Chaotic Characteristics of the Southern Oscillation Index

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Introduction

The Southern Oscillation (SO) is a phenomenon which affects broadscale atmospheric and oceanographic features of the tropical Pacific Ocean. The state of the oscillation can be characterized by indices based on variations in either sea surface temperatures, or differences in barometric pressures. Its best-known extremes are El Niño events. Analyses of the Southern Oscillation Index (SOI) and its relationships with hydrological phenomena have been presented by many researchers in recent decades [*e.g.*, *Trenberth*, 1984; *Gordon*, 1985; *Opoku-Ankomah and Cordery*, 1993; *Moss et al.*, 1994; *Mullan*, 1995].

Recent studies that consider the chaotic behaviour of a time series, such as sunspots, have indicated that better predictions can be made using developments in dynamical systems theory [*Mundt et al.*, 1991; *Jinno et at.*, 1995]. Chaotic dynamics arise in nonlinear deterministic systems very sensitive to initial conditions (so-called "butterfly effect") which yield outputs that are indistinguishable by standard techniques from a stochastic process [*Rodriguez-Iturbe and de Power*, 1989]. A chaotic time series originates from a nonlinear system with a small number of degrees of freedom, whereas a stochastic time series arises from a system with many degrees of freedom [*Jeong and Rao*, 1996]. There is now considerable interest in identifying chaos in natural or experimentally observed time series.

In this study, the SOI time series is analysed to determine its chaotic characteristics. We try to identify the essential features of the SOI when viewed as a dynamic system. If a time series can be identified as deterministic chaos, then the knowledge of these underlying characteristics will make possible to make short-term predictions (in this case of the SOI) by setting the system on a fractal trajectory (strange attractor), although chaotic systems are unpredictable in the long term.

Data

Several indices have been used to monitor the SO. One commonly used SOI is derived from values of monthly Mean Sea Level Pressure (MSLP) difference between Papeete, Tahiti (149.6°W, 17.5°S.) and Darwin, Australia (130.9°E, 12.4°S). The SOI data used in this study are the monthly series from January 1866 to December 1995, normalised to mean zero and a standard deviation of one. The method of calculation for the SOI is given by *Ropelewski and Jones* [1987] and *Allan et al.*[1991], who carefully infilled the all missing data by correlation with other observation stations. In order to extract the chaotic characteristics form a time series, a long continuous series is essential.

Methods

Various definitions have been proposed for deterministic chaos. According to *Ott*'s definition, 1) it is aperiodic, 2) its autocorrelation function converges to zero with the increase of lag time, 3) it shows extremely sensitive dependence to initial conditions. In this study, the following methods are used to identify the chaotic characteristics of SOI time series.

Noise Reduction

Observed hydro-meteorological time series generally contain noise. Methods for estimation of fractal dimension are extremely noise sensitive. Therefore, time series need firstly to be cleaned by a noise reduction scheme. *Berndtsson et al.* [1994] indicate that raw time series of sunspots, temperature and precipitation variables do not show any chaotic deterministic properties, but after noise reduction, all three variables display a low-dimensional chaotic behaviour. In this study, we use the algorithm by *Schreiber* [1993] for the above purpose. This is a simple nonlinear noise reduction method especially developed for dimension estimation.

Autocorrelation Function

The autocorrelation function of SOI time series is calculated to see whether it converges to zero with increasing lag time.

Spectral Analysis

Spectral analysis is carried out to check on periodicity and to see if the time series has the broadband spectra necessary for chaos. We use Maximum Entropy Method (MEM) for this purpose because it has a higher frequency resolution ability than other spectral analyses like Fast Fourier Transform (FFT).

Lyapunov Exponents

In order for a system to be chaotic it must possess at least one positive Lyapunov exponent, which results in sensitive dependence on initial conditions. We calculate the Largest Lyapunov Exponent (LLE) using the method of *Wolf et al.* [1985]. This algorithm is robust over a large range of input parameters and relatively accurate for small, noisy data sets.

Fractal Dimension

There are several ways to define the fractal dimension. In this paper we use the correlation dimension introduced by *Grassberger and Procaccia* [1983]. The dimension d of the strange attractor indicates how many variables are necessary to describe evolution in time. For example, d=2.5, indicates that a time series can be described by a system equation containing three independent variables. In this paper, firstly the algorithm according to *Grassberger* [1990] is used to estimate correlation dimension. The Grassberger-Procaccia (G-P) method is popular and commonly used for fractal dimension estimation, but some shortcomings are also pointed out. In this paper, an improved method by *Judd* [1992] is also used to estimate the fractal dimension.

Results

The results will be shown in the presentation at the symposium.

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