

On the added value of statistical post-processing of regional climate models to identify homogeneous patterns of summer rainfall anomalies in Germany

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Abstract

A fuzzy classification scheme that results in physically interpretable meteorological patterns associated with rainfall generation is applied to classify homogeneous regions of boreal summer rainfall anomalies in Germany. Four leading homogeneous regions are classified, representing the western, southeastern, eastern, and northern/northwestern parts of Germany with some overlap in the central parts of Germany. Variations of the sea level pressure gradient across Europe, e.g., between the continental and maritime regions, is the major phenomenon that triggers the time development of the rainfall regions by modulating wind patterns and moisture advection. Two regional climate models (REMO and CCLM4) were used to investigate the capability of climate models to reproduce the observed summer rainfall regions. Both regional climate models (RCMs) were once driven by the ERA-Interim reanalysis and once by the MPI-ESM general circulation model (GCM). Overall, the RCMs exhibit good performance in terms of the regionalization of summer rainfall in Germany; though the goodness-of-match with the rainfall regions/patterns from observational data is low in some cases and the REMO model driven by MPI-ESM fails to reproduce the western homogeneous rainfall region. Under future climate change, virtually the same leading modes of summer rainfall occur, suggesting that the basic synoptic processes associated with the regional patterns remain the same over Germany. We have also assessed the added value of bias-correcting the MPI-ESM driven RCMs using a simple linear scaling approach. The bias correction does not significantly alter the identification of homogeneous rainfall regions and, hence, does not improve their goodness-of-match compared to the observed patterns, except for the one case where the original RCM output completely fails to reproduce the observed pattern. While the linear scaling method improves the basic statistics of precipitation, it does not improve the simulated meteorological patterns represented by the precipitation regimes.

Keywords Summer precipitation regions · Germany · Climate models · Fuzzy classification · Bias-correction

1 Introduction

The impact of climate change on the water cycle and water resources are among the core interests of current climatological research. In this respect, climate models represent a key methodology since they are applicable for estimating projected changes in atmospheric and surface variables (e.g., Paeth et al. 2005, 2009) and for the analysis of processes (e.g., Abiodun et al. 2008; Druyan

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¹ Institute of Geography and Geology, University of Würzburg, Am Hubland, 97074 Würzburg, Germany et al. 2008; Ibebuchi 2021a). Climate change signals e.g. in precipitation extremes are expected to occur at regional scales (Trenberth 2007) and hydrological hazards are often associated with local precipitation extremes (Barros et al. 2014; Olsson et al. 2012). For this reason, higherresolution RCMs are often employed when it comes to the assessment of precipitation changes and associated extremes (Paeth and Diederich 2011). However, RCMs may inherit the bias from the driving GCM (Wu and Gao 2020). Bias correction (BC) is a commonly used statistical post-processing technique to improve the usability of RCMs by reducing their systematic biases (Maraun 2016). State-of-the-art BC techniques are mostly capable of improving the basic spatiotemporal statistical characteristics of individual output variables (e.g., Paeth 2011; Maraun 2016) whereas it is still uncertain how statistical post-processing affects the overall underlying physics of the resulting data sets and the simulated meteorological patterns (Ehret et al. 2012). In the regional context of Germany, where climate change is expected to alter the regional rainfall characteristics (e.g., Schwarzak et al. 2014), this study examines how BC impacts the simulated patterns of summer rainfall anomalies.

Precipitation exhibits high spatial heterogeneity (e.g., Kaufmann et al. 2017). This is due to the combination of manifold large-scale and local-scale atmospheric processes and boundary conditions that govern regional precipitation. The regionalization of precipitation can be used to group stations (or grid points) into climatologically homogeneous regions (e.g., Johnson and Green 2018). The reduced spatial complexity attained from the regionalization may enhance the understanding of the underlying large-scale meteorological processes associated with the time development of a given homogeneous precipitation region. It also enables a more focused analysis of projected changes in a specific region that exhibits high spatial coherency. However, given that the causal mechanisms of precipitation are fuzzy and largely overlap with each other, a clustering technique that results in physically interpretable meteorological patterns associated with precipitation in the region, and also maintains the fuzziness of the precipitation regions is desirable (Gong and Richman 1995). Gong and Richman (1995) compared the rotated S-mode (i.e., grid points are variable and observations are time series) principal component analysis (PCA) technique, which is inherently fuzzy by the nature of the PCA loadings, to other hard clustering techniques that allow a grid or station to be assigned to only one class. They found that the obliquely rotated S-mode PCA outperforms the other hard clustering techniques since the classification output preserves the underlying physics (i.e., the meteorological processes) that results in the time development of the homogeneous regions. Thus, the obliquely rotated S-mode PCA will be used in this work to regionalize the summer precipitation in Germany.

Several studies have regionalized rainfall over different domains in Germany. For example, Pluntke et al. (2010) regionalized hourly rainfall in the low mountain regions of Saxony. Kurbjuhn et al. (2010) regionalized precipitation data for the Free State of Saxony. In the present study, we go one step ahead by focusing on the whole of Germany and address the capability of RCMs (both raw and bias-corrected) to reproduce the observed patterns of homogeneous rainfall regions. Thus, the core focuses of this study are (i) to reduce the spatial complexity of boreal summer precipitation in Germany through the identification of homogeneous but fuzzy rainfall regions that can be physically interpreted; (ii) analysis of the capability of RCMs to replicate the observed precipitation regions. At the synoptic scale, this will enhance the understanding of the causes of the model biases; (iii) analysis of the added value of a simple bias correction approach in improving the capability of RCMs to identify the precipitation regions as observed; (iv) the impact of future climate change, under the RCP8.5 emission scenario, on the precipitation regions.

This study is structured as follows: Sect. 2 presents the data and methodology used; Sect. 3 presents the results of the regionalization and the capability of the RCMs to reproduce the observed patterns of the homogeneous precipitation regions. Discussion and conclusions are drawn in Sect. 4.

2 Data and methods

2.1 Study region

The study domain covers the whole of Germany which receives most of its rainfall during the Boreal summer season (Fig. 1). However, the summer months in this work are defined as May–August (MJJA) since, on average, these



Fig. 1 Seasonal climatology of precipitation in Germany for the 1981-2010 period from E-OBS



Fig. 2 Annual cycle of precipitation averaged over Germany for the 1981-2010 period from E-OBS

months receive the highest precipitation amount in Germany (Fig. 2). Thus the regionalization tends to isolate MJJA homogeneous regions of rainfall anomalies. From Fig. 1 some spatial differences become apparent: due to the proximity to the North Sea coast, the northwestern parts of Germany have an oceanic climate with more precipitation. The eastern parts of Germany are relatively drier with a more continental climate because they are downstream with respect to the dominating wind directions. The central parts can be classified as transition regions exhibiting both oceanic and continental climates with clearly visible windward and lee effects due to the low mountain ranges. The Alps, i.e. the southernmost mountainous region, receive the highest precipitation, especially during the summer season.

2.2 Data sets

Reanalysis data (10-m wind vectors, sea level pressure (SLP), and precipitation) are obtained from ERA5 (Hersbach et al. 2020). Observed precipitation is taken from the station-based gridded E-OBS data set version 23.1e (Cornes et al. 2018). The RCMs used are made available through the European Coordinated Regional Climate Downscaling Experiment (EURO-CORDEX) (Kotlarski et al. 2014; Jacob et al. 2014). The selected RCMs are CCLM4 and REMO, driven by ERA-Interim and MPI-ESM-LR for the historical period and emission scenario RCP8.5. The temporal resolution of the data sets is monthly for the MJJA months. The reanalysis data sets and E-OBS precipitation data are obtained for the 1979-2020 period (excluding the pre-satellite era), at a 0.1° horizontal resolution. The RCMs data sets are obtained from 1979 to 2005 (historical period) and 2070-2100 (future period under RCP8.5 scenario) at 0.11° resolution. The precipitation data sets are interpolated to a common 0.11° horizontal resolution using first-order conservative remapping (Jones 1999). Before the analysis, the precipitation data sets are detrended. This is because the analysis is not interested in this component of temporal variability (i.e., trend). Thus, MJJA rainfall anomalies are used for the analysis.

2.3 Classification of the homogeneous regions of rainfall anomalies

Obliquely rotated S-mode PCA, applied to the MJJA monthly rainfall anomaly, is used for classifying homogeneous regions of rainfall anomalies (Richman and Lamb 1985). The analysis aims to obtain grid points that covary over time. The grid points in the study region (c.f. Fig. 1) are related using the correlation matrix. Singular value decomposition is used to obtain the eigenvectors, eigenvalues, and PC scores. The eigenvectors are subsequently multiplied by the square root of the corresponding eigenvalues, making them longer than a unit length, referred to as PC loadings. The PC loadings are spatial variability patterns. The PC scores present the time series associated with the time development of the spatial patterns. The (oblique) rotation of the loadings aims to obtain the simplest configuration of the PC loadings, resulting in coherent spatial patterns (Richman 1986)-i.e., more near-zero values and fewer larger values of the loadings. Since the causal mechanisms of precipitation are fuzzy and overlap, some correlation between the scores is desirable. Thus, to preserve the meteorological processes that cause rainfall, an oblique solution might be preferred to an orthogonal solution (e.g., Gong and Richman 1995). In a situation the meteorological processes are orthogonal, an oblique rotation has the flexibility to also yield an orthogonal solution. The components are rotated obliquely using the Promax routine (Hendrickson and White 1964) at a power of 2 (i.e., the power at which the Varimax solution is raised) since in this case, the rotated PC loadings attain a simpler structure that matches well with the correlation patterns. The realism of the spatial patterns (i.e., the physical consistency of the meteorological patterns) according to Richman (1981, 1986) is based on relating the rotated PC loadings to the similarity matrix that generated them. Hence each Promax loading vector is compared to the correlation matrix that indexes the largest magnitude loading on that particular PC loading vector using the congruence coefficient (which does not remove the mean of each variable; see Eq. 1).

$$r_c = \frac{\sum XY}{\sqrt{\sum X^2 \sum Y^2}}.$$
(1)

 r_c is the congruence coefficient; X and Y are two distinct (PC loading) vectors.

As highlighted in Richman (1986), the following goodness-of-match can be used in interpreting the absolute value of the congruence coefficient: 0.98–1.00 (excellent match); 0.92–0.98 (good match); 0.82–0.92 (borderline match); 0.68–0.82 (poor match); less than 0.68 (terrible match). In this study, only rotated components with an absolute value of the congruence coefficient (i.e., goodness-of-match with the correlation structure) greater than or equal to 0.9 are retained. They are designated as realistic patterns that are physically interpretable and with the fuzziness of the precipitation region left intact. This is based on the finding of Richman (1981, 1986) that the rotated PC loadings can be interpretable insofar as they can be related to the correlation matrix that generated them and insofar as that correlation matrix reflects the meteorological processes associated with the modes.

The homogeneous rainfall patterns are tested for robustness, by first applying the classification scheme to the E-OBS and reanalysis data set for the 1979-2020 period and then to the 1979-2005 period for which the ERA-Interim and historical MPI-ESM driven RCMs are available. The patterns from the observed precipitation data sets are used as a benchmark to investigate the ability of RCMs to reproduce the MJJA homogeneous regions of rainfall anomalies in Germany when the same classification scheme is applied to the climate models. The congruence coefficient is used to examine the goodnessof-match between the patterns from the respective data sets. To assess the wind and SLP pattern anomalies associated with the time development of the homogeneous precipitation regions, composite anomalies of months when the PC scores are greater than |0.5| are calculated with respect to the MJJA climatology, and a test of statistical significance is done using the non-parametric block permutation test at a 95% confidence level. The 0.5 threshold is used in clustering the scores into a negative and positive phase to detect potential asymmetries

between these phases. Also, at a score magnitude of 0.5, there is a relatively greater similarity between the patterns of the homogeneous precipitation regions and the anomalies.

2.4 The linear scaling bias correction approach

The evaluation of the RCMs is done using the ERA-Interimdriven experiments that are closer to observation. The precipitation data sets from the GCM-driven RCMs are further biascorrected using linear scaling (LS) (Lenderink et al. 2007). The LS method is the simplest BC method and can improve the mean statistics of the data. While Berg et al. (2012) and Ibebuchi et al. (2022) compared a similar scaling approach with more sophisticated methods and found that such simpler methods correct the first moment of the distributions, but can have adverse effects on higher moments, Shrestha et al. (2017) reported that simple BC methods can be sufficient for hydrological analysis at monthly resolution. The reference data set for the BC is E-OBS. The analysis period (i.e., 1979 to 2005) is divided into 1979 to 1992, and 1993 to 2005. The BC transfer function is obtained for each period (i.e., training period), and then applied to the other period (i.e., validation period). Thus, the complete analysis period is bias-corrected. The correction factor is obtained for the MJJA climatological mean during the training period and then applied to the monthly precipitation estimates from the RCM during the validation period (Eq. 2). The correction factor is obtained and applied at each grid point in the study region to address the spatial heterogeneity of precipitation.

$$P_{RCM_{cor}}(t) = P_{RCM}(t) \times \left(\overline{P_{obs}}/\overline{P_{RCM}}\right).$$
(2)

 $P_{RCM_{cor}}(t)$ is the bias-corrected precipitation estimate from the RCM for a given month in the validation period, $P_{RCM}(t)$ is the raw precipitation estimate from the RCM for a given month in the validation period, $(\overline{P_{obs}}/\overline{P_{RCM}})$ is the ratio between mean MJJA observed precipitation value and mean MJJA raw RCM precipitation estimate in the training period. The ratio is the correction factor.

The added value of the BC and the stationarity of the transfer function are evaluated in the validation periods. The statistics considered for the validation of the bias correction are the mean values, standard deviation, 5 percentile, and 95 percentile rainfall estimates, at each grid box. The added value of the BC in terms of the observed homogeneous precipitation regions is tested by investigating whether the goodness-of-match is improved.

3 Results

3.1 Evaluation of the linear scaling bias correction

Figure 3 and Table 1 show the performance of the LS bias correction approach at each grid box in Germany. First, during MJJA, the raw RCMs simulated the monthly precipitation estimates in Germany with some biases. Generally, the precipitation estimates of when the RCMs are driven by ERA-Interim are closer to observed values, compared to when they are driven by MPI-ESM. The MPI-ESM has been reported to exhibit wet bias over Europe (Teichmann et al. 2013), which is evident from the mean precipitation values in Fig. 3 from both RCMs. The potential causes of the biases in the MPI-ESM model over Europe have been reported to include blocking frequency biases over Europe, sea surface temperature biases, representation of teleconnections such as the North Atlantic Oscillation, orographic effects, and cloud parameterizations (e.g., Muller et al. 2018). From Fig. 3, the stronger biases in REMO might be attributed to the challenges in simulating orographically induced precipitation (e.g., Feldmann et al. 2008). Also, compared to CCLM4, REMO has a low spatial correlation, probably due to the missing precipitation advection. Table 1 and Fig. 3 indicate that the source of the biases for REMO and CCLM4 has different causes.

The biases introduced by the GCM were dampened by the LS approach. Overall, the LS approach improved well the spatial variation of precipitation (measure by the spatial correlation coefficient) in Germany during MJJA. Also, the mean values and extreme value statistics of the precipitation estimates from the RCMs were brought closer to the observed. The added value of the BC is relatively lower for the standard deviation of precipitation, especially for the REMO model. From Fig. 3, there are few grid boxes where the BC worsens the standard deviations. However, from Table 1, when the spatial average is computed, improvement can be inferred since the grid boxes where the LS-approach seems to worsen the statistic are relatively few. The result also shows that the output of the BC can be dependent on the choice of RCM (e.g., Ibebuchi et al. 2022). For example, the largest contribution to the overall bias (mean absolute error) from the CCLM4 is coming from a few isolated grid points, mostly at the southernmost parts of Germany, and when these biases are dampened, the precipitation estimates from the RCM become quite closer to the observed relative to REMO.

3.2 Homogeneous regions of summer rainfall anomalies in Germany

Figure 4 shows the spatial patterns of the regions of MJJA rainfall anomalies in Germany from ERA5 and E-OBS. As explained in Sect. 2, only rotated components that match the correlation structure with a minimum congruence coefficient of 0.9 are retained. Hence following this criterion that ensures that the retained modes have a physical realism, four regions are classified which represent the western part of Germany (R1), the southeastern part including the Bavarian Alps (R2), the eastern part (R3), and the northern and northwestern parts that are close to the North Sea and the Baltic Sea (R4). The central part of Germany is characterized by an overlap of these four regions and hence, indicates the fuzziness of precipitation and its governing processes, supporting the idea of a transition zone with varying rain-producing or inhibiting influences. From Fig. 4, though the loading magnitudes appear to differ, E-OBS and ERA5 reveal very similar patterns. Indeed, Table 2 shows that there is a good match between the homogeneous precipitation regions as obtained from the two data sets. Further analysis of Fig. 4 will focus on the observed patterns from the E-OBS data.

Figure 4 shows that some regions have varying loading magnitudes, for example in the western region (R1), the loadings for the southwest are lower than in other domains in R1. The heterogeneity of the loading magnitudes in a given region can be an indication that the covariability of the grids has different extents. Significant effort is made by the classification to simplify the spatial complexity of the precipitation field, but the imprecise nature of the processes leading to the development of the regions can imply also that while the governing mechanism of precipitation is expected to be generally homogeneous for a given region (at least at the synoptic scale), nonetheless spatial heterogeneity of precipitation can still be expected within a classified homogeneous region. This can be due to local effects that modify the synoptic processes, which can translate, for example, to different precipitation amounts in a given homogeneous region.

Figure 5 shows the patterns of wind and SLP anomalies during the positive and negative phases of the homogeneous precipitation regions in Fig. 4. To have an idea of which phase in Fig. 4 is dry or wet concerning the region in question, we rely on the composite maps in Fig. 6. In the western region, the positive phase indicates a widespread cyclonic anomaly over Germany and the maritime regions. The wind anomalies are mostly southwest around the western domains. Figure 6 indicates that the positive phase of the western region is wet in the domains classified under it, whereas the negative phase comes along with dry conditions. From Fig. 5, an anticyclonic anomaly dominates over



Fig. 3 Validation of the Linear scaling bias correction technique for the 1993 to 2005 period. Biases are computed as precipitation estimates from RCM minus observed values from E-OBS

Table 1Spatial correlation coefficient (R) and mean absolute error(MAE)for the basic spatial statistics of the RCMs compared toE-OBSbefore and after bias correction of the RCMs driven by MPI-ESM, for the 1993 to 2005 validation period

Data	MAE (mm/month)	R
Mean		
REMO (ERA-Interim)	10.86	0.66
REMO (MPI-ESM RAW)	21.50	0.52
REMO (MPI-ESM BC)	8.63	0.97
CCLM4 (ERA-Interim)	14.40	0.93
CCLM4 (MPI-ESM RAW)	28.30	0.90
CCLM4 (MPI-ESM BC)	3.17	0.98
SD		
REMO (ERA-Interim)	5.21	0.43
REMO (MPI-ESM RAW)	5.43	0.42
REMO (MPI-ESM BC)	4.72	0.81
CCLM4 (ERA-Interim)	4.20	0.63
CCLM4 (MPI-ESM RAW)	10.60	0.80
CCLM4 (MPI-ESM BC)	2.53	0.87
5 percentile		
REMO (ERA-Interim)	6.47	0.71
REMO (MPI-ESM RAW)	21.09	0.41
REMO (MPI-ESM BC)	14.40	0.79
CCLM4 (ERA-Interim)	10.12	0.88
CCLM4 (MPI-ESM RAW)	11.20	0.88
CCLM4 (MPI-ESM BC)	3.62	0.90
95 percentile		
REMO (ERA-Interim)	21.82	0.53
REMO (MPI-ESM RAW)	25.75	0.50
REMO (MPI-ESM BC)	11.38	0.90
CCLM4 (ERA-Interim)	16.01	0.85
CCLM4 (MPI-ESM RAW)	45.23	0.84
CCLM4 (MPI-ESM BC)	10.04	0.91

Germany and the North Sea during the negative phase of the western region. On average the pattern is similar to Foehn conditions. The wind anomaly is dominantly northerly in the negative phase. The anticyclonic anomaly over the North Sea is equally an indication of suppressed convection.

Under the R2 regime (i.e., the southeastern region), Fig. 5 shows a weak pressure gradient between the North Sea and the southeastern parts of Germany. During the positive (negative) phase, a positive (negative) SLP anomaly is evident over the North Sea; as a result, the wind patterns are northwest (southerly) towards the regions of a relative enhanced cyclonic anomaly. In combination with orographic effects along the northern Alps, these patterns bring wet (dry) conditions over southern Germany. A further reason for the difference between precipitation in the positive and negative phase of R2 includes that the lower pressure over southern Germany (in the positive phase) steers moist air from the surrounding oceans into south-eastern Germany.

Under the positive (negative) phase of the eastern region, the pressure gradient indicates a cyclonic anomaly, situated at the south (widespread) over the landmasses in Germany; this results in maritime northeast (continental easterly) winds, over the landmasses in the eastern region; thus from Fig. 6, the positive (negative) phase of the eastern region is wet (dry).

Under the positive (negative) phase of the northern/northwestern region, a strong cyclonic (anticyclonic) anomaly dominates from the central to the northern parts of Germany. The wind patterns are dominantly southwest (northwest) towards the domains under the northern/northwestern region. This results in wet (dry) conditions in the northern/ northwestern region. The northerly wind anomaly during the negative phase might be dry since it could be related to the anticyclone that develops over Scandinavia.



Fig. 4 Leading four homogeneous regions of MJJA rainfall anomalies in Germany from E-OBS and ERA5 for the 1979–2020 period

Table 2Congruence coefficientbetween the precipitationregions classified from E-OBSand ERA5 for the 1979–2005period

Congruence coefficient		
0.97		
0.95		
0.96		
0.97		

In summary, the positive (negative) phases of all four rainfall modes denote wet (dry) conditions. The associated wind and SLP anomalies are in line with our basic understanding of rain-bearing (rain-suppressing) meteorological situations over Central Europe (e.g., Ibebuchi 2022). Yet, the positive and negative counterparts of all considered modes are mostly asymmetric. Moreover, there seems to be asymmetry in the contribution to the precipitation composites. For example, from Fig. 6, the positive phase looks similar for the eastern region, the northern/northwestern region, and partly the western region; whereas the negative phases match the patterns from Fig. 4. This can be a consequence of the fuzzy and overlapping nature of the large-scale meteorological processes that cause precipitation—the synoptic-scale processes associated with the formation of precipitation at a given region, modified by local geographical effects such as orography, can extend to other regions equally. In principle, the regions are not hard with step boundaries, especially when it comes to advective flow.



Fig. 5 SLP and wind anomalies during the positive and negative phases of the precipitation regions. The green vectors denote wind anomalies and the black contours indicate SLP in hPa. Contour inter-

val is 0.2 hPa. Dashed (thick) contour lines indicate negative (positive) SLP anomalies. Only values exceeding the 95% confidence limit based on the permutation test are plotted



Fig. 6 Precipitation composites of the positive and negative phases of the precipitation regions

3.3 Representation of the precipitation regions in the REMO and CCLM4 RCMs

Figures 7 and 8 show the precipitation regions as obtained from the CCLM4 and REMO compared to E-OBS,

respectively. Overall, the climate models can reproduce the regions as derived from observations and reanalysis data. Based on Table 3, the southeastern region is robustly captured by the models under all considered experimental settings, suggesting that the meteorological processes



Fig. 7 Patterns of the homogeneous regions of MJJA rainfall anomalies from E-OBS and as simulated in the CCLM4 for the 1979–2005 period. The simulations are for the ERA-Interim driven, MPI-ESM driven models for raw and bias-corrected data set

associated with the development of the southeastern region are well simulated in the models. However, REMO does not reproduce the western region when driven by MPI-ESM. As the western region is reproduced when REMO is driven by ERA-Interim, this is an indication that this bias stems from the MPI-ESM-REMO chain relationship, although CCLM4 performs better with input data from the same GCM. This suggests that under the REMO model, the GCM-RCM chain relationship fails to adequately capture the meteorological processes associated with the development of the western region. In general, CCLM4 performs better than REMO in many cases, especially when driven by the GCM data. For the eastern region and the northern/northwestern region, REMO performs better when using ERA-Interim as lateral and lower boundary conditions. Also, in some cases, for example, the northern/northwestern region from both RCMs, the raw GCM downscaling output seems to perform best in simulating the meteorological patterns compared to the ERA-Interim simulations. Thus, in this case, when having the meteorological patterns (i.e., the precipitation regimes) well simulated is the interest of the analysis, it might be better to either use the raw GCM downscaling output or apply a BC technique that improves the meteorological pattern.

3.4 Evaluation of the impact of bias correction on the simulated meteorological patterns

The added value of the BC in improving the goodness-ofmatch between the observed and simulated homogeneous precipitation regions can be equally assessed from Table 3,



Fig. 8 Same as Fig. 7 but for the REMO model

 Table 3
 Congruence coefficient between the precipitation regions

 classified from E-OBS and their counterparts from the various RCM

 simulations with different forcing for the 1979–2005 period

Data set	R1	R2	R3	R4
REMO (MPI-ESM Raw)	_	0.93	0.83	0.84
REMO (MPI-ESM BC)	0.75	0.92	0.82	0.84
REMO (ERA-Interim)	0.88	0.94	0.91	0.83
CCLM4 (MPI-ESM Raw)	0.90	0.93	0.94	0.85
CCLM4 (MPI-ESM BC)	0.91	0.92	0.94	0.85
CCLM4 (ERA-Interim)	0.95	0.96	0.87	0.79

(-) implies regions that are not reproduced in the model: based on visual inspection and terrible match (closer to zero) of the congruence coefficient

Figs. 7 and 8. For the REMO model, the BC has a positive effect with respect to the western region, though with a poor goodness-of-match, that was previously not reproduced by the GCM-RCM setup. Additionally, all the regions were reproduced after the BC which at least suggests that the BC does not alter the simulated weather pattern. However, there is no overall improvement in the goodness-of-match of the patterns after the BC or even there is slight deterioration in some cases. To this end, it should be noted that the temporal variations in the simulated time series, i.e., the sequence of positive and negative anomalies over the study period, remain unaffected by the BC approach and, hence, the PCA is based on more or less the same correlation matrix. In addition, it must be acknowledged that there is no clear added value by the BC approach in this work, on the simulated patterns, except for the western region in the REMO model.



Fig. 9 Patterns of the homogeneous regions of MJJA rainfall anomalies as simulated by the REMO and CCLM4 RCMs for the 2070–2100 period under the RCP8.5 scenario

3.5 Impact of future climate change on the meteorological patterns

Under radiative heating (i.e. towards the end of the twentyfirst century under the RCP8.5 scenario), Fig. 9 shows that the patterns of the precipitation regions were all reproduced, but with at least a borderline match with the historical patterns. Since the congruence match between the patterns from the historical and the RCP8.5 scenario are not in the excellent range, some changes in the configuration of the PC patterns under the RCP8.5 scenario can be inferred. Thus, two inferences can be made from Fig. 9 (i) the leading meteorological processes that govern wet or dry conditions in Germany, during boreal summer, remain the same and lead to more or less the same homogeneous summer rainfall regions across the country as observed under present-day conditions; (ii) the differences between the spatial structure of the historical and the RCP8.5 scenario patterns, suggest that while the meteorological processes associated with the development of the regions remain the same, climate change might be expected to impact some aspects of the governing meteorological processes, which translates to the future changes in the spatial structure of the precipitation regions. Here we use the bias-corrected RCMs. The correction factor was obtained during the historical period and, following the assumption of stationarity, was then applied to bias-correct the future data sets. While the temporal stationarity of the correction factor is often assumed and might not always hold under future radiative heating, Fig. 9 also suggests that this practice might not alter/constrain the simulated meteorological pattern of the bias-corrected future precipitation data set.

4 Discussion and conclusions

We applied the fuzzy rotated S-mode PCA (Richman and Lamb 1985; Gong and Richman 1995; Richman and Gong 1999) that maintains the underlying physics in precipitation to obtain MJJA homogeneous regions of rainfall anomalies in Germany. To ensure that the mathematical concept maintains the meteorological processes associated with rainfall, (i) the loadings are rotated obliquely (since the meteorological processes that cause rainfall naturally overlap and are fuzzy) to obtain a simple structure solution that makes the spatial patterns more coherent and also allows the PC scores to be inter-correlated; (ii) the rotated loadings are allowed to overlap under different classes, as the data permits, and are expected to resemble the correlation structure. Since the aim of the rotation is to make the rotated loadings fit the correlation pattern (Richman 1981, 1986), only PCs that have a congruence match of at least 0.9 with the correlation patterns are kept; (iii) the correlation structure (and the retained PCs that match well with the correlations) are expected to be physically interpretable in line with the basic knowledge of synoptic processes in the region. The method described here might be transferable to other regions or temporal changes, e.g., under future climate change conditions (c.f., Fig. 9).

Four major regions were classified: the western domains in Germany, the northern and northwestern domain, the southeastern domain, and the eastern part were found to represent homogeneous regions of summer rainfall. The regions exhibit some temporal stability as they were obtained from classifications done over a long and short time frame. According to our understanding of weather type effects and synoptic circulations over Central Europe (e.g., Ibebuchi 2022), very plausible variations in SLP gradients and wind patterns explained the large-scale synoptic conditions that can be associated with the time development of the respective homogenous rainfall regions.

Overall, the analyzed RCMs were able to reproduce the precipitation regions derived from observations and reanalysis data. CCLM4 outperformed the REMO model when the models are driven by MPI-ESM for all the simulated patterns and also for the western and southeastern regions when the models are driven by ERA-Interim. The REMO model outperformed CCLM4 for the eastern and northern/ northwestern region when the models are driven by ERA-Interim. In general, CCLM4 appears to be less prone to systematic errors inherited from the driving GCM compared with REMO. The REMO model failed to reproduce the western region when driven by MPI-ESM. However, the ability of the RCMs to reproduce all the regions when driven by reanalyses is promising and suggests that the RCMs can be applied to study the meteorological processes associated with rainfall formation in different parts of Germany.

Furthermore, Ibebuchi (2021a; b) found that within the regional context of southern Africa, climate change can impact the frequency distribution of synoptic circulations and also the amplitude of the circulation associated with synoptic geographical features. Here we found that the precipitation regions are reproducible under future climate change, given the stationarity of the large-scale processes associated with their development. However, based on the congruence match, the historical patterns are altered under future climate change scenarios. Thus, given that radiative heating can be expected to impact the frequency distribution of the synoptic circulation patterns and the synoptic geographical features (for example the strength of the circulation at the North Atlantic high-pressure that drives westerly winds to Germany), this can indeed cause the changes in the structure of the patterns under the RCP8.5 scenario.

Due to the low computational demand and simplicity, BC is a popular technique to improve the usability of climate data from RCMs. However, since BC corrects how much precipitation is allowed in each grid box, it is plausible that some aspects of the physical consistency in the field can be altered, e.g. the effects of microphysical and dynamical cloud processes on precipitation, depending on the grid box. Hence, it is arguable that BC might impact the simulated meteorological pattern in the RCM, as well as the correlation between different climatic variables (e.g., Maraun 2016). Since the classification scheme applied in this paper results in precipitation regions that are physically consistent, our study contributed to this issue by addressing the impact of BC on the simulated meteorological pattern of the data set. The major added value of the BC as found in this work is that a slightly better representation of the western region is achieved in the GCM-driven REMO run. The BC effect is rather small or does not exist in most other cases considered here. The simple BC approach applied here hardly affects the S-mode correlation matrix the PCA classification algorithm is based on. In summary, the linear scaling method has a positive effect on the basic statistical characteristics of simulated precipitation, i.e. in terms of mean, variability, and representation of extremes, while it barely impacts the spatiotemporal covariability of the simulated precipitation data sets. Therefore, there is no clear added value in the capability of the BC to improve the goodness-ofmatch with respect to the patterns of summer rainfall in Germany. When these patterns are deficiently simulated by climate models, there is a need for BC techniques that do not only improve the basic statistics of the corrected climate variables but equally adjust the underlying spatiotemporal covariability of the governing mechanisms.

To this end, studies have shown that before bias-correction, conditioning the time series by circulation patterns is plausible and correcting the time series based on circulation patterns rather than the monthly or seasonally conditioned values can result in the improvement of both the basic statistics of precipitation and the climatology/ pattern of precipitation under the classified circulation patterns (e.g., Bárdossy and Pegram 2011). Thus, we hypothesize that to improve the simulated meteorological patterns from the model output, a bias adjustment technique/ approach that focuses on improving the meteorological patterns might improve the congruence match between the simulated patterns and the observed patterns.

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Availability of data and materials ERA5 data are available at https:// cds.climate.copernicus.eu/cdsapp#!/dataset. The CMIP5 models are available at https://esgf-data.dkrz.de/projects/esgf-dkrz/. The E-OBS data is available at https://www.ecad.eu_

Code availability R studio was used for coding the methods as described in the methodology section. The codes are base packages in R (e.g. the PROMAX routine).

Declarations

Conflict of interest There are no conflicts of interest in this paper.

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