On the choice of reference database and calibration period of bias-corrected simulations: A case study for Hungary

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Abstract

The aim of the present study is to investigate the accuracy of bias-adjusted regional climate model (RCM) simulations using various calibration periods, demonstrated for the region of Hungary. High-resolution (0.11°) RCM simulations of daily near-surface mean air temperature, daily minimum and maximum air temperature, and daily precipitation provided by the EURO-CORDEX community are analysed. The model ensemble consists of 5 RCM simulations driven by 4 different general circulation models for the historical time period 1976–2005. The publicly available, most accurate, measurement-based and quality-controlled HuClim is used as the reference dataset. The internationally widely used percentile-based quantile mapping method is applied for the bias-correction and it is performed on a monthly level. The novelty of the present study is that we used two different calibration periods to create bias-corrected datasets: an earlier and a more recent 30-year long period, and made these new datasets available in Zenodo. In addition to these HuClim-based bias-corrected databases, another database, containing bias-corrected RCM simulations and produced by the EURO-CORDEX community is also investigated. The assessment is carried out for the period 1993–2005, which is the overlapping time interval of the different calibration periods. According to our results, the accuracy of the bias-correction depends on the chosen calibration period and on the analysed climate index, and the choice of the validation period also affects the results. As next step, we plan to extend our research on projections under RCP4.5 and RCP8.5 scenarios.

Keywords: EURO-CORDEX, HuClim, bias-correction, calibration period, validation, Hungary

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Introduction

Climate models have become key tools for climate research, providing not only information on past and present climate, but also numerical estimates of climate change (IPCC, 2013). General Circulation Models (GCMs) operate at a coarser horizontal resolution (100–500 km), therefore, they are unable to resolve complex topographical features that vary at finer scales. Regional climate models (RCMs), in contrast, are applied only to a limited area with a higher (10–50 km) horizontal resolution, thus, representing extreme events with higher accuracy and providing added value, especially in regions with complex topography (Torma, Cs.Zs. *et al.* 2015, 2020; Di Luca, A. *et al.* 2016; Rummukainen, M. 2016; Fantini, A. *et al.* 2018; Ciarlo, J.M. *et al.* 2021).

However, it is important to keep in mind that GCM and RCM simulations are encumbered with uncertainties from a variety of sources (Giorgi, F. 2005), thus, using raw RCM simulations can lead to unrealistic results. These uncertainties can be quantified and reduced by using bias-adjusted datasets and by evaluating several RCMs together, as members of an ensemble (Beniston, M. *et al.* 2007).

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The systematic bias of a climate model can be eliminated by post-processing the raw RCM data by applying a bias-correction method, which involves ensuring of equal mean values between the observation-based reference dataset and the bias-corrected climate model simulations (Déqué, M. *et al.* 2007). Previous studies have confirmed that bias-correction is required to improve the quality of RCM simulations (e.g. Ngai, S.T. *et al.* 2016; Jaiswal, R. *et al.* 2022) – it is particularly important, when RCM simulations are used for impact studies (e.g. wind energy generation: Costoya, X. *et al.* 2020; hydrology: Faghih, M. *et al.* 2022).

Several bias-correction methods have been developed to calibrate the raw RCM output against observations, and many studies have dealt with their comparison (Räty, O. *et al.* 2014; Casanueva, A. *et al.* 2020; Ji, X. *et al.* 2020; Mendez, M. *et al.* 2020). In addition to simpler approaches, including the delta method or linear scaling, there are also more complex methods that take into account the whole distribution of the meteorological variables (Themessi, M.J. *et al.* 2010). However, it is important to keep in mind that every method – even the best-estimated ones – has limitations since assumptions are made in all cases, such as the behaviour of the bias remains the same for the future with different climate conditions as it was in the past (Teutschbein, C. and Seibert, J. 2012; Van de Velde, J. *et al*. 2022). Moreover, a reliable, observation-based reference dataset of a good quality is required for a prosperous bias-correction (Casanueva, A. *et al.* 2020). The performance of the bias-correction method is sensitive to the choice of the length of the calibration period and at least a 30-year time period is recommended (Berg, P. *et al.* 2012; Reiter, P. *et al.* 2015; Ahn, K.H. *et al.* 2023).

This study focuses on the effect of the choice of calibration period on the bias-corrected RCM data. Our aim was to compare bias-adjusted databases produced by using the same method with different calibration periods, as well as using another bias-correction method with another calibration period and reference dataset (see *Appendix*, *Table A1*), and to investigate how the choice of different calibration periods affects the accuracy of the bias-correction. This is demonstrated by the validation of the different bias-corrected databases for the period 1993–2005. As far as we know, this latter aspect has never been analysed before with a special focus on the region of interest.

Data and method

Study area

Hungary, the region of interest, is located in East-Central Europe, between latitudes 45.7°–48.7°N and longitudes 15.9°–22.9°E *(Figure 1,* A*)*, surrounded by the Carpathians to the north and east, and by the Alps to the west. The Carpathians and the territory surrounded by the mountain range together form the Carpathian Basin, one of the largest basins in the world, covering an area of about 500,000 km^2, of which Hungary covers roughly 93,000 km^2. Although the Carpathian Basin has a complex topography (the elevation varies between 75 m and 2655 m), the orography of Hungary is less complex: the highest peak of the country, called Kékes, is located in the North Hungarian Mountains with an altitude of 1014 m, and the lowest point is situated in the Great Hungarian Plain (75 m a.s.l.). It is also important to note that two-thirds of the Hungarian territory lies below 200 m a.s.l. *(Figure 1,* B*)*.

The climate of the country is characterised by oceanic, continental and mediterranean effects – the features of the humid oceanic climate cause slightly varying temperatures; more extreme temperatures are the result of dry, continental air masses. The precipitation maximum occurs in May-June, and the driest season is winter. The influence of Mediterranean air masses is mainly manifested in the second precipitation maximum in autumn, which is mostly observed in the south-western part of Transdanubia (Mezősi, G. 2017). Although the Carpathians are outside of the borders of Hungary, its effect on

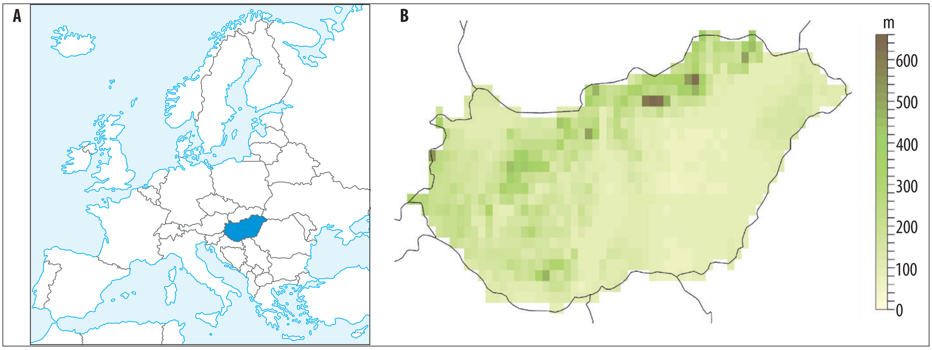

Fig. 1. The region of interest. A = Location of Hungary in Europe (filled with blue colour); B = The topography of Hungary on a 0.11° horizontal resolution. *Source*: Authors' own editing.

the climate of the country is not negligible – an important example is the blocking of cold air masses of Siberian origin (Spinoni, J. *et al.* 2014). Due to the various climatic effects, temperature and precipitation characteristics are investigated for Hungary on a yearly, seasonal and monthly scale.

Reference dataset

In this study, HuClim is used as a reference dataset for bias correction purposes and evaluation studies, which is produced by the HungaroMet Hungarian Meteorological Service and available on a daily basis and freely accessible via https://odp.met.hu/climate/. The data is available from 1971 and it is updated to the latest year (it is 2022 in the version used in the present study) for mean air temperature, maximum air temperature, minimum air temperature and precipitation. HuClim is a measurement-based dataset, which covers Hungary on a 0.1° × 0.1° horizontal grid and builds upon 500 precipitation and 112 temperature stations' data. Quality control is provided by the Multiple Analysis of Series for Homogenized Database (MASH) (Szentimrey, T. 2007) software, and the method of Meteorological Interpolation based on Surface Homogenized Database (MISH) (Szentimrey, T. and Bihari, Z. 2008) is used for gridding and interpolating the meteorological data. The importance of using HuClim data lies in the fact that this is the most accurate gridded, high-resolution, homogenized observational data currently available for the country: as it is well known that the quality of the reference database for bias adjustment is crucial (Casanueva, A. *et al.* 2020).

Model simulations and databases

Simulations of five RCMs driven by four different GCMs at a horizontal resolution of 0.11° are investigated in this study derived from the EURO-CORDEX framework (Jacob, D. *et al.* 2014). All historical simulations cover the period 1976–2005 and the projections were accomplished under the 4.5 and 8.5 Representative Concentration Pathways scenarios (RCP4.5 and RCP8.5, respectively) (Moss, R.H. *et al.* 2010). Details of the selected GCM-RCM combinations are listed in *Table 1.* During the selection procedure we focused on those RCM-GCM combinations, which were available for both RCP scenarios as well as for raw and bias-corrected versions. In addition, model performance was taken into account based on previous studies for East-Central Europe (Mezghani, A. *et al.* 2017; Torma, Cs.Zs. 2019; Lazic, I. *et al.* 2021; Simon, Cs. *et al.* 2023).

Table 1. Overview of the applied RCMs and their driving GCMs used in the present study

RCM	Driving GCM	Modelling group
CCLM4-8-17 (Rockel, B. *et al.* 2008)	MPI-ESM-LR (Jungclaus, J.H. *et al.* 2010)	Climate Limited-area Modelling Community, Germany
HIRHAM5 (Christensen, O.B. *et al.* 1998)	EC-EARTH (Hazeleger, W. *et al.* 2010)	Danish Meteorological Institute, Denmark
RACMO22E (Van Meijgaard, E. *et al.* 2012)	HadGEM2-ES (Collins, W.J. *et al.* 2011)	Royal Netherlands Meteorological Institute, The Netherlands
RCA4 (Kupiainen, M. *et al.* 2014)	CNRM-CM5 (Voldoire, A. *et al.* 2012)	Swedish Meteorological and Hydrological Institute, Rossby Centre, Sweden
REMO2009 (Jacob, D. *et al.* 2012)	MPI-ESM-LR (Jungclaus, J.H. *et al.* 2010)	Helmholtz-Zentrum Geesthacht, Climate Service Centre, Max Planck Institute for Meteorology, Germany

Four variables were used for this work: daily mean near-surface air temperature (*tas*), daily minimum near-surface air temperature (*tasmin*), daily maximum near-surface air temperature (*tasmax*), and daily precipitation (pr). Bias-adjusted model output from the EURO-CORDEX program was produced by using the MESAN reanalysis data (Häggmark, L. *et al.* 2000) for the time period 1989–2010, and a distribution scaling method (Yang, W. *et al.* 2010) was implemented for bias-correcting the RCM simulations. MESAN is an operational mesoscale analysis system developed by the Swedish Meteorological and Hydrological Institute (SMHI). The system is designed to provide high-resolution (about 11 km) analyses of meteorological variables, including precipitation and temperature. MESAN integrates various data sources such as weather radar observations, satellite data and ground-based measurements. Since climate model data and HuClim data are available on different horizontal resolutions, interpolation to a common 0.11° × 0.11° grid was performed using the CDO (Climate Data Operators; https://code.mpimet.mpg.de/projects/cdo/) software (Schulzweida, U. 2021) with a bilinear remapping method.

For the purpose of creating a new bias-corrected RCM dataset for Hungary based on the HuClim database – the use of which is not widespread, only a few studies (e.g. Kern, A. *et al.* 2024) applied it for this territory –, we have also corrected the raw EURO-CORDEX simulations (see details in section Bias correction method). This bias-adjusted RCM data produced by the use of HuClim are publicly available in the Zenodo repository (Simon, Cs. *et al.* 2024). Note that the bias-correction was implemented for the RCM simulations of the historical (1976–2005) and the scenario (2006–2099) periods, but in this study only the analysis of the historical simulations is considered.

Bias correction method

In order to correct the systematic bias present in raw RCM outputs, the internationally accepted, non-parametric, percentile-based quantile mapping method was applied, following the work of Mezghani, A. *et al.* (2017). This method is one of the most commonly used higher-skill bias-correction techniques in the climate research community (Teutschbein, C. and Seibert, J. 2013) which has been successfully applied in the East-Central European region (e.g. Torma, Cs.Zs. and Kis, A. 2022; Kern, A. *et al.* 2024). In general, the quantile mapping procedure matches the quantile-based distribution of the raw RCM simulations to that of the observed data. In the present study the bias-adjustment of the simulated time series was performed for each grid cell on the common 0.11° grid and the number of quantiles was set to 1000. In addition, the quantile mapping was performed for each month separately with the aim of investigating the behaviour of the bias and the accuracy of the bias-correction on a finer timescale. The length and the quality of the reference dataset is also a key tool, because quantile mapping is considered to be sensitive to that (Fowler, H.J. and Kilsby, C.G. 2007). To perform the quantile mapping method, two different 30-year calibration periods were selected from the observation-based HuClim database: an earlier (1976–2005, BC-HUCLIM-1) and a more recent (1993–2022, BC-HUCLIM-2) 30-year long period with different climatic characteristics, thus, creating two different bias-adjusted databases.

Noting that using different calibration periods of the same length and the same bias adjustment procedure can highlight the effect of the choice of the calibration period. However, the most recent period has characteristics of a warmer climate relative to the earlier period, which can lead to differences in relative biases, when different datasets based on different calibration periods are investigated. HuClim was also used by Kern, A. *et al.* (2024) to construct the FORESEE-HUN v1.0 database, which contains bias-adjusted RCM projections for the period 2022–2100 for Hungary, and for which a longer calibration period (1971–2020) was chosen.

Selected climate indices

Beside the investigation of average temperature and precipitation values, a total of eight climate indices were also chosen and analysed over the region of interest. *Table A2* in *Appendix* contains the details about the set of these indices, which can be separated into two categories: (1) threshold-related indices: count the number of days when a given (precipitation or temperature) threshold is exceeded; namely, summer days (SU), frost days (FD), tropical nights (TR) and wet days (RR1); (2) extreme-related indices: i.e. the warmest day (TXx) and the coldest night (TNn) of a period, the maximum of daily precipitation amount (RX1day), and extremely wet days (R99p).

Results

In this section, the performance of the different bias-adjusted databases is investigated for the evaluation period 1993–2005, which is the overlapping time interval of the three different calibration periods (1976–2005; 1989–2010; 1993–2022) used for the bias-corrections, furthermore, it contains only historical model simulations. Different metrics were selected for the evaluation: firstly, the mean precipitation and temperature characteristics are analysed on different timescales, and then the chosen climate indices are investigated over Hungary.

Mean precipitation and temperature characteristics

First of all, relative bias was calculated as the difference relative to the climatological average (as defined e.g. in the work of Vogel, E. *et al.* 2023) of the precipitation in the reference period shown in the first column of *Figure 2*. Relative bias was obtained from average annual values over the evaluation period. In the case of precipitation, relative bias shows positive values in most of the area for the raw simulations, especially in the North Hungarian Mountains with a positive bias of 35–55 percent, whereas in the south-western part of the country a negative bias of 5–15 percent occurs. BC-MESAN shows lower relative bias in the northern area, but the negative values are more pronounced. In terms of the two HuClim-based bias-corrected datasets the relative bias is closer to zero in comparison to the above-mentioned cases, but for the BC-HUCLIM-1 a negative bias of 5–10 percent is dominant over the country, while BC-HUCLIM-2 shows the same amount of positive bias in most of the area. In summary, the warming of recent decades has also affected annual precipitation totals. For temperature (*tas, tasmin, tasmax*) absolute biases are shown (columns 2–4 of *Figure 2*), which were calculated as the difference between the simulated and the observation-based values. Absolute biases are small (around 0.5 °C) for BC-HUCLIM-1 and BC-HUCLIM-2, but with an opposite sign, which can be related to the different climatic

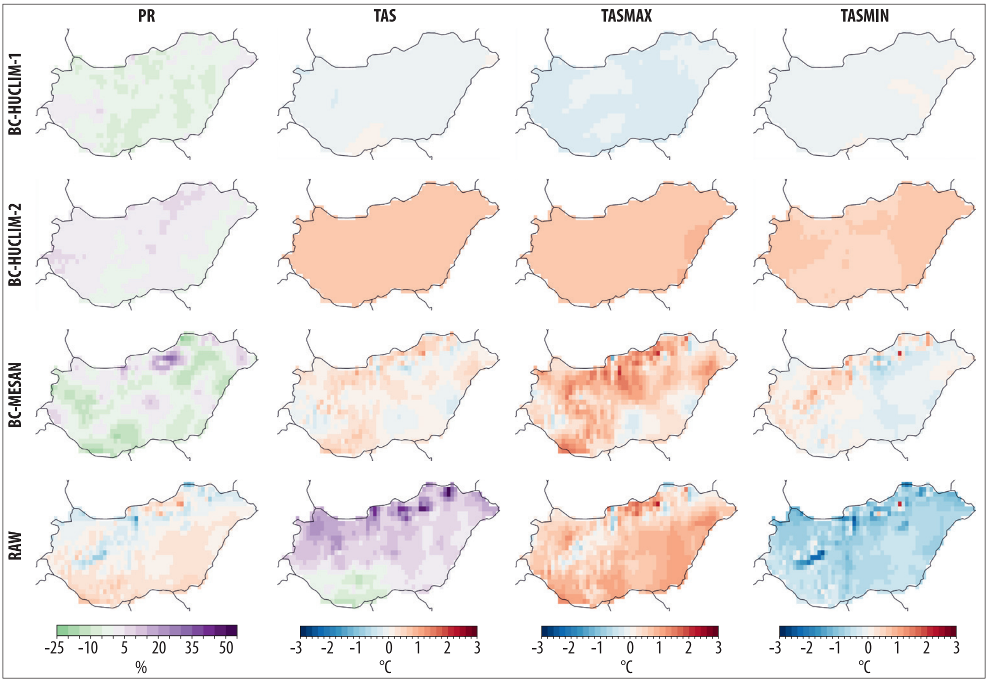

Fig. 2. Biases of the raw and bias-adjusted RCM simulations based on the multi-model ensemble mean for each variable and database for the period 1993–2005. *Source*: Authors' own editing.

conditions of the two calibration periods, i.e. while the database calibrated on the basis of a warmer climate shows an overestimation, the database bias corrected on the basis of a colder (earlier) period shows an underestimation. BC-MESAN is the most accurate for *tas* (±0.6 °C), but a relatively large bias appears in the case of *tasmin* (1–2 °C).

The performance of each RCM simulation was analysed by the difference of spatially averaged seasonal precipitation sum between the simulated values and HuClim, calculated and displayed for each database and expressed as a percentage *(Figure 3).* The difference between the climate models is higher in all seasons for the raw simulations, while for the bias-corrected results, these differences are reduced. Most of the raw RCM simulations underestimate summer precipitation by 15–30 percent, whereas in the other seasons an overestimation by 5–30 percent is found. For the two HuClim-based bias-corrected datasets, the difference between the individual RCMs is proved to be the smallest in spring and autumn. RACMO22E was found to be the most accurate among the RCMs and the worst performing models are HIRHAM5 and CCLM4-8-17. Based on the multi-model average of the differences, the variation is negligible in autumn for BC-HUCLIM-2 (-0.3%), and BC-HUCLIM-1 shows the best performance (-4%) in the case of winter. However, for spring and summer the results most consistent with observations were found in the case of the BC-MESAN multi-model average (+4.5% and -3.9%, respectively).

The performance of the individual RCM simulations was also investigated for the temperature-related variables. The average seasonal temperature characteristics were calculated based on the RCM simulations and compared to HuClim, which served as reference

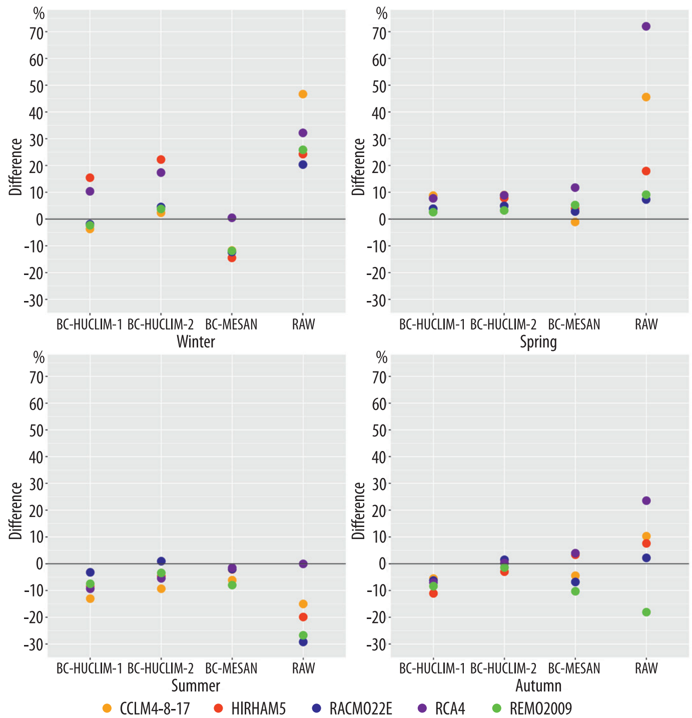

Fig. 3. The spatially averaged seasonal precipitation totals compared to HuClim for the period 1993–2005 displayed for the individual RCM simulations (indicated by different colours) and for the databases considered in this study. The differences are expressed as a percentage. *Source*: Authors' own editing.

(results can be seen in *Figure A1* in *Appendix*). The multi-model average and standard deviation of the variations have also been calculated and analysed. Similar to precipitation, raw RCM outputs show the largest standard deviation (between 0.6–2 °C), except for average summer *tasmin* (0.17 °C), which is comparable with BC-MESAN (0.15 °C). For BC-MESAN, the standard deviation is the smallest in autumn for all variables, and the most negligible for *tasmin* (0.08 °C), however, in the case of average seasonal *tas* and *tasmax*, the highest standard deviation values occur for all seasons in comparison with the other bias-corrected databases. The standard deviation is comparable for BC-HUCLIM-1 and BC-HUCLIM-2 and it ranges from 0.15 °C to 0.25 °C. Based on the multi-model average of the differences of the individual RCM simulations, BC-HUCLIM-2 shows the poorest performance characterised by a general overestimation. The best performance was found for BC-HUCLIM-1 in terms of average seasonal *tas* and *tasmin*, with an average difference of ±0.3 °C. For BC-MESAN a slight overestimation is more common for *tas* and *tasmax*. In the case of BC-HUCLIM-1 and BC-HUCLIM-2, CCLM4-8-17 was obtained to be the most accurate RCM simulation, and the performance of RCA4 was found to be the poorest in winter. For the other seasons, we cannot highlight any climate model as being the best one or an absolute outlier.

Finally, we evaluated the raw and bias-adjusted RCM data on a monthly basis. The annual cycle of the average monthly mean, minimum and maximum temperature and the average monthly precipitation sum over Hungary was investigated for the validation

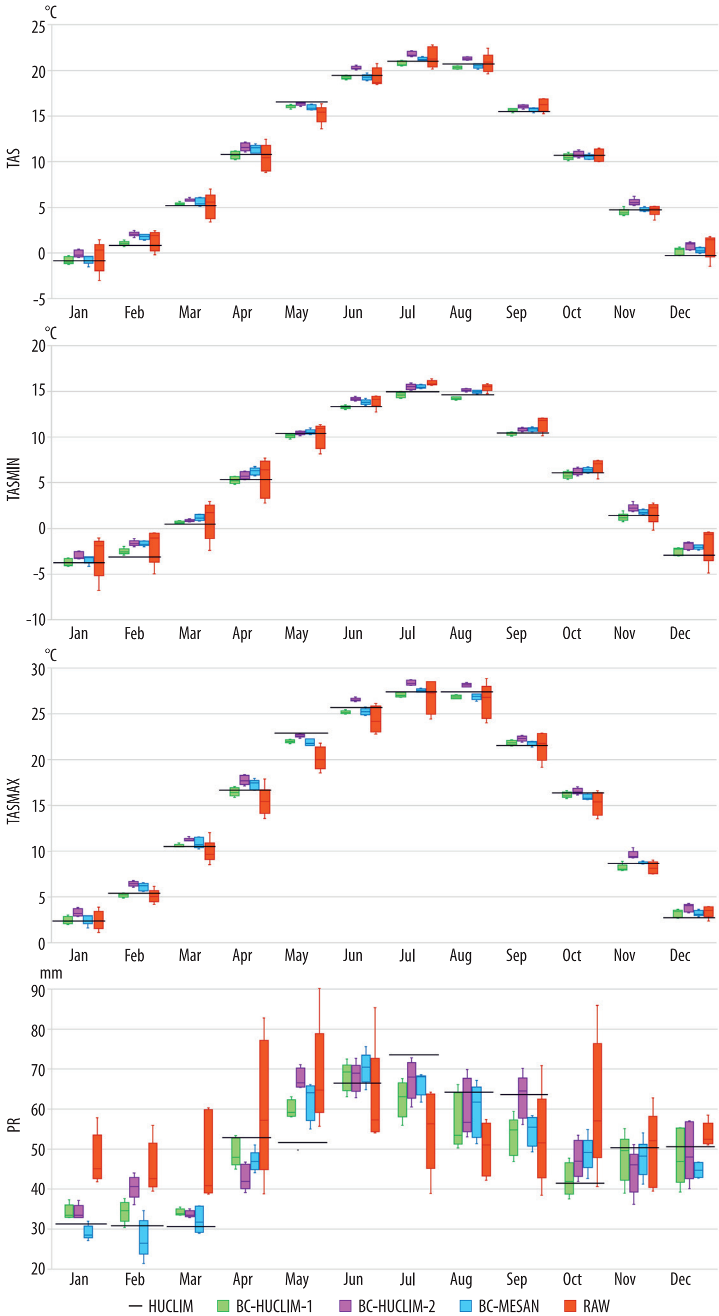

Fig. 4. The annual cycle of the average monthly temperatures (*tas, tasmin, tasmax*) and precipitation in Hungary during the period of 1993–2005 according to the raw and the different bias-adjusted RCM simulations (marked with different colours) in comparison with the measurement-based HuClim data (black horizontal lines). *Source*: Authors' own editing.

period according to the multi-model ensemble of the raw and the bias-corrected RCM simulations *(Figure 4).* In the one hand, for the temperature-related variables and for the raw RCM simulations, the spread of the models was found to be the largest (1.4–1.9 °C) in summer in the case of *tasmax*, but on the other hand, it was minimal (0.3–0.7 °C) for *tasmin*. The variance between the RCM simulations ranges between 0.6 °C and 1.7 °C for *tas*, with the greatest extent in winter and spring, and the smallest in autumn based on the raw data. The uncertainty was reduced by bias-adjustment regardless of the choice of the calibration period. The performance of BC-HUCLIM-1 was the best for temperature values in autumn and in the first part of spring (March and April), however, a general underestimation (with a median of 0.1–0.6 °C) can be observed in May and in the summer months (JJA).

In the case of BC-HUCLIM-2 an overestimation by 0.4–1.7 °C is dominant except for May and for October. BC-MESAN has the best performance in autumn and the poorest from February to April. For precipitation, a substantial overestimation (10–44 mm) was shown by the raw RCM simulations, especially in winter months, moreover, in May and October, when the uncertainty is the highest. A general underestimation of 9–35 mm was found for July, August and September based on the raw RCM simulations. After the bias-correction procedure, the variance between the RCM simulations decreased, and it was found to be the smallest in January and March in the two, HuClim-based bias-adjusted databases, but in some cases (in August and December) it remained comparable with the uncertainties of the raw simulations. The performance of the different bias-adjusted databases varies over the months: BC-HUCLIM-1 and BC-HUCLIM-2 show similar results in January, March, June, August and December, however, the boxes represent higher (lower) values for BC-HUCLIM-2 in comparison with BC-HUCLIM-1 in February, May, July, September and October (April and November). A clear overestimation (underestimation) appears in the case of May and October (July) regardless of the applied bias-correction and calibration periods.

Climate indices

This section presents the validation of the selected climate indices for Hungary. First, the spatial distribution of the annual number (amount) of threshold-based and extreme, temperature-related (precipitation-related) climate indices was investigated for the different datasets. *Figure 5* shows the results for summer days, tropical nights, frost days and wet days averaged over the period 1993–2005. The annual number of SU varies between 10–100 days over Hungary, with the minimum (10–25 days) in the mountainous areas. The highest occurrence (4–7 days per year) of the annual number of TR was observed at higher altitudes and on the southern slopes of the mountain ranges. This result can be explained by the presence of inversion stratification and as an effect of foehn wind, which occurs on the lee side of a mountain range (Brinkmann, W.A.R. 1971). The annual number of FD and its spatial distribution is also consistent with orography: over the highest peaks it reached 140–150 days, while in the southern part of Hungary it remained below 100 days per year. The annual frequency of RR1 is found to be relatively homogeneous across the country with 80–100 days.

Figure A2 in *Appendix* shows the spatial distribution of the bias fields with respect to the HuClim dataset. On the one hand, the ensemble mean of BC-HUCLIM-1 is in good agreement with the reference values for every threshold-based climate index apart from the underestimation of SU with 5–15 days in the Great Hungarian Plain and the slight underestimation of TR, especially in areas with higher altitudes. On the other hand, the average annual number of TR is overestimated by all databases except for BC-HUCLIM-1. In the case of SU, a general underestimation was found for BC-MESAN and a general overestimation appears based on BC-HUCLIM-2, especially in the south-eastern region of the target area. Raw simulations show 20–30 days overestimation for RR1 (mostly in the mountains), and the same extent of underestimation appears for FD compared to the reference values. These results are consistent with a warming trend in the region, i.e. the database calibrated to the most recent period gives an overestimation of the relevant indices compared to the earlier period.

Figure 6. compares the values of extreme-related climate indices and their spatial distribution over the period 1993–2005 based on the different databases investigated in this study. According to the reference data, the absolute minimum temperatures (around -28 °C) were detected in areas prone to frost, such as the north-eastern region and the northern valleys. Among the bias-corrected databases BC-HUCLIM-2 and BC-MESAN show relatively better agreement in terms of both spatial distribution and values. BC-HUCLIM-1 assumes lower temperatures over an extensive area. The highest temperatures (39–40 °C) occurred in the south-eastern part of the Great Hungarian Plain, while in the mountains TXx values of 30–32 °C were found. This index is best represented by BC-HUCLIM-1, however, BC-MESAN, as well as the raw simulations, overestimates TXx by 1–2 °C, mainly in the Great Hungarian Plain.

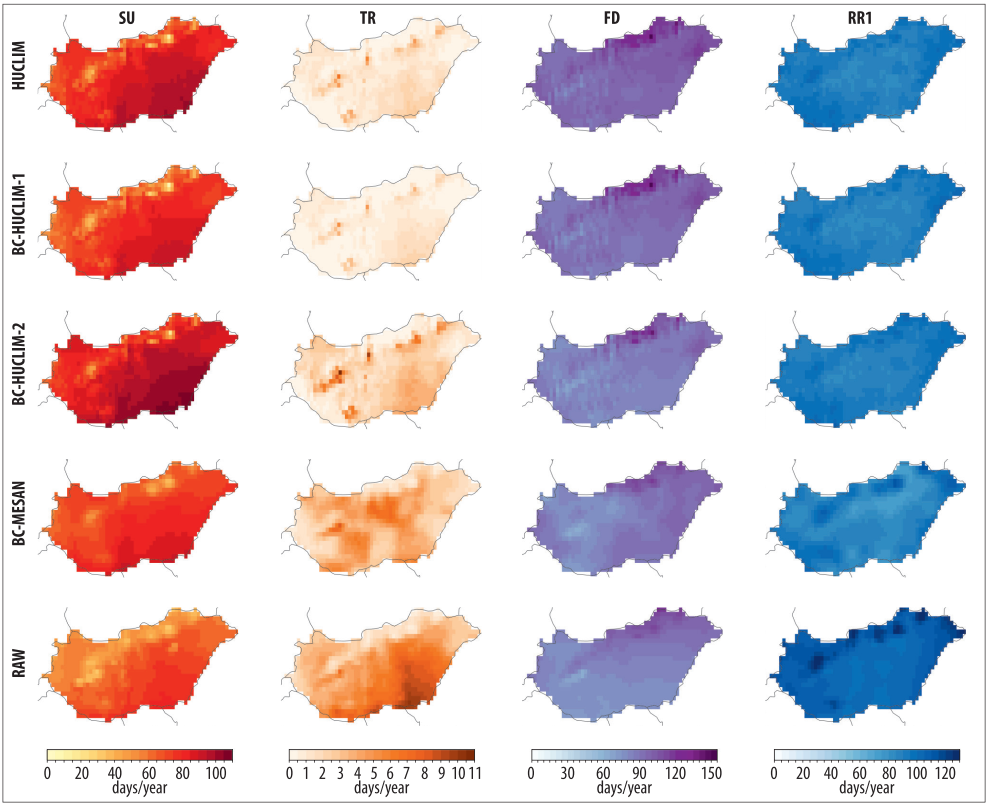

Fig. 5. Threshold-based climate indices (SU, TR, FD, RR1) over Hungary based on the multi-model averages of the different bias-corrected simulations (rows 2–4) and raw outputs (last row) in comparison with the HuClim reference data (first row) for the validation period of 1993–2005. *Source*: Authors' own editing.

Turning our attention to the extreme, precipitation-related climate indices, the highest daily precipitation sum (110–130 mm) was clearly related to Mátra mountain range, where Kékes is located. However, for R99p – which varies between 18–30 mm over Hungary –, the higher values were more prevalent in the south-western Transdanubian region and in the western border. These spatial patterns are well represented by BC-HUCLIM-1 and BC-HUCLIM-2, but according to BC-MESAN, a much more homogeneous spatial distribution appears for RX1day with a strong underestimation, especially in the mountains, where the values for this index are almost half as much as the reference. The spatial distribution of the bias fields with respect to the HuClim dataset is also shown in *Figure A3* in *Appendix*.

Normalized Taylor diagrams (Taylor, K.E. 2001) were also created in order to determine the degree of statistical similarity between the HuClim reference dataset and the various climate model simulations for each climate index. The closer a symbol is to this reference point (indicated by a black square), the better the performance of the related RCM simulation ensemble. *Figure 7* presents these statistical metrics for the average annual number of threshold-based climate indices for the target domain for the period 1993–2005. It can be

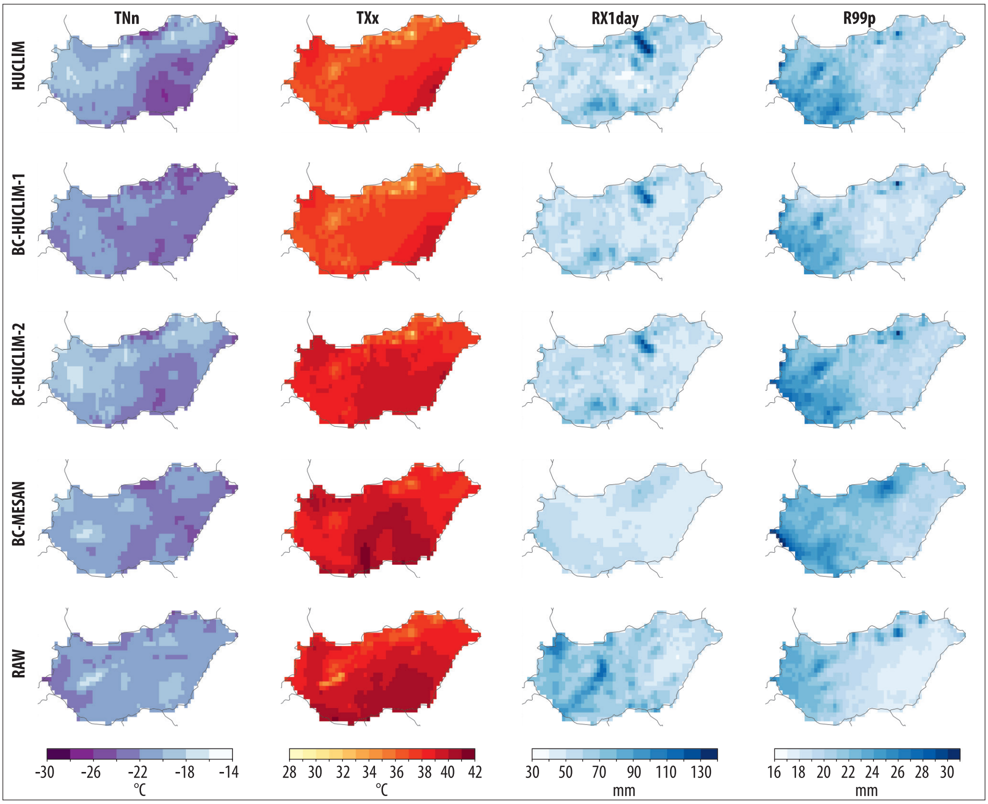

Fig. 6. The same as in *Figure 5*, but for extreme-related climate indices (TNn, TXx, RX1day, and R99p). *Source*: Authors' own editing.

seen that bias-correction based on HuClim data (regardless the calibration period) has obviously a positive effect, in addition, the two HuClim-based datasets provide similar statistical metrics, except for TR, where standard deviation values were found to be different – which means that BC-HUCLIM-2 exhibits larger spatial variability for tropical nights than BC-HUCLIM-1. These databases show the highest degree of similarity for SU and FD compared to the HuClim reference, for which the correlation coefficients are found to be above 0.99 and the RMSE values are minimal (< 1.2). It is interesting to see that the symbols of the multi-model ensemble of BC-MESAN and raw simulations are located on similar lines of correlation for each climate index.

Taylor diagrams for extreme-related climate indices for the period 1993–2005 can be seen in *Figure A4* in *Appendix*. In this case the effect of bias-adjustment using HuClim was also found to be favourable but less successful than for threshold-related indices. Similar statistical metrics were obtained for the HuClim-based databases in terms of extreme, precipitation-related climate indices, but more pronounced differences appeared for TNn and TXx. The degree of similarity regarding the spatial distribution of the lowest temperature was higher for BC-MESAN compared to BC-HUCLIM-1, however, BC-HUCLIM-1 showed the best performance in the case of TXx, for which the correlation coefficient is around 0.99 and the RMSE was found to be the smallest (0.15).

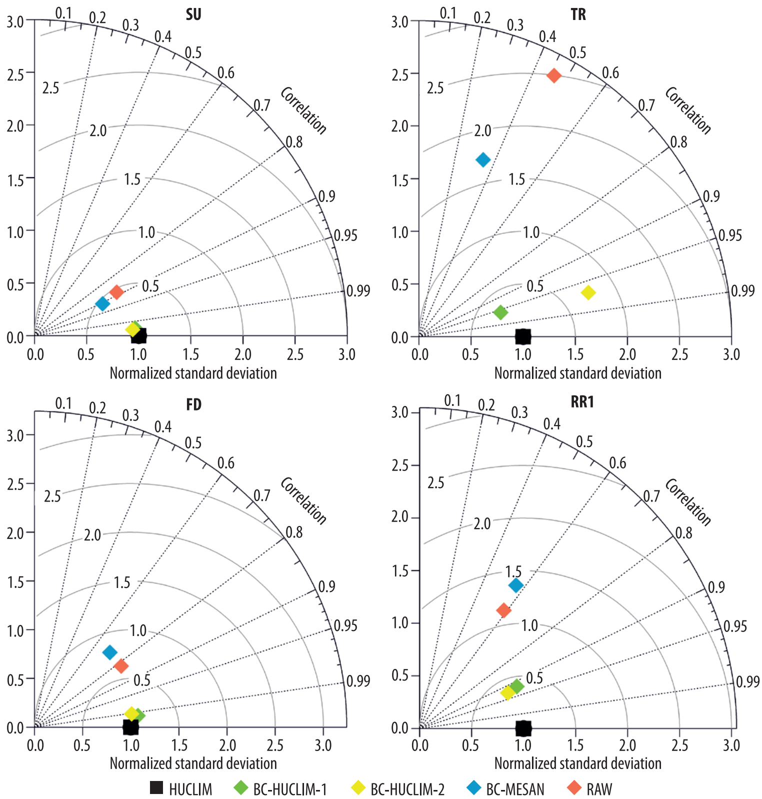

Fig. 7. Statistical characteristics summarized by Taylor diagrams for raw and bias-corrected multi-model data (coloured symbols) with respect to HuClim (black square) for the period 1993–2005. The four panels refer to the threshold based climate indices (SU, TR, FD, and RR1). *Source*: Authors' own editing.

Summary and final conclusions

The effect of the choice of the calibration period on the accuracy of the bias-correction was analysed in this study for Hungary, through the validation of three different bias-adjusted databases. Five RCMs were investigated from the framework of EURO-CORDEX at a horizontal resolution of 0.11° for the historical time period of 1976–2005 for four variables: daily mean temperature, minimum and maximum temperature, and precipitation. The percentile-based quantile mapping method was applied for the bias-correction, and was performed on a monthly scale. The observation-based HuClim dataset was used as a reference for the bias correction and the validation. Two, 30-year long time periods were selected from the HuClim database: 1976–2005 and 1993–2022, and as a result of the bias-correction, two different bias-adjusted databases were created based on these calibration periods. A third bias-adjusted database produced by the EURO-CORDEX community was also examined in this study. Two groups of climate indices were also assessed: (1) threshold-related climate indices: SU, TR, FD and RR1; (2) extreme-related climate indices: TXx, TNn, RX1day and R99p. The period 1993–2005 was selected as the validation period, since it is the overlapping time interval of the three calibration periods and contains only historical simulations.

In the validation period, the relative bias of the mean annual precipitation was the closest to zero (5–10%) in the cases of the two, HuClim-based bias-corrected databases, but with the opposite sign. This sign of absolute bias also appears for mean annual temperatures, since BC-HUCLIM-1 (BC-HUCLIM-2) has a bias of around -0.5 °C (+0.5 °C) over Hungary. The average seasonal temperature characteristics are similarly well approximated by BC-HUCLIM-1 and BC-MESAN, but a general overestimation appears for BC-HUCLIM-2. For the annual cycle of the average monthly mean, minimum and maximum temperature, BC-HUCLIM-1 is the most accurate bias-adjusted database, especially in autumn and in the first part of spring (March and April), however, a slight underestimation (with a median of 0.1–0.6 °C) appears during the summer months (JJA). For precipitation, the performance of each database shows a large variability between seasons and months. Note that the variation between the individual RCM simulations is reduced for each bias-corrected database in comparison with the raw model simulations. The annual number of threshold-based climate indices was in good agreement with the reference values in the case of BC-HUCLIM-1. The spatial distribution of the precipitation-related climate indices (RR1, RX1day, R99p) are well represented by the HuClim-based bias-corrected datasets, however, an excessively homogeneous spatial distribution appears for RX1day with a strong underestimation according to BC-MESAN. In general, the choice of calibration period is clearly influenced by the ongoing climate change. That is, the database corrected for the warmer period overestimates the average temperature and precipitation patterns compared to an earlier (and cooler) period, while the thresholds for the cold period are underestimated.

As a final conclusion, it can be said that the performance of the bias-corrected RCM simulations clearly depends on the analysed variable and chosen calibration period, as the results of the validation reflect the different climatic conditions of the calibration periods. (For example, the overestimation of the temperature-related variables or the tropical nights when using a more recent time period with more extreme events for bias-correcting the raw RCM data.) On the other hand, the results for precipitation are less affected by the choice of the calibration period, but they are more sensitive to the reference database. This can be explained by the fact that precipitation is one of the most variable meteorological elements not only in time but also in space. It means that using a database produced by a higher number of stations' measurement data provides more accurate results for precipitation. Overall, using the earlier calibration period (1976–2005) from the HuClim database proved to be the most accurate in the most cases during the validation. The next step in our research is to analyse the different bias-adjusted RCM simulations for the future.

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Appendix

Table A1. Overview of the databases analysed in our work

Name	Type	Bias-correction method	Reference dataset	Calibration period
RAW	raw	–	–	–
BC-MESAN BC-HUCLIM-1 BC-HUCLIM-2	bias-adjusted	distribution scaling quantile mapping quantile mapping	MESAN HuClim HuClim	1989–2010 1976–2005 1993–2022

Table A2. Description of the temperature and precipitation based climate indices used in this study

Label	Name	Category	Description	Unit
SU	Summer days	Threshold	Let TX be the daily maximum temperature on day *i* in period *j*. Count the number of days when $TX_{ij} > 25$ °C.	Days
FD	Frost days		Let TN be the daily minimum temperature on day *i* in period *j*. Count the number of days when $TN_{ij} < 0$ °C.	
TR	Tropical nights		Let TN be the daily minimum temperature on day *i* in period *j*. Count the number of days when $TN_{ij} > 20$ °C.	
RR1	Wet days		Let R be the daily precipitation amount on day *i* in period *j*. Count the number of days when $R_{ij} \geq 1$ mm.	
TXx	The warmest day	Extreme	Let TXx be the daily maximum temperature in month *k*, period *j*. The maximum daily maximum temperature each month is then: $TXx_{kj} = \max(TXx_{kj})$.	°C
TNn	The coldest night		Let TNn be the daily minimum temperature in month *k*, period *j*. The minimum daily minimum temperature each month is then: $TNn_{kj} = \min(TNn_{kj})$.	°C
RX1day	The highest daily precipitation sum		Let R be the daily precipitation amount on day *i* in period *j*. The highest daily precipitation sum over a time series is then: $RX1day = \max(R_{ij})$.	mm
R99p	Extremely wet days		Let R be a time series of the daily precipitation amount. Then R99p is the 99th percentile of the daily precipitation amount on wet days for a reference period.	mm

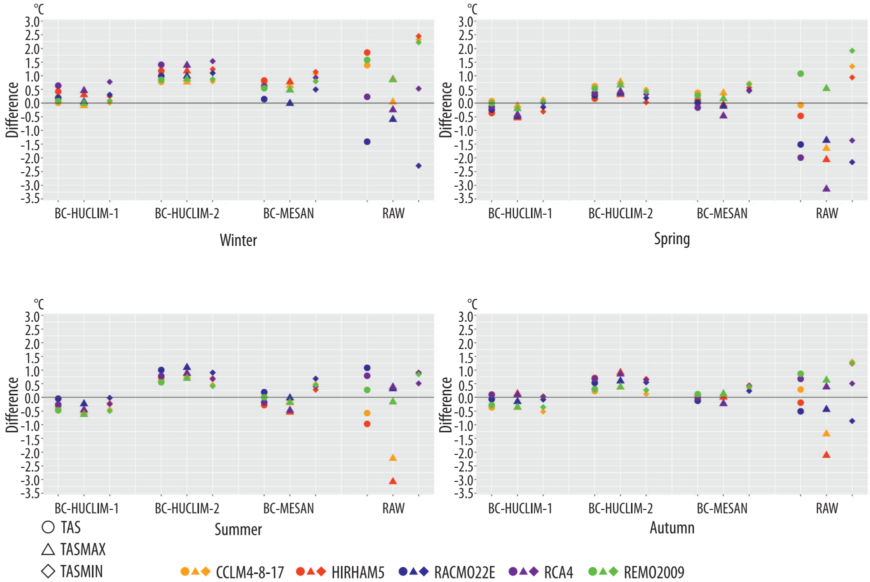

Fig. A1. The spatially averaged seasonal temperature characteristics compared to HuClim for the period 1993–2005 displayed for the individual RCM simulations indicated by different colours and for the four databases considered in this study. The differences are expressed in °C. *Source:* Authors' own editing.

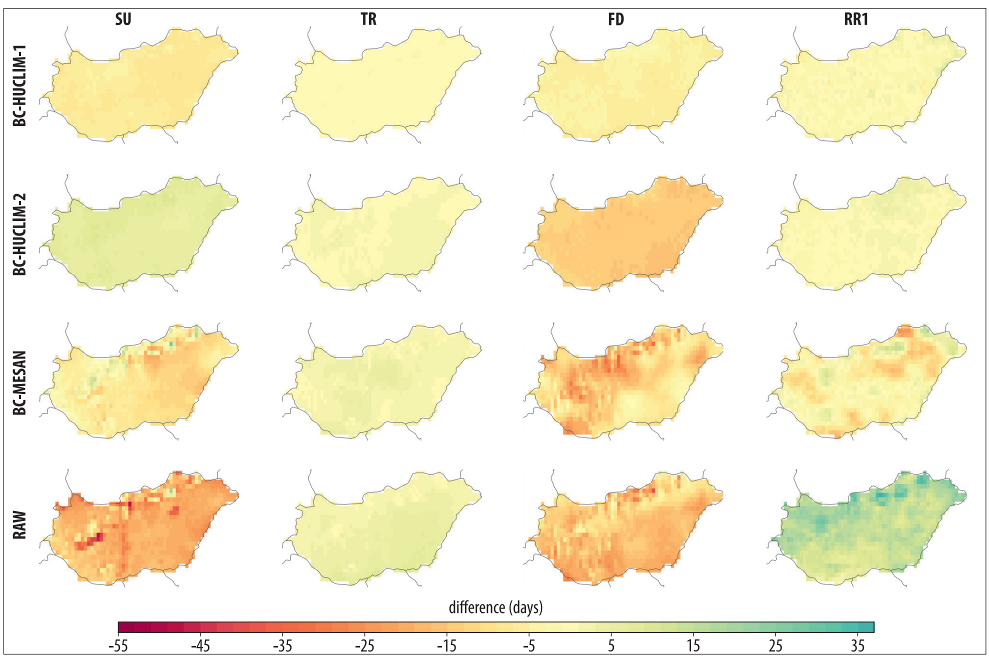

Fig. A2. Differences of threshold-based climate indices (SU, TR, FD, RR1) over Hungary based on the multi-model averages of the different bias-corrected simulations (rows 1–3) and raw outputs (last row) with respect to the HuClim reference data for the validation period of 1993–2005. *Source:* Authors' own editing.

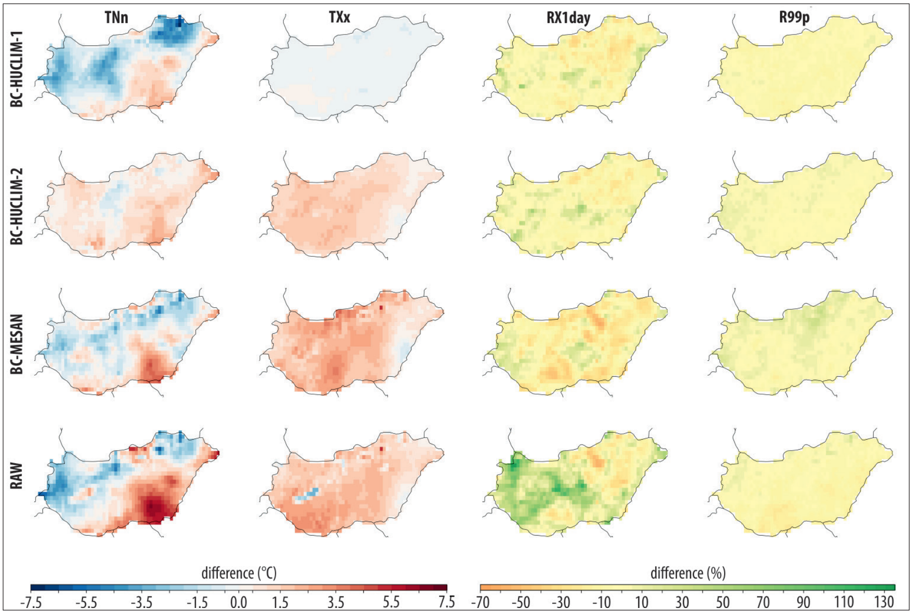

Fig. A3. The same as in *Figure A2*, but for extreme-related climate indices (TNn, TXx, RX1day, and R99p). *Source:* Authors' own editing.

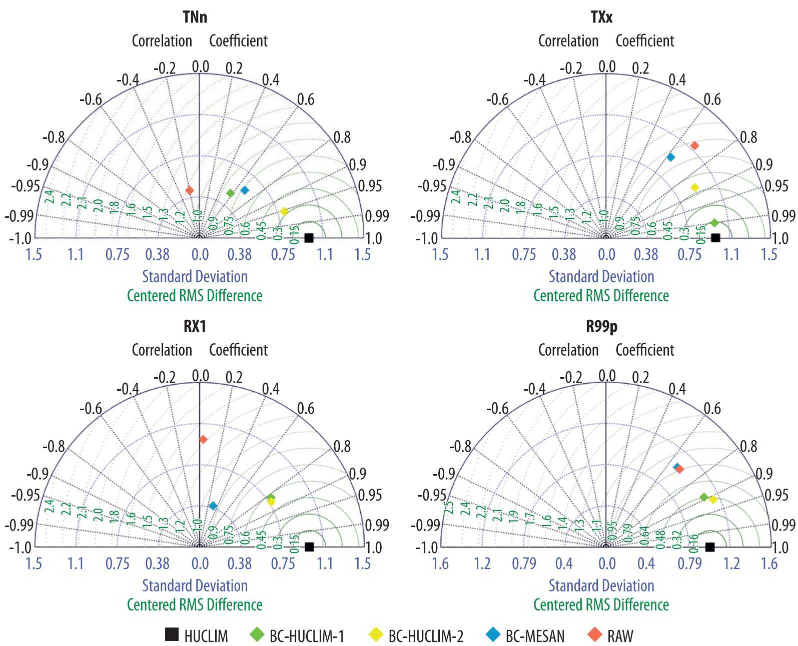

Fig. A4. Statistical characteristics summarized by Taylor diagrams for raw and bias-corrected multi-model data (coloured symbols) with respect to HuClim (black square) for the period 1993–2005. The four panels refer to the extreme-related climate indices (TNn, TXx, RX1, and R99p). *Source:* Authors' own editing.