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► **To cite this version:**

Pascal Yiou, D. Dacunha-Castelle, S. Parey, T. T. Huong Hoang. Statistical representation of temperature mean and variability in Europe. *Geophysical Research Letters*, 2009, 36 (4), pp.L04710. 10.1029/2008GL036836 . hal-03199482

HAL Id: hal-03199482

<https://hal.science/hal-03199482>

Submitted on 15 Apr 2021

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Statistical representation of temperature mean and variability in Europe

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Received 28 November 2008; revised 9 January 2009; accepted 23 January 2009; published 27 February 2009.

[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. **Citation:** Yiou, P., D. Dacunha-Castelle, S. Parey, and T. T. Huong Hoang (2009), Statistical representation of temperature mean and variability in Europe, *Geophys. Res. Lett.*, 36, L04710, doi:10.1029/2008GL036836.

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 $0.5 \times 0.5^\circ$ 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 material¹). 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 \times 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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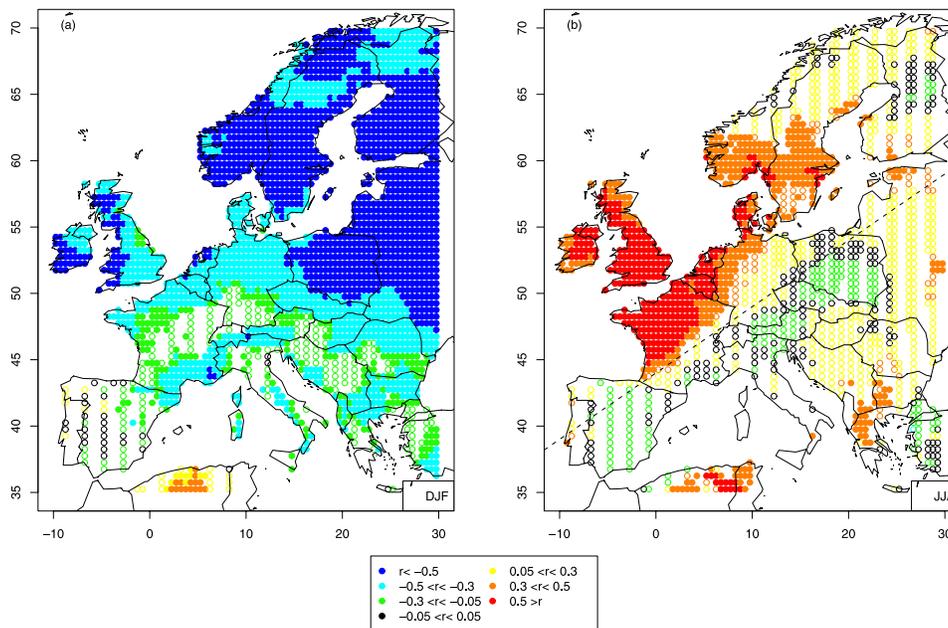


Figure 1. Rank correlations between mean daily temperature and its standard deviation for the gridded ECA&D dataset [Haylock *et al.*, 2008], between 1961 and 2007: (a) winter (December to February) and (b) summer (June to August). The dashed line represents a region north of which all correlations are 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

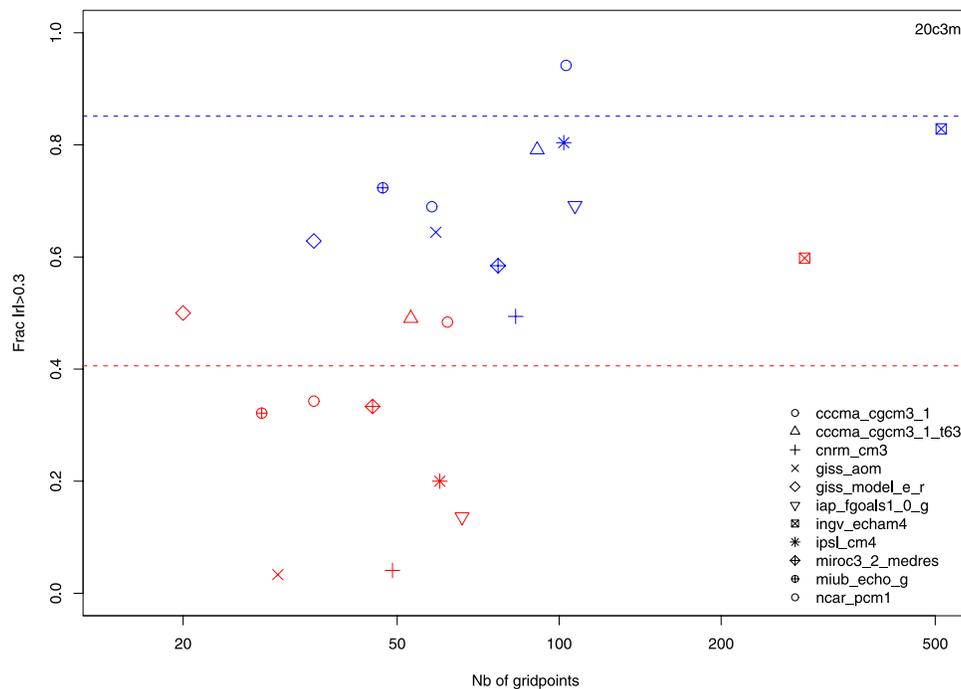


Figure 2. Fractions of gridpoints with $r < -0.3$ (winter: blue symbols) or $r > 0.3$ (summer: red symbols) and p-values < 0.01 in 11 of the CMIP3 data for the 20th century (between 1961 and 2000). The scores are plotted as functions of the number of gridpoints north of the Pyrenees (winter) or north 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.

[12] **Acknowledgments.** We acknowledge the climate dataset from the EU-FP6 project ENSEMBLES (<http://www.ensembles-eu.org>) and the data providers in the ECA&D project (<http://eca.knmi.nl>). We acknowledge the modeling groups, the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP's Working Group on Coupled Modelling (WGCM) for their roles in making available the WCRP CMIP3 multi-model dataset. Support of this dataset is provided by the Office of Science, U.S. Department of Energy. We thank an anonymous reviewer for suggesting the use of FDR.

References

- Beniston, M. (2004), The 2003 heat wave in Europe: A shape of things to come? An analysis based on Swiss climatological data and model simulations, *Geophys. Res. Lett.*, *31*, L02202, doi:10.1029/2003GL018857.
- Beniston, M., and D. Stephenson (2004), Extreme climatic events and their evolution under changing climatic conditions, *Global Planet Change*, *44*, 1–9.
- Benjamini, Y., and Y. Hochberg (1995), Controlling the false discovery rate: A practical and powerful approach to multiple testing, *J. R. Stat. Soc. Ser. B*, *57*, 289–300.
- Cassou, C., *et al.* (2005), Tropical Atlantic influence on European heat waves, *J. Clim.*, *18*, 2805–2811.

- Ciais, P., et al. (2005), Europe-wide reduction in primary productivity caused by the heat and drought in 2003, *Nature*, *437*, 529–533.
- Fischer, E., et al. (2007), Contribution of land-atmosphere coupling to recent European summer heat waves, *Geophys. Res. Lett.*, *34*, L06707, doi:10.1029/2006GL029068.
- Haylock, M. R., et al. (2008), A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006, *J. Geophys. Res.*, *113*, D20119, doi:10.1029/2008JD010201.
- Hurrell, J., Y. Kushnir, G. Ottersen, and M. Visbeck (Eds.) (2003), *The North Atlantic Oscillation: Climatic Significance and Environmental Impact*, *Geophys. Monogr. Ser.*, vol. 134, 279 pp., AGU, Washington, D. C.
- Intergovernmental Panel on Climate Change (2007), *Climate Change 2007: The Physical Science Basis: Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by S. Solomon, D. Qin, and M. Manning, 996 pp., Cambridge Univ. Press, New York.
- Klein-Tank, A., et al. (2002), Daily dataset of 20th-century surface air temperature and precipitation series for the European Climate Assessment, *Int. J. Climatol.*, *22*, 1441–1453.
- Meehl, G., and C. Tebaldi (2004), More intense, more frequent, and longer lasting heat waves in the 21st century, *Science*, *305*, 994–997.
- Piao, S. L., et al. (2008), Net carbon dioxide losses of northern ecosystems in response to autumn warming, *Nature*, *451*, 49–52, doi:10.1038/nature06444.
- Rosenzweig, C., et al. (2008), Attributing physical and biological impacts to anthropogenic climate change, *Nature*, *453*, 353–357, doi:10.1038/nature06937.
- Schaer, C., et al. (1999), The soil-precipitation feedback: A process study with a regional climate model, *J. Clim.*, *12*, 722–741.
- Schaer, C., et al. (2004), The role of increasing temperature variability in European summer heatwaves, *Nature*, *427*, 332–336.
- Storey, J. D. (2002), A direct approach to false discovery rates, *J. R. Stat. Soc., Ser. B*, *64*, 479–498.
- Vautard, R., et al. (2007), Summertime European heat and drought waves induced by wintertime Mediterranean rainfall deficit, *Geophys. Res. Lett.*, *34*, L07711, doi:10.1029/2006GL028001.
- Ventura, V., et al. (2004), Controlling the proportion of falsely rejected hypotheses when conducting multiple tests with climatological data, *J. Clim.*, *17*, 4343–4356.
- von Storch, H., and F. W. Zwiers (2001), *Statistical Analysis in Climate Research*, Cambridge Univ. Press, Cambridge, U. K.
- Yiou, P., and M. Nogaj (2004), Extreme climatic events and weather regimes over the North Atlantic: When and where?, *Geophys. Res. Lett.*, *31*, L07202, doi:10.1029/2003GL019119.

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