We would like to thank Prof. A. Bárdossy for his interest in this topic and for the valuable comments to improve our manuscript. Based on the comments some recalculations have been performed. Our point-by-point response to the comments is given in the following:

General Comments

The goal of bias correction is to provide time series which preserve the signal of the meteorological models, but are not biased with respect to the observations.

Comment 1

The methodology provides a set of realizations as time series. The evaluations are based on the mean of theses series. The mean is however not a good bias corrected series, as it has a different marginal (with reduced variance) than what was assumed. Thus the comparisons made with the mean of the realizations are misleading and do not reflect the quality of the corrected time series.

Answer

1. The major goal and motivation of this study is to develop a new framework for the bias correction of precipitation time series for subsequent modellers, e.g. in hydrology, based on the concept of Copulas. Our focus is on the introduction and demonstration of the methodology. We are not applying it to climate change analyses, trend analyses, or climate projections here. Subsequent modellers usually request one corrected value for each time step rather than a "Probability Density Function (PDF)". This is mainly due to practical reasons since they cannot handle the full PDF for subsequent analyses. However, the framework provides the possibility to obtain a large set of random realizations or alternatively give additional information about the PDF for each corrected time step (e.g. the spread of the distribution in form of the interquartile range) thus providing an additional quality criterion for the bias correction. If the spread of the sampled distribution is small, the corrected value (e.g. represented by the mean of the distribution) can be regarded to be more "trustworthy" compared to the corrected value based on a wide PDF.

2. We also agree that the mean will follow a different distribution with reduced variance. However, we are more interested in better correcting each time step separately instead of better matching the statistical distribution. Figure 1 shows the percentage of the corrected time steps that are closer to the observations in comparison of the Quantile Mapping method. It can be seen that the Copula-based correction in general provides a higher percentage of successful corrections for the whole domain. Based on the mean values for simulation, the bias is significantly reduced indicating the overall justification of this approach (Page 7224 in the manuscript).

3. Without any further a-priori knowledge, the mean or median value is a widely-accepted estimator which is frequently used in literature (e.g. Gao et al. (2007), Serinaldi (2008), Laux et al. (2011) and Vogl et al. (2012)). This approach can be regarded as a regression method (Nelsen (1999), Section 5.5).

   As mentioned already in the paper (Page 7203, Line 24-27 in the manuscript), we also tested the median and mode value for the correction and found that the mean value performs best. Both simulations based on the median and the mode tend to significantly underestimate the results (please see Figure 2). Therefore, we are convinced that the choice of the mean values is sound and acceptable.

Comment 2

It is unclear for me why the authors did not use the normal copula for the description of the dependence. There is no reason to assume tail dependence, and there are no evaluations with respect to extremes.

Answer

Initially, we did not consider the Gaussian Copula in this study due to the following reason: The Gaussian Copula is able to describe a similar dependence structure as the Frank Copula. In general, it exhibits a linear dependence with slightly higher densities in the lower and upper tails compared to the Frank Copula. Based on findings from our previous works (Laux et al. (2011), Vogl et al. (2012)), we excluded the Gaussian Copula to be a suitable candidate in our study.

We now followed the suggestions of the reviewer to include the Gaussian Copula as a potential candidate in our study and did a full recalculation of the Copula fitting and the GoF tests. Based on our GoF tests, the Gaussian Copula indeed is selected for numerous grid cells in the domain. Figure 3 shows the maps of the identified Copula families (now after adding the Gaussian Copula) for each season. It can be seen that most of the grid cells that were previously assigned to the Frank Copula are replaced by the Gaussian Copula. This is in agreement with our expectations since both the Gaussian and the Frank Copula are able to describe a similar dependence structure. The fraction of grid cells assigned to Gaussian Copula models which were previously assigned to the Frank Copula are 82%, 71%, 87% and 91% for MAM, SON, JJA and DJF, respectively.

We completely recalculated the bias maps for Germany including the Gaussian Copula. The new updated maps are shown in Figure 4 (annually) and 5 (seasonally). No significant differences between the original relative bias maps (based on Frank, Gumbel, Clayton) and the extended new ones (Gaussian in addition) can be seen at glance. The overall bias (integrated over all grid cells) is slightly reduced if compared to the previous bias map (page 7224-7225 in the manuscript).

Comment 3

It is not clear how the authors handle zero precipitation. Further how the problem of different zero precipitations for the model and the observations is treated? How is the distribution of the lower dry probability modified?

Answer

The strategy and procedure how to handle the different cases, including zero precipitation is described in detail in section 3.6 of the manuscript. In general, we have the following four cases:

1. (1,1): REGNIE and WRF precipitation $\geq$ pre-defined threshold
2. (0,1): REGNIE $<$ threshold, while WRF $\geq$ threshold
3. (1,0): REGNIE $\geq$ threshold and WRF $<$ threshold
4. (0,0): Both REGNIE and WRF $<$ threshold

The threshold is introduced to remove the drizzle behaviour of the RCM. It is described in more detail in the manuscript. Our concept is that the Copula-based correction technique is only applied for (1,1) cases (please see Figure 6), since the Copula can operate on positive pairs only. For the (0,0) case, there is no error to be considered. And we are keeping the values of the WRF simulations for both the (0,1) and (1,0) cases. As mentioned before, our main goal

of this study is to correct the precipitation values for each single time step rather than fitting (adjusting) the "Cumulative Density Function" (CDF). Using well-established approaches for adjusting dry probabilities such as e.g. the local scaling method allows only the correction of the fraction of dry days. However, it does not guaranty the correction for each single time step. A small example using one randomly selected grid cell from our domain is used to illustrate this. The four cases proportion can be seen from Table 1. Before the adjustment, the dry probabilities of REGNIE and WRF in the selected example grid cell are $0.07 + 0.21 = 0.28$, and $0.07 + 0.06 = 0.13$, respectively. After the local scaling adjustment, the dry probabilities are $0.14 + 0.14 = 0.28$, and $0.14 + 0.14 = 0.28$, respectively. However, from the table we can still see nearly the same proportion of (0,1) and (1,0) errors ($0.14 + 0.14 = 0.28$) after adjustment of the dry probability if compare to that ($0.21 + 0.06 = 0.27$) before the adjustment. This means that the dry probabilities are adjusted, but the error fractions still remain. Therefore, we do not correct the errors from (0,1) and (1,0) cases in this study. Instead we are keeping the values of the WRF simulations for both cases to preserve the signal of the WRF model.
Furthermore, we also investigated the proportion of four cases over our study area (please see also Figure 2 in the response to specific Comment #5 of reviewer #2). It can be seen that the high proportion has been taken by the (1,1) case. The proportion of both the (0,1) and (1,0) cases are low, especially for the (1,0) case.

Comment 4

It is unclear to me why the authors did not use truncated copulas as suggested in Bárdossy and Pegram (2009) which is referenced in the paper. This approach could help to avoid several problems with the zeros.

Answer

The truncated Copula suggested in Bárdossy and Pegram (2009) can describe the intermittent nature of rainfall and the dependence structure. The same can be achieved by a Copula-based mixed model following the approach of Serinaldi (2008). Both methods are able to produce time series that hold the same proportion of different cases ((0,0), (0,1), (1,0), (1,1) cases). Similarly to the above mentioned local scaling adjustment of the dry probabilities, these methods also can only correct the total number of dry days but cannot adequately correct and reduce the errors for the (0,1) and (1,0) cases.

Comment 5

The fit of a parametric distribution followed by a fit of the copula based on the empirical distribution is statistically not correct.

Answer

We were wrong in the description of the goodness-of-fit test. We checked that the calculation, however, is correct. We now changed the text (Page 7197, Line 7 in the manuscript) as follows: "Let $\{r_1(1), ..., r_1(n)\}$ and $\{r_2(1), ..., r_2(n)\}$ denote the ranks of observed and modelled rainfall from day 1 to day n, obtained from the original data." to "'Let $\{r_1(1), ..., r_1(n)\}$ and $\{r_2(1), ..., r_2(n)\}$ denote the values that are transferred from the fitted theoretical marginal distribution."

Comment 6a

Is a parametric fit of the local precipitation distribution really needed? In my opinion the empirical distributions or a non-parametric fit would do a better job. Further this would avoid some *problems with the spatial discontinuities imposed by taking different distributions.*

Answer

We do not fully agree to this comment. First, because the parametric fit of the local precipitation distribution is a well-accepted approach in literature (e.g. Dupuis (2007), Gao et al. (2007)). It gives further flexibility for the simulation of random realizations. Second, we want to illustrate the spatially distributed differences provided as fitted marginal family maps between WRF and the REGNIE data. This gives information about the performance of a regional atmospheric model. Albeit an interpretation of these results is difficult, we try to analyze them in terms of the underlying topography (Johansson and Chen (2003)). This finally helps to identify the problems (hotspot regions) of the WRF simulations. We will highlight and stress this additional objective and interest of our study more clearly in the updated manuscript.
Actually, the difference between non-parametric and parametric fitting is that the non-parametric can be regarded as the perfect fit. They behave similarly if the sum of the squared residuals between parametric and empirical distribution is small.
However, we followed the suggestion and recalculated the results by taking the non-parametric marginal fitting. The calculated relative bias maps are shown in Figure 7 and 8. It is seen that there are only small differences between the non-parametric and the parametric fitting based corrections. For the reasons mentioned above, we prefer to use the parametric approach.

Comment 6b

The use of different copulas for the different locations is also causing spatial ruptures.

Answer

From the fitted Copula family maps (Page 7222 in the manuscript), it is clear that the fitted Copulas vary over time and space due to the fact that the dependence structure mainly depends on the topography and prevailing circulation patterns. Using one common theoretical Copula such as the Gaussian model to describe the dependence over the whole domain may not be appropriate. In some areas, for instance, this does not adequately reflect the underlying dependence structures. The dependence may tend to be more concentrated in the lower or upper tails of the joint distribution, which cannot be captured well by one candidate exclusively (e.g. the Gaussian Copula).
Moreover, we are also interested in analyzing the spatial patterns of dependence across Germany (Copula family map) for our data sets (REGNIE and WRF). As an example, it is found that the dominated Copula in the summer season is Clayton, which means that the dependence between observed and modelled rainfall is stronger in the lower values.

Comment 6c

The method provides individual time series for each pixel. The simulated series are independent, thus there is no spatial coherence. This is a serious restriction of the suggested methodology, which can thus only be used for local and small scale studies.

Answer

Yes, the method corrects the time series for each pixel independently. However, our approach allows to preserve the spatial structure through the conditioning WRF model output (please see Figure 9). From the corrected precipitation field for the sequence of a few days, we can see that the corrected fields follows the pattern of raw WRF data, while the absolute values are slightly different. This is due to the reason that our Copula-based approach is conditioned on the WRF simulation. The method is adjusting the value of the WRF precipitation according to the fitted Copula model. Even though the Copula models are estimated for each grid cell, the spatial coherence is captured by the Copula model as both the Copula families as well as the marginal distributions are spatially clustered.

Comment 7

The evaluation of the series is only concentrating on the mean behavior of the simulated series. There are no attempts to look at other statistics, such as variance, dry probability etc.

Answer

As mentioned already before, our Copula concept is applied to the correction of the (1,1) cases. The dry probability is not further corrected in this study. Since the method is a stochastic technique, Monte Carlo simulations are performed. By taking a "typical" (mean) value of the realizations from the Monte Carlo simulations, the variance is reduced. To assess the performance of the proposed method, besides of the mean daily precipitation evaluation, we also looked at the mean monthly precipitation, the RMSE and the quantile RMSE values for selected grid cells (Page 7226-7227 in the manuscript). In addition, we calculated also the RMSE map for the whole domain to compare with the Quantile Mapping method (see Figure 10). For the Copula-based correction, we also included the mode regression (taking the highest probability value of the realizations as the "typical" value) and the median regression corrected time series. It can be seen that the mean regression performs best, and the Quantile Mapping even increases the RMSE values for the majority of grid cells in the domain.

Comment 8

The bias remaining after the correction is very high. It would be interesting to know how the observed and modelled precipitation itself was changing. Was the signal captured?

Answer

It can be seen from Figure 8 in the manuscript (Page 7224 in the manuscript) that most of the bias are removed after correction. In different seasons (Page 7225 in the manuscript), as mentioned in the manuscript, the average bias are reduced from 32% to 16% in spring (MAM), from -15% to -11% in summer (JJA), from 4% to -1% in autumn (SON) and from 28% to -3% in winter (DJF). The results show that the biases are corrected efficiently especially in winter. To investigate typical situations in detail, we also evaluated the monthly mean precipitation for selected grid cells (Page 7226 in the manuscript). It is shown that the biases are significantly reduced.

We are not sure, if the question of the reviewer also is directed towards climate trends. As stated in the first comment, we do not address climate trends in this study. The analysis of climate trends are beyond the scope of this study. For the response to the reviewer, however, we have now also evaluated the annual mean precipitation (original REGNIE, WRF, and bias corrected WRF) for the years 1986 till 2000 (please see Figure 11). No clear trend can be seen on the first sight. However it can be clearly seen that our bias corrected precipitation values are now much closer to REGNIE compared to the uncorrected WRF.

Comment 9

The possibly biggest problem with the method is its partial inability to reflect the signal of the meteorological model. The weaker the dependence between model and observations the less the model signal is reflected after bias correction.

This is illustrated with a small example. I simulated 500 realizations of modelled precipitation with a mean of 2mm using an exponential distribution. The observed precipitation has a mean of 3 mm and follows an exponential distribution. Copulas with different degrees of dependence ranging from full dependence to independence were used.
It is assumed that the model shows a precipitation increase of 50%. The corresponding bias corrected series were simulated, and the means were compared to the original mean (3mm for the observations). The increase in precipitation varied between 0 and 50% depending on the degree of dependence. The weaker the dependence the smaller is the signal which is captured. This is unfortunately not in the sense of bias correction, where the signal should be reflected.

Answer

Thank you very much for the time and efforts the reviewer spent to calculate this small artificial example. In order to analyze the signal-dependence relationship and inspired by the principle idea of the reviewer's example calculation, we repeated the calculations but used our algorithm for the conditional sampling instead. We followed the following procedure:

1. Simulate 500 realizations of modelled precipitation with a mean of 2 mm using an exponential distribution.
2. Assume that the observed precipitation has a mean of 3 mm and also follows an exponential distribution.
3. Assume that the dependence between modelled and observed precipitation follows a Gaussian Copula with a given rank correlation (dependence).
4. Conditional sampling: Generate 100 bias corrected precipitation time series and calculate their mean (variance) values to obtain a corrected time series of the 500 values.
5. Compare the mean (and variance) of the corrected series to the original mean (3 mm for the observation) and calculate the increase of the precipitation.
6. Repeat steps 3-5 for different rank correlations ranging from 1 (full dependence) to 0 (independence).

Apart from the results obtained by the reviewer, Figure 12 shows that the signal is nearly constant while the dependence is decreased. The increase of the modelled precipitation (50% as assumed) is always in the range of 50%. This gives strong indication that our method is able to preserve the signal of the input data (here: the WRF precipitation fields) and correct for the biases with respect to the observations. Besides the consideration of the mean, the variance of the corrected model series is found to be decreased if the degree of dependence is decreased (please see Figure 13).
In general, independently of potentially different simulation algorithms for this simple example, when reconsidering Figure 1 (Page C2295 in the referee comment #1) of the reviewer and bearing in mind our straight forward approach of bias correction (i.e. the corrected absolute value at every time step should be closer to the observation), we think that any "signal" > 0 correction (also in case of low rank correlations) is contributing to improve the time series for subsequent modellers, e.g. in hydrology.

Comment 10

Remark: The quantile/quantile transformation can be regarded as a special case of the suggested methodology with a fully dependent copula (rank correlation equal to one).

Answer

It is true that the Quantile Mapping method can be regarded as a special case of the proposed methodology as it corrects all the moments of modelled precipitation distribution under the assumption of the full dependence between the ranks. However, this full dependence assumption will not hold for the real world. In our study area, the rank correlation between the datasets varies between 0.3 and 0.6 (please see Figure 14), and we can see from Figure 10 that the RMSE are increased remarkably by the Quantile Mapping correction. In contrast, our Copula-based correction (mean regression) reduced the RMSE significantly, which is exactly the purpose of our method and this study.

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Table 1: The proportion of the aforementioned four cases before (top) and after (bottom) adjustment of dry probabilities following the local scaling approach.

	WRF_0	WRF_1
REGNIE_0	0.07	0.21
REGNIE_1	0.06	0.66

	WRF_0	WRF_1
REGNIE_0	0.14	0.14
REGNIE_1	0.14	0.58

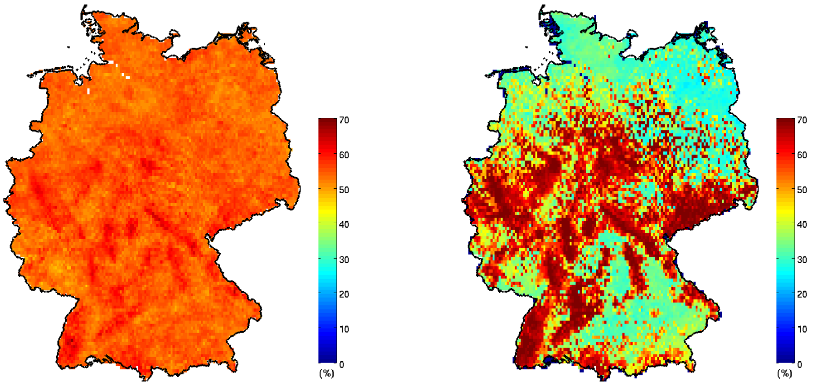

Figure 1: The percentage of the corrections that are closer to the observations. Left: Copula-based correction; Right: Quantile Mapping correction.

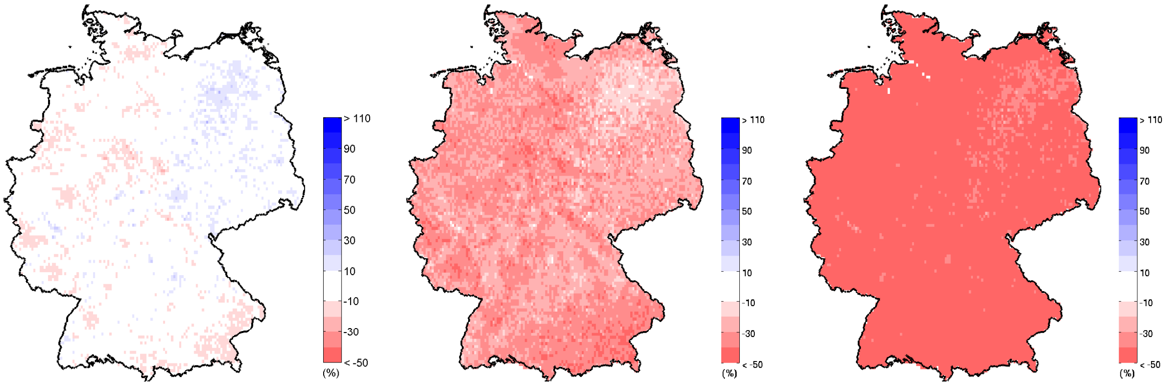

Figure 2: Relative bias map based on the mean (left), median (middle) and the mode (right) as estimator.

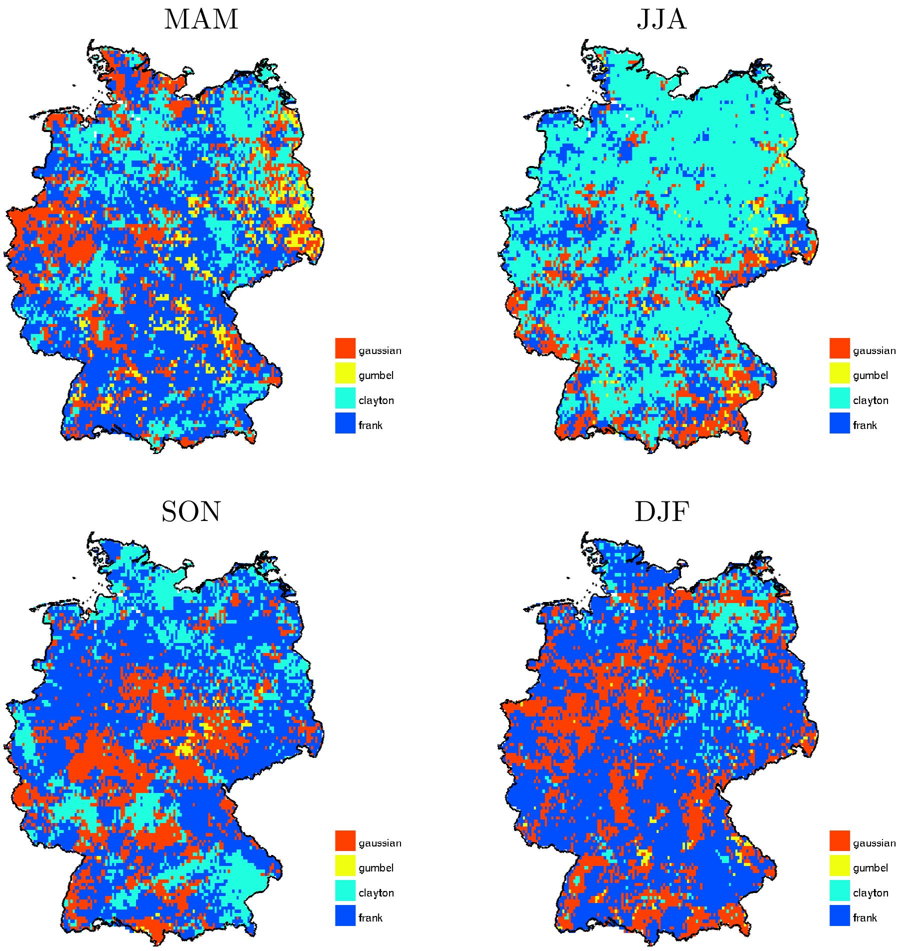

Figure 3: Fitted Copula model between REGNIE observations and WRF simulation results for the different seasons.

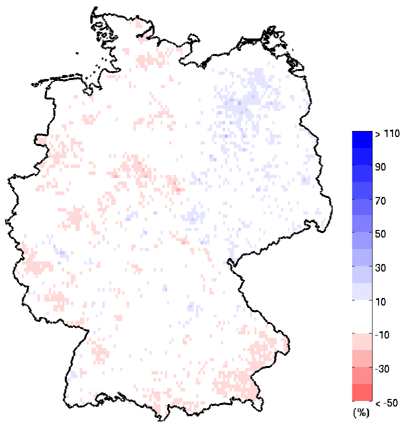

Figure 4: Relative bias map between REGNIE observations and WRF simulations (annually) based on four different Copula families, including the Gaussian Copula.

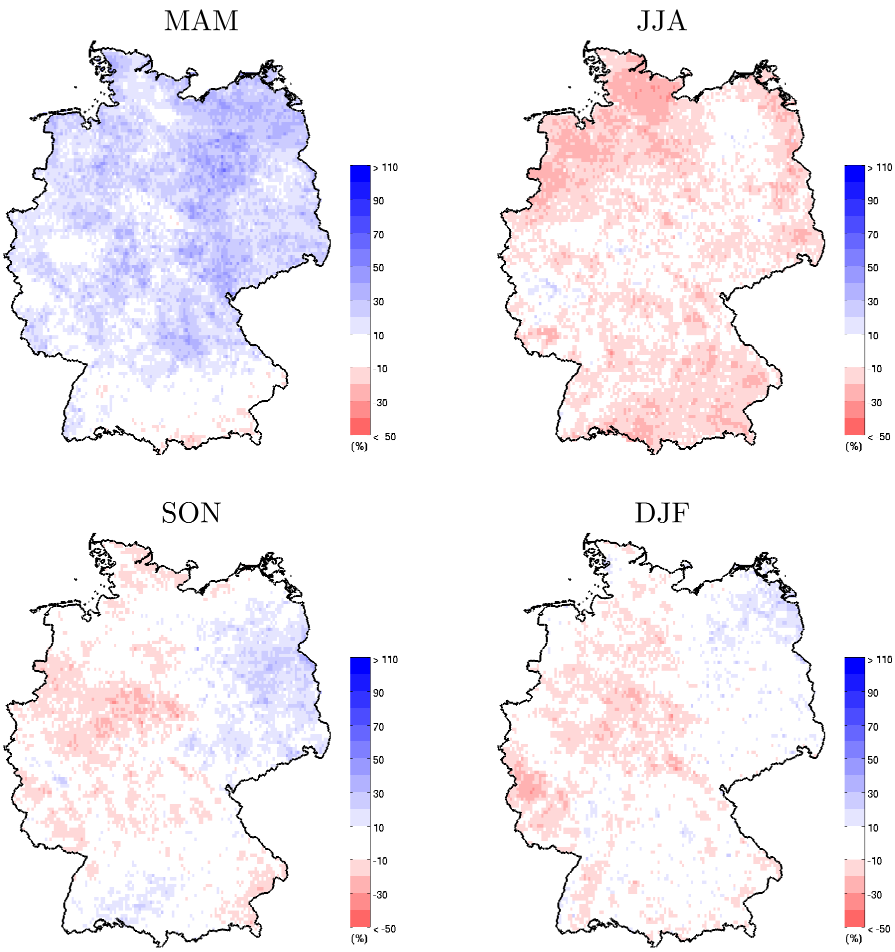

Figure 5: Relative bias map between REGNIE observations and WRF simulations (seasonally) based on four different Copula families, including the Gaussian Copula.

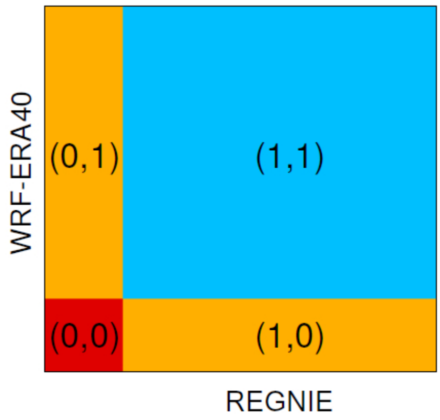

Figure 6: Four cases interpretation: (0,0) indicates that both REGNIE and WRF show no rain, (0,1) stands for an observation with no precipitation but the RCM model shows a rain event, while (1,0) indicates the opposite of (0,1), (1,1) implies that both are wet.

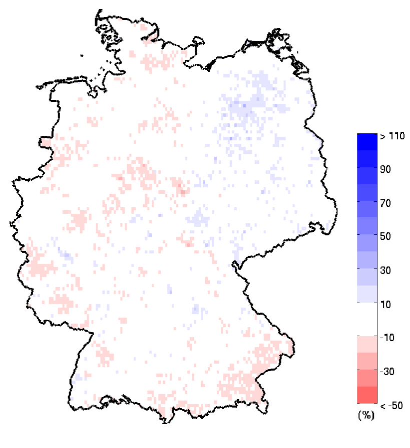

Figure 7: Relative bias map between REGNIE observations and WRF simulations (annually) based on non-parametric marginals and four different Copula families, including also the Gaussian Copula.

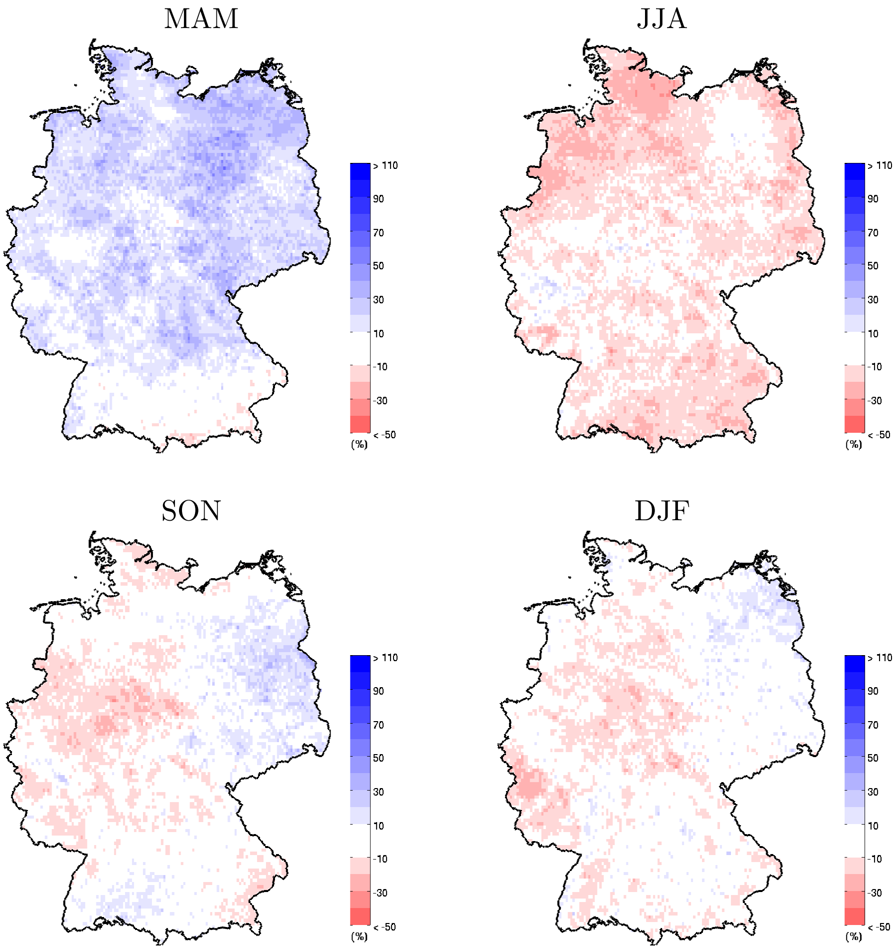

Figure 8: Relative bias map between REGNIE observations and WRF simulations (seasonally) based on non-parametric marginals and four different Copula families, including also the Gaussian Copula.

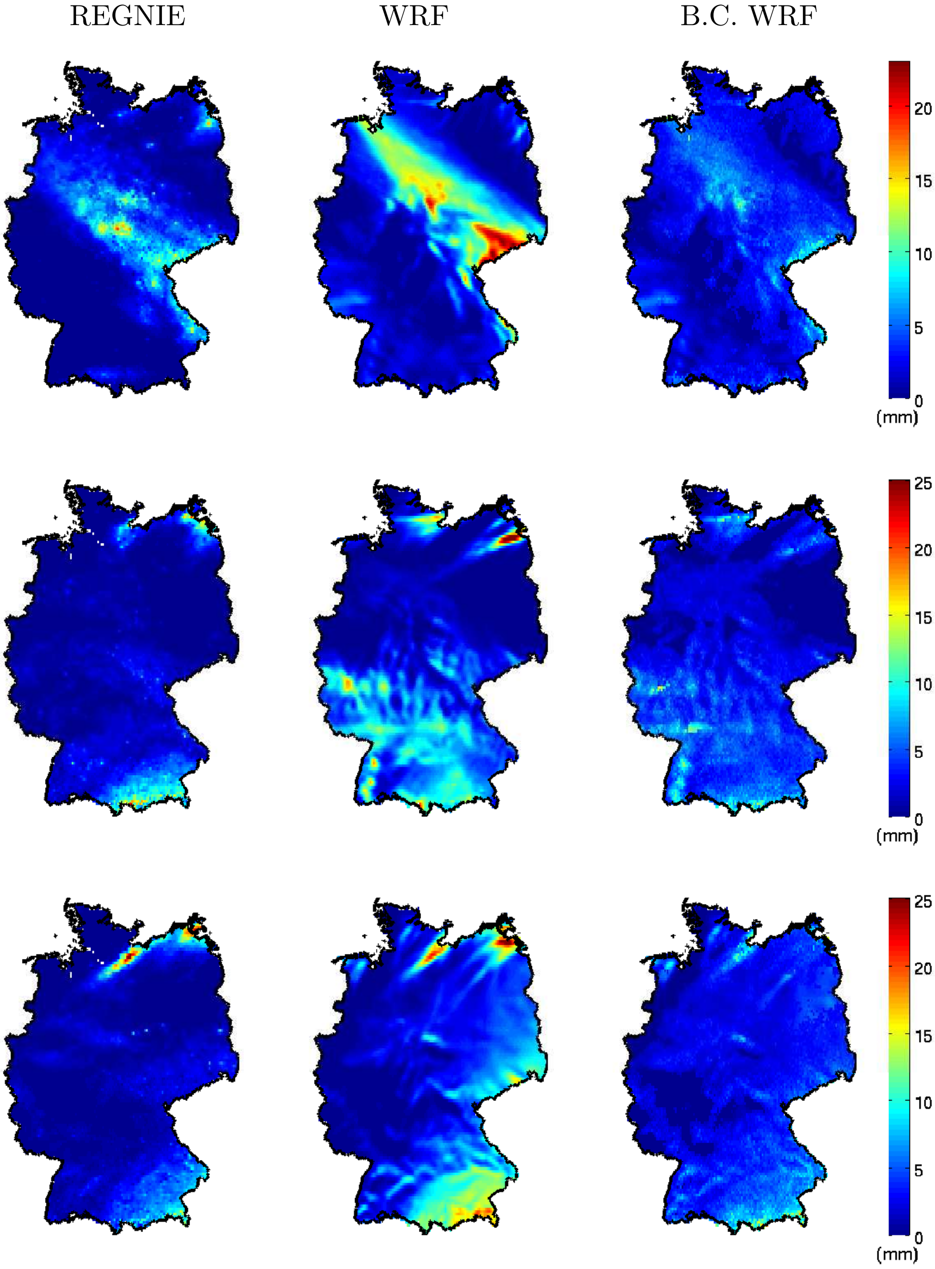

Figure 9: The precipitation field over Germany for the sequence of three days. From left column to right colum are REGNIE, WRF and bias corrected WRF, respectively. From top to bottom are the timesteps from January 9th to 11th, 1986.

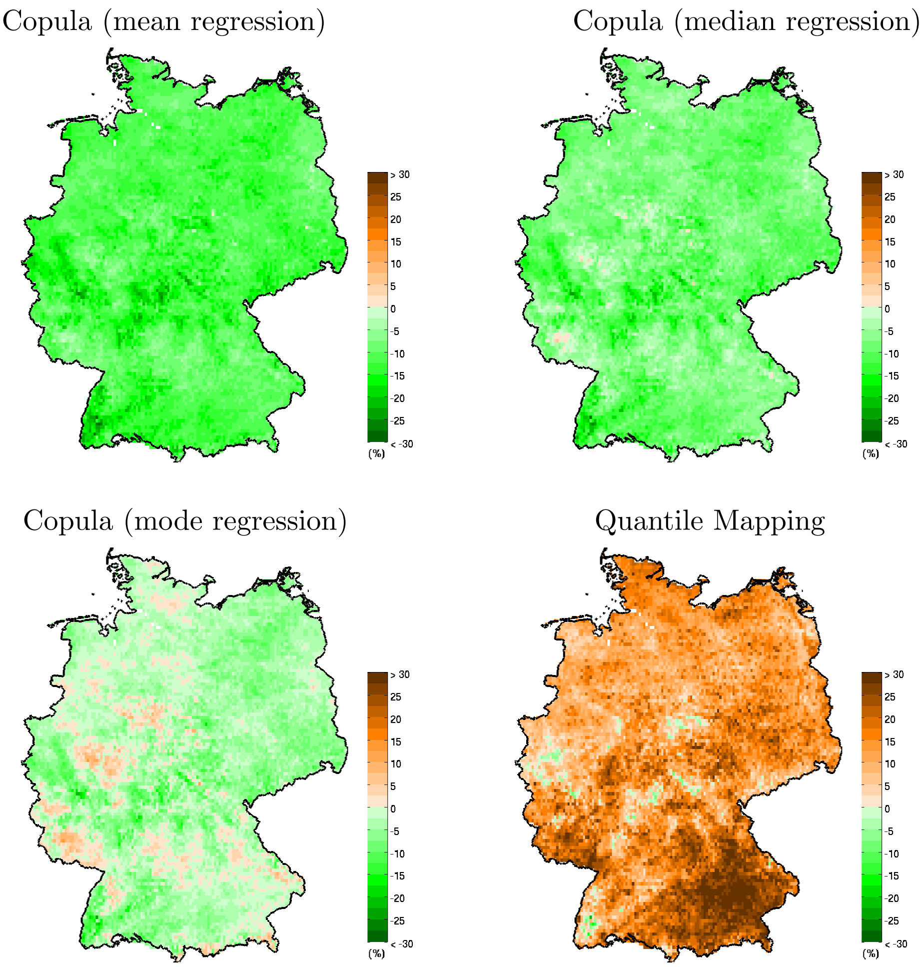

Figure 10: The RMSE between original REGNIE and bias corrected WRF for different methods.

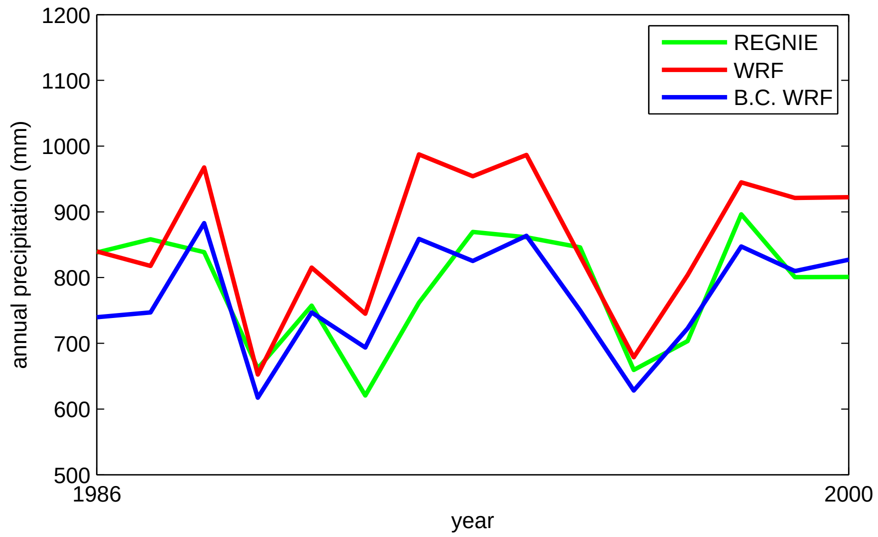

Figure 11: Annual mean precipitation for Germany from 1986 to 2000. The green line indicates the original REGNIE, the red line stands for the WRF and the blue line is the bias corrected WRF.

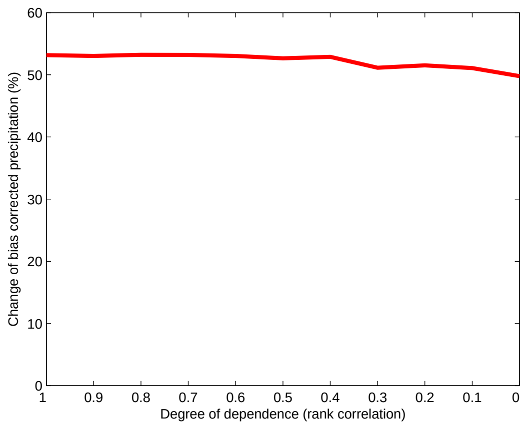

Figure 12: Change of the signal (mean value) in dependence of the rank correlation following our approach.

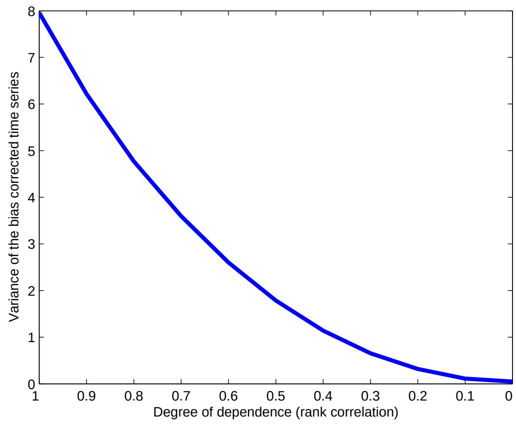

Figure 13: Change of the signal (variance) in dependence of the rank correlation following our approach

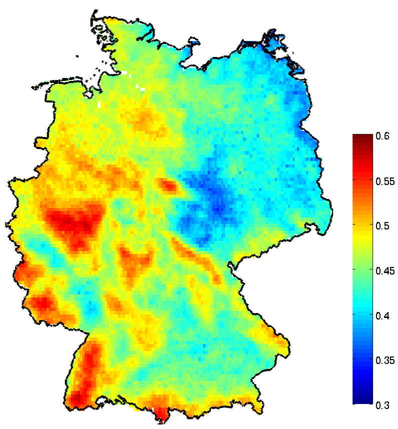

Figure 14: The rank correlation over the study domain