Atmospheric Environment 149 (2017) 47–54

Contents lists available at ScienceDirect

Atmospheric Environment

journal homepage: www.elsevier.com/locate/atmosenv

# Multifractal analysis of interactive patterns between meteorological factors and pollutants in urban and rural areas

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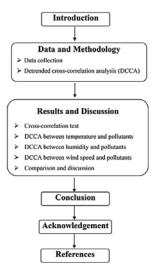
## HIGHLIGHTS

- Verify the existence of multifractal property between meteorological factors and pollutants.
- Reveal the difference of multifractal property between urban and rural areas.
- Clarify the influence of meteorological factors on cross-correlation behavior.
- Compare the difference of multifractal property for varied pollutants.

## GRAPHICAL ABSTRACT




## ARTICLE INFO

*Article history:*
Received 22 July 2016
Received in revised form
28 October 2016
Accepted 3 November 2016
Available online 12 November 2016

*Keywords:*
Cross-correlation behavior
Multifractality
Meteorological factors
Pollutants

## ABSTRACT

This paper seeks to enhance understanding of the cross-correlation patterns between meteorological factors and pollutants. The observed databases of daily meteorological elements (temperature, humidity and wind speed), as well as pollutants (CO, NOx, $PM_{10}$ and $SO_2$) levels during 2005–2014, is collected. Based on the database, the cross-correlation test is carried out firstly and the results indicate that cross-correlation behaviors exist statistically between them. Then the detrended cross-correlation analysis is performed for further analysis. With a detailed comparison, long-term cross-correlation behaviors are found to be more obvious in rural area. Beside, the influences of meteorological factors on multifractal property for pollutants are investigated. In contrast to humidity and wind speed, the long-term cross-correlation behaviors between temperature with pollutants are found to be more evident in both urban and rural areas. Furthermore, the difference of multifractal property for varied pollutants is explored. The strengths of multifractal spectra between meteorological factors with $PM_{10}$ are strongest while the corresponding values between meteorological factors with $SO_2$ are weakest. These findings successfully illustrate that the multifractal analysis is a useful tool for uncovering the interactive pattern in environmental issues.

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## 1. Introduction

Air pollution in Hong Kong is a complex issue and has attached much attention in recent years (Wong et al., 2001; Shi, 2014; Ai et al., 2016). In addition to the various anthropogenic emissions, meteorological condition has also been verified to appear a close relationship with pollution level (Tian et al., 2014; Trivedi et al., 2014; Zhang et al., 2015; Tang and Yu, 2016). Generally, the wind speed dominates the amount of pollutants dispersion while the temperature contributes transformation of pollutants. The relative humidity determines the deposition of pollutants and affects their life cycle in air. Meteorological factors play an important role in the pollutants dilution, diffusion, transportation and transformation

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http://dx.doi.org/10.1016/j.atmosenv.2016.11.004
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(Trivedi et al., 2014; Tiwari et al., 2016). Consequently, it is necessary to have a complete understanding of the relationships between meteorological factors and pollutants.

The relationship between meteorological factors and pollutants has been studied through statistical analysis methods such as regression analysis (Shi and Harrison, 1997; Wehner and Wiedensohler, 2003; Tang et al., 2015), cluster analysis (Oanh et al., 2005) and principal component analysis (Abdul-Wahab et al., 2005). However, statistics analysis is occasionally not in a position to fully characterize processes driven by certain physical and chemical laws but with a high degree of temporal variability. In addition, statistical results of the time series are based only on a single scale analysis (i.e., the observation time) and might not necessarily reflect the features of the time series over other scales. Fortunately, the application of the fractal theory provides alternative option to overcome such shortcomings (Varotsos et al., 2005; Podobnik et al., 2009; Jiang and Zhou, 2011). The fractal approach can divide the whole data into smaller self-similar fragment and discover the physical process of the data with a unique scaling behavior, which is associated with a power-law scheme. To date, there appear several fractal methods for revealing the fractal characteristics (Podobnik et al., 2009; Jiang and Zhou, 2011; Vassole and Zebende, 2012; Lu et al., 2014). Among them, the multifractal approach of detrended cross-correlation analysis (DCCA) is a proper tool to obtain a detailed description of the relationship between two time series (Podobnik et al., 2009; Jimenez-Hornero et al., 2010; Pavon-Dominguez et al., 2013; Shen et al., 2015; Xue et al., 2015).

The DCCA approach was put forward by Podobnik et al. in 2009 (Podobnik et al., 2009). This method is based on fractal theory for two non-stationary time series. It can effectively avoid the phenomenon of spurious correlation sequence due to the non-stationary nature between the two groups, and achieve quantitative analysis of non-stationary time series correlation and fractal characteristics in the most scientific and effective way. By detrending local trends, DCCA can ensure that the results are not affected by trend including linear, quadratic, and even higher order trends and periodic trends (Yuval and Broday, 2010; Kristoufek 2011). DCCA can provide information on whether one time series has long-term cross-correlation with another simultaneously recorded time series (Liu et al., 2014; Meraz et al., 2015; Gao et al., 2016).

In this paper, DCCA was adopted to explore the interactive relationships between meteorological variables and pollutants. In urban area, due to abundant of vehicle emissions, the influences of meteorological factors on pollutants variations present distinct behavior with that in rural area. Hence, in this research, the multifractal properties and interactive relationships between meteorological variables and pollutants in urban and rural areas are investigated respectively. The goals of this work are: (1) to verify whether the time series of meteorological variables and pollutants concentrations exhibit multifractal nature, (2) to reveal the difference of multifractal property between urban and rural areas, (3) to clarify the influence of meteorological factors on multifractal property, and (4) to compare the difference of multifractal property for varied pollutants.

## 2. Data and methodology

### 2.1. Data collection

Hong Kong is located on the southeast coast of China and faced to the South China Sea. The region is hilly and surrounded on three sides by sea. Due to its tropical location, Hong Kong has a subtropical ocean climate. Summer is hot and humid with high solar radiation, while winter is mild and usually starts sunny, becoming cloudier towards February. The meteorological characteristics of Hong Kong linked to the relevant industry, increasing population, and road traffic make its surroundings an area of special protection against air pollution.

In this study, the air pollution data of daily CO, NOx, $PM_{10}$ and $SO_2$, from 1 Jan 2005 to 31 Dec 2014, are collected from Hong Kong Environmental Protection Department. The meteorological factors of daily temperature, wind speed, humidity, and pressure are obtained from Hong Kong Observatory. For deeply exploring the influence of the meteorological factors on pollutants in varied areas, the raw pollution data in urban area (Causeway Bay) and rural area (Yuen Long) are collected in this study (Fig. 1). Since the meteorological factors were given out in term of daily values, the pollution data within the whole day were selected and averaged for a better comparison.

### 2.2. Detrended cross-correlation analysis (DCCA)

Let us assume that there are two time series x ($i$) and y ($i$) where i = 1,2, …, N. Where $N$ is the length of the time. The DCCA procedure is explained through the following steps (Podobnik et al., 2009; He et al., 2016).

Step 1: Determine new time series X ($i$) and Y ($i$) by the original time series x ($i$) and y ($i$).

$$\mathrm{X}(i) = \sum_{k=1}^{i} [x(k) - \overline{x}],\ i = 1, 2, \ldots N \tag{1}$$

$$\mathrm{Y}(i) = \sum_{k=1}^{i} [y(k) - \overline{y}],\ i = 1, 2, \ldots N \tag{2}$$

where $\overline{x}$ and $\overline{y}$ denote the mean values of x ($i$) and y ($i$) respectively.

Step 2: Divide the profile time series of X ($i$) and Y ($i$) into $N_s = [N/s]$ non-overlapping windows of equal length $s$. Since the length $N$ is not always a multiple of the considered time scale $s$, hence in order not to discard the section of series, the same procedure is repeated starting from the reverse end of each profile. Thus, $2N_s$ non-overlapping windows are obtained together.

Step 3: Obtain the detrended covariance for each segment v = 1,2,3, …, $N_s$


**Fig. 1.** Location of Yuan Long air quality monitoring station.

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