GCRI contribution to INDECIS D6.2:

Intercomparison of selected ECVs and indecis for the area of the Czech Republic

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1. Introduction

High-resolution information about future climate is needed for a proper adaptation and mitigation of the impacts of the climate change and variability. To obtain climate change information at the regional to local scale, different downscalling techniques are applied on GCMs (global climate models) outputs. Dynamical downscaling using a regional climate model (RCM) is an example of such a technique. The availability and reliability of RCM simulations for Europe has increased rapidly in recent years thanks to projects like PRUDENCE, STARDEX, ENSEMBLES and recently NARCCAP or CORDEX. However, RCMs feature considerable systematic errors, which hamper easy application of RCM results in climate change impact research.

Since model outputs suffer from systematic errors, it is necessary to correct them to obtain meaningful results on the simulated properties of the climate system. Especially for analysis of daily data and extreme values (like temperature maxima and minima, precipitation values over given thresholds, etc.), here the wrong statistical distribution of a given meteorological element simulated by a model may lead to wrong conclusions. To cope with distorted statistical moments of different order, generally the whole distribution, different model correcting techniques are applied (list of them is given e.g. in Themessl et al., 2012).

In this contribution we concentrate on validation of RCM's in the area of the Czech Republic. We analyzed 11 experiments coming from pair combination of 5 GCM and 5 RCM available within the Euro-CORDEX project (described later).

For the data processing, the software packages AnClim (Štěpánek, 2008), LoadData and ProClimDB (Štěpánek, 2010) were used. They offer complex solution, from tools for handling databases, through data quality control to homogenization of time series, as well as time series analyses, extreme value evaluation and model output verification and correction. The software is available on the web page www.climahom.eu.

2. Data and Methods

2.1. Station data.

For proper validation of RCM outputs and their later correction, proper reference datasets has to be used. Quality of reference datasets influences results (quality) of validation and correction of model outputs. If station data of high quality exists, such an option is naturally the best one that can be chosen. Applying ECA&D (its public version) or gridded E-OBS dataset is suitable in cases when proper station data are not available. In our case, we were able to work with station network data (coming from the Czech hydrometeorological institute), from which only certain portion is used for ECA&D creation and from which then E-OBS dataset is calculated.

When working with raw station data, first of all they should be subject of thorough quality control. Data quality control applicable on large datasets was developed by Štěpánek et al. (2009). The automation of the process (preserving good ratio of true and false alarms) has been achieved through combination of several methods of temporal and spatial analysis.

After the erroneous data are removed from the series during the quality control, the series are subject of homogenization applying several statistical tests for detection of inhomogeneities and found discontinuities are corrected in daily scale (again, several methods are applied to decrease uncertainty of the correction estimates). Further details about the homogenization can be found e.g. in Štěpánek et al. (2013) or documentation of the software (Štěpánek, 2010). Quality control and correction of inhomogeneities have been performed on a daily (sub-daily) basis for all key meteorological variables over the territory of the Czech Republic since 1961 (also for neighbouring countries, such as the Slovak Republic or Austria, within international projects).

After the quality control and homogenization, missing values were filled. The calculation of the "new" values was based on geostatical interpolation methods, improved by standardization of neighbor stations values to altitude of a given location by means of regional regression analysis (Štěpánek et al., 2011). Parameters settings of the calculation differ for each meteorological element and optimal settings were found by means of cross validation.

Data quality control, homogenization and filling missing values lead to the creation of the so-called "technical" series for mean, maximum and minimum temperatures, precipitation totals, sums of sunshine duration, relative humidity (mean water vapour pressure) and wind speed. They were calculated for 268 climatological and 787 rain-gauge stations of the CHMI network in the 1961–2018 period and actual values are continually added (for station locations please see Fig. 1). Despite the fact that a smaller number of stations was available for some of the studied characteristics (e.g. for sunshine duration or water vapour pressure), "technical" series were completely calculated (for arbitrary station location or regular gridded network – CZgrid dataset). In this way, we have a complex set of meteorological variables for each position of climatological station, which may be easily applicable for any climate analysis or impact study in this territory.

2.2. Model simulations

Our analysis of model outputs is based on regional climate model (RCM) simulations prepared within the European part of the global Coordinated Regional Climate Downscaling Experiment (CORDEX, www.cordex.org). The European domain of CORDEX is covered within the frame of

Euro-CORDEX sub-project (www.euro-cordex.net). Model experiments are performed here with two spatial resolutions: 0.44 degree and 0.11 degree. In our contribution we focus only on 0.11 degree resolution experiments. Following RCMs have been used in our study: ALADIN53, CCLM4-8-17, HIRHAM5, RACMO22E and RCA4. Two of five RCMs were driven by more than one GCM. These Euro-Cordex experiments were those first available to broader scientific community (already in 2015, compared to about 19 in 2019).

Table 1. Selected Euro-CORDEX experiments of regional and their driving global models.

RCM	Driving GCM	Scenarios
ALADIN53	CNRM-CM5	RCP4.5, RCP8.5
CCLM4-8-17	CNRM-CM5	RCP4.5, RCP8.5
	EC-EARTH	RCP4.5, RCP8.5
	MPI-ESM-LR	RCP4.5, RCP8.5
HIRHAM5	EC-EARTH	RCP4.5, RCP8.5
RACMO22E	EC-EARTH	RCP4.5, RCP8.5
RCA4	CNRM-CM5	RCP4.5, RCP8.5
	EC-EARTH	RCP2.6, RCP4.5, RCP8.5
	HadGEM2-ES	RCP4.5, RCP8.5
	IPSL-CM5A-MR	RCP4.5, RCP8.5
	MPI-ESM-LR	RCP4.5, RCP8.5

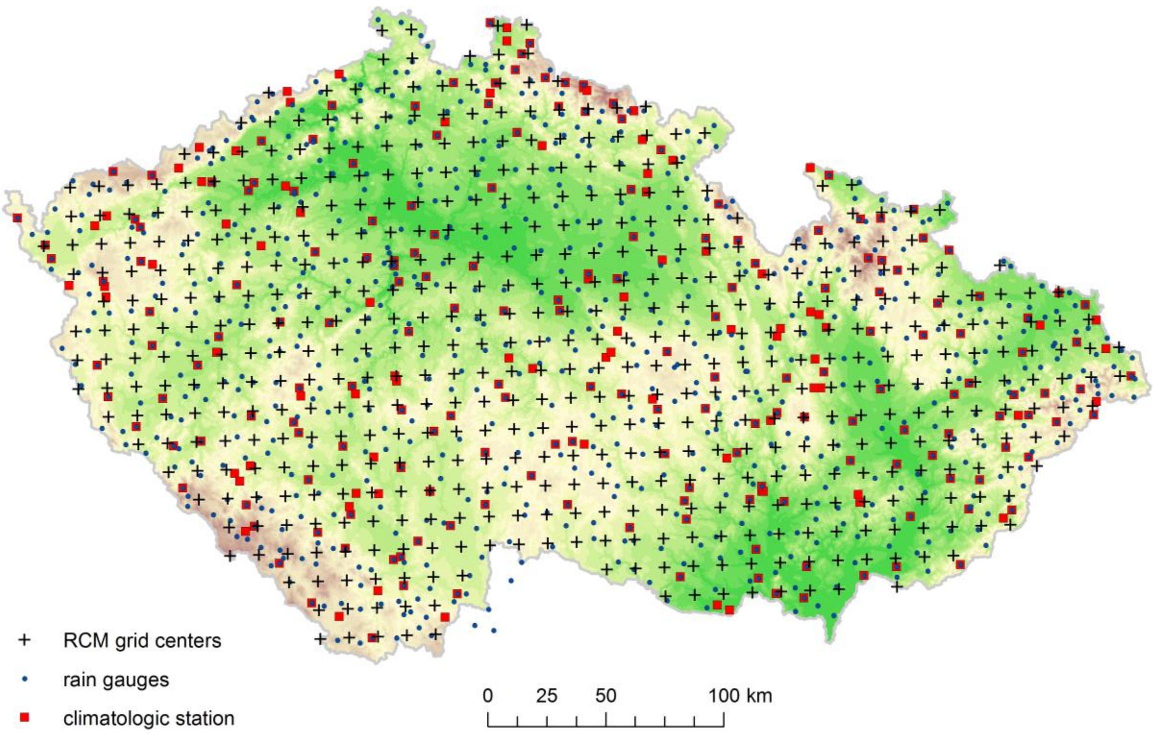

Fig. 1. Network of climatological (red squares) and precipitation stations (blue circles) together with positions of grid points of 0.11° Euro-CORDEX simulations (black crosses).

2.3. Bias correction

The climate simulated by numerical models shows systematic deviations from reality (true observed climate) which limits their applicability for impact models. Therefore, climate model outputs have to be post-processed to match the observed climate (Maraun, 2013, Christensen et al. 2008). One common way to deal with model errors in climate change impact studies is the "delta change approach". Besides the delta approach, more sophisticated RCM post-processing methods have been proposed and evaluated, their list is given e.g. in Themessl et al. (2012). These approaches belong to the family of Model Output Statistics (MOS), a concept developed in weather forecasting and now commonly used in climate science (Maraun et al. 2010).

In a comprehensive inter-comparison study of seven DECMs ("empirical statistical downscaling and error correction methods") for daily precipitation from a 10 km resolved RCM, Themessl et al. (2011) conclude that quantile mapping (QM) outperforms all other investigated DECM. Distribution mapping method was recommended as the best-performing correction method also by Teutschbein and Seibert (2013), where various bias correction techniques have been compared (Delta-Change Correction, Linear Transformation, Local Intensity Scaling (LOCI), Power Transformation, Variance scaling, Distribution Mapping), finding that QM was best able to cope with non-stationary conditions. Based on these results, QM was chosen for the bias correction purposes.

In our approach we come from quantile matching as described in Déqué (2007). It is applied as parameter-free (using empirical cumulative density distributions, ecdfs, rather than theoretical cumulative distribution functions). An empirical method is recommended over the parametric one since the latter one is not robust enough given the limited length of the time period (Gutjahr and Heinemann, 2013), and also, using theoretical distribution QM becomes less flexible in its application to different parameters and regions as a priori information about the shape of the probability density functions is needed (Themessl et al., 2012).

Based on validation of the QM method within model control runs, we further adopted some settings that suit best for the purpose of bias correction of various meteorological elements (including precipitation which are difficult to handle on both distribution tails). They are described with more details e.g. in Stepanek et al. (2016).

The QM method was applied on daily basis and for each grid cell / location separately. Correction for was performed using to the first (nearest) neighbor.

3 Results

3.1 Comparison of ECVs

As mentioned above, models suffer from biases. Given our knowledge about physical processes in atmosphere, computational possibilities etc., results usually have similar problems within the same group of models. Kotlarski et al. (2014) summarizes some of these biases evaluated from the ERAInterim-driven Euro-CORDEX regional climate models, like predominant cold and wet bias in most seasons and over most parts of Europe and a warm and dry summer bias over southern and southeastern Europe reflect common model biases. The other well-known issue concerns dry-day frequency being systematically underestimated by climate models, the frequency of light precipitation events between 0.1 mm/d and 1 mm/d ("drizzling-effect"; e.g. Gutowski et al. 2003),) as well as of heavy precipitation events are mostly overestimated by models (Themessl et al., 2012). We confirm similar bias patterns in our results for the Czech Republic, as follow from the following text.

Biases between prediction and reality were analyzed, in detail, mainly for five selected experiments. Control run were compared with real meteorological data. For spatial comparison, maps with values interpolated into 500m resolution were obtained, individually for each data source (station or model grid points).

3.1.1 Air temperature

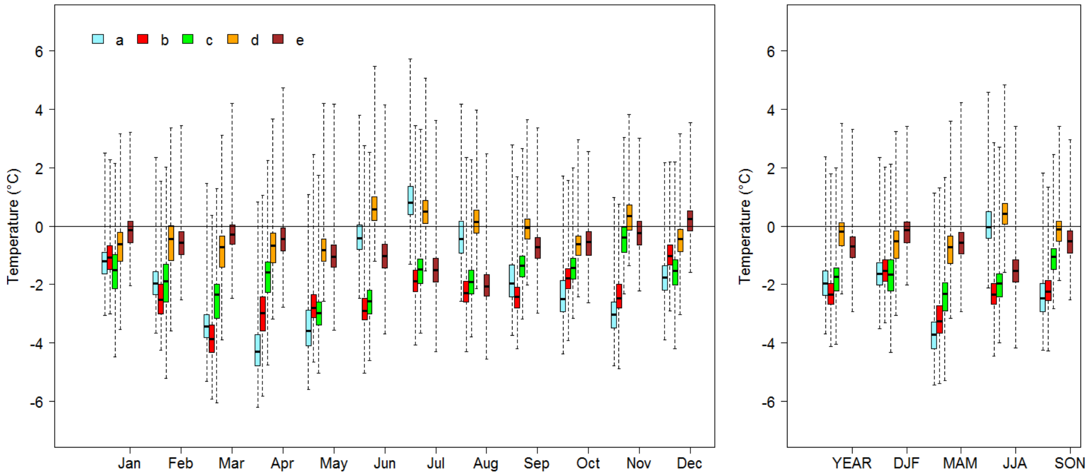

Fig. 2. Temperature bias, difference between original (uncorrected) model and reality, for 5 experiments: ***a****: CNRM-CM5_ALADIN (1961-2005),* ***b****: EC-EARTH_RACMO (1961-2005),* ***c****: EC-EARTH_RCA (1970-2005),* ***d****: HadGEM2-ES_RCA (1970-2005),* ***e****: MPI-ESM-LR_CCLM (1961-2005)*

Air temperature is underestimated by uncorrected models (Tab. 2). The highest differences were observed for the experiment EC-EARTH_RACMO. Average annual temperature is about 2.2°C lower than reality. In the spring it is underestimated even about 4°C. Lowest biases were achieved by HadGEM2-ES_RCA. The difference from reality is only -0.2°C. Overall for all the five selected experiments, the largest discrepancies were found in spring season (Fig. 2).

Table 2. Model bias for air temperature (°C) as difference between original (uncorrected) model and reality, areal averages for different altitudes

Altitude in m	CNRM-CM5 ALADIN	EC-EARTH RACMO	EC-EARTH RCA	HadGEM2-ES RCA	MPI-ESM-LR CCLM
0-300	-2	-2.46	-1.81	-0.3	-0.7
300-600	-1.92	-2.21	-1.76	-0.24	-0.66
600-900	-1.39	-1.92	-1.6	-0.06	-0.43
900-1200	-0.51	-1.42	-1.19	0.34	0.18
nad 1200	0.37	-0.4	-0.32	1.23	1.23
whole CZ	-1.83	-2.21	-1.74	-0.21	-0.62

Bias analysis was performed also with regards to different altitudes. We chose five levels – up to 300 m, 301–600 m, 601–900 m, 901–1200 and altitudes above 1200 m. The results are surprising. Highest model biases are observed within lower altitudes (up to 300 m), on the contrary for mountain regions model simulations are relative non-biased. Two experiments are different, HadGEM2-ES_RCA and MPI-ESM-LR_CCLM, which show quite accurate results. On the other hand, these two experiments in the highest mountains overestimate the temperature (Fig. 3).

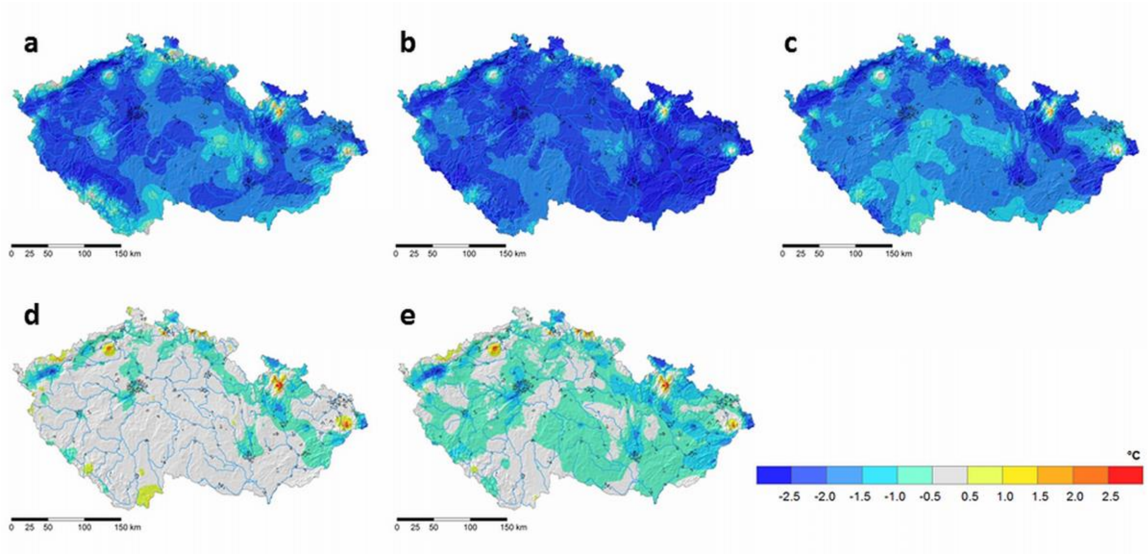

*Fig. 3. Temperature bias for 5 experiments: **a**: CNRM-CM5_ALADIN (1961-2005), **b**: EC-EARTH_RACMO (1961-2005), **c**: EC-EARTH_RCA (1970-2005), **d**: HadGEM2-ES_RCA (1970-2005), **e**: MPI-ESM-LR_CCLM (1961-2005).*

For a selected experiment (*EC-EARTH_RACMO22*) we tested whether the bias is constant or changes over time. Spatial biases for different decades of the control run are shown on Fig. 4. The biggest underestimation is observed in case of older values. Bias of about -2.5°C is found for the period 1961-1970 (Tab. 3), while bias of only -2°C is found in the last years of the control run (1991-2005). This means that modeled air temperature increase in the current climate is more rapid than it is in reality.

Tab. 3. Model bias for air temperature (°C) as difference between original (uncorrected) EC-EARTH_RACMO22 and reality, areal averages for the Czech Republic

Decade	average	minimum	maximum
1961-1970	-2.46	-4.18	0.38
1971-1980	-2.27	-4.11	0.66
1981-1990	-2.1	-3.89	0.84
1991-2000	-2.09	-3.8	0.97
2001-2005	-1.9	-3.69	1.28

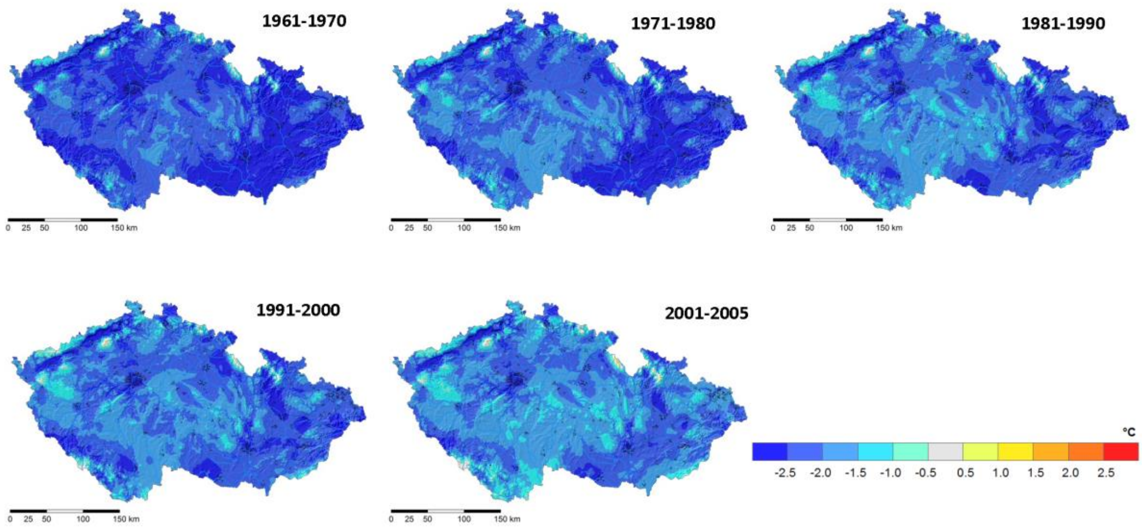

Fig. 4. Temperature bias for EC-EARTH RACMO, for indivivual periods (decades).

To better assess possible change based on all the available model simulations, from individual corrected model outputs an ensemble mean was created and is further worked with. Before creating ensemble mean, values of individual experiments were smoothed with 10 year low-pass Gaussian filter to get rid of incomparable individual yearly values.

To comprehensibly estimate change in climate for the whole area of the Czech Republic, simple means over all possible grid points were calculated. This is based on assumption that such spatial mean estimates are comparable. To answer a possible question about the role of locations density in the estimation of such areal average for the Czech Republic, we thoroughly compared results coming from several versions of datasets later used for the analysis. We have compared, for 30 years period (1981-2010), several characteristics: air temperature, number of tropical days, precipitation sum and number of days with precipitation 1 mm and higher. As reference dataset we used areal average based on 500m resolution grid layer obtained through geostatistical interpolation, namely regression kriging applying dependence of input station data (268 for temperature, 787 for precipitation) on various terrain parameters. Further datasets are: 523 grid points of Euro-CORDEX simulations – simple average over these values, and averages over 268, reps. 787 station locations. When comparing results from these four data sources, the results are practically the same, with difference maximum 0.1°C for air temperature or 4% in case of precipitation or number of days.

Fig. 5 shows fluctuations of air temperature for the whole Czech Republic according to original and bias-corrected model outputs. As for a level, corrected model outputs are in accordance with station measurements (black line). Raw model outputs are about 1°C lower than is reality. Different level of raw RCP2.6 values (compared to RCP4.5 and RCP8.5 within control run) is caused by different number of available models than is the case for RCP4.5 and RCP8.5, but anyway, after bias correction the level is again the same as reality.

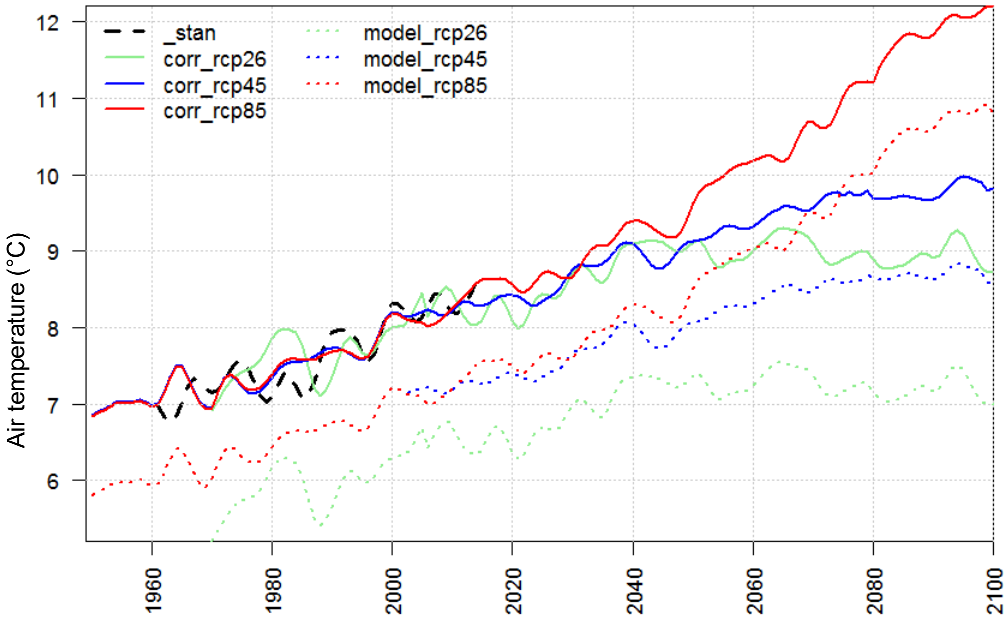

Fig. 5. Fluctuations of annual air temperature according to average of smoothed (10 year low-pass Gaussian filter) values of all 11 experiments (stan: reality, corr – bias corrected RCM outputs, model – original model outputs).

3.1.2 Precipitation sums

Precipitation sums are overestimated by uncorrected model outputs (see Fig. 6). From the selected 5 experiments, the most moisture conditions are modeled by MPI-ESM-LR_CCLM, its average daily precipitation is higher by about 0.65 mm (Tab. 4). On the contrary, almost bias free precipitations are simulated by EC-EARTH_RACMO experiment. The rest of the three models overestimated the precipitation by about 0.35 mm/day. Spring is more moisture compared to other seasons.

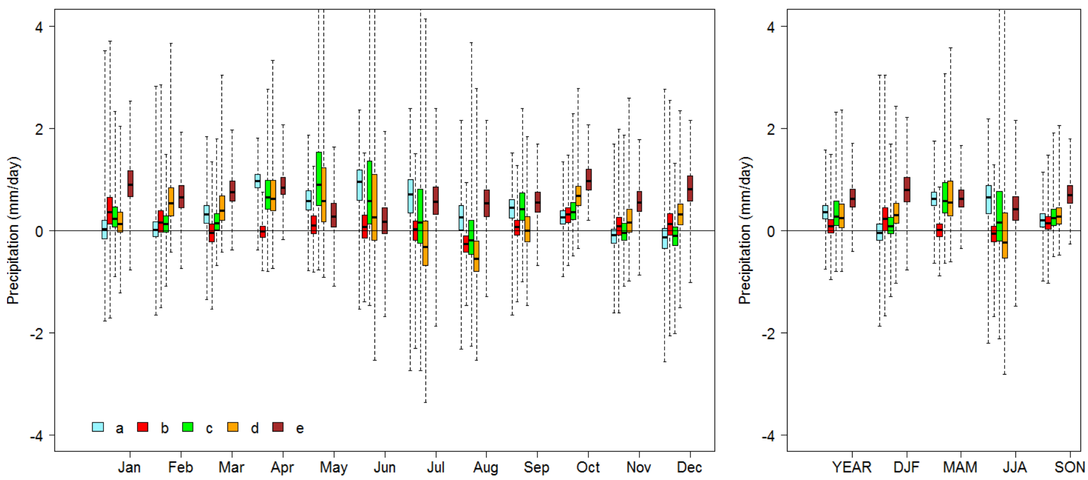

Fig. 6. Precipitation bias, difference of original (uncorrected) model and reality, for 5 experiments: ***a****: CNRM-CM5_ALADIN (1961-2005),* ***b****: EC-EARTH_RACMO (1961-2005),* ***c****: EC-EARTH_RCA (1970-2005),* ***d****: HadGEM2-ES_RCA (1970-2005),* ***e****: MPI-ESM-LR_CCLM (1961-2005)*

Tab. 4. Model bias for precipitation in mm/day as difference between original (uncorrected) model and reality, areal averages for different altitudes

Altitude in m	CNRM-CM5 ALADIN	EC-EARTH RACMO	EC-EARTH RCA	HadGEM2-ES RCA	MPI-ESM-LR CCLM
0-300	0.41	0.11	0.18	0.12	0.51
300-600	0.36	0.07	0.33	0.29	0.68
600-900	0.22	-0.01	0.68	0.67	0.78
900-1200	0	-0.25	0.97	0.97	0.66
nad 1200	-0.1	-0.48	0.98	0.98	0.27
whole CZ	0.34	0.06	0.36	0.32	0.65

More precipitation is simulated for Bohemia region than for Moravia (Fig. 7). Spatial differences of biases by altitude are not so evident as in the case of air temperature. The precipitation sums in lowlands are overestimated especially by CNRM-CM5_ALADIN and MPI-ESM-LR_CCLM experiments (Tab. 4). Mountain regions are modeled with higher amount of precipitation in case of EC-EARTH_RCA and HadGEM2-ES_RCA experiments. On the contrary EC-EARTH_RACMO experiment predicts, for altitude above 600 m, lower precipitation sums than is in reality.

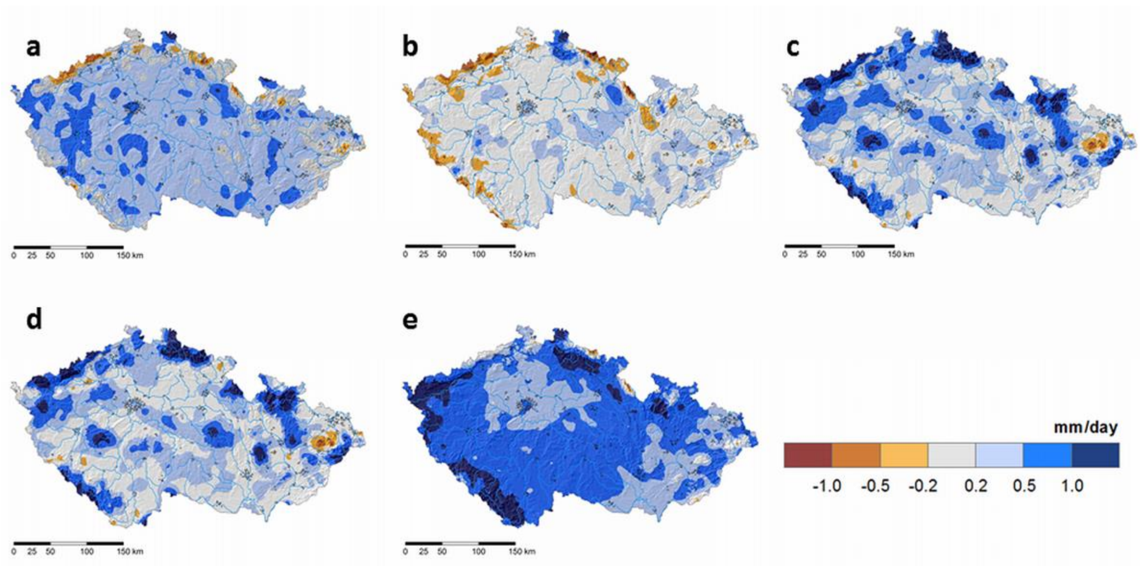

*Fig. 7. Precipitation bias for 5 experiments: **a**: CNRM-CM5_ALADIN (1961-2005), **b**: EC-EARTH_RACMO (1961-2005), **c**: EC-EARTH_RCA (1970-2005), **d**: HadGEM2-ES_RCA (1970-2005), **e**: MPI-ESM-LR_CCLM (1961-2005)*

Precipitation sums are distinguished by high spatially and temporal variability. This is determined mainly by atmospheric circulation, the amount of precipitation depends on the type of synoptic situation. Complex orography of the Czech Republic has a significant influence as well. Long-term changes in rainfall are not detected. The annual variability is stronger than the trend.

Prediction of the precipitation sums based on the all 11 experiments show slight increase of about 7-13 % for RCP 4.5 or 6-16% for RCP 8.5. Higher amount of precipitation are observed by the end of the 21st century (Fig. 8). Statistically significant trend (8.3 mm/10 years) is found for RCP 4.5 for the period 2061-2100. Emission scenarios 8.5 give statistical significant trend of 16 mm/10 years in the period 2021-2060 and 13 mm/10 years in the period 2061-2100. RCP 2.6 supposes increasing of the precipitation only in the first period 2021-2060 (14.7 mm/10 years). The biggest difference is observed for winter precipitation, whose increase can be up to 35% by the end of the 21st century (Tab. 6). On the contrary, the smallest change can be expected in summer precipitation (in summer we may expect even decrease of precipitation, even if annual sums are expected to increase).

Fig. 8 shows fluctuations of precipitation sums for the whole Czech Republic according to original and bias-corrected model outputs. Corrected model outputs are in accordance with station measurements (black line). Raw model outputs give about 100 mm higher annual precipitation sums. Different fluctuations of raw RCP2.6 values (compared to RCP4.5 and RCP8.5 within control run) are caused by different number of available models than is the case for RCP4.5 and RCP8.5.

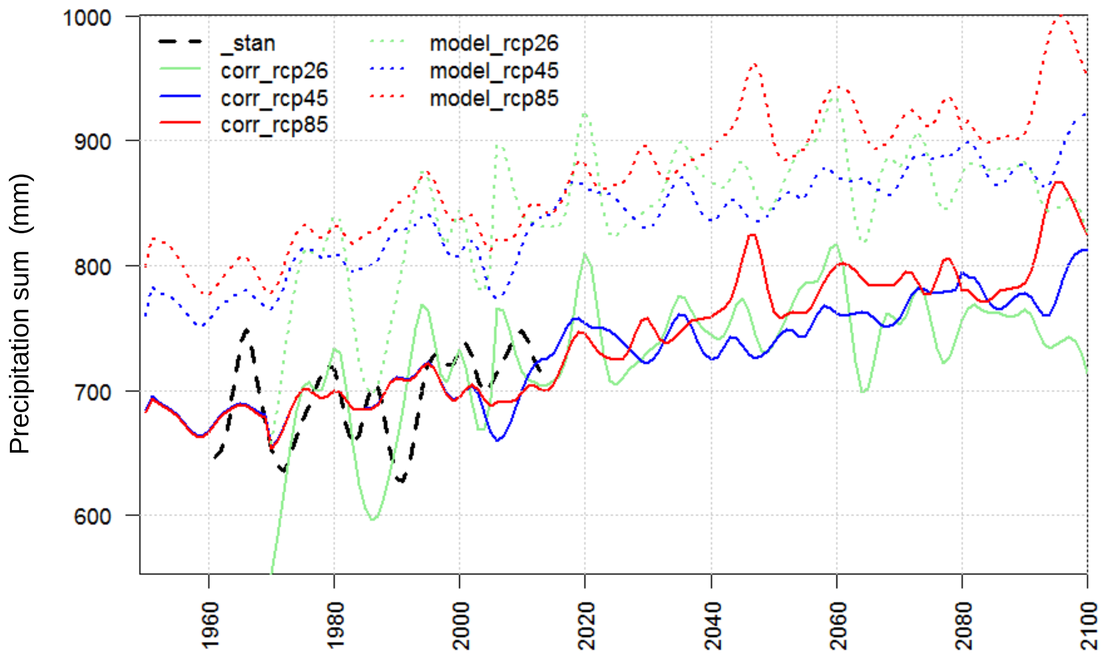

Fig. 8. Fluctuations of annual precipitation sums according to average of smoothed (with 10 year low-pass Gaussian filter) values of all 11 experiments (stan: reality, corr – bias corrected RCM outputs, model – original model outputs).

3.1.3 Further meteorological elements

Boxplots of biases in wind speed for the whole area of the Czech Republic for individual 11 RCM simulations within period of models control run (till 2005) are shown on Fig. 9. All the models, with exception of CNRM CM5_ALADIN53, show positive bias, reality is about 1 m/s lower. The bias is larger especially in the last years (marked as wind stilling, with cause still being investigated).

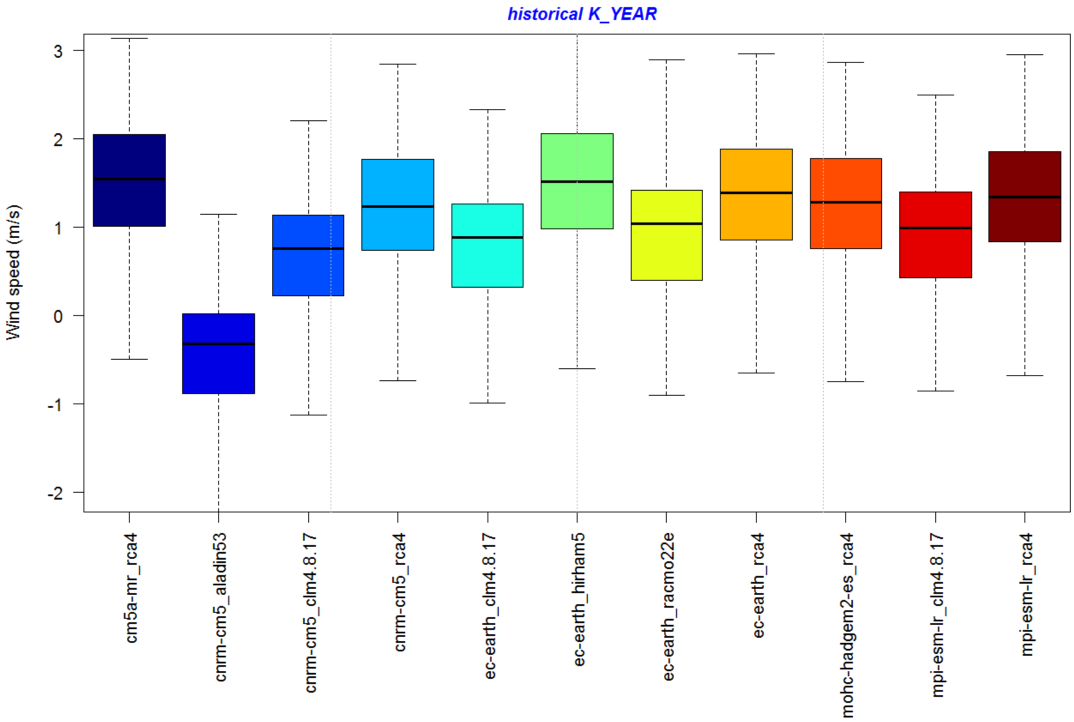

Fig. 9. Boxplots of wind speed biases for all locations (the whole Czech Republic) for individual 11 RCM simulations within control run (till 2005)

Boxplots of biases in relative humidity for the whole area of the Czech Republic for individual 11 RCM simulations within control run (till 2005) are shown on Fig. 10. Relative humidity is not available for all models (unlike specific humidity, but re-calculation to relative humidity and thus comparison with station measurements is not easy). Most of the models (except for EC-EARTH_HIRHAM5) show positive bias.

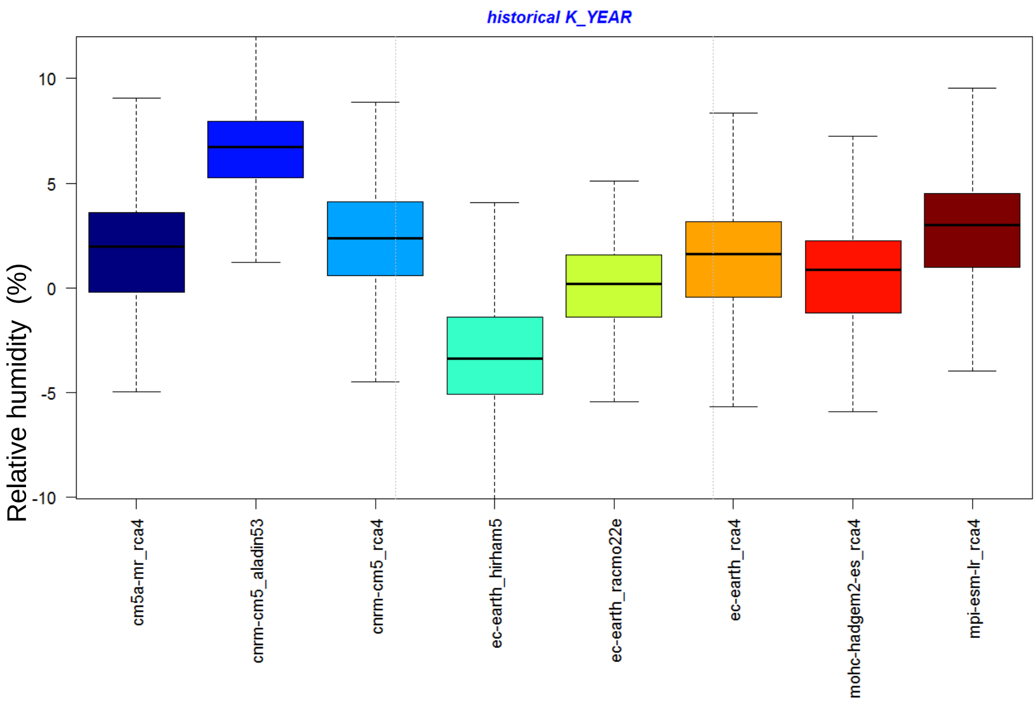

Fig. 10. Boxplots of relative humidity biases for all locations (the whole Czech Republic) for individual 11 RCM simulations within control run (till 2005)

3.1.4 Problems of some model simulations over the area of Central Europe

Some of the RCMs simulations showed critical biases for historical climate (control run). Here we show some examples. For this analysis, 19 simulations (combination of GCMs and RCMs as available in 2019), were used (plotted in the Taylor diagram).

- CNRM-CM5_ALADIN53: minimum temperature shows very low spatial correlations both in winter and summer (Fig. 11), and also relative humidity is not well represented (in winter).

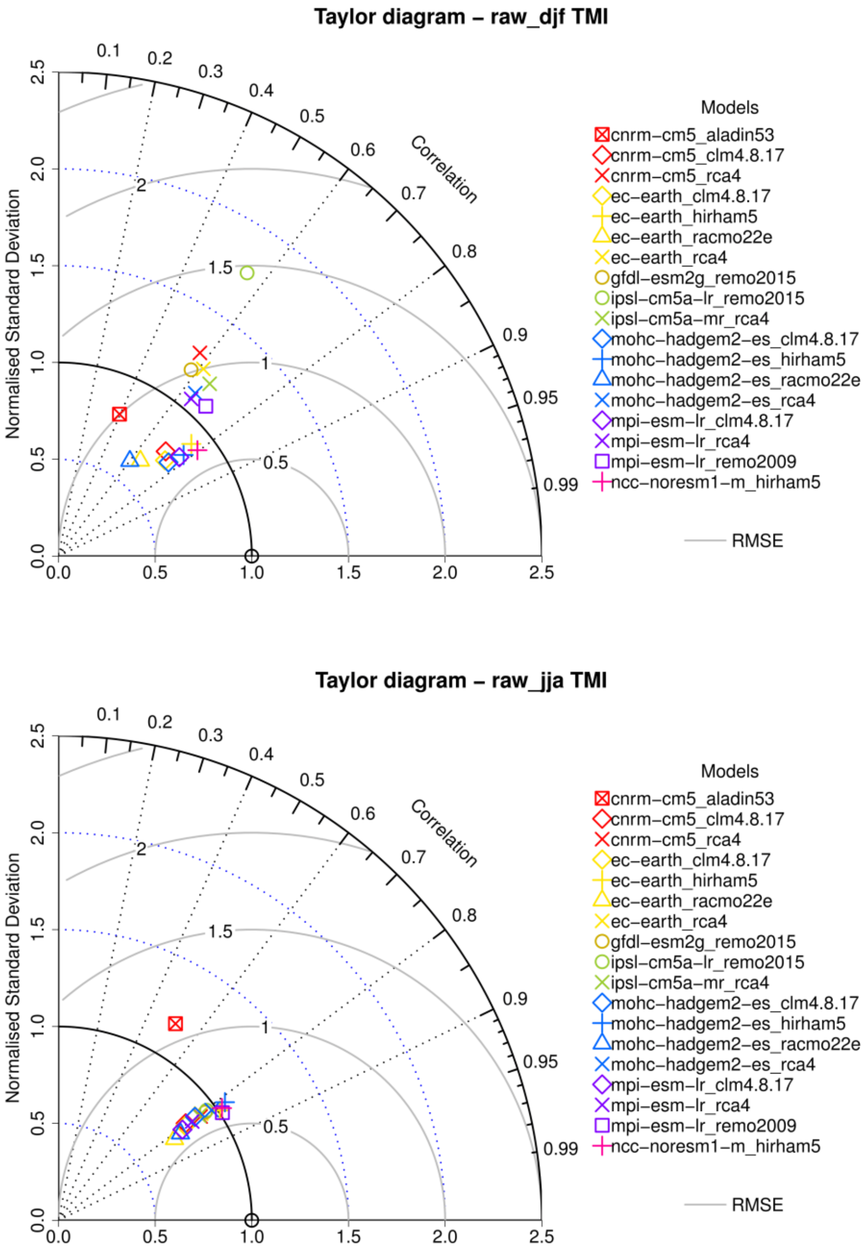

Fig. 11. Taylor diagrams for minimum temperature (DJF – winter – upper diagram, JJA – summer – bottom diagram) for original (non bias– corrected) model outputs.

- CNRM-CM5_CLM4.8.17: poor representation of annual cycle for precipitation and low spatial correlations for precipitation and solar radiation in summer (Fig. 12).

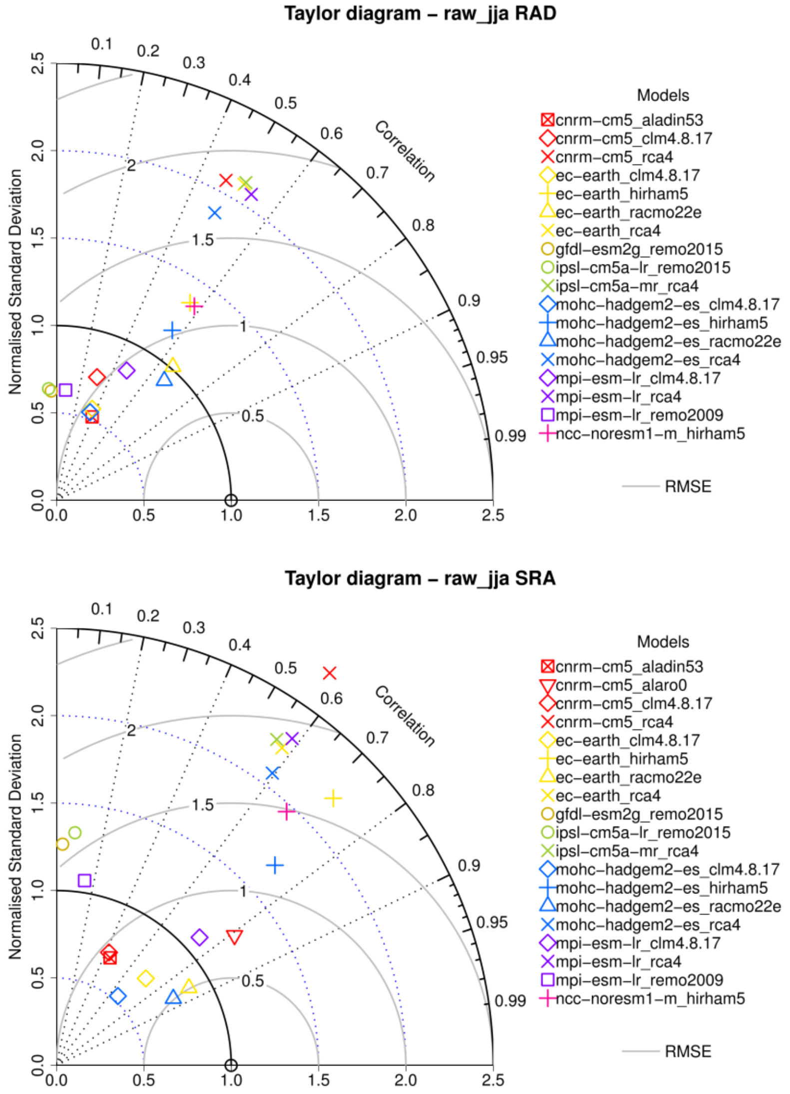

Fig. 12. Taylor diagrams for solar radiation in JJA – summer (upper diagram) and precipitation in JJA – summer (bottom diagram) for original (non bias– corrected) model outputs.

- RCMs REMO2009 and REMO2015 driven by various GCMs (not listed in the table 1 and not used otherwise throughout this contribution, but the results are interesting so they are presented here even being beyond scope of this contribution): these RCMs show very low spatial correlations for precipitation both in summer (Fig. 12 bottom) and winter (Fig. 13), remarkably lower values than other models. Moreover we see lower correlations for solar radiation in summer. For REMO2015 we also found problem with maximum temperature in summer and at the same time with minimum temperature in winter.

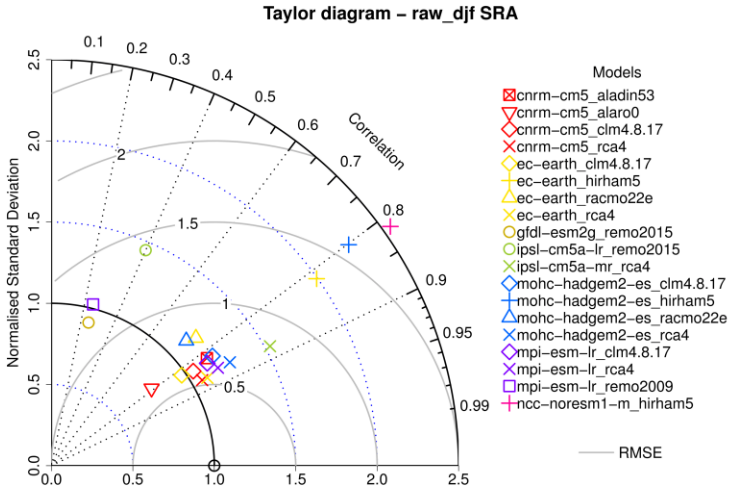

Fig. 13. Taylor diagrams for precipitation in DJF –winter for original (non bias– corrected) model outputs.

3.2 Comparison of climate indices

3.2.1 Number of days with precipitation above given level

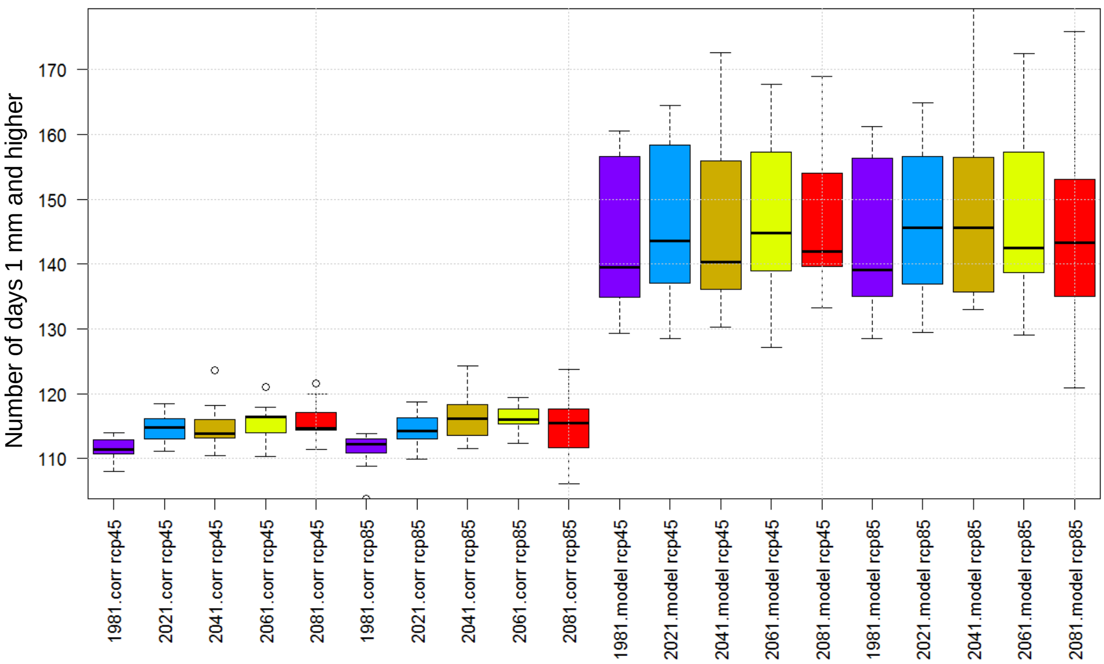

Fig.

*Fig 14. Boxplots over all 11 experiments for number of days with precipitation 1.0 mm and higher (**corr** – stands for bias corrected model outputs, **model** – stands for original model values), for 30 years (1981-2010) and future 20 years periods (beginning of the period is given in the description) and two scenarios RCP 4.5 and RCP 8.5*

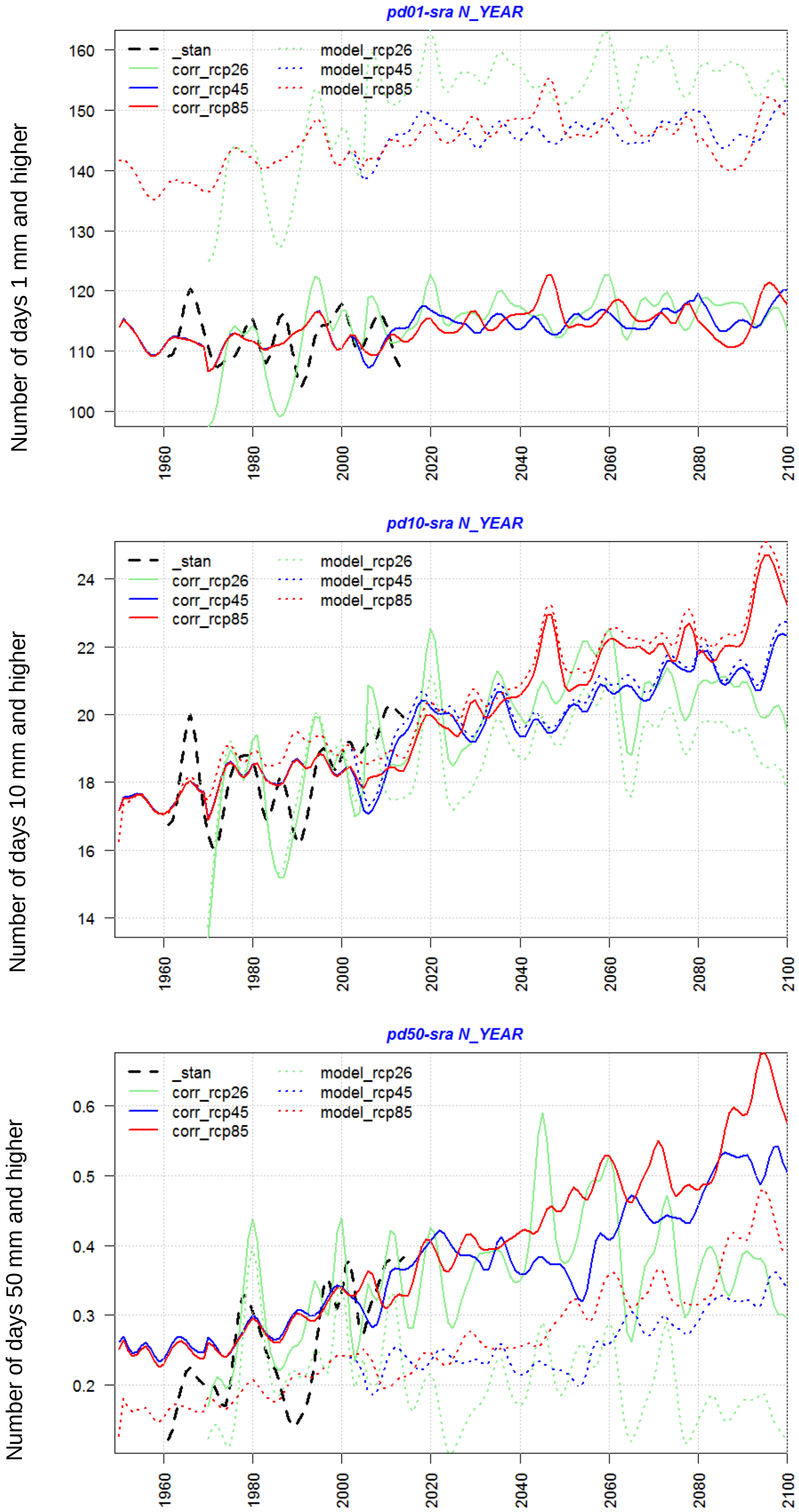

Fig 15. Fluctuations of number days with precipitation at least 1 mm (upper), 10 mm (middle) and 50 mm (bottom) according to average of smoothed (with 10 year low-pass Gaussian filter) values of all 11 experiments (stan: reality, corr – bias corrected RCM outputs, model – original model outputs).

After the bias correction, the results become more consistent in absolute values – initially large differences among individual experiments (as seen e.g. on Fig. 14), become more consistent. From this we can conclude that for impact studies, where absolute values play an important role (compared to climatological analysis usually based only on values change between various periods), bias correction is necessary to obtain meaningful results comparable with current station measurements.

Fig. 15 shows fluctuations of number of days with precipitation above given thresholds (1 mm, 10 mm and 50 mm and higher). As for 1mm precipitation, number of days is over-estimated in model outputs. For 10 mm threshold, level of corrected and original model values are in accordance, but for 20, 30 or 50 mm models give under-estimated results compared to reality. Moreover, while precipitation sums or number of days with precipitation 1 mm and more are without (statistically significant) trends, number of days with extreme precipitation increases from the past to far future (end of this century).

Number of tropical days (maximum temperature is 30°C or higher) is underestimated while number of ice days (minimum temperature dropped below 0°C are overestimated by models (not shown here).

Conclusions and outlook

- Especially for daily values and extremes generally, bias correction of model outputs Is necessary for further utilization of such outputs by impact studies
- While air temperature is underestimated by the models, precipitation sums and number of days with precipitation (1mm and higher) are overestimated) within the area of Central Europe. On the contrary, number of days with extreme precipitation are underestimated by models.
- Wind speed is overestimated by models, especially in the last years where we see negative trend in station observations while there are constant values from the past to future in model simulations
- Sunshine duration (solar radiation) is overestimated by model simulations

References

Christensen, J. H., F. Boberg, O. B. Christensen, and Lucas-Picher, P. (2008): On the need for bias correction of regional climate change projections of temperature and precipitation. Geophys. Res. Lett., 35, L20709, doi:10.1029/2008GL035694

Gutowski WJ, Decker SG, Donavon RA, Pan Z, Arritt RW, Takle ES (2003): Temporal-spatial scales of observed and simulated precipitation in central U.S. climate. J Clim 16:3841–3847

Kotlarski, S., Keuler, K. , Christensen, O. B., Colette, A., Déqué, M., Gobiet, A., Goergen, K., Jacob, D., Lüthi, D., van Meijgaard, E., Nikulin, G.. Schär, C., Teichmann, C., Vautard, R.. Warrach-Sagi, K., and Wulfmeyer, V. (2014): Regional climate modeling on European scales: a joint standard evaluation of the EURO-CORDEX RCM ensemble. Geosci. Model Dev., 7, 1297-1333, doi:10.5194/gmd-7-1297-2014

Maraun, D. et al. (2010): Precipitation downscaling under climate change: Recent developments to bridge the gap between dynamical models and the end user. Rev. Geophys., 48, RG3003, doi:10.1029/2009RG000314.

Maraun, D. (2013): Bias Correction, Quantile Mapping and Downscaling: Revisiting the Inflation Issue, J. Climate, 26, 2137–2143.

Štěpánek, P. (2008): AnClim - software for time series analysis. Dept. of Geography, Fac. of Natural Sciences, MU, Brno, 1.47 MB. http://www.climahom.eu/AnClim.html

Štěpánek, P. (2010): ProClimDB – software for processing climatological datasets. CHMI, regional office Brno. http://www.climahom.eu/ProcData.html

Štěpánek, P., Zahradníček, P., Farda, A. (2013): Experiences with data quality control and homogenization of daily records of various meteorological elements in the Czech Republic in the period 1961–2010. Időjárás, 117, 1, 123–141.

Stepanek, P., Zahradnicek, P., Farda, A., Skalak, P., Trnka, M., Meitner, J, Rajdl, K. (2016): Projection of drought-inducing climate conditions in the Czech Republic according to Euro-CORDEX models. Clim Res 70:179-193. https://doi.org/10.3354/cr01424, http://www.int-res.com/abstracts/cr/v70/n2-3/p179-193/

Štěpánek, P., Zahradníček, P., Huth, R. (2011): Interpolation techniques used for data quality control and calculation of technical series: an example of Central European daily time series. Időjárás, 115, 1-2, pp. 87-98.

Štěpánek, P., Zahradníček, P. a Skalák, P. (2009): Data quality control and homogenization of air temperature and precipitation series in the area of the Czech Republic in the period 1961–2007. Advances in Science and Research, 3, 23–26, http://www.adv-sci-res.net/3/23/2009/

Teutschbein, C. and Seibert, J. (2013): Is bias correction of regional climate model (RCM) simulations possible for non-stationary conditions?, Hydrol. Earth Syst. Sci., 17, 5061-5077, doi:10.5194/hess-17-5061-2013.

Themessl, M. J., Gobiet, A. and Leuprecht A (2011) Empirical-statistical downscaling and error correction of daily precipitation from regional climate models. Int J Climatol 31:1531–1544. doi:10.1002/joc.2168

Themessl, M. J., Gobiet, A. and Heinrich, G. (2012): Empirical-statistical downscaling and error correction of regional climate models and its impact on the climate change signal. Clim.Change, 112, 449-468, doi:10.1007/s10584-011-0224-4