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Long memory and the detectability of climate change

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A measure of the temporal dependence in a time series X is the autocorrelation function $C(\Delta) = \text{Exp}(X(t)X(t+\Delta))/\sigma^2$ for time lags $\Delta = 0, \pm1, \pm2$ ….

Conditional upon the "type of memory" the autocorrelation function may be approximated by

$C(\Delta) = \Sigma_i a_i^{\Delta}$ **Short memory / autoregressive**

$C(\Delta) \sim \Delta^{-\gamma}$ **Long memory;**
$\gamma = 2(1-d)$, d Hurst coefficient

Warning: sloppy language

Instead of
„system has long/short memory"
or
„presence of long/short memory"
a more accurate albeit somewhat clumsy formulation is
„the statistical properties of the time series X can be suitable described by the mathematical construct of long or short memory"

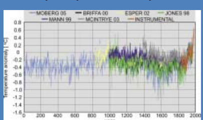
General significance

When time series exhibit short or long term memory, they contain less independent samples then the time series length. When the autocorrelation function of X is approximated as „short memory", it contains more independent samples than in the case of an approximation as long memory.
Tests of null hypothesis operating with short term memory are more liberal than tests operating with long memory assumptions.

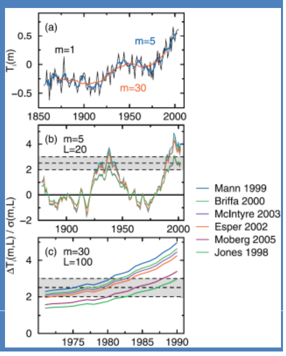
Case I: Inconsistency of long-term trends with natural variability

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 s(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 s(m,L) with the most recent temperature changes $DT_i(m, L)$ in the corresponding instrumental record and determine the year i_c where $DT_i(m, L)/s(m, L)$ 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.



Reconstructions of northern hemispheric temperature used to determine back-ground variability: Moberg et al. [2005], Briffa [2000], Esper et al. [2002], Jones et al. [1998]), Mann et al. [1999],and McIntyre and McKitrick [2003].
Also shown an instrumental temperature record of the Northern Hemisphere.

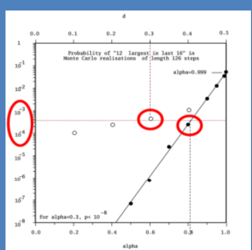


Instrumental Northern Hemisphere temperature diffe-rences compared with the corresponding standard deviations of the 6 *reconstructed* records considered here.
(top) Instrumental Northern Hemisphere temperatures between 1856 and 2004 with moving averages of window size m = 5 and m = 30.
(middle and bottom) The corresponding temperature differences $DT_i(m, L) = T_i(m) - T_{i-L}(m)$ divided by the standard deviations s(m,L) of the different *reconstructed* records, for m = 5, L =20 (middle) and m = 30, L = 100 (bottom).
The thresholds R = 2, 2.5 and 3 are shown as dashed lines.

Case II: Clustering of records

Previous statistical detection methods based partially on climate model simulations indicate that, globally, the observed warming lies very probably outside the natural variations. We use a more simple approach to assess recent warming at different spatial scales without making explicit use of climate simulations. It considers the likelihood that the observed recent clustering of warm record-breaking mean temperatures at global, regional and local scales may occur by chance in a stationary climate. Under two statistical null-hypotheses, autoregressive and long-memory, this probability turns to be very low: for the global records lower than p = 0.001, and even lower for some regional records. The picture for the individual long station records is not as clear, as the number of recent record years is not as large as for the spatially averaged temperatures.

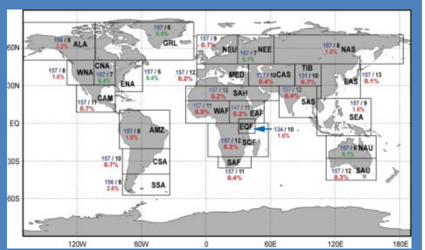
Citation: Zorita, E., T. F. Stocker, and H. von Storch (2008), How unusual is the recent series of warm years?, Geophys. Res. Lett., 35, L24706, doi:10.1029/2008GL036228.



Among the last 17 years, 1990-2006, there were the 13 **globally** warmest years since 127 years – how probable is such an event if the time series were stationary?

Monte-Carlo simulations taking into account serial correlation, either AR(1) (with lag-1 correlation a) or long-term memory process (with d).

Best guesses: $a \approx 0.8$; $d \approx 0.3$ (very uncertain) for global mean temperature



Record counting and assessing in **regional** Giorgi-boxes.
In **blue**: number of data (in years), in **black**: number of warmest years since 1990; in **red**/**green**: probability of such clustering under the assumption of long memory stationarity.
Note that the series are usually longer than the global series; thus less clustering contradicts the null hypothesis in many regions than on the globe.

The time series of global mean temperature is instationary.
For explaining the history of the record, in particular the recent end,
a reference to external factors is needed
– with other attribution studies pointing to GHGs.