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Atmospheric Chemistry and Physics

Technical Note: Long-term memory effect in the atmospheric CO_2 concentration at Mauna Loa

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Abstract. The monthly mean values of the atmospheric carbon dioxide concentration derived from in-situ air samples collected at Mauna Loa Observatory, Hawaii, USA during 1958–2004 (the longest continuous record available in the world) are analyzed by employing the detrended fluctuation analysis to detect scaling behavior in this time series. The main result is that the fluctuations of carbon dioxide concentrations exhibit long-range power-law correlations (long memory) with lag times ranging from four months to eleven years, which correspond to 1/f noise. This result indicates that random perturbations in the carbon dioxide concentrations give rise to noise, characterized by a frequency spectrum following a power-law with exponent that approaches to one; the latter shows that the correlation times grow strongly. This feature is pointing out that a correctly rescaled subset of the original time series of the carbon dioxide concentrations resembles the original time series. Finally, the power-law relationship derived from the real measurements of the carbon dioxide concentrations could also serve as a tool to improve the confidence of the atmospheric chemistry-transport and global climate models.

1 Introduction

A very important aspect of the climate problem consists in recognition of anthropogenically induced changes caused by increased CO_2 emissions to the atmosphere, taking, however, into account the complexity of all interactive processes including chemistry and dynamics of the atmosphere and hydrosphere (Jacovides et al., 1994; Crutzen et al., 1999; Kondratyev and Varotsos, 2001a, b; Varotsos et al., 2001; Schulz et al., 2001; Asher et al., 2004; Aziz et al., 2005). In this connection, highly uncertain quantitative estimates of anthropogenic impacts on global climate deserve special attention (Berger and Dameris, 1993; Dameris et al., 2005, Reid et al., 1998).

Recent years have been marked by an undoubtedly growing interest in the problem of complex studies of atmospheric CO_2 in connection with the necessity to obtain reliable estimates of the CO_2 (both natural and anthropogenic) impact on global climate. The global climate numerical simulation performed recently with consideration of not only anthropogenically induced growth of greenhouse gases concentrations, but also increasing content in the atmosphere of anthropogenic sulphate aerosol revealed a much more complicated pattern of climate formation than it was supposed before: the aerosol-induced climate cooling is mostly compensated from the greenhouse warming (Kondratyev and Varotsos, 1995; Varotsos, 2002a,b; Cartalis and Varotsos, 1994).

One of the main uncertainties and difficulties in assessment of the role of atmospheric CO_2 in climate changes is connected with the absence of adequate information about its temporal variability values, and, in particular, whether CO_2 observations remain residually correlated with one another even after many years (long-range dependence).

In an attempt to resolve the aforesaid problems, a modern method of statistical physics is herewith applied to the CO_2 observations that are collected at Mauna Loa, Hawaii. The necessity to employ a modern method of CO_2 data analysis stems from the fact that most of the atmospheric quantities obey non-linear laws, which usually generate non-stationarities. These non-stationarities often conceal the existing correlations into the examined time series and therefore, instead of the application of the conventional Fourier spectral analysis on the atmospheric time series, new analytical techniques capable to eliminate the non-stationarities in the data should be utilized (Lovejoy, 1982; Schertzer and Lovejoy 1985; Tuck and Hovde, 1999; Hu et al., 2001; Chen et al., 2002; Tuck et al., 2003; Grytsai et al., 2005).

Nowadays, the wavelet technique (e.g., Koscielny-Bunde

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et al., 1998) and the detrended fluctuation analysis (DFA) (Peng et al., 1994) are among the most often used tools along these lines. Experience gained from recent studies testifies to the fact that DFA has already proved its usefulness in several complex systems (e.g., Stanley et al., 1999; Zhu and Liu, 2003; Syroka and Toumi, 2001; Varotsos et al., 2002, 2003a, b, 2006c, d; Chen et al., 2005). Very recently, DFA has been applied to the time series of the surface air-pollutants (Varotsos et al., 2005), the aerosol index (Varotsos et al., 2006b), the total ozone content (Varotsos 2005a,b) and the tropospheric temperature (Varotsos and Kirk-Davidoff, 2006). More information about the DFA method is given below (Sect. 2).

The present paper examines the time scaling of the fluctuations of the atmospheric CO_2 concentrations by using the longest record of observations in the world (1958–2004). The results obtained, would help to the enhancement of the fidelity of the available climate models.

2 Methodology and data analysis

As has been mentioned above, the data employed in the present study have been continuously collected at Mauna Loa Observatory, Hawaii (19°32′ N, 155°35′ W), since 1958.

Four air samples are collected each hour and are analyzed by infrared spectroscopy for CO_2 concentrations. It has to be pointed out that Mauna Loa site is considered one of the most favorable locations for measuring undisturbed air because possible local influences of vegetation or human activities on atmospheric CO_2 concentrations are minimal and any influences from volcanic vents may be excluded from the records. In addition, the methods and equipment used to obtain these measurements have remained essentially unchanged during the 47-year monitoring program (Keeling and Whorf, 2005). Due to the fact that in the first year (1958) of the available time series 4 months of data were missing, this year was entirely ignored in our analysis. In addition, the existing very few gaps in the data were filled using polynomial interpolation. The averaged monthly mean values of the CO_2 concentrations are herewith analyzed by employing the DFA method (detailed information is given in Varotsos and Kirk-Davidoff, 2006 and in references therein), which is briefly described below.

In DFA, the nonstationary time series $y(t)$ is first integrated and then it is divided into segments of equal length, Δt. In each segment, a least squares line (or polynomial curve of order l, DFA-l) is then fitted, in order to detrend the integrated time series by subtracting the locally fitted trend in each segment. The root-mean-square fluctuations $F_d(\Delta t)$ of this integrated and detrended time series is calculated over all time scales (segment sizes).

More precisely, the detrended fluctuation function $F(\tau)$ is calculated as follows:

$$F^2(\tau)=\frac{1}{\tau}\sum_{t=k\tau+1}^{(k+1)\tau}[y(t)-z(t)]^2,\ k=0,1,2,\ldots,\left(\frac{N}{\tau}-1\right) \quad (1)$$

where $z(t)=at+b$ is the linear least-square fit to the τ data points contained into a segment.

Without dwelling upon details, for scaling dynamics, the averaged $F^2(\tau)$ over the N/τ intervals with length τ is expected to obey a power-law, notably:

$$\left\langle F^2(\tau)\right\rangle \sim \tau^{2\alpha} \quad (2)$$

and the power spectrum function scales with $1/f^{\beta}$, with $\beta=2\alpha-1$ (Kantelhardt et al., 2002).

We briefly mention that the slope α of the line on a log-log plot relating the average fluctuation and the segment size indicates the plausible presence of power-law scaling. A slope $\alpha\neq0.5$ implies the existence of long-range correlations, while $\alpha=0.5$ corresponds to the classical random (white) noise. If $0<\alpha<0.5$, power-law anticorrelations are present (antipersistence). If $0.5<\alpha\leq1.0$, long-range power-law correlations prevail; the case $\alpha=1$ corresponds to the so-called $1/f$ noise. In addition, when $1<\alpha<1.5$, then long-range correlations are again present (but are stronger than in the previous case) (e.g., Talkner and Weber, 2000; Chen et al. 2005).

It is worth to recall that a time-series is said to display long-range correlations when some properties of the time-series at different times are correlated and its correlation function decays much slower than exponential decay (e.g. power-law decay). It would be of interest to mention that wavelet-based estimators of self-similarity or long-range dependence scaling exponent lead to larger (smaller) mean squared errors for short (long) time-series comparing with DFA that is not wavelet-based (Audit et al., 2002; Chen et al., 2005; Varotsos et al., 2006c).

3 Application of DFA to the CO_2 time-series

In order to analyze the time series (shown in Fig. 1) it is important to investigate whether the CO_2 concentration at different times is actually correlated. The motivation for this investigation stems from the observation that many environmental quantities have values which remain residually correlated with one another even after many years (long-range dependence).

It is a truism that the standard tool to address this question is to derive the correlation function and the corresponding power spectrum (or frequency spectrum – spectral density) of the time series, which is simply the Fourier transform of the autocorrelation function. Usually, the short-range correlations are described by the autocorrelation function, which

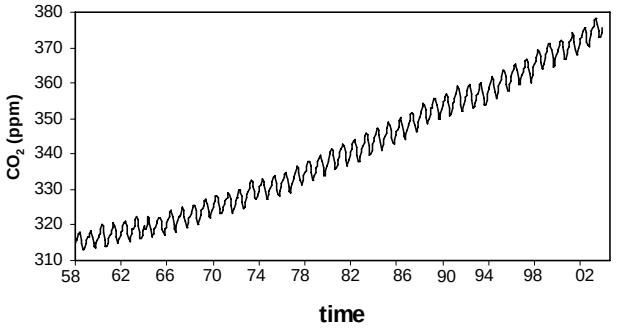

Fig. 1. Time series of CO_2 concentration observed at Mauna Loa Observatory, during 1958–2004.

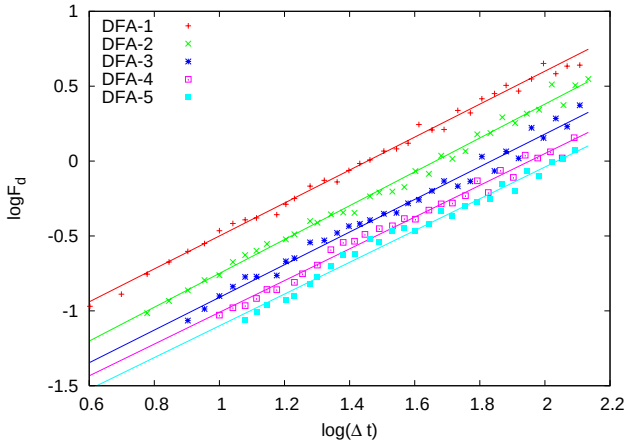

Fig. 2. Log-log plot of the DFA-l versus temporal interval Δt (in months) for detrended (by using the 10th order polynomial trend) and deseasonalized (by applying the Wiener filtering) CO_2 concentrations, during 1959–2004. The α-values for DFA-1, DFA-2, DFA-3, DFA-4, DFA-5 are 1.10 ($\pm$0.02), 1.13 ($\pm$0.02), 1.09 ($\pm$0.02), 1.06 ($\pm$0.02), 1.06 ($\pm$0.03), respectively.

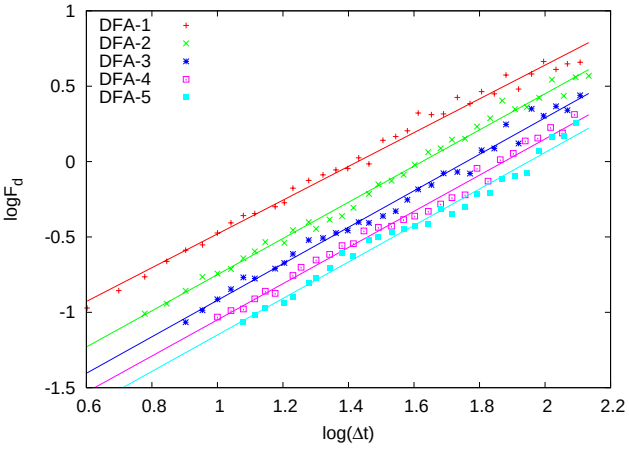

Fig. 3. Log-log plot of the DFA-l versus temporal interval Δt (in months) for detrended (treated as in Fig. 2) and deseasonalized (using the deviations of the monthly mean values from their normal values) CO_2 concentrations, during 1959–2004. The derived α-values for DFA-1, DFA-2, DFA-3, DFA-4, DFA-5 are 1.12 ($\pm$0.02), 1.20 ($\pm$0.02), 1.21 ($\pm$0.02), 1.20 ($\pm$0.02), 1.21 ($\pm$0.03), respectively.

declines exponentially with a certain decay time. In opposite, the long-range correlations imply that the autocorrelation function declines as a power-law in time rather than exponentially. However, the direct calculation of the autocorrelation function is usually not appropriate due to noise superimposed on the collected data and due to underlying trends of unknown origin. Furthermore, in practice, we do not know the appropriate scaling transformation factors, in advance, or if one does exist.

To quantify the fluctuations of the measured CO_2 concentrations we analyze the data following the steps of DFA (described in Sect. 2). However, as it is evident from Fig. 1, the CO_2 time series is characterized by strong long-term trend and seasonality, which can both be removed (detrending and deseasonalization, respectively) by using various statistical tools. For instance, the detrending may be simply achieved by applying polynomial best fit (e.g., 10th order polynomial trend) to the whole CO_2 time series, while the deseasonalisation can be implemented by applying the classical Wiener method (e.g., filtering out the seasonal – 3 months, terannual – 4 months, semiannual – 6 months, annual – 12 months and southern oscillation – almost here 44 months). Another filtering tool to deseasonalise the data is to employ the moving average filtering (e.g., 13-month moving average, thus cutting out the periodicities with periods lower than 13 months). Alternatively, a commonly used method for deseasonalization is to subtract the 46-year average of the CO_2 monthly mean values from those in each year (deviations from the normal).

In the following, the results obtained from the application of DFA to the detrended and deseasonalised CO_2 time series are presented and interpreted.

Assuming that the best deseasonalisation of the CO_2 time series (shown in Fig. 1) is effectively achieved by applying the Wiener filtering (as described above) and its detrending is accomplished by using the 10th order polynomial trend, then the resulting α-values of DFA-l have a mean 1.08 and standard deviation 0.03 (Fig. 2).

Next, let us treat the deseasonalisation using the deviations from the normal values, while the detrending accomplished as in the previous case. Then the α-values of DFA-l have a mean 1.20 and standard deviation 0.03 (Fig. 3).

It should be stressed that α-values obtained, at the aforesaid two cases, are in close agreement, to those reported in the comment by Sarlis and Skordas (2006b). It is also worthwhile to mention that a second comment by Sarlis and Skordas (2006a) demonstrated that removing the seasonality by the conventional "deviations from the normal" method, then α-values vary between 0.91–1.03. The latter verifies the α-

values obtained in Varotsos et al. (2006a), where the deseasonalization and detrending methods employed were a bit different (described above).

The main conclusion drawn from the above-mentioned multiple analyses is that the α- value of DFA ranges between (0.91, 1.21), independently of the deseasonalisation and detrending tool employed. Therefore, the fluctuations of the CO_2 concentrations exhibit long-range persistence (almost 1/f – type). The strong persistence found signifies that the fluctuations in CO_2 concentration, from small time intervals to larger ones (up to 11 years) are positively correlated in a power-law fashion. In other words, persistence refers to the "long memory" or internal correlation within the CO_2 concentration time-series. For example, there is a tendency an increase in the CO_2 concentration to be followed by another increase in the CO_2 concentration at a different time in a power-law fashion. The latter conclusion suggests that the correlations between the fluctuations in CO_2 concentration do not obey the classical Markov-type stochastic behavior (exponential decrease with time), but display more slowly decaying correlations.

One fact that attracts attention is that the persistence found above provides, in principle, a forecast for the CO_2 concentration, which assumes that the value of the CO_2 concentration in the "following time interval" (up to 11 years) will be the same as in the corresponding "current time interval". In reality, it apparently has a different meaning from the conventional forecast in climatology, which assumes that the value of CO_2 concentration in the "following" e.g., 11 years will be the same as the "overall climatological" CO_2 concentration mean.

It should be emphasized that the data analyzed above refer to CO_2 time series of around 5×10^2 data points. It was preferred to use DFA and not, for example, wavelet based estimators of self-similarity because recent studies, e.g., Audit et al. (2002), demonstrate that the wavelet transform modulus maxima (WTMM) estimator leads to larger mean squared errors when analyzing short time series of length 10^2 data points. In other words, Audit et al. (2002) showed that for time series of the aforementioned length, the DFA exponent is the best estimator.

In addition, an attempt has been made to compare the DFA-results of Mauna Loa data against South Pole, Antarctica (89°59′ S, 24°48′ W) CO_2 observation 1973–2004 time series (showing much less seasonal dependence). This time series is available at http://cdiac.esd.ornl.gov/trends/co2/sio-spl.htm. The DFA-1 applied to the detrended (with 9th order polynomial fitting) and deaseasonalized (using deviations from the normal) CO_2 record at South Pole gave that α=1.22, which reveals that persistent long-range correlations are again present (as in the case of Mauna Loa mentioned above).

Finally, we investigate whether the strong persistence found in CO_2 concentration time series stems from the values of CO_2 concentrations themselves and not from their time evolution. With this aim in view, the deseasonalized and detrended CO_2 concentrations were randomly shuffled. If the shuffled CO_2 values follow the random (white) noise, then the persistence found above does not come from the data, but from their time evolution (e.g., Varotsos et al., 2006a, b, d). Indeed the application of the DFA-1 to the shuffled CO_2 data gives α=0.49±0.02, which reveals that the shuffled deseasonalized and detrended CO_2 data are practically uncorrelated.

Therefore, the power-law relationship derived from the real measurements of the CO_2 concentrations eventually stems from their time evolution (temporal correlations). The latter could also be used to test the scaling performance of the climate prediction models under different scenarios of CO_2 levels (Ebel, 2001; Govindan et al., 2002).

4 Conclusions

Long-range correlations of the fluctuations of CO_2 concentrations measured at Mauna Loa, Hawaii during 1958–2004 were investigated by applying the DFA method. The main finding is that the fluctuations of the CO_2 concentrations exhibit strong long-range persistence (almost 1/f – type), which signifies that the fluctuations in CO_2 concentrations, from small time intervals to larger ones (up to 11 years) are positively correlated in a power-law fashion. This scaling comes from the time evolution and not from the values of the CO_2 data. Therefore the long-range correlations in the atmospheric CO_2 that deduced from the present analysis can help in recognition of anthropogenically induced changes caused by increased CO_2 emissions to the atmosphere on the background of natural atmosphere changes. More specifically, the scaling property detected in the real observations of CO_2 concentrations could be used to test the scaling performance of the leading global climate models under different scenarios of CO_2 levels and to improve the performance of the atmospheric chemistry-transport models. The latter is currently under investigation by employing daily CO_2 observations and the relevant results will appear elsewhere, soon.

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