On the robustness of the estimates of centennial-scale variability in heavy precipitation from station data over Europe

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Received 14 April 2005; revised 26 May 2005; accepted 16 June 2005; published 23 July 2005.

[1] The impact of missing values on the centennial-scale variability of heavy precipitation was analysed using daily data from European rain gauges. Sub-sampling was modeled according to the observed structure of gaps in daily precipitation records. Quantitative estimates of the sampling impact on the long-term variability derived from high-quality long-term station data were used for the homogenization of sampling in European time series and the estimation of long-term secular tendencies in heavy precipitation indices. Centennial linear trends of extreme precipitation based on different indices are quite robust in winter but less robust in summer, implying seasonality in the trend estimates especially in Western Europe. Estimates of annual indices derived for the locations where different indices shows significant trends imply primarily positive centennial-scale changes in heavy and very heavy precipitation with the strongest magnitudes of about 3–5% per decade in Eastern Europe. **Citation:** Zolina, O., C. Simmer, A. Kapala, and S. Gulev (2005), On the robustness of the estimates of centennial-scale variability in heavy precipitation from station data over Europe, *Geophys. Res. Lett.*, *32*, L14707, doi:10.1029/2005GL023231.

1. Introduction

[2] The analysis of in-situ precipitation measurements worldwide shows an increasing probability of heavy precipitation over Europe during the last several decades [*Frei and Schär*, 2001; *Groisman et al.*, 2005; *Klein Tank and Koennen*, 2003]. Despite the use of different indices for heavy rainfall, conclusions of these studies are quite consistent and reveal a stronger increase of heavy and very heavy precipitation when compared to the mean rainfall. Similar results were obtained from the NCEP/NCAR and ERA-40 reanalyses [*Zolina et al.* 2004]. However, continental scale analysis of centennial variability in heavy precipitation is limited by data availability and quality. Regional studies [*Frei and Schär*, 2001; *Brunetti et al.*, 2004] show a growing occurrence of heavy precipitation during the last century in the Alps and Northern Italy. The importance of the analysis of long-term changes in heavy precipitation is underlined by experiments with climate models [*Zwiers and Kharin*, 1998; *Semenov and Bengtsson*, 2002; *Watterson and Dix*, 2003], which suggest strong changes in the occurrence of heavy rainfall under the warming conditions. Besides the limited number of long records, a massive analysis of centennial changes in heavy precipitation is limited by the sampling inhomogeneity of the station daily data. Here we quantify the impact of sampling on the estimates of long-term trends in heavy precipitation indices over Europe on the basis of very high quality long-term daily records.

2. Data and Preprocessing

[3] We used daily rainfall data from the KNMI European Climate Assessment (ECA) data set [*Klein Tank et al.*, 2002], the collection of the Russian Institute for Hydrometeorological Information – World Data Center (RIHMI-WDC) and the German Weather Service (DWD) archive [*Zolina et al.*, 2004]. These comprise all together 295 stations for the time period 1804–2003 with 96 records spanning periods longer than 100 years. The data sets are characterized by the homogeneity of observational practices and reading procedures. Inhomogeneously distributed missing values in the records may, however, cause artificial time-dependent biases and therefore affect estimates of interannual variability. In order to quantify these effects we first selected 22 stations with completely gap-free daily records during 1900–2002. For these time series we simulated undersampling according to the gap structure derived from the analysis of all 96 stations. Two types of gaps occur in the 74 time series: continuous gaps due to missing complete months and seasons more frequent in the first half of the XX century (Type 1), and shorter gaps lasting from 1 to 20 days (Type 2). Type 1 gaps are responsible for 65% of missing records. Figure 1 shows for all data records the distribution of the relative number of missing days per season as well as of the duration of continuous gaps of Type 2. In 45% of the Type 2 gaps the records miss 1–2 days per season and in 8% 3–4 days. The remaining 47% of the Type 2 gaps are characterized by missing 5 to more than 40 days per season with relatively homogeneous probability distribution. The duration of Type 2 gaps varies from 1 day (56% of the Type 2 gaps) to 10–20 days (<4%). This analysis allows us to build up sampling structure models for the simulation of sub-sampling of the 22 gap-free time series.

[4] For the sampling limits of 10, 20, 30 and 40 missing days per season we simulated gaps in the 22 gap-free records according to the sampling models implied by Figure 1 by a random generator. For each calendar season the random simulation of Type 2 gaps of the prescribed durations was repeated 10 times. Type 1 gaps in the time series were simulated by the triply repeated elimination of a randomly chosen month of the calendar season. Thus, we obtained from the 22 gap-free records undersampled cen-

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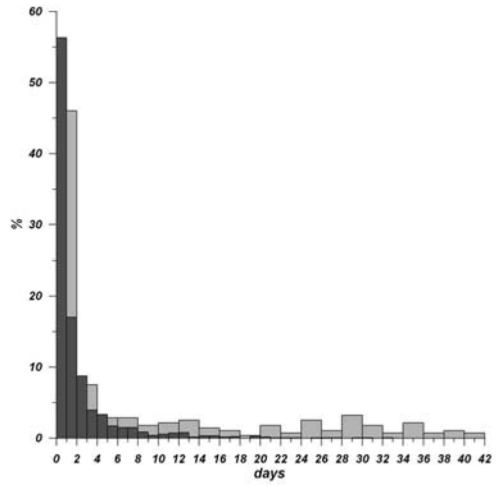

Figure 1. Statistical distribution of the relative number of missing days per season (light grey) and of the durations of continuous gaps (monthly and seasonal gaps are excluded) (dark grey) in all European centennial stations.

tennial daily records which are compared to the original gap-free data.

3. Estimation of Heavy Precipitation Indices and Their Variability

[5] Besides the seasonal totals p, the number of seasonal wet days n, and seasonal mean precipitation intensity ($p_i = p/n$), we used both the occurrence of the exceedance of a given threshold, e.g. 95% or 99% (*G95*, *G99*), corresponding to heavy and very heavy precipitation [*Groisman et al.*, 2005] and the percentage of the seasonal total precipitation sum obtained during very wet (>95%) days (*R95*) [*Klein Tank and Koennen*, 2003]. Additionally, we derived the 95% (p_{95}) and 99% (p_{99}) percentiles of precipitation from the estimated Gamma distribution for daily precipitation [*Wilks*, 1995; *Groisman et al.*, 1999; *Zolina et al.*, 2004]. Gamma PDFs were derived only for $n > 5$, and the Kolmogorov-Smirnov test was used to estimate the accuracy of the fit. All parameters were estimated for each calendar season from 10 sampling simulations and averaged afterwards. Linear trends in the seasonal values of precipitation indices for the period 1900–2002 were derived from the regularly sampled time series (RSTS) and from the undersampled (USTSn, n being the number of simulated gaps) time series for $10 < n < 40$. The trend significance has been estimated using the Student t-test and the *Hayashi* [1982] reliability ratio (H) which considers the confidence intervals of the statistical significance. If $|H| \gg 1$, the true value is close to its estimate. When $|H| > 1$, the null hypothesis (no trend) is rejected. When $|H| \leq 1$, confidence intervals can be quite high, even if the Student's t-test is formally satisfied. Additionally we used the Wilcoxon test, which may reject some estimates accepted by a Student t-test.

4. Results

[6] Differences in heavy precipitation indices derived form the RSTS and USTS data become detectable for 30–40 missing values per season. Seasonal means of p_{95} and p_{99} derived from the RSTS and USTS*40* time series, range from 0 to 5%, being typically 2–5 times smaller than for *G95* and *R95*. For p_{95} and *G95* the biases may be both positive and negative, while the values of *R95* typically decrease due to undersampling. Averaged over 22 stations root mean squared (rms) differences are 3.1 ± 1.7% for p_{95}, 8.0 ± 5.1% for *G95* and 6.2 ± 2.6% for *R95*.

[7] Sensitivity of the centennial trends in precipitation indices to the sampling can be detected only for >30 missing values. Figure 2 shows the significance of the differences between the trend estimates derived form the

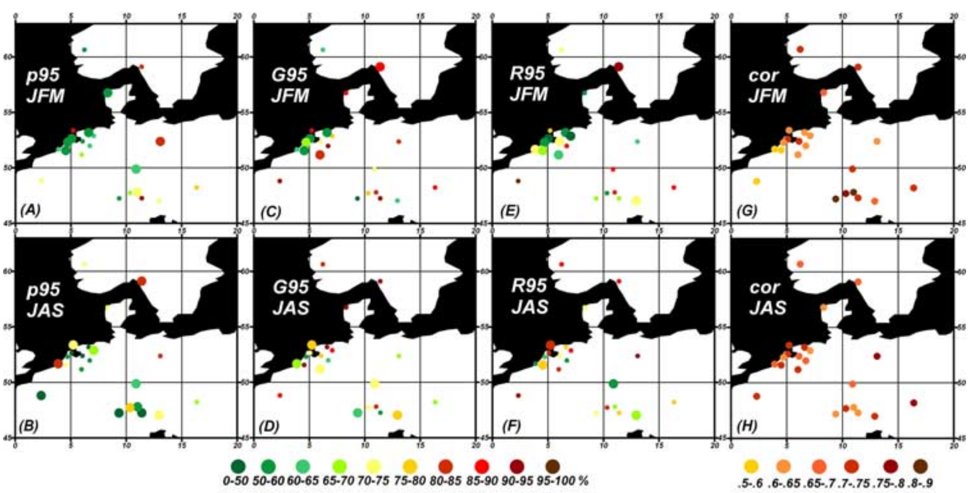

Figure 2. Significance (in %, t-test) of the differences between the trend estimates derived form the RSTS and USTS*40* daily time series of (a, b) p_{95}, (c,d) *G95* and (e, f) *R95* indices for winter (Figures 2a, 2c, and 2e) and summer (Figures 2b, 2d, and 2f) as well as correlation coefficients between de-trended time series of *R95* computed from RSTS and USTS*40* daily data for (g) winter and (h) summer. Large circles mark the locations where the trends themselves were significant according to t-test and *Hayashi* [1982] ratio.

Table 1. Root Mean Square Differences in the Linear Trend Estimates Derived From the RSTS and USTS40 Daily Precipitation Time Series ($d(a)$, %), Their Standard Deviations ($sig(d)$), Averaged Estimates of the Significance (%) of Differences Between the Trend Estimates From the RSTS and USTS40 Time Series (x, %) and Averaged Squared Correlation Coefficients Between RSTS and USTS40 Time Series ($r{**}2$, %) for Different Seasons

Season	$d(a)$, %	$sig(d)$	x, %	r^2, %
		p95		
JFM	0.35	0.28	68.3	84
AMJ	0.27	0.25	64.8	85
JAS	0.31	0.23	69.6	81
OND	0.25	0.22	66.1	84
		G95		
JFM	1.38	0.97	75.1	83
AMJ	1.15	0.86	79.5	81
JAS	1.12	0.98	77.2	80
OND	1.32	1.18	80.3	81
		R95		
JFM	0.57	0.43	71.3	81
AMJ	0.52	0.47	69.4	79
JAS	0.64	0.46	77.1	77
OND	0.48	0.38	72.6	81

RSTS and USTS*40* daily time series. Trend estimates in p_{95} derived from the RSTS and USTS time series show a better agreement with each other than *R95* and *G95* indices. Significance of differences for p_{99} (not shown) is higher than for p_{95}, but smaller than for *R95* and *G95*. For all indices the impact of sampling is more pronounced for mountain, island and coastal stations, which are stronger affected by convective precipitation. During summer sampling influences the trends in *R95* and *G95* in a stronger degree than p_{95}. Averaging of the trend estimates over the 22 stations (Table 1) implies that p_{95} index is less sensitive to the sampling compared to *R95* and *G95*. *G95* shows both the highest rms biases between the RSTS and USTS trend estimates and also larger standard deviations for the time series of the differences between RSTS and USTS.

[8] The impact of sampling on the interannual variability was quantified by the correlation between the de-trended index time series derived from RSTS and USTS data for the period 1900–2002. Although for the range of 0–20 missing values per season correlation is quite high, for n = 40 it may locally drop to 0.5–0.6 with higher values for p_{95}, and p_{99} compared to *G95* and *R95*. Averaged over the 22 stations the squared correlation coefficients (Table 1) give the highest values for p_{95}, and *G95*. Maps of the correlation coefficients between the RSTS and USTS time series of *R95* for winter and summer (Figures 2e and 2f) show the lowest winter correlation (0.53) in the Netherlands and the minimum summer correlation of 0.62 in the Alpine region of the Eastern Switzerland and Western Austria. Thus, sampling may locally produce 10 to 50% of interannual variability which is not explained by the gap-free time series for R95. For the other indices this estimate is somewhat lower (5–30 %).

[9] Being armed with the estimates of the potential impact of data gaps on the long-term variability of heavy precipitation, we employed all 96 European stations for estimation of long-term trends in the extreme precipitation indices for the period 1900–2002. In order to use the stations with continuous gaps of several years (39% of locations), we excluded time periods 1917–1921, 1942–1945, 1997–2002 and 2 single years from all records. For the remaining years we applied random sub-sampling of the daily time series for n = 40. The time series with the homogenized sampling were used for the estimation of linear trends in different precipitation indices.

[10] Trend estimates (in % per decade) for *R95* may exhibit locally significant differences with those for p_{95} (Figures 3a–3d). Trends in *G95* (not shown) are very close to p_{95}. During winter trends in p_{95} and *R95* are primarily positive in central and eastern Europe (2–7% and 3–10% per decade respectively). In 43 locations either index demonstrated significant changes, of which in 19 locations trends in all three indices are significant and show the same

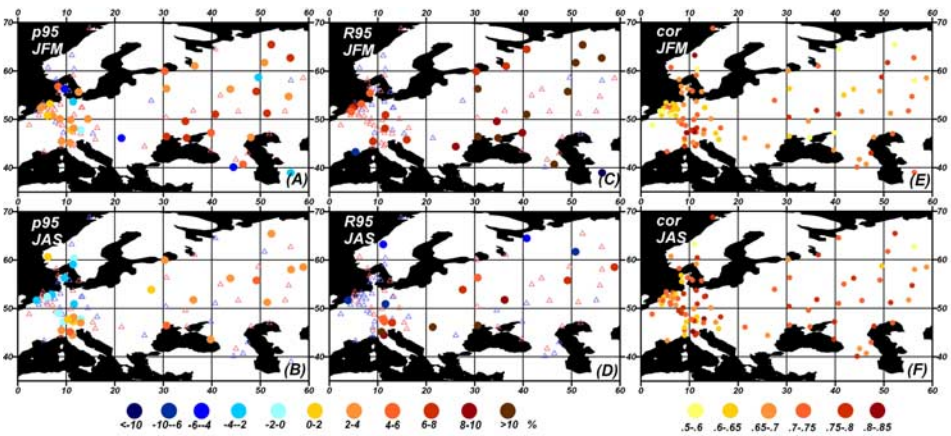

Figure 3. Estimates of linear trends in (a, b) p_{95} and (c, d) *R95* for the homogenized (n = 40) European centennial records for winter (Figures 3a and 3c) and summer (Figures 3b and 3d) as well as correlation coefficients between p_{95} and *R95* for (e) winter and (f) summer. Full circles correspond to the trends significant at 95% level according to t- and Wilcoxon tests and passing the Hayashi criterion, open triangles show the locations where trends are insignificant.

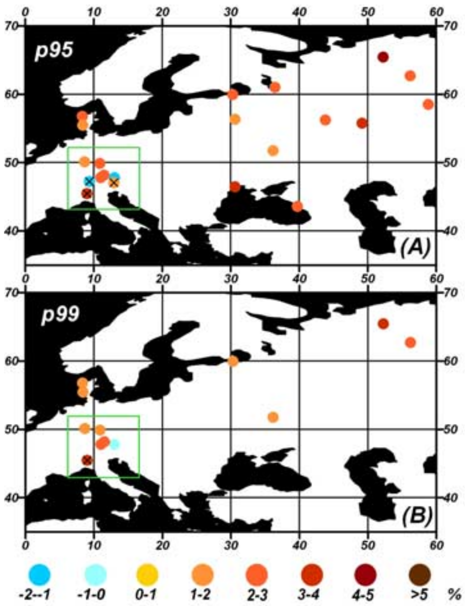

Figure 4. Estimates of linear trends in annual values of (a) p_{95} and (b) p_{99} in the locations where all three indices (p_{95}, *R95*, *G95*) computed from the homogenized time series are significant according to the chosen criteria. Rectangle shows the Alpine region for which the representaivness was estimated for 1960–1995 using 36 stations. Locations which were found to be not representative for this area are marked by crosses.

sign. In Western Europe in summer both indices show negative trends in the Netherlands, Northern Germany and Denmark and positive changes in the Alpine region of the Northern Italy. Summer trends of both indices in the eastern Europe are less consistent. Significant linear trends with the same sign exist only for 12 of 34 locations where either index demonstrated significant changes. In contrast to the secular trends the spatial consistency of interannual variability of the indices (Figures 3e and 3f) is stronger in summer than in winter. The number of stations where r (p_{95}, *R95*) is smaller than 0.7 is 51 and 32 (of 96 stations) in summer and winter respectively.

[11] An increasing frequency and intensity of heavy precipitation over most Europe in winter and south-north pattern in the trend estimates in the Western Europe in summer imply the seasonality of secular changes in heavy precipitation which can cause uncertainty in the trend estimates derived from the annual time series [*Klein Tank and Koennen*, 2003; *Groisman et al.*, 2005]. Figure 4a shows estimates of linear trends in annual values of p_{95} for the 21 locations where all three indices (p_{95}, *R95*, *G95*) computed from the homogenized time series are significant according to the chosen criteria, i.e. where secular centennial-scale trends are significant and robust to the sampling and to the choice of index. Such tendencies are positive in the most of Eastern Europe, where the strongest changes range from 3 to 5% per decade, while the trends exhibit more spatial variability in western Europe, varying from about −1 to +4% per decade. Field significance of this pattern according to the guidelines of *Livezey and Chen* [1983] is higher than 95%. The trends in p_{99} (Figure 4b) are significant in 12 locations only with primarily positive tendency and maxima of 3–4% per decade in the Northern European Russia. This pattern implies 90% field significance if the local significance is accepted at 95% level.

5. Summary and Conclusions

[12] The analyzed heavy precipitation indices are quite robust with respect to the sampling inhomogeneity in daily records. The spatial distribution of the estimated secular trends in heavy precipitation is somewhat more homogeneous in RSTS data than in USTS*n* (n > 30) time series. Nevertheless, sampling cannot fully explain the spatial noise in the estimates of long-term trends, also found by *Klein Tank and Koennen* [2003] and *Groisman et al.* [2005]. Meso-scale precipitation variability, which is usually higher in the areas with inhomogeneous terrain (mountain regions), and uncertainties associated with inaccuracy of data records still remaining after homogenization procedures are likely to be the reasons for this. The analysis of 100-year long homogenized time series shows that linear trends in heavy precipitation are influenced by seasonality, also found for the mean precipitation changes [*Zveryaev*, 2004]. Robust tendencies in heavy precipitation indices derived from annual records are found only in a few locations, being positive in most of cases. Analysis of the representativeness of these stations can even decrease the number of the locations with significant changes. This analysis involved comparison of the local trends with those derived form the area-averaged indices for 8 × 8 degree boxes for the period 1960–1995. Our estimates show that 1 of 6 stations for p_{99} and 3 of 8 stations for p_{95} are not representative for the Alpine area (Figure 4). The use of more objective indices based on estimated PDFs for daily precipitation, with separate analysis of different seasons appears to be the best strategy for estimating long-term tendencies in heavy precipitation.

[13] **Acknowledgments.** This study was supported by the North Rhine-Westphalian Academy of Science under the project "Large Scale Climate Changes and their Environmental Relevance", the NATO-SfP-981044 project "Extreme precipitation events: their origins, predictability and societal impacts" and RFBR (grants 03-05-64506 and 03-05-20016). European rain gauge data were made available by courtesy of KNMI (http://eca.knmi.nl), DWD and RIHMI-WDC. We thank the two anonymous reviewers whose comments largely helped to improve the manuscript. Discussions with P. Groisman of NCDC (Asheville), A. Hense of MIUB (Bonn) and V. Semenov of IFM-GEOMAR (Kiel) are very much appreciated.

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