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ORIGINAL PAPER

On correcting precipitation as simulated by the regional climate model COSMO-CLM with daily rain gauge observations

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Abstract Precipitation amounts simulated by the regional climate model COSMO-CLM are compared with observations from rain gauges at German precipitation stations for the period 1960–2000. The model overestimates precipitation by about 26 %. This bias is accompanied with a shift of the frequency distribution of rain intensities. The model overestimation varies regionally. A correction function is derived which adjusts rain intensities at every model grid point to the observations.

1 Introduction

Climate change is a global phenomenon, and its impact is usually studied with help of global circulation models (GCMs). The coarse spatial resolution of GCMs, however, makes it difficult to assess regional impacts. Thus, regional climate models (RCMs) are used to transfer GCM output to limited areas with higher spatial resolution by so-called dynamical downscaling (Von Storch et al. 2000; Murphy 1999). Downscaling results for Europe are available, e.g. from the regional climate model COSMO-CLM (Rockel et al. 2008). Like GCM runs, also RCM runs need to be validated for past periods for which observations are available, e.g. Jacob et al. (2001), Petrik et al. (2011) prior to their application for climate projections. In this study, we analyze the simulated precipitation from the so-called Consortial Runs (Hollweg et al. 2008) executed with COSMO-CLM, which provide the physical data base for several studies in the framework of the research program Klimazwei of the German Federal Ministry for Education and Research to support climate protection and adaptation (Bardt et al. 2009).

The amount of precipitation including its temporal and spatial distribution ranks among the most important climate parameters (Rutgersson et al. 2001). However, similar to weather prediction, simulated precipitation is also one of the most uncertain predictants. Feldmann et al. (2008) showed deficiencies of precipitation simulated by COSMO-CLM for south-western Germany. More critical with respect to expected precipitation changes is, however, eastern Germany, where already today annual precipitation falls below 500 mm in some regions. Further reductions would confront especially agriculture with considerable problems. In this study, we evaluate precipitation simulated with COSMO-CLM for Germany and derive a correction function, which corrects COSMO-CLM-predicted precipitation for future scenario runs.

Dobler and Ahrens (2008) corrected the COSMO-CLM precipitation bias by a two-step approach suggested by Schmidli et al. (2006). In a first step, the simulated rain day frequency is adjusted to the observed frequency, by selecting the appropriate rain day threshold for the model, while the observational threshold is set to 1 mm. In the second step, the rain day intensity minus the respective threshold is considered. These reduced intensities are corrected by a scaling factor in such a way that the rain amounts in model and observations are equal after the correction. For the second step, Dobler and Ahrens proposed an alternative approach. Here, the reduced intensities are fitted to a gamma distribution. The different scale and shape parameters for model and observations define the

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Table 1 Fraction of rain-free days for individual rain stations (row 1) and after averaging within the model grid cells as obtained for an increasing minimum number of stations; also, the model results are changing slightly, as for higher minimum numbers some grid boxes are no longer taken into account

	Observation	Model
Individual stations	0.5127	0.2894
At least 1 stations	0.4422	0.2894
At least 2 stations	0.4400	0.2895
At least 3 stations	0.4374	0.2896
At least 4 stations	0.4346	0.2892

conversion from uncorrected to corrected model rain. Both of the two-step versions ensures that two features of the corrected model rain are guaranteed: the number of rainy days and the total amount of rain are equal to that found in the observations.

In this study, we propose an even stricter approach to bring the distribution of the model in line with that of the observations. We apply the method of quantile matching, using the cumulative frequencies of the two data sets. This is a mapping method first inspired by Panowski and Brier (1968), which sorts the two distributions and connects the data pairs of each two corresponding rank numbers to each other. We assume temporal constancy of the mapping function as any possible change of the function due to global warming is detectable only by future observations.

2 Data

2.1 Data sets

We analyze the modelled precipitation of the Consortial Runs as provided by the model and data group at the Max

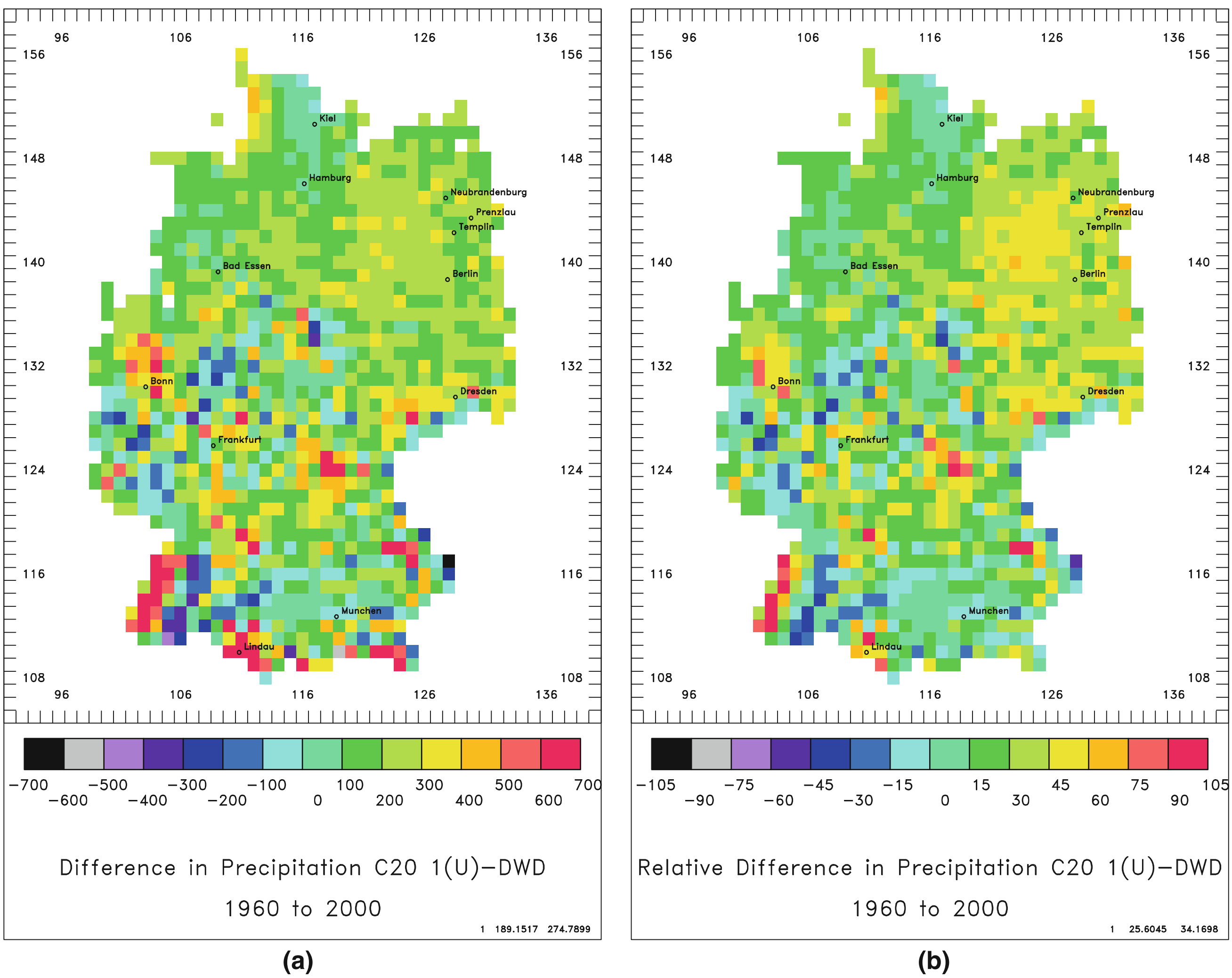


Fig. 1 Overestimation of the precipitation by the climate model COSMO-CLM compared to observations from rain stations in Germany for the period 1960–2000. On the *left panel* (Fig. 1a) the absolute difference in mm/a is given, *on the right* the relative difference in percent (Fig. 1b). The *grid box numbers of the model* are given at the edge of map

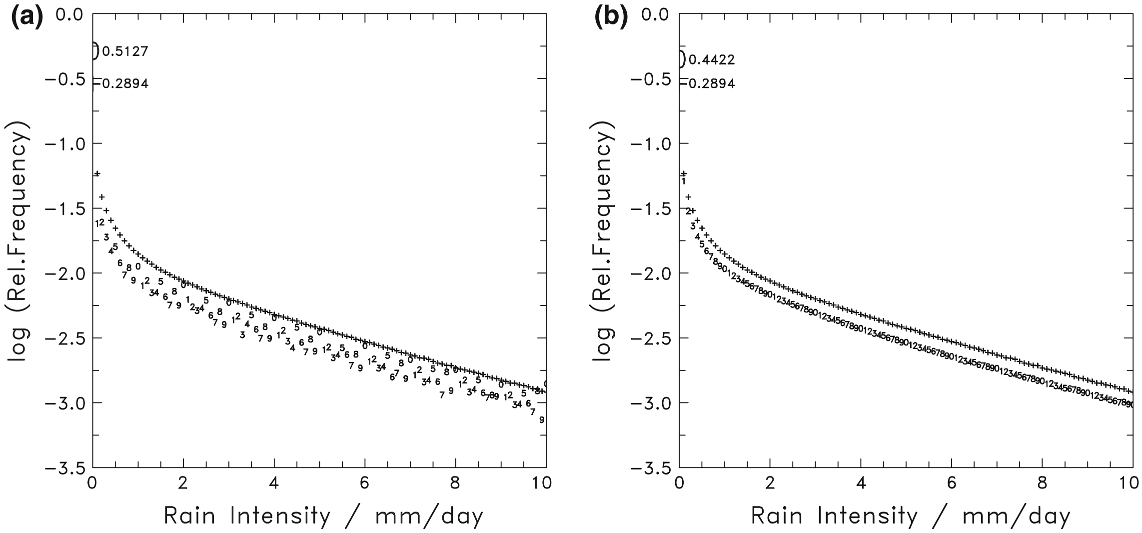


Fig. 2 Frequency distribution of rain intensity classes of 0.1 mm/day for the model (+) and for observations (0–9), where the digits denote the tenth of mm reported. On the *left panel* (Fig. 2a) individual observations are considered. No rain (<0.1 mm/day) occurs in the model with a frequency of 51.27 %, but is observed in only 28.94 % of the cases. These numbers are given explicitly. On the *right panel* (Fig. 2b), the observations are averaged within the model grid boxes

Planck Institute for Meteorology in Hamburg (Hollweg et al. 2008). The Consortial Runs are generated by the regional climate model COSMO-CLM (Rockel et al. 2008), which is based on the weather forecast model COSMO of Deutscher Wetterdienst (DWD) (Steppeler et al. 2003). The COSMO-CLM Consortial Runs have a horizontal resolution of 0.165° corresponding to about 18 km, and are nested one-way in the global climate prediction model ECHAM5 which has a resolution of about 1.8° (Roeckner et al. 2006). ECHAM5 runs of the current climate are available from 1860 on (see e.g. http://cera-www.dkrz.de/WDCC/ui/Entry.jsp?acronym=EH5-T63L31_OM-GR1.5L40_20C_1_6H) using the observed greenhouse gas forcings. Different future greenhouse gas and aerosol scenarios are taken from IPCC AR4 for simulating the future climate until the year 2100 (IPCC 2007).

We evaluate the present day COSMO-CLM simulations for the past 41 years (1960–2000). The three existing independent model realizations of the present day climate with COSMO-CLM (so-called C20 runs) were generated by nesting COSMO-CLM in three global model runs started at three arbitrary years taken from a 500 years control run. In Sect. 3.6, we will shortly discuss the precipitation changes as expected by climate projections following the moderate future scenario A1B (IPCC 2000).

The present day model output is compared to daily precipitation measurements from rain gauge stations operated by the DWD (Behrend et al. 2010). About 5,000 precipitation stations were recording during the period 1960–2000, which assures that on average each COSMO model grid box of 18 km width is sampled by several observing stations. This high-density precipitation data set has been used by many authors as a reference for the evaluation of model results and reanalysis output of precipitation (e.g. Zolina et al. 2004, 2008; Bachner et al. 2008; Ebell et. al. 2008). Following these authors, we abstain from any wind correction of the gauge estimates. We will show, however, that the observed model bias of 26 % is much larger than measurement errors, which would lead to corrections of only a few percent for most precipitation rates (Nespor and Sevruk

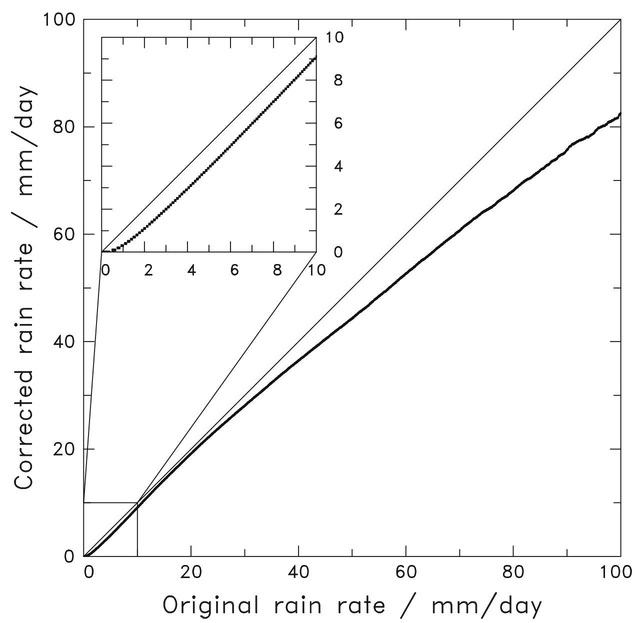


Fig. 3 General correction function for daily precipitation of COSMO-CLM. In the *upper left cut-out*, an enlargement for lower rain rates are given. Please note that all model rain rates below 0.45 mm/day are set to zero

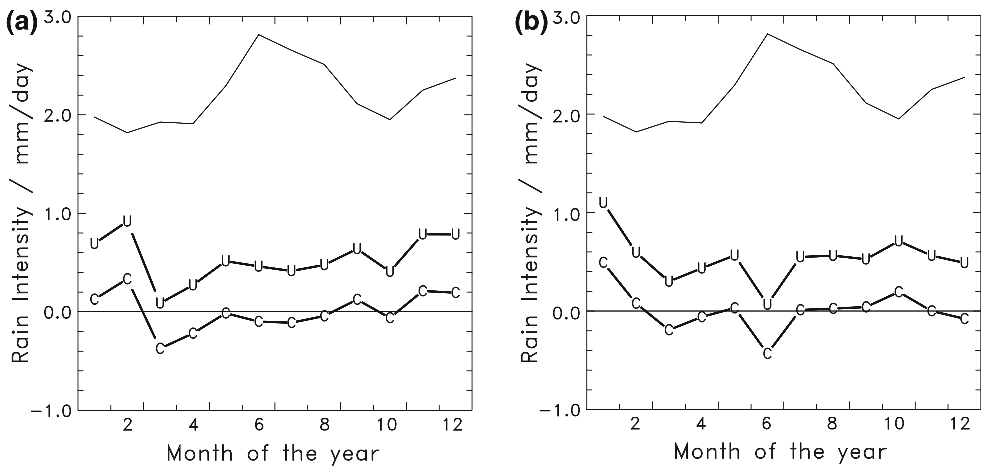


Fig. 4 **a** Monthly mean bias of the model run C20-1 compared to observations before (*U*) and after (*C*) the application of the general correction function as given in Fig. 3. For comparison, the *upper thin line* gives the precipitation as reported by the observations. **b** As Fig. 4a, but for the second model run C20-2

Table 2 Mean and standard deviation that is generated by the monthly precipitation bias of two COSMO-CLM runs; in the last row, it is not the annual cycle of the bias, but the root mean square (RMS) difference between the two runs, which is considered

	Mean (mm/day)	Std dev (mm/day)
Run_1	0.537	0.237
Run_2	0.538	0.241
Run_1_corr	0.006	0.200
Run_2_corr	0.009	0.218
Diff_1-2	0.001	0.264

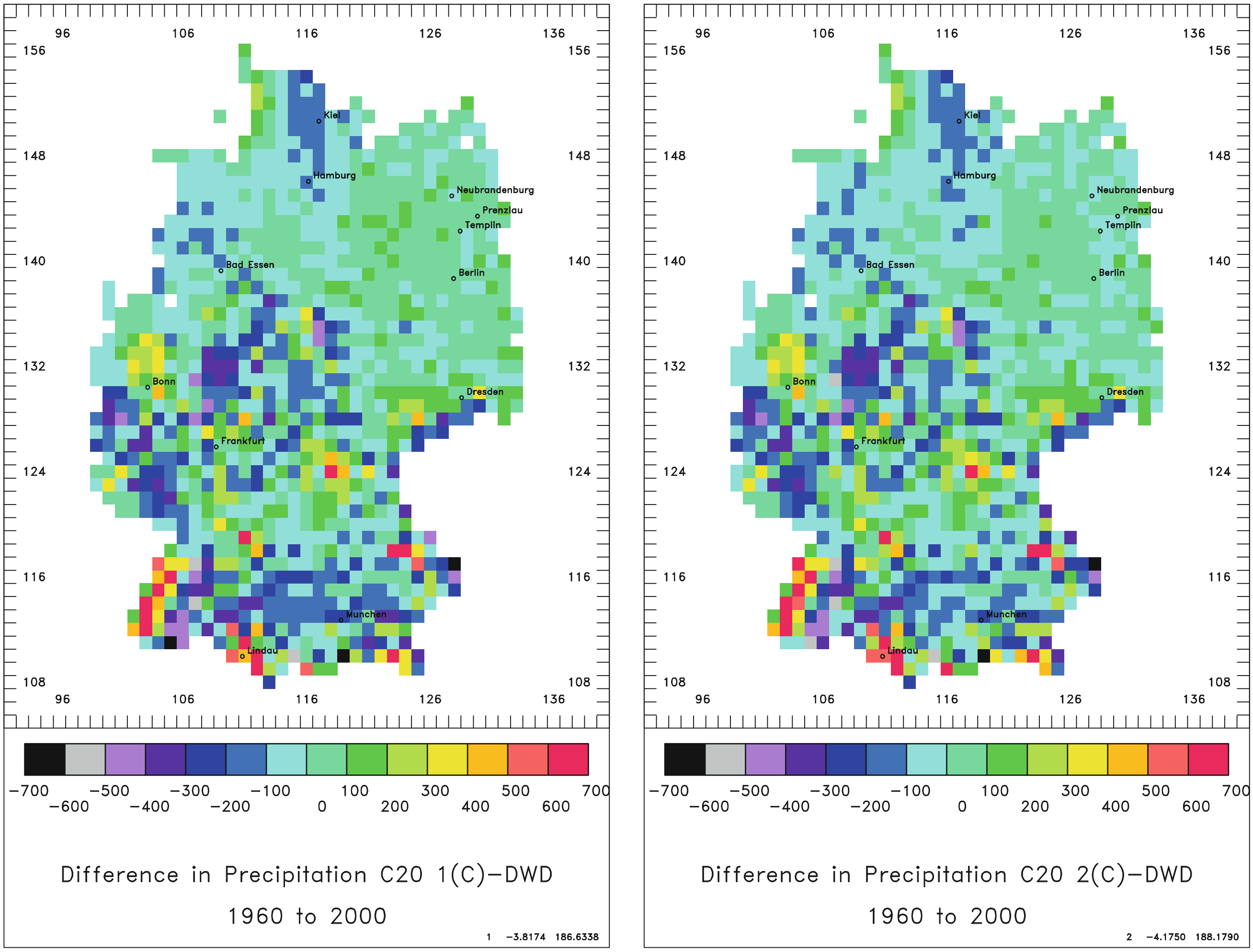
1998; Richter 1995). For very small precipitation rates corrections could amount to 10 % and above, but contribute only marginally to the daily precipitation amounts considered here. Thus, a possible, but relatively small, underestimation by the rain gauges must be kept in mind.

Hollweg et al. (2008) already reported an annual wet bias of the CLM-C20 for Germany of 153 mm, which corresponds to about 20 % of the total annual precipitation amount. They compared the Consortial CLM-C20 runs to so-called reference CLM runs, which are driven by reanalysis data and therefore closer to the true climate. These reference runs themselves have a wet bias compared to observations of in average 48 mm. Thus, both biases add up to about 25 %, which is consistent with our findings. We should mention, however, that Hollweg et al. (2008) consider the latter bias as insignificant because the observational data sets used in their study differ mutually by 85 mm.

2.2 Data processing

Precipitation measurements are known to suffer from deficiencies especially at very low rain rates (Nespor and Sevruk 1998). In these cases, evaporation and wind loss make it difficult to distinguish between dry and wet days. This becomes critical, if climate indices, as e.g. the maximum number of consecutive dry days (CDD), are considered. This parameter depends strongly on the ability to resolve especially the low rain rates. To avoid such problems, Peterson et al. (2001) recommended the usage of a precipitation threshold of 1 mm/day, which has been adopted by many authors, e.g. (Klein Tank and Können 2003; Zolina et al. 2010). However, the present study considers the rain rate itself and no indices based on it, so that a specifically increased threshold for dry days is not necessary here. Instead, the observational threshold of 0.1 mm/day is applied to both observed and model data to distinguish dry from rainy days.

In this study, we compare daily rain amounts observed by rain gauges with modelled precipitation. Due to their different spatial resolutions, the two data sets are not readily comparable. Model data are grid averages, whereas rain gauge measurements are point estimates, which do contain more variability. The surplus of variance of the observational data corresponds to the mean spatial variability within the model grid boxes. This scale problem can be overcome using the additivity of variance, as discussed e.g. by Lindau (2003) and Lindau and Ruprecht (2000). Concerning precipitation this scale problem is discussed in detail by Ruiz-Villanueva et al. (2012). They found extreme high maxima in individual point observations not reflected in radar measurements, which similar to model results are estimates of area averages. Thus, prior to the comparison of both data sets we average all observations within the boundaries of the model grid areas and compute daily precipitation sums from the model output.



(a) (b)

Fig. 5 Remaining bias of the model rain compared to observations as obtained after applying the general correction function as given in Fig. 3 to the C20-1 model run. **b** As Fig. 5a, but for the second model run C20-2

3 Methods and results

The resulting number of comparable data pairs is of the order of 10^7 (about 10^3 grid boxes cover Germany; 40 years contain about 10^4 days). Our aim is to convert every model value in such a way that the corrected data reflects the same statistical properties as they are found in the observations. This goal can be achieved by quantile matching, which sorts both data sets in ascending order with respect to precipitation amount and derives a suitable projection. The sorting, which is performed separately for both data sets, assigns a rank number to each individual daily grid box value. By comparing only the resulting ranks, the original model-measurement pairs are disconnected. Instead, precipitation amounts with same rank numbers in both data sets are connected. Since several million data pairs are related to each other, the transfer function is quite smooth and requires no further intermediate step, e.g. by fitting analytical functions.

One model run (C20-1) is used for the derivation of the transfer function and a second run (C20-2) is used for verification. Both runs describe only the past climate, thus it is cannot be guaranteed that the derived conversion function also applies for the future. In using the derived transfer function for future runs, we hypothesize that our transfer function does not change significantly in time.

In Sect. 3.1, we derive the 26 % model wet bias. In Sect. 3.2, a general correction function is derived by mapping the daily grid averages of the model to those of the observations. Using this general correction, monthly biases remain, but we show in Sect. 3.3 that these biases are random, because the standard deviation of the monthly biases is in the same range as the root mean square (RMS) difference between two independent model runs. When in Sect. 3.4, the same methodology is applied spatially, i.e. to grid box averages instead of monthly averages, the biases of two independent model runs are highly correlated, which calls for a separate correction of each grid box. In the final

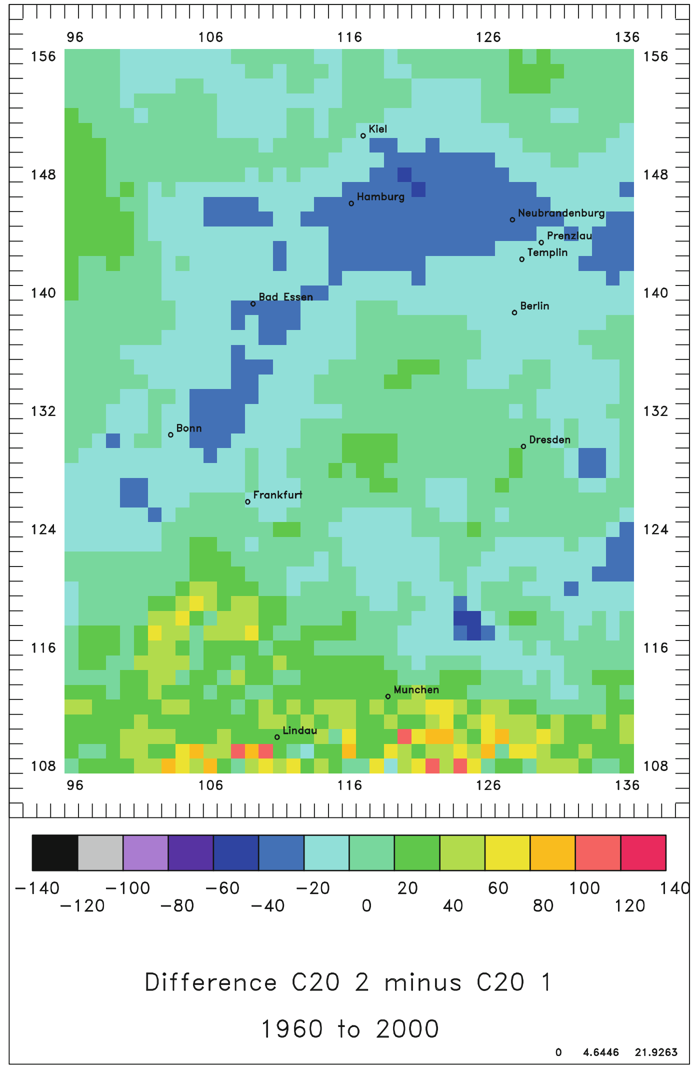


Fig. 6 Precipitation difference between the two model runs C20-1 and C20-2 for the period 1960–2000

Sects. 3.5 and 3.6, we discuss the change of precipitation as given by model scenarios for the coming decades and compare trends in the past of both model results and observations.

3.1 The model bias

As discussed in Sect. 2.2, we average the daily precipitation observations of all stations within the limits of a grid box prior to the comparison of model output and rain gauge observations. This will logically lead to a reduction of the number of dry days, because all stations within a model grid need to report no rain to generate a dry day. According to Table 1, the station average number of dry days is reduced from 51 to 44 %. We have to admit, however, that due to the regionally varying network density the number of stations included within the grid boxes varies also, which induces a small regionally varying bias that we did not correct for. We estimate this error by varying the minimum number of rain gauge stations within one model grid box from 1 to 4 (row 2–5 in Table 1). The fraction of dry days is decreasing for the observations most drastically, when moving from individual stations to areal averages (rows 1–2) as already discussed above. If we omit grid areas with only one, two, or three stations within a model grid area the probability of a precipitation-free day only slightly decreases from 44.2 to 43.5 %. A high minimum number of stations improves the reliability of the corresponding estimates; but a high quorum excludes large regions of northern Germany from the calculations due to the lower station densities, which in turn reflects the higher spatial representativity of stations in lowlands. Because of the weak decrease of dry days for different minimum numbers and to avoid an exclusion of any grid box, we consider in the following a minimum of one station per model grid box sufficient for our comparisons.

From our final twin data base of modelled and observed grid averages of daily precipitation we calculate the

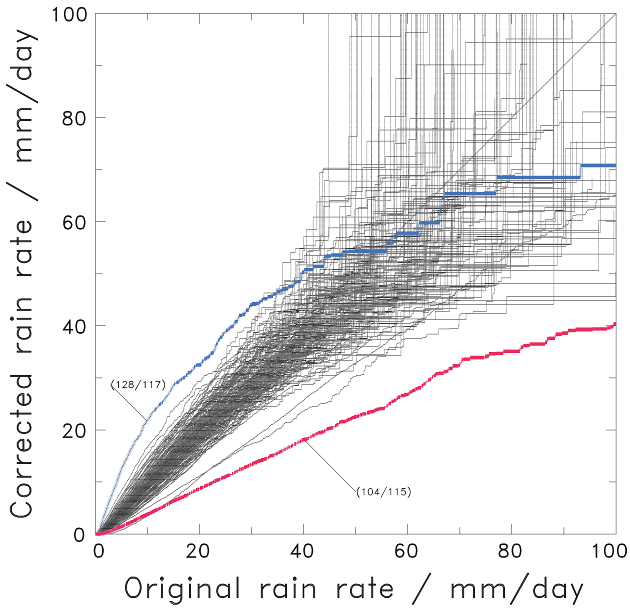


Fig. 7 Individual correction functions for every model grid box for daily precipitation of COSMO-CLM. For a better identification, only each 8th line is drawn (for each 4th grid box in east–west and each 2nd grid box in north–south direction). The two most extreme correction functions, those for the grid boxes (128;117) and (104;115) are marked exemplarily

41-year average for each model grid box. According to the observations, annual precipitation ranges from more than 1,000 mm/a at the foothills of the Alps, the Black Forest, and the Renish Slate Mountains to less than 600 mm/a for large areas of eastern Germany. The average for Germany of the gridded station data set is 785 mm/a, while COSMO-CLM generated 973 mm/a. Thus, averaged over Germany, the model is wetter by 188 mm/a (Fig. 1a).

While the overall model wet bias is 26 %, the regional bias over large parts of eastern Germany is even 50 % (Fig. 1b). We hypothesize is that this bias will project also to future scenarios. Strong regional biases also occur at the Black Forest with an overestimation of the rain at the windward side and opposite effects at the lee side of the mountains. Schwitalla et al. (2008) discuss these orographically induced errors and show that they can be largely reduced by enhancing the spatial resolution of the model. Another possibility to reduce the orographically induced bias would be to use the prognostic precipitation, which is newly implemented into COSMO (Seifert and Beheng 2006a, b).

3.2 The general transfer function for precipitation

Downscaling of precipitation should adequately reproduce, besides total areal precipitation amounts, also the number of dry/wet days and the intensity spectrum. This can obviously not be achieved by a simple reduction of the model precipitation by a fixed percentage. In Fig. 2, we compare the frequency distribution of modelled precipitation intensity classes with the observations. Although Fig. 2a shows the station observations, Fig. 2b reflects the grid box averages. The frequencies of precipitation intensities are depicted in logarithmic scale for better visibility. Model frequencies are consistently higher by an offset of 0.1 compared to the observations (Fig. 2b). Such a difference between the logarithms corresponds to a factor of 1.26, so that the model bias can be estimated to be about 26 %, which is in agreement with the bias found in Sect. 3.1. In turn, in the model simulations only 29 % of the days are precipitation-free, whereas this fraction amounts to 51 % in the raw observations (Fig. 2a) and still 44 % for the grid box averages (Fig. 2b).

We transform now the frequency distribution of the model data C20-1, which is considered to be erroneous, into the frequency distribution of the spatially on the model grid averaged observations, which is considered to be correct, using the method of corresponding cumulative frequencies (Kent and Taylor 1997). To this goal, both distributions are sorted separately according to their daily rain intensities. Any two intensities in both distributions having the same rank number are connected to pairs. These pairs define the transfer function to project model precipitation estimates into corrected estimates, which share their frequency distribution with observations. Since more than 62 million data pairs exist, a complete sorting of the two data sets is extremely time consuming. Instead, we resort to precipitation intensity classes with a class width of 0.1 mm/day. Figure 3 illustrates the resulting transfer function, which e.g. reduces model rain rate of 10 to 9.04 mm/day, because the exceeding probability for both precipitation intensities is 6.75 %. The procedure also ensures that modelled rain rates below 0.45 mm/day are set to zero to meet the correct number of dry days. After the correction both intensity distributions are identical, including the frequency of dry/rainy days, and of course also their means and standard deviations.

3.3 Monthly means

In the following, we analyze the impact of the derived general transfer function on the mean annual cycle. Figure 4a shows the monthly mean differences between both corrected and uncorrected model results against the observations. Obviously, the mean bias averaged over all 12 months vanishes after the correction, as required by the mapping method. However, if each month is considered separately, biases remain, which need to be tested for significance to justify a monthly detailed transfer function.

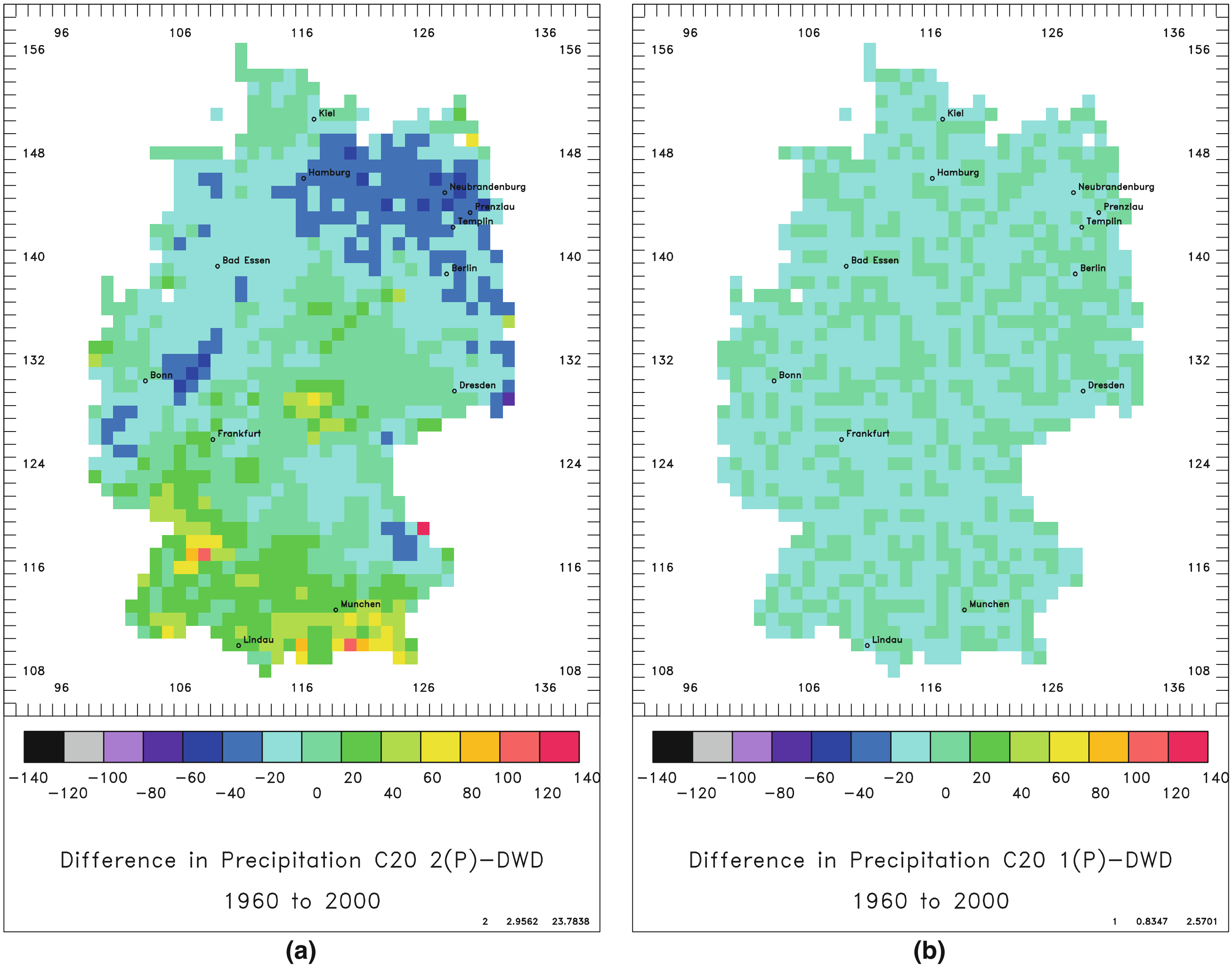


Fig. 8 Remaining error for the two model runs C20-1 (*left* 8a) and C20-2 (*right* 8b) as obtained after applying the individual correction function

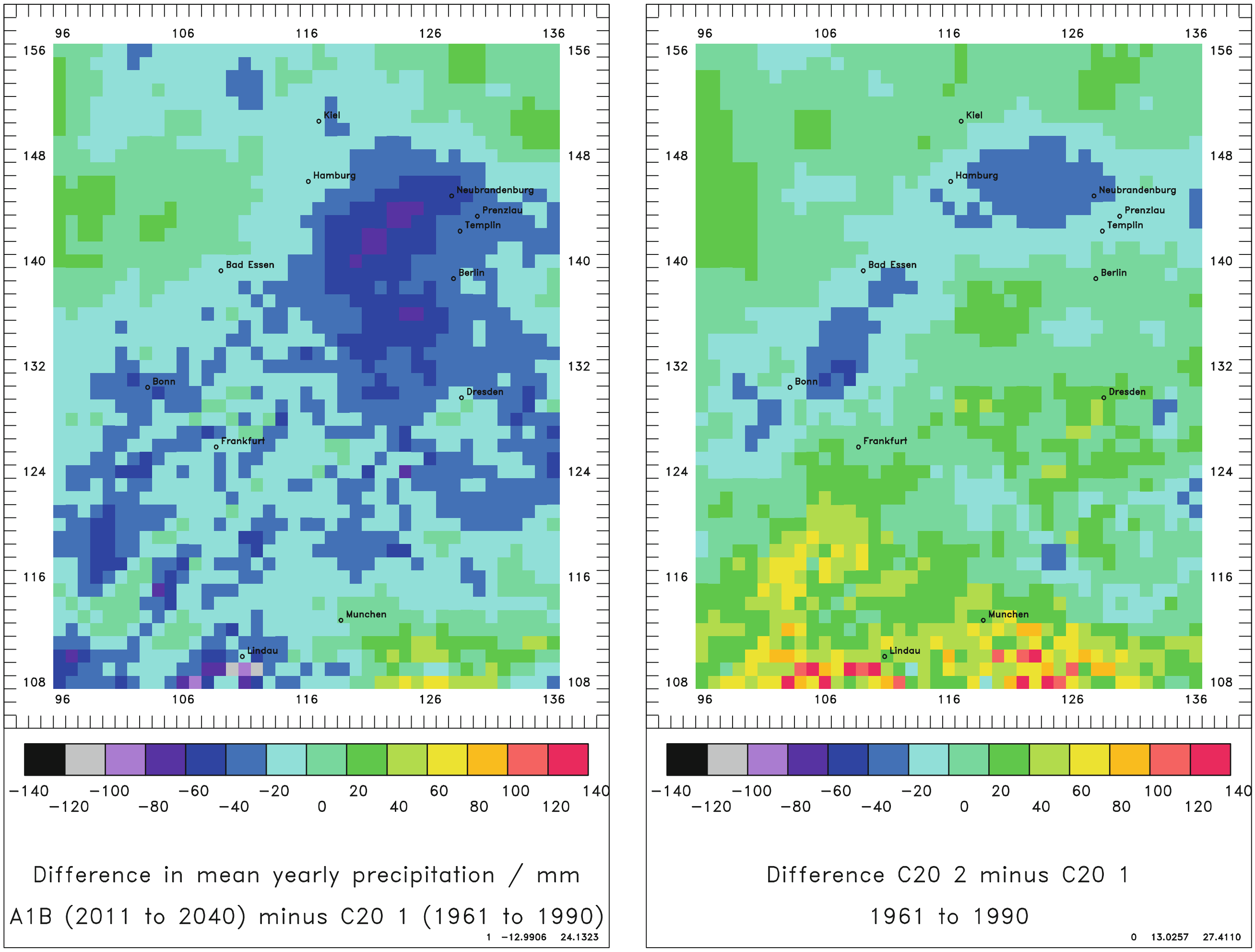
The decision can be based on the results of the second, independent run C20-2 (Fig. 4b). The monthly biases of the two model runs have standard deviations of 0.237 and 0.241 mm/day, respectively (Table 2). Since they are comparable to the standard deviation between the two runs (0.264 mm/day), the individual remaining monthly biases must be random and a monthly detailed transfer function is not required.

3.4 Spatial means and individual grid box correction

We analyze the impact of the general transfer function on the spatial distribution of the mean simulated precipitation for C20-1 and C20-2. Figures 5a and b, which show the remaining spatial bias distribution after applying the general transfer function, are rather similar for both independent runs; e.g. the contrast between the Upper Rhine Valley and the Black Forest is visible in both runs, as well as the generally large scatter of the model bias in western Germany.

Since both runs were corrected with the same general transfer function and compared to the same measurements, we can conclude that the spatial pattern of the long-term mean model precipitation is not random. Figure 6 shows the spatial distribution of the difference between both runs, which has a root mean square difference of only 22 mm/a. This is much smaller than the spatial variability of the individual runs (about 1,000 mm/a), indicating that the spatial bias pattern is significant.

Consequently, the spatial pattern of the model bias has to be included into the transfer function. To this goal, we apply the method of corresponding cumulative frequencies to each grid box individually, which results in the cohort of curves depicted in Fig. 7. The two most extreme curves are highlighted. For grid box (104;115), an area in the Upper Rhine Valley, modelled precipitation will be decreased, while for grid box (128;117), an area at the Czech–Austrian border, modelled precipitation is increased for all rain rates below about 50 mm/day.



(a) (b)

Fig. 9 **a** Change in annual precipitation for the period 2011–2040 (scenario A1B) compared to the period 1961–1990 (C20-1) given in mm/a. **b** As Fig. 9a, but for the difference between the two model realizations C20-1 and C20-2 for the period 1961–1990

The transfer function is derived by using model realization C20-1. Re-applying it to the same data is only a technical test for its correct derivation and should remove the model bias completely. The method of cumulative frequencies is, however, performed by comparing the number of class members instead of sorting the complete daily data as discussed already, and is the reason for the remaining weak scatter of the model bias. The mean bias is reduced from 188 to 0.83 mm/a, while the remaining root mean square error of an individual pixel is 2.57 mm/a (Fig. 8a).

When we apply the correction function to the independent second model realization (C20-2) a bias of 2.96 mm/a remains from the original bias of 188 mm/day and the error of an individual pixel is 23.78 mm/a (Fig. 8b). This error is mainly induced by the model uncertainty itself, because its spatial structure does not differ in a statistical sense from the pattern given in Fig. 6, where the difference between the two runs is shown. The last pattern is characterized by a mean bias of 4.6 mm/a and a standard deviation 21.9 mm/a. If differences between two model runs are considered to be unavoidable model uncertainties, an error of 21.9 mm/a for individual grid boxes and an overall error of 4.6 mm/a for the entire domain is expected. The characteristics for Fig. 8b are with 2.9 and 23.8 mm/a comparable. Since they are in the same range as the expected model errors, we conclude that the scatter shown in Fig. 8b is due to the model uncertainty.

3.5 Future precipitation changes

So far we considered model results for the past decades in order to identify and correct for the model bias by a comparison to observations. In the following we focus on

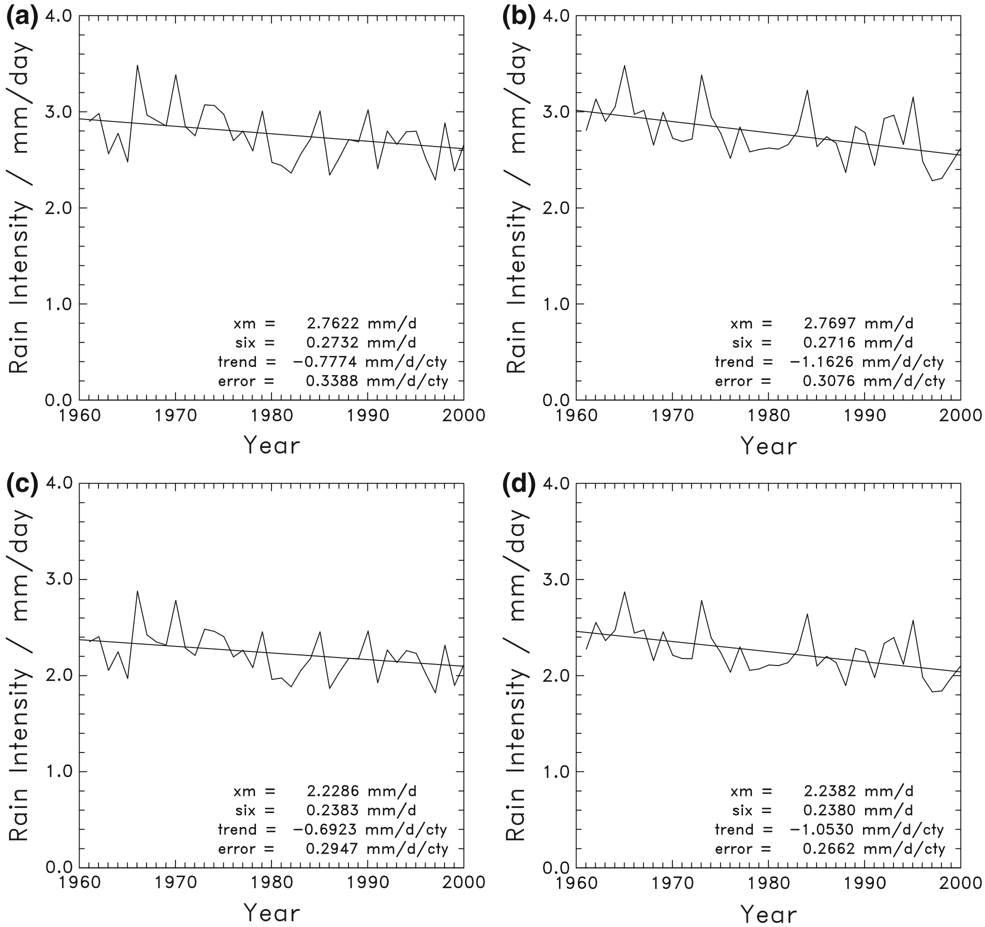


Fig. 10 **a** Time series of the annual precipitation for the period 1960–2000 for model run C20-1. Mean (xm), standard deviation (six) are given in mm/day. The linear trend and its error are given in mm/day per century. **b** As Fig. 10a, but for C20-2. **c** As Fig. 10a, but after applying the individual correction function as shown in Fig. 7. **d** As Fig. 10b, but after applying the individual correction function as shown in Fig. 7

precipitation trends generated by the model, when driven with global runs subject to future greenhouse gas scenarios. Figure 9a shows the change in annual precipitation amount when considering the moderate scenario A1B (IPCC 2007) for the decades 2011–2040 in the model simulations compared to the period 1961–1990 as provided by the C20-1 run. According to this projection, precipitation will be reduced on average over all grid points (Fig. 9a) by 13.0 mm/a. The standard deviation of the change for individual grid points, i.e. the RMS difference, is 24.1 mm/a. In order to decide whether this reduction is significant, we compare the two model realizations C20-1 and C20-2 for the period 1961–1990 (Fig. 9b). The mean annual precipitation difference between both runs is also 13.0 mm/a, and the RMS difference 27.4 mm/a. Both mean difference and RMS deviation are found to be equal or higher between two model realizations of an identical period than those found between two realizations of future 30 years periods with a time difference of 50 years. Thus, we can conclude that no significant change in precipitation is predicted by the model until 2025.

3.6 Precipitation trends

In Sect. 3.5, we showed that according to the model results no significant change is expected for the future annual precipitation amounts. We now investigate the reliability of trends in modelled precipitation for the past. To this goal, we compare the trends produced by the model for the period 1960–2000 with observed precipitation trends. From the model data, we can estimate four linear trends in annual precipitation for Germany, i.e. from the two independent runs both original and corrected with the spatially detailed transfer function (Fig. 10a–d). For all cases, the annual precipitation amount decreases considerably between 1960 and 2000. The trend magnitudes (between 0.69 and 1.16 mm/day/century) are 2–4 times larger than their uncertainties (exactly 2.29, 3.78, 2.35, and 3.96 times), rendering the detected decreases significant. The rationale is the following: the trends are expected to be t-distributed with 40 degrees of freedom. The 0.975 quantile is reached at 2.021, so that all four trends are significant on the 97.5 % level. An analogous analysis of the observations

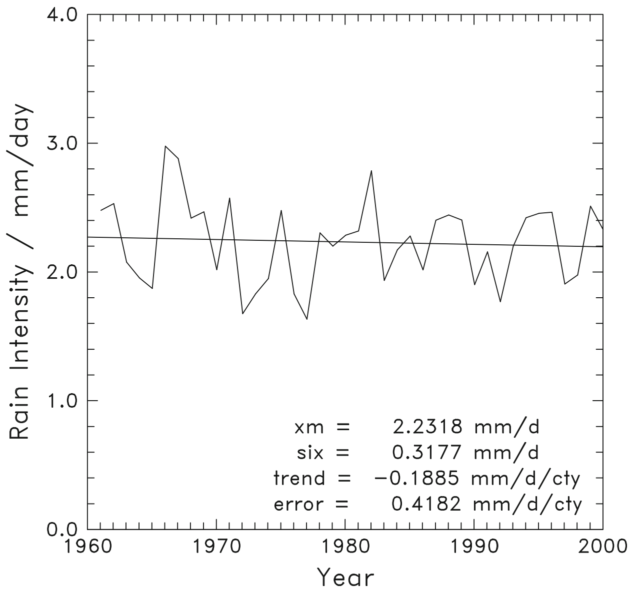


Fig. 11 Trend of the annual precipitation as obtained by measurement of German rain stations

indicates no significant trend (Fig. 11). Thus, the climate model produces trends in precipitation that are not found in observations. Precipitation trends derived from climate scenarios must be handled with considerable care.

4 Conclusions

COSMO-CLM when driven with the C20 global runs of the current climate overestimates precipitation as compared to observations from German precipitation stations. In this study, we derived a transfer function for the modelled precipitation based on the method of cumulative frequencies, which transforms the frequency distribution of the model into that observed at the rain gauges. Seasonal variations of the model bias are shown to be random; thus, a specific monthly correction is not required. In contrast, spatial variations of the model bias are significant. Consequently, our transfer function is derived separately for every model grid box. The overall effect of the correction reduces the modelled precipitation by 26 %. Owing to this large bias, the absolute values of modelled rain from COSMO-CLM are useful only after correction. In particular, uncorrected precipitation amounts from the model scenarios would be much higher than presently observed, even if the model would not produce any significant trend. Precipitation changes predicted for the next decades are, however, within the range of the model uncertainty.

The correction function presented here is assumed to be independent of time; thus, the trends found in the two independent model realizations of the past arise in both, the corrected and the uncorrected data. Surprisingly, the concordant trends do not occur in the observations for the period 1960–2000. We can conclude that statistically significant precipitation trends may well occur also for stable climates, even if they do not happen in reality.

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