Comparing precipitation bias correction methods for high-resolution regional climate simulations using COSMO-CLM

– Effects on extreme values and climate change signal

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Main question

How do bias correction methods influence the climate signal and the extremes? Are there differences between the methods?

1. Introduction

Model output is often biased, especially precipitation, and cannot be used directly as input data. This bias affects the whole distribution, not only the mean values. Extreme precipitation events are crucial for impact studies, since they may cause floods or distinction of a local species population. Therefore, an appropriate method for bias correcting the non-extremes and the extremes has to be applied. A combination of gamma and Pareto-distribution is used within Rhineland-Palatinate(RLP, Western Germany). Thereafter, effects on extremes and on the climate change signal are investigated.

2. Study area

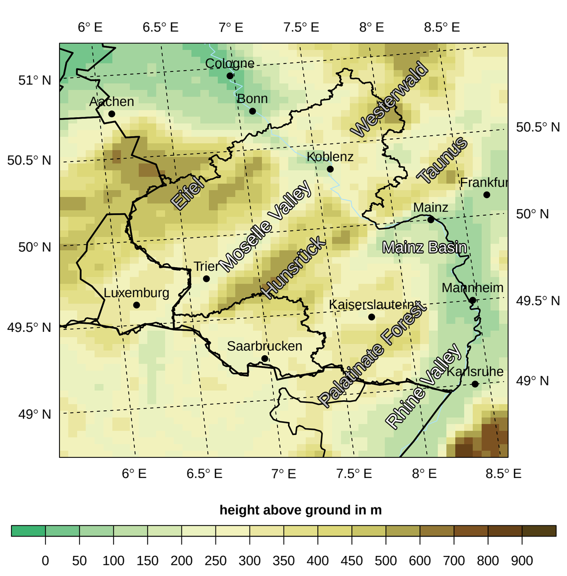

Figure 1a: The domain of the COSMO-CLM model with a resolution of 0.04° and the subdomain of the state Rhineland-Palatinate (black box); in addition the height of orography is plotted.

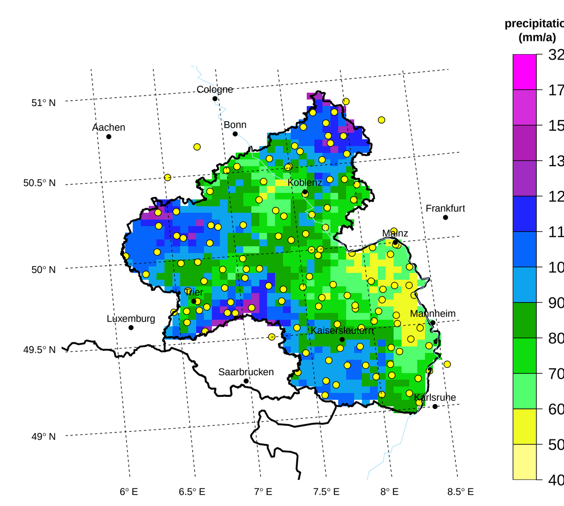

Figure 1b: Annual mean precipitation from REGNIE (1991- 2000). The yellow points mark the positions of the 121 precipitation stations used within this study (stations outside RLP are not considered).

3. Model and data

COSMO-CLM

- COSMO-CLM Version 4.8.11
- 10-year time slices: 1991-2000 (C20) and 2091-2100 (A1B)
- 1-h precipitation fields aggregated to daily fields
- Runge-Kutta scheme, Tiedtke scheme, graupel scheme, 40 levels, 5km resolution

Observations

- 121 stations from DWD and LUWG with daily precipitation data and no missing values and REGNIE data set (1991-2000) (Fig.1b)

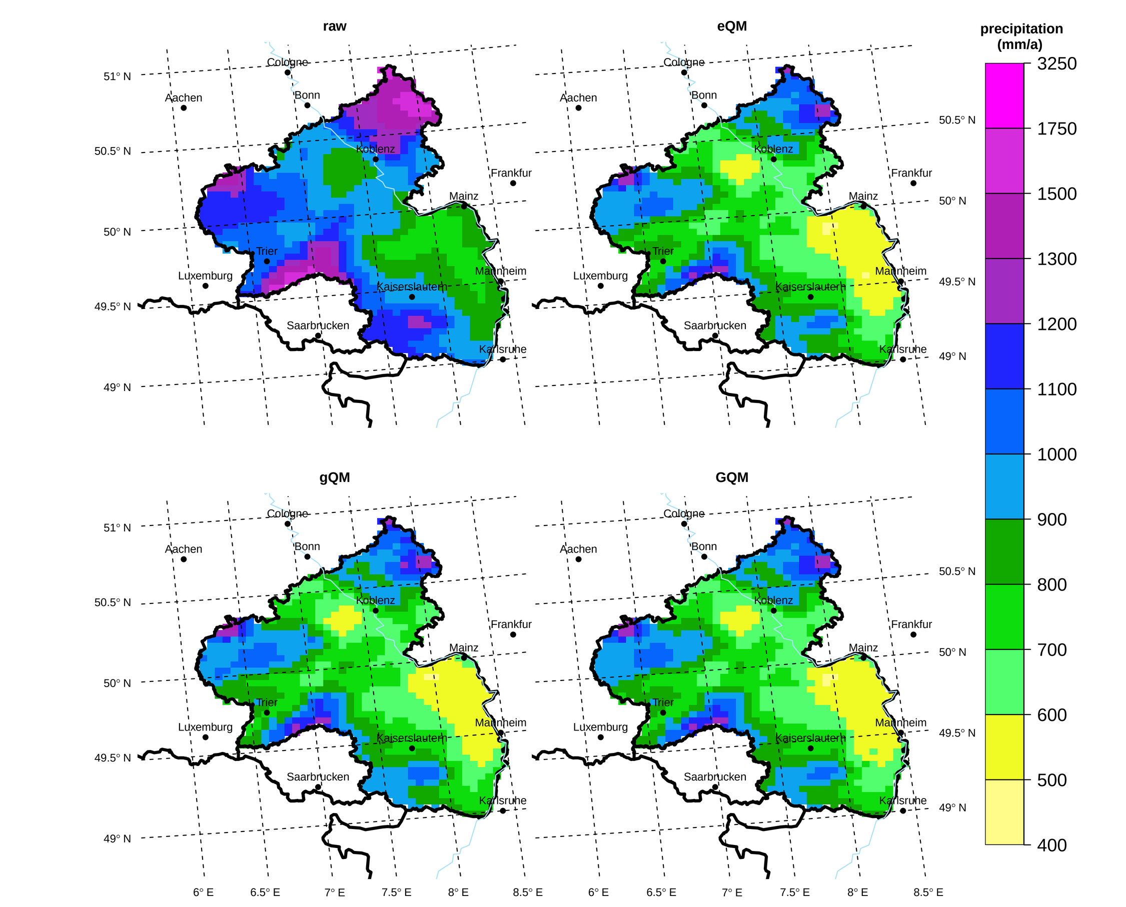

Figure 2: Annual mean precipitation (1991-2000) of the raw model output (raw, upper left) and after applying the three different bias correction methods (eQM: upper right, gQM: bottom left, GQM: bottom right).

4. Methods

Three different quantile matching methods are applied to correct the precipitation bias:

- empirical quantile matching (**eQM**; reference)
- gamma quantile matching (**gQM**; Piani et al. 2010)
- gamma+GPD quantile matching (**GQM**, based on Yang et al. 2010, new method)

The gQM and GQM are corrected for dry days probability first by finding a threshold, so that the number of dry days equals the observed number:
The GQM is a combination of fitting a gamma distribution Γ for precipitation values $\leq$ 95%-percentile and a general Pareto distribution (GPD, Coles 2001) for values $>$ 95%-percentile. After the estimation of the parameters with MLE, a quantile matching is applied:

$$y = \begin{cases} \Gamma^{-1}_{\alpha_{\text{obs}},\beta_{\text{obs}}}\left(\Gamma_{\alpha_{\text{cclm}},\beta_{\text{cclm}}}(x)\right), & \text{if } x \leq q95 \\ \text{GPD}^{-1}_{\xi_{\text{obs}},\sigma_{\text{obs}}}\left(\text{GPD}_{\xi_{\text{cclm}},\sigma_{\text{cclm}}}(x)\right), & \text{if } x \geq q95 \end{cases}$$

with x=precipitation from actual grid point. An inverse-distance weighting interpolation is used to interpolate the parameters from the three nearest neighbours (Casper et al. 2012). The MAEx skill score (Gudmundsson et al. 2012) is used for assessing the performance of the correction methods. The MAEx calculates absolute mean errors of quantile intervals (in 10% wide steps with 1000 substeps). Return values are calculated by fitting a "'peak-over-threshold"' model with declustering the exceeding extremes.

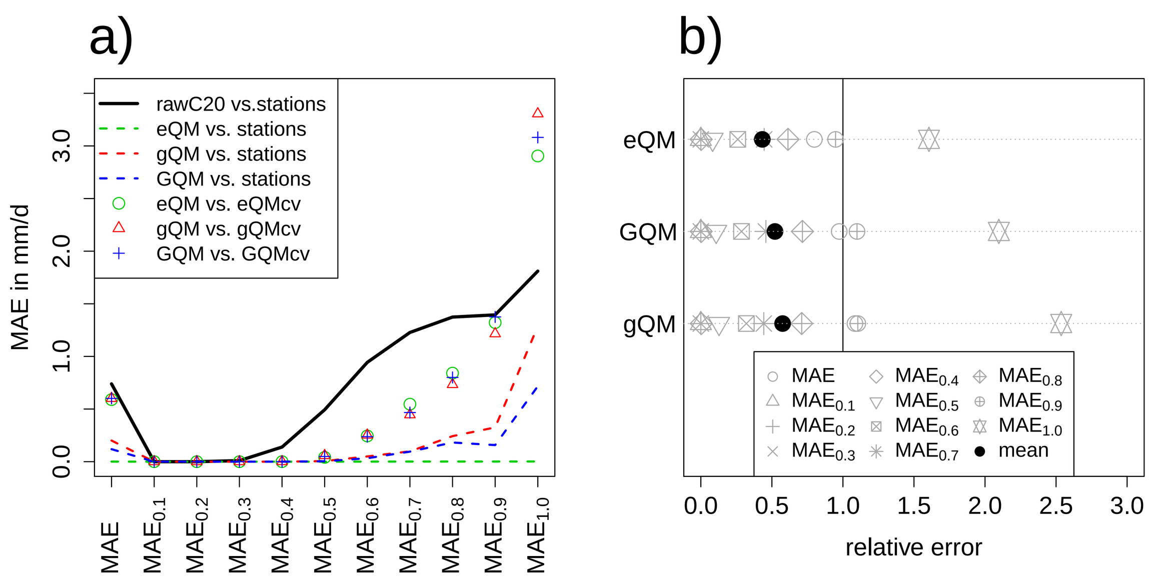

Figure 3: Temporal cross-validation: a) MAEx skill score for 10 year reference calibrations (solid and dashed lines) and for the cross-validations. In b) standardized ranking (dashed lines + points divided by black solid line), the black dot is the mean of all MAE and used for ranking.

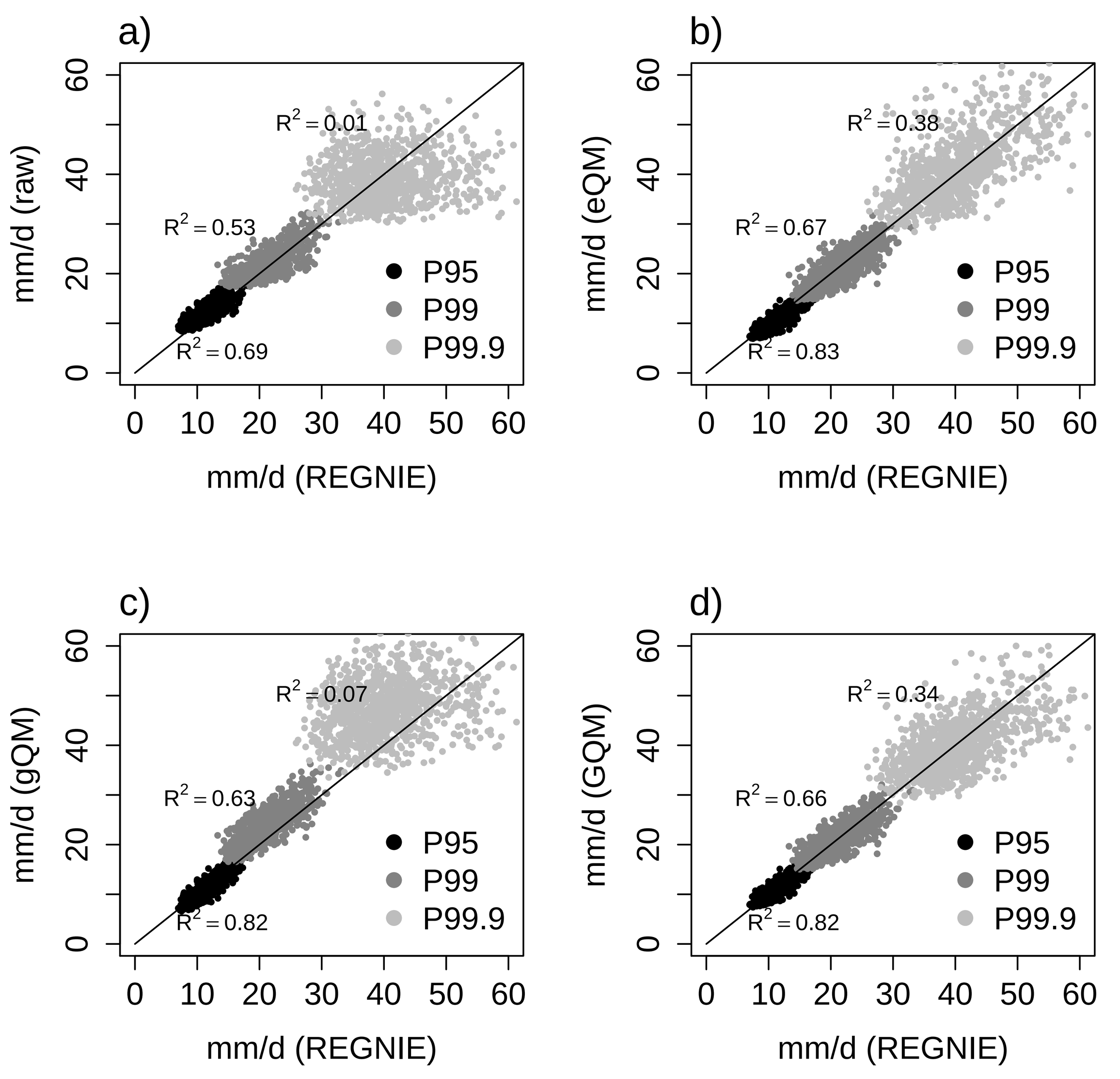

Figure 4: Scatterplots of the 95th, 99th and 99.9th percentiles (1991-2000) for all grid point pairs of REGNIE vs. a) original CCLM output, b) eQM corrected CCLM output, c) gQM corrected CCLM output and d) GQM corrected CCLM output. Additionally, the R^2 of linear regressions are shown.

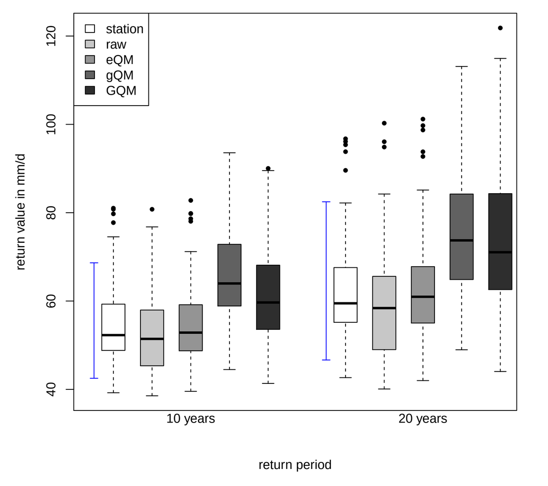

Figure 5: Estimated return values from the POT models for stations, raw, eQM, gQM and GQM. The blue vertical lines mark the mean 95%-confidence intervals obtained by bootstrapping (n=10000) each of the station time series and the black horizontal lines mark the median, respectively.

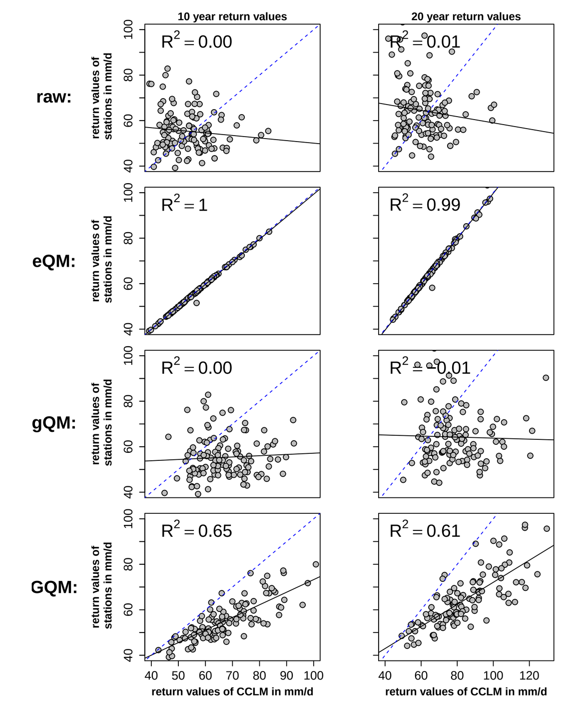

Figure 6: Scatterplots of the return values model vs. stations (left: 10yr, right: 20yr). Correlation between the estimated return values at the stations and from model data sets, (dashed: x=y) and the black continuous line is the regression line

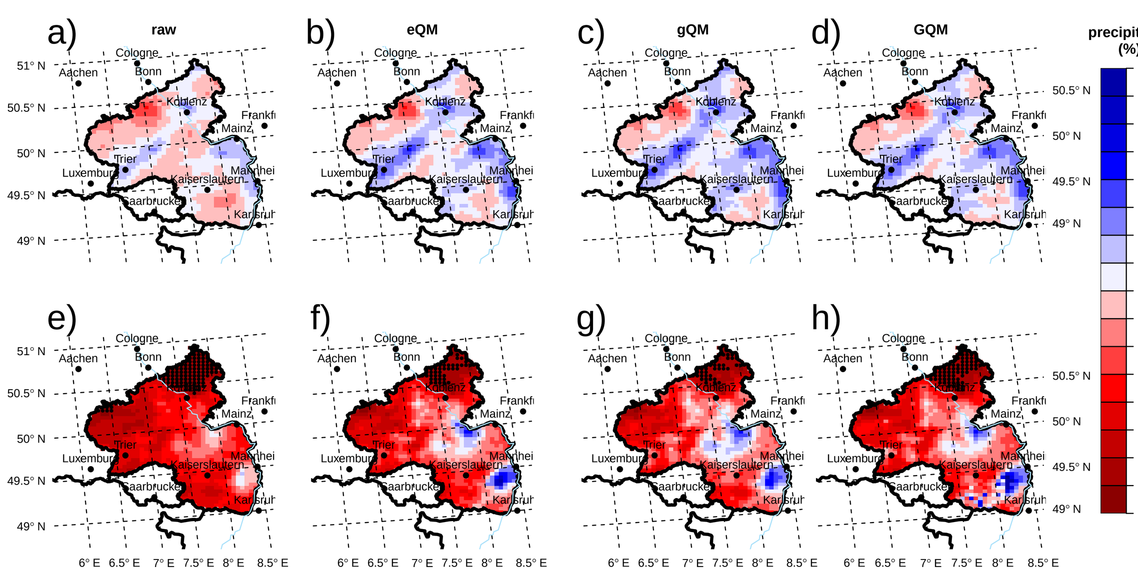

Figure 7: Seasonal climate change signal (2091-2100 - 1991-2000) for precipitation for winter (DJF, a-d) and summer (JJA, e-h). Significant grid points ($\alpha = 5\%$) are marked with black dots.

5. Results

- Mean annual precipitation is reduced in the whole domain (Fig.2) and the spatial pattern is preserved.
- eQM method shows best correction (Fig.3-6)
- gQM and GQM have problems due to the interpolation scheme (Fig.3) and wrong parameter estimation because of the short time series; therefore both methods overestimate the return values and produce outliers at some grid boxes
- GQM improves the correction of the extremes up to the 99.9th percentile (Fig.4,6); at higher percentiles the wrong parameter estimation becomes visible
- The climate change signal until 2091-2100 remains nearly constant in pattern, however positive signals are amplified whereas negative signals are dampened.

6. Discussion and conclusion

- Considering the distributions after the correction, there are some drawbacks:
  1. The time series are rather short, therefore uncertainty is introduced to the parameter estimation, in particular for the GPD shape parameter.
  2. During the interpolation, some outliers occurred with the GQM method. This happens if the shape parameter of the present and future GPD fit changes sign, or if the sign between the three nearest stations are different. A more sophisticated interpolation method will be tested.
- The influence of the parametric bias correction methods (gQM,GQM) on the climate change signal is not different to the influence of eQM.
- extremes are more sensitive to the chosen bias correction method than means

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CLM community

References

[1] Casper, M.C., Grigoryan, G., Gronz, O., Gutjahr, O., Heinemann, G., Ley, R., Rock, A. (2011): Analysis of projected hydrological behavior of catchments based on signature indices. *Hydrol. Earth Sys. Sci.*, 16, 409-421.

[2] Coles, S. (2001): An introduction to statistical modeling of extreme values. Springer, Berlin, 224 p.

[3] Déqué M. (2007): Frequency of precipitation and temperature extremes over France in an anthropogenic scenario: Model results and statistical correction according to observed values. *Global Planet. Change*, 57, 16-26.

[4] Gutjahr O., Heinemann G. (2013): Comparing precipitation bias correction methods for high-resolution regional climate simulations using COSMO-CLM – Effects on extreme values and climate change signal. *Theor. Appl. Climatol*,in print, doi:10.1007/s00704-013-0834-z.

[5] Gudmundsson L., Bremnes J.B., Haugen J.E., Engen-Skaugen T. (2012): Technical Note: Downscaling RCM precipitation to the station scale using statistical transformations – a comparison of methods.*Hydrol. Earth Syst. Sci.*, 16, 3383-3390.

[6] Piani C., Haerter J.O., Coppola E. (2010): Statistical bias correction for daily precipitation in regional climate models over Europe. *Theor. Appl. Climatol*, 99, 187-192.

[7] Yang W., Andréason J., Graham L.P., Olsson J., Rosberg J., Wetterhall F. (2010): Distribution-based scaling to improve usability of regional climate model projections for hydrological climate change impacts studies. *Hydrol. Res.*, 41, 211-229.