

**Long-term memory
effect in the
atmospheric CO₂
concentration**

C. Varotsos et al.

Technical Note: Long-term memory effect in the atmospheric CO₂ concentration at Mauna Loa

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Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Abstract

The monthly mean values of the atmospheric carbon dioxide concentration derived from in-situ air samples collected at Mauna Loa Observatory, Hawaii, 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, 2002a; Varotsos et al., 2001; Schulz et al., 2001; Asher et al., 2004; Aziz et al., 2005; Dameris et al., 2005). In this respect, highly uncertain quantitative estimates of anthropogenic impacts on global climate deserve special attention (Berger and Dameris, 1993; Hein et al., 2001; Dameris et al., 2005; Eyring et al., 2005).

Long-term memory effect in the atmospheric CO_2 concentration

C. Varotsos et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Long-term memory effect in the atmospheric CO₂ concentrationC. Varotsos et al.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[⏪](#)[⏩](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

Recent years have been marked by an undoubtedly growing interest in the problem of complex studies of atmospheric CO₂ in connection with the necessity to obtain reliable estimates of the CO₂ (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, 2002; Cartalis and Varotsos, 1994).

One of the main uncertainties and difficulties in assessment of the role of atmospheric CO₂ in climate changes is connected with the absence of adequate information about its temporal variability values, and, in particular, whether CO₂ 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 CO₂ observations that are collected at Mauna Loa, Hawaii. The necessity to employ a modern method of CO₂ 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 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; Talkner and Weber, 2000; Zhu and Liu, 2003; Syroka and Toumi, 2001; Varotsos

et al., 2002, 2003a, b, 2005; Chen et al., 2005). Very recently, the DFA method has been applied to the time series of the surface air-pollutants (Varotsos et al., 2005), the aerosol index (Varotsos et al., 2006), 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 CO₂ 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 CO₂ 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 CO₂ 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). The averaged mean monthly values of the CO₂ 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

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

$F_d(\Delta t)$ of this integrated and detrended time series is calculated over all time scales (segment sizes).

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

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

5 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:

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

10 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 box size indicates the plausible presence of power law scaling. A slope $\alpha \neq 1/2$ implies the existence of long-range correlations, while $\alpha=1/2$ corresponds to the classical random (white) noise. If $0 < \alpha < 0.5$, power-law anticorrelations are present (antipersistence). If $0.5 < \alpha \leq 1.0$, 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; Talkner and Weber, 2000).

20 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 (Chen et al., 2005).

25

Long-term memory effect in the atmospheric CO₂ concentration

C. Varotsos et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

◀

▶

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

3 Application of DFA to the CO₂ time-series

In order to analyze the time series (shown in Fig. 1) it is important to investigate whether the CO₂ 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 declines exponentially with a certain decay time. In opposite, the long-range correlations (long-range dependence) imply that the autocorrelation function declines as a power-law in time rather than exponentially. This implies that: a correctly rescaled subset of the original time series resembles the original time series. 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 CO₂ concentrations we analyze the data following the steps of DFA (described in Sect. 2). The application of DFA-1 to the deseasonalized and detrended CO₂ concentration time-series reveals $\alpha=1.05\pm 0.04$ (Fig. 2) for time scales between 4 months to 11 years. We found the same results by using a polynomial fit of order l (DFA- l) to the same time series of the CO₂ concentrations. More specifically, going from DFA-1 to DFA-5, the α -value was found to range from 0.98 to 1.08. Therefore, the fluctuations of the CO₂ concentrations exhibit $1/f$ – type long-range persistence. The strong persistence found signifies that the fluctuations in CO₂ 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-term memory effect in the atmospheric CO₂ concentration

C. Varotsos et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

“memory” or internal correlation within the CO₂ concentration time-series. For example, there is a tendency an increase in the CO₂ concentration to be followed by another increase in the CO₂ concentration at a different time in a power-law fashion. The latter conclusion illustrates that the correlations between the fluctuations in CO₂ 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 CO₂ concentration, which assumes that the value of the CO₂ concentration 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 CO₂ concentration in the “following” e.g. 11 years will be the same as the “overall climatological” CO₂ concentration mean.

Finally, it was investigated whether the persistence found in CO₂ concentration time series stems from the values of CO₂ concentrations by themselves and not from their time evolution. With this aim in view, the deseasonalized and detrended CO₂ concentrations were randomly shuffled. If the shuffled CO₂ 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., 2006). Indeed the application of the DFA-1 to the shuffled CO₂ data gives $\alpha=0.49\pm 0.02$, which reveals that the shuffled deseasonalized and detrended CO₂ data are practically uncorrelated. Therefore the power-law relationship derived from the real measurements of the carbon dioxide concentrations eventually stems from their time evolution. The latter could also be used to test the scaling performance of the climate prediction models under different scenarios of carbon dioxide levels (Ebel, 2001; Govindan et al., 2002).

Long-term memory effect in the atmospheric CO₂ concentration

C. Varotsos et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

4 Conclusions

Long-range correlations of the fluctuations of CO₂ 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 CO₂ concentrations exhibit 1/f – type long-range persistence, which signifies that the fluctuations in CO₂ 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 carbon dioxide data. The scaling property detected in the real observations of CO₂ concentrations could be used to test the scaling performance of the leading global climate models under different scenarios of CO₂ levels and to improve the performance of the atmospheric chemistry-transport models.

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Long-term memory effect in the atmospheric CO₂ concentration

C. Varotsos et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

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Long-term memory effect in the atmospheric CO₂ concentrationC. Varotsos et al.

Title Page

Abstract

Introduction

Conclusions

References

Tables

Figures

⏪

⏩

◀

▶

Back

Close

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Long-term memory effect in the atmospheric CO₂ concentration

C. Varotsos et al.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[⏪](#)[⏩](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

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Long-term memory effect in the atmospheric CO₂ concentrationC. Varotsos et al.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[⏪](#)[⏩](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

Long-term memory effect in the atmospheric CO₂ concentration

C. Varotsos et al.

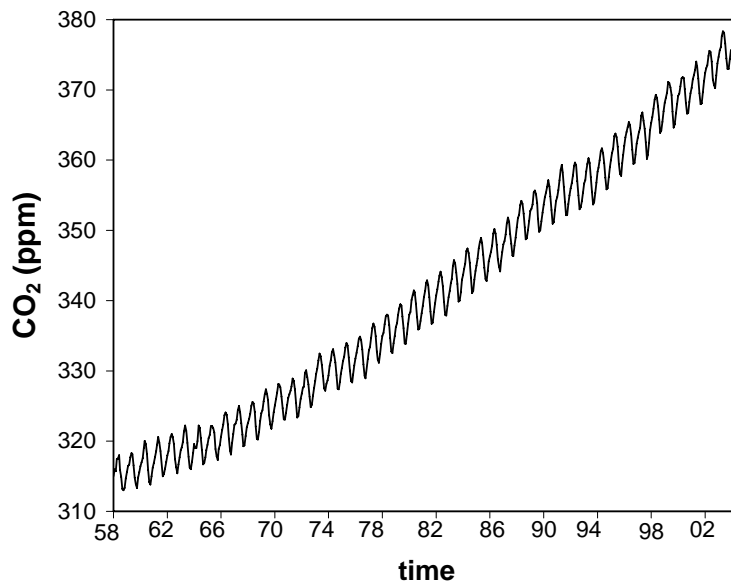


Fig. 1. Time series of CO₂ concentration observed at Mauna Loa Observatory, during 1958–2004.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

**Long-term memory
effect in the
atmospheric CO₂
concentration**

C. Varotsos et al.

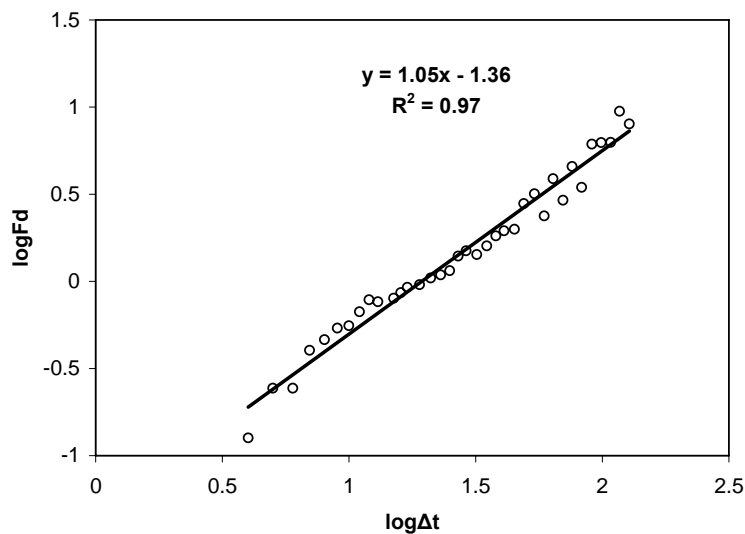


Fig. 2. Log-log plot of the DFA-function versus temporal interval Δt (in months) for detrended and deseasonalized CO₂ concentrations, during 1958–2004.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[⏪](#)[⏩](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

**Long-term memory
effect in the
atmospheric CO₂
concentration**

C. Varotsos et al.

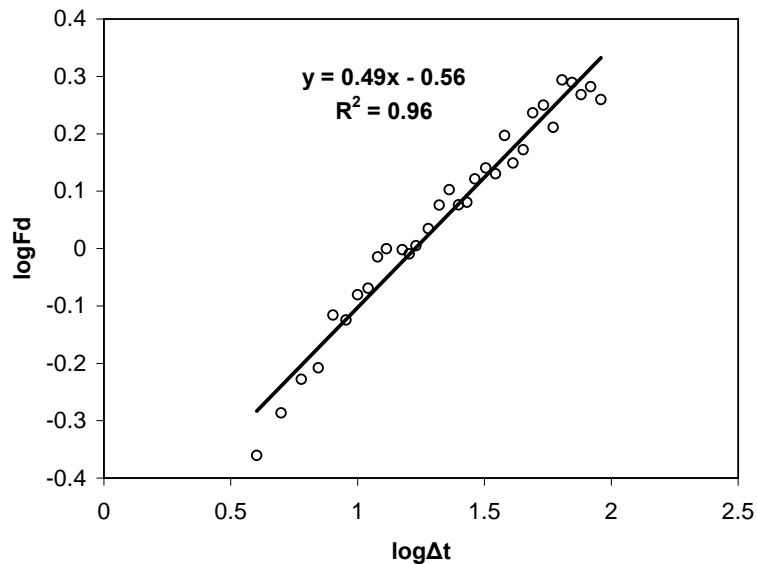


Fig. 3. Log-log plot of the DFA-function versus temporal interval Δt (in months) for the shuffled detrended and deseasonalized CO₂ concentrations, during 1958–2004.

[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[⏪](#)[⏩](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)