Comparison of parametric bias correction methods for high-resolution COSMO-CLM daily precipitation fields

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Main question

How can precipitation data from model output be corrected to achieve realistic statistics for impact modeling?

1. Introduction

Precipitation from raw model output needs to be bias-corrected in order to use it as forcing for impact models. A new parametric bias-correction method is compared to an existing non-parametric and parametric method. In addition, the effect of the bias correction on the climate change signal is investigated.

2. Model domain

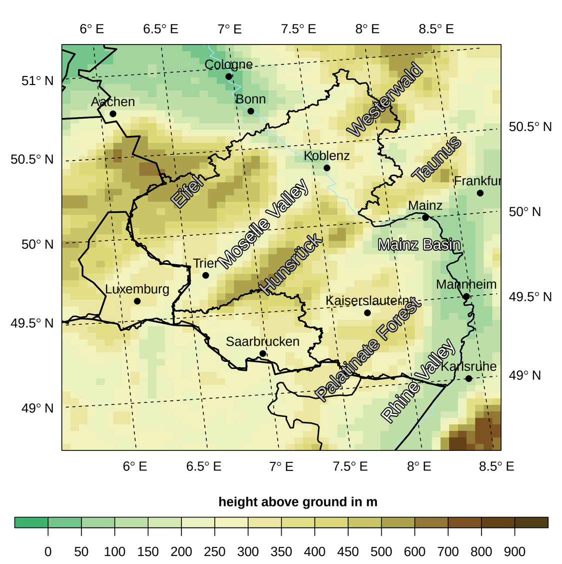

Figure 1: Left: Domain of Rhineland-Palatinate with orography and landscape names.

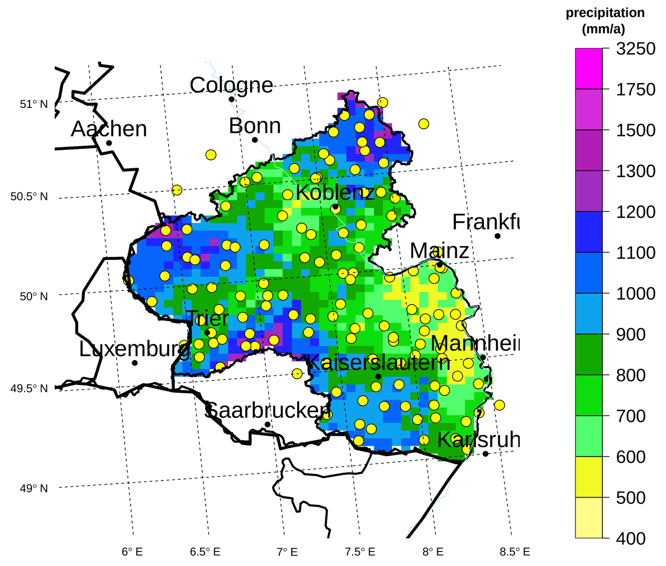

Figure 2: Annual mean precipitation from REGNIE (1991-2000). The yellow points mark the positions of the 128 precipitation stations used within this study.

3. Model and data

COSMO-CLM

- COSMO-CLM Version 4.8.11 "'Global Change"' project[1] in 0.04° resolution
- 10-year time slices: 1991-2000 (C20) and 2091-2100 (A1B)
- 1-h precipitation fields aggregated to daily fields

Observations

- 128 stations from DWD and LUWG with daily precipitation data and no missing values
- REGNIE 1991-2000 (DWD, interpolated station data, 1km interpolated on 0.04°)

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4. Methods

empirical quantile matching (**eQM**):

$$y = F^{-1}_{\text{obs}}(F_{\text{CCLM}}(x)). \tag{1}$$

parametric gamma quantile matching (**gQM**): first: optimize number of dry days with (2), second: replace F in (1) with CDF of fitted gamma distributions (3):

$$\underset{x_d \in \Re_+}{\operatorname{argmin}} |n - m(x_d)| \tag{2}$$

$$\Gamma(x) = \frac{(x/\beta)^{\alpha-1}\exp(-x/\beta)}{\beta\Gamma(x)} \quad x,\alpha,\beta > 0 \tag{3}$$

new parametric method, combination of gamma and General Pareto distribution (**GQM**): first: optimize number of dry days with (2),second: replace (1) with:

$$y = \begin{cases} F^{-1}_{\text{obs,gamma}}(F_{\text{CCLM,gamma}}), & \text{if } x < 95^{\text{th}} \text{percentile} \\ F^{-1}_{\text{obs,GPD}}(F_{\text{CCLM,GPD}}), & \text{if } x \geq 95^{\text{th}} \text{percentile} \end{cases} \tag{4}$$

with:

$$\text{GPD} = \begin{cases} 1 - \left(1 + \frac{\xi x}{\tilde{\sigma}}\right), & \text{if } \xi \neq 0 \\ 1 - \exp\left(-\frac{x}{\tilde{\sigma}}\right), & \text{if } \xi = 0 \end{cases} \tag{5}$$

These transfer functions are used for bias correcting the C20 and A1B scenario under the assumption of **stationarity**. To correct grid points where no station is located, an inverse-distance weighting with the three nearest stations is used. Extremes with a probability $P \leq 1 - 10^8$ are not corrected and treated as outliers.

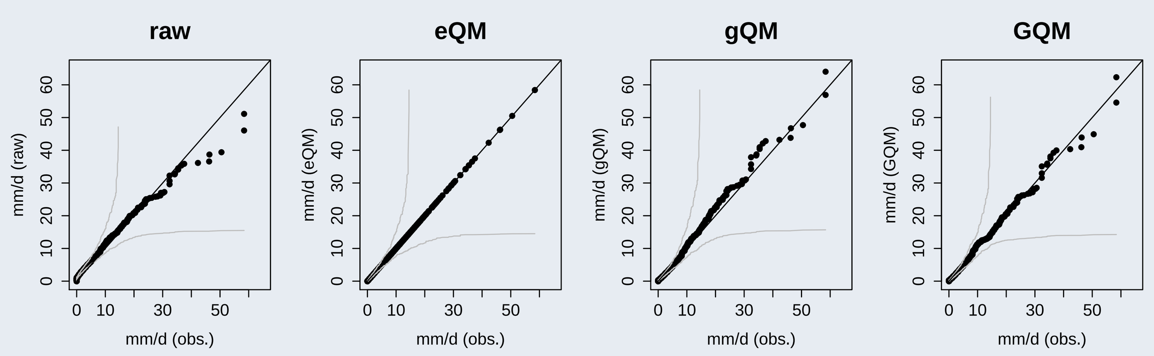

Figure 3: Quantile-Quantile plots at station Idar-Oberstein.

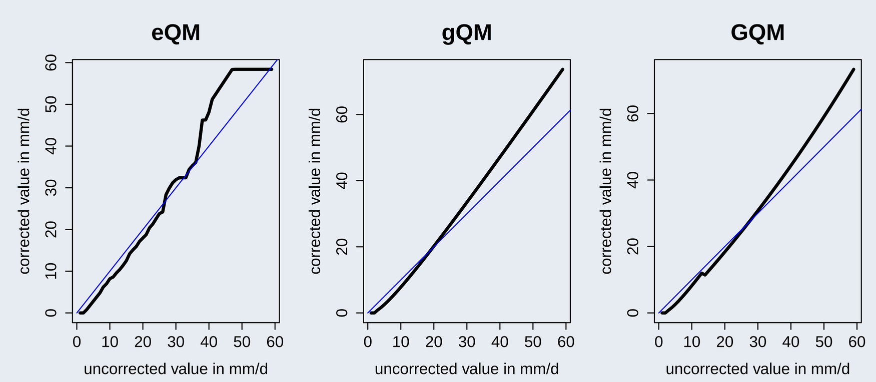

Figure 4: Transfer functions of the three quantile matching methods.

[1]**"Global Change" project:**
http://www.uni-trier.de/index.php?id=40193&L=2

5. Results of the bias correction

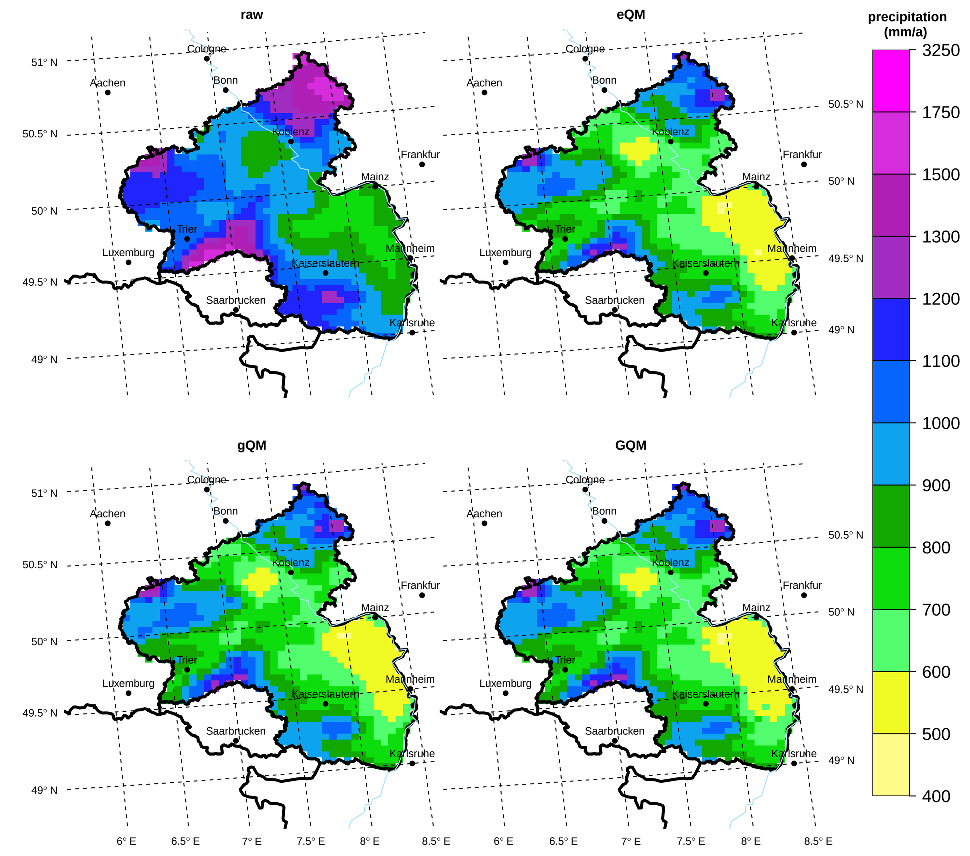

Figure 5: Annual mean precipitation of the raw model output (raw, topleft) and after applying the three different bias correction methods (eQM (topright), gQM (bottomleft), GQM (bottomright)).

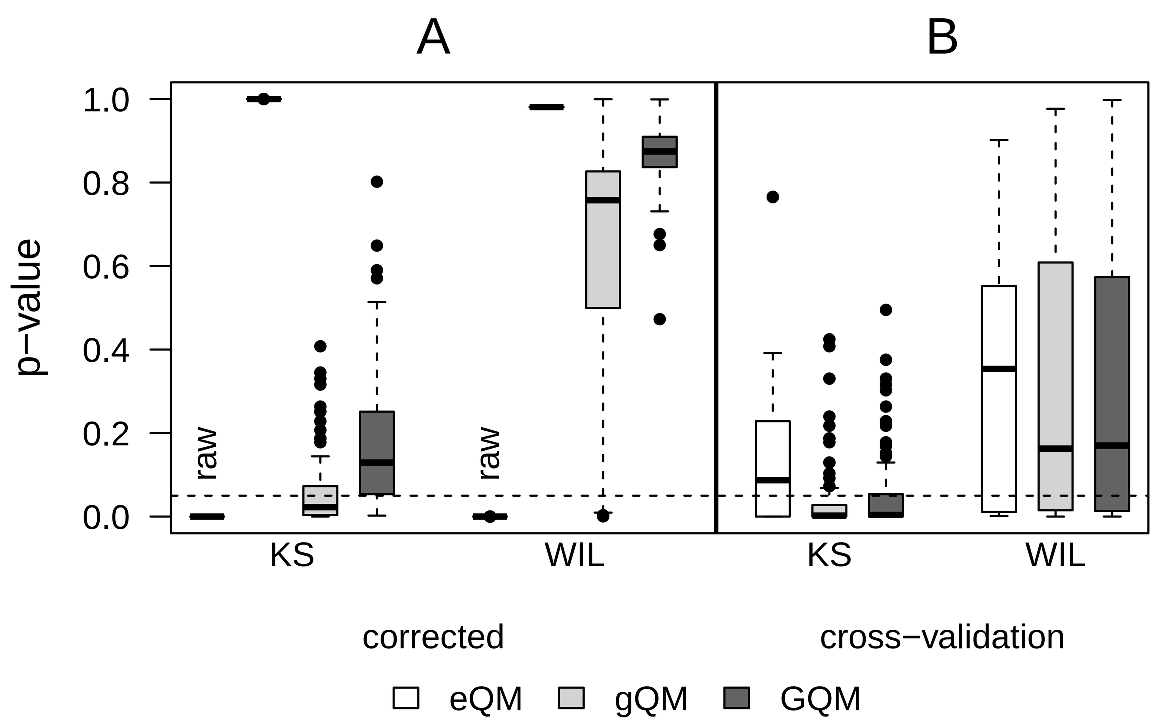

Figure 6: Results of Kolmogorov-Smirnov(KS) and Wilcoxon (WIL) tests. In part A, the p-values are shown before (raw) and after the corrections (eQM,gQM,GQM). The dashed line marks $\alpha = 5\%$. All p-values of raw are 0, i.e. neither location (WIL) nor distribution (KS) are from the same population. The eQM performs best, gQM fails in $> 50\%$ (KS), GQM succeeds in $> 75\%$ (KS). In part B, gQM and GQM fail during interpolation because of minimal deviations in low intensities, but no significant differences occur in WIL compared to eQM.

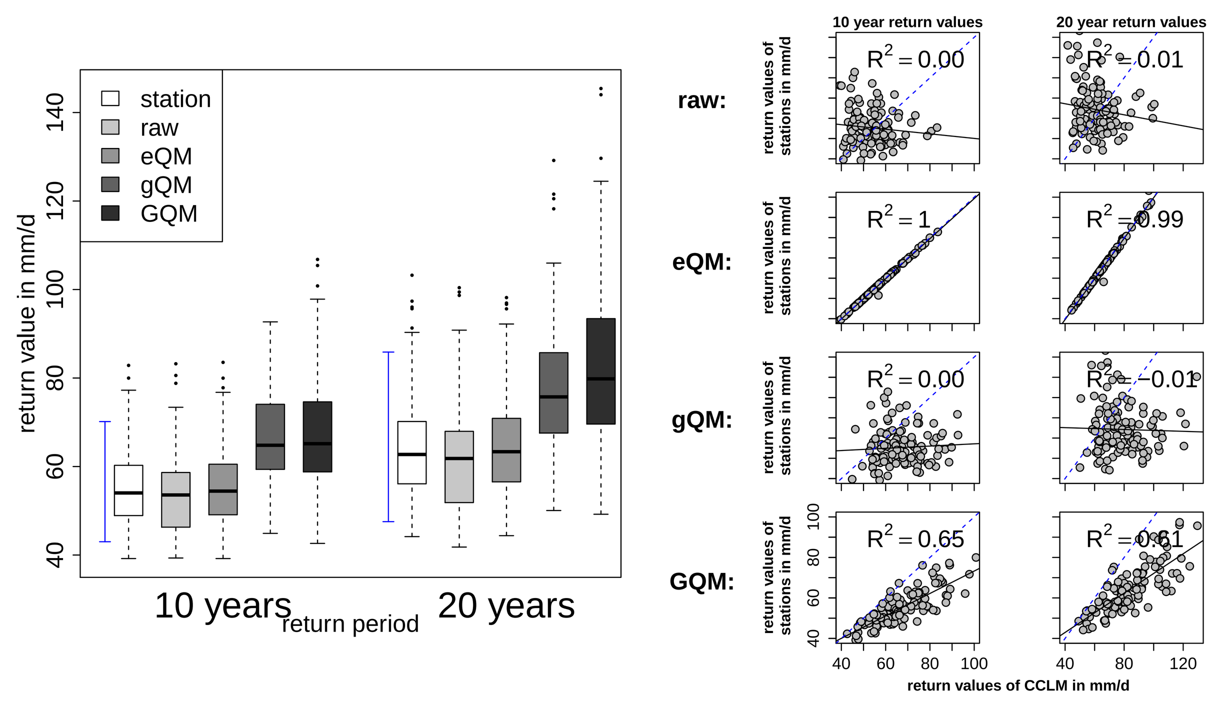

Figure 7: Left: 10 and 20 year return values overestimated by gQM and GQM. Right: Linear regression CCLM vs. stations. There is a clear dependency between GQM and stations compared to gQM and stations.

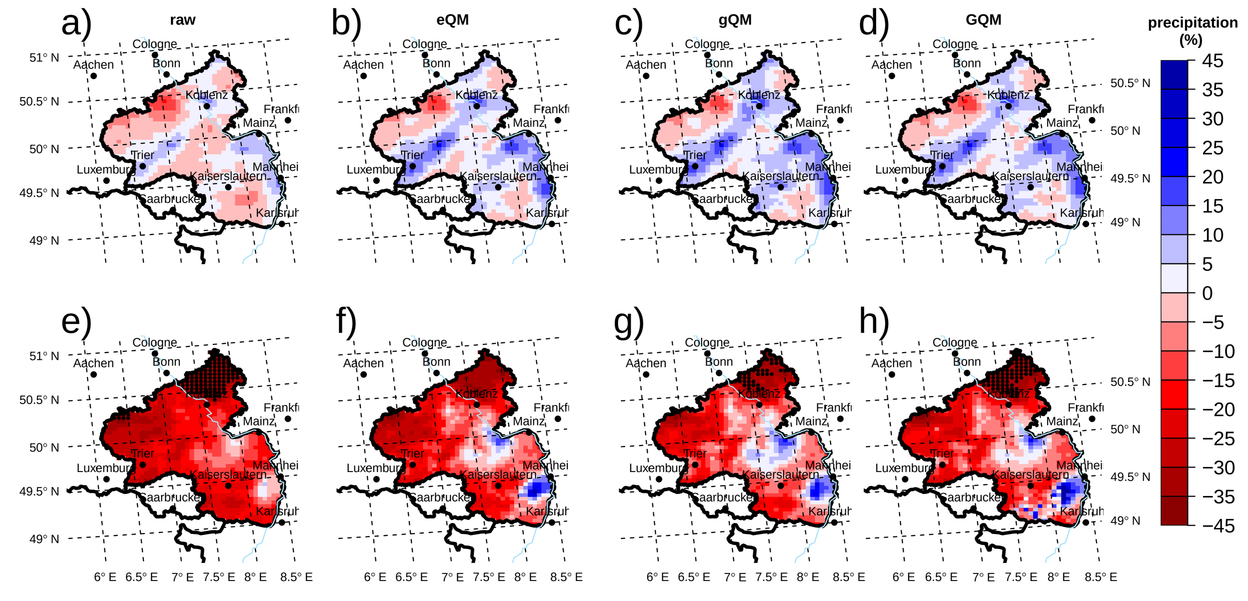

Figure 8: Seasonal climate change signal for precipitation (top: DJF, bottom: JJA). In winter (DJF, a-d), the precipitation increases in high elevations but decreases in low areas. None of the signals is significant, although the signals range between $\pm 20\%$, but the inter-annual signals are much larger. In summer, precipitation decreases in most areas of RLP (only significant in the NE RLP (t-test,$\alpha = 5\%$,black dots), except in the Rhine-valley and the Mainzer Basin.

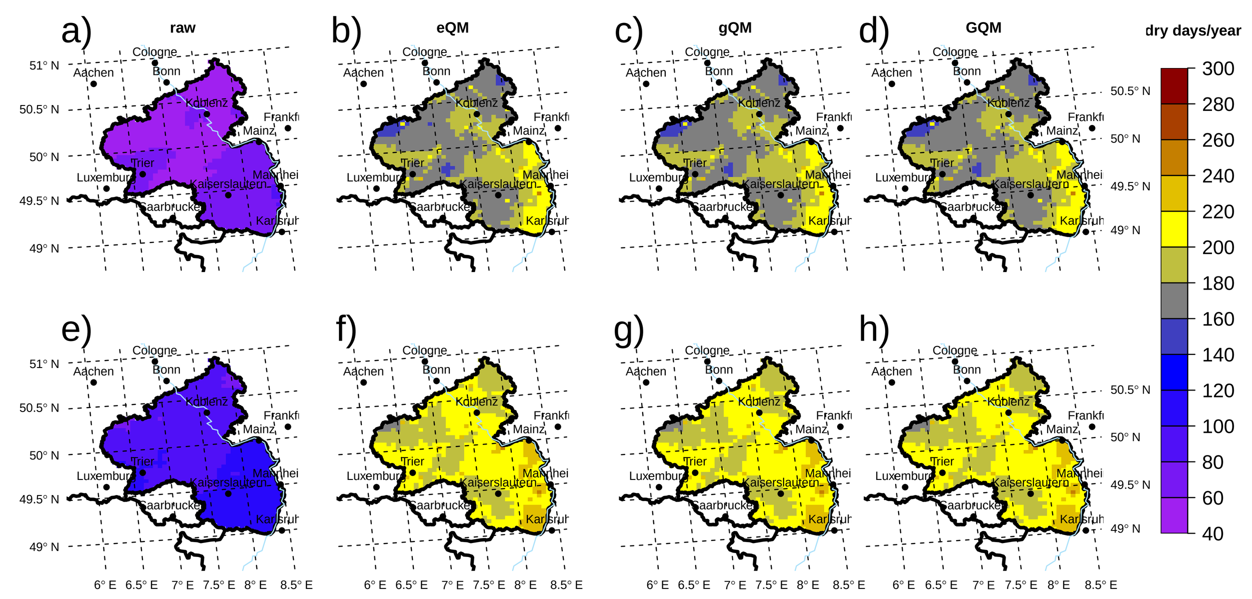

Figure 9: Climate change signal of the number of dry days per year (top: 1991-2000, bottom: 2091-2100). Since all grid points are significant (t-test, $\alpha = 5\%$), the markings (black points) are omitted for clarity. The raw signal (a and e) show nearly no spatial variability with 40-80 dry days per year and and increase of around 30 days in A1B. The bias correction alters dramatically the number of dry days and especially the pattern which becomes more differentiated. However, the signal reduces to $+20$ days in the mean (largest for high elevations).

6. Conclusion and Outlook

Methods:

- new method GQM is able to correct the bias with equally performance as gQM and eQM
- improvements at point-scale correction
- improvements of the extreme value correction with better spatial correlation than gQM
- too high extremes after corrections in A1B

Climate change signal:

- bias correction affects climate change signal (amplifies positive signal, dampens negative signal)
- but these alterations are not significant ($\pm 5\%$)
- large improvement of number of dry days (removing "'drizzle-error"')

Problems and future work:

- simple interpolation not optimal yet
- outliers occur after bias correction (improve filtering)

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CLM community

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