

RESEARCH ARTICLE

Bias-adjustment of high-resolution temperature CORDEX data over the Carpathian region: Expected changes including the number of summer and frost days

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Abstract

Climate model simulations' outputs are prone to biases compared to observations; furthermore, climate projections can be very different in modelling future temperature characteristics. One possible solution for reducing uncertainty and eliminating possible systematic errors within climate projections is the bias-adjustment of the raw climate model data. We used the quantile mapping method for bias-adjustment of a mini ensemble consisting of 8-member high-resolution (0.11°) regional climate model simulations provided by the CORDEX community. As the method requires a reliable observational dataset serving as reference data, we used the quality controlled and homogenized observational dataset: CARPATCLIM. Quantile mapping bias-adjustment technique was applied on the following variables: daily mean, minimum and maximum temperature. We analysed changes in mean temperature characteristics and of climate indices for future periods of 2021–2050 and 2070–2099 with respect to the reference period 1976–2005 for the Carpathian Region. The selected climate indices are based on minimum (frost days, FD) and maximum daily temperature data (summer days, SU). Our bias-adjusted RCM results suggest a similar degree of mean temperature change as the raw RCMs' data. Bias-adjusted and raw RCM data project a remarkable annual temperature increase on average under the RCP8.5 scenario (1.4°C and 3.9°C by 2021–2050 and 2070–2099, respectively). The highest temperature increase is likely to occur in summer: it is 4.3°C on average by the end of the 21st century. More pronounced differences were found for the projected changes of the number of summer and frost days based on the bias-adjusted and the raw RCM data. Our results draw attention to the fact that bias-adjusted RCM data are crucial for the provision of regional climate change impact and adaptation studies for the Carpathian Region.

KEYWORDS

bias correction, CARPATCLIM, Carpathian region, EURO-CORDEX, med-CORDEX, regional climate change, temperature, temperature climate indices

1 | INTRODUCTION

One of the greatest challenges that humanity has ever been faced with is climate change. Although, climate change is detected globally; observations and projections show remarkable regional characteristics of climate change (IPCC, 2014). Reliable information is needed in support of building proper mitigation and adaptation strategies at global and regional levels. Climate models can be useful tools for providing such valuable information on human induced climate change (IPCC, 2013). However, global and regional climate models (GCM and RCM, respectively) can provide information on climatic conditions only with uncertainties: climatic parameters derived from climate model simulations are encumbered with a certain degree of uncertainty as climate models are characterized by biases compared to observations (Torma *et al.*, 2008, 2011; Sillmann *et al.*, 2013; Kotlarski *et al.*, 2014; Torma, 2019). The main sources of uncertainties of climate projections can be attributed to different factors: internal variability, the implemented parameterization and model dynamics (model or response uncertainty), the prescribed greenhouse gas emission scenarios (scenario uncertainty), or climate model systematic errors (Giorgi, 2005).

In order to quantify existing uncertainties and provide credible climate change signals the assessment of RCMs as members of an ensemble is recommended (Beniston *et al.*, 2007). During the last two decades, several international projects have been accomplished based on RCM projections targeting the European continent. First of its kind was PRUDENCE (Predicting of Regional Scenarios and Uncertainties for Defining European Climate Change Risks and Effects, 2001–2004; Christensen and Christensen, 2007), followed by ENSEMBLES (Ensembles-Based Predictions of Climate Changes and Their Impacts, 2004–2009; Hewitt and Griggs, 2004) while CECILIA (Central and Eastern Europe Climate Change Impact and Vulnerability Assessment, 2006–2009; Halenka, 2007) ran in parallel with it.

Upon completion of the aforementioned European based projects another and still ongoing international initiative, the Coordinated Regional Downscaling Experiment (CORDEX, Giorgi *et al.*, 2009) was launched. CORDEX provides enormous amount of RCM data for several sub-regions of the world, with EURO-CORDEX (Jacob *et al.*, 2014) and Med-CORDEX (Ruti *et al.*, 2016) as its European branches. Noting that, these valuable RCM simulations may exhibit substantial systematic errors compared with observations. Post processing the raw climate simulation data in order to eliminate those systematic errors is called bias correction. During such process, we ensure the equal means between the reference dataset (observation) and the bias-corrected climate

simulation data (Déqué *et al.*, 2007). During the last decades several methods have been developed in favour of ensuring to fit the whole distribution of a given meteorological variable of climate model simulation to observations (Berg *et al.*, 2012; Lafon *et al.*, 2013). Considering several methods available, the non-parametric quantile mapping method is among the best methods in terms of reproducing statistical properties such as mean, standard deviation, quantiles, etc. The fact that the quantile mapping method is easy to implement makes it popular among the climate research community (Gudmundsson *et al.*, 2012; Fang *et al.*, 2015).

A crucial point for all bias correction methods is the reliable observational dataset that serves as reference. In general, a high-resolution, quality controlled and homogenized observational dataset is required by any bias correcting method. Following previous works (Torma, 2019; Torma *et al.*, 2020) the high-resolution and high quality observational CARPATCLIM (Szalai *et al.*, 2013) dataset served as reference for the present study. CARPATCLIM covers the Carpathians and its surrounding territories including the Carpathian Basin (hereafter the Carpathian Region). Present work focuses on bias adjustment of daily temperature data derived from RCM simulations along with their evaluation and assessment of projected changes including climate indices.

This work aims to provide supporting information on RCMs' performance over the Carpathian Region, which is considered essential for further research such as risk assessment, mitigation and impact studies. Overarching aim of the authors is to create a bias-adjusted temperature database in supplement of an available bias-adjusted precipitation dataset (Torma *et al.*, 2020) for the Carpathian Region, based on EURO- and Med-CORDEX regional climate model simulations for the selected periods: 1976–2005, 2021–2050 and 2070–2099. Final steps towards this purpose are reported here.

2 | DATA AND METHODS

2.1 | The region of interest: Carpathian region

Carpathian Region covers mostly central-eastern European territories within 44°–50° North and 17°–27° East. The Carpathian Region can be characterized as a region where warm dry Balkans meets with temperate Central Europe and cold continental Eastern Europe (UNEP, 2007), thus the climate across the Carpathian Region is considered as the synergy of oceanic, continental, and Mediterranean effects, as well as the complex orography (Torma and Giorgi, 2020). The altitude differences within the Carpathian

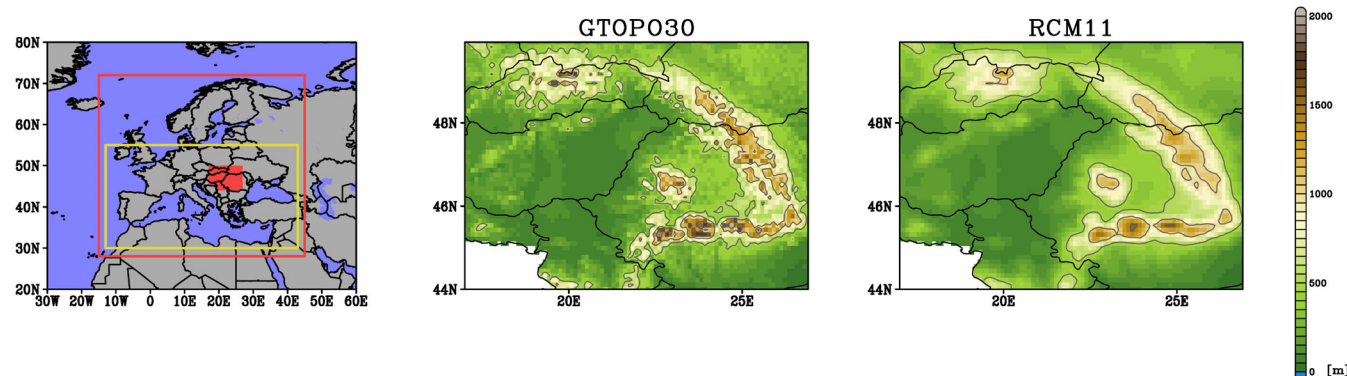


FIGURE 1 Location and topography of the Carpathian region. Location of the analysis region within the European domain (area filled with red colour on the panel to the left; red and yellow boxes depict EURO- and med-CORDEX domains, respectively); topography based on the GTOPO30 database (panel in the middle); the ensemble mean topography of the assessed high resolution RCMs (0.11°). Thin contour lines represent topography with intervals of 500 m. units are m. note that the territory of Bosnia and Herzegovina is not covered by the CARPATCLIM dataset [Colour figure can be viewed at wileyonlinelibrary.com]

Region exceed 2,500 m, as lowlands and mountain peaks lie between 27 and 2,655 m above sea level (Figure 1). Our analysis focuses on a region that hosts more than 20 million inhabitants, and is covered by the CARPATCLIM dataset, which partially encompasses the following countries: Austria, Czech Republic, Croatia, Hungary, Poland, Romania, Serbia, Slovakia, and Ukraine. Furthermore, rich biodiversity characterizes the Carpathian Region, which in fact embraces a significant part of the drainage basins of the two main rivers of the region: Danube and Tisza (UNEP, 2007). Several studies have discussed the climate of the Carpathian Region considering the CARPATCLIM dataset as reference (e.g., Birsan *et al.*, 2014; Spinoni *et al.*, 2015; Kis *et al.*, 2017).

2.2 | The reference dataset: CARPATCLIM

Since observational dataset serving as reference might have a larger impact on the projected possible changes in climate indices than the applied bias adjustment method, the selection of reference dataset for bias adjustment procedures is crucial (Casanueva *et al.*, 2020). The CARPATCLIM dataset serving as reference dataset for present study provides in total 16 meteorological variables on a daily basis and related derived indicators encompassing the Carpathian Region at $0.1^\circ \times 0.1^\circ$ horizontal grid resolution covering the period 1961–2010 (Szalai *et al.*, 2013). The CARPATCLIM database relies on station observations, its data is state-of-the-art quality controlled, covers the Carpathian Region (approximately 500,000 km²) and is freely available for scientific purposes through the following link: <http://www.carpatclim-eu.org>.

In total 415 stations from a network of weather stations covering the Carpathian Region were used in collecting near surface daily temperature data (Spinoni *et al.*, 2015). All data available under the framework of CARPATCLIM has been homogenized (Szentimrey and Bihari, 2006) and interpolated onto a regular grid (Szentimrey, 2007). CARPATCLIM is based on higher station density network than other available observational datasets covering the region of interest (e.g., E-OBS, Haylock *et al.*, 2008). Furthermore, in terms of data homogenization and data quality control this dataset can serve as basis for validation studies and for instance reference data for bias correction purposes over the Carpathian Region.

2.3 | Additional observational dataset

The E-OBS database (Cornes *et al.*, 2018) is also used for this study, as it served as an additional reference climate dataset for the validation of RCM simulations. E-OBS is an observation-based, gridded dataset, covering Europe with a horizontal resolution of $0.1^\circ \times 0.1^\circ$ and $0.25^\circ \times 0.25^\circ$. The purpose of the E-OBS database was originally the validation of RCM simulations, but it is also an appropriate tool to analyse European climate. Currently seven meteorological variables are available on a daily basis from 1950 until 2020 (it is updated every 6 months).

For our aim, to validate the RCM simulations, temperature fields were downloaded from E-OBS v22.0e on the finer grid and the seasonal average values were calculated for the Carpathian Region, for 1976–2005.

TABLE 1 Overview of regional climate models used in the present study. Models provided by the med-CORDEX framework labelled with an asterisk

Model	Modelling group	Reference
ALADIN 5.2*	Centre national de Recherches Meteorologiques, France	Colin <i>et al.</i> (2010)
CCLM 4.8.17	Climate limited-area modelling community, Germany	Rockel <i>et al.</i> (2008)
HIRHAM 5	Danish Meteorological Institute	Christensen <i>et al.</i> (1998)
RCA4	Swedish Meteorological and Hydrological Institute, Rossby Centre, Sweden	Kupiainen <i>et al.</i> (2011)
RACMO 2.2	Royal Netherlands Meteorological Institute, the Netherlands	Meijgaard <i>et al.</i> (2012)
RegCM 4.3*	International Centre for Theoretical Physics, Italy	Giorgi <i>et al.</i> (2012)
REMO	Climate Service Center, Germany	Jacob <i>et al.</i> (2001)
WRF 3.3.1	IPSL (Institut Pierre Simon Laplace) and INERIS (Institut national de l'Environnement industriel et des RISques), France	Skamarock <i>et al.</i> (2008)

2.4 | RCM simulations

Main motivation of present work was to extend the available CARPATCLIM based bias-adjusted precipitation RCM dataset for the Carpathian Region (Torma *et al.*, 2020) with additional variables as follows: mean temperature, minimum and maximum temperature. The selected mini ensemble includes the RCMs presented in the works of Torma (2019) and Torma *et al.* (2020) and consists of the eight RCM simulations, which are reported in detail in Table 1.

We analysed a mini ensemble, which consists of only individual RCM simulations (although, for several RCMs additional GCM-driven simulations are available) in order not to have a single RCM dominate the mini ensemble. All RCM simulations were accomplished under the framework of EURO-CORDEX and Med-CORDEX. More details of these integration domains are depicted in Figure 1 and reported in detail on the official CORDEX homepage: <http://cordex.org/>. In general, most CORDEX RCM

simulations are available at different horizontal grid spacings: 0.11° and 0.44°. For present study, we used only high-resolution RCM data at horizontal grid spacing of 0.11°, which corresponds to about 12.5 km. The members of the selected mini ensemble are ALADIN, RegCM (Med-CORDEX), CCLM, HIRHAM, RCA4, RACMO, REMO, and WRF (EURO-CORDEX). All selected RCM simulations follow the high-end RCP8.5 scenario (Moss *et al.*, 2010). RCP8.5 is a pessimistic scenario with a slow rate of economic development (Riahi *et al.*, 2011). It means that the radiative forcing surplus compared to the pre-industrial will be 8.5 W/m² by 2,100. RCP8.5 assumes high population, modest energy improvement (high fossil-intensity of the energy sector) and high greenhouse gas emission. The main sources of greenhouse gases are CO₂ (energy sector), N₂O (fertilizers) and CH₄ (rice, livestock).

In order to achieve evaluation of RCM simulations and furthermore do bias adjustment of simulations all data must share the same horizontal grid. For this purpose, all data were interpolated onto a common grid spacing of 0.11° by following previous work (Torma *et al.*, 2015). The interpolation was performed by using the Climate Data Operators software (CDO, <https://code.mpimet.mpg.de/projects/cdo>). The distance-weighted average remapping method was used as it was found to be the most spatial pattern consistent between different resolutions (Torma *et al.*, 2015). Hereafter all data are evaluated and reported on the common 0.11° grid.

2.5 | Bias adjustment method

In climate research, bias adjustment or bias correction is widely used in order to calibrate raw or biased climate model data to point-scale or gridded observational data (Rojas *et al.*, 2012; Casanueva *et al.*, 2018; Galmarini *et al.*, 2019). Several methods are available for such purposes including simple and more complex techniques (Lafon *et al.*, 2013; Sunyer *et al.*, 2015; Rajczak *et al.*, 2016; Kis *et al.*, 2017). It should also be highlighted that none of the available techniques, regardless of their complexity, is designed to address the fundamental shortcomings of the model used (Maraun, 2016). To minimize model shortcomings, the transient RCM simulations in CORDEX are preceded by careful tests to identify the best performing parameterization settings and physics configurations (Giorgi, 2019).

Following step-by-step the bias adjustment method reported in the work of Mezghani *et al.* (2017) and in accordance of our previous work (Torma *et al.*, 2020) the biases presented in our 8-member mini ensemble were adjusted by a percentile-based correction method or quantile mapping (Wang *et al.*, 2016). The applied bias adjustment technique is considered to be flexible and to

be a prominent representative of one of the most frequently used techniques by the climate research community for such purposes (Teutschbein and Seibert, 2013; Rajczak *et al.*, 2016; Kis *et al.*, 2017).

Quantile mapping employs a quantile-based transformation of distributions in order to adjust the variance of simulated distribution to match the variance obtained from the observations. As any other bias adjustment method quantile mapping has also specific limitations as it is considered to be sensitive to the quality and the length of the reference dataset (Fowler and Kilsby, 2007), which in fact especially reflects on the extremes as values that are possible, but not observed during the reference period cannot be taken into account (Thiemeßl *et al.*, 2010). All data was masked out for the region covered by CARPATCLIM (Figure 1). Following the work of Mezghani *et al.* (2017), the adjustment of all simulated daily temperature data (mean, minimum and maximum) to the observations was performed for each grid cell on that common grid. The correction factors were computed for each season for each grid cell in order to take into account the seasonal behaviour of biases. The quantiles of the RCM simulations for the control period (1976–2005) were mapped onto the corresponding quantiles in the observations using the entire 50-year reference period of CARPATCLIM (1961–2010). This was done in accordance with the above-mentioned limitation of the method used, in order to minimize the sensitivity of the choice of calibration period. Finally, the seasonal data were merged to construct the following 30-year periods: 1976–2005, 2021–2050 and 2070–2099.

2.6 | Temperature climate indices

Compared to the changes of monthly mean temperature, changes of extreme values may have larger effect for example, on human health and agriculture. Therefore, in the present analysis not only average temperature changes, but temperature related climate indices were also calculated. Of the 27 climate indices defined in total for climate studies by the Expert Team on Climate Change Detection and Indices (ETCCDI, for example, Sillmann *et al.*, 2013), we selected two. One of them is the number of summer days (SU), which means that the daily maximum temperature is greater than 25°C. The other one is the number of frost days (FD). An FD occurs, when the daily minimum temperature is below 0°C.

3 | VALIDATION OF RCM SIMULATIONS AGAINST CARPATCLIM

We present an evaluation of bias-adjusted daily temperature data and an assessment of expected changes in

temperature for the Carpathian Region. The results for the seasonal averages are reported first, followed by the results for the selected climate indices.

3.1 | Seasonal temperature means

Figure 2 presents the seasonal (winter: DJF; spring: MAM; summer: JJA and autumn: SON) mean temperature over the Carpathian Region (Figure 1) based on the raw and bias-adjusted individual RCM simulations, the E-OBS and the CARPATCLIM data for the reference period: 1976–2005. E-OBS is almost identical to CARPATCLIM. The difference in the seasonal mean temperature between these two data sets is less than 0.5°C.

In general, most RCMs underestimate the seasonal mean temperature over the region of interest for all seasons, with the exception of the summer months. Biases of the raw RCM simulations vary between -3.5°C (RACMO, MAM) and $+2.8^{\circ}\text{C}$ (RegCM, JJA). ALADIN, HIRHAM and RACMO underestimate CARPATCLIM data regardless of the season, while in the case of REMO an overall overestimation can be found. Taking into account the discrepancies in all the four seasons, RACMO shows the greatest bias (-2.3°C) on average, and CCLM presents the smallest ($+0.1^{\circ}\text{C}$).

The best performing simulation of minimum temperature values (Figure S1) is HIRHAM, while the greatest difference relative to CARPATCLIM ($+2.7^{\circ}\text{C}$) based on the average of the four seasons' biases occurs in the case of RACMO again. Analysing maximum temperature (Figure S2), the error is the largest for HIRHAM and the smallest for ALADIN (the annual discrepancies from the reference database are -2.1°C and $+0.8^{\circ}\text{C}$, respectively). The greatest negative ensemble average bias (T_{\min} : 1.9°C ; T_{mean} : 1.7°C ; T_{\max} : 2.1°C) occurs in spring, the smallest (T_{\min} : 1.1°C ; T_{mean} : 0.7°C ; T_{\max} : 0.5°C) in winter. Bias correction leads to negligible differences between the RCM simulations ($<0.2^{\circ}\text{C}$) and the reference database in the case of minimum, mean and maximum temperature as well (Figures S1 and S2).

We turn our attention to the spatial distribution of seasonal mean temperature fields during the period of 1976–2005 over the Carpathian Region. Figure 3 shows the spatial distribution of mean seasonal temperature for the ensemble mean of the eight RCMs along with the corresponding field in CARPATCLIM. Overall, the seasonal characteristics are well represented by the RCMs. In general, RCMs' performance in representing seasonal mean temperature over the Carpathian Region has substantially improved by the applied bias adjustment, which reflects in the spatial plots presented in Figure 3. The bias adjustment increases spatial variability in the

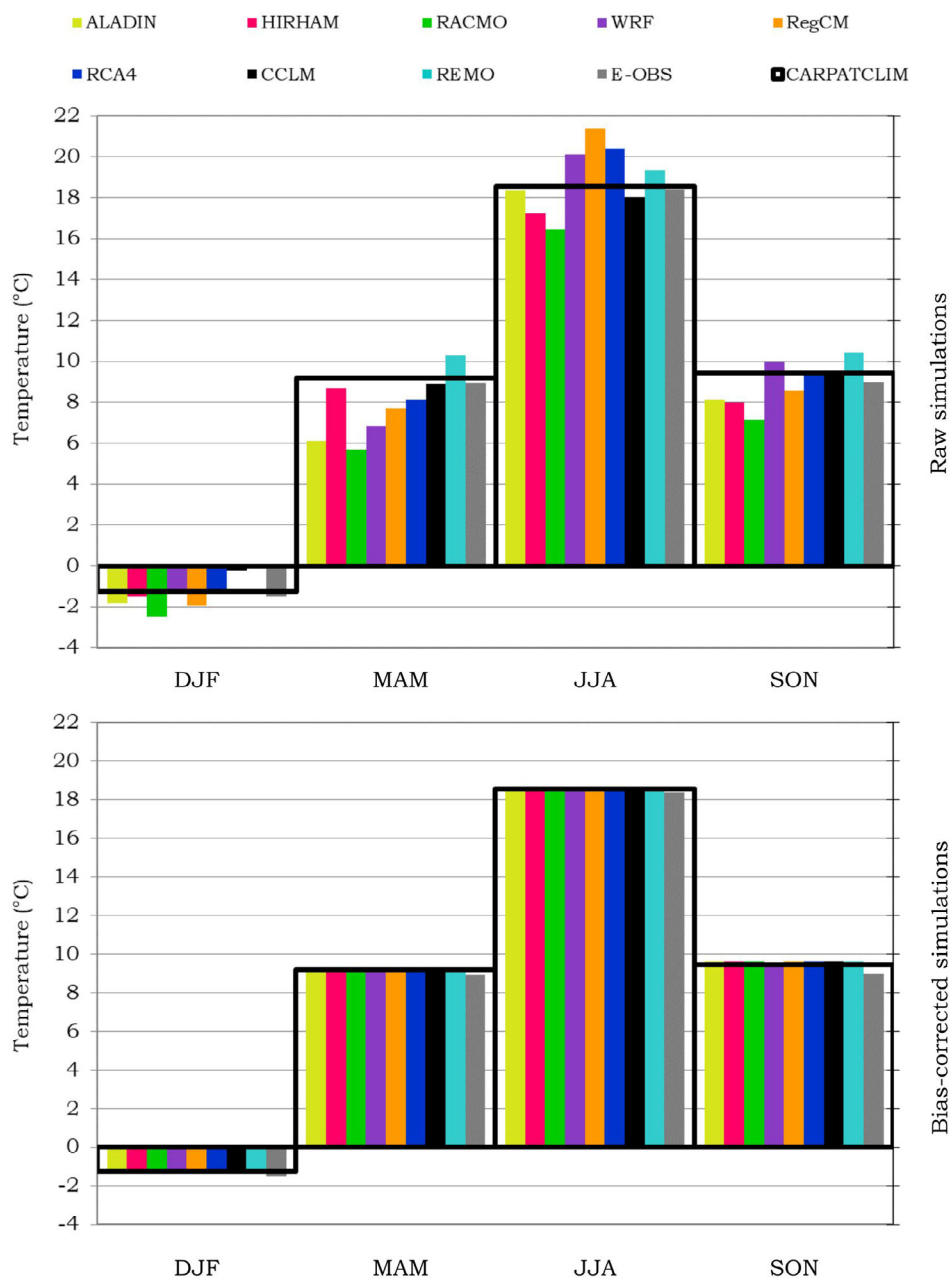


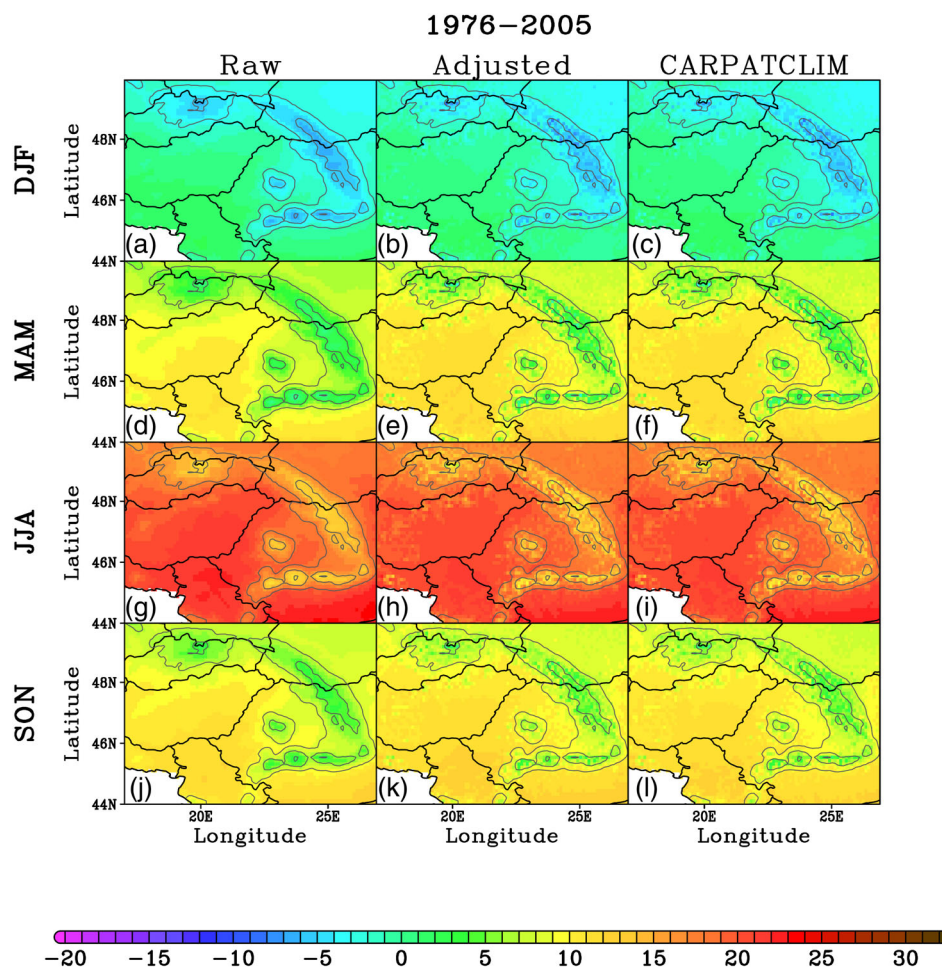
FIGURE 2 Seasonal mean temperature over the Carpathian region with (bottom) and without (top) bias correction for all RCMs (see Table 1) and the E-OBS database, for the period 1976–2005 compared to the CARPATCLIM dataset. Open boxes depict the reference database: CARPATCLIM [Colour figure can be viewed at wileyonlinelibrary.com]

temperature fields, especially in regions with distinct topography, which is in line with the observations.

In order to further explore the ability of RCMs' in reproducing present climatic conditions over the Carpathian Region, additional metrics were computed for the reference period 1976–2005 and are reported in Figure 4. The degree of statistical similarity between the climatic fields of RCMs and the reference dataset can be concisely quantified in the form of the normalized Taylor diagram (Taylor, 2001). The Taylor diagrams in Figure 4 show the centered (or bias removed) root mean square error (RMSE), spatial correlation and spatial standard deviation (STDV). The geometric relationship between these three metrics allows that the performance of each RCM

relative to the reference dataset (CARPATCLIM) can be directly compared on the same diagram (e.g., for each season separately). The azimuthal position of a symbol in Figure 4 gives information on the spatial correlation coefficient between the RCM simulation and the CARPATCLIM dataset. The radial distance from the pole of the sector to the symbol representing an RCM is proportional to the pattern STDV normalized by the reference standard deviation. Whilst, reference positioned along value 1 on axis x . In addition, the distance of any symbol from this point indicates the centered RMSE (noting that the centered RMSE values were also standardized with the STDV of the reference data). Consequently, perfect match with reference data would lead to a symbol located

FIGURE 3 Ensemble seasonal average of RCM simulations of near surface temperature based on raw (first column) and bias-corrected (second column) data. The reference dataset, CARPATCLIM is depicted on subpanels: C, f, i and l. the reference period is 1976–2005. Units are °C. thin contour lines represent the mean topography of RCMs with intervals of 500 m [Colour figure can be viewed at wileyonlinelibrary.com]



directly on the reference point, thus the symbol positioned closest to this reference point represents the best performing RCM.

The Taylor diagrams reported in Figure 4 are based on 30-year (1976–2005) seasonal means over grid points covering the Carpathian Region. The bias adjustment has an unequivocal effect on data as all bias-adjusted RCM data uniformly fit with CARPATCLIM (open circles in Figure 4). It is interesting to see, that our additional observational dataset (E-OBS) holds results similar to the best performing raw RCMs. Differences between E-OBS and CARPATCLIM can be attributed to the lower number of stations and different data processing techniques used for the E-OBS dataset compared to CARPATCLIM. It is also interesting to see the behaviour of each RCM over the four seasons: the spatial correlation coefficients are relatively high and found to be around 0.9 in all seasons, while highest differences among the RCMs are found for the summer period. Accordingly, RCA4 shows the lowest degree of similarity regarding the spatial distribution of mean temperature compared to CARPATCLIM during winter, meanwhile RCA4 is among the best performing RCMs

during summer. WRF exhibits qualitatively modest performances in winter and autumn. More specifically, during autumn and winter WRF exhibits the largest spatial variability (STDV ratio exceeds 1.5 in DJF) along with the largest centered RMSE. The STDV ratio is the lowest in case of RegCM regardless of the season. Considering all measures depicted on diagrams represented in Figure 4, CCLM and ALADIN are found to be among the best performing RCMs in all seasons. Similar findings are valid for the other bias-adjusted variables: minimum and maximum temperature (Figures S3 and S4).

3.2 | Climate indices

In addition to the seasonal means, it is essential to assess the bias-adjusted variables at much finer temporal scale (e.g., daily) in order to investigate climate extremes or climate indices especially over region with complex topography (Nemec *et al.*, 2013; Dumitrescu *et al.*, 2015; Torma *et al.*, 2015). We present results for the following indices based on different variables: FD (daily minimum temperature) and SU (daily maximum temperature).

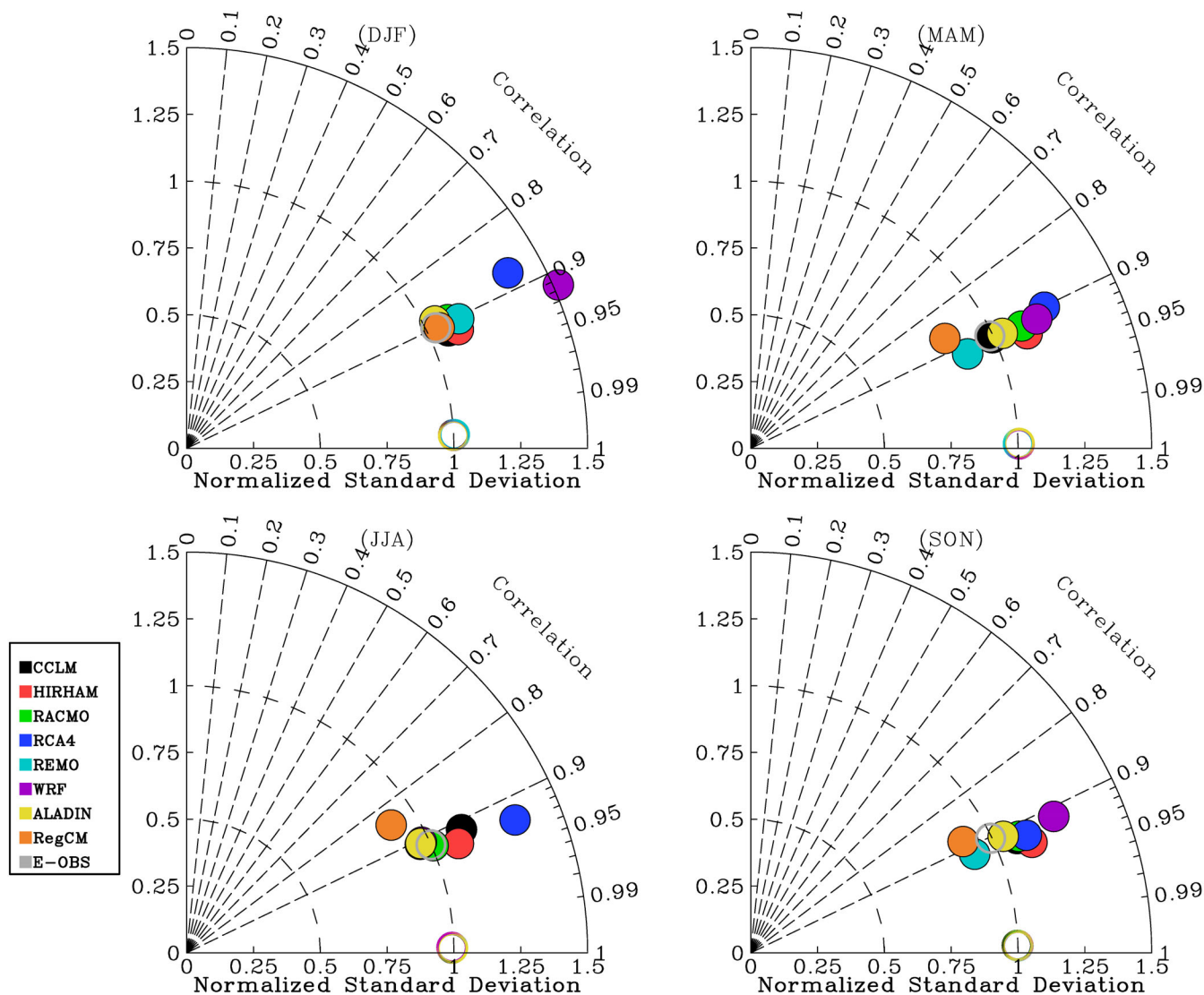


FIGURE 4 Taylor diagrams for summarizing the statistical characteristics of raw (filled circles) and bias-corrected RCM data (open circles) with respect to CARPATCLIM, for the period 1976–2005. The four panels refer to the four seasons (DJF, MAM, JJA, and SON). Noting that grey open circles refer to an additional observational dataset: E-OBS [Colour figure can be viewed at wileyonlinelibrary.com]

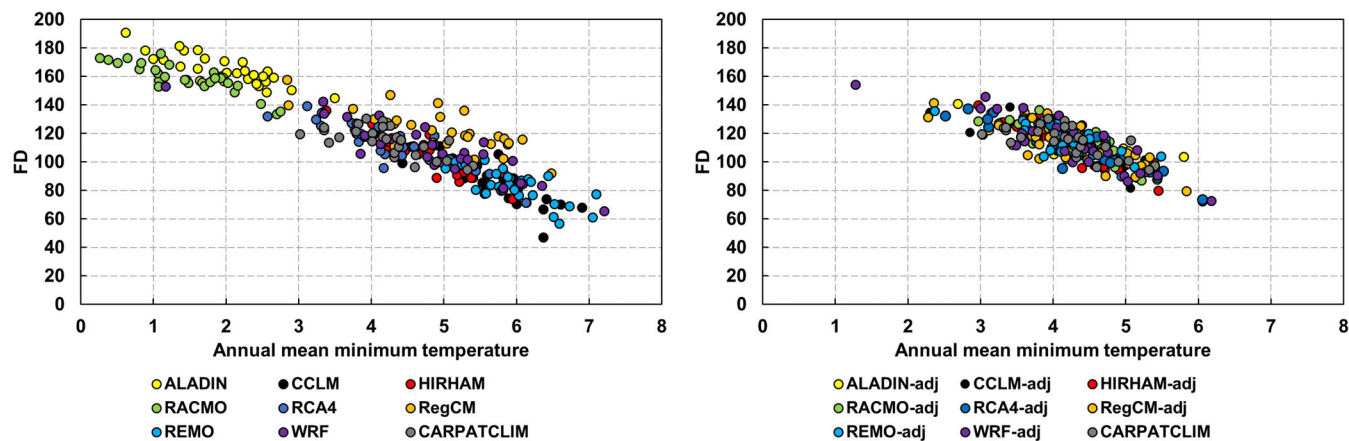


FIGURE 5 Number of Forst days (FD) versus annual mean daily minimum temperature during the reference period of 1976–2005. (each point represents 1 year.) the units are °C (x-axis) and days for FD [Colour figure can be viewed at wileyonlinelibrary.com]

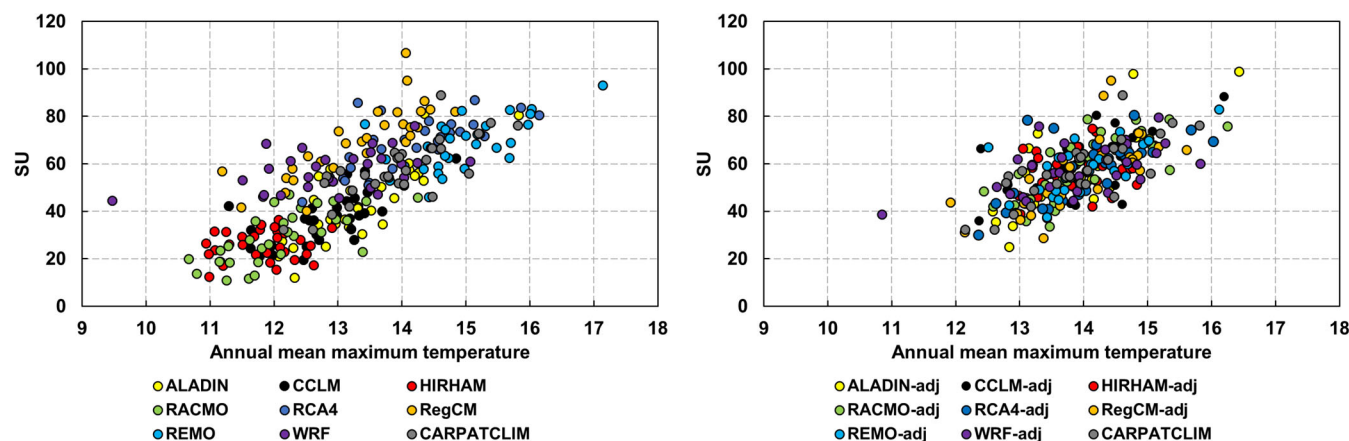


FIGURE 6 The same as Figure 5, but for the summer days (SU) and versus annual mean maximum temperature during the reference period of 1976–2005 [Colour figure can be viewed at wileyonlinelibrary.com]

The number of FD shows a strong correlation with annual mean minimum temperature for the period 1976–2005 (Figure 5). In the case of the adjusted simulations, the variability becomes smaller. While according to the raw values, FD varies between 40–200 days/year, after the bias correction it is between 70–160 days/year in the reference period. While the 30-year mean FD varies between the 8 RCMs as follows: 84–164 days/year and 110–113 days/year before and after the bias correction, respectively. In other words, the bias adjustment of the daily minimum temperatures led to lower variability of the simulated FD. Two simulations can be separated from the others and the CARPATCLIM, as they present colder conditions. Namely, ALADIN and RACMO show lower annual mean minimum temperature and more FD as well (see also Vautard *et al.*, 2021). After the bias correction, all the RCM-simulated values are in a smaller range and none of the RCMs can be separated easily from the others.

In the case of SU, similar conclusions can be drawn (Figure 6). The higher the annual mean maximum temperature, the more SU occurs in general. Variation of raw simulations is greater than variation of the adjusted values, but overall it is smaller compared to FD. Moreover, none of the RCM simulations can be separated by showing considerably warmer or colder climatic conditions. However, HIRHAM and RACMO simulate somewhat lower annual mean maximum temperatures in the reference period, but after the bias correction it has been eliminated. According to the adjusted RCM outputs, the annual number of SU is found to be between 20 and 100 days/year in 1976–2005. Specifically, the 30-year mean SU based on bias corrected RCM data varies between 57–58 days per year, while without the correction it is between 26 and 69 days per year.

4 | ESTIMATED TEMPERATURE CHANGES

4.1 | Projected mean temperature changes by 2021–2050 and 2070–2099 with respect to 1976–2005

In this section we turn our attention to the simulated changes for future periods (2021–2050 and 2070–2099), with respect to the historical 30-year period (1976–2005). The ensemble mean of bias-corrected RCM simulations shows a clear increasing trend in annual mean temperature; to smooth out year-to-year variability we also consider the 5-year moving average (Figure 7).

Naturally, in 1976–2005 there are cooler and warmer years compared to the 30-year average over the respective period considering the individual ensemble members. This is also true for 2021–2050, but in 2070–2099 the temperature anomaly is positive in every year according to every RCM simulation. Similar findings are valid for minimum and maximum temperature changes (Figures S5 and S6). In the reference period the average temperature was 9.1°C, while in 2021–2050 and in 2070–2099 it is 10.5°C (7.6–13.1°C) and 13.0°C (10.8–15.7°C), respectively. The minimum and maximum annual mean temperature changes simulated by the individual ensemble members range between −1.5°C and +4°C for the period 2021–2050 (with respect to 1976–2005). If we take into account all the RCM simulations and all the 30 years (2021–2050), only 2% shows negative anomaly. For 2070–2099 an increase by at least 2.8°C is projected, and in some years it can reach 4.7°C as well according to the ensemble mean of the RCM simulations. If we take into account the individual RCM simulations and years, the greatest change is of 6.7°C, while the smallest is of 1.7°C;

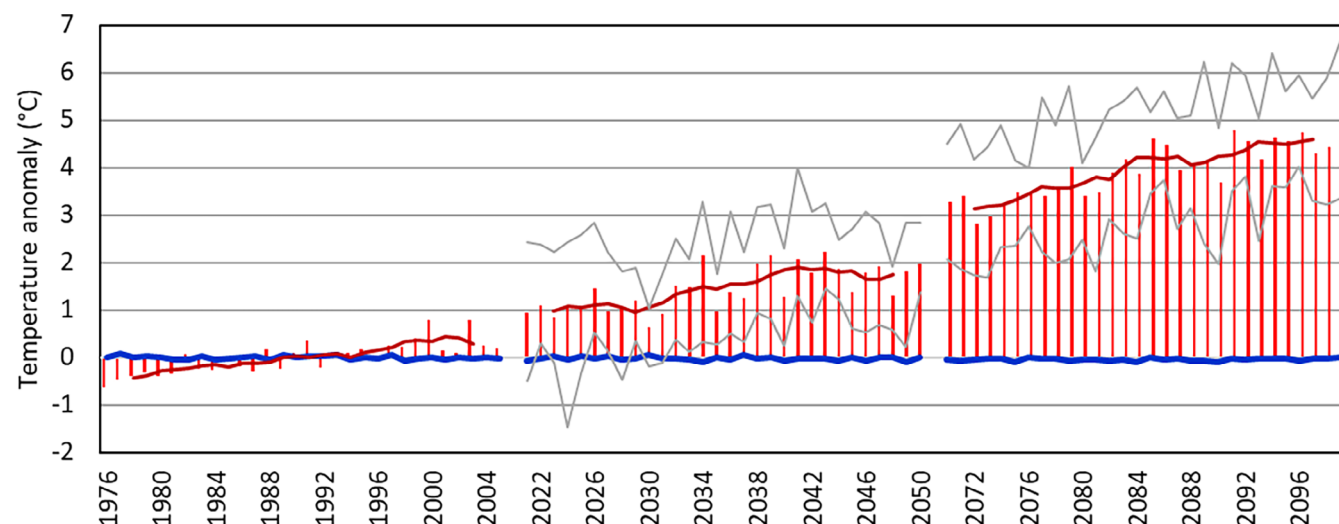


FIGURE 7 Mean temperature change based on the ensemble mean of bias-corrected RCM simulations compared to the 30-year average over the period 1976–2005. The red line represents the 5-year moving averages. The blue line shows the difference between the raw and bias-adjusted temperature anomalies with respect to their reference means, while grey lines depict minimum and maximum of the ensemble [Colour figure can be viewed at wileyonlinelibrary.com]

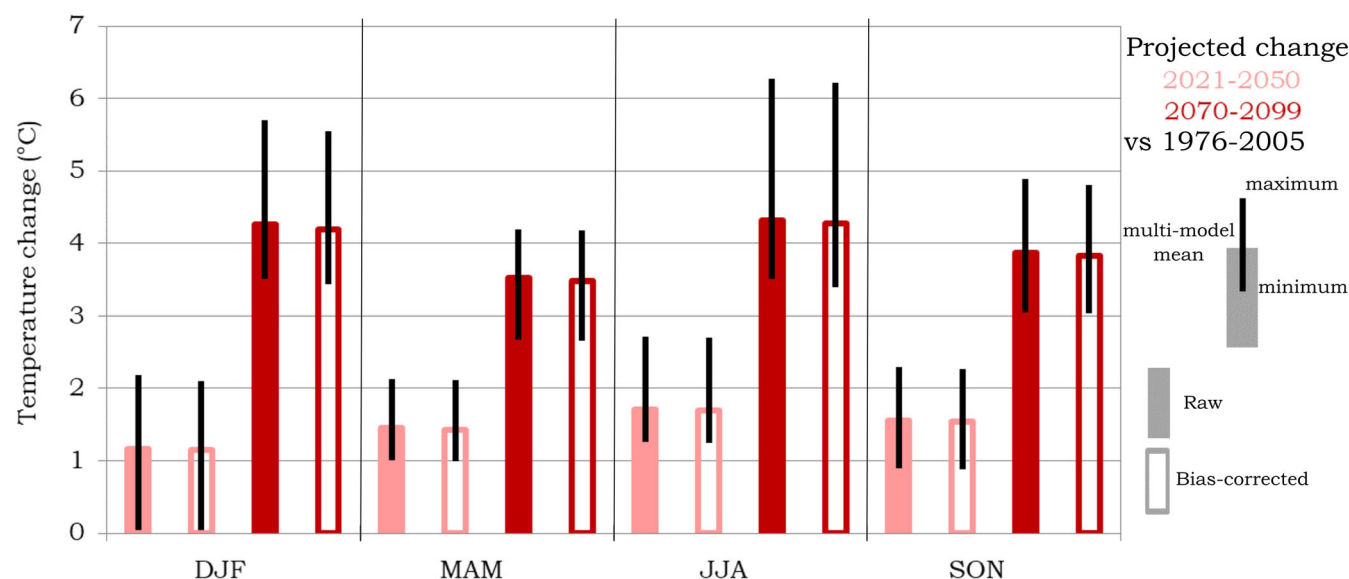


FIGURE 8 Mean temperature change for the periods 2021–2050 and 2070–2099 based on the ensemble mean of raw and bias-corrected RCM simulations with respect to 1976–2005 [Colour figure can be viewed at wileyonlinelibrary.com]

the standard deviation is about 1.0°C. The variability taking into account the individual RCM simulations averaged over the respective 30 years is somewhat higher in 2070–2099, when the standard deviation of temperature anomalies is 0.62°C (in 2021–2050 it is 0.40°C). We note that years in climate model simulations can not be regarded as real, calendar years (i.e., it is can not be expected, that in 2071 the average temperature will be higher exactly by 3.4°C compared to the reference period), instead we can use them as averages for longer time slices (e.g., 30 years).

The applied bias correction method did not alter the sign of the change: higher mean temperature values are simulated for the future in every season (Figure 8). The projected mean temperature change is clearly greater by the end of the 21st century compared to 2021–2050. With the greatest mean temperature increase occurring in summer: 1.7°C and 4.3°C on average, for 2021–2050 and 2070–2099, respectively. The smallest increase (<1.2°C) is simulated for winter for the near future, while by the end of the 21st century it is projected for spring (3.5°C). The ensemble spread exceeds 2°C in winter and in summer

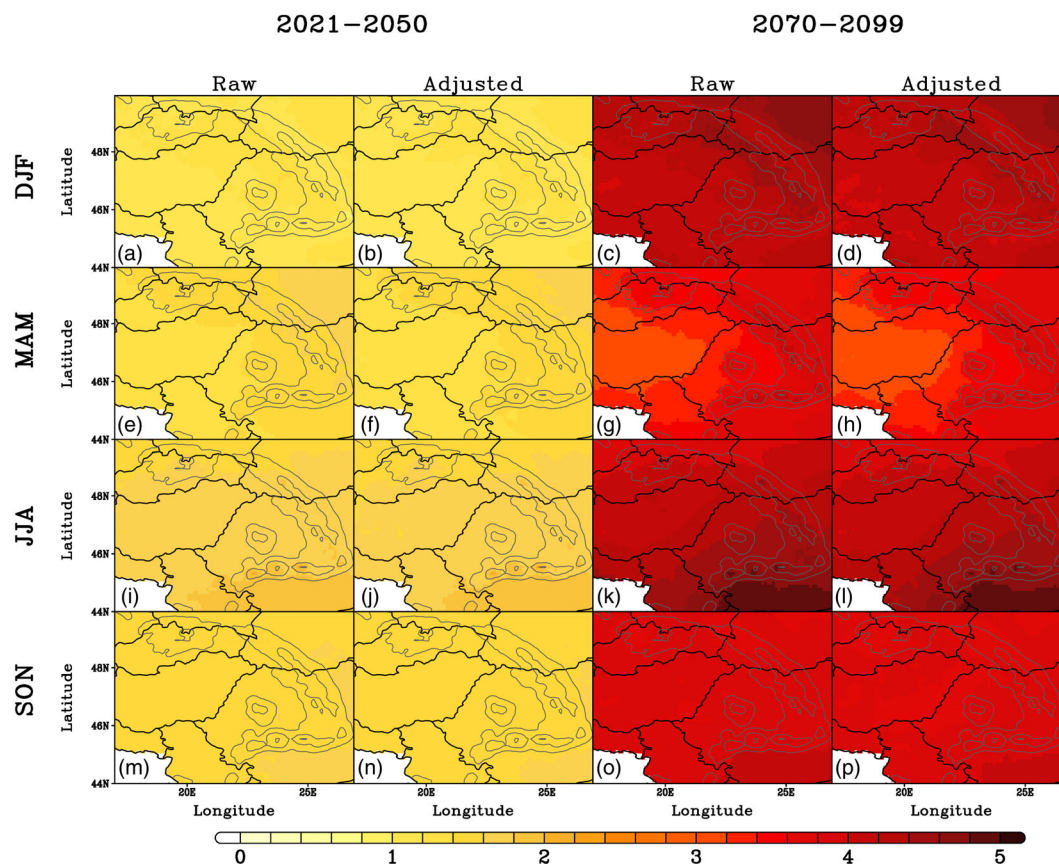


FIGURE 9 Ensemble seasonal average of RCM simulations of near surface temperature changes based on raw (first column) and bias-corrected (second column) data. The reference period is 1976–2005. Units are °C. thin contour lines represent the mean topography of RCMs with intervals of 500 m [Colour figure can be viewed at wileyonlinelibrary.com]

(in 2070–2099), while in the transitional seasons it remains under 1.8°C.

The projected spatial patterns of seasonal warming are very similar in the raw and bias adjusted RCM ensembles with the greatest increase in summer mean temperature occurring in the South-Eastern parts of the Carpathian Region (Figure 9). Specifically, in the high end RCP8.5 scenario RCM simulations projected a possible future where during JJA some of the highest peaks of southern flanks of the Southern Carpathians and the South-Eastern regions of the Carpathian Region might be exposed to warming of more than 5°C. In short, the JJA warming has its maximum signal over the Southern and its minimum over the Northern parts of the Carpathian Region, thus our findings confirm previous studies accomplished over European regions including our region of interest (Giorgi and Lionello, 2008; Giorgi and Coppola, 2010; Jacob *et al.*, 2014).

This JJA temperature change gradient might be attributed to MAM and JJA precipitation decrease leading to soil drying and less cloud cover (Coppola *et al.*, 2021). The well-known European winter temperature gradient can also be detected in the mean winter temperature change

present over the Carpathian Region (2070–2099), when the largest warming is projected in the northeast and the weakest warming in the southwest territories. This warming pattern to some extent is linked to the Arctic warming amplification, for which an important contribution (among others) is the snow albedo feedback that is largely governed by the continental snow cover loss (Walsh, 2014; Dai *et al.*, 2019; Coppola *et al.*, 2021).

In the transitional seasons, no similar temperature change gradients are present. In addition, spatial patterns in seasonal temperature changes (MAM and SON) show orographic origin. Accordingly, we identified temperature changes as robust in regions in which most of the models (6 out of 8 RCM in our case) agree on the sign of the signal. Furthermore, seasonal temperature changes presented in Figure 9 are robust and significant at the 90% confidence level (Student's *t* test) in all grid points regardless of season. Overall, we can conclude the bias adjustment did not significantly change either the extent of the seasonal temperature changes or their spatial distributions, but it rather had an impact on the absolute temperature values (Figure S7).

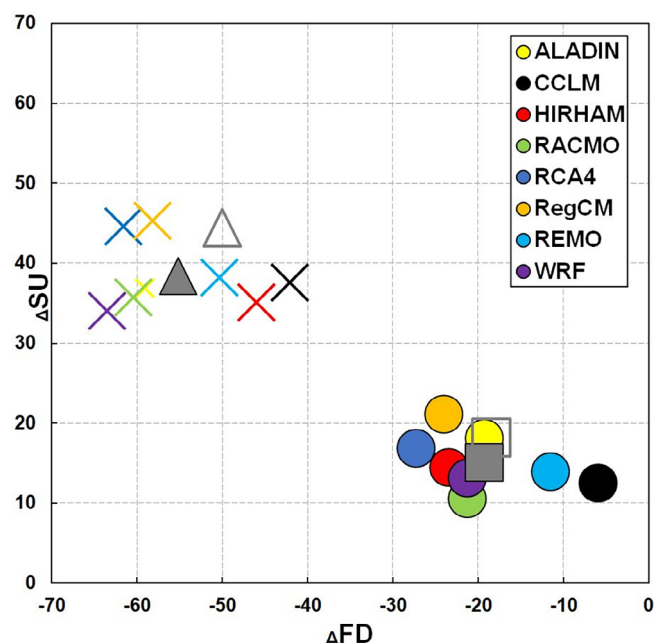


FIGURE 10 Changes in number of Forst days (FD) with respect to the change in the number of summer days (SU). Dots and squares are for near future (2021–2050), whilst crosses and triangles mark far future changes (2070–2099). Closed triangles and squares depict the ensemble mean of the analysed 8 raw RCMs, whilst the open triangles and squares represent the ensemble mean of the bias-corrected RCM data. The reference period is 1976–2005. The units are days [Colour figure can be viewed at wileyonlinelibrary.com]

4.2 | Projected changes of SUand FDby 2021–2050 and 2070–2099 with respect to 1976–2005

As both climate indices (SU and FD) might have significant impacts on agriculture, especially by the end of the century, it is important to assess their future characteristics. Climate change signals are compared for the selected climate indices for 2021–2050 and 2070–2099 with respect to 1976–2005 (Figure 10). Our results highlight an increasing frequency for SU along with a decreasing frequency for FD. The bias adjustment slightly affected the changes in climate indices, which effect is more evident for the far future. Bias adjustment was manifested in a stronger increase in SU and in a more modest decrease in FD for both time slices. Overall, RCMs projected greater decrease in FD (~50 days) than increase in SU (~44 days) by the end of the 21st century. Noting that, the number of frost days is also relevant for the energy sector and our results are in line with previous works (e.g., Coppola *et al.*, 2021; Vautard *et al.*, 2021).

5 | CONCLUSIONS

Temperature and temperature-related climate indices were analysed in this study for the Carpathian Region using CORDEX simulations. In the historical time period (1976–2005) mean temperature was underestimated by the RCM simulations in every season, except for summer. The bias adjustment was carried out on a seasonal basis and the reference was the CARPATCLIM dataset. After the correction, the variability between the individual RCM simulations decreased and the spatial distribution became more in line with observations (Figures 3 and 4), while the sign of the projected changes remained the same (Figure 9).

For 2021–2050 and 2070–2099 a remarkable annual temperature increase (on average 1.4°C and 3.9°C, respectively) is projected compared to 1976–2005 under the RCP8.5 scenario. The highest temperature rise is likely to occur in summer: it is 4.3°C on average by the end of the 21st century (however, the ensemble spread encompasses ~2°C). JJA warming has its maximum signal over the southern and its minimum over the northern parts of the Carpathian Region. In the mean winter temperature change, a gradient can also be detected, when the weakest warming is projected in the northeast and the strongest warming in the southwest territories. Seasonal temperature changes are robust and significant at the 90% confidence level in the entire domain regardless the season.

The number of SU and FD was also calculated for the region of interest, for the three 30-year long time slices as they might have important impacts on agriculture and health. In some countries in the Central European region a change of these indices is already detected. For example in most stations in Austria an increase of SU is experienced in the 1961–2000 time period (Nemec *et al.*, 2013). In Romania a significant increase of SU is detected (almost in the entire domain), and mainly in the central parts of the country and the southeastern regions the number of FD showed a significant decrease in 1961–2013 (Dumitrescu *et al.*, 2015). SU significantly increased (5.3 days per deacade) in Bosnia and Herzegovina as well between 1961 and 2015, while FD decreased by 3.3 days per decade (Popov *et al.*, 2018).

According to the present analyses, in the future time periods the number of SU will increase, while FD is likely to occur less frequently (Figures S8 and S9). Our results are in line with similar studies focusing on the European region. FD is projected to decrease by 26% in Europe, with the greatest absolute changes in the north western parts of the domain (Fallmann *et al.*, 2017). In Austria a general increase of SU is simulated by RCMs, it can exceed 40 days in the southeastern areas in the far future, in the case of RCP8.5 scenario (Olefs *et al.*, 2021). SU is

likely to increase in the near future in Croatia as well, especially in the coastal locations (by ~10 days; Brankovic *et al.*, 2012). RCM simulations show an increase in the number of SU and a decrease in the case of FD in Ukraine (Krakovska *et al.*, 2021), in Kolasin, Montenegro (Buric and Doderovic, 2020) and in Cluj Napoca, Romania (Ciupertea *et al.*, 2017).

As part of future studies, comparative investigations will be carried out over sub-regions within the Carpathian Region characterized by fundamentally different orography (lowland and mountainous). The bias-adjusted daily RCM data used for present study is publicly available at <https://doi.org/10.5281/zenodo.6393784>.

AUTHOR CONTRIBUTIONS

Csaba Zsolt Torma: Conceptualization; formal analysis; funding acquisition; investigation; methodology; supervision; validation; visualization; writing – original draft; writing – review and editing. **Anna Kis:** Investigation; validation; visualization; writing – original draft; writing – review and editing.

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