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Extreme winds over Europe in the ENSEMBLES regional climate models

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Abstract

Extreme winds cause vast amounts of damage every year and represent a major concern for numerous industries including construction, afforestation, wind energy and many others. Under a changing climate, the intensity and frequency of extreme events are expected to change, and accurate predictions of these changes will be invaluable to decision makers and society as a whole. This work examines four regional climate model downscalings over Europe from the "ENSEMBLE-based Predictions of Climate Changes and their Impacts" project (ENSEMBLES), and investigates the predicted changes in the 50 yr return wind speeds and the associated uncertainties. This is accomplished by employing the peaks-over-threshold method with the use of the Generalised Pareto Distribution. The models show that for much of Europe the 50 yr return wind is projected to change by less than $2\,m\,s^{-1}$, while the uncertainties associated with the statistical estimates are larger than this. In keeping with previous works in this field, the largest source of uncertainty is found to be the inter-model spread, with some locations showing differences in the 50 yr return wind of over $20\,m\,s^{-1}$ between two different downscalings.

1 Introduction

The case for anthropogenically forced climate change is now well established and it represents one of the most serious concerns currently facing mankind. The last report from the Intergovernmental Panel on Climate Change (IPCC) concluded that greenhouse gas forcing has very likely caused most of the observed global warming over the last 50 yr (Solomon et al., 2007). While this represents a significant risk in its own right, the impact of large-scale climate change will be felt most strongly on the local scale through the changes to the frequency and intensity of extreme events (Beniston et al., 2007). Europe has witnessed the impacts of extreme temperatures during the heat waves of 2003 and 2010 (Beniston, 2004; Grumm, 2011; Robine et al., 2008), and during the European cold wave of 2012 (WMO, 2012). While such events often result in a great loss of life, far more economic damage is done each year by extreme winds. The international reinsurance group, Munich RE, estimates that on average, 76 % of insured losses every year are due to extreme winds (Munich RE, 2011). Good knowledge of extreme winds at a given site is also vital for the safe design and construction of exposed structures, e.g. bridges, wind turbines, etc. Furthermore, such information also plays an important role in planning for the development of planted forests, since growth and survival rates are limited by the physiological and mechanical effects of the wind (Quine, 2000); and in the planning of future wind farm placements, since all turbines have a cut-out speed above which they cannot operate and a survival speed above which they cannot survive. With the damage from extreme winds rising each year (Munich RE, 2011) and wind power providing an ever greater proportion of the world's power, good predictions of extreme winds will be increasingly important over the coming decades.

There are numerous challenges with the prediction and investigation of extreme wind events under climate change. Firstly, due to the downscale energy cascade in geophysical turbulence, extreme winds are a local-scale effect, and their study in models therefore necessitates the fine-scale horizontal resolution found in regional climate models (RCMs). These models have some weaknesses including their dependence on the quality of the global model data that is used to drive them, and the various issues with their own model physics. A recent review of the state of regional climate models is given in Rummukainen (2010), but it has been shown that RCMs tend to underestimate wind speeds when compared to observations (Kunz et al., 2010). Unfortunately, regional climate models are also near the end of a long chain of predictions, namely: socio-economic assumptions, predicted emissions scenarios, carbon cycle response and concentration projections, global climate sensitivity estimates, regional climate simulations, and finally, the estimation of possible impacts (Jones, 2000). Each stage of this chain introduces more uncertainties into the final prediction from the RCM (Foley, 2011). In an attempt to put the extreme wind estimates from this work into context

ACPD
13, 1179–1199, 2013

of some of these uncertainties, estimates will be made for multiple simulations and their differences and uncertainties will be discussed.

The second major challenge in investigating extreme winds under a changing climate comes from the need to employ appropriate statistical techniques to both describe the events and to identify their change in frequency. A number of works have employed the Weibull method – this assumes the wind speeds can be fitted to a Weibull distribution and extreme events are then obtained by extrapolation (e.g. Quine, 2000; Lun and Lam, 2000; Koh et al., 2011). This method relies on a distribution that is well fitted to the non-extreme events that make up the largest proportion of the data. It also does not provide confidence intervals for the estimated return values (Perrin, 2006).

Alternative approaches come from extreme value theory; a branch of mathematics that deals with extreme distributions and determining the probability of an event occurring which is more extreme than any previously observed. In general terms there are two main approaches based on the two main theorems. The block maxima method, based on Fisher-Tippett theorem that states that the maxima of multiple samples (blocks) of independent, identically distributed data will converge in distribution to one of three classic distributions: the Gumbel, the Fréchet, or the Weibull distribution (Fisher and Tippett, 1928; Gumbel, 1958). These three distributions can be grouped into one family and described by the single Generalised Extreme Value (GEV) distribution. A serious criticism of the block maxima method is that it only considers a single value from each sample. This greatly reduces the amount of data available for analysis, and ignores sub-sample events, since only the largest event in any sample is included.

The second approach of extreme value theory is the peaks-over-threshold (POT) method. This is based on the Pickands-Balkema-de Haan theorem which states that the distribution of exceedances over a sufficiently high threshold will converge to a Generalized Pareto Distribution (GPD) (Balkema and de Hann, 1974; Pickands, 1975). The POT method has the advantage over the block maxima method that it extracts a larger number of extreme values, thereby increasing the sample size and decreasing the sampling uncertainty. A more detailed introduction to both of these methods, and

ACPD
13, 1179–1199, 2013

the theorems they are based upon, can be found in Coles (2001), and in references therein.

The POT method was chosen for this work due to its decreased uncertainties compared to the block-maxima method and its focus on extreme events compared to the Weibull method. It is used to examine the 50 yr return winds (U_{50}) in four RCM downscalings over Europe for a recent and a future period. The geographical distributions of predicted changes in U_{50} are shown, and these predicted changes are compared to the uncertainty associated with their derivation. Section 2 details the data sources while Sect. 3 details the statistical methods employed. The results are shown in Sect. 4, with a discussion and conclusions given in Sect. 5.

2 Source data

The data used in this project comes from the RCM simulations conducted as part of the ENSEMBLES project (van der Linden and Mitchell, 2009). The ENSEMBLES project created a matrix of experiments in which a range of GCMs were downscaled using various RCMs. This work uses the data from four of these downscalings where two GCMs were each downscaled by two different institutes, each using their own RCM (Table 1). The GCMs used were the Bergen Climate Model (BCM) (Furevik et al., 2003) and European Centre Hamburg Model version 5 coupled with the Max Planck Institute Ocean Model (ECHAM5/MPI-OM) (Roeckner et al., 2003; Marsland et al., 2003), while the RCMs used were the Rossby Centre Atmosphere climate model (RCA3) at the Swedish Meteorological and Hydrological Institute (Samuelsson et al., 2010), and the HIRHAM regional climate model version 5 at the Danish Meteorological Institute (Christensen et al., 2006). The HIRHAM acronym is a combination of the HIRLAM (High Resolution Limited Area Model) and ECHAM (European Centre Hamburg Model), since HIRHAM combines dynamics from these two models.

The RCM simulations all used the same domain covering Europe and had a horizontal grid resolution of 25 km, with 19 levels in the vertical. This work examines the daily

ACPD
13, 1179–1199, 2013

model output for two 30 yr periods: 1961–1990 (reference) and 2070–2099 (future). The length of the periods was chosen so as to provide sufficient data to determine 50 yr return events. The reference period has been commonly used in previous works (e.g. Solomon et al., 2007) and was selected so as to provide maximum compatibility. The simulations of the future period were all forced with the SRES A1B scenario; a mid-range scenario in terms of global warming at the end of the 21st century (Solomon et al., 2007).

While extreme wind speed calculations are often based on hourly, three-hourly, or six-hourly instantaneous data from models, this disjunct sampling does lead to an underestimation of the extreme winds due to the missed peak events that occur between the sampling times. Larsen and Mann (2006) demonstrated that taking hourly samples of ten-minute winds results in an underestimation of the extreme events by approximately 5 %, while for 6 h sampling this becomes approximately 15 %. This work examines the daily maximum wind speed, which is the highest wind speed at any given timestep during each day, thereby ensuring that all peak events are captured and avoiding the problem of disjunct sampling. A similar relationship has been found for the horizontal resolution of the model domain and the magnitude of the extreme wind speeds. Pryor et al. (2012b) identified that changing the model domain from a resolution of 50 km to a resolution of 6 km resulted in only a 5 % change in the mean 10 m wind speed, but with a change of over 10 % seen in the extreme winds. However, in this study, we are analysing pre-existing downscaling done with a 25 km horizontal resolution and cannot address this problem further.

3 Methods

In accordance with the Pickands-Balkema-de Haan theorem, the exceedances over a given threshold need to be determined once a suitable threshold has been selected. If the threshold is too high, very few exceedances will exist, leading to increased variance in the parameter estimation. Conversely, if the threshold is too low, the exceedances cannot be considered extreme events, and the GPD fit will no longer be appropriate, which results in a bias being introduced (Van de Vyver and Delcloo, 2011). One commonly used approach for determining a suitable threshold is to examine by eye plots of the sample mean excess (SME) for a range of thresholds (e.g. Supplement Fig. S1). The SME is the sum of the excesses above the threshold divided by the number of data points which exceeded the threshold. At high thresholds, the SME is fluctuating, while at low thresholds the SME is gradually increasing. Between these two cases, the SME is stable as a balance is achieved between the bias and the variance. The lowest threshold within this stable region is usually selected and used for the POT method.

In this work we want to create maps of return events based on the model domain. The problem is that there is no clear methodology to automate the threshold selection process which could handle the various wind regimes without introducing a large number of errors, and any such process would be computationally demanding to implement. For this reason, a simpler approach was employed in this work. The threshold was selected as the lowest of the annual maxima at each grid point. While this approach guaranteed a minimum of 30 exceedances for each of the 30 yr samples, it yielded between approximately 50 and 300 exceedances, representing the top 0.5 % to 2.7 % of wind events at each grid point. A number of locations were selected based on the different wind regimes they had, and the thresholds derived by using our approach were compared with those derived by examining the SME plot. This provided confidence for the threshold selection method used. Furthermore, the quality of the GPD fits based on the derived thresholds was also assessed at these locations, by using quantile-quantile plots and by comparing the cumulative distribution function plot to the empirical distribution (e.g. Supplement Fig. S2). The high quality of these fits provided further confidence that the thresholds were suitable.

Once the exceedances over the threshold were obtained, a simple de-clustering method was employed to ensure the independent nature of the extremes, as required by the POT approach. This method identified peak exceedances and removed exceedances that occurred on the adjacent days. Since the data was daily maximum

ACPD
13, 1179–1199, 2013

values, it was possible for two consecutive exceedances to be only a timestep apart if the first occurred at the end of a day and the second occurred at the beginning of the next day. The de-clustering meant that there was at least 24 h between any two exceedances, thereby ensuring their independence.

A maximum likelihood estimation method was used to fit a GPD to the resulting exceedances. This was accomplished by minimising the negative log-likelihood with respect to the parameters of the GPD. The Nelder-Mead simplex direct search algorithm was chosen for this task since it is a robust method for minimising an objective function in a many-dimensional space (Lagarias et al., 1998). The GPD was then used to estimate U_{50}. To determine confidence intervals on this estimate, a region of parameter space was defined based on the 95 % level of log-likelihood using a Chi squared distribution. A trust-region-reflective optimization algorithm was used to numerically find the range of U_{50} that occurred within the parameter space region. This approach differs from that of Pryor et al. (2012a), where the extreme return wind speed estimates are assumed to have a Gaussian distribution, in that it accounts for the non-linearity of the parameter space in deriving the confidence intervals. It also produces larger confidence intervals than the bootstrapping approach used by Naess and Gaidai (2009), demonstrating the sensitivity of the generalized Pareto distribution to the shape parameter. The equations for the Generalised Pareto Distribution are given in Appendix A and a more comprehensive introduction to the methods employed in this work is given in Coles (2001).

The final methodology was therefore as follows:

- Extract the 30 yr time series of daily maximum winds at a grid point in the reference period.

- Determine the annual maxima and set the lowest as the threshold.

- Extract the exceedances above this threshold from the time series.

- Apply a simple de-clustering method to isolate individual events.

ACPD
13, 1179–1199, 2013

– Use a maximum likelihood estimation method to determine the parameters of the GPD fit.

– Calculate U_{50} based on this GPD fit.

– Use the 95 % level of the Chi-Squared distribution of likelihood to derive confidence intervals in a profile likelihood approach.

– Repeat for every grid point in all four downscaling experiments.

– Repeat for the future period.

4 Extreme winds over Europe

The 50 yr winds show some remarkable differences between the four downscalings (Fig. 1). The most striking of which is that the return winds from the RCA3 downscalings are approximately 5 m s^{-1} lower than those from the HIRHAM5 downscalings. At some locations, this difference rises to over 20 m s^{-1}. Pryor et al. (2012a) identified that downscalings of ECHAM5 and ERA-40 reanalysis data produced very similar results when using HIRHAM5, but that downscalings using RCA3 showed a consistent negative bias in U_{50} compared to reanalysis, as previously identified by Höglund et al. (2009). A report by SMHI on this issue speculated that this was due in part to a poorly chosen roughness length within the planetary boundary layer scheme of RCA3 (Höglund et al., 2009). The difference depending upon which GCM is downscaled is less striking, with downscalings of ECHAM5 producing return wind speeds 0.5–1 m s^{-1} higher on average than those produced using the BCM. There are also differences in the distribution of U_{50} depending upon the GCM downscaled; with ECHAM5 producing higher wind speeds over the North Atlantic, and yet lower wind speeds over the Black Sea. Inter-model spread has already been identified as the main source of uncertainty in estimating return values from climate models (Kharin, 2007); however

ACPD
13, 1179–1199, 2013

Fig. 1 suggests that it is the spread between different RCMs that is most important when considering extreme winds.

Despite the differences, there are some clear commonalities between the four downscalings: the highest return wind speeds appear off the south east coast of Iceland where corner jets are frequent; high U_{50} over the eastern end of the Black Sea, near the Kaçkar mountains of Turkey and the Caucasus range in Georgia; increased wind speeds extend over the mountains of Norway; and isolated strips of locally higher U_{50} are seen over the Atlas mountains in Morocco, the Pyrenees mountains between France and Spain, and the Alps on the borders of France, Switzerland and Italy. This highlights the strong connection between extreme winds and orography, as previous studies have investigated (Outten et al., 2009; Renfrew et al., 2009; Smith, 1979). While the high U_{50} locations over land are less apparent in the RCA3 downscalings, they do perhaps possess a more interesting feature. The peak U_{50} is comparable to the continental average, and is only identifiable due to the lower than average U_{50} around it. For example, in BCM-RCA3, the mean U_{50} over Western Europe is approximately $10.7\,\mathrm{m\,s^{-1}}$, the mean U_{50} in the strip over the Alps (45.8° N, 7.4° W) is $10.8\,\mathrm{m\,s^{-1}}$, but the mean U_{50} either side of the strip over the Alps is $7.2\,\mathrm{m\,s^{-1}}$. This is also visible for the Atlas Mountains, the Pyrenees, and the mountains of Norway; and this feature remains unexplained.

Comparing the changes in U_{50} between the reference period and the future period (Fig. 2, left column), it is clear that at most locations, the change is less than $2\,\mathrm{m\,s^{-1}}$ in all four downscalings, as indicated by the light-beige regions. This is similar to the findings of Nikulin et al. (2011), who examined return events in the downscalings of six GCMs with a single RCM over Europe; and Pryor et al. (2012a), who examined only the Baltic Sea/Scandinavian region. Similar to their works, the downscalings presented here show little agreement in either the location or magnitude of changes greater than $2\,\mathrm{m\,s^{-1}}$. For example, the HIRHAM5 downscaling of the BCM shows regions of high change located in the mid-latitudes of the eastern Atlantic, the eastern half of the Black Sea, off the coast of Lebanon and Syria, and over northern Libya; while the RCA3

Discussion Paper | Discussion Paper | Discussion Paper | Discussion Paper |

ACPD

13, 1179–1199, 2013

Extreme winds over Europe in the ENSEMBLES regional climate

S. D. Outten and I. Esau

downscaling of the same GCM shows none of these locations as having significant change. It instead shows larger changes centred over the eastern and central Mediterranean.

Also shown in Fig. 2 are the confidence intervals at the 95 % level for the estimates of the return wind speed in the reference period. Comparing these to the plots of future change it is clear that at almost all locations, any change predicted by any of the models is comparable to, or more often smaller than, the uncertainty associated with the estimate of the return wind speeds. Hence the climate change signal for extreme winds in these RCM downscalings is indistinguishable from the noise associated with the uncertainties of estimating a 50 yr event. While the locations of highest uncertainty differ from downscaling to downscaling, they do correspond to the location of high return wind speed within each downscaling. It should also be noted that the confidence intervals are not evenly distributed around the maximum likelihood estimation (MLE). The upper limit of the confidence interval is invariably much further from the MLE than the lower limit (e.g.Supplement Fig. S2: profile likelihood). This is different from some works in which the confidence intervals are made considerably smaller by assuming they follow a Gaussian distribution (e.g. Pryor et al., 2012a).

One region of particular interest in recent studies of extreme winds has been the Southern North Sea, between Belgium and the UK. The four downscalings presented here all show different changes in this region, ranging from approximately 1 m s^{-1} to 8 m s^{-1}. The only significant change is predicted by the HIRHAM5 downscaling of ECHAM5, which shows a peak future change in U_{50} of 8.2 m s^{-1}, with a confidence interval of 3.6 m s^{-1}. It is one of the few locations where the predicted change is greater than the uncertainty. Wang et al. (2011) identified an increase in extreme winds in the Southern North Sea over the recent decades, however, these winds were geostrophic and calculated from sea-level pressure. Donat et al. (2011) also examined this region and found a similar increase in extreme winds in the NCEP/NCAR, ERA-40, and 20th Century reanalyses. In contrast, Van den Eynde et al. (2012) examined operation model wind fields from the Norwegian Meteorological Institute for this region covering

ACPD
13, 1179–1199, 2013

the period of 1955 to 2006. They found no significant trends in either the mean or extreme winds. One possible explanation for this discrepancy is the seasonality in the trends in the Southern North Sea, as identified by Wang et al. (2011). While this could be examined in the downscalings, it is beyond the scope of this work.

5 Discussion and conclusions

This work has examined the 50 yr return wind speeds over Europe in four different downscalings based on the peaks over threshold method and using the Generalised Pareto Distribution. For most locations over Europe the different downscalings all suggest a change in U_{50} of around 1–2 m s^{-1} in keeping with previous research (Pryor et al., 2012a; Nikulin et al., 2011). While the downscalings show some isolated areas where there is a greater change predicted in U_{50}, they do not agree on the location of these areas or the magnitude of the change. Indeed the inter-model spread, especially between different RCMs, appears to be the largest source of uncertainty.

Another source of uncertainty comes from the statistical estimation of a 50 yr event based on 30 yr of data. The average change in U_{50} in the HIRHAM (RCA3) downscalings was approximately 1.13 m s^{-1} and 1.8 m s^{-1} (0.69 m s^{-1} and 1.40 m s^{-1}) over the land and sea respectively, compared to the average confidence intervals of 4.39 m s^{-1} and 6.93 m s^{-1} (2.57 m s^{-1} and 4.59 m s^{-1}) respectively. Therefore the changes predicted by these models in the 50 yr return wind speed are well within the uncertainties of those predictions. Since this source of uncertainty stems from the method used, other methods were also considered. The annual-maxima method was employed, resulting in a Generalised Extreme Value distribution; however, since a 30 yr sample only provides 30 maxima, the uncertainties were considerably larger. Other works have made use of the Gumbel distribution (e.g. Pryor et al., 2012a). This is based on a modification of the block-maxima approach, where a likelihood ratio test is used to show that the two parameter Gumbel distribution provides an equally valid fit to the data as does the three parameter GEV. By reducing the problem to a Gumbel distribution, the

ACPD
13, 1179–1199, 2013

shape parameter to which the confidence intervals are so sensitive is removed, thereby reducing the uncertainty. When this method was applied in this work it was found that a considerable area of the domain failed the likelihood ratio test in either the current or future period (Supplement Fig. S3). This area was different in each model, making it an unviable method to use for intercomparison.

Given the value of good knowledge of extreme wind speeds to so many sectors, e.g. reinsurance, construction, wind energy, forestry planning, high-speed rails etc, it will become increasingly important to be able to accurately estimate both the return levels of wind speeds and the uncertainties associated with those estimates. While new techniques are being developed to improve the statistical tools (e.g. new estimator techniques for the shape parameter, Van de Vyver and Delcloo, 2011), the issue of inter-model spread in the RCMs remains a major problem.

Appendix A

Generalised Pareto Distribution

The approach used in this paper is a peaks-over-threshold (POT), extreme value method, thus it treats those values that exceed a given threshold, u, as being extremes. Like many such methods, it assumes that the values are independent and identically distributed (i. i. d.) in time (i.e. the values have no correlation or clustering). The second theorem of extreme value theory, or Pickands-Balkema-De Haan theorem, states that the magnitude of these exceedances can be approximated by a generalised Pareto distribution (GPD) and their frequencies by a Poisson distribution. The following is based on Coles (2001) and a more complete introduction to extreme value analysis is given therein.

Let $X = \{X_1, X_2, ...X_n\}$ be a random sample of an i. i. d. series with common distribution function F. The distribution of extreme events in the sample, defined as those exceeding the threshold u, is given by the conditional probability:

ACPD
13, 1179–1199, 2013

$$P\{X > u + y | X > u\} = \frac{1 - F(u+y)}{1 - F(u)}, \quad y > 0 \tag{A1}$$

Using a sufficiently high threshold, this distribution function converges to the Generalized Pareto Distribution as $n \to \infty$. The cumulative distribution function for the GPD is given by:

$$H(y) = \begin{cases} 1 - (1 + \frac{\xi y}{\sigma})^{-1/\xi}, & \xi \neq 0 \\ 1 - e^{-y/\sigma}, & \xi \neq 0 \end{cases} \tag{A2}$$

where ξ is the shape parameter and σ is the scale parameter. The GPD corresponds to the exponential, ordinary Pareto, and Pareto II type distributions when ξ =0, $\xi < 0$ and $\xi > 0$ respectively.

For a suitably chosen threshold, the number of exceedances can be assumed to approximate a Poisson distribution with parameter λ. This parameter gives the average rate of exceedances per year. The T-year return event, U_T, is an event (or quantile) which on average is only exceeded once every T years. This work considered the 50 yr return event. The T-year return event can be calculated from

$$U_T = \begin{cases} u + \frac{\sigma}{\xi}\left[(\lambda T)^{\xi} - 1\right], & \xi \neq 0 \\ u + \sigma \ln(\lambda T), & \xi = 0 \end{cases} \tag{A3}$$

In order to estimate the parameters of the GPD, the maximum likelihood method was used. Given that the values $y_1, y_2, ...y_n$ are the n excesses over the threshold u, the log-likelihood is given by:

$$L = \begin{cases} -n \ln \sigma - (1 + 1/\xi) \sum_{i=1}^{n} \ln(1 + \xi^{y_i/\sigma}), & \xi \neq 0 \\ -n \ln \sigma - 1/\sigma \sum_{i=1}^{n} y_i, & \xi \neq 0 \end{cases} \tag{A4}$$

ACPD
13, 1179–1199, 2013

The log-likelihood cannot be analytically maximised, hence the Nelder-Mead simplex direct search algorithm was used to numerically minimise the negative log-likelihood with respect to the parameters of the GPD.

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ACPD

13, 1179–1199, 2013

Extreme winds over Europe in the ENSEMBLES regional climate

S. D. Outten and I. Esau

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ACPD
13, 1179–1199, 2013

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ACPD
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Extreme winds over Europe in the ENSEMBLES regional climate

S. D. Outten and I. Esau

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ACPD
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Extreme winds over Europe in the ENSEMBLES regional climate

S. D. Outten and I. Esau

Table 1. The driving global model for each simulation is given in column 1. The regional climate model used and the institute who performed the downscaling are given in columns 2 and 3 respectively. The final column shows the abbreviation that is used in this paper for each of the simulations.

Global Climate Model	Region Climate Model	Institute	Abbreviation
Bergen Climate Model	HIRHAM5	Danish Meteorological Institute	BCM-HIRHAM5
	RCA3	Swedish Meteorological and Hydrological	BCM-RCA3
ECHAM5	HIRHAM5	Danish Meteorological Institute Institute	ECHAM5-HIRHAM5
	RCA3	Swedish Meteorological and Hydrological Institute	ECHAM5-RCA3

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ACPD
13, 1179–1199, 2013

Extreme winds over Europe in the ENSEMBLES regional climate

S. D. Outten and I. Esau

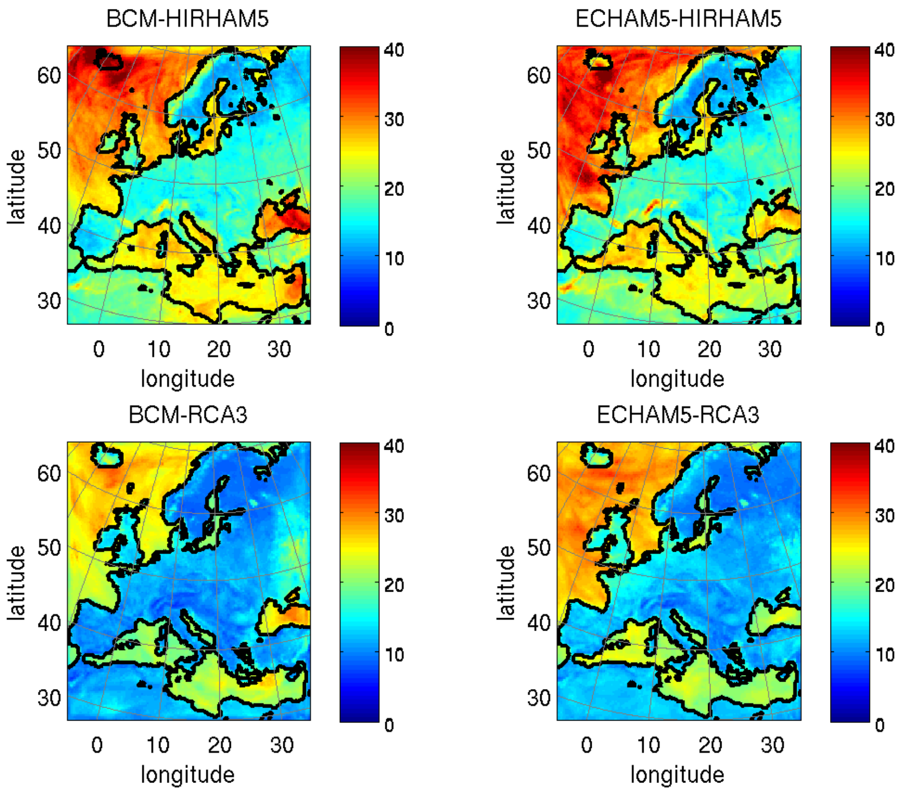

Fig. 1. The 50 yr return wind speed in m s^{-1} calculated using the GPD for four different down-scalings, with red/blue colours representing high and low return wind speeds respectively. The columns are using the Bergen Climate Model (left), and the ECHAM5 global climate model (right); while the rows are the HIRHAM5 (top) and the RCA3 (bottom) regional climate models.

ACPD
13, 1179–1199, 2013

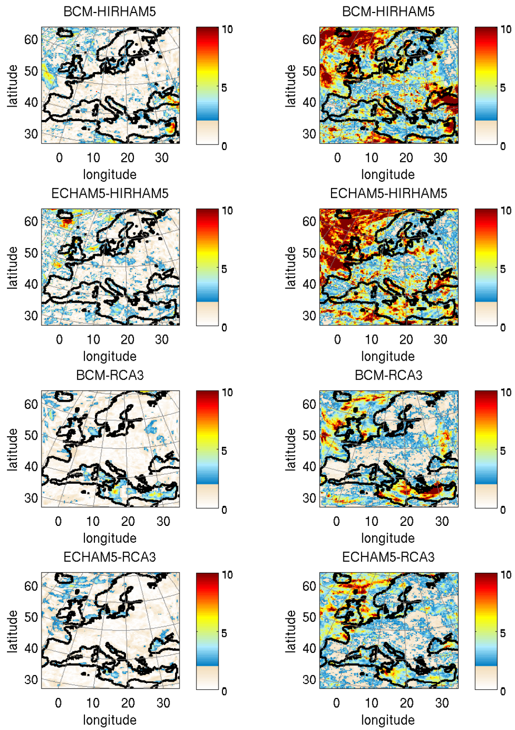

Fig. 2. The left column shows the magnitude of the change in 50 yr return wind speed between the reference 30 yr period (1961–1990), and the future 30 yr period (2070–2099). The right column show the size of the confidence interval associated with the maximum likelihood estimate of the 50 yr return wind speed in the reference period. All plots are in $m\,s^{-1}$ and are plotted on the same scale. The four rows show the results for the four different downscalings. The beige regions indicate locations with changes/confidence intervals (left and right column respectively) in their 50 yr return wind speeds of $2\,m\,s^{-1}$ or less. The coloured regions in the right column indicate locations with large confidence intervals in the estimate of the 50 yr return event.

ACPD
13, 1179–1199, 2013