Long-term persistence in climate and the detection problem

Diego Rybski,[1] Armin Bunde,[1] Shlomo Havlin,[2] and Hans von Storch[3]

[1]   We have analyzed six recently reconstructed records (Jones et al., 1998; Mann et al., 1999; Briffa, 2000; Esper et al., 2002; McIntyre and McKitrick, 2003; and Moberg et al., 2005) of the Northern Hemisphere temperatures and found that all are governed by long-term persistence. Due to the long-term persistence, the mean temperature variations $\sigma(m, L)$ between L years, obtained from moving averages over m years, are considerably larger than for uncorrelated or short-term correlated records. We compare the values for $\sigma(m, L)$ with the most recent temperature changes $\Delta T_i(m, L)$ in the corresponding instrumental record and determine the year i_c where $\Delta T_i(m, L)/\sigma(m, L)$ exceeds a certain threshold and the first year i_d when this could be detected. We find, for example, that for the climatologically relevant parameters $m = 30$, $L = 100$, and the threshold 2.5, the values (i_c, i_d) range, for all records, between (1976, 1990) for Mann et al. (1999) and (1988, 2002) for Jones et al. (1998). Accordingly, the hypothesis that at least part of the recent warming cannot be solely related to natural factors, may be accepted with a very low risk, independently of the database used.   **Citation:**   Rybski, D., A. Bunde, S. Havlin, and H. von Storch (2006), Long-term persistence in climate and the detection problem, *Geophys. Res. Lett.*, *33*, L06718, doi:10.1029/2005GL025591.

[2]   It is well accepted that the temperature of the Earth has been in the rise in the last hundred years, with a more pronounced increase in the last 25 years (Figure 1, red curve). The open question is how much of this increase can be attributed to natural fluctuations, and how much is of anthropogenic origin caused, for example, by the enhanced greenhouse gas (GHG) emissions in the last century. This is the detection and attribution problem [*Hasselmann*, 1993; *Hegerl et al.*, 1996; *Zwiers*, 1999; *Barnett et al.*, 2005], which plays a prominent role in the series of Intergovernmental Panel on Climate Change (IPCC) reports [*IPCC*, 2001, 1996].

[3]   In this Letter we study the variability of the temperatures of the Northern Hemisphere by analyzing six different reconstructions of Northern Hemisphere near-surface air temperature, that is, time series supposed to describe the historical development of this variable. They have been recently constructed with different methods from a variety of proxy data by *Jones et al.* [1998], *Mann et al.* [1999], *Briffa* [2000], *Esper et al.* [2002], *McIntyre and McKitrick*

[2003], and *Moberg et al.* [2005] (all data except *McIntyre and McKitrick* [2003] are available at the National Oceanic & Atmospheric Administration, World Data Center for Palaeoclimatology - Climate Reconstructions, Air Temperature, Northern Hemisphere: http://www.ncdc.noaa.gov/paleo/recons.html). We show that all records are characterized by pronounced long-term persistence, similar to those found in real climate records [*Koscielny-Bunde et al.*, 1998; *Pelletier and Turcotte*, 1999; *Eichner et al.*, 2003; *Blender and Fraedrich*, 2003; *Vyushin et al.*, 2004; *Kiraly and Janosi*, 2005; see also *Cohn and Lins*, 2005]. Here, the term "long-term persistence" refers to auto-correlation functions which decay by a power law and are characterized by an infinite correlation time. Due to the long-term correlations, the variability on long time scales is strongly enhanced.

[4]   In order to assess if the recent increase in temperature appears consistent with such long-term persistence, we compare the global mean temperature variations of the reconstructed records with the actual recent increase in temperature. Specifically, we perform a moving average over windows of m years and study the temperature differences $\Delta T_i(m, L)$ between moving-average points separated by L years. For each record, we compare the standard deviation $\sigma(m, L)$ with the corresponding actual temperature changes $\Delta T_i(m, L)$ in the instrumental record. We are interested in both short term changes (where we choose $m = 5$ and $L = 20$) and long term changes (where we choose $m = 30$ and $L = 100$). We find that in both cases, the large variability of the records due to their long-term correlations can only account for a part of the recent warming and specify the year where the ratio between $\Delta T_i(m, L)$ and $\sigma(m, L)$ exceeds certain thresholds above 2.

[5]   Figure 1 shows the reconstructed records of the annual temperatures of the Northern Hemisphere we consider here, together with the instrumental data of the past 149 years [*Jones and Moberg*, 2003](Climatic Research Unit, Northern Hemisphere average temperature 1856 to 2004, TaveNH2v: http://www.cru.uea.ac.uk/cru/data/temperature/). The recent increase in temperature as well as the warming period with a maximum at about 1000y ago are (clearly) seen. Figure 2a shows the scaled temperature distribution $P(T)$ of the six reconstructed records. One can see that for all records, $P(T)$ is well approximated by a Gaussian, being fully described by the standard deviation σ_0.

[6]   Next we show that the reconstructed records exhibit long-term persistence. Long-term persistent records $\{x_i\}$, $i = 1, \ldots, N$, with zero mean and unit variance are characterized by an auto-correlation function $C(s) = \langle x_i x_{i+s}\rangle \equiv 1/(N - s) \sum_{i=1}^{N-s} x_i x_{i+s}$ that decays by a power law, $C(s) \sim s^{-\gamma}$, where the correlation exponent γ is between 0 and 1. To test the temperature records for long-term correlations, we have employed the detrended fluctuation analysis (DFA2) [*Peng et al.*, 1994; *Bunde et al.*, 2000; *Kantelhardt et al.*, 2001].

[1]Institut für Theoretische Physik III, Universität Giessen, Giessen, Germany.
[2]Minerva Center and Department of Physics, Bar-Ilan University, Ramat-Gan, Israel.
[3]Institute for Coastal Research, GKSS Research Centre, Geesthacht, Germany.
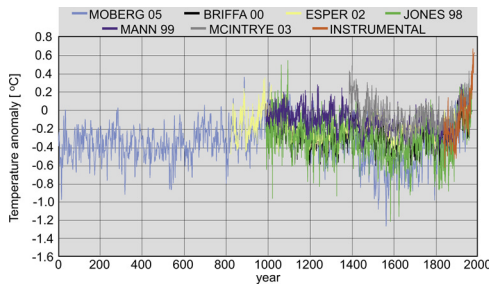
Figure 1. Considered reconstructions of northern hemispheric temperature: *Moberg et al.* [2005] (bright blue, 1–1979), *Briffa* [2000] (black, 1000–1993), *Esper et al.* [2002] (yellow, 831–1992), *Jones et al.* [1998] (green, 1000–1991), *Mann et al.* [1999] (dark blue, 1000–1980), and *McIntyre and McKitrick* [2003] (grey, 1400–1980). We show also an instrumental temperature record of the Northern Hemisphere (red).

In DFA2, one considers cumulated sums $Y_i = \sum_{j=1}^{i} x_j$, $i = 1, 2, \ldots, N$, and studies, in time windows of length s, the mean fluctuations $F(s)$ of Y_i around the best quadratic fit. For long-term correlated data, $F(s)$ scales as $F(s) \sim s^{\alpha}$, with $\alpha = 1 - \gamma/2$. To standardize the records, we subtracted each record by its mean and divided by its standard deviation. Figure 2b shows $F(s)$ for the six considered records. In the double logarithmic plot, the fluctuation functions are approximately straight lines, with slopes α roughly between 0.8 and 1, representing correlation exponents between about 0.4 and 0, as detailed in Table 1.

[7] To illustrate the effect of the long-term correlations on the variability of the records we compare, in Figures 3a and 3b, the longest reconstructed record [*Moberg et al.*, 2005] with an artificially long-term correlated record with the same exponent $\alpha = 0.86$ and the same standard deviation σ_0. In both figures, the annual data are shown in green, and the corresponding moving average with $m = 30$ is shown in black. The figure shows clearly the close similarity between the reconstructed record and the artificial long-term correlated one, and the effect of the correlations. Due to the persistence, warm years are more likely to be followed by warm years, and cold years by cold years, and the same holds for decades and centuries; it is this feature which leads to the pronounced mountain-valley structure we observe in Figures 3a and 3b and to the anomalous clustering of extreme events described by *Bunde et al.* [2005].

[8] To quantify the natural variability of the record T_i, we perform, as in Figure 3, a moving average over windows of m years $T_i(m)$, and study the temperature differences $\Delta T_i(m, L) = T_i(m) - T_{i-L}(m)$; by definition, $L + m/2 < i < N - m/2$, where N is the length of the record (the value of the moving average at year i, $T_i(m)$, is defined as $T_i(m) := \frac{1}{m}\sum_{j=i-m_-}^{i+m_+} T_j$ with $m_- = m_+ = \text{int}(m/2)$ if m is odd, and $m_- = m/2$, $m_+ = m/2 - 1$ if m is even). Since the original annual data are Gaussian distributed, also the temperature differences $\Delta T_i(m, L)$ are Gaussian distributed, with the standard deviation $\sigma(m, L)$. Accordingly, the knowledge of $\sigma(m, L)$ will enable us to detect the time when the recent increase in temperature can be explained by the natural variability only with a very

unreasonable low probability – for all considered temperature records.

[9] Figure 4 shows the dependence of $\sigma(m, L)$ on the time lag L, for two window sizes $m = 5$ and 30, for four representative reconstructed records [*Moberg et al.*, 2005; *Esper et al.*, 2002; *McIntyre and McKitrick*, 2003; *Mann et al.*, 1999]. We also show the theoretical standard deviation $\sigma(m, L)$ calculated from artificial long-term correlated records with the same α-value and the same length as the respective reconstructed record. The figure shows that for all records, $\sigma(m, L)$ is within the error bars of the artificial long-term correlated records. This very good agreement between artificial and reconstructed records is a further indication of long-term persistence in the considered records. We like to emphasize that there is no fit parameter in Figure 4, since the exponents α have been determined independently in Figure 2b. An approximate analytical expression for $\tau_i = T_i - \langle T \rangle$ and with the approximation $\langle \tau_i \tau_{i+s} \rangle \cong \langle \tau_i \tau_{i+1} \rangle s^{-\gamma}$ one can determine $\sigma(m, L)$ analytically: $\sigma(m, L) \cong \sqrt{2}\sigma_0 m^{-(1-\alpha)}[1 - \frac{1}{\sigma_0^2}\langle \tau_i \tau_{i+1}\rangle \left(\frac{L}{m}\right)^{-2(1-\alpha)}]^{1/2}$ for $0.5 < \alpha < 1$. Due to the long-term persistence, the natural variations are significantly larger than in uncorrelated or short-term correlated records. The standard deviations σ_0 and $\sigma(m, L)$ for two pairs of m, L are summarized in Table 1. The table shows that there are two groups of records: The first group [*Mann et al.*, 1999; *Briffa*, 2000; *McIntyre and McKitrick*, 2003; *Esper et al.*, 2002] is characterized by small standard deviations with, for example, $\sigma(30, 100)$ around 0.11 °C, while the second group [*Moberg et al.*, 2005; *Jones et al.*, 1998] is characterized by large standard deviations, for example, 0.16–0.18°C.
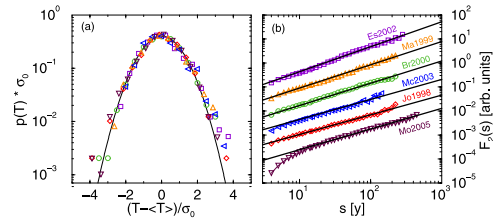

Figure 2. Distribution and correlation of the reconstructed temperature records of Figure 1, with standard deviations σ_0. (a) Normalized histogram using a bin-size of 0.5 σ_0: *Esper et al.* [2002] (squares), *Mann et al.* [1999] (vertical triangles), *Briffa* [2000] (circles), *McIntyre and McKitrick* [2003] (left-facing triangles), *Jones et al.* [1998] (diamonds), and *Moberg et al.* [2005] (downward-facing triangles). In order to scale the probabilities $p(T)$, the values in the abscissa are subtracted by the mean values $\langle T \rangle$ and divided by the standard deviation σ_0, whereas the ordinate is multiplied by the standard deviation. The figure shows that the histogram can be well approximated by a standard Gaussian (full line in the figure). (b) Second order detrended fluctuation functions (DFA2) of the considered records. The symbols correspond to those in Figure 2a. The straight lines have slopes $\alpha = 1.04 \pm 0.05$ [*Esper et al.*, 2002], $\alpha = 0.97 \pm 0.05$ [*Mann et al.*, 1999], $\alpha = 0.93 \pm 0.05$ [*Briffa*, 2000], $\alpha = 0.83 \pm 0.03$ [*McIntyre and McKitrick*, 2003], $\alpha = 0.82 \pm 0.03$ [*Jones et al.*, 1998] and $\alpha = 0.86 \pm 0.03$ [*Moberg et al.*, 2005].

Table 1. Values of the Standard Deviation σ_0 and the Fluctuation Exponent α of the Temperature Data and the Standard Deviation $\sigma(m, L)$ of Moving Average Differences $\Delta T_i(m, L)$ (with $m = 5$, $L = 20$ and $m = 30$, $L = 100$)[a]

| Reconstructed | σ_0 | α | $\sigma(m, L)$ | | i_c | |
			$m = 5$ $L = 20$, °C	$m = 30$ $L = 100$, °C	$m = 30$ $R = 2$, year	$L = 100$ $R = 2.5$, year
Mann et al. [1999]	0.13	0.97	0.11	0.11	<1971	1976
Briffa [2000]	0.14	0.93	0.12	0.11	<1971	1979
McIntyre and McKitrick [2003]	0.16	0.83	0.13	0.12	<1971	1980
Esper et al. [2002]	0.14	1.04	0.13	0.12	1972	1981
Moberg et al. [2005]	0.22	0.86	0.19	0.16	1981	1984
Jones et al. [1998]	0.23	0.82	0.18	0.18	1983	1988

[a]The table also shows the year i_c, when the ratio $\Delta T_i(m, L)/\sigma(m, L)$ exceeds $R = 2$ or $R = 2.5$ for the considered records (Figure 1). For obtaining σ_0, α, and $\sigma(m, L)$ from the reconstructed records, we only consider the time range before 1980.

[10] Next we consider the instrumental annual temperature data of the Northern Hemisphere that are available between 1856 and 2004. Figure 5a shows these data ($m = 1$) as well as the corresponding moving averages with $m = 5$ and $m = 30$. From Figure 5a we can deduce, for $m = 5$, the actual temperature differences $\Delta T_i(5, 20)$, where i runs from 1878 to 2002. Figure 5b shows the ratio R_i between these $\Delta T_i(5, 20)$ and the corresponding standard deviations $\sigma(5, 20)$ of the six records from Table 1. The figure shows two pronounced peaks, one at 1938 and one at 1996. The four records with the lower variability show R-values well above 3 at 1938 and well above 4 at 1996, while the two records with higher variability lead to R-values close to 2 at 1938 and between 2.5 and 3 in 1996. Since the ΔT_i are Gaussian distributed, the probability of finding a ΔT_i value above 2, 2.5 and 3 times σ is about 1/44, 1/161, and 1/769, respectively.

[11] Figure 5c shows the analogous analysis for $m = 30$ and $L = 100$. According to the definition of the moving average, the index i now represents the years between 1971 and 1990. Since $\Delta T_i(30,100)$ increases almost always monotonically, the intersection of $R_i = \Delta T_i(30, 100)/\sigma(30, 100)$ with one of the threshold values 2, 2.5, and 3 defines a threshold year i_c, above which the temperature increases can only be explained as a natural phenomenon with very low probability (1/44, 1/161, or 1/769, respectively). The threshold years for $R = 2$ and 2.5 are listed in Table 1. Since the calculation of i_c is based on a moving average over 30 y, from $i_c - 15$ to $i_c + 14$, the first year i_d when the effect can be detected in the record, is $i_d = i_c + 14$. We refer to this year as the detection year.

[12] In the past, often an R-value of 2 has been chosen [*Hasselmann*, 1993; *Hegerl et al.*, 1996; *Zwiers*, 1999; *Barnett et al.*, 2005]. Figure 5c shows that for $R = 2$, the threshold years i_c for the records from the first group are either below 1971 or in 1972 [*Esper et al.*, 2002], yielding detection years either below 1985 or in 1986 [*Esper et al.*, 2002]. For the records from the second group, $i_c = 1981$ for *Moberg et al.* [2005] and 1983 for *Jones et al.* [1998], and the detection years are 1995 and 1997, correspondingly. Even if we apply the stricter criterion with 2.5σ as a reasonable threshold, the recent temperature increases can hardly be regarded as natural. In this case, the detection year $i_d = i_c + 14$ ranges from 1990 [*Mann et al.*, 1999], 1993 [*Briffa*, 2000], 1994 [*McIntyre and McKitrick*, 2003], and 1995 [*Esper et al.*, 2002] to 1998 [*Moberg et al.*, 2005] and 2002 [*Jones et al.*, 1998].

[13] We conclude that the previous claim that the most recent warming, observed by quality controlled instrumental data, would be inconsistent with the hypothesis of purely natural dynamics [*Hasselmann*, 1993; *Hegerl et al.*, 1996; *Zwiers*, 1999; *Barnett et al.*, 2005] is supported by our long-term persistence analysis of different proxy-based reconstructions extending over many centuries and even up to two millennia. In case of the rather smooth reconstructions, the detection appears feasible even before 1985. An interesting detail is that the two fiercely arguing groups
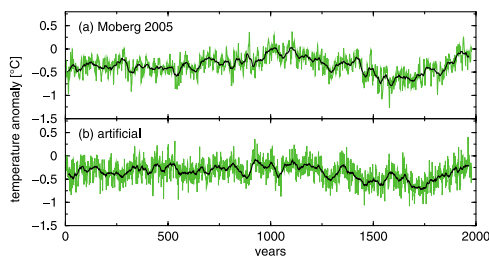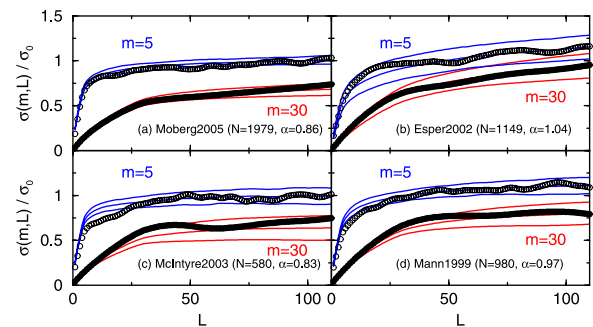

Figure 3. Comparison of (a) the Moberg-record and (b) an artificial long-term correlated record with fluctuation exponent $\alpha = 0.86$. The artificial record has been created by Fourier Filtering [*Makse et al.*, 1996]. Both records have identical standard deviation and average. The original records are plotted in green, while the corresponding moving averages with window-size $m = 30$ are drawn in black.

Figure 4. Normalized standard deviations $\sigma(m, L)/\sigma_0$ of moving average differences $\Delta T_i(m, L)$ for two window sizes $m = 5$ (open circles) and $m = 30$ (solid circles), as a function of the time lag L, calculated for the following records: (a) *Moberg et al.* [2005] (b) *Esper et al.* [2002] (c) *McIntyre and McKitrick* [2003] (d) *Mann et al.* [1999]. The centered solid lines represent $\sigma(m,L)$ obtained from 100 artificial configuration with the same fluctuation exponent α and the same record length N as the reconstructed record. The outer solid lines represent the error bars.
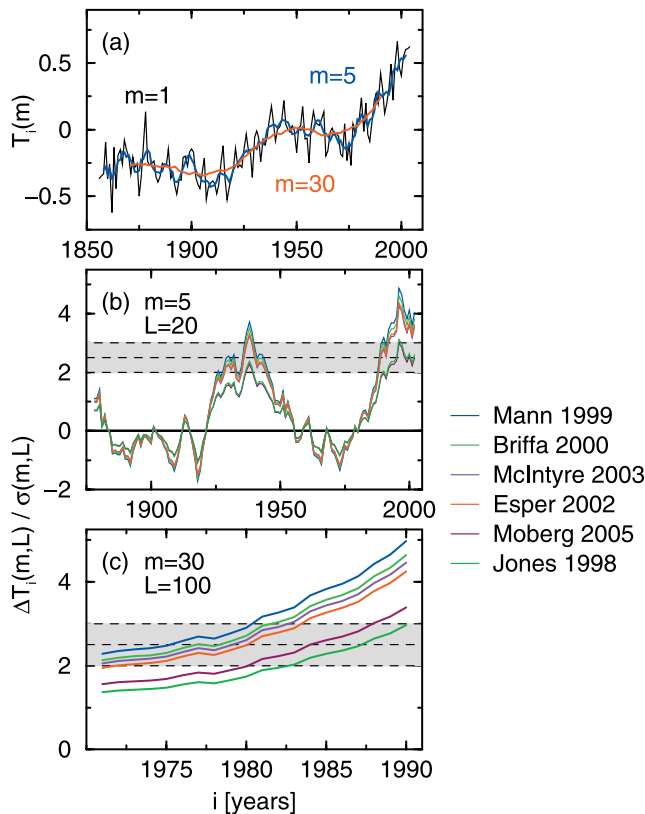
Figure 5. Instrumental Northern Hemisphere temperature differences compared with the corresponding standard deviations of the 6 reconstructed records considered here. (a) Instrumental Northern Hemisphere temperatures between 1856 and 2004 ($m = 1$) with moving averages of window size $m = 5$ and $m = 30$. (b and c) The corresponding temperature differences $\Delta T_i(m, L) = T_i(m) - T_{i-L}(m)$ divided by the standard deviations $\sigma(m, L)$ of the considered reconstructed records (Table 1), for $m = 5$, $L = 20$ (Figure 5b) and $m = 30$, $L = 100$ (Figure 5c). The thresholds $R = 2, 2.5$ and 3 are shown as dashed lines.

around Mann and McIntyre lead both to very early detections, while the most conservative detection result is obtained when the more "bumpy" reconstruction by Jones and coworkers is used.

References

Barnett, T., et al. (2005), Detecting and attributing external influences on the climate system: A review of recent advances, *J. Clim.*, *18*(9), 1291–1314.

Blender, R., and K. Fraedrich (2003), Long time memory in global warming simulations, *Geophys. Res. Lett.*, *30*(14), 1769, doi:10.1029/2003GL017666.

Briffa, K. R. (2000), Annual climate variability in the Holocene: Interpreting the message of ancient trees, *Quat. Sci. Rev.*, *19*(1–5), 87–105.

Bunde, A., S. Havlin, J. W. Kantelhardt, T. Penzel, J. H. Peter, and K. Voigt (2000), Correlated and uncorrelated regions in heart-rate fluctuations during sleep, *Phys. Rev. Lett.*, *85*(17), 3736–3739.

Bunde, A., J. F. Eichner, J. W. Kantelhardt, and S. Havlin (2005), Long-term memory: A natural mechanism for the clustering of extreme events and anomalous residual times in climate records, *Phys. Rev. Lett.*, *94*(4), 94048701, doi:10.1103/PhysRevLett.94048701.

Cohn, T. A., and H. F. Lins (2005), Nature's style: Naturally trendy, *Geophys. Res. Lett.*, *32*(23), L23402, doi:10.1029/2005GL024476.

Eichner, J. F., E. Koscielny-Bunde, A. Bunde, S. Havlin, and H. J. Schellnhuber (2003), Power-law persistence and trends in the atmosphere: A detailed study of long temperature records, *Phys. Rev. E*, *68*(4), doi:10.1103/PhysRevE.68.046133.

Esper, J., E. R. Cook, and F. H. Schweingruber (2002), Low-frequency signals in long tree-ring chronologies for reconstructing past temperature variability, *Science*, *295*(5563), 2250–2253.

Hasselmann, K. (1993), Optimal fingerprints for the detection of time-dependent climate change, *J. Clim.*, *6*(10), 1957–1971.

Hegerl, G. C., H. von Storch, K. Hasselmann, B. D. Santer, U. Cubasch, and P. D. Jones (1996), Detecting greenhouse-gas-induced climate change with an optimal fingerprint method, *J. Clim.*, *9*(10), 2281–2306.

Intergovernmental Panel on Climate Change (IPCC) (1996), *Climate Change 1995: The Science of Climate Change*, edited by J. T. Houghton et al., 88 pp., Cambridge Univ. Press, New York.

Intergovernmental Panel on Climate Change (IPCC) (2001), *Climate Change 2001: The Scientific Basis*, edited by J. T. Houghton et al., pp. 583–638, Cambridge Univ. Press, New York.

Jones, P., and A. Moberg (2003), Hemispheric and large-scale surface air temperature variations: An extensive revision and an update to 2001, *J. Clim.*, *16*(2), 206–223.

Jones, P. D., K. R. Briffa, T. P. Barnett, and S. F. B. Tett (1998), High-resolution palaeoclimatic records for the last millennium: Interpretation, integration and comparison with general circulation model control-run temperatures, *Holocene*, *8*(4), 455–471.

Kantelhardt, J. W., E. Koscielny-Bunde, H. H. A. Rego, S. Havlin, and A. Bunde (2001), Detecting long-range correlations with detrended fluctuation analysis, *Physica A*, *295*(3–4), 441–454.

Kiraly, A., and I. M. Janosi (2005), Detrended fluctuation analysis of daily temperature records: Geographic dependence over Australia, *Meteorol. Atmos. Phys.*, *88*(3–4), 119–128.

Koscielny-Bunde, E., A. Bunde, S. Havlin, H. E. Roman, Y. Goldreich, and H. J. Schellnhuber (1998), Indication of a universal persistence law governing atmospheric variability, *Phys. Rev. Lett.*, *81*(3), 729–732.

Makse, H. A., S. Havlin, M. Schwartz, and H. E. Stanley (1996), Method for generating long-range correlations for large systems, *Phys. Rev. E*, *53*(5), 5445–5449.

Mann, M. E., R. S. Bradley, and M. K. Hughes (1999), Northern Hemisphere temperatures during the past millennium: Inferences, uncertainties, and limitations, *Geophys. Res. Lett.*, *26*(6), 759–762.

McIntyre, S., and R. McKitrick (2003), Corrections to the Mann et al. (1998) proxy data base and northern hemispheric average temperature series, *Energy Environ.*, *14*(6), 751–771.

Moberg, A., D. M. Sonechkin, K. Holmgren, N. M. Datsenko, and W. Karlen (2005), Highly variable Northern Hemisphere temperatures reconstructed from low- and high-resolution proxy data, *Nature*, *433*(7026), 613–617.

Pelletier, J. D., and D. L. Turcotte (1999), Self-affine time series: II. Applications and models, *Adv. Geophys.*, *40*, 91–166.

Peng, C. K., S. V. Buldyrev, S. Havlin, M. Simons, H. E. Stanley, and A. L. Goldberger (1994), Mosaic organization of DNA nucleotides, *Phys. Rev. E*, *49*(2), 1685–1689.

Vyushin, D., I. Zhidkov, S. Havlin, A. Bunde, and S. Brenner (2004), Volcanic forcing improves Atmosphere-Ocean Coupled General Circulation Model scaling performance, *Geophys. Res. Lett.*, *31*(10), L10206, doi:10.1029/2004GL019499.

Zwiers, F. W. (1999), The detection of climate change, in *Anthropogenic Climate Change*, pp. 163–209, Springer, New York.

————————

A. Bunde and D. Rybski, Institut für Theoretische Physik III, Universität Giessen, D-35392 Giessen, Germany. (armin.bunde@theo.physik.uni-giessen.de)

S. Havlin, Minerva Center, Bar-Ilan University, Ramat-Gan, 52900 Israel.

H. von Storch, Institute for Coastal Research, GKSS Research Centre, D-21502 Geesthacht, Germany.