Response to reviewers

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Title: Assessment of the influence of bias correction on meteorological drought projections for Poland

Authors: M. Osuch, R. J. Romanowicz, D. Lawrence, and W. K. Wong

1 General response

We thank the reviewers and the editor for the time taken to review and process our manuscript. We are pleased that the reviewers find the work important as well as being of sufficient scientific quality and general interest to consider publication in HESS after revisions. The reviewers and the editor provided a number of suggestions to improve the manuscript. In response, we have made major revisions, clarifications, and/or additions to parts of the manuscript, as outlined in this document. In the following sections, we respond to each of the reviewers' remarks or questions.

2 Response to the Editor

I feel there has been some valuable discussion on this manuscript. All credit to the reviewers for stimulating this, and to the authors for responding in such detail.

The fundamental points raised by the reviewers relate to the suitability for the SPI when used in combination with bias correction. First amongst these is the fact that both involve normalisation. There are also the inevitable issues around the reference period being used, which to me are inherent challenges in using the SPI (or indeed any indicator in respect to a fixed reference period) in a non-stationary environment, as raised in many previous studies. This is problematic over past timescales and gets even more challenging to interpret in long transient projections.

On the question of normalisation, the authors have taken some steps to address reviewer 1's comments although have so far just presented correlation. There would be benefits in looking *at the other metrics (particularly given the possibility of differences at the extremes, as raised) and the new text needs to concisely capture the key points raised.*

The question of reference period is a vexed one, and the decision depends entirely on the objectives of the study. This clarification all needs to be articulated much more clearly, with some discussion on the reasons for the decision and how this affects interpretation. The authors have suggested they will add this discussion.

Answer: We updated the text related to the selection of the reference period.

Wu et al. (2005) recommended the use of the longest possible period for the derivation of the SPI, as short data sets could result in large errors of estimated values. For the comparison of indices between different locations the choice of the same period is suggested. Following that recommendation, the aggregated precipitation totals from the entire period (1971-2099) were normalized. The analysis of SPI values based on the entire time series gives an opportunity to estimate the tendency of changes in the SPI time series, which was one of principal aims of this work. However for the purpose of adaptation to climate change, the reference period to which the changes are related plays an important role. Namely, when the whole period is taken for the normalisation, normal conditions refer to the year 2035 which in the case of nonstationarity may lead to some difficulties in interpreting the results, as it changes the analyst's perspective.

In an alternative approach presented by Stagge et al. (2015) a nonlinear transformation (normalization) is developed for the present period (for example 1971-2000) and that transformation is further applied for future climate conditions. That approach also has some drawbacks. Future climate conditions could be different than the observed ones; therefore an application of a relationship based on the present conditions could lead to extrapolation outside the range of observed values. The second problem is related to interpretation of estimated SPI values for changed climatic conditions. The estimates of these values could be outside of the range [-3,3] that ensures comparability of the results. The third problem with the alternative approach is related to shorter time series that could results in errors in the fitting of the distribution and the normalization of the aggregated time series. This problem is mentioned in the work of Wu et al. (2007).

Most of the other points raised require relatively modest revisions and the authors' proposed changes seem reasonable. Both referees called for more discussion to be added, and the authors have already provided some new discussion text. This is encouraging and I hope the additional discussion is focused and well integrated with the existing text.

Answer: We have included an additional discussion in the text.

There was also a suggestion to shift emphasis and title away from droughts. I agree with this and I support the suggestion of a title change. I am not sure whether the new title is the best way of capturing the essence of the paper; "seasonally aggregated" could be misleading as the SPI is not necessarily seasonal. Would "monthly aggregated" be better? Or simply "…in projected SPI…". Worth giving further thought to a title that captures the work succinctly, but with impact.

Personally, given the points raised by the reviewers I wonder whether the title and emphasis should be moved away from bias correction too as that is just one element, and the paper is as much about the trends in the projections and differences between models, so the title could be more generally focused on met drought projections.

Answer: We have changed the title to " Trends in projections of Standardized Precipitation Indices in a future climate in Poland".

3 Response to Referee #1

The reviewer's comments are *in italic* and our response in normal font.

3.1 General Comments

The authors present a trend analysis for future projections of seasonal precipitation based on the meteorological drought index, SPI, for Poland. Projections are based on an ensemble of RCM runs, providing high spatial resolution. The projections show an overall increase in precipitation during the winter and a slight decrease in precipitation during the summer, with some model disagreement. The effect of bias correction on these projected trends was evaluated and found to have a small effect, but which is smaller than the variability among GCM/RCM model combinations. The paper is extremely well-written, clear, and easy to *understand. It provides high resolution projections and a non-parametric trend analysis of seasonal precipitation for Poland, which is worthy of publication, and asks an interesting research question – whether bias correction affects projections of the drought index, SPI. However, I have two major issues relating to the lack of a focus on drought and insufficient testing regarding bias correction. These are described below. Because of these fundamental issues, I recommend a major revision.*

Answer: We thank the reviewer for the encouraging words and helpful comments. The reviewer provides several very useful comments/suggestions for revisions. We address these in the revised manuscript, as per our responses to each comment below.

3.2 Major comments

I have 2 primary issues with the paper:

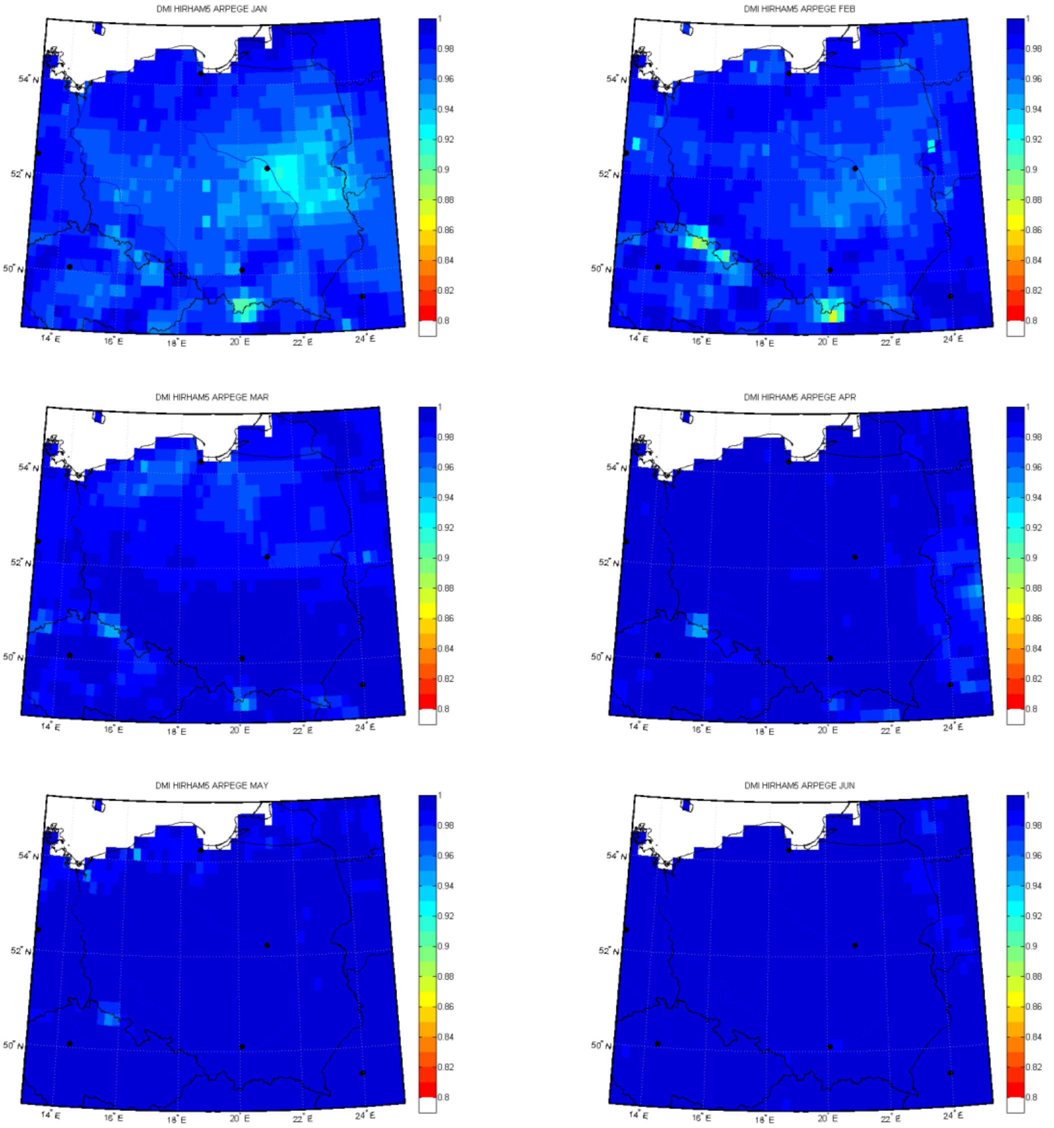
1. *The paper claims to be measuring trends in drought and discusses meteorological drought throughout. While the authors use the SPI, a drought index, they measure trends across the entire range of SPI values, which includes both wet and dry anomalies. Thus, the paper really deals with trends in seasonally accumulated precipitation, or general dryness/wetness. For example, extreme rainfall (SPI > 1) events increased in severity or frequency, while drought events (SPI < -1) remained the same, the trend would show an overall increasing trend in SPI, which the authors would incorrectly classify as a decrease in droughts. While overall wetness and droughts are potentially related, they are different and do not have to respond in the same way. The authors cite the study by Rimkus et al. (2012) which did specifically measure droughts, looking at trends in drought "intensity", defined as the sum of negative SPI values for a region. They later begin defining drought thresholds (Page 10341, Line 1), but this is never mentioned again. My recommendation is either to (a) change the title and text to reflect a focus on accumulated precipitation, or (b) focus analysis on drought occurrence, either based on area below a threshold or the sum of SPI below a threshold. The results shown here are interesting in their own right, so either choice would be acceptable.*

   Answer: This is a very valid point, and as we wish to retain the focus on seasonal wetness vs. dryness, we change the title as you have proposed, i.e. to "Trends in projections of Standardized Precipitation Indices in a future climate in Poland". The changes in text are included in the corrected version of manuscript.

2. *The title and much of the text focuses on the effect of bias correction on trends in SPI. I have serious questions with this premise and the conclusions that bias correction has a slight effect on trends in SPI values (Page 10336, Lines 8-11; Page 10350, lines 3-8; Section 3.3). SPI is a normalized index based on quantiles, though it uses a gamma distribution rather than the empirical cumulative distribution to calculate them. Thus, SPI uses a similar quantile fitting procedure as bias correction and thus bias correction should have nearly negligible difference. This can be seen in Figure 10, where the differences in significant trend areas are generally within 10% and are generally centered around 0 (except February). The only effect from bias correction should be due to (a) distribution fitting differences, (b) differences at the very extreme values, or (c) the difference between summing months first and normalizing (no bias correction) and first normalizing, summing, and then normalizing again (bias correction). The examples provided (e.g. Maurer and Pierce 2014) deal with bias correcting precipitation, rather than a relative metric like SPI, which is a very different question. Comparing differences between trends in bias-corrected and non-bias corrected SPI values skips the important step of determining whether there is a significant difference in SPI values themselves between the two. Given the above explanation, I doubt there is. In order to support your claim, I recommend quantifying the difference in corrected and non-corrected SPI time series using metrics like correlation, mean squared error, or mean absolute error.*

Answer: We present an analysis of the influence of bias correction on trends in precipitation totals and SPI values. We agree that factors such as errors associated with the fitting of the distribution for bias correction will may have an effect on the slope of trend. However, we have also presented an explanation on pages 10352-10353 illustrating how bias correction can change the slope, quite independently of such errors. Our explanation addresses two issues: (i) the effect of bias correction on the trend in the aggregated precipitation and (ii) the effect of that trend on the SPI values. It is shown that the application of bias correction by quantile mapping method does not change the sign of estimated trend of aggregated precipitation but may change the slope. The bias correction also influences the trends in the SPI values. Due to monotonic relationship between the aggregated precipitation and SPI the direction of changes in precipitation is reflected in changes of SPI, however these changes are much reduced in comparison with precipitation.

In reality, additional factors have an effect on the SPI, including uncertainty of distribution fitting applied in bias correction and the SPI calculation procedures. A test of differences between uncorrected and corrected SPI time series was performed using Person correlation coefficient as a criterion. The results of correlation analysis for six climate models and 12 months for all grid cells are presented in Tables 1-2 and Figure 1. In all cases the correlation is statistically significant at 5% level and the values of the minimum Pearson correlation coefficient are above 0.8 indicating nearly linear relationship between the indices.



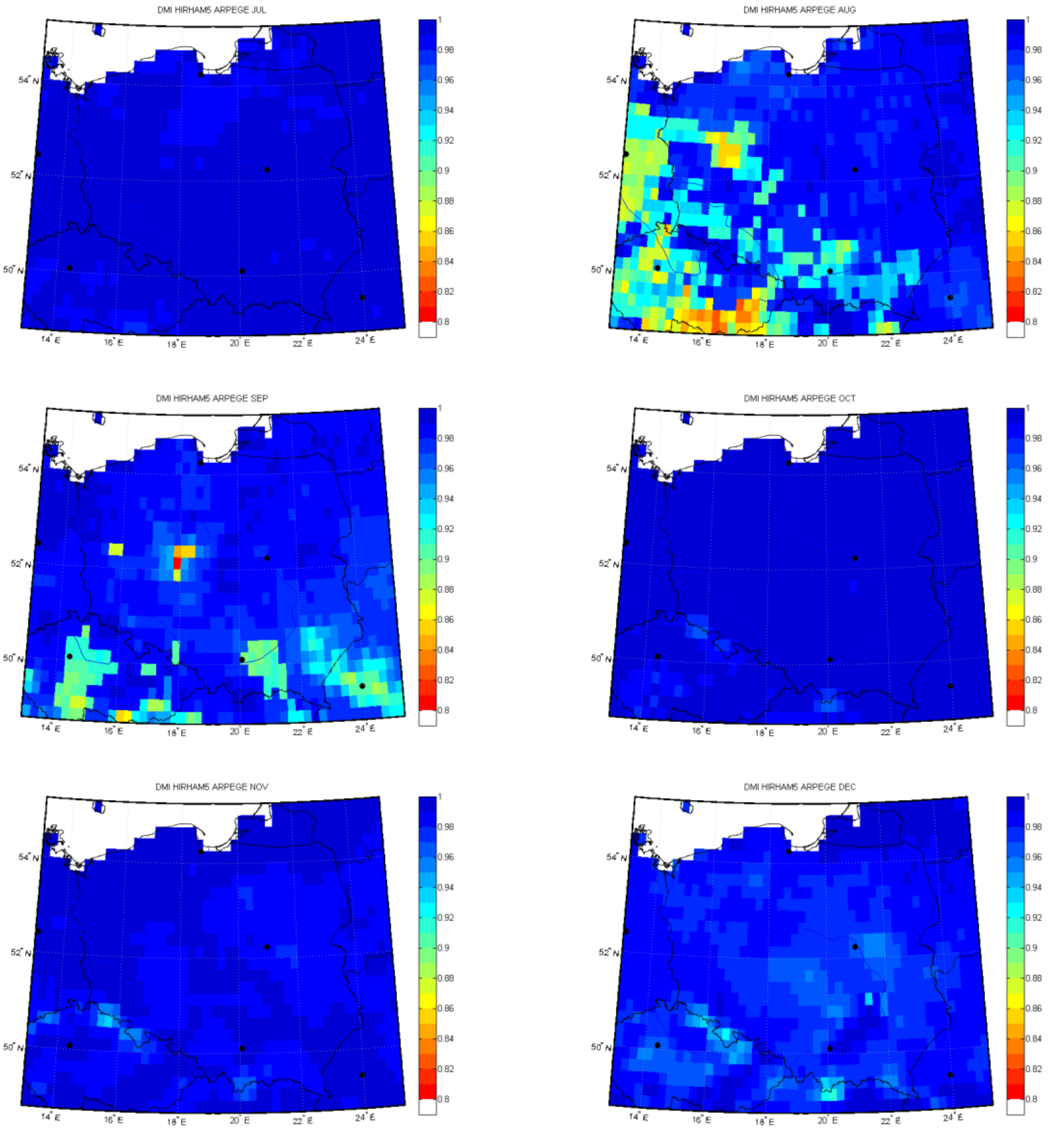


Figure 1 Estimated values of Pearson correlation coefficient between raw and corrected SPI 1 for DMI HIRHAM5 ARPEGE model

Table 1 Estimated minimum values of Pearson correlation coefficient between raw and corrected SPI 1 for six climate models and 12 months

	GCM	ARPEGE		ECHAM5		BCM	
Index	RCM	DMI HIRHAM	RM51	MPI M REMO	KNMI RACMO2	DMI HIRHAM	SMHI RCA
SPI 1	JAN	0.9002	0.9043	0.9434	0.9391	0.9134	0.9059
	FEB	0.8718	0.9104	0.9055	0.9252	0.8783	0.8932
	MAR	0.9452	0.9341	0.9502	0.9396	0.9018	0.9551

	APR	0.9436	0.8964	0.9638	0.9589	0.8939	0.9374
	MAY	0.9490	0.8897	0.9343	0.9680	0.9568	0.9711
	JUN	0.9738	0.8544	0.9440	0.9573	0.9582	0.9173
	JUL	0.9749	0.9368	0.9488	0.9698	0.9415	0.9798
	AUG	0.8200	0.9513	0.9436	0.9207	0.9217	0.9614
	SEP	0.8064	0.9730	0.9728	0.9619	0.9260	0.9702
	OCT	0.9601	0.9386	0.9666	0.9529	0.8253	0.9028
	NOV	0.9364	0.9592	0.9619	0.9591	0.9332	0.9161
	DEC	0.9103	0.9492	0.9687	0.9721	0.9138	0.9532
SPI 3	DJF	0.8679	0.9344	0.9580	0.9588	0.9215	0.9157
	MAM	0.9171	0.8450	0.9544	0.9542	0.9187	0.9604
	JJA	0.9376	0.9105	0.9436	0.9664	0.9224	0.9592
	SON	0.8758	0.9429	0.9462	0.9508	0.8788	0.9134
SPI 6	NOV-APR	0.9014	0.9348	0.9534	0.9660	0.9214	0.9220
	MAY-OCT	0.9077	0.9077	0.9369	0.9659	0.8874	0.9626
SPI 12	Calendar year	0.8522	0.8840	0.9450	0.9514	0.8680	0.9360
SPI 24	Two calendar years	0.8651	0.9029	0.9411	0.9479	0.8450	0.9137

Table 2 Estimated mean of Pearson correlation coefficient between raw and corrected SPI 1 for six climate models and 12 months

GCM	ARPEGE	ECHAM5	BCM

Index	RCM	DMI HIRHAM	RM51	MPIM REMO	KNMI RACMO2	DMI HIRHAM	SMHI RCA
SPI 1	JAN	0.9717	0.9745	0.9832	0.9823	0.9746	0.9694
	FEB	0.9770	0.9758	0.9765	0.9800	0.9728	0.9670
	MAR	0,9874	0.9757	0.9864	0.9861	0.9794	0.9848
	APR	0.9937	0.9529	0.9882	0.9928	0.9870	0.9864
	MAY	0.9948	0.9425	0.9884	0.9936	0.9940	0.9948
	JUN	0.9963	0.9481	0.9908	0.9955	0.9965	0.9882
	JUL	0.9937	0.9744	0.9906	0.9969	0.9916	0.9948
	AUG	0.9639	0.9834	0.9843	0.9860	0.9880	0.9921
	SEP	0.9751	0.9917	0.9962	0.9958	0.9882	0.9931
	OCT	0.9954	0.9845	0.9909	0.9833	0.9707	0.9717
	NOV	0.9904	0.9915	0.9938	0.9885	0.9846	0.9786
	DEC	0.9810	0.9885	0.9947	0.9933	0.9894	0.9884
SPI 3	DJF	0.9703	0.9784	0.9865	0.9831	0.9805	0.9757
	MAM	0.9867	0.9430	0.9839	0.9891	0.9786	0.9880
	JJA	0.9794	0.9680	0.9836	0.9932	0.9866	0.9902
	SON	0.9647	0.9782	0.9848	0.9766	0.9764	0.9802
SPI 6	NOV-APR	0.9770	0.9712	0.9848	0.9874	0.9811	0.9781
	MAY-OCT	0.9620	0.9649	0.9835	0.9860	0.9786	0.9861
SPI 12	Calendar year	0.9392	0.9542	0.9790	0.9806	0.9710	0.9832
SPI 24	Two calendar	0.9422	0.9559	0.9784	0.9815	0.9727	0.9851

years

In addition Figure 2 presents results of SPI 1 estimated for raw and corrected precipitation time series for one grid cell located close to Bialystok for the DMI HIRHAM5 ARPEGE model. In all cases the correlation is statistically significant at 5% level. The highest differences in the slope of the relationship between uncorrected and corrected SPI 1 values are achieved for winter months (January, February).

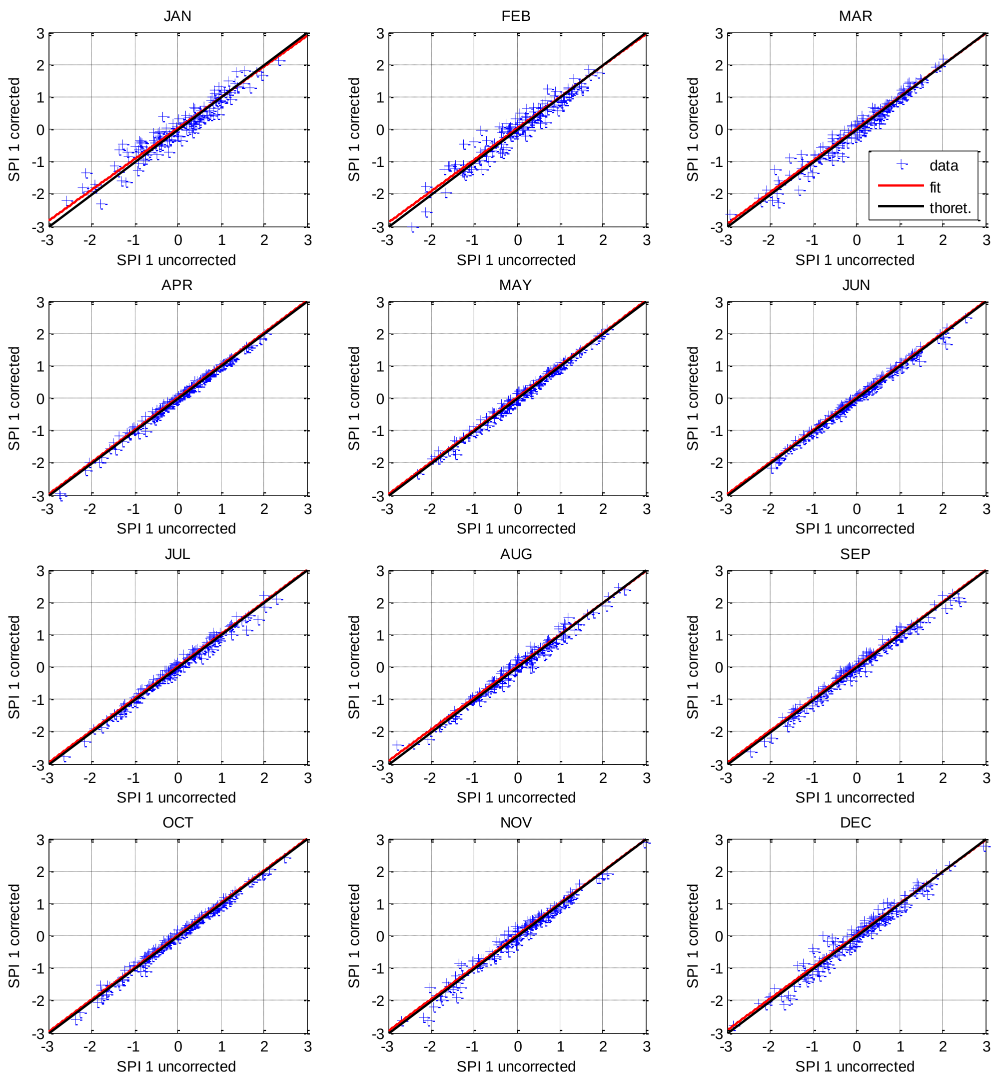


Figure 2 Scatterplots showing dependence between uncorrected and corrected SPI 1 values for one grid cell located close to Białystok for DMI HIRHAM5 ARPEGE model

Following the reviewer's comments, we recognise the importance of distinguishing between changes in the slope due to the fitting of the distribution and due to the bias correction itself. We also tested dependence of relative differences in monthly precipitation on the correlation in the SPI values. The outcomes for all grid cells are presented in Figure 3. A nonlinear relationship is visible for most of months and models that is statistically significant at 5% level except DMI HIRHAM ARPEGE and DMI HIRHAM BCM in June. The strength of these dependencies assessed with help of Spearman correlation coefficient (SCC) is varying from 0 up to 0.7954 with differences between months and models. The deviation from zero of SCC values quantifies influence of additional effects that include nonlinearity of the bias correction function, uncertainty in probability distribution of observed and simulated aggregated precipitation.

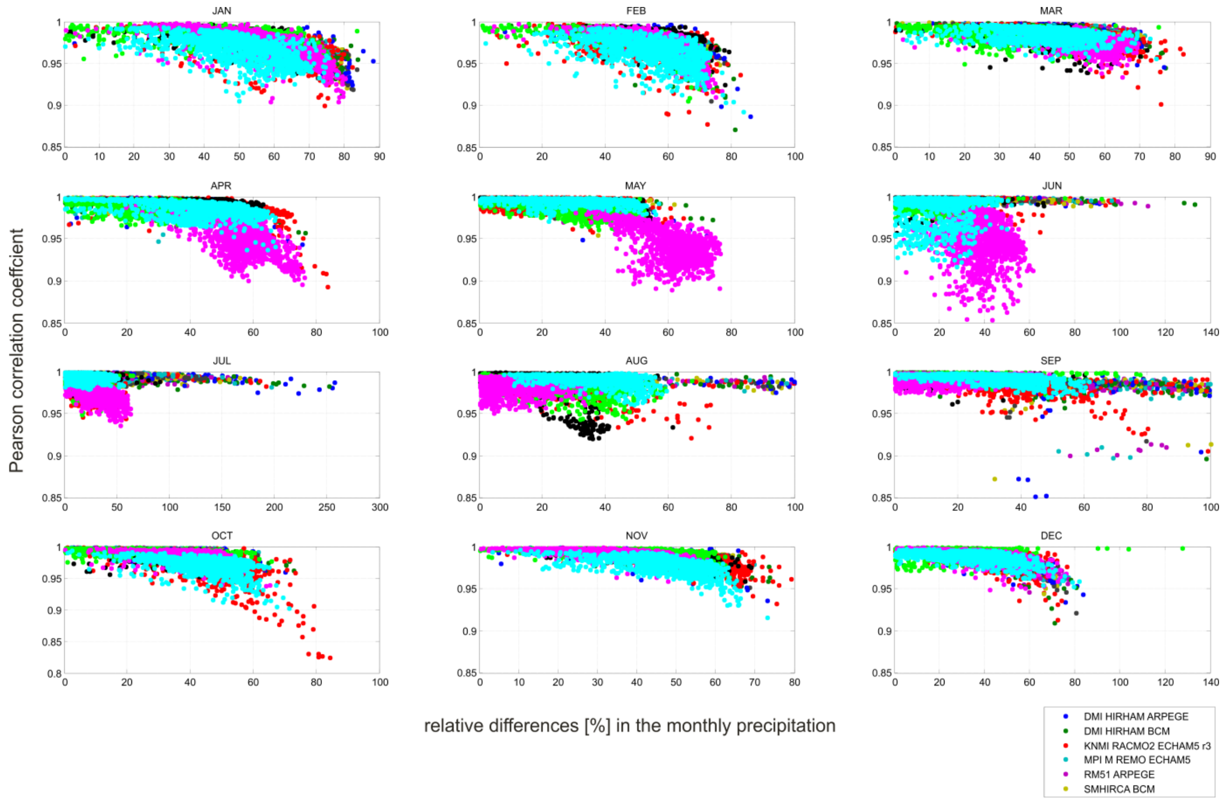


Figure 3. The scatterplots showing relationship between relative differences in the raw and corrected monthly sum of precipitation and Pearson correlation coefficient estimated for raw and corrected SPI 1 values for all grid cells.

3.3 Moderate Comments

1. *Title: Based on the above comments, I recommend adjusting the title to focus more on overall dry/wet trends, rather than on drought and bias correction.*

   Answer: As mentioned above, we have changed the title of the paper to address this issue.

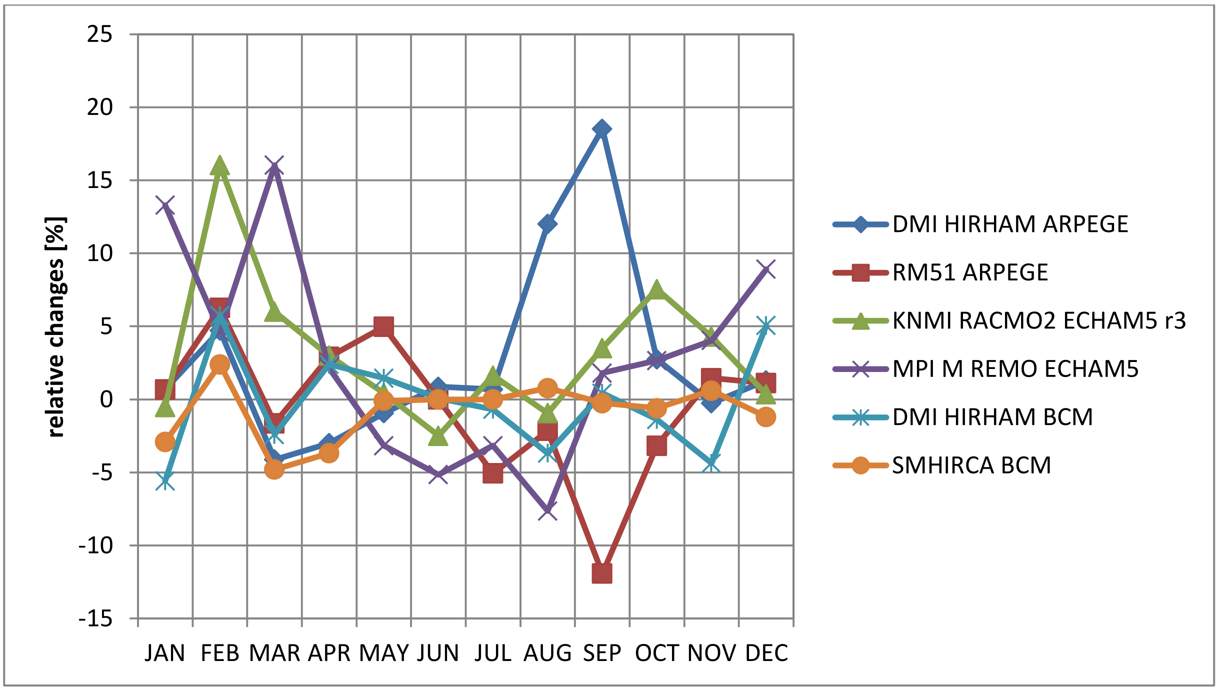
2. *Page 10341, Line 12: It would help if you distinguished between the reference period for bias correction (1971-2000) and the reference period for SPI normalization (1971-2099). It might also be helpful to add these reference periods to Figure 1 to help make this distinction. Tied into the issue of reference periods is your claim that it is better to use the entire period (1971-2099) to normalize SPI values based on Wu et al. (2005). By using the entire time series as a reference period, you force the SPI values to follow a normal distribution; however, it causes difficulties in interpretation when there is a detectable trend in SPI values. For a stationary timeseries, an SPI of 0 means that precipitation is near the median value of the reference period. But, for a non-stationary time series, this refers to the median value along the trend. For instance, if SPI was calculated based on a historical time series (e.g. 1971- 2000), an SPI of 0 would mean that precipitation was "typical" based on the reader's experience. But, using the full time series (1971-2099) with a linearly increasing trend, "typical" conditions should occur sometime around 2035. What the reader considers typical, i.e. historical and current climate conditions, would actually be considered drier than typical, with SPI values less than 0. As stated above, both reference periods allow for a valid analysis of trends as shown in this study, but there may be difficulty with interpretability moving forward.*

   Answer: Following the recommendation of Wu et al (2005) the aggregated precipitation totals from the entire period (1971-2099) were normalized. We agree that that assumption may lead to some difficulties in interpreting the results. The method proposed by the reviewer consists of developing a nonlinear transformation (normalization) for the present period (for example 1971-2000) and further applying that transformation for future climatic conditions. That approach also has some drawbacks. The most important are problems related to the extrapolation the nonlinear relationship for normalization. Future climatic conditions could be different than the observed ones; therefore an application of a relationship based on the present conditions could lead to extrapolation outside the range of observed values. The second problem is related to interpretation of estimated SPI values for changed climatic conditions. The estimates of these values could be outside of the range [-3, 3] that ensures comparability of the results. The third problem with the alternative approach is related to shorter time series that could results in errors in the fitting of the distribution and the normalization of the aggregated time series. This problem is mentioned in the work of Wu et al. 2007. They state that having an absolute value of the median smaller than 0.05 guarantees that the middle value of estimated SPI values is not greater than +-0.05.

In addition, the analysis of SPI values based on the entire time period gives an opportunity to estimate the tendency in changes in the SPI time series, and this is one of principal aims with this work. For these reasons, we wish to retain the approach we have used.

3. *Figure 10: This figure is unclear. Is this a stacked bar graph? If so, each GCM/RCM combination is independent and should not be added together. If they are not being added together, then showing them stacked is confusing. A simple line graph showing each GCM/RCM's progression through time would be more readable.*

   Answer: Updated



Discussion of the results should be expanded. The authors list several papers in the introduction that deal with climate projections and precipitation in Europe. The results show a consensus for wetter winters and generally drier summers, though there is more uncertainty in the summer. How does this compare, for instance, with Rimkus et al. 2012 or Liszewska et al. 2012? You may also compare with results from additional studies listed in the minor comments.

Answer: This expanded discussion is included in the revised version of the paper

Analysis of the potential impact of climate change on drought in Poland has been addressed by relatively few studies at a regional scale. Rimkus et al. (2012) analysed 50-year trends (1960-2009) under the recent climate and drought projections for the future climate (up to 2100) in the Baltic Sea region using the Standardized Precipitation Index (SPI). For the assessment of the observed climatic conditions, gridded precipitation time series at 1-degree resolution from the Climate Research Unit at the University of East Anglia were used. The trend estimated using a Mann-Kendall test indicated an increase in the SPI values for different time averaging periods over most of the studied area, except for Poland, where decreases were found. Future dryness was projected using COSMO Climate Limited-area Model (CCLM) driven by initial and boundary conditions from ECHAM5/MPI-OM GCM for two emission scenarios (A1B and B1). According to both scenarios, the intensity of drought will likely decline in most of the Baltic Sea area, except in southern areas, including Poland. Following the A1B scenario, drought occurrence will increase in the summer months in the future in those regions.

Some of the findings of Rimkus et al. (2012) can be compared with the results presented here. They both include simulations following the A1B emission scenario driven by ECHAM5 GCM. Our results in some aspects (e.g. tendency of changes of annual sum of precipitation) are similar to those presented by Rimkus et al. (2012) but also differences can be noticed. These differences result from different spatial resolution and an application of a different regional climate model.

The analysis of the impact of climate change on drought in Poland, carried out within the framework of the project “Development and implementation of a strategic adaptation plan for the sectors and areas vulnerable to climate change” with the acronym KLIMADA (klimada.mos.gov.pl), indicated that future predictions of annual total precipitation do not show any clear trends (Liszewska et al., 2012). The assessment of trends in seasons shows an increase in winter precipitation (DJF) of up to 20% in the eastern part of Poland and a decrease in summer precipitation in south eastern Poland. In contrast, changes in precipitation in spring and autumn tend to be much smaller (Liszewska et al., 2012). The number of dry days with daily precipitation of less than 1 mm shows an increasing trend. These changes are more pronounced in eastern and south eastern Poland (NAS, 2013). Those findings by Liszewska et al. (2012) are confirmed in this paper.

Analysis of an impact of climate change on drought using a meteorological water balance (defined as the difference between evapotranspiration and rainfall for a given period) for three periods 1971-2000, 2021-2050 and 2071-2100 was carried out by Osuch et al. (2012). The results of the assessment indicate significant differences between projections derived from the different climate models analysed. A comparison of the median of the ensemble of models in these three periods indicates an increase in water scarcity in Poland. These changes are more pronounced in the south eastern part of Poland. Those results confirm the SPI12 analysis outcomes presented in this paper.

Changes in European drought characteristics projected by PRUDENCE regional climate models were studied by Bleckinsop and Fowler (2007). In that work six climate model simulations were analysed following the SRES A2 emission scenario. Similarly to our findings, a considerable model uncertainty due to inter-model variability on regional and local scales was demonstrated. The projections indicate likely decreases in summer and likely increases in winter precipitation. For longer duration droughts, the projections indicate fewer droughts in northern Europe due to larger increases in winter precipitation and more droughts of increasing severity in the south. Our results confirm these general findings with differences due to different emission scenario as well as climate models. The study by Orlowsky and Seneviratne (2013) presents an analysis of the SPI12 at a continental scale. The results for Central Europe show an increasing trend in median SPI 12. The new study by Stagge et al. (2015) presents an analysis of meteorological drought using the most current climate models (23 simulations) for the three projected emission scenarios (rcp2.6, RCP4.5 and RCP8.5) for Europe at spatial resolution of 0.11 degree (~12.5 km). The meteorological drought was estimated with the help of SPI at 3, 6 and 12 month aggregation periods. In that work the relationship between aggregated precipitation and SPI was developed for the reference period (1971-2000). Then the same transformation was used for future scenarios (2011-2040, 2041-2070, and 2071-2100). The analysis of changes in SPI between future and present periods was conducted with the help of the parametric two sample t-test and the non-parametric Mann-Whitney test. The results indicate that precipitation is likely to increase in central and northern Europe therefore that area is likely to experience fewer precipitation-based droughts. In general, our study confirms the results of Stagge et al. (2015) with some differences due to different climate models, emission scenarios and change estimation methods applied. Our selection of climate models provides larger differences between meteorological projections. In addition, an analysis of SPI at shorter aggregation periods indicated an increasing trend of degree of dryness for summer months and decreasing for winter.

3.4 Minor Corrections

1. *Page 10333, Line 10: This should be “intense”, not “intensive”.*

   Answer: Corrected.

2. *Page 10334, Line 26: Because you have access to climatic water balance, it would be interesting in future studies to calculate trends in SPEI (Vicente-Serrano et al. 2010) and compare results to the SPI, a precipitation-based metric. This is not needed for this study, simply a suggestion for the future.*

   Answer: Thank you very much for this suggestion.

3. *Page 10334, Lines 23–26: There are some additional studies that attempt to project meteorological drought in Europe, either using coarse resolution (GCM) or high resolution (GCM/RCM). I suggest you consider some of the following:*
   a. *Blenkinsop, S. and H. J. Fowler (2007): Changes in European drought characteristics projected by the PRUDENCE regional climate models. International Journal of Climatology 27(12):1595-1610.*
   b. *Dai, A. (2013): Increasing drought under global warming in observations and models. Nature Clim. Change 3: 52–58.*
   c. *Orlowsky, B. and S. I. Seneviratne (2013): Elusive drought: uncertainty in observed trends and short- and longterm CMIP5 projections. Hydrol. Earth Syst. Sci. 17(5):1765-1781.*
   d. *Stagge, J.H., Rizzi, J., Tallaksen, L.M., and Stahl, K. (2015). "DROUGHTRSPI Technical Report No. 25 Future Meteorological Drought Projections of Regional Climate" DROUGHT-RSPI Project .*

      Answer: Thank you very much for the list of additional studies. We have included most of these in the corrected version of manuscript.

4. *Page 10335, Line 5: Hydrological drought may also refer to deficits in groundwater or reservoir storage.*

   Answer: Yes, a good point. Corrected.

5. *Page 10338, Line 4: The authors should mention that the scenarios are based on AR4 SRES scenarios (presumably) and not the RCP scenarios. This is not a problem, but should be mentioned in the methods.*

   Answer: The following sentence has been added to the manuscript. The A1B emission scenario belongs to SRES family described in the IPCC Special Report on Emission Scenarios (SRES) (Nakicenowic et al., 2000) and used to make projections for the IPCC Third Assessment Report (TAR) and in the IPCC Fourth Assessment Report (AR4).

6. *Page 10340, Lines 11-17: I appreciate the desire to cite all of this research, showing the importance of the SPI. But, I think this is citation list is a little excessive. I recommend trimming it to the most important references*

   Answer: The list of references has been shortened to include the most important recent papers as follows.

   The index is used for both research and operational purposes in over 60 countries (e. g. Bordi et al., 2009; Moreira et al., 2012; Sienz et al., 2012; Gocic and Trajkovic, 2013; Liu et al., 2013; Dutra et al., 2014; Zargar et al., 2014; Jenkins and Warren, 2015; Swain and Hayhoe, 2015; Zarch et al., 2015).

7. *Page 10341, Line 26: These papers discuss the use of normality testing to validate SPI values and check whether zeros cause a failure. They may be useful to cite:*
   a. *Kumar MN, Murthy CS, Sesha Sai MVR, Roy PS. 2009. On the use of Standardized Precipitation Index (SPI) for drought intensity assessment. Meteorol. Appl. 16 : 381–389, doi: 10.1002/met.136*
   b. *Stagge, J. H., Tallaksen, L. M., Gudmundsson, L., Van Loon, A. F. and Stahl, K. (2015), Candidate Distributions for Climatological Drought Indices (SPI and SPEI). Int. J. Climatol., 35: 4027–4040. doi: 10.1002/joc.4267*
   c. *Wu H, Svoboda MD, Hayes MJ, Wilhite DA, Wen F. 2007. Appropriate application of the standardized precipitation index in arid locations and dry seasons. Int. J. Climatol. 27 : 65–79*

      Answer: Thank you very much for these suggestions. The recommended references has been cited in the paper and the following sentence has been added “Different methods of normality testing of SPI values are reported in the literature, including, for example, the Shapiro-Wilk statistic and absolute value of the median smaller than 0.05 (Wu et al., 2007; Kumar et al., 2009; Stagge et al., 2015)”.

8. *Page 10342, Line 15: It would be good to mention in the text that the MannKendall test operates based on all possible combinations of points. This is mentioned for the Sen slope (Page 10343, Line 17), but should be introduced earlier in this section.*

   Answer: Updated. “The original Mann-Kendall test for trend is based on a rank correlation test for the observed values and their order in time and operates on all possible combinations of points”.

9. *Page 10347, Line 4 and elsewhere: You refer to figures out of order. In this case, you cite Figure 14 well before Figures 8-13.*

Answer: In that line Figure 7 should be cited and this has been corrected.

10. *Page 10351, Line 6 and elsewhere: Please be specific regarding the subset you are analyzing for longer duration SPI's. For instance, the SPI 12 is the annual time step, but it appears you are only considering the SPI 12 in December. The full SPI12 time series is a moving window that moves forward monthly (or daily), always looking back 12 months. I assume you are also using December for the SPI24, which should also be specified. The discussion of SPI3 is adequate, stating that you extracted values for February (DJF), May (MAM), August (JJA), and November(SON).*

Answer: Yes, the SPI indexes were calculated using aggregated sum of precipitation following the rule: SPI 3 – DJF the index was extracted for February, MAM the index was extracted for May, JJA the index was extracted for August, and SON the index was extracted for November. In the case of SPI 12 and SPI 24 the indexes were extracted for December.

11. *Table 1: I recommend using two column headings, one showing GCM and another showing RCM. By grouping the trends by GCM, it would be easier to look for trends among the forcing time series.*

Answer: Corrected.

Table 1. Results of trend analysis using the modified Mann-Kendall method for SPI 1 for one grid cell located close to Bialystok (NE Poland); ↗ - denotes statistically significant positive trend, ↘ - denotes statistically significant negative trend, - denotes no statistically significant trend.

	Bias corrected data						Uncorrected (raw) data					
GCM	ARPEGE		ECHAM5		BCM		ARPEGE		ECHAM5		BCM	
RCM	DMI HIRHAM	RM51	MPI M REMO	KNMI RACMO2	DMI HIRHAM	SMHIRCA	DMI HIRHAM	RM51	MPI M REMO	KNMI RACMO2	DMI HIRHAM	SMHIRCA
JAN	-	-	↗	↗	↗	↗	-	-	↗	↗	↗	↗
FEB	↗	-	-	↗	-	-	-	-	-	-	-	-

MAR	-	-	↗	-	↗	↗	-	-	-	-	↗	↗
APR	-	-	-	-	-	-	↘	-	-	-	-	-
MAY	-	-	-	-	-	-	-	-	-	-	-	-
JUN	-	-	-	↘	-	-	-	-	-	↘	-	-
JUL	↘	↘	-	-	↗	-	↘	↘	-	-	↗	-
AUG	↘	↘	-	-	-	-	-	↘	-	-	-	-
SEP	↘	↘	-	↗	-	-	↘	↘	-	↗	-	-
OCT	-	-	-	-	-	-	-	-	-	-	-	-
NOV	-	-	-	-	-	-	-	-	-	-	-	-
DEC	-	-	↗	↗	↗	↗	-	-	↗	↗	↗	↗

12. *Figure 7: Similar to my comment for Table 1, it would be helpful if these models were organized by GCM, rather than alphabetically to see how the GCM forcings differ and how the RCMs modify the forcings.*

Answer: Corrected.

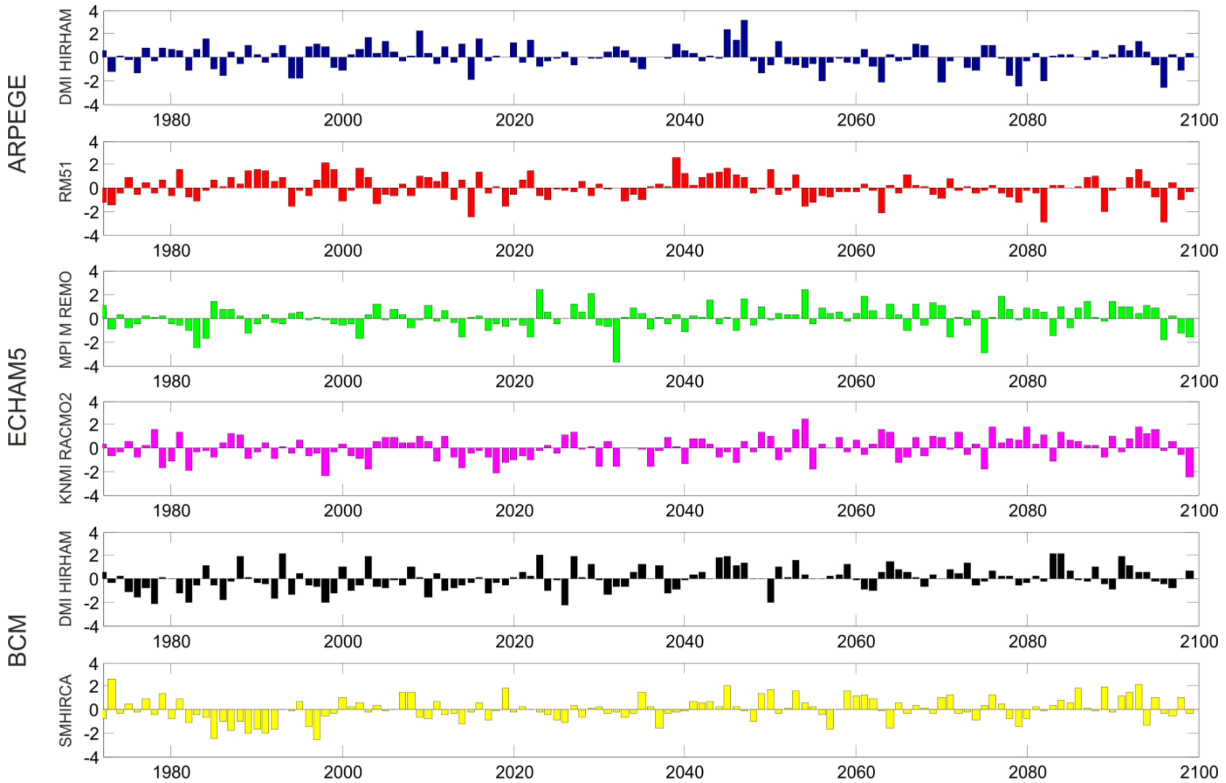


Figure 7. An example of SPI 12 time series for raw data: DMI HIRHAM ARPEGE, RM51 ARPEGE, MPI M REMO ECHAM5, KNMI RACMO2 ECHAM5 r3, DMI HIRHAM BCM, SMHIRCA BCM.

4 Response to Referee #2

The reviewer's comments are *in italic* and our response in normal font.

4.1 General Comments

The authors present an analysis using the Standardized Precipitation Index (SPI) to assess future trends in meteorological drought in Poland. They use high resolution climate simulations of the ENSEMBLES project of six different RCM/GCM combinations under the A1B emission scenario. The results show a positive trend of the SPI in winter and a slightly negative trend in summer. Additionally, the effect of bias correction on the trend signal is only weak. However, the spread between different model realisations introduces much more uncertainty. The paper is well written and structured. It provides information on future SPI trends and also on the very important topic of the effects of bias correction on the results. In *general I would recommend publishing the paper in HESS, however, some major and minor comments are summarized below and should be taken into account.*

Answer: We thank the reviewer for the encouraging words and very helpful and detailed comments.

4.2 Major Comments:

The authors use the linear trend of the SPI time series as a change indicator for meteorological drought occurrence in the future. I think, although the trend estimator is a very robust one, that the approach introduces some uncertainty and difficulty in interpretation. In the results maps are displayed showing the slope of the linear regression of the SPI values against time, indicating whether the SPI shows a negative trend (→ interpretation is increase in droughts) or a positive one (less droughts). These plain numbers make it hard to assess the magnitude of change. The SPI is a probabilistic drought index, indicating the chance of a certain precipitation amount to occur. For the reader and also for a deeper justification of the title of the manuscript (meteorological drought) it would be worthwhile to assess future drought occurrence in a more profound way. One possibility would be to fit the Gamma-distribution of the precipitation time series only in the reference period (1971-2000), but calculating the SPI for the whole time series (1971-2099). That would enable to assess possibly changing probability of drought occurrence (e.g. SPI below -1, or even -2) in a future time period (2070-2099) compared to the reference period, which should follow a unit normal distribution. I think the manuscript would benefit, if these kind of analysis is added. For examples two figures for winter and summer might be added to the results, or even to a Discussion section, although not existing. This is an additional point I'd like to make, that I think the manuscript would benefit from adding a Discussion section, adding a critical discussion on bias correction, possible introduced uncertainties thereof and the necessity for bias correction in the light of the presented results (Maybe section 3.3 could be included in a Discussion section and also some parts of the Conclusions). There is also much literature cited in the introduction. The Discussion section should pick up the main findings of these and discuss them in the light of the apparent results.

Personally, I think no matter how large the biases from the model data are, the differences between raw and corrected SPI should not be too big, since calculating the SPI is some kind *of quantile fitting as is the quantile mapping. As the first reviewer commented, the differences between raw and corrected SPI might come mostly from differences in the fitting of the distributions and/or differences in the extreme values, which is particularly of concern in quantile mapping.*

Answer: We thank the reviewer for very useful and constructive comments. We agree with the reviewer that the approach of drought assessment based on SPI indices introduces uncertainty and it is not straight-forward to interpret. We hope that our paper helps the reader to learn about those difficulties. We discussed the possibility of basing the SPI indices on the reference period in the response to the first reviewer. Taking into account the pros and cons we think our choice of using the whole future period is justified and we will add a discussion on that issue in the corrected version of the paper.

The reviewer's second comment refers to expanding the discussion part of the paper. In response to this comment we extended the discussion in the revised version of the paper (please see the response to minor comments).

4.3 Minor Comments:

- *Page 10332, Lines 1-2: Suggestion: ". . .drought severity in Poland are estimated applying an ensemble of six climate projections using. . ."; The ENSEMBLES project is described later and there is no need to introduce this abbreviation in the Abstract*

  Answer: Changed, as suggested.
- *Page 10332, Line 3: ". . .six different RCM/GCM runs. . ."; please also aim to avoid abbreviations in the Abstract. If it is ultimately necessary write the full name and the abbreviation in the Abstract and at that point in the text where it first appears.*

  Answer: Corrected. Instead of abbreviations such as RCM GCM, the full name is given. For example we changed "...six different RCM/GCM runs..." to " ..six different climate models runs …"
- *Page 10332, Line 7: ". . . spatial resolution of 25 km for the. . ."*

  Answer: Corrected.
- *Page 10332, Line 9: delete "25 km x 25 km"; ". . .projection and timescale. Additionally, results obtained. . ."*

  Answer: Deleted.

- *Page 10332, Line20: change "with different" to "driving different"*

  Answer: Corrected.

- *Page 10333, Line 20 – Page 10334 Line4: Just state shortly what Rimkus et al. (2012) found out. Shift most of the text to the Discussion section and discuss it in the light of your findings.*

  Answer: We include the following text: Analysis of the potential impact of climate change on drought in Poland has been addressed by a few studies at a regional scale. Rimkus et al. (2012) analysed 50-year trends (1960-2009) under the recent climate and drought projections for the future climate (up to 2100) in the Baltic Sea region using the Standardized Precipitation Index (SPI). For the assessment of the observed climatic conditions, gridded precipitation time series at 1-degree resolution from the Climate Research Unit at the University of East Anglia were used. The trend estimated using a Mann-Kendall test indicated an increase in the SPI values for different time averaging periods over most of the studied area, except for Poland, where decreases were found. Future dryness was projected using COSMO Climate Limited-area Model (CCLM) driven by initial and boundary conditions from ECHAM5/MPI-OM GCM for two emission scenarios (A1B and B1). According to both scenarios, the intensity of drought will likely decline in most of the Baltic Sea area, except in the southern parts, including Poland. Following the A1B scenario, drought occurrence will increase in the summer months in the future in those regions.

  Some of the findings of Rimkus et al. (2012) can be compared with the results presented here. They both include simulations following the A1B emission scenario driven by ECHAM5 GCM. Our results in some aspects (e.g. tendency of changes of annual sum of precipitation) are similar to those presented by Rimkus et al. (2012) but differences are also apparent. These differences result from different spatial resolution and an application of a different regional climate model.

  The analysis of the impact of climate change on drought in Poland, carried out within the framework of the project "Development and implementation of a strategic adaptation plan for the sectors and areas vulnerable to climate change" with the acronym KLIMADA (klimada.mos.gov.pl), indicated that future predictions of annual total precipitation do not show any clear trends (Liszewska et al., 2012). The assessment of trends in seasons shows an increase in winter precipitation (DJF) of up to 20% in the eastern part of Poland and a decrease in summer precipitation in south eastern Poland. In contrast, changes in precipitation in spring and autumn tend to be much smaller (Liszewska et al., 2012). The number of dry days with daily precipitation of less than 1 mm shows an increasing trend. These changes are more pronounced in eastern and south eastern Poland (NAS, 2013). Those findings by Liszewska et al. (2012) are confirmed in this paper.

Analysis of an impact of climate change on drought using a meteorological water balance (defined as the difference between evapotranspiration and rainfall for a given period) for three periods 1971-2000, 2021-2050 and 2071-2100 was carried out by Osuch et al. (2012). The results of the assessment indicate significant differences between projections derived from the different climate models analysed. A comparison of the median of the ensemble of models in these three periods indicates an increase in water scarcity in Poland. These changes are more pronounced in the south eastern part of Poland. Those results confirm the SPI12 analysis outcomes presented in this paper.

Changes in European drought characteristics projected by PRUDENCE regional climate models were studied by Bleckinsop and Fowler (2007). In that work six climate model simulations were analysed following the SRES A2 emission scenario. Similar to our findings, a considerable model uncertainty due to inter-model variability on regional and local scales was demonstrated. The projections indicate likely decreases in summer and likely increases in winter precipitation. For longer duration droughts, the projections indicate fewer droughts in northern Europe due to larger increases in winter precipitation and more droughts of increasing severity in the south. Our results confirm these general findings with differences due to different emission scenarios as well as climate models.

The study by Orlowsky and Seneviratne (2013) presents an analysis of the SPI12 at a continental scale. The results for Central Europe show an increasing trend in median SPI 12. The new study by Stagge et al. (2015) presents an analysis of meteorological drought using the newest climate models available representing 23 simulations for the three projected emission scenarios (rcp2.6, RCP4.5 and RCP8.5) for Europe at a spatial resolution of 0.11 degree (~12.5 km). Meteorological drought was estimated using the SPI at 3, 6 and 12 month aggregation periods. In that work the relationship between aggregated precipitation and SPI was developed for the reference period (1971-2000). Then the same transformation was used for future scenarios (2011-2040, 2041-2070, and 2071-2100). The analysis of changes in SPI between future and present periods was conducted using a parametric two sample t-test and a non-parametric Mann-Whitney test. The results indicate that precipitation is likely to increase in central and northern Europe, that area is, therefore, likely to experience fewer precipitation-based droughts. In general, our study confirms the results of Stagge et al. (2015) with some differences due to different climate models, emission scenarios and the change estimation methods applied. Our selection of climate models provides larger differences between meteorological projections. In addition, an analysis of SPI at shorter aggregation periods indicates an increasing trend in the degree of dryness during the summer months and a decreasing trend for the winter months.

- *Page 10334, Lines25-26: "or drought indices such as the climatic water balance, that are insufficient for adaptation purposes." Please clarify these statements: what is the climate water balance drought index? Do you mean the SPEI? Then you will have to add a reference (Vincente-Serrano et al. 2010). Why is it insufficient? Can you justify this statement?*

Answer: In Poland, the assessment of the degree of dryness is carried out using the climatic water balance defined as the difference between and potential evapotranspiration in the selected period. That index is an important variable using in drought monitoring. The usefulness of the climatic water balance is limited due to its simplified form and it does not include an estimation of actual evaporation or snow accumulation and melting. The analyses carried out with help of potential evapotranspiration are not bounded by physical conditions in the catchment, i.e. water availability.

- *Page 10334, Line29 – Page 10335, Line2: Merge this sentence with Page 10335 Lines 14-16, since there is much redundant information.*

Answer: Merged to eliminate redundancy.

- *Page 10338, Lines 4-10: Instead of listing all simulations in the text a small table would give a much better overview of the different runs and the RCM/GCM combinations.*

Answer: A table showing applied combination of climate model has been included in the revised manuscript, as shown below.

Table 3 GCM and RCM combinations used from ENSEMBLES project. The numbers denotes number of simulations

GCM / RCM	ARPEGE	ECHAM5	BCM	Total scenarios
DMI HIRHAM5	1	0	1	2
SMHIRCA	0	0	1	1
RM51	1	0	0	1
MPI M REMO	0	1	0	1
KNMI RACMO2	0	1	0	1
Total scenarios	2	2	2	6

- *Page 10338, Line 15: E-OBS is not a reanalysis in the usual climatological sense (like the ERA-40 or NCEP dataset). I would consider writing "E-OBS gridded observation data", or simply "E-OBS data". See also Line 27 on that page.*

  Answer: We changed this to "E-OBS gridded observation data".
- *Page 10339, Line 5: Dosio and Paruolo (2011) and Gudmunsson et al. (2012)*

  Answer: Corrected.
- *Page 10339, Line12: Please specify the threshold you applied for wet/dry day distinction.*

  Answer: Updated to P> 0mm/day
- *Page 10340, Lines 11-17: Please only cite the most important studies in the light of your investigation. This list is rather long.*

  Answer: The list of references has been shortened as follows to focus on the most important papers.

  The index is used for both research and operational purposes in over 60 countries (e. g. Bordi et al., 2009; Moreira et al., 2012; Sienz et al., 2012; Gocic and Trajkovic, *2013; Liu et al., 2013; Dutra et al., 2014; Zargar et al., 2014; Jenkins and Warren, 2015; Swain and Hayhoe, 2015; Zarch et al., 2015).*

- *Page 10340, Line 21: This is a rather sloppy formulation. Of course other distributions can be used, but what are the implications? When or where do I use other distributions?*

  Answer: Refined as follows: Time series of precipitation for a particular location are fitted to the gamma distribution following the recommendation by Stagge et al. (2015).

  Stagge, J. H., Tallaksen, L. M., Gudmundsson, L., Van Loon, A. F. and Stahl, K.: Candidate Distributions for Climatological Drought Indices (SPI and SPEI), Int. J. Climatol., 35, 4027–4040, doi: 10.1002/joc.4267, 2015.

- *Page 10341, Lines 10-13: This statement is not clear to me, please rephrase.*

  Answer: Changed to: “Wu et al. (2005) recommended the use of the longest possible period for the derivation of SPI as the short data sets could give large errors of estimated values. For the comparison of results between different locations the choice of the same period is suggested.”

- *Page 10344, Lines 3-5: Delete paragraph. It is not necessary.*

  Answer: Deleted, as suggested.

- *Page 10345, Line 4: rephrase: “. . .precipitation intensities are simulated by RCMs driven by ARPEGE.”*

  Answer: Corrected.

- *Page 10346, Line 16: raw should be row.*

  Answer: Corrected.

- *Page 10347, Line 4: Fig. 14: Please stick to the order of the Figures referenced in the text.*

  Answer: Corrected. Figure 7 should be cited there.

- *Page 10347, Line 12: Why did you choose exactly this station? Could you please justify this decision?*

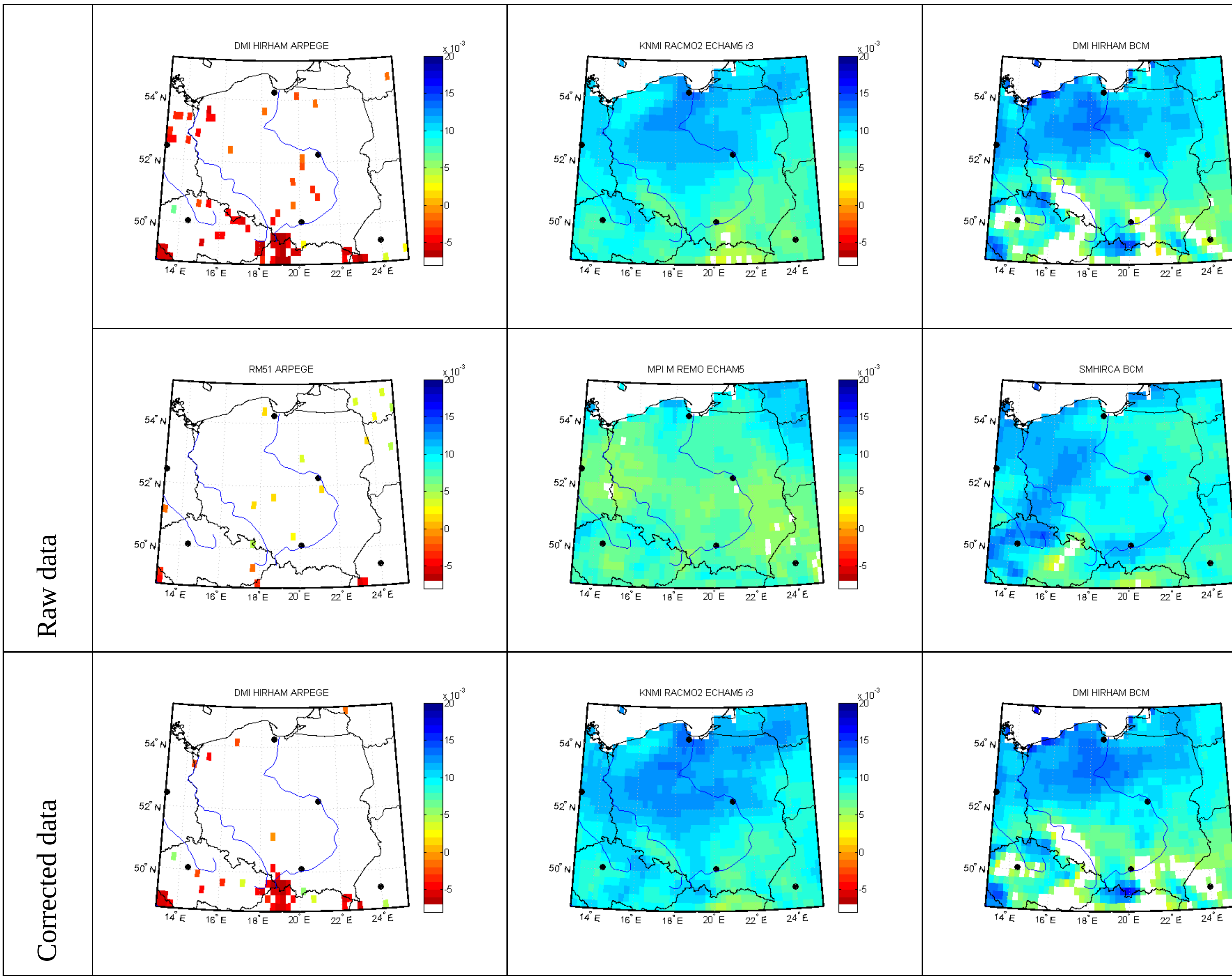
  Answer: We have chosen a grid cell located in the NE Poland close to Białystok to illustrate our results. This selection was made based on the results Liszewska et al. (2012). The largest changes in winter precipitation are projected to be in that area. We clarify this selection in the text.

- *Page 10349, Line 18: rephrase: ". . .depends on the climate model and month under consideration."*

  Answer: Corrected.
- *Page 10349, Lines 19-20: rephrase: ". . .of simulated data, therefore the most intense bias correction is applied in that case."*

  Answer: Corrected.
- *Page 10350, Lines 22-29: Where are these results shown? (Table, Figure)*

  Answer: The results of the SPI 6 for the cold season (November-April) are similar to those for the SPI 3 winter. The results are presented in the Supplementary materials (Figure S2).



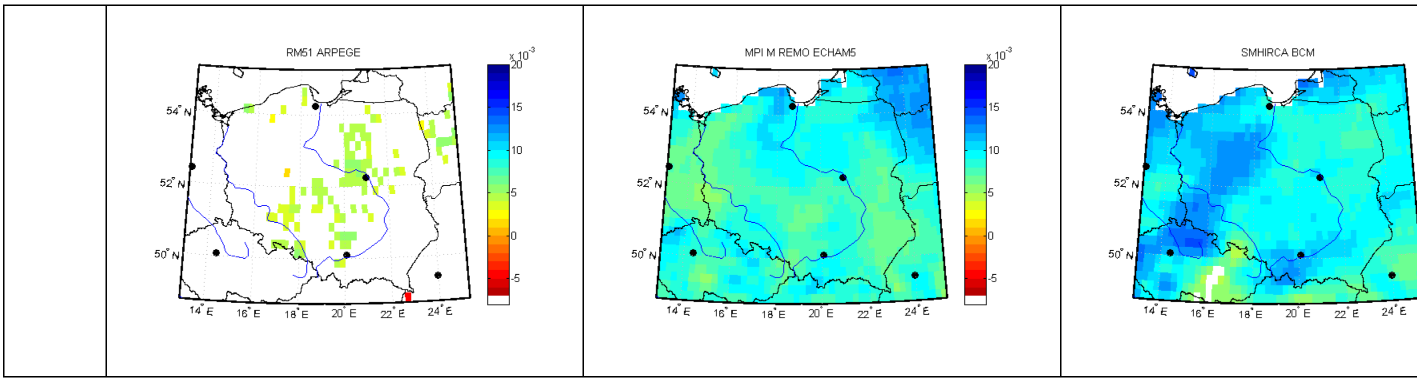


Figure S2. The results of modified Mann-Kendall trend analysis for SPI 6 cold season (NOV-APR). Colour scale denotes slope of the estimated trend. White colour denotes lack of trend.

- *Page 10353, Line 11: Why the "first six months"? Where is the justification for this? I would rather suggest using the four "core" months of the seasons: January, April, July and October.*
  Answer: In the updated version of manuscript we show the relationships for all months, as illustrated here.

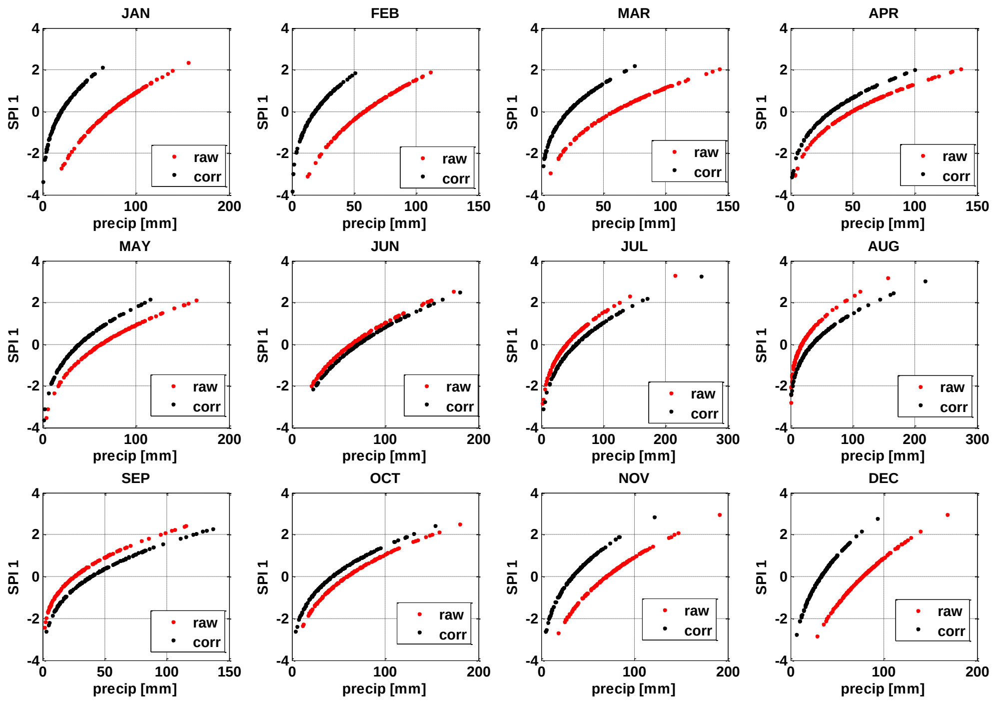


Figure 14 The scatterplots showing relationship between monthly sum of precipitation and estimated SPI 1 values for 12 months for one grid cell located close to Białystok (NE Poland) for DMI HIRHAM ARPEGE model. The colour denotes type of data used, red colour -uncorrected precipitation and SPI 1, black corrected ones.

- *Page 10354, Lines 4-6: Please add a reference to this statement.*
  Answer: Reference to Sunyer et al. (2015) is added.

- *Page 10354, Line 20: Reference of Maurer and Pierce (2014): the authors of this study analysed precipitation, not a precipitation index. This is a complete different thing, so I think this reference is not valid for the given statement.*

  Answer: We maintain this reference in order to explain bias correction methods necessary in our analysis of the influence of bias correction on SPI indices.

- *I could not find a reference in the text for Figure 7.*

  Answer: Corrected.

- *Figure 10 is a bit confusing. You produced a stacked bar chart, which is not appropriate in my opinion. A better way would be to draw the bars separately, grouped by month, or to have a line chart with one model representing one line in different colours.*

  Answer: Figure 10 was changed following the suggestions from both reviewers. :

Trends in projections of Standardized Precipitation Indices in a future climate in Poland

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Abstract

Possible future climate change effects on ~~drought severity~~dryness conditions in Poland are estimated for six ~~ENSEMBLE~~ climate projections using the Standardized Precipitation Index (SPI). The time series of precipitation represent six different ~~RCM/GCM~~climate model runs under the A1B SRES scenario for the period 1971-2099. Monthly precipitation values were used to estimate the Standardized Precipitation Index (SPI) for multiple time scales (1-, 3-, 6-, 12- and 24- months) for a spatial resolution of 25~~x25~~ km^2 for the whole country. Trends in the SPI were analysed using the Mann-Kendall test with Sen's slope estimator for each ~~25 x 25 km2~~ grid cell for each ~~RCM/GCM~~climate model projection and aggregation~~times~~ scale, and results obtained for uncorrected precipitation and bias corrected precipitation were compared. Bias correction was achieved using a distribution-based quantile mapping (QM) method in which the climate model precipitation series were adjusted relative to gridded E-OBS precipitation data for Poland. The results show that the spatial pattern of the trend depends on the climate model, the time scale considered and on the bias correction. The effect of change on the projected trend due to bias correction is small compared to the variability among climate models. We also summarise the mechanisms underlying the influence of bias correction on trends in precipitation and the SPI using a simple example of a linear bias correction procedure. In ~~the~~ both cases~~ of precipitation~~, the bias correction by QM does not change the direction of changes but can change the slope of trend, and the influence of bias correction on SPI is much reduced. We also have noticed that the results for the same

~~GCM~~global climate model, ~~with~~ driving different~~differing~~ ~~RCMs~~regional climate model, are characterized by a similar pattern of changes, although this behaviour is not seen at all time scales and seasons.

1 Introduction

Drought is an extreme event which can produce significant deleterious effects under both present and future climatic conditions according to the recent Special Report by the Intergovernmental Panel on Climate Change (IPCC) on Managing the Risk of Extreme Events and Disasters to Advance Climate Change Adaptation (SREX).

The assessment of future drought scenarios is crucial for many aspects of the national economy, including agriculture, energy, biodiversity, forestry, and the health and water sectors (Jenkins and Warren, 2015). Therefore, drought can significantly influence the well-being of society and its capacity for resilient development. Recent IPCC reports and scientific articles indicate that drought events have been increasing in frequency and intensity in some regions over the last part of the 20th century as a result of climate change (Kaczmarek et al., 1996; Alexander et al., 2006; Bartholy and Pongracz, 2007; Brazdil et al., 2009; Kiktev et al., 2009; Somorowska, 2009; Dai, 2011; KLIMADA, 2012; Seneviratne et al., 2012). Climate projections suggest that drought is likely to increase (at a medium level of confidence) and may become more intens~~iv~~e in some regions, including Central Europe (IPCC 2012), especially in areas with dry conditions in today’s climate (IPCC 2014 AR5). Poland has relatively limited water resources, and in some areas of Poland temporary difficulties in maintaining adequate water supply can occur. Previously published analyses of drought in Poland have mainly been concerned with the classification of drought types and the development of drought indices (Łabędzki, 2007; Łabędzki and Kanecka-Geszke, 2009; Tokarczyk, 2013), monitoring of drought conditions (Tokarczyk and Szalińska, 2013; Łabędzki and Bąk, 2014) and drought hazard assessment for periods when observations are available (Tokarczyk and Szalińska, 2014).

Analysis of the potential impact of climate change on drought in Poland has been addressed by a few other studies at a regional scale. Rimkus et al. (2012) analysed 50-year trends (1960-2009) under the recent climate and for drought projections for the future climate (up to 2100) in the Baltic Sea region using the Standardized Precipitation Index (SPI). For the assessment of the observed climatic conditions, gridded precipitation time series at a 1-degree resolution from the Climate Research Unit at the University of East Anglia were used. The trend estimated using a Mann-Kendall test indicated an increase in the SPI values for different time averaging periods over most of the studied area, except for Poland, where decreases were found. Future dryness was projected using COSMO Climate Limited-area Model (CCLM) driven by initial and boundary conditions from ECHAM5/MPI-OM GCM for two emission scenarios (A1B and B1). According to both scenarios, the intensity of drought will likely decline in most of the Baltic Sea area, except in the southern parts, including Poland. Following the A1B scenario, drought occurrence will increase in the summer months in the future in those regions.

The analysis of the impact of climate change on drought in Poland, carried out within the framework of the project "Development and implementation of a strategic adaptation plan for the sectors and areas vulnerable to climate change" with the acronym KLIMADA (klimada.mos.gov.pl), indicated that future predictions of annual total precipitation do not show any clear trends (Liszewska et al., 2012). The assessment of trends in seasons shows an increase in winter precipitation (DJF) of up to 20% in the eastern part of Poland and a decrease in summer precipitation in south eastern Poland. In contrast, changes in precipitation in spring and autumn tend to be much smaller (Liszewska et al., 2012). The number of dry days with daily precipitation of less than 1 mm shows an increasing trend. These changes are more pronounced in eastern and south eastern Poland (NAS, 2013).

Analysis of the impact of climate change on drought using a ~~meteorological~~ climatic water balance (defined as the difference between precipitation and potential evapotranspiration for a given period) for three periods 1971-2000, 2021-2050 and 2071-2100 was carried out by Osuch et al. (2012). The results of the assessment indicate significant differences between projections derived from the different climate models analysed. A comparison of the median of the ensemble of models in these three periods indicates an increase in water scarcity in Poland. These changes are more pronounced in the south eastern part of Poland.

Analyses of drought projections at continental scale were carried out ~~studied~~ by Bleckinsop and Fowler (2007). In that study six climate model simulations were analysed following the SRES A2 emission scenario. A considerable model uncertainty due to inter-model variability on regional and local scales was demonstrated. The projections indicate likely decreases in summer and likely increases in winter precipitation. For longer duration droughts, the projections indicate fewer droughts in northern Europe due to larger increases in winter precipitation and more droughts of increasing severity in the south.

Orlowsky and Seneviratne (2013) presented an analysis of SPI 12 at a continental scale. The results for Central Europe showed an increasing trend in median SPI 12.

A new study by Stagge et al. (2015) presents an analysis of meteorological drought using the most current climate models (23 simulations) for the three projected emission scenarios (RCP 2.6, RCP 4.5 and RCP 8.5) for Europe at a spatial resolution of 0.11 degree (~12.5 km). Meteorological drought was estimated with the help of SPI at 3, 6 and 12 month aggregation periods. In that work the relationship between aggregated precipitation and SPI was developed for the reference period (1971-2000). Then the same transformation was used for future scenarios (2011-2040, 2041-2070, and 2071-2100). The analysis of changes in SPI between future and present periods was conducted using the parametric two sample t-test and the non-parametric Mann-Whitney test. The results indicated that precipitation is likely to increase in central and northern Europe; therefore that area is likely to experience fewer precipitation-based droughts.

Results assessing the influence of climate change on drought in Poland which are available so far are limited to either a coarse resolution (1-degree), few climate models considered (e.g. only one RCM/GCM combination was used by Rimkus et al. (2012)) or to the choice of drought indices, e.g. climatic water balance, that are not suitable for adaptation purposes due to its simplified form with unlimited losses related directly to air temperature increase without limits (i.e. water availability).

~~This article aims to estimate changes introduced by climate variability on the meteorological drought in Poland using the Standardized Precipitation Index (SPI) at a spatial resolution of 25x25 km^2. In addition, we apply an ensemble of six GCM/RCM models in order to consider some of the uncertainty introduced by differences between climate model projections.~~

Three types of drought can be distinguished: meteorological drought which is evaluated on the basis of precipitation deficit, agricultural drought reflecting a soil moisture deficit, and hydrological drought resulting in a streamflow, groundwater or reservoir deficit. A meteorological drought often initiates agricultural and hydrological drought but other factors also have an effect on the occurrence and development of agricultural and hydrological drought. The term ‘drought’ has different meanings, depending on the end-user involved. For the description, monitoring and quantification of drought, several indices are used in research and in practice. A detailed review of these indices is presented in Dai (2011). In this article we focus on the description of the ~~meteorological drought~~degree of meteorological dryness using the Standardized Precipitation Index (SPI) developed by McKee et al. (1993). A description of this index is presented in the following section. Dryness, followed in this paper, reflects a wider range of conditions than drought as it describes a state of precipitation deficit in the range from normal conditions down to an extreme drought (Fischer et al, 20134).

Projections of ~~drought~~ dryness/wetness conditions under a future climate are carried out using simulated climate data obtained from regional climate models (RCM) which are run based on boundary conditions derived from global climate models (GCM). These models simulate the best available approximation of future climate conditions, although there remains uncertainty related to our insufficient knowledge of physical laws governing the atmosphere and the environment, differences in techniques for coupling RCM and GCM models, as well as assumptions related to global and regional economic and demographic development as represented by a given SRES greenhouse gas emission scenario.

Comparison of the simulations with observations indicates that climate models are able to simulate important aspects of current climate including many patterns of climate variability across a range of scales, for example annual patterns of air temperatures and storm tracks (Ehret et al., 2012; IPCC 2014 AR5). In particular, models lead to the same or similar tendencies in changes at large spatial and temporal aggregation scales (Ehret et al., 2012). The reliability of such simulations is, however, not proven for all climatic variables. Simulations of precipitation fields are highly biased due to the variety of complex processes leading to precipitation generation in the atmosphere, which includes microphysics of clouds, convection processes, processes in the planetary boundary layer and the interactions between the ground surface and the atmosphere. Errors occurring in simulated precipitation fields are due to necessary simplifications in the description of these processes in climate models. This problem is well known and reported by many authors (Piani et al., 2010; Hagemann et al., 2011; Liszewska et al., 2012; Osuch et al., 2012; Madsen et al., 2014; Sunyer et al., 2015; Vormoor et al., 2015). Therefore most studies considering the impact of climate change on processes related to precipitation use statistical downscaling and/or bias correction of the climate simulations relative to observations, rather than basing such analyses on raw (uncorrected) climate model outputs (Madsen et al., 2014).

An application of a bias correction significantly improves the simulations in the control time period, but at the same time, it changes a relationship between climate variables and can violate conservation principles (Ehret et al., 2012). Consistency between the spatio-temporal fields of a climate variable can also be altered. Other problems which potentially undermine a reliable interpretation of the results of projections include neglected feedback mechanisms and an assumption of stationarity of bias correction method parameters derived for a period with available observations but later used for changed conditions during future periods. Application of bias correction in the modelling chain can alter climate change signals (Hagemann et al., 2011; Cloke et al., 2013; Gutjahr and Heinemann, 2013; Teng et al., 2015). The ongoing discussion on the suitability of bias correction of data derived from climate model simulations was initiated by Christiansen et al. (2008) and has been taken further by Ehret et al. (2012), Muerth et al. (2013), Teutschbein and Seibert (2013), among others. Proposed solutions to this problem include presenting results for both bias corrected and non-corrected inputs and analysis of the worst case scenario. The best, but also the most challenging, solution could be achieved by the improvement of climate models (Ehret et al., 2012) such that bias correction is not required.

The aim of this paper is an estimation of potential local changes in the degree of dryness~~meteorological~~ ~~drought~~ in Poland resulting from future climate change, as interpreted from changes in the estimated Standardized Precipitation Index (SPI). We apply an ensemble of six GCM/RCM models in order to consider some of the uncertainty introduced by differences between climate model projections. The influence of bias correction on the resulting projections of trends in the SPI values is also analysed. Such work has not been previously undertaken for the whole of Poland, but is a necessary input for developing climate change adaptation policies related to the projected degree of meteorological dryness~~occurrence of meteorological drought~~.

The article is organized as follows. In section 2 we describe the methodologies used to develop precipitation and SPI projections for Poland. In section 3 a comparison of the simulated and observed precipitation time series is presented, together with the estimated tendencies in spatio-temporal changes in drought condition in Poland over the period 1971-

2099. The last section presents a discussion and summarizes the most important results of the study.

2 Methods

The chain of analysis underlying the estimation of changes in drought indices is illustrated in Figure 1. For these analyses, a multi-model ensemble of climate projections has been used in keeping with recommendations for such work (e.g. van der Linden and Mitchell, 2009; Knutti et al., 2010). Precipitation time series generated by the climate models have been bias corrected relative to observations and further details are given below. On the basis of the corrected precipitation series from the climate projections, the ~~meteorological~~ ~~drought~~meteorological dryness indices are calculated. Tendencies in changes are estimated using non-parametric trend analysis (Kundzewicz and Robson, 2004). For the assessment of the influence of the bias correction method on the temporal variability of the meteorological ~~drought~~dryness, the analyses are carried out for both uncorrected and bias corrected precipitation time series from the climate models.

2.1 Climate data

Climate variables have been obtained from the EU FP6 ENSEMBLES project (van der Linden and Mitchell, 2009), in the form of time series of precipitation derived from six different RCM/GCMs: DMI HIRHAM5 ARPEGE, SMHIRCA BCM, RM51 ARPEGE, MPI M REMO ECHAM5, KNMI RACMO2 ECHAM5 r3 and DMI HIRHAM5 BCM following A1B climate change scenario for the time period: 1971-2100. The A1B emission scenario belongs to the SRES family described in –the IPCC Special Report on Emission Scenarios (SRES) (Nakicenowic et al., 2000) and used to make projections for the IPCC Third Assessment Report (TAR) and in the IPCC Fourth Assessment Report (AR4). These six simulations are based on five RCMs (DMI HIRHAM5, SMHIRCA, RM51, MPI M REMO and KNMI RACMO2) driven by three different GCMs (ARPEGE, ECHAM5 and BCM). In two cases, the same RCM was used with different GCMs (ARPEGE and BCM). These combinations of RCM/GCM simulations are shown in Table 1. In this work we applied simulations of climate models transformed to normal grids (non-rotated) with a spatial resolution of 0.25° × 0.25°. The analyses were carried out for two periods: a reference period 1971-2000 and the entire available period 1971-2099.

The simulations in the reference period (1971-2000) were compared with observations from synoptic stations (point measurements) and also with the latest available version of the E-OBS gridded observation data~~reanalysis~~ (version 10) from the European Climate Assessment and Dataset (ECA&D; Haylock et al., 2008) of the Royal Netherlands Meteorological Institute (KNMI). The spatial resolution of the E-OBS grid cells is the same as the ENSEMBLES RCM domain (i.e. 0.25° × 0.25°).

2.2 Bias correction

Our previous analyses (Liszewska, et al., 2012; Osuch et al., 2012) indicated that raw climate simulations, especially for precipitation time series, are highly biased. Following the papers of Ehret~~d~~ et al. (2012) and Sunyer et al. (2015) we included an additional post-processing step, i.e. bias correction of climatic variables, which is a standard procedure for climate change impact studies. In this work we used a distribution-based quantile mapping (QM) method (Piani et al., 2010) applied to daily values subsampled on a monthly basis to correct biases in the precipitation time series derived from the climate models. The correction was done relative to E-OBS reanalysis precipitation data (Haylock et al., 2008), as this data set provides the best estimate of grid box averages and has the same resolution as the outputs from the climate models considered. Quantile mapping methods have a number of advantages over methods which only correct the mean and variance (Sunyer et al., 2015) and have been used in numerous previous studies, e.g. ~~Piani et al. (2010),~~ Dosio and Paruolo (2011) and~~,~~ Gudmundsson et al. (2012). The QM method is based on the assumption that a transformation (h) exists such that the distribution of quantiles describing the simulated time series of precipitation (P^{RCM}) can be mapped onto the quantile distribution of the observations (P^{obs}), i.e.:

$$P^{Obs} = h(P^{RCM}) \qquad (1)$$

In the application of this method here, observed and simulated time series were fitted to a gamma distribution. The distribution parameters were estimated using the maximum likelihood method. Only wet days (P>0.0 mm/day) were included in this analysis. The inverse of the derived gamma distribution for observed time series is used to correct the quantiles of simulations, following the transformation:

$$\hat{P}^{RCM}_{corr} = F^{-1}_{Obs}\left(F_{RCM}\left(P^{RCM}\right)\right) \qquad (2)$$

where F_{Obs} denotes the cumulative distribution function (cdf) of observations and F_{RCM} is the cdf of simulated values.

The relationship (eq. 2) between quantile-corrected and simulated data was parametrised using the power transformation:

$$\hat{P}^{RCM}_{corr} = \begin{cases} b(P^{RCM} - x_o)^c & for \quad P^{RCM} \geq x_o \\ 0 & for \quad P^{RCM} < x_o \end{cases}, \tag{3}$$

where coefficients b *and* c are calibrated for the best fit, x_0 *is* estimated threshold value of precipitation below which modelled precipitation is set to zero.

In addition to the correction of precipitation values, the number of wet days is also corrected based on the empirical probability of non-zero values in the observations. This is a necessary part of the bias correction, as RCMs tend to simulate too many wet days with low values of precipitation. All values for precipitation below this threshold (x_0) are set to zero for the simulated data. The transformation h and the wet day correction derived for the control period are further applied in the correction of precipitation data for future periods. The correction parameters are evaluated for every grid and every month separately.

2.3 Standardized Precipitation Index

Many different indicators of meteorological drought can be found in the literature (Mishra and Singh, 2010), although the Standardized Precipitation Index (SPI) is one of the most widely applied. The index is used for both research and operational purposes in over 60 countries (e.g. ~~Lloyd-Hughes and Saunders, 2002;~~ Bordi et al., 2009; ~~Costa, 2011;~~ Moreira et al., 2012; ~~Rimkus et al., 2012;~~ Sienz et al., 2012; ~~Dutra et al., 2013;~~ Gocic and Trajkovic, 2013; Liu et al., 2013; ~~Maule et al., 2013; Orlowsky and Seneviratne, 2013; Spinoni et al., 2013; Duan and Mei, 2014;~~ Dutra et al., 2014; ~~Soľáková et al., 2014;~~ Zargar et al., 2014; ~~Geng et al., 2015;~~ Jenkins and Warren, 2015; ~~Ryu et al., 2014; Spinoni et al., 2015;~~ Swain and Hayhoe, 2015; ~~Tue et al., 2015; Vu et al., 2015; Xu et al., 2015;~~ Zarch et al., 2015).

SPI has been developed by McKee et al. (1993). It is a relatively simple index based only on precipitation and quantifies a precipitation deficit for a sequence of data (Hayes et al., 1999; Seiler et al., 2002). Time series of precipitation for a particular location are fitted to the gamma distribution, ~~although other distributions can be used~~following the recommendation by Stagge et al. (2015). SPI values are then estimated by a transformation of the cumulative probability to a standard normal variable with a zero mean and a variance equal to one. Negative values of SPI indicate lower than median precipitation, whilst positive values denote higher than median precipitation. The calculated values of SPI give estimates of the degree of dryness for a given period and location. Different thresholds of SPI value are established to distinguish a meteorological drought. Originally McKee et al. (1993) proposed a threshold SPI = 0, although a later assessment by Agnew (2000) and Łabędzki (2007) suggested that drought conditions start at SPI = - 1. Due to the standardization of variables, SPI values can be used to represent wetter and drier areas in a comparable way.

The SPI can be used to quantify the precipitation deficit at multiple time scales (1, 3, 6, 12, 24 months). These time scales reflect the impact of drought on the short term water supplies which are important for agriculture, as well as on systems which may have more storage and, therefore, a longer response time such as water resources in the form of stream flow, reservoir storage and groundwater supplies.

In the assessment of a meteorological dryness using the SPI index, the length of the precipitation series and the probability distribution describing data are very important (Mishra and Singh, 2010). Wu et al. (2005) recommended the use of the longest possible period for the derivation of the SPI, as short data sets could result in large errors of estimated values. For the comparison of indices between different locations the choice of the same period is suggested. Following that recommendation, the aggregated precipitation totals from the entire period (1971-2099) were normalized. The analysis of SPI values based on the entire time series gives an opportunity to estimate the tendency of changes in the SPI time series, which was one of principal aims of this work. However for the purpose of adaptation to climate change, the reference period to which the changes are related plays an important role. Namely, when the whole period is taken for the normalisation, normal conditions refer to the year 2035 which in the case of nonstationarity may lead to some difficulties in interpreting the results, as it changes the analyst's perspective.

In an alternative approach presented by Stagge et al. (2015) a nonlinear transformation (normalization) is developed for the present period (for example 1971-2000) and that transformation is further applied to future climate conditions. That approach also has some drawbacks. Future climate conditions could be different than those observed; therefore an application of a relationship based on present conditions could lead to extrapolation outside the range of observed values. The second problem is related to the interpretation of estimated

SPI values for changed climatic conditions. The estimates of these values could be outside the range [-3, 3] that ensures comparability of the results. The third problem with the alternative approach is related to shorter time series that could result in errors in the fitting of the distribution and the normalization of the aggregated time series. This problem is mentioned in the work of Wu et al. (2007).

In this work the gamma distribution was chosen for description of the precipitation time series following the recommendation of McKee et al. (1993), Lloyd and Saunders (2002) and analyses of suitable statistical tests (Anderson-Darling, chi-square and Lilliefors). The distribution parameters were estimated using the maximum likelihood method. For locations where no precipitation occurs in the time series for a given period over analysed aggregation time scale, the cumulative probability *H(x)* is calculated from the following equation

$$H(x) = \begin{cases} q & \text{if } x = 0 \\ q + (1-q)G(x) & \text{if } x > 0 \end{cases} \qquad (4)$$

where q is the probability of no precipitation for the period estimated from the frequency of observations of zero, and *G(x)* denotes the cumulative probability derived from gamma distribution.

The SPI is the inverse of the normal cumulative distribution function corresponding to the normalised probability H(x). The influence of dry days on the normality of derived SPI values at different time scales was tested by the Anderson Darling test where the null hypothesis is that a sample comes from a population described by a normal distribution. The results indicated that the applied test fails to reject the null hypothesis at 0.05 level in all cases. Other methods of normality testing of the SPI values have been applied in other published studies, e.g. the Shapiro-Wilk statistic and absolute value of the median smaller than 0.05 (Wu et al., 2007; Kumar et al., 2009; Stagge et al., 2015).

2.4 Trend analysis

The last element in the applied modelling chain presented in Figure 1 is the trend analysis of the estimated SPI time series. There are many techniques which can be used to estimate trends in time series, such as linear regression, Spearman's rho test, Mann-Kendall test, seasonal Kendall test and also the application of time series models (Kundzewicz and Robson, 2004). In this work the Mann-Kendall test (Mann, 1945; Kendall, 1975) was applied to estimate monotonic trends in the SPI time series. In this approach it is assumed that the data are not serially correlated over time. There are no assumptions related to the distribution of residuals as is the case for a linear regression.

The original Mann-Kendall test for trend is based on a rank correlation test for the observed values and their order in time and ~~,~~ operates on all possible combinations of points. The Mann-Kendall test statistics S is calculated from the following equation:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} \operatorname{sgn}(x_j - x_k) = \begin{cases} +1 & if \quad (x_j - x_k) > 0 \\ 0 & if \quad (x_j - x_k) = 0 \\ -1 & if \quad (x_j - x_k) < 0 \end{cases} \tag{5}$$

where n is the number of observations. For independent and randomly ordered data for large n, the S statistics approximate a normal distribution with mean $E(S) = 0$ and a variance equal to $\mathrm{var}(S) = n(n-1)(2n+5)/18$.

The significance of a trend is tested by comparing the standardised Z test statistics with the standard normal cumulative distribution at a selected significance level. Positive values of Z statistics indicate a positive trend (an increasing trend) while negative Z values indicate a decreasing trend. The trend is statistically significant at $\alpha = 0.05$ level when the absolute value of Z is higher than 1.96.

The application of the Mann-Kendall test can be affected by a serial correlation of data and also by seasonality effects, as discussed by Hamed and Rao (1998). As we perform independent analysis for each month and season the seasonality effect is eliminated.

To avoid problems with autocorrelation a modified Mann-Kendall test has been developed (Hamed and Rao, 1998). The modification allows the test to be applied to data with serial correlation as is the case of SPI values for longer time steps (12 and 24 months).

To account for ~~the~~ an effect of ~~the~~ a serial correlation the correction ratio $n/n_S{}^*$ is introduced during the calculation of a variance of the S statistics.

$$\mathrm{var}^*(S) = \mathrm{var}(S)\,\frac{n}{n_S^*} \tag{6}$$

$$\frac{n}{n_S^*} = 1 + \frac{2}{n(n-1)(n-2)} \sum_{i=1}^{n-1} (n-i)(n-i-1)(n-i-2)\rho_S(i) \tag{7}$$

where ρ_S is the autocorrelation function.

The slope of trend can be estimated using the Sen's method where the trend is assumed to be linear (Wilcox, 2005). Following that method the slopes between all data pairs are calculated and then the overall slope is estimated using the median of these slopes. The median value is used such that the results are not strongly affected by outliers.

3 Results

3.1 Comparison of simulated and observed data for the reference period

~~Following the methodology presented in the previous section, the bias correction of the simulated precipitation time series are performed and the projections of meteorological drought are derived.~~

3.1.1 -Seasonal pattern of precipitation

In the first step of analysis, a comparison of observed and simulated (both uncorrected and bias corrected) average monthly precipitation for the reference period (1971-2000) was performed. The results in the form of annual runs for two grid cells located close to Białystok (NE Poland) and Wrocław (SW Poland) are presented in Figure 2. It can be seen that uncorrected RCM precipitation values (shown as red lines) overestimate the observations (black lines) and the observed seasonal pattern is not reproduced. For the uncorrected data, significant differences between the RCM/GCM combinations are evident especially during the summer months. Application of bias correction leads to an improvement relative to observed values. The bias corrected precipitation values are characterized by a similar seasonal pattern to that of the observed values, with a slight underestimation of monthly precipitation values relative to observed values. This is partly due to the fact that bias correction was undertaken using E-OBS data rather than station data. However, in addition, it must be remembered that bias correction is performed on individual daily precipitation values, rather than monthly totals. In addition, a gamma distribution is used as an approximation to the empirical distribution of values. Therefore, some differences in the final results are to be expected.

A comparison of the spatial patterns of the difference between average monthly precipitation based on uncorrected and bias corrected RCM data was performed, and an example for the month of February is shown in Figure 3. Red indicates negative and small positive differences between uncorrected and the bias corrected values, whilst blue indicates large differences (> 200%) after bias correction. Similarities between the climate models can be observed, and in all cases, the largest differences are found in the eastern and north-eastern regions of Poland. Figure 3 also suggests that the highest precipitation intensities are simulated by RCMs driven by the ARPEGE GCM, as the largest relative discrepancies shown in the figure are associated with that model.

The pattern of differences between corrected and uncorrected values for monthly precipitation varies between months. A comparison of the spatial pattern of residuals for July is presented in Figure 1 (Supplementary materials). Generally, the differences for July are smaller than in winter months. In the case of summer months the RCM results are not consistent, and significant differences in direction of changes and intensities are apparent.

In addition to the comparison of mean monthly values, the variability in the monthly precipitation during the reference period was also analysed. The results of that comparison for two grid cells located in the NE and SW Poland are presented in Figure 4. The results indicate similar tendencies in observed and simulated data, with higher variability in monthly values for precipitation during summer months and lower variability during winter months. Uncorrected RCM data overestimate the variability in monthly precipitation in the winter months and underestimate it in the summer period for most of models, relative to both observed stations and E-OBS data. Corrected data are characterised by similar variability throughout the year to the observed datasets.

A comparison of the spatial pattern of differences in the standard deviation of monthly precipitation is shown in Figure 5 for the month of February. The outcomes indicate a similar pattern of differences between the climate models, although the intensities vary between the models. The pattern is similar to those obtained for differences in mean value with the highest differences in eastern and north-eastern regions of Poland. The uncorrected ARPEGE model simulations again show the largest discrepancies relative to observed values, as indicated by large differences between uncorrected and corrected data.

3.1.2 Number of wet days

The number of wet days can be important for the estimation of meteorological drought. Figure 6 shows a comparison of the observed (E-OBS data and point measurements at meteorological stations) and the simulated mean monthly number of wet days for two grid cells located close to Białystok (NE Poland) and Wrocław (SW Poland). The number of wet days simulated by climate models is ~~different~~ significantly different from observations, both for annual and seasonal totals. Almost all uncorrected RCM simulations overestimate the number of days with precipitation relative to observations. The largest differences are associated with the RM51 ARPEGE climate model for the month of May for both locations. The DMI HIRHAM5 ARPEGE model gives a very low number of wet days in July, August and September. The bias corrected simulations reveal the observed annual of mean monthly number of wet days.

Figure 6 illustrates the dependence of the simulation results on the minimum rainfall threshold. The upper diagrams, which illustrate all of the days with precipitation, show that most of the models simulate continuous rain of varying intensity. Introducing a threshold of 1 mm (lower ~~raw~~ row in Figure 6) changes the seasonal pattern and makes it more comparable with the observed number of wet days.

The derived pattern of direction and intensity of local corrections for corrected and raw number of wet days is very similar to the seasonal pattern sum of precipitation presented in the previous section.

3.2 Future changes

Following the methodology presented in the previous section, SPI indices were calculated on the basis of simulated precipitation time series from the period 1971-2099. The analysis was carried out for:

- each grid cell (49x26) excluding 108 grid cells over the Baltic Sea,
- each climate model (6 models),
- 1-month (SPI 1), 3-month (SPI 3), 6-month (SPI 6), 12-month (SPI 12) and 24-month (SP 24) time scales,

An example of the SPI 12 time series for raw climate data for one grid cell located close to Białystok (NE Poland) is shown in Figure 7. It is seen that the results depend on the climate model considered and that for all models there is a high degree of interannual variability.

In order to examine the influence of bias correction on the meteorological ~~drought~~ dryness projections, the Mann-Kendall test for trend was applied and the slope of the SPI trend was estimated using Sen’s method for raw and corrected precipitation data.

3.2.1 SPI 1

The results of trend analysis for the SPI 1 for one grid cell located in the NE Poland close to Białystok are presented in Table ~~1~~2. This selection was made on the basis of the results of Liszewska et al. (2012). The largest changes in winter precipitation are projected to be in that area. On the left side of the table outcomes of the analysis for the bias corrected data are shown, whilst on the right side the trends for raw data are presented. It is clear that the sign of the estimated trends depends on the month, climate model and whether or not the data are bias corrected. The results for uncorrected data in February, May, October and November lack statistically significant trends. In those cases the results are consistent between models. In the other months there is no consistency between models with respect to the estimated trends. According to the estimated trends, the RCM-GCM models can be classified into wet vs. dry models. 'Dry' models (e.g. ARPEGE GCM) project a decrease in SPI values in the summer period and no statistically significant changes in winter. The opposite is true for the 'wet' models (ECHAM5 and BCM), for which an increase in SPI 1 values is projected in January and December with no statistically significant trend in summer.

The application of bias correction slightly alters the results of the trend analyses. In this case, DMI HIRHAM ARPEGEs project a decrease of the SPI 1 values in April and August using uncorrected data but does not for bias corrected data. The trends in SPI 1 in February for two climate models are statistically significant for corrected data. The results for other months are consistent for uncorrected and bias corrected data.

The results represent one grid cell point located in north eastern Poland. The same analyses were carried out for all grid cells in the analysed domain. The slopes of the estimated trends for the SPI 1 for the time series for January are shown in Figure ~~9~~8. It is seen that for the uncorrected data, the estimated slope of SPI 1 (January) in the period 1971-2099 strongly depends on the climate model and the region within Poland. For the ARPEGE GCM, there is no statistically significant trend across the whole of Poland. The outcomes from other models indicate an increase in the SPI 1 values (indicating wetter conditions), but the magnitude of the changes (as indicated by the slope of the trend) and the location of areas with or without statistically significant trends are not consistent.

~~The estimated trend in the SPI 1 (January) for the bias corrected data are presented in the lower part of Figure 8.~~ The application of the bias correction procedure slightly changes the results. In this case, the tendency of changes is similar as for uncorrected data (no trend for ARPEGE model and an increase in SPI values for BCM and ECHAM5 models). The magnitude of the changes varies between models, but in some cases it is slightly larger than for the corrected data.

A comparison of statistically significant trends in the SPI 1 for July is presented in Figure 9. There are significant differences between climate models. Trend results based on the ARPEGE climate model are characterized by a decrease in the SPI 1 values for the whole of Poland. The ECHAM5 climate model projects a decrease in SPI 1 in the south eastern part of Poland but no statistically significant changes in the rest of the country. A different tendency is seen for the trend analysis based on the BCM climate model; i.e. an increase in the SPI values in the north eastern and north western regions of Poland and no change in other areas.

Analyses of the estimated trend for raw and corrected data indicate similar tendency of changes with small differences in trends in the SPI 1 values as a result of the bias correction procedure.

To summarize the influence of the bias correction on the estimated trends of SPI 1 values, a comparison of the number of grid cells with statistically significant trends is presented in the Supplementary materials, Table 1. It is seen that the latter strongly depends on the month, climate model, and also on whether or not bias correction has been applied. The total area with statistically significant trends for the uncorrected data is the largest for analyses based on the BCM and ECHAM5 climate models for winter months (December, January and March) and for the ARPEGE model in summer months (July, August and September). The use of bias correction slightly decreases the area with statistically significant trends in summer months (June, July and August) and slightly increases in the other months (Figure 10). The largest differences are noted in September for DMI HIRHAM ARPEGE (18.51%) and RM51 ARPEGE (-11.92%), in February for KNMI RACMO2 ECHAM5 (16.04%), in March for MPI M REMO ECHAM5 (16.04%) and in August for DMI HIRHAM ARPEGE (12.01%). In the other months the differences in the areas with statistically significant trend between raw and bias corrected data are smaller than 10%.

In addition to changes in the area with a statistically significant trend for raw and corrected data also mean slope of trend is altered. The magnitude of these differences depends on a climate model and the month under consideration~~on a month~~. The highest differences were estimated for the ARPEGE models as an effect of the highest biases of simulated data, therefore the most intense bias correction is applied in that case.

3.2.2 SPI 3 and SPI 6

In addition to the SPI 1, the SPI 3 for four seasons (DJF – December, January and February, MAM – March, April and May, JJA – June, July and August, SON – September, October and November) and the SPI 6 for two seasons: a cold one (November - April) and a warm one (May – October) are also analysed. The 12 maps presenting the slope of the trend for the SPI 3 for the winter season (DJF) are shown in Figure 11. The outcomes for raw data presented in the upper part of Figure 11 indicate that the results for ARPEGE differ from those for other climate models. According to that model, the estimated trends are not statistically significant for almost the whole of Poland. The other four models project an increase in the SPI 3 values.

The application of bias correction slightly alters the findings of the analysis. In that case the results resemble the latter for uncorrected data. The differences in the projections of climate models are preserved. As an effect of bias correction the number of grid cells with a statistically significant trend is slightly increasing for almost all climate models except DMI HIRHAM BCM. The slope of trend is also slightly higher for corrected data indicating more rapid changes.

The results of the analyses for the SPI 3 calculated for the summer season are presented in Figure 12. The outcomes for uncorrected data in the upper part of figure indicate significant differences between the climate models. The simulations of the BCM global climate model project an increase in the SPI values in summer, corresponding to wetter conditions in the future. The other models simulate a decrease of the SPI which is equivalent to an increase of a degree of dryness.

The slope of the trend for the corrected data is statistically significant for a larger area for three models: DMI HIRHAM ARPEGE, DMI HIRHAM BCM and SMHIRCA BCM, and slightly lower for RM51 ARPEGE and ECHAM5 models. The bias correction also influences the mean (over study area) magnitude of changes. In the case of DMI HIRHAM ARPEGE the mean slope of trend increases due to bias correction. Results for the other two models (MPI M REMO and RM51 ARPEGE) show an opposite tendency – an increase in the mean slope.

The results of the SPI 6 for the cold season (November - April) are similar to those for the SPI 3 winter (Figure 2 in the Supplementary materials). The application of the bias correction procedure does not significantly change the outcomes obtained for the uncorrected data. There are still large differences in the tendency of the change between climate models.

For the warm period of the year (May – October), the estimated trends in the SPI 6 resemble those estimated for the summer months (JJA). The results are not similar between models. The ARPEGE GCM once again indicates an increase in the SPI values whilst the other climate models project a decrease. The application of bias correction leads to an increase in the area with statistically significant trends and the magnitude of the changes for DMI HIRHAM ARPEGE and corresponds to drier conditions. In the case of RM51 ARPEGE a decrease of number of grid cells with statistically significant trend and also its magnitude is achieved as a result of bias correction.

3.2.3 SPI 12 and SPI 24

The SPI was also estimated for longer time scales. The results for the annual scale (SPI 12,~~)~~ values extracted for precipitation totals over the calendar year, January – December) are shown in Figure 13. The outcomes for the uncorrected data indicate differences between models. The ARPEGE model projects a decrease in the SPI values whilst the other models show an increase in the SPI, corresponding to wetter conditions.

At the annual time scale the application of bias correction does not change the sign of the trend, but there are differences in the area affected and the magnitude of the changes. In the case of DMI HIRHAM ARPEGE and MPI M REMO ECHAM5, the correction of modelling biases leads to increases in the number of grid cells with a trend and also an increase in the magnitude of changes. On the other hand, the application of the bias correction procedure to RM51 ARPEGE model simulations leads to decreases in these factors.

The analysis of trends in the time series of the SPI 24 was also performed. Similarly to the outcomes for SPI 12, the estimated trends differ between the climate models. The results based on the ARPEGE model project a decrease in the SPI values (drier conditions). The other models indicate an increase in the SPI, corresponding to wetter conditions. The simulations of all global climate models (the ARPEGE, ECHAM5 and BCM) do not change the sign of the trend when bias correction is applied, but it makes a difference in the magnitude of the changes, leading to differences in number of grid cells with statistically significant trend.

3.3 Influence of bias correction on trend in precipitation and SPI values

The results shown in the previous section indicate that the influence of bias correction on the trends is small in comparison with the variability between climate models. In order to explain the mechanism by which bias correction influences trends in precipitation, let us analyse a simple example of a linear dependence of precipitation on time, for one grid cell and one month:

$$P^{RCM} = \beta_{RCM} t + \alpha_{RCM} \quad (8)$$

where β_{RCM} and α_{RCM} are coefficients of a linear trend.

After transformation using eq. (3) we get:

$$P^{RCM}_{corr} = b(\beta_{RCM} t + \alpha_{RCM} - x_0)^c \quad (9)$$

Assuming $c=1$ (i.e. that the relationship can be approximated as linear in our case) the equation can be simplified to

$$P^{RCM}_{corr} = b(\beta_{RCM} t + \alpha_{RCM} - x_0) = b\beta_{RCM} t + b\alpha_{RCM} - bx_0 \quad (10)$$

and the slope of corrected time series can then be estimated as

$$\beta_{corr} = b\beta_{RCM} \quad (11)$$

In the simplified case, the slope of corrected time series depends on the slope of uncorrected time series multiplied by the parameter *b* of the transformation function. The values of parameter *b* give the sign and magnitude of the biases. When P^{RCM} is higher than P^{Obs} the biases are positive and the values of parameter *b* are smaller than 1; therefore, the slope of the trend of corrected time series is smaller than that for the uncorrected time series. In the opposite situation with negative biases (i.e. $P^{RCM} < P^{Obs}$) the values of parameter *b* are higher than 1, and as a result the corrected slope is higher than the uncorrected one.

In the case of precipitation time series, the values of these series are non-negative; therefore, the values of parameter *b* (eq. 3) are also non-negative. These considerations lead to the conclusion that the application of bias correction does not change the sign of estimated trend, but its slope may be changed. Due to changes in slope, the number of grid cells with a statistically significant trend in the sums of precipitation may also change.

The bias correction also influences the trends in the SPI values, however to much smaller degree. The SPI is calculated by a nonlinear transformation of the precipitation time series from a gamma distribution into a standard normal distribution. An example of such relationship between monthly sum of precipitation and SPI 1 values for DMI HIRHAM ARPEGE model simulations for one grid cell located close to Białystok ~~in the first six months~~ is presented in Figure 14. In each case (month) two such curves are presented. The red and black curves denote the relationship for uncorrected and corrected variables, respectively.

Figure 14 shows that quite large changes in precipitation are transformed into small changes in the SPI 1 values. The transformation is monotonic, hence the direction of changes (trends) in precipitation is reflected in changes of SPI. However, due to the shape of the transformation these changes are ~~subdued~~reduced. The dependence between the values of the SPI and precipitation shown in Figure 14 for a specific model indicates that a simple relationship between the SPI values based on corrected and raw precipitation projections can be derived. In particular, under the assumption that bias correction is quasi-linear and follows eq. 3 with a power parameter $c=1$, the corrected SPI is linearly related to the SPI based on raw precipitation data with correlation parameters depending on the bias correction parameter b (eq. 3) and normalising transformation of precipitation sums into SPI values shown in Figure 14.

In reality, additional factors have an effect on the SPI, including an uncertainty of distribution fitting applied in bias correction and the SPI calculation procedures. A test of differences between uncorrected and corrected SPI time series was performed using the Pearson correlation coefficient as a measure of goodness of fit. The results of the correlation analysis for six climate models and 12 months for all grid cells are presented in Table 3. In all cases the correlation is statistically significant at the 5% level and the values of the minimum Pearson correlation coefficient are above 0.8, indicating a nearly linear relationship between the indices. We also tested the dependence of relative differences in monthly precipitation on the correlation in the SPI values. The outcomes for all grid cells are presented in Figure 15. A nonlinear relationship is visible for most months and models that is statistically significant at 5% level, excepting DMI HIRHAM ARPEGE and DMI HIRHAM BCM in June. The strength of these dependencies assessed using the Spearman correlation coefficient (SCC) varies from 0 up to 0.7954 with differences between months and models. The deviation from zero of the SCC values quantifies the influence of additional effects that include the nonlinearity of the bias correction function and uncertainty in probability distribution of observed and simulated aggregated precipitation.

4 Discussion and Conclusions

Potential future trends in the SPI index over the period 1971-2099 have been analysed using a modified Mann-Kendall test applied to precipitation time series derived from six ENSEMBLE RCM projections. Monthly precipitation time-series have been used for the estimation of Standardized Precipitation Index (SPI) for multiple time scales (1-, 3-, 6-, 12- and 24 months) at a spatial resolution of 25 km for the whole country. In the first stage, the simulated monthly sums of precipitation for the reference period (1971-2000) were compared with observed sums derived on the basis of the E-OBS reanalysis for the same period. We also compared those simulations with bias corrected precipitation time series. Results indicate that the uncorrected RCM time series overestimate precipitation values and that the annual pattern of monthly precipitation is not correctly reproduced. We also noticed large differences between results for ~~differing~~ various RCM/GCM combinations. The comparison of the simulated and observed number of wet days indicated that uncorrected RCM precipitation time series highly overestimate the total number of rainy days, as has been previously well established (Sunyer et al., 2015). Application of bias correction using the quantile mapping method leads to improved precipitation values with respect to the seasonal pattern of precipitation, monthly total precipitation and the number of wet days, when compared with observed values.

For the estimation of trends in the SPI, we used a modified Mann-Kendall trend test for the SPI time series for each grid cell, each climate model and multiple temporal aggregations (1-, 3-, 6-, 12- and 24 months). The choice of this approach was dictated by its relative simplicity and robustness. Projections of SPI values indicate a decrease in the degree of dryness (better water availability) during the winter months and an increase in the summer period (more water scarcity) that confirm findings by Bleckinsop and Fowler (2007), Liszewska et al. (2012), Osuch et al (2012), Rimkus et al. (2012), Stagge et al. (2015). The outcomes for longer time scales (SPI 12 and SPI 24) indicate an increasing trend in an ensemble SPI 12 (similarly to Orlowsky and Seneviratne, 2013) and considerable model-to-model variability on regional and local scales. The ARPEGE GCM driven RCM projections show a decrease of the SPI 12 and the SPI 24 whilst the other GCM driven RCMs show an increase in the SPIs, corresponding to wetter conditions. These results confirm the general findings of Bleckinsop and Fowler (2007) showing differences due to climate models. In general, our study confirms the results of Stagge et al. (2015) with some differences due to different climate models, emission scenarios and change estimation methods applied. In particular, our selection of climate models shows larger differences between climatic projections.

Results show that the spatial pattern of the trend depends on the climate model, the temporal aggregation considered and, to some extent, whether or not bias correction is applied. Differences between the climate model projections were found to be larger than the discrepancies introduced by bias correction for all aggregation scales (1, 3, 6, 12 and 24 months). These results contradict findings of Maurer and Pierce (2014) where uncertainty introduced by bias correction was found to be larger than the differences between climate models. This could reflect differences between the study areas, as precipitation projections for Poland are not consistent between the different climate models. We noticed also that results from the same GCM, but different RCMs, are characterized by similar patterns of change, although this behaviour occurs only at some temporal scales and seasons.

An analysis of the impact of bias correction on the trends in SPI values was carried out in two steps: (i) an assessment of the effects of bias correction on the trend of aggregated precipitation and (ii) an assessment of the effect of that trend on the SPI values. The results of the analysis indicate that bias correction may change the magnitude of the trend in precipitation values but not its direction. These changes vary throughout the year and between climate models, but spatial patterns showing areas with a statistically significant trend are preserved. These findings are confirmed by a theoretical investigation of the influence of bias correction on trends in precipitation using a simple example of a linear bias correction procedure. In that case the slope of the trend of the corrected precipitation time series is influenced by the parameters of the power relationship between uncorrected and corrected precipitation values in the reference period.

Where the SPI values are concerned, the influence of the bias correction has a similar character but are much reduced in comparison with precipitation due to the normalisation procedure included in both the bias correction and the SPI definition. The analysis of correlation between the SPI values based on corrected and uncorrected precipitation indicates a nearly one-to-one relationship between them. However, that correlation decreases when the relative differences between corrected and uncorrected precipitation increase.

The differences between SPI values for bias-corrected and raw precipitation projections depend on the month and climate model. Those monthly differences are consistent with the bias correction parameters (eq. 3). The largest differences occur for months when the bias correction is the strongest. In reality, additional factors have an effect on the trends in the SPI that include the nonlinearity of the bias correction function and uncertainty in the probability distribution of observed and simulated precipitation totals.

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Table 4 GCM and RCM combinations used from ENSEMBLES project. The number~~s~~ denotes number of simulations

GCM RCM	ARPEGE	ECHAM5	BCM	Total scenarios
DMI HIRHAM5	1	0	1	2
SMHIRCA	0	0	1	1
RM51	1	0	0	1
MPI M REMO	0	1	0	1
KNMI RACMO2	0	1	0	1
Total scenarios	2	2	2	6

Table 2. Results of trend analysis using the modified Mann-Kendall method for SPI 1 for one grid cell located close to Bialystok (NE Poland); ↗ - denotes statistically significant positive trend, ↘ - denotes statistically significant negative trend, - denotes no statistically significant trend.

	Bias corrected data						Uncorrected RCM data					
GCM	ARPEGE		ECHAM5		BCM		ARPEGE		ECHAM5		BCM	
RCM	DMI HIRHAM	RM51	MPI M REMO	KNMI RACMO2	DMI HIRHAM	SMHIRCA	DMI HIRHAM	RM51	MPI M REMO	KNMI RACMO2	DMI HIRHAM	SMHIRCA
JAN	-	-	↗	↗	↗	↗	-	-	↗	↗	↗	↗
FEB	↗	-	-	↗	-	-	-	-	-	-	-	-
MAR	-	-	↗	-	↗	↗	-	-	-	-	↗	↗
APR	-	-	-	-	-	-	↘	-	-	-	-	-
MAY	-	-	-	-	-	-	-	-	-	-	-	-
JUN	-	-	-	↘	-	-	-	-	-	↘	-	-
JUL	↘	↘	-	-	↗	-	↘	↘	-	-	↗	-
AUG	↘	↘	-	-	-	-	-	↘	-	-	-	-
SEP	↘	↘	-	↗	-	-	↘	↘	-	↗	-	-
OCT	-	-	-	-	-	-	-	-	-	-	-	-
NOV	-	-	-	-	-	-	-	-	-	-	-	-
DEC	-	-	↗	↗	↗	↗	-	-	↗	↗	↗	↗

Table 3 Estimated values of Pearson correlation coefficient between raw and corrected SPI time series for six climate models. A minimum value over all grid cells is shown.

	GCM	ARPEGE		ECHAM5		BCM	
Index	RCM	DMI HIRHAM	RM51	MPI M REMO	KNMI RACMO2	DMI HIRHAM	SMHIRCA
SPI 1	JAN	0.9002	0.9043	0.9434	0.9391	0.9134	0.9059
	FEB	0.8718	0.9104	0.9055	0.9252	0.8783	0.8932
	MAR	0.9452	0.9341	0.9502	0.9396	0.9018	0.9551
	APR	0.9436	0.8964	0.9638	0.9589	0.8939	0.9374
	MAY	0.9490	0.8897	0.9343	0.9680	0.9568	0.9711
	JUN	0.9738	0.8544	0.9440	0.9573	0.9582	0.9173
	JUL	0.9749	0.9368	0.9488	0.9698	0.9415	0.9798
	AUG	0.8200	0.9513	0.9436	0.9207	0.9217	0.9614
	SEP	0.8064	0.9730	0.9728	0.9619	0.9260	0.9702
	OCT	0.9601	0.9386	0.9666	0.9529	0.8253	0.9028
	NOV	0.9364	0.9592	0.9619	0.9591	0.9332	0.9161
	DEC	0.9103	0.9492	0.9687	0.9721	0.9138	0.9532
SPI 3	DJF	0.8679	0.9344	0.9580	0.9588	0.9215	0.9157
	MAM	0.9171	0.8450	0.9544	0.9542	0.9187	0.9604
	JJA	0.9376	0.9105	0.9436	0.9664	0.9224	0.9592
	SON	0.8758	0.9429	0.9462	0.9508	0.8788	0.9134
SPI 6	NOV-APR	0.9014	0.9348	0.9534	0.9660	0.9214	0.9220
	MAY-OCT	0.9077	0.9077	0.9369	0.9659	0.8874	0.9626
SPI 12	Calendar	0.8522	0.8840	0.9450	0.9514	0.8680	0.9360

	year						
SPI 24	Two calendar years	0.8651	0.9029	0.9411	0.9479	0.8450	0.9137

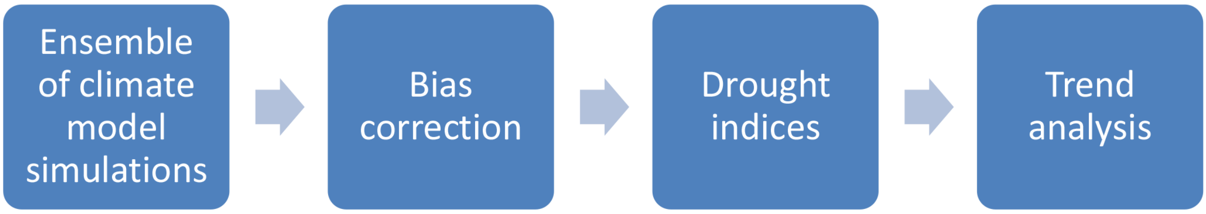

Figure 1. A scheme of the applied modelling chain.

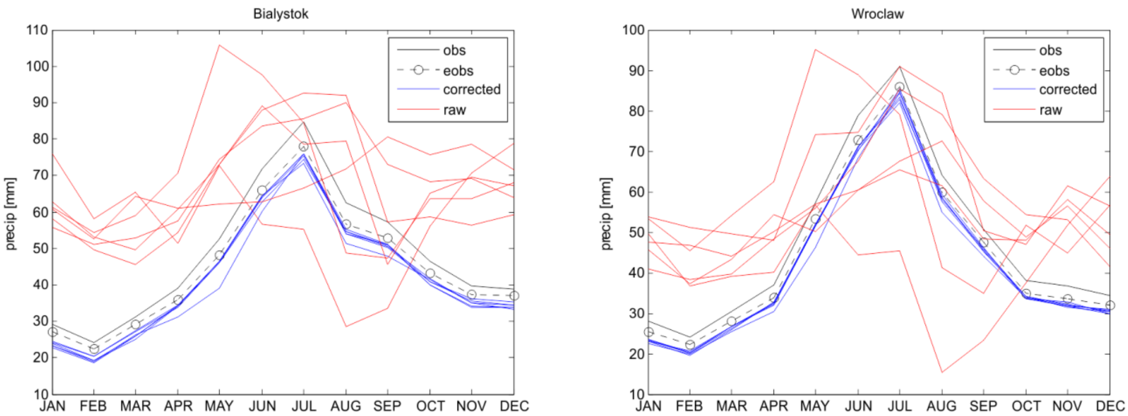

Figure 2. Comparison of mean monthly sums of precipitation calculated over the reference time period for two grid cells located close to Białystok (NE Poland) and Wrocław (SW Poland). Black continuous lines denote observations from meteorological stations, dashed lines denote observations from E-OBS reanalysis grid cells, red lines denote uncorrected precipitation series from the RCMs, and blue lines denote the bias corrected precipitation series.

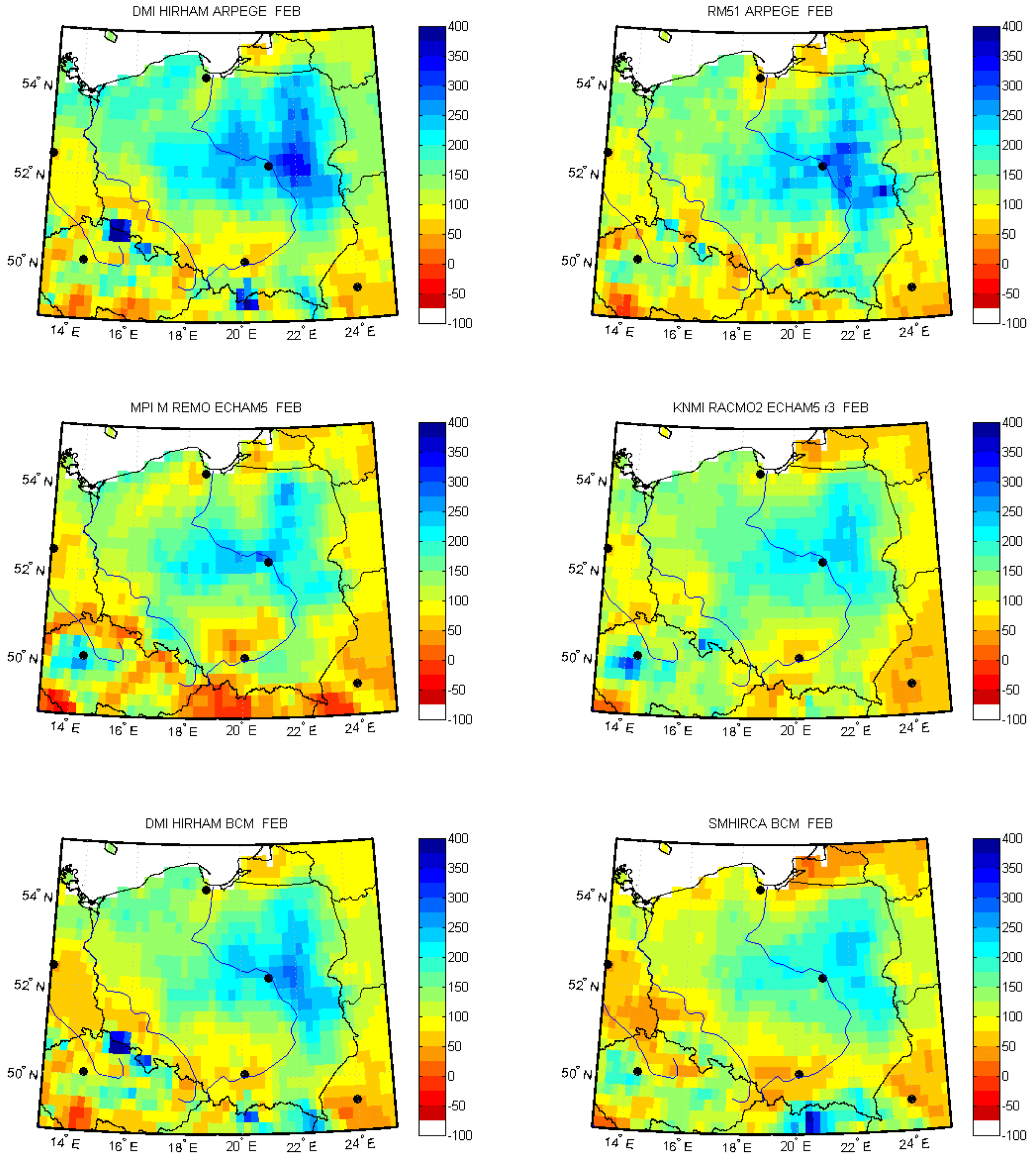

Figure 3. Comparison of spatial patterns of relative differences [%] in the average monthly precipitation in February between uncorrected and bias corrected data for the reference period 1971-2000.

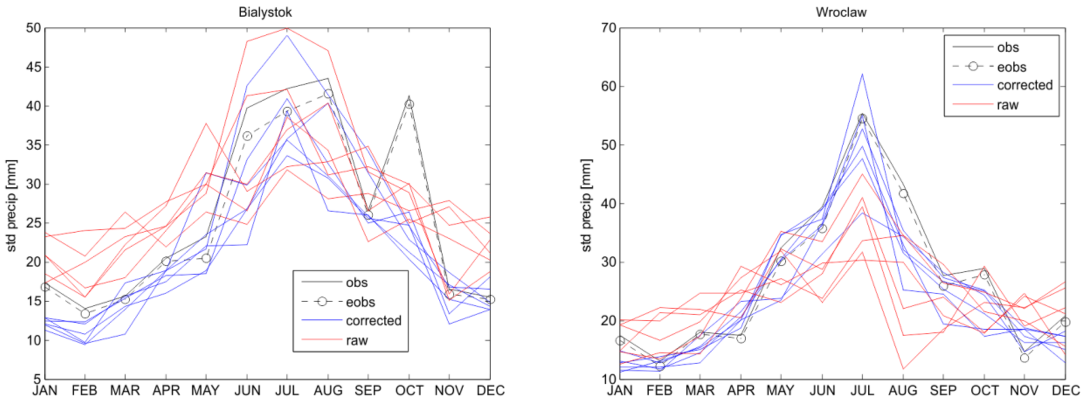

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Figure 4. Comparison of standard deviation of monthly sum of precipitation calculated over the reference time period for two grid cells located close to Białystok (NE Poland) and Wrocław (SW Poland). The black continuous line denotes observations from meteorological stations, black dashed lines denote observations from the E-OBS reanalysis, red lines denote precipitation values from uncorrected RCMs, and blue lines denote bias corrected RCM precipitation data.

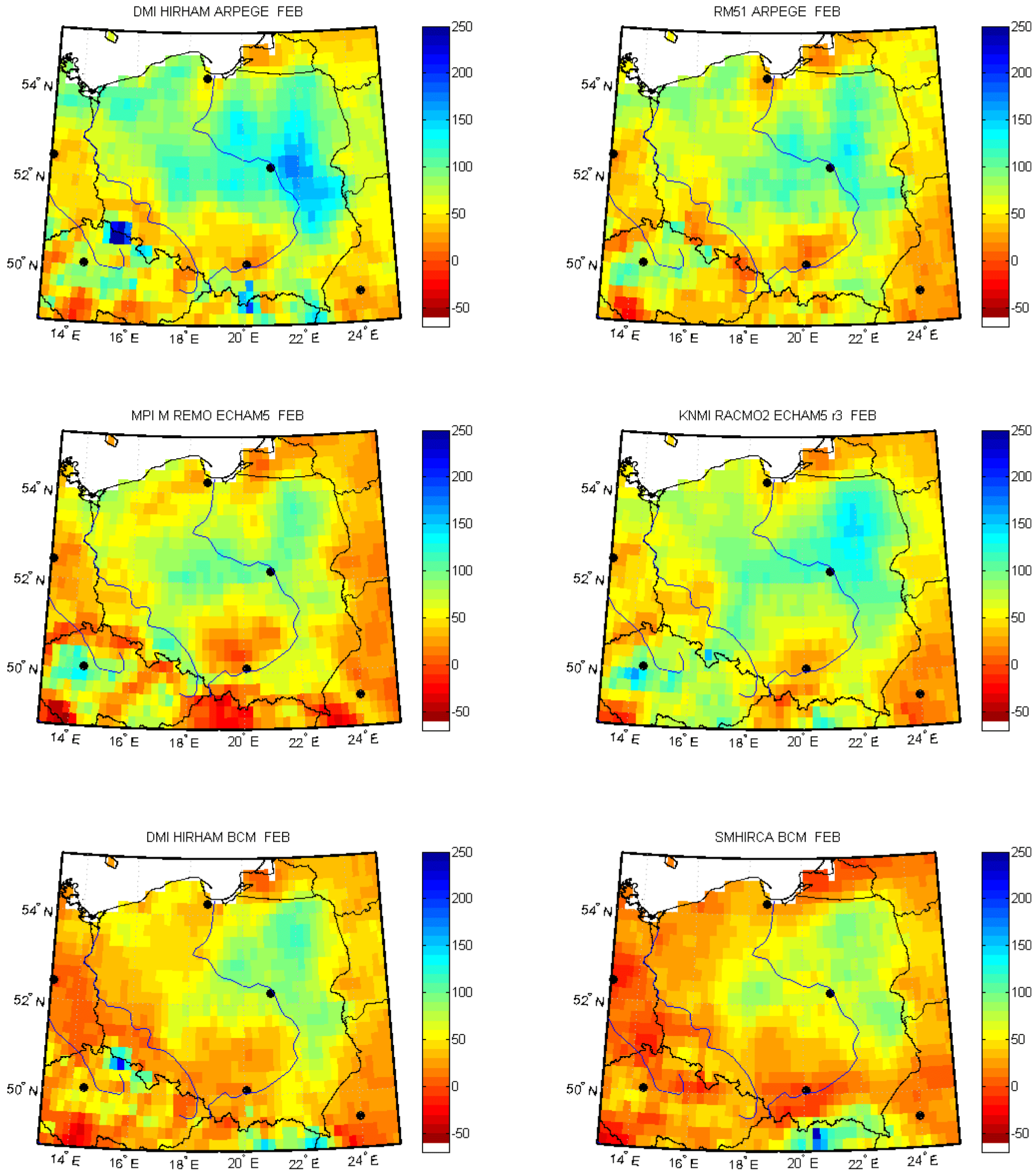

Figure 5. Comparison of spatial patterns of differences in the standard deviation of monthly precipitation for February for uncorrected relative to corrected RCM data for the month of February for the reference period 1971-2000.

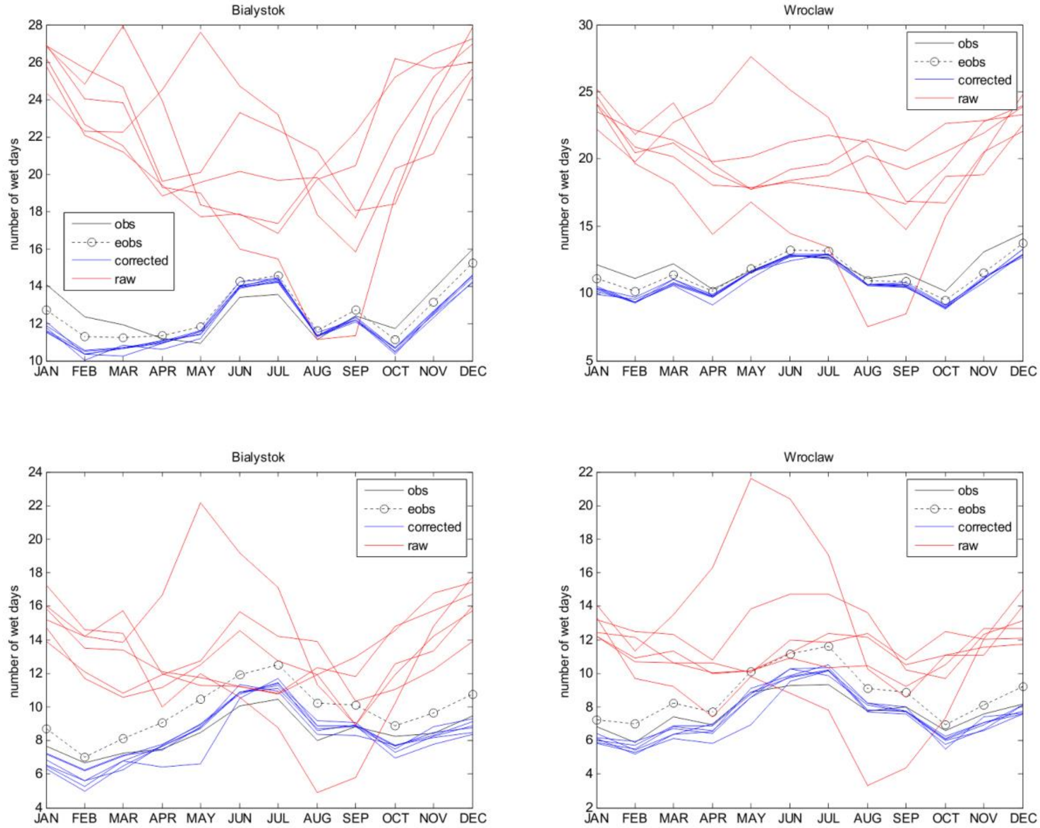

Figure 6. Comparison of mean monthly number of wet days with the minimum rain threshold values set to 0.1 mm (upper figures) and 1 mm (lower figures) for the uncorrected RCM data (raw), calculated over the reference time period for two grid cells located close to Białystok (NE Poland) and Wrocław (SW Poland). The black continuous line denotes observations from the meteorological stations, black dashed lines denote observations from the E-OBS reanalysis, red lines denote uncorrected precipitation values from the RCMs, and blue lines denote corrected RCM precipitation values.

Figure 7. An example of SPI 12 time series for raw data: DMI HIRHAM ARPEGE, RM51 ARPEGE, MPI M REMO ECHAM5, KNMI RACMO2 ECHAM5 r3, DMI HIRHAM BCM, SMHIRCA BCM.

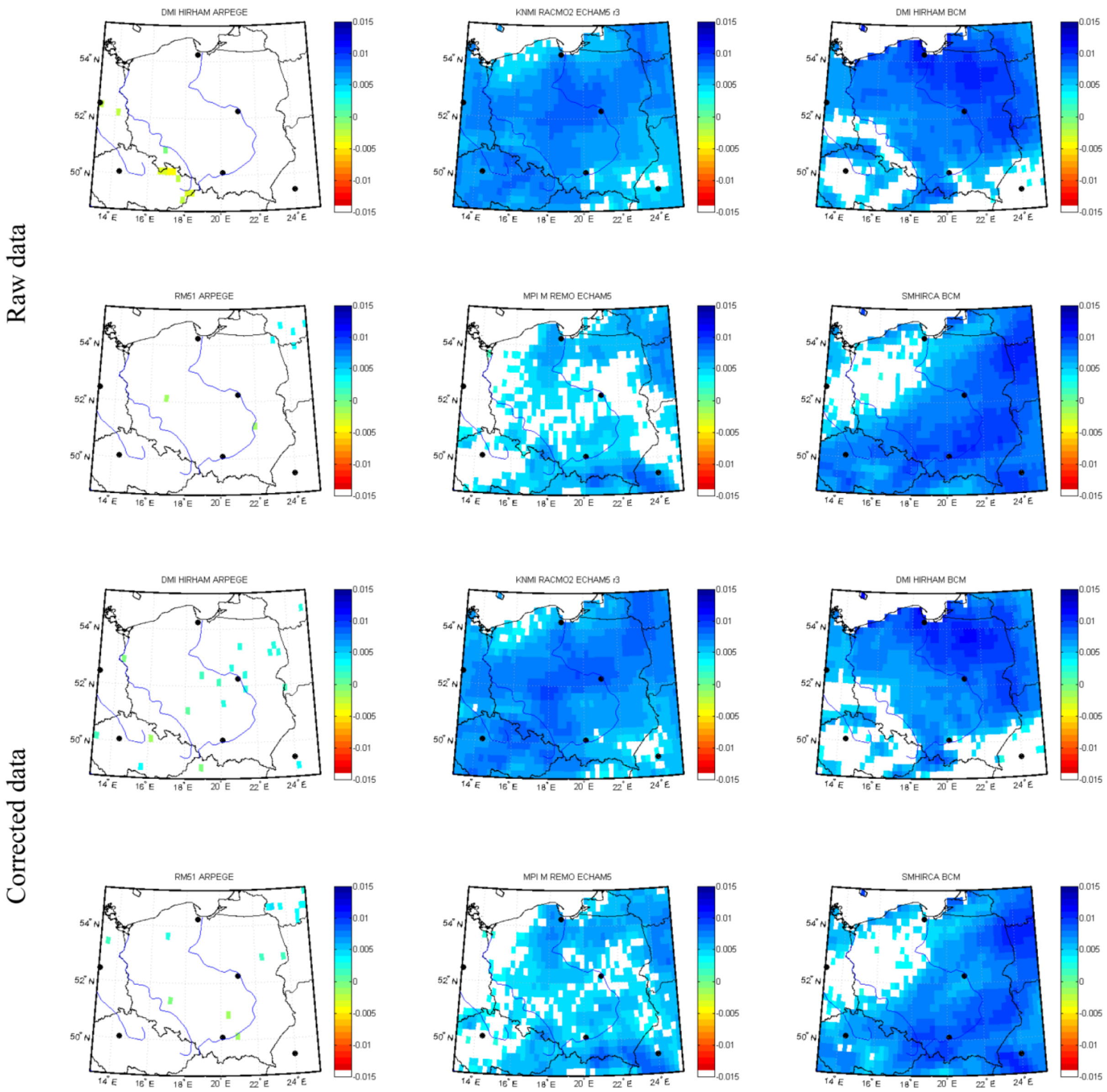

Figure 8. The results of the Mann-Kendall trend analysis for SPI 1 for January. The colour scale denotes the slope of the estimated trend. White colour indicates a lack of a statistically significant trend.

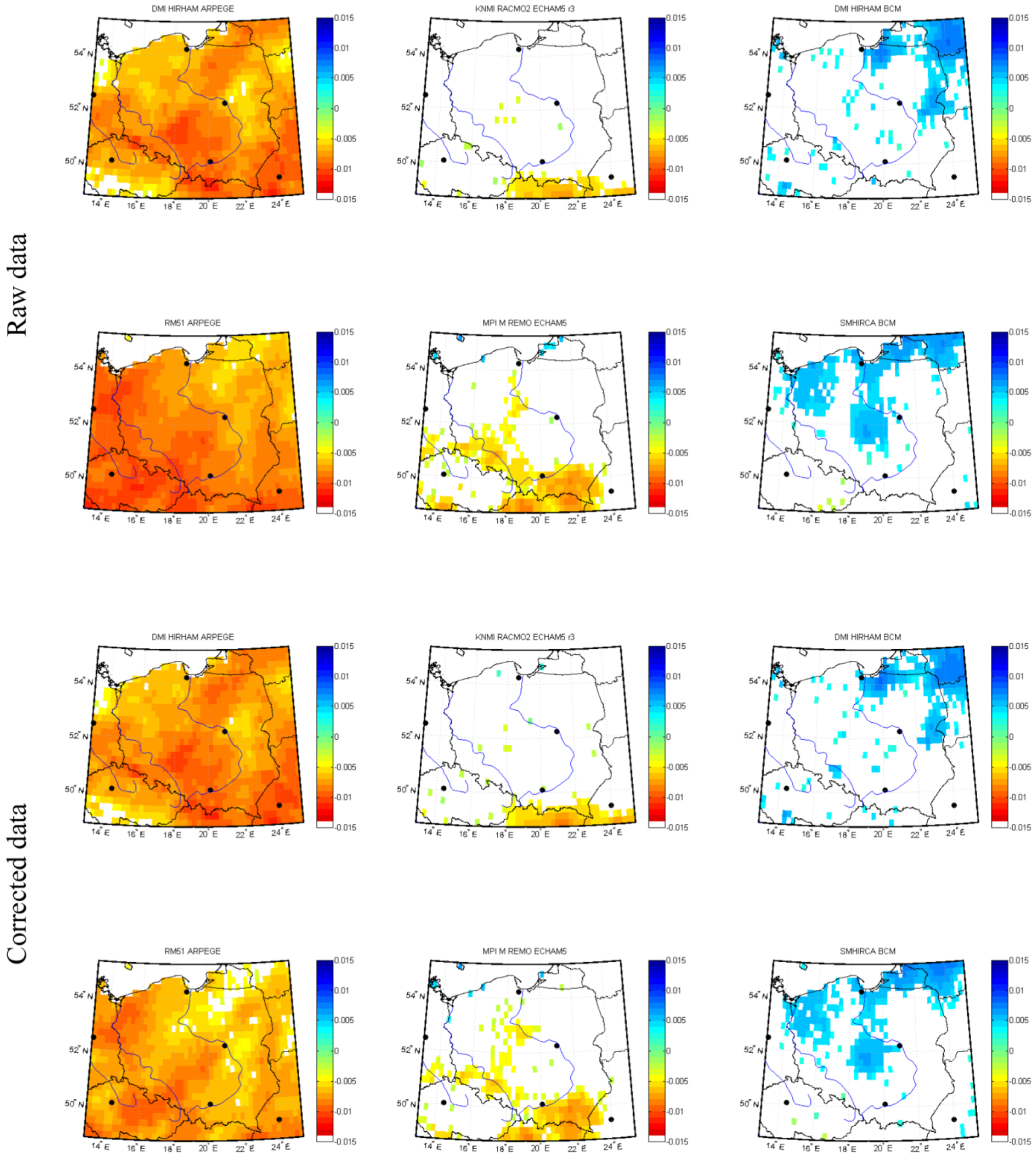

Figure 9. Results of the modified Mann-Kendall test for SPI 1 for July. Colour scale denotes the slope of the estimated trend. White areas indicate a lack of a statistically significant trend.

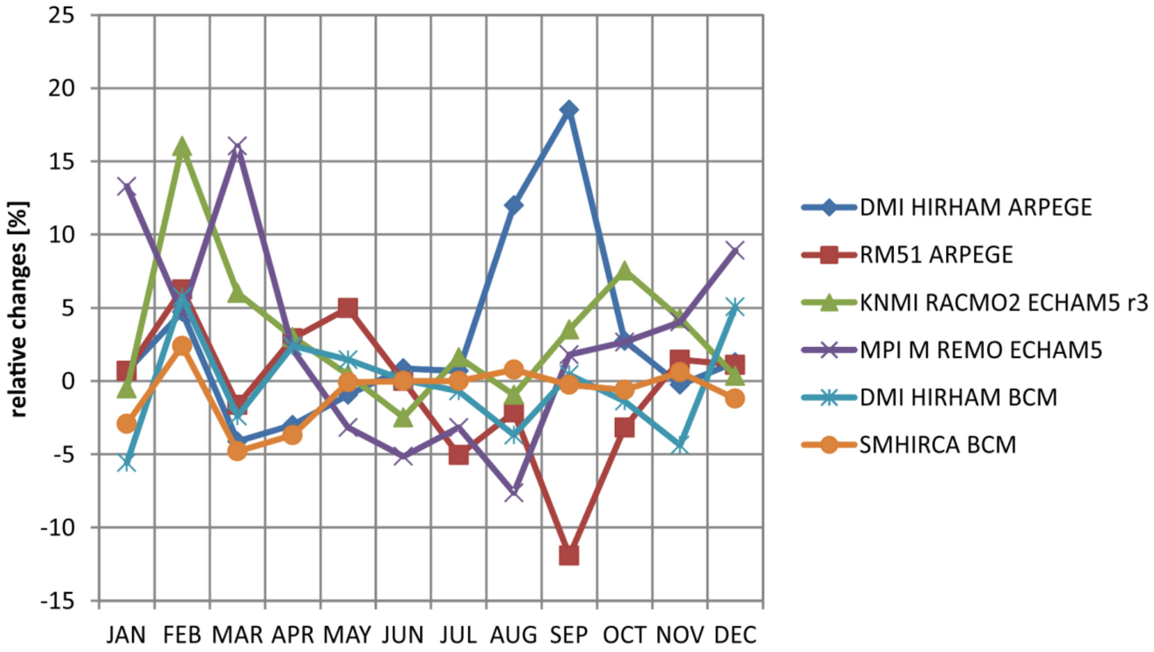

Figure 10. The relative differences [(corr-raw)/raw*100%] in the number of grid cells with a statistically significant trend for data with and without bias correction.

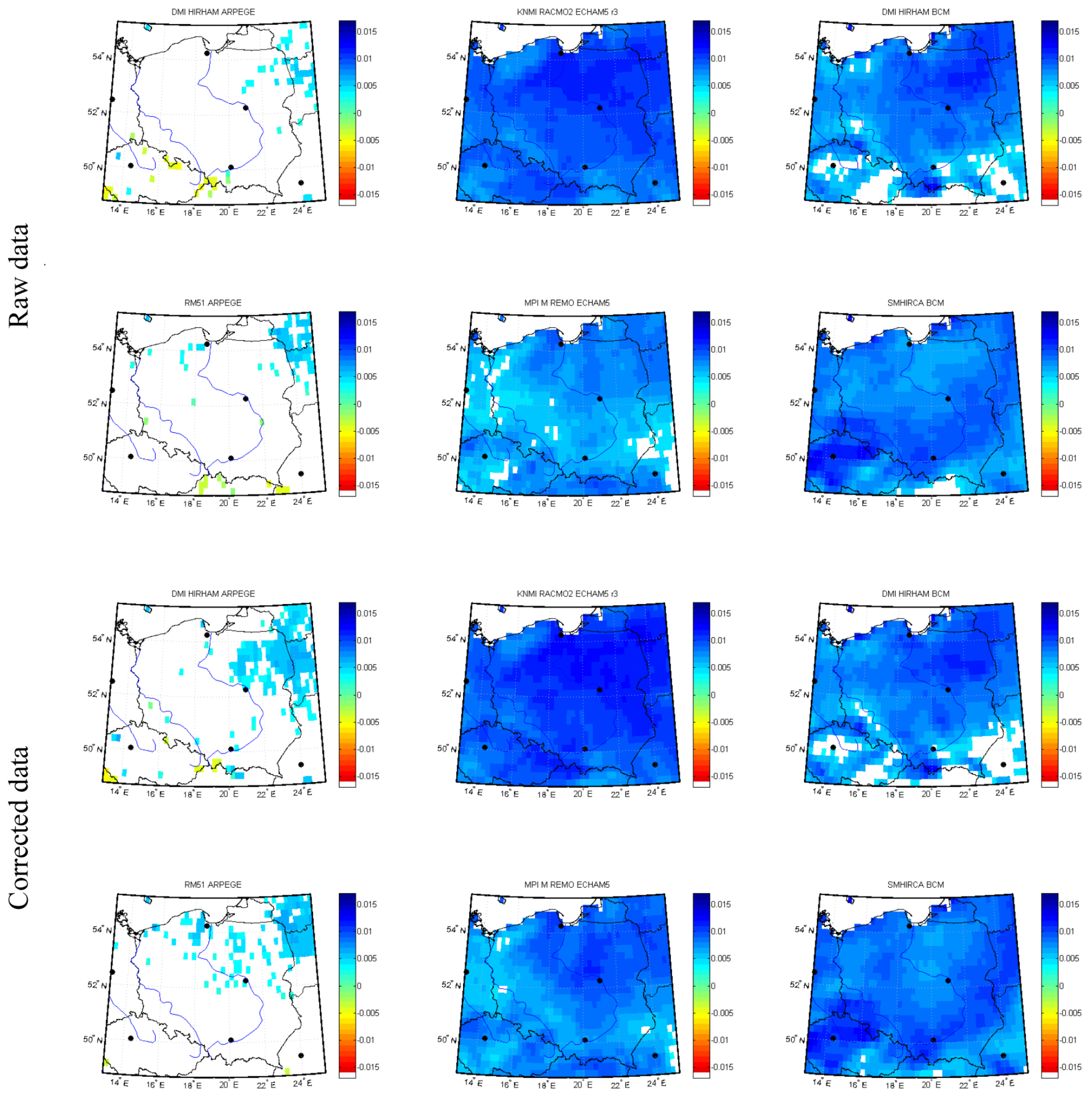

Figure 11. Results of the trend estimation using the Mann-Kendall method for the SPI 3 for the winter season (DJF). Colour scale denotes slope of the estimated trend. White colour denotes lack of statistically significant trends.

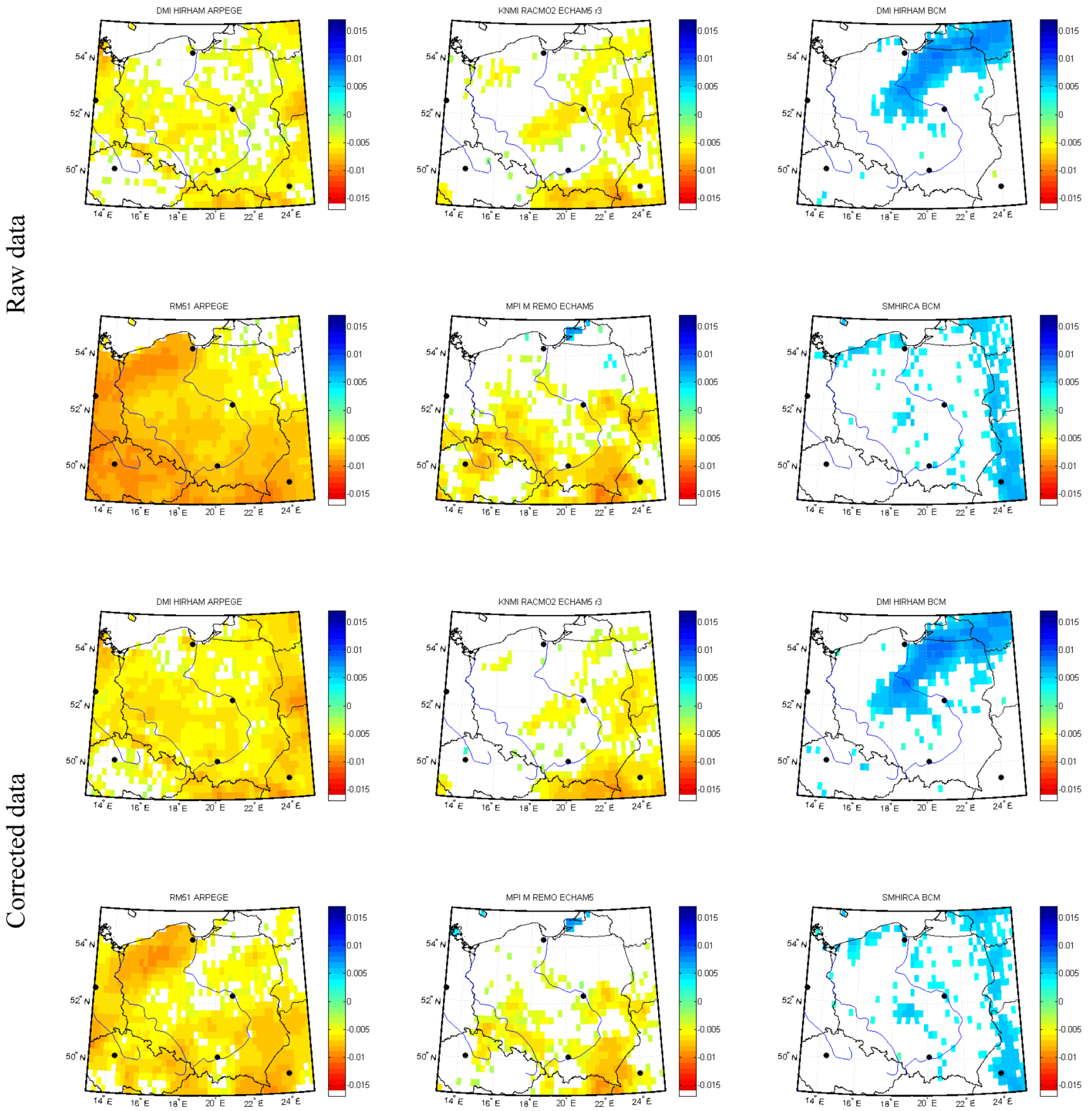

Figure 12. Trend for the SPI 3 for the summer period (JJA). The colour scale denotes the slope of the estimated trend. The white areas indicate the lack of a statistically significant trend.

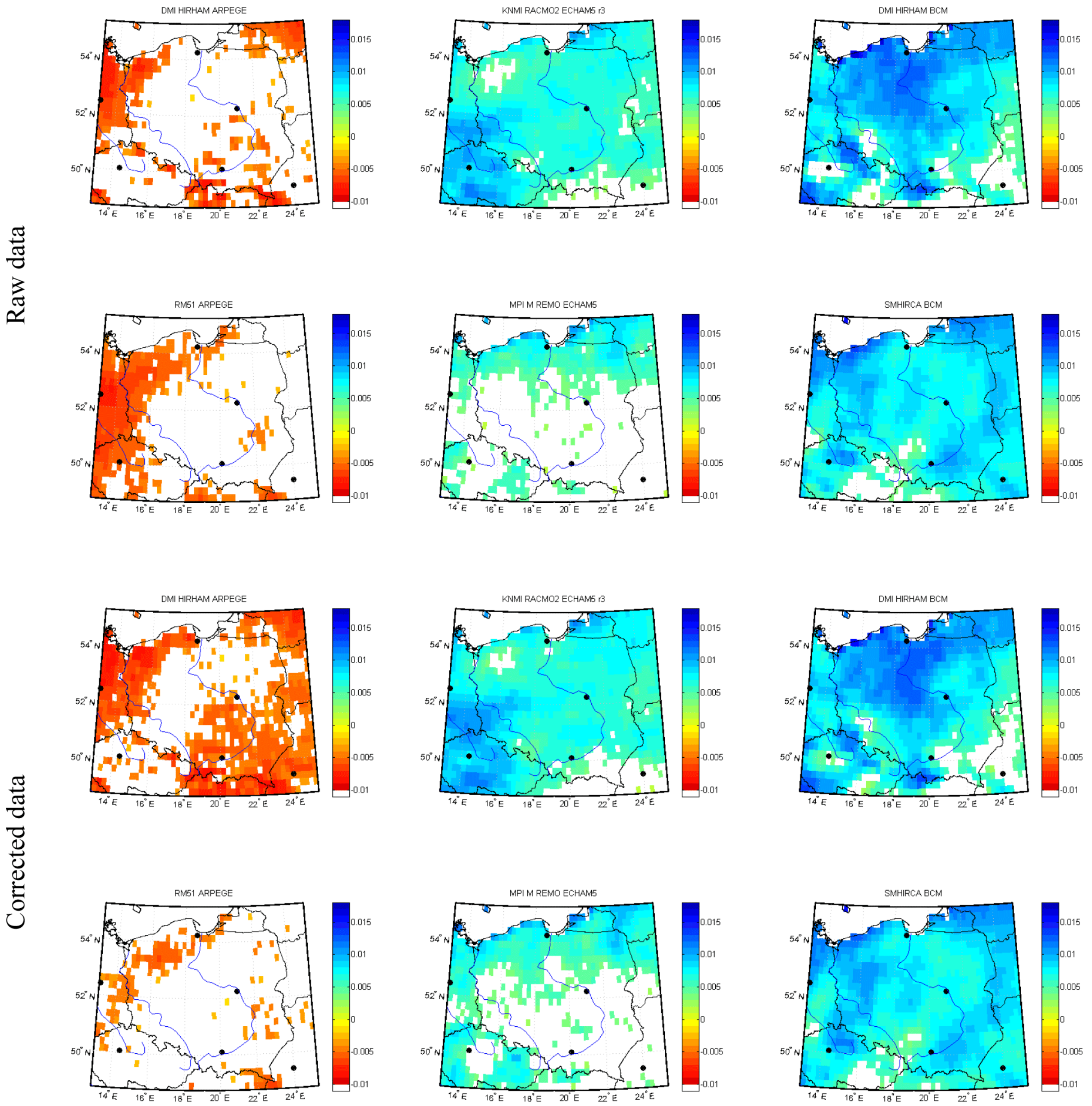

Figure 13. Trends in the SPI 12. Colour scale denotes the slope of the estimated linear trend. White areas indicate the lack of statistically significant trend.

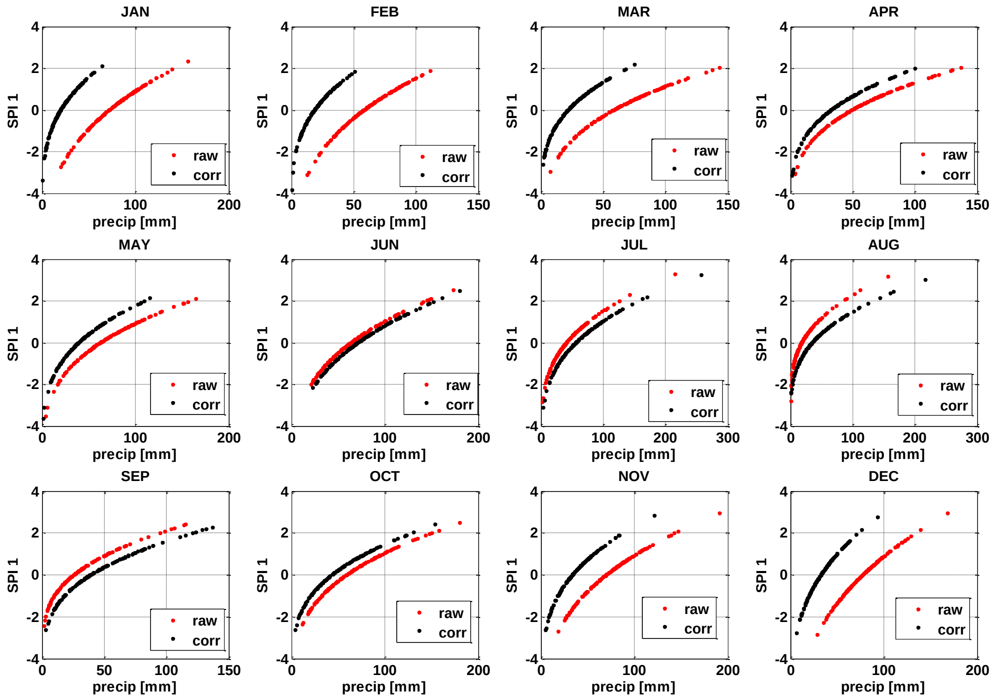

Figure 14. The scatterplots showing relationship between monthly sum of precipitation and estimated SPI 1 values for one grid cell located close to Białystok (NE Poland) for DMI HIRHAM ARPEGE model. The colour denotes type of data used, red colour -uncorrected precipitation and SPI 1, black corrected ones.

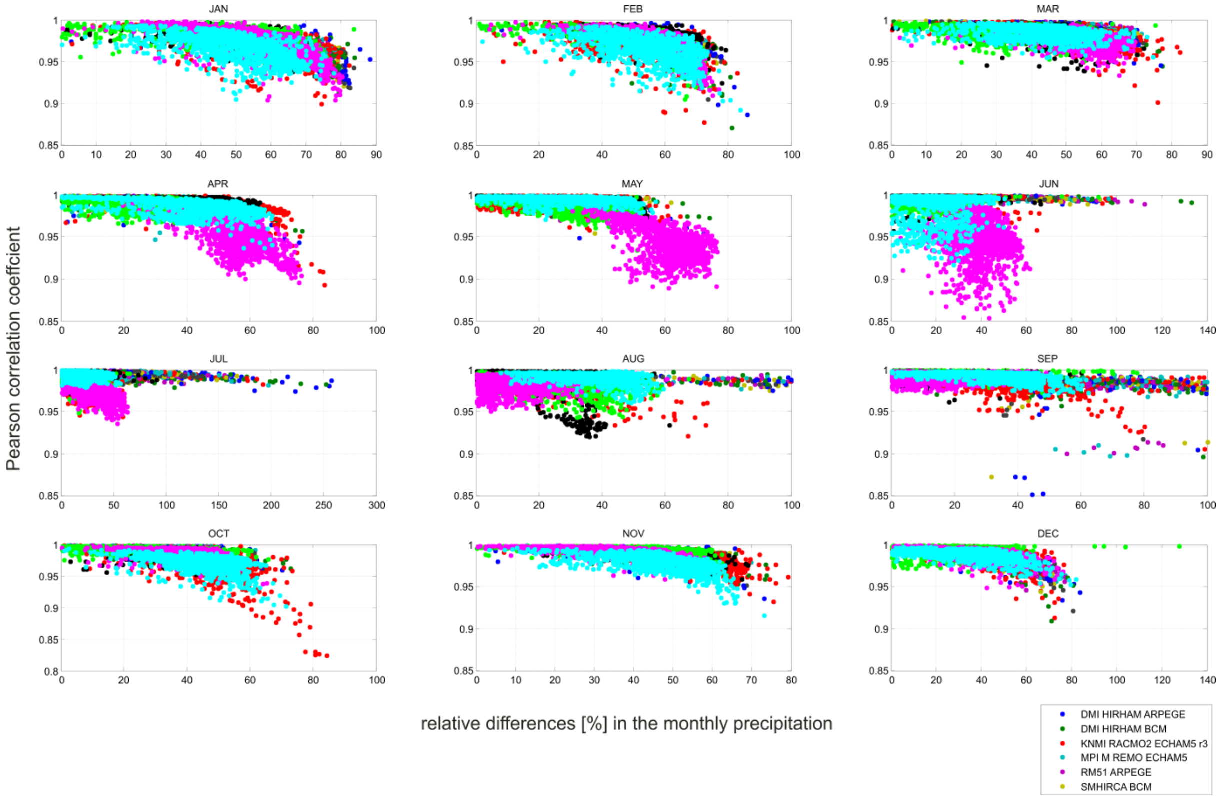

Figure 15. The scatterplots showing relationship between relative differences in the raw and corrected monthly sum of precipitation and Pearson correlation coefficient estimated for raw and corrected SPI 1 values for all grid cells.