Journal of Hydrology: Regional Studies 19 (2018) 25–41

Contents lists available at ScienceDirect

Journal of Hydrology: Regional Studies

journal homepage: www.elsevier.com/locate/ejrh

The impact of bias correcting regional climate model results on hydrological indicators for Bavarian catchments

Florian Willkofer[a,*], Franz-Josef Schmid[a], Holger Komischke[b], Jane Korck[b], Marco Braun[c], Ralf Ludwig[a]

[a] Department of Geography, Ludwig-Maximilians-Universtiät München, Luisenstraße 37, 80333, Munich, Germany
[b] Bavarian Environment Agency (LfU), Hans-Högn-Str. 12. 95030, Hof, Germany
[c] Ouranos, 550 Rue Sherbrooke West, West Tower, 19th Floor, Montreal QC H3A 1B9, Canada

ARTICLE INFO

Keywords:
Bias correction
Regional climate model
Climate change signal
Hydrological modeling
Runoff indicators
Bavaria

ABSTRACT

Study region: The Mindel river catchment, gauge Offingen, Bavaria, Germany.
Study focus: The study investigates the potential interference of climate change signals (CCS) in hydrological indicators due to the application of bias correction (BC) of regional climate models (RCM). A validated setup of the hydrological model WaSiM was used for runoff modeling. The CCS, gained by the application of three RCMs (CCLM, REMO-UBA, RACMO2) for a reference period (1971–2000) and a scenario period (2021–2050), are evaluated according to eight hydrological indicators derived from modeled runoff. Three different BC techniques (linear scaling, quantile mapping, local intensity scaling) are applied.

New hydrological insights for the region: Runoff indicators are calculated for the investigated catchment using bias corrected RCM data. The quantile mapping approach proves superior to linear scaling and local intensity scaling and is recommended as the bias correction method of choice when assessing climate change impacts on catchment hydrology. Extreme flow indicators (high flows), however, are poorly represented by any bias corrected model results, as current approaches fail to properly capture extreme value statistics. The CCS of mean hydrological indicator values (e.g. mean flow) is well preserved by almost every BC technique. For extreme indicator values (e.g. high flows), the CCS shows distinct differences between the original RCM and BC data.

1. Introduction

In recent years, large efforts have been made in climate research to improve process understanding and advance computation power to allow for higher resolution dynamical regional climate models (RCM) (Kotlarski et al., 2014). Meanwhile, a large number of RCM results have been made available to a growing user community, showing a broad range of variability and bias (Christensen et al., 2008; Giorgi et al., 2009; Kotlarski et al., 2014; van der Linden and Mitchell, 2009). Reasons for deviations from observations are manifold and encounter various sources of uncertainty, such as errors in reference data sets (Ehret et al., 2012), the spatio-temporal scale gap between RCMs and observations, differences in model parameterizations (e.g. for convection) (Maraun et al.,

* Corresponding author.
E-mail addresses: florian.willkofer@lmu.de (F. Willkofer), f.schmid@iggf.geo.uni-muenchen.de (F.-J. Schmid), holger.komischke@lfu.bayern.de (H. Komischke), jane.korck@lfu.bayern.de (J. Korck), braun.marco@ouranos.ca (M. Braun), r.ludwig@lmu.de (R. Ludwig).

https://doi.org/10.1016/j.ejrh.2018.06.010
Received 28 September 2017; Received in revised form 20 June 2018; Accepted 23 June 2018
Available online 31 July 2018

2010). The selection of SRES emission scenarios (SRES, Nakicenovic (2000)) or recently developed representative concentration pathways (RCP, van Vuuren et al. (2011)), however, affects the climate change signal for the future period. RCM data is made freely available through various data bases (ENSEMBLES (SRES) (van der Linden and Mitchell, 2009), CORDEX (RCP) (Giorgi et al., 2009)) and evermore climate change impact studies apply these data to assess the effects of potential alterations in climate on various physical, ecological and/or socio-economic aspects (e.g. runoff regimes, extreme discharge, biodiversity, water management) (Hattermann et al., 2014; Lenderink et al., 2007; Majone et al., 2012; Stagl and Hattermann, 2015). However, the increasing resolution of RCMs is mostly still too coarse for smaller scale investigations in hydrology, so additional downscaling techniques must be applied (Cloke et al., 2013). Besides this scale issue, RCMs often exhibit pronounced systematic deviations from any given reference period which are considered as bias (Ehret et al., 2012; Kotlarski et al., 2014; Maraun, 2016). If large enough, these biases can result in significantly and often non-linearly different outputs from subsequent models (e.g. for hydrological models) (Chen et al., 2011) which are usually calibrated against observations. Thus, the bias between the observations and the models has to be removed before the data is applicable for impact models. Several methods have been developed for this purpose and are often critically discussed (Ehret et al., 2012; Maraun et al., 2010). Recent studies indicate, that bias correction (BC) methods can have different effects on the distribution of any given parameter (e.g. precipitation), and can thus particularly impact its extreme values (Hagemann et al., 2011; Mudelsee et al., 2010). The underlying principle and thus the most crucial assumption is that the bias correction factors retrieved by any such methods must necessarily be considered valid for the future, assuming a temporal stationarity and thus introducing another, yet often neglected source of uncertainty (Teutschbein and Seibert, 2012). Hence, it must be argued that BC methods might falsify the original climate change signal (CCS) of RCMs with extreme values being stronger affected than means (Themeßl et al., 2012). Regarding the influence of the use of bias corrected data on hydrological modeling, Muerth et al. (2012) point out that individual simulations with a strong inherent bias visibly affect the CCS of hydrological indicators. The overall mean CCS of large RCM ensembles (i.e. multiple member of a RCM driven by the same GCM with changing initial conditions) however seem to be less sensitive to BC.

Many studies investigated the removal of bias in RCMs, resulting in a myriad of methods and various performances for specific purposes (e.g. Maraun et al. (2010); Themeßl et al. (2012)). The study by Muerth et al. (2012) investigated the influence of BC on the representation of observed runoff, the impact of CC on the runoff regime and the effect of BC on the future change in hydrological indicators over a single catchment in Bavaria. Hagemann et al. (2011) state that the hydrological CCS at certain locations and for specific seasons might be affected by the BC of raw GCM data. This impact of BC on the CCS of hydrological indicators is also significant if outputs from corrected RCMs are applied as a meteorological driver of hydrological models (Muerth et al., 2012). Cloke et al. (2013) investigated the impact of BC on the CCS of extreme discharges for the Upper Severn catchment, England, and found that it is even stronger than for mean flows.

To further investigate this specific topic in the course of its routine operations in water resources management (e.g. design of flood detention basins based on a threshold for extreme high flows), the Bavarian Environment Agency (Bayerisches Landesamt für Umwelt (LfU)) requested to analyze the performance of three bias correction methods (local intensity scaling, quantile mapping, linear scaling) for multiple Bavarian catchments in the framework of the BI-KLIM[1] project. These specific BC approaches are chosen for being considered state-of-the-art methods to adjust the systematic differences between RCM data and observations (Ehret et al., 2012). Hence, the purpose of this study was:

a) to determine the most sufficiently performing bias correction method as a standard approach for the Bavarian domain (see Fig. 1, upper left) and
b) to quantify and evaluate the effects of bias correction on the CCS of specific hydrological indicators for river catchments located in Bavaria, Germany.

This paper focuses on the effects of bias correction on the CCS of hydrological indicators. The climate simulations ensemble for this study includes three different RCMs: the COSMO-CLM (CCLM 4.8, Berg et al. (2013); Wagner et al. (2013)) of the Karlsruhe Institute of Technology (KIT)[2], the REMO-UBA[3], and RACMO (v2.1) of the KNMI (van Meijgaard et al., 2008), all driven by the same global circulation model (GCM, ECHAM5, Roeckner et al. (2003)) (further referred to as: CCLM, REMO, RACMO). The hydrological model WaSiM (Schulla, 2012) was applied to determine the impacts of BC to the CCS in the hydrology of several selected Bavarian catchments.

The performance of BC methods is evaluated by comparing long term flow regimes as well as specific flow indicators resulting from the hydrological modeling. A reference data set of observed data was set up at the beginning of the project. This dataset is further used as the observational reference for hydrological modeling and bias correction. The effects of BC on the CCS of the catchment's hydrology are investigated using the same hydrological indicators.

[1] Einfluss der Biaskorrektur dynamischer regionaler Klimamodelldaten auf die Wasserhaushaltsmodellierung und Klimafolgenabschätzung in Bayerischen Flussgebieten (BI-KLIM) (Impact of bias correction of dynamic regional climate model data on water balance modeling and assessment of climate impacts for Bavarian catchments).

[2] Institute of Meteorology and Climate Research, Department Troposphere Research (IMK-TRO) of the KIT, 2011. Provision of CCLM forcing data, version 4.8, calculated by the KIT for runoff models for KLIWA. Unpublished report on behalf of the Bavarian Environment Agency (LfU), Measurements and Environmental Protection Baden-Württemberg, and Water Management and Factory Department Rheinland-Pfalz.

[3] Max-Planck-Institute (MPI) under contract to the German Federal Environment Agency, 2006.

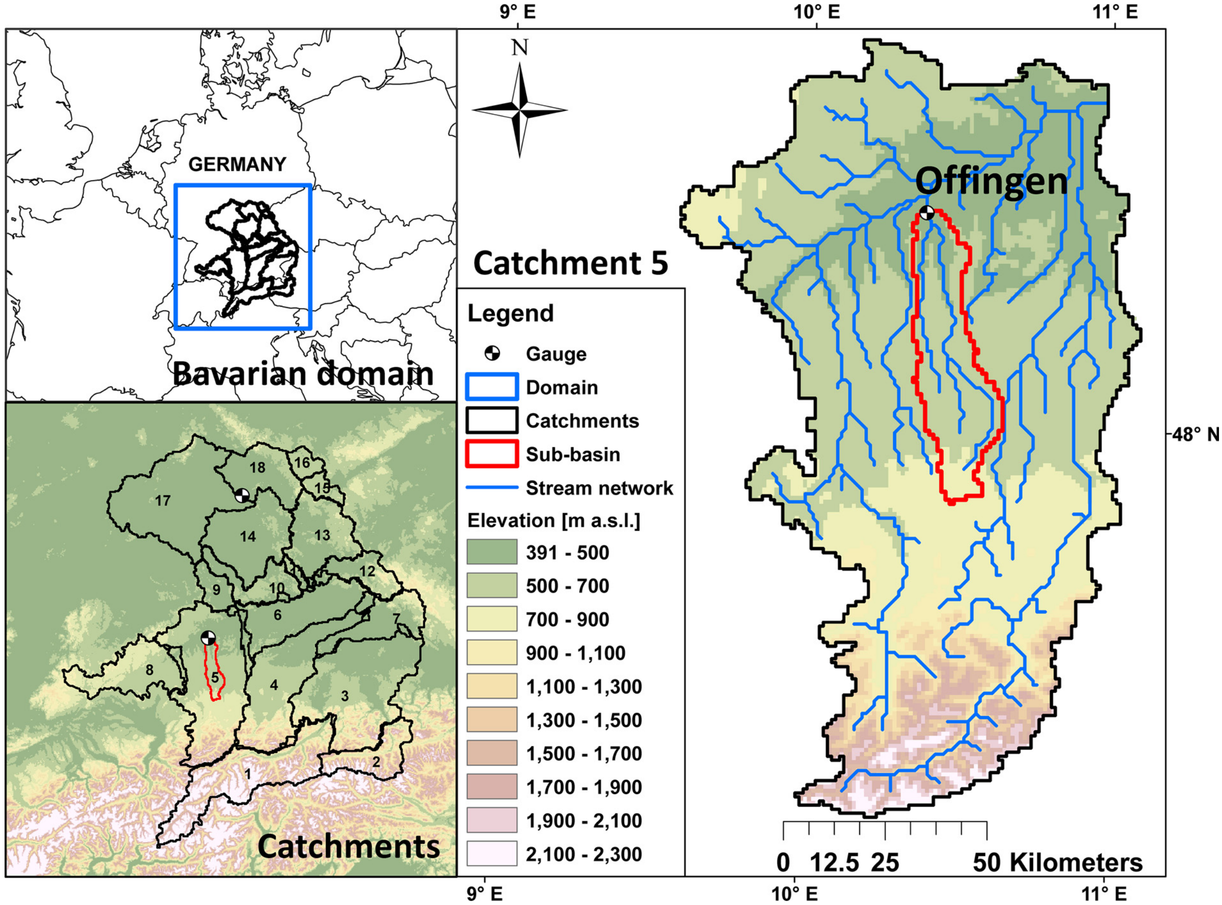

Fig. 1. Catchments of the hydrological Bavaria and the surrounding domain needed for scaling purposes. The Mindel sub-basin to the gauge Offingen (right, red boundary) is situated within the Iller-Lech catchment (5, lower left). The blue box in the upper left depicts the domain used for bias correction and spatial downscaling of RCM data.

2. Study area, data and methods

2.1. Study area

The study area covers the major Bavarian river basins including their headwaters in southern Germany and partly adjoining states (Austria to the south, Czech Republic to the east), furtherly referred to as “hydrological Bavaria”. It comprises 18 hydrological catchments modeled separately with the Water balance Simulation Model (WaSiM, Schulla (2012)) at the LfU as illustrated in Fig. 1 (left). Furthermore, this figure shows the surrounding domain (upper left, blue box) used for the bias correction of the RCM data for the Bavarian catchments (lower left). The following sections will focus on catchment 5 representing the Iller-Lech river system and parts of the Danube. In particular, results are shown for the Mindel river sub-basin up to the gauge Offingen (Fig. 1, right red outline) covering an area of about 929 km^2, since it represents a relatively pristine basin with only limited effects from water management infrastructure. Other catchments (Lech river to the East or Iller river to the West) are heavily impacted by artificial reservoirs and dams, which imposes additional challenges on the hydrological modeling outside the scope of this study.

This sub-basin is characterized by pre-alpine topography, showing a S-N gradient from the gauge in the north at 440 m a.s.l. to the highest peak in the south at 860 m a.s.l..The long term precipitation sums follow this gradient, ranging from 1100 mm in the southern part to 750 mm in the north. Mean temperatures range from −1 °C (January) to about 18 °C (August) and the mean annual evapotranspiration is around 570 mm. With a mean flow of 12.2 m^3/s, ranging from 11.5 m^3/s in the summer to 12.9 m^3/s in winter, the overall annual runoff variation in this pluvio-nival flow regime remains quite small.

2.2. Data

The data for this study is provided by the LfU covering the 18 catchments and including measured values from stream gauges and meteorological stations as well as grid based meteorological data.

Performing bias correction requires a meteorological reference to compute the change factors based on a distribution function or

Table 1
Meteorological dataapplied for the creation of a reference data set. Data is provided by the LfU. All data is based on interpolated measurements using different interpolation methods. The HYRAS data set was developed by the German Weather Service (DWD) and provided only for the German parts of the hydrological Bavaria.

Source	Data type	Parameter	Interpolation	References
HYRAS data set (DWD)	Raster, 1 x 1 km²	Precipitation [mm] (1) Air temperature [°C] (2) Rel. air humidity [1/1] (3)	REGNIE (1) Optimal Interpolation (2) & (3)	Rauthe et al. (2013), Frick et al. (2014) / Gandin (1965)
Interpolation from hydrological model	Raster, 1 x 1 km²	Precipitation [mm] Air temperature [°C] Rel. air humidity [1/1] Global radiation [Wh/m²] Wind speed [m/s]	Regionally different weighted combination of Inverse Distance Weighting (IDW) and altitude dependent regression	Pöhler et al. (2010)

simple deltas for the modification of the RCM values. Here, a reference data set based on a regular grid was created by combining meteorological data from different sources (Table 1) for different regions. Fig. 2 shows the spatial distribution of the different data sources and types for the climatological variables with station values covering the Danube tributaries to the south and HYRAS raster covering the northern tributaries as well as the Main catchment (except for air humidity (H) in two northern catchments). Wind speed (W) and radiation (R) are interpolated from station measurements for the entire hydrological Bavaria. All meteorological data are available on a daily basis.

The adjacent grids of each region of are spatially merged for each time step. In combination, both data sets provide a regular grid at the resolution of the hydrological model of 1 x 1 km² covering the entire Bavarian domain. The different data sets (HYRAS and interpolated station data) exhibit patterns due to the different development schemes. Hence, the Danube catchments show a more pronounced topographical pattern, while the Main catchment shows a more diffuse picture. The sharp transition between the regions might influence results of affected catchments. However, the different schemes have no impact on the findings shown in this study. The different sources of meteorological data are applied to the respective hydrological model for the catchments of Fig. 1.

The reference period for this study covers the period from 1971 to 2000. This period was chosen since meteorological data was available in sufficient spatial and temporal coverage. The presented investigation on the impacts of bias correction on CCS is based on data from three different RCMs, all using ECHAM5 as the driving GCM. Two were provided by the LfU: the CCLM and REMO. These RCMs are frequently used in other climate change related projects funded by the LfU (e.g. KLIWA, AdaptAlp, ClimChAlp)since their high spatial resolution is considered to be advantageous for applications in high relief terrain as Bavaria (especially over the Alps). In order to show the performance of BC on a coarse resolution model the RACMO RCM with a spatial resolution of 50 km was applied in this study. The respective characteristics of each RCM are given in Table 2.

The driving GCM and its members (i.e. GCM runs with slightly altered initial conditions) are the same for all three RCMs. Hence, the differences in the results using the different RCM ensembles (CCLM, RACMO, REMO) originate from the differences in the RCM configurations (e.g. resolution, domain size) However, as with the GCM members, variations between RCM members originate from their respective initial conditions. In contrast to RACMO and CCLM, with three members each, there is only one member available for the REMO RCM. Furthermore, the REMO precipitation shows a shift in precipitation fields in mountainous areas due to luv and lee effects. A minor precipitation event from clouds at 3000 m altitude might be shifted by up to 15 km if affected by wind speeds up to

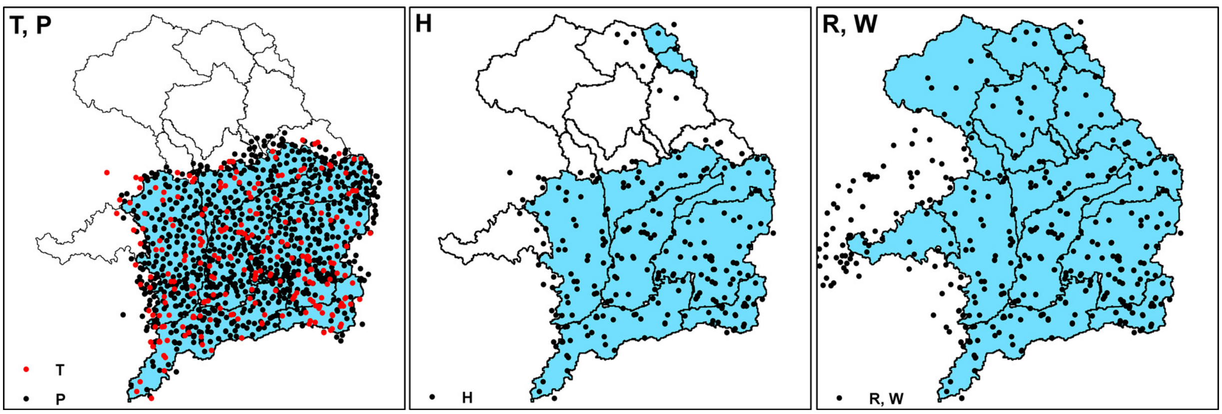

Fig. 2. Spatial distribution of the different data types available for the hydrological Bavaria. White indicates raster based interpolated measurements (HYRAS data, for air temperature (T), precipitation (P) and air humidity (H) only) whereas blue indicates interpolated point measurements from meteorological gauges. The dots in the frame show the distribution of the stations of the respective variable.

Table 2
Regional climate models applied in this study. The table shows the parameters, their spatial and temporal resolution, the period and driving GCM members available for this study.

Model	Parameter	Resolution	Period	Member (Scenario)
CCLM4.8	air temperature, precipitation, global radiation, wind speed, air humidity	7 x 7 km^2 daily	1971-2000 2011-2050	3x ECHAM5 Member 1 to 3 (A1B)
RACMO (v2.1)		50 x 50 km^2 daily	1950-2100	3x ECHAM5 Member 1 to 3 (A1B)
REMO		10 x 10 km^2 daily	1951-2100	1x ECHAM5 Member 1 (A1B)

10 m/s (Göttel, 2009). This spatial offset has to be considered in all further analysis. Table 3 illustrates the long term yearly mean values of the different meteorological variables of the reference data set and the raw RCMs as well as their respective absolute and relative biases.

The biases are considerable, especially for temperature and precipitation of all CCLM members and for temperature of the REMO RCM. Also precipitation biases for the RACMO RCM are significant (> 10%). Wind speed, global radiation and relative air humidity also exhibit strong relative biases. However, their absolute deviations are rather small. A proper correction of the bias of precipitation and air temperature is most important to allow hydrological models to produce reasonable outputs. However, since the hydrological model applied in this study requires all the above mentioned variables, they are also corrected for a better representation of the observed values.

2.3. Methods

For the purpose of analyzing the influence of the bias correction on the climate change signal a model chain was introduced (Fig. 3) with the BI-KLIM data base as central component. This data base includes all the pre- and post-processed RCM data (raw, scaled, and bias corrected). The bias correction is conducted at RCM resolution; thus, a spatial aggregation of the reference data set to the RCM scale was performed. After bias correction, the RCM data was further downscaled to the hydrological model grid, applying the scaling tool SCALMET (Marke, 2008). The influence of the bias correction on the climate change signal of the hydrological regimes was analyzed by applying all available raw and preprocessed data to the hydrological model WaSiM for the Mindel sub-basin within the Iller-Lech catchment.

2.3.1. Bias correction methods

RCM data usually display a statistical mismatch to recorded meteorological variables, a bias. In order to make the data better applicable and acceptable for users, various methods have been developed to correct such biases via transformation algorithms to statistically match the observations. A good overview of the various available approaches for bias correction is given by Teutschbein and Seibert (2012). The usual methods share the assumption that the retrieved correction factors and addendums are considered stationary in space and time. Thus, they are taken to be valid for the reference and the scenario period as well. This assumption is not challenged here, as the paper is focused on assessing the impacts of this common practice.

Table 3
Comparison (values, absolute and relative difference) of long-term yearly mean values between the reference data set and the raw RCM data.

Variable	Reference	RACMO			CCLM			REMO
		M1	M2	M3	M1	M2	M3	
Temperature [°C]	6.93	7.13	6.9	7.22	6.19	6.02	6.41	7.9
Precipitation [mm/a]	1048	1167	1175	1153	1668	1693	1674	1094
Relative air humidity [%]	75	81	81	81	86	86	85	74
Global radiation [Wh/m^2]	126	112	111	112	102	104	103	126
Wind speed [m/s]	2.05	2.92	2.9	2.91	3.56	3.55	3.54	3.41
		Absolute bias						
Temperature [°C]		0.2	−0.03	0.29	−0.74	−0.91	−0.52	0.97
Precipitation [mm/a]		119	127	105	620	645	626	46
Relative air humidity [%]		6	6	6	11	11	10	−1
Global radiation [Wh/m^2]		−14	−15	−14	−24	−22	−23	0
Wind speed [m/s]		0.87	0.85	0.86	1.51	1.5	1.49	1.36
		Relative bias						
Temperature		2.9	−0.4	4.2	−10.7	−13.1	−7.5	14.0
Precipitation		11.4	12.1	10.0	59.2	61.5	59.7	4.4
Relative air humidity		8.0	8.0	8.0	14.7	14.7	13.3	−1.3
Global radiation		−11.1	−11.9	−11.1	−19.0	−17.5	−18.3	0.0
Wind speed		42.4	41.5	42.0	73.7	73.2	72.7	66.3

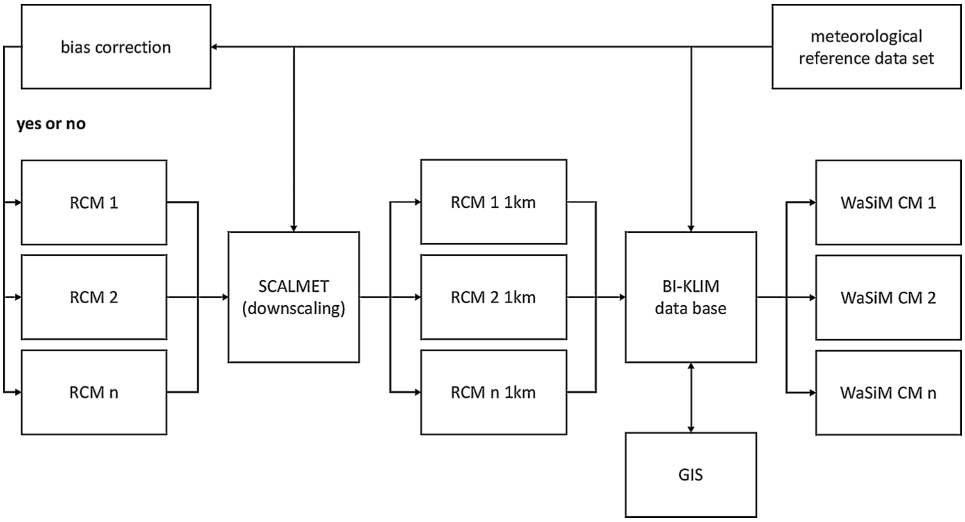

Fig. 3. Process chain with the BI-KLIM data base as most essential component including all of the processed data in the desired resolution for hydrological modeling applications. The GIS interface provides the opportunity to extract parameter values of each climate variable in table format for a single catchment. The bias correction is carried out on RCM resolution. (RCM: regional climate model; CM: climate model).

A common shortcoming of dynamic RCM data is the overestimation of the number of days with very little precipitation (Teutschbein and Seibert, 2012). This problem refers to the size of the raster cells of a RCM in combination with the convection of moist air. As the moist air reaches full saturation at a certain height with decreasing temperature, it will induce rainfall for a large area within a RCM. This process is further referred to as the 'drizzle-effect' (Dai, 2006). Dai (2006) also points out that this area-wide drizzle would not occur under natural conditions due to atmospheric instabilities and refers this effect to the model scale. Consequently, this particular portion of the RCM precipitation has to be removed in advance of the bias correction to avoid its influence on the modification factors. Kjellström et al. (2010) tested several thresholds for a minimum precipitation amount for handling the drizzle effect and found 1 mm/day to be a good value to remove excess drizzle precipitation from model data. Values up to this threshold do not significantly contribute to overall precipitation sums (Dai, 2001). Thus, this approach was applied for the elimination of the drizzle for all available RCM data in this study.

In contrast to the variability between the different RCMs, the changes in initial conditions of the driving GCM for the three members of the CCLM and RACMO induce an internal variability between these members of the particular RCM, which can be considered as natural variability (Elía and Côté, 2010; Muerth et al., 2012). To maintain this variability between the members of the CCLM and RACMO RCM, a multi member bias correction was performed. Here, a single set of correction factors is derived using the statistics of all the three respective members of the RCM (Muerth et al., 2012), instead of one set for each of the members. This allows for ascribing the differences in the annual course to the respective member of these small RCM ensembles. Furthermore, this ensures that a measure for the natural climate variability is maintained.

As mentioned above, for this study we used three different methods for bias correction which are briefly described here. The correction factors are calculated on a monthly (1 factor per month) as well as on a yearly (one factor per year) basis. Additionally, the multi member approach is applied to either of the sets of correction factors. Furthermore, values of relative air humidity are corrected in terms of dew point temperature, applying the Magnus formula for conversion. Since air temperature is required for the transformation, a good match between those two variables is maintained.

2.3.1.1. Linear scaling (ls). Linear Scaling is applied according to Lenderink et al. (2007), with slight changes regarding the long-term averages. For this approach we used the additive (air temperature [°C] (1)) or multiplicative (precipitation (2)) differences between the monthly (yearly) averages of the reference and the RCM data for the reference period similar to Teutschbein and Seibert (2012). The resulting correction factors are then applied to each daily (t) value of the entire time series of the RCM by addition or multiplication depending on the climate parameter to be corrected.

$$T_{RCM,cor}(t) = T_{RCM}(t) + (\overline{T_{obs}} - \overline{T_{RCM}}) \tag{1}$$

$$P_{RCM,cor}(t) = P_{RCM}(t) \cdot (\overline{P_{obs}} / \overline{P_{RCM}}) \tag{2}$$

The multiplicative approach also applies for the parameters wind speed and global radiation since these parameters have an absolute zero value like precipitation, whereas for air humidity the additive approach is used.

2.3.1.2. Quantile mapping (qm). The quantile mapping approach attempts to adjust the distribution function of values of the RCM to match the distribution function of observed values for the reference period (Sennikovs and Bethers, 2009; Teutschbein and Seibert, 2012). Thus, the correction factors depend directly on the values of both time series.

This study uses a modified empirical quantile mapping approach based on an daily translation after Mpelasoka and Chiew (2009). Apart from the usual multiplicative correction factors, the adapted approach of this study also provides additive factors to adjust temperature and relative air humidity (via dew point temperature). The distribution function for RCM and observed values is created by a division of the values using percentiles. In a first step, the values of each percentile i (with $i = 2k+1$, $k = [0,49]$) for both time series (observations and raw model data) are defined. If the percentile is in between two values of a time series a weighted mean will be calculated. The second step performs a cubic interpolation of the predefined percentile values to *n* percentiles. In order to prevent sharp edges between percentiles, the cubic interpolation to represent the fitting of the 50 percentile points is preferred over a linear interpolation in this study. The number *n* of percentiles can be altered and typically ranges between 0 and 100. For this investigation a value of 50 was chosen as this number was considered to sufficiently represent the distribution. Since every value of the time series is affected by the correction, also extreme values will be adjusted. Those new extreme values are achieved by an extrapolation of the percentile values > 99% and < 1% for the corrected model time series. This allows for the calculation of correction factors for the lowermost and uppermost percentile. In the last step the n percentiles are derived from the time series to be corrected. This also applies for the raw model time series for the future period. Hence, there are n values of the time series to be corrected and *n* correction factors for the respective percentiles. Afterwards, the correction factors closest to the respective percentile are assigned to the values of the original RCM time series. All these steps also apply for time series of single months which leads to *12n* correction values.

2.3.1.3. Local intensity scaling (LOCI). The local intensity scaling method (Schmidli et al., 2006) only applies for precipitation values. This approach is based on a scaling factor depending on wet-day intensities (3) and a wet-day threshold (WDT) derived from the wet-day frequency of daily observed (P_{OBS}) and model data (P_{RCM}).

$$s = \frac{\overline{P_{OBS}\colon P_{OBS} \geq P_{OBS}^{WDT}} - P_{OBS}^{WDT}}{\overline{P_{RCM}\colon P_{RCM} \geq P_{RCM}^{WDT}} - P_{RCM}^{WDT}} \tag{3}$$

The corrected time series is then calculated as follows:

$$P_{RCM,cor} = \max(P_{OBS}^{WDT} + s(P_{RCM}(t) - P_{RCM}^{WDT}), 0) \tag{4}$$

After the bias correction the new model data by definition have the same wet-day frequency and intensity as the observed time series (Schmidli et al., 2006). However, the overall precipitation sums may differ as for this method only the targeted statistics will match the statistics derived from the observation values (Muerth et al., 2012). In order to draw conclusions about the effects of this approach, the remaining parameters are corrected with the qm method.

2.3.2. The hydrological model WaSiM

The Water balance Simulation Model (WaSiM) was employed to perform the hydrological modeling. WaSiM is characterized as a distributed (grid based (regular / irregular)), mainly physically based, deterministic type of model using constant time steps with internally flexible sub time steps (Schulla, 2012). It is frequently applied for various climate change impact studies (Foltyn et al., 2017; Kleinn et al., 2005; Rößler and Löffler, 2010) or for the analysis on the need for bias correction (e.g. Muerth et al. (2012)). In this study, we applied existing calibrated and validated configurations of WaSiM for the catchments of the hydrological Bavaria and the following results focus on the results for the Mindel sub-basin (gauge Offingen) calculated using the model setup for the Iller-Lech river system (catchment 5, Fig. 1). The model was set up in 1 km spatial resolution and a daily time step and the parameters were derived for the calibration period from 1994 to 1998 and validated for the consecutive period between 1998 and 2003. These time slices were chosen since the number of available meteorological input data was larger. The authors of the model (UDATA, Pöhler et al. (2009)) evaluated the modeled discharge fit by the Nash & Sutcliffe Efficiency (Nash and Sutcliffe, 1970) for raw (NSE) and logarithmic (logNSE) model outputs. Furthermore, a long-term simulation run from 1971 to 2003 was evaluated to test the overall model performance including years with less available input data. The results for the different modeling periods (Table 4) for the Mindel catchment show a fairly good representation of the observed runoff by the model (NSE > 0.5 and logNSE > 0.65). The lack of available input data might influence the performance of the long-term simulation.

Table 4
Performance of the hydrological model WaSiM for the Mindel catchment at the gauge Offingen for different evaluation periods.

Period	NSE	logNSE
Calibration (1994–1998)	0.56	0.67
Validation (1998–2003)	0.59	0.72
Long term run (1971–2003)	0.53	0.68

Table 5
Codification of the multiple WaSiM model run results.

Code	Description
M*X*	Member *X* of the RCM
BC0 / BC1	Raw / bias corrected RCM data
OBS	Modeled using observed data (reference data set)
REF	Reference period
FUT	Future period
m / y	Monthly / yearly correction factors

3. Results

3.1. Bias correction results

The hydrological model for the Iller-Lech catchment is driven by the observed data (reference data set) as well as by the raw and corrected data of the dynamical RCMs. The modeled runoff obtained from driving the model with the reference data set forms the basis to assess the influence of the different bias correction methods. For the different hydrological model outputs a codification for the composition of the different RCM and bias correction methods is given in Table 5.

The long term flow regimes for the reference period between 1971 and 2000 shown in Fig. 4 illustrate the more or less distinct differences between the model runs using observed data (OBS) and those using the raw RCM data downscaled to the hydrological model resolution. While the regimes of the RACMO model mainly differ from the reference during the winter months, the results using the CCLM model overestimate the reference by almost 100% throughout all seasons due to significantly higher modeled precipitation. The runoff produced by the REMO model data, however, underestimates the reference entirely. Regarding the weak

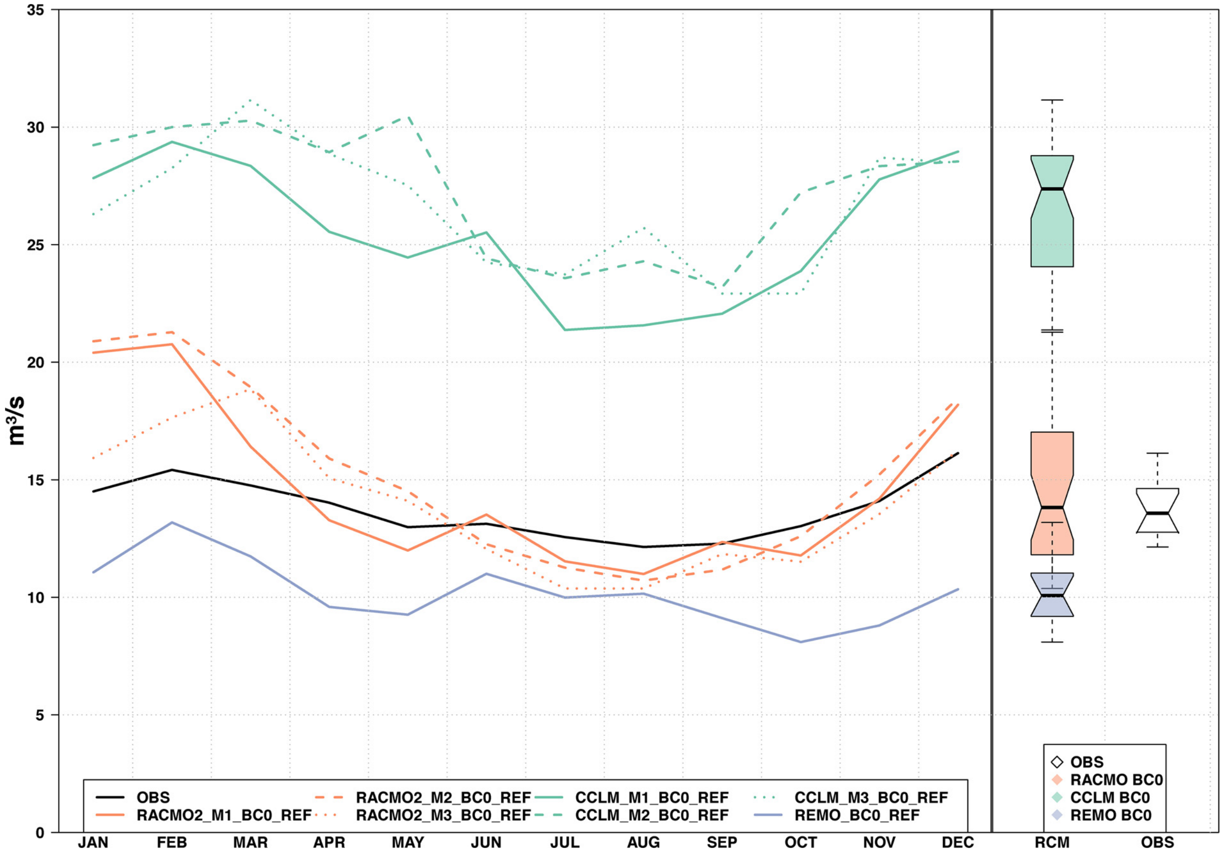

Fig. 4. Long term flow regimes for the reference period (1971–2000) of the river Mindel at the gauge Offingen. The regimes represent results of the hydrological modeling using observed data (reference data set) and raw data of the dynamical RCMs. The regimes using the raw RCM data show more or less significant deviations from the reference regime (REF). Especially the application of the members of the CCLM lead to a significant overestimation. The colored boxplots show the variability of the respective RCM dataset compared to the variability within the model results using observed data.

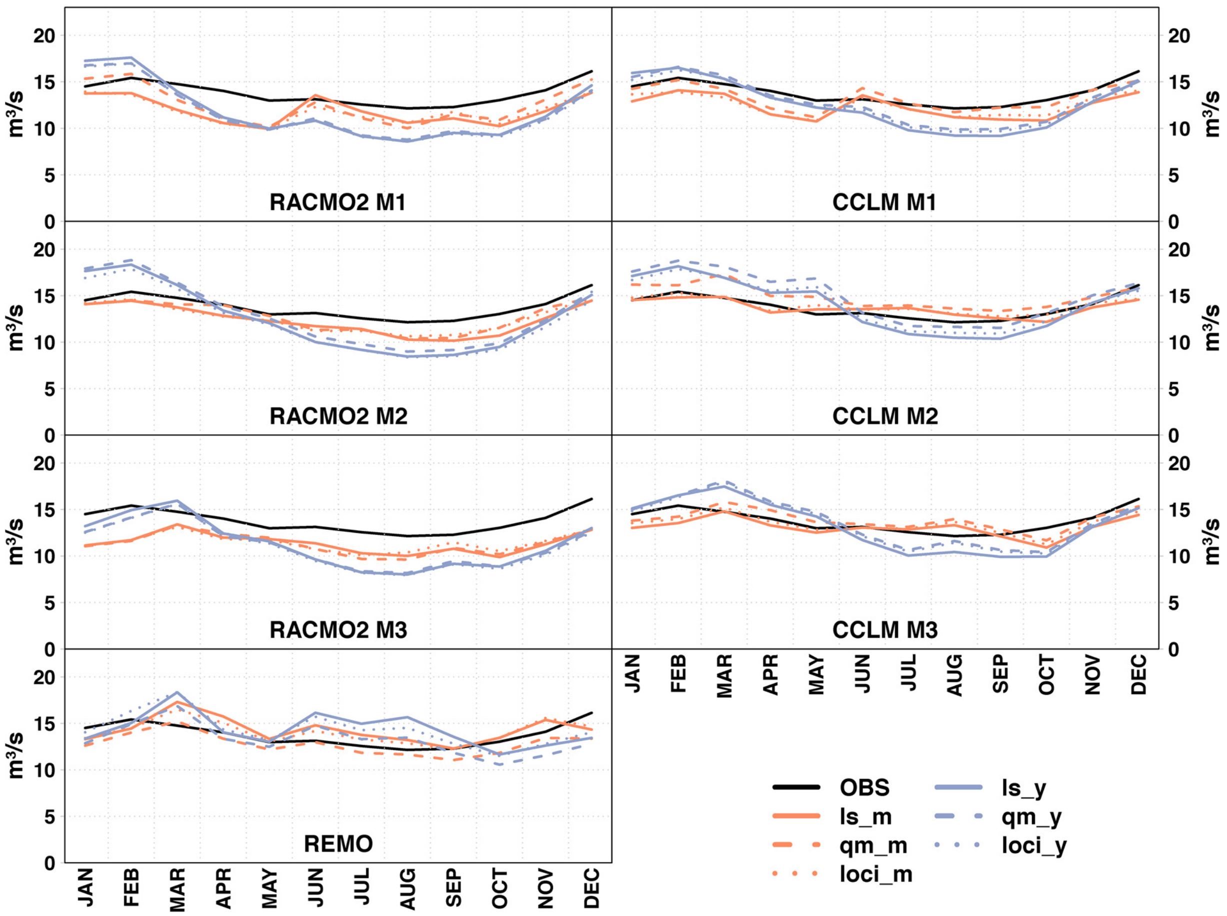

Fig. 5. Long term flow regimes for the reference period (1971–2000) of the river Mindel at the gauge Offingen showing model results using observed data (reference data set) and bias corrected RCM data. In general, approaches using monthly correction factors lead to a better adjustment to the reference. The regimes produced by RCM data using quantile mapping and monthly correction factors show the best results compared to other methods.

seasonal course the modeled regimes of the CCLM and REMO data show higher similarity to the reference. Furthermore, Fig. 4 shows the inter-annual variability of the simulations using raw RCM datasets (colored boxplots) compared to the variability of the model run produced with observed data (transparent box plot). Since there is no overlap between the upper or lower quantiles of simulations results of raw RCM data, these models differ significantly from each other. However, the variability of the RACMO model simulations is similar to the variability of the results using observed data since the notches of both boxplots as well as the median exhibit a good agreement. The variability of modeled results using raw CCLM and REMO RCMs in contrast differs significantly from the reference regime.

Fig. 5 shows the results of the hydrological modeling using the bias corrected RCM data (BC1). For the bias corrected RACMO data using monthly correction factors the results of the hydrological modeling are best for the 2nd member (-7.5% qm_m M2, > 8% for other members and BC methods, see Table 6) showing only minor differences of about 2 m^3/s (> 2 m^3/s for other members and BC methods, e.g. 4m^3/s in spring of M1) during the summer and fall season. In general, while the regimes produced by monthly corrected RACMO data systematically underestimate the observations (-4 m^3/s to -2 m^3/s throughout the year), the results with annual correction coefficients exhibit an overestimation in winter (1 m^3/s to 5 m^3/s) and underestimation in summer (up to -5 m^3/s in August). The flow regimes of the CCLM as well as REMO model show good adjustment, especially for member 2 and 3 of the CCLM with only minor differences regarding those produced with monthly correction factors. Despite the huge deviation of the raw CCLM data the bias correction is able to satisfactorily reproduce the observed runoff.

The results using yearly correction factors depict that the seasonal course of the results produced by raw RCM data is maintained in the corrected data. However, the correction leads to a shift of the respective regime to a slightly lower level. In most cases, this results in a slightly higher deviation from the observed data compared to the BC1 data based on monthly values.

The relative overall differences between the reference regime and those generated by the corrected RCM data given in Table 6 show that best adjustment is gained by the models CCLM member 2 and 3 as well as REMO. This is due to the finer resolution and an already better representation of the seasonal course in the raw data. Furthermore, these values illustrate that in most cases qm leads to the best adjustment. The differences of this approach are in most cases considerably lower (e.g. RACMO M1 qm_m -9.4%, locy_y

Table 6
Relative difference [%] of mean difference in runoff regimes produced by the application of the reference data set of observed data and those produced using the bias corrected RCM data.

BC Method	Overall relative difference [%]						
	RACMO M1	RACMO M2	RACMO M3	CCLM M1	CCLM M2	CCLM M3	REMO
ls_m	−13.4	−10.2	−17.2	−10.3	−0.3	−4.6	4.3
qm_m	−9.4	−7.5	−17.8	−3.3	8.6	1.5	−6.8
loci_m	−13.8	−8.8	−16.8	−9.3	1.6	−2.0	2.3
ls_y	−14.2	−10.1	−18.5	−9.3	1.4	−4.3	4.7
qm_y	−15.3	−6.8	−19.7	−6.4	8.8	−0.4	−3.5
loci_y	−16.1	−12.0	−21.0	−8.6	2.9	−2.1	4.6

Table 7
Flow indicators applied for the BI-KLIM project to determine the effects of bias correction of RCMs on hydrological climate change signals.

Flow indicator	Explanation
LF	Low flow, lowest flow of the entire runoff time series
MLF	Mean low flow, mean of the lowest flows of each model year of the runoff time series
7LF2	7 day duration low flow with a return period of 2 years
MF	Mean flow, over all mean of the entire runoff time series
MHF	Mean high flow, mean of the highest flows of each model year of the runoff time series
HF	High flow, highest flow of the entire runoff time series
HF2	High flow with a 2-year return period
HF100	High flow with a 100-year return period

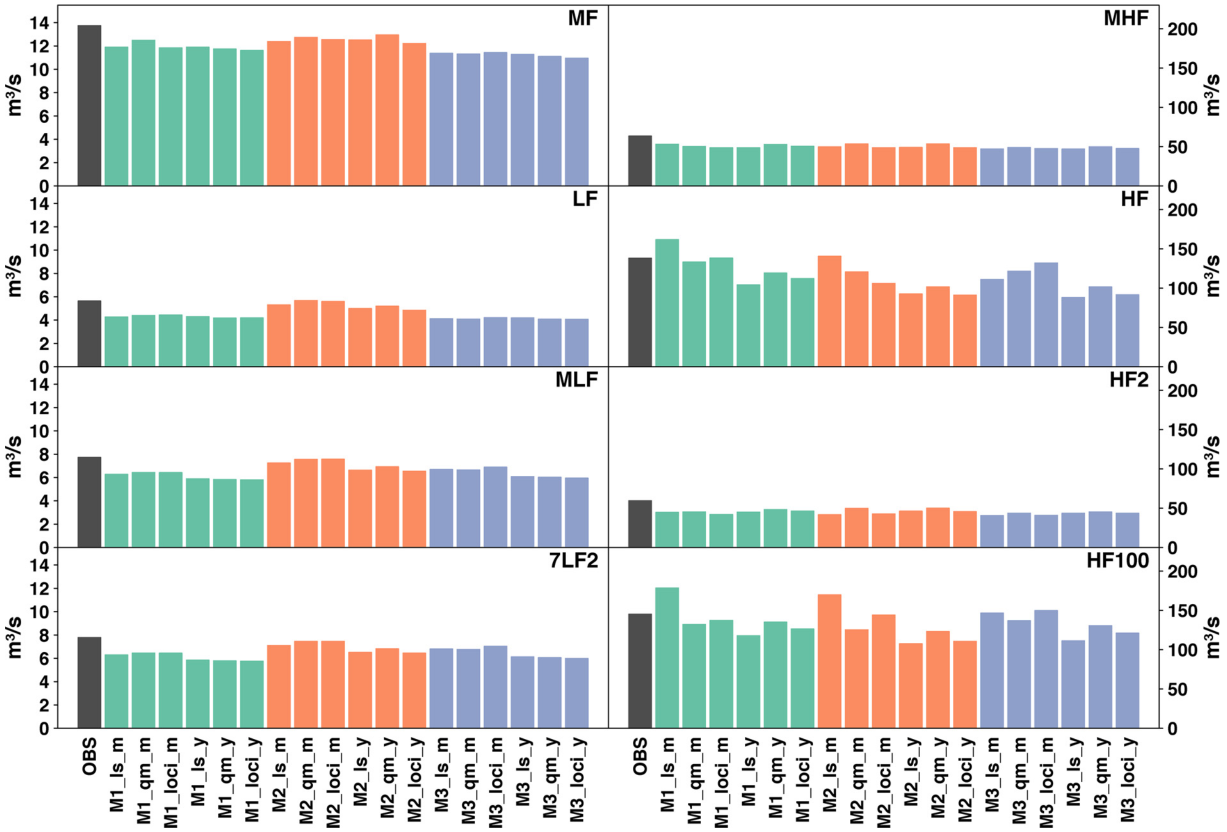

Fig. 6. Flow indicators for the gauge Offingen (Mindel river) for the reference period (1971–2000). The solid blue bar shows the reference values. The shaded bars represent the results of the model runs using bias corrected RCM data of the different members of the RACMO model (red: member 1, blue: member 2, green: member 3).

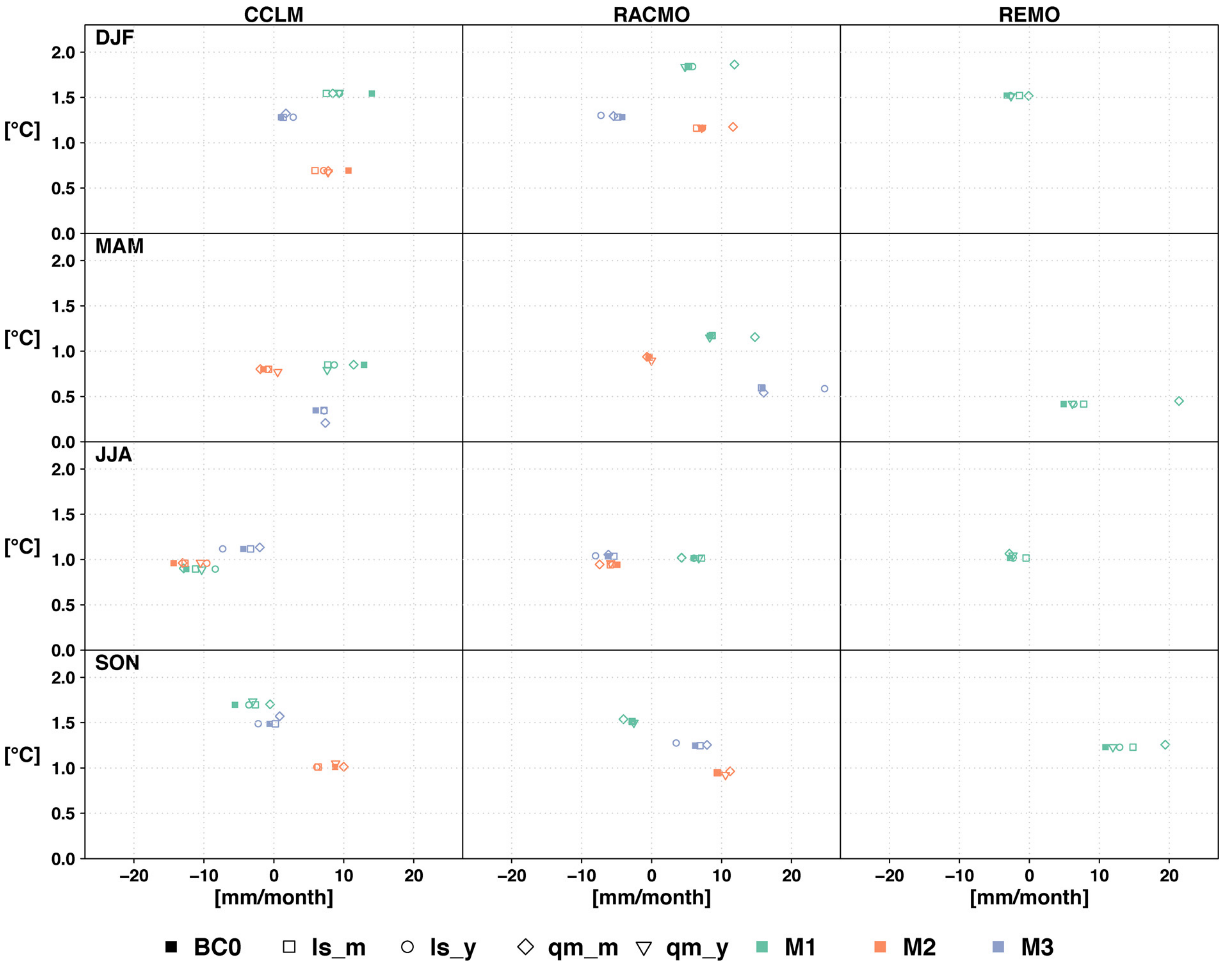

Fig. 7. Change signals of precipitation (x-axes) and temperature (y-axis) between the reference and future period for each season (DJF: winter, MAM: spring, JJA: summer, SON: fall) of raw (BC0) and bias corrected RCM data over the Offingen catchment.

-16.1%). Furthermore, yearly correction factors yield greater deviations for almost all RCMs. Also, the internal variations between the members of the CCLM and RACMO seem to be maintained by the multi member correction approach. The single set of correction factors for the REMO RCM however does not produce better results compared to the multi member approach, since the differences are comparable to those of the CCLM and RACMO (e.g. REMO qm_m -6.8% to RACMO qm_m -7.5%).

3.2. Changes in hydrological signals

The changes in hydrological signals are analyzed for the 'near future' scenario period ranging from 2021 to 2050 since data for the CCLM RCM is only available for this period. To determine the effects of bias correction of RCM data on the hydrological CCS we applied eight different flow indicators as described in Table 7. The extreme value statistics of the low and high flow indicators of a certain return period are based on the Pearson III distribution (DVWK, 1979, 1983).

The flow indicators for the reference period (1971–2000) show good agreement with observations for the hydrological data produced by bias corrected RCM time series in terms of mean flow, low flow and mean high flows compared to the reference (REF). However, the extreme high flow indicators show greater deviations. Fig. 6 exemplarily illustrates this behavior for the RACMO RCM and is representative for the results of the CCLM and REMO RCM as well. Whereas inter-member differences are very small for MF, LF, MLF, 7LF2, MHF, and HF2, the HF and HF100 depict significant variations between the different correction methods. These distinct differences in HF and HF100 for the various BC methods originate from their statistical characteristics. The HF index represents the highest runoff value of a chosen period (e.g. 30 years). Hence, the runoff simulations using BC data might not capture this specific value since the driving BC meteorology is possibly lacking a proper representation of extreme values. The HF100 is a statistical extrapolation based on yearly HF events of a certain period. Thus, the insufficient representation of HF values when using the BC meteorology directly affects the HF100 values. HF2 on the other hand is based on annual HF events. In this case an extrapolation is obsolete since the available runoff time series are sufficiently long (e.g. 30 years).

Fig. 7 shows the CCS for the different seasons (DJF, MAM, JJA, SON) of the raw and corrected RCMs. The different seasons exhibit

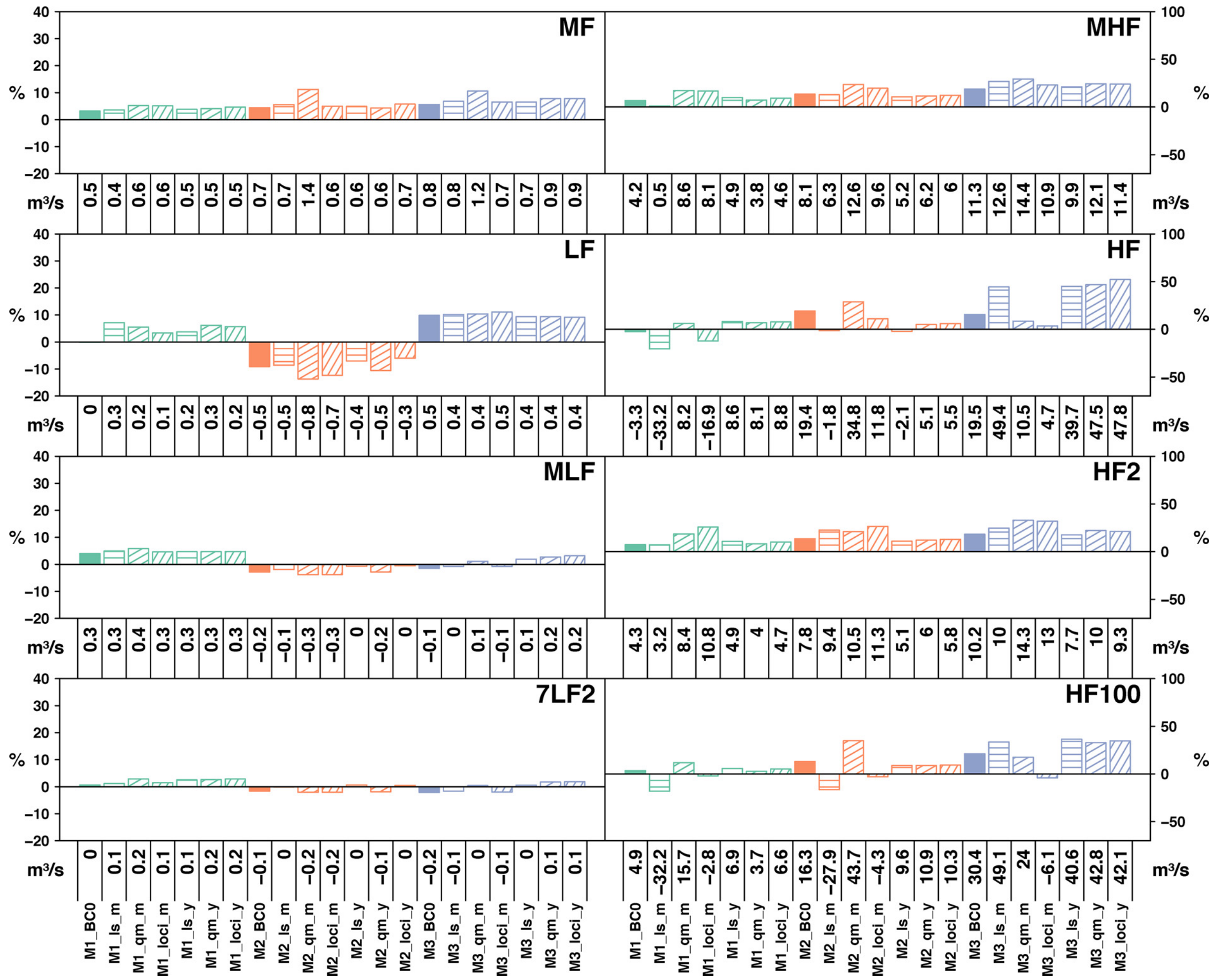

Fig. 8. Relative ([%]; bars) and absolute ([m^3/s]; numbers below graphs) hydrological climate change signals for the various flow indicators for the three RACMO RCM members.

various changes in the signal. The internal variability between the members of the CCLM and RACMO RCMs is visible and maintained by the applied correction methods (a warm and moist signal remains warm and moist). Signals in summer (JJA) are rather small for the REMO RCM, while in winter and spring they are larger for all RCMs. Apart from CCLM M1 and M3, and RACMO M1 and M3 for qm_m the CCS of BC1 data for the winter period show little deviations from the BC0 signal. This is also visible for the other seasons and the CCLM and RACMO model for almost all BC methods. Greater deviations in CCS between BC0 and BC1 data are present in the spring and fall season. The shift in precipitation fields, as described earlier, might be accountable for this larger change in signals by the various RCM methods since this shift is adjusted by the correction as well.

The following graphs (Fig. 8–10) show the results of the CCS analysis for streamflow. While the bars illustrate the relative [%] change signal (i.e. relative difference between reference and future scenario on RCM-to-RCM basis) of the flow indicators, the numbers below represent their respective absolute values [m^3/s]. It should be mentioned that the relative change signals might indicate a more severe change than the absolute value actually provides for; this is obviously pronounced for the low flow indicators. For the RACMO and CCLM RCMs the change signals of all three members are illustrated (member 1 red, member 2 blue, member 3 green). The solid bar represents the raw RCM (BC0) inherent climate change signal (CCS), the shaded bar the induced changes according to the bias corrected model data.

Fig. 8 illustrates the changes in the CCS of the original RCM and bias corrected model data for RACMO. The mean flow shows little to no difference between the change signals throughout all members regarding the absolute values (except for member 2 and 3 qm_m values, which is ascribed to a strong wet signal in winter, see Fig. 7) as well as the relative signals. Thus, in this case bias correction does not contribute to uncertainty in long-term water balance assessments (changes in mean flows under new climate conditions) since the CCS is not affected by the corrected data. Considering the LF, only member 1 and 2 show differences between the CCS of BC0 and BC1 (relative and absolute). Absolute and relative values of member 3 vary around the same magnitude. Furthermore, the LF depicts that natural variability between the three members is conserved by the multi member bias correction approach, with the 2nd member showing a negative signal whereas the other two members deviate positively. The absolute and relative CCS of the other low

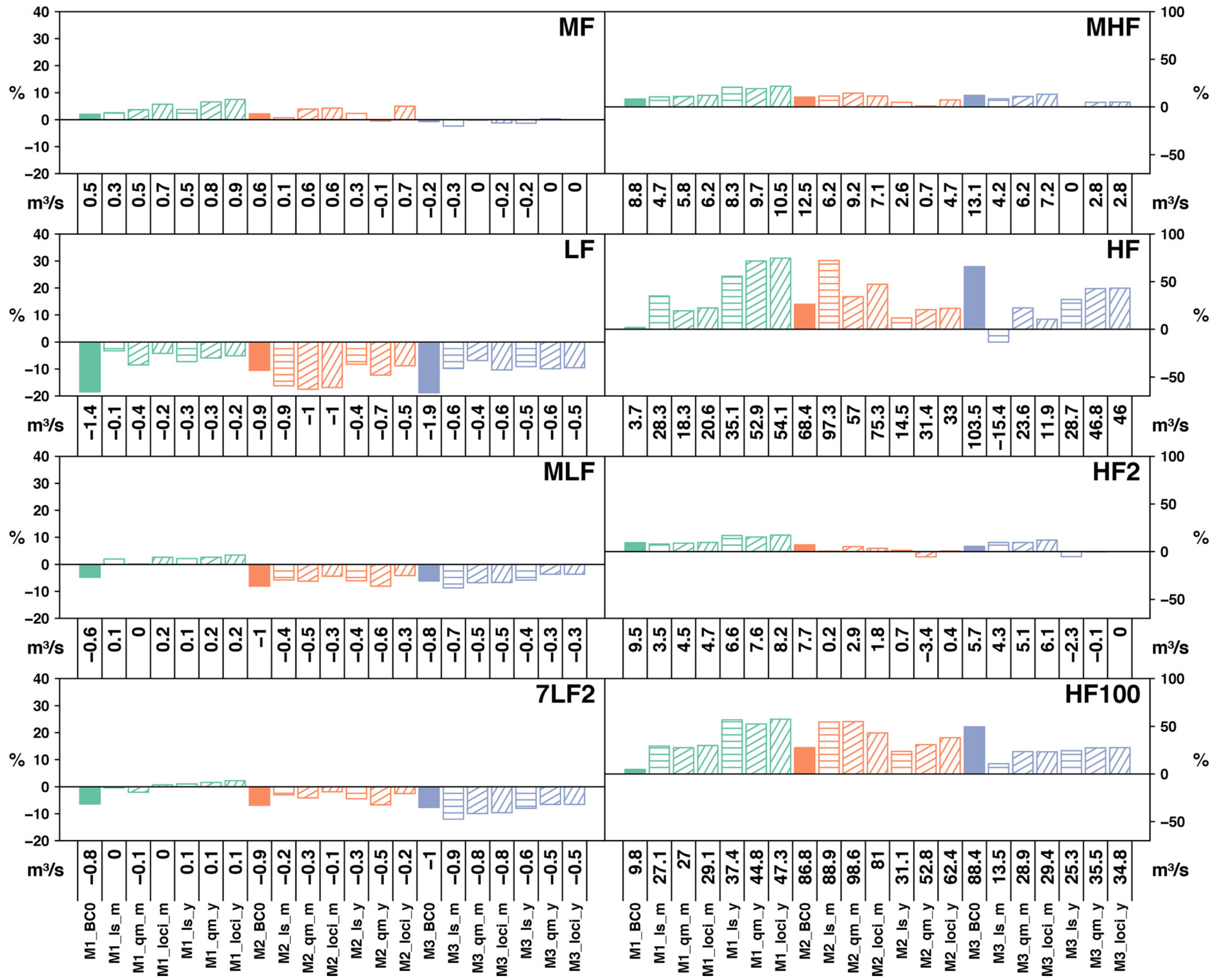

Fig. 9. Relative ([%]; bars) and absolute ([m^3/s]; numbers below graphs) hydrological climate change signals for the various flow indicators for the three CCLM RCM members.

flow indicators (MLF, 7LF2) vary just slightly. Since the absolute CCS values are close to zero the shift in direction may be neglected. The high flow indicators however show more distinct differences between the BC0 (raw RCM) CCS and those produced using bias corrected data. The MHF exhibits the least distinctive absolute and relative deviations as well as the HF2. Furthermore, the different methods lead to large differences between BC0 CCS and BC1 CCS which holds especially for the 3rd member of the HF indicator. Here, the relative BC0 CCS is below 20% but the BC1 CCS of the LOCI methods are 5% and greater 50%, respectively.

The absolute value of the loci_y method exceeds the BC0 value by over 100% (19.5 m^3/s BC0 to 47.8 m^3/s loci_y). In contrast to the low flow indicators, the shift in CCS direction within a member is more severe. Regarding the HF100 member 1 ls_m shows a decrease by 32.2 m^3/s whereas the BC0 displays a slight increase of 4.9 m^3/s.

The differences in CCS of the flow indicators are more pronounced for the CCLM model results (Fig. 9). The MF shows varying relative changes of the CCS (which is a direct response to the input data for all seasons, see Fig. 7), but the absolute values differ only very little. Compared to the RACMO model, the absolute differences of the CCS for the low flow indicators between the BC1 and BC0 are higher for CCLM data. Only the 3rd member, using the monthly adjustment factors, shows similarities to the raw RCM. However, the absolute changes are very small. Again, the high flow indicators show major differences in CCS between the BC1 and BC0 values for both, relative and absolute numbers. These changes are less severe for the MHF and in some cases for the HF2. However, the BC1 data in most cases overestimate the CCS of HF and HF100 for the members 1 and 2 by up to 145% (HF: BC1_M1_loci_y 54.1 m^3/s; BC0_M1 3.7 m^3/s) and underestimate the CCS for the 3rd member.

The REMO model data induce the most severe changes in CCS of the flow indicators between the original RCM and the BC1 results (Fig. 10). Here almost every indicator switches from a negative signal in BC0 to a positive in BC1 or vice versa, except for the MHF. While the BC0 data depict a reduction in MF and all low flow indicators, the BC1 data mostly show a slight increase. The CCS of the HF and the HF100 indicator exhibit considerable differences between BC0 and BC1 data. While the raw RCM data for these indicators depict an increase of less than 20%, the bias-corrected data reveal a significant decrease between about 30% (HF100, qm_m) and over 50% (HF, ls_y). As mentioned in Section 2.2 the BC0 REMO inherent spatial offset of precipitation fields might influence the CCS. All

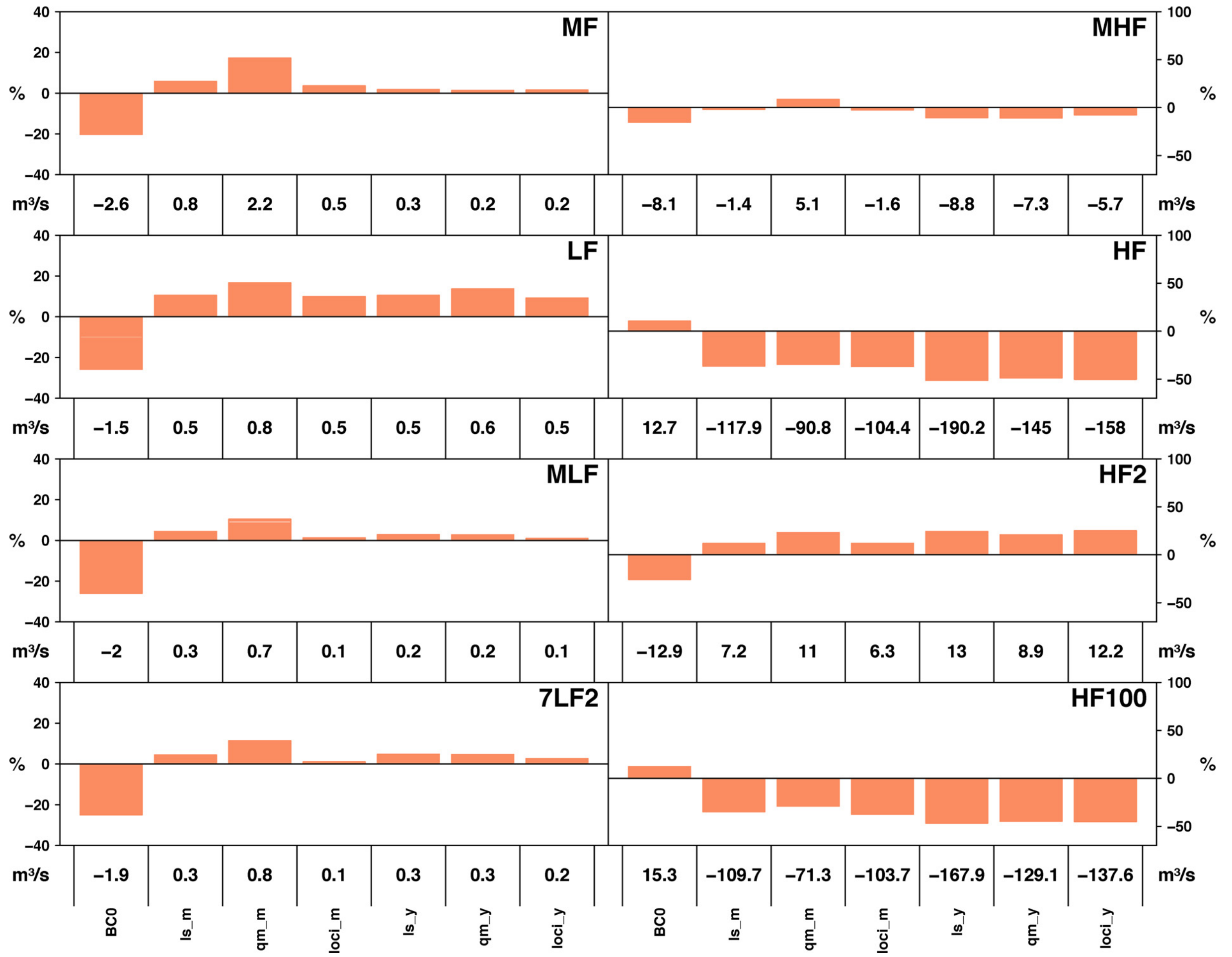

Fig. 10. Relative ([%]; bars) and absolute ([m³/s]; numbers below graphs) hydrological climate change signals for the various flow indicators for the REMO RCM.

bias correction methods remove this shift from the BC0 data.

4. Conclusions and discussion

The results of the hydrological modeling using the BC0 RCM data clarify the indispensable need for bias correction for climate impact studies, if the results significantly differ from observations and data are applied for subsequent hydrological applications (e.g. water management). The long term yearly flow regimes of the CCLM and REMO differ from the reference. However, apart from the winter season, the raw RACMO model shows a good regime representation. For the Mindel catchment, the different correction approaches account for good adjustment of the modeled runoff to the reference of observed data when applied to raw CCLM and REMO data. The regime simulated using the modified RACMO data on the other hand are at least comparable to the results using the raw data. In general, while in northern Bavaria the available models fit their respective reference equally well after correction (exemplarily shown in Fig. 11 for the gauge Kemmern, outlet of catchment 18, lower left map of Fig. 1), the RACMO model shows some greater differences in adjustment after the correction in the southern part of Bavaria.

Since the bias correction is performed on the RCM scale using the spatially aggregated reference data, localized small scale events within aggregation are also averaged and smoothed. Hence, this aggregation to the coarse RCM model resolution of 50 km is considered to be the major source for the partly huge deviations, especially in distinctive topography like the Alps. Considering the uncertainties added by applying bias correction to raw RCM data (e.g. by losing coherence between variables, assumption of temporal stationarity of correction factors, discrepancy in scales between RCM and observations) and the little effect it has on the RACMO data, the raw data might also be useful. However, judging from the indicators, the qm approach using monthly correction factors shows the best results and thus supports earlier suggestions by Themeßl et al. (2011). High flow indicators are an exception, which was also found by Muerth et al. (2012). However, it should be mentioned that the applied hydrological model WaSiM is not specifically calibrated for high flows. Thus, this must influence rare and single extreme high flow events like the HF and HF100. Combined with the BC1 RCMs, a sufficient match with the reference can hardly be achieved and might occur randomly. Such flood extremes are

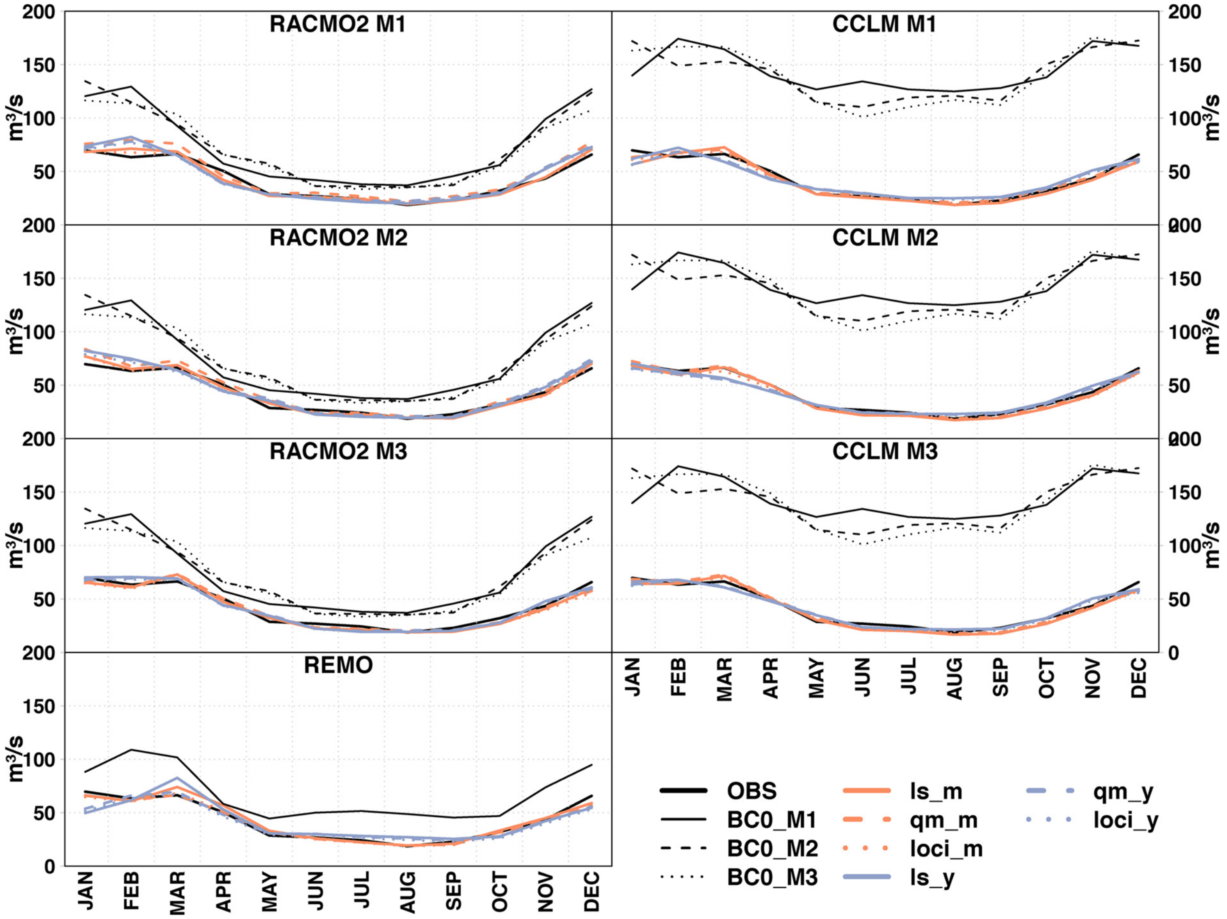

Fig. 11. Flow regimes of modeled runoff using observed (OBS), uncorrected (BC0) and bias corrected RCM data for the gauge Kemmern (Fig. 1, lower left map, outlet catchment 18).

usually triggered by extreme precipitation events at the far end of the cumulative distribution function or the highest percentiles of occurrence, for which the correction factors may only be able to provide insufficient approximations. IN conclusion, this study confirms that the qm approach applied to all meteorological variables results in a better representation of mean streamflow indicators across Bavaria than the other two investigated methods. Regarding extreme flow indicators (HF, HF100), these methods are still not able to reproduce the statistics of the observations at the upper end of the distribution for any Bavarian region. However, if extreme flow indicators are of particular interest (e.g. if a flood detention basin should be designed to store runoff up to a certain HF threshold) and other indicators (e.g. mean flow) are well represented by raw RCM data, Hattermann et al. (2014) suggest to correct discharge values by their return periods using extreme value statistics

The analysis for the gauge Offingen also shows that the bias correction of RCM data affects the CCS of hydrological indicators to an extent that may not be negligible for subsequent applications (e.g. hydrological modelling, water management or the design flood protection infrastructure). Differences in the relative CCS of mean flow indicators between raw and corrected data are small in most cases. The relative signals of BC1 low flow indicators show more severe deviations from the reference signal of the BC0 RCM data. This effect of bias correction on the CCS of mean indicators is also shown by Stagl and Hattermann (2015) and Muerth et al. (2012). Hence, in this case, raw RCM data can be considered useful, unless overall characteristics of these data (absolute values, seasonality) significantly differ from those of the observations. In this case, the RCM data might not be suitable for climate change impact assessment. Absolute values in CCS show less difference and are mostly of the same magnitude. This applies at least for the mean and low flow indicators. The bias correction depicts a stronger impact on the CCS for high flow indicators. Despite regional disparities in absolute quantities, this holds true for other catchments of the hydrological Bavaria that was analyzed for streamflow. Fig. 12 emphasizes this result showing the CCS for the RACMO RCM at the gauge Kemmern.

The REMO RCM shows significant deviations in the CCS across all indicators due to the correction of the inherent spatial drift of precipitation fields. Furthermore, since only a single member was available, a particular extreme event within this realization (e.g. high precipitation event during spring) affects the bias correction as well as the CCS. The member bound derivation of correction factors (i.e. deriving the factors using one member of a RCM only) might result in a misleading adjustment for this specific season. Hence, this may lead indirectly to a fraud of the CCS, which could be avoided by a multi member approach if more realizations would

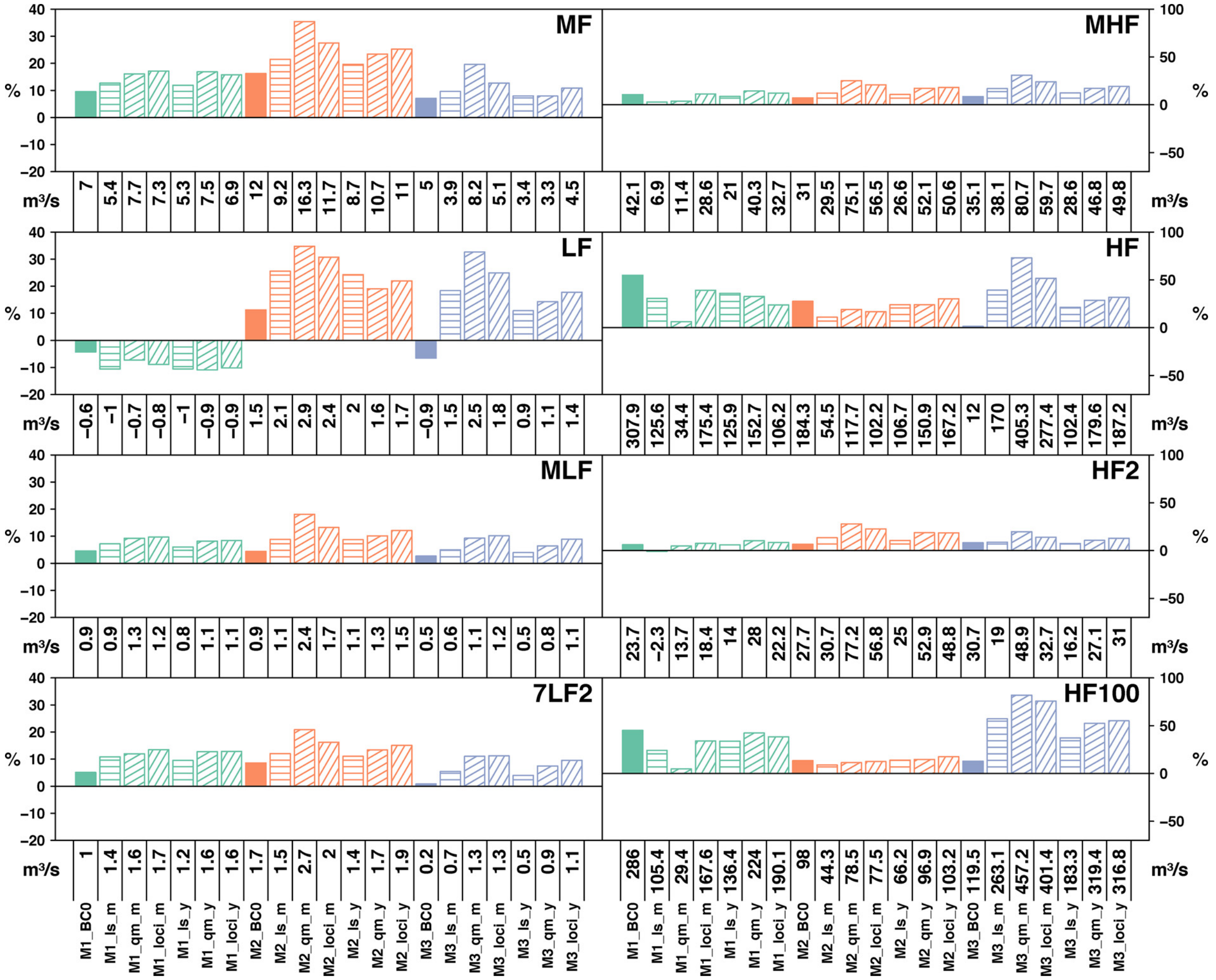

Fig. 12. Relative ([%]; bars) and absolute ([m³/s]; numbers below graphs) hydrological climate change signals for the various flow indicators for the three RACMO RCM members for the gauge Kemmern.

have been available showing different seasonal values. Therefore, this study shows that the application of bias corrected RCM data for hydrological modeling has an impact on the CCS of streamflow indicators derived for catchments situated in southern and northern Bavaria (catchment 5 and 18, Fig. 1, lower left map). Furthermore, the impacts on the CCS of extreme high flow indicators can be severe (up to or greater than 100%). Similar effects have been found by Cloke et al. (2013) over a catchment situated in England. Hence, the applicability of bias correction approaches for extreme values is still questionable and further development should be made to account for extreme value statistics.

Funding

This work was supported by the Bavarian Environment Agency (LfU).

Conflict of interest

I wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

References

Berg, P., Wagner, S., Kunstmann, H., Schädler, G., 2013. High resolution regional climate model simulations for Germany: part I—validation. Clim. Dyn. 40 (1–2), 401–414.

Chen, J., Brissette, F.P., Leconte, R., 2011. Uncertainty of downscaling method in quantifying the impact of climate change on hydrology. J. Hydrol. 401 (3), 190–202.

Christensen, J.H., Boberg, F., Christensen, O.B., Lucas-Picher, P., 2008. On the need for bias correction of regional climate change projections of temperature and precipitation. Geophys. Res. Lett. 35 (20).

Cloke, H.L., Wetterhall, F., He, Y., Freer, J.E., Pappenberger, F., 2013. Modelling climate impact on floods with ensemble climate projections. Q. J. R. Meteorol. Soc. 139 (671), 282–297.
Dai, A., 2001. Global precipitation and thunderstorm frequencies. Part II: diurnal variations. J. Clim. 14 (6), 1112–1128.
Dai, A., 2006. Precipitation characteristics in eighteen coupled climate models. J. Clim. 19 (18), 4605–4630.
DVWK, 1979. Empfehlungen zur Berechnung der Hochwasserwahrscheinlichkeit. DVWK Hamburg, Berlin.
DVWK, 1983. Niedrigwasseranalyse Teil I: Statistische Untersuchung des Niedrigwasser-Abflusses. DVWK Hamburg, Berlin.
Ehret, U., Zehe, E., Wulfmeyer, V., Warrach-Sagi, K., Liebert, J., 2012. HESS opinions" Should we apply bias correction to global and regional climate model data?". Hydrol. Earth Syst. Sci. 16 (9), 3391.
Elía, R., Côté, H., 2010. Climate and climate change sensitivity to model configuration in the Canadian RCM over North America. Meteorologische Zeitschrift 19 (4), 325–339.
Foltyn, M., Steinbauer, A., Kopp, B., 2017. Niedrigwasser in Bayern - Grundlagen. Veränderung und Auswirkungen, Augsburg.
Frick, C., Steiner, H., Mazurkiewicz, A., Riediger, U., Rauthe, M., Reich, T., Gratzki, A., 2014. Central European high-resolution gridded daily data sets (HYRAS): mean temperature and relative humidity. Meteorologische Zeitschrift 15–32.
Gandin, L., 1965. Objective Analysis of Meteorological Fields. Israel Program for Scientific Translation, Jerusalem, Jerusalem.
Giorgi, F., Jones, C., Asrar, G.R., 2009. Addressing climate information needs at the regional level: the CORDEX framework. World Meteorol. Organiz. (WMO) Bull. 58 (3), 175.
Göttel, H., 2009. Einfluss der nichthydrostatischen Modellierung und der Niederschlagsverdriftung auf die Ergebnisse regionaler Klimamodellierung.
Hagemann, S., Chen, C., Haerter, J.O., Heinke, J., Gerten, D., Piani, C., 2011. Impact of a statistical bias correction on the projected hydrological changes obtained from three GCMs and two hydrology models. J. Hydrometeorol. 12 (4), 556–578.
Hattermann, F.F., Huang, S., Burghoff, O., Willems, W., Österle, H., Büchner, M., Kundzewicz, Z., 2014. Modelling flood damages under climate change conditions–a case study for Germany. Nat. Hazards Earth Syst. Sci. 14 (12), 3151–3168.
Kjellström, E., Boberg, F., Castro, M., Christensen, J.H., Nikulin, G., Sánchez, E., 2010. Daily and monthly temperature and precipitation statistics as performance indicators for regional climate models. Clim. Res. 44 (2-3), 135–150.
Kleinn, J., Frei, C., Gurtz, J., Lüthi, D., Vidale, P.L., Schär, C., 2005. Hydrologic simulations in the Rhine basin driven by a regional climate model. J. Geophys. Res.: Atmos. 110 (D4).
Kotlarski, S., Keuler, K., Christensen, O.B., Colette, A., Déqué, M., Gobiet, A., Goergen, K., Jacob, D., Lüthi, D., van Meijgaard, E., 2014. Regional climate modeling on European scales: a joint standard evaluation of the EURO-CORDEX RCM ensemble. Geosci. Model. Dev. 7 (4), 1297–1333.
Lenderink, G., Buishand, A., van Deursen, W., 2007. Estimates of future discharges of the river Rhine using two scenario methodologies: direct versus delta approach. Hydrol. Earth Syst. Sci. 11 (3), 1145–1159.
Majone, B., Bovolo, C.I., Bellin, A., Blenkinsop, S., Fowler, H.J., 2012. Modeling the impacts of future climate change on water resources for the Gállego river basin (Spain). Water Resour. Res. 48 (1).
Maraun, D., 2016. Bias correcting climate change simulations-a critical review. Curr. Clim. Change Rep. 2 (4), 211–220.
Maraun, D., Wetterhall, F., Ireson, Am, Chandler, R.E., Kendon, E.J., Widmann, M., Brienen, S., Rust, H.W., Sauter, T., Themeßl, M., 2010. Precipitation downscaling under climate change: recent developments to bridge the gap between dynamical models and the end user. Rev. Geophys. 48 (3).
Marke, T., 2008. Development and Application of a Model Interface to Couple Land Surface Models With Regional Climate Models for Climate Change Risk Assessment in the Upper Danube Watershed, Munich.
Mpelasoka, F.S., Chiew, F.H.S., 2009. Influence of rainfall scenario construction methods on runoff projections. J. Hydrometeorol. 10 (5), 1168–1183.
Mudelsee, M., Chirila, D., Deutschländer, T., Döring, C., Haerter, J., Hagemann, S., Hoffmann, H., Jacob, D., Krahe, P., Lohmann, G., 2010. Climate Model Bias Correction und die deutsche Anpassungsstrategie. Mitteilungen Deutsche Meteorologische Gesellschaft, pp. 2–7 03/2010.
Muerth, M., Gauvin St-Denis, B., Ricard, S., Velázquez, J.A., Schmid, J., Minville, M., Caya, D., Chaumont, D., Ludwig, R., Turcotte, R., 2012. On the need for bias correction in regional climate scenarios to assess climate change impacts on river runoff. Hydrol. Earth Syst. Sci. Disc. 10205–10243.
Nakicenovic, N., 2000. In: Nakicenovic, Nebojsa, Swart, Robert (Eds.), Special Report on Emissions Scenarios, ISBN 521804930, 612.
Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models part I—A discussion of principles. J. Hydrol. 10 (3), 282–290.
Pöhler, H., Schultze, B., Stadelbacher, V., Scherzer, J., 2009. Vorhaben KLIWA: Wasserhaushaltsmodellierung für die südlichen Zuflüsse der Donau in Bayern / Kalibrierung und Validierung. UDATA - Umweltschutz und Datenanalyse, Neustadt.
Pöhler, H., Wendel, S., Schultze, B., Karl, S., Scherzer, J., 2010. Vorhaben KLIWA: Klimawandel und Wasserhaushalt: Teilprojekt AdaptAlp: Wasserhaushaltsmodellierung Inn und neue Niederschlagsregionalisierung Südbayern. UDATA - Umweltschutz und Datenanalyse, Neustadt.
Rauthe, M., Steiner, H., Riediger, U., Mazurkiewicz, A., Gratzki, A., 2013. A Central European precipitation climatology–Part I: generation and validation of a high-resolution gridded daily data set (HYRAS). Meteorologische Zeitschrift 22 (3), 235–256.
Roeckner, E., Bäuml, G., Bonaventura, L., Brokopf, R., Esch, M., Giorgetta, M., Hagemann, S., Kirchner, I., Kornblueh, L., Manzini, E., 2003. The Atmospheric General Circulation Model ECHAM 5. PART I: Model Description.
Rößler, O., Löffler, J., 2010. Potentials and limitations of modelling spatio-temporal patterns of soil moisture in a high mountain catchment using WaSiM-ETH. Hydrol. Process. 24 (15), 2182–2196.
Schmidli, J., Frei, C., Vidale, P.L., 2006. Downscaling from GCM precipitation: a benchmark for dynamical and statistical downscaling methods. Int. J. Climatol. 26 (5), 679–689.
Schulla, J., 2012. Model Description WaSiM (Water Balance Simulation Model), Completely Revised Version 2012. Hydrology Software Consulting, Zürich, Switzerland.
Sennikovs, J., Bethers, U. (Eds.), 2009. Statistical Downscaling Method of Regional Climate Model Results for Hydrological Modelling. Citeseer.
Stagl, J.C., Hattermann, F.F., 2015. Impacts of climate change on the hydrological regime of the Danube River and its tributaries using an ensemble of climate scenarios. Water 7 (11), 6139–6172.
Teutschbein, C., Seibert, J., 2012. Bias correction of regional climate model simulations for hydrological climate-change impact studies: review and evaluation of different methods. J. Hydrol. 456, 12–29.
Themeßl, J.M., Gobiet, A., Leuprecht, A., 2011. Empirical-statistical downscaling and error correction of daily precipitation from regional climate models. Int. J. Climatol. 31 (10), 1530–1544.
Themeßl, M.J., Gobiet, A., Heinrich, G., 2012. Empirical-statistical downscaling and error correction of regional climate models and its impact on the climate change signal. Clim. Change 112 (2), 449–468.
van der Linden, P., Mitchell, J.E., 2009. ENSEMBLES: Climate Change and Its Impacts-Summary of Research and results from the ENSEMBLES Project.
van Meijgaard, E., van Ulft, L.H., van de Berg, W.J., Bosveld, F.C., van den Hurk, B., Lenderink, G., Siebesma, A.P., 2008. The KNMI Regional Atmospheric Climate Model RACMO Version 2.1. Koninklijk Nederlands Meteorologisch Instituut.
van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.-F., 2011. The representative concentration pathways: an overview. Clim. Change 109 (1-2), 5.
Wagner, S., Berg, P., Schädler, G., Kunstmann, H., 2013. High resolution regional climate model simulations for Germany: part II—projected climate changes. Clim. Dyn. 40 (1–2), 415–427.