Persistent Regimes and Extreme Events of the North Atlantic Atmospheric Circulation

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Society is increasingly impacted by natural hazards which cause significant damage in economic and human terms. Many of these natural hazards are weather and climate related. Here we show that North Atlantic atmospheric circulation regimes affect the propensity of extreme wind speeds in Europe. We also show evidence that extreme wind speeds are long-range dependent, follow a Generalised Pareto distribution and are serially clustered. Serial clustering means that storms come in bunches and, hence, do not occur independently. We discuss the use of waiting time distributions for extreme event recurrence estimation in serially dependent time series.

Keywords: Circulation Regimes, Extremes, Long-Range Dependence, Clustering

1. Introduction

An important part of European weather and climate are wind storms. European wind storms can cause economic damage and insurance losses on the order of more than one billion Euro per year and rank as the second highest cause of global natural catastrophe insurance loss (Malmquist 1999). Many of these hazard events are not independent; for instance, severe storms can occur in trains of storms. Examples of such recurring storms include January 2008 (Paula and Resi) and March 2008 (Emma, Johanna and Kirsten) which each caused damages on the order of 1bn Euros (e.g. guycarp.com). Also the 2007 floods in the UK were caused by a succession of weather systems slowly moving across the UK which were likely caused by the jet stream located further south than normal (Blackburn et al. 2008). Another typical climate phenomenon in the North Atlantic region are nearly stationary blocking anticyclones which can cause heat waves, extreme cold spells (Cattiaux et al. 2010) and drought conditions.

The Intergovernmental Panel on Climate Change (IPCC 2012) has stated that it is likely that anthropogenic climate change leads to changes in the frequency and intensity of weather and climatic extreme events (Trenberth et al. 2007, Rahmstorf and Coumou 2011). The first six months of 2011 incurred insurance losses of about US$60bn which is about five times the average for the first six months of the year in the period 2001-2010 (Press release by MunichRe 2011). However, it is not clear how much of this loss increase is due to increasing populations in vulnerable regions, a significant increase in natural extreme events or random fluctuations in the rate of natural hazards. This illustrates the challenge society is facing in mitigating the effects of natural hazards.

It has long been recognised that low-frequency large-scale circulation patterns have a significant impact on surface weather and climate. These circulation patterns or regimes have been shown to affect extreme temperatures, cyclones, wind speeds and precipitation (Thompson and Wallace 2001, Yiou and Nogaj 2004, Raible 2007, Yiou et al. 2008, Yin and Branstator 2008). Since the regimes also affect cloud cover and the distribution of aerosols they may also influence the climate response to increasing greenhouse gas emissions and climate sensitivity. Since low-frequency waves are well represented in climate models this offers the potential to statistically extract information about extreme events (which might not be well represented in climate models) from simulations like the frequency of occurrence of extreme events. This might enable projections of how extreme events change in seasonal and decadal scale predictions and future climate projections. Many businesses and decision-makers need this kind of information.

Traditional extreme value statistics are based on the premise that extreme events occur independently from each other. However, this is rarely the case for weather and climatic extremes where these extreme events tend to serially cluster as discussed above. In the traditional framework no account is taken of the temporal dependency structure of weather and climate variables that are present in many natural time series. The temporal dependence can lead to the clustering of extremes and traditional extreme value statistics has to be adjusted to take account of this (Berman 1964, Leadbetter and Rootzen 1988, Bunde et al. 2005, Garrett and Müller 2008). This temporal dependence impedes our ability to estimate return periods, which now also requires the prediction of the clusters of extreme events, which are important for many practical applications.

The purpose of this contribution is to discuss the dependence structure and the empirical extreme value distribution of surface wind speeds and the occurrence of clustered wind speed extremes. We will also discuss how the regimes of the eddy-driven Atlantic jet stream (Franzke et al. 2011) affect the propensity of extreme events and the temporal dependence of wind speeds. We also provide evidence that surface wind speeds follow a Generalised Pareto extreme value distribution and that their amplitude is bounded; consistent with theoretical predictions. We will discuss the use of waiting time distributions as an alternative to return times inferred from extreme value statistics. Waiting time distributions are a natural measure for extremes of dependent data.

In section 2 we will describe the data, including the Jet Latitude Index (JLI) which is used as a proxy of North Atlantic climate variability (Woollings et al. 2010, Franzke and Woollings 2011, Franzke et al. 2011). Section 3 examines the persistence properties and extreme value characteristics of North Atlantic surface wind speeds while section 4 presents how persistent circulation regimes affect the propensity of extreme events. Here we focus on extreme wind speeds, deviations from Gaussianity in 500 hPa geopotential height as a first measure of extremes, and clustering of extremes. Previous studies mainly focused on the relationship between circulation regimes and temperature and precipitation extremes. A summary and discussion are given in section 5.

2. Data

Data are used from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA-40 Re-Analysis (Uppala et al. 2005). We use daily mean fields for zonal u and meridional v wind fields and 500 hPa geopotential height. The wind speed is computed as $\sqrt{u^2 + v^2}$.

As a North Atlantic climate variability proxy we use the jet latitude index (JLI) which is a measure of North Atlantic climate variability and in particular of the position of the lower tropospheric eddy-driven jet stream (Woollings et al. 2010, Franzke and Woollings 2011). This index covers the period 1 December 1958 through 28 February 2001. The JLI is derived in the following way: (1) A mass-weighted average of the daily mean zonal wind is taken over the vertical levels 925, 850, 775 and 700 hPa and over the Atlantic sector $0° - 60°$W. (2) Winds poleward of 75°N and equatorwards of 15°N are neglected. (3) The resulting wind field is low-pass filtered, only retaining periods greater than 10 days. (4) The JLI is defined as the latitude at which the maximum wind speed is found. (5) A smooth annual cycle is subtracted from the resulting time series. See Woollings et al. (2010) for more details, where it is also shown that this index describes jet stream variations which are associated with both the North Atlantic Oscillation (NAO) and the East Atlantic (EA) teleconnection pattern and, therefore, represents a good general proxy of North Atlantic climate variability. Based on the JLI we will compute composite fields of various quantities like skewness, kurtosis and extreme wind speeds. The composites of the wind speed data are computed from unfiltered data.

3. Persistence and Extreme Events

(*a*) *Persistence of the Atmospheric Circulation*

Persistence is one of the most fascinating and important characteristics of the atmosphere. By persistence we mean the atmosphere's tendency to maintain its current state. One of the simplest weather forecasting models is a persistence forecast where one predicts that tomorrow will be like today. This persistence forecast has a surprisingly good forecast skill. Such a forecasting model would be Markovian. The Markov property implies that the next state only depends on the current state but not on any past states. However, there is growing evidence that many climate variables have a more complicated temporal dependence structure (Koscielny-Bunde et al. 1998, Vyushin et al. 2009, Franzke 2010, 2012a, Ghil et al. 2011). This temporal dependence structure also indicates knowledge of the past is needed to forecast the next state. This temporal dependence of climate variables leads to so-called stochastic trends (Franzke 2010, 2012a) and the serial clustering of extremes (Bunde et al. 2005). Stochastic trends are trends which arise due to persistence and not due to external forcing like greenhouse gas emissions. Long-range dependent time series can exhibit stochastic trends over much longer periods of time than say a Markovian process and thus the detection of trends and attribution of drivers becomes much harder. The disentanglement of stochastic and deterministic trends is a field of active research (e.g. Barbosa 2011, Franzke 2010, 2012a).

A measure of the temporal dependence and persistence of a time series is the long-range dependency parameter d (Beran 1994). A process is long-range dependent when the prediction of its next state depends on the entirety of its past. An imprint of this dependence structure is that the covariance $r(k) = Cov(X(k), X(0))$ decays slowly, as $k \to \infty$, so that

$$\sum_{k=0}^{\infty} |r(k)| \to \infty. \tag{3.1}$$

The parameter d can be defined by specifying long-range dependence as a power-law like decay of the autocorrelation function. Thus, we define that a stationary process is long-range dependent if it has autocorrelation function r such that

$$r(k) \sim k^{2d-1} \text{ as } k \to \infty \tag{3.2}$$

where $0 < d < \frac{1}{2}$. This power law decay of the autocorrelation function is not integrable and will lead to a blow up as described by Eq. (3.1).

This slow decay of the covariances means that the values of the process X are strongly dependent over long periods of time. This contrasts with the more familiar short-range dependent process where $\sum_{k=0}^{\infty} |r(k)| = C < \infty$ and the correlations typically decay exponentially. In a short-range dependent process the next state only depends on the current state and the recent past. The archetype of a short-range dependent process is a first order Markov process where the next state depends only on the present state. See Beran (1994) for more details.

In order to estimate d we used the semi-parametric power spectral method of Geweke & Porter-Hudak (1983) and Hurvich and Deo (1999). Spectral methods find d by estimating the spectral slope of the low frequencies. The periodogram is used, which is an estimate of the spectral density of a finite-length time series and is given by:

$$\hat{S}(\lambda_j) = \frac{1}{N} \left| \sum_{t=1}^{N} X(t) e^{-i2\pi t \lambda_j} \right|^2, j = 1, ..., [N/2], \tag{3.3}$$

where $\lambda_j = j/N$ is the frequency and the square brackets denote rounding down. A series with LRD has a spectral density proportional to $|\lambda|^{-2d}$ close to the origin. Since $\hat{S}(\lambda)$ is an estimator of the spectral density, d is estimated by a regression of the logarithm of the periodogram versus the logarithm of the frequency λ. Thus having calculated the spectral density estimate $\hat{S}(\lambda)$, semi-parametric estimators fit a power law of the form $f(\lambda, b, d) = b\,|\lambda|^d$, where b is a scaling factor. The number of frequencies for the log-periodogram regression is computed with the plug-in selector derived by Hurvich and Deo (1999). Confidence intervals and bias correction for this estimator have been derived by Hurvich and Deo (1999) and the confidence intervals are asymptotically Gaussian distributed. The reliability of this estimator has been validated by Franzke et al. (2012).

The long-range dependence parameter $d = 0$ indicates that no temporal dependence is present in the data; thus the data are white noise. Positive d values indicate persistence and negative denote anti-persistence. Anti-persistence has a so-called blue noise power spectrum with the least power at low frequencies and with monotonically increasing variance towards high-frequencies. Furthermore, in a pure long-range dependent process for $d \to 0$ a singularity is approached and the dependence structure goes directly from long-range dependent to independent. The reason for this can be illustrated with the power spectrum. When testing for long-range dependence one is interested in the long-term behaviour of the time series and thus the low-frequencies. At these time scales the short-term dependent behaviour is negligible and is effectively white noise and independent at long time scales. If the time series exhibits long-range dependence then there will be a power-law like slope visible in the power spectrum for the lowest frequencies; otherwise the power spectrum is flat at low frequencies indicating white noise behaviour.

Fig. 1 shows the geographical distribution of d values which are significantly different from 0 for the North Atlantic region. The figure reveals that surface wind speeds are significantly long-range dependent. Most d values are positive, only a small area in the western North Atlantic has negative values. The largest d values occur over western North Africa, also the UK and Scandinavia have enhanced d values. We repeated this analysis with linearly detrended wind speed data and get very similar results (not shown). This suggests that the impact of possible trends is negligible. This provides evidence that surface wind speeds in the North Atlantic region are long-range dependent. Below we will put forward the idea that this long-range dependency might be the imprint of non-stationarities due to the regime behaviour of the jet stream.

(*b*) *Extremes of the Atmospheric Circulation*

In order to examine the extreme value characteristics of surface wind speeds we use a threshold exceedance approach and fit a Generalised Pareto Distribution (GPD, Coles 2001) whose PDF is given by

$$f_{(\xi,\mu,\sigma)}(x) = \frac{1}{\sigma}\left(1+\frac{\xi(x-\mu)}{\sigma}\right)^{(-\frac{1}{\xi}-1)} \tag{3.4}$$

where ξ denotes the shape parameter, μ the threshold (or location parameter) and σ the scale parameter. The shape and scale parameters are fitted with a standard maximum likelihood approach (Coles 2001). The GPD is generalised in the sense that it contains three special cases: (i) when $\xi > 0$ the GPD is equivalent to an ordinary Pareto distribution, (ii) when $\xi = 0$ the GPD becomes an exponential distribution and (iii) for $\xi < 0$ the GPD is a short-tailed Pareto type II distribution (Coles 2001). The standard asymptotic properties of the maximum likelihood estimator cannot be proven for shape parameters less than -0.5 and thus the confidence intervals cannot be reliably computed but this does not necessarily mean that the parameter estimates are not robust.

We estimate the GPD parameters from unfiltered wind speed data. Fig. 2 shows the shape and scale parameters of a GPD distribution. As a threshold we selected the 90th percentile value of the wind speed at each grid point. The parameter estimates are relatively stable for a range of different thresholds (see Fig. 2) and a visual inspection of quantile-quantile plots at some locations shows that the wind speed data follow a GPD (not shown). This provides confidence that surface wind speed extremes indeed can be described by a GPD. Furthermore, the shape parameter is negative. This indicates that extreme surface wind speeds are bounded. The shape parameter reaches its maximum over the central North Atlantic but also the UK, Scandinavia and Central Europe exhibit a large scale parameter. Our results are consistent with the study by Fawcett and Walshaw (2006) which also find that extreme wind speeds follow a GPD with mostly negative shape parameters.

That the unfiltered wind speed extremes are bounded is consistent with the theoretical findings of Majda et al. (2009). They show that while the normal form of stochastic climate models allows for a power-law like decay of the PDF tail over some range of values, the ultimate decay will be squared exponential (i.e. Gaussian; see their equation 11); thus very large values have a vanishing probability. This is in contrast to the results of Sardeshmukh and Sura (2009) and Sura (2011). They consider only a linear model with state-dependent noise and neglect the nonlinearity. Majda et al. (2009) and Franzke (2012b) have shown that the nonlinear interaction between slow and fast modes is producing the state-dependent noise in the normal form of stochastic climate models and is causing the tail of the PDF to decay according to a squared exponential function. This suggests that nonlinear interactions cannot be neglected and are a possible cause of the deviations from Gaussianity.

(*c*) *Clustering of Atmospheric Circulation Extremes*

While long-range dependence and extreme value statistics seem at first sight fairly unrelated to each other, in fact the opposite is the case. Long-range dependence has a rather strong impact on extreme value statistics, especially the return periods of extreme values. Long-range dependence leads to the clustering of extremes. Clustering of extremes means that there exist time periods where values are more likely to exceed the extreme value threshold than if they were to occur independent from each other. Likewise, there also exist periods where less extremes occur than one would expect if they were to occur independently. This means that extreme events are likely followed by other extreme events and that there are long periods when no extreme events occur. A prime example is the serial clustering of storms (Mailier et al. 2006) as alluded to in the introduction.

Traditional extreme value theory assumes that the data under consideration are independent and identically distributed (iid). For many climate time series this is not the case because these time series are autocorrelated and extreme value theory has been extended for dependent time series (Coles 2001, Beirlant et al. 2004). Extreme value theory can be extended to the case of short-range dependent time series by introducing the extremal index which adjusts the parameters of the GPD (Coles 2001). The extremal index is a measure of the clustering of extremes which adjusts extreme value distributions for serially short-range dependent time series (Coles 2001). In the presence of long-range dependence the GPD can still describe the amplitude distribution and we have provided empirical evidence for this in the previous section; see also Franzke (2012c). However, the presence of long-range dependence and thus clustering might affect the return period estimates based on the GPD in ways which one cannot account for solely with the extremal index and is an active area of research.

The extremal index θ is computed by using the method of Hamidieh et al. (2009). It characterises the extent of temporal dependency of extreme events and is inversely proportional to the average cluster size. The approach by Hamidieh et al. (2009) is based on the asymptotic scaling properties of block-maxima and resampling. The maxima of blocks of size m scale as $m^{\frac{1}{\alpha}}$, where α is the tail exponent. Thus, by examining a sequence of dyadic block sizes $m(j) = 2^j$ and resampling one can estimate the extremal index $\theta(j)$ and the corresponding uncertainty bounds (see Hamidieh et al. (2009) for more details). Evidence for clustering of extremes is given if θ turns out to be stable over a range of scales. An extremal index value close to 1 indicates almost independent extremes. In order to find θ values which are robust over a range of scales we use the non-parametric Kruskal-Wallis test (Hamidieh et al. 2009). We use this test to assess whether the medians over a scale range are statistically indistinguishable at a level of 5%. Furthermore, the resampling approach provides error intervals which provide a means to test whether the extremal index values are statistically significant different from 1. We also performed a field significance test (Livezey and Chen 1983) and found the results to be significant at the 5% level.

Fig. 3 shows the extremal index of surface wind speeds (only significant values at the 5% level are displayed). While the distribution of the extremal index is noisy the figure nonetheless provides evidence that extreme surface wind speeds are clustered in the North Atlantic region. Especially the UK, the Iberian peninsula, Germany and France as well as south-west Greenland, Latin America and Africa show extremal index values significantly different from 1 which indicate a propensity to clustering of wind speed events.

The fact that extreme wind speeds are clustered is consistent with the long-range dependence of wind speeds. In the next section we will provide evidence for regime behaviour which is one possible mechanism for the observed long-range dependence and clustering of extremes.

4. Persistent North Atlantic Regimes and Extremes

One of the most fascinating aspects of climate variability is that it can be described by just a few teleconnection patterns. This ability is attractive because this would not only allow for a very efficient description of the atmosphere but also offer the prospect of skillful long-range predictions. The quest to decompose the low-frequency atmospheric circulation into just a few recurring or preferred circulation patterns is long ongoing. The earliest attempts have been made by Defand (1924) and Walker and Bliss (1932). These studies identified the North Atlantic Oscillation (NAO) as the dominant teleconnection pattern in the North Atlantic region which exerts a significant influence on surface weather and climate. Other well known teleconnection patterns in the North Atlantic region are the East Atlantic (EA) and the Scandinavian patterns. These patterns are typically identified by Empirical Orthogonal Function (EOF) analysis (Barnston and Livezey 1987), Gaussian mixture analysis (Smyth et al. 1999), deviations from Gaussianity (Kimoto and Ghil 1993) or cluster analysis (Cheng and Wallace 1993, Cassou 2008).

In order to examine the relationship between persistent circulation regimes and extreme events here we are using the circulation regimes identified by Franzke et al. (2011). They used a Hidden Markov Model (HMM) to identify persistent regime states. A HMM identifies preferred persistent states in phase space by simultaneously estimating a Gaussian mixture model and a Markov transition matrix. The Markov transition matrix describes the temporal evolution of the regimes (Majda et al. 2006, Franzke et al. 2008, 2009, 2011). As a proxy of North Atlantic climate variability the JLI has been used and three significant persistent regime states have been identified which correspond to a Northern, Southern and Central jet state (see Fig. 2 of Franzke et al. (2011)). Franzke et al. (2011) show that the regimes well describe the storm tracks and that Rossby wave breaking plays a large role in the maintenence of the regimes.

The regime behaviour and long-range dependence are likely closely related. Regime behaviour is a case of non-stationarity which is able to induce long-range dependence (Klemes 1974). One of the simplest explanations of long-range dependence is that a system persists for long periods of time above or below its climatological mean value. This is exactly what happens for the jet stream regimes; they fluctuate for long periods of time around either their northern, southern or central states (Franzke et al. 2011). This suggests that the jet stream regime behaviour is a likely cause of the observed long-range dependence.

As we will show next these circulation regimes determine the propensity of extremes. One sign of the possible presence of extremes are deviations from Gaussianity. For instance, deviations from Gaussianity can indicate that large values occur more frequently than one would expect if they were from the Gaussian distribution. Nakamura and Wallace (1991) and Holzer (1996) provided evidence that deviations from Gaussianity in geopotential height fields are associated with extreme events. The first measures of deviations from Gaussianity are the skewness and kurtosis. Skewness indicates the degree of symmetry around the mean value; a Gaussian distribution has a skewness of zero. Kurtosis denotes the peakedness of the distribution; i.e. if it has more or less mass in the tail of its distribution than a Gaussian distribution. The skewness is defined as

$$s = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^3}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2)^{\frac{3}{2}}} \tag{4.1}$$

and the excess kurtosis as

$$k = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^4}{(\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2)^2} - 3 \tag{4.2}$$

where n denotes the length of the time series x_i, and $\overline{x}$ the mean value of the time series.

In Fig. 4 is displayed the skewness and in Fig. 5 the excess kurtosis of 500 hPa geopotential height. These figures show that the jet stream regimes have an impact on the deviations of Gaussianity in the upper tropospheric circulation in the North Atlantic region and over Europe. The Southern jet regime is associated with negative skewness and positive excess kurtosis on the equatorward flank of the jet stream and negative skewness and positive kurtosis over south-east Europe. The Northern regime is associated with positive skewness on the equatorward flank of the jet stream and negative skewness over central Europe and negative kurtosis over the Norwegian and Barents sea, while the Central jet regime is associated with positive skewness on the equatorward flank of the jet stream, positive skewness over central Europe and negative skewness west of the Iberian peninsula and negative kurtosis on the poleward flank of the jet stream.

These changes are likely due to changes in preferred locations of blocking in the jet regimes (Franzke et al. 2011). The northern jet regime is associated with blocking anti-cyclones mainly over southwestern Europe, the southern jet regime with Greenland blockings and the central jet regime with a reduction of blocking systems (Franzke et al. 2011). These changes in blocking and corresponding changes in deviations of Gaussianity are consistent with the findings of White (1980) and Rennert and Wallace (2009). On the other hand, Luxford and Woollings (2012) put forward the idea that the observed deviations from Gaussianity are just a consequence of the jet stream shifts and do not necessarily imply nonlinear dynamics and changes in blocking locations.

Next we examine how the regimes affect the occurrence of extreme wind speeds. For this purpose we computed the 99.9th percentile of unfiltered wind speeds. Fig. 6 reveals that the regime states also affect extreme wind speeds over the North Atlantic and the UK. During the Southern jet state extreme wind speeds are more likely to occur on the poleward side of the jet while during the Northern jet state they are more likely to occur on the equatorward side. During the Central jet state extreme wind speeds are likely to occur in a small band north-west of Ireland. The extreme wind speed results are robust against a change in the exact percentile level; choosing the 99th percentile level gives broadly the same results (not shown).

The statistical significance of the skewness, kurtosis and extreme wind speeds are tested by using a bootstrap approach. This tests whether the composite fields could have arisen from sampling issues. Our results suggest that the skewness, kurtosis and extreme wind speeds are unlikely to be the result of sampling variability. We also performed a field significance test (Livezey and Chen 1983) and found the results to be significant at the 5% level. These results reveal that circulation regimes of the North Atlantic jet stream have a statistically significant impact on the propensity of extreme events.

5. Summary and Discussion

In this contribution we have provided evidence that circulation regimes of the North Atlantic eddy-driven jet stream affect the propensity of extremes. In the case that seasonal-to-interannual prediction systems can skillfully predict the regime states of the jet stream or their changes in frequency of occurrence this would offer the prospect of probabilistic forecasts of the likely number of extreme events for the next season or year. This kind of information is needed by many businesses and decision-makers. It has to be noted that many climate models still have problems simulating blockings, which are strongly related to the jet stream regimes. This is likely related to the nonlinear wave breaking which is essential in the life cycle of blockings. Capturing the wave breaking features likely requires high horizontal resolutions.

We also provided evidence of long-range dependence of surface wind speeds. The occurrence of circulation regimes are a possible explanation of this property because they introduce non-stationary behaviour. It is well known that non-stationarity can cause long-range dependent behaviour. The fact that the wind speed extremes are serially clustered is consistent with both the long-range dependence and the regime behaviour (i.e. the non-stationarity). For instance, in Fig. 7 is displayed the wind speed time series at a grid point close to London. The time series looks non-stationary with periods with persistent high or low wind speeds. These persistent periods of high and low wind speeds are likely related to the regime behaviour of the jet stream and the long-range dependence.

This finding also has wider implications for climate change because long-range dependent processes can produce apparent trends over rather long periods of time

(Franzke 2010, 2012a) and there is evidence that surface temperatures are long-range dependent (Koscielny-Bunde et al. 1998). Also non-stationarities or regime behaviour can cause apparent trends. A typical HMM realisation, which is a paradigmatic non-stationary process, as displayed in Franzke et al. (2008) shows how regime behaviour can cause an apparent trend (see their Fig. 1b). However, there will be no trend for sufficiently long HMM realisations. The likely connection between climatic regime behaviour and climate trends needs further research.

Furthermore, the fact that extreme wind speeds cluster suggests that return periods are not necessarily a useful measure. This is even more complicated by the presence of long-range dependence which will link even far apart extreme events. This linking will negate traditional attempts to de-cluster the time series (Coles 2001). This calls for the need of new measures for describing the occurrence frequency of extremes, including the clustering of extremes, for serially dependent processes. Waiting time distributions are one promising measure of the reoccurrence properties of extremes. We estimated the exponential distribution and the empirical waiting time distribution for the grid point closest to London (Fig. 8; the results are insensitive to the exact location). The exponential distribution describes the waiting times of a memory-less Poisson process. As can be seen in Fig. 8 the empirical waiting time has a much fatter tail of waiting times than one would expect from a memory-less Poisson process. This is the imprint from the clustering which means that for long periods no extremes occur but when they occur they occur in bunches. The mean waiting time of the Exponential distribution is 14 days, while the empirically estimated mean waiting time is 33 days. This indicates that traditional extreme value statistics can be misleading if it does not take into account the dependence structure of the underlying process. The estimation of return periods of extremes becomes even more complicated when extremes tend to cluster. Then the return period becomes less meaningful. In principle then one would need two measures: the return period of clusters and the return period of extremes in a cluster. Of course, also outside of clusters extremes can occur. Some promising statistical approaches on clustered extremes are described in Fawcett and Walshaw (2006, 2007a, 2007b) and the relationship between long-range dependence and extremes is an active topic of current research.

While this study has mainly focused on wind speed extremes there are also other atmospheric circulation related extremes like heat waves and droughts which are associated with blocking. The principal difference between both kinds of extremes is that the first are more 'fast' extremes which last a day or two while the latter are more 'persistent' extremes which can last for weeks or longer. Examples are droughts and heat waves. The jet stream regimes are closely linked to blocking (Franzke et al. 2011) and thus will affect the 'persistent' extremes. For instance, the northern jet regime can last up to 3 weeks (Franzke et al. 2011). While most extreme value statistics is well suited to describe 'fast' extremes the statistical model of the 'persistent' extremes is less well developed. At a conceptual level the 'fast' extremes have highly non-Gaussian distributed increments while the 'persistent' extremes can have nearly Gaussian distributed increments. It is likely that the increments of the 'persistent' extremes are very small due to the quasi-stationary character of the phenomenon. An interesting approach to model natural 'persistent' extremes are so-called bursts (Barabasi 2005, Lowen and Teich 2005).

In Franzke et al. (2011) evidence has been provided for large interannual variability of the circulation regimes. Because of the potential that global warming might affect the regimes by e.g. changing their frequency of occurrence there is an urgent need for advanced statistical and mathematical tools to detect and attribute circulation changes and changes in extreme events. The approaches put forward by Horenko (2008, 2010) and O'Kane et al. (2012) are promising for this purpose. Possible processes causing the observed interannual variability are amongst others North Atlantic ocean variability (e.g. Atlantic Multidecadal Oscillation and the Meridional Overturning Circulation), Arctic sea ice decline, stratospheric circulation variability, variations in solar forcing or greenhouse gas emissions. More research is needed to disentangle these processes in a systematic way.

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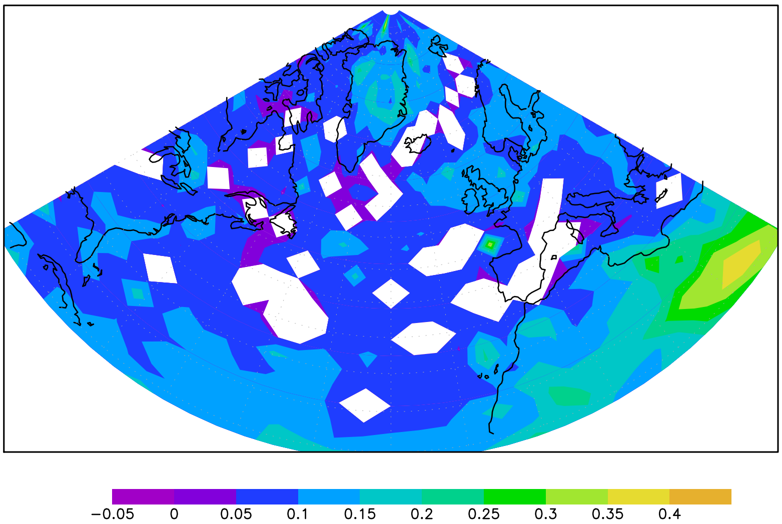

Figure 1. Long-range dependence parameter d of unfiltered surface wind speeds. Only values significant at the 5% level are displayed. Online version in color.

a) **Shape Parameter** b) **Scale Parameter**

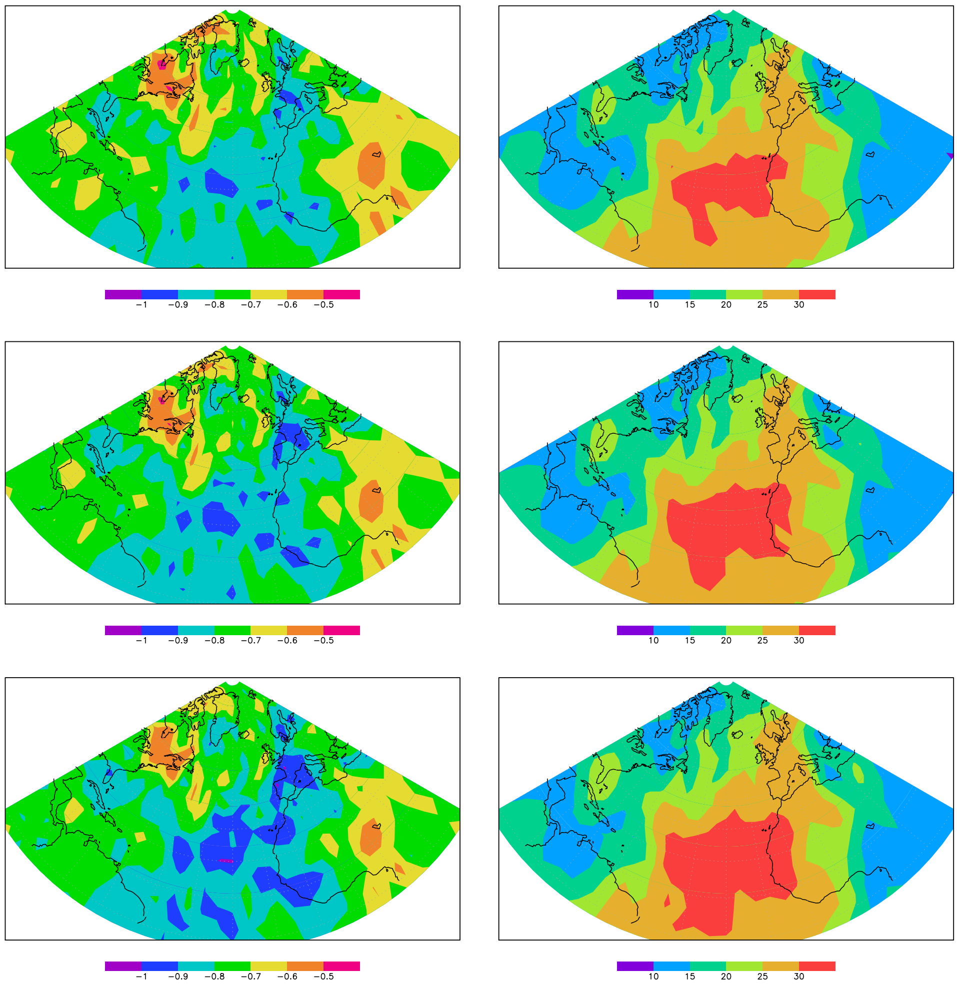

Figure 2. Shape and scale parameter of Generalised Pareto Distribution of unfiltered surface wind speeds for three different thresholds (Upper row: 88th percentile, middle row: 90th percentile and lower row: 92th percentile). Online version in color.

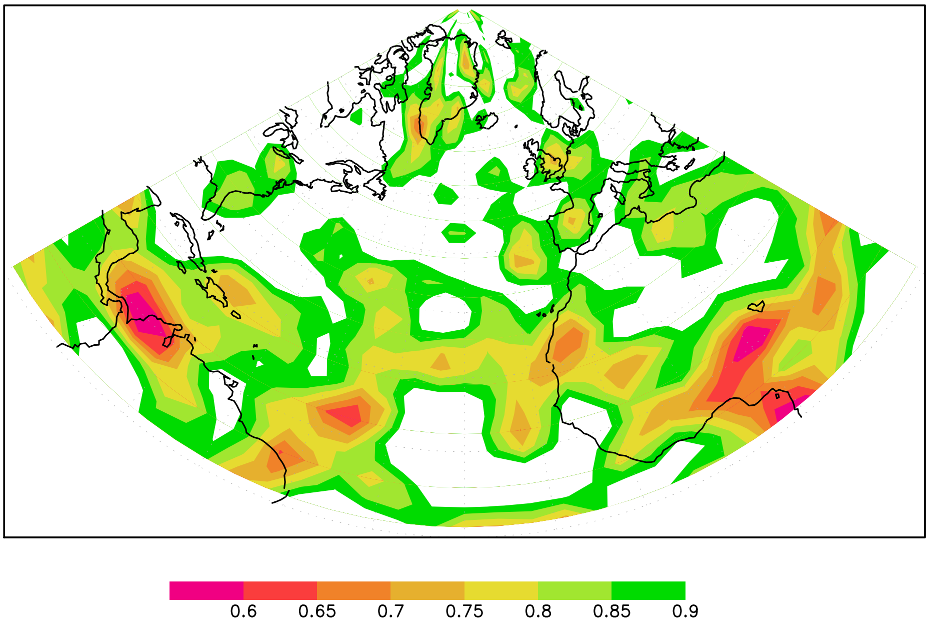

Figure 3. Extremal index of unfiltered surface wind speeds. Displayed are only values which are significant at the 5% level. Online version in color.

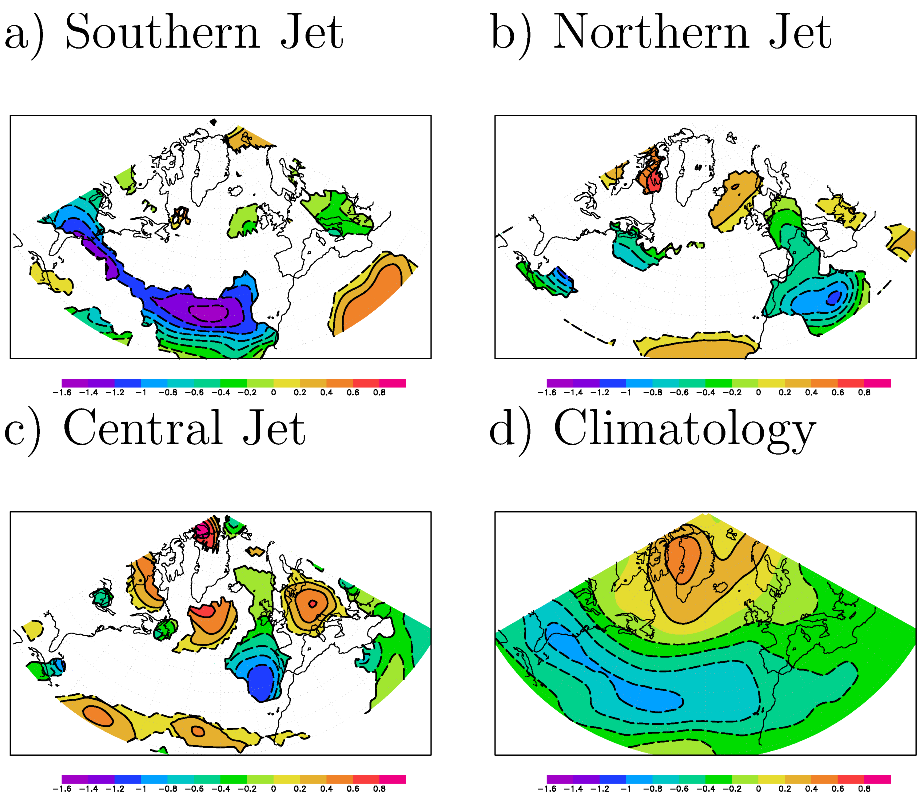

Figure 4. 500 hPa geopotential height skewness. Displayed are only values which are significant at the 5% level. Online version in color.

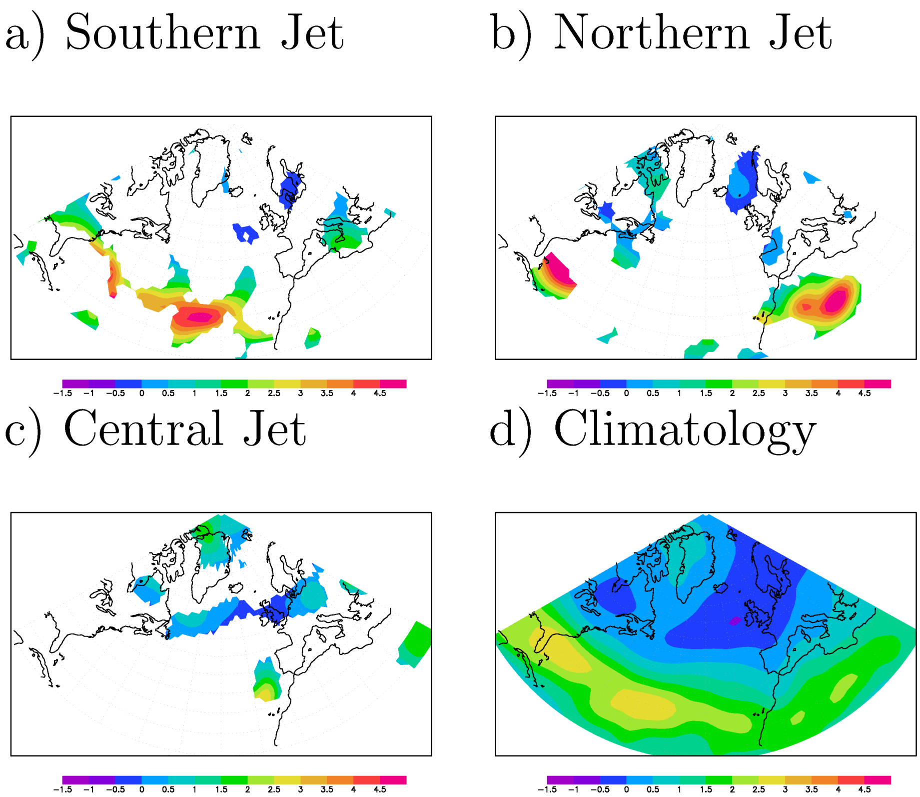

Figure 5. 500 hPa geopotential height kurtosis. Displayed are only values which are significant at the 5% level. Online version in color.

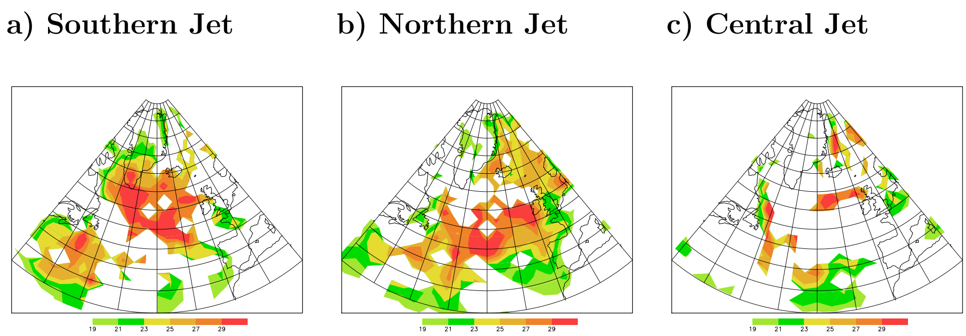

Figure 6. 99.9th percentile of unfiltered surface wind speeds. Displayed are only values which are significant at the 5% level. Online version in color.

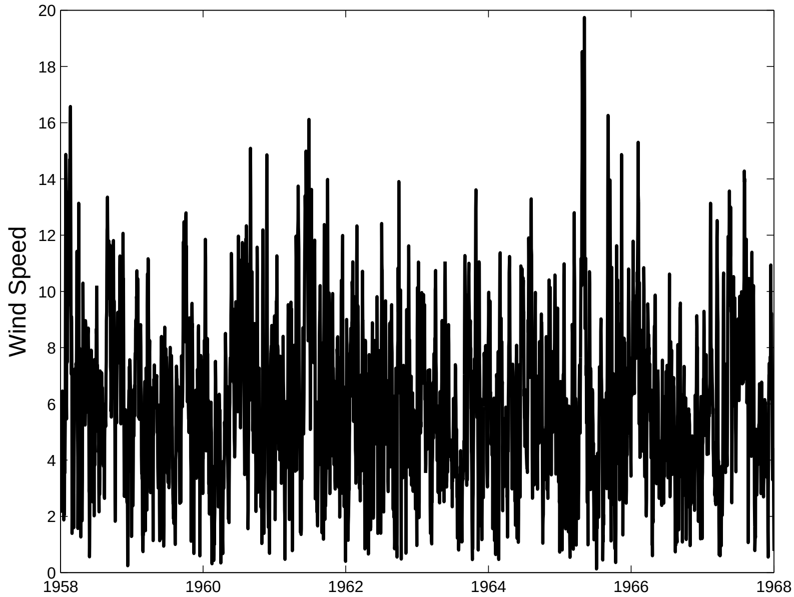

Figure 7. Wind speed time series at a grid point located close to London for the period 1958 through 1968.

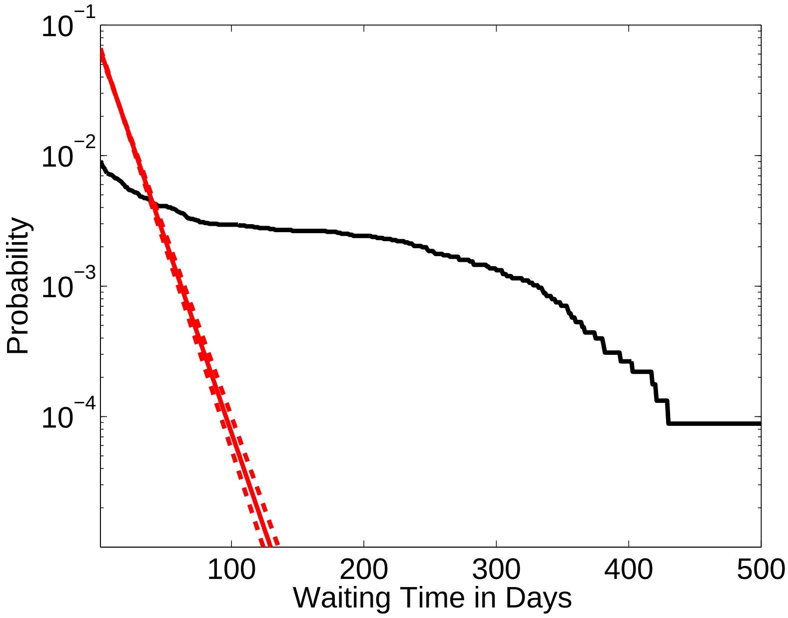

Figure 8. The cumulative waiting time distribution between consecutive 99th percentile threshold exceedances at a grid point located close to London (solid line). Plotted is the probability to exceed the waiting time in days (as given on the x-axis). The crosses denote the corresponding exponential distribution and the dashed lines indicate the 5th and 95th error bounds of the exponential distribution. Online version in color.