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Preface

This research was supported by the project ACER (A7) and the Tailoring project (Cs7), financed partly by the Dutch BSIK programme Climate Changes Spatial Planning. We thank Robert Leander and Jules Beersma for making available the computer code of the Nearest Neighbour Resampling and thinking along how to explain the bias correction. We also wish to thank Janette Bessembinder and Steven Weijs for their constructive comments. Finally, we thank Aline te Linde and Jeroen Aerts for the pleasant cooperation and their feedback on the previous versions on the generated time series.

Contents

Abstract

Extreme discharges of the Rhine are likely to change as a result of the changing climate. A common way to assess impacts of climate change is to use Regional Climate Model (RCM) output to drive impact models. For the assessment of very rare discharge events in a large river basin (e.g. with return periods of 1250 years) there are two major problems. First, available RCM simulations are usually way too short for the robust estimation of such rare events. Second, RCM output is generally too biased for direct use in impact models.

Nearest Neighbour Resampling (NRR) stochastically extends meteorological time series to any length. The generated synthetic time series are subject to the same characteristics as the reference time series and are generally thought to contain rare multi-day extremes in accordance with the time series length. The discharge of the Rhine at Lobith is closely related to the upstream precipitation of multiple preceding days. So, hydrological modelling on the basis of very long synthetic time series may result in more robust estimation of very rare discharge events at Lobith.

The RACMO simulation used for this study was nested in a simulation with the Global Circulation Model ECHAM5 forced by the SRES emission scenario A1B. The simulation is biased with respect to a reference observational data set with precipitation and temperature. Too high spatial and temporal coherency of the rainfall events result in too many wet days. A wet-day adjustment is developed that leaves the Probability Density Function (PDF) of wet-day amounts largely intact and slightly reduces the spatial and temporal coherency. These daily, local scale adjustments also improve the large-scale and multi-day variability. Yet, an additional power-law correction is necessary to efficiently reduce the remaining biases in average precipitation and the coefficient of variability (CV). For the daily temperature a shifting and scaling are sufficient to correct for biases in average temperature and standard deviation.

After the successive application of the Nearest Neighbour Resampling and the bias correction (BC) still some small biases remain. Yet, rare large-scale multi-day rainfall events in the bias-corrected RCM output are very well reproduced compared to the results of the synthetic time series based on historical data. This justifies the application of the generated and corrected time series for hydrological modelling and assessment of extreme discharges at Lobith.

Rare 10-day large-scale precipitation events upstream of Lobith with return periods between 10 and 1250 years increase 7% to 10% according the RACMO simulation and the proposed methods. Rare events with return periods of 1250 years in the current climate will have a 3 to 4 times higher occurrence probability around 2050.

1. Introduction

River dikes protecting the Netherlands against flooding along the Rhine are designed for discharges with a return period of 1250 years. Currently, the design discharge at Lobith amounts 16000m^3s^{-1} (*Te Linde et al.*, 2010). The estimation of such rare events from historical discharge series is very uncertain, since those series usually have a limited length. Therefore, KNMI and RIZA have developed a stochastic weather generator, the Rainfall Generator for the Rhine (*Beersma*, 2002). This Rainfall Generator is based on Nearest Neighbour Resampling (NRR) techniques, originally proposed by *Young* (1994). The resampling of historical time series in the Rhine basin has been optimised for the assessment of extreme discharges within various studies, for instance by *Wójcik et al.* (2000) and by *Beersma and Buishand* (2003).

As a result of climate change the distribution of extreme discharges is likely to change. To explore the range of plausible future climate conditions, climate simulations are performed with perturbed green house gas concentrations. For the assessment of regional climate change, Regional Climate Models (RCM's) are nested in coarse resolution Global Circulation Models (GCM's) (*Giorgi*, 2009). *Leander and Buishand* (2007) and *Leander et al.* (2008) resampled RCM output for the assessment extreme discharges of the Meuse. However, for successful hydrological modelling bias correction appeared necessary.

The objective of this study is to apply a comparable Nearest Neighbour Resampling scheme on RCM output and correct the generated time series for the most important biases. After the resampling and bias correction the time series should be suitable for hydrological modelling. The hydrological model output is used to explore plausible changes in extreme Rhine discharges at Lobith (*Te Linde et al.*, 2010).

For this study, a transient run (1950-2100) with the 2nd version of the KNMI Regional Atmospheric Climate MOdel (RACMO2) is used (*Lenderink et al.*, 2003). The output is stochastically extended (10000 years) with the help of Nearest Neighbour Resampling and is used as input for the hydrological model HBV. These models and the reference meteorological data are briefly introduced in chapter 2. Subsequently, chapter 3 extensively describes the biases in precipitation and temperature in the RACMO output with respect to the historical reference. Special attention is paid to the large scale multi-day variability and extremes, since the Rhine discharge at Lobith typically depends on the weather of multiple preceding days. In chapter 4 the bias correction is optimised and chapter 5 explains the combined effect of the resampling and subsequent bias correction.

2. Data and tools

2.1. HBV-Rhine domain

The meteorological time series are prepared for simulations with the hydrological model HBV[1] (*Lindström*, 1997). HBV-Rhine covers the whole Rhine basin upstream of Lobith, where the Rhine enters the Netherlands and distinguishes 134 subcatchments (*Eberle et al.*, 2005). It uses daily precipitation and temperature and monthly potential evapotranspiration as input. The potential evapotranspiration is indirectly obtained from air temperature within HBV-Rhine. For the spatial analysis of the meteorological data, the subcatchments have been divided over 14 regions, largely based on the main tributaries of the Rhine (Figure 2.1).

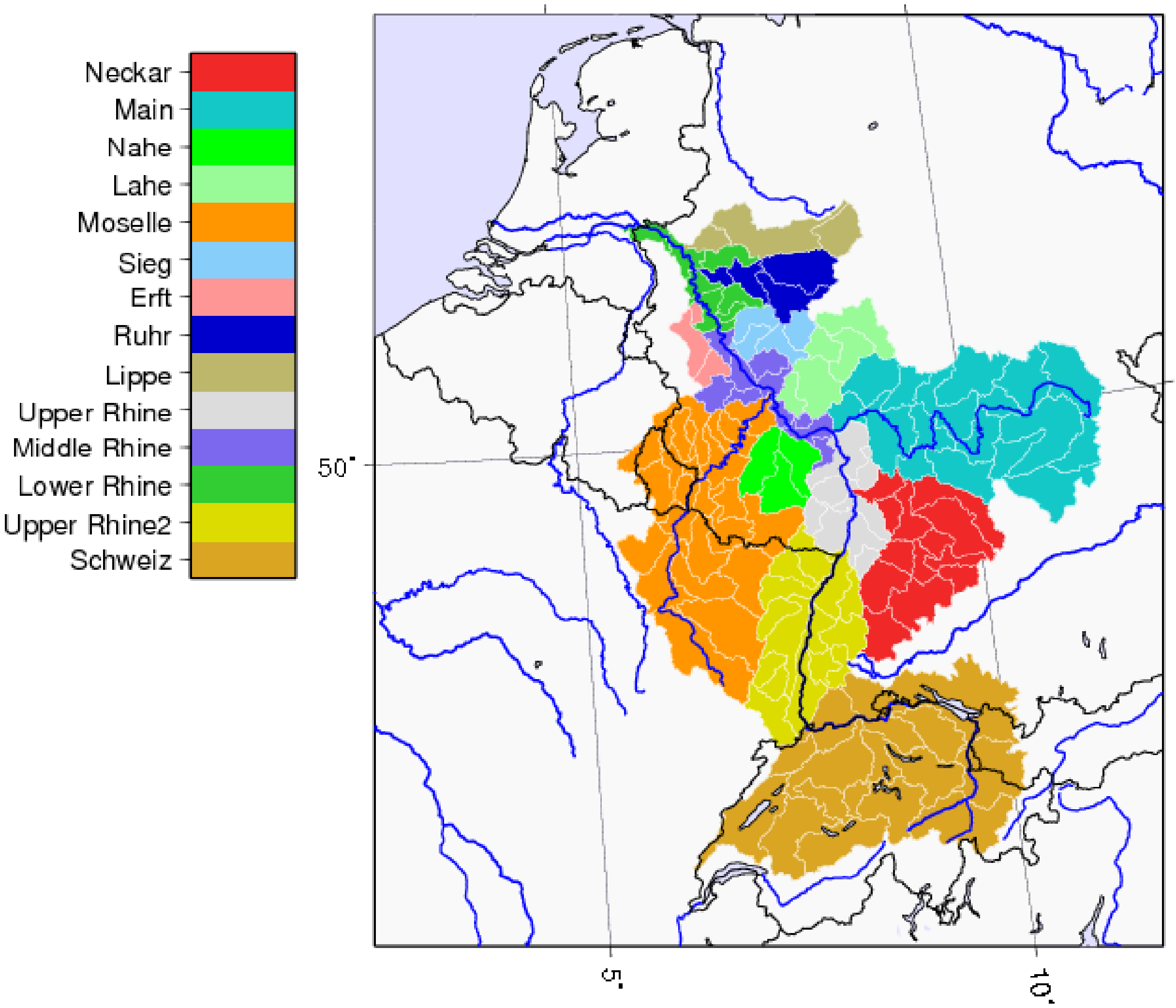

Figure 2.1 134 subcatchments used in HBV-Rhine divided over 14 regions

2.2. Reference data

Daily precipitation and temperature (1961-1995) obtained from the International Commission for the Hydrology of the Rhine Basin (CHR) serves as a reference for the validation and bias correction of the climate model output. The data has been compiled

[1] HBV (Hydrologiska Byråns Vattenbalansavdelning) is a Swedish abbreviation for a rainfall-runoff model based on the water balance which describes the hydrological processes at the catchment scale conceptually.

for the 134 subcatchments within HBV-Rhine (*Eberle et al.*, 2005). Per subcatchment, daily precipitation has been derived from gridded data,, where the area average was calculated from the arithmetic mean of the grid values within the subcatchment. For all German subcatchments except within the Moselle basin the REGNIE dataset (1 x 1 km^2 grid as provided by the Deutscher Wetterdienst (DWD)) has been used. For the Swiss part a 2 x 2 km^2 gridded data set (*Dällenbach*, 2000) and for the Moselle and French part a 7 x 7 km^2 gridded data set (*Helbig*, 2004) were used.

The temperature data have been derived from 49 meteorological stations from CHR, DWD, Metéo France and MeteoSchweiz. For the interpolation to mean subcatchment height, a correction of 0.6°C/100m has been applied.

2.3. RACMO2 simulations

In this study, the output of two simulations with the regional climate model RACMO2 is used (*Lenderink et al.*, 2003; *Van Meijgaard et al.*, 2008). The first simulation was nested in the reanalysis ERA40 (*Uppala et al., 2005*) and the second in a transient simulation (1950-2100) with the general circulation model ECHAM5 (*Jungclaus et al.*, 2006) forced by the SRES A1B scenario (*Nakicenovic et al.*, 2000). The simulations will be referred to as RA-ERA and RA-ECH respectively. According to *Demuzere et al.* (2009), the general circulation types over Western and Central Europe are well reproduced by ECHAM5 from October until April. From late spring to early summer (MJJAS) western type circulation patterns are significantly overestimated.

The RACMO domain covers Europe completely and a large part of the Northern Atlantic Ocean. Both simulations were run on a spatial resolution of about 25 x 25 km^2 and daily output has been made available within the ENSEMBLES project (*Van der Linden and Mitchell*, 2009).

RACMO2 showed good performance on precipitation (*Van den Hurk et al.*, 2005). The interannual variation in summertime temperature is well represented and relatively insensitive for circulation biases (*Lenderink et al.*, 2007). Thiessen interpolation has been used to translate the gridded RACMO output to subcatchment averages.

2.4. Nearest Neighbour Resampling

The Rainfall Generator for the Rhine has been developed and optimised for the hydrological modelling and assessment of extreme Rhine discharges (*Wójcik et al., 2000 Buishand and Brandsma, 2001)*. The Rainfall Generator applies Nearest Neighbour Resampling (NRR) of observed meteorological time series to obtain new sequences of any length (e.g. 1000 years and longer).

Nearest Neighbour Resampling involves the simultaneous sampling with replacement of various meteorological variables of a specific historical day (t). For the incorporation of autocorrelation the sampled day (t) depends on the characteristics of the previous sampled days (t-1, t-2, …) (*Young*, 1994; *Rajagopalan and Lall*, 1999). For day (t_s) in the stochastic series, a specific historical day (t) is randomly selected from the k=10 "nearest neighbours". The nearest neighbours are those historical days of which the characteristics are most similar to the characteristics of the previously selected historical day for t_s-1.

Smoothing meteorological data

The temperature (T) and precipitation (P) time series are standardised prior to the resampling. The temperature (at time t) is standardised by subtracting the estimated mean (m_d) and dividing by the estimated standard deviation (s_d) for the specific calendar day (d):

$$\tilde{T}_t = (T_t - m_d)/s_d , \qquad t = 1,2,...365J; \quad d = (t-1)\bmod 365 + 1$$

T_t and $\tilde{T}_t$ are the original and standardised temperature and m_d and s_d are smoothed estimates for the sample mean and sampled standard deviation for the specific calendar day. Daily precipitation is smoothed by dividing by the mean of the calendar days exceeding 0.3 mm of the specific calendar day.

Nearest neighbours and the feature vector

For the incorporation of seasonality, the nearest neighbours are selected from the 61 calendar days around the specific day (*Leander and Buishand*, 2007). A feature vector $\mathbf{D}_t$ is applied to determine the nearest neighbours in the historical record. $\mathbf{D}_t$ is formed out of q=3 standardised weather variables sampled for t. $\mathbf{D}_t$ contains the arithmetic mean of the standardised precipitation ($\tilde{P}_t$) and temperature ($\tilde{T}_t$) within the 134 subcatchments – in previous studies $\mathbf{D}_t$ has been determined from 34 meteorological stations (e.g. Beersma, 2002). $\mathbf{D}_t$ is completed by the fraction of subcatchments with more than 0.3 mm precipitation (*F*). *F* helps to roughly distinguish between large-scale and convective precipitation. The nearest neighbours in the historical record depend on the weighted Euclidean distance $\delta(\mathbf{D_t},\mathbf{D_u})$:

$$\delta(D_t, D_u) = \sqrt{\sum_{j=1}^{q} w_j \left(v_{tj} - v_{uj}\right)^2}$$

where v_{tj} and v_{uj} are the j^{th} components of $\mathbf{D_t}$ and $\mathbf{D_u}$ and w_1=w_2=w_3=1 are the scaling weights. For the random selection of one of the k=10 nearest neighbours, a kernel is applied that gives higher selection weights (p_n) to closer neighbours (*Lall and Sharma*, 1996):

$$p_n = \frac{1/n}{\sum_{i=1}^{k} 1/i}$$

2.5. Resampling of observed CHR data

The Nearest Neighbour Resampling (NNR) has been applied to extend the CHR precipitation and temperature time series. The long synthetic time series enable more robust estimation of extreme events with long return periods. Discharge of the Rhine at Lobith correlates rather well to 10-day basin-average precipitation ($P_{Rh\text{-}10}$). Figure 2.2 shows the reproduction of annual extremes of $P_{Rh\text{-}10}$ by NNR. The extreme value distributions seem to deviate somewhat for return periods larger than 10 years. It should however be noted that for return periods comparable to the length of the time series the return periods associated to the largest annual maxima are relatively uncertain.

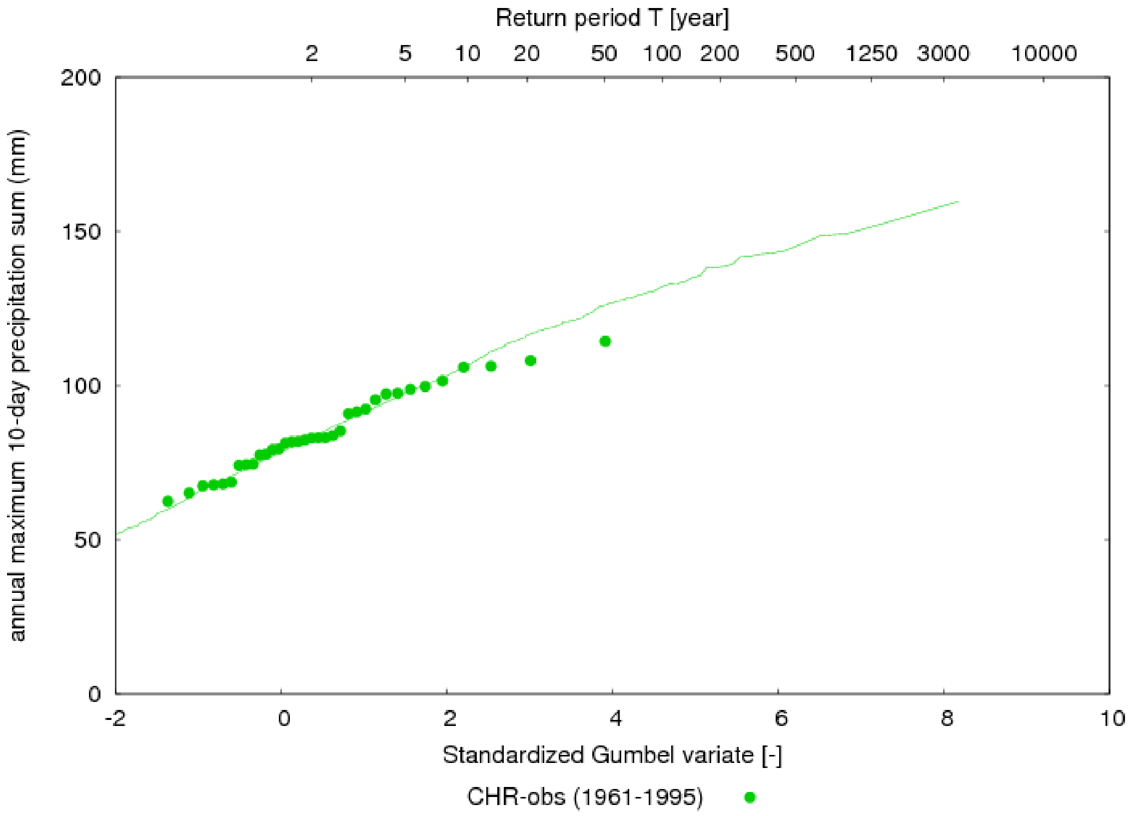

Figure 2.2 Return level plot for the 10-day basin-average precipitation including the annual maxima (dots) and the Nearest Neighbour Resampling extrapolation (continuous line) based on the CHR 1961-1995 P and T data.

3. Analyses of biases in climate simulation

A climate model is said to be biased if the statistical characteristics differ from the observed climate for the same period. In practice, all statistical properties of the climate model output, like the mean, the standard deviation and higher quantiles of a certain element are potentially biased. Since all these elements and their characteristics are mutually dependent, corrections of one bias will by definition change other characteristics: some other biases will be (partly) solved, but new biases and artefacts may be introduced. Therefore, it is very important to assess the biases of the main characteristics and to assess the characteristics which closely relate to the parameter of interest. The Rhine discharge at Lobith, for instance, is highly dependent on the 10-day precipitation sum in upstream the basin.

3.1. Mean precipitation

The mean precipitation in RA-ECH is strongly biased (Figure 3.1). Winter (djf) precipitation is in most sub-basins more than 20% larger than observed. The bias in summer precipitation is spatially more variable, roughly between -25 (west) and +25% (east).

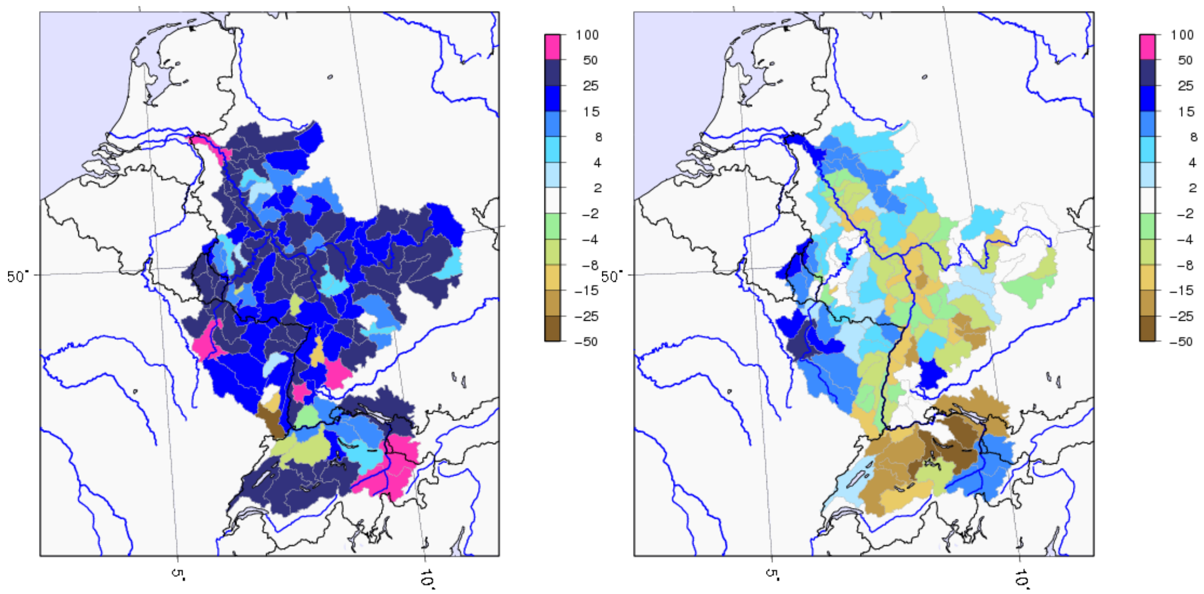

Figure 3.1 Bias of RA-ECH in mean precipitation (%). Left: winter (djf). Right: summer (jja)

Comparing RA-ECH and RA-ERA allows for disaggregating the bias into the individual contributions of ECHAM5 and RACMO2. In summer, RA-ECH gives much more precipitation in the north of Europe (including the entire Rhine basin) than when nested in ERA40 (Figure 3.2-right). This is a logical result of the too high relative contribution of westerlies in the ECHAM5 simulation. The negative bias in summer (Figure 3.1-right) should be attributed largely to the dynamical downscaling with RACMO2 (and not to the global climate simulation with ECHAM5).

Despite the fair reproduction of circulation types in the winter half year, ECHAM5 transports too much moisture into Europe (Figure 3.2-left). In winter, this bias is even strengthened by the dynamical downscaling with RACMO2 (not shown). This results in the very large discrepancies between observed and modelled precipitation for the Rhine basin in winter.

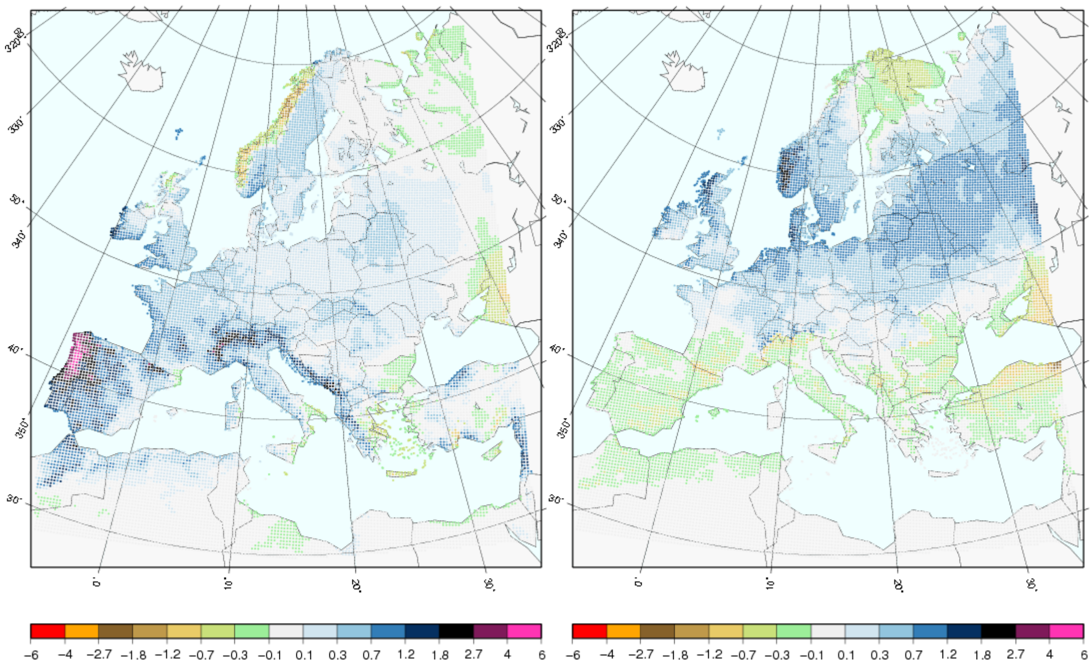

Figure 3.2 Absolute difference in daily precipitation between RA-ECH and RA-ERA [mm] Left: winter (djf). Right: summer (jja)

3.2. Wet days

The discrepancy in mean precipitation of RA-ECH compared to RA-ERA is mainly reflected in the wet day frequency (*fwet*: $P >= 0.05$ mm). Noticeably, the bias in *fwet* is rather constant through the entire basin (Figure 3.3). Yet, there is a distinct annual cycle, especially in the southern regions (Neckar, Upper Rhine 2 and Schweiz).

The bias in mean precipitation on wet days only (*mwet*) varies spatially far more than *fwet* (Figure 3.4). Like *fwet*, also the bias in *mwet* is characterised by a distinct annual cycle with a large underestimation of wet-day precipitation in summer and autumn. Obviously, the bias in *mwet* is much smaller than the biases in mean precipitation on all days (Figure 3.1).

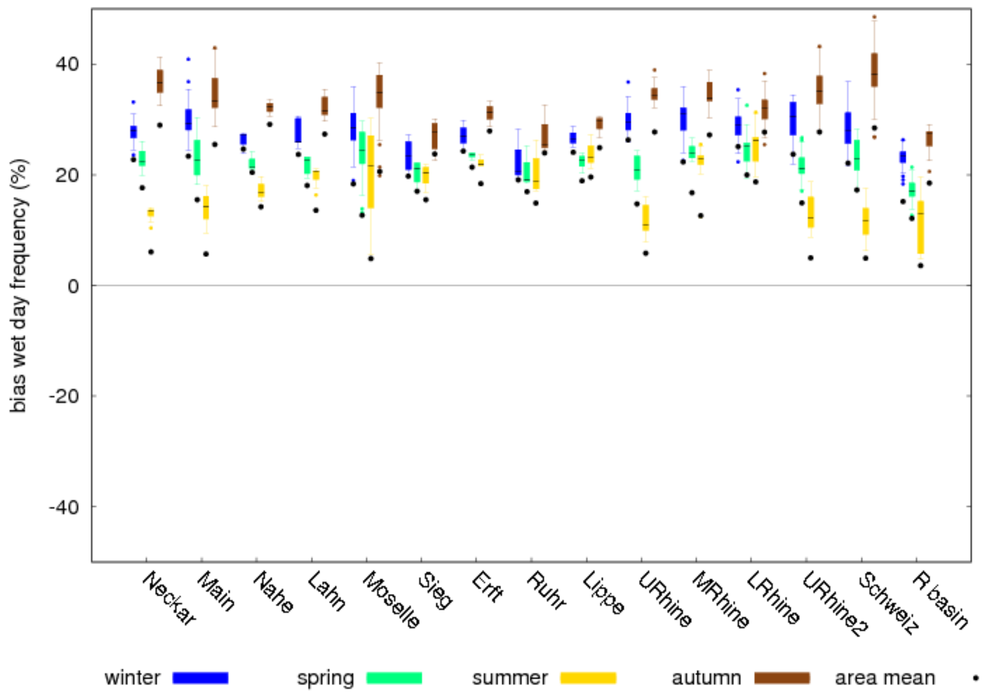

Figure 3.3 Bias in wet day frequency (fwet). Boxplots show the biases of the subcatchment per region. The colours give the biases per season. The black dots represent the biases for the region average precipitation. The rightmost boxplots give the biases per region and the accompanying dots the bias of the Rhine basin average.

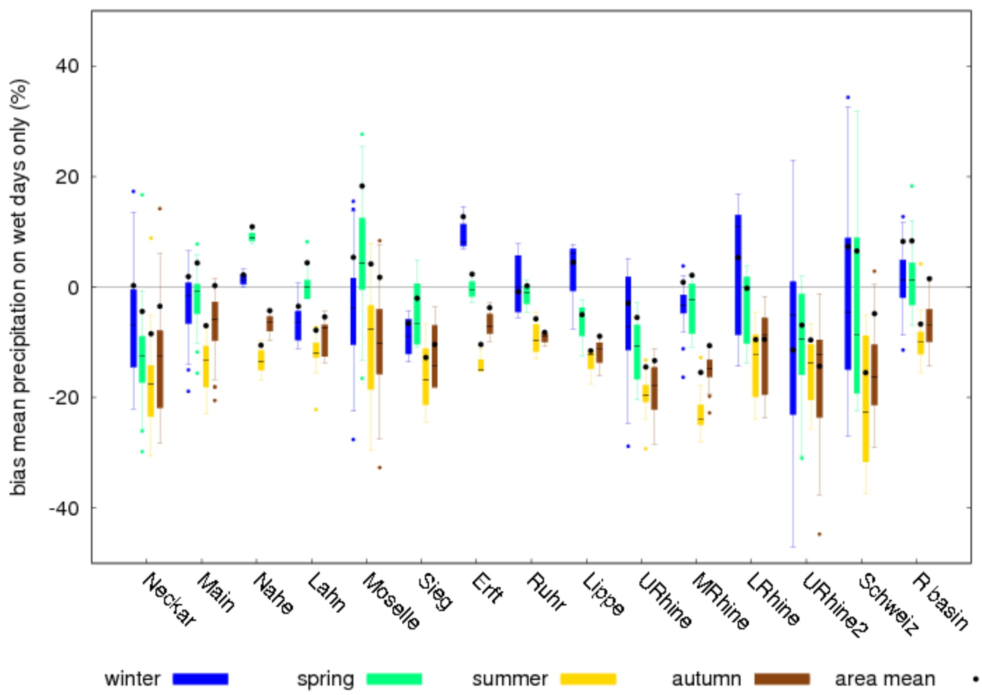

Figure 3.4 As Figure 3.3, but for biases in mean precipitation on wet days only, i.e. days with more than 0.05 mm precipitation (mwet).

3.3. Precipitation variability

As a consequence of the surplus of wet days, the variability of daily precipitation is generally too low (±-20% in winter). Figure 3.5 gives the distribution of bias in the Coefficient of Variation (CV)[2] per subcatchment and per season.

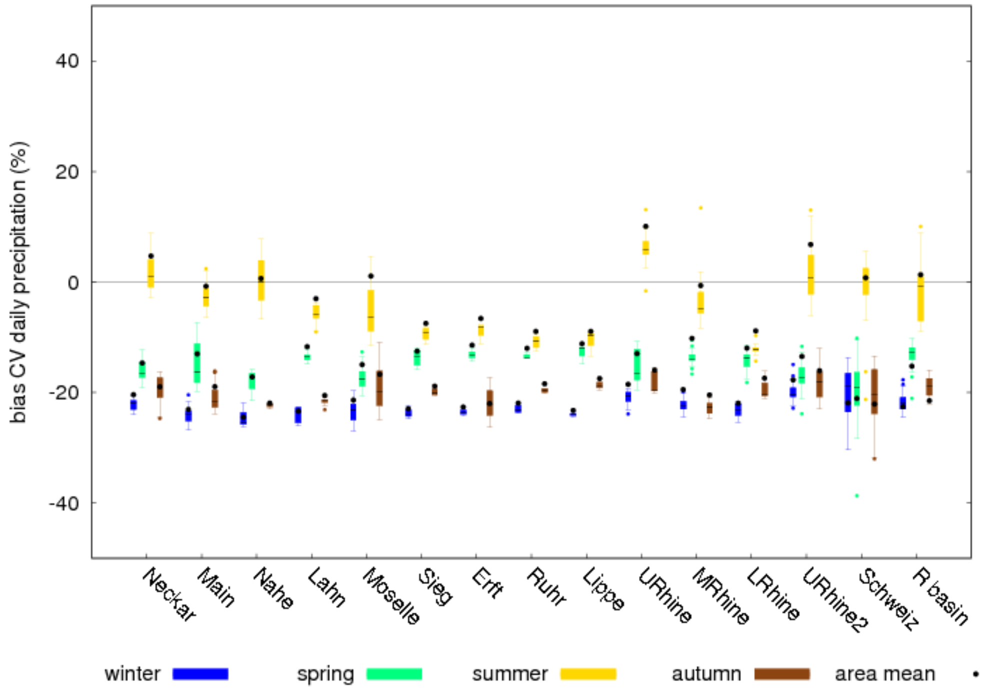

Figure 3.5 As Figure 3.3, but for biases in CV daily precipitation.

Taking into account the wet days only, the Coefficient of Variation (*cvwet*) is fairly well reproduced by RA-ECH, especially in the transition seasons (Figure 3.6). However, in summer *cvwet* is generally somewhat overestimated (+10%) and winter *cvwet* is generally underestimated (-10%).

As a result of the too low CV of daily precipitation, also the CV of multiple days is largely underestimated (Figure 3.7). Since the Rhine discharge at Lobith is typically dependent on multi-day precipitation, this will considerably affect the hydrological modelling.

[2] The Coefficient of Variation of daily precipitation equals the standard deviation of the daily precipitation divided by the mean daily precipitation.

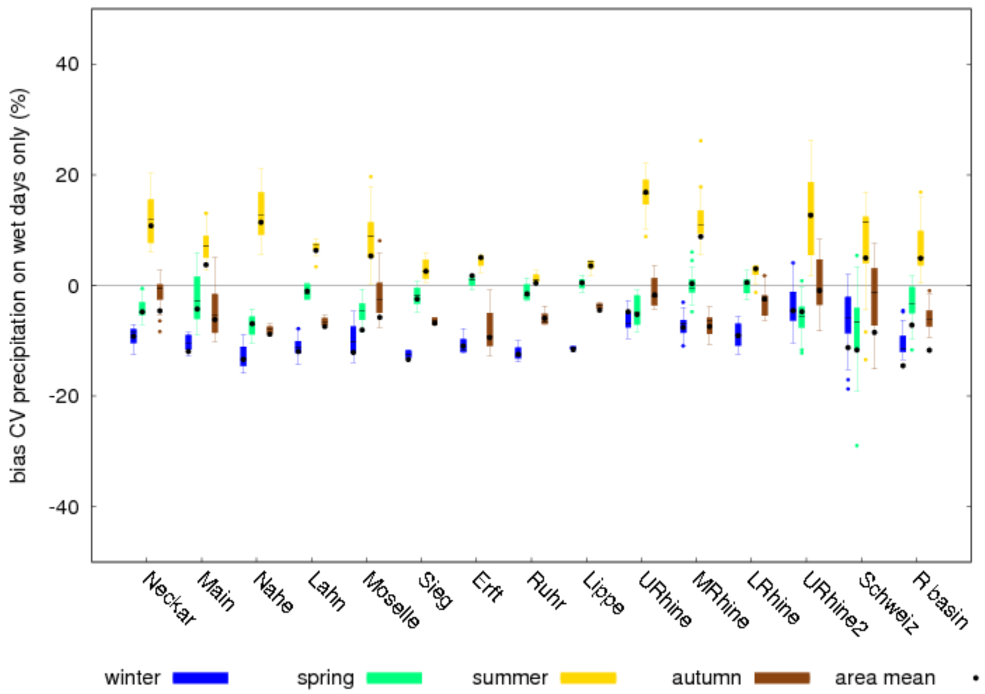

Figure 3.6 As Figure 3.3, but for biases in CV daily precipitation amounts on wet days only

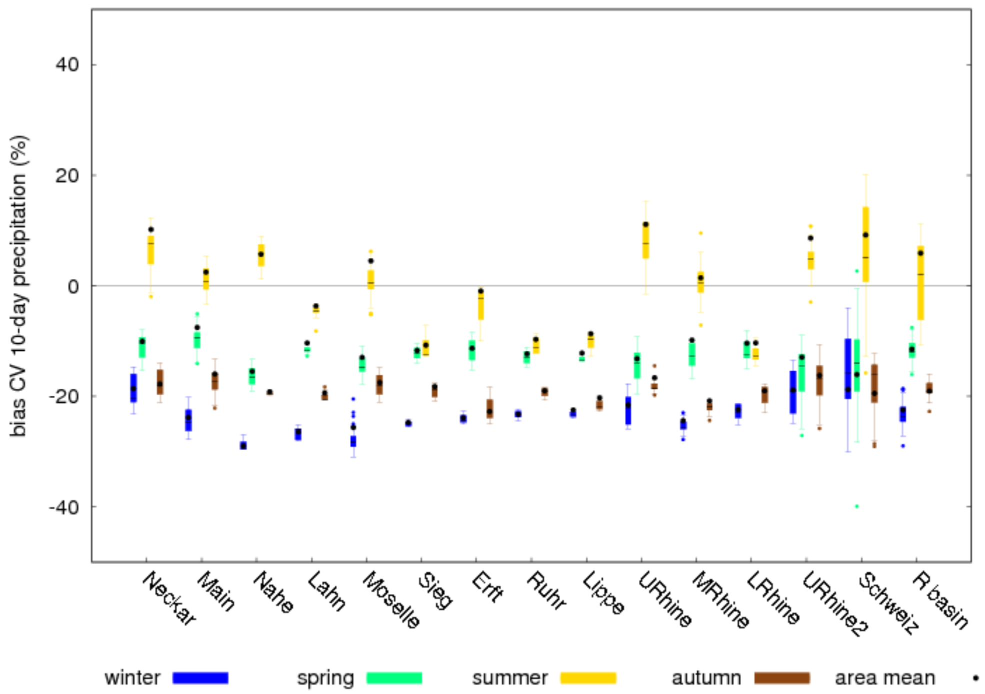

Figure 3.7 As Figure 3.3, but for biases in CV of 10-day precipitation sums.

3.4. Large scale 10-day precipitation extremes

Large scale 10-day precipitation (P_{Rh-10}) extremes according to RA-ECH compare rather well to the observed extremes (Figure 3.8). Yet, the slope of the distribution of annual extremes is too flat. So, the moderate extremes (i.e. with shorter return periods) are too high and the highest extremes (longer return periods) are too low. This is especially visible in the NNR extrapolations. The overestimation of the moderate extremes is caused by the too persistent supply of moisture, resulting in too many "very wet" 10-day periods. Conversely, the individual precipitation amounts in these "very wet" periods are generally too small. This is, amongst others, reflected in the underestimation (except for summer) of CV_{Rh-10} (Figure 3.7: black dots in rightmost Boxplots).

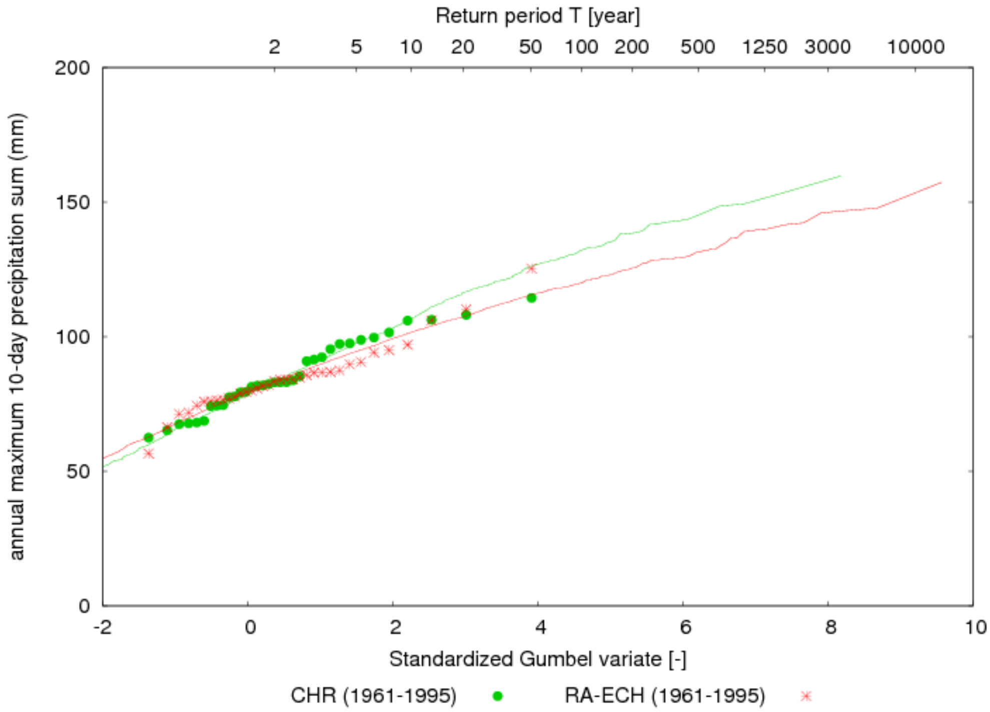

Figure 3.8 Return level plot for the 10-day basin-average precipitation including the annual maxima (dots) and the Nearest Neighbour Resampling extrapolation (continuous line). Green refers to CHR-data and red to uncorrected RA-ECH data.

3.5. Temperature

The simulated temperature is subject to serious biases too (Figure 3.9). The mean winter temperature is too high; mostly between 1 and 2°C in some subcatchments even more than 2,5°C. This is probably related to the large amount of moist air transported into Europe, which in winter is usually warmer than dry air from eastern direction and is heated due to the condensation process when rainfall occurs. Temperatures in the other seasons are reasonably reproduced. Yet, the temporal variability is generally too low (-0.5 – 0.0 °C, not shown).

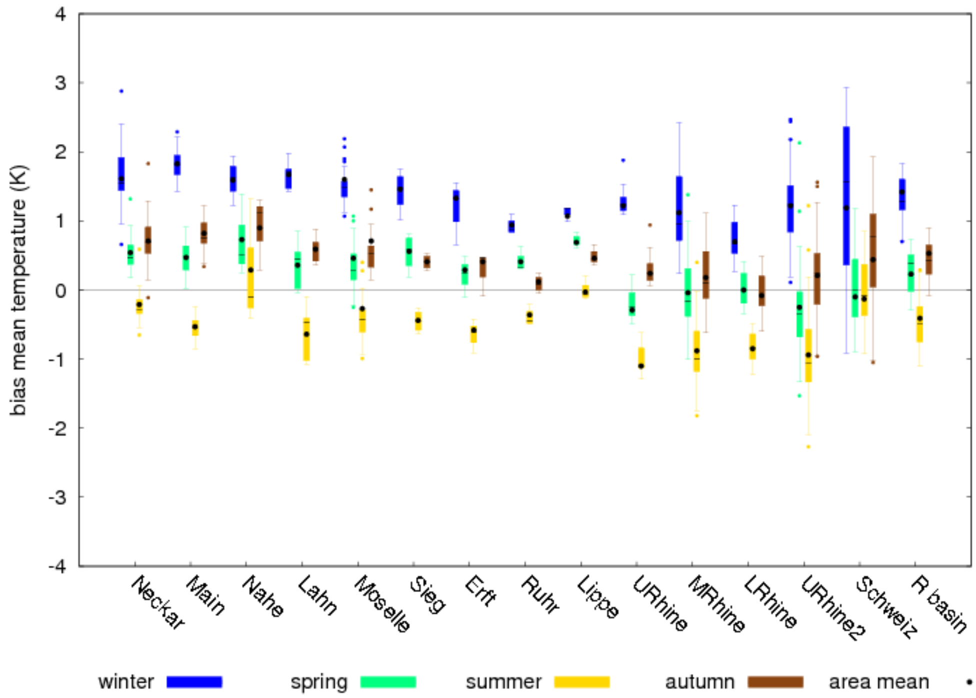

Figure 3.9 As Figure 3.3, but for biases in mean daily temperature.

4. Bias correction

4.1. General line of approach

Since all adjustments will introduce new biases and artefacts, it was tried to keep the bias correction (BC) as simple as possible. However, the correction should be able to efficiently remove the most important biases. After BC at least the general characteristics, like the mean, variability and autocorrelation structure, should be close to the observed climate. In addition we consider large-scale multiday variation and especially 10-day extremes as very important, since these characteristics largely determine the extreme discharge at Lobith.

The bias corrections are applied per calendar month. This largely smoothes the effect of natural variability, while the annual cycle is optimally maintained. No additional spatial smoothing is applied, since the spatial heterogeneity of the biases is larger than the natural variability.

The bias correction for precipitation consists of two steps. First, the number of wet days is adjusted. Second, a power law function is applied to correct for the mean and CV on wet days. The correction for the temperature is applied independently from the precipitation correction and may therefore introduce (small) physical inconsistencies.

The correction has been determined for the reference period 1961-1995 and it is assumed that the monthly bias does not change in time, i.e. the correction algorithm determined for the past/current climate is also applied to the future climate.

4.2. Correction of the number of wet days

A large part of the biases can be attributed to the large overestimation of the wet day frequency (*fwet*). Therefore first, *fwet* is adjusted. The applied method leaves the wet-day characteristics unchanged as much as possible (see below).

Wet days are "dried" by changing the precipitation amount to zero. In very few cases, in the RACMO simulation, *fwet* is slightly underestimated and dry days need to be "wetted". The correction for *fwet* is done as follows.

Selected precipitation amounts

The adjustment of *fwet* should not change the probability density function of the wet-day amounts (PDF-wet). This is achieved if the added or removed wet days are drawn from a similar distribution as the original PDF-wet. For example if nine wet days have to be dried, the selected days correspond to the 10%, 20% … 90% quantiles of PDF-wet.

In case of "wetting", the selected quantiles from PDF-wet are used to assign the amounts corresponding to these quantiles to the same number of originally "dry" days.

Selection criteria

Random selection of wet days for drying would considerably disturb the temporal structure of wet and dry days. For the reproduction of multiday variability and extremes of $P_{Rh\text{-}10}$, it is important to leave the temporal coherence largely intact. By trial and error the following selection criterion has been found; wet days are only available for drying if four of the six surrounding days are dry or moderately wet ($P \leq 1.0$ mm). For the wetting of dry days, the day should be preceded by a wet day.

The application of this selection criterion only slightly decreases the temporal and spatial correlation. In this specific case, this decrease is an improvement since the spatial and temporal correlation structure is generally too high in RA-ECH. Note that this selection criterion might be optimized differently for RCM simulations in which the spatial and temporal structure differs from that in RA-ECH.

Procedure

The wet days that initially satisfy the selection criterion generally belong to the lower quantiles of PDF-wet, since heavy precipitation amounts usually preceded and followed by several other wet days. To circumvent this problem, first the lower quantiles are selected. For every dried day, new wet days get available for drying (also higher amounts). As a result, enough wet days will become available for the higher quantiles.

In case of wetting, the added precipitation amounts exactly match the necessary quantiles/selected precipitation amounts. But additionally, the dry days to be wetted have to be selected. This is done by ranking the dry days on the basis of the preceding wet day amounts and matching the specific quantile and the dry-day quantile.

Characteristics after wet day adjustment

The adjustment of the number of wet days substantially improves the characteristics of the individual subcatchments. After adjustment, the biases in mean precipitation and CV (all days) are very similar to the biases in *mwet* and *cvwet* (not shown). The fwet adjustment considerably increases the multi-day variability. For winter, spring and autumn this is an improvement, but for summer the bias in multi-day variability gets bigger (Figure 4.1).

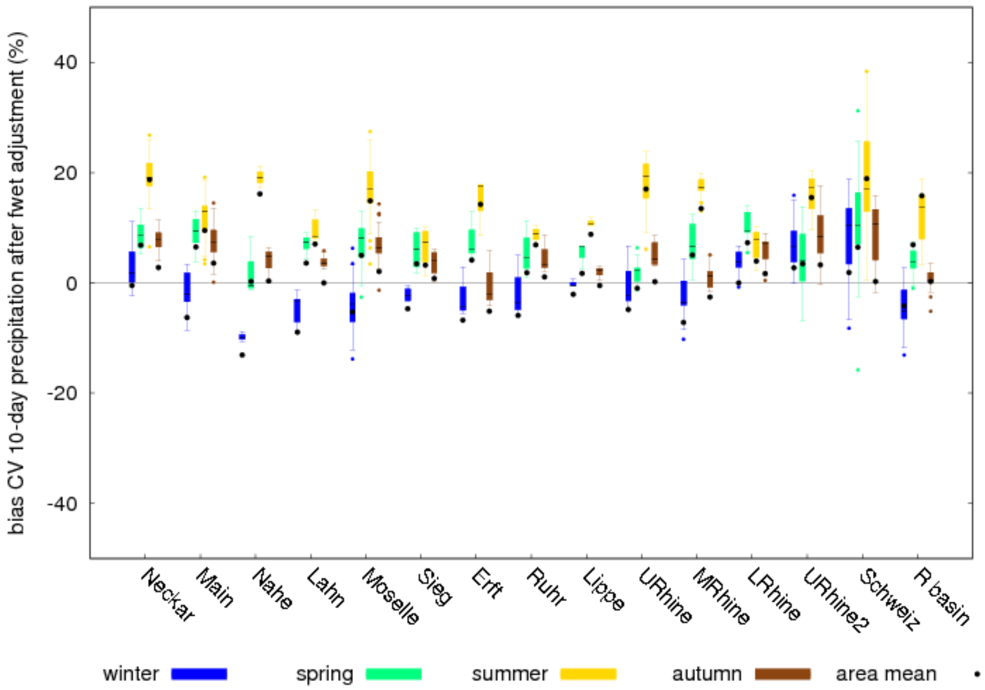

Figure 4.1 As Figure 3.7, but after adjustment of the wet-day frequency

Since the correction of *fwet* mainly involves drying of wet days, this correction obviously reduces the large-scale extremes (Figure 4.2). Yet, the slope of the annual extremes clearly improves. This is a result of the better representation of the CV of 10-day precipitation, especially in winter.

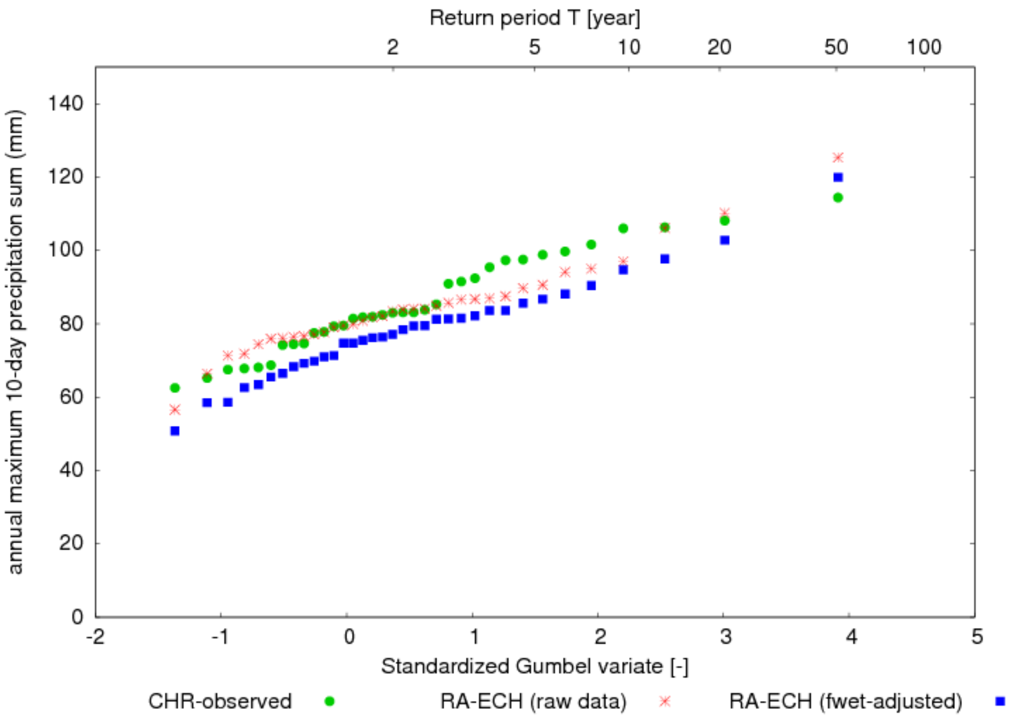

Figure 4.2 Annual maxima of the Rhine-basin average 10-day precipitation sums

4.3. Correction of mean and variability

Additional correction of the precipitation on wet days (PDF-wet) is necessary to improve the general daily characteristics and to increase the underestimated large-scale multi-day extremes. This is done by a power-law adjustment (*Leander and Buishand*, 2007).

$$P^* = a_i P^{b_i}$$

with *P* the modelled precipitation sum, *P** the corrected precipitation sum and a_i and b_i coefficients dependent on month i. The desired values for *mwet** and *cvwet** directly follow from the biases in *mwet* and *cvwet* in RA-ECH (1961-1995) as derived in chapter 3 and from the *mwet* and *cvwet* itself. Subsequently, the parameters a_i and b_i were iteratively determined such that *mwet** and *cvwet** exactly match the desired values.

In this study, the biases in mwet and cvwet are considered to be constant in time. This means that the parameters have to be determined separately for the reference period (1961-1995) and the future period (2036-2065). This is in contrast to the study of Leander and Buishand (2007) who determined the parameters a_i and b_i for the reference period and kept them constant in time.

Characteristics after complete correction

The proposed bias correction not only effectively removes the biases in daily characteristics, but also strongly improves large-scale multi-day variability, especially in winter and autumn (Figure 4.3).

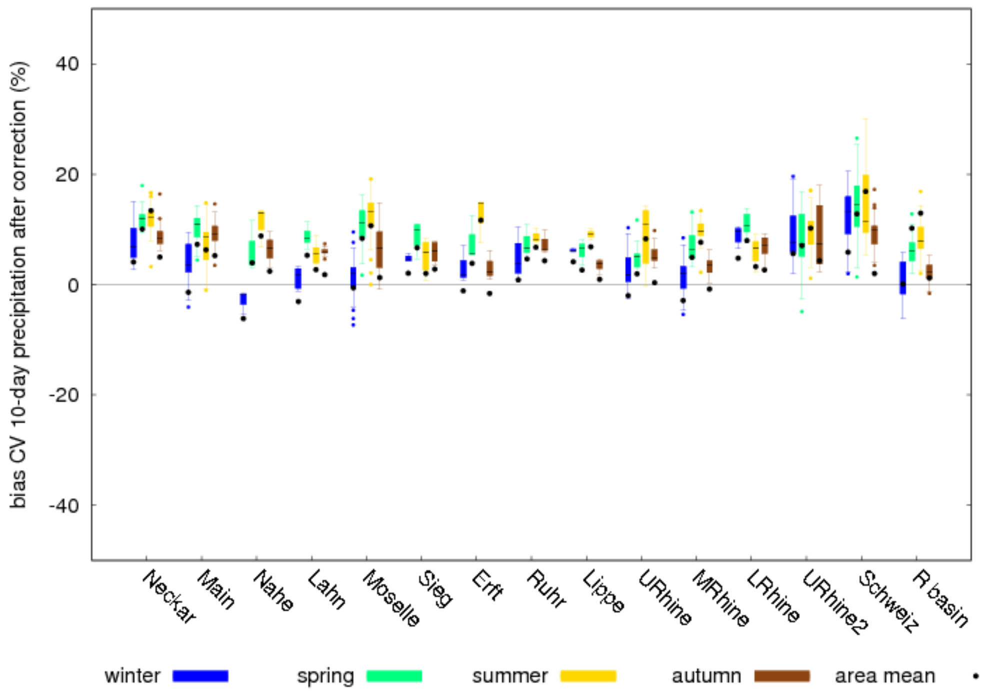

Figure 4.3 As Figure 4.1, but after applying the entire proposed bias correction

Especially, the reproduction of the 10-day large-scale extremes is good (Figure 4.4). First, the wet-day adjustment corrects for the slope of the extremes. Then, the power-law function ensures the observed and corrected RACMO extremes largely overlap. Only for return levels higher than 10 years the annual extremes deviate. Regarding the limited time series length, this is probably caused by statistical uncertainty.

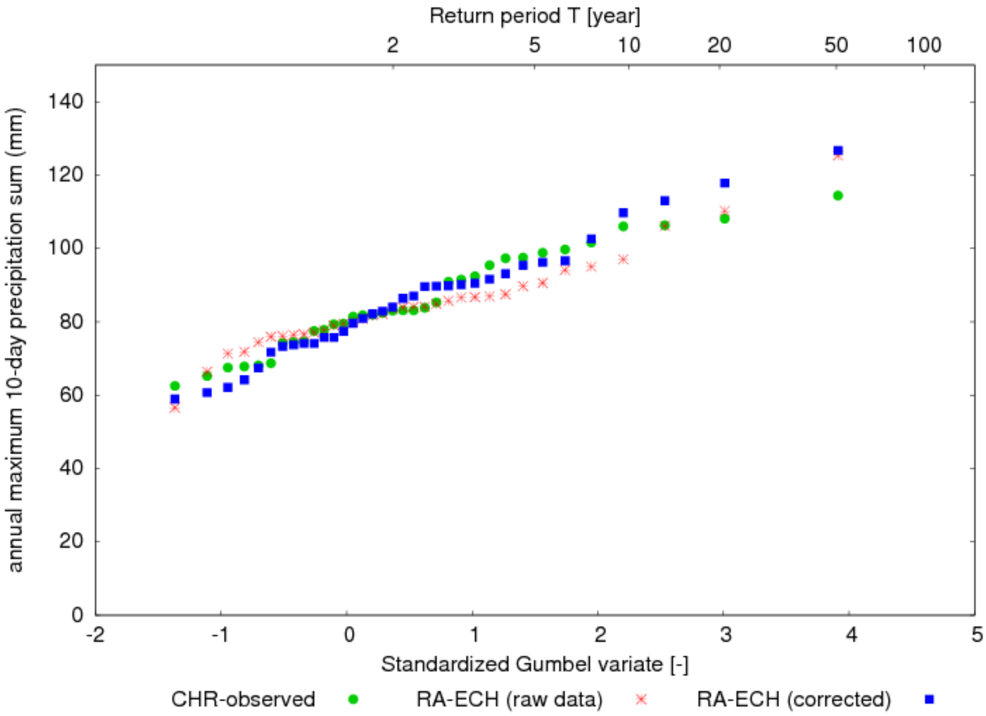

Figure 4.4 Annual maxima of the Rhine-basin average 10-day precipitation sums

4.4. Correction of temperature

The bias correction of temperature simply involves a shifting to adjust for the mean and a scaling to adjust for the standard deviation (*Leander and Buishand*, 2007).

$$T^* = \overline{T}_i^{obs} + \frac{s\left(T_i^{obs}\right)}{s\left(T_i^{\text{mod}}\right)}\left(T - \overline{T}_i^{\text{mod}}\right)$$

with *T* the modelled day-temperature, *T** the corrected temperature, $\overline{T}_i^{obs}$ and $\overline{T}_i^{\text{mod}}$ the mean temperature in month *i* and $s\left(T_i^{obs}\right)$ and $s\left(T_i^{\text{mod}}\right)$ the standard deviation of the daily temperature in month *i*.

Characteristics after complete correction

After correction, the bias in the mean and standard deviation of the daily temperature is by definition zero. The correction also considerably reduces the bias in multi-day temperature variation. For example, the standard deviation of 20-day mean temperature (subcatchments, regions, basin) varies from -0.2 – 0.1 °C after correction (not shown).

5. Bias-corrected resampled RCM output

5.1. Characteristics after resampling and correction

Biases after the subsequent use of Nearest Neighbour Resampling (NNR) and the proposed bias correction (BC) are larger than the biases after individual application of both techniques. The winter precipitation is for instance overestimated on average by 8.1% (Figures 5.1 and 5.2). Yet, these biases are small compared to the discrepancies between observed precipitation and raw RA-ECH output (Fig 3.1).

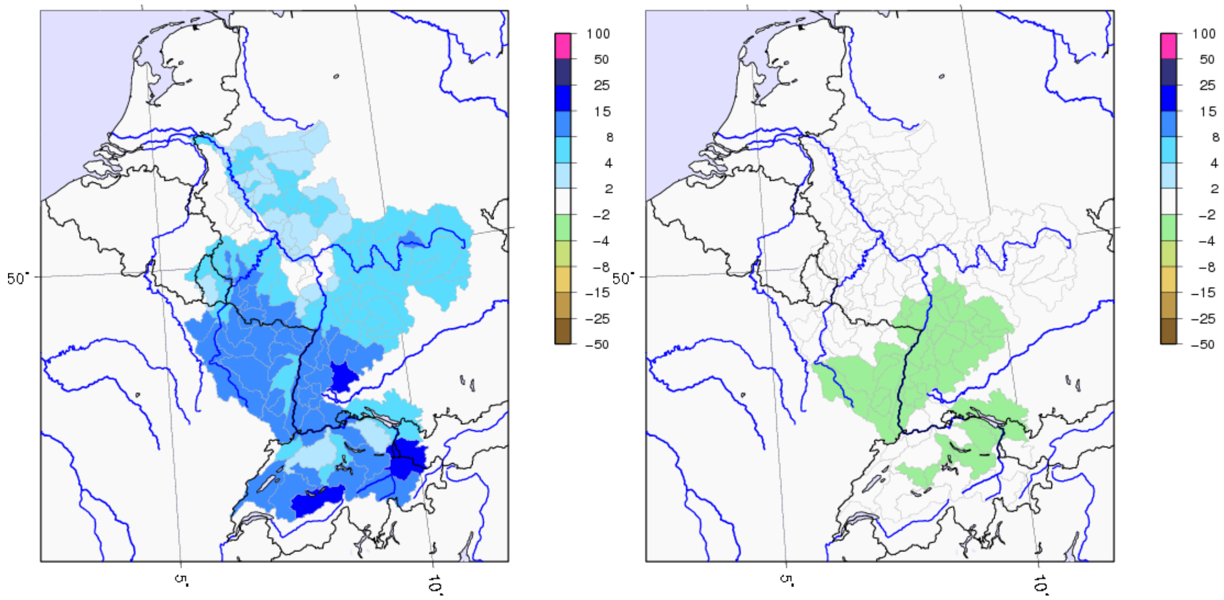

Figure 5.1 Bias in mean precipitation after resampling and bias correction (%). Left: winter (djf). Right: summer (jja)

The reproduction of the large-scale multi-day variability is hardly influenced by the resampling (Figure 4.3).

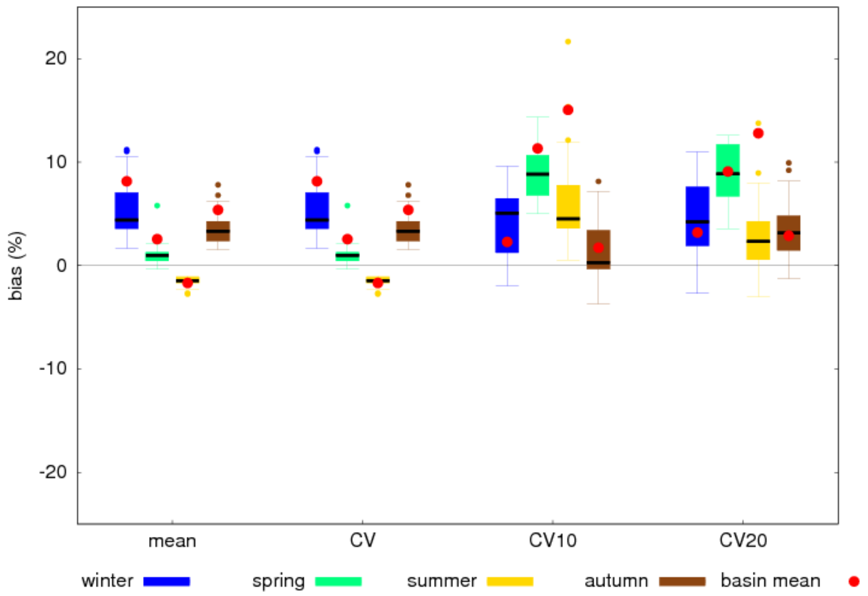

Figure 5.2 Biases in four precipitation characteristics after proposed resampling and bias correction. The boxplots give the distribution of the region-average biases and the accompanying red dots the bias of the Rhine basin average. The colours give the biases per season.

The additional discrepancy caused by the subsequent application of NRR and BC has two reasons. First, the resampling has been especially optimised for reproducing the annual extremes as good as possible. The reproduction of the general characteristics, like mean and daily variability, was given less weight. Second, the bias correction procedure has been constructed and calibrated from original short RACMO time slices and not from the long resampled RACMO time series – i.e. the coefficients a_i and b_i have not been re-calibrated for the resampled RACMO data.

5.2. Annual extremes

As a result of the overestimation of mean and standard deviation of daily Rhine basin-average precipitation P_{Rh}, the moderate extremes are slightly overestimated too. But after NRR and BC, the RA-ECH extreme events for return periods longer than 10-20 years are very similar to the CHR extremes after NRR (Figure 5.3).

Future extremes

Therefore, it can be justified to apply the bias correction to the generated time series for the assessment of changes of extreme discharges at the Rhine (Figure 5.3). According to the proposed method and the applied RACMO simulation, basin-average 10-day precipitation amounts with return periods between 10 and 1250 years will roughly increase between 7% and 10% in the period between 1995 and 2050. This is equivalent to a reduction of a return period of 1250 years (in the current climate) to about 300 years around 2050.

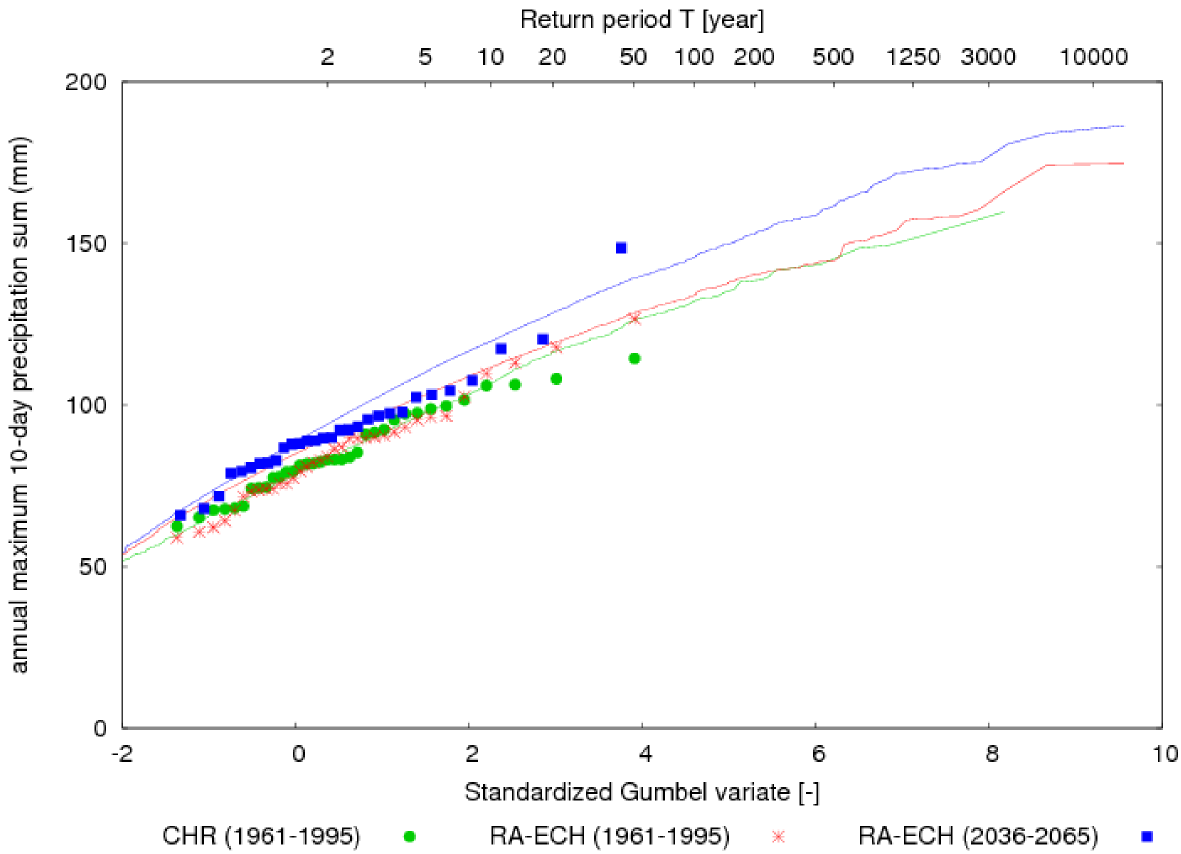

Figure 5.3 Annual maxima of the Rhine-basin average 10-day precipitation sums according to CHR-observations and bias-corrected RA-ECH output. Continuous lines give the extrapolation according to Nearest Neighbour Resampling.

6. Conclusions and discussion

RACMO output is biased and therefore not directly applicable in impact models. The biases in the wet day frequency are most pronounced, but also the mean and variability on wet days are seriously biased. The two-step correction involving first the wet day frequency and subsequently the mean and variability of precipitation on wet days per subcatchment also remarkably well reduces biases in multi-day and large-scale precipitation characteristics (Figures 4.3 and 4.4). Therefore, the generated time series are suitable for modelling hydrological extremes

Following the proposed method, large-scale 10-day precipitation extremes with return periods between 10 and 1250 years will increase by approximately 7% to 10%.

The Nearest Neighbour Resampling and the bias correction are separately tuned. Both methods slightly interfere and after successive application some biases remain. However, annual extremes with return periods longer than 10-20 years are well reproduced after resampling and correction. Combined tuning may improve the modelling results - i.e. the optimisation of the number of nearest neighbours (k), the elements (q) and scaling weights (w_j) within the feature vector ($\mathbf{D_t}$), the procedure of wet-day adjustment etc. The most straightforward way is to optimise the BC on the basis of NRR time series.

General applicability

The proposed method is not generally applicable, although the proposed method gives very satisfying results for large-scale multi-day variability and extremes in RA-ECH. Spatial and temporal biases in other RCM simulations are possibly of a very different nature than in RA-ECH. Before application of the proposed methods on other RCM simulations, the performance should be carefully checked and if necessary re-optimised.

The proposed method is optimised for the assessment of extreme Rhine discharges at Lobith, that typically depend on Rhine-basin average 10-day precipitation sums (in winter). For smaller catchments local (e.g. convective) precipitation extremes may dominate the discharge extremes rather than the large-scale multi-day (frontal) extremes.

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