Representation of precipitation and temperature by 8 ERA-Interim driven EURO-CORDEX regional climate models in Slovakia

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Abstract: To assess regional climate models' ability to simulate future climate, their ability to represent observed historical climate should be evaluated first. This article evaluates the performance of 8 ERA-Interim reanalysis driven EURO-CORDEX regional climate models, comparing their simulations of daily precipitation totals, daily temperature averages, maxima and minima over Slovakia to gridded observations dataset CarpatClim. Slovakia has complex orography, ranging from lowlands to high mountains (94 to 2654 m ASL). The evaluation of regional climate models in this study is detailed, examining both ensemble and individual model bias, including bias in spatial and temporal distribution. The results of the evaluation show that precipitation and temperature are represented relatively well by the regional climate model ensemble. Despite that, the ensemble shows bias: for precipitation namely wet bias for winter and dry bias for summer precipitation, weaker precipitation-elevation correlations, overestimation of longer dry spells occurrence, and underestimation of longer wet spells occurrence; for temperature namely warm bias of hot extremes, overestimation of the annual cycle amplitude, general underestimation of daily temperature maxima, and overestimation of longer heatwaves and cold spells occurrence. The model ensemble average generally outperforms any single model. Notable individual model biases include the lack of representation of precipitation-elevation correlations by REMO2015 and a strong underestimation of temperature by RACMO22E.

Key words: regional climate models, model evaluation, EURO-CORDEX

1. Introduction

Numerical global climate models (GCMs) provide simulations of past and future climate change using radiative forcing scenarios as input. GCM simulations have coarse resolution (100 to 250 km over land, 50 to 150 km over oceans) and therefore need to be downscaled to provide useful regional climate information. Regional climate models (RCMs) are numerical models over a limited area, allowing higher resolution (typically 10–50 km). They

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are used to dynamically downscale GCM simulations, resulting in a more detailed representation of complex orography, coastal areas, land surface properties and mesoscale circulation (*Feser et al., 2011*). To properly evaluate the ability of RCMs to represent historical climate, their performance can be evaluated separately from GCM performance by driving the RCMs with a reanalysis instead of GCM simulations.

Multiple studies have evaluated the reanalysis driven EURO-CORDEX RCMs over Europe. The review below pertains to the higher-resolution 0.11° simulations, as were used in this study.

Kotlarski et al. (2014) found that the evaluated RCM ensemble has a cold bias over Europe for most seasons, apart from summer, when the ensemble is warmer over some regions, including Eastern Europe. They found European temperature spatial patterns to be well represented, however the spatial variability was found to be overestimated in summer and underestimated in winter; the temperature annual cycle was found to be overpronounced. For precipitation, they found the RCM ensemble to be wetter in winter for most of Europe, particularly central and eastern regions. European precipitation spatial patterns were found to be represented less well than temperature, the spatial variability was found to be overestimated in summer and winter, and the representation of precipitation annual cycle was found to be deficient particularly over central and eastern Europe.

Vautard et al. (2013) examined the representation of European heatwaves and found that the evaluated RCMs simulate heatwave events too persistent, with an overestimated amplitude. They also found the number of hot days and interannual variability of summer temperatures to be overestimated for central and southern Europe. *Lhotka and Kyselý (2018)* found that over central Europe in winter the evaluated RCMs show both positive and negative daily minimum temperature biases, but only negative maximum daily temperature biases. *Fantini et al. (2018)* found the evaluated RCM ensemble to generally represent precipitation well over Europe, including spatial patterns, the seasonal cycle, daily precipitation probability distribution and mean intensity. Still, they found the occurrence of high intensity events to be overestimated for multiple regions, including the Carpathian region. Additionally, over the Carpathian region, the RCMs were found to overestimate winter precipitation, mean daily precipitation intensity, and the fraction of total precipitation above the 0.95 quantile.

Torma (2019) evaluated the representation of temperature and precipitation over the Carpathian region. It was found that the evaluated RCMs show both positive and negative temperature bias and overestimate the temperature annual cycle amplitude. For precipitation an underestimation in summer and a slight overestimation in winter was found (compared to observations with a precipitation undercatch correction); spatial correlations with observations were found to be high in summer, but lower in winter; the probability distribution of daily precipitation was found to be represented well with the exception of the right tail, as the frequency of high intensity precipitation events was found to be overestimated.

As model bias is often region specific, a more detailed RCM evaluation for Slovakia is of interest for local applications. Furthermore, since the studies mentioned above have been published, additional simulations have been released (two additional RCMs, and three newer versions of RCMs). This article will evaluate the representation of precipitation and temperature by 8 EURO-CORDEX RCMs driven by ERA-Interim reanalysis over the area of Slovakia. Ch. 2 describes utilised data and methodology, ch. 3 presents results of the evaluation for precipitation (3.1) and temperature (3.2) and ch. 4 discusses and summarises the results.

2. Data and methodology

Regional climate model simulations

Reanalysis-driven simulations of 8 RCMs from EURO-CORDEX (the European branch of the Coordinated Regional Climate Downscaling Experiment; *Giorgi et al., 2009*) have been used for the analysis: ALADIN63 (AL) from Centre National de Recherches Météorologiques, CCLM4-8-17 (CC) and COSMO-crCLIM-v1-1 (CO) from Climate Limited-area Modelling Community, HadREM3-GA7-05 (HA) from Met Office Hadley Centre, HIRHAM5 (HI) from Danish Meteorological Institute, RACMO22E (RA) from Royal Netherlands Meteorological Institute, REMO2015 (RE) from Climate Service Center Germany and WRF381P (WR) from Institut Pierre-Simon Laplace. The simulations were accessed through the Copernicus C3S Climate Data Store (*Copernicus C3S, 2019a*). The RCMs were driven by ERA-Interim (*Dee et al., 2011*) over the CORDEX Europe domain. All RCMs resolution is 0.11° ($\sim$12.5 km).

Simulations of four climate variables were used: daily precipitation totals (PR), daily near-surface temperature average (TAS), daily near-surface temperature maximum (TASMAX) and daily near-surface temperature minimum (TASMIN), with time series spanning 1989–2005. In addition, RCM elevation data were used for all RCMs except WR, for which the elevation file was not available. As AL has a different grid from the other RCMs (with similar resolution), its' daily fields were first regridded to the common RCM grid using thin-plate spline interpolation. This regridding method was chosen, as it has been shown to perform better than methods based on averaging (*McGinnis et al., 2010*), which can cause substantial smoothing (*Rajulapati et al., 2021*).

Reference observations

As a reference for the evaluation, two observations-based datasets were considered: gridded observations dataset CarpatClim (*Spinoni et al., 2015*) and reanalysis ERA5-Land (*Muñoz-Sabater et al., 2021*). Gridded observations-based data were chosen over station data, because while RCM simulations represent area averages, station data represent points, which can cause discrepancies in climate variable distributions solely rooted in the scale gap between a point and an area average (*Director and Bornn, 2015*). From both CarpatClim and ERA5-Land time series of PR, TAS, TASMAX and TASMIN spanning 1961–2005 and elevation data were used. The data were accessed through the Copernicus C3S Climate Data Store (*Copernicus C3S, 2013, Copernicus C3S, 2019b, Copernicus C3S, 2024*). Both CarpatClim and ERA5-Land have a slightly higher resolution than the RCMs (0.1°). The datasets were therefore first regridded to the common RCM grid using thin-plate spline interpolation (the same process as for regridding AL).

CarpatClim and ERA5-Land were then compared to data from 11 stations (station data provided by the Slovak hydrometeorological institute). Based on the results of this comparison, CarpatClim was chosen as the reference dataset for the RCM evaluation (Table S1; tables and figures denoted S1–S6 can be found in the Supplement). CarpatClim was found to generally represent the station data well including trends. Differences from stations include weaker extremes, lower daily precipitation intensities and higher precipitation frequency, although these can be at least partially explained by spatial averaging. Furthermore, in comparison to station data Carpat-

Clim shows a slight underestimation/overestimation of daily temperature maxima/minima and a slight overestimation of winter precipitation. From here CarpatClim will be referred to as 'observations' or 'OBS'.

Study domain

In this study, RCMs performance was evaluated over Slovakia (Fig. 1). Slovakia has complex orography with elevation ranging from 94 to 2654 m ASL. To evaluate model performance over different orographic features, two subregions have been selected: *lowlands* and *mountains* (Fig. 1). The elevation average for Slovakia is very similar to observations for all RCMs (RCM/OBS = 0.99 – 1.00), but RCMs generally have moderately smoother orography than OBS (*lowlands* average RCM/OBS = 1.00 – 1.06, *mountains* average RCM/OBS = 0.90 – 0.96). CC, CO, HA have smoother orography than AL, HI, RA, RE, WR.

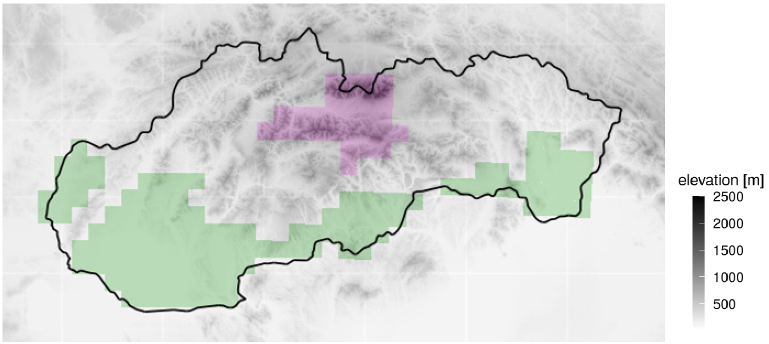


Fig. 1. Study domain – Slovakia and two selected subregions: lowlands (green) and mountains (Slovakia's highest mountains, pink).

Evaluated metrics

The evaluation of the RCMs for climate variables PR, TAS, TASMAX and TASMIN comprised out of four parts: 1) 1989–2005 area averages, 2) elevation dependence, 3) spatial distribution, 4) spell occurrences.

For the first part, a set of yearly statistics (statistics calculated for each year in the time series and each grid point) was temporally averaged over 1989–2005, then spatially averaged over Slovakia and subregions *lowlands* and *mountains*. The set of yearly statistics for precipitation includes yearly and seasonal sums (*Sum*, *SumMAM*, *SumJJA*, *SumSON*, *SumDJF*), number of days without precipitation (days with precipitation totals <0.1 mm, *DWOP*), quantiles of daily precipitation (calculated from days with precipitation totals ≥ 0.1, *Q10dwp*, *Q50dwp*, *Q90dwp*, *Q95dwp*), and yearly maximum of daily precipitation (*Max*). Note: before calculations, daily precipitation values for observations and RCMs were first rounded to one decimal point. The set of yearly statistics for temperature (TAS, TASMAX, TASMIN) includes yearly and seasonal means (*Mean*, *MeanMAM*, *MeanJJA*, *MeanSON*, *MeanDJF*), seasonal standard deviations of daily values (*SdMAM*, *SdJJA*, *SdSON*, *SdDJF*), yearly minimum and maximum of daily values (Min, Max), the 0.90 quantile of summer daily values (*Q90JJA*) and the 0.10 quantile of winter daily values (*Q10DJF*). This part of the evaluation serves as a base characteristic of RCM bias over Slovakia.

For the second part of the evaluation, the same set of yearly statistics was temporally averaged over 1989–2005, then correlations with elevation over all grid points in Slovakia were calculated for each statistic (the respective elevations for each RCM and observations). This part of the evaluation should verify, how well the RCMs represent the characteristic observed relationship of precipitation and temperature with elevation – generally observed precipitation increases and temperature decreases with elevation.

For the third part of the evaluation, again, the same set of yearly statistics was temporally averaged over 1989–2005. The resulting spatial fields for each statistic were then compared between observations and RCMs using Taylor diagrams (*Taylor, 2001*). In a single diagram, Taylor diagrams display spatial correlations between observed and simulated spatial fields, spatial variability of observed and simulated fields, and also the root-mean-square difference of the observed and simulated fields. This part of the evaluation examines the RCMs' ability to represent the observed spatial distribution of precipitation and temperature.

For the fourth and final part of the evaluation, occurrences of spells of different lengths were compared between observations and RCMs. Here, spells are defined as consecutive days with daily precipitation/temperature values above or below a certain quantile for the respective RCM/observations. Dry and wet spells are defined as consecutive days with daily precipitation under the 0.50 quantile and above the 0.90 quantile, respectively. The quantiles were calculated out of all days, including days without precipitation, so that the number of days above/below the thresholds is consistent between observations and all RCMs regardless of the precipitation frequency. Heatwaves and cold spells are defined as consecutive days with daily temperature maxima above the summer 0.90 quantile and daily temperature minima under the winter 0.10 quantile, respectively. The spell occurrences were calculated for each grid point and were subsequently spatially averaged over Slovakia.

3. RCM evaluation results

3.1. Daily precipitation totals (PR)

1989–2005 area averages

Table 1a shows averaged bias (expressed as ratio in % of RCMs and OBS) of different yearly precipitation statistics over Slovakia. As an ensemble the RCMs represent precipitation relatively well, as the ensemble average bias for all statistics is smaller than the observed interannual standard deviation. The ensemble average for yearly precipitation sum is close to observations (102% of OBS). However, the ensemble does show notable biases, particularly for seasonal sums: summer precipitation is underestimated (80% of OBS), and winter precipitation is overestimated (131% of OBS), resulting in a flatter annual cycle than observed. The RCMs have some trouble representing the number of days without precipitation (DWOP), as 5/8 RCMs show bias larger than the observed interannual standard deviation (77%–120% of OBS).

For the *mountains* area (Table 1b) some models show substantially larger biases, specifically AL, HI (strong overestimation) and RE (strong underestimation). However, the ensemble average bias for all statistics except *SumDJF* is still smaller than the interannual variability. For the *lowlands* area (Table S2) most RCM's biases are similar to their biases for the entire Slovakia.

Overall, the ensemble average shows better representation of observations than any single model. Out of the RCMs, CC performs the best, as all other models show substantial bias for some aspect of precipitation. AL, HI, and WR overestimate precipitation – AL and HI mainly over mountains (*Sum* 153%, 167% of OBS), WR for lowlands (*Sum* 126% of OBS). On the other hand, CO and RE underestimate precipitation – RE mainly over mountains (*Sum* 62% of OBS), CO for lowlands (*Sum* 82% of OBS); and

Table 1. 1989–2005 averaged bias (expressed as a ratio in % of RCMs and OBS) of precipitation statistics over a) Slovakia, b) *mountains* subregion; values in bold indicate bias larger than the observed interannual standard deviation.

a)	Sum	Sum MAM	Sum JJA	Sum SON	Sum DJF	DWOP	Q10 dwp	Q50 dwp	Q90 dwp	Q95 dwp	Max
AL	111	**131**	79	127	125	96	85	92	106	109	108
CC	100	119	**68**	102	**142**	101	116	105	96	97	110
CO	**84**	96	**51**	89	126	**120**	105	98	98	100	104
HA	103	113	72	106	**151**	**77**	75	**74**	86	89	103
HI	**118**	116	101	129	**142**	101	109	105	**114**	**119**	**141**
RA	98	101	81	100	128	**82**	85	**75**	**85**	87	102
RE	89	94	83	86	102	**109**	80	87	96	98	107
WR	**116**	**135**	102	106	**135**	**84**	112	110	101	98	94
AVG	102	113	80	106	131	96	96	93	98	100	109

b)	Sum	Sum MAM	Sum JJA	Sum SON	Sum DJF	DWOP	Q10 dwp	Q50 dwp	Q90 dwp	Q95 dwp	Max
AL	**153**	**182**	107	**179**	**176**	**79**	112	**144**	**132**	**130**	113
CC	100	119	**62**	109	**149**	104	120	114	98	97	103
CO	**83**	95	**49**	91	129	**126**	103	97	95	96	96
HA	99	109	**68**	112	**137**	**77**	**67**	**79**	87	89	99
HI	**167**	**175**	**140**	**184**	**195**	91	**134**	**149**	**152**	**156**	**168**
RA	95	99	77	103	120	**78**	80	**78**	**84**	86	96
RE	**62**	**63**	**57**	**58**	77	**132**	**63**	**60**	**77**	**79**	89
WR	102	110	77	98	**154**	93	101	98	98	95	95
AVG	108	119	80	117	**142**	98	98	102	103	103	107

[%] 250 100 40

simulate less frequent precipitation (*DWOP* 120%, 109% of OBS). HA and RA simulate more frequent precipitation (*DWOP* 77%, 82% of OBS) and smaller daily totals (*Q50* 74%, 75% of OBS).

Elevation dependence

Observed precipitation shows positive correlations with elevation (Table 2a) – strong for *Sum*, *SumMAM*, *SumJJA* (0.87–0.89), relatively weaker for *SumSON*, *Q50dwp*, *Q90dwp*, *Q95dwp*, *Max* (0.73 – 0.78), and only moderately strong for *SumDJF* and *Q10dwp* (0.64). *DWOP* are negatively correlated (−0.76).

Among RCMs, RE is an outlier and does not simulate any dependence between precipitation and elevation (correlations between −0.17 and 0.11), resulting in large bias (Table 2b). As an ensemble, the RCMs excluding RE represent the observed positive correlations with elevation relatively well (Table 2a), although the strength of the correlations is underestimated for all statistics except *SumSON* and *DWOP*, for which the strength is overes-

Table 2. a) Correlations of precipitation statistics with elevation – observations and RCM ensemble average excluding RE; b) Difference between RCM-simulated and observed correlation strengths (individual RCMs and ensemble average excl. RE); values in italics indicate simulated correlation of opposite sign than observed.

a)	Sum	Sum MAM	Sum JJA	Sum SON	Sum DJF	DWOP	Q10 dwp	Q50 dwp	Q90 dwp	Q95 dwp	Max
OBS	**0.87**	**0.89**	**0.89**	**0.73**	**0.64**	**-0.76**	**0.64**	**0.75**	**0.78**	**0.78**	**0.76**
**AVG	0.79	0.84	0.79	0.79	0.61	-0.85	0.61	0.66	0.63	0.61	0.59
b)											
AL	0.02	0.03	-0.02	0.17	0.14	0.14	0.07	0.05	0.10	0.10	0.09
CC	0.02	0.05	-0.10	0.17	0.17	0.10	0.14	0.05	-0.04	-0.07	-0.12
CO	-0.01	0.03	-0.08	0.11	0.06	0.11	0.02	-0.09	-0.10	-0.14	-0.24
HA	-0.16	-0.09	-0.12	-0.02	-0.26	0.06	-0.22	-0.19	-0.29	-0.31	-0.36
HI	-0.16	-0.17	-0.14	-0.04	-0.06	0.06	0.01	-0.14	-0.21	-0.20	-0.09
RA	-0.16	-0.12	-0.09	-0.04	-0.24	0.05	-0.19	-0.25	-0.35	-0.36	-0.33
RE	*-0.89*	*-0.94*	-0.78	*-0.88*	*-0.69*	-0.60	*-0.69*	*-0.92*	*-0.90*	*-0.89*	-0.71
**AVG	-0.07	-0.04	-0.09	0.06	-0.03	0.09	-0.03	-0.09	-0.15	-0.17	-0.18

1.00
0.00
-1.00

1.00
0.00
-1.00

timated. The underestimation of correlation strength is most apparent for extreme precipitation (*Max*, *Q95dwp*, *Q90dwp*; difference from OBS -0.18 to -0.15).

Concerning the representation of correlation strengths by individual RCMs – for sums, AL, CC and CO underestimate the correlation strength in summer and overestimate it in fall, winter and spring, whereas HA, HI and RA underestimate the correlation strengths for all seasons. *Q50dwp*, *Q90dwp*, *Q95dwp* and Max correlation strengths are underestimated by all RCMs except AL, which overestimates them. As WR had no elevation file available, it was excluded from the 'elevation dependence' section of evaluation.

Spatial distribution

Figure 2a shows a Taylor diagram for 1989–2005 averaged precipitation *Sum* spatial fields. Most RCMs represent the spatial distribution of precipitation yearly sums well; the ensemble average and 5/8 RCMs show high spatial correlations with observations ($\sim 0.8-0.95$) and spatial standard deviation similar to observations. These models also represent relatively well the spatial patterns of other precipitation statistics (seasonal sums, quantiles, *Max*, *DWOP*), however for extreme values (*Max*, *Q95dwp*, *Q90dwp*) the spatial correlations with observations are lower (~ 0.6) (Fig. 2b), and for *SumDJF*/*SumJJA* the models overestimate/underestimate the spatial

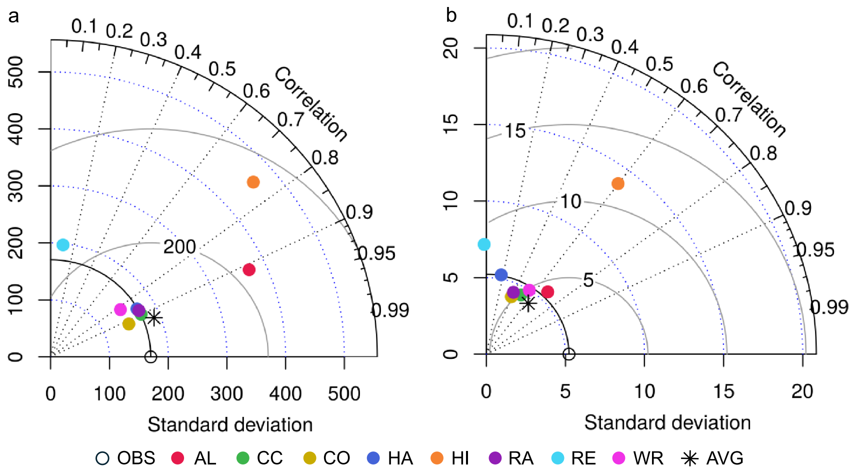


Fig. 2. Taylor diagram of observed and RCM-simulated 1989–2005 averaged a) precipitation *Sum* and b) precipitation *Max* fields.

standard deviation (Fig. S1).

The remaining three models – RE, HI, AL – show large differences from observations in spatial distribution of precipitation for all calculated statistics (sums, quantiles, *Max*, *DWOP*). An example of this is shown for *Sum* and *Max* in Fig. 2. RE shows very low spatial correlation with OBS (∼0.1). This is related to the model's inability to represent elevation dependence of precipitation (Table 2b, Fig. S2b). HI shows spatial standard deviation ∼2.5 times larger than observed, and lower spatial correlation with observations (∼0.7). Visually comparing HI precipitation *Sum* fields with OBS, it can be observed that for HI certain grid points over mountains have much higher values than their surrounding grid points, not corresponding to their difference in elevation (Fig. S2a). AL shows spatial standard deviation over 2 times larger than observed.

Spell occurrences

Table 3a shows the observed (averaged for Slovakia) number of wet spell events of different lengths and number of days within these wet spell events, and below that the ratio of simulated and observed number of days within the wet spells for each RCM. Here wet spells are defined as consecutive days with daily precipitation above the 0.90 quantile (the 0.90 quantile is 6.3 mm

Table 3. a) Wet spell occurrence (first two rows show number of observed wet spell events of different lengths (e.) and number of days within those events (d.) respectively, remaining rows show ratio of RCM-simulated and observed number of days within wet spell events expressed in %); b) Dry spell occurrence (equivalent to a)).

a)	l = 1	l = 2	l ≥ 3
OBS (e.)	**324**	**89**	**29**
OBS (d.)	**324**	**178**	**98**
AL	107	107	92
CC	109	104	88
CO	111	100	91
HA	108	101	98
HI	112	99	89
RA	111	101	90
RE	117	98	76
WR	118	91	84
AVG	112	100	88

b)	l = 1–7	l = 8–14	l ≥ 15
OBS (e.)	**918**	**73**	**11**
OBS (d.)	**2306**	**716**	**217**
AL	96	109	147
CC	94	116	121
CO	92	126	237
HA	102	93	95
HI	101	103	107
RA	99	106	96
RE	101	103	127
WR	99	78	158
AVG	98	104	136

[%]
250
100
40

for observations and 5.2 − 7.3 mm for the RCMs). From the table it is apparent that the RCMs overestimate the occurrence of one-day events (112% of OBS) and underestimate the occurrence of three-or-more-day wet spells (88% of OBS). RE and WR show highest bias, while HA performs best.

Table 3b shows an equivalent table for dry spells. Dry spells are defined as consecutive days with daily precipitation below the 0.50 quantile (the 0.50 quantile is 0.14 mm for observations and 0.03 − 0.32 mm for the RCMs). The table shows that the RCMs generally overestimate the occurrence of long (more than two weeks) dry spells (136% of OBS). CO, WR and AL show highest bias, while HA, HI, RE perform well.

3.2. Daily temperature averages, maxima and minima (TAS, TASMAX, TASMIN)

1989–2005 area averages

Table 4 shows averaged bias (expressed as a difference of RCMs and OBS) of different yearly temperature statistics over Slovakia. In general, the RCM ensemble represents temperature relatively well, as the ensemble average bias is smaller than the observed interannual standard deviation for most calculated statistics.

The RCM ensemble represents well the TAS yearly mean value (bias only −0.2 °C), but overestimates summer TAS (+0.8 °C and hot extremes (*Q90JJA* +1.5 °C, *Max* +2.2 °C, and underestimates winter TAS (−1.0 °C

Table 4. 1989–2005 averaged bias (expressed as a difference of RCMs and OBS) of a) TAS, b) TASMAX, c) TASMIN statistics over Slovakia; values in bold indicate bias larger than observed interannual standard deviation.

a)	Mean	Mean MAM	Mean JJA	Mean SON	Mean DJF	Sd MAM	Sd JJA	Sd SON	Sd DJF	Min	Q10 DJF	Q90 JJA	Max
AL	**0.7**	0.6	**2.1**	0.5	-0.6	0.1	**0.9**	0.5	-0.3	-0.5	0.1	**3.3**	**4.7**
CC	-0.4	-0.8	0.6	-0.4	-1.0	0.3	**0.5**	0.5	-0.4	-0.8	-0.6	1.1	**2.6**
CO	0.5	0.5	**1.5**	0.2	-0.1	0.4	**0.7**	0.6	-0.6	0.8	0.7	**2.6**	**3.5**
HA	-0.2	-0.7	**1.0**	0.0	-1.0	0.1	**0.5**	0.5	0.2	**-2.9**	-1.2	**1.7**	**2.3**
HI	-0.4	0.2	-0.1	-0.7	-1.2	0.3	0.2	0.4	0.3	-1.3	-1.5	0.3	0.2
RA	**-2.1**	**-2.4**	**-1.2**	**-1.8**	**-2.8**	0.7	0.2	0.3	0.1	**-3.5**	**-3.2**	-0.8	-0.4
RE	**0.6**	0.9	**1.1**	0.6	-0.1	0.0	0.3	0.5	-0.4	0.2	1.0	**1.3**	**2.0**
WR	-0.3	-0.7	**1.2**	-0.7	-1.0	0.8	**0.7**	**1.0**	0.2	**-2.2**	-1.1	**2.1**	**2.5**
AVG	-0.2	-0.3	0.8	-0.3	-1.0	0.3	**0.5**	0.5	-0.1	-1.3	-0.7	**1.5**	**2.2**

b)	Mean	Mean MAM	Mean JJA	Mean SON	Mean DJF	Sd MAM	Sd JJA	Sd SON	Sd DJF	Min	Q10 DJF	Q90 JJA	Max
AL	0.6	0.2	**1.7**	0.8	-0.2	-0.3	**0.8**	0.4	-0.2	-0.6	0.2	**2.8**	**4.5**
CC	**-1.5**	**-2.1**	-0.5	**-1.4**	**-2.1**	0.0	0.4	0.5	-0.5	**-2.2**	**-1.6**	-0.1	**1.8**
CO	-0.3	-0.5	0.8	-0.5	-1.2	0.0	**0.6**	0.7	-0.6	-0.7	-0.4	**2.0**	**3.2**
HA	**-0.8**	**-1.8**	0.6	-0.4	**-1.5**	-0.2	**0.6**	0.8	-0.4	-1.4	-1.1	1.5	**2.7**
HI	**-1.6**	-1.0	**-1.8**	**-1.8**	**-1.8**	-0.2	-0.1	0.0	0.2	**-2.8**	**-2.2**	**-1.9**	**-2.0**
RA	**-1.7**	**-1.9**	**-1.8**	**-1.2**	**-1.8**	-0.1	0.1	0.2	-0.2	**-2.5**	**-1.8**	-1.6	-0.8
RE	0.5	0.8	**1.2**	0.9	-0.9	0.0	0.3	**1.0**	0.1	-0.1	-0.3	1.4	**2.6**
WR	-0.5	**-1.1**	0.8	-0.3	-1.2	0.3	0.3	**1.0**	0.2	**-3.4**	-1.5	1.2	**2.1**
AVG	-0.7	-0.9	0.1	-0.5	-1.3	0.0	0.4	0.6	-0.2	-1.7	-1.1	0.7	**1.8**

[°C] 6 0 -6

c)	Mean	Mean MAM	Mean JJA	Mean SON	Mean DJF	Sd MAM	Sd JJA	Sd SON	Sd DJF	Min	Q10 DJF	Q90 JJA	Max
AL	0.3	0.3	**1.4**	0.2	-0.6	0.0	**0.6**	0.1	-0.5	1.0	0.4	**2.5**	**3.5**
CC	**0.8**	0.6	**1.8**	**0.8**	0.0	0.3	**0.3**	0.4	-0.6	2.2	1.0	**2.3**	**3.6**
CO	**1.5**	**1.8**	**2.1**	**1.2**	1.0	0.5	**0.5**	0.4	**-0.8**	**3.6**	2.3	**3.1**	**3.9**
HA	0.0	0.0	**0.8**	0.3	-1.0	0.2	0.2	0.3	**0.9**	**-4.7**	-2.1	**1.3**	**1.9**
HI	**0.9**	**1.5**	**1.7**	**0.8**	-0.5	0.5	0.1	0.5	0.0	1.0	-0.2	**2.0**	**2.3**
RA	**-2.6**	**-3.2**	**-1.3**	**-2.0**	**-3.8**	**1.1**	0.2	0.5	0.4	**-3.4**	**-4.2**	-0.8	-0.5
RE	**1.2**	**1.6**	**1.5**	**1.2**	0.8	-0.3	0.0	0.0	-0.3	-0.3	1.6	**1.6**	**2.2**
WR	-0.3	-0.5	**0.8**	**-0.8**	-0.8	0.6	**0.6**	0.7	0.0	-0.4	-0.5	**1.9**	**2.5**
AVG	0.2	0.3	**1.1**	0.2	-0.6	0.4	**0.3**	0.4	-0.1	-0.1	-0.2	**1.7**	**2.4**

and cold extremes (*Q10DJF* $-0.7\,°\mathrm{C}$, *Min* $-1.3\,°\mathrm{C}$ (Table 4a). These biases result in a more pronounced RCM-simulated annual TAS cycle than observed. The ensemble also overestimates the summer and fall TAS standard deviation ($+0.5\,°\mathrm{C}$). The summer and hot extremes biases are larger than the observed interannual standard deviation for 5/8 RCMs (6/8 for *Max*). In contrast to TAS, TASMAX is generally underestimated by the RCM ensemble, as yearly and seasonal means with the exception of summer show negative bias (-1.3–$-0.5\,°\mathrm{C}$) (Table 4b). For summer the RCMs show opposing biases, which result in an ensemble average bias close to 0. Other TASMAX statistics show similar bias to TAS (overestimation of hot extremes, summer and fall standard deviation and underestimation of cold extremes). For TASMIN, one RCM with a strong cold bias (RA) balances out the general warm bias from the rest of the ensemble, resulting in yearly, spring and fall TASMIN means ensemble average bias close to 0. Similarly to TAS, summer TASMIN is overestimated (+1.1 °C) and winter TASMIN is underestimated (−0.6 °C) by the ensemble. Hot TASMIN extremes show a positive bias similar to TAS, while cold TASMIN extremes show fairly large opposing biases resulting in an ensemble average bias close to 0.

For the *mountains* TAS, TASMAX and TASMIN area averages, compared to Slovakia averages, the RCMs simulate more pronounced negative winter mean and cold extremes biases, and less pronounced positive hot extremes biases (Table S3). The *lowlands* TAS and TASMIN area averages are similar to Slovakia averages for most RCMs and the ensemble. For the *lowlands* TASMAX area averages, compared to Slovakia averages, the RCMs simulate more pronounced positive hot extremes biases, and additionally simulate a positive summer mean bias (Table S4).

The ensemble average shows better performance than any single model. The comparatively best performing RCMs (when jointly considering Slovakia, *lowlands* and *mountains* area averages) differ between TAS and TASMAX – for TAS it is CC, for TASMAX it is CO. For TASMIN it is difficult to pick the best performing model, as all models show substantial bias for some aspect of TASMIN other than common biases. RA shows strong negative bias for all seasonal temperature means (up to −3.8 °C, Table 4), cold temperature extremes (up to −4.7 °C, Table S3), and also a slight negative bias for hot temperature extremes. Notably, it is the only model to simulate negative bias for most TASMIN statistics. AL shows strong positive bias for hot temperature extremes and summer temperature mean, particularly for *lowlands* (up to 5.7 °C, 2.9 °C, respectively) (Table S4). HA shows strong negative bias for cold TASMIN and TAS extremes, particularly for mountains (up to −8.6 °C) (Table S3).

Elevation dependence

Observed TAS shows strong negative correlations with elevation for all evaluated statistics except spring, summer and winter TAS standard deviations

(Table 5a). For *MeanDJF*, *Q10DJF*, *Min* and *SdSON* the correlations are strong ($-0.88 - -0.77$), and for *Mean*, *MeanMAM*, *MeanJJA*, *MeanSON*, *Q90JJA* and *Max* the correlations are very strong ($-0.98 - -0.96$). *SdMAM*, *SdJJA* and *SdDJF* show weak positive correlations with elevation.

The RCMs represent well the correlations for yearly and seasonal means, and hot extremes (the ensemble average shows no bias) (Table 5b). The strengths of the negative correlations of Min, and to a lesser extent *Q10DJF* are overestimated by the RCM ensemble (+0.12, +0.04, respectively). The RCM ensemble underestimates the strength observed negative *SdSON* correlation, however four of the models (AL, CC, CO, HI) show very low bias, while the remaining models (HA, RA, RE) show high bias. The correlations for *SdMAM*, *SdJJA* and *SdDJF* are clearly not represented well by the RCM ensemble.

Table 5. a) Correlations of TAS statistics with elevation – observations and RCM ensemble average; b) Difference between RCM-simulated and observed correlation strengths (individual RCMs and ensemble average); values in italics indicate simulated correlation of opposite sign than observed.

a)	Mean	Mean MAM	Mean JJA	Mean SON	Mean DJF	Sd MAM	Sd JJA	Sd SON	Sd DJF	Min	Q10 DJF	Q90 JJA	Max
OBS	-0.97	-0.97	-0.98	-0.97	-0.88	0.26	0.30	-0.84	0.23	-0.77	-0.85	-0.96	-0.96
AVG	-0.97	-0.98	-0.97	-0.97	-0.88	0.33	*-0.25*	-0.68	0.46	-0.88	-0.89	-0.96	-0.96
b)													
AL	0.01	0.01	0.00	0.00	0.04	*-0.52*	*-1.06*	0.04	0.63	0.18	0.08	0.01	0.02
CC	0.01	0.01	-0.01	0.01	0.03	-0.13	*-0.30*	0.02	0.12	0.13	0.07	-0.01	-0.01
CO	0.00	0.01	-0.01	0.00	0.05	0.28	*-0.64*	-0.05	-0.04	0.18	0.10	-0.02	-0.02
HA	0.01	0.01	0.00	0.00	0.05	0.53	*-0.77*	-0.52	0.61	0.16	0.08	0.01	0.01
HI	0.01	0.01	0.01	0.00	-0.02	0.27	-0.05	0.01	*-0.51*	0.11	-0.02	0.02	0.02
RA	-0.05	-0.05	-0.03	-0.04	-0.09	*-0.29*	*-0.50*	-0.20	0.52	0.07	-0.03	-0.04	-0.05
RE	-0.01	0.00	-0.01	-0.02	-0.06	0.31	*-0.50*	-0.46	0.31	-0.01	-0.01	0.00	-0.01
AVG	0.00	0.00	-0.01	-0.01	0.00	0.06	*-0.55*	-0.17	0.23	0.12	0.04	0.00	-0.01

1.00
0.00
-1.00

1.00
0.00
-1.00

For TASMAX, the observed correlations with elevations and the RCM performance are similar to TAS (Table S5). For TASMIN, the observed correlations with elevations and the RCM performance are also similar to TAS, with the exception of *Min*, *SdSON* and *SdDJF* (Table S6). The observed TASMIN Min negative correlation with elevation is weaker than for TAS (-0.63), but he RCMs simulate a similar correlation as for TAS (-0.87), resulting in larger bias. The observed TASMIN *SdSON* negative correlation is also weaker than for TAS (-0.51) and is not represented well by the RCMs.

As WR had no elevation file available, it was excluded from the 'elevation dependence' section of evaluation.

Spatial distribution

Figure 3a shows a Taylor diagram for 1989–2005 averaged TAS *Mean* spatial fields. The RCMs represent the spatial distribution of TAS yearly mean well; all models show very high spatial correlations with observations ($\sim 0.95-0.99$). The ensemble average slightly overestimates the spatial standard deviation, the largest overestimation is by AL. This description of RCM performance can be generalised to other TAS statistics (seasonal means, hot and cold extremes), although for *MeanDJF*, *Q10DJF* and *Min* the overestimation of the spatial standard deviation by HA and AL is more pronounced, and HA shows the largest bias; for TAS *Q10DJF* and *Min*, the spatial correlations are lower ($\sim 0.8-0.95$) (Fig. 3b).

For TASMAX, the results are similar to TAS, but AL is the model with largest overestimation of spatial standard deviation for all TASMAX statistics (means, hot and cold extremes), closely followed by CO for hot extremes (Fig. S3a,b). For TASMIN, the results are, again, similar to TAS, but WR shows a substantial underestimation of spatial standard deviation, particularly for summer mean and hot extremes, which causes the ensemble average to show smaller bias (Fig. S3c,d). Furthermore, for cold TASMIN extremes,

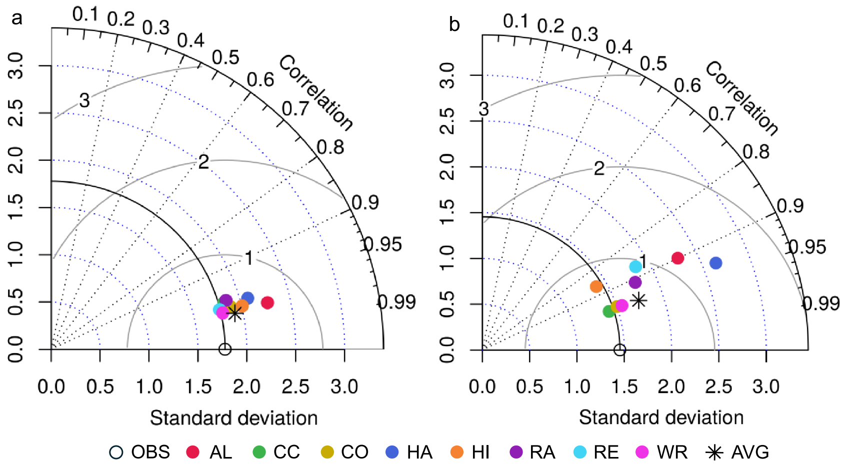


Fig. 3. Taylor diagram of observed and RCM-simulated 1989–2005 averaged a) TAS *Mean* and b) TAS *Q10DJF* fields.

the RCMs show lower spatial correlations (0.7 – 0.9 for *Min*) and a larger spatial standard deviation bias spread, with RE and RA showing large overestimation (Fig. S3e).

Spell occurrences

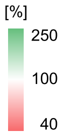
Table 6a shows the observed (averaged for Slovakia) number of heatwave events of different lengths and number of days within these heatwave events, and below that the ratio of RCM-simulated and observed number of days within the heatwaves for each RCM. Here heatwaves are defined as consecutive days with TASMAX above the summer 0.90 quantile (the summer 0.90 quantile is 29.3 °C for observations and 27.3 – 32.7 °C for the RCMs). The table shows that the RCMs underestimate the occurrence of 3 to 4-day heatwaves (72% of OBS) and overestimate the occurrence of longer heatwaves (138% of OBS). AL, RA and WR show highest bias, while CC performs best among the RCMs.

Table 6b shows an equivalent table for cold spells. Cold spells are defined as consecutive days with TASMIN below the winter 0.10 quantile (the winter 0.10 quantile is −11.9 °Cfor observations and −16.1 – −9.4 °C for the RCMs). The table shows that the RCMs underestimate the occurrence of shorter cold spells (1 to 2-day 93% of OBS, 3 to 4-day 79% of OBS) and overestimate the occurrence of longer cold spells (139% of OBS). AL, CO, HI and WR are models with higher bias, while CC, HA, RA and RE perform comparatively better.

Table 6. a) Heatwave occurrence (first two rows show number of observed heatwave events of different lengths (e.) and number of days within those events (d.) respectively, remaining rows show ratio of RCM-simulated and observed number of days within heatwave events expressed in %); b) Cold spell occurrence (equivalent to a)).

a)	l=1–2	l=3–4	l≥5
OBS (e.)	**29**	**12**	**5**
OBS (d.)	**62**	**57**	**38**
AL	93	52	183
CC	102	84	121
CO	97	71	148
HA	93	75	149
HI	120	83	93
RA	120	61	126
RE	113	76	116
WR	84	70	168
AVG	103	72	138

b)	l=1–2	l=3–4	l≥5
OBS (e.)	**25**	**10**	**6**
OBS (d.)	**58**	**53**	**41**
AL	85	83	145
CC	79	101	130
CO	96	67	150
HA	96	82	131
HI	90	75	149
RA	99	83	124
RE	104	76	127
WR	92	68	154
AVG	93	79	139



4. Summary, discussion and conclusions

This paper compared simulations of 8 EURO-CORDEX RCMs driven by ERA-Interim reanalysis to gridded observations dataset CarpatClim in order to evaluate the RCMs' representation of temperature and precipitation over Slovakia. Evaluation metrics included area averages (Slovakia, *mountains*, *lowlands*), elevation dependence and spatial distribution of multiple PR, TAS, TASMAX and TASMIN yearly and seasonal statistics. In addition, occurrence of wet/dry spells, heatwaves and cold spells was examined.

The results show that precipitation 1989-2005 area averages (Table 1) are represented relatively well by the RCM ensemble, as the ensemble average bias is mostly smaller than the observed interannual standard deviation, and is close to zero for yearly precipitation. The ensemble still shows notable biases, namely underestimation of summer precipitation and overestimation of winter precipitation. Furthermore, most of the RCMs misrepresent precipitation frequency. Overall, the RCM ensemble average outperforms any single RCM. Out of the RCMs, CC performs the best, as all other models show substantial bias for some aspect of precipitation. AL, HI and WR overestimate precipitation, while CO and RE underestimate precipitation and simulate lower precipitation frequency. HA and RA simulate higher precipitation frequency and smaller daily totals.

Observed precipitation-elevation correlations (Table 2) are qualitatively represented by all RCMs excluding RE, but their strength is underestimated by the RCM ensemble for most calculated statistics. RE simulates no correlation between precipitation and elevation. The spatial distribution of precipitation (Fig. 2) is represented well by 5 of the 8 RCMs – high spatial correlations with observations, and spatial standard deviation similar to observations for precipitation yearly sum and most other precipitation statistics. However, the spatial correlations are lower for extreme precipitation, and for winter/summer models overestimate/underestimate the spatial standard deviation. The three remaining models, RE, HI and AL, show large differences from observations in spatial distribution of precipitation for all calculated statistics, which are related to large biases of these models over the mountain subregion. For wet spells (Table 3a) the RCMs underestimate the occurrence of wet spells three days or longer while overestimating the occurrence of one-day events. As an ensemble, the RCMs also overestimate the occurrence of dry spells longer than two weeks (Table 3b).

The results for temperature 1989–2005 area averages show that the RCM ensemble represents temperature relatively well, as the ensemble average bias is smaller than the observed interannual standard deviation for most calculated statistics (Table 4). The TAS yearly mean is represented well, but the ensemble overestimates the summer mean and hot extremes, and underestimates the winter mean and cold extremes. Also overestimated are the summer and fall standard deviation. In contrast to TAS, TASMAX is generally underestimated by the RCM ensemble, as the yearly and seasonal means excluding summer show negative bias. Other TASMAX statistics show similar bias to TAS. For TASMIN yearly, spring and fall means, one RCM with a strong cold bias (RA) balances out the general warm bias of the rest of the ensemble, resulting in low ensemble average bias. Summer, winter and hot extremes biases for TASMIN are similar to TAS, while for cold TASMIN extremes the RCMs show large opposing bias, again resulting in low ensemble average bias. Overall, the ensemble average shows better performance than any single model. Out of the RCMs, the comparatively best performing model is CC for TAS and CO for TASMAX, for TASMIN the choice is ambiguous. Particularly large bias is shown by RA – strong negative bias for all seasonal temperature means, and cold temperature extremes.

Observed temperature-elevation correlations (Table 5) for yearly and seasonal means, and hot extremes are well represented by the RCM ensemble. The strengths of correlations of cold temperature extremes with elevation are overestimated (particularly for TASMIN), while the strength of correlation of fall temperature standard deviation is underestimated. Correlations of other seasonal temperature standard deviations are not well represented by the RCM ensemble. The spatial distribution of temperature is relatively well simulated (Fig. 3) – the spatial correlations with observations are high for all RCMs, however the ensemble slightly overestimates the observed spatial standard deviation. AL, HA (and WR for TASMIN) are models with the largest spatial standard deviation bias. For both heatwaves and cold spells, the RCMs overestimate the occurrence of events 5 days or longer and underestimate the occurrence of shorter events.

A number of these findings are in agreement with results of previous studies evaluating reanalysis driven RCMs over central/eastern Europe (ch. 1): positive TAS bias in summer and good representation of TAS spatial patterns (*Kotlarski et al., 2014*), wet winter precipitation bias when compared to observations without an undercatch correction (*Kotlarski et al., 2014; Fantini et al., 2018*), overestimation of the amplitude of the annual temperature cycle (*Kotlarski et al., 2014; Torma, 2019*), dry summer precipitation bias (*Torma, 2019*), underestimation of daily temperature maxima (*Lhotka and Kyselý, 2018*) and too persistent heatwaves (*Vautard et al., 2013*).

There are a couple of factors that add uncertainty to the presented results of the RCM evaluation. Firstly, it has been shown that gridded observation-based datasets can show considerable differences, leading to uncertainty that can in some cases be comparable to RCM bias (*Prein and Gobiet, 2017*). For this reason, it is imperative that the reference dataset for evaluation of RCMs is of high quality and representative of the actual climate. In this study, to utilise a dataset with best possible quality, two candidate datasets – CarpatClim and ERA5-Land were compared to station observations, and CarpatClim was chosen based on the results (ch. 2). It should be noted that neither CarpatClim nor the stations which it was compared to have a correction for precipitation measurement errors (undercatch). Precipitation undercatch in observations, especially for winter solid precipitation, can cause underestimation up to 25% (*Lapin et al., 1991; Adam and Lettenmaier, 2003*). Secondly, ALADIN63 and CarpatClim data had to be regridded to the common RCM grid. The regridding was done using the thin-plate splines interpolation method (ch. 2), and the choice of the regridding method is associated with additional uncertainty. Finally, the imperfect representation of historical climate by the ERA-Interim reanalysis utilised to drive the RCMs may have caused differences between observations and RCM simulations unrelated to RCM performance. A detailed analysis of uncertainty added by these factors is beyond the scope of this study but is an important topic for further research.

This study evaluates RCMs form an 'older' generation of EURO-CORDEX (CMIP5/ERA-Interim driven), as at the time of writing, new EURO-CORDEX simulations (CMIP6/ERA5 driven) have not yet been released. However, the results of this study can be used in the future to assess improvements of the newer generation of models compared to the previous generation.

As is evident from the results of this study and previous research, climate models show bias in comparison to observations, which then complicates the application of climate model projections. To reduce bias, numerous bias correction methods have been developed (e.g. *Gutiérrez et al., 2018*), including recent avenues such as deep learning-based correction (*Wang and Tian, 2022*). This study can also serve as a baseline for evaluation of bias correction methods.

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