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Technical Note: Downscaling RCM precipitation to the station scale using statistical transformations – a comparison of methods

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Abstract. The impact of climate change on water resources is usually assessed at the local scale. However, regional climate models (RCMs) are known to exhibit systematic biases in precipitation. Hence, RCM simulations need to be post-processed in order to produce reliable estimates of local scale climate. Popular post-processing approaches are based on statistical transformations, which attempt to adjust the distribution of modelled data such that it closely resembles the observed climatology. However, the diversity of suggested methods renders the selection of optimal techniques difficult and therefore there is a need for clarification. In this paper, statistical transformations for post-processing RCM output are reviewed and classified into (1) distribution derived transformations, (2) parametric transformations and (3) nonparametric transformations, each differing with respect to their underlying assumptions. A real world application, using observations of 82 precipitation stations in Norway, showed that nonparametric transformations have the highest skill in systematically reducing biases in RCM precipitation.

1 Introduction

It is well established that precipitation simulations from regional climate models (RCMs) are biased (e.g. due to limited process understanding or insufficient spatial resolution (Rauscher et al., 2010)) and hence need to be post processed (i.e. statistically adjusted, bias corrected) before being used for climate impact assessment (e.g Christensen et al., 2008; Maraun et al., 2010; Teutschbein and Seibert, 2010; Winkler et al., 2011a,b). In recent years a multitude of studies has investigated different post processing techniques, aiming at providing reliable estimators of observed precipitation climatologies given RCM output (e.g. Ines and Hansen, 2006; Engen-Skaugen, 2007; Schmidli et al., 2007; Dosio and Paruolo, 2011; Themeßl et al., 2011; Turco et al., 2011; Chen et al., 2011b; Teutschbein and Seibert, 2012). Among the most popular approaches are statistical transformations that aim to adjust (selected aspects of) the distribution of RCM (e.g. Ashfaq et al., 2010; Dosio and Paruolo, 2011; Rojas et al., 2011; Themeßl et al., 2011; Sunyer et al., 2012) and global circulation model (GCM) (e.g. Wood et al., 2004; Ines and Hansen, 2006; Boé et al., 2007; Li et al., 2010; Piani et al., 2010a,b; Johnson and Sharma, 2011) precipitation such that its new distribution resembles observations. However, there is no general agreement on the optimal technique to solve this task and the approaches employed differ at times substantially. Therefore, there is an urgent need for clarifying the relation among different approaches as well as for an objective assessment of their performance.

2 Statistical transformations

Statistical transformations attempt to find a function h that maps a modelled variable P_m such that its new distribution equals the distribution of the observed variable P_o. In the context of this paper, P_o and P_m denote observed and modelled precipitation, respectively. Following Piani et al. (2010b), this transformation can in general be formulated as

$$P_\mathrm{o} = h\left(P_\mathrm{m}\right). \tag{1}$$

Statistical transformations are an application of the probability integral transform (Angus, 1994) and if the distribution

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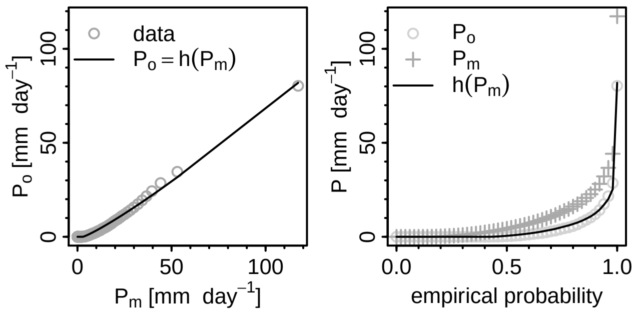

Fig. 1. Left: quantile–quantile plot of observed (P_o) and modelled (P_m) precipitation in Geiranger, Norway, as well as a transformation ($P_o = h(P_m)$) that is used to map the modelled onto observed quantiles. Right: empirical CDF of observed, modelled and transformed ($h(P_m)$) precipitation.

of the variable of interest is known, the transformation is defined as

$$P_o = F_o^{-1}(F_m(P_m)), \quad (2)$$

where F_m is the CDF of P_m and F_o^{-1} is the inverse CDF (or quantile function) corresponding to P_o.

Figure 1 illustrates statistical transformations for post processing RCM output using observed and modelled daily precipitation rates from Geiranger, in the fjords of western Norway. Modelled precipitation was extracted from a HIRHAM RCM simulation with 25 km resolution (Førland et al., 2009, 2011) forced with the ERA40 reanalysis (Uppala et al., 2005) on a model domain covering Norway and the Nordic Arctic. The left panel shows the quantile–quantile plot of observed and modelled precipitation as well as the best fit of an arbitrary function h that is used to approximate the transformation. The right panel shows the corresponding empirical CDF of observed and modelled values as well as the transformed modelled values. The practical challenge is to find a suitable approximation for h and different approaches have been suggested in the literature.

2.1 Distribution derived transformations

Statistical transformations can be achieved by using theoretical distributions to solve Eq. (2). This approach has seen wide application for adjusting modelled precipitation (e.g. Ines and Hansen, 2006; Li et al., 2010; Piani et al., 2010a; Teutschbein and Seibert, 2012). Most of these studies assume that F is a mixture of the Bernoulli and the Gamma distribution, where the Bernoulli distribution is used to model the probability of precipitation occurrence and the Gamma distribution used to model precipitation intensities (e.g. Thom, 1968; Mooley, 1973; Cannon, 2008). In this study, further mixtures, e.g. the Bernoulli-Weibull, the Bernoulli-Lognormal and the Bernoulli-Exponential distributions (Cannon, 2012), are also assessed. The parameters of the distributions are estimated by maximum likelihood methods for both P_o and P_m independently.

2.2 Parametric transformations

The quantile–quantile relation (Fig. 1) can be modelled directly using parametric transformations. Here, the suitability of the following parametric transformations was explored:

$$\hat{P}_o = b\,P_m \quad (3)$$

$$\hat{P}_o = a + b\,P_m \quad (4)$$

$$\hat{P}_o = b\,P_m^c \quad (5)$$

$$\hat{P}_o = b\,(P_m - x)^c \quad (6)$$

$$\hat{P}_o = (a + b\,P_m)\left(1 - e^{-(P_m - x)/\tau}\right) \quad (7)$$

where, $\hat{P}_o$ indicates the best estimate of P_o and a, b, c, x and τ are free parameters that are subject to calibration. The simple scaling (Eq. 3) is regularly used to adjust precipitation from RCM (see Maraun et al., 2010, and references therein) and closely related to local intensity scaling (Schmidli et al., 2006; Widmann et al., 2003). The transformations Eq. (4) to Eq. (7) were all used by Piani et al. (2010b) and some of them have been further explored in follow up studies (Dosio and Paruolo, 2011; Rojas et al., 2011). Following Piani et al. (2010b), all parametric transformations were fitted to the fraction of the CDF corresponding to observed wet days ($P_o > 0$) by minimising the residual sum of squares. Modelled values corresponding to the dry part of the observed empirical CDF were set to zero. Note, that the resolution of the precipitation observations used in this study (see Sect. 3) is 0.1 mm day^{-1} which implies a threshold of $\leq$ 0.1 mm day^{-1}.

2.3 Nonparametric transformations

2.3.1 Empirical quantiles (QUANT)

A common approach is to solve Eq. (2) using the empirical CDF of observed and modelled values instead of assuming parametric distributions (e.g. Panofsky and Brier, 1968; Wood et al., 2004; Reichle and Koster, 2004; Boé et al., 2007; Themeßl et al., 2011, 2012). Following the procedure of Boé et al. (2007), the empirical CDFs are approximated using tables of empirical percentiles. Values in between the percentiles are approximated using linear interpolation. If new model values (e.g. from climate projections) are larger than the training values used to estimate the empirical CDF, the correction found for the highest quantile of the training period is used (Boé et al., 2007; Themeßl et al., 2012).

2.3.2 Smoothing splines (SSPLIN)

The transformation (Eq. 1) can also be modelled using nonparametric regression. We suggest to use cubic smoothing splines (e.g. Hastie et al., 2001), although other nonparametric methods may be equally efficient. Like for the parametric transformations (Sect. 2.2), the smoothing spline is only fit to the fraction of the CDF corresponding to observed wet days and modelled values below this are set to zero. The smoothing parameter of the spline is identified by means of generalised cross-validation.

3 Data and implementation

The suitability of the different statistical transformations to correct model precipitation from the HIRHAM RCM forced with the ERA40 reanalysis was tested using observed daily precipitation rates of 82 stations in Norway, all covering the 1960–2000 time interval. The methods were implemented in the R language (R Development Core Team, 2011) and bundled in the package `qmap`, which is available on the Comprehensive R Archive Network (http://www.cran.r-project.org/).

4 Quantifying performance

To assess the performance of the different methods, a set of scores is needed that quantifies the similarity of the observed and the (corrected) modelled empirical CDF. Previously used scores include overall measures, such as the root mean square error (Piani et al., 2010b) or the Kolmogorov-Smirnov two sample statistic (Dosio and Paruolo, 2011). Other suggested scores assess specific moments of the distribution including the mean (Engen-Skaugen, 2007; Li et al., 2010; Dosio and Paruolo, 2011; Themeßl et al., 2011; Turco et al., 2011; Teutschbein and Seibert, 2012), the standard deviation (Engen-Skaugen, 2007; Li et al., 2010; Themeßl et al., 2011; Teutschbein and Seibert, 2012) and the skewness (Li et al., 2010). A variety of further scores are based on the comparison of the frequency of days with precipitation (Schmidli et al., 2006, 2007; Themeßl et al., 2011) and the magnitude of selected (mostly high) percentiles (Schmidli et al., 2006, 2007; Li et al., 2010; Themeßl et al., 2011; Teutschbein and Seibert, 2012). All these scores are either presented as maps or as spatial averages, which facilitate a quantitative comparison of methods.

4.1 Skill scores

One limitation of the scores above is that they can often not be summarised into one overall measure, e.g. due to different physical units or lack of normalisation. This renders a global evaluation, combining the advantages and drawbacks of different methods, difficult. Therefore, this study suggests a novel set of scores that aims at a global evaluation, while keeping track of many relevant properties of the distribution. Overall performance is measured using the mean absolute error (MAE) between the observed and the corrected empirical CDF. To assess the performance for more specific properties, for example related to the fraction of dry days, average intensities or precipitation extremes, further scores are needed. Here these properties are assessed using $\mathrm{MAE}_{0.1}$, $\mathrm{MAE}_{0.2}$, …, $\mathrm{MAE}_{1.0}$, the mean absolute errors computed for equally spaced probability intervals of the observed empirical CDF. The subscript indicates the upper bounds of 0.1 wide probability intervals. $\mathrm{MAE}_{0.1}$, for example, evaluates differences in the dry part of the distribution, indicating discrepancies in the number of wet days. Similarly, $\mathrm{MAE}_{1.0}$ indicates differences in the magnitude of the most extreme events. Note also that MAE can be computed as the mean of $\mathrm{MAE}_{0.1}$, $\mathrm{MAE}_{0.2}$, …, $\mathrm{MAE}_{1.0}$, which illustrates the consistency of these measures.

Statistical transformations, as any statistical technique, quietly assume that the modelled relation holds if confronted with new data. In the context of climate impact assessment this assumption is critical as it has to be expected that climate variables exceed the observed range in future periods. Further, highly adaptable methods, such as the nonparametric techniques used in this study, are prone to over fitting the data. Both issues require that model error is quantified using data that have not been used for calibration. A standard technique for this task is cross-validation (CV) (e.g. Hastie et al., 2001) which has been previously applied for evaluating statistical downscaling techniques (e.g. Themeßl et al., 2011, 2012). Here a 10-fold CV was employed to produce unbiased estimates of MAE and $\mathrm{MAE}_{0.1}$, $\mathrm{MAE}_{0.2}$, …, $\mathrm{MAE}_{1.0}$. First the data are split into 10 subsamples of continuous time intervals. The model is then calibrated using the data with one of the subsamples being removed. MAE and $\mathrm{MAE}_{0.1}$, $\mathrm{MAE}_{0.2}$, …, $\mathrm{MAE}_{1.0}$ are then estimated using the subsample that was not used for calibration. This procedure is repeated for each subsample and results in 10 estimates of model error. The mean of these 10 error estimates, the so called mean cross-validation error, is reported. In the remainder of this article MAE and $\mathrm{MAE}_{0.1}$, $\mathrm{MAE}_{0.2}$, …, $\mathrm{MAE}_{1.0}$ always refers to the mean cross-validation error to ease formulation.

4.2 Ranking of methods

In order to obtain a global comparison of the efficiency of the different methods their performance was ranked, closely following the procedure suggested by Reichler and Kim (2008). In a first step, relative errors are computed for each method by dividing the spatial averages of MAE and $\mathrm{MAE}_{0.1}$, $\mathrm{MAE}_{0.2}$, …, $\mathrm{MAE}_{1.0}$ by the corresponding scores of the uncorrected model output. In other words, the relative errors are defined as the individual points in Fig. 3 divided by the solid line. The relative errors range from an optimal value of zero to infinity. A value smaller than one indicates that the method causes an improvement; larger values indicate worsening. The relative errors where finally averaged for each method and ordered from the lowest (best method) to the highest value (worst method).

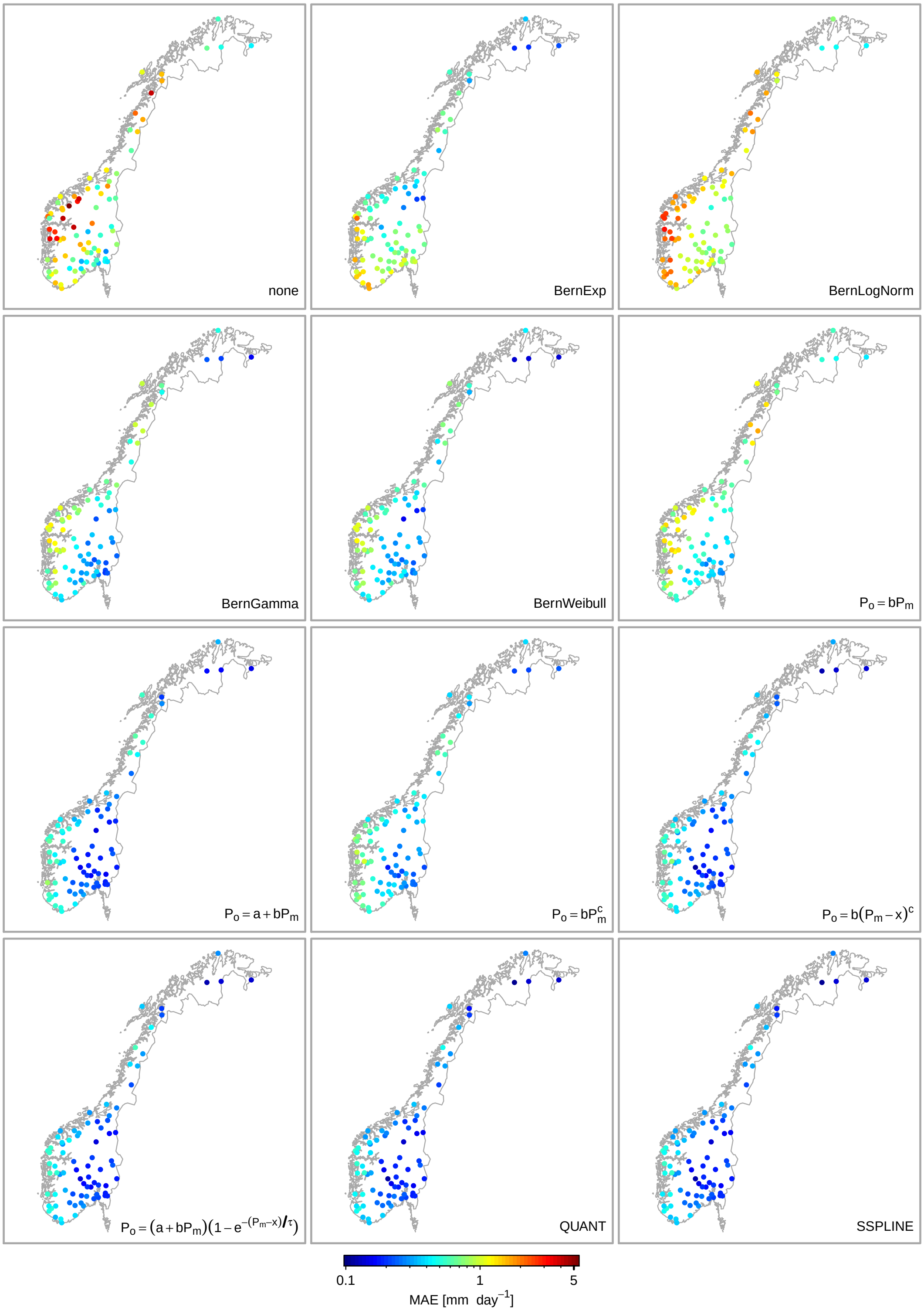

Fig. 2. Mean absolute error (MAE) between the observed and modelled empirical CDF for different statistical transformations, estimated using 10-fold cross-validation for the 1960–2000 time interval. "none" indicates uncorrected modelled values. Distribution derived transformations are based on the Bernoulli-Exponential (BernExp), the Bernoulli-Log-normal (BernLogNorm), the Bernoulli-Gamma (BernGamma) and the Bernoulli-Weibull (BernWeibull) distributions. Equations: parametric transformations. QUANT: statistical transformations based on empirical quantiles. SSPLINE: statistical transformation using a smoothing spline.

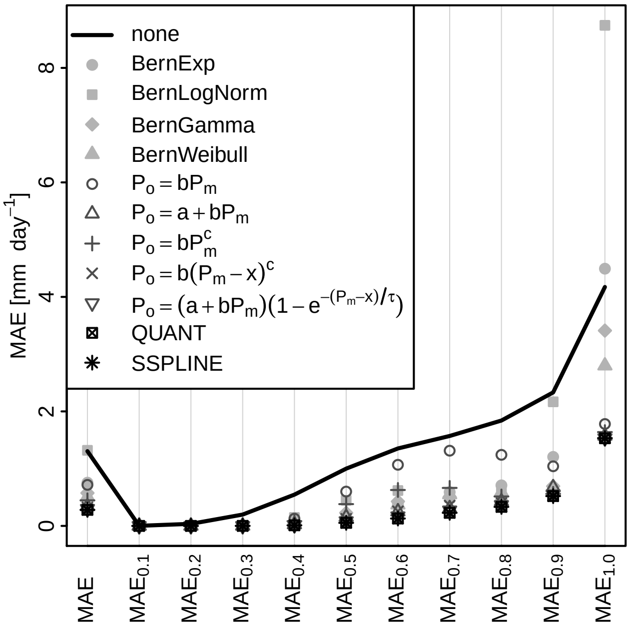

Fig. 3. Total mean absolute error (MAE) and the mean absolute error for specific probability intervals ($MAE_{0.1}$, $MAE_{0.2}$, …, $MAE_{1.0}$), averaged over all stations.

5 Performance

The MAE for all stations and all methods under consideration is shown in Fig. 2. For the uncorrected model output MAE has pronounced geographic variations. The largest errors are found along the west coast, where the model cannot resolve the orographic effect on precipitation with sufficient detail. Most methods reduce the error and even out some of its spatial variability. An exception is the transformation based on the Bernoulli-Log-normal distribution, which does not lead to any visible improvements. The largest improvements are achieved by parametric and nonparametric transformations, especially along the west coast.

The MAE and $MAE_{0.1}$, $MAE_{0.2}$, …, $MAE_{1.0}$ averaged over all stations are shown in Fig. 3. Most methods reduce both the total MAE as well as the MAE for the percentile intervals. The absolute improvements are in most cases largest for the upper part of the CDF ($p \geq 0.5$). Note however, that two of the distribution derived transformations (Bernoulli-Exponential and Bernoulli-Log-normal) increase the error for the most extreme values. In the lower part of the CDF, the absolute improvements are generally smaller, owing to the small (often zero) precipitation rates.

Figure 4 shows the ranking of the methods, based on the mean of the relative error (black dots). The hollow symbols show the relative errors for the total MAE and $MAE_{0.1}$, $MAE_{0.2}$, …, $MAE_{1.0}$. The two nonparametric methods SSPLINE and QUANT have on average the best skill in reducing systematic errors, also for very high (extreme) percentiles, being in line with other studies (Themeßl et al., 2011; Teutschbein and Seibert, 2012). The success of the nonparametric transformations is likely related to their flexibility as they do not rely on any predetermined function. This flexibility allows good fits to any quantile–quantile relation. As for all highly adaptable methods with many degrees of freedom, over fitting may be a concern. Recall, however, that all scores are estimated using cross-validation, and that the estimated model error is independent from the data used for calibration. This suggests that over fitting is no major problem if there are sufficient data. Nevertheless, over fitting may be an issue if the nonparametric transformations are calibrated using small data samples, i.e. time series that cover only a short period. Similarly it cannot be ruled out that the methods perform badly if the projected climatic conditions differ substantially from the calibration period.

The large spread in performance of parametric transformations is likely related to the flexibility of the different functions. Parametric transformations with three or more free parameters (Eqs. 6 and 7) are almost as efficient as their nonparametric counterparts. Transformations with less flexibility, in particular the simple scaling function (Eq. 3), do have worse performance.

The distribution derived transformations rank on average lowest. The best ranking distribution derived transformation is based on the Bernoulli-Weibull distribution. The transformation derived from the Bernoulli-Log-normal distribution has the lowest performance of all considered methods. Note also that all distribution derived transformations have particularly low performance with respect to the extreme part of the distribution. The low performance of distribution derived transformation may seem somewhat surprising, given the theoretical elegance of this approach. This is likely related to the fact that the parameters of the distributions are identified for P_o and P_m separately, which enables good approximations of the distributions of P_o and P_m but does not necessarily optimise the statistical transformation as defined in Eq. (1).

6 Possible limitations of statistical transformations for post-processing RCM putput

Prior to application of statistical transformations and related post processing methods it is important to recall that these techniques are designed with a limited scope: to adjust the simulated climate variable such that its distribution (or some aspects of it) matches the distribution of observed values. If applied in climate impact assessment it is then subsequently assumed that the difference between model output and observations is stationary, i.e. that the same corrections are applicable in future climates. The validity of this assumption cannot be fully assessed, as the variable of interest may exceed the observed range in a changing climate. However, the results of performance assessments using cross-validation, in this and in other studies (Themeßl et al., 2012, 2011),

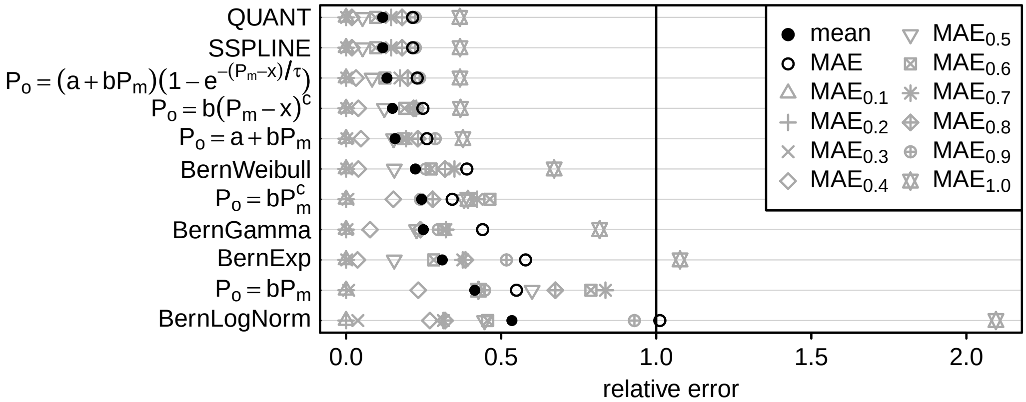

Fig. 4. Performance ranking of statistical transformations used for post-processing RCM output. Relative error (hollow symbols) is defined as the MAE of each method divided by the MAE of the uncorrected model output. The mean relative error (black dots) is used to rank the different methods.

indicate the stability of the methods. Further, numerical experiments on the global scale have shown that uncertainty related to the choice of calibration period is small compared to uncertainties related to choice of climate model and emission scenario (Chen et al., 2011a).

A related concern is the impact of post processing techniques on the climate change signal. Empirical investigations indicate that the impact of statistical transformations on the projected changes in mean conditions is comparably small but may systematically alter changes in nonlinearly derived measures, including characteristics of extreme events (Themeßl et al., 2011). Similarly statistical transformations and other bias correction techniques may have side effects on further statistical properties even if they are not explicitly designed to change these. Examples include changes in the amplitude of low frequency variability (Haerter et al., 2011) or the modification of measures characterising temporal persistence (Johnson and Sharma, 2012, 2011). However, whether these side effects are considered to be beneficial (correction of higher order properties), adverse (introduction of artifacts) or neutral (e.g. if only mean values are of interest) depends on particular applications and has to be evaluated on a case to case basis.

7 Conclusions

The three approaches using statistical transformation to post-process RCM output that were assessed in this paper differ substantially with respect to their underlying assumptions, despite the fact that they are all designed to transform RCM output such that its empirical distribution matches the distribution of observed values. A real-world evaluation of a wide range of statistical transformations showed that most of them are capable to remove biases in RCM precipitation. Despite this overall success, it was also demonstrated that the performance of the methods differ substantially. Therefore, we stress that these techniques should not be applied without checking their suitability for the data under consideration. The methods with the best skill in reducing biases from RCM precipitation through the entire range of the distribution are all classified as nonparametric transformations. These have the additional advantage that they can be applied without specific assumptions about the distribution of the data and are thus recommended for most applications of statistical bias correction.

Appendix A

Note on terminology

Throughout the preparation of this article issues concerning the terminology have been raised. Among the terms used for the presented techniques are "quantile mapping", "quantile matching", "cumulative distribution function (cdf) matching", "quantile–quantile transformation", "histogram equalisation or matching", "probability mapping", distribution mapping (see e.g. Maraun et al., 2010; Teutschbein and Seibert, 2012). In most instances these terms are used to refer to distribution derived transformations (Sect. 2.1) and nonparametric transformations (Sect. 2.3). However, some of these terms ("quantile mapping", "histogram equalisation or matching") have also been used to refer to parametric transformations as defined in Sect. 2.2 (Piani et al., 2010b), causing some ambiguity regarding the proper nomenclature. Further, "statistical bias correction" (Piani et al., 2010a,b), "direct error correction methods" (Themeßl et al., 2011) and "model output statistics (MOS)" (Maraun et al., 2010) have been used to refer to the methods under investigation. Unfortunately, this large variety in terminology can lead to misapprehensions regarding the actually used methods. Therefore, the more technical term "statistical transformation" was used in this study to emphasise the common objective of the presented techniques without interfering with previously used terminology.

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