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Statistical representation of temperature mean and variability in Europe

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[1] Understanding the relationship between mean temperature and its variance is essential for the prediction of temperature variability in the European region. Results on regional temperatures have been obtained for the climate of the 21st century but they mainly focused on monthly-to-seasonal variability. Since environmental variables such as plant phenology, net primary production or atmospheric pollution react on shorter timescales, it is necessary to investigate how daily variability is related to interannual temperature changes. Here, we assess the mean-variance seasonal dependence of observed daily temperatures over Europe. We find that extreme mean temperatures in the summer and winter tend to be associated with more variance. This assessment allows us to test whether 11 climate model simulations used in the IPCC AR4 can reproduce this relationship in cold and warm seasons. Most models yield a fair performance in the winter, but apart from four models, the mean-variance relationship is underestimated in the summer.

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1. Introduction

[2] The recent European summer heatwaves have generated many studies on the mechanisms of temperature variability [*Beniston*, 2004; *Schaer et al.*, 2004]. Such mechanisms include soil moisture feedbacks [*Fischer et al.*, 2007; *Vautard et al.*, 2007] and large-scale circulation [*Cassou et al.*, 2005]. In winter, temperature variability is mainly driven by large-scale atmospheric variability [*Hurrell et al.*, 2003]. In both seasons, temperature variability has an important impact on ecosystems [*Ciais et al.*, 2005; *Piao et al.*, 2008; *Rosenzweig et al.*, 2008]. Climate variability is often assessed on statistical features of temperature, i.e., a mean and a standard deviation [*Beniston and Stephenson*, 2004; *Meehl and Tebaldi*, 2004] and it is argued that climate change is susceptible to affect both parameters [*Intergovernmental Panel on Climate Change*, 2007]. Hence a major issue in future climate simulations is to be able to estimate correctly the regional temperature variability under a secular and large-scale forcing. Since environmental variables such as plant phenology [*Piao et al.*, 2008; *Rosenzweig et al.*, 2008], net primary production [*Ciais et al.*, 2005] or atmospheric pollution [*Vautard et al.*, 2007] react on shorter timescales, it is necessary to investigate how daily variability is related to interannual temperature changes for useful climate predictions. Some steps to derive those properties have been taken with a regional climate model, albeit focusing on monthly data [*Schaer et al.*, 2004]. This paper aims at revisiting a statistical description of temperature by determining the regional relation between the mean and standard deviation of temperature. We then explore the ability of a set of General Circulation Model (GCM) simulations to reproduce the properties shown by observations. This provides a new way to assess the behavior of GCMs, and suggests how improvements can be undertaken.

2. Data and Methods

[3] We use a gridded version of the European Climate Assessment and Data (ECA&D) [*Klein-Tank et al.*, 2002] of mean daily temperature [*Haylock et al.*, 2008]. The grid resolution is $0.5 \times 0.5°$ and the data span 1961 to 2007. The mean temperature m for each gridpoint, and cold and warm seasons (December-January-February, June-July-August) was computed. The standard deviation σ was computed on seasonal temperature anomalies with respect to the seasonal cycle. Hence we treat time series of seasonal means and seasonal standard deviations, computed from daily data. Then we determine the Spearman rank correlation r between m and σ for each station and the associated p-values [*von Storch and Zwiers*, 2001, section 8.2.3]. We consider here that r is significantly nonzero when the p-value is smaller than 0.02. The computations were checked on the station data of the ECA&D database [*Klein-Tank et al.*, 2002] starting in 1900, with similar results (see auxiliary material[1]). We obtained very similar results with linear correlations, or by considering the slope (and its significance) of a regression between the data.

[4] We applied this diagnostic to GCM output from the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset. The information on the individual models can be found at http://www-pcmdi.llnl.gov/ipcc/info_for_analysts.php. We treated 11 models with daily data for the period 1961 to 2000, and their preindustrial control simulations. The horizontal resolutions range between rather low (46 longitudes × 72 latitudes) to high (160 × 320) values.

3. Results

3.1. Observations

[5] We tested the collective patterns of correlation with a False Discovery Rate (FDR) test [*Ventura et al.*, 2004]. We

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[1]Auxiliary materials are available in the HTML. doi:10.1029/2008GL036836.

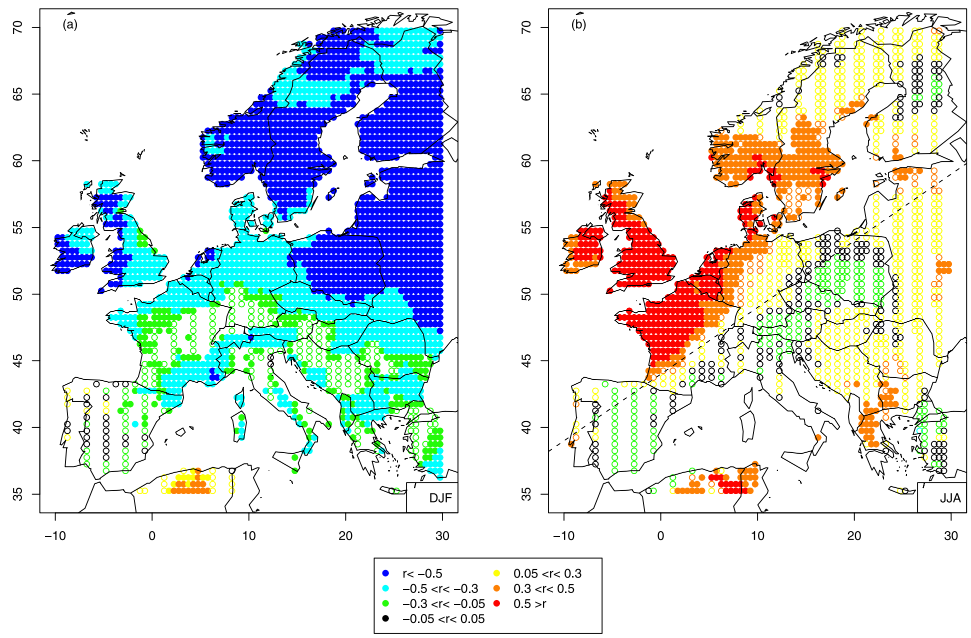

Figure 1. Rank correlations between mean daily temperature and its standard deviation for the gridded ECA&D dataset [*Haylock et al.*, 2008], between 1961 and 2007: (a) winter (December to February) and (b) summer (June to August). The dashed line represents a region north of which all correlations are positive (roughly north of the Gironde River in France). Solid circles have collectively significant correlations (p-values < 0.01) with an FDR test [*Ventura et al.*, 2004].

arbitrarily (but conservatively) prescribed a false rejection rate of $q = 0.01$ (i.e., 1%) on the null hypothesis of zero correlation, and computed the test on the p-values obtained from the correlation coefficients, following the method of *Benjamini and Hochberg* [1995] modified by *Storey* [2002]. *Ventura et al.* [2004] give heuristic arguments that this approach is robust to spatial dependency. From this test, 83% of the correlation coefficients with a p - value $< q$ obtained in the winter are significant (88% for the summer).

[6] We find that the mean and standard deviation of temperature north of the Pyrenees are negatively correlated in the winter (Figure 1a). Thus, colder winters have a higher variability. This can be explained by a snow-albedo feedback on temperature: when temperature goes below 0°C, snow can be maintained on the ground which increases the albedo and provides a positive feedback. If there is no snow, local temperature is mainly driven by atmospheric circulation. Thus, for a given negative mean temperature, those two types of behavior are responsible for a larger variance.

[7] The atmospheric circulation variability provides a complementary mechanism for this relation. The negative phase of the North Atlantic Oscillation (NAO-) is generally associated with extremely low temperatures in Europe [*Yiou and Nogaj*, 2004]. The temperature associated with NAO- also yields the highest variance (compared to other regimes), due to increased precipitation in Western Europe. The relative daily instability of this regime can account for increased variability.

[8] In summer, mean and standard deviation of temperatures are positively correlated north of the Gironde River in France (dotted line in Figure 1b). Thus, warmer summers have a higher variability. This relation can be due to soil-moisture and precipitation feedbacks, especially during convective events occurring during warm summers which tend to cool temperature rapidly [*Schaer et al.*, 1999]. Southern Europe does not have significant correlations. Indeed, warm summers are already dry in this region; hence local humidity feedbacks cannot induce much variability. The only apparent exception is Greece (with $r > 0$). When checking on the original ECA&D station data, it turns out that the gridded set is based on only one reliable station in Greece (see auxiliary material) so that Figure 1b might overemphasize this region. Therefore a discussion on climate variability in this region requires further data quality control that is beyond the scope of this study.

[9] This analysis has identified a regional and seasonal dependence between the variance and mean temperature in Northwestern Europe. Those results show that simple stochastic models of temperature are not sufficient to account for such dependence between mean and variance. For example, a Gaussian autoregressive process of order 1 [*von Storch and Zwiers*, 2001] does not have any correlation between its mean and variance. Nevertheless, this correlation-based diagnostic offers an integrated assessment of temperature variability that can be interpreted in terms of regional and seasonal feedbacks. Moreover, this illustrates how temperature variability features are regionally and seasonally dependent over Europe. This behavior could be summarized by the *skewness* of the temperature distribution, which is negative in winter and positive in summer (in Northwestern Europe). Besides avoiding the large uncertainties of skewness estimators [*von Storch and Zwiers*, 2001], our approach proposes a dynamic description of the mean-variance relationship that is potentially more useful.

3.2. Model Output

[10] For each of the 11 GCM simulations and the gridded observations, we extracted the land grid points either north of the Pyrenees (for winter) or north of the Gironde River

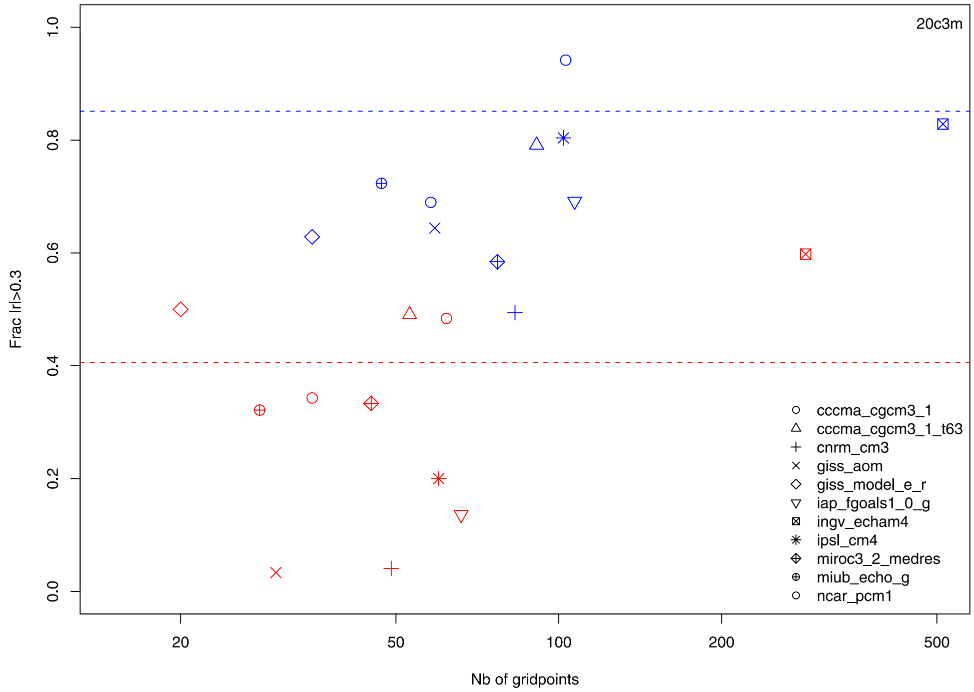

Figure 2. Fractions of gridpoints with $r < -0.3$ (winter: blue symbols) or $r > 0.3$ (summer: red symbols) and p-values < 0.01 in 11 of the CMIP3 data for the 20th century (between 1961 and 2000). The scores are plotted as functions of the number of gridpoints north of the Pyrenees (winter) or north of the Gironde River (summer). Horizontal dashed lines (winter: blue; summer: red) indicate the corresponding fractions for the ECA&D gridded data set [*Haylock et al.*, 2008].

(for the summer) and we determined the fraction of the number of grid points with negative (winter) or positive (summer) r and the corresponding p-values. The synthesis for all models (20th century experiment), as a function of the number of gridpoints in the delineated regions is shown in Figure 2. The model correlation patterns are generally fair for winter variability, all models exhibiting the similar behavior as observations ($r < 0$), although weighing the significance with p-values mitigates the performances (Figure 2). There is a large spread of behavior for the summer for the correlation patterns. This spread is accentuated when taking p-values into account, with only four models having scores larger than 0.5 (comparable to observations). Control simulations give similar results: fair scores in winter and a large spread of behavior in summer (not shown). High-resolution models tend to have better scores, but this is not a rule since a couple of medium resolution models yield fair scores (Figure 2). This suggests that physical feedbacks controlling temperature should be improved to provide a more accurate representation of its variability [*Fischer et al.*, 2007]. This synthetic presentation is a guide to outline potential biases in individual model simulations, and we stress that diagnostics shown in Figure 1 provide more accurate descriptions.

4. Conclusions

[11] We have shown the intrinsic property of daily temperature in Western Europe that extreme seasons (cold winters and warm summers) yield higher variability than mild seasons (warm winters and cool summers). The reasons for such dynamics remain to be elucidated. In a warming climate, it can be anticipated that European summers might be more variable, while winters becoming milder would have a decreasing intraseasonal variance. This study refines the results of *Schaer et al.* [2004] by treating explicitly statistical properties of daily data. We also have provided a test for the performance of climate models to simulate temperature variability in the European region. There is obvious room for improvement for European temperature variability in the GCM simulations we used, although such models were not specifically designed to reproduce such variability (especially the low resolution ones). The results we report are a simplified form of the diagnostics of S. Parey et al. (Mean and variance evolutions of the hot and cold temperatures in Europe, submitted to *Climate Dynamics*, 2008), who developed a more complex statistical approach based on nonparametric methods.

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