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Variability of weather regimes in the North Atlantic-European area: past and future

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Abstract

The concept of weather regimes represents a process-oriented method of organizing the varying states of the atmospheric circulation. We define weather regimes as preferred, or recurrent, circulation patterns. We use a suite of reanalysis products and general circulation model (GCM) simulations to assess the reproducibility and variability of the regimes. We find distinct variability of the regimes in observational periods as well as in future projections. Most notable is the high variability of the North Atlantic Oscillation (NAO) regime anomaly patterns in the GCM simulations which is not evident in reanalyses, and the substantial increase of variability regarding the frequency of occurrence of the Atlantic ridge regime and the NAO+ regime.

Keywords: **weather regimes; non-stationarities; climate change**

1. Introduction

The idea of classifying atmospheric dynamics in the extra-tropics into a defined number of states, so-called weather regimes (Vautard, 1990, Michelangeli *et al.*, 1995), evolves from the principle that to a certain degree the number of possible states of the large-scale circulation is finite. Regimes are defined as recurrent and/or persistent and/or quasi stationary states of the atmosphere (Michelangeli *et al.*, 1995, Stephenson *et al.*, 2004). The concept of weather regimes represents a process-oriented method of organizing the varying states of the atmospheric circulation. Over the North Atlantic-European domain weather regimes are highly correlated to anomalies of local surface temperature and precipitation (Plaut and Simonnet, 2001, Yiou and Nogaj, 2004). There are clear spatial patterns of precipitation and temperature associated with the regimes. The positive North Atlantic Oscillation (NAO) phase during winter, for example, is associated with above-normal precipitation and temperature over northern Europe and Scandinavia and below-normal precipitation over southern parts of central Europe, southern Europe as well as Northwest Africa (Wanner *et al.*, 2001, Hurrell *et al.*, 2003). Opposite patterns of temperature and precipitation anomalies are typically found during strong NAO− phases. During NAO− phases the cold-day frequency increases notably over Scandinavia due to cool or cold air advection from the northwest, whereas it decreases over Iberia due to more cyclonic conditions (Plaut and Simonnet, 2001). Concerning extremes, the NAO+ regime is connected with heavy precipitation over Northern Europe and drought periods over the Mediterranean area (Yiou and Nogaj, 2004). The NAO− regime causes heavy precipitation over Southern Europe. In contrast, the blocking regime controls the drought periods over large parts of Central Europe and Eastern Scandinavia. It also affects maximum temperatures over Scandinavia as well as minimum temperatures over south-eastern Europe (Plaut and Simonnet, 2001, Yiou and Nogaj, 2004). Thus, the practical interest in the classification of the large-scale circulation into a few recurrent patterns lies in the observation that local weather anomalies depend to a large extent on the large-scale atmospheric flow. If weather regimes can be reliably reproduced by general circulation models (GCMs), they provide a tool for inferring regional to local climate change via statistical downscaling which derives statistical relationships between the large scale (e.g. the atmospheric circulation) and regional to local scales (e.g. surface climate variables). The description of the large-scale circulation through weather regimes includes the advantage of being able to provide information on the physical processes of the atmosphere governing regional climate change.

In this study we focus on assessing the degree of correspondence of some GCMs of the most recent generation with reanalyses data. In addition, we address the degree of variability of weather regimes within the individual data sets. Thus, we assess the temporal variability of regimes in the reanalyses, compare GCMs versus reanalyses over the historical period, and evaluate differences between historical, Representative Concentration Pathways (RCP)4.5 and RCP8.5 scenario conditions. Section 2 describes data and methods used in this study. In Section 3 we present and discuss the results of our analysis, which is followed by the conclusions in Section 4.

2. Data and methodology

2.1. Data

National Centers for Environmental Prediction (NCEP) reanalysis (Kalnay *et al.*, 1996, Kistler *et al.*, 2001) for the period 1950–2010 and the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis for the period 1979–2012 (ERA-Interim, Dee *et al.*, 2011) were used. Daily geopotential height fields at the 700 hPa level in the North Atlantic-European area (20°N–70°N, 70°W–50°E) were obtained on a 2.5×2.5 degree horizontal resolution. Following earlier studies (Vautard, 1990, Michelangeli *et al.*, 1995), we chose the 700 hPa level, which represents a highly relevant level regarding precipitation processes over the European-Mediterranean area (Hertig and Jacobeit, 2013).

700 hPa geopotential height data were taken from a three-member MPI-ESM-LR (Max Planck Institute Earth System Model running on low resolution grid) ensemble with different initial conditions of each run, from HadGEM2-ES (Hadley Global Environment Model 2-Earth System), and from the first member of a five-member CanESM2 (second generation Canadian Earth System Model) ensemble. Model selection is not exhaustive, but serves to exemplarily highlight large-scale circulation variability within and across different GCM data sets. Runs with historical, RCP4.5 scenario, and RCP8.5 scenario (Van Vuuren *et al.*, 2011) conditions performed for the Coupled Model Intercomparison Project round 5 (CMIP5) were downloaded from the CMIP5 archive (http://pcmdi9.llnl.gov/esgf-web-fe/). We used the period 1950–2005 of the historical runs (1980–2005 in case of HadGEM2-ES) and the period 2006–2100 of the scenario runs (2006–2099 for HadGEM2-ES). The horizontal resolution of the model output data was fitted to that of the reanalysis data (2.5×2.5 degree) by ordinary kriging.

2.2. Methodology

Weather regimes are obtained by classifying the daily 700 hPa geopotential height fields in the North Atlantic-European area. As a first step we performed a principal component analysis (PCA, Preisendorfer, 1988) of the daily winter data (December to February, DJF), in order to reduce dimensions of the data. As results may be sensitive to the number of principal components (PCs) kept, we considered all solutions from 5 to 15 PCs, capturing between 55 and 90% of the total variance. To the corresponding PCs of each solution we applied the hierarchical clustering method of Ward (Ward, 1963, Cheng and Wallace, 1993) and used the resulting clusters as 'seeds' for the optimising k-means algorithm (Michelangeli *et al.*, 1995). We kept four clusters (regimes), providing a stable partitioning according to earlier publications (Vautard, 1990, Michelangeli *et al.*, 1995, Yiou and Nogaj, 2004). For each regime we calculated the geopotential composite patterns and the regime anomalies. Composites were derived by calculating the mean 700 hPa geopotential height field from all the days belonging to a specific regime. Anomalies were calculated as the deviations of the standardized composite pattern from the standardized long-term mean geopotential height field of all days in the time period considered. We applied no area weighting within pattern standardization. In addition, we computed the number of days per winter spent in each regime. For each data set considered, the similarity, given by the correlation coefficients, of the particular regime anomalies and the NCEP regime anomalies is used to select the optimum number of PCs.

The whole study period considered for a particular data set was split into 31-year sub-periods, each shifted by 1 year. When the end of the whole time series was reached, years from the beginning of the time series were successively included in order to avoid a more frequent inclusion of years located in the middle of the time series. For each 31-year period, we calculated the weather regimes using the statistical approach presented in the previous paragraph. No analysis was done for the HadGEM2 historical run as data was available only for the years 1980–2005.

For each regime we compare the regime anomalies from the different data sets by using Taylor diagrams (Taylor, 2001). These diagrams can be used to graphically summarize how closely the model anomaly patterns match a reference. NCEP reanalysis regime anomalies are used as 'observational' reference. The similarity between two patterns is quantified in terms of their correlation, their root-mean-square (RMS) difference, and their standard deviations.

3. Results and discussion

Significance testing in previous studies (Michelangeli *et al.*, 1995, Plaut and Simonnet, 2001) yields the result that the optimum solution is four classes (regimes) for the Atlantic domain. It should be noted, however, that there is an ongoing scientific debate on the appropriateness of the description of the large-scale circulation by multiple weather regimes (e.g. Stephenson *et al.*, 2004), and particularly by four classes for the Atlantic domain (e.g. Christiansen, 2007). We classified 5415 NCEP daily winter 700 hPa geopotential height maps in the North Atlantic-European area (20°N–70°N, 70°W–50°E) using seven PCs with 68% of explained variance (EV) and subsequent cluster analysis obtaining the four patterns displayed in Figure 1. The choice of seven PCs is motivated by the highest similarity of the resulting regimes to the patterns obtained in previous studies (Vautard, 1990, Yiou and Nogaj, 2004). We denote them according to Yiou and Nogaj (2004): NAO+ (the positive phase of the North Atlantic Oscillation, zonal pattern of Vautard, 1990), blocking, Atlantic ridge, and NAO− (the negative phase of the North Atlantic Oscillation, Greenland Anticyclone of Vautard, 1990). The anomaly

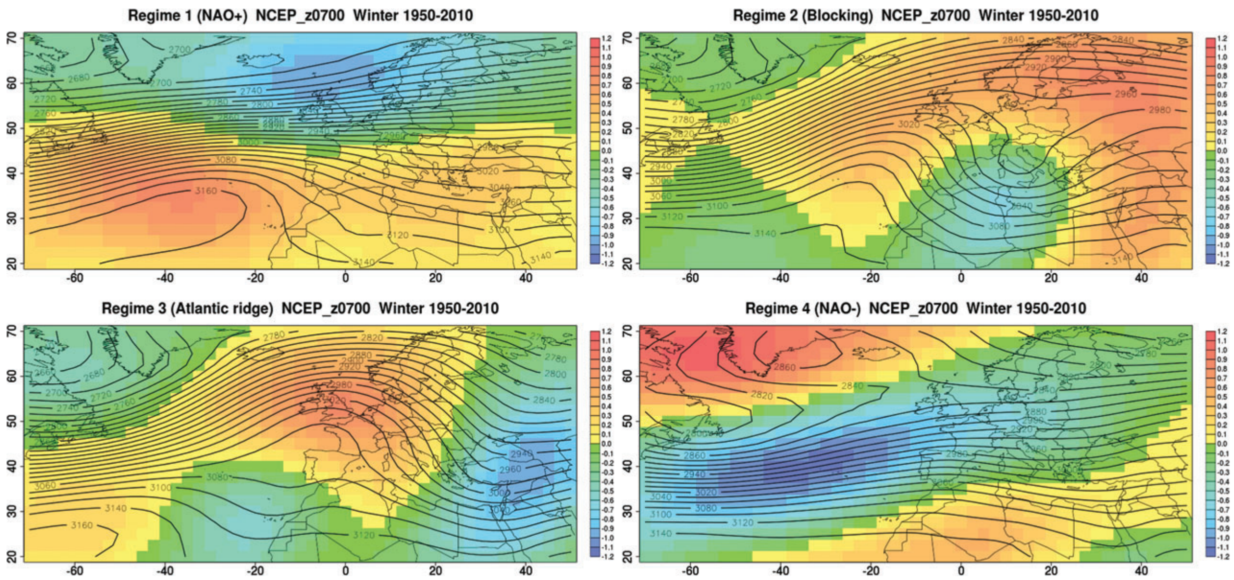

Figure 1. Weather regimes over the North Atlantic-European area. Shown are the regimes estimated from the 700 hPa daily winter (DJF) geopotential heights of the NCEP reanalysis. Colours indicate the regime anomalies and the contour lines show the geopotential composite pattern for each regime.

centre of the Atlantic ridge pattern is somewhat displaced to the east. The amplitude of the positive centre of the blocking pattern is weaker and the centre is more spread out. These differences can be attributed to differences in the clustering technique, height level, spatial domain, and time period considered. The correlation coefficients between the residence times (cumulative number of days spent in a cluster per season) of the two NAO regimes with the NAO index as published by the Climate Prediction Center (http://www.cpc.ncep.noaa.gov/data/teledoc/nao.shtml) are 0.74 (NAO+) and −0.78 (NAO−).

We also computed the weather regimes from the ERA-Interim data using eight PCs (71% EV). In addition, regimes were obtained from various GCM simulations comprising two different emission scenarios (RCP4.5 and RCP8.5), multiple runs for each scenario, and output of three different GCMs (MPI-ESM-LR, HadGEM2-ES, and CanESM2). Figure 2 indicates that the regime anomalies of the two reanalysis data sets are closely related with similar standard deviations and correlation coefficients mostly exceeding 0.9 (0.8 for the Atlantic ridge). The regimes can also be reproduced in the three MPI-ESM-LR historical runs using, depending on the particular run, 7, 12, and 5 PCs with EVs of 68, 85, and 57%, respectively. Figure 2 shows differences in the standard deviations mostly less than 0.1, RMS differences less than 0.3, and correlation coefficients greater than 0.7. Similar characteristics are found for the HadGEM2-ES historical run using 13 PCs (87% EV). In contrast, NAO+ and blocking regime anomalies computed from the CanESM2 historical run using 11 PCs (81% EV) diverge considerably from the NCEP regimes. Correlation coefficients drop below 0.5 and RMS differences reach values of nearly 0.4.

We also assessed the regimes under RCP4.5 and RCP8.5 scenario conditions using 11, 13, and 9 PCs for the three MPI-ESM-LR RCP4.5 runs (83, 87, and 77% EV), and 15, 10, and 11 PCs in case of the RCP8.5 scenario runs (91, 82, and 85% EV). For HadGEM2-ES 8 PCs (EV 74%) and 14 PCs (EV 90%), for CanESM2 5 PCs (EV 55%) and 9 PCs (EV 78%) are used to obtain the regimes under RCP4.5 and RCP8.5 scenario conditions, respectively. We compare the two scenarios, the different GCMs, and the runs under different initial conditions. The NCEP weather regimes are taken as a reference, again, in this context simply as an operational reference. We find no regularities or systematic behaviour regarding the reproducibility of the regime anomalies. Correlation coefficients, standard deviations, and RMS differences vary in a non-systematic way (Figure 2).

The number of PCs used to obtain the best solution in terms of highest correlation coefficients between the regime anomalies of a specific data set and the NCEP reference regimes, is highly variable across the different data sets. Looking at this characteristic in detail, we find that the methodology is sensitive to the choice of the number of PCs, hence that PCA dimensional reduction influences subsequent cluster results. Some PC solutions within a specific data set do not lead to a selective classification into the four regimes. However, for all data sets considered, at least one PC solution allows for a positive classification. As an alternative approach one could use common centroids (i.e. project anomalies of the GCMs onto the NCEP centroids), as done for example by Cattiaux *et al.* (2013). According to Cattiaux *et al.* (2013) similar patterns are obtained for the majority of the investigated 20 CMIP5 models when computing common centroids compared with centroids for each model individually, and the authors conclude that results are not sensitive to the centroid choice. This gives further confidence in our methodology. When applying the methodology of individual

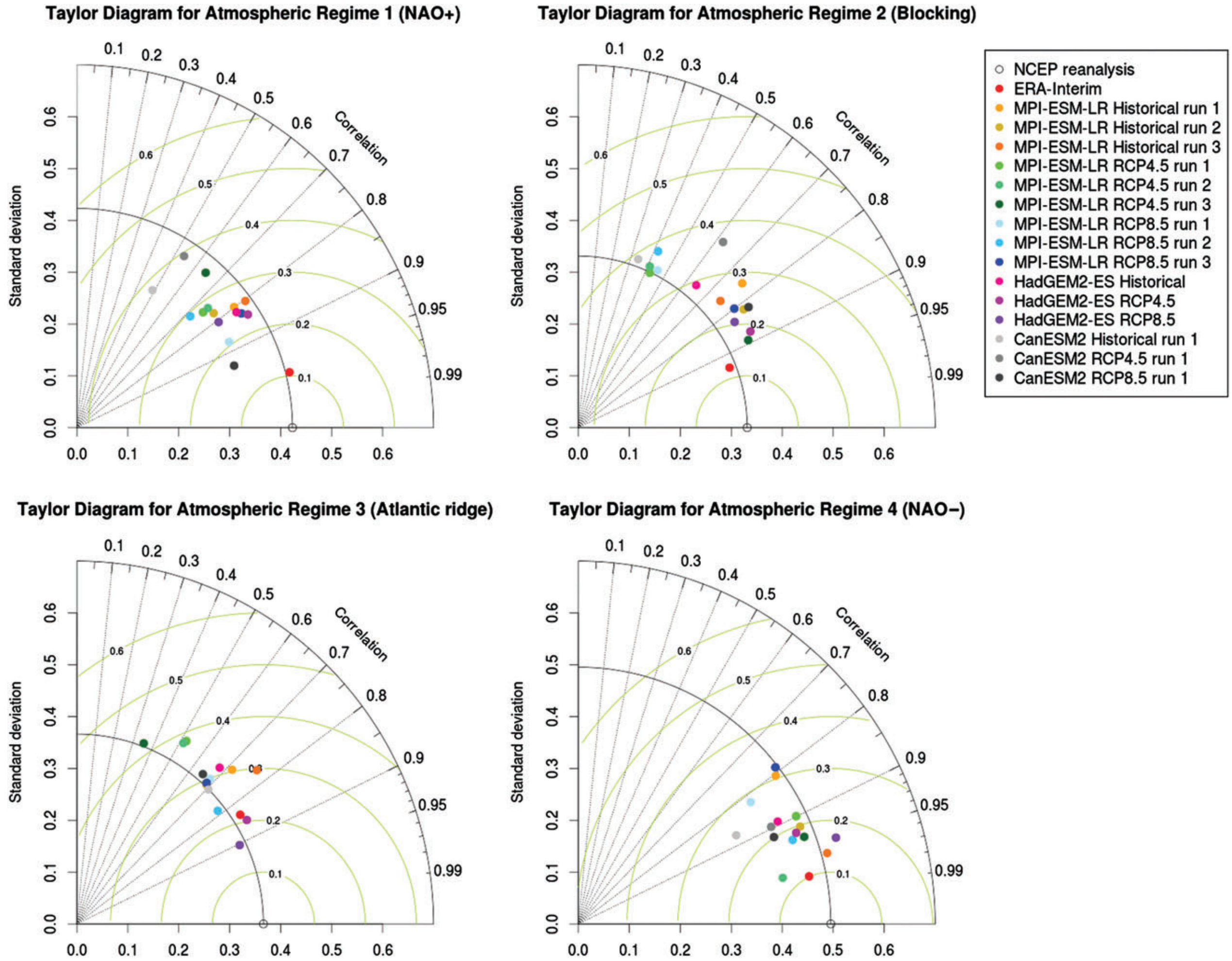

Figure 2. Taylor diagrams displaying the statistical comparison with the NCEP weather regimes of ERAInterim and GCM estimates. GCM data are historical runs, RCP4.5 runs, and RCP8.5 runs from three MPI-ESM-LR members, one HadGEM2-ES run, and the first member of CanESM2. Shown are, for each weather regime, the similarity of the anomaly patterns expressed in terms of the correlation, their root-mean square differences and their standard deviations.

cluster analyses to the 31-year sub-intervals, the choice is also motivated by the potential application of the weather regimes as predictors in a cross-validated statistical downscaling setting. However, the stability of the clustering results may depend on the period considered (Christiansen, 2007). Specific regimes occur more frequently in some sub-intervals due to decadal variability (for the NAO see, e.g. Wanner *et al.*, 2001). In the NCEP reanalysis the range of days belonging to a specific weather regime across the different sub-intervals is 16–28 days per winter (Table I), which yields cluster sizes between 496 and 868 days for a 31-year period. Thus, in all sub-intervals each regime is represented by a minimum of about 500 days. ERA-Interim and the GCM runs show similar results (with the exception of the HadGEM2-ES RCP8.5 run, see Table I).

In terms of overall reproducibility, the consistent stable regime across all data sets is clearly the NAO− regime with similar standard deviations and correlations nearly always greater than 0.8 (Figure 2). The anomalies of the NAO+ regime recur in the GCMs as well, however, with a systematic underestimation of the variance compared with the reanalyses due to relatively weaker anomalies in the GCMs. The anomalies of the Atlantic ridge regime and the blocking regime show higher variability between the various data sets. This is indicated by a large range of correlations caused by variations in the spatial position and the extent of the anomaly centres. In addition, standard deviations are mostly higher in the GCMs compared with reanalyses, indicating stronger anomalies in the GCMs.

Results from the analysis of running 31-year sub-intervals show further important aspects. A notable feature in Figure 3 and Supporting figures is the considerable intra-dataset spread of the regime anomalies across the 31-year sub-intervals. It points to substantial temporal non-stationarities of the regimes. Within the reanalysis data (NCEP Figure 3, ERA, Figure S4, Supporting Information) the temporal variations of the regimes are lowest for the NAO− regime and highest for the blocking regime. However, for the NAO− regime systematic differences between reanalysis and GCM historical and scenario runs can be seen with overall lower correlation coefficients as well as reduced

Table I. Mean number of days spent in each weather regime in winter (DJF). Indicated are, for each data set, the mean numbers over the whole time period considered and the range resulting from the analysis of 31-year sub-intervals.

		Regime 1 (NAO+)		Regime 2 (blocking)		Regime 3 (Atl. ridge)		Regime 4 (NAO−)	
Data set	**Time period**	**Mean number of days**	**Range in 31 years sub-intervals**	**Mean number of days**	**Range in 31 years sub-intervals**	**Mean number of days**	**Range in 31 years sub-intervals**	**Mean number of days**	**Range in 31 year sub-intervals**
NCEP reanalysis	1950–2010	24	17–28	23	17–27	23	16–27	20	16–27
ERA-Interim	1979–2012	22	18–29	22	17–28	26	17–29	20	17–27
MPI-ESM-LR historical run 1	1950–2005	27	20–30	19	17–28	22	16–27	22	17–27
MPI-ESM-LR historical run 2	1950–2005	26	21–30	18	18–26	23	14–28	23	16–28
MPI-ESM-LR historical run 3	1950–2005	19	19–30	25	17–28	26	15–25	20	15–27
MPI-ESM-LR RCP4.5 run 1	2006–2100	24	19–30	20	17–26	18	16–26	28	18–27
MPI-ESM-LR RCP4.5 run 2	2006–2100	24	18–30	17	16–27	23	16–28	26	15–27
MPI-ESM-LR RCP4.5 run 3	2006–2100	24	19–30	21	16–29	22	17–27	23	16–28
MPI-ESM-LR RCP8.5 run 1	2006–2100	25	12–32	23	15–30	19	12–29	23	14–26
MPI-ESM-LR RCP8.5 run 2	2006–2100	27	15–31	20	16–27	23	17–27	20	18–30
MPI-ESM-LR RCP8.5 run 3	2006–2100	27	18–29	20	16–29	21	14–30	22	15–29
HadGEM2-ES historical	1950–2005	26	–	21	–	19	–	24	–
HadGEM2-ES RCP4.5	2006–2099	24	18–29	19	17–28	25	17–27	22	16–27
HadGEM2-ES RCP8.5	2006–2099	17	11–32	23	13–29	27	6–30	23	12–28
CanESM2 historical	1950–2005	26	20–37	24	16–25	19	16–30	21	16–27
CanESM2 RCP4.5	2006–2100	25	18–30	24	16–27	19	14–26	22	17–30
CanESM2 RCP8.5	2006–2100	27	19–33	20	15–31	21	10–29	22	14–30

standard deviations in the GCM sub-intervals. This means a considerably reduced temporal consistency of the NAO− regime in the GCM simulations which is not evident in the reanalysis data. The other regimes hold a large but comparable intra-dataset spread in reanalysis and GCM data with regard to the pattern similarities as expressed by the correlation coefficients. However, the variability in the strength of the regime anomalies is higher in the GCM sub-intervals, indicated by a larger overall range of the standard deviations. Additionally, as already outlined in Figure 2, there is a systematic bias towards weaker regime anomalies for the NAO+ regime in the GCM data compared with reanalyses. Higher standard deviations and thus stronger anomalies are present for the blocking regime and the Atlantic ridge regime.

Table I illustrates notable variations in the mean number of days spent in each regime across the data sets as well as in the 31-year sub-intervals. The mean wintertime frequency of the NAO+ regime is 24 and 22 days in NCEP and ERA-Interim, respectively. Across the different GCM simulations it ranges from 17 days in the HadGEM2-ES RCP8.5 run to 27 days mainly in the MPI-ESM-LR and CanESM2 RCP8.5 scenario runs. Looking at the 31-year sub-intervals of the reanalysis data sets, all regimes show mean frequency differences of up to 12 days. A similar value is found for the GCM historical runs with the exception of the NAO+ regime in the CanESM2 sub-intervals with mean frequency differences of up to 17 days. Under scenario conditions, in particular concerning RCP8.5, the total range of the variations increases considerably. The mean number of days spent in the NAO+ regime varies up to 21 days in the different 31-year sub-intervals, up to 24 days for the Atlantic ridge regime, and up to 16 days for the NAO− regime and the blocking regime. We compare the variability in the frequency of occurrence between historical and scenario conditions by using the variance of the frequencies in the 31-year sub-periods and its 90% confidence limits from 1000 iterations of bootstrapping. Note that HadGEM2-ES RCP8.5, showing highest variability in the frequency of occurrence, is excluded, because data is too short for the historical period. Under RCP8.5 scenario conditions we find that the variances in the frequency of occurrence of the NAO+ regime and of the Atlantic ridge regime lie outside the 90% confidence intervals of the historical runs. We conclude that the variability in the frequency of occurrence increases under stronger greenhouse gas forcing, being significant for the NAO+ regime and for the Atlantic ridge regime. Whether this represents a real climate change signal or is due to model deficiencies has to be resolved yet.

4. Conclusions

Our study shows that the regimes exhibit considerable variability within the data sets as well as across the data sets considered. The NAO− regime specifications are highly varying with time in the GCM historical and scenario runs which is not the case in the reanalysis data. Owing to the consistency of this regime in reanalyses but not in the GCMs, our study suggests that the distinct spatial patterns of temperature and precipitation over Europe associated with this regime are not correctly captured in the GCM simulations. For the other regimes a notable variability can also be identified. However, variability of the regimes within the GCM data sets

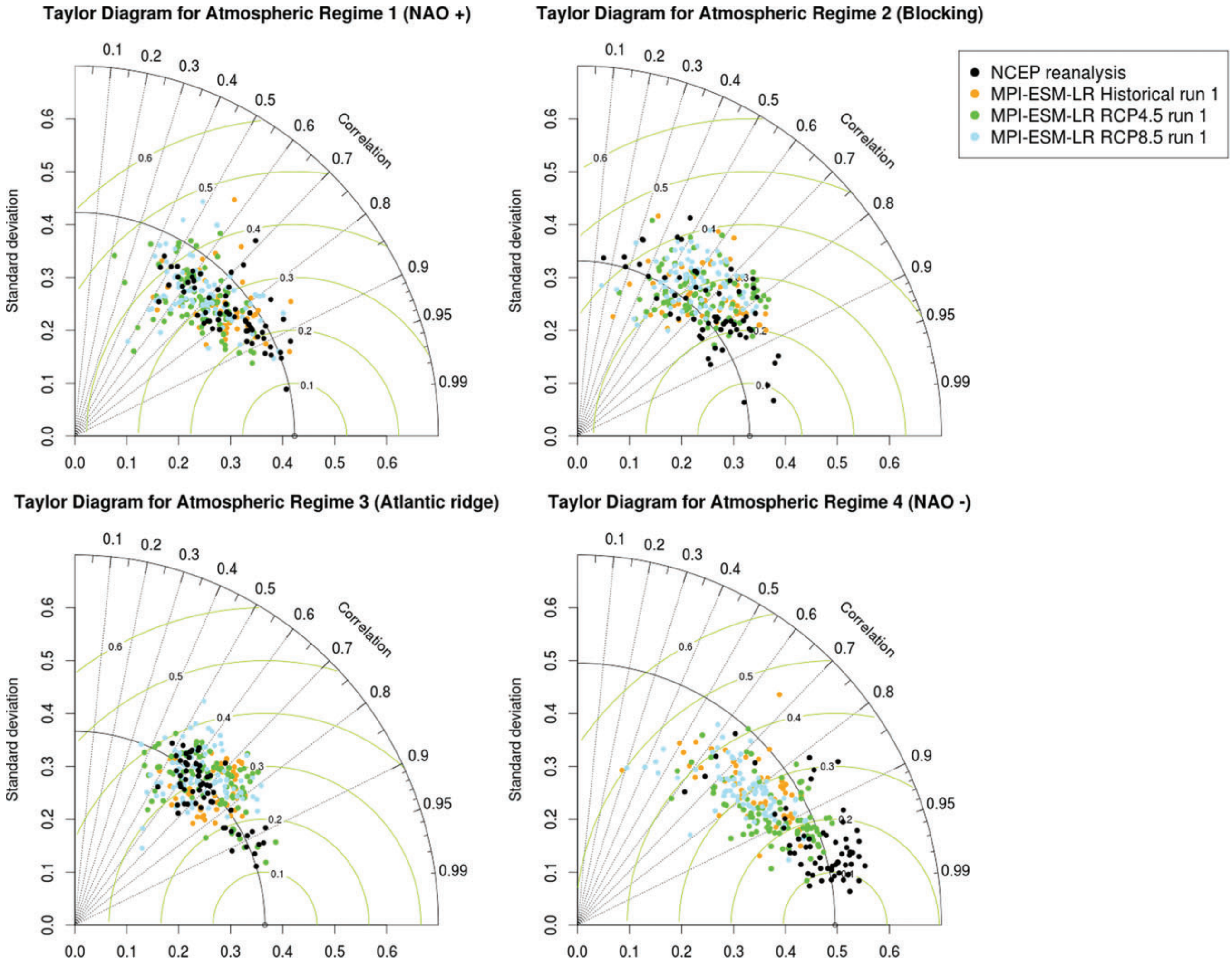

Figure 3. Taylor diagrams showing the similarity of the weather regimes in 31-year sub-intervals. Shown are, for each weather regime, the similarity of the anomaly patterns in 31-year sub-intervals with the NCEP weather regimes of the period 1950–2010. Illustrated are the 31-year sub-intervals of NCEP, and of the historical, RCP4.5, and RCP8.5 simulations of MPI-ESM-LR run 1.

is comparable to the spread seen in the reanalysis sub-intervals. These findings have major implications with respect to downscaling using the weather regimes as large-scale predictors. Despite the substantial variability of the NAO+ regime, of the Atlantic ridge, and particularly of the blocking regime, we expect that the consideration of the full range of observed variability will yield realistic projections of regime-dependent temperature and precipitation patterns under future climate change conditions. In contrast, regime-specific temperature and precipitation assessments will be more problematic for the NAO− regime. The close-confined reanalysis predictor–predictand relationships cannot be transferred one-to-one to the much broader GCM representations to make inferences about future regional climate changes.

We find considerable (real and/or model-induced) variations in the number of days per winter spent in each regime, most pronounced for the Atlantic ridge and the NAO+ regime under RCP8.5 scenario conditions. This leads to substantial modifications of the temperature and precipitation distributions in regions influenced by these regimes. Furthermore, the frequency changes of the regimes can increase or damp the effects of the above outlined variable regime-climate relationships by changing the proportion to which specific regime characteristics impact on the temperature and precipitation distributions.

Besides the variations of the frequency of occurrence and the modifications of the regime-climate relationships arising from the variability of the regime anomalies, other sources of non-stationarity can be relevant in the scope of future climate change. This concerns, for instance, changes of regime-specific temperature levels or thermodynamic processes. De Vries *et al.* (2013) find for western and central Europe that days in which the daily mean temperature falls below the freezing level, are strongly reduced under SRES A1B scenario conditions. The reduction is a consequence of the shift of the temperature distribution towards higher values. Furthermore, future days below the freezing level occur for more extreme circulation types associated with, on average, drier weather conditions. Hertig and Jacobeit (2013) analysed mean daily precipitation in the Mediterranean area and show that in the observational period non-stationarities occurred within the relationships between precipitation and circulation patterns and their within-type circulation and thermodynamic characteristics. The details of the effects of such 'within-type' (Barry *et al.*, 1981, Beck *et al.*, 2007) changes in the scope of regional climate change assessments using latest generation GCMs remain to be investigated.

Supporting information

The following supporting information is available:

Figure S1. Taylor diagrams showing the similarity of the weather regimes in 31-year sub-intervals of MPI-ESM-LR run 2. Shown are, for each weather regime, the similarity of the anomaly patterns in 31-year sub-intervals with the NCEP weather regimes of the period 1950–2010. Illustrated are the 31-year sub-intervals of the historical, RCP4.5 and RCP8.5 runs.

Figure S2. Taylor diagrams showing the similarity of the weather regimes in 31-year sub-intervals of MPI-ESM-LR run 3. Shown are, for each weather regime, the similarity of the anomaly patterns in 31-year sub-intervals with the NCEP weather regimes of the period 1950–2010. Illustrated are the 31-year sub-intervals of the historical, RCP4.5 and RCP8.5 runs.

Figure S3. Taylor diagrams showing the similarity of the weather regimes in 31-year sub-intervals of CanESM2 run 1. Shown are, for each weather regime, the similarity of the anomaly patterns in 31-year sub-intervals with the NCEP weather regimes of the period 1950–2010. Illustrated are the 31-year sub-intervals of the historical, RCP4.5 and RCP8.5 runs.

Figure S4. Taylor diagrams showing the similarity of the weather regimes in 31-year sub-intervals of HadGEM2-ES and of ERA-Interim. Shown are, for each weather regime, the similarity of the anomaly patterns in 31-year sub-intervals with the NCEP weather regimes of the period 1950–2010. Illustrated are the 31-year sub-intervals of the ERA-reanalysis and of the HadGEM2-ES RCP4.5 and RCP8.5 runs.

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