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Chaotic nature of total column ozone over tropical station by time series analysis

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ABSTRACT
The paper deals with monthly total column ozone concentration over Kodaikanal, Tamilnadu. The basic rationale is to investigate the existence of chaos within the relevant time series. Method of measuring trend, Mann Kendall trend analysis, measuring self similarity, Lyapunov exponent is adopted here as the preferred research methodology. After a rigorous investigation, a low dimensional chaos with the persistent behaviour is identified within the time series pertaining to monthly total column ozone concentration over Kodaikanal, Tamilnadu.

Key words: Trend, Ozone, Tropical station, Time Series Analysis, Mann Kendall trend analysis, self similarity, Lyapunov exponent, chaos.

INTRODUCTION

The forecasting plays a very important role in addressing weather related business, and environmental problems. Generally there are two approaches in the forecasting: time series approach and predictors approach. Time series approach has many advantages compared to predictor's method. To analyze time series data in terms of non-linear dynamics, chaos theory plays the role of apt direct link (Schrieber, 1998). Weigend and Gershenfeld (1993) discussed Impact of past decisions upon the future decisions in the situation of intrinsic chaos. Many areas of science, including biology, physiology, and medicine; geo- and astrophysics, hydrology, as well as the social sciences and finance have been diagnosed with chaotic properties (Khan et al., 2005). In recent decades, research on non-linear deterministic dynamics has created new insights in the problems associated with complex phenomena (Sivakumar et al., 2006). In non-linear dynamics, characterization of chaos from real world observations is a difficult problem (Khan et al., 2005). Systematic study of chaos started in the 1960s (Smale 1963).It started because the linear techniques dominating the field of applied mathematics found inadequate while dealing with chaotic phenomena; and in the case of amazing irregularities within non-linear deterministic systems, the linear methods identified them as stochastic.

In many forecasting situations, it is often difficult to determine whether a time series under study is generated from a linear or nonlinear underlying process or whether one particular method is more effective than the other in out of sample forecasting. Thus, it is difficult for forecasters to choose the right technique for their unique situation at the beginning. In order to remove the difficulty for the selection of best method some basic statistical and chaotic analysis are required. Study of potentially chaotic behaviour can be divided into three groups: identification of chaotic behaviour, modelling and prediction, and control (Kugiumtzis et al., 1995). Ozone is a molecule made up of three oxygen atoms, which is naturally formed by photolysis of normal oxygen by ultraviolet solar radiation at wavelengths below 242.5 nm in the stratosphere. A certain amount of ozone is also produced in the troposphere in a chain of chemical reactions involving hydrocarbons and nitrogen-containing gases. Though ozone is a minor atmospheric constituent, with an average concentration of about 3 parts per million volume (ppmv), the radiation properties of this "greenhouse" gas make it a significant contributor to the radiative energy balance of the atmosphere. It is also an important regulator of the ultraviolet solar radiation received at the Earth's surface. Most of the atmospheric ozone (90 per cent) is located in the stratosphere with a maximum concentration between 17 and 25 km. The concentration is dependent on location (particularly latitude) and season, where its presence causes stratospheric temperature inversion leading to maximum temperature at the stratopause. In addition to its radiation properties, ozone reacts with many other trace species, some of which are anthropogenic in origin. The geographical and vertical distributions of ozone in the atmosphere are determined by a complex interaction of atmospheric dynamics and photochemistry. Ozone near the ground is monitored because it is a product of industrial and urban pollution. Measurements of tropospheric and stratospheric ozone are used for the verification of models that simulate the photochemistry or general circulation of the real atmosphere. Ozone is also measured to determine attenuation of the ozone layer by man-made gases, to validate model estimations of changes in ozone. Many researchers have studied the influence of TOC (Total Ozone Column) Dobson (1926) noticed that high and low values of TCO (Total Ozone Column) are associated with cyclonic and anticyclonic conditions, respectively. Ozone data have been assimilated into numerical models for use in radiative transfer calculation (Nanopoulos et al., 2001; Peng Shi et al., 2013). Present study involves use of monthly total column ozone time series over Kodaikanal, Tamilnadu. Present study has taken in to cognizance influence of spatial and temporal factors. In other words analysis has been carried out at a particular location taking monthly total column ozone time series over Kodaikanal, Tamilnadu.

Study Area

Kodaikanal (10.2381° N, 77.4892° E) is a hill-city of the Dindigul district, Tamil Nadu, India. Kodaikanal sits on a plateau above the southern escarpment of the upper Palani Hills (2,133 metres above MSL), between the Parappar and Gundar Valleys. These hills form the eastward spur of the Western Ghats. Kodaikanal has a monsoon-influenced subtropical highland climate. It has a cool weather throughout the year due to the high elevation of the city.

Materials and Methods

A vast literature is available, where the theoretical concepts underlying the methodologies for the detection and modelling of nonlinear dynamical and chaotic components have been discussed (Khan et al., 2005). Present paper adopts the method of measuring trend, Mann Kendall trend analysis, measuring self similarity and Lyapunov exponent to detect the presence of chaos in the time series pertaining to the monthly total column ozone concentration over Kodaikanal, Tamilnadu between 1994 -2005. The data has been procured from IIT Website and also from the regional meteorological centre. Several techniques have been developed to find trend in the time series data. In the present paper we have employed the Mann Kendall Rank test to identify the turning point or the monotonic change in the total column ozone over Kodaikanal region. We then calculate the Hurst exponent. Through the H value, the given time series data is identified to be persistent, anti-persistent or chaotic. If the time series data shows persistent behaviour, then autoregressive process or moving average or auto regressive moving average methods are applied for their forecasting work analysis. If chaos is present in the system, the next step is to check for magnitude of chaos. The Lyapunov exponent is employed to analysis whether the data has low dimensional chaos or high dimensional chaos.

Measuring Characteristics of Time Series

A time series is the simplest form of temporal data and is a sequence of real numbers collected regularly in time, where each number represents a value. Time series can be described using a variety of qualitative terms such as seasonal, trending, noisy, non-linear and chaotic. This section presents a collection of measures that seek to quantify these descriptors. In addition to the standard statistical measures of a time series used by Nanopoulos et al., (2001), we have extended the scope to include a collection of special features such as long-range dependence and chaotic measures such as Lyapunov and Hurst exponents. These help to provide a rich portrait of the nature of a time series.

Measuring Trend

Trend is a common feature of time series, and it is natural to characterize a time series by its degree of trend. In addition, once the trend of a time series has been measured, we can de-trend the time series to enable additional features such as noise or chaos to be more easily detected. To estimate the trend, we can use smooth nonparametric method, for instance, penalized regression spline (Makridakis et al., 1998). Let Y_t be original data and $1\text{-}Y_t$ be detrended data. Then the measure of trend is

$$1- \frac{\text{var}(1-Y_t^{'})}{\text{var}(Y_t)}$$

Mann Kendall Trend Analysis

The Mann–Kendall does not require the data to follow a certain statistical distribution i.e., it is a nonparametric trend test, (Peng Shi et al., 2013). Mann–Kendall test is chosen to identify any trend in a time series without specifying whether the trend is linear or non-linear (Salas JD, 1993). Also, the Mann–Kendall test is rank order based, insensitive to missing values, and easy to calculate.

The computational procedure for the Mann Kendall test considers the time series of n data points and T_i and T_j as two subsets of data where i = 1,2,3,…, n-1 and j = i+1, i+2, i+3, …, n. The data values are evaluated as an ordered time series. Each data value is compared with all subsequent data values. If a data value from a later time period is higher than a data value from an earlier time period, the statistic S is incremented by 1. On the other hand, if the data value from a later time period is lower than a data value sampled earlier, S is decremented by 1. The net result of all such increments and decrements yields the final value of S (Drapela, K., Drapelova, I., 2011)

The Mann-Kendall S Statistic is computed as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(T_j - T_i)$$

$$Sign(T_j - T_i) = \begin{cases} 1 \text{ if } (T_j - T_i) > 0 \\ 0 \text{ if } (T_j - T_i) = 0 \\ -1 \text{ if } (T_j - T_i) < 0 \end{cases}$$

Where T_j and T_i are the annual values in years j and i, j>I, respectively. At a certain probability level H_0 (no trend in time series) is rejected in favour of H_1 (possible trend in time series) if the absolute value of S equals or exceeds a specified value $S_{\alpha/2}$, where $S_{\alpha/2}$ is the smallest S which has the probability less than $\alpha/2$ to appear in case of no trend. A positive (negative) value of S indicates an upward (downward) trend.

Measuring Self Similarity

The subject of self-similarity and the estimation of statistical parameters of time series in the presence of long-range dependence are becoming more common in several fields of science (Rose,1996). The definition of self-similarity most related to the properties of time series is the self-similarity parameter, Hurst exponent (H) (Mandelbrot.B.B, Wallis. J.R,1969). The Hurst Exponent was originally developed by Harold Hurst in 1951 for use in hydrology to determine optimal dam sizing for the Nile River. Hurst wanted to know how much a previous year's rainfall affected the height of the Nile River. The measure he developed gave him insight into how long a rainfall would cause an increase in the height of the Nile. The Hurst Exponent is a measurement that is non-deterministic in nature and measures what is observed. Currently, there are five methods for estimation of the Hurst Exponent (H). In no particular order they are: re-scaled range, autocorrelation, absolute moment method, aggregated variance method and periodogram method. The original method developed by Hurst was the re-scaled range method. We provide a concise summary of Hurst's rescaled range method below.

Let us assume we have 100 observations N (1), N (2)... N (100). We first start by removing any trend by subtracting the mean (m) from each observation and develop the series N'(1), N'(2), ...N'(100) where N'(t) = N(t) – m. Next, a set of partial sums are formed where N'' (1) = N'(1), N'' (2) = N'(1) + N'(2) etc. until N'' (n) = N'(1) + N'(2) + ... + N'(n). Since this series is a sum of a mean-zero variable, the series will be positive if the majority of variables is positive N'(n) and vice versa if negative. Next, the range R is defined as R = max N'' - min N''. Finally, the range is scaled by the standard deviation (s) of the series to get the re-scaled range = R / s.

Hurst found that (R/S) increments by power-law as time increases, which indicates $(R/S) = c, \tau^H$

H can be estimated as the slope of log-log plot of $(R/S)_\tau$ versus τ.

H describes the correlation between the past and future in the time series. For independent random processes with finite variances, the H value is 0.5. When H > 0.5, the time series is persistent, which means that an increasing trend in the past is indicative of an increasing trend in the future. Conversely, as a general rule, a decreasing trend in the past signifies a persistent decrease in the future. When H < 0.5, the time series is anti-persistent, which means that an increasing trend in the past implies a decreasing trend in the future and vice-versa. If H is more or less equal to 0.5 it indicates that the time series is random.

LYAPUNOV EXPONENT: Identifying a Dynamic System as Deterministic

Although it can be rather difficult to detect, there are ways to test a system for deterministic and chaotic behaviour. The most common test is that of the Lyapunov exponent. The Lyapunov exponent gives the quantitative value for a non-linear dynamical system. A positive largest Lyapunov exponent indicates chaos. It is thus useful to study the mean exponential rate of divergence of two initially close orbits using the formula (Dechert.W.D and Gencay.R, 1992)

$$\lambda = \lim_{t \to \infty} \frac{1}{t} \ln \frac{|\Delta x(X_0, t)|}{|\Delta x_0|}$$

This number, called the Lyapunov exponent "λ", is useful for distinguishing among the various types of systems. It works for discrete as well as continuous systems

$\lambda < 0$ Negative Lyapunov exponents are characteristic of dissipative or non-conservative system

$\lambda = 0$ A Lyapunov exponent of zero indicates that the system is in steady state mode or conservative.

$\lambda > 0$ A large positive Lyapunov exponent indicates the system is unstable and chaotic

Implementation procedure

The dataset explored in the present study consists of 16 years (1994-2005), that is, 192 months. Thus, the scalar time series of monthly total column ozone concentration over Kodaikanal contains 192 data points. The Time series components of trend, seasonal and random are computed for the whole data series. Figure 1 shows the time series components of trend, seasonal and random and Figure 2 shows the autocorrelation function for the monthly total column ozone time series over Kodaikanal, Tamil Nadu.

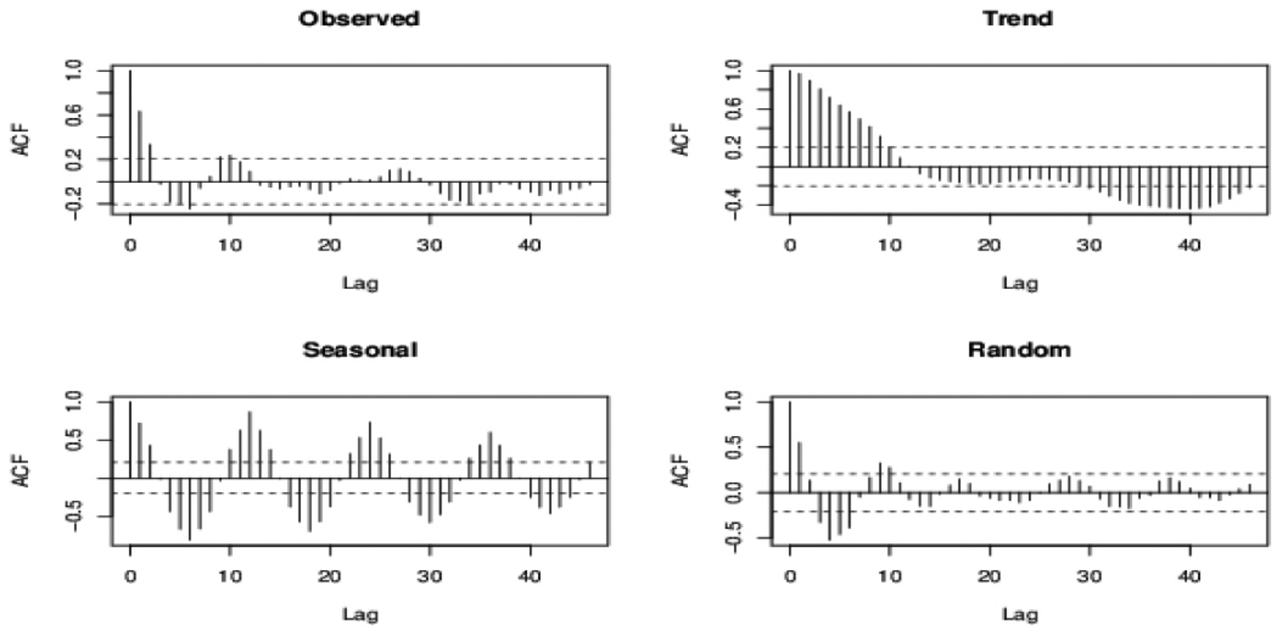

Figure 1. The Time series components of trend, seasonal and random.

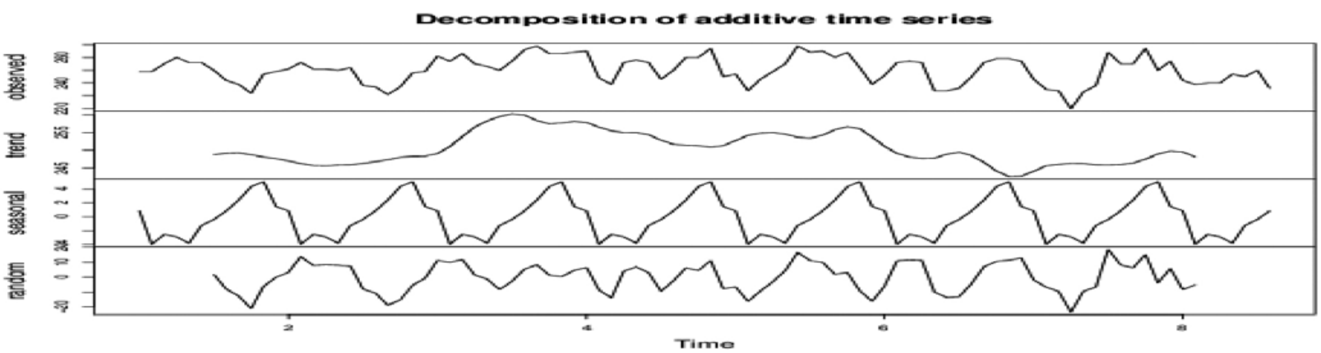

Figure 2. The Autocorrelation function for the monthly total column ozone time series over Kodaikanal, Tamil nadu.

Table 1. Mann Kendall results for monthly total column ozone over Kodaikanal

TCO	Mann Kendall Test				
	Mann Kendall statistics (S)	Var (S)	p- Value (two tailed test)	Alpha(α)	Test interpretation
MONTHLY	0.996	85084.000	< 0.0001	0.05	Reject H_0

Next the Mann Kendall test was run using Addinsoft's XLSAT 2012 software for the whole data series. The results obtained for Mann Kendall trend is tabulated in Table 1. If the p value is less than the significance level α =0.05, H0 is rejected. Rejecting H0 series, while accepting H0 indicates that there is a trend in the time. This in turn indicates that no trend was detected. From Table 1 it is inferred that the p value is less than α (0.05). Thus we reject the null hypothesis H_0 (no trend in the time series) and accept the alternative hypothesis (presence of significant trend in the time series). Thus we have a sufficient evidence to find trend in the total column ozone data in Kodaikanal. Figure 3 shows H is more or less equal to 0.5, thereby indicating that the time series is random. The values of the Hurst exponent and Lyapunov exponent are tabulated in Table 2. Thus, it can be concluded that the value of Lyapunov exponent 1.2942 shows that a low dimensional chaos is present in the Kodaikanal Ozone. Since the chaos is low dimension, it can be said that the time series of the monthly total column ozone concentration over Kodaikanal, Tamil nadu is characterized by the persistent behaviour. This also suggests that total column ozone over Kodaikanal has a trend.

Table 2. Hurst and Lyapunov Exponent Values of monthly total column ozone over Kodaikanal

Kodaikanal	**Hurst Exponent**	**Lyapunov Exponent**
Monthly total Column ozone	0.6455	1.2942

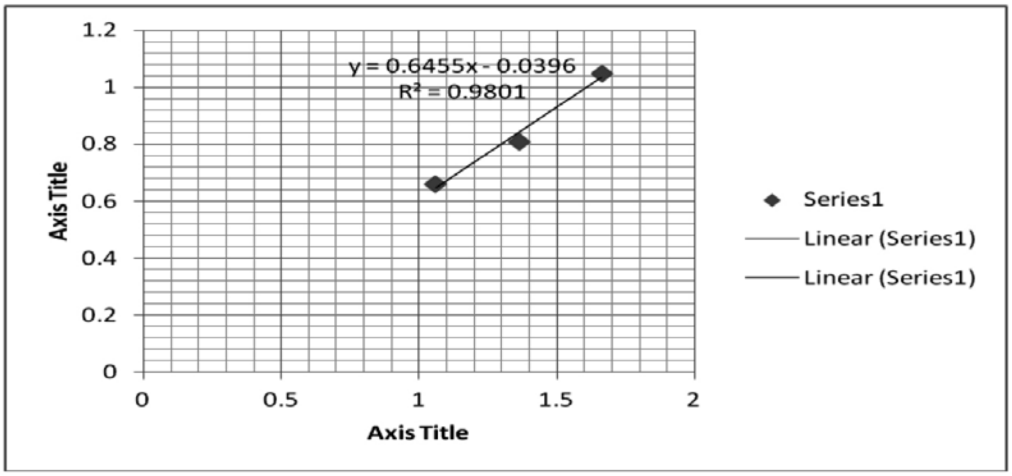

Figure 3. Hurst Exponent (R/S) graph for total column ozone data of Kodaikanal

CONCLUSIONS

Present study carried out three important analyses. These analyses are very essential for the forecasting. Generally trend identifies the behaviour of the times series. If no trend is presented in the time series data forecasting falling under the category of nonlinear model, in which ANN model is suitable, can be considered as suitable. The majority of the work supports that the linear pattern is presented in the time series data, since Lyapunov result shows presence of positive value in the time series data. Thus, nonlinear method of forecasting is applicable for total column ozone over Kodaikanal, Tamil nadu. Since low dimensional chaos is presented in the data, the forecasting is worth trying. Long term memory is also verified by Hurst method. This work brings out the importance of measurements of time series by statistical and chaotic methods. In future, it can be studied how the chaotic behaviour changes with the variability in the temporal scale.

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Compliance with Ethical Standards

The authors declare that they have no conflict of interest and adhere to copyright norms

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