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Downscaling precipitation using regional climate models and circulation patterns toward hydrology

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[1] The aim of this paper is to define a method for determining reasonable estimates of rainfall modeled by global circulation models (GCMs) coupled with regional climate models (RCMs). The paper describes and uses two new procedures designed to give confidence in the interpretation of such rainfall estimates. The first of these procedures is the use of circulation patterns (CPs) to define quantile-quantile (Q-Q) transforms between observed and RCM-estimated rainfall (the CPs were derived from sea level pressure (SLP) fields obtained from reanalysis of historical daily weather in a previous study). The Q-Q transforms are derived using two downscaling techniques during a 20 year calibration period and were validated during a 10 year period of observations. The second novel procedure is the use of a double Q-Q transform to estimate the rainfall patterns and amounts from GCM-RCM predictions of SLP and rainfall fields during a future period. This procedure is essential because we find that the CP-dependent rainfall frequency distributions on each block are unexpectedly different from the corresponding historical distributions. The daily rainfall fields compared are recorded on a 25 km grid over the Rhine basin in Germany; the observed daily data are averaged over the grid blocks, and the RCM values have been estimated over the same grid. Annual extremes, recorded on each block during the validation period, of (1) maximum daily rainfall and (2) the lowest 5% of filtered rainfall were calculated to determine the ability of RCMs to capture rainfall characteristics which are important for hydrological applications. The conclusions are that (1) RCM outputs used here are good at capturing the patterns and rankings of CP-dependent rainfall; (2) CP-dependent downscaling, coupled with the double Q-Q transform, gives good estimates of the rainfall during the validation period; (3) because the RCMs offer future CP-dependent rainfall distributions that are different from the observed distributions, it is judged that these predictions, once modified by the double Q-Q transforms, are hydrologically reasonable; and (4) the climate in the Rhine basin in the future, as modeled by the RCMs, is likely to be wetter than in the past. The results suggest that such future projections may be used with cautious confidence.

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1. Introduction

1.1. Outline of the Paper

[2] Global circulation models (GCMs) provide scenarios for the possible future development of climate. Unfortunately, their spatial resolution is coarse; thus, they cannot be used directly for the assessment of regional consequences of climate change. For this purpose downscaling methods have been developed. Regional climate models (RCMs) use the output of the GCMs and provide climate variables, including daily rainfall, at a finer spatial resolution. Unfortunately, these models inherit some of the biases of the GCMs.

[3] It is the purpose of this paper to link daily spatial rainfall to RCM-modeled rainfall produced by reanalysis so that projected future daily rainfall amounts might be estimated with minimum bias. The way this is achieved is described in the following six steps. The first step is to determine the link between circulation patterns (CPs), defined by sea level pressure fields obtained by reanalysis, with daily rainfall wetness patterns in a chosen geographical area. The region chosen was the Rhine basin in Germany, where there are approximately 600 long, good rain gauge records in an area of about 100,000 km². The 20 sets of rules defining these circulation patterns were obtained in a previous study using fuzzy rules and optimization by simulated annealing [Bárdossy, 2010]. These rules defining the CPs were used to determine the links between the CPs and the different daily rainfall regimes, in two 6 month seasons called summer (warm) and winter (cold), in the study leading to this paper.

[4] The second step is to take the rules determined in the first step and to identify the CPs (defined by the rules) which

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occur on each historical day in the 30 years from 1961 to 1990 and store this information. It is noted that the same CP is applicable on each day for all RCMs because the historical CPs were obtained by reanalysis. For each of the 25 km² grid blocks over the Rhine basin, on each day in each season, the spatial rainfall amounts (observed and modeled by the three RCMs) associated with the concurrent CP were identified and labeled as such.

[5] The third step is to determine the frequency distributions of the amounts of rain on each grid block on each day in each season, for each CP, for observed and RCM-based rainfalls during a 20 year (1961–1980) calibration period. Here two methods were used, one called universal downscaling and the other called CP-based downscaling; the latter is computationally more demanding than the former, and it was prudent to determine which offered better results. Universal downscaling required that all the observed and modeled rainfall values were collected for each block for each season (noting the CP associated with each day's data). These would then be used in quantile-quantile (Q-Q) transforms to downscale RCM rainfall during the calibration period, again noting (but not exploiting) the knowledge of the concurrent CP. In CP-based downscaling, the extra classification was the day's CP, so that each day's four rainfall values (observed and RCM based) on each grid block would be classified into two seasons and 20 CPs.

[6] The fourth step is the validation of the procedure outlined above in step three. A 10 year period (1981–1990) was selected, and the four spatial rainfall records were used in the following way. In universal downscaling, the estimated rainfall for each grid block for each day of each season was estimated by using a Q-Q transform from the respective RCM-based estimate to the observed value. In this universal downscaling procedure, although the concurrent CP was not used in the computation, it was noted for comparison purposes. In CP-based downscaling, the same procedure as universal downscaling was used with the addition that the CP on the day was used to select the appropriate Q-Q transform.

[7] The fifth step was to conduct other corroborative tests and comparisons, with a view to determining the modeled rainfall's effectiveness at capturing events which have marked hydrological impact. In particular, for flash flood events, the maximum rainfall on each grid block in the basin in a given year and season is of considerable interest. At the other extreme, the cumulative effects of dryness can have a devastating effect on reservoir storage and agriculture. To determine whether the models capture this behavior, an exponential filter of each block's rainfall was employed.

[8] In the sixth and last step, future (2021–2050) RCM-modeled rainfalls were downscaled using a double Q-Q transform. It was found that the rainfall frequency distributions, conditioned on each CP, were substantially different from the historical distributions. Using the historically derived Q-Q transforms directly on these estimates would destroy valuable information about future behavior which the RCMs had captured. Thus, the novel procedure was that on each block, on each day, the transform went from future modeled amount to historical modeled amount to the matching quantile of the observed amount back to the adjusted modeled amount at its own quantile level. The average accumulated rainfall for each grid block for each RCM output was

computed and was compared with the corresponding observed values.

1.2. Background to the Paper

[9] As introduced in section 1.1, the main goal in this paper is to exploit the classification-based link between the CPs and precipitation that was established by Bárdossy [2010] and to use this methodology in climate change scenarios. There are several other classification techniques based on different statistical methods such as empirical orthogonal functions [e.g., Hanachi *et al.*, 2006] and simulated annealing [e.g., Philipp *et al.*, 2007]. A thorough overview of circulation classification methods is given by Huth *et al.* [2008]. There are several methods which link surface weather variables (precipitation and temperature) to large-scale atmospheric variables such as sea level pressure (SLP) or geopotential elevations or other derived indices (vorticity and flow direction) on different time scales (daily or monthly). Wilby *et al.* [1998a, 1998b] give a good overview of different techniques.

[10] The outputs of regional climate models (precipitation, temperature, etc.) are potentially useful for impact assessment in hydrology. However, because of the biases of the model outputs, the direct use of regional climate model outputs in hydrological applications is a questionable approach because regional hydrology is very sensitive to precipitation and temperature, so that even small biases might change the hydrological equilibrium. Hydrological impacts cannot be usefully evaluated by comparing the results of hydrological models using unmodified RCM output of the control run and the climate change scenarios as input. Even though this is a frequently applied approach, because of the high nonlinearity of the hydrological cycle, the same climatic signal applied to a biased baseline might produce a completely different hydrological response.

[11] Two examples follow which explain this deficiency.

[12] 1. A 2°C bias of temperature in winter can change the hydrological behavior completely. Assume that the mean observed temperature in a catchment is −1°C, whereas the RCM mean is 1°C (2°C bias). A 3°C temperature increase would have an enormous effect in reality (a change of −1°C to 2°C would cause precipitation to fall as rain instead of snow), while change under positively biased conditions (a change of 1°C to 4°C) has only a minor effect on hydrology.

[13] 2. A bias in RCM precipitation in summer can change a water-limited situation to an energy-limited one or the opposite. For example, if, during the observation period, the summer average evapotranspiration (ET) exceeds the precipitation (P) and in the future the temperature rises so that ET > P, then streamflow is not much changed. If, on the other hand, P > ET during the observation period, an increase of temperature in the future resulting in an increase of ET so that ET > P, then streamflow will be affected negatively.

[14] The core of this paper is the development of a methodology which uses the outputs of RCMs as a basis for modeling future climate scenarios and combines them with circulation pattern-based statistical methods to obtain reasonable and unbiased inputs to hydrological models in order to assess possible consequences of climate change. In contrast to other statistical downscaling methods, we do not assume stationarity in the link between large-scale atmospheric

Figure 1. The 172 selected data points on a 25 km grid in the German part of the Rhine basin. The investigation area lies between 49°N and 52°N and 6°E and 8°E. The oval is used in Figure 3 to locate the basin.

variables and precipitation. Instead, we assume that RCMs are able to predict relative changes in the CP-precipitation relationship which can be scaled and bias corrected using the Q-Q transforms derived from the observation-RCM relationships. This means that if a given CP in the future produces wetter or drier patterns than what is observed, the shift will be modeled appropriately by adapting the already obtained Q-Q relationship to a double Q-Q transform; we do not adjust the future value by directly employing the historical Q-Q transform because this would destroy important information.

2. Data

[15] The main set of data (CPs and precipitation, RCM based and observed) used for the downscaling work in this study was made available via the European Union project ENSEMBLES supported by the European Commission's 6th Framework Program as a 5 year integrated program (2004–2009). The original RCM data sets cover the European continent to different extents and with spatial resolutions of 25 and 50 km grid sizes. The observed daily rainfall data had been averaged over 25 km grid blocks. The temporal resolution of observed gridded precipitation data sets was limited to daily data, while for RCMs, 6 hourly, 12 hourly, daily, and monthly mean data were available.

[16] The analysis conducted in this study was applied to the German part of the Rhine River catchment. On the basis of 25 km grid resolution, 172 of the grid blocks referred to above were selected within the catchment for analysis and evaluation (Figure 1). The output of three different regional climate models HadRM3 (developed by the Hadley Centre for Climate Prediction and Research, Met Office, United Kingdom), RACMO2 (developed by the Royal Netherlands Meteorological Institute, De Bilt, Netherlands) and REMO (developed by the Max-Planck-Institut für Meteorologie, Hamburg, Germany) had been estimated over the same 172 grid points, and these data were selected. For observational and RCM control runs the analysis was based on a common time period of 1961–1990, while for transient future runs, different time periods between 2001–2100 (2001–2099 in

the case of HadRM3 transient future runs) were considered for evaluation.

[17] Another, independent set of daily precipitation data obtained from the German Weather Service was used for the classification of the circulation patterns in the earlier investigation [Bárdossy, 2010]. These precipitation data comprised two sets of 24 daily precipitation records in the Rhine basin west of Frankfurt. To ensure that there was no crossover of information with the downscaling study, the data were not contemporaneous with the calibration and validation period used to monitor the success of downscaling the RCM precipitation. These were the data sets used for analysis, without any further preprocessing.

3. Methodology

[18] Although they are computed on finer grids than GCMs, RCMs unfortunately cannot provide modeled precipitation estimates with the spatial fidelity required for hydrological modeling. Figure 2 shows the mean daily precipitation on the grid blocks during the control or observation period (1961–1990) for the observations and the three RCMs. As can be seen, the spatial patterns of all RCM-based averages differ considerably from the observations (and also from each other). In fact, they seem not to reflect topographical influences correctly, which makes it

Figure 2. Observed and modeled mean daily precipitation amounts (mm) in the observation period (1961–1990).

Figure 3. SLP anomalies corresponding to selected circulation patterns (CP06, CP07, CP18, and CP20), with the associated precipitation wetness index (PWI) patterns for winter, over the Rhine grid during the observation period. The small green trapezoid indicates the scale of the SLP data.

Figure 4. Mean of the daily PWI for winter during the observation period (1961–1990) for the different CPs (observations).

difficult for hydrologists to obtain meaningful information from such products.

[19] The issues which need to be addressed in developing the downscaling methodology include the following: bias of precipitation estimation, variability of the bias, and changing relationships under different climates.

[20] 1. The precipitation estimates offered by the RCMs, realized as localized daily amounts, when summarized in the cumulative frequency distributions (cfd's), exhibit bias when compared to the cfd's of the observed data averaged over the same blocks on the grid during the observation period. This bias is location and season specific and needs to be corrected on individual blocks. Although there is spatial correlation between the rainfall amounts in the blocks, this correlation is not explicitly taken into account in the process.

It turns out that this omission is not an issue because the local bias is effectively removed by the adopted procedure, which improves the whole.

[21] 2. RCMs might produce different biases under different meteorological conditions; therefore, this variability needs to be assessed and then addressed where necessary. One might pool the relationships if the local variation is ignored (our so-called “universal” approach) or take special steps to address the local bias and variability conditional on the associated circulation patterns (our so-called “CP-based” approach).

[22] 3. It is possible (even likely, and, indeed, we show this to be so) that the precipitation associated with given CPs will change under different future climate change scenarios (of which the sea level pressure patterns are only one

Figure 5. Mean of the unadjusted daily PWI for winter during the observation period (1961–1990) for the different CPs (REMO).

Figure 6. Mean of the unadjusted daily PWI for winter during the observation period (1961–1990) for the different CPs (RACMO).

component), given that the precipitation characteristics depend on the full set of meteorological variables.

[23] Therefore, we trust the RCMs to produce their version of changes in precipitation behavior which integrates the effect of multivariate meteorological forcing, both during control (historical) runs and in the future scenarios, and correct the bias using the appropriate downscaling technique. We need to find a way of linking the associations in a realistic way, which we call the double Q-Q transform.

3.1. Universal Downscaling

[24] One possibility for the correction is a local scaling of the precipitation distributions in each season. In particular, the first way we choose to downscale precipitation is to

relate the distribution of the precipitation amounts generated by the RCM with the distribution of the observed amounts on each of the grid blocks. This downscaling method employed Gamma distribution mapping, as described by *Ines and Hansen* [2006]. *Thiemeßl et al.* [2010] essentially use universal downscaling in their “quantile mapping” method and find it superior to others. In this technique, they used empirical quantiles, which, they note, inhibits the modeling of extremes.

[25] This transformation corrects the modeled precipitation during the observation period. For the future scenarios the quantiles of the observation period are used for the transformation, without modification. In this way the downscaled precipitation signal becomes similar to the RCM-generated

Figure 7. Mean of the unadjusted daily PWI for winter during the observation period (1961–1990) for the different CPs (Hadley).

Figure 8. The spatially averaged PWI values of REMO, RACMO, and Hadley against the observed PWI averages for the winter season. Their rank correlations are 0.97, 0.99, and 0.98, respectively.

signal, but the bias is corrected. Let $Z_R(x, t)$ be the precipitation at location x and day t simulated by the RCM, and let $Z_O(x, t)$ be the observed precipitation at location x and day t within the observation period. The distribution function of the observed precipitation amounts (wet or dry) at location x is $F_O(z, x)$, and the corresponding RCM precipitation distribution for the RCM climate run is $F_R(z, x)$. The quantile-quantile downscaled precipitation $Z_D(x, t)$ can be obtained by taking

$$Z_D(x, t) = F_O^{-1}(F_R(Z_R(x, t), x), x). \quad (1)$$

This transformation ensures that if the RCM period and the observation period are identical, the model reproduces cumulative distribution functions,

$$F_D(z, x) = F_O(z, x).$$

[26] This quantile-quantile (Q-Q) transformation can be applied either over the whole year or during selected time periods (seasons) separately; we adopt the latter approach, splitting the year into two seasons: “winter” (November–April) and “summer”(May–October). There are three pos-

Figure 9. The spatially averaged PWI values of REMO, RACMO, and Hadley against the observed PWI averages for the summer season. Their rank correlations are 0.97, 0.97, and 0.96, respectively.

Figure 10. CP-dependent empirical frequency distribution functions (fdf's) of daily precipitation for pixel 104 for the different RCMs and the observations for the calibration period (1961–1980) before downscaling. The vertical axes show cumulative probabilities, and horizontal axes are in millimeters. Rainfall below 0.1 mm indicates a dry day; therefore, the diagrams implicitly indicate the probability of dryness. The lines indicate the following sources: solid line, observed; long-dashed line, REMO; short-dashed line, RACMO; medium-dashed line, Hadley.

sible natural choices for the distribution F_O . The first is to use the frequency (or empirical) distribution function (fdf). This method has the advantage that no distribution has to be fitted. The disadvantage is that the observed maximum cannot be exceeded in the downscaled series. (This is also a problem with all bootstrapping and reshuffling methods.) The other possibility is to assign to each location a probability of the site experiencing a dry day and fitting a cdf to

amounts on wet days. This approach can overcome the problem of maxima but at the cost of selecting an appropriate distribution and estimating its parameters. Another possibility is to fit a nonparametric distribution, but for most kernel functions the selected fit would artificially constrain the maximum, so the kernel would need to be selected with care. However, we note that there are solutions to this problem; *Mehrotra and Sharma [2010]* present a nonpara-

Figure 11. A sketch of the double quantile-quantile transform relating a given RCM future fdf to the observed cdf through the corresponding RCM cdf; the latter would be obtained from the observation period (see equation (2)). The vertical axes show cumulative probabilities, and horizontal axes are in millimeters. The sources are as follows: black line, observed cdf; gray line, RCM-based cdf (observation period); black diamonds, RCM future fdf. The RCM future point (large gray diamond) is matched with the same value on the observed RCM cdf, shifted at the same quantile level to the observed cdf and back to the same quantile level at the future value to give the point in the circle, in the process preserving the rank of the shifted value.

metric downscaling approach which uses a kernel with infinite support and a local bandwidth that assumes large values in the tails. In any event, we fitted Weibull cdf's to the wet amounts during the observation period and fdf's to the RCM-based future rainfall amounts because the maxima of the latter are not going to be exceeded in this study. The Weibull was chosen as it minimized the Akaike information criterion [Akaike, 1974] in comparison to the lognormal and exponential distributions when fitted by the method of maximum likelihood to samples of CP-dependent rainfall data.

[27] The Q-Q transformation provides a purely statistical correction of the RCM results, independent of the weather type. However, it is likely that RCMs have different bias behaviors in estimating the precipitation under different meteorological conditions. This was investigated using circulation patterns.

3.2. Circulation Pattern-Based Downscaling

[28] Modeling precipitation using RCMs is a difficult task. We found that the model calculates a physically reasonable precipitation which might be biased for different reasons. For example, the orographic influence is often not correctly represented, leading to a systematic error on the windward or lee sides of mountains. These types of biases are, however, different under different circumstances; for example, depending on the topography, they are related to

air mass flow directions. A downscaling (bias correction) procedure should thus consider the different circumstances leading to biases. Our suggestion is to take CPs directly into account.

[29] Circulation patterns in this study were defined in a semisupervised manner by Bárdossy [2010]. The relative wetness (number of wet stations on a day above a chosen threshold) of the gauge data on a day was used to identify the air pressure fields (CPs) using fuzzy rules, optimized using simulated annealing.

[30] Figure 3 shows the winter SLP anomaly maps for four selected CPs (out of 20) and the associated fields of observed mean block precipitation scaled by climatological mean, called a precipitation wetness index (PWI). The PWI for a given block and CP is calculated as the ratio of the mean precipitation for days associated with the given CP to the block's climatological mean. It is clear from this selection of pairs that the CPs have a considerable influence on the amount and location of precipitation, with second-order effects introduced by topography.

[31] The RCMs during the observation period are based on reanalysis of the meteorology, so the sequence of 20 daily CPs identified by the fuzzy rules determined in the prior study are the same for the RCMs and the observations. In the future scenarios, this CP classification procedure (using the same fuzzy rules) has to be done using the GCM-simulated SLP fields as the basis for the transfer of information.

Figure 12. Observed and CP-downscaled mean daily precipitation (mm) in the validation period (1981–1990), showing that the spatial distribution of rainfall is successfully recaptured by the procedure.

[32] Figure 4 shows the PWI patterns over the Rhine grid for observed winter precipitation for the 20 CPs. They have been ranked by spatially averaged PWI going from driest to wettest. There are two important observations to be made from the sequence of these patterns. The first is that there is a distinct sorting, even if it is gradual, according to the CPs, which suggests that pooling of the precipitation ignoring this classification will cause loss of valuable information. The second observation is that there is considerable structure in the patterns; for example, CP06 and CP07, with similar overall average PWI, show opposing amounts of precipitation almost everywhere, as if the one was the complement of the other. There is clearly strong topographical influence. It is precisely this detail that is important to capture for the purpose of sound hydrological modeling and decision making: the rainfall has to fall with the right intensity in the right place with the right frequency.

[33] Figure 5 shows the sequence of gridded Rhine PWI images, classified according to the same CPs in the same order as Figure 4 but for the raw output of the REMO RCM. For the other two RCMS the corresponding figures are Figure 6 for RACMO and Figure 7 for Hadley. Two striking observations are that Figures 4–7 are surprisingly similar and also that the general trend from dry to wet is very nearly

preserved for all models, although there is some minor shuffling at the dry end.

[34] Figure 8 is based on Figures 4–7 and compares the spatially averaged PWI values on the plots of Figures 4–7, demonstrating the ranking. The rank correlations of REMO, RACMO, and Hadley against the observed PWI averages are 0.97, 0.99, and 0.98, respectively. These high correlations indicate the excellent partitioning of the precipitation by the RCMS, which we are sure will please the climatologists. Figure 9 shows the same treatment for the summer PWIs. Figure 9 has the same ordering of CPs as Figure 8. It is interesting that the RCM-based PWIs follow the observed ones even though the responses of the CPs in summer are materially different from those in winter. The rank correlations are again high: for REMO, RACMO, and Hadley against the observed PWI averages they are 0.97, 0.97, and 0.96, respectively. These numbers reinforce what Figures 4–9 display, which is that the RCM-based rainfall estimates may not always be spatially accurate, but they are remarkably consistent in their ranking against the observed CP-based PWI maps.

[35] Note that these well-ordered patterns are not obtained from downscaled precipitation; they are simply due to the correct partitioning of the observed and RCM-based precipitation performed by the CPs. We note that compared to Hadley, the REMO- and RACMO-based patterns appear to differ less from the observed ones, so the CP responses are evidently RCM specific. It is differences such as these that cause the relatively poor accumulations of the raw RCM outputs, evident in Figure 2; this effect would be exacerbated if a CP pattern with poor spatial distribution of PWI occurs more frequently than the others.

[36] To remedy these biases, CP-based downscaling uses a Q-Q transform on each block, for each season, dependent on the CP. The fdf's for both the observed and the target period are first assembled. To each location's rainfall depth fdf, a Weibull cdf is fitted. The adjustment of the RCM-based observations was made using the corresponding quantiles of the fitted cdf's. The values of the target empirical fdf's are retained, but their quantiles are adjusted.

[37] These ideas are expressed in the following equation, which is an extension of equation (1). Here the dependence is on fitted Weibull cdf's corresponding to observations (O) and RCMS (R) associated with individual CPs (α):

$$Z_D(x, t) = F_{O\alpha(t)}^{-1}(F_{R\alpha(t)}(Z_R(x, t), x), x), \quad (2)$$

where $\alpha(t)$ is the circulation pattern on day t for either the observation or RCM sets during the validation period.

[38] Figure 10 shows the CP-dependent cumulative frequency distributions of daily precipitation during the calibration period, for a randomly selected grid point, number 104, before downscaling. As one can see, the distributions corresponding to the RCMS differ from the cdf of the observations; however, the differences for some CPs are small, while for others they are large. Further overestimations and underestimations are both possible.

3.3. The Double Quantile-Quantile Transform for Future Scenarios

[39] What distinguishes CP-based downscaling in the future scenario from the validation exercise in the obser-

Table 1. Spatial Averages Over the Rhine Basin of Local Means and Maxima During the Validation Period 1981–1990^a

Model	Mean			Maximum		
	RCM Downscaling	Universal Downscaling	CP-Based Downscaling	RCM Downscaling	Universal Downscaling	CP-Based Downscaling
Hadley	942.6	802.5	821.7	21.7	23.6	26.2
RACMO	722.5	769.9	794.6	15.4	24.1	24.5
REMO	782.4	758.0	782.9	26.4	24.5	28.8
Observation		815.1			30.5	

^aValues given in bold are the downscaled values closest to the observations.

vation period is the way in which the Q-Q transform is employed. This is key to allowing different responses of precipitation to the RCM outputs in the two periods. When it comes to downscaling the RCM-based rainfall estimates in the future period (2021–2050), we make use of two cdf's and one fdf in a double Q-Q transform. The reason this is done is because the rainfall distributions not only differ between CPs (a fact well illustrated in Figures 5–7), but as we will show, they also differ between those estimated in the future scenarios compared to those in the observed period. This temporal difference applies markedly to the distributions conditioned on CPs, a fact that will be demonstrated in future work.

[40] In Figure 11 are shown three curves that explain the method.

[41] The black curve is the Weibull distribution fitted to an observed fdf at a given location conditional on a chosen CP. The gray curve is the corresponding Weibull cdf fitted to one of the RCM precipitation estimates at the same location. These two curves are used to perform the downscaling during the validation period of observations, in the usual way. The empirical fdf shown using black diamonds comprises the future values offered by the RCM concerned. To obtain a downscaled futures CP-based estimate of the adjusted fdf, a value (the gray diamond) is matched to the same value in the RCM-based observed cdf, and its quantile is determined. This transform implicitly allows for changes in precipitation response from an RCM under a given future CP. To obtain the bias correction (the transform used in the validation period), the Q-Q transform of the value is obtained from the horizontal shift. This shift yields the CP-based Q-Q adjusted future point (circled), at the same quantile level as the gray diamond. Thus, changes in both the CP frequencies and in the CP-precipitation relationships produced by the

RCMs are jointly responsible for changes in modeled precipitation under climate change and are accommodated by this technique.

[42] The relationship can be described mathematically in the following equation, which is an adaptation of equation (2):

$$Z_{DF}(x, t) = F_{O\alpha(t)}^{-1}(F_{R\alpha(t)}(Z_{RF}(x, t), x), x), \quad (3)$$

where $\alpha(t)$ is the circulation pattern on day t from the observation period sets. The other symbols in the equation are as follows: DF refers to the downscaled future, O and R refer to the observation period, and RF refers to the RCM estimate in the future. The transform is done for members of each CP.

3.4. Extremes in Precipitation

[43] Very heavy rainfall locally causes flash floods, while long sequences of little or no rainfall cause drought. There are other worrying combinations that trouble hydrologists, but we concentrated on these two to determine the efficacy of the downscaling methods.

[44] For flash floods, a good indicator of damage potential in a region is the annual maximum rainfall. Therefore, we computed the average of the recorded annual maximum value on each block during the validation period, corresponding to the observed data, and for each RCM we computed the raw, universal, and CP-downscaled estimates of precipitation. In addition, the 95% quantile of the daily precipitation distribution of a given season was calculated.

[45] At the dry end of the scale, we looked not at daily minima but rather the lowest 5th percentile of an exponentially filtered value of the daily precipitation on each block. The idea is an old one in hydrology, called the antecedent precipitation index (API) [Linsley *et al.*, 1949], expressed as a linear difference equation.

Table 2. Sum of Squared Errors for the Validation Period (1981–1990) for the Different Downscaling Methods^a

Method		Daily Precipitation				Antecedent Precipitation Index			
		Winter		Summer		Winter		Summer	
		Max	95%	Max	95%	Min	5%	Min	5%
Hadley	RCM	6432.0	1963.1	17109.5	942.7	758.8	2542.9	283.0	1070.2
	Univ	5514.7	77.3	3053.0	208.4	34.3	123.0	201.1	316.2
	CP	3432.2	77.2	1320.6	140.2	47.8	164.8	202.1	266.2
RACMO	RCM	5234.5	1325.5	2159.8	1179.0	284.2	672.3	400.4	1539.2
	Univ	3327.2	104.8	5057.0	105.5	12.9	13.3	225.8	698.3
	CP	1043.4	113.9	2489.7	86.5	25.1	33.4	239.0	539.9
REMO	RCM	9131.4	1532.7	4733.6	659.2	134.4	441.7	394.6	1019.7
	Univ	4946.0	181.7	3538.6	91.2	83.0	136.9	405.8	811.4
	CP	1973.7	161.5	2136.9	75.2	48.5	68.4	367.6	673.5

^aValues given in bold are the lowest SSE for each treatment in each column for each RCM. Min, minimum; Max, maximum; RCM, regional climate models; Univ, universal downscaling; CP, circulation pattern downscaling.

Figure 13. Mean of the daily maximum precipitation (mm) in winter for the RACMO model in the validation period (1981–1990): (top left) observed data, (top right) raw RACMO estimates, (bottom left) the result of universal downscaling, and (bottom right) the field obtained by CP downscaling.

[46] The API for a day t and location x is defined as

$$A(x, t) = \beta A(x, t - 1) + Z(x, t), \quad (4)$$

with $0 < \beta < 1$ and $Z(x, t)$ being the precipitation (RCM, observed or downscaled). Low API values indicate low antecedent precipitation amounts which correspond well to droughts. For our investigation $\beta = 0.9$ was selected. With this value, the API is equivalent to a linear tank storage with 10 days retention time.

4. Application

4.1. Validation

[47] The first validation exercise that was carried out used split sample testing. The observed outputs and the three RCM modeled outputs available for the calibration time period of 1961–1980 were used to determine the relative frequencies of CP-dependent rainfall, hence the Weibull probability distribution parameters. Subsequently, downscaling was carried out for the time period of 1981–1990 (10 years) for all 172 grid blocks. Annual mean precipitation

amounts and annual maxima and minima of the antecedent precipitation index were compared.

[48] Figure 12 shows the CP-based downscaled mean daily precipitation amounts for the observations and the three selected RCMs during the validation period; note the improvement compared to Figure 2. One can see that the CP-based downscaling methodology is able to correct the spatial biases of the RCMs in every case. The downscaled precipitation pattern is similar to the observed one for all the CPs. This is reflected by the systematic low errors. The slight underestimation of the modeled precipitation is a consequence of the underestimation in the RCMs (the integral of the differences between the time periods being negative).

Figure 14. Observed and downscaled mean of the lowest 5% of the temporally filtered daily summer rainfall using the antecedent precipitation index (API) applied to the observed and the Hadley RCM-based precipitation during the validation period (1981–1990): (top left) observed data, (top right) raw Hadley estimates, (bottom left) the result of universal downscaling, and (bottom right) the field obtained by CP downscaling. The APIs for the two downscaling procedures in the bottom plots are an improvement over the raw RCM estimate. These images are very similar because the temporal filtering smooths the discriminatory influence of the CPs. Nevertheless, because the downscalings are performed blockwise, they recapture the spatial behavior of the observed field but with some bias.

Table 3. Mean Areal Maximum Precipitations (mm) for the Validation Period 1981–1990^a

	Observed	Hadley		RACMO		REMO	
		Universal	CP Based	Universal	CP Based	Universal	CP Based
Rhine	19.5	17.2	17.7	17.1	17.8	16.7	17.1
Neckar	22.9	20.4	20.7	21.0	21.9	20.6	20.7
Main	20.2	19.1	19.0	18.5	19.3	18.2	18.3

^aValues given in bold are the universal and CP-based values closest to the observed values for each subbasin.

[49] Table 1 summarizes the results in absolute terms. The raw RCM results are also included. One can see that RACMO and REMO show a strong bias in the mean precipitation amounts. Even though Hadley is better in the mean, the spatial distribution of the amounts is not as good as the other two RCM results. Extremes for all models are slightly underestimated. The CP-based downscaled precipitation has the correct pattern for the means and thus gives confidence for hydrological modeling.

[50] It can be seen that the universal methodology does not work as well as the CP-based methodology, both for the means and for the extremes. The validation period (1981–1991) was wetter than the calibration period slightly by 2% in the annual mean and 12% in the mean of the annual extremes. These changes were not captured by the methods; however, note that the CP-based method captures at least a part of the signal. The problem lies with the RCMs themselves; the raw (uncorrected) RCM precipitation amounts and extremes for the validation period are below the mean of the calibration period. This problem cannot fully be corrected using downscaling because if the RCMs cannot capture the signal, the downscaling procedure cannot correct it.

[51] The mean of the annual minima and the 5% quantile of the API distribution of a given season were calculated. The different downscaling methods were compared to the observations, and the sum of the squared differences (over all 172 grid points) was calculated. Table 2 shows the results. One can see that the raw RCMs produce the largest differences: both universal and CP-based downscaling improve the results considerably and, in most cases, the CP-based downscaling outperforms the universal. The reason for the poor performance of the RCMs is partly due to their inadequacy in the spatial representation.

[52] Figure 13 shows the CP-based downscaled mean of the daily maximum precipitation (mm) in winter for the RACMO model using the different downscaling methods. It is clear that the CP-based downscaling is highly successful at getting the means and locations right. Figure 13 (top right) and Figure 13 (bottom left) show the patterns obtained using the raw RCM and universal downscaling, respectively. These are typical of results obtained by the usual downscaling methods. It is clear that the extra effort expended in CP-based downscaling (Figure 13, bottom right) is rewarding.

[53] Figure 14 shows the CP-based downscaled mean of the lowest 5% of daily API values (mm) for the Hadley RCM in the three stages of refinement, compared to the observed values. The raw RCM-based image does not capture the spatial distribution as well as the two downscaling procedures. On that note, the universal and CP-downscaled images are remarkably similar. As observed in the caption of Figure 14, this is most likely due to the API filtering out the influence of the CPs.

[54] It is important to understand that the good correspondence between observed and simulated statistics was obtained not from a modification of the statistics alone as in universal downscaling but by CP-based blockwise downscaling. The deficiencies of the RCM patterns cannot be corrected simply by a single transformation because the overall and local biases are different for different meteorological states as represented by the different CPs.

[55] The suggested procedure cannot be validated using the precipitation distribution limited to individual points because the Q-Q modification of the distributions leads to the correct distribution for the validation period. Thus, validation can only be carried out on larger spatial and temporal scales. For example, distributions of areal averages

Figure 15. The distribution of the annual frequency of the 20 CPs during the observation (1961–1990) and future (2021–2050) periods.

Figure 16. Cumulative frequency distributions (cfd's) of daily precipitations after downscaling for the future period 2021–2050 at grid point 104 for different CPs (solid line, observed (1961–1990); short-dashed line, RACMO; long-dashed line, REMO; medium-dashed line, Hadley RCM).

and/or multiday precipitation amounts are investigated to this end. For this purpose the areal precipitation needs to be averaged over selected catchments. We chose three sub-basins of the Rhine: the Neckar, the Main, and the remainder of the Rhine.

[56] Table 3 shows the results of the comparisons. The closest values to the observed are all slightly lower than expected but do not differ much. Relatively speaking, however, the amounts modeled follow the ranks of the observed data correctly, indicating the capacity of the CP-based models (in all cases better than the universal approach) to adjust to terrain and climate.

4.2. Application to Climate Change Scenarios

[57] In Figure 15 the annual frequency of the 20 CPs during the observation and future period are compared. The ordering is on the increasing rank of the frequency of the CPs occurring in the observation period. It is seen that only three RCM future CPs (CP01, CP11, and, to a lesser extent, CP19) show material differences from their frequencies during the observation period, the remainder being in similar proportions. The suggestion is that any modeled changes in

the precipitation are going to be the consequence of changes in sea and land temperature (and other meteorological variables modeled by the RCMs) conditioned on the CPs.

[58] Figure 16 shows the CP-dependent daily precipitation depth distributions for block 104 after downscaling during the future period 2021–2050. Note that the distributions are relatively close to the observed one (corresponding to 1961–1990), but the method allows nonstationary behavior leading to modifications. For RACMO the distribution shows an increase of precipitation for CP06 and a decrease for CP18. This feature cannot be captured by the universal downscaling method.

[59] We note, however, that the downscaled series differ in their spatial distributions. The CP-based approach allows different spatial coherences due to the different CPs, while for universal downscaling the spatial structure is fully imported from the RCM.

[60] Figure 17 shows the mean daily precipitation amounts for the future period obtained for the three different RCMs compared to their precipitation in the observation period. It is worth noting at this juncture that the RCMs RACMO and REMO are downscaled from the same GCM, namely, ECHAM5, while Hadley is downscaled from

Figure 17. Mean daily precipitation for the for three RCMs obtained using CP-based downscaling for the transient period 2021–2050.

Had3CM. It is clear that the mean patterns of RACMO and REMO are very similar to each other but are quite different from Hadley. The differences become even more obvious if the difference in historical and future CP-based PWIs are calculated.

[61] Downscaling with the above-described methodology delivers spatially distributed daily precipitation series with improved change characteristics compared to universal downscaling. Some statistics for the selected three catchments are summarized in Table 4. Because the extremes play a central role in hydrology, values related to possible floods and droughts need to receive special interest. For

this reason the mean of the daily maxima and the mean of the minimum summer antecedent precipitation index are included in Table 4, giving numerical structure to Figures 12 and 13.

[62] Comparing the annual maxima in Table 4 with the corresponding ones in Table 3, we can draw the following conclusion: the CP-based downscaling of the future with either model suggests an increase in maximum rainfall in the future. This is after the CP-based method has modified the larger averages computed by the raw RCMs in both the observation (RCM control) and future (RCM) periods. This modification is the effect of the Q-Q transforms computed during the observation period. Hadley suggests generally little change from observed to future periods, whereas REMO suggests substantial changes for the Neckar and more modest increases for the other basins. The CP-based Q-Q transforms adjust these down to more modest increases.

[63] Finally, in Figures 18 and 19, we compare the results of the use of the three RCMs in their future estimations relative to those in the observation period for winter and summer for three selected CPs. The scale for each season and CP on each block is the shift in the PWI as a ratio of the predicted rainfall minus the observed rainfall divided by the observed mean rainfall. For example, if a block records a value of 0.2 and its average observed rain for that CP was 5 mm, the RCM predicts an average increase of 1 mm in the future. What we note for winter is that, with minor spatial differences, REMO and RACMO behave similarly and get wetter, whereas Hadley does not wet up as much. This is the effect for all 20 CPs. In summer, the three predictions are different; REMO wets up on all three CPs shown (and in 19 out of all 20), while RACMO gets wetter in only two out of three CPs (again in 19 out of all 20) and Hadley dries out on two out of three (and records 4 drier out of all 20 CPs). Not only are the counts different; the behavior of the CP-dependent change in PWIs is different.

[64] The interim conclusion is that differences in CP responses in different seasons show some positive agreement, some negative agreement, and some mixed agreement. We can definitely state that CPs' response in general is temporally and spatially nonstationary. RCM-modeled CP

Table 4. Selected Statistics for Two RCMs With Emphasis on Their Effect on Hydrology^a

Catchment	Hadley				REMO			
	RCM Control	RCM	Universal	CP Based	RCM Control	RCM	Universal	CP Based
<i>Annual Total</i>								
Rhine	954.5	1005.7	880.9	889.7	815.4	1013.3	1028.9	1042.8
Neckar	1105.0	1185.4	1053.3	1060.7	962.9	1171.1	1189.1	1209.6
Main	888.5	936.5	749.5	761.6	743.3	921.5	876.8	890.3
<i>Annual Maximum</i>								
Rhine	22.87	22.00	16.90	18.30	19.21	20.54	17.89	19.24
Neckar	26.12	28.65	21.77	24.20	22.73	27.52	23.83	24.79
Main	28.14	28.06	19.32	21.49	23.49	24.87	19.24	21.29
<i>Summer Minimum</i>								
Rhine	6.54	6.11	5.00	4.84	5.68	9.16	9.33	9.26
Neckar	8.17	7.62	6.07	5.88	6.57	10.90	10.82	10.65
<i>API</i>								
Main	5.33	4.84	3.50	3.36	4.24	7.22	6.94	7.01

^aThe four column headings under each RCM are RCM Control, averages obtained during the control run of all observed data from 1961 to 1990; RCM, raw RCM modeled values during 2021–2050; Universal and CP Based, downscaled estimates during 2021–2050.

Figure 18. A comparison of the winter PWI differences for the three RCMs: (top) RACMO, (middle) REMO, and (bottom) Hadley over three selected CPs: CP20, CP17, and CP06. All models exhibit different increases of average PWI across the CPs, with some similarity across the models. Generally, we found that all but one of the 60 winter CP/RCM plots showed an increase in PWI into the future.

downscaled precipitation behaves differently in the future compared to the past.

5. Discussion and Conclusions

[65] The main conclusion coming from this work is that CP identification is crucial for downscaling RCM outputs to local daily rainfall response as CPs have demonstrated high discriminative power in bringing useful corrections. The more that the CP-dependent precipitation differs from climatology, the more the CP-based downscaling tends to differ from the application of universal downscaling (which ignores the CP classification). RCMs produce biased pre-

cipitation compared to observations but nevertheless produce reasonable patterns for each CP (see Figures 4–7).

[66] The local (25 km²) Q-Q relationships established from the calibration period are determined from fitted Weibull distributions. This technique is different from the more commonly applied empirical (point to point) transform method and permits extremes larger than those observed to be scaled. This cdf-based Q-Q transform acknowledges that different CPs may give the same rainfall during the calibration or validation period but allows for different future behavior.

[67] There is a marked improvement in the patterns of the averaged rainfall occurring during the different seasons

Figure 19. Same as Figure 18 but in winter. These are not typical but have been chosen to show somewhat extreme results. All models again exhibit different increases of average PWI across the CPs, with disparity across the models.

when associated with the CPs rather than not. In addition, the CP-based Q-Q transforms during the validation period give the correct spatial distributions and patterns of extreme rainfall for both flood and drought applications, which is an important result for hydrological applications of the downscaling methodology. There are still a few problems to overcome; for example, the extent of rainfall fields for heavy precipitation is, even in the quantile sense, often underestimated by the RCMs, an effect that cannot be rectified by downscaling.

[68] The final conclusion is that the RCMs have faithfully preserved the partitioning of the rainfall via the CPs into regimes that are very close to the observed patterns. This comment applies for summer as well as winter. It is also

remarkable that although the frequency of occurrence of the CPs in the future scenario as modeled by the RCMs is not materially different from that observation period, the RCMs produce substantially different precipitation responses conditioned on the CPs, not so much between models as between periods. We assume that this is due to the effect of capably modeling changing meteorological responses in the future. Given the good performance of the CP-conditioned precipitation of the RCMs, we feel cautiously confident of the model outputs.

[69] Note that the basic assumption for all downscaling applications (including the presented one) is that the GCMs or RCMs are able to capture the change in climate even if they cannot perfectly reproduce present climate in detail. No

downscaling or bias correction procedure can produce a correct prediction from a wrong model.

[70] Looking to future work based on these results, it is likely that the inclusion of temperature, humidity, and other meteorological variables offered by the RCMs will aid in improving the discrimination of the CPs in rainfall prognostication. To that end, the work here was constrained by the grid scale of the RCMs; there is more to be done to take these results down to the station (or at least to intermediate) scales.

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