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GEOPHYSICAL RESEARCH LETTERS, VOL. 33, L10801, doi:10.1029/2005GL024251, 2006

Amplitude and frequency of temperature extremes over the North Atlantic region

M. Nogaj,[1] P. Yiou,[1] S. Parey,[2] F. Malek,[3] and P. Naveau[1]

Received 29 July 2005; revised 27 March 2006; accepted 31 March 2006; published 17 May 2006.

[1] Recent studies on extreme events have focused on the potential change of their intensity during the 20th century, but their frequency evolution has often been overlooked although its socio-economic impact is equally important. This paper focuses on extreme events of high and low temperatures and their amplitude and frequency changes over the last 60 years in the North Atlantic (NA) region. We analyze the temporal evolution of the amplitude and frequency of extreme events through the parameters of an extreme value distribution applied to NCEP reanalysis for the winter and summer seasons. We examine the relation of the statistics of extremes with greenhouse gas forcing and an atmospheric circulation index and obtain a spatial distribution of the trends of those extreme parameters. We find that the frequency of warm extremes increases over most of the NA while their magnitude does not vary as systematically. Apart from the Labrador Sea and parts of Scandinavia, the features of winter cold extremes exhibit decreasing or no trends. **Citation:** Nogaj, M., P. Yiou, S. Parey, F. Malek, and P. Naveau (2006), Amplitude and frequency of temperature extremes over the North Atlantic region, *Geophys. Res. Lett.*, *33*, L10801, doi:10.1029/2005GL024251.

1. Introduction

[2] Although a global warming trend since the beginning of the 20th century has been clearly identified in observations [*Intergovernmental Panel on Climate Change* (*IPCC*), 2001], large anomalies with respect to this secular trend do not necessarily have a simple temporal structure, as illustrated by *Meehl et al.* [2000]. Though previous studies mainly focused on the trends of the amplitudes of extreme temperatures [*Zwiers and Kharin*, 1998; *Folland et al.*, 1999; *Meehl et al.*, 2000], we model in this paper both the non-stationarity of these amplitudes and their occurrences with respect to a time-varying or constant threshold. Indeed, the pacing of such events, like heat wave episodes over Europe, can also have important environmental impacts [*Meehl et al.*, 2000], especially on the biosphere which might need a few years to recover from hot and dry summers [*Stott et al.*, 2004; *Schaer et al.*, 2004; *Ciais et al.*, 2005].

[1] Laboratoire des Sciences du Climat et de l'Environnement, CE Saclay l'Orme des Merisiers, Gif-sur-Yvette, France.

[2] Division Recherche et Developpement Departement Systèmes de Production et Environnement, Electricité de France, Chatou, France.

[3] Laboratoire de Modélisation Stochastique et Statistique, Université Paris-Sud, Orsay, France.

0094-8276/06/2005GL024251

2. Data

[3] We used the National Center for Environmental Prediction (NCEP) reanalysis data [*Kalnay et al.*, 1996] for daily surface temperatures, and focused on the NA region (80W–40E, 30N–70N, with a 2.5° by 2.5° resolution), from 1948 to 2004. This choice was motivated by the role of the North Atlantic Oscillation (NAO [*Hurrell et al.*, 2003]) on the climate variability of this region and its possible influence on extreme temperatures [*Yiou and Nogaj*, 2004].

[4] With respect to this data set, the extremes are defined as surface temperatures above (or below) a high (or low) threshold. Thus, to derive the statistical properties of these exceedances, we take advantage of the recent developments of the "Extreme Value Theory" (EVT) for non-stationary cases [*Katz*, 1999; *Coles*, 2001] (see section 3). More precisely, we studied high values of temperature in the summer (June to August) and low temperatures in the winter (December to February), yielding 57 seasons of 90 days. We checked that our results were insensitive to the seasonal cycle and the above season definition by removing the seasonal cycle and considering extended seasons.

3. Methodology

[5] One of the primary objectives of the statistical EVT is to describe the tail of the distribution of random variables when they exceed a high threshold [*Coles*, 2001]. If the distribution of a random variable X exceeding a high threshold u converges, it follows a Generalized Pareto Distribution (GPD) given by:

$$P(X > x|X > u) = \left[1 + \frac{\xi(x-u)}{\sigma}\right]^{-1/\xi}, \qquad (1)$$

with $1 + \frac{\xi(x-u)}{\sigma} > 0$, where σ is a scale parameter, and ξ a shape parameter [*Coles*, 2001]. The σ parameter is a variability indicator of extreme events. We shall consider that it varies with time. The sign of ξ indicates how fast the probability distribution in equation (1) converges to 0, i.e., the tail of the distribution. Positive ξ means a heavy tail, $\xi = 0$ means a moderate tail (e.g., an exponential law), and a negative ξ means a bounded variable (e.g., a uniform distribution). We perform our study under the assumption of a temporally constant shape parameter [*Parey et al.*, 2006].

[6] The probability of observing n occurrences of extreme events during a given interval of time is classically modeled by the Poisson distribution with parameter λ describing their average frequency where large λ implies more frequent events. This approach is similar to point process models [*Coles*, 2001]. When the exceedances

amplitudes and occurrences can be reasonably fitted by a GPD and Poisson distribution, the process can be represented by a Peak Over Threshold (POT) model. Extreme events can be defined with respect to an absolute fixed baseline, or with respect to an evolving baseline assuming that mean climate varies on a secular timescale. Thus, in the first step, threshold values were chosen as upper 95th (or lower 5th) quantiles of temperature for each grid point and each season. Those values form a spatial structure over the NA region that is similar to the mean seasonal patterns, with an offset of 3°C (−4°C) over the ocean and 6°C (−12°C) over the continents in the summer (winter). We treated the case of a varying threshold by removing a smoothing spline function of the seasonal mean of each gridpoint. The threshold is the 95th (5th) quantile of this modified data set. Removing the mean trend $m(t)$ is equivalent to a time-varying threshold $u(t) = m(t) + 95$th percentile. We hence discuss results with constant and varying thresholds.

[7] For each gridpoint of the NCEP reanalysis, considered independent in space, we introduce and model the temporal relation of the Pareto and Poisson parameters to a covariate, such as time (or equivalently any monotonic climate forcing, such as greenhouse gas concentration [*IPCC*, 2001]) or an atmospheric circulation index (e.g., the NAO index, i.e., the difference in sea-level pressure between the Azores and Iceland [*Hurrell et al.*, 2003]). This procedure allows the probability distribution of extremes to vary in amplitude (with σ) and in frequency (with λ). The chosen time-dependent model for σ and λ is a polynomial of degree less than, or equal to 2 (i.e., it can be either a constant, linear or quadratic function), for example:

$$\sigma(t) = \sigma_0 + \sigma_1 t + \sigma_2 t^2$$

in the quadratic case, with a similar equation for λ. By considering these two parameters (σ and λ) and their dependence to several covariates, this approach refines the work of *Kharin and Zwiers* [2005].

[8] Daily temperature time series are serially correlated. Hence we applied a declustering procedure to ensure the independence of extremes and justify the use of EVT. We defined clusters as aggregates of consecutive days exceeding a threshold and kept the maximum in each formed cluster. The size of the clusters is an interesting feature of extremes [*Laurini and Tawn*, 2003], but it will not be investigated here.

[9] The σ_i, ξ and λ_i parameters are obtained by a Maximum Likelihood Estimation (MLE), which provides estimates, log-likelihood scores and confidence intervals for each regression case (constant, linear and quadratic). The log-likelihood scores allow us to choose objectively the best polynomial fit through a likelihood ratio test (LRT). A goodness-of-fit test (Kolmogorov-Smirnoff test [*D'Agostino and Stephens*, 1986]) is applied to verify whether or not the statistically optimal choice of model indeed reflects observed climate trends. This LRT is a test between two nested models: by taking into account the number of parameters, it determines if a parameter-rich model is significantly better than a simple one. In this estimation procedure, the parameters σ and λ can have either increasing or decreasing trends or be constant. In addition, when a convex quadratic fit (i.e., with a positive coefficient) is found, we check that it corresponds to an increasing trend. If not, we replace it by the best linear model. This avoids statistical overfitting of both ends of a series.

[10] Return levels for given return periods are direct byproducts of EVT and can be convenient tools to diagnose the frequency of extreme events in a stationary case. In a non-stationary framework, their interpretation becomes rather non trivial [*Parey et al.*, 2006] and their discussion is beyond the scope of this paper.

4. Results for Extremes of Temperature

[11] We find that 80% of the ξ values are in (−0.37, −0.04) in summer and (−0.35, −0.04) in winter, showing mainly bounded tails over this region. The trends in the scale σ and Poisson intensity λ parameters for the summer and winter in the NCEP data validated by the goodness-of-fit tests are represented in Figure 1. In Figure 1a (summer), we identified connected grid points where the amplitude of extremes over the ocean and in eastern Europe indicates positive linear trends, while a constant σ gives us the best model over most of the continents. The trends in the frequency of warm events (Figure 1b) also show coherent regions, where extremely warm events become more prevalent, with the exception of the central NA.

[12] The variability of very cold temperatures over the NA is constant except for some regions of decreasing magnitude (Figure 1c). This result may be explained by the general warming trend which hinders the occurrence of cold events. Similarly, the frequency of winter cold waves over the NA ocean do not show trends, with the exception of a few small areas where the occurrence of cold spells is decreasing (Figure 1d).

[13] We tested the effect of a varying threshold on those two parameters for high temperatures. This gives a different definition for extremes, which prevents a direct comparison with Figure 1. The resulting amplitude trends, shown in Figure 2, are attenuated over the western Atlantic and eastern Europe. No trend is detected for the frequency of warm events above the varying threshold in southern Europe. However, the presence of the trends in NA shown in these graphs, depicts that, in addition to warmer summers, extremely high temperatures (with respect to an increasing baseline) still become either more intense or more frequent over the NA region. Figures 2c and 2d suggest that extreme low winter temperatures (below a varying threshold) yield constant features overall. We find that less variable but more frequent cold events occur over Romania and Bulgaria (∼20–30°E and ∼40–50°N).

[14] The temporal evolution of the mean summer and winter temperature and the POT parameters σ and λ are shown in the auxiliary material[1] for three different NA regions (over the western NA, southern NA and France). The range of σ variations can be as large as ∼0.6°C, which is the same order of magnitude as the mean summer standard deviation (∼0.5°C).

[15] Since the atmospheric greenhouse gas content is an increasing quasi-linear function of time over the 1948–2004 period, we substituted the covariate time with the

[1] Auxiliary material is available at ftp://ftp.agu.org/apend/gl/2005gl024251.

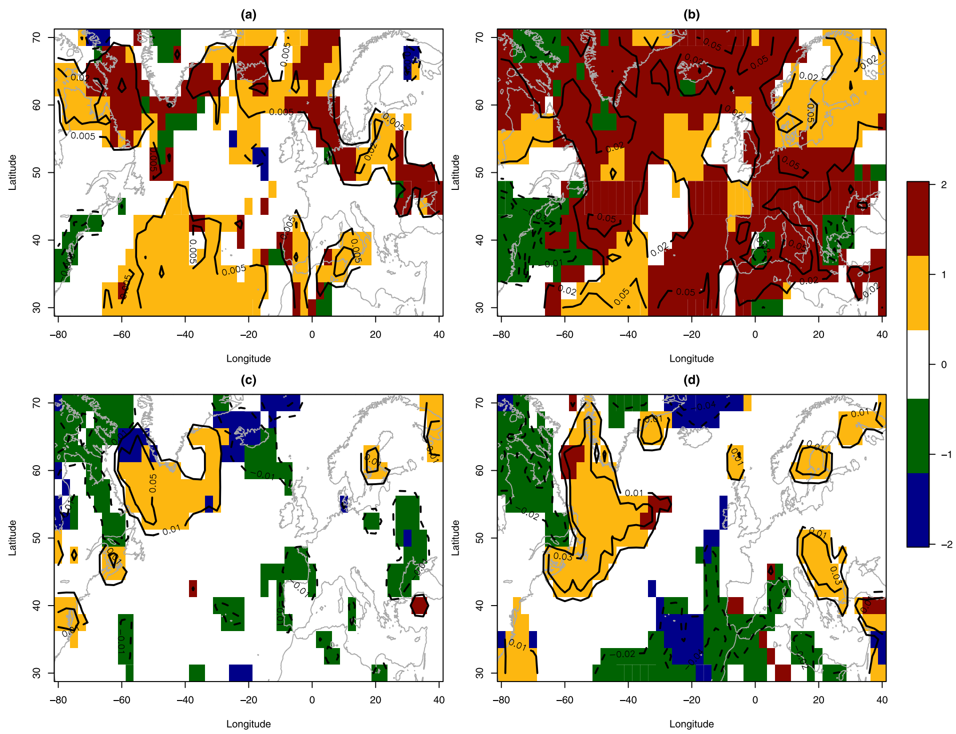

Figure 1. (a) Trends in the scale parameter σ of the high summer (June to August) temperatures over the North Atlantic. Orange (+1) and red (+2) gridpoints indicate linear and quadratic positive trends. Green (−1) and blue (−2) gridpoints indicate linear and quadratic negative trends. White (0) gridpoints yield no trend. (b) Same as Figure 1a for the frequency parameter λ. Increasing λ means more frequent extreme events. (c) Same as Figure 1a for low winter (December to February) temperatures. (d) Same as Figure 1b for low winter temperatures. Contours show the slope of the trends for σ [°C/year] and for λ (number of events per season per year).

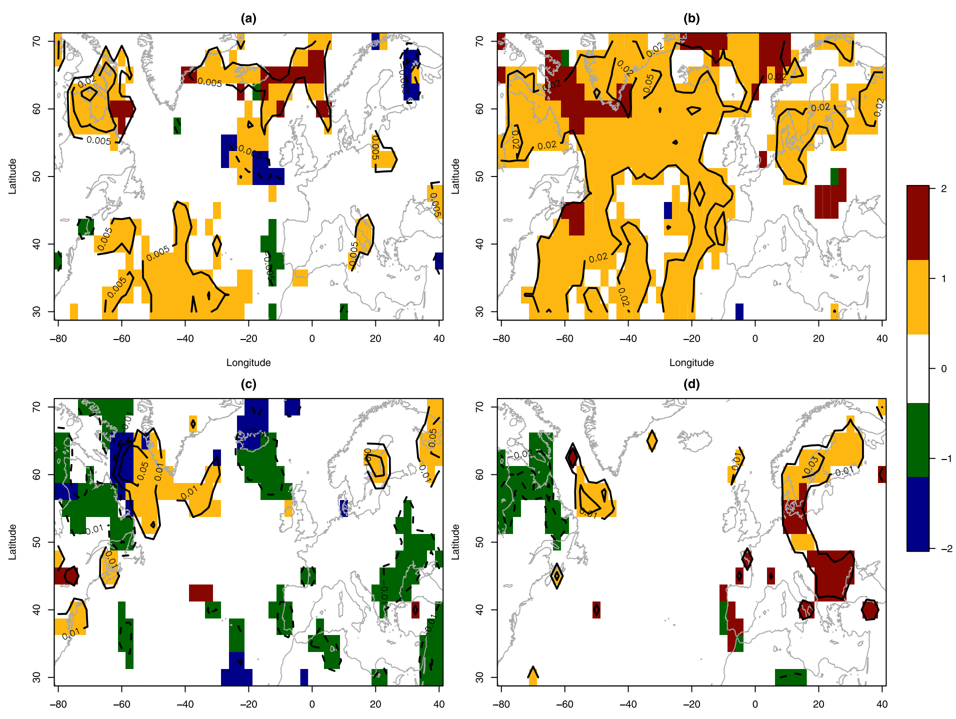

Figure 2. Same as Figure 1 but extremes are here considered with respect to a time-varying threshold.

equivalent radiative forcing of greenhouse gases [*IPCC*, 2001] (see section 3) and obtained the same results. Thus, the trends we observe can be considered as an effect of enhanced greenhouse gas forcing over the observed period.

[16] The North Atlantic Oscillation (NAO) index is a proxy for the intensity of westerly winds across the NA. It has been shown to yield correlation patterns with mean surface temperatures [*Hurrell et al.*, 2003]. We find that, north of 60°N, the NAO index has a signature on the high summer temperature amplitudes, but does not show significant regressions with those events in the midlatitudes (not shown). Moreover, this index has no regression with the frequency of temperature extremes. Hence we can associate the trends of warm extremes at latitudes below 60°N to greenhouse gas forcing, the influence of the NAO being less significant.

5. Discussion and Conclusion

[17] A few studies on extreme temperature indices based on observations are apparently at odds with our analysis of winter cold temperature extremes [*Yan et al.*, 2002; *Klein Tank and Können*, 2003]. However, their definitions for extremes and their statistical analyses are quite different from the one used in this paper, which may explain the discrepancy with our results. Our results on winter cold temperatures are consistent with the predictions for western Europe of *Zwiers and Kharin* [1998], who used a comparable EVT approach on climate simulations.

[18] A spatial extreme value analysis is out of the scope of this paper, but would be an interesting (if difficult) problem to look at. Significance testing that accounts for (or is robust to) spatial correlation [*Ventura et al.*, 2004] is also out of the scope of the paper, but it can be envisaged in a followup paper.

[19] The variability of extreme temperatures and their frequency are two distinct climatic features, with different impacts on environmental systems. *Ciais et al.* [2005] estimated that the 2003 European drought had a huge impact on the biomass productivity in Europe, and that it took more than a year to recover from this event. Hence, from our study, we can infer that even without increasing the severity of such events, their increasing frequency might have long-term effects on ecological systems if they do not have enough time to recover to favorable growing conditions.

[20] Our study confirms the regional increase in amplitude of hot events obtained by numerical simulations [*Meehl et al.*, 2000]. Our method makes appropriate distributional assumptions for extreme values through a joint GPD–Poisson model allowing for non-stationarity of the amplitudes and frequencies of extreme events, as opposed to the usual Gaussian approach [*IPCC*, 2001; *Schaer et al.*, 2004]. If the evaluated covariation remains correct when extrapolated, their frequency is prone to increase in the future. This type of diagnostic is being tested on model simulations to evaluate their ability to obtain realistic extremes of temperatures, and hence make better predictions. This paper raises the fundamental issue of the relation between the evolution of the mean and the extreme behavior. Many studies [*IPCC*, 2001, chap. 2.7] suggest connections between the mean and extremes. We have shown that time variations of average temperatures and POT parameters over selected regions (auxiliary material) do not show obvious relations.

[21] **Acknowledgments.** MN is supported by the Commissariat à l'Energie Atomique, the CLIMPACT centre and the région Ile de France. It is a pleasure to thank D. Dacunha-Castelle for constructive discussion. The two reviewers helped us improve the clarity of the manuscript. This work is part of the "Extreme Events: Causes and Consequences" (E2-C2) FP6 project.

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F. Malek, Laboratoire de Modélisation Stochastique et Statistique, Université Paris-Sud, F-91425 Orsay, France.

P. Naveau, M. Nogaj, and P. Yiou, Laboratoire des Sciences du Climat et de l'Environnement, CE Saclay l'Orme des Merisiers, F-91191 Gif-sur-Yvette Cedex, France. (yiou@lsce.saclay.cea.fr)

S. Parey, Division Recherche et Developpement Departement Systèmes de Production et Environnement, Electricité de France, 6 quai Walter, F-78401 Chatou Cedex, France.