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Quantile mapping for improving precipitation extremes from regional climate models

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ABSTRACT

The potential of quantile mapping (QM) as a tool for bias correction of precipitation extremes simulated by regional climate models (RCMs) is investigated in this study. We developed an extended version of QM to improve the quality of bias-corrected extreme precipitation events. The extended version aims to exploit the advantages of both non-parametric methods and extreme value theory. We evaluated QM by applying it to a small ensemble of hindcast simulations, performed with RCMs at six different locations in Europe. We examined the quality of both raw and bias-corrected simulations of precipitation extremes using the split sample and cross-validation approaches. The split-sample approach mimics the application to future climate scenarios, while the cross-validation framework is designed to analyse “new extremes”, that is, events beyond the range of calibration of QM. We demonstrate that QM generally improves the simulation of precipitation extremes, compared to raw RCM results, but still tends to present unstable behaviour at higher quantiles. This instability can be avoided by carefully imposing constraints on the estimation of the distribution of extremes. The extended version of the bias-correction method greatly improves the simulation of precipitation extremes in all cases evaluated here. In particular, extremes in the classical sense and new extremes are both improved. The proposed approach is shown to provide a better representation of the climate change signal and can thus be expected to improve extreme event response for cases such as floods in bias-corrected simulations, a development of importance in various climate change impact assessments. Our results are encouraging for the use of QM for RCM precipitation post-processing in impact studies where extremes are of relevance.

***Keywords*:** Extreme precipitation, bias correction, regional climate models, non-parametric methods, extreme value theory, new extremes

In recent years, there has been significant effort toward characterising future regional climate and the estimation of climate change impacts. Most often, climate scenarios used for this purpose originate from regional climate models (RCMs), for example from projects such as ENSEMBLES (van der Linden and Mitchell, 2009), or the recent CORDEX initiative (Giorgi *et al.,* 2006; 2011; Jones *et al.,* 2011). However, RCMs are still too coarse for direct application in local climate change impact studies (Mearns *et al*., 2003). As they are known to feature considerable errors, particularly regarding precipitation and their extremes (Jacob *et al*., 2007; Kjellström *et al*., 2010; Suklitsch *et al*., 2010). It requires further processing before applying as input for models used in climate change impact analysis such as hydrological and crop simulation models (Kaur *et al*., 2015; Dar *et al*., 2018). Here, empirical-statistical bias correction techniques play a vital role (Foley, 2010; Maraun *et al*., 2010). Different bias correction approaches are available, and an overview can be found in Themeßl *et al.* (2011), who compared seven different methods, concluding that quantile mapping (QM) offers the best performance, whilst a comparison of different implementations of QM by Gudmundsson *et al.* (2012) ranked the empirical (parameter-free) method in first place.

Quantile mapping corrects modelled data by fitting the cumulative distribution function (CDF) of a historical climate simulation to the CDF of observations. Thus, QM has frequently been applied to daily precipitation sums (Hageman *et al*., 2011; Gudmundsson *et al*., 2012; Piani *et al*., 2010; Themeßl *et al*., 2011; Wilcke *et al*., 2013) at station scale. Themeßl *et al.* (2012) also examined the performance of QM at higher quantiles and found that 'errors in the shapes of the daily precipitation probability density function (PDFs) are corrected adequately up to the 99th quantile'. Thus, QM proved to have a high correction potential for extreme precipitation, but at the same time has potential for further improvements, in particular in the context of "new extremes" i.e., extreme events beyond the range observed in the past. However, along with global warming, new extremes outside this range could occur (IPCC, 2001), and they are therefore highly relevant for adaptation and mitigation strategies. Themeßl *et al.* (2012) suggested a non-parametric implementation of QM that allows new extremes by extrapolation of the correction value at the highest and lowest quantiles of the calibration range. Gutjahr and Heinemann (2013) analysed a distribution-based application of QM, which inherently extrapolates beyond the observed range, i.e., a combination of a gamma distribution and a generalised Pareto distribution (GPD) for extreme precipitation, and concluded that the empirical implementations outperform distribution-based alternatives. Fitting theoretical distributions to the data (Dobler and Ahrens, 2008; Piani *et al*., 2009) offers one option to extrapolate the correction beyond the observed range, but this leads to a loss of information when compared to using the empirical distribution. Furthermore, there is a limitation in the flexibility of QM, which can be applied to any meteorological variable as long as empirical distributions are used. Owing to the above limitations, we propose a hybrid method that combines the non-parametric and parametric benefits using a mixed distribution approach. Similar mixed distribution approaches are already applied in practice to rainfall parameters. For example, Carreau *et al.* (2009) studied rainfall–runoff using a mixed hybrid Pareto model that is built by stitching a truncated Gaussian with a generalised Pareto distribution. By considering these arguments and the results of Gutjahr and Heinemann (2013), who demonstrated the superiority of non-parametric skill methods, we applied a theoretical distribution for high extremes only, but using the empirical distribution for the majority of the data. Our method integrates the advantages of non-parametric QM implementations with those of parametric implementations and takes advantage of extreme value statistics at the tails of the distribution. The method is flexible and can be easily adapted to meteorological variables other than precipitation. We implemented the method for daily precipitation and compared bias-corrected values to raw RCM output and a purely non-parametric QM method.

The main objectives of this work are, (a) assessment of QM general performance in the context of extremes, (b) identifying inherent limitations of bias correction methods employed for extremes (particularly new extremes), and (c) developing an improved method that extends these limits to produce more reliable climate scenarios for extremes, using the combination of non-parametric and parametric approaches. Cannon *et al.* (2015) suggest equi-ratio CDF matching to handle extremes more effectively, although it is not guaranteed to preserve changes in the mean.

MATERIALS AND METHODS

RCMs and observational data

Daily RCM outputs were derived from the multi-model dataset of the ENSEMBLES project (van der Linden and Mitchell, 2009). The ENSEMBLES RCMs have a horizontal grid spacing of 25 km and cover the European domain. The ENSEMBLES project provides hindcast simulations, with the lateral boundary conditions for the RCMs given by the European Centre for Medium-Range Weather Forecasts 40-year re-analysis (ERA-40) dataset (Uppala *et al*., 2005), covering the period from 1961 to 2000. Four simulations are analysed in detail: the RCA3 RCM performed at the Community Climate Consortium for Ireland, the REGCM3 RCM performed at the Italian Centre for Theoretical Physics (ICTP), the HIRHAM RCM, performed at the Norwegian Meteorological Institute, and the RCA RCM, performed at Sweden's Meteorological and Hydrological Institute.

In-situ station data were provided by the European Climate Assessment and Dataset Project (ECA&D) (Klok and Tank, 2009), providing daily precipitation (in mm). Six stations were selected (Fig.1 and Table 1), which represent an altitudinal gradient between 199 and 3,100 m above sea level (ASL) and annual precipitation ranging between 551 to 2500 mm.

The Brocken station, located at an altitude of 1142 m in Central Germany, experiences extreme weather conditions with severe storms and low temperatures, even in summer. Due to its significant elevation compared with the surrounding terrain, Brocken has the highest precipitation of any point in northern central Europe (excluding the Alps), with average annual precipitation (1961–1990) of 1814 mm. From a climatic and geographical perspective, the station at Zugspitze lies in the temperate zone at 2,964 m ASL. The Zugspitze presents a first obstacle to the prevailing westerlies when they reach the Alps. As a result, moist air accumulates releasing heavy precipitation in this region. By contrast, in the opposite direction, a dry, warm, down-slope wind (referred to as a foehn) occurs in the lee of the mountain range against the massif. The average annual precipitation on the Zugspitze is 2003 mm. Station Vienna is located in a flat region between the

Table 1: Geographical and precipitation details of the observational stations used in this study

Station	Latitude	Longitude	Height (m)	Annual precipitation (mm)
Col Du Grand St Bernard, Switzerland	+45:52:00	+07:10:00	2472	2368
Brocken, Germany	+51:48:00	+10:37:12	1142	1814
Sonnblick, Austria	+47:03:00	+12:57:00	3106	2500
Wien, Austria	+48:14:00	+16:21:00	199	620
Weiden, Germany	+49:40:02	+12:11:09	440	551
Zugspitze, Germany	+47:25:20	+10:59:12	2964	2003

north-eastern deviating veins of the Alps, in the north-western part of the Vienna Basin, at 199 m ASL. Vienna lies within a transition area of oceanic and humid continental climatic zones. Precipitation is generally moderate throughout the year, with an annual rainfall of 620 mm. Station Sonnblick is a very well-maintained meteorological observatory on top of the Hoher Sonnblick Mountain at an altitude of 3105 m with a very long time series and exposed to the free atmosphere. It has an average annual precipitation of 2500 mm. The station at Weiden presents a marine, west-coast climate with few extremes of temperature and significant rainfall throughout the year. It lies at an altitude of 440 m with an average annual rainfall of 551 mm. Finally, the station Col du Grand Saint-Bernard is situated on the ridge of the Valese Alps at an altitude of 2472 m and receives strong oceanic influences from the northwest (Pache *et al*., 1996). Average annual precipitation is 2368 mm.

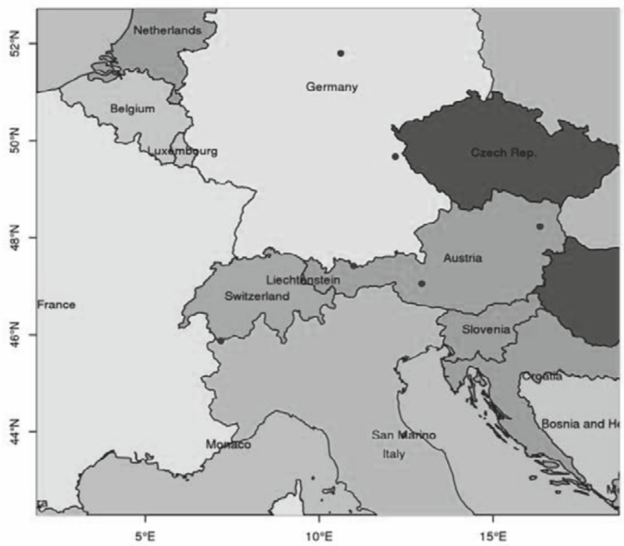

Fig. 1: Location of the six observation stations used in this study

Evaluation setup

In order to evaluate the performance of QM with regard to precipitation extremes, a split sample and a cross-validation approach were applied. In the split sample test, independent calibration (1961-1980) and validation periods (1981-2000) were used. This split-sample approach mimics the application for future climate scenarios, where observations of past precipitation are used for calibration and applied to simulate future precipitation. However, this approach made it difficult to judge the performance of the bias correction method systematically, because the results are affected by climate variability and consequently by potential different model error characteristics between the evaluation and calibration periods.

New extremes are not explicitly specified in the split sample setup. Due to this, a cross-validation framework with a particular focus on new extremes (out of sample extremes) was developed, which clearly displays the results for new extremes and excludes the effects of non-stationarity. In this frame, we used the 1961-2000 period as a primary dataset for calibration and evaluation. During the calibration period, it is neglected the 1% highest precipitation events for each season from observation, as well as models. In the evaluation, the neglected 1% of data was included again, and can be regarded as covering new extremes.

Quantile mapping methods

In this study, a new QM version (QMβ) was developed by combining parametric and nonparametric approaches. The new method replaces the empirical cumulative density functions (ECDFs) by combining an ECDF and a GPD for the high extremes. The new method preserves the major part of the empirical distribution by this means, but also sensibly extrapolates to new extremes at the tail of the distribution. The classical non-parametric QM method (QMα) is constructed as follows:

$$Y = F_{obs}^{-1}\left(F_{mod}(X)\right) \qquad (1)$$

Where, F is an ECDF and F^{-1} is the inverse of the ECDF, which is named the quantile function. The subscripts obs and mod indicate distributions that correspond to observed and modelled data, respectively. The probability of observing X mm per day (or less) in the model is transferred to the quantile of the observed ECDF, matching this probability exactly. Here, Y is the corrected precipitation value. In this non-parametric method, the correction of new extremes can be realised by applying the correction value of the highest observed quantile (Boe *et al*., 2007) and evaluated by Themeßl *et al.* (2012). Hereafter, this method will be referred to as QMα. In the new method (QMß), the distribution is divided into two parts separated by the 95th percentile (Yang *et al*., 2010). Values smaller than the 95th percentile are assumed to follow the empirical distribution, whereas values larger than this threshold are assumed to follow a GPD (Eqs. (2) and (3)).

$$F(X;\sigma,\xi) = 1 - \left[1 + \frac{X\xi}{\sigma}\right]^{-\left[1/\xi\right]} \qquad (2)$$

$$Y = \begin{cases} F_{obs,pem}^{-1}\left(F_{mod,emp}(X)\right), & \text{if } X < 95^{th} \text{ Percentile} \\ F_{obs,GPD}^{-1}\left(F_{mod,GPD}(X)\right), & \text{if } X \geq 95^{th} \text{ Percentile} \end{cases} \qquad (3)$$

Three parameters are relevant for the estimation of a GPD: a scale parameter (α), a shape parameter (ξ), and a threshold (μ), which is set to the 95th percentile in our case. The GPD is defined on {X: X> 0 and (1+ ξX / > 0)} with threshold μ and excess X = z – μ, where z is the observational or model data. We adopted the maximum likelihood estimation (MLE) method for estimating the parameters (Cloes, 2001). Palutikof *et al.* (1999) found that the MLE method provides stable parameter estimates over a range of thresholds. It should be noted that the 95th percentile threshold value is different for observed and predicted values. The shape parameter ξ is responsible for the "weighting" of the tail of the distribution. There are three distinctive regions of the GPD distribution, depending on the sign of ξ: if ξ > 0, the upper tail is unbounded and is heavy-tailed; if ξ = 0, the light-tailed with exponential; if ξ < 0, the upper tail is bounded and is shorter-tailed. Because a GPD with negative shape parameter has an upper bound (Coles, 2001), it limits the extrapolation of new extremes. We found that negative values of ξ often result in unrealistically high correction values. To mitigate this problem and to ensure the whole range of possible future extremes is captured, we introduced an additional version of QM by setting the lower bound of ξ to zero, similar to Kallache et al. (2011). In general, this constraint is suitable for stream flow or precipitation data (Katz, 2002; Katz *et al*., 2002; Reiss and Thomas, 1997). The new method, first without controlling the shape parameter and second with controlling the shape parameter is hereafter referred to as QMβ0 and QMβ1, respectively. The correction function is defined, as the statistical difference between RCM output and observations is constructed using equations (1) and (3). Daily correction functions are constructed for all stations in the study area, using a sliding window of 30 days and a similar method (Thrasher *et al*., 2010; Themeßl *et al*., 2012; Wilcke, 2014). In the sliding window approach, bias correction is applied on a single day of the year and collected data points from the surrounding 30 days (±15 days before or after the day of interest). This approach produces useful data sets with a better sample size. An example of 20 years calibration period hold 620 values. The three bias correction methods are implemented and subsequently compared.

RESULTS AND DISCUSSION

Correction function

As a first step, we compared the correction functions of QMα, QMβ0, and QMβ1. For illustration, we are showing the correction functions of a single station (Brocken) and a single model (the ICTPREGCM3) for day 15 of each month throughout the period 1961-2000 (Fig 2). In addition to this, for new extremes, we investigated the correction functions up to 10 mm greater than the model maximum precipitation value (vertical dashed line). Fig 2 demonstrates the unstable behaviour of bias correction at higher quantiles of the calibration range (left of the dashed line), with QMα (navy blue) in January, April, and August, whereas the correction with QMβ0 (green) and QMβ1 (sky blue) is smoother. Differences between the QMα and QMβ methods for new extremes (right side of the dashed line) are clearly visible (Fig 2), as an extrapolated constant correction value appearing with QMα (navy blue). Correction values of the QMβ (QMβ0 (green) and QMβ1 (sky blue)) were extrapolated by using extreme value statistics. The main advantage of the new bias correction method (QMβ) is that, it is possible to obtain more reasonable correction values for new extremes instead of constant correction values with QMα (right side of the dashed line). In most cases, QMβ0 and QMβ1 yielded identical results, but unrealistically large correction values were found for QMβ0 in February and March at precipitation values beyond the calibration range (right of the dashed line). Here, QMβ1 helped to maintain reasonably small correction values

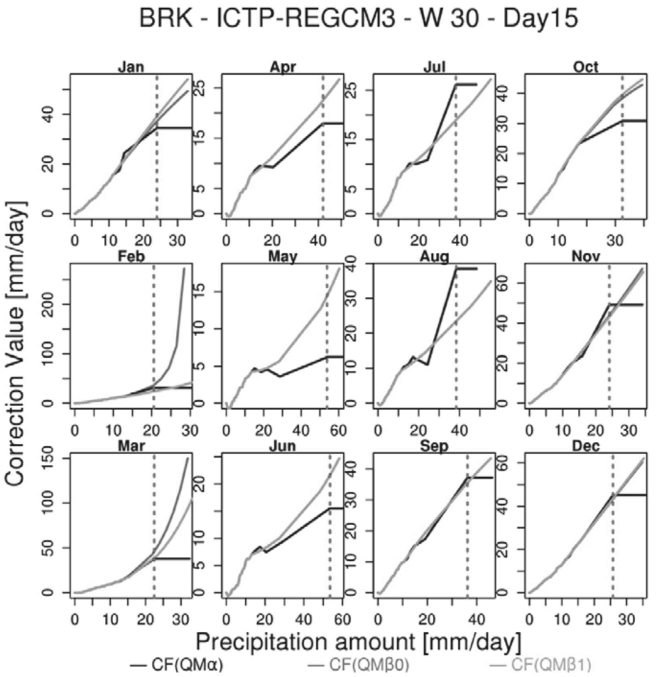

Fig. 2 : Daily correction functions of the three QM methods (QMα, QMβ0, and QMβ1) for the ICTP-REGCM3 model for station Brocken, Germany and the period 1961-2000. The red vertical line shows the start of the new extremes data.

in this range of "new extremes". Both QMβ0 and QMβ1 are identical when the fitted GPD has a positive shape parameter, which can be observed between April to September.

Quantile–quantile plots (q-q plots)

Split sample test

In the split sample test, independent validation and calibration periods were used. In this case, the calibration period was 1961-1980, while the data was validated in the independent period 1981-2000. The results of the split sample evaluation are presented as q-q plots, where model values were plotted against observed values, both are corresponding to the same probability. These are useful for checking the fit of external distributions, as they are particularly effective for highlighting discrepancies in the upper tail of the distribution. Season-wise q-q plots were created using observational, raw RCM, and bias- corrected data generated with three QM methods of the four RCMs and conducted for Weiden station (Fig. 3a to Fig. 3d). The model values correspond to the x-axis and the observed values to the y-axis. Uncorrected RCM data (red) was either overestimates or underestimates extreme precipitation events in all seasons, and in particular shows deficiencies for the less extreme precipitation events, compared to the bias-corrected results. All bias correction methods are able to rectify this issue, except (to some extent) for the highest extremes. The QMα version (navy blue) shows slightly larger over/underestimations of the highest quantiles than the uncorrected RCMs. The QMß versions (green and sky-blue), also show smaller errors than the uncorrected RCM for the highest extremes, in most cases. However, the effects of non-stationarity (which are inherent to the split-sample evaluation framework) make it hard to judge the performance of the QM implementations in more depth.

Cross validation (new extremes)

As described in Materials and Methods, a cross-validation framework with a particular focus on new extremes excluding the effects of non-stationarity was developed. In this frame, we used the same dataset used for calibration and evaluation, but neglect 1% of the highest precipitation events for each season from observation, as well as from the models during the calibration process. To cross-validate large events, we used data for the period 1961-2000 for calibration and neglected 1% data for evaluation. In the evaluation, the neglected 1% of data was included again and can be regarded as representing new extremes. Season-wise q-q plots were created using observational, raw RCM, and bias-corrected data generated with three QM methods for the Brocken station for four selected RCMs as shown in Figs.4a to Fig. 4d. All values above the red dotted line are new extreme events. Uncorrected RCM data (red) either overestimated or, as in the case of Brocken station, underestimated all new extreme precipitation events in all seasons. All the bias correction methods were capable to produce new extreme events, and were for the most part better than the raw RCM, with very few exceptions. The QMβ0 method (green) showed higher biases than the uncorrected data in some cases at very highest quantiles, due to high correction values generated by shape parameter issues. This deficiency was resolved in QMβ1 method by controlling shape parameter. The QMβ1 (sky-blue) reproduced new extremes with low biases in all seasons, compared to QMα and QMβ0 (Fig. 4). For other stations and models, the results were comparable. An average skill score over all the stations and models is presented in next section for a more systematic evaluation.

Ranking and mean absolute error (MAE)

We ranked the raw RCM output and QM implementations by using a mean absolute error (MAE) skill score, introduced by Gudmundsson *et al.* (2012). This score averages the absolute differences between model and observation in 0.1 wide probabilities in each interval, with the upper limit given by x (for example, 0.1 for the 0 to 10

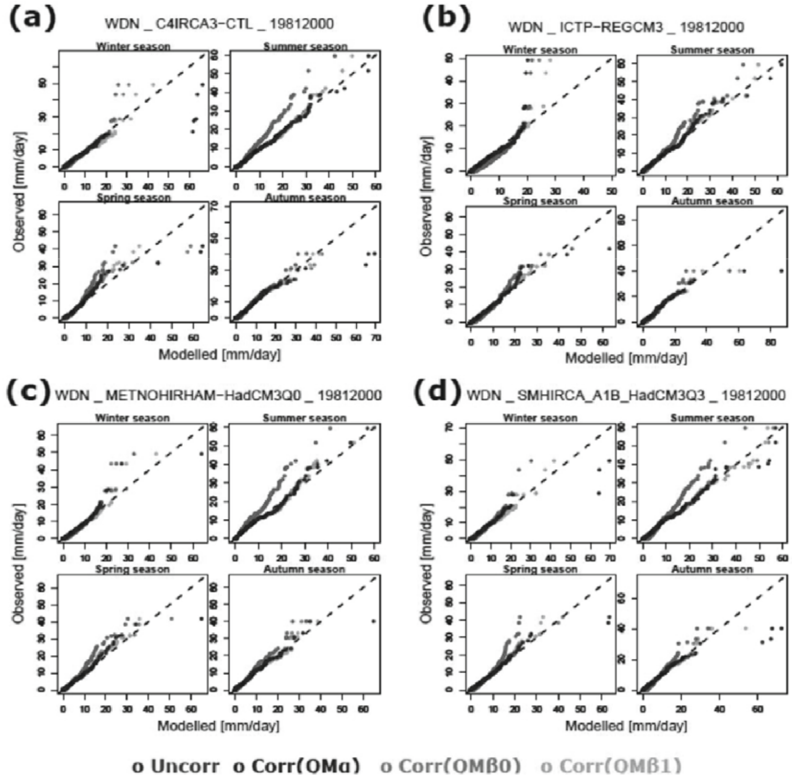

Fig. 3: q-q plots are shown to compare the daily precipitation distributions of uncorrected RCM data and three QM methods at the Weiden station for four RCMs (3a, 3b, 3c, and 3d).

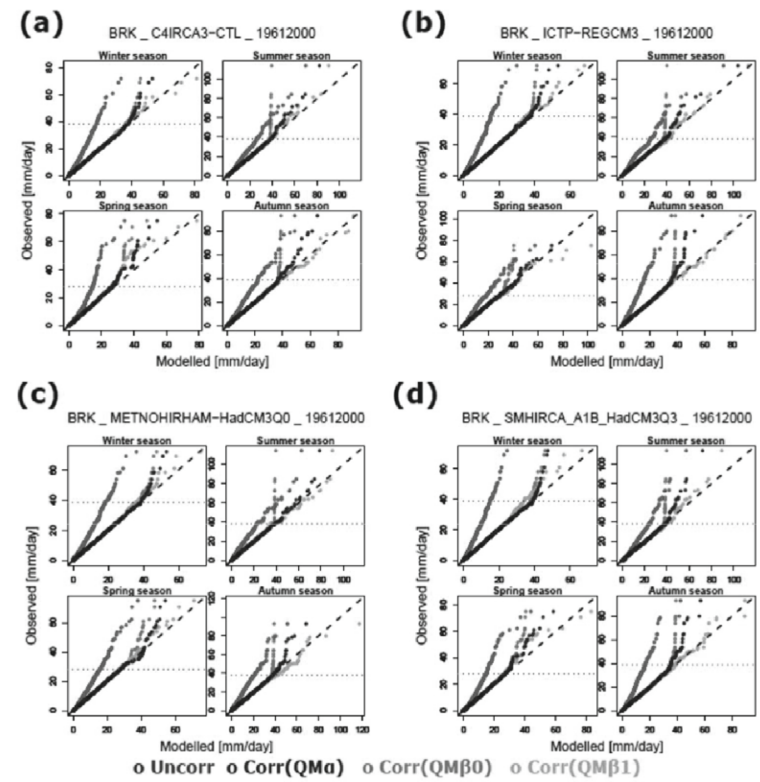

Fig. 4: q-qplots are shown for comparison of raw RCM output and different QM approaches for new extremes of daily precipitation at station Brocken, Germany for four RCM models (4a, 4b, 4c, 4d). The red horizontal line shows the start of the new extremes data.

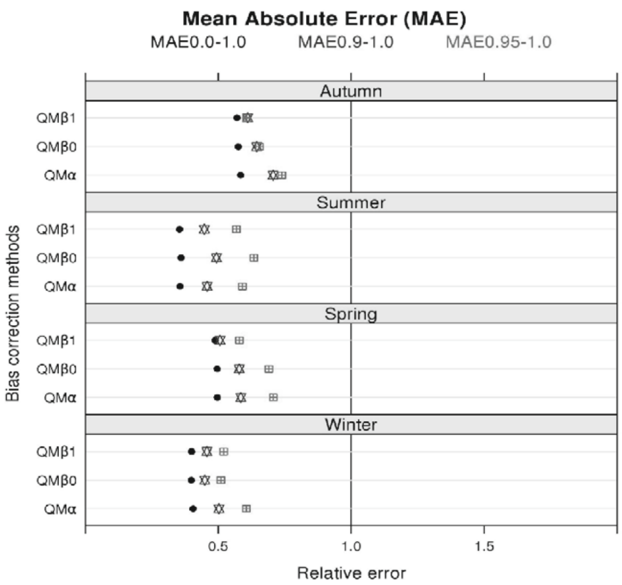

Fig. (5a) Split sample test

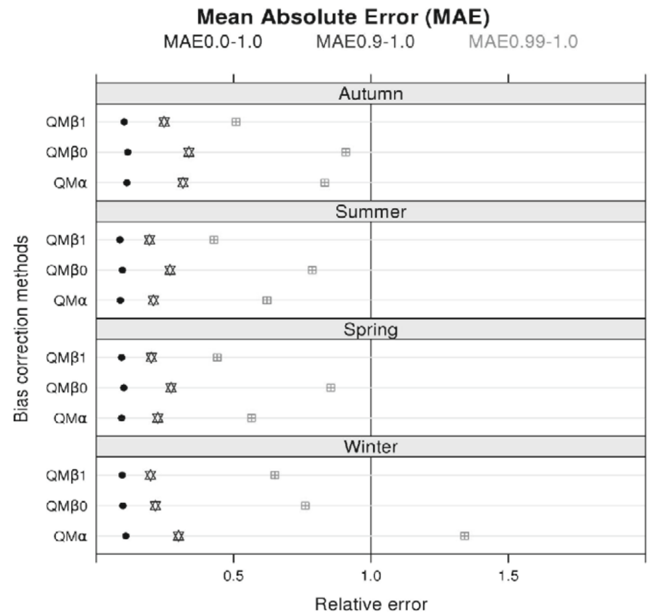

Fig. (5b) Cross validation test

Fig. 5a & 5b: Relative errors (MAE0.95-1.0, MAE0.99-1.0, MAE0.9-1.0, and MAE0.0-1.0) of the three QM implementations. a) Split sample test b) Cross Validation test

percentiles). Each interval is sub-divided into 1,000 steps. Thus, per interval, the absolute differences of 1,000 quantiles are averaged. Gudmundsson *et al.* (2012) calculated the $MAE_{0.1}$, $MAE_{0.2}$, . . ., $MAE_{1.0}$, where $MAE_{0.1}$ evaluates the dry part and $MAE_{1.0}$ the moderately extreme part of the distribution. Here, we applied the MAE skill score for split sample and the cross-validation framework and focused on extremes, not on the lower percentiles. Therefore, we additionally introduced $MAE_{0.99-1.0}$ and $MAE_{0.95-1.0}$. Here, $MAE_{0.99-1.0}$ focuses on new extremes in cross-validation framework, because it averages the 99 to 100 percentiles, that is, the 1% of precipitation events that we defined as new extremes. Focusing on the highest 5% of precipitation events, $MAE_{0.95-1.0}$corresponds to the part of the distribution where the GPD is fitted and represents more moderate extremes than $MAE_{0.99-1.0}$. All MAE_x scores were calculated season-wise for each station and model. Subsequently, the error (relative to the uncorrected RCM) was calculated by dividing the corresponding MAE_x of corrected RCM. If relative skill score is <1, an improvement is achieved. If relative error = 1 there is no improvement, and > 1 means a worsening has occurred. The relative errors were first calculated for seasonal for individual stations and models, and were then averaged over all the stations and models. In addition, the mean relative errors of all MAE_x were averaged, for example$MAE_{0.0-1.0,}$ which was used for ranking of the different bias correction methods by Gudmundsson et al. (2012).

Spit sample test (extremes)

The season-wise relative errors ($MAE_{0.95-1.0}$, $MAE_{0.9-1.0}$ and $MAE_{0.0-1.0}$) of the three QM implementations are presented for the split sample test (Fig. 5a). The results indicate that during all the seasons, three bias correction methods (QMα, QMβ0, and QMβ1), were able to reduce errors of the RCM (relative errors below 1), for extremes as well as for the mean absolute error ($MAE_{0.0-1.0}$). Further, the QMβ0 showed a better skill score than QMα except for summer season (Fig. 5a). Comparing the skill scores of all seasons, it was found that the performance of QMß1 was considerably better than QMβ0 for representing moderate extremes ($MAE_{0.95-1.0}$ and $MAE_{0.9-1.0}$). The relative error results indicate the following ranking: the QMß1 achieved the best performance, followed by QMβ0, and QMα.

Cross validation test (New extremes)

The season-wise relative errors ($MAE_{0.99-1.0}$, $MAE_{0.9-1.0}$ and $MAE_{0.0-1.0}$) of the three QM implementations (Fig. 5b) are presented for the cross-validation setup, which provides an opportunity to evaluate the performance with a particular focus on new extremes. As described in the previous Section, the $MAE_{0.99-1.0}$skill score focuses on new extremes. The relative errors were below 1 ($MAE_{0.99\text{-}1.0}$<1) for all three bias correction methods except QMα in winter. This means that under certain conditions, QMα may lead to a degradation of the simulation of new extremes, although in most cases it improved the simulation. This deficiency is removed in QMβ0 and QMß1, which significantly improved the simulation of new extremes during all seasons. In particular, QMβ1, which constrains the shape parameter, was clearly superior in this respect. The results also showed that, during all seasons the three bias correction methods were able to reduce errors very near to zero for the $MAE_{0.0\text{-}1.0}$. The $MAE_{0.0\text{-}1.0}$ was particularly low compared to the split sample test. This demonstrates the effect of non-stationary error characteristics, which play a role in the split sample test, but was excluded from the cross-validation test.

In summary, while considering the relative skill scores for ranking of the methods (Figs. 5a, 5b), all QM implementations improved simulated precipitation extremes simulated by RCMs, except for very few cases. The QMß implementations mostly performed better than the purely empirical QMα, and in particular QMβ1 was able to provide a stable improvement of the RCM output in any of the cases analysed here.

CONCLUSIONS

In this study, the problems of bias correction for extreme precipitation events as simulated by RCMs were addressed in detail as well as one of the most prominent bias correction methods, QM, was evaluated. A cross-validation framework with particular focus on new extremes excluding the effects of non-stationarity was developed, implemented, and tested. The error characteristics, q-q plots, and relative MAE skill scores tests showed that, the different QM implementations are very promising; particularly in a newly proposed method, that combines a parameter-free approach with extreme value theory at the tails of the distribution. The detailed analysis demonstrates that unstable behaviour of QM at higher quantiles with the purely empirical implementation QMα (but also with an unconstrained combined implementation QMβ1) leads to a sub-optimal performance in several cases. In some rare cases, QM even degrades the raw results of RCMs. An additional constraint in the fit of the GPD to the tail of the distribution (QMβ1) helps to maintain reasonably low correction values in such cases, and results in a bias correction method that considerably improves the simulation of precipitation extremes in all the cases evaluated. This refers to not only extremes in the classical sense, but also so-called new extremes, that is, values larger than those observed in the past.

These findings of the study are encouraging, because the new method has high skill and is easy to use. This makes it particularly attractive for RCM precipitation post-processing for impact studies. The method has the additional advantage that, it can be applied without specific assumptions about the distribution of the data. Therefore, it can easily be transferred to other meteorological parameters.

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