Supplement of the article: Impact of Climate Change on the Hydrological Regimes in Bavaria

Benjamin Poschlod, Florian Willkofer and Ralf Ludwig

Bias correction, statistical downscaling, WaSiM setup

In order to carry out the bias correction for the period 1981-2010, a reference dataset of observational data is created. Therefore, a statistical method using a combination between multiple linear regression (MLR) considering additional variables and inverse distance weighting similar to the method in Rauthe et al. [72] is applied to interpolate measurements of meteorological stations in a spatial resolution of 500 m. For each parameter, which is to be interpolated, different additional variables are used for the MLR. Precipitation and wind speed are interpolated considering elevation, exposition, as well as geographical latitude and longitude. The interpolation of air temperature and of the dew point temperature includes the elevation as additional variable. In order to interpolate the global radiation, the exposition of each grid cell is used.

The bias correction featuring the quantile mapping approach attempts to adjust the distribution functions of the respective CRCM5-LE parameter to match the distribution function of the parameter in the reference dataset [28]. For each monthly distribution of the RCM and reference dataset, the 1th to 99th percentiles are calculated. The 0th and the 100th percentiles would correspond to the minimal and maximal values of the dataset respectively, which is why for these values the percentiles are replaced by a piecewise cubic extrapolation of the 1th to 99th percentile [99]. After that, the ratio of the distribution of the reference dataset and of the distribution of the CRCM5-LE is used as scaling factor for the bias correction (for further details of this approach see [28]).

The differences between the non-bias-corrected and the bias corrected seasonal averages of air temperature and precipitation are given in Figures S1 and S2 in 0.11° spatial resolution. In large parts of the study are, the climate model slightly overestimates the temperature. A horizontal border between positive and negative differences is given by the northern pre-Alps, as the spatial resolution of the climate model is not able to resolve the topography within the Alps. Hence, the climate model underestimates elevation and therefore overestimates temperatures.

The largest differences in precipitation occur at the slopes of the Alps and other mountainous areas, as the CRCM5 shows high sensitivity to orographical precipitation. In addition, the undercatch of solid precipitation within the observational reference dataset amplifies the differences between BC0 and BC1, mainly during the winter season.

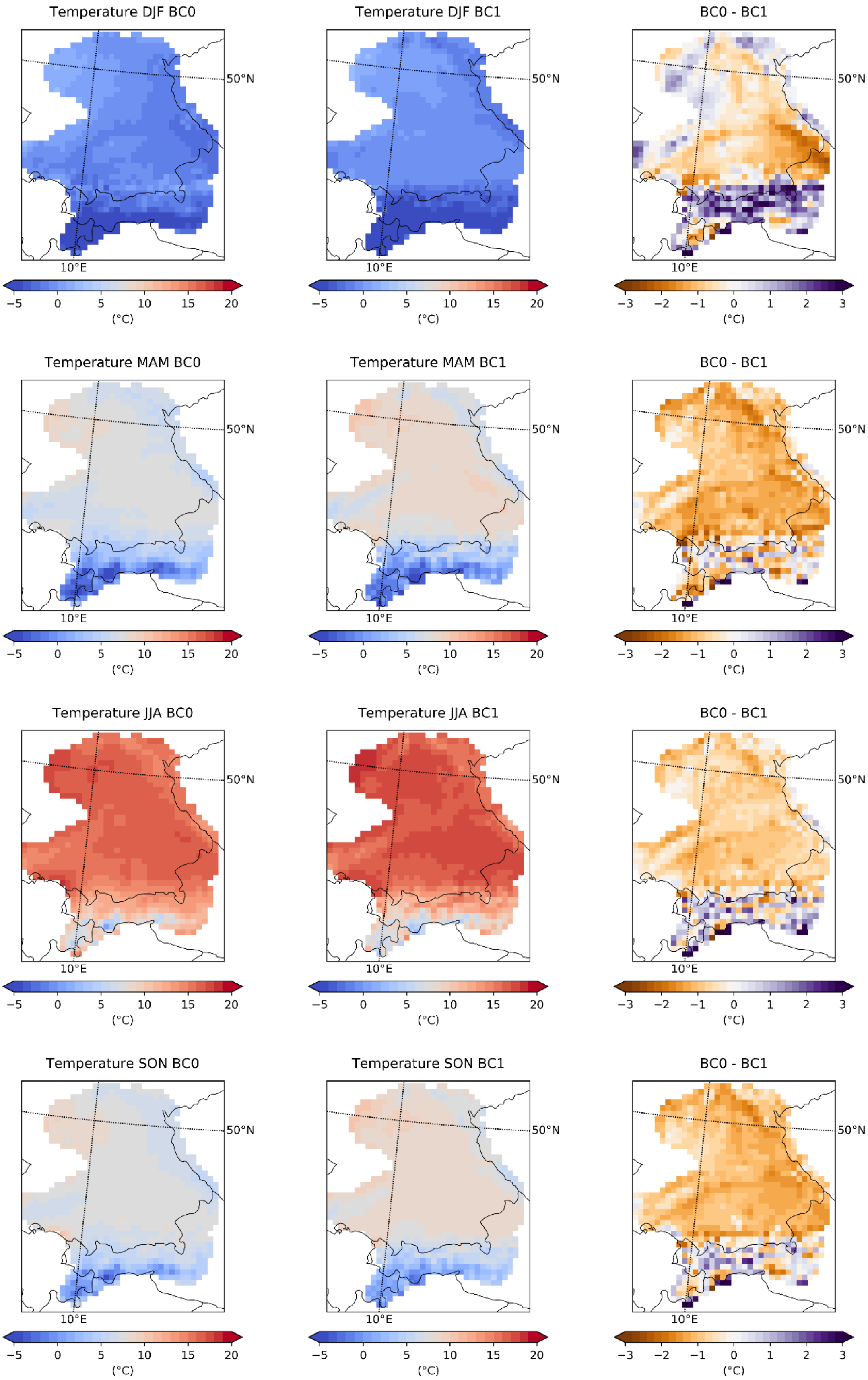

Figure S1. Median of the seasonal temperatures for the uncorrected (BC0) and bias corrected (BC1) climate model ensemble as well as their difference (BC0-BC1).

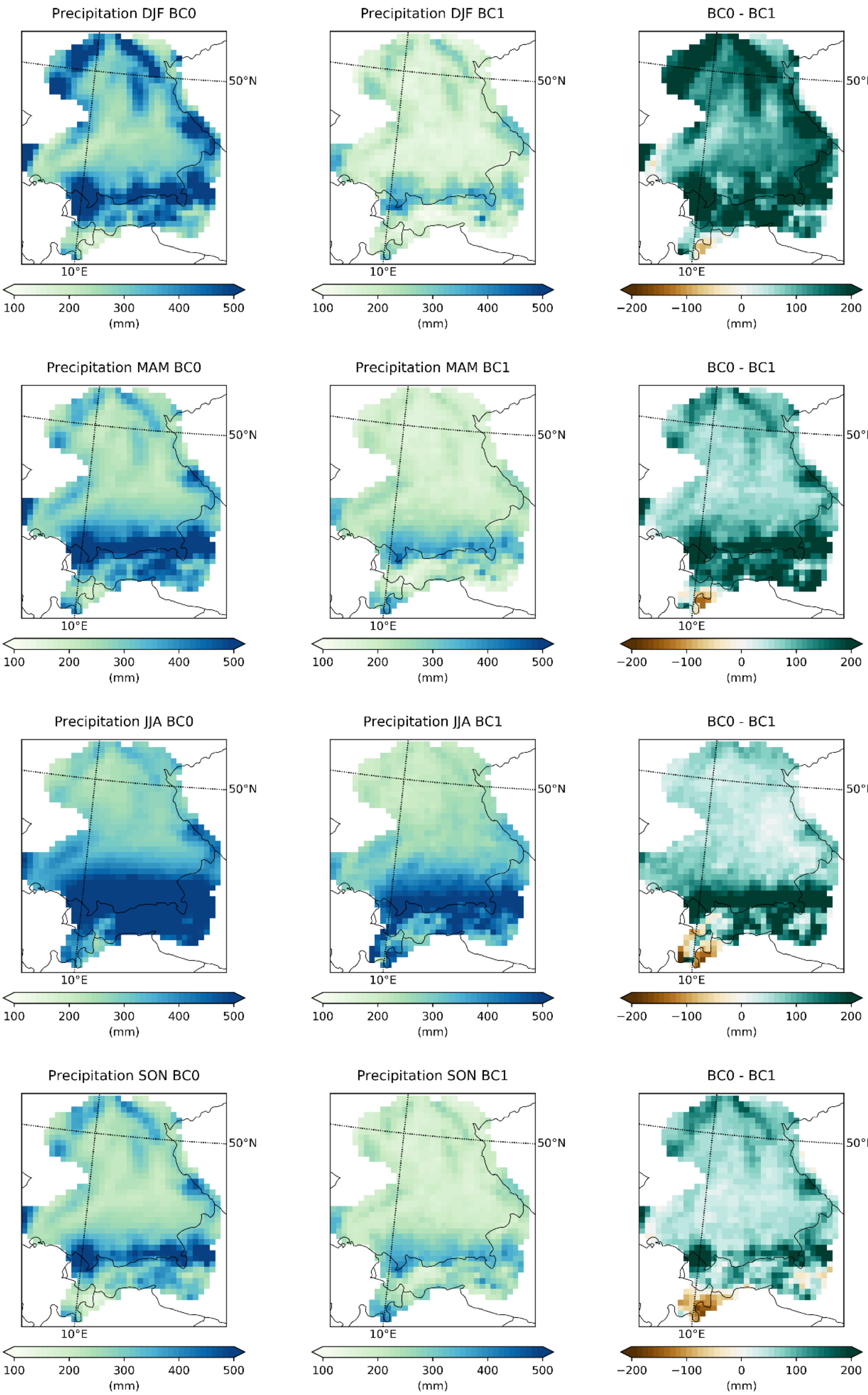

Figure S2. Median of the seasonal precipitation for the uncorrected (BC0) and bias corrected (BC1) climate model ensemble as well as their difference (BC0 – BC1).

This bias-corrected CRCM5-LE is then further downscaled. Treating the center points of each 0.11° grid cell as virtual meteorological stations, the same interpolation method as for the creation of the reference dataset is applied to statistically downscale the 50 members to a spatial resolution of 500 m. Afterwards, this interpolation is corrected in order to ensure conservation of mass for each downscaled 0.11° grid cell.

The resulting bias-corrected climate dataset with a spatial resolution of 500 m is used to drive the hydrological model WaSiM with a temporal resolution of 3 h. The input data for the WaSiM setup as well as the implemented modules are presented in Tab. S1 and Tab. S2.

Table S1. Data used for the WaSiM setup. All data were aggregated to the spatial resolution of 500 x 500 m².

Data	Resolution / Scale	Additional comments	Source
DEM	25 x 25 m²		EU-DEM [58]
Soil	1 x 1 km²		ESDB 2.0 [100]
Land cover	250 x 250 m²		CORINE LC v0.18 [101]
Groundwater conductivity	1:200000, 1:1500000	IMHE1500 further downscaled using slope as additional variable	HÜK200 [102] IMHE1500 [103]

Table S2. Modules applied in the WaSiM setup.

Module	Description
Meteorology	Module for processing meteorological input data (see [54])
Evapotranspiration, landuse table	Calculation of potential and real evapotranspiration according to Penman-Monteith (see [54])
Snow	Snowmelt using the approach of Warscher et al. [104]; extended energy balance method featuring lateral redistribution of snow and gravitational snow transport
Glacier	Dynamic glaciers with melting processes [104]
Lakes	Enables modelling lakes and reservoirs (see [54])
Groundwater	Groundwater model calculating base flow using Gauss-Seidel-iteration; lateral groundwater flow enabled (see [54])
Unsaturated soil zone, soil table	Richards-equation to model soil water fluxes; Application of identifier "MultipleHorizons" considering macropore runoff (see [54])

Cluster validity

In order to evaluate the cluster validity (choice of number of clusters) we applied 27 indices provided by the R package NbClust [77]. The results of these indices are summarized in Table S3.

Table S3. Optimal number of clusters for 4900 Pardé coefficients chosen by 27 different indices. The indices have been restricted to the range of four to ten cluster classes.

Index	**Frey**	**CH**	**Silhouette**	**Duda**	**PseudoT2**	**Beale**	**McClain**	**Ratkowsky**	**SDindex**
#clusters	**3**	**4**	**4**	**4**	**4**	**4**	**4**	**4**	**4**
Value	NA	3717	0.2975	0.9676	69.17	0.2494	0.9922	0.3464	5.454

Index	Gap	PtBiSerial	Hartigan	KL	Scott	Marriott	TrCovW	TraceW	Friedman
#clusters	**4**	**5**	**5**	**6**	**6**	**6**	**6**	**6**	**6**
Value	-0.2707	0.5605	948.1	19.968	4385	8.9+e19	7764	144.9	10.57

Index	DB	Ball	Dunn	DIndex	Hubert	Rubin	CIndex	CCC	SDbw
#clusters	**6**	**6**	**6**	**6**	**9**	**9**	**9**	**9**	**10**
Value	1.0824	63.27	0.0477	graphical	graphical	-0.6681	0.3298	46.98	0.1771