TEMPORAL VARIABILITY IN LOCAL AIR TEMPERATURE SERIES SHOWS NEGATIVE FEEDBACK

by

Olavi Kärner

Reprinted from

ENERGY &
ENVIRONMENT

VOLUME 18 No. 7+8 2007

MULTI-SCIENCE PUBLISHING CO. LTD.
5 Wates Way, Brentwood, Essex CM15 9TB, United Kingdom

TEMPORAL VARIABILITY IN LOCAL AIR TEMPERATURE SERIES SHOWS NEGATIVE FEEDBACK

Olavi Kärner
Tartu Observatory, 61602 Tõravere, Estonia
E-mail: olavi@aai.ee

ABSTRACT
Long daily surface air temperature series from 24 European and Asian stations are analyzed, among them the Central England temperature dataset (1772 – 2005). The mean seasonal cycle in each series is removed and correlations between the consecutive increments of various increment intervals for the anomaly series are calculated. The sample correlations appear to behave similarly for all series. A positive coefficient between the short-term (daily etc) increments rapidly changes to the negative side while the increment interval increases. The value of the coefficient saturates at the level -0.5 and stays at that level for long range of intervals from 20 to 2000 days. The feature is a testimony to the regulating role of (cumulative) negative feedback in the climate system during the last two centuries.

1. INTRODUCTION

One of the largest challenges in the understanding of the behavior of the Earth's climate variations consists in an adequate estimating of the influence of feedbacks in the climate system. The sign of the cumulative feedback (i.e the overall effect of all feedback loops in the climate system) is the key element to show the system's reaction to outside forcing including the effect of increasing CO_2 concentration in the atmosphere.

Climate Change (2001) writes: *An interaction mechanism between processes in the climate system is called climate feedback, when the result of an initial process triggers changes in a second process that in turn* influence*s the initial one. A positive feedback intensifies the original process, and a negative feedback reduces it.*

The definition is simple, but the climate system is too complicated to estimate the feedbacks directly. There is a strong seasonal cycle of the solar radiation at the top of the atmosphere (TOA) that dictates the system's main variability. This means that it is difficult to separate the changes caused by outside forcing from those caused by any feedback. That may be the reason why the IPCC relies on model computations to estimate the sign and strength of the feedbacks (e.g Soden and Held 2006).

IPCC (AR4) considers water vapor, lapse rate, surface albedo and cloud feedbacks as the key processes and uses model calculations to estimate their magnitudes. Soden and Held (2006) applied a consistent methodology to compare feedback strengths in 14 ocean-atmosphere models using a coordinated set of 21st century climate change experiments generated for the 4th Assessment of the Intergovernmental Panel on Climate Change (AR4). They computed the feedbacks as products of two terms, one dependent on the radiative transfer, and another on the climatic response. The first term was calculated by means of a particular model (GAMDT, 2004). The second term (climatic response) for each variable x was computed by differencing the projected climate of years (2000-2010) from that of (2100-2110). Soden and Held (2006) summarize:

The analysis confirms two widely-held beliefs about the behavior of climate feedbacks in models:

i) that water vapor provides the largest positive feedback and that the strength of this feedback can be estimated assuming constant relative humidity in all models.

ii) that clouds provide the the largest source of uncertainty in current model predictions of climate sensitivity.

This work also identifies some less well recognized aspects of climate feedbacks:

i) that clouds appear to provide a positive feedback in all models, and

ii) that inter-model differences in lapse rate response stem primarily from differences in the meridional distribution of surface warming, with these differences in turn responsible for much of the intermodel spread in water vapor feedback.

As a result the model calculated feedbacks show the domination of positive feedback. Three of the four key processes (water vapor, surface albedo and cloud) give positive feedback on the basis of the model comparison by Soden and Held (2006). As a result, the estimated cumulative feedback ('all feedbacks' as term by IPCC) should be positive.

At the same time several opposite views were obtained examining the climate system variability. Rial et al. (2004) illustrated how the presence of several types of amplifying (positive) and controlling (negative) feedbacks, some physical, some biogeophysical, and some biogeochemical can be deduced from observations. The authors conclude *that the relatively stable global temperature and benign climate the earth has enjoyed for billions of years is testimony to the action of regulating negative feedbacks which balance and neutralize amplifying positive feedbacks continuously.* The same conclusion is also reached by Douglass et al. (2004) who directly determined the sensitivity and time delay of earth's surface temperature response to annual solar irradiance variations from 60 years of data.

Lindzen et al. (2001) estimated the magnitude of cloud feedbacks based upon radiance measurements of Japan's Geostationary Meteorological Satellite (GMS). They found that the high-level cloud amount averaged over a large oceanic region in the western tropical Pacific decreases with increasing sea surface temperature (SST) underneath clouds. Using a 3.5 box radiative-convective model, they further found that the response of high level clouds to SST had a negative climate feedback. Lin et al. (2002) reassessed this phenomenon by analyzing the radiation and clouds inferred from the Tropical Rainfall Measuring Mission (TRMM) Clouds and the Earth Radiant Energy System (CERES) measurements. They found a weak positive feedback between high-level clouds and the surface temperature. Chou et al. (2002) determined that the difference in the feedback factor between the two studies is due to a larger contrast in albedos and a smaller contrast in the outgoing longwave radiation (OLR) between the high-level cloudy region and the surrounding regions as derived by Lin et al. (2002) when compared with that specified by Lindzen et al. (2001).

In the model by Lindzen et al. (2001), the Tropics is divided into a dry region, a clear moist region and a cloudy moist region. the fractional coverages of these regions are assumed to be 0.50, 0.28, and 0.22, respectively. The factors responsible for the difference between the results from two approaches appeared to be the high level cloud cover and the high level cloud albedo. Chou et al. (2002) concluded that using realistic values for these variables in the radiative-convective model gives negative feedback, but Lin et al. (2002) significantly underestimated the high level cloud cover and overestimated the high level cloud albedo and, hence, overestimated the sensitivity of shortwave radiation to high-level clouds.

In the present paper the daily surface air temperature series from Europe and Asia are used to estimate the sign of the overall feedback in the Earth's climate system. It is evident that any separation of the changes in the climate system due to individual forcing is impossible on the basis of a data analysis. But it is easy to study the temporal variability of the local temperature response on the basis of several temperature records. Because concentration of the main disputable forcing (the CO_2 concentration in the Earth's atmosphere) has been permanently increasing during the last century (Climate Change 2001) the variability in various temperature series also describes the influence of that increase to the whole system. Because the response is formed under the circumstances where plenty of feedback loops are operating, the corresponding estimate should be called the *cumulative feedback*.

In order to get rid of the influence of the seasonal cycle the anomaly series are used in the analysis. The growth rate of the second moment for the time series of increments as a function of the increment interval (the structure function or variogram, see Monin and Yaglom 1975 or Malamud and Turcotte 1999 for details) is used to estimate the temporal variability.

Mandelbrot (1982) defined the fractional Brownian motions (FBM) with the growth rate proportional to τ^{2H}, where $0 < H < 1$ and τ is the interval between the data points in the time series. In FBM's the value of H is uniquely connected to the correlations between the consecutive increments of the process. The latter correlation sign corresponds to the feedback sign dominating in the physical processes generating the series (Mandelbrot 1982).

Previous studies of the temporal variability in various air temperature series revealed behavior similar to FBM's in certain time scales (e.g Lovejoy and Schertzer 1986, Kärner 2005). But the exponent H appeared to be dependent on the increment interval. Large scale variability is characterized by small values of H and the result is an indication of the domination of negative feedback (Kärner 2005). More detailed description of the structure function growth rate for the air temperature series is presented in the next but one section.

A change in the growth rate of structure function is linked to changes in correlations between the time series' increments (see equation (3)). This means that an estimate about the feedback sign can be found in a direct way: analyzing the correlations between the increments. In the present paper the corresponding approach will be carried out. In the air temperature series the structure function growth rate is not uniform for different increment intervals. Initial rapid growth rate changes to a slow one as τ grows beyond some weeks. Thus, the correlations between the increments are also changing as the increment interval increases. In a study of the climate feedback we are interested in long term correlations. The governing idea of the current study is simple. If the correlations between the increments are negative then the system is influenced by a negative feedback, because an increment showing a positive deviation in respect to the balanced situation is followed (on average) by a negative one and *vice versa*. The negative correlations express a tendency of the values of increments to compensate each other to prevent for the series from blowing up too fast. Positive correlations imply a tendency of growth for the occurred deviations, indicating a positive feedback. The corresponding correlations are analyzed in detail for the series from 24 locations and the results will be presented in the following sections. It is important to note that the increment intervals studied start from significantly shorter intervals than traditionally used in climate studies. This is caused by the scale break in terms of H in between two and four weeks (e.g. Lovejoy and Schertzer 1986, Kärner 2005). More details will be presented later.

2. DATA

Surface air temperature data from 20 meteorological stations in Europe and 4 in Asia (Table 1) are used to estimate the cumulative feedback using daily mean time series. 18 of them are downloaded from http://eca.knmi.nl (see Klein Tank and coauthors 2002 for details). The Central England temperature (CET) series from 1772-2005 (Parker et al. 1992) is downloaded from http://www.badc.rl.ac.uk. These datasets contain daily mean temperature values from the corresponding stations. Temperature values for the local noon at Tartu from 1865 – 1941 are also analyzed in order to find any possible difference between the results for daily mean and noontime observations. Data for 4 Asian stations are downloaded from http:www.meteo.ru. The record length in series varies from 50 to 250 years.

A few illustrations about the extent of temporal variability of the time series are shown in Figure 1. Its left panel shows the annual amplitude calculated from the available samples in two places. The Central England temperature (CET) series appears to have a low amplitude among the analyzed stations, and the Verkhoyansk dataset has one of the highest among them. The seasonal cycle is calculated by averaging separately the observed temperature values for each calendar day (including February 29).

The right panel in Figure 1 shows the variability of annual mean air temperature in ˚C for two station (Stockholm and Praha) air temperatures over the available record length of more than two centuries. The annual mean values are used to make the picture more readable. All the calculations for the present paper are carried out using daily anomaly values defined as the difference between the recorded value and the averaged value for that day.

Table 1. Summary information about the situation of stations and their record lengths

Station, Country	LAT	LON	Years	Length *n* (days)
Stockholm, SE	59.35	18.05	1756 – 2006	91584
Central England, GB	52.42	-1.83	1772 – 2005	85467
Praha-Klementinum, CZ	50.09	14.42	1775 – 2005	84127
Bologna, IT	44.48	11.25	1814 – 2002	68807
Uccle, BE	50.80	4.35	1833 – 2006	63460
Zagreb, HR	45.82	15.99	1861 – 2006	52899
Armagh, GB	54.35	-6.65	1865 – 2001	49703
Tartu, EE	58.3	26.73	1865 – 1941	27604
Vestervig, DK	56.72	8.31	1874 – 2006	48272
Kremsmäunster, AT	48.05	14.13	1876 – 2006	47755
Potsdam, DE	52.38	13.07	1876 – 2006	47755
Hamburg Bergedorf, DE	53.48	10.25	1879 – 2006	42276
Hohenpeissenberg, DE	47.80	11.02	1879 – 2001	44925
St. Petersburg, RU	59.96	30.30	1881 – 2006	45928
Archangelsk, RU	64.50	40.73	1881 – 2006	45532
Tomsk, RU	56.43	85.01	1884 – 1995	40571
Orenburg, RU	51.68	55.10	1986 – 1999	41484
Halle, DE	51.48	11.98	1900 – 2006	38989
Lisbon, PT	38.72	-9.15	1901 – 2006	38624
Davos, CH	46.81	9.85	1901 – 2003	37986
Marseille, FR	43.30	5.40	1901 – 2000	36890
Verhoyansk, RU	67.55	133.38	1926 – 1995	25346
Kluchi, RU	56.30	160.80	1931 – 1995	23376
Ashgabat, Turkm	38.00	58.4	1951 – 1995	16436

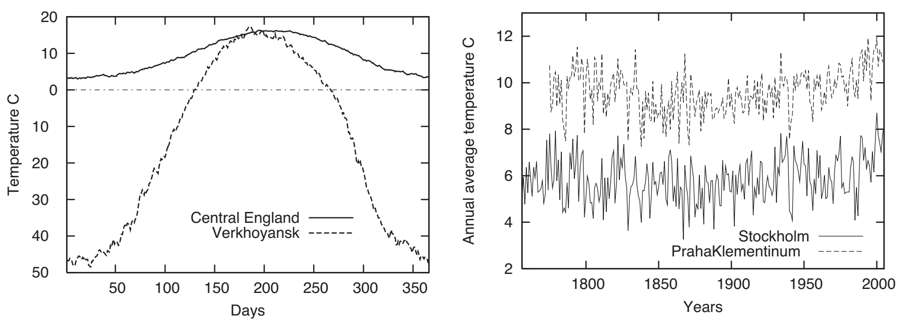

Figure 1. Two examples about the temporal variability in the series.
Left panel: Low and high amplitude of the seasonal cycle.
Right panel: Annual mean temperature series for 2 stations.

3. QUANTIFYING THE TEMPORAL VARIABILITY

A value from the time series $X(t)$, $t = 1, 2; \ldots, n$ at the time instant t can be presented by

$$X(t) = \sum_{i=0}^{n-1} x(t-i), \tag{1}$$

where $x(t) = X(t) - X(t-1)$ is the corresponding increment during the time step t. In the current approach $X(0)$ is set equal to the sample mean of X's.

The temporal structure of a non-stationary series $X(t)$ can be studied on the basis of the growth rate of variance for the increment

$$X(t+\tau) - X(t) = x(t+1) + \ldots + x(t+\tau), \tag{2}$$

where $t = 1, \ldots, n - \tau$, as a function of τ.

The necessary function representing this growth rate (structure function or variogram) can be written as (e.g Kärner 2005):

$$\begin{aligned} D(\tau) &= \frac{1}{n-\tau}\sum_{i=1}^{n-\tau}(X(i+\tau) - X(i))^2 \\ &= \frac{1}{n-\tau}\sum_{i=1}^{n-\tau}(x(i+1) + \ldots + x(i+\tau))^2 \\ &= \tau C(0) + 2[(\tau-1)C(1) + (\tau-2)C(2) + \ldots + C(\tau-1)] \\ &= \tau[C(0) + 2\sum_{i=1}^{\tau-1}(1 - i/\tau)C(i)], \end{aligned} \tag{3}$$

where $C(i)$ stands for the auto-covariation of the increments $x(t)$ at the lag i,

Expression (3) shows that the growth rate for $D(\tau)$ depends upon the correlations between the increments (over the range $1 \ldots (\tau - 1)$). It is customary to describe the growth rate by means of a special (Hurst) exponent H (e.g Davis et al 1996) defined by the relation $D(\tau) \propto \tau^{2H}$, where $0 < H < 1$. The value of H determines some important classes among the non-stationary series:

1. If $C(i) = 0$ for all $i > 0$, then expression (3) shows that the growth rate for $D(\tau)$ is proportional to τ, and consequently $H = 0.5$. The process is often called random walk (RW).
2. If positive correlations are dominating in the term $\sum_{i=1}^{\tau-1}(1 - i/\tau)C(i)$, the function $D(\tau)$ has a faster growth rate than in the previous case. Positively correlated increments tend to have the same sign, so the process, produced by such increments, tends to increase in the future if it has had an increasing tendency in the past. And *vice versa* it has a tendency to decrease in the future if it has had a decreasing tendency in the past. Such a feature is called *persistence* (P) (Mandelbrot 1982). Physically, a persistent system is going to increase a deviation, thus a positive feedback generally dominates in the system that

governs the time series. In terms of the FBM the persistent processes have the growth rate of $D(\tau)$ proportional to τ^{2H}, where $0.5 < H < 1$.

3. If over some interval $\tau_0 < \tau < \tau_1$ the function $D(\tau)$ is growing more slowly than in case (1) so that $D(\tau) \propto \tau^{2H}$, where $0 < H < 0{:}5$, negative correlations dominate in the system. Being negatively correlated, the increments tend to be rich in opposite signs, so that the process has a tendency to decrease in future if it has had an increasing tendency in the past and *vice versa*. The feature is called *anti-persistence* (AP). It expresses a tendency of the values of increments to compensate for each other to prevent the process from blowing up too fast. The physical processes governing the behavior of the system over this time interval tend to eliminate deviations showing a negative feedback in aggregate.
4. If $H = 0$. the necessary condition for stationarity of $X(t)$ is satisfied (Monin and Yaglom 1975).

To get the actual estimate, the exponent H is fitted to the change of $D(\tau)$ change over some finite interval for the time lag $\tau : \tau_0 \le \tau \le \tau_1$ by means of the linear equation $\log D(\tau) = 2H \log(\tau)$ + some constant. The latter constant has no significance for the current study.

The growth rate for $D(\tau)$ can be calculated for every sample of the time series. The rate can be quantified by H over the parts where it is approximately linear. The results can be characterized by means of the feature of (anti-)persistence (AP or P) in the same way as for the FBM's. The scheme enables us to estimate the sign of the feedback on the basis of the assigned AP or P property (as a function of the time scale). The corresponding estimation has been carried out for various surface air temperature series by Kärner (2005).

Figure 2 shows the growth rate for $D(\tau)$ for 5+5 temperature anomaly series of various length from different European and Asian stations.

The growth rate of $D(\tau)$ in this example shows a scale break in terms of H. The function $D(\tau)$ grows rapidly ($H \approx 0{:}35$) for $1 < \tau < 16$ days due to the strong synoptic scale variability (e.g Lovejoy and Schertzer 1986). The growth rate slows down drastically ($H \approx 0$) for the range $\tau > 30$ days. All the analyzed series behave on the same manner. Formula (3) shows that a change in H should be caused by some change in the correlations between the increments of the series. This means that focusing on the long-range feedback studies we need to examine the behavior of the correlations up to sufficiently long ranges. It turns out that the scale break showing the upper end of a strong non-stationarity in the temperature variability takes place much earlier than one can expect the lower end (some decades) of the climate scale. But the same regime on the basis of $H \approx 0$ persists beyond decades. This means, that the condition $H \approx 0$ advises the beginning of the increment interval where the correlation studies should start. Next we show that the same feedback sign can be figured out on the basis of sample correlations between the consecutive increments.

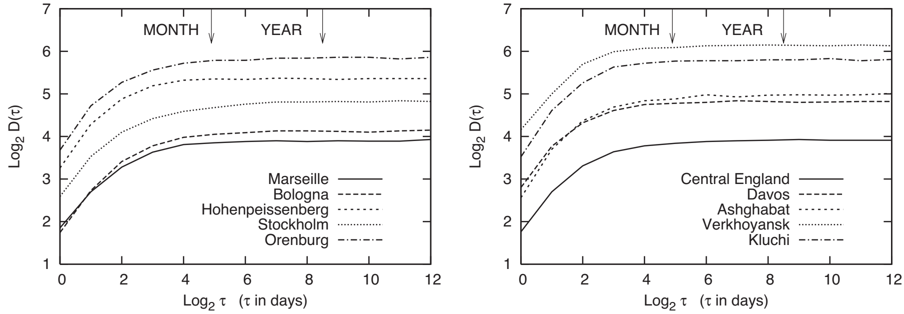

Figure 2. The growth rate of $D(\tau)$ for 5 different station daily temperature anomaly series on both panels

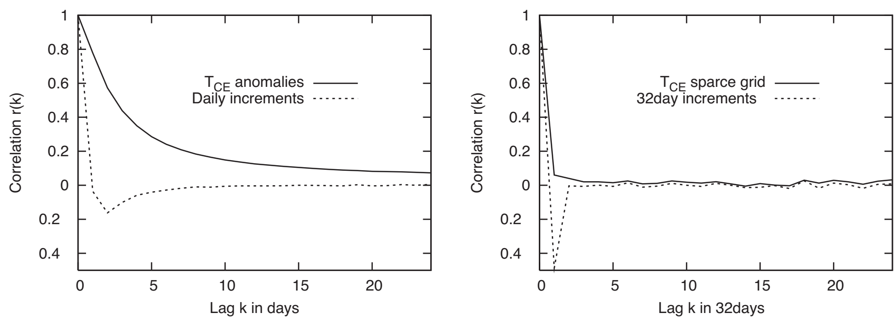

Figure 3. Autocorrelations for 4 samples from the Central England T_{CE} daily series over the period 1772 – 2005. Left panel: For the anomaly and daily increment series. Right panel: For the anomaly and increment series calculated over a sparse (32 day) grid.

4. CORRELATION BETWEEN THE INCREMENTS

Small H values (i.e $H < 0.5$) indicate the predominance of negative correlations between the series' increments. To become sure of that it is easy to calculate the corresponding correlations directly on from the increment records. Sample values for the correlation calculated from different modifications of the initial series enable us to explain the task. Figure 3 shows 4 examples of sample correlation for the CET anomaly and increment series calculated using two different time resolutions, the daily and the 32-day time step.

The left panel shows that there lasts a strong positive correlation between the anomalies up to considerably long lags. At the same time, the correlations between the daily increments are negative although quite weak for the lags extending up to a couple of days. Right panel of the Figure 3 shows average autocorrelations for the anomaly and increment series calculated over a sparse (32 day) grid. This example explains the effect of using a wider grid to get rid of the influence of short-range dependence between the anomalies. Two important details can be seen in the right panel. Firstly, there is still a signal of long memory among the anomalies (i.e the autocorrelations are small but still positive). A remarkable difference can be seen between the correlations for the increments. The lag one correlation for daily increments is nearly negligible (left panel) but turns out to a remarkably negative one for the series for 32-day increments. All the coefficients for longer lags are practically zero.

The panel reveals a practical need to study the increments over the time steps considerably longer than one day, because the correlation between the increments during the consecutive nonoverlapping time intervals appears to change while τ increases. In actual calculations we need to use the all dataset and calculate the lag one correlations $r_\tau(1)$ between the consecutive increments over wide range of increment intervals τ, but omitting short intervals. The task can be simplified dividing the initial series into groups of sub-series. Each group contains τ sub-series, (i.e the same amount as to the currently considered increment interval), and the obtained sub-series are numbered correspondingly. Time series $X(t)$ where $t = 1, 2, 3, \ldots, n$ can be unfolded into the τ sub-series $j = 1, 2, \ldots, \tau$ of increments as follows:

$$x_{\tau,j}(t) = X((t+1)\tau + j) - X(t\tau + j). \quad (4)$$

Here, τ is the increment interval, $j = 1, 2, \ldots, \tau$ denotes the sub-series, and t the time: $t = 1, 2, \ldots, n_1$, where $n_1 = n/\tau - 1$. The initial series is divided to τ sub-series having n_1 terms in each. Autocovariations for the j-th sub-series at the lag $k = 0, 1, \ldots, m$ are calculated as follows

$$C_{\tau,j}(k) = \frac{1}{n_1 - k} \sum_{i=1}^{n_1-k} (x_{\tau,j}(i) - \overline{x}_{\tau,j})(x_{\tau,j}(i+k) - \overline{x}_{\tau,j}) \quad (5)$$

Sample mean values $\overline{x}_{\tau,j}$ for the sub-series will generally differ from zero even for anomaly series.

Thus, it is important to take them into account. In the present study we are interested in behavior of the correlation between the consecutive increments only, i.e. the case of $k = 1$. As every j presents a sub-series of non-overlapping increments, a representative value for the coefficient $r_\tau(1)$ is recoverable by averaging over the all subseries:

$$r_\tau(1) = \frac{1}{\tau} \sum_{j=1}^{\tau} \frac{C_{\tau,j}(1)}{C_{\tau,j}(0)} \quad (6)$$

The correlations are calculated over a remarkably wide increment interval $\tau = 1, 2, 3, \ldots, \Lambda$, in order to get an idea about their dependence on τ.

Calculating the correlations between the increments of different increment intervals enables us to follow an important feature in the temperature increment series: the strengthening of the negative correlation between the consecutive increments up to saturating at some level. An even and remarkably strong negative correlation between the consecutive increments appears to be a common characteristic for the station based temperature anomaly series (see also Kärner 2005). It springs up for τ values corresponding to the scale break transition period (about two weeks) and saturates rapidly near the level $r_\tau(1) = -0.5$ as τ increases.

The feature is illustrated on two panels in Figure 4. The left panel shows a rapid decay of the correlations between the consecutive increments as the interval increases from 1 to 5 days. Some difference in decay rate can be observed between the results from various stations for the shorter intervals. The curves of r_τ (1) saturate rapidly at the level –0.5 as τ becomes larger than 10 days. Examples of the sample coefficients r_τ (1) up to the increment interval of 100 days are shown in Figure 4 (right panel). It shows the correlation r_τ (1) curves for 3 other surface air temperature anomaly series. The saturation appears to hold for all the analyzed daily mean series as well as the noon record from Tartu (not shown). The value for τ corresponding to the first (approximate) approach to the saturation level corresponds to the scale where the short-range nonstationarity loses its influence. More stationary long-range variability rules the variability over the longer scales. The nearly saturated behavior of $D(\tau)$ when $\tau > 1$ month shows that the temporal variability of the temperature anomalies is close to stationary because the increment variance grows very slowly as τ oncreases. The saturation of the correlation between the consecutive increments r_τ (1) as τ grows beyond one month shows than in that τ region the correlation between the consecutive increments is stable and independent of τ. And the saturation level at the negative side of the correlations is a confirmation of the domination of negative feedback in the climate system.

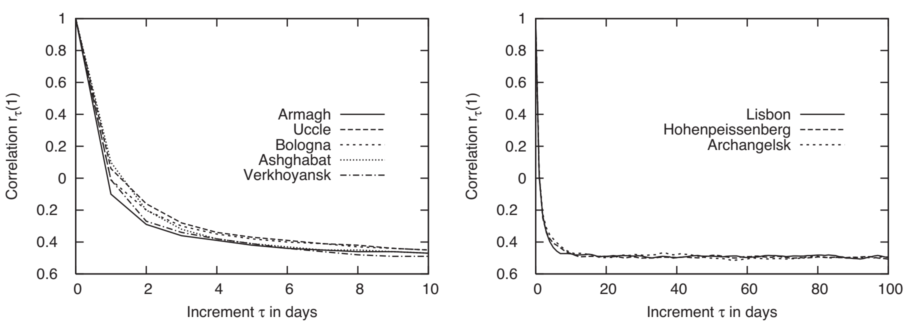

Figure 4. Change of the correlation r_τ (1) between the consecutive increments as the increment interval increases. Left panel: A rapid decay of the coefficient for the short increments. Right panel: A saturation at the level –0.5 at longer τ values

5. STATISTICAL BACKGROUND OF THE FEATURE

The existence of the strong negative correlation between the time series increments during a remarkably wide time interval can be commented on the basis of a simple statistical model. Let us consider the model $X(t) = a(t)$, where $a(t)$ consists of independent, identically distributed random variables with a common variance σ_a^2 (i.e *white noise* WN). It is evident that the corresponding model for its increments is written as

$$X(t) - X(t-1) = a(t) - a(t-1) = b(t), \tag{7}$$

where the variance for b(t) equals $2\sigma_a^2$. Correlation between the consecutive increments during equal time intervals equals –0.5 and is independent of the interval over which the increment is calculated (e.g Mandelbrot 1982). It is also evident that there exists no statistical model to reduce the variance of WN. This means that if there exists a physical system that operates under the influence a large variety of outside forcing, still generating a WN, it should should be regulated by a strong negative feedback, sufficient to keep the increment's variance constant while τ increases. Let's call it full feedback. For $X(t)$ it means that the full feedback would maintain the variance σ_a^2. This means that any model, based on increments and capable to describe the full feedback of the system must obey the property of halving the variance of the increment time series (that is the value of $2\sigma_a^2$ to σ_a^2 in the current example).

In our case, the temperature anomaly sub-series are not expected to behave like WN, but our task is similar, to use the behavior of increments for describing the series behavior. The given example is useful for comparing the correlations between the consecutive increments of various temperature anomaly series. Figure 4 shows that the correlation between consecutive increments in the temperature anomaly series is very close to the magic value of –0.5 for a certain τ range. This is a statistical attestation about the possibility of existence of full feedback in the governing system over some short increment interval. The behavior of the correlations appears to be very similar for all the analyzed series. Using Figure 4 one can expect that the full feedback loop range for the temperature anomaly series is about one or two months. The correlation starts to weaken when τ grows beyond that.

Question about the τ range where $r_\tau(1) \approx -0.5$ is important for better understanding of the climate system. The answer improves our knowledge about the temporal extent of negative feedback in the system. There are 3 long time series of local measurements – for Central England, Stockholm and Praha-Klementinum, that enable us to calculate correlations between the consecutive increments up to very long increment intervals. Figure 5 shows r_τ (1) values calculated for these 3 long temperature series. The increment range span from 100 to 10000 days (i.e up to 27 years).

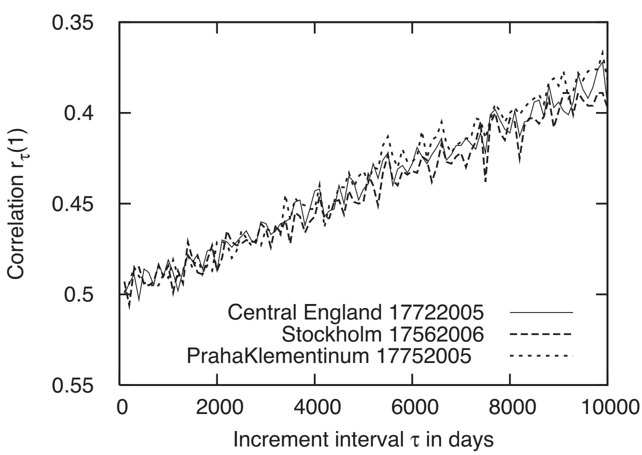

Figure 5. Correlation $r_\tau(1)$ between the consecutive increments for various intervals τ. for the three longest daily temperature anomaly series

There is a slow tendency of increase in r_τ (1) as τ increases. The Figure shows a very similar weakening rate of negative correlation as τ increases for all three series. Although the Central England record does not belong to one station only (Parker et al. 1992), its weakening rate is similar to that for the others. This is an indication of weakening negative feedback in the Earth climate system, perhaps disappearing if the time scale grows far enough. One possible explanation of the weakening may be connected to finite lengths of actual feedback loops in the climate system. They will loose their influence gradually as the increment interval increases. At the same time, other loops that were initiated after the time t and whose effective length is less than τ, increase the random component of the output. One needs also to bear in mind continuous low amplitude random fluctuations of the *solar constant* at the top of the atmosphere (e.g Fröhlich and Lean 1998). That component gradually increases helping to weaken the correlation between the response's increments for large values of τ.

Assuming the same rate of weakening, correlation between the consecutive increments over 120 years should reach zero. The tendency does not contradict a possible random walk type temperature change for the surface air temperature at these stations provided that the increment interval is more than 100 years and the variability in solar irradiance holds the same level than during the last 250 years. Climate on that scale would consist of the independent increments.

No signal of the IPCC predicted positively correlated increments (which is a necessary sign to indicate the positive feedback) was found on the basis of the current analysis. The latter hypothesis about the linear weakening of the negative correlation is quite weak. There is no information available about the long range stability of the total solar irradiance. The modern satellite measured *solar constant* record began only in 1978 (Fräohlich and Lean 1998). Even less grounded seems to be the assumption about the validity of the provisional linearity in that process. But an examination of those variations is beyond the present task.

6. SUMMARY

The IPCC WG I accepts the feedbacks obtained by means of comparing the projected climate of years (2000-2010) with that of (2100-2110) (Soden and Held 2006). In adopting this position where models are preferred to data, the IPCC shows that it has no intention to estimate the cumulative feedback in the contemporary climate system.

The aim of the paper was to determine about the sign of the current cumulative feedback in the climate system on the basis of the surface air temperature series registered at different stations in Europe and Asia. Unlike the IPCC we used the history not prediction to estimate it.

A crucial step in order to estimate climate feedback is the elimination of the short-range signal from the observations. The $D(\tau)$ growth rate shows that it disappears as the increment interval extends beyond three or four weeks. Analyzing the daily series over a sparse temporal grid enables us to remove the effect of the short range variability. Correlations between the consecutive increments essentially depend upon the interval over which the increment is computed. Only the statistical properties of longer increment intervals can determine the long-range variability in the temperature series. All the analyzed temperature anomaly time series behave in the same way showing strong negative correlation between the consecutive increments over a large interval of increment intervals.

A negative correlation between the consecutive increments in the time series is an indication of domination of the negative feedback in the physical system generating the series at that time interval. An explanation for the series with a constant variance is simple: the negative correlation coefficient means that an increase of the current temperature increment is likely followed by a decrease of the next increment. The strong correlation takes place only between the consecutive increments during the equal time intervals. The sample value of the correlation coefficient changes very slowly as the increment interval grows from 30 days to 200 days and beyond. This means that the effective loop for the cumulative feedback is relatively short. The obtained feedback sign coincides with that obtained by Douglass et al. (2004) and Kärner (2002, 2005).

Time series analysis results on the basis of 24 long temperature series from various European and Asian stations do not support the IPCC conclusion about the dominant role of positive feedback (e.g Soden and Held 2006) as long as the cumulative feedback sign is considered. *Vice versa*, the variability of the air temperature at these stations during the last centuries shows that the influence of growing CO_2 concentration in the atmosphere has been totally eliminated by the system's negative feedback. One can expect that the IPCC used four key feedbacks represent too weak tool to properly describe the cumulative effect of all actually operating feedback loops in the climate system. Its results are therefore not relevant for understanding the current climate system variability.

ACKNOWLEDGMENTS

I thank the editor and unknown reviewer for their strong effort to improve the paper's readability.

REFERENCES

Chou M-D., R.S. Lindzen, A.Y. Hou, 2002: Comments on "The Iris hypothesis: A negative or positive cloud feedback?" *J. Climate,* **15,** 2713-2715.

Climate Change 2001: Summary for Policymakers and Technical Summary of theWorking Group I Report. WMO/UNEP, Cambridge University Press, 98 pp.

Douglass D.H., E.G. Blackman, and R.S. Knox, 2004: Temperature response of Earth to the annual solar irradiance cycle. *Phys. Lett.,* **A 323,** 315-322.

Davis A., A.Marshak, W.Wiscombe, and R.Cahalan. Multifractal characterizations of intermittency in nonstationary geophysical signals and fields. In *Current Topics in Nonstationary Analysis* (G. Trevino et al. eds) World-Scientific, Singapore, 1996, 97-158.

Fröhlich C. and J. Lean J, 1998. Total Solar Irradiance Variations, in: F.L.Deubner et al., Eds., *New Eyes to see inside the Sun and Stars*, Proceedings IAU Symposium 185, Kyoto, August 1997, Kluwer Academic Publ., Dordrecht, The Netherlands, pp. 89-102.

GAMDT (The GFDL Global Atmospheric Model Development Team), 2004: The new GFDL global atmosphere and land model AM2-LM2: Evaluation with prescribed SST simulations. *J. Climate,* **17,** 4641-4673.

Kärner O. 2005: Some examples of negative feedback in the earth climate system. *Centr. European J. Phys.,* **3,** 190-208.

Klein Tank A.M.G. and coauthors, 2002. Daily dataset of 20th-century surface air temperature and precipitation series for the European Climate Assessment. *Int. J. Climatol.,* **22,** 1441-1453.

Lin, B., B. Wielicki, L. Chambers, Y. Hu, and K-M. Xu, 2002: The Iris hypothesis: A negative or positive cloud feedback? *J. Climate,* **15,** 3-7.

Lindzen, R.S., M-D. Chou, and A.Y. Hou, 2001: Does the earth have an adaptive infrared iris? *Bull. Amer. Meteor. Soc.,* **82,** 417-432.

Lovejoy S. and D. Schertzer, 1986: Scale invariance in climatological temperatures and the local spectral plateau. *Ann. Geophys.,* **4B**, 401-410.

Malamud B.D., and D.L. Turcotte, 1999: Self-affine time series: I. Generation and analyses. *Adv. in Geophys.,* **40,** 1-90.

Mandelbrot, B.B., 1982: *The fractal geometry of nature*, W.H.Freeman, New York.

Monin A.S. and A.M. Yaglom, 1975: *Statistical Fluid Mechanics*, Vol 2., MIT Press Boston Massachusetts.

Parker D.E., T.P. Legg, and C.K. Folland: 1992. A new daily Central England Temperature Series, 1772-1991. *Int. J. Climatol*, **12,** 317-342.

Rial J.A., R.A. Pielke Sr., M. Beniston, M. Claussen, J. Canadell, P. Cox, H. Held, N. de Noblet-Ducoudre, R. Prinn, J.F. Reynolds, and J.D. Salas, 2004: Nonlinearities, feedbacks and critical thresholds within the earth's climate system. *Climatic Change,* **65,** 11-38.

Soden, B.J. and I.M. Held, 2006: An assessment of climate feedbacks in coupled ocean-atmosphere models. *J. Climate,* (in press)