.*

   We have rephrased the respective sections accordingly.

10. *page 13, line 12: "(ie underestimation of negative magnitude)" is not very clear consider rephrasing as "(ie more negative values)"*

    We have rephrased the section containing this sentence.

11. *page 19, line 32: "as well as the number of breaks set within this range" I am not quite certain about the meaning of this phrase. Could you please clarify?*

    Both methods employ a sequence of thresholds that are generated based on a specified range and resolution of values. We have revised the entire paragraph (also with reference to the comment of Reviewer #2) to improve readability.

1.2 Technical Comments

All technical comments have been implemented as proposed by the reviewer.

1.3 References

- Ganaraska Region Conservation Authority: Technical and Engineering Guidelines for Stormwater Management Submissions, available from: `http://www.grca.on.ca/Guidelines_for_swm_submissions-_FINAL.pdf` (Accessed 24 February 2017), 2014.
- EPA: Addressing Green Infrastructure Design Challenges in the Pittsburgh Region. Abundant and Frequent Rainfall, available from `http://www.3riverswetweather.org/sites/default/files/Rainfall%20white%20paper.pdf` (Accessed 24 February 2017), 2014.
- Stedinger, J. R., Vogel, R. M. and Foufoula-Georgiou, E.: Frequency analysis of extreme events, Chapter 18 in Handbook of Hydrology, edited by DR Maidment, McGraw-Hill., 1993.

2 Response to Reviewer 2

We also would like to thank Dan Rosbjerg for his useful feedback. Our response is given below, with referee comments in italics, and our responses in standard format.

1. *Only one specific method for selecting an appropriate threshold for POT events has been applied. This choice might be crucial for the results and the conclusions, and it is not verified that the choice is optimal, although it is argued that some graphical criteria have been fulfilled. Another choice might lead to somewhat different conclusions.*

   We agree that different thresholds might lead to somewhat different conclusions. However, appropriate threshold choice is one of the most discussed issues related to the threshold excess approach (e.g. Scarrot and MacDonald, 2012). We have discussed this issue in the discussion section "Secondly, threshold selection in the threshold excess method is a legitimate subject for debate..."
   In this study, 100 time series (i.e. 25 stations with 4 meteorological indicators each) have been analyzed. In order be able to perform a standardized and reproducible threshold selection for this large number of time series, we decided to use

some sort of supervised automated threshold selection method.
In this respect we have tested several automated threshold selection methods, to be precise ATSM (automated threshold selection method) by Thompson et al. (2009) and MTM (multiple threshold selection method) by Deidda (2010). However, both methods yielded dissatisfying and inconsistent thresholds. Threshold values of similarly distributed time series obtained by ATSM varied considerably, and parameter estimates of MTM were depending on range and resolution of the thresholds considered. While certain patterns of convergence were found based on sensitivity analysis, we argue that these procedures somehow replace the threshold selection problem with that of selecting an appropriate range and an appropriate number of breaks (c.f. response #11 to reviewer 1).
Having tested several options, the square-root-rule criterion by Ferreira et al. (2003) – which has been used in various other studies as well (Scarrot and MacDonald, 2012) – has been employed. The results have been double-checked by means of diagnostic plots for threshold selection (mean residual life plot, parameter stability plots), which are the sole basis for threshold selection in many other studies (c.f. Coles, 2001; Della-Marta et al., 2009; Scarrott and MacDonald, 2012). Results show that the thresholds derived in this way provide reasonable results (c.f. also Figure 8). We have revised and enhanced the discussion section accordingly (also, with ref. to Reviewer 1) in order to clarify the issues pointed out by the reviewer.

2. *The assessments are based on conditional root-mean-square deviation and conditional mean absolute error as metrics. With the condition applied ($T > 10$ yr) the number of observations available for calculation of the metrics is drastically reduced. For example, if the AMS sample is covering 30 yr, only the three largest observations are applicable for calculating the metrics; in a 50 yr sample only the five largest observations can be used. Taking into account that the variance of the order statistics is strongly increasing towards the upper end of the ordered sample, it is evident that the metrics become highly uncertain.*

   Note that we are not solely analyzing conditional errors for the desired extremes ($T > 10$ *yr*), but also the overall G.O.F. We think this specific assessment of the desired extremes is important, as the overall G.O.F is mainly representing the non-extreme part which is usually of little relevance. However, we agree that the proposed metrics are of limited robustness, especially if time series are short and the condition is selected for high return periods.
   Depending on the length of the time series available, the value for x should be chosen accordingly. In our study, most of our time series date back to the period between the world wars, or even further back as early as 1895. Choosing $T > 10$ *yr* seems feasible in these cases.
   We have added this point to the discussion.

3. *For assessment of empirical probabilities in the ordered sample the Weibull plotting position has been selected. While the choice of plotting position formula in many cases is of minor importance, it might be influential in the present case with overly*

weight on the upper order statistics. If F indicates a chosen probability distribution, and y_m is the m'th order statistic in a sample of size N, then the Weibull plotting position stems from the fact that $E[F(y_m)] = m/(N+1)$. However, with M denoting the median operator, we have $F-1(m/(N+1)) < M[y_m] < E[y_m]$. Thus $F-1(m/(N+1))$ is relatively close to the modal value of y_m (where this exists), but far from being unbiased. A more balanced and consistent choice of plotting position would be the median plotting position as, independently of F, we have $M[F(y_m)] = F(M[y_m]) \approx (m-0.3)/(N+0.4)$.

The choice of a plotting position (PP) was mainly important when distribution parameters were estimated graphically from a probability paper. In this paper, according to common standard, parameters are estimated using analytical equations (e.g. based on L-moments method or maximum likelihood method) which do not depend on the choice of plotting positions. The choice of a specific plotting position is therefore of minor relevance for our paper.

Only the conditional performance measure depends, to some extent, on the chosen PP, as it uses a quantile estimate related to $T = 10$ years to select extreme values. To assess the sensitivity of the measure to the choice of the PP, we computed G.O.F. results with two alternative measures (i.e. based on Beard (median) and Gringorton plotting position) for the GEV case. We found that differences in CRMSE_{10} and CMAE_{10} values are only minor. As far as Weibull PP and median PP are concerned, mean absolute deviations in CRMSE_{10} values are around 0.09 – 0.17 °C for the different temperature indices and 1.15 mm for precipitation. Summary statistics of absolute CRMSE_{10} deviations between Weibull PP and median PP (including parameter estimation based on both MLE and LMOM for each of the four meteorological indicators) are presented below:

```
> sapply(delta_abs_crmse, summary)
          dt        precip   tmax       tmin
 Min.     0.008714  0.08059  0.0005396  0.02376
 1st Qu.  0.060140  1.12000  0.0513100  0.13130
 Median   0.084670  1.69500  0.0863700  0.15180
 Mean     0.093220  1.68000  0.0960000  0.16620
 3rd Qu.  0.100400  2.15100  0.1263000  0.17920
 Max.     0.218600  3.69600  0.2328000  0.35560
```

```
> sapply(delta_abs_cmae, summary)
          dt       precip   tmax      tmin
 Min.     0.00146  0.01179  0.002527  0.0009262
 1st Qu.  0.03299  0.53900  0.033770  0.0968800
 Median   0.06176  1.16600  0.060990  0.1352000
 Mean     0.07185  1.22500  0.074560  0.1432000
 3rd Qu.  0.07904  1.67300  0.086700  0.1693000
 Max.     0.20000  2.96400  0.218500  0.3472000
```

When using median PP instead of Weibull PP, results in terms of best fitting estimation method change in 16 % of all cases. However, in these cases, effects on results in terms of return level estimates are only minor, since – except for one case – changes occurred in cases where both estimation methods yield very similar parameter estimates. Results of the differences in return levels based on Beard and Weibull PP are presented below:

```
# return levels w/ Beard PP - return levels w/ Weibull PP

> delta_rl
$analysis_dt
   rl10  rl20  rl50 rl100
1 -0.09 -0.15 -0.21 -0.26
2 -0.03 -0.02  0.01  0.03
3  0.02 -0.01 -0.07 -0.16
4 -0.04 -0.04 -0.03 -0.01

$analysis_precip
   rl10  rl20  rl50  rl100
1 -0.44 -2.12 -5.97 -10.47
2 -0.45 -0.73 -1.16  -1.52
3  0.09 -0.39 -1.46  -2.64
4 -0.04 -0.05 -0.14  -0.26
5 -0.67 -0.80 -0.91  -0.95

$analysis_tmax
   rl10  rl20  rl50 rl100
1 -0.12 -0.21 -0.35 -0.46

$analysis_tmin
   rl10  rl20 rl50 rl100
1  0.22  0.50 0.92  1.23
2 -0.07 -0.04 0.05  0.15
3  0.34  0.73 1.25  1.61
4  0.33  0.51 0.76  0.94
5  0.13  0.57 1.26  1.85
6  0.17  0.40 0.70  0.91
```

Additional plots showing a graphical comparison between Weibull, Beard and Gringorten PP for all four parameters and for all 25 stations each are attached in the supplement.

In addition, our decision to use Weibull PP is based on the fact that we wanted to find a common ground regarding PP. Weibull PP is the one most commonly used in extreme value analysis and has been applied in most reference works in this area (e.g. Coles, 2001). We basically followed the argumentation of Lasse Makkonen (2005, 2008, 2013), who argues that the Weibull plotting position is the most suitable plotting position, independent of the underlying distribution $f(x)$. For further information, see the following publications and the cited references (also including opposing views) therein:

- Makkonen, L. (2005): Plotting Positions in Extreme Value Analysis. Journal of Applied Meteorology and Climatology, 45: 334–340. Available at: `http://journals.ametsoc.org/doi/pdf/10.1175/JAM2349.1`.
- Makkonen, L. (2008): Bringing Closure to the Plotting Position Controversy. Communications in Statistics - Theory and Methods, 37: 460–467.
- Makkonen, L.; Pajari, M. & Tikanmki M. (2013): Closure to Problems in the extreme value analysis (Struct. Safety 2008:30:405419). Structural Safety, 40: 65–67.

4. *There is a basic difference between calculation of the return periods in AMS and POT, which is important for $T < 10$ yr. For example, a 2 yr POT event corresponds to approximately a 2.54 yr AMS event, and a 5 yr POT event to a 5.52 AMS event. It is not evident how the difference between POT and AMS return periods has been handled.*

   Thanks for pointing this out; it is perfectly right that AMS return periods (T) and POT return periods (T_*) are not the same, they are rather related in the form of

$$\frac{1}{T} = 1 - e^{\frac{-1}{T_*}}.$$

   This inequality was considered by converting AMS return periods to PDS return periods (in order to avoid underestimating the probability of occurrence). However, it turned out that this has not been done in Fig. 5. We have clarified this issue in the methodology section and made corrections to Fig. 5. References to Langbein (1949), Rosbjerg (1977) and Madsen et al. (1997) have been added.

Extreme weather exposure identification for road networks – a comparative assessment of statistical methods

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Abstract. The assessment of road infrastructure exposure to extreme weather events is of major importance for scientists and practitioners alike. In this study, we compare the different extreme value approaches and fitting methods with respect to their value for assessing the exposure of transport networks to extreme precipitation and temperature impacts. Based on an Austrian data set from 25 meteorological stations representing diverse meteorological conditions, we assess the added value of partial duration series over the standardly used annual maxima series in order to give recommendations for performing extreme value statistics of meteorological hazards. Results show the merits of the robust L-moment estimation, which yielded better results than maximum likelihood estimation in 62 % of all cases. At the same time, results question the general assumption of the threshold excess approach (employing partial duration series, PDS) being superior to the block maxima approach (employing annual maxima series, AMS) due to information gain. For low return periods (non-extreme events) the PDS approach tends to overestimate return levels as compared to the AMS approach, whereas an opposite behaviour was found for high return levels (extreme events). In extreme cases, an inappropriate threshold was shown to lead to considerable biases that may outperform the possible gain of information from including additional extreme events by far. This effect was neither visible from the square-root criterion, nor from standardly used graphical diagnosis (mean residual life plot), but from a direct comparison of AMS and PDS in ~~synoptic~~combined quantile plots. We therefore recommend performing AMS and PDS approaches simultaneously in order to select the best suited approach. This will make the analyses more robust, in cases where threshold selection and dependency introduces biases to the PDS approach, but also in cases where the AMS contains non-extreme events that may introduce similar biases. For assessing the performance of extreme events we recommend the use of conditional performance measures that focus on rare events only in addition to standardly used unconditional indicators. The findings of the study directly address road and traffic management, but can be transferred to a range of other environmental variables including meteorological and hydrological quantities.

1 Introduction

Reliable information about the exposure of road infrastructure networks to extreme weather events is of major concern for road authorities, governmental institutions and safety researchers all over the world (TRB, 2008; Koetse and Rietveld, 2009; Eisenack et al., 2011; Doll et al., 2013; UNECE, 2013; Meyer et al., 2014; Michaelides, 2014; Schweikert et al., 2014a, 2014b; Matulla et al., 2016). In a changing climate (IPCC, 2012) and due to extensive soil sealing (Nestroy, 2006) the impact of extreme weather events are likely to increase in both frequency and intensity (APCC, 2014). Against this background, the resilience of transport systems with respect to weather hazards has become increasingly important.

A basic requirement for foresightful road infrastructure management are data about both the probability and magnitude of severe weather events. This information can be derived from long-term records of weather quantities such as precipitation and temperature, by means of statistical extreme value modelling. While extreme value theory provides a methodological framework that is commonly used in various scientific disciplines, such as hydrology (Katz et al., 2002), finance (Embrechts et al., 2003), engineering (Castillo et al., 2005) and climate sciences (Katz, 2010; Cheng et al., 2014), the application of these tools for road network exposure analysis is a relatively uncharted area. In particular, formal comparative assessments of the various statistical methods that can be applied for estimating return levels of extreme events are rare.

Two basic approaches have been proposed for deriving extreme value series (Coles, 2001), which are both widely applied in studying extreme meteorological events (e.g. Smith, 1989; Davison and Smith, 1990; Parey et al., 2010; Villarini, 2011; Papalexiou and Koutsoyiannis, 2013). On the one hand, the maximum value per year can be used in the block maxima approach, resulting in an annual maxima series (AMS). On the other hand, all values exceeding a certain threshold can be considered extreme, leading to the threshold excess approach based on partial duration series (PDS). Once the extreme value series has been derived, an appropriate distribution function is fitted to these observations by using different parameter estimation methods, such as maximum likelihood estimation, method of moments or Bayesian methods for parameter estimation. Clearly, there are a number of possible combinations of the approaches that may lead to different, often equally plausible results.

Several efforts have been made to compare the performance of block maxima and threshold excess approaches. While some studies only provide a qualitative description of resulting parameter estimates and estimated return levels for both methods (Jarušková and Hanek, 2006), more formal assessment approaches are based on the asymptotic variance of the T-year event estimator (Cunnane, 1973) or on various goodness-of-fit tests and model performance metrics (Madsen et al., 1997a, 1997b; Bezak et al., 2014). Controversial conclusions have been drawn. For instance, Madsen et al. (1997a) found for extreme discharges that the most suitable approach depends on the sample size and the shape parameter of the fitted functions. However, Ben-Zvi (2009) and Bezak et al. (2014) argue that a Generalized Pareto distribution fitted to partial duration series yields the best results for modelling rainfall and discharge extremes. Mkhandi et al. (2005), again, found that AMS and PDS methods result in similar predictions of flood magnitudes. All of these studies document the importance of extreme value analysis in hydrology, but ~~we are not aware of~~ similar studies on temperature extremes~~,~~ that are equally important as rainfall impacts for road networks, are rare. Based on a literature review, Grotjahn et al. (2016) argue in favour of using PDS for analysing extremes in large scale meteorological patterns, but their review did not contain any direct quantitative comparisons based on a common dataset. Moreover, ~~the~~ studies so far did not specifically assess the performance of methods with respect to rare events, such as 100-year events, which are more relevant for risk assessment~~s~~ than events at the moderate tail of the distribution.

In this study, we compare the different extreme value approaches and fitting methods with respect to their value for assessing the exposure of transport networks to extreme weather impacts. Based on an Austrian data set from 25 meteorological stations representing diverse meteorological conditions, we assess the added value of partial duration series over the standardly used annual maxima series in order to give recommendations for performing extreme value statistics of meteorological hazards.

2 Materials and methods

2.1 Data – Meteorological indicators

This study focuses on several meteorological indicators that can be used to assess the exposure of road networks to two main meteorological quantities: precipitation and temperature. These two variables are considered to have the most serious influence on damage to infrastructure (Matulla et al., in press). They are measured by meteorological services on a regular basis so the data quality is usually high. Nevertheless, the methodology presented in this paper is applicable to various other meteorological quantities (e.g. maximum wind speed), if time-series of about 30 years or more are available.

Four meteorological indices are used in this study. Temperature impacts are considered by daily minimum (T_{min}) and daily maximum temperature (T_{max}). In addition, maximum daily temperature difference ($T_{\Delta} = T_{max} - T_{min}$) is analysed, with all temperature indices in [°C]. Regarding precipitation impacts, the daily precipitation sum [mm/d] has been chosen.

In order to identify suitable meteorological stations that represent the main climate features of the highway network in Austria, all monitoring stations operated by the national weather service Zentralanstalt für Meteorologie und Geodynamik (ZAMG) served as a starting point. The selection of suitable stations was carried out in a stepwise procedure with respect to the following considerations: Firstly, the spatial proximity of available measuring stations to the highway network was considered, by excluding stations with a distance greater than 10 kilometres from the data set. Secondly, data availability and data quality were considered. As sufficiently long time series are a prerequisite for reliable return level estimation, only stations with more than 30 years of record (i.e., since 1 January 1985) and with less than 5% missing values were selected. Finally, topographic conditions and regional peculiarities were taken into account for selecting evenly spread and climatically representative stations. This step was guided by visual inspection of climate maps (Hiebl et al., 2011) and the digital hydrological atlas of Austria (BMLFUW, 2007; Fürst et al., 2009). The dataset so obtained consists of 25 hot spots representing climatically homogeneous regions of Austria (Fig. 1).

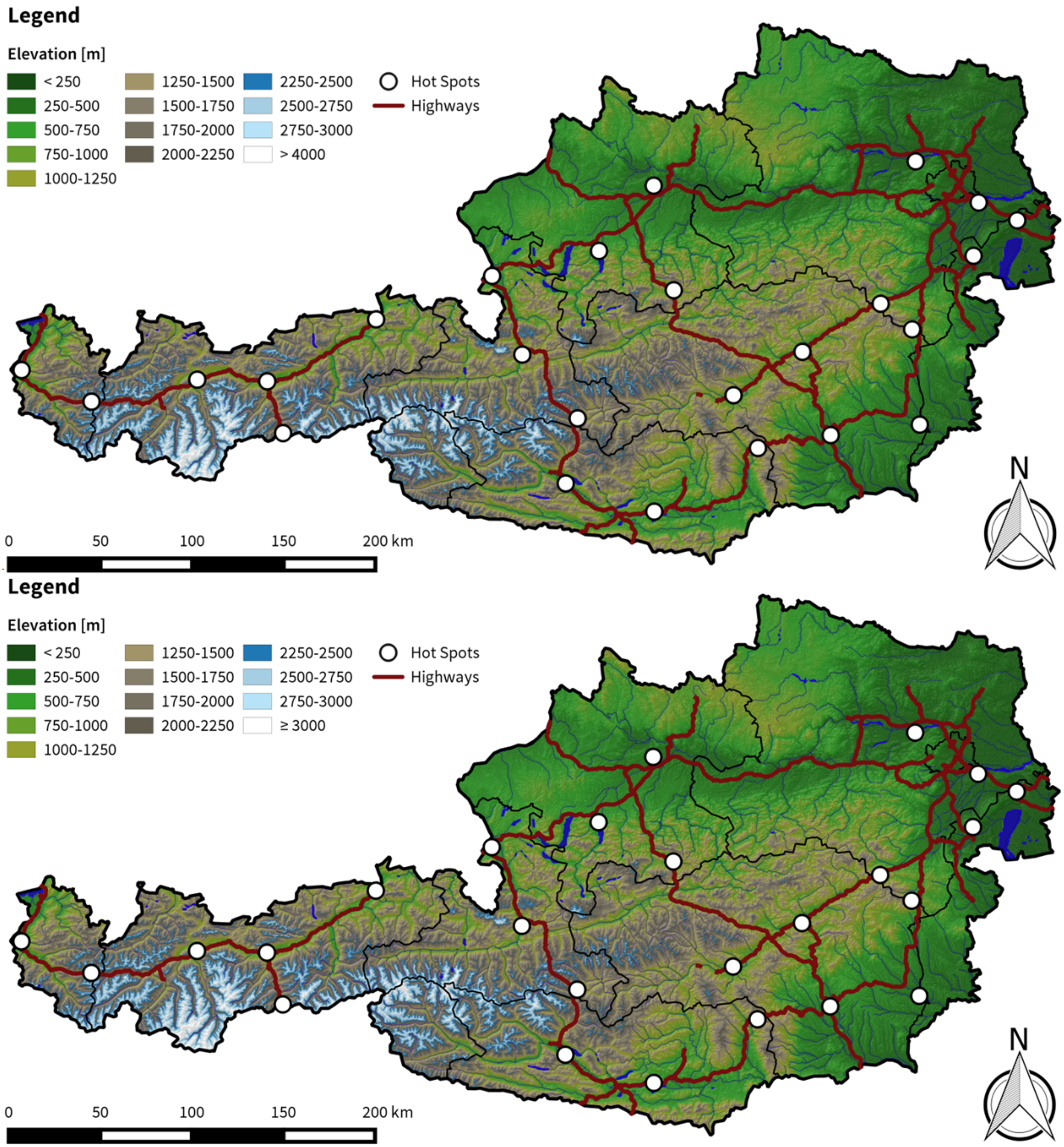


Figure 1: Location of the selected meteorological stations used for extreme value analysis.

2.2 Extreme value selection

2.2.1 Block maxima method

The first approach for deriving extreme value series consists in selecting maximum (or similarly minimum) values of the observations within subsequent time intervals (blocks) of constant length. While the block size is freely selectable, a trade-off has to be made between bias (small blocks) and variance (large blocks). Most commonly, the length of the block is chosen to correspond to a calendar year (Coles, 2001), resulting in an annual extreme value series. This was also the case in our study.

Based on the Fisher–Tippett–Gnedenko theorem, a generalized extreme value (GEV) distribution is appropriate for modelling the resulting annual maxima series (Fisher and Tippet, 1928; Gnedenko, 1943). The cumulative distribution function of the GEV is defined by

$$G_{\mu,\sigma,\xi}(z) = exp\left\{-\left[1+\xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \quad \textbf{(1)}$$

for the set $\left\{z: 1+\xi\left(\frac{z-\mu}{\sigma}\right) > 0\right\}$ where μ is the location parameter, σ is the scale parameter and ξ is the shape parameter. Alternative formulations with inverse sign of ξ are also common (e.g. Hosking, 1990). In both cases, the parameters satisfy $-\infty < \mu < \infty$, $\sigma > 0$ and $-\infty < \xi < \infty$ (Coles, 2001).

The GEV comprises three different types of distributions, which can be distinguished by the sign of their shape parameter: Gumbel, Fréchet and Weibull distribution (Fréchet, 1927; Gumbel, 1958; Coles, 2001; Embrechts et al., 2003; Basrak, 2014). The Gumbel distribution is commonly applied for maxima that are not limited towards an upper bound, whereas the Weibull case is more appropriate for minima which are often limited by a lower bound (Tallaksen and van Lanen, 2004).

2.2.2 Threshold excess method

In some cases, fitting distributions to block maxima data is a wasteful approach as only one value per block is used for modelling. A threshold excess approach potentially provides more information on extremes (Coles, 2001).

Analogous to the choice of the block size in the block maxima approach, the selection of the threshold value in the threshold excess method is also subject to a trade-off between bias (due to selecting non-extreme events if the threshold is low) and variance (due to a small number of exceedances when selecting a high threshold). Hence, the choice of a suitable threshold is important. The basic aim is to select the potentially lowest threshold, given the prerequisite that the extreme value model must provide a reasonable approximation to exceedances above this threshold and shall not contain non-extreme events (Coles, 2001). According to the Pickands–Balkema–de Haan theorem, a Generalized Pareto (GP) distribution is suited for modelling the resulting threshold excesses (Balkema and de Haan, 1974; Pickands, 1975): It states that, for some large threshold u, the distribution function of $(X-u)$, conditional on $X > u$ can be well approximated by the Generalized Pareto distribution, which is defined by

$$H_{\xi,\sigma}(z) = \begin{cases} 1 - \left[1 + \xi\left(\frac{z-\mu}{\sigma}\right)\right]^{-1/\xi} & \text{for } \xi \neq 0 \\ 1 - exp\left(-\frac{z-\mu}{\sigma}\right) & \text{for } \xi = 0 \end{cases} \tag{2}$$

where the support is $z \geq \mu$ in the case $\xi \geq 0$, and $\mu \leq z \leq \mu - \sigma/\xi$ when $\xi < 0$. This is valid for $x_1, x_2, \ldots, x_n$ being a sample of *n* independent and identically distributed realizations of a random variable *X* following some common distribution function *F* (Coles, 2001).

A number of approaches have been proposed for selecting an appropriate threshold. Coles (2001) suggests to let the selection be guided by graphical diagnostics about bias (i.e. mean excess, see Ghosh and Resnick (2010) for a detailed discussion) and stability of the scale and shape parameter. Despite these criteria are well justified from a theoretical point of view, its application involves substantial elements of subjectivity leading to ambiguous results (Scarrott and MacDonald, 2012; Northrop and Coleman, 2014). To overcome this problem, we employed the deterministic square root rule $k = \sqrt{n}$ (Ferreira et al., 2003) for pre-selecting the threshold level in an objective way, using the k^{th} upper order statistic as a threshold, which is related to the total time series length *n*. Albeit this rule does not properly account for threshold uncertainty on subsequent inferences (Scarrot and MacDonald, 2012), it satisfies the intermediate sequence of order statistics that formally ensures tail convergence (Leadbetter et al., 1983). The so-obtained threshold was subsequently validated by the graphical criteria of Coles (2001) for bias and parameter stability.

2.3 Dealing with non-stationarity and dependency

Extreme value theory assumes that data are independent and identically distributed (Coles, 2001; Gilleland and Katz, 2011; Katz, 2010; Katz, 2013; Cheng et al., 2014). To test for non-stationarity in the expected value we perform separate Mann-Kendall trend tests (Mann, 1945; Kendall, 1976; Gilbert, 1987) at a significance level of $\alpha = 0.05$ (Zhang et al., 2004) for the extreme value series of each meteorological indicator. In case of significant trends, detrending was performed with respect to the last year of the time series (i.e. 2015). The trend-corrected estimation of a meteorological indicator *z* at time *t* is obtained as

$$\hat{z}_t = y_t - \hat{y}_t + \hat{y}_{2015} \tag{3}$$

where y_t is the measurement at time *t* and $\hat{y}_t$ is the trend at time *t* obtained from the linear trend model

$$\hat{y}_t = \beta_0 + \beta_1 t \tag{4}$$

with intercept β_0 and slope β_1, and $\hat{y}_{2015}$ being the trend estimate for 2015.

For climate variables independence of data is usually a minor issue for the annual maxima approach as multi-annual dependencies are usually low for most climates (Madsen et al., 1997a; Katz et al., 2002). Regarding the threshold excess method, threshold exceedances on consecutive days will likely violate the assumption of independence. Dependent values in the threshold excess series are eliminated by a declustering procedure that consists in removing threshold exceedances within the autocorrelation length on both sides of the local maxima (Jarušková and Hanek, 2006). Based on sensitivity analysis an autocorrelation window of 5 days was chosen for the three temperature indicators, while a window of 3 days was chosen for ~~the~~ accumulated daily precipitation.

2.4 Parameter estimation

Once the extreme value series is available, a theoretical distribution needs to be fitted. Two different methods of parameter estimation are used within the scope of the present analysis.

The first method, maximum-likelihood estimation (MLE), was formally introduced by Fisher in the early 20th century (Fisher, 1912; Aldrich, 1999; Hald, 1999). Let x_1, x_2, …, x_n be a sample of n independent and identically distributed realizations of a random variable with the unknown probability density function $f(x|\theta_0)$. As the true value of the parameter vector θ_0 is unknown, an estimate $\hat{\theta}$ which is as close to θ_0 as possible is found by maximizing the likelihood function

$$L(\theta) = \prod_{i=1}^{n} f(x_i|\theta) \qquad \textbf{(5)}$$

i.e. by maximizing the accordance of the extreme value model with the observed data (Coles, 2001).

The second method, L-moments estimation (LMOM), evolved from modifications of probability weighted moments of Greenwood et al. (1979). They are linear combinations of first order statistics and are hence more robust to measurement errors or sampling uncertainty than conventional moments (Hosking, 1990). The r^{th} population L-moment of a random variable X is defined as

$$\lambda_r \equiv r^{-1} \sum_{k=0}^{r-1} (-1)^k \binom{r-1}{k} EX_{r-k:r}\ , \qquad r = 1, 2, \ldots \qquad \textbf{(6)}$$

As compared to MLE, L-moments are superior for fitting GEV distributions in terms of bias and variance, in particular for small sample sizes (Hosking et al., 1985).

As far as reliability of the fitting results is concerned, confidence intervals play a major role for assessing uncertainty. The most common way to derive a $(1-\alpha)$ confidence interval for a particular component θ_i of a parameter vector θ is by using the formula $\hat{\theta}_i \pm z_{\alpha/2} \times \sigma/\sqrt{n}$, with $\hat{\theta}_i$ denoting the estimate for θ_i, $z_{\alpha/2}$ indicating the $\alpha/2$ quantile of the standard normal distribution and $\sigma/\sqrt{n}$ indicating the standard error of the estimate.

The approach assumes Gaussian distributed parameter estimators, which may be inappropriate for extreme value distributions. For LMOM estimators resampling methods have been recommended (Burn, 2003). Thus, nonparametric bootstrapping with 500 iterations was applied in this study. MLE offers a more accurate method for deriving confidence intervals based on the profile likelihood (Coles, 2001). The profile log-likelihood for θ_i is defined as

$$L_p(\theta_i) = \max_{\delta} L(\theta_i, \delta) \qquad \textbf{(7)}$$

where δ denotes all components of parameter vector θ excluding θ_i. That is, for each value of θ_i, $L_p(\theta_i)$ is the maximized log-likelihood over all remaining elements of θ.

2.5 Assessment method

There are various performance measures that are regularly employed in model evaluation, including the root-~~-~~mean-~~-~~square~~d~~ error (RMSE) and the mean absolute error (MAE). These metrics provide a comprehensible and objective basis regarding the assessment of the fitted functions.

~~In addition~~However, most events of the extreme value series are only moderate and these will have an overly excessive influence on the performance measure. In order to specifically assess the accuracy of the fitted models for higher quantiles (i.e. for larger return periods), we propose conditional variants of the root-mean-square ~~deviation~~ error (CRMSE_{T^*} ~~CRMSE_T~~) and mean absolute error (CMAE_{T^*} ~~CMAE_T~~). These metrics are ~~conditional on the return period T of the underlying data and~~ specifically consider the upper tail of the fitted functions above some return period T^*. Using Weibull plotting positions as empirical probability estimator (Weibull, 1939; Makkonen, 2006~~5~~), these measures are defined as

$$\mathrm{CRMSE}_{\cancel{T}T^*} = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n_{\cancel{t}T^*}}} \forall y_i : \left[-\frac{1}{\ln\left(\frac{m}{N+1}\right)}\right] \geq \cancel{T}T^* \tag{8}$$

$$\mathrm{CMAE}_{\cancel{T}T^*} = \frac{\sum_{i=1}^{n}|\hat{y}_i - y_i|}{n_{\cancel{t}T^*}} \forall y_i : \left[-\frac{1}{\ln\left(\frac{m}{N+1}\right)}\right] \geq \cancel{T}T^* \tag{9}$$

where $\hat{y}_i$ denotes the model prediction or the i^{th} element of the extreme value series, y_i is its observed value, m is its order statistic (with $m = 1$ for the minimum and $m = N$ for the maximum), and $n_{\cancel{T}T^*}$ is the number of elements with an empirical return period greater than $\cancel{T}T^*$. Hence, the conditional performance measures are calculated by using only the residuals of observations and theoretical distribution above some relevant return level T^*~~T~~. The value for T^* should be chosen depending on the length of the time series available. Since the records at the stations used for this study date back to the period between the world wars in most cases, or even further back to as early as 1895~~In this study~~, T^*~~T~~ $= 10$ years has been chosen as the base value of the conditional performance measure, and ~~the~~ CRMSE_{10} and CMAE_{10} are calculated accordingly. Similar return periods (about 5 – 10 years) are often considered as a minimum requirement in storm infrastructure design (e.g. GRCA, 2014; EPA, 2014). Hence, such a level appears well suited to separate extreme and non-extreme events.

Distribution-fitting tests such as Kolmogorov-Smirnov, Anderson-Darling or Cramér-von Mises are not used in this study. Such tests are primarily useful for gaining an appreciation whether a lack of fit is statistically significant, or rather an effect of sampling uncertainty, but they have little discriminative power to identify the “true” or “best” distribution to use (e.g. Stedinger et al., 1993). Instead,

~~In addition to the goodness-of-fit analysis~~ we perform~~ed~~ graphical diagnosis of the extreme value series and the fitted distributions in quantile plots, which allow a more complete assessment. ~~For AMS, p~~Plotting of empirical distributions is straightforward. The return level (i.e. magnitude) z_T of each observed extreme event is plotted against its return period (i.e. recurrence interval) T_{GEV} ~~T~~ $= 1/(1 - P)$, using Weibull plotting positions as an estimator of empirical recurrence probability P. For AMS, the T-year return level is obtained using the quantile function of the GEV:

$$z_{T,AMS} = \begin{cases} \mu - \dfrac{\sigma}{\xi}\left[1 - \{-\ln(P)\}^{-\xi}\right] & \text{for } \xi \neq 0 \\ \mu - \sigma \ln\{-\ln(P)\} & \text{for } \xi = 0 \end{cases} \qquad \textbf{(10)}$$

with parameters according to Eq. For PDS, the quantile function provides *N*-observation return levels rather than *T*-year events, with *N* being the number of threshold exceedances. When calculating *T*-year return levels, ~~1. In the case of PDS~~ the return period *T* needs to be transformed from an ~~observation~~ annual scale to an ~~annual~~ observation scale by taking the ratio of threshold exceedances and years of record into account ~~the number of threshold exceedances within the observation period~~ (Coles, 2001). Hence, the *T*-year return level is obtained from the quantile function of the GP by:

$$z_{T,PDS} = u + \frac{\sigma}{\xi}\left[\left(T\lambda\cancel{n\zeta_u}\right)^{\xi} - 1\right] \qquad \textbf{(11)}$$

where λ is the mean number of threshold exceedances per year, u is the threshold, ~~n is the number of observations per year, ζ_u is the sample proportion of threshold exceedances,~~ and remaining parameters according to Eq. 2. Although Eq. 10 and 11 yield consistent return levels for both types of extreme value series, the return periods of AMS/GEV and PDS/GP are not fully comparable. As pointed out by Langbein (1949) and Rosbjerg (1977), their relationship can be well approximated by an exponential equation of the form ~~The so obtained return levels were used for synoptic plotting of AMS and PDS.~~

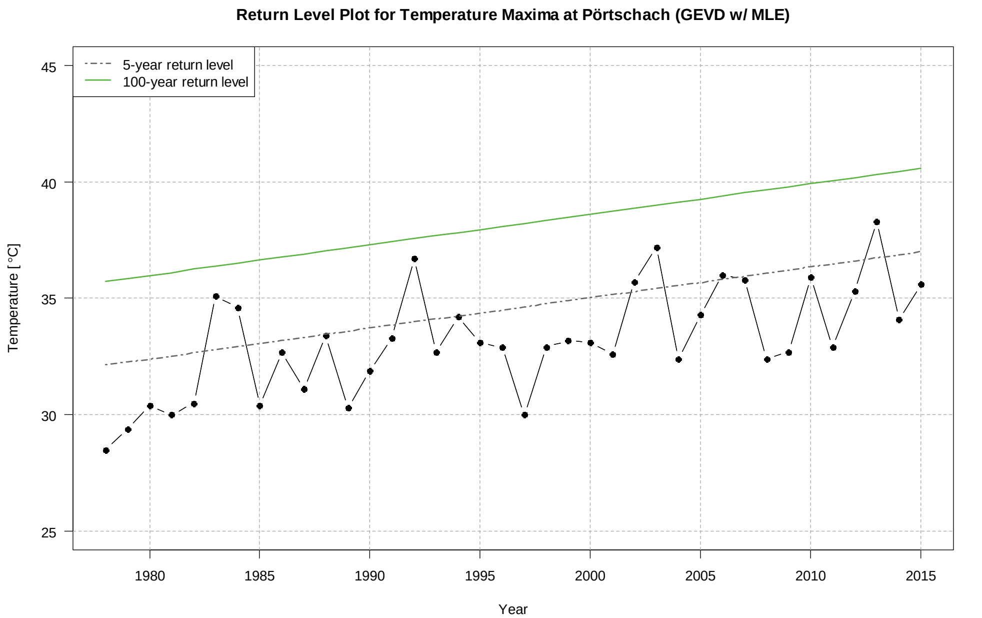
$$\frac{1}{T_{GEV}} = 1 - e^{(-1/T_{GP})} \qquad \textbf{(12)}$$

and the return periods of one approach need to be transformed to obtain consistent plots. Following the convention of the `extRemes` package (Gilleland and Katz, 2016), the PDS/GP-based *T*-year event definition is applied in this paper, and we transformed AMS/GEV return periods accordingly. Note, however, that the transformation difference is mostly relevant for small return periods, as differences between T_{GEV} and T_{GP} become negligible for return periods of more than five years (Langbein 1949; Rosbjerg 1977; WMO, 2009).

3 Results

3.1 Non-stationarity

~~Linear trends were considered by incorporating dependency on time by means of precedent detrending within model estimation.~~ Extreme value series were checked for stationarity. Most of the temperature hot spots showed a significant ~~change over time~~trend in at least one of the temperature indicators, but often maxima and minima series were simultaneously affected. All significant trends were incorporated in the model. ~~The observed positive temperature trends lead to both an increase of daily maximum temperatures and at the same time to an increase of daily minimum temperatures.~~ As illustrated by Fig. 2, the consequence of incorporating a trend model in the analysis are non-stationary return levels that refer to a specific time. We will give results for the end of the observation period.



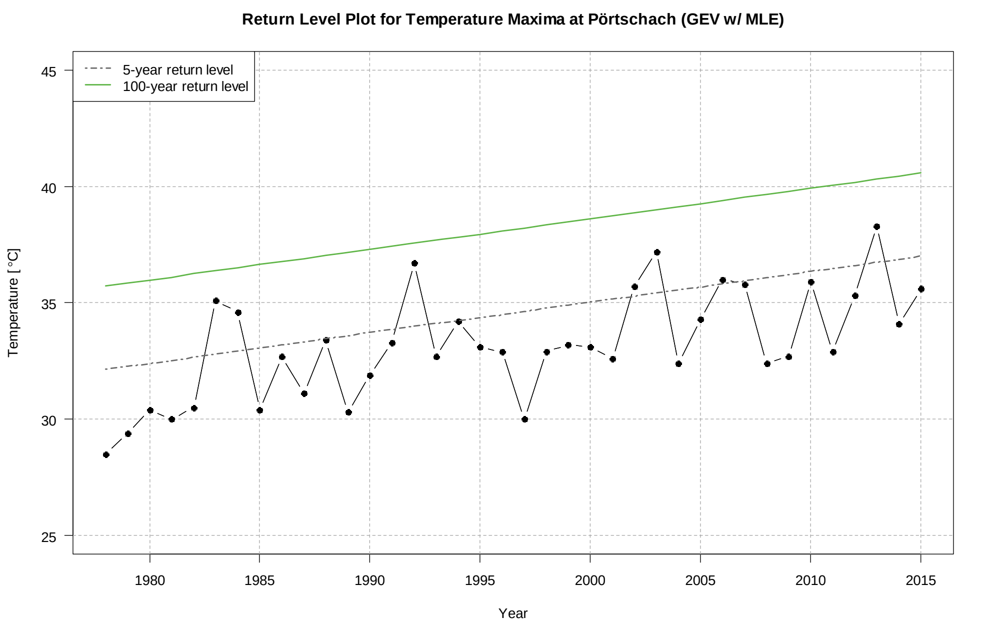


Figure 2: Return level plot of temperature maxima at Pörtschach (Carinthia) with linear trend correction. The trend is visible in the lines depicting the 5-year return level (gray dashed line) and the 100-year return level (green solid line). This is an illustrative example of temperature trends that are commonly observed at the selected stations for both temperature maxima (increasing trend) and temperature minima (decreasing trend).

For precipitation, non-stationarity seems less important than for temperature indicators: About 85 % of the hot spots of our study area showed no trend in the annual extremes. This is consistent with the expectation of the Austrian Panel of Climate Change (APCC, 2014) that climate impacts on precipitation will mainly lead to seasonal shifts rather to changes in total annual precipitation.

3.2 Parameter estimation method

The two approaches have been tested for the four meteorological indicators. In summary, it becomes apparent that the relative performances of MLE and LMOM are strongly situation-dependent. For instance, while the return level plots for temperature maxima at *Schwechat* in the eastern lowlands show that the function fitted on the basis of LMOM behaves more robust, which appears to be beneficial in this case (Fig. 3), return level plots of daily rainfall at *Brenner* on the Austrian-Italian border indicate that the less robust MLE offers better fit for higher quantiles (Fig. 4).

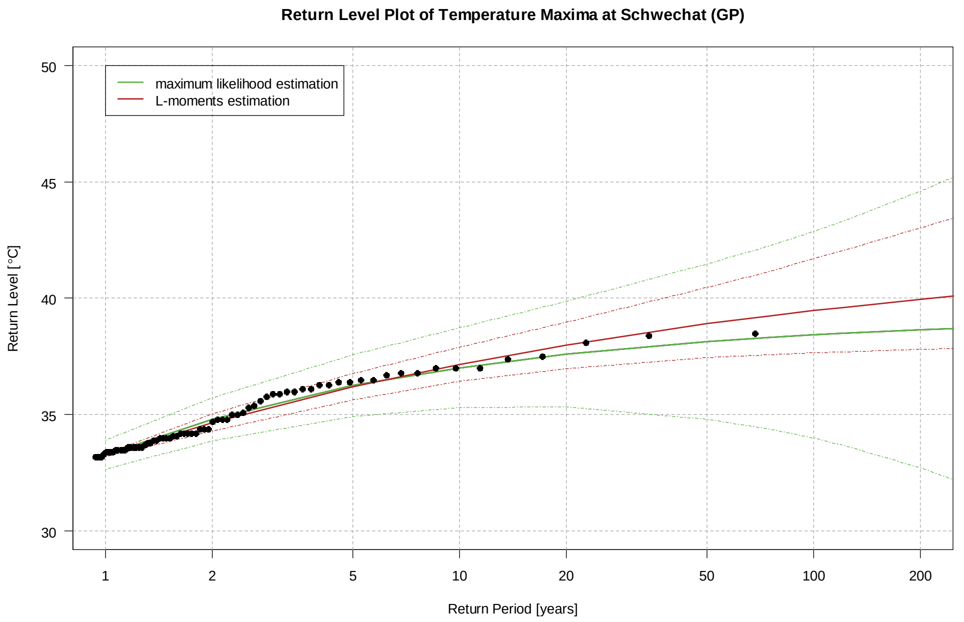


Figure 3: Return level plot of temperature maxima at *Schwechat*. Return level estimation is based on the threshold excess approach with two different parameter estimation methods (MLE and LMOM-estimation). Solid lines show the mean estimate, while dashed lines indicate the 95% confidence intervals for the fitted functions.

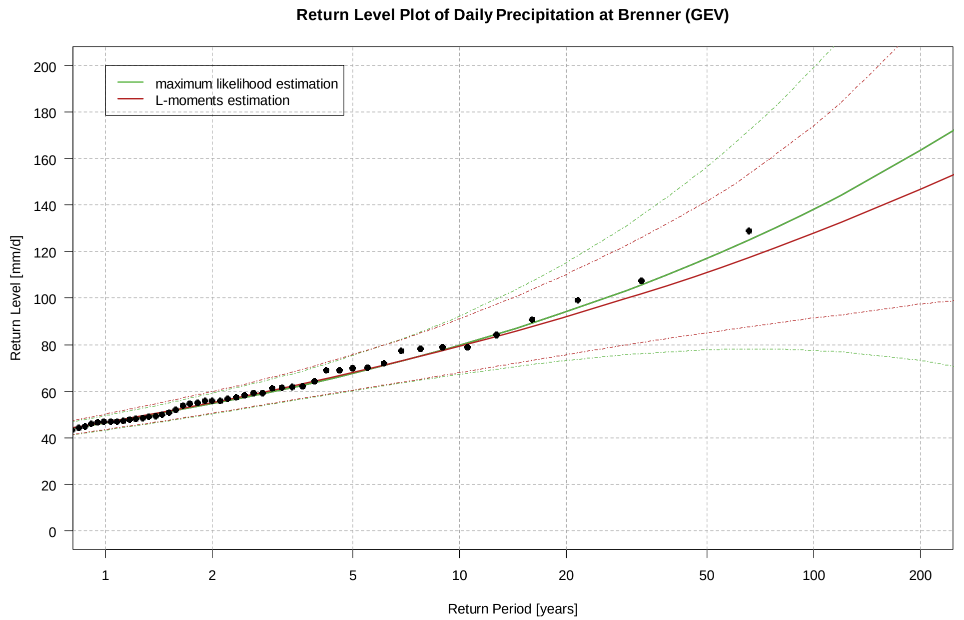


Figure 4: Return level plot of daily rainfall events at Brenner. Return level estimation is based on the block maxima approach with two different parameter estimation methods (MLE and LMOM-estimation). Solid lines show the mean estimate, while dashed lines indicate the 95% confidence intervals for the fitted functions.

Tab. 1 summarizes the overall goodness-of-fit for the 100 climate records (25 stations x 4 indicators) assessed in this study for the AMS approach. LMOM performed better in 69 % of the cases when assessed by the RMSE, and in 94 % when assessed by the MAE (note that for 100 climate records one percent corresponds to one record). Since the MAE favors overall model accuracy and gives little weight to outliers with large errors, the better overall fit achieved by LMOM nicely illustrates the greater robustness of this method. These differences apply to most individual meteorological indicators. The sole exception is daily minimum temperature, which yields similar success rates of MLE and LMOM for both goodness-of-fit measures. This is attributable to several larger residuals in these time series.

Table 1: Comparison of parameter estimation methods for the AMS approach based on goodness-of-fit measures RMSE and MAE. Numbers indicate success ~~rates (% of records)~~cases of MLE and LMOM.

Indicator	RMSE (MLE)	RMSE (LMOM)	MAE (MLE)	MAE (LMOM)
Precipitation	7	18	4	21
T_{min}	13	12	1	24
T_{max}	5	20	0	25
T_{Δ}	6	19	1	24
Total	**31**	**69**	**6**	**94**

The relative performances turned out to be more balanced with respect to the PDS approach. As indicated by Tab. 2, MLE performed better in 56 % and 53 % of the cases when judged by the RMSE and MAE, respectively. Again, daily minimum temperature deviates from the general picture, by showing clear advantages in favor of LMOM-estimation in this case.

Table 2: Comparison of parameter estimation methods for the PDS approach based on goodness-of-fit measures RMSE and MAE. Numbers indicate success ~~rates (% of records)~~cases of MLE and LMOM.

Indicator	RMSE (MLE)	RMSE (LMOM)	MAE (MLE)	MAE (LMOM)
Precipitation	14	11	13	12
T_{min}	9	16	12	13
T_{max}	17	8	14	11
T_{Δ}	16	9	14	11
Total	**56**	**44**	**53**	**47**

Apart from the overall goodness-of-fit it is interesting to assess how the fit depends on the return period of events. This has been done by visual inspection of the distribution plots, such as the examples shown in Fig. 3 and Fig. 4. In most cases there were only minor differences between MLE and LMOM when considering return levels below 10 years, but often considerable differences for larger return periods. For the 100-year events, e.g., results of the temperature indicators differed by about 0.5 °C on average, and by up to 2 °C for single stations. With maximum differences around 10 mm/d, the 100-year precipitation events showed even greater variation.

As the objective of extreme value analysis is usually related to return periods of 10 years or more, we specifically assessed the performance of the extreme upper tail of the distribution by the conditional goodness-of-fit measures $CRMSE_{10}$ and $CMAE_{10.}$ Results indicate again a favorable performance of LMOM-method for AMS series (Tab. 3), when judged by the $CRMSE_{10}$ (58 %) and the $CMAE_{10}$ (62 %).

Table 3: Comparison of parameter estimation methods for the AMS approach based on conditional goodness-of-fit measures $CRMSE_{10}$ and $CMAE_{10}$. Numbers indicate success ~~rates (% of records)~~cases of MLE and LMOM.

Indicator	$CRMSE_{10}$ (MLE)	$CRMSE_{10}$ (LMOM)	$CMAE_{10}$ (MLE)	$CMAE_{10}$ (LMOM)
Precipitation	11	14	11	14
T_{min}	11	14	10	15
T_{max}	12	13	8	17
T_{Δ}	8	17	9	16
Total	**42**	**58**	**38**	**62**

In contrast, results for the PDS showed, again, a slight advantage of MLE when assessed with the goodness-of-fit measures for the conditional variants. Both measures indicate a preference towards MLE in 58 % of the cases. The better performance of the MLE method is against the expectation based on robustness and will be examined in more detail in the following section.

Table 4: Comparison of parameter estimation methods for the PDS approach based on conditional goodness-of-fit measures CRMSE$_{10}$ and CMAE$_{10}$. Numbers indicate success ~~rates (% of records)~~cases of MLE and LMOM.

Indicator	CRMSE$_{10}$ (MLE)	CRMSE$_{10}$ (LMOM)	CMAE$_{10}$ (MLE)	CMAE$_{10}$ (LMOM)
Precipitation	14	11	14	11
T_{min}	9	16	10	15
T_{max}	19	6	19	6
T_{Δ}	16	9	15	10
Total	**58**	**42**	**58**	**42**

3.3 Extreme value selection

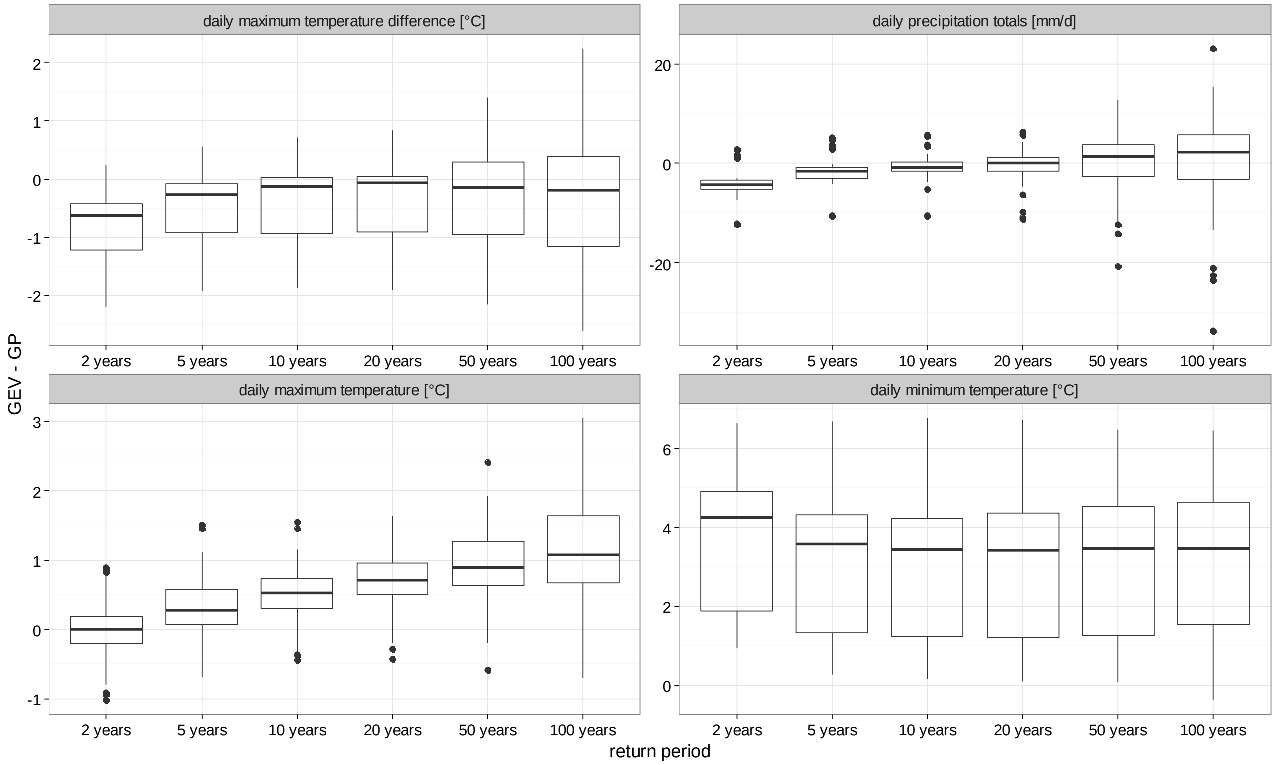
Tab. 5 presents the relative performances of AMS and PDS approaches based on the two parameter estimation methods. Albeit overall results show advantages for the AMS approach in terms of goodness-of-fit for the upper tail of the underlying distributions, results largely depend on the underlying meteorological indicators. While precipitation and daily maximum temperature difference offer a better fit when using GEV distributions of AMS, GP distributions of PDS appear better suited for modelling daily temperature maxima and minima.

Table 5: Comparison of AMS and PDS approach based on conditional goodness-of-fit measures CRMSE$_{10}$ and CMAE$_{10}$ for two parameter estimation methods MLE and LMOM. Numbers indicate success ~~rates (% of records)~~cases of approaches.

Indicator	Fitting Method	CRMSE$_{10}$ (GEV)	CRMSE$_{10}$ (GP)	CMAE$_{10}$ (GEV)	CMAE$_{10}$ (GP)
Precipitation	MLE	18	7	19	6
Precipitation	LMOM	19	6	20	5
T_{min}	MLE	9	16	8	17
T_{min}	LMOM	10	15	10	15
T_{max}	MLE	10	15	11	14
T_{max}	LMOM	13	12	14	11
T_{Δ}	MLE	16	9	17	8
T_{Δ}	LMOM	17	8	16	9
Total		**112**	**88**	**115**	**85**

To perform a direct comparison, Fig. 5 presents the deviations between return levels derived via AMS and PDS approach for the four meteorological indicators. ~~A common~~Interesting patterns regarding the magnitude of the estimated return levels can be observed. For precipitation, PDS/GP estimates result in slightly higher return levels for lower return periods (indicated by negative deviations) and this behavior changes to the opposite for higher return periods. Maximum temperature shows the same tendencies as precipitation, but the PDS/GP always yields higher return levels than the AMS/GEV, suggesting that differences mainly occur at higher return periods. Temperature minima, however, show a rather constant overestimation (i.e., underestimation of negative magnitude) of PDS compared to AMS regardless of the frequency of events, with patterns of temperature difference being a combination of the effects of temperature maxima and minima. Overall, the average deviations between methods mostly increase with the return period, and the variability between cases increase as well. This issue will be further explored in the discussion section.

~~While GP estimates seem to result in higher return levels for lower return periods (indicated by negative deviations), this behavior changes to the opposite for higher return periods. This issue will be further explored in the discussion section. Nonetheless, it shall be noted that daily minimum and maximum temperature do not fully fit into these patterns. Albeit maximum temperature shows the same tendencies as precipitation, the PDS always yields higher return levels than the AMS, suggesting that differences mainly occur at higher return periods. Temperature minima, however, show a rather constant overestimation (i.e., underestimation of negative magnitude) of PDS compared to AMS regardless of the frequency of events.~~


daily maximum temperature difference [°C]
daily precipitation totals [mm/d]
daily maximum temperature [°C]
daily minimum temperature [°C]
GEV - GP
2 years
5 years
10 years
20 years
50 years
100 years
return period

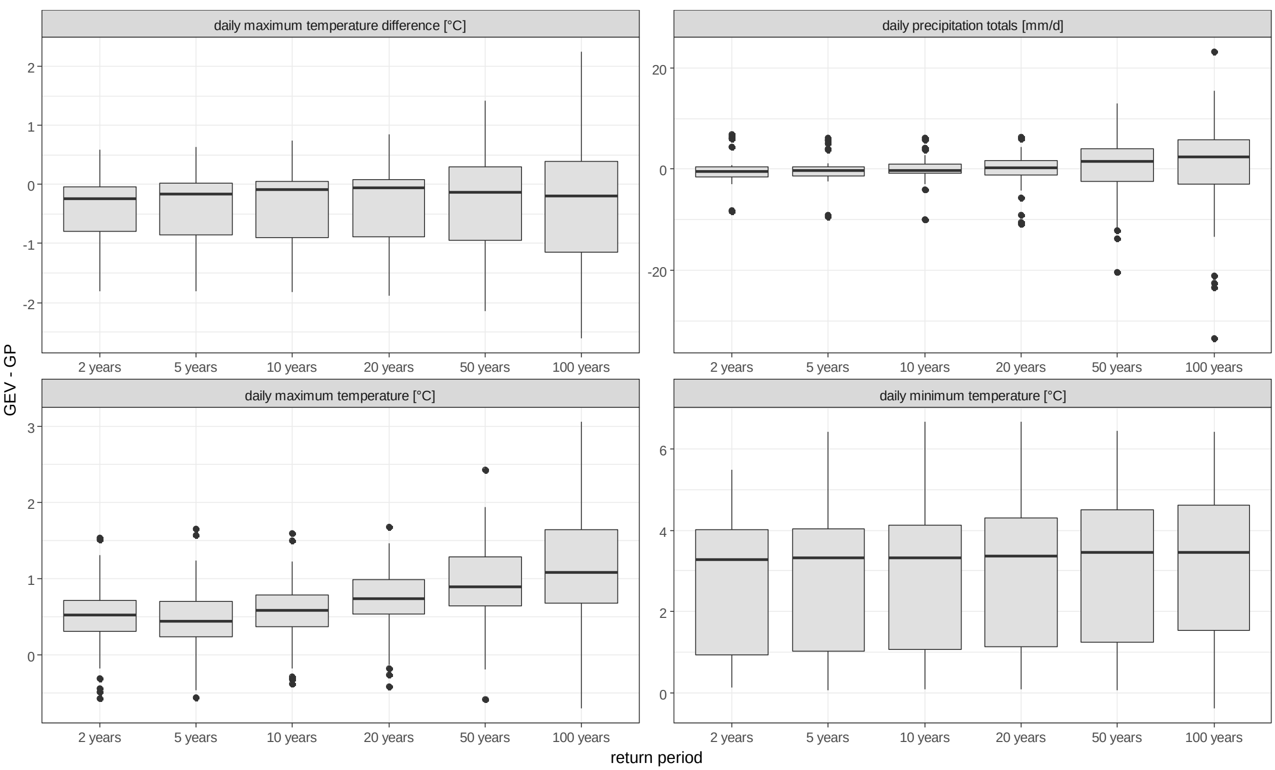

daily maximum temperature difference [°C]
daily precipitation totals [mm/d]
daily maximum temperature [°C]
daily minimum temperature [°C]
GEV - GP
2 years
5 years
10 years
20 years
50 years
100 years
return period

Figure 5: Differences in estimated return levels between GEV and GP models for six selected return periods. These differences are calculated by subtracting the GP estimate from the GEV estimate, given the same parameter estimation method. This results in *n* = 50 observations per boxplot.

Finally, Tab. 6 summarizes the success rates of all methods based on $CRMSE_{10.}$ Results show an overall advantage of using L-moments estimation as compared to MLE. As far as the two different methods of extreme value selection are concerned, the AMS approach seems to slightly outperform the threshold excess approach in this study. While results are basically quite balanced between all four methods, AMS fitted on the basis of LMOM estimation turned out to yield the best results in about 35% of all cases.

Table 6: Success rates of methods according to $CRMSE_{10}$. The bold value in the center of each field indicates the overall count. The four smaller numbers in the corners display the counts with respect to temperature minima (top left), temperature maxima (top right), temperature difference (bottom left) and precipitation totals (bottom right). Bold values indicate better performance.

		Distribution		
		GEV	**GP**	**Total**
Fitting method	**MLE**	3 4 **19** 4 8	5 **12** **19** 1 1	**38**
	LMOM	7 5 **35** **12** **12**	**10** 4 **27** 8 4	**62**
	Total	**54**	**46**	**100**

4 Discussion

We compared the relative merits of the block maxima method and the threshold excess approach. In addition, two different fitting methods have been contrasted. This results in four possible combinations of extreme value model parameter estimation, all of which have certain strengths and weaknesses. Concerning the fit of the distributions to sample, we found a slight advantage of using LMOM instead of MLE, especially in combination with AMS/GEV. For PDS/GP there was a slight advantage of using MLE. But overall, the differences were not huge.

The conditional assessment of the individual deviation between return levels of AMS/GEV and PDS/GP yielded deeper insight in the relative performances of methods. Most importantly, we found ambiguous systematic deviations between both approaches (Fig. 5), depending on the meteorological indicators under consideration: Concerning temperature minima, PDS/GP was found to consistently overestimate return levels compared to the AMS/GEV approach, while results for temperature maxima and – albeit to a lesser extent – temperature differences show just the opposite. Regarding daily rainfall events, ~~For low return periods (non-extreme events)~~ the PDS/GP approach tends to slightly overestimate return levels for low return periods (non-extreme events) as compared to the AMS/GEV approach, while an ~~. An~~ opposite behavior was found for high return levels (extreme events). To assess the reasons for this systematic behavior, we selected four example series that represent extreme cases, where results of approaches differ significantly.

The first two examples are daily precipitation at Sankt Michael (Fig. 6a) and Brenner (Fig. 6b), where extreme value series deviate from the ideal, smooth behavior of a homogeneous extreme value series. These fluctuations point to either measurement errors or process heterogeneity that will introduce uncertainty into extreme value analysis. In the case of Sankt Michael, the most extreme events appear as outliers that deviate from the general behavior of the sample. In general, LMOM will give lower weight to such leverage points but this seems not the case here where the GP fitted by LMOM seems more attracted. A plausible ~~explication~~ explanation would be that the upper-tail behavior is resulting from the attraction of the distribution at the lower end, because of the limited flexibility of the GP. In the case of Brenner, the extreme values seem to follow the same distribution ~~than~~ as the remaining sample so one would have more confidence in the validity of these values. However, extreme values are always prone to higher uncertainty than the remaining sample. The MLE estimate gives more weight to these values and shows a better fit at the upper tail in this case, whereas LMOM gives less weight to these values, and makes visible that they are not perfectly following the shape of the entire distribution. The choice of the parameter estimation method will finally depend on the weight one tends to give to the extreme values as compared to the remaining sample.

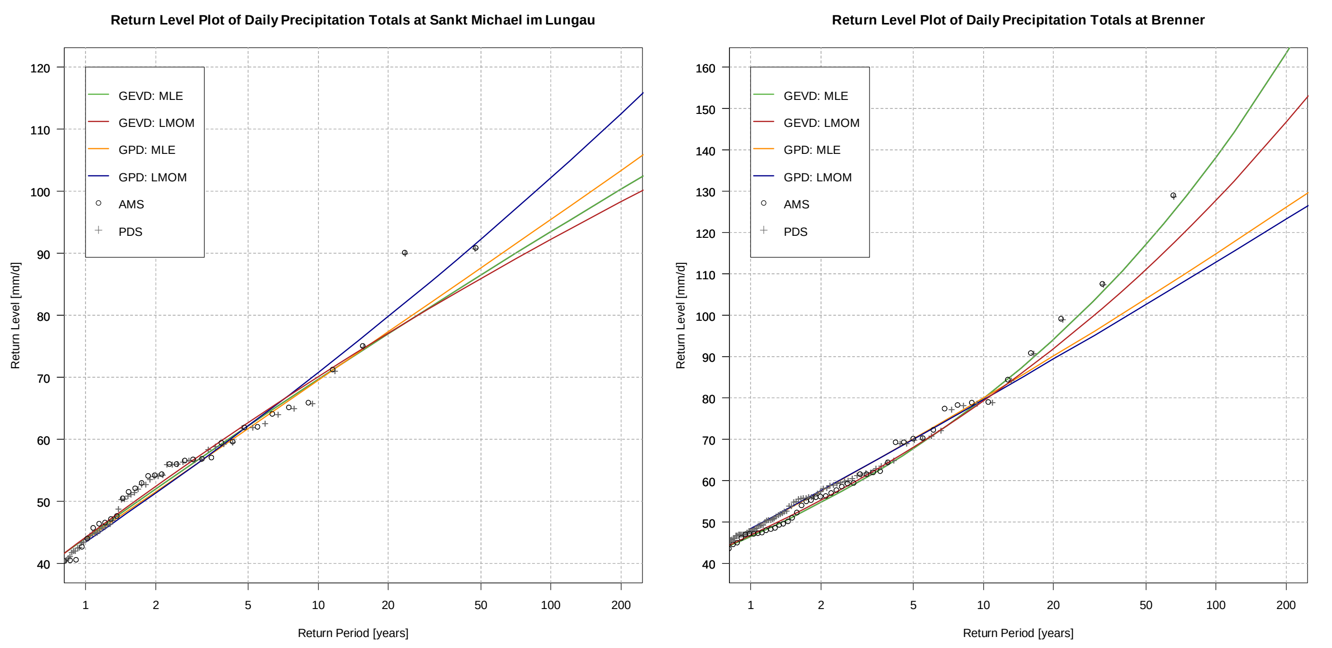


Figure 6: Return level plots of daily rainfall events at the hot spot in (a) *Sankt Michael im Lungau*, which is located in the Central Eastern Alps and (b) *Salzburg*, located at the northern edge of the Alps. Return level estimation is based on the block maxima approach and on the threshold excess approach with two different parameter estimation methods (MLE and LMOM-estimation). Based on the $CRMSE_{10}$, GP fitted on the basis of LMOM-estimation was found to be the most appropriate method for Sankt Michael, while GEV with MLE was found to be most suitable in Salzburg. Please note that functions are plotted without associated confidence intervals for the sake of clarity.

It is also interesting to analyze extreme cases where AMS/GEV and PDS/GP methods yield contrasting results (Fig. 7). When focusing on the empirical distributions, we observe that only the ~~highest~~ more extreme events (three in the case of *Bruck an der Mur*, and two in the case of *Graz*) have almost identical empirical probabilities in both extreme value series. At the lower end, we observe that there are several events in the AMS/GEV below the threshold level of PDS, which fit well to the distribution of the higher values so we find no evidence to exclude them from the analysis. The shift in the distribution can therefore be regarded as an effect of threshold level selection, which determines the lower end and therefore the shape of the lower part of the PDS/GP distribution. Between the undisturbed upper part and the disturbed lower part a breakpoint at $T = 15$ years in the PDS/GP is clearly visible from the robustly fitted GP~~D~~ distribution using the LMOM method. This illustrates an inherent danger of the PDS/GP approach: An inappropriate threshold may entail considerable biases that outperform the possible gain of information by the method by far. This was neither visible from the square-root criterion nor from the graphical diagnosis (residual life plot, Fig. 8) which yielded indeed almost no bias in both cases (in the case of *Bruck an der Mur*, mean excess = 2.99 for the threshold of -17.1 °C, and in the case of *Graz*, mean excess = 1.63~~82~~ for threshold of 32.~~1~~6 °C).

Similar shifts may arise if the extreme value series contains dependent events. Non-extreme events are generally more likely to cluster than extreme events because they are generated by exceptional process combinations, which are unlikely to occur more often during one extreme weather situation. Thus, dependencies may possibly affect all parts (but more likely the lower part) of the distribution apart from the maximum, which remains unchanged. In consequence, the empirical distribution is stretched at the lower tail (shifted to the left), with similar consequences on lower and upper tail as described for the case of data uncertainty and leverage points. Such artifacts are difficult to detect in quantile plots of one extreme value series alone, but are often visible from direct comparison of AMS/GEV and PDS/GP approaches. Albeit both AMS/GEV and PDS/GP may be affected by dependency of events, AMS/GEV behaves more robust since it selects only one event per year.

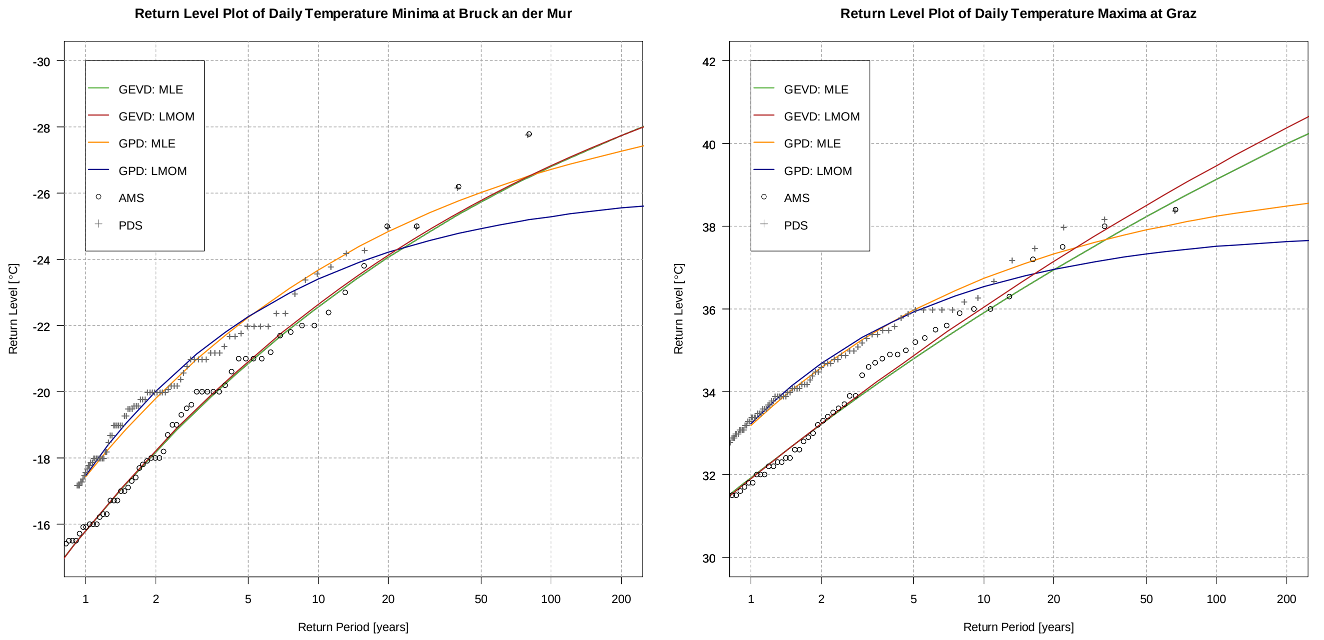
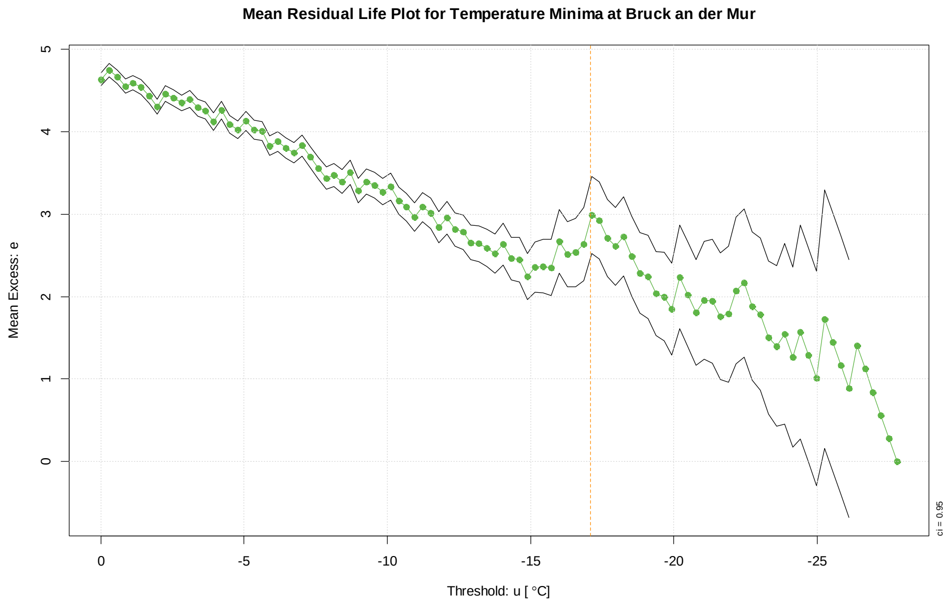
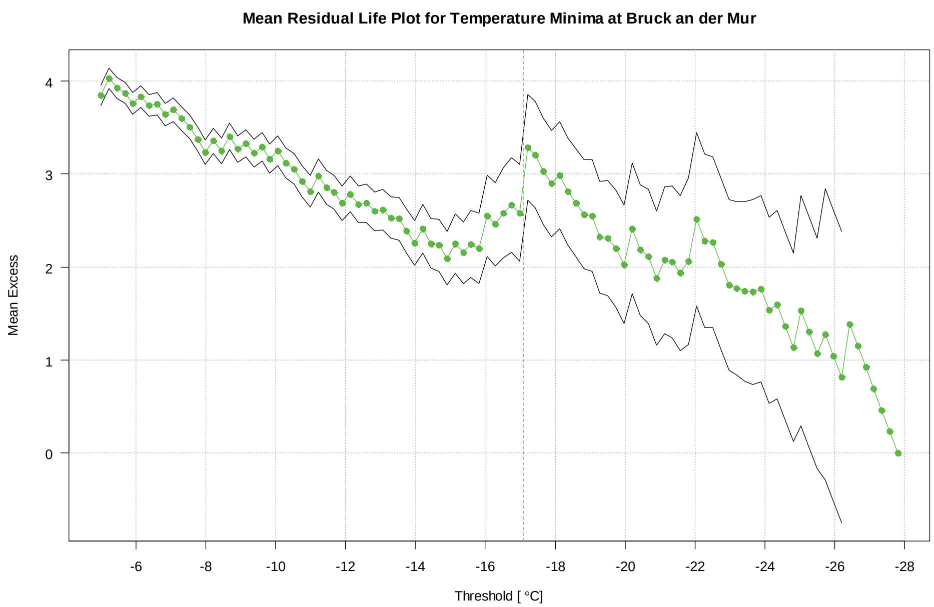


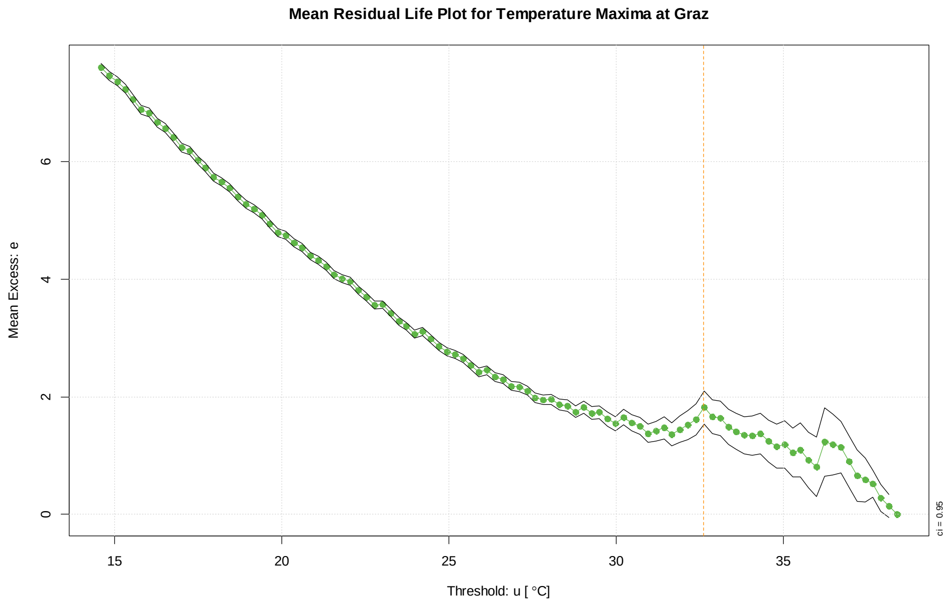
Figure 7: Return level plots of (a) temperature minima at *Bruck an der Mur*, and (b) temperature maxima at *Graz*. Return level estimation is based on the block maxima approach and on the threshold excess approach with two different parameter estimation methods (MLE and LMOM-estimation).

~~We did not expect these findings, which~~These findings are against our initial expectation and contradict to the spirit of most existing studies that aimed to recommend the best performing method for a variable or situation. Instead of recommending either block maxima or threshold excess method, ~~W~~we recommend performing both approaches, as their ~~synoptic~~combined assessment by means of diagnostic plots together with overall and conditional goodness-of-fit measures offers a more complete diagnosis of the quality of extreme series and the resulting distributions.

Concerning the parameter estimation method, there are also benefits and disadvantages that have to be balanced against each other. MLE has some merit with respect to calculating reliable confidence intervals via profile likelihood. Confidence intervals for estimation via LMOM were derived with non-parametric bootstrapping, which is arguably less trustworthy for indicating the uncertainty of the estimates. However, LMOM-estimation has been shown to yield more robust estimation results for small sample sizes (Hosking et al., 1985; Hosking and Wallis, 1987), which can be especially beneficial when analyzing environmental data like temperature or precipitation indicators, which are derived from raw measurements at meteorological measuring stations. Regarding the overall results, LMOM-estimation turned out to offer a better fit than MLE, which is consistent with previous findings (Hosking et al., 1985; Hosking and Wallis, 1987; Bezak et al., 2014).


Mean Residual Life Plot for Temperature Minima at Bruck an der Mur
Mean Excess: e
Threshold: u [°C]
ci = 0.95


Mean Residual Life Plot for Temperature Minima at Bruck an der Mur
Mean Excess
Threshold [°C]



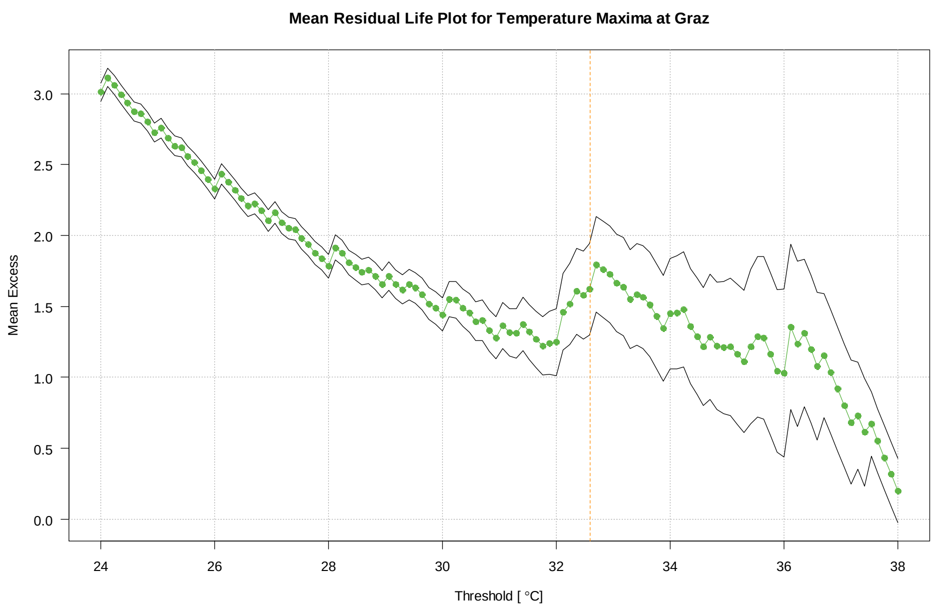


Figure 8: Mean residual life plots of (a) temperature minima the hot spot in *Bruck an der Mur* and (b) temperature maxima at *Graz*. Black lines indicate the 95% confidence interval for the mean excess and orange lines indicate the threshold selected by means of the square root rule.

Concerning the comparison based on the goodness-of-fit of the distributions it shall be noted that a formal comparison of the two extreme value selection approaches is not straightforward. Measures of goodness-of-fit are not fully conclusive, as the underlying extreme value series are derived by different methods and thus are not directly comparable. Our analysis demonstrates that the choice between these approaches has to be based on the statistical properties of the extreme value series, which are related to the indicators under consideration and on data availability. The conditional measures proposed in this paper help to perform a more specific assessment for extreme events, but they are also not a remedy to overcome this problem. They are a way to assess the goodness of fit at the upper tail of the distribution and facilitate the comparison between AMS/GEV and PDS/GP. These metrics can assist, but not substitute careful analysis of assumptions. We show that contrastive plotting methods can strongly support these analyses.

While the methodology of this study can be easily generalized and extended to cover other environmental variables, ~~two~~ four possible limitations have to be discussed. First~~ly~~, the seasonality of temperature and precipitation extremes has not been taken into account. While maximum/minimum temperatures will always occur in the same season, which will factor out any seasonal heterogeneity, this is not genuinely the case for extreme precipitation events, where ~~different~~ seasonal~~ity of~~ occurrence may be associated~~linked~~ with diverging~~different~~ processes (Hundecha et al., 2009). In order to account for seasonal effects, a common approach is to split the events into process-homogeneous subsets. This can be either based on seasonality (e.g. Laaha and Blöschl (2006) for low streamflows)~~,~~ or on a typology of processes (e.g. Merz and Blöschl (2003) for floods based on rainfall types and catchment preconditions), or ~~on~~ a temporal stratification of records is applied (e.g. Méndez et al. (2008) for wave height and Maraun et al. (2009) for heavy precipitation). For each subset extreme value analysis is performed separately, leading to process-specific return levels, such as summer and winter low flows in the case of minimum discharges. These quantities may be combined by a mixed distribution model to yield overall return levels (e.g. Hundecha et al., 2009). For further discussion of modelling dependent and non-stationary time series extremes, the reader ~~it~~ is referred to Chavez-Demoulin and Davison (2012).

Secondly, threshold selection in the ~~threshold excess~~PDS/GP method is a legitimate subject for debate. In recent years, efforts have been made to overcome the problem of visual threshold selection, e.g. by robust threshold selection (Dupuis, 1999), ~~additional~~ likelihood-based ~~procedures for supplementing~~ visual diagnostics (Wadsworth and Tawn, 2012; Wadsworth, 2016), Bayesian approaches (Tancredi et al., 2006; Lee et al., 2014), approaches based on goodness-of-fit tests (Roth et al., 2016) and extreme value mixture models (MacDonald et al., 2011). In addition, attempts were made to develop more automated approaches for extreme value threshold estimation, including the automated threshold selection approach (ATSM) by Thompson et al. (2009), the multiple threshold method (MTM) by Deidda (2010) and the automatic threshold and run parameter selection by Fukutome et al. (2015). While these approaches are appealing from a theoretical perspective, their practical value is often reduced by numerical issues and sampling effects. At least for the time series tested in this study, both the ATSM and MTM yielded inconsistent results: Threshold values of similarly distributed time series obtained by ATSM varied considerably, and parameter estimates were depending on range and resolution of the thresholds considered. ~~Several automated threshold selection methods (ATSM by Thompson et al., 2009; MTM by Deidda, 2010) which have been tested for the time series under consideration yielded dissatisfying and inconsistent thresholds: Threshold values for time series which exhibit similar empirical distributions varied considerably and it was noticed that results were depending strongly on the range over which the functions are fit as well as the number of breaks set within this range. While~~

~~certain patterns of convergence were found using brute force methods, it is argued~~One could think that automatic threshold selection~~these~~ procedures ~~somehow~~ replace the threshold selection problem with that of selecting an appropriate range and resolution of the thresholds to be tested~~ an appropriate number of breaks~~.

However, the authors are aware that also the semi-supervised method applied in this study may not be optimal in all cases. Rather than performing in-depth analysis of single time series, we have given priority to analyzing a large amount of time series covering a range of environmental conditions. Therefore, the application of the square-root-rule in combination with graphical diagnostics is argued to be a feasible approach that led to satisfactory results in the present study.

Thirdly, the conditional performance metrics depend, to some extent, on the chosen plotting position. While the choice of plotting position formula is only of minor importance in many cases, it might be influential in the present case with emphasis on the upper order statistics. However, a sensitivity analysis based on Beard (i.e. median) plotting positions has shown that effects on results in terms of return level estimates are small in this study, since changes mainly occur in cases where both estimation methods yield very similar parameter estimates.

Finally, it has to be noted that the conditional metrics are of limited robustness, especially if time series are short and the condition is chosen inappropriately. Since the variance of the order statistics strongly increases towards the upper end of the ordered sample, the conditional metrics may be subject to high uncertainty, particularly if inadequate (i.e. too high) return periods are selected. Thus, the authors want to emphasize that an appropriate base value has to be chosen depending on the length of the time series under consideration. For small samples, priority should be given to robust error metrics such as CMAE_{T^*}.

5 Conclusion

We compared statistical methods for extreme value analyses based on four climate indicators related to daily precipitation and temperature. While the indicators were selected for studying the exposure of road infrastructure to extreme weather events, the assessments are equally relevant for a range of other environmental variables including meteorological and hydrological quantities. We first analyzed the goodness-of-fit of distributions to extreme value series consisting of annual maxima (AMS/GEV) and threshold exceedances (PDS/GP) using two parameter estimation methods.

Results for the parameter estimation methods vary considerably between stations and approaches. For the AMS/GEV approach, LMOM yielded, on average, better fitted distributions than MLE. The goodness-of-fit turned out to be more balanced with respect to the PDS/GP approach, with a slight advantage of MLE. In most cases there were only minor differences between MLE and LMOM when considering return levels below 10 years, but often considerable differences for larger return periods.

Concerning extreme value selection, the relative performance of AMS/GEV and PDS/GP approaches vary between meteorological indicators. For precipitation and temperature difference the AMS/GEV data outperformed the PDS/GP approach. For temperature maxima and minima the PDS/GP approach appeared better suited.

Regarding goodness-of-fit for extreme events that are typically used as design-values (T of 10 years and more), results show an overall advantage of using L-moments estimation as compared to MLE, and that the AMS/GEV approach slightly outperforms the threshold excess approach. The AMS/GEV fitted on the basis of LMOM estimation method performed better than all other combinations of approaches in this study.

We further examined the conditional performances of AMS/GEV and PDS/GP approaches with respect to the return period in more detail. From conditional performance measures and ~~synoptic~~combined plots, we found systematic deviations between AMS/GEV and PDS/GP approaches. For low return periods (non-extreme events) the PDS/GP approach tends to overestimate return levels as compared to the AMS/GEV approach, whereas an opposite behavior was found for high return levels (extreme events). The assessment of extreme cases where approaches differed significantly suggests that this behavior may be related to two factors, sampling uncertainty and threshold selection.

Regarding sampling uncertainty, we found that outliers may not only attract the distribution at the tail where they occur, but they may also bend the curve at the opposite tail as a consequence of limited flexibility of the extreme value distributions. Such leverage effects can be handled by careful inspection of quantile plots. Regarding threshold selection, the analysis of extreme cases within the data set revealed that an inappropriate threshold may lead to considerable biases that may outperform the possible gain of information from including additional extreme events by far. Selecting a high threshold will determine the lower end of the extreme value distribution whereas the upper tail remains unchanged. This may introduce an inflection point in the distribution, which is against its ideal shape according to extreme value theory, resulting in poor estimates of the theoretical distribution. This effect was neither visible from the square-root criterion, nor from the graphical diagnosis (mean residual life plot) which yielded indeed no atypical biases for the analyzed cases. Similar effects may arise when the extreme value series contains dependent events that may stretch the empirical distribution at the part where they occur. These findings w~~h~~ere against our expectations that the estimation of the theoretical distribution will greatly profit from the gain of information that is provided by the PDS/GP approach.

We emphasize ~~the~~that reliable extreme value statistics require controlling for sample effects in order to avoid biased models. In our study, the differences and relative merits of methods were best visible from a direct comparison of AMS/GEV and PDS/GP approaches. We therefore recommend performing both analyses and carefully analyze the ~~fit of~~ distribution fit relative to the respective sample and relative to each other, by means of ~~synoptic~~combined quantile plots. This will make the analyses more robust, in cases where threshold selection and dependency introduce~~s~~ biases to the PDS/GP approach, but also in cases where the AMS/GEV contains non-extreme events that may introduce similar biases. For assessing the performance of extreme events we recommend conditional performance measures such as $CRMSE_{10}$ and $CMAE_{10}$ in addition to unconditional indicators.

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