UNCERTAINTIES IN THE ASSESSMENT OF FUTURE TEMPERATURE AND PRECIPITATION EXTREMES IN CENTRAL EUROPE

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With 11 figures and 1 table
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Summary: In the context of global warming, changes in climate and weather extremes are of particular relevance, although their assessment is subject to many sources of uncertainty. In this study, we address to what extent the estimate of projected temperature and precipitation extremes in Central Europe is sensitive to i) the choice of a theoretical extreme value distribution, ii) to a random sample of given data and iii) to the initial conditions of a model experiment. When evaluated with empirical extreme values, the Gumbel distribution is outperformed by the other considered extreme value distributions, especially for temperature. The above-threshold distribution is characterized by the highest flexibility and the best fit at many grid boxes. Projected changes in temperature and precipitation extremes are more sensitive to the chosen statistical model than to initial conditions. The discrepancies are largest in mountainous regions. Using the best statistical fit at every model grid box reveals a mostly significant tendency towards warmer temperature extremes and more intense heavy precipitation, particularly in the Alpine region.

Zusammenfassung: Im Zusammenhang mit der globalen Erwärmung sind Veränderungen von Klima- und Wetterextremen von besonderer Relevanz. Die Erfassung solcher Veränderungen ist jedoch durch verschiedene Arten von Unsicherheit gekennzeichnet. In der vorliegenden Studie untersuchen wir, in welchem Ausmaß die Schätzung zukünftiger Temperatur- und Niederschlagsextreme in Mitteleuropa von der Wahl der i) theoretischen Extremwertverteilung, ii) von der gegebenen Zufallsstichprobe und iii) von den Anfangsbedingungen eines Modellexperiments abhängt. Im Vergleich zu empirischen Extremwerten wird die Gumbel-Verteilung von allen anderen berücksichtigten Extremwertverteilungen übertroffen, vor allem im Hinblick auf Temperaturextreme. Die schwellwertüberschreitende Verteilung zeichnet sich durch die größte Flexibilität und die beste Anpassung an die Modelldaten in den meisten Gitterboxen aus. Projektionen zukünftiger Temperatur- und Niederschlagsextreme erweisen sich sensitiver gegenüber dem gewählten statistischen Modell als gegenüber den Anfangsbedingungen. Die Unterschiede zwischen den Extremwertschätzungen sind in gebirgigen Regionen am deutlichsten ausgeprägt. Auf der Grundlage der jeweils besten statistischen Anpassung in jeder Modellgitterbox zeichnet sich eine überwiegend signifikante Tendenz zu wärmeren Temperaturextremen und intensiveren Niederschlagsereignissen ab. Dies gilt insbesondere im Alpenraum.

Keywords: Meteorological extremes, extreme value statistics, uncertainty, climate change, Central Europe

1 Introduction

The evidence of anthropogenic climate change is steadily increasing. This is particularly true for near-surface global mean temperature, which directly reflects changes in radiative forcing (IPCC 2013). More uncertainty is still associated with the regional dimension of climate change that also relates to the mediating role of circulation changes, and with the assessment of changes in the frequency and intensity of climate and weather extremes. Extreme events are seldom and, hence, badly represented in a statistical sense (Palmer and Räisänen 2002). In addition, many climate models have limited skill in simulating extremes, mainly depending on their resolution (Brown et al. 2014; Cretat et al. 2014; Mishra et al. 2014). Nonetheless, changes in extremes are of crucial relevance, e.g., for food production systems, development and the insurance industry (Easterling et al. 2000; Dlugolecki 2008; IPCC 2012). Especially precipitation extremes are in the focus of current research because tendencies towards more intense droughts and floods can already be observed and threaten human societies and ecosystems (Milly et al. 2002; Lehner et al. 2006). Moreover, precipitation extremes may be more sensitive to radiative heating than precipitation sums due to non-linear feedbacks through moisture holding capacity and cloud processes (Hennessy et al. 1997).

Statistically, extremes are defined to be noticeably distant from a mean state (Beirland et al. 2004). In the climate system, changes in means and

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extremes are expected to be asymmetric. Therefore, specific statistical distributions are required to describe extreme events and their instationarities (Christidis et al. 2010). As no extreme value distribution (EVD) appears to be superior to all others for every region, season nor variable (cf. Keim and Faiers 2000; Papalexiou and Koutsoyiannis 2013; Renard et al. 2013; Serinaldi and Kilsby 2014), the choice of an EVD represents one source of uncertainty when assessing future changes of climate extremes (Gomez and Guillou 2014). Additional uncertainties arise from the limitations of global and regional climate models in terms of parameterizations and resolution (Easterling et al. 2000; Brown et al. 2014; Cretat et al. 2014; Mishra et al. 2014), the unknown initial conditions of climate simulations (Palmer and Anderson 1994; Palmer and Williams 2008), and the assumed emissions scenario (Schenk and Lensink 2007). Previous studies suggest that the model spread is particularly high for simulated precipitation in general and for rainfall and wind extremes in particular (Paeth and Hense 2002; IPCC 2007, 2013; Nikulin et al. 2011; Paeth et al. 2011).

The present study is dedicated to some of these sources of uncertainty when estimating daily temperature and precipitation extremes over Central Europe. In contrast to Frias et al. (2012), we do not focus on climate model uncertainty, but on the effect of choosing different statistical models to describe the distribution and response of weather extremes. For this purpose, four commonly used extreme value distributions are validated in terms of empirical quantiles based on high-resolution regional climate model (RCM) simulations. In addition, two ensemble members with identical radiative forcing, but different lateral boundary conditions, i.e., two global coupled general circulation model (GCM) runs that start from slightly different initial conditions in 1860, are compared. Results will be interpreted in regional and seasonal contexts. Finally, future changes of temperature and precipitation extremes until 2100 will be derived from the best statistical fit at each grid box.

Central Europe was chosen for two reasons: First, a two-member ensemble of RCM simulations at 0.088° (~10 km) resolution is available for Central Europe (cf. Fig. 1). This resolution is noticeably higher than the one realized in the coordinated RCM initiative ENSEMBLES (www.ensembles-eu.org) and similar to the targeted resolution in CORDEX (www.euro-cordex.net) and realistically represents the spatial characteristics of daily temperature and precipitation extremes as a function of the spatially heterogeneous terrain across Central Europe (Jacob et al. 2008). In addition, the systematic bias in terms of the distribution function of daily precipitation as reported by Zolina et al. (2004) may be less pronounced (cf. Tapiador et al. 2009). The RCM experiments are realized with REMO, nested in ensemble members of the coupled global GCM ECHAM5/MPIOM with different initial conditions in the starting year 1850 and increasing greenhouse gas concentrations until 2100 according to emissions scenario A1B (Jacob et al. 2008). REMO is a hydrostatic limited-area model based on primitive equations with a terrain-following vertical coordinate (Jacob 2001). It has been widely used for climatological applications all over the globe (e.g., Jacob 2001; Paeth and Hense 2005; Paeth et al. 2011). The hydrostatic approximation is a limiting factor towards higher resolutions. However, it could be shown by Jacob et al. (2008) that REMO performs well in terms of important measures of temperature and precipitation climatology and variability. Some noticeable deficiencies were identified in parts of the Alpine region, especially for precipitation. Feldmann et al. (2008) revealed an added value of REMO at this high resolution with respect to spring and summer rainfall, whereas winter precipitation was systematically overestimated and close to the patterns simulated by the driving larger-scale global climate model. The REMO runs that were analysed here cover the time period 1950–2100, using observed greenhouse gas concentrations until 2000 and A1B emissions scenario thereafter (Nakicenovic and Swart 2000).

The second reason for choosing Central Europe is that this region is already characterized by noticeable changes in observed temperature and precipitation extremes. Against a background of remarkable warming since the Little Ice Age (Luterbacher et al. 2004) there is also a clear tendency towards warmer temperature and heavier precipitation extremes in Central Europe (Moberg et al. 2006; Kürbis et al. 2009), leading to more summer dryness (Briffa et al. 2009) and, at the same time, to intermittent extreme rain events (Lehner et al. 2006; Kunz et al. 2009; Zolina et al. 2010) with return times becoming progressively shorter (Christensen and Christensen 2003; Fowler and Kilsby 2003). In the recent past, the most prominent extreme event in Central Europe certainly was the 2003 heat wave (Schär et al. 2004). It was the warmest summer since 1500 (Stott et al. 2004) with a large-scale temperature anomaly of 3.4 °C above long-term climatology (Schönwiese et al. 2004). While extreme events in Central Europe mainly relate to specific large-scale patterns of weather or circulation types (Jacobeit et al. 2009; Kunz et al. 2009), heat stress may also arise from complex

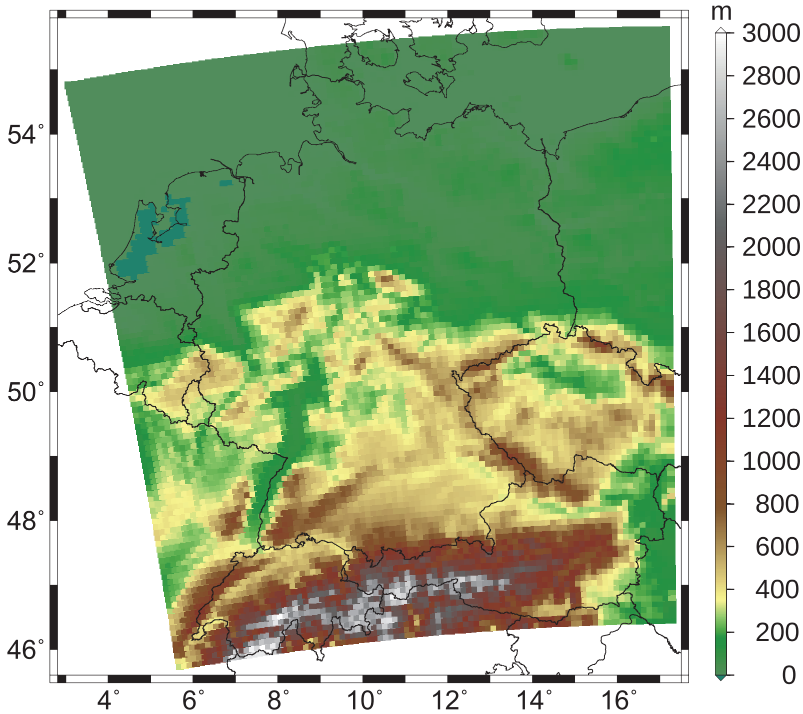

Fig. 1: Model domain and model topography

feedbacks with the land surface (Seneviratne et al. 2006). Other meteorological extremes to be noted in Central Europe are storms (Pinto et al. 2010) and, in the case of 2009/2010, even winter cold (Ouzeau et al. 2011). Central Europe also appears to be very sensitive to changes in temperature, precipitation and wind extremes, e.g., with regard to tourism (Endler and Matzarakis 2011) and agricultural sectors (Lippert et al. 2009). Climate model projections into the 21st century mostly draw a picture of enhanced heat events and increasing flood risk in Central Europe (Cattiaux et al. 2012; Feyen et al. 2012). The frequency of present-day heat waves has already increased by a factor of 10 since the mid-20th century and will further increase into the future, making them a typical event until 2100 (Kyselý 2010). Nikulin et al. (2011) have shown on the basis of their RCM ensemble for Europe that heat and heavy rain events with a current return time of twenty years will occur every 1–2 years and 6–10 years, respectively, until the end of the 21st century.

Overall, the considered REMO experiments represent a consistent, spatially and temporally complete and homogeneous data set that can be used to investigate present-day and future meteorological extremes. Note that emissions scenario and model physics as sources of uncertainty are not accounted for in this study (cf. Frias et al. 2012). In addition, the focus is not on the validation of simulated daily temperature and precipitation extremes with respect to station data which, by the way, is not straightforward, especially for precipitation (cf. Zolina et al. 2004). The goal rather is to assess uncertainties related to statistical models, i.e., extreme value distributions, excluding the interference by inhomogeneities and gaps in long-term observational data. In this context, the analysed REMO runs represent useful case studies that may serve as a benchmark for applying the method to other RCM or GCM simulations.

The following section is dedicated to the extreme value statistics that are compared. The evaluation of the statistical models is described in section 3. The uncertainties of future projections are presented in section 4 along with the presumably ‘best’ projections. Results are discussed in section 5 and conclusions are drawn in section 6.

2 Extreme value statistics

As the description of extreme events requires specific statistical distributions (Christidis et al. 2010) and no established EVD has yet been identified that is universally valid in the climate system

(Keim and Faiers 2000), we rely on four well-known theoretical distributions classically used for meteorological extremes. These are the Gumbel distribution (GUM), the generalized extreme value distribution (GEV), the Pearson type 3 distribution (PE3), and the generalized Pareto distribution (GPD). Note that this choice is not exhaustive but also not arbitrary: We wanted to refer to EVDs that have often been used for weather and climate extremes issues (see references below).

The first three EVDs belong to the category of statistical distributions, which are based on block maxima (Coles 2001). According to most previous studies, block maxima are defined as the highest daily temperature and precipitation value, respectively, within each month. In terms of temperature, we rely on the daily-mean instead of daily maximum temperature. As many climate models have deficiencies in terms of radiation and cloud processes and the resulting diurnal temperature range, the former is characterized by a smaller model bias (Kothe et al. 2011; Evans and Westra 2012; Li et al. 2013). The GPD is an above-threshold distribution that rests upon the highest values beyond a given threshold, typically a higher quantile (Coles 2001). Our analysis addresses daily temperature and precipitation extremes per month aggregated to the four classical mid-latitude seasons (DJF, MAM, JJA, SON). Thus, each season comprises three extreme values per year. An alternative way is to use only the seasonal maximum, which leads to a smaller sample size for fitting the EVDs and is, hence, not realized here. The seasonal view in the more maritime middle latitudes of Central Europe implies that the independent and identically distributed (iid) assumption is reasonable because the block maxima for each month typically belong to different weather situations (Jacobeit et al. 2009; Kunz et al. 2009). This is more critical for the above-threshold approach when consecutive extreme days may relate to the same heat wave or storm event (cf. Kunz et al. 2010).

The GUM was among the first EVDs to be applied to issues of rainfall extremes (Hershfield 1961; Nadarajah 2006; Maclado et al. 2010). It is also appropriate for hydrological risks (Clarke 2002), maxima of snow cover (Graybeal and Leathers 2006), and even sea level peaks (van den Brink and Können 2011). Its probability density function is given by

$$f(x) = \alpha^{-1} e^{-\frac{x-\xi}{\alpha}} e^{-e^{-\frac{x-\xi}{\alpha}}} \tag{1}$$

and comprises two parameters: A location parameter ξ, indicating the position along the x-axis, and a scale parameter a, denoting the dispersion, i.e., the spread of the distribution.

The GEV is the most common EVD to represent block maxima. It reliably fits precipitation extremes in various regions (Maraun et al. 2009; Hanel and Buishand 2011) and also works for simulated rainfall (Min et al. 2009). Rusticucci and Tencer (2008) selected the GEV for extremely hot temperatures. Besides location and scale parameter, the probability density function contains a third parameter, shape parameter $\varkappa$ that describes the skewness of the distribution with $\varkappa = 0$ signifying a symmetric shape, and has the following form:

$$f(x) = \alpha^{-1} e^{-(1-\kappa)y - e^{-y}} \tag{2}$$

with

$$y = \begin{cases} -\kappa^{-1} log\left(1 - \dfrac{\kappa(x-\xi)}{\alpha}\right) : \kappa \neq 0 \\ \dfrac{(x-\xi)}{\alpha} : \kappa = 0 \end{cases} \tag{3}$$

It must be noted that at $\varkappa = 0$, GEV is identical with GUM (Kotz and Nadarajah 2000). Thus, compared with the latter, GEV is characterized by a higher flexibility when fitted to data. As both EVDs are frequently used and in order to assess the gain by the shape parameter, they are both addressed in this study.

Our third EVD tends to be less frequently applied to climatological issues than the other considered EVDs. Kumar et al. (2003) successfully used the PE3 to assess severe floods in India. In their hydrological study, Hussain and Pasha (2009) compared PE3 with GEV and GPD and concluded that the former is similar to the GEV but still outperformed by the GPD. The PE3 is derived from the Gamma distribution by introducing a location parameter ξ that marks the lower boundary for the following probability density function:

$$f(x) = \frac{1}{\beta\Gamma(A)} \left(\frac{x-\xi}{\beta}\right)^{A-1} e^{-\frac{x-\xi}{\beta}} \tag{4}$$

for $x \geq \xi$ with Gamma function

$$\Gamma(A) = \int_0^\infty t^{A-1} e^{-t} dt \tag{5}$$

and

$$A = \frac{4}{\kappa^2} \tag{6}$$

$$\beta = \kappa\left(\alpha - \xi\right)\left|\kappa\right| \tag{7}$$

The cumulative distribution function of PE3 does not exist in closed form. It is estimated via a frequency factor that depends on the skewness.

In contrast to the other EVDs described so far, the GPD is an above-threshold distribution. This threshold is a higher quantile, which may affect the shape and location of the GPD considerably. It must be set based on prior knowledge. A higher threshold implies a smaller sample of basic values to be fitted, while a lower threshold enlarges the sample at the expense of enhancing the risk that the subset of values does not follow a Poisson process. If prior knowledge is not assured, Coles (2001) suggests sampling the arising uncertainty by varying the threshold. In this study, the GPD is applied to different thresholds based on all days for temperature and rainy days with values larger than 0.1 mm/day for precipitation. We use quantiles between 85 % as the lower boundary in order to exclude too many 'normal' events, and 95 % as the upper boundary to account for a certain minimum of data for the fitting procedure. Applications of the GPD have been found to be appropriate for daily temperature and precipitation extremes (Paeth and Hense 2005), severe flood events (Hussain and Pasha 2009), as well as ozone minima and maxima (Rieder et al. 2010). The probability density function contains location, scale and shape parameters and is:

$$f\left(x\right) = \frac{1}{\alpha} e^{-(1-\kappa)y} \tag{8}$$

with y according to Eq. 3.

The location parameter ξ, scale parameter a and shape parameter $\varkappa$ of all considered distributions were estimated by the method of L-moments (Hosking 1990). This approach is based on order statistics and particularly efficient for relatively small samples – as a typical situation of extreme value issues – and in the presence of outliers (Kunz et al. 2010). There are many successful examples in the literature, e.g., for meteorological (Paeth and Hense 2005) and hydrological (Saf 2009; Gubareva and Gartsman 2010) applications.

Given the limited number of extreme events, the estimate of the EVD parameters may still be subject to considerable sampling errors. Therefore, a Monte Carlo approach is used: Once an EVD is fitted to the original model time series, new samples are drawn based on uniformly distributed random numbers and the quantile function of each EVD (cf. Kharim and Zwiers 2000). Thereby, 100 new samples are created with each having its own EVD and related parameters and return values. We carried out sensitivity studies and found that 100 new samples appropriately reflect the uncertainty of the EVD fit. Park et al. (2001) showed that return values arising from such a Monte Carlo resampling technique are normally distributed with mean and confidence intervals over the random samples. We use the confidence intervals as a measure of uncertainty in terms of small samples and to assess the statistical significance of future changes in temperature and precipitation extremes (cf. Paeth and Hense 2005): A change is defined to be significant when the confidence intervals of a time slice in the past and in the future overlap by less than 5 %. According to $\sqrt{0.05}$ this relates to the 77 % confidence interval.

To compare and evaluate the considered EVDs, empirical return values for various return periods of length P_i are computed from the same simulated time series of daily temperature and precipitation at every model grid box. For return periods that are shorter than the available time series, this can easily be done by means of order statistics, taking the quantiles that separate a certain range of data at the upper tail as return value for a given return period. Based on the current WMO climate normal period 1961–1990, sliding windows of length P_i are considered and the mean over all return values is used as the comparative value for the theoretical return values derived from the EVDs. We mainly consider two return periods: 30 years as an indication of very rare and severe events and 1 year as an example of more frequent extreme events for which we expect a lower level of uncertainty in terms of the statistical models. For 30-year return periods, only one return value is retained that is the highest daily value over 30 years. In terms of 1-year return periods, the empirical reference value is the mean over 30 annual maxima. In order to test whether the theoretical statistical distributions represent an appropriate model for the data, the Kolmogorow-Smirnow (KS) test is applied to empirical and theoretical return values (Wilks 2006). It is a non-parametric test for statistical distributions that is quite robust in view of small samples and most frequently used for issues like the one addressed here. However, note that a typical shortcoming of such issues is that the same data is used for the estimation of the parameters and the goodness-of-fit assessment (Wilks 2006; Nuzzo 2014). The test variable of the KS test is a function of the largest difference between empirical and theoretical return values. The fit is defined to be successful when the alternative hypothesis H_1: $F_t(x) \neq F_e(x)$ is rejected. This means that the theoretical and empirical cumulative distribution functions are identical, implying that the test variable of the KS test is smaller than the critical value at a given error level p and degrees of freedom Φ. While the KS test is a qualitative criterion for the fit of the EVDs, we also compute the root mean square error (RMSE, Wilks 2006) between empirical and theoretical return values over all return times as a quantitative measure of the goodness-of-fit.

3 Evaluation of statistical models

Figure 2 displays the statistical fit of the cumulative distribution functions of the four considered EVDs to summer temperature and precipitation extremes at one exemplary model grid box in southwestern Germany (47.65°N, 7.72°E, 420 m a.s.l.). Summertime is predominantly addressed in this study because changes are expected to be most severe during this season in Central Europe (Jacob et al. 2008; Lippert et al. 2009; Endler and Matzarakis 2011). In addition, table 1 lists the p-values from the KS test for this grid box. The p-value indicates the error level when accepting the alternative hypothesis (see section 2). A high p-value denotes that the alternative hypothesis, which states that the theoretical and the empirical distributions are different, is accepted with a high error probability and, hence, is typically rejected. This implies that the theoretical and empirical distributions are not inconsistent with each other (Wilks 2006). Thus, the highest p-value among the considered EVDs identifies the distribution for which the alternative hypothesis will most likely be rejected or,

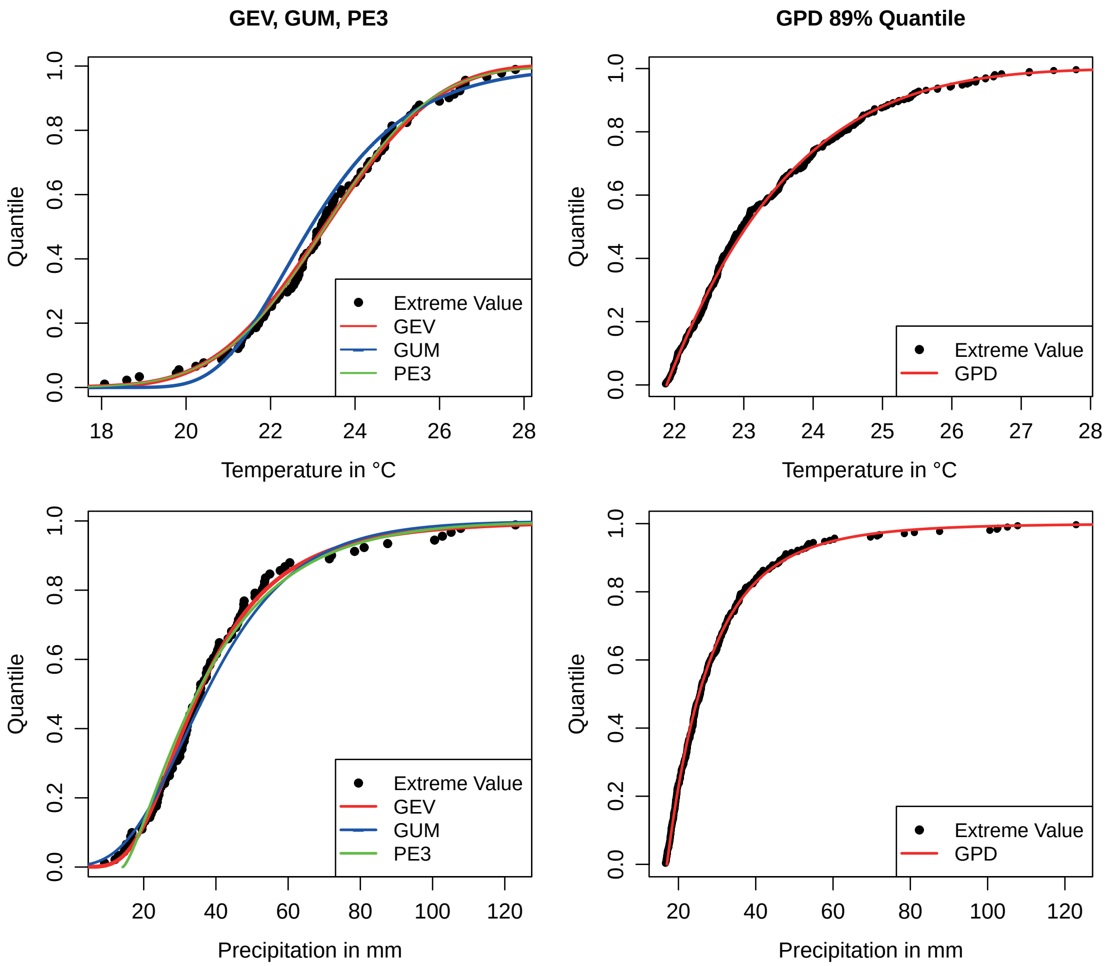

Fig. 2: Statistical fit of EVDs to simulated extreme summer (JJA) temperature (top) and precipitation (bottom) during period 1961–1990 at one exemplary grid box in southwestern Germany from model run 1: GUM, GEV and PE3 are fitted to the monthly maxima during summertime (left), whereas GPD is based on all extremes above the 89% quantile

Tab. 1: p-values from KS test for the exemplary grid box in figure 2

variable	GPD	GEV	GUM	PE3
temperature	0.83	0.93	0.34	0.93
precipitation	0.94	0.88	0.53	0.52

in other terms, the best EVD is the one with the highest p-value. At a first glance, GUM appears to be less appropriate than GEV and PE3, particularly for the lower tail of temperature. GEV and PE3 can hardly be distinguished from each other. Both of them are close to the block maxima from which they are estimated. Except for PE3, the fit is generally better for precipitation rather than temperature, especially in the range of highest extremes. This likely arises from the fact that the considered EVDs have been designed for precipitation and hydrological processes rather than for temperature (e.g., Hershfield 1961; Clarke 2002; Kumar et al. 2003; Maraun et al. 2009; Hanel and Buishand 2011). GPD tends to provide the best fit for precipitation extremes and the second best fit for temperature extremes at this individual grid box. Note that GPD relies on a larger number of basic values that are yet not necessarily independent (see section 2) but, still, the upper tail of the distribution is badly represented because daily extremes beyond 29 °C and 100 mm, respectively, are seldom in southwestern Germany under present-day climatic conditions. Considering another quantile threshold, season or model run leads to the same general picture, identifying GUM as the worst and GPD as the best statistical fit for simulated extremes (not shown).

Extending this view to the entire model domain, figure 3 identifies the best EVD at every model grid box as measured by the p-value of the KS test. In general, the p-values are quite high across Germany, im-

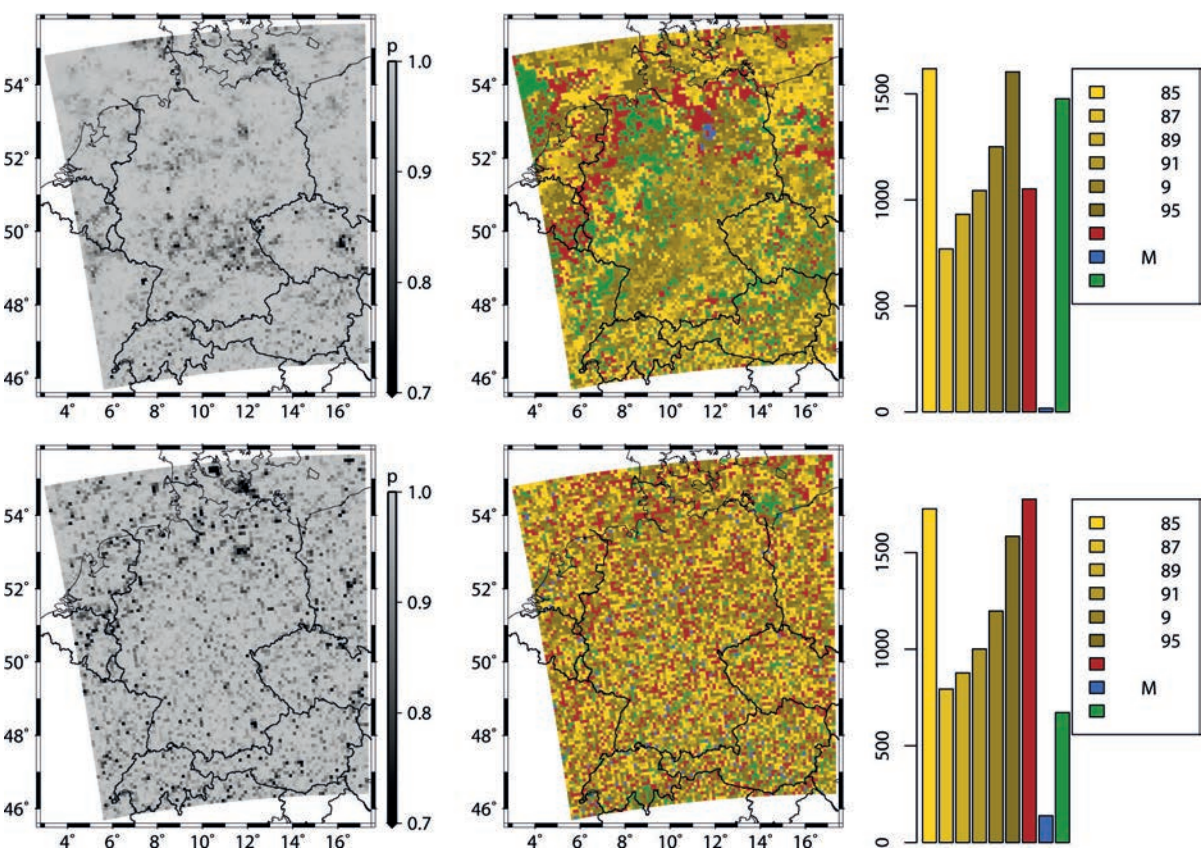

Fig. 3: Best statistical fit of the EVDs to simulated extreme summer temperature (top) and precipitation (bottom) during period 1961–1990 at every grid box from model run 1: the identified best EVD (middle) with respective p-value from the KS test (left) and the counts of each EVD identified as best overall model grid boxes (right)

plying that there is a suitable theoretical distribution to be fitted to simulated temperature and precipitation extremes almost everywhere. Over almost 75% of the model domain, GPD represents the best fit, especially for relatively low and high quantile thresholds. While the former allows for a larger amount of data and, hence, a more robust statistical fit, the latter can be more focused on the highest extremes. In parts of northern Germany, e.g., along the coasts, GPD is outperformed by GEV and PE3 concerning temperature, whereas the picture is less coherent for precipitation. GUM hardly plays a role for temperature and also does not perform as well as the other EVDs for precipitation. This result was confirmed for the other seasons and for model run 2 (not shown).

In order to provide a more quantitative measure of the quality of fit compared with the p-value, the RMSE between theoretical and empirical temperature extremes was determined over all model grid boxes for different return times and for the considered four EVDs (Fig. 4). It is obvious that GUM is characterized by a noticeably higher RMSE than all other EVDs. For shorter return times of winter temperature extremes (top left), GPD outperforms GEV and PE3 with rather small errors around 0.3 °C. For return times of 30 years, the RMSE of GPD is in the same range as for GEV and PE3, which is around 1 °C. There is some dependence of the GPD fit on the quantile threshold but only for longer return times: The RMSE decreases with higher thresholds simply because rare events are better represented if the statistical fit is based on the highest extremes. In general, the RMSE is higher for winter rather than summer temperature extremes, according to higher temperature variability in winter. Likewise, spring and autumn show up with intermediate RMSE (not shown). Astonishingly, the RMSE is not systematically higher for 30-year rather than 1-year return times, except for GUM. Obviously, most EVDs tend to adjust to the highest extremes no worse than to the more frequent events. This equity arises from the order statistics in the method of L-moments (Hosking 1990).

For winter and summer precipitation extremes, the picture is partly inverted (Fig. 5). For shorter re-

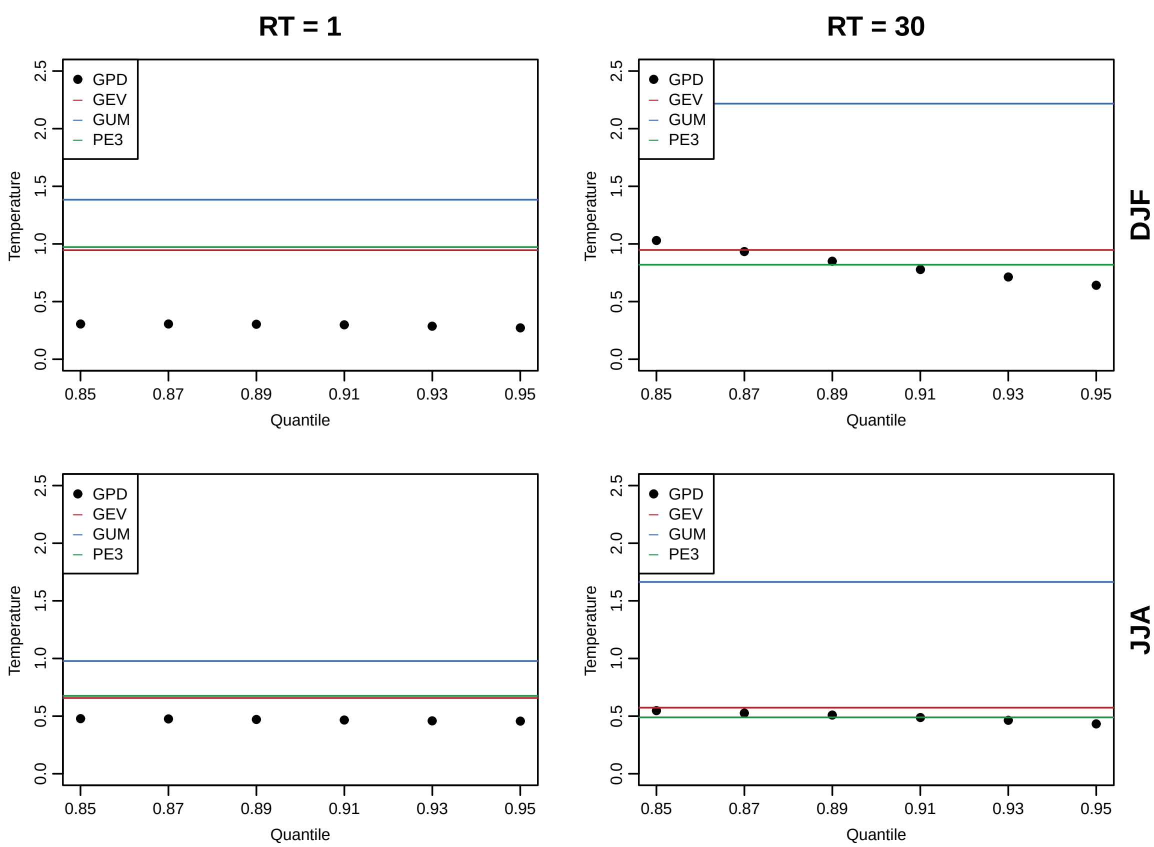

Fig. 4: RMSE between empirical extreme winter (top) and summer (bottom) temperature and RVs derived from the theoretical distributions with a return time of 1 year (left) and 30 years (right) during period 1961–1990 over all grid boxes from model run 1: the RMSE of GPD – in contrast to GUM, GEV and PE3 – is a function of quantile threshold

turn times, GPD still tends to provide a noticeably better fit but now also GUM slightly outperforms GEV and PE3. However, GUM is clearly worse for particularly heavy rain events while GPD, GEV and PE3 are in the same range. Moreover, 30-year RVs are not as well represented as 1-year RVs. This particularly holds for summer extremes where the RMSE ranges between 29 and 41 mm, which is enormous given that typical 30-year RVs across Central Europe amount to 70–140 mm (see below). This implies that convective precipitation extremes during summertime are badly represented by all considered EVDs (cf. Paeth and Hense 2005). It should be noted that GPD clearly outperforms all other EVDs in the spring and autumn (not shown).

4 Future projections

Given the fact that we rely on two simulations from one RCM and undertake no validation study of present-day simulated temperature and precipitation extremes, the projected changes presented here must not be overestimated in the sense of a multi-model agreement (cf. Paeth et al. 2013). In order to compare the effect of different EVDs and initial conditions on projected climate extremes, figure 6 displays the 30-year RVs of warm temperature extremes for the end of the 20th century and figure 7 illustrates the corresponding changes until the end of the 21st century. Adding the changes from figure 7 to the present-day means from figure 6 reveals that future heat extremes will range between 24 °C along the Baltic Coast and 34 °C in the Upper Rhine Valley. Note that this refers to daily means, not daily maxima. Warm extremes below 20 °C will occur in the Alps. Except for GUM, the ensemble members are characterized by some minor differences, indicating that initial conditions only marginally affect the projection of future temperature extremes. Nonetheless, run 1 tends to project a stronger intensification of heat events in the southern part of the model domain, i.e., southeastern Central Europe and the Alpine region. GPD, GEV and PE3 also

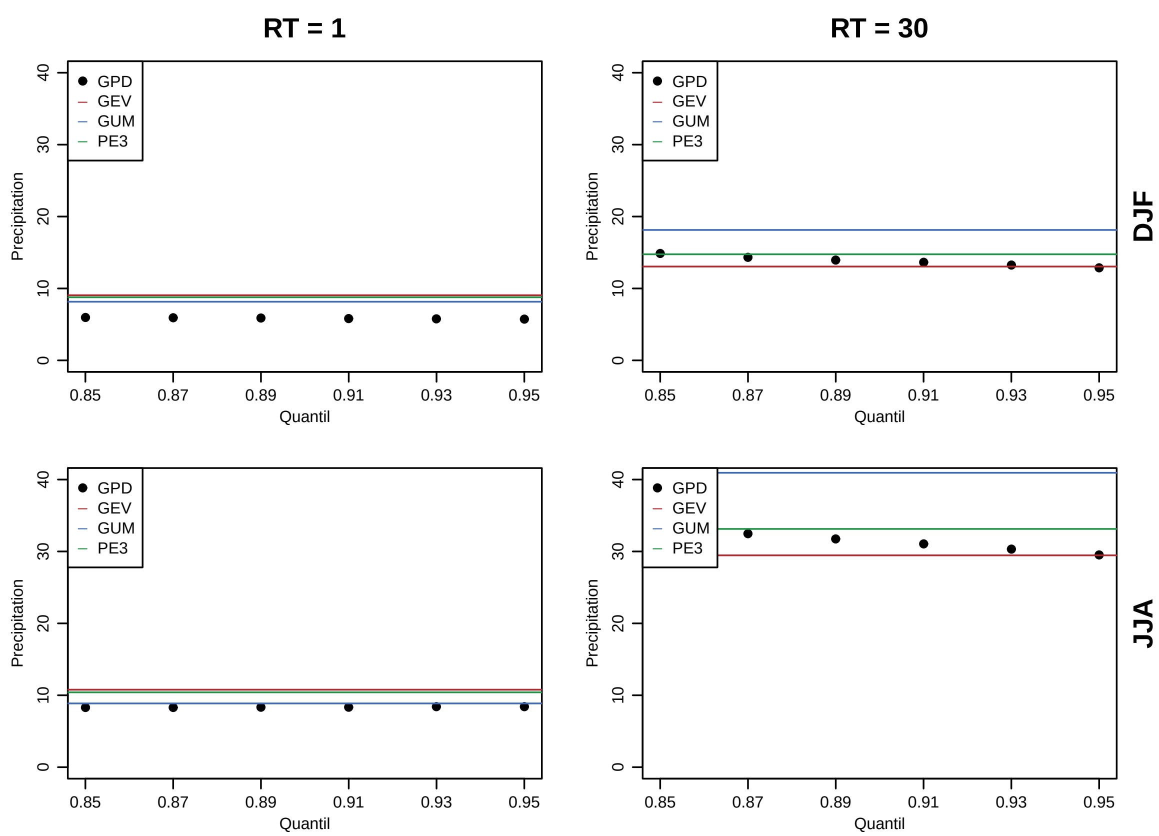

Fig. 5: RMSE between empirical extreme winter (top) and summer (bottom) precipitation and RVs derived from the theoretical distributions with a return time of 1 year (left) and 30 years (right) during period 1961–1990 over all grid boxes from model run 1: the RMSE of GPD – in contrast to GUM, GEV and PE3 – is a function of quantile threshold

draw very similar pictures that reflect some robustness in the assessment of future heat events. In contrast, GUM leads to systematically warmer 30-year RVs. The difference is in the order of 4 °C on average and, hence, considerable. Moreover, both ensemble members differ noticeably by up to 6 °C. As such, GUM is somewhat alone-standing and in combination with the findings in section 3 less confident for the estimate of present-day and future temperature extremes. Basically the same results can be obtained for the other seasons, of course with other RVs for 30-year temperature extremes (not shown).

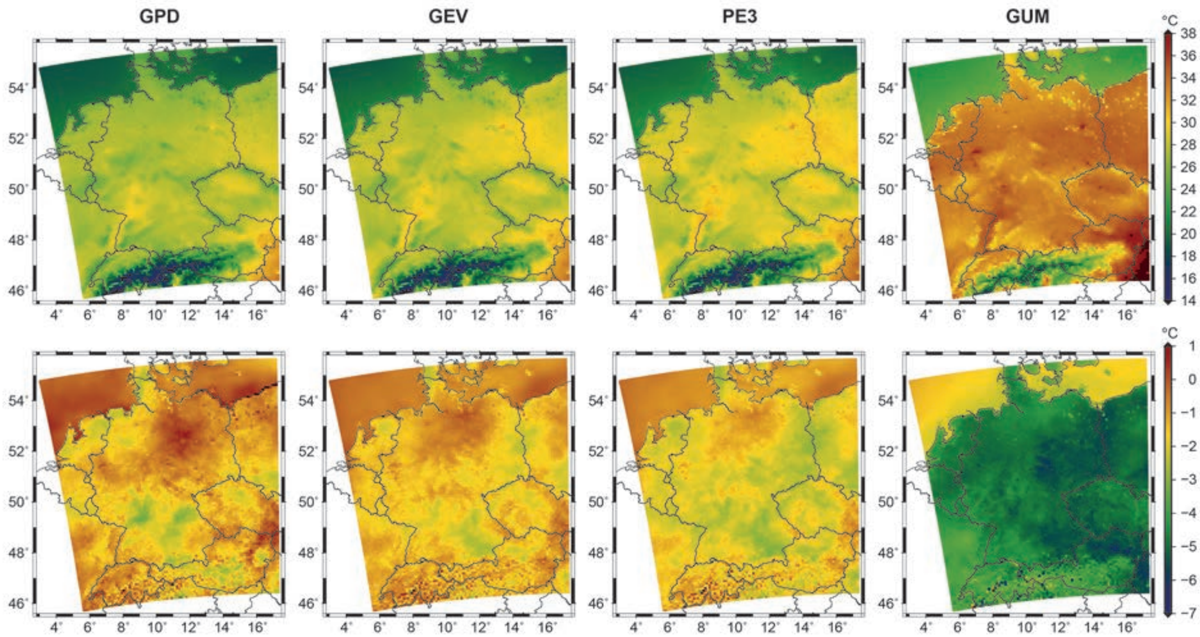

Fig. 6: Present-day RVs of extreme summer temperature with a 30-year return time during period 1971–2000 from run 1 (top) and differences of run 2 from the former one (bottom) based on all four considered EVDs (from left to right), GPD refers to the 89% quantile threshold

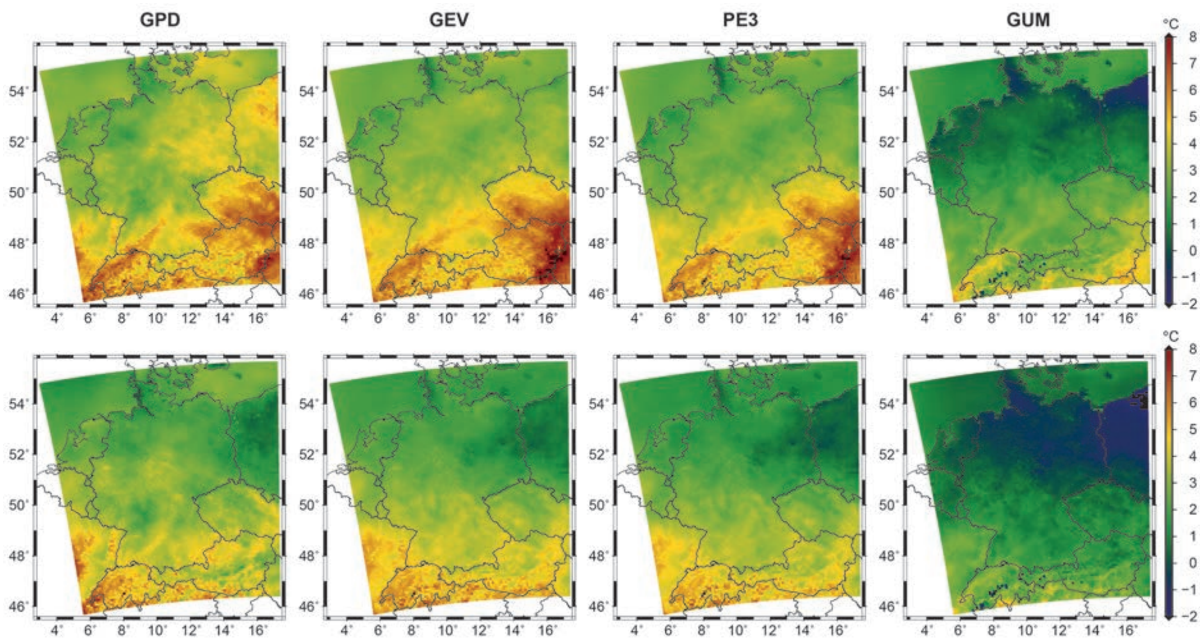

Fig. 7: Future changes in extreme summer temperature with a 30-year return time between period 2071–2100 and period 1971–2000 from run 1 (top) and run 2 (bottom, using run 1 present-day as a reference) based on all four considered EVDs (from left to right), GPD refers to the 89% quantile threshold

For heavy rain events, the discrepancies between different model runs and different EVDs are more pronounced (Figs. 8 and 9). The general structure with strongest increases over parts of the Alps, along the mid-mountain ranges in southern Germany, over the Baltic Sea and in northwestern Italy is common to all projections, reaching regional maxima of more than 200 mm per day during the 2071–2100 period. Over the rest of Germany, no coherent pattern of future precipitation extremes is simulated. One may attribute some of the enhanced extremes to orographic effects but,

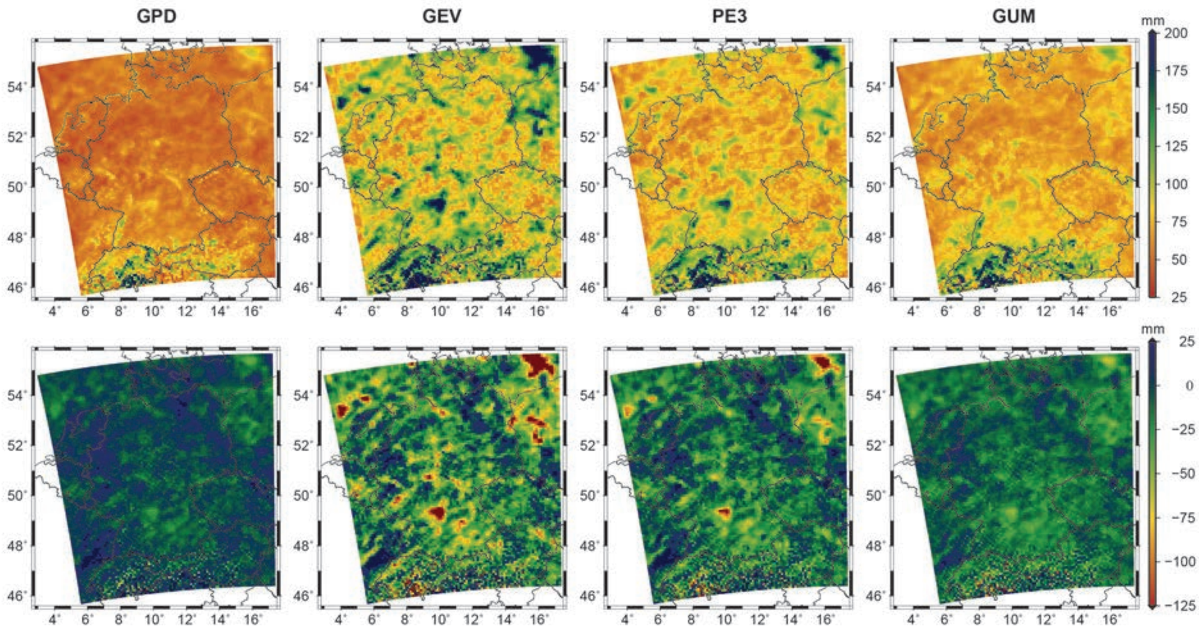

Fig. 8: Present-day RVs of extreme summer precipitation with a 30-year return time during period 1971–2000 from run 1 (top) and differences of run 2 from the former one (bottom) based on all four considered EVDs (from left to right), GPD refers to the 89 % quantile threshold

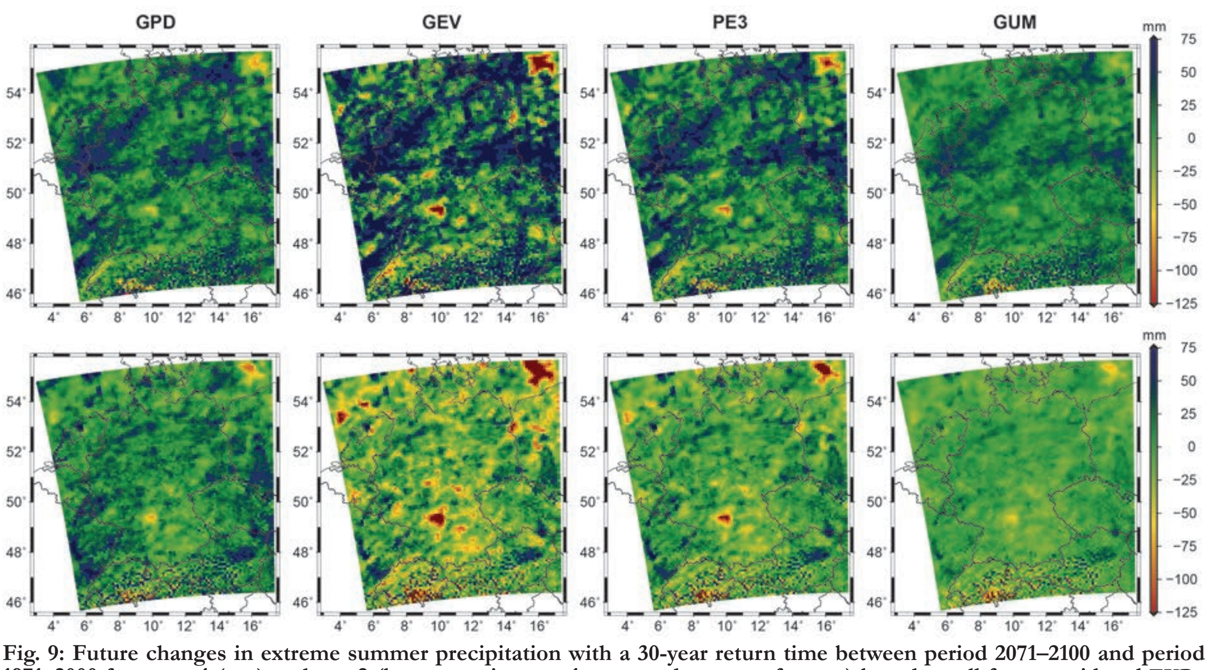

Fig. 9: Future changes in extreme summer precipitation with a 30-year return time between period 2071–2100 and period 1971–2000 from run 1 (top) and run 2 (bottom, using run 1 present-day as a reference) based on all four considered EVDs (from left to right), GPD refers to the 89 % quantile threshold

actually, approximately the same spatial heterogeneity can be diagnosed over the relatively flat region of northern Germany. GUM does not stand out as much from the other EVDs as for temperature. In fact, systematically lower values of 30-year precipitation RVs occur, but GPD, GEV and PE3 are less consistent with each other. In addition, initial conditions play a major role, which is a typical feature for precipitation signals (e.g., Paeth and Hense 2002; IPCC 2007). In fact, the sensitivity to different EVDs itself varies from model run to model run: For example, GEV tends to reflect noticeably higher RVs in the past and future than all other EVDs but only in model run 1. In summary, present-day and future precipitation extremes are subject to a higher degree of uncertainty as compared to heat events.

Figure 10 is dedicated to the climate change signals in terms of warm temperature extremes with return times of 1 (left) and 30 (right) years. In this figure, each model grid box is represented by the best fitted EVD during present-day climate according to figure 3, assuming that this leads to the best estimate of future changes in temperature extremes given this RCM and emissions scenario. Note that it is conceivable that the best fit itself is sensitive to climate change when the processes leading to meteorological extremes basically change. Over most of the model domain, 1-year heat events may rise by about 3 °C until the end of

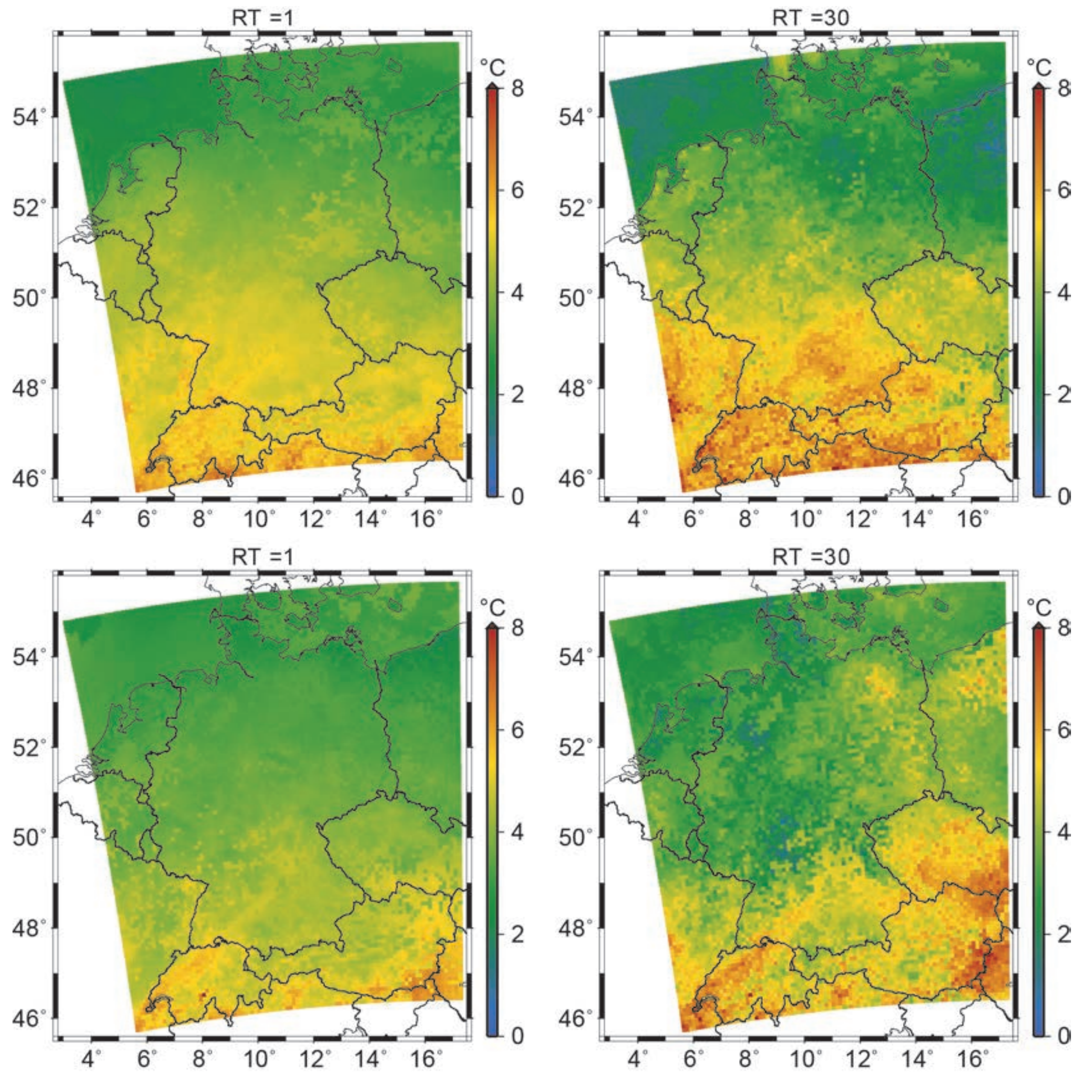

Fig. 10: Future changes in extreme summer temperature with return times of 1 year (left) and 30 years (right) between periods 2071–2100 and 1961–1990 from run 1 (top) and run 2 (bottom) based on the best statistical fit at every model grid box. Only changes statistically significant at the 5% level are plotted

the 21st century. In the Alpine region, the increase may even amount to partly more than 6 °C. All changes are statistically significant at the 5 % significance level. Both ensemble members are quite close to each other in terms of the general pattern but differences in amplitude still occur. For 30-year temperature extremes some changes are more pronounced, the pattern is spatially more heterogeneous and the model runs differ to a larger extent, which is due to the fact that the uncertainty of the extreme value estimate (cf. section 2) increases with return time (cf. Paeth and Hense 2005).

Precipitation extremes may also be enhanced until 2100 in many parts of Central Europe (Fig. 11). The intensification is typically below 10 mm per day for 1-year RVs, but in the Alps stronger increases of up to 20 mm per day are projected. Not all grid boxes experience significant changes because the bootstrap samples differ substantially, which lead to large confidence intervals for late-20th and late-21st century precipitation extremes (cf. Kharim and Zwiers 2000; Paeth and Hense 2005). This is particularly true for longer return times where heavy rain events may intensify by up to 80 mm per day in many regions of western and central Germany (right panels). At the same time, their intensification may be reduced in some parts of southern Germany. According to figure 11, changes in precipitation extremes are clearly sensitive to the initial conditions of the model run.

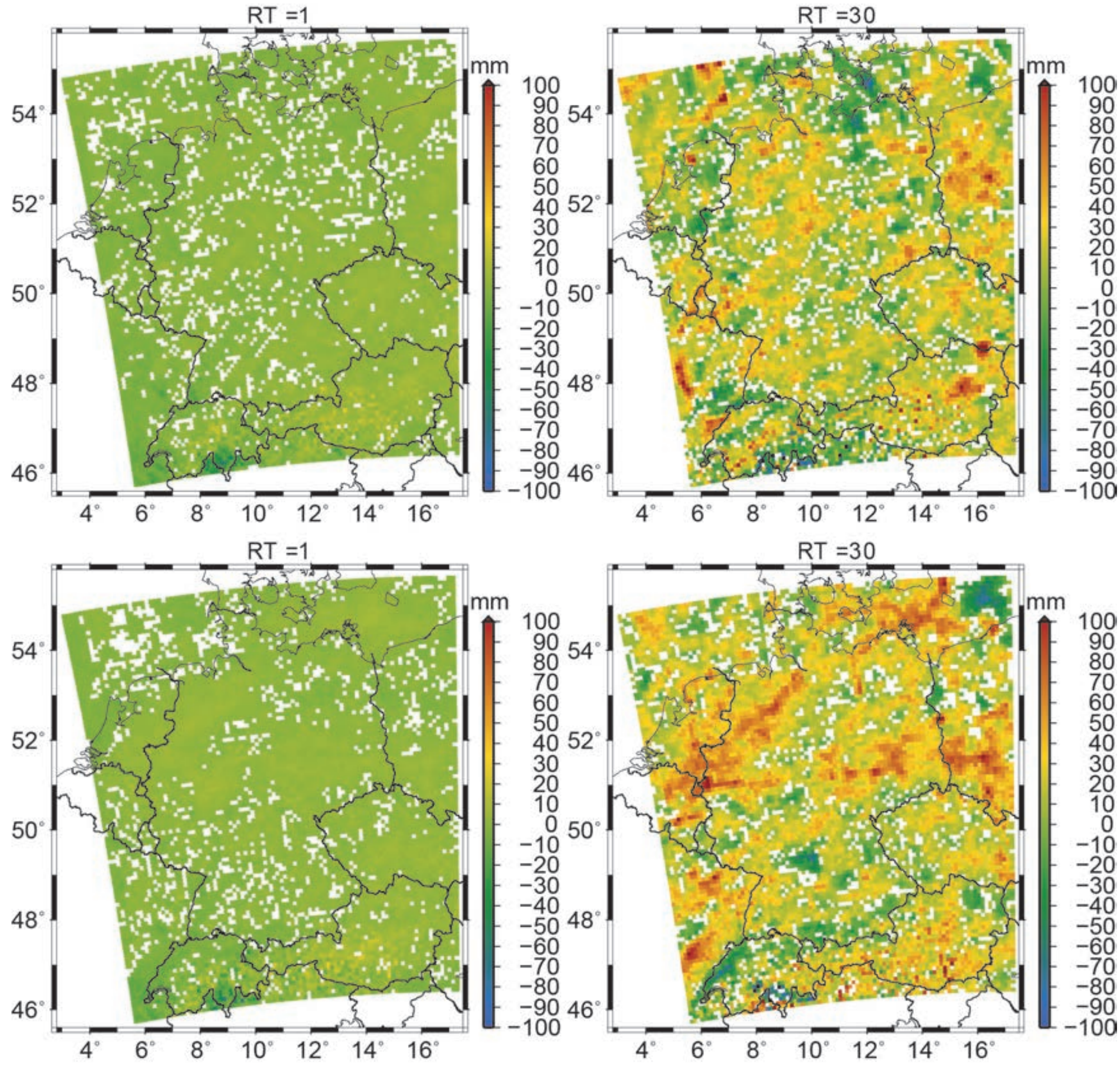

Fig. 11: Future changes in extreme summer precipitation with return times of 1 year (left) and 30 years (right) between periods 2071–2100 and 1961–1990 from run 1 (top) and run 2 (bottom) based on the best statistical fit at every model grid box. Only changes statistically significant at the 5 % level are plotted

5 Discussion

The assessment of future changes in climate and weather extremes is subject to substantial uncertainty. In this study, three sources of uncertainty are addressed: Initial conditions of climate model experiments, small sample sizes for extreme values, and assumptions on extreme value distributions. In contrast, uncertainties that arise from model physics and emissions scenarios are not taken into account. The analysis is based on daily temperature and precipitation extremes from high-resolution regional climate model simulations over Central Europe, using the A1B scenario until 2100. As Jacob et al. (2008) showed that temperature increase and reduction of seasonal rainfall amount is particularly pronounced during summer, this season is the focus of our extreme value analysis.

First, we can confirm that none of the considered EVDs outperformed all others at all grid boxes or seasons (cf. Keim and Faiers 2000). Nonetheless, GPD mostly provided the best fit to daily precipitation and temperature extremes in Central Europe. The GPD fit is based on a larger sample of extreme values compared to GUM, GEV and PE3 that refer to block maxima. In addition, GPD allows for some flexibility by varying the quantile thresholds. Relatively low and high thresholds were found to perform best, either profiting from a larger sample or from a subset of very rare events that possibly arise from the same physical processes. GEV and PE3 lead to virtually the same results and, hence, can be regarded as one EVD choice (cf. Hussain and Pasha 2009). GUM is not an appropriate model for warm temperature extremes, it is more adjusted to hydrological issues (Clarke 2002; Machado et al. 2010). Extreme events with shorter return periods tend to be better represented by EVDs than 30-year RVs, especially in terms of summer rain events. This was also reported by Paeth and Hense (2005) for the Mediterranean region. In contrast, heat events with longer return times are relatively well-assessed by GPD, GEV and PE3, likely due to the method of L-moments (Kunz et al. 2010). From a seasonal point of view, temperature and rainfall extremes react differently: The former are better fitted during the summer, whereas EVDs perform better for heavy precipitation events in the winter.

Projections of future temperature extremes are quite robust with respect to different ensemble members and when using the GPD, GEV or PE3. GUM differs substantially from the other estimates and, hence, should not be considered. Future precipitation extremes appear to be more sensitive to the choice of an EVD and to the initial conditions of the model run. GUM is closer to the other EVDs but still distinguishable. Paeth and Hense (2002) demonstrated that mean temperature represents a more reliable detection variable than precipitation totals. In that sense, it is not surprising that this also holds true for temperature versus precipitation extremes.

In terms of the climate change signals, a statistically significant tendency towards more intense heat events is simulated in both ensemble members and for 1-year and 30-year RVs. Such a trend was also observed (Schär et al. 2004; Moberg et al. 2006; Briffa et al. 2009; Kyselý 2010) and confirmed by other modeling studies (Stott et al. 2004; Lehner et al. 2006). The changes are even more pronounced for the strongest heat events, but the pattern is spatially more heterogeneous (cf. McGuffie et al. 1999). The fact that most changes are statistically significant implies that the confidence intervals over the 100 bootstrap samples are small and, hence, the assessment of temperature extremes works well also for small sample sizes (Kharim and Zwiers 2000; Paeth and Hense 2005). This large signal-to-noise ratio arises from two facts: (1) temperature variability is relatively low and temperature directly responds to radiative forcing, in contrast to most other climate variables, such as precipitation and wind (cf. Paeth and Hense 2002; Paeth and Pollinger 2010).

Concerning future changes in daily precipitation extremes during summer, the picture is more diverse. For shorter return times, a slight intensification of heavy rain events prevails that is mostly significant across Germany. Observations and climate model simulations confirm a certain tendency towards more frequent or more intense precipitation extremes in Central Europe (Lehner et al. 2006; Moberg et al. 2006) and the UK (Palmer and Räisänen 2002; Fowler and Kilsby 2003). 30-year RVs may increase dramatically, especially in western and central Germany (cf. Kunz et al. 2009), whereas a slight reduction is simulated over the southern part. However, the pattern is quite incoherent as also reported by Bell et al. (2004) for California and not all model grid boxes are characterized by statistically significant changes. In addition, the ensemble members differ more clearly from each other. This reflects the uncertainties in the assessment of heavy rain events that arise from the initial conditions as an indication of strong internal variability and the small sample sizes, making precipitation extremes a less clear indicator of man-made climate change (cf. Paeth and Hense 2002, 2005; IPCC 2007). Against the background of decreasing summer totals of rainfall in Central

Europe (Christensen and Christensen 2003; Jacob et al. 2008), the tendency towards more intense daily rain events is particularly critical. Such asymmetries in mean and extreme changes relate to the fact that different processes with different sensitivities to radiative forcing are at work (Christidis et al. 2010).

6 Conclusions

A major conclusion from this study is that various EVDs should be considered and that the estimate of future meteorological extremes is then based on the EVD that best matches the data at a specific location. From a practical point of view, this may lead to the best guess of extreme changes. However, from a physical and statistical point of view, this is problematic: By choosing different EVDs at neighboring grid boxes it is assumed that different processes lead to a particular extreme event, since a statistical distribution represents a specific model for a real-world process (e.g., Wilks 2006). From our physical understanding of the climate system, it is unlikely that the processes, which lead to a heat or heavy rain event, differ from grid box to grid box, especially at a horizontal resolution of 10 km. Indeed, heat weaves are spatially homogeneous and extend over hundreds of kilometers, while rainfall extremes in summer may be more localized. Therefore, it is more consistent to choose one EVD for the entire model domain or, at least, for coherent sub-regions. From our analysis, we suggest that the GPD is the most appropriate statistical model for the assessment of daily temperature and precipitation extremes in Central Europe. It should be used in combination with a bootstrap sampling approach in order to test the statistical significance of changes in extreme events (cf. Kharim and Zwiers 2000; Paeth and Hense 2005). In terms of the quantile thresholds, a choice should be made for relatively high (i.e., q=95 %) thresholds.

A shortcoming of this conceptual study is that model and scenario uncertainties are not taken into account. In fact, Paeth et al. (2011) showed that the inter-model spread among different regional climate models can be larger than the climate change signals, in this case for African rainfall. Model uncertainty also plays an important role in Central Europe, especially for the estimate of rainfall extremes during the summer when subgrid-scale convective processes prevail (Frei et al. 2006). This problem is further aggravated because temperature and precipitation extremes are also related to larger-scale circulation patterns (Jacobeit et al. 2009) which, themselves, are subject to substantial uncertainty in global climate change simulations (Paeth and Pollinger 2010). Model-specific climate sensitivity, included feedbacks, emissions scenarios and the interplay of natural and anthropogenic climate drivers represent additional sources of uncertainty when assessing future climate change (Stott et al. 2000; Roe and Baker 2007; Schenk and Lensink 2007). Nonetheless, the general tendency towards more intense heat and partly also heavy rain events across Central Europe, as identified in this study, could meanwhile be corroborated in a multi-model ensemble context on the basis of regional and global climate models (Nikulin et al. 2011; Cattiaux et al. 2012; Frias et al.2012) and, thus, can be regarded as a quite robust indication of regional climate change. As a matter of further investigation we plan to test whether the GPD can be approved as a best statistical fit to meteorological extremes when applied to experiments from various regional climate models. Thereby, we may quantify the uncertainty range of future changes in temperature and precipitation extremes in a broader probabilistic sense according to Räisänen and Palmer (2001). Finally, more sophisticated test statistics and verification scores for the goodness-of-fit of EVDs could be tested in this context (cf. Luceño 2006; Friederichs and Thorarinsdottir 2012; Toreti et al. 2013).

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