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Bias correction of temperature and precipitation data for regional climate model application to the Rhine basin

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Abstract

In many climate impact studies hydrological models are forced with meteorological forcing data without an attempt to assess the quality of these forcing data. The objective of this study is to compare downscaled ERA15 (ECMWF-reanalysis data) precipitation and temperature with observed precipitation and temperature and apply a bias correction to these forcing variables. The bias-corrected precipitation and temperature data will be used in another study as input for the Variable Infiltration Capacity (VIC) model. Observations were available for 134 sub-basins throughout the Rhine basin at a temporal resolution of one day from the International Commission for the Hydrology of the Rhine basin (CHR). Precipitation is corrected by fitting the mean and coefficient of variation (CV) of the observations. Temperature is corrected by fitting the mean and standard deviation of the observations. It seems that the uncorrected ERA15 is too warm and too wet for most of the Rhine basin. The bias correction leads to satisfactory results, precipitation and temperature differences decreased significantly. Corrections were largest during summer for both precipitation and temperature, and for September and October for precipitation only. Besides the statistics the correction method was intended to correct for, it is also found to improve the correlations for the fraction of wet days and lag-1 autocorrelations between ERA15 and the observations.

1 Introduction

Hydrological models have become an important tool for predicting streamflow generation in river basins around the world. Many hydrologists use hydrological models for climate impact studies, e.g. de Wit et al. (2007) investigated the impact of climate change by applying the HBV (Bergström and Forsman, 1973; Lindström et al., 1997) model to the Meuse basin, Kleinn et al. (2005) investigated the impact of climate change to the Rhine basin, by forcing the WaSiM-ETH model with regional climate model (RCM) output and Hurkmans et al. (2009) investigated the impact of climate change on streamflow dynamics of the Rhine basin by forcing the Variable Infiltration Capacity (VIC) model (Liang et al., 1994) with different climate scenarios. A distinction can be made between lumped and spatially distributed hydrological models. Lumped models are often capable of simulating historical streamflows quite well, because they are easy to calibrate. It is, however, questionable if the resulting calibration parameters will still be valid for a changing climate. Examples of lumped water balance models for the Rhine include HBV (Bergström and Forsman, 1973; Lindström et al., 1997), Rhineflow (Kwadijk, 1993) and STREAM (Aerts et al., 1999, 2006). Examples of spatially distributed models include the Variable Infiltration Capacity (VIC) model (Liang et al., 1994), TOPMODEL (Beven and Kirkby, 1979) and SHE (Abbott et al., 1986). Water balance models often use emperical or statistical methods to estimate potential evaporation on the basis of temperature. Spatially distributed models, like e.g. VIC (Variable Infiltration Capacity model) (Liang et al., 1994), on the other hand, derive evapotranspiration from coupled water and energy balance simulations, and are able to utilize additional information provided by RCM output, such as solar radiation, wind speed and specific humidity (Hurkmans et al., 2008). The original purpose of spatially distributed models was to represent the land surface in (regional) climate models and numerical weather prediction models (Hurkmans et al., 2008).

Nowadays, modelers are aware of the uncertainty involved in modeling, and the necessity to quantify the model output reliability (Beven, 1989). Spatially distributed models are often forced with regional climate model output (e.g., REMO Jacob, 2001), because observations are scarce on the spatial and temporal resolution at which these spatially distributed models are run. However, in many of these climate impact studies (e.g., Middelkoop et al., 2001), the hydrological model is forced with RCM data, without an attempt to assess the quality of the RCM data. Obviously, the reliability of the spatially distributed model output is strongly dependent on the quality of the climate forcing data. Christensen et al. (2008) state that one inherent source of uncertainty comes from the RCM's inability to simulate present-day climate conditions accurately. Therefore it is of major importance that RCM output is validated with historical obser-

vations, before calibrating the hydrological model with the RCM data. Applying a bias correction to the RCM data often seems necessary to match the RCM data with the observations (Shabalova et al., 2003; Kleinn et al., 2005; Leander and Buishand, 2007). It is hoped that the model skill scores under present day conditions are carried over to future climate conditions.

The objective of this study is to compare observed precipitation and temperature data with downscaled ERA15 data, investigate if there exists a certain bias between the latter two, and finally apply a bias correction to correct for this bias. The downscaled ERA15 data consists of ERA15 extended with operational re-analysis data to have a total period of 17 years (ECMWF re-analysis[1], 1979–1995). Several studies have been performed in which a bias correction method was applied to RCM data. For example, Hay et al. (2002) applied a gamma transform to correct RegCM2 precipitation data and Leander and Buishand (2007) applied a power law transform, which corrects for the coefficient of variation (CV) and mean of the precipitation values. Hay et al. (2002) found that the corrected precipitation data did not contain the day-to-day variability which was present in the observed data set. For this reason we have chosen to apply the method developed by Leander and Buishand (2007) in this study, because for calibration purposes we think it is important that the day-to-day variability of precipitation remains preserved.

The importance of this study for ongoing research (e.g., Hurkmans et al., 2009) is to use the bias-corrected downscaled ERA15 data for calibrating the VIC model and use the calibrated VIC model for climate impact studies. We hope the results of this bias correction study will facilitate other hydrologists in their search for a suitable bias correction method. The bias correction method employed in this study can easily be applied to other river basis if there is enough forcing and observational data available. Climate impact studies could be evaluated by applying a bias correction to future climate scenarios and a climate scenario of the 20th century and compare the latter two. The Max Planck Institute for Meteorology, for example, has developed three climate

[1]http://www.ecmwf.int

scenarios for the entire 21st century and a climate run for the second half of the 20th century. These scenarios were created by forcing their ECHAM5 GCM with IPCC carbon emission scenarios (A1B, A2 and B1; IPCC, 2000) and finally downscale them with REMO (Jacob, 2001).

Section 2 describes the area of interest for this study. This study uses data from a meteorological model. The meteorological forcing data and observed data are subject of Sect. 3. Section 4 explains the method used to correct for the bias. The results of the analyses are described in Sect. 5.

2 Study area

The Rhine basin is one of the largest river basins in western Europe. The river Rhine originates in the canton of Graubünden in the Swiss Alps and it drains portions of Switzerland, Germany, France, Austria and the Netherlands before draining into the North Sea. Approaching the Dutch border, the Rhine has an annual mean discharge of 2395 $m^3 s^{-1}$ and an average width of 400 m. Because of the various bifurcations in the lower Rhine, only the part upstream of Lobith (the point where the river crosses the German-Dutch border) is considered in this study. The area of the Rhine upstream of Lobith is about 185 000 km^2 (Hurkmans et al., 2008). Figure 1 represents the Rhine basin upstream of Lobith.

3 Models and data

The downscaled and bias corrected ERA15 data is used as input for calibrating the spatially distributed macro-scale hydrological model VIC (Variable Infiltration Capacity; Liang et al., 1994). With the calibrated VIC model we want to assess the effect of climate change on streamflow generation for the Rhine basin. The calibration of VIC and the impact of climate change on streamflow generation are not covered in this paper but are reported in Hurkmans et al. (2009).

The bias correction is determined for downscaled ERA15 reanalysis data for the period 1979–1995. ERA15 contains reanalyses of multi-decadal series of past observations, and it has become an important and widely utilized resource for the study of atmospheric and oceanic processes and predictability. ERA15 was downscaled in two steps at the Max Plack Institute for Meteorology in Hamburg, Germany, to a resolution of 0.088°, using their Regional Climate Model (RCM) REMO (Jacob, 2001). To run the VIC model, several forcing parameters are necessary (i.e., precipitation, temperature, radiation, humidity, wind speed and air pressure). The bias correction is determined for precipitation and temperature only, because no observations were available at the appropriate resolution for the remaining parameters. Therefore these parameters are left uncorrected. The downscaled ERA15 data set will be refered to as ERA15d in the remainder of this paper.

Observations of precipitation and temperature were made available by the International Commission for the Hydrology of the Rhine basin (CHR) (Sprokkereef, 2001). They provide daily values of precipitation and temperature for 134 sub-basins (Fig. 2) throughout the Rhine basin for the period 1961–1995. These observations are based on several measurement locations in each of the sub-basins. Combining the period 1979–1995 of ERA15d with the period 1961–1995 of the observations results in the overlapping period 1979–1995 (17 years) for detecting the bias.

4 Method

4.1 Introduction

With the bias correction we try to match the most important statistics (CV, mean and standard deviation on a scale of 65 days) of the ERA15d data with those of the CHR observations. The bias correction applied in this study is based on that proposed by Leander and Buishand (2007) for a Meuse basin study. They found that a relatively simple non-linear correction, adjusting both the biases in the mean and variability, leads to a better reproduction of observed extreme daily and multi-day precipitation amounts than the commonly used linear scaling correction. This method of bias correction does not correct for the fraction of wet and dry days and lag-1 autocorrelation. The bias correction of temperature was found to be more straightforward than that of precipitation, involving shifting and scaling to adjust the mean and variance, respectively. In this section, the method used to calculate the bias correction for precipitation and temperature will be described in detail.

4.2 Precipitation

Because the bias in precipitation and temperature was found to vary spatially, bias corrections were carried out for each of the 134 subbasins individually. Leander and Buishand (2007) used a power transformation, which corrects the CV (Coefficient of Variation) as well as the mean. In this nonlinear correction each daily precipitation amount P is transformed to a corrected P^* using:

$$P^* = aP^b \tag{1}$$

The effect of sampling variability is reduced by determing the parameters a and b for every five-day period of the year, including data from all years available, in a window including 30 days before and after the considered five-day period (Leander and Buishand, 2007). The determination of the b parameter is done iteratively. It was determined such that the CV of the corrected daily precipitation matches the CV of the observed daily precipitation. In this way, the CV is only a function of parameter b according to:

$$\mathrm{CV}(P) = \mathrm{function}(b) \tag{2}$$

in which P is the precipitation in a block of 65 days times 17 years. With the determined parameter b, the transformed daily precipitation values are calculated using:

$$P^* = P^b \tag{3}$$

Then the parameter a is determined such that the mean of the transformed daily values corresponds with the observed mean. The resulting parameter a depends on b. The parameter b depends only on the CV and is independent of the value of parameter a. At the end, each block of 5 days has its own a and b parameter, which are the same for each year. The bias correction for the ERA15d data set needs to be calculated for the period 1979–1995, which has a total length of 17 years. Figure 3 illustrates the division of a year into 73 blocks of 5 days. For every 5-day block, a different set of a and b parameters is determined using the method described above. The top panel of Fig. 3 represents the daily precipitation throughout the year. The bottom panel zooms in to the first 65 days of the year resulting in 13 blocks of 5 days each. Parameters of block 7 are calculated using 30 days before and 30 days after the considered block, and taking into account all years for which the bias correction is applied. This results in 1105 (=17×65) values for the calculation of the CV and the mean.

4.3 Temperature

For correcting the daily temperature a different technique is used. The correction of temperature only involves shifting and scaling to adjust the mean and variance (Leander and Buishand, 2007). For each sub-basin, the corrected daily temperature T^* was obtained as:

$$T^* = \overline{T}_o + \frac{\sigma(T_o)}{\sigma(T_m)}(T_u - \overline{T}_o) + (\overline{T}_o - \overline{T}_m) \tag{4}$$

where T_u is the uncorrected daily temperature from ERA15d, T_o is the observed daily average temperature from the CHR data set and T_m is the corresponding basin average temperature obtained from ERA15d. In this equation an overbar denotes the average over the considered period and σ the standard deviation. This method was not appropriate for precipitation because it might cause negative values. Again both statistics were determined for each 5-day block of the year separately, using the same 65-day windows as for the bias correction of daily precipitation.

5 Results

5.1 Introduction

In the following sections the data are analyzed spatially and temporally. We analyse how well the important statistics (CV, standard deviation and mean) of the corrected ERA15d data match those of the observations after the bias correction has been applied. Extended analyses are done on the behaviour of extremes, fraction of wet days and lag-1 autocorrelations. This is done for precipitation and temperature seperately. The sensitivity of the determined *a* and *b* parameters is investigated by using bootstrapping.

5.2 Precipitation

5.2.1 Spatial precipitation difference

The average precipitation is corrected to match the average precipitation for each window of 65 days times 17 years. It would also be of interest if the daily average precipitation over the entire period has improved as well. For calibration purposes it is important that the spatial differences between ERA15d and the observations are as small as possible. Therefore the average daily precipitation over the period 1979–1995 has been calculated for each sub-basin seperately. The difference in average daily precipitation between the observations and the uncorrected and corrected ERA15d data is shown in Fig. 4. A positive difference means that ERA15d is wetter than the observed precipitation value for that specific sub-basin. As can be seen from Fig. 4, the difference between the uncorrected ERA15d and the observations varies between −2 and +2 mm d^{-1}. The uncorrected ERA15d precipitation is too wet for most of the Rhine basin, especially in the Alps and in areas close to where the river Rhine is located. From the right panel of Fig. 4 it can be concluded that the bias correction leads to satisfactory results. Differences between the corrected ERA15d and the observations

have decreased significantly. The spatial variation in the spread of yearly precipitation differences per sub-basin, is quantified by the root-mean-square-error (RMSE) of the yearly averaged daily precipitation (Fig. 5). The RMSE of the bias-corrected precipitation has decreased significantly for the entire Rhine basin, especially for the Black Forest and some sub-basins in the Alps. It can be concluded that the spread in yearly precipitation differences has decreased considerably.

5.2.2 Temporal precipitation difference

The Rhine basin is subject to a stong seasonal pattern in which wet winters and dry summers are quite common. This aspect is important for the correct timing of flood peaks. Therefore we are interested in how well the bias-corrected ERA15d precipitation performs temporally. We already noticed that the daily average over the entire period has improved significantly (Fig. 4). However, it is certainly possible that the average monthly precipitation sums of the corrected ERA15d data differ from those of the observations, but that the average ERA15d precipitation over the entire period is unbiased. Figure 6 represents the average monthly precipitation sums for the observations and the uncorrected and corrected ERA15d data. Averages are calculated as weighted (based on sub-basin size) averages over the period 1979–1995. Large differences between the observations and the uncorrected ERA15d can be seen during May, June, July, September and October. However, the bias correction seems to correct for this bias reasonably well. It has some difficulties in correcting the precipitation during September and October. This suggests that the employed method, is less capable of correcting the precipitation sum if the observed precipitation is increasing from one month to the next, while the ERA15d precipitation is decreasing from one month to the next.

As Fig. 6 already suggested, precipitation is corrected from a wet to a drier situation for almost the entire year. In September and October the correction is the other way around, and according to Fig. 6 the described method has some difficulties in correcting for this shift. Figure 7 represents the ratio of the area-weighted average corrected preciptitation over the area-weighted average uncorrected precipitation. The 10th and 90th percentile for the spread in ratios between the various sub-basins are shown as well. This figure confirms the results as obtained from Fig. 6, namely that the bias correction method tries to correct from a dry to a wetter situation in September and October, but that the difference is too large to obtain satisfactory results during these months. The spread in ratios between the sub-basins is largest during summer. However, considering the good obtained results from Fig. 6 during summer, it can be concluded that the bias correction leads to satisfactory results for this time of year.

5.2.3 Variation and sensitivity of parameters

The determined *a* and *b* parameters affect the corrected daily precipitation value. It is of major importance how sensitive these parameters are to the chosen period of time. What would happen with the parameters if we had chosen a shorter, longer or different time period for determing the parameters? Figure 8 shows a boxplot of the *a* and *b* parameters throughout the year. These boxplots are calculated for each block of 5 days taking into account the values from all sub-basins. Outliers are defined as values larger than 1.5 times the interquartile range and are indicated with red crosses. It is clear that parameter *a* is smaller than one during almost the entire year. Parameter *a* was determined to fit the mean of ERA15d with that of the observations. It can be concluded that the average precipitation has to be corrected from a wet to a drier situation for almost the entire year. This correction is especially large during summer, as was allready noticed from Fig. 6. However, the spread in the *a*-parameter is smallest during summer. This spread is large during winter, which denotes a large variation in the *a*-parameter for the various sub-basins. It could be that the uncertainty of the *a*-parmeter is large during winter. Outliers indicate sub-basins, especially during the first 280 days of the year, for which the *a*-parameter is significantly higher or lower than for most of the sub-basins. Sub-basin 1 (see Fig. 2) is an outlier during almost the entire year. Sub-basin 119 (eastern part of Switzerland) has an *a*-parameter which is smaller than 1.5 times its interquartile range for the 26th and 27th block. The spread in the

b-parameter (Fig. 8 bottom panel) is less significant as was the case for parameter *a*. Outliers can be found throughout the entire year, except for the first 55 days of the year. Outliers for a large *b*-value occur mainly in sub-basin 107. Small outliers for *b* occur mainly for sub-basin 1. Parameter *b* is larger than one during almost the entire year. The CV has to be corrected the most during summer months.

To address the uncertainty concerning the determined *a* and *b* parameters, we applied bootstrapping for block 55 and sub-basin 1. This is done because for this block the spread in both *a* and *b* is quite significant and both *a* and *b* contain sub-basin 1 as an outlier for this block and we have noticed that sub-basin 1 seems to be a frequently occuring outlier. In our case we took 10 000 random samples of 65 days from the 17 years of data available for block 55 and sub-basin 1, and determined for each sample a new *a* and *b* parameter. The results of this analysis are shown in Fig. 9. It can be concluded that the uncertainty range for parameter *a* is larger than for parameter *b*. Considering the range of the 95% confidence interval, it can be seen that the width of this interval for parameter *a* is almost 3 times larger than for parameter *b*. In other words, the largest uncertainty is associated with correcting the mean of the precipitation values.

5.2.4 Statistics

In Sect. 4 we described the method of the bias correction, that is employed to fit the mean and CV for the precipitation data. Figure 10 shows several scatter plots for the fitting statistics as well as for the fraction of wet days (f_{wet}) and the lag-1 autocorrelations. These statistics are calculated for each of the sub-basins seperately, resulting in 134 data points for each graph. The observed statistics are plotted versus those of the uncorrected and corrected ERA15d data.

Of course the mean, standard deviation and CV of the observations match those of the corrected ERA15d almost perfectly, because those were the fitting criteria. Interestingly, also the correlation between the fraction of wet days in the observations and in ERA15d has improved significantly for the corrected ERA15d data. Also the lag-1 autocorrelations of the corrected ERA15d data match those of the observations better than the uncorrected ERA15d data. These results can be considered as good, because the method of bias correction applied in this study was only intended to correct for the CV and mean, not for the fraction of wet days or the lag-1 autocorrelation.

As mentioned before, we intend to use the bias-corrected ERA15d precipitation for the calibration of the VIC model. With that we want to evaluate the impact of climate change on streamflow generation in the Rhine basin by forcing the VIC model with several climate scenarios. For climate impact studies it is important that the hydrological model is capable of simulating the runoff generated by large multi-day precipitation events well enough. These large multi-day precipitation events often result in floods. Therefore we have selected all 10-day precipitation sums occuring during winter. The exceedance probabilities for these 10-day precipitation sums have been investigated in Fig. 11. According to Furrer and Katz (2008) a Generalized Pareto distribution is capable of fitting high intensity precipitation data. Therefore we have fitted a Generalized Pareto distribution through the data. The Generalized Pareto distribution function is given by:

$$y = f(x|k,\sigma,\theta) = \left(\frac{1}{\sigma}\right)\left(1 + k\frac{(x-\theta)}{\sigma}\right)^{-1-\frac{1}{k}} \tag{5}$$

where k is the shape parameter, σ is the scale parameter and θ is the threshold parameter. The parameters are estimated using the maximum likelihood method. Both the uncorrected and corrected ERA15d data match the observations well for return periods larger than 20. However, for return periods smaller than 20 the uncorrected ERA15d matches the 10-day precipitation sums of the observations better than the corrected ERA15d does. These differences are however quite small. More important is that the distribution of the 10-day precipitation sums is not significantly disturbed by applying a bias correction.

5.3 Temperature

5.3.1 Spatial temperature difference

The difference in average daily temperature between the observations and ERA15d for each sub-basin is shown in Fig. 12. These differences are averaged over the period 1979–1995. A positive value corresponds to a higher temperature for the uncorrected ERA15d data set. Differences in average temperature vary between −1.5 and +3.5°C for the uncorrected ERA15d data. The average temperature difference is positive for the largest part of the Rhine basin, which means that the uncorrected ERA15d is warmer than the observations for that part of the Rhine basin. The right panel of Fig. 12 shows the differences between both data sets after the correction has been applied. It can be concluded that the bias correction for temperature leads to good results. Differences have decreased significantly to values between −0.4 and +0.4°C. Another point of interest is the spatial variation in the spread of yearly temperature differences per sub-basin. This is quantified by the RMSE of the yearly averaged daily temperature (Fig. 13). Although the RMSE for the uncorrected case is not large, there is an improvement visible in the RMSE for the bias-corrected ERA15d.

5.3.2 Temporal temperature difference

Average monthly temperatures for the period 1979–1995 are shown in Fig. 14. Averages are calculated as area-weighted averages over the entire Rhine basin. With the bias correction we hope to capture the seasonal pattern of temperature. It can be concluded that the bias correction for temperature leads to satisfactory results. The bias-corrected ERA15d temperature matches the observed temperature almost perfectly for each month. Corrections are largest during the summer months and smallest during winter. This is mainly caused by the difference in mean temperature as shown later in Fig. 15.

5.3.3 Standard deviation and mean

As mentioned in Sect. 4 the correction of temperature is more straightforward than for precipitation. It only involves correcting for the mean and the standard deviation. Therefore it is interesting to know how the ratio of the ERA15d standard deviation over the observed standard deviation for temperature varies during the year. The spread in ratios for all sub-basins, before the correction is applied, is represented in the boxplot of Fig. 15 (top panel). A seasonal pattern can be distinguished from this figure. From January on, there is an upward trend until the start of summer, which suggests an increasing variation in temperature for ERA15d when approaching summer. During summer this ratio again approaches one, suggesting an almost similar standard deviation for the observed and ERA15d temperature. Around mid-summer this ratio is increasing again, resulting in a larger spread in temperature for ERA15d during this period. The area-weighted average ratio of 1.05 suggests that the average spread in temperature for ERA15d is larger than that for the observations.

The bottom panel of Fig. 15 represents the spread in average temperature differences between the ERA15d ($\overline{T}_m$) and observed temperature ($\overline{T}_o$). Differences are shown for each 5-day block in a boxplot. Especially during summer the difference between $\overline{T}_m$ and $\overline{T}_o$ tends to be larger, suggesting a much warmer 17-year average for ERA15d than for the observations. The 17-year average temperature appears to be warmer for ERA15d throughout the entire year for almost all sub-basins.

The overal area-weighted average temperature difference of 0.86°C suggests that the average temperature for ERA15d is larger than that for the observations.

5.3.4 Statistics

The most important statistics for the uncorrected and corrected ERA15d temperature are plotted against those of the observations in Fig. 16 in four scatter plots. The considered statistics are the mean, standard deviation, CV and lag-1 autocorrelation. They are calculated over the entire period 1979–1995, for each sub-basin seperately. As

mentioned before, the chosen method of bias correction only corrects for the mean and the standard deviation. This is clearly visible in the plots of the mean, standard deviation and CV, where the corrected ERA15d statistics are almost similar to those of the observations. Despite the fact that the correlation coefficients between the lag-1 autocorrelations for ERA15d and the observations have increased for the corrected situation, the points have moved further away from the $x=y$ line. However, considering the scale of the y-axis this results seems to be of minor importance.

5.4 Relation between precipitation and temperature

The employed bias correction method adjusts precipitation and temperature seperately. It is possible that there exists a certain relation between these variables and that this relation is disturbed after applying a bias correction. Dependencies between the daily precipitation and temperature are shown in Fig. 17 for sub-basin 119 in the Alps. This sub-basin is chosen because the uncorrected precipitation and temperature for this sub-basin were significantly different from that of the observations. Results are shown for the observations and the uncorrected and corrected ERA15d data. The extremely low R^2 for the correlation between precipitation and temperature indicates the absence of correlation. From this figure we can conclude that the pattern of points and correlation coefficient are not drastically disturbed after the bias correction is applied.

6 Conclusions and discussion

In this study a bias correction has been applied to ERA15d data to correct for a bias in precipitation and temperature. ERA15d was downscaled at the Max Planck Institute for Meteorology in Hamburg in two steps (with their REMO model; Jacob, 2001) to a resolution of 0.088 degrees. Observations for 134 sub-basins at a temporal resolution of one day were made available by the International Commission for the Hydrology of the Rhine basin (CHR) (Sprokkereef, 2001). The purpose of this study is to minimize the bias between the observed and ERA15d data to make the data suitable for calibrating hydrological models, in particular the VIC model. Precipitation is adjusted to fit the mean and CV of the observations, while temperature is adjusted to fit the mean and standard deviation of the observations.

The uncorrected ERA15d precipitation was found to be too wet for most of the Rhine basin when compared with the observations. Especially areas in the Alps and close to the Rhine valley were far too wet. The bias correction minimizes the difference between ERA15d and the observations drastically. Corrections are largest during May, June, July, September and October. However, the method has some difficulties in correcting the precipitation during September and October. This suggests it is less capable of correcting the precipitation if the observed precipitation is increasing from on month to the next where ERA15d is decreasing from one month to the next. Bootstrapping resulted in uncertainty ranges considering the determined a and b parameters. It can be concluded that the 95% confidence intervals for parameter a are almost 3 times larger than for parameter b. This means that the uncertainty about the mean precipitation is larger than for the CV of the preciptiation. The employed method of bias correction was intended to correct for the mean and CV of the observations only, but it seems to correct other statistics as well. In particular, the correlation between the fraction of wet days in the observations and ERA15d has improved significantly for the corrected ERA15d data. The same is true for the lag-1 autocorrelations, although less significant than for the fraction of wet days.

10-day winter precipitation sums were selected and plotted against their return periods. The occurrence of 10-day winter precipitation events often results in floods and is therefore important for the calibration of a hydrological model. The bias correction does not disturb the distribution of these 10-day winter precipitation sums. Only for large return periods, the uncorrected 10-day winter precipitation sums match those of the observed better, but these differences are relatively small.

The standard deviations for the uncorrected ERA15d temperature tend to be much larger than for the observations. These differences seem to be largest at the begin-

ning and end of summer. Considering the spatial distribution of average temperature differences we see that the uncorrected ERA15d temperature is too warm for most of the Rhine basin. However, the bias correction method seems to correct for these differences very well. Differences between the observed and corrected ERA15d temperature are in the order of 0.4°C. The largest corrections are applied during summer months. The means, standard deviations and CVs for the corrected temperature match those of the observations almost perfectly. This result is expected because that is what the method of bias correction is based on. Despite the fact that the correlation coefficients between the lag-1 autocorrelations for ERA15d and the observations have increased for the corrected situation, the points have moved further away from the $x=y$ line. However, this result seems to be of minor importance.

The bias correction employed does not introduce a spurious correlation between precipitation and temperature.

This study employed a bias correction for temperature and precipitation data only. The VIC model, however, needs other meteorological forcing data as well, such as surface air pressure, specific humidity, upward solar radiation, net solar radiation, upward thermal radiation, net thermal radiation and wind speed. Unfortunately there were no observations available for these variables and they were therefore left uncorrected. For calibration purposes we expect the precipitation and temperature to be the most important parameters to correct for. More research considering the remaining VIC forcing variables is recommended. A final point of attention is the temporal and spatial resolution at which the bias correction is applied. The bias correction in this study is determined at a temporal resolution of one day and at the scale of sub-basins. We intend to run the VIC model at a 3-hourly temporal resolution for grid cells with a size of 0.05 degrees. More research considering bias corrections at such resolutions is recommended.

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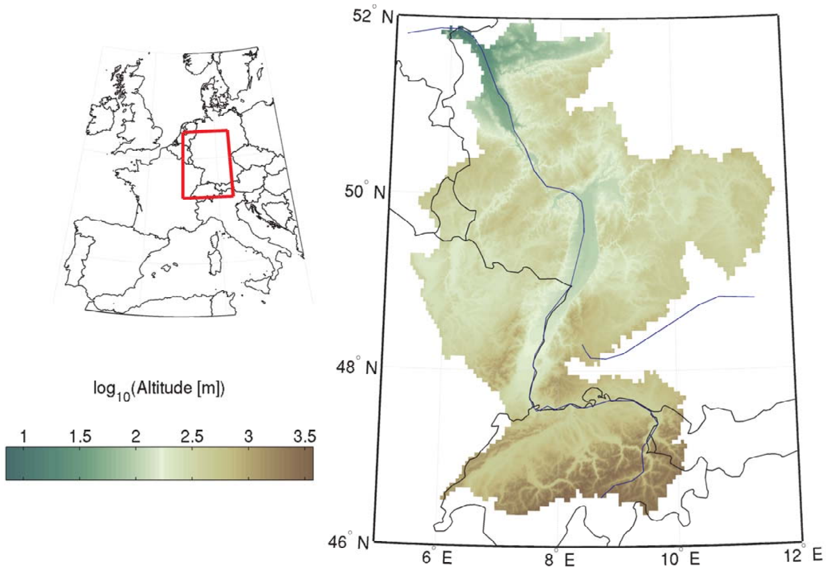

Fig. 1. Location and elevations of the Rhine basin upstream of the German border.

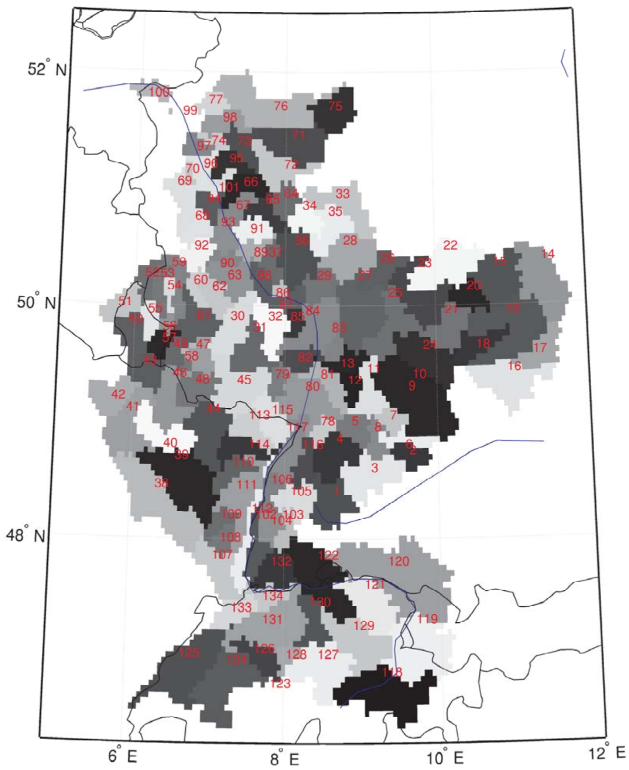

Fig. 2. Location of the 134 sub-basins for which observations are available at a temporal resolution of 1 day.

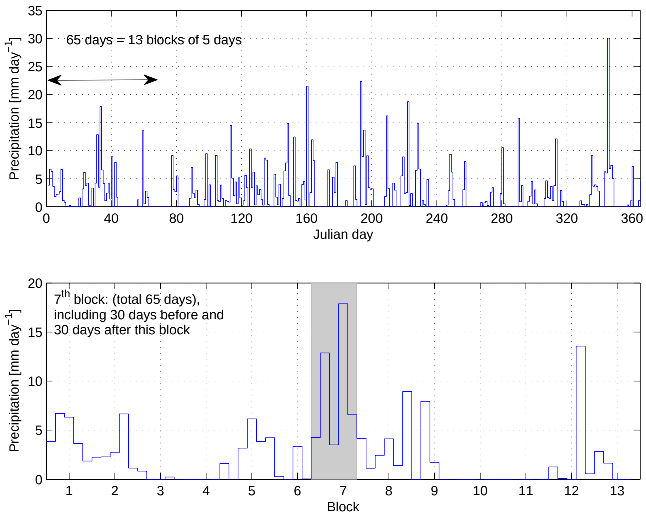

Fig. 3. Schematisation of the division of a year into 73 blocks of 5 days each for which the *a* and *b* parameters are determined. Top panel: daily precipitation throughout the year; bottom panel: first 65 days of the year resulting in 13 blocks of 5 days each.

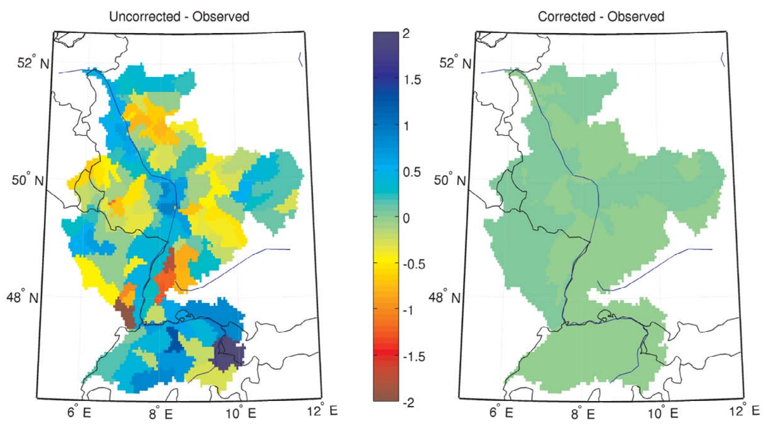

Fig. 4. Difference in average daily precipitation [mm] between the observations and the uncorrected (left panel) and corrected (right panel) ERA15d data for the period 1979–1995.

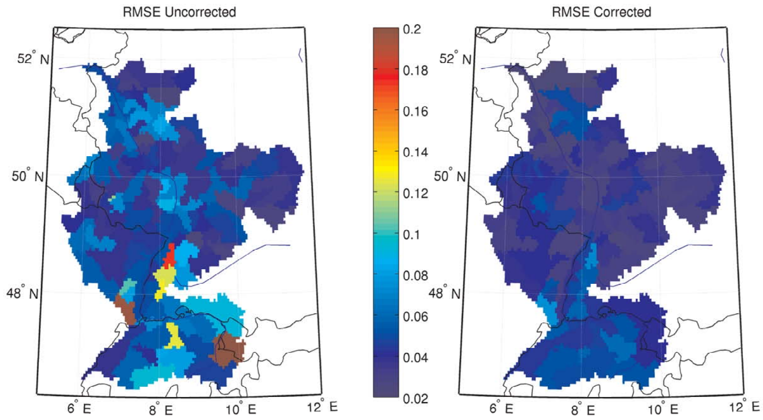

Fig. 5. RMSE of the yearly averaged daily precipitation per sub-basin for the uncorrected (left panel) and corrected (right panel) for the period 1979–1995.

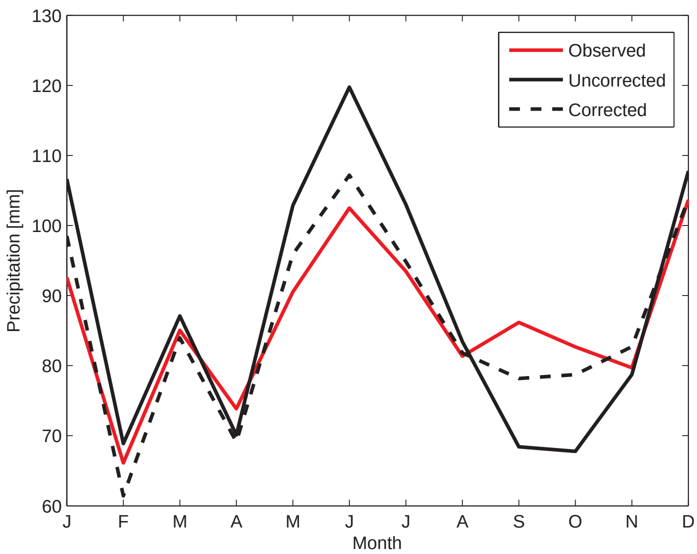

Fig. 6. Average monthly precipitation sums [mm] for the observations and the uncorrected and corrected ERA15d data. Averages are calculated as weighted (based on sub-basin size) averages over the period 1979–1995 for the entire Rhine basin.

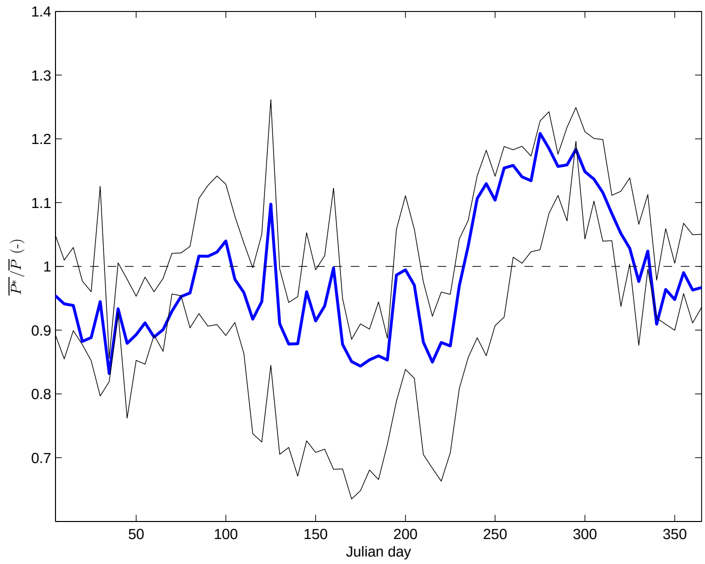

Fig. 7. Ratio of area-weighted average corrected precipitation and the area-weighted average uncorrected precipitation (bold line) for the entire Rhine basin. The thin black lines represent the 10th and 90th percentile of that ratio.

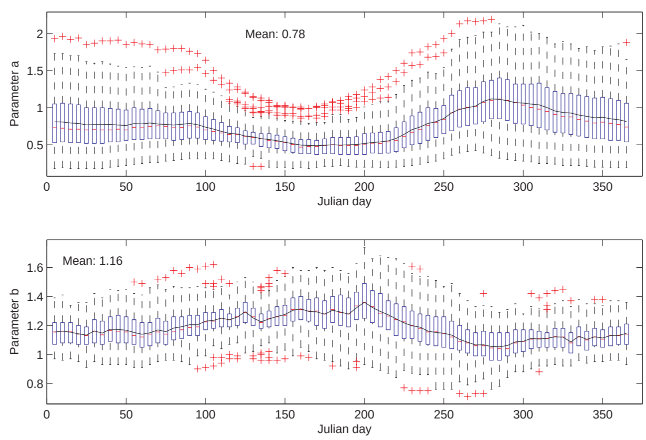

Fig. 8. Boxplots of the parameters *a* (top panel) and *b* (bottom panel) for each block of 5 days. Boxplots are calculated taking into account the values from all sub-basins. Median values are represented with the horizontal red lines. Area-weighted average *a* and *b* parameters are shown with the black solid line. Outliers (red crosses) are calculated as values larger than 1.5 times the interquartile range.

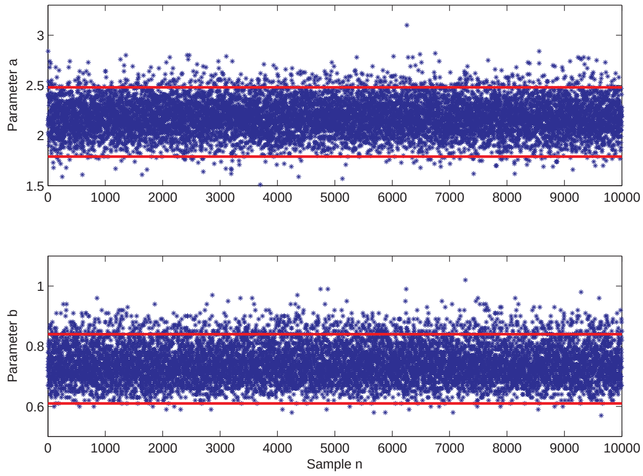

Fig. 9. Values for *a* (top panel) and *b* (bottom panel) for 10 000 random samples of 65 days from 17 years of data. Samples are taken from sub-basin 1 and from block 55, including 30 days before and after this block. 95% confidence intervals for both *a* and *b* are indicated with the solid red lines.

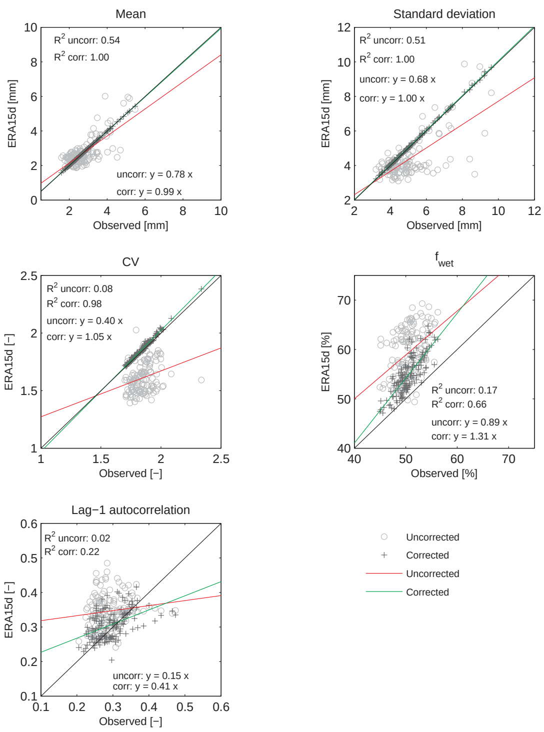

Fig. 10. Scatter plots of the statistics of the observed precipitation versus the corrected and uncorrected ERA15d precipitation. The statistics are calculated for each sub-basin over the period 1979–1995. The fraction of wet days (f_{wet}) is the percentage of days where P>0.3 mm. In each subplot the square of the correlation coefficient (R^2) and slope of the linear regression line are plotted. The black line represents the x=y line.

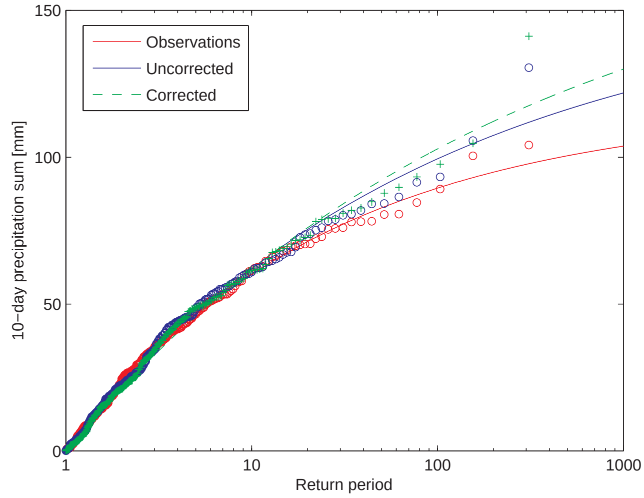

Fig. 11. Return periods of basin-averaged 10-day winter precipitation sums for the period 1979–1995. The 10-day precipitation sums are area-weighted averages.

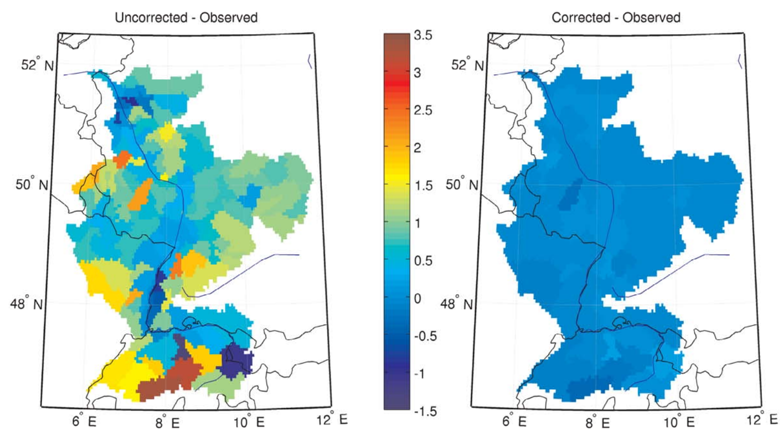

Fig. 12. Difference in average daily temperature [°C] between the observations and the uncorrected (left panel) and corrected (right panel) ERA15d data for the period 1979–1995.

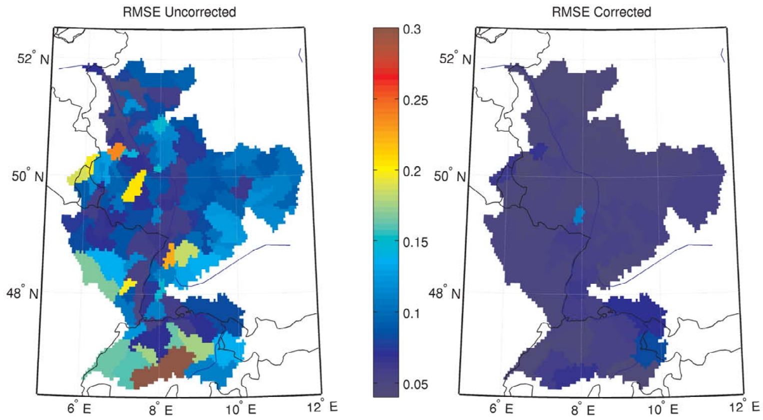

Fig. 13. RMSE of the yearly averaged daily temperature per sub-basin for the uncorrected (left panel) and corrected (right panel) for the period 1979–1995.

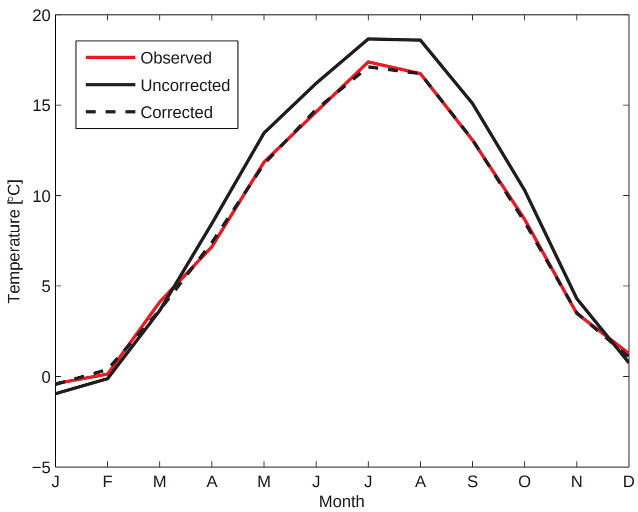

Fig. 14. Area-weighted monthly temperature [°C] over the entire Rhine basin for the period 1979–1995. Results are shown for the observations and the uncorrected and corrected ERA15d.

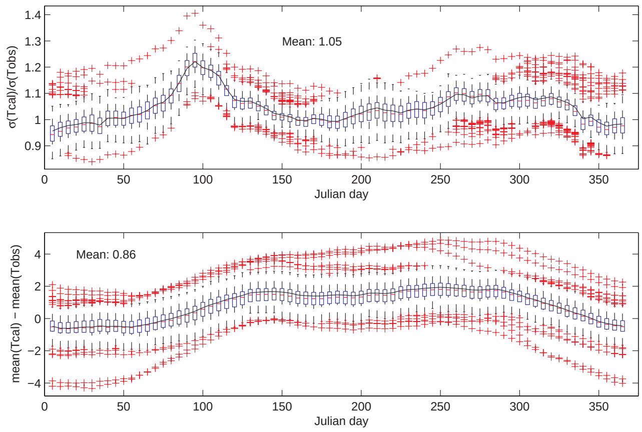

Fig. 15. Boxplot for the ratios of the ERA15d standard deviations over the observed standard deviations (top panel). Boxplot for the differences between the ERA15d average temperatures and observed average temperatures (bottom panel). Boxplots are shown for each block of 5 days in which each box represents the spread between all sub-basins. Area-weighted averages for each block of 5 days are represented with the solid black line. Median values are represented with the horizontal red lines while outliers are indicated with the red crosses and are calculated as values larger than 1.5 times the interquartile range.

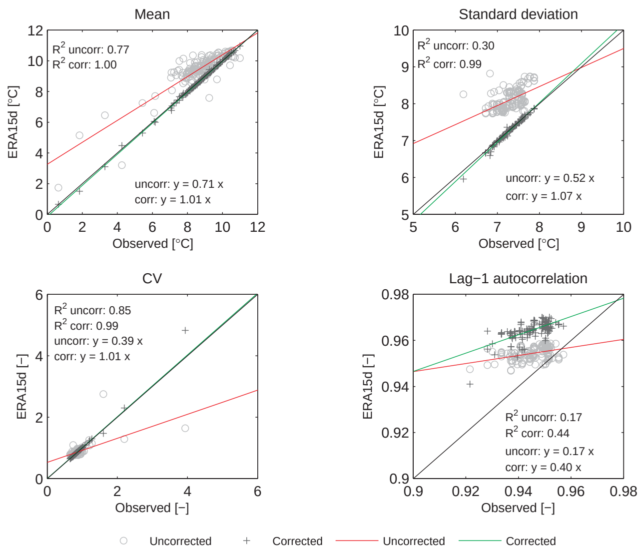

Fig. 16. Scatter plots of the statistics of the observed temperature versus the corrected and uncorrected ERA15d temperature. The statistics are calculated for each sub-basin over the period 1979–1995. In each subplot the square of the correlation coefficient (R^2) and slope of the linear regression line are plotted. The black line represents the $x = y$ line.

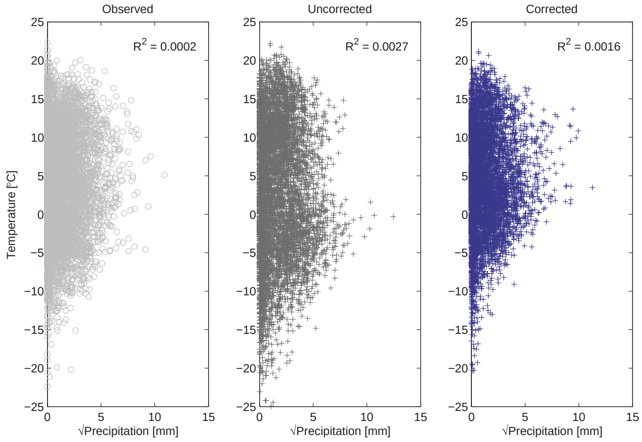

Fig. 17. Dependency between the daily precipitation and temperature of the observed and uncorrected and corrected ERA15d data for sub-basin 119 in the Alps for the period 1979–1995. The units on the x-axis are [$\sqrt{mm}$]. The squared correlation coefficient for the correlation between precipitation and temperature is shown as well.